SIGNAL ANALYSIS BASED ON HAND ACTIVITY: IMPLICATIONS FOR PROSTHETIC DEVELOPMENT

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ABSTRACT: This study examines electromyography (EMG) signal pattern recognition to elucidate the relationship between EMG signals, hand movement, and biceps muscle force. The exercises were performed at angles of 45°, 90°, and 120° relative to the elbow joint. The research uses Matlab for EMG signal optimal features parameters to focus on hand movements under varying loads (2kg, 4kg, and 6kg). Data acquisition involved tasks of lifting and holding, with EMG signals analyzed across different phases of muscle activation. Results indicate a positive correlation between EMG signal amplitudes and load and motion angles, revealing distinct muscle activation phases during lifting, holding, and releasing. The results show that the normalized average peak force at different loading levels increases if the load increases. If the load decreases, the amplitude decreases for trained and untrained subjects. The findings underscore the potential for these insights to inform the development of flexible prosthetic arms and assistive technologies.

***KEYWORDS**: Electromyography (EMG); Signal pattern recognition; Hand movement; Muscle activation; Prosthetic arms.*

1.0 INTRODUCTION

An individual's capacity to do daily tasks can be significantly impacted by the partial or total loss of an upper limb, a vital human body component [1]. The hand, forearm, and arm are the three parts that make up the human upper limb. The relationship between the musculoskeletal system, the neurological system, and its environment must be coordinated for each portion to move. Coordination of the shoulder, elbow, wrist, and finger joints is necessary to carry out various daily tasks involving a wide range of motions with many degrees of freedom. Even though these synchronized motions are repetitive, they might be useful for carrying out difficult tasks. All these typical hand control capabilities should be closely matched to an artificial hand, allowing the user to accomplish daily tasks more efficiently and customized. Because the coordinated control of the human hand is intricate, it is very challenging to precisely mimic it in a prosthetic hand [2].

A typical prosthetic hand involves three main connected parts: an input signal acquisition unit, a processing and control unit and an end effector. Nowadays, almost all high-performing artificial hands (or prostheses) use surface electromyography signals (sEMG or myosignals) to control their end effectors. Surface electromyography records the muscle movements electrically from the surface of muscle cells when they are electrically or neurologically activated [1]. Electromyography (EMG) is a technique focused on the development, recording, and analysis of myoelectric signals, which arise from physiological changes in muscle fibre membranes [1]-[3]. During muscle contractions, these electrical activities generate EMG signals [4]. The signals are produced by ion exchanges across muscle fibre membranes, which precede muscle force generation. This process involves the nervous system controlling muscle activity during contraction and relaxation [4]. When an action potential, initiated in the brain, travels along nerve fibres through the spinal cord to skeletal muscles, it stimulates muscle contractions that move human limbs [5].

The recorded EMG signal represents the superimposed electrical potentials from numerous muscle fibres, forming a time-varying signal. Each motor unit action potential (MUAP) contributes to the overall EMG signal, reflecting muscle responses to neural stimulation [2], [6]. EMG signals are typically modelled as a filtered impulse process, with MUAPs acting as filters. The raw surface EMG signal is unprocessed and comprises superimposed MUAPs. According to Yacoub and Raoof [7], EMG signals have a frequency range of 0 to 2000 Hz, with dominant energy concentrated between 20 and 500 Hz. The signal amplitude ranges from 0 to 10mV, and noise is a common issue

[1], [6].

Recording EMG signals involves electrodes, and several external factors, including tissue characteristics, physiological cross-talk, geometry changes between muscle and electrode, and electrode quality, can influence the signals. Proper circuit design and skin preparation can mitigate some of these issues [2]. However, various types of noise, including electrical noise from equipment and ambient electromagnetic radiation, remain challenging [8]. Modern technology, including electronics and differential amplification advancements, has improved the ability to measure surface EMG signals with low noise and high fidelity. Differential amplifiers with high common mode rejection rates and high input impedance are typically used, along with bandpass filters ranging from 10-20 Hz for high-pass to 500-1000 Hz for low-pass filtering [9].

EMG has been used extensively in performance analysis for exercise and rehabilitation, helping to evaluate muscle recruitment, activity levels, and fatigue through amplitude and frequency analysis of the signals [10]-[12]. These signals provide critical insights into neuromuscular activities and are vital in clinical and engineering applications, including sports training, gait analysis, and physical therapy [2], [13]. The raw EMG signal is complex and influenced by physiological, anatomical, and instrumentation factors, varying from person to person [14]. Noise from tissue characteristics, cross-talk, and surrounding environments can distort the signal [1]. Effective EMG applications, such as controlling prostheses and assistive devices, leverage the direct correlation between EMG signal amplitude and muscle force [15]. Analyzing EMG signals helps understand muscle force utilization, execution of movements, and muscle rest dynamics [16]. Accurate EMG signal recording requires careful electrode selection and placement. Invasive methods using needle electrodes provide precise and high-resolution measurements of electrical activity, particularly for deep muscles [17]. Although more intrusive, these methods offer bandwidth and specific muscle targeting advantages, which are essential for detailed neuromuscular studies [1], [19].

In this paper, electromyography (EMG) technology aims to collect EMG data based on various hand movement activities to analyze the electrical signal activity across different angles of movement. By examining these signals, the research seeks to understand the relationship between EMG signal amplitude and the weight involved in these movements, providing insights into how muscle activation varies with different loads and positions.

The paper is structured as follows. In the Material and Methods section, the tools and methods utilized for EMG data acquisition and processing are detailed and explained. The Results & Discussion section highlights the differences observed in EMG signal characteristics based on electrode placement, arm movements, and applied loads, discussing the implications of these findings. Lastly, the Conclusion section summarizes the key findings regarding electrode placement's impact on EMG signal quality and its relevance for applications in prosthetic control and rehabilitation technologies.

2.0 MATERIAL AND METHODS

This section discusses the process of the study, starting with choosing the samples for the experiment and ending with the analysis of the results of the produced signals.

Step-1:

The criteria for selecting suitable participants for this study are outlined in Table I. Factors such as the amount of fat in the biceps muscle, and the condition of the upper limb are also considered. Participants with excessive fat are excluded, as it can introduce noise into the electromyography signal. Fifteen healthy subjects were selected to minimize the risk of injury.

Table I: Criteria for selecting a suitable subject for the experiment

Criteria	Specification
Number of Subjects	15 male right-handed individuals
Age (years old)	24.00 ± 0.93
Weight (kg)	70.60 ± 12.89
Height (m)	1.67 ± 0.01
Health Condition	Normal and healthy
BMI	25.25 ± 3.79

Participation is voluntary, and each subject is required to sign a consent form. This consent form ensures that participants volunteer willingly, fully understand the experiment, and know the potential consequences. This precautionary measure safeguards the participants and the study in case of post-experiment issues.

Step-2:

In the second step, the authors ensure the consistency and validity of the raw EMG data collection, and standardized experimental procedures are followed, as illustrated in Figure 5. The experiments are conducted in a quiet room to minimize noise interference and enhance signal quality. Participants lean against a wall to maintain a straight and upright posture, preventing the use of their body for weight support. Data is recorded continuously throughout the experiment. Vernier EKG Sensor, Flex Sensor, Electrode and Dubell shown in Figures 1,2,3 and 4 were used in this experiment.

Figure 1: Vernier EKG sensor

Figure 2: Flex sensor

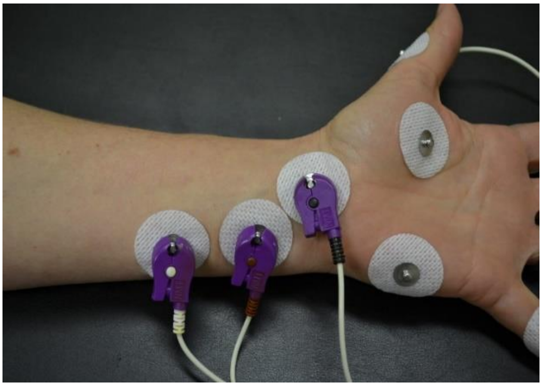


Figure 3: Surface Electrodes

Figure 4: Dumbell of different Weight

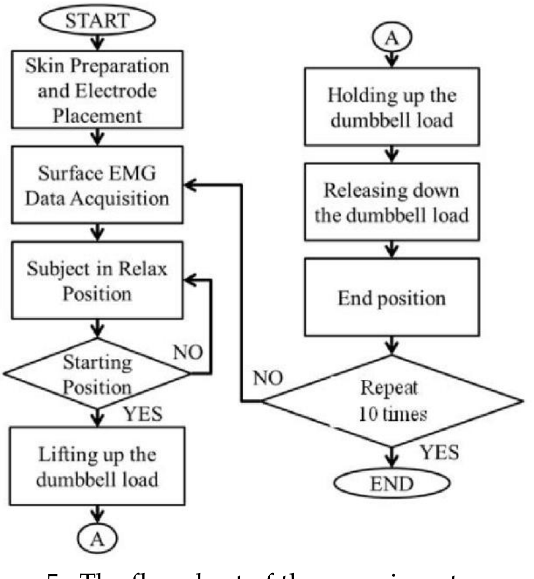


Figure 5: The flowchart of the experiment

Figure 6 shows an overview of the EMG signal pattern recognition. First, we acquire EMG data using experimental procedures and then process the data using feature extraction. Lastly, we use the Matlab app to see the expected outcome.

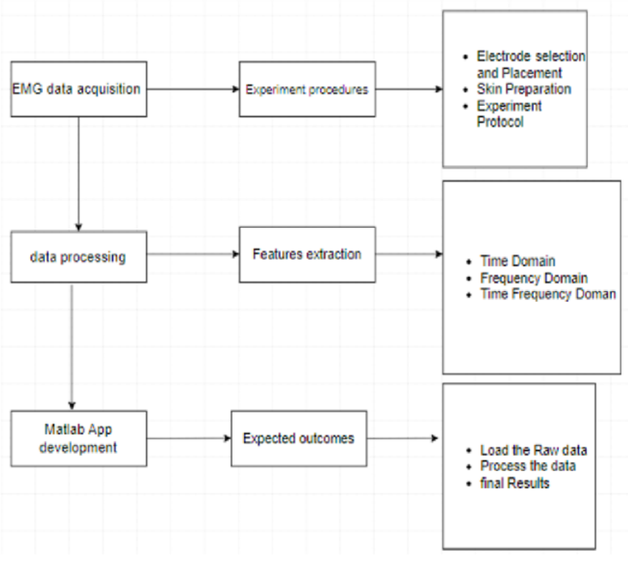
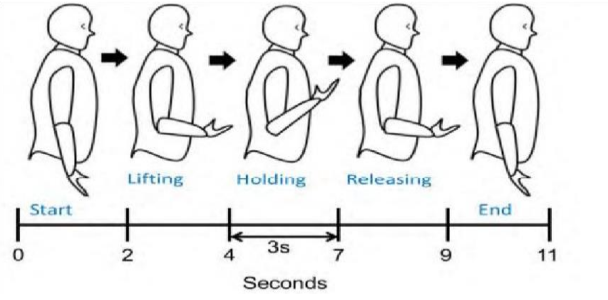


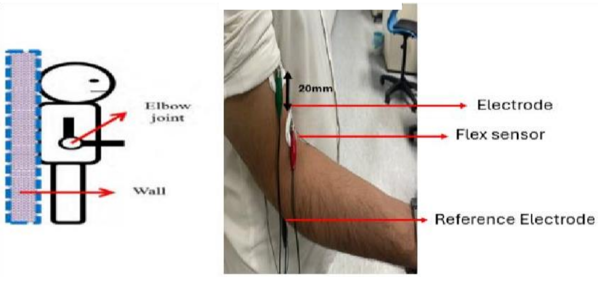
Figure 6: An overview of EMG Signal Pattern Recognition

Step-3:

In this step, participants are instructed to lift their hands freely without any load and then with dumbbell loads of 2kg, 4kg, and 6kg. Each task is repeated ten times under observer supervision. Figure 7(a) shows the different positions of the experiment from start to end. The movement of the participants during the experiment is shown in Figure 7(b). The 6kg load is selected as the maximum load for an average, healthy individual, applicable for males, using a single hand. The right hand is used in this experiment to minimize interference from heartbeat signals (electrocardiogram, ECG).



(a)



(b)

Figure 7: Steps during the experiment (a) different hand position (b) Experimental setup for the subject during the experiment.

Step-4:

In the last step, the data acquisition phase, EMG signals are measured according to several tasks defined in the experimental procedures. The measured EMG signals undergo a feature extraction process in the data processing phase. Achieving the first objective involves completing both data acquisition and data processing. Data classification and validation phases are necessary for the second and third objectives. In the data classification phase, the extracted features from the EMG signal are used for neural network training. Post-training, the EMG signals are classified based on force (using load) and motion (in degrees). The developed EMG signal pattern recognition system is tested on new, randomly selected subjects to assess its performance in the data validation phase.

3.0 RESULTS AND DISCUSSION

This research collects EMG data while participants lift a dumbbell weighing 2kg, 4kg, and 6kg at different arm motion angles (45°, 90°, and 120°). Analyzing these EMG signal characteristics reveals the fundamental relationship between arm motion angles, the loads, and the changes in EMG signal amplitudes. This analysis comprehensively explains the interaction between EMG signals, muscle force, and arm motion.

The graphs presented in Figures 9.1, 9.2 and 9.3 depict data from a single subject, categorized into three phases: phase I (lifting), phase II (holding), and phase III (releasing). In phase I (lifting stage), the biceps muscle expends increased energy or force to lift the load from 0 to the target angle (45°), evidenced by a rapid increase in EMG signal amplitude. The peak amplitude at the start of the lifting stage indicates the maximum muscle effort required for initiating the lift. During phase II (holding stage), when the subject maintains the load at 45°, the EMG signal amplitude stabilizes, reflecting consistent muscle activation to sustain the load. However, the amplitude gradually decreases over time, illustrating the non-stationary nature of the EMG signal, wherein signal frequency changes over time. In phase III (releasing stage), the EMG signal amplitude decreases rapidly as the subject releases the load, reaching zero force at 0°. These findings underscore the relationship between EMG signal amplitude variations, muscle exertion, and arm movement.

TABLE II. Maximum EMG Signal Amplitude at Different Load

Load (kg)	Maximum EMG signal amplitude (mV)
2	120
4	220
6	240

Further analysis aimed at understanding the characteristics of the EMG signal focused on its relationship with muscle force under varying loads. Additionally, Table II. and Figure 8. present the maximum amplitude of the EMG signal across different loads. Maximum amplitude was chosen as a feature because it represents the peak energy or force exerted by the biceps muscle during the experiment. This result demonstrates that the biceps muscle expends greater energy or force to lift the load as the load increases, resulting in higher EMG signal amplitudes. Moreover, the tested data shows a clear and obvious comparison between the intensity of the load and how widely spread the arm is, which is represented by the arm motion angle in degree.

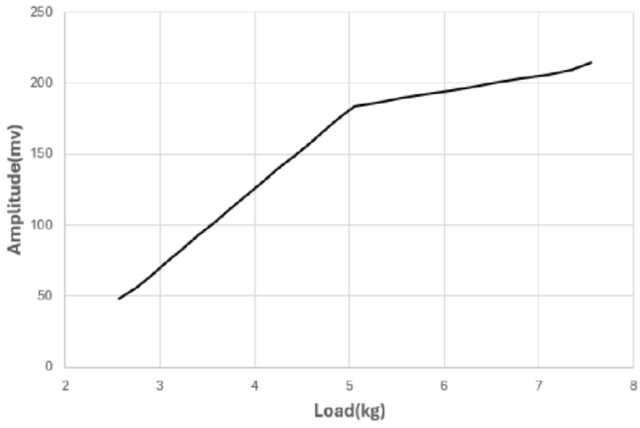


Figure 8: Max EMG signal to load relation

The comparison between the weight of the subject arm and the force exerted by the biceps muscle is illustrated in Table III. This insight, for instance, shows that a higher arm weight does not necessarily mean higher force exerted by the biceps muscle.

TABLE III. Sample comparison of the subject physical and force exerted by biceps muscle

Subject, N	Weight of arm, $Warm$(kg)	The force exerted by the biceps muscle, $Fbiceps\ muscle$(N) x102
1	1.08	3.58
2	1.33	3.78
3	3.52	3.27
4	2.13	4.09
5	1.94	3.05
6	2.10	3.42

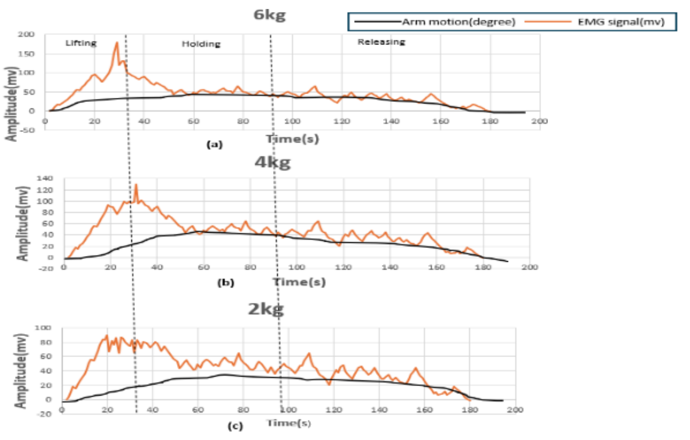


Figure 9.1: Comparison of the EMG Signal Amplitude for 45 of Elbow Angle at Different Load: (a) 2kg, (b) 4kg and (c) 6kg

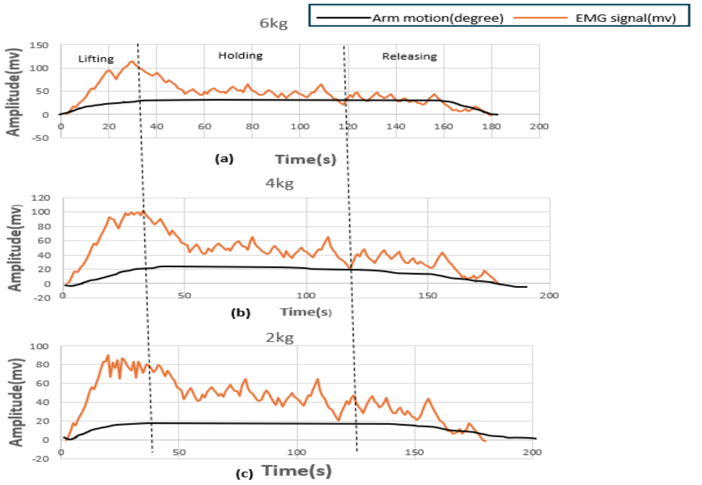


Figure 9.2: The graphs presented in Figure 9.2 depict data from a single subject, categorized into three phases: phase I (lifting), phase II (holding), and phase III (releasing). In phase I (lifting stage), the biceps muscle expends increased energy or force to lift

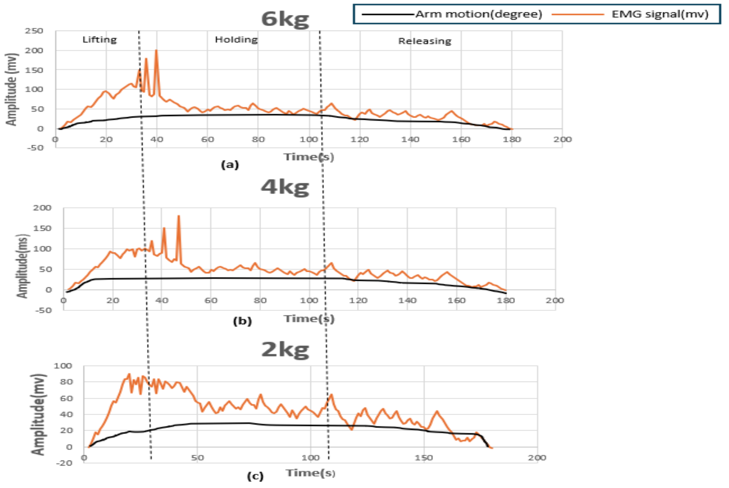


Figure 9.3: Comparison of the EMG Signal Amplitude for 120 of Elbow Angle at Different Load: (a) 2kg, (b) 4kg and (c) 6kg

The EMG data used in this study were obtained while hand load-lifting dumbbell loads of 2, 4, and 6 kg at various arm motion angles. Figures 9.1, 9.2, and 9.3 display the properties of the EMG signal for varying arm motion degree values (angle), which are 45, 90, and 120, respectively. The essential relationship between changes in arm motion (angle) and loads and changes in EMG signal amplitudes are revealed by studying the signal characteristics. This feature analysis explains the link between the EMG signal, muscle force, and arm motion (angle). So, Figures 9.1, 9.2 and 9.3 show that if the load increases, then the amplitude in Mili-volts also increases and if the load decreases, the amplitude also decreases.

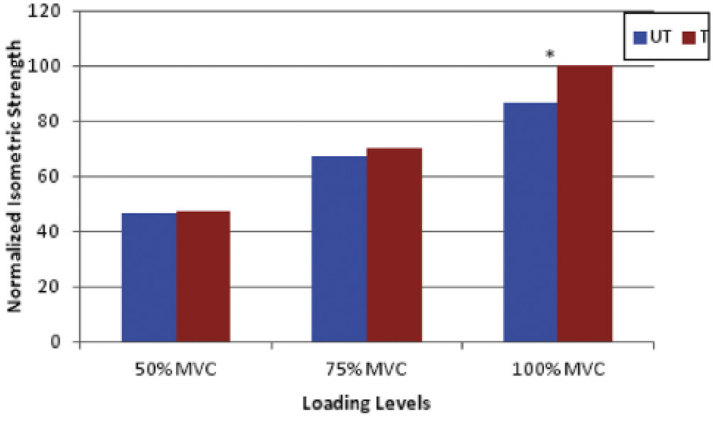


Figure 10.1: Comparative plot of normalized average peak force at different levels of MVCs for trained and untrained subjects.

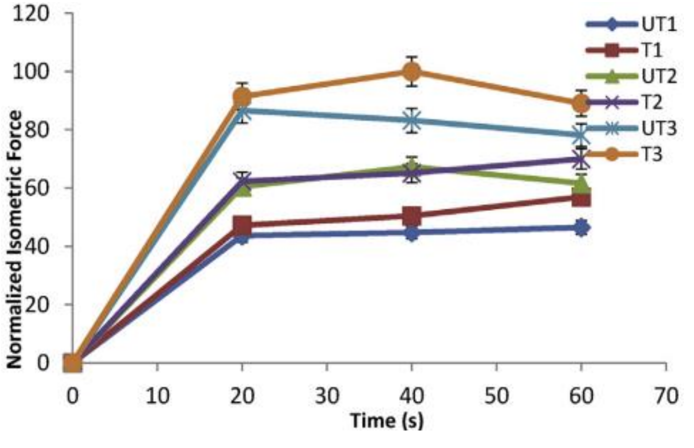


Figure 10.2: Normalized average forces for subjects at different levels of MVCs

Figure 10.1 illustrates how the strength of the biceps brachii was found to be 13.41% greater in trained subjects than in untrained subjects. As the amount of Maximal Voluntary Contraction (MVC) increased, the muscular force increased for both groups. The muscle force rose by 32.38% and 30.04% in trained participants. However, as the degree of MVC increased from L1 to L2 and L2 to L3, respectively, the muscular force increased by 30.97% and 22.3% for the untrained subjects, as shown in Figure 10.2.

4.0 CONCLUSION AND FUTURE WORK

This study explored EMG signal pattern recognition and investigated its correlation with hand motion and force exertion by the biceps muscle. A Python model was developed for EMG signal pattern recognition, and its performance was evaluated through data acquisition, processing, and classification. The relationship between hand motion and biceps muscle force was analyzed, revealing a strong association. These findings offer potential applications for enhancing the flexibility and functionality of prosthetic arms. Additionally, the study discusses how changes in hand movements correspond to EMG signal variations and changes in biceps muscle force.

Future research should focus on identifying optimal feature parameters for input into the EMG pattern classifier. Features are extracted from individual time segments to form a comprehensive feature set representing the myoelectric pattern. Determining the number of time segments is critical for defining the quantity of feature parameters. Investigating the impact of segment length on classification accuracy is essential to strike a balance between preserving class information and minimizing feature estimation errors.

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