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LINEAR MODELING OF RELATIONSHIP BETWEEN EMG AND FMG: TOWARD HOME-BASED POST-STROKE REHABILITATION

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Abstract

Neurological injuries such as stroke and cerebral palsy frequently result in substantial loss of arm function. While rehabilitation therapies are essential for recovering motor skills, many current devices targeting muscle strength deficits are impeded by their bulk, cost, and weight, limiting their regular use in clinics or home settings. This paper aims to describe variable resistance rehabilitation methods, emphasizing the advantages and disadvantages in contemporary device development. The study also examines the effect of applied resistance on muscles during hand flexion and extension using electromyography (EMG) and force myography (FMG). The findings underscore the potential of FMG to serve as a low-cost alternative to EMG in home-based rehabilitation systems. Designed linear model using the data collected from 10 healthy subjects demonstrates that EMG increases linearly with FMG, with a slope of 17.5 µV per Volt of FMG. This suggests a direct relationship between EMG and FMG.

Keywords: Stroke, rehabilitation, resistance training, automation, physiotherapy.

1. INTRODUCTION

Stroke is a leading global cause of premature death and disability [1]. The age-adjusted prevalence ranges from 84–262 per 100,000 in rural areas and 334–424 per 100,000 in urban areas. Economically disadvantaged populations are disproportionately affected due to the high costs of post-stroke care. Many stroke survivors face long-term functional impairments, placing a significant financial and emotional burden on their families.

A common consequence of stroke is spasticity—a neuromuscular disorder affecting approximately 75 million people globally [1]. Stroke-induced spasticity, particularly in the upper limbs, impacts up to 70% of survivors and may worsen even a year after the event. Individuals with spasticity often suffer from reduced mobility, pain, bone deformities, loss of independence, and lower quality of life. Without early intervention, spasticity can lead to muscle stiffness, joint contractures, and pressure sores. Around 35% of stroke patients develop spasticity, which resists normal muscle stretching and hinders movement [2].

Early assessment of spasticity, especially in the hand, is crucial for predicting motor recovery and optimizing rehabilitation outcomes [3]. Traditional assessment tools like the Modified Ashworth Scale (MAS) often lack accuracy and objectivity, prompting the need for improved evaluation methods [4]. Various treatments exist—including medication, Botox injections, physical and occupational therapy—but physiotherapy is often the preferred, cost-effective approach, focusing on strengthening and improving mobility through targeted exercises.

Loss of arm function is another common post-stroke complication, often due to reduced strength and motor control [4]. This impairment can significantly impact quality of life, sometimes more than lower limb disabilities. As the global population ages, the prevalence of neurological disorders is expected to rise [5]. However, access to rehabilitation remains limited due to shortages of therapists, caregiver

availability, and insurance restrictions, highlighting the need for affordable, effective, and scalable rehabilitation solutions.
Current manual rehabilitation methods depend heavily on therapists' subjective assessments, with limited tools for tracking recovery progress objectively. Among available rehabilitation strategies are surgery, functional electrical stimulation [6], medications, and assistive technologies. Isometric and isotonic exercises—especially those involving wrist joints—play a crucial role in strengthening and improving function. In particular, isotonic movements, where muscles contract while joints move, are effective in enhancing muscle strength [7].
Recent trends emphasize the use of assistive devices for hand rehabilitation. These devices can support recovery but often fall short in clinical applicability. A better understanding of muscle performance under different conditions is essential for improving these tools.
This study investigates the effect of applied resistance on muscle activity during wrist flexion and extension using electromyography (EMG). EMG data was collected from 10 healthy individuals under varying resistance levels, following a standardized task protocol. Key features such as Mean Absolute Value (MAV) and Root Mean Square (RMS) were extracted, revealing notable differences in muscle performance across resistance levels. Further analysis using forcemyography (FMG) confirmed these findings. This research lays the groundwork for future studies involving patients with spastic hemiparesis, aiming to explore the impact of resistance-based training on their motor recovery.

2. LITERATURE SURVEY

Various techniques have been explored in the literature for the treatment and management of spasticity. In addition to surgical and pharmacological interventions, several conventional and non-invasive approaches have shown promise. These include functional electrical stimulation (FES), transcranial direct current stimulation (tDCS), repetitive transcranial magnetic stimulation (rTMS), transcutaneous electrical nerve stimulation (TENS), mental imagery, sensory stimulation, mirror therapy, use of static and dynamic splints, constraint-induced movement therapy (CIMT), bilateral training, virtual reality, electromyography (EMG) biofeedback, and robot-assisted therapy.
Non-invasive brain stimulation methods such as rTMS and tDCS are used to modulate the activity of specific neuronal populations by altering cortical excitability. FES and TENS, on the other hand, stimulate peripheral muscles but are less effective for facilitating precise, fine motor movements. In mental imagery therapy, patients visualize specific motor tasks, which activates cortical areas similar to those engaged during actual movement. Tactile stimulation methods help redirect the patient's attention to the affected limb, enhancing sensory-motor integration. Mirror therapy leverages visual feedback: the patient observes the unaffected limb's movement reflected in a mirror placed at the body's midline, creating the illusion that the limb is moving. This visual feedback can stimulate motor cortex activity and support recovery.
Splints, both static and dynamic, are used to apply controlled forces over prolonged periods to mobilize joints and stretch soft tissues. Constraint-induced movement therapy (CIMT) involves intensive training of the affected limb while restricting use of the unaffected side using a glove or bandage. This approach encourages neural reorganization and improved motor function. Conversely, bilateral training involves coordinated use of both limbs; however, its effectiveness remains under debate, as it may sometimes lead to overreliance on the contralesional hemisphere.
Virtual reality (VR) systems offer immersive and interactive environments that provide real-time visual and sensory feedback, increasing patient engagement through gamified experiences. EMG biofeedback enables patients to monitor and regulate muscle activation in real time, which has been shown to influence cortical plasticity.
Robotic-assisted therapy utilizes robotic devices to assist with passive or active movement of the affected limb. In active-assisted modes, the robot initiates movement based on the patient's intention signals from the impaired limb. Combining multiple rehabilitation modalities—such as robotics,

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stimulation techniques, and physiotherapy—can enhance treatment outcomes. Below are two commonly used medical interventions for managing spasticity:

A. Surgical methods

Spasticity can sometimes result from abnormal neural signals to specific muscles. *Selective dorsal rhizotomy (SDR)* is a surgical procedure that targets this issue by removing specific nerve roots in the spinal cord responsible for transmitting these abnormal signals. This technique is typically reserved for severe cases of leg spasticity, especially in individuals with cerebral palsy. By carefully cutting selected sensory nerve fibers, SDR reduces muscle stiffness while preserving other neurological functions.

B. Drugs

Several oral medications—such as Baclofen, Gabapentin, Benzodiazepines, and Imidazolines—are prescribed in combination with physical therapies. These are usually recommended when symptoms significantly disrupt sleep or daily activities. For more severe cases, *Intrathecal Baclofen Therapy (ITB)* may be used. This involves the surgical implantation of a pump that delivers a continuous dose of Baclofen directly into the spinal fluid via a catheter, offering more effective and targeted relief from spasticity.

C. Brain Stimulations

Electrical Stimulation (ES) involves the use of electrical currents delivered through electrodes to activate muscles [8]. This technique has been in practice since the 1960s and is effective in improving movement in affected limbs. ES is commonly used to treat a variety of conditions, including Multiple Sclerosis, spinal cord injuries, Parkinson's disease, and Cerebral Palsy.

D. Physiotherapy

Physiotherapy focuses on reducing muscle tension and stress in the affected areas. Its goal is to enhance the patient's strength and mobility, enabling them to perform daily activities with greater independence. Various therapeutic methods, such as moist heat, electrical stimulation, low-level laser therapy, casting or orthotics, and cryotherapy, are employed to alleviate pain and muscle tension. Through these treatments, physiotherapy helps individuals regain function and mobility.

E. Robotic Assist Devices

Robotic rehabilitation devices have shown significant promise due to their ability to provide safe and adaptable interactions with patients [9]. These devices, including customizable and affordable soft robotic hand exoskeletons, are used for rehabilitation and can be remotely controlled and monitored [10].

Robotic research focuses on different design strategies, such as continuous passive motion (CPM) systems, which support and guide the limb throughout its entire range of motion [11][12]. In contrast, active rehabilitation systems require the patient to engage in active movements. One example of an active system is a brain-controlled hand exoskeleton, where EEG sensors measure brain activity to drive the device based on the patient's attention levels [13]. There is increasing demand for functional rehabilitation systems capable of supporting actions like hand grasping [14]. These systems use motion intent signals to control the device with an accuracy of up to 80.45%, offering significant benefits for individuals with limited mobility [15].

Electromotive Resistance

Washabaugh E. et al.[8] introduced a Passive Rehabilitation Robot (PaRRo) that employs kinematic redundancy in its mechanical design to apply forces that oppose user movement. This system uses low-cost eddy current brakes to deliver scalable resistance. These brakes work by moving a conductor through a magnetic field, inducing circular currents (eddy currents). The magnetic field generated by the eddy currents opposes the original magnetic field, resulting in a resistive force that is proportional to the relative velocity between the conductor and the magnetic field.

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One of the key advantages of eddy current brakes over traditional friction-based systems is that they are non-contact and velocity-dependent, providing a smooth experience and greater durability. They also handle a wide range of resistive loads effectively. However, their performance drops significantly at low speeds, making them less suitable for patients with severe impairments or very limited movement.

In a related study, Amanda Peattie et al. developed a system that combines robot-assisted therapy with augmented reality [16]. Their device features an automated, variable-resistance arm skate integrated with a virtual reality exercise platform. This setup enables users to engage in therapy across various resistance levels and training modes. Despite its potential, clinical adoption has been limited—primarily due to high implementation costs.

Wheel braking systems

Programmable resistance devices often use disc braking systems, where patients control the device by pushing a handle connected to a rope that is carefully unspooled. The braking system is a component designed to counteract the force exerted by the patient. An advanced control system adjusts the internal brake mechanism in real time to precisely match the patient's pulling force. Resistance is regulated by disc brakes managed through an Arduino controller. A retraction mechanism safely returns the rope to its starting position after use. The device also collects and analyzes performance data, which is displayed on a mobile application via Bluetooth. A key benefit of this system is its ability to offer adjustable, programmable resistance tailored to the individual's rehabilitation needs. However, as the device is currently in the prototype phase, its clinical effectiveness remains to be validated.

Another study by Hu S. et al. [17] designed a braking system to provide resistance in the Gait Propulsion Trainer (GPT). The device features a cable mechanism that is reeled in using a brake and control system. During training, the user stands in front of the GPT and the session continues until the user is no longer able to move forward. he system achieves a friction reduction of 0.06 N·m.

Additionally, Niels de Ruiter et al. developed a method to adjust mechanical resistance according to the user's effort. This approach allows for the design of rehabilitation devices tailored to the varying resistance needs of different patients and can be adapted for different stages of physiotherapy [18]. A wheel braking system using a simple clutch brake is employed to increase resistance, giving physiotherapists the flexibility to modify the difficulty level based on the patient's progress.

Sensor based systems

Another important area of research focuses on the use of surface electromyography (sEMG) and various sensors to support rehabilitation. This technique employs superficial electrodes to record electromyographic signals, which provide valuable insights into muscle performance across different age groups [19][20]. Robotic rehabilitation devices often incorporate soft fabric sEMG sensors to capture these signals and use them to drive movement, enhancing therapy outcomes and improving daily activities for patients undergoing elbow training, spinal cord injury (SCI) rehabilitation, and stroke recovery [21][22]. Additionally, EMG signals can serve as control inputs to activate functional electrical stimulation, helping to boost muscle activation as well as static and dynamic balance in stroke patients [6].

However, since EMG has certain limitations, alternative methods such as force myography (FMG) and mechanomyography (MMG) are also used to measure muscle activity [23]. Force-sensitive resistors (FSRs) are commonly employed for muscle monitoring and activity recognition, demonstrating better performance than accelerometers and significantly improving classifier accuracy [24]. Comparative studies indicate that FSR sensors are effective for force measurement [25]. FMG sensors provide stable signals during dynamic and non-stationary movements, showing promise for use in user-machine interfaces [26]. Moreover, multi-sensor systems combining accelerometers, flex sensors, and force-sensitive resistors have been integrated into arm rehabilitation devices, offering portable data logging capabilities [27][28] [29].

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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3. MATERIALS AND METHODS

In this work we are studying the effect of resistance on muscle performance using Electromyogram (EMG) and Forcemyogram (FMG) signal. Performance of FMG is evaluated in literature to find its potential application in rehabilitation and assistive tools during daily life activities

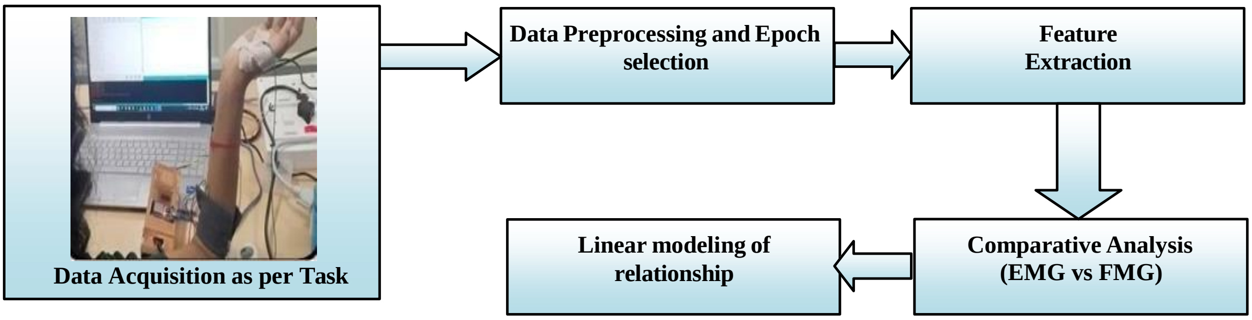

Fig.1. Block diagram of methodology adopted

[27]. FMG showed good results in classification of different wrist movements like wrist flexion/extension, grip squeeze, pinch squeeze and tripod squeeze [26]. Superficial EMG (sEMG) is a good tool to detect muscle fatigue [19]. It is also used to study the characteristics of extensors in hand during rehabilitation that shows direct correlation with respect to muscle performance scales such as Barthel index score and Fugl-Meyer score [20]. This section discusses the material and methods used in present work as shown in figure 1.

3.1 Task design and Data Acquisition

Data were collected from 10 healthy participants using an RMS EMG system

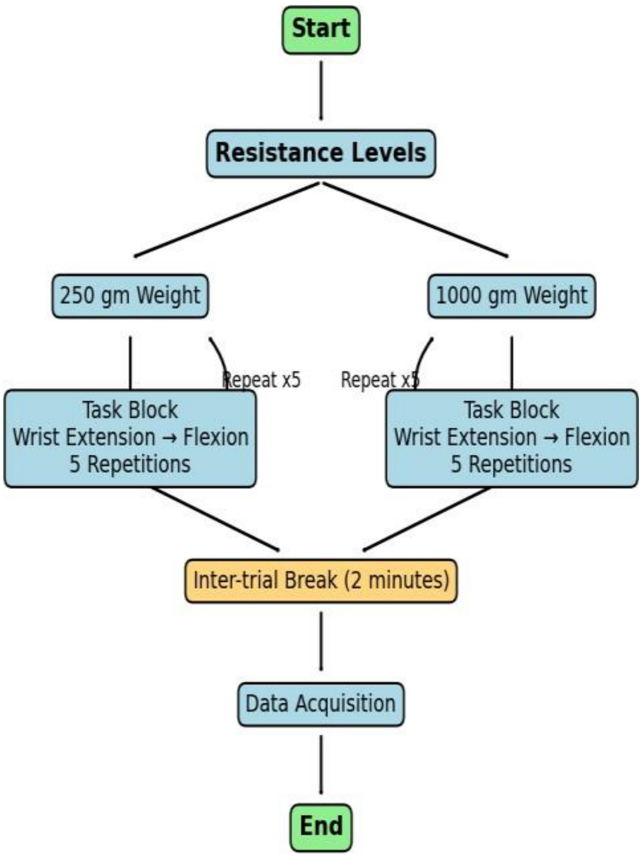

Fig. 2. Flowchart of task block employed for data acquisition

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with Ag/AgCl surface electrodes, following informed written consent. The skin was cleaned with alcohol prior to electrode placement to minimize impedance. Data acquisition adhered to the task protocol illustrated in Figure 2. Two resistance levels (250 g and 1000 g) were employed. Each task block consisted of wrist extension followed by wrist flexion, performed for five repetitions at each load, with a two-minute inter-trial rest period."

3.2 Data Preprocessing and Epoch selection

The acquired signals were band-pass filtered between 10–500 Hz. To further eliminate ECG and power-line interference, a fourth-order notch Butterworth filter was applied in the 58–72 Hz range [11]. The Butterworth filter was selected for its ability to balance effective noise suppression with minimal distortion of signal characteristics. Subsequently, the data were segmented to define windows for feature extraction. This segmentation process enabled detection of muscle activation associated with wrist movement activity [30]. For analysis, 300 data points following the onset of muscle activity (identified at the signal peak) were extracted."

3.3 Feature extraction

Mean absolute value and root mean square error features were extracted using the processed dataset

1. Mean Absolute Value (MAV): MAV is a statistical measure used to quantify the average magnitude or intensity of a signal over a specified time interval. Equation 1 is used to calculate MAV.

$$\text{MAV}=\frac{1}{N}\sum_{i=1}^{N}|\mathrm{x_i}| \qquad \ldots\ldots\ldots\ldots\ldots(1)$$

Where; x represents the EMG signal, in the interval i, |x| denotes the absolute value of the EMG signal in the given time interval.

2. Root Mean Square Error (RMSE): RMSE gives the indication of constant force and non-fatigue contractions of the muscles. Equation 2 is used to calculate RMS.

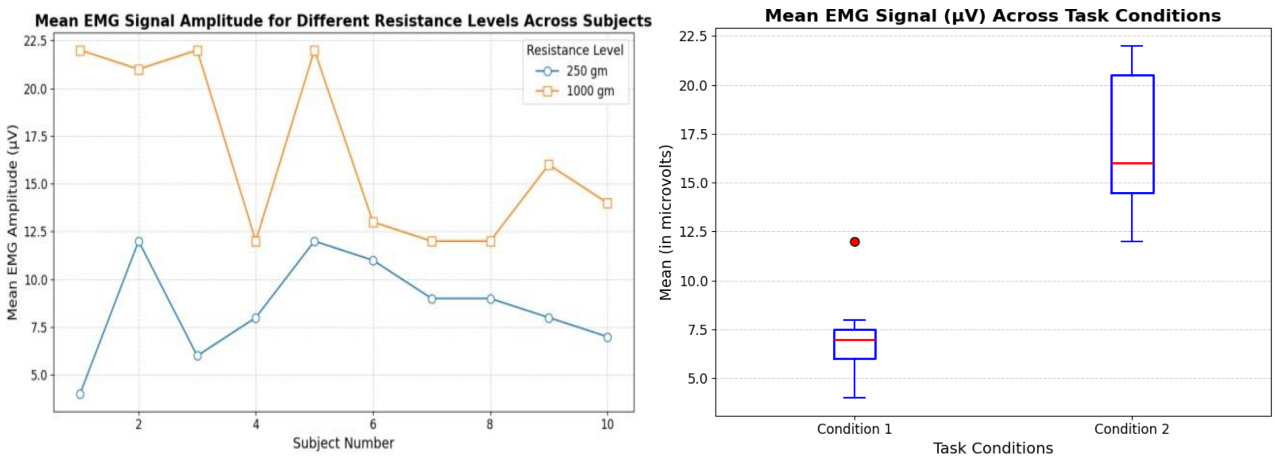
$$\text{RMS}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}|\mathrm{x_i}|} \qquad \ldots\ldots\ldots\ldots\ldots(2)$$

Where; x represents the EMG signal, in the interval i, |x| denotes the absolute value of the EMG signal in the given time interval.

4. RESULTS

4.1 Feature distribution

MAV and RMSE features are calculated for the ten subjects and compared for the two task conditions.



(a) (b)

Fig. 3. Mean features plotted over 10 healthy subjects (a) Mean (b) Error bar plot

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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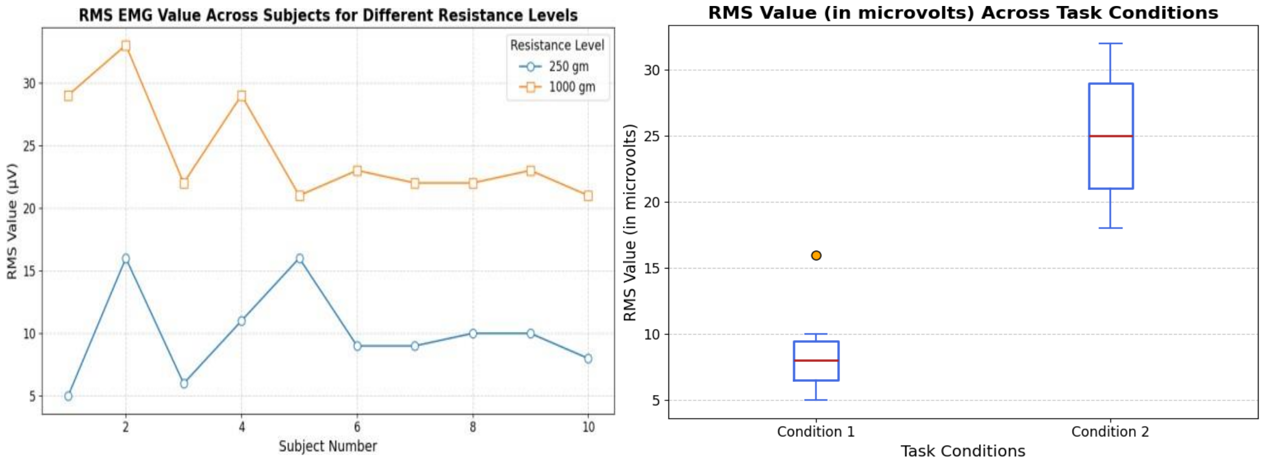
Figure 3 (a) shows the MAV feature distribution over 10 subjects. Results suggest a distinct difference between the MAV values across all subjects for two task conditions. Figure 3(b) shows error bar graph for MAV feature over a population size of 10. Result displays a clear distinction between two task conditions. RMSE feature shows similar distribution over 10 subjects as shown in Figure 4 (a) and (b) MAV and RMS features display an increase in MAV and RMS value as resistance increases. RMSE feature shows similar distribution over 10 subjects as shown in Figure 4 (a) and (b). MAV and RMS features display a significant increase in MAV and RMS value as resistance increases.



(a) (b)

Fig. 4. RMS features plotted over 10 healthy subjects (a) Mean (b) Error bar plot

4.2 Force Myography (FMG)

Electromyography (EMG) remains the established benchmark for muscle analysis. Complementing this, Force Myography (FMG) presents a practical, low-cost method for assessing muscle function by measuring volumetric changes in the underlying musculotendinous structures. For this study, FMG signals were acquired from the forearm using a custom-designed band equipped with two FSR402 sensors as shown in figure 5. These force-sensitive resistors, strategically placed on the flexor and extensor sites, transduce muscle activity into a variable resistance. This analog signal is subsequently digitized via a microcontroller's analog-to-digital converter (ADC) for analysis during specific wrist movements.

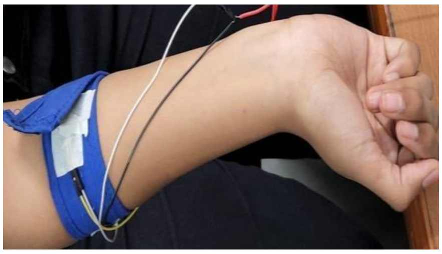


Fig. 5. FMG band and sensor placement

A calibration was performed on the Force-Sensing Resistors (FSRs) using known weights of 50g and 100g. Recordings from the extensor sensor (Figure 6a and 6b) demonstrate a clear signal response: a rapid rise during active wrist extension followed by a sharp fall when the wrist returns to rest. This data indicates that greater force corresponds to lower FSR resistance (and higher output voltage), which is consistent with established EMG principles. For future improvements, the voltage divider circuit could be reconfigured to map the sensor's output across the entire 0-3.3V range of the microcontroller, thereby enhancing measurement resolution.

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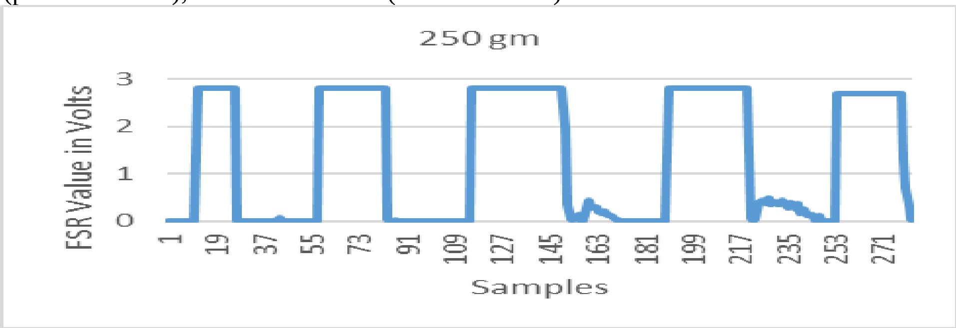
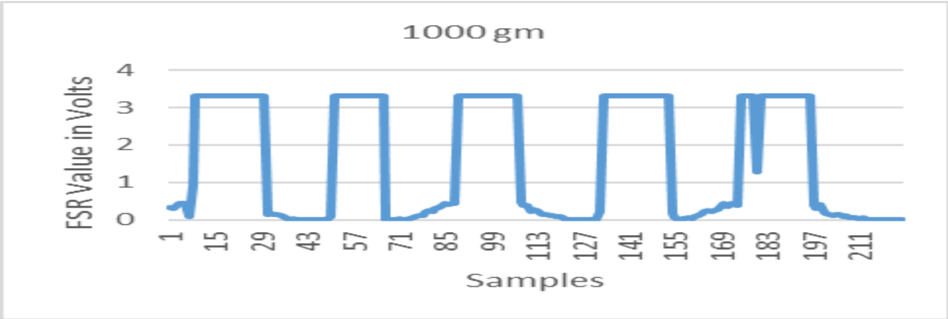


(a)



(b)

Fig. 6. FMG recorded with (a) 250 gm (b) 1000gm resistance values

4.3 Comparative analysis of EMG and FMG

A comparison of the mean feature values for EMG and FMG is presented in Table 1.

Table 1 Comparison of EMG and FMG mean feature value

Signals	Resistance (in grams)	
	250GM	1000G M
EMG Mean Value	7μV	14μV
FMG Mean Value	2.8V	3.2V

The analysis indicates a proportional relationship for EMG, where its mean value doubles as resistance doubles. For FMG, the mean value demonstrates a positive but different correlation with increasing resistance. These observations across the studied population support a linear model between the two variables, with EMG as the dependent variable (y) and FMG as the independent variable (x). This model is constructed from two key data points [31], [32]:

$$P1: (x1, y1) = (2.8, 7)$$

$$P2: (x2, y2) = (3.2, 14)$$

We can model the relationship as linear:

$$y = a * x + b \qquad \text{…………..(3)}$$

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Volume 38 No. 11s 2025,
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where y is EMG (in µV) and x is FMG (in V).

First, calculate the slope (a):

$$a = (y2 - y1) / (x2 - x1) = (14 - 7) / (3.2 - 2.8) = 17.5$$

Using point P1= (2.8, 7); Intercept:

$$b = 7 - 49 = -42$$

So, equation (3) can be written as:

$$y = 17.5 * x – 42$$

or

$$EMG = 17.5 * FMG – 42 \qquad \text{………………(4)}$$

This equation holds for the given data points. It is important to note that this is a linear approximation based on only two points; for more accuracy, more data points would be needed.

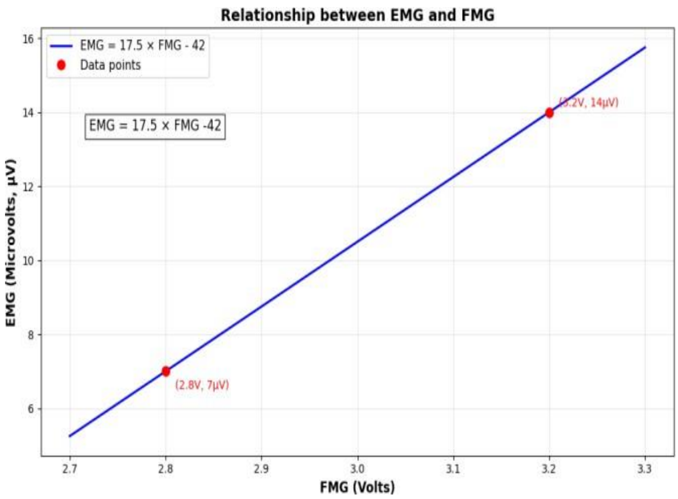

Fig. 7. Linear Model representing relationships between EMG and FMG

The graph in figure 7 demonstrates that EMG increases linearly with FMG, with a slope of 17.5 µV per Volt of FMG. This suggests a direct relationship between EMG and FMG considering the data acquired from 10 subjects.

5. CONCLUSION

Rehabilitation relies on diverse measurement techniques, with significant global research focused on developing practical wearable sensors to quantify and facilitate recovery. A primary goal is creating home-based tele-rehabilitation systems that improve efficiency for patients and clinicians while enhancing quality of life. Examples include effective Virtual Reality (VR)-based Rehabilitation Gaming Systems (RGS) [33] and low-cost, internet-enabled platforms for upper-limb motor rehabilitation [34][35], such as the Neuro-rehabilitation Training Toolkit (NTT). There is a growing need for systems that provide support during daily activities and in work environments [36]., necessitating accelerated development, research standardization, and a sustained multidisciplinary effort [37].

Rehabilitation accelerates recovery and helps restore normal function. This study investigates the effects of resistive therapy on healthy individuals by applying two resistance levels (250g and 1000g) and recording muscular response via EMG and FMG. Results indicate increased extensor muscle effort with higher resistance, providing a basis for analyzing and monitoring resistive therapy in patients with

Received: August 11, 2025

conditions like spastic hemiparesis.

Key Findings on FMG:

FMG presents a promising, cost-effective alternative to EMG but requires further development for clinical use. The current setup reveals a linear relationship between EMG and FMG signals with respect to applied resistance over 10 subjects. Signal acquisition can be enhanced by improving the FSR voltage scaling and employing a higher-resolution analog-to-digital converter (ADC) to better utilize the 3.3V range. Future work will focus on designing an automated hardware setup for administering resistive therapy, enabling effective treatment in the comfort of a patient's home.

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