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FEASIBILITY OF FORCE SENSING RESISTOR (FSR) TO MEASURE UPPER LIMB ACTIVITY

N. I. F. Anwar[1], N. H. D. Nordin*[1], A. S. Ghazali[1] and M. A. Husman[1]

[1] Department of Mechatronics, Faculty of Engineering, International Islamic University Malaysia, Gombak, 53100, Kuala Lumpur, Malaysia.

corresponding: nhdiyana@iium.edu.my

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Abstract— This study explores the feasibility of using Force Sensing Resistor (FSR) sensors as a non-invasive, cost-effective alternative to electromyography (EMG) for detecting muscle activation in the upper limbs. While EMG is a widely used technique for measuring muscle activity, it suffers from several limitations, including susceptibility to motion artifacts, variability due to electrode placement, and discomfort associated with invasive intramuscular recordings. These challenges hinder its practicality for real-time, wearable, or long-term applications in rehabilitation, prosthetics, and biomechanical monitoring. In response, this work investigates the

Limb Activity	potential of FSR sensors, which detect changes in applied force, to offer a simpler and more robust solution. FSRs were placed on the forearm to record sensor output during controlled gripping tasks. The data showed a clear increase in FSR signal during muscle contraction (grip phase) and a corresponding decrease during relaxation (release phase), reflecting the mechanical force generated by the muscles. These results suggest that FSRs can serve as reliable indicators of muscle activity, supporting their integration into future low-cost, user-friendly systems for clinical and biomechanical use.

I. Introduction

Upper limb activity monitoring is crucial for assistive technologies in biomedical applications. Specifically, upper limb activity can be measured upon the detection of muscle contraction and relaxation. The study and method of detecting muscle activity are commonly referred to as myography. There are several types of myography, including electromyography, mechanomyography, and force myography, which differ in their principles and characteristics. Traditionally, electromyography (EMG) sensors are utilized for monitoring upper limb activity by evaluating electrical signals captured from muscle contraction. The type of widely used EMG sensor is an invasive needle electrode inserted through the skin [1]. However, challenges such as high cost, system complexity, and inter-individual variability continue to pose limitations [2, 3]. In contrast, non-invasive myography, such as surface electromyography (sEMG), mechanomyography (MMG), and force myography (FMG), has gained significant interest in upper limb activity, specifically in biomedical applications.

Notably, FMG is particularly promising due to its ease of integration and less signal interference. In the context of muscle activity detection, Force Sensing Resistors (FSRs) play a significant role in FMG, a method that analyzes lateral force changes arising from muscle contractions. (FMG) operates on the principle that muscle contraction induces localized swelling, which exerts force on the overlying skin [4]. This pressure may be successfully monitored with pressure-sensitive sensors, such as FSRs. FSRs are thin, flexible sensors that detect changes in force or pressure by altering their electrical resistance in response to applied load [5]. Due to their lightweight structure, low cost, and ease of integration, FSRs have gained attention in various applications, including robotics, prosthetics, and biomedical sensing.

Within non-invasive myography research, sEMG is widely employed due to its non-invasive nature and suitability for real-time monitoring to assess the electrical potential in muscle fibers. Notably, a study by [6] emphasized real-time detection of five hand motions and suggested a hand gesture recognition model employing a Myo armband with 8 EMG dry surface electrodes. By using the dataset originally generated by [7], this study utilized spectrogram-based feature representation paired with CNN and CNN-LSTM architectures, followed by a post-processing approach to remove incorrect predictions. The suggested CNN-LSTM model exhibited a mean recognition accuracy of 90.55%, exhibiting good performance despite substantial inter-user EMG variability. However, as reported in [7], the study revealed a significant drawback, which includes significant user variation produced by changes in muscle activation patterns, electrode displacement, and physiological variability among individuals. Likewise, a study by [8] successfully established a real-time control approach for a prosthetic hand that employs

EMG signals to accurately detect finger motions. Yet, the effectiveness and performance of the systems are restricted by sensor position, which possibly results in excessive signal noise as several electrodes are activated. Similarly, Choi et. al [9] presented a transfer learning strategy for estimating motion intention using EMG data as the source domain and FSR with IMU as the target domain, demonstrating the possibility of multimodal sensor integration. However, the approach they used was not tested using deep learning frameworks, which limits its applicability to more complex rehabilitation applications.

In addition, other studies have investigated MMG, which detects muscle vibrations during contractions. Specifically, Han and Kim [10] used Active Muscle Stiffness Sensors (aMSS) for MMG, which measure muscle stiffness and vibrations during contraction to estimate muscular contraction. Accelerometers are commonly used to gather extra motion data to improve muscle stiffness measurements. In contrast, Wattanasari et al. [11] demonstrated that a wearable MMG wristband constructed with six microphone-based MMG sensors and an Inertial Measurement Unit (IMU) has been effective in detecting five hand motions across different arm postures. The microphone-based MMG sensors measure the mechanical vibration during muscle contractions, meanwhile, the IMU is used to verify the arm positioning. Next, the process starts with the signals being converted into Continuous Wavelet Transform (CWT) scaleograms and categorized using a Domain-Adversarial Convolutional Neural Network (DACNN) to increase robustness for posture variation. The system attained an average accuracy of 87.43% inside the same posture and 64.29% across numerous postures, which improved to 92.32% and 71.75% with a 600 ms window. However, the results of both studies indicated existing limitations, such that thermal drift and skin layer thickness might lead to data errors and inconsistencies.

In the context of force myography (FMG) for muscle activity analysis, Li et al. [12] used piezoelectric force-sensitive resistors to perform FMG for motion identification and obtained an average classification accuracy of 95.5% for dynamic muscle contraction detection. However, limitations arise with sensor stability and performance under variable environmental circumstances. Recent studies for non-invasive myography, highlighting the sensor setups, applications, and performance are summarized in Table 1.

Table 1: Overview of Non-Invasive Myography Techniques by the Current Research

Myography Type	Sensors Type	Signal Type	No. of Sensors	Application	Sensor Placement	Accuracy	Ref.
EMG	sEMG electrodes	Bio electrical	8	Hand gesture recognition	General forearm area	90.55 %	[6]
EMG	sEMG electrodes	Bio electrical	5	Finger motion	General forearm area	-	[8]
Hybrid	sEMG (4) + FSR (2) + IMU (1)	Mixed	7	Motion identification	Upper arm area	-	[9]
MMG	Active Muscle Stiffness Sensor (aMSS)	Bio mechanical	1	Motion intent recognition	Single point on forearm	-	[10]
MMG	Microphone-based MMG sensor (6) + IMU (1)	Bio mechanical	7	Hand gesture recognition	General forearm area	-	[11]
FMG	FSR Sensor	Bio mechanical	8	Motion identification	Forearm band array	95.5%	[12]

In general, the literature reveals limitations related to the use of complex sensor arrays, non-specific sensor placement, and insufficient methodological evaluation under varying load conditions. This work seeks to address these gaps by employing a simple sensor configuration, using muscle-specific sensor placement, and systematically assessing performance across a wide range of load levels. In contrast to previous studies, the present work utilizes targeted sensor placement based on palpation and precise FSR positioning informed by muscle anatomy. This approach minimizes variability due to inconsistent sensor placement and inter-user differences, thereby supporting a more standardized and effective methodology that directly responds to shortcomings identified in earlier research.

The integration of FSRs into FMG-based systems presents potential for accurate muscle activity monitoring with a low-cost, easy system setup and a specific sensor placement for advanced rehabilitation and assistive technology. This study analyzed the viability of deploying FSR sensors in an FMG-based framework for upper limb activity detection, with a particular focus on their sensitivity to fluctuations in grip force activity rather than motion of the upper limb. Thus, the focus of this work is to demonstrate the feasibility of using a commercial FSR sensor circuit setup for upper limb activity detection, especially in grip force assessment.

Conversely, this study focused on individual muscle placement using palpation and a precise FSR placement depending on muscle anatomical position. Thus, the variability caused by inconsistent sensor placement and inter-user variability can be reduced, resulting in a more effective standardized approach that directly addresses the constraint identified in most studies. The integration of FSRs into FMG-based systems presents potential for accurate muscle activity monitoring with a low-cost, easy system setup and a specific sensor placement for advanced rehabilitation and assistive technology. This study analyzes the viability of deploying FSR sensors in an FMG-based framework for upper limb activity detection, with a particular focus on their sensitivity to fluctuations in grip force activity rather than motion of the upper limb. Thus, the focus of this work is to demonstrate the feasibility of using a commercial FSR sensor circuit setup for upper limb activity detection, especially in grip force assessment.

II. Methodology

A. Calibration of FSR

The FSR sensor circuit was composed of a voltage divider and a voltage follower that transformed resistance changes into a steady voltage signal while preserving signal quality. Equation (1) defined the voltage output as a function of the supply voltage (V_{in}), the sensor resistance (R_{fsr}), and a fixed resistor (R), which is 100 kΩ. Figure 1 depicts a schematic diagram of the circuit consisting of the FSR sensor connection, which is an A0 analog input, the voltage divider, and the voltage follower. The voltage divider converts the FSR's resistance changes into a proportional voltage output, while the voltage follower circuit ensures signal stability by preventing loading effects on the voltage divider. The sampling rate of the signal recorded is 10 Hz.

$$V_{out} = V_{in}\left(\frac{R}{R_{fsr} + R}\right) \quad (1)$$

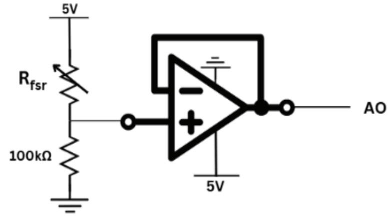
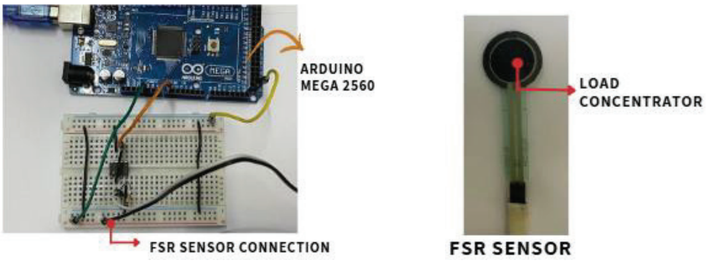


Figure 1: Schematic diagram of the FSR circuit

Before data collection, the FSR sensor was calibrated to provide accurate and consistent results. The calibration involved applying known weights to the sensor and monitoring the voltage output. On the other hand, a load concentrator with the same diameter as the active area of the FSR sensor had been mounted on the FSR to guarantee consistent force distribution. Figure 2 presents the circuit connections for the FSR sensors with the Arduino

Mega 2560 and the load concentrator, showcasing the integration of components for data acquisition.



(a) (b)

Figure 2: (a) Circuit connections. (b) Load concentrator on the FSR sensor

B. Sensor calibration results

During the calibration process, eight known weights were placed on the sensor, representing forces ranging from 0 N to 4.9 N, and the voltage outputs were recorded. Essentially, an inverse logarithmic model was recommended as a suitable fitting model for the FSR sensor utilized in this study [13]. Then, the calibration was executed along with the load concentrator, and the collected data were employed to generate a calibration equation using the inverse logarithmic model, which accounted for sensor variability and environmental circumstances. The correlation between the applied force (F) and the sensor's voltage output (V) was further represented by Equation (2), where a, b, and c were constants obtained from the fitting model. Figure 3 shows the calibration setup for the FSR sensor.

$$F = ae^{bV} + c \qquad (2)$$

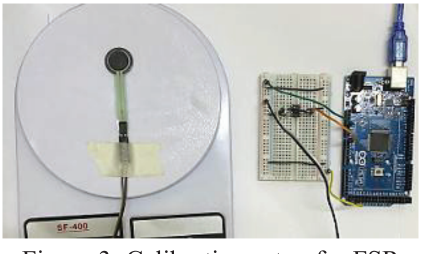


Figure 3: Calibration setup for FSR sensor

Figure 4 presents the FSR calibration curve, which represents the relationship between the applied force (N) and the sensor output voltage (V) using an inverse logarithmic function. The red markers reflect the data that was collected from the eight known varied weights, while the green curve shows the calibration model that was fitted. This nonlinearity correlates with the findings by Schofield et al. [13], which showed an exponential connection between force and voltage in FSR sensors.

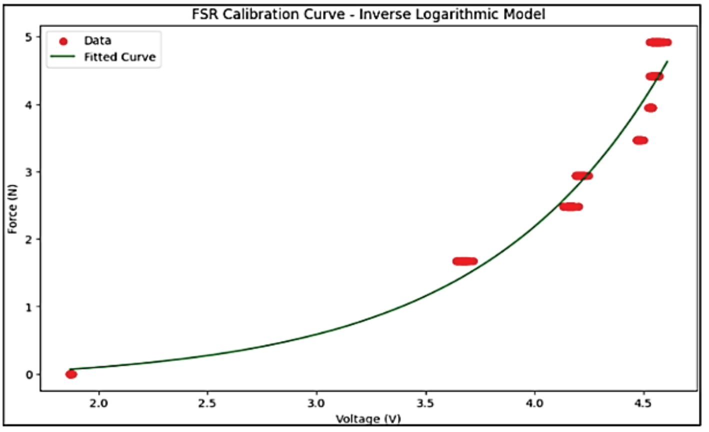


Figure 4: Calibration curve of FSR sensor

This calibration ensured that force measurements were dependable in future tests by incorporating differences in sensor response and surrounding situations. The curve's exponential structure shows that force sensitivity grew as voltage levels rose, which was consistent with the sensor's behavior. The calibration equation depicted in Equation (3) was developed to properly convert voltage data to force levels.

$$F = 0.0197e^{1.1900V} - 0.1167 \quad (3)$$

C. FSR Sensor Placement

In this work, the placement of the FSRs on three targeted forearm muscles; Flexor Digitorum Superficialis (FDS), Flexor Carpi Radialis (FCR), and Brachioradialis (BR), as shown in Figure 5 were studied. The FSR sensor would be placed on the surface of the skin in the corresponding anatomical location of the muscle. These muscles were chosen because they are essential for forearm tasks, particularly those that require hand gripping [14]. During hand grasping, the FDS muscle aids in finger flexion. Furthermore, the FCR muscle controls wrist flexion and stabilizes the wrist during gripping, influencing the grip strength. Finally, the brachioradialis contributes to overall grip strength by supporting the forearm when gripping and aiding with elbow flexion. By attaching the FSR sensor to these muscles, muscular activity can be measured efficiently during handgrip activity.

The placement of the FSR sensor on each targeted muscle was positioned in a specific anatomical region of the muscle. Palpation was performed to determine precise sensor position; participants used particular hand motions to locate the muscle bellies for the best signal measurement. The FDS is located on the anterior forearm and extends to the fingers from the humerus's medial epicondyle and the ulna's coronoid process. The sensor was positioned partially toward the ulnar side, above its muscular belly [14, 15].

Next, for Flexor Carpi Radialis (FCR), the muscles span downward the radial side of the forearm and have the sensor immediately lateral to the FDS [16]. Finally, is the Brachioradialis (BR), which runs from the lateral supracondylar ridge of the humerus to the distal radius on the lateral forearm, and the sensor was recommended to be attached to the muscle belly [17]. Figure 5 illustrates the anatomical region for all the targeted muscles on the forearm.

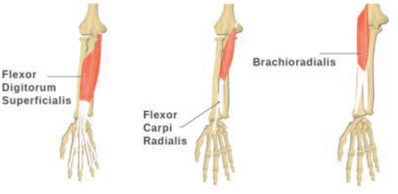


Figure 5: Anatomical region of targeted muscles [18-20]

D. Experimental Setup

The experimental procedure of this study involved isometric handgrip activity with load variations. This experimental procedure was approved by IREC IIUM. The tests were carried out by completing three grip trials at various load levels (Low, Medium, and High) to assess changes in muscle activity. Following the procedure by Buniya, Al-

Timemy, Aldoori, and Khushaba [21], each trial consisted of the 6s isometric grip protocol, including a 6s rest period before each grip. Figure 6 depicts the block diagram of the Grip Trial framework in seconds for each load variation.

Figure 6: Block diagram of Grip Trial

To achieve a controlled posture, the tests were executed with participants in a sitting position with the elbow flexed at a 90° angle, shoulder neutral (0° angle), and wrist neutral. Ultimately, the FSR sensor was attached to the skin with tape and velcro straps to ensure sensor stability and steady contact with the surface of the skin throughout the conducted test. It reduced the effects of motion and eliminates displacement when doing handgrip exercises. Figure 7 illustrates the position setup during the test.

The experimental approach followed an organized sequence. The experiment session started with a 6s baseline recording, then three sets of 6s isometric grips at each load level. For preventing muscle fatigue, a 5minute rest interval was provided between each load condition. Following each load session, participants filled out a form to measure their perceived effort. The trial ended with a 5minute cool-down time.

Figure 7: Experimental position setup

III. Results and Discussion

A. Upper limb activity detection signal

The preliminary findings of this study focused on reviewing raw voltage data from targeted forearm muscles. Prior to conducting a more extensive investigation, this pilot study was conducted with a single participant to assess the feasibility of employing an FSR to measure upper-limb activity. The primary goal at this stage had not been to accomplish quantitative estimation, but rather to discover whether the

FSR sensor could reliably measure significant activity-related shifts under controlled conditions. Whilst the procedure used in the experiment was repeated three times to verify procedure reliability, the supplementary experiments were not documented for formal analysis and were only utilized to assess the repeatability and stability of the research setup. The data was collected during a hand gripping activity under low, medium, and high load circumstances, utilizing an FSR sensor connected to an Arduino Mega 2560.

Figure 8 exhibits the voltage-time graph for one muscle on the forearm, which shows muscle activation patterns during both the grip and release phases for light load. The grip phase generates a rise in voltage, indicating muscular contraction, whereas the release phase results in a voltage decrease, showing muscle relaxation. The fluctuations in voltage levels across varied loads and muscle locations indicate that the FSR sensor is capable of accurately measuring muscle activity variations.

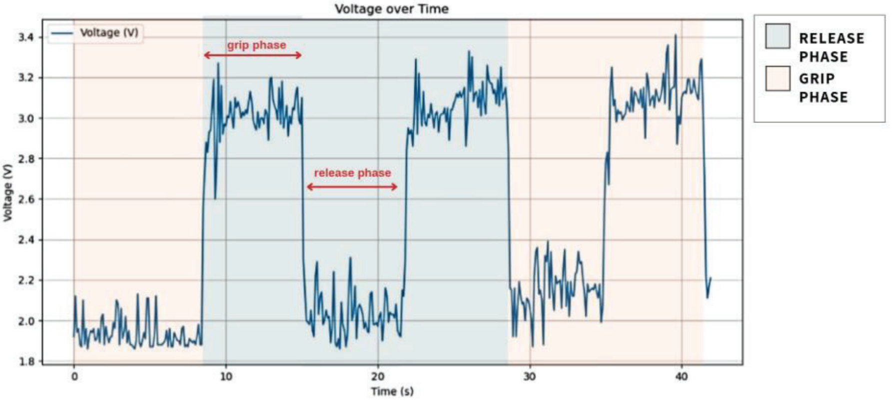
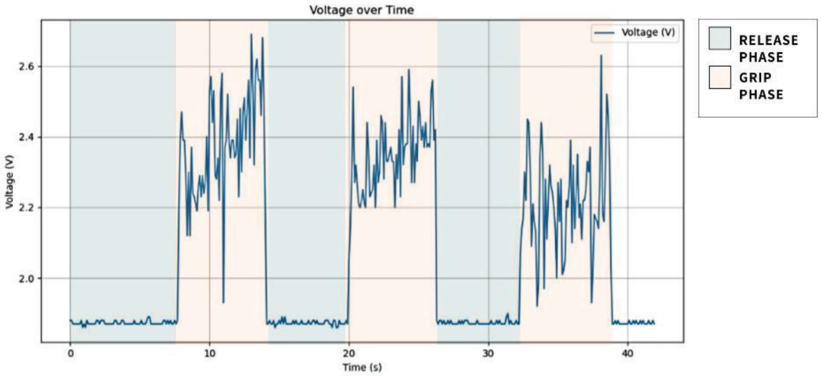
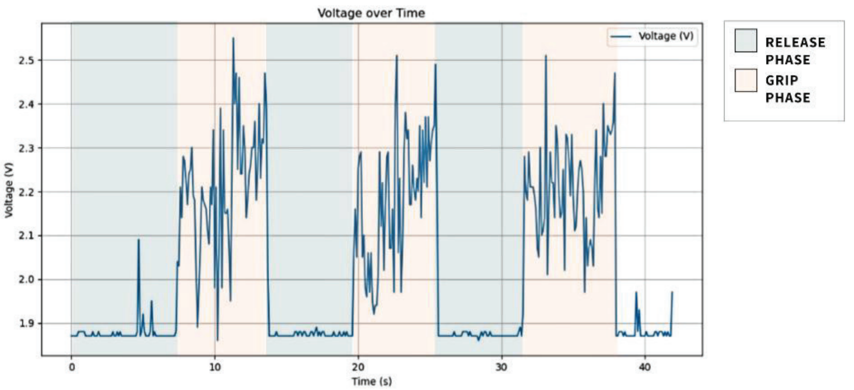


Figure 8: Raw FSR Signal

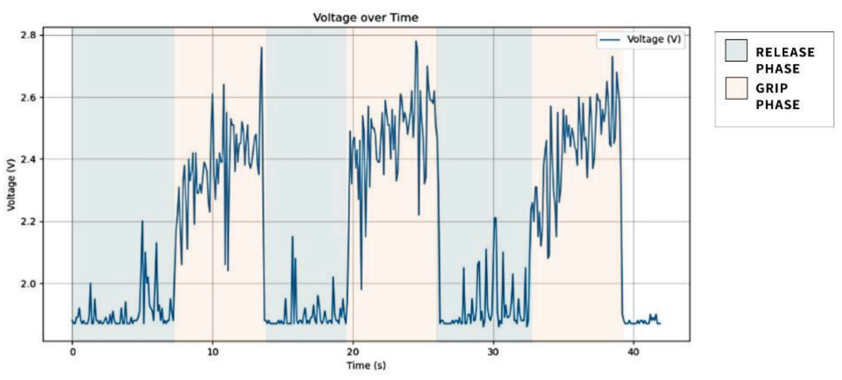
Furthermore, Figure 9 depicts voltage-time graphs for the FDS muscle at three distinct load levels, which are light, medium, and high. The phases of the muscle, which consist of the grip phase and the release phase, are emphasized in different colours accordingly. The observation concluded that as the load increases, the voltage amplitude and signal fluctuations become more noticeable, suggesting more muscle activity.



(a) Light Load



(b) Medium Load



(c) High Load

Figure 9: Comparison of voltage signals over time for the FDS muscle

Across the three different load conditions, the raw FSR signal voltage output showed a noticeable increase in peak voltage, rising over about 2.60 V for the light load, 2.50 V for the medium load, and exceeding 2.70 V for the high load. Although this pattern reflects the load-dependent fluctuations in upper-limb activity, the slightly higher peaks for the light condition compared to the medium condition indicate that further study with a larger sample size and controlled conditions of load is required to establish a quantitative relationship between applied force and raw FSR voltage output. The findings from the data demonstrate the feasibility of FSR sensors for activity-based applications and justify their ongoing utilization in future studies with more extensive data collection and processing procedure.

IV. Conclusion

This study has demonstrated the possibility of utilizing an FSR sensor as a suitable instrument for monitoring upper limb muscle activity during grip-based activities. The results have shown its ability to detect patterns in muscle contraction and relaxation. The recorded signals successfully distinguish between these phases, with rising load levels causing larger signal amplitudes. This trend emphasizes the sensor's sensitivity to force fluctuations, indicating its potential for applications such as rehabilitation and muscle function evaluation. Future work will concentrate on advanced signal processing techniques and real-time implementation to improve accuracy and extend usefulness in both clinical and research environments.

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