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Monitoring Leg Muscle Strength Symmetry via Electromyography †

Fu-Jung Wang [1], Liang-Sian Lin [1,*], Chun-Kai Tseng [1], Cheng-Hsiang Chan [1], Zhe-Yu Lee [1] and Ting-An Yeh [2]

[1] Department of Information Management, National Taipei University of Nursing and Health Sciences, Taipei 112303, Taiwan; 102214221@ntunhs.edu.tw (F.-J.W.); 102214238@ntunhs.edu.tw (C.-K.T.); 102214242@ntunhs.edu.tw (C.-H.C.); 102214202@ntunhs.edu.tw (Z.-Y.L.)
[2] Department of Leisure Industry and Health Promotion, National Taipei University of Nursing and Health Sciences, Taipei 112303, Taiwan; 112314003@ntunhs.edu.tw
* Correspondence: lianghsien@ntunhs.edu.tw
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Abstract: Many movements of the human body's muscles rely on the leg muscles for power or weight-bearing. However, leg muscle symmetry is often ignored. Therefore, it is necessary to monitor uneven or asymmetric muscle strength between the legs. We developed a system using electromyography (EMG) and an HW827 sensor for detecting leg muscles and monitoring the heart rate. In the system, the data are displayed on the Node-RED dashboard and are stored in the SQLite database. These experimental results show that for two subjects at a moderate level of exercise intensity, their non-dominant leg EMG values are higher than those for the dominant leg.

Keywords: EMG; heart rate; muscle symmetry

1. Introduction

Humans rely on muscles to function, such as walking, exercising, or even breathing [1]. Janssen et al. [2] indicated that the percentage of skeletal muscle in males between the ages of 18–29 years old is 40–45%, while in females between the ages of 18–29 years old, it is 31–33%. As people age, muscle mass begins to decrease. Especially after 75 years old, men's muscle mass reduces to about 30%, but no significant differences are observed in women. To monitor uneven muscle strengths in the human body, electromyography (EMG) is used. In using EMG [3], all actions generated require combining muscle fibers as motor unit action potentials (MUAPs). EMG electrodes are used to collect multiple MUAPs from each skeletal muscle.

Lanshammar and Ribom [4] examined 159 non-athlete women aged 20–39 years old and found that the knee flexor strength of the dominant leg was 8.6% weaker than that of the non-dominant leg, while the knee extensor strength was 5.3% stronger, indicating asymmetry in leg muscle strength. Mondal et al. [5] selected 10 soccer players, 5 players using their right leg and 5 players using their left leg as the dominant leg. Based on data from the calves, quadriceps, and hamstrings in a standing position, they found EMG activity values were significantly higher in the dominant leg than the non-dominant leg. EMG is also used to detect muscle fatigue. For 10 subjects aged 19–27 years old, their muscle fatigue during exercise was analyzed [6]. Hofmann and Tschakert [7] noted that heart rate is the most common variable for detecting exercise training intensity, where the heart rate between 40 and 50% indicates moderate-intensity exercise, or up to 85% indicates high-intensity exercise.

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We developed an EMG-based system to monitor leg muscle strength symmetry. The developed system includes an EMG detector for measuring muscle strength and an HW827 sensor for monitoring the subject's heart rate. We measured the subject muscle strength while climbing stairs. By comparing differences in muscle between the right and left legs, we observed a phenomenon where the non-dominant leg bears more weight load, thereby strengthening its muscles.

By measuring exercise intensity [8], we determined whether subjects met the exercise standards in the experiment period. In the experiment, we identified exercise intensity according to the subject's heart rate. The maximum heart rate (MHR) is calculated by $220 - \text{age}$ [9]. The relationship between heart rate and exercise intensity, proposed by Norton et al. [8], is listed in Table 1.

Table 1. Heart Rate And Exercise Intensity.

Exercise Intensity Level	Heart Rate (HR)
Sedentary	<40% MHR
Light	40–55% MHR
Moderate	55–70% MHR
Vigorous	70–90% MHR
High	>90% MHR

2. Developed System

Figure 1 shows the developed system with the message queuing telemetry transport (MQTT) protocol [10] for real-time data transmission. Arduino serves as the Publisher, and sensor data from EMG and HW827 is delivered on the Raspberry Pi 4 [11] via D1 mini ESP-8266, sourced from WEMOS Technology Co., Ltd., Shenzhen, China. The Node-RED [12] acts as the subscriber, where the data from EMG and HW827 sensors are displayed on the Node-RED Dashboard UI and stored in the SQLite database across the Raspberry Pi 4, sourced from Sony UK Technology Centre, Pencoed, UK.

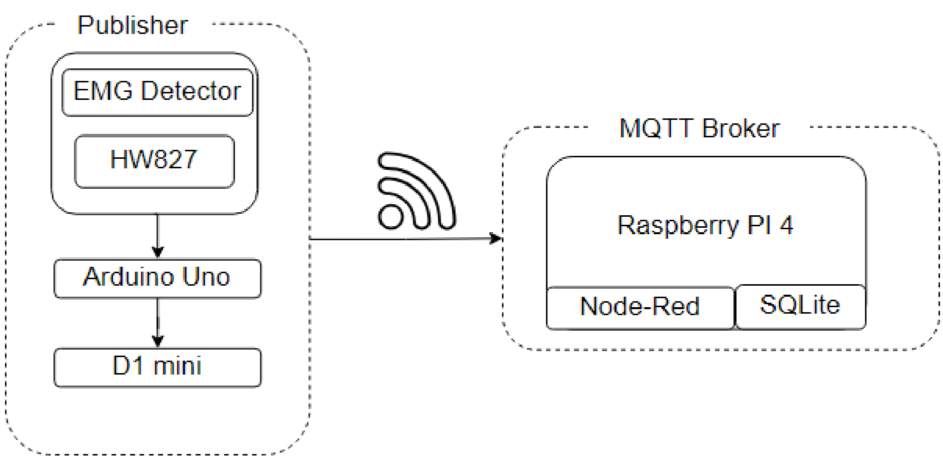
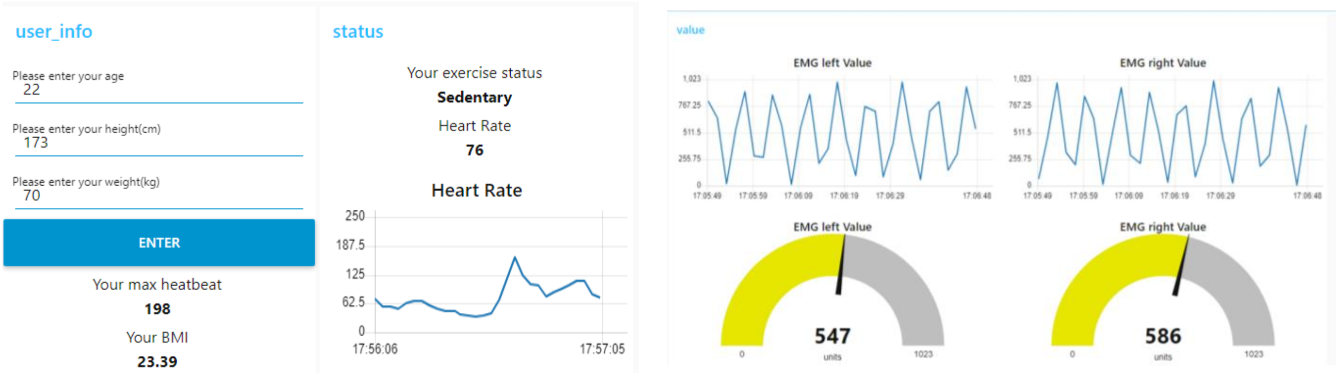


Figure 1. Proposed system.

A subject can input age, height, and weight on our system (Figure 2a). The subject's body mass index (BMI) is displayed on the system. The maximum HR is calculated by subtracting the subject's age from 220 [9]. The real-time HR in one minute is illustrated on a line chart. Figure 2b presents EMG data in line and gauge charts. The line chart displays data in one minute, and the gauge chart shows the latest EMG value. These values are updated every two seconds on the Node-Red platform, and they are stored in the SQLite database through Raspberry Pi 4. The flow of the proposed system is shown in Figure 3.



(**a**) User page (**b**) Emg values

Figure 2. Node-RED dashboard. (**a**) enter subject's information; (**b**) visualization of subject's EMG values.

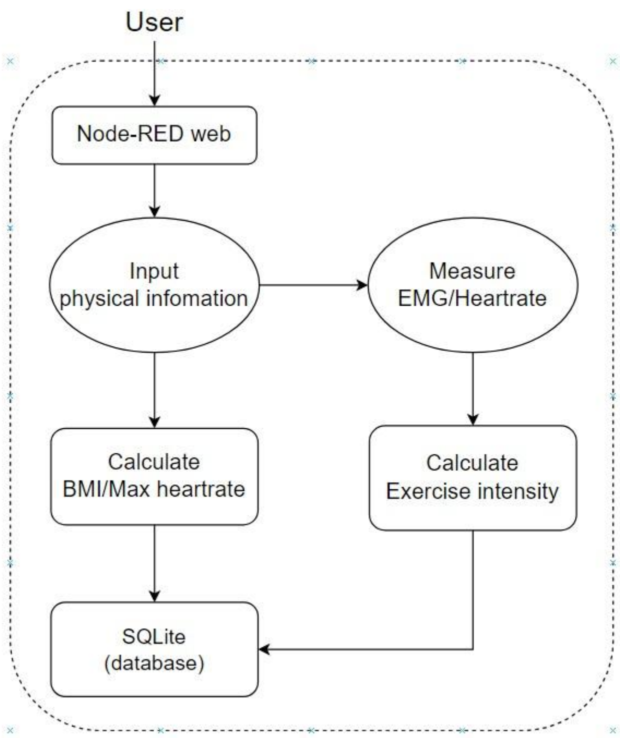


Figure 3. Flowchart of the developed system.

The hardware devices used in the system include two Grove-EMG Detector, sourced from Seeed Studio Co., Ltd., Shenzhen, China, noted as EMG-left and EMG-right, and a HW827 sensor, sourced from Shenzhen Yike Technology Co., Ltd., Shenzhen, China. These sensors are activated using the Arduino UNO controller, sourced from Arduino S.r.l., Scarmagno, Italy. All sensor data are transmitted to the Node-Red dashboard and SQLite database through the D1 mini Wi-Fi module (ESP-8266), sourced from WEMOS Technology Co., Ltd., Shenzhen, China, as shown in Figure 4.

The specifications of sensors and devices used in the system are listed in Table 2.

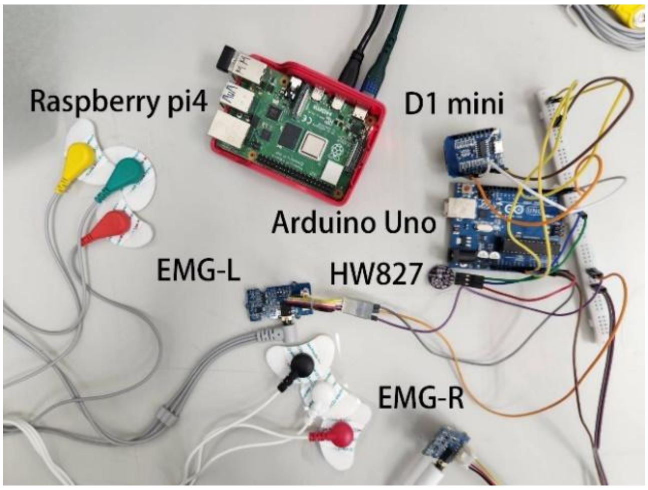


Figure 4. System hardware.

Table 2. Sensor and Devices.

Name	Function	Specification
Arduino UNO	Microcontroller board	Based on the ATmega16U2 chip
D1 mini Wi-Fi	Wi-Fi microcontroller board	The ESP-8266 chip features built-in Wi-Fi capabilities.
Grove-EMG Detector	Muscle activation detecting	Operating Voltage: 5 V
HW827	Heart rate monitoring	Operating Voltage: 5 V

3. Experiment

One male and one female participated in the experiment. Both had no history of leg injuries. The male subject participated on 31 July 2024, from 16:09:00 to 16:10:12, while the female subject on 31 July 2024, from 18:01:02 to 18:02:11. Tables 3 and 4 present their EMG and HR data, respectively. Before the experiment, the subjects determined their dominant leg via kicking a ball [13]. In the experiment, two EMG devices were used, with the sensors attached to both legs' quadriceps. The two subjects climbed a three-story staircase, respectively, for 70 s. The quadriceps' performance was monitored to observe differences between the dominant and non-dominant legs. Average EMG values were recorded to assess if the dominant leg quadriceps exhibited stronger performance.

To reduce the negative influence of noise, EMG values below 300 μV and HR values above 200 bpm or below 50 bpm were excluded. The male subject showed a BMI of 24.39 (=173 cm/73 kg), which falls into the "Normal weight" category, and his dominant leg was the right leg. The female subject has a BMI of 23.53 (=157 cm/58 kg), which also falls within the "Normal weight" category, and her dominant leg was the right leg. BMI was defined as BMI = weight (kg)/height (m)^2.

When starting stair climbing, the male subject's HR was 71 bpm, and the female subject's HR was 79 bpm, both classified as "Sedentary" on exercise intensity. Both subjects exhibited significant increases in HR within 70 s. The male subject's maximum HR reached 120 bpm, while the female subject's maximum HR reached 132 bpm.

Both subjects had normal BMI and achieved a "Moderate" exercise intensity level, indicating that the exercise intensity in the experiment was a general physical activity. The EMG data from the testing period showed that the non-dominant leg had higher EMG than the dominant leg. The average EMG of the male subject was 604 μV for the right leg and 617 μV for the left leg, indicating that the non-dominant left leg's EMG was higher than the dominant right leg. For the female subject, the average EMG was

516 µV for the right leg and 529 µV for the left leg (Figure 5). The average EMG data of the female subject's non-dominant left leg was also higher than that of her dominant right leg (Figure 6). This indicates that the non-dominant leg has more muscle load during exercise, thereby reflecting muscle asymmetry and potentially increasing the risk of injury.

Table 3. Sensor Data For Male Subject.

Time	EMG-Left (µV)	EMG-Right (µV)	HR (bpm)	Exercise Intensity Level
16:09:16	558	561	71	Sedentary
16:09:20	639	636	74	Sedentary
16:09:24	736	668	80	Light
16:09:44	492	409	88	Light
16:09:52	762	735	94	Light
16:09:56	654	635	98	Light
16:09:58	643	637	103	Light
16:10:00	479	462	114	Moderate
16:10:06	718	716	116	Moderate
16:10:12	876	851	120	Moderate

Table 4. Sensor Data For Female Subject.

Time	EMG-Left (µV)	EMG-Right (µV)	HR (bpm)	Exercise Intensity Level
18:01:04	477	484	76	Sedentary
18:01:10	859	536	79	Sedentary
18:01:18	483	476	83	Light
18:01:22	758	732	88	Light
18:01:26	482	344	91	Light
18:01:28	524	492	95	Light
18:01:36	768	668	109	Light
18:01:49	478	437	118	Moderate
18:01:57	533	497	122	Moderate
18:02:11	799	891	132	Moderate

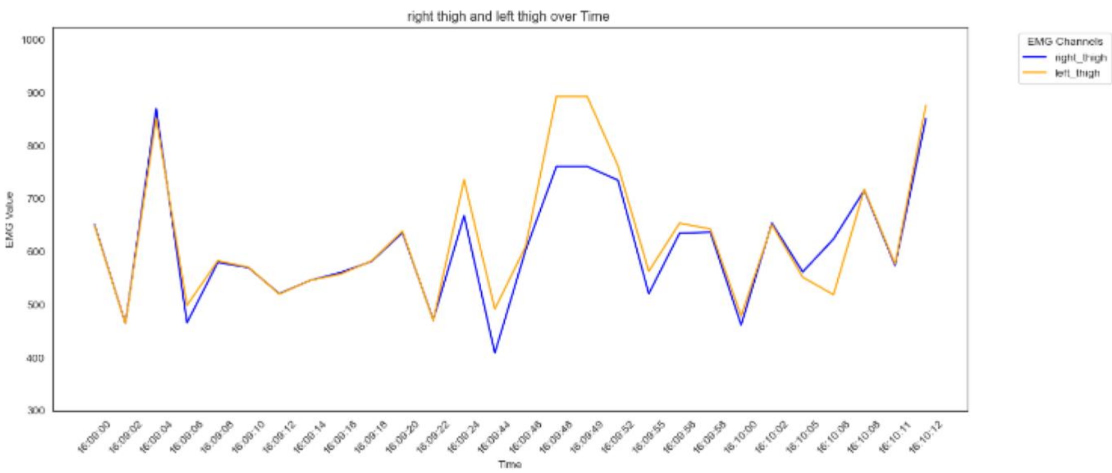


Figure 5. EMG data for male subjects.

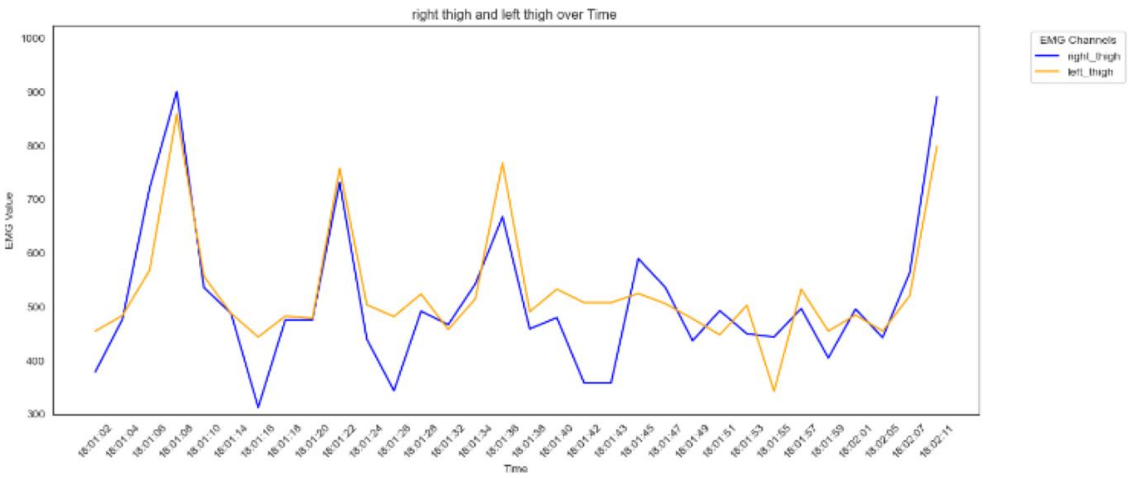


Figure 6. EMG data for female subjects.

4. Conclusions

When subjects' exercise intensity reached "Moderate", the non-dominant leg had higher EMG than the dominant leg. This indicates that the non-dominant leg has more muscle loading, potentially increasing the risk of injury during exercise. Therefore, we recommend that subjects engage in exercises such as squats and leg presses to strengthen the muscles of the non-dominant leg. The system developed in this study helps users identify muscle loading on the non-dominant leg and further strengthen non-dominant leg muscles.

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