UTS UNIVERSITY OF TECHNOLOGY SYDNEY

EMG-based Assessments for Rehabilitation Application

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under the supervision of

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and
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Certificate of Original Authorship

I, Ghada Muneer Bani Musa, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Computer Science at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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List of Abbreviations

AD	Deltoid Anterior
ANN	Artificial Neural Networks
AP	Action Potential
APR	Automatic Posture Response
BI	Biceps Brachii
Brac	Brachioradialis
C	Consist Parameter
CBGWO	Competitive Binary Grey Wolf Optimizer
CNMF	Concatenated Non-Negative Matrix Factorisation
CNN	Convolutional Neural Network
CNS	Central Nervous System
COP	Centre of Pressure
ELM	Extreme Learning Machine
EMG	Electromyography
ERM	Empirical Risk Minimization
FD	Frequency Domain Features
FIM	Functional Independence Measure
FNN	Feedforward Neural Network
FNNs	Feedforward Neural Networks
FP	Feature Projection
FS	Feature Selection
FSM	Finite State Machines
Gamma (γ)	Kernel Parameter
HCI	Human Computer Interaction

Hjorth	Hjorth Parameters
IDI	Inter Discharge Intervals
IPI	Inter-Pulse Interval
IS	Infraspinatus
kEMG	Kinesiology Electromyography
kNN	k-nearest Neighbour
LD	Latissimus Dorsi
LDA	Linear Discriminant Analysis
LKF	Linear Kernel Function
MAE	Mean Absolute Error
MAV	Mean Absolute Values
MFAP	Muscle Fibre Action Potential
MKF	Multi-Kernel Function
MLP	Multilayer Perceptron
MME	Multilevel Mixed-Effects
MPR	Myoelectric Pattern Recognition
MS	Myoelectric Signal
MSE	Mean Square Error
MU	Motor Unit
MUAP	Motor Unit Action Potential
MUAPT	Motor Unit Action Potential Train
nEMG	Neurological Electromyography
NMF	Non-Negative Matrix Factorisation
PKF	Polynomial Kernel Function
PM	Pectoralis Major
PSD	Power Spectral Density

PSO	Particle Swarm Optimisation
RC	Rotator Cuff
RBF	Radial Basis Function
RMS	Root Mean Square
RMSE	Root Mean Square Error
sEMG	Surface Electromyography
SENIAM	Surface EMG for Non-Invasive Assessment of Muscles
SBS	Sequential Backward Selection
SFN	Single Feedforward Network
SFS	Sequential Forward Selection
SIAS	Stroke Impairment Assessment Set
SKF	Sigmoid Kernel Function
SKW	Sample Skewness
SLFNs	Single Hidden Layer Feedforward Networks
SSC	Slope Sign Change
STFT	Short Term Fourier Transform
SVM	Support Vector Machine
T	Triceps Brachii
T_{Thr}	The Threshold
TD	Time Domain
TFD	Time–Frequency Domain Features
TM	Teres Major
TSD	Time Scale Domain
V_{EMG}	Electromyography Voltage
VAF	Variance Accounted for Threshold
WHO	World Health Organization

WL	Waveform Length
WPT	Wavelet Packet Transform
WT	Wavelet Transform
ZC	Zero Crossings

Abstract

Biomedical signals–based human control systems have been studied in the biomedical field to improve quality of life. The muscle signal—electromyography (EMG)—is one of the main types of biomedical signals. The muscles are controlled by the central nervous system (CNS). The CNS does not directly control the activation of a large number of muscles, but it still shapes voluntary synergy motion. This research investigated and developed pattern-recognition approaches for EMG signals by studying the automatic body response and voluntary actions to support and understand how the CNS shapes voluntary synergy motion. The purpose of this study is extended to investigate the possible recovery improvement of human rehabilitation movement for stroke patients. This thesis answer core questions: How the automatic body response and voluntary movements can help to improve the quality of life for people with disability?, How can we predict rehabilitation for post-stroke patients?, and how to predict the possible recovery performance ahead of three months?.

My doctoral study contributes to knowledge both theoretically and practically. The main research objective was to develop computational intelligence-based EMG for upper limb rehabilitation applications.

After building stable procedures for signal processing, we predicted the functional motor recovery of severe, moderate, and mild post-stroke patients during their rehabilitation programs based on support vector machine regression (SVMR). The EMG signals from the upper limb muscles of the patients during their initial rehabilitation sessions were used to train the model. In this thesis we achieved good results with error < 0.5.

We developed the non-negative matrix factorisation (NMF) method to extract the synergy EMG to express some features that could support the CNS in shaping the voluntary movement and reducing error. After building our model and extracting the synergy, we calculated the Variance Accounted for Threshold (VAF) to identify the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs; our result was > 95% VAF overall.

We developed the multilevel mixed-effects (MME) model to predict human recovery based on biomarker assessment sets. We also predicted future rehabilitation for post-stroke patients three months ahead using time series prediction based on synergy EMG.

In summary, this pilot study's results promise the ability to predict the future muscle performance of post-stroke patients based on their current motor ability as well as this summary aims to be easiest for the reader to know upfront everything in the coming chapters.

Chapter 1: Introduction

The successful research in the rehabilitation field needs the developing of classifiers for the electromyography (EMG) signal for the upper limb rehabilitation application and devices.

However, there are still limitations in the clinical application of using the rehabilitation device in a real-time environment. Understanding the upper limb rehabilitation problems and the requirement to use an accurate real-time classifier could be achieved by using an accurate real-time environment application. This chapter first establishes the motivations for this doctoral research and the aspiration to discover and learn new things. It then presents the research contributions, questions and objectives and details the organisation of the thesis. The last section lists publications produced during the doctoral study, and then provides a chapter-by-chapter summary as per the thesis

1.1 Background

Many countries throughout the world have sizeable populations of disabled individuals. According to the 2009 Survey of Disability, Ageing and Caring, 4.4 million Australians have a disability (Temple, Batchelor, Hwang, Stiles, & Engel, 2021). The physical and mental disability percentage in 2018 was 17.7%. This was down from 18.3% in 2015 and 18.5% in 2009 (Khairul Anam & Al-Jumaily, 2021). 5.5 million people die each year as a result of stroke, while 80 million survive globally from stroke each year. Many live with short term stroke, long term stroke or permeant stroke (World-heart-federation). In 2020, disabled people in Australia used the National Disability Agreement specialist support at the cost of $4.2 billion (Health & Welfare, 2020).

In the United States, 18.4% of the population, or 54.4 million individuals, are disabled somehow; 12% are severely disabled. The situation is similar in many countries. As a result, numerous attempts have been made to provide a variety of facilities to meet the needs of disabled people in public places, as they have the same right to live in the world as non-disabled people. The World Health Organization (WHO) has urged its members to take this issue seriously and has produced a study to assess how seriously they are taking it (World Health, 2001).

Disability can be psychological, mental, or physical. Physical disabilities account for the majority of disabilities. Physical disabilities require more medical attention than other forms of disability to be resolved. Stroke represents one of the major causes of physical

disability's problems and can affect the upper limbs. These problems require specialist forms of therapy. The type of therapy is determined based on the type of disability and the underlying conditions of the disability.

The WHO defines 'rehabilitation' as a process that aims to allow the patient with disability to reach their optimal sensory, acknowledgeable, physical or social connection level as an ordinary person (World Health, 2001). Rehabilitation includes procedures to provide and/or restore function limitations. The initial care given to a stroke patient at the beginning of their medical care plan does not include rehabilitation activities. The rehabilitation activity is only introduced after the patient has received a certain level of medical care. Rehabilitation aims to help patients return to their everyday lives and restore weakness that cannot be addressed medically (Akdogan & Adli, 2011; World Health, 2001).

The most frequent disability problem is hand disability. This can be caused by either muscular dystrophy and stroke or motor function problems. Muscular dystrophy is a form of a physical disability that can cause hand problems that this study seeks to help resolve. Developing the perfect technology for hand rehabilitation is a challenging task. A robotic hand exoskeleton that has a hand's functionality that helps the patient to do the exercise to help move their hand (Khairul Anam & Al-Jumaily, 2021). However, these prosthetic hands need more advanced computations and advanced technology so that their wearers can move and 'feel' with their prosthetic hands in real-time. Further, they should work in agreement with the patients wearing them.

The focus of this study was to provide new methodologies to help the patients who lost upper limb hand mobility as a result of their stroke and improve their upper limb function weakness by using electromyography (EMG) and a group of muscles (Synergy EMG).

EMG is the most important and effective signal to create a smooth connection between human and rehabilitation devices. Thus, the robotic hand will work as a natural extension by capturing the message sent from the central nervous system (CNS) to the muscle and then using it to drive the robot after processing the required action.

An EMG signal that records the myoelectric signal (MS) from muscle activity has been widely used as a record to detect users' movements, and the user could be a healthy or unhealthy person (Aidan, Hubertus, Dario, & Oskar, 2014). EMG electrodes are placed in the human limb, either invasively (via wires or needles inserted directly into the muscle) or non-invasively (recording the electrodes placed on the skin surface overlying the investigated muscle) (F. Hug & Dorel, 2009; Merletti & Di Torino, 1999).

Most people do not like to plant electrodes inside their bodies, preferring to use the surface electrodes instead. Nevertheless, surface electrodes have several disadvantages, such as crosstalk from other muscles. However, it is not easy to obtain an EMG signal from deeper muscles, which means it is not easy to handle MS processing using EMG. Another problem is that the extrinsic muscles that cause flexion, extension, abduction and adduction are located in the middle (flexor digitorum superficialis muscle) and deep (flexor digitorum profundus muscle) layers of the upper limb. Therefore, surface electromyography (sEMG) will not provide the precise signal from the intended muscles. Conversely, extension is mostly located in the superficial layer (extensor digitorum).

Another problem is caused by the skeletal muscles of a human body; one muscle is responsible for moving in a specific way, either individually or in combination. Of course, this increases the difficulty of myoelectric control for the upper limbs. In addition, different testing environments may change the characteristics of EMG signals. For example, a trial conducted on a particular day may have a different set-up to subsequent trials and might thus attain different results. This raises concerns about collected EMG.

Pattern recognition–based EMG and synergy EMG can treat various upper limb problems. Pattern recognition in the upper limb has been studied for years. This indicates support for EMG-based non-pattern recognition. The sEMG based has a big challenge to analyse and process the movement that requires a final clarifier which respond to EMG signal nature and environmental change.

Uchida classified hand movements with an accuracy of 86% using fast Fourier transform features (Uchida et al., 1992). His method is not used now because it takes too much time to process. Similarly, Tsenov used multilayer perceptron (MLP), developing a hand movement recognition system using time-domain (TD) features extraction and achieving 93% accuracy when using two EMG channels as input and 98% accuracy when using four EMG channels (Tsenov et al., 2006). In 2011 (Cipriani et al., 2011), Cipriani used k-nearest neighbour (kNN) as a classifier. kNN, linear discriminant analysis (LDA) and support vector machine (SVM) have been used extensively in many areas like biology and medicine (R. N. Khushaba, Kodagoda, Takruri, & Dissanayake, 2012; Oskoei & Hu, 2008).

Less mobile persons need specialised care to improve muscle strength, since muscular dystrophy causes them to have a very limited range of motion.

1.2 Problem Statement

The purpose of this study is to investigate the possible recovery improvement of human rehabilitation movement for stroke patients. This research aims to find out the possible system or tools that can facilitate objectives based on artificial intelligent system judgement complementary to medical experts. Also, to help these experts identify the affected areas more efficiently and predict upper limb recovery more accurately rather than waste treatment time and cost.

This doctoral research is based on Electromyography (EMG) muscle signal analysis. EMG signal will be useful to provide indication for the upper limb movement problem for stroke patients. We used the collected EMG signal to predict the upper limb recovery after stroke and to provide e specialist forms of therapy. The type of therapy is determined based on the type of disability and the underlying conditions of the disability.

1.3 Scope of Work

Our project aims to help the muscles to regularly work every time and as a real function to help the CNS shape voluntary action. We specifically look at people who affected by stroke and suffered from lost upper limb mobility as a result. It also seeks to predict rehabilitation performance for post-stroke patients.

1.4 Research Gap

The disability to hold, gasp and manipulate, inability to feel, and express emotions, that are partially reflected member's situation imposed by limbs (Demofonti, Carpino, Zollo, & Johnson, 2021; Ingram, Butler, Brodie, Lord, & Gandevia, 2021). Stroke is one of a leading cause of short term, long term or permanent disability worldwide in upper limb (Boehme, Toell, Lang, Knoflach, & Kiechl, 2021). Many studied highlighted the fact that the upper limb functional recovery is higher in the first few days post stroke and weeks following that (Chinnavan, Ragupathy, & Wah, 2020; J. Lee et al., 2021). Consequently, the best therapy result achievement is in a short time frame followed stroke. Therefore, medical experts have only a brief time to value the upper limb damage to the brain and decide on the best course choice of therapeutic to control intervention (Stinear, Lang, Zeiler, & Byblow, 2020). As well as, any delay in the stroke assessment process it can cause a delay in the treatment course and delay the importance of early rehabilitation, and increase in the cost (Chowdhury, Baskar, & Bhaskar, 2021). Thus, building a system that can provide advice to the expert about possible rehabilitation procedure and help them

for short-term, and long-term rehabilitation performance index is vital to avoid long term or permanent disability and shorten the rehabilitation time and reduce the cost.

1.5 Thesis Motivation

This thesis proposes a computational intelligence-based automated body response and voluntary action via EMG signal in the upper limbs to predict human rehabilitation. Upper limb stroke affects many people, and the main objective for this thesis applying minimum recording EMG signals was to predict rehabilitation performance for post-stroke patients on a daily basis in relation to their upcoming motor activities. Another objective was to predict the possible recovery performance ahead of three months' time.

EMG pattern recognition has had several experimental achievements (Oskoei & Hu, 2008) but is frequently overtaken by machine-learning methods in a wide range of occupations. Moreover, various machine-learning techniques with different inputs have been studied in the context of upper limb problems. Consequently, to provide a new methodology that can improve the quality of the life of people with disability, a new pattern-recognition system is needed. It is essential to develop computational tools that can overcome the problem and improve the reliability of the process for automated rehabilitation diagnosis that operates on a quantitative measure.

Such tools can facilitate objective mathematical judgement complementary to that of medical experts. It can also help these experts identify the affected areas more efficiently and predict upper limb recovery more accurately rather than waste treatment time and cost.

1.6 Thesis Contributions

This doctoral study contributes to knowledge both theoretically and practically. The main research objective was to develop computational intelligence-based EMG for upper limb rehabilitation applications. These contributions can solve problems that occur in real-time applications. To achieve this objective, several methods and algorithms were examined and developed with actual data and systems. The thesis presents and discusses all theoretical and practical contributions and briefly explains the requirements for collecting sEMG data signals from upper limbs.

The main research contributions of the work presented in this thesis:

- Provide a new methodology to help the CNS shape the voluntary movement that can help to improve the quality of the life for needed people. This thesis demonstrates that EMG data collected using the manipulandum Delta technology can be used to construct models that aim to help the CNS to shape the voluntary movement.
- Develop a pattern recognition system based on EMG data that is used to classify the muscle synergy to help the CNS shape the voluntary action.
- Investigated the possibility of a machine-learning algorithm using support vector machine regression (SVMR).
- Identification of two robotic biomarkers for prediction of future ability. Generally, Biomarkers generated from a set of activities/behaviours tasks that are used robotic to estimate the daily activities. In this thesis the activities measures are based on Functional Independence Measure (FIM) and Stroke Impairment Assessment Set (SIAS) biomarkers. Identification of these two biomarkers can prospect be used as a guide-base for the targeted exercise of rehabilitation therapy.
- Build a predictive model for the current ability to predict the future ability to perform usual daily activity. This thesis explains how to use the EMG data to predict a set of clinical scores and motor functional recovery for post-stroke patients during their rehabilitation program.
- Predict recovery performance ahead of three months. This thesis objectively aims to predict a set of motor function in line with estimates provided by clinical scores at approximately three months ahead.
- Develop a Multilevel mixed effect model for predicting recovery performance.

1.7 Thesis Questions

The main research questions and objectives are as follows.

- How the automatic body response movements and voluntary movements can help to improve the quality of life for people with disability?
- How can we predict rehabilitation for post-stroke patients based on a daily basis in relation to their upcoming motor activities?
- What is the possibility to predict the possible recovery performance ahead of three months?

1.8 Thesis Objectives

The objectives of this thesis are three main objectives:

- The first object concerns to provide a new methodology that can improve the quality of life of people with disability by developing a stronger understanding of the CNS voluntary movement effect. It also sought to develop a pattern-recognition system and apply it to the EMG data, which can be used to classify the muscle synergy to help the CNS shape voluntary action. This object is achieved by using Dual Manipulandum robot technology to quantify a range of behavioural capabilities of individuals, providing a rich set of EMG data then use it in a computational model. This objective is discussed in Chapter 4.
- Investigate the possibility of a machine-learning algorithm using support vector machine regression (SVMR) to predict motor functional recovery for post-stroke patients during their rehabilitation program. This is discussed in Chapter 5.
- Predict rehabilitation for post-stroke patients by developing a multilevel mixed-effects (MME) model, predicting recovery performance ahead of three months' time based on time series prediction and then comparing the results with the Functional Independence Measure (FIM) and Stroke Impairment Assessment Set (SIAS) biomarkers. By providing a rich set of Biomarkers of sensory function and motor function, we use the data set in computational models to estimate present and future clinical score to predict the ability for participants post stroke to perform daily rehabilitation activities following stroke. We sought to motivate the patients to complete their designed rehabilitation programs and to help their therapists assist them by executing the proper rehabilitation program. To achieve this objective, data from the biomarker set were used for assessment of motor function and sensory function. This is discussed in Chapter 6.

1.9 The Organisation of the Thesis

The thesis contains eight chapters plus an appendix and references. The chapters proceed as follows.

Chapter 1: Introduction.

This chapter introduces the study background, scop of works, this thesis motivations and outlines this thesis contributions, questions, and objectives.

Chapter 2: Literature Review

This chapter reviews the literature on upper limb anatomy, stroke, and the EMG signal.

Chapter 3: EMG and Synergy EMG Signal for Upper Limbs

This chapter gives background on the EMG signal for upper limbs and synergy EMG.

Chapter 4: Shape Voluntary Movement Based on EMG Using Pattern Recognition and CNMF

This chapter details how automatic body responses could be used as a reference in the body movement to familiarise the voluntary efforts to help the CNS system shape voluntary movements and develop rehabilitation performance.

Chapter 5: Upper Limb Recovery Prediction After Stroke Rehabilitation Based on the Regression Method

This chapter explains how we motivated patients to complete the designed rehabilitation program or changed their rehabilitation programs, with assistance from their therapists, depending on the predictions that we were able to make about the patients' recovery. We investigated the possibility of a machine-learning algorithm using the SVM to predict the motor functional recovery of post-stroke patients during their rehabilitation program.

Chapter 6: Upper Limb Recovery Prediction Based on MME EMG Synergy and Biomarker Value

This chapter details our use of a robot and clinical biomarkers associated with upper limb function quantified in the first few days post-stroke to estimate the effectiveness of rehabilitation recovery.

It also illustrates how to predict rehabilitation for post-stroke patients by developing the MME model using robot-based biomarkers in both the FIM and SIAS for EMG signals. Finally, it presents the synergy of the affected and non-affected sides of the body for post-stroke patients that can help predict their ability to recover based on their performance of daily activity rehabilitations, and that represents the level of recovery and improvement potential for a given rehabilitation technique.

Chapter 7: Thesis Summary, Conclusion and Future Study

This chapter concludes the thesis and presents future research directions.

1.10 Definition of Terms

- Electromyogram: is a technique that used to collect the EMG data from the integration of action potentials spreading through muscular fibres under an electrode. It recorded the bioelectrical muscle activity that generated from the muscle fibres (McManus et al., 2021). It can detect the wave EMG data using the needle EMG or surface EMG along muscle fibre (Grabow, Block, Kelekis, Filippiadis, & Murphy, 2020).

- Stroke: These days, stroke is the commonly caused of human disability worldwide. It is damage in central nervous system function that increase the upper limb function problem. It cause loss of sensation, movements and difficulties surrounding daily living activities (Zhou et al., 2021).

- Electromyography (EMG): is the essential biological signal in the human body that used in biomedical field in hand pattern recognition and rehabilitation system. It is used to classify, predict and study the human motor muscles (A. A. Al-Jumaily, Matin, & Hoshyar, 2021; Bi, Feleke, & Guan, 2019). It can be detected from the muscle fibres using needle or surface technique. EMG signal been extensively used in robotic assistive for stroke and hand rehabilitation.

- Synergy EMG: It is the recorded EMG signal of a group of muscles that worked together to perform the human movement as one muscle. It is provide a high level to control the neural information (Xiong, Zhang, Zhao, Chu, & Zhao, 2021).

- Manipulandum Delta 3. robot: Is a machine that integrating a hardware system and interface software system that appear in the manipulandum screen Infront of the user. The software system responds to the user's action by moving hand a specific movement with an organised resistance. The resistance sometimes from the user or from the manipulandum, which depends on the experiment (Neibling, Jackson, Hayward, & Barker, 2021).

1.11 Publications

Papers and presentations published during my doctoral studies are as follows:

Journal:

- Musa, G.M.B., Al-Jumaily, A., Alnajjar, F. and Shimoda, S., 2017. Analyze the human movements to help CNS to shape the synergy using CNMF and pattern recognition. Procedia Computer Science, 105, pp.170-176 (Bani Musa, Al-Jumaily, Alnajjar, & Shimoda, 2017).
- New journal paper going to be submitted.

Conference:

- M. Bani Musa, Ghada & Alnajjar, Fady & Al-Jumaily, Adel & Shimoda, Shingo. (2019). Upper Limb Recovery Prediction After Stroke Rehabilitation Based on Regression Method: Proceedings of the 4th International Conference on NeuroRehabilitation (ICNR2018), October 16-20, 2018, Pisa, Italy. 10.1007/978-3-030-01845-0_76 (Bani Musa, Alnajjar, Al-Jumaily, & Shimoda, 2019).

Chapter 2: Literature Review

This chapter reviews the literature on upper limb anatomy to understand the structure of the hand rehabilitation device and the upper limb muscles involved in rehabilitation movement. The chapter also introduce the stroke, different types of strokes, and the main stroke statistic. At the end of this chapter, we will also present basic information about EMG.

2.1 The Upper Limb Anatomy

The upper limb is the most freely moveable area in the body. The upper limb structurally and functionally is complex. To understand the upper limb anatomy, it is necessary to study the upper limb bones and muscles to determine how rehabilitation devices are designed. The following subsections discuss the upper limb bones, joints and muscles.

2.1.1 The Upper Limb Bones

The upper limb bones are found in the arm, forearm and hand (Etrusco et al., 2017; Forro & Lowe, 2019). The single upper bone arm is called the humerus and is located between the shoulder and the mid joint of the hand. The forearm bones comprise the ulna and radius bones; they are located between the mid joint of the hand and the wrist joint. The hand, which is located after the wrist joint, includes carpal bones, metacarpal bones and phalanx bones, which contain eight bones, five bones and 14 bones, respectively (Marieb & Hoehn, 2010; Nordin, 2020), as shown in Figure 2.1.

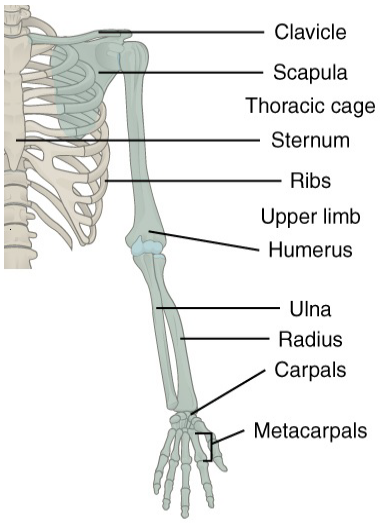


Figure 2.1: Upper Limb Bones (Brack & Amalu, 2021)

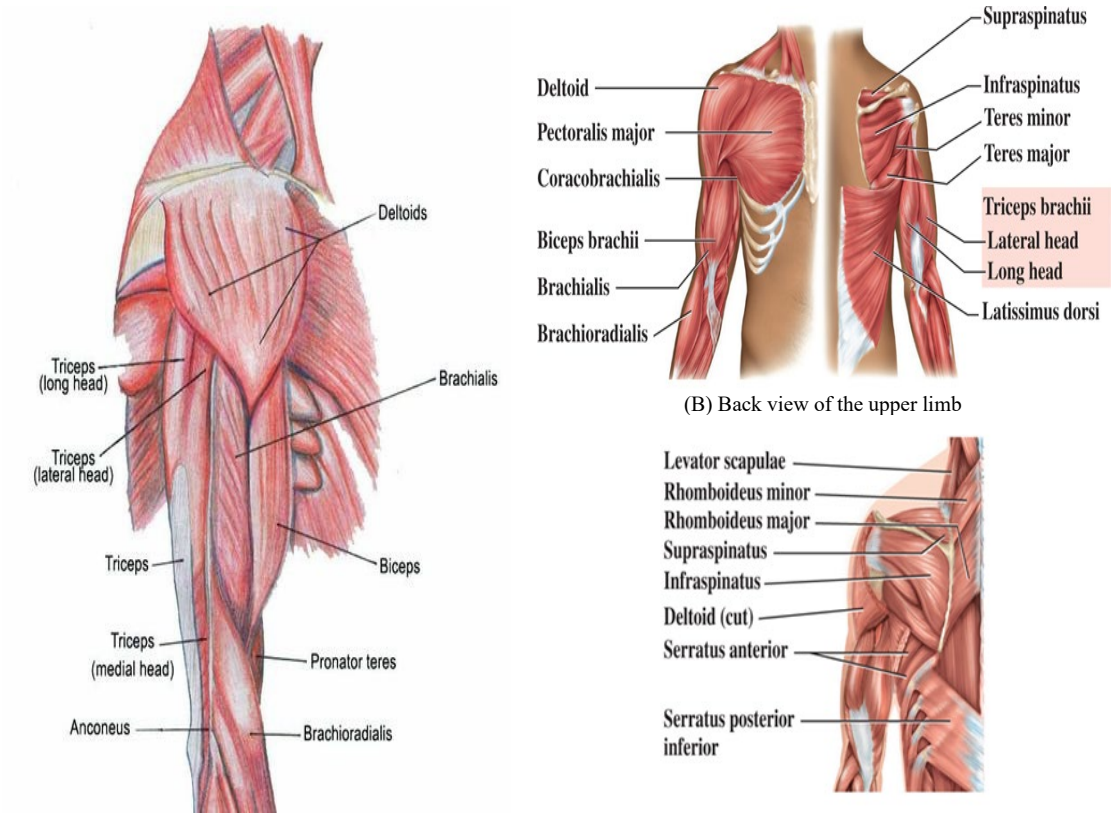
2.1.2 The Upper Limb Muscles

The upper limb muscles are divided into two main types: extrinsic muscles and intrinsic muscles (Dawson-Amoah & Varacallo, 2019). The extrinsic muscles are located outside the hand and comprise the arm and forearm muscles. The extrinsic muscles drive the upper limb. These muscles generate an electrical signal to generate muscle movement, which is called an EMG signal. The strength of the electrical current generated by the muscle varies depending on the muscle strength. To measure the electrical current from

the biomedical signal and the muscle activities, relaxations, performance and recovery prediction, the filtered EMG signal has been used in prior studies (Piskorowski, 2013).

The intrinsic muscles are located inside the hand and perform independent action. The coordination action from the inside upper limb muscles and the outside upper limb muscles are accomplished by the dextrous movement of the upper limb. The extrinsic muscles control the flexion and extension of muscle movement (Heo, Gu, Lee, Rhee, & Kim, 2012; Schwarz, 1955).

Figure 2.2 represent the upper limb muscles. Figure 2.2 (a) represent the side view of the upper limb of the body. Figure 2.2 (b) shows the back view of the upper limb muscle. Figure 2.2 (c) shows the front views of the upper limb. The flexor and extensor are classified as extrinsic muscles.



(A) Side view of the upper limb

(B) Back view of the upper limb

(C) Front view of the upper limb

Figure 2.2: Upper Limb Muscles ((A) Side View, (B) Back View and (C) Front View) (Dawson-Amoah & Varacallo, 2019; Etrusco et al., 2017)

The clavicle and scapula link the upper limb appendicular part of the Skelton to the trunk through the sternoclavicular joint (Etrusco et al., 2017). The muscle that gives roundness to the shoulders is called the deltoid and is made from three motor fibres: the clavicular part, acromial part and scapular part (Etrusco et al., 2017).

Figure 2.3 shows the arm and forearm muscles that determine and controlling flexor and extensor movement (Marieb & Hoehn, 2010).

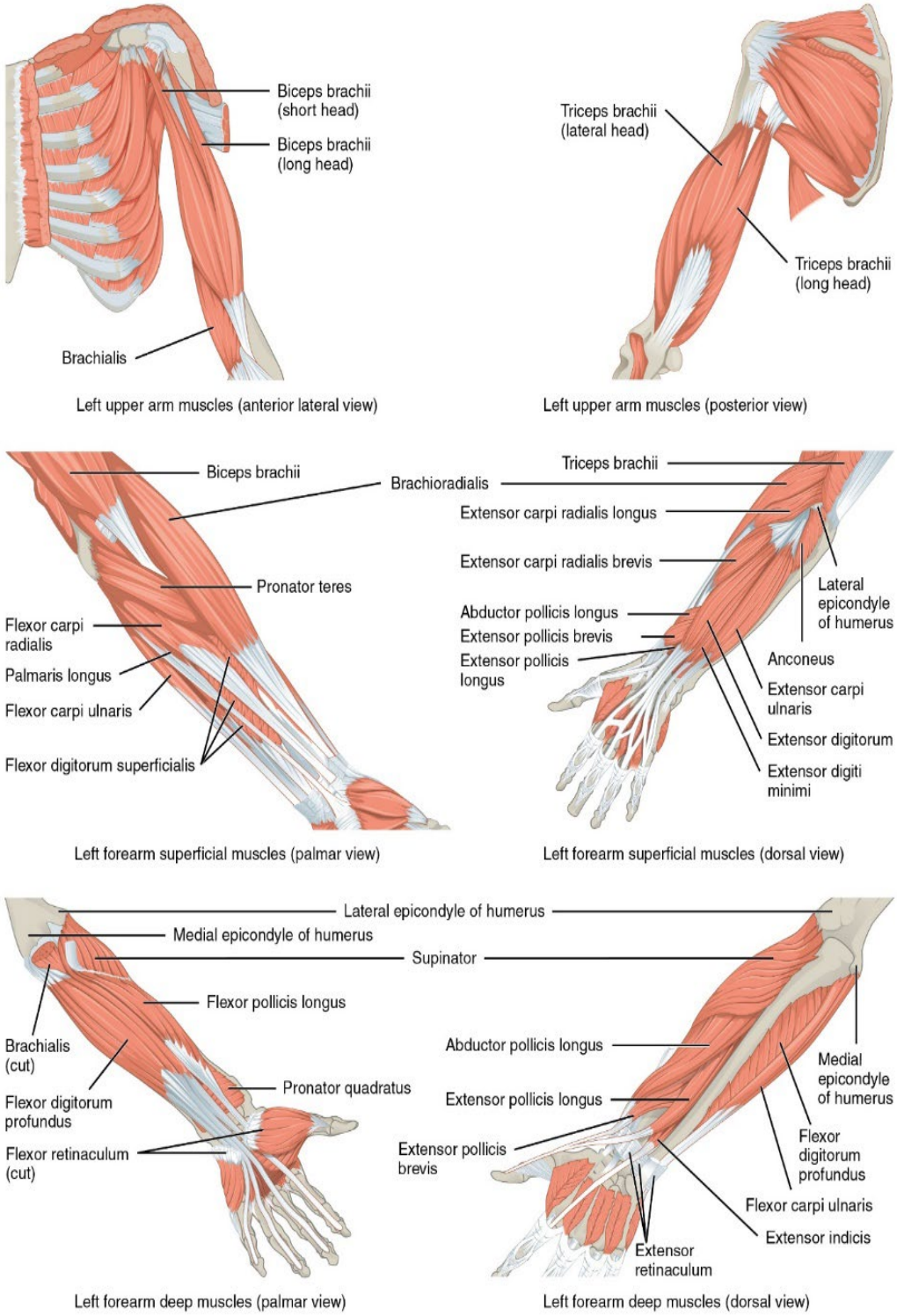


Figure 2.3: The Arm and Forearm Muscles (Pale, Atzori, Muller, Muller, & Scano, 2020)

2.1.3 The Upper Limb Muscles Anatomy

Structurally, the upper limb contains a wide range of anatomical variant. It can relate to any body movements. There are many different parts in the upper limb (Orellana-Donoso et al., 2021). The first part is the arm region, which features the biceps brachii, brachialis and the triceps brachii. The second part is the forearm, which features the brachioradialis, anconeus, pronator teres and supinator. The biceps brachii, brachialis and brachioradialis are the forearm flexion muscles. The triceps brachii and anconeus are the extensors. The following muscles are the muscles that we collected the EMG data from in this thesis:

Deltoid anterior: deltoid started from the spine of the scapula. It is lateral third of the clavicle. The deltoid muscle and the rotator cuff (RC) functionally working together as one unit to enable the shoulder movements. The shoulder active motion can raises the arm from 0^{o} to 180^{o} degree (Elzanie & Varacallo, 2022; Hecker et al., 2021).

Pectoralis major: pectoralis major muscle is located in the front of the thorax and very important to protect the axillary cavity. It performs several upper limb extremity movements. It help the shoulder to do the contraction, flexion, rotation, and adduction on a horizontal plane (Lulic-Kuryllo, Negro, Jiang, & Dickerson, 2022).

Biceps brachii: The biceps brachialis muscle originates with two origins: long head from supraglenoid tubercle of the scapula bone and short head from the coracoid process of the scapula. It is very important in upper limb flexor. Any weakness of biceps causes loss of strength in the whole upper limb. (Enix, Scali, Sudkamp, & Keating, 2021).

Brachialis: This muscle located in the forearm. It is superficial muscle. This muscle primarily helps the forearm to flexes. It is very important in supinate or pronate depends on the forearm rotation. It is the largest muscle in the forearm. It connect the distal end of the upper limb bone into the distal end of the forearm bone (Lung, Ekblad, & Bisogno, 2021).

Triceps brachii: The triceps brachii is the larger muscle on the back part of the upper arm. It is formed from three parts (related to the name: tri mean three and cep mean head): the long head, lateral head, and medial head. This muscle is very important to extension the elbow joint (Tiwana, Sinkler, & Bordoni, 2019).

Latissimus dorsi: It is flat muscle, and it forms the majority of the lower posterior thoracic cavity. It is very important muscle. It takes into account a muscle of contributing to thoracic and brachial motion. It is the most important internal rotator muscle. It is the most important for the extension (spin-extension), flexion(lateral flexion), and rotation of the shoulder (Jeno & Varacallo, 2021).

Teres major: this muscle is small muscle. It is the inner shoulder muscle. It is extended from lateral edge of the scapula. It is very important to provide the shoulder with the, extension, flexion, and internal rotation (Juneja & Hubbard, 2021).

Infraspinatus: Infraspinatus is a thick muscle. It is look like triangular in the shape. It is occupying from the infraspinous fossa of the scapula shoulder. Mainly, it is important in external and lateral rotation of the shoulder joint (Williams, Sinkler, & Obremskey, 2018).

Supraspinatus: Subscapularis is the large and stronger muscle. It is triangular shape. It is very important to help the humaerus bone to rotate internally. It is work together as one unit with supraspinatus, infraspinatus, and teres minor muscles to compose the rotator cuff apparatus (Aguirre, Mudreac, & Kiel, 2021).

2.2 Muscle Physiology

A muscle contains a number of motor units (MUs), depending on its size. The MU is made up of a motor neuron and muscle fibres in the spinal cord (Daube, 2006). The MU is the smallest functional unit that is responsible for neural control of the muscle (Kleissen, Buurke, Harlaar, & Zilvold, 1998). It controls the muscle movements through upper motor neurons (Z. Chen, Fan, Li, Yuan, & Xu, 2020). It is a laborious but indispensable keystone of EMG diagnosis (Andrade, Nasuto, & Kyberd, 2007). The tissues support electrical conductivity in the muscle fibres. At the same time, this provides depolarisation of the fibres. The electrical signal generated from the muscle in the same MUs is the EMG signal (the EMG signal is discussed in more detail in this chapter). Motor neurons has long axons. Which work as part of a nerve cells (M. Chen, Bashford, & Zhou, 2022). Each axon connected to different muscle fibres on the same endplate. Usually, the motor neurons located in the middle of the fibre to support group of muscle fibres. It communicate sensory with muscles, skin tissue, and all body organs (A. Al-Jumaily & Olivares, 2009). Figure 2.4, Figure 2.5 and Figure 2. 6 shows MU in the CNS, the MU structure, and the motor unit axons, respectively.

As depicted in Figure 2.4, an electrical impulse from the muscle fibres travels down the axon and arrives at the end of the motor is known as an endplate, because the CNS activates the MU. Before impulse arrival, neurotransmitters appear that cause depolarisation waves to propagate along both ends of muscle fibres.

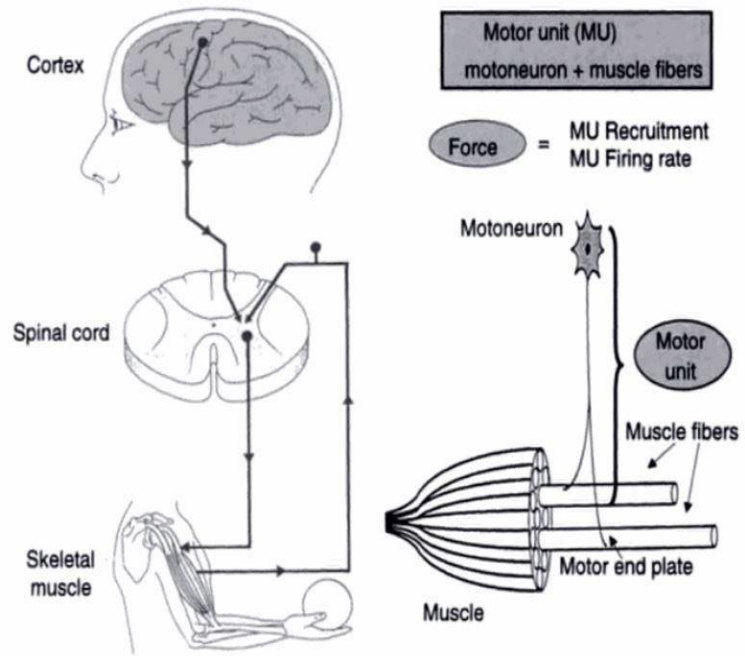


Figure 2.4: The MU Control System (Atkinson, 2018)

Figure 2.5 represents the MU schematic and has two MUs. The number of anterior horn cells or the axons controlling the muscle determines the number of MUs (Daube, 2006; Moritani, Stegeman, & Merletti, 2004). The number of MUs in each muscle may range from 100 to 1,000 or more for small and large muscles, respectively (Moritani et al., 2004). The amplitude of the EMG signal depends on the number of active MUs, their size and the relative position of the recording surface electrode (Farina, Merletti, & Enoka, 2004).

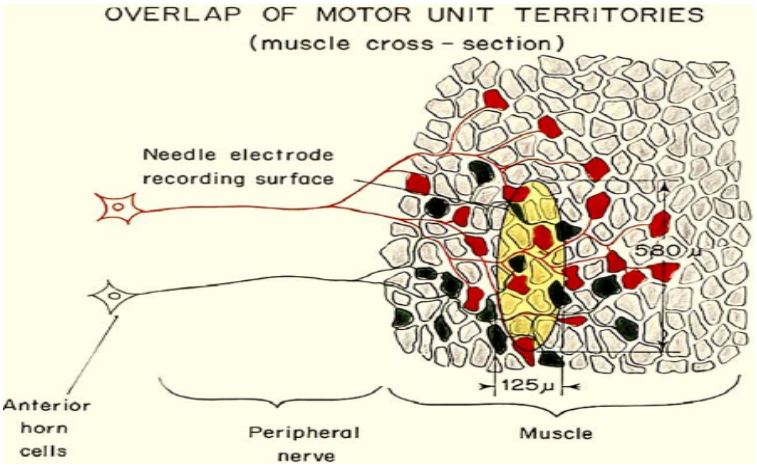


Figure 2.5: MU Structure (Daube, 2006)

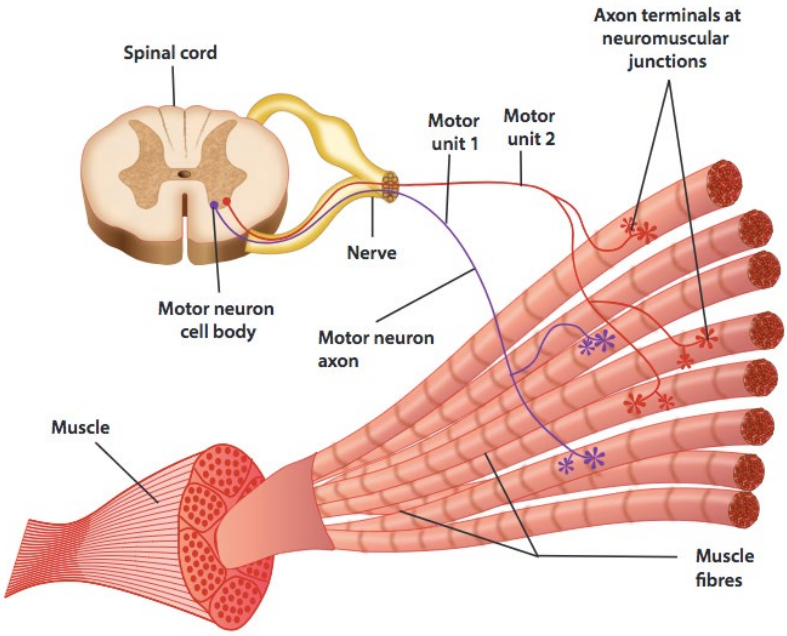


Figure 2. 6: Axon of Motor Neuron and Muscle Fibres (Heckman & Enoka, 2004).

Figure 2. 6, shows the spinal cord and the axon of motor neuron and muscle fibre. The motor neuron and axon and nerve are extended from the middle of the spinal cord to the muscle. It sends motor neuron axons to the muscle fibres. Each muscle control hundreds of motor neurons. After the central nervous system activates the motor unit, an electrical impulse signal of the muscle fibres travels down on the axon and arrives to the end of the motor. This signal collected from the muscle via an electric needle(injection), surface electrode that connected to the skin surface, or wire sensors connected to the muscle tissue (Lee, Shin, Jang, Jeong, & Ahn, 2021).

There is an electrical effect on an electrode and a signal observed by this electrode. This is called the motor unit action potential (MUAP). The MUAP is the EMG signal source. It contains important information such as muscle force, muscle impedance and human arm motion (Du, Lin, Shyu, & Chen, 2010). MUAP was developed to investigate the amplitude and frequency spectrum contributions of MUs. The electrode could be located at various depths within the muscle or at the top of the skin surface to detect the EMG signal (Alkan & Gunay, 2012).

The EMG signal reading affected by the stroke. Usually, stroke divided to two damage zones: first zone is the core zone, which is the most severe damage cells will cause damage in muscle tissues with neurons die, brain damage. The second damage zone is surface region damage which is mildly affected the muscle tissue. Usually in the surface zone, the cells remain alive post stroke for several hours (Rulaningtyas et al., 2021).

Next, we will talk more about the stroke, stroke types, stroke statistics, followed by addressing the EMG signal.

2.3 Stroke

Stroke is damage in central nervous system function that increase the human body function problem by intermission of blood-flowing to the brain. When the blood does not flow to the brain it causes shortage of oxygen then death within 60s -90 seconds. It causes loss of sensation, movements and difficulties surrounding daily living activities. Currently, stroke is the major commonly caused of human disability worldwide. Globally, each year more than 17 million people (different ages) are predictable to suffer from stroke. 80% of the stroke can cause impairment in the upper limb. 50% of the post stroke patients can recover the upper limb daily activities and 50% could remain the same or worse in upper limb function (Bernhardt & Mehrholz, 2019; Zhou et al., 2021).

In united states, stroke increasingly spread in non-elderly people (for ages less than 65 years old). 150000 cases death every year as a result of stroke. The hospitalization period in United states it cost around $30 billion each year. (R. T. Nguyen, Khan, Valero-Elizondo, Cainzos-Achirica, & Nasir, 2022; Tsao et al., 2022). 13000 cases death every year because of stroke in Canada. The hospitalization period in Canada cost exceeds $2.5 billion each year. 60,000 stroke cases were occurred in Australia in 2011 (Aung & Al-Jumaily, 2012).The hospitalization post stroke needs a rehabilitation process from a health care system as well as that increase the cost. In Chapter 6, we highlighted this problem and I find a solution to help physicians to do the right rehabilitation recovery to reduce the cost. Many studies predicted that by 2030, for United states, Canada, European countries and Australia, the stroke cases will increase (Olié et al., 2022).

The recovery from the stroke depends on the stroke effectiveness/strength on the human body. The stroke strength (sever, moderate or mild) to the brain can be different depends on the size and location of the injury. It can affect a wide range of sensory, gripping, or motor functions (Antonis, 2021). The hospitalization length post stroke in Canada is 17 days. Which is longer compared to other diseases, that depends on the stroke strength as well.

There are two types of strokes that can affect the human body: Ischemic stroke and Hemorrhagic stroke (Hakoupian et al., 2021). Ischemic stroke is stop blood flowing to the part of brain due to atherosclerosis, embolism in any intravascular solid or vessel disease. Approximately 85-87% of all stroke are ischemic stroke (Mendelson & Prabhakaran, 2021).

Hemorrhagic stroke happened as a result of break of blood vessels. It accounts for 13%-15% of the stroke cases. This stroke damage the brain tissue by blood clots due to coagulopathy, loss of blood pressure control because of high blood pressure, or surgical hematoma (Bahader et al., 2021; Montaño, Hanley, & Hemphill III, 2021). Which cause a risk of rapid rice pressure in local tissue which cause cell death.

Many numbers of risk factors that linked to the stroke. It is divided to two main risk factors: non-intervention (non-modified) and intervention (modified). Non-intervention could be but not limited to: age, gender, or genetic. The invention risk factors which includes: high blood pressure, cholesterol, smoking, and diabetes, im-proper lifestyle (Guo et al., 2022).

Since upper limb daily activities recovery is the most important and challenging post stroke, there is an essential requirement to study EMG signal extensively as it is the most

important signal in driving the rehabilitation and using assistive robotic for stroke. Next, we will highlight the EMG signal and in chapter 6 will explain experiment and methodology, result related to human stroke.

2.4 EMG Signal

Biomedical signals have been studied to develop the human movement control system and to improve the quality of life. They are a combination of electrical signals that occur in any organ of the body. EMG (or MS), electroencephalography (EEG), electrooculogram (EOG) and electrocardiogram (ECG) are examples of biomedical signals, it used to diagnosis of muscle activity, brain diseases, heart diseases, and more related to the body (De Luca, 1997; Shahid, Walker, Lyons, Byrne, & Nene, 2005). The EMG signal is one of the main types of biomedical signals. It is controlled by the nervous system and depends on the physiography of muscles, which help to control those muscles. The EMG signal has been widely studied, used and applied. It is widely used in electrophysiological research. EMG as a bio-signal is used to record muscle activities, amplitude, phase, features and more. Usually, the EMG data generated during muscles activities or relaxation. Mainly, the EMG used to detect and analyze the myoelectric activities of muscles (Khairul Anam, Rosyadi, Sujanarko, & Al-Jumaily, 2017; De Luca, 1997). There are many types of EMG signal, including sEMG, kinesiology electromyography (kEMG) and neurological electromyography (nEMG). While sEMG is an essential tool for clinical analysis, kEMG is used to study muscle movements, and nEMG is used to study the neuromuscular system and more. sEMG is generated using a model constructed to closely resemble the physiology and morphology of skeletal muscle, combined with line source models of commonly used electrodes and positioned in a way that is consistent with clinical studies (Hamilton-Wright, Stashuk, Power, amp, & Energy Society General, 2005). Next, we explain the EMG background, definition and process in details.

2.4.1 EMG Signal Background

In the last few decades, the EMG signal has had a respectable volume of efforts to study it for different aims. In 1666, Francesco Radi was the first to begin investigating the EMG deeply. Once he had assembled good documentation, efforts to study the EMG signal increased (Kleissen et al., 1998).

In 1792, Galvani's publication 'De Viribus Electricitatis in Motu Muscular Commentarius' showed that muscle contractions could cause electricity (Galvani, 1792).

Other studies indicated that the EMG could generate electricity and that this electricity could initiate muscle contractions (Kleissen et al., 1998). From 1890 to the 1950s, researchers discovered that 'it was possible to record electrical activities during a voluntary muscle contraction' (Cram, 2005).

Following this, researchers started to study the EMG signal more widely in an effort to better understand it. Some scientist researchers started to develop clinical methods, such as scanning different types of muscles using an EMG sensing device (Cram, 2005).

Few years later, researchers have provided a respectable understanding of sEMG. It is increasingly used for recording the information from muscles, where intramuscular electrodes are used for deep muscles only. It provides easy access to physiological processes that cause the muscle to generate forces and produce movements. There are many applications for using EMG signals. They can be applied in human-computer interaction systems and used for neurological and neuromuscular problems, biomechanics, motor control, neuromuscular physiology, movement disorders, postural control and physical therapy (Md R. Ahsan, Ibrahimy, & Khalifa, 2011). Next, we define the EMG and explain the EMG signal in detail, including how to process it and how to detect its information.

2.4.2 EMG Definition and Characteristics

2.4.2.1 EMG Definition

EMG is a signal for evaluating and recording muscle activation signals. It has the information about muscles achievements'. It is measured using an instrument called an electromyogram (Harivardhagini, 2021). The EMG signal is useful for both clinical application and the human-machine interface. It is applied in many areas of muscle research and patient care, such as human movement sciences, rehabilitation, ergonomics, sports and clinical decision-making (Hewson, Hogrel, Langeron, & Duchêne, 2003; Staudenmann, Roeleveld, Stegeman, & van Dieen, 2010).

EMG is commonly used in the study of muscle activity since it provides the only non-invasive index of the level of muscle activation (Y. Fang, Zhu, & Liu, 2013; Hewson et al., 2003; Lapatki, Van Dijk, Jonas, Zwarts, & Stegeman, 2004).

EMG detects the electrical potential generated by muscle cells when these cells contract and rest. In our research, we collected information from the upper limb muscles by connecting an electrode to the surface of the following muscles: deltoid anterior, pectoralis major, biceps brachii, brachialis, triceps brachii, latissimus dorsi, teres major,

infraspinatus and supraspinatus, as shown in Figure 2.2. These muscles gave important information, such as muscle force, muscle impedance, and human hand and arm motion (Du et al., 2010). This process of placing the electrodes on the muscle surface is called sEMG, which is mainly used to analyse the myoelectric activity of each muscle (Onishi et al., 2000).

Figure 2.6 depicts the electrode connected to the muscle's surface to collect the information.

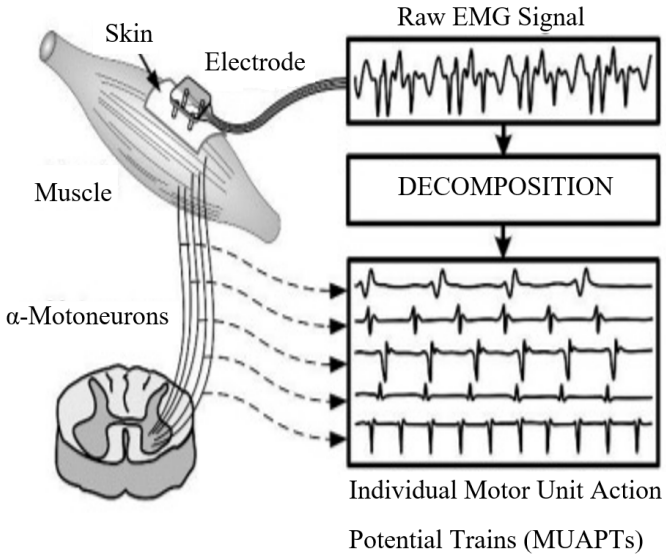


Figure 2.7: EMG Signal Collecting Process (Stratton, 2015)

The information extracted from the EMG (usually using two electrodes connected to the muscle's surface that record the EMG data to detect activity at a single MU) is often considered a global measure of MU activity (Farina et al., 2004). Moreover, the extracted information from the EMG is different each time (Christie, Greig Inglis, Kamen, & Gabriel, 2009). Next, we explain EMG characteristics.

2.4.2.2 EMG Signal Characteristics

The EMG signal is random. The amplitude range can be between 0 mV to 10 mV (peak to peak) or 0 mV to 1.5 mV (root mean square [RMS]).

Figure 2.7 shows the amplitude. It is defined as the time-varying standard deviation of the EMG (De Luca, 1997). The frequency range is between 0 and 500 Hz, and the noise energy range is between 50 and 150 Hz (Clancy, Morin, & Merletti, 2002; Uchiyama, Lee, Kazama, Minagawa, & Tsurumaki, 2015).

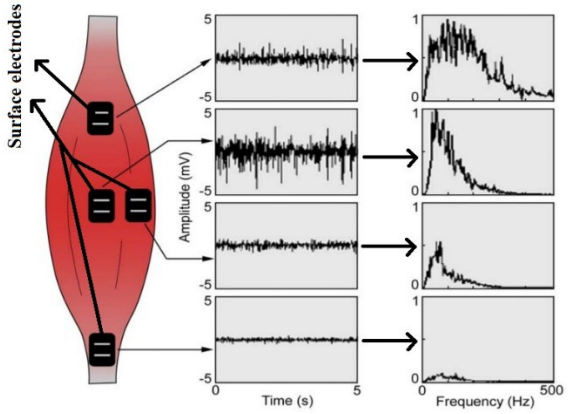


Figure 2.8: The EMG Signal Time and Frequency Spectrum (De Luca, 1997)

EMG signals make noise while travelling through different tissues. This noise is an electrical signal that will affect the EMG signals. It is inherent to electronics equipment and cannot be eliminated, but high-quality electronic components can reduce it. Other noises that may affect the EMG signal are motion artefacts. These could be caused by the electrode interface or the cable and can lead to irregularities in the data. This noise can be reduced by proper electronic circuitry design and setup. The ambient noise and inherent instability of the signal can also affect the EMG signal.

A high-quality EMG signal can be achieved by gathering the highest amount of quality information from the EMG signal as possible in the signal-to-noise ratio. At the same time, the distortion of the EMG signal must be as minimal as possible, which can be done by applying the necessary filtration. The next section explains the EMG signal collection technique.

2.4.3 EMG Signal Detection

Generally, the EMG signal is an electrical signal generated by the motor neuron and recorded by the electrodes. It is useful because it offers insight into muscle activity and, therefore, into muscle force production during functional movements (Staudenmann et al.). The human skeletal, muscular system is mainly responsible for providing the required forces to perform various actions to increase the force level (Md R. Ahsan et al., 2011; Md Rezwanul Ahsan, Ibrahimy, Khalifa, & th International Conference on, 2011; Subasi, 2013).

EMG recording can be performed in two different ways: invasively (wires or needles inserted directly into the muscle) (Merletti & Di Torino, 1999; Rossetti, Kateb, & Cicoira, 2021) or non-invasively (recording electrodes that are placed on the skin surface over the investigated muscle) (F. Hug & Dorel, 2009). The surface electrode records the electrical activity directly underneath the electrode placed on the skin over the muscle while the muscular needle records the EMG signal from the inner muscle tissue (Hewson et al., 2003; Stratton, 2015). Hargrove (Hargrove, Englehart, & Hudgins, 2007) shows that collecting the EMG data from the skin surface and collecting it from the inner muscle tissue both take around the same time, but with wire electrodes, the volume of muscle from which the signal is recorded is relatively small (a few cubic millimetres) and may not represent the total muscle mass involved in the exercise (F. Hug & Dorel). Conversely, surface EMG provides information from a large mass of muscle tissue and thus is more directly correlated to the mechanical outcome. However, various factors can influence the signal and must be taken into consideration for proper interpretation (F. Hug & Dorel). Generally, a basic assumption for sEMG is that the recorded potentials originate from the muscle directly under the electrodes (van Vugt & van Dijk). The non-physiological factor can influence the signal in the form of crosstalk and motion artefacts. Even if motion artefacts can be eliminated by carefully fixing all the cables and by using pre-amplifiers close to the electrode, avoiding crosstalk is more difficult. This thesis considers the sEMG signal.

The sEMG signal represents the sum of the electrical signals made by individual MUAPs as detected by surface electrodes (Hewson et al., 2003; Stratton, 2015). Accordingly, sEMG for the non-invasive assessment of muscles (SENIAM) provides recommendations for the correct electrode placement over the targeted muscle (Hermens et al., 1999). SENIAM contributed to the development of hardware for signal detection and software for how to extract the information (Hermens et al., 1999; F. Hug & Dorel, 2009; Merletti & Farina, 2008). Figure 2.6 and Figure 2.8 show the position of the surface electrode that connects to the muscles to collect the data.

While collected the data, some noises may occur, that could be caused by the electrode–skin interface. This noise consisted of voltage and current noise. Some noise will always be removed from the signal using a filter, such as a high-pass filter (15–28 Hz) (De Luca, Donald Gilmore, Kuznetsov, & Roy, 2010). To detect a good EMG signal with less noise, the signal is segmented to generate possible MUAP waveforms. The threshold (T_{Thr}) eliminates the areas of low activity and identifies the peaks of the signal, which depends

on the maximum discrete value of the EMG signal and the mean absolute value (MAV) ($1/L\ \sum_{i=1}^{L}|X_i|$) of the EMG signal, where X_i are the discrete values of the EMG signal and L the number of samples.

The following equation was used to calculate the threshold (T):

$$IF\ max\{X_i\} > \frac{30}{L}\sum_{i=1}^{L}|X_i|,\ \ Then\ T = \frac{5}{L}\sum_{i=1}^{L}|X_i| \quad ,else\ T = max\frac{\{X_i\}}{5} \qquad \textbf{2.1}$$

The T calculated for the EMG segmentation was introduced to provide a wide range of amplitude variations in the recorded signal (Christodoulou & Pattichis, 1999; Katsis, Goletsis, Likas, Fotiadis, & Sarmas, 2006). Next, we explain EMG processing in more detail.

2.4.4 EMG Processing

In our research, we connected electrodes to the top of the upper limb muscle surface, as shown in Figure 2.8.

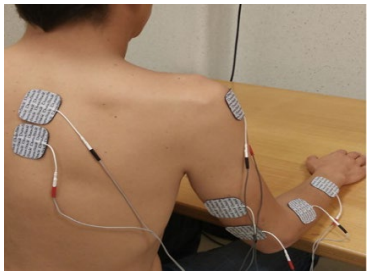


Figure 2.9: Electrode Connected Points

After connecting the electrodes to the electromyogram, we started collecting the data. To keep the muscle producing a good EMG signal, two techniques can control muscle power higher levels:

1. The number of active MUs in one muscle can be changed.
2. Each active MU induces MUAPs, which causes the motor unit to fire. The electrodes pick up MUAPs from more than one active MU. The sum of MUAPs on the electrode is the EMG signal, which is induced by the individual units. Any increase in the MU's activity will cause a greater sum and stronger EMG signal.
3. The firing frequency of each active MU can be changed.
4. If the MUAPs are generated with an increasing force level per unit of time, it will cause a greater sum and stronger EMG signal. The EMG signal is a good indicator of the level of muscle activation and can help control muscle movements (Kleissen et al., 1998).

In the following subsections, we discuss the EMG process in detail.

2.4.4.1 Motor Unit (MU) Recruitment And Firing Behaviour

To obtain the required muscle force, the MU recruitment and firing coding rate vary across different muscle types. The MU recruitment and firing behaviour in the muscle has to be known in a model for the interference pattern; this model is known as Henneman's size principle (D. F. Stegeman, Blok, Hermens, & Roeleveld, 2000). Usually, a larger MU value means that stronger muscle is required to do the following:

1. understand the data and process it
2. specify and analyse the hand movement's speed and direction.

For example: we connected the surface electrode to stronger upper limb muscles depending on the specific tasks those muscles would be attempted to carry out so that we could analyse the hand movement. Generally, this process is a challenge for sEMG analysis because it estimates the available number of MU to understand and analyse the rehabilitation movement (Roeleveld, Stegeman, Vingerhoets, & Oosterom, 1997; D. F. Stegeman et al., 2000). Every change in the MU firing frequency will affect mechanical output for the muscles. MU firing processes can be described as follows (D. F. Stegeman et al., 2000):

1. inter-pulse interval (IPI) statistics distribution of a single MU
2. IPI statistics distribution between different active MUs
3. synchronisation of the firing moments of the different MUs.

2.4.4.1.1 Single MU Inter-Pulse Interval (IPI)

To describe the MU firing process in terms of successive IPI is to look at each MU as independent sample of a variable value. Person and Kudina (Person & Kudina, 1972) and Kranz and Baumgartner (Kranz & Baumgartner, 1974) found that the IPI histograms were a little skewed at a low firing rate and became identical at higher firing rates.

2.4.4.1.2 IPI Across Different MUs

The MU firing rate will increase with increasing force. The IPI within a single MUAP train varies. Usually, MUs at a higher force level present a higher initial firing rate. Usually, firing at a lower rate requires MUs at the same force level (D. F. Stegeman et al., 2000).

2.4.4.1.3 MU Synchronisation

The synchronisation of the firing between different MUs can be performed by generating the firing instants of a first train and then linking the firing instants of a consecutive train

to them. Some researchers have used a Gaussian distribution to model firing synchronicity to decrease the median frequency considerably depending on the number of MUs that have synchronised activity and the extent to which they are synchronised (D. F. Stegeman et al., 2000).

2.4.4.2 EMG Composition

A MU is an alpha motor neuron and controls the fibres. MUAP is the sum of the muscle fibre action potential (MFAP). During MUAP detection, the waveform travels along with a number of fibres inside the muscles of the MU, which are known as the $MFAP_i(t)$. The MUAP waveform shape differs because of the variation in the delay of the fibre potential of the surface electrode connected to the muscle fibres. The MUs generate MUAPs by spending time in inter-discharge intervals. A sequence of MUAP is called the motor unit action potential train (MUAPT). The large MU will produce large MUAPs (Stashuk, 2001). The diameter of the fibre will determine the $MFAP_i(t)$ benefit. A larger fibre diameter size means a larger MFAP and more benefit. The MFAP location is relative to the surface electrode placement (Stashuk, 2001). Suppose $MUAP_j(t)$ is the potential detected when the j_{th} MU fires.

$$MUAP_j(t) = \sum_{i=1}^{N_j} MFAP_i(t - \tau_i)s_i \qquad \textbf{2.2}$$

$$where: \begin{cases} N_j: number\ of\ MU\ fibers \\ j: the\ size\ of\ MU \\ \tau_i: the\ temporal\ offset\ of\ MFAP_i(t) \\ i_{th}: the\ number\ of\ fibers\ on\ the\ neuromuscular\ junction's location\ duration\ velocity \\ s_i: the\ binary\ variable\ that\ represent\ neuromuscular\ junction\ function, 1\ if\ fiber\ fires\ and\ 0\ if\ fiber\ blocked \end{cases}$$

$$MUAPT_j(t) = \sum_{k=1}^{M_j} MUAP_{jk}(t - \delta_{jk}) \qquad \textbf{2.3}$$

$$where: \begin{cases} MUAPT_j(t): is\ MUAP\ of\ j_{th}\ MU \\ MUAP_{jk}(t): is\ the\ MUAP\ generated\ during\ k_{th} firing\ of\ j_{th} MU, it\ is\ unique\ due\ to\ variety\ of\ the\ MUAP\ shape \\ M_j: the\ number\ of\ times \\ j_{th}: the\ MU\ fires \\ \delta_{jk}: the\ k_{th} firing\ time\ of\ the\ j_{th}\ MU \end{cases}$$

Generally, the number of fibres and the diameter of the closest few fibres within the MU can determine the MUAP size. The sum of all potential contributions from the muscle fibre activity is the EMG signal.

$$EMG(t) = \sum_{j=1}^{N_m} MUAPT_i(t) + n(t), \qquad \textbf{2.4}$$

$$where: \begin{cases} MUAPT_j(t)\ the\ j_{th} MUAPT \\ N_m\ is\ the\ number\ of\ active\ MU \\ n(t) is\ the\ background\ instrumentation\ noise \end{cases}$$

As shown in Equation (2.4), the EMG signal is composed from all active potential fibres in the muscle. The EMG data differ each time because of the differences in signal movements (Christie et al., 2009). The distance between the muscle fibres and the surface electrode will cause a radio signal separation and a lower level of signal detection with a high level of noise. To reduce the noise and obtain high amplitude and current, good EMG signal detection is required. It is important to select the right location for the surface electrode. Wire surface electrodes are suitable for collecting the EMG data to reduce the difference in information each time (Christodoulou & Pattichis, 1999; Kaplanis, Pattichis, Hadjileontiadis, Panas, & Proceedings of 10th Mediterranean Electrotechnical Conference, 2000; Onishi et al., 2000; Õunpuu, DeLuca, Bell, & Davis, 1997).

2.4.4.3 EMG Decomposition

EMG signal decomposition (as shown in Figure 2.9) is the process of resolving a composite EMG signal into its constituent MUAPs.

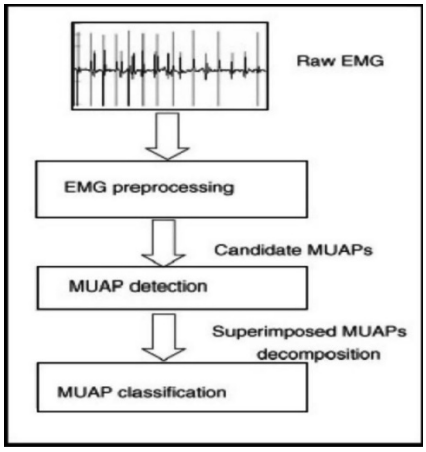


Figure 2.10: EMG Decomposition

The main purpose of decomposing the EMG is to assist with muscle diagnosis and nerve disorders and analyse the neuromuscular system, and it could be considered a classification problem (Katsis et al., 2006; Rasheed, Stashuk, & Kamel, 2007). Decomposing EMG allows MUAPs to be collected over a broad range of force levels given the size principle of MU recruitment (Boe, Stashuk, Brown, & Doherty, 2005). There are four main steps to EMG signal decomposition:

1. signal processing
2. MUAP detection
3. clustering
4. MUAP classification.

The following subsections describe each step.

2.4.4.3.1 Signal Processing, MUAP Detecting and Clustering

Good MUAP values in the filtered signal are detected using the threshold-crossing technique. This is the basic step in EMG decomposition and gives important information about the neuromuscular system through MUAP firing time. Each MUAP is represented using 2.56 ms of filtered data samples cantered in its peak value (Andrade, Kyberd, & Nasuto, 2008; H. Parsaei & Stashuk, 2013).

In the cluster of MUAP, the average and the template shape are automatically detectable through the code running (Jain & Murty, 1999; Katsis, Fotiadis, Likas, & Sarmas, 2003; Katsis et al., 2006). The cluster obtains the essential information required for the classifier to detect the MUAP in a specific portion of the EMG signal. This information is important for detecting the MUAP in the MUAPT (H. Parsaei & Stashuk, 2013).

SVM is the common classifier. It is proposed to estimate the validity of the extracted MUAPT using either the extracted MU firing pattern, MUAPT shape features or both (Hossein Parsaei & Stashuk, 2012). In each event, the decomposition process works sequentially, compared to a time-dependent library of the distinct action potential templates. The decomposition process will involve one of the following scenarios (Erim, Winsean, Power, amp, & Energy Society General, 2008):

1. If the event is similar to any library value of the templates, it is assigned to the cluster of action potentials with the same template.
2. If there is no similarity, another resolution algorithm is employed. In this case, the faster position is employed to determine if the current event can be assigned as a combination with any set of subsets of the library template.
3. The event is assigned as a new first member of a new cluster if no sufficient match could be found by the previous combination.
4. If the event does not include a certain number of APs, it is considered unstable and the events belonging to these clusters are marked as unassigned.

After the event is assigned to a library template, the decomposition process algorithm starts to merge any two similar clusters by taking into account the firing statistic observed.

2.4.4.3.2 Motor Unit Action Potential (MUAP) Classification

The classification task of EMG signal decomposition is not easy. Pattern recognition in the classification decomposition process is difficult; the process is repeated a number of times in uncertainty and contains high-dimensional patterns, large numbers of classes and noisy inputs, but it can be solved efficiently using a combination of multiple classifiers

(Katsis et al., 2003; Katsis et al., 2006; Rasheed, Stashuk, & Kamel, 2008). The detected MUAPs are appointed to MUAPTs using a supervised classifier. The main purpose here is to specify each MUAP to the MUAPT for which the MUAP's time of occurrence and shape are more consistent with the estimate for the MU firing times and MUAP shapes of the selected MUAPT, in order than for other MUAPTs (Erim et al., 2008; H. Parsaei & Stashuk, 2013).

2.5 EMG Signal Acquiring Limitation for EMG Signal Processing

EMG signal is an important source to record useful information from the muscles about the muscle's activities. There are still limitations and difficulties in recording the suitable EMG signal from the muscles and sometimes there is a shortage of information that collected from the patients for the control of multiple functions. Sometimes the patient unable to produce EMG signal or have difficulty repeated the movement (Enders & Nigg, 2016).

The other limitation that could happened during collecting the EMG data is shifting the electrode locations or changing skin conditions such as the skin getting sweat that can cause unreliable in the information. On the other hand, the electrodes shape, dimension, material, and the electrode location on the skin surface could affect the EMG signal. The major limitation of surface EMG is the EMG decomposition. The EMG decomposition output is sensitive because it is related to the muscle investigated, the properties volume of the muscles and the muscles contraction intensity (Del Vecchio et al., 2020).

2.6 Related Works Advantages and Limitations of EMG Signal Processing

Various research groups used different technique to analyse the upper limb movement based on pattern recognition method. Different studies and works used different method to filter and classify the EMG data. Kim in his EMG analysis works, used the notch and the band pass filter to filter the data and used convolutional neural network (CNN) to classify and perform the figures movement directions to improve the EMG simultaneous (Kim, Stapornchaisit, Miyakoshi, Yoshimura, & Koike, 2020). Zia on his work, demonstrate the performance of myoelectric control for the upper limb using the LDA classification to improve the performance and to increase robustness over time (Zia ur Rehman et al., 2018). (Mendez et al., 2017), achieved accuracy of 91.67± 6.89 by attempting to classify different upper limb movement using LDA classification. (Wahid, Tafreshi, Al-Sowaidi, & Langari, 2018) achieved 94.45 ± 5.20 accuracy by classifying three upper limb movements and achieved 97.6 ± 1.99 accuracy. Chen (H. Chen, Zhang,

Li, Fang, & Liu, 2020) extracted the EMG features and then find the hand motion classification using the SVM classifier and he got 93.95 accuracy (Yinfeng Fang, Yang, Zhou, & Ju, 2022). Other related work that extracted the features and the useful information from the EMG signal by analysing and recognise the law frequency in EMG signal, using wavelet packet transform (WPT) (Shanmuganathan, Yesudhas, Khan, Khari, & Gandomi, 2020). For the feature reduction most of studies use it to evaluate the most informative features that evaluate the optimal features from the original feature set. (Too, Abdullah, Mohd Saad, Mohd Ali, & Tee, 2018) proposed competitive binary grey wolf optimizer (CBGWO) for feature reduction and he obtain an accuracy of 92.69. Table 2. 1 represent the advantages and limitations for pattern recognition stages.

Table 2. 1: The Advantages and Limitations for Different Stages of Pattern Recognition

Methodology	Advantages	limitations
Using the Band Pass filter (Kim et al., 2020)	- Minimise the noise signal from the original signal	- It might remove the original signal from the EMG
Windowing	- The EMG signal can be windowing using two different procedures: Overlapped or non-overlapped. - The overlapped windowing segments, process idle time to produce more classified output (Dehghani, Sarbishei, Glatard, & Shihab, 2019).	- The limitation of windowing is when calculating the average of more than one window. The output average will distorted the important information in the EMG signal (Ullah, Ali, Khan, Khan, & Faizullah, 2020).
Feature Extraction	- It passes the signal through several levels to determine the signal quality.	- It could cause loss of information when the data has high frequency (Shanmuganathan et al., 2020)
Time Domain features (TD)	- It can be used in real time applications. - It is required low computational complexity. - It is easy implementation. - It has good calculation and performance in low noise environment. (Al-	- Working with non stationary signals like sEMG signals. -

	Taee & Al-Jumaily, 2018)	
Time frequency domain features (TFD)	- It is more accurate. - It can control the energy in EMG signal in time and frequency domain. ex: wavelet transform (WT), WPT, short time Fourier transform (STFT)	- The time frequency domain transformation needs a lot of computations.
Frequency domain feature (FD)	- It has frequently been used in fatigue analysis. - The FD features are exacted from Power spectral density (PSD). - It can decode higher capacity tags.	- Moderate to resistant to interface. - Low in Signal processing complexity (Aliasgari, Forouzandeh, & Karmakar, 2020).
Feature reduction	- Remove redundant and not important information and reduce the unnecessary complexity without changing the main features (Too et al., 2018).	- The feature reduction results are assumed to be large feature sets. The feature dimension was D; is the dimension of features. The feature combination is 2^D. (Too et al., 2018)
Classification	- Classification commonly used to diagnose stages that is important for reading the features in order to process the input signal. - It used a different classification method that statistically important to diagnose the input signal.	- The classification needs a good classifier that can train, test, process and diagnose the EMG signal. (Inam et al., 2021)
LDA classifier	- Lower classification error and good classification performance (Sifaou, Kammoun, & Alouini, 2018).	- The classification required to classify the data from the training set. (Joshi, Prasad, Mewada, & Saurabh, 2020)
SVM classifier	- Optimised the variable data and does not get trapped in a local optima (Gu et al., 2018).	- Finding the right way to optimise the parameters efficiently and effectively (J. Wang & Shi, 2013)

2.7 Summary

Generally, to record the information from any physiological processes, the electromyogram is used, which is the device for recording the EMG signal from the muscle. The EMG signal is also used in many types of research laboratories, including those for biomechanics, motor control, neuromuscular physiology, movement disorders, postural control and physical therapy. It provides information about the capabilities of the neuro system and muscles. Muscle activity and relaxation are controlled by the nervous system and depend on muscles' anatomical and psychological properties.

EMG as a function of time can describe muscle amplitude, frequency and phase. It is random, continuous and nonlinear. These properties reveal that the EMG is to be processed in order to get a good model for the researcher's target. However, limitations still exist in terms of detecting and characterising the EMG signal because of EMG's derivation of normality. Generally, we used the EMG signal to give us indications about muscle performance and measure that performance, to review muscle activity, and to monitor rehabilitation progress. In subsequent chapters, we explain how we filtered this signal, processed it and used the EMG data to recognise the movement. We detail the methodology used to develop and improve the EMG detection technique to reduce noise and acquire accurate EMG signals. All of this is important to analysing movement rehabilitation, predicting recovery and reducing treatment costs.

Chapter 3: EMG and Synergy EMG Signal for Upper Limbs

This chapter presents basic information about the EMG pattern-recognition and non–pattern recognition techniques, gives examples of the upper limb rehabilitation device base control source, and details the robot used to collect the data for this study. Furthermore, to increase our understanding of CNS mechanisms for movement and to give rise to exploring the potential of muscle synergies, we studied the complex interaction between neural circuits and biomechanics; subsequent chapters discuss this in detail. That followed by highlighted in details the new concept of a group of muscles, the synergy muscle that we used in our work to develop that of previous researchers.

3.1 EMG Control System

An easy way to extract information from the less activity muscle of motor control is to generate the electrical signal from the activated EMG (F. Hug & Dorel, 2009). In fact, sEMG provides information from a large mass of muscle tissue (J. Liu, Li, Li, & Zhou, 2014). The EMG signal can be used in the control system by EMG pattern recognition, as illustrated in Figure 3.1, or EMG non-pattern recognition, as illustrated in Figure 3. 2. EMG pattern recognition can recognise and classify hand movements, but EMG non-pattern recognition does not classify hand movements (Gopura, Bandara, Gunasekara, & Jayawardane, 2013), so it may use the EMG signal as a threshold control system.

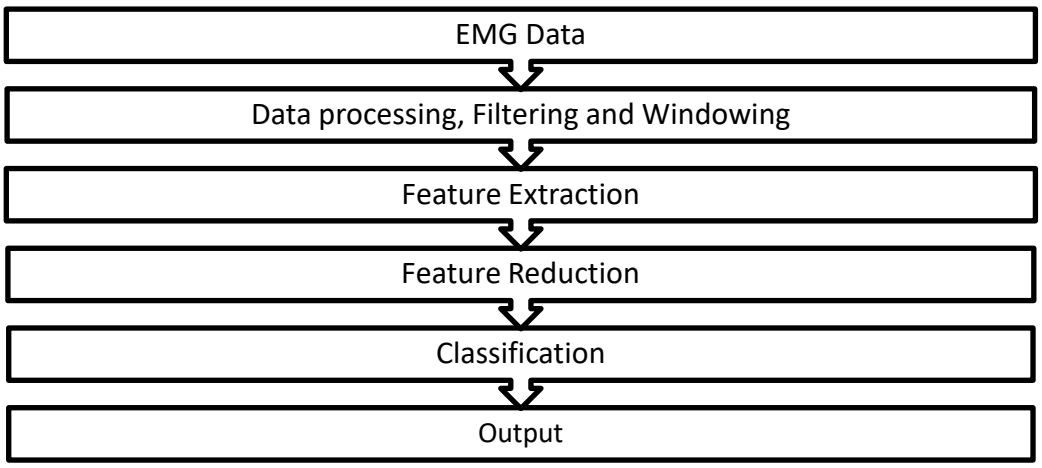


Figure 3.1: Pattern-Recognition Method for Classifying Hand Movements

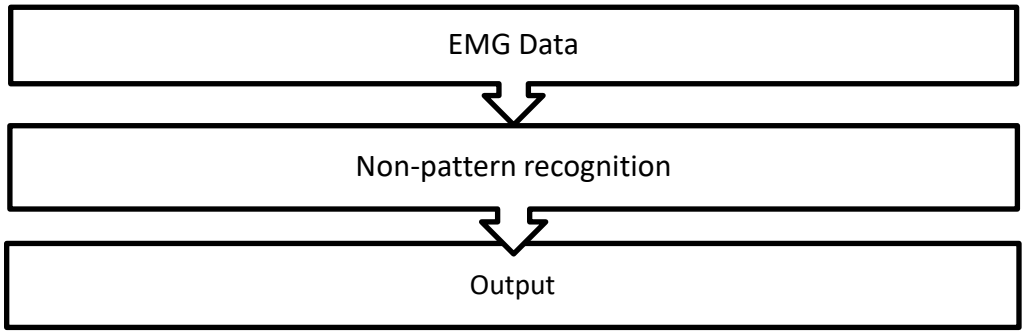


Figure 3. 2: Non–Pattern Recognition Method

3.1.1 Myoelectric Pattern Recognition (MPR)

Myoelectric pattern recognition (MPR) with a large number of EMG channels is one approach for assessing motor control information from the recorded muscles. It is aiming to classify the collected data. Pattern recognition is one integral part in most machine learning system that created to make decision. Pattern recognition is very important method which help to drive the improvement of various applications in different fields, and it form the basis of most applications. Pattern recognition method can be used and applied in machine intelligent artificial applications, such as: power electronics, orthognathic surgery, antimicrobial resistance, statistical pattern recognition, Neural networks, applications of Support Vector Machine (SVM), Data clustering. The pattern recognition technology is applicable in different area such as: Artificial neural network, speech recognition algorithms, fuel smart speakers, self-driving cars, and more (Haenlein & Kaplan, 2019; Wu & Feng, 2018).

There are five major steps for myoelectric pattern recognition:

1. Collecting the data using the electromyogram device
2. Data processing, Filtering, and windowing
3. Feature Extraction
4. Feature Reduction
5. Classification

This part of this thesis will address and clarify the myoelectric pattern recognition step by step. They described in detail in the following subsections.

3.1.1.1 Collecting the Data Using the Electromyogram

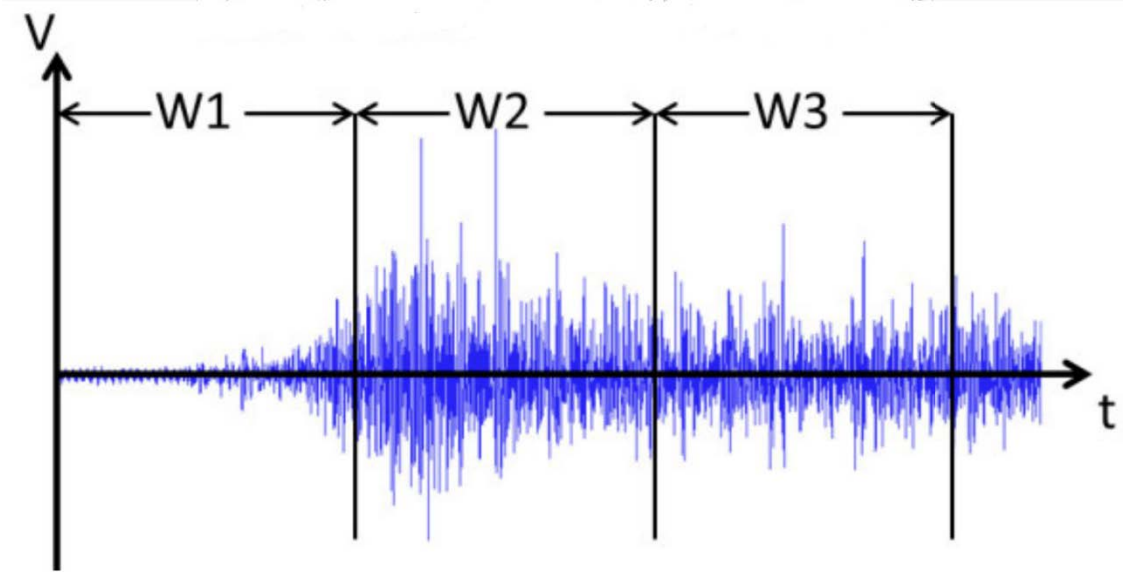
An easy way to obtain muscular information is via the electromyogram; which is an integration of action potentials spreading through muscular fibres under an electrode. This signal is called EMG voltage (V_{EMG}). During electrical stimulation, the V_{EMG} signal takes on a particular shape known as the M wave. This shape varies over the stimulation and

can estimate muscular fatigue. In Yochum's study (Yochum, Bakir, Lepers, & Binczak, 2013), he introduced a system that can perform an electrically evoked stimulation and record EMG signals at the same time (Yochum et al., 2013). Chapter 2 discussed the EMG data collection process; the following chapters detail our technique and the robot used to collect the data.

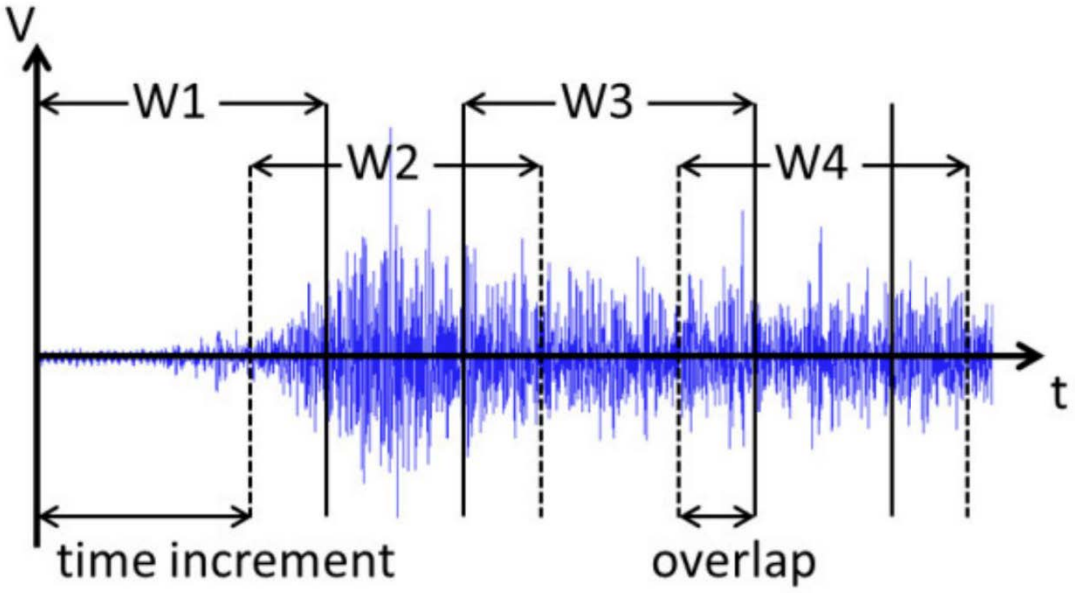
3.1.1.2 Data Filtering and Windowing

After collecting the EMG signal using the electromyogram, we used the filter to minimise and distract as much as possible noise signal from the original signal. The filters to remove the noise could be the band-pass filter and low-pass filter, power noise filter, and notch filter. The band-pass filter allows signals between two specific frequencies to pass but discriminates against signals at other frequencies, which could be 20–500 Hz or 50–500 Hz (Khairul Anam & Al-Jumaily, 2018; Kieliba et al., 2018; H. Parsaei & Stashuk, 2013). Conversely, the low-pass filter passes signals with a frequency lower than the cut-off frequency value and attenuates signals with frequencies higher than the cut-off frequency (0.5 Hz, 4 Hz, 10 Hz, 20 Hz cut-offs) (Kieliba et al., 2018; H. Parsaei & Stashuk, 2013), the power noise filter signal between (50 Hz and 60 Hz), and the notch filter of (50 Hz to 60 Hz) (Simao, Mendes, Gibaru, & Neto, 2019).

In the other hand, the windowing procedure. Which is procedure to extract the essential features information from the EMG data. This features help to evaluate the performance of the pattern recognition system (Al Taee, Khushaba, Al-Timemy, & Al-Jumaily, 2020). The EMG can be windowing into two different types, as illustrated in Figure 3. 3. Firstly, Disjoint (non-overlapped). Which mean adjust the window size to simplify the EMG process. Secondly, Overlapped. Which mean adjust the window size as well as the window increment (Cao et al., 2020). These two procedures: overlapped segments and non-overlapped segments be the same value in one case, which is, when the window increment and the window size the same.



(A) Disjoint (non-overlapped).



(B) Overlapped

Figure 3. 3: Myoelectric Signal Time Windowing Procedure. (A) Disjoint (non-overlapped). (B) Overlapping. (Ortiz-Catalan, Brånemark, & Håkansson, 2013)

3.1.1.3 Feature Extraction

Feature extraction is a very important step of the EMG data process: it aims to extract the best EMG information data for neuromuscular system control strategies. It is a vital step in successfully classifying the EMG signal (Alkan & Gunay, 2012; Andrade et al., 2007; Angkoon Phinyomark, Phukpattaranont, & Limsakul, 2012). Generally, EMG feature extraction is divided into three main groups: TD, frequency domain (FD) and time-frequency or time–scale representation (A. Phinyomark, Nuidod, Phukpattaranont, & Limsakul, 2012). Chapter 4 addresses these in detail.

3.1.1.4 Feature Reduction

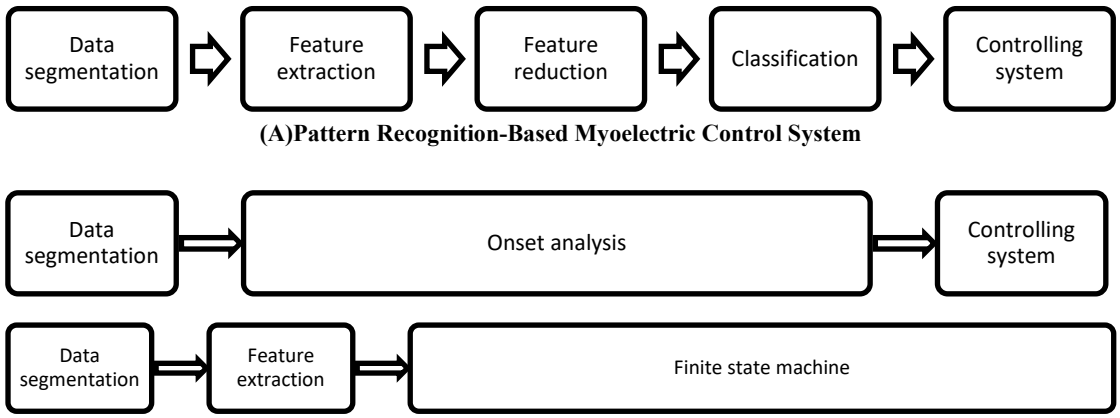
After extracted the features in the previous step, the features assumed to be very large feature sets. These features must be stay under control all the time without any damages or any changes to the features meanings. To dominate the extracted features, the feature reduction should be used. Feature reduction aim to improve performance of the classifier. The output from the feature reduction is the input for the classification training and testing. Generally, Feature reduction divided to two dimensionality reductions method: firstly, Feature Selection (FS), such as: sequential forward selection (SFS), Sequential Backward Selection (SBS), Genetic algorithms, and Particle Swarm Optimisation (PSO) (Takruri, Mahmoud, & Al-Jumaily, 2019). Secondly, Feature Projection (FP) (Mursalin, Islam, Noman, & Al-Jumaily, 2019). Unsupervised methods such as: Linear discriminant analysis (LDA) and principal component analysis (PCA) with feature projection, can be used to extract features from huge data sample. Commonly, feature reduction choose the best sub-set elements from the original features. (Phukpattaranont, Thongpanja, Anam, Al-Jumaily, & Limsakul, 2018).

3.1.1.5 Classification

The classification task of the EMG signal is a difficult pattern-recognition problem—it abounds in uncertainty and involves high-dimensional patterns, large numbers of classes, and noisy inputs, but it can solve problems efficiently using a combination of multiple classifiers (Katsis et al., 2003; Katsis et al., 2006; Rasheed et al., 2008). The classification step is very important to improving the myoelectric control system performance (Chan, Yong-Sheng, Lam, Yuan-Ting, & Parker, 2000). Chapter 4 addresses this in detail.

3.1.2 Myoelectric non-Pattern Recognition

As shown in Figure 3.2, the EMG based on non-pattern recognition could not classify any rehabilitation movement. Examples of non-pattern recognition EMG control systems are finite state machines (FSM), onset analysis, proportional control, simultaneous propositional control and threshold control (Khairul Anam et al., 2017; Asghari Oskoei & Hu, 2007). In Figure 3.3, the first diagram shows the pattern recognition–based EMG control system, and the second diagram shows the non-pattern recognition–based EMG control system.



(A)Pattern Recognition-Based Myoelectric Control System

(B) Non-Pattern Recognition-Based Myoelectric Control System

Figure 3.4 (A): Pattern Recognition (B) Non-Pattern Recognition (Asghari Oskoei & Hu, 2007)

As depicted in Figure 3.3, the pattern recognition–based EMG control has a classification process, while the non-pattern recognition–based EMG control system does not—this is why it cannot be used to classify rehabilitation movement. The following subsections briefly explain the non-pattern recognition examples of FSM, onset analysis, proportional control, simultaneous propositional control and threshold control (Khairul Anam et al., 2017; Asghari Oskoei & Hu, 2007).

3.1.2.1 Finite State Machine (FSM)

As we see in Figure 3.3, in the non-pattern recognition-based myoelectric control system, FSM is used to perform rehabilitation devices. It is composed of some states. Switching between these states can be prompted by a timer or be based on the EMG contraction level (Khairul Anam et al., 2017).

3.1.2.2 Onset Analysis

Onset non-pattern EMG control analysis is based on ON/OFF activity detection rather than slow muscle activity detection. As we continue collecting the EMG data, the onset

analysis was not affected because of an instant collecting value (Asghari Oskoei & Hu, 2007).

3.1.2.3 Proportional Control

Proportion myoelectric control gives a more advanced control signal. It proportionates to the contraction level of the EMG control signal for the upper limb rehabilitation device. It estimates the specific strength parameter of the muscle control, such as angle, speed or force (Khairul Anam et al., 2017; Asghari Oskoei & Hu, 2007).

3.1.2.4 Simultaneous and Propositional Control

Simultaneous and propositional myoelectric control is a more advanced schematic than proportional myoelectric control. It controls the joints simultaneously and propositionally from the collected EMG signal. It estimates all the physical parameters that are recorded from the collected EMG data (Asghari Oskoei & Hu, 2007).

3.1.2.5 Threshold Control

Threshold myoelectric control is a control source that activates or deactivates the action used from the contraction of the EMG signal level as it estimates the human rehabilitation parameters, such as the angle of the elbow or the force while collecting the data. It is known as a binary myoelectric control system because it is based on an ON/OFF state (Khairul Anam et al., 2017).

3.2 EMG Signal for Upper Limb Rehabilitation Device

MPR is an advanced technique concerned with EMG detection, processing and classification and with applying EMG signals to control human rehabilitation devices. There are many examples of robotic hand technologies, such as the robotic hand with realistic thumb pronation (Grimm, Arroyo, & Nechyba, 2002), Robonaut hand (Bridgwater et al., 2012) and Harada hand (Keymeulen & Assad, 2001) , shown in Figure 3.4, Figure 3.5 and Figure 3.6, respectively.

Figure 3.5: Realistic Thumb Robotic Hand (Grimm et al., 2002)

Figure 3.6: Robonaut Robotic Hand(Bridgwater et al., 2012)

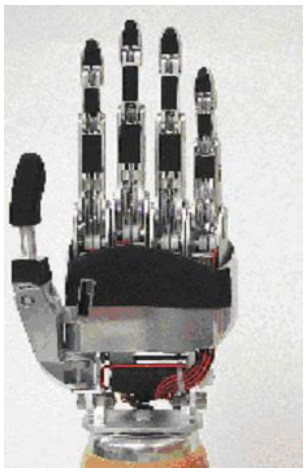


Figure 3.7: Harada Robotic Hand(Keymeulen & Assad, 2001)

In our study, we used the Delta.3 manipulandum device (Bani Musa et al., 2017) to collect the EMG data (see Appendix A), which has high performance and capability, as well as this device can help to train the body first for the motion then the body will respond with the same trained motion. Chapter 4 details the EMG signal for the upper limb and how we detected and analysed the data.

3.3 Synergy EMG

3.3.1 Background and Definition

In 1889, Hughlings Jackson recognised that the CNS control muscles in groups rather than separately. In 1966, Gelfand and Tsetlin studied a group of muscles as a particular example of structural units within a neuromotor system. In 1967, Bernstein proposed that the CNS uses a group of muscles to solve the motor redundancy problem. Others used synergies to solve this problem by decreasing the number of variables needed to manipulate the controller. The biomedical experts named muscle synergy to the group of muscles. Muscle synergy is defined as a group of muscles that are constrained to act in a concerted manner. It refers to groups of muscles within the neuromuscular system that allows the CNS to deal with muscle redundancy (F. S. Alnajjar et al., 2014; Krishnamoorthy, Latash, Scholz, & Zatsiorsky, 2003; Saltiel, Wyler-Duda, D'Avella, Tresch, & Bizzi, 2001; Y. Wang & Asaka, 2008). Activating flexible combinations in these muscle synergies allows the CNS to control muscles by producing a wide repertoire of movements. The identification of muscle synergies had strong implications for the organisation and structure of the nervous system. If synergy is activated at a given time, all muscles within that synergy are active (Li, Sheng, Liu, Zhu, & Loughlin, 2014; Ting & McKay, 2007).

In 1967, Bernstein (Ting & Macpherson, 2005) assumed that each muscle belonged to only one synergy and identified muscle synergy as a strategy for a group of output variables to simplify controlling the muscles (Shaharudin & Agrawal, 2015; Ting & Macpherson, 2005; Tytus, Fady, Shingo, & Hidenori, 2014). But a single muscle can simultaneously belong to multiple synergy sets, and it is the weighted combinations of these synergy groups that determine global muscle activation patterns (Ajiboye & Weir, 2009; Henry, Fung, & Horak, 1998). Recently, the biomedical expert extracted the synergies from the active EMG signal using the non-negative matrix factorisation (NMF) technique (Ting & Macpherson, 2005). The algorithm for this technique is that each muscle can be activated by multiple synergies simultaneously. No two muscle activation patterns are exactly the same, and significant partial correlations may exist across many muscles. Because there is no two muscles activation the same patterns, the CNS may use a limited set of control signals to activate a large number of muscles (Ting & Macpherson, 2005). When the synergy is extracted from the active EMG signal, it reflects only the simultaneous muscle activity without taking into account the neural coupling between

muscles (Ranganathan & Krishnan, 2012). If synergy is activated at a given time, all muscles within that synergy are active. Generally, muscle synergies are recommended as a solution to the degrees of freedom problem faced in motor control instead of having to control many thousands of MUs or dozens of single muscles (Tresch & Jarc, 2009).

3.3.2 Synergic Concept

Recent research suggests that the CNS controls muscles by activating flexible combinations of muscle groups to produce a wide range of movements. These muscles work together as a building block. Selecting a small number of synergies can define the activation pattern across multiple muscles that perform similar functions. Muscle synergies have significant implications for the structure of the CNS because they provide a strong mechanism for choosing a task level whereby MUs are translated into low-level muscle activation patterns (Lencioni et al., 2021; Overduin, D'Avella, Carmena, & Bizzi, 2014; Roh, Rymer, & Beer, 2015; Saltiel et al., 2001; Ting & McKay, 2007).

McKay (McKay & Ting, 2008) studied the muscles and groups of muscles in a cat. He demonstrated that a set of five functional muscle synergies were sufficient to characterise both hind limb active muscles and forces during automatic postural responses while the cat occupied different postural configurations. McKay and Ting (Lemon & Bolam, 2007; McKay & Ting, 2008) used flexible combinations of a few synergy muscles that are part of complex muscle activation patterns to produce the wide repertoire of MU behaviour. They make a case for muscle synergies being the main feature determining the organisation of the CNS motor system. Generally, the concept of ‘muscle synergies’ has been proposed as a working hypothesis to explain how the CNS coordinates the frequent degrees of freedom of the musculoskeletal system.

3.3.3 Mechanisms of Synergy

Ishida (Ishida, Karatsu, & Sakaguchi, 2007) extracted and analysed muscle synergies from recorded surface EMG signals during grasping movements of the right forearm. The EMG patterns detected during movements to achieve different goal postures and execution times were represented by combinations of the same set of synergies (Ishida et al., 2007). It is important to determine how the CNS generates an appropriate command for a motor system that has a large number of degrees of freedom for a given MU task. With respect to this problem, each motor command is represented as a combination of a few basic patterns.

Some researchers have attempted to extract basic muscle synergies patterns from EMG muscle activity patterns and have demonstrated the combinations of several synergies approximating the muscle activities while reaching or grasping movements. Other researchers have proposed that the brain calculates the motor command at a lower computational cost using parametric motor representation, which includes the synergy model. The synergy strategy model could provide an attractive and easy strategy for reducing the number of output patterns that the nervous system has to specify (François Hug, Turpin, Dorel, & Guével, 2012; Ishida et al., 2007).

Yun and Asaka (Y. Wang & Asaka, 2008) investigated multi-muscle synergies during preparation to push a load forward. They used different support conditions for these load-pushing tasks and recorded no changes to the multi-muscle synergy composition during the task. They collected EMG data from 12 muscles in eight healthy humans who performed load-pushing tasks and released load tasks. They performed these experiments to assess muscles grouping with a shift of the centre of pressure (COP) of the CNS, in particular about the way the muscles behaved (Y. Wang & Asaka, 2008).

Therefore, our first hypothesis in this thesis is that synergy can help analyse human movement. Generally, synergy muscles have been studied as building blocks that simplify the construction of MU behaviours (François Hug et al., 2012). Each synergy muscle is supposed to be controlled by a single neural command signal. It has a clinical application that could offer us a better understanding of the neural signal structure (François Hug et al., 2012). Our other hypothesis is that muscle synergy extraction is a better technique for evaluating and predicting post-stroke patient rehabilitation.

3.4 Summary

In previous studies, muscle synergy was mainly computed by averaging the data. However, these computations emphasised the similarities of the muscles involved in muscle synergy. Understanding the automatic body response is a challenging research topic that can provide insight into the properties of motor unit neural. This chapter provided information about analysing the body's voluntary and automatic responses and muscle synergy. Chapter 4 discusses and develops the methods used to compute muscle synergy that helps the CNS shape voluntary action to provide a new methodology that can improve the quality of life for those with a disability.

Chapter 4: Shape Voluntary Movement Based on EMG Using Pattern Recognition and CNMF

Human upper limb movements and movement changes are controlled by the CNS. They comprise exhibit different actions, such as lifting an object, moving hands down or up and carrying objects. The MU in all these movements and more differs depending on the movement type. One of my publications for this thesis (Bani Musa et al., 2017) illustrates how we helped the CNS shape voluntary movement by providing a new method that can improve the quality of the life of people. Generally, motor control strategies for redundant movement and the complexity of the musculoskeletal and musculature systems remain unclear and complex and that these strategies differ across different studies. As is well known, EMG-based techniques are used for assessing, analysing and recording data by detecting the EMG signals generated during the relaxation of muscles. Conversely, the Synergy EMG demonstrates how the CNS controls groups of muscles and is a more effective way of generating healthy and dynamic movement (Hardesty, Boots, Yakovenko, & Gritsenko, 2019; Shaharudin & Agrawal, 2015). Muscle synergies have been used to solve the redundancy problem. Synergy EMG views muscle synergies as a specific example of structural units, which are tasked with particular ensembles of elements within a neuromotor system. Two main movements can help the CNS activate a group of muscles: automatic body response (reflexes) and voluntary movement (Adolph & Robinson, 2013; F. S. Alnajjar, Berenz, & Shimoda, 2013; Burke, 2016).

Based on previous experiment results, it has been proposed that the automatic response in humans is automatic movements (F. S. Alnajjar et al., 2013). Within this automatic action, the CNS can store the movement to create a voluntary movement, which is the reaction movement. That means automatic human body responses could be used as a reference to explain the voluntary movement. This has been validated by analysing human voluntary movement and the automatic motions from muscle synergy, the automatic response in humans formed of automatic movements (F. S. Alnajjar et al., 2013). Automatic and voluntary action are two main movements that can help the CNS shape the synergy muscle movement (Bani Musa et al., 2017).

NMF can help the automatic synergy motion express some features that could support the CNS in shaping voluntary synergy motion. By developing NMF into concatenated non-negative matrix factorisation (CNMF), human movements from muscle synergy can be

analysed to help the CNS shape synergy movement and improve the quality of life of people with disability.

MPR has been widely used and successfully applied in biomedical research. It is used as an interface machine to control the different hand movements of robotic hands. Multi-EMG channels are necessary for successful hand control pattern recognition (Z. Lu, Tong, Zhang, Li, & Zhou, 2019).

As mentioned in Chapter 3, there are four major steps to classifying human movement—as shown in Figure 3.1, to classify the human movement using the MPR method, we must extract the movement features after filtering the EMG data and then classifying it. This chapter offers a detailed explanation of the feature extraction and classification method.

This chapter presents two different methods for analysing human movement. The first is shaping synergy EMG using pattern recognition, and the second is shaping synergy EMG using the CNMF method. We compare the results of both methods to determine if they can help the CNS shape synergy movements and which method is more accurate. The work in this chapter has been published in IRIS 2017 (Bani Musa et al., 2017).

4.1 Method 1: Shape and Extract Synergy EMG Using Pattern Recognition

EMG pattern recognition with large numbers of EMG channels provides an approach for assessing the signal information available from the recorded muscles. Using this method, hand movements are classified using the pattern-recognition system for EMG signals, as shown in Figure 4. 1. The feature data collected from the original EMG data were consistently used in the training and testing parts of the experiments described in this chapter. The raw EMG data were used with a window size of 200 ms and Butterworth filter frequency of 20–450 Hz to reduce the power line noise to 50 Hz. Then, the features were being extracted using SSC, ZC, WL, Hjorth, SKW, MAV and the MWP feature. The following sections describe the pattern-recognition stages for classifying the movement. In addition, this chapter involves different kinds of classifications. In general, there are many available classification algorithms based on the structure of the network, such as kNN, LDA, ANN and SVM. Moreover, this chapter presents the performance of LDA with other classification algorithms to classify the movement-based pattern-recognition method.

Figure 4. 1: Pattern-Recognition Method for Classifying Hand Movements

4.2 Method 2: Shape and Extract Synergy EMG Using CNMF

The second method in this chapter is: shape and extract synergy using CNMF. CNMF is used to extract the characteristic frequency components and obtain the corresponding connectivity matrices across conditions and subjects (Boonstra et al., 2015; Shourijeh, Flaxman, & Benoit, 2016; Wojtara, Alnajjar, Shimoda, & Kimura, 2013)

In this method, the hand movements are classified using the CNMF system for EMG signals.

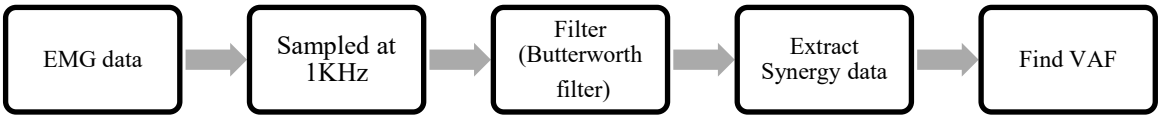


Figure 4. 2: CNMF Method

Figure 4. 2 illustrates the process for analysing synergy EMG.

In Equation 4.1, a matrix with a dimension of m = 6 (the number of muscles) was extracted from the processed EMG data of each experimental trial. It was multiplied by the recorded time t (variables based on the task). In each trial, synergy activation coefficients were identified using the synergy muscle space (*W*), which weighted the muscles based on their activations and the neural command (*C*); *n* denoted the number of synergies; *E* was the residuals between the recorder *M* and the calculated *WC* (F. S. Alnajjar et al., 2013; Shibata Alnajjar, Wojtara, Kimura, & Shimoda, 2013).

$$M_{m\times t} = W_{m\times n}C_{n\times t} + E_{m\times t} \quad \textbf{4. 1}$$

VAF was measured with a threshold of > 90% using Equation 5.2. It was adopted to detect the minimum number of muscle synergies. In this study, the threshold was used to ensure that the estimated number of synergies would effectively preserve the characteristics of the recorded EMG data (Bani Musa et al., 2017).

$$VAF = 1 - \frac{\|E\|_F^2}{\|M\|_F^2} \quad \textbf{4. 2}$$

The following subsections discuss every stage of both methods in detail and present the methodology, results and conclusions.

The following subsections discuss every stage of both methods in detail and present the methodology, results and conclusions.

4.3 Data Acquisition and Processing

4.3.1 Participants

The EMG data used in this work were recorded in the Intelligent Behavior Control Unit, Brain Science Institute, BSI-TOYOTA Collaboration Centre of RIKEN, Nagoya, Japan (F. S. Alnajjar et al., 2013). Three neurologically healthy participants, all right-handed and with no reported muscular impairment on the upper limb, participated in this study. The study protocol was discussed with and explained to the participants to familiarise them with the objective of the study. Three participants, weight 69.25 ± 9.1kg, height: 175 ± 6.2 cm, age: 34.5 ± 5.1 yr) took part in the study (F. S. Alnajjar et al., 2013). The participants were sitting on an adjustable chair. There hand holding the side of the knob of the robotic Manipulandum, see Figure 4.6. A display screen placed in front of the participant to assist there movements through different tasks. The RIKEN ethics committee approved that protocols to collect the data for all participants (F. S. Alnajjar et al., 2013). The EMG signals came from six EMG channels located on the upper limb, as shown in Figure 4.3 and Figure 4.4.

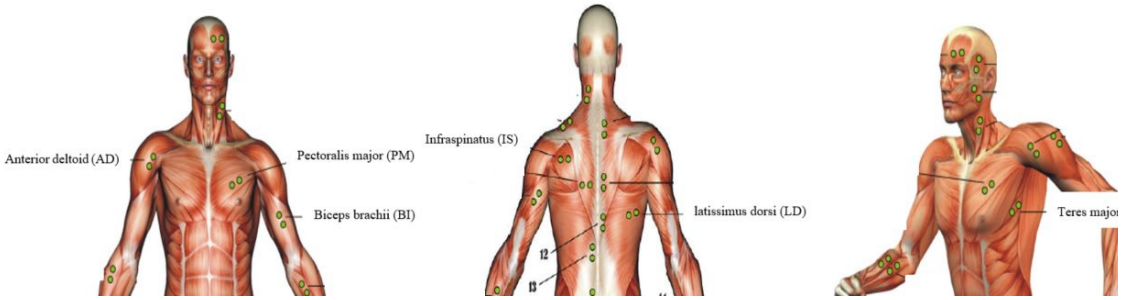


Figure 4. 3: Locations of EMG Electrodes (Front View, Back View and Side View, respectively)

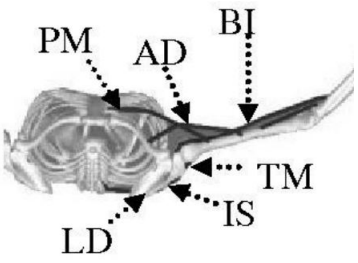


Figure 4. 4: Locations of EMG Electrodes (top view)

4.3.2 Acquisition Device

The device used in our project was a Delta.3 manipulandum (Bani Musa et al., 2017) from Force Dimension, as shown in Figure 4.5 (see Appendix A for the manipulandum fact sheet). It had an adjustable stand and was 260 mm high and 40 mm in diameter. This device has a wide range of uses, such as a medical robot, training system, virtual simulation, research and more. The important value of this manipulandum device is their ability quantify upper limb motion accurately and objectively. As well as, this robotic devise has the ability to control the upper limb movements and apply mechanical loads that can be performed by simulate some properties for real time tasks. Furthermore, this manipulandum connected to a computer monitor displaying visual targets that indicating the limb position. That allowed the position of the upper limb movements to be viewed directly together with visual movement assessment. In our work, we used it as a training system and collected the required EMG data to ascertain whether we could prove our hypotheses. Participants sat on a modifiable chair next to the manipulandum, holding its robotic knob, with a display screen in front of them to assist their movements through the experiment stages, as shown in Figure 4.6 (F. S. Alnajjar et al., 2013; Bani Musa et al., 2017). The participants controlled Delta.3 manipulandum and used it to apply different resistances in various tasks. They rested between each movement and repeated each movement several times. The knob position and force were sampled at 100Hz (F. S. Alnajjar et al., 2013; Bani Musa et al., 2017), and the EMG data were stored for analysis.

Figure 4.5: Manipulandum Device

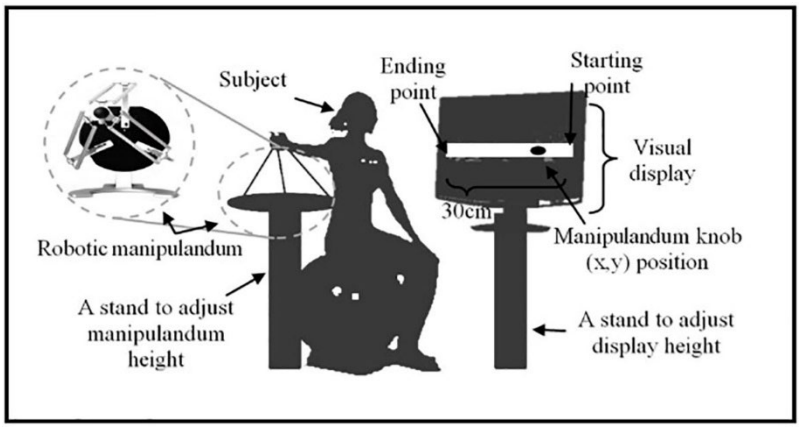


Figure 4.6: Participant Positions While Holding the Manipulandum

4.3.3 Experiment Protocol

In this work, we sought to evaluate the real-time pattern recognition control of hand motions in four different environments: reflex response (Rx), voluntary action (Vc), voluntary action in a modified environment (Vm) and adaption to the modified environment (Vn). We deployed two methods. First, we used the experiment EMG data to the pattern-recognition process with a significant change in using the features and classification methods. Second, we used the experiment EMG data to analyse the four movements, this time with the advanced NMF method.

Generally, the study's results support the hypothesis that automatic synergy powerfully shapes the formation of voluntary synergies. It also supports the notion that this effect may increase when a person performs an unfamiliar movement by creating a reaction movement (voluntary motion) (F. S. Alnajjar et al.), demonstrating how many synergies are used in each movement. The healthy subjects performed these combined movements only. All trials in a movement were combined and labelled with a class related to the movement.

Voluntary synergy actions and automatic synergy actions relationship were verified through the experimental work. The four main movement groups that were considered to support and verify the hypothesis are as follows:

A. Reflex response (Rx): In this experiment, we aimed to collect the EMG data for each participant. This measured the automatic responses from their manipulandum with zero resistance from the participants. The participants were seated in the adjustable chair, holding the knob of the manipulandum, and their arm was positioned at 90 degrees straight, as shown in Figure 4.6 and Figure

4.7(A) (top view). Each participant was relaxed and was not required to perform any reaction. In this movement, 10 random time series were applied.

B. Voluntary action (Vc): At this point, there was no resistance produced by the Delta.3. Just with this movement and before starting this experiment and collecting the data, the participants had a trial period in which they could familiarise themselves with the device. When the data were being collected, each participant sat on the chair grasping the manipulandum knob and performed 10 trials movements, each one second in duration —the movement was just from the participant, with zero resistance from the manipulandum robot, and each participant started the trial from the zero position as displayed on the screen, as shown in Figure 4.6 and Figure 4.7 (B) (top view), and start moving the manipulandum to the endpoint within one second as displayed in Figure 4.6. By the end of this task, participants were familiar with the movements.

C. Voluntary action in a modified environment (Vm): The participant position in this experiment was the same as in the previous movement, but with a slight difference in technique. The participant sat on the chair holding the manipulandum knob and looking at the display screen to reach the endpoint when they moved the knob. The difference in this movement was the manipulandum resistance, which was 70% and applied randomly by Delta.3, as shown in Figure 4.7(C) to record the participant action. In this part of the experiment, resistance was randomly applied from the manipulandum with a reaction from the participant. This unexpected manipulandum resistance helped support our hypothesis, which is that automatic movement can help to shape the voluntary movement.

D. Adaption to the modified environment (Vn): Two identical modified environment sets were applied in this experiment. Each comprised 15 trials, each one-minute duration with two minutes' rest to minimise the possibility of fatigue. The aim was to collect the EMG data in different modified environments to determine how the participant could familiarise themselves with the manipulandum resistance. The participants could also adjust the movement to the modified environment through training and could modify the environment continuously by adjusting the manipulandum by adding a planned or un-planned force or resistance. The manipulandum resistance direction was from the endpoint side, as shown in Figure 4.7(D).

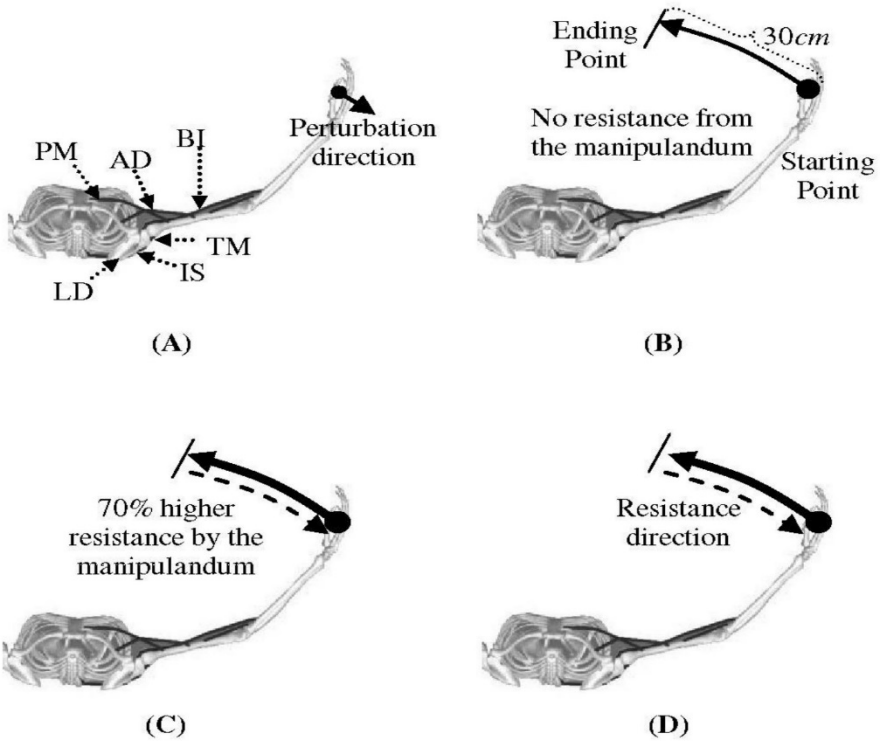


Figure 4.7: Top View of a Layout for the Four Experiments: (A) Rx, (B) Vc, (C) Vm, (D) Vn

4.3.4 The EMG Channel Number and Electrode Placement

The performance of the system model is affected by the number of EMG channels used in MPR. In general, at least two single surface electrodes are often used in a simple task to connect to the human upper limb to make a close pre-amplifier circuit to help get a result. For the work described in this chapter, we used six sEMG signals. The electrodes were located in six upper limb shoulder muscles: pectoralis major, deltoid anterior, infraspinatus, teres major, latissimus dorsi and biceps brachii, as shown in Figure 4.3. These locations were used in such a way that the muscle movement gave an indication and good reading about human movement (Bani Musa et al., 2017). The sEMG electrodes were located in the upper limb muscles in accordance with the guidelines of the SENIAM European Community projects 8 and 9 (Hermens et al., 1999; D. Stegeman & Hermens, 2007). These guidelines suggest locating the electrode halfway along with the muscle and not close to the muscle ends (tendons and ligaments). They recommend placing the electrode on the skin surface away from the edges of the hand. In this work, EMG signals were sampled at 1 kHz and filtered by Butterworth filter with 30 Hz, with LDA used for data classification (LDA is applied to the classification problem in pattern recognition). The EMG data, rectified using RMS and smoothed using a moving average with a

window of length 10 samples (Bani Musa et al., 2017). EMG data were synchronised with the data collected from the manipulandum using a common clock and trigger.

4.4 Data Processing

To support our hypothesis (that the automatic synergy powerfully shapes the formation of voluntary synergies), we worked on the synergic EMG signal. To work on synergy EMG, we processed the EMG signal and extracted the synergy EMG signal, as shown in Figure 4. 1, Figure 4. 2. Figure 4. 1 shows the use of pattern recognition to classify the movement by using new features and classifications to calculate the synergy EMG result. This starts with the raw EMG data, which was filtered using a Butterworth filter. The results were applied to extract features and also applied to a classification system as a form of muscle synergy data that helped classify the hand movement to obtain a better result. Figure 4. 2 explains the process for analysing synergy EMG. This started with raw EMG data and involved several steps in extracting the muscle synergy using CNMF; with this technique, each muscle could be activated by various synergies. Consequently, there are no two similar muscle activation patterns. These findings imply that the nervous system may use a limited set of control signals to activate a large number of muscles (Tresch & Jarc, 2009). When the EMG signal was used for analysis, the synergy reflected only synchronised muscle activity. If synergy is active at a given time, all muscles within that synergy are active (Ranganathan & Krishnan, 2012). Generally, muscle synergies are suggested as a solution to a muscle's degree of freedom problem in motor control action potential instead of having to manage many thousands of MUs or dozens of muscles. However, using the CNMF concatenates the original EMG data of individual trials or all trials (Oliveira, Gizzi, Farina, & Kersting, 2014; Smale, Shourijeh, & Benoit, 2016) while keeping the synergy pattern fixed among those trials. By keeping the synergy adjusted among participants, signal variability between the trails is limited to the coefficients and therefore is a stronger approach (Shourijeh et al., 2016; Smale et al., 2016). After the CNMF was applied, The VAF threshold was found to identify the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs and explain the variance (F. S. Alnajjar et al., 2013; Bach, Daffertshofer, & Dominici, 2021).

4.5 Filter

It helps to remove some unwanted components (noise) or features from a signal—that is, eliminating some unwanted frequencies to reduce background noise. Since EMG is affected by noise, a Butterworth filter was applied in this study.

4.6 Feature Extraction

Feature extraction is the second crucial step after preparing the data to start processing it. The pattern recognition converts to a feature using the feature extraction step (T. T. Nguyen, Krishnakumari, Calvert, Vu, & van Lint, 2019). The process of feature extraction in the MPR algorithm means transferring the EMG signal's pattern to segments that help find features that contain distinguished and helpful features of the EMG signal that help the next step of the MPR algorithm (Rami N. Khushaba, 2010).

The feature extraction step is important to finding the highest suitable feature sets from the EMG signal that have low misclassification, keeping the classes separate in the noisy environment of the feature space (robustness), having lower calculation complexity and reducing error (Al Taee et al., 2020; Rami N Khushaba, Al-Ani, Al-Timemy, & Al-Jumaily, 2016; R. N. Khushaba, Lei, & Kodagoda, 2012). As well as, feature extraction proposed to improve the biomedical signal interpretations (Chahid, Khushaba, Al-Jumaily, & Laleg-Kirati, 2020).Generally, the feature extraction in MPR comprises three different groups (Angkoon Phinyomark et al., 2012):

1. Time Domain (TD)
2. Frequency Domain (FD), sometimes called spectral-domain (SD)
3. Time-frequency domain (TFD), sometimes called time–scale domain (TSD).

4.6.1 Time Domain (TD)

Time Domain (TD) features have been used globally in Biomedical field, especially in EMG pattern recognition. The TD features are less complex when computing the features and perform well in the noisy environment of the feature space (robustness), which means that scientists use TD widely in EMG pattern-recognition processors (Al-Timemy, Bugmann, Escudero, & Outram, 2013; Hargrove et al., 2007; Oskoei & Hu, 2008; Angkoon Phinyomark et al., 2012).

The TD features are the most used in the field are as follows:

1. Slope Sign Change (SSC)

This feature counts the number of times that the EMG signal slope sign changes (Hudgins, Parker, & Scott, 1993).

$$SSC = \sum_{k=1}^{N} Z_k, \qquad Z_k = \begin{cases} 1 & (x_k > x_{k-1}\ and\ x_k > x_{k-1}) or \\ & (x_k < x_{k-1}\ and\ x_k < x_{k-1})\ and \\ & |x_k - x_{k-1}| \geq threshold\ or \\ & |x_k - x_{k-1}| \geq threshold \\ 0 & else \end{cases} \quad \textbf{4.3}$$

2. Zero-Crossing (ZC)

This represents the frequency information of the signal at the TD. It counts the number of times that EMG signal amplitude values cross the zero-amplitude level (Hudgins et al., 1993). It is defined as follows:

$$\mathrm{ZC} = \sum_{k=0}^{n} Z_k\ , Z_k = \begin{cases} 1, & x_k x_{k+1} < 0\ and\ |x_k - x_{k+1}| \geq threshold \\ 0, & else \end{cases} \quad \textbf{4.4}$$

3. Waveform Length (WL)

This is a measure of the complexity of the EMG signal. It is defined as the increasing length of the EMG waveform over time and is defined as follows:

$$WL = \sum_{k=1}^{N} |x_k - x_{k-1}| \quad \textbf{4.5}$$

4. Hjorth Parameters (Hjorth)

These are the normalised slopes used in EMG. Moreover, Hjorth is used for signal processing as surface detection and feature extraction in three TD features (Mouzé-Amady & Horwat, 1996):

$$Activity: \quad m_0 = var(x(t)) \quad \textbf{4.6}$$

$$Mobility: \quad m_1 = \sqrt{\frac{m_0\left(\frac{dx(t)}{dt}\right)}{m_0(x(t))}} \quad \textbf{4.7}$$

$$Complexity: \quad m_2 = \frac{m_1\left(\frac{dx(t)}{dt}\right)}{m_1(x(t))} \quad \textbf{4.8}$$

5. Sample Skewness (SKW)

This is a measure of the asymmetry of a signal or measure of x order:

$$SKW = E\left[\left(\frac{x-\mu}{\sigma}\right)^{x}\right] \quad \textbf{4.9}$$

6. Mean Absolute Values (MAV)

This is a standard and easily implemented feature of the TD. It finds the mean of the EMG amplitude values over the sample length of the signal (Hudgins et al., 1993) and is defined as follows:

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|x_k| \quad \textbf{4.10}$$

The MAV slope is different and is defined as follows:

$$MAVS = MAV_{k+1} - MAV_k \quad \textbf{4.11}$$

7. RMS (Root Mean Square)

The RMS is the square root measure of the average magnitude of the error. It can be calculated as follows:

$$RMS = \frac{1}{N}\sum_{k=1}^{N}x_k^2 \quad \textbf{4.12}$$

8. Autoregressive Feature (AR)

The EMG signal could be viewed as a stationary Gaussian function using this feature. The EMG signal can be demonstrated as follows:

$$x_k = \sum_{i=1}^{m} AR.x_{k-i} \qquad m^{th}\ order\ AR\ model \quad \textbf{4.13}$$

4.6.2 Frequency Domain Features (FD)

The features are mostly obtained in the FD domain from power spectral density. This domain is commonly used when obtaining the features from fatigue analysis. The two types of FD are as follows:

1. Mean Frequency (MNF)

As shown in Equation 4.14, the frequency average is obtained from the sum of the multiplication between the frequency and the power spectrum divided by the sum of the total power spectrum:

$$MNF = \sum_{k=1}^{N} f_k P_k \Big/ \sum_{k=1}^{N} P_k \qquad \textbf{4.14}$$

2. Median Frequency (MDF)

MDF is the FD when the power spectrum (P_k, as in Equation 4.13) is divided into two equal regions with the same amplitudes.

$$\sum_{K=1}^{MDF} P_k = \sum_{k=MDF}^{N} P_k = \frac{1}{2}\sum_{k=1}^{n} P_k \qquad \textbf{4.15}$$

4.6.3 Time-Frequency Domain Features (TFD)

The TFD can manage the EMG signal energy in the TD and FD (Englehart, Hudgins, Parker, & Stevenson, 1999); as a result, the TFD is described as more accurate than the previous two FDs.

With the pattern-recognition method, after extracting the EMG signal's features and as a result of processing the data, we extracted a huge pool of data with a large dimension that had to be reduced without losing the useful main features. Two different feature reduction methods can be used to achieve this. The first is feature selection (FS), which involves selecting the subset of a feature's subset from the original features to reduce the dimension. The second is feature projection (FP), which reduces the dimension by transforming the original features spaces to new feature spaces.

Generally, the FP reduction method is more likely to be used in EMG feature reduction for huge EMG data readings because it is more effective than FS. We used the FP method in this study. FP can classify using a supervised or unsupervised method. Next, we explain how feature projection can be classified (Englehart et al., 1999; Rami N. Khushaba, 2010).

EMG feature extraction is one of the necessary procedures for extracting useful information from the EMG signal. No additional signal transformation was needed in this work. For the work described in this chapter, we used the following TD and TFD features (Altin & Er, 2016; H. Huang et al., 2016; Hudgins et al., 1993; Mouzé-Amady & Horwat, 1996; Reis, Saraiva, & Bakshi, 2008). After extracting the features from the EMG signals, they were ready for classification.

4.7 Classification System

As shown in **Figure 3.1**, classification is the fourth step. It is one of the main stages of the pattern-recognition procedure. In the biomedical field, classification is used to reduce the features into certain classes. MLP and feedforward neural network (FNN) was used frequently in the biomedical field to classify the features, but it needed more time for training. In addition, kNN, LDA, artificial neural networks (ANN), SVM and extreme learning machine (ELM) are all types of classification methods. Next, we explain the LDA, SVM and ELM.

4.7.1 Linear Discriminant Analysis (LDA)

LDA is the preferred method in the biomedical field as it has faster processing than the MLP, and it is as accurate as of the FNN (de Castro, 2012). The main goal of using LDA is to search for the best vectors that discriminate among classes instead of searching for vectors that best describe the feature data (Naskar, Nandeshwar, & Das, 2018). LDA is a supervised classification method that contains the movement class information, and it is demonstrated as follows:

$$a^* = arg_a max \frac{a^T S_b a}{a^T S_w a} \text{ , where } \begin{cases} S_w: \quad within-class\ scatter\ matrix \\ S_b: between-class\ scatter\ matrix \end{cases} \text{(de Castro, 2012)} \qquad \textbf{4.16}$$

The researchers are encouraged to use the LDA method when the number of classes is greater than the number of samples (Cai, He, & Han, 2007). The LDA algorithm is based on the scatter matrix, which divides into two matrices: between-class matrix and within-class matrix. LDA seeks to maximise and minimise those respective matrices. The within-class matrix can be demonstrated as follows:

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{N_j} (x_i^j - \mu_j)(x_i^j - \mu_j)^T \text{ , where } \begin{cases} x_i^j: the\ i^{th} sample\ of\ j \\ \mu_j: the\ mean\ within-class\ parameter\ of\ j \\ c: the\ classes's\ numbers \\ N_j: the\ samples's\ number\ in\ class\ j \end{cases} \qquad \textbf{4.17}$$

The between-class matrix can be demonstrated as follows:

$$S_b = \sum_{j=1}^{c} (\mu_j - \mu)(\mu_j - \mu)^T \qquad \textbf{4.18}$$

As Equation 4.18 shows, by maximising the objective function, we reach the goal of LDA classification.

4.7.2 Support Vector Machine (SVM)

SVM is one of the most techniques used to classify data and diagnose diseases in the Biomedical field. For example, it is used to diagnose skin cancer disease (Arora, Dubey, Jaffery, & Rocha, 2020) and for sleep apnoea classification (W.-C. Huang, Lee, Liu, Chiang, & Lai, 2020; Maali & Al-Jumaily, 2011). National Health and Nutrition Examination Survey (NHANES) created SVM to predict the classification models for people with diabetes and pre-diabetes as well as predict depression (Rudd, Waller, & Smith, 2018) as well as in other field the use the SVM for solar and renewable energy forecasting (Zendehboudi, Baseer, & Saidur, 2018). Khushaba notes that SVM has a better performance compared with classification methods, such as LDA, kNN or FNNs, because it uses optimised parameters to reach the maximum SVM value (R. N. Khushaba, Lei, et al., 2012)—this is one of the reasons SVM is used widely in classification applications and regression problems (G. B. Huang, Zhou, Ding, & Zhang, 2012; Rudd et al., 2018). SVM is a machine-learning model based on binary classification, and it is an arithmetical learning theory (Vapnik, 1999). The SVM training algorithm could be an example of linear separation and multi-kernel function (MKF).

The MKFs in SVM are sigmoid kernel function (SKF), polynomial kernel function (PKF) and radial basis function, which are defined as follows:

1. SKF: $$K(x_i, x_j) = e^{-\gamma|x_i - x_j|^2} \quad \textbf{4.19}$$
2. PKF: $$K(x_i, x_j) = (x_i x_j + 1)^q \quad \textbf{4.20}$$
3. SKF: $$K(x_i, x_j) = tanh(\gamma x_i^T x_j + c) \quad \textbf{4.21}$$

The two main parameters in SVM classification are cost parameter C and kernel parameter γ, where the ranges are (2_{-9}, 2_{-8}, …, 2_9,2_{10}). SVM has two different learning features:

1. In a nonlinear mapping (ω(x) function), the sample trained data are mapped in the high-dimensional domain.
2. The representative SVM optimise feature is applied to discuss the maximisation the value of the variable by targeting the low error in the feature domain.

Like the other methods, SVM has advantages and disadvantages, but scholars have tried to obtain good results using SVM because it is a reliable method for nonlinear data. One advantage to using SVM is particularly advantageous in training because it optimises the unstable line of the cost purpose. It has also been used in background propagation neural networks as a safety method.

SVM has two different principles:

1. structural risk minimisation, which is less affected in case of overfitting in some cases
2. empirical risk minimisation.

Generally, SVM works in many movement classes (Rami N. Khushaba, 2010; R. N. Khushaba, Lei, et al., 2012). In the case of a multi-classification class, SVM can be used as many times as needed, but this will add more time to the data processing. In Chapter 5, we use SVM as a regression method.

4.7.3 Extreme Learning Machine (ELM)

ELM is very similar to SVM in terms of its performance working the parameter dependency (G. B. Huang et al., 2012). In his ELM research (G. B. Huang et al., 2012), Huang states that ELM is a method that simplifies the single hidden layer feedforward networks (SLFNs). That to avoid the iterative tuning in the hidden layer and output layer. The goal of using the ELM is to achieve and minimise the output error and minimise the norm of the output layer, which differs from the SLFNs. As a result, researchers obtain a result that shows the training speed in ELM is much better than in SLFNs. Further, like SVM, ELM has two main parameters, parameter C and kernel parameter γ, and that a particular parameter affected ELM performance (G. B. Huang et al., 2012). The basic single feedforward network (SFN), as shown in Figure 4.1 (Mo, Zhang, Li, & Qu, 2019), is the original concept of the ELM.

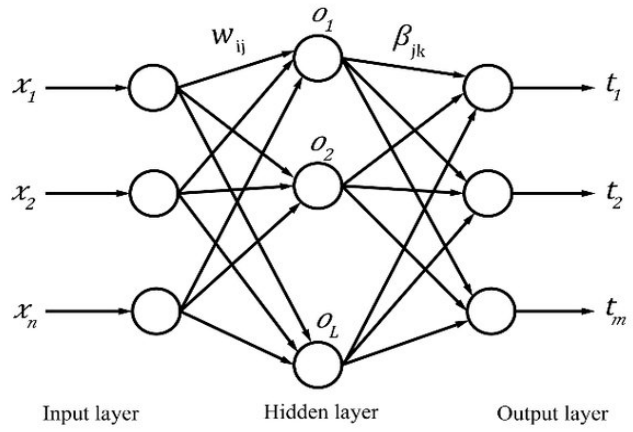


Figure 4.8: Single Feedforward Network for ELM (Mo et al., 2019)

Figure 4.8 shows that if there are too many inputs and outputs (x_i, y_i), then the input $x_i = [x_{i1}, x_{i2}, \dots, x_{ik}]^T \in R^k$ and $y_i = [y_{i1}, y_{i2}, \dots, y_{im}]^T \in R^m$, and the SFN with L hidden layers is shown by the following equation:

$$f_i(x) = \sum_{j=1}^{l} \beta_i g(w_j . x_i + b_j) = G\beta, \qquad where \begin{cases} i = 1, \dots, N \\ w_j = [w_{j1}, w_{j2}, \dots, w_{jk}]^T \\ \beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{il}]^T \end{cases} \quad \textbf{5.22}$$

Where w_j is the weight vector relating to the j^{th} hidden neuron for the input and the β_i is the weight vector relating to the ith hidden neuron for the output, b_j is the jth hidden neuron threshold and G is the hidden node function.

After the EMG signal features were extracted, they were ready for classification. There are many available classification algorithms. The most common are the kNN, LDA, ANN and SVM. In this work, we used the LDA, which is applied to classification problems in pattern recognition. We decided to proceed with LDA in the hope that it would provide better classification compared with other classification algorithms (J. Lu, Mamun, & Chau, 2015).

4.8 Data Analysis

Voluntary and automatic actions experiment stretch reflex magnitude was measured using the EMG data. The baseline was eliminated by processing the EMGs. CNMF was used to extract the muscle synergy from the recorded EMG data. Raw EMG data were applied to the classification method.

4.9 Results

Using the TD and TFD features, and LDA classifier, Figure 4.9 and Figure 4.10 showed that the results were achieved with 0% error and 100% accuracy.

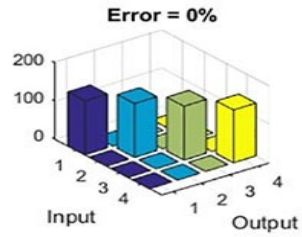


Figure 4.9: Classification Results for Four Movements

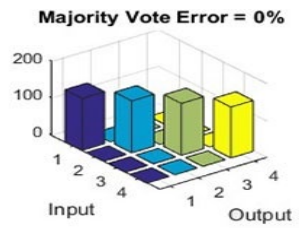


Figure 4.10: Classification Results (Majority Vote) for Four Movements

All participants completed the tasks based on Equation 652. Figure 4. 11, Figure 4.12 and Figure 4.13 show the average of the utilized number of synergies by three participants when they performing the tasks. Figure 4. 11, Figure 4.12, and Figure 4.14 shows the VAF of all possible number of muscle synergies that recorded from the EMG dataset which required to achieve > 90% overall VAF and > 75% VAF.

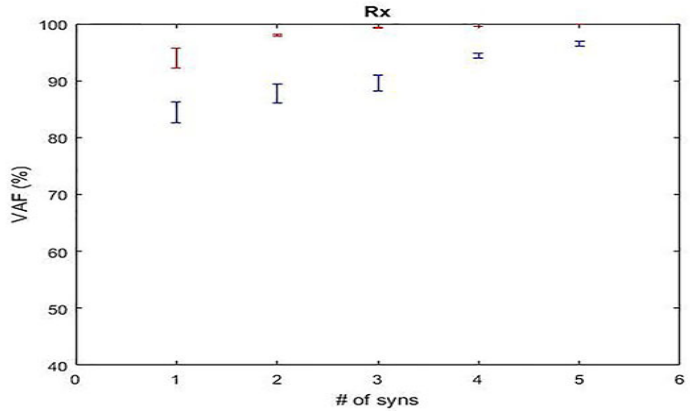


Figure 4. 11: VAF of all Possible Identified Synergies from the Recorded EMG Data-Set in Reflex Response (Rx)

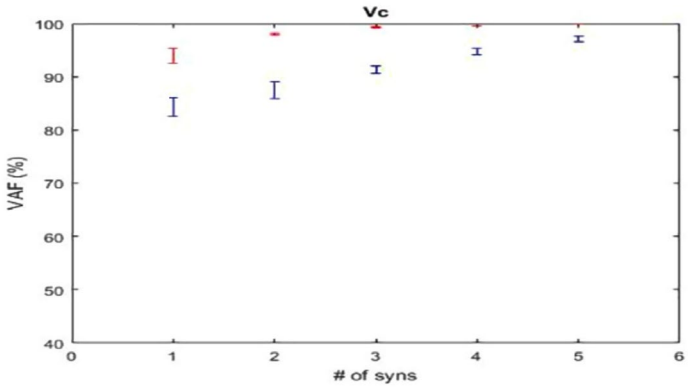


Figure 4.12: VAF of all Possible Identified Synergies from the Recorded EMG Data-Set in Voluntary Action (Vc)

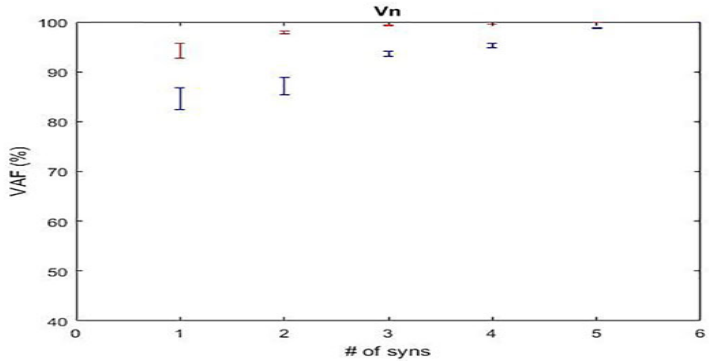


Figure 4.13: VAF of all Possible Identified Synergies from the Recorded EMG Data-Set in Modified Environment (Vn)

As we see in Figure 4. 11, Figure 4.12 and Figure 4.13, there were two muscle synergies required to reconstruct a feature of the recorded EMG data. These synergies were used in automatic and voluntary actions and helped shape the movement. Figure 4.14 shows that one synergy was enough to reconstruct the EMG data and shape the movement (F. S. Alnajjar et al., 2013), and this was achieved > 95% VAF.

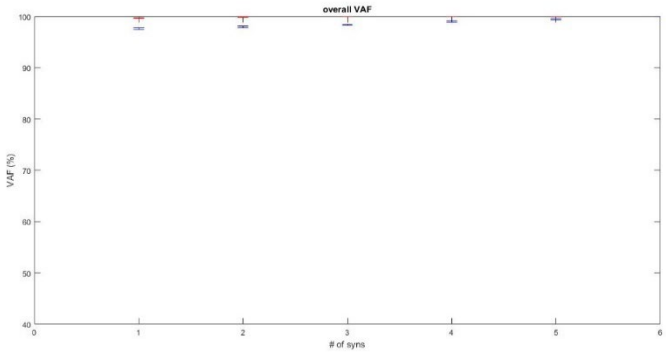


Figure 4.14: VAF of all Possible Identified Synergies from the Recorded EMG Data-Set in Adaptation to the Modified Environment (Vm)

Comparing both methods with previous researchers results (F. S. Alnajjar et al., 2013), shows that the pattern-recognition method helps the CNS shape movement with 100% accuracy and the CNMF method with > 95% overall VAF. The VAF result was > 90, which is important to identify the minimum number of used synergies that adequately to reconstructed the characteristics of the recorded EMG to help the CNS shape the movements. If the body performs an unusual task in an unusual environment, the CNS deploys the used synergy to cope with the new task. This supports our hypothesis for analysing automatic movements and voluntary movements for helping the CNS system shape synergy movement. Thus, we have successfully determined that synergy can help the CNS shape voluntary movement by calculating the VAF.

4.10 Summary

This chapter presented background information for the research feature extractions and classifications used in the subsequent thesis chapters. The chapter reviewed the classifiers and feature extractions that helps to develop pattern recognition auto control and a diagnostic system for upper limb performance recovery prediction. Some of the conditions that affect pattern recognition development and performance were reviewed and reported.

In this research, many techniques were used to analyse and control the synergy EMG signal. Automatic body response movements and voluntary movements can help the CNS shape synergy. Using the CNMF method and the pattern-recognition method with > 95% overall VAF and 0% error, respectively, helped the CNS shape synergy movements with good results. In future work, we want to improve the repeatability and reliability of automatic body movement and voluntary action movement for shaping muscle synergy analysis using a new approach. The results in this chapter are published because it is accepted as worth researching (Bani Musa et al., 2017).

Chapter 5: Upper Limb Recovery Prediction After Stroke Rehabilitation Based on the Regression Method

Neurological disorders following brain stroke are classified as one of the leading causes of long-term motors disabilities worldwide. Such motor disabilities may not only affect survivors' quality of life but also can affect their communities. Motor disabilities after stroke are not necessarily identical in terms of the injury location and size; it is thus difficult for therapists to predict the evolution of the disability, the optimal treatment and the recovery period (Mostafavi, Glasgow, Dukelow, Scott, & Mousavi, 2013).

The muscle bio-signal, EMG, has been studied extensively in an effort to understand the development of human control systems to improve rehabilitation techniques (F. Alnajjar et al., 2015; Bani Musa et al., 2017; Shibata Alnajjar et al., 2013). However, predicting motor recovery after stroke is still an important topic to address (Stinear, Byblow, Ackerley, Barber, & Smith, 2017). In this pilot study, we used the recorded EMG data from three moderate post-stroke patients during their rehabilitation sessions to investigate the possibility of predicting their upcoming motor activities. Specifically, we investigated the possibility of a machine-learning algorithm using SVMR to predict the motor functional recovery of these patients during their rehabilitation program. To train the model, we used the recorded EMG signals from the patients' upper limb muscles during their initial rehabilitation sessions. We then tested the trained model to predict the patients' later muscle performance during the same sessions. The results are promising, and the data were, to some extent, predictable. We believe this research could help motivate patients to complete their designed rehabilitation programs and assist therapists with designing proper rehabilitation programs for individual patients. The work of this chapter has been published in *Converging Clinical and Engineering Research on Neurorehabilitation III: Proceedings of the 4th International Conference on NeuroRehabilitation* (Bani Musa et al., 2019).

5.1 Support Vector Machine Regression (SVMR)

Recently, stroke have become very common. The researchers focus more on rehabilitation programs containing movement evaluation and training. There are many algorithms used for the movement evaluation and training. SVMR is a good algorithm for such purpose. It is a prediction algorithm based on SVM. The SVM is a good classification technique that classify the data to diagnose diseases (Masood, 2016). It separates a set of training vectors to two different classes (x_1,y_1), $(x_2,y_2),\ldots,(x_m,y_m)$. Different researches examined the prediction performance based on different SVM kernel functions (Abakar & Yu, 2014; Song, Zhou, & Han, 2018). Most popular kernels are:

1. Linear Kernel: $K(x_i, x_j) = \left(x_i . x_j + k\right)^d$.
   Where *k* is constant, when *d=1* it means linear kernel.
2. Polynomial: $K(x_i, x_j) = \left(x_i . x_j + k\right)^d$
   Where *k* is constant, *d* is the kernel of degree.
3. Gaussian (Radial Basic Function (RBF)): $K(x_i, x_j) = \exp\left(-\left\|x_i, x_j\right\|/2\gamma\right)^2$
   Where $\gamma > 0$ is the parameter that control the width of the Gaussian. γ control the flexibility of the resulting classifier.

The choice of the kernel is based on the data nature.

The main and basic point of using SVMR is to schedule the original EMG data into a high dimension space, then find the optimal plan in high dimension space to analyse the data ad predict the recovery rehabilitation (Qijun & Fangteng, 2021). The main advantage point to use SVMR algorithm because it has a good non-linear generalization ability and mapping ability (Park, Forman, & Lievens, 2021; Zhang et al., 2022). In this thesis, I used SVMR to predict the motor functional recovery of the patients during their rehabilitation program.

5.2 Methodology

Three unilateral moderate post-stroke patients (age: 52+/-2, SIAS score: 3) were recruited for this study. Eighteen EMGs data channels were recorded from the patients' upper limb muscles while they performed a driving simulation task, as shown in Figure 5. 1 (Costa, Itkonen, Yamasaki, Alnajjar, & Shimoda, 2017). Nine of those EMGs data channels were recorded from the muscles on the stroke-affected side, and the remaining nine were recorded from the non-affected side. Data were collected from two independent sessions (with 30 minutes' rest between the two sessions) of approximately 60 movements each.

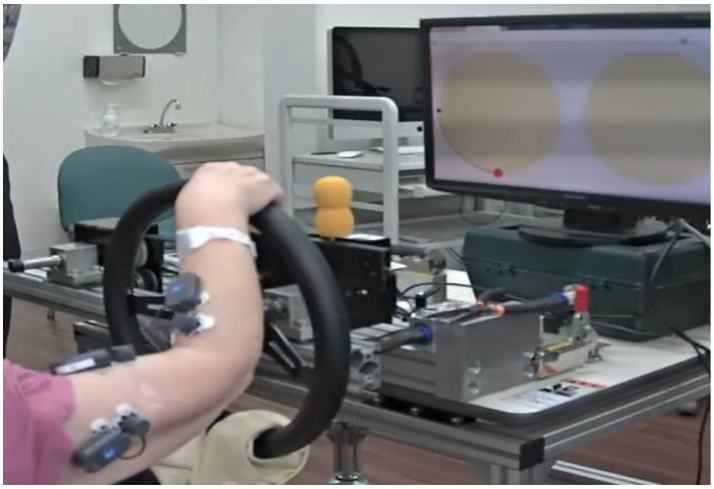


Figure 5. 1: Participant Position While Holding the Dual Steering Wheel

The initial 80% of the collected EMGs data for each session were considered the training dataset. The remaining 20% were considered the testing dataset. The training data were band-pass filtered before being processed by a regression model using SVMR. Different kernels were tested. We used root mean square error (RMSE), mean square error (MSE) and mean absolute error (MAE) to check the error between the predicted data and the actual data (the testing data). The kernel with the minimum error, the fine Gaussian kernel in this study, was used.

5.3 Results and Discussion

For Patient 1, the results of sessions 1 and 2 are shown in Figure 5. 2and Figure 5. 3, respectively. The solid brown circles represent the actual results, and the solid blue circles represent the predicted outputs.

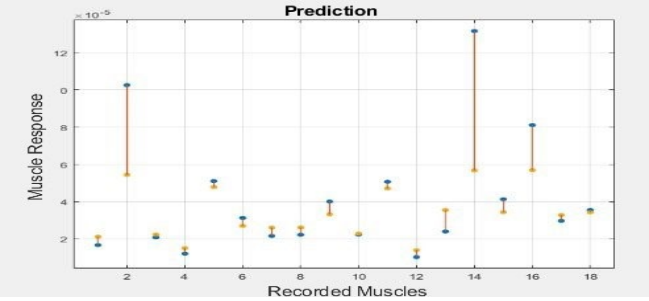


Figure 5. 2: Patient n1 (Session 1), RMSE 3.3e–05, MSE 1.3e–09, MAE 2.3e–05

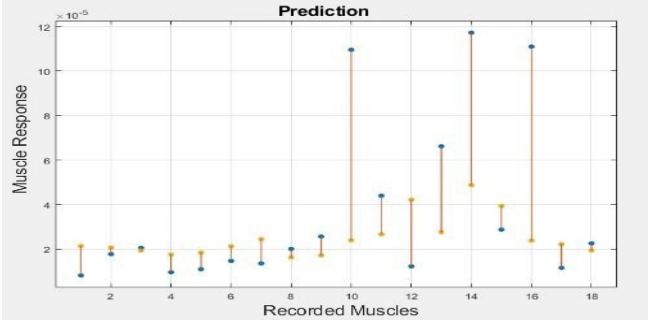


Figure 5. 3: Patient n1 (Session 2), RMSE 2.2e–05 MSE 4.9e–10, MAE 1.1e05

In Figure 5. 2 and Figure 5. 3, the first nine points of the x-axis are for the stroke-affected side, and the remaining nine points are for the non-affected side. The same pattern is displayed in Figure 5. 4 and Figure 5. 5 and in Figure 5. 6and Figure 5. 7, which display the data for the second and third patients, respectively.

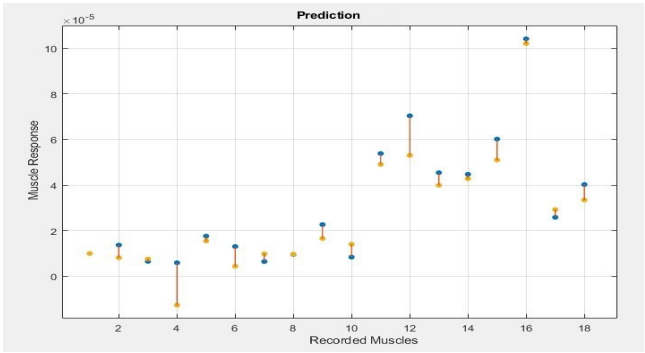


Figure 5. 4: Patient n2 (Session 1), RMSE 2.2e–05, MSE 4.8e–10, MAE 1.6e–05

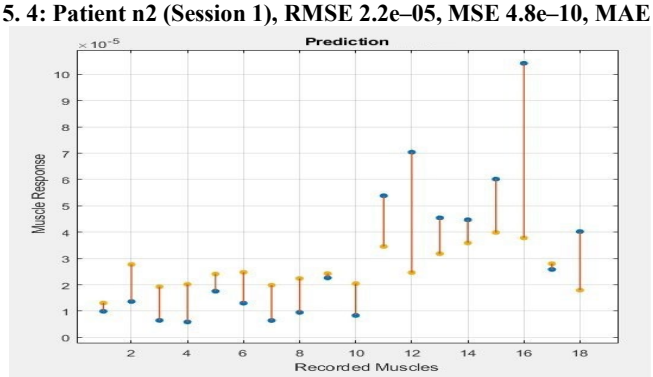


Figure 5. 5: Patient n2 (Session 2), RMSE 7.3e-06, MSE 5.3e-11, MAE 5.4e-06

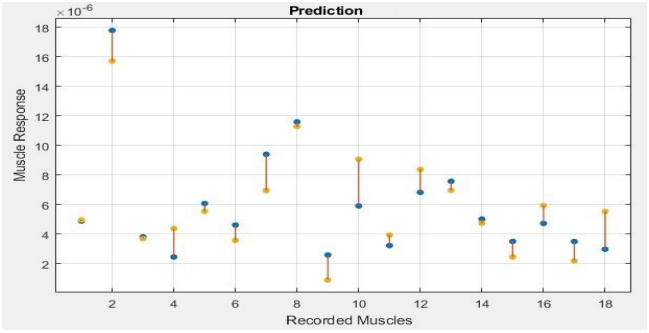


Figure 5. 6: Patient n3 (Session 1), RMSE 6.6e–06, MSE 4.3e–11, MAE 5.1e–06

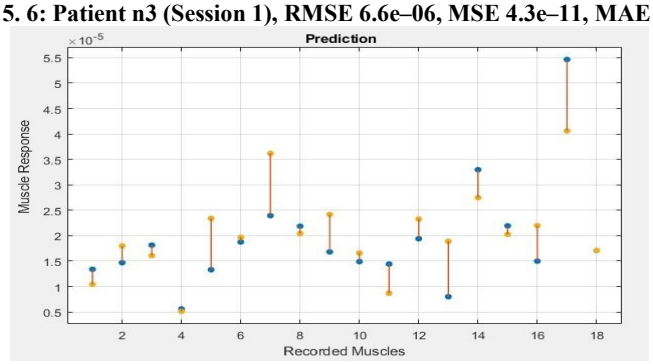


Figure 5. 7: Patient n3 (Session 2), RMSE 1.5e–06, MSE 2.4e–12, MAE 1.3e–06

Table 5. 1: Comparison of The Predictive of SVM in Different Kernels

SVM Kernel	Error		
	RMSE	MSE	MAE
Polynomial Kernel (Abakar & Yu, 2014)	5.369		
RBF Kernel (Abakar & Yu, 2014)	.911		
RBF kernel (first patient) Session 1	**3.3e–05**	**1.3e–09**	**2.3e–05**
RBF kernel (first patient) Session 2	**2.2e–05**	**4.9e–10**	**1.1e05**
RBF kernel (second patient)	**2.2e–05**	**4.8e–10**	**1.6e–05**
RBF kernel (second patient) Session 2	**7.3e-06**	**5.3e-11**	**5.4e-06**
RBF kernel (third patient)	**6.6e–06**	**4.3e–11**	**5.1e–06**
RBF kernel (third patient) Session 2	**1.5e–06**	**2.4e–12**	**1.3e–06**

From the above figures and Table 5. 1, we could observe that our trained model could predict, to some extent, the recorded data of the patients. In Session 1, for instance, eight out of nine of the stroke-affected muscle activities were well predicted for patients 1 and 2 (two to five of the stroke-affected muscles were predicted in Session 2 for the same patients). However, Patient 3 had five out of nine acceptable predictions for the affected-side muscles in both sessions. The less predictive ability could be observed in the muscles

of the non-affected side for all three patients. The results show that it is possible for the machine-learning algorithm using SVMR to predict the motor functional recovery of moderate post-stroke patients during their rehabilitation programs (Bani Musa et al., 2019; Shibata Alnajjar et al., 2013).

5.4 Summary

This chapter presented a pilot study examining the ability to predict the future muscle performance of post-stroke patients based on their current motor ability. The prediction model used the SVMR method, trained using the actual EMGs activities of post-stroke patients and validated by their future muscle performance. A statistical validation and of this work would be made possible by increasing the dataset size, which is what we intend to do in future research. The results in this chapter are published because it is accepted as worth researching (Bani Musa et al., 2019).

Chapter 6: Upper Limb Recovery Prediction Based on MME EMG Synergy and Biomarker Value

Stroke is damage of function of the central nervous system (CNS). It caused by fail of blood flow to the brain tissue. It causes of short, long term or permanent disability. It is one of the mortality worldwide (Phipps & Cronin, 2020; Stinear et al., 2020).

Immediately after a stroke, the primary concern of the patient, relatives, and caregivers is the potential of recovery and the possibility of doing daily rehabilitation basis. In most cases, clinical based on visual or patient physical examination are used for stroke assessments. Therefore, the results from the previous mentioned stroke assessment methods are suffer from lake of resolution (Canosa-Carro et al., 2022).The need for improve the stroke assessment methods for effective stroke rehabilitation is increased. To address this concern and to aid in clinical management, improved patient recovery predictions are needed. Information based on observation of average recovery patterns may have little relevance to an individual patient or healthcare provider. Analytical studies on outcomes after stroke have tended to concentrate on predicting the outcome at a specific time point (e.g., three months after stroke). This type of prediction does not aid clinical decisions about whether or not to continue an intervention, such as a rehabilitation program, nor does it identify the causes of recovery failure (G. Chen, Taylor, Shin, Reynolds, & Cox, 2017; Pinheiro & Bates, 2000).

The patient's rate of recovery also has important implications for the costs of care, especially the length of hospital stays.

Such probabilities for recovery may vary according to treatment regimen or patient characteristics. It has been emphasised (Mostafavi et al., 2013; Pilarski, Dick, & Sutton, 2013) that standard patterns of recovery from a stroke should be established as a guide to monitoring the future recovery of patients. However, there is a lack of carefully designed statistical models for the development of such recovery patterns.

This chapter proposes a system that helps stroke patients achieve specific benchmarks by predicting their ability to recover. The proposed system also assists physiotherapists to decide whether or not to change the exercise regimen for patients. Such exercise aids recovery and independence in activities of daily living by a given time point after stroke, allowing the patient to recover part or all of their former health, motor capabilities and upper limb function as well as helping to reduce hospital stay costs.

Recent research has focused on rehabilitation using different types of artificial intelligence, as our previous work in (Rahman & Al-Jumaily, 2013) required a certain type of hand control (Khairul Anam & Al-Jumaily, 2012). While electromyography (EMG) muscle signals have been used as one of the control signals as well as rehabilitation performance measurement indication and developed many algorithms to process for biomedical application, few works related to that were published (K. Anam & Al-Jumaily, 2017; Rami N Khushaba, Al-Ani, & Al-Jumaily, 2009).

Research on the prediction and accuracy of rehabilitation performance is limited and could be improved by an appropriate selection of EMG signal inputs (Sanchez et al., 2004; Westwick, Pohlmeyer, Solla, Miller, & Perreault, 2006) (G. Chen, Saad, Britton, Pine, & Cox, 2013; D. Lu, Tripodis, Gerstenfeld, & Demissie, 2018).

To achieve more accurate prediction results and to better predict rehabilitation performance recovery, we developed a multilevel mixed-effect method (MME) to create a more flexible and accurate framework to predict recovery.

The purpose of this chapter is to describe the use of artificial intelligence and clinical biomarkers associated with upper limb function. This is quantified in the first period of time post-stroke, which could be days or months, depending on the willingness of the patient to allow data to be collected from them. With data collected from patients, it is possible to estimate the ability of the patients to perform daily activities and to predict their skills at three months post-stroke. In particular, recent developments in robot-based behavioural tasks provide a rich set of biomarkers on sensory and motor function, including the performance of both the affected and unaffected upper limbs. In this study, we observe possible rehabilitation recovery and compare the results with the Functional Independence Measure (FIM) and the Stroke Impairment Assessment Set (SIAS) scores prior to and following rehabilitation.

To start the observation, we trained part of the recorded EMG signals from the upper limb muscles of the patients during their initial rehabilitation sessions. We target to motivate the patient to complete the designed rehabilitation program. The results can then be used by the therapist to tailor an appropriate rehabilitation program for each patient.

This chapter covers our use of a robotic data and clinical biomarkers associated with upper limb function data that collected and measured for post-stroke patients to estimate the efficiency of rehabilitation recovery.

It also illustrates how to predict rehabilitation recovery for post-stroke patients by developing the MME model using robot-based biomarkers in both the FIM biomarker

and SIAS biomarker for EMG signals. Finally, it presents the synergy of the affected and non-affected sides of the body for post-stroke patients that can help predict their ability to recover based on their performance of daily activity rehabilitations, and that represents the level of recovery and improvement potential for a given rehabilitation technique.

6.1 Stroke Assessment

Generally, stroke causes long-term disability, with the patient suffering from physical weakness or paralysis of the limbs, usually on one side of the body. The patient will also experience difficulty gripping or holding objects and will have reduced joint mobility, which makes biomarker assessment problematic (Le Sant et al., 2019). The assessment procedure can be time-consuming, which can increase patient recovery time and cost. FIM and SIAS are two types of biomarker assessments. These assessments generally describe the patient's ability to recover or improve after stroke to perform daily activities of living.

6.1.1 Functional Independence Measure (FIM)

FIM is widely accepted as a body functional assessment of the patient's ability to perform daily rehabilitation tasks (Hamilton, Laughlin, Fiedler, & Granger, 1994; Ottenbacher, Hsu, Granger, & Fiedler, 1996). It is an instrument was developed and used to measure the disability for different verity of movement (Mayur, Adiga, Ananthan, & Adiga, 2021). FIM contains a total of 18 tasks, rated on up to 7 scales (Chehata, Shatzer, & Cristian, 2019). Table 6. 1 summarises the FIM measurement features. These are divided into two categories: 13 motor items (assessing self-care, sphincter control, mobility, and locomotion) and five cognitive items (assessing communication, psychosocial, and cognitive functioning) (Cech & Martin, 2012; Gillen, 2009).

Generally, FIM reliability and validity have a good interrater reliability score. FIM evaluates the recovery rehabilitation depending on the independence score from 1 to 7 to complete the 18 items. The maximum score for FIM is $18 \times 7 = 126$ (for motor items and cognitive items), which indicates complete independence ability. The minimum score is $18 \times 1 = 18$, which means the lowest end of the task dependence (Gillen, 2009). The maximum score for motor and cognitive items is $13 \times 7 = 91$ and $5 \times 7 = 35$, respectively. The minimum score for motor and cognitive items is $13 \times 1 = 13$ and $5 \times 1 = 5$, respectively.

Table 6. 1: FIM Features of Measurement

Motor Items	Cognitive Items
Self-care Items	Communication Items
1. Feeding	1. Comprehension
2. Grooming	2. Expression
3. Bathing	
4. Upper body dressing	
5. Lower body dressing	Psychosocial Adjustment
6. Toileting	1. Social interactions
7. Bladder control	
8. Bowel control	
9. Bed, chair, wheelchair	Cognitive
10. Toilet	1. Problem-solving
11. Tub or shower	Memory
12. Walking, wheelchair locomotion	
13. Stairs locomotion	
Motor Score /91	Cognitive Score /35

6.1.2 Stroke Impairment Assessment Set (SIAS)

The SIAS is a standardised measure of stroke damage and is used clinically to evaluate upper limb and lower body movement ineptness (Osu et al., 2011). Generally, the range of SIAS scores, according to symposium recommendations, is between 1 to 5 for each item (M. Liu et al., 2002). The SIAS score is divided into sub-categories of motor function, tone, and sensory function, including a range of motion, pain, feeling, visualisation function, speech, and sound function, among others, as illustrated in Table 6.2.

The scores are rated from 0 (severe) to 3 (normal) for Muscle tone, Sensory Function, Range of motion, Pain, Trunk balance, Visuospatial, speech, Grip and unaffected side. Other categories are: Motor function: the Proximal and Distal, the score rated 0 (severe) to 5 (normal) for the motor function category (F. Alnajjar et al., 2020; Chino & Melvin, 1996; Tsuji, Liu, Sonoda, Domen, & Chino, 2000).

Table 6.2: SIAS Scores

Item	Upper Limb and Lower Limb Scaling	
Categories	U/E	L/E
Motor function		
1. Proximal	0–5	(0–5) Hip (0–5) knee
2. Distal	0–5	(0–5)
Muscle tone		
1. Deep tendon reflexes DTR)	0–3	(0–3)
2. Tone	0–3	(0–3)
Sensory function		
1. Touch	0–3	(0–3)
2. Position	0–3	(0–3)
Range of motion (ROM)	0–3	(0–3)
Pain	0–3	
Trunk balance	0–3	
Visuospatial	0–3	
Speech	0–3	
Grip	0–3	
Unaffected side	0–3	(0–3)
The Total score for the upper limb side and the Lower side is 76 (normal function)		

The scores in Table 6.2 are used to plot a chart on a radar chart program to indicate the stroke patient's status (F. Alnajjar et al., 2020; Chino & Melvin, 1996). Figure 7.1 and Figure 6.2 shows two examples of a SIAS radar chart. This chart considered SIAS feature; it can show the patients score in different angles way. Figure 6. 1 shows the example of a 73-year-old male. This patient was first tested 26 days after the stroke; his SIAS assessment score was severe for the upper and lower limbs. After 251 days, the test was readministered, and the SIAS score was recorded as moderate. Thus, the patient's status improved from severe to moderate, and he totally recovered on some severe strokes like motor simulation and the pain reduced by time. Figure 6.2 shows the SIAS radar chart for a 59-year-old male. This patient was first tested 52 days after the stroke and again after 187 days. His SIAS assessment score shows some recovery in his lower and upper limbs (F. Alnajjar et al., 2020; Chino & Melvin, 1996).

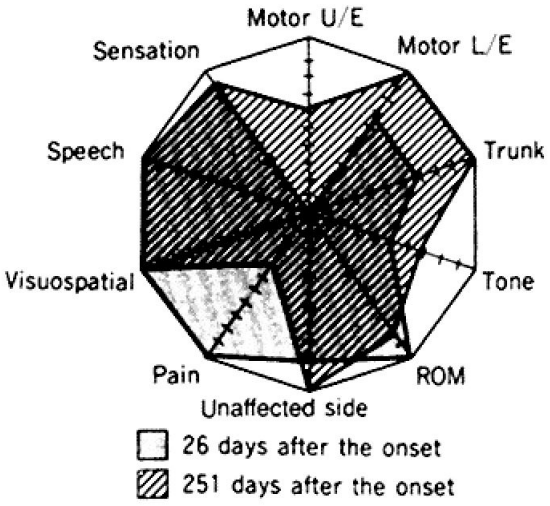


Figure 6. 1: SIAS Radar Chart for 73 years male

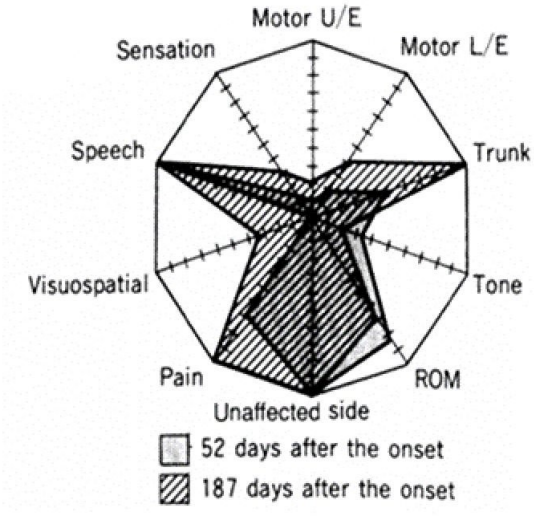


Figure 6. 2: SIAS Radar Chart for 59 years male

6.2 SIAS Radar Chart for Our Data

By considering SIAS features as in Table 6.2 for our data, we can chart the patients score for the original data and the prediction data in different angles way.

Figure 6. 3 shows the SIAS radar chart for our first patients. This patient was tested as a moderate stroke. We predict patient SIAS, and it shoes recovery in patient Motor L/E, Muscle tone, and sensory function. **Figure 6. 4** shows the SIAS radar chart for the second patient. Patient SIAS assessment score was sever for the upper and lower limbs. We predicted patient SIAS, and it shows that the patient needs more time to recover. Figure 6. 5 shows the SIAS radar chart for our third patients. Patient SIAS assessment score was Mild. We predicted patient SIAS, and he recovered in Motor L/E, Trunk Balance, Range of motion (ROM), Visuospatial, sensory function, and Motor U/E.

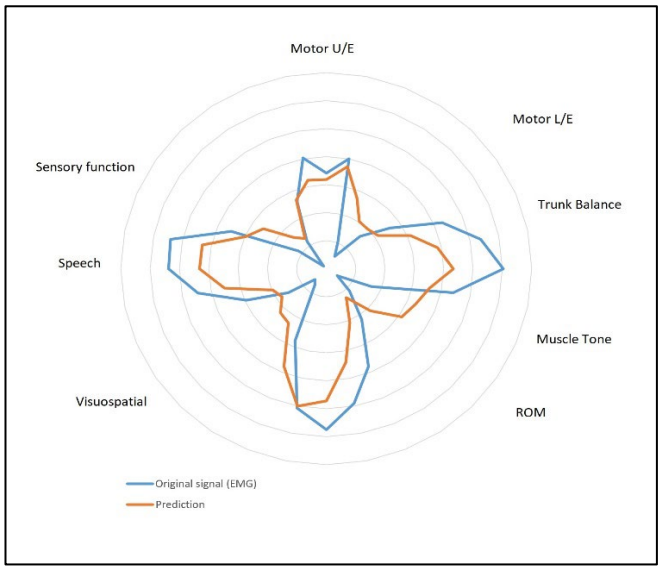


Figure 6. 3: SIAS Chart for the Second Patient (moderate)

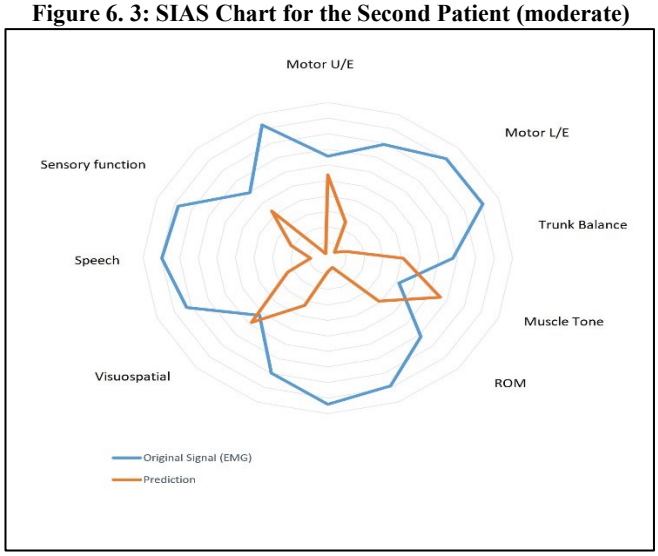


Figure 6. 4: SIAS Chart for the Third Patient (severe)

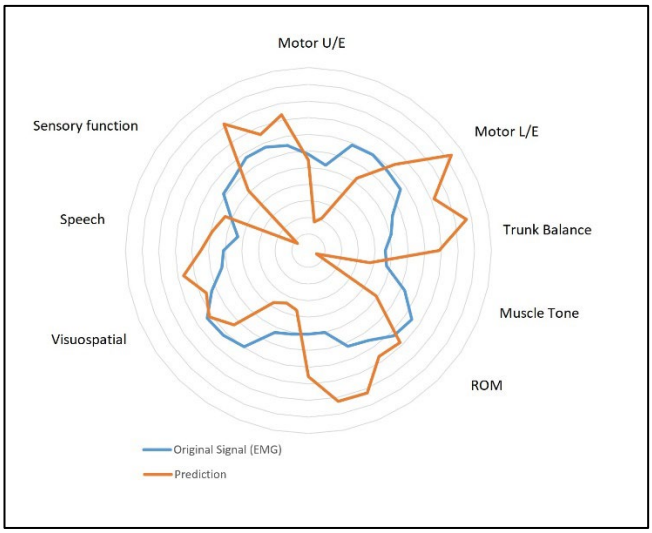


Figure 6. 5: SIAS Chart for the First Patient (mild)

Comparing Figure 6. 1,Figure 6. 2,Figure 6. 3,Figure 6. 4, and Figure 6. 5 we can see that the prediction is deferent from patient to patient depends on the stroke zone and how it affects the human body.

Health care providers such as physiotherapists, nurses, or therapists score the FIM scale or SIAS scale based on direct input from the patient (Tsuji et al., 2000). Generally, for FIM and SIAS, standard errors (SE) are taken into account (Tsuji et al., 2000).

Numerous studies have also been conducted to predict the clinical assessment (FIM and SIAS) value and predict the patient's length of stay (Sprint, Cook, Weeks, & Borisov, 2015).

In this study, we use either FIM or SIAS clinical assessment or both, based on biomarkers, to compare the biomarker value with our prediction results. In our study, we used both values to obtain more accurate results. If the proposed method success to obtain a result toward the biomarker of FIM, or SIAS results, then the proposed method successfully predicts future rehabilitation recovery. This study represents a development insofar as it uses MME to predict the patient's rehabilitation performance as well as evaluate that prediction.

The next section explains the use of MME as a prediction method, followed by a detailed description of the materials and methodology used in this study.

6.3 Multilevel Mixed-Effects (MME) Prediction

The MME model is generally used to identify how to process various changes of non-linear prediction. Thus, it helps to process single EMG channels. It is good prediction method because it estimate the value between the subject variability in motion as well as estimate the case observation (Sebri & Dachraoui, 2021). In this study, we extended the MME to predict variability in the human body for multi-EMG channels. This method provides an accurate result when based on FIM/SIAS biomarkers by adding regression coefficient parameters (discussed in greater depth in the materials and methodology section). This step reduces the final prediction error in predicting the rehabilitation recovery for the affected side of the body by using the unaffected side as a reference. The MME for each EMG signal has different intercepts and slopes across time. MMEs have become important tools in recovery prediction. They allow the analyst to treat the effects of the collected data through the prediction process. EMG data vary from patient to patient and muscle to muscle; there are even variations within the one muscle depending on movement type, movement force, movement angle, and surface electrodes. Thus, such a data structure lends itself to analysis via mixed-effects models. The most important element in rehabilitation application is the modelling, and especially, the prediction of rehabilitation (Hall & Clutter, 2004). In this study, we describe how we improve the MME model to fit multiple EMG channels.

6.4 Material and Methodology

This section specifies how we modify and predict rehabilitation movement using the EMG data. It also describes how we predict movement using a multi-EMG data channel.

6.4.1 Participants

Three stroke patients were recruited for this experiment. The data were collected from each patient at different times, as shown in **Table 6.3** In the table, ID refers to the three patients, identified as P1 (Patient 1), and so on. G/A indicates gender and age, respectively. A-side indicates the affected side. The first data collection for this patient occurred on 1 December 2016. Overall, data we collected from this patient 12 times over four months. For Patient 2, data were collected 14 times over six months, whereas for Patient 3, data were collected 9 times over four months. The age of Patient 1 was 93 years, Patient 2 was 72 years, and Patient 3 was 52 years. The first two patients were female, and the third patient was male.

Table 6.3: Patient Collection Data Dates

			2016 (Y)			2017 (Y)																	
ID	G/A	A-side	12			1		2					3			4			5			6	
P1	F/93	R	1	7	14	16	30	6	13	20	27	6	13	27									
P2	F/71	L					30	6	13		27	6	13	27	3	10	17		15	22	5	12	
P3	M/52	L							13		27	6	13	27	3	10	17	8					

Table **6.4** shows the patients' stroke strength based on SIAS/FIM biomarkers rated as severe, moderate, or mild. The table also shows the stroke date for each patient. For example, for Patient 1 (P1), the date on which the stroke occurred was 7 November 2016. Also, Table **6.4**, show the SIAS biomarker and the FIM biomarker reading date and results before and after treatment, respectively. The table shows SIAS biomarker results before treatment and after treatment. These reflected the improvement in the patients' status, meaning that the patients had recovered. The same data are presented for the FIM biomarkers also showing improvement, with the motor item (see **Table 6. 1**).

Table 6.4: Patient Information

	Ref ID	G/A	Stroke Date	Stroke type	SIAS Before training		SIAS After training		FIM Before training		FIM After training	
					Date	UE	Date	UE	Date	motor	Date	motor
1	P1	F/93	7.11.16	moderate	1.12.16	1	2.4.17	3	1.12.16	20	2.4.17	71
2	P2	F/71	25.12.16	severe	30.1.17	0	12.6.17	2	30.1.17	20	12.6.17	62
3	P3	M/52	23.1.17	light	13.02.17	3	23.6.17	4	13.2.17	58	23.6.17	87

6.4.2 Rehabilitation Device

The dual steering system is used to perform symmetrical tasks at the upper limb level, as shown in Figure 6.6A. This robotic device can quantify many areas of brain by collecting the EEG signal or collecting the EMG data using set of movement tasks. The data provided in this task on the robot can potentially be used as diagnostic for different neurological deficits and disorders. Figure 6.6B illustrate the graphical interface, which signals to the patient to synchronise subject movement with the desired cycling frequency. The system allows three working modes depending on the interaction between the steering axes: free mode (FREE) in which the axes rotate independently, asynchronous mode (ASYM), and synchronous locked mode (SYM) in which both axes are connected, experiencing the same angle of rotation in an asymmetric or asymmetric direction Figure 6.6C. The system also permits the use of different rotating elements, such as steering wheels and cranks, as shown in Figure 6.6D and Figure 6.7. First, the patient makes a voluntary movement before using the dual steering system. This movement trains the central nervous system (CNS), indicating that there is a new movement that the body

will make. The CNS will assign new neurons to carry out this exercise. This movement was discussed in detail in one of our previous studies (Bani Musa et al., 2017). Second, the patient is seated in front of the dual steering system. For accessible EMG recordings, the data were collected with a sampling frequency of 1000 Hz by using surface electrodes positioned according to the surface electromyography (sEMG) guidelines (Bani Musa et al., 2017; Costa et al., 2017), as shown in Figure 6.7, Several independent sessions were conducted with rest in between to minimise potential fatigue. Some of these sessions took place on the same day, some took place on different days, and some were conducted after a few months, as we see in Table 6.3.

6.4.3 MME Prediction and Time Series Prediction

MME is commonly used in economy, biostatistics and sociology. It is usually used for single prediction items, such as the performance of the economy to predict the growth of a country in the coming year (G. Chen et al., 2013; Stinear et al., 2017).

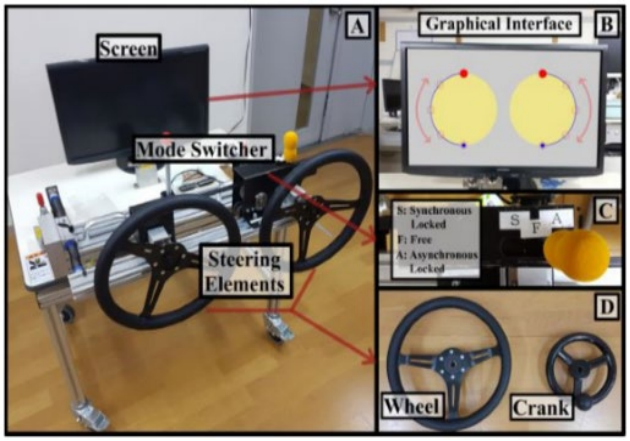


Figure 6.6: Experimental Environment: A) Dual Steering System, B) Graphical Interface to Synchronise Subject Movement With the Desired Cycling Frequency, C) Switcher to Select the Working Mode, D) Steering Elements

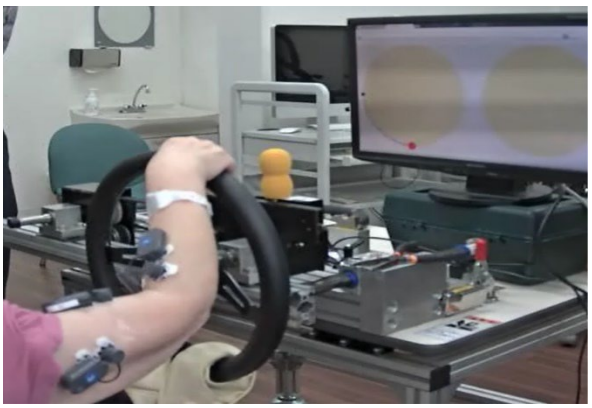


Figure 6.7: Participant Positions While Holding Dual Steering Wheel

We developed and calculated the MME prediction based on the FIM/SIAS biomarker by combining groups of EMG data for the affected muscles to predict rehabilitation recovery. We took the unaffected side as a reference to determine the prediction recovery for the affected side. EMG data were collected from the affected and unaffected sides using the dual system with a sampling frequency of 1000 Hz.

EMG data were obtained using 18 EMG channels, which recorded data from the upper limbs and back and chest muscles of the patients while performing the driving simulation tasks (Bani Musa et al., 2019; Costa et al., 2017). Nine surfaces of EMG were recorded from the muscles on the affected side, and nine sEMG data were recorded from the unaffected side according to the sEMG guidelines (Costa et al., 2017; Hermens et al., 1999) with the following distribution: brachio radialis, protanor teres, biceps, triceps, anterior deltoid, posterior deltoid, pectoralis major, infra spinatus and elector spinae.

We use the unaffected EMG signals (the healthy side) as an indication in the prediction procedure to determine whether the affected side prediction results are going to be similar or close to the unaffected side EMG signal value. If the affected prediction results values were close to the unaffected side EMG signal value, this indicated that the affected side had recovered.

6.4.4 Methodology and Results

As shown in Figure 6.8, the MME prediction process started with raw EMG data that were collected using the dual steering system. The data were then sampled at 1000 Hz and filtered between 20 and 450 Hz using the Butter filter. Then, the signal was smoothed using a moving average filter to obtain better results, as in Figure 6.9.

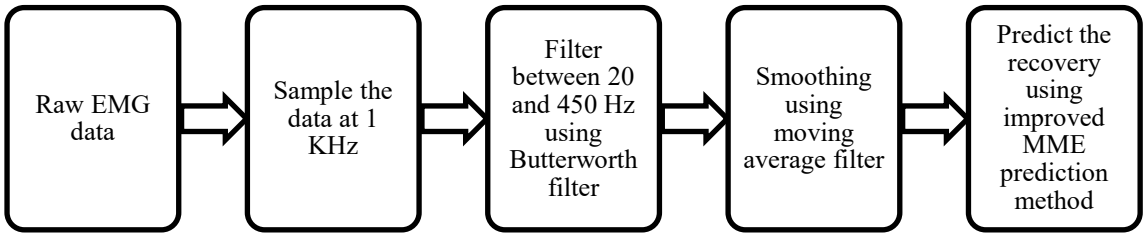


Figure 6.8: MME Prediction for EMG Signal

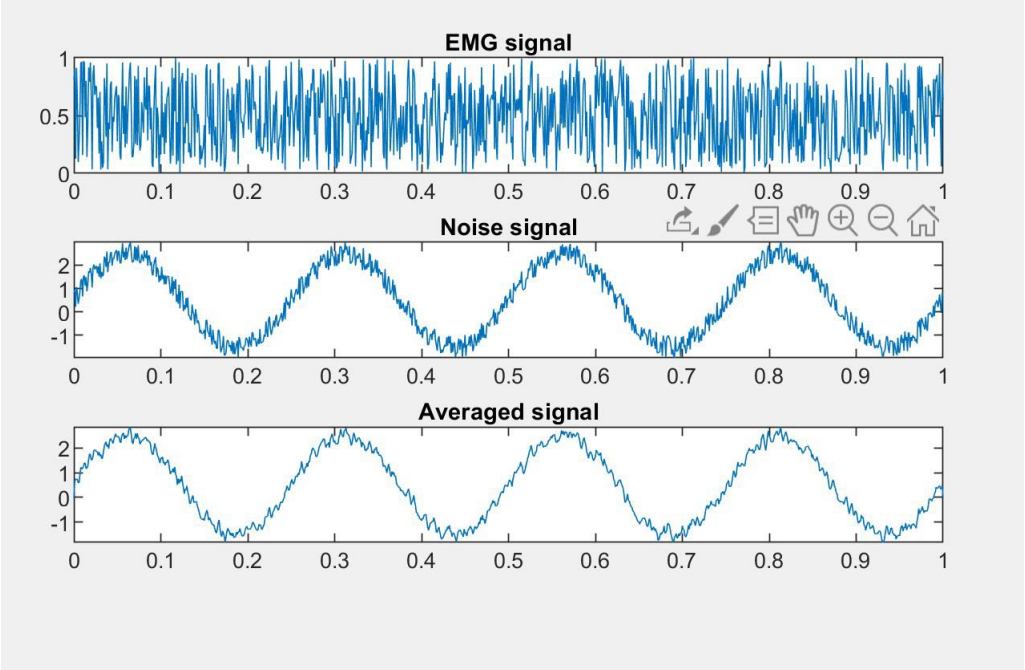


Figure 6.9: EMG and Average Signal

We calculated the average signal values, as in Equation 7.1:

$$\mathrm{Y(n)} = \frac{X(n-1) + X(n) + X(n+1)}{3} \quad , \begin{cases} X(n) = noise\ effected\ signal \\ Y(n) = Averaged\ Signal \end{cases} \qquad \textbf{6.1}$$

Note: In order to validate the real meaning of (n-1) and (n+1), the average loop starts from 2: n-1

Time series prediction is a useful tool to predict future behaviour. Time series data are usually modelled through a random probability distribution process and used the data that function of time (Sapankevych & Sankar, 2009; Thissen, Van Brakel, De Weijer, Melssen, & Buydens, 2003). We built a new time series model to predict future rehabilitation based on extracted synergy.

Figure 6.10 illustrates our time series prediction methodology model. The model starts with raw EMG data, but after smoothing the signal, we extracted the synergy EMG using concatenated non-negative matrix factorisation (CNMF) for the unaffected and affected sides. In particular, we used the CNMF extracting method rather than the NMF method to improve the efficiency of the CNMF, as in one of our previous studies (Bani Musa et al., 2017).

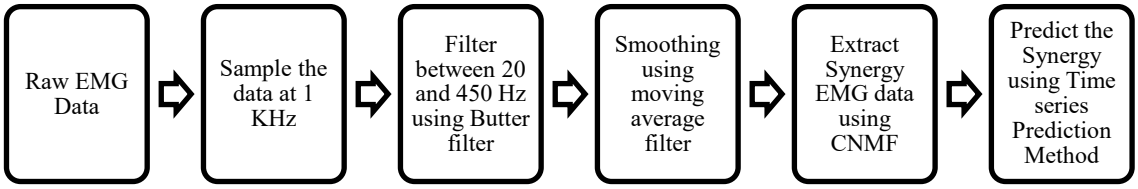


Figure 6.10: Time Series Prediction for Synergy EMG

We calculated the final prediction error (FPE) for the MME as in Equation 6.2 and mean square error (MSE) as in Equation 7.3, between the filtered EMG data and the Prediction EMG data. This is defined in the equation below:

$$FPE = \left(\frac{1+\frac{d}{N}}{1-\frac{d}{N}}\right) * V \qquad 6.2$$

Where d is the regression coefficient, which describes the prediction relationship value between the unaffected side and the affected side. The coefficient sign (+/−) indicates the direction of the relationship between the unaffected and affected sides. The positive sign means that the muscle will recover, whereas the negative sign means that the muscle will not recover (S. Wang & Cui, 2020). N is the length of the data record (observation data). V is the loss function for the structure (Fryer, Odegard, & Sutton, 1975)

$$MSE = \frac{1}{n}\sum_{i-1}^{n} \left|\theta_i - \widehat{\theta}_i\right|^2 \qquad 6.3$$

Where n is the number of observation values in each EMG channel(number of the collected data), θ the true value for the estimate of interest, and $\widehat{\theta}_i$ is the estimate of interest obtained from the i_{th} simulation (Rombach, Jenkinson, Gray, Murray, & Rivero-Arias, 2018).

The simple regression model has explained the relation between y (the regression output) and one independent variable, x, as in Equation 6.4. We used this equation to predict the EMG single channel.

$$y = \beta_0 + \beta_1 x + \varepsilon \qquad 6.4$$

For the MME regression model, we developed Equation 6.4 to fit the various EMG data. Equation 6.5 explains the relation between y and more than one independent variables

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad 6.5$$

Where: $\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ are the parameters, and ε is the error.

We developed Equation 6.5 to fit our EMG data. We used a sample to estimate the multiple prediction equation based on the least square method. Since the calculation for

the parameters: β_0, β_1, *and* β_2 are not known, it was necessary to use sample statistics to estimate these parameters. We calculated the coefficient for each EMG channel to calculate the recovery prediction. We used the sample statistics to develop the parameters in Equation 6.5. The developed parameter, as in Equation 6.6, is obtaining the multiple prediction equation. This allowed us to find the best line that fitted our data by adding the coefficient parameter to Equation 6.5.

$$\hat{y} = b_0 + b_1 c_1 + b_2 c_2 + \cdots + b_n c_n + \varepsilon \quad \textbf{6.6}$$

Where: b_0, b_1, ..., b_n are the EMG values for each observation, c is the coefficient for each muscle, n is the signal value, which is 9 in our study (9 EMG channel).

Equation 6.7 is the least square equation; it calculates the least square error between the observed EMG data and the prediction value.

$$\min \sum (y_n - \hat{y}_n)^2 \quad \textbf{6.7}$$

Where:

y_n : is the observed value of the y for the nth observations.

$\hat{y}_n$: is the predicted value of y for the nth observations.

From Equation 6.7, we obtained two values: the observed value (the unaffected side reference value) and the predicted value (which is the prediction recovery for the affected side). The best regression line that affects the data can be found by minimising the mean square error between the observed value (y_n) and predicted value ($\hat{y}_n$).

By testing the significance of the individual parameters, we suppose the following:

$$\begin{cases} H_0: \beta_i = 0, & p - value \leq \alpha, \alpha = 0.025.\ The\ value\ is\ sygnificant, posibility\ of\ recovery \\ H_n: \beta_n \neq 0, & otherwise\ , No\ recovery \end{cases} \quad \textbf{6.8}$$

In Equation 6.8, we predicted H_0 if the $p - value \leq \alpha$ or using the critical value approach, which is: If $p - value \leq \alpha$ that mean $\beta_i = 0$. In turn, this means that there is a relationship between the affected side and unaffected side prediction values. Therefore, it is possible to predict the recovery of the patient.

By calculating the *p*-value in each session for each EMG channel, we can predict whether the muscle will recover or not. Table 6.5 Present the results for each muscle to determine an indication parallel with the SIAS biomarker to enable recovery prediction. The table shows the sample values for the three patients for multiple sessions with moderate, severe, and mild stroke, respectively. We calculate the intercept, multiple R, R squared, and the standard error to find the signal prediction output.

Table 6.5 shows that the values for the multiple R and the R square is towards 1. This means that the patients recovered, but they needed more practice. When these results are compared with those in Table 6. 1 and Table 6.2, we find that after training, the patient showed a moderate recovery (which is 3 SIAS and 71 FIM), the second patient showed minimal recovery (which is 2 SIAS and 62 FIM) and the third patient showed the greatest recovery (which is 4 SIAS and 87 FIM). After calculating the previous parameters for each EMG for all sessions for each patient, the results are presented in Figure 6.11, Figure 6.12 and Figure 6.13.

As in Equation 6.8, after calculating (α-(p_value)) for each single EMG channel, we placed zeros in the negative value as we see in Table 6.6 to simplify and understand the prediction results.

Table 6.5: MME Prediction for the ES-EMG Channel for Unhealthy Side

	Sessions	Intercept	ES (EMG_9)	Multiple R	R Square	Standard Error
P1	1	-3.8E-11	-0.021995	0.67	0.45	2.61433E-05
	2	7.65E-11	8.61E-02	0.76	0.57	1.10175E-05
	3	-8.3E-10	-2.33E-02	0.90	0.81	3.51754E-05
	4	-2.9E-09	1.21E-03	0.85	0.73	1.82951E-05
	5	-1.1E-10	-3.02E-03	0.28	0.08	8.62527E-06
	6	1.74E-11	-1.21E-03	0.69	0.48	1.02802E-05
	7	-2.1E-11	-1.70E-02	0.74	0.55	1.9213E-05
	8	-6.2E-11	2.40E-02	0.56	0.31	1.85957E-05
	9	-4.6E-10	-1.30E-01	0.86	0.74	1.42564E-05
	10	-1.8E-10	-6.26E-01	0.92	0.85	1.51882E-05
	11	-5.8E-11	1.52E-01	0.49	0.24	1.23125E-05
	12	-2.8E-11	-1.13E+00	0.94	0.87	1.20597E-05
P2	1	2.78E-11	3.29E-01	0.85	0.73	1.25563E-05
	2	1.83E-10	5.97E-03	0.31	0.10	1.07049E-05
	3	-3.9E-11	8.38E-02	0.91	0.82	1.67023E-05
	4	1.94E-10	-8.17E-03	0.86	0.74	9.71386E-06
	5	7.18E-12	1.93E-01	0.34	0.11	1.02255E-05
	6	1.19E-10	2.59E-02	0.84	0.70	1.03589E-05
	7	-2.7E-10	4.77E-02	0.92	0.85	1.46256E-05
	8	4.96E-10	-9.07E-02	0.82	0.67	5.25837E-05
	9	7.75E-11	1.70E-03	0.05	0.00	9.84463E-06
	10	-3.4E-11	-2.27E-02	0.18	0.03	9.41904E-06
	11	-9.7E-12	-1.96E-04	0.35	0.12	8.95578E-06
	12	-3.1E-10	-2.44E-03	0.04	0.00	1.51845E-05
P3	1	8.36E-12	4.48E-04	0.89	0.79	7.6842E-06
	2	1.23E-11	5.71E-03	0.57	0.32	1.70211E-05
	3	2.12E-12	1.24E-01	0.66	0.43	1.73212E-05
	4	7.07E-11	1.15E-01	0.74	0.54	1.1864E-05
	5	1.37E-10	-6.00E-02	0.59	0.35	3.68439E-05
	6	-2.1E-11	1.65E-02	0.83	0.69	7.70275E-06
	7	-2.3E-10	2.52E-01	0.82	0.68	1.27693E-05
	8	9.51E-12	6.85E-01	0.55	0.31	1.61569E-05
	9	2.97E-10	3.26E-01	0.60	0.36	9.80951E-06
	10	4.81E-11	-1.11E-02	0.69	0.48	1.48361E-05
	11	5.08E-10	1.72E-02	0.73	0.53	1.0308E-05
	12	-1.1E-10	-4.86E-02	0.92	0.85	7.30509E-06

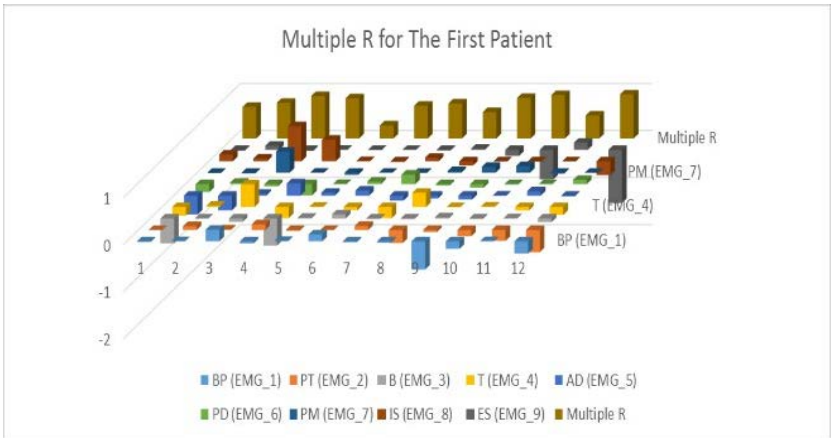


Figure 6.11: Multiple R for First Patient

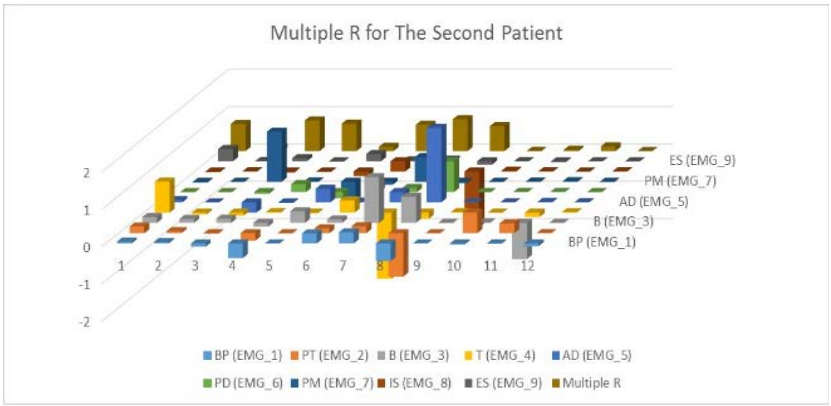


Figure 6.12: Multiple R for Second Patient

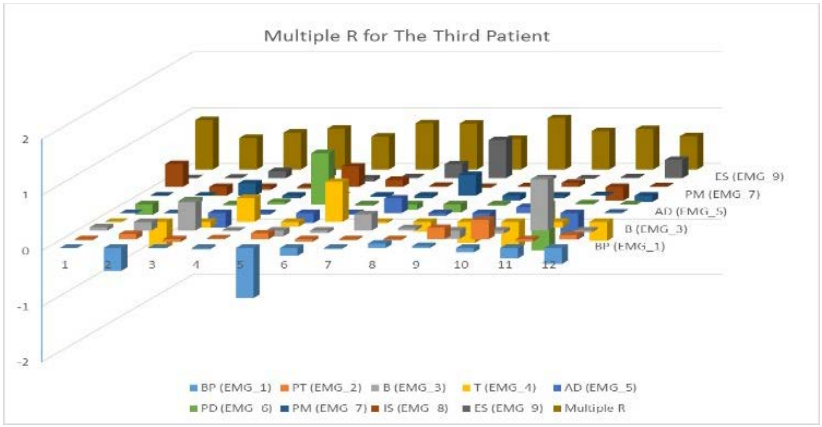


Figure 6.13: Multiple R for Third Patient

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Table 6.6: (α-(p_value)) for all EMG Signal

	Sessions	BP (EMG 1)	PT (EMG 2)	B (EMG 3)	T (EMG 4)	AD (EMG 5)	PD (EMG 6)	PM (EMG 7)	IS (EMG 8)	ES (EMG 9)
First patient	1	2.500E-05	2.611E-01	0	0	0	0	2.227E-14	0	8.073E-51
	2	6.907E-04	0	2.625E-02	2.146E-136	0	3.848E-77	2.297E-07	0	0
	3	0	1.976E-01	1.706E-211	0	3.097E-18	3.366E-76	0	0	1.955E-19
	4	5.338E-23	9.467E-36	0	0	1.404E-163	5.424E-285	1.188E-02	0	7.173E-01
	5	6.997E-60	4.711E-23	3.520E-200	1.242E-63	0	6.381E-06	3.435E-133	1.458E-07	1.764E-03
	6	0	5.349E-02	2.241E-219	0	0	0	2.202E-02	4.892E-56	5.641E-05
	7	4.833E-50	0	3.673E-12	0	0	0	3.292E-20	0	1.245E-101
	8	7.701E-66	0	4.266E-27	0	0	1.088E-62	2.821E-57	0	1.648E-32
	9	0	2.774E-166	1.818E-108	2.334E-23	1.256E-258	0	0	1.731E-03	0
	10	0	0	6.782E-07	1.448E-31	1.433E-01	3.607E-02	0	1.113E-03	0
	11	1.501E-08	0	1.766E-10	3.833E-189	0	1.579E-02	8.616E-14	1.360E-01	0
	12	0	0	0	0	3.135E-29	4.292E-212	5.263E-02	0	0
Second Patient	1	1.085E-01	6.169E-04	2.511E-02	8.587E-70	0	2.928E-13	1.379E-288	6.971E-01	7.584E-03
	2	0	1.319E-220	4.281E-161	0	6.994E-14	7.273E-01	1.610E-22	6.031E-17	0
	3	2.364E-92	1.920E-26	0	7.233E-85	4.892E-01	6.703E-01	4.476E-01	1.576E-02	1.067E-13
	4	0	3.024E-03	4.628E-01	7.397E-68	0	0	1.418E-164	1.459E-248	0
	5	0	6.101E-37	0	0	0	3.313E-214	0	2.018E-58	1.655E-75
	6	1.959E-13	7.226E-31	3.264E-01	8.350E-58	6.061E-04	8.671E-88	7.440E-01	4.219E-28	5.447E-34
	7	0	0	0	9.166E-242	9.672E-25	0	7.422E-53	5.726E-02	1.391E-27
	8	4.659E-80	2.489E-115	0	2.108E-149	1.149E-63	3.450E-02	2.911E-17	4.670E-40	6.361E-54
	9	5.325E-254	0	0	7.605E-16	0	0	1.074E-37	0	1.710E-55
	10	9.611E-01	4.148E-04	0	2.278E-02	9.018E-157	6.047E-105	0	6.224E-08	2.607E-187
	11	0	0	0	1.275E-27	1.113E-15	1.340E-01	3.656E-22	7.776E-08	3.157E-08
	12	0	1.529E-100	6.515E-176	0	5.748E-05	0	1.161E-135	0	1.559E-08
	13	0	2.045E-82	0.000E+00	0	0	6.242E-202	0	2.874E-110	1.026E-61
	14	0	2.932E-230	1.918E-129	0	0	8.501E-120	1.185E-13	4.527E-100	1.723E-90
	15	1.282E-128	0	0	1.075E-241	0	0	8.468E-21	0	4.551E-158
	16	3.221E-01	5.953E-02	7.588E-01	4.301E-01	2.490E-11	3.970E-01	6.958E-08	3.766E-02	0
	17	5.370E-01	5.582E-01	1.358E-01	8.076E-06	3.118E-03	9.578E-03	4.495E-01	3.129E-45	4.296E-01
	18	1.230E-06	0	1.648E-22	2.688E-01	6.069E-01	2.342E-02	4.152E-03	2.577E-02	2.207E-10
	19	1.971E-01	1.083E-210	0	3.301E-262	2.454E-12	1.671E-05	1.184E-14	1.293E-01	9.186E-01
	20	2.006E-01	3.382E-01	1.292E-01	1.317E-02	8.644E-01	7.437E-02	5.889E-01	5.474E-01	4.369E-02
	21	3.388E-03	6.418E-01	3.512E-01	1.408E-04	1.201E-01	4.432E-01	3.946E-01	3.623E-02	5.664E-01
	22	5.210E-01	2.433E-08	5.327E-09	1.176E-135	0	8.191E-32	0	0	1.003E-160
Third Patient	1	0	0	0	5.302E-01	0	0	1.100E-10	0	6.188E-01
	2	0	0	0	0	6.899E-01	1.203E-33	1.244E-01	0	1.513E-02
	3	0	3.021E-61	1.555E-215	2.957E-117	2.020E-41	3.526E-01	2.152E-03	6.649E-19	1.624E-09
	4	1.918E-01	5.135E-106	0	1.716E-177	0	1.860E-18	2.088E-242	2.319E-28	0
	5	3.040E-19	1.305E-22	9.040E-04	0	1.378E-64	2.190E-115	9.965E-234	6.028E-24	0
	6	1.617E-13	0	7.954E-74	1.174E-27	5.295E-35	4.217E-42	0	0	0
	7	0	0	4.531E-11	5.899E-20	0	0	0.000E+00	0	0
	8	0	6.820E-12	3.266E-88	8.697E-24	9.621E-52	0	0	2.823E-185	3.699E-22
	9	5.631E-218	8.204E-31	2.988E-116	5.410E-07	7.029E-10	0	1.425E-11	0	4.664E-103
	10	0	6.559E-232	0	0	8.800E-110	9.819E-77	1.486E-126	0	8.075E-40
	11	1.135E-11	3.608E-14	0	3.955E-28	0	3.615E-154	4.510E-100	1.866E-15	0
	12	6.240E-172	4.530E-17	1.069E-04	1.131E-128	2.402E-37	1.215E-281	0	3.476E-10	0
	13	0	2.395E-11	8.557E-01	1.078E-07	6.405E-67	0	0	4.992E-164	2.256E-82
	14	8.293E-225	3.292E-217	0	7.145E-32	0	1.419E-114	1.586E-275	6.884E-106	0
	15	0	3.384E-12	9.868E-27	1.560E-05	1.015E-30	1.288E-09	2.775E-08	2.015E-34	4.583E-19
	16	2.672E-05	2.099E-286	0	5.848E-153	0	1.317E-81	6.909E-277	1.738E-10	1.043E-51
	17	4.063E-166	0	5.782E-160	0	0	0	1.525E-147	4.108E-23	1.146E-02
	18	7.223E-17	0	1.047E-59	0	7.894E-175	0	4.470E-12	4.271E-164	6.737E-02
	19	0	5.499E-138	0	1.879E-134	0	2.200E-25	7.746E-16	0	8.373E-31
	20	1.124E-97	3.699E-03	0	2.341E-13	1.299E-12	0	8.770E-02	0	1.151E-03
	21	7.561E-274	6.555E-127	5.724E-120	0	4.532E-11	5.395E-02	6.489E-107	7.803E-13	0

Figure 6.14, Figure 6.15 and Figure 6.16 indicate which muscles will help recovery during the single sessions for each patient.

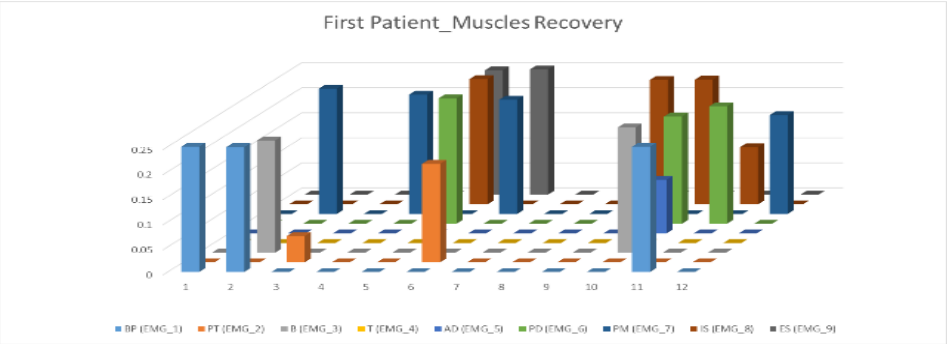

Figure 6.14: Muscles Recovery Prediction for the First Patient

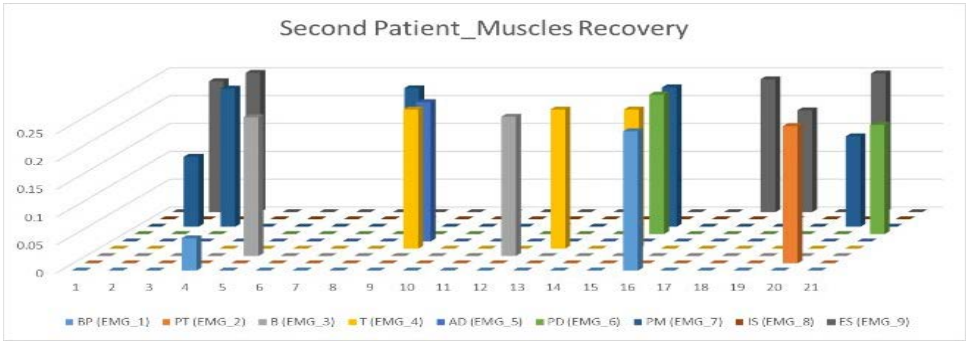

Figure 6.15: Muscles Recovery Prediction for the Second Patient

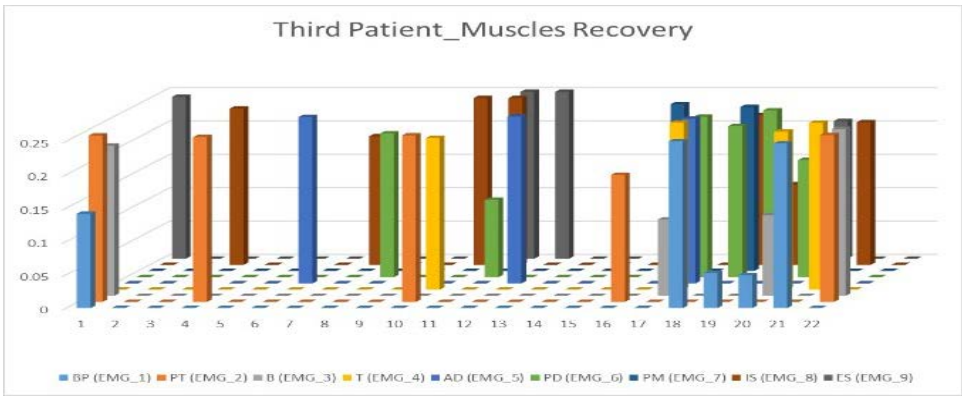

Figure 6.16: Muscles Recovery Prediction for the Third Patient

From Table 6.6 and Figure 6.14, the first patient has 12 data collection sessions. Table 6.6 and Figure 6.15, the second patient had 21 data collection sessions. Table 6.6 and Figure 6.16 third patient had 22 data collection each session. Some muscles had recovered, whereas others had not. Therefore, we can conclude that this patient's recovery was moderate. As shown in Table 6.6 and Fig. 12, for the second patient, only a few muscles recovered with each session. Therefore, we can conclude that this patient had a severe stroke. As shown in Table 6.6 and Fig. 13, for the third patient, many muscles

recovered with each session. After we compare our results chart and the SIAS and FIM results in Table 6.6, we can see that the recovery results are very close because the high value in SIAS that indicates full recovery is 5, whereas the lowest value of 0 indicates no recovery. Our prediction method and results match the SIAS results in Table 6.6. This means that the MME prediction for multi-EMG channels successfully predicts stroke patients' rehabilitation.

We demonstrated how the time series prediction method could predict the rehabilitation recovery using the synergy EMG for stroke patients of the upper limbs for the near future results.

Figure 6.17, Figure 6.18 and Figure 6.19 represent the first, second and third patients time series synergy prediction, respectively.

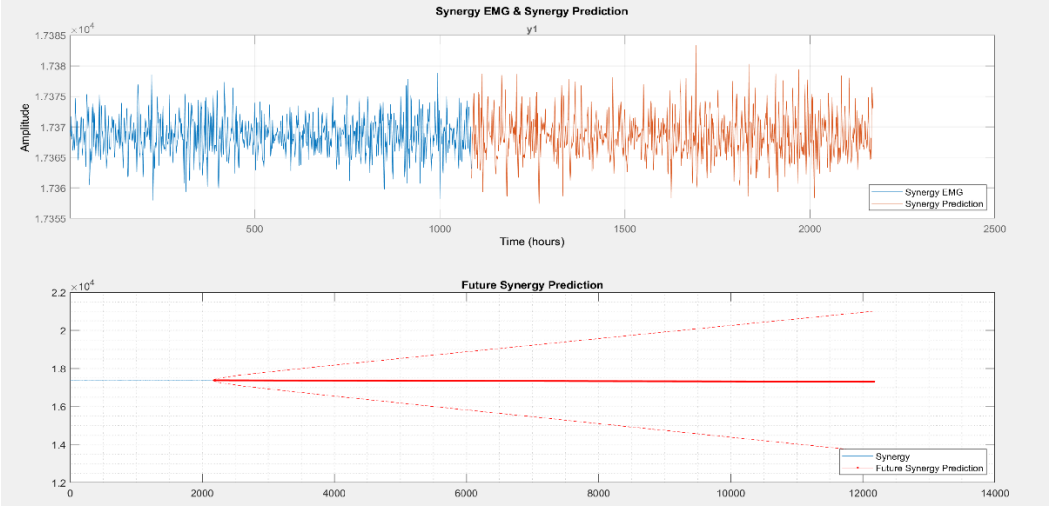

Figure 6.17 First Patient Synergy Prediction

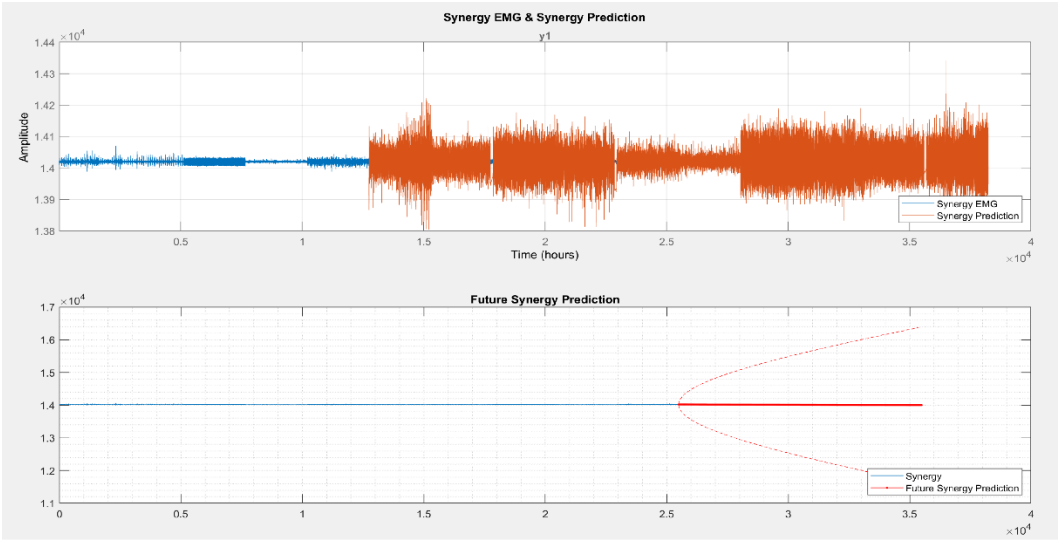

Figure 6.18: Second Patient Synergy Prediction

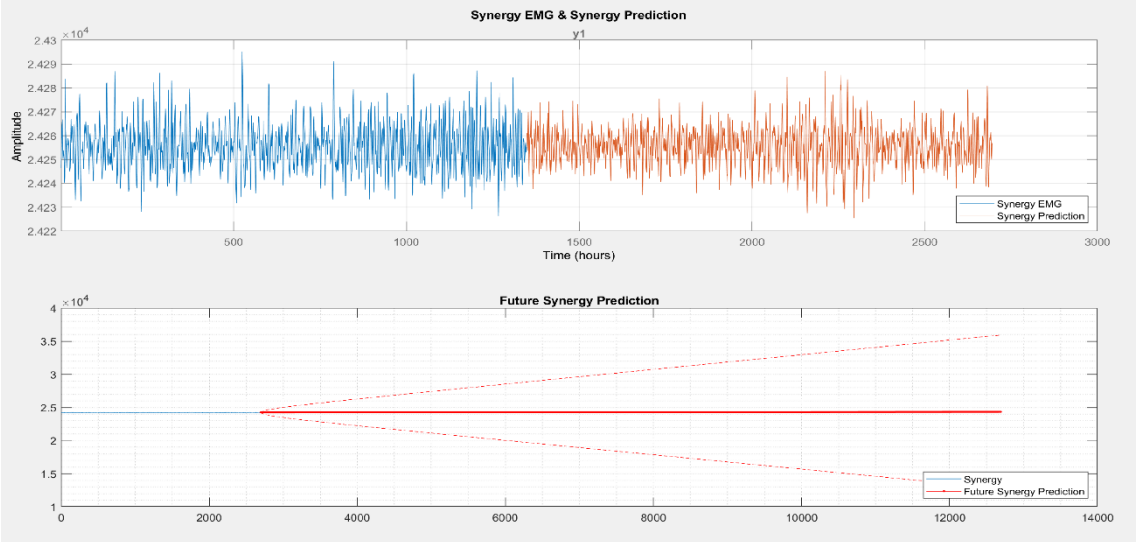

Figure 6.19: Third Patient Synergy Prediction

In Figure 6.17, Figure 6.18 and Figure 6.19, the first simulation shows the synergy prediction in the short term. The second simulation shows the time series prediction after three months. The first patient has recovered moderately, taking into account the amplitude range. The second patient has recovered with a small amplitude. This means that the stroke was severe, not all muscles will recover, and recovery time will be longer. The third patient also has an increased amplitude range, which means that his recovery is different from the first and second patients'. These results are compatible with the SIAS biomarkers to predict future rehabilitation recovery.

6.5 Summary

In this study, we predicted the recovery of severe, moderate, and mild stroke patients during their rehabilitation program. We successfully anticipated their rehabilitation possibility using the MME method and predicted their future recovery performance based on muscle synergy using time series prediction. This study modelled and developed the MME for the collected EMG data, demonstrating that the MME provides a significantly superior method to predict the rehabilitation recovery performance of stroke patients using multi-EMG channels. This improved prediction method can help researchers to identify the possibility of stroke patients' recovery and ability to perform daily rehabilitation tasks. This was proved by comparing our results with the clinical FIM or SIAS biomarkers. This study also demonstrated predicted future rehabilitation movement recovery for stroke patients based on synergy data, which facilitates the efficient selection of essential muscles.

Chapter 7: Thesis Summary, Conclusion and Future Work

This chapter summarises the thesis and its major findings. It also offers recommendations for future research in the same field.

7.1 The Significant of The Research

Stroke is the major factor causing disability in people of all age groups. The stroke patients required rehabilitation to recover their function movements. The main aim of this thesis was to introduce two computational intelligence-based human movement types—automatic body action and voluntary action based on EMG signal in the upper limb of the body to predict muscle rehabilitation performance. We studied the biomedical signal to improve muscle strength and develop human control systems to improve quality of life by predicting recovery, which can help physiotherapists predict training outcomes and clarify the best rehabilitation training programs. This study studied upper limb movements and applied recorded EMG signals to predict rehabilitation performance for post-stroke patients in terms of their daily upper limb motor activities. The study sought to help improve muscle strength via specialised care by giving patients the right exercises and predicting their recovery performance ahead of three months. To achieve these aims, we studied EMG pattern recognition. As pattern recognition has made numerous experimental results achievements which are frequently overtaken by machine-learning methods, we investigated and developed EMG pattern-recognition approaches to help the muscles to regularly work every time and as a real function to support and understand how the CNS shapes voluntary motion.

7.2 Thesis Summary and Results

This thesis has success to add new knowledge to the field. **Chapter 1** reviewed an introduction for this thesis including the contributions, objectives, questions, and publications. **Chapter 2** reviewed the literature on upper limb anatomy and presented an overview of EMG signals. **Chapter 3** provided background on EMG and synergy signals for the upper limbs. **Chapter 4** explained how automatic body responses could be used as a guide to familiarise and understand voluntary movement to help the CNS system shape voluntary motions and improve rehabilitation performance. The first part of the chapter explained how to shape the movement by extracting synergy EMG based on pattern recognition. We extracted the features for the EMG using the following TD and time-frequency features: MAV, SSC, ZC, WL, Hjorth, MWP and SKW. We then used

the LDA classifier because it has the ability to cope with a large dataset such as the one we used. We obtained 0% error in the pattern-recognition classification. The second part of the chapter detailed how to shape the movement by extracting synergy EMG based on CNMF. Here, we did not use a classifier (which is new to not using classification in the pattern recognition methodology). We developed the NMF to CNMF to reduce the error and found the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs—we obtained > 95% VAF overall. The results of this chapter were published it IRIS 2017 (Bani Musa et al., 2017).

Chapter 5 predicted post-stroke patient rehabilitation. We investigated the possibility of the machine-learning algorithm using SVMR to predict functional motor recovery for post-stroke patients during their rehabilitation programs. In this chapter, we compared the actual results with the predicted output results, finding that some muscles would recover completely, some would slightly recover, and some needed more time than the duration of the planned rehabilitation program. The kernel that achieved the minimum error in SVMR was the fine Gaussian kernel. The results for this chapter were published on ICNR 2019 (Bani Musa et al., 2019).

Chapter 6 predicted rehabilitation for post-stroke patients by developing the MME and predicting rehabilitation performance ahead of three months based on time series prediction. It also presented the synergy of the affected and non-affected sides of the body for post-stroke patients, which can assist in predicting their ability to recover daily activity. This can indicate the extent of a patients' recovery and improve the potential of post-stroke patients and help guide rehabilitation strategies. We compared our results with the FIM and SIAS biomarkers and found that we successfully predicted rehabilitation recovery for a particular number of post-stroke patients. Further, we helped therapists assist post-stroke patients by devising a proper rehabilitation program for them.

7.3 The Limitation of The Research

- The data used were collected using the Delta 3 manipulandum device.
- This data recorder for around 3 months' time.
- We use the data to predict performance.
- Limitation on the number of participants.

7.4 Future Work

It is advised that future research in this area seek to achieve the following:

- improve the repeatability and reliability of automatic body movement and voluntary action movement by predicting the movement type
- Develop the pattern-recognition methodology. Currently, pattern recognition is used to classify upper limb movement, but our future work aims to predict the upper limb motor movement type for post-stroke patients with considering the real-time. This work will help physiotherapists choose the right recovery exercises and thus reduce recovery time and cost.
- Increase the performance of the pattern-recognition system using other machine-learning techniques, such as the ELM, on the synergy signal to reduce the prediction error, as the ELM is fast to learn, requires less training and saves recovery time
- Develop the ELM method to predict the post-stroke patient rehabilitation movement type
- Develop the ELM method by optimising the main parameters to be the Swarm-ELM regression method, which can help predict the movement type for post-stroke patients.

7.5 Conclusion

This thesis adds to knowledge a particular theoretical and practical understanding of a particular area. The major goal of this study was to introduce a new computational intelligence-based EMG signal for use in upper limb rehabilitation. Its three main contributions helped achieve this purpose and have the potential to solve issues that arise in real-time applications. The first contribution was to successfully analyse the automatic body response and voluntary action. We successfully found that synergy can help the CNS shape voluntary action by calculating the VAF. We used the CNMF method and the pattern-recognition method with > 95% overall VAF and 0% error, respectively. The second contribution was to successfully predict future muscle rehabilitation for post-stroke patients using SVMR. The third contribution was to successfully examine the ability to predict the future muscle performance of post-stroke patients based on their current motor ability. This motivated the patients to complete their designed rehabilitation program. This study successfully anticipated rehabilitation potential using the MME method based on a robot-based biomarker in both FIM and SIAS for EMG signals. This

saves physiotherapists significant time and advises patients which types of exercise are useful or not after one or two months. In addition, we successfully predicted future rehabilitation for post-stroke patients based on synergy data, which allows the accurate selection of essential muscles.

Through these contributions, the synergy of the affected and non-affected sides of the body can successfully help predict the ability and the level of post-stroke patients' performance recovery of their daily movement activity and improve rehabilitation techniques for these patients.

Appendix a: Manipulandum Device

force dimension

delta.3 haptic device

force feedback interface

The **delta.3** is a high performance force feedback interface based on the delta manipulator. It offers 3 active degrees-of-freedom in translation and features a **larger workspace** than omega.x devices. Thanks to its unique parallel mechanical design, the **delta.3** can convey **large continuous forces** anywhere in its workspace.

applications

The **delta.3** provides 3D active force feedback for a wide range of applications:

- medical and space robotics
- micro and nano manipulators
- teleoperation consoles
- virtual simulations
- training systems
- research

force dimension

delta.3

workspace	translation	∅ 400 x 260 mm
forces	translation	20.0 N
resolution	translation	0.02 mm

electronics

interface	standard	USB 2.0
	refresh rate	up to 4 KHz
power	universal	110V - 240V

software

platforms	Microsoft	Windows
	Linux	all distributions
	Apple	macOS
	Blackberry	QNX
	WindRiver	VxWorks
software	haptic SDK	
	robotic SDK	

features

structure	delta-based parallel kinematics
	active gravity compensation
calibration	automatic
	driftless
user input	1 haptic programmable button
safety	velocity monitoring
	electromagnetic damping
option	right- or left-handed

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Appendix b: Published Paper

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Analyze The Human Movements To Help CNS To Shape The Synergy Using CNMF And Pattern Recognition

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Abstract

The Biomedical Signals have been studied for developing human control systems to improving the quality of life. The EMG signal is one of the main types of biomedical signals. It is a convoluted signal. This signal (EMG signal) controlled by the Central nervous system (CNS). It has been a long time expected that the human central nervous system (CNS) uses flexible combinations of some muscles synergy (MS) to solve and control redundant movements. Synergy muscles activities are different in a single muscle. In the concept of Synergy muscle, the CNS does not directly control the activation of a large number of muscles. There are two main movements can help CNS to shape the synergy. The automatic body response and the voluntary actions. These activities remain not too bright. Some studies support the hypothesis that the automatic body responses could be used as a reference to familiarize the voluntary efforts. It has been validating by analyzing the human voluntary movement and the automatic mechanical motions from the muscle synergy. Based on the validation, there was a proposition that the automatic synergy motion may express some features which could support the CNS to shape the voluntary synergy motion using the nonnegative matrix factorization (NMF). Thus the target of the presenting work is to analyses the human movements from the muscle synergy to help CNS shapes the synergy movement by suggestion using the concatenated non-negative matrix factorization (CNMF) method and the pattern recognition method. Then compare the two results and see if that help CNS to shape the synergy movements and which method has more accuracy.

Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2016).

Keywords: Muscle Synergy; Electromyography (EMG); Central nervous system (CNS); automatic body response; voluntary action component; classification; pattern recognition.

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Peer-review under responsibility of organizing committee of the 2016 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2016).

1. Introduction

Electromyography (EMG) based techniques are used for assessing, analyzing and recording the data by detecting the EMG signals generated during the relaxation of muscles or powerful muscles. On the other hand, the Synergy EMG (SyEMG) has known that the CNS control muscles in groups, more confident than individually to generate healthy and dynamic movements[1]. Muscle synergies had been used to solve the redundancy problem. SyEMG has viewed Muscle synergies (MS's) as a specific example of structural units, which are task particular ensembles of elements within a neuromotor system. There are two main movements can help CNS to deal with muscles to activate a group of muscles: The automatic body response (reflexives) and the Voluntary movements[2-4]. The automatic body response (automatic synergy) in structuring the voluntary movements (voluntary synergy) still needs to resolve. Some hypothesis based on the experiments results found that the automatic response in human formed as automatic movements[4]. Within this automatic action, the CNS can store the movement to create a voluntary movement which is the reaction movements.

This paper aims to simplify the human movements to shape the muscle synergy using CNMF, and then to use a typical pattern recognition method to classify the muscle synergy.

Nomenclature

m	The muscles number
n	Number of synergies
t	Time
E	Residuals between the recorded M and the calculated WC
$\|\|\ \|\|_F$	Frobenius norm of a matrix

2. Synergy EMG Using Pattern Recognition

Pattern recognition is researching object description and classification method. It is a collection of mathematical, statistical and inductive techniques. It includes many methods which help the development of numerous applications in different fields. CNS use many surface electromyography (sEMG) channels that show a vast ability to control the combined muscles (Synergy EMG). However, this control needs to be adapted when applied for upper limb muscles. Combining of EMG data from upper limb muscles can be used to classify hand movements[5].

This paper aims to evaluate real-time pattern recognition control of hand motions in four different environments, (Rx, Vc, Vm, Vn). This work uses two methods: using the experiment data with CNMF matrix and then apply same experiment's EMG data to the pattern recognition process with a significant change in using the features and classification methods.

The present work is to support the hypothesize that the automatic synergy powerfully shapes the formation of voluntary synergies. It also supports that this effect may increase whenever facing unfamiliar movement by mean of creating a reaction movement (voluntary motion)[4], also demonstrate how many synergies used in each movement.

3. Data Acquisition

3.1 Participants

The used data in this paper support the hypothesis to apply the new method. It had been recorded in Intelligent Behavior Control Unit, Brain Science Institute, BSI-TOYOTA Collaboration Centre of RIKEN, Nagoya, Japan. Three neurologically healthy participants, right-handed with no reported muscular impairment on the upper limb had been engaged in this study.

The study protocol was discussed and explained to the participants to be familiar with the objective of the study. They were [(means ± SD), weight 69.25 ± 9.1kg, height: 175 ± 6.2cm, age: 34.5 ± 5.1yr] participated in the study[4]. The RIKEN ethics committee approved the protocols of all participants[4].

3.2 Equipment

Participants were holding a robotic manipulandum sitting on a fixed chair beside, as shown in Fig.1(a) Delta.3 manipulandum (260mm height and 40mm diameter) has been used to collect the data[4].

Delta.3 was controlled and used to apply different resistances in various tasks. The knob position and force have been sampled at 100Hz[4].

4. Electromyography (EMG) Methods

Surface EMGs recorded from six shoulders prime muscles: deltoid anterior (AD), pectoralis major (PM), biceps brachii (BI), latissimus dorsi (LD), teres major (TM) and infraspinatus (IS). The electrodes have been placed in accordance position to the sEMG's guidelines. EMG data has been synchronized with manipulandum through the experiment. To Support the previous hypothesis, we suggest working on Synergic EMG signal. To work on Synergy EMG, we have to process the EMG signal and extract the Synergy EMG signal as shown in Fig. 1(b) and Fig.1 (c). Fig. 1(b) illustrates the process to analyze synergy EMG. It starts from raw EMG data through several steps to extract the muscle synergy using CNMF; using this technique, each muscle can be activated by various synergies.

Consequently, there are no similar two muscle activation patterns. These findings imply that the nervous system may use a limited set of control signals to activate a large number of muscles[6]. When the EMG signal is used for analysis, the synergy reflected only synchronized muscle activity. If a synergy is active at a given time, all muscles within that synergy are active[7]. Generally, muscle synergies are suggested as a solution to muscle's degree of freedom problem in motor control action potential instead of having to manage many thousands of motor units or dozens of muscles, However, using the CNMF concatenates the original EMG data of individual trials or all trials[8, 9] and while keeping the synergy pattern fixed among those trials. By keeping the synergy adjusted among participants, signal variability between the trails is limited to the coefficients and therefore is a stronger approach[8, 10]. After the CNMF had been applied, the variance accounted for (VAF) threshold was found to identify the minimum number of synergies that adequately reconstructed the characteristics of the recorded EMGs[4].

Fig.1 (c) shows the using of pattern recognition for classification method, to classify the movement by using new features and classification to get the synergy EMG result. It starts with the raw EMG data, filter the data using the butter filter, apply the result to extract features, and apply it to a classification system as a muscle synergy data, that helps to classify the hand movement to get a better result.

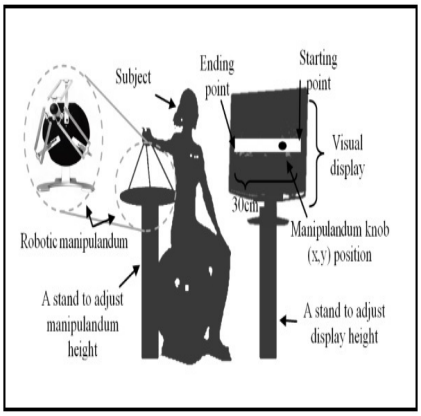
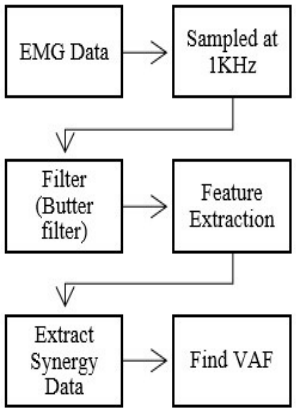
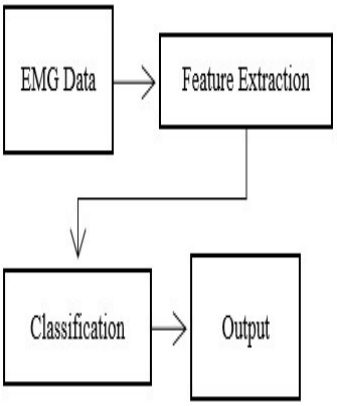


Fig.1. (a) Delta.3 manipulandum devise



(b) CNMF extracting method



(c) Pattern recognition method

4.1 Filter

It helps to remove some unwanted components (noise) or features from a signal. In other words, eliminating some unwanted frequencies to reduce background noise. Since EMG is affected by noise, a butter filter is applied.

4.2 Feature Extraction

EMG feature extraction is one of the necessary procedures to extract the useful information from the EMG signal. No additional signal transformation is needed. We used the following features[5, 11-14]:

- Slope sign change (SSC): Counts the number of times that EMG signal slope sign changes. This presents the frequency information of the EMG signal.
- Zero crossings (ZC): A representation of frequency information of the signal at time domain. It counts the number of times that EMG signal amplitude values cross the zero amplitude level.
- Waveform length (WL): A measure of the complexity of the EMG signal. It is defined as increasing length of the EMG waveform over the time.
- Hjorth parameters (Hjorth): Is normalized slope used in EMG. Moreover, Hjorth parameters are used for signal processing as surface detection and feature extraction.
- Sample skewness (skw): Is a measure of the asymmetry of a signal or measure of X order.
- Absolute values (MAV): A standard and easily implemented feature of the time domain. It finds the mean of EMG amplitude values over sample length of the signal.
- Multiscale wavelet packet (mwpf): An alternative means of extracting time-frequency information from vibration signals. It is a combination of wavelets. A recursive algorithm computes the coefficients, making each newly computed wavelet packet coefficient sequence the root of its analysis tree.

4.3 Classification System

After extracting the EMG signals features, they are ready for classification. There are many available classification algorithms. The most common classification algorithms are the K-Nearest Neighbour Algorithm (KNN), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN) and Support Vector Machines (SVM). In this work, Linear Discriminant Analysis (LDA) algorithm is used. The use of LDA for data classification is applied to classification problem in pattern recognition.

We decided to proceed with LDA in hopes for providing better classification compared to other classification algorithms[15].

5. Experiments Protocol

Voluntary and automatic actions synergies relationship have been verified through the experimental work[4], the following are the four main movements that was considered in the experiments to support the hypothesis:

5.1 Reflex response (Rx)

This measures the automatic responses from the manipulandum with zero resistance of the participants. Seated participants have been grasping the knob of the manipulandum, and the arm was positioned 90 degrees straight.

5.2 Voluntary action

At this point, there was no produced resistance from Delta.3. The movement was just from the participant with zero resistance from the manipulandum robot. By the end of this task, the movement will be familiar to the participants.

5.3 Voluntary action in a modified environment (Vm)

The experiment position is the same as above (shown in Fig.1 (a)) with 70% resistance applied randomly by the manipulandum. On this part of the experiment, there is resistance from the participant. It is random depends on the manipulandum action.

5.4 Adaption to the modified environment (Vn)

Participants can adjust the movement to the modified environment through training. In two identical sets for fifteen trials, Participant has modified the environment continuously using the previous position.

6. Data Analysis

Voluntary and automatic actions experiments stretch reflex magnitude was measured using the EMG data. The baseline was eliminated through processing the EMGs. Concatenated non-negative matrix factorization (CNMF) was used to extract the Muscle synergy from the recorded EMG data. Raw EMG data was applied on classification method.

6.1 CNMF Methodology

Concatenated non-negative matrix factorization (CNMF) is used to extract the characteristic frequency components and obtain the corresponding connectivity matrices across conditions and subjects[10, 16, 17]. In equation 1, a matrix with a dimension of m=6 (the number of muscles) was extracted from the processed EMG data of each experimental trial. It is multiplied by the recorded time t (variables based on the task). In each trial, synergy activation coefficients were identified using the synergy muscle space (W) which weights the muscles based on their activations and the neural command (C)[4, 18].

$$M_{m\times t} = W_{m\times n} C_{n\times t} + E_{m\times t} \tag{1}$$

VAF is measured with a threshold of >90% was adopted to detect the minimum number of muscle synergy. In this study, the threshold used to ensure that the estimated number of synergies would well preserve the characteristics of the recorded EMG data[4].

$$VAF = 1 - \|E\|_F^2 / \|M\|_F^2 \tag{2}$$

6.2 Pattern recognition Methodology

EMG pattern recognition with a large number of EMG channels provides an approach to assessing the signal information available from the recorded muscles. The feature data collected from the original EMG data are consistently used in the training and testing parts. The raw EMG data is used with window size of 200 ms, and processed them to a butter filter between 20 and 450 Hz. Then, the features have been extracted using: Slope sign change (SSC), Zero crossings (ZC), Waveform length (WL), Hjorth parameters(hjorth), Sample skewness (skw), Absolute values (MAV), Multiscale wavelet packet (mwpf). After extracting the features from the EMG signals, they are ready for classification. The LDA classiffication method was used.

7. Results

All participants completed the tasks based on equation 2. Fig.2 (a), Fig.2(b), Fig. 3(a) shows the number of muscle synergies required to achieve >90% overall VAF and >75% VAF which are two muscles synergy in this case which mean two synergies required to reconstruct to a feature of the recorded EMG data, these synergies were utilized in the automatic and the voluntary actions in the regular environment and help to shape the movement. Fig. 3(b) shows that one synergy is enough to reconstruct the EMG data and shape the movement[4] and it is achieved > 95% VAF.

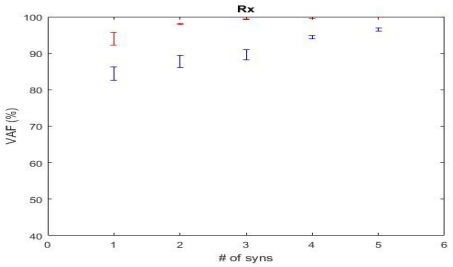
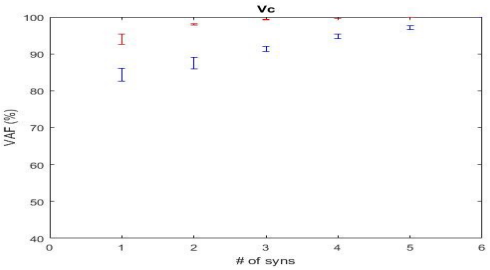


Fig.2 (a)VAF of all possible synergies from Rx



(b) VAF of all possible synergies from Vc

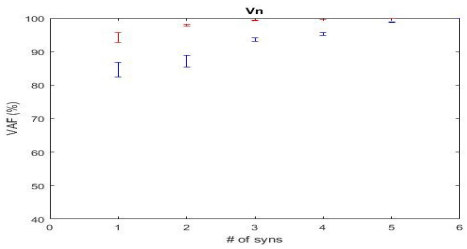
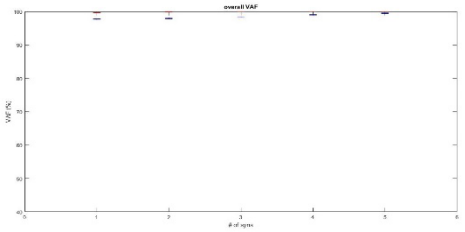


Fig. 1. (a) VAF of all possible synergies from Vn



(b) VAF of all possible synergies from Vm

Using the pattern recognition method, Fig. 4 (a) and Fig. 4(b) have been achieved with 0 % error and 100% accuracy. Comparing both methods, the pattern recognition method helps the CNS to shape the movement with 100% accuracy and the CNMF method with > 95% overall VAF. This supports our hypothesis for analyzing the automatic movements and the voluntary actions movements for helping the CNS system to shape the synergy movement.

8. Conclusion

Many techniques were used to analyze and control the synergy EMG signal with limited achievement results. The automatic body response movements and the voluntary actions movements can help CNS to shape the synergy. Using the CNMF method and pattern recognition method with >95% overall VAF and 0% error, respectively, helped the CNS to shape the synergy movements with good results. On our future work, we want to improve the repeatability and reliability for automatic body movement and voluntary action movement for shaping the muscle synergy analysis using a new approach.

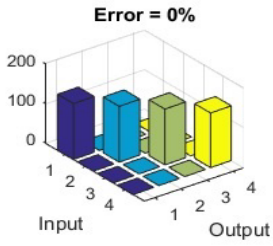
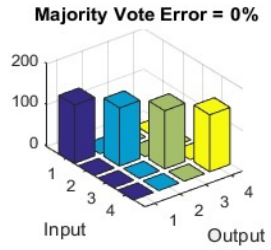


Fig. 4. (a) Classification results (Error) for four movements.



(b) Classification results (Majority vote) for four movements

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Upper Limb Recovery Prediction After Stroke Rehabilitation Based On Regression Method

Ghada M. Bani Musa, Fady Alnajjar*, Adel Al-Jumaily and Shingo Shimoda

***Abstract*— In this paper, we investigate the possibility of a machine-learning algorithm using the Support Victor Machine Regression (SVMR) to predict the motor functional recovery of moderate post stroke patients during their rehabilitation program. To train the model, we used the recorded electromyography (EMG) signals from the upper limb muscles of the patients during their initial rehabilitation sessions. Then we tested the trained model to predict the later muscles performance of the patient during the same sessions. The results of this pilot study were promising; data were, to some extent, predictable. We believe such research direction could be essential to motivate the patient to complete the designed rehabilitation program and can assist the therapist to innovate proper rehabilitation menu for individual patients.**

Keywords—Upper Limb, Rehabilitation, Regression, SVMR.

INTRODUCTION

NEUROLOGICAL disorders following brain stroke are classified as one of the leading cause of long-term motors disabilities worldwide. Such motor disabilities may not only affect the survivors' quality of life (QOL), but also can affect their surrounding community.

Motors disabilities after stroke do not necessarily have to be identical in terms of the location and the size of the injury, thus it is difficult for the therapist to predict the evolvement of disability, the optimal treatment, and the recovery period [1].

The muscle bio-signal, Electromyography (EMG), have been studied by many research teams to understand the development of human control systems to improve rehabilitations techniques [2][3][4]. Prediction of motor recovery after stroke, however, is still a hot topic to be addressed. In this pilot study, we used the recorded EMG data from three moderate post-stroke patients during their rehabilitation sessions to investigate the possibility to predict their upcoming motor activities.

METHOD

Three unilateral moderate post-stroke patients (age: 52+/-2, SIAS score: 3) were recruited for this study. 18 EMGs data was recorded from the upper limb muscles of the patients while performing driving simulation task [5]. Nine EMGs data was recorded from the muscles on stroke-affected side, and remaining 9 EMGs data was recorded from the non-affected side. Data were collected from two independent sessions (30 minutes were rest given between the two sessions) of approximately 60 movements each.

The initial 80% of the collected EMGs data for each session was considered as the training data set. The remaining 20% were considered as the testing data set. The training data was band-pass filtered before being processed by a regression model using the Support Victor Machine Regression (SVMR) [6]. Four different kernels were tested. We used the root mean square error (RMSE), mean square error (MSE) and mean absolute error (MAE) to check the error between the predicted data and the actual data (the testing data). The kernel with the minimum error, the fine Gaussian Kernel in this study, was used.

RESULTS AND DISCUSSION

For patient (n=1), results of session 1 and 2 are as shown in Fig.1 and Fig.2, respectively. Where the brown solid circles represent the actual result and the blue solid circles represent the predicted outputs.

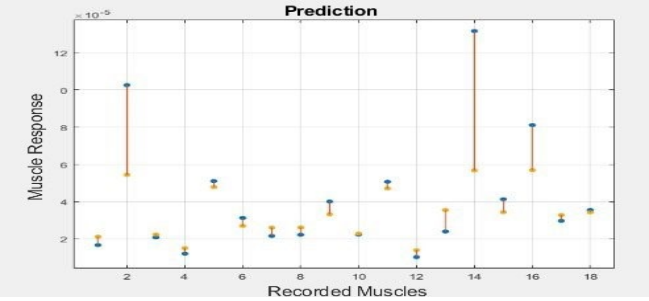

Fig. 1. Patient n1 (session 1), RMSE 3.3e-05, MSE 1.3e-09, MAE 2.3e-05.

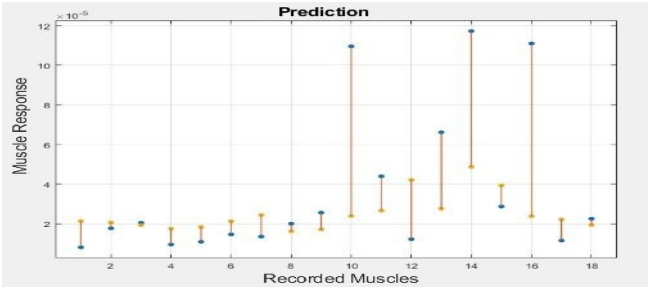

Fig. 2. Patient n1 (session 2), RMSE 2.2e-05 MSE 4.9e-10, MAE 1.1e05.

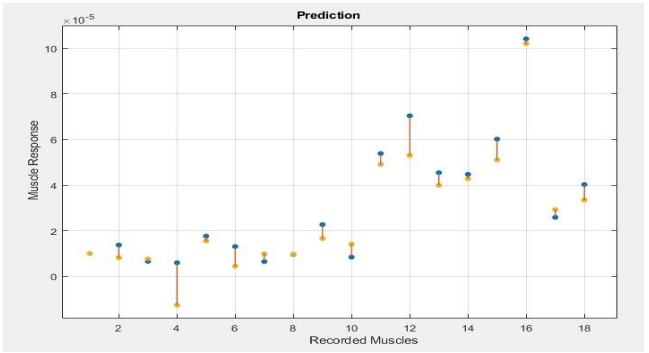

Fig. 3. Patient n2 (session 1), RMSE 2.2e-05, MSE 4.8e-10, MAE 1.6e-05.

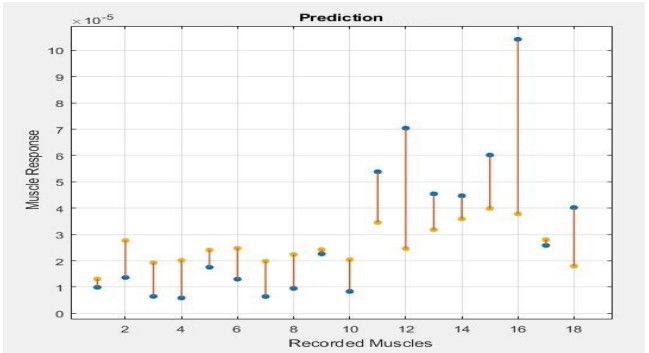

Fig. 4. Patient n2 (session 2), RMSE 7.3e-06, MSE 5.3e-11, MAE 5.4e-06.

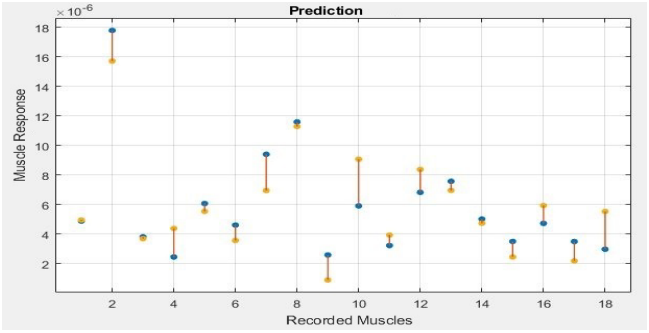

Fig. 5. Patient n3 (session 1), RMSE 6.6e-06, MSE 4.3e-11, MAE 5.1e-06.

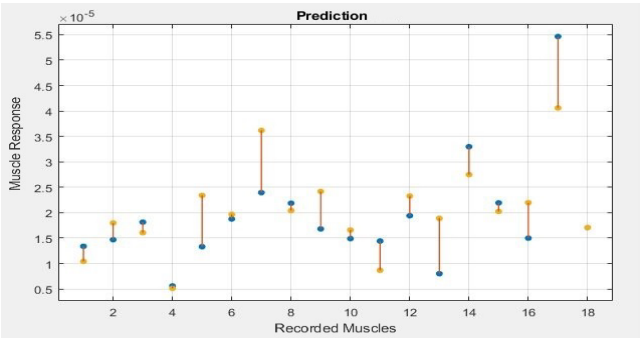

Fig. 6. Patient n3 (session 2), RMSE 1.5e-06, MSE 2.4e-12, MAE 1.3e-06.

From Fig.1&2, the first 9 points of the x-axis are for the stroke-affected side, while the remaining 9 points are for the non-affected side. As on the same pattern of Fig.1&2, Fig.3 & Fig.4/(Fig.5 & Fig.6) represent data of patient n=2/(n=3).

From the above figures, we could observe that the trained model could predict, to some extent, the recorded data of the patients. For session 1, for instance, eight out of the nine of the stroke-affected muscles activities were well predicted for patients 1&2 (2 to 5 of the stroke-affected muscles were predicted for session-2 for the same patients). Patient 3, however, showed 5 out of 9 acceptable prediction of the affected-side muscles in both the sessions. Less predictions ability could be seen from the muscles in the non-affected side for all the three patients.

From the above results, although limited participants/data, we believe that the prediction level of the muscles on the stroke-affected is promising and open the challenge to continue the research on this direction. More data, in term of the number of subjects, as well as, number of recorded muscle activity history of each subject is essential to conclude better this study.

Regarding the poor ability of trained model to predict the muscle perforce of the non-affected side could be due to the high redundancy of healthy muscles activities compare to stroke affected muscle activities [7].

CONCLUSION

This paper presented a pilot study examines the ability to predict future muscle performance of post-stroke patients based on their current motor ability. The prediction model utilized SVMR method, trained by actual EMGs activities of stroke patients, and validated by their future muscle performance. A statistical validation and conclusion of this work would be possible by increasing the data-set size, which what we are planning for future direction.

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