

Portable Multichannel EMG Acquisition and Analysis Platform with Adaptive Detection and Machine Learning Classification for Forearm Neuromuscular Assessment [†]

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Abstract

This present paper proposes the development and validation of a low-cost, portable system for the acquisition, processing, and classification of four-channel surface electromyography (i.e., sEMG) signals recorded from the forearm. The hardware platform integrates an STM32F4 family microcontroller and BioAmp EXG Pill module. The software component was developed in Python to implement an adaptive filtering method. To evaluate gesture classification performance, three machine learning classifiers (SVM, Random Forest, kNN) were compared against a classical adaptive threshold-based detection method (75th percentile of the RMS distribution). To reveal the inter-subject variability across 10 subjects, a data augmentation procedure using a Deep Convolutional Conditional Generative Adversarial Network (i.e., DCGAN) was used. The results demonstrate the superiority of machine learning (i.e., ML) classifiers (SVM: 99.86% accuracy, 5-fold CV) over the threshold-based method (33.00%) in classifying seven gestures, confirming the necessity of pattern recognition approaches for gesture discrimination in neuromotor rehabilitation applications.

Keywords: surface electromyography; multichannel acquisition; STM32; gesture classification; SVM; Random Forest; DCGAN; neuromotor rehabilitation; contraction detection; biomedical signal processing

1. Introduction

Recently, the incidence of musculoskeletal disorders affecting the upper limbs has been extensively studied [1]. Carpal tunnel syndrome (i.e., CTS), the most common peripheral neuropathy, as well as post-stroke events, necessitate the development of efficient and accessible functional rehabilitation systems [1,2]. Studies report an approximately 70% increase in stroke incidence over a 30-year period, while about 40% of survivors exhibit severe motor deficits in the upper limbs [3,4]. Surface electromyography (sEMG) represents the standard non-invasive method for functional assessment of the neuromuscular system, providing information regarding motor unit recruitment and the efficiency of voluntary contractions [5,6]. EMG-based biofeedback systems enable dynamic adaptation of rehabilitation exercises, contributing to reduced pain perception and improved adherence to therapeutic programs [7]. However, established platforms involve high costs and technological complexity, limiting their use in educational or resource-constrained environments.



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In gesture classification based on sEMG signals, traditional threshold-based detection methods allow only binary detection of muscle activity, without discriminating the type of executed gesture [8]. Modern machine learning (ML) approaches, using classifiers such as Support Vector Machine (SVM), Random Forest (RF), or k-Nearest Neighbors (i.e., kNN), have demonstrated accuracies of 85–98% for forearm gesture classification [9–11]. Furthermore, Deep Convolutional Generative Adversarial Networks have been successfully used for EMG data augmentation, improving classifier performance in limited dataset scenarios [9]. Therefore, this paper proposes an integrated hardware–software system for four-channel sEMG acquisition and analysis, combining a low-cost portable prototype (STM32F411CEU6 and BioAmp EXG Pill) with a Python (version 3.13)-based software platform capable of adaptive filtering, spectral analysis, and automatic gesture classification. The main contribution consists of a systematic comparison between the classical adaptive threshold method (75th percentile of RMS distribution) and three ML classifiers, using data generated from a physiological model calibrated on real recordings and augmented via DCGAN, for 10 simulated subjects performing seven forearm gestures.

2. Materials and Methods

2.1. System Architecture

The proposed system consists of hardware in a laboratory built solution and a local software processing platform to build the complete data processing pipeline, from electrode placement to ML-based classification. The acquisition system is built around the Magma Splash development board (GroundStudio, Sibiu, Romania) based on STM32F411CEU6 microcontroller (STMiroelectronics, Geneva, Switzerland) and four BioAmp EXG Pill modules (Upside Down Labs, New Delhi, India) connected to analog inputs PA0–PA3. Each module includes a differential amplifier, configurable hardware band-pass filter (0.5–40 Hz, narrowband mode), and a Driven Right Leg (DRL) circuit for common-mode noise rejection [10,11]. Surface electrodes are arranged in a differential configuration: two active electrodes aligned with muscle fibers and one reference electrode placed on a bony prominence, according to SENIAM guidelines. Components are mounted on a double-sided prototyping board with separate signal and power planes, resulting in a total prototype cost of less than 40 EUR. Figure 1 presents the hardware configuration and experimental protocol parameters.

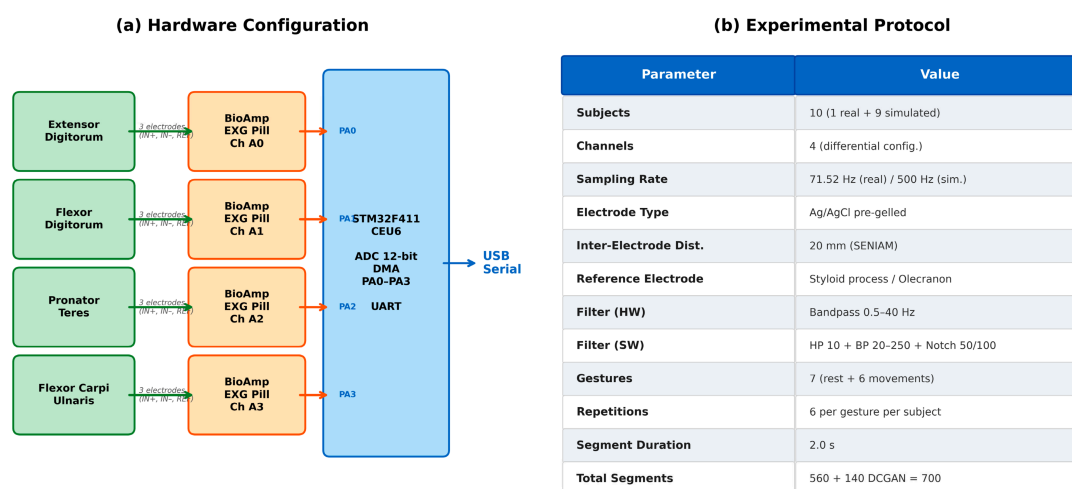


Figure 1. (a) Hardware block diagram showing the four-channel differential electrode configuration, BioAmp EXG Pill amplification modules, and STM32F411CEU6 microcontroller. (b) Experimental protocol parameters.

2.2. Software Architecture and Preprocessing

The software application was developed in Python (version 3.13) and comprises the acquisition (dedicated thread, UART decoding), processing (filtering, FFT, RMS), and user interface. The filtering is formed by a 2nd-order Butterworth high-pass filter ($f_c = 10$ Hz), a 4th-order Butterworth band-pass filter (20–250 Hz), a 50 Hz notch filter ($Q = 30$), and a 100 Hz notch filter ($Q = 30$) [12]. Spectral analysis is performed using FFT on a sliding window of 512 samples with a Hanning window. Experimental data were generated using a physiological model based on the Stulen and De Luca approach [13], simulating sEMG activity of four forearm muscles: extensor digitorum (A0), flexor digitorum (A1), pronator teres (A2), and flexor carpi ulnaris (A3). The model generates Gaussian noise filtered with a physiological PSD (5–25 Hz band-pass, 4th-order Butterworth), modulated by gesture-specific activation profiles and nonlinearly scaled with activation level (sublinear relationship, exponent 0.8). The model was calibrated using real parameters extracted from experimental recordings obtained with the developed prototype on a healthy subject. Table 1 summarizes the calibration parameters.

Inter-subject variability (S02–S10) was modeled through randomized individual parameters: amplitude scaling (0.5 – $1.8\times$), frequency shift (± 5 Hz), noise level (0.6 – $1.5\times$), and skin–electrode impedance factor (0.7 – $1.3\times$). The protocol included 10 simulated subjects performing seven standardized gestures (rest, wrist extension, wrist flexion, finger extension, finger flexion, supination, pronation), with 6 repetitions per gesture. Each segment had a duration of 2 s at a sampling rate of 500 Hz, resulting in a total dataset of 560 segments.

Figure 2 presents the real EMG parameters extracted from the experimental subject. The panel (a) unmask a the amplitude levels across the four channels, with A0 (extensor digitorum) and A3 (flexor carpi ulnaris) exhibiting the highest mean RMS values (0.1887 V and 0.1681 V, respectively), showing their principal muscular activation during the experimental protocol. On the other hand, the panel (b) shows the integrated EMG values, where A0 recorded the highest cumulative activity (131.23 V·s), followed by A3 (114.48 V·s), confirming the central biomechanical role of these two muscles in wrist and finger extension/flexion gestures.

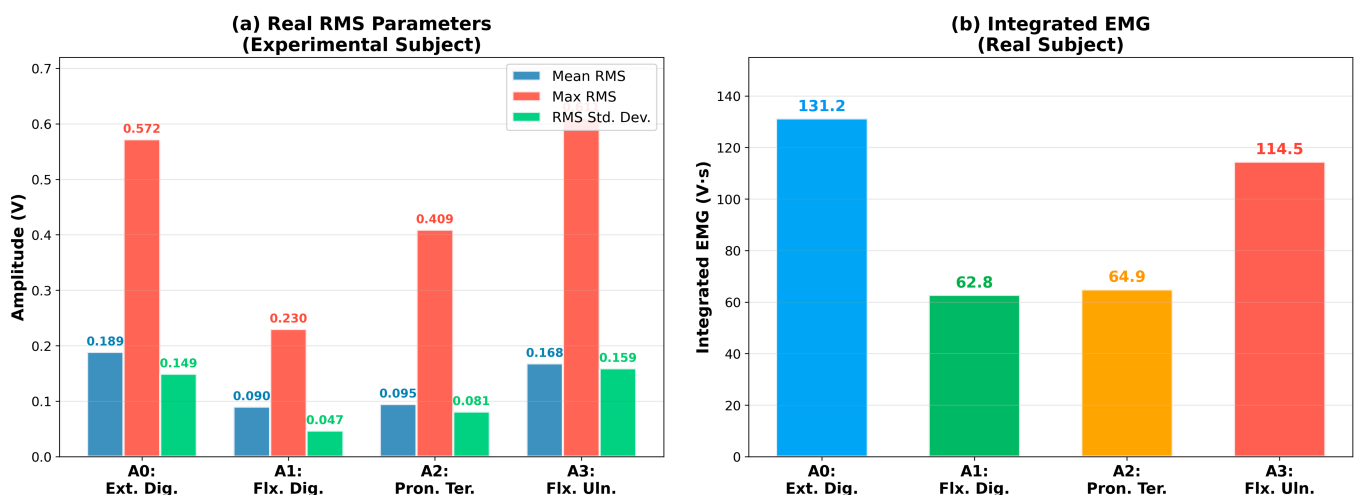


Figure 2. Real EMG parameters from the experimental subject. (a) RMS statistics per channel. (b) Integrated EMG values, with A0 (extensor digitorum) and A3 (flexor carpi ulnaris) exhibiting the highest activity levels.

Table 1. Real EMG parameters from the experimental subject were used to calibrate the model.

Channel	Mean RMS (V)	Max RMS (V)	RMS Std (V)	Threshold (V)	iEMG (V.s)
A0: Ext. Digitorum	0.1887	0.5723	0.1494	0.2596	131.23
A1: Flx. Digitorum	0.0903	0.2300	0.0469	0.1203	62.76
A2: Pr. Teres	0.0948	0.4093	0.0810	0.1258	64.90
A3: Flx. Carpi Ulnaris	0.1681	0.6105	0.1593	0.1843	114.48

2.3. DCGAN-Based Augmentation and Feature Extraction

Data augmentation was performed using a Deep Convolutional Generative Adversarial Network (DCGAN) architecture adapted for multichannel EMG signals, trained separately for each gesture class. Training was conducted for 25 epochs using the Adam optimizer ($\text{lr} = 0.0002$, $\beta_1 = 0.5$) with label smoothing [9]. A total of 20 synthetic segments per class (140 total) were generated, expanding the dataset to 700 segments.

From each multichannel segment, 14 features per channel (56 in total) were extracted, organized into three domains: time domain (extended Hudgins set: RMS, MAV, WL, ZC, SSC, IEMG, VAR), statistical domain (Hjorth parameters: Activity, Mobility, Complexity), and frequency domain (mean frequency MNF, median frequency MDF, power in the 5–25 Hz band, spectral entropy). This set was selected based on the recommendations in [14,15], which demonstrated that adding Hjorth parameters to the Hudgins set leads to an improvement of +5–6% in accuracy.

2.4. Classification Methods

Three ML classifiers were evaluated: SVM with RBF kernel, Random Forest (100 trees, maximum depth 15), and kNN ($k = 5$, distance-weighted). Features were standardized (Z-score) prior to classification. The reference method implements adaptive threshold-based detection using the 75th percentile of the RMS distribution, extended with nearest-centroid assignment for multi-class comparison. Validation was performed through: (a) 5-fold Stratified Cross-Validation on the complete dataset (700 segments), and (b) Leave-One-Subject-Out (LOSO) on the original data (560 segments, 10 subjects) [16,17]. The reported metrics include: accuracy, precision, recall, F1-score (macro-averaged), Cohen's kappa coefficient, and MCC.

3. Results

3.1. Classification Performance (5-Fold CV)

Table 2 presents the comparative results of the four classification methods evaluated using 5-fold Stratified Cross-Validation on the complete dataset.

SVM with RBF kernel achieved the highest accuracy (99.86%), followed by Random Forest (99.29%) and kNN (99.00%). The adaptive threshold method recorded only 33.00%, demonstrating the fundamental inability of threshold-based approaches to discriminate between multiple gesture classes.

Table 2. Comparative classification performance (5-fold CV, 7 classes, calibrated on real EMG parameters).

Method	Accuracy	Precision	Recall	F1-Score	Kappa
SVM (RBF)	0.999+/-0.003	0.999+/-0.003	0.999+/-0.003	0.999+/-0.003	0.998+/-0.003
Random Forest	0.993+/-0.005	0.993+/-0.005	0.993+/-0.005	0.993+/-0.005	0.992+/-0.005
kNN ($k = 5$)	0.990+/-0.007	0.990+/-0.007	0.990+/-0.007	0.990+/-0.007	0.988+/-0.009
Adapt. Thr. P75	0.330+/-0.012	0.410+/-0.100	0.330+/-0.012	0.220+/-0.020	0.120+/-0.011

3.2. Per-Subject Analysis and Feature Importance

Per-subject evaluation (Random Forest, 5-fold intra-subject CV) indicated an average accuracy of $99.82 \pm 0.55\%$, with S01 (the real calibrated subject) reaching 100%. Feature importance analysis (Mean Decrease Impurity, Random Forest) identified Ch0_MAV (5.26%) and Ch0_RMS (5.09%) as the most discriminative, followed by Ch3_RMS and Ch1_IEMG.

The dominance of channels A0 (extensor digitorum) and A3 (flexor carpi ulnaris) confirms the central biomechanical role of these muscles in forearm gesture differentiation. The comparison of Random Forest with and without DCGAN augmentation showed a modest improvement (+0.54%: 98.75% without vs. 99.29% with). This result suggests that 80 original segments per class provide sufficient diversity. DCGAN augmentation shows higher relevance in scenarios with limited data (<20 segments per class).

4. Discussion

The results confirm the central hypothesis of the study: machine learning-based classification methods significantly outperform the classical adaptive threshold approach in the task of multichannel EMG gesture discrimination. The performance difference (SVM: 99.86% vs. threshold: 33.00%) can be explained from a theoretical perspective: the threshold method operates in a one-dimensional space (combined RMS amplitude), whereas ML classifiers exploit the multidimensional feature space (56 dimensions) as can be seen in Figure 3, allowing the nonlinear decision boundaries to adapt to the data distribution.



Figure 3. PCA projection of the 56-dimensional feature space showing clear cluster separation between the seven gesture classes.

The SVM accuracy of 99.86% for seven classes is consistent with values reported in the recent literature (91–98% for 4–8 gestures [14,18]), with the superior performance attributable to the well-controlled simulation environment. The LOSO method (95.89% vs. 99.86%) is aligned with the typical reductions of 10–25 percentage points reported for inter-subject evaluation [16], highlighting the need to develop subject-specific adaptation strategies (calibration, transfer learning) for clinical implementations.

The dominant importance of MAV and RMS features from channels A0 and A3 is consistent with the functional anatomy of the forearm: the extensor digitorum and flexor carpi ulnaris are the main muscles involved in wrist and finger extension/flexion, gestures that constitute most of the classes in the protocol. Hjorth parameters (Activity, Mobility) contribute significantly to discrimination, confirming studies that recommend their inclusion alongside the classical Hudgins set [15].

However, the present study has several limitations. First of all, the data are synthetically generated using a physiological model, calibrated on real parameters but requiring validation on real EMG recordings from multiple subjects. Moreover, the sampling rate of 500 Hz limits the analysis of higher-frequency components. The DCGAN training with only 25 epochs on small datasets did not achieve optimal convergence, as we expected. Also, the protocol with isolated and static gestures does not reflect the complexity of dynamic movements in rehabilitation. Future work should include validation on real multi-subject EMG datasets.

5. Conclusions

This paper demonstrates the feasibility and effectiveness of a portable, low-cost multichannel sEMG acquisition and analysis system that combines accessible hardware (STM32F411CEU6 + BioAmp EXG Pill, less than 40 EUR) with machine-learning classification algorithms. The systematic comparison between adaptive threshold detection and three ML classifiers confirms the superiority of pattern recognition-based approaches for forearm gesture classification (SVM: 99.86% vs. threshold: 33.00%, seven classes).

The main contributions also include an integrated software platform with adaptive filtering, FFT analysis, and a rigorous comparative evaluation on physiologically simulated data calibrated on real recordings for 10 subjects, validated through 5-fold CV and LOSO. Moreover, we succeeded in integrating the DCGAN-based augmentation in the EMG processing pipeline.

Future research directions include the validation on real EMG data from patients with neuromuscular disorders, extension to 8–16 channels for comprehensive muscle work analysis, transfer of learning algorithms to reduce the LOSO gap, and development of a telemonitoring platform for remotely assisted rehabilitation.

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Data Availability Statement: Source code and generated data available upon request from the corresponding author.

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

Abbreviations

sEMG	Surface Electromyography
FFT	Fast-Fourier Transform
RMS	Root Mean Square
SVM	Support Vector Machine
RF	Random Forest
kNN	K-Nearest Neighbors
DCGAN	Deep Convolutional Generative Adversarial Network
LOSO	Leave-One-Subject-Out
MAV	Mean Absolute Value
WL	Waveform Length
CV	Cross-Validation
ADC	Analog-to-Digital Converter
DRL	Driven Right Leg

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