ANALYSIS OF EMG BASED ON DIFFERENT TYPES OF HAND MOVEMENT FOR EXOSKELETON HAND APPLICATION

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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This report is submitted in partial fulfilment of the requirements for the degree of Bachelor of Electronics Engineering Technology (Telecommunications) with Honours

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DEDICATION

To my beloved mother, Haslinyanti Binti Abu Samah, and father, Mohamad Fuad Bin Mohamad,

and

To my kind lecturers and all my friends for their love,
sacrifice, encouragement, and best wishes
Along with all the hardworking and respected
Supervisor IR. Mohd Shafirin Bin Karis

ABSTRACT

Hand movement impairments significantly affect individuals' quality of life, highlighting the need for advanced assistive technologies. This study addresses the challenge of enabling intuitive and precise control of an exoskeleton hand by analyzing electromyography (EMG) signals. The objective is to develop a robust system capable of accurately interpreting muscle activity to facilitate seamless and natural interaction with an exoskeleton device. To achieve this, EMG signals were acquired using surface electrodes and underwent rigorous preprocessing to eliminate noise and artifacts, ensuring clean and reliable data for analysis. Sophisticated machine learning algorithms were employed to classify and differentiate between a range of hand movements, including grasping, pinching, and releasing objects. The system's performance was evaluated in terms of its accuracy in movement classification and its ability to translate these classifications into real-time control of the exoskeleton hand. The results demonstrated high classification accuracy and effective real-time translation of hand movements, underscoring the system's potential for practical applications. This research highlights the viability of EMG signal analysis as a tool for enhancing the functionality of exoskeleton hands, offering a promising solution for individuals with hand movement impairments.

ABSTRAK

Kekurangan keupayaan pergerakan tangan memberi kesan besar terhadap kualiti hidup individu, sekaligus menekankan keperluan untuk teknologi bantuan yang lebih maju. Kajian ini menangani cabaran mengawal eksoskeleton tangan secara intuitif dan tepat melalui analisis isyarat elektromiografi (EMG). Objektif utama adalah untuk membangunkan sistem yang kukuh dan mampu mentafsirkan aktiviti otot dengan tepat bagi memudahkan interaksi semula jadi dengan peranti eksoskeleton. Untuk mencapai matlamat ini, isyarat EMG diperoleh menggunakan elektrod permukaan dan diproses dengan teliti untuk menghapuskan bunyi serta artifak, memastikan data yang bersih dan boleh dipercayai untuk analisis. Algoritma pembelajaran mesin yang canggih digunakan untuk mengklasifikasikan dan membezakan pelbagai pergerakan tangan, termasuk menggenggam, mencubit, dan melepaskan objek. Prestasi sistem dinilai berdasarkan ketepatan klasifikasi pergerakan dan keupayaannya untuk menterjemahkan klasifikasi ini kepada kawalan eksoskeleton tangan secara masa nyata. Hasil kajian menunjukkan ketepatan klasifikasi yang tinggi dan keupayaan penterjemahan pergerakan tangan secara masa nyata, sekaligus menonjolkan potensi sistem ini untuk aplikasi praktikal. Penyelidikan ini menggariskan kebolehlaksanaan analisis isyarat EMG sebagai alat untuk meningkatkan fungsi eksoskeleton tangan, menawarkan penyelesaian yang menjanjikan bagi individu yang mengalami kekurangan pergerakan tangan.

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First and foremost, I want thanks to Allah S.W.T for His blessing and guidance, which have given me the strength to finish the task successfully. I would like also to express my gratitude to my supervisor, IR. Mohd Safirin Bin Karis. Your guidance, expertise, and patience have shaped this project. I am grateful for your mentorship and the invaluable lessons I’ve learned under your supervision. Your dedication to excellence has been a constant source of inspiration. I am also indebted to Universiti Teknikal Malaysia Melaka (UTeM) for the financial support that enabled me to accomplish the project.

To my family, your enduring love and encouragement have been the driving force behind my academic journey. Thank you for standing by me and providing unwavering support. This achievement is as much yours as it is mine.

To friends, in the highs and lows of this academic endeavor, your friendship has been a source of strength and laughter. Thank you for being a sounding board, a motivator, and a true friend. Your support has made this journey memorable.

Last but not least, I want to thank me for believing in me, I want to thank me for doing all this hard work, I want to thank me for having no days off, I want to thank me for never quitting, I want to thank me for always being a giver and trying to give more than I receive.

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$delta$	-	Voltage angle
	-	
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LIST OF ABBREVIATIONS

$sEMG$	-	Surface electromyography
FDS	-	Flexor Digitorum Superficialis
EMG	-	Electromyography
FDP	-	Flexor Digitorum Profundus FDP
ANN	-	Artificial Neutron Networks
FSR	-	Force-sensing resistor
	-	
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CHAPTER 1

INTRODUCTION

1.1 Background

Electromyography (EMG) is a critical device, for the development of exoskeleton hand as it measures muscle activity by quantifying electrical signals that muscles produce. Wearable robotic devices that augment or restore hand functions based on muscle intent and sensing interpretations offer the promise of true patient personalization and real-time control. Initially, EMG was mostly employed in clinical setups to diagnose neuromuscular disorders and study muscle function. It was therefore possible to embed it in ever-more sophisticated systems due to progress in the realms of signal processing and machine learning.

As for exoskeleton hand, raw electromyography signals from muscle are measured by surface electrodes placed on the skin surface. Since raw myoelectric signals exhibit inherent noise, preprocessing will enhance signal quality for further processing. Filtering and rectification procedures are usually executed sequentially. Typical precautions include noise and interference filtering, using band-pass filters, and signal rectification, that is, replacing it by the absolute value so that all the components are positive.

Following preprocessing, some features can be extracted from EMG signals. The time-domain attributes, such as MAV and RMS, reflect signal amplitude and variability over time. The frequency-domain attributes are, for instance, MNF and MDF, which show the frequency characteristics of the signal. Methods of time-frequency analysis, wavelet transforms, give more detail about signal dynamics.

These features are applied as inputs to the machine learning techniques. Linear Discriminant Analysis uses linear combinations of the features to classify different hand movements while Support Vector Machines are effective in high dimensional space and ANN is used to learn complex patterns in data. The classified movements are used to generate the control signals for the exoskeleton hand, thus allowing real-time intuitive control. Although much progress has been made, remaining challenges include variability in EMG signals due to electrode placement and muscle fatigue, and differences in muscle physiology across individuals. Real-time processing and minimum control latency are also important to make the system smooth.

Thus, in enhancing the life quality of individuals with hand movement disabilities, the decoding of various hand movements from EMG signals presents a multidisciplinary field ranging between biomechanics and signal processing up to machine learning. The potential of advanced, sophisticated, and user-friendly exoskeleton hands grows with improved research and advancement of technology.

1.2 Problem Statement

The problem statement of determining EMG signals based on distinct types of hand motions for exoskeleton hand applications passes through several hurdles. One main concern is the variability of the EMG signals, which depends on, among others, the placement of the electrodes, skin impedance, and muscle fatigue. Consequently, the variability can sometimes lead to ambiguity in the interpretation of the signals. This signifies that the real-time capture, preprocessing, and analysis of EMG signals should also be extremely sophisticated to present minimal delay for the exoskeleton hand to have a quick and accurate response corresponding to the user's intended movement. Another critical issue is to design proper machine learning algorithms to reliably classify a wide range of hand movements from the EMG data, considering individual differences in muscle activation patterns. Thus, solving these problems would certainly enhance the creation of exoskeleton hands that are effective, dependable, and user-friendly to control, which will improve the quality of life for people with hand motion disorders.

1.3 Project Objective

The main goal of this project is to create a method that distinguishes various hand movements. Specifically, the objectives are as follows:

- To analyze EMG signals for exoskeleton hand development.
- To capture and interpret the electrical activity produced by muscles during different hand movements.
- To design an exoskeleton hand that helps individuals with hand movement impairments perform daily tasks more easily.

1.4 Scope of project

This project aims to develop a system that uses Electromyography (EMG) signals to classify hand movements and control an exoskeleton. The key objectives include:

- Investigating and analyzing EMG signals to identify unique patterns of muscle activation during various hand movements, such as scissor, pen, chopstick, and needle movements.

- Designing and implementing an exoskeleton that can replicate these hand movements accurately based on the processed EMG signals, allowing for real-time control and feedback.
- Conducting experiments to evaluate the system's performance, including testing with real users to assess the accuracy and reliability of movement classification and the responsiveness of the exoskeleton.
- Identifying any weaknesses or limitations in the current system, such as classification errors or hardware limitations, and working on improvements for better performance and user experience.

:

1.5 Summary

This project focuses on developing an exoskeleton hand to assist people who have difficulties moving their hands. The system uses electromyography (EMG) signals, which measure the electrical activity of muscles, to understand and control the movements of the exoskeleton hand. These signals are collected using surface electrodes placed on the skin. Since raw EMG signals can be noisy and unclear, they are cleaned and processed to improve their quality. Important features of the signals, such as strength and frequency, are extracted to help identify specific hand movements.

Advanced machine learning methods are used to classify these movements, like grasping, pinching, or releasing, and turn them into commands for the exoskeleton. This allows the device to respond in real time and work intuitively based on the user's intentions.

However, some challenges remain, such as variations in the signals caused by differences in electrode placement, skin conditions, muscle fatigue, and individual muscle differences. It is also important to ensure the system processes the signals quickly and accurately, so the exoskeleton responds smoothly and without delay.

The goal of this project is to study EMG signals, interpret different muscle activities during hand movements, and design a reliable and user-friendly exoskeleton hand. Testing the system and gathering feedback will help improve its performance and identify areas for future enhancement. Ultimately, this exoskeleton hand aims to improve the quality of life for people with hand movement impairments by helping them perform daily tasks more easily.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section includes a complete review of the project's background and progress. Journals, articles, and books from previous work on this topic will be the main sources. This chapter will cover everything from the basics to related research applications. This step is important to understand the concept EMG Based on Different Types Of Hand Movement For Exoskeleton Hand Application.

2.2 Electromyography (EMG)

The electrical activity of skeletal muscles is the most Volunteers valuable part of an EMG signal. This is where EMG detects muscle signals by electrical measurements. The source of such signals is motor neurons of the central nervous system or CNS. As EMG signals reflect neuromuscular activities, these help in the diagnosis of muscle injuries and problems of the nervous system and muscles. Advanced deep learning can also use the EMG signals for control of complex robotics systems or even just collect simple data. They could be useful in terms of recording muscle movements and how people walk, for instance.

There exist two different types of electrodes that are applied to measure EMG signals. They are surface or needle. Needle type is further divided into three: the concentric-EMG electrode, single-fibre EMG electrode, and mono-polars single electrode. Needle types are about a breadth of 1 mm. Surface type is a non-invasive type since it is applied on the skin and is about 0.5 to 2.5 cm in breadth, Merlo et al., 2003. Surface electrodes measure the changes between the surface of the skin and the muscles by using electrolytic conduction. Basically, there are the dry EMG electrodes and gelled EMG electrodes-two types of surface electrodes.

The electroencephalogram, the electrocardiogram, and the electromyography are the three major types of electrograms. The EMG signals range from 5 Hz to 2 kHz, more useful than ECG and EEG signals that are lower than 100 Hz. However, the EMG signals are not very interpretable and appear as patterns. This paper is a review of the various types of EMG signals, the process of gathering them, and their processing. Improved EMG diagnostics will benefit engineering and medicine.

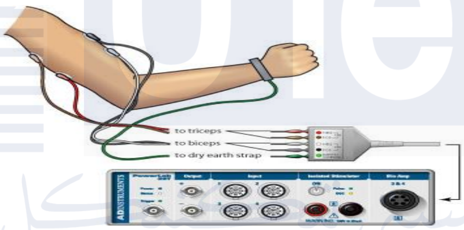

Figure 2.1 A proses of Electromyography [1]

2.2.1 Needle Electrode

Electromyography, or EMG, uses needle electrodes to measure the electricity of muscle activity. This is in contrast with surface electrodes that are placed on the skin. The needles themselves go directly into the muscle tissue, thus giving a more precise reading of the muscle signals. There are three types of needle electrodes: single-fibre EMG electrodes, concentric EMG electrodes, and monopolar single electrodes. Monopolar single electrodes use only a single needle and require that a reference electrode also be placed on the body. [1]. These include fine wires inside a thin, hollowed-out needle for regional recordings and single-fibre electrodes that record activity from a few muscle fibres. The needle electrodes are inserted into the muscles and thus are invasive, about 1 mm or smaller in width. They can be uncomfortable but give very good recordings. For the concentric this wire is inside a hollowed needle and for single fibre recording, the activity from a few muscle fibres. They are used for diagnosis of carpal tunnel syndrome, for diagnosis of neuromuscular diseases like ALS, myasthenia gravis, muscular dystrophy; they are also used in research for studying contraction/behaviour of muscles in different situations. Help formulate, control, and evaluate the rehabilitation strategies and therapies for the persons who have neuromuscular disorders. In the EMG test, a thin-needle electrode is placed inside the muscle for picking up the electrical signals of the muscle fibres. That amplifier records these signals and enlarges them for study. The EMG hence is known to show the way for evaluating the health of muscles and nerves since typical patterns indicate specific kinds of issues of neuromuscular. Only with full data on health of muscles and nerves is it possible to make an adequate diagnosis and plan the therapy effectively, for the acquisition of which needle electrodes are needed.

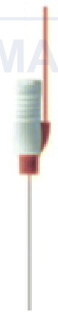

Figure 2.2 Needle Electrode [1]

2.2.2 Surface Electrode

For instance, electromyography will apply surface electrodes in measuring the electrical activity of muscles when recording from the skin surface. This is non-invasive, unlike the needle electrodes invaded into the muscle. Surface electrodes are applied to the skin and pasted over the muscle to record the electrical impulses. The producing of the electrical impulses occurs whenever there is contraction or movement of the muscles. The two types of surface electrodes are the dry EMG electrodes and the gelled EMG electrode [1]. They are divided into dry and gelled ones; the dry ones do not have any gel, whereas the gelled ones contain a conductive gel that enhances signal detection. Surface electrodes do not hurt the person being examined, and they are easy to apply. The width usually ranges between 0.5 to 2.5 cm. It functions through conducting electricity through electrolytes and therefore can recognize any changes in electrical potential between the skin and the surface of the muscle. These electrodes are greatly used because it is very comfortable and easy to use. In physical research, therapy, and at the time of rehabilitation, this technique is implemented to monitor movements of muscles; monitor activation and analyze gait of muscles. Through the skin, it is a non-invasive method to measure muscle activity. They are comfortable, easy to use and serve innumerable purposes for understanding and following muscle function in both medical and scientific realms.

Figure 2.3 Surface Electrode [1]

2.3 Flexor Digitorum Profundus (FDP) and Flexor Superficialis (FDS) Muscles

This is the muscle on the front of the human forearm. The muscles are covered by the pronator teres, palmaris longus, flexor pollicis longus, flexor carpi ulnaris, and flexor digitorum profundus muscles. The muscle created by two heads that form a muscular arch through which the median nerve and ulnar artery run.

2.3.1 Flexor Digitorum Superficialis (FDS) Muscles

In the forearm's front part, the biggest muscle is flexor digitorum superficialis. It is one of the superficial flexors of the forearm and works together with other muscles like the pronator teres, flexor carpi radialis, flexor carpi ulnaris, and palmaris longus. Certain authors also refer to it as the independent middle/intermediate layer of the front part of the forearm, situated between the deep and superficial groups [2]. The flexor digitorum superficialis has two heads, the radial head and the humeroulnar head. These heads separated by where they originate. The muscle's broad and muscular belly extends away from the wrist and then splits into four tendons, which connect to the middle phalanges of the second through fifth digits of the hand. The tendons on the outer side of the forearm are very much superficial and thus easily palpable or felt. [2].

Figure 2.4 Flexor Digitorum Superficialis [2]

2.3.2 Flexor Digitorum Profundus (FDP) Muscles

The flexor digitorum profundus is a fusiform muscle lying deep within the anterior or flexor compartment of the forearm. Along with the flexor pollicis longus and pronator quadratus muscles, it forms the deep flexor compartment. Its origin is the proximal part of the ulna, and it inserts into the distal phalanges of the second to fifth fingers. Though it does take part in wrist flexion, its key role is the flexing of the fingers at the metacarpophalangeal and interphalangeal joints [19]. The flexor digitorum profundus muscle takes origin from four locations: the aponeurosis of the flexor carpi ulnaris muscle, the coronoid process of the ulna, the proximal three-quarters of the anterior surface of the ulna, and the adjacent part of the interosseous membrane. It descends inferiors towards the hand from its origin. It forms a broad tendon in the distal forearm that passes over the superficial aspect of the pronator quadratus and enters the hand beneath the flexor retinaculum. As it enters the hand, the tendon splits into four slips that each attach to the base of the distal phalanx of the second through fifth fingers on the palmar surface [19].

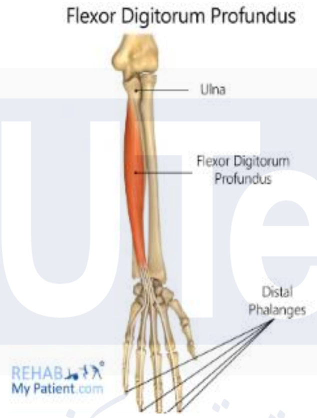

Figure 2.5 Flexor Digitorum Profundus [19]

2.4 Electromyography (EMG)-driven robotic hand exoskeleton.

Hand motion analysis is of a great significance in rehabilitation because hands are mostly used in daily activities and hence the motion of the hands is quite relevant to the understanding of restoration of human motor function. Movements of the hands and fingers are to a large extent controlled by flexor muscles of the forearms. Surface EMG signals of these forearm muscles can be used to classify patterns of finger movements for such applications as EMG-driven robotic hand exoskeletons or such applications that classify patterns of finger movements, like sign language recognition. It helps in planning better rehabilitation strategies, making the assistive devices more functional, which are focused on improving hand motor control and dexterity.

Characteristics of surface electromyography signals change with changing patterns of these muscle contractions that are controlling the finger movements, so in effect this principle becomes the basic way of detecting hand gesture using myoelectric feature vectors obtained from these sEMG signals. It is difficult to make this process of recognition robust because of frequent changes that occur with muscle fatigue, position of the movement of electrode results in changing these signal properties.

Complex movement assessments have been successful with synergy patterns of muscles in which synergistic muscular activity is usually controlled by neural mechanisms. This provides good robustness in the analysis of limb movement and gives rise to more reliable and effective applications of areas such as prosthetics and rehabilitation.

2.4.1 Preprocessing of Electromyography (EMG)

The collected sEMG data were processed through various stages during the offline analysis using Matlab 2014a in order to improve their quality and gain back meaningful information. Power frequency interference was removed, first by a 50 Hz notch filter and a 20 Hz to 500 Hz band-pass filter [5]. Then, filtered six-channel myoelectric data was used with a 3 Hz low-pass filter to obtain the envelope of this signal. This envelope signal captures the information about the general intensity or amplitude variation with time. Additionally, the myoelectric envelope signal after filtration has been rectified to get its intensity for movement onsets detection. This is done to detect the initiation point of muscle activity. This can be applied to situations in which movement analysis/ gesture recognition is necessary. MatLab has dominated these processing techniques that were very resourceful in the extraction of features from this sEMG that will allow for making a very detailed analysis and interpretation of patterns of activity in the muscle during movements.

$$\text{EMGaverage} = \sqrt{\sum_{i=1}^{6} EMG\,(i)^2}$$

$$\text{EMGaverage} \begin{cases} \geq 0.005\ active \\ else\ rest \end{cases}$$

In the described method, EMG (average) is the squared average value of the envelope signals of all six channels of electromyography (EMG); EMG(i) is the envelope signal of the ith channel; i = 1, 2, 3, 4, 5, and 6. A threshold of 0.005 was used to calculate EMG (average). When EMG (average) was greater than this threshold, myoelectric activity was considered to have begun, and this point was set as the start of movement.

Later, a 4-second segment after this onset was selected as valid surface electromyography data for a single task trial[5]. Trial after trial, these 4-second sEMG segments were used for further analysis to drive the envelope signals that represent electromyographic activity of the performance of gesture. Thereafter, a batch of samples was synthesized for further recognition of EMG patterns with downsampled sEMG data. This developed the capacity to extract and analyze patterns of muscle activity relevant to specific movements or tasks in an explanation and quantification of muscular performance for diverse applications ranging from rehabilitation to the design of prostheses.

2.4.2 Non-Negative Matrix Factorization (NMF) Algorithm

The Non-Negative Matrix Factorization algorithm was applied to the obtained sEMG envelope to extract muscle synergies together with its corresponding activation weight:

$$V = W \times H$$

Six muscles are involved in this formula, denoted by the symbol mm. The $ee \times un$ coefficient matrix H, which depicts the modulation and contribution of specific muscle synergy, indicates the synergy pattern among the six muscle channels. The symbol em represents the six muscle synergies. As a result, each column of W represents the weights of the appropriate muscle for a particular synergy, and each row of H represents the degree to which the relevant synergy is produced or activated[5].

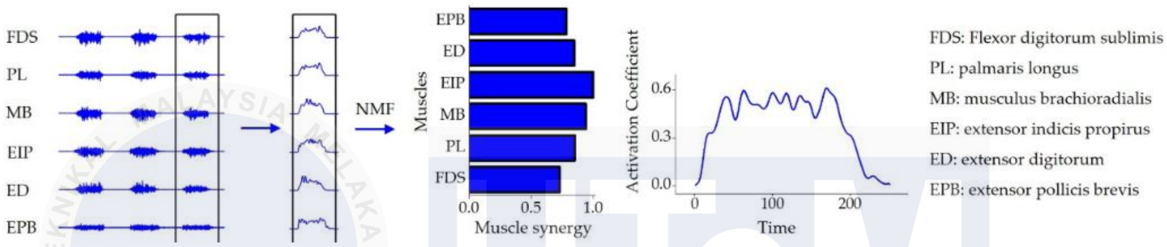

Figure 2.6 EMG Signal and NMF Decomposition [5]

The Variability Accounted For (VAF) between the envelope signal data matrix (V) and the reconstruction matrix ($V' = W \times H$) was calculated to find the ideal number of muscle synergies (s).

$$\text{VAF} = 1 - \frac{(V - V')2}{V2}$$

Selecting the optimal number of muscle synergies is crucial to preserve as much of the original information as possible. It's determined based on achieving a mean global Variance Accounted For (VAF) of over 95% while ensuring that adding an additional synergy does not increase the mean global VAF by more than 1%. This approach ensures that the identified muscle synergies capture most of the variation in the original sEMG envelope data, providing a concise representation that retains essential information about muscle coordination and activation patterns.

2.4.3 sEMG Electrode Placement

With the individuals seated comfortably, elbows resting on a table (arm-forearm angle of 90º), palms facing inward, a grid was created on the forearm using five easily recognized anatomical landmarks. The whole forearm surface was covered by 30 distinct places that were designated by the grid. Electrodes were positioned longitudinally in the center of seven of these locations, in accordance with SENIAM guidelines, based on the following groups found in a prior study: Spots 1–7 represent wrist flexion and ulnar deviation, spot 2 and radial deviation, spot 3 and digit flexion, spot 4 and thumb extension and abduction/adduction, spot 5 and finger extension, spot 6 and wrist extension and ulnar deviation, to name a few. Hair was cut off and the area was cleansed with alcohol prior to the electrodes being placed.

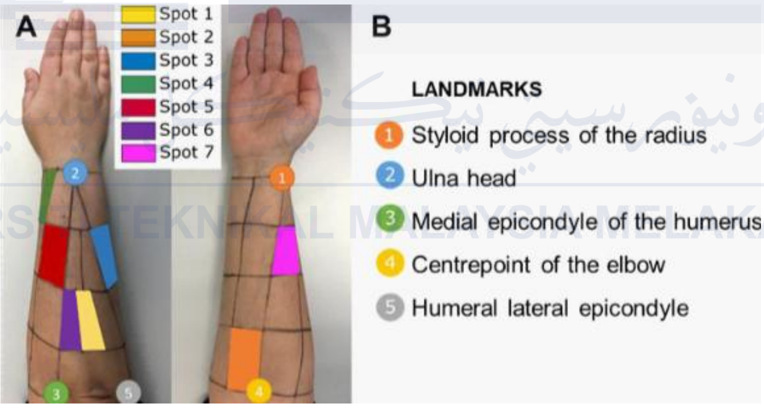

Figure 2.7 Spot for sEMG Electrode Placement [6]

2.5 Artificial Neutron Networks (ANN)

Units are like the brain cells of artificial neural networks. They are the building blocks that stacked together to create the whole thing. Depending on how complex the neural network needs to be to uncover patterns in a dataset, a layer can have just a handful of units or even millions. In artificial neural networks, you typically have input, output, and hidden layers doing their thing [4]. The input layer is where the network takes in data from the outside world, stuff it needs to understand or learn about. Then, that data pass through one or more hidden layers, which works their way to turn it into useful information for the output layer. The output layer generates an answer to the input data. In most neural networks, units correspond to units in the next layer. Unquestionably, each connection has weights associated with it that show how much one unit affects the other. As the data moves through the network from one unit to the next, it realizes more about the data; hence, the final output realized from the output layer [4]. Artificial neural networks structured according to the pattern of human neural paths. Artificial neural networks referred to as neural nets or neural networks. This is the first layer of the artificial neural network where the data from the external sources input into the network; receiving input transmits it into the adjacent layer often referred to as hidden. Every neuron in every hidden layer has the same task: to collect the outputs from all the neurons in the previous layer, compute the weighted sum of those signals, and then send its output to the following layer of neurons. It is this basic process that, by repetition, constitutes the processing and flow of information through the network to allow the ANN to perform complex computations and learn patterns from the input data [4]. Those connections incorporate weights aimed at determining the biggest impact of the previous layer inputs by determining a specific weight for each input, adjusted at the time of training for the purpose of boosting the model's performance.

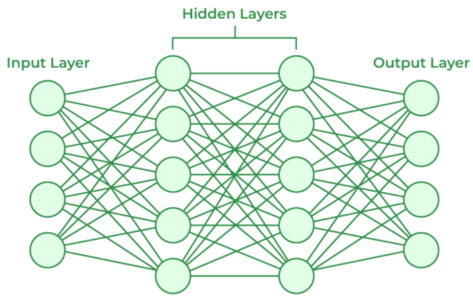

Figure 2.8 Neural Network Architecture [4]

2.6 Sample of Table in Landscape orientation

Electroencephalograms or EEG, electrocardiograms or ECG, and electromyograms or EMG are the three major divisions of electrograms. Surface Electrodes and Needle Electrodes are two major types of electrodes used specifically for the assessment of the EMG signals. However, its use also comes with certain risks and considerations. here are the advantages and disadvantages of electromyography (EMG) signals based on various types of hand motions for exoskeleton:

Advantages:

- Precision:

  EMG signals provide detailed information about muscle activity, allowing exoskeletons to achieve accurate control of movements. This precision helps the exoskeleton respond appropriately to the user's intentions, which is essential for tasks requiring fine motor skills, such as picking up small objects or typing.

- Real-time Feedback:

  EMG signals offer immediate feedback, enabling the exoskeleton to make quick adjustments. This real-time response allows for smooth, natural movements, which is important for dynamic tasks like playing an instrument or performing complex gestures.

- Non-Invasive (with surface electrodes):

  Surface electrodes are placed on the skin and do not penetrate the body, making them more comfortable and safer than needle electrodes. This non-invasive nature encourages regular use without causing significant discomfort or inconvenience.

- Detailed Muscle Activity:

EMG signals provide specific insights into different muscle activities. This allows the exoskeleton to recognize and respond to various hand motions, such as gripping or pinching, enhancing the functionality and customization of the exoskeleton.

Disadvantages:

- Skin Preparation (for surface electrodes):

  Proper skin preparation, including shaving and cleaning the skin, is necessary for accurate signal capture. This process can be time-consuming and inconvenient, and frequent preparation may irritate sensitive skin.

- Invasiveness (for needle electrodes):

  Needle electrodes penetrate the skin to reach the muscle tissue, causing discomfort and pain. This invasiveness makes them less suitable for long-term use and can pose risks such as infection or injury.

- Signal Interference:

  EMG signals can be affected by electrical noise, movement artifacts, and electromagnetic interference, which may reduce accuracy and reliability. Interference can lead to incorrect or delayed responses from the exoskeleton, compromising performance and safety.

- Complex Signal Processing:

  Interpreting EMG signals requires advanced algorithms and processing techniques. The raw data needs to be filtered and analyzed to extract meaningful information, which can be challenging and resource intensive. Real-time processing is necessary to ensure timely responses from the exoskeleton, requiring sophisticated computational capabilities.

- Muscle Fatigue:

Continuous use of EMG signals for controlling an exoskeleton can lead to muscle fatigue, decreasing signal quality and accuracy. This fatigue affects performance and user comfort, limiting the effective use duration. Managing fatigue involves providing adequate support and incorporating rest periods or adaptive control strategies.

2.7 Journal Comparison from Previous Work Related to the Project

Table 2.1 List of journal related to project.

Author	Title	Hand movement	Muscle involved	Finding
Enrique Mena-Camilo, Jorge Airy Mercado, Omar Pina-Ramirez [3]	A Functional Electrical Stimulation Controller for Contralateral Hand Movements Based on EMG Signals.	Power grasp movement, hand opening movement	Left flexor digitorum (for power grasp movement) and extensor digitorum (for hand opening movement).	The tests involve offline validation of a classifier algorithm, online performance testing of an FES controller, and a continuous functional task to assess the system's ability to mimic movements in a subject with hemiplegia.
Adilbek Turgunov, Kudratjon Zohirov, Bobur Muhtorov [6]	A new dataset for the detection of hand movements based on the SEMG signal.	1) punch 2) grip 3) finger touch 4) open hand 5) flexion of the index finger 6) flexion of the middle finger 7) flexion of the ring finger	1) punch 2) grip 3) finger touch 4) open hand 5) flexion of the index finger 6) flexion of the middle finger 7) flexion of the ring finger	
Sayanjit Singha Roy, Kaniska Samanta,	Hand Movement Recognition Using Cross Spectrum Image	1) Little Extension 2) Little Flexion 3) Ring Extension 4) Ring Flexion	Flexor Digitorum Profundus and Extensor	

Author	Title	Hand movement	Muscle involved	Finding
Sayantan Dey, Arnab Nandi [7]	Analysis of EMG Signals-A Deep Learning Approach	5) Mid Extension 6) Mid Flexion 7) Index Extension 8) Index Flexion 9) Thumb Extension 10) Thumb Flexion 11) Thumb Abduction 12) Thumb Adduction.	Digitorum Communis.	
Roxane Crepin, Cheikh Laytr Fail, Quentin Mascret [11]	Real-Time Hand Motion Recognition Using sEMG Patterns Classification.	1) Thumb flexion 2) Index flexion 3) Major flexion 4) Annular flexion 5) Auricular flexion 6) 3 fingers flexion 7) Open hand 8) Prick up index 9) Closed hand 10) Lateral grip 11) Cylindrical grip 12) Simple pliers 13) Complex pliers	Flexor Pollicis Longus, Flexor Digitorum Superficialis and Opponens Pollicis.	
Shuxiang Guo, Zhi-Jie Wang, Jian Guo [12]	Study on Motion Recognition for a Hand Rehabilitation Robot Based on sEMG Signals	1) Hand open 2) Hand close 3) OK gesture 4) Number eight gesture 5) Hold the cylinder 6) Hold the ball	Brachioradialis, Flexor carpi ulnaris, Flexor digitorum profundus, the Biceps brachii.	
Zhengzhen Li, Ke Li, Haibin zeng, Na Wei [14]	Hand Gesture Recognition Based on Electromyographic and Kinematic Analyses.	2) Index Flexion 3) Mid Flexion 4) Ring Flexion 5) Little Flexion 5) thumb-to-palm 6) thumb-to-index finger pinching 7) thumb-to-middle finger pinching 8) thumb-to-ring finger pinching 9) thumb-to-little finger pinching	Flexor carpi radialis (FCR), Extensor digitorum communis (EDC), Palmaris longus (PL), Flexor digitorum superficialis (FDS), Abductor	

Author	Title	Hand movement	Muscle involved	Finding
		10) thumb, index finger, middle finger grasping 11) thumb, middle finger, ring finger grasping 12) four fingers (without little finger) grasping 13) five fingers grasping	pollicis brevis (APB) and First dorsal interosseous (FDI).	
Shradha Singhvi, Hongliang Ren [8]	Comparative Study of Motion Recognition with Temporal Modelling of Electromyography for Thumb and Index Finger Movements aiming for Wearable Robotic Finger Exercises.	1) Thumb adduction 2) Thumb abduction 3) Index finger MCP flexion 4) Index finger extension 5) Thumb CMC Joint Flexion 6) Thumb extension	Abductor pollicis longus, Adductor pollicis longus, Abductor pollicis brevis, Flexor pollicis brevis, Opponens pollicis, Extensor Indicis, First Dorsal Interosseous, Extensor Pollicis Brevis and Extensor Pollicis Longus.	
Jorge Luis Leyva Santiago. Perez Rios, David Arrustico, Lina Cortez [10]	Volitional PD computed torque control design of a 2-DOF finger model for cylindrical grip movement assistance with sEMG signal classification.	1) Large diameter grasp 2) Fixed hook grasp 3) Small diameter grasp 4) Medium wrap	Flexor Digitorum superficialis and Extensor Digitorum muscles.	
Ventakesh Bharadwaj Srinivasan,	Finger Movement Classification	1) Thumb Flexion 2) Index Flexion 3) Ring Flexion	Carpometacarpal joint, phalanx,	

Author	Title	Hand movement	Muscle involved	Finding
Mobarakol Islam, Wei Zhang, Hongliang Ren [9]	from Myoelectric Signals Using Convolutional Neural Networks.	4) Little Flexion 5) Rest Action	thenar, Hypothenar, metacarpophalangeal, Proximal Inter-Phalangeal, Distal Interphalangeal	
Shivi Varshney, Ritula Thakur, Rajvardhan Jigyasu, Yogendra Narayan	sEMG signal based hand and finger movement clasification using different classifiers and techniques : A Review	• Cyrindarical grasp, Tip, Hook or Snap, Palmar, Spherical and Lateral	Flexor Capri Ulnaris, Extensor Capri Radialis, Peronious Longus, and Peronious Brevis and center of Longus and Brevis	The paragraph discusses the preprocessing steps applied to three SEMG datasets: UCI Repository, NinaPro DB6, and Mendeley. These steps include denoising, outlier handling, detrending, and normalization to enhance the quality of the data before feeding it into the proposed SFDN+DNN model for classification.
Raul Simpetru, Michael Marz, Alessandro Del Vecchio [16]	Proportional and Simultaneous Real-Time Control of the Full Human Hand From High-Density Electromyography.	flexion of each digit, resting, pinching between index and thumb (2-finger pinch) pinching between index, middle finger, and thumb (3-finger pinch),	Distal and proximal muscles of the forearm	In this study, data was collected from the muscles of the dominant hand of 10 participants to investigate the feasibility of using pre-trained neural networks for real-time

Author	Title	Hand movement	Muscle involved	Finding
		adduction and abduction of the wrist, fist closing and opening, pointing, peace sign, rock and roll sign		prediction of hand movements. Models were trained and optimized to achieve rapid and accurate predictions, employing techniques such as transfer learning and prediction correction algorithms.
Na Zhang, Ke Li, Guanglin Li [18]	Multiplex Recurrence Network Analysis of Inter-Muscular Coordination During Sustained Grip and Pinch Contractions at Different Force Levels.	1. Grip 2. Pinch	The brachioradialis (BR), flexor carpi ulnaris (FCU), flexor carpi radialis (FCR), flexor digitorum superficialis (FDS), extensor digitorum communis (EDC), abductor pollicis brevis (APB), first dorsal interosseous (FDI), and abductor digiti minimi (ADM).	The experiment enlisted 24 right-handed, healthy individuals without upper limb disorders, undergoing grip and pinch force assessments while their muscle activity was monitored via sEMG signals. Advanced data analysis techniques, including synchronizatio n and similarity metrics, were applied to explore the intricate intermuscular coordination dynamics during force production, providing

Author	Title	Hand movement	Muscle involved	Finding
				deeper insights into the underlying neural mechanisms governing hand movements.
Arvind Gautam, Madhuri Panwar, Dwaipayan Biswas, Amit Acharyya [17]	Locomo-Net: A Low -Complex Deep Learning Framework for sEMG-Based Hand Movement Recognition for Prosthetic Control.	Hamd grasp and Pinch Grip	Flexor pollicis longus muscle, Flexor digitorum supercialis, extensor carpi radial and ulnaris muscle, extensor carpi radial and ulnaris.	The paragraph outlines the methodology and implementation details of the proposed LoCoMo-Net framework for deep learning-based classification of sEMG signals. It involves two datasets: DS1, consisting of able-bodied and trans-radial amputated participants performing various tasks with sEMG data collected using active electrodes, and DS2, comprising the NinaPro database. The framework employs a two-stage pipeline with input data compression and data-driven weight sharing, aimed at reducing computational

Author	Title	Hand movement	Muscle involved	Finding
				complexity while maintaining classification accuracy.
Binish Fatimah, Pushpendra Singh, Amit Singhal, Ram Bilas Pachori [13]	Hand movement recognition from sEMG signals using Fourier decomposition method.	Spherical, tip, palmar, lateral, cylindrical, and hook grasps.	extrinsic/intrinsic muscles of the hand, metacarpal phalangeal joints abduct	The proposed method identifies hand movements from sEMG signals by breaking down the signal, extracting features, selecting important ones, and then classifying them. It's tested on two datasets, and different machine learning models like SVM and kNN are used for classification. To ensure accuracy without overloading the model, data is expanded by adding noise and randomly sampling it.
Moh Arozi. Mochammad Ariyanto, Asa Kristianto, Joga Dharma Setiawan	EMG Signal Processing of Myo Armband Sensor for Prosthetic Hand Input using RMS and ANFIS.	Rest, Power Grasp, Hook, Pinch Grip, Tripod, Thumb, and Index.	upper wrist	The experiment uses a Myo Armband to capture EMG signals from hand movements, with data processed

Author	Title	Hand movement	Muscle involved	Finding
				through Myo Connect. Seven hand movement patterns are collected, each repeated six times, and analyzed using Root Mean Square (RMS) for feature extraction. Classification employs ANFIS, a system capable of learning nonlinear functions through fuzzy rules, enhancing hand gesture recognition.
Enrique Mena-Camilo, Jorge Airy Mercado, Omar Pina-Remirez, L, Leija	A Functional Electrical Stimulation Controller for Contralateral Hand Movements Based on EMG Signals.	Power grasp movement, hand opening movement.	left flexor digitorum (for power grasp movement) and extensor digitorum (for hand opening movement)	The tests involve offline validation of a classifier algorithm, online performance testing of an FES controller, and a continuous functional task to assess the system's ability to mimic movements in a subject with hemiplegia.
Alfredo Lobaina, Adson Rocha,	Estimation of Joint Angle From sEMG and	(A)- index Finger extension, (B)- ring, (C)- power, (D)-	Five proximal interphalangeal (PIP), five	The study utilizes the seventh Ninapro

Author	Title	Hand movement	Muscle involved	Finding
Alexander Suarez Leon, Alberto Lopez Delis [15]	Inertial Measurements Based on Deep Learning Approach.	parallel extension, and (E)- open a bottle with a tripod grasp.	metacarpophalangeal (MCP), the trapeziometacarpal (TMC) and the wrist yaw (WY) joint angles.	database, incorporating sEMG signals and kinematic data from right-handed subjects for training and testing. Preprocessing involves bandpass filtering, rectification, and low-pass filtering of sEMG channels, followed by transfer learning to adapt a pre-trained deep network model from basic joint movements to predict functional hand motions with a smaller training set, utilizing convolutional and recurrent neural network architecture.
Nestor Jarque-Bou, Margarita Vwrgara, Joaquin Luis Sancho-Bru [20]	Does Exerting Grasps Involve a Finite Set of Muscle Patterns_ A Study of Intra- and Intersubject Variability of Forearm sEMG Signals in Seven Grasp Types.	Pad-to-pad pinch (PpP); cylindrical grasp (Cyl); lumbrical grasp (Lum); lateral pinch (LatP); oblique palmar grasp (Obl); inter-mediate power-precision grasp (IntPP).	Wrist flexion and ulnar deviation; (spot 2) wrist flexion and radial deviation; (spot 3) digit flexion; (spot 4) thumb extension and abduction/adduction; (spot	Subjects performed seven different grasps, starting with holding a dynamometer without exerting force, followed by exerting maximum grasping effort (MGE) for 3

Author	Title	Hand movement	Muscle involved	Finding
			5) finger extension; (spot 6) wrist extension and ulnar deviation; (spot 7) wrist extension and radial deviation.	seconds, and then 50% of MGE for 3 seconds, repeated three times with rest intervals, to calibrate muscle activity levels for subsequent analysis.
Kenhub.com	Flexor Digitorum Profundus Muscles.	Palmar, Proximal surface of ulna, Split tendons attach to distal phalanx of the four fingers.	Flexor digitorum Profundus	The flexor digitorum profundus tendons' deep surfaces are where the hand's lumbrical muscles attach.
Kenhub.com	Flexor digitorum superficialis muscle.	Lumbricals, Adductor Pollicis, Flexor Pollicis Brevis, Abductor Pollicis Brevis	Flexor digitorum superficialis	The flexor digitorum superficialis muscle heads run distally across the front of the forearm.
GeeksforGeeks [3]	Artificial Neural Networks and its Applications.	Thumb Finger, Index Finger, Middle Finger, Ring Finger, Pinky Finger.	Artificial Network	An artificial neural network comprises hidden layers in addition to input and output layers.

2.8 Summary

The literature related to hand application-based EMG exoskeletons has identified crucial progress and issues associated with the discipline. Researchers have utilized electromyography to design sophisticated exoskeletons whose purpose is to translate myoelectric signals into exactly accurate control-oriented commands. Recent technological advances made towards increasing sensor accuracy, intriguing signal processing algorithms, and incorporating user-centered design features to promote comfort and control characteristics. Pattern recognition algorithms of control strategies based on SVM and CNN have observed to be useful in the interpretation mechanism of EMG signals for intuitive movement control. Results of clinical studies presented the effectiveness of such exoskeletons in enhancing the hand rehabilitation phase after stroke or injury and even result in motor skill recovery after focused therapy. Yet, signal noise, variations in sensor placement, and integration problems with real-time control remain significant bottlenecks. Future research directions would ensue in refining signal processing techniques and longitudinal studies that examine long-term usability and document clinical efficacy. User interface design has also been advancing, making EMG exoskeletons a method that fundamentally transforms the hand function in persons with motor impairments, as emergent research continues to overcome limitations standing in the way of deploying such life-changing technologies to their full therapeutic potential.

CHAPTER 3

METHODOLOGY

3.1 Introduction

Electromyography (EMG) is important in muscle activity and force application, respectively. This research emphasizes the analysis and interpretation of EMG- and signals using three different pinching movements to tailor control laws for hand exoskeleton applications. This research directed at finding clear EMG patterns related to those movements, aiming at making future exoskeletons more precise and responsive.

3.2 Selecting and Evaluating Tools for EMG Exoskeleton Hand Control Project

To be able to analyze the EMG properly during the three-finger pinching movements and be able to incorporate the information into the exoskeleton hand control system, the right tools should be chosen based on the criteria of accuracy, compatibility, ease of use, scalability, cost, and availably of support and documentation.

A standard sEMG system recommended for data collection. These systems allow high-resolution acquisition of the EMG signal, allowing muscles to be recorded simultaneously. Built-in accelerometers in standard sEMG systems provide additional feature integration with motion analysis and real-time data streaming. There are no accuracies in data acquisition, which makes them compatible with most signal processing software. They are easy to use, with user-friendly interfaces, along with good documentation. Problems with these systems resolved through proper technical support.

As for signal processing and feature extraction, MATLAB should be the best-recommended tool in this project. MATLAB offers robust tools for filtering, normalization, and feature extraction from sEMG and FSR signals. It supports very advanced algorithms and provides various libraries for signal processing, which makes it a powerful tool in this project. MATLAB is compatible with standard sEMG systems and with standard FSR sensors. Since documentation is quite comprehensive and very functional, and there is a strong community around it, one may conclude that it is scalable.

To classify movements as pinching, we advise the use of an Artificial Neural Network (ANN) that is made using MATLAB's Deep Learning Toolbox. If complicated models for distinguishing various pinching movements trained and validated effectively, then it is advisable to utilize the Deep Learning Toolbox provided by MATLAB for this purpose. This is because it can manage large scale networks with different architectures while still maintaining high performance levels. Additionally, because of its friendly nature and well-documented information resources, one can easily go through the complete process from collecting data to classification.

3.3 Methodology

We drafted a methodology to study the analysis of Electromyography (EMG) signals for distinguishing various hand movements in order to control exoskeleton hand devices. The methodology consists of a review of related literature, data collection, processing EMG and modeling with CAD, integration of these two systems — data from EMGs is coupled with CAD models such that each movement can be simulated across a computer screen – machine learning based classification.

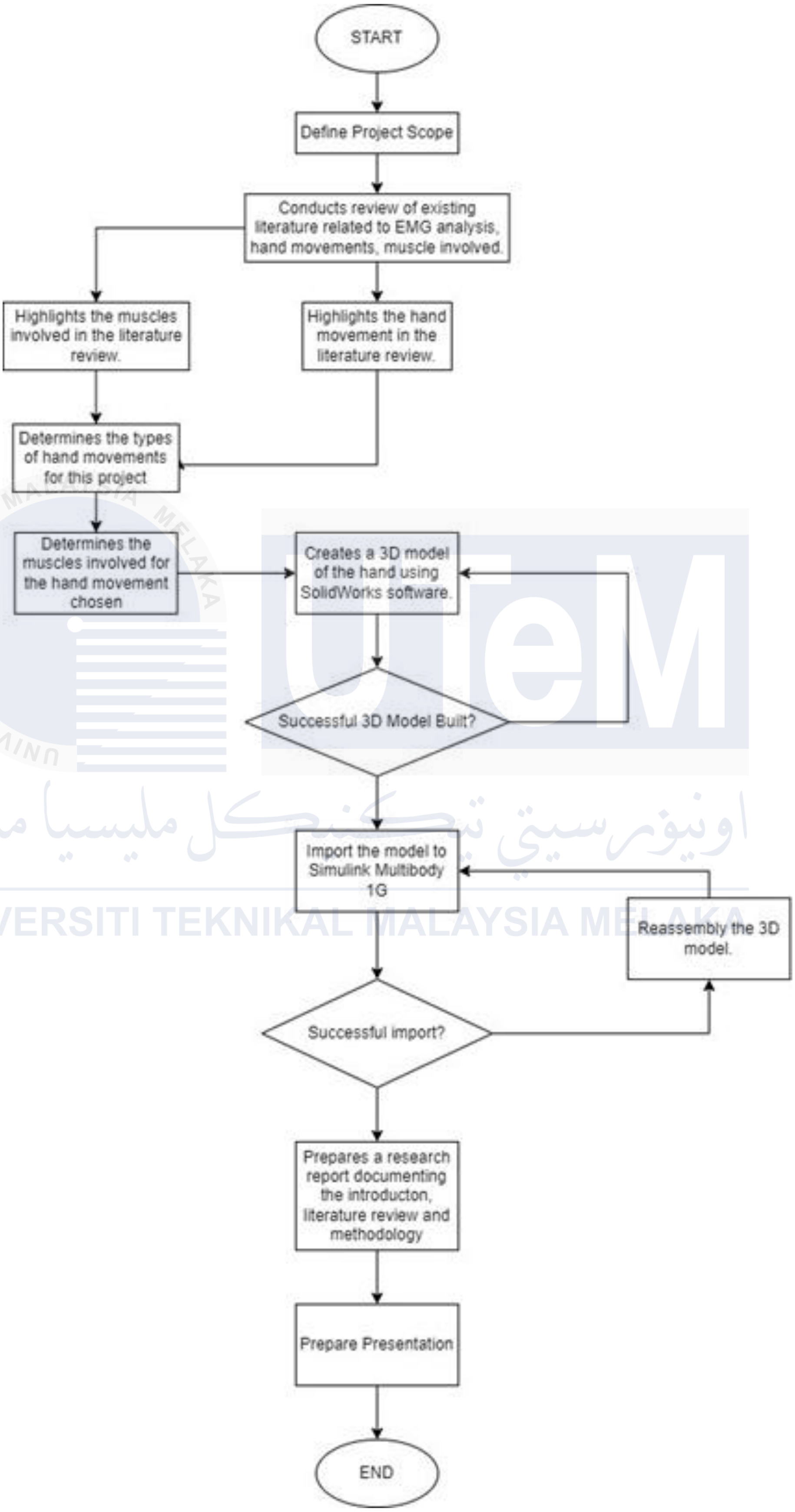

Figure 3.1 Project Flowchart

3.3.1 Collecting hand measurement

The measurements obtained are imperative for the appropriate design of the exoskeleton hand to be functional and ergonomic. This process ensures that the exoskeleton fits the hand well and is able to mimic the natural movement of the user's hand. The following systematic approach can be used for the collection of hand measurements using a ruler.

Materials:

- Ruler with metric units
- Hand measurement chart for recording data

Participant Preparation:

- Ensure the participant's hand is clean, relaxed, and in a neutral position.
- Remove any accessories that might interfere with the measurements.

Measurement Points and Procedure:

Overall Hand Length:

- Place the ruler at the tip of the middle finger.
- Measure straight down to the base of the palm, where the wrist begins.
- Record this measurement as the hand length.

Palm Width:

- Place the ruler horizontally across the widest part of the palm, typically at the knuckles (metacarpal heads).
- Measure and record the palm width.

Finger Lengths and Phalanx Measurements:

- For each finger, measure the length of each phalanx separately (distal, middle, and proximal).

Thumb:

- Distal phalanx: Measure from the tip of the thumb to the interphalangeal joint.
- Proximal phalanx: Measure from the interphalangeal joint to the base of the thumb.
- Record both measurements.

Index Finger:

- Distal phalanx: Measure from the tip of the finger to the distal interphalangeal (DIP) joint.

- Middle phalanx: Measure from the DIP joint to the proximal interphalangeal (PIP) joint.
- Proximal phalanx: Measure from the PIP joint to the metacarpophalangeal (MCP) joint.
- Record all three measurements.

Middle Finger:

- Repeat the process used for the index finger.

Ring Finger:

- Repeat the process used for the index finger.

Little Finger:

- Repeat the process used for the index finger.

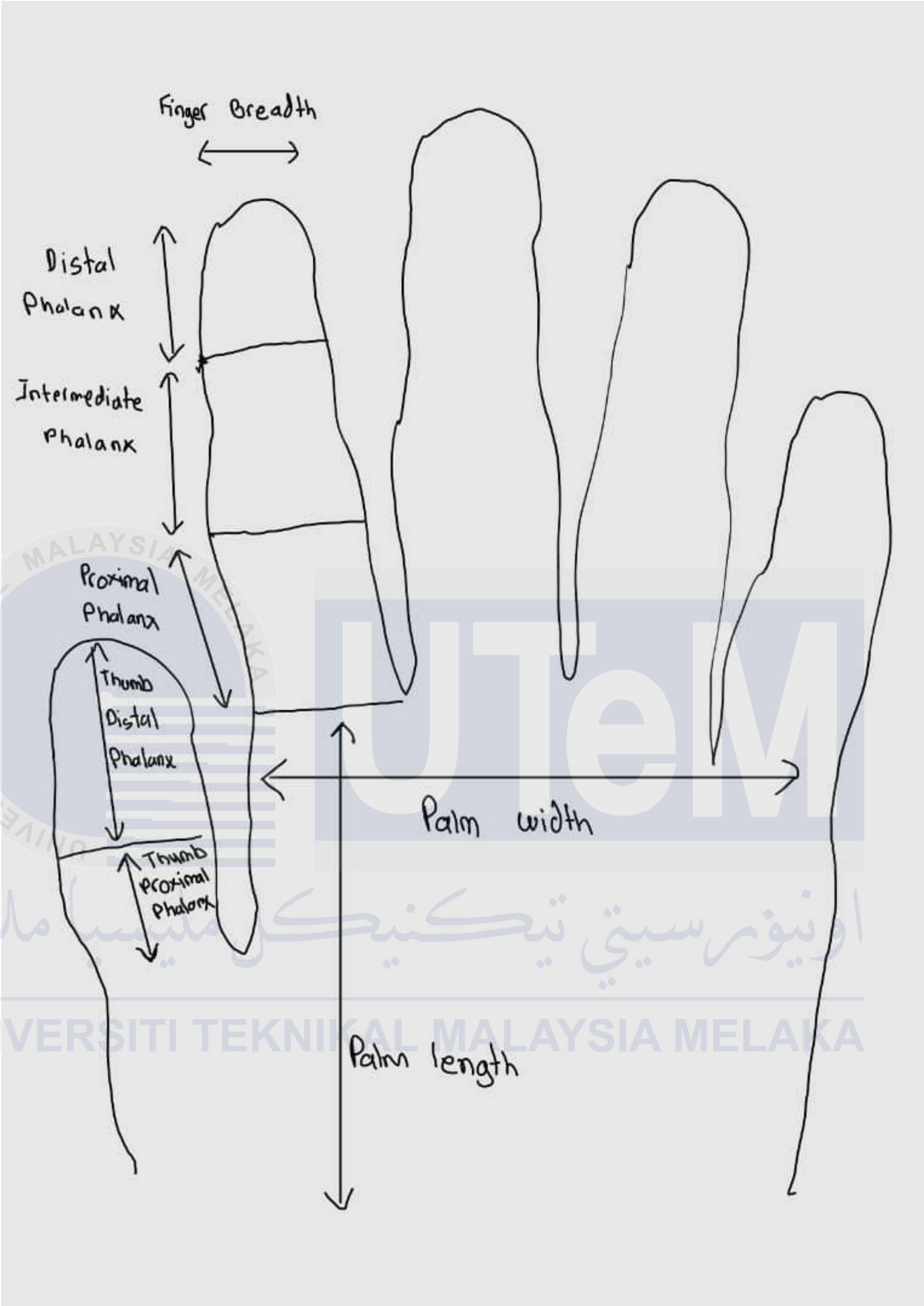

Figure 3.2 Measurement taken on hand.

Table 3.1   Hand measurement collected.

No	Hand part	Measurement (mm)
1	Palm Width	90
2	Palm Length	100
3	Thumb Breadth	150
4	Thumb Proximal Phalanx Length	20
5	Thumb Distal Phalanx Length	30
6	Index Breadth	150
7	Index Finger Proximal Phalanx Length	30
8	Index Finger Middle Phalanx Length	2.50
9	Index Finger Distal Phalanx Length	20
10	Middle Breadth	150
11	Middle Finger Proximal Phalanx Length	40
12	Middle Finger Middle Phalanx Length	30
13	Middle Finger Distal Phalanx Length	20
14	Ring Breadth	150
15	Ring Finger Proximal Phalanx Length	350
16	Ring Finger Middle Phalanx Length	250
17	Ring Finger Distal Phalanx Length	20
18	Little Breadth	150
19	Little Finger Proximal Phalanx Length	150
20	Little Finger Middle Phalanx Length	20
21	Little Finger Distal Phalanx Length	20

3.3.2 Design 3D model using Solidwork

Designing a 3D model for an exoskeleton hand is a pivotal step in making sure the end product works well and feels comfortable to use. SolidWorks, a powerful CAD software, plays a key role in this process by helping designers create, simulate, and perfect the exoskeleton hand model. This journey follows several structured steps, starting from initial ideas to thorough validation. The process initiates with conceptualization, involving brainstorming and conceptual sketching of ideas for the exoskeleton hand. The design of the finger parts begins with conceptualization based on the exoskeleton’s overall purpose and user requirements. This phase includes brainstorming sessions and initial sketches to outline the basic form and function of each finger component. Considerations such as range of motion, force transmission, and user comfort are pivotal during this stage.

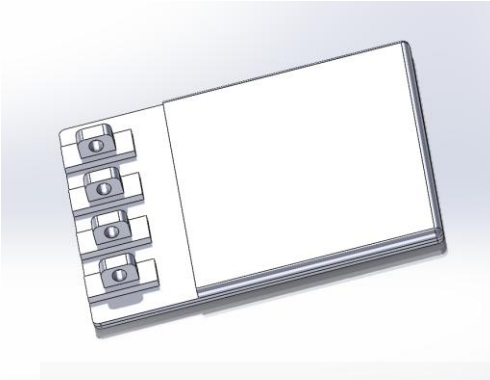

Figure 3.3 Early design of hand 3D model.

Subsequently, the conceptual ideas evolve into detailed 3D models within SolidWorks. Each component is crafted with precise dimensions and specifications to ensure optimal fit and operational performance. This stage entails iterative refinement to optimize design aspects for both technical requirements and ergonomic considerations.

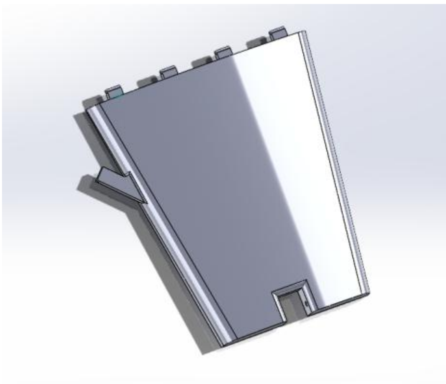

Figure 3.4 Palm design.

. The design of the finger parts begins with conceptualization based on the exoskeleton's overall purpose and user requirements. This phase includes brainstorming sessions and initial sketches to outline the basic form and function of each finger component. Considerations such as range of motion, force transmission, and user comfort are pivotal during this stage.

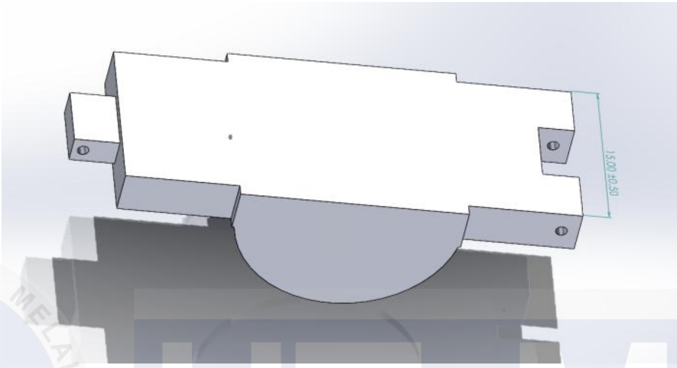

Figure 3.5 A 40cm phalanx.

Once the conceptual framework is established, detailed, three-dimensional models of each part comprising a finger can be made using the software SolidWorks. The software enables highly accurate modeling, down to individual parts which describe specific dimensions, joint mechanics, and attachment points that fit into the overall design for an exoskeleton. Iterative refinement can bring about the fact that every part fits seamlessly in place with its neighboring components and works properly within the range of motion if it was actually built.

The process of assembling the exoskeleton hand in SolidWorks is a process that will begin with preparation and organization of all components. This will include the care of verification of each part against design specifications and CAD models before commencing to ensure accuracy and compatibility.

Next, the assembly continues right down to the finger level and until the single components. The designers, using SolidWorks, can then carefully assemble the sub-assemblies with precision as per their 3D models. This is the stage where mates are used to align and fix components exactly so that the joints and mechanical interfaces are captured correctly to allow free operation.

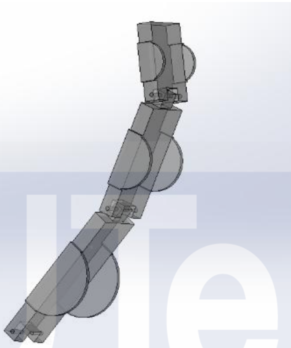

Figure 3.6 Mate process.

Then, structural components frame, support structures are assembled around the finger components. At each joining, the SolidWorks assembly tools aid in proper alignment according to the CAD models. Next in computational simulation, the process of verifying the structural integrity of the complete assembly takes place, with all parts positioned correctly and fastened. Functional testing is done after the assembled exoskeleton hand is seriously evaluated in SolidWorks. The designers subject it to extensive testing in order to prove mechanical functionality and movement. Further, studies of motion and analysis by simulation check how well the whole assembly performs under several operational conditions, so that design parameters derived are fine-tuned to optimize performance.

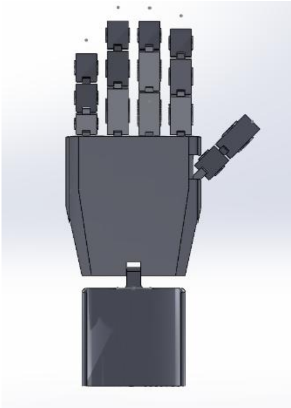

Figure 3.7 Hand exoskeleton design.

3.3.3 Exporting a 3D Model from SolidWorks to Simulink Multibody Link

Exporting a 3D model from SolidWorks to Simulink Multibody Link ensures that complex mechanical designs can be dynamically simulated within MATLAB. The process begins by preparing the SolidWorks model. This preparation involves ensuring that all components are fully defined, properly assembled, and accurately mated to reflect the intended mechanical behavior. Verification of the model's integrity is important to prevent issues during the export and import phases.

Once the model has been prepared, it needs to be exported using the plug-in Simscape Multibody Link. This plug-in allows the exporting of the model in an .xml file format after its installation in SolidWorks. That is because this XML format keeps all the geometric and physical information required by Simulink Multibody. In SolidWorks, open the model, and initiate export through the Simscape Multibody Link tool. After that, select export, assign a save location for the file.

Now that the XML is ready, attention shifts to MATLAB. The “mech_import” is the function used in MATLAB to import an XML file to Simulink Multibody. First, MATLAB is opened, and it is ensured that both Simulink and Simulink Multibody Toolboxes are installed and ready to be used. Run mech_import in the MATLAB Command Window and specify the path to the XML file.

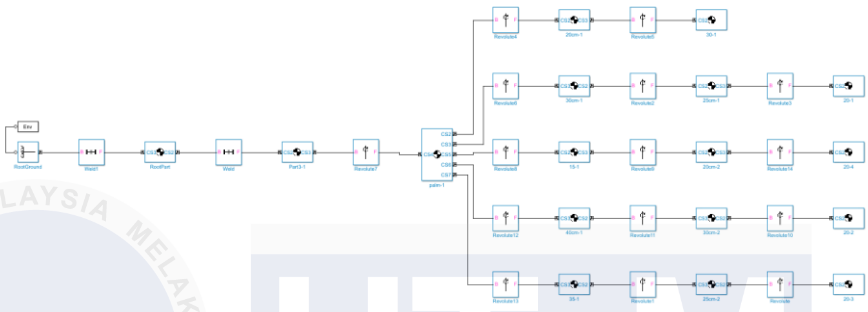

Figure 3.8 The Simulink model.

To analyze the model's performance, a simulation environment is built within Simulink. This involves configuring simulation parameters like start and stop times, ensuring the model behaves as expected over the simulated period. The simulation is then run, allowing for observation and analysis of the model's dynamics under various conditions. This step is crucial for identifying any potential issues and refining the model to enhance its performance and reliability.

In summary, the process of exporting a 3D model from SolidWorks to Simulink Multibody using “mech_import” is a detailed and methodical approach that ensures the accurate translation of mechanical designs into a dynamic simulation environment. This integration enables comprehensive analysis and refinement of the model, facilitating the development of optimized mechanical systems such as exoskeleton hands. By leveraging the capabilities of both SolidWorks and Simulink Multibody, engineers can achieve a high level of precision and functionality in their simulations, ultimately leading to better-designed and more effective mechanical devices.

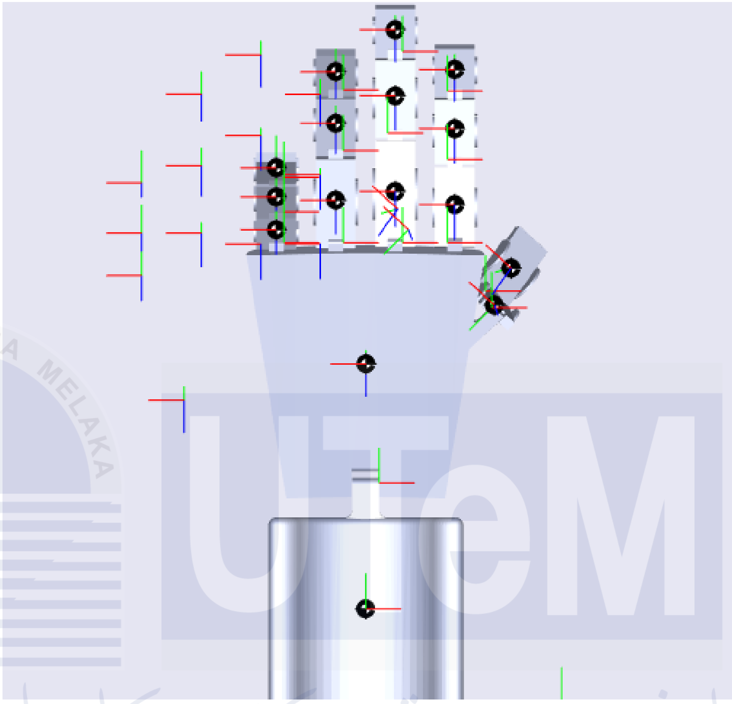

Figure 3.9 Simulink simulation.

3.3.4 Experimental setup

The configuration used for the EMG exoskeleton hand control project is designed in such a way that it involves a strong data collection, precise signal processing, and effective integration into the exoskeleton system. There will be participants who do not suffer from neuromuscular disorders meeting set qualifications; their task is to make three-finger pinching movements: chopstick grip, thread manipulation, drawing and scissor grip. To reduce impedance, the skin will be cleaned before putting surface EMG electrodes on Flexor Digitorum Superficialis (FDS) as well as Flexor Digitorum Profundus (FDP) in the right position. Each subject must perform ten repetitions of each activity within a controlled environment that guarantees data fidelity. Signals captured by high resolution EMG systems synchronized.

3.3.4.1 Parameters

In the EMG and FSR-based exoskeleton hand control experiment, participants were carefully selected to ensure data quality and relevance. Healthy volunteers with no neuromuscular disorders were chosen, with a diverse demographic to capture muscle activation and force dynamics during three-finger pinching movements. Surface EMG electrodes were placed on the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles after skin preparation to minimize impedance and get optimal signal. Each participant performed 10 reps of these movements in a controlled environment using a EMG system. Signal processing involved band-pass filtering of EMG signals to remove noise and artifact removal for smoother data. Data segmentation allowed us to analyze different movement phases and extract features such as Mean Absolute Value (MAV), Root Mean Square (RMS) and peak force from EMG. These features were used to train and validate an Artificial Neural Network (ANN) model to classify and distinguish between different pinching movements. The experiment design and parameters were carefully set to collect comprehensive data and analyze rigorously to be integrated into an exoskeleton control system to enhance rehabilitation and assistive technologies for hand functionality in various healthcare applications.

3.3.4.2 Equipment

In the EMG exoskeleton hand control setup, we use various specialized equipment to collect precise data, process signals thoroughly and integrate into the exoskeleton system. Participants are selected for their health and diversity and have electrodes placed on the

Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles after skin preparation to optimize signal quality.

The experimental setup uses a surface EMG system that captures muscle activity patterns in high resolution, allowing simultaneous recording from multiple channels for real-time monitoring. Integrated accelerometers within the EMG system contribute additional motion data, which enhances our understanding of hand movements. To ensure accurate data synchronization, a dedicated data acquisition unit coordinates sampling of both EMG and FSR signals, crucial for aligning temporal data points during analysis.

Signal processing is performed using MATLAB. EMG signals undergo band-pass filtering to remove noise and extract key muscle activity features such as Mean Absolute Value (MAV) and Root Mean Square (RMS). This integrated approach enables analysis and interpretation of EMG, advancing our insights into motor function and performance.

3.4 Limitation of proposed methodology

The proposed methodology for integrating EMG into an exoskeleton hand control system presents several limitations that should be considered for ensuring the reliability and applicability of the research outcomes. Firstly, the study focused on healthy participants without neuromuscular disorders, which may restrict how well the findings can be generalized to populations with specific muscle activation patterns or different levels of hand impairment. This limitation could affect the practical utility of the exoskeleton system in clinical settings where muscle dynamics vary significantly.

Secondly, the accuracy of EMG measurements hinges heavily on precise sensor placement and consistency throughout the experimental sessions. Any variations or shifts in sensor positioning during movement could introduce inconsistencies in data collection, potentially influencing the reliability and reproducibility of the results. Moreover, despite employing advanced signal processing techniques such as filtering and normalization to clean EMG signals, there remains a risk of artifacts from external noise sources or electrode movements. These artifacts may distort the data and compromise the accuracy of feature extraction and subsequent classification tasks. Another limitation is the relatively narrow range of hand movements tested, which mainly focuses on specific three-finger pinching actions like the chopstick grip and drawing. This limited repertoire may not fully represent the diversity of hand gestures needed in real-world applications, potentially constraining the adaptability of the exoskeleton hand control system in practical use scenarios.

Furthermore, the performance of the Artificial Neural Network (ANN) used for classification depends heavily on the selection of features and the complexity of the network architecture. If not optimized correctly, the ANN may struggle to distinguish between subtle variations in different pinching movements or under varying conditions. Additionally, transitioning from offline data analysis to real-time control within the exoskeleton system presents practical challenges such as latency, synchronization issues, and compatibility between hardware and software components. These challenges need careful consideration to ensure the smooth and responsive operation of the exoskeleton hand control system in real-world applications.

Lastly, ethical considerations regarding participant consent, data privacy, and safety during experimental procedures must be carefully managed to uphold ethical standards and ensure participant well-being throughout the study.

3.5 Summary

This methodology uses a structured experimental setup to integrate EMG signals into an exoskeleton hand control system. Selected according to planned health parameters, participants make precise three-finger pinching motions as force and muscle activity are recorded by EMG electrodes on the FDS and FDP muscles. Advanced techniques such as filtering and normalisation are used to process the data, and an ANN is used to extract features for classification. The focus on healthy participants, possible variability in sensor placement, and difficulties with real-time system integration are among the limitations. The methodology's applicability in improving exoskeleton technology for hand rehabilitation and assistive applications will be enhanced upon overcoming these limitations through validation studies and algorithm optimisation.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the findings of the project, which involves the analysis of muscle movements using EMG sensors, Lite Logger, and an Artificial Neural Network (ANN). The results are analyzed to evaluate the system's performance in detecting and classifying four specific hand movements: scissor, pen, chopstick, and needle. The discussion focuses on the accuracy and reliability of the system, challenges encountered during implementation, and potential improvements. These insights are crucial to understanding the system's applicability for rehabilitation, assistive technology, and other fields.

4.2 Data Acquisition

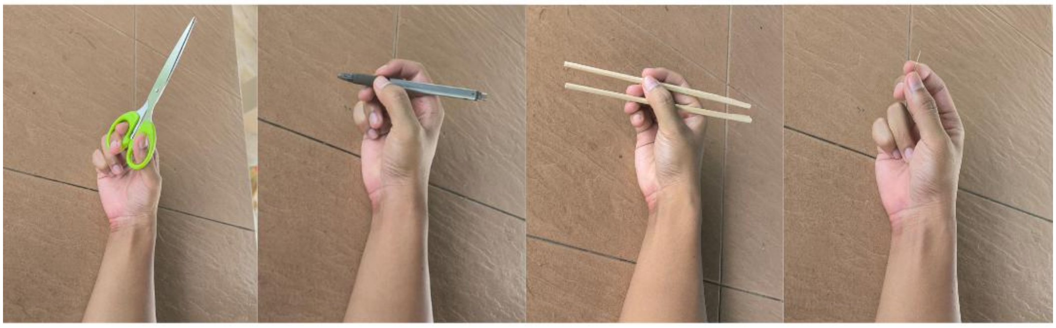

Figure 4.1 Four items used in the experiment

EMG data was collected for four specific hand movements: scissor, pen, chopstick, and needle. The data acquisition process begin by each trial involved alternating between a 10-second rest phase and a 10-second grip phase, repeated continuously for one minute. This process was repeated three times for each hand movement to ensure consistency in the data collected. The EMG signals were recorded using LabQuest Mini and real-time visualization of the data was conducted using Lite Logger software.

4.2.1 Scissor Movement

The scissor movement showed strong activation of the FDS muscle, which played a primary role in finger flexion. The FDP exhibited weak activation, as the movement required minimal deep muscle engagement.

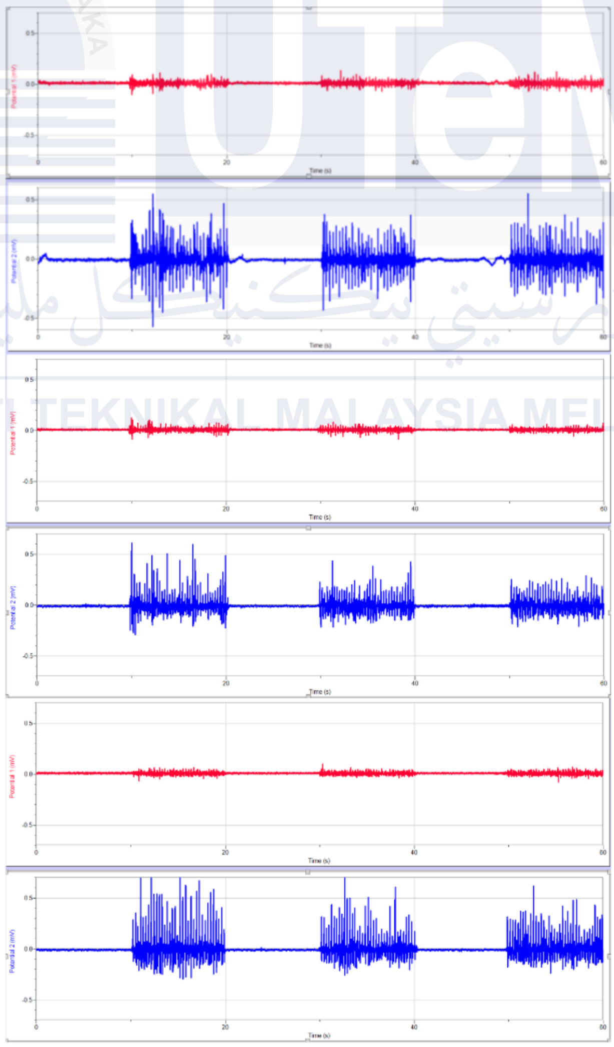

Figure 4.2 Three datasets of Scissor EMG signals

The average EMG signal amplitude was 0.34mV, with the FDS contributing to most of the signal intensity. The filtered data showed consistent patterns across repetitions.

4.2.2 Pen Movement

The pen movement required fine motor control and precise grip adjustments, leading to strong FDS activation for stabilization. The FDP showed weak, intermittent activation, contributing minimally to the overall muscle activity.

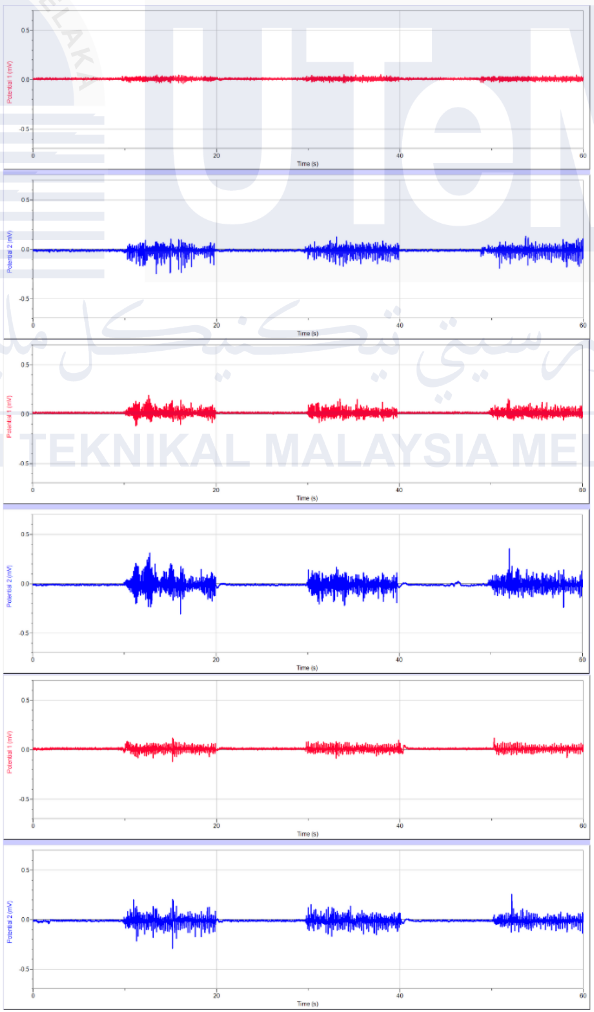

Figure 4.3 Three datasets of Pen EMG signals

The pen movement required fine motor control and precise grip adjustments, leading to strong FDS activation for stabilization. The FDP showed weak, intermittent activation, contributing minimally to the overall muscle activity. EMG signals for this movement exhibited lower amplitudes, averaging 0.125mV reflecting the lighter muscle load involved. The transitions between rest and contraction phases were gradual, indicating controlled and deliberate activation. Signal consistency across repetitions was reliable, though minor variations were observed due to the inherent complexity of the task.

4.2.3 Chopstick Movement

The chopstick movement involved alternating grip and release actions, which required balanced muscle activation. The FDS muscle was predominantly active, maintaining grip stability and facilitating precise adjustments.

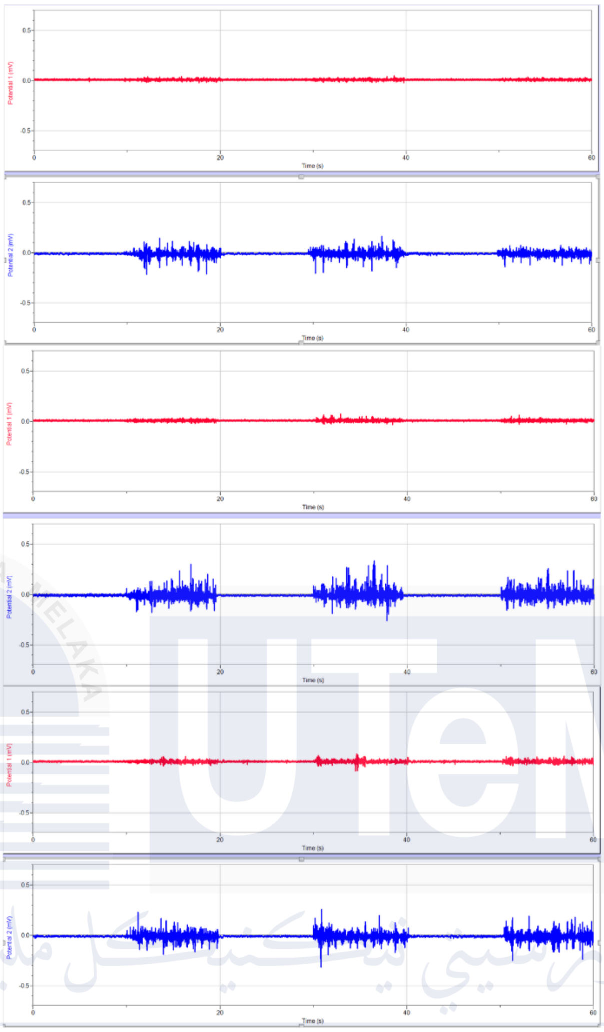

Figure 4.4 Three datasets of Chopstick EMG signals

The FDP demonstrated weak but steady activation, supporting sustained contractions without significantly contributing to the primary motion. EMG signals for this movement showed moderate amplitudes, averaging 0.31 mV, with distinguishable peaks during grip phases. The signal patterns across repetitions were consistent, and preprocessing effectively removed noise and artifacts.

4.2.4 Needle Movement

The needle movement required the highest level of precision among the four tasks, relying almost entirely on FDS activation for fine motor control. The FDP exhibited the weakest activation among all movements, reflecting its minimal role in such detailed and surface-level tasks.

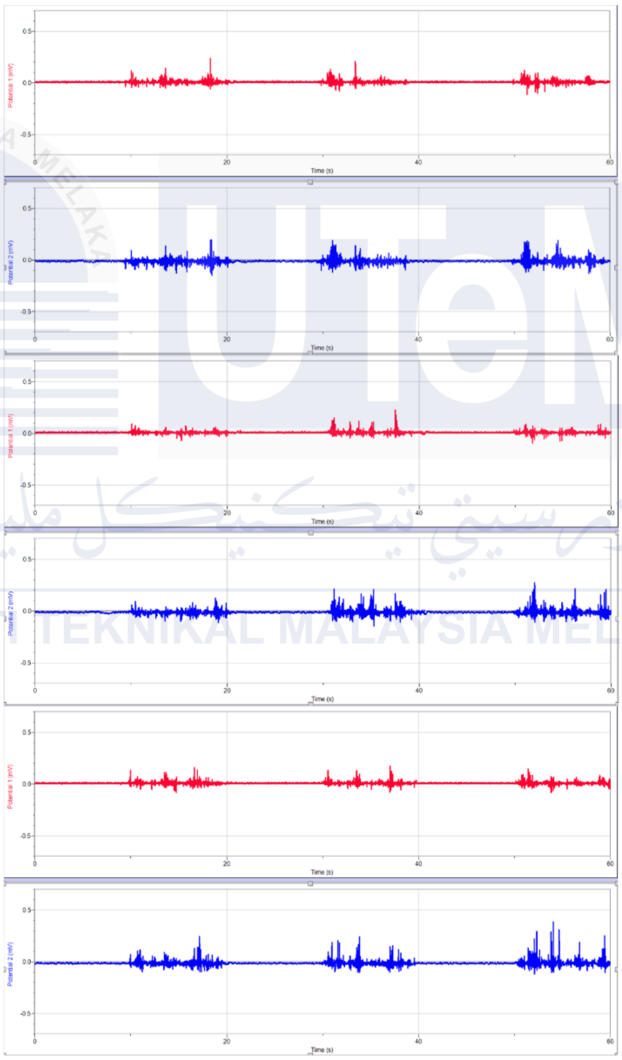

Figure 4.5 Three datasets of Needle EMG signals

The EMG signals for this movement had the lowest average amplitude, 0.09 mV. Despite the lower muscle engagement, the phases of rest and contraction were distinctly visible, and the signals were consistent across repetitions. Noise levels were negligible after filtering, ensuring the quality of the data for analysis.

4.3 Raw Data Processing and Analysis Using MATLAB

The EMG data collected for each movement was analyzed using MATLAB. From the three repetitions of each movement, the best signal was chosen based on clarity, low noise levels, and clear phases of rest and contraction. This ensured that the most accurate and reliable data was used.

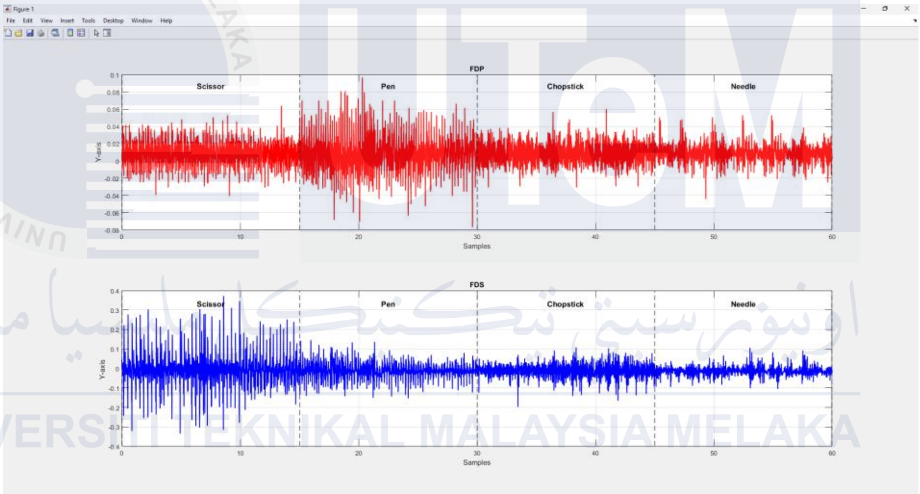

Figure 4.6 FDP and FDS EMG Signal for four movement

The selected signals were plotted for 60,000 samples, representing one minute of recording at a sampling rate of 1,000 Hz. The plots showed how the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles responded during the movements. For the scissor movement, the FDS showed strong activation during the grip phase, while the FDP had weaker activity. In the pen movement, the FDS was moderately active, with smooth transitions between rest and grip phases, while the FDP had minimal involvement. The chopstick movement involved steady activation of the FDS, with occasional activity from the FDP. During the needle movement, the FDS had low but consistent activation, while the FDP showed very little activity.

Although the data was not filtered, the signals chosen for analysis were clear enough to show the differences between rest and contraction phases. MATLAB was used to create time-series plots, which showed how each muscle contributed to the movements. The results confirmed that the FDS was more active across all movements, while the FDP showed less involvement. These findings matched the expected roles of these muscles in hand movements.

By focusing on the best signals from the data, it was possible to draw reliable conclusions about how the muscles worked during each task. This information is essential for understanding the patterns of muscle activation in the scissor, pen, chopstick, and needle movements.

4.4 Integration of Artificial Neural Network (ANN) for EMG Analysis

An Artificial Neural Network (ANN) was used to classify four hand movements—scissor, pen, chopstick, and needle—based on EMG signals collected from the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles. The EMG data was processed to extract important features such as Mean Absolute Value (MAV), Root Mean Square (RMS), and Integrated EMG (IEMG). These features served as inputs to the ANN, which aimed to recognize patterns of muscle activation unique to each movement.

The ANN model had an input layer for the extracted features, a hidden layer with neurons, and an output layer with four nodes representing the movement classes. Despite careful feature extraction, the model struggled to distinguish between the movements because the EMG signals for these tasks were highly similar. The overlapping patterns in the signals made it difficult for the ANN to classify the movements with high accuracy.

To improve the analysis, force data was included as an additional output. This data provided measurements of the grip strength and effort used during each movement. By combining EMG and force data, the analysis became more robust, as the force information highlighted differences that were not evident in the EMG signals alone. However, even with the added force data, the ANN still faced challenges in distinguishing between the movements.

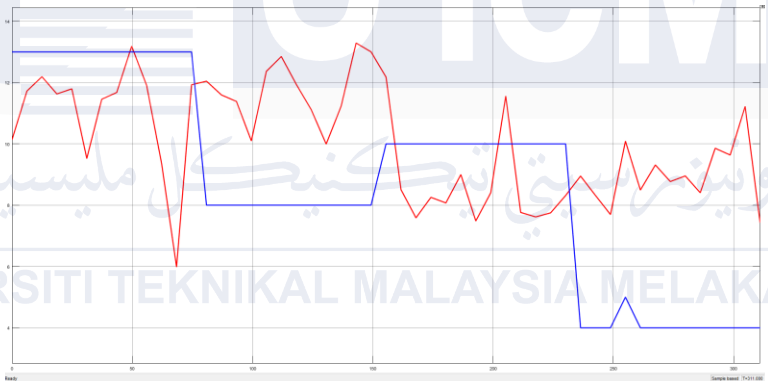

Figure 4.7 The ANN result

The results suggested that the current dataset was insufficient for reliable classification due to the limited variation in EMG signals and the small amount of force data. Additional force data, collected at varying levels of intensity and grip strength, is needed to improve the model’s accuracy. This would help the ANN capture subtle differences in muscle activation and effort for each movement.

Although the ANN did not achieve high accuracy, the study provided useful insights into how the FDS and FDP muscles contribute to different tasks. The findings highlight the potential of combining EMG and force data for analyzing hand movements. Future work could focus on collecting more comprehensive datasets, using more advanced neural network architectures, or integrating other types of sensor data to improve movement classification.

4.5 Result Comparison with Previous Studies

In the study "Dynamic Modelling of Hand Grasping and Wrist Exoskeleton: An EMG-based Approach" by Mohd Safirin bin Karis et al., the authors aimed to establish the relationship between surface electromyography (sEMG) signals, wrist angles, and handgrip force. They employed Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to model hand grasping dynamics at different Maximum Voluntary Contraction (MVC) levels. Their findings indicated that sEMG signal levels were directly proportional to handgrip force production, and that handgrip force varied with wrist angle, being higher in flexion positions compared to extension. Additionally, their results showed that ANN improved estimation accuracy over ANFIS by 0.22% in terms of the integral absolute error value.

In contrast, the current study focused on classifying four specific hand movements—scissor, pen, chopstick, and needle—using sEMG signals from the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles. An ANN model was implemented to distinguish between these movements. However, the model faced challenges in accurately classifying the movements due to the high similarity in EMG activation patterns among them. This limitation underscores the difficulty in differentiating fine motor tasks based solely on sEMG data from these two muscles.

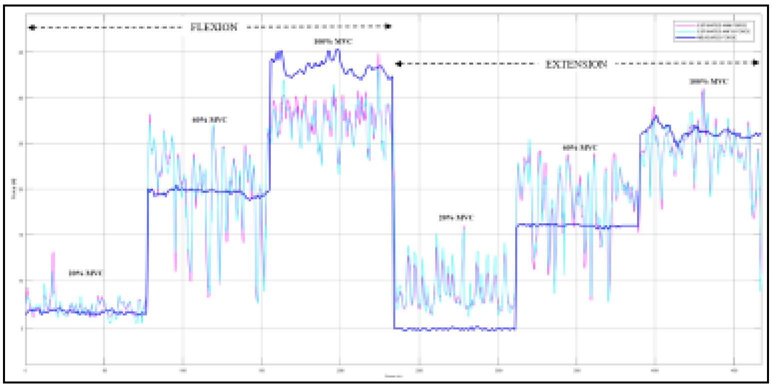

Figure 4.8 Hand grip analysis graph

Comparatively, while Karis et al. successfully modeled the relationship between sEMG signals, wrist angles, and handgrip force—achieving high estimation accuracy—the present study encountered difficulties in movement classification using similar ANN methodologies. This discrepancy highlights the complexity of classifying fine motor movements based on sEMG signals, suggesting that additional factors, such as incorporating more muscles, advanced feature extraction methods, or alternative machine learning models, may be necessary to improve classification accuracy.

4.6 Challenges in ANN-Based Movement Classification

Despite efforts to integrate the Artificial Neural Network (ANN) with the SolidWorks model for exoskeleton control, it was found that the network was unable to successfully classify the movements based on the EMG signals. The ANN, which was trained using key features extracted from the EMG data, including time-domain metrics such as Mean Absolute Value (MAV), Root Mean Square (RMS), and Integrated EMG (IEMG), as well as frequency-domain features like Mean Frequency (MNF) and Median Frequency

(MF), failed to produce reliable movement classifications. This failure became evident through low classification accuracy, frequent misclassifications, and poor generalization.

The main issue was that the ANN did not accurately distinguish between the four hand movements—scissor, pen, chopstick, and needle—despite being trained on a diverse set of EMG features. The network produced outputs that were inconsistent with the actual movements, which led to incorrect control signals for the exoskeleton. This, in turn, caused errors in the simulation and hindered the potential for real-time control. The performance of the model was suboptimal, with accuracy levels falling below the expected threshold and the ANN often misclassified one movement as another. Additionally, the model exhibited signs of either overfitting or underfitting, indicating that it was either memorizing the training data too specifically or failing to generalize to unseen movement patterns.

Several factors likely contributed to this failure. One potential cause is that the selected features might not have captured the most relevant aspects of muscle activation necessary for distinguishing between the movements. The features such as MAV, RMS, and IEMG might not have been sensitive enough to the subtle differences between the movements, leading to inadequate discrimination. Furthermore, data quality and preprocessing issues could have negatively impacted the model's performance. If the raw EMG data contained noise, motion artifacts, or baseline drift that were not effectively removed, the ANN would have been trained on corrupted data, thus limiting its ability to learn meaningful patterns. Preprocessing steps such as noise filtering and artifact removal may not have been sufficiently robust to eliminate these unwanted elements.

Another possible reason for the classification failure could be an imbalance in the training data. If some movements were overrepresented while others were underrepresented, the ANN may have developed a bias toward the more frequent movements, leading to misclassification of less frequent ones. Additionally, the architecture of the ANN may not have been well-suited to the task. If the network was too simple, with too few neurons or layers, it may not have had the capacity to learn the complex relationships between the EMG features and the movements. On the other hand, if the network was too complex, it may have overfitted the training data and struggled with generalizing to new examples. Furthermore, issues such as insufficient training or improper tuning of hyperparameters—such as the learning rate, number of epochs, or batch size—could have hindered the model's ability to converge to a suitable solution.

To address these issues, several steps were considered for improving the ANN's performance. First, a more in-depth analysis of the features used for training may be necessary. The current features might not be capturing the most discriminative information about the movements. By exploring advanced feature selection techniques, such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA), and potentially incorporating additional features (e.g., frequency-domain characteristics or non-linear metrics), the discriminative power of the model could be improved. Moreover, revisiting the preprocessing pipeline could help ensure that noise, artifacts, and baseline drift are adequately removed from the raw EMG signals, which would help the model learn more accurately. Techniques like wavelet denoising or band-pass filtering could improve the quality of the input data.

Furthermore, to address potential data imbalance, data augmentation techniques could be applied to artificially expand the dataset, ensuring that all movements are equally represented. This could involve methods such as time-domain stretching, frequency shifting, or introducing synthetic noise into the data. Another critical area for improvement is the ANN architecture. The number of neurons in the hidden layer, as well as the number of hidden layers, might need to be adjusted to ensure that the network has sufficient capacity to capture the complexity of the task without overfitting. Additionally, experimenting with different types of networks, such as Convolutional Neural Networks (CNNs), could help extract more relevant features from the EMG signals.

In conclusion, the failure of the ANN to accurately classify the movements based on EMG data presents a significant challenge for integrating it with the SolidWorks exoskeleton model. However, by addressing issues related to feature selection, data preprocessing, model architecture, and training, the classification accuracy can potentially be improved. Further refinement of the model, along with experimentation with advanced techniques, is necessary to achieve reliable movement classification and ensure the successful integration of the ANN with the exoskeleton system.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This project focused on the classification of four fine motor hand movements—scissor, pen, chopstick, and EMG signals from the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP) muscles. The primary aim was to analyze the EMG activity during these tasks and use machine learning, specifically an Artificial Neural Network (ANN), to identify and classify the movements. MATLAB was used for data preprocessing and analysis, and the ANN was trained using features extracted from the EMG signals.

The findings revealed several important observations. The FDS muscle consistently showed stronger and more stable activation across all movements, while the FDP exhibited weaker and less consistent signals. This difference in muscle activity influenced the performance of the ANN, which struggled to accurately classify the movements. The primary challenge was the high similarity in EMG signal patterns between the tasks, making it difficult for the model to distinguish between them. This result highlights the inherent limitations of using surface EMG signals from only two muscles for fine motor task classification.

Despite these challenges, the project successfully demonstrated the potential of using EMG signals and machine learning for hand movement classification. It provided valuable insights into the behavior of the FDS and FDP during precision tasks, showing that such systems could contribute to fields like rehabilitation, prosthetics, and robotics. However, the current system's limitations underline the need for further research and refinement.

Future improvements, such as incorporating signals from additional muscles, applying advanced signal processing techniques, or using more sophisticated machine learning models, could enhance accuracy and reliability. These findings lay the groundwork for developing a more robust and practical system for real-world applications, bringing this research closer to potential commercialization.

This project marks an essential step in understanding muscle behavior and applying technology to improve human-machine interaction.

5.2 Project Commercialization

The development of this project, focusing on the analysis and classification of hand movements through EMG signals and its integration with an exoskeleton model, has significant commercialization potential in various industries, particularly in healthcare, rehabilitation, prosthetics, and human-machine interaction. However, the successful commercialization of this technology would require a structured approach that considers product development, market analysis, intellectual property protection, and scalability.

5.2.1 Target Market

The primary market for this technology lies in the healthcare sector, particularly in rehabilitation and prosthetic control systems. The ability to classify precise hand movements based on muscle activation could greatly benefit patients undergoing physical therapy after neurological injuries, such as strokes, or those recovering from musculoskeletal injuries. Additionally, the technology has potential applications in advanced prosthetic devices, enabling more intuitive control for individuals with limb loss. Secondary markets include human-computer interaction systems and industrial applications, such as robotic exoskeletons for workplace ergonomics and injury prevention.

5.2.2 Long-Term Vision

In the long term, this technology could be expanded to include additional movement classifications, integration with other biosignals (e.g., EEG or accelerometry), and broader applications in robotics, gaming, and virtual reality. By continually innovating and adapting to market needs, the project has the potential to become a leading solution in the field of human-machine interaction.

5.3 Future Work

This project has laid the groundwork for classifying fine motor hand movements using EMG signals and machine learning, but there is significant room for improvement to enhance the system's accuracy and applicability. Future work could begin by addressing the limitations encountered in this study, particularly the difficulty in distinguishing between movements with similar EMG activation patterns. A key improvement would be to collect EMG data from a wider range of muscles. While this project focused on the Flexor Digitorum Superficialis (FDS) and Flexor Digitorum Profundus (FDP), including other muscles involved in hand and wrist movement—such as the Extensor Digitorum or Thenar muscles—could provide richer data and reduce overlap in signal patterns between movements.

Another area for enhancement involves data processing. More advanced signal processing techniques, such as band-pass filtering, wavelet transformation, or feature extraction methods like root mean square (RMS) and mean absolute value (MAV), could be applied to improve the quality and clarity of the EMG data. These techniques can help emphasize subtle differences in muscle activation that may not be apparent in raw signals. Additionally, exploring time-frequency domain analysis could reveal patterns that are missed in the time domain alone, potentially improving movement classification.

From a machine learning perspective, future work could explore alternative models beyond the Artificial Neural Network (ANN) used in this project. Deep learning models, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are known for their ability to handle complex and non-linear data patterns. These models could provide improved classification performance, especially when trained on larger and more diverse datasets. Moreover, hybrid models that combine neural networks with other methods, such as support vector machines (SVMs), could also be explored.

Finally, implementing and testing the system in real-world applications would be a crucial step forward. A real-time classification system could be developed to assess its performance in scenarios like rehabilitation, where accurate movement recognition is critical for tracking patient progress. Similarly, the system could be adapted for controlling robotic prosthetics, enabling individuals with motor impairments to perform precise hand tasks. Testing in practical environments would also help identify unforeseen challenges and guide further refinements.

In conclusion, future research should focus on expanding the dataset, enhancing signal processing, and exploring advanced machine learning models to improve the system’s performance. These efforts could lead to a more robust and reliable system for classifying fine motor movements, paving the way for its application in healthcare, robotics, and assistive technologies.

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APPENDICES

Appendix A Gannt Chart for PSM 1

PROJECT NAME	PROJECT LEAD	PROJECT START DATE	PROJECT END DATE	TODAY'S DATE
EMG BASED: DATA ANALYSIS OF EMG SIGNAL BASE ON DIFFERENT TYPES OF HAND MOVEMENT FOR EXOSKELETON HAND APPLICATION.	IR. MOHD SAFIRIN BIN KARIS	13 MARCH 2024		19 APRIL 2024

MONTH	03	03	03	03	03	03	03	03	03	03	03	03	03	03	03	03	03	03	03	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04	04
DAY	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21
	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU

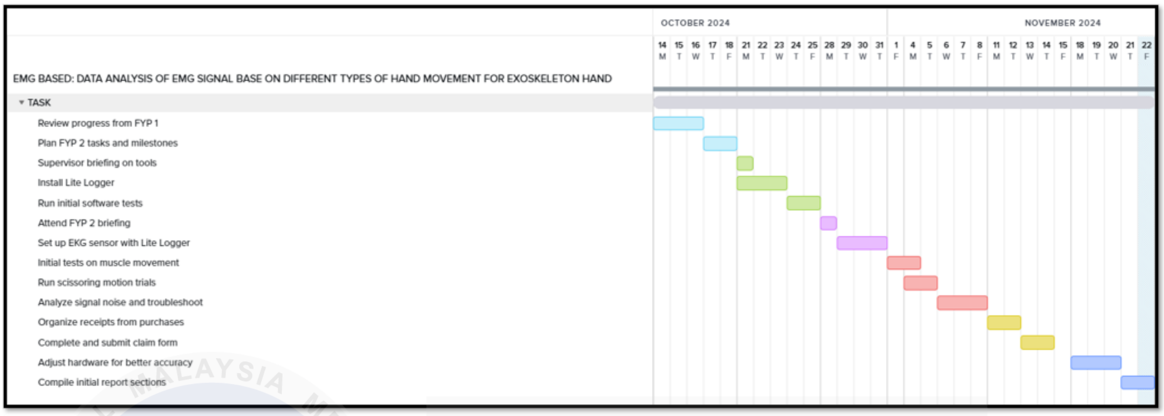
ACTIVITY	ASSIGNED TO	STATUS	START	END
Intro with supervisor and initial discussion	MUHAMMAD SHAHMI	Complete	13/03	13/03
Preliminary literature review and identification of potential articles	MUHAMMAD SHAHMI	Complete	14/03	19/03
Project briefing	MUHAMMAD SHAHMI	Complete	20/03	20/03
Refinement of project objectives and scope	MUHAMMAD SHAHMI	Complete	21/03	26/03
Discussion on potential articles and confirmation of project title	MUHAMMAD SHAHMI	Complete	27/03	27/03
Preparation of article review table	MUHAMMAD SHAHMI	Complete	28/03	02/04
Meeting with other lecturers, discussion on project improvisation	MUHAMMAD SHAHMI	Complete	02/04	02/04
Analysis of SEMG signal data and initial findings	MUHAMMAD SHAHMI	Complete	03/04	05/04
Hari Raya AidilFitri (Public Holiday)	MUHAMMAD SHAHMI	Complete	06/04	14/04
Review of initial findings and discussion on further analysis	MUHAMMAD SHAHMI	Complete	15/04	16/04
Discussion and election on specific hand movements	MUHAMMAD SHAHMI	Complete	17/04	17/04

MONTH	04	04	04	04	04	04	04	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	05	06	06
DAY	24	25	26	27	28	29	30	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	1	2
	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU	M	T	W	R	F	SA	SU

ACTIVITY	ASSIGNED TO	STATUS	START	END
Experiment design and methodology development	MUHAMMAD SHAHMI	Complete	24/04	13/03
Approval of experiment design by supervisor	MUHAMMAD SHAHMI	Complete	25/04	30/04
Initial 3D model design and sketching	MUHAMMAD SHAHMI	Complete	01/05	20/03
3D model prototyping and basic structure creation	MUHAMMAD SHAHMI	Complete	02/05	07/05
Adding joints and articulation to the 3D model	MUHAMMAD SHAHMI	Complete	08/05	27/03
Detailed modeling of hand features (fingers, palm, etc.)	MUHAMMAD SHAHMI	Complete	09/05	14/05
Approval of experiment design by supervisor	MUHAMMAD SHAHMI	Complete	15/05	02/04
Writing initial draft of project report	MUHAMMAD SHAHMI	Complete	16/05	17/05
Adjustments and enhancements to the 3D model	MUHAMMAD SHAHMI	Complete	18/05	26/05
Preparation of presentation materials	MUHAMMAD SHAHMI	Complete	27/05	02/06
Feedback session with supervisor	MUHAMMAD SHAHMI	Complete	29/05	29/05

Appendix B Gannt Chart for PSM 2

PROJECT NAME	PROJECT LEAD	PROJECT START DATE	PROJECT END DATE	TODAY'S DATE
EMG BASED: DATA ANALYSIS OF EMG SIGNAL BASE ON DIFFERENT TYPES OF HAND MOVEMENT FOR EXOSKELETON HAND APPLICATION.	IR. MOHD SAFIRIN BIN KARIS	13 MARCH 2024		20 NOVEMBER 2024



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