Real-time approach for the effect of arm position using Fitts' Law

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March, 2021

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science in

Biomedical Engineering

Supervisor: Dr. Asim Waris

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H-12, Islamabad, Pakistan

March, 2021

FORM TH-4

National University of Sciences and Technology

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Acknowledgements

I am grateful to my parents for supporting me to pursue my higher studies. I thank my teachers who helped me along this tough journey and guided me towards my best. I thank Dr.Asim Waris for supporting me and helping me in understanding many critical topics regarding my research study. His dedication towards me will always be the best part of my life.

I thank my friends who helped me during my research study especially Younas Khan, Mazhar Shehzad, Tufail Ahmad, Junaid Yousafzai, Mubashir Khan, Muhammad Asif, Farooq Saeed, Khizer Jan, Malik Naveed, Jibran Ishtiaq, Hashim Khan, Kamran Mangi, Ammad Din, Hassan Ashraf, Fazeel Ghafoor and Afaq ahmad. I thank my elder brother Shakeel Ahmad for believing in me and having faith in me. I thank Sehrish Raja for helping me during my thesis.

The journey of my masters would have been impossible without the help of my famil, my teachers and my friends.

Contents

List of Figures

List of Tables

Abstract

Electromyography is a method or technique that is utilized to evaluate or record the electrical activity of muscles. These recorded signals can reveal some notable observations that can be used to enhance myo electric-based prosthetic devices. The prosthetic devices that are commonly available have changed the lives of people significantly with upper limb amputation. However, currently available devices are calibrated in a single position, which gives rise to problems that can affect these devices accuracy and efficiency. The “limb position effect” is a prominent problem in prosthetic devices. The recognition of limb positions and motions plays a vital role in both healthcare and engineering. But as mentioned earlier, most of these devices are calibrated in a single position, leading to a faulty performance at other positions. This study aimed to find out the effect of limb position in real time using Fits’ law and compare the real time outcomes with the offline analysis. Twelve healthy subjects and two trans-radial amputees were studied. Four motions, such as closed hand, open hand, hand flexion, hand extension along with resting position, have been recorded.

Four performance metrics, overshoot, completion rate, throughput, and path efficiency were observed in real time. During group analysis for healthy and amputees, higher completion rates were observed while training and testing in the same position. Whereas between groups testing yielded in lower completion rates as compared to within group testing. Offline analysis was performed using ANN classifier with one layer and fifteen neurons. Six features were extracted namely; slope sign change, zero crossing, willision amplitude, waveform length, cardinality and mean absolute value. Similar training and testing scenarios were assessed during offline analysis as well; within group and between groups training and testing. Offline analysis yielded in high classification accuracies during within group testing and lower classification accuracies during between group testing. The results of real time and offline were compared to find the variability between these two approaches. This comparison revealed some notable observations, revealing that real-time analysis are necessary as the two observations were different. The outcome of this study suggests that in an attempt to minimize the effect of arm position, the device should be calibrated in multiple positions.

Chapter 1

1 Introduction

1.1 Motivation

Human beings are bestowed with many natural capabilities, due to which they are able to perform many daily life activities. However, if someone is missing even a single part of their body, there daily life activities are effected greatly e.g. limb amputation. If a person is missing any part of their body, his life is affected in many ways, e.g., lack of confidence, lack of working capability, lack of mental satisfaction, etc. But gladly, the current advancement in technology has filled up most of the loopholes capable of effecting human lives, such as prosthetic limbs. The prosthesis is an electronic device that works as an extension to the missing part of the human body. These prostheses can help normalize human lives by performing most of the activities that a normal human limb can perform. These electronic gadgets are helpful in many ways, but still, they are lagging in performing some activities. Researchers are currently working on the performance parameters of prostheses by implementing different techniques and methods. Many clinical problems have been solved in this current era by implementing different engineering techniques, especially in prostheses. The close link between clinical problems and engineering techniques implementation has led to many great inventions. Hence, this study is directed towards improving lives of people with limb amputation by suggesting a method to enhance the currently available prosthetic devices [1].

1.2 Different Types of Amputation

There are many types of amputation but the four main types are as follow:

1.2.1 Transtibial Amputation

This is a type of amputation which occurs below the knee as depicted in the picture below:

Figure 1-1: Transtibial Amputation

1.2.2 Transfemoral Amputation

This is a type of amputation which occurs above the knee as depicted in the picture below:

Figure 1-2: Transfemoral Amputation

1.2.3 Transradial Amputation

This is a type of amputation which occurs below the elbow as depicted in the picture below:

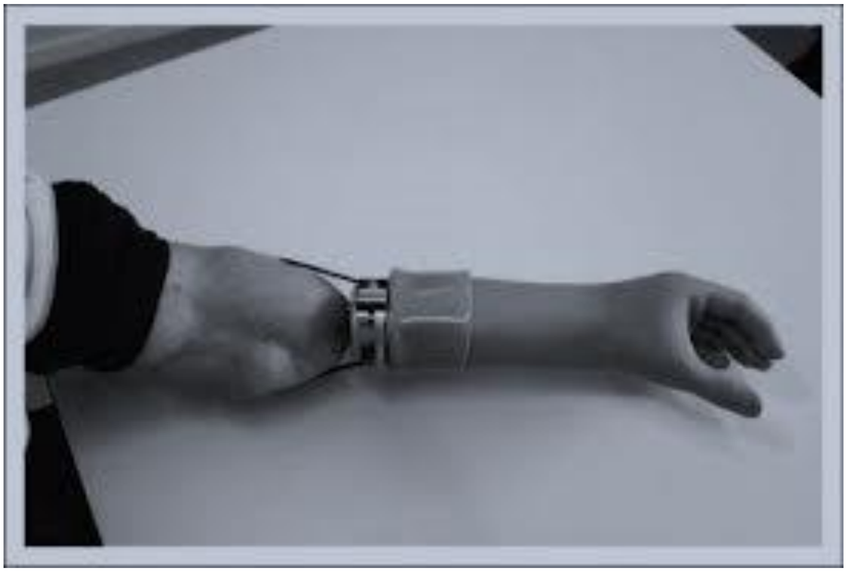

Figure 1-3: Transradial Amputation

1.2.4 Transhumeral Amputation

This is a type of amputation which occurs above the elbow as depicted in the picture below:

Figure 1-4: Transhumeral Amputation

1.3 Different Prosthetic Devices

In this current era, many prosthetic devices are available that used worldwide by many people for performing their daily life activities. These prosthetic devices are mainly divided in to two major categories: Body powered prostheses and Electric powered prostheses. Figure 1-1 and 1-2 shows body powered and electric powered prostheses respectively. Many people use the body powered prostheses for two main reasons: cheap price and easy repairing. These devices are not able to perform a diverse range of motions. They utilize different parts of human body to operate. Body powered prostheses are tough and they can be used in rugged environment and are really excellent for completing specific tasks. The electric powered prostheses are a much better option and replacement to body power prostheses because they can perform more motions. These devices are also called myoelectric prosthetic devices because they operate on electric signals (generated by muscles). Myoelectric prostheses remain expensive and is better suited for people who want to have a natural-appearing replacement for the lost limb. The currently manufactured prostheses have changed people's lives by helping them conduct many activities, which in return helped restore their lost confidence and motivation. Mostly, people are satisfied with their prosthetic implants, but these prostheses can still not work as efficiently as a healthy human limb.

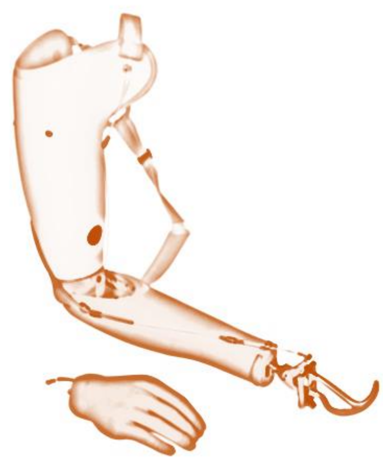

Figure 1-5: Body Powered Prosthetic Arm

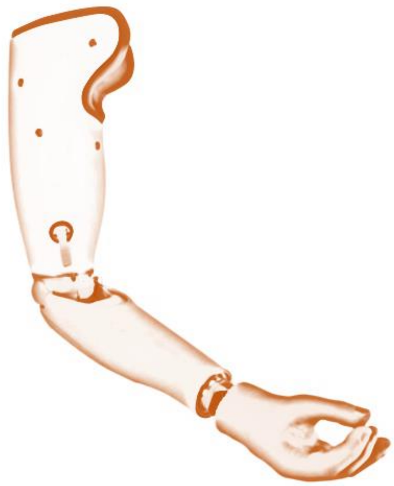

Figure 1-6: Electric Powered Prosthetic Arm

1.4 Literature Review

1.5 Conventional Myoelectric Control Strategies

There are many types of control strategies that are being implemented in myoelectric prosthetic devices, such as:

- On/off myoelectric control
- Proportional myoelectric control
- Direct myoelectric control
- Finite state machine control
- Pattern recognition based myoelectric control

1.5.1 "On/Off" Myoelectric Control

During on or off control the amplitude of EMG signal is measured and then compared with a certain threshold. If the value is above a certain threshold, it will turn on the motor and vice versa. This control scheme operates for two-degree of freedom. Also, the prosthetic device is operated at a constant speed which is not dependent upon the strength of the EMG signals. This type of control scheme is good where simple hand motions are required without involving complex motions for example simple hand rotation in clockwise and anti-clock wise direction [2].

1.5.2 Proportional Myoelectric Control

During proportional myoelectric control, the amplitude of the EMG signal is measured which is mapped against a single mechanical output. This mechanical output can be position, velocity, force etc. The input voltage of the motor is modified with respect to the output of motor controller. The voltage feeded to motor is proportional to the strength of the EMG signals. Such control schemes are applicable for general hand motions which donot require multiple degrees of freedom [3, 4].

1.5.3 Direct Myoelectric Control

The direct myoelectric control works similar to the proportional myoelectric control but with a slight difference. It involves the implementation of multiple sensors where the output of each sensor is mapped against an individual function corresponding to mechanical ouput. Similarly to proportional myoelectric control, the input voltage of the motor is modified with respect to the ouput of motor controller. As direct myoelectric control involves multiple sensors, the controlling of individual finger movements is achieveable. But this is a difficult objective as there is always crosstalk between the EMG signals. This task can be achieved by involving intramuscular EMG [5].

1.5.4 Finite State Machine

In finite state machine, the hand positions are pre-defined as states and the change in these states is also pre-defined. These type of control schemes are implemented where a fixed number of positions are required and no complex positions are involved. Postures involving multiple degree of freedom cannot be achieved with FSM control [6, 7].

1.5.5 Pattern Recognition Control

During pattern recognition the EMG signals are segmented and then features are extracted from these EMG signals. The extracted features are classified to operate the motor control. Multiple degrees of freedoms can be achieved with pattern recognition control scheme.

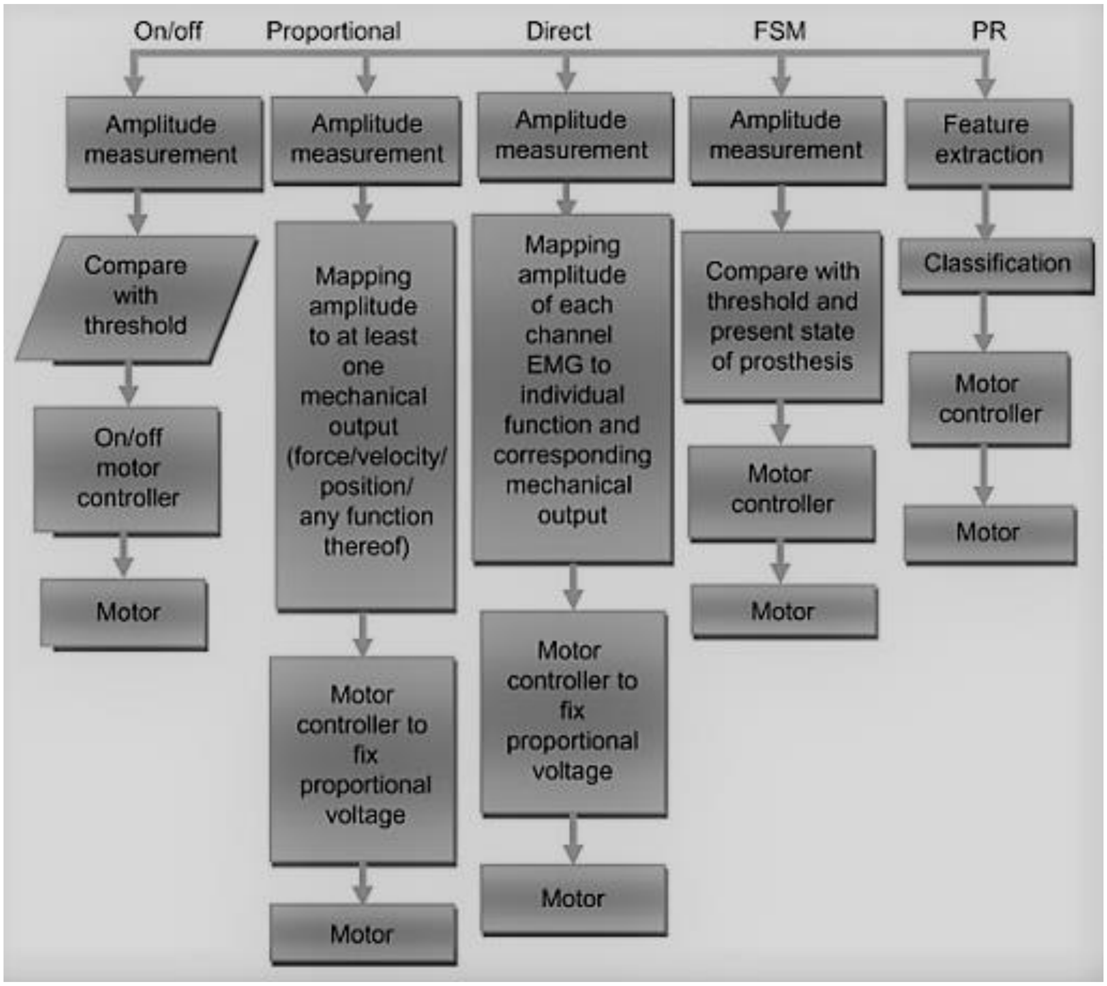

Figure 1-7: Flowchart of Different myoelectric control schemes

1.6 Improtance of Pattern Recognition based Myoelectric Control

Pattern recognition based controls are better and efficient than other myoelectric control strategies. The conventional myoelectric controls were successful in providing a limited number of degrees of freedoms. The pattern recognition overcome this shortcoming by controlling multiple degrees of freedoms by recognizing specific patterns in EMG signals. This implies that with the help pattern recognition we are able to perform various types of hand motions such as open hand, close hand, wrist flexion, wrist extension, pronation, supination, chuck grip, extended index and many other hand motions which we cannot achieve with conventional myoelectric controls [8].

1.7 Significance of Pattern Recognition based MECs

The electromyography signal reflects the electrical potential field produced by the depolarization of the surface muscle-fiber membrane known as sarcolemma. The use of invasive or non-invasive electrodes located at a certain distance from the source requires detecting these EMG signals. A so-called volume conductor acts as the tissue separating the source and recording electrodes. The volume conductor's properties largely define the detected signals' characteristics in terms of the frequency content and the distance within which the signal can no longer be detected. An invasive technique for monitoring muscle function from inside the muscle is intramuscular EMG. Usually, a monopolar or concentric needle electrode is implanted through the skin into the muscle tissue to conduct intramuscular EMG. The needle is then moved to several relaxed muscle locations to measure both contraction and relaxation activity. Surface EMG measures muscle behavior from the surface of the skin above the muscle. The injection of electrodes directly into the muscle enables the detection of electrical potentials very close to the source, due to which the impact of the volume conductor is lower. Surface EMG may only include a small assessment of muscle function. Surface/non-invasive EMG can be reported either by a pair of electrodes or by a group of multiple electrodes. More than one electrode is required because the EMG recordings show the potential difference (voltage difference) between two different electrodes. Barriers of this strategy include the fact that surface electrode recordings are confined to superficial muscles and are affected by the depth of the subcutaneous tissue at the recording position, which can differ greatly depending on the patient's weight accurately distinguish between adjacent muscle discharges. The EMG signal is the building block unit of myoelectric-based prosthetic devices and is fed as an input to these devices [9, 10].

The advancement in medical and engineering is progressing rapidly with each coming day. To derive meaningful and significant information from EMG signals, several different techniques have been developed. This information is mostly used in upgrading and enhancing myoelectric prosthetic devices. The technique that many research groups have used is commonly known as Pattern recognition (PR) technique. PR is the process of identifying patterns by using different machine learning techniques. Multiple methods based on PR have been investigated to enhance myoelectric-based prosthetic devices' performance and working capability. *Park et al.* proposed an EMG pattern recognition system to recognize different motion controls for prosthetic arm control through evidence acquisition with multiple parameters. A series of evidence accumulation procedures have indicated that the proposed approach effectively recognized the target motion with several incomplete parameters. And the test of separability has shown that ACV is better for the recognition of EMG patterns than for the other parameters. Furthermore, the recognition system's error rate has resulted in the proposed methodology of recognition better and more efficient than the other EMG pattern recognition methods. The proposed strategy to EMG pattern recognition emphasizes producing relatively accurate results with less computation time using the extracted feature parameters and very little subject training, which appears to be beneficial over other techniques requiring considerable training and time. Further work is suggested to find the optimal functional parameters to be used as inputs to the EMG pattern classifier and develop the decision algorithm for more effective pattern recognition systems with the accumulated data [11]. *Christodoulos et al.* stated that an important source of information for diagnosing neuromuscular disorders is the structures, design, and firing rates of the motor unit action potentials (MUAPs) in electromyographic (EMG) signals. To obtain this data from the muscle signals that is recorded at low-moderate force levels, it's required to: i) define the EMG signal of "MUAP", (ii) classify MUAPs (iii) decompose MUAP waveforms. Two different pattern recognition approaches were explained for the identification of MUAP, i) an unsupervised learning-based artificial neural network (ANN) technique, the tweaked version of the self-organizing feature map (SOFM) technique and the technique of learning vector quantization (LVQ), and ii) a Euclidean distance-based statistical pattern recognition process. For the ANN model, the prediction accuracy was 97.6%, and the statistical method was 95.3%. A cross-correlation technique for the organization of the MUAP and a blend of Euclidean distance and area measurements were used for the decomposition of the superimposed waveforms to classify the decomposed waveforms. The decomposition protocol performance rate was 90% [12].

The manufacturing companies are introducing different types and designs of myoelectric prosthetic devices. But the characterization of hand motions performed via prostheses is studied in a fixed location. This is a huge drawback of these prostheses because a normal human hand can generate different EMG signals at other positions. Due to the change in EMG signals, PR-based myoelectric control devices' performance is affected significantly.

1.8 Objectives

This study was mainly focused on developing new method for the currently available myoelectric prosthetic devices to improve its efficiency and working performance. Many problems can affect the working capability of myoelectric prosthetic devices. However, the problem addressed in this study was to solve the limb position effect in myoelectric prostheses in real-time. The limb posture effect can greatly reduce the performance of prosthetic devices. This problem was addressed due to the fact that mostly prosthetic devices that are being currently used by people are calibrated in a single posture. The disadvantage of calibrating a prostheses in a single posture is that it will not perform efficiently at multiple angles (positions). And secondly, no research group has solved this problem in real-time environment.

Chapter 2

2 Multiple Arm Position Effect Problem and Different Methods

2.1 Arm Position Effect and Offline Analysis

As mentioned earlier, performing hand motions in multiple postures produce different EMG signals. The accuracy of PR techniques is greatly influenced due to performing motions in multiple postures. There is a lot of evidence to prove this phenomenon that shifting limb posture and performing various types of motions in these postures can adversely affect the classification accuracy. *Jiang et al.* investigated arm posture's effect on the efficiency of a simultaneous and proportional myoelectric control system on both trans-radial amputees and healthy subjects. The authors found that changing arm posture negatively affects the algorithm's efficiency for both groups of subjects, but that this effect is less prominent in amputee subjects than in able-bodied subjects. It was proposed that the effect of arm posture on myoelectric control could not be inferred from the effects on healthy subjects and should be studied specifically in amputee subjects [13]. *Muraki et al.* measured the pressure on the supraspinatus, the infraspinatus, and the posterior portion of the deltoid in the healthy cadaveric shoulders in each posture to assess the most suitable contracting posture for each muscle. It was suggested that the findings of this study could overcome uncertainty about stretching practices and be extended to the correct stretching of weak shoulder muscles to treat and prevent injury to the shoulder of athletes [14]. *Zuckerman et al.* determined the influence of arm posture and capsular discharge on the restoration of rotator cuffs. Artificial faults were made in the rotator cuff to include either the supraspinatus (small) or both supraspinatus and infraspinatus (large). Faults were restored in a normal fashion, with the shoulder abducted 30 degrees at the glenohumeral joint. Strain gauges were positioned on the lateral cortex of higher tuberosity and measurements were reported in 36 separate configurations of abduction, flexion/extension and medial/lateral rotation. Observations were collected before and after the release of the capsule. With small tears, stress in the repair increased dramatically with movements from 30 degrees to 15 degrees of abduction, but was minutely influenced by changes in flexion or rotation. Capsular release greatly decreased the force at 0 degrees and 15 degrees abduction. In case of broad tears, abduction of 30 degrees or more with lateral rotation and extension consistently provided the lowest values. Capsular release led in 30% less force at 0 degree abduction [15]. *Mourad et al.* confirmed the important effect of arm posture on auscultative blood pressure. Such an impact occurs in sitting and standing poses as well as in an oscilometric system. Moreover, it is now clear that the higher the BP, the greater the error created, especially in the measurement of SBP. Considering the current focus on diagnosis and treatment of systolic hypertension, the possibility for false readings should pose problems. The Indirect calculation of BP is vulnerable to multiple errors due to poor procedure and even the presence of back support while sitting can affect BP. However, the marked impact of the placement of the arm on BP was relatively overlooked, presumably because the agreed position of the heart level is vague and subject to misinterpretation. Even a relatively insignificant downward arm motion with a borderline or high BP in a patient could profoundly affect diagnosis and care [16].

2.2 Variability between Offline and Real-Time Analysis

It has been proved by many studies that real-time tests and offline tests do not result in similar results. This is a very important fact in the field of PR based myoelectric control as most of them are solely based upon the outcomes of offline tests. *Savur et al.* proposed a Real-Time Sign Language recognition method using the Electromyography surface system (sEMG). For this purpose, for all twenty-six movements of the American Sign Language, the sEMG data was obtained from the right forearm subject. Raw sEMG data has been filtered, extracted, and graded. For multi-class grouping, Support Vector Machine (SVM) with one vs. all method was introduced. The offline test resulted in a 91 % classification precision and 82.3 % accuracy of the real-time system classification output. This system's results have shown that the SEMG signal can be used for real-time SLR systems [17]. *Parajuli et al.* presented a brief introduction to EMG-PR techniques and explores the work done on real-time myo-activated prostheses based on pattern recognition control over the years. Some of the important methods needed to enhance EMG-PR's current real-time applications for hand prosthesis have been addressed through available literature. Although smart pattern recognition control methods have been well studied for many degrees of freedom for hand prosthesis, their real-time functionality is still complicated by a range of factors. The normal neuromuscular control of the prosthesis should be proportionate and many degrees of freedom should be investigated. Nevertheless, while reviewing existing literature, they find that EMG is used for most real-time prostheses, i.e. multiple channels that influence different residual muscles to create other synchronous control signals. Owing to the proximity of the muscles/electrodes, etc., the question is much greater than a single degree of independence. For real-time scenarios in the future, this should be well studied. [18]. *Sattar et al.* presented a feedback control of the prosthetic arm. This helps people who, based on electromyography (EMG) signals, deal with trans-humeral amputation. Collected signals are used to generate a control order for elbow joint movements. These will mask the weakening of the proximal radio-ulnary articulation of the forearm joint by the ulna-humeral joint and wrist pronation flexion-extension motion. The Myo armband was used to receive an EMG signal from the muscles of the biceps and tricepsThe data collection and classification of the target motion was aided by integrating simulations with real-time monitoring of EMG signals from selected muscles. With ten competent people, the accuracy of both offline and online classification was checked by experiments.The offline training was conducted using Artificial Neural Networks with an accuracy of 94%. Support Vector Machine was used for real-time analysis with an accuracy of 85%. Raspberry Pi was utilized for high-speed and versatile processing as it provides high functionality. Five control commands were also obtained to control device motions, including elbow extension and flexion, wrist pronation and supination along with rest condition. Feedback control of 2 degrees of freedom prosthetic arm was modeled and applied using the PID control algorithm [19]. The investigations of the studies mentioned above revealed a very important point in the field of myoelectric control. This breakthrough gave rise to conducting real-time tests along with offline tests.

2.3 Different Types of Real-Time Analysis

Different research groups performed several studies to evaluate different types of real-time tests. Mostly, the researchers tend to use two types of real-time tests. The one is called Fitts' test, and the second is called Target achieving control. Both of these tests are capable of conducting the real-time analysis. *Rasool et al.* presented a novel approach that uses task-specific muscle synergies and state-space expression of neural signals to solve the difficult challenge of myoelectric control of lower arm prostheses. The suggested structure provides details on muscle arrangements, e.g., muscles behaving synergistically or in agonist/antagonist combinations, using the concept of muscle synergies. The synergistic activation coefficients are established as the latent machine state and are calculated using a constrained Kalman filter. These task-dependent coordinated activation coefficients are calculated in real-time from electromyogram (EMG) data and are used to differentiate between different tasks. Task distinction was assisted by a post-processing algorithm that utilizes post-processing probabilities. The suggested method was efficient and computationally intensive, resulting in a conclusion with higher classification accuracy. The algorithm's real-time efficiency and reliability were analyzed by using the Targeted Performance Control (TAC) test.

The suggested methodology surpassed typical machine learning algorithms for both single-and multi-degree-of-freedom (DOF) activities in offline classification accuracy and real-time reliability [20]. *Zhuang et al.* proposed electromyography (EMG)-based admittance controller (EAC) to enhance the human-robot coordination, particularly in comparison to that accomplished by the use of a torque-sensing-based admittance controller (TAC). Computations and experiments have been performed to explore the performance of the EAC and the TAC. The simulation results demonstrated that the postponement between the human's voluntary torque and the exoskeleton robot's assistive torque noticeably deteriorated the human-robot cooperation movement's performance when the TAC was implemented. The experimental outcomes showed that the jerk value, the interaction torque, and the EMG level of the tibialis anterior acquired with the EAC were considerably lower than those reported with the TAC. Particularly in comparison to the TAC, the EAC has a benefit in enhancing the movement of human-robot coordination. The EAC can prevent delays between the human voluntary torque and the exoskeleton robot's assistive torque [21].

2.4 Fits' Law and Performance Parameters

As mentioned earlier in the literature that researchers have used different types of real-time tests. However, Fitts' test is used preferred by many research groups because it is less challenging and easy to perform as compared to other real-time tests, e.g. TAC test. *Belya et al.* conducted a detailed relation of EMG-based and FMG-based systems using both regression and classification controllers. Two-degree-of-freedom Fitts' law style virtual target acquisition activity relying on both FMG and EMG classification and regression control systems has been used. The performance was assessed based on the conventional Fitts law testing of metrics throughput, path efficiency, and average speed, number of timeouts, overshoot, stopping distance, and simultaneity. The FMG-based prediction system performed better than the EMG-based prediction system for both throughput and path efficiency. Likewise, FMG-based regression significantly performed better than EMG-based regression in throughput and path efficiency. They concluded that FMG-based schemes outperformed EMG-based schemes despite which controller was utilized [22]. A non-invasive electromyography (EMG) signal-based computer interface and a

Fittspsila law-based performance appraisal system were identified by *Choi et al.* To obtain the intentions of the participants, the signals of the EMG produced by voluntary wrist movements were received from four locations in the lower arm, and six groups of wrist movements were distinguished by the implementation of an artificial neural network. To maneuver the mouse using the advanced platform, press buttons and write text on the screen. The research rig was designed to assess five participants with intact limbs tested the developed platform and the mouse. Compared with the industrial non-invasive brain signal interface's reliability, the built machine interface and mouse performance were measured. The results indicate that the built interface was smarter than the commercial interface but less adequate than the computer mouse. Though other problems remain fixed, the established EMG interface can naturally and intuitively help people with motor disabilities access computers and Internet situations [23]. *Ameri et al.* validated the CNN regression model's functionality for the first time, using an online Fitts Law Style Test with both individual and simultaneous wrist movements. The outcomes were compared to the support vector-based regression system with a group of commonly used extracted features. Despite these excellent features' proven efficiency, the CNN-based system surpassed throughput for support vector machine (SVM) due to increased regression accuracy, particularly with high EMG amplitudes. These findings suggest that the CNN model can retrieve the underlying motor control information from EMG signals during single and multiple degree-of-freedom (DoF) activities. The benefit of CNN's regression over CNN's (previously studied) classification is that it enables independent and simultaneous control of movements [24]. Many other research groups have efficiently implemented Fitts' law for EMG-based control systems [25-27].

2.5 Research Gap

The studies mentioned above regarding the limb position effect are mainly related to research studies performed on pre-recorded data. As mentioned earlier, we cannot rely on offline tests, and real-time tests should also be performed. Many researchers have solved the problem of the limb position effect by suggesting different techniques and methods. However, all these techniques and methods solely rely on offline tests and not real-time tests. The main purpose of conducting this study was to see the limb position effect in the currently available PR-based myoelectric prosthetic devices in real-time environment. This was a crucial research gap as no study has been conducted in the past regarding this. The novelty of this work was the observation of the outcomes of real-time analysis regarding limb position effect.

Chapter 3

3 Methodology

3.1 Subjects

Healthy (12) and amputated (2) subjects were recruited to record data and real-time tests. Each subject was consulted and requested to experiment, and all healthy subjects and amputees voluntarily participated. However, the amputated subjects were consulted in their desired location. Due to the COVID-19, it was difficult to recruit many amputees in the study. All subjects were given a written agreement to conduct this experiment.

3.2 Data Collection

Myo is a lightweight elastic armband made up of a series of electrodes that track electrical activity in the forearm's muscle to relay movements you make through Bluetooth with your hand to a connected computer. It is quick enough to synchronize with the armband with a USB dongle that plugs into the laptop. The number of electrodes in Myo armband is eight, which are surface electrodes. The sampling frequency of myo armband is fixed at 200 Hz [28, 29]. Figure 3-1 illustrates raw data collected through 8 channels and Figure 3-2 illustrating myo armband for movement recording.

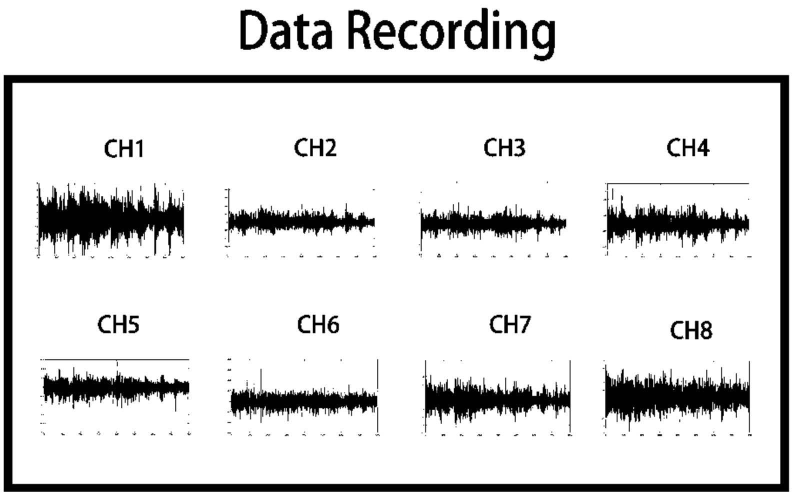

Figure 3-1: Raw EMG signals recorded for open hand motion using Myo armband.

Figure 3-2: Myo armband for Data Recording

3.3 Motions and Positions

The motions that were recorded from every subject using myo armband were Hand Open, Hand Close, Hand Extension and Hand Flexion and rest motion (No Motion). Each and every subject recorded these motions in three different postures (0^0 , 45^0 and 90^0) as shown in Figure 3-4. The contraction time for each motion was six seconds which were then followed by rest time of six seconds. Each subject performed a total of ten sessions. Each session consisted of recording each of the above mentioned motion. The time break between two consecutive sessions was set to twelve seconds.

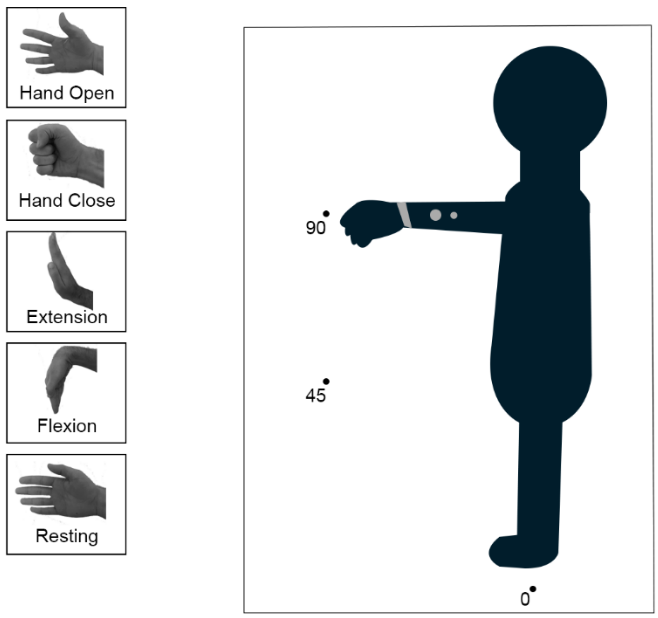

Figure 3-3: Graphical representation of 5 motions and 3 positions.

3.4 Signal Processing, Classifier and Features

As mentioned earlier that motions were recorded for a duration of six seconds. These motions were segmented by clipping the starting one second of the motion and the last second of the motion to remove any redundant content. There are two major types of segmentation techniques: disjoint windowing and overlapping window. During disjoint windowing no content from the previous segment is added into the next segment. Whereas during the overlapping window, a small portion of the last segment is added into the next segment. In this experiment, the overlapping window was used, having a size of 200ms and an overlap of 50ms. Many classifiers could have been used during this experiment.

Artificial neural networks were implemented during this experiment as it has been proved by many studies that ANN outperforms other classifiers like LDA, SVM etc. Whether real-time or offline, in both scenarios, ANN was implemented to avoid biases between these two techniques' results. As we know that human brain consists of neurons that processes information in the form of electric signals. Artificial Neural Network (ANN) is a classifier that works similarly to the human brain and is used to develop algorithms that can be used to model complex patterns and prediction problems. ANN consists of three layers: input layer, hidden layer and output layer. Each layer consists of neurons that are connected with each other. During the implementation of ANN the complete data is divided into three sets namely: training set, validation set and testing set. The ANN architecture used in this experiment consists of one hidden layer with fifteen neurons. Signal features extraction is an important part of machine learning. The extracted features help understand the ANN architecture to distinguish between different types of signals generated for different types of motions. The features that were extracted in this study were: zero crossing, mean absolute value, slope sign changes, waveform length, willison amplitude and cardinality [30, 31].

3.5 Real-time Analysis Methodology

3.5.1 Graphical User Interface

Figure 3-6 shows a Graphical User Interface (GUI) which was used in order to record data for motions from subjects. The interface of GUI was user-friendly and every motion was prompted on the GUI that the subjects have to perform. All the possible motions were shown on the right side of GUI which can be seen in the Figure 3-6. However, only four motions were recorded and tested in real-time. A protocol was designed for recording of motions in various positions. According to the designed protocol, each and every subject was instructed about the environment of GUI and were made familiar with all the motions that they were asked to perform in the experiment.

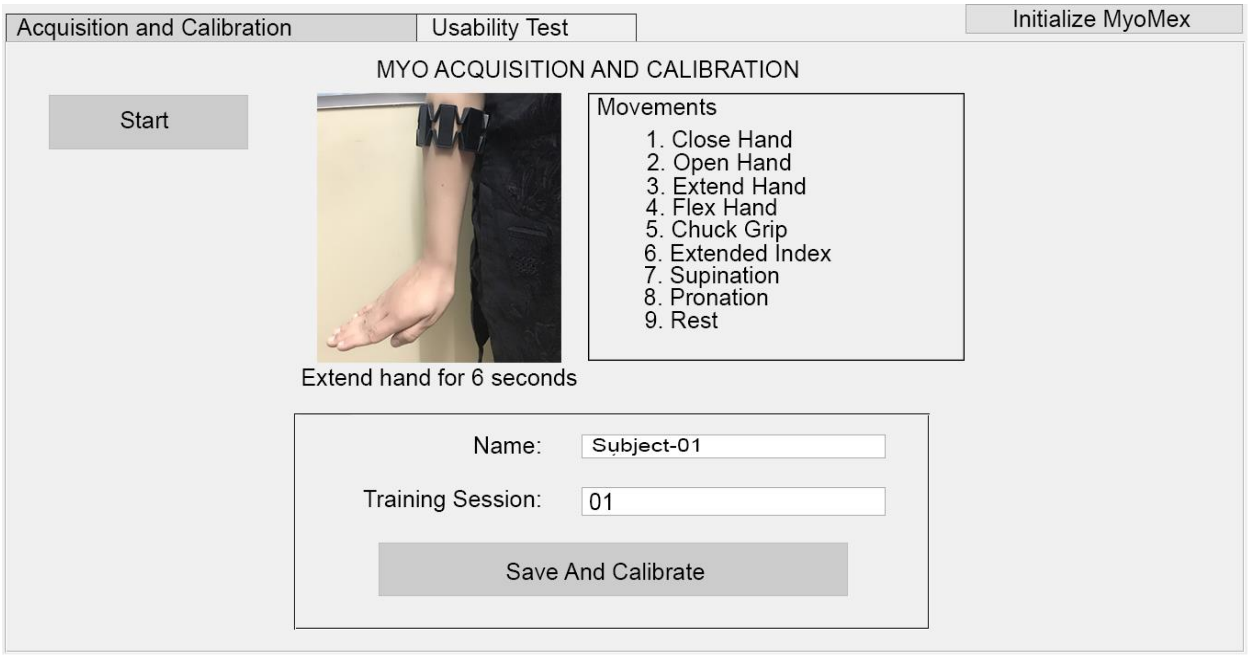

Figure 3-4: Graphical User Interface for recording data at different positions

3.5.2 Fits' Law and Performance Parameters

Fits' law states that the index of difficulty is a function of the distance to the target divided by the target's size. The formula through which different index of difficulties was calculated is given below:

$$\text{Index of Difficulty} = \log_2(\frac{D}{W} + 1)$$

Four performance metrics were assessed to quantify real-time system performance: completion rate, path efficiency, overshoot, and throughput. The completion rate describes the overall success rate of the system within the allowed period. Path efficiency represents the quality of control by checking how efficiently the subject has achieved the target in selecting the best path. Overshoot describes the ability to stop on a target. This shows the subjects ability to stop on the target efficiently for 1-s before leaving the target. Throughput is defined mathematically as the ratio between the ID and the time of movement (MT), which is the time taken (in seconds) to achieve the goal. It is a measure of the amount of knowledge that the subject can communicate to the mission from a specific command source. Table 1: Index of difficulties and their corresponding Distances and Widths

Distance	Width	ID
50	5	3.46
50	10	2.59
50	20	1.81
100	5	4.39
100	10	3.46
100	20	2.59

3.5.3 Experimental Procedure

Figure 3-5 shows the real-time environment where Fitt's law was implemented for various training and testing scenarios. The figure shows position of all the possible targets with their respective IDs. These targets were prompted one at a time and subjects were ask to achieve these targets by moving a cursor from center point. These targets were picked randomly after every trial. The overall time allocated to complete a trial was fifteen seconds and the subjects were asked to keep the cursor at the target position for at least one second after hitting the target. If, within the time slot, the subjects did not meet the target, the trial was declared unfinished and the cursor was reset back to the origin, ready to begin the next trial. Different target sizes show different index of difficulties as shown in Table 1. Each motion was tested six times with varying IDs. The Fitt's law was implemented in various limb positions.

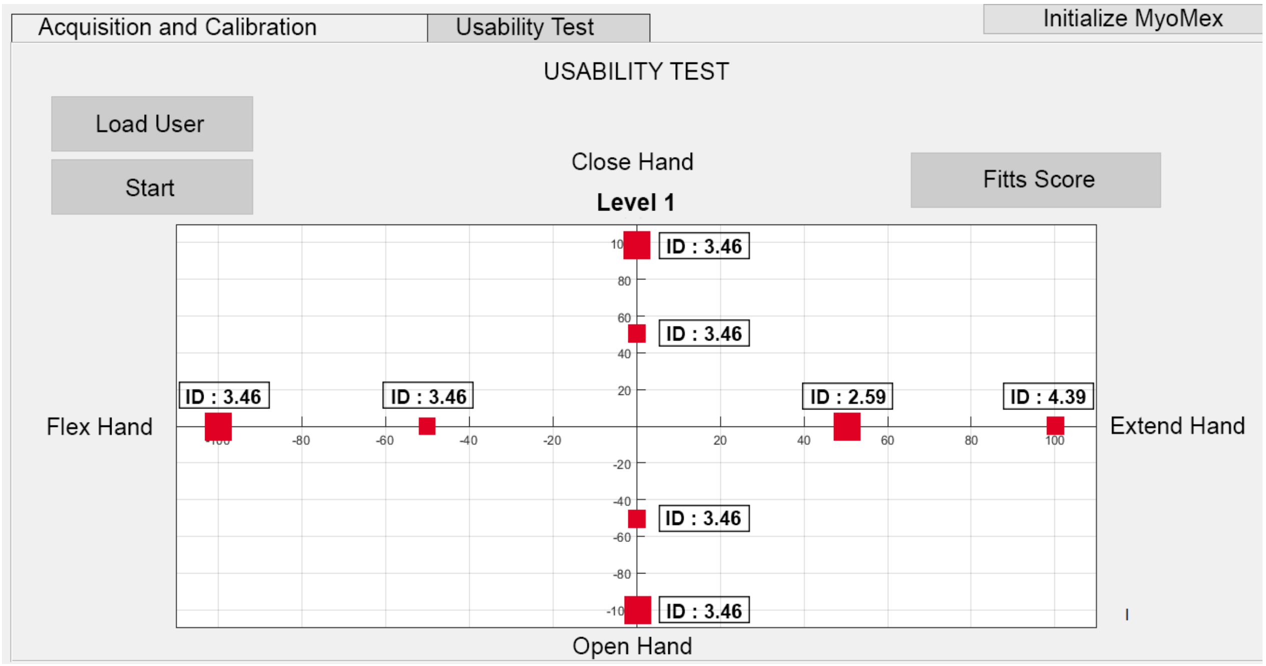

Figure 3-5: Fitt's Test for Different Hand Motions and Positions

3.5.4 Training and Testing Schemes

Multiple real-time training and testing schemes were followed to check the effect of multiple positions on performance metrics. The Table 2 below shows multiple training and testing schemes for real-time analysis.

Table 2: Notations for Multiple Training and Testing Scenarios

	Testing 0°	Testing 45°	Testing 90°
Training 0°	$ZT0^0$	$ZT45^0$	$ZT90^0$
Training 45°	$FT0^0$	$FT45^0$	$FT90^0$
Training 90°	$NT0^0$	$NT45^0$	$NT90^0$

3.6 Offline Analysis Methodology

After the successful experimentation of real-time test using Fitt's law, the offline tests were performed on pre-recorded data. ANN classifier with one hidden layer and fifteen neurons was used as mentioned earlier in the manuscript. The same set of features were implemented as well.

However, K-fold cross validation was used during training and testing of classifier in same positions. During K-fold the data is split into small chunks. Usually the number of active motions is the number of K-fold. In this experiment we investigated four active motions, so four-fold cross validation was implemented to avoid over-fitting. Over-fitting occurs when the model learns too much from training data and isn't able to generalize the underlying information. When this happens, the model is able to describe training data very accurately but loses precision on every dataset it has not been trained on. Figure 3-6 shows the graphical representation of offline analysis.

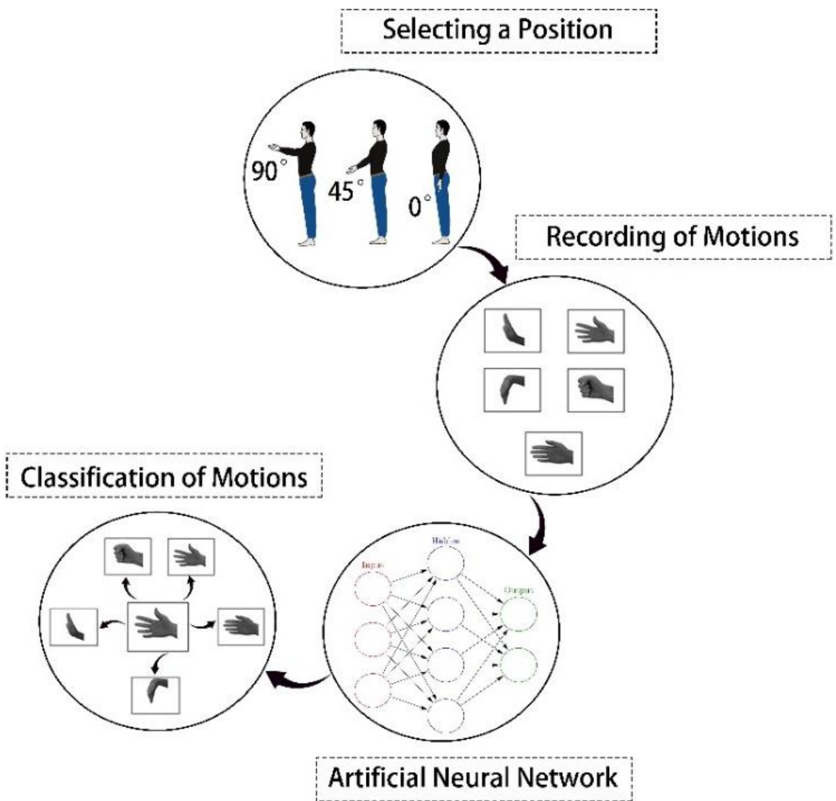

Figure 3-6: Offline Analysis Graphical Map

3.7 Statistical analysis

A one-way repeated measures ANOVA test was implemented to see the effect of different training and testing scenarios on real-time and offline tests. The one-way rmANOVA is used to determine whether there are any statistically significant differences between the means of independent groups. During rmANOVA test, different parameters like F-value, P-value and degree of freedom were assessed. All the P-values that were less 0.05 were considered significant. All significant tests were followed by Tukey honest significant different posthoc test.

Chapter 4

4 Results and Discussions

The experiment performed was divided into two sections for the better understanding of each protocol. In order to further simplify the understanding of this research the results have been into two sections: Real-Time analysis and Offline analysis.

4.1 Real-time Analysis

4.1.1 Real-time Analysis (Healthy)

In a within-group analysis for real-time, completion rate, overshoot and throughput showed no significant difference (p-value > 0.05) for ZT0^0 - FT45^0 , ZT0^0 - NT90^0 and FT45^0 - NT90^0 , however, for path efficiency, one-way rmANOVA revealed that FT45^0 was performing significantly better than ZT0^0 (p-value $\leq$ 0.01) also, NT90^0 was performing markedly better than ZT0^0 (p-value $\leq$ 0.01). A significant difference was observed between groups analysis for completion rate, where ZT0^0 was performing significantly better (p-value $\leq$ 0.01) than ZT90^0 . Similarly, FT45^0 was performing significantly better than (p-value $\leq$ 0.005) FT0^0 and (p-value $\leq$ 0.03) FT90^0 as shown in Figure 4-1. For overshoot, one-way rmANOVA revealed that NT45^0 was resulting in significantly lower (p-value $\leq$ 0.03) overshoot than NT0^0 , whereas no significant difference was observed for other training and testing groups as depicted in Figure 4-2. Similarly, for path efficiency, ZT45^0 was performing significantly better (p-value $\leq$ 0.03) than ZT0^0 . Also, FT45^0 was out performing FT90^0 by a significant difference (p-value $\leq$ 0.04) as shown in Figure 4-3. The last observed performance metric was throughput, where no significant difference was observed for any training and testing scenario as shown in Figure 4-4.

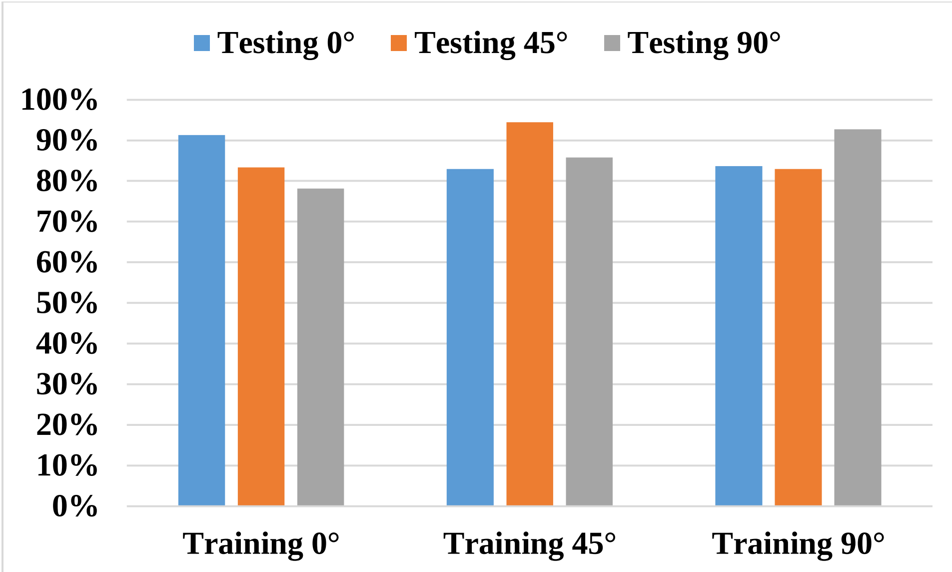

Figure 4-1: Completion rates (%) for different training schemes (Healthy)

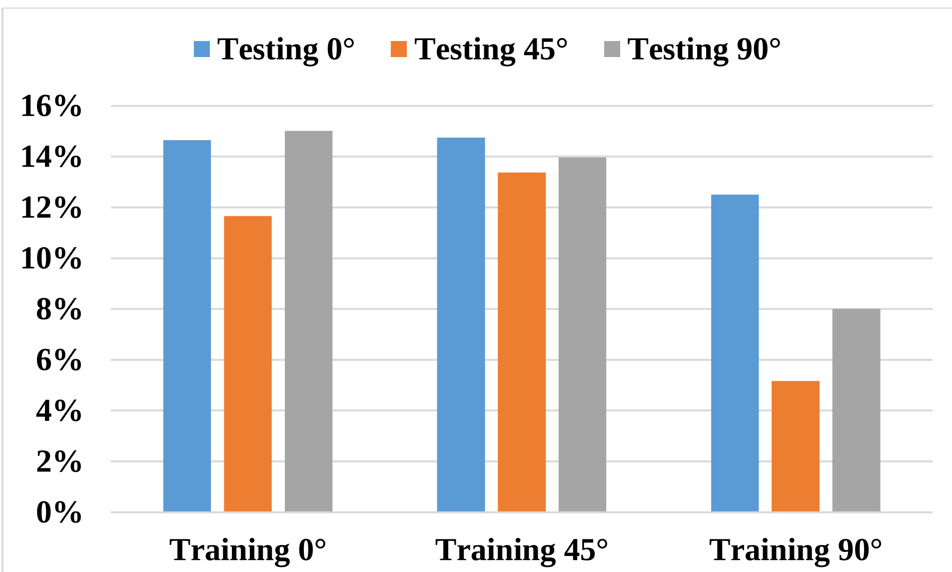

Figure 4-2: Overshoot (%) at different training and testing schemes (Healthy)

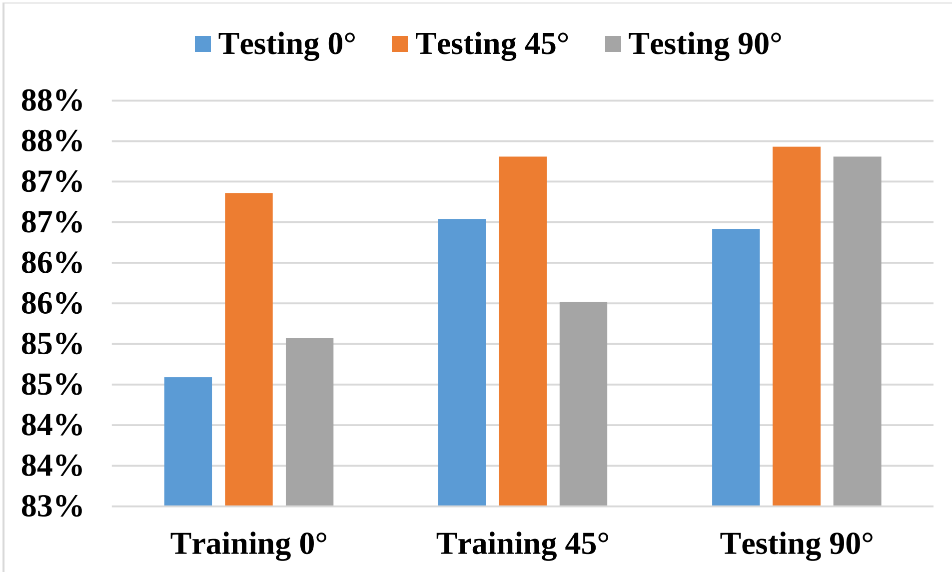

Figure 4-3: Path efficiency (%) at different training and testing schemes (Healthy)

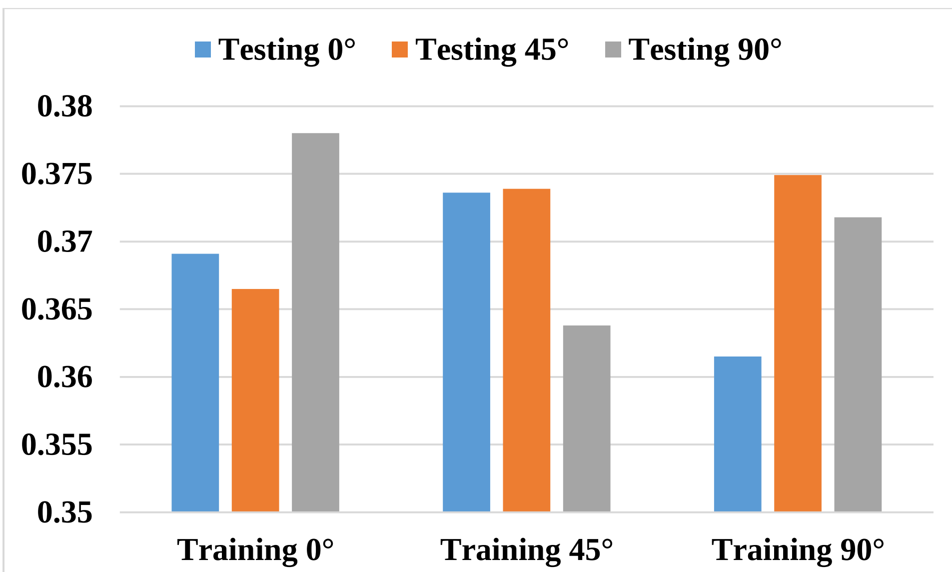

Figure 4-4: Throughput (bits/sec) at different training and testing schemes (Healthy)

4.1.2 Real-time Analysis (Amputees)

Within-group analysis in real-time for amputees, one-way rmANOVA showed no significant difference (p-value > 0.05) for completion rate, overshoot, path efficiency, and throughput for ZT0^0 - FT45^0 , ZT0^0 - NT90^0 and FT45^0 - NT90^0 . A significant difference was observed for completion rate during group analysis, where ZT0^0 was performing significantly better than (p-value ≤ 0.04) $ZT45^0$ and (p-value ≤ 0.01) $ZT90^0$ as depicted in Table 4-5. At the same time, no significant difference was observed for other groups while keeping the completion rate. The other performance metrics, overshoot, path efficiency, and throughput, showed no significant difference for any training and testing scenario shown in Table 4-6, 4-7, and 4-8.

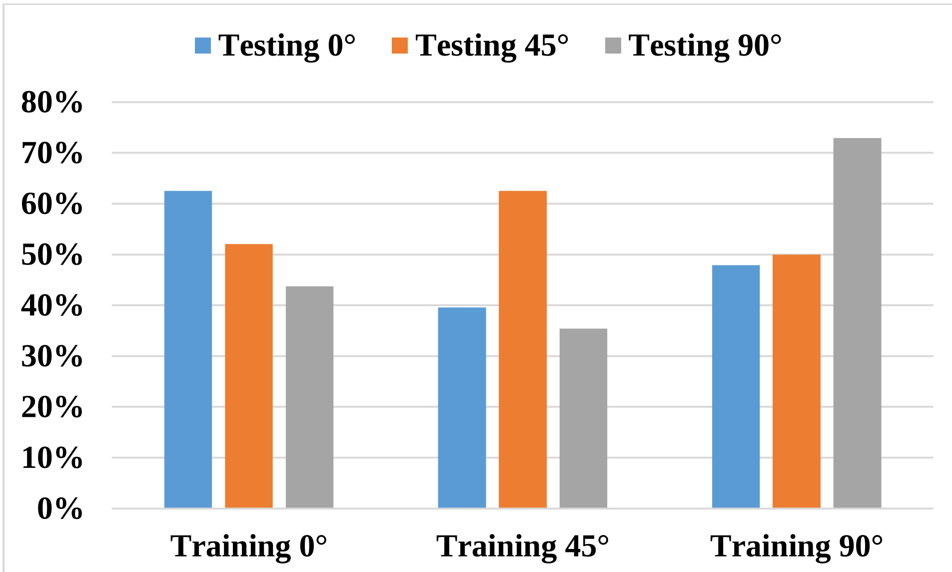

Figure 4-5: Completion rates (%) for different training schemes (Amputee)

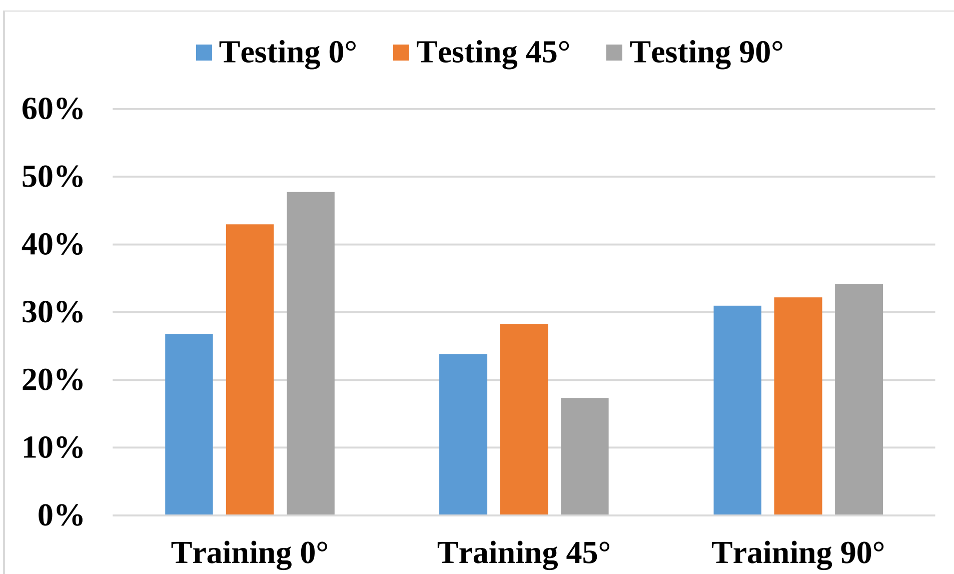

Figure 4-6: Overshoot (%) at different training and testing schemes (Amputee)

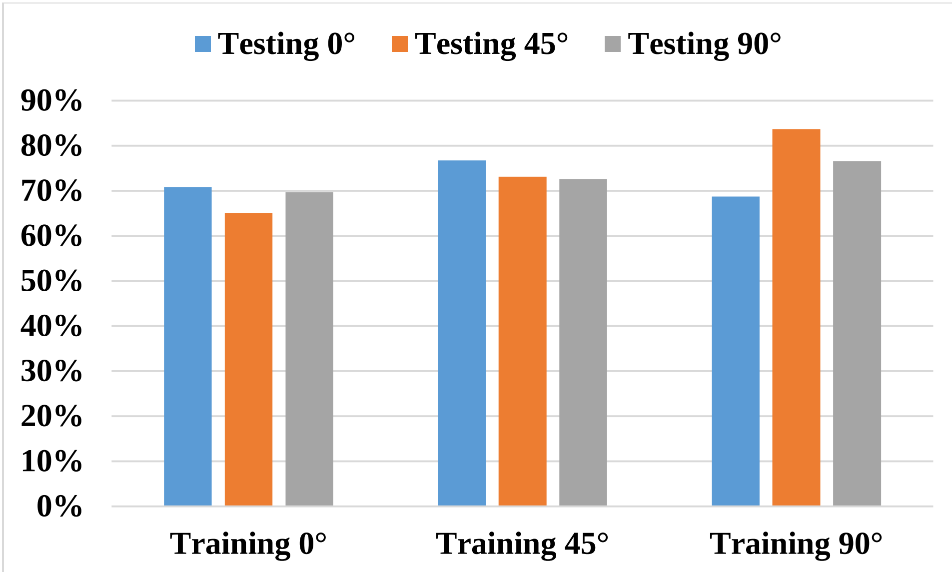

Figure 4-7: Path efficiency (%) at different training and testing schemes (Amputee)

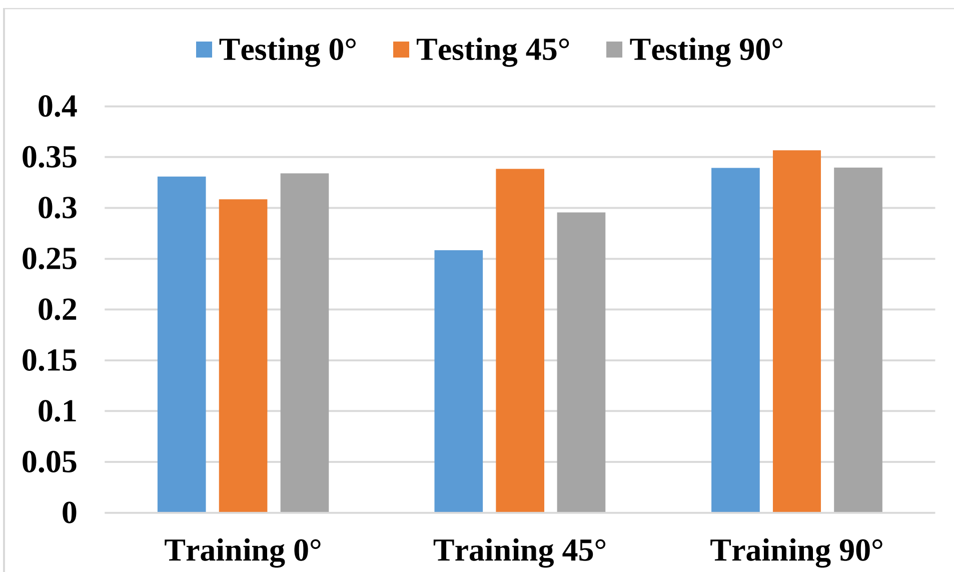

Figure 4-8: Throughput (bits/sec) at different training and testing schemes (Amputee)

4.2 Offline analysis

4.2.1 Within Group Results (Healthy)

During group testing, 4-fold cross validation was implemented to avoid overfitting and obtain accurate classification accuracy. When the system was trained with data from 0° and tested with data from 0°, the system's overall classification accuracy was 99.3%, with a classification error of 0.7%. Similarly, when training and testing were done for 45°, the overall accuracy was 99%, with 1% error. A similar trend was seen for training and testing at 90°. The overall accuracy for the 90° train-test was 97.9%, with misclassification of 2.1%. One-way rmANOVA showed no significant difference between ZT0^0 and FT45^0 (p-value ≥ 0.74). However, a significant difference (p-value < 0.05) was observed for ZT0^0 and NT90^0. Similarly, one-way rmANOVA also revealed a significant difference (p-value < 0.05) for FT45^0 and NT90^0. The offline analysis was showing better results than their corresponding real-time completion rates. The results are shown in Figure 4-9.

4.2.2 Within Group Results (Amputees)

While observing within-group analysis for amputees, the same 4-fold cross-validation method was implemented to avoid overfitting and obtain accurate and precise classification accuracy. When the system was trained with data for 0^0 and tested with the data from 0^0 degree, the classification accuracy was 95.8% with a misclassification error of 4.2%. Similarly, when training and testing were done at 45^0, the classification accuracy was 93.7%, with 6.3%. The final position for training and testing was 90^0, which yielded 92.5% accuracy with an error of 7.5%. One-way rmANOVA revealed no significant difference (p-value > 0.05) during within-group analysis. Figure 4-10 shows the overall results for within-group classification accuracies for amputees.

4.2.3 Between Group Results (Healthy)

For training and testing in different positions, the classification accuracies dropped by a huge margin. I was training the classifier with data from 0^0 and testing at 45^0 and 90^0 yielded accuracies of 64.4% and 54.2% with misclassification of 35.6% and 45.8% respectively. Similarly the system was trained with data from 45^0 and later tested with data from 0^0 and 90^0. The resulting accuracies were 63.8% and 70.6%, with a classification error of 36.2% and 29.4%, respectively. After training the classifier with data from 90^0 and testing with data from 0^0 and 45^0, the system yielded accuracies of 53.5% and 64.5%, with misclassification of 46.5% and 34.5%. One-way rmANOVA revealed that ZT0^0 was performing significantly better (p-value ≤ 0.05) than ZT45^0 and ZT90^0. Also, FT45^0 was performing significantly better than FT0^0 and FT90^0. Similarly, NT90^0 was performing significantly better than NT0^0 and NT45^0. The results are shown in the Figure 4-9 below.

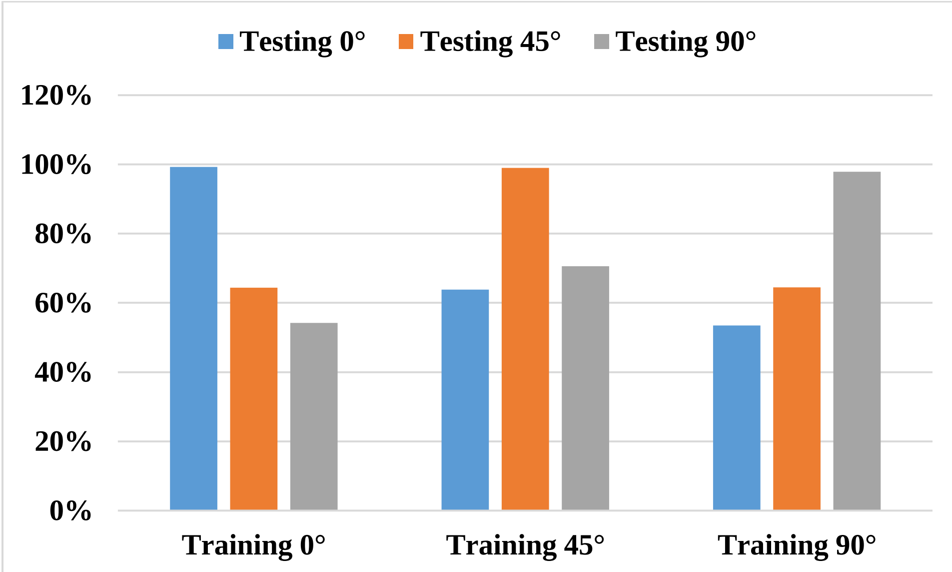

Figure 4-9: Classification accuracies for different training and testing schemes (Healthy)

4.2.4 Between Group Results (Amputees)

While performing the between groups training and testing for amputees, the amputees' classification accuracy dropped similar to as previously observed for healthy subjects. When training was done at 0^0 and tested at 45^0 and 90^0, the classification accuracies were 62.1% and 43.2%, with a misclassification of 37.9% and 56.8%, respectively. Similarly, when the classifier was trained with data from 45^0 and tested with 0^0 and 90^0, the reported classification accuracy was 70% and 41% with a classification error of 30% and 59%, respectively. Finally, when the system was trained with data from 90^0 and tested with data from 0^0 and 45^0, accuracy was 44.8% and 33.9%, with misclassification accuracy of 55.2% and 66.1%, respectively. The classification accuracies for between-groups analysis are shown in Figure 4-10. During one-way rmANOVA test, no significant difference (p-value > 0.05) was observed for any possible training and testing scenario.

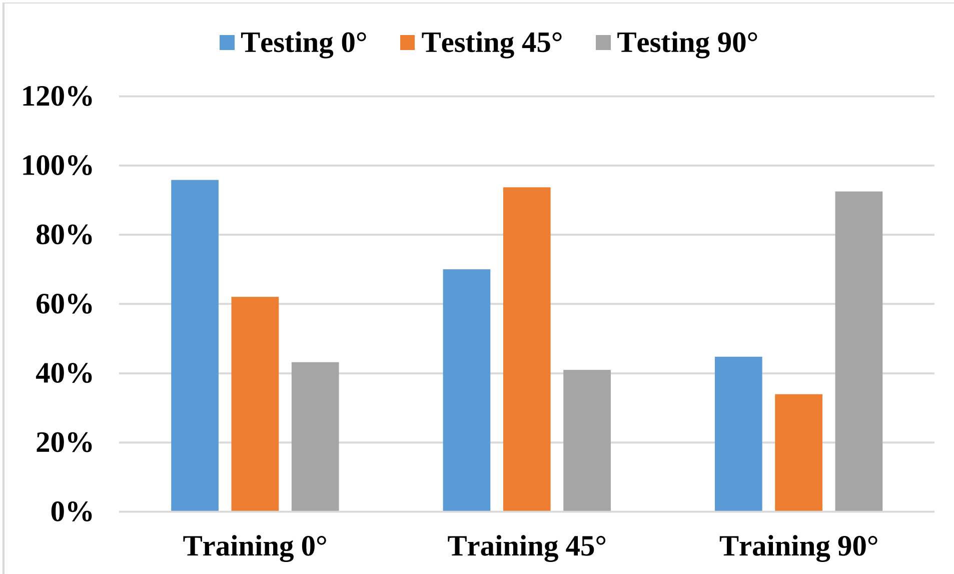

Figure 4-10: Classification accuracies for different training and testing schemes (Amputee)

4.3 Discussion

Like other bioelectric signals, SEMG offers a systematically added advantage for evaluating the organ that produces it. Information on skeletal muscle activation has many forms. It is useful in many areas, varying from orthopedics and neurorehabilitation to fitness and exercise movement analysis, from aging to gnathology, obstetrics to occupational medicine, and space medicine. Much of the relevant research on SEMG involves technical issues and proof of concepts, mainly on healthy subjects. There are few research trials in large patient populations and case studies and case-series in tiny amounts. This doesn't mean that the methods developed do not have practical significance or do not address clinical reasoning. Instead, it implies that there is a significant gap in the application of methods to the clinical setting.

In this study, sEMG was used to solve an important loophole in PR-based myoelectric prosthetic devices. Previous studies addressed this problem but all these studies suggested a solution based solely on offline classification accuracies. However, in the research, a solution for the limb position effect was proposed based on real-time tests and offline tests. Furthermore, a comparative study was also performed between real-time results and offline results.

While conducting real-time tests for healthy subjects, it is clear from the graphs that completion rate was the performance metric that was affected the most during different training and testing scenarios. The completion rates were relatively high for $ZT0^0$, $FT45^0$ and $NT90^0$ than $ZT45^0$, $ZT90^0$, $FT0^0$, $FT90^0$, $NT0^0$ and $NT45^0$. Similarly, when assessing completion rate for amputees, the completion rates were higher for $ZT0^0$, $FT45^0$ and $NT90^0$ than $ZT45^0$, $ZT90^0$, $FT0^0$, $FT90^0$, $NT0^0$ and $NT45^0$. However, the completion rates observed for amputees were lower as compared to healthy subjects. Observing other performance metrics like overshoot, path efficiency and throughput for healthy subjects, it is clear from the result section that no major difference was observed between them for different training and testing schemes. However, compared with the results of amputees, the observed overshoot for amputees was higher than the overshoot of healthy subjects. Similarly, the path efficiencies for healthy subjects were higher as compared to observed for amputees. The least affected performance metric was throughput where no major difference was observed for both amputees and healthy subjects.

After the successful performance of real-time tests, offline tests were performed to verify different training and testing schemes' outcomes. While performing offline analysis, it was concluded that low classification errors were observed when training and testing of classifier was done in same position. However, the classification errors increased when training and testing of classifier was done in different positions. The classification errors for training and testing in the same position were lower than their corresponding completion rates error. But the classification errors for training and testing in different positions were higher as compared to the corresponding completion rates error. Similarly for amputees, the offline analysis were conducted as well. However, classification errors for amputees were higher in the same position and different positions scenarios than healthy subjects.

The outcomes of real-time test and offline tests were compared and it was concluded that the results differ in both cases which further satisfies the previous research studies where it was mentioned that we cannot rely solely on offline analysis. This study's significance is huge as it will bring a great impact on the currently available PR-based myoelectric prosthetic devices.

The findings of this study are an important breakthrough in the field of prostheses. As mentioned earlier that manufacturing companies are making prostheses that are calibrated and set in a single position. This study has proven that calibrating a prosthetic device in a single posture is not enough. The prostheses should be calibrated in multiple postures. This will help the amputees perform motions and activities that require prosthetic movement in various angles. This research study can be further improved by increasing the number of recruits, increasing the number of motions performed, and increasing limb positions. These are some major points that can help develop an ideal prosthetic device that will be more close to a healthy human hand in terms of working and performance. As we know that the psychological impact of amputation on life is as severe as physical challenges. Body image, self-esteem and quality of life can be significantly reduced as a result of amputation. The increased use of better myoelectric prosthetic devices is associated with high levels of employment, increased quality of life, decrease in the phantom limb pain and general levels of psychiatric symptoms.

Chapter 5

5 Conclusion

This study aimed to implement Fits' law to evaluate the variability of different training and testing schemes in the same position and different positions. The findings of this study showed that completion rates and classification accuracies of five motions are affected by arm positions. This means that the prosthetic limb should not be calibrated in a specific position. Calibrating the prosthetic in a specific position will result in bad performance in other positions. Therefore, to overcome this hurdle, it is highly recommended to calibrate the prosthetics in different positions. Calibrating the prosthetic devices in different positions will significantly increase performance at all positions, thus overcoming the limb position effect more efficiently.

5.1 Future Recommendations

This study has highlited some of the important issues that are being faced in PR based myoelectric prostheses. This study has further proven some of the previous research studies which clearly indicates that real-time tests are necessary along with offline testing. Also, we cannot rely on the outcomes of healthy subjects only. Amputees are necessary in every study as their results are greatly different from healthy subjects. Any prosthetic device whether its for transradial, transhumeral, tranfemoral or transtibial, we had to include amputees along with healthy subjects. All the studies that have been performed only on pre-recorded data must be performed in real-time as well. This is because the offline analysis hasn't corresponded to real-time analysis. In future, other problems associated with PR based myoelectric controls must be addressed in real-time as well.

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