# Usability of Upper Limb Electromyogram Features as Muscle Fatigue Indicators for Better Adaptation of Human-Robot Interactions

By

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A dissertation submitted to the University of Hertfordshire in partial fulfilment of the requirements of the degree of DOCTOR OF PHILOSOPHY in the School of Computer Science.

JANUARY 2019

# Abstract

Human-robot interaction (HRI) is the process of humans and robots working together to accomplish a goal with the objective of making the interaction beneficial to humans. Closed loop control and adaptability to individuals are some of the important acceptance criteria for human-robot interaction systems. While designing an HRI interaction scheme, it is important to understand the users of the system and evaluate the capabilities of humans and robots. An acceptable HRI solution is expected to be adaptable by detecting and responding to the changes in the environment and its users. Hence, an adaptive robotic interaction will require a better sensing of the human performance parameters. Human performance is influenced by the state of muscular and mental fatigue during active interactions.

Researchers in the field of human-robot interaction have been trying to improve the adaptability of the environment according to the physical state of the human participants. Existing human-robot interactions and robot assisted trainings are designed without sufficiently considering the implications of fatigue to the users. Given this, identifying if better outcome can be achieved during a robot-assisted training by adapting to individual muscular status, i.e. with respect to fatigue, is a novel area of research. This has potential applications in scenarios such as rehabilitation robotics. Since robots have the potential to deliver a large number of repetitions, they can be used for training stroke patients to improve their muscular disabilities through repetitive training exercises.

The objective of this research is to explore a solution for a longer and less fatiguing robot-assisted interaction, which can adapt based on the muscular state of participants using fatigue indicators derived from electromyogram (EMG) measurements. In the initial part of this research, fatigue indicators from upper limb muscles of healthy participants were identified by analysing the electromyogram signals from the muscles as well as the kinematic data collected by the robot. The tasks were defined to have point-to-point upper limb movements, which involved dynamic muscle contractions, while interacting with the HapticMaster robot. The study revealed quantitatively, which muscles were involved in the exercise and which muscles were more fatigued. The results also indicated the potential of EMG and kinematic parameters to be used as fatigue indicators. A correlation analysis between EMG features and kinematic parameters revealed that the correlation coefficient was impacted by muscle fatigue. As an extension of this study, the EMG collected at the beginning of the task was also used to predict the type of point-to-point movements using a supervised machine learning algorithm based on Support Vector Machines. The results showed that the movement intention could be detected with a reasonably good accuracy within the initial milliseconds of the task. The final part of the research implemented a fatigue-adaptive algorithm based on the identified EMG features. An experiment was conducted with thirty healthy participants to test the effectiveness of this adaptive algorithm. The participants interacted with the HapticMaster robot following a progressive muscle strength training protocol similar to a standard sports science protocol for muscle strengthening. The

robotic assistance was altered according to the muscular state of participants, and, thus, offering varying difficulty levels based on the states of fatigue or relaxation, while performing the tasks. The results showed that the fatigue-based robotic adaptation has resulted in a prolonged training interaction, that involved many repetitions of the task. This study showed that using fatigue indicators, it is possible to alter the level of challenge, and thus, increase the interaction time.

In summary, the research undertaken during this PhD has successfully enhanced the adaptability of human-robot interaction. Apart from its potential use for muscle strength training in healthy individuals, the work presented in this thesis is applicable in a wide-range of human-machine interaction research such as rehabilitation robotics. This has a potential application in robot-assisted upper limb rehabilitation training of stroke patients.

# Dedication and acknowledgements

I would like to express my sincere gratitude to my supervisor Dr. Farshid Amirabdollahian for the continuous support of my Ph.D research, for his motivation, advice, knowledge, and constant encouragement throughout this research. I express my appreciation for the guidance that he offered all the time of research and writing of this thesis. I would also like to personally thank him for the flexibility that I enjoyed during this PhD balancing my work and family life.

My sincere thanks also go to my secondary supervisor Dr. Volker Steuber for offering constructive advices, valuable suggestions, and feedback on all my publications and the thesis drafts during my study at the University of Hertfordshire.

Thanks to my friends and colleagues in the Adaptive Systems Research Group and in particular, Sudhir Sharma, Udeshika Dissanayake, Adeline Chenasu, Alessandra Rossi, and more for their help in various phases of my research. Also, I would like to thank all the participants who took part in my studies for their valuable time and feedback. I would also like to thank all my friends who helped me to recruit participants for the experiments.

Special thanks to the ladies in the Research office for being very friendly and guiding me through the university's processes.

I owe special gratitude to my parents and I can hardly imagine getting to this stage of my research without their support and encouragement. I am particularly grateful to my lovely daughter, Farha and my dear wife, Shadiya for all their love and patience.

I would also like to acknowledge the financial support provided by the University of Hertfordshire, UK. The work reported in this thesis was supported by the research studentship from the School of Computer Science, University of Hertfordshire, and sincere thanks to the school for the support.

## Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the university's regulations and code of practice for research degree programmes, and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of others, is indicated as such. Any views expressed in the dissertation are those of the author.

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# Glossary

**AA** Active-Assisted.

**AvgP** Average Power.

**BB** Biceps Brachii.

**BMI** Body Mass Index.

**DLT** Deltoid.

**DLTF** Deltoid Frontal.

**DLTM** Deltoid Middle.

**EMG** Electromyogram.

**Fx** Force - x component.

**Fy** Force - y component.

**Fz** Force - z component.

**GUI** Graphical User Interface.

**HM** HapticMaster.

**MAV** Mean Absolute Value.

**MedF** Median Frequency.

**MJT** Minimum Jerk Trajectory.

**MVC** Maximum Voluntary Contraction.

**MVC-Eq** Maximum Voluntary Contraction Equivalent.

**NS** Non-Significant.

**PSD** Power Spectral Density.

**RMS** Root Mean Square.

**RMSE** Root Mean Squared Error.

**S1** Segment 1.

**S2** Segment 2.

**S3** Segment 3.

**S4** Segment 4.

**SMUAP** Single Motor Unit Action Potential.

**SSC** Slope Sign Change.

**STD** Standard Deviation.

**SVM** Support Vector Machine.

**TB** Triceps Brachii.

**TRP** Trapezius.

**VR** Virtual Reality.

**WL** Waveform Length.

**ZC** Zero Crossing Rate.

# Chapter 1

# Introduction

Human-Robot Interaction (HRI) study is used to understand, design, and evaluate different robotic systems for use by or with humans, which involves communication between robots and humans [79]. Human-robot interaction is the process of humans and robots working together to accomplish a goal with the objective of making the exchange beneficial to humans. This requires evaluating the capabilities of humans and robots, and designing the technologies and training that produce desirable interactions. Some of the widely accepted goals for an acceptable HRI solution are the usability, usefulness, and adaptation. The usability and minimizing the amount of human training required to interact with robots are key factors in human-robot interactions for therapeutic purposes for children, autistic individuals, or mentally challenged individuals. Similar is the case for "edutainment" robots, which include robots designed for use in classrooms and museums, for personal entertainment, and for home use. An HRI system is expected to be adaptable by detecting and responding to the changes in the environment and its users [79]. Designing an appropriate HRI interaction scheme and interface requires an understanding of the users of such a system. A good adaptive HRI will require a better sensing of the human performance parameters. Human performance is found to be influenced by their state of muscular and mental fatigue during active interactions.

It is anticipated that robots will become more like personal training tools in the future, as already available by some of the existing products. Robots have the potential to deliver a large number of repetitions in training exercises. Physically challenged people can get help from robots for lifting the weight of their limbs, and thus can perform tasks for a longer duration. Assistive robots can sense, process the sensory information, and perform actions that benefit seniors and people with disabilities [50]. Assistive robots can substitute or act as tools for health care professionals, when they are not available for a physical therapy. The availability of robots to successively repeat movements as well as their ability to record movements makes them suitable for rehabilitation training, that can be delivered without the constant presence of a therapist. Closed-loop control and adaptability to individuals are important criteria for the acceptance of rehabilitation solutions.

Adaptive robotic interactions for upper limb training have been studied by many researchers ([149], [115], [148], [208], [76]), however, a commercially accepted solution for robot-assisted muscle training considering muscle states could not be found yet [75][67]. Past research in this area has not been successful enough to deliver a solution that makes the robot or the training environment adaptive to the user's state of fatigue. Existing human-robot interactions are designed without sufficiently considering the implications (pain or state of fatigue) to the participant [149][195][60]. Given this, identifying if many repetitions and better outcomes can be achieved by adapting to individual muscular status, i.e. with respect to fatigue, is a novel area of research. Electromyogram (EMG) based fatigue indicators from upper-limb muscles can be explored to be used as adaptation parameters for robot-assisted training. EMG features from the involved muscles can be used to understand the current physical state and the effort exerted by the participant [149][195], and then to alter the intensity of the training.

The main hypothesis for this research was that the system's awareness of the extent of physical fatigue in the involved muscles during a human-robot interaction will enable us to have more user-adaptive interactions with the help of fatigue indicators derived from physiological measurements such as electromyogram (EMG). One of the applications of this could be in robot-assisted muscle strength training based on standard sports science protocols, where an adaptive robotic system could be used to change its environment to achieve a large number of task repetitions and a prolonged interaction. Sports science protocols for strength training suggest to quantify the task difficulty levels based on the maximum voluntary strength of participants, and use a proportional increment of the difficulty at regular intervals [49]. Such a protocol was implemented as part of this research, which helped to achieve a prolonged progressive strength training exercise with the help of a fatigue-based robotic adaptation compared to the training interactions which were based on manual/no adaptation.

Apart from its potential use for robot-assisted muscle strength training in healthy individuals, the work presented in this thesis is also applicable in a wide-range of human-machine interaction research such as stroke rehabilitation. In stroke patients, due to their reduced muscular and cognitive capabilities they can easily come to a state of fatigue during rehabilitation training exercises. To prevent this, the adaptive robot-assisted strength training protocols suggested by sports science literature may be applied also to the scenario of stroke rehabilitation training to reduce or delay the muscle fatigue during the interaction. Since, more repetitions in rehabilitation training are thought to impact on neuro-plasticity, that aids the recovery after stroke [69], the results of this research have a potential to be used in this context. Hence, a future work will consider applying the proposed method for robot-assisted upper limb rehabilitation training of stroke patients, which will help to utilize their limited physiological resources better. Thus rehabilitation therapies can be made more patient-adaptive.

## 1.1 Scope of the Thesis

The long-term aim of the research is to offer a user-adaptive robotic system to assist people during upper-limb training exercises that result in a prolonged interaction. This thesis contributes to the development towards that goal. The research involved the HapticMaster robot, which could be configured in either passive, active or active-assisted modes of operation [10]. This was similar to a past rehabilitation project, GENTLE/S, which studied the upper-limb training of stroke survivors using haptic robotic interactions (using the HapticMaster robot), however, this did not perform any robotic adaptation based on the muscular state of the patients [10][128]. An EMG acquisition hardware was used to collect the muscle EMG during the robotic interactions. The indications of muscle fatigue were studied by analysing the EMG measurements and also kinematic data measured by the robot. Later, a robotic algorithm was developed, which adapted the training environment according to the upper-limb muscle fatigue detected based on the calculated EMG features. Additionally, physiological measures such as height, weight, BMI, muscle composition, and body fat were studied to see if they had any significance in the development of fatigue. A subjective assessment of muscle fatigue was also conducted by providing appropriate pre and post-fatigue questionnaires. Finally, an adaptive robot-assisted progressive muscle strengthening protocol based on standard sports science protocols was proposed using the findings of the experiments as shown in Figure 1.1.

## 1.2 Research Questions

This research was aimed at exploring the potential of fatigue indicators based on EMG and kinematic measurements to improve the adaptability of human-robot interaction. The major motivation behind the current research is stated as below.

**Motivation:** *"It is possible to improve the adaptability of human-robot interaction using the EMG features collected from the main muscles involved in the interaction."*

This leads to the following major research questions, which were addressed in this research. Figure 1.2 maps the different research questions onto the major explorations planned through the different experiments in this research.

**Question 1:** Can the state of muscle fatigue during human-robot interactions be effectively represented by Electromyogram (EMG) from upper-limb muscles and kinematic measurements from the robot?

Electromyogram signals from upper limb muscles have been used in many of the past studies on human-robotic interaction for controlling exoskeletons and upper limb virtual models [91], [80], [186], [38], [146] and for detecting hand gestures and movements [60]. However,

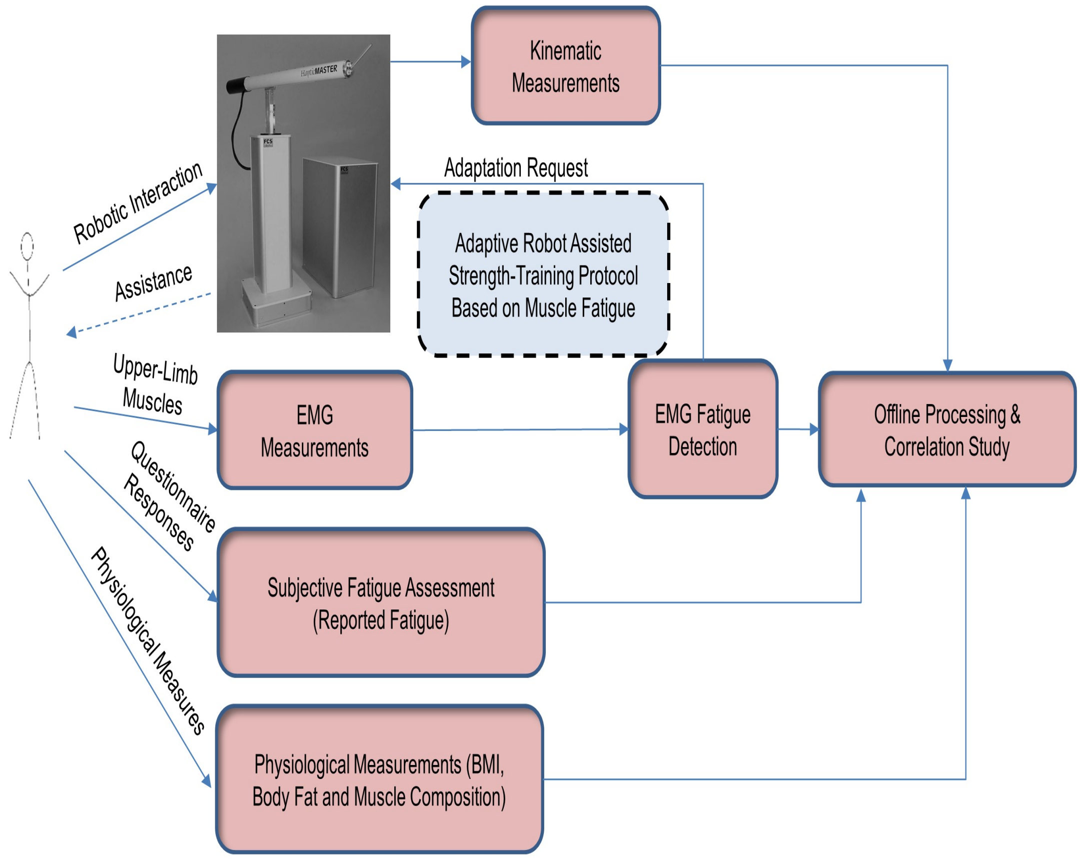


Figure 1.1: The Overall Context of the Research.

very few studies have explored fatigue indicators based on EMG and kinematic features in a context of rehabilitation with robotic assistance. Past research has indicated a high and significant correlation between upper limb muscles and brain activity during high and low precision repetitive tasks [211]. Muscle fatigue during upper limb exercises was found to affect mental simulation of action [55]. This implies that if a patient gets mentally and physically fatigued during a training exercise, this is going to affect their performance in the training interaction.

In this research, the fatigue indicators from the upper limb muscles of participants were identified by collecting the EMG signals from the involved muscles, while interacting with the HapticMaster robot following different experiment protocols. The kinematic measurements from the robot were also studied to identify potential indicators of fatigue. The fatigue detection was implemented through an off-line signal processing algorithm, and then the EMG and kinematic features representing muscle fatigue were identified. As an extension to this study, an additional research question was also derived to explore if the EMG collected at the beginning of above upper-limb exercise can be used for predicting the motion intention and if it has a potential to

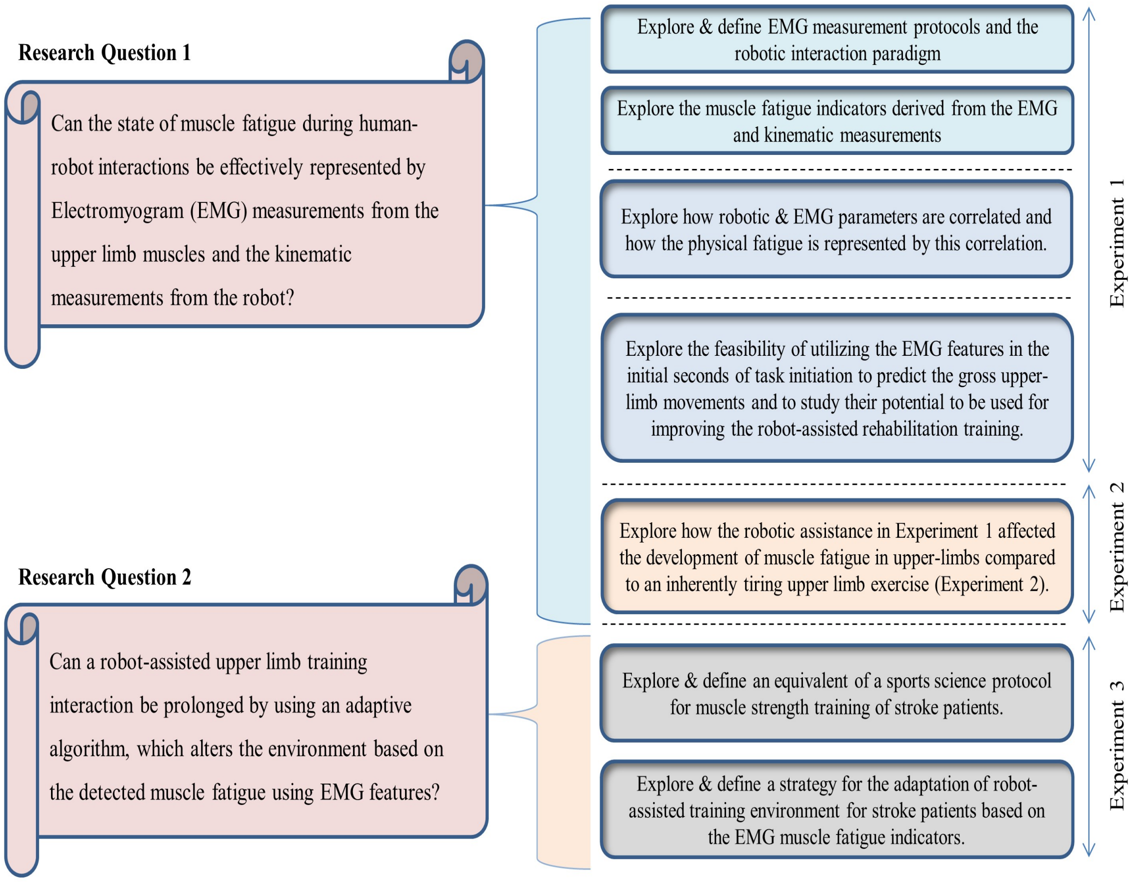


Figure 1.2: Mapping Research Questions onto Experiments.

further inform the rehabilitation exercise plan during a robot-assisted training.

**Question 2:**

Can a robot-assisted upper limb training interaction be prolonged by using an adaptive algorithm, which alters the environment based on the detected muscle fatigue using EMG features?

Few studies involving robotic interactions have measured the fatigue state of participants using methods like subjective analysis and game scores. For example, the studies by Octavia et al. [148], [149] measured fatigue using EMG signals, but did not use them to feed back to the robot and to improve the interaction. Few other studies such as [81] and [117] have also investigated the EMG based fatigue indicators during a robotic interactions. However, the EMG fatigue indicators were not utilized for demonstrating any method that would make the robot or the training environment adaptable to the user's state of fatigue. The above literature suggested that physiological signal parameters as fatigue indicators were not utilized for building an adaptive robotic interaction. They stated that the muscle fatigue parameters can be detected from upper limb muscle locations. The state of muscle fatigue of participants can be feed back to the robotic system so that the degree of assistance can be adapted accordingly. An interactive and motivating training environment (game/virtual reality (VR)) that would adjust its difficulty level according to some parameters derived from the biological sensor data (like EMG) could possibly improve the adaptability of human-robotic interaction. The complexity of rehabilitation training environments could be altered according to the participant's disability and tiredness, which could be measured through suitable algorithms for physical fatigue detection. This could result in a prolonged training interaction.

## 1.3 Thesis Layout

In order to address the research questions, a total of three experiments were planned. Suitable robotic interaction paradigms were explored and protocols were defined for the experiments using the measured EMG features. The overall organisation of the thesis is as follows.

Chapter 2 presents the past studies, which were relevant to this study and the current gaps. The chapter discusses different topics including muscle physiology, electromyogram, muscle fatigue, rehabilitation robotics, robotic adaptation, rowing tasks, and muscle strengthening exercises for stroke rehabilitation.

Chapter 3 describes the design and results of Experiment 1, where the upper-limb muscle fatigue and kinematic measurements from the robot are studied. The experiment protocol, methodology and the outcome of the study are discussed. This chapter partially covers Research Question 1. Experiment 1 was conducted to validate how effectively the EMG features from the upper-limb muscles can be used to represent muscle fatigue during human-robot interactions. The HapticMaster robot was used in the experiment to provide assistance based on kinematic measurements during upper limb tasks, which also allowed users to be monitored by sensing the user's hand movements through its end effector. The robot was previously used in a stroke rehabilitation project, GENTLE/S, where different interaction modes were developed [10]. The robot is capable of rendering high stiffness, near-to-zero friction and zero end effector weight, offering a very low-impedance motion [126]. As an input device, the robot allows users to interact with some software applications/games by sensing the user's hand movements and as an output device, it can provide haptic feed back to the user [148]. In the active-assisted mode of HapticMaster, the subject only had to initiate the activity, after which the robot would assist/guide the subject for the rest of the movement [10][34]. In Chapter 4, an extension of the above study is presented detailing a movement classifier based on the measured EMG from the upper limbs during Experiment 1. The study explored the possibility of using the EMG for predicting the type of gross-upper limb movements based on the EMG collected at the beginning of the movements.

Chapter 5 explains the study protocol, methods, and results of Experiment 2, where the EMG based muscle fatigue indicators from Experiment 1 were validated. This chapter covers the rest of Research Question 1. Since the previous experiment (Experiment 1) was performed in active-assisted mode, the robot provided assistance to the participants, and hence, there was less effort from the participants to move the end-effector along the different segments. This resulted in a reduced muscle fatigue. To ensure that the EMG features in Experiment 1 could indeed identify fatigue correctly, Experiment 2 was planned with an inherently fatiguing set-up without robotic assistance. The study helped to validate how the features of the EMG could represent the extent of fatigue during the tasks.

Chapter 6 describes the details of Experiment 3, where adaptation of a human-robot interaction based on muscle EMG was implemented, which addressed Research Question 2. The experiment was conducted to implement the adaptability of robotic interaction by using the EMG fatigue indicators from the upper limb muscles. The participants interacted with HapticMaster robot with a progressive muscle strength training protocol similar to standard sports science protocols for muscle strengthening. The EMG features representing muscle fatigue were identified and the fatigue detection was performed by an on-line signal processing algorithm. The result of this detection was then used by the robotic algorithm to adapt the robotic environment accordingly. The robotic (HapticMaster) assistance was altered according to the fatigue indicators and thus offering a different difficulty level for performing the tasks.

Finally, Chapter 7 presents the conclusion of different experiment results, discussions and possible future work. The flow diagram of the study is chronology explained in Figure 1.3.

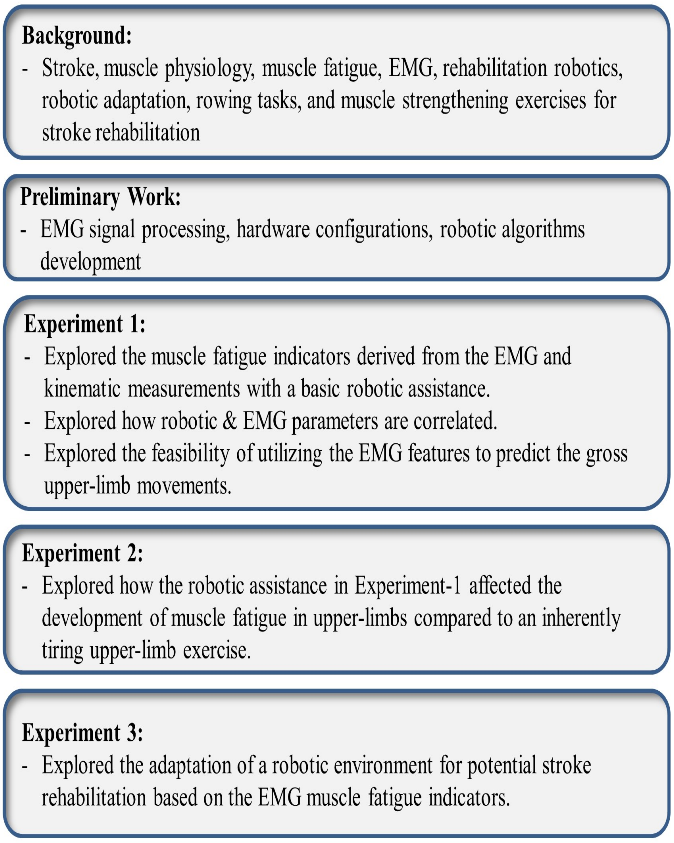


Figure 1.3: Flow Diagram Showing the Study Chronology.

CHAPTER 2

# BACKGROUND

## 2.1 Robotics and Human-Robot Interaction

Robots are intelligent machines with capacities of perception and action in the physical world. The interaction between robots and humans becomes more and more important as robotic technology advances, and the robots start moving out of the research laboratories in to the real world. It is anticipated that robots will become more like personal training tools in the future, as already available by some of the existing products. For example, robotic systems have been used in the context of rehabilitation for more than two decades. Robots are also used in "edutainment" purposes, where they are designed for use in classrooms, museums, and personal entertainment. The use of production robots in industrial automation can lead to considerable savings in the cost of labour and products. Robots can not only support humans, but also involve in various lifesaving functions such as medical diagnostics, and for inspection and assessment of dangerous objects in hard-to-reach areas without putting humans at risk. One of the advantages of using robots is that, they can not be distracted by fatigue, which results in an improvement in the efficiency and a better control of the task performance. Hence, they can be very useful in applications, where higher accuracy and repetitive tasks are involved.

Human-Robot Interaction (HRI) study is used to understand, design, and evaluate different robotic systems for use by or with humans, which involves communication between robots and humans [79]. Human-robot interaction is the process of humans and robots working together to accomplish a goal with the objective of making the exchange beneficial to humans. This requires evaluating the capabilities of humans and robots, and designing the technologies and training that produce desirable interactions. Designing an appropriate interaction scheme and interface requires an understanding of the users of such a system. The usability and minimizing the amount of human training required to interact with robots are key factors in human-robot interactions for therapeutic applications. Many past studies explored HRI problems such as factors that improve usability, the way information is exchanged between human and robot, developing means to support a productive interaction, and making user interfaces that reduce the cognitive load of the user. An HRI system is expected to be adaptable by detecting and responding to the changes in the environment and its users [79]. This will require a better sensing of the human performance parameters. Human performance is found to be influenced by their state of muscular and mental fatigue during active interactions. Hence, assistive robots used in therapeutic HRI systems are programmed to sense, process the sensory information, and perform actions that benefit seniors and people with disabilities [50].

## 2.2 Muscle Physiology

The functional unit of muscles are the motor units (MU), that consists of alpha motor neurons and fibers innervated by it. Muscle fibers are the structural units of muscle contraction and one MU can have from 3 to 2000 muscle fibers, depending on the degree of control and strength required by the muscle [113]. As shown in Figure 2.1, each MU consists of an anterior horn cell or motor neuron, Axon and muscle fibers innervated by the axon. The hatched fibers belong to one motor unit and the non-hatched fibers belong to other motor units. The fibers of one MU are interspersed with the fibers of other MUs [167].

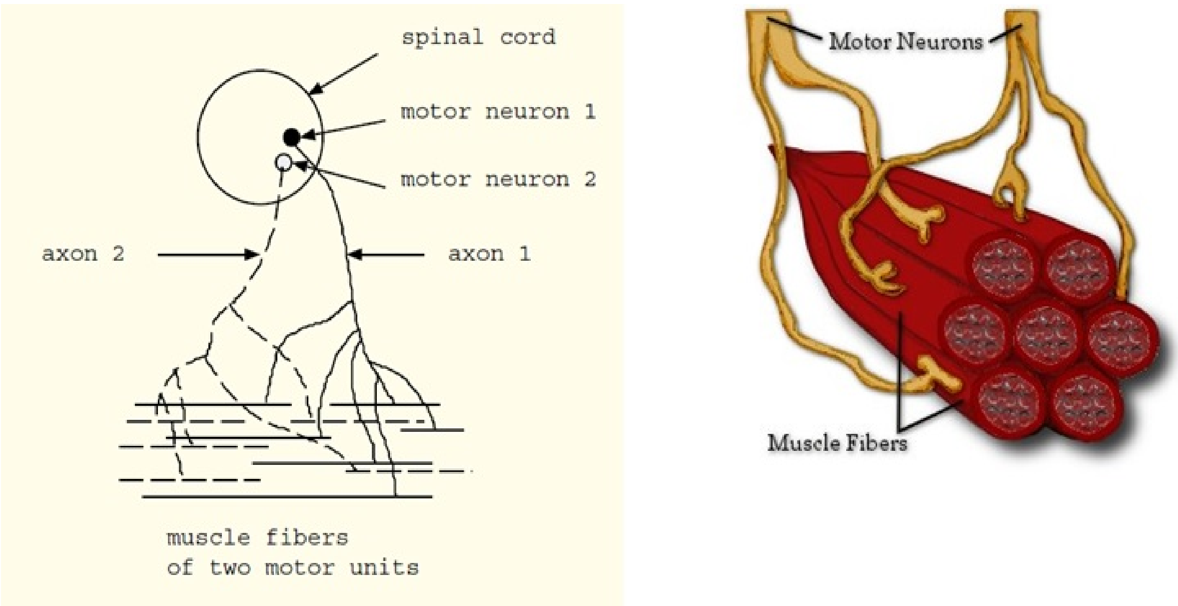


Figure 2.1: The motor units of muscle fibers [167].

The ability of a muscle to generate tension/muscle strength is a result of nerve stimulation originated from the brain. A sensory input from muscles travels via afferent pathways to the central nervous system (CNS), where it triggers the recruitment of motor neurons that stimulates muscle fibers. This results in the generation of muscle strength. Muscular contraction levels are controlled in two ways with increasing effort: In one way through a spatial recruitment by activating new MUs and secondly, through a temporal recruitment by increasing the frequency of discharge or firing rate of each MU. The muscles, which control fine movements and require precise but low strength have fewer fibers per MU. The large muscles, which control gross movements and requiring greater strength, may contain 100 to 1000 fibers per MU [113]. The contraction of muscle fibers occurs when the muscle cells fire an action potential due to a motor neuron command. When the action potential reaching the motor neuron and axon terminal exceeds the threshold of depolarization in the post-synaptic membrane of the neuromuscular junction, it becomes a muscle action potential. The muscle action potential is propagated in both directions of the muscle fiber, triggering the process of the sliding of actin filaments on myosin (the major contractile proteins of the myofibrils). This promotes muscle contraction based on the moving filament theory [27] as explained in Figure 2.2.

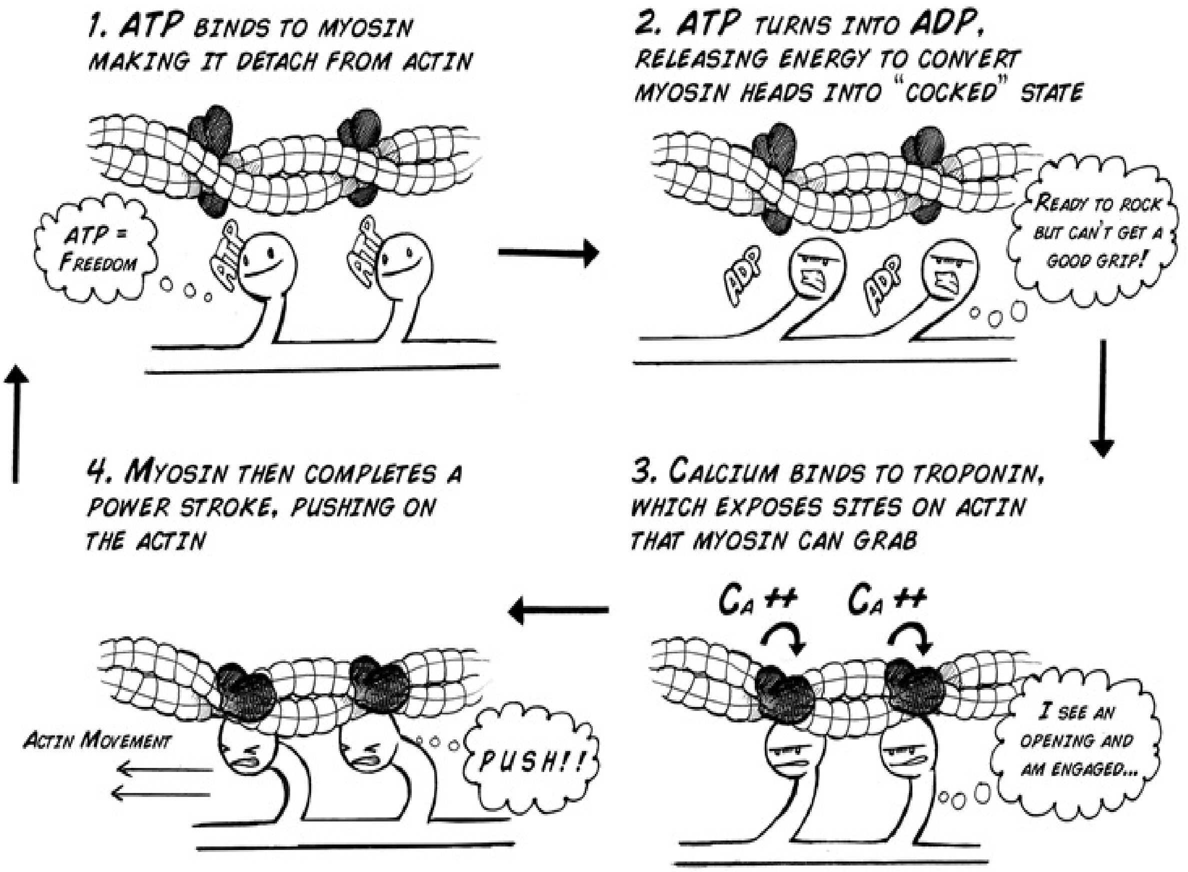


Figure 2.2: Muscle Contraction and Moving Filament Theory [27].

The fibers do not remain contracted; instead they relax after each activation, and this results in a repeatability of activation, which is called the frequency of MU activation. The synchronization of activation refers to the temporal coincidence of the pulses of two or more MUs firing in combination. During voluntary contractions, muscle force is modulated by the central nervous system, which combines recruitment with the frequency of MU activation and synchronization. The more the ability to recruit MUs simultaneously, the higher the force produced by the muscle [113].

As the level of the contraction increases, additional motor units are recruited, and the firing rate of motor units increases [52]. Contracting muscles do not produce a smooth or steady force. These fluctuations increase both during and after sustained contractions as the muscle becomes fatigued. When a muscle contracts, the central nervous system regulates muscle force production by varying the two main motor unit parameters: the recruitment of new motor units and the modulation of firing rates of active motor units. During isometric contractions, the fluctuation of the force output of muscles increases as the muscle fatigues and the contraction is sustained to exhaustion [44].

## 2.3 Muscle Fatigue

Muscle or physical fatigue is defined as the decline in the ability of muscles to generate force or power during a physical task. Fatigue usually results in a feeling of tiredness or forces a person to take rest because of the lack of strength and it develops gradually during a physical activity [39]. Muscle fatigue is the consequence of a variety of physiological changes within the working muscle and is typically mild or temporary in duration and this discomfort normally disappears when the exercise is stopped [14][27][39][144][66][136]. Fatigue is also defined as any exercise or non-exercise-induced loss in total performance due to various physiological factors, athlete reported psychological factors, or a combination of the two [207].

The main reasons for muscle fatigue are the limitations of a nerve's ability to generate a sustained signal (called as mental fatigue) and the reduction in the ability of the muscle fibers to contract (called as muscle fatigue). Central fatigue is related to the brain and the spinal cord and it originates at the central nervous system (CNS), which decreases the neural drive to the muscle. Peripheral fatigue is the failure to maintain an expected power output and it occurs within the muscle [207]. During high intensity exercises the demand for oxygen can become greater than the supply (anaerobic contraction). The 'Metabolic Fatigue' is defined as the reduction in muscular force due to the effects of shortage of substrates and the accumulation of substances (metabolites) within muscle fibers. This accumulation results in the release of calcium (Ca2+) or it affects the ability of calcium to stimulate muscle contraction. Since the anaerobic contraction results in the generation of waste products like accumulation of Lactic acid, the pH decreases and this results in a sense of pain in the muscles as shown in Figure 2.3 [27].

The shape of the action potential (hence the EMG) is affected by the conduction velocity (CV)

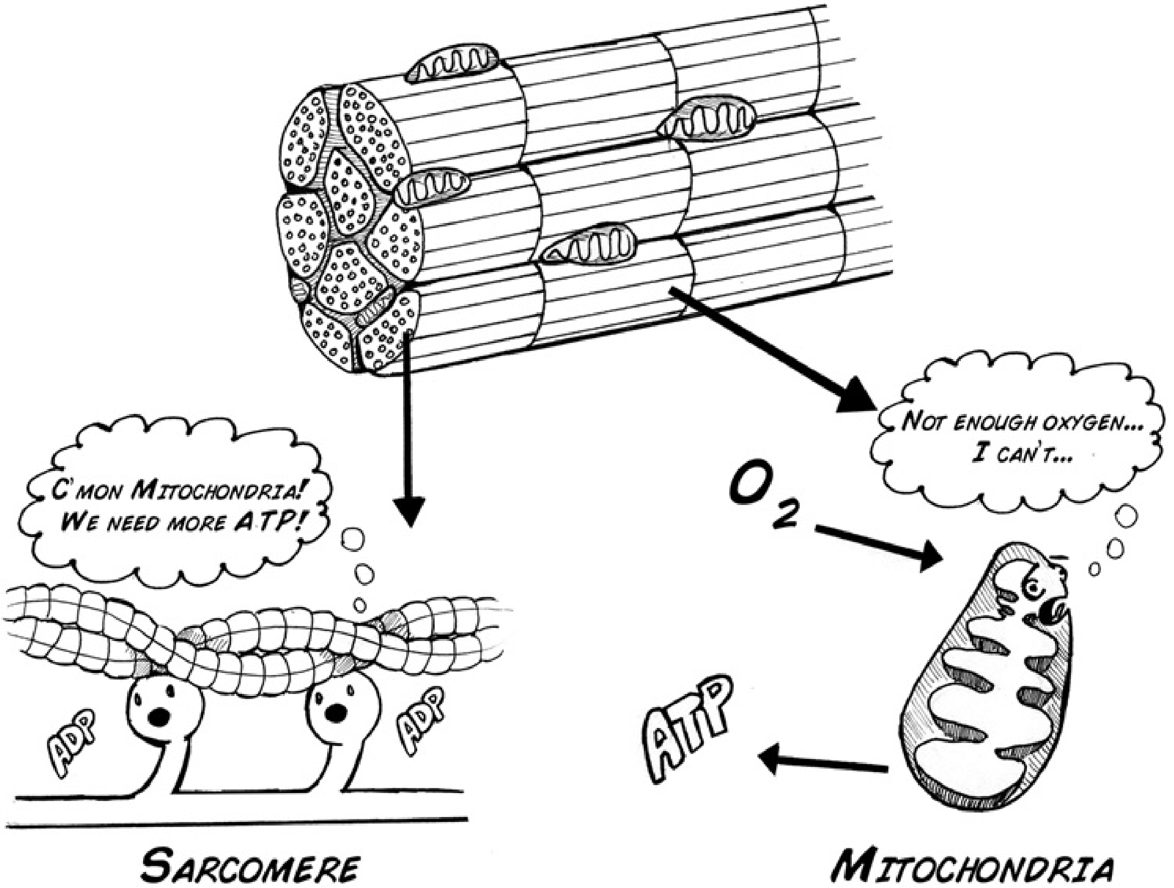


Figure 2.3: Formation of Muscle Fatigue [27].

of the action potential along the muscle fibers. Due to the accumulation of Lactic acid (decrease of pH), an increase of H+ concentration happens, which increases the positive charge outside the cell. This creates an opposition to the propagation of action potentials. Since the conduction velocity decreases, the depolarization current would require more time to traverse the fixed distance along the fibers. So, the time duration of the action potential increases and, hence, a decrease in the firing frequency and also a decrease in the force [27]. So, fatigue results in a shift in the frequency spectrum of the MUAPs and the EMG signal. This causes a relative increase in the lower-frequency components and a decrease in the higher-frequency components on the EMG. As a muscle is progressively more fatigued additional motor units are recruited, to maintain a constant force, and this also results in an increase in the EMG amplitude. At low levels of force requirement, both the recruitment and firing rate changes are actively used to generate the muscle force. At higher levels of force, since most of the motor units are already recruited, changes in muscle force are caused by changing motor unit firing rates [189].

### 2.3.1 Effects of Fatigue

A more muscular effort results in an increased demand on the recruited muscle fibers and more recruitment of motor units (MUs), which leads to a faster rate of muscular fatigue [168]. Effects of muscle fatigue on task performance were evaluated by Demougeot et al. [55] who tried to examine if mental movements were influenced by muscle fatigue, using the EMG collected from the right arm muscles. Participants were asked to execute an actual and an imaginary mental arm movement in a particular way. Both types of movements were performed before and after a fatiguing exercise and EMG data was collected in both cases. It was found that before the occurrence of fatigue both the movement duration were same. But after occurring fatigue there were discrepancies in the duration. It was reported that the muscle fatigue significantly affected the neural drives, which are sent to fatigued muscles.

Studies suggest that when the muscle fatigue occurs, the stability of surface EMG of muscles reduces. Researchers have tried to overcome the impact of fatigue during human-machine interactions using EMG feed back and improved classification methods [209]. It is possible to identify, which muscles come to a state of fatigue during a training interaction by analysing the progress of muscle EMG. For example, during a study by Minning et al. [141], the fatigue rate of some selected shoulder muscles during an isometric shoulder elevation task was explored, and the results stated that the middle deltoid muscle reached a state of fatigue faster than other shoulder muscles. So, while designing a rehabilitation training or game, a sequence of upper limb exercises may be designed in such a way that it does not cause fatigue in the specific muscles [141]. Another study which explored the effects of muscle fatigue concentrated on how fatigue affected the position sense in upper limbs during a reaching task [198]. Two precision tasks were conducted before and after a fatiguing exercise to see the impact of fatigue on the reaching performance. The results suggested that muscle fatigue need to be considered as an important parameter during the treatment of musculo-skeletal injuries as well as athletic training. EMG measurements from upper limb muscles were used to detect fatigue in order to validate the results.

**Prevalence of Fatigue in Patients** Fatigue after stroke feels like 'hitting a wall' or feeling suddenly overwhelmed with the desire to sleep and its causes can be both physical and emotional. For example, movement impairments cause to spend more energy than before stroke and the post stroke pain causes the need of immense energy to cope with. There are also emotional causes of fatigue like post stroke depression and anxiety from fear of having another stroke. Even for a mild stroke, the patients can still feel extreme fatigue [73] and muscle fatigue may place the stroke patients at greater risk [154]. The symptom of Post Stroke Fatigue (PSF) has been commonly described as one of the most difficult for the patients to cope with. The negative impact of post stroke fatigue hampers their attempts to return to normality and regain independence. At least 30-60% of stroke patients are reported to have experienced fatigue sometime during their recovery, which lasted for weeks, months or even years afterwards [15]. Guidelines suggest that the patients need to recognise their limitations and set realistic goals for improvement, with carefully designed assistance protocols [15].

The impact of fatigue on patients with multiple sclerosis (MS) has been reported as very prevalent and severe. Fatigue has a significant effect on the mental health and general health status of MS patients [70]. Fatigue is considered as one of the main reasons for the impaired quality of life in multiple sclerosis (MS) patients [112]. It makes the patients resuming previous roles and daily activities more difficult and thus making them socially isolated. Fatigue is one of the most commonly reported symptoms by at least 75% of MS patients at some point in their diseased stage [111][123]. Fatigue after MS patients have also been reported to have caused significant socioeconomic consequences including loss of work hours and loss of employment [184].

### 2.3.2 Monitoring Muscle Fatigue

Muscle force production involves a series of events that include cortical excitation, motor unit activation, excitation-contraction coupling, and finally muscle activation. Changes at any level in this pathway will impair force generation and contribute to the development of muscle fatigue [200].

During stroke rehabilitation training, the motor tasks need to be not only actively and repetitively practiced, but also challenging enough to stimulate individuals to go beyond the current state of their motor capacity, and thereby achieve the adaptive brain reorganization driving behavioral improvements [147]. However, an increased perception of fatigue and fatigability during the training sessions can result in a decrease in the neural activation required for the neuroplastic processes mediating motor gains [147]. Fatigue can critically decrease the individual's physical capacity and ability to actively engage with the repetitive practice of progressive motor tasks [78]. Muscle fatigue may place the stroke patients at greater risk [154]. Also, training under high-levels of fatigue can result in little to no training adaption. Hence, monitoring the amount of fatigue is important for optimizing the training performance [212]. Monitoring fatigue can provide important feed back required to adjust training loads accordingly [207]. Enhancing the control scheme by lessening the effects of muscle fatigue would make a better use of the time available for a rehabilitation session [208]. Therefore, it is important to detect the onset of muscle fatigue and then use this for adapting the training environment so that the fatigue can be delayed or avoided.

Developing resistance to fatigue through muscle strength training has been explored by many past studies. Studies suggest that prevention of fatigue during rehabilitation training is therapeutic. Prevention or delaying of fatigue during rehabilitation training can help in a prolonged interaction that helps to perform more repetitions. Recent studies have reported that patient motion can became more stable and resistive to fatigue as the recovery stage progressed through increased repetitions [196]. Body of evidence supports the use of exercise training for stroke survivors, which helps to improve the ability to perform activities of daily living. Low to moderate-intensity aerobic activities, and muscle-strengthening activities are suggested to be promoted for physical activity in stroke survivors. Physical activity goals and exercise prescription for stroke survivors need to be customized for the individual to maximize long-term adherence [178]. The fundamental mechanisms underlying neuro-plasticity can be induced by skills training and by exercise programs designed to increase muscle strength and cardiovascular fitness. Training interventions that depend on repetitive task-oriented practice at suitable intensity and duration can help to reacquire the affected motor skills [61].

Muscle fatigue can be overcome through suitable muscle strength training tasks. Spending energy on high intensity training exercises can help to reduce fatigue in a long run. Intensive training could help the stroke patients to rebuild stamina and they will eventually start using less energy to perform the tasks, which will help reduce the post fatigue [41]. Studies have reported that specific strength training improves muscular fatigue resistance and reduces pain of the upper limb [188]. Fatigue after stroke will naturally decrease as you work to overcome your movement impairments and improve your stamina through rehabilitation exercises [72]. Other similar studies also report that training delays the onset of muscle fatigue during maximal exercise testing [87].

## 2.4 Electromyogram (EMG)

### 2.4.1 Formation of Electromyogram

Electromyography (EMG) is a technique used for recording the electrical signals produced by skeletal muscle cells when they are activated [204]. An EMG signal measures the electrical activity of muscles at rest as well as during contraction. EMG signals are used in many clinical and biomedical applications, which includes controlling prosthetic devices in rehabilitation. The amplitude of muscle EMG is dependent on many factors like the diameter of the muscle fiber, properties of the electrode, distance, and the nature of tissue between the muscle fibers and detection site.

The body fluids surrounding the muscle cells contain charged atoms/ions. During the resting state, the semi-permeable membranes of the excitable muscle cells permit the entry of K+ and Cl- ions, but block Na+ ions. This constitutes a resting potential of the order of -60 to -100 mV across the cells. Resting state is a state of equilibrium established with a potential difference across the cells, polarised with the inside of the cell negative with respect to the outside as shown in Figure 2.4 [167]. Depolarization happens when a muscle cell is excited by a stimulus, and the membrane changes its characteristics allowing Na+ ions to enter the cell [108].

Brain recruits motor units to innervate muscles while initiating a movement. When the potential exceeds the threshold of depolarization in the post-synaptic membrane of the neuromuscular

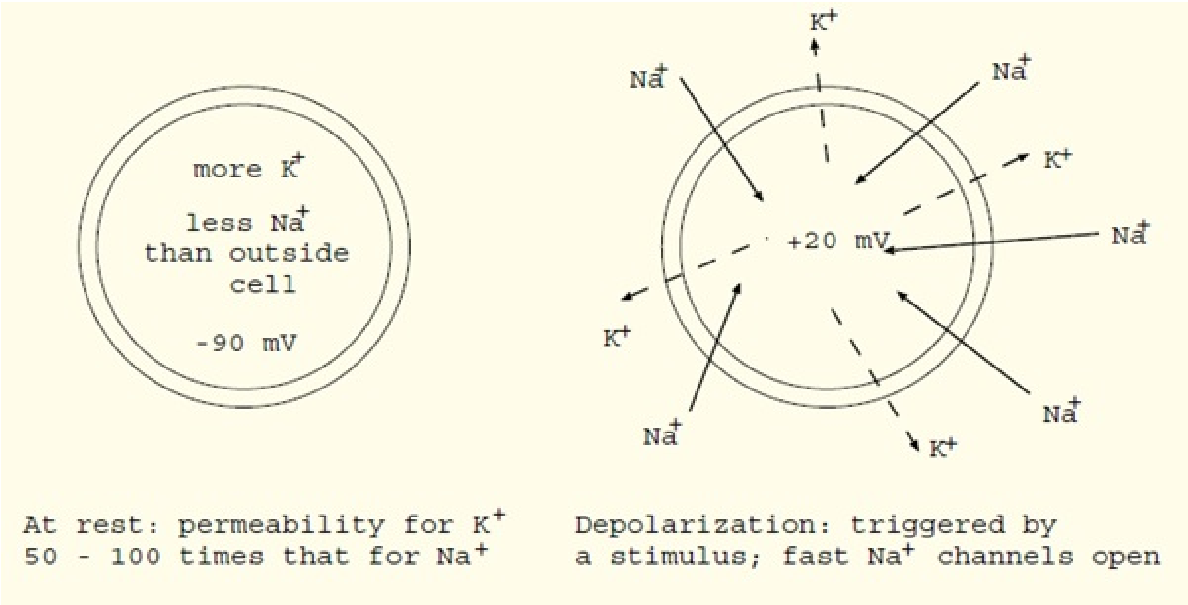


Figure 2.4: Resting state and depolarisation of a cell [167].

junction, it becomes a muscle action potential. The membrane depolarization, accompanied by movement of ions, generates an electromagnetic field in the vicinity of the muscle fibers, and an electrode located in this field will detect the potential or voltage (with respect to ground) [51]. When stimulated by a neural signal each motor unit contracts, and a summation (spatio-temporal superposition) of the action potentials of all the constituent cells is known as the single-motor-unit action potential (SMUAP) or MUAP [167].

In a normal muscle, the peak-to-peak amplitude of a MUAP detected with indwelling electrodes (needle or wire) range from a few $\mu$V to 5 mV (typical value of 500 $\mu$V). In human muscle tissue, the amplitude of the action potentials is dependent on the diameter of the muscle fiber, the distance between the active muscle fiber and the detection site, and the filtering properties of the electrode. The firing pattern of each motor neuron is represented by an impulse train. Each system hi(t) shown in the figure Figure 2.5 represents a motor unit that is activated and generates a train of MUAPs [51][16]. The spatio-temporal summation of several such single motor unit action trains results in an interference pattern called EMG as shown in Figure 2.5. This myoelectric energy is detected by surface electrodes and this is measured as the EMG.

The raw EMG amplitude can range between 5 and -5 mV and the typical frequency range is 6-500 Hz, with the most frequency between 20 and 150 Hz approximately [108]. Due to the wide frequency spectrum typical sampling rate for EMG acquisition is 1000 Hz or greater. The frequency spectrum of the action potentials will be affected by the tissue between the muscle fiber and the detection site. The presence of this tissue creates a low-pass filtering effect whose bandwidth decreases as the distance increases.

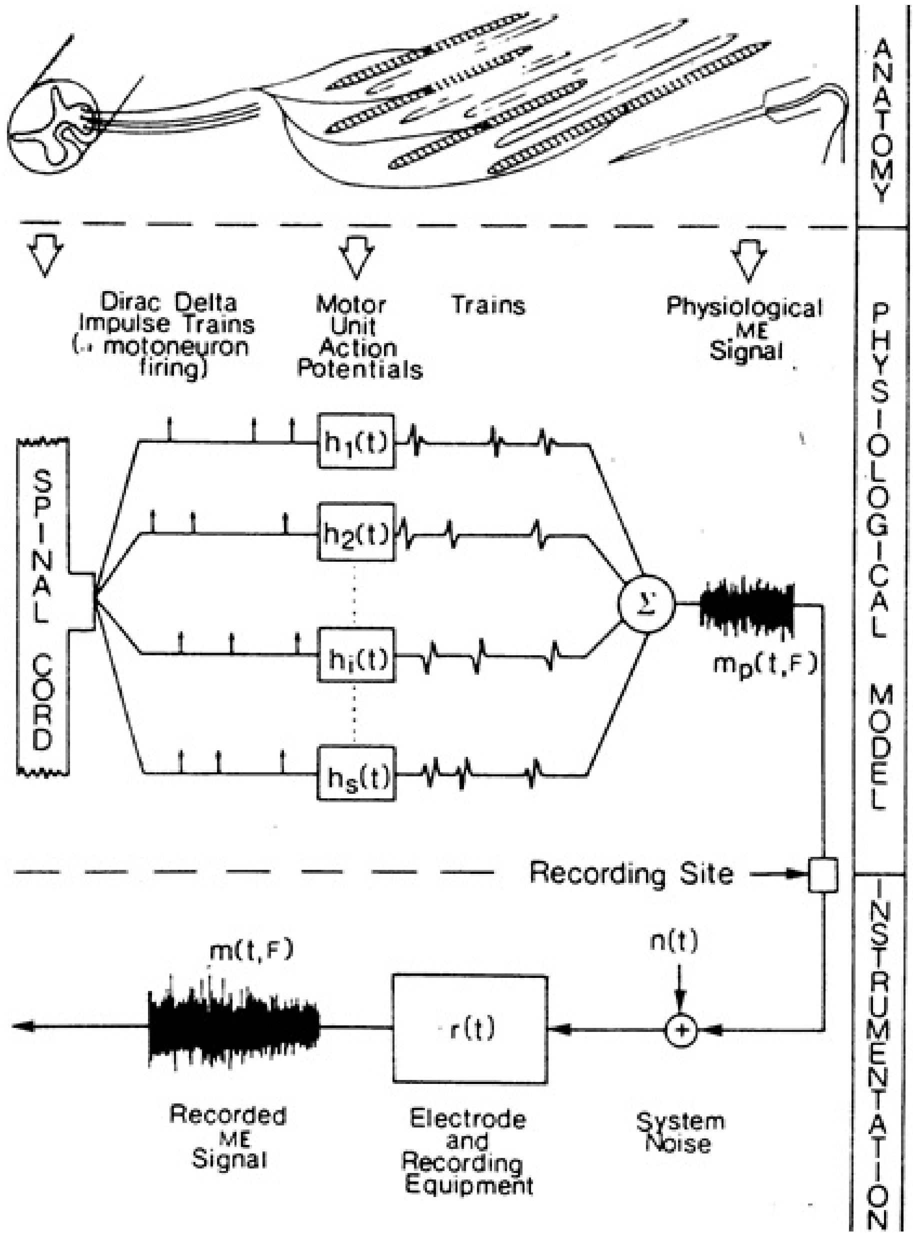


Figure 2.5: Formation of EMG as a spatio-temporal summation of several single motor unit action (SMUAP) trains [51][16].

### 2.4.2 EMG Based Studies on Upper Limbs

Researchers have conducted various studies on EMG signals from upper limb muscles for different purposes such as muscle activation studies, gesture recognition, prosthesis control, and development of control models [38][146][139][140]. Upper limb EMG signals can be used to interact with computers (Human-Computer Interaction) which can provide an alternative way of accessing computers for individuals with motor disabilities [38]. The EMG signals from upper limb muscles were utilised by Choi et al. [38] in order to interface with a computer using residual muscle activities without using a mouse or keyboard. A means to improve human-computer interaction by utilising the information such as muscle fatigue gathered from EMG measurements needs to be explored further.

**EMG in Rehabilitation Studies:** In the context of rehabilitation exercises for patients who are subjected to reduced muscular or cognitive capabilities, EMG features can provide us with a better picture of the development of muscle fatigue as a measure, the extent of muscle tiredness and it's effect on prediction accuracy of the intended movement. EMG data have been used in developing control models for upper limb orthosis [197][2]. In the study by Vaca et al. [197], the position and the force sensor measurements from the orthosis and EMG measurements from upper limb muscles were used as inputs for the control models. Al-Jumaily et al. [2] proposed an EMG and Virtual Reality (VR) based human arm model to control virtual prosthetic prototypes. However, neither of these studies explored the usability of muscle fatigue during the design of the control models. None of them dealt with any interaction that considered muscle fatigue in the upper limbs for adaptation of the environment.

**Detecting Muscle Activation Using EMG:** EMG can be used to detect the extend of muscle activity in the upper limbs [160][1][24]. In a study by Bonnefoy at al. [24], the influence of reach distances on the activation of four upper limb muscles was examined. The levels of muscle activation during upper limb reach-to-grasp movements was identified as higher for increased reach distances [24]. The identification of upper limb muscle activations using a single channel EMG was explored by Phinyomark et al. [160]. A method termed "Detrended Fluctuation Analysis" was used to identify the low-level muscle activations, which can be used in a number of rehabilitation and HCI applications. Muscle activations in Biceps Brachii muscle between the dominant and non-dominant arms were compared by Ahamed et al. [1]. The EMG data from the muscles were higher in amplitude in the dominant arm compared to the non-dominant arm. The differences in the mean value of EMG amplitude were higher in eccentric muscle movements than in the concentric movements. The level of muscle activation is found to be different for different types of movements; however, within a defined set of upper limb movements the muscle EMG could further show variations as the muscles become tired due to task repetitions. The above studies did not take into account any such variations as the muscles become fatigued.

**Gesture Classifier in Upper Limbs Using EMG:** A number of previous studies have conducted EMG based experiments on hand gesture recognition during steady state muscle contractions, and different forearm gestures were classified at high accuracy [186][100][105][26][74]. The EMG signals collected from both forearm and upper arm muscles were studied.

In a study that involved EMG measurements from forearm muscles during wrist and hand movements, the combined effect of forearm orientation and muscle contraction levels on the EMG pattern was explored [105]. A gesture classifier trained with the EMG signals collected at multiple forearm orientations with medium muscular contractions could achieve classification accuracies of up to 91% [105]. In another study on forearm muscles involving upper limb motions, the accuracy of classifiers for different feature combinations (from among 50 different EMG features) was compared [161]. The hand movements were also studied by [85] using the EMG signals from two forearm muscles, where different EMG features such as variance, zero-crossings and auto-regressive model were analysed. The discrimination system could achieve a success rate of 85% for off-line test and of 71% for online test. The classifier accuracy in detecting different hand gestures based on EMG collected from 4 forearm muscles was investigated by Oskoei et al. [150]. The forearm motions involved hand flexion, extension, abduction, adduction, and keeping the hand straight, where each motion was held fixed for the 5 seconds. The accuracy of classification was computed using the EMG data corresponding to the steady state of muscle contraction. A window length of 200 ms was used for EMG feature extraction that was sufficient for the steady state processing. A study by [11] has recently identified a number of hand grasp gestures using wireless Myo armband and support vector machine classifiers, where different kernel functions and electrode combinations were studied. An overall accuracy of 94.9% was obtained using the data from 8 electrodes, and 72% using only four electrodes. However, the study was not targeting the upper arm gross muscles. Moreover, the off-the-shelf Myo armband device limits its usage to a set of muscles, which are close to each other. All the above studies were focussed only on a set of fixed hand gestures involving steady state muscle contractions of the forearm muscles. The EMG activation and muscular fatigue during a dynamic muscle contraction task was not considered or explored.

Studies have also explored gesture recognition using the EMG from major upper arm muscles such as Biceps, Triceps, Deltoid, and Brachioradialis muscles [95][20][153]. In a study by Hu et al. [95], even though the classifier resulted in an improved accuracy, the experiment only involved a limited range of upper arm movements. EMG data from both upper arm and forearm muscles were also studied by [20] during reach and grasp tasks. The results indicated that the grasps could be classified with 90% accuracy for three typical grasps. The muscular activity was found consistent across different grasp tasks within subjects, but were significantly different across subjects. However, the study involved a large number of electrodes (15 electrodes) which made the system complicated. As mentioned before, only the EMG corresponding to steady state muscle contractions were used in these studies, and no dynamic muscle contractions or muscle fatigue were explored.

**Detect User Intention for Upper Limb Movements Using EMG:** One of the major applications of hand prosthetics for physically disabled are the detection of intention to move the upper limb. This requires prediction of the intended destination using muscle activation [186]. Even though dynamic upper limb movements and orientation can be sensed by using accelerometer sensors, EMG measurements, which are direct estimates of muscle activation could be more useful here. The study by Soma et al. [186] investigated an on-line classification method for discriminating around-the-shoulder muscle activity during a reaching task. The main goal was to detect the user intention from EMG and accelerometer measurements, which can then be used to coordinate the prosthetic arm position and movements in a dynamical way. The classification of different arm positions and grips while reaching for an object was explored. EMG features like mean value, subtract value, point value were used. It was noticed that using accelerometer along with EMG sensors helped in improving the discrimination rate and most of the contributions to the discrimination of arm movements were by the accelerometer measurements. The median classifier accuracy seems to be approximately 90% or less among all the 3 subjects and there seems to be a high variation in the accuracy across subjects. However, the EMG analysis conducted here does not seem to be powerful due to the less number of participants took part in the study. Also, considering other EMG based features could possibly help to improve the movement prediction and to explore the implications of muscle fatigue on the classifier accuracy.

A study by [153] explored continuous recognition of upper limb movements during rehabilitation training sensing EMG from both upper arm and forearm muscles. Autoregressive (AR) model was used to extract the feature of the filtered EMG signals. Backpropagation Neural Networks (BPNN) was applied to realize the recognition of the patterns in the upper limb movements [153]. However, the study only involved a minimal activation of the BB and TB muscles for the movements due to the simple upper arm flexion and extension movements. The study did not look into the prediction of gross upper limb activities like away-from-body movements involving the muscles such as Trapezius and Deltoid muscles.

In general, the majority of the studies on the prediction of upper limb movements used the steady state EMG features to classify only the hand gestures, and they did not classify the gross spatial upper limb movements, which involved the major muscles of upper-arm. To my knowledge, there are no studies that have investigated the gross movements of upper limb based on EMG corresponding to the dynamic state of muscle contraction. Hence, it is worth exploring the prediction of movements involving dynamic muscle contractions as mentioned in Section 1.2, as an extension of the Research Question 1. Such a movement classifier using the EMG collected at the beginning of the task would also be useful in predicting the motion intention in applications like adaptive rehabilitation training. Furthermore, the muscle fatigue state will impact on the muscle activation, which can further inform the rehabilitation exercise plan.

### 2.4.3 Muscle Fatigue Detection Using EMG

Muscle fatigue can be detected by analysing the electromyogram signals collected from the involved muscles [16][93]. Electrodes are attached to the corresponding muscles and a configurable data acquisition device attached to the electrodes helps to sample the signals and save them accordingly. The collected EMG data is then processed online or offline using suitable signal processing algorithms in order to extract features out of it. Various features such as EMG RMS value, average power, median frequency, mean frequency, and Dimitrov index have been suggested as fatigue indicators by many past studies [93][198][179][59].

#### 2.4.3.1 EMG Fatigue Indicators

According to Lalitharatne et al. [116], muscle fatigue can be indicated by 3 features: RMS value, mean power frequency (MPF), and a feature called spectral index as proposed by Dimitrov [58]. An increase of RMS value and the spectral index as well as a decrease in the MPF were noticed as indicators of fatigue.

**EMG Amplitude Features:** EMG amplitude has been identified as a feature that can provide indications of muscle fatigue. The development of muscle fatigue results in an increase in the Root Mean Square (RMS) amplitude [93][198][179]. Significant changes in the RMS value of EMG were noted by Santy et al. [179] as well as by Zadry et al. [211], where a positive slope of the RMS value was considered to detect muscle fatigue. An increase in the mean EMG amplitude during upper limb muscle fatigue was also reported by Octavia et al. [149], where only the low frequency (0.8-2.5Hz) EMG was used to calculate the features.

**EMG Median Frequency/Mean Frequency:** EMG median frequency or mean frequency have also been proposed by past studies as useful features to indicate fatigue. The development of muscle fatigue can be indicated by a decrease in mean or median frequency of the EMG signals [93][198][179]. Studies report that muscle fatigue results in a shift in the frequency spectrum towards low frequency end [16][81][93]. Median and mean frequency of EMG signal power spectrum were studied by [59] for detecting muscle fatigue and these parameters were found to be linearly decreasing during fatigue. This was also supported by Zadry et al. [211] who investigated the effects of repetitive tasks of high and low precision on upper limb muscles using EMG measurements. A decrease in Mean Power Frequency (MPF) indicated muscle fatigue, and the slope of the MPF with respect to time was analysed for this. A negative slope of the MPF, when it exceeded 8% of the initial value was used to detect the fatigue [211]. However, there is no sufficient information on a standard threshold parameter of fatigue available as of now, which can be used to predict a possible muscle injury or fatigue. So, future research may target to identify a threshold, which can be used to limit the task intensity for a person before getting injured.

**Joint Analysis of EMG Spectrum and Amplitude (JASA):** The EMG amplitude as well as the spectrum do not only depend upon the fatigue state, but also upon the produced muscle force. In case of fatigue, a left shift in the EMG spectral distribution was consistently found. However, for the force dependency of the spectral distribution, inconsistent findings were reported depending on the muscle under test and the force level. Hence, for varying muscle load conditions a joint analysis of EMG spectrum and amplitude (JASA) was suggested to detect muscle fatigue

[130]. The method used concurrent analysis of both amplitude and spectrum of sEMG to provide information on whether the changes in EMG were fatigue-induced or force-related. The JASA method suggested that an EMG variation is considered 'fatigue-induced', when an increase in the EMG amplitude occurs together with a decrease in the median/mean frequency. The separate use of the increase in the EMG amplitude or the left shift in the EMG spectrum for the indication of fatigue is possible, if the force production is similar for all EMG sections which are included in the analysis of the EMG time course. This method was also used by Madden et al. [102], who suggested to check for an increase in the amplitude together with a decrease in the median frequency (MF) for detecting fatigue. The method is referred in Experiment 3 of the current study (Chapter 6).

#### 2.4.3.2 Time to Fatigue

A more muscular effort results in an increased demand on the recruited muscle fibers and more recruitment of motor units (MUs), which leads to a faster rate of muscular fatigue [168]. The time taken by muscles to come to a state of fatigue (time-to-fatigue parameter) has been explored [3][7]. Three different stages of muscle fatigue (Non-Fatigue, Transition-to-Fatigue, and Fatigue) were identified, while using a fatigue-detecting wearable system based on EMG signals from upper limbs. The time-to-fatigue parameter was estimated using EMG signal processing and artificial neural network classification algorithms [3]. In a context of a fatigue-based adaptive robotic training, this parameter can be used to study the time taken to reach the first fatigue, the time difference between successive fatigue/relax cycles, and so on as planned in Experiment 3 of the current study (Chapter 6).

### 2.4.4 Correlation Between EMG and Kinematic Parameters

#### 2.4.4.1 Low Frequency Correlation Between EMG and Force

Few studies have explored the correlation between kinematic force and EMG measurements [143][125]. The power spectrum for force and EMG was reported to contain the most of the power below 0.5 Hz and they were found to be correlated [143]. The low-frequency components (low pass filter at ≤ 0.5Hz) of a rectified EMG during constant force tasks were found to be correlated with the interference (actual) EMG signals in the frequency band of 35-60 Hz. On the other hand, a study by [125] on fatigue effects during isometric contractions stated that the power spectrum of a rectified EMG signal displayed a reduction in the gamma EMG oscillations (40-60 Hz of EMG signals) when fatigue occurred.

A correlation of EMG signals with exerted force parameters was also indicated by studies of [210], but the study was concentrated on the steady sub-maximal force values rather than varying forces. The study stated that the smoothed motor unit discharge rates were more correlated with rate of change of force than with the force parameters directly. A correlation was also noticed with the low-frequency component of rectified and smoothed EMG. But these studies were concentrated on isometric force tasks rather than dynamic muscle contractions.

#### 2.4.4.2 Effects of Fatigue on Correlation Coefficients

During dynamic muscle actions both linear and non-linear relationships between EMG amplitudes and resultant force have been identified by researchers ([98], [185]), however, the relation is not completely clear. Theory states that the EMG amplitude in isometric muscle contractions is directly proportional to the square root of the resultant force when the motor units are activated independently [122]. Solomon et al. [185] stated that a linear relation between EMG and force can occur when full motor unit is recruited before motor unit (MU) firing starts increasing. A non-linearity will start when MU recruitment and MU firing frequency contribute together. Hence, different muscles will have different EMG-force relationships since they have different strategies for MU recruitment [122]. However, another research [189] stated that during low levels of muscular force both the MU recruitment and the firing rate changes were used to change muscle force. But during higher levels of force (approximately more than 30% of maximum voluntary contraction (MVC) value), most of the muscles motor units remain already recruited. In such a case, the changes in muscle force are caused by change in firing rates of motor units.

The above studies were mainly concentrated on isometric contractions (where the length of muscles does not change during the contractions), but the current scenario of research is on non-isometric/isotonic muscle contractions (contractions, which generate force by changing the length of the involved muscles [25]). Similar to the findings by [98], the non-linearity in the relation between the muscle force and EMG amplitude during fatigue might probably affect the correlation coefficient in an isotonic context also. As stated by [57], the EMG signal amplitudes showed an increase when force was maintained at the target level. But during fatigue (i.e; beyond task failure), the EMG amplitude started reducing and the target force could not be maintained any longer. This indicates that during fatigue, the linear relation between EMG and force is not completely clear yet, since it depends on multiple neuro-muscular conditions.

## 2.5 Robotic Rehabilitation

The field of rehabilitation robotics is meant for assisting the rehabilitation of disabled people through a prescribed use of robotic devices. Physically challenged people can get help from robots for lifting the weight of their limbs, and thus can perform tasks for a longer duration. Robotic systems have been used in the context of stroke rehabilitation for more than two decades. Robots have shown a potential to speed up the recovery process in stroke patients and help to improve the quality of life by assisting people with disabilities. The availability of the robot to successively repeat movements as well as the ability to record movements makes them suitable for rehabilitation training that can be delivered without constant presence of a therapist. A high-intensity, repetitive and task-specific treatment of the upper limbs provided by robot-assisted training was found to be useful for a successful neurological rehabilitation [19][114].

Much previous research has investigated the robotic rehabilitation of upper limb; some of them using adaptive systems, few using physiological feed back, few others using interactive and intuitive training games in virtual environments, and so on. A review on the past research shows that the upper limb adaptive robotic rehabilitation still need to be improved towards their usability in practical solutions. Literature also shows that methods for system training and control of upper limb prostheses is not yet matured enough compared to the currently available advanced multi-function prostheses and interpretation methods [75]. Farina et al. [67] stated that over the past 60 years, academic research in the field of myo-electric control systems has advanced a lot but the research output have not been successfully used in commercial solutions. Even though the laboratory results are promising, the current gap between industrial solutions and academia is mainly due to relatively less amount of functional improvements reflected in practical use. None of these solutions offer the most needed acceptance criteria by end users: intuitiveness, closed loop control, adaptability, minimal training, less number of electrodes, robust real-time control and less complex.

Freemann et al. [76] investigated an Iterative Learning Control (ILC) based muscle model for robot-assisted upper limb stroke rehabilitation. Iterative learning control algorithms exploit the repeating nature of the rehabilitation training tasks to improve the task performance by learning from experience. This helps ILC to respond to physiological changes in the system, such as spasticity and the presence of a patient's voluntary effort [76]. The work described how robotic and Functional Electrical Stimulation (FES) controllers can be combined to make a complementary assistance driven by clinical need. As the training progresses, the control action helps patients to apply an increased effort with each trial and thus a decrease in the level of FES applied. However, there were no EMG muscle fatigue indicators used in this study to improve the adaptability of robotic interaction. It was discussed that the voluntary effort by muscles using EMG signals were not incorporated into the model.

Amirabdollahian [9] and Alexander [6] have previously worked on a rehabilitation system for stroke survivors called "Supervised Care and Rehabilitation Involving Personal Tele-robotics (SCRIPT)" for upper limb training with a proprietary hand exoskeleton. Two user-interfaces were used, one for the patient and the other for the health care professional. The health care professional would remotely monitor the therapy and also provided feed back to the patients. The advantage of this system was that the training environment with an interactive game was motivating, enabling progressive exercise environment for the patient and allowing the patient to train independently with continuous access to treatment facilities. But the robotic hand was not really adaptive enough to consider the user's state of fatigue. The muscle fatigue measured through the upper limb EMG was not taken as a feed back parameter to improve the adaptability of the training environment.

### 2.5.1 HapticMaster Robot

The HapticMaster robot is developed by MOOG BV, The Netherlands. The robot follows an admittance control strategy, where the user's applied force is measured and the end effector reacts with the proper displacement. From this the position, velocity, and acceleration (PVA) can be calculated using a virtual model. This makes the HapticMaster robot capable of rendering high stiffness, near-to-zero friction and zero end effector weight, giving a very low-impedance "free space" motion [126]. As an input device, the robot allows users to interact with some software applications/games by sensing the user's hand movements through its end effector. As an output device, it can provide haptic feed back to the user during the experiment corresponding to the exerted forces by the user [148].

The robot has been utilised in a stroke rehabilitation project, GENTLE/S, where 3 different interaction modes were developed [10]. HapticMaster can be operated in Patient Passive (P), Active-Assisted (AA) or Patient-Active (A) mode. In the passive mode the participants are asked to gently hold the end effector of HapticMaster and follow its path to execute the activity and, hence, the subject remains passive here. In the active mode the participants are asked to take charge of the activity by applying suitable force on the ball gimbol of HM to move it along the prescribed path. While in active-assisted mode the subject has to just initiate the activity then the HapticMaster (HM) robot will assist/guide the subject for continuing the rest of the movement [34]. Different kinds of movements in point-to-point or curved paths are possible using HapticMaster arm and suitable protocols need to be defined for different training experiments accordingly.

### 2.5.2 Robotic Rehabilitation Using EMG

Electromyogram signals from upper limb muscles have been used in human-robotic or human-computer interaction, as control signals for exoskeletons and upper limb virtual models [91][118] [190]. EMG measurements were used for pattern recognition and for detecting patient's intention to move, and then a robot was used to assist the movements [60][190][118]. Tang et.al [190] used EMG signals from upper limb muscles to assist an exoskeleton actuated by pneumatic muscles by a proportional myoelectric control algorithm based on the user's motion intention in real time. The reliability of the control scheme and power-assist effectiveness were studied, and the results indicated that the exoskeleton could be controlled by the user's motion intention, which can be applied to assist in elbow rehabilitation after neurological injury [190]. But these studies did not explore muscle fatigue or the adaptability of the systems based on fatigue.

Muscle fatigue during robot assisted upper limb exercises has been explored by [181] and [81]. Grover et al. [81] investigated the correlation of EMG fatigue indicators with robot-collected fatigue indicators. The purpose of the study was mainly to determine fatigue generation trends. The study was conducted on the upper limb muscles of healthy participants in an experiment using a robot, where EMG data was be used to detect muscle fatigue during the exercise. EMG based Dimitrov index was used as the fatigue indicator. The study stated that using an upper limb rehabilitation robotic device will cause localized muscle fatigue even for healthy participants, and that the fatigue onset can vary greatly between participants. However, the fatigue indicators were only planned to be used in the future to develop the robot's Artificial Intelligence (AI) model to assist a post-stroke recovery. Also, the study did not demonstrate any method that makes the robot or the training environment adaptive to the user's state of fatigue.

EMG was used for robotic rehabilitation in a recent study [145] in which a framework for the objective evaluation of upper limb muscle fatigue during robot-mediated movements was proposed. The study involved a haptic wrist rotation task (flexion and extension) in a resistive visco-elastic force field, while holding a robotic manipulandum, until the forearm muscles showed signs of fatigue. The onset of fatigue was calculated based on the mean frequency of the EMG signals collected from the forearm muscles of healthy subjects. However, this study did not consider any adaptation of the robotic environment based on the detected fatigue.

In a study by Severijns et al. [181], the muscle fatigue in MS patients and healthy individuals were compared during a robot mediated upper limb training exercise using HapticMaster robot and a virtual game. The root mean square (RMS) amplitude and median frequency of EMG signals from the Deltoid muscles were studied during vertical movements (e.g., lifting tasks) of upper limbs. The study showed that the game performance was not affected by fatigue possibly due to the contribution from other compensatory muscles and there was no relation between the subjective and objective fatigue indicators for the MS patients. However, the interaction was not guided by the robot and, hence, the experiment rythm was not fixed. The detected fatigue information was not used for any robotic adaptation. Also the kinematic trajectory (position) parameters could have been utilised to adapt the environment.

The above robotic rehabilitation studies were either limited to exploring a fatigue detection framework for rehabilitation, gesture recognition or movement classification of upper limbs based on the measured EMG features. Few of them only dealt with an exoskeleton that was controlled based on the user's intention to move the upper limb, and compensating the effects of fatigue during an EMG based control. The studies did not concentrate on making the robot or the environment adaptive to the user's state of fatigue. Even though some studies tried to address the adaptability of rehabilitation training using EMG in some ways, the participant's state of fatigue is still an overlooked area, which can potentially benefit the adaptation algorithms.

### 2.5.3 Adaptation in Robotic Rehabilitation

During the process of rehabilitation training, robots can benefit from additional performance markers to aid safety as well as define the optimal interactions for the best recovery. Research to date has shown that repetitive task-specific robot-assisted training can be an effective method to help motor recovery in stroke patients [110][156][173][103][40]. Adapting the training environment based on task performance can help to increase the number of task repetitions. Building robotic systems capable of adapting its behavior to user's physiology or muscular state so as to provide an engaging and motivating training environment is a difficult task. Hence, among the different acceptance criteria in assisted training solutions, adaptation of the interaction has become an active area of research.

Some relevant studies on upper limb rehabilitation have explored kinematic features measured by the robot to adapt rehabilitation training environment. Octavia et. al [172] explored a rehabilitation training environment, where the adaptation was achieved by adjusting a personalized difficulty level of virtual training games by forming user models. The HapticMaster robot was used for developing the adaptive personalized training system. However, this research did not involve any EMG fatigue studies and adaptation of robotic parameters. A second study [148] also tried to address the adaptability of games by automatic adjustment of difficulty levels during the training exercises for MS patients. But the adaptation algorithm was not the major focus here and the study was more towards observing the patient's response with respect to the adjustment of difficulty levels. With some robotic assistance the fatigue would reduce further.

The HapticMaster robot was used to assist (through anti-gravity compensation) in improving the difficulty in reaching away movements by chronic stroke survivors during shoulder abduction tasks [63]. An adaptive algorithm in the HapticMaster robot was used for specifically targeting the abnormal joint torque coupling impairment in chronic stroke survivors. An increase in the upper limb reach area was achieved through robot assisted progressive shoulder abduction loading exercises, which reduced the abnormal coupling of shoulder abduction with elbow flexion. Even though this robotic intervention provided an adaptive training environment for the patients to help in improving reaching work area, the user's state of fatigue was not covered in the study. As a possible expansion of this study, robotic assistance in combination with muscle EMG studies were also proposed [63]. Another research experimented HapticMaster based upper limb rehabilitation training in a virtual learning environment [68]. The effects of intensive robot-assisted training were studied in multiple sclerosis (MS) patients. The hand path ratio was used as an indicator for the variation from the optimal trajectory between the start position of the hand and the target position. However, the idea of the paper was not to develop a solution that can directly read the physiological state of the patient, for example, by using the muscle EMG. None of these studies explored the user's state of fatigue and the possibility of using EMG features as fatigue indicators.

As an extension of the studies by [10] and [128], Chemuturi et al. [35] presented the HapticMaster robot based adaptive rehabilitation system, which investigated the contribution of the participants and the HapticMaster robot during different human-robot interaction modes, and aimed to identify who led (the robot or the person) this interaction. The goal was to identify who led (robot or the person) the interaction by comparing the actual performance of the participant against the minimum jerk model followed by the robot. The results showed that the leading or lagging role of a subject can be identified [35]. An adaptive algorithm based on a lead-lag performance model was then developed by altering the movement duration and stiffness parameter of the robot to change the difficulty level of tasks. The adaptability of the system using HapticMaster robot was then tested against the performance of the user [36]. The test involved point-to-point movements using a combination of embedded and virtual reality training environment using HapticMaster robot arm. The parameters recorded by the HapticMaster robot were used as performance indicators by the rehabilitation system to identify the leading/lagging performance. A performance based training algorithm was then developed and evaluated with healthy participants [36]. However, these studies did not consider the upper limb fatigue of the participants while performing the rehabilitation exercises, and the muscle EMG was not utilised either. Also, using the force measured at the robotic end-effector can be misleading and often not conclusive to measure the performance of the user. So, a combination of the kinematic measurements from the robot and the muscle EMG from the upper limbs was chosen as an exploration for this PhD.

A solution that can sense the muscular state (for example state of pain or stiffness) of patients can help to improve the adaptability of the training environment. Muscular activation can be obtained through electromyogram (EMG) measurements during the interaction. EMG is a very useful resource that is being increasingly used by the research community. It has a potential to be used as a measure of muscle tiredness/fatigue during training interactions.

#### 2.5.3.1 Adaptive Robotic Rehabilitation Using EMG

EMG has also been used for the adaptation of robotic environment in the context of rehabilitation [91][195][60]. The strategy for adaptation was mainly detecting the user's intention to move the upper limb and then assisting accordingly. In a work by Ho et al. [91], an exoskeleton hand robotic training device was used to train the impaired hand of stroke survivors using EMG feed back from hand opening and closing tasks. The exoskeleton detected the user's intention of movement using EMG signals from two muscle locations, and assisted in the tasks. However, the study involved only the hand opening and closing tasks, and no upper arm muscles around the shoulder were studied. The algorithm for the assistance was just based on the detection of user's intention (threshold of 20% MVC), and no fatigue studies were involved.

Dipietro et al. [60] presented a system for EMG based robot-assisted therapy for stroke survivors. Any attempt by the patient to move was detected by monitoring the EMG from the selected muscles, then the robot was programmed to assist him to perform the movement. Tong et al. [195] explored an interactive and motivating robot-assisted stroke rehabilitation training system using EMG feed back. An interactive training game was controlled through detecting user's intention (muscle activation from flexor and extensor muscles) and feed back though real-time continuous EMG signal amplitude measurements. The results indicated some improvements in the spasticity on the joint and better coordination was observed on the wrist and elbow joints. Even though continuous EMG signals were used as real time feed back for controlling the rehabilitation training, this did not involve the adaptation of the environment according to user's state of fatigue. The system only considered the user's intention as an input, and not the fatigue.

#### 2.5.3.2 Muscle Fatigue During Adaptive Robotic Rehabilitation

Active participation and repetitive training being key factors in deciding recovery time, also require some knowledge of the current muscular state of the stroke patients during the training interactions. The knowledge of muscle fatigue can help to protect weak muscular resources in stroke patients and to avoid risk of further damage to the available muscles [154]. Hence, muscle fatigue is considered as an important parameter during the treatment of musculoskeletal injuries [198][141] and stroke rehabilitation.

Octavia et al. [149] explored the fatigue state of patients in a robotic environment using subjective analysis and game scores. Here, the HapticMaster robot and adaptive games were used for the rehabilitation training of multiple sclerosis (MS) patients based on the EMG data from shoulder muscles (Deltoid and Trapezius). The main upper limb movements involved in the training game were the lifting and holding tasks. A decreased performance and higher subjective fatigue perception levels were observed in the MS group. The HapticMaster robot in this study was used just as a haptic input/output device and no robotic assistance was used during the exercise. Hence, all the participants seemed to have fatigued and the EMG fatigue indicators represented significant fatigue in both the muscles, Deltoid (DLT) and Trapezius (TRP). In presence of robotic assistance/guidance the impact of fatigue would have been reduced and the fatigue indicators would indicate lesser fatigue. Hence, a robotic adaptation using the muscle fatigue indicators could have been explored. However, the study only proposed a possible robotic adaptability using anti-gravity support as a future work. In this study, fatigue was used but not for any adaptation; instead the games were adaptive. The EMG data was used only to check if muscle fatigue was developed in the patients. Also, a kinematic study could have helped to understand the corresponding kinematic implications of muscle fatigue.

In an effort to improve the fatigue state detection of upper limb movements, a study by Lalitharatne et al. [115] used fuzzy-neuro modifiers for compensation of the effects of muscle fatigue on EMG based control of an upper limb exoskeleton. A combination of EMG RMS value, mean power frequency (MPF) and a "Fatigue Index" parameter was used in the study. A reduction of torque was observed after using the proposed method for compensation of the effects of muscle fatigue. The method helped to reduce overshoots of the robot motions that occurred due to the effects of muscle fatigue while controlling the exoskeleton. However, no motivating factors were involved in the study other than verbal encouragement so that patients would perform more iterations using a intuitive game or virtual environment. In another recent study an upper limb exoskeleton was used by Ali et al. [8] that adapted based on fatigue. The study investigated the effect and performance of the exoskeleton in dealing with human muscle fatigue in a virtual environment and provided support as needed. The human joint fatigue model developed by Ma et al. [131] was used in this study, and an algorithm based on PID (Proportional, Integration and Derivative) control was developed to activate the exoskeleton accordingly. Fatigue was detected when the maximum voluntary contraction of the torque reduced to 80% of its initial value. The results indicated that the participant was able to prolong the task by wearing the exoskeleton. However, no EMG measurements were used in this study and the fatigue was only detected based on the joint torque.

Few studies suggested using muscle fatigue models to adapt the robotic assistance [208]. A functional electrical stimulation (FES) based iterative learning control algorithm for robotic-assisted upper limb stroke rehabilitation was proposed by [208]. The effects of upper limb muscle fatigue were considered for developing a robotic control scheme that removed or reduced the effects of fatigue, which helped the patients to complete the exercises. The control system used a muscle model (based on the Hill-type model [90][129]), which calculated the input to regulate the stimulation (FES) applied to the muscles of patients, that would result in an accurate tracking of a reference trajectory for the upper limb movements. The isometric recruitment curve (IRC) of a muscle that depends strongly on the past history of muscle activation [62] was found to be influenced by muscle fatigue. When fatigue occurred, a substantial drop in the magnitude of the IRC results were noted and, hence, the performance of the control scheme degraded. This problem was addressed by increasing the frequency of the applied FES. However, fatigue indicators based on EMG were not considered in the study for developing the model, which could have helped improving the adaptability of the robotic interaction.

All the above literature suggests that physiological signal parameters such as muscle EMG features as fatigue indicators are not fully utilized for building an adaptive robotic interaction.

#### 2.5.3.3 Strategies for Robotic Adaptation

Different strategies for robotic adaptation have been proposed by past studies [110][128][17][22] [159][134]. Adaptation of the training environment by adjusting task difficulty tailored to the muscular state of the patients can be a useful strategy for rehabilitation, and past studies have suggested that increasing the task repetitions can help motor recovery [110].

A strategy for robotic-adaptation that delivers therapy "on demand" with accurate objective measurements of a patient's progression has been suggested by Loureiro et al. [128]. The control strategy was based on the minimum jerk theory in a system based on haptics and virtual reality using HapticMaster robot. The interaction required task initiation by the patient, and then the robotic assistance helped the patients to complete the task. In patient Active-Assisted mode of operation, the haptic interface would start moving as soon as the patient initiated a movement in the direction of the pathway.

A rule-based framework (an intelligent decision-making system) was suggested by Biagetti et al. [22] to decide the training intensity/mode based on muscle fatigue and repetition rates, and thus to optimize the training strategy. Both the exercise repetition frequency (cadence) and the muscular fatigue were simultaneously measured by using a novel method using a fuzzy engine. The output of the fuzzy engine was used as the guideline for optimizing and customizing individual training sessions. The output logic was designed to select the next training load (weight) to be used for the exercise. The training difficulty was reduced when high fatigue and slow movements were detected during the exercise [22].

A strategy of performance-based progressive robot therapy based on impedance control algorithm was suggested by Krebs et al. [110], which used speed, time, or EMG thresholds to initiate robotic assistance. The algorithm provided a mechanism for the patient to evolve from hemiplegic to normal arm movement. MIT-MANUS robot was used to deliver the therapy. If the person was unable to move the upper limbs in the prescribed path, the robot guided the hand to the target in a similar manner as a therapist would do during a conventional therapy. A minimum-jerk model was used to calculate the ideal trajectory for movement. Four performance measures (PM) were used to grade patients' ability to initiate movement (PM1), to move from a starting position to the target (PM2), to aim the movement along the target axis (PM3), and to reach the target position (PM4). This rewarded the patients for relaxing their arms, and the robot helped to move their hands closer to the target [110].

A strategy for adapting the physical behavior of robot according to the muscle fatigue in human-robot co-manipulation tasks was recently suggested by Paternel et al. [159]. In the study, the robot initially imitated the human to perform a collaborative task in a leader-follower manner, using a feed back about the human motor behavior. The robot also simultaneously learned the skill in an online manner. When a fatigue threshold was reached, the robot used the learned skill to take over the task, which reduced the human effort. The human continued to supervise the operation and only executed the aspects of the task, which the robot could not fully take over (i.e. cognitive and those, which require collaborative effort). The human partner could then partially relax and recover some of the physical strength while continuing to perform the collaborative aspects that the robot could not take over by itself. The estimation of fatigue was done using a fatigue model, which was based on the human muscle activity measured by the EMG. This was similar to the previously proposed models based on muscle force [131].

Basteris et al. [17] developed a challenge point framework for classification of session types based on the patterns observed during rehabilitation training sessions that are expected to improve motor learning and neuro-motor recovery. The study suggested that an adaptive mechanism that makes the exercises not too easy or not too challenging will be most favorable to improve the upper arm functions. A balancing between supporting and challenging will allow an optimal learning. This can be achieved by promoting active movements by allowing errors and variability and continuously adapting the amount of support based on the task performance. Task difficulty was altered by varying the speed of exercise based on the lag-lead performance during the interaction. Average value of lag-lead score across a session was used to indicate the performance of the subject. Among the 5 types of sessions defined in the framework, "challenging" and "challenging-then supporting" were found to be leading to higher number of movement repetitions with respect to other 3 types "supporting", "under-challenging" and "under-supporting". The average number of repetitions were higher for "challenging-then-supporting" sessions. Another exploration by Basteris et al. [19] suggested a robot-mediated therapy in the Active-Assisted mode to be most consistent to improve the upper arm function. A pushing force in combination with lateral spring damper or EMG modulated assistance can show favorable results on body function level. The study also suggested that the active nature of training interactions can be maintained by forcing the patients to initiate movements and keep being challenged in a progressive way throughout the exercise. In a further work, Basteris et al. [18] experimented this framework on people with Stroke while exercising at home by playing video games using a passive-actuated orthosis for the wrist. The movement speed was adapted to the game-performance based on the Optimal Challenge Framework. The adaptation algorithm reduced the difficulty when the participants become tired during the robotic interaction. This made the game easier for the subjects who were often in delay with respect to the reference trajectory (failure), and harder for those able to anticipate it (success).

### 2.5.4 Protocols for Robot-Assisted Strength Training

A robot-assisted strength training can be effective if it is progressive and challenging based on the patient's abilities [152][43]. To achieve this, the performance of the patient need to be assessed and the training environment need to be adapted accordingly. In order to utilise EMG based fatigue indicators for improving the adaptation of robot assisted training environments, suitable training protocols need to be defined. There is no universally accepted protocol available for the upper limb rehabilitation of stroke patients, and the treatment programs vary in the duration, intensity, and frequency of the rehabilitative therapy [5].

#### 2.5.4.1 Control Schemes for Strength Training

There are different control methods used in muscle strength training; isometric, isokinetic, isotonic and shared control [183]. Among the different exercise modes, isokinetic and isotonic exercises are widely used for strength rehabilitation [83]. Isokinetic exercises make the patients contract their muscles at a constant speed regardless of force that they exert. This results in a high muscle activation throughout a wide range of motion (ROM) and, hence, good for rehabilitation. However, the therapist has to adjust the operation speed to change the exercise intensity and this does not guarantee the patient to increase the exercise intensity equally. Isotonic exercise is similar to the conventional weight training exercise. For example, lifting a dumbbell is an isotonic movement. With isotonic exercises, patients contract their muscles under constant force for all the range of motion. This method is widely used because it is easy to perform. As the subject works against a resistive torque applied to the muscle, the muscle activation is linear and proportional to the resistive torque. Therefore, the exercise intensity can be easily adjusted through the resistive torque [183].

Some studies such as Remaud et al. [170] reported that both isotonic and isokinetic exercises can provide similar results in terms of the number of task repetitions, total external amount of work and mean angular velocity. However, a recent work by Sin et al. [182] reports different results while comparing isotonic and isokinetic strengthening exercises in stroke patients. The results suggested that the isokinetic mode makes efficient dynamic muscle action and contributes more to increase motor unit recruitment, which was in line with the theoretical concept. Theoretically, isokinetic contraction works better than isotonic contraction because the isokinetic tasks induce maximum loading to muscles through the overall range of motion, whereas isotonic tasks can load only at the weakest mechanical points during motion [182].

Another method called shared control is used for the strength rehabilitation using robots, which is based on impedance/admittance control. With the help of impedance/admittance control, it is possible to create virtual effects like weight, virtual drag or haptic sensation in the training, and the resistive environment can be easily adjusted by the robotic algorithm [183]. A robotic equivalent of isometric, or isokinetic behavior will be created. Rehabilitation through strength training using shared control with robots have been reported to be helpful for gain in motor skills [187][201][42][183]. While studying how different control parameters affected the muscle activation during a robot-assisted strength rehabilitation training, Sin et al. [183] noticed that in shared control, the exercise intensity increased as the desired damping increased. However, the slope of the muscle activation started decreasing as the damping increased because the speed of movement decreased [183].

Since rehabilitation treatment by using robot can provide low cost and high accessibility to patients, while ensuring intensive and repetitive training, a shared control method seems to be best suited for an adaptive robot-assisted strength training protocol. For a robot-assisted strength training protocol for stroke patients, a possible control strategy could be to reduce training intensity when fatigued. Once the onset of fatigue is detected, the difficulty level/resistance may be reduced by 50% of the MVC force as mentioned by Chang et al. When relaxed, the difficulty level may be increased again in steps of 10%MVC to follow the sports science protocol for strength training [32]. The further challenge here is to design a robotic intervention that quantifies the training difficulty based on the maximum force capabilities of patients, which require a way to mimic/resemble MVC force as used in general sports science protocols.

#### 2.5.4.2 Rowing Exercises for Strength Training

Rowing is an excellent activity for developing physical fitness and studies suggest that rowing exercises can help rehabilitation. Exercises for a range of motion, muscular strength and cardiovascular endurance help redevelopment of proprioception by contracting muscles and moving joints. Rowing exercises can contribute to proprioception while developing range of motion, muscular endurance, and/or muscular strength [155].

There have been studies on the lower body muscle activities during rowing exercises [96][163] [162][29][82]. An indoor rowing exercise model was designed by Hussain et al. [96] for rehabilitation of lower body function through the application of functional electrical stimulation (FES). The effect of the muscle fatigue was reduced by adaptation of muscle stimulation pulse width required to drive FES-rowing using a fuzzy logic control (FLC). The algorithm was aimed at minimising the error between the reference and actual trajectories. However, the adaptation was only achieved using the pre-trained (offline) artificial neural network. The muscle fatigue was not used as a parameter for the adaptation and no EMG studies were involved [96]. Others studied the muscle activity and coordination in the lower body muscles during the rowing task using EMG measurements. They mainly concentrated on the changes in kinematics and trunk EMG, lower body muscles activation and the effects of repetitive motion on the muscle activities [163][162][29][82].

## 2.6 Stroke Rehabilitation

Studies report that 15-17 million people per year suffer from stroke worldwide, and around one third of them are left permanently disabled [157][76]. Stroke patients often suffer from severe physical and mental disabilities that significantly impact their daily life. Stroke is usually caused when blood clots in a vessel in the brain or when a vessel ruptures and leaks blood into the surrounding areas in brain. This might result in destroying some of the connecting nerve cells, and the person might suffer partial paralysis on one side of the body [76]. They often need to use extensive rehabilitation training to regain the lost motor functions.

Even though the damaged brain cells can not regrow, the brain has an interesting ability to make new connections. The brain can gradually adapt by leaning new skills, and the redundant connections will be disappeared [76]. The human brain is able to compensate for the damages caused by stroke and recover the functions by a reorganizing process called neuroplasticity or brain adaptability [101]. The current belief is that stroke patients benefit from rehabilitation through physiotherapy that induces neuroplasticity [120][124]. A stroke patient who relearns the motor skills goes through a similar process like a baby learning to walk, which however requires sensory feed back during the repeated practice of a task [76]. Additionally, a motivational environment for rehabilitation training was suggested to help towards recovery [30][133]. Furthermore, active involvement of the patient when selecting therapies is known to have positive impacts on their motivation [92].

The upper limbs play a important role in the performance of activities of daily living since the ability to reach and grasp is required for the majority of the daily life tasks. Hence, in stroke survivors, an improved upper extremity recovery will have a positive impact on the quality of life [202]. Rehabilitation of upper limb function after stroke is still a major challenge in stroke therapy. Motor impairments of the upper limb are one of the most common consequences of stroke, leading to lack of coordination, lack of motor control and importantly, loss of functional movement [137]. Studies state that less than 40% of the stroke survivors continue to suffer from some functional disabilities and only 11% of them recover the complete upper limb functions [45]. In the stroke patients with impaired shoulder and elbow movement, excessive compensatory movements are also reported during pointing and reaching tasks. However, excessive use of compensatory movements usually cause additional complications like joint misalignment and pain, which can affect the speed of the upper limb functional recovery [202]. Therefore, upper limb rehabilitation constitutes an important research topic in rehabilitation.

### 2.6.1 Muscle Strength Training for Stroke Rehabilitation

High intensity training (HIT) sessions in healthy subjects has been suggested for improving general fitness by different studies [97][138]. An interesting report by [138] explains the advantages of performing intensive physical activity over traditional 'walking 10,000 steps a day'. In the study, the subjects who did three brisk 10-minute walks a day (Active 10 group) were found to have done 30% more 'moderate to vigorous physical activity' than the subjects who did 10,000-steps a day, even though they moved for less time. Getting out of breath and increasing the heart rate in lesser time had greater health benefits compared to those who did "walking 10,000 steps a day". Studies have also suggested that the optimal intensity for strength training is maximal or near maximal [104]. However, in the context of stroke rehabilitation, training at high intensity as well as low intensity have been reported as effective.

**High Intensity Training** An important question in stroke rehabilitation is, "does intensive muscular training help stoke rehabilitation?". Many studies suggest that muscle strength training is useful for stroke rehabilitation [180][5][164]. The long-term benefits of conducting intensive rehabilitation training in patients with moderate-to-severe disabilities were investigated by Albert et al. [5]. The results stated that gains in motor function can be visible even years after a stroke. Resistance training/functional muscle strengthening is found to be helpful for rehabilitation and there are evidences to support "increased dose" of exercises for stroke rehabilitation. Significant improvement in maximal oxygen consumption, workload, and exercise time and, hence, improvements in sensorimotor function has been reported by Potempa1 et al. [164] after receiving intense exercise and aerobic training. Similarly, increased exercise duration has been reported to have helped stroke recovery [84].

**Does Repetitions Help Stroke Recovery?** There is a body of evidence that supports the "more is better" argument in the context of neurological rehabilitation. Repetitive tasks are thought to reinforce plastic changes in brain [156][173][40] and can help to improve functional ability after stroke [77][5][206][171][86]. Research by Karni et al. has shown that repetition and practice improved the task performance and could cause neural processes that continue to evolve many hours after the practice had ended [103]. Cortical reorganization and outcome after stroke rehabilitation are positively associated with repetitive task-specific practice [151][193]. More repetitions and altered environments can help in motor relearning [107]. In human stroke survivors the number of repetitions per session is typically 30 [119]. The motor system responds to altered environment in order to regain former levels of performance, acquiring new patterns of muscle activation to achieve higher levels of performance and higher number of repetitions helps this. Thus intense motor learning protocols could lead to gains in function and increasing the number of task repetitions could be an effective method for improving the task performance [107]. High-intensity, repetitive, task-oriented upper limb training was studied by Albert et.al [5], in an intensive robot-assisted therapy for stroke survivors with moderate-to-severe upper limb impairment. Significant improvements in motor capability and motor-task performance was observed.

**Low Intensity Training** Evidences also support low intensity and sub-maximal training exercises for stroke rehabilitation [99][49][48][28]. High mental effort training combined with low-intensity (30% maximal voluntary contraction [MVC]) physical exercise could be an effective method for muscle strengthening and this approach can be beneficial for patients who have difficulty in undergoing strength training [99]. The extent of muscle protein synthesis after a resistance training is not entirely dependent on the load, but is also related to the number of repetitions, which results in full motor unit activation and muscle fiber recruitment [28]. Hence, a training mode with lower weight and higher repetitions can be more effective than a high-load low volume exercises for improving muscle growth [28].

**Progressive Strength Training** Progressive strength training is an exercise that builds physical strength, especially in a weak or injured body part, through a progressively difficult task according to a formula based on the subject's maximum strength at the starting point [56]. The techniques of progressive resistance exercise as defined almost 60 years ago suggested 3 principles, which are, (1) to perform a small number of repetitions until fatigue, (2) to allow sufficient rest between exercises for recovery, and (3) to increase the resistance as the ability to generate force increases [191]. These principles are detailed in the guidelines of the American College of Sports Medicine (ACSM) [109]. Progressive resistance training can be the most effective treatment to improve the muscle strength in stroke patients and studies suggest that there are long-term benefits for this [205][71][64]. A progressively increasing upper limb training intensity used in the rehabilitation of stroke patients using dedicated virtual reality environments can deliver high rehabilitation doses and intensive training [157]. However, further research has been suggested in this area to optimize the strength training and to transfer the strength gains to functional tasks in stroke survivors [64].

## 2.7 Chapter Summary

Existing human-robot interactions are designed without sufficiently considering the implications to the participants. Past research has not been successful enough to deliver a solution that makes an HRI environment adaptive to the user's state of fatigue. Given this, identifying if better outcomes can be achieved by adapting to individual muscular status based on fatigue is a novel area of research. Electromyogram features from the involved muscles can be used to understand the current physical state and the effort exerted by the participant, and then to alter the environment. Studies have reported that training exercises involving concurrent augmented feed back and virtual environments help to enhance motor learning in complex motor tasks. A rowing exercise that involves progressive difficulty levels as suggested by sports science protocols in combination with augmented feed back through visuals and haptic sensation could be useful for better HRI and rehabilitation systems. To the best of my knowledge, none of the past studies have focused on adaptive robot-assisted rowing exercises using EMG based fatigue features from upper limb muscles. Hence, this research was planned to implement a robot-assisted progressive muscle strength training based on standard sports science protocols, where an adaptive robotic system was used to change its environment to achieve a large number of task repetitions and a prolonged interaction.

# Chapter 3

# Experiment 1: Indication of Muscle Fatigue by EMG and Kinematic Features in Robot Assisted Training

## 3.1 Introduction

The previous chapters had presented the need for adaptive robot-assisted sessions to improve rehabilitation training for stroke patients and past studies towards achieving this. They draw attention to the recent developments in rehabilitation robotic devices given their capability to offer repetitive task-oriented training and potentials to augment therapies with more interactive mediums. As described in Subsection **??**, stroke patients usually have limited muscular capacity, which means that they can be fatigued easily and the fatigue may not let them complete the exercises, which in turn can affect their possibility of getting better. So, a personalisation of the training sessions can potentially have an impact on their adherence to the training and this may help in getting better. Personalisation of training can be achieved by introducing adaptation and to make a rehabilitation training more adaptive, rehabilitation robotic devices can utilize the muscular state of patients during the interaction. The fatigue indicators may be used to inform the therapists about the progress of the recovery and thereby allow them to tailor the training according to the muscular state of the patient. In the process of this initial investigation, Experiment-1 was conducted and is presented in this chapter.

The aim of this experiment was to identify the fatigue indicators in an environment similar to the one used for stroke patients undergoing robot-assisted training. The EMG features and correlation between the EMG and kinematic features were analysed. EMG measurements from the upper limb muscles were used to extract features that could indicate the onset of muscle fatigue during a training interaction. The HapticMaster robot that is capable of recording various parameters of the user movements like the positions, velocities, and forces was used as the robotic component. It was aimed to take advantage of the different parameters and explore the alignment of upper limb muscle fatigue with the task performance recorded kinematically.

This chapter is organized as follows: Section 3.2 presents the key research question addressed by Experiment 1. Section 3.3 describes the experimental set-up and methodology used for the study. Section 3.5 presents the results based on various analysis methods. Section 3.6 conducts a detailed discussion on the results. Finally, in Section 3.7 conclusion and next steps are briefly explained.

## 3.2 Research Question

Can the state of muscle fatigue during human-robot interactions be effectively represented by Electromyogram (EMG) from upper limb muscles and kinematic measurements from the robot?

## 3.3 Experiment Design

The experiment studied the fatigue development in the upper limb muscles of 10 healthy individuals using EMG and kinematic features recorded. The study was designed to use a training set up, where the participants would move their upper limbs in a robot assisted environment that results in a less tiring exercise due to the presence of robotic assistance. The protocol for the experiment was designed and the ethics approval was obtained from the University of Hertfordshire under approval reference: COM/PGT/UH/02002.

### 3.3.1 Experiment Setup

The experiment involved interaction with the robot in active assisted mode [10], where the robot and human participant both contributed to activities and the corresponding position of the robot end-effector was measured during the interaction.

#### 3.3.1.1 Configuration of HapticMaster

The study used HapticMaster (HM) as the robotic platform (Figure 3.1), which followed an admittance control strategy, where the user's applied force was measured and the end effector was controlled to move proportionally to the force (Section 2.5). The active-assisted (AA) mode of HapticMaster robot was utilized in this study, where the robot automatically compensated for the lag or lead in subject's arm position with reference to an internal trajectory model by offering support to achieve the task in time [35][36]. The participants were asked to hold the ball attached to the end effector of HM with their right hand and move between various points as shown on the monitor in Figure 3.1.

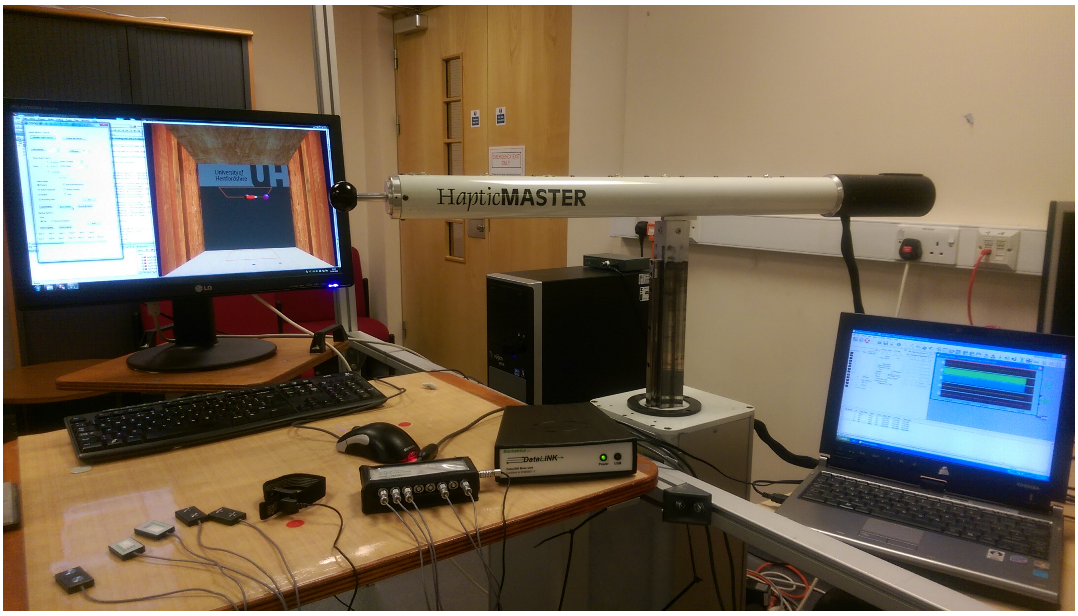


Figure 3.1: HapticMaster, EMG Device and Virtual Reality Environment.

#### 3.3.1.2 Virtual Environment

A C++ code running on a Windows 7 (64 bit) machine using Visual Studio 2009 was used to configure the virtual reality environment and the HapticMaster. Data during the robotic interaction were captured using comma separated files at a rate of approximately 32 samples per second. The Virtual Reality (VR) environment and the graphical user interface (GUI) were already developed with the help of OpenGL libraries [36] and displayed on a 24 inch wide LCD monitor. A simulated 2D environment was created to make the user feel that the planned movement paths were reached by the user accordingly. A user interface was also provided for configuring different HapticMaster parameters like stiffness, inertia, operation modes and so on (Figure 3.2).

#### 3.3.1.3 Electromyography Recording

EMG signals were collected using Biometrics Ltd DataLINK signal acquisition device. The DataLINK hardware consisted of two main units (Subject Unit and Base Unit), sensors and some connecting cables as shown in Figure 3.3. A pre amplifier/sensor electrode (Biometrics SX230) was used for capturing high quality EMG signals. The electrodes were fixed using a double sided adhesive tape (T350) and a ground reference cable (R206) was attached to the subject using the elastic wrist band. The procedure described by the manufacturer was followed for configuring the DataLINK hardware unit [23]. Before connecting the EMG sensors to the upper limb muscles, skin was wiped with a wet tissue [54] including the area of skin, which will come into contact with the elastic ground strap. The EMG electrodes were attached to the gross upper limb muscles, Biceps Brachii (BB), Triceps Brachii (TB), Anterior Deltoid (AD) and

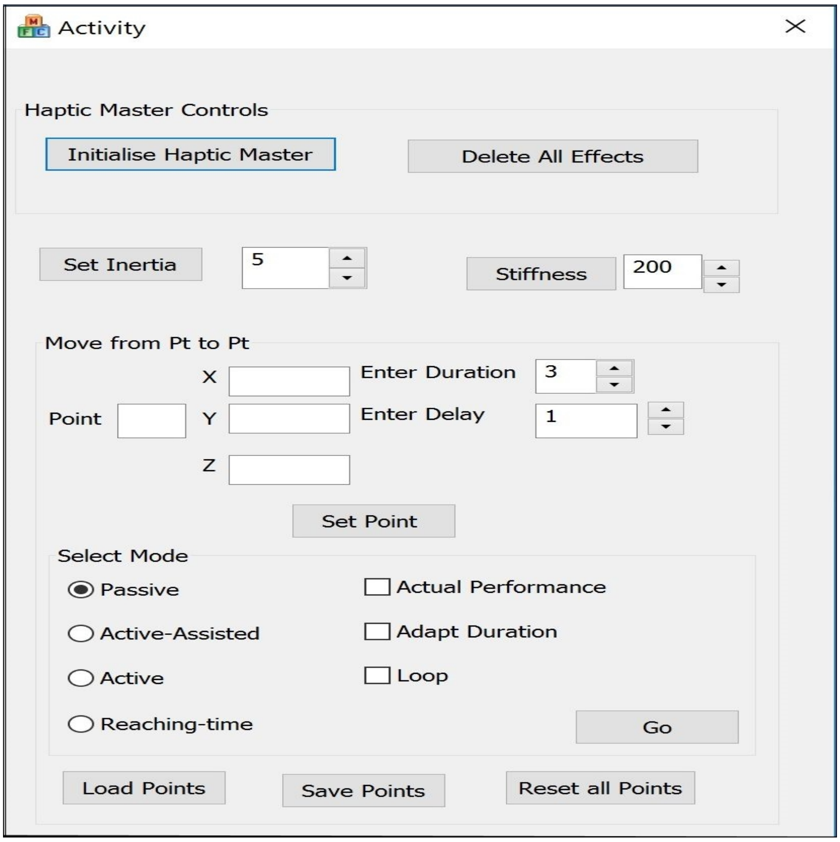


Figure 3.2: User Interface to Configure HapticMaster and Virtual Environment

Trapezius (TRP). The electrodes were connected to the skin immediately while it was still moist. The wrist strap was placed some distance away from the electrodes on an electrically neutral tissue such as over a bony area.

### 3.3.2 Experiment Protocol

The study was concentrated on the gross movement of upper limb that involved larger muscles. 10 right-handed healthy participants of at least 20 years of age took part in the experiment. Subjects with no history of injury to the upper limb and back were included in the study to minimize the variation in the measured EMG data [4]. Duration of the experiment for each participant was around 50-60 minutes. As explained in the experiment protocol in Figure 3.4, there was a preparation stage before the experiment and then, a familiarization stage followed by a performance session.

The sitting position and upper limb position of participants during the experiment were as shown in Figure 3.6. During the exercise, the participants moved the robotic arm in a prescribed path in a two-dimensional horizontal plane. The path between a source point and a destination point was termed a 'Segment' and the movements consisted of four segments S1, S2, S3, and S4.

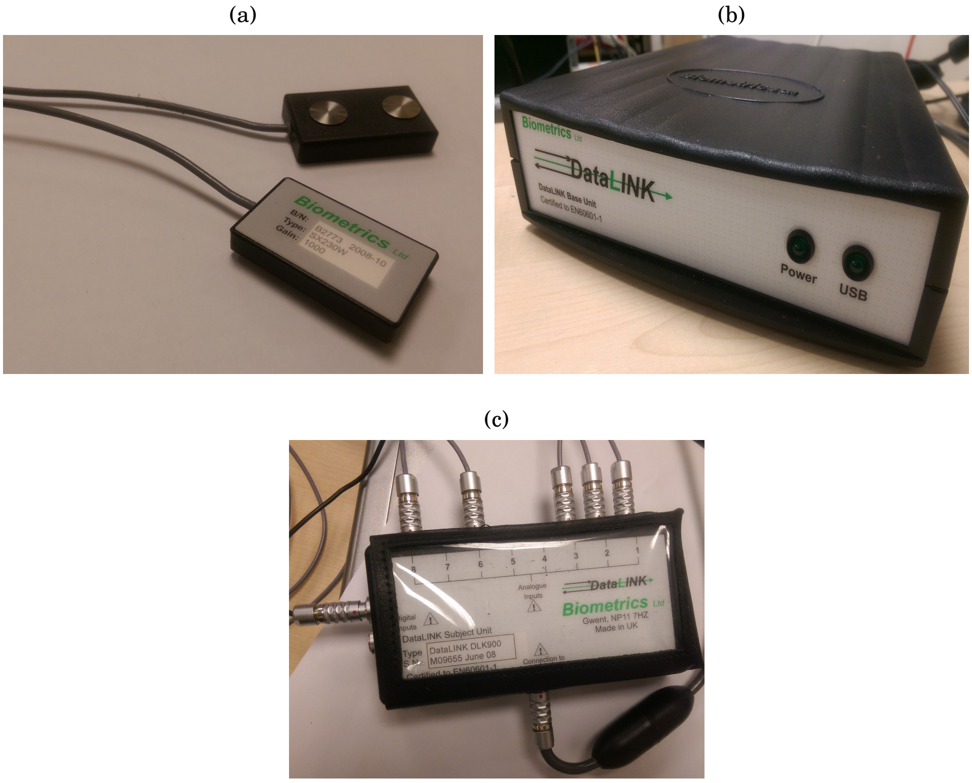


Figure 3.3: (a) EMG Pre Amplifier SX230. (b) DataLINK Base Unit. (c) DataLINK Subject Unit.

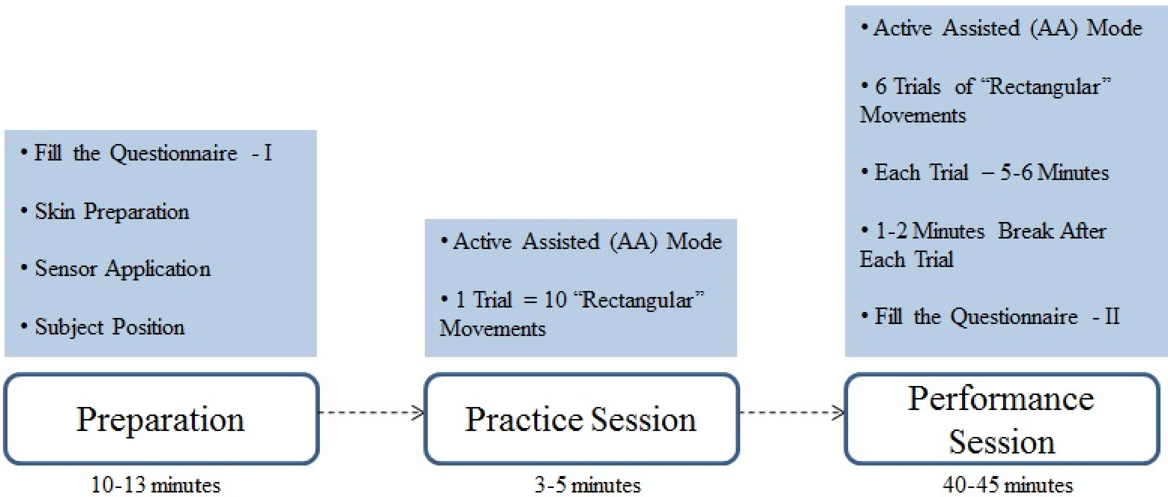


Figure 3.4: Experiment Protocol.

The experiment consisted of 6 trials, and each trial included 10 repetitions of the rectangular motions as shown in Figure 3.6(a). The experiments would stop if a total of 6 trials were completed, or if the participant reported fatigue. The scope of the experiment protocol with the details about the number of subjects, trials, iterations, and segments during the experiment are briefly explained in Figure 3.5.

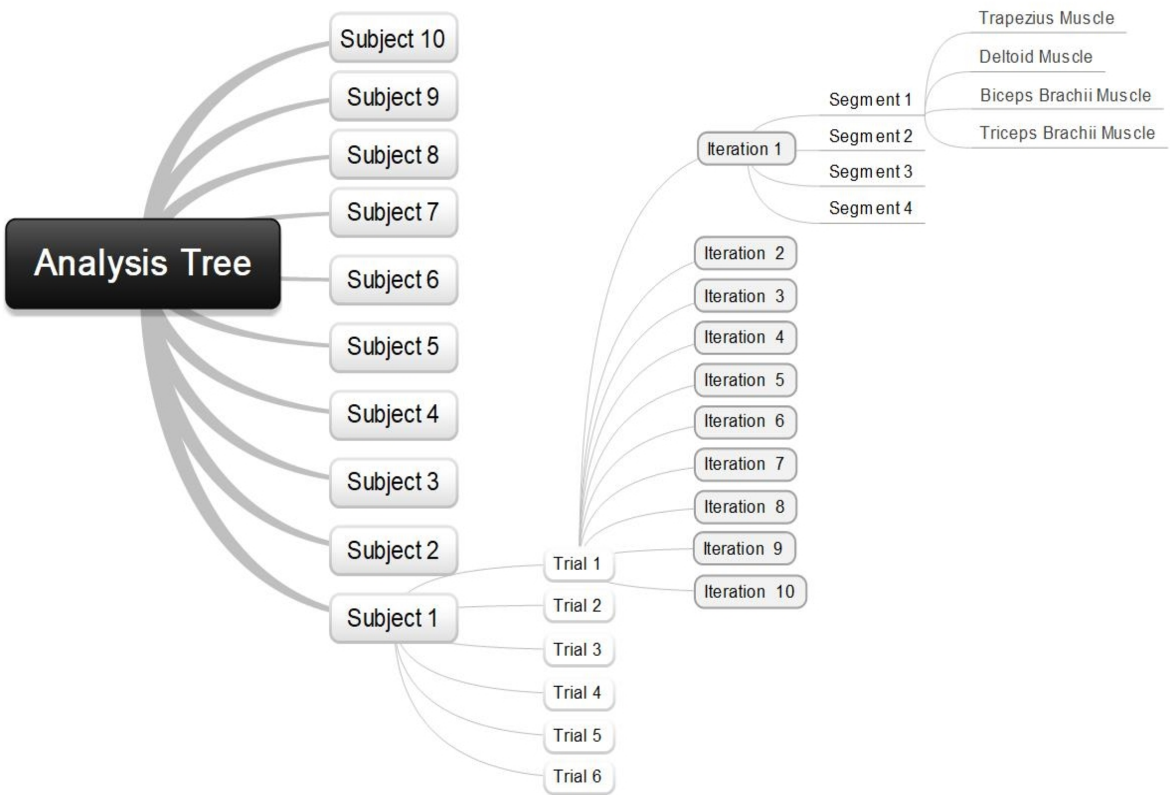


Figure 3.5: Tree Diagram Representing the Scope of the Experiment Protocol.

#### 3.3.2.1 Preparation

Participants were asked to sit straight with the hand involved in the experiment not externally supported. The opposite hand was allowed to rest on any external support like table or chair. A "Rectangle" shaped movement pattern was defined in XY plane of the Virtual Reality (VR) environment on the LCD monitor to guide the participants for segment movements in space, which involved 4 segments as shown in Figure 3.6(a). By maintaining 90 degree shoulder abduction angle for the shoulder the arm movements were constrained to a plane that was in line with the shoulder centre of rotation. This position was thought to help in creating fatigue for the upper limbs around the shoulder, since the hand and the elbow were positioned at shoulder height [63], [47]. The subjects were directed to follow each segment path visually as well as through audio messages (Text-to-Speech).

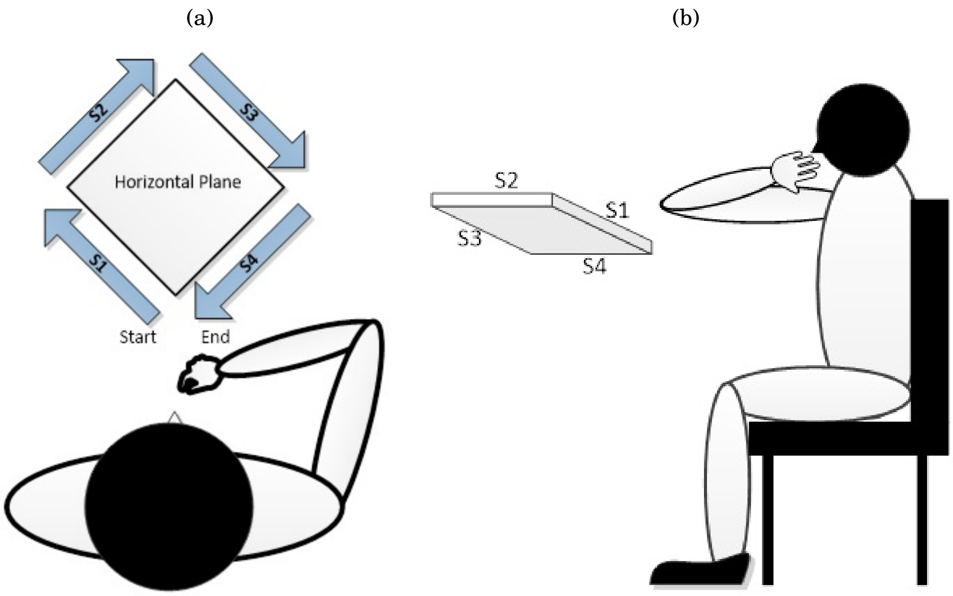


Figure 3.6: Sitting Position of Participants During the Experiment. (a) Top view. (b) Side view.

#### 3.3.2.2 Practice Session

The participants were given a practice session to get familiar with the HapticMaster movements in active assisted mode. This session would also help in identifying any discomfort due to placement of electrodes for the participant and re-fix it accordingly. A small yellow ball in the Virtual Reality environment represented the robot end-effector and this was directly mapped to the movement of robotic end effector in the actual space [35]. A grey coloured cylinder represented the path to be followed by the robot according to minimum jerk trajectory (MJT) [10][128]. A red coloured cylinder represented the actual path achieved by the robot when the participant interacted with the environment. The subject was asked to hold the gimbal of HM end effector and move according to the trajectory directed on the monitor.

#### 3.3.2.3 Performance Session

The duration of this session was around 35-40 minutes for each participant. HapticMaster was configured in AA mode. So, the participant had to initiate each movement by applying force on the ball end-effector and the robot helped to complete the movement. The session consisted of a "Rectangle" segment movement as directed by the audio message and visual feed back on the monitor. Each session consisted of a total of 6 trials for each participant. Each trial consisted of 10 iterations and 1 iteration was a sequence of segment movements named S1, S2, S3, and S4. Each trial lasted for around 6 minutes including the 5 seconds break in between iterations. After each trial there was a short break period of 1-2 minutes. The logging of EMG and HM data was stopped after each trial. Kinematic data from HM data was logged during the session. Audio feed back was given regarding the start and end of each trial. The session was conducted until the subject reported high fatigue or until the maximum number of trials were reached. In case of any feeling of high fatigue or discomfort participants were allowed to stop. The session could be ended in such cases in order not to hurt the subject. At the end of the experiment, a subjective assessment of fatigue detection was done through a second questionnaire and the feed back about the experiment session was taken.

## 3.4 Methodology

The segment-wise analysis of EMG features across trials was conducted by calculating the corresponding EMG features (Average Power, Median Frequency and Peak PSD) using signal processing algorithms in MATLAB version R2015b and statistical analysis was carried out using IBM SPSS v22.

### 3.4.1 Electromyogram Processing and Feature Extraction

A general nature of EMG signals as described by [16] and [174] was that they had a wide frequency spectrum (20-500 Hz), sampling rates of 1000 Hz or greater, and amplitude range between 50 $\mu$V to 20-30 mV depending on the type of activated muscle. EMG pre-processing usually involve methods like line (AC) interference removal, band-pass filtering, and full wave rectification [53].

**Filtering** For removing the power line interference a narrow notch filter was used (e.g., 49.5-50.5 Hz) [174]. The frequency range and, hence, the power spectral density of EMG signals are within the boundary of 5-500Hz. For the current study the usual band of 20-450 Hz was adopted for the band-pass filtering ([174], [60], [176], [139], [13]). A Chebyshev Type II filter was used to select this band of frequencies in order to achieve a steeper roll-off, however allowing some ripples in the stop band.

The study used the following EMG features for fatigue analysis and they were implemented in MATLAB accordingly:

- Average Power
- Peak Power Spectral Density (PSD)
- Median frequency

**Average Power:** At any particular time 't', the power of a signal is equal to its amplitude squared. The average power of EMG signal is defined as the energy contained in the signal over a defined time interval. Average power is explained by [121] as,

$$AverageP ower = \frac{1}{T}\int_{t=1}^{T} EMG(t)^2 dt \tag{3.1}$$

where T is the time interval and $EMG(t)$ is the EMG signal amplitude.

**Peak Power Spectral Density:** Power of a signal can also be represented through its spectrum. The spectrum of a signal represents the power of each frequency components of the signal. For any signal, a plot between frequency components (x-axis) and signal power (y-axis) is called the power spectrum with units 'Watts per Hertz'. It is also called as Power Spectral Density (PSD). The power spectrum is not a measure of the total or average power of the signal; instead it only shows the power contained in individual spectral components. The total power of a signal in a particular frequency range can be calculated by integrating the power spectrum over the frequency range [121].

**Median Frequency:** Median frequency is defined as the frequency, which separates the power spectrum of signals in two equal parts with the same power. It also divides the area under the Amplitude-Frequency curve into two equal regions as shown in Figure 3.7. It is found that as the muscle fatigue occurs, the frequency spectrum and, hence, the median frequency will start shifting to lower frequency side [174].

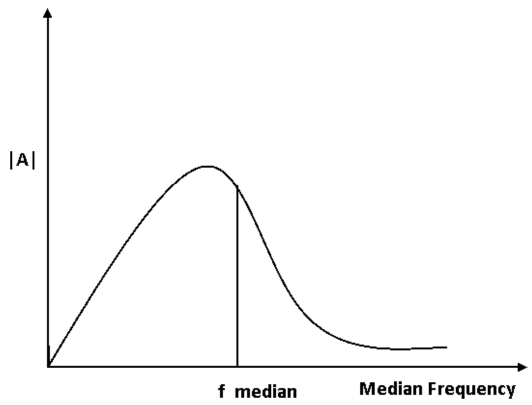


Figure 3.7: Median Frequency.

### 3.4.2 Kinematic Data Processing

#### 3.4.2.1 Feature Extraction

**Minimum Jerk Trajectory (MJT) Position:** Minimum Jerk Trajectory (MJT) position coefficients were calculated from the actual position parameters as described by [10] and [128]. Minimum Jerk Trajectory is defined as the smooth trajectory followed during interactions between human and haptic interfaces. A $5^{th}$ order polynomial was used by the HapticMaster robot to define the trajectory and control the robot arm to achieve minimum jerk movements. Since the MJT position parameters were not logged during the experiment, the same parameters were also calculated off-line using MATLAB algorithms. The MJT projection for position was then calculated by performing the dot product of the MJT position vector ($x_{MJT}$, $y_{MJT}$ and $z_{MJT}$) with the actual position vector as shown in Figure 3.8, where the actual vector is lagging behind the MJT vector, which is represented by the red and grey coloured cylinders respectively. The MJT projection and the variance of MJT projection were used to assess the progress of fatigue in different trials.

$$Projection = x * x_{MJT} + y * y_{MJT} + z * z_{MJT} \tag{3.2}$$

where, x, y, and z are the actual position components and $x_{MJT}$, $y_{MJT}$ and $z_{MJT}$ are the calculated MJT position components.

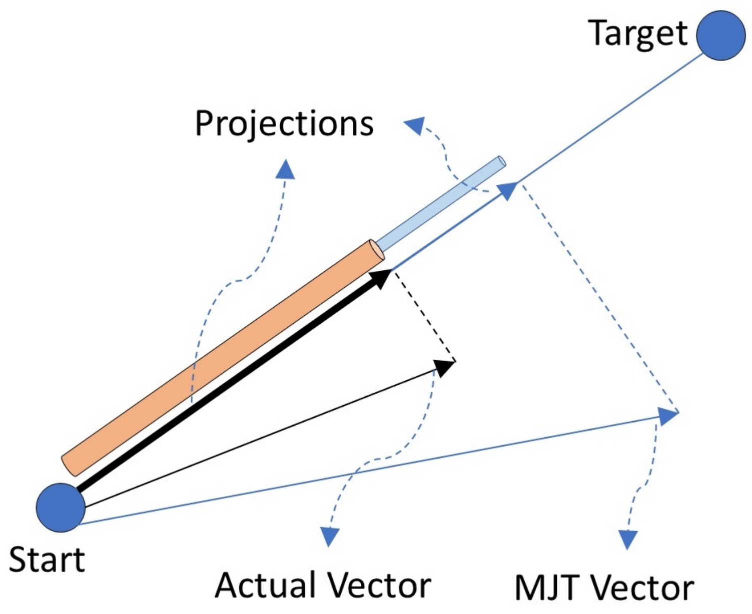


Figure 3.8: Vector Representations of MJT and Actual Position: The dot product of MJT and actual position vectors was performed.

The Root Mean Square Error (RMSE) can be calculated from the actual position and the expected MJT position as follows,

$$RMSE = \frac{\sqrt{(x - x_{MJT})^2 + (y - y_{MJT})^2 + (z - z_{MJT})^2}}{\sqrt{N}} \tag{3.3}$$

where N is the number of samples considered.

**Force Parameters:** The force components were low pass filtered and analysed below 0.5 Hz as directed by [143]. A second order Chebyshev Type II filter with cut-off frequency of 0.5 Hz was designed to extract the low frequency components of force. Then the RMS value was calculated from the filtered forced components $F_x$, $F_y$ and $F_z$. The sampling frequency of the logged kinematic force data was approximated to 32 samples per second as could be observed from the HapticMaster log files.

#### 3.4.2.2 Feature Analysis

The kinematic features derived from the position and force measurements were analysed using SPSS and MATLAB plots. Box Plots were generated in order to analyse the distribution of features as the trials progressed. The shift of median values of the features across the trials was noted for each subject. A summary table was created at the end of analysis based on the variation of features as the trials progressed.

### 3.4.3 Muscle Fatigue Detection

As explained in Subsection 2.4.3, muscle fatigue can be identified from the EMG measurements by analysing the average power and median frequency. Studies have also identified non-linearity in the EMG vs force relationship when the muscles get fatigued, as explained in Subsubsection 2.4.4.2. In addition, studies by Chemuturi et.al [36] and Basteris et.al [17] have identified reduced task performances indicated by the lag-lead parameters measured during robot-assisted interactions. The lagging performance by the participants could be a possible indicator for the development of fatigue. Hence, it was decided to also explore the parameters like MJT projection and RMSE error of kinematic position. Hence, in this study, the detection of upper limb muscle fatigue based on EMG and kinematic measurements was investigated using the below methods.

- Increase of EMG average power and decrease of EMG median frequency (as explained in Subsection 2.4.3).
- Increase in the variance of MJT projection of the kinematic position, decrease in MJT projection and increase in RMSE error in position [36][17] .
- Change/decrease of correlation between EMG and kinematic data (as explained in Subsubsection 2.4.4.2)

### 3.4.4 Data Preparation and Correlation

Correlation between the EMG and the kinematic data was studied after conducting a mapping between the EMG and kinematic measurements based on the HapticMaster time log and segment information. The EMG data corresponding to different segments were separated after this mapping. In order to map the data between EMG and HapticMaster robot in terms of time and segment, a Python code was developed. The segment parameters were read from the HM log file and the corresponding time-stamp information was mapped with the time in EMG data log file. Based on this mapping, the EMG and kinematic data could be divided into four segments in a mapped file, which then was used for further analysis. Since the kinematic features were not normally distributed, Spearman's method was used for the correlation study.

The correlation study was conducted in two ways. Initially, the EMG feature and kinematic force features (RMS value of force components) were compared. The features derived from EMG were used to see if there was a relation with the features derived from kinematic force components and it was investigated how the correlation was affected as the trials progressed. The average power of EMG and the RMS value of force components ($F_x$, $F_y$, and $F_z$) were compared segment-wise for each muscle separately. The correlation study was then conducted segment-wise for each muscle separately, by using each iteration of the segment to calculate one value each for the features (Figure 3.5). Initially, each segment was split into four equal-sized windows and the EMG average power was calculated for each window. The 'segment' information from the kinematic log file (which maps EMG and HapticMaster data) was used as the parameter to divide the EMG data into equal sized windows between start and end of each segment. Hence, each segment iteration corresponded to 4 values of average power. So, 10 iterations of a trial corresponded to 10x4 values of average power.

In the second method, the correlation between EMG features and raw force components were studied. During the analysis, the raw values of force components were used to avoid the averaging effect while calculating the kinematic features across each segment. The correlation study was conducted between the raw kinematic force and the EMG average power of relatively smaller windows. The window size for the EMG analysis was decided based on the number of samples per segment of the kinematic data. The sampling rates for EMG and kinematic data were different and the HapticMaster robot was logging the kinematic data at a rate of 151 samples per segment. The EMG signals were acquired at a frequency of 1000 samples per second. So, before the correlation study, in order to make the number of features on both sides equal, each iteration per segment of EMG data was divided into 151 number of windows/blocks of equal length. A few numbers of replications had to be made at the end of each segment to make the total size divisible by 151 and thus to make them of equal length. The last element in the array was replicated 1-3 times to make the whole length divisible by 151. Nevertheless, these replications to adjust the window width would not propagate to the next segment since the total windows in each iteration of a segment were bounded by the start and end of the segment. Thus, for each of the 151 windows, the average power was calculated. The corresponding raw values of force components ($F_x$, $F_y$ and $F_z$) were low-pass filtered at 0.5Hz for removing the high-frequency variations. Now, each value of force component corresponds to a single value of EMG average power. Then, the correlation was studied between these 2 features for each segment separately. Initially, the correlation was studied by considering all the subjects together, and also by considering the subjects separately.

Finally, each trial was considered separately for each of the subjects, which were then used to assess how the muscle fatigue would affect the correlation coefficients as the trials progressed. The overall research context for the experiment is described in Figure 3.9.

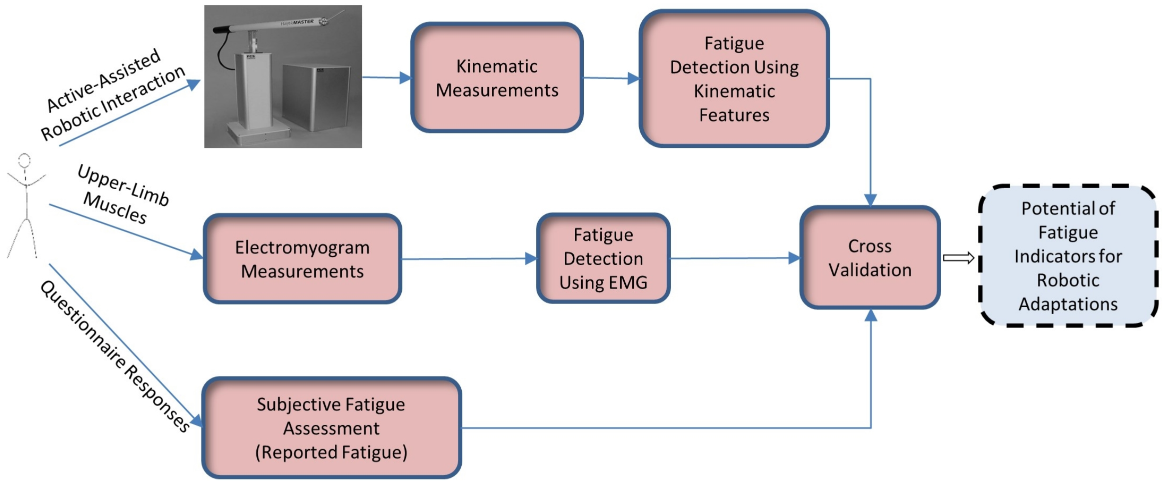


Figure 3.9: Research Context for the Experiment.

## 3.5 Results

### 3.5.1 EMG Features

The analysis was aimed to check if there was any trend in the EMG features between trials in different subjects and different segments. The mapped files were used as input to the signal processing algorithms to generate a feature list for different EMG features. The EMG features were calculated considering each segment separately. Subject 2 could only complete four trials because of high fatigue during the experiment. So, empty data was inserted manually corresponding to trials 5 & 6 to make uniformity in SPSS analysis.

Box plots of the features were generated for each segment to identify trends in median values of EMG features as the trials progressed. The box plots for average power and median frequency as the trials progressed for a typical subject for the Trapezius muscle and 1st segment are shown in Figure 3.10 and Figure Figure 3.11. A decrease of median frequency and an increase of average power could be noted as the trials progressed [93][181].

Linear regression test of EMG features was also conducted to see if there was a significant trend as the trials progressed. For average power for example; in case of subject 1 for the Trapezius (TRP) muscles during all the four segments it was noticed that there was a significant increase of median value of average power in all the segments (S1, S2, S3 and S4) as the trials progressed. A strong positive correlation (0.809, 0.779, 0.820, 0.826) was noticed between Average power and the Trials, supported by significant p values. Also a major percentage (65.4%, 62.1%,

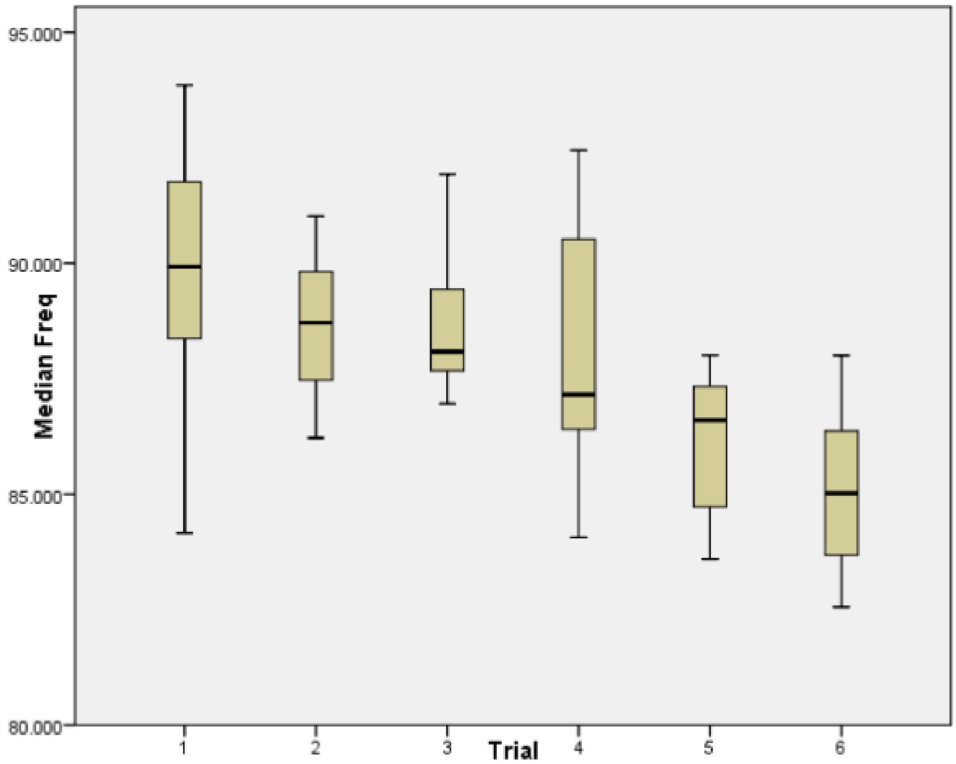


Figure 3.10: Box Plots for Median Frequency in Trapezius Muscle and Segment 1.

67.5%, 68.6%) of the total variance of average power was explained by the independent variables "Trial" & "Iteration" together. But the results were not similarly significant in all the subjects. It was noticed that the break period between trials, the robotic assistance and the 5 seconds break between each iteration helped all the participants to some extent recover from fatigue developed during each trial. The break period between trials was around 1-2 minutes duration depending on when the subjects decide to start the next trial. Hence, a linear regression study across all trials of a subject often resulted in a non-significant slope depending on how well the muscles recovered from fatigue; which was often subjective. So, instead of looking for significant regression slopes across all the trials, it was decided to conduct a comparison study of features between the first an last trials to see any indication of fatigue. Summary tables were created based on this comparison.

#### 3.5.1.1 Summary Tables

Summary tables were created based on the variation of different EMG features across trials as shown in Table 3.1 and Table 3.2. Since the EMG features were normally distributed, the mean value of features in each trial for each segment was used to make decisions on the state of fatigue. The mean values between the initial and final trials were compared. The hypothesis for fatigue detection using average power parameter was that the mean value of average power in

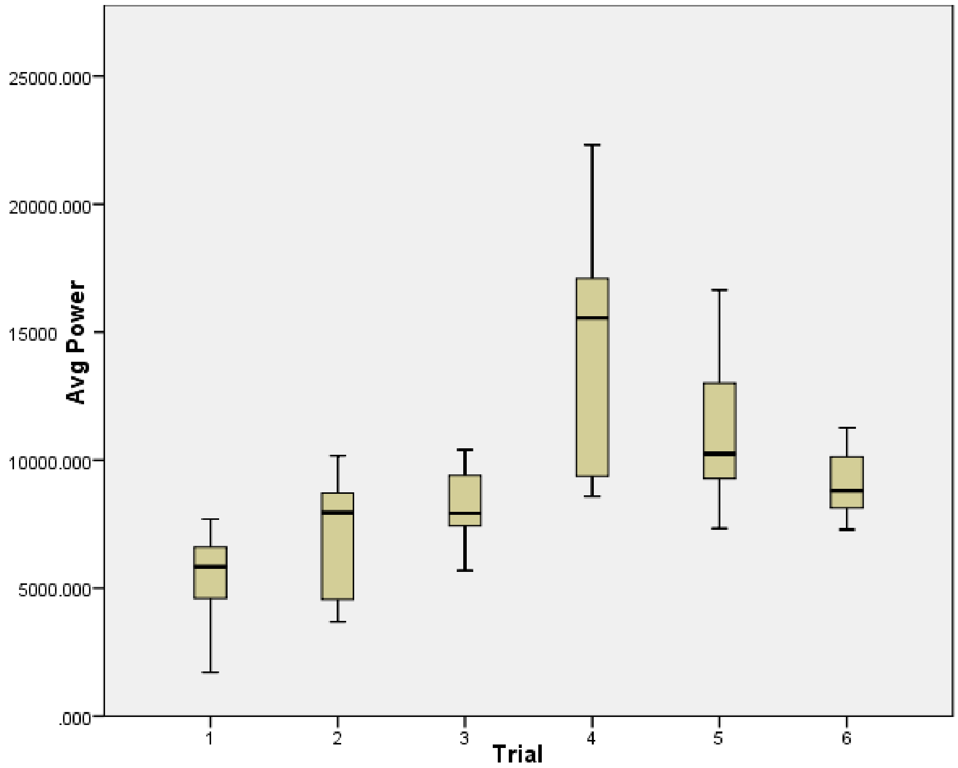


Figure 3.11: Box Plots for Average Power in Trapezius Muscle and Segment 1.

the first trial will be smaller that the last trial [93][211]. A "1" in the corresponding cell indicated that the hypothesis was true; meaning that there was an increase in the average power as the trials progressed. A "0" indicated that there was no increase or there was a decrease in its mean value between trials. The table highlights that for the majority of cases, the average power of EMG displays an increasing trend as the trials progressed. As seen in Table 3.1, a majority of the analysed cases in Trapezius and Deltoid muscles showed an increasing trend (60% and 70% respectively) compared to the Biceps and Triceps muscles (37.5% and 40% respectively).

Similarly, the hypothesis for fatigue detection using median frequency parameter was that the mean value of the feature in the first trial will be larger that of the last trial [81][59]. A "1" in the corresponding cell indicated that the hypothesis was true, which meant that there was a decrease in the median frequency as the trials progressed. A "0" meant that there was no decrease or there was an increase in its mean value. As seen in Table 3.2, the median frequency of EMG displayed a decreasing trend as the trials progressed in Trapezius and Deltoid muscles in the majority of the analysed cases (57.5% and 62.5% respectively) compared to Biceps and Triceps muscles (37.5% and 27.7% respectively). This might be probably due to the increased fatigue state of TRP and DLT muscles compared to the BB and TB muscles.

The peak PSD parameter was giving similar result as the average power as explained in Table 3.3.

Table 3.1: Summary Table for EMG Average Power.

| Feature -> | EMG Average Power | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hypothesis -> | The mean value of EMG Average Power in the first trial is smaller than that of the last trial (1 = TRUE, 0 = FALSE, NA = Not Known) | | | | | | | | | | | | | | | |
| Methodology -> | Compare the mean values of the parameter between 1st and last trials to see if there is an increase. Each trial includes 10 iterations. | | | | | | | | | | | | | | | |
| Muscles -> | TRP | | | | DLT | | | | BB | | | | TB | | | |
| Segments -> | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 |
| Subject 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Subject 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Subject 3 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Subject 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| Subject 5 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 |
| Subject 6 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Subject 7 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Subject 8 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Subject 9 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Subject 10 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| TOTAL | 6 | 7 | 6 | 5 | 6 | 8 | 7 | 7 | 2 | 2 | 7 | 4 | 5 | 3 | 5 | 3 |
| Fatigue Score | 24 | | | | 28 | | | | 15 | | | | 16 | | | |
| Percentage % | 60 | | | | 70 | | | | 37.5 | | | | 40 | | | |

### 3.5.2 Kinematic Position

A segment-wise analysis of position components was conducted by generating the corresponding minimum jerk trajectory (MJT) parameters. Since the kinematic features were not normally distributed, non-parametric test (independent samples median test) was used to compare medians between the different trials.

**MJT Projection of Position Values** The MJT projection (dot product) of position was studied by generating median line plots through a MATLAB script, and the trend in the features across different trials was analysed. As shown in Figure 3.12, the median plots were drawn considering each trial of a subject and a line joining them across the trials. All the segments were studied separately for each subject. As shown in the figure, it was noticed that there was a reduction in the MJT projection as the trials progressed. The overall result of this analysis is shown in the summary table (Table 3.4).

Summary Tables were generated based on the kinematic features as the trials progressed by comparing the median values of first and last trials using MATLAB. In the summary table corresponding to MJT projection (Table 3.4), a value of 1 means that there was an decrease in the

Table 3.2: Summary Table for EMG Median Frequency.

| Feature -> | EMG Median Frequency | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hypothesis -> | The mean value of EMG Median Frequency in the first trial is higher than that of the last trial (1 = TRUE, 0 = FALSE, NA = Not Known) | | | | | | | | | | | | | | | |
| Methodology -> | Compare the mean values of the parameter between 1st and last trials to see if there is a decrease. Each trial includes 10 iterations. | | | | | | | | | | | | | | | |
| Muscles -> | TRP | | | | DLT | | | | BB | | | | TB | | | |
| Segments -> | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 |
| Subject 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| Subject 2 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| Subject 3 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| Subject 4 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Subject 5 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| Subject 6 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 |
| Subject 7 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Subject 8 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| Subject 9 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Subject 10 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| TOTAL | 7 | 6 | 4 | 6 | 5 | 7 | 7 | 6 | 2 | 3 | 6 | 4 | 2 | 1 | 3 | 5 |
| Fatigue Score | 23 | | | | 25 | | | | 15 | | | | 11 | | | |
| Percentage % | 57.5 | | | | 62.5 | | | | 37.5 | | | | 27.5 | | | |

median value of the MJT projections (dot product) as the trials progressed. A value of 0 means there was no decrease or there was an increase in median values as the trials progressed. 60% of the cases for S3 segment followed the hypothesis, which meant that there was a decrease in the median values of MJT projection. The S3 segments for the majority of the subjects (6 out of 10) involved too many variations at the reaching point of the segment due to the difficulty in accurately judging the end position of the segment S3. Hence, the actual position was not found in line with the MJT position. This inaccuracy might have increased when the subjects get fatigued as the trials progressed. This might have resulted in a decreased median values of projection in the final trials of S3 compared to the initial trials.

On the other hand, S4 segments displayed an increase or no trend in the MJT projection (dot product) as the trials progressed for 80% of the subjects and this was the highest compared to all other segments. S1 segments also displayed 70% of increasing trend. S4 segments involved movements in space, where the upper limb was closer to the body as well as moving towards

Table 3.3: Summary Table for EMG Peak PSD Values.

| Feature -> | Peak Power Spectral Density (PSD) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hypothesis -> | Is the mean value of EMG Peak PSD in the first trial is smaller than that of the last trial?<br>(1 = TRUE, 0 = FALSE, NA = Not Known) | | | | | | | | | | | | | | | |
| Methodology -> | Compare the mean values of the parameter between 1st and last trials to see if there is an increase. Each trial includes 10 iterations. | | | | | | | | | | | | | | | |
| Muscles -> | TRP | | | | DLT | | | | BB | | | | TB | | | |
| Segments -> | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 | S1 | S2 | S3 | S4 |
| Subject 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Subject 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| Subject 3 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 |
| Subject 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 |
| Subject 5 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| Subject 6 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 |
| Subject 7 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Subject 8 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Subject 9 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Subject 10 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| TOTAL | 6 | 5 | 7 | 5 | 5 | 6 | 6 | 5 | 3 | 4 | 6 | 3 | 4 | 3 | 3 | 2 |
| Fatigue Score | 23 | | | | 22 | | | | 16 | | | | 12 | | | |
| Percentage % | 57.5 | | | | 55 | | | | 40 | | | | 30 | | | |

the body and this might make the S4 movements easier than the other segments. This might mean that the subjects were in a more comfortable upper limb position during S4 movements or it was more easy to follow the robot in this segment. Hence, even in a state of fatigue, being in a comfortable segment they were able to do more adaptation (by learning from previous trials) to the S4 movements compared to the other segments.

When the variance of the MJT projection was analysed an increase of variance was noted as the trials progressed. As shown in Table 3.5, 80% of the subjects displayed an increase of variance for the S3 segments, whereas S4 segment had the least number of cases (20%) of increase in variance. This was in accordance with the previous results using projection parameter, where an increased variation in the projection was noticed for S3 segment. The smaller percentage for the S4 segments might be due to the near-the-body movements as described before. A similar result (fewer variations) was also noticed for S1 segments (40%), where the movements were again close to the body of the participant. As seen in the summary table (Table 3.5), 'near-the-body'

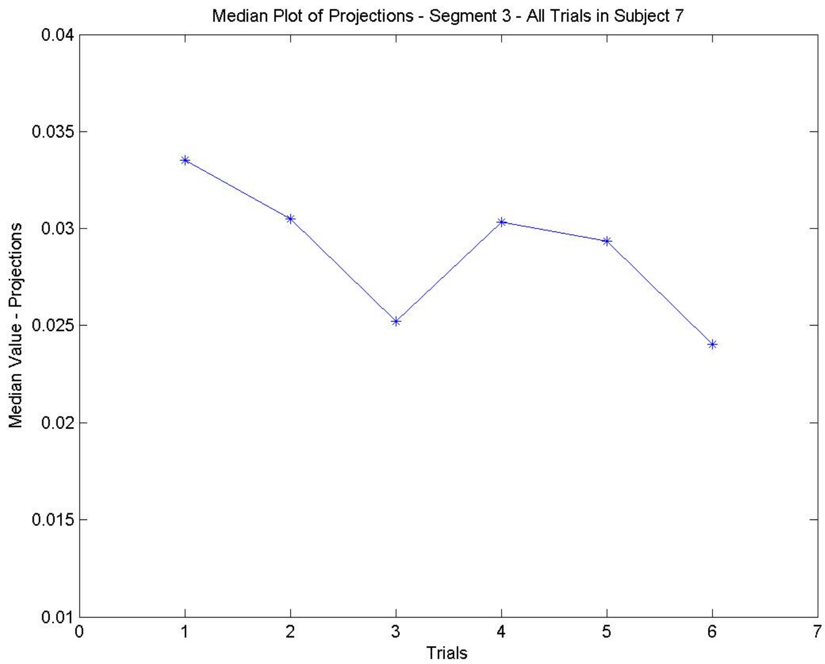


Figure 3.12: Progress of MJT Projection of Position Along All Iterations & Trials - Subject 7

Table 3.4: Summary Table for MJT Projection

| Feature -> | Projection (Dot Product) of Actual Position Vector on MJT Position Vector | | | |
|---|---|---|---|---|
| Hypothesis -> | Is the median value of the projection in the first trial is higher than that of the last trial? (1 = TRUE, 0 = FALSE, NA = Not Known) | | | |
| Methodology -> | Compare the median values of the parameter between 1st and last trials to see if there is a decrease. Each trial includes 10 iterations. | | | |
| Segments -> | S1 | S2 | S3 | S4 |
| Subject 1 | 0 | 0 | 0 | 0 |
| Subject 2 | 0 | 0 | 0 | 0 |
| Subject 3 | 0 | 1 | 1 | 0 |
| Subject 4 | 1 | 0 | 1 | 0 |
| Subject 5 | 0 | 1 | 1 | 1 |
| Subject 6 | 0 | 0 | 0 | 0 |
| Subject 7 | 1 | 1 | 1 | 0 |
| Subject 8 | 1 | 0 | 1 | 0 |
| Subject 9 | 0 | 1 | 1 | 1 |
| Subject 10 | 0 | 0 | 0 | 0 |
| TOTAL | 3 | 4 | 6 | 2 |
| Percentage | 30% | 40% | 60% | 20% |

movements (S1 and S4 segments) were having less position variance compared to the 'away-from-body' movements (S3 and S4 segments). This can be related to the findings of Chemuturi et al.[36], which stated that the 'reaching away' movements were longer than the 'returning towards' movements.

Table 3.5: Summary Table for Variance of MJT Projection

| Feature -> | Variance of Projection (Dot Product) of Actual Position Vector on MJT Position Vector | | | |
|---|---|---|---|---|
| Hypothesis -> | Is the median value of the variance in the first trial is smaller than that of the last trial? (1 = TRUE, 0 = FALSE, NA = Not Known) | | | |
| Methodology -> | Compare the median values of the parameter between 1st and last trials to see if there is an increase of variance. Each trial includes 10 iterations. | | | |
| Segments -> | S1 | S2 | S3 | S4 |
| Subject 1 | 0 | 0 | 0 | 0 |
| Subject 2 | 1 | 1 | 1 | 0 |
| Subject 3 | 0 | 1 | 1 | 1 |
| Subject 4 | 0 | 0 | 1 | 0 |
| Subject 5 | 0 | 0 | 1 | 1 |
| Subject 6 | 0 | 1 | 1 | 0 |
| Subject 7 | 1 | 1 | 1 | 0 |
| Subject 8 | 1 | 0 | 1 | 0 |
| Subject 9 | 1 | 1 | 1 | 0 |
| Subject 10 | 0 | 0 | 0 | 0 |
| TOTAL | 4 | 5 | 8 | 2 |
| Percentage | 40% | 50% | 80% | 20% |

**Root Mean Square Error (RMSE) analysis** An increase of variance could also mean that there was an increase in the Root Mean Square Error (RMSE) between the actual and the expected position trajectory. Hence, the RMSE feature was studied using SPSS box plots and MATLAB plots and summary tables were generated by comparing the median values of first and last trials. An increase of RMSE error was noted between the first and last trials. In the summary table (Table 3.6), a value of 1 means that there was an increase in the error between first and last trials. A value of 0 means there was no increase or there was a decrease in the error. The hypothesis was that there will be an increase of RMSE error between first and last trials when the muscles come to a state of fatigue. 70% and 60% of the subjects displayed an increase of RMSE for the S2 and S3 segments respectively, whereas S1 and S4 segments had the least percentage (40% for both). The RMSE fatigue indication was hence, more during S2 and S3 segments than during the S1 and S4 segments. This might be possibly due to the fatigue developed during the trials in association with the 'away-from-body' movements involved in S2 and S3 segments.

Table 3.6: Summary Table for RMSE Error in Position Parameter

| Feature -> | Root Mean Square Error (RMSE) between Actual Position Vector on MJT Position Vector | | | |
|---|---|---|---|---|
| Hypothesis -> | The median value of RMSE parameter in the FIRST trial is smaller than that of the LAST trial (1 = TRUE, 0 = FALSE, NA = Not Known) | | | |
| Methodology -> | Compare the median values of the parameter between 1st and last trials to see if there is an increase of error. Each trial includes 10 iterations. | | | |
| Segments -> | S1 | S2 | S3 | S4 |
| Subject 1 | 0 | 0 | 0 | 0 |
| Subject 2 | 0 | 0 | 0 | 0 |
| Subject 3 | 0 | 1 | 1 | 1 |
| Subject 4 | 0 | 1 | 1 | 0 |
| Subject 5 | 1 | 1 | 1 | 1 |
| Subject 6 | 0 | 1 | 0 | 0 |
| Subject 7 | 1 | 1 | 1 | 1 |
| Subject 8 | 1 | 1 | 1 | 1 |
| Subject 9 | 1 | 1 | 1 | 0 |
| Subject 10 | 0 | 0 | 0 | 0 |
| **TOTAL** | 4 | 7 | 6 | 4 |
| **Percentage** | **40%** | **70%** | **60%** | **40%** |

### 3.5.3 Correlation Between EMG and Kinematic Data

The experiment involved dynamic muscle contraction, where different combinations of muscles were activated that result in different positions and directions of upper limb movements in space. Hence, a change in force at the robotic end-effector could be correlated to the combined action of different muscles, which also varied across subjects. The different segments separated by color for the EMG signals as well as force components are shown in Figure 3.13 and Figure 3.14. The "wait" states (of around 5 seconds) between iterations in each trial were removed from the plots. The force plot was drawn against the total number of samples along the x-axis (151 Samples x 4 Segments x 10 Iterations) for each trial. The figures clearly show which muscles were more involved in the task and in which segment they were highly active. As in the figures, visually there was a correlation observed between the EMG amplitude for different muscles and corresponding force amplitudes ($F_x$, $F_y$ and $F_z$ components) measured by the HapticMaster robot.

#### 3.5.3.1 EMG Feature vs Kinematic Force Features

The EMG features and RMS force were found to have a similar number of peaks as the trials progressed. The correlation of the number of peak points between EMG average power in TRP muscles and the RMS value of force x-components after low pass filtering at 0.5Hz are shown in Figure 3.15. The plot corresponded to the Subject 1, Trial 1, Segment 1 and 10 iterations, with each iteration divided into 4 windows. Matching of peaks was one of the initial indicators of the

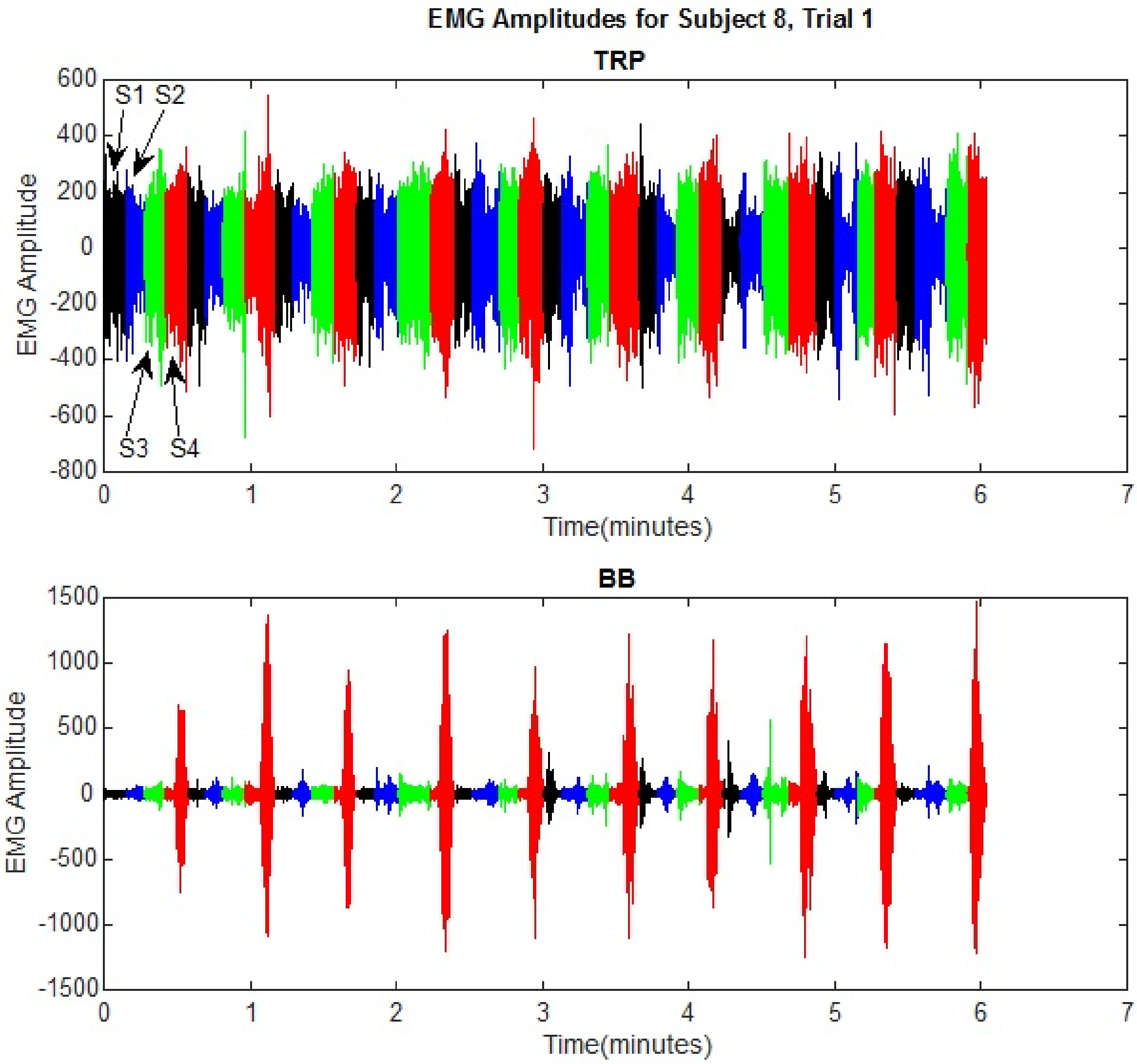


Figure 3.13: EMG with Segments Separated by Colours After Removing Wait States

correlation between the two features.

#### 3.5.3.2 EMG Feature vs Raw Force Components

Correlation tables considering all the subjects together, separated by different segments and different muscles are described in Table 3.8. While analysing the correlation results considering all the subjects together, the sign of the correlation coefficients for $F_x$ and $F_y$ components in all significant cases were found to follow a pattern as presented in Table 3.7. For example, corresponding to BB and TB muscles, there was a pattern that represented the directions of movement of the four segments. The $F_x$ and $F_y$ components during Segment 1 had a pattern of "positive" and "negative" respectively, whereas Segment 2 had a pattern of "negative" and

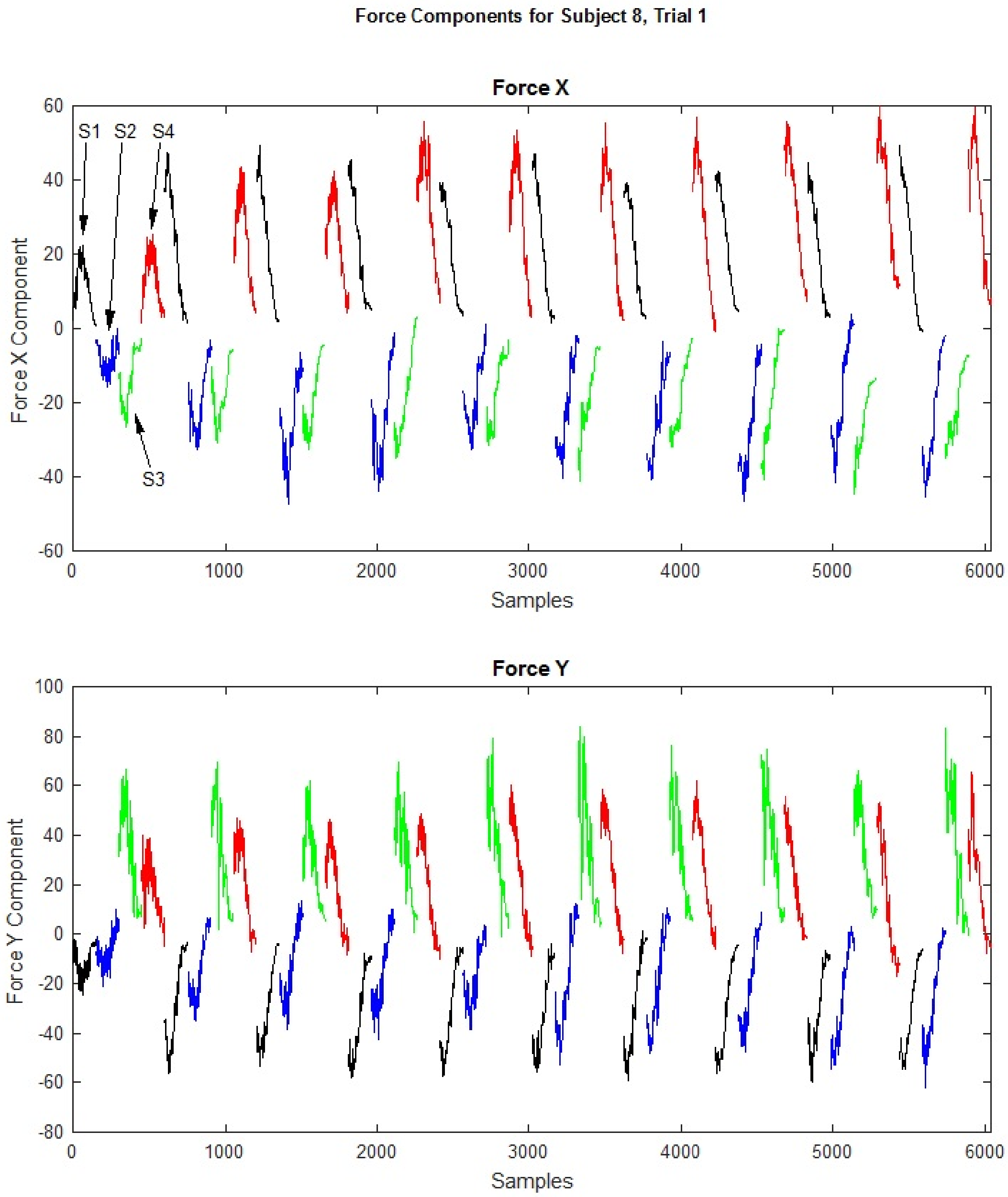


Figure 3.14: Force with Segments Separated by Colours After Removing Wait States

"negative" respectively. A "positive" sign means that the EMG average power for the particular segment increases with an increase in the force components measured by the HapticMaster. In Segment 1, the average power increased with an increase in $F_x$, and decreased with an increase in $F_y$. This analysis was conducted considering all the subjects together in the correlation study. A similar analysis was also conducted considering individual subjects to check if there were deviations from this observation due to possible subject-specific variations. This gave a similar pattern of sign-changes for the $F_x$ and $F_y$ components in the majority of the subjects.

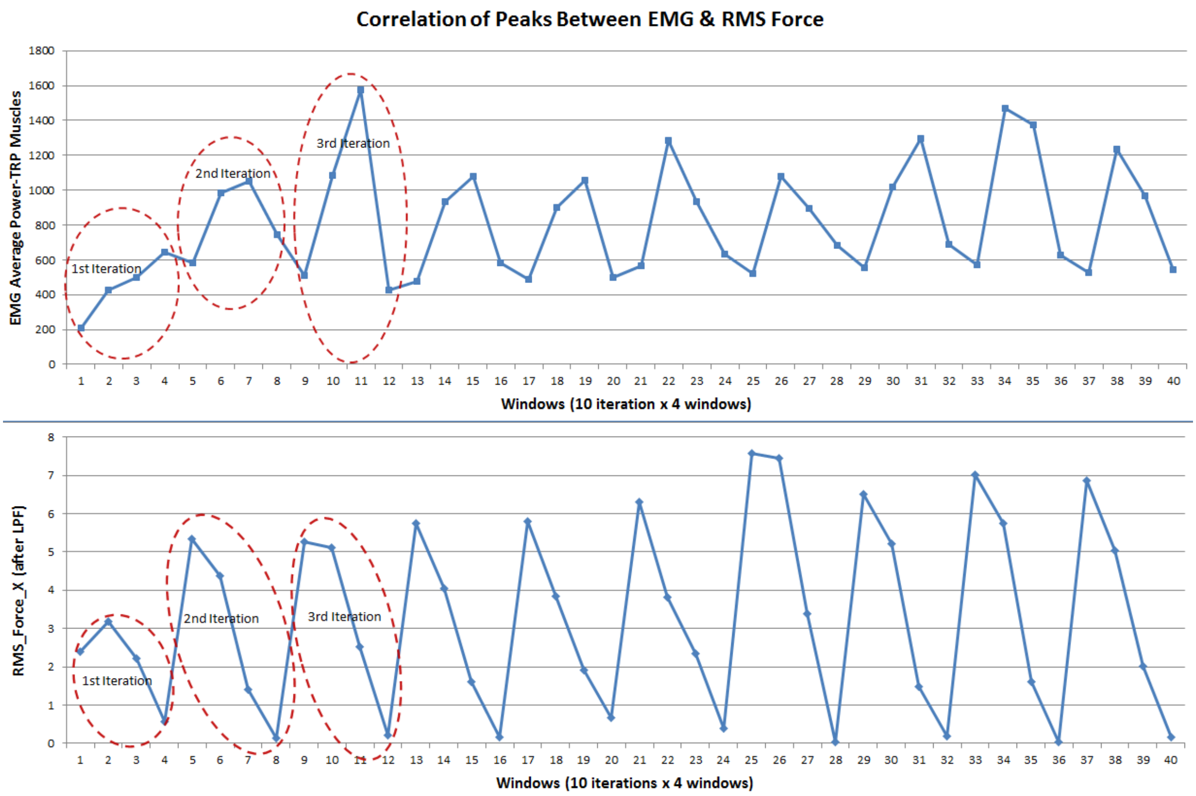


Figure 3.15: Correlation of Peaks Between EMG Average Power in TRP Muscle & RMS Force X Component - Segment 1

Table 3.7: Pattern Displayed by BB and TB Muscles in Terms of Sign of Correlation Coefficients: Correlation was performed between the row force components ($F_x$ and $F_x$) and EMG average power considering 151 windows per segment. Each pattern represents the movement direction of the corresponding segment.

| | Force $F_x$ | Force $F_y$ |
|---|---|---|
| Segment 1 | +ve | -ve |
| Segment 2 | -ve | -ve |
| Segment 3 | -ve | +ve |
| Segment 4 | +ve | +ve |

**Correlation Considering Each Trial of Individual Subjects:** Having noticed that the low-frequency force components were correlated with the EMG average power as in Table 3.8, any trend in the values of correlation coefficient was investigated in order to see if this can represent muscle fatigue as the trials progressed. Past studies had given some indications on the effect of fatigue on force-EMG correlations (Subsubsection 2.4.4.2). Hence, different trials of each individual subjects were studied separately for each segment. A change of correlation coefficient (mostly a decrease in value compared to the initial trial) was noticed as the trials progressed in the majority of subjects. The results are described in the summary table (Table 3.9). The

Table 3.8: Correlation Table Based on Raw Force Components and EMG Average Power for All Subjects Together - Considering 151 windows for each segment and each muscle.

**Segment 1 - Correlations between HM Raw Force Components and EMG Features**

| | | | EMG_AvgPower_TRP | EMG_AvgPower_DLT | EMG_AvgPower_BB | EMG_AvgPower_TB |
|---|---|---|---|---|---|---|
| Spearman's rho | Force_X | Correlation Coefficient | -.235** | .283** | .129** | .370** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Y | Correlation Coefficient | .229** | -.293** | -.168** | -.419** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Z | Correlation Coefficient | .290** | -.087** | .176** | .101** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

**Segment 2 - Correlations between HM Raw Force Components and EMG Features**

| | | | EMG_AvgPower_TRP | EMG_AvgPower_DLT | EMG_AvgPower_BB | EMG_AvgPower_TB |
|---|---|---|---|---|---|---|
| Spearman's rho | Force_X | Correlation Coefficient | .299** | .164** | -.187** | -.492** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Y | Correlation Coefficient | .292** | .116** | -.099** | -.471** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Z | Correlation Coefficient | .165** | .199** | .246** | .045** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |

**Segment 3 - Correlations between HM Raw Force Components and EMG Features**

| | | | EMG_AvgPower_TRP | EMG_AvgPower_DLT | EMG_AvgPower_BB | EMG_AvgPower_TB |
|---|---|---|---|---|---|---|
| Spearman's rho | Force_X | Correlation Coefficient | .118** | .259** | .038** | -.485** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Y | Correlation Coefficient | -.034** | -.362** | -.047** | .175** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Z | Correlation Coefficient | .136** | -.071** | .065** | 0.001 |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .769 |

**Segment 4 - Correlations between HM Raw Force Components and EMG Features**

| | | | EMG_AvgPower_TRP | EMG_AvgPower_DLT | EMG_AvgPower_BB | EMG_AvgPower_TB |
|---|---|---|---|---|---|---|
| Spearman's rho | Force_X | Correlation Coefficient | .141** | -.102** | .414** | .252** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |
| | Force_Y | Correlation Coefficient | 0.003 | -.105** | .378** | .262** |
| | | Sig. (2-tailed) | .504 | .000 | .000 | .000 |
| | Force_Z | Correlation Coefficient | .403** | .222** | .130** | .099** |
| | | Sig. (2-tailed) | .000 | .000 | .000 | .000 |

summary table was formed based on the trend in correlation coefficients as the trials progressed. The hypothesis was that there will be a decrease in the value of correlation coefficient as the trials progressed. A value of "1" indicated that there was a decrease in the correlation in the last trial compared to the first trial.

Table 3.9: Summary Table Based on the Trend in Correlation Coefficients as the Trials Progressed in Segment 1.

| Correlation of Force Components with EMG Average Power | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hypothesis: There will be a decrease in the value of correlation coefficient as the trials progress (1 = TRUE, 0 = FALSE, NA = Unknown) | | | | | | | | | | | | |
| | Force_X_LPF | | | | Force_Y_LPF | | | | Force_Z_LPF | | | |
| | TRP | DLT | BB | TB | TRP | DLT | BB | TB | TRP | DLT | BB | TB |
| Subject 1 | 1 | NA | 0 | NA | 1 | NA | 1 | NA | 0 | 1 | 0 | NA |
| Subject 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | NA | 1 | 1 | 0 | 1 |
| Subject 3 | 0 | 1 | NA | 1 | 0 | 1 | NA | 1 | 0 | 1 | 0 | 0 |
| Subject 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | NA | 1 | NA |
| Subject 5 | 1 | 0 | NA | 1 | 1 | 0 | NA | 1 | 1 | 1 | 0 | 1 |
| Subject 6 | 1 | NA | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Subject 7 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | NA |
| Subject 8 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| Subject 9 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |
| Subject 10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| TOTAL | 7 | 6 | 6 | 8 | 8 | 6 | 7 | 7 | 7 | 8 | 5 | 6 |
| Percentage | 70% | 60% | 60% | 80% | 80% | 60% | 70% | 70% | 70% | 80% | 50% | 60% |
| Fatigue Score | 27 | | | | 28 | | | | 26 | | | |
| Overall Percentage % | 68% | | | | 70% | | | | 65% | | | |

### 3.5.4 Questionnaire Responses

The visual observation during the experiment indicated that the majority of the subjects were in a state of fatigue in the middle of each trial. They were not able to hold the upper limb in the suggested position (Figure 3.6) throughout the experiment. However, by the end of the experiment when all the trials were finished, this fatigue was not accumulated enough to represent a significant state of fatigue possibly due to the break period and robotic assistance as described before. Probably due to this reason, the majority of the subjects mentioned in the questionnaires that they were only feeling "Somewhat fatigued" after the last trial of the experiment was finished. This is described in the summary of questionnaires in Table 3.10. Only one out of ten subjects mentioned that the experiment was difficult and only one subject reported to be "Very fatigued". All the subjects were ready to continue the experiment further if required.

Table 3.10: Summary of Questionnaires From All Subjects.

| | Subject 1 | Subject 2 | Subject 3 | Subject 4 | Subject 5 | Subject 6 | Subject 7 | Subject 8 | Subject 9 | Subject 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Fatigue Status? | Not Fatigued | Very fatigued | Somewhat | Somewhat | Somewhat | Somewhat | Somewhat | Somewhat | Somewhat | Somewhat |
| Can continue the exercise? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Was the experiment challenging? | Somewhat | Yes | Yes | Yes | Not at all | Yes | Yes | Not at all | Somewhat | Yes |
| Duration of the experiment | Moderate | Moderate | Moderate | Moderate | Moderate | Very Long | Moderate | Moderate | Moderate | Moderate |
| Was the experiment difficult? | Easy | Moderate | Moderate | Too Easy | Moderate | Moderate | Moderate | Moderate | Somewhat Easy | Difficult |
| Which movement was difficult? | Away from Body | Away from Body | Towards Body | Towards Body | Towards Body | Away from Body | Towards Body | Towards Body | Away from Body | Towards Body |

## 3.6 Discussion

### 3.6.1 Discussion on EMG Analysis

It was noticed that most of the participants were challenged especially on the DLT and TRP muscles due to the horizontal position of the upper limb. It was observed that none of the participants were able to hold their upper limb in the horizontal position continuously (as it was supposed to be). This was due to the intentionally complex movement requirements [63]. Subjects could only complete the trials by lowering their upper limb below the shoulder level (hence, by not following the preferred position in the experiment design).

In the experiment, the HapticMaster robot was configured in the Active Assisted mode. Hence, the robot was providing some assistance to the participant when there was less effort from the participant to move the end-effector along the different segments. Additionally, all the participants in the experiment were healthy individuals. The experiment protocol also defined 1-2 minutes of break period between each trial. This period was introduced in order not to harm the participant's muscles due to any prolonged interactions. But this break period often resulted in a recovery from the state of muscle fatigue developed during the trial (short-term fatigue) before they started the next trial. Hence, the continuity of any trend in the features used as fatigue indicators was partly lost. So the experiments could have been made a bit more difficult and the break period could be avoided so that the muscles are sufficiently tired to produce better indications of fatigue. Probably due to this reason, at the end of the experiments, all the participants stated (through a questionnaire as in Table 3.10) that they were only slightly fatigued. The information about the short-term fatigue during the intermediate stages was not captured through a questionnaire and, hence, not recorded. This was a missing step in the current protocol that will be considered in future experiments.

During the analysis of EMG signals, the expectation was that there will be an increasing trend for the average power and a decreasing trend in median frequency as the trials progressed. The results had indicated that both the parameters displayed such a trend as explained by the summary tables, Table 3.1 and Table 3.2. In the current experiment, the fatigue was mainly caused by the horizontal position of upper limb hence, the fatigue had affected mainly the DLT and TRP muscles. Comparison of mean values of EMG features across trials displayed higher percentage fatigue scores for Trapezius and Deltoid muscles in the majority of the analysed cases (60% and 70% respectively) compared to Biceps Brachii and Triceps Brachii muscles (37.5% and 40% respectively).

### 3.6.2 Discussion on Kinematic Data Analysis

The study of the kinematic features showed that there was an increase of RMSE error more visible in S2 and S3 segments than in S1 and S4 segments. This could be because S2 and S3 were the most difficult segments, which were away from the body and, hence, tracking error was more visible in them. To ascertain if the increase of RMSE error between first and last trial was due to fatigue or perception error, the error between the first and second trial was compared. Another summary table was formed by comparing the median values of RMSE error between the first and second trials as in Table 3.11. The fatigue percentage for S2 and S3 segments were found to be 40% and 50% respectively in this case compared to the case considering the first and last trials (70% for S2 and 60% for S3). This indicated that the RMSE error due to fatigue was not as visible in the second trial as was the case in the last trial in the majority of the analysed cases. This study implied that the increased fatigue score during S2 and S3 segments was not attributed to the perception error in locating the 3-dimensional reach points but was due to the development of fatigue as the trials progressed.

Table 3.11: Summary Table for RMSE Error in Position Considering 1st and 2nd Trials

| Feature -> | Root Mean Square Error (RMSE) between Actual Position Vector on MJT Position Vector | | | |
|---|---|---|---|---|
| Hypothesis -> | The median value of RMSE parameter in the FIRST trial is smaller than that of the SECOND trial (1 = TRUE, 0 = FALSE, NA = Not Known) | | | |
| Methodology -> | Compare the median values of the parameter between 1st and 2nd trials to see if there is an increase of error. Each trial includes 10 iterations. | | | |
| Segments -> | S1 | S2 | S3 | S4 |
| Subject 1 | 0 | 0 | 0 | 0 |
| Subject 2 | 0 | 0 | 0 | 0 |
| Subject 3 | 0 | 0 | 1 | 1 |
| Subject 4 | 0 | 0 | 0 | 0 |
| Subject 5 | 1 | 1 | 1 | 1 |
| Subject 6 | 0 | 1 | 0 | 0 |
| Subject 7 | 1 | 1 | 1 | 1 |
| Subject 8 | 1 | 0 | 1 | 1 |
| Subject 9 | 0 | 1 | 1 | 0 |
| Subject 10 | 0 | 0 | 0 | 0 |
| **TOTAL** | 3 | 4 | 5 | 4 |
| **Percentage** | **30%** | **40%** | **50%** | **40%** |

The S2 and S3 segments for the majority of the subjects involved too many variations at the reaching point of the segment possibly due to the difficulty in accurately judging the end position of the segments. It seems that this inaccuracy increased when the subjects got fatigued as the trials progressed. This might have resulted in an increased RMSE in the final trials of S2 and S3 segments compared to the initial trials as implied by the higher percentage scores. On the other hand, the smaller percentage for the S1 and S4 segments (40%) might be because they involved movements in space, where the upper limb was closer to the body. This might make the movements easier than the other segments. This might mean that the subjects were in a more comfortable upper limb position during S1 and S4 movements or it was more easy to follow the robot in these segments. These results can be related to the findings of [36], which stated that the 'reaching away' movements were longer than the 'returning towards' movements. However, there could be a further explanation for the error in movements away from the body. The perception errors when trying to reach virtual objects away from the body could cause larger tracking errors due to overestimation of the distance to peripheral targets, which might lead to overshooting reaching movements [175][21][88].

The results of EMG fatigue analysis had indicated that the DLT and TRP muscles were fatigued more. Similarly, the results from the analysis of RMSE error had indicated that S2 and

S3 segments displayed more error and variation in position compared to S1 and S4 segments. Hence, it can be inferred that the indication of fatigue by EMG signals (mainly from TRP and DLT muscles) were kinematically correlated with the errors and variations in position mainly in the segments, which were difficult to execute (S2 and S3) as shown by the summary tables of kinematic and EMG features.

### 3.6.3 Discussion on Correlation Study

In the correlation study between EMG and force, the effective kinematic force at the robotic end effector was used instead of the force in the near proximity of muscles, where the EMG was measured. The force was the result of a combined action by multiple upper limb muscles. The study used individual force components ($F_x$, $F_y$, and $F_z$) instead of using the resultant force values. The robotic interaction involved dynamic muscle contraction tasks, where the length of muscles changed during different segment movements.

During the correlation study between EMG and kinematic data, considering all subjects and trials, a gradual change (mostly decrease) in correlation coefficient was noticed as the trials progressed (noticed mainly in S1, S2, and S3). This may be an indication of fatigue. This was observed mainly for $F_x$ and $F_y$ force components. During fatigue, the non-linearity in the correlation between the muscle force and EMG amplitude might have caused the particular behaviour of correlation coefficients as the trials progressed. But this decrease in correlation coefficient might not help to differentiate which muscles were fatigued or which muscles had caused the decrease.

Since the results from subject-wise correlation (mainly in BB and TB muscles) were in line with the findings from the correlation analysis using all subjects together, it seems that the subject-specific variations did not significantly affect the sign-pattern of correlation coefficients in these muscles. It was noticed that the TRP and DLT muscles did not show a consistent sign-pattern for the correlation coefficients in individual subjects probably because they were in a more fatigued state compared to the BB and TB muscles. Previously, the EMG analysis in Subsection 3.5.1 had indicated that DLT and TRP muscles were more fatigued than the BB and TB muscles. So, it seems that muscle fatigue had affected the correlation between the EMG and kinematic force since the fatigued muscles displayed the least correlation in the majority of the subjects. Possibly due to this reason, the sign-pattern was more profound in the BB and TB muscles as shown in Table 3.7. It seems that a pattern existed for the correlation sign when there was a state of less-fatigue or no-fatigue. The muscles BB and TB did not seem to play a significant role in the shoulder position; instead they played more role in determining the direction of movement along the four segments. Probably due to this reason, these muscles were found to have strongest EMG-Force correlation compared to TRP and DLT muscles. The TB muscle was found to be the most correlated in almost all the segments, whereas BB muscle was found to be more correlated in the towards-body and close-to-the body segment S4.

## 3.7 Chapter Summary

The research studied quantitatively which muscles were involved and fatigued in a robot-assisted exercise in a 3-dimensional space in presence of a virtual environment. The EMG analysis indicated that the Trapezius (TRP) and Anterior Deltoid (DLT) muscles were more in a state of fatigue compared to the Biceps Brachii (BB) and Triceps Brachii (TB) muscles. The study also looked into how the kinematic features from the robot represented the muscular fatigue. The variation in tracking error during the robot-assisted upper limb interactions was found to indicate physical fatigue in the muscles involved.

Similar to the study by [63], it was identified that the DLT and TRP muscles were fatigued more. This was because of the role of the two muscles in lifting the arm to the shoulder height in order to perform the activity. The higher fatigue indication in the Trapezius and Deltoid muscles can be mapped to kinematic indications of fatigue mainly in the segments S2 and S3, which were away from the body because these muscles were actively contributing to keeping the horizontal position of the upper limb. The extracted features have shown the potential to identify the fatigued muscles as expected. The study also showed that the EMG and kinematic features have a potential to be used to highlight the extent of muscle involvement, as the positioning of the segments and the required articulations for performing those segments relate to the EMG observations. For example, the increase of RMSE error was the least in S1 and S4 segments, which were comfortable 'near-the-body' movements and considering musculoskeletal physiology, Biceps Brachii and Triceps Brachii muscles play the major roles in these segments. The summary tables for tracking error also implied that the increased fatigue score during S2 and S3 segments was not attributed to the perception error in locating the 3-dimensional reach points but due to the development of fatigue by the end of the experiment.

In the experiment, the HapticMaster robot was configured in the Active-Assisted mode and all the participants in the experiment were healthy individuals. The robot was providing some assistance/guidance to the participant when there was less effort from the participant to move the end-effector along the different segments. A limitation of this study was that the robotic assistance resulted in a reduced the muscle fatigue to the participant. However, it was also noticed that the indications of fatigue were observed even with this robotic assistance. Additionally, the experiment protocol had also defined 1-2 minutes of break period between each trial. This period was introduced in order not to harm the participant's muscles due to over challenging. However, this break period could result in a recovery from the state of muscle fatigue developed during the trial (short-term fatigue) before they started the next trial. Hence, the continuity of any trend in the features used as fatigue indicators was partly lost. Hence, the experiments could have been made a bit more difficult and the break period could be avoided so that the muscles are sufficiently tired to produce better indications of fatigue. Probably due to this reason, at the end of the experiments, 8 out of the 10 participants stated (through a questionnaire) that they were only slightly fatigued. The state of fatigue during or in the middle of different trials could also have been captured through the questionnaire. These issues were planned to be addressed in Experiment-2, where an inherently tiring exercise was designed to confirm the findings from this study.

To conclude, even though a decrease of correlation coefficient could be a possible indication of fatigue, this needs to be confirmed further in an inherently tiring exercise. Moreover, this way of detecting fatigue requires both EMG and kinematic data to be collected during the interaction and, hence, need not be an optimal solution to implement in a real rehabilitation training environment. The MJT based kinematic features are used mainly for point-to-point movements and, hence, might not be a generally usable parameter in a training scenario, where various directions of upper limb movements in space are involved. Hence, as shown in the results and discussions, the EMG based features could be the possible fatigue indicators usable to implement an adaptive robotic training environment.

CHAPTER 4

# DETECTING USER INTENTION TO MOVE DURING HUMAN-ROBOT INTERACTION

## 4.1 Introduction

The possibility of using electromyogram signals for classifying point to point upper limb movements in the initial moments of dynamic muscle contraction exercises is explored in this chapter. One of the major applications of hand prosthetics for physically disabled are the detection of intention to move the upper limb. This requires prediction of the intended destination using muscle activation [186]. Even though dynamic upper limb movements and orientation can be sensed by using accelerometer sensors, EMG measurements, which are direct estimates of muscle activation could be more useful here. In the context of rehabilitation exercises of stroke patients who are subjected to reduced muscular or cognitive capabilities, EMG features can also provide us with a better picture of the development of muscle fatigue as a measure, the extent of muscle tiredness and it's effect on prediction accuracy of the intended movement. This also helps to employ measures to avoid causing fatigue for example, by offering break periods.

The majority of the studies on the prediction of upper limb movements as described in Subsection 2.4.2 used the steady state EMG features to classify only the hand gestures, and they did not classify the gross spatial upper limb movements, which involved the major muscles of upper-arm. Previously, in the context of steady state muscle activities, [150] and [199] suggested a window length of 100-200ms for the EMG analysis based on the voluntary reaction time as suggested by human muscle physiology. However, during gross upper limb movements, multiple co-contractions occurs between muscle pairs and supporting muscles. Past studies have identified a non-linear EMG-Force relationship during non-isometric muscle contractions compared to isometric (steady state) contractions [203]. This would result in higher EMG variations during dynamic muscle contractions than during fixed gestures over the course of a chosen task. Hence, for predicting such movements, a steady state EMG analysis might not be sufficient and the dynamic EMG variations need to be considered. Also, there is a need to explore what could be a better window length for EMG analysis in such a context.

The hypothesis for the current study was that predicting the end position of upper limb movements based on the EMG variations during the initial seconds after a task initiation would have applications in a variety of human machine interaction applications including adaptive rehabilitation training. Furthermore, the fatigue state of muscles will impact on muscle activation, which can further inform the rehabilitation exercise plan. Hence, the EMG signals recorded in Experiment 1 (Chapter 3) from four gross upper limb muscles (Biceps Brachii, Triceps Brachii, Anterior Deltoid and Trapezius) were used for the purpose of this study. The experiment and results obtained from this study have been published in [192].

## 4.2 Research Question

Can the EMG collected at the beginning of upper limb exercises be used for predicting the motion intention during robot-assisted rehabilitation training?

## 4.3 Materials and Methods

The EMG data collected during the HapticMaster robot interaction while making segment movements in Experiment 1 was used in this study to predict the type of the upper limb movement. The EMG signals were band pass filtered in the frequency band of 20-450 Hz using Chebyshev Type II filter to achieve a steeper roll-off [60][174][139]. The power line interference at 50 Hz was removed before the signal analysis using a notch filter.

### 4.3.1 EMG Feature Extraction

Various features for EMG feature extraction have been explored in the past studies such as [150] who suggested the Waveform Length (WL) as one of the best single features to recognise hand gestures. EMG features like Mean Absolute Value (MAV), Zero Crossing Count (ZC), Slope Sign Change (SSC) and Waveform Length (WL) have already been used in the past to control upper extremity prostheses [65]. In contrast, another study [127] that examined the classification of seven hand movements using EMG, suggested that the temporal features like Slope Sign Change (SSC) and WL do not help much for the recognition except the mean absolute value (MAV). In the current study the same set of EMG features were used. Each segment (S1 to S4) was a point to point movement defined in space. The EMG signals collected during each segment movement were used to calculate the EMG features during each window of analysis. In the first stage of analysis, each segment iteration of around 5 seconds duration was considered as one window to calculate the features. In the second stage, each segment was divided in to windows of width 100 milliseconds and the corresponding features were calculated for each window. This was different from the window size of 200ms used by Oskoei et al. [150] who conducted the EMG analysis only for fixed hand gestures. Different combinations of EMG features (WL, MAV, ZC and SSC) from four upper limb muscles/electrodes (TRP, DLT, BB, TB) were experimented. Different combinations of muscles (TRP+DLT+BB+TB, TRP+DLT, BB+TB) were also studied. The following features were used in the study.

***Average Power***: Average power of EMG is defined as the energy contained in the signal over a defined time interval and is interpreted as the energy in a single pulse of the signal as represented by Equation 3.1.

***Waveform Length (WL)***: Waveform Length measures the cumulative changes in amplitude from time sample to time sample over the entire time period. This is equivalent to treating both ends of the waveform like the ends of a jumbled string, pulling on them until it forms a straight line and then measuring the straight-line distance [194].

***Zero Crossing Rate (ZC)***: ZC rate is defined as the number of times the signal crosses the reference within a specified interval. ZC rate increases as the high frequency content of the signal increases [194].

***Slope Sign Change (SSC)***: Slope sign change is related to signal frequency and is defined as the number of times that the slope of the EMG waveform changes sign within an analysis window [194].

***Mean Absolute Value (MAV)***: This feature is the mean of the absolute values of the signal in an analysis time window with a specified number of samples [194].

### 4.3.2 Classifier

The EMG features were used for classifying the different segment movements using supervised machine learning techniques. Supervised learning is the machine learning task of learning a function, which maps an input to an output based on example input-output pairs. It infers a function from a labeled training data set consisting of training examples [177][142]. There will be input variables (x) and an output variable (y) and the algorithm will learn the mapping function from the input to the output. The goal is to approximate the mapping function so well that when we have a new input data (x), then we can predict the output variables (y) for that data. It is called supervised learning because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. We know the correct answers, the algorithm iteratively makes predictions on the training data and is corrected by the teacher. Learning stops when the algorithm achieves an acceptable level of performance.

The support vector machine (SVM) is a supervised machine learning method, which can generate input-output mapping functions from a set of labelled training data and can be used for both classification or regression challenges. However, it is mostly used in classification problems.

SVM is a discriminative classifier formally defined by a separating hyperplane. In other words, given a labelled training data, the algorithm computes an optimal hyperplane, which categorizes new examples. In a two-dimensional space this hyperplane is a line dividing a plane in two parts, where each class lay in either side. SVM based classifier was used in the current study due to its ease of use and the ease of tuning the parameters. Also, its strategy of determining maximum-margin hyperplane is one the best to reduce the prediction errors. SVMs can efficiently perform a non-linear classification using kernels, implicitly mapping their inputs into high-dimensional feature spaces. There are two configuration parameters required when using an SVM classifier, the cost (c) and gamma parameters. The cost parameter determines the trade-off between minimising the training error and maximising the size of margin. The parameter gamma is used for setting the type of kernel to be used for the classification.

In the current study, the EMG classifier code was developed in python using 'libsvm' library [94][31]. The SVM model was configured with a linear kernel type, with the cost and gamma parameters calculated at run time. The 'grid.py' (a handy python script available from LIBSVM Tools) was used to determine the optimal values of the SVM parameters through a systematic grid search. The script would assess the classifier performance versus the parameter combination in order to decide the best values for the cost and gamma parameters. The script was customised to return the optimal parameters when called from the main program. In order to defend against both under-fitting and over-fitting, grid.py used an n-fold cross-validation, where the default value was n = 5. In 5-fold cross-validation, the data was split into 5 groups of approximately equal size. The model was trained using 4 groups and then tested on the one remaining. The whole process had 5 iterations, so that each of the groups will have had a turn at being the testing set. After the last iteration, the average accuracy across all the 5-folds was used by the script to identify the best values for the parameters to be used by the classifier [94][31]. The research used the EMG features corresponding to only one of the subjects (subject 1) for the cross-validation to calculate these parameters.

The SVM model was generated using the function 'svm_train()' provided by the LIBSVM [37]. The model was configured as a multi-class classifier (C-SVC) with a non-linear kernel function and using the calculated optimal cost and gamma parameters. Then the function 'svm_predict()' from the LIBSVM was used to predict the segments using the test data and SVM model. The test data and the corresponding labels were passed into the function 'svm_predict()', which returned the results after prediction using the trained SVM model. The evaluation of the prediction results for the individual segments was done by comparing 'true labels' against the 'predicted labels' using the function 'evaluations()'; one of the utility functions provided by 'svmutil'. The function calculates the accuracy, mean squared error and squared correlation coefficient using the true values and predicted values. The function calculated the classifier accuracy based on Equation 4.1, and the results were then saved into corresponding output files.

$$AccuracyPercentage(ACC) = \frac{TotalCorrectlyClassifiedLabels}{TotalNumberLabels} * 100 \tag{4.1}$$

Two types of analysis windows were used to generate the train/test features for the classifier. In the first method, the whole segment of around 5 seconds duration was used as one window to generate the features and all the segments were used in the classifier. A segment was defined as a point-to-point upper limb movement in space, and the corresponding EMG data represented the muscle activation from the start to the end of each segment iteration. In this segment based analysis, the EMG features for each segment iteration (segment based analysis) were analysed to study if the dynamic upper limb movements were classifiable. The training and testing data samples for each subject were generated using the EMG features corresponding to each segment movement. Before selecting the training and test sets for each subject, the features corresponding to each segment group were separated and randomised/shuffled to make it uniform. 75% of the samples from each segment were used as training data as shown in Figure 4.1. The remaining 25% of samples were used for testing the performance of the classifier. 75% of the randomised samples selected from each of the 4 segments were combined, converted to the SVM data format, and then saved into a separate 'train_data.csv' file for each subject. This formed the classifier training data input for that subject. The remaining samples were saved to a 'test_data.csv' file for that subject. This was repeated for all the 10 subjects. The training set included EMG features from a combination of 4 muscles. Different combination of EMG features (Waveform Length, Mean Absolute Value, Zero Crossing count and Slope Sign Change) corresponding to the four muscles (TRP, DLT, BB and TB) were used for training the SVM classifier. The results were statistically analysed using SPSS box plots.

In the second method, EMG features corresponding to 100$ms$ windows during the initial 1 second (initial 1 to 10 windows) of each segment were used as the input data for SVM classifier as shown in Figure 4.2. The analysis started with using only 1 window for training, then 2 windows, and so on, upto 10 windows. With the window width of 100$ms$ duration, using 10 successive windows for training the classifier would correspond to 1 second. The EMG data corresponding to each segment movement was divided into a number of windows and for each window the EMG feature values were calculated. The classifier data set were created for individual features like MAV, WL and AvgPow as well as for feature combinations like WL+AvgPow, WL+MAV, WL+MAV+ZC+SSC, and WL+AvgPow+ZC+SSC. The data set were also generated individually for each of the muscles BB, TB, DLT, and TRP as well as for the different muscle combinations, TRP+DLT, BB+TB, and TRP+DLT+BB+TB. From each of these combinations, only the mentioned number of feature samples were selected (corresponding to the number of windows under analysis). As described previously in Subsection 3.3.2, each trial involved 10 repetitions/iterations of each segment movement (S1 to S4). For generating the training and test data for the classifier, the input data was read by a python algorithm from a csv file that contained the calculated EMG features for each subject. This file was previously generated by a MATLAB algorithm

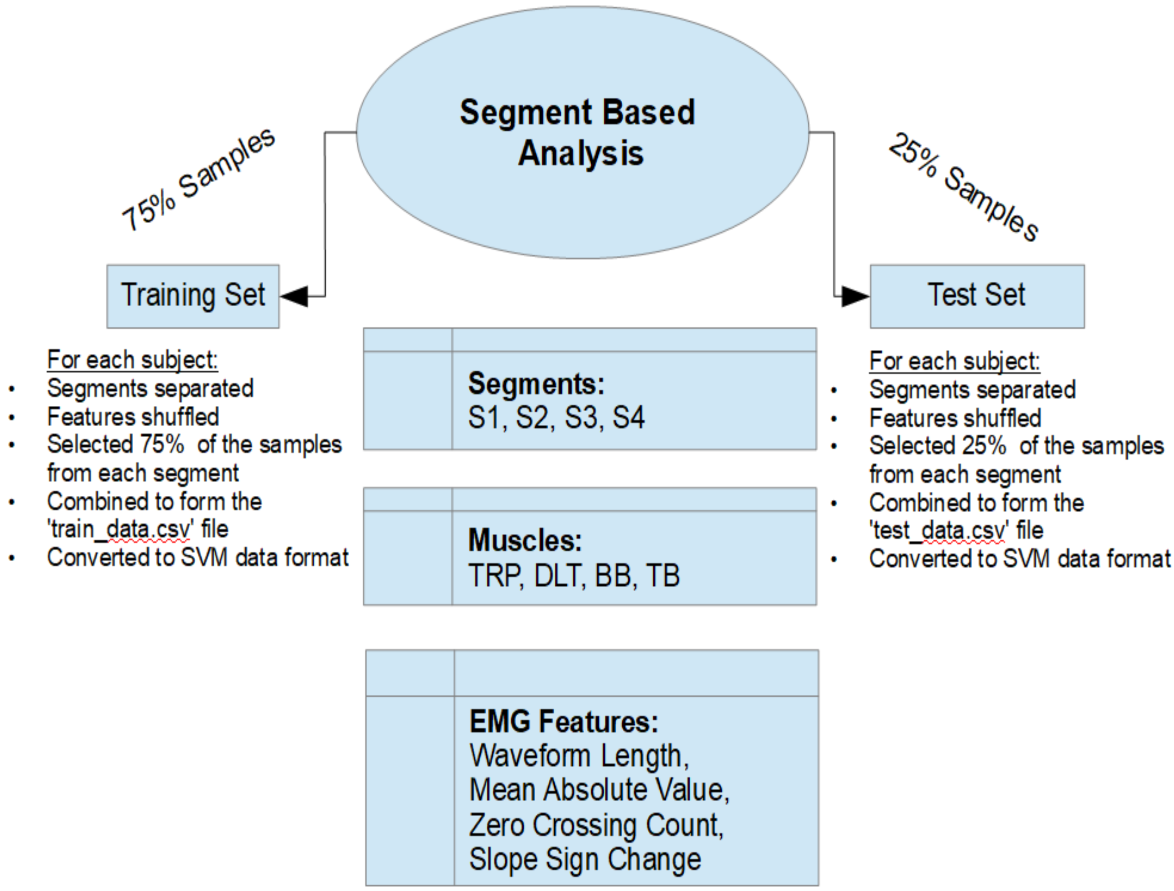


Figure 4.1: Segment Based Analysis: The training and test set for the classifier were selected from all the 4 segment movements (S1, S2, S3 and S4) for different combinations of EMG Features, and muscle groups. The EMG corresponding to one whole segment was considered to generate a feature value.

using the collected raw EMG data. The feature values were then loaded into a python array, and then sorted based on both the segment and the iteration columns to create the uniform set of training and test data. For forming the training and test data sets, the features corresponding to iterations were selected as below. For each subject, considering the 10 repetitions during a trial for each type of segment movement, a training data set was formed by selecting EMG features corresponding to the segment iterations 1, 2, 4, 5, 7, 8, and 10. The iterations 3, 6 and 9 were used for creating the test data as shown in Figure 4.3. Selecting the data set this way would also make sure that any slight amount of fatigue developed within the initial trials would be balanced in both the training and testing sets of the classifier. A maximum training set using 10 windows corresponding to 1 second analysis consisted of 280 feature samples (7 iterations x 4 segments x 10 windows). Similarly, the testing set consisted of 120 feature samples (3 iterations x 4 segments x 10 windows). Then the selected number of data samples from each of the 4 segments were concatenated for each subject, each feature and muscle combination, and then, converted into

SVM data format using a python algorithm. These were then saved into 'train_data.csv' and 'test_data.csv' files for the training and test data respectively, and this was repeated for all the 10 subjects. The SVM classifier was then trained using the training data set per subject for each of these features and muscle combinations. Finally, statistical analysis of the classifier accuracy for different segments was conducted using IBM SPSS version 22.

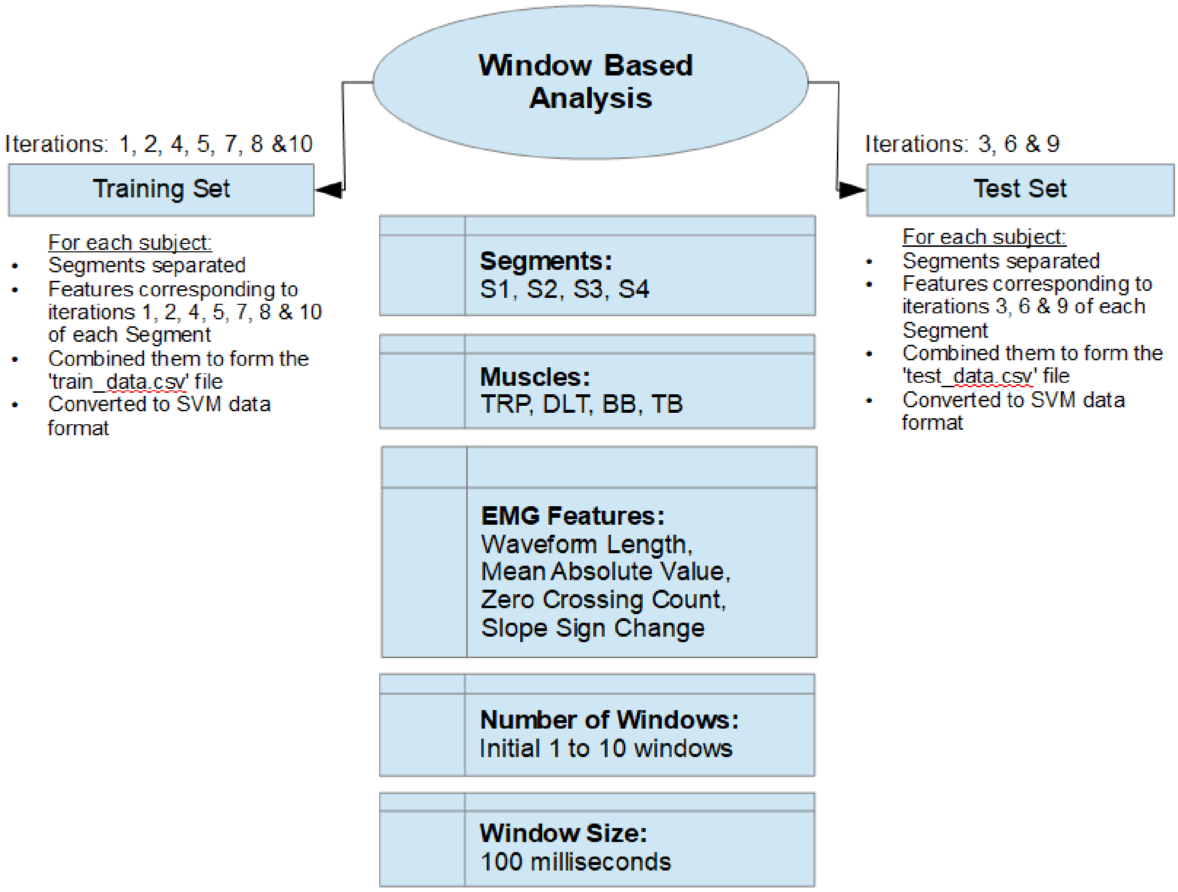


Figure 4.2: Window Based Analysis: The training and test set for the classifier were selected from all the 4 segment movements (S1, S2, S3 and S4) for different combinations of EMG Features, and muscle groups. 1 trial involved 10 iterations of each Segment. A window size of 100 milliseconds was used to calculate the EMG features. Different number of windows (1 to 10) were used for training the classifier. Iterations 1, 2, 4, 5, 7, 8, and 10 were used for training and the iterations 3, 6 and 9 for testing.

## 4.4 Results

The accuracy of classifier was tested using the EMG features for each subject. The accuracy represented the percentage of the number of correctly classified segment labels compared to the total number of known/actual segment labels.

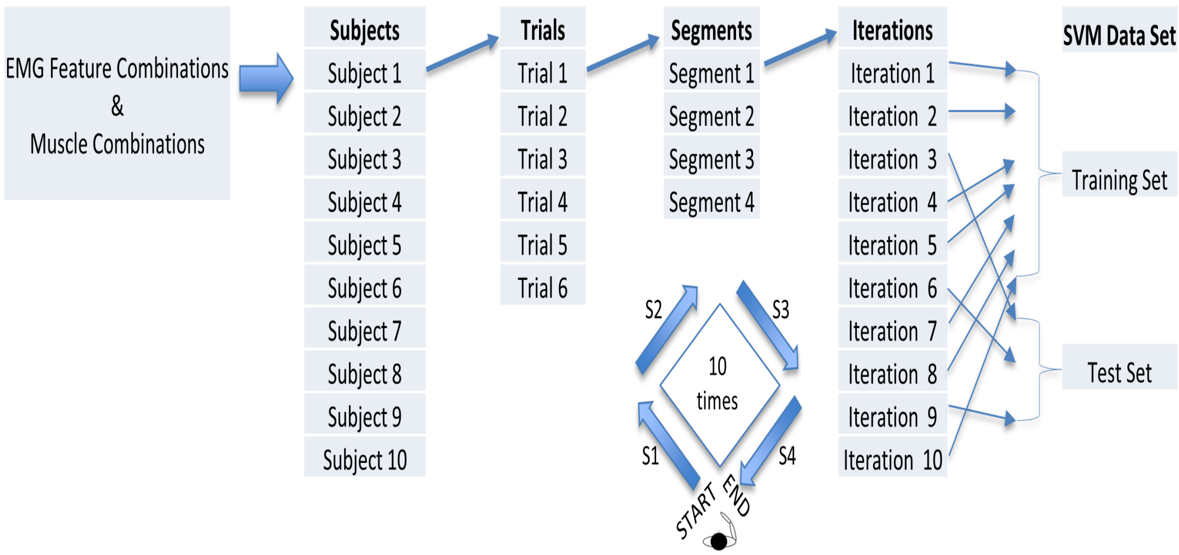


Figure 4.3: Window Based Analysis: Forming the training and test sets for the SVM classifier

### 4.4.1 Segment Based Analysis

Then the accuracy for the recognition of different segment movements was assessed for each segment. Based on the studies of [150], the box plots were created for the classifier accuracy using the combined features WL+MAV+ZC+SSC, as shown in Figure 4.6. The minimum value of median classifier accuracy in the four segments was found to be 88.19% and the maximum was 95%. A similar analysis on a single feature (WL) and the feature combination (WL+MAV) provided a minimum median classifier accuracy of 87.5% and 73.5% respectively as shown in figures 4.4 and 4.5.

Even though the results provided good median accuracy, the variation of accuracy as seen in the box plots were high for some segments. Moreover, taking the whole segment for classification does not make the prediction of movement intention accurate. Hence, it was decided to conduct a window based analysis on each segment iteration.

### 4.4.2 Window Based Analysis

In order to make the prediction of movement intention possible and to reduce the variability in accuracy of the classifier, a window based analysis was carried out using a window width of 100 milliseconds. Different numbers of windows were studied during the initial 1 second of each iteration. Each feature set used in the study was either a single feature (WL, MAV etc.) or a combination of features (WL+MAV+ZC+SSC) and for a single muscle or a combination of muscles (TRP+DLT+BB+TB).

Box plots showing the variation in accuracy across different subjects as the number of windows increased for each segment is shown in Figure 4.7. The feature combination WL+MAV+ZC+SSC

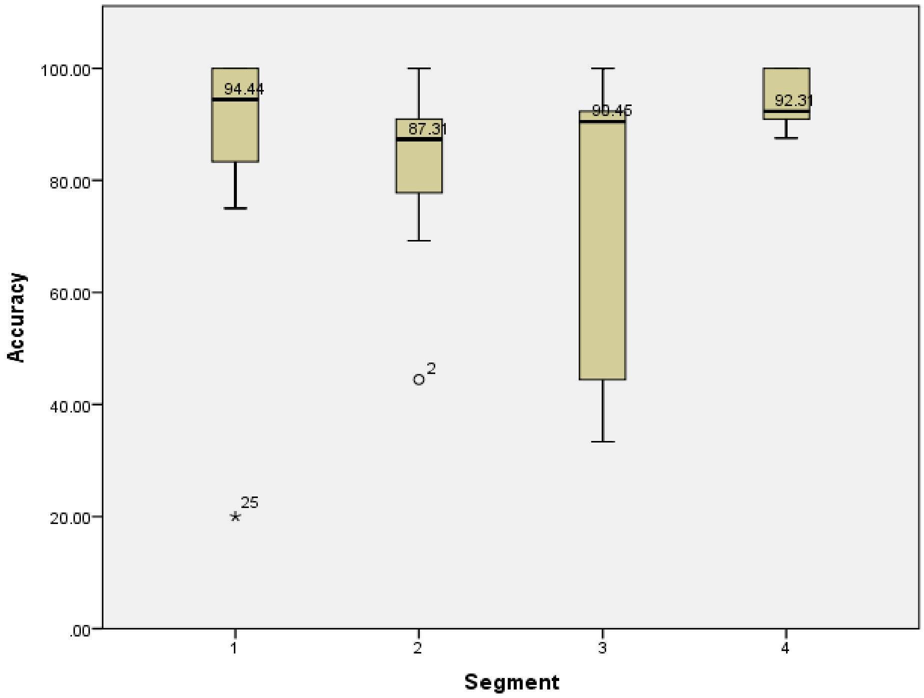


Figure 4.4: Segment Based Analysis: Accuracy(%) of Classifier for each Segment using the EMG Single Feature - WL

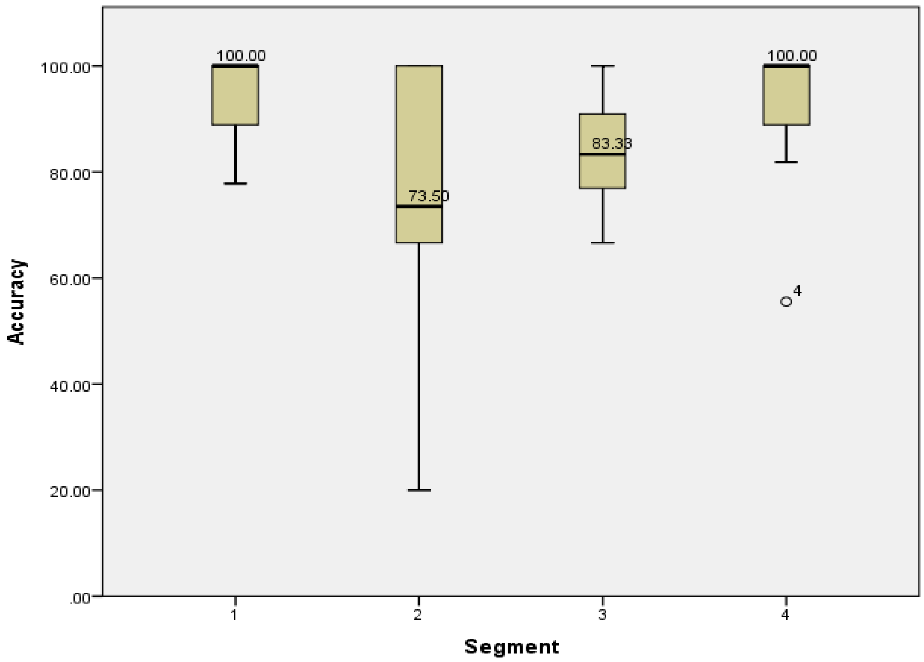


Figure 4.5: Segment Based Analysis: Accuracy(%) of Classifier for each Segment using the Combination of EMG Features, WL + MAV

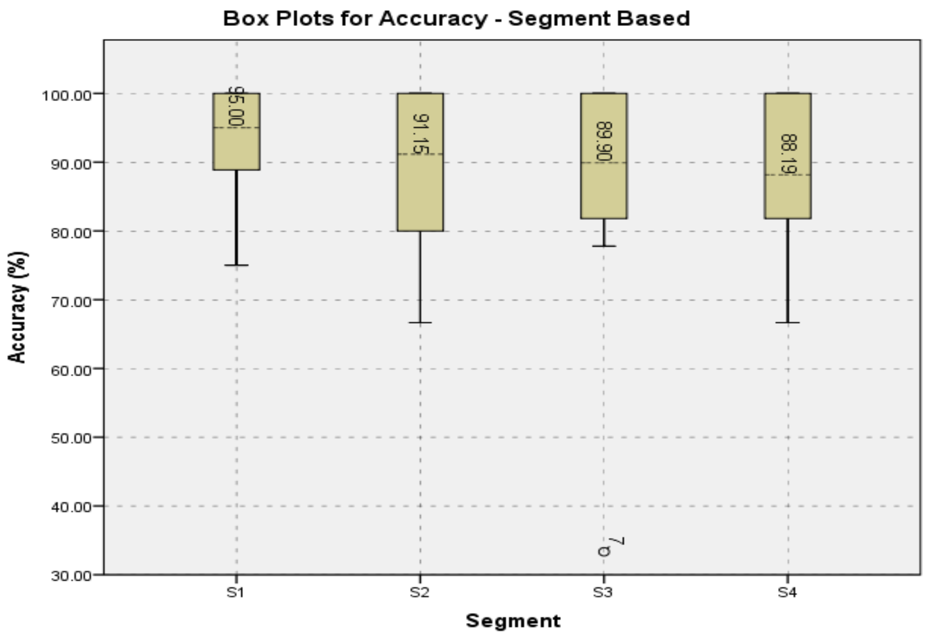


Figure 4.6: Segment Based Analysis: Accuracy(%) of classifier for each segment using the combination of EMG Features, WL+MAV+ZC+SSC

considering all the muscles together was used to plot this. Using 7 or 8 number of windows of 100 milliseconds width resulted in good accuracies with lesser variations simultaneously in all the segments S1, S2, S3, and S4. Even though the smaller number of windows also gave high accuracies in few subjects, the variations across different subjects were high and, hence, the results were less reliable. Using more number of windows resulted in reasonably good accuracy with lesser variations across the subjects.

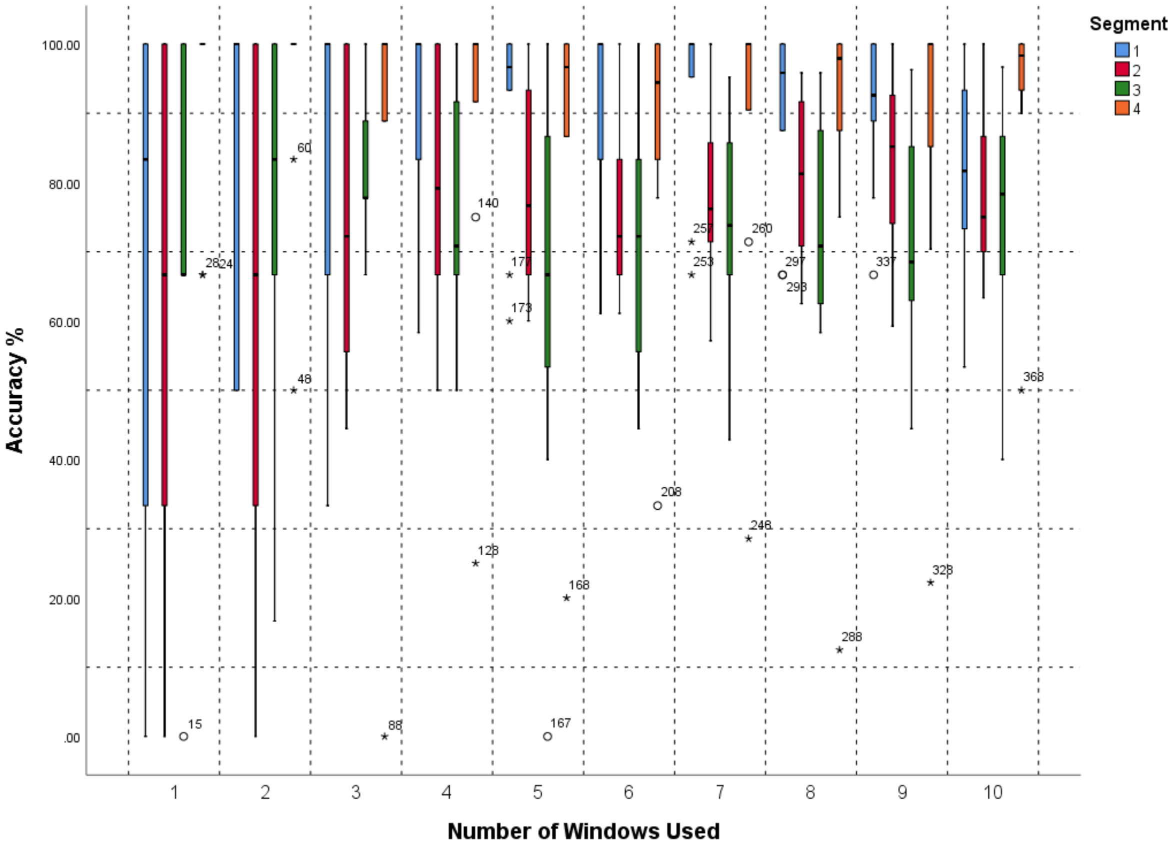


Figure 4.7: Accuracy as a Function of the Number of Windows Used: Box plots showing the progress of classifier accuracy(%) for each segment as the number of windows increased. The combination of EMG features WL+MAV+ZC+SSC was used considering all the muscles together.

Figure 4.8 depicts the accuracy of classifier corresponding to the different features and muscles using 7 windows of EMG feature combination WL+MAV+ZC+SSC.

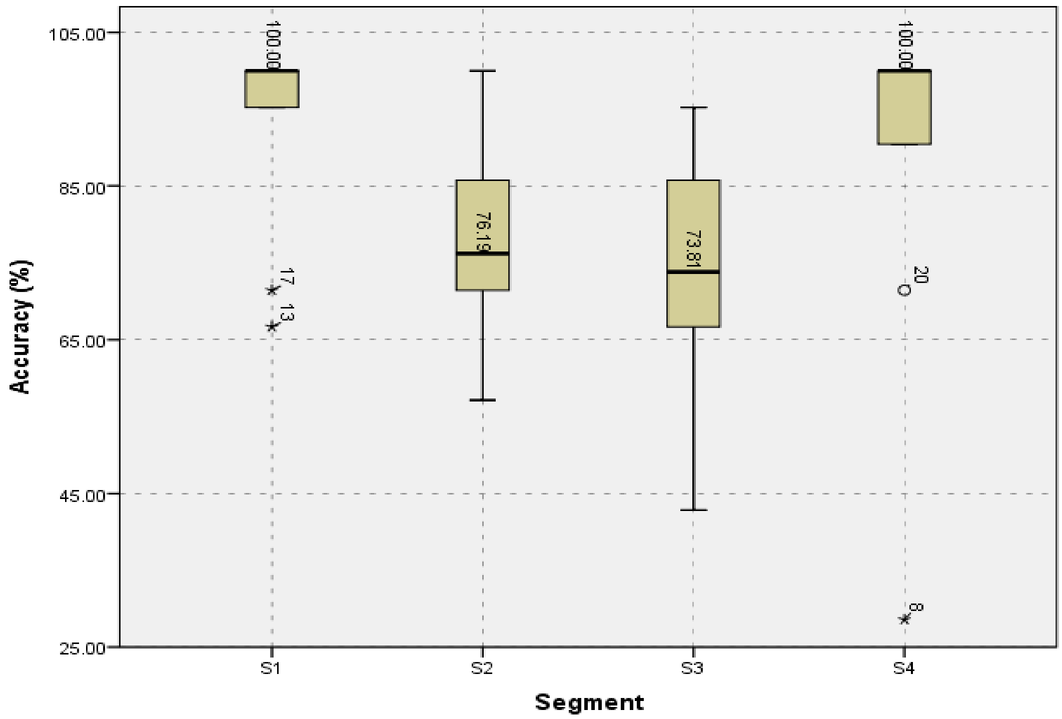


Figure 4.8: Window Based Analysis: Box plots for classifier accuracy. 100msec window based analysis using combined EMG features WL+MAV+ZC+SSC for all the muscles. 7 such windows were used to train the SVM classifier.

The descriptive statistics from different combinations of the EMG features as well as chosen muscle combinations for each classifier for the case of 7 windows are offered in Table 4.1.

Table 4.1: Classifier Accuracy and Descriptive Statistics for Combinations of EMG Features and Muscles: Window based analysis using initial 7 windows of width 100 msec.

| **Feature Combination** | **Muscle Combination** | **Segment** | **Median Accuracy** | **Inter-Quartile Range (IQR)** |
|---|---|---|---|---|
| WL | TRP+DLT+BB+TB | S1 | 100 | 11.9 |
| | | S2 | 76.1905 | 26.19 |
| | | S3 | 66.6667 | 26.19 |
| | | S4 | 100 | 9.52 |
| | TRP+DLT | S1 | 73.8095 | 44.05 |
| | | S2 | 71.4286 | 29.76 |

| | | | | |
|---|---|---|---|---|
| | | S3 | 35.7143 | 77.38 |
| | | S4 | 80.9524 | 42.86 |
| | BB+TB | S1 | 80.9524 | 55.95 |
| | | S2 | 71.4286 | 20.24 |
| | | S3 | 73.8095 | 33.33 |
| | | S4 | 95.2381 | 29.76 |
| WL+MAV | TRP+DLT+BB+TB | S1 | 100 | 15.48 |
| | | S2 | 80.9524 | 26.19 |
| | | S3 | 80.9524 | 35.71 |
| | | S4 | 100 | 19.05 |
| | TRP+DLT | S1 | 66.6667 | 57.14 |
| | | S2 | 52.381 | 53.57 |
| | | S3 | 57.1429 | 27.38 |
| | | S4 | 73.8095 | 38.1 |
| | BB+TB | S1 | 95.2381 | 17.86 |
| | | S2 | 71.4286 | 26.19 |
| | | S3 | 73.8095 | 26.19 |
| | | S4 | 100 | 28.57 |
| WL+MAV+ZC+SSC | TRP+DLT+BB+TB | S1 | 100 | 16.67 |
| | | S2 | 76.1905 | 16.67 |
| | | S3 | 73.8095 | 26.19 |
| | | S4 | 100 | 14.29 |
| | TRP+DLT | S1 | 59.5238 | 55.95 |
| | | S2 | 66.6667 | 38.1 |
| | | S3 | 40.4762 | 67.86 |
| | | S4 | 71.4286 | 29.76 |
| | BB+TB | S1 | 85.7143 | 38.1 |
| | | S2 | 52.381 | 44.05 |

| | | | | |
|---|---|---|---|---|
| | | S3 | 61.9048 | 22.62 |
| | | S4 | 90.4762 | 32.14 |

The overall accuracy considering all the segments together for different feature sets was higher for the muscle combination (TRP+DLT+BB+TB) compared to all other combinations as shown in Figure 4.9.

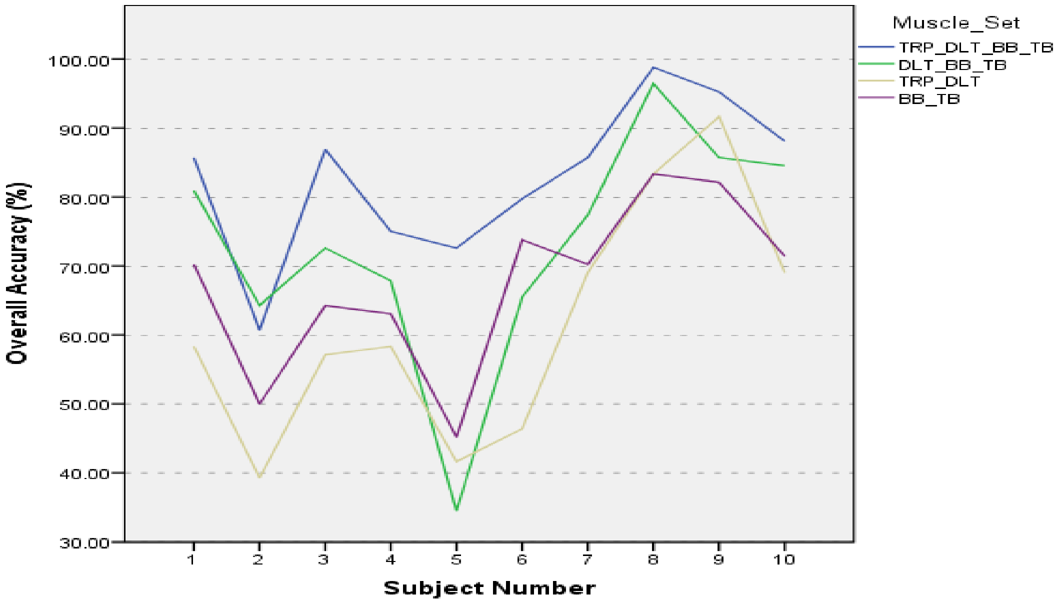


Figure 4.9: Overall Classifier Accuracy(%) Considering All Segments Together: Different muscle combinations for the combined feature set WL+MAV+ZC+SSC displayed the highest accuracy for the muscle combination TRP+DLT+BB+TB.

## 4.5 Discussion

The accuracy of classifier for single and multiple feature/muscle combinations indicated that the upper limb segment movements in space can be classified with a reasonable accuracy even in cases of dynamic muscle contractions for gross muscles. The study suggests that for complex upper limb motions it is not necessary to consider the EMG features corresponding to the fixed gestures (steady state) for training the classifiers as done by Oskoei et al. [150].

The segment-wise analysis conducted initially indicated the usability of EMG features to be used for classifying the gross muscle's spatial movements. The idea here was to initially explore this potential considering a large window first (one whole segment movement), and see if the collection of EMG data during the movement is unique for each segment. The prediction results indicated a reasonably good accuracy for the different combinations of features. Among all the feature combinations, WL+MAV+ZC+SSC was found to be the best as shown in Figure 4.6. Here, all the segments provided a good accuracy with less variation across subjects. The maximum accuracy observed was 95% for segment S1. Since the classifier results were promising, the EMG features seemed to be usable for the purpose of predicting the upper limb gross movements. However, in this case the feature sets were considered for all the segments together (S1 to S4) to calculate the classifier accuracy. Considering such a long window for the EMG analysis could possibly violate the assumption of signal stationarity. Hence, in order to confirm if the results answer the research question correctly, the further analysis was done using smaller window sizes.

The window-based study was conducted to see if the upper limb movements are predictable during the initial seconds of the segment iterations. Hence, only the features corresponding to the initial EMG windows during iterations in the first trial were used. This corresponded to task initiation during the initial milliseconds of each segment, where the intention of movement will be more visible. Afterwards the robotic assistance contributed to spatial movement and was likely affecting the recognition accuracy due to creating a dynamic interaction. It was noticed that for a number of 5 or fewer windows, even though there were some good median accuracy for the segments there were also high amount of variations in the accuracy (higher Inter Quartile Range). Some subjects had poor/nearly zero accuracy. But as the number of analysis windows increased beyond 5 windows, which corresponded to above 500 milliseconds from the start of each segment iteration, the accuracy started improving with lesser variations. This suggests that using small number of windows can be unreliable as a predictor for gross muscle movements.

Among all the cases of different feature and muscle combinations, both 7 and 8 number of windows gave good results as shown in Figure 4.7. Using 7 windows gave a higher median accuracy for the segments S1, S3, and S4 compared to 8 windows. Using 7 windows (so, total 700 milliseconds) for the classifier provided the best accuracy especially for the segments S1 and S4 with the least variations in accuracy (IQR). When the number of windows were increased further this did not result in a better accuracy, and in some cases even resulted in a reduced accuracy as shown in Figure 4.7. The figure also shows that the S2 and S3 accuracy values were lower than that of the S1 and S4 segments in the majority of the cases.

In the window based analysis, as shown in Table 4.1 the median value of the accuracy for the combined features WL+MAV+ZC+SSC displayed only slight improvement compared to the feature WL. The feature combination WL+MAV displayed an improved accuracy with reduced variance for S2 and S3 segments compared to other feature combinations. However, for S1 and S4 segments the accuracy variations across subjects were higher than that of single feature WL and the feature combination WL+MAV+ZC+SSC. It seems that the features ZC and SSC only slightly improved the classifier accuracy. This could be due to the fact than the features waveform length (WL), zero crossing rate (ZC), and slope sign change (SSC) are related, and hence, a change in WL might also result in changes in ZC and SSC. It was noticed that the classifier accuracy in case of the combined EMG features were better than that of single feature in majority of the subjects. This was in line with the findings of [150], which also stated that the time domain multi-feature set MAV+WL+ZC+SSC outperformed the other features.

It was also observed that out of the four segments studied, the accuracy of classifier for the segments S2 and S3 were comparatively lower than that of segments S1 and S4. For example, for the all muscle combination (TRP+DLT+BB+TB) as shown in Table 4.1, the median values of classifier accuracy for the single feature WL for S2 and S3 segments were 76.19% and 66.67% respectively. Similarly, for the combined feature set WL+MAV+ZC+SSC, the accuracy were 76.19% and 73.81% for the S2 and S3 segments respectively. It could be noticed that the corresponding accuracy in the case of feature combination WL+MAV was 80.95% and 80.95% respectively. The previous study [165] had discussed the effect of fatigue on the away-from-body movements during robot assisted interactions. The segments S2 and S3 were the segments that required more effort in reaching the end positions. However, in the current analysis only the data taken from the initial 1 second of each iteration and only upto 10 number of windows were used for the classifier. Hence, the later trials consisting of more fatiguing episodes were not included in the training or testing set. So, it is possible that the movement difficulty in away-from-body segments is affecting the performance accuracy in these cases.

The classifier accuracy was found to be affected based on different muscle combinations. When single muscles were studied using 7 windows for different combinations of features, the accuracy was not found better than the muscle combinations. For the single muscles analysis, different feature combinations were also analysed. All the feature combinations provided a recognition accuracy of around 50-60% except for the combination WL+MAV, which provided an accuracy of 90.48%, 61.90%, 83.38%, and 97.62% for the segments S1, S2, S2 and S4 respectively. Hence, single muscles do not seem eligible to be considered for the overall movement prediction because, it is the combination of muscle, which causes the gross arm movement predictable and not the individual muscles alone. Among the different muscle combinations, the combination of four muscles TRP+DLT+BB+TB always gave the highest accuracy compared to individual muscles. Irrespective of the number of windows considered, the muscle combination TRP+DLT as shown in Table 4.1 provided a poor accuracy with higher variations in most of the analysed cases. This could be because the involvement of these two muscles in combination was not the main deciding factor for the segment movements; instead they were mainly used to hold the upper arm in the horizontal position parallel to the shoulder. Hence, the use of TRP+DLT combination alone for prediction of segment movements could be unreliable. The DLT, BB, and TB seems to be the major contributors for movement accuracy because, taking out TRP muscle did not result in a significant change in the accuracy. For the muscle combinations TRP+DLT+BB+TB and DLT+BB+TB, accuracy were comparable and were found more stable and higher for S1 and S4 segments than S2 and S3 segments.

## 4.6 Chapter Summary

The results show that EMG features from upper limb during dynamic muscle contraction exercises can be used to classify point to point spatial movements that involve gross muscles. The initial study using the whole segments proved that there is a potential to classify the gross movements using EMG features. Later, the window based analysis could prove that there is a potential to predict the segment movements during the initial windows within each segment. The movement intention could be detected with a reasonably good accuracy within the initial 700 milliseconds that corresponded to 7 number of 100 millisecond windows.

The overall accuracy was found to increase when a combination of EMG features was selected for classification, compared to the individual features, which was in-line with the findings from past studies. Using individual muscles could not give a good accuracy but the accuracy was improved when all the four major upper limb muscles were considered for training the classifier. It was also found that the high variation and lower accuracy for the muscle combination TRP+DLT could be an indication that these two muscles did not play the major role in deciding the movement direction, and rather work in supporting the arm. In the majority of the analysed cases, the segments S1 and S4 segments displayed a high accuracy of prediction probably because they were "near-the-body" movements compared to the "away-from-body" movements of S2 and S3 segments. Possible applications of the study could be the detection of user intention during various human machine interactions and rehabilitation robotics.

CHAPTER 5

# Experiment 2: How Well Do The EMG Features Indicate Muscle Fatigue?

## 5.1 Introduction

The previous experiment (Experiment 1) on healthy individuals had explored how upper limb muscle fatigue can be estimated using EMG and kinematic features in a robot-assisted environment (Chapter 3) [165]. A potential trend in the features was observed and the results indicated the potential of EMG parameters to be used as fatigue indicators during human-robot interaction. However, the majority of the participants only reported slight fatigue after the experiment. As the experiment was performed in an active-assisted mode, the robot provided assistance/guidance to the participant and there was less effort from the participants to move the end-effector along the different segments. This seems to have resulted in a reduced muscle fatigue. Questionnaires had also stated that there was a low level of fatigue experienced by the participants after the experiment. The majority of the participants stated that they were "Somewhat Fatigued". The difficulty level of the experiment was reported as easy/moderate by most of the participants. All the participants responded that they could still continue the experiment. This did not ensure the suitability of the EMG features for fatigue estimation, in the chosen context of human-robot interaction. Hence, it was decided to conduct a second experiment, designed to be inherently fatiguing, to validate how the features of the EMG could represent the extent of fatigue. To ensure that the EMG features could indeed identify fatigue correctly, a second experiment was planned, which involved an inherently fatiguing set-up without any robotic assistance.

## 5.2 Materials and Methods

The experiment was designed as a pilot study to verify how fatigue indicators perform when there is a high level of fatigue as a result of a tiring upper limb exercise. For this purpose, with assistance from colleagues in sports science studies, a dumbbell lifting experiment was formulated. Ethics approval was obtained from the University of Hertfordshire (Protocol number: COM/PGR/UH/02741). The experiment was subsequently conducted on healthy individuals. Informed consent was obtained from all individual participants included in the study.

### 5.2.1 Experiment Setup

The experiment set-up included an EMG acquisition device (g.USBamp) from g.tec medical engineering GmbH, which is a multimodal biosignal amplifier for any type of electrophysiological signals. An electrode cable with a clip lead was attached to disposable electrodes to measure EMG signals from 3 major upper limb muscles of participants as shown in Figure 5.1. The data acquisition parameters (sampling rate, channel selection and so on) for the g.USBamp amplifier were configured using Simulink. Three EMG electrode channels were configured in bipolar mode with a sampling frequency of 1200Hz. The measurements were taken during each trial, as described in the Simulink model (Figure 5.2).

### 5.2.2 Protocol

The aim of this study was to identify the level of muscle fatigue induced by intensive upper limb exercise. Twenty (14 males, 6 females) healthy participants of at least 18 years old with no history of injury to the upper limb and back were involved in this experiment. Participants were students or staff members of the University of Hertfordshire or volunteers from outside the university. They were asked to sit straight on a non-rotating chair. Three gross upper limb muscles, Biceps Brachii, Triceps Brachii, and Deltoid were studied and three EMG electrodes were attached to the participants' upper limb. The task involved elbow flexion and extension movements as directed by visual instructions on the screen. The instruction also enforced uniform timing of flexion and extension for all participants. The participants were asked to hold the weights/dumbbell using their dominant arm. The experiment progressed from no weight (trial 1) to low-weight (trial 2), and then high-weight (trial 3). The initial trials also helped to warm up the muscles reducing the risk of injury. A short break period of 1 minute was given between each experiment trial.

The initial two trials were conducted until a defined number of iterations was reached. Trial 1 recorded the relaxed state of muscles which involved elbow flexion and extension tasks with no weight. This task was repeated 10 times continuously, where the starting time was guided by a "Beep" sound. The beep would repeat every 10 seconds since each iteration was defined to take 10 seconds to complete. In Trial 2, the participants were asked to hold a small load of 500g weight, while performing the elbow flexion and extension tasks and repeating this 10

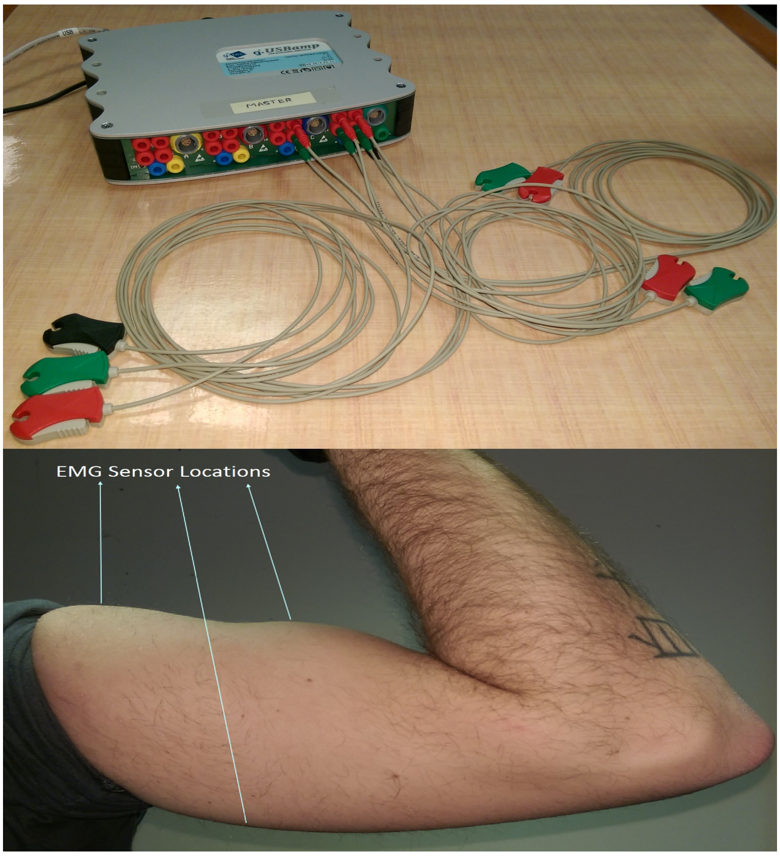


Figure 5.1: Experiment 2: Setup and Electrode Locations: Gross Upper Limb Muscles Biceps Brachii, Triceps Brachii and Deltoid muscles were studied.

times continuously or until the muscles become fatigued. The start of each iteration was again signalled by a beep. In Trial 3, the participants were asked to carry a heavy load (10kg for a male participant and 7.5kg for a female participant) and this involved elbow flexion and extension tasks continuously until the muscles were fatigued. The start of each iteration was signalled by a beep. The participants were allowed to stop the repetition when they were highly fatigued or unable to continue. In addition to the EMG measurements from muscles, a subjective measurement of fatigue at different stages was also taken at the end of the experiment using a questionnaire.

### 5.2.3 Methodology

The experiment was conducted mainly to verify if the low level of fatigue in many subjects measured through EMG fatigue indicators could be due to the robotic assistance during Experiment 1. EMG average power was calculated from the measured EMG data. Two types of analysis were conducted. Initially, variations in EMG average power were compared across trials 1, 2, and 3 in each participant. Secondly, a trend in EMG average power within trial 3 was studied. Trial 3 was designed to be the most difficult task that would cause muscle fatigue in the participants. In both

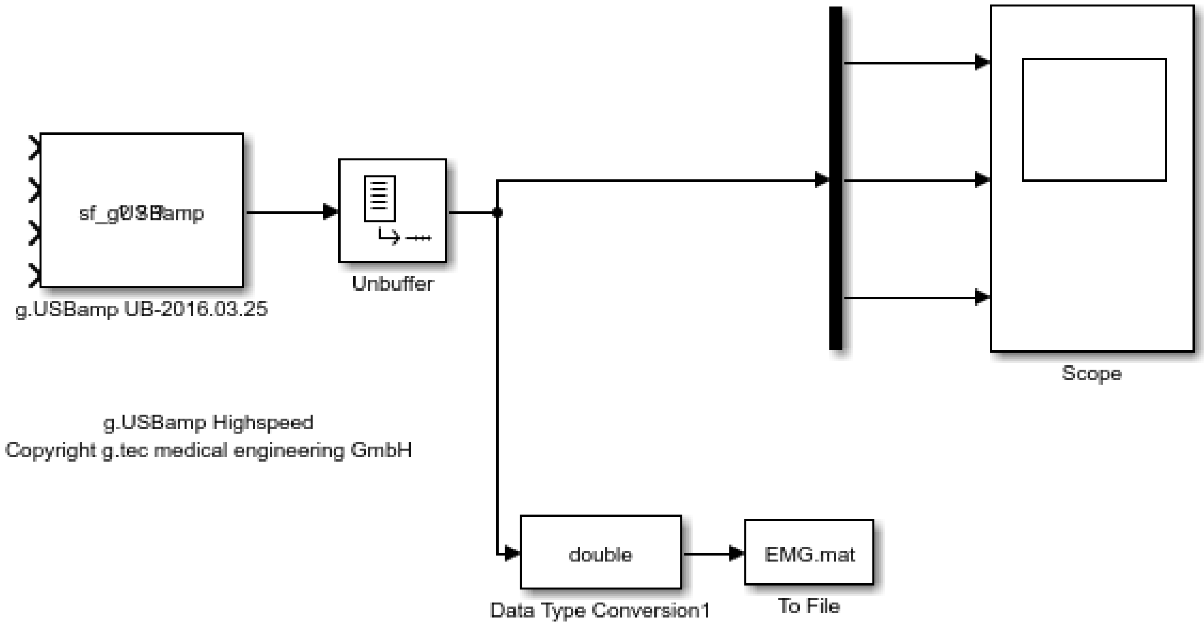


Figure 5.2: Experiment 2: Simulink Model to Collect EMG Data and Save to a .mat File.

methods, linear regression coefficients were calculated. Regression line slopes with significant p-values were used to state if there was a trend in the EMG features as the windows/trials progressed.

Since each iteration of flexion/extension tasks lasted for 10 seconds, non-overlapping windows with a length of 10 seconds were used to analyse the EMG data. Many participants did the first iteration very fast without looking at the screen or without keeping in sync with the visual directions on the computer monitor. Hence, during the analysis, the initial window (10 seconds) was skipped, which also helped to avoid random peaks at the beginning of the lifting task.

The collected EMG signals were filtered using an IIR notch filter to remove power line interference at 50Hz. The signals were then band-pass filtered using two different frequency bands in order to explore which of the two EMG frequency bands was more useful as fatigue indicator. Initially, for the analysis of average power, the signals were band-pass filtered in the frequency band 0.8-2.5Hz as used by [149]. However, in contrast to this study, the signals were not full-wave rectified since it was noticed that a rectification process would alter the frequency content of the EMG and the median frequency analysis would be affected. The median frequency analysis was conducted within the whole frequency band of 20-450Hz [176][139]. A non-overlapping moving window of 10 seconds width that corresponded to each iteration was used for generating each EMG feature value. The existence of a trend in the EMG features was studied by performing a linear regression of the feature values as the analysis windows progressed. Summary tables were formed based on significant regression slopes of EMG features.

In the summary table, a trend in average power or median frequency as the windows progressed in trial 3 was marked as '+', '-' or 'NS' (positive slope, negative slope or Non-Significant slope respectively, where a positive slope represented an increase in the EMG feature as the windows progressed, whereas a negative slope represented a decrease in the EMG feature).

## 5.3 Results

### 5.3.1 EMG Feature Analysis

In the previous experiment, most of the participants had reported through a questionnaire that they were only slightly fatigued. During this experiment, trials 1 and 2 were completed easily by most of the participants and trial 3 was completed with difficulty. During the analysis, average EMG features across trial 1, trial 2 and trial 3 were compared. The average EMG power of BB and TB muscles for trial 3 was significantly higher compared to trials 1 and 2 in both male and female participants (shown in Figure 5.3). The median EMG frequency of the BB and TB muscles also displayed a significant difference between trials (shown in Figure 5.4). These significantly different EMG feature values could be due to the obvious need of increased muscle force to lift the heavy dumbbell during trial 3 or due to muscle fatigue.

Hence, the trial 3 data alone were also analysed to see how the EMG features varied as the windows progressed within the trial. Regression lines were plotted within the trial for different muscles in all the subjects. A positive trend in average power and a negative trend in median frequency were observed as the windows progressed in trial 3 [174][211][181].

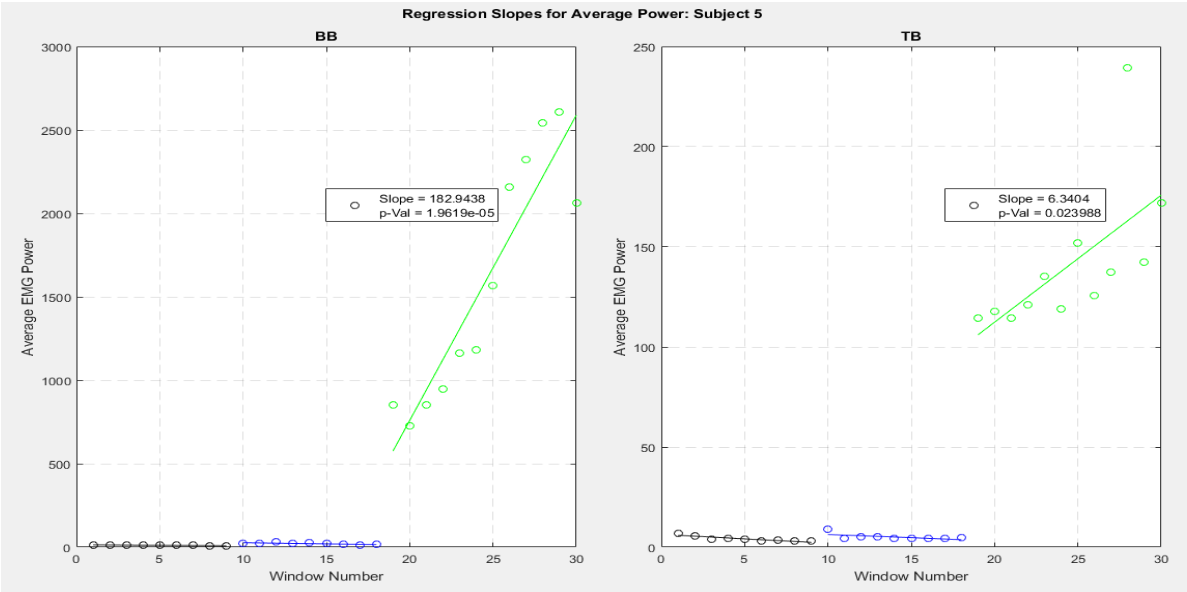


Figure 5.3: Regression Slope Across Trials for Average Power - Subject 5: Regression slopes across the trials displayed a positive trend with significant p-values as the windows progressed. The trials 1 and 2 were similar but trial 3 had high values of average power for all the three muscles as the windows progressed.

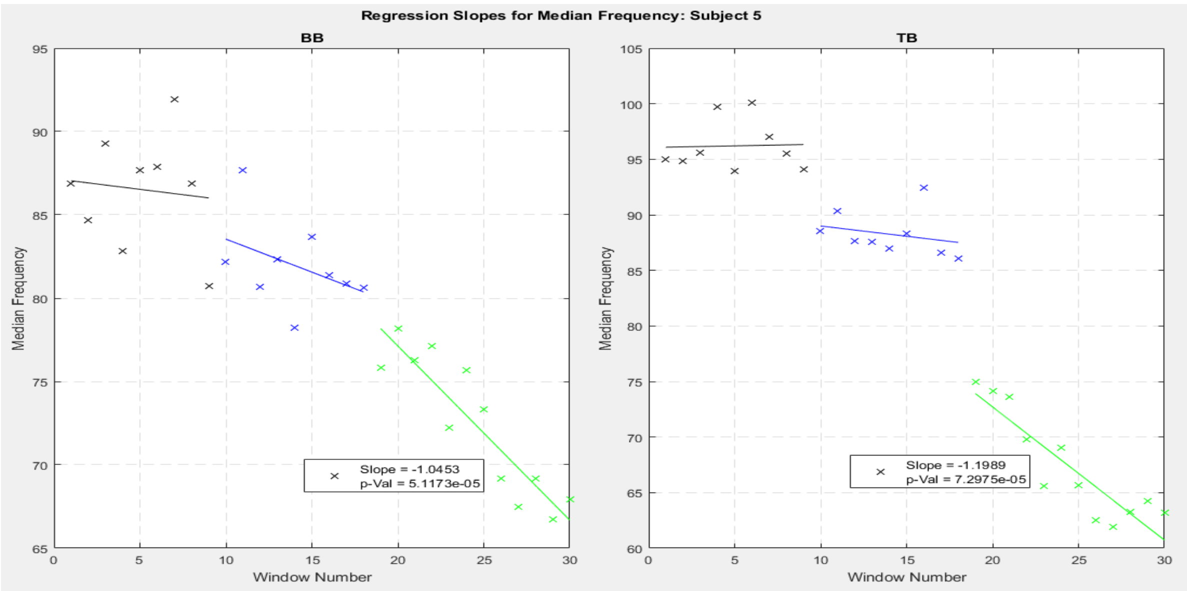


Figure 5.4: Regression Slope Across Trials for Median Frequency - Subject 5: Regression slopes across trials 1, 2 and 3 displayed a negative trend with significant p-values as the windows progressed. The median frequencies for trials 1 were found to be significantly different compared to trial 3 for BB and TB muscles.

The maximum number of iterations during trial 3 for each subject was also analyzed as shown in Figure 5.5, although it is understood that it is also dependent on the muscle strength of the participants.

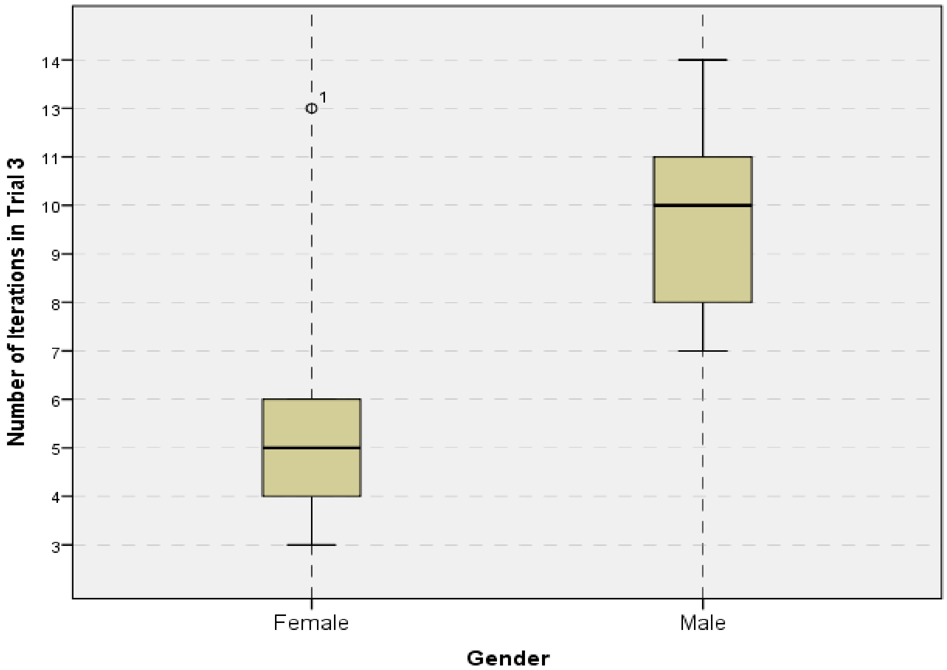


Figure 5.5: Iterations During Trial 3: Male and Female Participants: The number of iterations of flexion and extension tasks in trial 3 were significantly different between male and female participants. Female participants were asked to lift a dumbbell of weight 7.5kg and for male participants it was 10kg.

#### 5.3.1.1 Male Participants:

As shown in the summary tables for male participants, Table 5.1 and Table 5.2, the majority (92% & 85.7% for EMG average power & median frequency respectively) showed indications of fatigue by the end of trial 3. This was also supported by the post-experiment questionnaires. The *average power* in the frequency band 0.8-2.5Hz were significantly different from the initial values (shown in Figure 5.3 for a typical participant Subject 5). However, Subject 4 displayed a non-significant increase even though the regression analysis appeared to provide a positive slope. Similarly, the regression slopes for median frequency in the frequency band 20-450Hz (shown in Figure 5.4) indicated a statistically significant negative slopes for the majority of the male participants. This meant that the median frequency was significantly different from the initial values. This was more visible in the BB and TB muscles than in the DLT muscle as shown in the Table 5.2.

Table 5.1: Summary Table for Average Power in Male Participants: The summary table that shows significant regression slopes for the majority of the male participants as the iterations progressed in trial 3. This was more significant in BB muscles than TB muscles. "+" sign indicates statistically significant slopes with p-value <0.05 and "NS" indicates non-significant slopes. Some sample statistics are shown in Appendix C.

| **Feature ->** | **Average Power (0.8-2.5Hz) - Male Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There is a positive trend in average power as the windows progressed in Trial 3. ( + =>Positive, - =>Negative, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear Regression test on the values of average power considering moving window of 10 seconds duration corresponding to each iteration carrying 10Kg weight. The EMG was band pass filtered at 0.8-2.5Hz.** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 2 | + | + | NS |
| Subject 3 | + | + | + |
| Subject 4 | NS | NS | + |
| Subject 5 | + | + | + |
| Subject 6 | + | + | + |
| Subject 7 | NS | + | NS |
| Subject 9 | + | + | NS |
| Subject 11 | + | + | + |
| Subject 12 | + | + | - |
| Subject 15 | + | + | NS |
| Subject 16 | NS | + | NS |
| Subject 17 | + | + | + |
| Subject 18 | NS | + | + |
| Subject 19 | NS | + | + |

Table 5.2: Summary Table for Median Frequency in Male Participants. The summary table for median frequency shows significant negative regression slopes for the majority of the male participants as the iterations progressed in trial 3 for the majority of the muscles. Some sample statistics are shown in Appendix C.

| **Feature ->** | **Median Frequency (20-450Hz) - Male Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There is a negative trend in median frequency as the windows progressed in Trial 3.<br>( + =>Positive, - =>Negative, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear regression analysis on the values of median frequency considering moving window of 10 seconds duration corresponding to each iteration carrying 10Kg weight. The EMG was band pass filtered at 20-450Hz.** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 2 | - | - | NS |
| Subject 3 | - | NS | - |
| Subject 4 | NS | NS | - |
| Subject 5 | - | - | - |
| Subject 6 | NS | - | NS |
| Subject 7 | + | - | - |
| Subject 9 | NS | - | - |
| Subject 11 | NS | - | - |
| Subject 12 | NS | - | - |
| Subject 15 | - | - | - |
| Subject 16 | NS | - | - |
| Subject 17 | NS | - | - |
| Subject 18 | NS | - | - |
| Subject 19 | NS | - | - |

The answers to the questionnaires stated that 10 out of 14 male participants were fatigued or very fatigued. The remaining 4 male participants reported being "Somewhat Fatigued" as explained in the Fatigue Chart (Figure 5.6). The female participants reported different levels of fatigue (2 of them reported "Very Fatigued", 1 reported "Fatigued", 1 reported "Somewhat Fatigued", and another 2 reported "Not Fatigued").

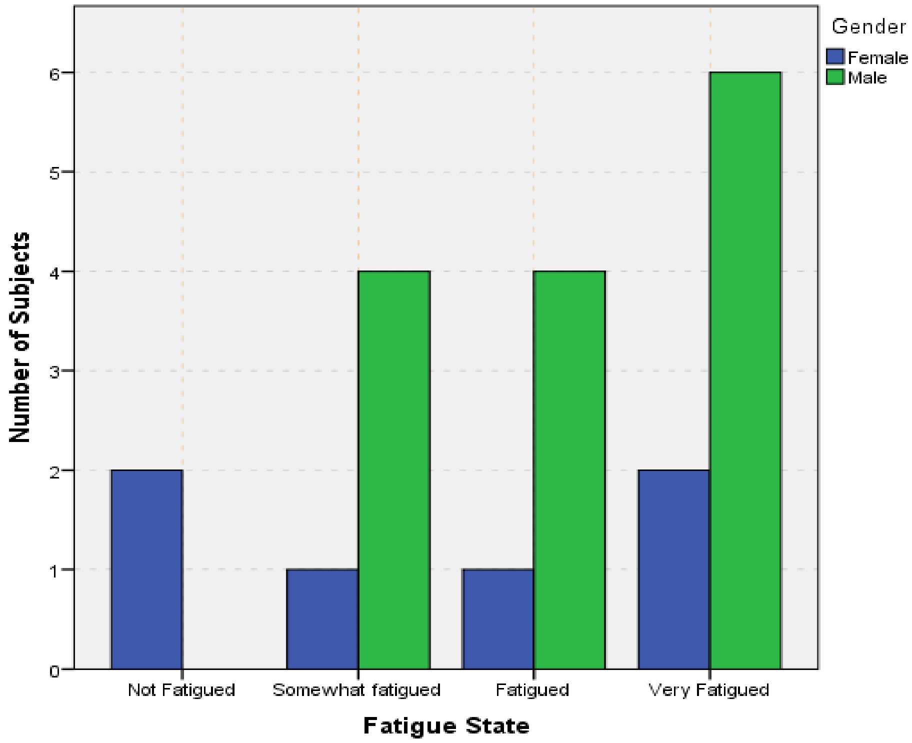


Figure 5.6: Fatigue Chart: Male and Female Participants. The responses about the state of fatigue from post-experiment questionnaire were consolidated separately for male and female participants. All the male participants reported some level of fatigue, whereas the female participants had a mixed response due to different reasons.

#### 5.3.1.2 Female Participants:

In all the female participants the features average power and median frequency were not significantly different from the initial values as indicated by the regression slopes within trial 3 (using a 7.5kg dumbbell). The *average power* in the frequency band of 0.8-2.5 Hz in the majority of the female participants except for Subject 1 resulted in regression slopes tending towards positive but lacking statistical significance (Figure 5.7). The case was similar for the regression slopes of *median frequency* in the band of 20-450 Hz as shown in Figure 5.8 for a typical female participant. In their responses to Questionnaire, three female participants stated being "Fatigued" or "Very Fatigued", whereas one stated being "Somewhat Fatigued" and 2 others stated "Not Fatigued". The measurements from one of the female participants (Subject 1) were not suitable to be compared with other results due to incomplete flexion and extension movements after visual assessment of recorded performance videos.

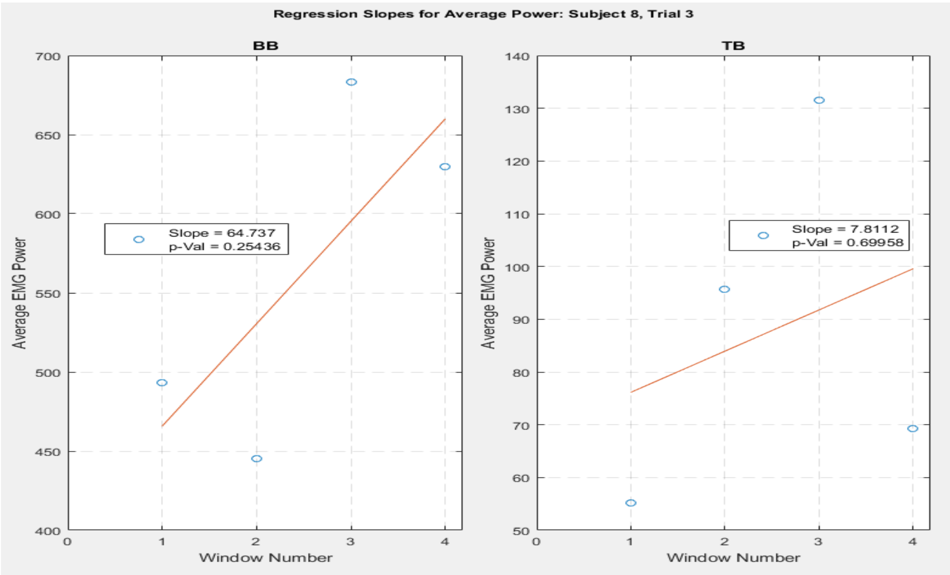


Figure 5.7: Average EMG Power in Female Participant - Subject 8 During Trial 3: Regression slopes within trial 3 for subject 8 were not statistically significant. The slopes for all the female participants were non-significant because, the heavy weight of the dumbbell did not allow them to comfortably lift it. Hence, most of them could not do the iterations properly.

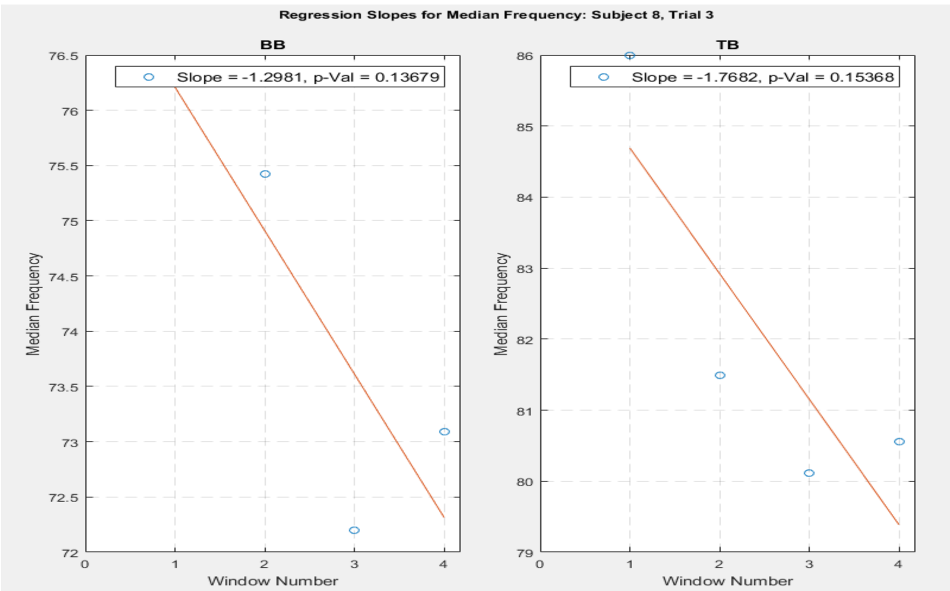


Figure 5.8: Median Frequency in Female Participant - Subject 8 During Trial 3: Regression slopes within trial 3 for a typical female participant subject 8 were not statistically significant.

The summary tables for female participants showed non-significant results for all the muscles in case of both the EMG features as in Table 5.3 and Table 5.4.

Table 5.3: Summary table for Average Power in female participants which shows non-significant regression slopes for the majority of the female participants in trial 3.

| **Feature ->** | **Average EMG Power (0.8-2.5Hz) - Female Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There is a positive trend in average power as the windows progressed in Trial 3.<br>( + =>Positive, - =>Negative, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear Regression test on the values of average power considering moving window of 10 seconds duration corresponding to each iteration carrying 7.5Kg weight. The EMG was band pass filtered at 0.8-2.5Hz.** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 1 | NS | NS | - |
| Subject 8 | NS | NS | NS |
| Subject 10 | NS | NS | NS |
| Subject 13 | NS | NS | NS |
| Subject 14 | NS | NS | NS |
| Subject 20 | NS | NS | NS |

## 5.4 Discussion

In the current experiment, it was observed that the average power and median frequency after the tiring exercise clearly represented the upper arm muscle fatigue. As suggested by muscle physiology, when there is a development of muscle fatigue, more recruitment of motor units occurs, which results in an increased EMG amplitude [93][211]. The values of average power corresponding to each EMG window within trials 1 and 2 did not increase as the iterations progressed. This could be because there were only 10 iterations of flexion and extension in trials 1 and 2, without holding any weight and with a weight of 0.5kg respectively. Hence, these tasks were easy to execute. In the case of trial 3 at the beginning, the EMG signals had an increased amplitude compared to the trials 1 and 2. However, it was noted that the EMG average power displayed a further increase from its initial value within trial 3 as the iterations progressed, as shown in Figure 5.3. Trial 3 iterations were carried out until the participants were completely exhausted or unable to continue. This ensured that the majority of participants tried their best to maximize the number of iterations in trial 3, which resulted in their gross upper limb muscles becoming fatigued. The EMG signals were analysed using both frequency bands 0.8-2.5Hz and

Table 5.4: Summary table for Median Frequency in female participants which shows non-significant regression slopes for the majority of the female participants in trial 3.

| Feature -> | **Median Frequency (20-450Hz) - Female Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There is a negative trend in median frequency as the windows progressed in Trial 3.<br>( + =>Positive, - =>Negative, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear regression analysis on the values of median frequency considering moving window of 10 seconds duration corresponding to each iteration carrying 7.5Kg weight. The EMG was band pass filtered at 20-450Hz.** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 1 | - | - | - |
| Subject 8 | NS | NS | NS |
| Subject 10 | NS | NS | NS |
| Subject 13 | NS | NS | NS |
| Subject 14 | NS | NS | NS |
| Subject 20 | NS | NS | NS |

20-450Hz.

In male participants, fatigue charts as shown in Figure 5.6 indicated that all of them had some level of fatigue after lifting a weight of 10kg during trial 3. The average number of iterations in all the male subjects was approximately 10 as shown in Figure 5.5. There was a statistically significant difference between the number of iterations in male and female participants. Considering the fatigue indicator based on EMG average power in male participants, there was a significant difference between the initial and final trials as indicated in Figure 5.3. This implied that there was a significantly increased muscle activity due to a larger force required to lift the higher weight. This increase was observed in all the participants. However, this does not give a clear picture of muscle fatigue development and, hence, it was decided to study the progress of the EMG feature within trial 3 where the heavy load was used.

For the average power in male participants within trial 3, the use of frequency band 0.8-2.5Hz resulted in a summary table as shown in Table 5.1. The majority of the male subjects displayed statistically significant positive slopes with p-value $<0.05$ as shown in the summary table. It was noticed that the BB muscle displayed the highest indication of fatigue in 13 out of 14 male participants (92.85% of the cases) compared to the TB muscle (57%). Both the BB and TB muscles were expected to play a major role in the flexion/extension tasks. However, the results for the TB muscles were not statistically significant in a few subjects, even though the slopes tended towards positive direction. The lesser significance for TB muscles compared to BB muscles could be due to the participants resting their elbow on their laps and thus getting support during the extension movements. This support could potentially have resulted in a smaller EMG amplitude in the TB muscles. One of the male subjects (Subject 4) displayed unexpected results in terms of both EMG features, where the BB muscles displayed non-significant (NS) regression slopes. However, the participant stated being "Fatigued" in the questionnaire. The smaller significance of EMG features from the BB muscles could potentially be explained by the EMG electrode positions. The average power analysis using the 20-450Hz frequency band as shown in Table 5.5 resulted in lesser significant results than using the 0.8-2.5Hz band as shown in Table 5.1. This indicated that the amplitude based study may be better in the low-frequency ranges of EMG as also suggested in the studies of Octavia et al. [149].

Similarly, the summary table based on the EMG median frequency also displayed significant negative slopes in 12 out of 14 male subjects as the windows progressed within trial 3. While using median EMG frequency as fatigue indicator with a frequency band of 20-450Hz, the summary table (Table 5.2) showed that BB and TB muscles had a maximum percentage of cases with significant regression slopes 85.71% and 85.71% respectively. On the other hand, using the frequency band of 0.8-2.5Hz for calculating median frequency resulted in a less clear indication of fatigue, where the BB and TB muscles only had significant slopes in 71.42% and 71.42% of the cases respectively as shown in Table 5.6. Even though the EMG amplitude values for the TB muscle were affected due to the elbow support during extension, this did not seem to affect the median frequency values possibly due to the physiologically different reason behind the reduction in median frequency. A decrease in median frequency during muscle fatigue is due to a decrease in the conduction velocity, which results in an increase in the time duration of action potentials. An increase the EMG average power is mainly due to the additional motor units recruited, to maintain the required force [168][16][81]. Hence, in comparison to the results for average power, a less clear fatigue indication could not be noticed in the TB muscles than in the BB muscles while using the median frequency parameter.

Table 5.5: Summary Table for Average Power in Male Participants in the Frequency Band 20-450Hz: The summary table shows many non-significant regression slopes for average power compared to that using the frequency band of 0.8-2.5Hz. A "+" sign indicates statistically significant slopes with p-value <0.05 and "NS" indicates non-significant slopes.

| **Feature ->** | **Average Power (20-450Hz) - Male Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There a positive trend in average power as the windows progressed in Trial 3.<br>( + =>Positive Slope, - =>Negative Slope, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear Regression test on the values of average power considering moving window of 10 seconds duration corresponding to each iteration carrying 10Kg weight** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 2 | + | NS | NS |
| Subject 3 | NS | + | + |
| Subject 4 | NS | NS | NS |
| Subject 5 | + | + | - |
| Subject 6 | + | NS | NS |
| Subject 7 | + | + | NS |
| Subject 9 | + | + | - |
| Subject 11 | + | + | NS |
| Subject 12 | + | + | - |
| Subject 15 | + | + | - |
| Subject 16 | NS | NS | - |
| Subject 17 | + | NS | NS |
| Subject 18 | NS | + | NS |
| Subject 19 | + | + | NS |

Table 5.6: Summary Table for Median Frequency in Male Participants in the Frequency Band 0.8-2.5Hz: The summary table shows many non-significant regression slopes in this case compared to the analysis using the frequency band of 20-450Hz.

| **Feature ->** | **Median Frequency (0.8-2.5Hz) - Male Participants** | | |
|---|---|---|---|
| **Hypothesis ->** | **There a negative trend in median frequency as the windows progressed in Trial 3. (+ =>Positive Slope, - =>Negative Slope, NS =>Non Significant )** | | |
| **Methodology ->** | **Linear regression analysis on the values of median frequency considering moving window of 10 seconds duration corresponding to each iteration** | | |
| **Muscles ->** | **DLT** | **BB** | **TB** |
| Subject 2 | NS | - | NS |
| Subject 3 | - | NS | NS |
| Subject 4 | NS | - | - |
| Subject 5 | - | - | - |
| Subject 6 | - | - | - |
| Subject 7 | + | NS | NS |
| Subject 9 | NS | - | - |
| Subject 11 | NS | NS | - |
| Subject 12 | + | - | + |
| Subject 15 | NS | - | - |
| Subject 16 | NS | - | - |
| Subject 17 | NS | - | - |
| Subject 18 | NS | NS | - |
| Subject 19 | + | - | - |

In female participants, it was noticed that the EMG fatigue indicators (median frequency and average EMG power) displayed non-significant regression slopes as described in Figure 5.7, Figure 5.8, Table 5.3, and Table 5.4. The physical strength of the female participants was not considered, while selecting the weight of 7.5kg for the task, instead this decision was made after consulting with some colleagues from the school of sports science. As per the results obtained, this weight seems to be too heavy for the them to perform the tasks for a sufficient duration. Few female participants struggled to lift the weight comfortably and few others could not repeat the task more than 3-4 iterations. 5 out of 6 female participants reported in the questionnaire that the weight of 7.5kg during the trial 3 was too heavy to lift and, hence, could not continue the iterations properly. As noted from the questionnaire and the recorded videos, it was understood that the heavy weight resulted in performing only a small number of iterations by the majority of the female participants, which was not sufficient for the purpose of regression analysis. Majority of the cases showed non-significant results ("NS") as in the summary tables Table 5.3, and Table 5.4. Even though most of the results for the female participants were non-significant, the regression slopes seemed to be moving in a positive direction for average power and in a negative direction for median frequency as seen in Figure 5.7, Figure 5.8. The gender factor and hence, the muscle strength of the participants could have some effect on the fatigue indicators. However, it seems that the non-significant results as shown in the summary tables need not be only due to fatigue, but could also be due to the insufficient number of samples available for the regression analysis. Standardising the task difficulty based on the muscle strength of participants could possibly neutralise the effect of gender factor on the results.

In contrast to this experiment, the previous study (Chapter 3) with robotic assistance had shown that EMG features in presence of robotic assistance displayed only non-significant indications of muscle fatigue. The horizontal position of the upper limb in parallel to the shoulder was expected to produce a good level of fatigue. However, since the robot was configured in active-assisted mode, there was only a limited "reported-fatigue" to validate the observations. Participants were not showing a maximum effort to actively become involved in the interaction; instead many were seeking some assistance from the robot to complete the movements. This resulted in a less clear indication of fatigue through the EMG features in the majority of the participants. The questionnaires also supported this observation since 80% of the participants in Experiment 1 reported being "Somewhat Fatigued". However, in the majority of the subjects, the EMG features indicated the presence of muscle fatigue in the most active upper limb muscles. The trend in EMG features was more visible in TRP and DLT muscles in comparison to BB and TB muscles (Table 3.1). A possible explanation for these differences between muscles is that TRP and DLT muscles played a more active role in lifting the arm to shoulder height for performing the tasks.

Based on the findings from both the experiments, it was concluded that the EMG features can be indicative of fatigue, and the results from the first experiment could indeed be an indication for successful assistance offered by the robot. The results showed that with robotic assistance the participants reported "Somewhat Fatigue", whereas without robotic assistance, the participants reported high fatigue. The extent of fatigue with and without assistance varied significantly. Due to the complex nature of muscle fatigue, no literature has as yet clearly identified a standard method to quantify the level of muscle fatigue based on EMG features. In an effort towards this, based on the results, it was noted that a baseline range calculated from statistical significance test (2 times standard deviation) of the EMG features may be used to set the threshold to detect muscle fatigue by checking if a new value of EMG feature lies within the range. In order to study how different could a "High Fatigue" be compared to "Fatigued" and "Somewhat Fatigued", the fatigue scores reported through the questionnaire in all the subjects after trial 3 of Experiment 2 were analysed. On a scale of 0 to 10, the participants who reported a state of "High Fatigue" mostly gave a fatigue score between 7 to 10. Two subjects (Subject 15 and 17) marked a score of 10 for "Somewhat Fatigued". A score of 10 must correspond to the highest level of fatigue and, hence, this seems incorrect. However, further exploration is required to see for which values of the EMG features do the muscle states transit from a "Fatigued" state to a "High Fatigued" state and from a "Somewhat Fatigued" state to a "Fatigued" state. It is also interesting to compare the accuracy of fatigue state identification methods when the fatigue thresholds are based on a 2STD range, 3STD range and so on.

## 5.5 Chapter Summary

The present study showed that the EMG features average power and median frequency can display a clear indication of fatigue across the full range of participants, but statistically significant fatigue trends were only observed in healthy male individuals. The study also confirmed that the formulation of the previous experiment had impacted the observed fatigue, either via the use of robotic assistance or the type and duration of activities performed.

Both experiments were conducted on healthy participants. However, in a real scenario of rehabilitation training, the patients (for example stroke survivors) will exhibit reduced muscular or cognitive capabilities. It is likely that their muscles can easily come to a state of fatigue even in a robot-assisted environment. A state of fatigue in the patients can deplete their limited resources if there is no mechanism to detect this and avoid them becoming highly fatigued. A fatigue indicator has the potential to be used to alter the training intensity by changing the robotic assistance parameters like stiffness, training duration and so on based on the level of muscle tiredness before damaging their muscles.

It was also noted that the lower band of frequencies (0.8-2.5Hz as used by [149]) was more suitable for the amplitude/average power based features than considering the whole band of 20-450Hz. Interestingly, for the median EMG frequency as fatigue indicator, the EMG frequency band of 20-450Hz was found to provide the best fatigue indication as compared to the band of

0.8-2.5Hz. It was also noted that the rectification of EMG signals is not recommended during the feature extraction stage if median frequency analysis is planned for fatigue detection. It seems that not all EMG changes amount to fatigue. However, a statistically significant increase in the EMG average power or a significant decrease in the median frequency indicated fatigue, which was supported by the subjective reporting of fatigue through the questionnaire. Hence, a 2 times standard deviation (2STD) check of the EMG features was found to be useful for fatigue detection during training interactions with a constant load. However, this method needs to be tested further in training environments with varying loads, for example during progressive muscle strengthening exercises and adaptive environments.

The task difficulty could have been selected according to the muscular strength or body mass index of the participants. In a robot-assisted training interaction, the task difficulty may be set based on the muscular strength and force generation capabilities of the participants. This is addressed in the next study. It was also realized that the dumbbell weight used in trial 3 for female participants could have been selected better so that they could do more iterations to make the muscles tired through repetitions rather than making them unable to lift it or to use compensatory strategies for lifting. This, however, does not affect the findings of this study, since the intention of the study was mainly to verify if the EMG fatigue indicators can indicate muscle fatigue and allow proceeding to the next study, regarding how they can be used to improve robotic adaptation as planned in the future experiments. The results obtained from the male participants' EMG data have indeed verified that episodic fatigue measurement is possible. As also indicated by the results of the first experiment, the EMG features like average power and median frequency are potential parameters, which can be used to improve the adaptation of robot-assisted rehabilitation. Hence, utilizing EMG fatigue indicators to improve the adaptability of human-robot interactions and rehabilitation training is explored in the next experiment.

CHAPTER 6

# EXPERIMENT 3: ADAPTIVE ROBOTIC TRAINING BASED ON MUSCLE FATIGUE

## 6.1 Introduction

Rehabilitation training for stroke patients is suggested to involve protocols for developing muscle strength and relearning the lost motor skills. But, due to their reduced muscular and cognitive capabilities the patients can easily come to a state of fatigue during the exercises. To prevent this the strength training protocols suggested by sports science literature may be applied to the scenario of rehabilitation training to reduce or delay the muscle fatigue during the interaction. Sports science protocols suggest to quantify the task difficulty levels based on the maximum voluntary strength of participants and use a proportional increment of the difficulty at regular intervals [49].

A rehabilitative training is considered to be useful if it can help the patients to train more at the initial stages of recovery and to make the task progressively challenging. Many studies as described in the literature (Subsection 2.6.1) have suggested that stroke rehabilitation can benefit from intensive muscle training, and a progressive strength training is helpful for stroke recovery by improving the muscle strength. Increasing the number of task repetitions is known to help motor relearning significantly and thus help the recovery of upper limb functions during stroke rehabilitation [151][193][107][77]. Hence, the aim of this chapter's investigation is to explore the usability of a high-intensity strength training protocol for stroke rehabilitation.

Previous work by Octavia et al. [149] had explored the muscle fatigue developed in the participants during a robotic training interaction, and the proposed EMG based features indicated muscle fatigue significantly in all the participants. However, the fatigue indicators were not used for any robotic adaptation. In the previous experiments, the elements of fatigue onset in robotic experiment were identified, and the fatigue indicators were verified during an inherently fatiguing exercise (Chapter 3 and Chapter 5). These provided the material for the final experiment of this work where fatigue indicators were used to automatically change the interaction difficultly during human-robot interaction. Hence, the current study labelled as Experiment 3 was designed to test a robot-assisted training interaction that adapted the task difficulty based on EMG-based detection of muscle fatigue. The experiment followed a protocol for increasing the muscle strength by progressive strength training. This was an implementation of a known method in sports science for muscle training [32], in a new domain of robotic adaptation in muscle training.

The experiment involved a robot-assisted incremental strength training exercise for upper limbs, where the robot would adjust the task difficulty based on the detected muscle fatigue, which thus results in a delay in the onset or decrease of fatigue. During the experiment, EMG was used to monitor muscle fatigue and to enable relaxed exercise so that fatigue can be alleviated allowing a prolonged exercise cycle. Robotic adaptations were used to reduce the fatigue during the interaction by automatically adjusting the task difficulty. Fatigue was detected based on the EMG measured from three gross-muscles of the upper limb in 30 healthy participants. The study also compared how the change in task difficulty levels was perceived by the participants when the robot adjusts the difficulty, when the difficulty was manually adjusted as well as when there was no difficulty adjustment at all. Three experimental conditions were chosen, one benefiting from robotic adaptation (the intervention group) and the other two presenting control groups 1 and 2. The hypothesis for this study was that the participants can perform a prolonged progressive strength training exercise with more repetitions with the help of a fatigue-based robotic adaptation compared to the training interactions which are based on manual/no adaptation. The results of the study were expected to be extended to stroke patients in the future.

The rest of the chapter is organized as follows: section 6.2 presents the second research question addressed by Experiment 3. Section 6.3 describes the experimental set-up and methodology used for the study. Section 6.4 presents the results based on the adaptive and non-adaptive algorithms. Section 6.5 conducts a detailed discussion on the results. Finally, in Section 6.6 conclusion and next steps are briefly explained.

## 6.2 Research Question

Can the human-robot interaction dynamics be altered automatically based on EMG fatigue indicators to prolong the interaction by delaying the muscle fatigue during high-intensity progressive muscle training exercises?

## 6.3 Materials and Methods

The overall context of the experiment is explained in Figure 6.1.

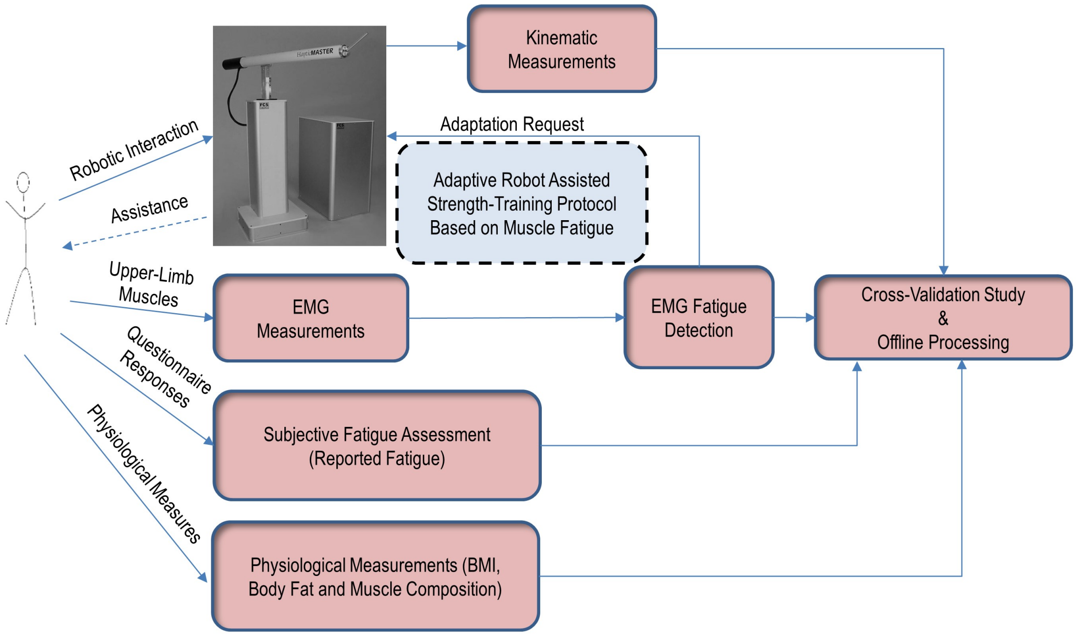


Figure 6.1: Context for the Experiment.

### 6.3.1 Experiment Setup

The experiment set-up included the HapticMaster robotic interface configured for a rowing task. In order to support an aesthetically pleasing interactive task for the participants, an animated rowing environment embedded with audio cues and haptic sensation of underwater viscosity were created using the HapticMaster robot. A user-interface and the animated environment were developed using Visual C++ and with Open GL programming in a Windows PC. The background on a wide-screen 43 inch LCD monitor would display the front-end of a rowing boat with flowing water as in Figure 6.2, which would potentially motivate the participants for an active involvement in the task. A suitable audio for water flow was played in the background. The HapticMaster robot was programmed to deliver different viscosities under water and above water while rowing. The starting time, the break period and the stopping time of the experiment were guided by audio cues. The user interface for configuring the experiment protocol for the different subject groups and the robot was as shown in Figure 6.3.

A non-invasive EMG acquisition device (CE marked g.USBamp) from g.tec medical engineering GmbH, was used to acquire the EMG signals from the upper limb muscles. The data acquisition parameters (sampling rate, channel selection and so on) for the g.USBamp amplifier were configured using a Simulink model. Three EMG electrode channels were configured in bipolar mode with a sampling frequency of 1200Hz.

An electrode cable with a clip-lead was attached to sterile disposable non-invasive electrodes to measure EMG signals as shown in Figure 6.5. A bipolar electrode configuration was used for


Figure 6.2: The experiment set-up including the EMG acquisition device, HapticMaster robot, visual guidance and the animated background.

the EMG acquisition and the electrode placement errors were minimised by following SENIAM guidelines [89]. The measurement of physiological parameters (refer the protocols in Subsection 6.3.2.1 for details) was conducted using OMRON digital weight scale (Figure 6.6).

### 6.3.2 Methods

The experiment was designed for performing an upper limb exercise that simulates boat rowing using a robotic arm. The participants were asked to hold the robotic end-effector using their right hand with an animated boat rowing environment on an LCD monitor in front. They were free to move the robot in any path for rowing on the right side of the boat. The number of rowing iterations and the time duration of the tasks were studied when the task was not auto-adjusted according to user's state of fatigue (control groups) as well as when using an adaptive algorithm for altering the difficulty (the intervention group). Ethics approval was obtained from the University of Hertfordshire (Protocol number: aCOM/PGR/UH/03221(1)). Written consent was obtained from all individual participants included in the study.

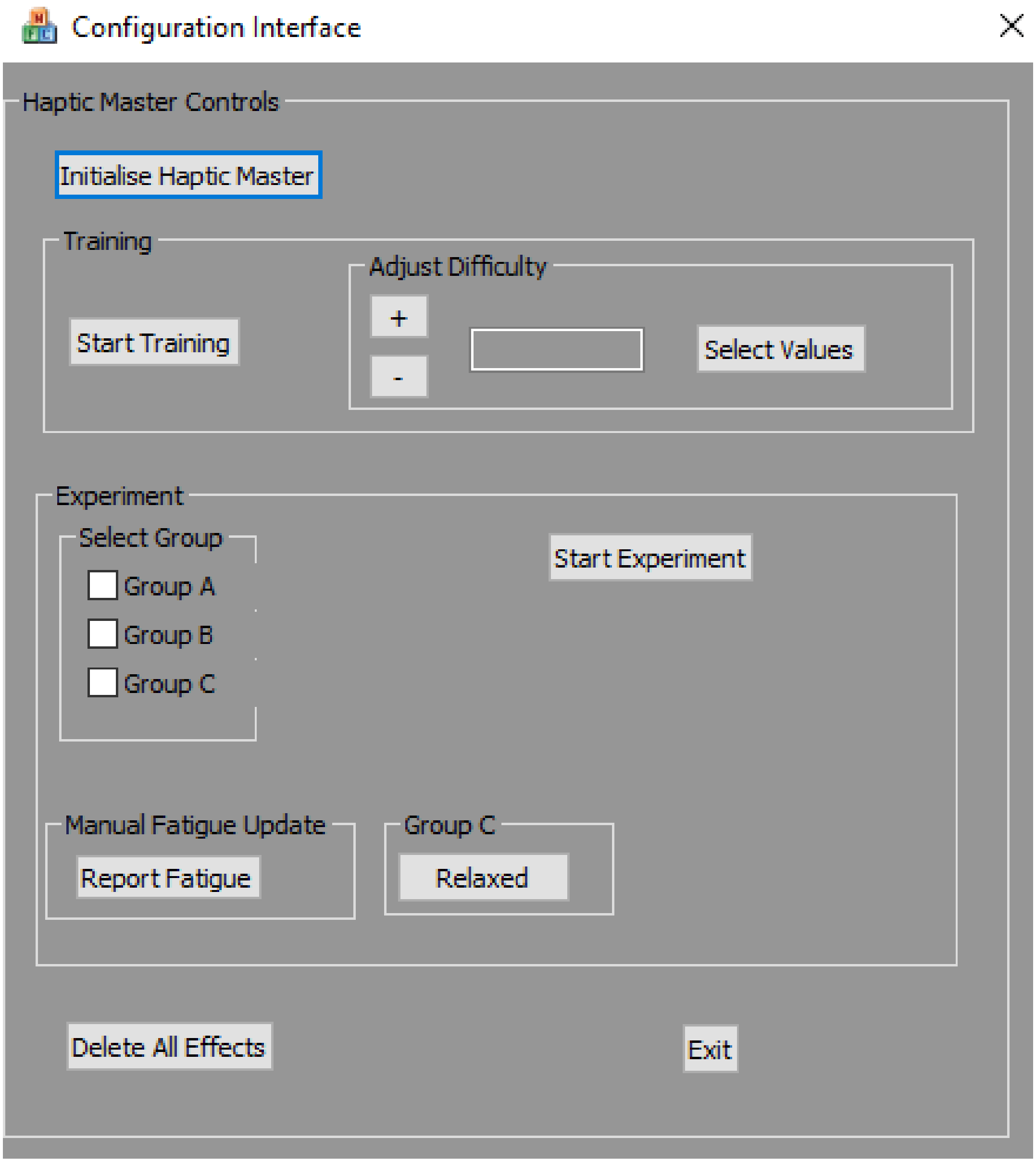


Figure 6.3: User Interface for Configuring the Experiment Protocol for Different Subject Groups and the HapticMaster.

#### 6.3.2.1 Protocol

Sports science studies have a training protocol for muscle strengthening as described in the literature Subsection **??**. The protocol for the current experiment was defined based on the study of Chang et al. [32] where the participants would be performing maximum voluntary contraction (MVC) trials at first, then taking a recovery break, then starting with a low-intensity task, and then gradually increasing the difficulty level. The protocol included a preparation stage, followed by initial measurements, a familiarisation session and finally a performance session as described


Figure 6.4: The EMG acquisition device with g.USBamp amplifier, 3 bipolar electrodes and a ground electrode.

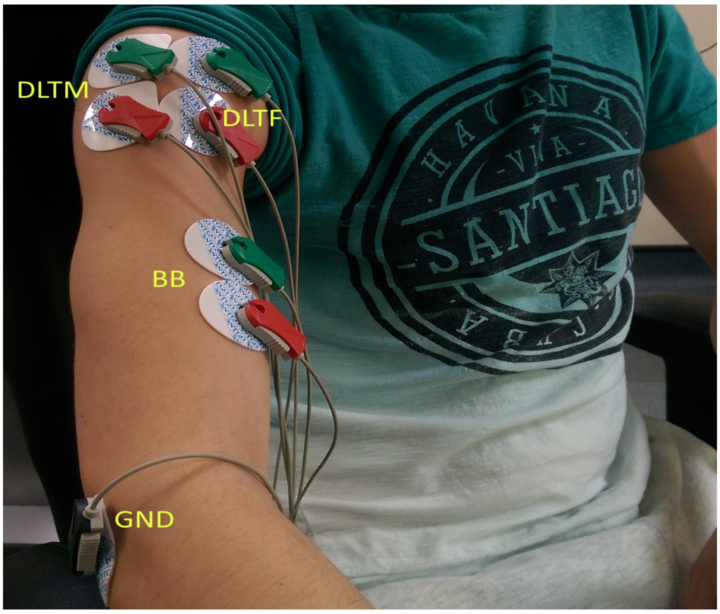


Figure 6.5: EMG electrodes are connected to three upper limb muscle locations (Biceps Brachii (BB), Anterior Deltoid (DLTF), and Middle Deltoid (DLTM)). The corresponding EMG data were termed EMG1, EMG2, and EMG3 respectively. The ground electrode was connected to a bony area near the elbow.

in Figure 6.7.

Thirty (30) healthy participants (13 female and 17 male) of at least 18 years old (mean ± SD: 31.8 ± 10.6 years) and with no history of injury to the upper limb and back were involved


Figure 6.6: OMRON digital weight scale

in the experiment. The total duration of the experiment, including the set-up time for each participant, was normally 40-55 minutes. Audio feedback was given regarding the start and end of the experiment cycles as well as during break periods. In case of any feeling of fatigue or discomfort during the experiment, participants were allowed to stop and the session could be ended in cases of discomfort. A questionnaire was given as part of the experiment as shown in Appendix A. The participants were asked to fill in a part of the questionnaire at the beginning of the experiment (Page 1 of Appendix A). They were also requested to update the fatigue state in the questionnaire after finishing the experiment (Pages 1 and 2 of Appendix A).

**Preparation:** EMG sensor electrodes were connected to the skin on the upper limb locations. The skin area for the sensor application was prepared by cleaning with a wet wipe. Participants were assisted to fix the EMG electrodes on the three specific upper limb muscles (Biceps Brachii (BB), Anterior Deltoid (DLTF), and Middle Deltoid (DLTM)). The corresponding EMG data were termed EMG1, EMG2, and EMG3 respectively. The ground electrode was connected to a bony area near the elbow as shown in Figure 6.5. The participants were asked to sit straight on a non-rotating chair during the experiment. The hand involved in the experiment was not externally supported. The opposite hand was allowed to rest on any external support like a table or chair to maintain an upright posture. Participants were advised to wear a loose garment for the ease of fixing the electrodes on the upper limb.

**Initial Measurements:** Since the rowing task is of a dynamic nature each participant will apply different levels of force according to their physical strength and the current state of fatigue. This will make it difficult to compare the results across the subjects. Also, the robot's maximum force is not comparable to the range of maximum force variations in a normal healthy individual.

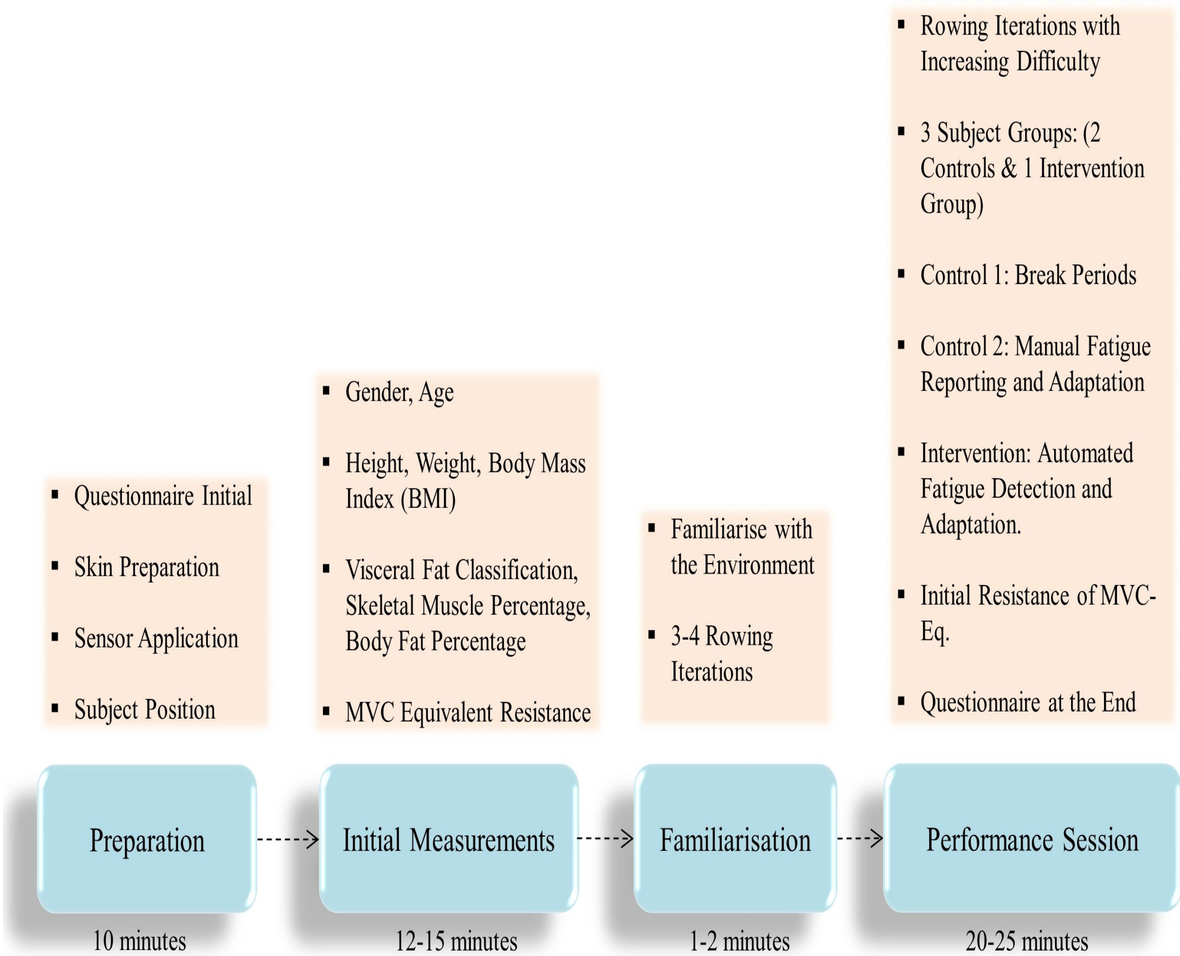


Figure 6.7: Experiment 3 protocol - Description of the different stages.

So, a personalised assessment was used to identify the maximum feasible force. Since the fatigue was planned to be produced through the resistance offered by the robot, it was decided to make the measurements of an isometric quantifiable nature by standardising the applied force/resistance across the different participants. Hence, the most feasible and highest robotic resistance for the rowing task was measured for each participant. This was done by using a user-interface as shown in Figure 6.3. The robotic resistance was gradually increased to the comfortable highest level by adjusting the damping coefficient of the robotic end-effector and verbal feedback about the task difficulty was collected from each subject. The value of damping coefficient corresponding to the highest feasible force was noted. Three such MVC measurements were conducted. There was a break period of at least 30 seconds between each MVC trial [46][188][182]. The average value of the three readings was calculated [32]. This was termed as MVC-Equivalent (MVC-Eq) and was approximated as each subject's MVC force, which was used to set the initial task difficulty for each subject. After the three MVC trials, there was a break period for 10 minutes or until a self-reported full recovery before starting the rowing task [32].

The EMG measurements were taken from the 3 upper limb muscles of the participants as in Figure 6.5. The body weight, Body Mass Index (BMI), visceral fat classification, skeletal muscle percentage and body fat percentage of participants were measured before the experiment. The gender, age, and height of the participants were also measured. The participants were allowed to take these physiological measures with them on a card if they wanted to so that they can learn a bit about their own fitness level. Different parameters like subject group name, MVC-Equivalent, number of rowing iterations, kinematic measurements such as the end-effector position, velocity and force were logged into a file at a rate of 10 samples per second approximately. The different states of muscle fatigue were also logged during the experiment (reported fatigue, detected fatigue and relaxed state).

**Familiarisation and Performance Sessions:** After the initial measurements were completed, all the participants familiarised themselves with the robot and the environment in a practice run, which was then followed by the performance session. There were three experimental conditions and hence, three groups of participants in this study. They were randomly assigned to a group and each group was assigned 10 participants each as described in Table 6.1.

Table 6.1: Participant table with gender, age and experiment groups. Group-A and Group-C represents the participants involved in "Control 1" and "Control 2" studies respectively. Group-B represents the participants who took part in the "Intervention" study.

| Subject No | Group | Group Description | Age (Years) | Gender |
|---|---|---|---|---|
| 1 | B | Intervention | 21 | Male |
| 2 | C | Control 2 | 20 | Male |
| 3 | A | Control 1 | 27 | Female |
| 4 | C | Control 2 | 18 | Male |
| 5 | C | Control 2 | 33 | Male |
| 6 | C | Control 2 | 36 | Female |
| 7 | B | Intervention | 29 | Female |
| 8 | A | Control 1 | 25 | Male |
| 9 | B | Intervention | 30 | Male |
| 10 | A | Control 1 | 32 | Male |
| 11 | B | Intervention | 42 | Male |
| 12 | B | Intervention | 32 | Female |
| 13 | C | Control 2 | 41 | Male |
| 14 | B | Intervention | 20 | Male |
| 15 | A | Control 1 | 21 | Male |
| 16 | A | Control 1 | 35 | Male |
| 17 | A | Control 1 | 21 | Male |
| 18 | B | Intervention | 36 | Female |
| 19 | B | Intervention | 26 | Female |
| 20 | B | Intervention | 19 | Male |
| 21 | B | Intervention | 40 | Female |
| 22 | C | Control 2 | 60 | Female |
| 23 | C | Control 2 | 23 | Male |
| 24 | C | Control 2 | 39 | Male |
| 25 | A | Control 1 | 53 | Female |
| 26 | C | Control 2 | 23 | Female |
| 27 | A | Control 1 | 35 | Female |
| 28 | A | Control 1 | 35 | Female |
| 29 | A | Control 1 | 29 | Male |
| 30 | C | Control 2 | 52 | Female |

The Groups A and C were considered as the control groups and Group B as the intervention group. The intervention group (Group-B) was designed to involve the participants in a fatigue-adaptive robotic environment, where the subjects would receive varying resistance from the robot automatically based on their muscular state (fatigue) detected using EMG features. Control Group 1 (Group-A) was meant for studying the performance of the subjects in a similar environment as in the intervention group, but instead of receiving a robotic adaptation they were given break periods at regular intervals and then an increased resistance after the break. They did not receive any adaptation from the robot during the interaction. Control Group 2 (Group-C) was designed for exploring the task performance during the same adaptive robotic environment as in the intervention group, but instead of receiving an automatic adaptation, the subjective state of muscular fatigue was used for the robotic adaptation. During these three experimental conditions, participants were asked to perform the exercise until they were unable to continue or until they reported fatigue three times or until the maximum feasible robotic resistance was reached.

During the performance session, the 3 groups of participants involved in each experiment branch received incremental robotic resistance at some intervals (1 minute). The experiment started at a low difficulty level of 20% maximum feasible MVC equivalent (MVC-Eq) resistance [33], then this was progressively incremented by 10% MVC-Eq in each trial, and then normally continued until the robotic resistance reached 100% MVC-Eq [32]. The part where the current difficulty was incremented by 10% MVC was termed MVC+ part. However, there were different strategies for the break period or reducing the difficulty level in the 3 subject groups. The subjects were requested to report fatigue when they were in a state of pain or unable to continue, which helped to assess their psychological perception of fatigue. Participants of all groups were allowed to report fatigue orally during the interaction, which was then recorded as a subjective measure of fatigue. The experiment would continue until the participants reported fatigue 3 times or until the robotic resistance reached the 100% of MVC-Eq. A maximum duration of the rowing tasks was set to 20 minutes after which the experiment was manually stopped in order not to exceed the maximum experiment duration of 45-60 minutes.

**Group-A Participants (Control-1 Group):** In Control-1 group participants the sports science procedure of increasing difficulty for muscle training with break periods in between each trial was implemented. The participants did not receive any adaptation from the robot and there were no reducing of difficulty levels during the robotic interaction. While the status of the muscle fatigue was recorded, there was no intervention based on the detection of fatigue, instead, the participants could only report fatigue. The participants were asked to perform each trial for a duration of 1 minute [32] or until they felt tired before they could take a break of 30 seconds [135], [106], [12]. After each break, the next trial lasted for 1 minute. After the break period, the robotic resistance was incremented by 10% MVC-Eq before the next trial. During the break period, the EMG acquisition was stopped and the measurements were saved to a file.

**Group-B Participants (Intervention Group):** In the Intervention group, the protocol was designed to follow the sports science procedure for muscle training using robotic assistance when fatigued. The participants interacted with an adaptive robotic environment which was designed to adjust the difficulty level of the exercise automatically based on EMG fatigue indicators from the upper limb muscles. In addition to automatic fatigue detection, the participants were also allowed to report fatigue when needed. However, the reported fatigue was only used to log it into a file and not used for any adaptation. There were no break periods given; instead, there was a single continuous trial that incremented the difficulty level by 10% MVC-Eq every 1 minute. When the algorithm detected fatigue, the difficulty level was automatically decreased to 50% of the current value. The action when the value that caused fatigue was reduced to half and repeated was termed 'reduce difficulty' action. When relaxed, the robotic resistance was again incremented by 10% MVC-Eq after 1-minute trial and then the trials were repeated until the resistance reached 100% MVC-Eq.

**Group-C Participants (Control-2 Group):** There may be a delay in reporting fatigue compared to the fatigue that can be detected using EMG. This was studied by recruiting Control-2 group participants, where the subjective fatigue was reported by each participant and the robotic adaptation was performed based on this. Similar to the Intervention group, there were no break periods between trials instead, there was a single continuous trial that incremented the difficulty level by 10% MVC-Eq after every 1-minute trial. The robotic resistance was adapted only based on the subject-reported fatigue and did not use the status of automatically detected fatigue. When the fatigue was reported by the participant, the difficulty level was decreased to 50% of the current value. After 1 minute, the robotic resistance started incrementing by 10% MVC-Eq and then the trials were repeated until the resistance reached 100% MVC-Eq.

#### 6.3.2.2 EMG Data Processing

MATLAB 2016b was used to develop the EMG acquisition and processing algorithms in Simulink and the processing of EMG was performed almost entirely online. A de-multiplexer block was used to separate the individual EMG data from each electrode (Figure 6.8). Then, for each EMG channel, Simulink buffers were used to split the individual EMG data into blocks of fixed sizes. The average time taken to complete a single iteration rowing task was around 6 seconds. Hence, a buffer size of 7200 samples was used in the model (an average of 6 seconds per iteration x a sampling rate of 1200) to split the EMG into blocks. This buffer size was then used as the window length for EMG processing and analysis. For visual analysis of the signals and EMG features in Simulink, "Time scopes" were used which would display the EMG signal variations as the time progressed. MATLAB Function blocks were used to develop custom functions that processed the EMG data frames from the three muscles simultaneously and generated a fatigue status from all the 3 muscles separately. These function blocks calculated the EMG features (median frequency and average power) corresponding to one buffer length of the EMG from 3 muscles as shown in Figure 6.8. Within each function block, a notch filter was used at 50Hz to remove the power line interference. For average power calculation, the EMG was band-pass filtered at 0.8-2.5Hz [149] and for the calculation of median frequency, at 20-450Hz as used in the previous study Subsection 5.2.3. During the experiment, the EMG raw values and the calculated features were logged into two separate csv files.

The EMG features calculated from the initial EMG blocks for each muscle were also saved into global arrays to calculate a baseline range to be used for fatigue detection. This baseline feature range corresponded to a muscle state before any occurrence of fatigue during the exercise. The baseline range was later used as a threshold to compare with the features from the later EMG measurements as the exercise progressed. The initial 3 frames (corresponding to the initial 15 seconds) were ignored to avoid random fluctuations at the beginning of the EMG data which might result in a wrong calculation of the baseline range. The features corresponding to the next frames were saved into the feature array and were used for the calculation of the baseline range as described in Equation 6.2 [158][166][169]. The mean and standard deviation (STD) of the first 5 elements of the feature array were calculated which corresponded to the movements during the initial 30 seconds approximately, ignoring the skipped initial frames. The duration of 30 seconds was approximated based on the inferences during the pilot trials which would not have had an instance of fatigue at the initial stages of the exercise.

$$UpperLimit = mean(x) + 2 * STD(x) \tag{6.1}$$

$$LowerLimit = mean(x) - 2 * STD(x) \tag{6.2}$$

where $x$ was the input baseline array of features.

As per the previous study, a statistically significant increase in the average power and median frequency was identified as an indicator of muscle fatigue. Hence, a 2 times standard deviation check based on Equation 6.2 was used to decide if a new value of EMG feature was within the range or outside the range. For each muscle, if the feature values were out of range for more than 3 times continuously then a corresponding fatigue flag was set. When the features were within the baseline range the fatigue flag was cleared.

It was noticed during the pilot studies that the MVC+ step added some additional force requirement on the muscles while performing the rowing task, which resulted in an increase in the EMG amplitude and, hence, also in the average power. In a shared control where impedance/admittance control methods are used for robot-assisted strength training, the exercise intensity was found to increase as the desired damping increased [183]. The muscle activation was linear and proportional to the resistive load. Also, when the damping coefficient goes high the speed of the task would also decrease. Hence, the result of using a 2-STD check for fatigue detection using EMG average power can be an indication of both muscle fatigue and the higher force requirement due to the MVC+ increments. However, this does not seem to be the case for median frequency due to the different physiological reasons behind the shift in frequency spectrum during fatigue (Subsection 2.4.3). Since the average power was always showing an increase due to the MVC+ increments, only the median frequency was used in the fatigue detection algorithm. This makes the method similar to the JASA method mentioned in Subsection 2.4.3. However, the average power was also logged during the experiment for the off-line analysis.

**Simulink Model for Fatigue Detection** As shown in the Simulink model (Figure 6.8), processing of the EMG measurements from the three muscles and detecting the corresponding muscular fatigue were done in parallel. If any of the three muscles indicated fatigue, a corresponding fatigue flag was set to 1. The final state of the upper limb fatigue was indicated by a separate fatigue flag, and this was done based on a logical OR operation on the 3 individual fatigue flags corresponding to each EMG electrode. The final state of fatigue was then communicated to the HapticMaster control software through a shared csv file. The fatigue state was checked by the robotic algorithm by reading this file approximately every 6 seconds corresponding to one buffer size of EMG data. Since the robotic adaptation was not too time-critical, this way of communication was sufficient to feed back the state of muscles. If the robotic assistance had helped to reduce the fatigue, the muscle activation was supposed to be back to the normal range (within the baseline range). The fatigue flags were reset by the algorithm when the feature values returned to their baseline range. The individual muscles were considered relaxed when the corresponding fatigue flags were reset to zero. The upper limb was considered relaxed only when all the individual muscles were identified as relaxed. The relaxed state of the muscles was then updated in the shared csv file accordingly which would inform the robot that the upper limb muscles were relaxed.

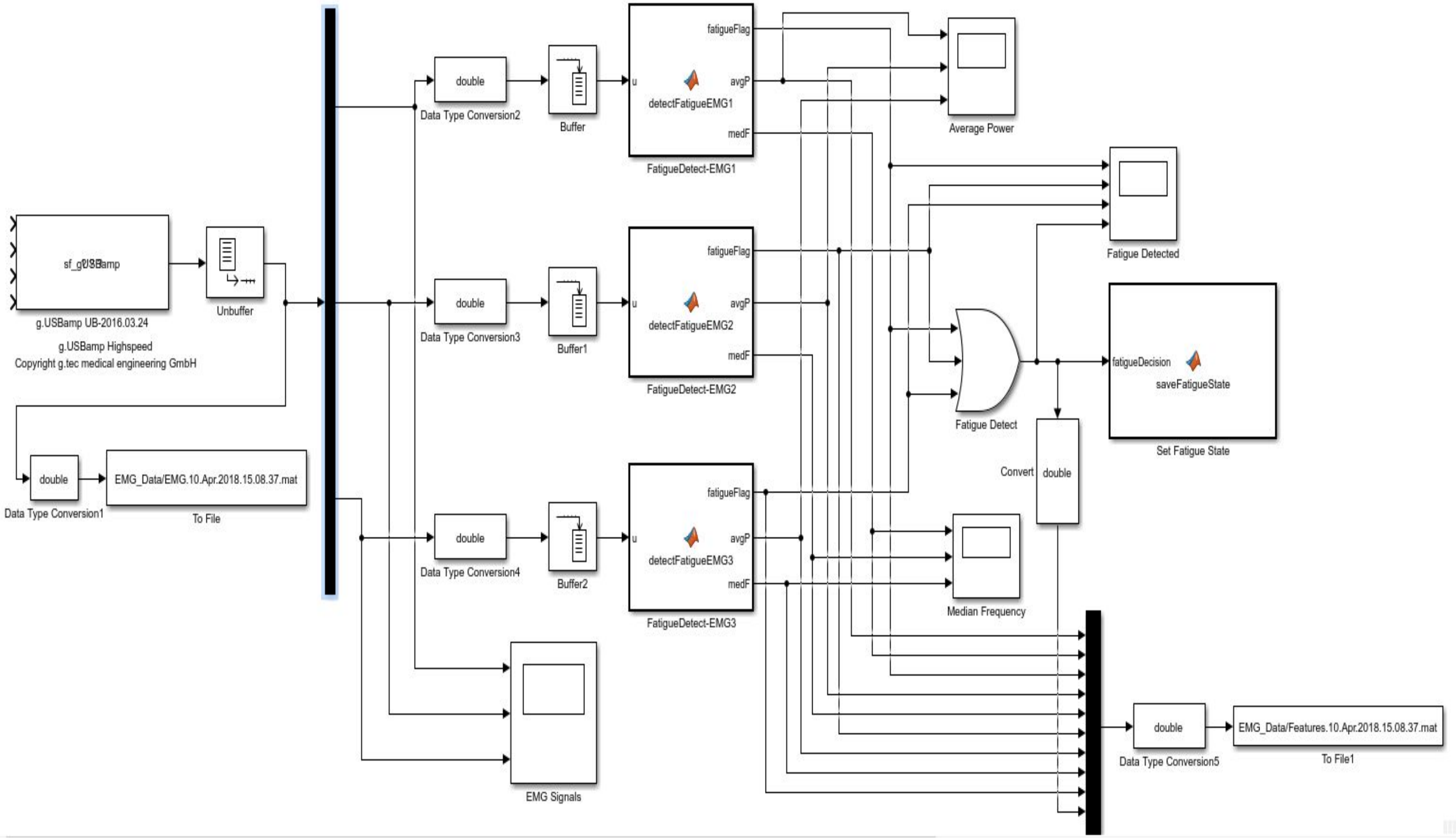


Figure 6.8: The Simulink model for performing EMG data acquisition and processing the collected data. The model has a signal processing algorithm that performs the fatigue detection for each muscle simultaneously. The detected fatigue state was communicated to the HapticMaster control algorithm.

#### 6.3.2.3 Adaptive Robotic Algorithm

The adaptive robotic algorithm was designed to support the intervention group (Group-B) participants when fatigue was detected based on the changes in the EMG features. The fatigue flag was checked by the robotic algorithm to adapt its behaviour accordingly. As explained in the protocol (subsubsection 6.3.2.1 and Figure 6.9), after detecting fatigue the robotic resistance was reduced to 50% of the present value that caused the fatigue. The 'reduce difficulty' action continued as long as the fatigue flag was set. Once the difficulty was reduced by 50%, the next 'reduce difficulty' action would only happen after the current trial of 1-minute duration was completed or after the muscles are relaxed once. Hence, if a fatigued state continued even after receiving the 'reduce difficulty' action once, the difficulty would further reduce by 50% in the next trial and so on until all the muscles were relaxed. Since there was a possibility that one of the muscles get fatigued and then never relaxed, the assistance algorithm had to make sure that all the muscles were relaxed. This was done by the robot by providing an additional anti-gravity support temporarily when the difficulty level reached the lowest value. This support was withdrawn once the muscles were relaxed at the lowest level of difficulty and the MVC+ increments started again.

#### 6.3.2.4 Off-line Data Analysis

An off-line data analysis was conducted on the different parameters calculated/obtained from the experiment. The parameters such as the time taken to automatically detect fatigue, the time of reported fatigue, fatigue/relax cycles, the variation in the difficulty levels, the total duration of the experiment, the number of task repetitions/iterations, and the repetitions per minute were studied. For Control-1 group participants, the time-to-fatigue was calculated off-line from the EMG features since there was a break period between different trials (of 1 minute duration), and the EMG data acquisition was stopped after each trial. A continuous progress of the EMG fatigue indicators could not be understood directly from the individual trials. Hence, the individual mat files containing the EMG data from each trial were merged to form a single combined mat file for each subject. This was then analysed to detect fatigue as the trials progressed. However, some unexpected signal spikes were observed at the beginning of each trial after each break period when the device started capturing the EMG data. This appeared as an unexpected increase of EMG amplitude and hence, resulted in a wrong fatigue detection by the algorithm. Hence, during the off-line EMG analysis, while combining the different mat files corresponding to each EMG acquisition, the initial spikes were avoided by ignoring the initial second of EMG data from each trial. Additionally, after combining the files, the initial 12 seconds of combined EMG data corresponding to the first two frames were also skipped during the off-line processing. However, during the on-line EMG processing for the Groups B and C, there was one additional empty frame of data at the beginning that was generated by the Simulink buffer block and this occurred when the model started running. Hence, this additional frame was also skipped during the on-line processing, which made the total number of skipped initial frames 3. But, in off-line processing,

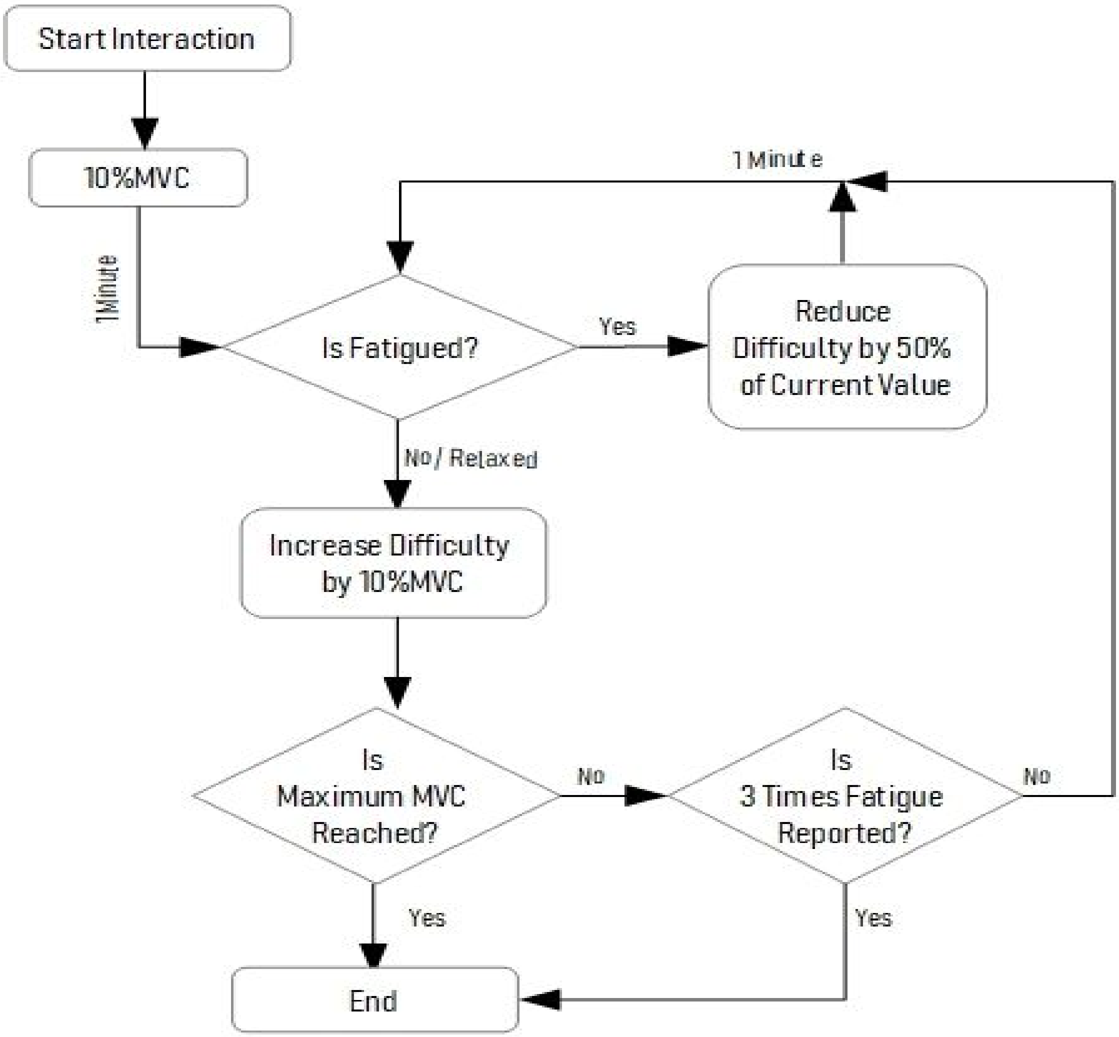


Figure 6.9: The flow chart of the adaptation algorithm for Intervention group participants.

this was not required since this additional empty frame did not exist, and hence, only 2 frames were skipped.

During the analysis, the time-to-fatigue for Intervention group and Control-2 group participants were calculated based on the data read from the HapticMaster log file using an algorithm developed in python. The log file contained different information like the time stamps, end-effector position, velocity, and force, detected and reported state of fatigue, iterations, and task difficulty level. The time stamp corresponding to the state of fatigue was noted and used to calculate the time-to-fatigue. However, for Control-1 group participants, the time-to-fatigue was measured from the values of fatigue detection flags set by the off-line algorithm in MATLAB and by noting the corresponding window numbers. The corresponding window numbers were then multiplied by the window length to get the corresponding time-to-fatigue. Since the kinematic data corresponding to the break period between different MVC+ trials was also ignored, the time duration of the exercise in Control-1 group was calculated after skipping these periods. The number of task repetitions and the speed of repetitions (per minute) [22] were also analysed. A comparison was also done between the results considering the 2-STD threshold against 3-STD, 4-STD, and 5-STD thresholds in the algorithm for fatigue detection.

## 6.4 Results

### 6.4.1 Median Frequency Analysis

Similar to the results from the previous experiments, an increase in average power and a decrease of median frequency were observed and confirmed during the analysis. In the current study, a decrease in median frequency was never accompanied by a decrease in the amplitude as verified during the off-line analysis. Hence, a decrease in muscle force was not the probable cause for the above response of the EMG features, instead, it was the muscle fatigue which caused this. However, the detection algorithm only looked at a decrease in the median frequency to detect fatigue, due to the reason mentioned in Subsubsection 6.3.2.2.

Feature line plots that show the progress of EMG features as the different muscles get fatigued and relaxed during the adaptive robotic interaction are shown in Figure 6.10 for subject 20. The median frequency in the Intervention group participant displayed both increases and decreases based on the robotic adaptation. The doted regions indicated a significant decrease of median frequency in the DLTM muscle which caused in the detection of fatigue. The initial values showed that the muscle fatigue was detected when the EMG feature went outside the 2-STD threshold range and relaxed when the feature was back in the normal range. It could also be noted that the EMG median frequency stayed outside the normal range for a long duration after approximately 450 seconds without getting relaxed further. The corresponding state of fatigue flags for each muscle was also plotted as in Figure 6.11. The final fatigue flag was set based on the individual fatigue flags for each muscle. The doted regions indicated the detection of fatigue in the DLTM muscle which decided the final state of fatigue in this case, as shown in Figure 6.11. The other muscles, even though underwent many cycles of fatigue and relaxation, were not the deciding factors in the final decision about fatigue.

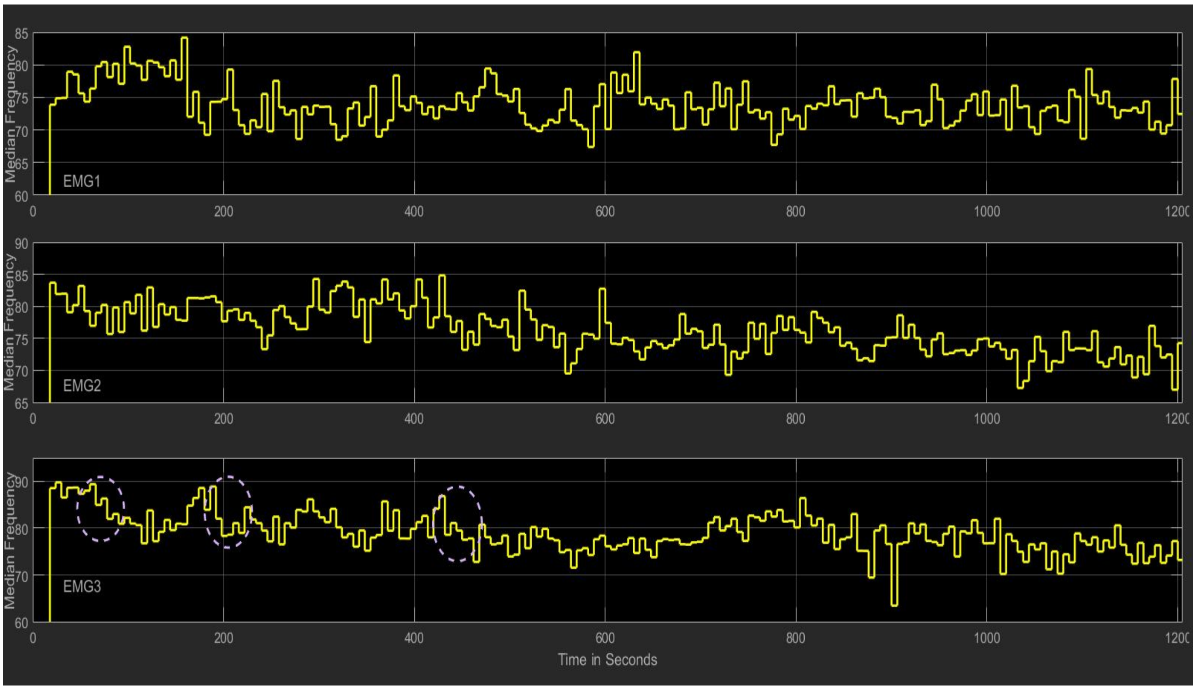


Figure 6.10: The progress of EMG median frequency in a typical Intervention group participant (Subject 20) who received adaptive robotic assistance based on the detected muscle fatigue using EMG features. The doted regions represent the significant decrease in median frequency which resulted in the detection of fatigue.

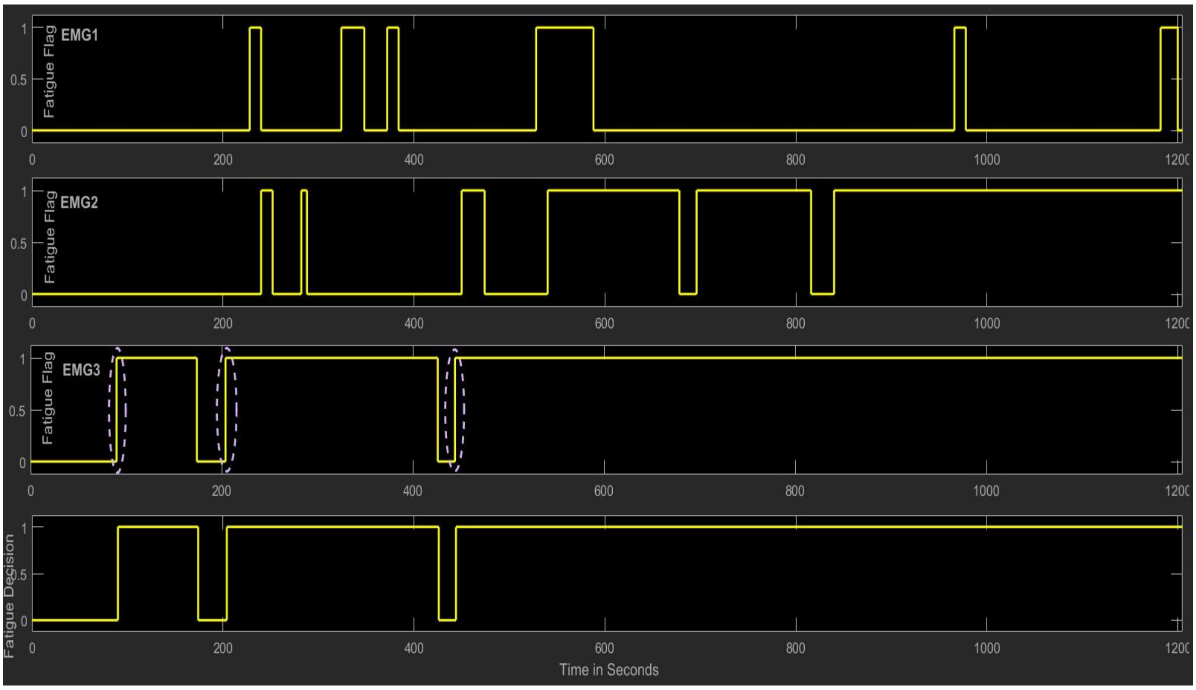


Figure 6.11: The status of fatigue flags in a typical Intervention group participant (Subject 20) who received adaptive robotic assistance based on the detected muscle fatigue. The doted regions represent the detection of fatigue in the DLTM muscle which decided the final state of fatigue.

### 6.4.2 Number of Fatigue/Relax Cycles

The number of fatigue/relax cycles after the first detected fatigue was studied as shown in Figure 6.12. A value of 0 meant that no fatigue was detected at all or that there was no cycle of fatigue/relax states after the first fatigue detection (the fatigue was detected only once during the experiment). The number of fatigue/relax cycles displayed an increased value for the Intervention group participants compared to Groups A and C as shown in Figure 6.12.

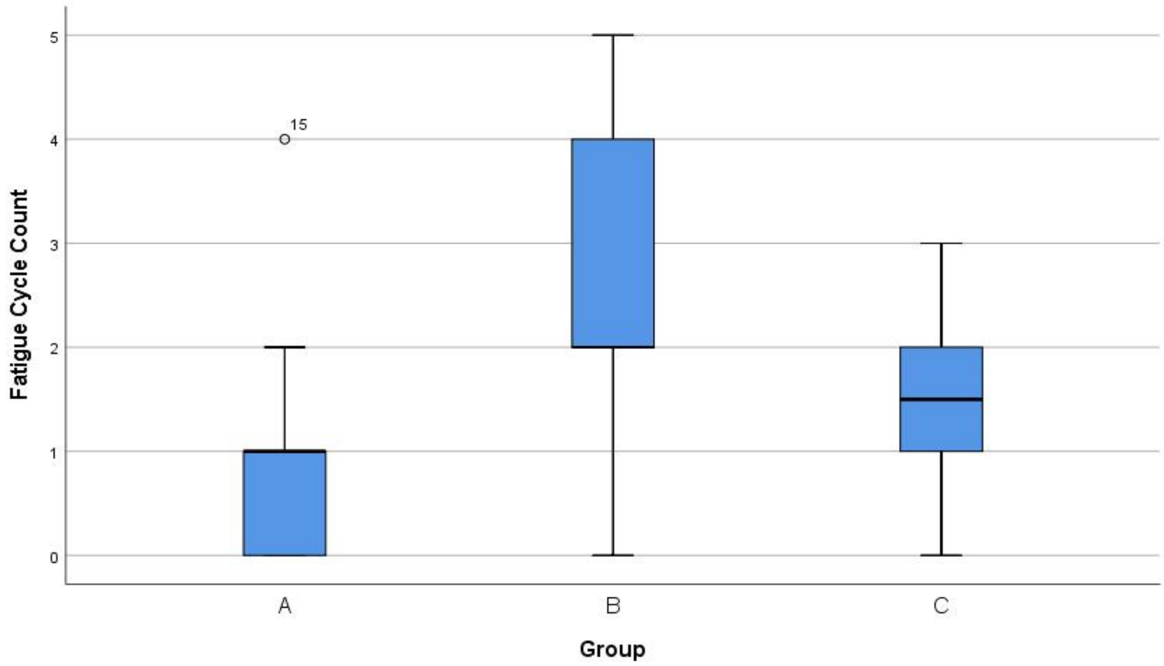


Figure 6.12: The number of fatigue/relax cycles after the first detected fatigue where the Intervention group displayed a higher value compared to the groups A and C.

### 6.4.3 Difficulty Level (Robotic Damping Coefficient)

The progress of the difficulty levels/damping coefficients during the rowing task for the three groups of participants was plotted as in Figure 6.13, Figure 6.14, and Figure 6.15. The Control-1 group performed the experiment with difficulty taking much effort to complete, however, was not able to do many iterations due to the progressively increasing difficulty after every 30 seconds break period as shown in Figure 6.13. After the experiment, only 2 subjects in the Control-1 group reported fatigue and 4 subjects reported "somewhat fatigued" through the final questionnaire. The break period introduced to avoid fatigue seemed to have helped many of them to recover before each trial. In Control-2 group participants, a subjective reporting of fatigue during the experiment was used to manually reduce the task difficulty by 50% of the current value as shown in Figure 6.15 which helped them to prolong the exercise. When the subjects reported relaxed, the difficulty started increasing by 10% MVC as shown in the figure. The questionnaire response after the experiment stated that 5 subjects reported "fatigued" and the remaining 5 reported "somewhat fatigued".

Intervention group participants could do many iterations of rowing task and several of them could continue the experiment until the maximum duration of 20 minutes was reached. Many did not report fatigue until the end and the experiment had to be stopped since the time limit was exceeded. Few subjects in Intervention group reported fatigue only once, and then stopped the exercise after a prolonged interaction. They did not want to continue further after fatigue was reported for the first time. However, as shown in the plot of difficulty levels in Figure 6.14, it was noticed that muscle fatigue was detected by the algorithm many times during the task and the difficulty was adjusted by the algorithm accordingly. The difficulty was reduced to 50% of the current value each time when fatigue was detected by the algorithm. The difficulty started increasing further by 10% MVC increments when a relaxed state was detected by the algorithm. This showed that the automatic detection of fatigue based on EMG features by the algorithm resulted in a switching of the task difficulty. This helped the participants to avoid or delay a state of fatigue during the interaction and hence, to have more repetitions and a prolonged robotic interaction.

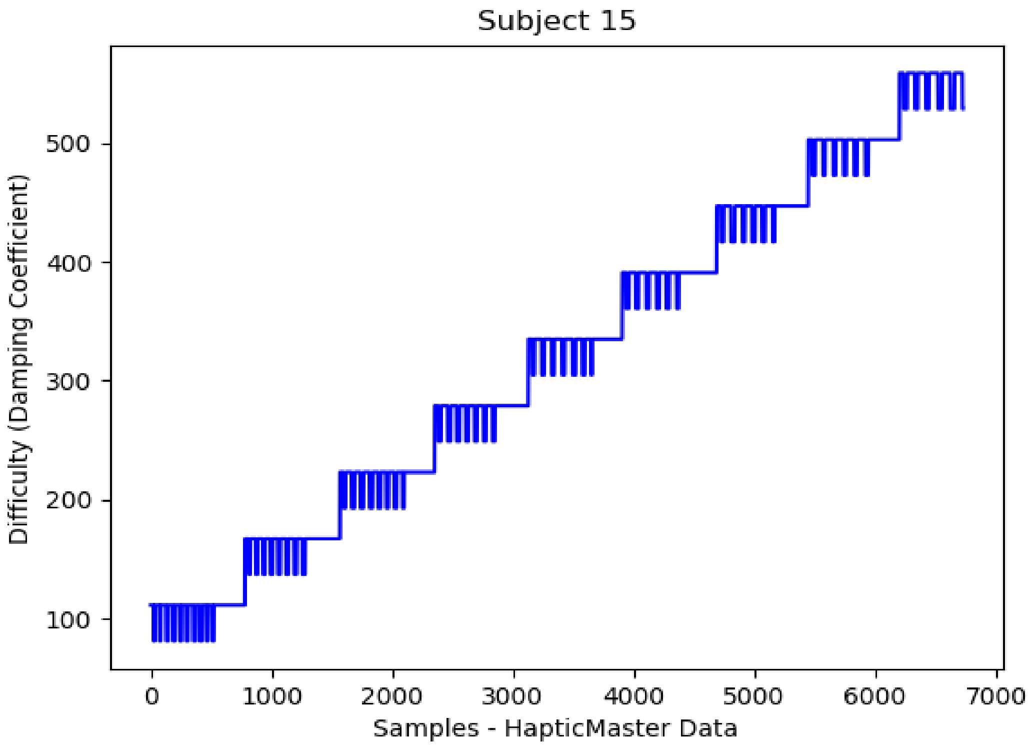


Figure 6.13: The progress of task difficulty in Control-1 group participants who received 30 seconds break period after each trial of 1-minute duration before the MVC+ increment. This group did not receive any robotic adaptation based on muscle fatigue.

Since the task difficulty was decided by the algorithm based on the muscular state of the

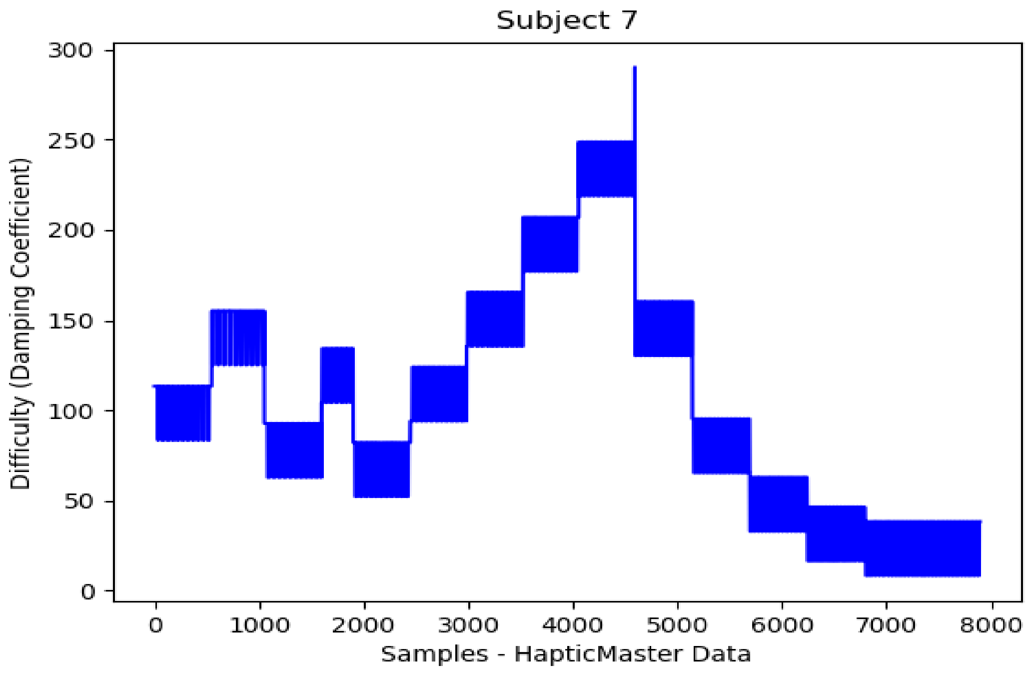


Figure 6.14: The progress of task difficulty in Intervention group participants who received an automatic robotic adaptation based on the detected fatigue using EMG features.

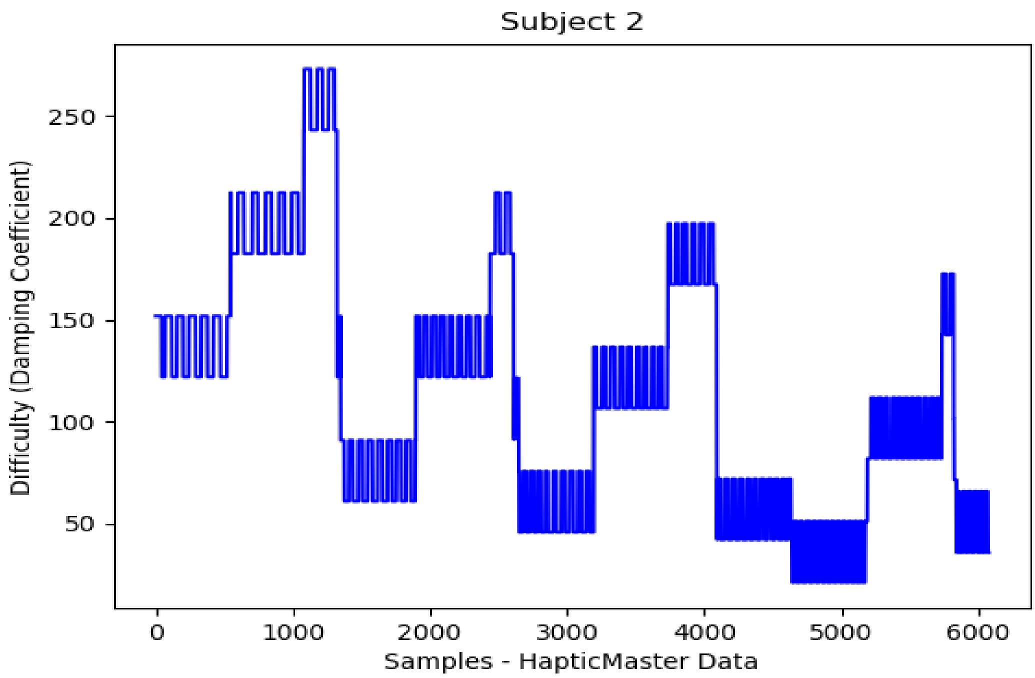


Figure 6.15: The progress of task difficulty in Control-2 group participants who received a manual robotic adaptation based on subjective fatigue reported.

participants, the average damping coefficient was considered as an output of the algorithm. Analysing the average task difficulty faced by different subjects during the experiment among the 3 participant groups as shown in Figure 6.16 indicated that Control-1 group participants faced the highest task difficulty. The Intervention group received the least task difficulty which was significantly different from both groups A and C.

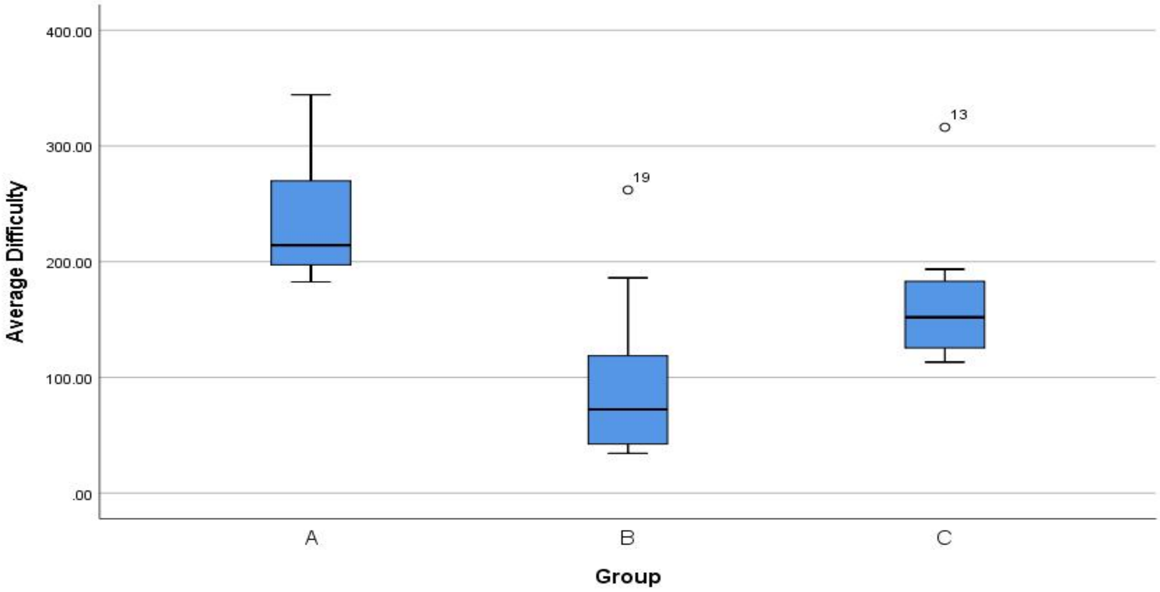


Figure 6.16: Box plots showing the average task difficulty experienced by the 3 subject groups.

### 6.4.4 Experiment Duration

Analysing SPSS box plots of the duration of the experiment among the 3 subject groups as shown in Figure 6.17 indicated that the Intervention group participants who received adaptation had the highest duration compared to Control-1 group who did not receive any adaptation. In Control-1 group, the 30 seconds of break period between different trials were ignored while calculating the duration. Control-2 group displayed a better duration compared to Control-1 group but less than that of the Intervention group participants.

### 6.4.5 Task Repetitions

The number of repetitions during the rowing task was compared using the box plots as shown in Figure 6.18. There was a statistically significant difference in the number of repetitions in the three groups, where the Intervention group displayed the highest values compared to groups A and C. The number of task repetitions per minute was also calculated and analysed as shown in Figure 6.19. A similar result as in Figure 6.18 and Figure 6.17 was observed, but a less significant difference among the 3 subjects was noted.

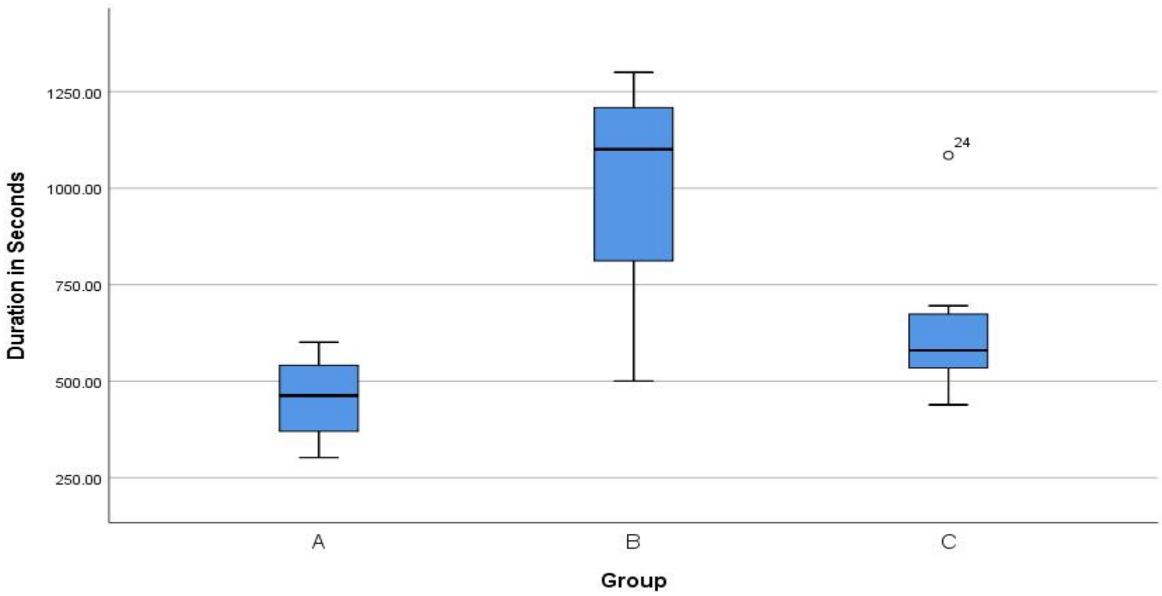


Figure 6.17: Box plots showing the duration of the experiment in the 3 groups of participants.

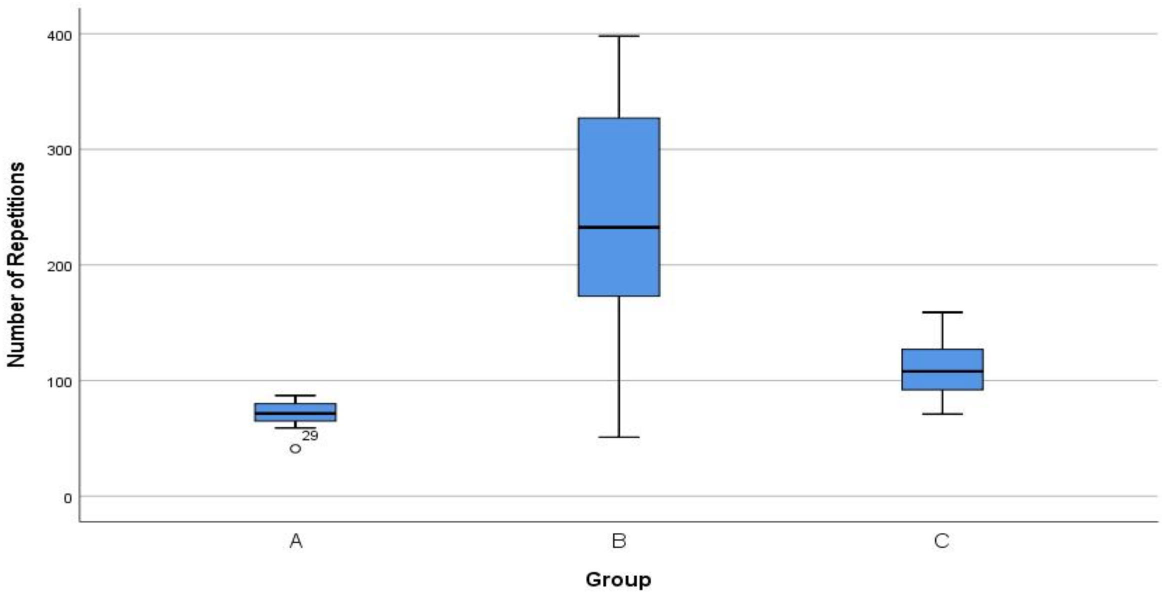


Figure 6.18: Box plots showing the number of repetitions of the rowing task in the 3 groups of participants.

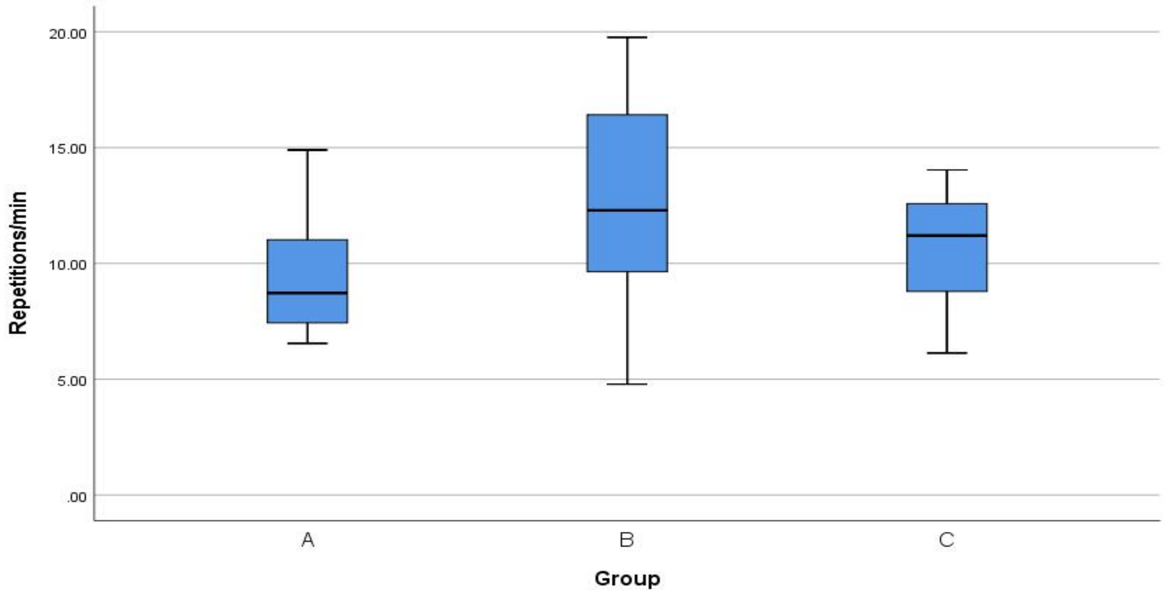


Figure 6.19: Box plots showing the rate of task repetitions (repetitions/minute) of the rowing task in the 3 groups of participants.

### 6.4.6 Time to Fatigue

The time taken to reach the first reported state of fatigue was also analysed using box plots as shown in Figure 6.20. The Intervention group was found to have taken more time to reach a state of fatigue as indicated by the higher values compared to groups A and C.

During the off-line processing, fatigue flags were also generated using algorithms based on 3-STD, 4-STD and 5-STD thresholds for studying the time of occurrence of the first fatigue. This was then compared against the time of first reported fatigue. It was noticed that using a 5-STD threshold for the fatigue detection algorithm resulted in closer values of time-to-fatigue between the reported and the detected fatigue. As an example, the difference between the time to first reported fatigue and the time to first detected fatigue considering different thresholds in few subjects was as shown in Table 6.2. The difference between the two was smaller in the case of the 5-STD threshold compared to the other thresholds.

| | **2-STD** | **3-STD** | **4-STD** | **5-STD** |
|---|---|---|---|---|
| **Subject 18** | 376.438 | 250.438 | 16.438 | 4.438 |
| **Subject 30** | 91.181 | 49.179 | 43.179 | 7.179 |

Table 6.2: Difference between the time to detected fatigue and the time to reported fatigue in seconds using different thresholds for the fatigue detection algorithm

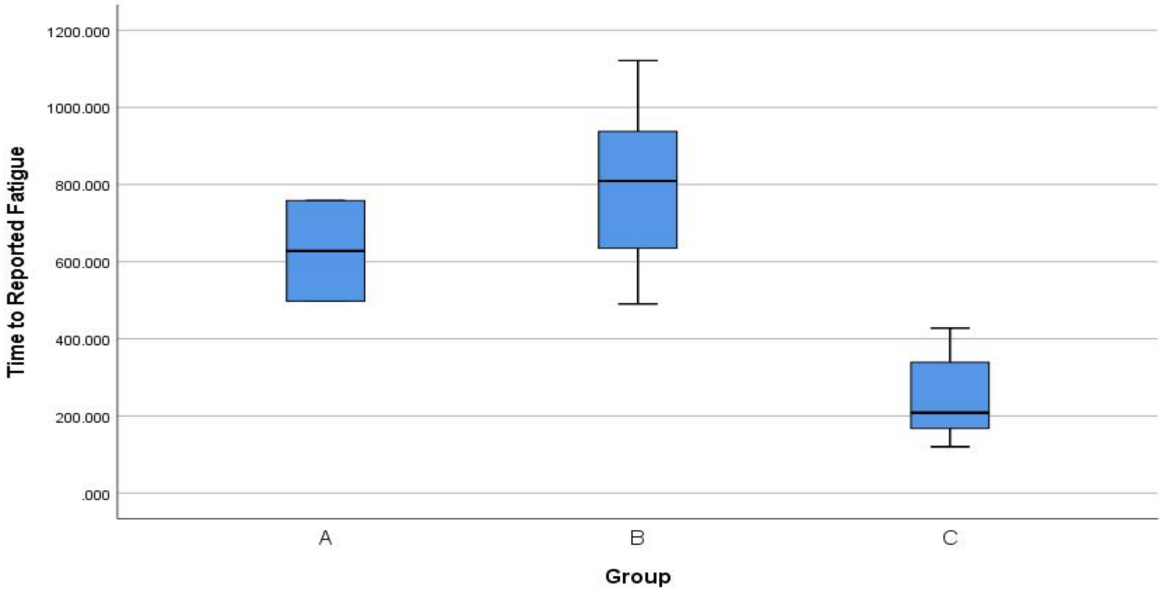


Figure 6.20: Box plots showing the time taken to reach the first reported state of fatigue in the 3 groups of participants.

## 6.5 Discussion

The results from Control-2 group showed that the manually reported fatigue in the majority of cases happened a few minutes after the automatically detected fatigue. The algorithm used for the Intervention group for automatic adaptation of the difficulty level was based only on the detected fatigue. Hence, the first detected fatigue did not involve any effects of adaptation. The adaptation would start working only after the first detection of fatigue and then, the difficulty level was reduced and, thus, the participant was assisted to perform the tasks more easily. The intention of having Control-2 group participants was to study if the automatic fatigue detection algorithm in the Intervention group actually detected the fatigue sooner or later than the reported fatigue. The same algorithm was used in Control-2 group to adjust the difficulty level, but, this was based on the reported fatigue instead of the detected fatigue. In the majority of the cases, the detected fatigue occurred before the reported muscle fatigue by the participant during the interaction. This was anticipated because EMG can give a direct measure of the muscle activation and the muscles may start showing the indication of fatigue onset through the EMG features directly. Hence, the detection of muscle fatigue based on EMG features can be earlier than the actual perception of fatigue. The subjective reporting of muscle fatigue will usually happen when the subject feels pain or is unable to continue after trying his/her level best. Since the reported fatigue happened minutes later than the detected fatigue, the time of occurrence of the reported fatigue was found to have also been influenced by the adaptation process because the reduced difficulty helped the participants to do more iterations.

Control-1 group participants performed the rowing task with difficulty due to the progressively increasing robotic resistance after each 1-minute trial. Some Control-1 group participants even though they performed the difficult task without any assistance from the robot, did not report a high fatigue. The subjects were observed to perform the task with a smaller number of repetitions, lesser duration and slower speed of task execution as shown in Figure 6.18 and Figure 6.17. Also, the break period of 30 seconds after each 1-minute trial seemed to have resulted in a recovery of the involved muscles. The experiment was designed in this way so as to mimic the sports science protocol for muscle strengthening, which involved 1 minute of training task followed by 30 seconds of break period, with incremental difficulty levels after each break period. However, as shown by the progress of damping coefficients in Figure 6.13 and Figure 6.16, Control-1 group subjects faced a progressively increasing difficulty level after each 1-minute trial.

The Intervention group participants switched between a state of fatigue and relaxation throughout the experiment (Figure 6.11). Hence, they could perform a large number of iterations with higher speed of execution as shown in Figure 6.19, Figure 6.18 and Figure 6.17. However, most of the participants reported fatigue after the prolonged robotic interaction. But this was at the cost of an increased number of task iterations and an increased duration of the exercise. Even though multiple muscles were involved in the movements some of the muscles were in a prolonged state of fatigue (for example, EMG3 in Figure 6.11 which corresponded to the DLTM muscle), and hence, had a major influence on the final decision on fatigue detection. This could be because the DLTM muscle had a higher involvement in the particular movement in Subject 20, and his could vary across different subjects based on their muscle composition.

In Control-2 group participants, the robotic adaptation happened based on the manually reported fatigue during the task and the corresponding changes in the task difficulty level were explained by Figure 6.15. Since the reported fatigue always happened after the automatically detected fatigue, the participants in the Control-2 group always received the task adaptation later than that for the Intervention group participants. Hence, the Control-2 group subjects were finding it more difficult to achieve more iterations and a prolonged interaction as explained in Figure 6.17 and Figure 6.18.

The increased effort in performing the high difficulty task in Control-1 group participants was compensated by reducing the task repetitions and a reduced duration of the experiment. Hence, even though the fatigue rate in the Control-1 group was not as high as expected, the duration for which the participants could perform the progressive strength training task was considerably small. A similar observation was made for the number of task repetitions. As previously stated, the number of task repetitions is one of the important criteria for better stroke rehabilitation (Subsection 2.6.1). Here, it was noticed that the task repetitions could be significantly increased in the Intervention group participants by using a fatigue-adaptive training environment compared to both the manual-adaptive (Control-2 group) and the non-adaptive (Control-1 group) cases.

The context of the current experiment included an automated way to measure the upper limb muscle fatigue and its rate of change in a human-robot interaction experiment that mimics a standard sports science exercise for muscle strengthening. The time taken to relax after the occurrence of fatigue was expected to be different between the 3 groups of participants. The number of fatigue and relax cycles after the occurrence of the first fatigue was counted for comparison across the different subject groups. The effect of robotic or manual assistance on the fatigue cycle count in Groups B and C only started from the first fatigue onwards, since, until this, there was no automatic or manual difficulty adjustment, which differentiated the 2 subject groups. The Intervention group participants displayed a higher number of fatigue cycles, due to frequent switching between fatigued and relaxed states. The adaptive robotic algorithm automatically detected the onset of muscle fatigue when the EMG features crossed the threshold range and then reduced the task difficulty to 50% of the current difficulty level. This level of difficulty continued for 1 minute. If the muscle fatigue continued to exist, the difficulty was further reduced by 50% of the current value. If the muscles were relaxed any time, by the end of the current 1-minute trial, the difficulty level started increasing by 10% MVC after every 1-minute of the rowing task. This switching between fatigued and relaxed states caused the higher number of the fatigue cycle count in the Intervention group as shown by Figure 6.12.

The results from the analysis could not find any particular correlation of the "time-to-fatigue" with parameters like age, body weight, Body Mass Index (BMI), visceral fat classification, skeletal muscle percentage or body fat percentage. This seems in accordance with the findings of Ma et al. [132], where, no significant effects of BMI, muscle mass or age was noticed on the joint muscle strength; instead this was dependent on the different compositions of muscle fibre types. Ma et al. [132] also stated that fatigue rates were positively correlated with maximum joint moment strength, and higher joint moment strength resulted in faster fatigability in the muscles.

The correlation study of the physiological measures against the fatigue time and experiment duration across the three groups did not give significant results. The intervention group was expected to show the least correlation between the total exercise time and the muscle composition since there would be more frequent switches between fatigued and relaxed states due to the robotic adaptation. On the other hand, the control groups 1 and 2 should show more correlation since there was no automatic adaptation involved. A person with more physical strength should ideally be able to do more iterations and hence, achieve longer experiment duration. However, the results did not show any significant correlation in any of the groups. This could be probably due to the standardisation using MVC-Eq to set the initial task difficulty level. Hence, the subject specific variations such as muscle composition and BMI did not show significant correlation with the experiment duration.

It was also noticed that at the end of the experiment, especially for Control-1 group, the iterations were very slow and hence, the chosen window/buffer size corresponding to 6 seconds does not seem to completely include the EMG corresponding to a full rowing task. This resulted in the calculated EMG features at the end stage of the experiment not representing the muscle activations corresponding to a complete rowing movement. The features might have a different composition compared to that of a full cycle of rowing task. This was due to the fixed buffer size of 6 seconds.

During the off-line analysis of the EMG data for Control-1 group participants after combining the individual mat files for each trial omitting the break periods, it was noted that some subjects (for example, Subject 8) did not show a detected fatigue even though the overall regression lines considering all the feature values were statistically significant. The linear regression analysis displayed statistically significant slopes while considering the combined mat file. However, as per the logic implemented in the algorithm for fatigue detection, any temporary reduction in the median frequency was ignored by checking the EMG feature values 3 times continuously using a fatigue counter. Since the feature values did not cross the calculated 2-STD lower limit for median frequency continuously, no fatigue detection happened according to the algorithm. If any out-of-range value occurred once and then returned to its normal range in the next sample, the fatigue counter was reset to 0 and would again wait for another 3 times continuous occurrence of out-of-range values before detecting fatigue. On the other hand, the overall regression analysis would ignore such a condition check and hence, the regression lines were found statistically significant.

It was noticed that many subjects in the Intervention group reported "relaxed" not too late after receiving the robotic adaptation. It could be that the fatigue detected by the current algorithm based on the 2-STD threshold might be an indicator of just the onset of fatigue and not that of a high state of fatigue. Hence, the time taken to come to a state of relaxation was not too long. There are many applications for the automatic fatigue detection algorithm like in human-robot interaction, rehabilitation training, muscle building or strength training exercises, where the detected muscle fatigue may be utilized in different ways, for example, for delaying/avoiding fatigue or causing fatigue. As explained in Table 6.2, depending on the application, the fatigue threshold may be adjusted such that the detected fatigue comes closer to the reported fatigue. Increasing the fatigue threshold to higher values like 5-STD threshold could be more accurate to be used in algorithms that adapt based on a high level of fatigue. However, more explorations need to be done in this area. Some recent studies have also reported that despite a reasonable rest period after a fatiguing protocol, while the performance recovered, there was even further progression of fatigue when measured by EMG. Hence, it would also be interesting to look at different time-frames following the fatigue protocol to underpin the time required for sufficient recovery from fatigue during a robot-assisted interaction.

## 6.6 Chapter Summary

As described in the literature (Subsection 2.6.1), progressive strength training has been suggested to help in stroke rehabilitation protocols. In this study, a robotic interaction protocol that mimics conventional sports science protocol for muscle strength training was suggested to be used in rehabilitation training. The robotic assistance could be used for an adaptive interaction by switching between different intensities based on the detected muscle fatigue. The results indicated that a progressive increase of task difficulty and adaptation of the difficulty level based on the onset of muscle fatigue resulted in a prolonged training interaction and increased task repetitions. The features derived from the EMG measurements from the upper limb muscles were found effective to be used as fatigue indicators for adaptive rehabilitation training.

CHAPTER 7

# DISCUSSIONS AND CONCLUSIONS

## 7.1 Conclusions

Adaptable HRI systems are known to be able to detect and respond to changes in the environment and their users. A means to sense the state of tiring of people during an HRI interaction can be utilised in a wide range of applications such as "edutainment" or rehabilitation. The major aim of the research presented in this thesis was to enhance the adaptability of a robot-assisted upper limb training environment and to achieve a prolonged and repetitive training interaction. Such a system can potentially assist patients to train independently with minimal supervision from a therapist. Through an extensive review of the literature on myoelectric signals from upper limbs and their usability in rehabilitation robotics, the work in this thesis has offered a comprehensive overview of the topic for present and future researchers in the field (Chapter 2). The literature review has revealed that the methods for robotic adaptation need further research in order to achieve acceptable solutions for adaptive rehabilitation training. The thesis has addressed the topic of robotic adaptation based on muscle fatigue detected during a rowing task with a progressively increasing difficulty.

Research Question 1 was "Can the state of muscle fatigue during human-robot interactions be effectively represented by Electromyogram (EMG) from upper limb muscles and kinematic measurements from the robot?". In the first experiment (Chapter 3), this research question was addressed by exploring the potential of using myoelectric measurements from gross upper limb muscles and kinematic measurements from the robot for detecting fatigue. The study also looked into how the kinematic features from the robot represented muscular fatigue, where the variation in tracking error (RMSE) during the robot-assisted upper limb interactions was found to indicate physical fatigue in the muscles involved. The results showed that the EMG features average power, and median frequency could be good indicators of physical fatigue during a dynamic muscle contraction exercise which involved gross upper limb muscles. The EMG analysis indicated that the Trapezius and Deltoid muscles which played a larger role in the dynamic muscle contraction task during the 4 segment movements, were more in a state of fatigue compared to the other muscles (Biceps Brachii and Triceps Brachii). The higher fatigue indication in these muscles could be mapped to kinematic indications of fatigue (through RMSE) mainly in the movements S2 and S3 which were away from the body because these muscles were actively contributing to keeping the horizontal position of the upper limb. The study showed that the EMG and kinematic features have a potential to be used to highlight the extent of muscle involvement, as the positioning of the segments and the required articulations for performing those segments relate to the EMG observations. However, the majority of the participants only reported slight fatigue after the experiment. As the experiment was performed in an active-assisted mode, the robot provided assistance/guidance to the participant. Hence, there was less effort from the participants to move the robotic end-effector along the different segments and this could have resulted in reduced muscle fatigue. To ensure that the EMG features could indeed identify fatigue correctly, a second experiment was planned with an inherently fatiguing set-up without robotic assistance.

Experiment 2 (Chapter 5) confirmed the findings from Experiment 1, stating that a statistically significant increase in EMG average power or a significant decrease in median frequency was a good indicator of muscle fatigue during dynamic muscle contraction tasks. The results from Experiment 2 also suggested that the lower band of frequencies (0.8-2.5Hz as used by [149]) was more suitable for the amplitude/average power based features than considering the whole band of 20-450Hz. Interestingly, for median frequency as the fatigue indicator, the EMG frequency band of 20-450Hz was found to provide the best fatigue indication as compared to the band of 0.8-2.5Hz. It was also noted that the rectification of EMG signals is not recommended during the feature extraction stage if median frequency analysis is used for fatigue detection.

Additionally, the feasibility of utilising the EMG features from Experiment 1 during the task initiation of upper limb movements was also explored for predicting the type of movements (in Chapter 4). This has a potential to be used for identifying the intention of gross movements during stroke rehabilitation. Different features (WL, MAV, ZC, and SSC) calculated from the EMG measurements during the dynamic muscle contraction task in the first experiment were used to classify the upper limb movements using an SVM classifier. The results showed that the movement intention of upper limbs could be detected with a reasonably good accuracy within the initial 700 milliseconds after the initiation of the task. The accuracy of the classifier for single and multiple feature/muscle combinations indicated that the upper limb segment movements can be classified with a reasonable accuracy, even in cases of dynamic muscle contractions for gross muscles. The study suggested that it is not necessary to consider the steady state EMG features for training the classifiers for complex upper limb movements and that instead, the features corresponding to dynamic muscle contractions are sufficient for this.

Research Question 2 was "Can the robot-assisted training interaction for upper limb rehabilitation be prolonged by using an adaptive algorithm which alters the environment based on the detected muscle fatigue using EMG features?". To address this research question, in Experiment 3 (in Chapter 6), the thesis proposed a progressive muscle strengthening protocol that would adjust its difficulty level based on the fatigued or relaxed state of the participants at run-time, measured by the upper limb EMG features. Based on the findings from the prior two experiments, the EMG features that were identified as fatigue indicators were used in an adaptive robot-assisted rowing environment for upper limb training. The adaptation strategies were designed based on a standard sports science protocol for muscle strengthening to suit for stroke rehabilitation. Experiment 3 demonstrated that delaying muscle fatigue by detecting fatigue and adaptation can result in a prolonged robotic interaction. The intervention group (group B) participants who received the robotic adaptation performed a significantly larger number of repetitions and exercise duration compared to the control groups (groups A and C) who did not receive any automatic adaptation based on fatigue.

## 7.2 Contribution to Knowledge

In conclusion, my research during this Ph.D. could successfully enhance the adaptability of a robot-assisted rehabilitation system based on the detected fatigue from upper limb muscles. From the overall analysis it turned out that the proposed method based on EMG-based muscle fatigue indicators can be effectively used as input to a robotic control algorithm to adapt the robot-assisted muscle strength training exercises. The research demonstrated the efficacy of the EMG parameters as muscular fatigue indicators and they could become key contributors to the design of experimental set-ups and studies in clinical settings. With an increasing number of EMG-based control approaches for assistive robots, the proposed method is beneficial to deal with many problems faced during stroke rehabilitation. One of such problems is an early termination of rehabilitation training sessions due to the patients easily coming to a state of fatigue even with mild exercises. This usually results in de-motivation in the patients and, hence, a slow recovery from stroke. The results have shown that the fatigue-based adaptive robotic control has helped to prolong the rowing exercise, which resulted in switching many times between fatigued and relaxed states of the involved upper limb muscles. The intervention group who received an automatic adaptation was found to achieve a prolonged interaction compared to the control groups. Therefore, the thesis has contributed to the long-term goal of offering an adaptive solution for prolonged and repetitive training interaction for stroke patients as well as for the end-users of upper limb prostheses.

Additionally, during the kinematic feature analysis in Experiment 1, it was noticed that there was an increase of root mean square error (RMSE) between actual and expected position trajectories as the muscles became fatigued. It was noticed that this increase in RMSE was smallest during the comfortable 'near-the-body' movements compared to 'away-from-body' movements. Considering the musculoskeletal physiology of upper limbs, the Biceps Brachii and Triceps Brachii muscles played the major role in these 'near-the-body' movements and, hence, these muscles were less fatigued compared to the Deltoid and Trapezius muscles who played a major role in the 'away-from-body' movements. The results implied that the increased kinematic fatigue score during 'away-from-body' movements was attributed to the development of fatigue by the end of the experiment. Hence, the indication of muscle fatigue by EMG features (mainly in the TRP and DLT muscles) was kinematically correlated with the errors and variations in position mainly in the movements which were difficult to execute.

Also, during the correlation study between EMG and kinematic force, a gradual change (mostly decrease) in correlation coefficients was noticed as the trials progressed, which could be an indication of fatigue. This was observed mainly for the horizontal force components ($F_x$ and $F_y$). The non-linearity in the correlation between muscle force and EMG amplitude during fatigue might have caused this particular behaviour of correlation coefficients. Moreover, the sign of correlation coefficients for $F_x$ and $F_y$ components was found to follow a pattern as shown in Table 3.7. The more fatigued muscles (Deltoid and Trapezius) did not show a consistent sign-pattern compared to the less fatigued muscles (Biceps Brachii and Triceps Brachii). It seems that the profound sign-pattern in the BB and TB muscles was due to the state of less-fatigue or no-fatigue. This could be because the BB and TB muscles played roles mainly in determining the direction of movements along the four segments, but not in holding the upper limb in the shoulder position. Probably due to this reason, these muscles also displayed the strongest EMG-Force correlation compared to the TRP and DLT muscles. Previously, the EMG analysis during the initial studies indicated that the DLT and TRP muscles were more fatigued compared to the BB and TB muscles. Hence, the study shows that muscle fatigue affected the correlation between EMG and kinematic force since the fatigued muscles displayed the least correlation in the majority of the subjects.

The work reported in this thesis has contributed to the publications listed below which include two international conference papers and two journal articles (to be submitted). The first author of these articles conducted the research studies and produced a complete draft of the articles. The co-authors guided and supported during the design, development and evaluation process of the studies and also provided feedback on the drafts of the articles.

- **Paper 1:** Azeemsha Thacham Poyil, Farshid Amirabdollahian, Volker Steuber, "Study of Gross Muscle Fatigue During Human-Robot Interactions", ACHI 2017: The Tenth International Conference on Advances in Computer-Human Interactions, Nice, France, March 19 - 23, 2017 (Appendix B).
  The paper investigated the usability of kinematic features, EMG median frequency, and average power as fatigue indicators during an upper limb exercise while operating the HapticMaster robot in the active-assisted mode of operation. The features were identified to have a potential to be used in an adaptive robot-assisted system for stroke rehabilitation, however, many participants seemed to have taken the assistance from the robot.
- **Paper 2:** Azeemsha Thacham Poyil, Farshid Amirabdollahian, Volker Steuber, "Classification of Gross Upper Limb Movements Using Upper Arm Electromyographic Features", RO-MAN 2017: Proceedings of the 26th IEEE International Symposium on Robot and Human Interactive Communication, Lisbon, Portugal, August 28-31, 2017 (Appendix B).
  The paper explored the efficacy of using the initial EMG measurements during the task initiation of upper limb movements to be used for predicting the type of movements. This has the potential to be used for identifying the intention of gross upper limb movements during stroke rehabilitation.
- **Paper 3 (to be submitted)**: This was a continuation of the study from Paper 1 and was planned to confirm the findings from the paper by performing an inherently tiring exercise for causing fatigue. The EMG features median frequency, and average power were found to display a statistically significant trend as the muscle fatigue developed in the upper limb muscles. This confirmed the results from Paper 1.
- **Paper 4 (to be submitted)**: This study investigated the efficacy of using the EMG fatigue indicators to be used for adaptation of a progressive muscle strength training protocol in stroke patients. A robotic interaction protocol that mimics a conventional sports science protocol for muscle strength training was suggested to be used in rehabilitation training. The study was conducted on 30 healthy individuals. The results indicated that a progressive increase of task difficulty and adaptation of the difficulty level based on the onset of muscle fatigue resulted in a prolonged training interaction and increased task repetitions.

## 7.3 Limitations and Future work

As discussed previously, the major limitation of the study was the robotic assistance used in the first experiment, which resulted in a smaller fatigue in the participants, whereas the expectation was a high fatigue at the end of all trials. This led me to conduct the second experiment which could have been avoided otherwise. Additionally, the break period between trials also caused recovery from the state of muscle fatigue before starting the next trial. Hence, the continuity of any trend in the fatigue indicators was partly lost. Hence, the experiments could have been made a bit more difficult and the break period could be avoided so that the muscles are sufficiently tired to produce better indications of fatigue. The state of fatigue during or in the middle of different trials could also have been captured through a questionnaire. Another area in this study that needs improvement could be the on-line fatigue detection logic used during Experiment 3. If the feature values do not cross the baseline range three times in a row, fatigue detection would not occur according to the algorithm. If any out-of-range value occurred once and then returned to its normal range in the next sample, a fatigue counter was reset to zero and the algorithm would again wait for another 3 times continuous occurrence of out-of-range values before detecting fatigue. This logic of using "3 times check" for confirming the detected muscle fatigue was arbitrary, and there could be other possible strategies to do this in a better way.

The results presented in this thesis have demonstrated the effectiveness of the proposed methods and approaches, and an obvious future study would be recruiting stroke patients and assessing their performance with and without fatigue-based robotic adaptation. It may be noted that the current results are only based of healthy individuals, however, in the real scenario of stroke patients, there could be a faster rate of fatigue and a different response rate between fatigued and relaxed states.

Based on the work presented in this thesis, there are several possible future lines of research. A possible future study based on Experiment 1 could be to utilise the kinematic fatigue indicators based on MJT parameters and RMSE for a fatigue-adaptive robotic-assisted training protocol. As an extension of the study described in Paper 2, the predictability of gross upper limb movements during the training exercises may be used in association with a fatigue based adaptive robotic environment to improve the assistance strategy based on the predicted movement type. Future research may exploit this possibility. Another possible future study as an extension of Experiment 3 could be to explore if the fatigue detected by the current algorithm based on the 2-STD threshold was only an indicator of the onset of fatigue. It may be investigated how to quantitatively measure the different levels of fatigue such as "Somewhat Fatigued", "Moderately Fatigued", "Highly Fatigued", and "Extremely Fatigued". It would also be interesting to look at different time-frames following the fatigue protocol to underpin the time required for sufficient recovery from fatigue during a robot-assisted interaction. Some of the contributions from this work may also be applicable to myoelectric control of lower-limb prostheses. Future studies may also look into the possibilities of using interactive games with adaptable complexity parameters based on the user's state of fatigue identified through EMG and kinematic fatigue indicators.

APPENDIX A

# APPENDIX A

# Research Questionnaire

Thank you for participating in the study. Please place a [X] mark in the corresponding box of your answer or write your answer in the provided space. The answers will be anonymous and will only be used for the experimental result analysis.

---

## About you

1. **Subject ID:** ____________________
2. **Your name:** ______________________________________
3. **Age:** _____ years.
4. **Gender:** ☐ Male ☐ Female
5. **Dominant Arm:** ☐ Right Handed ☐ Left Handed

---

**Before the Experiment:**

6. **Current Level of Muscle Fatigue:**
   ☐ Not Fatigued. ☐ Somewhat Fatigued. ☐ Fatigued. ☐ Very Fatigued. ☐ Extremely Fatigued.

---

**After the Experiment:**

7. **Level of Muscle Fatigue After the Experiment:**
   ☐ Not Fatigued. ☐ Somewhat Fatigued. ☐ Fatigued. ☐ Very Fatigued. ☐ Extremely Fatigued.
8. **How difficult was the experiment for you?**
   ☐ Too Easy. ☐ Somewhat Easy. ☐ Difficult. ☐ Very Difficult. ☐ Extremely Difficult.
9. **Do you think that your performance during the exercise was affected by fatigue?** ☐ Yes ☐ No
10. **Do you feel that the robot assisted/helped you (by reducing the task difficulty) at some point while performing the task?** ☐ Yes ☐ No

**If selected "Yes" for the above question, please answer the these**

11a. **Did you receive the robotic assistance when you really needed it?**
- ☐ Yes, exactly when I needed.
- ☐ Before I actually needed it.
- ☐ No, some time after I actually needed it.
- ☐ I do not remember.

11b. **Did the robotic assistance help you to perform more iterations?**
☐ Yes ☐ No

11c. **How do you feel that the robotic assistance worked?**
- ☐ Assisted me only once.
- ☐ It switched between assistance and difficulty mode many times.
- ☐ I do not remember.
- ☐ If in some other ways, please write here:

______________________________________________

______________________________________________

______________________________________________

______________________________________________

**11d. Do you feel that the level of robotic assistance was sufficient?** ☐ Yes ☐ No

**12. Which muscles did you find as most tired after the experiment?** Tick in the area near the muscle locations in the image below.

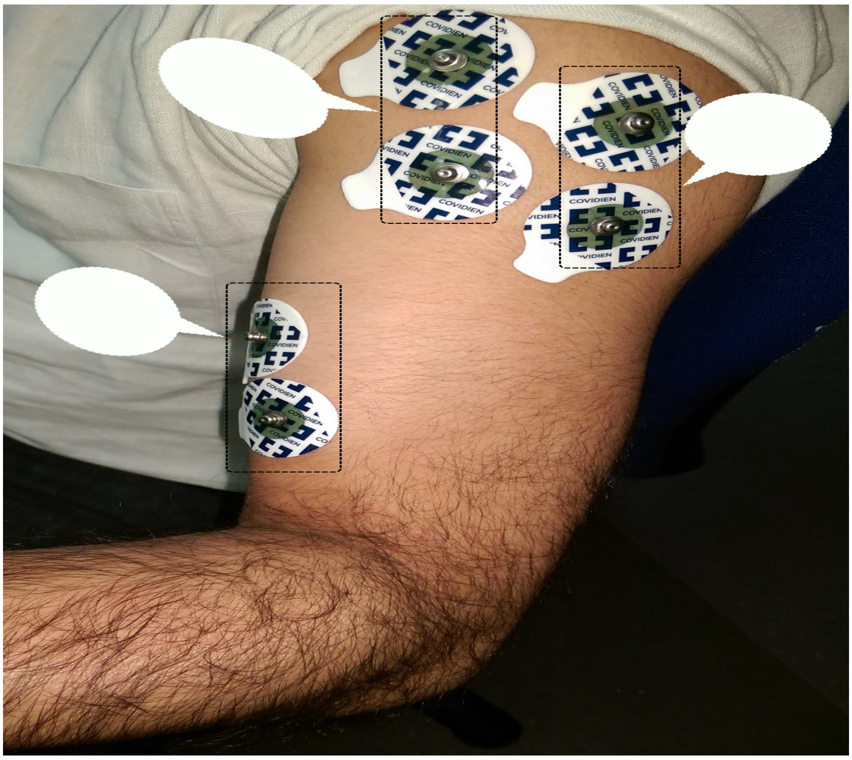


Figure 1: Muscle Locations.

**13. Would you like to write some more lines on how you felt about the experiment?. Do you have any suggestions on how to improve the experiment?**

________________________________________

________________________________________

________________________________________

________________________________________

## Experiment Measures (To be entered by the principal investigator)

14. **Height:** ________ cm.
15. **Weight:** ________ Kg.
16. **Body Mass Index:** ___________ .
17. **Visceral Fat Classification:** ___________ .
18. **Skeletal Muscle Percentage:** ___________ .
19. **Body Fat Percentage:** ___________.

# APPENDIX B

**Paper 1:** Study of Gross Muscle Fatigue During Human-Robot Interactions

**Authors:** Azeemsha Thacham Poyil, Farshid Amirabdollahian, Volker Steuber

**Abstract:** This study explores the utility of Electromyogram (EMG) signals in the context of upper-limb exercises during human-robot interaction considering muscle fatigue of the participant. We hypothesise that the Electromyogram features from muscles and kinematic measurements from the robotic sensors can be used as indicators of fatigue and there is a potential to identify the muscle contribution during the activity where the Electromyogram data is correlated with the kinematic data. Electromyogram measurements were taken from four upper limb muscles of 10 healthy individuals. HapticMaster robot in active assisted mode together with a virtual environment was used to guide the participants for moving the robotic arm in a prescribed path in a horizontal plane consisting of four segments. The experiments were conducted until the participants reached a state of fatigue or until a defined maximum number of 6 trials were reached. Comparing the first and last trials indicated that the muscle fatigue had caused an increase in the average power and a decrease in the median frequency of EMG, which was more visible in Trapezius (TRP) and Anterior Deltoid (DLT) muscles in most of the analysed cases compared to Biceps Brachii (BB) and Triceps Brachii (TB) muscles. As the muscles came to a state of fatigue, the kinematic position also showed an increase in tracking error between the first and last trials. The "near-the-body" segment movements (S1 and S4 segments) were found to have less increase of tracking error compared to the "away-from-body" movements (S2 and S3 segments). A further analysis on this proved that the tracking error observed was mainly due to fatigue building up over the number of trials when performing "away-from-body" movements, and not a bi-product of perception errors. We identify that Deltoid and Trapezius muscles were

fatigued more. These EMG fatigue indications can be mapped to kinematic indications of fatigue mainly in the segments S2 and S3, which required away from body movements because of the role of these two muscles in lifting the arm to the shoulder height in order to perform the activity. Our extracted features have shown the potential to identify the fatigued muscles as expected. The study also showed that the Electromyogram and kinematic features have a potential to be used to highlight the extent of muscle involvement.

**Conference:** The Tenth International Conference on Advances in Computer-Human Interactions

**Location:** Nice, France

**Pages:** 187 to 192



**Publication date:** March 19, 2017

**ISBN:** 978-1-61208-538-8

**Paper 2:** Classification of gross upper limb movements using upper arm electromyographic features

**Authors:** Azeemsha Thacham Poyil, Farshid Amirabdollahian, Volker Steuber

**Abstract:** This research paper explores the possibility of using Electromyogram (EMG) signals for classifying point to point upper limb movements during dynamic muscle contraction in the context of human-robot interactions. Previous studies have mostly focused on classifiers for gesture recognition using steady state EMG. Only few studies have used non-steady-state EMG classifier when gross upper arm muscles are in motion. To investigate it further, our study was designed to take EMG measurements from 4 upper limb muscles of 10 participants while interacting with HapticMaster robot in assisting mode. The participants were asked to move the robotic arm in a rectangular path consisting of 4 segments named S1 to S4. The EMG signals were analyzed by splitting them into non-overlapping windows of 100 milliseconds width. The initial windows within the initial 1 seconds of each segment iteration were considered to train and test a Support Vector Machine classifier. Various EMG features were calculated for different number of windows and used for classifying different segments. For the different combinations of features and muscles, it was noticed that the near-the-body segments S1 and S4 displayed the highest median accuracy for the feature combination (Waveform Length + Mean Average Value + Zero Crossing Count + Signal Slope Change) which were 100% each. For the same feature combination, it was also noticed that the segments S2 and S3 had the least accuracy, 76.2% and 73.8% respectively, possibly due to the away-from-body movements. In general, the accuracy was found to be more stable and higher for S1 and S4 segments. Considering 700 milliseconds (so 7 windows) for classification provided the best accuracy and the best muscle combination was Trapezius + Deltoid + Biceps Brachii + Triceps Brachii.

**Conference:** 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)

**Location:** Lisbon, Portugal

**Date of Conference:** 28 Aug.-1 Sept. 2017

**Publication date:** 14 December 2017

**Electronic ISSN:** 1944-9437

APPENDIX

C

# APPENDIX C

## Regression Statistics for Average Power (Experiment 2)

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| AvgPower_BB | 1133.51667 | 95.682785 | 12 |
| Window | 6.50 | 3.606 | 12 |

a. Selecting only cases for which Subject = 1

### Correlations[a]

| | | AvgPower_BB | Window |
|---|---|---|---|
| Pearson Correlation | AvgPower_BB | 1.000 | -.159 |
| | Window | -.159 | 1.000 |
| Sig. (1-tailed) | AvgPower_BB | . | .311 |
| | Window | .311 | . |
| N | AvgPower_BB | 12 | 12 |
| | Window | 12 | 12 |

a. Selecting only cases for which Subject = 1

### Model Summary

| Model | R Subject = 1 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .159[a] | .025 | -.072 | 99.077964 |

a. Predictors: (Constant), Window

### a,b

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 1160.926 | 60.978 | | 19.038 | .000 |
| | Window | -4.217 | 8.285 | -.159 | -.509 | .622 |

a. Dependent Variable: AvgPower_BB

b. Selecting only cases for which Subject = 1

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| AvgPower_BB | 2413.90000 | 699.894956 | 7 |
| Window | 4.00 | 2.160 | 7 |

a. Selecting only cases for which Subject = 2

### Correlations[a]

| | | AvgPower_BB | Window |
|---|---|---|---|
| Pearson Correlation | AvgPower_BB | 1.000 | .930 |
| | Window | .930 | 1.000 |
| Sig. (1-tailed) | AvgPower_BB | . | .001 |
| | Window | .001 | . |
| N | AvgPower_BB | 7 | 7 |
| | Window | 7 | 7 |

a. Selecting only cases for which Subject = 2

### Model Summary

| Model | R<br>Subject = 2 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .930[a] | .864 | .837 | 282.523662 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 1209.143 | 238.776 | | 5.064 | .004 |
| | Window | 301.189 | 53.392 | .930 | 5.641 | .002 |

a. Dependent Variable: AvgPower_BB

b. Selecting only cases for which Subject = 2

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| AvgPower_BB | 54.87387 | 19.743078 | 8 |
| Window | 4.50 | 2.449 | 8 |

a. Selecting only cases for which Subject = 3

**Correlations**[a]

| | | AvgPower_BB | Window |
|---|---|---|---|
| Pearson Correlation | AvgPower_BB | 1.000 | .930 |
| | Window | .930 | 1.000 |
| Sig. (1-tailed) | AvgPower_BB | . | .000 |
| | Window | .000 | . |
| N | AvgPower_BB | 8 | 8 |
| | Window | 8 | 8 |

a. Selecting only cases for which Subject = 3

**Model Summary**

| Model | R<br>Subject = 3 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .930[a] | .865 | .843 | 7.821459 |

a. Predictors: (Constant), Window

**Coefficients**[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 21.131 | 6.094 | | 3.467 | .013 |
| | Window | 7.498 | 1.207 | .930 | 6.213 | .001 |

a. Dependent Variable: AvgPower_BB

b. Selecting only cases for which Subject = 3

**Descriptive Statistics**[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| AvgPower_BB | 246.75273 | 43.076717 | 11 |
| Window | 6.00 | 3.317 | 11 |

a. Selecting only cases for which Subject = 4

### Correlations[a]

| | | AvgPower_BB | Window |
|---|---|---|---|
| Pearson Correlation | AvgPower_BB | 1.000 | .139 |
| | Window | .139 | 1.000 |
| Sig. (1-tailed) | AvgPower_BB | . | .342 |
| | Window | .342 | . |
| N | AvgPower_BB | 11 | 11 |
| | Window | 11 | 11 |

a. Selecting only cases for which Subject = 4

### Model Summary

| Model | R Subject = 4 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .139[a] | .019 | -.090 | 44.966270 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 235.923 | 29.078 | | 8.113 | .000 |
| | Window | 1.805 | 4.287 | .139 | .421 | .684 |

a. Dependent Variable: AvgPower_BB

b. Selecting only cases for which Subject = 4

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| AvgPower_BB | 1582.20750 | 715.223875 | 12 |
| Window | 6.50 | 3.606 | 12 |

a. Selecting only cases for which Subject = 5

### Correlations[a]

| | | AvgPower_BB | Window |
|---|---|---|---|
| Pearson Correlation | AvgPower_BB | 1.000 | .922 |
| | Window | .922 | 1.000 |
| Sig. (1-tailed) | AvgPower_BB | . | .000 |
| | Window | .000 | . |
| N | AvgPower_BB | 12 | 12 |
| | Window | 12 | 12 |

a. Selecting only cases for which Subject = 5

### Model Summary

| Model | R Subject = 5 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .922[a] | .851 | .836 | 289.996757 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 393.069 | 178.481 | | 2.202 | .052 |
| | Window | 182.944 | 24.251 | .922 | 7.544 | .000 |

a. Dependent Variable: AvgPower_BB

b. Selecting only cases for which Subject = 5

## Regression Statistics for Median Frequency (Experiment 2)

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 24.42829 | 3.126314 | 7 |
| Window | 4.00 | 2.160 | 7 |

a. Selecting only cases for which Subject = 2

### Correlations[a]

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.979 |
| | Window | -.979 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .000 |
| | Window | .000 | . |
| N | MeanFreq_BB | 7 | 7 |
| | Window | 7 | 7 |

a. Selecting only cases for which Subject = 2

### Model Summary

| Model | R Subject = 2 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .979[a] | .958 | .950 | .700472 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 30.095 | .592 | | 50.835 | .000 |
| | Window | -1.417 | .132 | -.979 | -10.701 | .000 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject = 2

## Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 30.13738 | 1.404109 | 8 |
| Window | 4.50 | 2.449 | 8 |

a. Selecting only cases for which Subject = 3

## Correlations[a]

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.572 |
| | Window | -.572 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .069 |
| | Window | .069 | . |
| N | MeanFreq_BB | 8 | 8 |
| | Window | 8 | 8 |

a. Selecting only cases for which Subject = 3

## Model Summary

| Model | R Subject = 3 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .572[a] | .327 | .214 | 1.244518 |

a. Predictors: (Constant), Window

## Coefficients[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 31.612 | .970 | | 32.599 | .000 |
| | Window | -.328 | .192 | -.572 | -1.706 | .139 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject = 3

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 35.04300 | 1.248165 | 11 |
| Window | 6.00 | 3.317 | 11 |

a. Selecting only cases for which Subject =  4

### Correlations[a]

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.585 |
| | Window | -.585 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .029 |
| | Window | .029 | . |
| N | MeanFreq_BB | 11 | 11 |
| | Window | 11 | 11 |

a. Selecting only cases for which Subject =  4

### Model Summary

| Model | R Subject =  4 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .585[a] | .342 | .269 | 1.067158 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 36.364 | .690 | | 52.693 | .000 |
| | Window | -.220 | .102 | -.585 | -2.163 | .059 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject =  4

**Descriptive Statistics[a]**

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 32.63542 | 3.697640 | 12 |
| Window | 6.50 | 3.606 | 12 |

a. Selecting only cases for which Subject = 5

**Correlations[a]**

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.930 |
| | Window | -.930 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .000 |
| | Window | .000 | . |
| N | MeanFreq_BB | 12 | 12 |
| | Window | 12 | 12 |

a. Selecting only cases for which Subject = 5

**Model Summary**

| Model | R Subject = 5 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .930[a] | .864 | .851 | 1.428525 |

a. Predictors: (Constant), Window

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 38.833 | .879 | | 44.168 | .000 |
| | Window | -.953 | .119 | -.930 | -7.981 | .000 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject = 5

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 30.71200 | 3.848055 | 8 |
| Window | 4.50 | 2.449 | 8 |

a. Selecting only cases for which Subject = 6

### Correlations[a]

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.914 |
| | Window | -.914 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .001 |
| | Window | .001 | . |
| N | MeanFreq_BB | 8 | 8 |
| | Window | 8 | 8 |

a. Selecting only cases for which Subject = 6

### Model Summary

| Model | R Subject = 6 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .914[a] | .836 | .808 | 1.684609 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 37.175 | 1.313 | | 28.321 | .000 |
| | Window | -1.436 | .260 | -.914 | -5.525 | .001 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject = 6

### Descriptive Statistics[a]

| | Mean | Std. Deviation | N |
|---|---|---|---|
| MeanFreq_BB | 27.97786 | 2.510819 | 7 |
| Window | 4.00 | 2.160 | 7 |

a. Selecting only cases for which Subject = 7

### Correlations[a]

| | | MeanFreq_BB | Window |
|---|---|---|---|
| Pearson Correlation | MeanFreq_BB | 1.000 | -.766 |
| | Window | -.766 | 1.000 |
| Sig. (1-tailed) | MeanFreq_BB | . | .022 |
| | Window | .022 | . |
| N | MeanFreq_BB | 7 | 7 |
| | Window | 7 | 7 |

a. Selecting only cases for which Subject = 7

### Model Summary

| Model | R Subject = 7 (Selected) | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .766[a] | .586 | .504 | 1.769182 |

a. Predictors: (Constant), Window

### Coefficients[a,b]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 31.538 | 1.495 | | 21.092 | .000 |
| | Window | -.890 | .334 | -.766 | -2.662 | .045 |

a. Dependent Variable: MeanFreq_BB

b. Selecting only cases for which Subject = 7

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