

sensors

Special Issue Reprint

Advanced Sensors for Real-Time Monitoring Applications II

Edited by
Olga Korostynska and Alex Mason

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Advanced Sensors for Real-Time Monitoring Applications ||

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Guest Editors

Olga Korostynska

Alex Mason



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Guest Editors

Olga Korostynska
Faculty of Technology, Art
and Design
Oslo Metropolitan
University (OsloMet)
Oslo
Norway

Alex Mason
Faculty of Science
and Technology
Norwegian University of Life
Sciences (NMBU)
Ås
Norway

Editorial Office

MDPI AG
Grosspeteranlage 5
4052 Basel, Switzerland

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About the Editors

Olga Korostynska

Olga Korostynska is a Professor in Biomedical Engineering at Oslo Metropolitan University (OsloMet), Oslo, Norway, a member of the ADEPT research group, and a coordinator of the Master's in Electronics and Biomedical Systems specialization. In addition to OsloMet, she has research and lecturing experience from the Norwegian University of Life Sciences, Liverpool John Moores University in the UK, Dublin Institute of Technology, and the University of Limerick in Ireland. She was involved in research projects funded by the Marie Curie EU Fellowship, IRCSET, Enterprise Ireland, EU FP7 and Horizon Europe, Cancer Research UK, Daiwa foundation and the Norwegian Research Council. Her research interests include sensors for biomedical engineering, electromagnetic wave sensors and their applications, including for real-time water quality monitoring and smart tools. Prof. Korostynska has co-authored 2 books, 15 book chapters, 5 UK patents, and over 300 scientific papers in peer-reviewed journals and conference proceedings.

Alex Mason

Alex Mason is a Professor in Sensors, Robotics, and Automation at the Norwegian University of Life Sciences and the Director of Emnisense AS, also in Norway. He has professional interests in sensor development, particularly microwave-based, in addition to robotics and general automation. He participates in R&D projects related to these topics and has led national-level projects in the UK and Norway, as well as at the international level via European Horizon and Life programs. Over a career spanning 15 years, he has approximately 280 research-related publications, in addition to being an inventor in 10 granted patents.

Preface

This reprint contains a collection of 15 research papers published in the Sensors Special Issue entitled “Advanced Sensors for Real-Time Monitoring Application II”, which is the second reprint in this series, guest-edited by Prof. Olga Korostynska and Prof. Alex Mason. This reprint serves as an academic forum to document the development, optimization, practical validation, and new applications of sensors in a range of key areas, such as environmental monitoring, cognitive mechatronics and robotics, sustainable agriculture and animal health, and signal processing. It is of interest to students and researchers in many engineering areas, as sensors are an integral part of almost all technological solutions today.

Olga Korostynska and Alex Mason

Guest Editors

Advanced Sensors for Real-Time Monitoring Applications ||

Olga Korostynska ^{1,*} and Alex Mason ²

¹ Department of Mechanical, Electronic and Chemical Engineering (MEK), Faculty of Technology, Art and Design (TKD), Oslo Metropolitan University (OsloMet), 0166 Oslo, Norway

² Faculty of Science and Technology (REALTEK), Norwegian University of Life Sciences (NMBU), 1432 Ås, Norway; alex.mason@nmbu.no

* Correspondence: olga.korostynska@oslomet.no

Abstract

In the world of electronics, sensors are more than just components—they are the eyes, ears, and touchpoints of modern technology. From self-driving cars that rely on LiDAR and ultrasonic sensors to navigate complex environments, smart watches that detect your every move and heartbeat, to advanced brain chip implants that can sense your thoughts and translate them into physical moves with the assistance of exoskeletons, sensors bridge the gap between the physical world and digital systems. The rapid arrival of advanced Artificial Intelligence (AI) and Large Language Models (LLMs) has transformed almost every part of technology, especially data processing. However, the development of sensors remains a vitally important topic. Sensors form the foundation of innovation in electronics; novel sensors provide reliable data across a broad range of application areas and are a foundation for intelligent systems. Notably, knowing the capabilities and limitations of each sensor type is crucial for selecting the right sensor for a specific application, troubleshooting issues, and optimizing system performance. This book, entitled “Advanced Sensors for Real-Time Monitoring Applications II”, demonstrates developments of real sensors for a range of applications, including descriptions of fundamental principles of operation, concepts, theory, and practical validation of the results, as well as a review of current state-of-the-art and future directions.

Keywords: healthcare; biopotential; heart rate; PPG; residual cancer burden; motion capture; photoacoustic spectroscopy; intelligent transportation systems; biodegradable implants; remote monitoring

1. Introduction

The human body is a remarkable example of how sensory schemes seamlessly integrate sensory information with biomechanical and physiological processes to enable effective functioning [1]. Sensors enable us to perceive the world, interact meaningfully, and make informed decisions based on our experiences [2]. Thus, sensory information is not merely a passive data stream, but a dynamic and multifaceted landscape that holds invaluable clues about our health and well-being [3]. Sensory schemes can also be harnessed to personalize rehabilitation therapies [4,5], optimize athletic performance [6], and enhance human–computer interactions. Sensor research is paving the way for a future where personalized healthcare is not a distant dream but a tangible reality, empowered by sensors and electronics [7].

Healthcare and related applications take the central place in this book, with a comprehensive review on biopotential signal monitoring systems in a rehabilitation setting,

setting the tone in Contribution 1. It is followed by articles focusing on heart rate estimation (Contribution 2), residual cancer burden (Contribution 3), cognitive load with heart rate variability monitoring (Contribution 4), remote responders bio-signal monitoring (Contribution 5), biodegradable implants status (Contribution 6); plantar pressure monitoring (Contribution 7), assembly posture recognition (Contribution 8) and activity monitoring (Contributions 9 and 10).

Another set of articles reports on advanced sensors for real-time monitoring applications of gas sensing (Contributions 11 and 12), intelligent transportation systems (Contribution 13), water velocity (Contribution 14), and temperature monitoring (Contribution 15). A more detailed overview of each contribution is given in the next section.

2. Overview of Contributions

A timely review of biopotential signal monitoring systems in rehabilitation is offered in Contribution 1. This paper provides a state-of-the-art review of the recent advances in electroencephalogram (EEG), electrocardiogram (ECG), and electromyogram (EMG) signal monitoring systems and sensors, both commercial and research, that are relevant to the field of tele-rehabilitation and health monitoring. Future advancements in sensor technology must focus on developing low-cost, miniaturized, comfortable, and clinically relevant wearable devices designed for real-life conditions to bridge this gap and support widespread home-based and remote healthcare applications.

Precision heart rate estimation using a PPG sensor patch was achieved in Contribution 2. With the help of new algorithms of pre-quality checking and Hankel decomposition, motion artifacts due to subjects' hand motions and walking were considerably reduced. The proposed method achieved the best accuracy of 3.78 bpm in mean absolute errors among all previously reported studies for hand-moving scenarios.

Residual cancer burden is a prognostic tool widely used to estimate survival outcomes in breast cancer, and a novel optical sensory system for its assessment is reported in Contribution 3. It is based on machine learning of data acquired from 15 patients undergoing neoadjuvant chemotherapy and has achieved an accuracy of 0.98 in predicting RCB number/class based on the changes in optical properties measured by the Opti-scan probe. These findings suggest that the reported approach has considerable potential as a valuable non-invasive tool for monitoring breast cancer patients' response to NAC and guiding treatment decisions.

Cardiac surgery is one of the most complex and high-risk areas of medicine. Effective team coordination requires the management of interruptions and distractions as well as awareness of the context of the surgical procedure. Cognitive load, a measure of how mentally occupied or stressed a team member is at a particular time, provides a useful metric for understanding how team members' attention and mental load vary through the stages of a surgical procedure. An open-source, interoperable architecture for generating real-time surgical team cognitive alerts from heart-rate variability monitoring was the scope of the work reported in Contribution 4. This novel work demonstrates for the first time the feasibility of acquiring multiple ECG waveforms, applying an interoperable pipeline capable of filtering the ECGs, identifying IBIs, calculating HRV metrics, estimating team cognitive load states, and generating alerts in response. For example, if the ECG is sampled at 100 Hz, each sample covers a 10 ms time period, and then the errors become similar in magnitude to the beat-to-beat variability being measured. This prototype application requires a sample rate of 500 measurements per second or higher to reduce the magnitude of timing measurement errors.

Remote responder bio-signal monitoring in a cooperative human-robot architecture for search and rescue (SAR) in disaster scenarios was investigated in Contribution 5. The

roles of emergency responders are challenging and often physically demanding, so it is essential that their duties are performed safely and effectively. The integration of a set of health monitoring sensors suitable for detecting stress, anxiety, and physical fatigue in an Internet of Cooperative Agents architecture for search and rescue missions was proposed, which allows remote control and communication between human and robotic agents and the mission control center. Proof-of-concept experiments were performed with a bio-signal sensor suit worn by firefighters in two high-fidelity SAR exercises. ECG, EDA, PZT, and EEG data, a key combination of bio-signals for physical fatigue, anxiety, and stress detection, were monitored. The proposed designs were assessed by a Fire Brigade Consortium in two workshops in a 90,000 m² area plot, divided into several zones. Notably, the gain of EEG sensors (41,782) was much higher than the gains of the other sensors (e.g., 1100 for ECG, and 1 for PZT), so EEG is more sensitive to electromagnetic noise and may not be reliable in some environments.

Biodegradable materials such as magnesium (Mg) and its alloys have increasingly been used in orthopedic surgery for bone fixation. The use of near-infrared spectroscopy for the in vivo monitoring of such biodegradable implants is reported in Contribution 6. It is a non-destructive, non-invasive technique used to monitor tissue oxygenation in various clinical settings. NIR light is estimated to reach a 3–3.5 mm depth, and the diffuse light is detected by the optical fiber inside the probe. The purpose of this study was to investigate the effects on hemoglobin changes and tissue oxygen saturation (StO₂) after the implantation of Mg-alloy (WE43) and titanium (Ti) implants using a multiwavelength optical probe. Interestingly, the StO₂ values of days 0 and 45 for the Mg-implanted animals were similar, but StO₂ mainly changed postoperatively from day 0 to day 3, possibly due to bubble gas formation, a well-known side effect associated with the initial fast degradation of Mg implants. It was shown that applying the modified Beer–Lambert law (MBLL) to particular measurement conditions related to the effect of Mg degradation within tissues can enhance the reliability of data on the target tissue’s physiological state and biochemical content.

The study of human walking, namely gait analysis, can be used as a valuable diagnostic tool to distinguish between normal and pathological gait. A novel 3D-printed capacitive smart insole for plantar pressure monitoring was presented in Contribution 7. The sensor exhibited a sensitivity of 1.19 MPa^{−1}, a wide working pressure range (<872.4 kPa), excellent stability and durability (at least 2.280 cycles), great linearity ($R^2 = 0.993$), fast response/recovery time (142–160 ms), low hysteresis ($DH < 10\%$) and the ability to support a broad spectrum of gait speeds (30–70 steps/min). Authors state that depending on the 3D printing systems, one can have a pair of smart insoles ready within a day, which makes them perfect for personalized applications.

A novel, cost-effective method for recognizing assembly postures in Industry 4.0 settings using Inertial Measurement Units (IMUs) is presented in Contribution 8. It proposes a low-cost human motion collection system, combining BMI160 IMU modules with ESP8266 WiFi for real-time data transmission. This data is then used to calculate human posture by mapping IMU trackers to a digital human skeleton in Unity, enabling synchronized 3D visualization, with a reported average accuracy of 98.24%. The study validates this approach through experiments simulating assembly tasks in a virtual reality environment, collecting motion data from six key joints.

Activity monitoring based on the structural vibration of ambient objects was the focus of the research reported in Contribution 9. Here, a vibration sensing device using a six-axis IMU and an optimized beam structure achieved a 6.2-times-higher vibration amplitude and an increase in signal energy of 480% when compared to a directly mounted IMU

without a beam. The sensor fusion algorithm provided a noise reduction of 5.6% by fusing accelerometer and gyroscope data at 103 Hz.

Another physical activity monitoring paper by the same authors also focused on the non-contact method using a multi-axial IMU in animal husbandry, Contribution 10. The activity was classified as resting, stationary activity, and locomotion with over 90% accuracy.

Detection of SO_2F_2 using a photoacoustic two-chamber approach was the focus of the study reported in Contribution 11. SO_2F_2 is highly toxic to humans and the environment, but is widely used for termite control in buildings, warehouses, and shipping containers. Thus, reliable real-time detection is necessary, and the novel system for that was developed based on the photoacoustic detection method. The results show that concentrations below 1 ppm SO_2F_2 can be reliably detected.

Drone-mountable gas sensing platform using graphene chemiresistors for remote in-field monitoring was the focus of the research reported in Contribution 12. An array of graphene-based field-effect transistors in combination with commercial humidity and temperature sensors is used to relay data on the presence of airborne chemicals over distances of 1 km by wireless communication. A system on a drone was controlled by a mobile application for real-time data transmission, compatible with Internet of Things (IoT) applications. The information collected by all sensors comprised in the platform was registered every 210 ms (at a rate of 4.8 Hz). However, the device performs a moving average to reduce noise, yielding a time resolution of ~ 1 s and matching the time resolution of the BME280 sensor.

The increasing attacks on traffic signals worldwide indicate the importance of intrusion detection, and this issue was researched in Contribution 13, where an intelligent transportation system was proposed with a technique to detect such intrusions. Specifically, it is based on the real-time observation of traffic parameters, namely, traffic flow, average vehicle speed, phase time of the signal, and their historical values for Melbourne Central Business District, combined with an approach based on Shannon's entropy to incorporate the uncertainty of observed data. An overall accuracy of 79.3% for intruded traffic conditions was demonstrated.

Monitoring flow velocity in storm and wastewater systems is crucial for environmental applications, including pollution load estimation and normalization of pathogen concentrations in wastewater. The work in Contribution 14 presents a low-cost, low-power water velocity sensor utilizing acoustic Doppler measurement. This sensor is significantly cheaper than the typical commercial alternatives and is very energy-efficient: 2 mW for 10 measurements an hour. Its compact size also supports the deployment of the sensor for real-time monitoring in large quantities.

A fiber optic sensing system consisting of a fiber Bragg grating (FBG) sensor, optical circulator, optical band pass filter, and photodetector was developed to monitor the real-time temperature response of a structure under a dynamic thermal loading in Contribution 15. This system showed a fast response during $40\text{ }^\circ\text{C}/\text{min}$ thermal loading and is suitable for online structural health monitoring.

3. Conclusions

Despite the unprecedented rise in AI data processing algorithms in the last year, real-time sensors remain the indispensable source of information for countless applications, forming the bedrock upon which intelligent systems are built. This book details developments in healthcare, activity and posture monitoring, gas detection, environmental, traffic, and infrastructure monitoring, and search and rescue operations. Advanced sensors for

real-time monitoring applications will continue to play a pivotal role in the future, enabling smarter decision-making, enhanced safety, and greater efficiency across all areas.

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List of Contributions:

1. Palumbo, A.; Vizza, P.; Calabrese, B.; Ielpo, N. Biopotential Signal Monitoring Systems in Rehabilitation: A Review. *Sensors* **2021**, *21*, 7172.
2. Thakur, S.; Chao, P.C.-P.; Tsai, C.-H. Precision Heart Rate Estimation Using a PPG Sensor Patch Equipped with New Algorithms of Pre-Quality Checking and Hankel Decomposition. *Sensors* **2023**, *23*, 6180.
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Review

Biopotential Signal Monitoring Systems in Rehabilitation: A Review

Arrigo Palumbo ¹, Patrizia Vizza ^{2,3,*}, Barbara Calabrese ¹ and Nicola Ielpo ¹

¹ Department of Medical and Surgical Sciences, Magna Græcia University, 88100 Catanzaro, Italy; a.palumbo@dimes.unical.it (A.P.); calabreseb@unicz.it (B.C.); nicola.ielpo@unical.it (N.I.)

² Mater Domini University Hospital, 88100 Catanzaro, Italy

³ Interdepartmental Center of Services (CIS), Magna Græcia University, 88100 Catanzaro, Italy

* Correspondence: vizzap@unicz.it

Abstract: Monitoring physical activity in medical and clinical rehabilitation, in sports environments or as a wellness indicator is helpful to measure, analyze and evaluate physiological parameters involving the correct subject's movements. Thanks to integrated circuit (IC) technologies, wearable sensors and portable devices have expanded rapidly in monitoring physical activities in sports and tele-rehabilitation. Therefore, sensors and signal acquisition devices became essential in the tele-rehabilitation path to obtain accurate and reliable information by analyzing the acquired physiological signals. In this context, this paper provides a state-of-the-art review of the recent advances in electroencephalogram (EEG), electrocardiogram (ECG) and electromyogram (EMG) signal monitoring systems and sensors that are relevant to the field of tele-rehabilitation and health monitoring. Mostly, we focused our contribution in EMG signals to highlight its importance in rehabilitation context applications. This review focuses on analyzing the implementation of sensors and biomedical applications both in literature than in commerce. Moreover, a final review discussion about the analyzed solutions is also reported at the end of this paper to highlight the advantages of physiological monitoring systems in rehabilitation and individuate future advancements in this direction. The main contributions of this paper are (i) the presentation of interesting works in the biomedical area, mainly focusing on sensors and systems for physical rehabilitation and health monitoring between 2016 and up-to-date, and (ii) the indication of the main types of commercial sensors currently being used for biomedical applications.

Keywords: biomedical signal; monitoring system; rehabilitation; signal processing

1. Introduction

Biomedical wearable sensors allow the measurement of physiologic parameters in a continuous, real-time and non-invasive way, including a wide range of advances in electrocardiogram (ECG), electromyogram (EMG) and electroencephalogram (EEG)-based sensing platforms [1–3]. These platforms and their related sensors have different diagnostic and monitoring applications [4,5]. For example, physiological monitoring could support both diagnosis and ongoing treatment for many diseases involving movement disorders [6]. Furthermore, home-based motion sensing could assist the subject in rehabilitation path and falls prevention, helping him/her improve his/her independence and lifestyle [7]. Moreover, sensors acquire and analyze biomedical signals to monitoring the effectiveness of home-based rehabilitation therapies, for example, in stroke survivors, in patients undergoing surgery, in subjects involved in accidents or to evaluating the use of mobility assistive devices in older adults [8–10]. Moreover, the monitoring of physiological signals and parameters could also be a good support in many clinical and non-clinical applications, e.g., in sporting activities to evaluate performance and physical condition of athletes [1,11], in postural control to correct stability, or in a physiotherapy context after injury [12,13]. Generally, the measurement of physical activity parameters

aids in guiding many types of applications; e.g., (i) monitoring physical activity during rehabilitation or in a physical therapy setting; (ii) evaluating the success of an intervention and tracking physical activity post-surgery; (iii) evaluating patient mobility; (iv) all (risk) detection; and (v) monitoring physical activity in patients with chronic diseases and disabilities involving movement disorders. Most recently, the coronavirus disease 2019 (COVID-19) pandemic has affected access to standard rehabilitation services, highlighting the need to define new rehabilitation perspectives as telemedicine [14,15]. During this period, the rehabilitation concept considerably changed: the need for home medical assistance for a new idea of rehabilitation phase in older people both with and without COVID-19, in patients affected by neuro-motor disease, in subjects with limited movements after injury or accident and athletes is becoming essential to help these people in maintaining their daily activities. In this context, tele-rehabilitation became an effective and well-accepted method of providing outpatient and community rehabilitation services to support family and caregivers in the assessment of the home environment, patient monitoring and outpatient therapies [16–18]. In emergencies such as the COVID 19 pandemic, access to health services is restricted due to the risk of infections and limitations of health resources [14,19]. For this reason, telemedicine services have proved extremely useful by providing home monitoring and rehabilitation solutions and thus minimizing the risk of infection. Survivors of COVID-19-associated pneumonia may experience a long-term reduction in functional capacity and muscle strength. Telerehabilitation (TR) programs could be effective for patients after COVID-19 [14]. However, few studies have assessed whether telerehabilitation for COVID-19 patients is an effective tool. In [20,21], telerehabilitation programs consist of home exercises for aerobic reconditioning, muscle strengthening, and healthy lifestyle education. The physiotherapist (PT) contacts the patient via video call via a dedicated platform to monitor progress. Moreover, physicians can add chest physiotherapy exercises for lung expansion and strengthening of the respiratory muscles. In these programs, a pulse oximeter as a monitoring device is also used.

Many healthcare devices for rehabilitation provide biosignals, such as blood pressure, blood glucose levels, EEGs, ECGs and EMGs [22]. The main bioelectrical signals are generated by the heart, the brain and the muscles, producing ECGs, EEGs and EMGs, respectively. ECG, EEG and EMG signals are characterized by low amplitude (generally, expressed in mV—millivolts) and low operating frequencies, from frequency Hz to some kHz range [23]. The acquisition, analysis and interpretation of these signals are fully reported in the literature [24–31]. Physical activity is often associated with the cardiovascular and muscular systems. Therefore, electrical signal variations cause ECG and EMG during athletic activities, and they are essential and commonly adopted parameters for healthcare management and rehabilitation protocols. In particular, EMG signal is the typical clinical recording method used to diagnose and monitor neuromuscular behaviours. Surface EMG (sEMG) allows extraction of information on muscle activation during a movement or effort, identifying impairment and functional alteration useful in clinical evaluation [32,33]. This information can be presented in different forms (e.g., amplitude, timing, morphology, muscle fibre conduction velocity or muscle coordination). They are relevant in many fields, from orthopaedics and neurorehabilitation to movement analysis in exercise and sport or aging [34,35]. This review aims to focus on EMG signal acquisition devices, also combined with other biosignals ECG and EEG, in rehabilitation pathways, especially for telemedicine applications. This contribution is proposed as a review by addressing questions such as (i) what are the most recent contributions in literature? (ii) what are the commonly used medical devices? (iii) how do these contributions and medical devices support physiological monitoring in rehabilitation? and (iv) what are the future directions and opportunities for EMG signal acquisition and analysis in a rehabilitation context? Many reviews are presented in the literature regarding biosignal acquisition devices for rehabilitation applications, but to the best of our knowledge, EMG signal has been considered only in specific context for single review. This review is thus

a general but detailed comprehensive overview of EMG monitoring systems aiming to resume and to discuss the different and important solutions of EMG applications in different rehabilitation contexts. The key contributions of this review are outlined as follows. Section 2 presents a summary of basic concepts such as bioelectrical signals and medical devices aiming to identify their main features and characteristics. These concepts are required background knowledge to this review. Section 3 reports the research methodology applied to define this review. Section 4 proposes an intense state-of-the-art about the last 5 years' contributions in wearable sensors and platforms to summarize recent developments in the field of wearable sensors and systems used for rehabilitation. In Section 5, most commercial biomedical signal acquisition and processing sensors and devices have been reported comparing physical and performance characteristics. Section 6 has also been formulated to summarize and discuss the literature on EMG signal acquisition devices in rehabilitation and to explore their challenges and their future direction. Finally, Section 7 provides conclusions of the article.

2. Background

This section summarizes fundamental concepts needed to consider this review.

2.1. EMG and Rehabilitation

In the last decade, the new advanced devices and the increasing of computer science technologies have improved telemedicine applications [36]. A most important application regards telerehabilitation, which is still a new field in rapid growth. The advantage of telerehabilitation consists in the reduction of the costs both for health care providers and patients compared with traditional inpatient or person-to-person rehabilitation. Furthermore, telerehabilitation helps patients who live in remote places, allowing them to benefit from this technology. The primary application of telerehabilitation is regarding physiotherapy [37], and it is often associated with telemonitoring, referred to as the remote monitoring of physiological parameters, including ECG, blood pressure and oxygen saturation in patients with chronic diseases [38]. Physiotherapy applied to telerehabilitation is a valid approach both for musculoskeletal disorders and some physical diseases. Moreover, it contributes to improve patients' posture and movement, supporting caregivers in creating a customized physical exercise program for physical rehabilitation [39–41]. In the rehabilitation field, the evaluation and the monitoring of the muscular conditions are needed to define a pathway aiming to develop and make stronger the correct voluntary muscle movements. The EMG signal is able to detect voluntary muscle activation giving information to encourage the correct patterns of activity. This EMG signal together with a robust, reliable and user-friendly acquisition and analysis system could be a strong support in rehabilitation cases to be used in assistive technology for helping people with severe disabilities [42]. The information about muscle activation can be expressed in different way, e.g., as amplitude, timing, morphology or spectral features, and it could be very useful and relevant in many fields ranging from orthopedics and neurorehabilitation to movement analysis in exercise and sport, from aging to obstetrics up to occupational and space medicine [33]. In the following sections, we report the potential clinical applications based on sEMG sensors in rehabilitation medicine with specific focus on (i) neurorehabilitation, (ii) stroke rehabilitation and (iii) sporting rehabilitation.

2.1.1. EMG in Neurorehabilitation

Neurological rehabilitation medicine and its clinical research demonstrate that the damaged limb motor function can be restored to some extent through an efficient rehabilitation process. During this process, physicians must acquire and monitor the physical condition and physiological parameters to evaluate the training effect and, eventually, correct the follow-up rehabilitation training program. Information on muscle activation supports the physician in the clinical evaluation furnishing a reference for impairment and functional alterations. The ability of EMG signal in the measurement of this muscle

activation makes this electrodiagnostic medicine technique very useful and relevant in neurorehabilitation, especially in the last four decades [43,44]. The application of sEMG techniques in neurorehabilitation is proposed in [34]. First, the authors report a review about the applications of EMG in neurological rehabilitation as support for the assessment and treatment of muscle spasticity and overactivity due to EMG's ability to quantify alterations associated with these disorders. Moreover, the authors discuss their limited clinical applications. Another survey concerning the use of surface electromyography in neurorehabilitation is addressed by Manca et al. [45]. The authors collect information on (i) the current use of sEMG and its clinical potential, (ii) the professional figures primarily dealing with sEMG, (iii) the educational aspects and lastly, (iv) the possible reasons for its limited use in neurorehabilitation field. This survey research proposes and discusses different aspects of sEMG in neurorehabilitation ranging from current trends in its use; educational, technical and methodological features; and the translational outreach and potential utility of this technique for clinicians and patients.

The applications of surface EMG signals in neurorehabilitation regard: (i) the monitoring of neuromuscular pathologies, (ii) the prevention of work-related disorders and occupational therapy and (iii) the monitoring of neuromuscular changes and progress in severe patients. Information concerning the muscle activation during a movement or effort help physicians to evaluate and provide a clinical overview of both impairment and functional alteration. Another current common development of device in neurorehabilitation is represented by the acquisition of both EMG and EEG signals through biosignal amplifiers aiming to use physiological data to enhance their functionality in Brain Computer Interface (BCI) application. For example, the patient's upcoming movements could be predicted by using electroencephalography (EEG) or electromyography (EMG). Always in BCI applications, EEG and EMG can be combined to either predict as many movements as possible or to enhance the reliability of movement prediction [46].

2.1.2. EMG in Stroke Rehabilitation

Stroke represents one of the major causes of chronic motor disability among adults worldwide [47]. In addition, many stroke survivors suffer from hemiplegia, which makes walking difficult or even impossible. Therefore, rehabilitation represents an important treatment for the post-stroke patient to recover their muscle strength and motor coordination as well as to retrieve their nervous system [48]. Motor training and rehabilitation aim to be effective in enhancing muscle activity and improving neuromuscular control [49]. In this context, EMG-based methods could be a valid support in the detection of residual EMG activity and consequently in the control of exoskeletons in patients unable to generate sufficient joint torque, training them during the post-stroke period [50–52]. Electromyography, together with a controlled Neuromuscular Electrical Stimulation (NMES), generate the most benefits on motor recovery of upper limb function in clinical trials for patients with stroke [53]. In this direction, Monte-Silva et al. [54] propose a systematic review and meta-analysis concerning the effects of EMG-NMES on stroke upper limb recovery. Another significant contribution is furnished by Hameed et al. [55]. The authors discuss robotic devices as valuable tools to help patients with hand deficits in daily activities and restore hand functions by rehabilitation. Specifically, they highlight the potential of using sEMG in controlling hand robotic devices, including gloves and exoskeletons, for rehabilitation and assistance in daily activities. Furthermore, the authors in [56] investigate the possible use of EMG to detect hand/wrist extension movement intention to trigger robot-assisted training in individuals without residual movements. Specifically, they compared movement intention detection using an EMG detector with a sensorimotor rhythm-based EEG-BCI (Brain–Computer Interface) using only ipsilesional activity. The results show that EMG-based assisted therapy should be a valid and practical way to trigger robot-assisted training, furnishing also an easier interface and more compact dimensions than EEG-BCI devices.

2.1.3. EMG in Sports Rehabilitation

Surface EMG can evaluate the status of skeletal muscles, assisting in muscular training and rehabilitation. Surface EMG is becoming a popular research tool in sport and rehabilitation sciences. In athletes' rehabilitation, EMG is useful to analyze muscle dysfunction, to detect not-correct muscle activation patterns and to assist in establishing and assessing treatment outcomes [57–59]. The correct utilization of muscles and the rapid identification of anomalous muscle pattern activation help the athletes to improve their activities and to prevent the risk of injury [60]. The dynamic analysis of muscles performed by sEMG is particularly interesting in sport, especially in injury prevention. For example, the analysis of the sEMG signal could improve the performance of a task by evaluating the muscular activation and/or muscular fatigue [61]. An important application of EMG in sporting rehabilitation regards the fatigue analysis in triceps brachii. Hussain et al. [62] report an interesting review summarizing and analyzing the research findings regarding analysis of fatigue in the human triceps brachii (TB) muscle through surface electromyography (sEMG) observations. Other applications are in postoperative rehabilitation following rotator cuff repair, as reported in [63], or in monitoring different responses of skeletal muscles subjected to external stimuli such as hypoxia and physical activity [64]. Wearable biosensors are becoming most important in real-time physiological monitoring useful in athletic performance analysis, injury and recovery time assessment, thus supporting athletes, trainers and coaches in characterizing the daily demands of sports [65]. A sports rehabilitation monitoring system based on wearable sensors and Internet of Things technology has been developed in [66]. This system includes sensors to acquire and monitor ECG signals, EMG signals, motion posture, body temperature and other physiological parameters. The experimental results show that the system can closely monitor changes in vital signs while providing real-time monitoring and feedback. Furthermore, the acquired physiological data can be analyzed to support physicians in formulating effective rehabilitation training programs. Another contribution in the wearable system for EMG acquisition and analysis to evaluate athlete performance is proposed in [67]. The authors investigate the validity and reliability of their proposed sEMG system to characterize muscle activation patterns during isokinetic knee extension and flexion.

2.2. EMG Signal Acquisition: General Considerations

The main bioelectrical signals are generated by the heart, the brain and the muscles, producing ECGs, EEGs and EMGs, respectively. The acquisition, analysis and interpretation of these signals are fully reported in literature [24–28]. Electrical signal variations generate EMG signals during muscular activities [68]. Therefore, in physical activity monitoring and the evaluation of muscle conditions, EMG has become an important and commonly adopted parameter for healthcare management and rehabilitation protocols. High-quality recording of EMG signal is performed by well-designed instrumentation, and it is important to guarantee a correct processing and feature extraction [69].

2.2.1. EMG Signal Features

EMG is an electrodiagnostic medicine technique to evaluate and record the muscular electrical signal generated by skeletal muscle activities [70]. The EMG signal measures electrical currents generated in muscles during their contraction, representing neuromuscular activities [71]. Thus, EMG provides excellent information about the health of muscles and the function of motor neurons, which transmit electrical signals to muscle cells allowing their contraction. Generally, EMG signals are characterized by a frequency range from 20 up to 2000 Hz and by amplitude from about 50 μ V to 20 mV [72]. The features analysis of EMG signal could offer body muscle activity information, such as fitness, fatigue and endurance level and gesture, such that the biomechanics of human medical abnormalities or activity levels can be detected and analyzed. The evaluation of muscle activation during a movement or effort provides useful information on impairment

and functional alteration. It is widely used in medical rehabilitation, human–machine interface, biomedical research and other fields. The current applications of EMG mostly regard physiological investigations, monitoring of neurological disorders, planning of treatments, assessment of interventions and control of prostheses and robots [73]. Electromyography can be performed using two electrodes: surface (or skin) electrodes or inserted (or wire and needle) electrodes. Surface electrodes are used to monitor the overall activity of a muscle, while the second type is generally used to reveal the electrical activity of a nerve [12]. EMG signals represent the state of limb muscle activity, reflecting the movement of skeletal muscle and the command information of the nervous system, which are very useful in stroke rehabilitation treatment. The acquisition and the analysis of EMG signals are useful to classify and recognize different limb movements, supporting the identification and the study of limb movements and their characteristics. Specifically, sEMG provides a non-invasive and global measurement of muscle activity, and it may be suitable for applications in movement analysis requiring frequent assessments or information on the patterns of activation of multiple muscles [74]. For example, surface EMG could be a valuable tool in sport, rehabilitation and clinical assessment to quantitatively measure progress and evaluate treatment outcomes.

2.2.2. EMG Instrumentation Characteristics

The EMG signal is a complex and non-stationary physiological signal characterized by a low amplitude and low frequency values. Therefore, its acquisition is not easy to perform due to noise. The noise includes three main components: (i) the noise of the electronic acquisition equipment, (ii) the noise generated by skin-electrode contact and (iii) the noise added by the power frequency interference. Therefore, a well-specified acquisition and analysis system must be designed to improve the quality of EMG signal acquisition and its spatial and temporal resolution. Generally, an EMG acquisition system is composed of: (i) electrode, (ii) preprocessing stage (pre-amplifier and filtering), (iii) processing stage (amplifier), (iv) analog to digital conversion, (v) power supply and (vi) wireless transmission module [75], as shown in Figure 1.

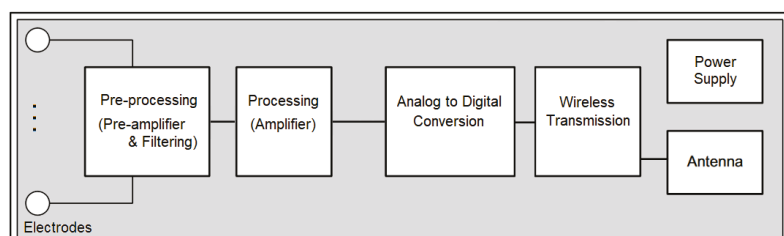


Figure 1. General EMG acquisition system.

Synthetically, the amplifier magnifies the difference in voltage between the inputs, attenuating the unwanted noise, aided by analog filters; then, the amplified signal is measured using an analog-to-digital converter (ADC), and this digitized signal allows further computerized analysis. Moreover, the signal acquisition can be performed into two different modalities: the monopolar acquisition performs the difference between a signal detected on the electrode concerning a remote reference placed in an electrically inactive area; the bipolar acquisition, instead, performs the difference between the signal detected on the electrode concerning another electrically active electrode. Finally, the wireless transmission module aims to connect the system with an external PC for EMG data analysis and processing as well as display, control, storage and query functions. This module is also the key element to achieve a portable performance of rehabilitation training. As reported above, EMG signal is affected by the environment, physiological and equipment noise components, so the acquired EMG signal contains a lot of information, useful and not. Therefore, a pre-processing module is necessary to remove baseline drift and power frequency by using a filtering stage composed of a low-pass filter and a high-

pass filter [70]. The denoising and the removal of baseline wander are useful to reject the useless frequency signals cleaning the EMG signal by unwanted components. Moreover, a 50/60 Hz filtering (known as notch filter) eliminates 50/60 Hz power line frequency and harmonic noise in EMG. In particular, high-pass filters attenuate low-frequency components in the signal, and its low-frequency cutoff must be accurately chosen because it could cause initial amplitude loss of slowly changing signals, waveform distortion, decreasing the latency to the peak of the waveform and introducing artefacts [69]. On the other hand, low-pass filters attenuate high frequencies, and in this case, its high-frequency cutoff must also be opportunely chosen due to its influence in the reduction of the amplitude and rise time. EMG signal in output from the conditioning stage (preprocessing and processing modules) should be sent to an acquisition device for data recording, analysis and/or storage. This system is generally composed of an Analog-to-Digital Converter (ADC) that discretizes the signal in both time and amplitude, assigning a digital value to the amplitude at defined time points. This procedure is needed to further perform signal analysis for both clinical and research diagnostic purposes. Generally, the EMG front-end system should be satisfied well-defined specifications. The main specifications regard [76]:

- Accuracy: this characteristic is related to the implementation of the differential amplifier, ADC and several other components connected to inherent noise; the aim is to optimize each used component to minimize noise, ensuring accuracy;
- Sensitivity: this features on the ADC resolution and consequently the overall resolution of the system; it allows the physicians to understand the limits of their reading;
- CMRR: this is the Common-Mode Rejection Ratio, and it expresses the ability of the differential amplifier to reject common-mode signals; it plays a crucial role in avoiding 50–60 Hz power line interference;
- Input impedance: the optimization of this value is relevant in differential amplifier selections and implementations related to different user skin types and electrode interfaces;
- Input range: this specification regards hardware implementation and ADC, specifying the range of the biosignal that can be picked up without saturating the amplifier. A larger input range is preferred to acquire the entire signal, but this requires an expansion of signal resolution;
- SNR: this is the Signal-to-Noise Ratio, and it is the ratio between the signal's amplitude and the background noise.

3. Research Methodology

This review has been conducted following the Preferred Reporting Items for Systematic Reviews and MetaAnalyses (PRISMA) item [77]. This research aims to investigate and provide a review of existing research on biosignal monitoring systems in the rehabilitation field. Scientific contributions and commercial devices have been chosen based on their contents and applications, closely related to the objective of this paper.

For scientific papers, the chosen databases were PubMed, MDPI, Springer, ACM Digital Library and Science Direct, as reported in Table 1.

Table 1. Databases used for this review.

Database	URL	Date Access
PubMed	https://pubmed.ncbi.nlm.nih.gov/	30 June 2021
MDPI	https://www.mdpi.com/	30 June 2021
Springer	https://link.springer.com/	30 June 2021
ACM Digital Library	https://dl.acm.org/	30 June 2021
Science Direct	https://www.sciencedirect.com/	30 June 2021

The main research questions (RQ) of this study are:

- RQ1: what are the most recent contributions in literature?
- RQ2: what are the commonly used medical devices?
- RQ3: how do these contributions and medical devices support physiological monitoring in rehabilitation?
- RQ4: what are the future directions and opportunities for EMG signal acquisition and analysis in a rehabilitation context?

Based on these research questions, while reviewing the existing research on keywords *Biosignals*, *Acquisition device*, *Wearable device*, *Monitoring*, *Rehabilitation* and *Telemedicine*, a total of 856 were identified as interesting for the topic of this review from 2004 to the present. From these resulting articles, 743 were removed because they did not fully satisfy the requirements of this review. Starting from these 113 remain papers, 15 contributions were also excluded because they did not report explicit considerations about EMG signals. Finally, from 98 studies, 20 contributions about wearable monitoring systems were chosen among papers published in the literature in the last 5 years to be analyzed in depth. A flow diagram illustrating our review methodology process is shown in Figure 2.

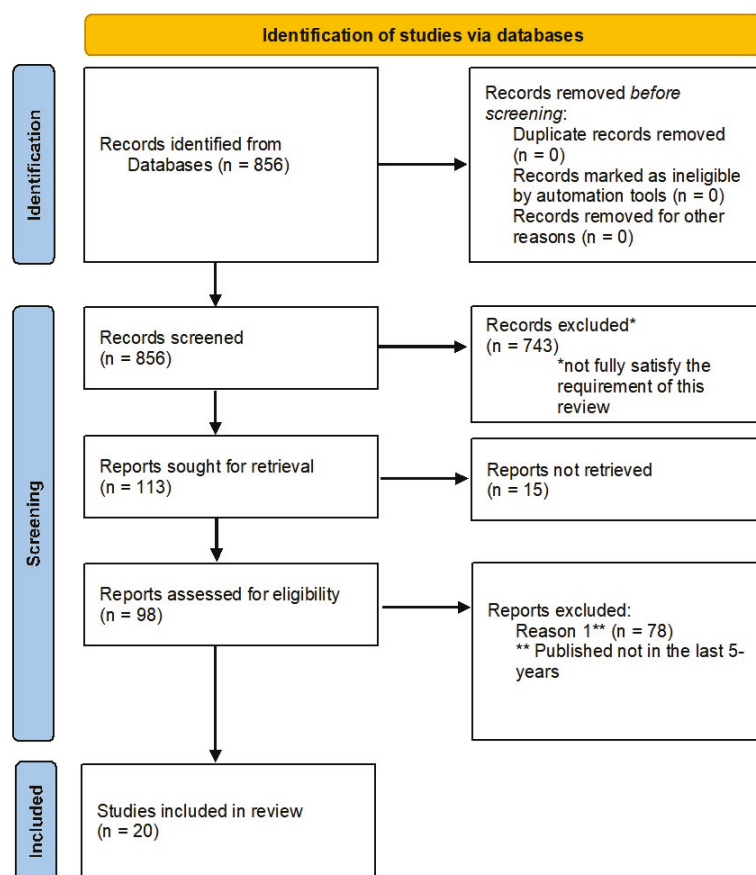


Figure 2. Flow diagram about research methodology.

4. Wearable Devices for Rehabilitation

Rehabilitation consists of an iterative process involving assessments and specialized training, which unfortunately are often limited by healthcare centres' restricted resources. To overcome this limitation, wearable technology should be an important, potential and valid solution to objectively assess and monitor patients inside and/or outside clinical environments. The information extracted by the use of this technology should provide a more detailed evaluation of the impairment, also allowing the identification of rehabilitation therapies [78]. The advantage of wearable devices in terms of portability, low cost and

unobtrusive sensors makes this technology highly efficient in tracking movements aiming to enhance patient care with neurologic or musculoskeletal conditions. Furthermore, these sensors enable quantification of motor behaviour useful in compensation motor recovery mechanisms, remote monitoring, telerehabilitation and robotics [79–81].

Electrical biosignals are important indicators of the health and fitness condition of the human body. The acquisition and analysis of biosignals such as ECG, EMG and EEG through real-time e-health monitoring systems allow the extraction of relevant and useful information to achieve better healthcare in terms of observation, diagnosis and treatment [82]. A general setup of these systems is reported in Figure 3:

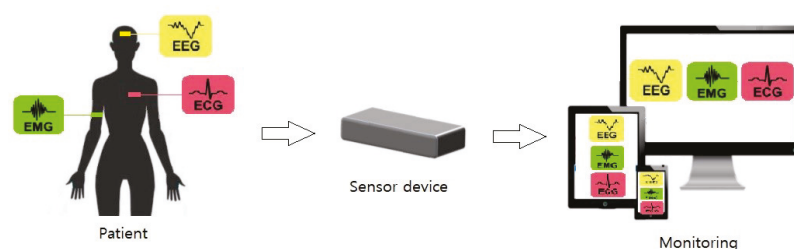


Figure 3. General setup of biosignal monitoring system.

EEG, ECG and EMG signals are extracted by electrodes placed on the patient and acquired by sensor devices able to process these signals and transmit them on accurate instrumentation for monitoring.

Generally, these systems present heavy drawbacks regarding the limitation in acquiring and sending data at high rates, the low energy efficiency and the restricted portability due to their large size and weight. To overcome these limitations and make these systems more efficient, wearable devices are becoming essential in daily and clinical practice to allow continuous monitoring of human activity in terms of changes in biological signals. The increasing trends of wearable devices and the multimodal acquisition of different biosignals are crucial for advancing disease-diagnosis and treatment. Wearable devices perform activity monitoring through two main processes: (i) data acquisition and preprocessing; (ii) transmission, analysis and classification of acquired data. Signal preprocessing, for example, includes amplification and filtering stage; signal analysis, instead, involves averaging or extraction of relevant features to be used as training data for classifier [83].

In literature, many contributions are available concerning the design and the implementation of wearable sensors aiming to define platforms of multimodal acquisition and recognition of different biosignals, such as electroencephalography, electromyography and electrocardiography, for continuous and automatic monitoring of human health status, improving diagnosis, follow-up and therapeutic strategies of several disorders. Wearable devices usually involve smart sensors to detect and monitor a set of physiological parameters aiming to support their continuous monitoring for diagnostic, therapeutic and control purposes [84]. The great demand of the aging population for healthcare management needs the use of these wearable medical devices to monitor personal health information in real-time to prevent diseases and emergency health risks. Today, many wearable healthcare devices provide biosignals, such as EEGs, ECGs, EMGs, blood pressure or blood glucose levels. Electrical signal variations cause ECG and EMG during muscular activities, and they are important and commonly adopted parameters for healthcare management and rehabilitation protocols.

Zhao et al. [84] propose a wearable monitoring device for upper limb rehabilitation. This device integrates ECG/EMG sensors with data acquisition boards to obtain accurate signals during robotic glove assisting training. The ECG/EMG signals are acquired, preprocessed, digitized and transmitted to a remote receiver via a low-energy Bluetooth module. In addition, a software platform was developed for data analysis by integrating different algorithms to visualize ECG/EMG information and extract patterns of interest.

EMG and ECG sensors monitor the hand activities and the relative changes in the physiological status of a subject, respectively. The results show that monitoring ECG and EMG signals assist the subject in improving upper limb rehabilitation according to specific treatment conditions and the users' demands.

Liu et al. in [85] propose a portable and wireless acquisition system to acquire physiological signals. The system mainly consists of a portable device, a graphic user interface (GUI) and an application program for displaying the signals on a computer or a smart device. This device is characterized by eight measuring channels, a powerful microcontroller unit, a lithium battery, Bluetooth 3.0 data transmission and a built-in 2 GB flash memory. The results show that as this system can measure signals in real-time, supporting physicians and researchers can perform experiments collecting physiological signals of interest.

Park et al. [86] report about an energy-efficient integrated circuit architecture of a 128-channel Δ -modulated $\Delta\Sigma$ analog front-end (Δ - $\Delta\Sigma$ AFE) for 1024-channel neural recording microsystems. The proposed platform is based on the modularity of 128 channels and consists of eight multi-shank neural probes connected to individual AFEs. In addition, a spectrum equalization scheme has been implemented to reduce area and energy consumption, taking advantage of the inherent spectral characteristics of neural signals (most of the energy is present in low frequencies). The following features characterize the designed Δ - $\Delta\Sigma$ AFE: each single-channel AFE consumes $3.05\ \mu\text{W}$ from 0.5 and 1.0 V supplies in an area of $0.05\ \text{mm}^2$ with 63.8-dB signal-to-noise-and-distortion ratio and 3.02 noise efficiency factor.

An analog front-end AFE with two-channel acquisition is described in [87]. It is characterized by high impedance for low power application of bioelectrical activity. The proposed architecture comprises a programmable gain amplifier (PGA) and a 10-bit $\Sigma\Delta$ (SDM-ADC). The overall gain is programmed through the flip-over-capacitor feedback and proposed reconfiguring in the PGA. The AFE measured frequency response from 50 Hz to 360 Hz with an SNR of 63 dB, power consumption of 11 mW, programmable gains from 52.6 dB to 72 dB and an input-referred noise of $3.5\ \mu\text{V}$ in the amplifier bandwidth.

In [88], a multi-channel data acquisition system to record bio-electrical signals is proposed. The system consists of eight front-end acquisition modules and a synchronization module useful for reliable synchronization of all acquired signals. Each front-end acquisition module uses a separated universal serial bus data link to the computer. It is synchronized with other modules by an external clock, providing the time-base for the microcontrollers. The generated synchronization error is smaller than $10\ \mu\text{s}$, so the system is suitable for real-time analysis of movements. Furthermore, each analog front-end circuit is based on the highly integrated chip ADS1299, which contains analog filters and simultaneous digitalization of eight bipolar channels. Therefore, the proposed system can support real-time recordings of up to 64 bipolar channels. Lastly, raw data are analyzed and stored on a personal computer or a single-board computer.

A most recent contribution is given by Tran et al. in [89]. The authors present a four-channel, power-efficient and low-noise neural recording analog front-end (AFE) integrated circuit (IC). The overall architecture is composed of a four-channel neural recording analog front-end. Each front-end channel consists of a low-noise amplifier (LNA), a programmable gain amplifier (PGA) and buffers. The four-channel AFE is followed by a 4-to-1 multiplexer (MUX) and the analog-to-digital converter (ADC). The overall system presents a programmable gain range from 45 dB to 63 dB, and it achieves integrated input-referred noise of $3.16\ \mu\text{VRMS}$ within the 10 kHz bandwidth, a noise efficiency factor of 2.04, a power efficiency factor of 4.16 and a power consumption of $2.82\ \mu\text{W}$ per channel powered from the 1-V supply voltage.

A modular and wearable system for the acquisition and wireless transmission of biological signals is proposed in [90]. This system has been configured for different signals, such as ECG and EMG signals, and it is based on the ADS1294 Medical Analog Front End and the CC3200 microcontroller, both from Texas Instruments. It is a portable solution

supplied by two Li-ion charged batteries. The results are promising in size, physical reduction, robustness in the wireless transmission and reliability in data acquisition and processing.

Another contribution is proposed in [91] by Sarker et al. A compact and wearable portable bio-signal acquisition device has been designed and implemented. It is characterized by real-time data wireless transmission and low energy consumption. The system has been defined to acquire ECG and EMG signals at eight channels with a 24-bit resolution/channel configuration and 500 samples/s. Moreover, the device has been used in an IoT-based system as an example of possible integration.

Mazzetta et al. [92] propose a stand-alone wearable sEMG system for monitoring muscle activity in real time. This system can detect the muscle activation potentials, and it embeds the complete real-time data processing thanks to an integrated low-power microcontroller. The system is optimized for power consumption, compactness and energy autonomy, so it can be used for valuable diagnostic data sets for patients during their day-to-day life. Moreover, the results in testing the system report an achieved specificity and sensitivity in recognizing exact activity timing over 87% and 82%, respectively, with the advantage of being wireless and comfortably wearable.

The system presented in [93] consists of a non-contact ECG sensor with a fully integrated analog front-end (AFE), a temperature sensor, an accelerometer and a Bluetooth Low Energy (BLE) module for multiparameter real-time monitoring. Small dimensions characterize it, and it can be used by inpatient, outpatient, people with disabilities or aging people who live alone. Data processing is performed by an Android application, sending alerts to authorities in case of an emergency.

Kim et al. [94] present a low-power, multimodal analog front-end (AFE) for wearable health monitoring sensors. It is based on novel system architecture and very large scale integrated circuit design methods with CMOS technology. Three sensors for bio-potential, photoplethysmography (PPG) and bioelectrical impedance analyzer (BIA) are integrated for low dimension and power consumption. Results showed high-quality AFE permitting users to effortlessly self-monitor multiple clinically relevant physiological parameters.

Authors in [95] proposes a novel analog front-end (AFE) to investigate three features: (i) voltage-dependent input impedance, (ii) bandpass amplification and (iii) stray capacitance reduction by using capacitive electrocardiogram (cECG) or capacitive electromyogram (cEMG) measurements in seven human subjects. Performance evaluation indicates that the proposed AFE can provide a feasible balance between sensitivity and stability in capacitive biopotential measurements (CBMs). Thus, it could be a versatile replacement for the conventional voltage follower used in CBMs.

Biagetti et al. [96] present a low-cost wearable wireless system for the acquisition of surface electromyography (sEMG) and accelerometer signals aiming to monitor human activity when performing sport and fitness activities, as well as in healthcare applications. The proposed system consists of several ultralight wireless sensing nodes that can acquire, process and efficiently transmit the motion-related (biological and accelerometer) body signals to one or more base stations through a 2.4 GHz radio link using an ad hoc communication protocol designed on top of the IEEE 802.15.4 physical layer. In addition, a user interface software for viewing, recording and analyzing the data was implemented on a controlled personal computer connected through a USB link to the base stations. To demonstrate the system's capability to detect the user's activity, data recorded from a few subjects were used to train and test an automatic classifier to recognize the type of exercise being performed. The system was tested on four different exercises performed by three people; the automatic classifier achieved an overall accuracy of 85.7% combining the features extracted from acceleration and sEMG signals.

Another contribution proposed by Biagetti et al. [97], following the previously developed system, regards the design of a wireless sensor device for the real-time acquisition of bioelectrical signals, such as EMG and ECG. This device aims to furnish a complete stream of data suitable for human activity detection, motion analysis and technology-assistance

for people with physical or cognitive impairments. Six electrodes are considered to allow up to three independent bioelectrical channels, each with 24 bits of resolution and a sampling rate up to 3.2 kHz. Moreover, a Bluetooth Low Energy wireless link has been chosen to interact with many consumer electronics devices. Specifically, this contribution investigates data rate restrictions imposed by these devices proposing a strategy aiming to maximize the available bandwidth and reliability of the transmission.

Xian Li and Ye Sun [98] present a button-like wearable wireless non-contact system for long-term multiple biopotential signal (ECG, EMG and EEG) monitoring. This system is based on an ultra-high input impedance of the analog front-end for non-skin contact detection. The system is powered by a 150 mAh rechargeable Li-ion battery and packaged into a 39 mm × 32 mm × 17 mm 3D printed small box for a total weight of 24.0 g. A power management circuit is included to provide a dual power supply for operational amplifiers. The system's performance has been evaluated through multiple motion scenarios with different types of cloth, and the results show the feasibility of long-term biopotential monitoring for daily application without affecting daily activities.

In [99], the authors present a single-channel amplifier to simultaneously acquire the ECG signal and the impedance respiration signal. The system is based on the over-sampling and fast digital lock-in technology. It uses capacitive reactance of a capacitor changing with the signal's frequency to satisfy the different impedance requirements of both the respiratory impedance signal and ECG signal. The preprocessing stage has been designed to improve the common-mode rejection ratio (CMRR) and the signal-to-noise ratio (SNR). ADS1294R (four-channel 24-bit ADC with integrated respiration impedance and ECG front-end) has been included to detect the ECG signal, and respiration signal and STM32F103RET6 has been adopted for signal processing. The results show as the designed circuit can support the simultaneous acquisition of multiple human physiological signals in a signal channel. Moreover, it can also detect other impedance variation signals and bioelectrical signals such as EMG, EOG and EEG signals.

The authors of [100] propose their contribution in the design of a portable device for ECG, EMG, EEG and Electrooculogram (EOG) signal monitoring aiming to support diagnosis and the evolution of several diseases. The processor satisfies the suppressing of baselines wander (0.1–0.5 Hz) and power line interference noise (50/60 Hz), and it provides to switch between low noise–high CMRR mode and average noise-average CMRR mode. Moreover, a bandpass and a band-stop FIR filter have been developed. The processor also contains a Successive Approximation Register (SAR) DAC for the controlling signal. It is designed in Spartan-3E FPGA and 0.18 µm CMOS TSMC technology for a total of 33,005 µm² area and power consumption of 0.382 mW.

Lee et al. [101] present a novel wireless ExG sensor tag with a multi-channel physiological signal acquisition (PSA) system aiming to acquire biopotential signals, such as ECG, EOG and EMG. Furthermore, a mixed-signal processor system-on-chip (SoC) and Bluetooth Low Energy (BLE) chip have been implemented for real-time recording and wireless transmission, respectively. This system is optimized for power efficiency, and it can be easily achieved in 12 h with a 200 mA H battery of continuous recording of ExG signals in healthcare applications.

Flexible architecture of a multi-purpose physiological signal (e.g., ECG, EMG) recorder is presented in [102], supporting wired and wireless body sensor networks. It allows a wide range of hardware settings, data processing and reporting options. The proposed architecture is based on three main layers, including data acquisition, processing and communication modules. A programmable analog front-end ADAS1000 with five configurable gain single-ended channels has been implemented. In addition, a 24-bit resolution analog-to-digital converter with a programmable data rate up to 128 kHz has been designed. Moreover, three channels are provided for immediate communication and storage of results of physiological measurement in either raw or processed form.

A noise-power-area optimized biosensing front-end application specified integrated circuit (ASIC) for wireless body sensor nodes, and implantable medical devices are

presented in [103]. The ASIC is implemented in a 0.18 μm CMOS process, and it is reconfigurable to accommodate different biopotentials with the high-pass and low-pass cutoff frequencies being 0.5–300 Hz and 150–10 kHz, respectively. An antialiasing filter is also available for the switching-optimized 10-b successive approximation register (SAR) analog-to-digital converter (ADC). The analog front-end (AFE) allows a programmable gain from 38 to 72 dB. Moreover, a power management unit provides the power supply, multiple reference voltages and bias currents to the entire chip. In terms of performance, the following characteristics can be identified: (i) AFE and ADC dissipate 5.74 μW and 306 nW, respectively, (ii) the measured input-referred noise is 2.98 μVRms , (iii) the noise efficiency factor is 2.6, (iv) the power efficiency factor is 9.46 and (v) the area of the AFE is 0.0228 mm^2 .

A summary of these contributions about wearable monitoring systems chosen among the papers in the literature published in the last 5 years is made in Table 2.

Table 2. Summary of selected wearable monitoring system included in this review.

Authors	Signals	Channels	Platform Characteristics	Features
Tran et al., 2021	Bio-potentials	4 channels	Four-channel neural recording analog front-end composed by a low-noise amplifier (LNA), a programmable gain amplifier (PGA) and buffers; 4-to-1 multiplexer (MUX) and analog-to-digital converter (ADC)	Programmable gain from 45 dB to 63 dB, input-referred noise of 3.16 μVRMS within the 10 kHz bandwidth, noise efficiency factor of 2.04, power efficiency factor of 4.16, power consumption of 2.82 μW per channel powered from 1 V supply voltage
Yin et al., 2021	Bio-potentials, impedance respiration	Single 1 channel	Oversampling and fast digital lock-in technology, ADS1294R, STM32F103RET6 for signal processing	Improve the common-mode rejection ratio (CMRR) and the signal-to-noise ratio (SNR) of the signal
Zhao et al., 2020	ECG/EMG	N.A.	Low-energy Bluetooth module	Wearable monitoring device, software platform for data analysis
Biagetti et al., 2020	Bio-potentials	3 channels	Six electrodes, 24 bits of resolution and a sampling rate up to 3.2 kHz for each channel, Bluetooth Low Energy wireless link	Wireless sensor, real-time acquisition, maximization of the available bandwidth, reliability of the transmission
Nakamura et al., 2020	ECG/EMG	N.A.	Analog front-end (AFE)	Capacitive measurements
Liu et al., 2019	Bio-potentials	8 channels	Powerful microcontroller unit, lithium battery, Bluetooth 3.0 data transmission and built-in 2 GB flash memory	Portable device with a graphic user interface (GUI) and an application program for displaying the signals on a computer or a smart device
Park et al., 2018	Bio-potentials	128 channels	Energy-efficient integrated circuit architecture of a Δ -modulated $\Delta\Sigma$ AFE with multi-shank neural probes connected to individual AFEs	The Δ - $\Delta\Sigma$ AFE is characterized by a consume of each single-channel AFE of 3.05 μW from 0.5 and 1.0 V supplies in an area of 0.05 mm^2 with 63.8 dB signal-to-noise-and-distortion ratio and 3.02 noise efficiency factor
Raheem et al., 2018	Bio-potentials	2 channels	Programmable gain amplifier (PGA) and 10-bit $\Sigma\Delta$ (SDM-ADC)	High impedance, power consumption of 11 mW, programmable gains from 52.6 dB to 72 dB and input referred noise of 3.5 μV in the amplifier bandwidth
Mazzetta et al., 2018	EMG	Differential 1 channel	32 bit ARM® Cortex®-M4, microSD, Bluetooth 4.0, 592 mWh battery, micro-USB connector, 30 × 30 × 15 mm dimensions, weight of 10 g	Power consumption, compactness and energy autonomy, wireless and comfortably wearable

Table 2. Cont.

Authors	Signals	Channels	Platform Characteristics	Features
Biagetti et al., 2018	sEMG	N.A.	Ultralight wireless sensing nodes, base station for data transmission through a 2.4 GHz radio link, communication protocol designed on top of the IEEE 802.15.4 physical layer	Low-cost wearable wireless system, user interface software for viewing, recording and analyzing data
Kast et al., 2017	Bio-potentials	Bipolar 64 channels	Up to eight front-end acquisition modules with synchronization module, a separated universal serial bus data-link to the computer and an ADS1299	Raw data are analyzed and stored on a personal computer or a single-board computer
Sarker et al., 2017	ECG/EMG	8 channels	24 bit resolution/channel and 500 samples/s, IoT-based system	Compact and wearable portable bio-signal acquisition device, real-time data wireless transmission, low energy consumption
Li et al., 2017	ECG/EMG	N.A.	150 mAh rechargeable Li-ion battery, packaged into a $39 \times 32 \times 17$ mm 3D printed small box, total weight of 24.0 g, power management circuit, dual power supply for operational amplifiers	Wearable wireless non-contact system, ultra-high input impedance, feasibility of long-term biopotential monitoring
Senepati et al., 2017	ECG/EMG	N.A.	Band pass and band stop FIR filters, Successive Approximation Register (SAR) DAC, Spartan-3E FPGA and 0.18 μ m CMOS TSMC technology	Area of 33,005 μ m ² area, power consumption of 0.382 mW, suppressing of baselines wander and power line interference noise (50/60 Hz)
Bhamra et al., 2017	ECG/EMG	N.A.	ASIC technology in a 0.18 μ m CMOS process, high-pass and low-pass cutoff frequencies being 0.5–300 Hz and 150 Hz–10 kHz, antialiasing filter, successive approximation register (SAR) analog-to-digital converter (ADC), power management	Wireless, programmable gain from 38 to 72 dB, AFE and ADC dissipation of 5.74 μ W and 306 nW, measured input-referred noise of 2.98 μ Vrms, noise efficiency factor of 2.6, power efficiency factor of 9.46, area of the AFE of 0.0228 mm ²
Kim et al., 2016	Bio-potentials, PPG, BIA	N.A.	CMOS technology, low-power and multimodal analog front-end (AFE)	Wearable health monitoring, low dimension and power consumption
Mahmud et al., 2016	ECG	N.A.	Fully integrated analog front-end (AFE), temperature sensor, accelerometer, Bluetooth Low Energy (BLE) module	Multiparameter real time monitoring, small dimensions, Android application, Alerts
Piccinini et al., 2016	ECG/EMG	N.A.	ADS1294 Medical Analog Front End, CC3200 microcontroller, two Li-ion charged batteries	Portable solution, size physical reduction, robustness in wireless transmission, reliability in data acquisition and processing
Lee et al., 2016	ECG/EMG	N.A.	Mixed-signal processor system-on-chip (SoC), Bluetooth Low Energy (BLE) chip, 200 mAh battery	Wireless transmission, power efficiency, 12 h of continuous recording
Augustyniak et al., 2016	Bio-potentials	Single-ended 5 channels	Programmable AFE ADAS1000, 24-bit resolution analog-to-digital converter with programmable data rate up to 128 kHz	Wired and wireless body sensor networks, configurable gain for channel

5. Commercial Wearable Devices

Wearable portable systems aim to daily acquire and process different health data, providing early detection of pathological signs and improving the treatment and the continuous monitoring of disease. Many commercial EMG and ECG sensors are available, and they are designed and created to satisfy different specifications. In this section, the review proposes a description of the common commercial biosignal acquisition systems for physiological monitoring. These systems have been chosen to be the most used devices in health practice presenting similar characteristics to be compared.

Biometrics Ltd offers different data acquisition systems to collect analog and digital data from various sensors and are available in wireless, portable and laboratory configurations. Wireless systems furnish total freedom of movement without being constrained by wires [104]. They are available in 2-, 4-, 8- and 16-channel configurations to acquire EMG signals by using surface, small and lightweight sensors, allowing muscle activity readings to be smooth and robust with a range of up to 30 m from its receiver. The main features of these types of sensors are (i) a bandwidth from 10 Hz to 250 Hz through to 10 Hz to 5000 Hz and (ii) a sensitivity for the peak to peak measurements ranging from ± 60 mV to ± 6000 mV [105]. Portable systems are comprehensive packages of sensors and instrumentation for static and dynamic measurements in a clinical setting, a research centre, or at any remote location such as an office, workplace or home. Biometrics offers three different versions of EMG sensors: (i) surface EMG sensors, (ii) wireless surface EMG sensors and (iii) surface EMG amplifier.

Shimmer offers a set of individual sensors for different parameters measurement [106]. Shimmer3 EMG Unit provides a configurable digital front-end useful for the acquisition and measurement of EMG signals [107]. This unit uses a non-invasive sensor allowing registration of the activity of the whole muscle. It provides two channels of EMG data with a common reference electrode in a wireless solution. It can also acquire ECG data, but EMG and ECG data cannot be measured simultaneously from a single unit. Shimmer3 EMG unit contains an MSP430 microcontroller, a Bluetooth Radio (RN-42) and an integrated 8 GB micro SD card, and it is supplied by a 450 mAh rechargeable Li-ion battery. The Shimmer3 ECG unit is equivalent to the Shimmer3 EMG unit, but it is optimized for the measurement of physiological signals for ECG [108]. It is a four-lead ECG solution to measure bipolar limb leads chosen from V1–V6; moreover, it offers respiration demodulation from ECG data and allows lead-off detection.

BioSemi instrumentation proposes ActiveTwo biopotential measurement systems for research applications [109]. This system is characterized up to 256-channel DC amplifier, 24-bit ADC per channel and active electrodes. These active electrodes are smaller with less cable weight while offering even better specs in terms of low-frequency noise and input impedance. Specifically, the ActiveTwo system provides: (i) up to 256 + 8 electrode +7 sensor channels in a single ultra-compact box, (ii) battery-powered front-end with fiber optic data transfer, (iii) reliable measurements without skin preparation, (iv) improved digital resolution with LSB value of 31 nV and (v) user-selectable sample rate of 2, 4, 8, 16 kHz/channel. Moreover, it is suitable for EEG, ECG and EMG measurements, and it offers graphical programming in LabVIEW.

FreeEMG is an electromyography device with wireless probes for the dynamic analysis of muscle activity. It is a 4G technology device for surface EMG analysis characterized by signal accuracy, absence of wires, lightness and reduced size of the probes. FreeEMG is largely used for orthopedic and neurological disorders; pharmacological treatments; the evolution of motor deficits; rehabilitation and follow-up; and athletic task optimization. PLUX develops innovative biosignal acquisition and monitoring platforms integrating wearable body sensors such as EMG and ECG combined with wireless connectivity and software applications [110]. Two of these platforms are BITalino and Biosignalsplux.

BITalino (r)evolution kit is an all-in-one board with all the blocks pre-connected and ready to work out-of-the-box [111]. This model is fitted with Bluetooth communication. Its EMG sensors are specially designed for surface EMG. The bipolar configuration is ideal for low-noise data acquisition, and the raw data output enables it to be used for human–computer interaction and biomedical projects alike.

Biosignalsplux represents an advanced wireless toolkit to collect and analyze reliable and high-definition biosignal data [112]. It offers a set of cabled and wearable sensors. The biosignalsplux electromyography (EMG) sensor is a high-performance bipolar sensor with low noise for seamless muscle data acquisition. This sensor is designed to monitor muscular activity, and the bipolar configuration is ideal for uncompromised low-noise data acquisition. The raw data output provides medical-grade data enabling it to be used for advanced and highly accurate biomedical biomechanics and sports

research. Its main features are (i) bipolar differential measurement, (ii) pre-conditioned analog output, (iii) high signal-to-noise ratio and (iv) medical-grade raw data output. It is also ready-to-use, and it is miniaturized. The wireless single-channel EMG device for real-time muscle sensing is muscleBAND. It is an integrated single-channel EMG sensor with a triaxial accelerometer and magnetometer for real-time acquisition of muscle activity and motion data with an integrated dual Bluetooth module. This sensor allows data acquisitions with up to 16-bit resolution at up to 1000 Hz sampling rate, with the internal battery providing enough power for continuous data streaming.

Delsys proposes complete wireless EMG-based solutions for monitoring human movement in research, clinical and educational settings [113]. These solutions are composed of (i) research, mobile and lite systems, (ii) EMG sensors, (iii) mobile software and (iv) software for devices integration. The most used EMG sensor is Trigno Avanti Sensor, which can capture muscle activity and movement data accurately. It is designed to work with all Trigno systems, and it is characterized by (i) patented technology, (ii) improved RF performance, (iii) cable-free design, (iv) selectable EMG bandwidth settings and (v) on-board signal processing. It also allows differential EMG input acquisition in a very small dimension and weight. Trigno Research+ is a high-performing device designed to make EMG signal detection reliable and easy, offering a full set of physiological and biomechanical monitoring tools to simplify complex research and provide the highest quality data. Proprietary RF protocol guarantees synchronization between all sensors and allows data transmission from Trigno wireless sensors to a Trigno base station. Table 3 reports the main characteristics of the selected wearable monitoring systems.

Table 3. Main characteristics of the commercial wearable monitoring systems.

Features	Biometric	Shimmer	Biosemi	BTS Bioengineering	Biosignal Plux	BITalino	Delsys
Type of sensor	Wireless EMG Sensor	Shimmer3 EMG Unit	ActiveTwo	FreeEMG 1000 H ₂ O	Electro-myography Sensor	Electro-myography Sensor	Trigno Avanti Sensor
Size (mm × mm × mm)	42 × 24 × 14	65 × 32 × 12	120 × 150 × 190	Probes: 41.5 × 24.8 × 14	28 × 70 × 12	12 × 27	27 × 37 × 13
Weight	17 g	31 g	1.1 kg	13 g—battery included	25 g	N.A.	14 g
# channels	1	2	8 up to 256	1	1	1	1 differential input
Input impedance	>100 Mohms	N.A.	>100 M @ 50 Hz		>100 GOhm	10/7.5 GOhm/pF	
Input range	+/-6 mV	Approx. 800 mV @ gain = 6	+262 mV to -262 mV	N.A.	Up to 10 mV	±1.64 mV @ VCC = 3.3 V	11 mV/22 mV rti
Gain	+/-60 mV to +/-6000 mV	1,2,3,4,6,8,12 (software configurable)	N.A.	N.A.	1000	1009	11 mV/22 mV rti
CMRR	>96 dB (typically 110 dB) @ 60 Hz	N.A.	>90 dB @ 50 Hz	N.A.	100 dB	86 dB	<-80 dB
Consumption	N.A.	N.A.	4 Watt @ 280 channels	N.A.	1 mA	0.17 mA	N.A.
Bandwidth	0–250, 470, 950, 5000 Hz	8.4 kHz	Up to DC—3200 Hz @ -3 dB	N.A.	25–500 Hz	25–482 Hz	10–850 Hz 20–450 Hz

Table 3. Cont.

Features	Biometric	Shimmer	Biosemi	BTS Bioengineering	Biosignal Plux	BITalino	Delsys
Data transmission	Wireless	Bluetooth Radio – RN-42	Fiber optic	Wireless IEEE 802.15.4	Bluetooth Low Energy	N.A.	2.400–2.483 GHz ISM Band, Proprietary RF Protocol - BLE V4.2
Resolution	N.A.	24 bit	24 bit	16 bit	12 bit	N.A.	16 bit
Sample rate	N.A.	125, 250, 500, 1000, 2000, 4000, 8000 SPS	2048 Hz–4096 Hz–8192 Hz–16,384 Hz	N.A.	N.A.	N.A.	4370 sa/sec
Battery type and life	Rechargeable Li-ion Polymer, Up to 8 h	450 mAh rechargeable Li-ion battery	Battery power with >10 h @ 144 channels, >72 h @ 16 channels	Battery Li-Po, Up to 6 h	N.A.	Battery Li-Po 700 mAh	Rechargeable Li-Po Battery Up to 8 h

6. Discussion

The acquisition and analysis of biopotentials (e.g., EEG, ECG and EMG) are relevant in a diagnostic and therapeutic context to monitor and identify normal and/or abnormal physical conditions. In the rehabilitation field, these biopotentials became important to support human activity monitoring. Surface EMG is a widely used technology in rehabilitation research. It furnishes quantifiable information on the myoelectric signal of a muscle. Nevertheless, there is a strong contrast between the application of sEMG in clinical practice and research findings. This contrast is due to several issues including: (i) limited time and resources due, for example, to electrodes and skin preparations, electrode placements and equipment setup; (ii) clinically inapplicable sEMG system features mainly caused by the limited spatial resolution of sEMG; and (iii) lack of training and confidence in utilization of sEMG technology. Common example of issues are technical and regard signal processing and information extraction algorithms which do not directly produce clinically relevant information. Other issues concerns the user-unfriendliness of some equipment. Finally, the cost of the devices and the timing procedure to perform a measurement and to obtain a clinically useful information have also a negative impact. In terms of sensor technology, the main characteristics of a wearable system include low-energy operations, light weight and safety requirements. In addition, a wearable device must be compact and comfortable enough to be easily used. Moreover, it must be portable and guarantee continuous monitoring of human behavior through a battery power supply and wireless connectivity, respectively. Today, many commercial sensors are available to meet these requirements, and they offer different personalized solutions regarding specific needs. These sensors are characterized by small dimensions and portable configurations, making them more useful in patient control in clinical structure and at home. The limitation of modern commercial sensors is mainly due to the high cost and the complexity of the system used by a single subject. Moreover, they are not always easy to use. One of the main problems of existing biosignal technology is the high cost of commercial devices that is higher in devices with wireless technologies, which makes it easier to install on the muscle and connect with the computer; however, this requires a more complex system configuration. Very often, these commercial sensors present complex design, mainly based on sophisticated hardware with little attention toward a comfortable sensor–patient interface. Another problem regards the fact that these sensors are designed based on bench tests, models and patient simulators, ignoring the key component and working well in the simulation phase but revealing problems under real-life conditions. To improve these limitations, research prototypes are becoming very important because the newest sensor technology must meet the needs of clinicians and patients. The new generations of sensor-driven technologies should individuate the potential clinical need, identifying the key biosignals related to a specific physiological processes and seeking the development of platforms based on novel sensing technologies. These new platforms must be able to monitor the physiological processes from useful locations using novel transduction mechanisms. The hardware also should be designed and developed around these constraints and requirements. In the future, these sensors will support home-based physiological data collection, preventive healthcare programs and also facilitate remote care and rehabilitation protocols. For this

reason, the future steps will regard the development of miniaturized and economic devices which will be used on a large population.

7. Conclusions

This contribution is proposed as a review of the most common physiological monitoring systems in the rehabilitation field. It focuses on the EMG signal front-end as one of the main platforms to support physicians, patients and general subjects in rehabilitation protocols. In this review, many references in the literature have been presented to highlight the importance of the acquisition, analysis and monitoring of EMG signals to muscular activity control. Moreover, different commercial available EMG sensors have also been described and compared to identify the most common features of these devices in EMG acquisition. The main characteristics are portability and wireless data transfer, aiming to ensure a practical use in rehabilitation.

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Abbreviations

The following abbreviations are used in this manuscript:

EEG	Electroencephalogram
ECG	Electrocardiogram
EMG	Electromyogram
sEMG	Surface Electromyography
IC	Integrated Circuit
NMES	Neuromuscular Electrical Stimulation
BCI	Brain–Computer Interface
ADC	Analog-to-Digital Converter
CMRR	Common-Mode Rejection Ratio
SNR	Signal-to-Noise Ratio
AFE	Analog Front-End
PGA	Programmable Gain Amplifier
LNA	Low-Noise Amplifier
BLE	Bluetooth Low Energy
BIA	Bioelectrical Impedance Analyzer
CBM	Capacitive Biopotential Measurements
SoC	System-on-Chip
ASIC	Application Specified Integrated Circuit

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Article

Drone-Mountable Gas Sensing Platform Using Graphene Chemiresistors for Remote In-Field Monitoring

Jaewoo Park, Franklyn Jumu, Justin Power, Maxime Richard, Yomna Elsahli, Mohamad Ali Jarkas, Andy Ruan, Adina Luican-Mayer and Jean-Michel Ménard *

Department of Physics, University of Ottawa, Ottawa, ON K1N 6N5, Canada; jpark4@uottawa.ca (J.P.); fjumu014@uottawa.ca (F.J.); jpowe074@uottawa.ca (J.P.); mrich154@uottawa.ca (M.R.); yelsa078@uottawa.ca (Y.E.); mjark066@uottawa.ca (M.A.J.); a2ruan@uwaterloo.ca (A.R.); luican-mayer@uottawa.ca (A.L.-M.)

* Correspondence: jean-michel.menard@uottawa.ca

Abstract: We present the design, fabrication, and testing of a drone-mountable gas sensing platform for environmental monitoring applications. An array of graphene-based field-effect transistors in combination with commercial humidity and temperature sensors are used to relay information by wireless communication about the presence of airborne chemicals. We show that the design, based on an ESP32 microcontroller combined with a 32-bit analog-to-digital converter, can be used to achieve an electronic response similar, within a factor of two, to state-of-the-art laboratory monitoring equipment. The sensing platform is then mounted on a drone to conduct field tests, on the ground and in flight. During these tests, we demonstrate a one order of magnitude reduction in environmental noise by reducing contributions from humidity and temperature fluctuations, which are monitored in real-time with a commercial sensor integrated to the sensing platform. The sensing device is controlled by a mobile application and uses LoRaWAN, a low-power, wide-area networking protocol, for real-time data transmission to the cloud, compatible with Internet of Things (IoT) applications.

Keywords: microcontroller; graphene gas sensor; drone mountable; in-field performances

1. Introduction

Detection and identification of volatile compounds in remote locations for air quality monitoring are crucial to establish and enforce environmental policies on greenhouse emission or provide early warning for dangerous air-borne agents. To enable these applications, gas sensors must not only feature high sensitivity and selectivity to specific molecules, but also have practical in-field characteristics, such as being compact, light-weight, deployable, and low cost [1–3]. One strategy consists of miniaturizing the design of gas sensing technologies first developed in research in laboratories. This approach was used for gas chromatography/liquid chromatography-mass spectroscopy (GC/LC-MS) [4,5], and ion mobility spectroscopy (IMS) [6–8]. In these contexts, such an approach can ensure high sensitivity as well as selectivity, but the structural complexity of these devices puts a limit on their minimal size and cost.

Previous work demonstrated that, when exploring new compact sensing technologies, graphene-based chemiresistors satisfy many requirements for gas sensing applications [9, 10]. For example, their lightweight, low power consumption, and chemical stability position them advantageously to play a key role in future sensing technologies [11–15]. Notably, graphene-based sensors have an especially high gas detection sensitivity that can be attributed to the two-dimensional nature of the material, ensuring that adsorbed molecules on the surface significantly affect its macroscopic electrical properties [16,17]. Scalable approaches to fabrication of graphene, for example by chemical vapor deposition (CVD) or liquid phase exfoliation (LPE), provide a pathway to large-scale fabrication of sensor arrays [18]. Those advantages combined with recent progress on improving selectivity of graphene-based chemiresistors have made possible to envision the large-scale deployment

of this technology for environmental monitoring and warfare agents detection [10,19]. Finally, graphene-based sensors have demonstrated mechanical strength and flexibility, which are essential characteristics to many devices used in real-life applications [20].

In parallel to the development of smaller gas sensing devices, programmable 32-bit microcontrollers (μ C), such as ESP32, are increasingly used to achieve compact and portable processing platforms [21–24]. In addition to their small size and low cost, they are energy efficient and can readily interface with electronic hardware and components, such as Wi-Fi and Bluetooth transmitters. These hardware features are critical to enable Internet of Things (IoT) applications and allow emerging technologies, such as in-field gas sensing, [21,22,25,26] to be integrated into the design of unmanned automated vehicles. Among those, drones offer the ability to sample large remote areas, including those otherwise inaccessible due to geographical landscape or safety concerns. Therefore, there is considerable interest in developing sensing platforms with an architecture compatible with drone sizes, shapes, and movements [27]. A specific challenge is ensuring that sensing devices can be operated over large distances for remote monitoring and provide accurate readings despite the drone's rapid movement and environmental fluctuations. In particular, changes in humidity and temperature are known to induce changes in graphene's electrical properties, potentially leading to a high noise level when graphene is used as a chemiresistor [28–31]. Recent research showed that environmentally induced signal variations can be resolved when the device is kept at a high temperature of 110 °C [27]. However, this technique requires a heat-resistant hardware configuration and demands a higher power consumption, which reduces the battery lifetime. In other work, fluctuations were counterbalanced by real-time computer normalization using a model provided by a trained artificial neural network (ANN) [32]. Although showing promise, this technique requires a large dataset to train the algorithm and ultimately reach the desired accuracy.

Here, we report a drone-mountable sensing platform using a graphene chemiresistor array fabricated integrated to a battery-powered μ C development board and accessible with short- and long-range wireless communication systems. More importantly, we demonstrate the possibility to integrate graphene-based sensing technology into a drone-mountable platform for real-life applications. We propose a compact design and explore some of the main limitations, including environmental noise caused by temperature and humidity fluctuations. In a lab setting, the device reading accuracy is similar to the one provided by a state-of-the-art multi-meter (Model 2400, Keithley Instruments, Solon, OH, USA). Tests performed during flights and under rapidly changing environmental conditions show a significant increase in noise level. We were able to reduce signal fluctuations by about an order of magnitude when normalizing the signal against independent temperature and humidity readings from a commercial sensor also integrated into the sensing platform.

2. Materials and Methods

We design a compact and light-weight (185 g) sensing platform using commercially available μ C devices and compatible components (see Figure 1). The functional component is an ESP32-based development board, which controls the general operations of the device. The sensor array contains three graphene chemiresistors, which consist of 0.7×0.7 cm CVD graphene layers placed onto a 1.0×1.0 cm Si/SiO₂ substrate with parallel gold electrodes deposited on the surface. The chemiresistors are fabricated following the technique described in [17]. Although the board can accommodate a fourth graphene sample, in this experiment we use instead a commercial static resistor, which monitors the electronic stability of the system.

A high-accuracy 32-bit analog-to-digital converter (ADC) monitors real-time resistance of the four devices by measuring the voltage across four reference resistances directly mounted on the sensor board. Note that the ADS1262 ADC model used in this configuration could allow up to eight channels to be read simultaneously. The μ C performs a circuit calculation using these voltages to retrieve the resistance of each three chemiresistors and the static resistor (details in Supplementary Materials). These values are sent in

data packets to another remote μC device, referred here as the gateway, via Semtech's LoRa protocol using a 915 MHz center-frequency. The gateway then unpacks the packets and sends the resistance digital values to either: (i) a computer via serial cable or (ii) a smartphone running a mobile application allowing data transfer over Bluetooth. The LoRa communication in our application has been tested to work consistently at distances up to 1 km from the operator while sending a steady stream of data. This range can be improved by using higher gain antennas. Components used in the device configuration, such as the μC , ADC converter, and fan, are commercially available; here we present an original design, assembly, and overall architecture involving these components to demonstrate a drone-mountable sensing platform.

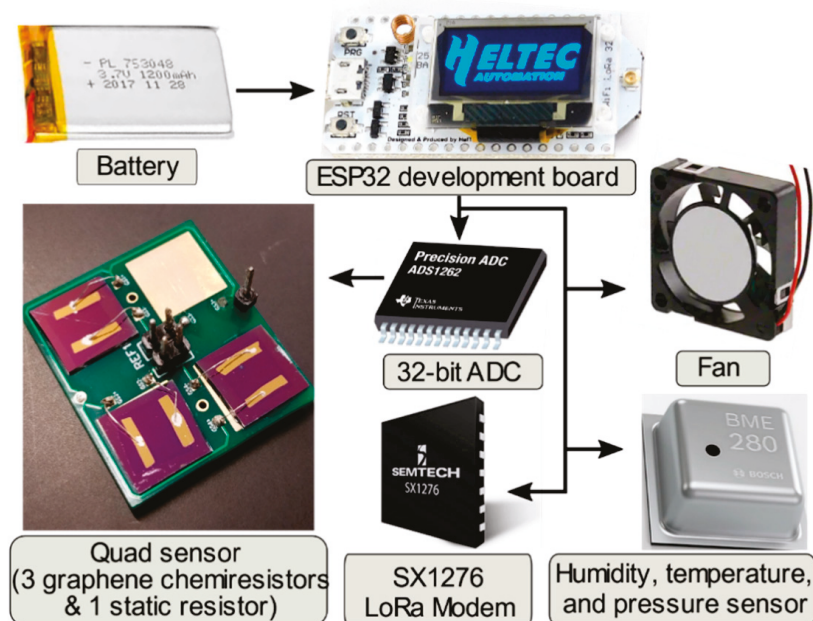


Figure 1. Diagram of the main functional components of the gas sensing platform. A battery powers the development board (ESP32 μC), which controls the graphene chemiresistor array via a 32-bit analog-to-digital converter (ADC). A fan, a long-range communication (LoRa) module and a commercial humidity/temperature/pressure sensing device are also accessible by the ESP32 μC using the I2C communication bus.

A commercial temperature and humidity (TH) sensor (model BME280) monitors environmental fluctuations. Its readings are used to normalize the graphene sensors' response as we demonstrate later. A comprehensive functional diagram including all device components can be found in Figure S3 (see Supplementary Materials). The information collected by all sensors comprised in the platform is registered every 210 ms (or at a rate of 4.8 Hz). However, the device performs a moving average to reduce noise, yielding a time resolution of ~ 1 s and matching the time resolution of the BME280 sensor.

The sensing platform architecture is adapted to the drone size and shape (see Figure 2). The 3D printed casing has a length and width of ~ 85 mm and a height of 46 mm. An intake fan located at the top of the device allows air to flow across the sensing chamber, which contains both the quad sensor panel and TH sensor, and then exit by the exhaust located on the side of the casing. USB ports are used to charge the lithium-ion battery (right port) and access the ESP32 μC (left port) for firmware updates. PCB boards are stacked vertically to minimize lateral footprint. An adapter at the base of the casing ensures solid mounting of the device on the top of the drone. Note that the platform could not easily be located under the drone as it tends to obstruct optical sensors necessary for the drone's advanced obstacle avoidance system.

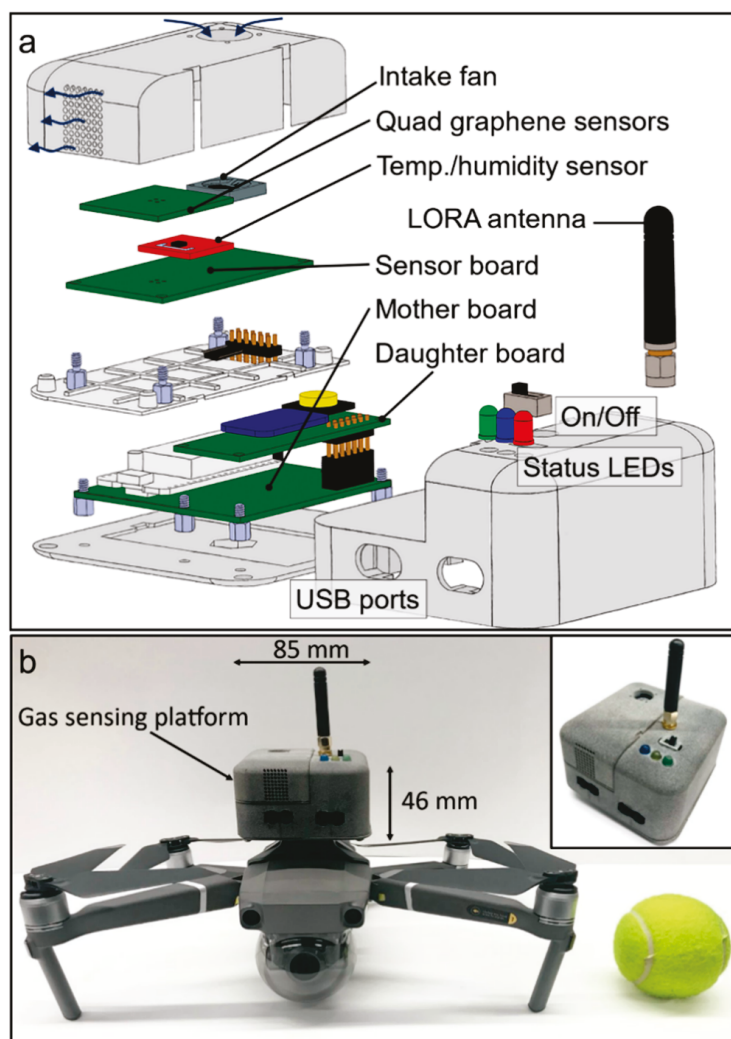


Figure 2. (a) Schematic of the gas sensing platform showing components and configuration. (b) Photo of the gas sensing device mounted on top of a drone, and unmounted in inset, with dimensions comparable to a tennis ball.

We demonstrate the practicality of the device by testing it under different experimental conditions: (1) in a laboratory setting, inside an enclosure under a controlled environment, (2) mounted on a drone during an indoor flight, and (3) outdoor while being exposed to wind and sun. In the laboratory, experiments are conducted with a standard configuration (see Figure 3) for evaluating the sensing platform's response when exposed to precise concentrations and exposure times of two target analytes: ethanol and water vapour. Although graphene-based chemiresistors are not especially sensitive to ethanol [33], here we use this low-cost, easily accessible, and low-toxicity chemical to demonstrate the concept of a compact and portable sensing platform. Three mass flow controllers (MFCs) are used to control the concentration of gases supplied inside a plexiglass enclosure in which the sensing platform is placed. Two gas lines are connected to a bubbler to provide saturated vapours of ethanol and water. Computer-automated 3-way valves allow us to determine the precise exposure time to each analyte. Indoor flight tests are conducted inside a $10\text{ m} \times 5\text{ m} \times 4\text{ m}$ drone area, allowing us to investigate the effect of the drone movement on the sensors. We also explore the ability to detect humidity changes while flying the drone. In these experiments, the drone is initially placed at one end of the drone cage, and a commercial humidifier at the opposite end. We fly the drone within 1 m of the water vapour jet of the humidifier for the detection test. Finally, in the third experimental setting,

the sensing platform was tested outdoor under rapidly fluctuating conditions due to wind and sun exposure.

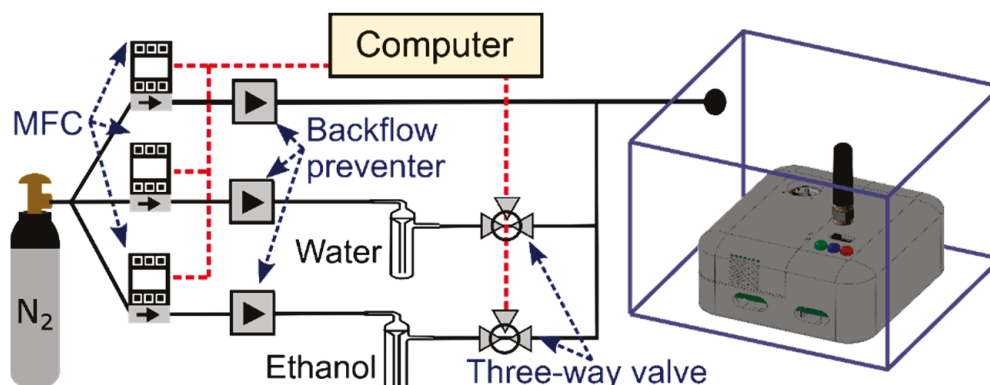


Figure 3. Schematic of the automated experimental setup used to characterize the sensor responsivity to different chemicals species (ethanol and water vapour) diluted in a N_2 carrier gas. The sensing platform is located inside a plexiglass enclosure.

3. Results and Discussion

3.1. Tests in a Laboratory Setting

In a first experiment, the sensing platform is placed inside a plexiglass enclosure under steady conditions and we investigate the optimal sensitivity of the device by analyzing the noise characteristics with a series of continuous measurements. Figure 4a shows the corresponding data points collected by the sensing platform's ESP32 μC and ADC components during a period of 575 s. Figure 4c shows that the distribution of data points is Gaussian-like and has a standard deviation of $\Delta R/R_0 = 0.012\%$. The response $\Delta R/R_0$ provided by a sensor is defined as the change of resistance ΔR of the graphene sheet divided by its resistance R_0 at the beginning of the experiment. We performed a similar series of measurements using a state-of-the-art sensor monitoring system. This system extracts the electrical resistance from the linear I - V characteristic curve obtained by a multimeter (Keithley 2400) by keeping the voltage constant and reading the current. Results shown in Figure 4b,d indicate a noise level that is only larger by a factor of two ($\Delta R/R_0 = 0.006\%$). Considering that the standard laboratory data acquisition equipment is significantly more bulky and expensive than our compact sensing platform, we believe this comparison not only demonstrates the ability to use μC -based infrastructure for sensitive remote gas sensing, but also its potential to replace standard data acquisition equipment to save space and costs. All data acquisition in Figure 4 is performed at the common sampling rate of ~ 1 Hz.

In another experiment, also performed in the laboratory setting described in Figure 3, the sensing platform monitors devices' resistance changes when we introduce analytes into the plexiglass enclosure. Figure 5a shows the recorded resistance changes of the three graphene sensors, $G1$, $G2$, and $G3$, and the static resistance, R_{Static} , (top panel), as well as the recorded relative humidity and temperature provided by the TH sensor (bottom panel). In this experiment, water vapour is first introduced in the enclosure. We see a correlation between the humidity level (blue line) and the signal ($\Delta R/R_0$) provided by the three graphene sensors, where R_0 is the resistance at time 0 s. The fact that R_{Static} remains constant during the experiment demonstrates the stability of the electronic configuration and reliability of the resistance readings.

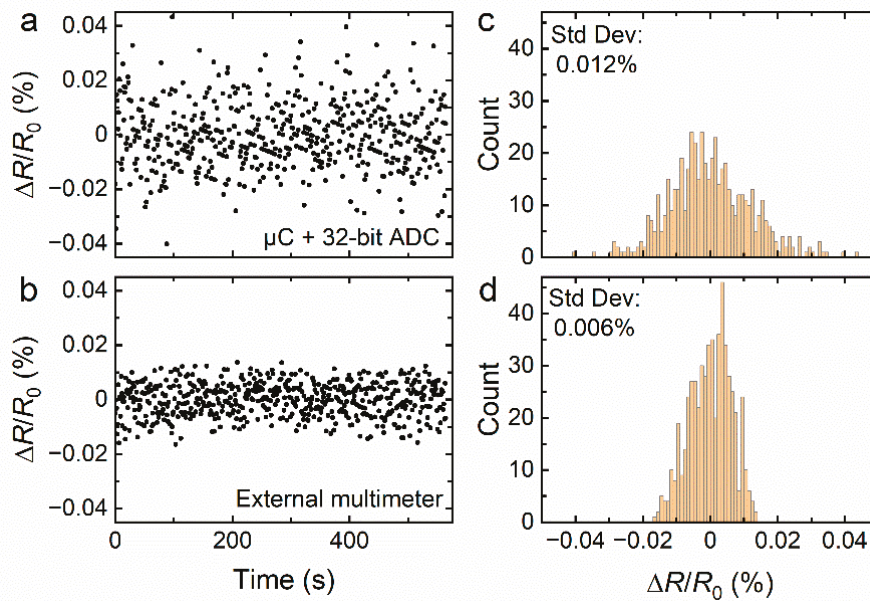


Figure 4. Resistance measurements of a graphene sensor under steady state conditions (a) measured with our sensing platform combining a μC and 32-bit ADC, and (b) extracted from the linear I - V characteristic curve obtained by an external multimeter (Keithley 2400) by keeping the voltage constant and reading the current. (c,d) show the statistical distribution of the time-dependent data presented in (a,b), respectively.

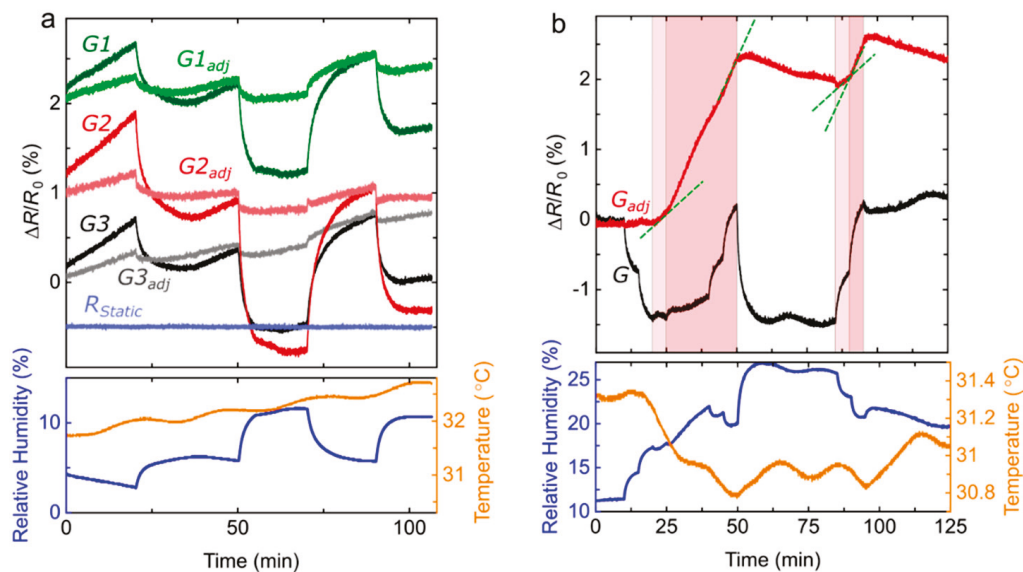


Figure 5. (a) The sensing platform inside an enclosure allows us to remotely monitor the signal ($\Delta R/R_0$) of three graphene sensors, $G1$, $G2$, and $G3$, one static resistance R_{Static} (top panel, with a vertical offset of 1% between all readings), as well as the relative humidity and temperature provided by the TH sensor (bottom panel). As we introduce varying concentrations of water vapour inside the enclosure a correlation is observed between the G 's and the humidity. We use Equation (1) to adjust the graphene sensors' response to a signal, G_{adj} , more independent to fluctuations in humidity and temperature. (b) The experiment is repeated with one graphene sensor while introducing different concentrations of ethanol vapour (red regions) and water vapour (not indicated with background color but traceable from the relative humidity readings). The light red region corresponds to an ethanol vapour concentration of 7800 ppm and the darker red region to a higher concentration of 13,700 ppm.

The signal $G = \Delta R/R_0$ of a graphene sensor depends on ambient humidity and temperature, which are varying parameters difficult to control in real-life applications. In practice, this can result in signal fluctuations reducing the sensor's sensitivity to a targeted gas. Here, we independently measure humidity and temperature and use signal processing to account for the effects of these two environmental parameters on the sensor. We build a model, based on previous work [13,31], to calculate G_{mod} , the projected signal derived from humidity and temperature readings only:

$$G_{mod} = a\Delta H_{abs}e^{\frac{E_d}{N_A k_B T}} + b(T - 273.15)^c \quad (1)$$

where T is the temperature in K, $\Delta H_{abs}(T)$ is the change in absolute humidity, $N_A k_B$ (referred as the gas constant 8.314 J/mol K) is the Avogadro's number multiplied by the Boltzmann constant, and E_d is the energy for water desorption (4.64×10^4 J/mol [34]). The variables a , b , and c , are determined for each individual graphene sensor, as the relationship between the signal and the parameters in Equation (1) depends on intrinsic graphene electrical properties, such as the doping level [34]. These three variables are determined by minimizing the adjusted signal ($G_{adj} = G - G_{mod}$) during an experiment performed under rapidly fluctuating environmental conditions. We use the same values, listed in Table 1, in all other experiments to obtain the adjusted signal. Signal variations due to changes in humidity or temperature can then be significantly decreased, by about an order of magnitude (Figure 5a).

Table 1. Fitting parameters used in Equation (1) to remove humidity and temperature dependence on signals from the three graphene devices in our sensing platform.

	$a (\times 10^{-9})$	$b (\times 10^{-4})$	$c (\times 10^0)$
G1	4	1.5	2.8
G2	7.5	1.6	2.85
G3	4.9	1.65	2.7

Figure 5b demonstrates the practicality of this normalization step to detect ethanol vapours. In this experiment, we trace the signal of a single graphene sensor while varying the concentrations of water and ethanol, both successively and simultaneously, inside the enclosure containing the sensing platform. The monitored relative humidity (blue line, bottom panel) indicates significant and random-like modulations, which are also reflected in the original signal G . After adjustment, most of these modulations are cancelled out and we are left with a signal perfectly correlated with the exposure times to ethanol. More strikingly, the slope of $\Delta R/R_0$ (green dashed lines) is changing accordingly to the ethanol concentration, which is equal to 7800 ppm in the light red region and 13,700 ppm in the darker red regions. Chemiresistors used in this work have a response time of ~20 min [10], which is defined as the time required for the sensor in a lab setting to display a signal $\Delta R/R_0$ reaching 90% the maximum signal associated with a constant analyte concentration. For real-life applications, other features, such as the maximum slope of the time-dependent signal, or a comparison between the responses provided by different types of sensors, could be monitored to reduce the time necessary to detect and identify chemicals [19]. Furthermore, a shorter response time and recovery time can be achieved by structural modifications of the sensing platform, e.g., by optimizing the chamber design [35], implementing a functionalization of the graphene surface [36], or using of a heterodyne sensing configuration [37]. The tests performed in a controlled laboratory setting show promises for the sensitive detection of specific gases in field applications under fluctuating environmental conditions. However, more external factors can potentially influence the signal when the sensor is mounted on a flying drone.

3.2. Indoor Flight Tests

As a first step towards assessing the performance of the drone platform in real-life environments, we mounted the sensing platform on a drone while collecting data with the sensors on-board. Figure 6a shows the signal measured while the drone is in motion. After switching on the sensing platform electronics and before activating the drone propellers (still switched off), we observe a slow but gradual rise in temperature causing a drift in the signal of all sensors. When the drone is in flight mode and starts hovering 0.5 m above the floor, the signal initially oscillates significantly but, within a minute, tends towards a plateau due to the increased air flow contributing to regulating the temperature. The drone is then kept at a constant height and repetitively moved over an 8 m distance at different speeds, first at ~ 1 m/s and then ~ 3 m/s. No significant changes can be observed due to the motion of the drone in the horizontal direction. We draw the same conclusion when the drone is repetitively moved vertically from 0.5 m to 3.1 m during the last series of measurements for this test.

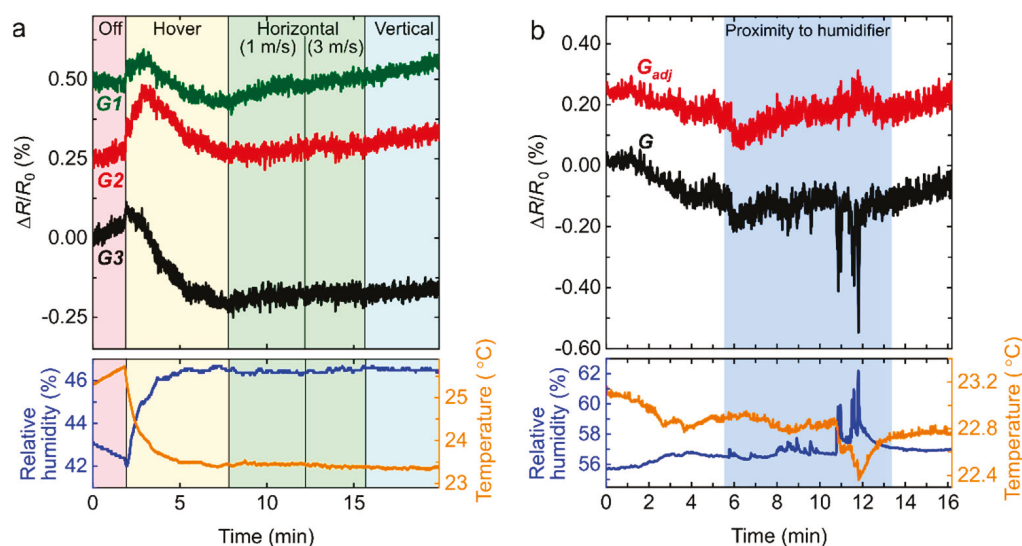


Figure 6. The sensing platform mounted on a flying drone measures and relays in real-time the changes in resistance of graphene sensors while also monitoring the relative humidity and temperature with a commercial sensor (bottom panel). (a) The changes in the sensing response as a function of drone motion is investigated by performing measurements when the drone is powered off and on the ground (red region), hovering (yellow region), moving horizontally at speeds of 1 m/s and 3 m/s (green regions), or moving vertically (blue region). (b) As the flying drone is approaching a humidifier, the signal G relayed by the graphene sensors (only one is shown here) features large irregular oscillations. Equation (1) and parameters listed in Table 1 allow us to calculate G_{adj} , a signal independent of environmental variations such as humidity and temperature changes.

We also investigated the response of the graphene sensors to a sudden increase in humidity during in-flight tests by approaching the flying drone to a humidifier releasing a jet of water vapour (Figure 6b). Interestingly, the monitored humidity varies irregularly in time and the largest related signal is observed during the time period corresponding to 11 to 12 min. We attribute the irregular fluctuation to the local increase in humidity induced by the humidifier jet, which is periodically sampled by our sensing platform as the drone propellers mix up different volumes of air in a turbulent manner. By monitoring the humidity and temperature with a TH sensor, we then use Equation (1) and the parameters listed in Table 1 to calculate G_{adj} and significantly reduce the effects of fluctuating humidity.

3.3. Outdoor Tests

In a final experiment, we investigate the response of the sensing platform when it is left outdoor (under direct sunlight at an ambient temperature of 24 °C, humidity 27%, and wind speed 11.3 km/h), while being exposed to fluctuating environmental conditions. The results are presented in Figure 7. After switching the device on, we immediately notice an increase in temperature due to the electronics warming up the device, but more importantly because of the direct sunlight exposure. This leads to a gradual increase in the graphene sensor signal, which simultaneously shows relatively large and fast fluctuations correlated to the varying relative humidity. We apply the normalization procedure based on Equation (1) to reduce the influence of these environmental factors and notice a significant decrease in signal fluctuation in the adjusted signal G_{adj} . The standard deviation of the three signals from the graphene sensors ($G1$, $G2$, $G3$) decreases, on average, from 0.53% to 0.08%. In other words, the noise decreases by a factor of ~ 7 . For the experiment shown in Figure 7, the commercial TH sensor is an HDC1080 (instead of the BME280 used in previous experiments) with a time response approaching 10 s. As a result, a 50-sample moving average is applied on the graphene sensor signals to optimize the signal synchronization between all sensors. We would expect to significantly improve noise reduction using a TH and graphene sensors having a perfectly matching temporal response.

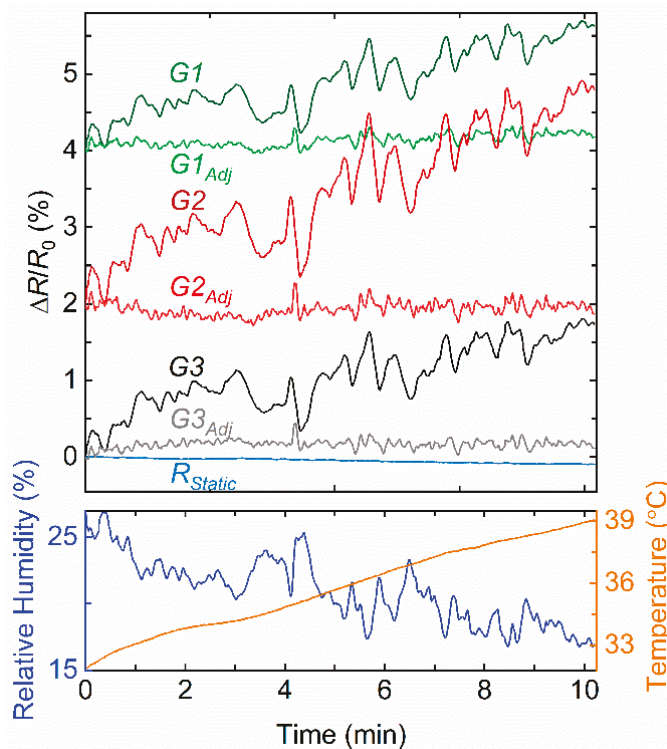


Figure 7. The sensing platform located outdoor allows us to remotely monitor the signal ($\Delta R/R_0$) of three graphene sensors, $G1$, $G2$, and $G3$, one static resistance R_{Static} (top panel), as well as the ambient relative humidity and temperature provided by the TH sensor (bottom panel). Equation (1) is used to decrease the effects of the change in humidity and temperature on G , to obtain the adjusted signal G_{adj} . A vertical offset of 2% for $G2/G2_{adj}$ and 4% for $G1/G1_{adj}$ is added for clarity.

4. Conclusions

We demonstrate the use of a microcontroller (μC) and related components to produce a lightweight, compact, and low-cost platform, which can be mounted on a drone for remote gas monitoring over distances of 1 km. Under controlled conditions, our platform can relay a signal G ($\Delta R/R_0$) with relatively low noise (0.06%), only two times higher than the one measured with standard, state-of-the-art laboratory equipment. When exposed to water and ethanol vapours, graphene sensors show a clear response. We build a model of the

graphene response as a function of monitored changes in humidity and temperature, and use it to obtain an adjusted signal G_{adj} independent of these two environmental parameters and distinctively revealing the presence of specific gases. We demonstrate this concept by exposing our sensors to fluctuating water vapour concentrations while detecting ethanol. Indoor flight tests show that the flying drone motion does not significantly affect the sensing response, especially when the platform temperature has reached an equilibrium. Finally, we demonstrate that fast-varying outdoor environmental conditions increase graphene-based chemiresistor noise. This poses a major obstacle to the deployment of sensing technologies in the field. However, cross-data analysis on data provided by a commercial temperature/humidity (TH) sensor and graphene sensors can be used in real-time to decrease unwanted signals created by environmental fluctuations. We demonstrate a noise reduction approaching an order of magnitude with room for further improvements, which can be achieved by perfectly matching the time response of the TH and graphene sensors. In our experiment, three graphene chemisensors fabricated with the same technique are tested simultaneously to demonstrate reproducibility. This compensation method for temperature and humidity is software-driven and can be easily applied to graphene-based sensor systems. In a lab-setting, we demonstrate that our platform can achieve a signal-to-noise comparable to the one obtained with high-quality commercial multimeters. Previous work has established correlations between air flow and the relative positioning of the sensors. The fan included in our device architecture helps sample the surrounding area but a more in-depth study of the placement and orientation of the air intake could still improve the overall performances of our gas sensing platform [38–40]. In future experiments, selected graphene-based sensors could be functionalized chemically or optically [33] to enhance sensitivity to specific gases and improve selectivity. A different sensing board design could also accommodate a larger number of sensors with graphene sheets of smaller area [41].

Supplementary Materials: The following are available online at <https://www.mdpi.com/article/10.3390/s22062383/s1>, Figure S1: High-level circuit schematic of resistance monitoring module of the graphene sample (a) Sensor board, (b) Analog to digital converter (ADC), (c) ESP32 microcontroller, Figure S2: Schematic of the circuit and sample calculation to retrieve the resistance of the graphene chemiresistor $G1$. V_0 is provided by an external battery and voltage regulator, R_{G1} is the actual resistance of the graphene sensor $G1$, $R1_{Ref}$ is a 1 k Ω commercial resistor and V_1 is the voltage read by the ADC. The same technique is applied to monitor the resistance of other graphene samples on-board the sensing platform as well as the static resistor, Figure S3: Complete functional schematic of the sensing platform.

Author Contributions: Draft preparation: J.P. (Jaewoo Park) and J.-M.M.; Project management: F.J. and J.-M.M.; In-lab test: J.P. (Jaewoo Park) and J.P. (Justin Power); Prototype development and in-field tests: F.J., J.P. (Justin Power), M.R., Y.E., and M.A.J.; Software development: J.P. (Justin Power), F.J., M.R., and A.R.; Data analysis: J.P. (Justin Power), F.J., M.R., and J.-M.M.; Supervision: A.L.-M. and J.-M.M. All authors have read and agreed to the published version of the manuscript.

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Article

Non-Contact Activity Monitoring Using a Multi-Axial Inertial Measurement Unit in Animal Husbandry

Pieter Try and Marion Gebhard *

Group of Sensors and Actuators, Department of Electrical Engineering and Applied Sciences,
Westphalian University of Applied Sciences, 45897 Gelsenkirchen, Germany; pieter.try@w-hs.de

* Correspondence: marion.gebhard@w-hs.de; Tel.: +49-209-9596-380

Abstract: In this work, a novel method is presented for non-contact non-invasive physical activity monitoring, which utilizes a multi-axial inertial measurement unit (IMU) to measure activity-induced structural vibrations in multiple axes. The method is demonstrated in monitoring the activity of a mouse in a husbandry cage, where activity is classified as resting, stationary activity and locomotion. In this setup, the IMU is mounted in the center of the underside of the cage floor where vibrations are measured as accelerations and angular rates in the X-, Y- and Z-axis. The ground truth of activity is provided by a camera mounted in the cage lid. This setup is used to record 27.67 h of IMU data and ground truth activity labels. A classification model is trained with 16.17 h of data which amounts to 3880 data points. Each data point contains eleven features, calculated from the X-, Y- and Z-axis accelerometer data. The method achieves over 90% accuracy in classifying activity versus non-activity. Activity is monitored continuously over more than a day and clearly depicts the nocturnal behavior of the inhabitant. The impact of this work is a powerful method to assess activity which enables automatic health evaluation and optimization of workflows for improved animal wellbeing.

Keywords: inertial measurement unit; activity classification; structural vibrations; machine learning; data fusion

1. Introduction

The monitoring of physical activity is a widespread tool to evaluate physical health in humans and animals alike. Physical activity is a complex multi-dimensional behavior that is characterized by frequency, duration, intensity and mode [1,2]. Typical metrics to quantify activity are locomotion (e.g., steps and traveled distance) and heart rate. The state of the art is wearable devices which contain various sensors to obtain objective measurements of activity [3,4]. However, wearable devices have some disadvantages that make them inconvenient and even unsuitable in some applications. For example, elderly people can forget to put the wearable device on and may be discouraged by the inconvenience of frequent charging. In addition, wearables are unsuitable for target groups such as small animals due to the relative weight of the wearable device, which has a strong negative impact. For these target groups, non-contact activity monitoring methods are employed which use cameras [5] and other sensing methods [6–8].

A major use case for non-contact activity monitoring is to evaluate health and wellbeing in the husbandry of mice. Mice husbandry, e.g., at the Institute for Laboratory Animal Science Aachen (VTK) which houses over 20,000 mice, is a large scale operation which requires a large workforce. Here, non-contact activity monitoring is used for behavioral studies and to ensure wellbeing of the animals. Sensing systems employed in this use case are cameras [9–11], radar sensors [12,13], capacitive sensing arrays [14] and arrays of radio-frequency identification (RFID) scanners [15,16]. However, these systems are only used on a small scale for studies and are not widespread in the husbandry where most animals reside. This is due to disadvantages such as high computation cost for camera systems, large sensing devices, invasive components (such as RFID-chips) and poor scalability.

Promising non-contact methods for activity monitoring have been presented previously [6–8,17–21], which are based on measurements of structural vibrations. These methods demonstrate how various activities and non-activity are detected in different use cases based on structural vibrations using various computational methods. State of the art in vibration sensing is the use of geophones, e.g., the SM-24 Geophone [22] which is used in most works mentioned above. Geophones have a common frequency bandwidth of 10 to 250 Hz, very low noise and high sensitivity which makes them suitable to measure small vibrations [22,23]. However, commercial multi-axial inertial measurement units (IMUs) have improved significantly in sensing performance and cost. One reason is the widespread adoption of micro-electro-mechanical system (MEMS) motion sensing devices in consumer electronics. A comparison of MEMS accelerometers and geophones is performed in a study [24,25]. In this study a single axis MEMS-based accelerometer for seismic applications is compared to several geophones. The results show that a MEMS-based accelerometer for seismic applications is competitive to geophones. However, as geophones are dedicated vibration sensing devices their performance in terms of noise and sensitivity is superior to commercial multi-axial IMU which are most often used for motion sensing. On the other hand, MEMS IMU have superior frequency bandwidth and integrate multiple sensor types in a highly integrated system on a chip (SOC). For example, the widespread 9-axis IMU or sometimes called magneto-inertial measurement unit (MIMU) hosts three triads of orthogonally oriented accelerometers, angular rate sensors and magnetometers in a package with a size of $3 \times 3 \times 1 \text{ mm}^3$.

Looking at the state of the art, there is a lack of scalable non-contact methods for activity monitoring in animal husbandry. Such a method would allow for large scale automated activity and health assessment, which represents a major benefit for both animal welfare and caregiver workload. Furthermore, it is evident that multi-axial IMU are not yet state of the art for vibration measurement, despite the clear advantages of these sensors. Therefore, in this work, we propose a novel non-contact method for continuous activity monitoring, which uses a single commercial multi-axial IMU to measure the structural vibrations of a husbandry cage. Based on the cage vibrations, activity of the cage inhabitant is estimated and classified as resting, stationary activity and locomotion. For this, a setup is developed, which consists of an multi-axial IMU and a reference system. These are used to monitor the activity of a mouse inside a commercially available husbandry cage. The IMU sensor is mounted on the outside of the cage in the center of the cage floor. For reference of the activity of the inhabitant, a camera-based reference system is used. It uses a camera with a fish eye lens mounted in the cage lid and sophisticated algorithms for markerless motion tracking. Activity classes representing common activity patterns are defined based on the horizontal movement of the inhabitant. For activity classification based on structural vibration data, eleven features are extracted from multiple sensors of the IMU and used to train a supervised machine learning model. Training and evaluation is performed using 16.17 h of data.

This paper presents the proof of concept for a sensitive and selective activity classification method based on structural vibrations measured with an multi-axial IMU SOC. The results clearly show that IMU are suitable for measuring activity-induced structural vibrations with very small amplitudes. It is shown that various cage vibrations in the three spatial directions are measured by the triads of orthogonally oriented sensors of the IMU SOC. Furthermore, it is shown that these vibrations contain non-redundant information that is fused to achieve increased activity classification accuracy. The evaluation further shows very good accuracy in identifying resting phases versus phases with activity. The activity of horizontal locomotion is identified in about half of the cases, which is detected based on unique vibrations induced by foot steps. Finally, it is demonstrated how the proposed method is used to monitor the activity over a period of 26.67 h. The results clearly show expected activity patterns such as the activity cycle of a nocturnal creature.

2. Concept, Setup and Reference

In this work, a proof of concept is presented for activity monitoring based on structural vibrations measured with a multi-axial IMU. Two major questions are explored for this proof of concept. First, IMUs are assessed for their performance in measuring structural vibrations as well as the activity-related information contained in it. Furthermore, metrics for measuring activity are assessed and classes of activity defined. For this, data of cage vibrations in the scenario of mice husbandry are acquired and analyzed. Afterwards, a method is researched to classify activity based on structural vibrations that are measured by the IMU. This method is developed based on observations from the acquired data.

In this section, the setup for data acquisition is presented as well as the initial analysis of IMU data with regards to activity-induced vibrations. Furthermore, the metrics are described by which activity is measured in this work. Afterwards, in Section 4, a method is presented to classify physical activity based on IMU measurements, which is built on the findings of this section.

2.1. Concept and Application Scenario

Physical activity monitoring is a valuable tool to evaluate health because of the correlation between health and physical activity. Generally speaking, physical activity is a complex behavior that is described by many characteristics. The commonly used metrics for activity are the amount of motion such as steps and travelled distance.

The movements that are performed during activity, apply dynamic forces to surrounding objects (e.g., the floor, a chair or a cage) which cause mechanical vibrations. Impulsive forces are mainly generated by localized impacts such as steps or an object dropping on the floor. These impulses create rapidly decaying vibrations which contain frequency components of the natural frequency of the excited object. Vibrations of objects on which activity takes place, for example vibrations of the floor or a husbandry cage, are referred to as structural vibrations. The structural vibrations created during different activities exhibit activity-dependent characteristics. For example during locomotion, short impulse-induced vibrations will occur at regular intervals corresponding to the frequency of the steps. In addition, the characteristics of vibrations vary due to the different strength and duration of impulsive forces. By measuring and analyzing structural vibrations for these characteristics, it is possible to identify the activity that is performed.

In mice husbandry, animals are held in rectangular plastic containers, shown in Figures 1 and 2. These containers, consist of a cage tub and a cage lid. The cage tub is filled with one to two centimeters of bedding which is made from wood chips or similar material. The bedding provides a soft floor and absorbs moisture to improve hygienics. Two primary ventilation concepts are used, active ventilation and passive ventilation. In active ventilation, cages of type individually ventilated cage (IVC) are stored in racks which have an active ventilation system pumping fresh air through each cage individually. Passive ventilation relies on cutouts with air filters on the cage lid which provide fresh air. The mice held in large scale husbandry have a weight of approx. 25 g and typically inhabit cages in groups of up to six. However, this work will focus on a scenario with one mouse per cage.

In this use case scenario, a mouse is the subject which performs physical activity in a husbandry cage which is the surrounding object. During different activities, impulsive forces are applied to the cage by the inhabitant, which causes structural vibrations. Locomotion, digging and vertical stretching are some activities that are expected to cause structural vibrations. The forces generated during activity are very small due to the small size and weight of about 25 g. Correspondingly, the amplitude of vibrations is also small. In addition, activity induced forces are transferred to the cage indirectly through the soft bedding which dampens and decreases the amplitudes.

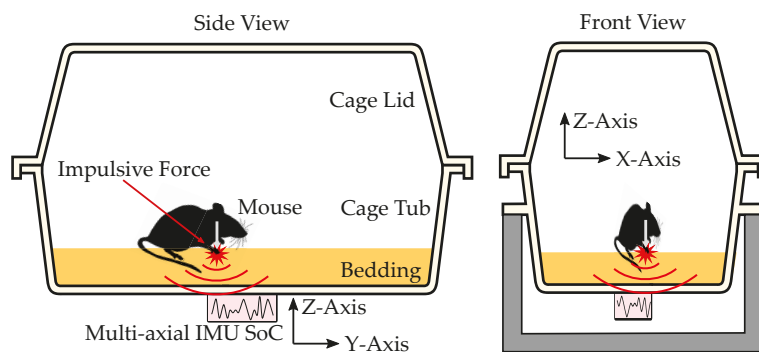


Figure 1. This drawing visually depicts the concept of the proposed method for activity detection and classification based on measurements of structural vibrations with an multi-axial inertial measurement unit.

In this work, activity of the mouse is estimated by measuring the structural vibrations of the cage with a 9-axis IMU SOC as shown in Figures 1 and 2. The proposed sensor integrates nine sensors in a single SOC and measures acceleration, angular rate and magnetic fields in the three spatial directions X, Y and Z. In this application, data of the magnetometer is omitted. The individual sensors are layered on top of each other in an integrated SOC using MEMS manufacturing techniques. The complete package has a size of $3 \times 3 \times 1 \text{ mm}^3$. Although IMUs are better described as sensor modules, in this work IMUs will be referred to as a sensor. When mounted to the cage floor, the IMU measures the vibrations of the cage at the mounting point as acceleration and angular rate in the three axis X, Y and Z. An advantage of the small dimensions of the IMU is the minimal influence on the natural frequencies of the cage. The acceleration measurements depict linear deflection and motion while the angular rate measurements depict twisting and rotational oscillations. The structural vibrations measured by the IMU are expected to exhibit different properties in the three spatial directions due to the geometry of the cage. In Z-axis a membrane-like vibration of the cage floor is expected. In X- and Y-axis vibration is expected to originate from oscillation of the whole cage, because these axes are aligned parallel to the plane of the cage floor. For concise monitoring and depiction of activity, metrics and classes have to be defined to describe different activity patterns of the inhabitant. This is described in Section 3.1.

The proposed method involves sensitive measurement of small cage vibrations to extract activity-specific information for activity classification. For this reason, it is of high interest to increase the signal to noise ratio due to the relatively large noise of the IMU, when compared to geophone sensors. However, the inherent noise of the IMU is relatively uniform in the frequency domain. Therefore, it is proposed to filter and extract activity-induced vibrations in the frequency domain where useful signals can be differentiated from the noise floor. In addition, the multiple information sources of the multi-axial vibration measurement are fused to achieve improved activity classification.

2.2. Setup and Measurements

The goal of the measurements is to collect IMU measurements of structural vibrations of a husbandry cage in the scenario that a mouse in the cage performs its regular activities undisturbed. For this, a measurement setup is used which simulates the environment found in regular husbandry and includes a camera reference system. It is shown in Figure 2 and used to acquire ground truth of physical activity using camera images. It is described in detail in Section 2.3. The setup consists of an unmodified Zoonlab HRC500 IVC [26], a cage lid with cutouts for the camera system, the camera reference system and the ICM20948 9-axis IMU from STMicroelectronics [27]. The IMU is mounted on the outside of the cage floor as shown in Figure 1. The camera reference system is mounted in the lid and provides a top-view of the inside of the cage. The top-view video images are later used to estimate physical activity with an algorithm, which serves as the ground truth for training and

evaluation of algorithms. The cage is placed on a dedicated aluminum stand. The raw data streams of the IMU and camera are recorded and synchronized by a raspberry pi 4 using a program written in Python. In the measurements two setups, shown in Figure 2, were used in parallel to increase the amount of data collected.

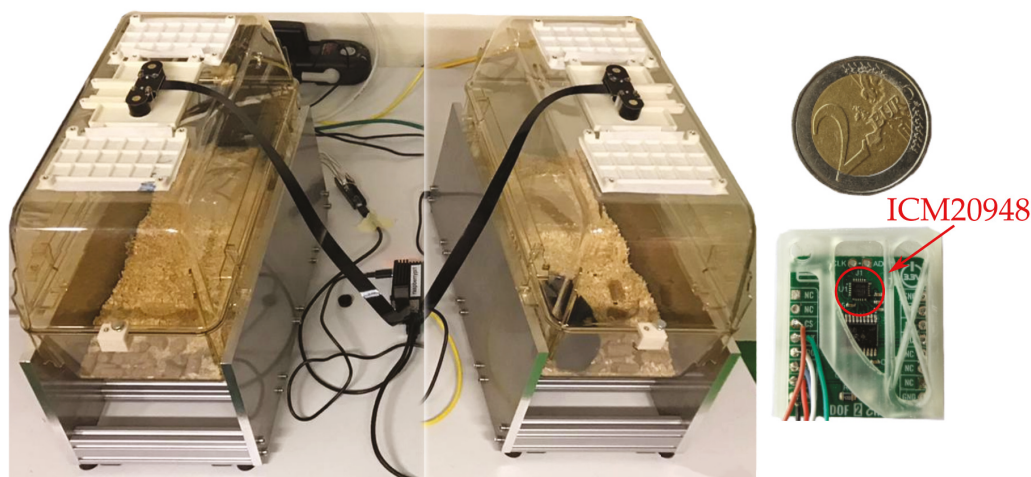


Figure 2. Figure shows the two measurement setups employed at the Institute for Laboratory Animal Science Aachen on the left. On the right the ICM20948 [27] is shown with a 2 Euro coin as reference for size.

The ideal mounting position of the sensor, meaning a place with maximum vibration amplitude, was determined using finite element method (FEM) analysis of the empty cage. The result indicates that the cage floor exhibits a membrane-like oscillation when excited by an impulsive force. The center of the cage floor is the anti-node of this oscillation and has the highest amplitude of deflection. In addition, the FEM predicts a 1st harmonic natural frequency at 130 Hz. It should be mentioned that the exact material properties of the cage are not known and that the bedding and other objects inside the cage are neglected. Therefore, a lower natural frequency is expected in the real world scenario. Based on these results, the center of the cage floor is chosen as the mounting position of the IMU sensor. In order to prevent interference with the inhabitant, the sensor is mounted on the outside under the cage. The X-axis of the IMU is aligned to the short side, the Y-axis to the long side and the Z-axis perpendicular to the cage floor. The sensor is mounted using thin double sided tape of the brand tesa®, which allows for non-permanent attachment of the sensor. Lab tests showed that vibration measurements are uninfluenced when using this tape for mounting. The IMU accelerometer data are obtained with a sampling rate of 4500 Hz (3 dB cutoff at 1248 Hz) and a resolution of 61.04 $\mu\text{g}/\text{LSB}$. The manufacturer specifies a noise density of 190 $\mu\text{g}/\sqrt{\text{Hz}}$ which amounts to a theoretical noise of 6.7 mg root mean square (RMS). The IMU gyroscope data are obtained with a sampling rate of 9000 Hz (3 dB cutoff at 12,106 Hz) and a resolution of 7.63 mdeg/LSB. The manufacturer specifies a noise density of 15 mdeg/ $\sqrt{\text{Hz}}$ which amounts to a noise of 1.65 dps RMS.

The measurements were carried out at the VTK [28]. Animal handling and cage preparations were performed by trained personnel. Prior to the measurements, the cages were cleaned and fitted with new bedding (approx. 2 cm thick), food (45 g) and water (74 g). The measurements were performed in a room with certification for animal husbandry, which features automatic climate and light control for day night cycling. Four female mice, age 56 to 64 weeks of strain CD56/Black6 were used in the measurement. The measurements were performed as follows. The animals were placed inside the cages, the lid was closed and the data recordings were started. During measurements no humans were present in the room except for a short period to change out the cage inhabitants. Raw data of the IMU and the camera reference system are saved in packages of 10-min length. Data processing was performed after the measurement.

All in all, three datasets were collected: 27.67 h with one mouse (28 g) in the cage, 21.5 h with two mice (28 g and 27 g) and 9 h with three mice (28 g, 27 g, and 26 g). Each dataset consists of six IMU data streams at 4500 Hz (acceleration and gyro data each in the three axis) and a video stream at 1296×972 30 fps. However, only the first dataset with one mouse will be discussed in this work.

According to the ethical statement provided by the Landesamt für Umwelt-, Natur- und Verbraucherschutz of NRW Germany, these measurements are a pure observation without intervention in the habitat of the animals and therefore it is assessed not to be an animal experiment. Furthermore, food and water were provided in accordance to EU Directive (2010/63 EU) and the legal provisions of German Animal Welfare Act (TierSchG). Due to these circumstances ethical review and approval are waived.

2.3. Camera Reference System

It is necessary to determine the ground truth physical activity of the inhabitant for training of models, data analysis and evaluation. A camera-based reference system was developed for this, due to the availability of the deeplabcut framework for animal pose estimation [10] and because videos can be reviewed by humans. The system consisted of a PiCam NoIR-V1 camera module with a 160° field of view (FOV) lens. It was mounted in the lid of the cage which is modified with cutouts. The camera provided a top down view of the inside of the cage. A raspberry pi 4 was used to capture the camera images. The videos were processed afterwards, since deeplabcut is not real-time capable on the raspberry pi 4 hardware.

Physical activity can be described by many metrics and characteristics. In this work, velocity is chosen as a metric for activity, because it is a quantifiable measure of movement and can be reliably determined using deeplabcut by tracking the position of the inhabitant. The deeplabcut software package features pre-trained networks that are able to estimate the pose of various animals in various scenes. The pre-trained networks are retrained using a few manually annotated video frames. In this case, a deeplabcut network was retrained using 80 manually annotated video frames. The retrained deeplabcut network is then used to analyze a total of 16.17 h of video images. The deeplabcut network outputs the pose of the mouse as well as the likelihood of each label for each frame. Figure 3 shows a cropped video frame and the pose labels. The body shape of mice and the relative position of body parts varies drastically depending on the pose. In order to get a reliable velocity estimate, the head of the mice is chosen for velocity calculation, because it is rigidly coupled to the skeleton by the skull. Additionally, the head leads the motion of the body in most activities. The head velocity, in the following referred to as velocity, is calculated based on the position of the two ears and the headbase. The headbase is a point which lies between the ears. First the absolute velocity of each point is calculated separately using the position difference between two consecutive frames. Afterwards, the smallest of the three values is extracted for velocity estimation. This approach eliminates sudden velocity spikes that are caused by misclassification of individual points, which falsely suggest large movements. However, it leads to underestimation of velocity in rotational movements when velocity is different for the three points. However, in this case underestimation is more preferred than overestimation.

In order to determine activity classes based on velocity, seven clips of ten minutes each were manually labeled on a frame to frame basis using the activity labels: walking, digging, stretching, rotating, grooming and resting. These hand labels were chosen, because they are distinguishable from a top down view. Using these manually obtained activity labels, velocity-based activity classes are defined to establish the ground truth of physical activity.

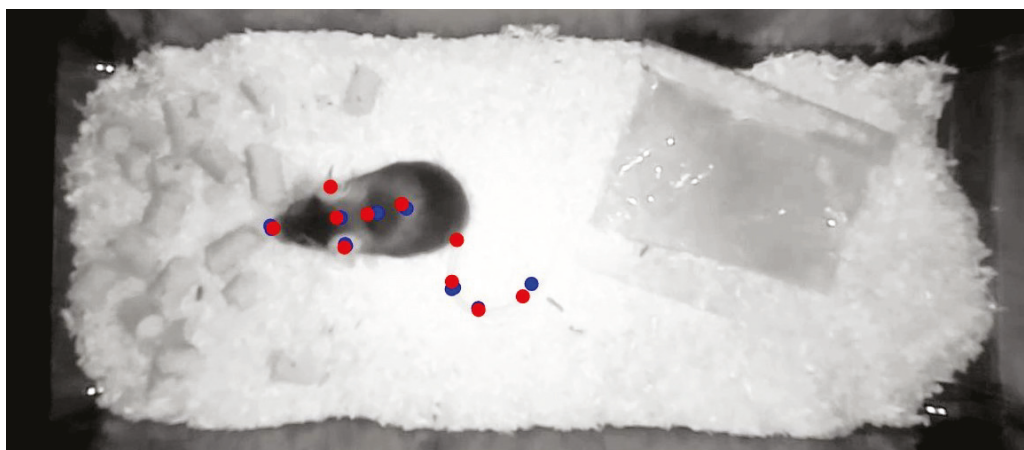


Figure 3. This figure shows a video frame of the camera reference system. The red dots illustrate manually set pose labels. The blue dots are estimates of a retrained deeplabcut network.

3. Activity Classes and Their Correlation to IMU Measurements

The data acquired using the measurement setup described in Section 2.2 holds important information that: (a) is used to define a metric for objective activity estimation in our use case and (b) shows correlation of certain cage vibrations and activities. These results are presented in the following.

3.1. Definition of Camera-Based Activity Classes

The analysis of the deeplabcut data shows that the position of the body parts right ear, left ear and headbase are estimated most reliably based on their average likelihood. Therefore, it is confirmed that these points are suitable for reliable velocity estimation.

The Figure 4 shows two graphs with four plots containing activity and velocity data of one of the aforementioned seven clips which were manually annotated with activity labels. These plots show ten minutes of mouse activity with (A) the raw velocity values as explained in Section 2.3 (B) the raw velocity values averaged over an interval of 15 s (C) the activity labels by visual inspection and (D) the velocity-based activity labels.

When looking at the activity labels obtained by visual inspection (C) shown in Figure 4, it is observed that activities such as walking, digging and grooming are rarely performed continuously over a longer period of time. Instead, these activities are alternated in short intervals of a few seconds. This can be seen in the latter half of the plot where the activities walking, stretching and rotating are quickly switched between. The only activity that is performed over longer periods is resting which is depicted in the first half of the charts. This type of behavior is also observed in the other six clips which were manually inspected. From these observations, it is concluded that the activity classes resting, grooming, rotating, stretching, digging and walking, which were defined for manual annotation, are too detailed and unrepresentative of typical activity patterns. Therefore, three new activity classes are proposed which summarize certain individual activities to describe the most common activity patterns. These classes are used as the ground truth of physical activity in the rest of this work. Furthermore, it is determined that activity classification is not reliable on a frame to frame basis. The reason for this is that the activity patterns only become apparent over longer periods of time. Therefore, it is proposed to evaluate activity based on intervals with a timeframe of 15 s. The 15 s length is chosen based on observations that show a typical minimum activity duration of about 15 s.

In order to achieve a reliable ground truth for activity classification, it is proposed to use the velocity of the mouse, as the metric for classification. The velocity is obtained from pose estimation using deeplabcut and is shown as (A) in Figure 4. For classification of an 15 s interval, the average velocity (B) is calculated from the raw velocity data (A). The class is then determined with thresholds which are derived from correlations between the velocity and the common activity patterns seen in the activity labels obtained by visual

inspection. This correlation can be seen in Figure 4 when comparing the plots of the two graphs. A detailed description of the activity classes and thresholds is given in the following. For reference, the mouse observed here has a length of approx. 200 px.

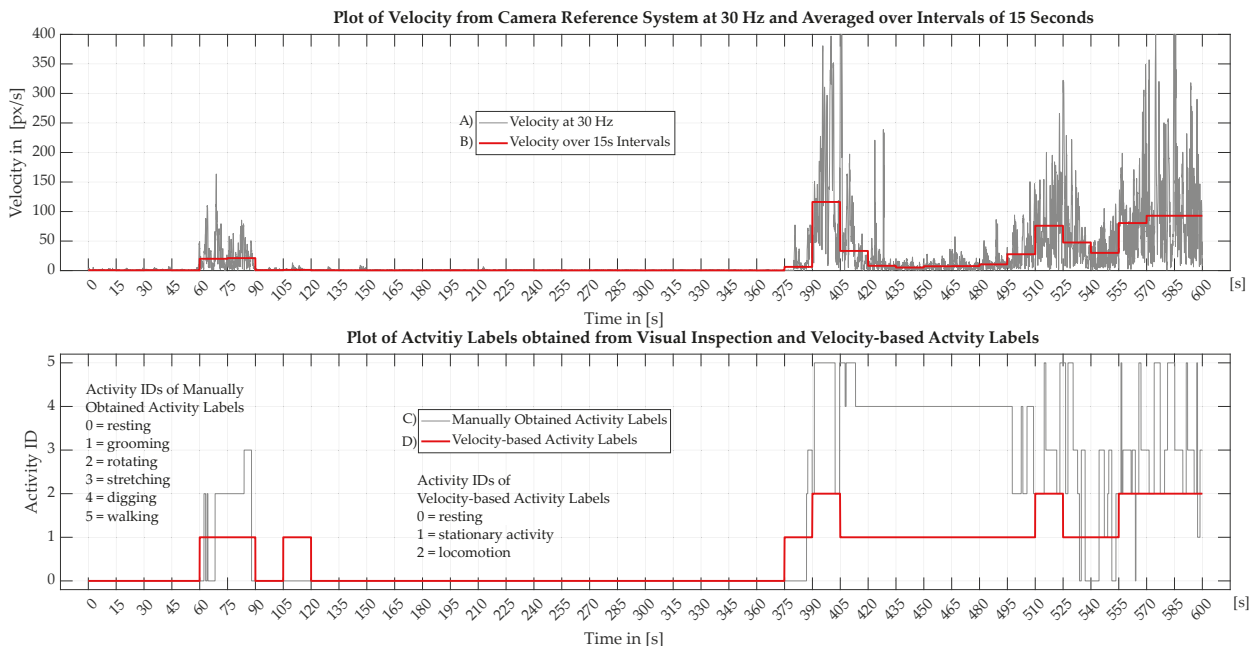


Figure 4. This figure shows two graphs with four plots containing various activity labels and the velocity of the mouse of a 10-min excerpt. The upper graph depicts the velocity of the mouse obtained from the camera reference system at 30 Hz as well as average values over intervals of 15 s. The lower graph illustrates activity labels from visual inspection of the camera images as well as velocity-based activity labels. The activity classes are depicted as activity IDs ranging from 0 to 5 for plotting purposes. The X-axis of the charts are synchronized.

Resting In phases where activity is manually labeled as resting, the mouse exhibits a particular lack of motion in a sleep-like state which is clearly distinguishable from all other activities. Therefore, a velocity-based activity class is defined for the activity resting. When looking at the velocity of several timeframes which only contain resting, an average velocity of 0.45 px/s with a standard deviation of 0.04 px/s is observed. Based on this observation, the velocity-based label *resting* is assigned to all timeframes with an average velocity lower than 1 px/s. This means that timeframes with an average velocity above 1 px/s most certainly contain activity.

Locomotion Locomotion is characterized by walking or a behavior where walking, digging, grooming, stretching and rotating are mixed up. It can range from slow walking to hopping. Timeframes during locomotion activities show an average velocity of 115.22 px/s with a standard deviation of 43.0 px/s. Based on this, timeframes with an average velocity of over 50 px/s are classified as locomotion. Due to the large standard deviation caused by the wide range of locomotion types, some misclassification is expected, for example during very slow walking.

Stationary Activity The class stationary activity contains all activities which are performed on the spot such as grooming, digging, rotation and stretching. During timeframes with the aforementioned activities but without walking, an average velocity of 20.73 px/s with a standard deviation of 17.0 px/s is observed. Based on this, all timeframes with average velocities between 1 px/s and 50 px/s are considered stationary activity. The velocity distribution during stationary activity lies between the other classes. However, some overlap to locomotion may occur which is a source of misclassification.

The velocity-based activity labels as defined above are depicted as (D) in Figure 4. In this graph it can be seen that these activity classes have good correlation with the patterns exhibited in the manually obtained activity labels. Therefore it is considered to be a reliable ground truth of physical activity.

Apart from that, there are less frequent cases of activities which are atypical for their classes. For example, sometimes the mouse lifts and moves the water filled jellypack, which involves another type of motion typically not observed during stationary activity. These cases are not represented in the activity classes.

3.2. Correlation of IMU Data and Activity

Based on the three activity classes defined in the previous section, characteristics of cage vibrations measured with the multi-axial IMU are analyzed with regards to different activities. The cage vibrations, respectively the IMU data, are analyzed in the frequency and time domain using Fourier and short Fourier transformation. The Figure 5 illustrates correlations by showing synchronized plots containing activity labels and accelerometer data in the frequency domain over a time of ten minutes.

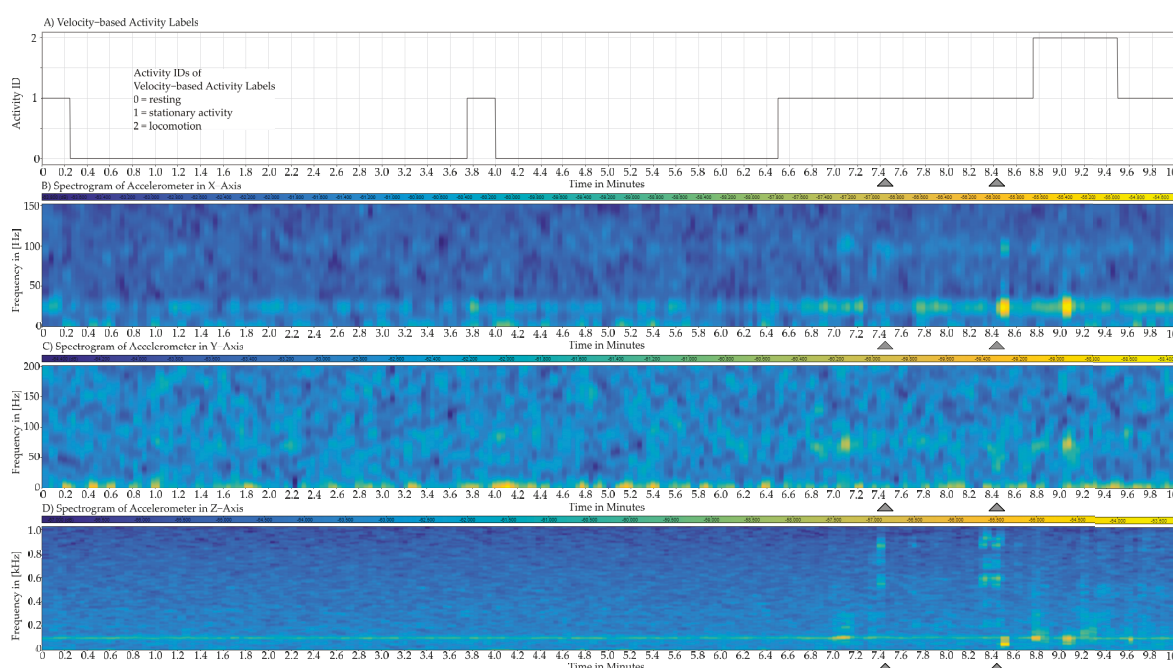


Figure 5. This figure shows four synchronized plots over a length of ten minutes which contain ground truth activity labels and the spectrogram of all accelerometer axis. The gray triangles mark two special case activities, that were observed by manually viewing the video recordings.

The Figure 5 shows four plots of a ten minute excerpt which depict the physical activity and the spectrogram of the accelerometer data. The spectrograms show the short time Fourier transformation of each of the three accelerometer axes. The Fourier coefficients are color coded, where blue represents a weak amplitude and yellow represents a strong amplitude. This figure serves to visualize correlations between the occurrence of vibrations in the three axes at certain frequencies and physical activity. With this visualization, multiple ten minute excerpts of data were analyzed and the observations are described in the following.

3.2.1. Data of the Accelerometer

In the X-axis, which corresponds to vibrations along the short horizontal side of the cage, vibrations are observed at a frequency of 25 Hz while activities take place. During resting phases, the 25 Hz vibration has a very low amplitude which is indistinguishable from the noise floor in some cases. This can be seen in the first half of the graphs in Figure 5.

In some instances when the inhabitant moves more strongly than usual, vibrations with higher frequency components are observed in a range of 100 Hz. This can be seen at the minute 8.5 and 9. Based on these observations, it is concluded that activity-induced vibrations most likely appear in a small frequency band around 25 Hz.

In the Y-axis vibrations with high amplitude are observed in the range of under 10 Hz. However, these have no apparent correlation with physical activity. Vibrations with weak amplitude in the range of 75 Hz to 80 Hz are infrequently observed during locomotion and stationary activity. During resting, these are indistinguishable from the noise floor. Based on these observations, activity-induced vibrations most likely appear in a range of 75 Hz to 80 Hz with small amplitude.

In the Z-axis, which lies perpendicular to the cage floor, a weak permanent vibration at 100 Hz persists regardless of the activity of the inhabitant. During locomotion and stationary activity, vibrations with frequency components in a range of 80 Hz to 250 Hz are observed. Most of the energy is concentrated around 120 Hz. These appear frequently during locomotion and are less common during stationary activity. This observation is made on several occasions including the clip shown in Figure 5. In some instances during locomotion or stationary activity, the inhabitant shows uncommon behavior with strong movements. For example, the mouse lifts and drops the jellypack during stationary activity which is not represented in the activity labels and has to be identified by manually viewing the video recordings. While this behavior occurs, vibrations with frequency components of 500 Hz to 1000 Hz are observed. These can be seen in Figure 5 where they are marked with the grey triangles. From these observations it is concluded that activity-induced vibrations commonly appear in a range of 50 Hz to 250 Hz.

In some instances not shown in Figure 5, high amplitude broadband vibrations are measured in all sensor axis. Velocity-based activity labels and manual reviewing of video material do not show any correlation to the behavior of the inhabitant.

In separate tests, measurements were made to evaluate the base sensors noise of the ICM20948 IMU. The results show a RMS noise of 6.6 mg, 6.5 mg and 6.4 mg for the X, Y and Z-axis of the accelerometer which lie within the margin of error of the value of 6.7 mg specified by the manufacturer.

3.2.2. Data of the Gyroscope

In viewing the angular rate sensor data with regards to the velocity-based activity labels, activity-induced vibrations above the noise floor were not observed. Consequently, no activity related information could be obtained from the angular rate sensor of the IMU used in the measurement.

In separate tests, measurements were made to evaluate the base sensors noise of the ICM20948 IMU. The data of the gyroscope shows a RMS noise of 1.278 dps, 1.991 dps and 1.691 dps for the X, Y and Z axis which is slightly higher than the value of 1.65 dps specified by the manufacturer.

4. Method for IMU-Based Activity Classification

The result of the activity-induced vibration analysis, described in Section 3.2, suggests a strong correlation between the occurrence of certain signals in the three axis of the accelerometer data and the activity of the cage inhabitant. With these results, a feature set and a classification model are developed to classify the physical activity of the inhabitant only using data of the IMU. Classification is performed of 15 s intervals as previously defined in Section 3.1. A multi-class supervised approach is chosen based on the activity classes of the reference method defined previously. The classification model is trained using the Matlab Classification Learner app.

The feature set consists of statistical and frequency-domain features of the three IMU accelerometer axis. Features in the frequency domain are calculated using fast Fourier transform (FFT) algorithm and defined based on the findings of Section 3.2. The features are calculated over the 15 s timeframe and are listed below:

The dataset for training and testing is derived from 16.17 h of IMU measurements of cage vibrations and camera-based ground truth of physical activity. For obtaining the dataset, first the continuous data stream is divided into sections with a timeframe of 15 s. Each section is processed individually and represents one data point. A data point consists of two elements: (a) the 11 IMU-based features (b) the associated velocity-based activity label which represents the ground truth.

The whole dataset consists of 3880 data points. 1000 data points (26%) are randomly selected and withheld for testing. The remaining 2880 data points (74%) are used for training and validation of classification models. After evaluation and testing of the classification model, a final classifier is trained using all available data points. Multiple classification models are automatically trained and validated using the Matlab Classification Learner app, including decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naive Bayes, kernel approximation, ensemble, and neural network classification. Five-fold cross-validation is used for validation during training.

4.1. Method for Continuous Activity Monitoring

The continuous activity monitoring of the inhabitant of the husbandry cage is performed with the classification algorithm described above by analyzing consecutive intervals of the continuous IMU data stream. The continuous data stream is divided into sections with a duration of 15 s. The time at the beginning of each section is recorded in order to assign the activity classification to a point in time. Then, activity is estimated as described above by calculating the features and applying the classification model. The result is continuous monitoring of activity with a time resolution of 15 s.

5. Results on IMU-Based Activity Classification

All in all, 3880 data points (74% of the dataset) containing the features listed in Table 1 were used in the training of multiple classification models. Another 1000 data points (25.7%) were used for testing. The training dataset contains 1105 (38.37%) samples of the activity class resting, 1317 (45.73%) samples of the class stationary activity and 458 (15.9%) samples of class locomotion. The test dataset contains 321 (32.1%) samples of the activity class resting, 510 (51.0%) samples of the class stationary activity and 169 (16.9%) samples of class locomotion. The results of the evaluations are presented in the following.

Table 1. Feature set for classification of physical activity based on 3-axis accelerometer data of a cage mounted inertial measurement unit.

Number	Axis	Description
1	X	Relative average of FFT coefficients in the interval 23 Hz to 27 Hz
2	X	Absolute average of FFT coefficients in the interval 23 Hz to 27 Hz
3	X	RMS of time-domain signal
4	Y	Relative average of FFT coefficients in the interval 62 Hz to 80 Hz
5	Y	Absolute average of FFT coefficients in the interval 62 Hz to 80 Hz
6	Y	RMS of time-domain signal
7	Z	Relative average of FFT coefficients in the interval 80 Hz to 120 Hz
8	Z	Absolute average of FFT coefficients in the interval 80 Hz to 120 Hz
9	Z	Relative average of FFT coefficients in the interval 60 Hz to 180 Hz
10	Z	Absolute average of FFT coefficients in the interval 60 Hz to 180 Hz
11	Z	RMS of time-domain signal

5.1. Best Fit Classification Model

In multiple training runs involving all classification models available in the Matlab Classification Learner app, validation accuracy between 68% and 80% are observed. The optimizable ensemble classification model achieved the best results in validation and test accuracy persistently. Consequently, it was deemed best fit to this classification problem and used in the following evaluations.

5.2. Classification Accuracy

The optimizable ensemble classification model achieves a validation accuracy of 82.3% and a test accuracy of 79.8% when all features are used. The confusion matrix is presented in Figure 6. In testing, the class resting has the highest true positive rate (TPR) of 94.1% with a PPV of 84.8%. The class stationary activity ranks second and achieves a TPR of 82% with a positive predictive value (PPV) of 80.2%. The class locomotion achieves a TPR of 46.2% with a PPV of 63.4%.

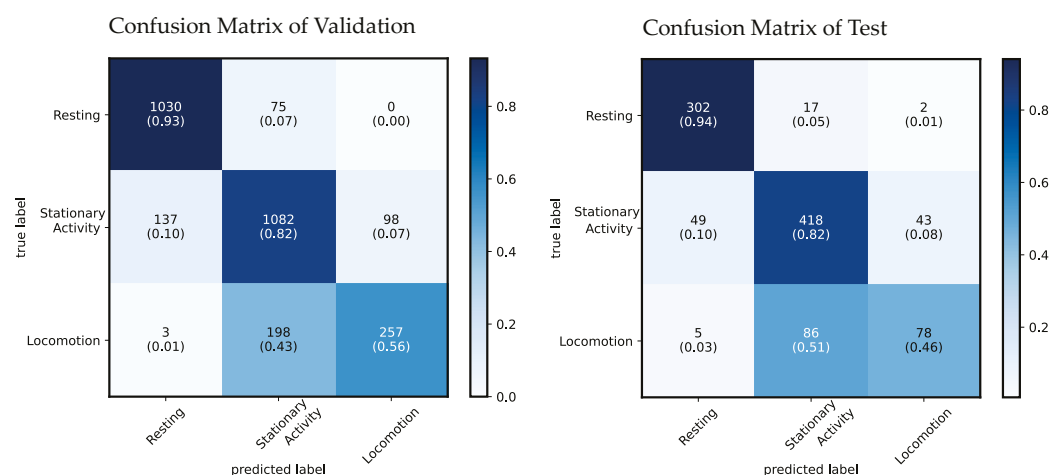


Figure 6. This figure shows the confusion matrix of an optimizable ensemble classification model which computes eleven features. The numbers in the boxes show the amount of samples. The numbers in the brackets below show the relative amount of samples. Validation results are displayed on the left and test results on the right.

When comparing the results of the validation during training and the results achieved on unseen test data, the total accuracy differs by 2.5%. In the classes resting and stationary activity the TPR between validation and testing differs by less than a percent. In the class locomotion a difference of about 10% is observed.

5.3. Results of Using Features from Different Vibration Axes

In order to evaluate the information contained in the data of each accelerometer axis, five optimizable ensemble classification models were trained with different features. The results are presented in Table 2.

The best accuracy is achieved by the classification models which use all features and features from the X- and Y-axis accelerometer data combined. They are followed by the model using Z-axis features, then the model using X-axis features and at last the model using Y-axis features.

Table 2. This table shows the test results of five ensemble classification models. The models were trained using different sets of features which is described in the left most column. TPR stand for true positive rate and PPV for positive predictive value.

Classes	Resting		Stationary Activity		Locomotion		Accuracy
	TPR	PPV	TPR	PPV	TPR	PPV	
All Axis	94.1%	84.8%	82.0%	80.2%	46.2%	63.4%	79.8%
X- And Z-Axis	93.5%	85.7%	83.5%	80.1%	46.2%	66.1%	80.4%
Only X-Axis	86.6%	84.5%	83.1%	71.7%	25.4%	53.8%	74.5%
Only Y-Axis	79.8%	48.6%	41.4%	59.1%	32.0%	46.6%	52.1%
Only Z-Axis	93.1%	77.1%	71.8%	79.2%	49.1%	55.3%	74.8%

5.4. Final Classification Model

The final classification model is trained using all 3880 available data points. All features are used in the training of this optimizable ensemble classification model. The validation result is shown in Figure 7.

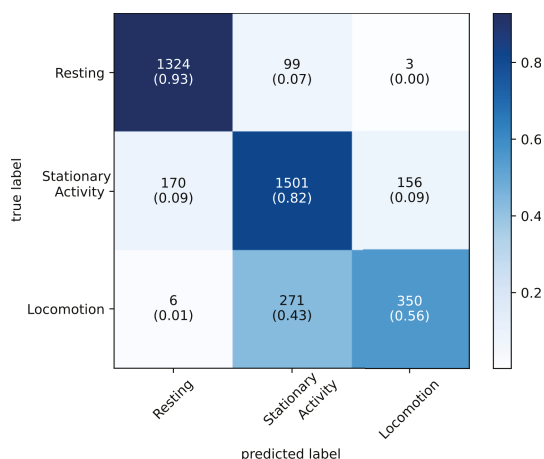


Figure 7. Confusion matrix of the final classification model using all available data points. The numbers in the boxes show the amount of samples. The numbers in brackets below show the relative amount of samples.

Validation shows an accuracy of 81.8%. The class resting has the highest TPR of 92.8% with a PPV of 88.3%. The class stationary activity ranks second and achieves a TPR of 82.2% with a PPV of 80.2%. The class locomotion shows a TPR of 55.8% with a PPV of 68.8%.

5.5. Application of Continuous Activity Monitoring

Using the method described in Section 4.1, continuous activity monitoring is demonstrated on the measurements obtained at the VTK. The final classification model, which is trained using 16.17 h of data, is used to analyze the 27.67 h of data collected during the measurements at the VTK. The 16.17 h of data used for training are contained in the 27.67 h of data. For continuous activity monitoring, the data are divided into sections with a timeframe of 15 s length. Each timeframe is classified individually. The output of this operation is an array with 6640 elements. Each element contains the point of time and the activity label. The output array is plotted in Figure 8.

Figure 8 shows the result of the proposed method for continuous activity monitoring over a timespan from 9:23 to 15:30 of the next day. The figure shows two plots. The upper plot contains each individual activity classification which has a duration of 15 s. The lower graph shows a summarized representation where activity is described by the percentage of occurrence of each label over an interval of 30 min. The activity classes are color coded. The color black stands for resting, gray for stationary activity and red for locomotion. The mouse is placed in the measurement cage a few minutes prior to the start of the measurement period. The room where the cages were placed was only visited in the period which is marked by the circled number two. Otherwise no humans intervened during the measurements. The light of the room is dimmed between 19:00 and 7:00 to simulate the night which is marked by the bar with the circled number 3. Between 5:30 and 8:20 the sensor detached from the cage which is clearly indicated in the IMU data. As a result, no IMU data are collected in this time span. At around 8:20, the sensor is reattached and the data acquisition is continued.

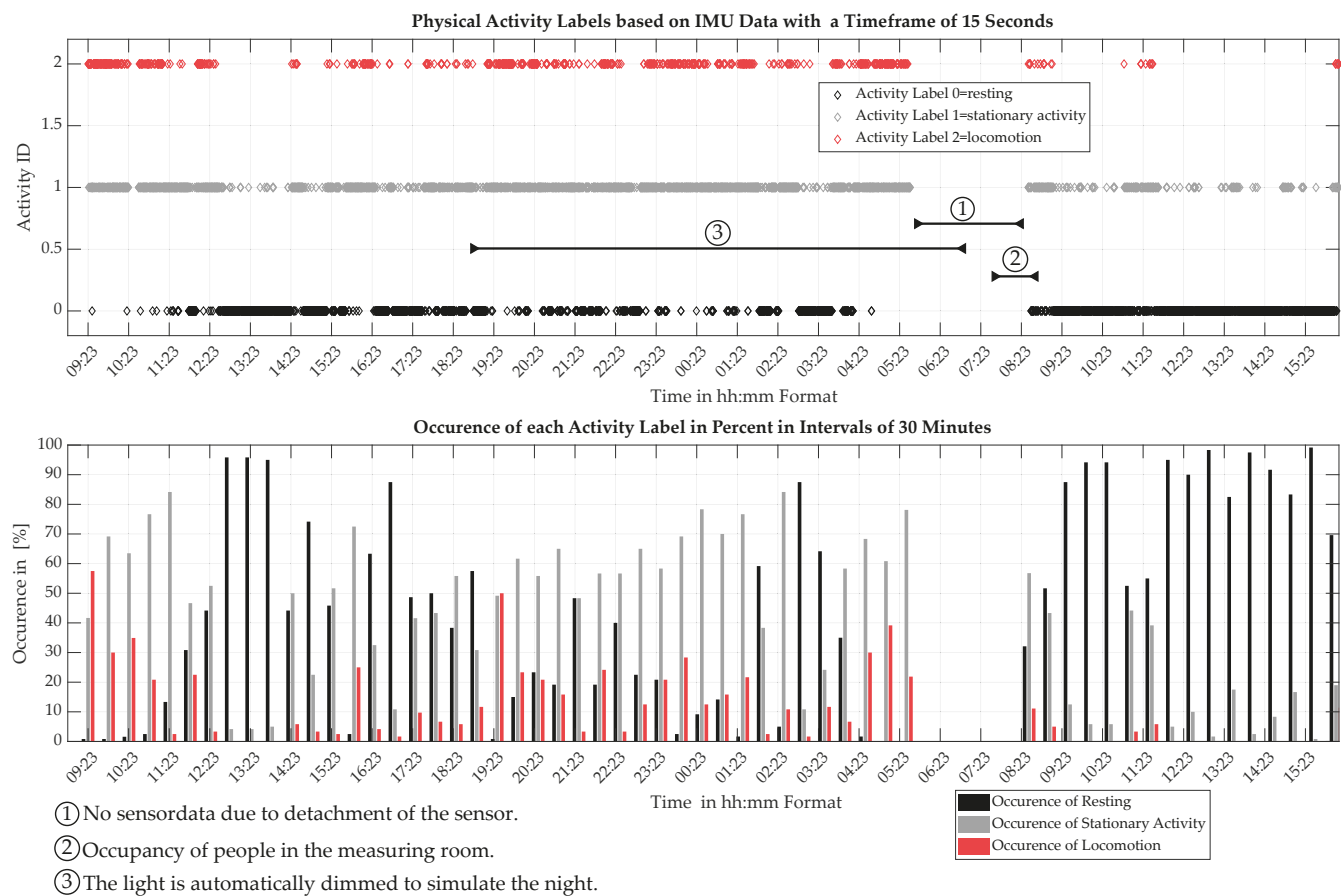


Figure 8. This figure shows the physical activity of the inhabitant of the husbandry cage over one and a quarter of a day. The activity labels are estimated from cage vibrations measured with an 9-axis IMU. The upper plot shows 6640 data points of activity labels which represent the activity patterns of 15 s intervals. The lower plot shows the occurrence of each activity in an interval of 30 min in percent. Special events are marked using bars.

The graphs shown in Figure 8 clearly depict patterns of activity which change over time. In the time period between 9:30 and 11:30 a lot of locomotion is observed at the beginning which decreases more or less linearly. This is followed by a phase dominated by resting which lasts until 19:00. Between 19:00 and 5:40 higher activity levels are seen with increased locomotion of around 10% to 20% and little resting phases as well as a lot of stationary activity at over 50%. The time period from 8:23 to 16:00 is dominated by resting which is interrupted by the occasional stationary activity and locomotion. In total, the activity is monitored over 27.67 h. The inhabitant is observed to rest for a total of 13.09 h. In sum, stationary activity is observed over 11.44 h and locomotion over 3.13 h

6. Discussion

In this work, a proof of concept is presented for a method to continuously monitor activity based on measurements of structural vibrations using a multi-axial IMU. In order to proof the feasibility of the concept, two major questions were explored. These are the performance of multi-axial MEMS IMU in measuring structural vibrations as well as physical activity monitoring based on data of an IMU mounted on a husbandry cage. The results are discussed in the following chapter.

6.1. Mechanics of Activity-Induced Cage Vibrations

The measurements of the IMU depict the vibration of the cage at the mounting point in the three spatial directions. The vibrations in the three axis exhibit different characteristics

in frequency, amplitude, decay rate and occurrence. In the analysis, various patterns are evident that correlate with the physical activity of the inhabitant. Based on the rather high frequency of these vibrations, it is evident that these vibrations do not directly correspond to periodic impulsive forces such as footsteps or grooming. It is hypothesized that these vibrations are natural vibrations of the cage which are induced by non-periodic impulsive forces generated during activity.

Based on this hypothesis, vibrations measured in the Z-axis of the IMU, which exhibit a typical frequency of 120 Hz, most likely correspond to the membrane-like natural oscillation of the cage floor. This theory is supported by the FEM result which predicts oscillation of the cage floor at 130 Hz. The lower frequency seen in the measurements is explained by the added mass of the bedding and the mouse inside the cage, which are neglected in the simulation.

The vibrations measured in the X- and Y-axis of the IMU most likely correspond to an oscillatory movement of the cage in the horizontal plane. These can either be deformations or movement of the cage in the suspension. Nevertheless, the vibration characteristics such as frequency and amplitude are determined by the geometry and material properties and are different in the X- and Y-axis.

In summary, the analysis of the IMU data clearly shows three dimensional activity-induced structural vibrations of the husbandry cage. The observed activity-induced vibrations exhibit frequencies in the range of 0 Hz to 250 Hz with higher frequency vibrations generated by strong movements in the range of 500 Hz to 1000 Hz. From these results it is concluded that commercial MEMS IMU are capable of measuring activity-induced structural vibrations for classification of activity. Furthermore, these sensors have the necessary frequency bandwidth to measure the natural oscillations of the cage which are induced by activity.

6.2. Quality of Reference Activity Labels

The camera reference system classifies activity based on the two dimensional velocity of the mouse inside the cage which is used as ground truth to classify activity based on cage vibrations measured with an IMU. Three activity classes are defined for velocity-based classification which represent the most frequent behavior patterns resting, stationary activity and locomotion. When comparing data of the velocity-based activity classes to the activity labels obtained by visual inspection, it is observed that the velocity-based activity classes are a good representation of mice behavior. However, the three classes only represent an approximation of activity, due to the complex nature of physical activity.

In comparison, the velocity-based activity class resting is well distinguished from the other classes due to the narrow distribution of velocities during resting phases. Therefore, good separation of non-activity (resting) and activity (the other two classes) is achieved. However, due to the wide distribution of velocities in the classes stationary activity and locomotion, some uncertainty remains in the distinction of the two classes. Among other things, this is due to the fact that the intensity and quantity of movement varies drastically in the defined classes. Due to these circumstances, the velocity by itself is not conclusive enough for correct classification of the behavior. In order to improve the activity estimate, additional metrics such as distance traveled in a timeframe is proposed to be used.

6.3. Performance of Activity Classification Using IMU-Based Cage Vibrations

In the evaluation of the classification model, similar results were achieved in the validation of the training dataset and testing of the test dataset. It is concluded that generalization error of the classification model is small which makes it suitable to analyze previously unseen data.

The results presented in Section 5.3 provide insight into the activity-related information contained in the vibrations measured in each axis. All in all, the classification model which uses all features achieves the best results. The classifier which uses data of the X- and Z-axis achieves similar results. A significant difference could not be determined. The classification

model, which only uses features from the vibrations in the Y-axis, achieves poor accuracy and PPV of around 50%. These results suggest activity-related information contained in the data of the Y-axis is small. The classification models, that use data of the X- or the Z-axis exclusively, achieve a similar accuracy. However, significant differences are seen when comparing the TPR and PPV of the models in different classes. From these results, it is concluded that the information contained in the data of different axes are non-redundant and enable better overall classification when information is fused for classification.

Furthermore, the evaluation of the models shows that classification performance differs significantly between the classes. In the following, classification performance of the individual activity classes is discussed:

Resting: Very good performance is achieved in the classification of resting with a TPR of about 94% and a PPV of about 85%. The results from Section 5.3 show that resting is best classified when features from the X- and Z-axis are used in combination. This is supported by the analysis from Section 3.2 which shows that activity-induced vibrations have a particularly low amplitude and occurrence during resting. The observations show that the mouse sleeps or is in a sleep-like state during resting phases. In this state, the mouse almost does not move which in turn generates almost no vibrations. As a result, resting can be differentiated well even from stationary activity.

Stationary Activity: The class stationary activity is classified reliably with a TPR of 82.0% and a PPV of 80.2%. Stationary activity is misclassified as resting in about 10% of cases. This is in part explained by phases with little movement that sometimes occur during time periods with stationary activity. In other cases, stationary activity is misclassified as locomotion which is in part due to strong movement on the spot which induces vibrations in the Z-axis of the cage floor. One exemplary case is when the mouse interacts with the jellypack and throws it to the ground which generates strong vibrations in the Z-axis. Table 2 shows that the model only using X-axis features achieves better TPR in classifying stationary activity by about 11%, compared to the model only using Z-axis features. This is attributed to the observations, that vibrations in the X-axis occur very reliably during any sort of activity, while vibrations in Z-axis mostly occur in locomotion activity shows that stationary activity has a higher TPR in the model only using X-axis

Locomotion: The class locomotion is classified unreliably with a 56% TPR and 63.4% PPV. However, when locomotion is misclassified, it is almost exclusively misclassified as stationary activity. Locomotion is only misclassified as resting in 1% to 3% of cases. This suggests that the information extracted from the IMU data is not sufficient to reliably distinguish between stationary activity and locomotion. The results presented in Table 2 show that the model using Z-axis features has a 23.7% better TPR than the model using X-axis data. This result shows that features from the Z-axis are the best predictors of locomotion. This is supported by the observations in Section 3.2 which indicate that vibrations in the Z-axis are measured more frequently during locomotion than during the other two classes. The vibrations in Z-axis are thought to be membrane-like vibrations of the cage floor that are induced by impulsive forces generated by steps. However, the analysis also shows that these vibrations appear unreliably during locomotion which is a contributing factor to the unreliable classification of locomotion. It is likely that step induced vibrations occur more frequently than measured but exhibit an amplitude that is indistinguishable from the sensor noise.

6.4. Continuous Activity Monitoring

The method for continuous activity monitoring described in Section 5.5 is used on the IMU measurements of over one and a quarter day made at the VTK. It demonstrates the continuous monitoring of the activity of a mouse inside a husbandry cage. The monitoring

data, shown in Figure 8, depicts clear trends and behavioral patterns that are discussed in the following.

In the beginning of the measurement period, the data shows high activity levels with little to no resting and a lot of locomotion which decreases almost linearly in the timespan between 9:23 and 11:30. This behavior is attributed to an acclimatization phase due to being put into a freshly cleaned and replenished cage. Furthermore, data suggests a nocturnal behavior where higher levels of activity are observed in the evening hours between 19:00 and 8:30 and lower levels of activity during the day, especially between 8:30 and 15:30 of the second day. These observations coincide with the expected nocturnal behavior of mice and suggests that general behavioral patterns can be deduced from the activity monitoring data.

Over the whole measurement period of 27.67 h, monitoring data shows a total resting time of 13.09 h and a total active time of 14.57 h. This results suggests a sleep duration of 47% per 24 h, although this value is somewhat imprecise due to the data loss between 5:30 and 8:20 in the morning. However, the observed resting time coincides with literature [29] which suggests that mice spend about 40% to 50% of a day sleeping or in a sleep-wake state.

In conclusion, the data derived from the proposed continuous activity monitoring method shows clear behavioral patterns that coincides with the expected behavior described in the literature. Therefore, it is concluded that this method is able to monitor the activity of the mouse to such an extent that reliable statements about the general behavior can be made. In addition, the method also enables the estimation of activity duration such as time spend sleeping per day. However, for confirmation if activity durations can be extracted reliably, more data must be collected for evaluation.

7. Conclusions

In this work, a novel method is presented for physical activity classification and monitoring, which uses a multi-axial IMU SOC to measure structural vibrations in multiple axes. The method is demonstrated in the use case of continuous activity monitoring of a mouse in a shoe-box-style husbandry cage. In this use case, an IMU is mounted in the center of the underside of the cage floor to measure structural vibrations in the three spatial directions. The vibrations are measured in three axes as acceleration and angular rate. A reference system is developed which uses top-view video recordings to classify physical activity into the classes resting, stationary activity and locomotion. These classes are defined using observations obtained by visual inspection of videos and reflect the most common physical activity patterns. The reference system is assembled in the lid of a husbandry cage. This setup is used to obtain 27.67 h of IMU data of cage vibrations as well as synchronized video recordings. Based on this data, different activity-induced vibration modes of the cage are identified as well as their correlation to certain activity patterns. From this, eleven features are defined as predictors of activity classes which contain and fuse information from the X-, Y- and Z-axis accelerometer data. These features are used to train a classification model with a dataset containing 16.17 h of IMU cage vibrations and ground truth activity labels. The resulting classification model achieves a TPR of 94% in classifying resting, 82% in classifying stationary activity and 46% in classifying locomotion on previously unseen data which was withheld from training. Using this classification model, continuous activity monitoring is demonstrated on the 27.67 h of collected IMU data which spans a period of 9:30 a.m. to 15:30 p.m. of the next day. The results of the proposed monitoring method clearly illustrate the behavioral patterns of the mouse which coincide with the expected behavior described in literature. Additionally, the method is able to measure the duration of activities such as sleeping which is useful for the assessment of health.

In summary, a novel method is demonstrated which enables continuous activity monitoring of a mouse in a husbandry cage using a non-contact non-invasive sensing method. This sensing method, allows for the monitoring of physical activity in regular husbandry cages where mice spend most of their lives. In addition, hardware requirements only consist of an IMU, which is mounted on the outside of the floor of the cage. Furthermore,

it is shown that more information is extracted and better activity estimation achieved, when structural vibrations are measured in multiple axes and the data fused. As a result, excellent results are achieved in the distinction between activity (the classes stationary activity and locomotion) and non-activity (the class resting). The impact of this work is a powerful method to continuously monitor physical activity using a low-cost IMU. This method for activity monitoring provides a tool to assess the activity of an animal inside its regular habitat on a large scale, which opens up many possibilities to automatically monitor wellbeing and create optimized work flows.

8. Future Work

Based on the promising results in this work, one goal of future work is to expand the application scenario to the activity monitoring of multiple inhabitants in one husbandry cage. Data of this scenario was previously collected which is described in Section 2.2.

As described in Section 6.3 it is likely that many activity induced vibrations in the Z-axis remain undetected due to sensor noise. In addition, no activity-induced signals are observed in the data of the angular rate sensor. For this reason, other commercial IMU with lower sensor noise are to be investigate for improved sensing of activity-induced structural vibrations. Furthermore, the use of magnetometers in a sensor system for sensing structural vibrations will be investigated due to the full market penetration of low cost 9-axis IMU in portable devices. These sensor modules contain nine orthogonally mounted triads of accelerometers, angular rate sensors and magnetometers.

In analyzing the results, there is evidence for cage vibrations in X- and Y-axis. It is beyond the scope of the work presented here, which is a proof of concept for activity monitoring, to discuss structural dynamics in depths. Therefore, extensive FEM modal analysis of the cage is planned, to identify oscillation modes of the cage and their correlation to activity-induced impulsive forces.

A major aspect of future works is research on algorithms, classification methods and sensors for more accurate activity monitoring. First, more sophisticated algorithms will be investigated to analyze the individual activity-induced structural vibration. For example, wavelet transformation-based filtering of time domain signals which will be used to detect individual activity-induced vibrations in the time domain. It is also investigated, how activity-related information can be obtained from the angular rate sensor and magnetometers, which will be fused to improve activity classification. In addition, more secure mounting solutions are developed to prevent detachment of the IMU from the cage. At last, due to their small size it will be investigated how multiple IMU can be integrated into a sensor system to achieve more accurate detection of activity-induced structural vibrations and in turn improve activity classification.

Lastly, the camera reference system is to be improved and made real-time capable in classifying activity using top-view video images. This enables longer measurement periods for evaluation and training purposes which were challenging previously due to the massive amount of video data produced.

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Conflicts of Interest: The authors declare no conflict of interest.

Ethical Statements: The measurements in this work were performed in the regular habitat of the animals and the animals were not influenced or interacted with in any way. The measurements served only to measure cage vibrations. Our setup meets all guidelines of the EU Directive 2010/63 and the German Tierschutzgesetz. Therefore, the measurements performed here are not classified as animal experiments and do not need approval.

Abbreviations

The following abbreviations are used in this manuscript:

FOV	field of view
IMU	inertial measurement unit
MEMS	micro-electro-mechanical system
RFID	radio-frequency identification
IVC	individually ventilated cage
FEM	finite element method
SOC	system on a chip
RMS	root mean square
FFT	fast Fourier transform
TPR	true positive rate
PPV	positive predictive value
MIMU	magneto-inertial measurement unit
VTK Aachen	Institute for Laboratory Animal Science Aachen

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Real-Time Temperature Monitoring under Thermal Cycling Loading with Optical Fiber Sensor

Shiuh-Chuan Her * and Jr-Luen Tasi

Department of Mechanical Engineering, Yuan Ze University, Chung-Li 320, Taoyuan 32003, Taiwan;
s985033@mail.yzu.edu.tw

* Correspondence: mesch@saturn.yzu.edu.tw; Tel.: +886-3-463-8800

Abstract: A fiber optic sensing system consisting of a fiber Bragg grating (FBG) sensor, optical circulator, optical band pass filter and photodetector is developed to monitor the real-time temperature response of a structure under a dynamic thermal loading. The FBG sensor is surface-bonded on a test specimen and integrated with an optical band pass filter. As a broadband light source transmits into a FBG sensor, a specific wavelength is reflected and transmitted into an optical band pass filter. The reflected wavelength is significantly affected by the temperature, while the output light power from the optical band pass filter is dependent on the wavelength. By measuring the light power with a photodetector, the wavelength can be demodulated, resulting in the determination of the temperature. In this work, the proposed optical sensing system was utilized to monitor the dynamic temperature change of a steel beam under a thermal cycling loading. To verify the accuracy of the fiber optic sensor, a thermocouple was adopted as the reference. The experimental results illustrate a good agreement between the fiber optic sensor and thermocouple. Electronic packages composed of various components such as a solder joint, silicon die, mold compound, and solder mask are frequently subjected to a thermal cycling loading in real-life applications. Temperature variations' incorporation with mismatches of coefficients of thermal expansion among the assembly components leads to crack growth, damage accumulation and final failure. It is important to monitor the temperature to prevent a thermal fatigue failure. A fast response and easy implementation of the fiber optic sensing system was proposed for the real-time temperature measurement under thermal cycling loading.

Keywords: fiber Bragg grating; optical band pass filter; thermal cycling loading; real-time

1. Introduction

Sensing technology plays an important role in structural health monitoring, since in-service monitoring can provide real-time information to improve the safety and performance of engineering structures. Various sensors with different working principles have been proposed for structural health monitoring [1,2]. Traditional strain or temperature sensors such as a strain gauge and thermocouple mainly rely on electrical working principles to detect strain or temperature. The major drawbacks of these sensors include the sensitivity, cross talk, vulnerability to harsh environmental conditions and their sizes [3]. Fiber optic sensors have several advantages over traditional sensors, such as a compact size, corrosion resistance, multiplex capability, and immunity to electromagnetic interference [4,5]. Moreover, fiber optic sensor exhibits a broad bandwidth, which permits a fast transmission of a huge amount of information in the same optical fiber [6]. With the rapid progress of optical fiber sensing technologies, many fiber optic sensors based on different operational principles have been developed, such as reflectometry-based sensors (Brillouin and Rayleigh scattering), grating-based sensors (FBG), and interferometry-based sensors (Mach–Zehnder and Michelson) [7,8]. Choi et al. [9] detected the impact location and residual strain of a composite pressure vessel using a phase-modulated optical fiber

sensor based on Brillouin frequency. Lu et al. [10] developed a distributed optical fiber sensing system to discriminate temperature and strain based on coherent Rayleigh scattering. Zhao et al. [11] proposed a low-frequency vibration sensor based on the Mach–Zehnder Interferometer with a maximum error of 0.27%. Li et al. [12] developed a highly sensitive optical sensor based on the Michelson interferometer with a measured sensitivity of up to 77 pm/mm for a water level ranging from 0 to 40 mm.

FBG sensors based on the shift of the reflecting particular wavelength of light are the most common fiber sensing technology for structural health monitoring (SHM) [13]. They are highly sensitive to changes in both the strain and temperature. Due to the mature processing technology and low fabrication cost, a variety of applications for FBG sensors have been proposed. Szebenyi et al. [14] demonstrated the capability of FBG sensors integrated between the reinforcing layers of composites for cyclic creep strain monitoring and fatigue failure prediction. Hong-kun et al. [15] reported an optical fiber pressure sensor using two FBGs to reduce the cross-sensitivity between the temperature and pressure, leading to a high pressure sensitivity of 1.198 nm/MPa in the range of 0–1 MPa. Lv et al. [16] developed an optical fiber sensor consisting of two FBGs for simultaneous measurements of the flow rate and temperature in a pipeline, with an accuracy of 2.27% and ± 1 °C, respectively. Jang and Kim [17] utilized an FBG sensor to detect impact-generated acoustic emission (AE) signals and to analyze the wavelet transform (WT) method for real-time delamination monitoring of a composite plate. Weisz–Patrault et al. [18] evaluated the contact stress during a cold rolling process with FBG sensors. Tsukada et al. [19] investigated the residual strain distribution in a thick thermoplastic composite during a high-rate manufacturing process using FBG sensors. Anastasopoulos et al. [20] developed a novel damage detection method based on the strain modal shape obtained from fiber-optic Bragg grating strain sensors.

Temperature sensors have been widely used for temperature monitoring in many different applications such as machinery components, power plants, electric devices, kitchen appliances, heating ventilation and air conditioning devices. There are many different types of temperature sensors, based on different working principles, that are used to measure the temperature. Among them, thermocouples and thermistors are the most common temperature sensors that are used. Both thermocouples and thermistors are point-wise sensors, and their lacking capability in terms of continuum-wise measurements is their major drawback. On the contrary, FBG sensors are highly sensitive to the temperature, and their multiplex capability can be prepared in a series of same optical fibers in order to conduct continuum-wise measurements. In this work, an FBG sensor is incorporated with an optical band pass filter and a photodetector to monitor the temperature of structures. The wavelength shift of the FBG sensor induced by a temperature change is converted to a variation of light power through an optical band pass filter. The light power is measured by a photodetector. A fast response of the photodetector allows for the real-time monitoring of the structural temperature. Thermal cycling is an environmental test that is commonly used to evaluate the reliability of materials or electronic devices and to detect any manufacturing defects early during the thermal fatigue. Electronic packages composed of various components such as a solder joint, silicon die, mold compound, and solder mask are frequently subjected to a thermal cycling loading in real-life applications [21]. Temperature variations' incorporation with mismatches of coefficients of thermal expansion among the assembly components leads to crack growth, damage accumulation and final failure [22]. It is important to monitor the temperature to prevent a thermal fatigue failure. The proposed FBG sensor was employed in order to monitor the real-time temperature response under a thermal cycling loading.

2. Bragg Wavelength Shift

FBG possesses a periodic variation in the core refractive index along a length of an optical fiber. When a broadband light transmits into FBG, a specific wavelength known as Bragg wavelength λ_B is reflected, while the remaining portion of the broadband light

passes through. The Bragg wavelength can be expressed in terms of the grating period Λ and refractive index n_0 as follows:

$$\lambda_B = 2n_0\Lambda \quad (1)$$

The changes of the grating period and refractive index due to the mechanical strain ε and temperature variation ΔT exerted on the FBG induce a Bragg wavelength shift $\Delta\lambda_B$, which can be expressed in terms of the sum of the strain and temperature contributions as follows [23]:

$$\frac{\Delta\lambda_B}{\lambda_B} = k_\varepsilon\varepsilon + k_T\Delta T \quad (2)$$

$$k_\varepsilon = 1 - \frac{1}{2}n_0^2[(1 - \nu_f)p_{12} - \nu_f p_{11}] \quad (3)$$

$$k_T = \left[1 - \frac{1}{2}n_0^2(p_{11} + 2p_{12})\right]\alpha_f + \frac{\xi}{n_0} \quad (4)$$

where k_T and k_ε represent the temperature and strain coefficients of the FBG sensor, respectively, n_0 , ν_f , α_f and ξ are the refractive index, Poisson's ratio, coefficient of thermal expansion and thermo-optic coefficient of the optical fiber, respectively, and p_{11} and p_{12} denote Pockel's constants.

The Bragg wavelength shift of an FBG sensor adhering to a host structure due to a temperature change can be attributed to the temperature change ΔT and the thermal strain ε_T induced by the mismatch of the thermal expansion between the optical fiber and host structure. The thermal strain ε_T has been reported by Her and Huang [24]. Substituting the temperature change ΔT and thermal strain ε_T into Equation (2) leads to the determination of the Bragg wavelength shift of an FBG sensor as follows:

$$\begin{aligned} \Delta\lambda_B = & \left\{1 - \frac{1}{2}n_0^2[(1 - \nu_f)p_{12} - \nu_f p_{11}]\right\}\varepsilon_T\lambda_B \\ & + \left\{[1 - \frac{1}{2}n_0^2(p_{11} + 2p_{12})]\alpha_f + \frac{\xi}{n_0}\right\}\Delta T\lambda_B \end{aligned} \quad (5)$$

In the experimental test, a steel beam bonded with an FBG sensor was placed in a thermal chamber and heated from room temperature to 100 °C. The Bragg wavelength shift of the surface-bonded FBG sensor due to the temperature change was detected by an optical spectrum analyzer (AQ 6331, Ando Electric Co., Tokyo, Japan). The experimental measurements of the Bragg wavelength shift were compared with the theoretical prediction of Equation (5), as illustrated in Figure 1. The grating temperature coefficient of 25 pm/°C extracted from Figure 1 is higher than that of the normal grating temperature coefficient of 10 pm/°C due to the thermal strain transferred from the host structure to the FBG sensor. The coefficients of the thermal expansion of the FBG sensor and steel host structure are $0.5 \times 10^{-6}/^\circ\text{C}$ and $12 \times 10^{-6}/^\circ\text{C}$, respectively. The mismatch of the thermal expansion between the optical fiber and host structure induces a thermal strain leading to an additional Bragg wavelength shift. The theoretical prediction is in good agreement with the experimental measurement. A linear dependence between the Bragg wavelength shift and temperature change was observed.

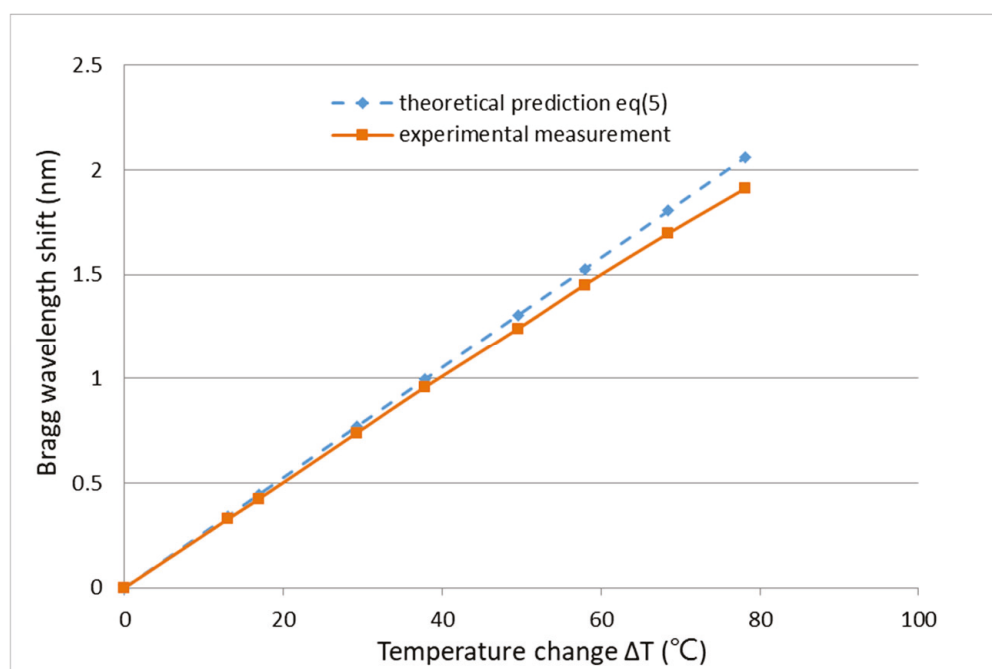


Figure 1. Bragg wavelength shift of a fiber Bragg grating (FBG) sensor induced by a temperature change.

3. Temperature-Induced Light Power Variation

The working principle of FBG sensors exists according to the correlation between the Bragg wavelength shift and the temperature change and applied strain, as presented in Equation (2). A wavelength meter is widely employed to measure the wavelength. However, a slow response of the wavelength meter is inappropriate for online and real-time measurements. In this study, the Bragg wavelength shift is converted to a modulation of light power through an optical band pass filter and detected by a photodetector. The fast response of a photodetector provides the feasibility of the measurement for real-time responses. The proposed FBG sensing system is schematically illustrated in Figure 2. The sensing system is composed of a broadband light source (ASE 1550A, Faztec Optronics Corp., Taipei, Taiwan), an optical circulator, an optical band pass filter (TBF-1550-1.0, Newport Corp., Irvine, CA, USA) and a photodetector (ET3010, Throlabs Inc., Newton, NJ, USA). The initial Bragg wavelength of the FBG sensor used in this study is 1524.66 nm, as shown in Figure 3, while the range of the optical band pass filter is 1523.8~1527.2 nm, as shown in Figure 4. When a broadband light is transmitted to the FBG, a narrowband spectrum of the Bragg wavelength is reflected back from the FBG sensor and guided into an optical band pass filter. The light power is modulated by the optical band pass filter according to its wavelength. To ensure the one-to-one correspondence between the wavelength and light power, the Bragg wavelength reflected from the FBG sensor was restricted to a range of 1523.8~1525.7 nm in this study. In this wavelength region, the output of the light power from the optical band pass filter increases with the increase of the wavelength. Thus, a one-to-one correspondence between the temperature and light power can be achieved. In this work, a Bragg wavelength of 1524.66 nm was used for the FBG sensor since it falls in the valid region of 1523.8~1525.7 nm. The light power is converted to an electrical voltage through a photodetector, yielding to the determination of the temperature.

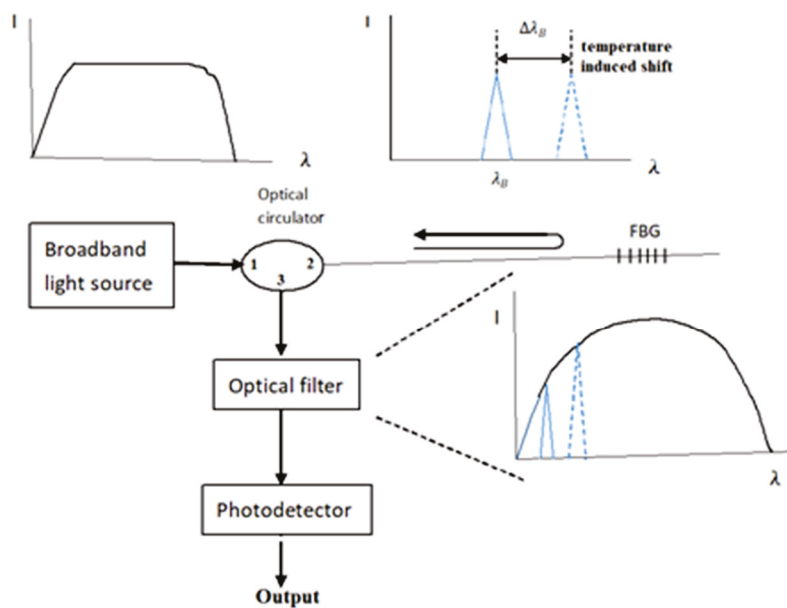


Figure 2. Schematic diagram of the FBG sensing system [25].

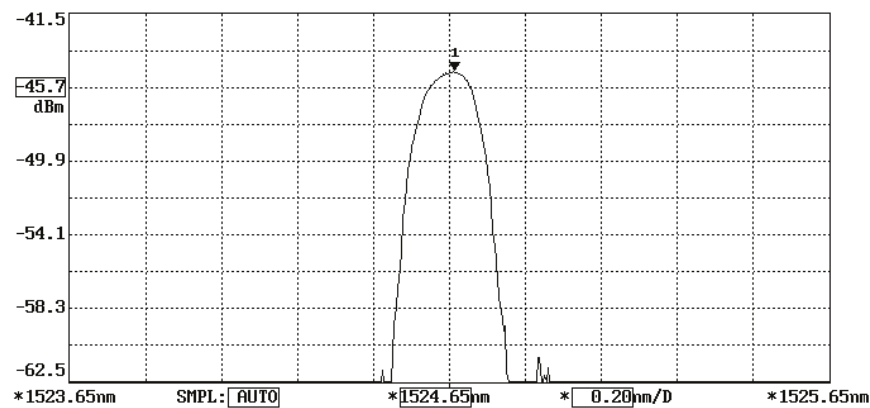


Figure 3. Bragg wavelength reflected from the FBG sensor.



Figure 4. Band pass from the optical filter.

To correlate the temperature with the light power, experimental tests of an FBG sensor adhering to a steel beam under a series of temperature changes were conducted. The Bragg wavelength of the FBG sensor used in this study at its initial state is $\lambda_B = 1524.66$ nm, as shown in Figure 3, which is in the left half region of the optical band pass filter, as shown in Figure 4. The output light power of the optical band pass filter increases with the increase of the temperature due to the increase of the Bragg wavelength reflected from the FBG

sensor. In the experimental tests, the test specimen was heated from room temperature to 70 °C in a thermal chamber. The temperature change and light power change were recorded and plotted in Figure 5. The linear relationship fitting between the temperature change and light power variation exhibits a reasonable linearity, with the coefficient of determination being approximately 0.99. The linear relationship between the temperature change ΔT and light power variation ΔV is obtained as follows:

$$\Delta T = 124.56\Delta V \quad (6)$$

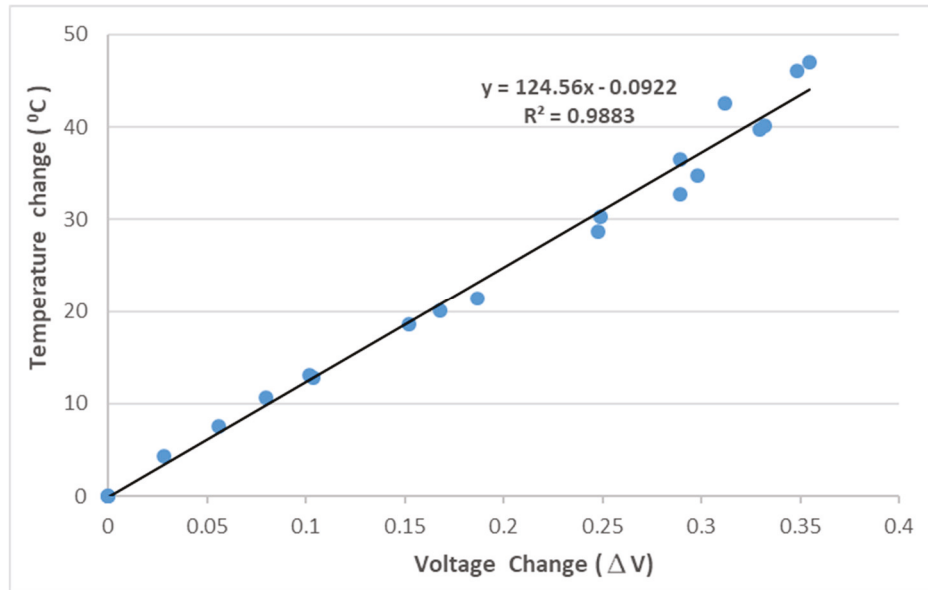


Figure 5. Relationship between the temperature change and light power variation.

4. Thermal Cycling Test

A thermal cycling test is a process of temperature change at a high rate for materials or devices. It is considered to be an environmental stress test that can be used to evaluate the durability and safety of products. A thermal cycling test can quickly unravel the potential failure or defects of an electronic product to improve product design and reliability. In general, electronic devices are under a non-uniform strain distribution in a working environment. The non-uniform strain distribution of the electronic component could affect the Bragg wavelength shift of the attached FBG sensor. An FBG sensor with a small size can provide a point-wise measurement. Moreover, the non-uniformity within the small area is insignificant. In this work, an FBG sensor was employed to monitor the temperature change in a thermal cycling test. A steel beam surface-bonded FBG sensor, using epoxy and with a length of 2 cm, was placed in a thermal cycling test chamber (TSR-A4, KingSon Technology Co., New Taipei City, Taiwan), as shown in Figure 6. In addition, a K-type thermocouple with a diameter of 2 mm was placed next to the FBG sensor as a reference. Two different heating rates, 10 °C/min and 40 °C/min, were adopted in the thermal cycling test. The valid wavelength range for the optical band pass filter with a one-to-one correspondence between the wavelength and light power was 1523.8~1525.7 nm. The temperature variation was 50 °C in the experimental tests to make sure that the Bragg wavelength reflected from the FBG sensor was in the range of 1523.8~1525.7 nm. The light power detected by the photodetector in the thermal cycling test with a heating rate of 10 °C/min is plotted in Figure 7. The initial temperature T_0 and light power V_0 were 22.80 °C and 0.1268 V, respectively. Substituting the light power from Figure 7, the initial temperature T_0 and the light power V_0 into Equation (6), the dynamic temperature response of the specimen in the thermal cycling test can be detected, as shown in Figure 8. The temperature measured by the FBG sensor was compared with the results recorded by a thermocouple. It can be seen

that a close agreement with a difference of less than 2% was achieved between the FBG sensor and thermocouple. Next, the heating rate was increased to 40 °C/min. Figures 9 and 10 show the variation of light power and temperature response of the specimen during the thermal cycling test, respectively. It demonstrates that the FBG sensor is capable of monitoring the real-time temperature response at a high rate of 40 °C/min.



Figure 6. Experimental setup of a test specimen in a thermal cycling chamber.

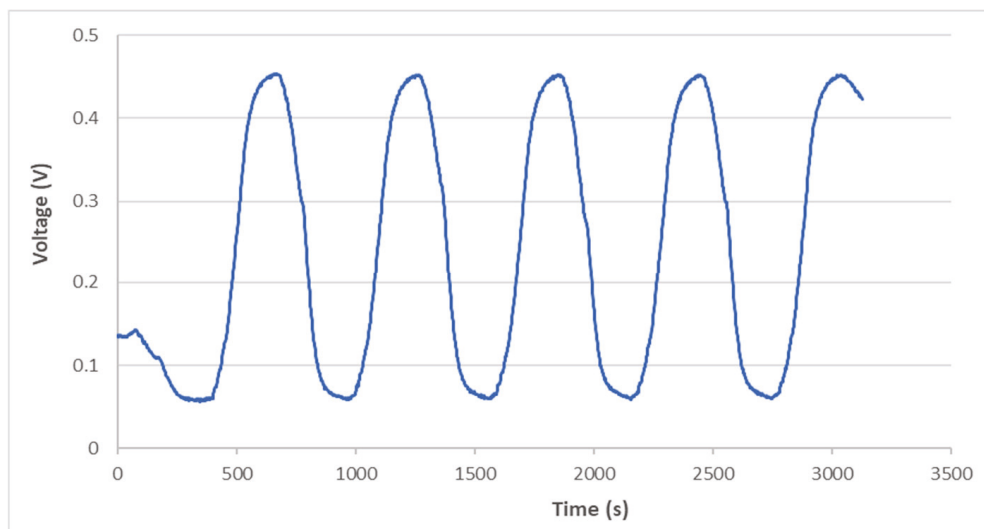


Figure 7. Variation of light power during the thermal cycling test with a heating rate of 10 °C/min.

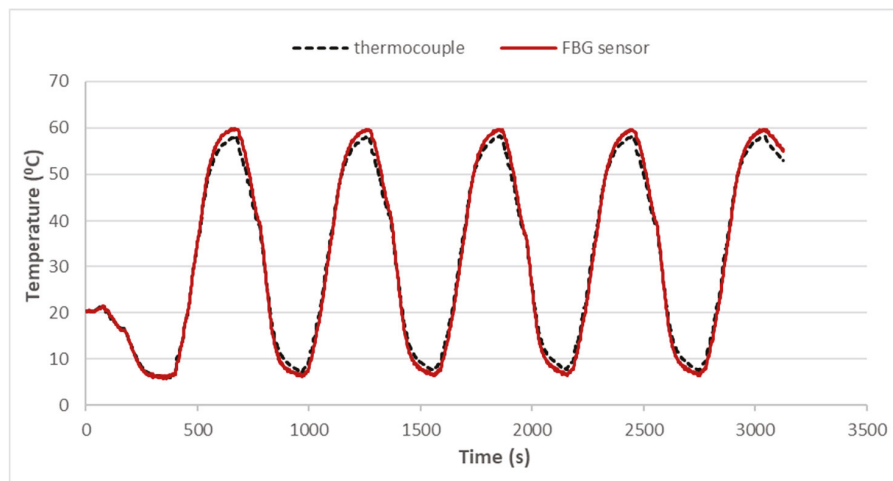


Figure 8. Dynamic temperature response of the specimen in the thermal cycling test with a heating rate of 10 °C/min.

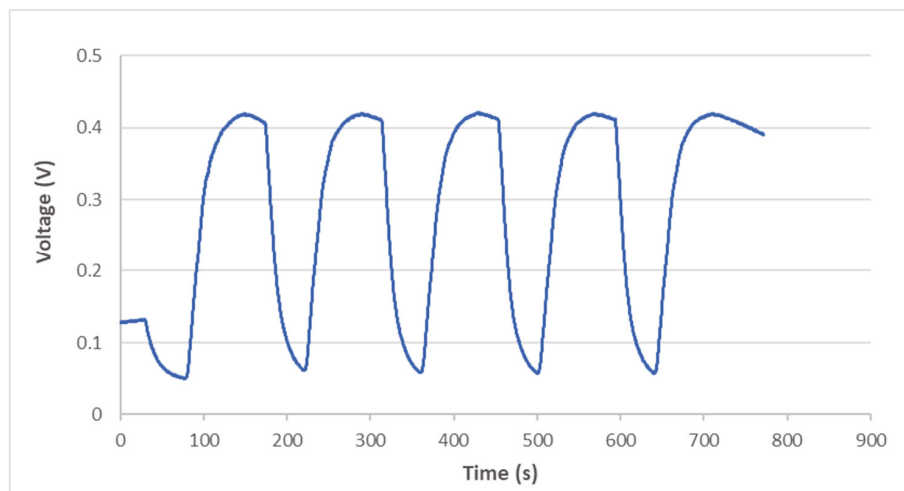


Figure 9. Variation of light power during the thermal cycling test with a heating rate of 40 °C/min.

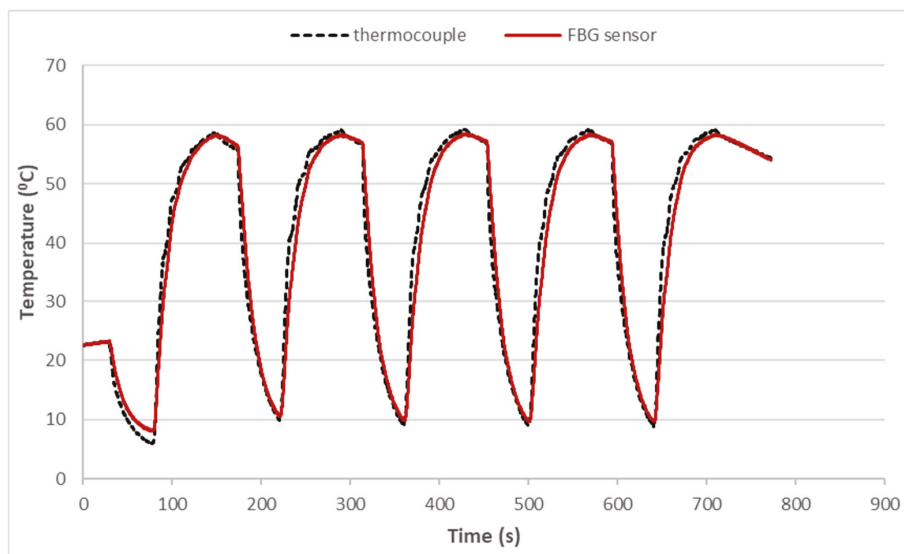


Figure 10. Dynamic temperature response of the specimen in the thermal cycling test with a heating rate of 40 °C/min.

5. Conclusions

FBG sensors have been well recognized as being more suitable for structure health monitoring than conventional electrical sensors, with capabilities of immunity to electromagnetic interference and multiplexed measurements. In this study, a fiber optic sensing system consisting of an FBG sensor, optical band pass filter, and photodetector was developed to monitor the real-time temperature response of a structure subjected to a dynamic thermal loading. The shift of the Bragg wavelength reflected from the FBG sensor induced by the temperature change is converted to a light power variation through an optical band pass filter and detected by a photodetector. Through a fast response of the photodetector, in situ monitoring of dynamic temperature change is possible. The FBG sensing system was employed to conduct temperature monitoring during a thermal cycling loading with a high rate of 40 °C/min. The FBG measurement was verified by a thermocouple, with a difference of less than 2%. Moreover, the proposed optic fiber sensing system has the advantages of having a compact size, good accuracy, low cost and easy fabrication. The present work provides an FBG sensing system with a fast response, online monitoring and easy implementation, which is helpful and useful for structural health monitoring.

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Article

A Low-Cost, Low-Power Water Velocity Sensor Utilizing Acoustic Doppler Measurement

Stephen Catsamas, Baiqian Shi, Boris Deletic, Miao Wang and David T. McCarthy *

BoSL Water Monitoring and Control, Department of Civil Engineering, Monash University,
Melbourne, VIC 3800, Australia

* Correspondence: david.mccarthy@monash.edu

Abstract: Current commercial sensors to monitor water flow velocities are expensive, bulky, and require significant effort to install. Low-cost sensors open the possibility of monitoring storm and waste water systems at a much greater spatial and temporal resolution without prohibitive costs and resource investment. To aid in this, this work developed a low-cost, low-power velocity sensor based on acoustic Doppler velocimetry. The sensor, costing less than 50 USD is open-source, open-hardware, compact, and easily interfaceable to a wide range of data-logging systems. A freely available sensor design at this price point does not currently exist, and its novelty is in enabling high-resolution real-time monitoring schemes. The design is capable of measuring water velocities up to 1200 mm/s. The sensor is characterised and then verified in an in-field long-term test. Finally, the data from this test are then used to evaluate the performance of the sensor in a real-world scenario. The analysis concludes that the sensor is capable of effectively measuring water velocity.

Keywords: acoustic Doppler velocimetry; field verification; low cost; low power; open hardware; real-time environmental monitoring; sensor design; stormwater monitoring; urban water; water velocity

1. Introduction

The velocity of stormwater, wastewater, and surface water is an essential parameter that requires continuous monitoring to estimate the discharge volume and conduct further analyses, such as pollution load estimation [1], flow and water quality modelling [2,3], and normalisation of pathogen concentrations in wastewater [4,5]. Current sensors available on the market to measure water velocity in storm and waste water systems are expensive, are high-power, are not available freely as open-source or open-hardware, and/or require significant preparation and overhead to setup and maintain [6–8]. Such sensors are not feasible for research and water operations where the objective is to collect higher spatial resolution data to, for example, further improve the accuracy of water models [9] and the performance of sewer surveillance programs [10]. Other drivers for low-cost velocity sensors include the improvement in existing flow measurement stations that simply rely on stage-discharge relationships, where the determination and updating of flow rating curves is costly and time-consuming, and often requires extrapolation for extreme events [11,12]. Instead, a low-cost velocity sensor could allow for a permanent installation to collect continuous and real-time velocity data for more accurate discharge information; if truly low cost, then continuous and simultaneous measurements across the stream's cross section could be obtainable. A wide range of technologies have been explored for new low-cost, low-power velocity sensors, including time of flight measurement, Doppler shift techniques, and velocity dependent force sensing.

Doppler shift techniques have been explored in [13,14]. The authors of [13] demonstrated the feasibility of non-contact measurements of surface velocity using a radar-based sensor and a novel sensor data processing algorithm to extract this surface velocity. The authors focused on a demonstration of this technology as an accurate and low-cost method

for measuring surface velocity rather than the implementation of the principle into a field-ready self-contained sensor. The authors of [14] established the potential of utilising visible light as a carrier wave for Doppler-based velocity measurement. It further develops the signal processing methods and provides experimental verification of using visible light in low-cost velocity sensors. Again, more emphasis is applied to demonstrating the principle as opposed to its implementation in deployable sensors.

Low-cost contact and non-contact sensors have been proposed by [15]. Both the contact- and non-contact-type sensors are tested and produce accurate measurements of the water velocity. The contact-type sensor uses a hall effect device to measure the rotational speed of a pinwheel located in the water. The non-contact-type sensor uses video from a digital camera to detect the movement of surface features in particle image velocimetry. These methods, while accurate, are ultimately unsuitable for long-term monitoring applications. For the contact sensor, the moving pinwheel will become clogged and require maintenance, while particle image velocimetry techniques require large amounts of computational resources, leading to high power usage and bulky installation.

Methods based on the velocity dependent force exerted by a water flow on a mast or cantilever are used in [16,17]. The authors of [16] demonstrated that low-cost bidirectional sensing of water flows in a pipe can be achieved by measuring the deflection angle of a thin metallic cantilever in the flow and found that the technique can achieve small error. It is acknowledged that further work on this sensor would be needed for a low-cost and onboard method of measuring this deflection angle. A sensor for a near-bed velocity measurement incorporating the measurement of the frequency of vortex-induced vibrations of a mast submerged in the flow for the determination of velocity is presented in [17]. This novel method was successfully implemented in a low-cost sensor for continuous in-field measurement; however it specialises in measuring the velocity in the immediate vicinity of the channel bed and not the bulk water velocity.

Other velocity methods have been proposed by [18], based on aerial particle image velocimetry, and by [19], based on ultrasonic time-of-flight methods. These require either open-channel and visible flows for the expensive but novel method in [18] utilising a remotely piloted aircraft or full-pipe flows, as in [19]. While these are novel methods to measure velocity, they are not applicable to the smaller scale, underground storm and sanitary sewer systems.

As such, this paper will fill the research gap identified in the literature by developing and validating a low-cost, low-power velocity sensor, which can be used to continuously measure flows in storm and sanitary sewer systems. The sensor's design is freely available and is based on continuous wave (CW) ultrasonic Doppler; this technology was chosen for its relative simplicity and, thus, abilities to be implemented at low cost and to be optimised for low power. While work discussing velocity sensing have mainly focused on novel measurement principles and their implementation, this sensor is a waterproofed and integrated design that addresses the need for a 'field-ready' velocimeter suitable for real-time monitoring of open channel flows able to be deployed at scale. The deployment of the sensor at this scale is supported by its low-cost and low-power usage, which enables it to be installed for long periods of time without maintenance. This research has three major objectives: (1) to develop the low-cost sensor architecture including the circuitry and the sensor case, (2) to develop the sensor data processing algorithm, and (3) to validate the performance of the sensor under typical installation scenarios. The sensors design files and firmware are made freely available under an open hardware licence to allow the reader to construct and modify the sensor design.

2. Materials and Methods

A detailed description of the sensor's design and design choices is provided. Following this, power testing is conducted to measure the current consumption of the sensor in various operational modes and to verify its low power status. Flume testing of the prototype designs is used to optimise and help develop the digital signal processing algorithm used

to extract the velocity measurements. Following sensor calibration, the sensor is deployed in an 8-week field trial to validate and characterise the performance of the sensor in a realistic installation scenario. A flowchart of the studies framework is provided in Figure 1.

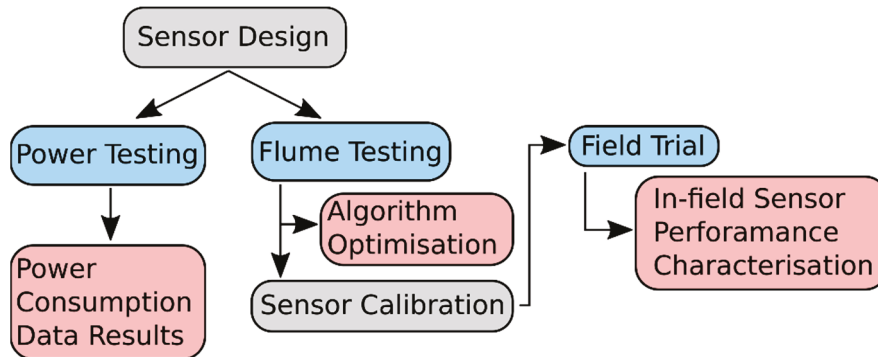


Figure 1. Flowchart describing the design, validation, and characterisation procedures used in this study; major experiments are in blue, and outcomes are in red.

2.1. Sensor Design

The sensor's reading is based on CW ultrasonic Doppler. This reflects an acoustic pressure wave off particles and impurities in the water [20]. Based on their velocity, the returning acoustic wave has its frequency shifted by what is known as the Doppler shift Δf . The equation which governs this phenomenon is

$$\Delta f = \frac{2f}{c} v \cos \theta, \quad (1)$$

where f is the transmitted ultrasonic frequency, c is the speed of sound in water, v is the flow velocity, and θ is the angle between the ultrasonic beam and the water velocity [21]. For the sensor, f , c , and θ are controlled or known from theory. Hence, a measurement of Δf can be used to determine the flow velocity via

$$v = \frac{c \Delta f}{2f \cos \theta}. \quad (2)$$

The relative simplicity of the CW ultrasonic Doppler principle reduces the complexity of the sensor design. This aids in achieving low-cost designs as it both reduces the component count of the design and allows the sensor to be built from non-specialised components, which often do not carry the price premium of more specialised components. To supplement the minimal design of the sensor, digital signal processing (DSP) is used in the measurement of the Doppler frequency shift, Δf . Fourier methods have been shown to be a powerful technique in Doppler frequency estimation, particularly when there is a high signal to noise ratio [22]. Hence, the Fast Fourier Transform (FFT) is utilised to analyse the data in the frequency domain.

The sensor has three major subsystems: (1) the Doppler signal generation and detection subsystem, (2) the digital signal acquisition subsystem, and (3) the sensor interface subsystem. Each of these subsystems are described in detailed below. A block diagram of their relationships is provided in Figure 2, and a circuit diagram is provided in Figure 3.

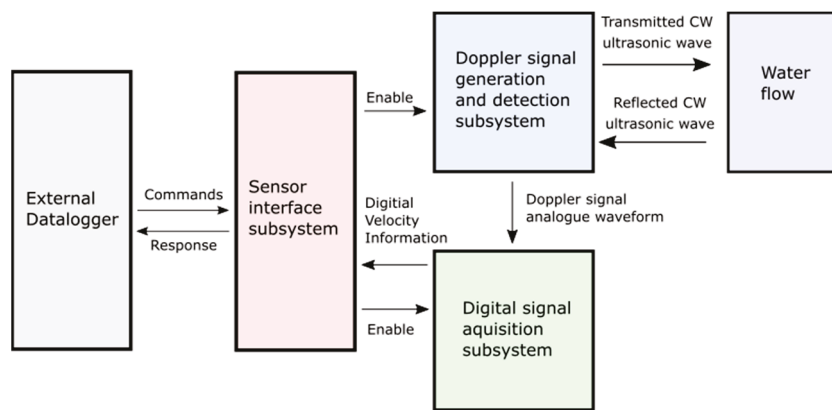


Figure 2. Functional block diagram of major sensor subsystems. Interaction between subsystems displayed on arrows. The sensor consists of the Doppler signal generation and detection subsystem (see Section 2.1.1), digital signal acquisition subsystem (see Section 2.1.2), and sensor interface subsystem (see Section 2.1.3). The sensor interacts with the water via the ultrasonic transducers and is connected to the external datalogger via electrical cable.

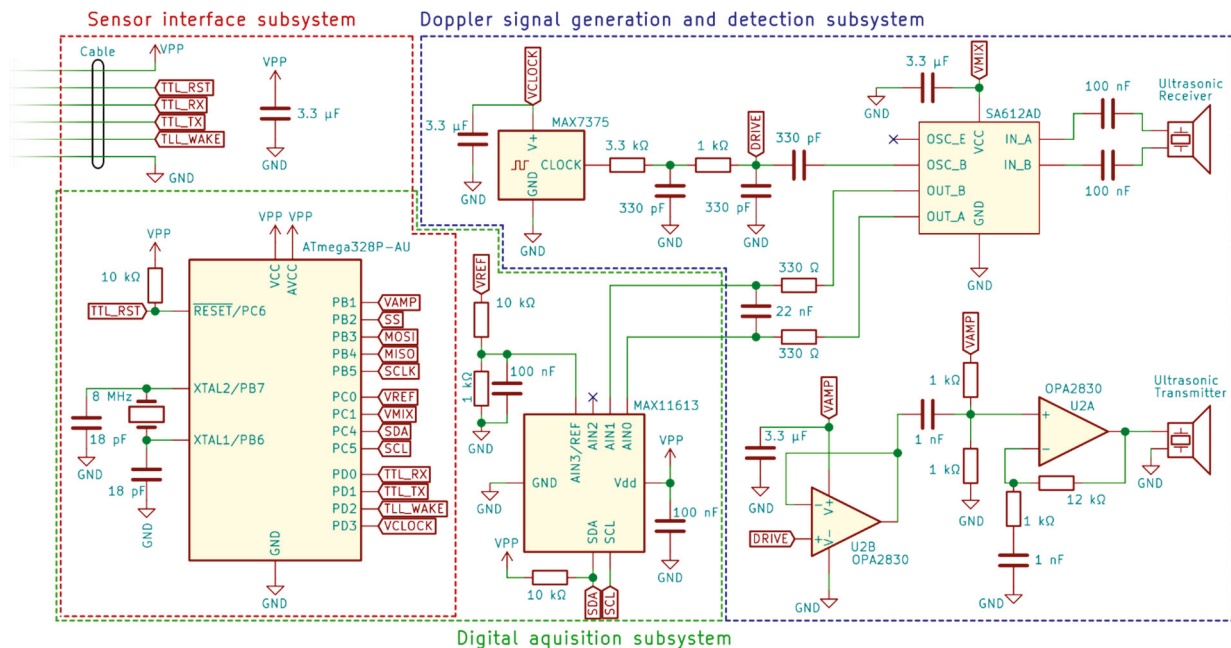


Figure 3. Circuit diagram of sensor. Components corresponding to each subsystem are contained within the dashed line coloured: blue, Doppler signal generation and detection subsystem (Section 2.1.1); green, digital signal acquisition subsystem (Section 2.1.2); and red, sensor interface subsystem (Section 2.1.3). Note that the digital acquisition subsystem and sensor interface subsystem contain components in common. For a complete set of design files, please see the Supplementary Materials.

2.1.1. Doppler Signal Generation and Detection Subsystem

The implementation of the Doppler velocity principle of measurement used in this sensor can best be understood through a procedural explanation. CW ultrasonic Doppler requires a known frequency to be transmitted into the water for the Doppler shift to be measured. The MAX7375 oscillator IC was used as it outputs a 1 MHz 5 V peak-to-peak square wave [23]. A waveform of this output is measured in Figure 4a. The 1 MHz frequency matches the resonance frequency of the SMFM21F1000 ultrasonic transducers used for the emitter and receivers. Each transducer is 12.95 mm in diameter. The signal from the oscillator is filtered through two passive low-pass filters with cut-off frequencies

of 150 kHz and 480 kHz. Two filters are used to achieve second order roll-off, suppressing the harmonics of the square wave to produce a better approximation of a 1 MHz sine wave. The waveform after the first filter is shown in Figure 4b, and that after the second filter is shown in Figure 4c. The low-pass filters result in a waveform with 6% total harmonic distortion. The choice of this square wave generator over a pure sine wave generator is due to its simplicity, requiring only the low-cost MAX7375 and passive components. The cut-off frequencies of 150 kHz and 480 kHz are below the 1 MHz fundamental frequency and, thus, attenuate the 1 MHz component. This is intentional as it brings the amplitude to an appropriate level for later use in the SA612AD mixer IC.

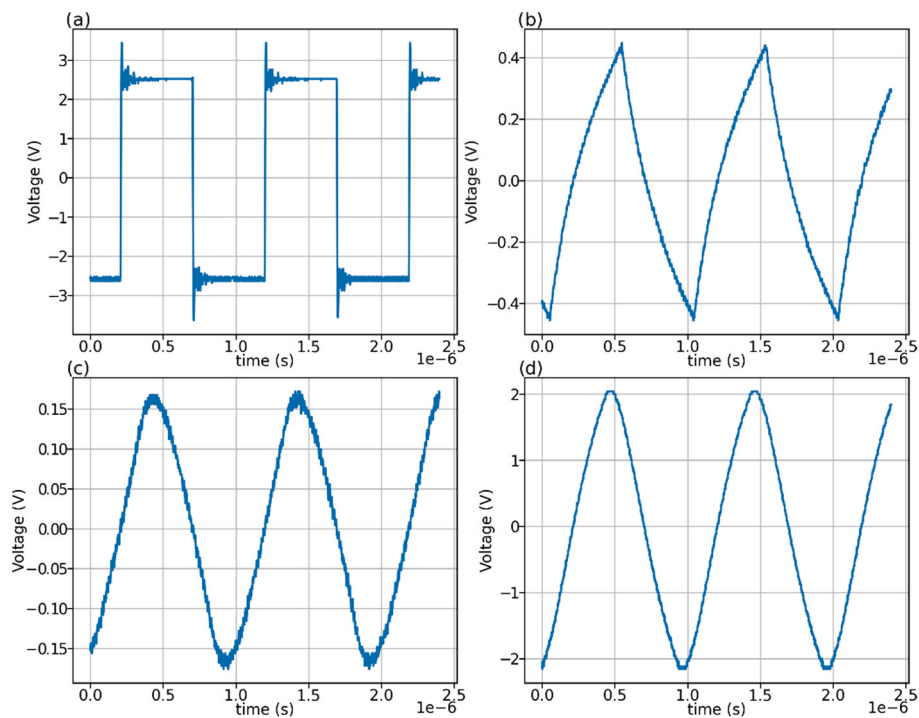


Figure 4. Measured waveforms for Doppler signal generation subsystem. All waveforms recorded with AC coupling at 1 GSa/s. (a) MAX7375 output. (b) First low-pass filter output. (c) Second low-pass filter output. (d) Ultrasonic emitter drive signal.

This signal is then split into an AC-coupled high-bandwidth operational amplifier and into the local oscillator (LO) input of the SA612AD mixer (OSC B). The high-bandwidth operation amplifier is configured as an AC-coupled amplifier that amplifies the high impedance 1 MHz sine wave output of the oscillator to a low impedance 4 V peak-to-peak waveform with 5% total harmonic distortion (Figure 4d). This is then used to drive the ultrasonic transmitter. Other commercial ultrasonic Doppler systems operate on greater voltages of 12 V or higher [24–26]. This aids greatly in increasing the output power of the ultrasonic transmitter as it is proportional to the square of the input voltage. The design goals of this sensor are low power and wide compatibility with 5 V microcontroller systems; however, the sensor is restricted to the use of a 4 V signal to drive the ultrasonic transmitter.

The reflected Doppler shifted signal is then detected by the ultrasonic receiver, which outputs a voltage proportional to the incoming acoustic signal. The receiver is connected to the mixer IC via a balanced connection. Internally, the SA612AD uses a Gilbert cell to mix the LO input signal with the received Doppler signal. It also provides an amplification of 6 dB [27]. Theory states that the mixing of two sine waves of frequencies f_1 and f_2 produces a signal with output frequencies of $|f_1 + f_2|$ and $|f_1 - f_2|$. Critically, since the ultrasonic transmitter was driven from the same 1 MHz frequency source, f , as the LO input, the input frequencies into the mixer are $f + \Delta f$ and f , where Δf is the Doppler shift. Therefore, the mixer outputs at frequencies $|\Delta f|$ and $|2f - \Delta f|$. It is noted that the presence of the $|\cdot|$ in

the demodulation removes any information about the direction of flow. This is a limitation compared to other demodulation techniques such as quadrature demodulation; however, quadrature demodulation requires duplicates of many components to accommodate an additional channel [13,28]. This increases the complexity and cost of the sensor. Furthermore, the surface water systems for which the sensor is targeted have unidirectional flows, as such the direction of the water flow does not need to be determined.

The mixed signals are output from the mixer to a balanced low pass filter, which has a cut-off frequency of 11 kHz. The cut-off frequency is chosen to be similar to that of the sampling rate and above the Doppler shift frequencies corresponding to the highest velocities that the sensor can measure. The low-pass filtering is necessary to filter out the signal component of frequency $|2f - \Delta f|$, preventing aliasing when the signal is digitally sampled. This signal is then output to the digital signal acquisition subsystem.

2.1.2. Digital Signal Acquisition Subsystem

The digital signal acquisition subsystem consists of a differential analogue-to-digital converter (ADC) and the ATmega328P microcontroller unit (MCU). The differential ADC samples the balanced signal output from the Doppler signal generation and detection subsystem. Using a differential ADC over a single sided output enables a 3 dB gain in signal amplitude, critical for aiding in the detection of weak signals. It also eliminates the need for biasing circuitry as the input is not sampled in reference to circuit ground. The ADC samples the signal at a frequency of 11 kHz, along with the DSP, this caps the maximum measurable velocity of the sensor to 1200 mm/s. The ADC converts the analogue signal into a 12-bit signed digital readings. The conversions are sent over an I2C bus to the MCU, where they are recorded for digital signal processing. The digital signal processing algorithm is discussed in detail in Section 2.1.6.

2.1.3. Sensor Interface Subsystem

An ATmega328P microcontroller is used to control subsystems of the velocity sensor, to compute necessary digital signal processing, and to provide a digital I/O interface. The use of the ATmega328P was selected as it is a low-cost solution to managing these tasks; is relatively simple to program for; and is compatible with the Arduino IDE, a popular and easily accessible platform for programming MCUs. The latter two reasons aid in making the design more accessible to end users who want to modify the sensor to better fit their application but are relatively unfamiliar with MCU programming. For lower power consumption and higher signal processing performance, the ATmega328P may be substituted for an STM32L412 or similar.

To reduce power consumption the sensor is kept in a low power sleep mode with the Doppler signal generation and detection subsystem and parts of the digital signal acquisition subsystem isolated from the supply voltage. When the microcontroller receives a request for a velocity measurement over the IO interface, these systems are woken up to begin a measurement. This helps significantly with reducing the current consumption of the sensor, particularly when measurements are temporally sparse.

The sensor communicates to a datalogger via a USART interface at a baud rate of 9600. This has been proven to be stable for cables up to 20 m in length. Commands can be sent to the sensor, including to make a velocity measurement, query the sensor ID and firmware version, or send the sensor to sleep. There is also a wake line necessary to be pulsed to wake the sensor from its low power sleep state. A reset line is also available. This allows the sensor to be reprogrammed, to add more functionality, or to customise the sensor to the end users' requirements. Power is provided through a 5 V and GND line to the sensor.

2.1.4. Physical Overview

The sensor's housing was constructed using 3D printing technology. It is printed out of a PET-G filament. An image of the sensor is provided in Figure 5. The housing is filled with a two-part potting mixture, which waterproofs the sensor's electronics. The

front of the sensor contains the two ultrasonic transducers, which are angled such that their acoustic beam is elevated 30 degrees from the horizontal. This is done to have the reading obtain information from a larger range of flow depths as opposed to if the transducers were angled in the horizontal. It has been shown that this orientation gives a more representative reading of the mean flow velocity and with less dependence on the water depth [29]. The optional attachment wings aid in affixing the device to a channel bed via an anchor bolt. The wiring for the sensor exits through a CAT5 four-pair cable. The total current cost to manufacture the sensor is less than 50 USD. As the sensor is only currently in boutique production, it is thought that this could be further reduced with mass production techniques.

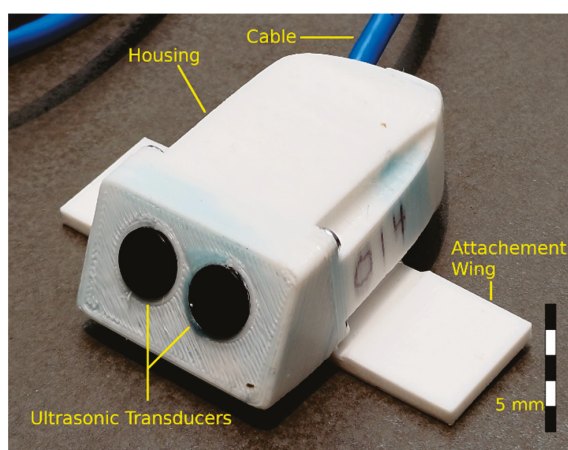


Figure 5. Picture of the velocity sensor with approximate scale overlayed. Key external features of the sensor have been labelled. The sensor measures 75 mm by 44 mm by 25 mm without the optional attachment wings.

2.1.5. Calibration

Calibration of the sensor is necessary to quantify its background noise profile, that is the measurement at no flow. This profile is then filtered out of the sensor data as part of the DSP. Specifically, a power spectral density (PSD) that quantifies the amount of noise at each frequency in the digitised Doppler shift signal is estimated. The variability in the construction of the sensor is such that each sensor requires its own calibration before deployment. To measure this PSD, the sensor is placed in still water. The transducers are oriented such that there is at least 20 cm of unobstructed water in front of them. Then, 256 samples are taken from the ADC at a sampling frequency of 11 kHz. At least 2000 of such 256 sample segments are taken. Welch's method is then used on these segments with a 0% overlap and hamming windowing to produce the PSD estimation [30].

2.1.6. Digital Signal Processing Algorithm

The principle task of the digital signal processing algorithm is to estimate the central Doppler signal from the sampled data to calculate flow velocity. This is a task made more challenging by the high SNR environment. The algorithm is run on the MCU and is thus subject to considerable memory and processing power constraints. Many Doppler velocity sensors determine the Doppler frequency by calculating the mean of the measurement power spectrum. For this sensor, it was found based on laboratory flume testing (Section 2.2.2) that an algorithm that looks for the dominant falling edge in the reflected power spectrum performs better at obtaining the Doppler frequency. A flowchart overview of this algorithm is provided in Figure 6. Let $s[t]$ be t -th sample in the array of data captured by the ADC from the received signal (Figure 6, $s[t]$ captured, and Figure 7a). An algorithm to remove the DC component of $s[t]$ is applied. Under this algorithm the array is updated,

$$s[t] := s[t] - \langle s \rangle, \quad (3)$$

where $\langle s \rangle$ is the arithmetic mean of all samples, $s[t]$ (Figure 6, DC removal). The data are then transformed via an FFT to convert it to the frequency domain. This yields an array of frequency domain data, $S[f]$. As $s[t]$ was purely real, then $S[f]$ is symmetric about its midpoint, the 128-th element. The data beyond the 128-th element in $S[f]$ are therefore discarded to save memory (Figure 6, FFT).

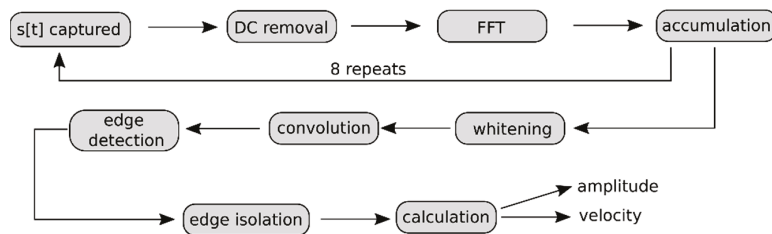


Figure 6. Digital signal processing flowchart. Each step is displayed in the grey boxes. Example data for the processed signal after certain steps can be found in Figure 7. The algorithm begins at $s[t]$ captured.

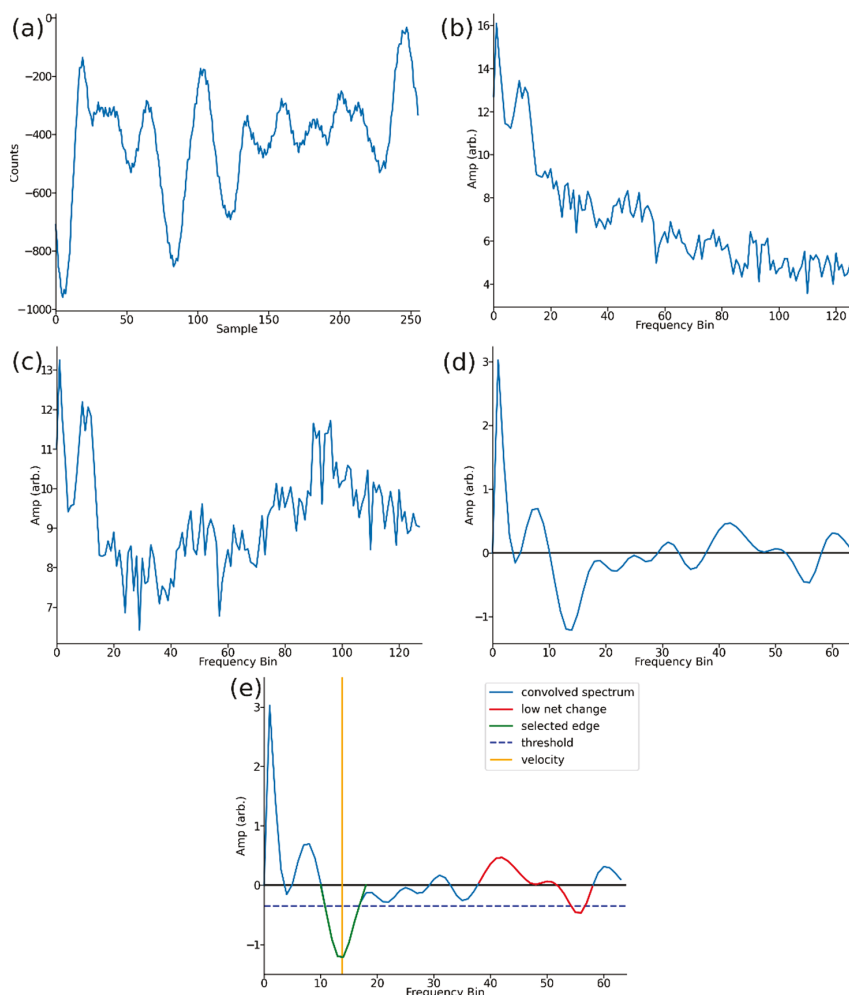


Figure 7. Signal waveform after points in digital signal processing pipeline: (a) raw $s[t]$ captured data, (b) waveform after FFT accumulation and logarithm, (c) waveform after whitening, (d) waveform after convolution, and (e) waveform showing edge detection and final velocity reading. The edge detection threshold is shown in dashed blue, an edge rejected due to a low net change is shown in red, and the selected edge is shown in green. The orange vertical line displays the frequency bin corresponding to the final measured velocity.

The square of the magnitude of each element in $S[f]$ is then accumulated into a new array $S_{acc}[f]$, according to the following:

$$S_{acc}[f] += S[f]S^*[f], \quad (4)$$

where $*$ denotes the complex conjugate and $S_{acc}[f]$ is initialised to zero for the first dataset. New data are sampled and accumulated into $S_{acc}[f]$ for a total of eight times (Figure 6, accumulation). This is done to calculate the average power spectrum density (PSD) over a short period of time, reducing the variability seen in any single measurement. Once this is complete the square root of each element is taken,

$$S_{acc}[f] := \sqrt{S_{acc}[f]} \quad (5)$$

To give a final PSD, for debugging and testing purposes, the PSD at this point is sent to the datalogger and recorded on an SD card. The next steps of the algorithm are dedicated to estimating the Doppler frequency of the recorded spectrum in S_{acc} . The algorithm attempts to detect the frequency at which a falling edge in the PSD occurs, that is where the reflected signal due to the particles in the water significantly drops off in power.

The natural logarithm of each element $S_{acc}[f]$ is taken (Figure 7b), and then, the array is whitened according to

$$S_{acc}[f] := S_{acc}[f] - C[f] \quad (6)$$

where $C[f]$ is the sensor's calibration PSD and corresponds to the relative background noise at the frequency f (Figure 6, whitening and Figure 7c). $C[f]$ is determined as in Section 2.1.5.

S_{acc} is then convolved with a Gaussian derivative kernel of standard deviation 2 bins to produce array, D_{acc} . The edge data in S_{acc} are now present as peaks in the D_{acc} , and the use of the Gaussian derivative helps to inhibit the effect of noise appearing as an edge by smoothing the data. The values $D_{acc}[f]$ for $f = 0, 1, 2$ and $f > 64$ are discarded. This is due to a high SNR for these frequency bins due to the inherent noise of the sensor (Figure 6, convolution and Figure 7d).

The last local minimum (highest frequency) of D_{acc} above a pre-set threshold is found; this corresponds to a falling edge. Let this occur at $D_{acc}[f']$. A check is then conducted to test if this edge corresponds to a sustained increase in the reflected power or a 'bump'. This is achieved by calculating the net change in D_{acc} over the found falling edge at f' and previous rising edge, if this net change is below a given threshold, the edge is discarded and a prior falling edge at a lower frequency is considered. This is repeated until a falling edge is found, which fulfils the above criteria (Figure 6, edge detection).

Once a falling edge that meets the required condition is found, the falling edge is isolated; that is, only the data of D_{acc} between the zero crossings on either side of $D_{acc}[f']$ are considered (Figure 6, edge isolation and Figure 7e). Finally, the height difference in the edge is assigned to the signal strength of the datapoint and the mean frequency of the isolated peak in D_{acc} is taken to be the Doppler frequency. A conversion between Doppler frequency and velocity is performed via (2) (Figure 6, calculation).

2.2. Lab and Field Testing Setup

2.2.1. Lab Power Usage Testing

For measurements of the power usage of the sensor, an ammeter was placed in series with the 5 V supply line; the sensor was then connected to an Arduino Uno [31], from which the sensor received its power and communications. Three different power states were investigated: measurement, active, and sleep, with these representing typical states in the operation of the sensor. The measurement state had all devices in their full power states, as would be the case when a measurement is occurring. The active state had the devices in the digital signal acquisition and sensor subsystem in their active states and devices in the Doppler signal generation and detection subsystem powered down. Hence, in this state, the device is ready to accept commands. In the sleep state, all devices were in

their low power states. For each of these states, the current displayed on the ammeter was recorded. Commands over the UART were used to switch between the power states.

2.2.2. Flume Testing

To aid in the development and prototyping of both the sensor and signal processing algorithms, laboratory tests were conducted. In this test series, the velocity sensor was installed facing up-stream near the invert of a flume channel so as to remain submerged through the tests. The flume was able to produce flow velocities ranging from 100 to 400 mm/s and was measured using the Flo-Mate Model 2000 portable flow meter also mounted in-line with the velocity sensor. At various flow rates, diagnostic engineering data were collected from the sensor, including raw transducer output, ADC samples, and formatted velocity data. The results from successive tests were used to inform the design of the sensor hardware and algorithm. The results will not be discussed here as they were conducted with previous iterations of the sensor. To evaluate the sensor's real-world performance and to overcome the limited flow velocities achievable in the laboratory setup, we focus our performance study on in-field testing.

2.2.3. Field Trial

For testing, the sensor was installed at the bed of Dandenong Creek, Australia, facing upstream and with the ultrasonic detection cone positioned azimuthally. The sensor was set to a measurement interval of 2 min. It was connected to an Arduino Uno datalogger, which recorded the averaged FFT data of the sensor after each measurement. Installed next to the sensor was a HACH Submerged Area Velocity Sensor [24]; this logged the velocity of the water every minute and was used as the source of comparison for the sensor under test. The data points from the sensor and those from the HACH probe were associated by pairing the datapoints nearest in time. For the analysis, it was assumed that HACH probe had negligible uncertainty, which, while we acknowledge is not correct, was carried out to compare our low-cost sensor to this well-established, industry-leading sensor. The weekly retrieval of data from the site was conducted for eight non-consecutive weeks beginning 2020 July and ending in 2020 October. The velocity sensor received its power from the Arduino Uno datalogger over a 20 m cable, which was also used for data transfer between the sensor. The collected data from the sensor was the processed externally using the described algorithm to obtain the velocity and signal strength reading. This was carried out to aid in adjusting the algorithm for Doppler frequency estimation. For the data analysis, a filter was applied to the sensor's data to remove low-signal-strength points with velocities higher than 250 mm/s. Low-signal-strength high-velocity readings occur mostly at low water depths [32]. As they are not an accurate measure of the water velocity and are clearly distinguishable from the typical high signal strengths seen at high velocities, they are filtered from the analysed data set.

3. Results

3.1. Lab Power Usage Testing

A sleep current of 100 μ A was found for the sensor. This moderately low sleep current supports the design criteria of the sensor being compatible for long-term instalment as a low-maintenance real-time monitoring device (Table 1). Given the measurement time of 4 s, supply voltage of 5 V, and measurement current of 27 mA, this leads to an energy per measurement of just 0.6 J. For a measurement regime with 10 measurements per hour, a calculated total consumption over 1 year of logging is 3500 mAh, about the typical capacity of an 18650 Li-ion cell. A lower measurement frequency would extend the logging lifetime; however, at lower measurement frequencies, the proportion of current used in sleep, which depends only slightly on the logging interval, would increase from the 25% in the above scenario.

Table 1. Results of lab power usage testing. Measured current consumption for velocity sensor in various power modes.

Mode	Current
Measurement	27 mA
Active	12.8 mA
Sleep	100 μ A
Yearly power use (6 min measurement intervals)	3.5 Ah

At 10 measurements per hour, the average continuous power consumption is 2 mW. This compares very favourably to current state-of-the-art commercial sensors. This information is summarised in Table 2. Both the continuous current consumption and the energy per measurement of the sensor are reduced by more than an order of magnitude compared to the HACH Submerged Area/Velocity Sensor. The continuous power consumption of the sensor is also lower than the 50 mW to 500 mW of the OTT SLD and 20 mW of the SonTek-IQ. This reduction in power usage enables smaller batteries to be used in remote logging applications. This facilitates the lower-cost and easier installation of the sensor when compared to current solutions.

Table 2. Comparison of power usage of velocity sensors to state-of-the-art commercial sensors. Data for commercial sensors are taken from manufacturers documentation. Continuous power consumption is the average power used during use. For the sensor in this work, this is 10 measurements per hour. The range of continuous power consumptions for the OTT SLD is due to variable measurement frequency.

Power Usage	This Work	HACH Submerged Area/Velocity Sensor [24]	SonTek-IQ [25]	OTT SLD [26]
Energy per measurement	0.6 J	<15 J	not specified	not specified
Average continuous power consumption	2 mW	<1.2 W	>20 mW	50–500 mW
Supply voltage	5 V	9–15 V	9–15 V	12–16 V

There is also scope for the power consumption of the sensor to be reduced further. While fundamental properties of the FFT algorithm used necessitate a minimum amount of time for which data need to be collected to maintain the velocity resolution of the sensor, giving a lower bound to measurement time, this lower bound has not yet been achieved due to the large portion (3.5 s) of time spent computing the signal processing algorithms to extract the velocity. Future work could involve optimisation of this algorithm to bring further power savings.

3.2. Field Trial

A correlation plot between the sensor measured velocities and velocity as measured by the HACH probe is shown in Figure 8. Both probes indicate that most of the velocities ranged from 0 mm/s to 1200 mm/s. The data display a linear trend for flow velocities up to 1200 mm/s—the measurement ceiling of the sensor. Calculating a line of best fit gives a gradient of 0.94, an R^2 value of 0.78, and the probability of the null hypothesis that the gradient is zero is $p < 0.0001$, supporting the sensor can accurately measure the velocity. Whilst a linear trend is present, there are also other qualities to the velocity measurements. It is seen that there are a cluster of points at a sensor's velocity from 100 mm/s to 200 mm/s and a very wide range of HACH velocities. That is, the sensor may sometimes significantly underestimate the flow velocity according to the HACH sensor (17% of datapoints) and this underestimation occurs more frequently at low velocities rather than at higher velocities. Significant overestimation of the HACH velocity (sporadically high readings) are seen much less commonly. It is important to note that this is in part due to the filtering of datapoints with low signal strengths, as before this filtering, there was a large clustering of great overestimations at low flow velocities. It is possible that further optimisation of the

signal strength filter could achieve a more reliable measurement by eliminating a greater proportion of measurements that significantly underestimate or overestimate the flow.

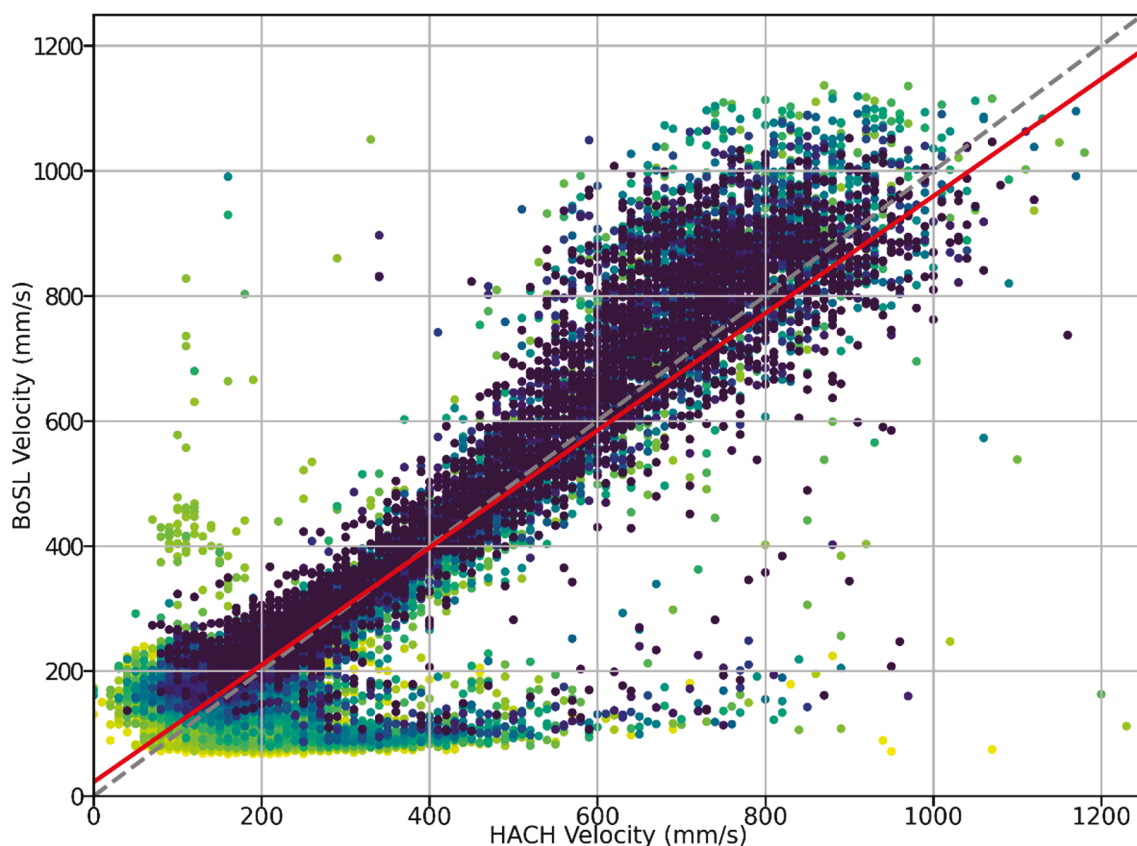


Figure 8. Plot of the sensor measured velocity on the y-axis vs. HACH probe measured velocity on the x-axis. Points are coloured according to signal strength, with darker points having a higher signal strength. Red: line of best fit with gradient 0.94 and y-intercept 22 mm/s, R^2 value 0.78, probability of null hypothesis of gradient equal to zero $p < 0.0001$. Linear regression calculated using SciPy [33]. Grey dashed line: 1:1 correlation. A few data points are beyond the plot range; the full data extends to 3000 mm/s on the x axis.

To better characterise the behaviour of the sensor, it is also helpful to plot the velocity measurements against time (Figure 9). The sensor records similar velocity measurements to the HACH probe during flow events. Importantly, the maxima of the flow events as recorded by the sensor in this work and the HACH sensor are similar. This indicates that the upper measurement range of the sensor is sufficient to capture the event and not clip the data. It is confirmed here that the sporadically high readings occur almost entirely at low depth, which is a typical feature of ultrasonic Doppler-based velocity sensors [20]. Additionally, the density of sporadically high points is comparable to that of the data from the HACH sensor. Figure 9 also highlights that the minimum velocity at which useful velocity measurements are obtained is at the filter cut-off of 250 mm/s, since below this, velocity readings from the sensor are distributed from 0 to 250 mm/s regardless of the HACH measurement. It is known that the HACH sensor performs multiple velocity scans per recording interval to improve its measurement accuracy, and it is poorly documented whether the resultant velocity output is processed further based on past measurements. If so, this would likely increase the ‘smoothness’ of the HACH data when compared to the velocity sensor.

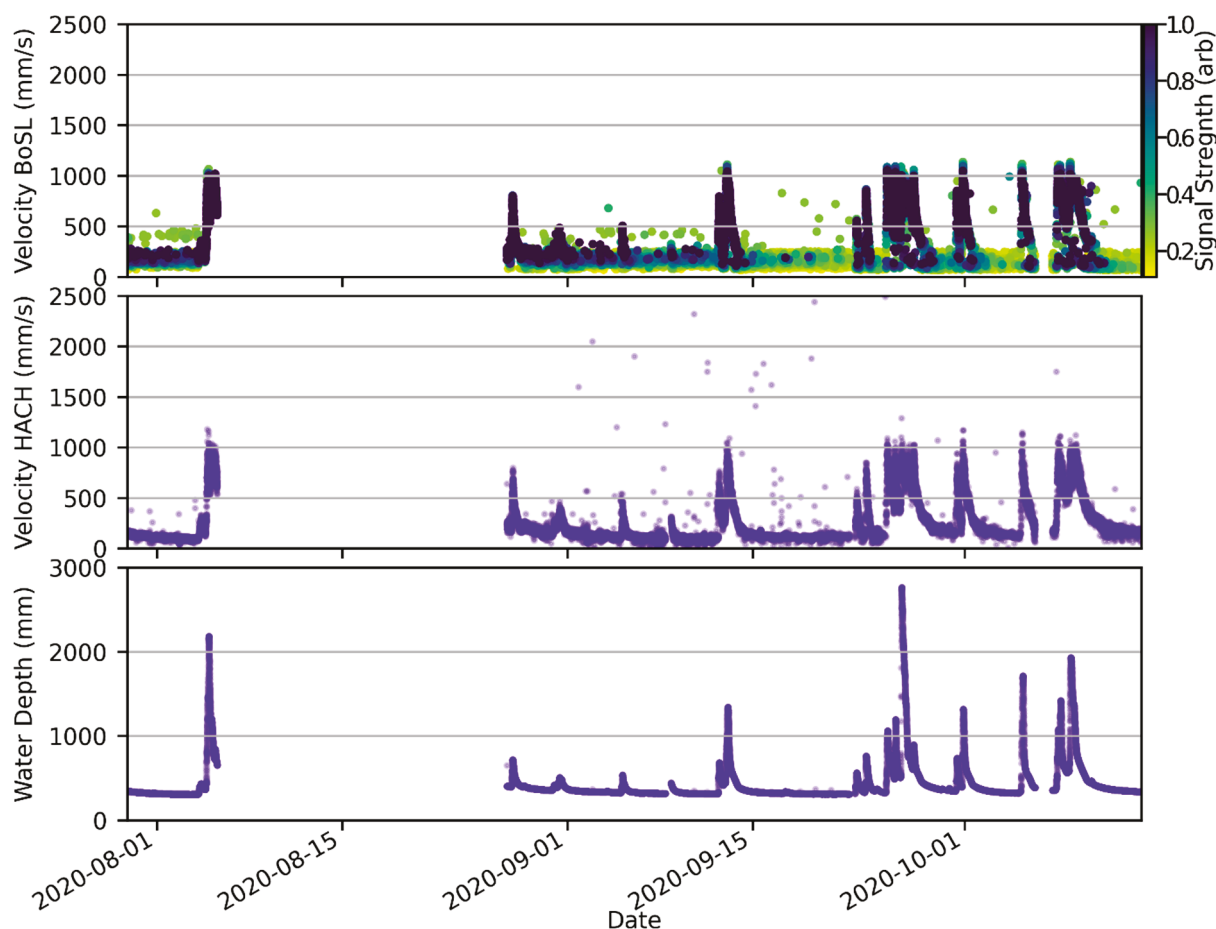


Figure 9. Top: Plot of the velocity measurement of the sensor over time. Middle: HACH probe velocity measurements over time. Bottom: HACH probe depth measurements over time. The x-axis on all plot is the same. There was a pause in data collection from 2020 AUG 5 to 2020 AUG 27. A few data points are beyond the plot range; the full data extends to 3000 mm/s on the y-axis.

The root mean square (RMS) error for the sensor's measurement when compared to the HACH measurement was calculated for measured flow velocities in 200 mm/s bins (Table 3). This was performed to obtain a better description of the measurement error at different flow velocities. The RMS error falls below 30% above flow velocities of 400 mm/s. Larger errors occur at flow velocities below 400 mm/s, particularly below 200 mm/s; however, this is expected as velocities below 250 mm/s are out of the sensor's designed measurement range. The mean error for the sensor is least at above 400 mm/s, where it remains within $\pm 11\%$. Below 400 mm/s, particularly 200 mm/s, the mean error increases in magnitude significantly, though still remaining less than 30%.

Table 3. Sensor error characterisation. RMS error calculations for the sensor measurement in in-field testing. A negative mean error corresponds to the sensor under-reading. Data are binned according to the velocity recorded by the HACH sensor.

Velocity Range (mm/s)	Number of Points	RMS Error (%)	Mean Error (%)
0 to 200	15,867	65	+30
200 to 400	6204	43	−23
400 to 600	2463	29	−3
600 to 800	2516	23	+10
800 to 1000	1130	17	+1
1000 to 1200	70	20	−11

To further understand the performance of the sensor, causes for the error of the sensor should be analysed. The accuracy of the HACH probe used to compare the sensor's measurements to is a clear first consideration. The HACH corporation claims a measurement error of less than 3% in ideal conditions [24]. Studies using data from the HACH probe in real-world conditions, however, claimed that the uncertainty could be underestimated significantly, especially at low water velocity, and therefore have taken a more conservative estimate of ± 100 mm/s [34,35]. This absolute uncertainty would contribute significantly to the relative uncertainty estimated at low flow velocities and may partly explain the high error seen at the 0 to 200 mm/s and 200 to 400 mm/s velocity ranges (representing an RMS error of 50% for 200 mm/s and 25% for 400 mm/s). At higher velocities this error from the HACH probe will contribute less significantly to the uncertainty in the measured error for the velocity sensor.

It should also be reiterated that it is not well-documented what post processing the HACH sensor performs on its data. It is a common practice to perform data cleaning of the velocity measurements both to overcome the random error from the sensor and to reduce high-frequency variations in the water velocity induced by pulsation and turbulence [36]. Use of the data should perform some similar data processing, which will result in a reduction in the RMS error.

The sensor does not compensate for temperature. It is hypothesised that temperature could affect the velocity measurement through changes to the speed of sound in water or by altering the frequency of the LO. At 20 °C, the speed of sound in water is 1480 m/s with a variation of 3 m/s·K [37]. The speed of sounds affects the velocity measurement; however, over an extreme 20 °C swing in temperature, a 5% error of the velocity measurement occurs. Likewise, the MAX7573 oscillator used has temperature dependence on its output frequency; this similarly affects the velocity. However, a 20 °C swing here produces a less than 1% variation in output frequency [23]. The sensor also compares favourably to other current works on velocity sensing. The low-cost contact- and non-contact-type water velocity sensors presented in [15] have root sum of squares errors of 10% and 12% over six data points over a range of 0.21 to 1.4 m/s for the contact type and 0.2 to 0.5 m/s for the non-contact type. While these errors are smaller than those for the sensor presented here, they are not too dissimilar and the small number of data points limits the confidence of any conclusion. Furthermore, the sensor presented here has the advantage of containing no moving components, which are likely to be blocked by debris, limiting the reliability of the sensor, or the computationally expensive and high power algorithms needed for particle image velocimetry methods.

Another non-contact method for velocity sensing via a flying optical-based method can be found in [18]. It finds an uncertainty from 5% to 26%. While this sensor performs better at lower velocities, the overall uncertainty range is similar to the sensor in work. The design produced by [18] also serves a different use case of instantaneous measurement of a large number of sites rather than the long-term real-time monitoring application that is the focus of this work.

The recent low-cost hydro-mast for measurement of the velocity near the bed of the channel [17] was tested with a similar field validation method by comparison against a commercial acoustic Doppler sensor. In the velocity range from 0.35 to 1.2 m/s, the sensor was found to have a mean error of at most 95 mm/s. This is just slightly lower than the maximum mean error found for this sensor at 130 mm/s (−11% at 1200 mm/s). Again, while the sensor from [17] is valuable for understanding the flow dynamics in the near-bed. The sensor proposed here measures the mean velocity, more suitable for obtaining a reading representative of the flow across the channel. As discussed, our sensor compares favourably in performance to recent developments in the water sensing space and fulfills the gap of a sensor suitable for long-term, low-cost, real-time monitoring.

Future work should focus on studying the sensor in a large-scale deployments for real-time monitoring and should investigate the benefits and considerations of the sensor to this application. Incremental improvement to the sensor's design should also be another

focus of future research. This may include enhancement of the sensors' electronics and data processing to increase the sensors' accuracy, performance at lower velocities, and data reliability.

4. Conclusions

The sensor presented has been shown to effectively measure the water velocity via data from an in-field test. The performance of the sensor is best at 400 to 1200 mm/s, where RMS error is below 29% and mean error ranges from -11% to $+10\%$. While this does not match the manufacturer's quoted performance of current commercial sensors in ideal lab conditions, the performance becomes significantly more comparable in field applications, where there is an increase to the uncertainty. The novelty of the sensor is in enabling the measurement of velocity at a cost of 50 USD, significantly cheaper than the typical thousands of dollars for commercial sensors. Along with the low power usage of the sensor—2 mW for 10 measurements an hour—and its compact size, it supports the deployment of the sensor for real-time monitoring in large quantities. This opens up the possibility to new scientifically interesting monitoring schemes, such as high spatial and temporal data resolution collection in environmental monitoring programs.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/s22197451/s1>. Please find complete design files necessary to modify and build the sensors along with the data used in the analysis of this study in the Supplementary Materials.

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Article

A 3D-Printed Capacitive Smart Insole for Plantar Pressure Monitoring

Anastasios G. Samarentsis ^{1,†}, Georgios Makris ^{1,†}, Sofia Spinthaki ², Georgios Christodoulakis ³, Manolis Tsiknakis ³ and Alexandros K. Pantazis ^{1,*}

¹ Institute of Electronic Structure and Laser, Foundation for Research and Technology Hellas, 70013 Heraklion, Greece

² Department of Physics, University of Crete, 70013 Heraklion, Greece

³ Department of Electrical and Computer Engineering, Hellenic Mediterranean University, 71410 Heraklion, Greece

* Correspondence: alepa@iesl.forth.gr; Tel.: +30-2810-39-4111

† These authors contributed equally to this work.

Abstract: Gait analysis refers to the systematic study of human locomotion and finds numerous applications in the fields of clinical monitoring, rehabilitation, sports science and robotics. Wearable sensors for real-time gait monitoring have emerged as an attractive alternative to the traditional clinical-based techniques, owing to their low cost and portability. In addition, 3D printing technology has recently drawn increased interest for the manufacturing of sensors, considering the advantages of diminished fabrication cost and time. In this study, we report the development of a 3D-printed capacitive smart insole for the measurement of plantar pressure. Initially, a novel 3D-printed capacitive pressure sensor was fabricated and its sensing performance was evaluated. The sensor exhibited a sensitivity of 1.19 MPa^{-1} , a wide working pressure range ($< 872.4 \text{ kPa}$), excellent stability and durability (at least 2.280 cycles), great linearity ($R^2 = 0.993$), fast response/recovery time (142–160 ms), low hysteresis ($DH < 10\%$) and the ability to support a broad spectrum of gait speeds (30–70 steps/min). Subsequently, 16 pressure sensors were integrated into a 3D-printed smart insole that was successfully applied for dynamic plantar pressure mapping and proven able to distinguish the various gait phases. We consider that the smart insole presented here is a simple, easy to manufacture and cost-effective solution with the potential for real-world applications.

Keywords: gait analysis; wearable sensors; 3D printing; capacitive pressure sensors; smart insole; real-time plantar pressure monitoring

1. Introduction

Human gait, as natural and as simple as it seems, is the product of a complicated and cooperative process involving the brain, spinal cord, nerves, muscles, bones and joints. Gait is a typical activity for healthy human beings but also characteristic of a person's style and quality of life. Proper gait functionality is essential for maintaining an abundant lifestyle, healthier and happier, while any deviation from the standard can drastically affect everyday experiences.

The study of human walking, namely gait analysis, can be used as a valuable diagnostic tool to distinguish between normal and pathological gait. Abnormal gait patterns are related to the pathology of the human locomotor system, which can be caused by various pathological conditions including neurodegenerative, musculoskeletal or other peripheral disorders [1]. For example, apraxic gait is characterized by the deterioration of neurons, loss of locomotion control and eventually inability of proper movement as a result of diseases such as Parkinson's [2], Alzheimer's [3] or cerebral palsy (CP) [4], etc. Limited mobility and dysfunctional gait, e.g., antalgic patterns, may be the effect of chronic musculoskeletal pain arising from age-related conditions such as knee osteoarthritis [5],

osteoporotic hip fractures [6], etc. In this respect, a quantitative gait analysis at a specific moment, or through continuous monitoring and re-evaluation over time, can support early diagnosis of diseases, credible clinical decisions, optimization of treatment protocols and assessment of patient outcomes [7]. Apart from clinical applications, the reliable analysis of human gait characteristics is one of the main interests in the fields of sports science [8], rehabilitation [9], security monitoring [10] and robotics [11].

The traditional/old-fashioned approach to human gait analysis is based on the observation of a patient's gait performed in a clinic by experienced specialists, aided with patient self-reporting. However, this method is considered unreliable and oversimplified, i.e., the evaluation is subjective and lacks of quantitateness [1]. The progress of new technologies has given rise to more delicate, advanced techniques which allow for an accurate, objective and quantitative measurement of gait parameters [12]. The standard method for gait analysis, adopted by the majority of specialized clinics, is a vision-based motion analysis captured by digital video cameras and thoroughly analyzed through image processing techniques [13]. Alternatively or in combination, force platforms can be used to extract gait information; they are located on the floor and utilize a pressure mattress to measure ground reaction forces (GRFs) during walking [14]. Nonetheless, the aforementioned methodologies are relatively expensive, time-consuming and require expertise [15]. Moreover, the examination procedure is strictly performed to controlled environmental settings, where the patient is aware of his/her movements and usually with markers attached to the body; hence, the results do not reflect real-world activities [15].

In the last decade, wearable insole-based sensor systems have shown great potential as gait analysis tools, intending to overcome the aforementioned limitations of stationary force platforms [16–18]. These wearable technologies allow for continuous gait monitoring in both indoor and outdoor environments on a daily basis without any constraints on an individual's natural gait during measurements. Most often, they are used to measure the plantar pressure distribution, despite the fact that other gait features can also be obtained, including the center-of-pressure (CoP), step count, duration of gait cycle, swing and stance duration [19]. Insole-based plantar pressure sensors produce an electrical signal upon pressure loading during human gait. Based on their working mechanism, they can be divided into three major, widely used types: piezoelectric [20–22], piezoresistive [23–26] and capacitive [27–30]. Each sensing mechanism exhibits its own merits and limitations [16,18], none of them has a clear edge and it is rather hard to develop a sensor device with ideal characteristics [31]. The basic parameters to determine the performance of plantar pressure detection sensors are sensitivity, linearity, range of detection, response time, hysteresis, stability, durability and interferences from external sources such as temperature, humidity or electromagnetic interference [32]. Apart from sensor performance characteristics, multiple factors have to be considered prior to the development of a new insole sensing system, including sensing elements layout, electronics circuit design, signal processing algorithms, energy consumption, manufacturing cost and user comfort [7,16,18].

Capacitive pressure sensors have been established as a compelling candidate for insole-based plantar pressure monitoring due to their simple structure, low power consumption, good reliability, repeatability and dynamic performance [16,17,33]. Nonetheless, their performance can be affected by humidity, temperature and electromagnetic interference [16]. Many attempts have been made over the years to integrate capacitive pressure sensors into smart insoles. In order to increase plantar pressure sensitivity, capacitive sensors with porous polydimethylsiloxane (PDMS) as the dielectric material have been repeatedly presented in the literature [34–36]. In another approach, Zhang et al. developed a low-cost, capacitive-based plantar pressure sensor composed entirely of fabric [37]. Tao et al. established a real-time pressure mapping smart insole system with a rubber dielectric layer and studied various motions and postures [29]. Aqueveque et al. presented a gait segmentation method using a custom-made capacitive insole [28]. Sorrentino et al. developed a capacitive insole prototype with temperature compensation and high spatial resolution [27]. Recently, De Guzman et al. created a low-cost, capacitive insole for

plantar pressure measurement as a possible alternative to more expensive systems [30]. However, the insoles presented in the aforementioned studies are characterized by complex and expensive fabrication processes or inadequacy for cost-effective mass production. In addition, a few capacitive-based insole products have become commercially available in the last two decades. For example, the Pedar[®] (Novel GmbH, Munich, Germany) pressure distribution measuring system is a widely used and well-tested in-shoe device based on 99 capacitive sensors [38–40]. Another product worth mentioning is Moticon's (Moticon GmbH, Munich, Germany) OpenGo[®] sensor insole system which consists of 16 capacitive pressure sensors and is capable of measuring plantar pressure distribution and acceleration in three dimensions [41–43]. PODOSmart[®] (Digitsole SAS, Nancy, France) insoles have also been validated for normal walking measurements using a stereophotogrammetry-based system [44]. Despite the above solutions having been proven in terms of accuracy and repeatability, they are characterized by a relatively high cost.

In recent years, the application of three-dimensional (3D) printing technology for the manufacturing of sensors has attracted a significant amount of research interest both in industry and academia [45]. When compared to traditional semiconductor processing techniques, 3D printing offers several advantages, including lower fabrication costs, reduced manufacturing time, lesser number of processing steps, a range of different materials and prototypes that can be easily customized according to application [46]. Various types of 3D-printed sensors such as force, acoustic and ultrasonic, optical and electromagnetic have been developed for engineering [45,47] and biomedical applications [46,48,49]. Several 3D-printed capacitive-based, flexible strain and tactile sensors can be found in the literature [50,51], but to the best of our knowledge, a 3D-printed capacitive smart insole for plantar pressure monitoring has not been developed up to now.

In this study, we present the development of a 3D-printed smart insole suitable for plantar pressure monitoring. The insole incorporates 3D-printed pressure sensors based on the capacitive sensing principle. At first, the capacitive sensors were tested under dynamic loading conditions to assess their performance by measuring their principal characteristics. These include sensitivity, linearity, pressure detection range, durability, stability, hysteresis and response/recovery time. The 3D-printed sensors were integrated into a 3D-printed insole, demonstrating the potential use of the system for recording gait-related data.

2. Materials and Methods

2.1. A 3D-Printed Capacitive Pressure Sensors

Capacitive pressure sensors were fabricated using 3D printing technology, employing the Fused Filament Fabrication (FFF) method. Specifically, 3D printing was performed with the TENLOG TL-D3 Pro Dual Extruder 3D Printer (TENLOG 3D solutions, Shenzhen, China). The sensors were designed via the Fusion 360 CAD software (Autodesk, San Rafael, CA, USA), while the Ultimaker Cura 4.6.2 software (Ultimaker B.V., Utrecht, The Netherlands) was used for the slicing of the object into layers.

Capacitive pressure sensors consist of two conductive plates separated by a dielectric material. As it is shown in Figure 1, the in between section of the two plates consists of two dielectric materials, in separate levels: First, an air cavity with a thickness of 1.0 mm and then a 0.2 mm solid flexible material (Filaflex 70A). This architecture was chosen as it offers greater sensitivity than the classic plate–dielectric–plate structure [52]. We should mention here, that prior to the presented architecture, we had already tested various versions of the classic capacitive structure (data not shown), where the dielectric was either solid or had a grid pattern (20% to 100% infill). However, in this case the system demonstrated a poor signal response/sensitivity. In general, the pressure sensitivity of a capacitive pressure sensor S_c can be expressed as [34]:

$$S_c = \frac{(\Delta C / C_0)}{\Delta P} \quad (1)$$

where ΔC is the change in capacitance, C_0 is the initial capacitance without the application of pressure and ΔP is the pressure change.

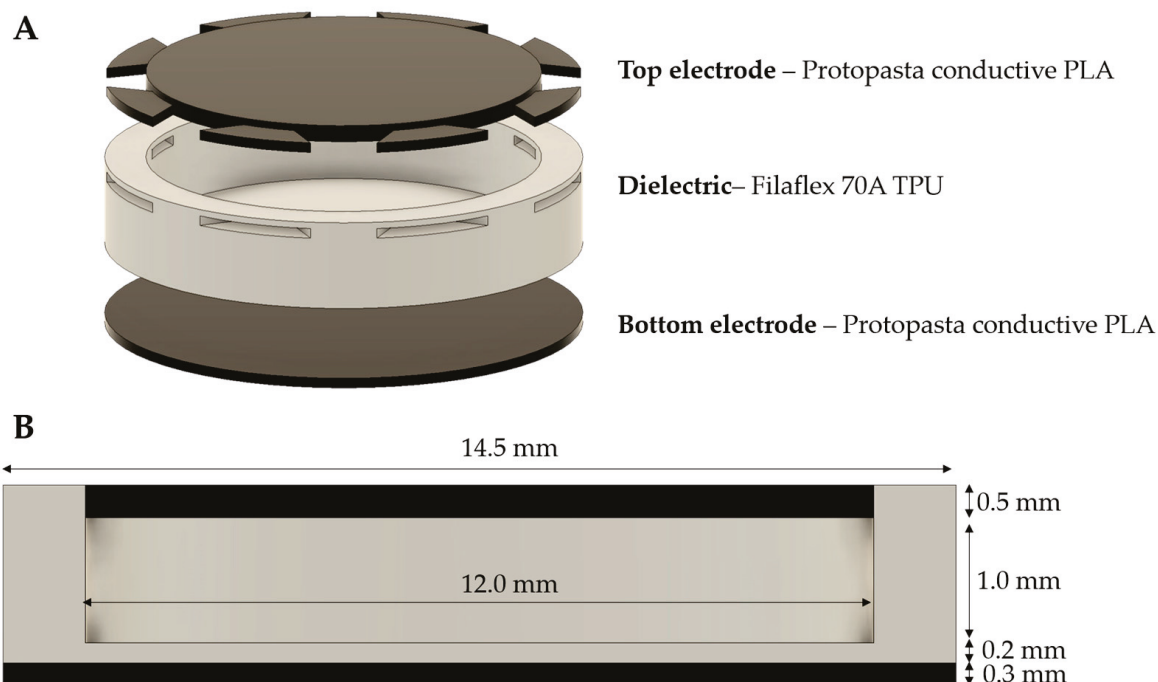


Figure 1. (A) Layers of the structure and (B) cross-section of the 3D-printed capacitive pressure sensor.

The optimized model of the capacitive pressure sensor incorporates two conductive plates made of Protopasta CDP11705 composite conductive PLA (Protoplant, Vancouver, Canada) while the middle dielectric layer is made of Filaflex 70A TPU (Recreus Industries S.L., Elda, Spain) (Figure 1). The overall thickness of the sensor is $t = 2$ mm and its diameter $d = 14.5$ mm with layers of the following thicknesses: bottom electrode—0.3 mm, top electrode—0.5 mm and dielectric in total—1.2 mm. The settings for the 3D printing of the different materials used for the fabrication of the capacitive pressure sensors are summarized in Table 1.

Table 1. Printing parameters applied for the 3D printing of the different materials.

3D Printing Settings	Protopasta Conductive PLA	Filaflex 70A/82A TPU
Infill (%)	100	
Extruder temperature (°C)	215	230
Bed temperature (°C)	45	
Print speed (mm/s)	15–20	
Layer height (mm)	0.1	
Nozzle diameter (mm)	0.6	
Flow rate (%)	110	
Flow width (mm)	0.6	
Retraction speed (mm/s)	60	

The capacitance for two dielectric layers in series can be found easily from basic electrodynamics equations [53] and expressed as:

$$C = \frac{\epsilon_0 \times A}{\frac{d_1}{k_1} + \frac{d_2}{k_2}} \quad (2)$$

where ϵ_0 is the dielectric constant of free space, A is the area of the plate, d_1 , d_2 are the thicknesses of the two dielectric materials and k_1 , k_2 are the relative permittivity of the two dielectrics, respectively.

When pressure is applied on the capacitance sensor, the two plates (top and bottom) come closer. Thus, the total distance ($d_1 + d_2$) between the two electrodes is reduced on the system and the capacitance changes (Equation (2)).

On both plates, we fix the cables with an adhesive conductive glue and on top of the glue we place a small piece of insulation tape as a protective layer.

2.2. Experimental Set-Up for Dynamic Measurements

An in-house experimental set-up was designed and manufactured to facilitate dynamic measurements by simulating a pressure point. This is performed through an aluminum shaft (piston) that moves up and down. The shaft moves through a flanged linear ball bearing (8 mm), which is fixed on the structure (wooden crate). The sensor is located on the bottom side of the structure, just below of the shaft's tip (area of the tip is equal to the area of sensor). On the top part of the shaft, the crate supports the installment of a pulley system that enables the movement of the shaft on the vertical axis (Figure 2). Additionally, the pulley system is easily disengaged from the shaft in order to place on it 0.5 kg disk weights. In this direction, the pulley system transmits the motion to the piston through a stepper motor (Nema 23 57BYGH115 from Wantai motors), which is located on the side of the crate, and is connected to a motor driver (TB6600), both controlled by an Arduino Nano system (Arduino LLC, Boston, MA, USA). This way, the shaft applies periodic force on the sensor. Two potentiometers control the speed and the elevation of the shaft, which are modified in real time. The gait speed is displayed on a microdisplay (1.3" OLED Display Module from Waveshare) as steps per minute per foot. A second Arduino Nano board is used for the system's output acquisition and data are recorded using a code written with the open-source Arduino software language (IDE). The total time of the measurement and the sampling period are defined by the user. The sensor is fixed at this position with adhesive tape (3M™ Acrylic Adhesive 300MP) before the experiment initiation. The set-up makes it possible to measure the sensor's response as a function of different mass loading conditions ranging from 0.7 (weight of shaft) to 14.7 kg (which in pressure units is 41.5 kPa to 872.4 kPa). The environmental conditions of the sensor tests were 20 °C and 55–60% humidity.

2.3. A 3D-Printed Smart Insole

The fabricated 3D-printed capacitive pressure sensors were used for the design and development of a 3D-printed smart insole. The architecture, circuit connection and images of the 3D-printed capacitive smart insoles are presented in Figure 3. The upper and lower layer of the insole are made of Filaflex 82A (Recreus Industries S.L., Elda, Spain) and the printing parameters are the same as those presented in Table 1. Each insole incorporates 16 capacitive pressure sensors which are fixed to the lower flexible case and adequately electrically connected. The sensors are distributed in the insole as depicted in Figure 3A. The total thickness of the insole is 3.8 mm, with a length up to 25 cm and width up to 8.5 cm, corresponding to a No.39 EU size shoes. The two layers (upper and lower) are glued together at the perimeter of the insole.

2.4. Smart-Insole Graphical User Interface (GUI) Implementation

The GUI presented in the current investigation is a Java-based desktop application developed in IntelliJ IDEA [54]. It makes use of a "lightweight" GUI Framework, called "Swing", which contains a set of classes to provide powerful and flexible GUI components [55]. The application communicates with the insole, and particularly with the electronics module, with the use of the *Serial Communication* protocol, through a USB cable, or, alternatively, a wireless Bluetooth module working as a serial (Rx/Tx) pipe. It receives and converts in real-time the sensor readings, acquired from the A/D converter of

the electronics module, into pressure values, and subsequently, it presents in a graphical manner the pressure variations of each individual sensor and the center of pressure (CoP) in total too. In the implementation of the individual pressure variations, the insole, scaled into the monitor resolution, is divided into 227 grids as shown in the middle of Figure 4. Then, a group of nearby grids is assigned to every sensor, which, depending the current pressure value, change color accordingly, with yellow indicating the lowest and red the highest pressure. Next to the grid implementation, the individual pressure values may also be presented in a chart-type implementation as shown at the left and the right side of Figure 4.

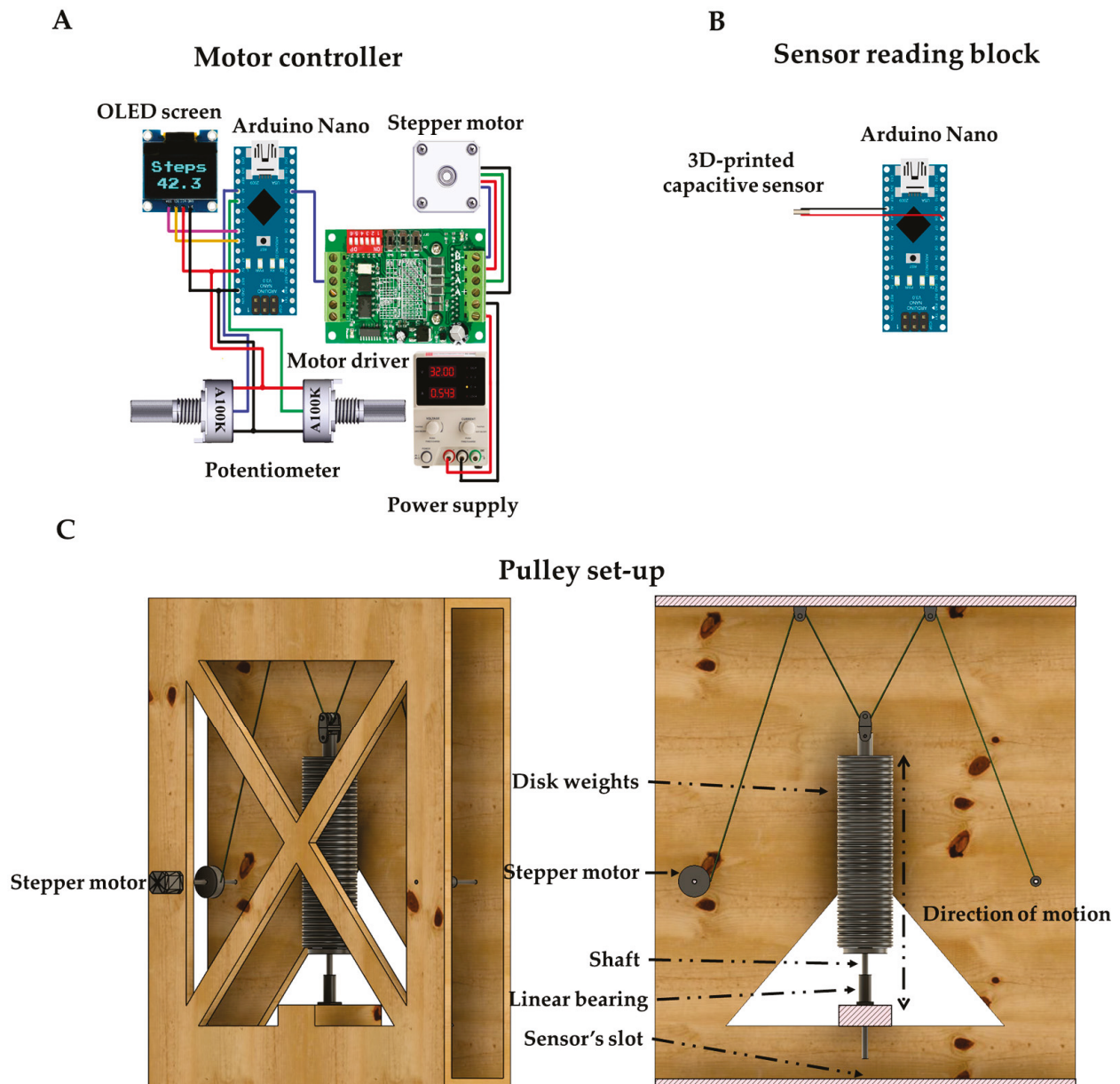


Figure 2. Experimental set-up for dynamic measurements; (A) motor control circuit, (B) capacitive sensor reading block and (C) pulley set-up system.

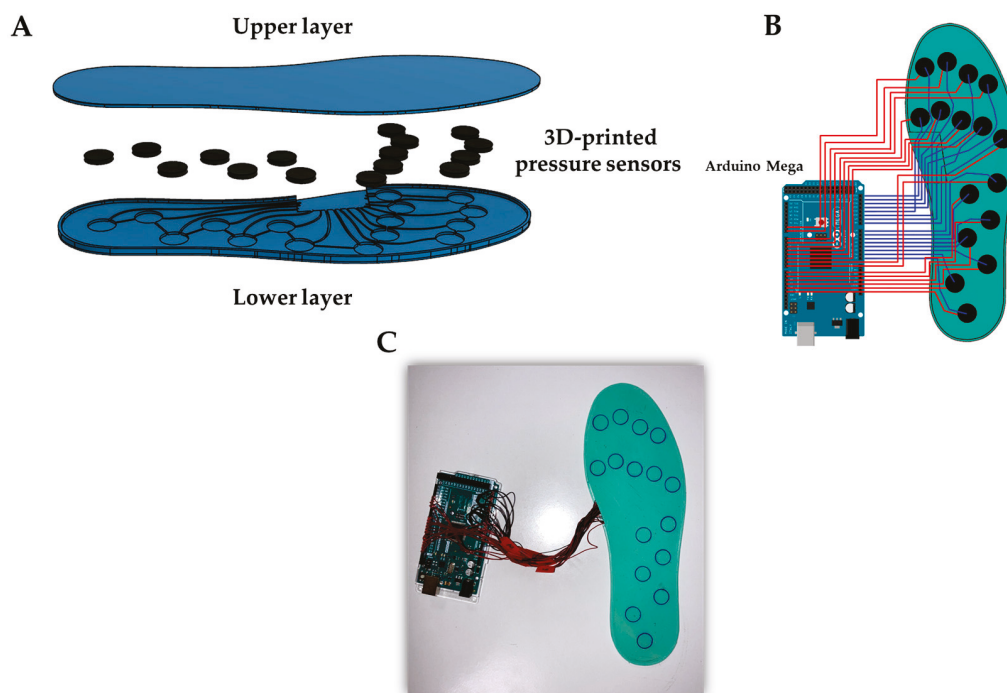


Figure 3. Schematic illustration of 3D-printed smart insole; (A) general structure, (B) electrical circuit and (C) image of the capacitive 3D-printed smart insole.

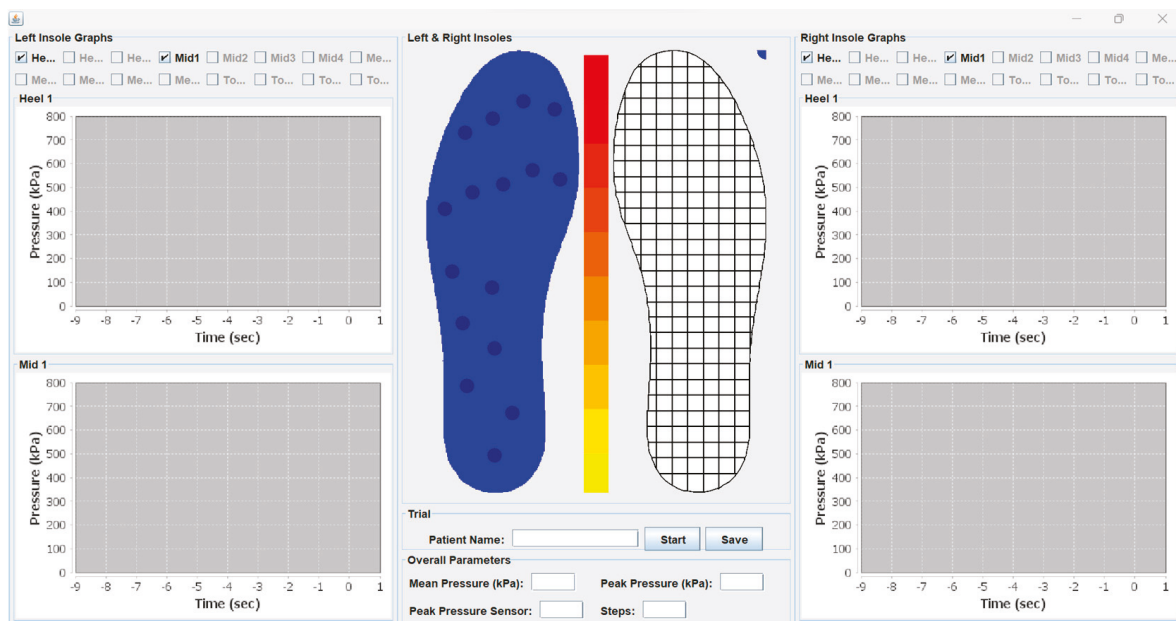


Figure 4. Smart insole graphical user interface (GUI) implementation.

3. Results and Discussion

3.1. Sensor Evaluation

In order to evaluate the sensing performance of the 3D-printed capacitive pressure sensors, we conducted a series of experiments that enabled to assess their basic characteristics. The real-time sensor responses under dynamic pressure loading were used to obtain an estimation of their sensitivity, both in and out of the insole. In addition, we investigated other key parameters correlated to sensor performance including linearity, limit of detection (LoD), detection range, effect of loading frequency, stability, durability,

repeatability, hysteresis, response and recovery time. In this manner, their potential for practical applications such as plantar pressure monitoring was verified.

3.1.1. Real-Time Measurements

The real-time capacitance changes of a typical 3D-printed capacitive pressure sensor as a function of varying external pressure are demonstrated in Figure 5. The dynamic experiments were performed under a loading frequency that was kept constant at 40 steps/min. The applied pressure ranged from 41.5 kPa to 872.4 kPa with an incremental increase of 59.35 kPa, while one-minute recordings were obtained at every pressure. In these graphs, we present the dynamic responses of the sensors at selected pressure values (step = 118.7 kPa) under three loading/unloading cycles. As observed, the capacitance response gradually increases with pressure and its value is clearly distinctive among all steps. Moreover, the sensor is characterized by a stable and repeatable capacitance response under every pressure in the range tested. The results indicate that the sensors can efficiently operate at this pressure range without any damage, since in all cases they rapidly recover to their initial baseline value.

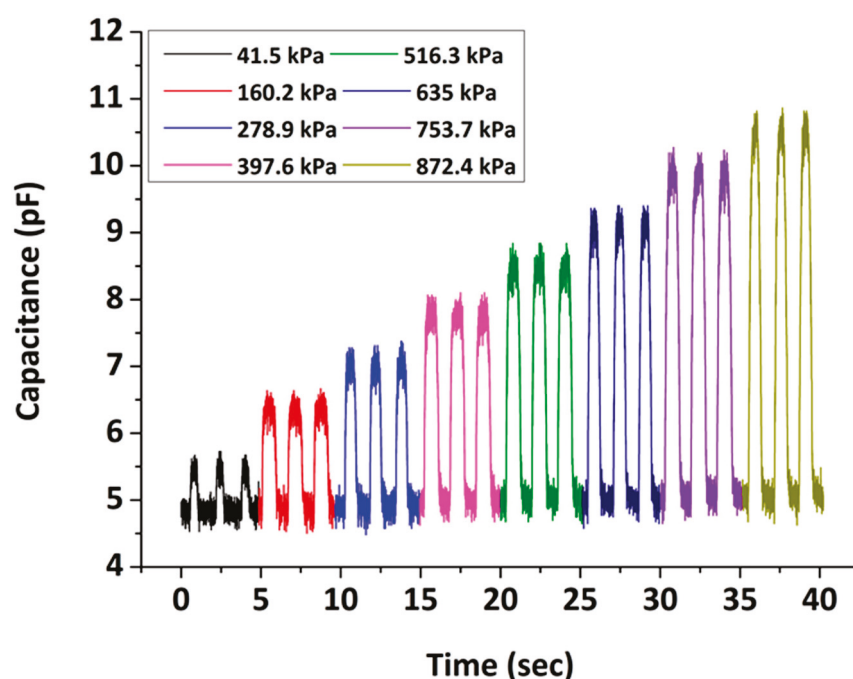


Figure 5. Real-time capacitance response of a typical 3D-printed capacitive pressure sensor at different external pressures under three loading/unloading cycles.

3.1.2. Sensitivity

In order to assess the sensitivity of the 3D-printed capacitive pressure sensors, we measured their relative responses versus external pressure. In Figure 6, the relative capacitance change, the average of 16 sensors, is presented under varying external pressures ranging from 41.5 kPa to 872.4 kPa, using a step of 59.35 kPa. In this range, the mean sensor response was proved to be linear with pressure, while the slope of the curve was used to estimate the sensitivity. As shown in Figure 6, the average sensitivity of the capacitive sensors is $1.19 \pm 0.03 \text{ MPa}^{-1}$, showing a great linear trend ($R^2 = 0.993$) under the pressure range tested up to 872.5 kPa. The LoD is 41.5 kPa, which means that below this point it is not possible to reliably detect any pressure changes. The sensitivity found here is higher than that of other capacitive pressure sensors with similar working pressure ranges reported previously in the literature [34,37]. Our results suggest that the developed capacitive sensors are well-suited for applications with a broad pressure range.

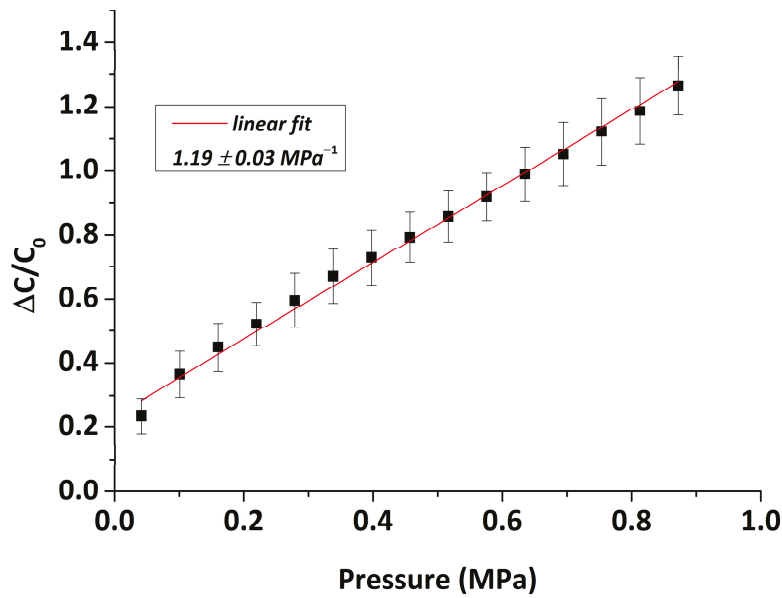


Figure 6. Average relative capacitance variation of 16 sensors as a function of the external pressure applied (0.04–0.87 MPa); the red line represents a linear fit of slope $1.19 \pm 0.03 \text{ MPa}^{-1}$.

3.1.3. Loading Frequency

Considering the specific application envisaged for the capacitive pressure sensors, i.e., gait analysis, it is important to verify the sensor response at different loading frequencies, which correspond to altering gait speeds. In this direction, Figure 7 shows the capacitance response of a typical 3D-printed capacitive pressure sensor as a function of different loading frequencies under a pressure load of 872.5 kPa. The range of the tested gait speed is between 30 and 70 steps/min, simulating slow, normal, fast and dynamic gait. As shown, no dependence of the sensor response was found on the gait speed. This means that the operation of the capacitive sensor remains stable regardless of the gait pace. In this graph, the initial C_0 and final C_f capacitance values are depicted, as well as their difference ΔC .

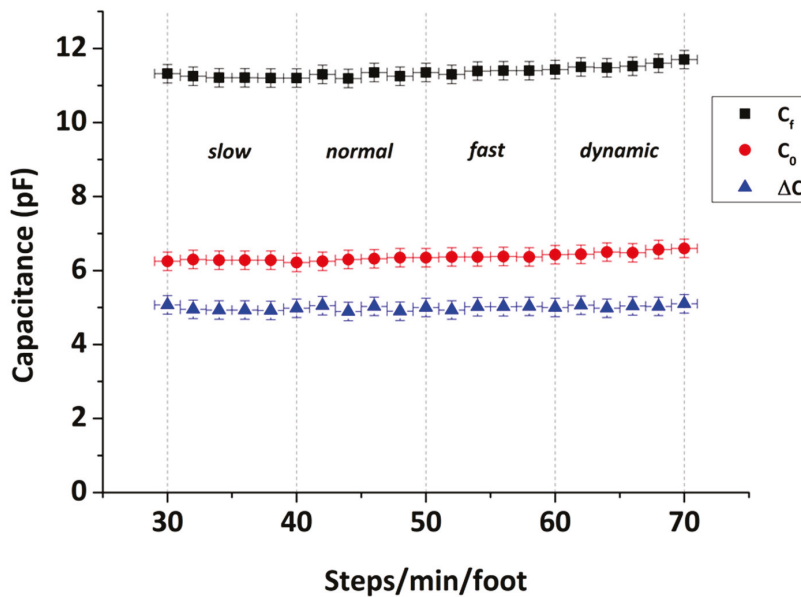


Figure 7. Capacitance response of a typical 3D-printed capacitive pressure sensor at different gait speeds (30–70 steps/min) under an applied pressure of 872.4 kPa; C_0 —initial value, C_f —final value and $\Delta C = C_f - C_0$.

3.1.4. Durability

In Figure 8, we present the capacitive sensor response during 1 h of continuous measurements (2.280 cycles of loading/unloading) under an applied pressure of 872.4 kPa. The experiment is used as a reliability test in order to assess the durability of the capacitive sensor. The inset figures demonstrate the first and final minute of the measurements. As seen, the response of C_0 and C_f remains the same, confirming the excellent stability and durability of this type of sensor.

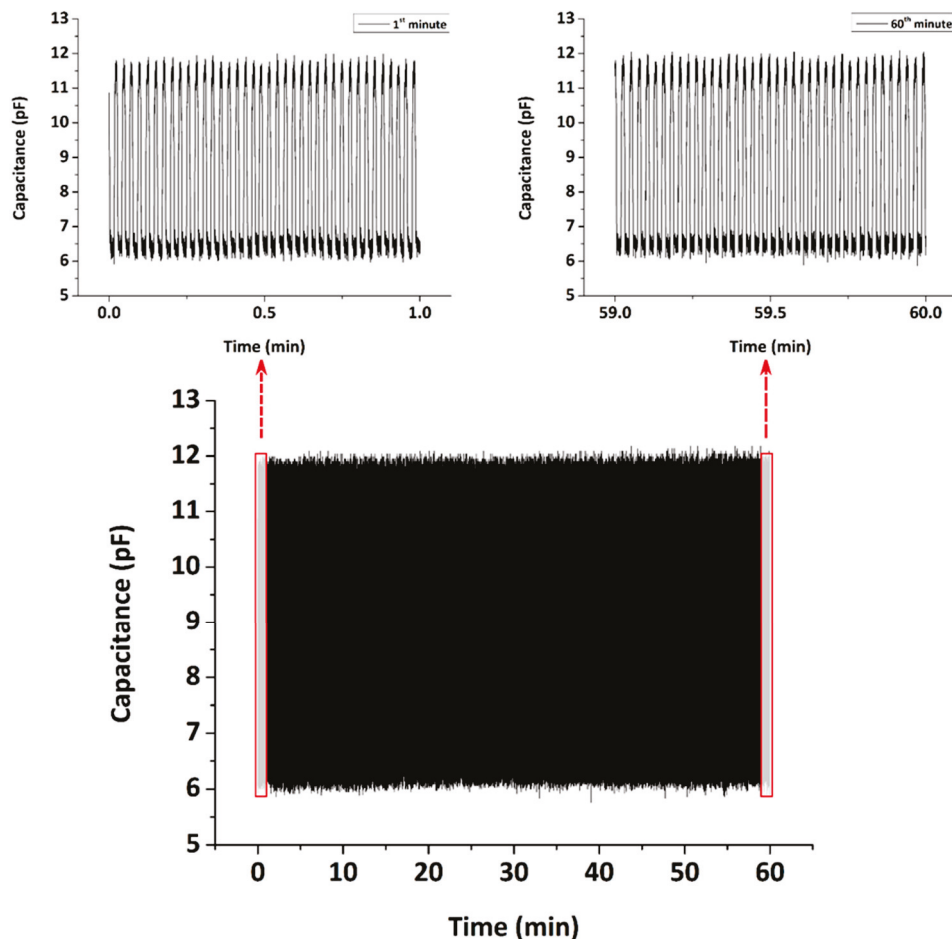


Figure 8. Capacitance response of a typical 3D-printed capacitive pressure sensor during 1 h of continuous measurements at 40 steps/min gait speed under an applied pressure of 872.4 kPa.

3.1.5. Hysteresis

Hysteresis is a critical parameter to be evaluated considering the practical applicability of any pressure sensor. Hysteresis can be defined as the difference in the output signal between consecutive loading and unloading cycles [56]. Negligible or low hysteresis is a desirable property that allows for consistent and accurate measurement of pressure variations over time. Due to the fact that the sensor has to operate under repeated dynamic conditions, potential unrecoverable deformations could introduce significant measurement errors. Figure 9 depicts the measured hysteresis curves, forward and reverse, as obtained from three consecutive linear loading–unloading pressure cycles. According to this graph, two different responses are distinguished with the unloading curve being slightly higher compared to the loading cycle. Nevertheless, the sensor only exhibits low hysteresis, indicating its capability to obtain reliable and accurate pressure signals.

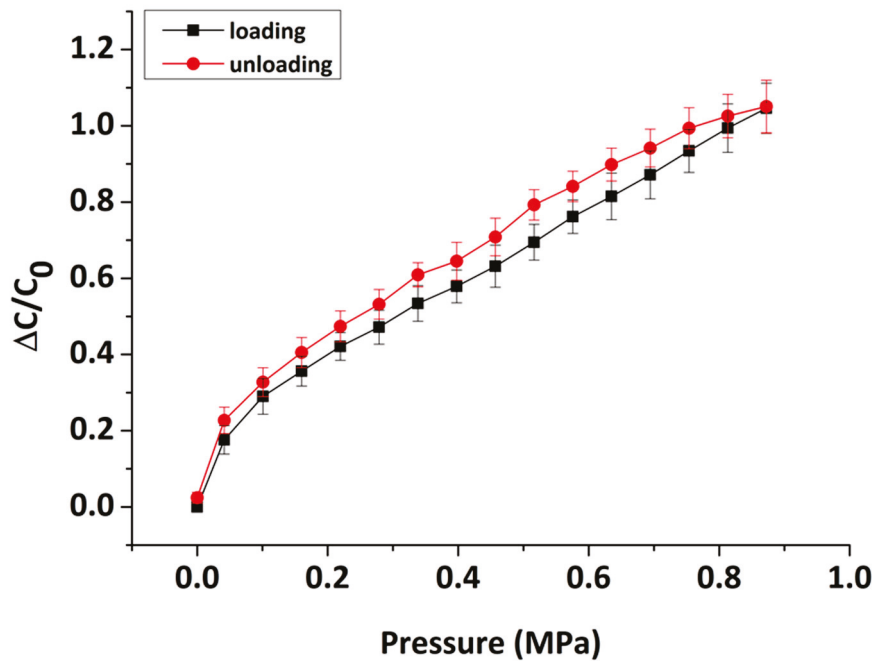


Figure 9. Hysteresis curves of the sensor obtained from three consecutive linear loading–unloading cycles of pressure.

Quantitatively, hysteresis can be assessed using the equation for the degree of hysteresis (DH) which is defined as the percentage of the relative difference in the area underneath the loading and unloading curves, calculated by the following equation [56]:

$$DH(\%) = \frac{A_{\text{Unloading}} - A_{\text{Loading}}}{A_{\text{Loading}}} \times 100 \quad (3)$$

where A_{Loading} and $A_{\text{Unloading}}$ are the areas underneath the curves in Figure 9, corresponding to the loading and unloading cycles, respectively. For our sensor, the DH value was estimated to be 9.8%, implying a relatively good hysteresis level.

3.1.6. Response/Recovery Time

Real-time pressure monitoring requires sensors that exhibit fast response and recovery times. Response time is the interval needed for the sensor output to reach its final value upon a pressure change. Reversely, recovery time is the interval required for a sensor to return to its base value upon pressure release. In this study, the response time was estimated as the time in which the capacitance changes from 10 to 90% of its maximum change upon pressure loading while the recovery time was from 90 to 10% upon pressure unloading [57]. The response/recovery time can be seen in Figure 10, where the sensor response is presented under the loading–unloading of 872.4 kPa. As illustrated, the response/recovery time of our device was found to be in the millisecond range. Specifically, the sensor can detect pressure changes with a response time of 142 ms and a recovery time of 160 ms. This means that the developed sensing device can successfully monitor plantar pressure variations, at least in cases where the stride frequencies are in the range of 30–70 steps/min. The response/recovery time found in this study is similar to that of other capacitive pressure sensors [29,35].

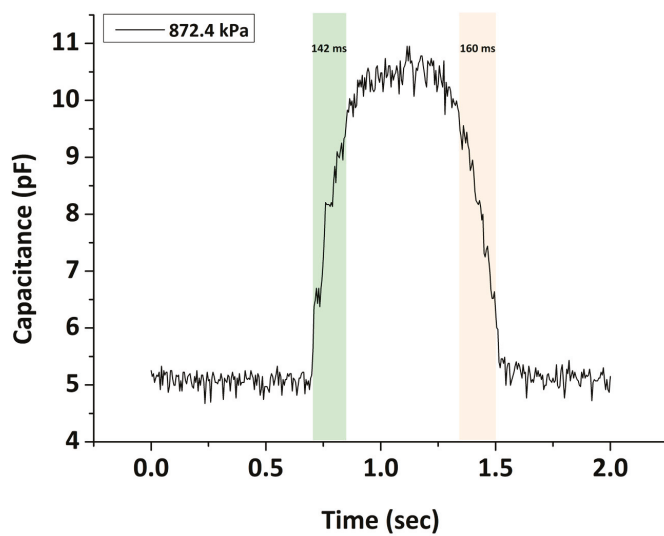


Figure 10. Sensor response and recovery times under an applied pressure of 872.4 kPa.

3.1.7. Insole Sensitivity

Since the capacitive pressure sensors developed in this research are meant to be fixed inside an insole, one should consider investigating the effect of the insole and electrical connections on the sensor's performance. For this purpose, the same sensors were placed inside the designed 3D-printed insole and re-calibration was performed using the same experimental parameters (see Section 3.1.2). The average relative capacitance change ratio ($\Delta C/C_0$) of sixteen sensors as a function of increasing applied pressure, both outside and inside the insole, is presented in Figure 11. Again, the slope of the curve reveals the average sensitivity of the capacitive pressure sensor. As anticipated, the insole has a noticeable impact on the sensor's response, i.e., the sensitivity decreases 2.1 times, specifically from 1.19 to 0.55 MPa^{-1} . Even so, the linearity is still high ($R^2 \sim 0.989$), and the working pressure range remains the same while the average error level drops to 10%. The insole sensitivity may be further improved by reducing the thickness of the insole's upper/lower cases and minimizing the electrical noise by upgrading/optimizing the external electrical circuit and hardware.

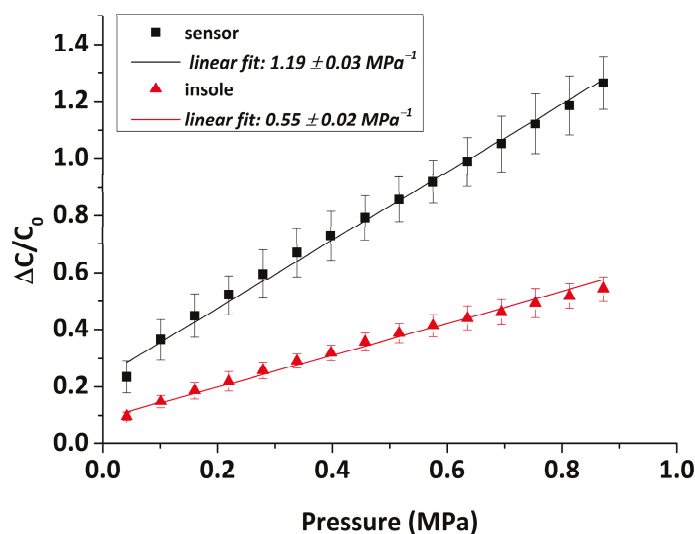


Figure 11. Average relative capacitance response of the 3D-printed capacitive pressure sensors as a function of the applied pressure measured outside (black) and inside the insole (red). The slopes correspond to the sensitivities.

3.2. Plantar Pressure Mapping

To demonstrate the relevance of the developed 3D-printed capacitive pressure sensors for practical applications, we placed the sensors inside a 3D-printed smart insole, which was subsequently used for real-time plantar pressure measurements and gait analysis. The smart insole was designed to incorporate 16 pressure sensors, distributed appropriately across the main pressure areas of the foot during walking. Specifically, the sensors were fixed at four areas: phalanges (T1, T2, T3, T4), metatarsals (ME1, ME2, ME3, ME4, ME5), plantar arch (M1, M2, M3, M4) and calcaneus (H1, H2, H3). The arrangement of the sensing elements inside the smart insole is depicted in Figure 12G.

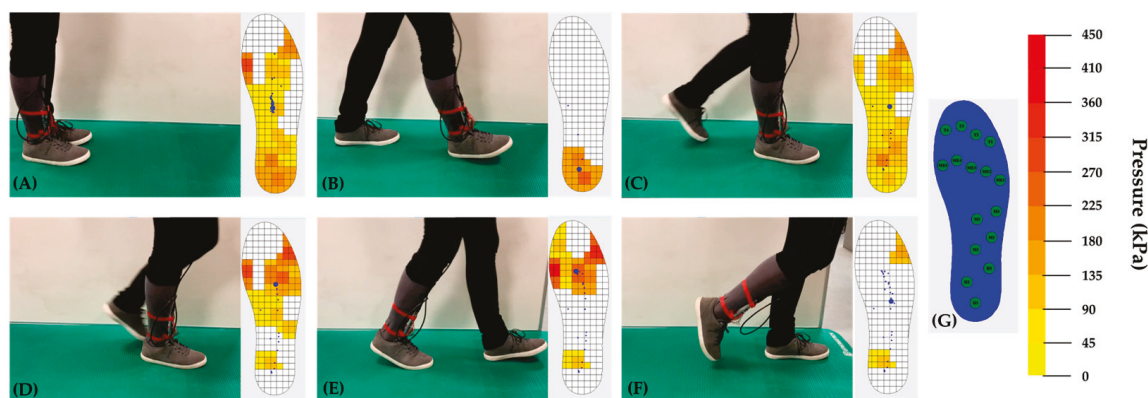


Figure 12. Plantar pressure distribution (heatmap) of the right foot under the main phases of a normal gait cycle: (A) stance, (B) heel strike, (C) foot flat, (D) midstance, (E) heel off and (F) toe off, (G) insole sensors arrangement and color map of the pressure range.

The smart insole system was fixed at the right foot of a volunteer subject and real-time recordings were obtained during repeated gait cycles. The subject recruited for these experiments was a healthy female, 27 years old, 59 kg in weight and 1.69 m in height with a European 39 shoe size. No discomfort was reported from the volunteer while wearing the insole. The plantar pressure distribution during a dynamic gait cycle is presented in Figure 12. The heatmaps shown in this graph correspond to the main stance phases of a gait cycle including stance, heel strike, foot flat, midstance, heel off and toe off. The plantar pressure mapping is based on a color scale of ten regions (0–450 kPa), ranging from yellow (low pressure) to red (high pressure). It can be clearly seen that the developed smart insole system was able to assess dynamic pressure variations and successfully determine gait events during a gait cycle. The plantar pressure distribution changes depend on the specific gait phase. In the stance and foot flat phases, a relatively even distribution of the pressure across the foot is observed. In the heel strike stage, ground contact is initiated, which results in the activation of the heel sensors that reach their peak value while the rest of the sensor remains inactive. The midstance posture is characterized by the relocation of the pressure loading mainly on midfoot and forefoot as recorded by the metatarsal and toe sensors. During the heel off phase, the pressure is concentrated on the metatarsals zone and the big toe. Finally, as displayed in the graph, at heel off all sensors return close to zero pressure values, despite the fact that some signal drift or delay is observed. In Figure 12, the trajectory of the center-of-pressure (CoP) is also shown (blue marker) during the gait cycle and its transition through the subphases is revealed. As expected, the CoP is initially located near the heel at the time of heel strike and gradually moves forward to the forefoot near the toes at the heel off stage, indicating a regular variation of the CoP. It should be noted that a proper estimation of the CoP, its trajectory and velocity, is an important parameter to evaluate the balance ability of an individual.

The real-time plantar pressure signals, as collected from the sixteen sensors of the insole during the normal gait cycle, are displayed in Figure 13. All heel sensors are activated at the first three phases, namely stance, heel strike and foot flat with the highest amplitude

of pressure measured at sensor H1 during heel strike (~ 295 kPa). The hallux area, represented here by the sensing element T4, experienced a pressure value of ~ 127 kPa in the transition between midstance and heel off. At the same time point, the highest pressure value in the phalanges zone was reported at sensor T1 (~ 370 kPa). The metatarsals area is for the most part loaded between the end of heel strike and the start of heel off. The maximum pressure recorded in this zone was of value ~ 380 kPa at sensor ME5, which is located lateral to the first metatarsal. The plantar arch received the lowest pressure and it was activated primarily at the foot flat stage with pressures remaining below 150 kPa. Sensors T2 and T3 of the middle toes area did not bear any pressure throughout the gait cycle. The results presented above confirm the applicability of the proposed 3D-printed smart insole system for plantar pressure monitoring in real time with adequate accuracy and time resolution. However, it should be noted that the results depend firmly on the architecture of the sensors, their position within the system (including how close they are packed together), on the manufacturing materials and on the general design of the insole and how it may absorb the pressure during a gait analysis.

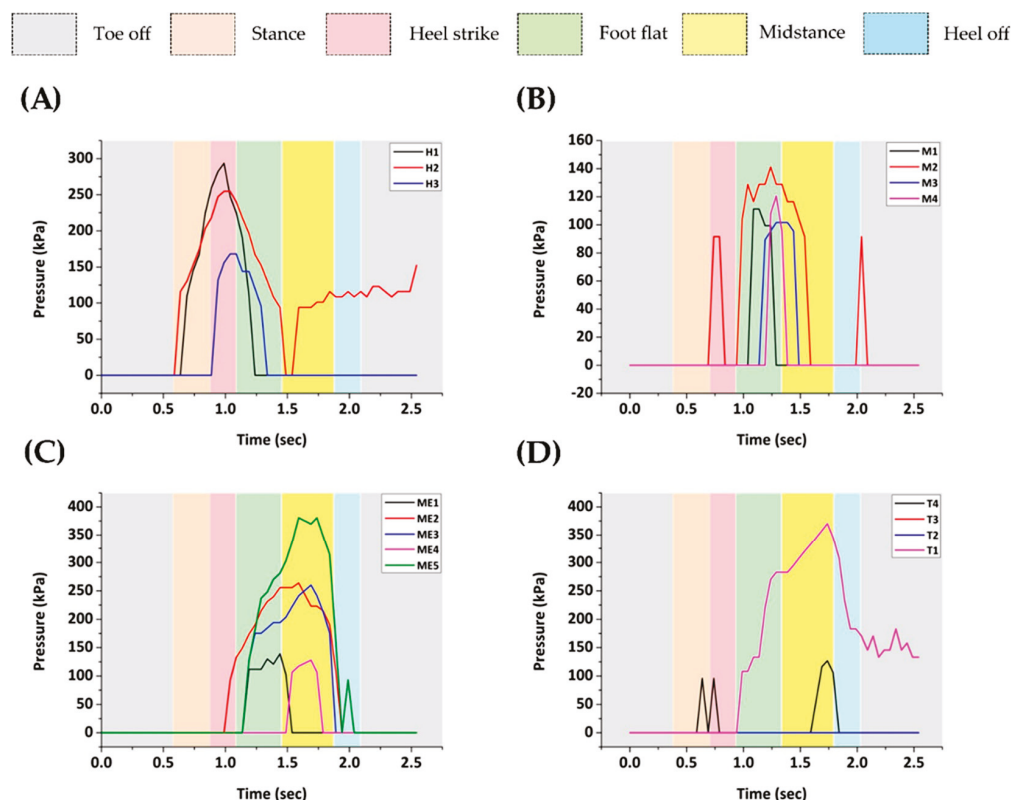


Figure 13. Real-time plantar pressure signals obtained from the right foot of the subject during a normal gait cycle using the developed smart insole system. Sensors monitored four areas: (A) calcaneus, (B) plantar arch, (C) metatarsals and (D) phalanges.

4. Conclusions

In this work, a 3D-printed smart insole system was established, aiming to monitor the plantar pressure distribution during human gait. The insole system consists of 16 3D-printed pressure sensors employing capacitive sensing. The capacitive sensors were tested under dynamic loading conditions using a custom-built experimental set-up that was developed for gait simulation experiments. The experimental set-up allows to evaluate the response of the sensors under repeated loading/unloading cycles and by varying the loading frequency and amount of pressure. As a result, it was possible to assess the performance of the sensors in terms of real-time dynamic response, sensitivity, linearity, pressure detection range, stability, durability, hysteresis, response/recovery time and gait

speed. It was confirmed that the sensors exhibit a very positive performance for their specific application, i.e., real-time human gait monitoring. Using the smart insole and dedicated software, it was possible to obtain plantar pressure maps at different gait phases, to demonstrate the capabilities of our system for gait signal analysis. Moreover, this smart insole system is characterized by a fast and low-cost fabrication process. Depending on the 3D printing systems, one can have a pair of insoles ready within a day. According to Table 2, the manufacturing costs of the 3D-printing parts per sole is a little bit less than EUR 6. The total cost of the insole pair, including the external recording unit, reaches EUR 60. Additionally, the process offers the ability to easily redesign an insole that will specifically meet the requirements of a process and the specificity of a person's/patient's foot. This makes the use of the aforementioned smart insole system perfect for personalized applications.

Table 2. Analysis of the cost per sole.

3D Printing			
Part	Mass (gr)	Material	Cost (EUR)
Insole case (top and bottom)	82	Filaflex 82A	4.57
Sensor—Conductive parts	4	Protopasta	0.50
Sensor—dielectric	4	Filaflex 70A	0.38
Electronics			
Part	#	Characteristic	Cost (EUR)
Cables	32	30 AWG	4.00
Microcontroller	1	Arduino mega	41.00
USB cable	1		2.00
Other			
Part			Cost (EUR)
Adhesive conductive glue			4.00
Adhesive glue			1.00
Insulation tape			0.50
		Full insole (including cables)	14.95
		Monitoring system	41.00
		Total	57.95

Author Contributions: Conceptualization, G.M. and A.K.P.; methodology, A.G.S., G.M. and A.K.P.; software, G.C. and M.T.; validation, A.G.S., G.M., S.S. and A.K.P.; formal analysis, A.G.S., G.M. and S.S.; resources, A.K.P.; writing—original draft preparation, A.G.S., G.M. and A.K.P.; writing—review and editing, A.G.S., G.M., S.S., G.C., M.T. and A.K.P.; supervision, A.K.P.; project administration A.K.P.; funding acquisition, M.T. and A.K.P. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of University Hospital of Patras (protocol code 279/14-5-2021 and date of approval 14.05.2021)." for studies involving humans.

Informed Consent Statement: Written informed consent has been obtained from the volunteer to publish this paper.

Data Availability Statement: The study did not report any data.

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Article

Enabling Remote Responder Bio-Signal Monitoring in a Cooperative Human–Robot Architecture for Search and Rescue

Pablo Vera-Ortega, Ricardo Vázquez-Martín *, J. J. Fernandez-Lozano, Alfonso García-Cerezo and Anthony Mandow

Robotics and Mechatronics Lab, Institute for Mechatronics Engineering & Cyber-physical Systems, Universidad de Málaga, 29071 Málaga, Spain

* Correspondence: rvmartin@uma.es

Abstract: The roles of emergency responders are challenging and often physically demanding, so it is essential that their duties are performed safely and effectively. In this article, we address real-time bio-signal sensor monitoring for responders in disaster scenarios. In particular, we propose the integration of a set of health monitoring sensors suitable for detecting stress, anxiety and physical fatigue in an Internet of Cooperative Agents architecture for search and rescue (SAR) missions (SAR-IoCA), which allows remote control and communication between human and robotic agents and the mission control center. With this purpose, we performed proof-of-concept experiments with a bio-signal sensor suite worn by firefighters in two high-fidelity SAR exercises. Moreover, we conducted a survey, distributed to end-users through the Fire Brigade consortium of the Provincial Council of Málaga, in order to analyze the firefighters' opinion about biological signals monitoring while on duty. As a result of this methodology, we propose a wearable sensor suite design with the aim of providing some easy-to-wear integrated-sensor garments, which are suitable for emergency worker activity. The article offers discussion of user acceptance, performance results and learned lessons.

Keywords: real-time monitoring; bio-signals; remote sensors; cloud robotics; 5G communications; search and rescue

1. Introduction

Fitness-For-Duty (FFD) refers to the physical and mental ability of a worker to safely perform the essential functions of his or her job [1]. The roles of emergency services are challenging and often physically demanding because they need to adapt to the extreme conditions of disaster environments. Readiness to meet these challenges and demands is a fundamental requirement for staff to work safely and effectively [2]. First responder is a substantial term that includes emergency workers, such as firefighters, police officers and paramedics [3]. For these workers, efficiency in their tasks is decisive because it has a direct impact on time employed on victim recovery and assistance.

In this article, we focus on first responders' health while on duty, which involves both physical fatigue and psychological aspects such as stress and anxiety. Stress is an immediate response of the body to stimuli that disturb the mental or physical equilibrium of a person [4]. Continuous exposure to stress can cause anxiety and hinder concentration on assigned tasks [5]. Moreover, not only mental but also physical fatigue can provoke an immediate increase in the risk of committing errors and causing accidents [6]. In the long-term, stress has been linked to the three leading physical causes of death in the general population: heart disease, stroke, and cancer [7]. Two of these, heart disease and cancer, are prevalent causes of mortality in firefighters [8].

The resilience and cognitive readiness of emergency workers can benefit from increasing research interest in wearable sensors for biological signal monitoring and analysis. The availability of inexpensive and small sensors for real-time monitoring and connectivity

technologies has enabled recent applications such as healthcare [9–11], human–machine interfaces [12] and monitoring of workers [13] or elderly people [14].

In previous works, we presented a mission-oriented Internet of Cooperative Agents architecture for search and rescue (SAR) missions (SAR-IoCA) [15] that integrates robotic and human agents in the field with the mission control center. SAR-IoCA allows remote control and communication [16], integrating hybrid sensor networks [17], victim close detection [18] and requests from rescuers [19]. In this work, our goal is to enable remote first responder bio-signal monitoring during SAR interventions. For this purpose, the employed methodology starts with the definition of a set of sensors to measure the main signals of the responder in order to monitor the most interesting aspects of their health. This sensor suite is integrated into SAR-IoCA and used in several realistic experiments. The experience of these experiments in disaster scenarios with actual first responders demonstrates the feasibility of real-time monitoring in extreme conditions while on duty. As a result, a survey to the target community was conducted to obtain useful information to finally propose a design of a wearable sensor suite for bio-signal monitoring. The main contributions of this article are:

- We performed proof-of-concept experiments with a bio-signal sensor suite worn by firefighters in two high-fidelity simulated SAR disaster scenarios. This sensor suite is integrated into a cloud robotics architecture for real-time bio-signal monitoring and data transmission to a Forward Control Center (FCC) via 5G for expert mission supervision.
- A survey was conducted among Spanish firefighters with the aim of collecting their opinion and interest in bio-signal monitoring while on duty.
- Based on learned lessons from these experiments and survey results, we propose a sensor suite with a non-invasive and easy-to-wear design that has reduced interference with emergency worker activities.

This article is structured as follows: after this introduction, Section 2 reviews related work. Section 3 presents the objectives and methodology. Section 4 defines measured biological signals, their features and sensor arrangement on the first responder's body. Section 5 describes the integration of these sensors in the SAR-IoCA architecture for real-time bio-signal monitoring. Section 6 describes the proof-of-concept in two experiments in high-profile SAR missions. Section 7 analyzes firefighters' survey results. In Section 8, we propose a wearable sensor suite. Finally, Section 9 offers conclusions and ideas for future work.

2. Related Work

Many studies on assessments of common daily-life activities and some types of on-duty workers can be found in the literature with the aim of preventing situations of stress, anxiety or fatigue. In [20], an assessment carried out to detect fatigue in car drivers and aircraft pilots reviewed non-invasive neurophysiological measures, such as electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOG) and eye movements and concluded that a single method for fatigue evaluation is not sufficient. Bio-signals were also recommended for improving the ergonomics of heavy equipment operation and worker's health [21], where EEG is not feasible due to electromagnetic noise inside heavy machinery, being the most informative bio-signals ECG and galvanic skin response (GSR) data. Furthermore, studies in nuclear power plant workers were conducted in [22] for monitoring psychological distress using EEG at certain brain areas where reduced alpha and increased beta activity in cortical areas are associated with anxiety, but conclusions were limited by the small sample size and the difference of EEG signals for each person. In [23], an evaluation was performed to develop a concept for the assessment of fatigue, acute stress and combat/cognitive readiness in military battle tank crews by recording the ECG and the physical activity and eye movements during sleep, but no experiments were shown. Studies were also out to detect intimate partner violence [24], where monitoring of heart rate (HR), pulse, body temperature, electrodermal activity (EDA) and the brain's electrical activity was proposed

for training machine learning algorithms to generate automatic aggression alarms without the victim's conscious action, but no experimental validation is available.

In the field of biological signal analysis, solutions for some specific tasks have been proposed by processing and extracting useful features from bio-signal data. Some applications have been human-machine interfaces, such as robot control using three electromyography (EMG) signals from a human arm [25] or hand gesture recognition also using EMG [26]. In the development of new human-machine interfaces using non-invasive methods to decode a user's intentions, a review of sensor fusion methods can be found in [12]. The review concluded that the fusion of two or more myography methods leads to better performance. Moreover, near-fall detection for the elderly and people with Parkinson's disease using EEG and EMG [27] and machine learning based on stroke disease prediction using ECG and photoplethysmography (PPG) [28] are examples of applications in medical settings. Another specific application is real-time emotion classification, where [29] proposed a convolutional autoencoder based on PPG and GSR signals from experiments where subjects watched a short video and marked self-assessment labeling of two or three classes (positive, negative or neutral emotions). Similarly, Ref. [30] addressed emotion classification using ECG, PPG, a respiratory belt and a thermal infrared camera to register facial skin temperature to train a feedforward neural network for four classes.

This interest in the analysis of biological signals requires the existence of datasets and benchmarks, where the research community may find a large amount of data to train their machine learning algorithms and propose new methods. AffectiveROAD [31] included physiological and environmental sensors for driver attention assessment. In [32], biometric data were collected from nurses in a hospital during the COVID-19 outbreak, using a wristband while on duty. WESAD [33] is a multimodal dataset where subjects were exposed to stressful activities, even if it is limited by low sample size and lack of diversity.

Some works have focused on firefighters and emergency responders. Thus, the firefighter assessment of stress test (FAST) [8] proposed a behavioral-analytic model for situational analysis through tests and cognitive interviews to identify stressful scenarios, but the main evaluated factors were related to office tasks, such as responding to calls, administrative stress and overwork. In the field, work with firefighters has been carried out to propose smart helmets as wearable devices for emergency issues or potential harm by monitoring bio-signals. A human-centered design of a smart helmet named FireWorks [34] was proposed, collecting user needs by interviewing 80 firefighters. FireWorks includes an array of sensors to collect body temperature, HR and motions and is connected to a smartphone through Bluetooth Low Energy (BLE) to collect data locally and to synchronize with a cloud database using a radio link. A similar design was proposed in [35] using a LoRa (Long-Range Radio) wireless protocol to achieve long-range and low-power communication with the cloud database. Both designs were proposed to alert the supervisor of potential health or emergency issues, such as dehydration, potential falls or abnormal heart rates. We are interested in monitoring an extended set of bio-signals that is not limited to the head, including other body parts, such as the forearm for EDA and the chest for ECG and breathing. For this purpose, integrated platforms, such as Multimed [36], are interesting. Multimed offers hardware and open-source control and processes software for real-time bio-signal monitoring. However, this platform is designed for laboratories and is not appropriate for wearable devices for on-duty workers. Commercial products can be found for military [37] or first-response [38] but with a limited set of sensors.

Therefore, there is an increasing interest in biological signal monitoring and analysis, where a combined set of sensors is needed to study situations of stress, fatigue or anxiety. However, there is a significant gap in the development of real-time biosensor systems and experimentation in a huge variety of domains.

3. Objectives and Methodology

3.1. Objectives

The objective of this study is enabling remote first responder bio-signal monitoring during realistic SAR missions, integrating a set of biosensors in the first responders' body without disturbing their duty. We note the following milestones:

- Selecting a set of biological sensors to monitor relevant first responder bio-signals, useful for subsequent analysis to detect stress, anxiety or fatigue.
- Proof-of-concept experiments for remote bio-signal monitoring in SAR-IoCA architecture in SAR missions during first responder interventions. In order to achieve continuity in bio-signal data, two schemes are considered: real-time communication and local data storage to prevent data lost during transmission to the mission control center.
- Design proposals based on the acquired experience in experiments to improve the performance in future exercises.

3.2. Methodology

In order to meet challenges on first responder health monitoring while on duty during realistic SAR missions, this problem is addressed in the following steps:

1. A sensor suite is proposed to measure the appropriate biological data that meet the requirements of monitoring the most important factors in first responders' health, such as stress, fatigue and anxiety.
2. Once selected, the sensor suite is integrated into a cloud robotics architecture for remote control and communication between agents in the field (human and robotic) and the mission control center.
3. Some experiments in high-impact SAR exercises in simulated disaster scenarios are conducted with real first responders during real-time interventions.
4. After the on-field experience in SAR missions on biological signal monitoring, a survey among the end-users is conducted with the aim of obtaining useful information with only a few questions. These questions were designed to know the firefighters' interest in bio-signal monitoring and their willingness to participate in this line of research.
5. Finally, as a result of the experiences on the field and the survey results, an easy-to-wear design to put on the sensor suite easily is proposed in order to avoid sensor fixing problems and reduce sensor arrangement before first responder interventions.

The following sections describe and illustrate the development and design of a wearable sensor suite for real-time biological sensor monitoring of first responders during interventions in SAR missions.

4. Measured Bio-Signals

According to the objectives defined in Section 3, this work proposes a set of measurable signals that are suitable to monitor and detect both psychological (anxiety and stress) and physical (fatigue) aspects for first responders on duty. In particular, we propose measuring ECG, EDA, respiration data and EEG brain waves, as shown in Figure 1. Examples of measured signals are illustrated in Figure 2.

Regarding psychological aspects, anxiety is related to EEG and EDA signals. EEG measures brain electric activity, which can be indicative of concentration or relaxation states, and EDA values increase with the presence of anxiety [20,22]. Moreover, for stress detection, although the four bio-signals are used, the most important feature is EDA because of its relationship with the sympathetic nervous system (SNS), since this system acts as a trigger for stress. HR and respiration rate increase and EEG gamma waves appear with a stress state [20,22,24,39].

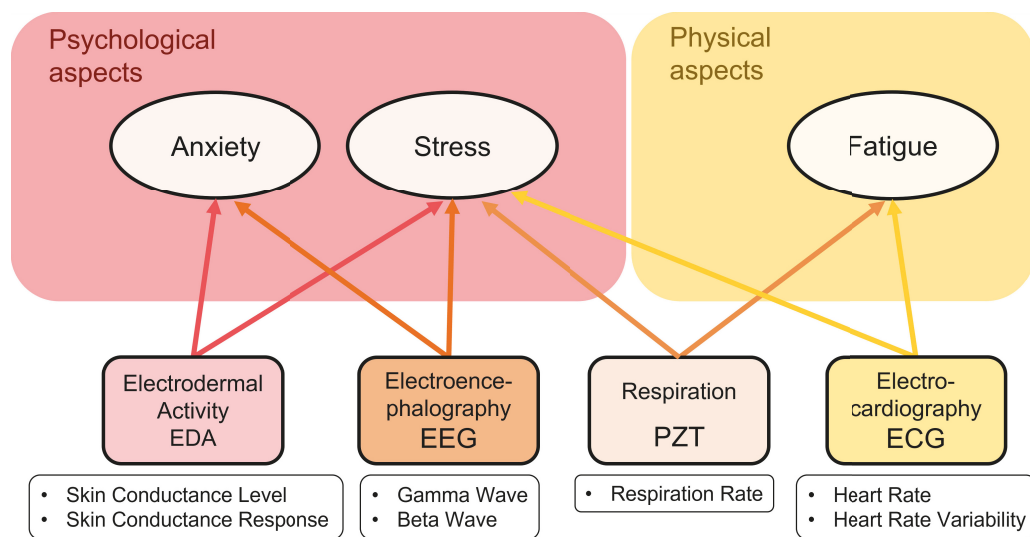


Figure 1. Relation between measured bio-signals and psychophysical aspects.

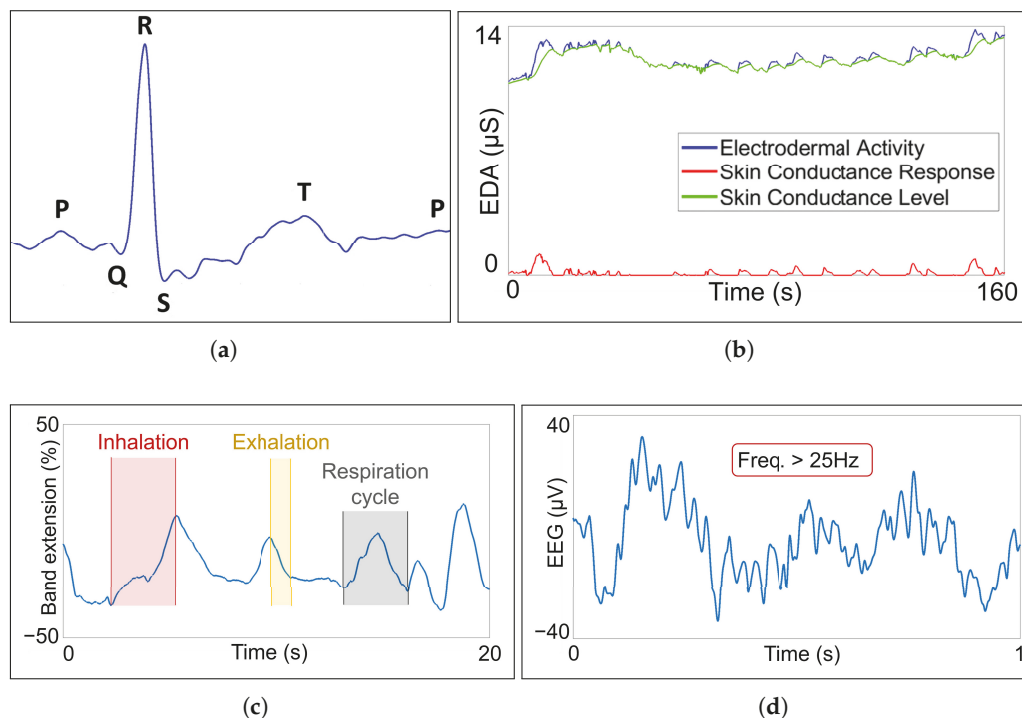


Figure 2. Measured bio-signals: (a) ECG with characteristic points: P, Q, R, S and T; (b) EDA with skin conductance response and skin conductance level components; (c) PZT signal with one inhalation, one exhalation and one complete respiration cycle highlighted; (d) gamma wave EEG signal, with a frequency higher than 25 Hz.

Physical fatigue (referred to just as fatigue) is linked to PZT and ECG signals. ECG measurement allows monitoring the effort during interventions. The respiration (PZT) sensor gives information about breathing, whose rate will tend to increase when physical effort raises [20].

ECG measurement (see Figure 2a) allows knowing HR and its variability (HRV). HR will increase during exercise and will decrease while resting. HRV measures the difference in time between heartbeats.

EDA monitoring gives feedback about sweat gland secretion, which is related to SNS activity. Arousal or relaxation states are translated into sweat production or its absence, respectively. EDA consists of two components, as seen in Figure 2b:

- The skin conductance level (SCL) is a tonic component that changes over time constantly depending on factors such as hydration.
- The skin conductance response (SCR) is a phasic component with short-lasting changes provoked by stimuli.

The respiration rate is obtained from the PZT sensor (see Figure 2c). Hyperventilation or hypoventilation states can be detected thanks to PZT sensor information.

Electric activity of different zones of the brain is recorded by EEG sensors. Each brain zone has different functions, and the recorded signal wave type is dependent on the signal frequency. Beta (12–25 Hz) and gamma (>25 Hz) (see Figure 2d) waves are expected to appear in experiments as representative of active mind and concentration states, respectively. The other three types of EEG waves, alpha (8–12 Hz), theta (4–8 Hz) and delta (0–4 Hz), are representative of restful or sleepy states.

Finally, requirements for a wearable monitoring system are measurement accuracy and reliability, ability to present (high level) real-time readiness information, data transfer reliability, durability and ruggedness, small size and weight, long battery life, fault-tolerance and easiness to wear, use and maintain [23]. It is also important that the system does not cause harm to first responders, nor compromise their performance.

5. Integration in a Cloud Robotics Architecture

This section presents the architecture that integrates devices described in the previous section and the particularities of this integration.

5.1. SAR-IoCA Overview

In a previous work, an Internet of Cooperative Agents architecture (X-IoCA) was presented [15]. It consists of a cloud robotics scheme that integrates heterogeneous sensor networks and robots, multi-edge computing and fifth generation of mobile network (5G) communications in cooperative field tasks between humans and robots. X-IoCA has two components:

- An Internet of Robotic Things (IoRT).
- A feedback information system (FIS).

The first part of the X-IoCA is the IoRT, composed of sensor networks and entities that carry or wear end-devices, such as sensors or actuators. End-devices belong to two different network types:

- Hybrid heterogeneous wireless transceiver network (H2WTN), which detects sensor events at long-range for obtaining data from sensor-nodes or concentrator-nodes in the area of operation and at short-range for detection of agents, i.e., vehicles, people or animals.
- ROS-based sensor network, which obtains information from integrated sensors on agents, such as acceleration from inertial measurement units (IMU), position from global positioning system (GPS), mapping and localization, recording via video or audio and monitoring of bio-signals.

The other part of X-IoCA is the FIS, consisting of two components for data monitoring and processing:

- X-FIS, which collects data from non-ROS sensors of H2WTN for the purpose of monitoring the operation field and generating points of interest and controlling cooperative robots in response to the received information, thanks to an integrated global path planner.
- ROS-FIS [16], which processes and monitors information of the ROS-based sensor network, with a main computer (MPC) in each edge sharing local area network (LAN) with secondary PCs (SPC).

The IoRT and the FIS are connected through multi-access edge computing (MEC) centers, which can be either cloud or local edges. Cloud edges are remote edges, while local edges correspond to local hosts in the operation area. Both types of edges are distributed

between FIS elements, while only local edges are available as IoRT elements. This way, information and data do not share the same physical site, so any agent can use resources that are not physically accessible. All communication is conducted through 5G, which supports high bandwidth, low latency (10–12 ms) [15] and real-time requirements [40]. Moreover, 5G includes features, such as quality of service (QoS) aware applications which may prioritize a part of the traffic [41]. It is even possible to create an ad hoc private 5G network, independent of public operators, to serve a limited geographic area in the event of an emergency [42].

A classification attending to the constituents and their physical location is:

- End-devices at the physical site where data is acquired.
- Fog, composed of cloud and local edges, and switches and 5G customer-premises equipment, which allow sharing data between their respective PCs and hosts.
- Cloud elements, which present no physical location, belonging to independent processing centers: (1) a virtual machine host, (2) a computing center and (3) the master node of the ROS network.

The implementation of X-IoCA for SAR missions is called SAR-IoCA. This architecture presents two MEC centers:

- The Forward Control Center (FCC), which acts as a local edge in the operation area.
- The Base Control Center (BCC), acting as a cloud edge located in a distant lab building and a replica of the FCC, provides redundancy to the system.

Biosensors are integrated into this architecture because of previous and successful applications for robot and human communication and control in disaster scenarios [15–19].

5.2. Integration of Bio-Signal Monitoring in SAR-IoCA Architecture

First responder monitoring requires just a part of the SAR-IoCA architecture. H2WTN and SAR-FIS (X-FIS version for SAR missions) are not required in this particular case.

Regarding the part of the SAR-IoCA architecture shown at Figure 3 and the earlier classification of the physical position of X-IoCA elements, it can be distinguished:

- Bio-signal sensors and a smartphone, which records audio, as end-devices.
- The FCC and the BCC inside the Fog.
- The ROS master node launched in a virtual machine, both belonging to the Cloud.

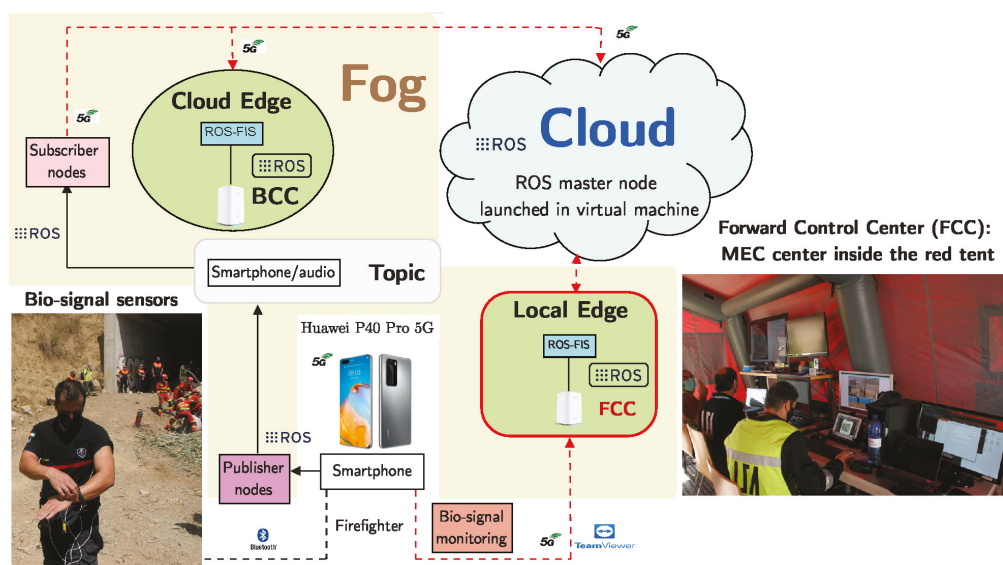


Figure 3. Part of the SAR-IoCA architecture for real-time bio-signal monitoring.

In this particular case, Fog and Cloud elements constitute the ROS-FIS. The smartphone takes part in the ROS-based sensor network, publishing audio recorded from its

integrated microphone [19] during a first responder intervention. The ROS master node hosted in the Cloud allows the MPC at the FCC to subscribe to the audio node published by the smartphone, obtaining the audio information. Likewise, the MPC at BCC can subscribe to the audio node too if desired. The smartphone also acts as an intermediate node between the BITalino board, which transmits via Bluetooth bio-signals recorded by physiological sensors on a SAR agent, and the FCC, where real-time bio-signals of the agent are displayed on a screen thanks to the 5G network and remote access software.

According to the requirements for a wearable monitoring system referred to in Section 4, the device used to measure physiological data from a responder is a BITalino Core BT (see Figure 4), developed by PLUX (Lisbon, Portugal) [43], which consists of a board with:

- Eight analog ports.
- Three digital ports.
- Connection via Bluetooth, with approximately 10 m of range.
- Sampling rate at 1, 10, 100 or 1000 Hz.
- Energy consumption about 65 mA.
- 3.7 V 700 mAh lithium-ion polymer Li-Po battery.

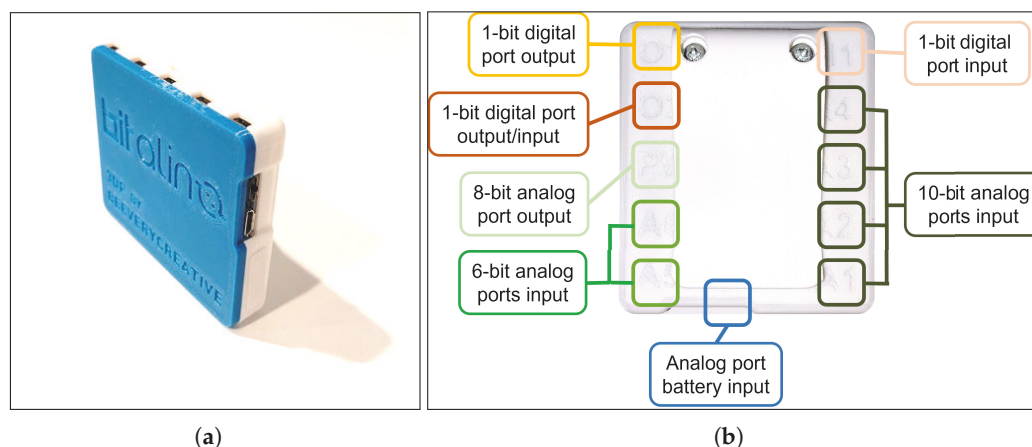


Figure 4. BITalino Core BT board: (a) assembled board for measuring bio-signals; (b) device ports where sensors and actuators can be connected.

Bio-signals are measured thanks to pre-gelled self-adhesive disposable Ag/AgCl electrodes shown in Figure 5. Sensors and actuators are connected by cable to the sockets of the board. The BITalino case has a docking clip to attach the device to any garment. BITalino can be linked via Bluetooth to a computer or a smartphone in order to show data collected by sensors thanks to the OpenSignals software suite, also developed by PLUX. This suite allows starting and finishing the recording, showing real-time acquired bio-signals and storing recorded sensor raw data in the internal memory of the device linked to BITalino. Board recorded and transmitted data require a conversion from raw data (10 or 6 bits size) to International System of Units (SI) data using transfer functions provided on sensor datasheets [44–47].

ECG electrode placement on the responder is based on the lead I Einthoven configuration (see Figure 5a,b), measuring from the right collarbone (negative electrode, sensor black sleeve) to the left collarbone (positive electrode, sensor red sleeve), with the reference electrode (sensor white sleeve) positioned on the left iliac crest. This configuration is the closest placement to the right arm, the left arm and the left foot, respectively, considering the 30 cm long cables used by the ECG sensor.

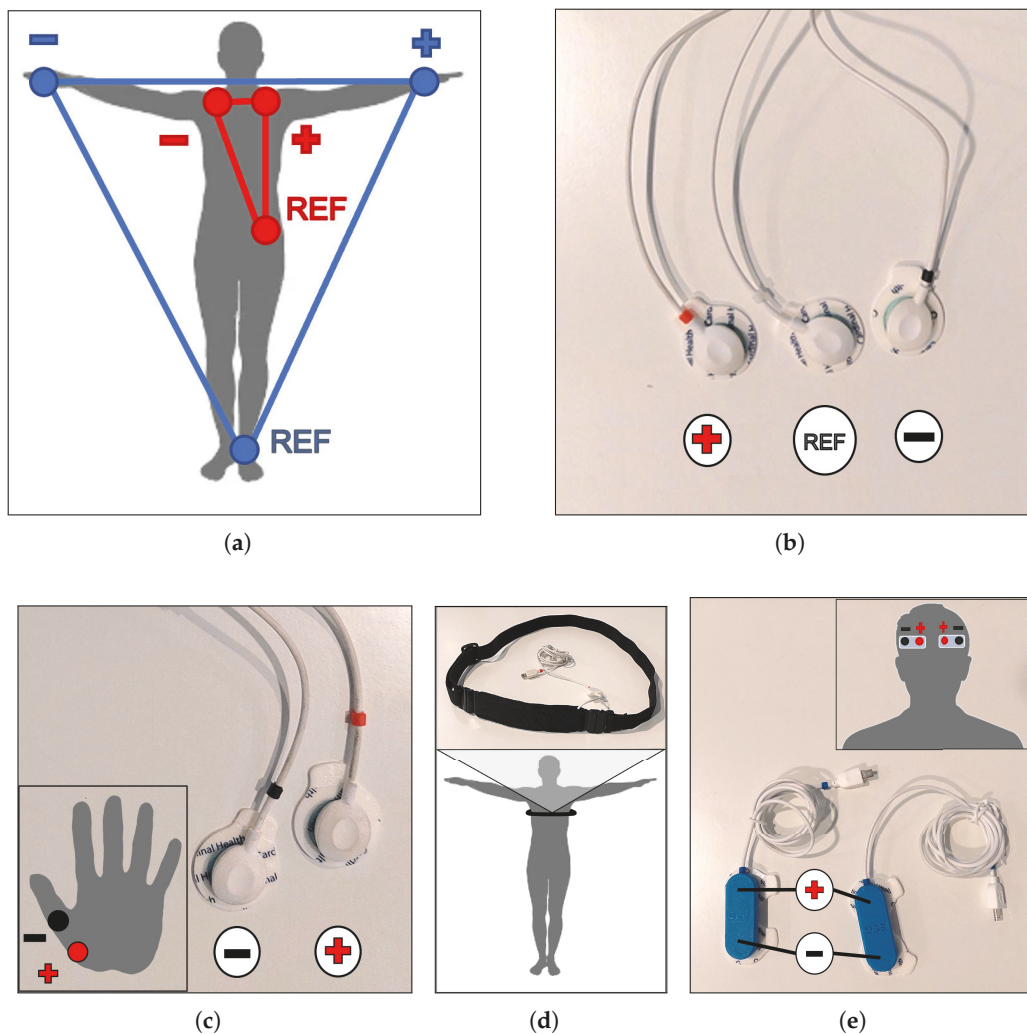


Figure 5. Sensor placement: (a) lead I Einthoven configuration; (b) ECG electrodes; (c) EDA electrodes and their placement on the palm; (d) PZT chest-band and its location around the chest; (e) EEG electrodes and their location on the forehead.

EDA electrodes were placed on the non-dominant hand of first responders, with the negative electrode (sensor black sleeve) located on the metacarpus of the thumb and the positive one (sensor red sleeve) put on the scaphoid, as shown in Figure 5c. This disposition was recommended by PLUX in the EDA sensor datasheet although electrodes can also be placed on other parts of the body, such as feet, armpits, abdomen or chest. The ergonomics of responders was the major factor in the electrode arrangement decision.

The PZT sensor is integrated into a wearable chest belt and measures displacement variations during respiratory cycles. The chest belt was placed under the chest of the first responders, with the sensor on the front. Upper or lower position was also possible, but volunteers felt more comfortable with the belt in that position (see Figure 5d).

EEG electrodes were disposed on the forehead of the responder, the only place not covered by the helmet (see Figure 5e). This way, the electric activity of the frontal lobe, which controls planning, problem solving, speech, voluntary movements and emotions, was measured.

6. Experiments

The exercises were conducted as part of an annual workshop organized by the chair of security, emergencies and disasters at Universidad de Málaga (UMA). Exercises were held in two different workshops, on 18 June 2021, and 3 June 2022, respectively. The purpose

of the workshops is providing a framework for testing and evaluating new technologies under realistic conditions with the cooperation of members of governmental and non-governmental emergency response organizations. The exercise site was located within the UMA campus, in a 90,000 m² plot called the area of experimentation in new technologies for emergencies (LAENTIEC). LAENTIEC was divided into several zones (see Figure 6). Although exercises were carried out in two different years, zones remained unchanged:

1. Zone 1, a natural ravine, a creek and a storm drain tunnel.
2. Zone 2, a rubble zone.
3. FCC, located in a tent, where FIS is the interface with vehicles and sensors in the field.
4. BCC, in a laboratory out of the area of operations, being able to share tasks with the FCC to reduce workload.



Figure 6. Aerial view [48] of the area of experimentation in new technologies for emergencies (LAENTIEC), where areas indicate relevant locations.

In previous work using hybrid sensor networks in SAR missions [17], some experiments were conducted in 2018 and 2019 to test the continuity in sensor data transmission in poor coverage conditions. These experiments consisted of data transmission from mobile sensor nodes, allowing local storage to maintain continuity in sensor data and then transferring their local database when the nodes were back to the coverage area. Following this strategy, the 2021 exercise focused on first responder real-time monitoring, while the aim of the 2022 exercise was on local database recording of bio-signals.

6.1. Real-Time Monitoring Exercise

On the 2021 Workshop, the experiment consisted of a SAR mission in a disaster scenario, which simulated moments after an earthquake that caused a fire with victims trapped inside crushed vehicles into a stormwater drain tunnel (Zone 1 in Figure 6). Figure 7 represents the location of the main milestones in the exercise. Access to the tunnel was possible both from the creek and a hatch located next to Paraninfo metro station

(points 2 and 4, respectively). The tunnel has a thickness of about 1 m and a length of about 100 m between the entrance and the hatch and 185 m in total, with a tunnel height of about 7 m and metro tracks above it.

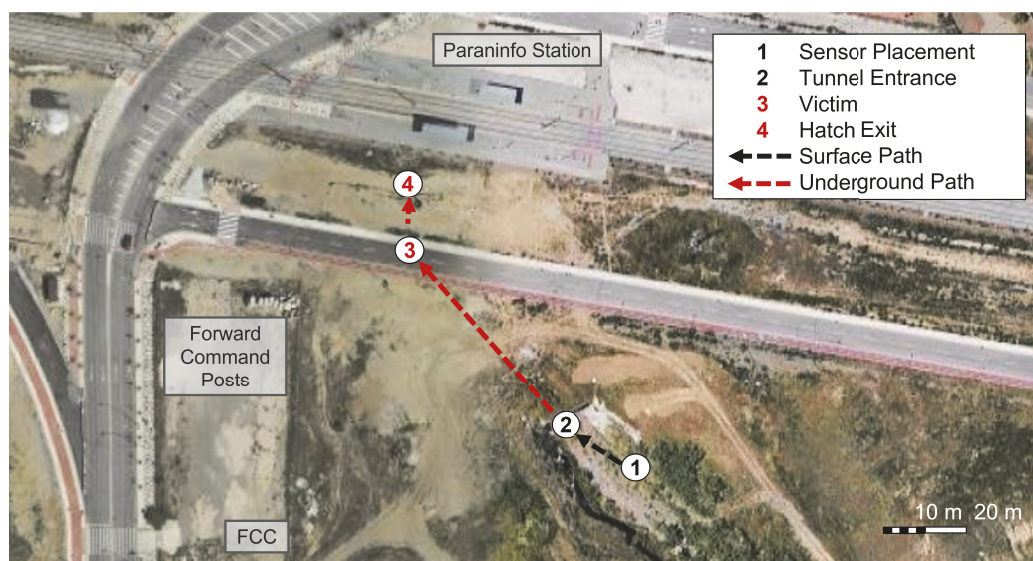


Figure 7. Aerial view [48] of Zone 1. Surface operations in black; underground operations in red.

A fireman from the Royal Fire Department of Málaga volunteered for being monitored with ECG, EDA and PZT sensors. BITalino Core BT, sampling at 1000 Hz, was connected to a smartphone, a Huawei P40 Pro 5G (Shenzhen, Guangdong, China), which had the OpenSignals app installed. The smartphone was operated remotely from the FCC thanks to the TeamViewer app, developed by TeamViewer AG (Göppingen, Waden-Württemberg, Germany). This app also allowed data transfer generated by OpenSignals and stored in the phone's internal memory to a computer. The smartphone was connected to a 5G network to allow communication with the FCC. Audio was transmitted through ROS thanks to the specially designed UMA-ROS-Android app [49] running in background mode. To avoid any kind of undesired interaction with the tactile screen of the phone, the Touch Lock app from Brink Technologies (Veliko Tarnovo, Bulgaria), was used. No instructions were planned to be given from the FCC to the fireman through the cell phone or any other device. Communication from the FCC to the operation area was limited to a phone call to a researcher in charge of the field real-time experiment, if necessary.

Before beginning the exercise, at point 1, skin zones where electrodes were going to be placed were cleaned with alcohol. Then, the PZT belt was adjusted to the thorax of the firefighter, and electrodes were stuck on their positions (see Figure 8a). Next, the board was attached to the belt of the fireman, and the smartphone was stored in one of the pockets of his vest. The exercise started at point 2 (see Figure 8b). A group of firemen, including the monitored one, initiated the tunnel exploration searching for potential victims inside.

After 45 min of exercise, firemen exited by the hatch, and the volunteer took off the chest-belt and electrodes, giving sensors, board and smartphone back and proceeding to explain the development of the exercise inside the tunnel: A victim was found at point 3, next to some stairs, which connected with the hatch. The victim needed medical evacuation on a scoop stretcher, so firemen decided to evacuate exiting through the hatch. The space in the stairs was too narrow to let the stretcher move, and such after several attempts, the evacuation was cancelled, concluding the exercise due to accumulated exercises during the day. The fireman also stated that the sensors did not interfere during the exercise except for EDA electrodes which peeled off, so electrodes had to be stuck again.



Figure 8. Real-time monitoring exercise: (a) deployment of bio-signal measurement devices on first responder in the initial area of operations; (b) tunnel entrance. Left side entrance was used.

Despite the duration of the experiment being 45 min, bio-signals could not be recorded during the whole intervention. Real-time bio-signals were monitored for two different intervals of 126 and 509 s corresponding to the initial phase of exploration (see Figure 9). When the OpenSignal app stopped working for the first time, a new bio-signal recording was initialized. Finally, the connection was completely lost because of the interruption of the 5G signal inside the tunnel. Thus, the period where the highest level of stress or fatigue was expected was not recorded.

6.2. Local Recording Exercise

The second experiment was held on 3 June 2022. Several modifications were implemented regarding last year's exercise:

1. The exercise took place in zone 2 (see Figure 6), a rubble zone with concrete pipes laid out to simulate, e.g., wells (Figure 10 includes the location of main milestones along the exercise).
2. The volunteer belonged to the Fire Department of Benalmádena, being a different fireman from the previous year.
3. A Samsung S20 FE 5G, by Samsung (Seoul, Republic of Korea) was used instead of the Huawei device.
4. Two EEG sensors were placed on the forehead of the firefighter, in addition to the previously used ECG, EDA and PZT sensors.
5. Electrodes were fixed with tape to the skin of the volunteer for avoiding detachment in the course of the exercise.
6. A wearable 2-megapixel video camera connected to a cloud-based video service delivery platform, BlueEye, manufactured by RedZinc (Dublin, Ireland), was mounted on the helmet of the fireman, with camera connection to the smartphone via a cable with type-C USB connector. This service included accessories, such as the cell phone used in this experiment and its docking clip case.
7. No direct communication between the researcher and the FCC nor phone and the FCC was planned, so the bio-signal recording would be stored in the internal memory of the phone, and video and sensor recording would initialize on site.

Originally, the volunteer was supposed to go into a well (point 5 in Figure 10) to rescue a trapped victim inside. According to the planned exercise, with the aim of interfering the least, the board and the smartphone were attached to the belt at the back of the fireman after skin cleaning and putting ECG, EDA and EEG electrodes and the PZT chest-belt on. The sampling rate of the board was 1000 Hz. However, following instructions from the fire chief, the firefighter participated in a different exercise, which consisted of a fire inside a concrete pipe (point 4) to be suppressed with a cutting extinguisher—a kind of fire hose connected to a water pump on one side and to a hand lance, which mixes water

and abrasive for drilling materials, on the other. This new exercise included driving a fire truck and parking next to the water pump. Sensor placement was interrupted several times because of the new instructions received by the fireman, lasting about 15 min.

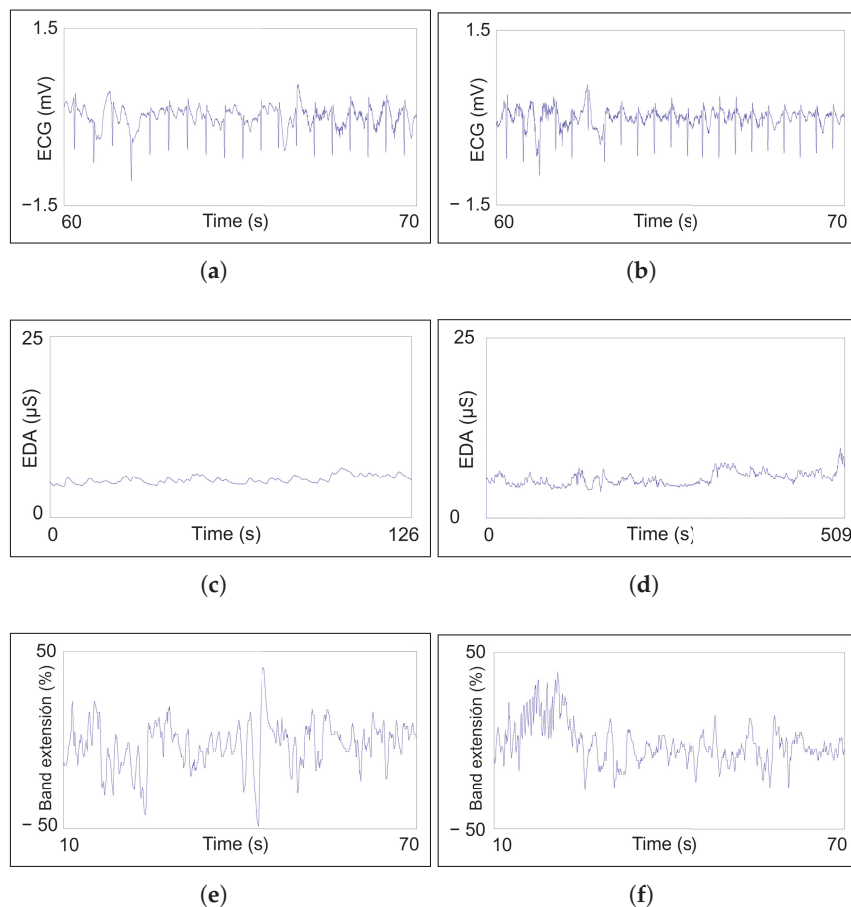


Figure 9. Bio-signals recorded during a real-time monitoring exercise. On the left, recordings corresponding to the first measured interval (126 s). On the right, recordings of the second measured interval (509 s): (a,b) 10 s sample of ECG recording to show ECG signal intervals; (c,d) complete EDA recording; (e,f) one-minute sample of PZT recording.

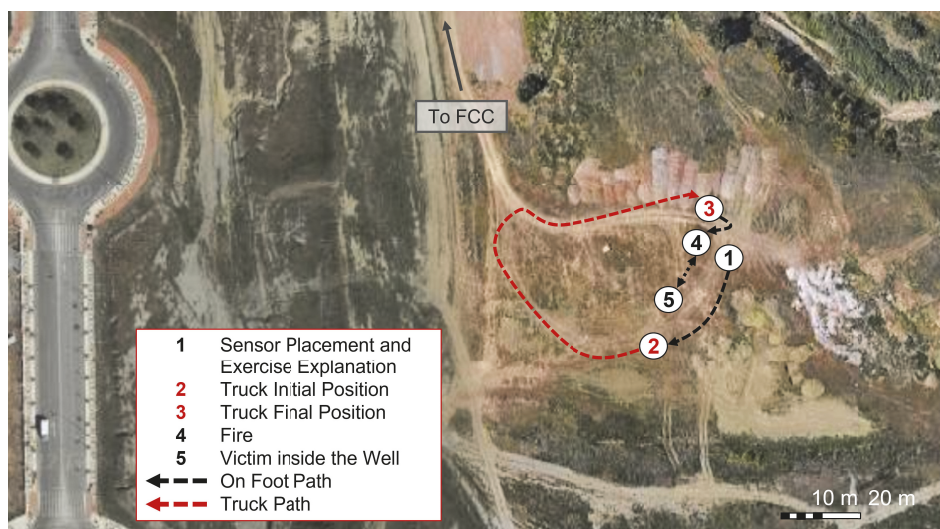


Figure 10. Aerial view [48] of Zone 2. Truck operations in red; on-foot operations in black. Note that fireman moved in both directions between the fire and the victim inside the well.

The exercise started at point 1, with the fire chief explaining the exercise and how to use the cutting extinguisher. After this first part, the firefighter ran alone to the truck (point 2) to store several tools (see Figure 11a). After closing all compartments, the fire truck was driven to point 3, near the water pump and the concrete pipe (see Figure 11b). While seated in the truck, the phone came out of the case. As the fireman got out of the cabin of the truck, the cable disconnected from the smartphone, which fell onto the seat. The image of the video recording froze immediately but audio from inside the cabin continued being recorded. The Bluetooth connection of BITalino was maintained, although when the firefighter started to unload tools from the bottom of the truck, data acquisition began to save wrong values of bio-signals, swinging between threshold values of the sensors, until the distance between the smartphone and the board exceeded Bluetooth range [43] and the transmission ended. The exercise continued with no one having noticed the lack of the smartphone in its case; after several attempts, the water pump was started, and the fire was extinguished by the volunteer (see Figure 11c) from different sides of the pipe (the rescue at the well, see Figure 11d, was in between).



Figure 11. Sequence of the local recording exercise: (a) closing truck compartments; (b) driving the fire truck; (c) using cutting extinguisher; (d) Helping at well evacuation.

Just after finishing the exercise, the fireman approached to give back the cell phone and the board and be interviewed, realizing that the phone had fallen somewhere, being

found on the seat of the truck. During the interview, the volunteer stated that sensors had not interfered with his duty, although ECG electrodes had fallen off at the end of the exercise. Even though it was his first use of the cutting extinguisher and it took several attempts to start the water pump, the firefighter stated that he had not felt any kind of stress during the exercise because of his training to deal with dangerous and extreme situations, but he reported that the high working pressure of the cutting extinguisher caused fatigue and stiffness in his arm muscles. In the end, a recording 464 s long (7 min, 44 s) of the exercise was stored (see Figure 12) and documented with several videos and photos.

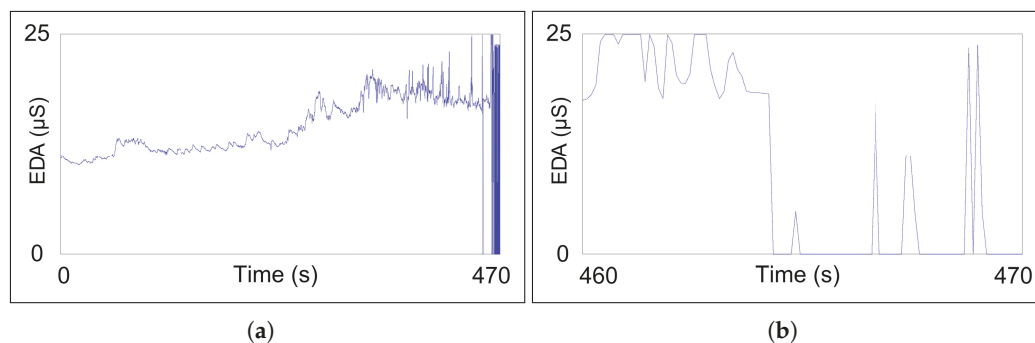


Figure 12. Parts of EDA recorded during local recording exercise: (a) sample from the start until the 470th second, showing the difference between the normal recording and the final wrong values; (b) beginning of wrong EDA recording at the 464th second. This error occurred in the other four measurements.

6.3. Evaluation of the Exercises

The experiments carried out were used for measuring and monitoring firefighters during SAR missions developed in open-field realistic exercises. Time required for electrode placement was similar on both exercises, about fifteen minutes (from 12:03 until 12:18 in 2021, and from 12:21 until 12:36 in 2022). Several interruptions happened during these preparations, so this time can be reduced easily in future experiments.

The first exercise allowed us to check that a real-time monitoring of a fireman was possible in a 5G network with a set of physiological sensors (ECG, EDA and PZT) transmitting health information to the FCC. BITalino Core BT was demonstrated to be effective for bio-signal acquisition (not invasive, enough battery life and reliable data transfer to the via-Bluetooth-connected cell phone). By contrast, electrodes did not remain stuck to the skin of the responder in a situation that implies movement and sweating, hindering his labour. As the exercise took place inside the tunnel, the 5G connection was compromised, losing signal soon after the firefighter went into the tunnel. This is a limitation imposed by the trade-off offered by 5G between favorable low latency and data rate against low obstacle penetration [50]. LoRa technology is limited by requirements for public use of a frequency band, which decreases the length of sent packets and the sending frequency in a way that precludes obtaining enough data to represent high-frequency bio-signals, such as ECG. Furthermore, LoRa transmission characteristics are not suitable for monitoring a high number of first responders. BLE and ZigBee technologies have a short range, which limits the direct transmission of bio-signals to the MEC or requires a larger infrastructure compared to the use of a 5G network, adding more complexity [51]. Furthermore, the lack of video recording meant that the only way to know what had happened during the exercise was the subsequent interview with the volunteer. From a 44 min and 22 s exercise, 10 min and 35 s of biosensor signals were recorded, 23.85% of the total time.

The second exercise, during the 2022 Workshop, served for implementing a new strategy aimed at storing recorded data in a low coverage 5G signal scenario instead of real-time monitoring and trying to solve two of the problems that were found the previous year:

- Electrode fastening was improved with adhesive tape.
- A video camera was mounted on the helmet of the fireman to obtain footage from a first-person perspective.

Moreover, two EEG sensors were added to the previous year bio-signal acquisition setup.

The smartphone and the board were attached to the firefighter's belt to interfere with fire extinguishing tasks as little as possible. However, during the exercise, the firefighter had to drive a fire truck. The placement of the smartphone was not suitable and fell out of its flexible case and stayed in the truck, losing video and Bluetooth connection. While exercise duration was 38 min and 10 s, just 7 min and 44 s of bio-signals were recorded properly, 20.26% of the total time.

From one year to another, the fastening of electrodes improved with adhesive tape as an "easy but effective" solution, and a video recording system was added, although it caused new errors. Design failures detected on the smartphone case and cable connection were reported to RedZinc, improving their performance with a more rigid case and a tighter cable connection to the USB port.

Regarding energy consumption, the BITalino Core BT consumption is about 65 mA with a capacity of 700 mAh, resulting in an autonomy of about 10 h. Moreover, the battery level of the smartphone after the real-time monitoring exercise (44 min duration) was 76% and after the local recording exercise (38 min duration) was 85%.

In general, the experiments provided some insight regarding applicability issues such as electromagnetic interference and energy consumption. As for electromagnetic interference in communications, this was not explicitly considered in the experiments, as the different technologies in the SAR-IOCA architecture used different bands: 3.5 GHz for 5G, 2.4 GHz for Bluetooth and 868 MHz for LoRa. However, it is an important point for future work in case of monitoring several first responders at the same time. The gain of EEG sensors (41,782) was much higher than the gains of the other sensors (e.g., 1100 for ECG, and 1 for PZT) [44–46], so EEG is more sensitive to electromagnetic noise and may not be reliable in some environments [21]. In addition to the required improvements regarding electrical shielding, the proposed sensor configuration offers some redundancy for stress and anxiety detection by combining EEG and EDA.

In both exercises, firemen valued as "remarkably positive" the research on real-time monitoring of bio-signals, not just for stress, but for any kind of health glitch which could lead to dangerous circumstances, bearing in mind extreme situations that firefighters have to face in their duty. Both assessed that time to set up electrodes and devices should be reduced as much as possible.

7. Firefighter Survey for Bio-Signal Monitoring

A survey was conducted in order to gather firefighters' opinions on bio-signal monitoring and analysis while on duty. After the on-field experience in realistic scenarios, the aim of this survey was to check the end-user interest in bio-signal monitoring, asking their opinion about the most important aspects of mental and physical health in their duty and which parts of the body should be avoided for placing sensors in order not to hinder their work. Answers were completely voluntary and anonymous.

After an informed agreement and some personal data (age group and gender), the four main questions were:

1. Do you think that monitoring your physical and mental state during an intervention can be useful?
2. Which of the following factors do you think would be the most important to monitor while on duty? This question offers up to 15 non-exclusive possible answers (see Figure 13).
3. Would you be willing to be monitored with biological sensors during an intervention?
4. In which of the following parts of your body do you think the sensor arrangement may interfere with your work during an intervention? This question provides up to 14 possible answers, non-exclusive (see Figure 14).

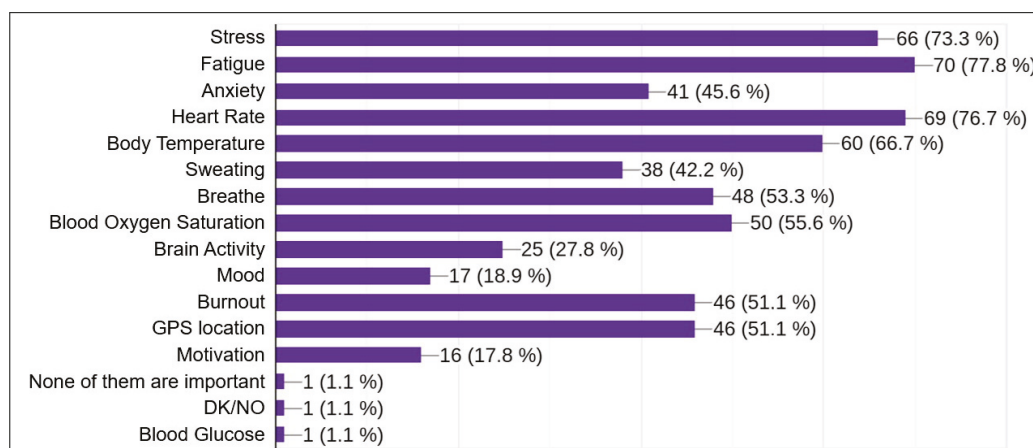


Figure 13. Answers to question: Items to be investigated in bio-signal monitoring.

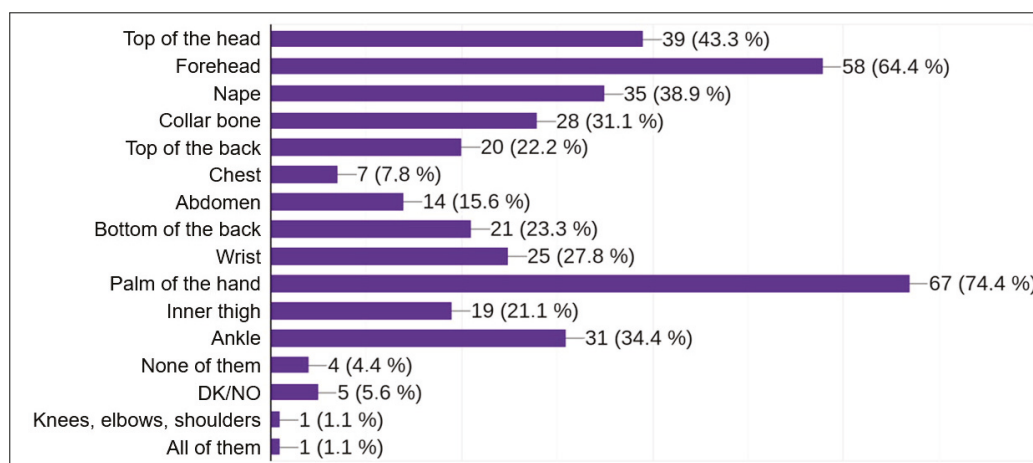


Figure 14. Answers to question: parts of the body where sensor placement would hinder your duty.

This survey was sent to the Fire Brigade consortium of the Provincial Council of Málaga, which serves over 2 million inhabitants. Every question had an option for not answering (referred to as DK/NO in Figures 13 and 14). A total of 95 answers were received, and 95.8% of the respondents participated in this data collection for research purposes. The gender of the participants was 95.6% male, 2.2% female and 2.2% did not answer. Regarding the age range, 7.7% were more than 55 years old, 45.1% were between 46 and 55 years, 41.8% were between 31 and 45, 4% were between 18 and 30 and, finally, 1.1% did not answer this question.

Regarding the main questions of this survey, oriented to the use of biological sensors, 97.8% of respondents agreed about the usefulness of monitoring their physical and mental state while on duty. In the question about the most interesting factors to analyze using these sensors, the most selected items were stress (72.5%), fatigue (78%), heart rate (76.9%) and body temperature (67%). A complete set of results is shown in Figure 13. Most of the firefighters surveyed were willing to be part of an experiment with biosensors while on duty (91.3%). Finally, when asked about where not to attach sensors, their main answers were the forehead (65.2%) and the palm of the hand (75%). All the results to this question can be seen in Figure 14.

This survey was composed of only a few questions to avoid disturbing firefighters' work and revealed the interest of firefighters in biological signal monitoring in order to analyze their mental and physical conditions while on duty. Answers to the more detailed questions in the survey showed their interest in issues such as stress and fatigue, and where sensor placement would interfere with their duties: the forehead and the palm of the hand.

8. Wearable Sensor Suite Design

The diversity of scenarios of first responders reveals the importance of a highly reliable system for measuring their bio-signals during an intervention. The position of devices or the grasp of electrodes must not interfere with the work of responders or preclude bio-signal measurements.

The need of decreasing the time to place sensors and improving their adherence can be solved with the development of adjustable integrated-sensor garments, which take into account ergonomics [52]. According to our experience with the exercises and the answers to the survey, a proposal of three prototypes is shown in Figure 15:

- A T-shirt with integrated ECG electrodes and PZT chest-band.
- A wristband with integrated EDA electrodes.
- A cap with integrated EEG electrodes.

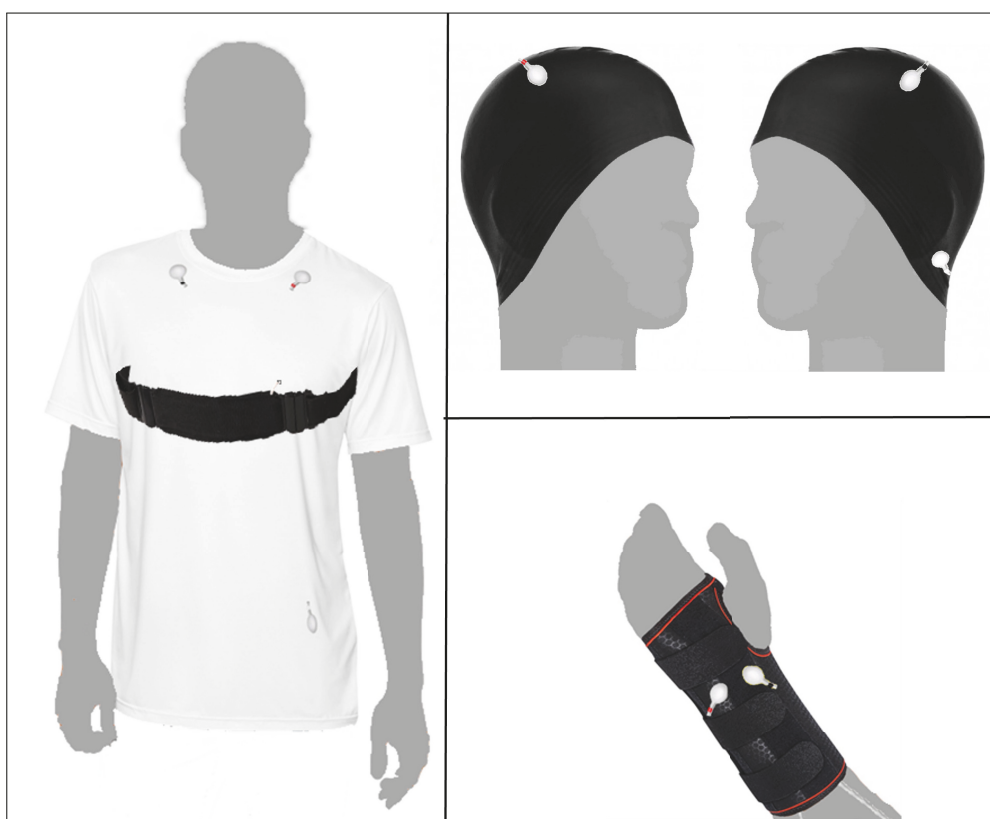


Figure 15. Proposal of integrated-sensor garment. Clockwise, starting from left: T-shirt with ECG and PZT sensors, integrated-EEG-sensor cap and wristband with integrated EDA sensors.

The T-shirt with a fit design similar to the one currently used by firefighters integrates ECG electrodes in the position presented in Section 4, which is appropriate for fatigue and stress detection, heart rate information through an ECG signal and the PZT chest-band to monitor fatigue. The EDA signal is monitored in the wrist instead of face and palms, taking into account answers from firefighters in Section 7. This setup is not the best for stress detection but suitable according to [53]. The design of the wristband allows wearing gloves and a jacket. Finally, a cap with integrated EEG electrodes is also proposed. The placement of electrodes on the top of the head reflects concerns of firefighters for helmet comfort, avoiding the former position on the forehead. It also integrates the reference electrode behind the ear. Although mental state monitoring was not among the most selected items to be investigated during an intervention, the cap prototype has also been included to anticipate possible requirements from psychology experts.

9. Conclusions

This work presents a validation of remote first responder bio-signal monitoring in high-fidelity SAR scenarios while on duty. To the best of our knowledge, this is the first time that proof-of-concept experiments in disaster situations have been carried out. Furthermore, two different strategies were implemented: (1) real-time monitoring and (2) local recording of bio-signal data. For these experiments, we previously selected a sensor suite for monitoring ECG, EDA, PZT and EEG data, a key combination of bio-signals for physical fatigue, anxiety and stress detection. This set of sensors was integrated into the SAR-IoCA architecture and proven in realistic SAR missions.

With the lessons learned from these experiments, a survey was conducted among the Fire Brigade consortium of the Provincial Council of Málaga to learn whether they consider bio-signal monitoring while on duty important and their willingness to participate in future exercises. The main questions in the survey were addressed to collect their opinion about the most interesting issue to be investigated in health monitoring and in which part of their body they think that sensor arrangement may interfere with their work. Answers to these questions, along with learned lessons from the exercises, provided a reference to design three prototypes of integrated sensor garments: (1) a T-shirt, (2) a wristband and (3) a cap. Moreover, data collected from the survey and the bio-signal monitoring and recording are stored in a restricted access folder.

In the future, we plan to continue validation of the proposed wearable sensor suite design through new experiments and recording more biosensor data to accumulate a massive dataset in realistic SAR exercises. Finally, issues such as coexistence with other networks, energy consumption, and data integrity will be considered in future works.

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Article

Near-Infrared Spectroscopy for the In Vivo Monitoring of Biodegradable Implants in Rats

Hafiz Wajahat Hassan ¹, Eduarda Mota-Silva ^{2,3}, Valeria Grasso ^{4,5}, Leon Riehakainen ^{2,3}, Jithin Jose ⁴, Luca Menichetti ² and Peyman Mirtaheiri ^{1,*}

¹ Faculty of Technology, Art and Design, Department of Mechanical, Electronic and Chemical Engineering, Oslo Metropolitan University, 0130 Oslo, Norway

² Institute of Clinical Physiology, National Research Council (IFC-CNR), 56124 Pisa, Italy

³ Institute of Life Sciences, Sant'Anna School of Advanced Studies, 56127 Pisa, Italy

⁴ FUJIFILM VisualSonics, 1114 AB Amsterdam, The Netherlands

⁵ Faculty of Engineering, Institute for Materials Science, Christian-Albrecht University of Kiel, D-24143 Kiel, Germany

* Correspondence: peymanm@oslomet.no

Abstract: Magnesium (Mg) alloys possess unique properties that make them ideal for use as biodegradable implants in clinical applications. However, reports on the in vivo assessment of these alloys are insufficient. Thus, monitoring the degradation of Mg and its alloys in vivo is challenging due to the dynamic process of implant degradation and tissue regeneration. Most current works focus on structural remodeling, but functional assessment is crucial in providing information about physiological changes in tissues, which can be used as an early indicator of healing. Here, we report continuous wave near-infrared spectroscopy (CW NIRS), a non-invasive technique that is potentially helpful in assessing the implant–tissue dynamic interface in a rodent model. The purpose of this study was to investigate the effects on hemoglobin changes and tissue oxygen saturation (StO₂) after the implantation of Mg-alloy (WE43) and titanium (Ti) implants in rats' femurs using a multiwavelength optical probe. Additionally, the effect of changes in the skin on these parameters was evaluated. Lastly, combining NIRS with photoacoustic (PA) imaging provides a more reliable assessment of tissue parameters, which is further correlated with principal component analysis.

Keywords: biodegradable implants; in vivo monitoring; Mg alloys; near-infrared spectroscopy (NIRS); oxygen saturation (SO₂); photoacoustic imaging (PAI); principal component analysis (PCA); tissue oxygen saturation (StO₂)

1. Introduction

Biodegradable materials such as magnesium (Mg) and its alloys have increasingly been used in orthopedic surgery for bone fixation [1]. Although the cellular responses of surrounding tissue are important, their mechanism of action remains unclear [2]. Due to their osteogenic properties and biodegradability, Mg implants have been gaining significant attention among degradable materials as a superior alternative to bio-inert implants [3,4]. Titanium alloys are considered the gold standard for stabilizing fractured bones, also referred to as a bio-inert metallic implant [5]. Magnesium hydroxide temporarily inhibits osteoclastic activity and stimulates bone formation, but emphysema can occur if hydrogen gas production exceeds the tissue's ability to absorb and transport the gas [6–8]. The formation and composition of the degradation layer alter physiological parameters such as the temperature, pH, ionic content, and protein content after implantation [9]. Currently, imaging techniques such as X-ray imaging, computed tomography (CT), synchrotron-radiation-based computer microtomography (SRCT), positron emission tomography (PET), PET-CT, magnetic resonance imaging (MRI), and ultrasound photoacoustic (USPA) can be used to assess Mg degradation and its effects in vitro/in vivo. However, these methods

are costly and time-consuming, and not all of these techniques can be translated into a clinical context due to patient safety restraints [10–13]. Near-infrared spectroscopy (NIRS) technology enables the measurement of oxygen delivery, pH, and blood flow in tissues, which can be used to assess metabolic and respiratory health [14–17]. NIRS and partial least square regression (PLSR) can be applied to estimate the change in pH values in vivo and in vitro, as discussed in our previous studies [18,19].

NIRS is used as a rapid and cost-effective solution for in vivo monitoring [18,20]. NIRS allows for the non-invasive and continuous monitoring of tissue oxygenation [21]. Imaging techniques such as NIRS and USPA are commonly applied to soft tissues to access blood- and tissue-related properties [18]. As blood keeps cells in close contact with the external environment, measurements in the tissue bed can provide information about the interface between the implants and tissue. However, because the Hounsfield Unit (HU) of Mg alloys is similar to the bone structure, it is challenging to differentiate the Mg particles from bone tissue using microCT [22,23]. Therefore, NIRS can analyze Mg degradation's effects, regardless of it having the same HU unit as bone, and in vitro studies have evaluated this degradation effect [19]. A device must be developed to be used in in vivo clinical procedures that can also be used in real-life scenarios to monitor the Mg alloy's degradation effect. To the authors' knowledge, no study has examined the tissues' in vivo response to Mg reactions by using NIRS. As NIRS enables measuring oxyhemoglobin (HbO₂) and deoxyhemoglobin (Hb) concentrations changes, information related to changes in tissue hemodynamics and oxygenation can be obtained [24]. Monitoring tissue oxygen saturation (StO₂) can be used to measure peripheral hypoperfusion and tissue hypoxia [25,26]. Assessing StO₂ in the implantation site is a relatively new approach to evaluating tissue healing [27,28]. The proposed study uses a novel optical probe with wavelengths from 650 nm to 1050 nm that probes into the specific region of interest at the implant tissue interface non-invasively. In one of our previous studies, we provided detailed information on the optical probe's feasibility for optical phantoms [29]. An NIR optical probe can provide valuable information about the absorption reflectance properties of tissues. There are thousands of data points in a spectral dataset, many of which are noise, background, isosbestic, or dark regions or highly correlated information (i.e., broad absorption or emission bands) [30]. In order to visualize NIRS data, principle component analysis has been found to be a useful tool. PCA is commonly employed in NIRS studies to reduce data dimensionality, reduce noise impact, visualize data patterns, and identify trends that are not immediately evident, hence increasing accuracy and interpretation [30,31].

This study's main objective was to verify the effectiveness of the NIRS technique when combined with Principal Component Analysis (PCA) for extracting information about tissue oxygenation and the correlation between different groups of spectral data when comparing Mg with titanium (Ti)-implanted animals and sham animals (animals without an implant, to which only bone defect was performed). In statistics, information is extracted from noisy data by converting it into a set of variables made up of uncorrelated linear combinations of the original variables (for example, principal components (PCs) containing most of the variability of the original variables within a dataset). Finally, photoacoustic imaging has validated the extracted tissue components [32].

2. Materials and Methods

In this pilot experiment, 15 12-week-old female Wistar rats were used. The animals were anesthetized with an intraperitoneal injection of 5 mg/kg Xylazine (Rompun Elanco, Italia, Florence, Italy) and 10 mg/kg Zoletil (Virbac, Opfikon, Gluttbrugg, Switzerland), while the depth of anesthesia was evaluated by the toe pinch response technique. Before surgery, the animal's legs were shaved using a depilatory cream (Veet, Reckitt Benckiser Healthcare (Italia), Milano, Italy) and carefully cleaned to avoid skin burns from contact with the cream. An incision was made laterally on the leg, and the muscles were carefully teased away to expose the diaphyseal region of the femur. A drill with a 1.55 mm diameter was used to create a transcortical hole in the femur. A low drilling rotational speed was

selected, and physiological saline (Fresenius Kabi, Verona, Italy) was dripped to minimize the frictional heat and thermal damage to the tissue. A pin implant with a length of 8 mm and a diameter of 1.6 mm made of either Mg-alloy (WE43) or Ti was implanted. The cylindrical implant was inserted by gentle tapping, resulting in a uniform press fit. After the pin placement, the wound site was cleaned with sterile cotton tips for the remaining bone debris, and the wound was closed with resorbable sutures (Johnson & Johnson Medical, Spa, Rome, Italy). The contralateral side was operated on similarly, using the same implant type. Figure 1 shows the implanted Mg pin in the CT image.

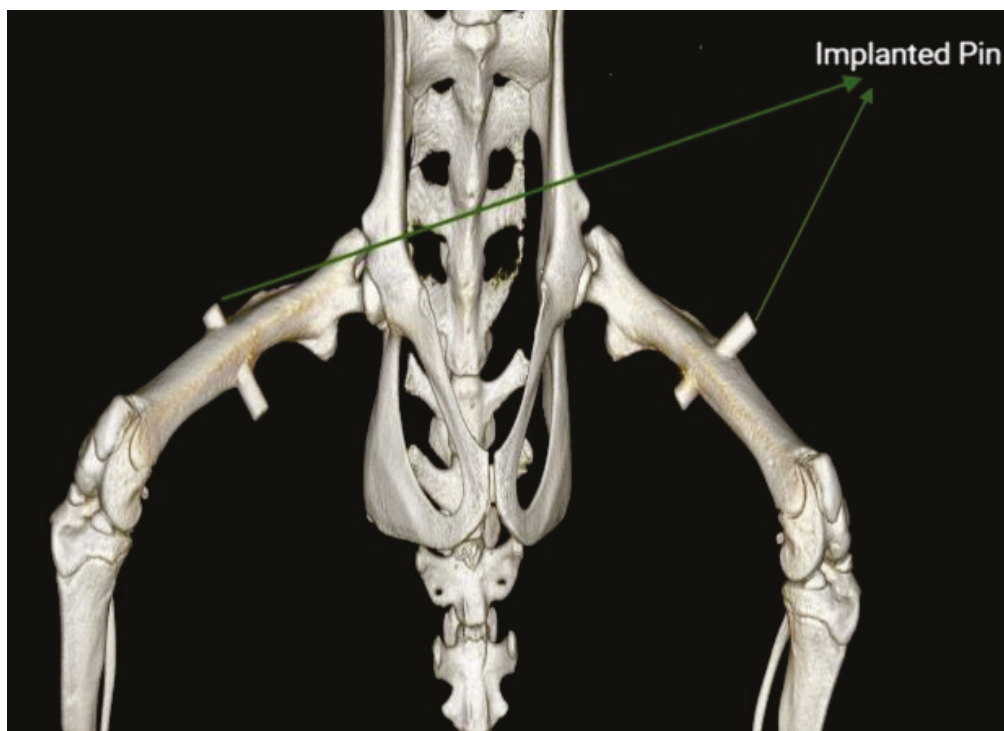


Figure 1. CT image showing the Mg implant positioning on day 7. Acquired with an IRIS PET/CT scanner (Inviscan Imaging System, Strasbourg, France), visualized in an OsiriX DICOM Viewer (Pixmeo, Switzerland).

2.1. Experimental Workflow

Our study involved implanting pins into rat femurs. To determine the oxygen saturation, we performed sequential NIRS and USPA acquisitions, followed by the application of MBLL on the NIRS data and of SPAX on the USPA data. We utilized PCA on the NIRS data to improve the presentation of the data for a short case study and a longitudinal evaluation of the bone-healing process. Our approach combines NIRS and PCA analysis and USPA validation to provide a comprehensive evaluation of the spectral measurements. Additionally, a flowchart was created to illustrate the steps involved in our study, as shown in Figure 2. The flowchart provides a clear visualization of the processes carried out, starting from the implantation of pins and ending with the analysis of the spectral measurements. In this study, oxygen saturation was measured using both USPA and CW-NIRS, resulting in the measurement of SO_2 and StO_2 , respectively. The distinction between these two measurements arises from the differing principles and technologies utilized by each method.

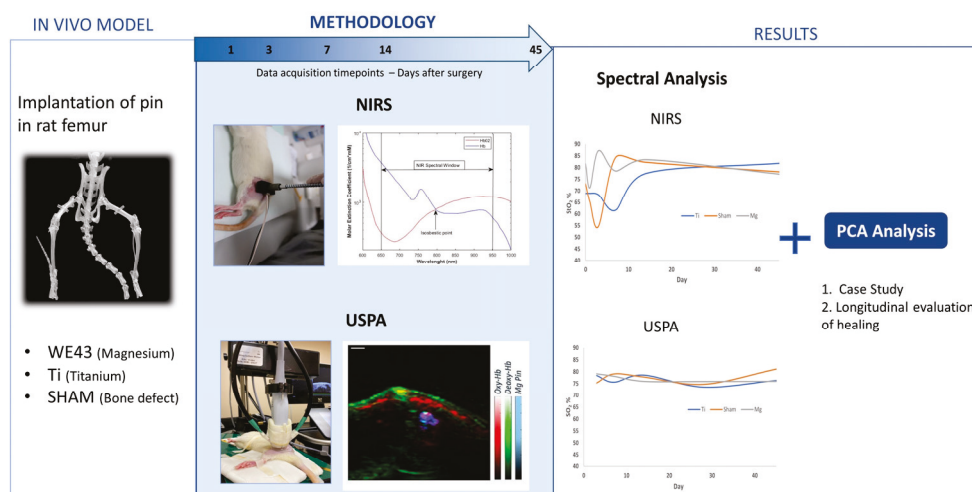


Figure 2. Illustration Summarizing the Workflow of the Study.

2.2. NIRS Acquisition

NIRS acquisitions were made prior to surgery, immediately after surgery, and on days 3, 7, 14, and 45. The animals were anesthetized with isoflurane (2.5% in pure oxygen) and placed laterally on a stereo-foam platform to help prevent rapid heat loss. When necessary, the regrowth fur was removed using the depilatory cream (Veet) prior to the acquisition. In this case, the acquisition was made 2–3 min after shaving to account for possible changes in the skin microcirculation due to friction while shaving and cleaning. The acquisitions were always made in the same room, with an average temperature of 25 °C, and on reduced luminosity conditions to reduce background noise. Figure 3a illustrates the NIR probe placement, and Figure 3b shows the obtained raw spectra with multiple acquisitions. The NIRS optical probe used for this experiment, which was developed at our lab at Oslo Metropolitan University, Oslo, Norway, has a source-detector distance of 8 mm. This specific value was chosen for a 3–3.5 mm penetration depth at the implant–tissue interface [29]. The optical light source of the probe operated in wavelengths between 650 and 1050 nm. To calculate the HbO₂ and Hb, 740 nm and 840 nm wavelengths were chosen based on the prior differential path length factor (DPF) information from Geoffrey D.V et al. [33]. The spectra data were collected from the Avantes Spectrometer (Avaspec-2048x14), which operates between 600 and 1100 nm.

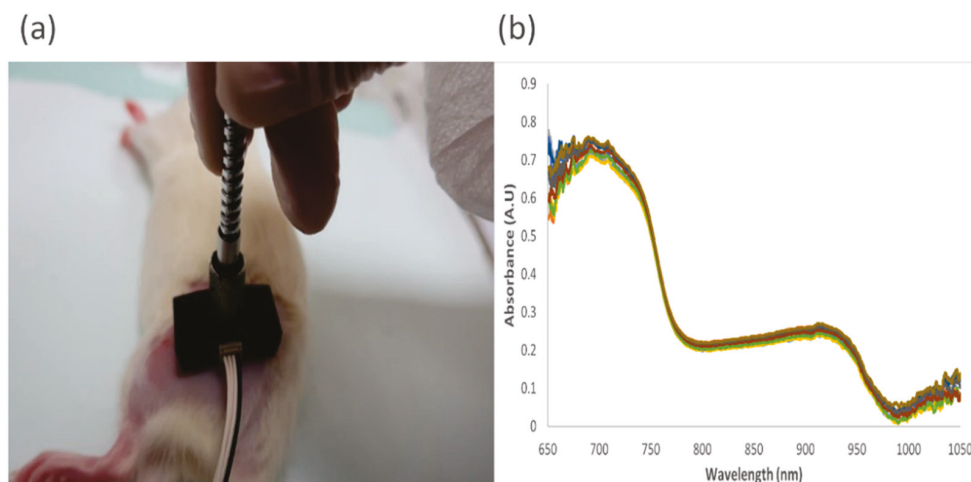


Figure 3. (a) The test bed for NIRS acquisition; (b) the raw absorption spectra for multiple measurements on a single point.

2.3. Modified Beer–Lambert Law (MBLL)

The modified Beer–Lambert law (MBLL) is the foundation of CW NIRS [34]. MBLL can be used to model what is known as CW wavelength-dependent diffuse reflectance [35].

$$I(\lambda) = I_0(\lambda)e^{-(\mu_a(\lambda) \cdot DPF(\lambda) \cdot d + G)} \quad (1)$$

where $I(\lambda)$ is the wavelength-dependent diffuse reflected light intensity, $I_0(\lambda)$ is the incident light, $\mu_a(\lambda)$ is the absorbance of the tissue, d is the source-detector distance, the differential pathlength factor is $DPF(\lambda)$, and the constant G is a medium- and geometry-dependent constant. (1) can be written as:

$$\begin{aligned} OD(\lambda) &= -\ln\left(\frac{I_0(\lambda)}{I(\lambda)}\right) = \mu_a(\lambda) \cdot d \cdot DPF(\lambda) - G \\ OD(\lambda) &= -\ln\left(\frac{I_0(\lambda)}{I(\lambda)}\right) = \mu_a(\lambda) \cdot DPF(\lambda) \cdot d + G \end{aligned} \quad (2)$$

where $OD(\lambda)$ stands for optical density. When more than one chromophore contributes to the total absorption $\mu_a(\lambda)$, Equation (2) can be further rewritten as:

$$OD(\lambda) = -\ln\left[\frac{I_0(\lambda)}{I(\lambda)}\right] = \sum_{i=1}^n [\varepsilon_i(\lambda) C_i] \cdot DPF(\lambda) \cdot d + G \quad (3)$$

where n is the number of chromophores, $\varepsilon_i(\lambda)$ is the extinction coefficient at the wavelength with the i th substance, and C_i is the concentration of the given substance. Obtaining a total concentration estimate is impossible without knowledge of the geometry-dependent term. If the extinction coefficients $\varepsilon_i(\lambda)$ are known for individual wavelengths, and measurements are treated differentially in time, it will be possible to cancel out G because it is usually assumed to be constant. Changes in the concentration are of primary interest in NIRS and are independent of G , specifically in CW-NIRS, unlike in the frequency domain or the time domain NIRS [36]. It is hypothesized that, at times t_1 and t_2 , the extinction coefficient ε_i , DPF, D_1 , and G remain unchanged for measurements. The change in absorption is computed and removes factor G , resulting in a change in the concentration [36–38]. Equation (3) reduces to:

$$\begin{aligned} \Delta OD(\lambda) &= OD(t_2, \lambda) - OD(t_1, \lambda) \\ \Delta OD(\lambda) &= \varepsilon(\lambda) C_2 \cdot DPF(\lambda) \cdot d + G(\lambda) - \varepsilon(\lambda) C_1 \cdot DPF(\lambda) \cdot d - G(\lambda) \\ \Delta OD(\lambda) &= \varepsilon(\lambda) \cdot \Delta C \cdot DPF(\lambda) \\ \Delta OD(\lambda) &= \sum_{i=1}^n [\varepsilon_i(\lambda) C_i] \cdot DPF(\lambda) \cdot d \end{aligned} \quad (4)$$

where Δ identifies the time-dependent changes. In order to approach the problem, at least two wavelengths are needed to calculate HbO_2 and Hb , which are, in principle, the only absorbing compounds that show a time-dependent modulation. By rewriting Equation (4) in matrix format, we will have:

$$\begin{bmatrix} \Delta OD(\lambda_1) \\ \Delta OD(\lambda_2) \end{bmatrix} = d \cdot \begin{bmatrix} \varepsilon_{O_2Hb}(\lambda_1) DPF(\lambda_1) & \varepsilon_{Hb}(\lambda_1) DPF(\lambda_1) \\ \varepsilon_{O_2Hb}(\lambda_2) DPF(\lambda_2) & \varepsilon_{Hb}(\lambda_2) DPF(\lambda_2) \end{bmatrix}^{-1} \begin{pmatrix} \Delta O_2Hb \\ \Delta Hb \end{pmatrix} \quad (5)$$

When measuring ΔOD from empirical measurements for the hemoglobin concentration, the above equation must be inverted. Please note that the a priori parameters of Equation (5) are the extinction coefficients of HbO_2 and Hb at the two wavelengths $\varepsilon_i(\lambda)$ and the DPFs at the two wavelengths. The geometrical inter-optode distance d and the changes in optical densities ΔOD are measured empirically.

$$\begin{pmatrix} \Delta HbO_2 \\ \Delta Hb \end{pmatrix} = \frac{1}{d} \frac{1}{[\varepsilon_{HbO_2}(\lambda_1) \varepsilon_{Hb}(\lambda_2) \quad \varepsilon_{Hb}(\lambda_1) \varepsilon_{HbO_2}(\lambda_2)] DPF(\lambda_1)}$$

$$\begin{bmatrix} \varepsilon_{Hb}(\lambda_2) & -\frac{\varepsilon_{Hb}(\lambda_1)DPF(\lambda_1)}{DPF(\lambda_2)} \\ -\varepsilon_{HbO_2}(\lambda_2) & \frac{\varepsilon_{HbO_2}(\lambda_1)DPF(\lambda_1)}{DPF(\lambda_2)} \end{bmatrix} \begin{bmatrix} \Delta OD(\lambda_1) \\ \Delta OD(\lambda_2) \end{bmatrix} \quad (6)$$

A measurement of the tissue perfusion StO_2 can be taken with NIRS by measuring changes in HbO_2 and Hb concentrations, using the following predictors of the Hb and HbO_2 relative concentrations:

$$StO_2 = \frac{HbO_2}{HbO_2 + Hb} \times 100\% \quad (7)$$

Due to the assumption that the tissue scattering and pathlength remain constant throughout the measurement period, CW-NIRS does not provide absolute oxygen saturation values. The modified Beer–Lambert law is used instead to provide a semi-quantitative estimate.

2.4. Ultrasound and Photoacoustic Imaging

High-resolution Ultrasound (US) and Photoacoustic (PA) imaging (USPA) were acquired using the platform Vevo LAZR-X (FUJIFILM VisualSonics, Inc., Toronto, ON, Canada). The USPA imaging was performed sequentially after the NIRS measurement. This methodology was chosen to ensure that the results from the two techniques would be comparable and provide a comprehensive understanding of the samples. A linear US transducer array (MX 550) consisting of 256 elements at a nominal center frequency of 40 MHz and a bandwidth of 25–55 MHz is coupled with thin optical fibers and mounted on either side of the transducer. Homogenous light illumination is guaranteed by placing the sample to be imaged on the converging area of the two light beams. Spectral photoacoustic imaging (sPAI) was performed, within the wavelength range of 680–970 nm, with a 5 nm step. The imaging acquisition was made on days 3, 7, 28, and 45 after surgery. The rats were anesthetized with isoflurane (2–3% by volume with 0.8 L/min gas flow) and positioned in lateral recumbency, and the transducer was aligned perpendicularly to image the region of interest in the rats' hindlimbs.

The automated detection of the HbO_2 and Hb content was obtained from sPAI utilizing a newly developed superpixel data-driven unmixing (SPAX) framework, described in detail elsewhere [39]. The framework implements an SVD-based analysis to distinguish the relevant spectral information above the noise level automatically. SPAX is also extended to compensate for the spectral coloring artifact combining US image segmentation and spectral Monte Carlo (MC) light fluence simulations based on a predefined library of optical tissue properties. The advanced superpixel subsampling integrated within SPAX enables the detection of the least and most prominent components without a priori information.

Finally, the SO_2 has been calculated from the normalized unmixed maps of HbO_2 and Hb , obtained as the output of the SPAX analysis. Furthermore, the characteristic broad absorption spectrum of the metallic implant and its spatial distribution have also been obtained by the unsupervised SPAX approach.

2.5. Principal Component Analysis

Principal component analysis (PCA) was applied to NIRS data to extract practical information regarding the various factors affecting the Mg degradation. To perform exploratory analyses of NIRS data, PCA was applied on raw NIRS data. PCA is a mathematical procedure for resolving datasets into orthogonal components whose linear combinations approximate the original data by any desired degree of accuracy. The PCA method allows dominating patterns to be extracted from an NIRS data matrix. Two PCs were selected by examining the eigenvalues plot; outliers were detected and removed from the NIRS data after confirming their presence with spectral analysis. The dataset, including information about the implant types, rat group details, femur information (left and right), and time-points (0, 3, 7, 14, and 45) was compiled. These data were preprocessed using normalization, one of the most commonly used preprocessing techniques. For subjects with damaged skin,

a separate PCA was performed. In our study, PCA was performed using the open-source software R, in Rstudio.

3. Results

3.1. NIRS

StO₂ was measured on the implanted site pre-operatively (day 0) and 1, 3, 7, 14, and 45 days postoperatively. On day 0, two measurements were taken pre-operatively and post-operatively. For the simplicity of the visualization of the data, pre-surgery is chosen as day 0, and post-surgery is written as day 1. The StO₂ obtained from CW-NIRS for Mg-, Ti-, and sham-implanted rats is shown in Figure 4. Despite the reduced number of animals used for Ti-implanted and sham animals, it seems that Mg-implanted animals present a higher variability at the initial timepoints. The proposed study compared the spectroscopic characteristics of different implanted rats to assess StO₂.

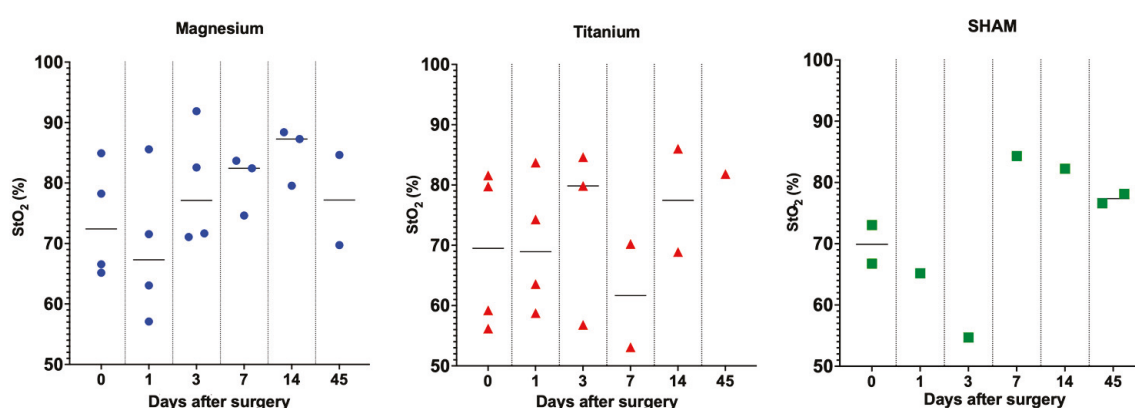


Figure 4. The tissue oxygen saturation (StO₂%) values calculated for each animal for all timepoints (0, 1, 3, 7, 14, 45) are represented in the distribution plot.

3.2. NIRS and USPA—Spectral Analysis

The NIRS spectral region exhibited typical differences in the spectra of Hb and HbO₂. Figure 4 shows how Hb and HbO₂ have different wavelength dependences regarding extinction coefficients. The DPF values for the wavelength at 740 nm and 840 nm are 3.50 and 3.01, respectively, which are used to obtain the relative information about Hb and HbO₂ based on the literature [33]. The wavelength dependency of blood absorption can be used to determine the blood StO₂ level. The blue curve in Figure 5a represents the extinction coefficient of Hb, and the red and green curves represent the extinction coefficient of HbO₂ and THb, respectively. Figure 5b shows the unmixing of the Hb, HbO₂, and Mg pin from PAI. Figure 5c,d show a semi-quantitative analysis of the oxygen saturation calculated from spectral photoacoustic unmixing and NIRS. Here, we focused on NIRS evaluations, and USPA has been used to identify the anatomical structures and validate the molecular evaluations extracted from the entire region of interest. The graphs show a typical pattern of longitudinal variation in StO₂ in the soft tissue around Mg and Ti implants. Similar trends have been retrieved from NIRS and USPA.

We used USPA imaging to study the possible presence of bubbles at the implant–tissue interface as a factor contributing to the higher variation in StO₂ in the surrounding soft tissue of the Mg implant on day 3. Figure 6a,b show the ultrasound and photoacoustic images of the implanted rat femur at day 3, where the tip of the Mg pin is depicted in the short axes view. Figure 6c shows the spatial distribution of the unmixed components such as the HbO₂, Hb, and Mg pin.

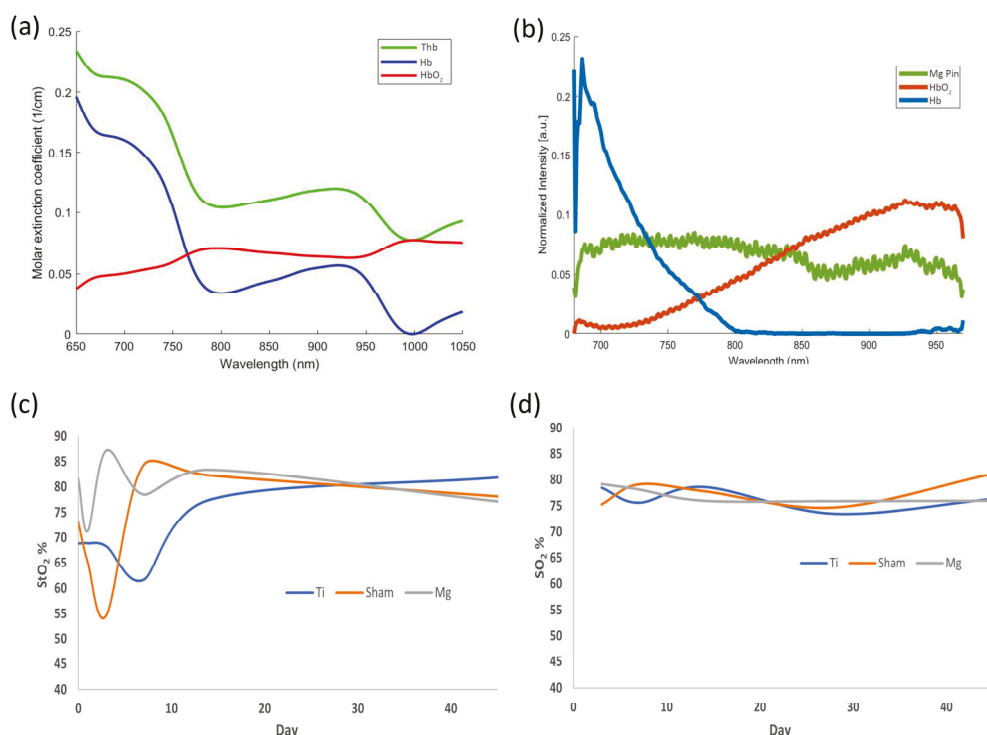


Figure 5. (a) The molar extinction coefficients of Hb, HbO₂, and THb, as calculated from MBL; (b) Unmixed spectra of the Hb, HbO₂, and Mg implant pin after normalization; (c,d) Comparative analysis of oxygen saturation at the implant–tissue interface: (c) Near-infrared spectroscopy (NIRS); (d) Photoacoustic (PA) imaging.

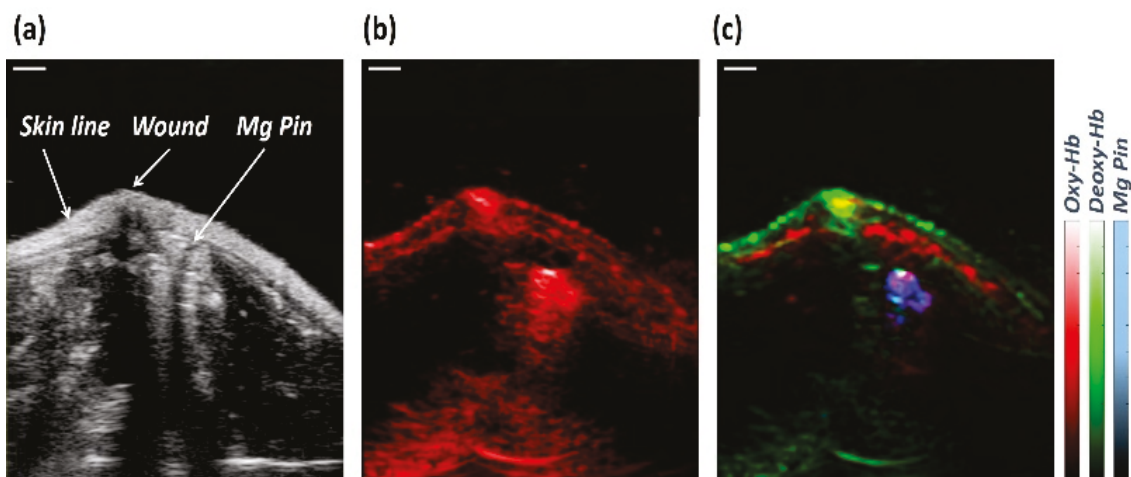


Figure 6. (a,b) The Ultrasound and Photoacoustic images of the Mg-implanted rat's femur on day 3 after surgery in grey and red scales, respectively; (c) Overlapped unmixed distribution maps of the Oxy-, Deoxy-hemoglobin, and Mg pin in red, green, and blue scales, respectively, automatically obtained from sPAI. The scale bar size is 2 mm.

3.3. PCA Detects Significant Physiological Changes

3.3.1. Case Study

On day 3, one of the Ti-implanted rats developed a skin rash as an allergic reaction to the shaving cream that persisted until the end of the study. We found a measurable difference by analyzing the StO₂ values and comparing a Ti-implanted animal with normal skin to a rat with skin rash. The data obtained at different timepoints were also visualized

using PCA. In Figure 7, the PCA score plot shows the effect of damaged skin in terms of correlation at Timepoints 3, 7, and 14.

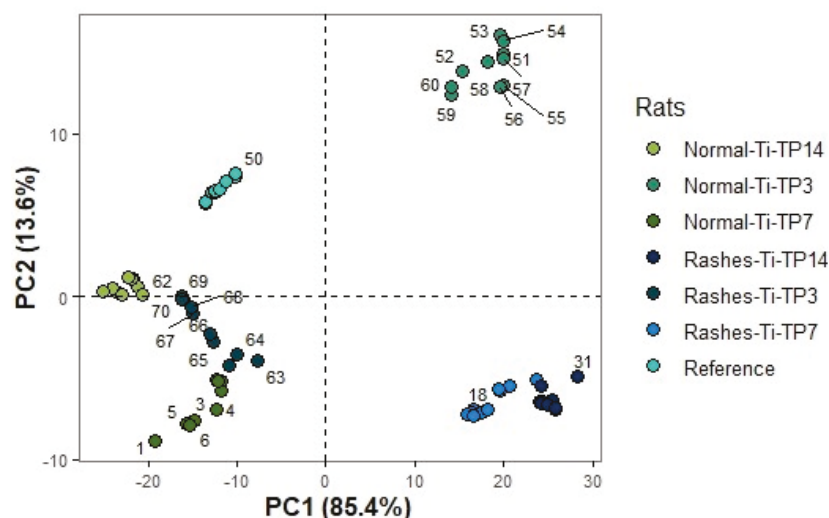


Figure 7. PCA score plot of normal vs. skin rash rats before surgery and on days 3, 7, and 14.

3.3.2. Longitudinal Evaluation of Healing

Furthermore, to assess the evolution of healing, we compared the measurements of the last timepoint, day 45, with the measurements performed before the surgery, day 0. The PCA score plot, represented in Figure 8, shows a significant spectral correlation at day 45 with day 0 on the Mg-implanted rats. Improbably, the Ti and Sham animals present a less significant correlation between the same timepoints. The same trend was observed in terms of the StO₂ values of Mg-implanted rats; day 45 presented StO₂ values similar to those of day 0. Although preliminary, these results suggest that there is a difference between Mg-implanted animals and Ti-implanted or sham animals.

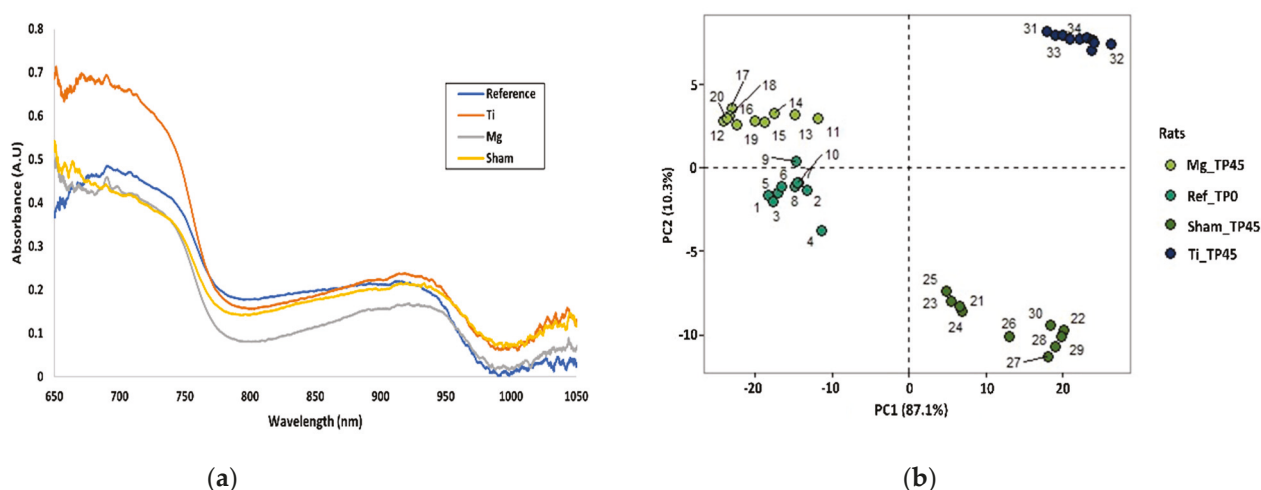


Figure 8. (a) Preliminary results in terms of absorption directly from the spectrometer, and (b) PCA score plot of all rats pre-operatively at Day 0 and post-operatively at Day 45; for reference, Mg-, Ti-, and sham-implanted rats are shown.

4. Discussion

The modified Beer–Lambert approach is extensively used in the biomedical optics community due to its simplicity [35]. Researchers have used CW light to measure blood oxygenation and blood volume changes over time [24,37]. The present paper extends the modified Beer–Lambert approach to calculate the oxygen saturation of the tissues

surrounding an implant. The NIR spectrometer Avaspec (Avantes, BV) can be used to measure the StO₂ levels in the soft tissue located under a sensor probe to measure the oxygen content of the hemoglobin in the soft tissue. The spectra are captured in real time by radiating broadband NIR light, and only two selective wavelengths (740 nm and 850 nm) were used in MBLL to measure changes in HbO₂ and Hb. Based on diffusion theory, it is possible to calculate the depth to which diffuse light will penetrate tissue as a function of the source-detector separation (d). Using a simple dependence, Weiss found that the photon depth before being detected is proportional to the square root of the source-detector separation (d) [40]. On average, the penetration depth of photons in the tissue is around 1/2 to 1/3 of the source-detector distance [41]. NIR light is estimated to reach a 3–3.5 mm depth, and the diffuse light is detected by the optical fiber inside the probe [29,42]. The same optical probe was recently used to validate the spectral absorption curves obtained from USPA [43]. As shown in Figure 5, we have used the molar extinction coefficient values to estimate the change in Hb and HbO₂ using an optical probe developed at Oslo Metropolitan University, Oslo, Norway [29]. In order to investigate different wavelengths, we must have DPF values for each wavelength. Minor changes in DPF values could result in incorrect results [44]. It is assumed that these changes are minor, and, thus, a DPF value was chosen based on the literature that uses a DPF value based on the source-detector distance we selected.

NIRS studies have shown that oxygenation changes in the expected direction; however, absolute values can vary among studies and devices [45,46]. While CW-NIRS, such as the one used in this study, cannot estimate absolute concentrations, they are able to provide relative changes compared to a baseline, unlike FD-NIRS and TD-NIRS. The StO₂ differences between some of the most commonly used commercial NIRS devices typically range from 10 to 15%, but they can be as high as 20% at low StO₂ levels [46]. As a result of this variability across devices, it is challenging to establish thresholds for StO₂ that can guide clinical management. Several equations were recently derived from converting values from one device to another to standardize oxygenation measurements across devices [45]. However, the StO₂ values obtained through the NIRS probe, as reported in the proposed paper, are in line with the measurements obtained from USPA. One phenomenon associated with Mg implants degradation is the formation of gas bubbles around the implantation site, particularly at early timepoints after implantation, such as day 1 and day 3. This is challenging to measure with USPA, but NIRS presents a significant advantage in this sense. Therefore, NIRS can be used to investigate the bubble formation behavior of StO₂, particularly in the case of Mg alloy implantation. Upon implantation, magnesium and its alloys degrade in the body, releasing corrosion products such as H₂ in the local environment [47]. For the *in vivo* study, maximum gas volumes were formed from earlier days until day 5 [48]. Rats implanted with Mg had the highest StO₂ variation on days 1 and 3 relative to their baseline values on day 0 compared to rats implanted with Ti or sham implants.

Ultrasound (US) and photoacoustic (PA) imaging technology has been used to assess the SO₂ changes in the vicinity of the implant. The combination of USPA with a recently developed unsupervised unmixing framework named superpixel photoacoustic unmixing (SPAX) has enabled the automated detection of the Mg-based implant, HbO₂, and Hb as a prominent absorber [39]. Thus, this methodology was used as a comparison to benchmark the NIRS assessments *in vivo*. Although the sPAI unmixing provides results about the molecular tissue components' spectra and their distribution maps, the SO₂ evaluation is not an absolute measure. Thus, to obtain the absolute quantification in PA imaging, an improved measurement of the system response, optical tissue properties, and Grüneisen parameters are required. In the future, we aim to address the absolute quantification by implementing deep learning approaches based on non-explicit light fluence estimation, leading to high-fidelity SO₂ estimations.

There have been a few studies that suggest that StO₂ levels are significantly affected by the skin blood flow. NIRS measurements were shown to be affected by the skin blood

flow by Buono et al. [49]. Our case study results showed that the animal with the skin rash presented a higher StO_2 level associated with the abnormally high blood flow to the injured area. Furthermore, PCA was used in our study to demonstrate the potential for effectively differentiating between the spectral signatures collected from healthy and abnormal skin conditions. The results, although limited to one case, suggest the potential for PCA to be used in future studies to differentiate between healthy and diseased tissue. On a last note, our study uses albino rats, and the skin rash is easily detectable by visual observation; yet, NIRS could have more meaningful use in cases where skin pigmentation is higher and, thus, it is more difficult to detect changes visually.

In this study, we used PCA to detect differences between the timepoints (0, 1, 3, 7, 14, and 45). The PCA score plot for days 0 and 45 for all rats can be seen in Figure 7. Interestingly, on day 45, the rats implanted with Mg seemed closer to their pre-implanted state, day 0, when compared to the rats of the other groups. Moreover, the StO_2 values of days 0 and 45 for the Mg-implanted animals were similar. This result seems to be in accordance with recent studies showing that Mg implants' degradation promotes tissue regeneration and leads to a faster soft tissue homogeneity [47,50]. Although preliminary, our study shows that NIRS and PCA can detect these changes and are suitable tools for monitoring Mg implants degradation, particularly in an initial stage of soft tissue regeneration.

Our study presents a purely descriptive pilot study. However, to our knowledge, this study is the first longitudinal study using NIRS and PCA to assess, *in vivo*, the implant soft tissue–interface. With our NIR optical probe, we demonstrated that StO_2 mainly changed postoperatively from day 0 to day 3, possibly due to bubble gas formation, a well-known side effect associated with the initial fast degradation of Mg implants. By using our approach, it is demonstrated that StO_2 changes over time after implantation and that PCA can detect meaningful correlations with physiological reasoning. Further experiments with a larger group of animals should be conducted in order to significantly validate our findings. Furthermore, NIRS combined with multivariate techniques such as PLS and PCA and complemented with morphological information from USPA can provide a quick, objective, and reliable measure of the implant–tissue interface.

5. Conclusions

Applying the modified Beer–Lambert law (MBLL) to particular measurement conditions related to the effect of Mg degradation within tissues can enhance the reliability of data on the target tissue's physiological state and biochemical content. NIRS is a non-destructive, non-invasive technique used to monitor tissue oxygenation in various clinical settings. This study shows that it may be a valuable method for measuring tissue oxygen levels and monitoring the tissue healing associated with Mg implant degradation. We use NIR spectroscopy techniques along with PCA analysis to assess the tissues surrounding the implant–tissue interface over time and detect significant changes. By combining NIRS and USPA, many other tissue parameters can be measured non-destructively and non-invasively. Furthermore, NIRS combined with multivariate techniques such as PLS and PCA and complemented with morphological information from USPA can provide a quick, objective, and reliable measure of the implant–tissue interface.

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Institutional Review Board Statement: All in vivo experiments were carried out in accordance with the National Ethical Guidelines (Italian Ministry of Health; D.L.vo 26/2014) and the guidelines from Directive 2010/63/EU of the European Parliament. The protocol was approved by the Istituto Superiore di Sanità on behalf of the Italian Ministry of Health and Ethical Panel (Prot. n° 299/2020-PR) and the local ethics committee. Additionally, the protocol conformed to the ARRIVE guidelines.

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Article

An Open-Source, Interoperable Architecture for Generating Real-Time Surgical Team Cognitive Alerts from Heart-Rate Variability Monitoring

David Arney ^{1,2,*}, Yi Zhang ¹, Lauren R. Kennedy-Metz ³, Roger D. Dias ⁴, Julian M. Goldman ^{1,2} and Marco A. Zenati ⁵

¹ Medical Device Plug-and-Play Interoperability and Cybersecurity Program, Massachusetts General Hospital, Boston, MA 02115, USA

² Department of Anaesthesia, Harvard Medical School, Boston, MA 02115, USA

³ Department of Psychology, Roanoke College, Salem, VA 24153, USA

⁴ STRATUS Center for Medical Simulation, Department of Emergency Medicine, Brigham and Women's Hospital, Boston, MA 02115, USA

⁵ Division of Cardiac Surgery, Veterans Affairs Boston Healthcare System, Department of Surgery, Brigham and Women's Hospital, Harvard Medical School, Boston, MA 02115, USA

* Correspondence: darney@mgh.harvard.edu

Abstract: Clinical alarm and decision support systems that lack clinical context may create non-actionable nuisance alarms that are not clinically relevant and can cause distractions during the most difficult moments of a surgery. We present a novel, interoperable, real-time system for adding contextual awareness to clinical systems by monitoring the heart-rate variability (HRV) of clinical team members. We designed an architecture for real-time capture, analysis, and presentation of HRV data from multiple clinicians and implemented this architecture as an application and device interfaces on the open-source OpenICE interoperability platform. In this work, we extend OpenICE with new capabilities to support the needs of the context-aware OR including a modularized data pipeline for simultaneously processing real-time electrocardiographic (ECG) waveforms from multiple clinicians to create estimates of their individual cognitive load. The system is built with standardized interfaces that allow for free interchange of software and hardware components including sensor devices, ECG filtering and beat detection algorithms, HRV metric calculations, and individual and team alerts based on changes in metrics. By integrating contextual cues and team member state into a unified process model, we believe future clinical applications will be able to emulate some of these behaviors to provide context-aware information to improve the safety and quality of surgical interventions.

Keywords: surgical data science; interoperability; cognitive load; smart alarms; heart-rate variability

1. Introduction

Cardiac Surgery is one of the most complex and high-risk areas of medicine. Four teams (Surgery, Anesthesia, Perfusion, and Nursing), each comprised of 2–3 individuals, need to cooperate and interact with medical cyber-physical systems to achieve the desired cardiac intervention (e.g., repair a defective mitral valve) effectively, safely, and expeditiously [1]. Effective team coordination requires the management of interruptions and distractions as well as awareness of the context of the surgical procedure. Cognitive load, a measure of how mentally occupied or stressed a team member is at a particular time, provides a useful metric for understanding how team members' attention and mental load varies through the stages of a surgical procedure.

A context-aware operating room (OR) is one in which patient data are integrated with information about surgical processes, medical devices, and clinician mental states in order to provide OR providers, in real time, with an overall status of the surgical process,

alerts and guidance about current and anticipated hazardous situations. Thus, the real-time monitoring and alerting of the cognitive load of surgical team members during the procedure can be an important application of the context-aware OR.

To establish context-aware OR infrastructures and applications, the emerging field of surgical data science strives to leverage the data-rich environment in the OR through the capture, formatting, analysis, and modelling of data to ultimately improve surgical care [2]. Building a context-aware OR requires multidisciplinary collaboration to not only capture disparate data sources, but also integrate device data, clinician mental state monitoring, and process modelling and monitoring. These new intelligent spaces offer great potential to improve patient safety and outcomes as well as to build rich new data stores for better understanding and improving clinical processes.

Unfortunately, current technologies capturing and integrating important patient data from clinical environments, such as widely used anesthesia record systems and electronic health records (EHR), suffer from significant limitations in recording key information necessary for understanding clinical processes. These systems are not suitable for building real-time alarms and closed-loop control applications, or for supporting the context-aware OR vision described above. For example, there may be delays of up to several minutes from the time a medication administration or other data element is entered at the bedside until it appears in the EHR report from that patient and detailed information from patient monitors such as waveforms are usually not recorded.

In this paper, we propose a framework and describe a novel application that both makes use of, and adds additional contextual information to, a context-aware OR based on the OpenICE (Open Integrated Clinical Environment) medical device interoperability framework [3]. This effort builds on previous work on surgical process modeling, behavioral and cognitive engineering [4], and an offline dashboard for cognitive load analysis [5]. In particular, we apply the OpenICE platform to the surgical subspecialty of Cardiac Surgery in order to enable a ‘smarter’, or more context-aware, operating room by developing real-time processing, monitoring, and alerting based on measures of individual and overall team cognitive load. We call this adaptation COR-ICE for the Cardiac Operating Room Integrated Clinical Environment.

OpenICE is an open-source implementation of the AAMI (Association for the Advancement of Medical Instrumentation) 2700-1:2019 standard on the patient-centric integrated clinical environment (ICE) interoperability architecture [6]. It is a platform for medical device integration that supports rapid development of bedside clinical applications including data collection, smart alarms and data dashboards, and closed-loop control of devices. OpenICE software code is freely available online: <https://www.openice.info> (accessed on 10 January 2023).

In this work, we extend OpenICE with new capabilities to support the needs of the context-aware OR including a modularized data pipeline for simultaneously processing real-time electrocardiographic (ECG) waveforms from multiple clinicians to create estimates of cognitive load.

This real-time ECG pipeline leverages previous work [5] on developing a dashboard for offline analysis of cognitive load estimates derived from heart-rate variability (HRV) metrics as well as extensive related work on HRV metrics and ECG signal processing and analysis algorithms [7,8].

Unobtrusive physiological sensors and the accompanying algorithms applied to the waveforms generated by them [9] have contributed substantially to our understanding of psychophysiological states. Devices and software designed to receive and filter physiological waveforms, identify features of interest, calculate relevant metrics based on those features, and present information on the underlying physiological status back to the user form the backbone of real-time biofeedback approaches [10,11]. These types of sensors and algorithms have been successfully implemented to train users to improve physical symptoms (i.e., vestibular imbalances [12]), mental symptoms (i.e., depressive states [13]), and a variety of other clinical symptoms.

Biofeedback approaches relying on the detection of cardiovascular changes are particularly prevalent given the prominent and relatively isolated amplitude of the R-peak appearing within ECG waveforms, which represents ventricular contraction of the heart [14]. Subsequently, sensors designed to monitor cardiovascular changes have contributed substantially to the understanding of autonomic nervous system (ANS) changes [15]. For these approaches to be successful, it is critical that the feedback loop underpinning them operates in real-time or near real-time. While the shortest duration for traditional HRV analysis of ECG waveforms was historically identified as five minutes [16], more nuanced methods are required in order to accomplish on-line analysis. Specifically, this calls for ultra-short-term analytical approaches to calculate upon incoming data, which has become increasingly utilized in recent years [17].

Further, to ensure accuracy in real-time calculations, consideration must be given to the nature of the calculations, including the physiological processes they represent. HRV metrics consist of time-domain, frequency-domain, and geometrical approaches and can broadly be categorized according to the branch of the ANS contributing to its measurement [7]. In particular, the high frequency (HF) band (0.15–0.40 Hz) reflects respiratory sinus arrhythmia, which is vagally mediated and reflects parasympathetic dominance. The low frequency (LF) band (0.04–0.15 Hz), in contrast, has been demonstrated as a proxy for sympathetic dominance by some, and sympatho-vagal balance by others [16]. The LF/HF ratio thus reflects an input from both branches of the ANS and, given their respective oscillation frequencies and generally slower sympathetic responsiveness, requires a minimum time window of one minute of data to discriminate between high and low arousal states accurately [18], and to perform on-line processing with accuracies equivalent to a 5-min time window [19,20]. Additionally, previous work has suggested a relationship between the LF/HF ratio and emotional states such as frustration [21], mental stress [22], and cognitive workload [23].

Insights into the surgical team members' mental state and changing cognitive workload can be extrapolated according to underlying physiological changes via non-invasive sensors [24]. Estimation of intra-operative cognitive workload in particular is most often approached through HRV acquisition and analysis [25]. Previous work has demonstrated the sensitivity of capturing intra-operative HRV from multiple team members, analyzed according to surgical phase [26] and according to intra-operative events [27].

In addition to integrating data representing the progress of the surgical procedure and patient data, monitoring clinicians' mental workload state may provide a more comprehensive snapshot of the COR context. In fact, clinician workload represents a unique data stream/input incorporated into the COR-ICE platform. The tenets of mental workload theory are the assumptions that individuals have a limited cognitive capacity, demands imposed and resources required vary according to the task at hand, and individuals differ in the degree of cognitive resources required to perform a given task [28]. Thus, monitoring individual operators during the course of a multi-task, multi-step procedure reflects personalized insights into cognitive efficiency. In the future, tying these insights to a process model of the specific procedure would allow immediate feedback based on both the current step in the process as well as predicted likely future states and actions. In surgery in particular, cognitive factors are the major contributors to human performance deficiencies and adverse events [29], necessitating a nuanced understanding of these cognitive workload changes over time.

In addition to deriving individual indicators of mental states using sensor technology, capturing and representing team cognitive load states is still facing a particularly compelling knowledge gap. Effective implementation of team cognitive load calculations has been demonstrated through off-line analysis in the domains of submarine navigation [30] and cardiac surgery [31,32], but its real-time implementation has received less attention.

The goal of this work is to develop an interoperable pipeline on an open-source platform to enable the real-time representation of a team cognitive load estimate derived from the simultaneous acquisition of ECG measurements from multiple team members.

2. Methods

We designed an architecture for real-time capture, analysis, and presentation of HRV data from multiple clinicians and implemented this architecture as an application and device interfaces on the OpenICE platform.

2.1. COR-ICE: OpenICE-Centered Context-Aware Operating Room

The COR-ICE architecture shown in Figure 1 brings together physiological data from multiple clinicians into an interoperable processing pipeline that supports individualized and team-based alerts and notifications. COR-ICE includes interfaces for the clinical team that provide a summary of the current data sources and HRV metrics for each clinician and a dashboard of team status.

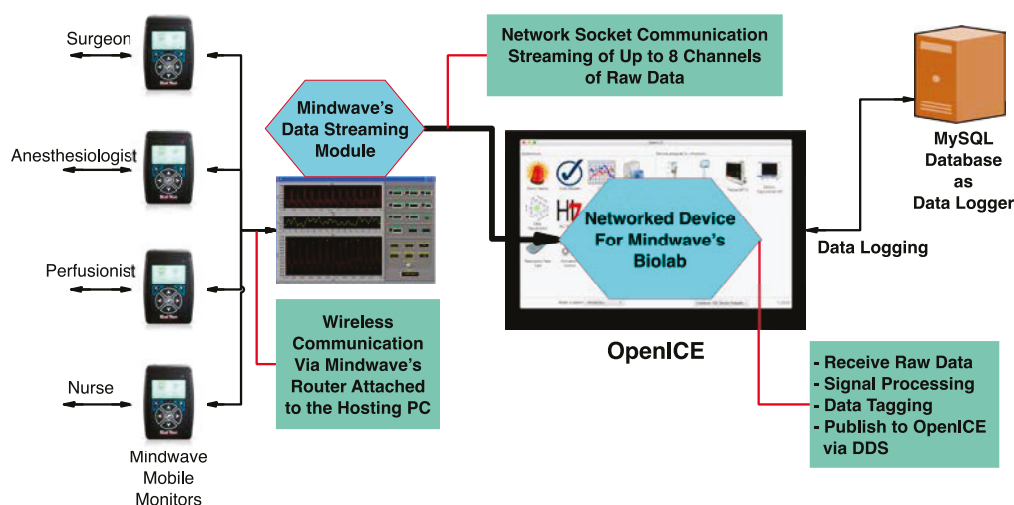


Figure 1. COR-ICE Architecture.

OpenICE (OpenICE source code is freely available at github.com/mdpnp (accessed on 10 January 2023) and OpenICE.info) is intended as a distributed system centered on a single patient. One of the foundational insights in its design was that healthcare is already a distributed system; caregivers learn about the patient and their condition and share information with each other in both structured and un-structured ways as the information is needed and available. COR-ICE builds on this foundation to add multiple streams of clinician physiological data that can be associated with the clinical role and a specific patient, enabling alerts that could also take into account that patient's status.

The design of OpenICE mirrors this architecture, with independent agents such as medical equipment interfaces and applications sharing data elements as needed via a publish/subscribe middleware. In a publish/subscribe communication pattern, data producers publish the produced data to different pre-defined topics, while data consumers who are interested in using the produced data for their tasks subscribe to these topics. In this pattern, topics can be considered as buffers from which data consumers can receive the latest data produced by data producers. We have found that these publish/subscribe patterns map well onto many clinical applications and that building on existing and familiar communication patterns enhances explainability; the way data moves around makes sense to many clinicians because it matches how they are used to working. OpenICE shares goals with other medical device interoperability projects such as the 11073-SDC (Service-oriented Device Connectivity) family of standards developed by the OR.net organization [33,34].

OpenICE emphasizes bedside networks and the capacity for closed-loop control based on requirements from specific clinical scenarios, while 11073-SDC has an emphasis on linking devices to enable data sharing using established web-services protocols. Both groups have complementary approaches and share the goals of improving the safety and quality of clinical care.

The COR-ICE architecture shown in Figure 1 supports connecting a wide variety of sensors and data sources. As many sources of contextual data are available for use in OR, COR-ICE provides a generalized, standards-based terminology set and means to capture and share data from sensors. The ICE standard explicitly includes the healthcare providers (HCP), connections to non-medical equipment in the room; tracking sound/noise levels and equipment state provides important contextual cues [35]. This aligns with the ultimate goal of this work—supporting the cardiac surgical team with relevant contextual information [36].

A wide range of monitoring modalities are available. In previous work, we proposed to monitor HRV and map this psychophysiological measure to cognitive workload [26]; we are extending this in COR-ICE to additionally monitor clinician eye-tracking, electroencephalography (EEG), Near Infrared Spectroscopy (NIRS), heart rate (ECG), pulse oximetry, body temperature, blood pressure, electrodermal activity (EDA), and voice recognition.

In this work, we integrate with OpenICE portable monitors that the team members can wear that will stream ECG and other physiologic signals from all of the participants simultaneously. Preoperative domain knowledge, patient information, and staff profiles could also be securely made available to the COR-ICE from the hospital PACS (Picture Archiving and Communication System) through the COR-ICE external interface and HL7 FHIR (Fast Healthcare Interoperability Resources) interfaces, though this would require further system integration work.

Software applications for the cardiac OR mostly fall into two categories: (1) smart alarms and dashboards that monitor the output of one or several connected devices and create alarms and alerts based on the data they receive; and (2) closed-loop control applications that automatically control the care delivery by one device based on sensor data from one or more other devices. These software applications are safety critical and will usually need to be hosted close to the patient rather than on a server in a datacenter; this reduces the risks of network delay and accidental disconnection, simplifies patient identification and association, and allows direct feedback to the clinicians at the patient's side. These software applications for the cardiac OR can be implemented as 'apps' hosted inside the ICE Manager in OpenICE that is deployed close to the patient.

2.2. Deriving Cognitive Load Estimates and Alerts from Heart-Rate Variability Metrics

Dias et al. [5] introduced a dashboard for visualizing cognitive load of multiple clinicians in a surgical team. The proposed dashboard used recorded data and a commercial HRV analysis program to do offline analysis and visualization. We build on this work by creating an open-source processing pipeline for real-time monitoring and alerting based on live streams of data from the surgical team members, where components of the pipeline can be easily changed and reordered to accommodate different formats and quality levels of the input ECG data streaming.

2.3. Processing Pipeline

The process of going from individual clinician ECG measurements to alert notifications based on the team's cognitive load estimate includes six major stages as illustrated in Figure 2, including: (1) acquisition of ECG data; (2) ECG filtering to remove noise; (3) Beat detection and inter-beat interval (IBI) calculation; (4) HRV metric calculation; (5) cognitive load estimation; and (6) alert management. The inputs and outputs of each stage are enumerated in Table 1.

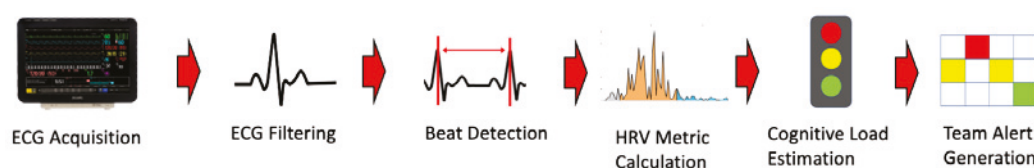


Figure 2. Stages of the Processing Pipeline.

Table 1. Processing Pipeline Stages, Inputs, and Outputs.

Stage	Input	Output
ECG Acquisition	Physiologic measurement	Standardized ECG waveform
ECG Filtering	Standardized ECG waveform	Standardized ECG waveform
Beat Detection	Standardized ECG waveform	IBI Series
Metric Calculation	IBI Series	HRV Metrics Series
CL Estimation	HRV Metrics Series	CL Estimate Series
Alerting	CL Estimate Series	Team CL Alerts

ECG acquisition starts with a medical device measuring electrical potential from multiple points on a person’s skin. This system was developed and tested with different devices: Mindware Mobile monitors, a Philips MX800 patient monitor, and a software simulated ECG device built into OpenICE. ECG waveforms at this stage include noise and artifacts from motion, poor electrode contact, and other causes.

ECG data originates as voltages measured using electrodes attached to the skin. Electrical potential differences between pairs of electrodes are represented by convention as virtual Leads. We used Lead II as the input for this processing pipeline. The Mindware Mobile, Philips MX800, and most other medical devices output data encoded in proprietary terminologies and communicate using proprietary protocols. The OpenICE equipment interfaces use these proprietary protocols to communicate with the devices and then republish the data in a standardized encoding. This encoding uses the ISO 11073-10101 [37] term “MDC_ECG_Lead_II” and represents the data as a series of voltage measurements with a sampling rate determined by the acquisition device. OpenICE bundles together 250 ms of waveform data into each waveform publication. The Mindware Mobile samples at 500 samples per second, so each MDC_ECG_Lead_II waveform publication would include 125 samples and a timestamp for the first sample in the array. This format is used between several of the stages of the processing pipeline and also in other applications, allowing easy use of other ECG acquisition devices and easy replacement or reordering of processing pipeline stages.

The filtering stage takes a standardized ECG waveform as input, applies signal processing to remove noise and artifacts, and outputs the ‘cleaned-up’ ECG as another standardized ECG waveform. We followed the approach of Chen et. al. [8] and designed our prototype application with three stages of filtering: wavelet denoising, linear high-pass filter, and non-linear low-pass filter. Any number of filtering stages could be applied here; each consumes and produces an ECG waveform so they can be combined in any desired order. Related work in de-noising and classifying individual beats [38–40] could plug in at this stage to reduce the effects of missed beats and noise on the downstream calculations of inter-beat intervals.

Accurate beat detection is critically important for the HRV analysis. Our implementation uses an adaptive threshold algorithm that continuously monitors the ECG signal to determine the highest voltage values (corresponding to R-wave peaks) over the last 10 s, then sets a slightly lower threshold value. When the input waveform exceeds this threshold, the algorithm watches for a change in sign—when the voltage switches from increasing to decreasing—that marks the peak of the R-wave. The time of this peak is the time of a heartbeat, and the time interval between this and next peaks is the R-R interval or inter-beat interval. Much related research in beat detection, for instance [41], could be leveraged here to improve performance.

The ECG sampling rate must be high enough to allow peak detection with minimal errors. Errors in the timing of R-waves will directly affect the accuracy of inter-beat intervals and all downstream metrics. Sampling rate relates to the accuracy of the timing measurements because the R-wave peak will fall within one to two sample periods. The interval depends on the time of two beats, so each interval has an error of ± 2 sample

periods. If the ECG is sampled at 100 Hz, each sample covers a 10 ms time period and the errors become a similar magnitude to the beat-to-beat variability being measured. This prototype application requires a sample rate of 500 measurements per second or higher to reduce the magnitude of timing measurement errors.

The sequence of IBIs is the basic input to the HRV metric calculations. There are many HRV metrics [7]; previous work [5] has found that RMSSD and LF/HF ratio are the most relevant for the cognitive load estimation stage that will use these metrics as input.

The modular architecture of the processing pipeline allows for easily providing additional inputs at any stage. Some devices, for instance the Polar H10 monitor [42], directly output and stream IBI sequences in real-time. Feeding these IBI sequences into the pipeline replaces the Acquisition, Filtering, and Beat Detection stages with the H10's built-in algorithms. This has advantages for reducing the complexity of the system at the expense of also reducing flexibility—it is not possible, for instance, to change how the H10 filters ECGs before beat detection.

Our COR-ICE prototype implementation allows playback of recorded IBI sequences from Polar or processed output of programs such as Kubios that take ECG records as input, perform highly-configurable processing, and output IBI sequences. Analysis programs such as Kubios are useful tools for offline analysis but do not generally support real-time streaming or alert generation.

The six stages of our data pipeline are modularized and interoperable, meaning that their inputs and outputs of each stage are defined in a standardized terminology and the OpenICE platform provides a standardized means for communicating the data elements between stages or applications.

3. Results

We have built a prototype implementation of COR-ICE, an interoperable system for capturing and real-time analysis of multiple streams of ECG data and performed pre-clinical bench testing to verify that it meets key design metrics. It should be noted that this prototype does not intend to validate specific HRV metric calculations or cognitive load estimation algorithms. Rather, it intends to verify the system architecture, particularly the data pipeline described above, for future integration with and application in the context-aware OR to support clinical research on surgical process monitoring and modeling.

System Implementation

Our COR-ICE prototype is implemented as an app on the OpenICE platform. As such, it inherits many capabilities and interfaces from the platform, including the real-time data bus and equipment interfaces. Figure 1 shows the main components of this app.

Multiple Mindware Mobile monitors are connected via a dedicated WIFI network to a computer running Mindware's Biolabs software. The Mindware Data Streaming Module is used to collect and relay one channel of ECG data per monitor as a data stream over ethernet to an OpenICE equipment interface. The equipment interface receives the data stream, associates each ECG waveform with a unique device identifier, and publishes the data as an MDC_ECG_LEAD_II waveform on the DDS data bus. The data streaming module supports eight simultaneous waveform streams. The monitoring app is designed to support simultaneous monitoring of up to four members of the surgical team, but there is no fundamental limit preventing expansion to monitoring up to eight people with a single data streaming module or multiples of eight people with multiple Biolabs systems.

The COR-ICE app subscribes to these waveform data streams, calculates the HRV metrics, and creates a real-time display of metrics and cognitive load estimates. Data, including the calculated metrics and waveforms, is also recorded by the OpenICE's built-in data logger (complying with the AAMI 2700-2-1: ICE Forensic Data Logging Standard [43]) with a coordinated timestamp to support future analysis and research.

One challenge in developing this app is that the ICE architecture has primarily been used to host applications supporting the care of a single patient. While there is still a

single patient in the cardiac operating theatre, the system must now track physiologic data from multiple individuals. This is handled in the HRV Analysis app by providing a user interface (shown in Figures 3 and 4) with means for the user to associate ECG waveforms with a clinical role and, optionally, clinician name. In this implementation, the team roles are “Surgeon”, “Anesthesiologist”, “Perfusionist”, and “Nurse”.

Surgical Team Cognitive Load Monitoring App

Source 1
 Sensor Connection: **Connected**
 ECG Waveform
 Sensor ID: **Sensor_XXX**
 Team Member: **Dr. XXX**
 Role: **Surgeon**
 Cognitive Load: **Normal**
 IBI: **2200** ms SDNN: **500** ms RMSSD: **500** ms LF/HF: **34** %

Source 2
 Sensor Connection: **Connected**
 ECG Waveform
 Sensor ID: **Sensor_XXX**
 Team Member: **Dr. XXX**
 Role: **Anesthesiol**
 Cognitive Load: **Normal**
 IBI: **2200** ms SDNN: **500** ms RMSSD: **500** ms LF/HF: **34** %

Source 3
 Sensor Connection: **Connected**
 ECG Waveform
 Sensor ID: **Sensor_XXX**
 Team Member: **Dr. XXX**
 Role: **Perfusionist**
 Cognitive Load: **Normal**
 IBI: **2200** ms SDNN: **500** ms RMSSD: **500** ms LF/HF: **34** %

Source 4
 Sensor Connection: **Connected**
 ECG Waveform
 Sensor ID: **Sensor_XXX**
 Team Member: **RN Karen**
 Role: **Nurse**
 Cognitive Load: **Normal**
 IBI: **2200** ms SDNN: **500** ms RMSSD: **500** ms LF/HF: **34** %

Time Window Size: **Dr. XXX** seconds

Start/Stop

Figure 3. Application Design Wireframe.

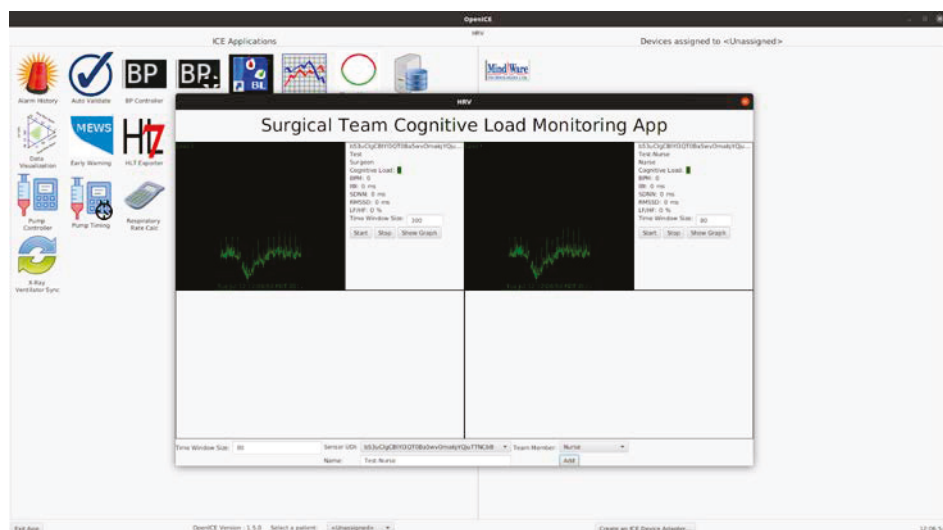


Figure 4. COR-ICE HRV Analysis App UI.

Much of the complexity of the data processing pipeline is not exposed on the user interface. The user can specify the time window over which the HRV metric calculations are made, ranging from 10 s to 300 s. The average heart rate over this interval, SDNN, RMSSD, and LF/HF ratio over this time window are displayed for each clinician and the values are updated once per second.

The last layer of interpretation is estimating clinician cognitive load from the HRV metrics. The app will generate some threshold-based alerts from the HRV and/or Cognitive Load metrics. The cognitive load estimation and alerts are still under development. We

plan to map terciles of LF/HF ratio to low/medium/high cognitive load estimates and display a ‘traffic light’ style section for each clinician, illustrated in Figure 4 as a small green box. For team alerts, we plan to assign a score of 1 to 3 to each tercile and set a team alarm under two conditions: if the sum of the four scores is ≥ 7 OR if two team members are in the red.

Validation that the cognitive load measurements accurately reflect the clinician’s actual cognitive load and that alerts are triggered at correct times will require running the app against recorded data sets where events and cognitive load levels are manually annotated. We are in the process of collecting such a data set and will pursue validation of the cognitive load estimation algorithm as future work. One key benefit of our approach is that any algorithm for cognitive load estimation based on ECG signals or sequences of HRV metrics can easily plug into other pipeline stages, allowing for quick testing and comparison of algorithms without needing to recreate data collection and filtering stages.

4. Conclusions

We have presented an overview of the COR-ICE architecture, an example scenario of the type of applications we are planning to address, and the data sources, including surgical team monitoring, that drive the awareness of context. We believe all of these elements are necessary to build a context-aware operating room for cardiac surgery.

Beyond the technical ‘bricks and mortar’ that make up the COR-ICE, we have a shared vision of how applications in a context-aware operating room will need to interact with the surgical team. Current medical devices and clinical applications typically trigger alarms and alerts based on a single monitored variable such as heart rate or blood pressure. Monitors and decision support systems that lack clinical context create non-actionable nuisance alarms that are not clinically relevant and cause distractions during the most difficult moments of a surgery. In contrast, we believe COR-ICE applications will be able to interact with the surgical team more like another team member. Communication between team members takes into account where they are in the surgical workflow, how busy or mentally occupied each team member is, and knowledge of who needs to know what to respond to expected and unexpected occurrences. By integrating contextual cues and team member state into a unified process model, COR-ICE applications will be able to emulate some of these behaviors to provide context-aware information to improve the safety and quality of surgical interventions.

This novel work demonstrates for the first time the feasibility of acquiring multiple ECG waveforms, applying an interoperable pipeline capable of filtering the ECGs, identifying IBIs, calculating HRV metrics, estimating team cognitive load states, and generating alerts in response. The real-time, multi-agent nature of this open-source platform advances the current state of sensor-derived signal analysis, with implications for providing cognitive support to teams operating in complex environments.

In the future, we envision further extensions to COR-ICE that will enable recording, in a common terminology and time-base, data from a rich variety of inputs including RGB-D cameras, real-time location systems, posture, gesture, instrument, and eye motion tracking, as well as object recognition, action detection, and detection of person-object interactions. Together with the current capability to stream and record vital signs and other information from the patient and clinical team, this will support integration with the workflow and process modeling to add awareness of the current status and stage of the surgical procedure.

Though preliminary, the demonstration of this pathway is unique in its utilization of data acquired in the naturalistic and complex environment of the cardiac operating room. Subsequent efforts will target validating the team cognitive load estimates derived algorithmically by observing event logs, team non-technical skills, and self-reports of stress and cognitive workload corresponding to the associated times. Excessive team cognitive load estimates will be validated against audio/video data capturing the procedures included in this analysis.

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Article

An Evidence Theoretic Approach for Traffic Signal Intrusion Detection

Abdullahi Chowdhury ¹, Gour Karmakar ^{2,3}, Joarder Kamruzzaman ^{2,3}, Rajkumar Das ⁴ and S. H. Shah Newaz ^{5,6,*}

¹ School of Computer and Mathematical Sciences, The University of Adelaide, Adelaide, SA 5005, Australia

² Centre for Smart Analytics, Federation University Australia, Ballarat, VIC 3350, Australia

³ Institute of Innovation, Science and Sustainability, Federation University Australia, Ballarat, VIC 3350, Australia

⁴ Information Technology Services, Federation University Australia, Mount Helen Campus, Ballarat, VIC 3350, Australia

⁵ School of Computing and Informatics, Universiti Teknologi Brunei, Jalan Tungku Link, Gadong BE 1410, Brunei

⁶ KAIST Institute for Information Technology Convergence, 291 Daehak-ro, Yuseong-gu, Daejeon 34141, Republic of Korea

* Correspondence: shah.newaz@utb.edu.bn; Tel.: +673-2461020 (ext. 5235)

Abstract: The increasing attacks on traffic signals worldwide indicate the importance of intrusion detection. The existing traffic signal Intrusion Detection Systems (IDSs) that rely on inputs from connected vehicles and image analysis techniques can only detect intrusions created by spoofed vehicles. However, these approaches fail to detect intrusion from attacks on in-road sensors, traffic controllers, and signals. In this paper, we proposed an IDS based on detecting anomalies associated with flow rate, phase time, and vehicle speed, which is a significant extension of our previous work using additional traffic parameters and statistical tools. We theoretically modelled our system using the Dempster–Shafer decision theory, considering the instantaneous observations of traffic parameters and their relevant historical normal traffic data. We also used Shannon’s entropy to determine the uncertainty associated with the observations. To validate our work, we developed a simulation model based on the traffic simulator called SUMO using many real scenarios and the data recorded by the Victorian Transportation Authority, Australia. The scenarios for abnormal traffic conditions were generated considering attacks such as jamming, Sybil, and false data injection attacks. The results show that the overall detection accuracy of our proposed system is 79.3% with fewer false alarms.

Keywords: traffic signals; intrusion detection; intelligent transportation systems

1. Introduction

Traffic signals control traffic flows in different directions. This control reduces traffic jams and delays and bypasses incidents. Therefore, traffic signals are the heart of the city’s traffic management of an intelligent transportation system. Intelligent transportation systems (ITSs) aim at making reliable, efficient, and protected transportation systems by integrating smart transportation management and control systems through communication networks and computing techniques [1]. Reliable and efficient traffic signals save lives by bypassing incidents and responding to emergency vehicles so that they can meet the target response time [2,3]. Traffic controllers control the traffic signals dynamically based on the traffic conditions derived from wirelessly collected sensor data. These sensors are installed in external places, such as being buried in the roads and equipped with roadside units. These sensors, their communication systems, and traffic signals are vulnerable to cyber attacks. Hackers or cybercriminals can easily create traffic disruptions or diversions by compromising the traffic signals to achieve the benefits they are interested in [4,5]. The chance of hacking or intruding traffic signals is sharply increasing over time because the signals are being equipped with more and more smart electronic devices and are

increasingly dependent on wireless and internet-based data communications. The cyber security threats in the traffic signals will culminate at the peak when Autonomous Vehicles (AVs) hit the city's roads. AVs are a key component of an ITS. These AVs are equipped with advanced sensors and communication systems that allow them to operate without human intervention. Although there are many benefits of AVs, they are also vulnerable to cyber attacks because of their reliance on a range of connected devices and systems, such as GPS, sensors, and wireless communication networks. Hackers could potentially take control of an AV, causing it to malfunction or even crash [6–8].

The authors of [9] showed that disabling as few as seven signals in peak time periods for a couple of hours using a max vehicle affected model can cost around US USD 0.93 million, while the maximum vehicle flow targeting method can cost around US USD 0.98 million if 26 signals are impacted. The authors employed dynamic traffic assignment to show the consequences of traffic signal assaults and to mimic network-wide repercussions of intersection failures. The green traffic signal phase time analysis was also performed in [10]. It is imparted that the analysis of the patterns of green traffic signal phase time can be exploited to detect potential intrusion. However, in this study, a theoretical model for intrusion detection and its evaluation and validation were not specifically performed. In the current literature, there exist congestion-based attack analysis [11] and intrusion detection techniques [12] that exploit traffic image features. Additionally, with intrusion detection considering a specific attack, the other loopholes of these approaches rely on a selected set of traffic image features and an image preprocessing technique (background separation) that usually leads to being more computationally expensive. To advance the research in this area and introduce a more generic approach capable of detecting intrusion under various attacks, we introduced an approach for identifying traffic signal intrusion, which was published in [13]. However, the main problems of this approach are that important traffic signal parameter vehicle speed was not considered and mass value functions for flow rate and speed were not properly formulated. Additionally, there is uncertainty associated with probabilistic measures and converting the flow rate and vehicle speed data into normal distributions was not performed. By addressing these research issues, in this paper, we introduced a traffic signal Intrusion Detection System (IDS) with the following contributions:

- We developed a theoretical model for our proposed IDS, leveraging the Dempster–Shafer (DS) decision theory. Our model incorporates real-time observations of vehicle flow rate, vehicle speed, and traffic signal change duration, as well as relevant historical data obtained from transportation authorities. By utilising this decision theory, we sought to enhance the performance of our proposed system, leading to a more efficient and effective traffic control system. Our approach enables the integration of both historical and real-time data, facilitating the system's ability to make more precise and informed decisions.
- The historical data associated with traffic flow and vehicle speed were transformed into normal distributions. A heuristic mass function was introduced by assigning higher probabilities to those phase time values that are most frequently observed and are closer to the most observed value.
- To assess the uncertainty associated with our observations, we utilised Shannon's entropy. In order to verify and validate our proposed IDS, we developed a simulation model that is based on the SUMO traffic simulator [14]. Our simulation model incorporates real-world scenarios and utilises data collected by the Victorian Transportation Authority, Australia (VicRoads). The results of our simulations demonstrate that our proposed IDS is highly effective in detecting intrusions on traffic signals while reducing false alarms.

Since our proposed IDS is based on anomaly detection, it has the ability to detect intrusions created by the spoofed vehicles proposed in [11], as our method picks up any anomaly caused by intrusions, including intrusions in roadside sensors and traffic controllers and signals. Flow rate, phase time, and vehicle speed are affected by the

attacks in a traffic signal irrespective of their types. Therefore, in contrast to image analysis techniques, as mentioned before, our IDS is more generic because it detects by identifying the inconsistencies between the traffic flows, vehicle speeds, and phase time of the observed and normal traffic conditions. In summary, the overall advantages of our proposed solution are: (i) it is more generic and comprehensive in response to the intrusion of various forms, and (ii) it does not require any image capture and analysis as required by the above studies.

The organisation of the paper is as follows. Section 2 presents the related works on the impact of attacks on traffic signals and intrusion detection in traffic signals. Our proposed IDS along with its theoretical modelling is provided in Section 3. Finally, the experimental results and conclusions are given in Sections 4 and 5, respectively.

2. Related Works

To reduce traffic congestion and travel time, enhance traffic flow management, and protect the safety of road users, intelligent traffic systems, including traffic signals, are utilised [15]. Malicious disruption or manipulation of the lights of a traffic signal can result in catastrophic events such as massive delays, financial loss, and loss of life. Many traffic lights have recently been revealed to have been tampered with throughout the world, emphasising the necessity of precise intrusion detection. Since VANETs are an important part of an ITS, a survey on machine learning based IDSs is presented in [16]. As VANET is an ad hoc vehicular network comprising vehicles and road side units (RSUs), this survey did not consider IDSs for traffic signals.

Feng et al. [6] indicated that intruders could send malicious, spoofed, and corrupted data to the traffic signal control units. These exposures exhibit the pressing need to develop an intrusion detection system for traffic signals. So far, some research studies exist for assessing the impact of attacks on and detecting intrusions in traffic signals. These studies are presented in the following sections.

2.1. Intrusion in Traffic Signals

Intrusion attacks in intelligent traffic signals can cause significant safety hazards and traffic disruptions. Intrusion in traffic signals and traffic control systems refers to any unauthorised access, attack, or disruption of the system's functionality, which can compromise the safety, privacy, and security of the system and its users. Intelligent transportation systems use advanced technology and communication networks to optimise traffic flow, reduce congestion, enhance safety, and improve overall transportation efficiency. These systems rely heavily on connected devices, sensors, data processing, and communication networks, making them vulnerable to cyber threats.

Intrusion threats in intelligent traffic signals can be launched by intruders from outside the network using various methods. Some common intrusion attacks include replay attacks, jamming attacks, Sybil attacks, and false data injection attacks. A jamming attack is an intrusion attack in which an attacker sends messages to a specific RSU, disrupting the communication between the targeted RSU and other RSUs in the network. This can prevent the RSU from receiving essential messages or updates, leading to potential safety hazards or traffic disruptions. Replay attacks intercept the messages exchanged between sensors in the ITS network and re-transmit them to impersonate and steal their identity. This can allow an attacker to gain unauthorised access to the network or impersonate a legitimate user, potentially leading to data theft or other malicious activities. Sybil attacks are another type of intrusion attack where an attacker uses multiple identities to deceive other sensors by reporting fake road congestion. By flooding the network with false information, the attacker can disrupt traffic flow or cause congestion in specific areas, leading to potential safety hazards or traffic disruptions. False data injection is another type of intrusion attack, where an attacker sends false information about the current traffic situation on the road. This can lead to traffic disruptions or congestion, potentially causing safety hazards or delays for drivers.

A ransomware attack hit San Francisco's Municipal Transportation Agency in November 2016, preventing the agency from collecting fares and leading to several key systems shutting down. The attackers demanded a ransom payment of 100 Bitcoin (around USD 73,000 at the time) to restore the systems [17].

The city of St. Louis' traffic system was hacked, causing the city's traffic lights to go dark for several hours. The attack disrupted traffic and caused several accidents, highlighting the potential danger of hacking into critical ITS infrastructure [18].

Implementing robust security measures to prevent unauthorised access and manipulation is important, including access controls, encryption, network segmentation, and ongoing monitoring and testing of their systems to identify and address vulnerabilities.

2.2. *Evaluating the Impact of an Attack on Traffic Signals*

The U.S. Department of Transportation (USDOT) uses the Intelligent Traffic Signal System (I-SIG) to increase traffic management efficiency, reduce traffic congestion, and increase safety [19]. An approach presented in [20] to perform a data spoofing attack on I-SIG demonstrated that the data spoofing could be highly effective in manipulating the signal control algorithm. The spoofed trajectory analysis of the study shows that one single attack could increase the traffic delay by up to 68.1%. Introducing I-SIG improves traffic mobility by 26.6%, but only a single attack can make the traffic condition 23.4% worse than the traffic condition without using I-SIG [21]. Anomalies in traffic control systems not only increase traffic congestion but can also contribute to substantial financial loss. An intruder was able to attack the security cameras used in the Carmel Tunnels toll on a major road network in Haifa, Israel, on 8 September 2013. This cyber attack caused around eight hours of disruption, created enormous logistic issues, and cost hundreds of thousands of dollars [22].

2.3. *Detecting Intrusions in Traffic Signal*

Traffic congestion is considered a severe challenge to urban areas as it harms economic growth, increases gas emissions, and may lead to increased numbers of accidents [23]. Therefore, intelligent traffic signal management is crucial. The algorithms governing intelligent traffic signals are vulnerable to connected vehicle data spoofing attacks, resulting in the creation of congestion at road intersections. To overcome this problem, the foremost important step would be timely and accurate congestion attack detection and identification.

Xiang et al. [11] applied empirical studies to detecting intrusions in traffic signals. From a range of traffic images (vulnerable to potential data spoofing attacks), the solution measures the traffic flow characteristics and predicts whether there would be any attacks that would be able to cause congestion with a certain probability. Additionally, to verify any congestion occurrence, the authors proposed a tree-regularised gated recurrent unit-based approach that analyses the underlying relation between the congestion attack and traffic flow features at a given time. Therefore, when there is an attack that may lead to congestion with high probability, as well as if any congestion development is observed from the subsequent traffic flows, a congestion attack can be inferred. Based on an experiment, the authors imparted that the solution performs well in terms of attack detection accuracy and timeliness. They also proposed to validate their prediction by using traffic parameters in an intersection to determine if congestion really occurs as a result of placing spoofed vehicles in the intersection. Although this model can detect intrusion created by spoofed vehicles, it cannot detect intrusion created by malicious users modifying the data through unauthorised access to the traffic controller unit. This scenario will create congestion in intersections without having any indication from the image generation model.

The authors of [24] highlighted that the existing solutions for identifying congestion attacks have the disadvantage of delay. Considering that a congestion attack is made continuously and periodically, the authors developed a solution for predicting congestion attacks and attack frequency and the timely forecast of future congestion attacks. The prediction mechanism uses supervised machine learning algorithms where historical data are fed in.

The solution collects traffic flows of variable spoofing frequencies and, then, the flows that lead to congestion are used to extract important features. It implements ensemble learning to establish correlations between various traffic flow features and abnormal congestion and attack frequency. The authors demonstrated the significance of their solution based on experimental results.

Li et al. [12] introduced a traffic image feature-based attack prediction mechanism. They claimed that, based on feature-based learning, it is possible to understand the relationship between attack and the caused congestion. Using a cycle generative adversarial network, the authors proposed a prediction mechanism where L1 regularisation loss is made to understand and recognise the difference between the last-vehicle and the first-vehicle attack.

Even though the image analysis technique was adopted as a universal technique for road safety, the 5th-generation adaptive traffic signal management system [25] employs self-learning capabilities and real-time computations to enhance the quality of traffic management for both conventional and autonomous vehicles by observing real-time traffic situations using different in-road sensors and RSUs. The traffic management system can independently learn traffic management strategies and make wise choices to optimise traffic flow, reducing the computational decision-making load incurred by image analysis techniques.

Most Adaptive Traffic Systems (ATs), such as SCATS [26], SCOOT [27], and OPAC [27], use sensors to count vehicles and pedestrians and monitor vehicle speed. These ATs use vehicle count sensor data, average vehicle speed data, and cell arrival and departure data. Most traffic signal intrusions occur by compromising roadside sensors [28]. So, it is crucial to develop a traffic signals intrusion detection system that utilises data collected from roadside sensors rather than relying on image analysis techniques. Other inherent issues associated with image analysis techniques are selecting optimised feature sets and separating background images, further contributing to its high computational requirements.

The framework developed by the authors of [10] allows for the identification of potential attacks on traffic control systems through the use of visual analytics and data collected from traffic signals. This framework provides a comprehensive overview of traffic signal data by breaking down traffic light cycles and calculating statistics on their duration and distribution over a given time period. By normalising individual traffic light cycles, the framework can detect potential abnormal patterns, making it possible to differentiate normal from abnormal traffic signal behaviour. This method of analysis can be an effective tool for identifying and mitigating potential security threats to traffic control systems.

The paper [13] describes our initial work on detecting intrusions in traffic signals by analysing vehicle flow rate and phase time at intersections. The DS decision theory was used to combine the evidential observations of these two traffic characteristics, using historical data provided by the Victorian Transportation Authority in Australia (VicRoads) and the SUMO traffic simulator to simulate intruded and typical traffic scenarios. We evaluated the performance of the proposed IDS under both normal traffic conditions and induced intrusions.

However, the intrusion detection approach described in [13] has some limitations. Firstly, it does not consider vehicle speed, which is an important traffic characteristic. Moreover, the mass value function defined for flow rate and phase time is not adequately specified, since the minimum value of the mass function is set to 0.5, whereas in reality, the mass function values should range from 0 to 1. Additionally, it does not address the uncertainty associated with the signals being normal or abnormal. This paper focused specifically on addressing these practical research issues to improve the accuracy and effectiveness of intrusion detection in traffic signals.

3. Proposed Intrusion Detection System

Anomaly-based intrusion detection can be particularly effective for detecting new or unknown threats that may not be detected by signature-based intrusion detection methods,

which rely on known patterns or signatures of known threats. Anomaly-based detection is useful because it can detect previously unknown attacks and it does not require prior knowledge of the attack signature. For detecting an intrusion in an intelligent traffic signal, these merits motivated us to propose an anomaly-based intrusion detection system in this paper. This system involves creating a baseline of normal traffic patterns and behaviour using historical traffic data and then monitoring the traffic for any deviations from this baseline that indicates a potential intrusion.

The implementation of anomaly-based intrusion detection for intelligent traffic systems involves several steps:

- Data collection: Traffic data are collected from the intelligent traffic system, including information on traffic flow rate, vehicle speed, and phase time.
- Baseline generation: A baseline is generated from the collected traffic data, which represents the normal traffic patterns and behaviour for the system.
- Anomaly detection: The traffic data are continuously monitored for any deviations from the baseline. Significant deviation from the baseline is flagged as potential anomalies and investigated further.
- Response: Once an anomaly is detected, the system sends an alarm to the traffic controller.

Details of our proposed model are given below.

3.1. Overview of the Proposed IDS

Our proposed system primarily monitors the state of a current traffic light, which is statistically calculated based on the flow rate, vehicle speed, and the traffic signal's phase time. The current state of the traffic signal is compared and contrasted with the relevant status of the traffic signals obtained from the related historical data collected by its Traffic Management System (TMS) [29] infrastructure to determine if it is functioning normally or abnormally. The operational flow chart of the proposed IDS is depicted in Figure 1. There are seven steps in our proposed intrusion detection system. The intrusion detection process starts in Step 1. In Step 2, our system collects data on road traffic, including flow rate, average vehicle speeds, and phase time. The details of the simulation used for the data collection are given in Section 4.1. In the third step, the mass values in probabilistic terms for each traffic condition (flow rate, vehicle speed, and phase time) are calculated. Sections 3.3–3.5 describe the details of this step. The mass values are then fused to find the belief value of the normal traffic condition in the fourth step. In the next step, the system checks if the fused value equals or exceeds the threshold value (defined in Section 4). If the value is above the threshold value, the traffic condition is determined to be normal and the system continues observing the traffic data. If the value is below the threshold, our system goes to Step 6 and sends an intrusion detection alarm to the traffic controller. Step 7 ends the intrusion detection process.

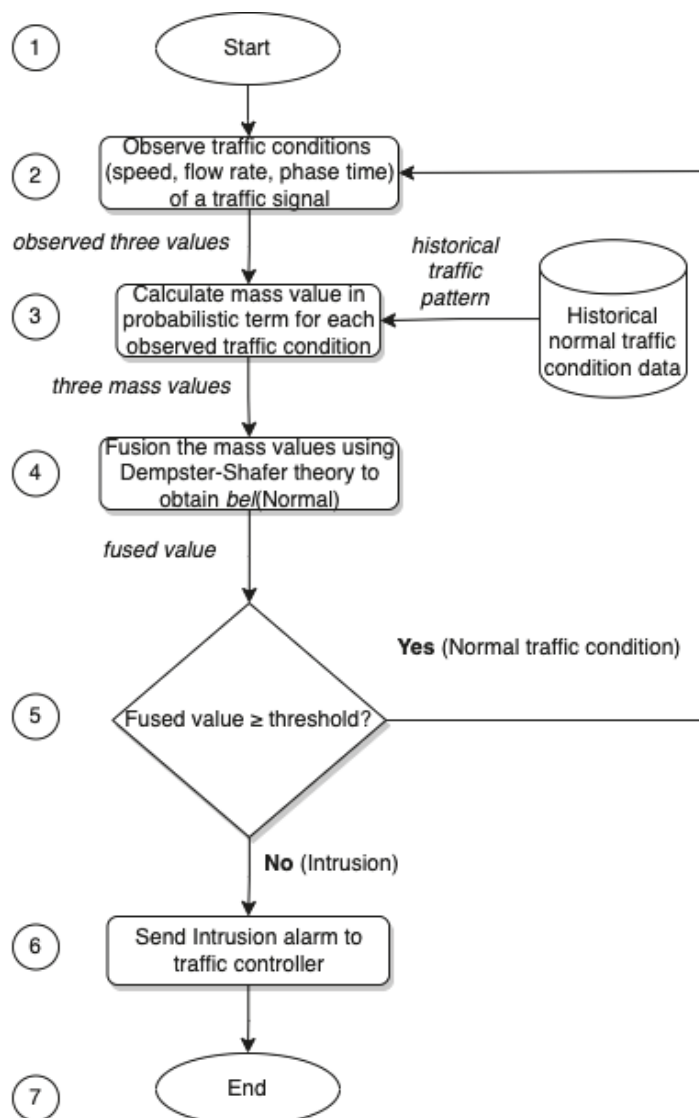


Figure 1. The operational flow chart of the proposed IDS.

3.2. Monitoring the Status of the Traffic Signal

Our suggested technique starts the intrusion detection assessment process in the second step by using a historical traffic pattern probability mass function that has not been tampered with by an intruder at a certain moment inside a specific time window (e.g., from 08:00 a.m. to 09:00 a.m. on Monday).

We acquired all relevant data from VicRoad's traffic data [30] for this research because we wanted to use previous data to monitor the state of a current traffic light at a certain moment. After this, we go through how to estimate the probability mass function of these data for a certain time window.

In the second phase, we need to calculate the continuous observed values of the traffic signal attributes for intrusion detection. We selected the three most important traffic attributes, namely traffic flow rate, signal phase time, and average vehicle speed. Attackers can change the phase time information manually and/or change the phase time by changing the flow rate information in an intersection and/or modify the average vehicle speed to falsify the traffic data. For example, hackers can extend the signal phase time to create disruption for plotting terrorist activity or a thief can extend a green signal phase time to pass quickly by a stolen vehicle. Vehicle speed was selected as it is also profoundly affected by traffic signal disruption. The impact of their changes only stays for one or two cycles, not being sufficient to create considerable disruption.

To determine whether a traffic signal is functioning normally or abnormally, we employed an inference method based on DS decision theory [31]. This theory, which is an extension of Bayesian theory, provides distributed support for various propositions based on temporal evidence. Our system defines the frame of discernment using three propositions: N , $\neg N$, and $(N \vee \neg N)$, which represent the current observation being normal, not normal, and uncertain, respectively.

Since flow rate, vehicle speed, and phase time are measured by individual sensors, the belief function contributing to each proposition must be statistically measured for each sensor. Let R_{jw} denote the id of a sensor located at intersection j with sensor type w , where $w \in F, S, P$ represents the observed events of flow rate, vehicle speed, and phase time, respectively. As these events are observed over a time period for a given intersection, we utilised probability mass functions based on historical data from the corresponding time window of that day to determine the probability of a particular observation is normal. These time windows may differ for working and non-working days and are typically one hour in duration (e.g., 08:00 a.m. to 09:00 a.m. or 09:00 a.m. to 10:00 a.m.). The lower limit of the probabilistic value of j^{th} intersection being normal for y events can be defined using the belief function of the DS theory [32]:

$$bel_j(N) = \frac{1}{1-k} \times \sum_{\cap E_w(t)=N \neq \emptyset} \prod_{1 \leq w \leq y} m_j(E_w(t)), \quad (1)$$

where k is defined as:

$$k = \sum_{\cap E_w(t)=\emptyset} \prod_{1 \leq w \leq y} m_j(E_w(t)). \quad (2)$$

According to the Shannon information theory [33], the uncertainty is the highest when $m_j(E_w(t)) = m_{jw}(N) = 0.5$. Note, here, $m_{jw}(N)$ denotes the probabilistic value of a mass function for w^{th} event ($E_w(t)$) with the j^{th} intersection being normal. If the value of $m_{jw}(N)$ moves in either direction from 0.5, the uncertainty decreases. Applying the principle of Shannon information theory, the uncertainty associated with $m_{jw}(N)$ i.e., the probability, $m_{jw}(N \vee \neg N)$ is defined as:

$$m_{jw}(N \vee \neg N) = -m_{jw}(N) \log_2 m_{jw}(N) - (1 - m_{jw}(N)) \log_2 (1 - m_{jw}(N)). \quad (3)$$

Since $m_{jw}(N \wedge \neg N)$ denotes the null hypothesis, i.e., $m_{jw}(N \wedge \neg N) = 0$, $m_{jw}(\neg N)$ is derived as,

$$m_{jw}(\neg N) = 1 - m_{jw}(N) - m_{jw}(N \vee \neg N). \quad (4)$$

The upper limit (plausibility) of the j^{th} intersection being normal is defined as:

$$pl_j(N) = 1 - bel_j(\neg N). \quad (5)$$

For obtaining the uncertainty value and then the belief value using (3) and (1), respectively, we need to calculate $m_j(E_w(t))$ for the flow rate, vehicle speed and phase time.

An attacker may attempt to intrude on one or more of the sensors used to collect data for the TMS. To detect whether a sensor has been compromised, we can compare its observed values with the corresponding original (i.e., unaltered) historical values. This process involves the development of probability mass functions, denoted by $m_j()$, which are used in the DS theory-based fusion approach defined in (1) and (5). By comparing observed and historical values, our approach enables the identification of abnormal or anomalous sensor behaviour, which can be indicative of a security breach.

3.3. Development of the Probability Mass Function

We developed a formula (refer to (6)) to calculate the mass value that identifies an intrusion from a regular traffic signal based on the assumption that the underlying historical data are normally distributed. In the following section, we present an analysis of the validity of such assumptions and converted the data to follow normal distributions when the assumption did not hold true.

3.4. Data Conversion into Normal Distribution

As discussed in the previous section, we assumed that the traffic data follow the normal distribution. However, since the traffic data are not normally distributed, we transformed the data so that they follow the normal distribution. For example, the flow rate and vehicle speed distributions before and after normal transformation for Intersection 1 are shown in Figures 2 and 3.

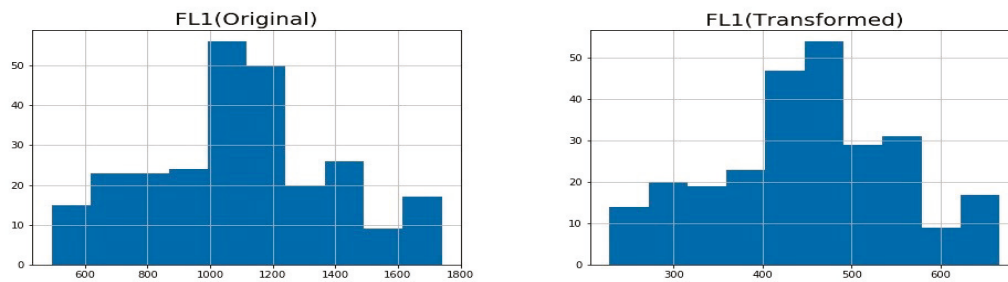


Figure 2. Histograms for flow rate for original and transformed data.

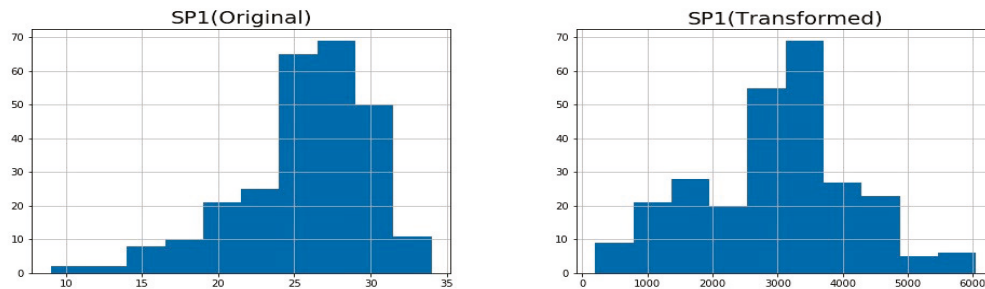


Figure 3. Histograms for vehicle speed original and transformed data.

We applied the BoxCox transformation [34], which can transform the data to a normal distribution. The following equation defines BoxCox transformation.

$$y = \begin{cases} \frac{(x^\lambda - 1)}{\lambda} & \text{for } \lambda \neq 0 \\ \log(x) & \text{for } \lambda = 0. \end{cases} \quad (6)$$

Here, x and y represent data before and after the BoxCox transformation, respectively, and λ is a transformation parameter.

The calculation method for the probability of the observed evidence (e.g., flow rate, vehicle speed, and phase time) developed from the historical data using the probability mass functions is described below.

3.5. Probabilities of Observed Evidence for Flow Rate and Vehicle Speed

For an event w and the observed value x_w , the probability of the evidence can be calculated using (7).

$$m_j(x_w) = \begin{cases} 1 - \frac{\sqrt{2}}{\sqrt{\pi}} \int_0^{z_w} e^{-\frac{x^2}{2}} dx & \text{if } z_w \geq 0 \\ 1 - \frac{\sqrt{2}}{\sqrt{\pi}} \int_{z_w}^0 e^{-\frac{x^2}{2}} dx & \text{otherwise,} \end{cases} \quad (7)$$

where $z_w = (x_w - \mu_w)/\sigma_w$, $x_w = E_w(t)$, and σ_w and μ_w are the standard deviation and mean of the probability mass function, respectively.

3.6. Probability of Observed Evidence for Phase Time

The probability of observed phase times was computed. As the phase times observed take values from a limited set, they usually do not follow the normal distribution. Consequently, the probabilities were computed based on the frequency of observed phase times and the relative distance between an individual phase time with the most observed one. In calculating the probabilities, we used the two following rules, i.e., (i) assigning higher probabilities to those phase time values that are more frequently observed, and (ii) assigning higher values to those that are relatively closer to the most-observed value. The following equations capture such probabilities:

$$m_j(x_w) = \begin{cases} \alpha - \alpha \times \frac{(\min(X) - x_w)}{\min(X)} & \text{if } x_w < \min(X) \\ \alpha \times \frac{(CT - x_w)}{CT} & \text{if } x_w > \max(X) \\ e^{\left(\frac{A+B}{2} - 1\right)} & \text{if } \min(X) \leq x_w \leq \max(X), \end{cases} \quad (8)$$

where

$$A = \frac{f(x_w)}{\max(f(X))} \quad (9)$$

and

$$B = \left(1 - \frac{|(x_w - \operatorname{argmax}(f(X)))|}{\max(X) - \min(X)}\right). \quad (10)$$

Here, A and B are the two rules described above capturing the frequency of occurrence and the relative distance of an observation from the most frequently observed one. $\min(X)$ and $\max(X)$ represent the minimum and maximum phase time values observed in the historical data. $f(x_w)$ and $f(X)$, respectively, represent the frequency of the phase time value x_w and the frequency distribution of all phase times observed in the historical data X . $\operatorname{argmax}(f(X))$ represents the phase time that occurred most in the data set. Finally, CT represents the cycle time with a typical value of 180, and α is a chosen parameter that controls the behaviour of the probability function defined in (8), when the phase time observation falls beyond the minimum and maximum values in the historical data and α is chosen as 0.4.

4. Evaluating the Traffic Signal to Detect Intrusion

In the next step, we evaluated the status of a traffic signal to detect an intrusion in that traffic signal. The standard behaviour profile of a traffic signal was determined using the evaluated status of that traffic signal. Once the value of current events (e.g., $E_F(t)$, $E_S(t)$, $E_P(t)$) are determined, their probabilities can be calculated as $m_j(E_F(t))$, $m_j(E_P(t))$, and $m_j(E_S(t))$ using (7) and the μ and σ of their corresponding probability mass functions. After this, the probability of being N , i.e., $bel_j(N)$ defined in (1), needs to be determined. If $bel_j(N) \geq \Phi$, the traffic signal of j^{th} intersection is considered to be normal, otherwise, it is not normal (intruded). Here, Φ is an intuitively-selected threshold that is used in Step 5 of our model (ref to Figure 1). The performance metrics of our proposed methods depend on the value of Φ . In an ideal case, the value of Φ can be considered 0.5.

4.1. Simulation Environment

We used the map of Melbourne CBD and VicRoads' traffic data [35] for five critical intersections and created a simulation environment in SUMO using a popular microscopic traffic model presented in [14] and the Krauss car following model [36,37]. The selected intersections were (i) Lonsdale and Russel Street, (ii) Collins and Kings St, (iii) Elizabeth and Latrobe St, (iv) Collins, and Swanston St, and (v) Flinders and Swanston St Melbourne. For traffic data, we selected the peak-time traffic data from 08:00 a.m. to 10:00 a.m. Monday.

Normal and intrusion scenarios: for normal traffic conditions, the flow rate, vehicle speed, and phase time of an intersection for a particular scenario were derived through our above-mentioned simulation model developed using SUMO. The traffic distributions were initiated with the respective and normal (non-compromised) historical traffic information obtained from the VicRoads online data [30] in our simulation environment. To emulate the current traffic in the simulation, the density, vehicle speed, and phase time of the incoming and outgoing traffic of an intersection of interest were randomly selected from the range of the [minimum, maximum] value of the respective historical data for that day and time period collected from three years (2016–2018) of data available on the VicRoads website. Traffic volumes for the freeways and arterial roads data were taken from [38], signal details for simulation were taken from [39], and traffic signal volume data were taken from [40].

Figures 4 and 5 show the traffic flow of Intersection 1, namely Lonsdale and Russel Street, for its normal and intruded conditions, respectively.

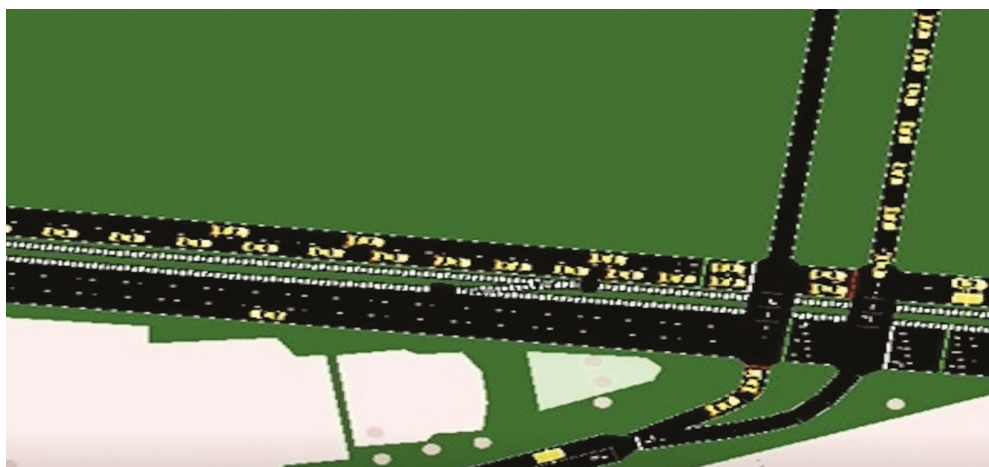


Figure 4. The traffic condition of the simulation environment for the normal scenario.

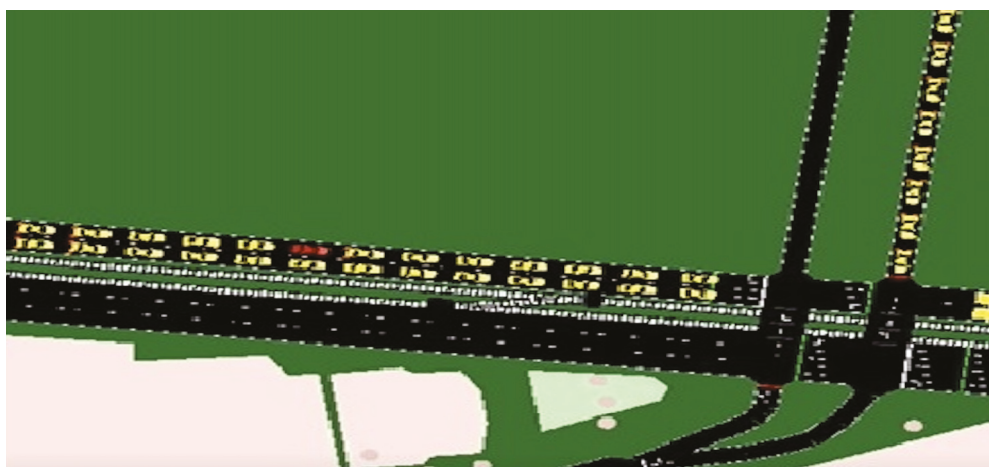


Figure 5. The traffic condition of the simulation environment for the intruded scenario.

As described in Section 2.1, traffic signals can be the victim of the intrusion. For simulating intrusions to the traffic signals, the flow rate of an intersection and/or average

vehicle speed for a particular scenario was changed by intuitively induced phase time and vice versa. The induced average vehicle speed of an intersection was also inserted while phase time and the flow rate were normal. If the intersection is intruded for a very short time (e.g., less than one cycle time), flow rate, vehicle speed, and phase time data will remain within the range of 68% to 95% confidence intervals. If the duration of the intrusion is higher, flow rate, vehicle speed, and phase time will go outside the 95% confidence interval. To consider both cases (e.g., short and long time intrusion), the flow rate, vehicle speed, or phase time were induced in such a way that they remain within 68% to 95% confidence intervals in some cases (Scenario 2 and Scenario 4) and outside 95% confidence intervals of the relevant historical data for the other cases.

We used historical data to observe the current status of a traffic signal for a given point in time. Four different scenarios were created to test 40, 41, 39, 42, and 44 pieces of evidence for Intersection 1, Intersection 2, Intersection 3, Intersection 4, and Intersection 5, respectively. Scenarios 1 to 4 described in Section 4.3 show how different types of evidence (e.g., flow rate, phase time, and vehicle speed) were used. Using the normal historical data taken from the VicRoads website [30], initially, we simulated normal traffic scenarios. We simulated different malicious and abnormal traffic situations. The abnormal situations include incidents, vehicle breakdowns, unusual vehicle stops, and malicious driving behaviour to see the impact of these scenarios on traffic conditions. Note that, in normal traffic conditions, vehicle breakdown creates a traffic jam which reflects the jamming attack. Using Sybil attack, vehicles can be stopped or redirected. Therefore, consideration of unusual vehicle stops is regarded as the impact of a Sybil attack. By injecting false data in GPS or traffic signals, the driving behaviour of a vehicle can be manipulated, representing the false data injection attacks in the situations used in abnormal traffic scenario generation. Abnormal traffic scenarios (Scenario 2 and 4) were created considering the types of attacks mentioned here affecting flow rate, vehicle speed, and phase time of a traffic signal.

The simulation was modified in six different ways to create intruded scenarios. These modifications are described below:

Type 1: Congestion attack scenario

The number of vehicles on the route was falsely increased by modifying the following parameters. This modification would create an incorrect flow rate and cause the traffic controller to miscalculate the average speed. This scenario represents congestion attacks because it falsely increases on-road traffic.

Type 2: False vehicle number injection scenario

By changing the state of the lane area detector, the actual number of vehicles on the detector is overridden, leading to miscalculation of congestion on the cell and disrupting the dynamic adaptation of the traffic light phases.

Type 3: Replay attack scenario

Induction loop state values were replayed at certain intervals and transmitted to the regional traffic controller. This attack modifies flow rate count and average vehicle speed.

Type 4: Sybil attack scenario

The simulation environment is tampered by introducing a multitude of fake vehicles and sensors, which sent erroneous traffic data to the traffic controller system in such a manner that may create congestion on the roadways.

Type 5: False traffic light state injection

A false traffic light state was injected to modify the phase times, creating an impact of false traffic control.

Type 6: Jamming attack scenario

The lane attributes can be changed by transmitting false values or man-in-the-middle attacks. Examples of such attributes include the allowed speed limit, permitted vehicle categories, restricted vehicles, acceptable turns, and lane change permissions. These changes force vehicles to make incorrect turns, travel at varying speeds, and prevent certain vehicles from entering the lane.

The above scenarios consider most attacks that were previously observed in traffic signal intrusions (see Section 2.1).

4.2. Performance Metrics

Widely used standard performance metrics such as specificity, sensitivity, overall accuracy, and F-Score were employed to evaluate our model. If the normal (non-intruded) event is detected correctly, it is considered a True Positive (TP). Conversely, when an intruded event is detected as normal, it is marked as False Positive (FP). When the system is able to detect the intruded event correctly, it is considered a True Negative (TN), but when the system detected a normal event as an intruded event, it is considered a False negative (FN) value. The accuracy, sensitivity, specificity, and F-Score are defined as follows:

$$Accuracy = \frac{TN + TP}{TP + TN + FP + FN}; \quad (11)$$

$$Sensitivity = \frac{TP}{TP + FN}; \quad (12)$$

$$Specificity = \frac{TN}{TN + FP}; \quad (13)$$

$$F\text{-Score} = 2 \times \frac{Sensitivity \times Precision}{Sensitivity + Precision}. \quad (14)$$

4.3. Results and Analysis

We used 206 observations for the five intersections for each piece of evidence (FP, FS, PS, and FPS) and scenario. Therefore, the total number of observations we used was $206 \times 4 \times 4 = 3296$. These 206 observations were distributed to 40, 41, 39, 42, and 44 observations for Intersections 1 to 5, respectively. As a representative sample, Tables 1–4 show the probabilities of signals being normal (N), not normal ($\neg N$), and the uncertainty ($N, \neg N$) for Scenarios 1–4 having various flow rates, average speeds, and phase times. Note, Scenarios 1 and 3 were created using the original data collected from VicRoads to emulate normal traffic conditions without intrusion. Scenarios 2 and 4 were created to induce intrusions by using the same data but manipulating a combination of flow rate, phase time, and average vehicle speed.

Table 1. Detection results for Scenario 1. In the simulation, all intersections operated in normal conditions. The values that are highlighted in bold represent the combination that produces the best outcome.

	Normal (N)				Not Normal ($\neg N$)				Uncertainty ($N \vee \neg N$)			
	FS	FP	PS	FPS	FS	FP	PS	FPS	FS	FP	PS	FPS
1	0.58	0.65	0.71	0.76	0.3	0.29	0.27	0.16	0.12	0.06	0.02	0.08
2	0.75	0.58	0.64	0.72	0.23	0.31	0.29	0.17	0.02	0.11	0.07	0.11
3	0.48	0.52	0.67	0.58	0.39	0.36	0.29	0.21	0.13	0.12	0.04	0.21
4	0.61	0.61	0.76	0.63	0.31	0.29	0.21	0.25	0.08	0.1	0.03	0.12
5	0.57	0.52	0.58	0.59	0.32	0.39	0.3	0.22	0.11	0.09	0.12	0.19

Table 2. Detection results for Scenario 2. In the simulation, all intersections were intuitively intruded (not normal). The values that are highlighted in bold represent the combination that produces the best outcome.

	Normal (N)				Not Normal ($\neg N$)				Uncertainty ($N \vee \neg N$)			
	FS	FP	PS	FPS	FS	FP	PS	FPS	FS	FP	PS	FPS
1	0.41	0.38	0.24	0.41	0.51	0.53	0.64	0.5	0.08	0.09	0.12	0.09
2	0.32	0.27	0.32	0.38	0.62	0.64	0.57	0.56	0.06	0.09	0.11	0.06
3	0.27	0.48	0.32	0.46	0.66	0.44	0.62	0.43	0.07	0.08	0.06	0.11
4	0.19	0.24	0.21	0.33	0.72	0.69	0.71	0.55	0.09	0.07	0.08	0.12
5	0.23	0.17	0.26	0.28	0.63	0.72	0.62	0.54	0.14	0.11	0.12	0.18

Table 3. Detection results for Scenario 3. In the simulation, all intersections operated in normal conditions. The values that are highlighted in bold represent the combination that produces the best outcome.

	Normal (N)				Not Normal ($\neg N$)				Uncertainty ($N \vee \neg N$)			
	FS	FP	PS	FPS	FS	FP	PS	FPS	FS	FP	PS	FPS
1	0.68	0.61	0.59	0.74	0.27	0.33	0.35	0.2	0.05	0.06	0.04	0.06
2	0.42	0.48	0.50	0.51	0.51	0.42	0.51	0.32	0.07	0.1	0.06	0.12
3	0.65	0.58	0.66	0.51	0.30	0.36	0.34	0.47	0.05	0.06	0.06	0.03
4	0.67	0.71	0.65	0.72	0.26	0.20	0.26	0.16	0.04	0.09	0.09	0.13
5	0.65	0.63	0.67	0.69	0.33	0.35	0.30	0.25	0.02	0.02	0.03	0.06

Table 4. Detection results for Scenario 4. In the simulation, all intersections were intuitively intruded (not normal). The values that are highlighted in bold represent the combination that produces the best outcome.

	Normal (N)				Not Normal ($\neg N$)				Uncertainty ($N \vee \neg N$)			
	FS	FP	PS	FPS	FS	FP	PS	FPS	FS	FP	PS	FPS
1	0.20	0.24	0.22	0.22	0.74	0.71	0.65	0.6	0.06	0.05	0.12	0.14
2	0.18	0.16	0.17	0.14	0.71	0.65	0.72	0.70	0.10	0.19	0.11	0.16
3	0.01	0.02	0.02	0.09	0.92	0.91	0.88	0.78	0.08	0.07	0.11	0.13
4	0.23	0.22	0.18	0.27	0.73	0.67	0.72	0.56	0.04	0.11	0.10	0.17
5	0.31	0.26	0.34	0.38	0.53	0.62	0.57	0.40	0.16	0.11	0.09	0.22

We used four different types of combinations for two different observations of an intersection. Four different combinations of two observations are (i) flow rate and phase time (FP), (ii) flow rate and vehicle speed (FS), (iii) phase time and vehicle speed (PS), and (iv) flow rate, phase time, and vehicle speed (FPS).

Tables 1 and 3 present the intrusion detection results and their uncertainty values produced by our system for Scenarios 1 and 3, where no intrusions happened in any of the five intersections. Note, since uncertainty values are shown separately in all tables, throughout the chapter, belief values obtained by (1) denote the results. In contrast, Tables 2 and 4 show the results for Scenarios 2 and 4 where intersections were intruded. Therefore, Scenarios 1 and 3 represent normal intersections, while Scenarios 2 and 4 are for the intruded intersections. The probability values highlighted with bold text represent which combination provides the best result. It also shows the combinations that have the lowest uncertainty.

4.3.1. Detection Probability

In the case of intrusion in an intersection, the results produced by combining two pieces of evidence (e.g., FP, FS, PS) provide better detection than the results achieved using all

three pieces of evidence (FPS). For example, in Table 4, our proposed method obtained the maximum detection probability values (e.g., 0.74, 0.72, 0.921, 0.73) for being not normal for four intersections using FS, while for Intersection 5, it (e.g., 0.62) was for FP. Table 4 also shows that the lowest uncertainty values (e.g., 0.06, 0.10, 0.07, 0.04) were obtained for the maximum number of intersections (4/5) using FS. Table 2 also supports a similar trend in the results. The detection probabilities obtained using FPS for Intersection 3 of Scenario 2 (see Table 2) and Intersection 5 of Scenario 4 (refer to Table 4) are 0.43 and 0.40, respectively, which are lower than the selected threshold 0.50, indicating the ineffectiveness of exploiting all three pieces of evidence for capturing intrusion. These results indicate that phase time is a major factor in intrusion detection. If a hacker can intrude on the sensor to change the phase time, it creates more congestion. Phase time impacts the traffic flow and average vehicle speed immediately. In the simulation, Intersection 5 and Intersection 2 had intruded phase time in Scenario 2 and Scenario 4, respectively. For Intersections 5 and 2, Tables 2 and 4 present the high detection values exhibiting the efficacy of phase time consideration in spotting intrusion.

When the intersection is not intruded, i.e., normal, a combination of all three pieces of evidence (FPS) provides better detection results than the others. These results are above 0.50 for all intersections of the two scenarios. For example, for FS, the probability value for Intersection 3 shown in Table 1 is 0.48, while it is 0.58 for FPS. Table 3 shows that the probability values for Intersection 2 are 0.42, 0.48, and 0.50 for FP, FS, and PS, respectively, compared with 0.51 for FPS. These superior detection outcomes vindicate the use of FPS (three or more pieces of evidence) for the accurate detection of normal traffic conditions. The only loophole of FPS utilisation is that its uncertainty value is higher than that of others but not that high as its maximum value of 0.12. This higher uncertainty value is justified by the fact that, in a normal scenario, the real traffic conditions are dynamic. Traffic conditions may change due to many different reasons, such as different times (peak, off-peak), weather conditions, special events (e.g., road works, sports events), and school time. Flow rate, average vehicle speed, and phase time are affected because of the dynamic characteristics of the traffic conditions.

From the results discussed so far, it is evident that FPS is effective at identifying normal traffic conditions, but not so effective for intruded intersection detection. However, if we use the maximum probabilistic values, highlighted in bold, of an intersection in Tables 1–4, our proposed system is able to detect the correct state (normal or intruded) of all intersections. For example, for intersections being normal, the maximum values for Intersection 3 in Table 1 and Intersection 2 in Table 3 are $\max(0.48, 0.52, 0.67, 0.58) = 0.67$ and $\max(0.42, 0.48, 0.43, 0.51) = 0.51$, respectively. Note, since for both intersections, these two maximum values (0.67 and 0.51) are above 0.50, our proposed system can detect normal traffic conditions accurately.

To show how our proposed IDS works to detect both traffic conditions for each intersection, we calculated the average value of the probabilities for both scenarios. Figures 6 and 7 show these average detection results for the normal and intruded traffic conditions, respectively. In Figures 6 and 7, for each intersection, there are 12 bars. The first four bars represent the probability of an intersection being normal, bars five to eight denote the probability of an intersection being not normal, and the last four bars show the uncertainty values. For the normal traffic conditions, as with the results shown in Tables 1 and 3, for FS, the detection probabilities shown in Figure 6 are higher and above or equal to 0.62 for all interactions except Intersection 3. For these intersections for FPS, Figure 6 also shows higher uncertainty values. However, for the intruded traffic conditions, the probability values for FPS for all intersections are less than those of the others having higher uncertainty values except for Intersection 4.

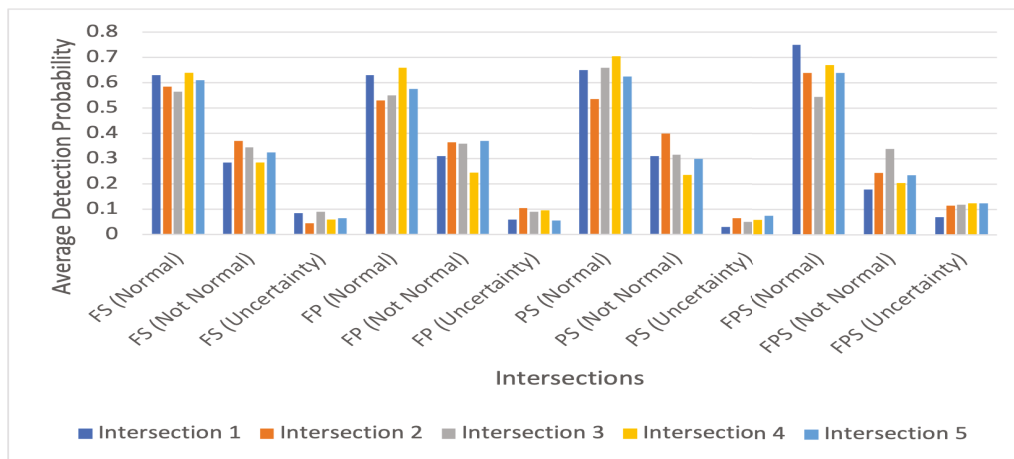


Figure 6. Average detection probability for normal intersections.

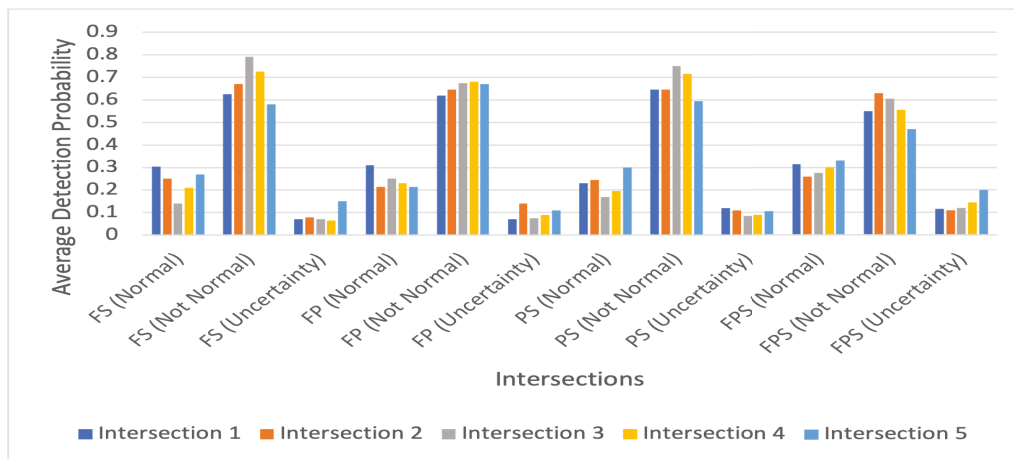


Figure 7. Average detection probability for intruded intersections.

4.3.2. Class Separability

As we know, the wider separation gap between the value of two decisive parameters makes the system robust and decisions more accurate. For this reason, to show the robustness of our proposed IDS in deciding whether an intersection is normal or not normal, we calculated the separation gap between the average probability values for all pieces of evidence being normal or not normal for any particular intersection.

The separation band of the values of an intersection being normal or intruded is shown in Figures 8 and 9, respectively. The highest gap calculated is for Intersection 4, shown in Figure 8, which has a probability of being not normal of 0.76, and of being normal of 0.27. So, the gap is 0.59. The lowest gap is for Intersection 5, shown in Figure 9. The probability of being normal is 0.615, and not normal is 0.38, and thus the lowest gap is 0.235. The wide separation gap ranging from 0.235 to 0.59 vindicates that our system can conveniently differentiate the normal and intruded intersections.

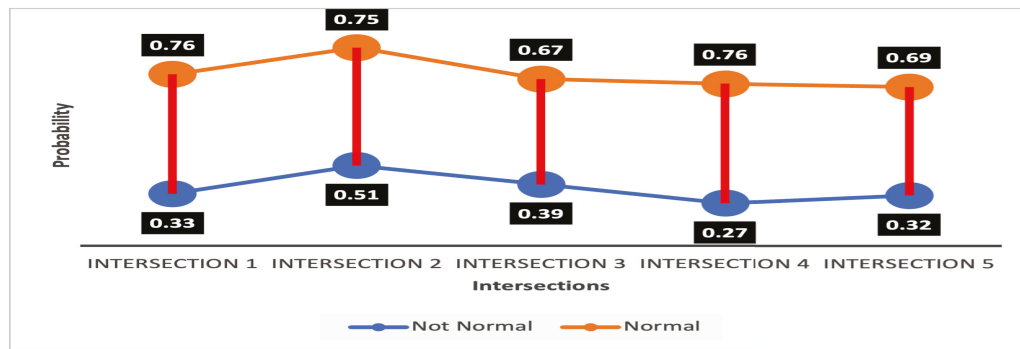


Figure 8. Separation gap between the probability of intersection being normal.

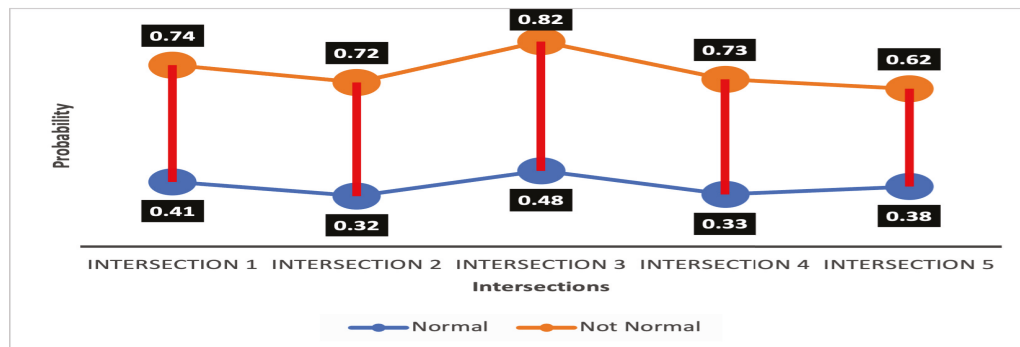


Figure 9. Separation gap between the probability of intersection being intruded.

4.3.3. Detection Performance

We demonstrated the performance of the proposed model in terms of its ability to detect intruded and non-intruded scenarios accurately. For this, we calculated the value of four performance metrics—sensitivity, specificity, accuracy, and F1-Score—using Equations (13) and (14); this is shown in Table 5.

Table 5. Detection results in terms of standard performance metrics. Here, TP = (True Positive), TN = (True Negative), FP = False Positive, FN = False Negative, Sen. = Sensitivity, Spec. = Specificity, Acc. = Accuracy, and F1 = F1-Score.

		TP	TN	FP	FN	Sen.	Spec.	Acc.	F1
FP	1	1960	678	122	536	0.79	0.85	0.80	0.82
	2	2052	306	194	444	0.82	0.61	0.79	0.70
	3	2316	664	136	380	0.86	0.83	0.85	0.84
	4	2157	513	287	439	0.83	0.64	0.79	0.72
	5	2324	505	295	572	0.80	0.63	0.77	0.71
PS	1	2352	619	181	414	0.85	0.77	0.83	0.81
	2	2025	578	222	471	0.81	0.72	0.79	0.76
	3	2435	626	174	382	0.86	0.78	0.85	0.82
	4	2187	606	194	309	0.88	0.76	0.85	0.81
	5	2343	582	218	453	0.84	0.73	0.81	0.78

Table 5. Cont.

		<i>TP</i>	<i>TN</i>	<i>FP</i>	<i>FN</i>	Sen.	Spec.	Acc.	F1
FS	1	2074	577	223	322	0.87	0.72	0.83	0.79
	2	2295	612	188	401	0.85	0.77	0.83	0.81
	3	2377	613	187	512	0.82	0.77	0.81	0.79
	4	1866	589	211	430	0.81	0.74	0.79	0.77
	5	2203	613	187	393	0.85	0.77	0.83	0.81
FPS	1	2126	458	342	612	0.78	0.57	0.73	0.66
	2	2052	473	327	444	0.82	0.59	0.77	0.69
	3	2352	466	334	472	0.83	0.58	0.78	0.69
	4	1826	413	387	417	0.81	0.52	0.74	0.63
	5	2192	496	304	452	0.83	0.62	0.78	0.71
Overall						0.82	0.71	0.79	0.80

Table 5 displays the performance metrics of different models based on the combination of input features (flow rate, phase time, and vehicle speed). The performance of each model was evaluated using True Positive, True Negative, False Positive, False Negative, sensitivity, specificity, accuracy, and F1-Score. Five different instances (1 to 5) are reported for each model, possibly indicating different test sets or cross-validation results.

1. Flow rate and phase time:
The model utilising flow rate and phase time as features has sensitivity values ranging from 0.79 to 0.86, specificity values between 0.61 and 0.83, accuracy values varying from 0.77 to 0.85, and F1-Scores ranging from 0.70 to 0.84. This model seems to have a relatively good overall performance with varying levels of specificity.
2. Phase time and vehicle speed:
This model, based on phase time and vehicle speed, shows sensitivity values between 0.81 and 0.88, specificity values ranging from 0.72 to 0.78, accuracy values varying from 0.79 to 0.85, and F1-Scores ranging from 0.76 to 0.82. The performance of this model is consistent and generally good across all instances.
3. Flow rate and vehicle speed:
For the model using flow rate and vehicle speed as features, sensitivity values range from 0.81 to 0.87, specificity values are between 0.72 and 0.77, accuracy values vary from 0.79 to 0.83, and F1-Scores range from 0.77 to 0.81. This model demonstrates a fairly consistent and good performance across all instances, with a slightly lower specificity compared to the phase time and vehicle speed model.
4. Flow rate, phase time, and vehicle speed:
The model that includes all three features—flow rate, phase time, and vehicle speed—has sensitivity values ranging from 0.78 to 0.83, specificity values between 0.52 and 0.62, accuracy values varying from 0.73 to 0.78, and F1-Scores ranging from 0.63 to 0.71. This model shows a drop in performance, especially in specificity, when compared to the other models.
The models with the best performance are those that utilise two features: phase time and vehicle speed or flow rate and vehicle speed. The phase time and vehicle speed model shows a slightly better performance than the flow rate and vehicle speed model, with higher specificity values. The model using all three features (flow rate, phase time, and vehicle speed) exhibits the lowest performance, especially in specificity. Based on these findings, it is recommended to use the phase time and vehicle speed model or the flow rate and vehicle speed model for further analysis or deployment.

Our system is able to detect most of the normal and intruded traffic conditions used in our simulation successfully. Due to the dynamic characteristics, the traffic condition deviates highly from the ideal condition. These dynamic characteristics cause some False Positives and False Negatives. The results presented in Table 5 show that none of the pieces of evidence achieve a superior performance in terms of all metrics. This is because, as mentioned before, there are some situations in which our system could not detect normal traffic conditions accurately.

5. Conclusions

In this paper, we introduced a technique to detect intrusion at the traffic signal of an ITS. Our technique is based on the real-time observation of traffic parameters, namely, traffic flow, average vehicle speed, phase time of the signal, and their historical values. Using the past and currently-observed values, probabilistic estimation of those parameters being normal or abnormal was derived using the DS theory. We also used an approach based on Shannon's entropy to incorporate the uncertainty of observed data in the detection system. To validate the efficacy of the proposed IDS, simulation scenarios were built using the SUMO platform and the real road network of Melbourne CBD, utilising the actual data from road transport authority on traffic flow, phase time, and vehicle speed. Intrusion scenarios were created by intentional perturbation of those traffic parameters and the proposed system's capability to identify traffic signal intrusion was assessed in terms of the widely used metrics of detection accuracy, sensitivity, specificity, and F1-Score. The proposed IDS demonstrated an overall accuracy of 79.3% for intruded traffic conditions. Further investigation into the behaviour of the system showed that detection fails if the intrusion is very short-lived in the range of one to two cycles only. This is because such short intrusion fails to produce enough impact in the traffic system to cause a significant deviation from normal data.

The next-generation ITS will be highly complex, comprising autonomous and semi-autonomous vehicles, intelligent sensors connected wirelessly to TMS infrastructure, and all requiring ultra-low latency interactions among themselves and with road-side infrastructure. All these expose ITS to new attacks and vulnerabilities. Future work will focus on improving the detection of intrusion and types of intrusion.

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Article

An Optical Sensory System for Assessment of Residual Cancer Burden in Breast Cancer Patients Undergoing Neoadjuvant Chemotherapy

Shadi Momtahn ¹, Maryam Momtahn ¹, Ramani Ramaseshan ^{1,2} and Farid Golnaraghi ^{1,*}

¹ School of Mechatronic Systems Engineering, Simon Fraser University, Surrey, BC V3T 0A3, Canada; shadi_momtahn@sfu.ca (S.M.); maryam_momtahn@sfu.ca (M.M.); ramasesh@sfu.ca (R.R.)

² Department of Medical Physics, BC Cancer, Abbotsford, BC V2S 0C2, Canada

* Correspondence: mfgolnar@sfu.ca

Abstract: Breast cancer patients undergoing neoadjuvant chemotherapy (NAC) require precise and accurate evaluation of treatment response. Residual cancer burden (RCB) is a prognostic tool widely used to estimate survival outcomes in breast cancer. In this study, we introduced a machine-learning-based optical biosensor called the Opti-scan probe to assess residual cancer burden in breast cancer patients undergoing NAC. The Opti-scan probe data were acquired from 15 patients (mean age: 61.8 years) before and after each cycle of NAC. Using regression analysis with k-fold cross-validation, we calculated the optical properties of healthy and unhealthy breast tissues. The ML predictive model was trained on the optical parameter values and breast cancer imaging features obtained from the Opti-scan probe data to calculate RCB values. The results show that the ML model achieved a high accuracy of 0.98 in predicting RCB number/class based on the changes in optical properties measured by the Opti-scan probe. These findings suggest that our ML-based Opti-scan probe has considerable potential as a valuable tool for the assessment of breast cancer response after NAC and to guide treatment decisions. Therefore, it could be a promising, non-invasive, and accurate method for monitoring breast cancer patient's response to NAC.

Keywords: biosensor; machine learning; breast cancer; chemotherapy; residual cancer burden

1. Introduction

Breast cancer is a common disease that causes significant morbidity and mortality worldwide, with an estimated 43,250 women expected to have died from breast cancer in the US in 2022 [1]. Neoadjuvant chemotherapy (NAC) is a standard treatment for locally advanced and inoperable breast cancer [2]. However, measuring tumor response to NAC is challenging, and no gold standard exists for assessing tumor response before surgery [3]. Pathological complete response (pCR) is often used as a marker of chemosensitivity and survival outcomes [4,5]. Still, it does not provide precise information on the amount of residual tumor [6,7], making it difficult to predict overall survival [8] accurately.

The residual cancer burden (RCB) method is a pathological approach that quantifies the residual disease in the breast or regional lymph nodes after chemotherapy [9]. RCB provides a standard for classification of the extent of residual disease based on a computed RCB index that uses the tumor bed area (TBA), the extent of in situ disease (IS) and invasive cancer (IC), and the number of involved lymph nodes (LNs) [9]. RCB is scored on a scale of 0–3, with RCB-0 (RCB score = 0) corresponding to pCR, RCB-I ($0 < \text{RCB score} \leq 1.36$), RCB-II ($1.36 < \text{RCB score} \leq 3.28$), and RCB-III (RCB score > 3.28) [10]. However, RCB has been highly validated as reproducible and prognostic, small cohorts limit its accurate prognosis in breast cancer subtypes [7].

Near-infrared (NIR) biosensing devices, such as diffuse optical tomography (DOT), have shown promise for breast cancer detection and monitoring. These techniques utilize the unique optical properties of biological tissue to detect biomarkers and molecular changes associated with cancer lesions. NIR-DOT is a non-invasive, easy-to-use point-of-care bedside tool [10] that can potentially measure responses to NAC for clinical decision-making and prognostication [11], providing critical indicators of treatment response, such as tumor hemoglobin distributions [12] and metabolism [13]. For example, researchers used NIR-DOT with ultrasound localization to image heterogeneous hemoglobin distribution in large breast cancers [14]. In contrast, others introduced a compact ultrasound-guided NIR-DOT system for non-invasive imaging of breast cancer [15] and used both MRI and diffuse optical tomography to improve breast cancer detection [13]. However, accurately predicting optical parameters from conventional NIR-DOT imaging techniques can be challenging due to nonlinear photon scattering and fewer known measurements than unknowns [16].

To address this challenge, ongoing research is being conducted at Simon Fraser University (SFU) to develop a proprietary near-infrared optical breast-scanning (Opti-Scan (US Patent: US20220409058—HANDHELD PROBE AND SYSTEM FOR IMAGING HUMAN TISSUE)) probe to detect breast cancer. The Opti-Scan probe collects backscattering light intensity from the breast surface to identify abnormalities [10]. Four generations of the probe have been designed and successfully tested for cross-sectional imaging. The first generation introduced in 2014 utilized eLEDs with a multiwavelength pointed-beam illumination source, and subsequent developments led to the 2016 generation, which underwent clinical trials on patients with known breast cancer, demonstrating high accuracy at the Jim Pattison Outpatient Care and Surgery Centre (JPOCSC) [10]. The current Opti-Scan probe was developed to further enhance the probe's performance, incorporating improvements in the linear CCD sensor, light intensity control, noise reduction, and data collection process. In addition, the imaging system of the previous version, which was based on the diffusion equation (DE) and had some limitations, was improved by introducing the modified diffusion equation (MDE). This improved imaging system accurately determines absorption values and provides clearer images of various breast phantoms [17] and breast tissues [18]. However, since the MDE was slow in real-time imaging, a machine learning (ML) algorithm was developed to predict scattering coefficients of breast tissues [19], and an ML ensemble method was used to classify liquid phantoms into healthy and unhealthy classes [20]. The absorption coefficient needs to be measured to enable image reconstruction and accurate calculation of RCB. Therefore, in collaboration with BC Cancer (BCCA) in Abbotsford, we developed a new method that utilizes a machine learning algorithm to estimate the absorption coefficients, potentially improving the accuracy of the Opti-Scan probe. This method was tested on fifteen breast cancer patients undergoing neoadjuvant chemotherapy (NAC) and monitored periodically by the probe. The ML model accurately differentiated between cancerous and non-cancerous tissues, demonstrating the probe's potential as a non-invasive diagnostic biosensor for breast cancer detection.

The RCB index/class is predicted according to calculations of the area under the curve of residual disease based on changes in each patient's optical properties. This approach shows promise in accurately classifying patients based on their response to treatment and predicting their prognosis. Utilizing the Opti-Scan probe with the RCB index/class prediction methods shows promise as a more comprehensive and non-invasive method for monitoring breast cancer treatment efficacy and improving patient outcomes. However, further studies with larger patient cohorts are needed to validate these findings and determine the clinical utility of this approach.

2. Materials and Methods

2.1. NIR Opti-Scan Probe for Breast Tissue Imaging and Cancer Detection

The NIR Opti-Scan probe (Figure 1) is a portable device designed for optical imaging of breast tissues. It is a non-invasive imaging modality that utilizes the near-infrared (NIR) region of the electromagnetic spectrum, where biological tissues' absorption and scattering properties are relatively low, allowing for deeper tissue penetration and imaging [17]. The probe consists of a charge-coupled device (CCD) with 2048 active pixels and a 14 μm pixel pitch, providing an effective imaging area of 28.672 mm ($2048 \times 14 \mu\text{m}$). Two encapsulated light-emitting diodes (eLEDs) are mounted 15 mm away from the two sides of the CCD detector to provide symmetrical light illumination. Each eLED can illuminate light with selectable wavelengths of 690, 750, 800, and 850 nm in the NIR region [21]. These specific wavelengths were selected based on the large difference between extinction coefficients in the four primary components in breast tissue, including oxyhemoglobin (HbO₂), deoxyhemoglobin (Hb), fat, and water (H₂O) [22]. Previous studies have shown that the absorption coefficients of these components depend on the wavelength [12,23]. Thus, the selected wavelengths allow for optimal sensitivity to the breast tissue composition. For more details about the probe specifications, please refer to Table 1.

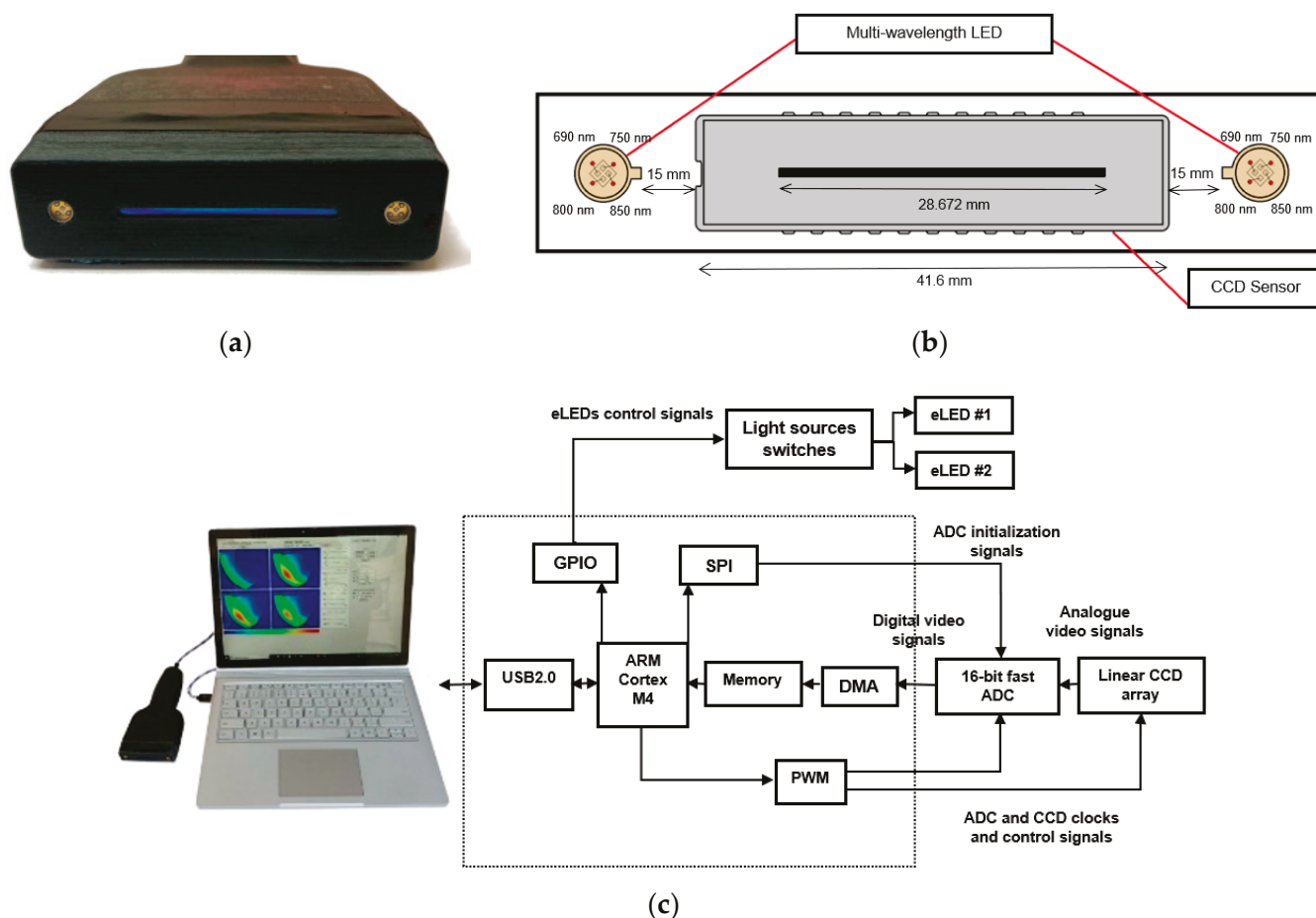


Figure 1. Overview of the Opti-Scan probe and system: (a) front-end view of the probe, showing the light sources and linear CCD; (b) diagram illustrating the CCD sensor and LED arrangement in the head of the probe; (c) photograph of the Opti-Scan probe connected to a laptop running custom software and a schematic diagram of the sensory system, highlighting the different components.

During imaging, reflectance versus the distance to the light source is collected by the CCD and acquired by a computer simultaneously. The software interface communicates with the probe via USB 2.0 and contains a graphical user interface (GUI) for the operator's ease of use. The GUI comprises a series of tabs and data graphs for various operations, including manual and periodic light source selection, CCD integration time setting, and data collection mode [21].

The image reconstruction algorithm is a crucial NIR handheld Opti-Scan probe component. The algorithm involves the collection of raw data obtained from 2048 pixels in the CCD array, which are acquired from the surface of the tissue. These raw data are then processed using a series of computational steps to reconstruct an image of the tissue's internal optical properties. To reduce noise in the raw data, the reflectance data are averaged from 16 contiguous pixels, resulting in 128 points of raw reflectance data. Then, the tissue's optical properties, including absorption and scattering coefficients, are determined by fitting the experimental reflectance obtained by the CCD to the theoretical reflectance values calculated by the modified diffusion equation (MDE) solution. Finally, the optical parameters calculated for each position in the tissue are converted to cross-sectional optical images.

Table 1. Specifications of the NIR handheld Opti-Scan probe.

Parameter	Value
Imaging technology	Near-infrared optical imaging
Detector type	Linear CCD
Detector resolution	2048 pixels
Image resolution	128 × 128 pixels
Imaging area	28,672 mm (2048 × 14 µm)
Pixel pitch	14 µm
Detector sensitivity	1800 (V/Lx.S) @ 660 nm
Light source	Encapsulated light-emitting diodes (eLEDs)
Wavelengths	2 × (690, 750, 800, and 850 nm)
Distance from CCD	15 mm
Max. frame rate	24
Power consumption	100 mA @ 5V
Radiated power	20 mA

The Opti-Scan probe's potential for non-invasive and accurate imaging of biological tissues, particularly for breast cancer diagnosis and monitoring, has been demonstrated in various studies. One such study presented a reconstructed 2D image based on the absorption parameters for a physical phantom with a spherical abnormality of size 4.5 mm in the center, as shown in Figure 2 [17]. In another recent study [18], the Opti-Scan probe's MDE imaging was used to measure the optical properties of 15 breast cancer patients accurately. The probe used different slices of images to map each patient's blood concentrations to optical 3D imaging reconcentration, as shown in Figure 3a. The 3D optical images of a patient were captured using 12 slices at 690 nm, and a 3D volume model of the tumor was created using MATLAB rendering capabilities, as shown in Figure 3b. These findings highlight the Opti-Scan probe's potential for precise breast cancer detection and monitoring.

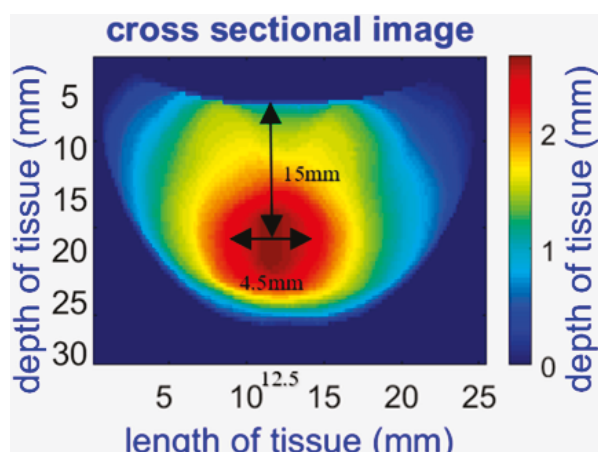
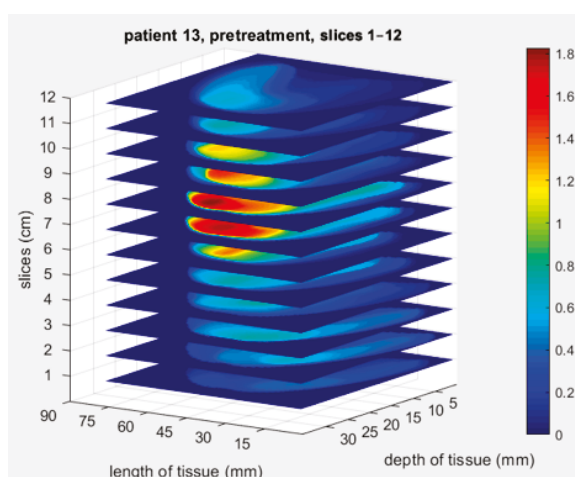
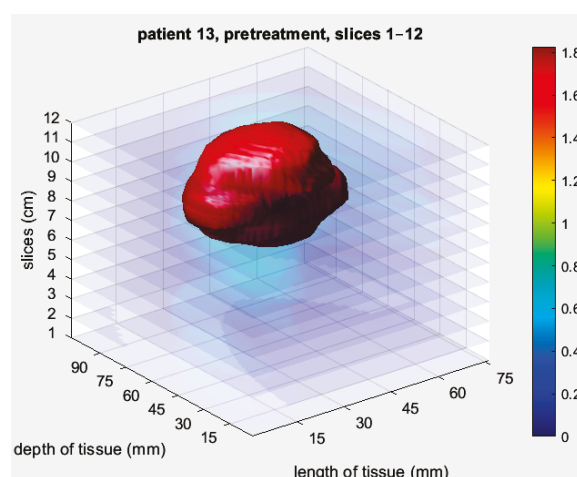


Figure 2. Optical image of a physical phantom with a 4.5 mm spherical abnormality at the center captured at 690 nm [17].



(a)



(b)

Figure 3. Reconstructed 3D optical image of a patient's tumor using 12 slices at 690 nm: **(a)** reconstructed image using the Opti-Scan probe's MDE imaging; **(b)** 3D volume model of the tumor created using MATLAB rendering capabilities, with gaps between the adjacent slices interpolated [18].

2.2. Study Design and Scanning Procedure

This preliminary study included fifteen female patients (mean age: 61.8 years) diagnosed with early breast cancer and eligible for neoadjuvant intravenous systemic therapy at BC Cancer Abbotsford. The patients received six to eight cycles of treatments, and optical scans were performed separately for each patient before and after each treatment cycle to evaluate the tumor's response to treatment. Two trained Ph.D. students conducted the optical scans, following a standardized scanning procedure established by the scanning team. The procedure included the determination of the reference location, the optimal direction of the scan, the probe's location and orientation, the number of slices required to capture the whole tumor, and the interval distance between each slice (see Figure 4). The optical scans were performed on both the cancerous lesions and the healthy regions of the contralateral breast, with the reference selected based on the approximate location of the tumor underneath the skin.

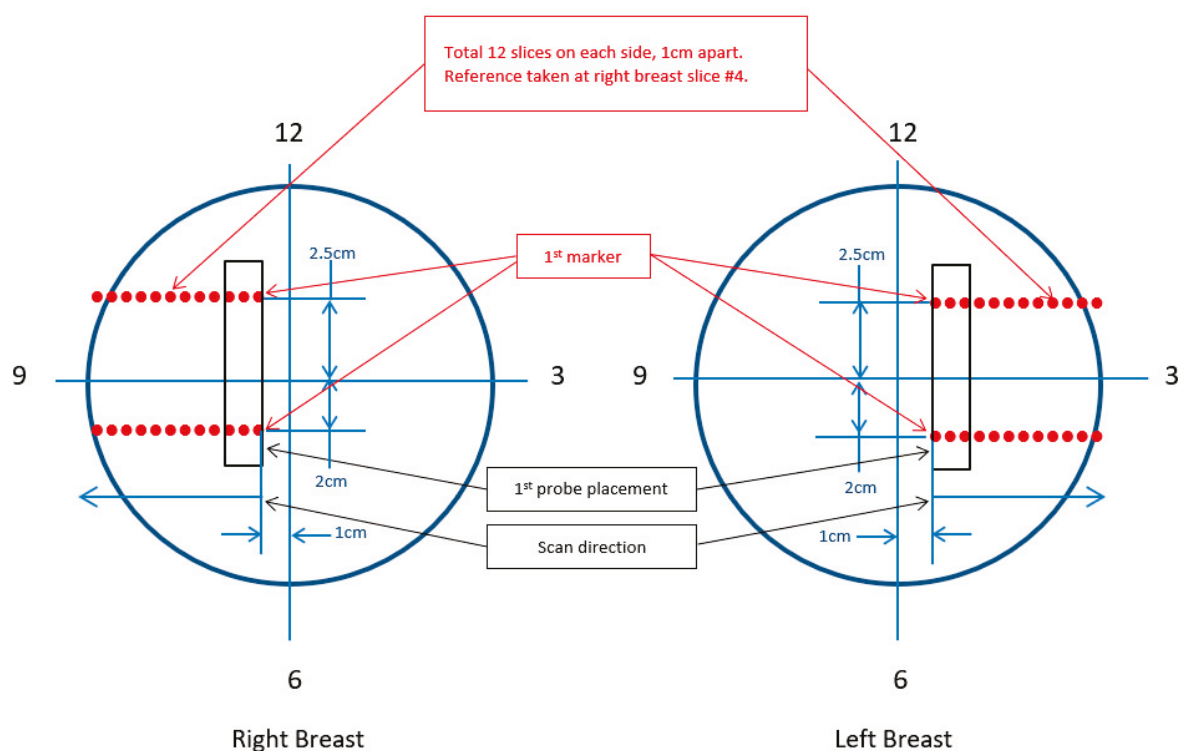


Figure 4. Tumor localization scanning procedure. This figure shows the tumor localization scanning, including the determination of the reference location, optimal scan direction, probe placement, and number of slices needed.

To evaluate the accuracy of the optical measurements, three metrics were compared: pathology, palpation (PALP), and ultrasound (US). Pathological information about each tumor was obtained through a needle biopsy, which served as the gold standard for tumor size measurement. The oncologist assessed the tumor size and texture by palpation during each visit to determine the treatment progress. The patients received ultrasound screening before, during, and after the treatment cycle to evaluate the tumor's response to treatment. Table 2 presents the tumor size (cm) before and after treatment measured with palpation and ultrasound for a subset of 3 of 15 enrolled patients. As an example, the ultrasound measurement of patient 13's tumor size during the pretreatment screening was $5.0 \times 5.1 \times 4.1$ cm (length $\times$ width $\times$ depth).

Table 2. Patient characteristics and treatment progress: tumor size (cm) before and after treatment measured with palpation (PALP) and ultrasound (US). Note: “NP” indicates “not palpable” and “NA” indicates “not available”.

Patient	Tool	Tumor Size (cm)							
		Pretreatment	Post-Treatment 1	Post-Treatment 2	Post-Treatment 3	Post-Treatment 4	Post-Treatment 5	Post-Treatment 6	Post-Chemo
12	PALP	2.5×2.5	3×3	NP	NP	NP	NP	NP	NA
	US	$3.2 \times 1.3 \times 2.0$	NA	NA	NA	NA	NA	NA	NA
13	PALP	10×9	7×8	5×6	3.5×3.5	2.5×2	2.5×2	NP	NA
	US	$5.0 \times 5.1 \times 4.1$	NA	NA	NA	NA	$3.2 \times 1.4 \times 1.7$	NA	NA
26	PALP	8×10 3	4×3	NA	5×5.5	3	NA	5.5×5.5	NA
	US	$3.8 \times 3.9 \times 2.3$ $1.9 \times 1.7 \times 1.9$	NA	NA	NA	$1.0 \times 1.3 \times 0.9$ $1.0 \times 1.0 \times 0.5$	NA	NA	$0.9 \times 1.0 \times 0.7$ $0.4 \times 0.4 \times 0.5$

2.3. Machine Learning Models for Breast Optical Properties and Residual Cancer Burden

In this study, we aimed to use an innovative approach to measure pathological residual cancer burden (pRCB) values, considering the complexity of pRCB measurements. We utilized the Opti-Scan probe to measure optical RCB values, referring to them as optical residual cancer burden (oRCB). By estimating breast tissue's optical properties, including absorption and scattering coefficients, we established the correlation between pRCB and oRCB values. The absorption coefficients were measured using reflectance data obtained from the probe, serving as the basis for determining the optical RCB value and predicting corresponding pathological RCB values. To accurately calculate optical properties based on reflectance measurements, we utilized machine learning (ML) techniques.

Review of Current ML Methods for Breast Optical Properties and Residual Cancer Burden

This section reviews several ML models used to estimate breast optical properties and residual cancer burden. Conventional image reconstruction algorithms estimate optical tissue property distributions ($\hat{x}^*$) by minimizing the regularized objective function in Equation (1) [24]:

$$\hat{x}^* = \operatorname{argmin} \left\{ \frac{1}{2} \|F(\hat{x}) - y\|_2^2 + \lambda R(\hat{x}) \right\} \quad (1)$$

where λ is the regularization hyperparameter, and $R(\cdot)$ is a regularization term, usually the standard Tikhonov regularization ($R(x) = \lambda \|x\|^2$). These model-based algorithms are computationally expensive, limiting their practicality and real-time applications [25].

Recently, machine learning applications have shown the potential to improve the accuracy of reconstructed images and solve inverse scattering problems [26]. For example, Feng et al. [27] proposed a multilayer perceptron (MLP) feedforward neural network for 2D-DOT image reconstruction, but its performance was reduced significantly for limited-angle acquisition. Yoo et al. [28] designed a convolutional neural network for 3D-DOT inverse scattering problems to determine the nonlinearity of the inverse scattering problem. Machine learning algorithms have also been used to estimate residual cancer burden (RCB). Ref. [29] highlights the potential of machine learning with multiparametric MRI (mpMRI) to predict the complete pathological response (pCR) to neoadjuvant chemotherapy (NAC) in breast cancer patients. In another study [30], deep-learning-derived volumes of locally advanced breast cancer on MRI showed comparable performance to functional tumor volume in predicting residual disease after chemotherapy (AUC = 0.76). These findings suggest the potential of deep-learning-based segmentation for accurate assessment of tumor load and residual cancer burden in breast cancer patients. A related study [31] investigated artificial intelligence-based segmentation of residual tumor burden after neoadjuvant therapy as an objective and reproducible solution for tumor response scoring. Despite various ML models for residual breast measurement using MRI and other technologies, there remains a need to evaluate breast optical properties and residual cancer burden, specifically through diffuse optical tomography (DOT) technologies. To address this need, our study was focused on leveraging highly accurate ML algorithms and optimizing the performance of the Opti-Scan probe for accurate estimation of breast optical properties and residual cancer burden.

2.4. Proposed ML Model for Breast Optical Properties and Residual Cancer Burden

In this study, we aimed to predict optical properties in breast tissue using regression analysis. The training dataset (D) consisted of 640 phantom data collected using various breast phantoms, each with 128 different reflectance, scattering, and absorption values. These phantoms simulate breast tissue with varying absorption levels, which can mimic the optical properties of normal and cancerous breast tissue. The absorption coefficients were measured using the MDE [17], which utilizes the modified diffusion equation to measure the optical properties of phantoms.

The test dataset (T) contains 15 sets of testing data, each comprising 128 data reflectance values collected by the probe for each patient, denoted as $X_1, X_2, \dots, X_{128}$. The ML-optical model aims to train the training dataset based on phantom data and predict the corresponding unknown absorption coefficients ($Y_1, Y_2, \dots, Y_{128}$) of normal and cancerous breast tissue based on the reflectance values obtained from the breast phantoms.

To estimate the optical properties, we employed a predictive model (F) that uses k-fold cross-validation, where the training set was split into k smaller subsets. Given the exponential nature of the reflectance curve in the patient data, polynomial regression was selected as the appropriate method. To determine the optimal polynomial degree, we fit polynomials of varying degrees to the training data and compared their performance on the testing data.

We employed the gradient descent algorithm during the training process and specified two important hyperparameters: the learning rate and the iteration count. The learning rate controlled the step size for each iteration, and we set it to 0.5 in this study. The iteration count determined the number of times the model updated the weights and biases, and we performed 10,000 iterations to ensure convergence and optimize the model's performance. We monitored the convergence by calculating the cost function at each iteration. We visualized the results by plotting the cost against the number of iterations, demonstrating the successful training of the polynomial regression model with a degree of 4.

To assess the accuracy of our model, we evaluated two metrics on the testing data: the mean square error (MSE) and the R^2 score. The MSE was calculated to quantify the average squared difference between the predicted and actual absorption coefficients, yielding an impressive value of 0.011%. Additionally, the R^2 score, which measures the proportion of the variance in the target variable explained by the model, demonstrated an accuracy of 90%. These metrics provided valuable insights into the model's performance in capturing the optical coefficients for normal and cancerous breasts across patients, slices, and treatments using eLED1 and eLED2.

Figure 5 depicts the path of light through breast tissue; two light paths from eLED1 and eLED2 converge at $(X1, Y1)$ to measure the absorption coefficient as a superposition of the coefficients of both eLED. Figure 6a displays absorption curves for healthy and unhealthy breast tissue by combining estimated absorption properties obtained by each eLED. The oRCB values were subsequently derived by subtracting absorption values from cancerous breast tissue from corresponding normal tissue values for all patients, slices, and treatments. The area under the curve (AUC) of residual disease was computed from the absorption difference (i.e., error) between healthy and unhealthy tissue values for all slices in each treatment, as illustrated in Figure 6b.

This dataset and methodology formed the foundation for developing and evaluating the machine learning (ML) model. The ML model uses reflectance data to predict the optical properties of breast tissue, which, in turn, allows for the estimation of optical residual cancer burden. The oRCB values are correlated with the pRCB index. To calculate the oRCB values for fifteen patients, we compared the AUC values of residual disease for each treatment. Then, we divided the smallest value (usually for the last treatment) by the largest value (usually for pretreatment).

Furthermore, another regression analysis was employed to determine the unknown pRCB values based on available values. The new training dataset consisted of eight oRCB values and their eight corresponding known RCB values obtained from the BC Cancer Agency. This training dataset was used to develop a regression model. The test dataset, which we used to evaluate the model's performance, consisted of seven oRCB values as input and seven corresponding unknown RCB values as outputs. We could predict the unknown pRCB values for each of the seven cases by applying the regression model to the test data.

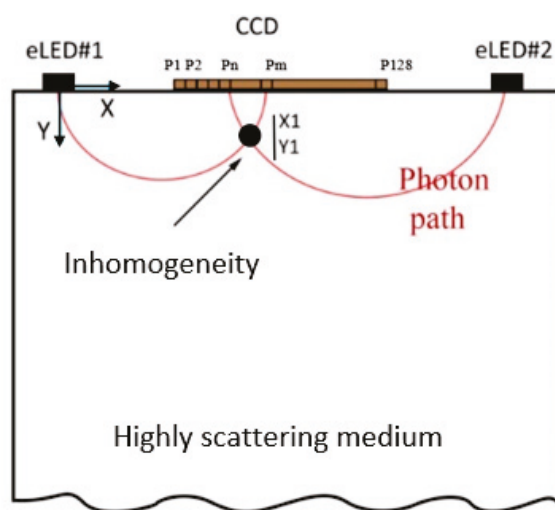


Figure 5. Sketch of light propagation and absorption measurement in breast tissue using two eLEDs [17].

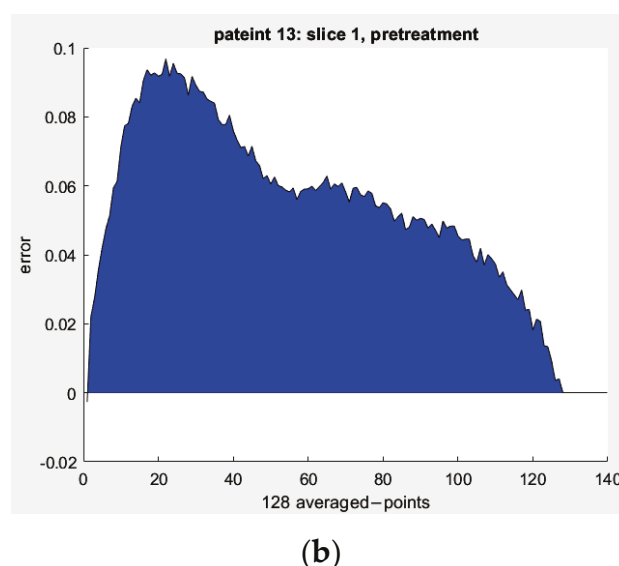
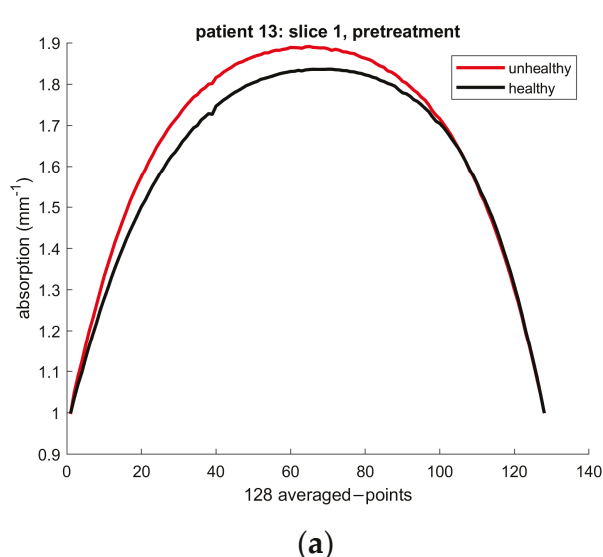


Figure 6. Absorption curves of patient 13's healthy and unhealthy breast tissue for slice 1 during the pretreatment screening at 690 nm: **(a)** the absorption curves of healthy (black) and unhealthy (red) tissue; **(b)** the AUC for residual disease calculated by subtracting the absorption values of the cancerous breast from the corresponding values of normal tissue.

3. Results: Machine-Learning-Based Method for Breast Tissue Optical Property Determination and Treatment Response Monitoring

3.1. Optical Property Determination

In this section, we present our study's results in using a machine learning (ML) predictive model to determine the optical properties of healthy and unhealthy breast tissues. Figure 7 shows the absorption curves for each patient's healthy and unhealthy breasts, represented by the black and red curves. The black curves were used as a baseline to detect changes in optical parameters. The red curve should fit the black curve when there is no tumor. However, deviations indicate changes in the optical properties due to the tumor's presence.

3.1.1. Patient 12

For patient 12, the ML model indicated that slice #4 had the highest absorption concentrations, consistent with palpation (palpation reported slice #4 as the reference). The noticeable changes in optical properties observed in slices #3 to #5 are clear evidence of the presence of the tumor.

3.1.2. Patient 13

For patient 13, the model indicated that slice #7 (or #8) reflected the highest absorption concentrations. The largest optical changes reflecting the tumor were observed in slices #5 to #9.

3.1.3. Patient 26

For patient 26, the absorption curve in slice 1 was large, likely due to the nipple effect. This patient had two tumors, and palpation reported slice #3 as the reference. The model found a tumor on the right side of slice #3, representing a higher concentration of the larger tumor, but the smaller tumor was not reflected in this slice. Slice #6 showed the largest total changes in optical properties since it showed both tumors' optical properties.

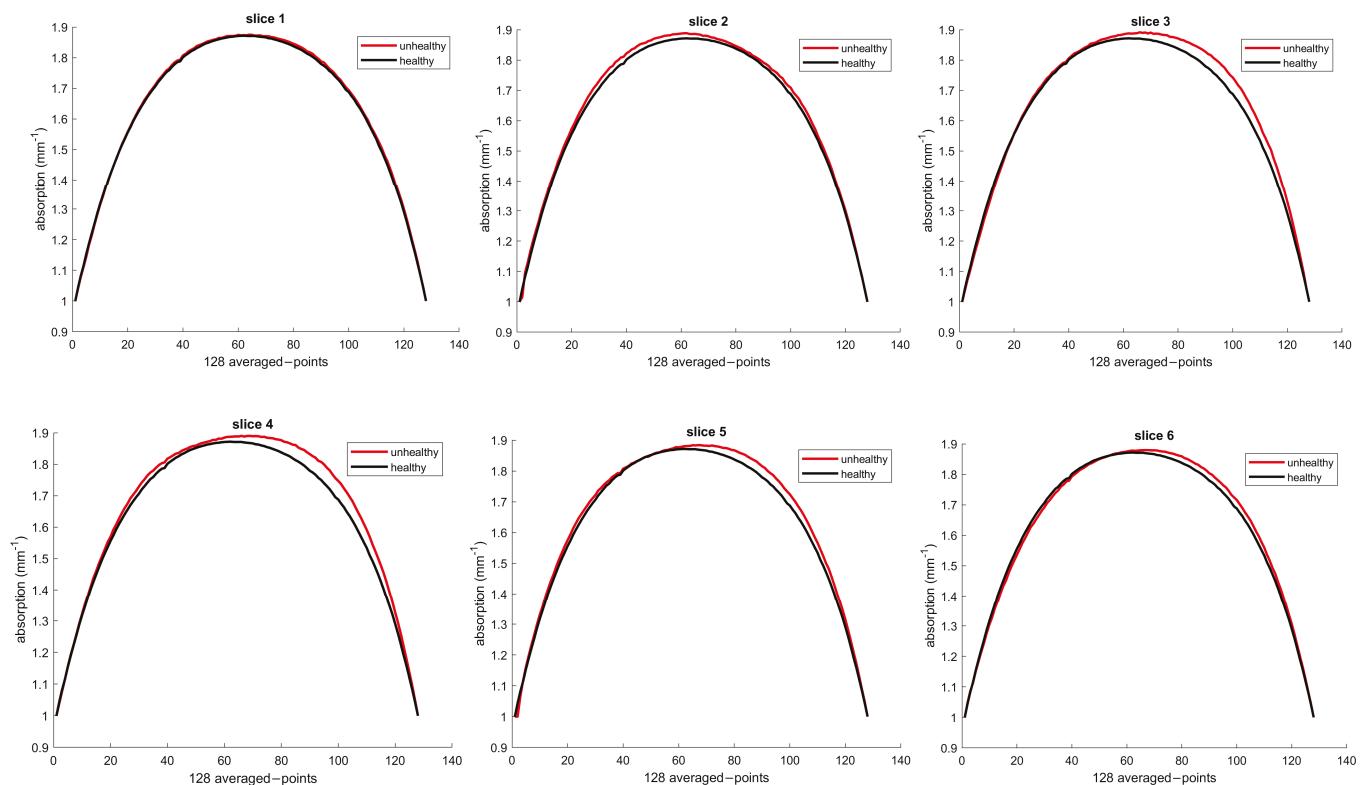
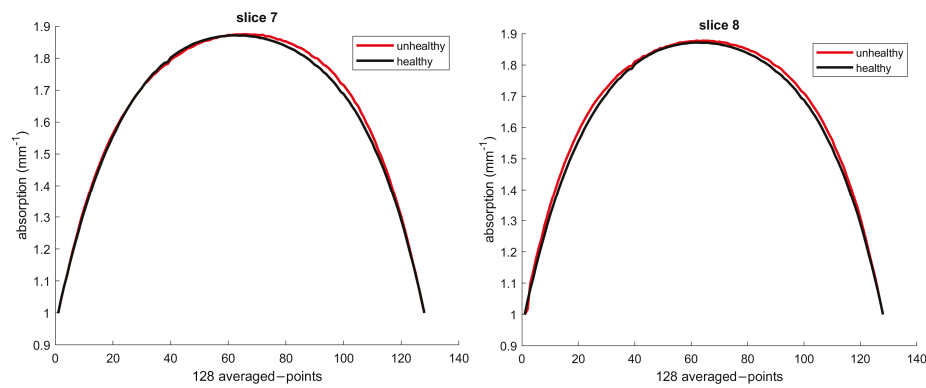
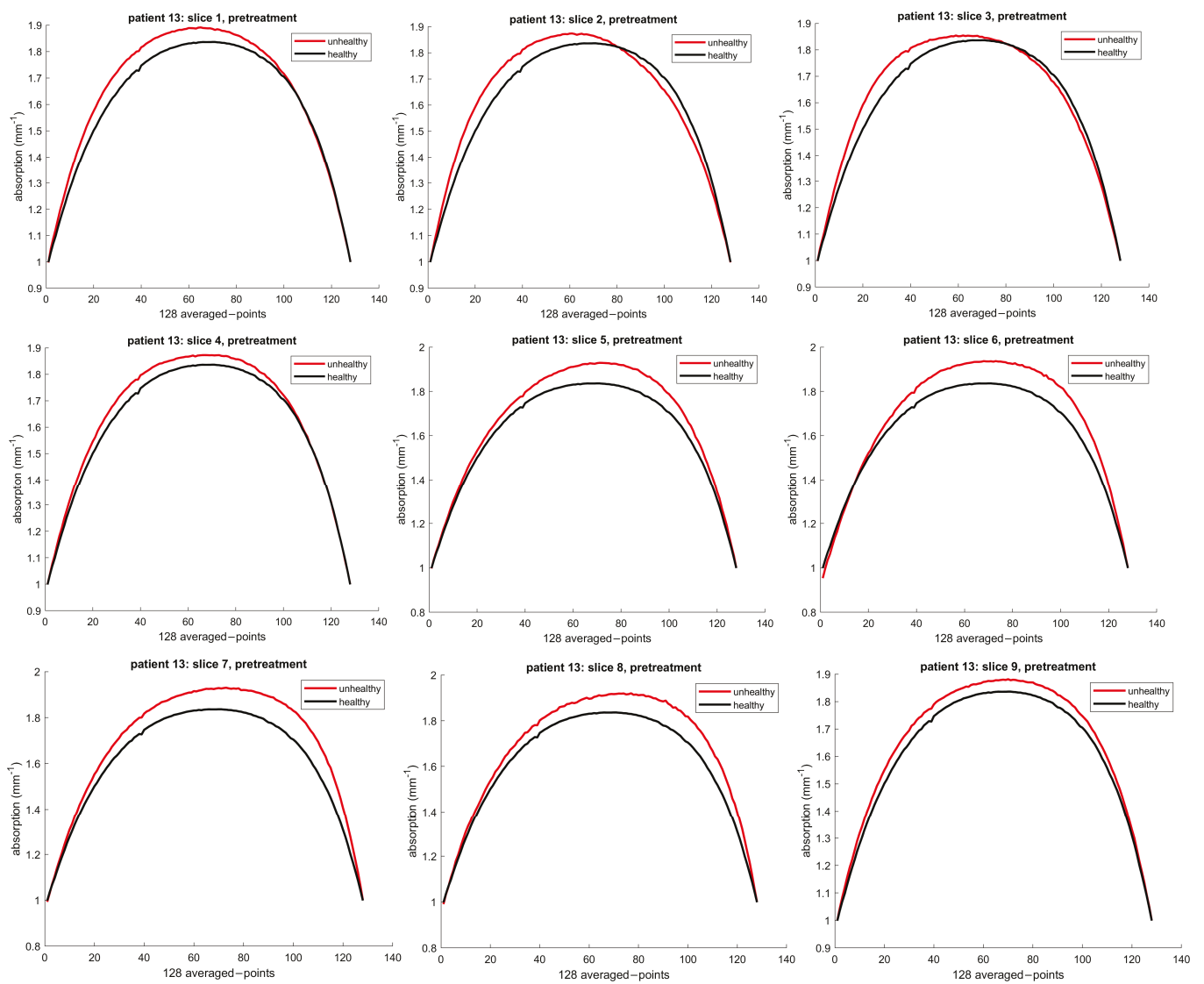


Figure 7. Cont.



(a) Patient 12.



(b) Patient 13.

Figure 7. Cont.

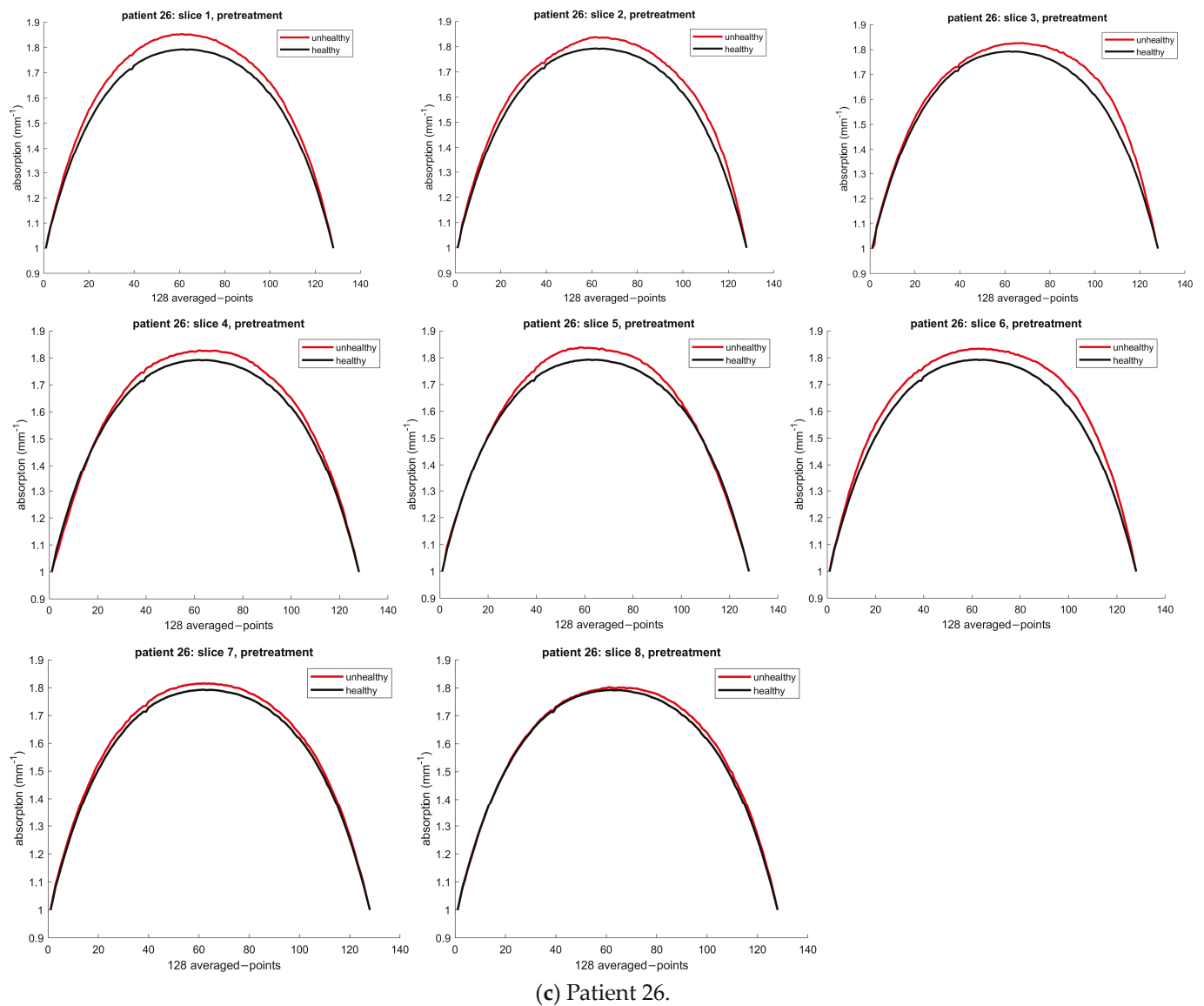


Figure 7. Absorption curves at 690 nm were generated by ML for patients (a) 12, (b) 13, and (c) 26 during pretreatment screening. Black curves: healthy breast tissue. Red curves: unhealthy tissue affected by the tumor. Deviations from the black curve signal change in optical properties due to tumor presence.

3.2. Treatment Response Monitoring and Residual Cancer Burden (RCB)

In this section, we present the results of the ML model for treatment response monitoring and prediction of residual cancer burden in breast tissues. Figure 8 shows the AUC of residual disease for all slices and treatments for selected patients, providing valuable information about patient response to treatments.

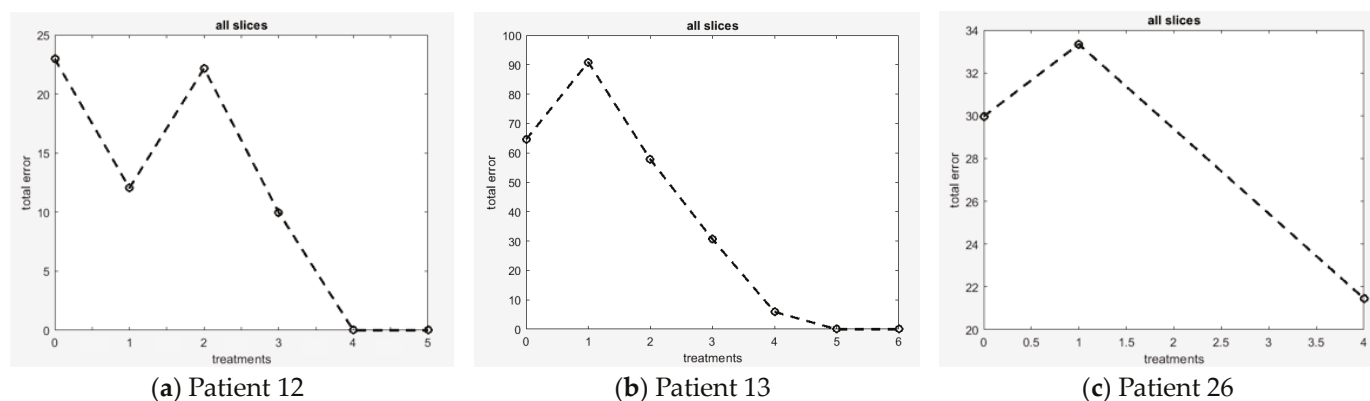


Figure 8. ML-based treatment response monitoring for all slices and treatments at a wavelength of 690 nm in patients (a) 12, (b) 13, and (c) 26, showing the absorption differences (total errors) between healthy and unhealthy tissue values and providing valuable information about patient's response to treatments.

3.2.1. Patient 12

As shown in Table 2, the tumor volume decreased and became not-palpable (NP) after the second post-treatment scan, indicating a complete response ($\text{pRCB}\# = 0$). The ML model confirmed the reduction in tumor size after the second post-treatment scan and further validated the continued reduction, indicating a complete treatment response ($\text{pRCB}\# = 0$).

3.2.2. Patient 13

Patient 13 received seven cycles of NAC, and the tumor volume decreased gradually ($\text{pRCB}\# = 0$), also confirmed by the ML model. The model indicates that patient 13 responded completely to the chemotherapy drugs without any residual cancer burden ($\text{pRCB}\# = 0$).

3.2.3. Patient 26

Patient 26 had multiple tumors in her right breast, some shrank during chemotherapy, but others remained after the treatment. Despite undergoing six treatment cycles, residual tumors were observed in post-treatment scans. As shown in Table 2, the tumor volume decreased initially on the post-chemotherapy scan, but the subsequent scans showed incomplete elimination of the tumor. The ML model confirmed the presence of residual disease after neoadjuvant chemotherapy.

Table 3 shows the estimated AUC of residual disease for the healthy and unhealthy sides of three patients across all slices and treatments and their corresponding errors. The oRCB values were calculated as the proportion of the area containing cancer by comparing the AUC values of residual disease for each treatment and dividing the smallest value (usually for the last treatment) by the largest value (usually for pretreatment).

Table 4 displays the known pRCB values and classes, with "NA" representing the unknown values we aimed to calculate using Opti-Scan. The information provided in Table 3, including the errors for treatments, is also shown in Table 4 for all patients, allowing us to estimate the oRCB for all 15 patients. Negative oRCB values were replaced with zero since they are not biologically plausible. Then, the unknown pRCB values for fifteen patients were predicted using AUC of residual disease values and oRCB values, with patient 18 excluded due to the lack of data. Table 4 also indicates the predicted pRCB values and the corresponding classes using cut points at 0, 1.36, and 3.28.

Table 3. Estimated AUC of residual disease for healthy and unhealthy sides of patients 12, 13, and 26 for all slices and treatments, along with corresponding errors.

Patient	AOC	Pretreatment	Post-Treatment 1	Post-Treatment 2	Post-Treatment 3	Post-Treatment 4	Post-Treatment 5	Post-Treatment 6
12	Unhealthy	1680.1	1669.2	1679.3	1667.2	1649.3	1652.1	NA
	Healthy	1657.1	1657.1	1657.1	1657.1	1657.1	1657.1	NA
	Error	22.96	12.04	22.17	9.98	0.00	0.00	NA
13	Unhealthy	1902.9	1929.2	1896.1	1869.0	1844.2	1833.2	1821.5
	Healthy	1838.4	1838.4	1838.4	1838.4	1838.4	1838.4	1838.4
	Error	64.56	90.88	57.77	30.63	5.89	0.00	0.00
26	Unhealthy	1633.6	1627.3	NA	NA	NA	NA	1627.2
	Healthy	1603.7	1593.0	NA	NA	NA	NA	1605.7
	Error	39.97	34.34	NA	NA	NA	NA	21.46

Table 4. Prediction of unknown pathological residual cancer burden (pRCB) values and classes using optical residual cancer burden (oRCB).

Patient	Known pRCB Value	Known pRCB Class	Treatment	Unhealthy	Healthy	Error	Predicted oRCB	Predicted Unknown pRCB Value	Predicted Unknown pRCB Class
10	3.93	RCB-III	Pre-t	1914.8	1839.3	75.45	53.54	NA	NA
			Post-t7	1882.9	1842.4	40.40			
12	0.00	RCB-0	Pre-t	1680.1	1657.1	22.96	0.00	NA	NA
			Post-t5	1652.1	1657.1	0.00			
13	0.00	RCB-0	Pre-t	1902.9	1838.4	64.56	0.00	NA	NA
			Post-t6	1821.5	1838.4	0			
14	2.51	RCB-II	Pre-t	1657.7	1614.1	43.64	37.37	NA	NA
			Post-t7	1630.4	1614.1	16.31			
15	2.18	RCB-II	Pre-t	1707.1	1601.6	105.51	25.75	NA	NA
			Post-t7	1630	1602.8	27.176			
16	NA	NA	Pre-t	2144.2	1983.3	160.95	81.34	5.88	RCB-III
			Post-t3	2122.5	1991.6	130.92			
17	NA	NA	Post-t1	2035	1981.5	53.463	8.75	0.67	RCB-I
			Post-t7	1995.6	1990.9	4.679			
18			Lack of Data						
19	1.6	RCB-II	Pre-t	1860.5	1815.4	45.15	22.7	NA	NA
			Post-t5	1825.6	1815.4	10.25			
21	NA	NA	Post-t4	1603.5	1588.8	14.69	54.15	3.93	RCB-III
			Post-t7	1615.5	1607.6	7.96			
22	NA	NA	Post-t1	2034.5	1995.8	38.72	23.47	1.73	RCB-II
			Post-t6	2014.5	2005.4	9.09			
26	NA	NA	Post-t1	1627.3	1594.0	33.34	64.37	4.66	RCB-III
			Post-t6	1627.2	1605.7	21.46			
29	0.00	RCB-0	Post-t2	2074.2	2073.3	0.89	0.00	NA	NA
			PC	2028	2054.8	0.00			
30	NA	NA	Pre-t	2018.2	1983.3	34.91	2.67	0.23	RCB-I
			Post-t5	1976.6	1975.7	0.93			
31	NA	NA	Pre-t	2025.3	1999.3	25.99	0.00	0.00	RCB-0
			Post-t5	2001.1	2015.3	0.00			

For model training, the dataset consisted of known oRCB values as features and corresponding known pRCB values as targets. Regression analysis was used to predict the unknown pRCB values based on the corresponding known oRCB values.

Table 5 compares the oRCB and the predicted pRCB values for the selected patients, considering the initial unknown pRCB and predicted values. The table also provides the corresponding lower and upper confidence intervals, indicating the certainty range associated with the predicted pRCB values.

Figure 9 presents the prediction of pRCB values using oRCB values. Panel (a) shows the estimated oRCB values for patients with known pRCB values, while panel (b) presents the predicted pRCB values for patients with an unknown pRCB index. The scatter plot displays the relationship between the oRCB and pRCB values. The blue dots represent the oRCB values, while the red dots represent the predicted pRCB values. The solid red line represents the linear regression model's predictions. The light gray area indicates the confidence intervals for the predicted pRCB values, providing a range of certainty associated with the predictions. The model achieved an accuracy of 98.301%, as measured by the coefficient of determination (R^2), indicating a strong correlation between the oRCB and predicted pRCB values. Additionally, the model's mean squared error (MSE) is 2.775%, representing the average squared difference between the actual and predicted pRCB values.

Table 5. Comparison of oRCB and predicted pRCB values with their corresponding lower and upper confidence intervals for selected patients.

Patient	oRCB Value	pRCB Value	Lower Confidence Interval	Upper Confidence Interval
16	81.34	5.88	3.70	8.06
17	8.75	0.67	−1.51	2.85
21	54.15	3.93	1.75	6.11
22	23.47	1.73	−0.45	3.91
26	64.37	4.66	2.49	6.84
30	2.67	0.23	−1.94	2.41
31	0.00	0.00	−2.13	2.22

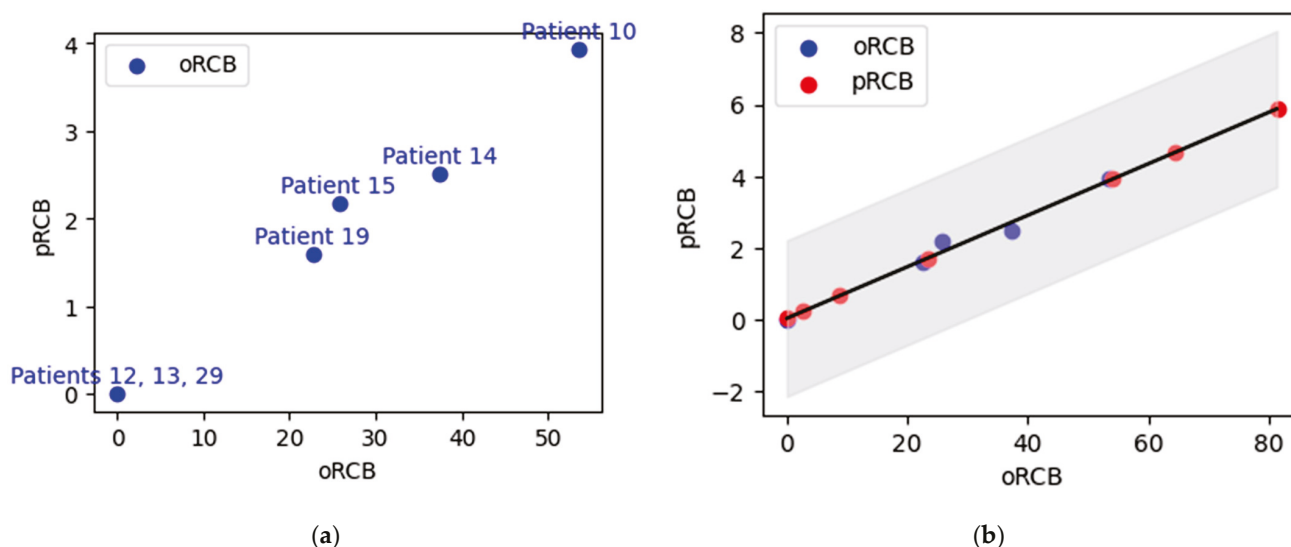


Figure 9. Prediction of unknown pathological RCB values using optical RCB values: (a) the estimated oRCB values for patients with known pRCB values; (b) the pRCB values predicted for patients with unknown pRCB values. The light gray area indicates the confidence intervals for the predicted pRCB values.

The oRCB values for all fifteen patients were consistent with the corresponding pRCB values, indicating the effectiveness of the ML model in predicting treatment response. The absorption differences (i.e., total errors) between healthy and unhealthy tissue values for all slices in each treatment concentration change inside a tumor provided valuable information about patient response to treatments. These results demonstrate the potential of ML-based methods to predict residual cancer burden and monitor treatment response in breast tissue.

4. Discussion

The results of this study indicate that the ML model is a reliable and effective tool for the determination of the optical properties of breast tissue. Our findings suggest that the ML-generated optical properties can be used to obtain optical images, which may aid in diagnosing breast cancer. However, further studies are needed to investigate the clinical utility of our ML model for breast cancer diagnosis.

In terms of treatment response monitoring, the ML method showed potential in detecting gradual tumor volume reduction and confirming complete treatment response in patients 12 and 13. However, limitations were observed in patient 26, for whom the ML method was not able to detect remaining tumors after treatment completion. Combining the ML and MDE [17] methods may enable more accurate treatment response monitoring in breast tissue.

Furthermore, the predicted pRCB values were found to be highly accurate, with an accuracy of 0.98%, which is an important clinical implication of this study. The ML model can provide a more objective and quantitative assessment of treatment response, allowing for earlier identification of non-responders and potential adjustments to the treatment plan.

Although the findings of this study are promising, it is important to note that the training dataset size was relatively small and limited to breast phantoms, with only fifteen patients tested. Therefore, further studies with larger dataset sizes and diverse patient populations are needed to validate the findings. Additionally, while we used a regression analysis algorithm in this study, evaluating the performance of other ML algorithms, such as transfer learning and ensemble learning, in this context would be beneficial.

Overall, the results of this study suggest that ML has the potential to improve the accuracy and objectivity of breast cancer treatment response monitoring and RCB estimation. However, further studies are needed to confirm these findings and evaluate the clinical utility of the ML model for breast cancer diagnosis and treatment.

5. Conclusions

In conclusion, using the Opti-scan probe, this study demonstrates the successful application of machine learning methods to assess residual cancer burden (RCB) in breast cancer patients undergoing neoadjuvant chemotherapy (NAC). The use of regression analysis and cross-validation allowed for the calculation of the optical properties of healthy and unhealthy breast tissues. The ML model trained on the optical parameter values and breast cancer imaging features obtained from the Opti-scan probe data achieved a high accuracy of 0.98 in predicting RCB number/class based on changes in optical properties. These findings suggest that the Opti-scan probe has considerable potential as a valuable non-invasive tool for monitoring breast cancer patients' response to NAC and guiding treatment decisions. In future work, we plan to design machine-learning models based on patients' optical data to recreate optical blood concentration images. Overall, this study provides a strong foundation for further investigation into using machine-learning-based NIR biosensors for assessing residual cancer burden in breast cancer patients.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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Article

Precision Heart Rate Estimation Using a PPG Sensor Patch Equipped with New Algorithms of Pre-Quality Checking and Hankel Decomposition

Smriti Thakur, Paul C.-P. Chao * and Cheng-Han Tsai

Department of Electronics and Electrical Engineering, National Yang Ming Chiao Tung University, Hsinchu 300, Taiwan

* Correspondence: pchao@nycu.edu.tw

Abstract: A new method for accurately estimating heart rates based on a single photoplethysmography (PPG) signal and accelerations is proposed in this study, considering motion artifacts due to subjects' hand motions and walking. The method comprises two sub-algorithms: pre-quality checking and motion artifact removal (MAR) via Hankel decomposition. PPGs and accelerations were collected using a wearable device equipped with a PPG sensor patch and a 3-axis accelerometer. The motion artifacts caused by hand movements and walking were effectively mitigated by the two aforementioned sub-algorithms. The first sub-algorithm utilized a new quality-assessment criterion to identify highly noise-contaminated PPG signals and exclude them from subsequent processing. The second sub-algorithm employed the Hankel matrix and singular value decomposition (SVD) to effectively identify, decompose, and remove motion artifacts. Experimental data collected during hand-moving and walking were considered for evaluation. The performance of the proposed algorithms was assessed using the datasets from the IEEE Signal Processing Cup 2015. The obtained results demonstrated an average error of merely 0.7345 ± 8.1129 beats per minute (bpm) and a mean absolute error of 1.86 bpm for walking, making it the second most accurate method to date that employs a single PPG and a 3-axis accelerometer. The proposed method also achieved the best accuracy of 3.78 bpm in mean absolute errors among all previously reported studies for hand-moving scenarios.

Keywords: heart rate (HR); photoplethysmogram (PPG); motion artifact; notch filter; Hankel matrix; singular value decomposition (SVD); beats per minutes (bpm)

1. Introduction

The first on-market PPG (photoplethysmogram) sensor was the pulse oximeter, which was commercialized around 1980 for hospital use [1]. This PPG sensor device consists of two alternating LEDs in red/infrared and a photodetector (PD) to obtain information about blood vessel pulsations from the output signals of the PD. The devices are now available on the market in the form of wearable smart watches, earphones, etc. [2]. The non-invasiveness, ease of use, and variety in price, design, and uses have made this industry of wearable smart watches flourish within a few years. However, further advances of this PPG technology are nowadays seriously hampered by the unavoidable contamination of PPG signals by noises mainly from motion artifacts (MAs) [2–5], which are caused by significantly unavoidable changes in the optical power paths from LEDs and PDs during motions, resulting in undesired components to be measured in the PPG signals. These noises become worse when the sensor is dislocated or in loose contact with the body. With MAs, obtaining the correct heart rate (HR), blood oxygen saturation (SpO_2), and blood pressure (BP) based on PPGs becomes very difficult and sometimes impossible due to the absence of uncontaminated PPG signals measured from wearable devices.

Many reported studies have been dedicated to detecting, evaluating, mitigating, and/or removing motion artifacts (MAs) from PPG signals. The detection of MAs can

be carried out by statistical means. Rajet Krishnan et al. [3] used kurtosis and skewness in both time and frequency domains to distinguish between clean and MA-corrupted data. Some researchers, such as Hanyu et al. [6], have also used the standard deviation and mean error along with selected parameters to detect MAs and remove them. Another method is to consider the spectral analysis of measured raw PPG signals based on ensemble empirical mode decomposition (EEMD) with spectrum subtraction (SS) [7,8]. In this method, corrupted PPG signals are classified into corrupted, moderately corrupted, and clean by the thresholds on the amplitudes and frequencies of dominant peaks. Bashar et al. [9] developed a method of variable frequency complex demodulation (VFCDM) and applied this to a set of 200 subjects for PPGs measured at fingers and wrists as well as with elbow movements. They acquired 449 recordings, with the result that 156 were misclassified and 29 were false-positives. Once detected, the MAs can be removed. Kong et al. [10] also used VFCDM. Some other studies, such as [11,12], conducted motion artifact removal (MAR) with assistance from reference signals from multiple LEDs (blind separation methods, Kalman filtering, etc.) and/or an accelerometer (adaptive filter). With multiple LEDs, Raghuram et al. [11] and Hara et al. [12] showed an accuracy of 0.392 bpm using PPG with finger motions, achieving a RMSE of 6.5 for walking, running, and jumping. On the other hand, using accelerometers, Lin and Ma [13] adopted discrete wavelet transforms for noise reduction. They calculated and tracked heart rates using the Kalman Filter. Mahdi Boloursaz et al. [14] utilized accelerometer signals before applying an LMS filter for MAR. Other techniques include an independent component analysis (ICA), adopted by [15–19]; empirical mode decomposition (EMD), used by [11,20–25]; least mean squares (LMS), used by [26–29]; wavelet transform (WT), used by [30–32]; a notch filter, used by [33]; or recently, in 2022, adaptive filters, used by [34]. With advances in technology, some very recent attempts at using machine learning for MAR have also been reported [35–39]. Most recently, in 2023, attention has been turned to lightweight machine learning modules [40] that are implementable in wearable devices.

Different from all the previous studies, this study proposes two sub-algorithms in a series to remove motion artifacts, which were applied to cases of hand movements and walking. The first was a new quality-assessment criterion to disregard highly noise-contaminated PPG signals, while the second employed the Hankel matrix and the associated SVD to remove motion artifacts. The aforementioned pre-screening of noises by the first quality-check sub-algorithm, and the capability of the subsequent Hankel matrices and the associated SVD to identify, decompose, and remove the motion components in measured PPG were expected to deliver a high-precision HR estimation. Two cases of walking and hand movement were considered to demonstrate the effectiveness of the proposed MAR algorithm. The IEEE Signal Processing Cup 2015 dataset was used for performance evaluation. The average error result was 0.7345 ± 8.1129 bpm, with a mean absolute error (MAE) of 1.86 bpm (beats per minute); the second-best of all the reported results. As for hand-moving, this study showed the best accuracy of 3.78 bpm in MAE compared with all the reported studies.

The remainder of this article is organized into four sections. Section 2 describes how the PPG signals were collected. Section 3 details the first algorithm of the quality check on measured PPG signals, while Section 4 describes the algorithm of motion artifact removal using the Hankel matrix and the associated SVD. Section 5 presents the experimental validation of the performance of the proposed method. Finally, Section 6 concludes this study.

2. PPG Signals and Motion Artifacts

2.1. Measuring PPG

A typical PPG signal at the wrist artery, where most wearable devices measure PPG, is shown in Figure 1a, which was measured by the PPG sensor patch developed exclusively by [41], as given in Figure 1b. This typical PPG waveform consists of AC and DC components. The AC component reflects the pulsatile component of blood vessel pulsations

synchronized with heart beats, while the DC component is the non-pulsatile component resulting from light absorption in tissue, skin, and bones along the optical paths between LEDs and PD of the PPG devices. To find the best wavelength of LEDs and the best location to measure PPG, a series of experiments with the subject sitting still were conducted with the PPG sensor in Figure 1 emitted at different wavelengths and attached at different locations 1–3, as illustrated in Figure 2a–c. It can be seen from Figure 2a–c that both green and infrared (IR) LEDs lead to larger AC components, while locations 1 and 3 lead to larger ACs in the measured PPGs as opposed to others. This is, in fact, due to the presence of arteries under the locations as shown in Figure 2a, like seen in [42]. For the remainder of this study, to develop the algorithm for removing motion artifacts, the PPG sensor patch in Figure 1b is attached at location 1, as seen in Figure 2b, to obtain the PPG measured from the green LED. Typical PPGs contaminated by motion artifacts, measured by the green LED at location 1 on the wrist artery, are shown in Figure 3a,b, which are those during walking and with hand motion, respectively. Based on the comparison between Figure 3a,b, it can be seen that the PPG waveforms measured with hand movement exhibit much smaller DC drifts than walking, while the AC components of both cases are close to each other. Additionally, the large DC drifts, especially in the case of walking, present a serious, negative effect of motion artifacts on estimating the heart rate, blood oxygen, and/or blood pressure based on measured PPG waveforms.

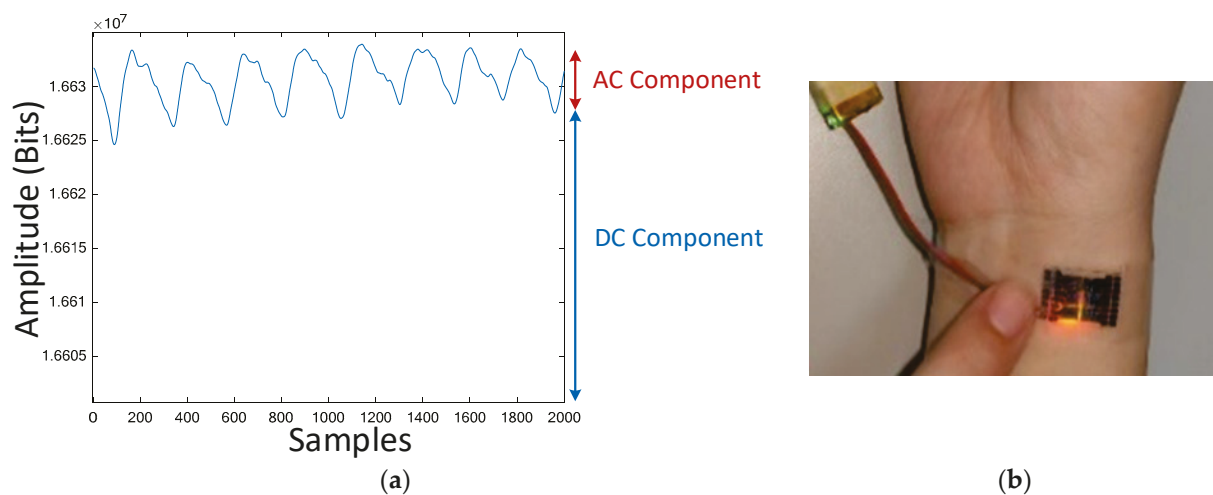


Figure 1. (a) AC and DC components of a typical PPG signal; (b) PPG sensor patch developed by [41].

2.2. Classification of Motion Artifacts

Motion artifacts are understood nowadays as having two different magnitudes, micro and macro motions, as shown in Figure 4. The micro-motion artifacts have been defined as those due to measuring position adjusting, gesture changing, or finger tapping, while the macro-motion artifacts are those having consistent body motion, such as walking, jogging, and running. Figure 4 shows the measured PPGs contaminated by the micro- and macro-motion artifacts due to finger tapping, measuring position adjusting (both leading to micro-MAs), and walking (macro-MAs). It can be seen from this figure that both micro- and macro-motion artifacts cause much more significant fluctuations to the measured PPG signal than sedentary gestures of the subject. All the aforementioned motions could range between 0.1 and 20 Hz, which is right within the frequency range for heart rate (1–4 Hz), causing much trouble for estimating heart rate based on measured PPG signals. Figure 5 shows the frequency response of a contaminated PPG signal with a few components away from the given frequencies. With the presence of micro and macro motions, the estimation accuracy of heart rate could be seriously compromised. To remedy this problem, two algorithms are proposed herein for motion artifact reduction (MAR), as described in the ensuing Sections 3 and 4.

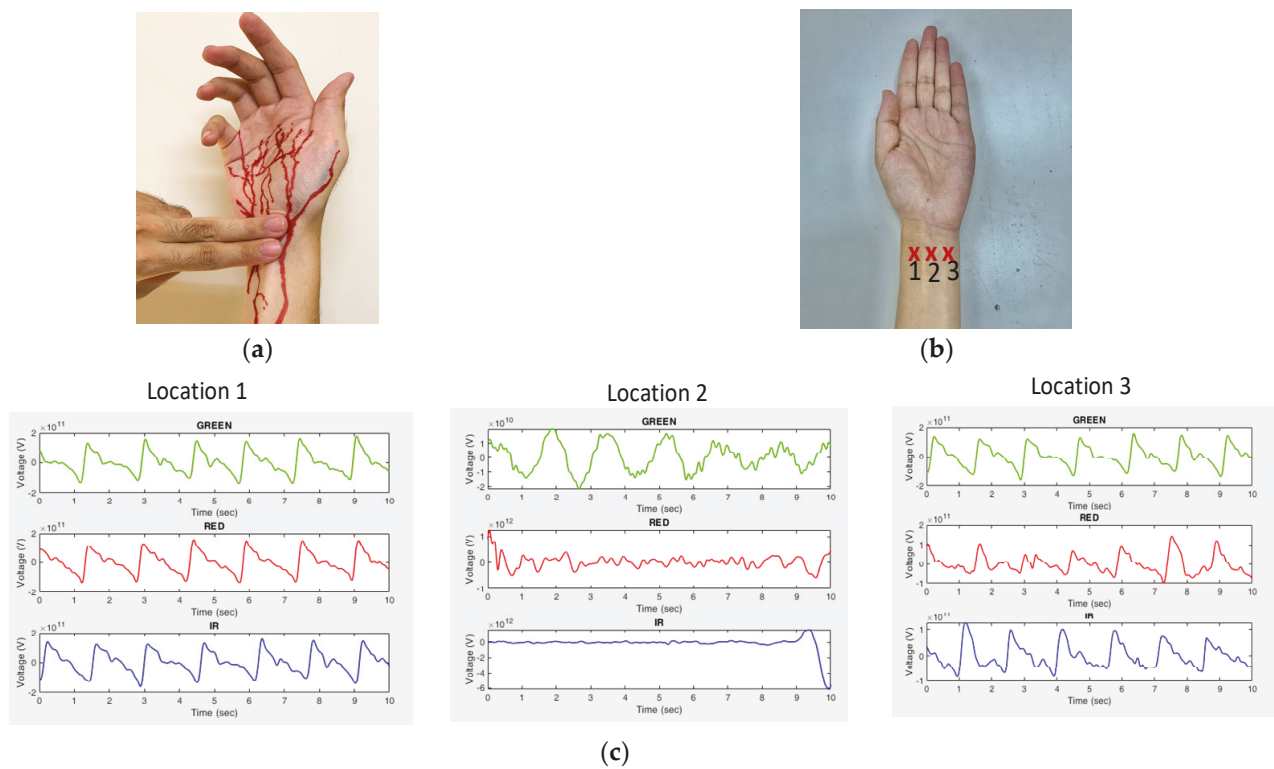


Figure 2. (a) Human arteries at wrist; (b) three different locations on the wrist to measure PPG; (c) measured PPGs using green, red, and infrared LEDs at three different locations.

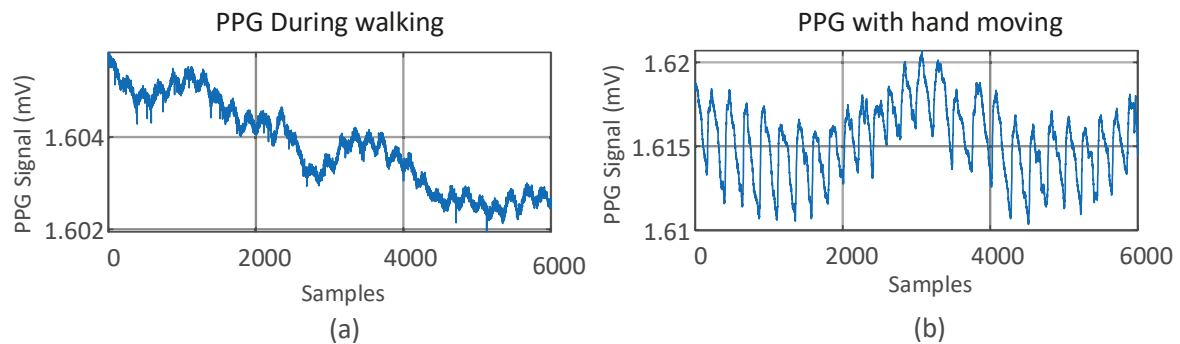


Figure 3. PPGs measured at a wrist artery contaminated by two different motion artifacts: (a) walking; (b) hand movement.

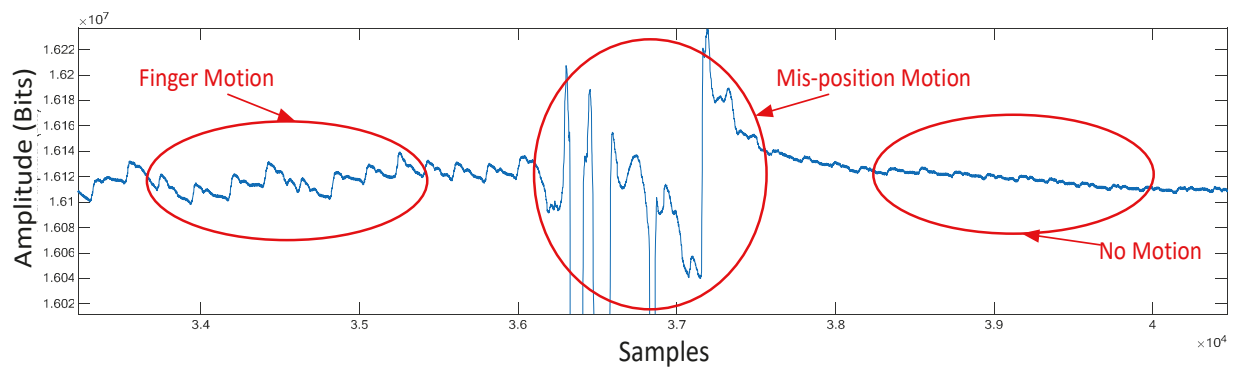


Figure 4. PPG contaminated by motion and mispositioning.

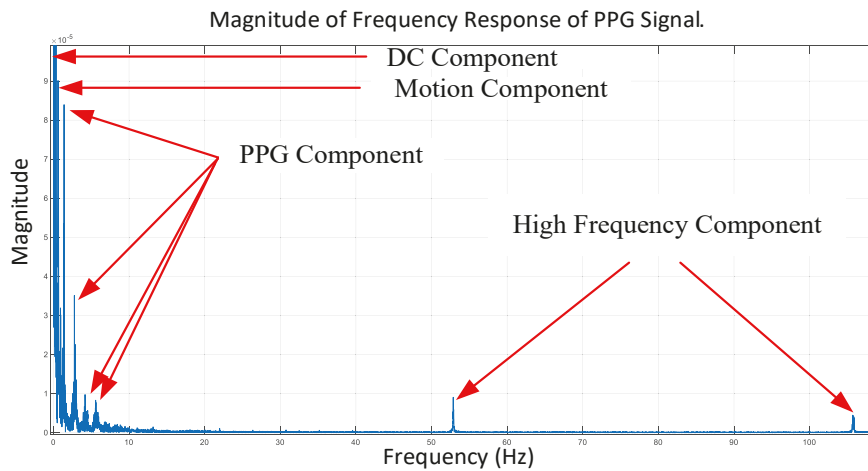


Figure 5. Frequency response of the measured PPG signal.

3. The First Sub-Algorithm of Quality Check on Measured PPG Signals

The algorithm proposed by this study consists of two sub-algorithms to increase the accuracy of heart rate estimation with serious motion artifacts in PPGs measured by the wearable device. The first sub-algorithm is designed to check the quality of real-time raw PPGs measured to rule out those seriously contaminated and keep the information of heart rate still embedded in the measured PPGs. With this first sub-algorithm, the accuracy of estimating heart rate is expected to increase. To this end, a new algorithm for signal quality checking on measured PPG has been developed. Figure 6 elaborates on its computation flow. Note that a qualified PPG signal at the end is defined as the one that is periodic in time domain and has the largest frequency component remaining within a limited range close to that of the legitimate heart rate. Accordingly, specific conditions in a sequence for checking are defined below for subsequent analysis to extract precision heart rate in the next section.

- (1) The number of valleys and peaks of the measured PPG signal is calculated, and then it is checked if

$$(\text{Number of Valleys}) \leq (\text{Number of Peaks}) \pm 1, \quad (1)$$

to affirm the presence of pulsation in the measured PPG; otherwise, the signal is labeled as “unqualified” and we then return to stage one for motion artifact reduction.

- (2) The t_i values are defined as the time intervals between peaks that can be extracted from measured PPGs, as shown in Figure 7. It is next checked if all differences between consecutive t_i values,

$$\Delta t = t_{i+1} - t_i, \quad (2)$$

are each less than or equal to ± 0.1 of t_i . If this condition is true, the signal is labelled as “qualified,” and then we go to the next step in Figure 6; otherwise, the signal is labelled as “unqualified” and we stop the computation.

- (3) The statistical measures of kurtosis, mean, and standard deviation of the qualified PPG segments are calculated further at each cycle. If all calculated statistical values are within pre-defined thresholds, as shown in Figure 8a, the measured PPG is identified as “qualified;” otherwise, it is determined as “unqualified” and then the computation is stopped. Note that a similar approach was used by [3] for motion artifact detection.
- (4) A marker SQT (Signal Quality Token) is defined as either ‘0’ or ‘1’ to label the measured PPG segment as qualified or unqualified. Figure 8b shows three representative examples of PPG marked with different SQTs. Only the PPG with SQT = 1 is passed on to calculate heart rate based on the Hankel matrix and SVD decomposition.

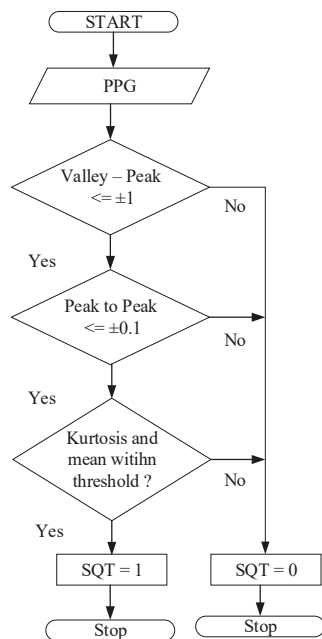


Figure 6. Computation flow of the quality-check algorithm on the measured PPG.

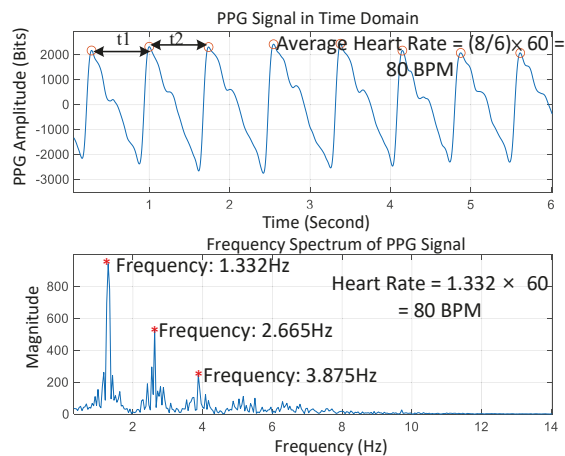


Figure 7. Measured PPG signal in time and frequency domains.

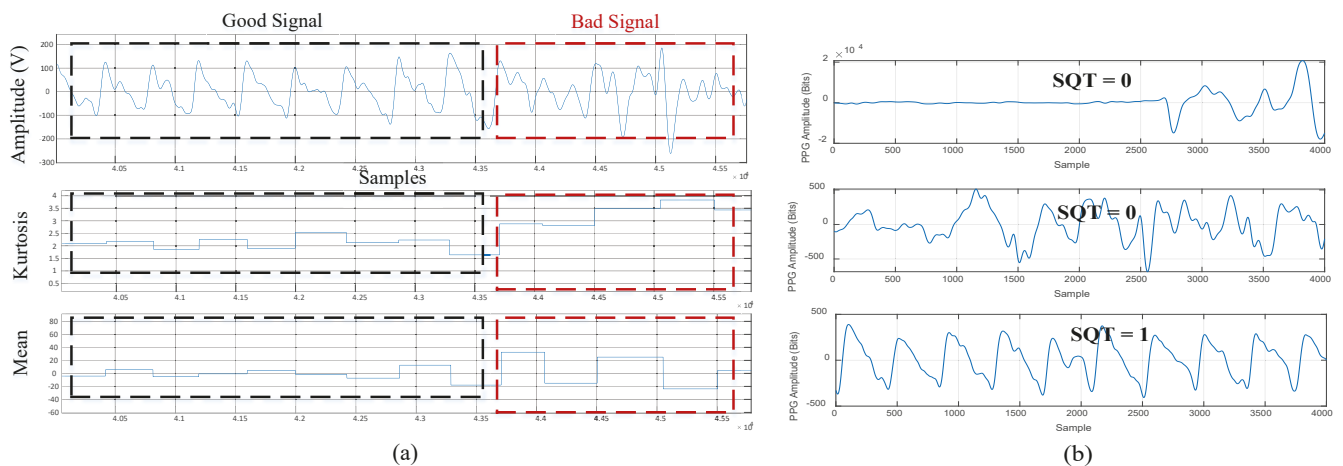


Figure 8. (a) Mean and kurtosis for qualified and unqualified PPG signals; (b) SQT for the PPG signal.

4. The Second Sub-Algorithm for Motion Artifact Removal

The PPG signals determined as “qualified” by the first sub-algorithm of quality checking in the previous section are next processed with the motion artifact removal (MAR) algorithm proposed herein.

4.1. The Hankel Matrix and Its SVD

Precision estimation of heart rate is carried out herein by singular value decomposition on the Hankel matrix of the measured PPG and motion via an accelerometer also attached to the PPG sensor, as shown in Figure 1b. The PPG and accelerometer signals are measured and recorded for six seconds and then first organized into Hankel matrices [43], $\mathbf{H}_{\text{ppg}}$, $\mathbf{H}_x$, $\mathbf{H}_y$, and $\mathbf{H}_z$, respectively, for PPG and accelerations along x, y, and z. For example, $\mathbf{H}_{\text{ppg}}$ is in the form of

$$\mathbf{H}_{\text{ppg}} = \begin{bmatrix} a(t_1) & a(t_2) & \dots & a(t_n) \\ a(t_2) & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ a(t_n) & \dots & \dots & a(t_{2n}) \end{bmatrix}, \quad (3)$$

where $a(t)$'s are PPG data at times of t 's, and there are in total $2n$ PPG data in the sampled window of six seconds. Next, the single value decompositions (SVDs) [44] are conducted on each of $\mathbf{H}_{\text{ppg}}$, $\mathbf{H}_x$, $\mathbf{H}_y$, and $\mathbf{H}_z$, leading to

$$\mathbf{H}_{\text{ppg}} = \mathbf{U}_{\text{ppg}} \mathbf{\Sigma}_{\text{ppg}} \mathbf{V}_{\text{ppg}}^T, \quad (4)$$

$$\mathbf{H}_x = \mathbf{U}_x \mathbf{\Sigma}_x \mathbf{V}_x^T, \quad (5)$$

$$\mathbf{H}_y = \mathbf{U}_y \mathbf{\Sigma}_y \mathbf{V}_y^T, \quad (6)$$

$$\text{and } \mathbf{H}_z = \mathbf{U}_z \mathbf{\Sigma}_z \mathbf{V}_z^T \quad (7)$$

respectively, where $\mathbf{U}$, $\mathbf{\Sigma}$, and $\mathbf{V}$ correspond to orthogonal, diagonal, orthogonal matrices. $\mathbf{U}$ contains the orthogonal basis for the column space of $\mathbf{H}$, while $\mathbf{V}$ contains the orthogonal basis for the row space of $\mathbf{H}$. $\mathbf{\Sigma}$ contains the eigenvalues of matrix $\mathbf{H}$. The eigenvalues of the diagonal matrices $\mathbf{\Sigma}$ are stored as $\mathbf{\Lambda}_{\text{ppg}}$, $\mathbf{\Lambda}_x$, $\mathbf{\Lambda}_y$, and $\mathbf{\Lambda}_z$ for further processing. In the next steps, the eigenvalues with the associated components highly correlated to motion artifacts are removed. To this end, the correlation matrix of PPG and 3-axis accelerometer signals can be calculated; that is [45],

$$\rho_{x,y} = \text{corr}(\mathbf{x}, \mathbf{y}) = \frac{\text{cov}(\mathbf{x}, \mathbf{y})}{\sigma_x \sigma_y} = \frac{E(\mathbf{x} - \mu_x) E(\mathbf{y} - \mu_y)}{\sigma_x \sigma_y}, \quad (8)$$

where the correlation value $\rho_{x,y}$ gives the similarity index between the two signals, with expected values μ_x and μ_y , and standard σ_x and σ_y of the two signals. The components in measured PPG that are highly correlated to accelerations are removed. Then, the time-domain PPG signal without motion artifacts can be restored by recovering the frequency response with the non-MR-related components only via the inverse Fourier transform, as seen in Figure 9.

4.2. The Computational Flow of the Proposed MAR Algorithm

A new algorithm of motion artifact removal (MAR) is engineered herein for reconstructing MR-free PPG signals based on the decomposed Hankel matrices in Equations (5)–(7) and their mutual correlation in Equation (8). The associated computation flow is shown in Figure 10, while the pseudo-code is given below. The algorithm (Algorithm 1 in pseudocode) consists of five stages, (a) synthesizing the Hankel matrices $\mathbf{H}_{\text{ppg}}$, $\mathbf{H}_x$, $\mathbf{H}_y$, and $\mathbf{H}_z$ in the forms of (3); (b) Conducting singular value decomposition (SVD) on $\mathbf{H}$'s; (c) Calculating correlation to remove MR-related components; (d) Conducting discrete Fourier transform on the MR-free PPG signals and then finding the heart rate

by taking the maximum peak of the spectrum as the heartbeat component; (e) Finally, the heart rate is estimated again to see if the consecutive estimated heart rates are close to each other to ensure the robustness of the algorithm.

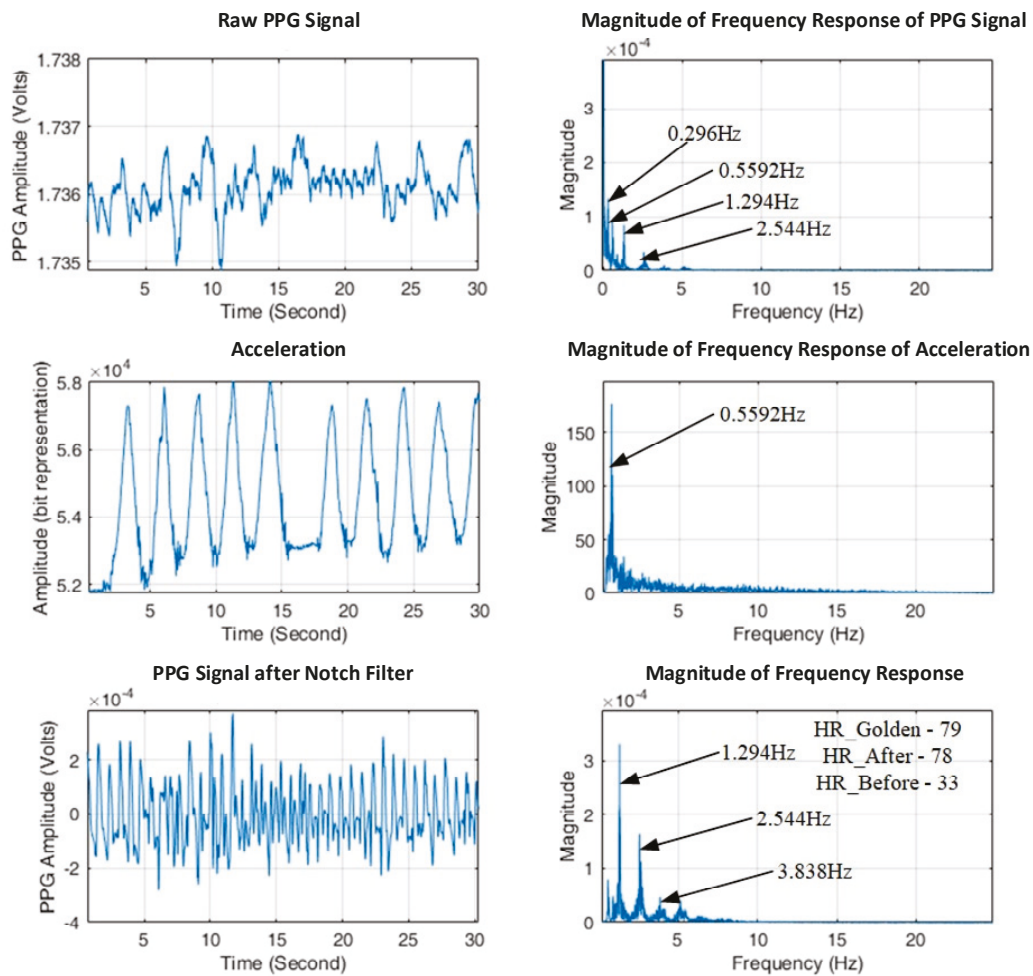


Figure 9. Estimating heart rate for hand movement using the proposed algorithms.

Algorithm 1 In pseudocode: Motion Artifact Algorithm for Walking.

- 1: **Procedure** Record PPG signal and accelerometer signal x,y,z for 8 s
 - 2: Initialize $HR_est = 78$
 - 3: Construct Hankel matrix H_{ppg} for PPG
 - 4: Construct Hankel matrix H_x for x
 - 5: Construct Hankel matrix H_y for y
 - 6: Construct Hankel matrix H_z for z
 - 7: Find SVD of matrix obtained from step 3, 4, 5, 6
 - 8: Construct a correlation matrix between the 3-axis accelerometer and PPG
 - 9: Select eigenvalues
 - 10: Reconstruct using inverse SVD
 - 11: Find DFT of the reconstructed signal
 - 12: Find HR
 - 13: Heart rate estimation
 - 14: **End procedure**
-

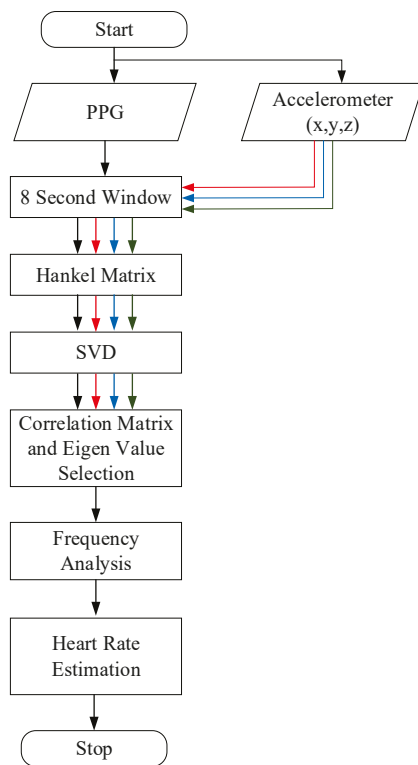


Figure 10. Computation flow of the proposed second sub-algorithm.

5. Experimental Results

Experiments were conducted for the cases of hand movement and walking, as shown in Figure 11, to validate the performance of the two sub-algorithms built. A commercially certified oximeter was utilized to provide reference heart rates for validating the performance of the two designed sub-algorithms. All experiments for collecting data were conducted at room temperature, 28~31 °C. The skin temperature of the subject during the experiment is noted to be 35~37 °C. The PPG signals and the accelerometer signals are recorded simultaneously using a printed circuit board (PCB). A Bluetooth connection was established, allowing the subject to freely move his/her arm and walk.

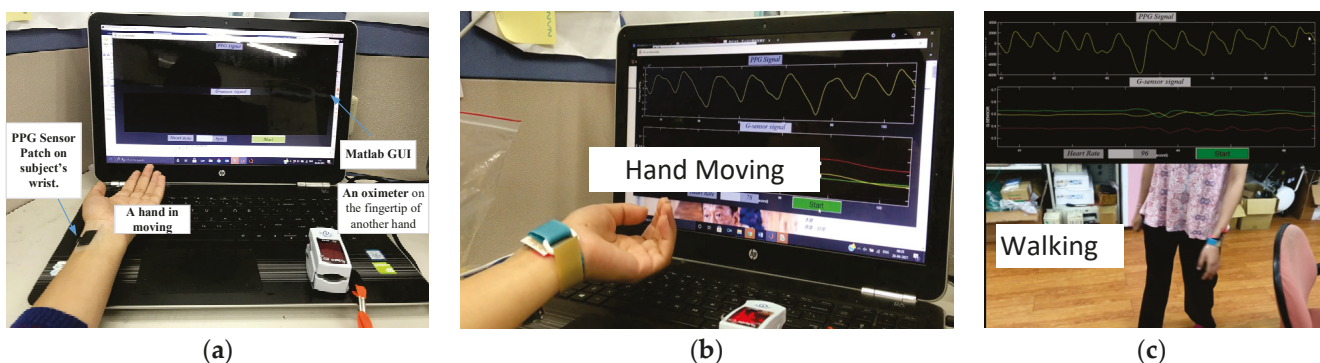


Figure 11. (a) Experiment setup for (b) hand movement and (c) walking.

5.1. Hand Movement

The experiment setup with hand movement is shown in Figure 11a,b. A PPG sensor was attached to the wrist artery of a subject, while the fingertip of another hand was clamped with the aforementioned oximeter for reference. The subjects were asked to sit and relax for some time, and then their information, such as skin color, temperature, and reference heart rate from the oximeter, was recorded and noted. Then the subjects were

allowed to move the hand up and down with the PPG sensor patch worn at the wrist. The algorithm (consisting of two sub-algorithms) was tested on 10 subjects of three different skin tones (beige, honey, and bronze). The results are shown in Figure 12. The proposed system achieves an accuracy of 0.6525 ± 4.7 bpm with a window of 6 s. The Pearson correlation is 0.6, while the average absolute error (MAE) is 3.78 beats per minute (bpm).

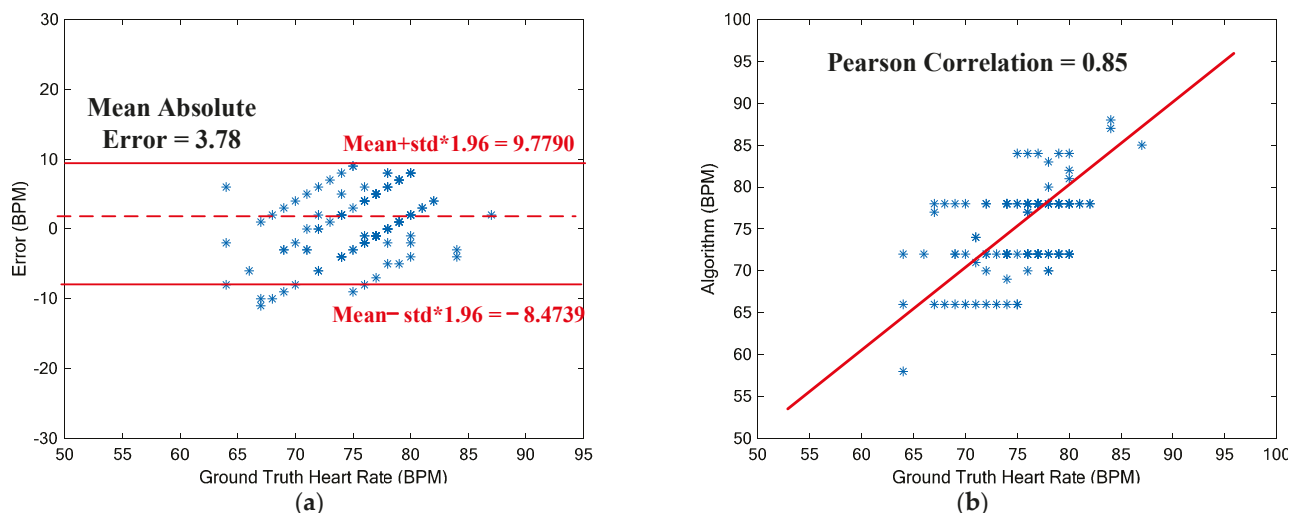


Figure 12. (a) Bland–Altman plot for heart rate estimation. (b) Correlation plot of estimated HRs vs. ground-truth HRs for the case of hand movement.

5.2. Walking

The proposed MAR algorithm for walking was tested again on these 10 subjects for walking, as seen in Figure 11c, while the datasets of the IEEE Signal Processing Cup 2015 were used to evaluate the performance of the developed algorithms. The results are shown in Figure 13. Seen in Figure 13a is the Bland–Altman plot of the results predicted by the proposed algorithm for 8-s windows of walking. The resulting average error is as low as 0.7345 ± 8.1129 bpm (beats per minute), with a mean absolute error (MAE) of 1.86 bpm. The associated Pearson correlation is 0.9499, as seen in Figure 13b. Note herein that the MAE of 1.86 bpm for walking being lower than 3.78 bpm for hand-moving is due to much smaller hand-waving amplitudes during walking than intentional hand movement of the subjects.

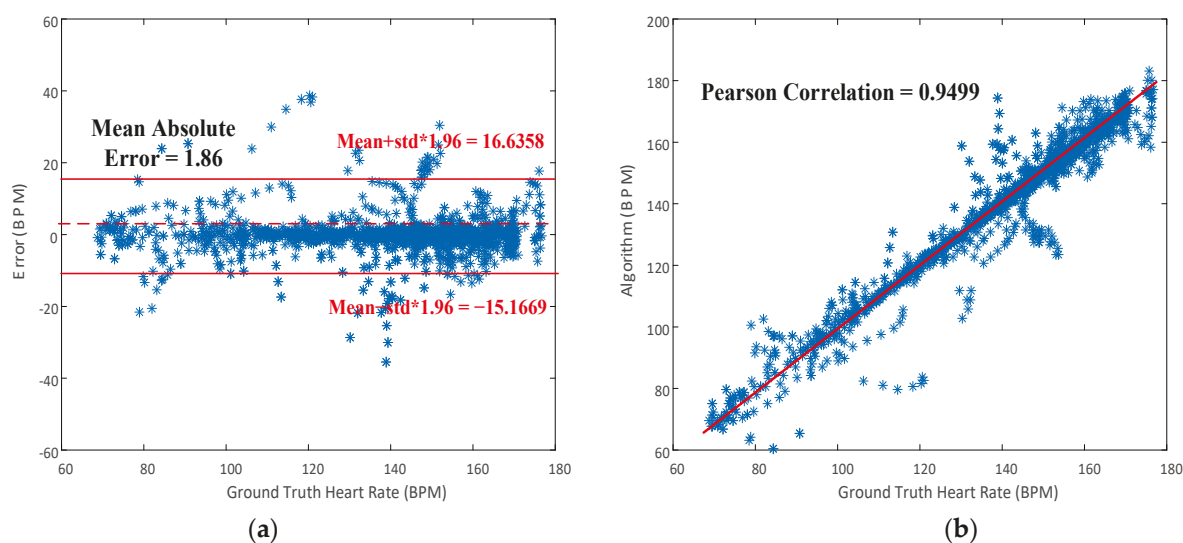


Figure 13. (a) Bland–Altman plot for heart rate estimation; (b) Correlation plot of estimated HRs vs. ground-truth HRs for the case of walking.

5.3. Discussion

The performance of the proposed two sub-algorithms is compared herein to the results delivered by other reported past studies. Table 1 [6,13,19] and Table 2 [8,10,22–25,29,46] show the comparison among the algorithms for hand movement and walking, respectively. The mean absolute error (MAE) is considered the main metric for performance comparison. Table 1 gives the performance comparison with other reported studies on MAR for hand movement, while Table 2 does for walking. It can be seen from Table 1 that the present study shows the best accuracy of 3.78 bpm in mean absolute error (MAE) as compared to all the reported studies. The reasons that the present study renders better results compared to other studies [6,13] are the use of the accelerometer signals as a reference and the much better quality checking offered by this work. In comparison to [19], this work identifies the pulsation from PPG before estimating HR, while the work in [19] relies only on a single accelerometer.

Table 1. Comparison among various techniques for MAR on hand movement.

	Year	Technique	Sensors (Database)	Reference Signal	Movement	Mean Absolute Error in (bpm)	Mean Error (bpm)	Measurement Location
This study	2023	Quality Check and Notch Filtering with peak selection and current and gain tuning	One-channel PPG and 3-axis accelerometer signals recorded in the lab	Accelerometer	Waving the hand	3.78 95% of HR estimation within ± 9.3 bpm	0.6525	Wrist
Lin and Ma [13]	2016	DWT	PPG signals	None	Waving the hand	6.87	NA	NA
Hanyu and Xiao hui [6]	2017	Statistical Evaluation	PPG signals	None	Finger tapping or hand swinging	7.85	NA	NA
Chao Zhao et al. [19]	2021	ICA, VMD, WSST, SSA, and Kalman Smoothing	A three-axis acceleration signals	None	Finger tapping or hand swinging	95% of HR estimation within ± 8.86 bpm	NA	Wrist

As for walking, the mean absolute error (MAE) offered by our algorithm for walking is 1.86 bpm (beats per minute), the second best but very close to the best [46] of all the reported results. Among all the studies in Table 2, most of them [8,10,22,23,29,46] render better results, with MAEs under 3 bpm, where two-channel PPGs and an accelerometer are employed for HR estimation, the same as in this study, to achieve favorable performance. On top of these studies are those [29,46] that achieve MAEs under 2 bpm for walking. Arunkumar and Bhaskar in 2020 [29] achieved an MAE of 1.89 bpm by developing the recursive least squares (RLS) and normalized least mean squares (NLMS) adaptive filters to remove MAs in the frequency domain. As for the work by Motin et al. in 2019 [46], recursive Wiener filtering was employed. Since Wiener filtering has been considered effective in removing MAs by many studies, the result showed a very favorable low error of HR estimation of 1.85 bpm. Even with very low MAEs [29,46], it could be difficult to remove MAs accurately if the frequency of motion (walking) is close to HR. The methods of Hankel and SVD proposed by this study are based on correlations, which are supposedly more capable of identifying and then removing MAs in the frequencies close to HR. In a nutshell, the favorable precision of HR estimation is due to the pre-screening of noises by the quality-check sub-algorithm and the capability of the subsequent Hankel matrices and the associated SVD to identify, decompose, and remove the components in measured PPGs that are highly correlated to motions.

Table 2. Performance comparison among various techniques for MAR on walking.

	Year	Technique	Sensors (Database)	Reference Signal	Movement	Mean Absolute Error (bpm)	Mean Error (bpm)	Measurement Location
This Study	2023	Hankel Matrix, SVD and Spectral Analysis	Two-channel PPG signals, three-axis accelerations	Accelerometer and a single PPG	Walking	1.86	0.7345	Wrist
Amirhossein Koneshloo et al. [22]	2019	Joint Basis Pursuit Linear Program	Two-channel PPG signals, three-axis accelerations	Accelerometer and PPG signal.	Walking and running	2.61	NA	Wrist
Mohammad Abdul Motin et al. [46]	2019	Recursive Wiener Filtering	Two-channel PPG signals, three-axis accelerations	Accelerometer and PPG signal	Walking and running	1.85	NA	Wrist
Wenwen He et al. [23]	2020	Motion tracking, Sparse Representation-based MA elimination, and Spectral Peak Tracking for HR	PPG signals with 3-axis accelerometer signal	Accelerometer	Quasi-periodic motions.	2.40	NA	Wrist
Deniz Alp Savaskan et al. [24]	2020	SPECMAR, TROIKA and JOSS methods along with pre and post processing	Two-channel PPG signals, three-axis acceleration signals for 12 samples	Accelerometer and PPG signal	Walking and running	4.19	NA	Wrist
Youngsun Kong et al. [10]	2019	VFCDM approach, Cubic Spline	Two-channel PPG signals, three-axis acceleration signals	Accelerometer and PPG signal	Walking and running	2.94	NA	Wrist
			Two-channel PPG signals, three-axis acceleration signals (lab)	Accelerometer and PPG signal	Walking and running		NA	Forehead
Nicholas Huang et al. [25]	2020	TAPIR Method	Two-channel PPG signals, three-axis acceleration signals	Accelerometer and PPG signal	Walking	9.21	NA	Wrist
K.R. Arunkumar et al. [29]	2020	Recursive Least Squares (RLS) and Normalized Least Mean Squares (NLMS)	Two-channel PPG signals, three-axis acceleration signals recorded for 23 samples	Accelerometer and PPG signal.	Walking and running	1.89	NA	Wrist
S. Friman et al. [8]	2022	Electromyogram (EMG) and accelerometer (ACC)	PPG signals with three-axis acceleration signals	Accelerometer, EMG and PPG signal	Walking and running	2.83	NA	Wrist

6. Conclusions

Effort was dedicated to developing new algorithms for motion artifact removal (MAR) to accurately estimate heart rate when the subject is in motion, such as hand movement and walking. The proposed algorithm consists of two sub-algorithms. The first is a new quality-assessment criteria to disregard highly noise-contaminated PPG signals, while the second employs the Hankel matrix and SVD to remove motion artifacts. The second sub-algorithm for MAR (motion artifact removal) is built upon (1) assembling Hankel matrices of PPG and accelerations and (2) singular value decomposition to remove the frequency components related to motions for accurate heart rate estimation. The result shows a mean absolute error (MAE) of 1.86 bpm (beats per minute) for walking, the second best but close to the best among all the reported results. As for hand movement, the algorithm shows the best accuracy of 3.78 bpm in MAE as compared to all the other reported results.

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Article

A Vibration Sensing Device Using a Six-Axis IMU and an Optimized Beam Structure for Activity Monitoring

Pieter Try * and Marion Gebhard

Group of Sensors and Actuators, Department of Electrical Engineering and Applied Sciences,
Westphalian University of Applied Sciences, 45897 Gelsenkirchen, Germany; marion.gebhard@w-hs.de

* Correspondence: pieter.try@w-hs.de; Tel.: +49-209-9596-380

Abstract: Activity monitoring of living creatures based on the structural vibration of ambient objects is a promising method. For vibration measurement, multi-axial inertial measurement units (IMUs) offer a high sampling rate and a small size compared to geophones, but have higher intrinsic noise. This work proposes a sensing device that combines a single six-axis IMU with a beam structure to enable measurement of small vibrations. The beam structure is integrated into the PCB of the sensing device and connects the IMU to the ambient object. The beam is designed with finite element method (FEM) and optimized to maximize the vibration amplitude. Furthermore, the beam oscillation creates simultaneous translation and rotation of the IMU, which is measured with its accelerometers and gyroscopes. On this basis, a novel sensor fusion algorithm is presented that adaptively combines IMU data in the wavelet domain to reduce intrinsic sensor noise. In experimental evaluation, the proposed sensing device using a beam structure achieves a 6.2-times-higher vibration amplitude and an increase in signal energy of 480% when compared to a directly mounted IMU without a beam. The sensor fusion algorithm provides a noise reduction of 5.6% by fusing accelerometer and gyroscope data at 103 Hz.

Keywords: inertial measurement unit; sensor fusion; signal processing; structural vibration measurement; activity estimation

1. Introduction

The measurement and analysis of structural vibrations has a wide range of applications. Traditionally, it is used in predictive maintenance to detect the failure of rotating machines [1–3]. The constant vibration of rotating machinery and the high correlation of failure modes and vibration patterns make this application very useful and particularly widespread. Vibration monitoring is also used in structural health monitoring, where vibration sensors are used to assess the condition of buildings and civil structures [4,5]. A key application is monitoring of the occurrence, formation and propagation of damage.

Another application is demonstrated in recent studies, where structural vibration of ambient objects is used to detect and estimate the activity of living creatures. These methods are able to obtain a wide range of information such as human occupancy [6], foot step location [7], different human activities [8,9] as well as animal activity of pigs [10] and mice [11]. When living creatures perform physical activities, they interact with ambient objects such as the floor, walls and furniture. These interactions cause the ambient objects to vibrate. The vibration contains different frequency components that are related to the oscillation modes and are unique for different interactions. The main challenges are the measurement of small vibrations and the data analysis to detect and classify activity. In most instances, geophones are used to measure vibrations because they provide low noise due to their large proof mass. However, geophones have several weaknesses that make them unsuitable in some scenarios.

In our previous work, non-contact activity monitoring of mice is demonstrated, which uses a commercially available multi-axial inertial measurement unit (IMU) to measure

activity-induced structural vibrations of the husbandry cage [11]. This method enables activity monitoring in large-scale mouse husbandry, where thousands of mice are held in individually ventilated husbandry cages that are stacked in racks. There are established methods for activity monitoring of mice which are not suitable for large-scale husbandry due to cost. These use radar [12], cameras [13,14] or electromagnetic detection methods [15,16]. A method using low-cost sensors enables large-scale monitoring, reducing the workload for human caretakers, improving response time for animal care and providing continuous long-term activity data for studies. In our previous work, the IMU is mounted in the center on the outside of the cage floor and continuously monitors cage vibrations in three spatial directions. These data are split into 10 s intervals and preprocessed, then a classification algorithm is used to estimate the activity level of the mouse inside. In this scenario, geophones are unsuitable, because they cannot physically fit below a cage due to the cages being stacked in racks. A large geophone would also interfere in the handling of the cages. Furthermore, the husbandry cage is observed to exhibit vibrations with a frequency of over 250 Hz, which is above the frequency range of commonly used geophones [17]. In contrast, IMUs provide many benefits in this use case, including small size, low weight, high performance-to-cost ratio, high sampling rate and multiple sensors in a single chip. Especially, the multiple sensors are shown to provide additional information that improves classification accuracy. However, a disadvantage of commercial micro-electro-mechanical systems (MEMS) sensors is their intrinsic noise. As a result, very small vibrations cannot be detected, thus impacting the classification accuracy. A promising technique used in several applications is the functional use of the supporting structure e.g., efficient energy harvest [18]. This approach is also shown to improve state estimates in robotics by taking the flexibility of the robotic limbs into account [19].

In this work, a sensing device is proposed that uses a mechanical beam structure to achieve improved vibration sensing with a single multi-axial IMU. The beam is integrated in the printed circuit board (PCB) of the device, where the IMU is mounted on one end of the beam and the other end is mounted to the ambient object. This arrangement significantly increases the vibration amplitude at the IMU location, thereby increasing the signal-to-noise ratio (SNR). Furthermore, a sensor fusion algorithm is presented that combines the data from the accelerometers and gyroscopes to reduce the intrinsic noise of the sensor. The sensor fusion is based on the correlation of the linear acceleration and angular rotation of the IMU, which occurs due to certain oscillation modes. The key contributions of this work are as follows:

- A novel method is presented to enhance the vibration sensing capabilities of multi-axial sensors, such as IMUs, and the concept is evaluated in simulation and experiment.
- A PCB-based vibration amplifying beam structure is designed, optimized and experimentally validated.
- A novel sensor fusion algorithm is presented, which uses the unique oscillation modes of the beam structure to combine multiple sensor signals to reduce noise. The algorithm is suitable for arbitrary multi-axis sensors and beam structures.
- An experimental study is devised to evaluate the concept in an application environment, where the desired vibration amplification and noise reduction through sensor fusion is successfully demonstrated.

2. Materials and Methods

In previous work [11] it is observed that many physical activities only induce very small vibrations z_1 , which are below the noise floor of commercial IMUs. The proposed sensing device aims to amplify these vibrations to improve the detection of activities that only generate very small vibrations. Sections 2.1 and 2.2 outline the generalized model for the oscillation of ambient objects. Sections 2.3 and 2.4 illustrate the FEM simulation to analyze the use case and generate an optimized beam design. In Section 2.5, the sensor fusion algorithm is presented, which combines accelerometer and gyroscope data to reduce

the intrinsic sensor noise. The experimental setup is shown in Section 2.6, which serves to evaluate the proposed concept.

2.1. Physical Model of Activity-Induced Vibration

Previous work has shown that living creatures create structural vibrations through different force pulses during physical activity. These forces cause the vibration and natural oscillation of ambient objects. A generalized physical model of an environmental object is given by a spring mass damper system. The forces that are generated by physical activity act on the mass and cause oscillation. This model is illustrated in (A) of Figure 1.

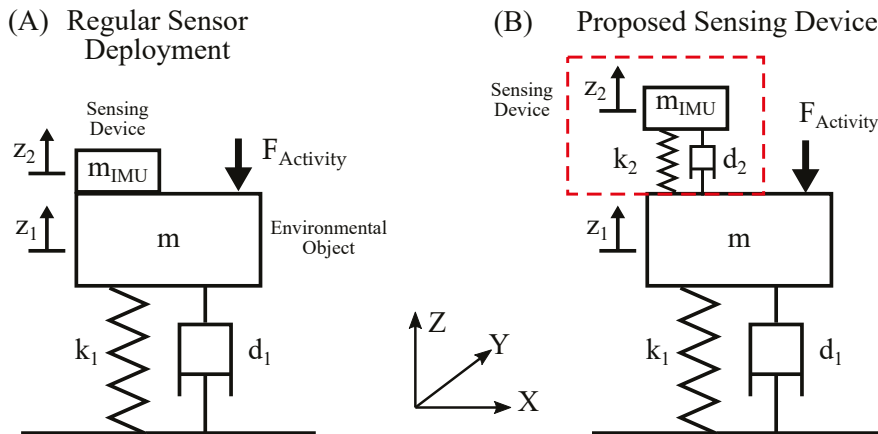


Figure 1. This figure illustrates the generalized physical model of the proposed sensing device. Subfigure (A) shows a regular directly mounted IMU and (B) shows an IMU with an added spring mass damper system as proposed.

In the regular setup labeled as (A), the sensor is directly mounted to the object. The environmental object usually has a mass m that is much greater than the mass of the IMU m_{IMU} . Thus, the influence of the IMU can be neglected. Physical activity of living beings applies force pulses $P = \int F_{Activity} dt$ on the object, which generates dampened natural oscillations. Given the rigid mounting of the sensor, the position of the sensor z_2 is equal to the position of the environmental object z_1 .

2.2. Beam Structure for Vibration Amplification

The proposed sensing device employs an additional spring mass damper system situated between the environmental object and the IMU, which is shown in (B) of Figure 1. By optimizing the parameters m_{IMU} , k_2 and d_2 of this spring system, an amplified oscillation $z_2 > z_1$ can be achieved. This setup forms a two-mass-spring damper system. Depending on the scenario, the influence of the sensing device on the environmental object cannot be neglected. Analytical analysis of systems with complex geometry is near impossible and numerical methods are generally used to find solutions. In this work, finite element method (FEM) analysis in Ansys Mechanical [20] is employed to analyze the oscillating system, which is presented in Sections 2.3 and 2.4.

It is proposed to implement the additional spring mass damper system as a beam structure. One end of the beam is mounted to the ambient object and the IMU is mounted on the other end. Furthermore, the beam is integrated in the PCB of the device and contains the electrical connections. This approach has many benefits, such as ease of manufacturing and implementation in devices. The beam is designed and optimized using FEM simulation, which is described in detail in Section 2.4. Although not suitable for determining vibration characteristics, the classical equations for the deflection of a beam under load [21] are helpful in formulating design criteria. The forces that act on the sensing device are shown in Figure 2.

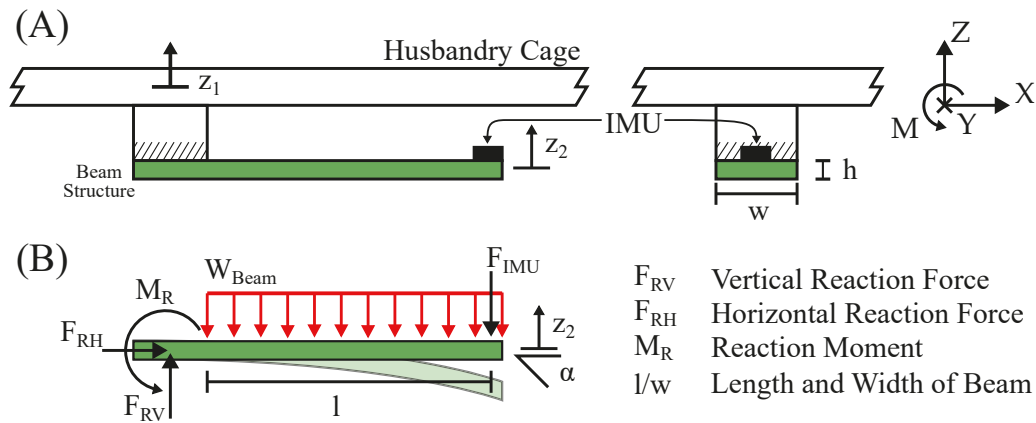


Figure 2. This figure illustrates the forces acting on the beam structure and IMU of the sensing device. In (A), a conceptual drawing shows a sensing device mounted on the floor of a husbandry cage. In (B), a mechanical drawing illustrates the forces acting on the beam.

An activity-induced force pulse $P = \int F_{Activity} dt$ acts vertically on the cage floor, causing a natural oscillation of the cage. As described in Section 2.3, the cage floor oscillates like a membrane. The displacement z_1 of the cage floor oscillation exerts a force on the sensing device. This force acts as a vertical reaction force F_{RV} on the base of the beam. It is directly opposed by the inertial force of the beam W_{Beam} and sensor F_{IMU} . In order to calculate the displacement at the end of the beam, where the IMU is located, F_{IMU} is neglected as it is much smaller than $W_{Beam}l$. The tilt angle and displacement are calculated as:

$$\theta = \frac{W_{Beam}l^3}{6EI_y}, \quad (1)$$

$$z_2 = \frac{W_{Beam}l^4}{8EI_y} = \theta \frac{4l}{3}, \quad (2)$$

where z_2 is the displacement, θ is the tilt angle, E is the Young's modulus and I_y is the moment of inertia [21]. Equation (2) further shows that the displacement z_2 and the tilt angle θ are linearly correlated. As a six-axis IMU is capable of measuring both variables directly, this circumstance allows for sensor fusion, which is further described in Section 2.5.

For proof of concept, a first design of the beam is proposed here. Other designs will be explored in the future. This design resembles a bending beam, which is split laterally and folded to form two parallel braces that are shaped around the base. This design shifts the center of mass further to the base of the beam, which reduces the moment generated by the beam. It is shown in Figures 3 and 4. The manufacturing of the prototype requires some design restrictions: The beam needs a surface to mount to the cage and one to mount the IMU, where the surfaces have a size of $17 \text{ mm} \times 17 \text{ mm}$ each. The braces need a minimum width w of 3 mm to accommodate the data lines. The interspace in the beam needs to be at least 4 mm wide.

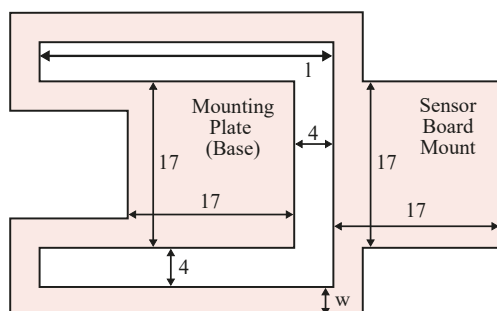


Figure 3. Technical drawing of the beam structure design.

For prototyping purposes, the system on a chip (SoC) of the IMU is not mounted directly to the beam structure but to a small daughter board shown in Figure 4, which contains the IMU. This daughter board is easily desoldered and mounted on another prototype for testing without damaging the delicate SoC.

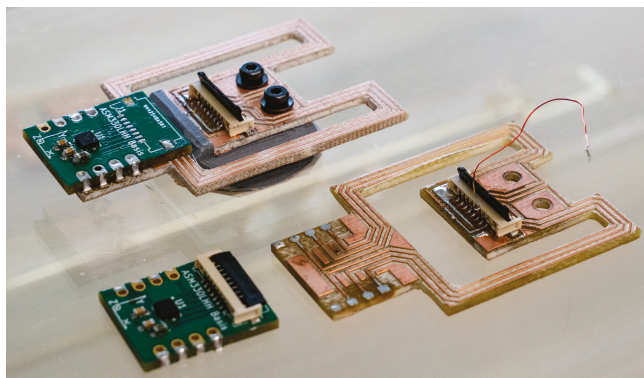


Figure 4. This figure shows two different beam structures and two sensor boards with the ASM330LHHTR 6-axis IMU. The upper beam is fully assembled and has braces with a width of 3 mm and a length of 30 mm. The lower beam has braces with a width of 3 mm and a length of 27 mm.

2.3. FEM Analysis of the Ambient Object

The design of the beam structure needs to be adapted to the vibration characteristics of the object. The ambient object in this use case is the husbandry cage HRC500 from Zoonlab, which is evaluated in the finite element analysis (FEA) software Ansys Mechanical. Some simulation results are illustrated in Figure 5. The simulation uses a CAD model of the HRC500 cage from Zoonlab [22]. The parameters for the PSU material of the cage were adopted from the Ansys library with a change to the density to match the real weight of the cage. The cage is fixed on its lateral side rails, which are on either side of the cage. In addition, a distributed mass of 200 g is applied to the bottom of the cage to simulate the wood flocking that typically covers the floor.

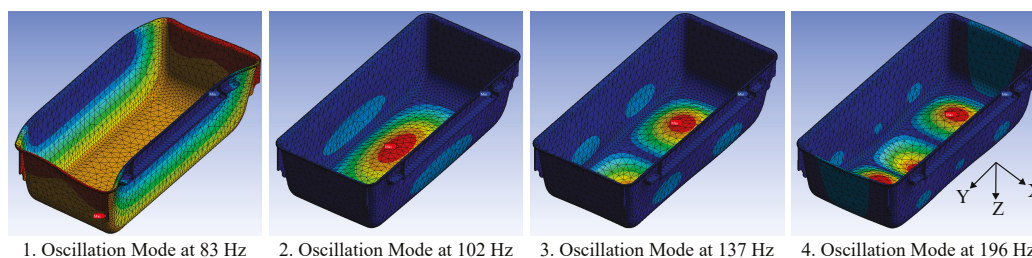


Figure 5. This figure illustrates the first four oscillations modes of the husbandry cage from a modal analysis.

Figure 5 illustrates the first four oscillation modes of the Zoonlab HRC500 husbandry cage. The 1st mode shows a lateral displacement of the entire cage. The 2nd to 4th modes are membrane-like oscillations of the cage floor with different numbers of peaks and nodes. The 2nd mode has one peak and no nodes. The 3rd mode has two peaks and one node, while the 4th mode has three peaks and two nodes. The simulation predicts many more oscillation modes that follow a similar pattern.

The simulation results suggest that the cage primarily exhibits a membrane-like oscillation of the cage floor. This is also observed in previous work [11]. Furthermore, when the cage floor is excited by a vertical force pulse, the 2nd mode has the highest displacement. It is therefore concluded that the center of the cage floor is the ideal location for the IMU.

2.4. FEM Analysis Beam Design

In order to optimize the design shown in Figure 3, a large number of parameters and dimensions can be adjusted. Some parameters are already set due to manufacturing, assembly and mounting requirements. The remaining parameters are the length, height, width, Young's modulus and mass. While the mass is proportional to the overall size, the height and Young's modulus can only be changed by using a different raw material. Therefore, the main parameters for optimizing the design are the length and width. These are defined in Figure 3 as the width w of each of the symmetrical braces and the length l of the outer brace.

In order to analyze the beam structure in its intended use case scenario, the simulation includes the cage as described in Section 2.3. The beam structure is mounted in the middle of the cage floor with a spacer to allow for oscillation. The geometry of the sensor board is not modeled since it does not influence the oscillation characteristics, but the mass of the sensor board is simulated with a surface mass. The IMU is represented by a $2\text{ mm} \times 3\text{ mm} \times 2\text{ mm}$ rectangle and assembled on the sensor board mount surface. The material characteristics of the beam are set to a standard FR-4 glass-reinforced epoxy laminate material from the Ansys library.

The modal analysis depicts the oscillation characteristics of the beam when mounted on the cage and shows that the beam exhibits many oscillation modes. However, some of them have a similar form of deformation and typically occur in the same frequency range. The oscillation modes are grouped together based on their deformation form. In Figure 6 four different deformation forms are presented of a beam structure with $w = 3\text{ mm}$ and $l = 29\text{ mm}$.

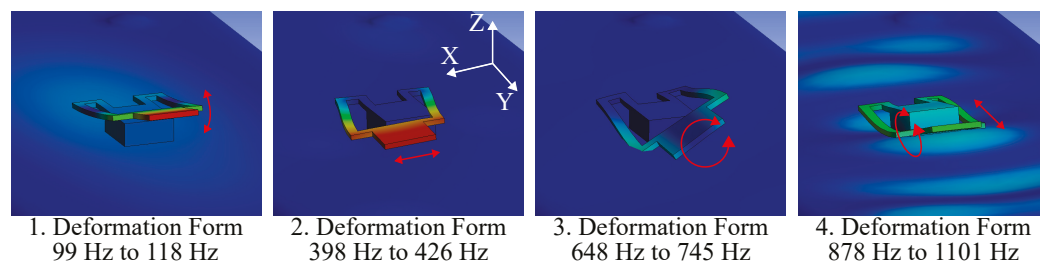


Figure 6. This figure shows four types of oscillation of a sample beam structure. The beam has braces with a width of 3 mm and a length of 29 mm. The deformation is shown exaggerated and the red arrows visualize the displacement.

The first deformation form appears in the range of 99 Hz to 118 Hz and exhibits a bend in the z -axis, which is accompanied by a rotation around the x -axis. The second form shows a sideways movement in the x -axis and occurs between 398 Hz to 426 Hz. The third form shows a twisting deformation around the y -axis and appears in the range of 648 Hz to 745 Hz. The fourth form shows a twisting motion around the x -axis and a back-and-forth movement in the y -direction. It occurs in the range of 878 Hz to 1101 Hz. Beam structures with similar dimensions exhibit the same deformation forms at different frequencies.

A transient structural FEM analysis is performed to evaluate the activity-induced structural vibration of the cage. The simulation is 0.3 s long with a step time of $50\text{ }\mu\text{s}$. At 1 ms, a force pulse of $P = 0.15\text{ N} \times 1\text{ ms} = 150\text{ }\mu\text{Ns}$ is applied to the center of the cage floor. Afterwards, the system continues its dampened oscillation undisturbed. The result of the simulation is the acceleration at the location of the virtual IMU in the x -, y - and z -direction. The amplitude of the oscillation modes is evaluated in the frequency domain by Fourier transforming the output acceleration data.

Based on this simulation setup, a design with maximum vibration magnitude is identified in Section 3.1 by comparing beams with different w and l dimensions to determine optimal dimensions.

2.5. Sensor Fusion Algorithm

The IMU data consist of six signals, which are the three acceleration signals a_x , a_y and a_z and the three angular rate signals ω_x , ω_y and ω_z . In the standard configuration, where the sensor is mounted directly on an object, the different sensor signals of the IMU are not directly correlated and cannot be fused in the time domain e.g., to reduce noise. This is shown in [11] where statistical information from different sensors is combined to improve classification accuracy. However, the signals could not be combined on a per-sample basis to reduce noise or increase the SNR.

The simulation of the beam structure in Section 2.4 shows that certain oscillation modes of the beam are composed of displacement in multiple axes. This creates a mechanical coupling between the different signals of the IMU, which enables sensor fusion. Using prior knowledge of the oscillation modes, a sensor fusion algorithm is proposed that combines multiple correlated sensor signals to create a single signal with lower noise. As the SNR varies between signals, a main signal is determined first, which has the highest SNR. The correlated signals are then combined to reduce the noise of the main signal.

The sensor signals are modeled as a vibration f with additive Gaussian noise with zero mean. The noise of the different signals is uncorrelated, since the intrinsic sensor noise is mainly due to the thermal noise of the proof mass in each sensor. The underlying theory is presented in the following. Two signals of different sensors are denoted as:

$$x = f + \mathcal{N}_x(\mu = 0, \sigma_x^2), \quad (3)$$

$$y = f + \mathcal{N}_y(\mu = 0, \sigma_y^2), \quad (4)$$

where x and y are the two measurements, $\mathcal{N}$ denotes the corresponding additive noise, σ^2 is the variance of noise and f is the vibration. A weighted estimator z is constructed to combine the signals x and y :

$$z = cx + (1 - c)y, \quad (5)$$

$$z = f + \mathcal{N}_z(\mu = 0, \sigma_z^2), \quad (6)$$

$$\sigma_z^2 = c^2\sigma_x^2 + (1 - c)^2\sigma_y^2, \quad (7)$$

where $\mathcal{N}_z$ is the noise of the estimator z , σ_z is the noise variance and c is the weight. By minimizing σ_z in Equation (7), the optimal value of c is determined as:

$$c = \frac{\sigma_x^{-2}}{\sigma_x^{-2} + \sigma_y^{-2}} \quad (8)$$

In the ideal case $\sigma_x = \sigma_y$, the weight is $c = 0.5$. Using Equation (7), the standard deviation of noise of the estimator is calculated as $\sigma_z \approx 0.707\sigma_x$. For an example with two signals with $\sigma_y = 2\sigma_x$, the weight is $c = 0.8$ and the standard deviation of the estimator is $\sigma_z \approx 0.89\sigma_x$.

There are three main challenges in fusing IMU data. First, the sensor signals of the IMU, which are supposed to be fused, are correlated but do not have the same amplitude, which is denoted as f above. Therefore, the signals must first be transformed to equalize the amplitude. For this purpose, a linear transformation is proposed as it maintains the normal distribution of the noise. Second, the structural vibration measurement contains many oscillation modes simultaneously and the correlation as well as transformation between the signals depend on the mode. However, since each mode has a different frequency, it is possible to fuse signals by combining data with regard to the frequency. Third, the noise variance is required to calculate the optimal weights and needs to be estimated.

Figure 7 presents an overview of the sensor fusion algorithm. The first step in the sensor fusion algorithm is preprocessing, which involves discrete differentiation of the angular rate signals ω_x , ω_y and ω_z to obtain the angular accelerations $\dot{\omega}_x$, $\dot{\omega}_y$ and $\dot{\omega}_z$. The signals

are then decomposed using multi-level discrete wavelet transformation (MLDWT) [23], which is a key element and enables the frequency-dependent fusion of IMU data.

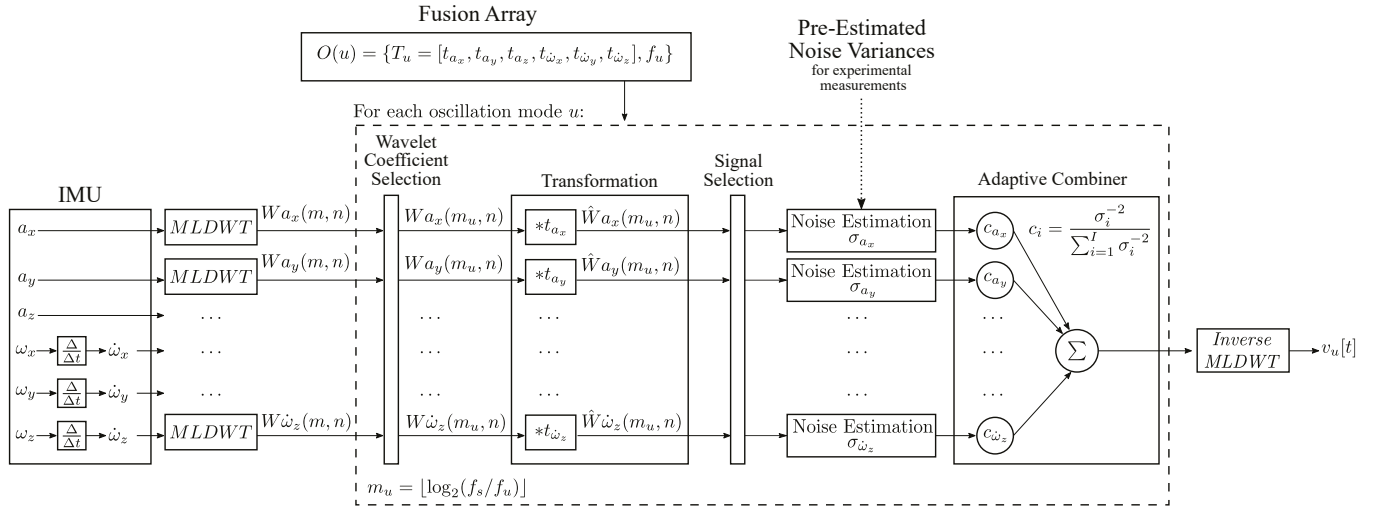


Figure 7. This diagram illustrates the structure of the sensor fusion algorithm.

MLDWT is a wavelet-based analysis method for discrete signals, which extracts time-frequency features by decomposing time signals into low-frequency and high-frequency subseries on multiple levels. The MLDWT decomposes a discrete time signal into one approximation coefficient and M detail coefficients. Each coefficient represents time-frequency information of a unique range of frequencies. By fusing the wavelet coefficients of different signals at a specific level, signals can be fused with regard to frequency. The result of the fusion is a single wavelet coefficient. The appropriate mother wavelet for the MLDWT is determined experimentally by minimizing the error of a sample signal with vibrations and the transformed and recomposed version of the same signal. It is chosen to be a Coiflet wavelet with five vanishing points. Furthermore, the number of decomposition levels is $M = \lfloor \log_2(N) \rfloor$, where N is the length of the signal.

In the next step, data fusion is performed for each previously defined mode. The wavelet level m_u , which contains the frequency component f_u of an oscillation mode u , is calculated as:

$$m_u = \lfloor \log_2(f_s/f_u) \rfloor, \quad (9)$$

where u is the index of the mode, f_s is the sampling rate and f_u is the frequency of the oscillation mode. The level m_u is then used to extract the relevant wavelet coefficients. Fusion at each oscillation mode requires some prior knowledge of the system, which is provided by the fusion array $O(u)$. Each element of the fusion array contains a vector with six coefficients t_{a_x} to t_{ω_z} and the frequency f_u of the oscillation. The coefficients t_{a_x} to t_{ω_z} describe the transformation between the signals. The coefficients are determined experimentally by measuring high amplitude vibrations and numerically estimating the transformation coefficients by minimizing the mean squared error (MSE).

A transformation coefficient of 1 is assigned to the main signal with the highest SNR. As a result, the other signals are transformed to match the amplitude of the main signal. Signals that are not correlated by the beam oscillation have a coefficient of zero and are removed by the Signal Selection Filter. An example for an element of the fusion array is shown in Equation (24). The transformation of wavelet coefficients is a multiplication with the transformation coefficient:

$$W\hat{S}(m_u, n) = t_S Ws(m_u, n), \quad (10)$$

where $WS(m_u, n)$ is the wavelet coefficient of a signal from the IMU, t_S is the corresponding transformation coefficient and $W\hat{S}(m_u, n)$ is the transformed value. After transformation, uncorrelated signals are removed by the Signal Selection Filter, which removes signals with a total sum of zero. In the next step, signals are combined by the adaptive combiner. The optimal weights are calculated as:

$$c_i = \frac{\sigma_i^{-2}}{\sum_{i=1}^I \sigma_i^{-2}}, \quad (11)$$

where i is the index representing the different signals for fusion, c_i is the optimal weight for signal i , σ_i is the standard deviation of noise of signal i and I is the total number of signals to fuse. The result is a single wavelet coefficient containing the combined sensor signals. The time signal of the fusion result is obtained using inverse MLDWT. The result is a time signal with a narrow frequency band, as it only represents the oscillation of a single oscillation mode.

The noise standard deviation σ_i of each signal needs to be estimated. The implemented estimator is based on [24] and estimates the noise variance by calculating the median of the wavelet coefficients in a section where f is piecewise smooth. This is a section where little or no vibration occurs. The standard deviation of the noise is estimated to be:

$$\sigma_i = \frac{Med(|S_i|)}{0.6748}, \quad (12)$$

where $Med(|S_i|)$ is the median of the signal S_i . The analysis of the sensor noise shows that the noise in the accelerometers has a uniform noise density and Gaussian distribution. In this case, the best estimate is calculated by analyzing the finest-scale wavelet coefficient. The noise in the gyroscope signals is unevenly distributed in the frequency domain and increases at higher frequencies. Because the noise is level-dependent, it must be estimated for each wavelet coefficient individually.

In the real-world scenario, piecewise smooth sections need to be identified to update the noise estimates. In the experimental measurements presented here, no piecewise smooth section is available for noise estimation. Therefore, the noise variance is estimated prior using a separate measurement without vibrations. It is provided as the noise matrix:

$$\sigma_{IMU} = \begin{bmatrix} \sigma_{a_x 1} & \cdots & \sigma_{a_x M} \\ \vdots & \ddots & \vdots \\ \sigma_{\dot{\omega}_z 1} & \cdots & \sigma_{\dot{\omega}_z M} \end{bmatrix} \quad (13)$$

2.6. Experimental Setup

The proposed concept is validated experimentally by measuring structural vibrations of a husbandry cage using different sensor arrangements. The vibrations are generated with a custom-built force pulse generator. The experimental setup emulates activity-induced structural vibrations with force pulses that act vertically on the cage floor. The setup includes: mice cages of type Zoonlab HRC500 [22], 200 g of wood flocking, an aluminum stand for the cages, a force pulse generator, a heavy aluminum base to reduce external vibrations and several microcontrollers. The components are shown in Figure 8.

There is a wide selection of commercial multi-axial IMUs available such as the Bosch BMI270 [25], STMicroelectronics ASM330LHHTR [26] and the TDK InvenSense ICM20948 [27]. For this work, the ASM330LHHTR was chosen due to its superior noise characteristics and sampling rate. It has a noise density of $60 \mu\text{g}/\sqrt{\text{Hz}}$ for the accelerometers and $0.005 \text{ dps}/\sqrt{\text{Hz}}$ for the gyroscopes, which is lower than the other IMUs mentioned. Furthermore, it has a maximum sampling rate of 6667 Hz for all sensors.

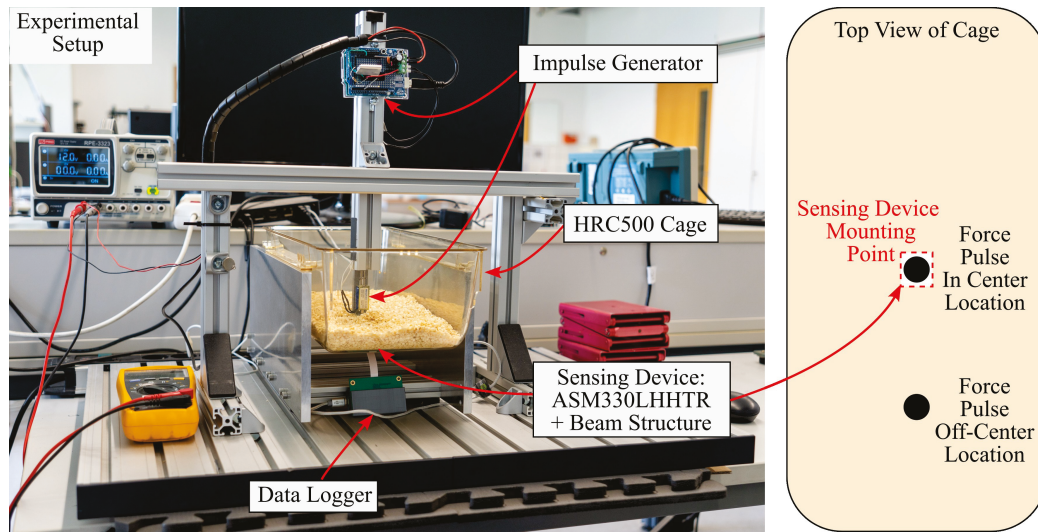


Figure 8. This figure shows the experimental setup. It depicts the force pulse generator, the cage stand, the base plate and a mice cage. On the right, the location of the sensor and the force pulses are shown as a schematic.

Two sensor arrangements are evaluated, which are shown in Figure 9. The first arrangement serves as reference and has an IMU directly mounted in the center of the cage. This location is deemed the optimal location in Section 2.3. The second cage has an IMU with the proposed beam structure. The beam uses the optimal design that is covered in Section 3.1. The prototype is milled from a piece of FR-4 PCB material. Both arrangements use the same STMicroelectronics ASM330LHHTR sensor.

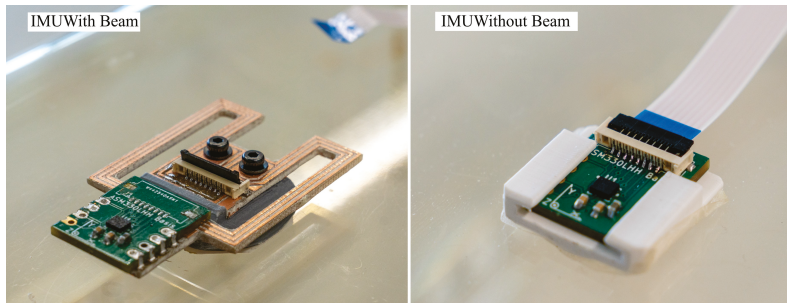


Figure 9. This figure shows the two sensor arrangements that are evaluated in the experiment.

Another parameter of the experiments is the location where the force pulses act on the cage. Two excitation locations are defined to investigate whether amplification also occurs when the cage is excited at different locations. The first location is the center of the cage floor. The second location is beside the center and about half the distance towards the short side of the cage. The locations are illustrated in Figure 8.

2.6.1. Force Pulse Generator

The experiment requires a purpose build force pulse generator, which is able to generate very small force pulses. The force pulse generator uses a magnetic actuator and is driven with a rectangular signal of 12 V. The pulse amplitude is controlled by the duration of the rectangular control signal and is modulated between 0 s and 1000 μ s. At 12 V, the actuator generates a constant force of 2.16 N, which amounts to a force pulse range of 0 to 2.16 mN s. The force pulse is calculated as:

$$|\vec{p}| = |\vec{F}| \Delta t, \quad (14)$$

where Δt is the duration of power supplied to the actuator and $|\vec{F}|$ is the force generated by the actuator. The repeatability error of the experimental setup is explored in Section 2.6.3.

For comparison, the pulse of a free-falling object can be calculated as $|\vec{p}| = m|\vec{v}| = m\sqrt{2gh}$ when air resistance is ignored. A 25 g mouse would therefore create a pulse of 7.83 mN s when it lands from a height of five millimeter.

2.6.2. Experimental Measurements

The experimental evaluation aims to explore the characteristics of the proposed sensing device compared to a directly mounted sensor for different force pulse strengths and excitation locations. In the experiment, force pulse sweeps are used to investigate the aforementioned characteristics. The individual force pulses are spaced apart by 0.5 s, which allows each structural vibration to decay before the next starts. Each measurement begins with a starting sequence of four force pulses, after which 100 force pulses are generated at a rate of 2 Hz. The pulses go up in equidistant steps. In this work, several experiments are presented which have different amplitude ranges and location of force pulse application depending on the evaluation. A sample of a measurement is shown in Figure 10.

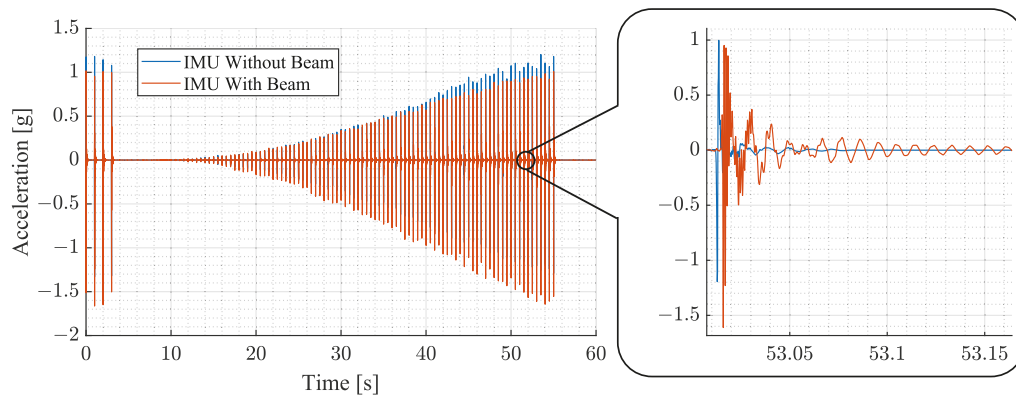


Figure 10. This figure shows a sample of the experimental measurements. It depicts the magnitude of acceleration over a span of 60 s. The plot in blue represents results of an IMU directly mounted to the cage without a beam. The plot in orange depicts the results using an IMU with the proposed beam structure.

2.6.3. Repeatability of Experimental Setup

The repeatability error of the experimental setup is assessed throughout the entire range of force pulse amplitudes. For this, twenty amplitude sweeps are recorded using an IMU without the beam structure. The amplitude sweep consists of 100 pulses from 21.6 $\mu\text{N s}$ to 2160 $\mu\text{N s}$ and the force pulses are located in the center. Based on the acceleration data, the vibration magnitude is calculated for each force pulse. Afterwards, the mean and standard deviation are calculated to determine the average magnitude and error. As a measure of magnitude, the energy of the acceleration magnitude $|\vec{a}|$ is calculated. The energy is calculated over a period of 0.2 s, which is the longest duration of a decaying vibration. The magnitude and energy are calculated as follows:

$$|\vec{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2}, \quad (15)$$

$$E[i] = \sum_{n=1}^{N=[0.2s \times f_s]} |\vec{a}[n]|^2, \quad (16)$$

where $E[i]$ is the energy at a certain force pulse i , N is the number of samples and f_s is the sampling rate of the sensor. The mean and standard deviation of $E[i]$ are shown in Figure 11.

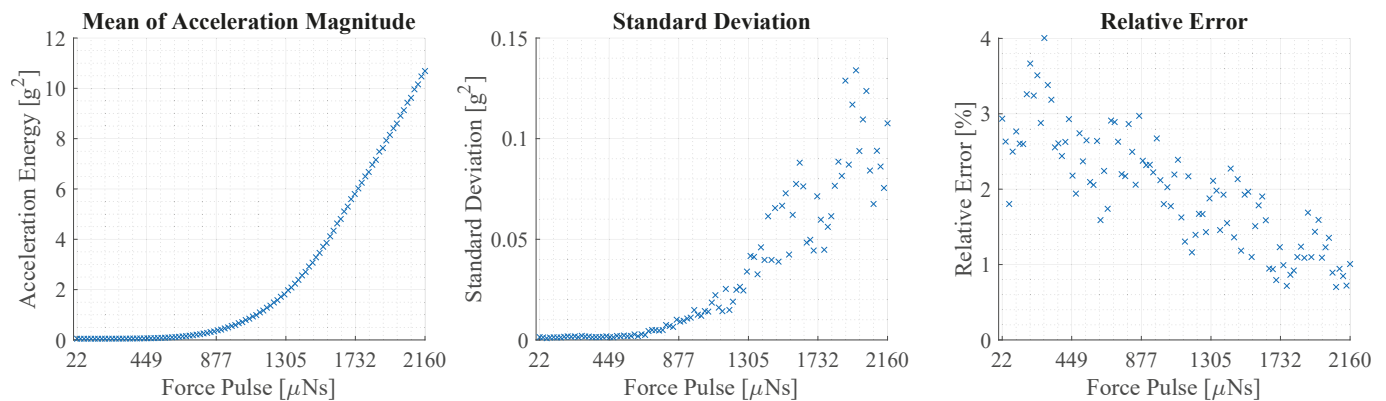


Figure 11. This figure illustrates the repeatability error of the experimental setup. The left plot displays the average vibration magnitude of 20 measurements at force pulses between 21.6 μNs and 2160 μNs . The plot in the middle shows the standard deviation. The plot on the right shows the relative error, which is the standard deviation divided by the average.

The average vibration magnitude in the left plot of Figure 11 has a flat slope at the beginning that becomes steeper as it progresses. The error depicted in the plot in the middle follows a similar path and increases with the magnitude of the vibration. The relative error shown in the right plot is calculated as the fraction of error and average. It shows a declining trend with a variation of about $\pm 1\%$. In the beginning, the values average about 3% and decline to about 1% at the end.

The results illustrate that the experimental setup is capable of generating structural vibrations with a high degree of repeatability. Furthermore, it is observed that the energy of the vibration magnitude does not rise linearly with the force pulse amplitude. Although starting at about 1550 μNs , the average energy appears to enter a quasi-linear region.

3. Results

The performance of the proposed sensing device is evaluated based on measurements of structural vibrations, which are generated with a highly repeatable experimental setup. This allows for a direct comparison between a rigidly mounted sensor and the proposed IMU using a PCB beam structure. The results of the FEM simulation and experimental evaluations are presented in the following.

3.1. Beam Optimization

As described in Section 2.4, the structural vibration of the system of cage and beam structure is simulated to determine an optimal design of the beam that maximizes the vibration amplitude. The best result is achieved using a beam with a width of 3 mm and a length between 27 mm and 36 mm. The results are shown below and a simulation without a beam structure is included for reference. In the context of the beam structure, the width corresponds to the variable w and the length to l as described in Section 2.4.

Figure 12 illustrates the acceleration observed at the location of the virtual IMU. The x -axis depicts the different simulations. For each simulation, the bars depict the signal energy E_i for the x -, y - and z -axis, respectively, as well as the total energy E_{Total} . The signal energies are calculated as:

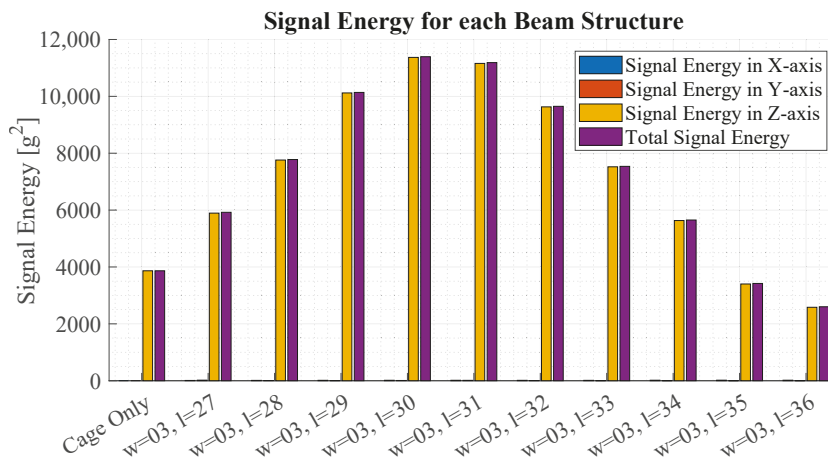


Figure 12. This figure shows the signal energy of the IMU using beam structures with different lengths from 27 mm to 36 mm in the FEM analysis. The bars illustrate the signal energy in the x -, y - and z -axis, respectively, as well as the energy of the magnitude. All beams have a width of 3 mm.

$$E_i = \sum_{n=1}^N a_i^2, \quad (17)$$

$$E_{Total} = E_{a_x} + E_{a_y} + E_{a_z}, \quad (18)$$

where a_i is one of the three acceleration signals and N is the number of samples. The bars show that most of the signal energy is contained in the z -axis. Starting from the left, the total signal energy rises up to the beam of length 30 mm, which has the highest signal energy. Compared to the simulation without a beam, the beam exhibits a 1.72-times-higher signal energy.

From these results, it is concluded that the beam structure with a width of 3 mm and a length of 30 mm exhibits the highest signal energy, which makes it the most optimal design to achieve a high SNR.

3.2. Vibration Spectrum in Simulation

The four beams, from Section 3.1, with the highest signal energy are analyzed further by Fourier transforming the acceleration data. The spectrum of acceleration for the x -, y - and z -axis, respectively, is shown for beams with a length 29 mm to 32 mm in Figure 13.

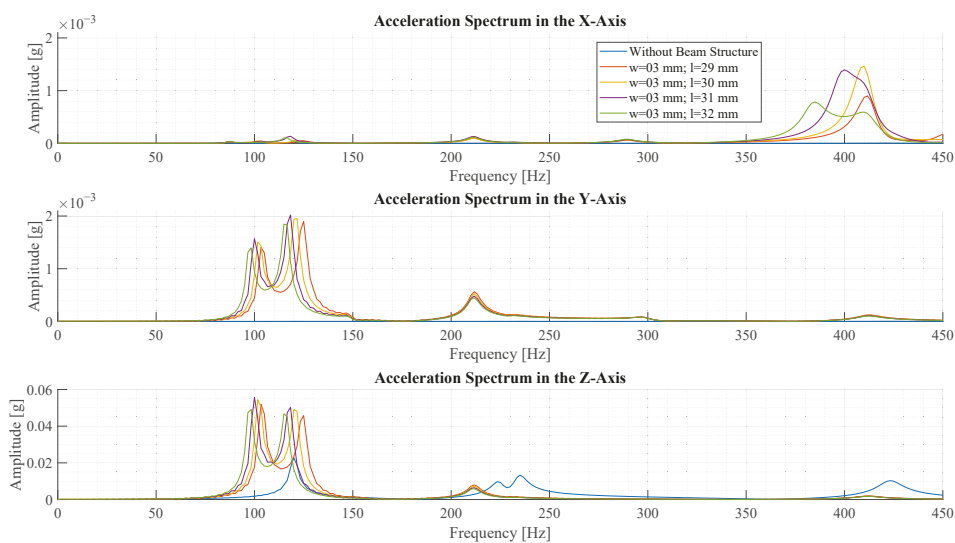


Figure 13. This figure illustrates the frequency spectrum of vibrations with different beam structures in a transient structural simulation. The vibration is created by a simulated force pulse of 150 $\mu\text{N s}$.

The spectrum of the IMU without a beam only exhibits a few small peaks in the z-axis. The results using a beam structure show multiple peaks in all axes. Between these results, the peaks exhibit similar frequency and magnitude. It is observed that a longer beam results in oscillation of lower frequency. Due to the resolution of the Fourier transform, the exact amplitude at the peak can only be estimated, but the beams with length 29 mm and 30 mm exhibit the highest amplitude at a frequency of around 102 Hz.

The spectra of simulations with a beam depict the deformation forms described in Section 2.4. The big peak in the z-axis and the smaller peak in the y-axis around 100 Hz correspond to the first deformation form. The peak at 400 Hz in the x-axis corresponds to the second deformation form. Since the sensor is in the axis of rotation of the third form, there is no acceleration peak at 700 Hz. Frequency components corresponding to the fourth form are not visible in the spectrum.

Comparing the 30 mm beam to the simulation without a beam, based on the amplitude of the highest peaks, a 2.4-times-higher amplitude is observed with the beam. All in all, the simulation shows that the signal amplitude and energy are amplified by using a beam to sense vibration.

3.3. Experimental Vibration Amplification

The experimental evaluation involves multiple measurements with force pulse sweeps from 21.6 μN s to 2160 μN s, where two characteristics are explored. The first is the amplification of vibration achieved by the proposed sensing device. For this, measurements using an IMU without a beam are compared with measurements of an IMU with the beam structure. Secondly, the location-dependency of the vibration amplification is explored by changing the location of the force pulses between the center and an off-center location shown in Figure 8. Twenty measurements are recorded for each combination of sensor arrangement and excitation location for a total of 80 measurements.

In the first assessment, the vibration magnitude is evaluated. It is calculated as the energy of the acceleration magnitude. The acceleration magnitude and energy are calculated as:

$$|\vec{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2}. \quad (19)$$

$$E(|\vec{a}|) = \sum_{n=1}^{N=[0.5s \times f_s]} |\vec{a}|^2[n]. \quad (20)$$

where f_s is the sampling rate. The magnitude of very small vibrations is significantly influenced by the sensor noise. In Section 2.5, the sensor noise is modeled as additive Gaussian noise with zero mean. Using the characteristic function of a Gauss distribution, it is found that the acceleration magnitude $|\vec{a}|$ also has additive Gaussian noise. Therefore, the true signal energy is estimated according to the following equations:

$$X = |\vec{a}| + \sigma, \quad (21)$$

$$E(X) = \sum X^2 = \sum |\vec{a}|^2 + \sum \sigma^2 + \sum 2|\vec{a}|\sigma, \quad (22)$$

$$E(|\vec{a}|) \approx E(X[n]) - E(\sigma[n]), \quad (23)$$

where X represents the measurement, $|\vec{a}|$ represents the true acceleration and σ represents the additive sensor noise. Equation (22) shows that the energy of the measurement is comprised of the energy of the desired value $E(|\vec{a}|)$, the energy of the noise $E(\sigma[n])$ and a remainder $\sum 2|\vec{a}|\sigma$. Since σ has zero mean, the remainder is small compared to $E(X[n])$ and $E(N[n])$. Therefore, it is neglected and the true vibration magnitude is estimated by subtracting the energy of the noise. In the experiment, the energy of the noise is estimated in a section, where no vibrations occur.

The results in Figure 14 show the average noise-compensated signal energy of the acceleration magnitude. The results for an IMU without a beam and an IMU with a beam

are shown in different colors and the x -axis depicts the force pulse amplitude. The graph on the left shows the results with force pulses located in the center and the graph on the right shows results for force pulses off-center. The error bars depict the standard deviation. The amplification, which is the ratio of the measurements with a beam and without a beam, is shown as a percentage with black diamonds. The percentages are shown on the right vertical axis.

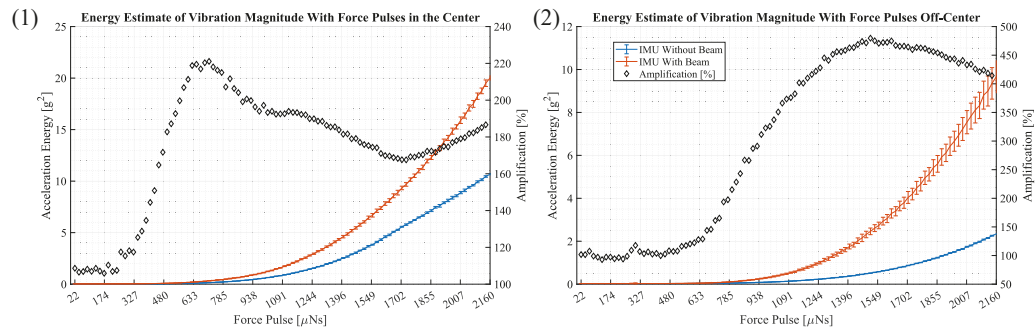


Figure 14. This figure shows the average energy of the acceleration magnitude at force pulses from 21.6 μ N s to 2160 μ N s. It depicts measurements of an IMU without a beam in blue and an IMU with a beam structure in orange. The error bars depict the standard deviation. The black diamonds illustrate the amplification in percent, which is the ratio of signal energy from the IMU with a beam and the IMU without a beam. The percentages are shown on the right vertical axis. Figure (1) and (2) depict results for force pulses in the center and off-center.

Both results in Figure 14 depict an amplification of vibration when using the proposed beam structure. In plot (1), where force pulses are applied in the center, a maximum amplification of 221% is observed at a force pulse of 713 μ N s. In plot (2), where force pulses are applied off-center, a maximum amplification of 480% is observed at a force pulse of 1512 μ N s.

In order to evaluate the oscillation modes in the measurements, the Fourier transformed acceleration and angular rate are evaluated in the following. In Figure 15, the frequency spectra of measurements with and without the beam are shown, where force pulses are applied in the center. For the IMU without a beam, vibration is only observed in the z -axis and it is distributed over a large frequency range. For the IMU with a beam, many distinct peaks are observed in all but the z -axis of the gyroscope. Comparing the largest peaks in the acceleration z -axis, the measurement with a beam structure shows a 4.4-times-higher amplitude.

Based on the oscillation forms shown in Section 2.4 and the peaks in the spectrum depicting the measurements with a beam, it is hypothesized that certain signal components are correlated. These are the signal components in a_z and ω_x at 100 Hz and a_y and ω_x at 1000 Hz.

Figure 16 illustrates the results of measurements with force pulses off-center. Comparing the largest peaks in the acceleration z -axis, the measurement with a beam structure shows a 6.2-times-higher peak amplitude over the measurement without a beam.

The spectra in Figures 15 and 16 show some differences. In the measurements with a beam structure, the peaks are at a similar amplitude, but the peaks at 1000 Hz and 450 Hz are less pronounced. In the measurements without a beam, the overall amplitude is smaller and higher frequency components are reduced significantly.

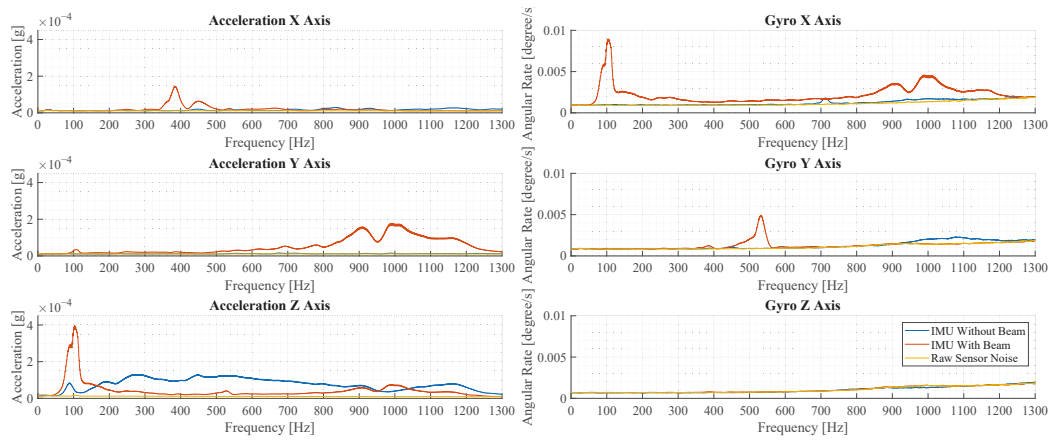


Figure 15. This figure illustrates the results of the experimental vibration measurement for force pulses in the center of the cage floor. Depicted are six plots that show the spectrum of the accelerometers and gyroscopes in the three spatial directions.

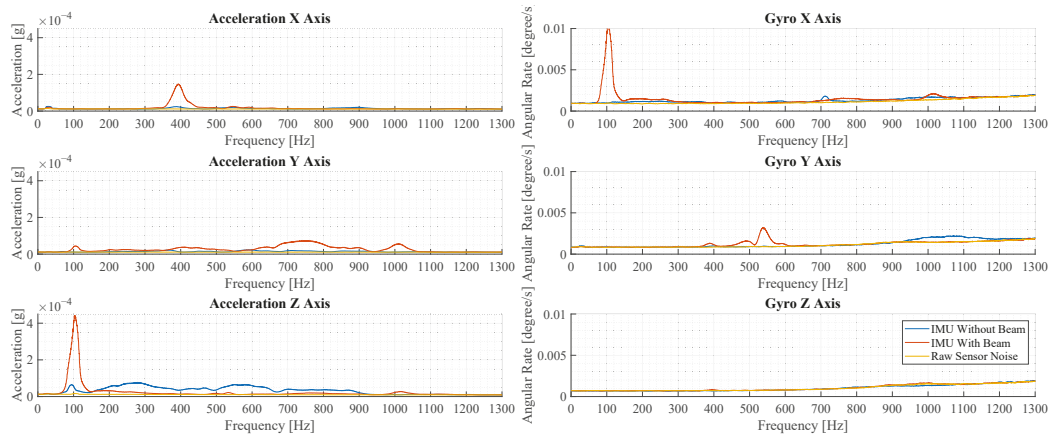


Figure 16. This figure illustrates the results of the experimental vibration measurement for force pulses off the center of the cage floor. Depicted are six plots that show the spectrum of the accelerometers and gyroscopes in the three spatial directions.

3.4. Sensor Fusion in Experiment

The sensor fusion algorithm combines the six sensor signals a_x , a_y , a_z , ω_x , ω_y and ω_z of the IMU to reduce the intrinsic noise. For fusion, the angular rate is differentiated to obtain the angular acceleration $\dot{\omega}_x$, $\dot{\omega}_y$ and $\dot{\omega}_z$.

Combining the findings of Section 2.4 and the spectra in Section 3.3, two oscillation modes are identified for sensor fusion. The first oscillation mode is at 103 Hz and creates a correlated oscillation of a_z and $\dot{\omega}_x$, where a refers to acceleration and $\dot{\omega}$ refers to angular acceleration. Examining further, the oscillation at 103 Hz actually consists of two modes at 90 Hz and 103 Hz. These two modes have the same oscillation form and exhibit very similar transformation coefficients. In addition, they fall into the same wavelet level due to their close proximity frequency-wise. For the purpose of sensor fusion, they are treated as one oscillation mode. The second oscillation mode is at 1000 Hz and involves oscillation of a_y and $\dot{\omega}_x$. The information describing the oscillation modes is stored in the fusion array:

$$O(1) = \{[0, 0, 1, -7.2 \times 10^{-5}, 0, 0], 103 \text{ Hz}\}, \quad (24)$$

$$O(2) = \{[0, 1, 0, -6.8 \times 10^{-6}, 0, 0], 1000 \text{ Hz}\}, \quad (25)$$

where O depicts the fusion array. In the first element $O(1)$, the main sensor signal is a_z and $\dot{\omega}_x$ is correlated by a factor of -7.2×10^{-5} . In $O(2)$, the main sensor signal is a_y and $\dot{\omega}_x$ is correlated by a factor of -6.8×10^{-6} .

The sensor fusion performance is evaluated experimentally by using the algorithm on a test measurement and examining the noise characteristics before and after the sensor fusion has been used. The test measurement has a force pulse amplitude sweep from $6.48 \mu\text{N s}$ to $648 \mu\text{N s}$. The fusion algorithm requires noise estimations, which are obtained as described in Section 2.5 using another measurement where no vibrations occur. Equations (7) and (8) are used to calculate the expected noise reduction. The noise estimates are given in Table 1.

Table 1. Noise estimates derived from an experimental measurement and the predicted noise reduction.

	O(1) at 103 Hz	O(2) at 1000 Hz
Noise of Main Signal	$5.306 \times 10^{-3} \text{ g}$	$3.771 \times 10^{-3} \text{ g}$
Noise of 2nd Signal	$13.532 \times 10^{-3} \text{ g}$	$50.534 \times 10^{-3} \text{ g}$
Estimated Noise of Fusion	$4.9398 \times 10^{-3} \text{ g}$	$3.761 \times 10^{-3} \text{ g}$
Noise Reduction	$0.37 \times 10^{-3} \text{ g}$ or 6.9%	$0.01 \times 10^{-3} \text{ g}$ or 0.276%

In order to estimate the noise contained in the experimental measurement, a wavelet-based denoising method is used to separate the vibration and noise signal. The standard deviation of the noise signal is then calculated to evaluate the noise level. The denoising method uses a threshold filter in the wavelet domain and is based on [24]. The method applies a hard threshold to the wavelet coefficients of a signal to remove the noise. The threshold value T is based on the Universal Threshold proposed in [28] and is calculated as follows:

$$T = \sigma \sqrt{2 \log N} \times 0.67, \quad (26)$$

where T is the threshold value, σ is the theoretically calculated standard deviation of the noise and N is the length of the wavelet coefficient. The factor of 0.67 is determined manually to extract most of the vibration components. The noise signal is obtained by subtracting the denoised signal from the original signal. The different signals that are calculated are shown in Figure 17.

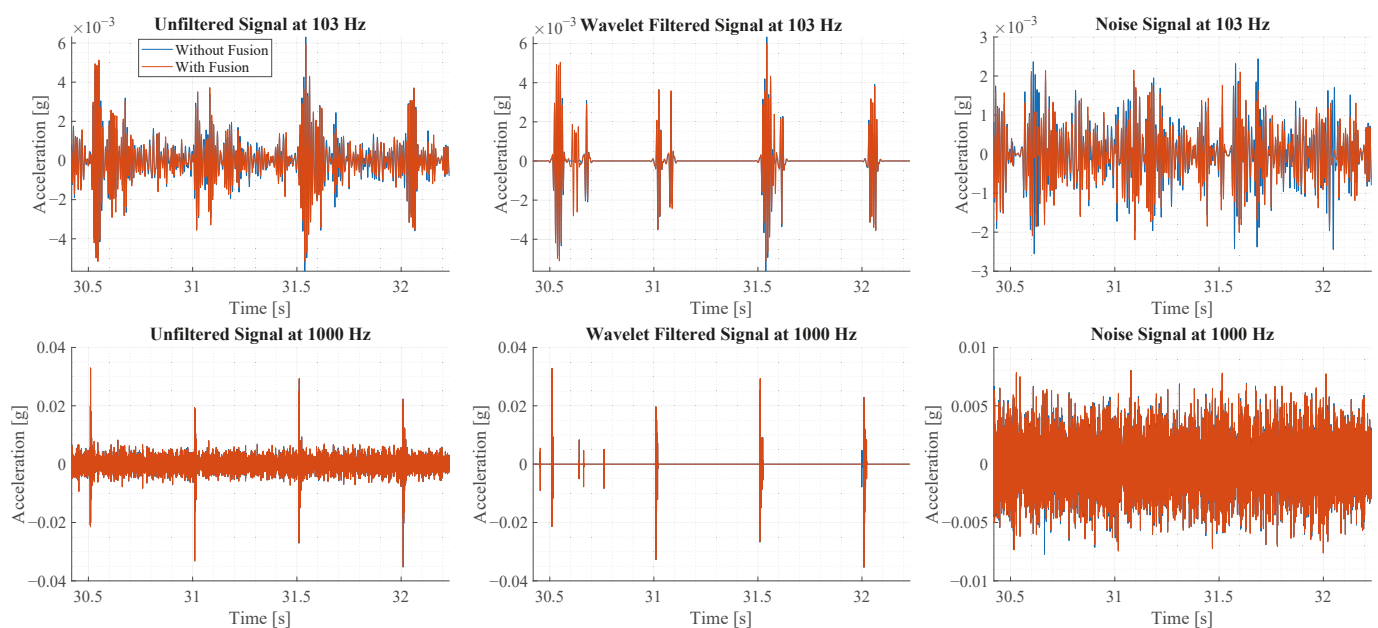


Figure 17. This figure illustrates the sensor signal before and after the sensor fusion for two oscillation modes. Furthermore, for each oscillation mode the original signal, the wavelet denoised signal and the noise signal are illustrated.

A sample of 2 s is shown in Figure 17. The rows of the plots show the result of the two oscillation modes, while the columns illustrate the unfiltered signal, the wavelet-denoised signal and the noise signal. In the first row of plots, the signals with sensor fusion appear less noisy than the original signal, as observed visually. In the second row, the signals with and without sensor fusion show little visual difference at this scale.

Based on the noise signals, shown in the third column, the noise is estimated by calculating the standard deviation. For the oscillation at 103 Hz, the signal without sensor fusion has a noise of 0.66149×10^{-3} g and 0.6246×10^{-3} g with fusion. This corresponds to a noise reduction of 0.0369×10^{-3} g or 5.573%. For the second oscillation at 1000 Hz, the noise standard deviation is 18.782×10^{-3} g without fusion and 18.738×10^{-3} g with fusion. This corresponds to a noise reduction of 0.044×10^{-3} g or 0.23%. In comparison to the values in Table 1, the noise reduction achieved in experiment is smaller than theoretically calculated.

3.5. Influence of Ambient Temperature

A change in ambient temperature affects the mechanical properties of the beam structure and characteristics of the sensing device. However, temperature fluctuations are very unlikely in this use case scenario because the room temperature is kept constant for the wellbeing of the animals. The temperature influence is investigated in simulation by evaluating the signal energy at the location of the virtual IMU for different temperatures.

Figure 18 illustrates the vibration characteristics of a sensing device with a beam of $l = 30$ mm and $w = 3$ mm. The vibration energy is practically unchanged in a range of -30 °C to 20 °C. At higher temperatures, the signal energy decreases.

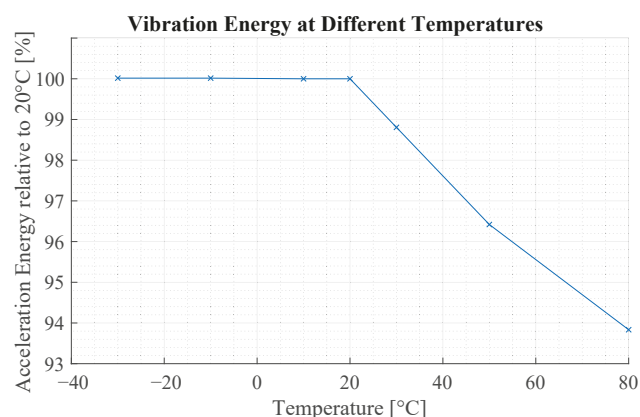


Figure 18. This figure shows the influence of temperature on the vibration characteristics of the beam structure. The y-axis shows the relative vibration energy compared to 20 °C of a beam with $l = 30$ mm and $w = 3$ mm.

4. Discussion

The results illustrate that the proposed concept achieves the desired effect of amplifying structural vibration to increase the SNR. The results also illustrate a number of other features, which will be discussed in more detail here.

4.1. Experimental Setup

In Section 2.6.3, it is shown that the experimental setup is capable of generating structural vibrations with a high degree of repeatability. Based on the energy of the vibration, an error of about 1% up to 3% is observed depending on the amplitude of the force pulse. The experimental setup is sufficient to evaluate the vibration amplification of the proposed concept, where differences of several hundred percent are observed.

While the repeatability error is small, the actual amplitude of the force pulses is not calibrated. A calibrated force pulse generator is useful to assess the correlation between force pulse strength and structural vibration magnitude, which is not subject of this work.

Because of the short duration of the force pulses, a force measurement method with a high sampling rate is needed. Piezo-electric force transducers have a sampling rate in the upper kilohertz range.

4.2. Optimal Beam Design

The experiment shows a greater amplification than the simulation results. In the spectrum, the simulation predicts an amplification of 2.4 and the experiment shows an amplification of 4.4 times. In terms of signal energy, an amplification of 221% is observed in experiment and the simulation predicts an amplification of 172%. The cause of these differences are inaccuracy of parameters and idealizations in the simulation model, which are discussed in detail in Section 4.4.

The results indicate that the simulation setup is sufficiently accurate to design a beam structure with the intended vibration amplification characteristics. However, when employed in the real world, these designs may not perform optimally. A proposed solution to guarantee optimal vibration amplification is the implementation of a tuning component. It is used to adjust the oscillation characteristics in the operating environment in order to adapt to the oscillation characteristics of the real-world environment. A tunable weight is proposed as a tuning component, which is mounted at the end of the beam. The beam characteristics are adjusted by changing the mass of the weight or the position of the weight. Another approach is to mount the beam using laterally oriented slits instead of round holes. This allows for adjustment of the free-standing beam length and in turn adjust the effective length of the beam. A longer beam results in a lower oscillation frequency. However, this type of adjustment requires recalibration up on reassembly and is very tedious in practice.

4.3. Vibration Amplification in Application

In the experimental evaluation, a significant amplification of vibration is observed. The evaluation in Section 3.3 shows that the desired effect is achieved whether the cage is excited in the center or closer to the walls of the cage. This is important in the application, as it increases the sensitivity of the system in all scenarios. Furthermore, it is observed that the amplification is higher when the cage is excited off-center. This effect is very beneficial, as force pulses at the periphery generally generate weaker vibrations. In the application, this could help in the detection of physical activity in the periphery. Furthermore, when comparing Figures 15 and 16, the composition of oscillation modes changes depending on the location of the force pulse. In the future, this phenomenon could be used to extract location-specific information by analyzing the composition of the oscillation modes.

The correlation between amplification and vibration magnitude is investigated in Section 3.3 and the results are shown in Figure 14. In this examination, a series of force pulses generate vibrations with increasing magnitude, starting with vibrations with a magnitude below the sensor noise. It is evident that the sensing device produces an amplification effect throughout the tested amplitude range. It is observed that the amplification is highest at lower amplitudes, which supports the intended use of amplifying very small vibrations that would otherwise be masked by noise. At higher magnitudes, the amplification is smaller but still very significant at over 165%. At smaller amplitudes, the deformation of a bending beam is approximately linear. At higher amplitudes, the deformation causes non-linear effects, which are believed to reduce the amplification.

4.4. Deviation of Simulation and Experiment

In Section 3.3, the experimental data of a beam using the optimal design from Section 3.1 is obtained. The experimental data are compared to the simulation results in the frequency domain, where signal peaks are a representation of different oscillation modes. The comparison shows many similarities such as the peaks in a_z at around 100 Hz, the peaks in a_y at around 100 Hz and the peaks in a_x at around 400 Hz. However, the exact frequency and amplitude of the peaks differs between experiment and simulation. Furthermore, the experimental data show additional signal components in the a_y axis at 900 Hz to

1000 Hz, which are not present in the simulation results. Based on the modal analysis in Section 2.4, these correspond to the oscillation type titled as fourth oscillation form.

The differences between simulation and experiment are attributed to three main causes. First, the material parameters like the Young's modulus and damping coefficient of the cage and the beam are estimated using standard values from a library. The inaccuracy of these parameters is accepted, because more accurate estimations would require extensive and destructive testing, which was not feasible. Another inaccuracy is the weight of the sensing board, which fluctuates due to the inconsistent amount of solder used for mounting. Secondly, the simulation model is idealized in some aspects to reduce computational cost and complexity. The wood flocking used to fill the floor is simulated as a surface mass, which neglects damping properties. The data lines that are milled into the beam are able to reduce the mechanical stiffness but were neglected. The third cause of disparity are the tolerances in manufacturing and assembly. The milling operation has good tolerances, which have minimal influence on the oscillation characteristics of the beam. The assembly is conducted by hand, which has an error of about 1 mm in the worst case. However, the assembly error alone does not explain the observed deviation, since beams with lengths between 29 mm and 32 mm show less deviation between each other in the simulation than compared to the prototype beam.

4.5. Noise Reduction with Sensor Fusion

In Section 3.4, the proposed sensor fusion algorithm is successfully validated by fusing accelerometer and gyroscope data in an experiment. The IMU data are first preprocessed to obtain the acceleration and angular acceleration for each spatial axis, which are then selectively fused to produce a single signal with reduced noise.

The sensor fusion algorithm achieves a noise reduction of 5.573% for the oscillation at 103 Hz and 0.23% at 1000 Hz in the experiment. The theoretical calculation predicts a noise reduction of 6.9% at 103 Hz and 0.276% at 1000 Hz in an ideal case, which is higher than the results of the experiment. This is explained by the error of estimated parameters, which reduces the effective noise reduction. Parameters that are estimated are the noise levels and the transformation coefficients. The experiment shows that the proposed sensor fusion algorithm achieves the desired effect. Furthermore, the noise reduction in the experiment approaches the theoretical maximum, which shows that the estimated parameters are sufficiently accurate.

Table 1 shows that the noise of the angular acceleration is significantly higher than the acceleration. As explained in Section 2.5, the maximum noise reduction is achieved when the noise level is equal in all signals. To maximize the noise reduction, the amount of angular rotation during oscillation must be increased for a higher SNR in the angular acceleration sensor signals. The relationship between the translation z and rotation θ for a point load at the end of the beam is:

$$\theta = \frac{3}{2l}z, \quad (27)$$

according to [21]. For a uniform surface load, the relationship is:

$$\theta = \frac{4}{3l}z. \quad (28)$$

These equations indicate two methods of increasing the angular acceleration. First, the rotation is anti-proportional to the length of the beam. Therefore, a shorter beam should create more rotation at a given translation z . Secondly, the factor that is dependent on the type of load is more advantageous for a beam with a point load at the end. This means that most of the mass of the free-standing beam should be concentrated at the end. Further, it may even be advantages to place a mass at the end of the beam to move the center of mass further towards the end.

4.6. Limitations

In the discussion of the proposed concept, two main limitations stand out. First, the beam structure needs to be redesigned and adapted to each new application because the beam has to be tuned to the specific vibration of the ambient object. A possible solution is given in Section 4.2. Using a tuning component, the vibration characteristics of the beam can be adjusted in the application environment to achieve vibration amplification. Secondly, the proposed beam structure massively alters the vibration characteristics and is probably unsuited for unbiased quantitative vibration analysis, e.g., seismic exploration. For vibration-based activity estimation, however, physical quantity is not as important because the relationship between activity and vibration is derived by analyzing exemplary datasets. The proposed sensing device could also be beneficial in applications where detection of vibration is the main goal.

4.7. Comparison of SNR

The signal-to-noise ratio at a given force pulse amplitude can be derived from the results in Figure 14. The SNR is equal to the ratio of the signal energy of the measurement and the energy of the noise, which is about 0.1 g^2 . At a force pulse of $1512 \mu\text{N s}$ in the experiment where force pulses are applied off-center, the IMU without a beam shows a signal energy of 0.51 g^2 and the IMU with the beam structure an energy of 2.46 g^2 . These values correspond to an SNR of 5.1 and 24.6, which clearly illustrates the benefit of the proposed beam structure.

A direct comparison to geophones needs to take the frequency of the signal into consideration, due to the difference in the frequency response of the sensors. In order to compare the IMU results to a geophone, SNR is calculated as the ratio of signal amplitude of the acceleration in the z-axis at 100 Hz as shown in Figure 16. The IMU without a beam shows an amplitude of $8.7 \times 10^{-4} \text{ m s}^{-2}$ and a noise of $1.86 \times 10^{-4} \text{ m s}^{-2}$, which amounts to an SNR of 4.7. The IMU with a beam shows an amplitude of $3.9 \times 10^{-3} \text{ m s}^{-2}$ and a noise of $1.85 \times 10^{-4} \text{ m s}^{-2}$, which amounts to an SNR of 21.1.

The noise floor of a geophone is estimated by the voltage noise of the amplifying electronics, which is the main source of noise [29]. The noise of the amplifier varies between models but is about $0.3 \mu\text{V}$ on average [30]. The commonly used SM-24 from sparkfun has a sensitivity of 28.8 V/m/s , which amounts to a noise of $1 \times 10^{-8} \text{ m s}^{-1}$. At a frequency of 100 Hz, this is equivalent to an acceleration noise of $6.6 \times 10^{-6} \text{ m s}^{-2}$. Assuming that the geophone would show a similar amplitude as the IMU without a beam, the SNR is estimated to be 131.4.

The comparison shows that the proposed sensing device massively increases the SNR compared to a directly mounted IMU. While the geophone has a 28-times-higher SNR over a directly mounted IMU, the geophone SNR is only 6.2 times higher than the proposed sensing device, which makes it much more competitive to geophones. Furthermore, this comparison ignores the fact that high-frequency signals above 250 Hz can only be measured by an IMU.

5. Conclusions

In this work, a novel method is proposed to enhance vibration sensing with IMUs using an optimized beam structure. It presents the design process for the beam structure, as well as a sensor fusion algorithm for combining the multiple sensor signals of an IMU to reduce the intrinsic noise. The concept is evaluated in an experimental use case where vibrations of a husbandry cage are measured. The results show that a significant increase in signal amplitude and signal energy is achieved by the proposed beam structure. In addition, the amplification is independent of the location of the excitation and the magnitude of the vibration. Amplification is therefore achieved in all activity related scenarios of the application. In terms of amplitude in the frequency domain, up to 6.2 times amplitude amplification is achieved. In terms of signal energy, a maximum amplification of 480% is observed. Furthermore, the experimental evaluation of the sensor fusion algorithm shows a

noise reduction of 5.6% when fusing the acceleration in the z-axis and angular acceleration around the x-axis at 103 Hz.

In summary, this work presents a new sensor device using a six-axis IMU that achieves a significant amplification of structural vibrations, increasing the SNR and enabling the detection of smaller vibrations. It is experimentally validated that the desired effect is independent of the location of excitation and magnitude of vibration.

6. Future Work

In future work, the performance of the beam structure will be further optimized by integrating a tuning component to adjust the vibration characteristics in the operating environment. This allows for optimal performance in the real world by compensating for inaccuracies. A promising approach is an adjustable weight at the end of the beam, which can be changed or moved along the beam.

The sensor fusion algorithm shows promising results in the experiment. Two approaches are proposed to increase the effectiveness of the sensor fusion algorithm in the future. First, the beam is optimized to produce more rotation at a given deflection, which increases the SNR of the gyroscope measurements. Secondly, the number of oscillation modes of the beam suitable for sensor fusion is increased.

Vibration-based activity monitoring applications are differentiated by the observed subject, the environment and the information derived from the structural vibration. In the future, our proposed sensing device will be transferred to other applications, where it can provide a much higher sampling rate and multi-dimensional vibration data at a lower cost when compared to conventionally used geophones.

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Abbreviations

The following abbreviations are used in this manuscript:

IMU	inertial measurement unit
MEMS	micro-electro-mechanical systems
FEM	finite element method
FEA	finite element analysis
SoC	system on a chip
SNR	signal-to-noise ratio
PCB	printed circuit board
MLDWT	multi-level discrete wavelet transformation
MSE	mean squared error

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Article

Detection of SO₂F₂ Using a Photoacoustic Two-Chamber Approach

Hassan Yassine ^{1,†}, Christian Weber ^{1,2,†}, Andre Eberhardt ², Mahmoud El-Safoury ², Jürgen Wöllenstein ^{1,2} and Katrin Schmitt ^{1,2,*}

¹ Department of Microsystems Engineering IMTEK, University of Freiburg, 79110 Freiburg, Germany; hassan.yassine@imtek.uni-freiburg.de (H.Y.); christian.weber@imtek.uni-freiburg.de (C.W.); juergen.woellenstein@imtek.uni-freiburg.de (J.W.)

² Fraunhofer Institute for Physical Measurement Techniques IPM, 79110 Freiburg, Germany; andre.eberhardt@ipm.fraunhofer.de (A.E.); mahmoud.el-safoury@ipm.fraunhofer.de (M.E.-S.)

* Correspondence: katrin.schmitt@imtek.uni-freiburg.de

[†] These authors contributed equally to this work.

Abstract: The wide use of sulfuryl difluoride (SO₂F₂) for termite control in buildings, warehouses and shipping containers requires the implementation of suitable sensors for reliable detection. SO₂F₂ is highly toxic to humans and the environment, and moreover, it is a potent greenhouse gas. We developed two photoacoustic two-chamber sensors with the aim to detect two different concentration ranges, 0–1 vol.-% SO₂F₂ and 0–100 ppm SO₂F₂, so that different applications can be targeted: the sensor for high concentrations for the effective treatment of buildings, containers, etc., and the sensor for low concentrations as personal safety device. Photoacoustic detectors were designed, fabricated, and then filled with either pure SO₂F₂ or pure substituent gas, the refrigerant R227ea, to detect SO₂F₂. Absorption cells with optical path lengths of 50 mm and 1.6 m were built for both concentration ranges. The sensitivity to SO₂F₂ as well as cross-sensitivities to CO₂ and H₂O were measured. The results show that concentrations below 1 ppm SO₂F₂ can be reliably detected, and possible cross-sensitivities can be effectively compensated.

Keywords: photoacoustic spectroscopy; sulfuryl difluoride (SO₂F₂) detection; two-chamber photoacoustic sensors

1. Introduction

The extensive use of sulfuryl difluoride (SO₂F₂), mostly as replacement for methyl bromide, for termite control in buildings, warehouses and shipping containers has led to a significant increase in global emissions and therefore the atmospheric mixing ratios from 1.8 parts-per-trillion (ppt) in 2011 to 2.6 ppt in 2019 [1,2]. SO₂F₂ is highly toxic to humans [3] and the environment, and moreover, it is a potent greenhouse gas with a global warming potential of 4780 and an atmospheric lifetime of 36 years [4,5]. Due to its toxicity, occupational safety requires the monitoring of SO₂F₂, e.g., in workplaces or during the fumigation of buildings. The occupational exposure limit (OEL) of SO₂F₂ is 5 parts-per-million (ppm) and an immediate danger for life and health starts from 200 ppm [3], so suitable sensors need to be able to monitor the lower ppm range, better reaching the parts-per-billion (ppb) level. A large variety of sensors has been reported in recent years. Many of them are chemical sensors based on different material complexes, e.g., Mo-, W-, Hf, or Co-based [6–10], NiO- or TiO-based [11–13], or they implement transition metals [14,15]. Generally, chemical sensors are designed to sense the target gas in low concentration ranges, yet the material systems often suffer from cross-sensitivities to other gases and do not have sufficient long-term stability. Apart from their detection using chemical sensors, gases often can be monitored using optical sensors, making use of their characteristic absorption properties [16,17]. Gas absorption can be observed in the ultraviolet but also in the visible

and infrared wavelength range. Simple sensors employ the non-dispersive infrared (NDIR-) principle with broadband sources and detectors and optical filters for measuring the absorption of the target gas within a defined optical path. More complex and cost-intensive, but also up to several decades more sensitive, are laser-based systems. Both principles have already been proposed for SO_2F_2 detection [18–21]. NDIR sensors can be designed in a size- and cost-efficient way but often lack sensitivity, whereas laser-based systems are more complex but show better performance. Laser-based systems are often still laboratory-based due to their complexity, which limits their applicability in field applications.

Therefore, we decided to employ the principle of photoacoustic detection in our SO_2F_2 sensor. Photoacoustic devices are highly selective and, depending on their mode of operation, also highly sensitive with detection limits in the ppb range, which makes such devices highly suitable for many application fields [22,23]. Generally, resonant devices can achieve such low detection limits, but they are much more complex and expensive than non-resonant sensors. Resonant photoacoustic sensors have already been proposed for SO_2F_2 sensing but are restricted to laboratory use [24–28]. If the modulation of the light source is operated at a frequency that is much smaller than the smallest resonance frequency of the photoacoustic cell (PA) cell, this is referred to as non-resonant operation. In this case, the sound wave has a wavelength much larger than the dimensions of the cell. This means that no standing wave can form in the cell, as is the case for resonant devices [29]. Non-resonant systems, although they only show detection limits in the ppm range, might be more suitable for field use. Such sensors can be equipped with micro-electromechanical system (MEMS) components, and they are already available commercially, e.g., for CO_2 sensing from the companies Infineon or Sensirion.

We propose to use a non-resonant, two-chamber photoacoustic setup as schematically illustrated in Figure 1. In this setup, we employ an IR emitter, a measurement/absorption chamber to be filled with the gas mixture to be measured and a second chamber (detection chamber) filled with the target gas or a suitable substitute gas. In our previous publication, we have reported detailed simulations on the sensor design and optical path length, considering different gases for the detector chamber [30]. The idea is to use a non-toxic substituent gas with similar absorption characteristics in the photoacoustic detector chamber for indirect, but still selective, SO_2F_2 sensing. Photoacoustic detectors were designed, fabricated and then filled with either pure SO_2F_2 or pure substituent gas, the refrigerant 1,1,1,2,3,3,3-heptafluoropropane (R227ea), to detect SO_2F_2 . Absorption cells with optical path lengths of 50 mm and 1.6 m were built for both concentration ranges. The sensitivity to SO_2F_2 as well as cross-sensitivities to carbon dioxide (CO_2) and water vapor (H_2O) were measured. We also compare the results to our simulations and other SO_2F_2 photoacoustic sensors reported in the literature. The results showed that our photoacoustic sensor with the absorption cell with an optical path length of 1.6 m can monitor the OEL of SO_2F_2 and can therefore be deployed in various applications in the future.

2. Materials and Methods

2.1. Photoacoustic Sensors Setups

Our photoacoustic two-chamber sensors consist of an infrared radiation source, an absorption cell and a photoacoustic detector. The JSIR 350-4-AL-R-D6.0-2-A7 IR emitter (Micro-Hybrid Electronic GmbH, Germany) offers a sufficiently high optical output power and spectral range for the intended SO_2F_2 sensor. Figure 1 shows the working principle of our sensor and its components schematically. The graphs illustrate the emitted spectral power of the IR emitter $I_{\text{Em}}(\lambda)$ between 2.5 μm and 15 μm at an emitter temperature of 550 °C (electrical input power of 0.36 W) calculated using Planck's law from [31] and the information provided in the datasheet [32]. Radiation losses resulting from the transmission through the window of the IR emitter were not considered. Furthermore, the absorption of an SO_2F_2 detector is shown, calculated according to the Beer–Lambert law from [33] with a detector length of 1.5 mm. The transmission through the detector window was considered here. In the absence of SO_2F_2 in the absorption chamber, the detector signal is maximum,

and it decreases when SO₂F₂ is present. Due to the absorption of part of the IR radiation by the SO₂F₂ molecules in the absorption chamber, the absorption by SO₂F₂ in the detector decreases and thus also the detector signal decreases.

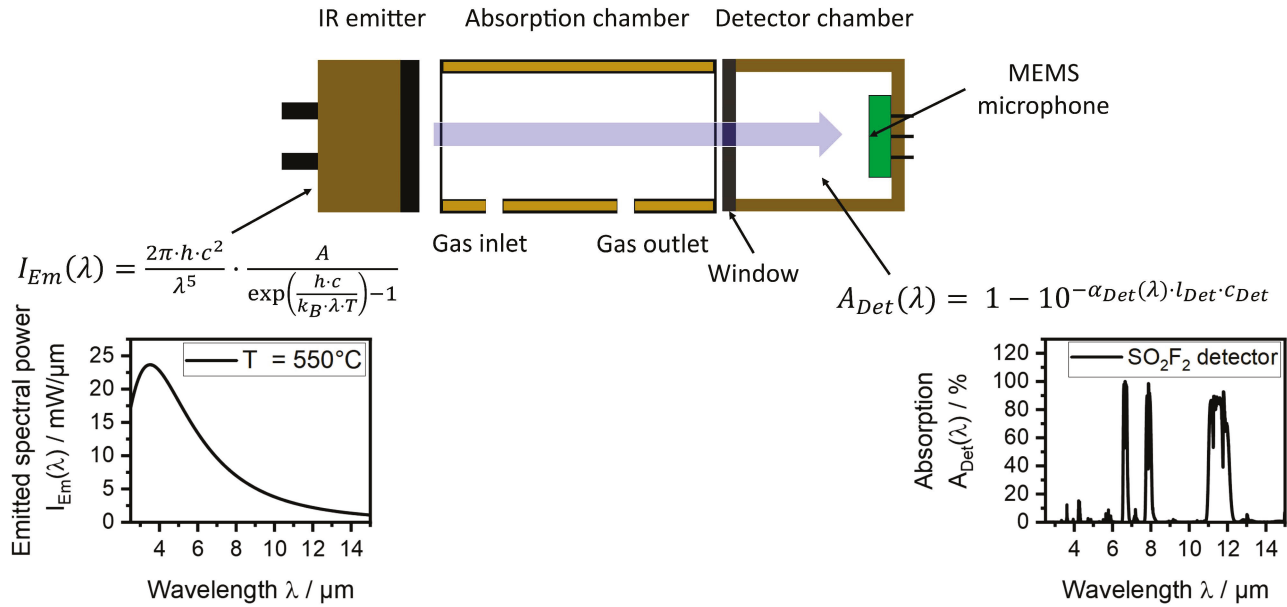


Figure 1. Schematic illustration of the photoacoustic sensor setup using the two-chamber approach. The graphs show the emitted spectral power $I_{Em}(\lambda)$ of the JSIR 350-4-AL-R-D6.0-2-A7 IR emitter used (Micro-Hybrid Electronic GmbH, Germany) between 2.5 μm and 15 μm at an emitter temperature of 550 °C (electrical input power of 0.36 W), calculated using Planck's law from [31] and the information provided in the datasheet [32]. Radiation losses resulting from the transmission through the window of the IR emitter were not considered. It shows the absorption $A_{Det}(\lambda)$ of a SO₂F₂ detector with a detector length l_{Det} of 1.5 mm, calculated using the Beer–Lambert law.

In addition to the choice of the radiation source, both the geometry of the photoacoustic detector and that of the absorption cell play an important role for the sensor signal, the sensitivity of the sensor and the resulting detection limit. The detector (5 mm × 5 mm × 4 mm) shown in Figure 2 was milled from 1.1730 steel and then nickel-plated ($d = 5\text{ μm}$) and gold-plated ($d = 1.5\text{ μm}$) by SIMEK Silikat-, Metall- und Kunststofftechnik GmbH, Vilsbiburg, Germany. A SPV1840LR5H-B MEMS microphone (Knowles Electronics, Santa Clara, CA, USA) was integrated into the detector chamber, and its contacts were led outside the detector chamber via a gas-tight glass feedthrough manufactured also by SIMEK GmbH. Afterwards, copper tubes (1 mm × 0.5 mm) were soldered into the sides of the detector chamber to fill the detector with gas. A 500 μm double side polished <110> 4-inch Si wafer was used as a detector window. A metallization layer for soldering was applied onto the wafer, and the wafer was then cut into quadratic windows (4.8 mm × 4.8 mm). The metallized Si window was soldered to the detector, sealing the gas cavity.

The simulation results in [30] showed that the refrigerant R227ea could be a suitable substituent gas for SO₂F₂ in the detector gas filling. Thus, the detectors were prepared and then flushed with either 100 vol.-% SO₂F₂ or 100 vol.-% R227ea. After that, the ends of the filling tubes of the detectors were crimped and then soldered.

For the concentration range 0–1 vol.-% SO₂F₂, an absorption cell (Figure 3a) with an optical path length of 50 mm and an internal diameter of 3 mm was designed. It was manufactured from brass and subsequently chemically Au-coated. For manufacturing reasons, the absorption cell consists of four individual segments. The photoacoustic detector was then fixed to the first end of the absorption cell and the IR emitter to the other end. For the concentration range 0–100 ppm SO₂F₂, a multi-pass White cell with an optical path length of 1.6 m was designed according to [34] and built. As the sensor signal of a two-

chamber photoacoustic sensor changes according to the Beer–Lambert law, extending the optical path length l in Equation (1) increases the sensitivity. Hence, lower concentrations c can be detected [33].

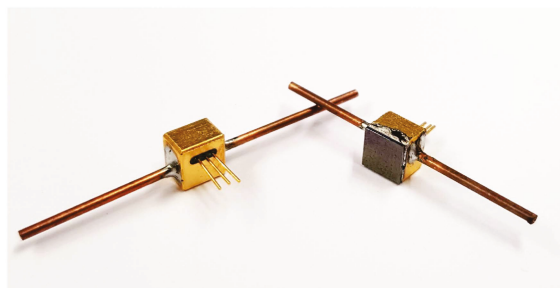


Figure 2. Picture showing the back side (**left**) and front side with detector window (**right**) of the constructed detector chamber (5 mm × 5 mm × 4 mm). Two copper tubes (1 mm × 0.5 mm) were soldered into the sides of the detector chamber to fill the detector with gas and a 500 μm double side polished <110> 4-inch Si window with a metallization layer was soldered to the detector. The MEMS microphone is integrated into the detector chamber, and the contacts are led outside the detector chamber via a gas-tight glass feedthrough.

$$I = I_0 \cdot 10^{-\alpha \cdot l \cdot c}, \quad (1)$$

where I and I_0 are the radiation intensity and initial radiation intensity, respectively, and α is the decadic absorption coefficient. Figure 3b shows a photograph of the overall setup of the multi-pass cell with the IR emitter and the photoacoustic detector. The IR emitter was mounted in the opening on the right side while the detector was mounted in the opening on the left side.

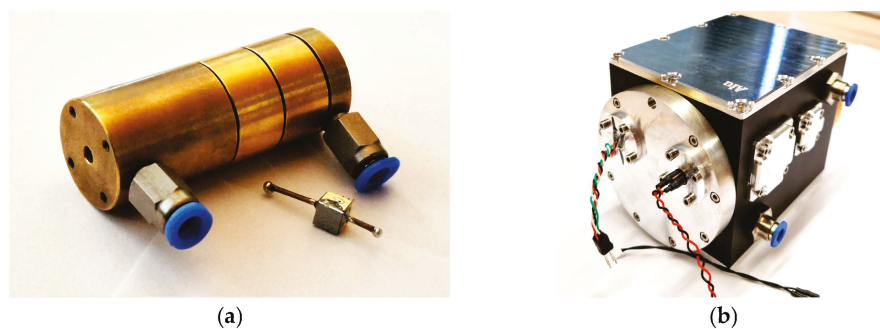


Figure 3. (a) Picture of the absorption cell (20 mm × 50 mm) made of brass, consisting of four segments together with a photoacoustic detector in the foreground. The optical path length is 50 mm and the diameter of the optical path is 3 mm. The photoacoustic detector was mounted to the first end of the absorption cell and the IR emitter to the second end. (b) Overall setup of the multi-pass White cell with an optical path length of 1.6 m, with the IR emitter and the photoacoustic detector. The IR emitter was mounted in the opening on the right side, while the detector was mounted in the opening on the left side.

2.2. SO₂F₂ Gas Measurements

All measurements were performed with an electronic board similar to the one described in [35]. The analog and digital signal processing, including a digital lock-in algorithm, as well as the control and modulation of the emitter were performed with this electronic board. The effect of the modulation frequency of both photoacoustic detectors, the SO₂F₂ detector and the R227ea detector, on the sensor signal was investigated. Both measurements were performed in a nitrogen (N₂) atmosphere using the sensors with the 50 mm absorption cell.

After that, measurements determining the sensitivity of both photoacoustic detectors to SO_2F_2 were performed. First, SO_2F_2 concentrations between 0 and 1000 ppm in steps of 100 ppm and a duration of 30 min for each SO_2F_2 step were applied (cf. Figure S1). After that, SO_2F_2 concentrations below 400 ppm, in steps of 50 ppm also lasting 30 min each, were applied. The IR emitter was modulated with a frequency of 35 Hz in both systems and the lock-in time constant was set to 20 s. In addition, measurements of possible cross-sensitivities of both photoacoustic detectors to CO_2 and H_2O were performed. The same driver current, modulation frequency and lock-in time constant as in the previous measurement were used. CO_2 concentrations of 400 ppm, 600 ppm, 800 ppm and 1000 ppm as well as relative humidity contents of 20% r.H. to 80% r.H. (at $T = 30^\circ\text{C}$) in 20% r.H. steps were applied in these measurements.

Based on the observed sensor performance, experiments with the multi-pass White cell ($l = 1.6\text{ m}$) were set up. SO_2F_2 concentrations between 0 and 100 ppm in concentration steps of 10 ppm and a duration of 1h each were applied in this measurement (cf. Figure S2). Furthermore, SO_2F_2 concentrations of 2 ppm, 10 ppm, 15 ppm and 20 ppm with the same duration were applied additionally. The IR emitter was modulated with a frequency of 35 Hz and the time constant of the lock-in filter was set to 20 s. Measurements of cross-sensitivities of both photoacoustic detectors to CO_2 and H_2O were also carried out. CO_2 concentrations of 400 ppm, 600 ppm, 800 ppm and 1000 ppm as well as relative humidity contents of 10% r.H. to 60% r.H. (at $T = 30^\circ\text{C}$) in 10% r.H. steps were used as concentration setpoints.

3. Results

3.1. Sensor Setup for the Measuring Range 0–1 vol.-% SO_2F_2

3.1.1. Characterization of the Sensitivity of the Sensors to SO_2F_2

The dependence of the signal of both photoacoustic detectors (SO_2F_2 detector and R227ea detector) on the modulation frequency of the IR emitter is shown in Figure 4. Both photoacoustic detectors show a similar change with modulation frequency. Between 20 Hz and 35 Hz, the signal of both detectors is higher than 85% of its maximum value. At 500 Hz, it decreases to less than 5%. This was expected due to the decrease in the modulation depth of the IR emitter with higher frequencies as well as the $1/f$ signal decrease of photoacoustic detectors. At the same time, the $1/f$ noise of the microphone decreases with the modulation frequency. So, as a trade-off between the absolute signal of the photoacoustic detectors and their noise, a modulation frequency of 35 Hz was used in all measurements.

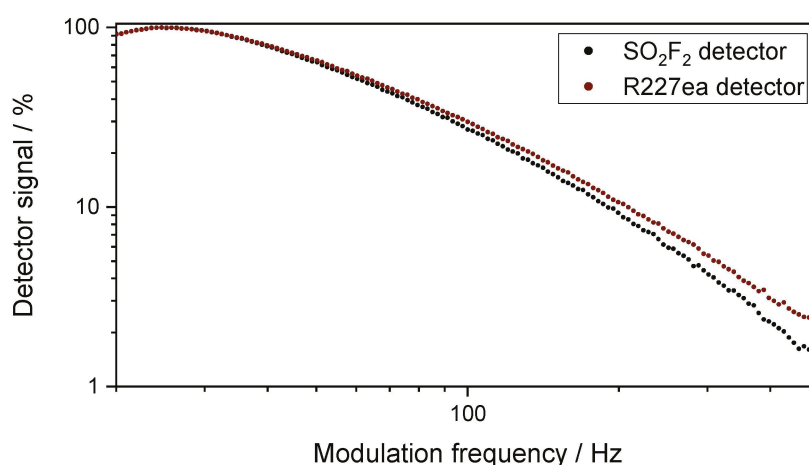


Figure 4. Variation in the signal of the SO_2F_2 photoacoustic detector and the R227ea photoacoustic detector with respect to the change in the modulation frequency of the IR emitter in the range between 20 Hz and 500 Hz. The detector signal decreases with the increase in modulation frequency. These measurements were performed with the sensor setup with the 50 mm absorption cell in N_2 atmosphere.

Figure 5a shows the signal of the SO₂F₂ photoacoustic detector as well as that of the R227ea photoacoustic detector with respect to the concentration change of SO₂F₂ in the 50 mm absorption cell between 0 and 1000 ppm. The higher the given concentration, the lower the detector signal is. Both photoacoustic detectors show a non-linear response to the concentration change in SO₂F₂ in the absorption cell. A logistic function as in Equation (2) describes the detector response well:

$$y = \left(\frac{a - b}{1 + \left(\frac{x}{x_0} \right)^p} \right) + b, \quad (2)$$

where, a , b , x_0 and p are fit parameters. The relative signal change of the SO₂F₂ photoacoustic detector to the SO₂F₂ concentration change in the absorption cell is higher than the relative signal change of the R227ea photoacoustic detector to the SO₂F₂ concentration change in the absorption cell. In the presence of 1000 ppm SO₂F₂ in the absorption cell, the SO₂F₂ photoacoustic detector shows a detector signal of 93.75%_{FS} (FS = full scale), whereas that of R227ea decreases to 98.35%_{FS}. The detector signal of the SO₂F₂ detector was 99.59%_{FS} at 50 ppm SO₂F₂, while that of R227ea was 99.85%_{FS}. The 3 σ noise was 0.16%_{FS} for the SO₂F₂ detector at 0 ppm SO₂F₂, while that of the R227ea was 0.174%_{FS}. Considering the 3 σ noise of both detectors and the sensitivity of the detectors to different SO₂F₂ concentrations, the detection limit and the 3 σ resolution of the sensors can be determined.

Figure 5b shows the sensitivity of both photoacoustic detectors in %_{FS}/50 ppm to SO₂F₂ in the concentration range of 50–1000 ppm SO₂F₂. The first derivative of the logistic fit with respect to the concentration yields the sensitivity of the photoacoustic detectors versus the concentration. The derivative of the fit is chosen over the derivative raw data for obtaining continuous data with less discretization at the cost of some accuracy. The sensitivity of the SO₂F₂ photoacoustic sensor in the range of 0–1000 ppm SO₂F₂ is 2.5 $\times$ to 6 $\times$ higher than the sensitivity of the R227ea detector. The higher the SO₂F₂ setpoint concentration, the lower the sensitivity of both photoacoustic detectors. Considering the 3 σ noise of both detectors as well as the sensitivity of both detectors to SO₂F₂ concentrations shown in Figure 5b, detection limits of 20 ppm for the SO₂F₂ detector and 60 ppm for the R227ea detector at 0 ppm SO₂F₂ were determined. The 3 σ resolution for the SO₂F₂ detector is 34 ppm at 1000 ppm SO₂F₂, while it is 180 ppm for the R227ea detector. This is due to the lower sensitivities at higher SO₂F₂ concentrations. The response time t_{90} of the sensor is 20 s, which is dominated here by the lock-in integration time required for the measurements and not by the volume of the absorption chamber. If the volume of the absorption chamber (approx. 360 μ L) dominated here, the sensor would have to have a time constant t_{90} of less than 0.5 s at an SO₂F₂ flow rate of 0.5 L/min. Figure 6a,b compare the simulated and the measured signal of the two photoacoustic detectors as a function of the SO₂F₂ concentration in the range of 0–10,000 ppm. An in-depth explanation on how the simulations were conducted can be found in [30]. The simulations consider the Beer–Lambert law seen in Equation (1) spectrally to determine the absorption in the detector chamber and at the absorption chamber. There is a difference between the simulated and measured signal of both photoacoustic detectors as can be noticed from Figure 6a,b. The higher the SO₂F₂ concentration setpoint in the absorption cell, the greater the difference between simulated and measured signal. The difference in the simulated and the measured signal of the SO₂F₂ photoacoustic detector is probably due to the fact that the simulations were calculated under ideal conditions by assuming that the detector chamber was filled with 100 vol.-% SO₂F₂. In reality, the detector chamber might still contain traces of interfering gases generated during the soldering, so that it is not filled with pure SO₂F₂. This leads to a change in the sensitivity of the SO₂F₂ photoacoustic detector to various SO₂F₂ concentrations in the absorption cell. The utilized IR emitter has a Si window with an anti-reflective coating which was also not considered in the simulation. Furthermore,

flux residues or dirt particles on the surface of the Si window affect the IR transmission through the window, which leads to a change in the sensitivity of the detector. In addition, the absorption cell consists of four segments, which significantly increases the probability of IR radiation loss. These could also be reasons why the R227ea photoacoustic detector has a higher sensitivity in the measurements than in the simulations. Moreover, the IR radiation rays could pass the absorption cell diagonally via several reflections, causing an extension of the effective optical path length and thus leading to a higher sensitivity.

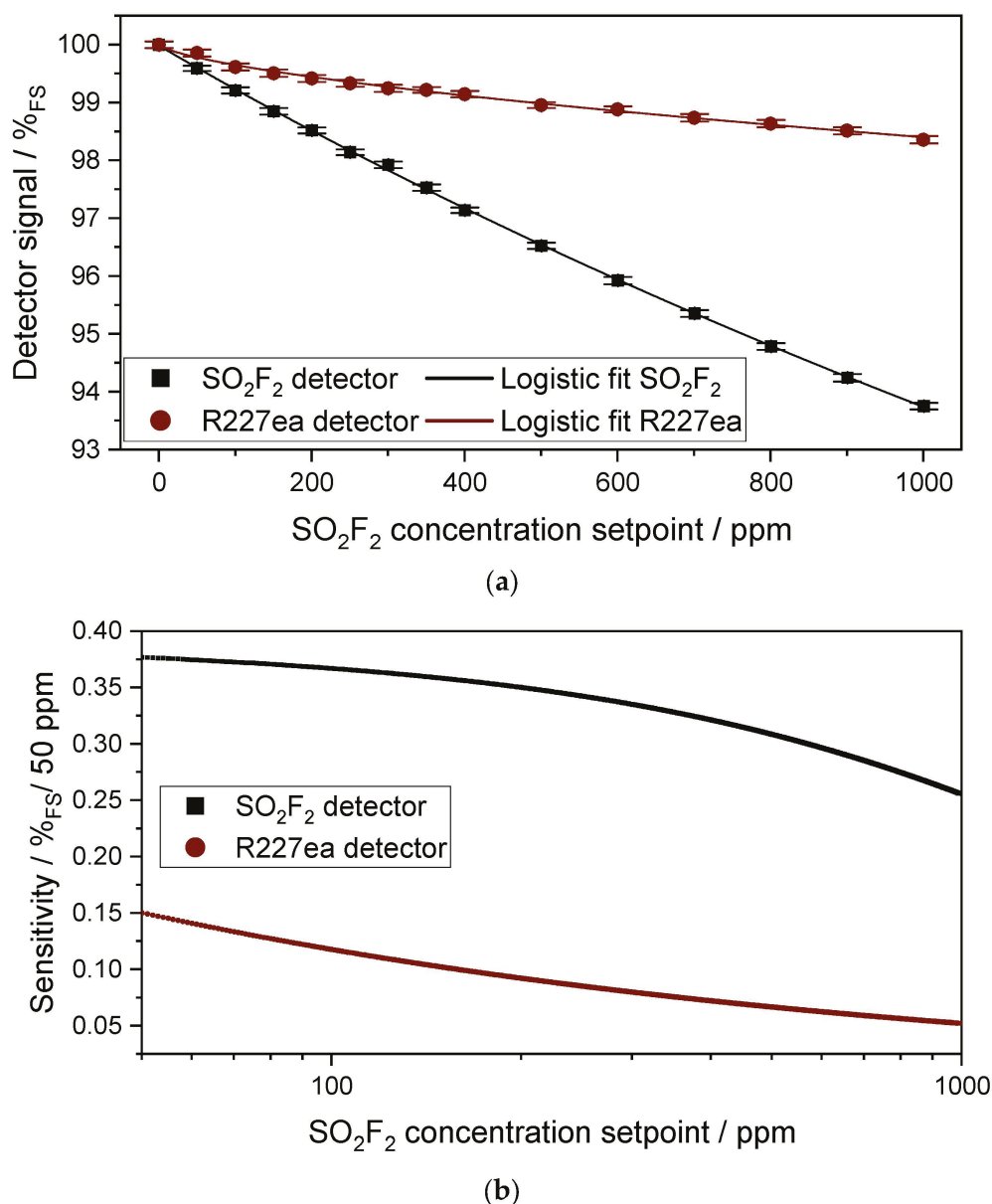


Figure 5. (a) Variation in the sensor signal of both photoacoustic detectors as a function of the SO_2F_2 concentration change in the absorption cell ($l = 50$ mm). A logistic function as in Equation (2) describes the detector response well. (b) Sensitivity of both photoacoustic detectors in % FS /50 ppm in concentration range between 50 and 1000 ppm SO_2F_2 .

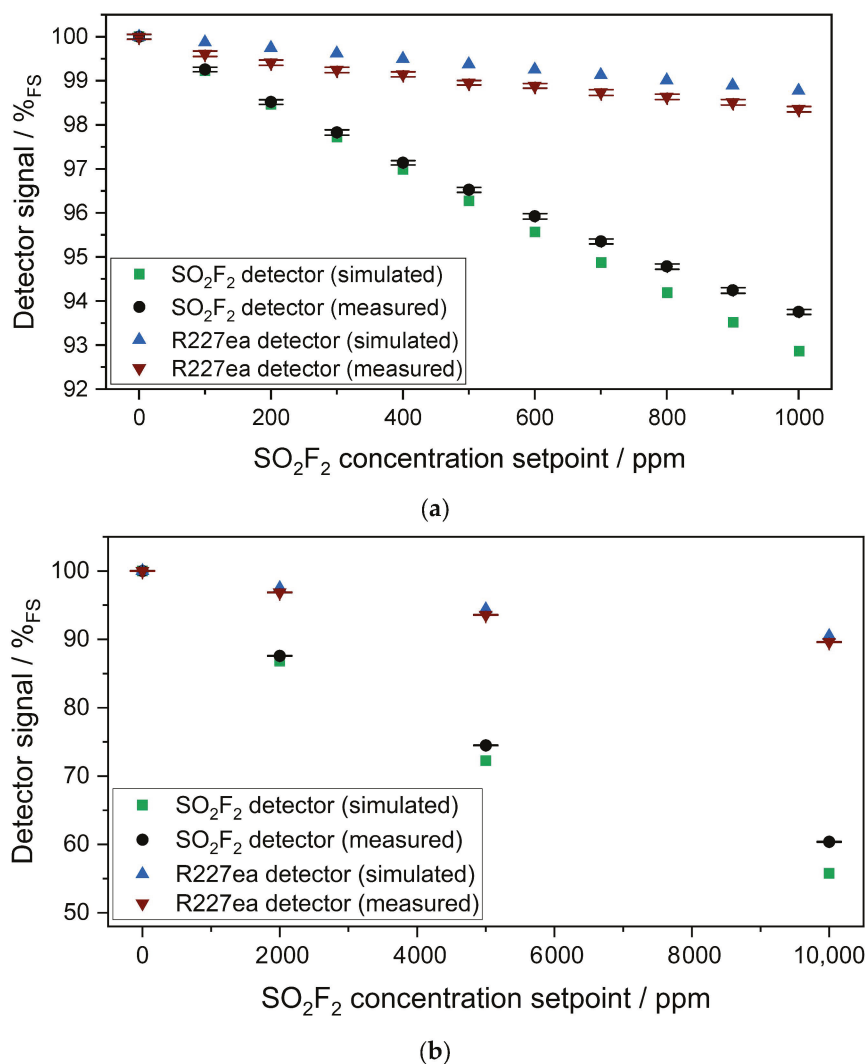


Figure 6. (a) Variation in the measured and the simulated signals of both photoacoustic detectors as a function of the SO_2F_2 concentration in the absorption cell ($l = 50$ mm) between 0 and 1000 ppm as well as that at SO_2F_2 concentrations of 2000 ppm, 5000 ppm and 10,000 ppm in the absorption cell ($l = 50$ mm) in (b).

3.1.2. Characterization of the Cross Sensitivity of the Sensors to CO_2 and H_2O

The results of the measurements regarding the cross-sensitivity of the two photoacoustic detectors towards CO_2 and H_2O are shown in Figure 7a,b. The SO_2F_2 detector shows slightly higher cross-sensitivity to CO_2 than the R227ea detector. This is due to SO_2F_2 having more overlapping absorption lines with CO_2 than R227ea. In addition, interfering gases in the detectors may increase the cross-sensitivities to other gases as well. The relative signal change of the SO_2F_2 photoacoustic detector when the CO_2 concentration in the absorption cell was changed from 400 ppm to 1000 ppm is about 0.5%_{FS}, which corresponds to a similar relative signal change when the SO_2F_2 concentration in the absorption cell was changed from 0 to 65 ppm. In contrast, when the CO_2 concentration in the absorption cell changed from 400 ppm to 1000 ppm, the relative signal change of the R227ea photoacoustic detector was about 0.4%_{FS}, corresponding to a similar relative signal change when the SO_2F_2 concentration in the absorption cell was changed from 0 to 150 ppm. Depending on the application field of the sensor, an IR filter that blocks the wavelength range below 5 μm could be mounted onto the IR emitter to minimize this cross-sensitivity.

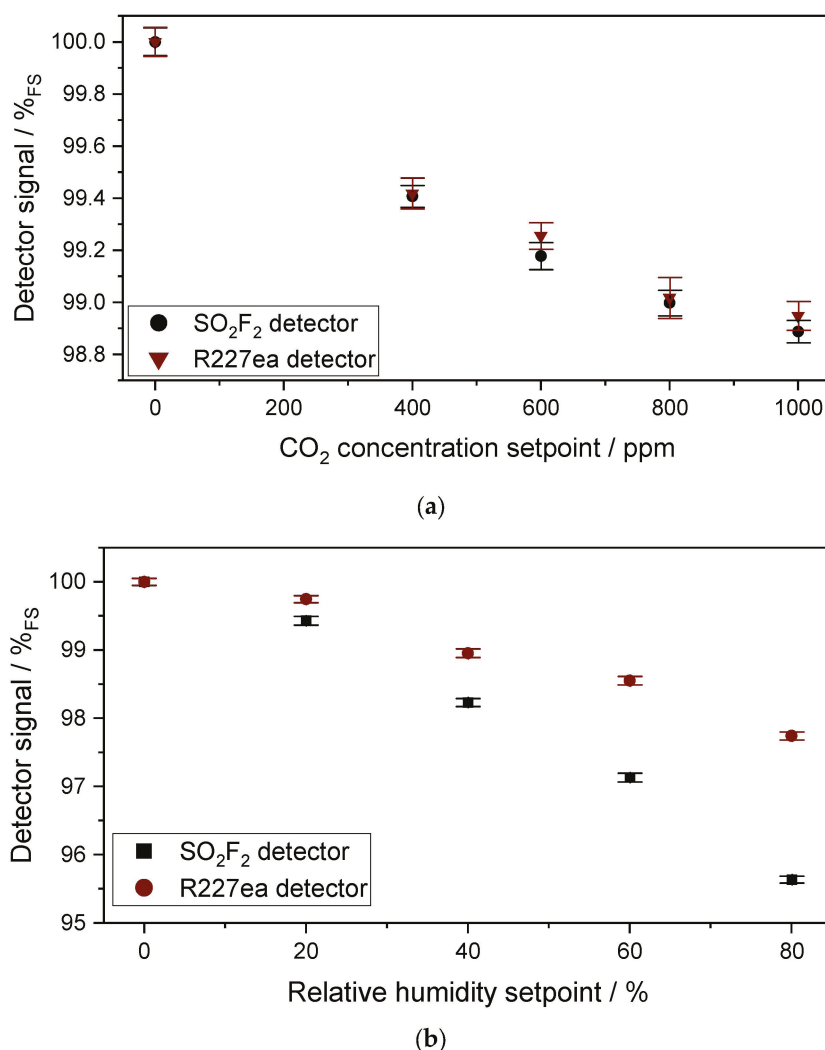


Figure 7. (a) Measured signal of both photoacoustic detectors with 400 ppm, 600 ppm, 800 ppm and 1000 ppm CO₂ in the absorption cell ($l = 50$ mm) and (b) 20%, 40%, 60% and 80% relative humidity (at $T = 30$ °C).

A change in relative humidity has a higher effect on the signal than CO₂ in the sensors with both detectors. The sensor with the SO₂F₂ detector shows higher cross-sensitivity to humidity than the R227ea photoacoustic detector. The relative signal change of the SO₂F₂ photoacoustic detector when the relative humidity in the absorption cell was changed from 40% r.H. to 80% r.H. is about 2.6%_{FS}, which corresponds to an equivalent of 360 ppm SO₂F₂. The relative signal change of the R227ea detector following the relative humidity change from 40% r.H. to 80% r.H. is about 1.2%_{FS}, which corresponds to a SO₂F₂ concentration change from 0 to 650 ppm. One strategy to mitigate this cross-sensitivity would be the implementation of a humidity sensor into the system for compensation.

3.2. Sensor for the Measuring Range 0–100 ppm SO₂F₂

3.2.1. Characterization of the Sensitivity of the Sensors to SO₂F₂

As with the sensor setup with the 50 mm absorption cell, which was analyzed in detail in the previous subsection, experiments were also carried out with the sensor setup with the 1.6 m multi-pass absorption cell. Figure 8a displays the signal of both photoacoustic detectors with respect to the concentration change of SO₂F₂ between 0 and 100 ppm in the 1.6 m multi-pass absorption cell. As in the experiments with the 50 mm cell, both photoacoustic detectors again show a non-linear response to the concentration change in SO₂F₂. In the presence of 100 ppm SO₂F₂ in the absorption cell, the SO₂F₂ photoacoustic

detector shows a detector signal of 82.34%_{FS}, whereas that of R227ea decreases to 96.1%_{FS}. Considering the sensitivity results of the two photoacoustic detectors displayed in Figure 8b, as well as the 3σ noise of 0.08%_{FS} of the SO₂F₂ detector and 0.11%_{FS} of the R227ea detector, a detection limit of 0.5 ppm can be achieved with the SO₂F₂ detector and 2 ppm with the R227ea detector. The 3σ resolution of the SO₂F₂ detector is 1.25 ppm at 100 ppm SO₂F₂, while it is 4.25 ppm for the R227ea detector. This is due to the lower sensitivities at higher SO₂F₂ concentrations. The response time t_{90} of the sensor is 40 s at a SO₂F₂ flow rate of 2 L/min, which is dominated here by the volume of the absorption chamber (approx. 500 mL) and the time required for the gas exchange in the chamber to reach the SO₂F₂ concentration setpoint.

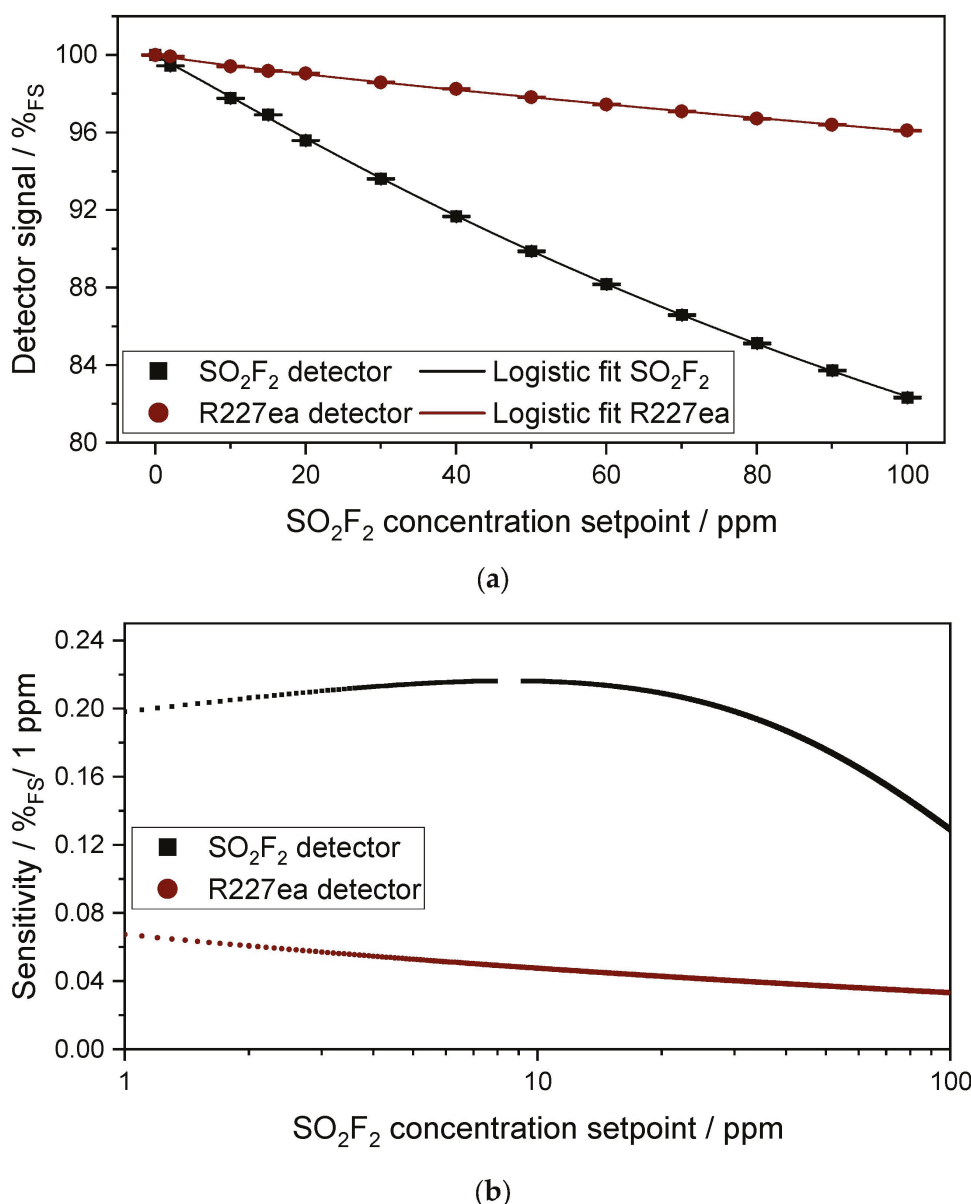


Figure 8. (a) Variation in the sensor signal of both photoacoustic detectors as a function of the SO₂F₂ concentration change in the absorption cell ($l = 1.6$ m). A logistic function as in Equation (2) describes the detector response well. (b) Sensitivity of both photoacoustic detectors in %_{FS}/1ppm in concentration range between 1 and 100 ppm SO₂F₂.

Figure 9 compares the simulated and measured signal of the two photoacoustic detectors. As in the previous experiments with the 50 mm absorption cell, there is a

difference between the simulated and measured signal of both photoacoustic detectors. However, the difference between the simulated and measured signal of both photoacoustic detectors seems to be smaller here with the 1.6 m cell than with the 50 mm cell. This seems feasible because the IR radiation losses at characteristic wavelengths are larger in the 50 mm absorption cell than in the 1.6 m multi-pass absorption cell, which in turn has an influence on the signal change. Due to manufacturing reasons, the 50 mm absorption cell consists of four segments, which leads to higher IR radiation losses. In addition, the surface quality of the mirrors of the multi-pass absorption cell is much better than the surface quality of the optical path of the 50 mm absorption cell, which leads to lower radiation losses. Of course, the reasons already mentioned in the discussion with the 50 mm absorption cell play a role here as well.

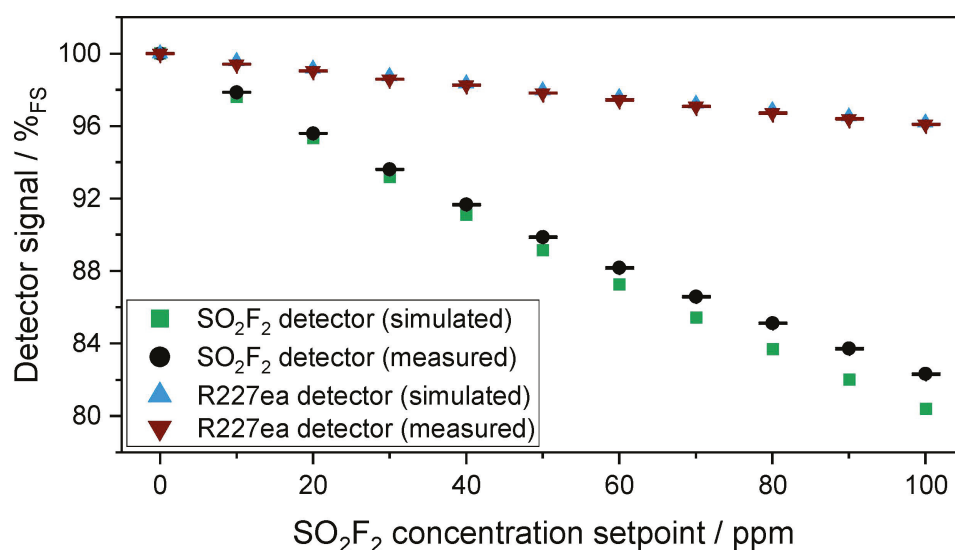


Figure 9. Variation in the measured and the simulated signals of both photoacoustic detectors as a function of the SO₂F₂ concentration change in the absorption cell ($l = 1.6$ m) between 0 and 100 ppm.

3.2.2. Characterization of the Cross-Sensitivity of the Sensors to CO₂ and H₂O

Figure 10a,b show the results of the measurements on the cross-sensitivity of the two detectors to CO₂ and H₂O, with the optical path length of 1.6 m. The effect of the cross-sensitivity becomes higher compared to the 50 mm cell. The relative signal change of the SO₂F₂ photoacoustic detector when the CO₂ concentration was changed from 400 ppm to 1000 ppm in the absorption cell is about 1.4%_{FS}, which corresponds to a concentration change of SO₂F₂ from 0 to 6.3 ppm in the absorption cell. In contrast, when the CO₂ concentration changed from 400 ppm to 1000 ppm in the absorption cell, the relative signal change of the R227ea photoacoustic detector was about 0.9%_{FS}, corresponding to a concentration change of SO₂F₂ from 0 to 19.9 ppm.

As before with the 50mm cell, the change in relative humidity has a much higher effect on the signal of both photoacoustic detectors than CO₂. The SO₂F₂ photoacoustic detector shows higher cross-sensitivity to humidity than the R227ea photoacoustic detector. The relative signal change of the SO₂F₂ photoacoustic detector with a humidity change from 30% to 60% is about 5.9%_{FS}, which corresponds to a concentration change of SO₂F₂ from 0 to 27.4 ppm. The signal change of the sensor with the R227ea detector with a relative humidity change from 30% to 60% is about 2.5%_{FS}, which corresponds to a concentration change of SO₂F₂ from 0 to 59 ppm. The response of the SO₂F₂ detector to H₂O is higher than the R227ea detectors, but due to the higher sensitivity of the SO₂F₂ detector to SO₂F₂ than R227ea, the equivalent cross-sensitivity of the SO₂F₂ detector is smaller.

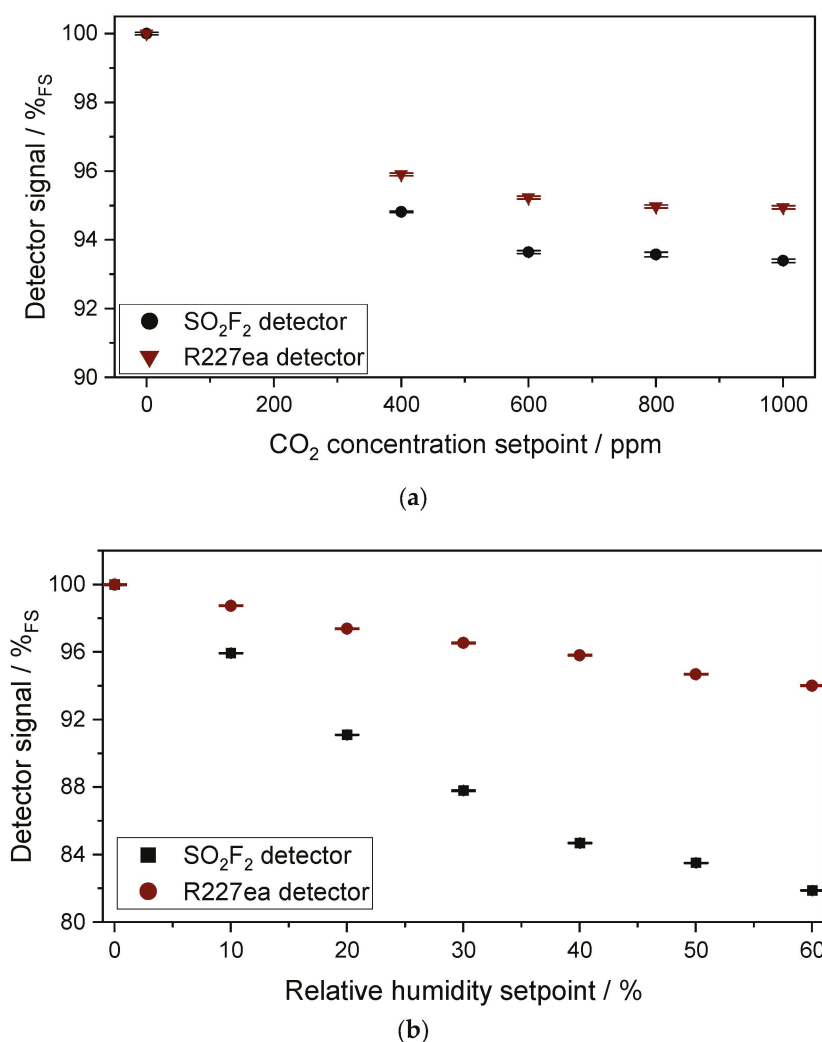


Figure 10. (a) Measured signal of both photoacoustic detectors to 400 ppm, 600 ppm, 800 ppm and 1000 ppm CO₂ in the absorption cell ($l = 1.6$ m) and (b) to 10%, 20%, 30%, 40%, 50% and 60% relative humidity (at $T = 30$ °C).

4. Conclusions

Two photoacoustic sensor setups for the detection of SO₂F₂ in two concentration ranges (0–1 vol.-% SO₂F₂ and 0–100 ppm SO₂F₂) were presented. Both sensors are based on the photoacoustic two-chamber approach, consisting of an IR emitter, an absorption cell and a photoacoustic detector. The first sensor setup has an absorption cell with an optical length of 50 mm for detecting SO₂F₂ in the concentration range of 0–1 vol.-% SO₂F₂, while the second setup has a multi-pass absorption cell with an optical path length of 1.6 m for detecting SO₂F₂ in the concentration range of 0–100 ppm. The photoacoustic detector was designed as a hermetically tight gas cavity that was equipped with a MEMS microphone and sealed by soldering a Si window. After that, the detectors were filled with either pure SO₂F₂ or a substituent gas, the refrigerant R227ea. The sensitivity to SO₂F₂ and cross-sensitivity to CO₂ and H₂O were measured for both photoacoustic detectors with both absorption cells and strategies for their mitigation discussed. Using the sensor setup with the 50 mm absorption cell, a detection limit of 20 ppm was obtained with the SO₂F₂ photoacoustic detector and 60 ppm with the R227ea photoacoustic detector. With the multi-pass absorption cell, a detection limit of 0.5 ppm was obtained with the SO₂F₂ photoacoustic detector and 2 ppm with the R227ea photoacoustic detector. Although these detection limits are approximately two decades higher than those that can be achieved with resonant photoacoustic systems [25,29], our sensor is able to monitor the OEL in different

applications in the future. A direct comparison with sensing devices relying on chemical principles (cf. [6–15]) is difficult because these studies investigated the sensing ability of different materials but did not yet set up sensor devices. The next steps in our sensor development include improvements in sensor integration and the testing of the sensor systems in field applications, e.g., in freight containers.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/s24010191/s1>, Figure S1: Sensor response to SO₂F₂ using the 50 mm cell; Figure S2: Sensor response to SO₂F₂ using the 1.6 m cell.

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Article

A Low-Cost Inertial Measurement Unit Motion Capture System for Operation Posture Collection and Recognition

Mingyue Yin ¹, Jianguang Li ^{1,*} and Tiancong Wang ²

¹ School of Mechatronics Engineering, Harbin Institute of Technology, Harbin 150001, China; 21b908117@stu.hit.edu.cn

² School of Astronautics, Harbin Institute of Technology, Harbin 150001, China; 17862700589@163.com

* Correspondence: meigli@hit.edu.cn

Abstract: In factories, human posture recognition facilitates human–machine collaboration, human risk management, and workflow improvement. Compared to optical sensors, inertial sensors have the advantages of portability and resistance to obstruction, making them suitable for factories. However, existing product-level inertial sensing solutions are generally expensive. This paper proposes a low-cost human motion capture system based on BMI 160, a type of six-axis inertial measurement unit (IMU). Based on WIFI communication, the collected data are processed to obtain the displacement of human joints' rotation angles around XYZ directions and the displacement in XYZ directions, then the human skeleton hierarchical relationship was combined to calculate the real-time human posture. Furthermore, the digital human model was been established on Unity3D to synchronously visualize and present human movements. We simulated assembly operations in a virtual reality environment for human posture data collection and posture recognition experiments. Six inertial sensors were placed on the chest, waist, knee joints, and ankle joints of both legs. There were 16,067 labeled samples obtained for posture recognition model training, and the accumulated displacement and the rotation angle of six joints in the three directions were used as input features. The bi-directional long short-term memory (BiLSTM) model was used to identify seven common operation postures: standing, slightly bending, deep bending, half-squatting, squatting, sitting, and supine, with an average accuracy of 98.24%. According to the experiment result, the proposed method could be used to develop a low-cost and effective solution to human posture recognition for factory operation.

Keywords: motion capture; inertial measurement unit; human posture recognition; BiLSTM model

1. Introduction

In the era of Industry 4.0, motion capture systems will find broader applications in engineering for digital human modeling [1]. In the factory, the recognition of human body movement contributes to human–machine collaboration [2] and human factor analysis [3]. In contrast to optical cameras, inertial sensors are more flexible and resistant to obstruction, making them suitable for scenarios such as automotive assembly [4,5]. Researchers have established methods for capturing full-body motion by sparse inertial sensors. Susperregi et al. [6] proposed the fusion of multiple low-cost sensors and cameras to capture human behavior, addressing data bias through data fusion. Caputo et al. [4] utilized a motion capture system to estimate the basic segment positions of the human body. He et al. [7] introduced a wavelet tensor fuzzy clustering scheme for analyzing multisensor signals to capture human behavior, achieving higher recognition accuracy compared to the fuzzy mean clustering method. Liu et al. [8] developed a segmentation procedure based on a moving average window algorithm, and introduced a double-threshold technique for automatic recognition and segmentation of calibration postures. Yi et al. [9] tracked human motion using only six inertial sensors, combining a neural kinematic estimator and a physical perception motion optimizer. Previous work has provided good guidance

for achieving low-cost inertial sensor dynamic capture, giving IMUs potential application prospects in the engineering field.

Due to the inevitable presence of a large number of metal objects in the factory environment, the negative impact on magnetometers needs to be considered. Therefore, we have chosen the cost-effective six-axis sensor chip BMI160, along with the ESP8266-NodeMCU chip, IP5306 BMS charging board, and li-ion battery, to collectively form our tracker; the total cost is USD 3.60. A comparison of prices and performance of other IMU solutions is presented in Table 1, covering aspects such as price, sampling rate, accelerometer rate noise spectral density, gyroscope rate noise spectral density, interface mode, and battery life. The IMU solutions commonly used in human motion recognition research, such as Xsens MTw Awinda [10], MetaMotionR [10], Next-Generation IMU [11,12], MetaMotionC [13], Shimmer3 [14], and InvenSense MPU-9250 [15], were chosen. Through comparison, our solution demonstrates advantages in terms of pricing. Moreover, for the collection of human body movements, the sampling rate and accuracy within our solution fall within acceptable ranges, and the interface and the battery life employed in our solution are also sufficient for human motion capture.

Table 1. Comparison of prices and performance of common IMUs.

Ref.	IMU Models	Price (1 IMU)	Sampling Rate	Acc. Noise [$\mu\text{g}/\sqrt{\text{Hz}}$]	Gyro. Noise [$^{\circ}/\text{s}/\sqrt{\text{Hz}}$]	Interface	Battery Life
[10]	Xsens MTw Awinda	\$437.2	120 Hz	200	0.01	Wireless 2.4 GHz	6 h
[10]	MetaMotionR	\$98.4	100 Hz	300	0.007	Bluetooth LTE 2.4 GHz	1 to 14 days
[11,12]	NG IMU	\$273.3	50 Hz/100 Hz	NA	NA	Preconfigured Wi-Fi router	4 to 12 h
[13]	MetaMotionC	\$75	NA	300	0.007	Bluetooth 4.0	1 to 14 days
[14]	Shimmer3	\$945.5	51.2 Hz	72.5	0.007	Bluetooth	NA
[15]	InvenSense MPU-9250	\$10.9	120 Hz	300	0.01	I ² C – SPI	NA
	This work	\$3.60	100 Hz	300	0.007	Wireless 2.4 GHz	6 h

Machine learning is commonly used in human motion recognition research, for example, the support vector machines classification model [16], Markov model [17], and random forest (RF) [18]. In the past few years, deep learning algorithms have found extensive applications in the realm of human motion recognition [19], demonstrating superior recognition performance compared to traditional algorithms [20,21]. Akkaladevi et al. [22] proposed a multilabel human action recognition framework using a spatiotemporal graph convolutional network (ST-GCN) to capture spatial and temporal relationships between joint sequences. Tang et al. [23] introduced a novel dual-branch interactive network (DIN) that incorporates the strengths of both CNNs and transformers for managing multichannel time series. Wang et al. [24] explored adaptive networks that can dynamically adjust their structure based on available computing resources, allowing for a trade-off between accuracy and speed. Dey et al. [25] utilized a three-layer stacked temporal convolutional network to predict foot angular positions. Oh et al. [26] employed a pattern recognition method based on an artificial neural network algorithm to detect different gait states. Seenath et al. [27] proposed the conformer-based human activity recognition model, which leverages attention mechanisms to better capture the temporal dynamics of human motion and improve recognition accuracy. Considering that IMU motion capture data contain both temporal and spatial information, Chen et al. [28] used a deep convolutional neural network with a bidirectional long short-term memory network (DCNN-BiLSTM) to recognize and estimate four swimming styles. Based on deep learning algorithms, the accuracy of human motion

recognition can reach around 90%. Based on existing research, we will carry out IMU-based human operation posture recognition.

Existing product-level inertial motion capture devices generally require high purchasing costs. This paper aims to explore a low-cost operation motion capture system and an operation posture recognition solution based on IMU. The cost-effective core components are used to build the human motion capture system, and experimental tests are conducted in virtual factory environments. A deep neural network model is used to recognize multiple basic operation postures offline based on experimental datasets. This paper is organized as follows: Section 1 offers an overview of the research status and significance of IMU-based human motion capture and operation posture recognition. Section 2 introduces the low-cost assembly operation motion capture scheme based on IMU from the aspects of hardware configuration, motion signal processing, and human motion reproduction. Section 3 describes the operation motion capture experiment and the operation posture recognition method based on the BiLSTM model. Section 4 discusses the proposed research methods and suggests future research directions; Section 5 summarizes the proposed research work.

2. Design of a Low-Cost Motion Capture System Based on IMU

2.1. Overall Solution

This paper proposes a low-cost human motion capture system based on IMU. As shown in Figure 1, the system consists of four main components: a firmware module, a hardware module, a signal processing module, and a synchronized visualization module. In the hardware part, the core modules include the inertial measurement, communication, and charging modules. The inertial measurement module utilizes BMI160. The communication module uses the ESP8266 chip for wireless communication via WiFi. The charging module consists of a charging integration board, a battery, and a switch. The BMI160 is driven by the CH341SER. The firmware code is compiled and run in PlatformIO IDE (VSCode). The tracker signals are transmitted to the host computer via WiFi, where the collected data are processed to obtain the pose information of the sensors. The trackers are assigned to the corresponding joint positions of the digital human body based on their actual wearing positions. Combined with the hierarchical relationship of the human skeleton, the real-time calculation of human posture is performed. Finally, using the Open Sound Control (OSC) network transmission protocol, the system synchronously visualizes human motion through a 3D digital human model in Unity3D.

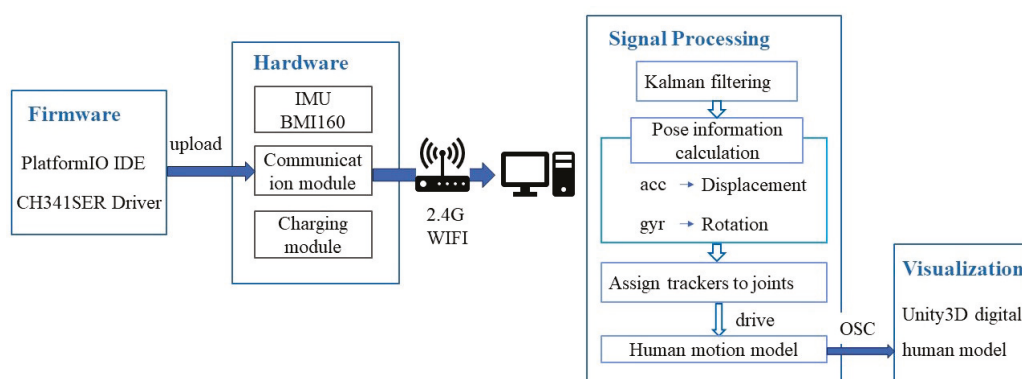


Figure 1. The structure of the low-cost motion capture system based on IMU.

2.2. Hardware

The main functional components of the action tracker are the BMI160 IMU module, the ESP8266-NodeMCU module, and the IP5306 BMS charging module. Considering usability and price, the BMI160 was chosen to implement the inertial measurement function. The BMI160 chip module includes a three-axis accelerometer and a three-axis gyroscope. The chip features three 16-bit analog-to-digital converters (ADCs) for digitizing the accelerometer outputs and three 16-bit ADCs for digitizing the gyroscope outputs with standard

IIC (up to 1 MHz)/SPI communication protocol. The chip can monitor an acceleration range of ± 4 g and an angular velocity range of $\pm 250^\circ/\text{s}$. The sampling rate is 100 Hz. In coordination, the ESP8266 Node MCU module, which is a version containing the ESP-12F WIFI unit with a peak power consumption of approximately 1.5 W, was selected for communication, supporting WIFI connections in the 2.4 G frequency band. Additionally, the charging module was designed using the TP4056 Type-C charging chip, an input voltage of 5 V, and a maximum charging current of 1000 mA. The 3.7 V, 1500 mAh lithium battery was chosen. Finally, two-position toggle switches were selected to control the tracker's on and off functions. The circuit diagram and physical diagram of the tracker are shown in Figure 2a. The wires were soldered in a tightly arranged manner to minimize the size of the tracker. The tracker's housing was 3D printed, with a total length of 54 mm, a total width of 39 mm, and a total height of 29 mm. The strap width is 25 mm, as shown in Figure 2b. In this paper, six motion trackers are used, strapped respectively to the chest, and waist, above the left knee joint, above the left ankle joint, above the right knee joint, and above the right ankle joint of the human. From top to bottom, these trackers represent the movements of the chest, waist, knee end of the femur bone, and the ankle end of the tibia bone. The wearing positions and directions of IMU are shown in Figure 2c. When wearing, the direction of the BMI160 inside each tracker is consistent, with the Y-axis pointing towards the ground and the Z-axis pointing towards the front of the body. The length values of each segment of the experimenter's body have been pre-inputted into the terminal, and the movement status of the trunk and lower limbs can be obtained by providing joint displacement and angle. Before the motion capture experiment, the experimenter needs to make two designated postures: upright posture and skiing posture, to calibrate the initial direction of each tracker.

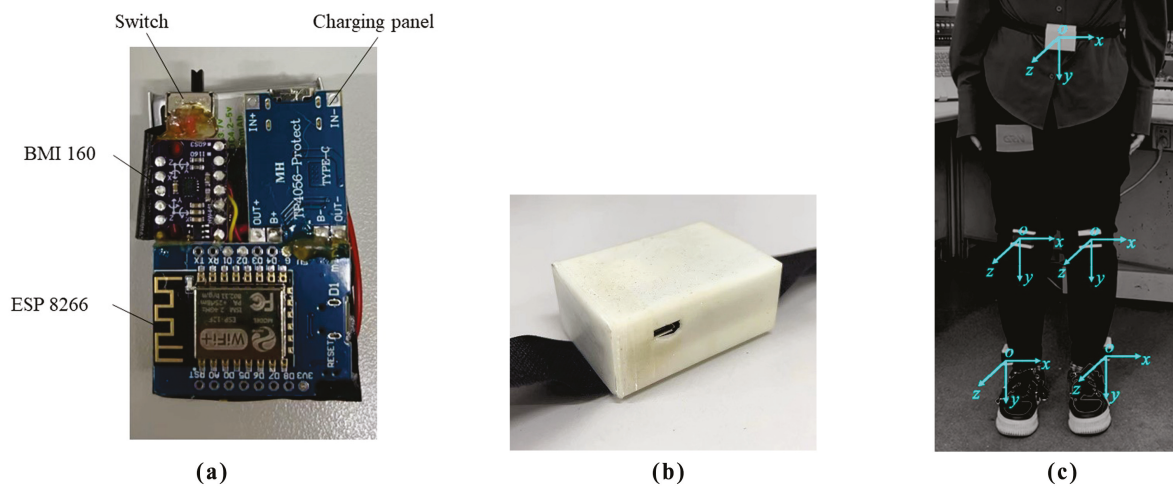


Figure 2. The circuit diagram and physical diagram of the tracker. (a) The status of completed welding. (b) The tracker with casing and straps attached. (c) The tracker placement.

2.3. Signal Processing

The processing of motion signals involves two main parts: filtering and drift compensation of IMU signals. Kalman filtering algorithm is used for filtering. Human motion is irregular but within a certain activity space. The Kalman filtering algorithm is a classic method for processing IMU signals, which consists of predicting the position of the next time step, and correcting the position of the current state. The specific implementation principle is as follows.

$$\hat{X}_k = A_k \hat{X}_{k-1} + B_k u_k \quad (1)$$

$$P_k = A_k P_{k-1} A_k^T + Q \quad (2)$$

Above are prediction equations. In Equation (1), $\hat{X}_k$ represents the prior state estimation at time k , and $\hat{X}_{k-1}$ represents the posterior state at time $k-1$, respectively. A_k is a transformation matrix that represents the proportion of the previous state's correction to the current state result. B_k represents the control variable matrix, and u_k is the state control vector. In Equation (2), P_k represents the prior estimate covariance at time k , and P_{k-1} represents the posterior estimate covariance at time $k-1$, Q is the covariance of the system process noise.

$$K_k = \frac{P_k H_k^T}{H_k P_k H_k^T + R} \quad (3)$$

$$\hat{X}_k = \hat{X}_k + K_k (Z_k - H_k \hat{X}_k) \quad (4)$$

$$P_k = (I - H_k K_k) P_k \quad (5)$$

Equation (3) calculates the Kalman gain (K_k), in which H_k represents the prediction matrix and R is the covariance matrix of the measurement noise. Equation (4) uses two predicted values and a ratio to calculate the output $\hat{X}_k$, the posterior state estimation at time k . Z_k is a measurement vector. Equation (5) prepares the posteriori estimation covariance at time $k(P_k)$ for the prediction of the next time step.

The drift compensation part mainly involves applying inverse rotation to compensate drift of the IMU. In this study, signal processing and fusion are based on the Slime VR open-source software, a recently matured open-source motion capture solution based on IMUs. Based on our experimental environment and equipment, after multiple tuning and testing sessions primarily focusing on the accuracy and stability of reproducing human motion, we finally set the filtering strength to 50% and drift compensation strength to 20%. The original signals collected by IMUs consist of XYZ tri-axis acceleration signals and XYZ tri-axis gyroscope signals. The displacement information can be obtained by integrating the acceleration signal, while the rotation angle information can be obtained by integrating the gyroscope signal.

The calculation method for obtaining the current pose from two frames of IMU data is as follows. For the acceleration data, calculate the average acceleration between the current time t and the next time $t+1$. This average acceleration over the time interval is used to approximate the velocity and displacement at $t+1$, given the initial velocity and displacement at t . Since the IMU acceleration data is represented in the body coordinate system, it needs to be transformed to the world coordinate system using the corresponding pose. Before the transformation, the bias needs to be subtracted, and after the transformation, the gravitational acceleration needs to be subtracted. For the gyroscope data, the average angular velocity over the time interval is calculated between t and the next time $t+1$. With this average angular velocity and the current pose, the pose at $t+1$ can be approximated. Equations (6)–(12) show the entire integration process.

$$a_{t,w} = Q_t(a_{t,b} - B_a) - g \quad (6)$$

where $a_{t,w}$ is the acceleration of IMU at time t in the world coordinate system, Q_t is the quaternion of IMU at time t , $a_{t,b}$ is the acceleration at time t in the body coordinate system, B_a is the deviation of the body coordinate system, and g is the gravitational acceleration.

$$\bar{\omega}_t = \frac{1}{2}(\omega_t + \omega_{t+1}) - B_g \quad (7)$$

$$Q_{t+1} = Q_t(\omega_t \Delta t) \quad (8)$$

In Equations (7) and (8), $\bar{\omega}_t$ is the average angular velocity, ω_t is the angular velocity at time t , ω_{t+1} is the angular velocity at time $t + 1$, and B_g is the gyroscope bias, Q_{t+1} is IMU Quaternion at time $t + 1$.

$$a_{t+1,w} = Q_{t+1}(a_{t+1,b} - B_a) - g \quad (9)$$

$$a_{t,w} = \frac{1}{2}(a_{t,w} + a_{t+1,w}) \quad (10)$$

In Equations (9) and (10), $a_{t+1,w}$ is the acceleration in the world coordinate system at time $t + 1$, $a_{t+1,b}$ is the acceleration in the body coordinate system at time $t + 1$, and $a_{t,w}$ is the average acceleration.

$$V_{t+1} = V_t + a_{t,w}\Delta t \quad (11)$$

$$D_{t+1} = D_t + V_t\Delta t + \frac{1}{2}a_{t,w}\Delta t^2 \quad (12)$$

In Equations (11) and (12), V_t is the velocity at time t , V_{t+1} is the velocity at time $t + 1$, D_t is the displacement of the IMU at time t , and D_{t+1} is the displacement of the IMU at time $t + 1$.

2.4. Online Synchronized Display of Human Body Motion

The online synchronized display of human body movements is achieved based on the tracker's pose information and the hierarchical relationship of the human body skeleton. This study uses a simplified digital human model to focus on the operational movements of the human torso and lower limbs. A 3D digital human model was built on the Unity platform. The joint composition of the digital human includes thoracic joints, lumbar joints, left and right hip joints, left and right knee joints, and left and right ankle joints. In constructing the digital human model, the thoracic, lumbar, and hip joints comprise three independent subjoints capable of generating rotation, pitch, and yaw movements. The ankle joint is generally considered a ball joint with two independent axes of rotation, while the knee joint has only one axis of rotation. The head and upper limb segments are set to default states. Figure 3 shows the skeletal and digitized human models with skinning. The lengths of the body segments are set according to the experimenter's height (1580 mm) and standard body proportions.

Unity and the IMU host can communicate through the OSC protocol to achieve an online synchronized display of human body movements. Figure 4 shows the real-time human body movement at a certain moment and the corresponding movements of the digital human model at the same moment.

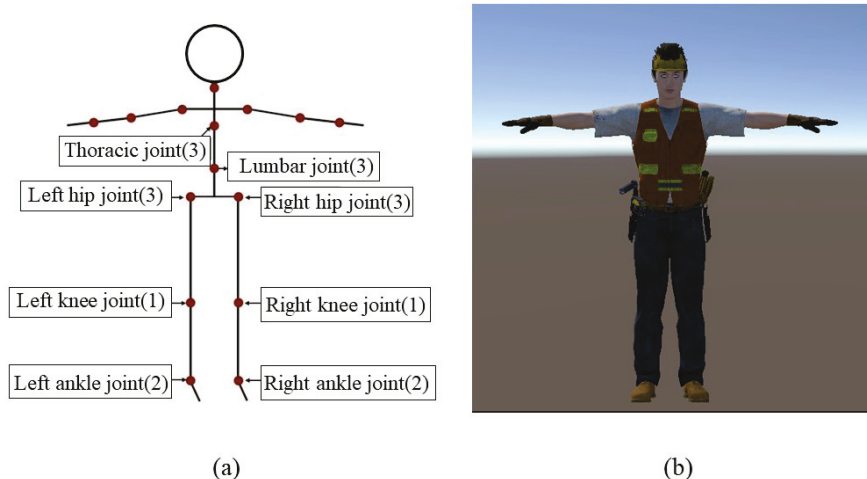


Figure 3. The digital human model. (a) Skeletal model. (b) Digital human model with skinning.



Figure 4. Real-time human body and digital human model.

3. Human Posture Recognition with Assembly Operations

3.1. Basic Operation Postures

By observing the assembly and maintenance operation processes of large-scale equipment, several common assembly basic postures that facilitate exerting force could be summarized: standing posture, slightly bending posture, deep bending posture, half squatting posture, squatting posture, sitting posture, and supine posture. Operators could perform upper limb actions based on these basic postures, such as pushing (pulling), tightening (loosening), gripping, tapping, etc. The labels, names, and reference images of the basic working postures are shown in Table 2. The definition of postures mainly considered the range of bending angles of the torso, the range of bending angles of the hip joint, and the range of bending angles of the knee joint. Labels have been defined for these basic postures.

3.2. Operation Posture Collection Experiment

As shown in Figure 5, an immersive assembly scene was set up to facilitate participants making corresponding assembly movements based on prompts using Tecnomatix software and HTC VIVE devices. The participant wearing the tracker completed the operation tasks under instructions. The router was not connected to other devices to obtain sufficient bandwidth during the experiment, and the entire experiment process was recorded. At the same time, we tried to avoid other 2.4 G signals to prevent excessive data transmission delay caused by frequency congestion in the experimental environment. The experiment was conducted within a radius of 5 m from the router to ensure low data transmission delay. The average latency during the actual testing process was approximately 3 ms. With time, the BMI160 may experience drift, causing body parts to face the wrong direction after some time. Therefore, a calibration of the wearable device was required every 10 min.

The participants sequentially completed seven different types of work tasks under voice prompts. Each work task corresponds to a category of basic working postures. A rest period was scheduled between the fourth and fifth tasks for device reset. Table 3 displays the duration of each operation task. The experiment involved a participant with a mechanical engineering background familiar with assembly processes. The participant's height is 1580 mm, and weight is 55 kg.

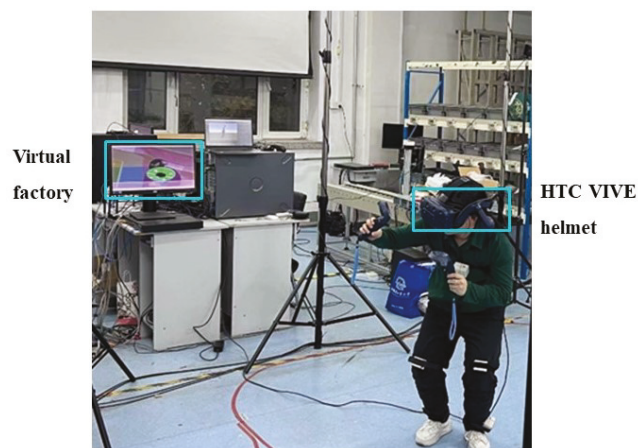


Figure 5. Operation posture collection experiment scene.

Table 2. The basic postures.

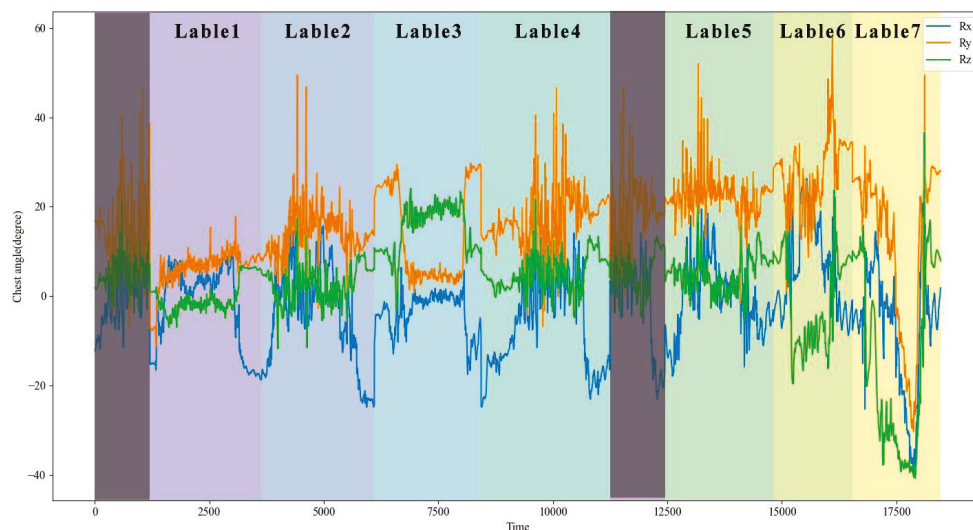
Lable	Gesture Name	Gesture Picture	Torso Bending Angle (°)	Hip Joint Bending Angle (°)	Knee Joint Bending Angle (°)
1	standing posture		−15–15	−17–5	−3–5
2	slightly bending posture		15–40	5–50	5–60
3	deep bending posture		40–84	70–116	5–70
4	half squatting posture		15–40	50–116	60–100
5	squatting posture		15–40	50–116	100–150
6	sitting posture		−15–15	30–70	−3–5
7	supine posture		−5–40	50–100	5–60

Table 3. The duration of each operation task.

Task Name	Duration (ms)
Preparation	60,000
Installing bolts in standing posture	121,800
Installing bolts in slightly bending posture	123,250
Installing bolts in deep bending posture	116,550
Installing bolts in half squatting posture	140,600
Break time	60,000
Installing bolts in squatting posture	118,350
Installing bolts in sitting posture	86,500
Installing bolts in supine posture	96,300

3.3. Operation Posture Recognition Method

After signal processing, the experiment data were organized as the cumulative displacement of six joints and the joint angles of six joints over time. In preparation for posture recognition, removing the preparation and rest periods and labeling the remaining periods with corresponding posture labels is necessary. As shown in Figure 6, Taking the curve of chest joint angle over time as an example, the gray area in the graph represents the excluded periods. In the remaining periods, each color represents a category of working posture.

**Figure 6.** Chest joint angle over time, each color represents a category of working posture, the gray area is the excluded periods.

BiLSTM is a deep learning model suitable for sequential data, and particularly effective for data with a temporal structure, such as time series. BiLSTM effectively captures contextual relationships and long-term dependencies in sequential data by combining forward and backward information. In recent years, the BiLSTM model has been commonly applied in research on IMU-based human posture recognition, demonstrating excellent recognition performance. Based on the experiment data, the BiLSTM model was used to recognize the seven basic operation postures: standing posture, slightly bending posture, deep bending posture, half-squatting posture, squatting posture, sitting posture, and supine posture. The operation posture recognition network structure is shown in Figure 7. Labeled experimental data were transformed into the dataset using a sliding window technique. The window length is 50 and the sliding size is 5; a total of 16,067 labeled samples were obtained for training. The input features included the displacement and rotation angles of six joints (chest, waist, left hip, right hip, left ankle, right ankle) in the XYZ direction, resulting in 36 features. The input layer of the network module is a $16,067 \times 36$ matrix. The

input sequence is processed by two separate LSTM layers, each observing the sequence in both the forward and backward directions. The number of hidden neurons in each LSTM layer is 64. The input time-series data first pass through the forward layer. For each time step, the forward LSTM unit updates its internal state and produces an output. Similarly, the input sequence data also go through the backward layer. For each time step, the backward LSTM unit updates its internal state and produces an output. The outputs from both the forward and backward directions are merged. The merged representation is then passed to a fully connected layer. Finally, it is fed into an output layer for classification, using the softmax activation function to generate a probability distribution over the classes. The outputs of multiple neurons are mapped to the range of 0–1 to obtain the predicted probability distribution, which represents the probability of belonging to each category and enables posture prediction. This model was compiled using the cross-entropy loss function and adaptive moment estimation (Adam) optimizer. We divided the dataset into training and testing sets in a 4:1 ratio, the random state was set to 42. The epochs and batch size were set to 10 and 32. The initial learning rate was set as 0.001. L2 regularization with a dropout of 0.5 was selected to prevent overfitting of the model.

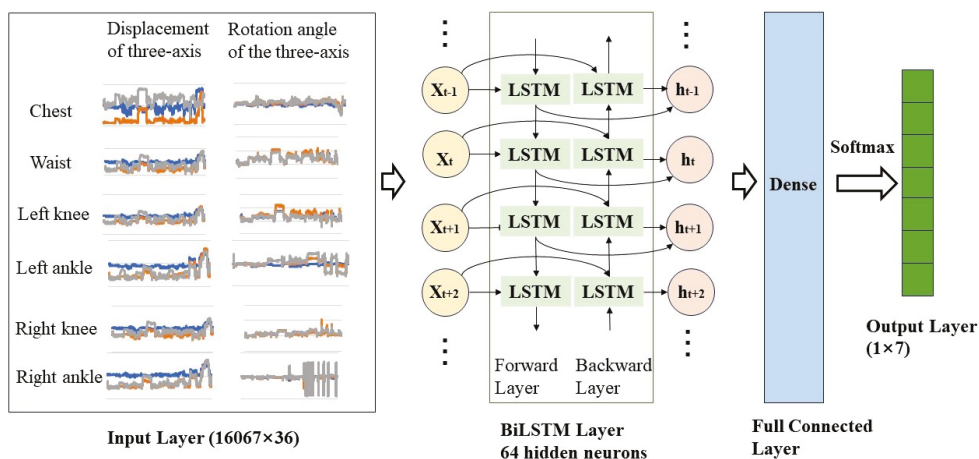


Figure 7. The operation posture recognition network structure.

3.4. Operation Posture Recognition Result

The offline test was conducted on a workstation with an Intel Core i7-1165G7 CPU and NVIDIA GeForce MX 450 GPU. To reduce the random effects of the training tests, the sample order was randomly shuffled and the training test was repeated five times. The average training time was 75.08 s. Figure 8 shows the training and validation loss as the number of iterations increases. It can be observed that the loss curves of the training set and validation set tend to flatten after the 8th iteration. After the 10th generation, the test set loss remained stable below 0.05.

After the test, the average accuracy of posture prediction was 98.24%. The posture prediction transition time, including data preprocessing time and inference time, is 31 ms. Table 4 shows the accuracy, recall, and F-score of each posture prediction result. Each calculation result in the table is the average of 5 tests.

The results are summarized in Table 4, which shows that (1) the precision of the seven postures are all above 96%, with the highest precision for the bending posture at 99.74% and the lowest for the squatting posture at 96.80%; (2) the recall of the seven postures are all above 96%, with the highest recall for the bending posture at 99.45% and the lowest for the half-squatting posture at 96.57%; (3) the F-score of the seven postures are all above 97%, with the highest F-score for the bending posture at 99.56% and the lowest for the half-squatting posture at 97.42%. Overall, the recognition performance is best for the deep bending posture, while the recognition performance for the half-squatting and squatting postures is relatively poor. Figure 9 shows the distribution of the test set confusion matrix

from five tests. From the confusion matrix, it can be visually observed that the model performs well in classifying most postures. In comparison, the standing posture and half-squatting posture are more prone to be misclassified as a slightly bending posture.

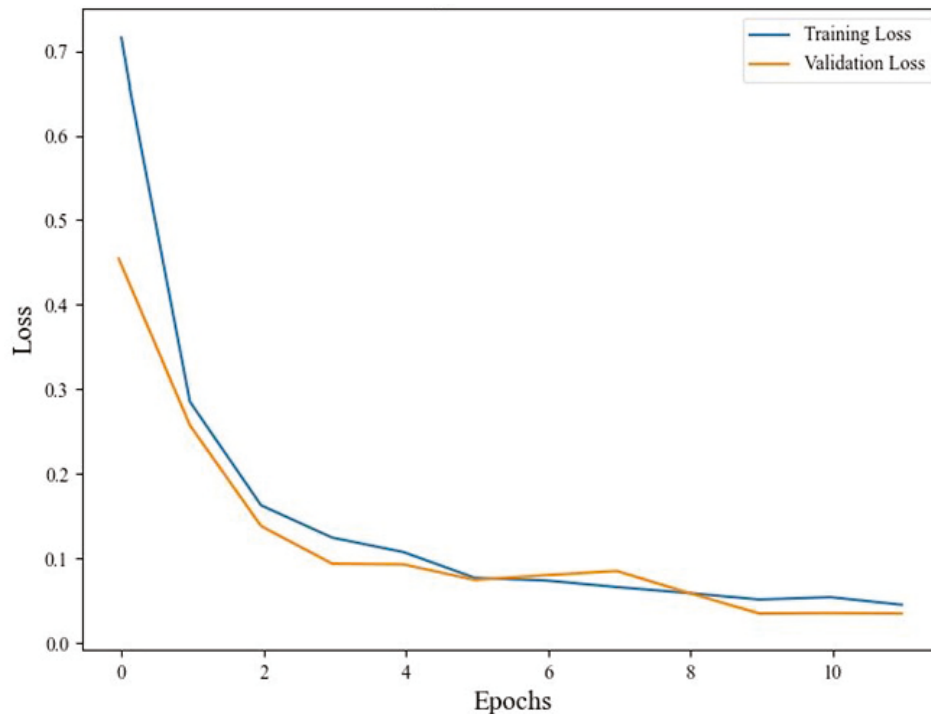


Figure 8. Training and validation loss.

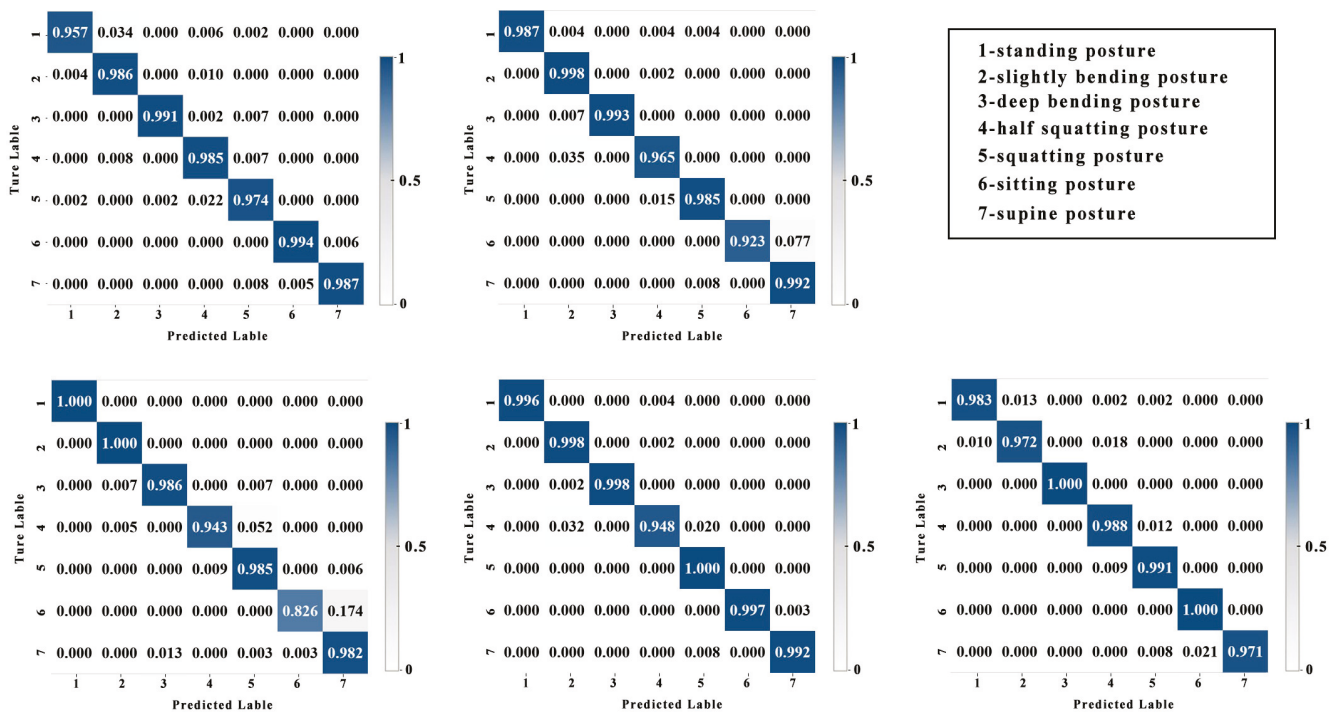


Figure 9. The confusion matrix from five tests.

Table 4. Classification accuracy of the test set.

Posture Category	Precision	Recall	F-Score
1—standing	0.9940	0.9859	0.9905
2—slightly bending	0.9764	0.9909	0.9800
3—folding	0.9974	0.9945	0.9956
4—half-squatting	0.9832	0.9657	0.9742
5—squatting	0.9680	0.9871	0.9773
6—sitting posture	0.9936	0.9721	0.9823
7—supine posture	0.9752	0.9850	0.9859

The comparison of the results with existing research is shown in Table 5. In aspects of accuracy and time cost, we compared our work with other IMU-based human posture recognition works. The number of recognition classes and the number of IMUs are also shown in the table. In terms of accuracy, our work achieved a 98% accuracy for the classification of seven postures using six trackers, placing it in a relatively high position compared to similar studies. Regarding the time cost, we took into account the posture prediction transition time (including data preprocessing time and inference time), as well as the IMU sampling rate. While our method does not match the performance of the approach described in reference [28], we were able to identify a greater number of postures with more considerable accuracy.

Table 5. Comparison of the human posture recognition results.

Ref.	Model	Accuracy	Prediction Time	Sampling Rate	Recognition Classes	Number of IMUs
[29]	ANN	82.74%	NA	50 Hz	8	2
[13]	CLN model	90.00%	NA	NA	7	5
[12]	LSTM	94.44%	170 ms	100 Hz	3	4
[28]	DCNN-BiLSTM	96.00%	8.47 ms	120 Hz	4	3
[30]	RBF-SVM	97.35%	120 ms	62 Hz	8	3
[11]	LSTM-RNN	99.00%	277 ms–488 ms	50 Hz	7	4
This work	BiLSTM	98.24%	31 ms	100 Hz	7	6

4. Discussion

This paper focuses on operation posture collection and recognition based on low-cost IMU. The proposed method is available, and the accuracy of basic posture classification recognition is satisfactory. Integrating more features and employing more complex machine learning models may result in higher recognition accuracy, but it also comes with relatively higher time costs. Based on the data in this experiment, we compared the recognition accuracy of the LSTM and BiLSTM models. We conducted five training and testing times and calculated the average accuracy of classification on the test set. The average accuracy of LSTM is 95.81%, while the average accuracy of BiLSTM is 98.24%. Compared to LSTM, BiLSTM has a greater advantage in basic posture classification for assembly tasks. However, due to the complexity of the model, BiLSTM requires longer training time. In our test, LSTM took 34.82 s and BiLSTM took 75.08 s. However, the difference in prediction time between the two models is not significant: LSTM took 15ms and BiLSTM took 31 ms.

Using wireless network transmission of data can enhance convenience, but it may lead to sudden posture distortion when the network signal is unstable, as shown in Figure 10. The occurrence of abnormal postures is related to the network signal quality. In the experimental environment, the occurrence of anomalies is rare (1–2 times/10 min) and quickly recovers to normal. However, in environments with poorer signal quality, it can be foreseen that sudden abnormal postures will affect the observation of operation movements and the accuracy of posture recognition to some extent. How to identify and

ignore exceptional signals is a research question that needs to be further studied. Because abnormal postures often manifest as sudden drifts in joint positions, a possible solution is to set a threshold for joint position changes and identify abnormal postures accordingly. Alternatively, based on gathering a sufficient number of data samples, machine learning models can be employed to differentiate between normal and abnormal states. We will attempt to address this issue in future work.

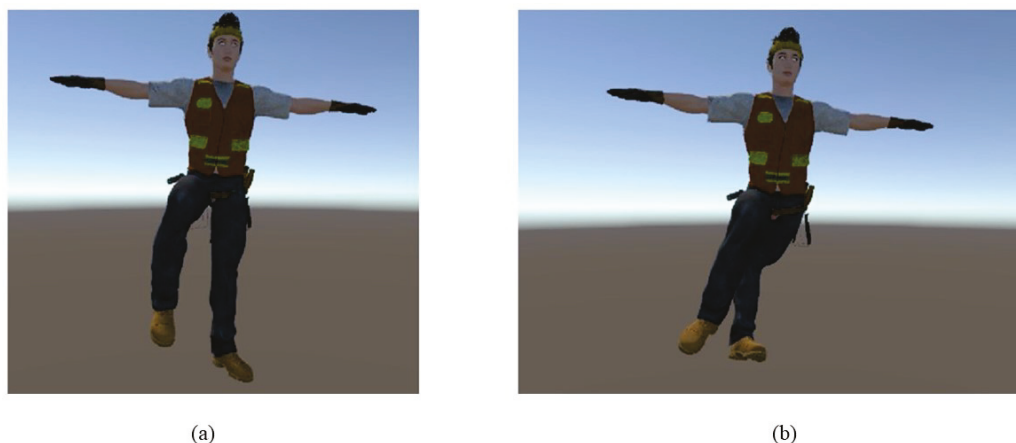


Figure 10. The sudden posture distortion when the network signal is unstable. (a) The normal posture. (b) The abnormal posture.

5. Conclusions

For the demand for operation posture recognition in the Industry 4.0 era, this paper explores a low-cost method for collecting assembly actions and recognizing assembly postures based on IMU. The study includes the following aspects:

A low-cost human motion collection system based on IMU has been proposed. The BMI160 inertial measurement module is combined with the ESP8266 communication module to create the motion collection tracker. Motion signals are transmitted via WiFi to the computer to obtain sensor pose information. The tracker is assigned to the corresponding joint positions of the digital human body based on the actual wearing position. Real-time calculation of human posture is performed by combining the hierarchical relationship of the human body skeleton. The Unity development platform receives human motion information and presents synchronized online visualization through a 3D digital human model;

We experimentally validate the feasibility of the action collection scheme. We have simulated various assembly tasks in a virtual reality environment and collected motion information for six joints of the subjects: chest, waist, left knee, left ankle, right knee, and right ankle, which included the rotation angles around XYZ directions and the displacement in XYZ directions. The BiLSTM model was used to identify seven common assembly postures: standing posture, slightly bending posture, deep bending posture, half-squatting posture, squatting posture, sitting posture, and supine posture. The model performs well in classifying these operation postures.

Based on the experiment results, the system could serve as a low-cost solution for the basic operation posture recognition of operation tasks. Subsequent research will focus on enhancing the operation posture recognition system and testing it in real factory environments.

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