A Study of Controlling Upper-Limb Exoskeletons Using EMG and EEG signals

BY

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Abstract

Among the many fields of robotics, assistive robotic technologies have attracted a lot of attention among the research community as well as the common society. Especially assistive robots such as exoskeletons, prosthetics are playing major roles in assisting and rehabilitation processes for a range of people including physically weak, old, injured or disabled individuals to improve their quality of life. An upper-limb exoskeleton robot is one of the most effective assistive robots that can be used to assist or rehabilitate the motions of upper-limbs of a physically weak individual. Controlling upper-limb exoskeletons however, requires sophisticated technologies or methods, as they always interact with human users. More importantly, upper-limb exoskeletons are required to control according to the motion intention of the user. Apart from torque/force sensor signals, Electromyography (EMG) and Electroencephalography (EEG) signals are identified as two potential input signals for these control methods in order to monitor the motion intention of the exoskeleton users. Although there has been tremendous progress in the last decade in control methods for upper-limb exoskeletons, there are several problems which need further research effort. Therefore, the objective of this thesis is to address issues related to the control of upper-limb exoskeletons using EMG and EEG signals. More specifically this thesis focuses on the issue of muscle fatigue in EMG-based control and the feasibility of using EEG signals for evaluation of the perception-assist in upper-limb exoskeletons.

The first half of the thesis addresses the problem of muscle fatigue on EMG-based control. At the beginning, experiments were carried out to find out the effects of muscle fatigue on EMG signals and EMG-based control in human upper-limb power-assist. The results of these experiments revealed that only an EMG amplitude feature such as EMG Root mean square (RMS) is not adequate as an input for accurate EMG-based control during the muscle fatigue conditions and highlighted the importance of using frequency domain EMG features as additional input features to EMG-based control. To compensate for the effects of muscle fatigue on EMG-based control, this thesis proposed a novel method based on multiple fuzzy-neuro modifiers which used EMG mean power frequency (MPF) in addition to EMG RMS as an input to identify the muscle fatigue conditions. Experiments were performed with elbow flexion/extension motions to control a robot arm and the proposed method was able to reduce the overshoots of the robot motions that occurred due the effects of muscle fatigue conditions. From the overall analysis, it turned out that the proposed method based on multiple fuzzy-neuro modifiers with EMG RMS and MPF features as inputs could be effectively used to compensate for the effects of muscle fatigue on EMG-based control. With increasing number of EMG-based control approaches for assistive robots, the proposed method is beneficial to deal with the problem of muscle fatigue.

The second half of the thesis investigates the feasibility of EEG signals for evaluation of the perception-assist control performed by the upper-limb exoskeletons. Perception-assist has been introduced in addition to the power-assist for upper-limb exoskeletons to avoid the undesired motion intentions by the users with deteriorated perception abilities. Perception-assist needs to be learned by the exoskeleton itself and in this learning process; it is required to judge the correctness or incorrectness of the perception-assist performed by the exoskeleton. EMG is one of the potential signals to judge the perception-assist control performed by the exoskeleton. On the other hand, EEG signals are also another candidate for evaluation of the perception-assist control. Experiments were carried out using a wrist assist exoskeleton with perception-assist while monitoring EMG and EEG signals. Results of the analysis of EMG signals during perception-assist signified that EMG signals are sometimes not adequately changed for the judgments of the perception-assist. Moreover, for a particular user, it might be difficult to measure the EMG signals or required muscles may simply be unavailable. For these reasons, in addition to EMG signals, this thesis explored the possibility of utilizing EEG signals. Correctness or incorrectness of the perception-assist was judged using a combination of EMG-EEG signals and the results showed a relatively higher accuracy compared to EMG signals alone. Moreover, an attempt was made to judge the perception-assist based on only EEG signals. Even though the accuracy of the judgment was above the chance level in this approach, it was lower than that of EMG only or EMG-EEG approaches. Eventually, this study suggested that to use a combination of EMG and EEG for higher judgment accuracy of the perception-assist. It also highlighted that depending on the situation and condition of the user, either EMG, EEG or combination of EMG-EEG can be switched in between to judge the correctness or incorrectness of the perception-assist.

Approval

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CERTIFICATE OF APPROVAL

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Dedication

To my *father* and *mother*,
To my *brother*,
To my *wife*,
for their love and endless support.

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Writing this thesis would not have been possible without the help and support of many people around me.

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Thilina Lalitharatne
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Chapter 1

Introduction

In the last few decades, robots and robotic technology have progressed from machines in science fiction to nearly commercialized products. A few decades ago, robots were mainly utilized as tools in manufacturing facilities to perform tasks like welding, drilling, machining and assembling. However, with the advancement of technology, the field of robotics expanded rapidly. More and more researches are carried out in different fields of robotics such as industrial robots, arial robots, mobile robots, cooperative robots, assistive robot and biorobotics, underwater robots etc.

Among many fields of robotics, assistive robotic technologies have been able to attract much attention in the current research community around the world. Recent developments in assistive robotic technology serves in many ways to improve the quality of life for a range of people including physically weak, old, injured or disabled individuals. It is also a well known fact that in current global society, the number of aged population and the percentage of aged population are increasing rapidly [1]. The main reasons of this rapid increment of aged population are the decrease in the total fertility rate and the increase in the life expectancy [2]. In addition, a significant numbers in the population suffer from physical disabilities such as full or partial loss of functions. These disabilities largely occur due to diseases including trauma, strokes, spinal cord injuries, occupational injuries and sports related injuries. To add to this, with increasing number of physically weak people (aged, injured, slightly disabled or handicapped), the working percentage is decreasing and taking care of physically weak individuals has become a problem. Therefore, usually such physically weak individuals are forced to take care of themselves. However, it may not be an easy task to maintain a normal daily life for such individuals in the society. In light of these problems, assistive robotic technology has opened new paths to assist and improve the living standards of those people. Especially, assistive robots are playing a major role in assisting and rehabilitating of physically weak, old, injured or disabled people.

Exoskeleton or exoskeleton robot is one of the promising applications among assistive robotics technology. The exoskeleton robot is a robotic device that is used to assist or rehabilitate the limb motions of physically weak individuals. Based on the body part or parts where the exoskeleton is used to assist, usually the exoskeletons are categorized as upper-limb exoskeletons [7,30,31,107], lower-limb exoskeletons [8] or full body exoskeletons [9]. As upper-limb motions are very important to perform daily activities, many research and development projects and studies are carried out on upper-limb exoskeletons. Especially, assisting motion of the upper-limb of physically weak people brings a lot of benefit to ease their daily lives and that makes them more productive to the society. Many promising upper-limb exoskeleton robots [7,30,31,107] have been developed to date. However, a majority of the exoskeleton robot systems are still at the experimental stage or clinical testing levels. More research effort is essential to bring them out of the laboratory.

Controlling any exoskeleton, however, requires sophisticated technologies or methods, as they always interact with human users. Therefore main requirements such as accuracy, long-term reliability and safety are vital for exoskeletons and their control methods [21]. As a result, several promising control methods have been proposed to meet those requirements. However for any control method, the basic task is to translate the user's motion intention to drive the exoskeleton robot. Thus, it is necessary to find an appropriate input signal to the control method that reflects the motion intentions of the exoskeleton user. Basically, input signals to the control method of exoskeleton can be categorized as non-biological signals and biological signals. Input signals from force/torque sensors which can be considered as non-biological signals have been successfully used to control the exoskeletons [75, 76]. On the other hand, it is necessary for any input signal of exoskeleton control methods to provide the information about the motion intention of the user as soon as it occurs because, exoskeletons should operate in real time without any delays. In this context, electromyography (EMG) has been one of the frequently used biological signals in the control methods of bio-robotics applications such exoskeletons and prosthetics, because

EMG directly reflects the human motion intention or muscle activity of the user. Many effective control methods have been developed for exoskeleton robots taking EMG signals as input information [11, 24, 26–28, 106]. On the other hand, with recent advancements of technology, brain-machine interfaces (BMI) have attracted a lot of interest in the assistive robotics field. Such interfaces may open new paths to directly decode the user's brain signals to control equipment such as prosthetics, exoskeletons. Among the several methods of capturing brain signals, electroencephalography (EEG) is identified as a non-invasive and convenient method which may be suitable for practical systems. Several attempts to implement EEG signal based control methods have been reported in case of exoskeleton robots [3,4]. However, unlike EMG signals which has one to one mapping between motion intentions or limb movements, EEG signals do not reflect such clear and direct connections. Therefore, extracting motion intention from the EEG signals is much more challenging in comparison to EMG signals.

Although there has been tremendous progress in the last decade in control methods for upper-limb exoskeletons, there are several problems which need more research effort. While some of the problems in EMG-based control methods such as physical tremor or unintentional limb movements have been explored [44–46] adequately, relatively less attention has been given to issues such as muscle fatigue and problems related to perception-assist control. Therefore, the objective of this thesis is to address these issues related to the control of upper-limb exoskeletons using EMG and EEG signals: more specifically issue of muscle fatigue in EMG-based control and problems associated with the perception-assist control in upper-limb exoskeletons.

Muscle fatigue can occur in any exoskeleton user and may have a higher possibility of occurring in older people. As the body gets older, the skeletal muscle fibers become smaller in size and less powerful which may lead to reduction of strength and endurance, and tendency to fatigue rapidly [32]. Muscle fatigue can affect the estimation of the correct motion intention of the user in the EMG based control as muscle fatigue has an influence on variations of the EMG amplitude and frequency [95, 96, 99, 100]. Muscle fatigue can significantly modify the EMG to EMG-based torque relationship, and therefore assistive robots such as exoskeletons, prosthetics should consider this alteration and comply with it in order to maintain accurate control. Therefore, when the user's muscles get fatigued, it is required to consider the variety of EMG signals on the EMG-based controllers and compensate for the effects. In light of these issues, the first half of this thesis aims to explore the problem of muscle fatigue on EMG-based control.

On the other hand, many of the proposed upper-limb exoskeleton systems assume that the exoskeleton user has good environment perception abilities. However, this assumption may not be valid for each and every user. Therefore, in addition to the basic assist, perception-assist control methods have been proposed [40–43] for upper-limb exoskeletons. In the perception-assist control, exoskeletons generate additional modification forces to the user's motions based on information of environment monitoring sensors to ensure safety of the user's motion. As it is difficult for the exoskeleton to plan all proper perception-assist for each and every task, tool, and environment, basically exoskeletons are required to learn the proper perception-assist on its own [42, 43]. In this learning process, it is necessary to judge the correctness or erroneous of the perception-assist performed by the exoskeleton. Specifically, second half of this thesis aims to study this problem of evaluating or judging the perception-assist control in upper-limb exoskeletons. In addition to EMG signals, the feasibility of utilizing EEG signals for the evaluation of perception-assist control in upper-limb exoskeletons are explored in the second half of this thesis.

1.1 Thesis Contributions

The research work presented in this thesis basically addresses the issues related to control of upper-limb exoskeletons using EMG and EEG signals. More specifically, major contributions of this thesis are outlined as follows:

- Show that only an EMG amplitude feature such as EMG RMS is not adequate as an input for effective EMG-based control during the muscle fatigue conditions and highlight the importance of using frequency domain or spectral EMG features as additional input features to EMG-based control. Experiments are carried out to support these claims.

- Propose multiple fuzzy-neuro modifiers based method for compensation of the effects of muscle fatigue on EMG-based control. Both amplitude (time domain) and spectral (frequency domain) features of EMG signals are used to identify the muscle fatigue conditions. In the proposed method, multiple fuzzy-neuro modifiers are trained to adapt to the muscle fatigue conditions and those modifiers are used to modify the EMG-based torque output in order to compensate the effects of muscle fatigue on EMG-based control. Effectiveness of the proposed methods are experimentally validated.

- Show that variations of EMG signals are sometimes not adequate to be used in perception assist control learning approaches where EMG signals are basically used to evaluate the correctness or incorrectness of the perception-assist performed in upper-limb exoskeletons.

  - Investigate the feasibility of utilizing EEG signals in addition to EMG signals to evaluate the correctness or incorrectness of the performed perception-assist tasks by upper-limb power-assist exoskeletons. In this investigation, combinations of EMG and EEG signals are tested to judge to the performed perception-assist tasks of the upper-limb exoskeletons. Moreover, possibilities of using EEG signal alone for this purpose are also explored. Effectiveness of the propose methods are validated by performing experiments.

1.2 Thesis Organization

This thesis consists of five chapters including Introduction chapter. The overall structure of the thesis depicts in fig. 1.1. The contents of next chapters are stipulated as below.

Chapter 2: Background

This chapter starts with a brief introduction on existing exoskeleton robots with a major focus on upper-limb exoskeletons. More importantly, an in-depth review of controlling

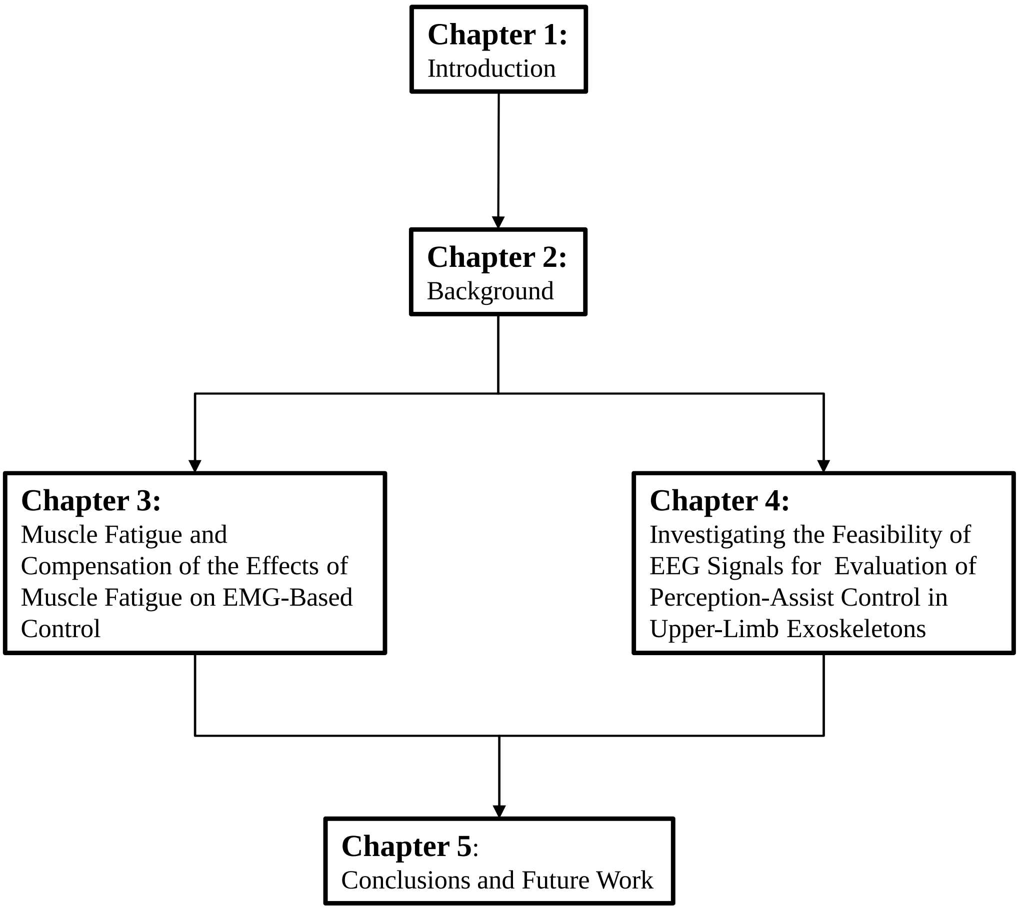


Figure 1.1: Structure of the Thesis

methods of upper-limb exoskeletons using EMG and EEG signals which have been reported in the literature are presented, discussed and limitations of those methods are identified. Moreover, specific information on the existing control method that has been proposed for Saga University upper-limb exoskeleton system in previous work are also presented since, it is essentially the basic framework of the research work of this thesis.

Chapter 3: Muscle Fatigue and Compensation of the Effects of Muscle Fatigue on EMG Based Control

This chapter presents a study which aims to address one of the challenges in EMG-based control: Muscle Fatigue. In this chapter, studies that carry out to analyze the effects of muscle fatigue on EMG-based control in human upper-limb power-assist are presented.

Moreover, a novel method based on fuzzy-neuro modifiers for compensation of the effects of muscle fatigue on EMG-based control to be used in upper-limb exoskeletons are proposed. Proposed methods are experimentally validated and results are presented with a discussion.

Chapter 4: Investigating the Feasibility of EEG Signals for Evaluation of Perception-Assist Control in Upper-Limb Exoskeletons

This chapter reports a study which aims to address the problems in perception-assist control learning of upper-limb exoskeletons. This chapter illustrates an attempt to use EEG signals recorded from human brain in addition to EMG signals to judge the correctness or incorrectness of performed perception-assist control by the upper-limb exoskeletons. Methods of using combination of EEG-EMG signals and EEG signals alone to evaluate the preformed perception-assist control are investigated. Effectiveness of the methods are compared with the approach that use EMG signals alone to judge the correctness of the perception-assist. Moreover, this chapter highlights the advantages of using EEG signals for evaluation of perception-assist control in upper-limb exoskeletons.

Chapter 5: Conclusions and Future Work

The final chapter includes new contributions of the thesis, conclusions, and suggestions for the future directions.

Chapter 2

Background

This chapter contains background knowledge on exoskeletons and exoskeleton control methods. It starts with a brief review on different types of existing exoskeleton systems and especially focusing on the upper-limb exoskeletons. More importantly, this chapter focuses on control methods of upper-limb exoskeletons using EMG and EEG signals. First, a non-exhaustive review of existing EMG-based control methods of upper-limb exoskeletons is presented. As mentioned in the introduction, EEG signal is also another biological signal that has potential to be used as an input signal in upper-limb exoskeletons control. Therefore, part of this chapter is dedicated to identify the potential uses of EEG signals and analyze EEG-based control approaches that have been proposed for upper-limb exoskeleton control. Moreover, a relatively new approach: hybrid EMG-EEG based control methods that have been proposed for upper-limb exoskeletons and other similar assistive robotic applications are briefly reviewed in this chapter. The research work presented in this thesis was inspired by the overall framework of EMG-based control methods of Saga University upper-limb exoskeleton. Therefore at the end of this chapter, it contains a brief background on those methods which have been developed to date. This will help to provide a clear understanding about the research work that is going to present in next few chapters of this thesis.

2.1 Exoskeletons or exoskeleton robots

The basic concept of exoskeleton has been emerged from biology. Some creatures such as turtles and crabs have external structures called exoskeletons. These exoskeletons usually offer safety from environment and predators, as sensory mediums to outside world and attachments for muscles etc [5]. In robotics field, an exoskeleton or exoskeleton robot is a

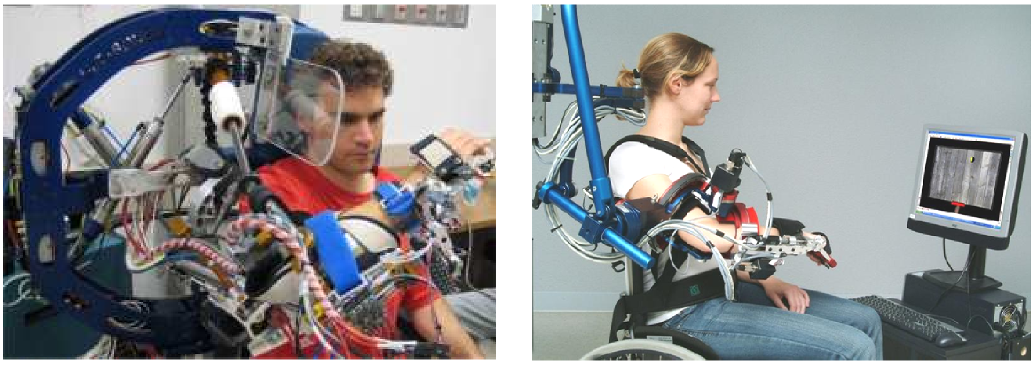
(a) (b) (c)

Figure 2.1: Different types of Exoskeletons (a) CADEN)-7 : Upper-Limb [7] (b) Berkeley Lower-Limb [8] (c) HAL full body exoskeleton [9]

machine consisting basically of an outer framework worn by a human. This machine could be a passive device or an active device such as a powered system of motors or hydraulics. Basically, the structure of an exoskeleton robot consists of joints and links which are corresponding to the human body. Exoskeleton robots can be classified according to the place where it supports the human body. This includes upper extremity, lower extremity and full body exoskeletons. Figure 2.1 shows examples for such mentioned three categories of exoskeletons that have been reported.

2.2 Upper-limb exoskeletons

Upper-limb motions are vital for humans to maintain natural daily activities. However, for people who do not privilege to have such functional upper-limbs, upper-limb exoskeletons have been proposed to get external assistances. Human upper limb mainly consists of seven degree of freedom (DOF). Some researchers have developed 7 DOF upper-limb exoskeleton robots [7, 107] in order to assist the complete upper-limb motions. On the hand in some of the proposed designs [10–12], number of DOFs have been limited than seven. Figure 2.2 depicts few examples of reported upper-limb exoskeleton systems.



(a) (b)

Figure 2.2: Upper-Limb Exoskeletons (a) BONES, University of California [30] (b) University of Zurich, Switzerland ARMin-Robot [31]

It is not a straight forward task to design the mechanical systems of an exoskeleton. Many factors such as biomechanics of the upper-limb, safety measures, types of acquisitions, power sources, material and weight of the systems need to be considered when designing exoskeleton systems [6]. On the other hand, controlling upper-limb exoskeletons according to human motion intention is not an easy task [13, 14] as well. When controlling an exoskeleton, the selection of a proper control input signal that reflect correct motion intention of the user is really important. So far research is being carried out considering different biological signals and especially Electromyography(EMG) have shown a promising potentials. On the other hand, with the advances of brain signal monitoring methods, Electroencephalography (EEG) signals based control approaches for upper-limb exoskeletons have been gained much attention recently in addition to EMG-based methods.

2.3 Electromyography (EMG)

Electromyography(EMG) signal indicates the amount of electrical potential generated by the muscle cells when at contraction or rest. In other words, the EMG signal is the algebraic summation of the motor unit action potentials within the measured area of the EMG electrode being used [15]. In the case of muscle contraction, it can be voluntary or involuntary. Because of the fact that EMG signal can directly reflet the motion intention, EMG signal is often considered as a strong candidate to be used in control approaches of assistive robots as an input signal.

2.3.1 Characteristics of EMG signal

Amplitude of the EMG signals is usually stochastic or random in nature and so it can be represented by a Gaussian distribution function approximately. The peak to peak value of the EMG signal amplitude is usually within 0-10 [mV] range. The usable energy of the signal is typically around 0 to 500 [Hz] frequency range, with the dominant energy being in the 50-150 [Hz] range [16]. Variations of EMG signals are different from person to person. Moreover, EMG signals are differed for the same motion even with the same person. On the other hand, physical conditions such as tiredness, muscle fatigue, sleepiness, etc. and psychological conditions such as stress, etc. can affect the EMG signals. Therefore, these characteristics should be considered carefully when developing control method for assistive robots such as exoskeletons using EMG signals.

2.4 EMG signal acquisition systems

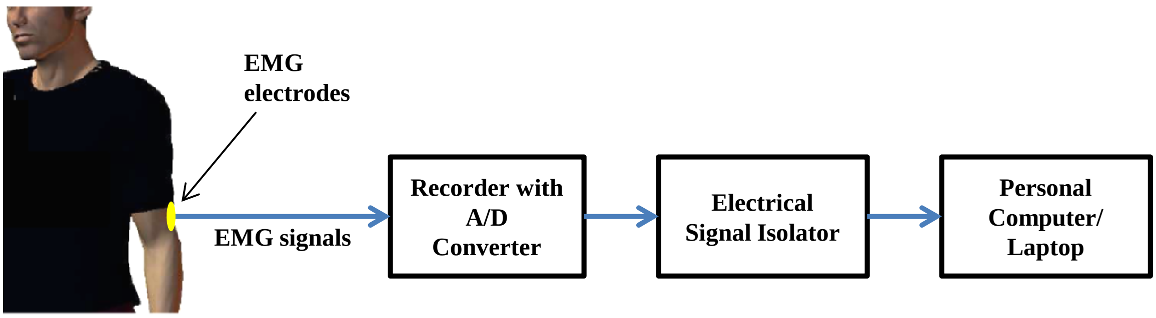


Figure 2.3: Typical set up of EMG signal acquisition

Typical equipments in EMG signal acquisition setup is shown in fig 2.3. First step of the EMG signal acquisition is the detection of EMG signals using electrodes. Detection of EMG signals can be done mainly in two ways namely non-invasive and invasive methods. The EMG signals detect from skin surface of the muscles are called surface EMG which is a non-invasive method. On the other hand, the EMG signals acquire from inside of the muscles or by invasive methods are called as intramuscular EMG. Both of these EMG recording methods have their own advantages and disadvantages. Placement of surface EMG electrodes is comparatively easier than intramuscular EMG electrodes. Moreover, surface EMG works well for the large muscles and muscles which are easily accessible. However, for a small muscle or a deep muscle which can not be accessible using surface EMG, intramuscular EMG is beneficial. Also, intramuscular EMG can be used when specifically a muscle need to be isolated from a muscle group. In this context for the practical applications like exoskeletons or prosthetics, surface EMG is preferred over the intramuscular EMG simply because of non-invasive nature of the surface EMG.

To record the surface EMG, the electrode should be placed over the interested muscle after cleaning the skin surface. Usually, alcohol based liquids are applied to removal of dirt, oil, and dead skin. Under ideal conditions shaving excess hair should be carried out if necessary though, it is not feasible in many practical cases. There are a several types of surface electrodes that can be found in the field. Some types need a gel [17] to be applied between the skin and the electrode whereas other type [18] use an adhesive tapes to ensure proper contact between the muscle and the electrode instead.

(a) (b) (c)

Figure 2.4: Commercially available EMG acquisition systems. (a) Bio Semi [19] (b) Delsys [18] (c) Nihon Kohden [17]

Then signals from the electrodes are passed into an input box and subsequently fed to an amplifier. In order to cancel out the noise, a differential amplifier is used when amplifying the weak EMG signal. There after, the output of the amplifier is fed into an analog to digital converter (A/D converter) to digitized the amplified analog EMG signal. Finally, this digitized signal is sent to a personal computer or a laptop to use in the whatever the application. However, in order to safely isolate the electrical connection between computer side and the user (through EMG electrodes), an electrical isolation method is used in between. There are a number of commercially developed EMG acquisition systems available [17–20]. Most of them can be used for both clinical and research purposes. Some of the existing EMG acquisition system manufacturers are Nihon Kohden Co. [17], Delsys [18], BioSemi [19], and Cambridge Electronic Design [20]. Some of these systems are shown in fig. 2.4.

2.5 A brief review on EMG-based methods proposed for assistive robots control

EMG-based control methods have commonly been used in many of the assistive robots such as exoskeletons. Basically, EMG based control methods of assistive robots can be categorized based on the structure of the EMG control method. Considering the architecture of the controller, the EMG based control methods can be categorized mainly as pattern recognition based and non-pattern recognition based [22, 23]. Non-pattern recognition based control method consists only a few steps and basically a simple structure. In most cases it uses simple ON/OFF type controllers [22,27]. Therefore, the accuracy of this method basically is not high with compared to the pattern recognition based methods. On the other hand, simple on-off control is one of the primary levels of controlling assistive robots such as exoskeletons and practically this type of prosthetic/ exoskeletons control may not adequate to be used in assisting the complex daily life activities.

Therefore, many control methods for assistive robots are implemented with pattern recognition based control methods and they provide accurate controls compared to non-pattern recognition based EMG based control [22]. Basically, pattern recognition based

EMG processing consist of four major stages namely; EMG data acquisition, data segmentation, feature extraction and classification as shown in fig 2.5. Moreover, fig 2.6 depicts different methods and algorithms typically find in each of these steps. Usually, the accuracy of pattern recognition based control methods can be improved by selecting proper feature extraction methods and applying appropriate classification algorithms [22, 23].

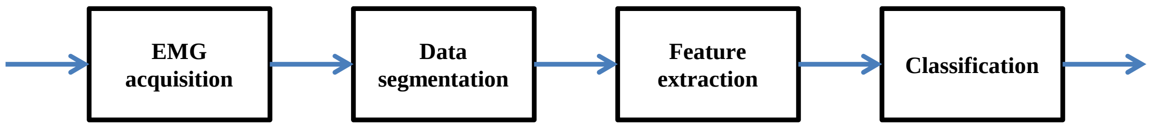


Figure 2.5: Typical EMG processing flow in pattern recognition based control

In EMG pattern recognition based methods, data segmentation is performed after the data acquisition. Data segmentation can be performed with two major techniques as overlapping segmentation [22, 23] or disjoint segmentation which uses segments with predetermined length for feature extraction. However, overlapping segment method increases processing time [23] and better for the data segmentation [22].

After data segmentation, feature extraction is carried out. Practically, it is difficult to provide all the data of EMG signals directly to the classifier [26, 107] due to large number of EMG channels and random nature of the raw EMG signals. Furthermore, success of any pattern recognition methods depends on accurate selection and extraction of relevant features. On the other hand, dimension of the feature vector should be minimized as possible without discarding the important information. According to the previous studies on this field, basically these features fall into one of three categories as time domain, frequency domain and time scale domain [23]. Many assistive robots have used time domain features in most cases and RMS is widely adapted for feature extraction [25, 107]. On the other hand, assistive robots based on frequency domain and time frequency domain are not often be found.

Extracted features then need to be classified into respective classes for the recognition of the desired motion patterns. Speed of the classifier is a vital aspect for generating required output from the controller. Usually training of the classifier is necessary to improve

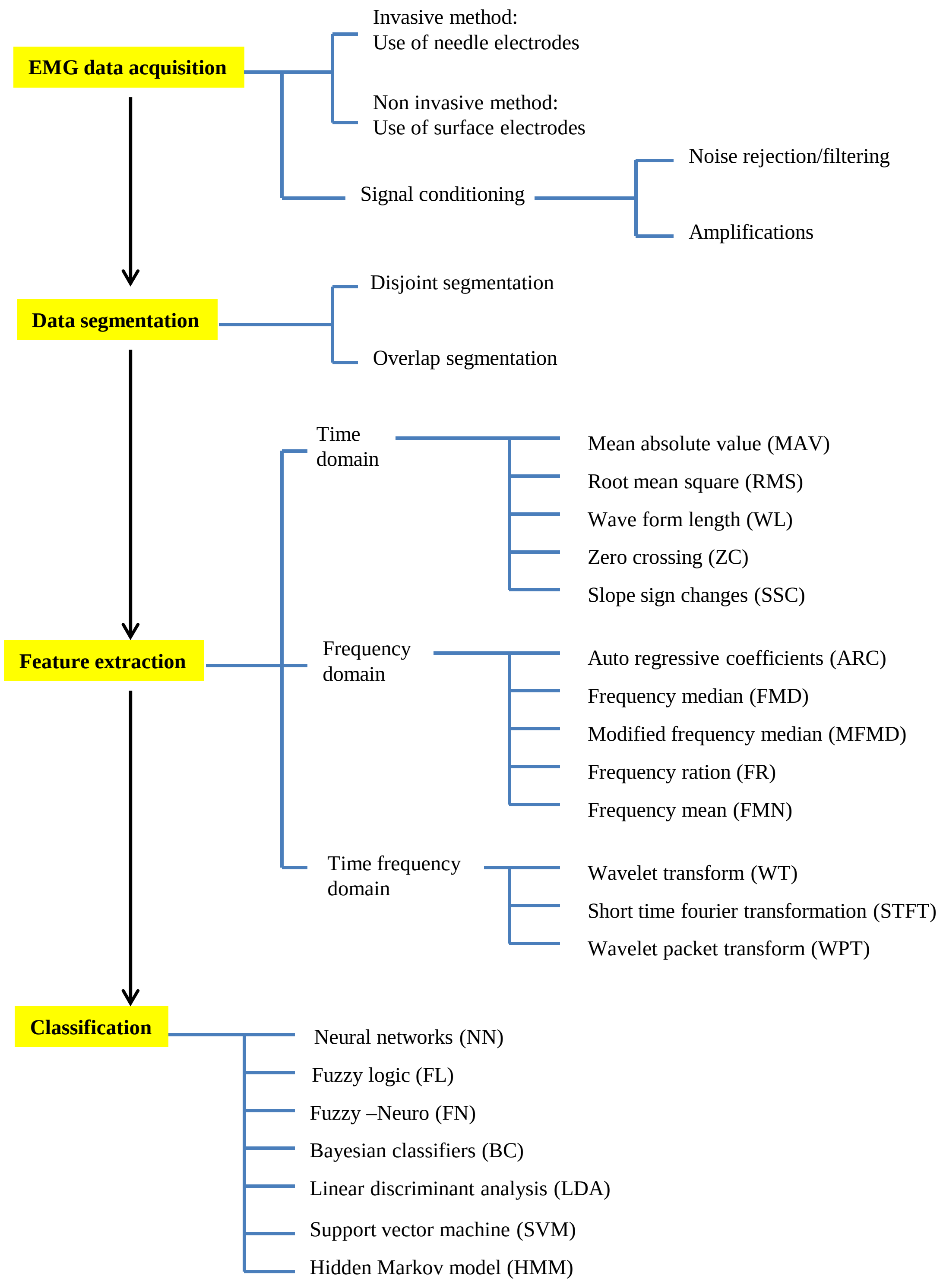


Figure 2.6: Different methods used in each step of pattern recognition based EMG processing as presented in [21]

the response of the control system of the assistive robot. Depending on the performance of the subject, practice required for rehabilitation etc can be customized through training of the classifier. In previous studies, several methods have been used for EMG features classifications. Some of the popular methods are Neural network [22, 25], Fuzzy logic [23], Neuro-fuzzy [22, 23], Probabilistic approach etc.

Instead of aforementioned non pattern recognition based EMG based control methods such as simple on-off/binary control of robots using EMG signals, proportional controlling methods been developed [24, 28]. The rationale behind those methods are that the control output is estimated by a proportional controller, where the level of the assistance or proportionality constant of the exoskeleton is controlled by varying the gains linked to each EMG signal. In the meantime, muscle models such as Hill-based muscle model [29] are also employed in some studies [11] . However, due to the nature of the biological signal such as EMG which is usually a non-linear and non-stationary signal, aforementioned types of control methods might have to suffer from few challenges in complex control of exoskeletons or prosthetics. Moreover, EMG signals are known to be user dependent and therefore, a custom developed controller for a particular user may not be used by another user without any modifications to the EMG-based controller. These reasons urge the importance of the use of adaptive EMG-based control methods [26, 106]. In these types of EMG-based control methods, it has the possibility to adapt the assistive robot or exoskeletons to be used with any user by the means of learning.

On the other hand apart from the basic requirement of assisting, it is required to address the other related issues in EMG-based control as well. Effects of physical tremor or unintentional limb movements on EMG-based control is one of the challenges in EMG-based control. The tremor is a commonly found disorder especially in older people, which causes rhythmic oscillation of a body part. People with upper limb tremor, in particular, usually show difficulties in performing activities of daily living. These unintentional movements generate EMG signals that do not represent the actual motion intentions of the users. Therefore, it is important to identify and cancel the tremor effects on EMG-based control approaches of the assistive robots such as exoskeletons. Several research groups have studied on this area already and they have proposed few solutions [44–46] to compensate this problem. However, these methods need to be perfected and suggest the important of further research requirements.

Most of these assistive robots such as exoskeleton systems assume that the user has good environment perception abilities. However, this assumption may not valid for each and every user. For an example, elderly or disabled individuals may suffer from not only reduced motor ability, but also limited environment-perception ability as well. For such individuals, it is important for exoskeletons to have some sort of environment perception ability in order to prevent undesired or accidental motions performed by the user. In light of these requirements, perception-assist control methods have been proposed for exoskeletons [40–43] in addition to the basic power assist. Nevertheless, more research effort is needed to further improve and verify these methods.

On the other hand, effects of muscle fatigue on EMG-based control is one of the other issues which has not been paid much attention to date. This issue also needs to be considered in order to enhance the reliability and robustness of the EMG-based control.

2.6 Brain Machine Interface (BMI)

Even though, the advances of EMG-based control methods in assistive robots such as exoskeletons are enormous, these EMG-based control approaches used alone have some disadvantages that depend on the user and on the application. In cases where the user cannot generate enough muscle signals, EMG-based approaches are not beneficial as an input. For example, a person who has a totally paralyzed upper limb may not be able to use a device such as an exoskeleton because of the lack of getting control signals from the muscles of the paralyzed limb.

On the other hand, with recent advancements of technology, brain machine interfaces (BMI) have attracted a lot of interest in the bio-robotics area. A BMI is a direct communication pathway between the brain and an external device. This device or application can be

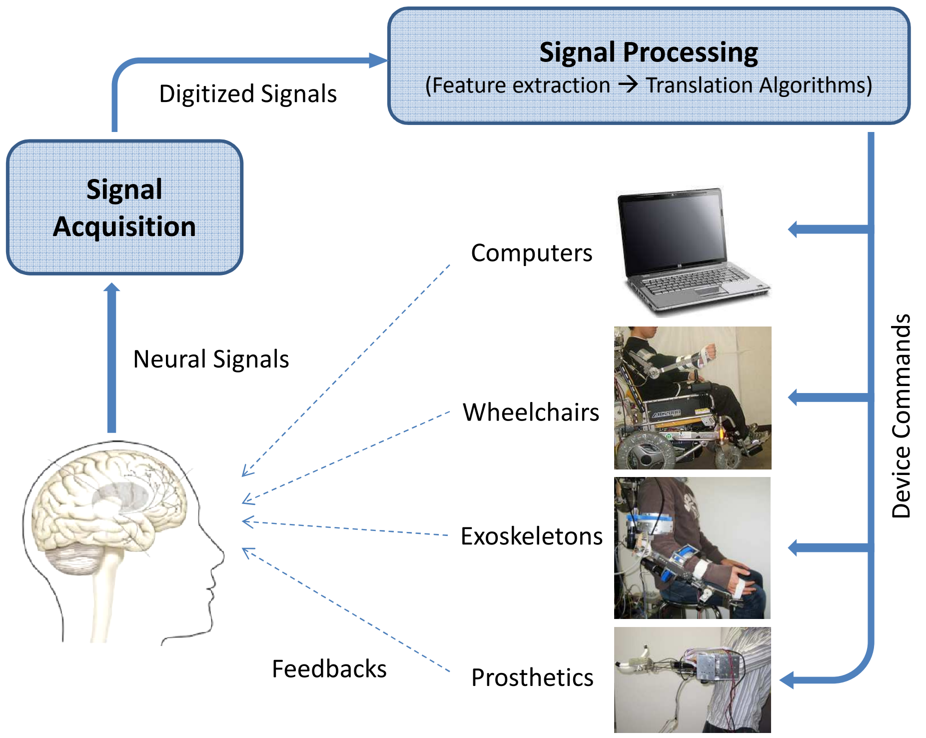
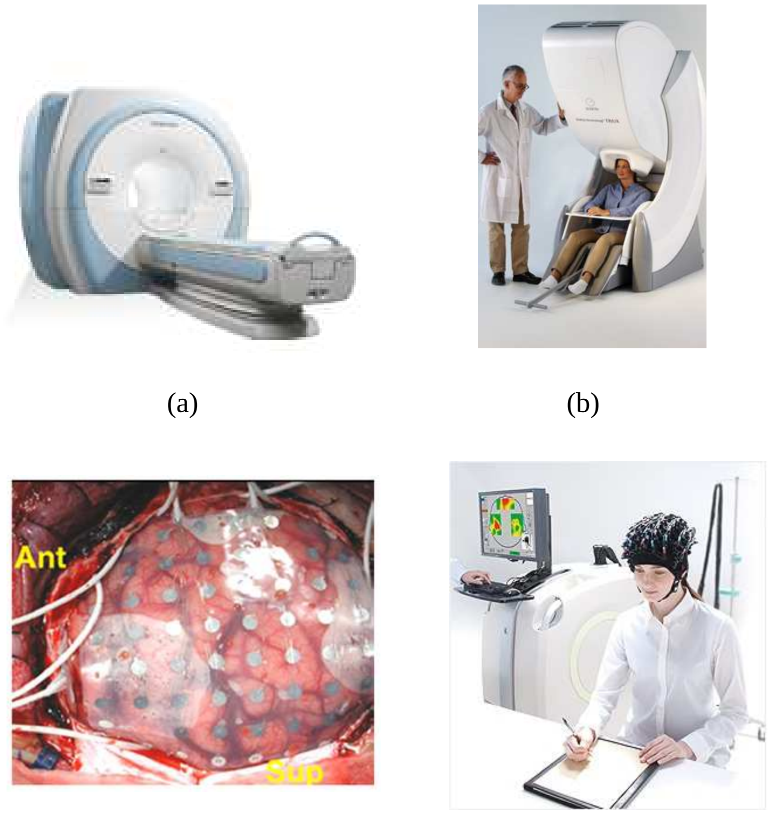


Figure 2.7: Brain Machine Interface (BMI)

a simple cursor control program on a computer, intermediate application such as controlling a wheel chair or controlling a complex device such as a prosthetic or an exoskeleton. Fig 2.7 shows a systematic diagram of such a BMI system. These interfaces may open new paths to directly decode the users brain signals to control equipment such as prosthetics, exoskeletons or wheelchairs as mentioned; for example, even though a user cannot make any efficient movements of his limbs, he may still be capable of generating commanding brain signals, which can be used in such a brain control interface to drive an exoskeleton.

There are several methods exist to study about the brain functions or brain neural signals (see fig. 2.8) such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET) , magnetoencephalography (MEG), nuclear magnetic resonance spectroscopy, electrocorticography (ECoG), Single-photon emission computed tomography, near-infrared spectroscopy (NIRS), and Event-related optical signal (EROS) other than EEG. Each of these methods has respective advantages and disadvantages.

Among these several methods of capturing brain signals, electroencephalography (EEG)



(a) (b) (c) (d)

Figure 2.8: Sevaral brain function monitoring methods other than EEG. (a) fMRI (Toshiba [36]) (b) MEG (Elekta Neuromag TRIUX [37]) (c) ECoG (Adopted from [38]) (d) NIRS (LABNIRS [39])

is identified as a non-invasive and convenient method which may be suitable for practical systems. Therefore in next section, a brief introduction of EEG signals, its characteristics, relative advantages and disadvantages of EEG signals are discussed.

2.7 Electroencephalography(EEG)

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. The EEG can be defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media [33]. Local current flows are produced when brain cells (neurons) are activated. The EEG measures mostly the currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex [34]. Differences of electrical potentials are caused by summed post synaptic graded potentials from pyramidal cells that create electrical dipoles between soma (body of neuron) and apical dendrites (neural branches) [34]. Brain electrical current consists mostly of Na+, K+, Ca++, and Cl- ions that are pumped through channels in neuron membranes in the direction governed by membrane potential [35]. When large populations of active neurons produce electrical activities it can be measured on the head surface using EEG electrodes. However, between electrodes and neuronal layers there exist many layers such as skin, skull and several other layers which cause weakening the current signal. Therefore, these weak electrical signals discovered by the EEG electrodes are needed to massively amplify before use.

Despite the relatively poor spatial sensitivity of EEG, it gives several advantages over other methods or techniques in studying brain functions mentioned previously. Some of the advantages of EEG include:

- Noninvasive
- EEG has high temporal resolution
- EEG sensors can be applied in more places than other brain signal monitoring methods such as fMRI or MEG, since those methods often consist of bulky and immobile equipments.
- Hardware costs are relatively lower with compare to most other techniques
- EEG does not involve user to get exposure in such as high-intensity magnetic fields etc.

However, there are few relative disadvantages as well.

- Low spatial resolution on the scalp.
- EEG can pickup poorly the neural activity that occurs in the cortex.
- Signal-to-noise (SNR) ratio is poor, therefore advanced data analysis and relatively large numbers of subjects are require to extract useful information from EEG.
- EEG system preparation and connection time to subject may take long time and may complex depend on the type of the EEG system used.

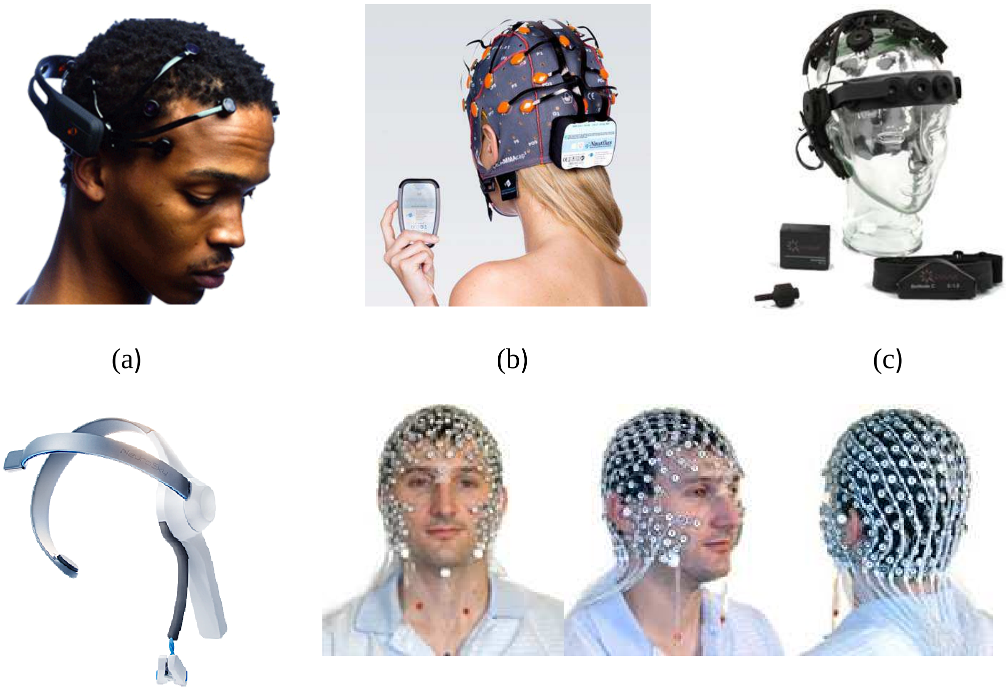
Considering these points, many research attempts can be found that using EEG signals in bio robotics applications such exoskeletons, prosthetics etc. Especially with the rapid development of the technology, some of the latest version of EEG systems have been able to reduce or even avoid some of the mentioned disadvantages. Therefore, the popularity has been increased of using EEG signals among researchers as a potential method of acquiring brain signals.

2.7.1 Characteristics of EEG signals

As discussed earlier, the EEG is a recording of the electrical activity of the brain from the scalp. The measured waveforms reflect the cortical electrical activity. Signal intensity of EEG activity is often quite small and measured in microvolt (μV) range. On the other hand, it is possible to differentiate EEG signal as alpha (α), beta (β), delta (δ), and theta (θ) waves as well as spikes associated with epilepsy [52] based on signal frequency. The alpha waves are known to be in the frequency spectrum of 8-13 Hz and can be measured from the occipital region in an awake person when the eyes are closed. The frequency bandwidth of the beta waves is 13-30 Hz and beta waves can be detected over the parietal and frontal lobes. The delta waves have the frequency range of 0.5-4 Hz. The delta waves are detectable in usually infants and sleeping adults. The theta waves are in the frequency spectrum of 4-8 Hz and these waves also are obtained from children and sleeping adults [52].

2.8 EEG signal acquisition systems

EEG acquisition system is one of the most important parts in any application that used EEG signals. Different types of EEG signal acquisition systems have been developed and their features and capabilities may different from each other. However, basically in any EEG acquisition system, EEG signals are measured by EEG electrodes. Normally these EEG electrodes are holding on a cap that can be wore over the head. Then as the measured signals are weak, they are amplified. Finally, those amplified analog signals are digitized before sending to a computer. Figure 2.9 depicts some of the existing EEG acquisition systems that are being used among research community.



(a) (b) (c)

(d) (e)

Figure 2.9: EEG acquisition systems. (a) Emotiv EEG Headset [47] (b) g.Nautilus wireless EEG system [48] (c) DSI 10/20 Dry sensor interface [49] (d) NeuroSky MindWave headsets [50] (e) EGI dense array EEG [51]

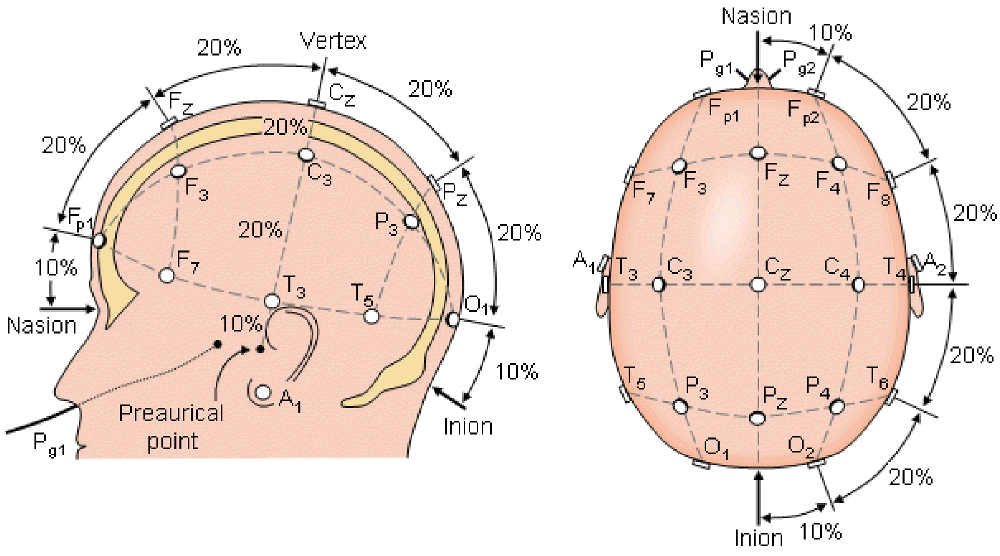
Some of the EEG acquisition systems need more time to prepare the EEG system. In those types of systems, it takes considerably long time to connect a subject to EEG, as it needs accurate placement of many electrodes around the head and the use different kinds of gels, saline solutions, and/or pastes to keep them in place [51] . However, recently introduced EEG systems do not need such an extensive preparation. Some of them are using dry EEG electrode technologies [49] and therefore, those systems can be connected to an user much faster. Moreover, newer version of EEG acquisition systems are comparably small in size and are capable of wireless data transmissions [48] . Another important fact is the number of EEG electrodes. Some of the EEG systems are only consisted of few EEG electrodes [47, 50], whereas several EEG systems boast high density EEG electrodes such as 128 or 256 electrodes [51]. High density EEG systems are helping to increase the spatial resolution of EEG signals. Moreover, most of these EEG acquisition systems can measure or record EEG signal data at high sample rates such as even up to the 20 [kHz] in some cases.

As mentioned above, there are some advantages as well as limitations of each EEG acquisition system, therefore it is necessary to select an appropriate EEG acquisition system that required for particular research application or device.

2.9 International 10-20 system: standard locations of scalp EEG electrodes

In order to measure the EEG signals of a subject, EEG electrodes should be placed over his/her brain using arrangements such as shown in fig 2.9. The placements of EEG electrodes should have some sort of standard in order to make sure the reproducibility of the results across the subjects and over the time. International 10-20 system [53] is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment. This method is based on the relationship between the location of an EEG electrode and the underlying area of cerebral cortex. The ”10” and ”20” refer to the actual distances between adjacent electrodes are either 10% or 20% of the total front back or right left distance of the skull. In this system, 21 electrodes are located on the surface of the scalp as shown in fig 2.10.

Each channel location has a letter to identify the lobe and a number to recognize the hemisphere location. Frontal,central,temporal, parietal, and occipital lobe areas of brain are represented by letters F, C, T, P and O, respectively. An electrode placed on the midline is referred to ”z” (zero). On the other hand, the letter A, Pg and Fp are used to represent the earlobes, nasopharyngeal and frontal polar areas respectively. Even numbers refer to EEG electrode positions on the right hemisphere and odd numbers represent to those on the left hemisphere of the brain. It is necessary to position these EEG electrodes over the scalp. Two anatomical landmarks are normally used for this purpose as shown in fig 2.10 (b). They are the nasion and the inion points. In addition to these basic 21 electrode sites, intermediate 10% electrode positions have been introduced (see fig 2.11) [54] as well.



(a) (b)

Figure 2.10: The international 10-20 system seen from (A) left and (B) above the head. A = Ear lobe, C = central, Pg = nasopharyngeal, P = parietal, F = frontal, Fp = frontal polar, O = occipital (Adopted from [52])

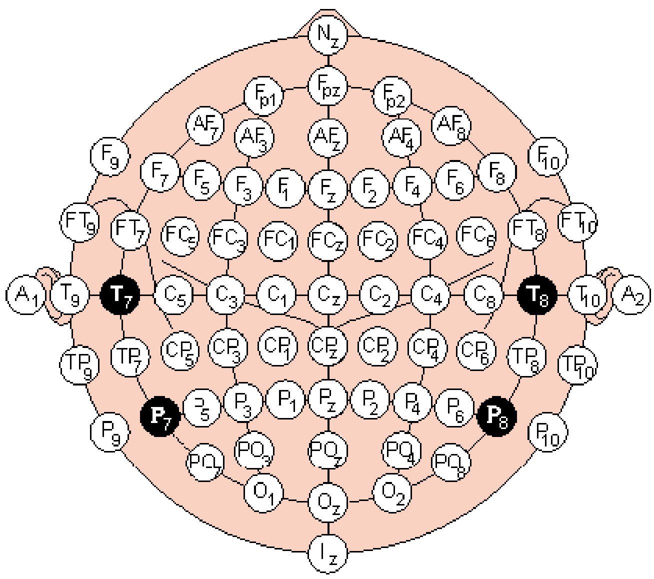


Figure 2.11: Location and nomenclature of the intermediate 10% electrodes, as standardized by the American Electroencephalographic Society (Adopted from [52])

2.10 EEG artifacts

One of the biggest challenges in monitoring EEG signals is artifact. Unlike in EMG, there are several types of artifacts commonly found in EEG. However, basically EEG artifacts can be classified in to two main groups. One of them are patient related artifacts such as movement, sweating, ECG, eye movements [55]. Other artifacts are related to technical problems such as 50/60 Hz main lines artifact, cable movements, electrode paste-related [55] etc. Many artifact rejection and removal methods have been proposed [56,57] in order to deal with the problems when utilizing EEG signals. However, each of these artifacts may have to be handled differently according to the situation or application.

2.11 A brief review on EEG-based methods proposed for assistive robots control

As discussed previously, large number of EMG-based control methods have shown high effectiveness in assistive robots control such as upper-limb exoskeletons control. However, given the potential advantages of using EEG-based control methods, increase number of researches are reported on designing and developing EEG-based control methods for assistive robots. In fact during the last decade, it has shown remarkable advances in neural decoding and assistive brain machine interfaces to reconstruct motor function, control of robotic limbs, and orthoses in real time. Dexterous control of assistive robot such as upper-limb exoskeleton using direct EEG signals is a challenging task even at the present. However, researchers have already taken initiatives target this goal.

Different characteristics of brain signals have been explored by the researchers in order to use in control methods of assistive robots. Motor imagery (MI) [59] is one of the mental activities that has frequently been used to build BCIs. MI represents the result of conscious access to the content of the intention of a movement that is normally performed unconsciously during movement preparation. It has been found that a physical movement or preparation for the movement of a particular limb is usually accompanied by the μ and β waves decreasing. This variation is called event-related desynchrohization (ERD) [64].

Moreover, an increase of μ waves (this is called event-related synchrohization (ERS) [64]) is observed during and post limb movements. More importantly, these ERD and ERS variations are also observed during motor imagery and classifications of these variation can be used in assistive control methods.

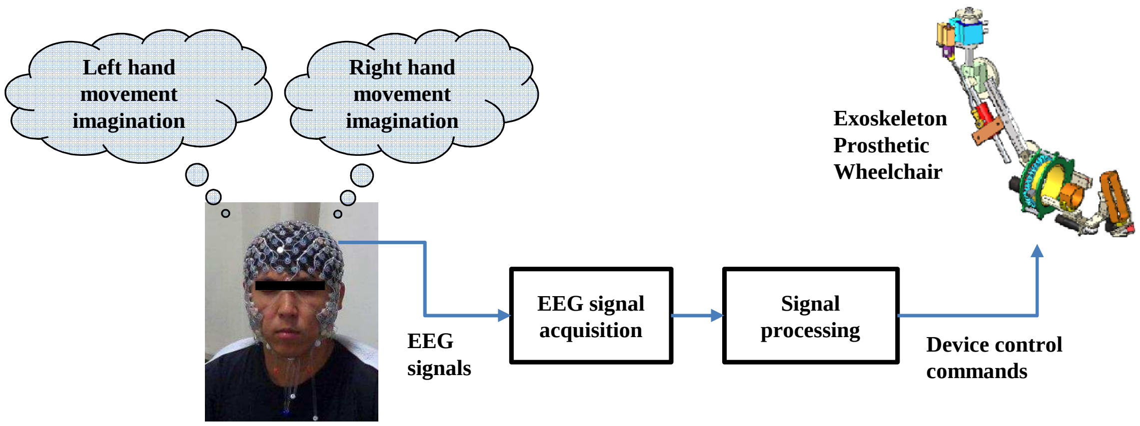


Figure 2.12: Structure of an interface that use motor imagery (MI) related EEG signals to control assistive devices

For an example, as shown in fig 2.12 when person imagine his or her left and right hands movement, EEG signals variations from the right side and left side of the brain can be used to identify the respective imaginary motions. Processed EEG signals then can be mapped in to control devices such as exoskeletons or prosthetics. As a reference, MI based method has been used to control of a hand orthosis [58]. This system is capable of driving the powered orthotic hand which opens and closes the subjects hand to be used in rehabilitation processes following a stroke. In that study of hand orthosis control, MI of hand motions were classified using EEG signals and those classification results were mapped in to the control of hand orthosis open/close motion. However, this simple on-off type control can be taken as the basic level of exoskeleton control. Recently, a research on the feasibility of using motor imagery EEG-based brain computer interface in chronic tetraplegics for assistive robotic arm control has been reported [60]. In this study, four mental tasks of motor imagery as left,right,foot and relax were classified using EEG signals to control the external assistive robot arm. Moreover, a recent paper discusses about the possibility of the rehabilitation of patients with motor disorders through the BCI based on motor imagery and the upper-limb exoskeleton control [62].

As shown in above studies, motor imagery can be recognized using EEG signals and can be used in control methods of assistive robots such as exoskeletons. By improving accuracy of the classifications, therefore more robust and reliable control can be archived. Many classification algorithms such as linear discriminant, support vector machines, neural networks classifiers and probabilistic classifiers have been used in the reported studies. A comprehensive review of classification algorithms for EEG-based BCI interfaces can be found in [63]. These classifiers are trained using EEG data of training sessions and those trained classifiers are used to classify the new EEG data. One of the most important requirements is the real time control of the assistive robots. Therefore, classification and control methods should be capable of working real time.

Real time methods open new paths to improve the EEG based control methods in assistive robots. Especially, in real time systems feedbacks can be given to the user when he or she control assistive device such as an upper-limb exoskeleton using EEG signals during training sessions. These feedbacks may improve the emission of particular brain signals along with the training period and therefore might improve the classification results. Therefore, these feedbacks are critical in a MI-based assistive robot controls. For example, a similar approach has been reported in a study that use left vs right vs rest motor imageries to control a hand orthosis [69]. In that study, two training stages were carried out. In the first training stage, a fresh subject was trained to control a cursor position using motor imaginary movements. During this training stage visual feedbacks were displayed to the subject. Once the subject achieve higher success rate in controlling the cursor, he was trained to control the hand orthosis through BCI during the second training stage. Results of that study observed that pre-training with visual feedback made the subjects perform imaginary movements efficiently, so that the subjects could operate the orthotic hand accurately. In another attempt, in order to address the question whether proprioceptive feedback affects the regulation of brain oscillations and therefore the final control, a study has been conducted using a BCI coupled on-line with a robotic hand exoskeleton [61]. Results of this study showed that proprioceptive feedback (feeling and seeing hand movements) improved BCI performance significantly. However, this type of motor imagery-based BMIs to control orthosis normally requires long training times to gain control over brain waves. This is a major disadvantage of motor imagery based approaches for assistive robots control.

Use of visual evoked potential (VEP) is one of the other approaches that some of the proposed BCI and BMI have used. VEPs are generated by sensory stimulation of a person's visual field, and visual information processing mechanisms are reflected in the brain [66]. VEP based BCI is a tool that can identify a target on which a user is visually fixated via analysis of concurrently recorded EEG. Fig. 2.13 shows the system diagram of a VEP based control interface. In a VEP based BCI, each target is prepared to emit a unique stimulus pattern which in turn evokes the relevant VEP pattern.

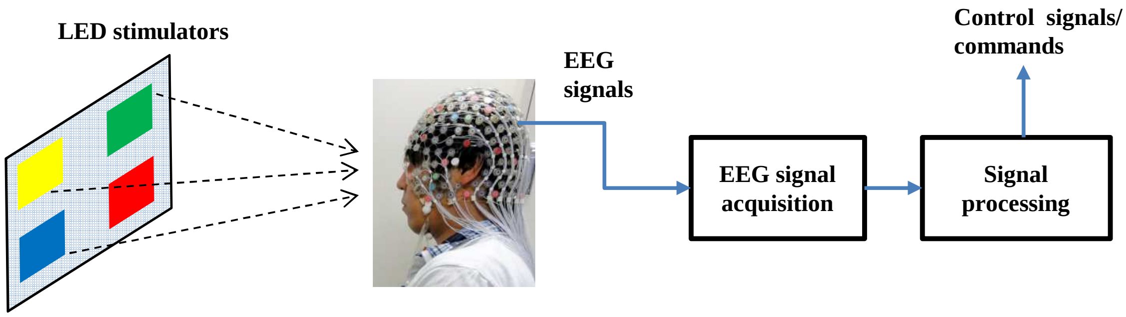


Figure 2.13: Structure of an interface that use visual evoked potential (VEP) related EEG signals to control assistive devices

Steady-state VEPs (SSVEPs) is a sub class of VEPs which occurs when the brain reaction to stimuli of a frequency higher than 6 Hz [65]. SSVEPs are less susceptible to artifacts occurred by blinks and eye movements and to EMG noise contamination [67] and therefore are typically used for BCI and BMI. As an example, control of an electrical prosthesis with an SSVEP-based BCI has been proposed in [78]. In that study, an asynchronous (self-paced) four-class BCI based on SSVEPs was used to control a two-axes electrical hand prosthesis. That hand prosthetic consisted with four light emitting diodes and each of them associated with a control command. From the results of that study suggested that the SSVEP-based BCI while operating in an asynchronous mode can be used for controlling the neuro prosthetic devices with the flickering lights mounted on its surface. In similar attempt, a SSVEP BCI to control a hand orthosis for persons with tetraplegia has been proposed [70]. In recently published paper, a BMI-based occupational therapy assist suit which asynchronous control by SSVEP has been proposed [68]. In that study, the subjects were able to control BMI-based occupational therapy assist suit effectively using SSVEP. EEG signals recorded from the visual cortex were used in classification. Paper also confirmed that the system could be operated with little training and system could be driven asynchronously whenever the wearer wished to. These studies shows the effectiveness of the SSVEP based approach to control assistive robots like exoskeletons. One of the major advantages of SSVEP-based approach to control assistive robots such as exoskeletons is it needs less training time than motor imagery-based control. However, it requires focused attention to the external stimulus such as blinking lights mounted on an orthosis which consider as a disadvantage.

On the other hand, several research groups have introduced combine use of several approaches to control assistive devices such as exoskeletons. Recently, a self-paced control of SSVEP-based orthosis with MI based brain switch has been proposed and evaluated [71]. The brain switch based on ERS in MI was used to activate the four-step SSVEP-based orthosis only when required for control and to shutoff the flickering LEDs during resting periods. In this case, two EEG channels; as one over the motor cortex and one over the visual cortex were used.

One of the problems in almost all the previously mentioned approaches such as MI or SSVEP based methods is that they are discrete systems which capable of sending only a limited set of commands to the device such as an exoskeleton. However, ultimate goal should be the dexterous control of assistive robot such as upper-limb exoskeleton using direct EEG signals. In this context, recently some researchers have shown interest in decoding natural actions using EEG signals. This approach aims to decode the natural motor plan to control the impaired or intact limb. Basically in this approach at first, a decoder that maps neural activity to natural limb movements is prepared. Then it is used to predict limbs movements from only the recorded neural activity. Several studies have been reported on decoding of upper limbs movement such as decoding hand directions [72], decoding elbow joint velocities [74] and reconstructing three dimensional hand movements [73] using EEG signals. These studies are important because, successfully predicted kinematics of limb movements can be used to continuous control of assistive robots such as exoskeletons as contrast to the previously mentioned discrete approaches.

Nevertheless, it can be observed that EEG signal has gained as a potential biosignal to use in control approaches of assistive robots such as exoskeletons. Given the advantages of using EEG signals, there are still many challenges to sort out in these EEG-based approaches. Especially, BCI or BMIs which use the EEG signals alone as the primary input are not yet fully acceptable in applications like in assistive robots due to difficulties such as low reliability, low accuracy, low user adaptability and low data transfer rates [79, 91, 92].

2.12 Hybrid EMG-EEG based control approaches

In order to compensate problems with both EEG and EMG based control methods, a combination of both systems, building on the merits of each signal while diminishing the limitations of each might be a promising approach. For example, in a device like exoskeletons, some muscles needed for acquiring EMG signals might be disconnected or paralyzed, or some nerves to the relevant muscles might be disconnected. In these cases, EEG can be used to compensate for the missing EMG signals. Even if all needed muscles for EMG are available, EEG can still be applied to get rid of the effect of fatigue or undesired tremor.

The main idea behind a hybrid EMG-EEG based control interface is the fusing of EEG and EMG signals in the control method. Figure 2.14 depicts a typical graphical interpretation of such a hybrid EMG-EEG based control interface. The fusion of the signals may be carried out in many different ways, and may depend on factors such as the specific application, and the abilities of the users. Applications of the hybrid approaches may change from a simple game control application for an healthy person through to a artificial robotic arm control application for an amputee subject. As discussed previously, there are many different ways to fuse the EMG and EEG signals, within a particular control approach, to enhance the effectiveness.

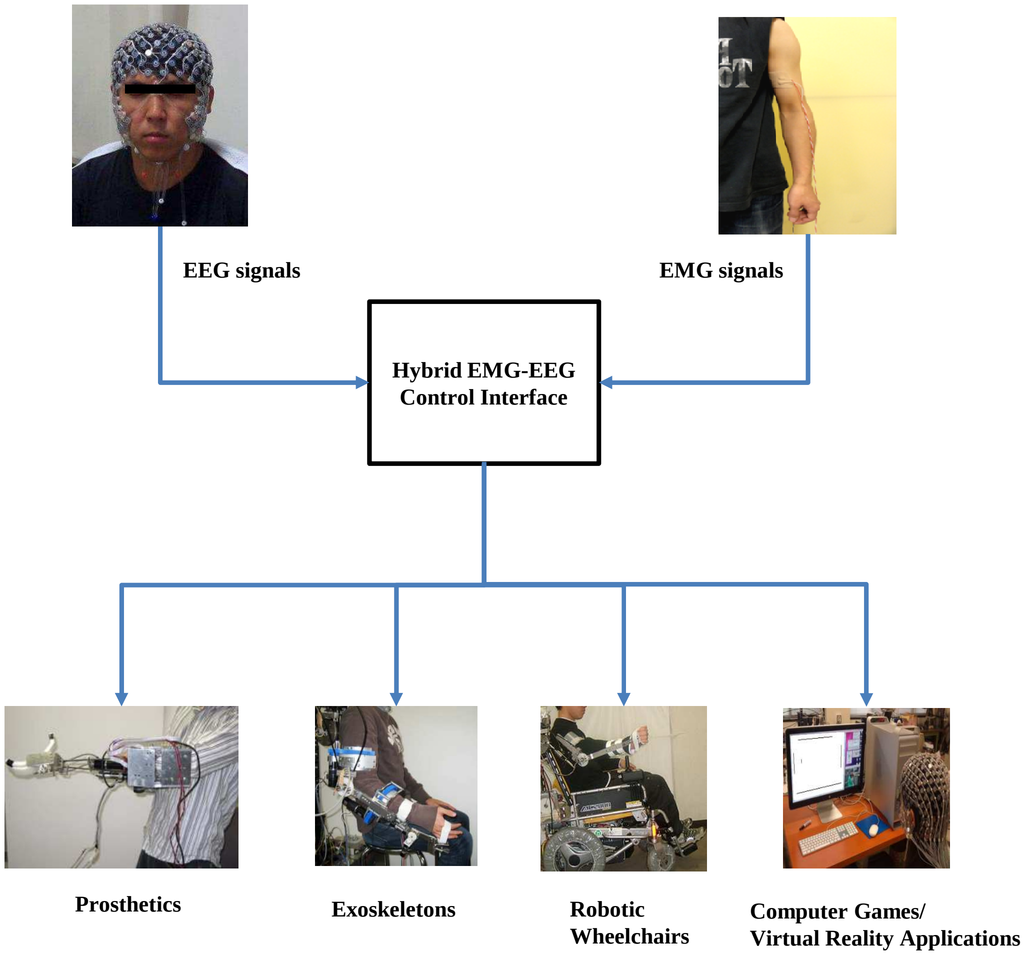


Figure 2.14: A graphical interpretation of a typical hybrid EMG-EEG control interface

2.13 A brief review on hybrid EMG-EEG based methods proposed for assistive robot control

The EEG or EMG signals can be used to control individual parts of a device, such as parts in an assistive robotic device. On the other hand, all of them can be combined as well. The latter approach will allow users to smoothly transfer from one control signal to the other, depending on their preference and performance. Several criteria can be used to distinguish the hybrid EMG-EEG control approaches in assistive robotic applications, such as the particular applications/devices (e.g. prosthetics, exoskeleton, wheelchair) or the input processing methods. As a two-input system, a hybrid EEG-EMG approach can either work on the inputs simultaneously or sequentially. Nevertheless, it is important to ensure that, a higher effectiveness is achieved from the fusion approach of EEG-EMG signals, than from methods that use either EMG or EEG signals alone.

Few studies [81–84] have attempted compensation for problems associated with the EMG-based control methods in assistive robotics applications by using the hybrid approaches. One such problem which may be occurred when using EMG signals alone is muscle fatigue. For such cases, instead of depending on the EMG signals alone, it is possible to utilize the EEG signals as an additional input signal to deal with the muscle fatigue situation in the control approaches. Such an attempt of a fusion of muscle and brain signals for a hybrid-BCI were reported [81, 82]. In those papers, a parallel use of EMG and EEG depending on the user availability and reliability were proposed for a hand-control task. The experimental results of those studies suggested that the classification accuracy improved with the combined approaches as compared to the approaches when EEG and EMG inputs were used independently.

Recently, a novel multimodal sensor fusion approach for tremor suppression was proposed [83]. In that study, a multimodal BCI-mediated soft, wearable robot capable of compensating for upper limb tremor through functional electrical stimulation (FES) was proposed. Moreover in that study, the control signal to drive the FES-based wearable robot was supposed to be estimated based on a combination of EEG, EMG and inertial sensor signals. The hybrid fusion method used in this case can be classified as a sequential fusion method. This study emphasized the importance of fusion and integration of different modalities in order to improve the accuracy, and the robustness, of the detection and characterization of voluntary and tremorous components of movement.

Especially, the hybrid EMG-EEG control methods are effective when a particular person lacks the ability to generate control signals to command an assistive robotic device such as an active prosthetic arm. In the case of an above elbow amputee, for example, the muscles which are required to generate forearm, wrist and hand motions are not present, even if he/she may have the muscles for performing elbow joint motions. To address this issue, a five degree of freedom (DOF) myoelectric arm which uses shoulder and elbow motions

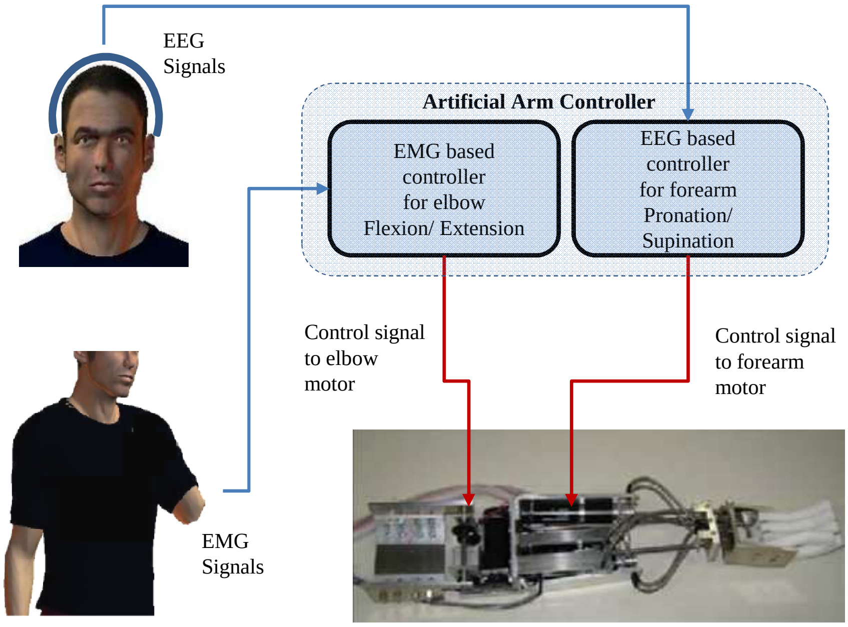


Figure 2.15: Combined use of EEG and EMG signals in controlling an artificial arm for an above-elbow amputee

as additional input signals was proposed [85, 87] (fig 2.15). It was not, however, easy to estimate various daily life motions with this method. Therefore, later on a combination of upper-limb EMG signals and EEG signals was used to control this artificial arm [86]. Control of the forearm pronation/supination motions of the prosthetic arm was controlled using EEG signals, whereas the elbow flexion/extension motions were operated by the EMG signals of the remaining bicep and triceps muscles. Therefore, this hybrid EEG-EMG based control approach showed its potential advantages by realizing a control channel for the additional degree of freedom (forearm pronation/supination). Even though, the aforementioned study was based on the upper-limb prosthetic, a similar method could be applied to control an upper-limb exoskeleton in the case of user unable to generate adequate EMG signals from particular muscles.

Moreover, few researchers have suggested the integration of EEG and EMG signals in control approaches for use in assistive robotics applications such as exoskeletons. In projects like MIND WALKER (Web: https://mindwalker-project.eu/), the researchers proposed an integrated brain-computer approach basically based on EMG and EEG signals related to human locomotion. Then the same research group has also proposed a hybrid BCI-based device with multimodal feedback to assist post-stroke motor rehabilitation of the upper limb [88]. On the other hand, few studies [89,90] have introduced conceptual designs of hybrid sensor fusion in BCIs. Not only EEG and EMG signals, but also additional inputs such as signals from simple switches and motion sensors are fused in those designs in order to enhance the effectiveness. These proposed design basically highlighted that depending on the user preference and/or availability, the hybrid interfaces could be able to decide which input channels, or combinations of fused channels, offer the most reliable signals for controlling the assistive robotic devices.

In light of these background, several advantages of the hybrid EMG-EEG based control approaches can be highlighted. The hybrid approaches can improve in several performance criteria such accuracy, reliability or robustness in comparison to individual use of EEG or EMG based control methods. Fusing EMG-EEG control approaches can also improve the potential of assistive robotic applications such as prosthetics and exoskeletons by introducing an additional degree of freedom, and also improves the robustness of the control approaches. For example, even if all necessary muscles for EMG-based control methods are available, EEG signals can still be utilized during some common issues in the EMG-based control such as undesired tremor or the effects of muscle fatigue. Furthermore unlike fully EEG-based control approaches, where users may need to have high concentration on his/her activity, these hybrid approaches may help to reduce the mental effort of the users while they operating assistive robotic devices.

Even though with the aforementioned merits, there are several issues that have to be encountered in the case of hybrid EMG-EEG approaches. One of the main challenges with hybrid approaches is the difficulty in realizing flawless fusion of EMG and EEG based methods. Although different techniques can be applied to combine EMG and EEG based methods, it is important be cleared that not all the combinations are feasible and effective. The performances of a non matching EMG-EEG combined approach may be less than that of EEG or EMG alone. It is therefore vital to critically consider the ways of combining both signals within the control approaches for a particular application in order to gain better results. On the other hand, all the issues involved in EEG or EMG based control methods alone, will still be problems for the hybrid EMG-EEG approaches as well. In this sense, the technology is one of the regulating factors for hybrid EMG-EEG based control approaches. EEG systems with larger number of electrodes can explore a lot of details, but it is sometimes not convenient to use such systems when they cover the whole head of the user. Therefore, compact, low-weight and portable systems for EEG and EMG data measuring need to be introduced. On the other hand, in the case of assistive robotics devices such as exoskeletons or prosthetics, there is a high possibility of EEG signals being affected by movement artifacts. It is, therefore, necessary to incorporate motion artifact filtering and removal techniques in those control approaches. Moreover, because of the complexity of hybrid EMG-EEG based control approaches, sometimes those systems may be difficult to train or adapt by users. Therefore, additional consideration has to be focused to the training experiments and protocols used in the hybrid EMG-EEG based control approaches.

2.14 Saga University upper-limb power-assist exoskeleton and its control method

In order to get a better understanding about the research work which is going to present in this thesis, it is important to have an idea about the previous work done so far on this research. Therefore, this subsection presents the details about the existing exoskeleton hardware system and the EMG-based control methods which have been developed to date. Latest version of the Saga University Upper-limb exoskeleton robot consists of 7 degree of freedoms (DOF) [105, 107] and is shown in fig 2.16. It consists of seven dc motors and those motors have in-built encoders or potentiometers to measure each joint angle. Apart from those, force/torque sensors (PD3-32, Nitta Corporation) are fitted in the forearm and wrist parts to monitor the force between the user and the robot.

In the exoskeleton system, the shoulder vertical, shoulder horizontal, shoulder rotation, and elbow motions are controlled by the motor 1,2,3 and 4 respectively. The torques generated by these motors are transferred to the robot joints using pulleys and cable drives. This exoskeleton was designed to be installed on a wheelchair as it is reasonable to think

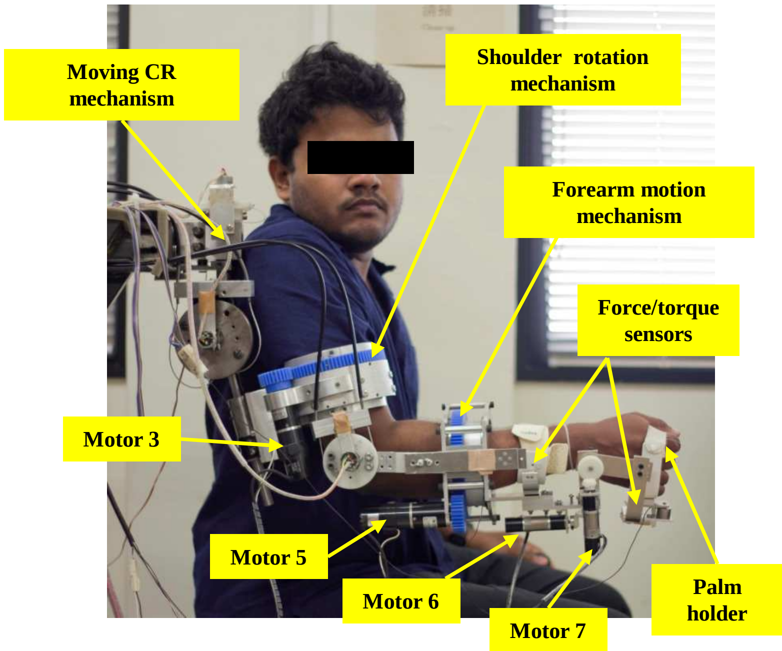


Figure 2.16: Structure of the upper-limb exoskeleton robot

that many physically weak individuals may prefer use a wheelchair. On the other hand, in order to provide safety and the convenience of users, these motors have been placed to the rear frame of the wheelchair. Rest of four motors are fixed to the robot directly using spur gears. Three hook-and-loop-fastener type holders are used for the user to wear the robot. They are located over the biceps, the forearm and on the palm.

As this exoskeleton continuously interacts with the user, the highest priority has been given to safety of the user. Therefore, both in the software and the hardware safety measures are considered to prevent unexpected motions and accidents. In the software level, maximum torque and maximum velocity are limited whereas in the hardware case, physical stoppers are included for each joint in order to regulate the joint motion within the movable range of human upper limb.

The primary way of controlling this exoskeleton is based on EMG signals. In the proposed method, sixteen channels of EMG are utilized as main input signals to estimate the upper limb motion intention of the user. The locations of EMG electrodes positions are shown in fig 2.17. Each EMG channel basically corresponds to one muscle, as shown in Table 2.1. In addition to those EMG signals, the forearm force , the hand force , and the

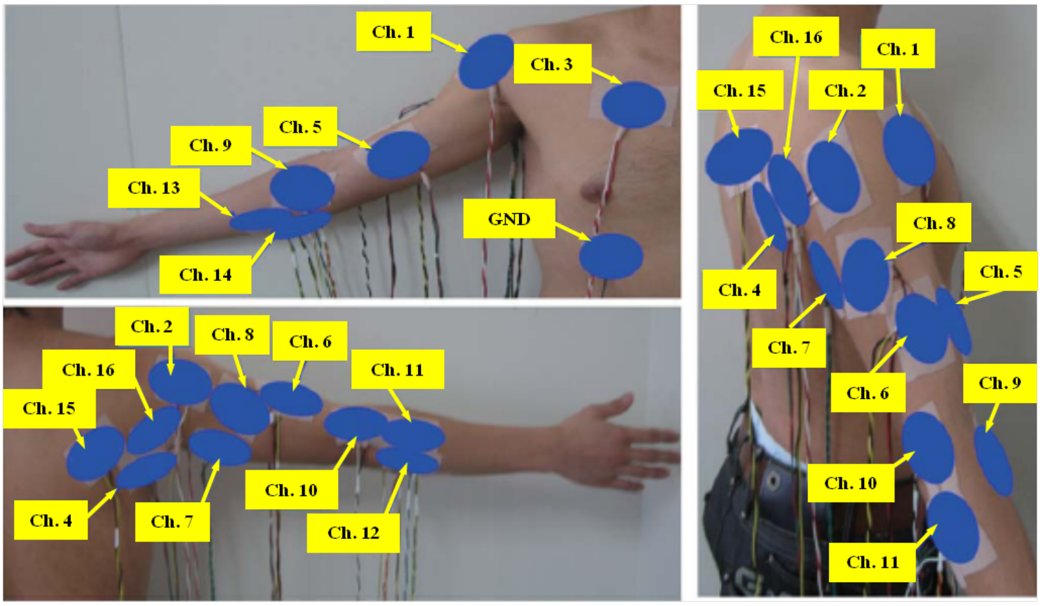


Figure 2.17: Location of the EMG channels [77]

Table 2.1: Muscles related to each EMG channel

EMG channel	Muscle
Ch.1	Deltoid-anterior
Ch.2	Deltoid-posterior
Ch.3	Pectoralis major-clavicular
Ch.4	Teres major
Ch.5	Biceps-short head
Ch.6	Biceps-long head
Ch.7	Triceps-long head
Ch.8	Triceps-lateral head
Ch.9	Pronator teres
Ch.10	Supinator
Ch.11	Extensor carpi radials brevis
Ch.12	Extensor carpi ulnaris
Ch.13	Flexor carpi radials
Ch.14	Flexor carpi ulnaris
Ch.15	Infraspinatus
Ch.16	Teres minor

forearm torque are also used as input signals for the controller. The overall structure of the controller is shown in fig 2.18. In this control method, at beginning, user's upper limb joint torque vector is estimated based on EMG signals and/or force/torque sensor signals.

Then, the user's hand force vector is calculated based on the estimated joint torque vector. Eventually, the impedance control is applied to generate the user's hand force vector. In a situation where the user does not activate the muscles actively, the force/torque sensor based control is applied. However, in this case the robot only follows the user's upper limb motions without the power assist so that the robot does not obstruct the user's motion [77].

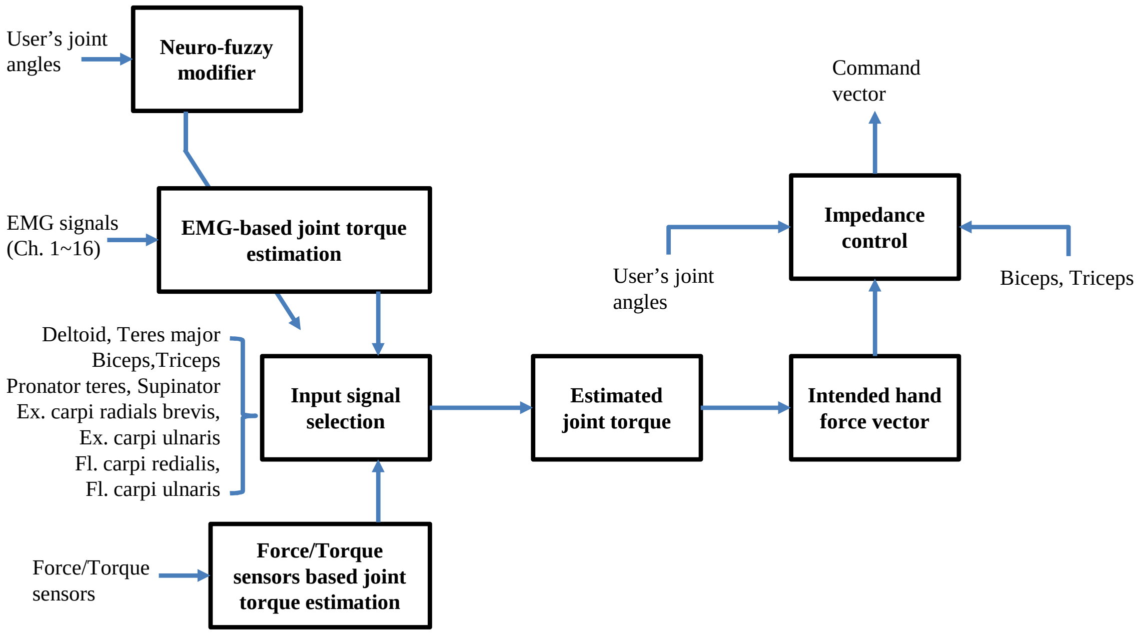


Figure 2.18: Overall structure of the controller

Basically, the raw EMG signals are not appropriate as input signals to the controller and suitable features from the EMG raw signals should be extracted. Therefore, the root mean square (RMS) of the EMG signal is calculated and used as an input for the controller in this method. As mentioned before, the joint torque of the user is estimated based on EMG signals and/or force/torque sensor signals. The input signals utilized for the joint torque estimation are automatically switched depending on the EMG signal levels of the user. In the case of EMG signal level of the user is high, EMG signals are used to estimate the user's motion to be assisted by the exoskeleton. Conversely, force/torque sensor signals are used to estimate the user's motion when the user's muscle activation levels are low as the increment of the noise ratio in the EMG signals. On the other hand, when the user's EMG signal levels are in-between, both the EMG signals and the force/torque sensor signals are simultaneously used in the control approach. Basically, the EMG levels of corresponding muscles for each joint motion are employed to switch the signals for each joint motion.

The relationship between the joint torque vector and the 16 EMG RMSs used for the EMG-based torque estimation is modeled as follows.

$$\tau_{est} = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \\ \tau_4 \\ \tau_5 \\ \tau_6 \\ \tau_7 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{115} & w_{116} \\ w_{21} & w_{22} & \dots & w_{215} & w_{216} \\ w_{31} & w_{32} & \dots & w_{315} & w_{316} \\ w_{41} & w_{42} & \dots & w_{415} & w_{416} \\ w_{51} & w_{52} & \dots & w_{515} & w_{516} \\ w_{61} & w_{62} & \dots & w_{615} & w_{616} \\ w_{71} & w_{72} & \dots & w_{715} & w_{716} \end{bmatrix} \begin{bmatrix} ch.1 \\ ch.2 \\ . \\ . \\ . \\ ch.15 \\ ch.16 \end{bmatrix} \tag{2.1}$$

where τ_{est} is the joint torque vector and τ_1-τ_7 are the joint torques for each joint motion. w_{ij} is the weight value for the j th EMG signal to estimate the joint torque τ_i, and ch_j represents the RMS value of the EMG signal measured in channel j. This weight matrix (i.e., the muscle-model matrix [106]) in 2.1 can be approximately defined using the priori knowledge of human upper-limb anatomy and/or using the results of preliminary experiments. Moreover, in this method, the initial weight matrix was prepared considering the relationship between the muscle and the direction of the rotation of the joint. Thus, the joint torque vector generated by the muscle force can be estimated if every weight for the EMG signals is properly selected. It is not that easy, however, to define the proper weight matrix for the user at the beginning because of the differences across the persons. Moreover, the posture of the upper limb have an influence in the relationship between the EMG signals and the generated joint torques, because of anatomical reasons such as the change of the moment arm. As a result, the effect of the posture differences of the upper limb need to be considered in order to estimate the accurate upper limb motion for the power assist. Therefore, a fuzzy-neuro muscle-model matrix modifier is introduced to take into account the effect of the upper-limb posture difference of the user.

The fuzzy-neuro modifier generates the coefficient for each weight of the muscle-model matrix shown in 2.1 to modify the weight matrix in real time based on the upper-limb posture of the user. The generated coefficients are applied to adjust the weight matrix in real time (on-line) by multiplying the weight by the respective coefficient in accordance with the upper-limb posture of the user in a way that the effect of upper-limb posture differences can be effectively compensated. Moreover, it also produces the similar effect of adjusting the weight matrix itself to be adapted for each user.

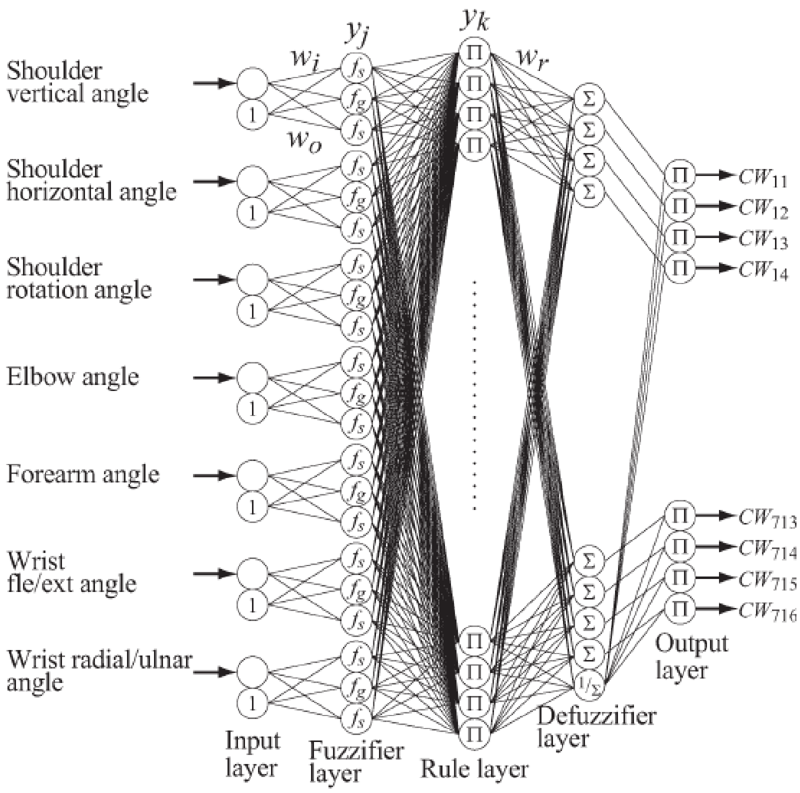


Figure 2.19: The structure of the fuzzy-neuro modifier [77]

The structure of the fuzzy-neuro modifier is basically similar to a neural network, and the process of the signal flow in the fuzzy-neuro modifier is same as that in fuzzy reasoning [77]. This fuzzy-neuro modifier has five layers (input, fuzzyfier, rule, defuzzifier, and output layers) as depicted in fig 2.19. Input variables to this fuzzy-neuro modifier are joint angles of the user's upper limb and at first those input variables are fed in to the input layer. Then, three fuzzy linguistic variables are arranged for each joint angle in the fuzzifier layer. The sigmoidal functions f_s and the Gaussian functions f_g are used to represent the membership functions in the fuzzifier layer. In the rule layer, the coefficient for each weight is reasoned for any combination of upper-limb joint angles. Finally, the output variables from this fuzzy-neuro modifier are coefficients related to the components of the weight matrix.

It is important to train the fuzzy-neuro modifier to adjust its output for each user during the training before its normal operation. At first, the output of the fuzzy-neuro modifier is set to be 1.0 for every weight of the muscle-model matrix. During the training period, the exoskeleton is supposed to produce the motion as close as to the estimated motion of the user in real time. In order to train the fuzzy-neuro modifier, the error-backpropagation learning method is employed to minimize the squared error functions to minimize the error of the muscle-model matrix. Therefore, if the muscle-model matrix with the fuzzy-neuro modifier correctly performs, the generated exoskeleton motion are supposed to be similar to the user's motion. Here, the amount of the error can be measured using the force/torque sensors, as the force/torque sensors measure the force/torque caused by the motion differences between the user and the exoskeleton. So, the squared error function used in this research is calculated as follows.

$$E = \frac{1}{2} f_{err}^2 \tag{2.2}$$

where E and f_{err} is the error function to be minimized and the measured force/torque between the user and the robot respectively. The output of the force/torque sensors should become zero if the generated exoskeleton robot motion and the user's intended motion are identical [77]. Therefore, the joint torque vector of the user can be estimated based on the muscle model matrix with the properly trained fuzzy-neuro modifier. On the other hand, if user cannot move his/her upper limb adequately even though he/she can generate EMG signals, a motion indicator which is manipulated by any other movable part of the user can be used to prepare the amount of motion error for the learning [125].

Then hand force vector is calculated based on the estimated joint torque vector. In this step, the estimated joint torque vector is transferred to the hand force vector of the user using the Jacobian matrix as follows:

$$F_{hand} = J^{-T} \tau_{est} \tag{2.3}$$

$$F_{avg,hand} = \frac{1}{N} \sum_{i=1}^{N} F_{hand}(i) \tag{2.4}$$

where F_{hand} is the hand force vector (6-D vector) of the user, J is the Jacobian matrix, and $F_{avg,hand}$ is the average of F_{hand} in N number of samples. Then, the desired hand acceleration vector is calculated as follows:

$$\ddot{X}_d = M^{-1} F_{avg,hand} \tag{2.5}$$

where $\ddot{X}_d$ is the desired hand acceleration vector (6-D vector) and M is the mass matrix of the robot and the user's upper limb. Then, in order to realize the user's intended motion, impedance control scheme as shown in following equation is applied to get the resultant hand force vector F:

$$F = M\ddot{X}_d + B(\dot{X}_d - \dot{X}) + K(X_d - X) \tag{2.6}$$

where $\dot{X}_d$ and X_d are the desired hand velocity vector and position vector, which are calculated from 2.5, respectively. B and K are the viscous coefficient matrix and the spring coefficient matrix, respectively. It has been known that the impedance parameters of the human upper limb are changed based on the upper-limb posture and the relationship between agonist and antagonist muscles. Therefore, the impedance parameters of the exoskeleton are also varied based on those factors in the proposed method in order to realize natural and comfortable power assist [77]. In the proposed method, the impedance parameter matrix B and K in 2.6 are varied based on the upper-limb posture and the activity levels of activated upper-limb antagonist muscles in real time. Finally, the joint torque command vector for the seven dc motors is derived as follows:

$$\tau_{motor} = kJ^T F \tag{2.7}$$

where τ_{motor} is the joint torque command vector for the seven DC motors and k is the power-assist rate.

Effectiveness of this proposed method has been experimentally validated in the previous studies and reported literature can be found in [77, 106, 107].

As mentioned in section 2.5, there are few other issues associated with upper-limb exoskeletons control such as physical tremor, perception-assist and muscle fatigue. It is important to pay attention to these problem as well. To this moment, several studies have already been conducted to address some of these issues. Physical tremor and its effects has been studied in detail and several methods have been proposed for compensation of the effects of tremor in EMG-based control in the upper-limb exoskeleton [45, 46]. Moreover, several studies have been carried out to include perception abilities to the exoskeletons [40–43]. In those studies, for the individuals with deteriorated perception abilities, perception-assist in addition to the power-assist has been proposed. Nevertheless, more research efforts on these topics are needed to enhance the effectiveness, reliability and robustness of the control methods for upper-limb exoskeletons.

2.15 Summery

This chapter introduced the background information of upper-limb exoskeletons and especially their controlling methods using EMG and EEG signals. Basics and characteristics of EMG signals, a typical EMG signals acquisition method and different EMG signal acquisition systems were studied. More importantly, different EMG-based control methods which have been proposed for controlling upper-limb exoskeletons were reviewed. Moreover, existing problems and challenges in EMG-based control were highlighted. In addition to EMG signals, EEG signals measured from brain can be used as an input signal to control assistive robots such as upper-limb exoskeletons. Therefore, EEG-based control methods proposed for assistive robots such as upper-limb exoskeleton were reviewed.

Characteristics of EEG signals, standard use in EEG studies and various EEG signal acquisition systems were studied. Moreover, challenges and limitations of EEG-based control methods were discussed. To overcome the individual weakness of EMG and EEG, a relatively new approach: hybrid EMG-EEG based control methods that have been proposed for upper-limb exoskeletons and other similar assistive robotic applications were briefly reviewed in this chapter. Moreover, potential advantages, disadvantages and challenges in hybrid EMG-EEG based approaches were identified. This chapter also introduced the existing EMG-based control methods that have been proposed for controlling Saga University Upper-Limb Exoskeleton. Also, limitations of the current methods and areas need to be more focus were identified.

Chapter 3

Muscle Fatigue and Compensation of the Effects of Muscle Fatigue on EMG-Based Control

This chapter reports a research work which aims to address one of the challenges in EMG-based control: *Muscle Fatigue*. Numerous EMG based control methods have been proposed, validated and implemented for assistive robotic applications such as exoskeletons, prosthetics, rehabilitation robots to date as reviewed in the previous chapter. However, some challenges still need to be addressed in the case of EMG based control methods. One of the challenges that had not been considered in such EMG-based control in common is the muscle fatigue. Muscle fatiguing effects of user can deteriorate the effectiveness of the EMG-based control in the long run, because the effects of muscle fatigue can alter the relationship between EMG signal and EMG-based control output. First half of this chapter presents a study that carries out to find out the effects of muscle fatigue on EMG based control in upper-limb power-assist control. Then, the second half of this chapter proposes a method of using fuzzy-neuro modifiers for compensation of the effects of muscle fatigue on EMG-based control to be used in upper-limb exoskeletons. Preliminary studies, proposed methods for compensation of the effects of muscle fatigue on EMG-based control and experimental validation of the proposed methods are comprehensively presented in this chapter.

3.1 Muscle fatigue

Muscle fatigue is basically the decline in the ability of a muscle to generate force. Muscle cells work by detecting a flow of electrical impulses from the brain which signals them to contract through the release of calcium by the sarcoplasmic reticulum [93]. Muscle Fatigue can be caused by various mechanisms such as the accumulation of metabolites within muscle fibres or the generation of an inadequate motor command in the motor cortex. However, it is difficult to derive a global mechanism responsible for muscle fatigue. Relatively, the mechanisms that cause fatigue are specific to the task being performed [94]. As the body gets older, the skeletal muscle fibers become smaller in size and less in power which lead to reduction of strength and endurance and tendency to fatigue rapidly [32]. Because of these reasons, one could consider the possibility that especially such as older individuals may have to face the muscular fatigue more often as they become more and more tired of their physical actions. Analysis of Electromyography (EMG) signal is a well known research method which have shown interest among researchers all over the world. Those analysis permit them to look at muscle recruitment in various conditions, by quantifying electrical signals. Especially, EMG signal based analyses are often been used to understand the muscle fatigue conditions.

3.2 Relationship between EMG signals and muscle fatigue

Several previous studies have shown the evidence of strong relationship between muscle fatigue and EMG signals. Of them many studies show that amplitude often increases and spectral frequency features such as mean/median power frequency usually decreases with fatigue conditions [95–97]. Nonetheless, the median power frequency is normally seen as less sensitive to noise, but on the other hand mean power frequency (MPF) is proposed as a more reliable measure of fatigue in practice, even though the MPF can be affected by the noise [98]. On the other hand, it is important to understand the variations of these amplitude and spectral features during the dynamic contractions, as in the most practical applications such as exoskeletons, it is required to analyze the EMG features in dynamic conditions. In many studies which were conducted to study on dynamic muscle fatigue conditions, the EMG amplitude has been observed to increase during dynamic tasks and the EMG spectral frequency features have been reported as decreasing pattern during the dynamic tasks [99, 100].

However, the explanation of muscle fatigue from the EMG signals for dynamic conditions is considered to be much more difficult, as it introduces additional factors such as effects of muscle kinematics that affect the characteristics of surface EMG amplitude and frequency during muscle fatiguing dynamic contractions [99]. In this context, some studies have proposed methods for monitoring the muscle fatigue continuously throughout dynamic movements that the results might be applicable to normal occurring activities [101]. However, most of these results indicate that, it is not a straight forward task to derive an analytical model which associates the muscle fatigue with specific individual features of the EMG signals. Therefore, to overcome these issues, different methods have been proposed in the literature. One of the methods was the analysis of EMG amplitude and spectrum changes in simultaneously to discrimination between fatigue-induced and force-related EMG changes [102]. Several studies have used artificial neural networks (ANN) to predict the muscle fatigue or related measurements [103, 104] by using time and spectral domain features as the inputs. The main intention of these approaches was that the ANN would estimate the relationship between EMG signals and the muscle fatigue by learning, as oppose to an analytical approach that would be much more complex.

Therefore, these studies show the importance of analyzing the EMG signals during muscle fatigue situations and necessity of studying about the effects of muscle fatigue on EMG-based control.

3.3 EMG signal acquisition setup

In order to analysis the EMG signals, first step is to measure the EMG signals from human subjects. Detection or measuring methods of the EMG signals vary according to its type (i.e: based on invasive or non-invasive methods). As it is more practical and convenient to use the non-invasive EMG signal recording methods and almost all of the EMG-based control methods have used non-invasive surface EMG signals, the surface EMG signal

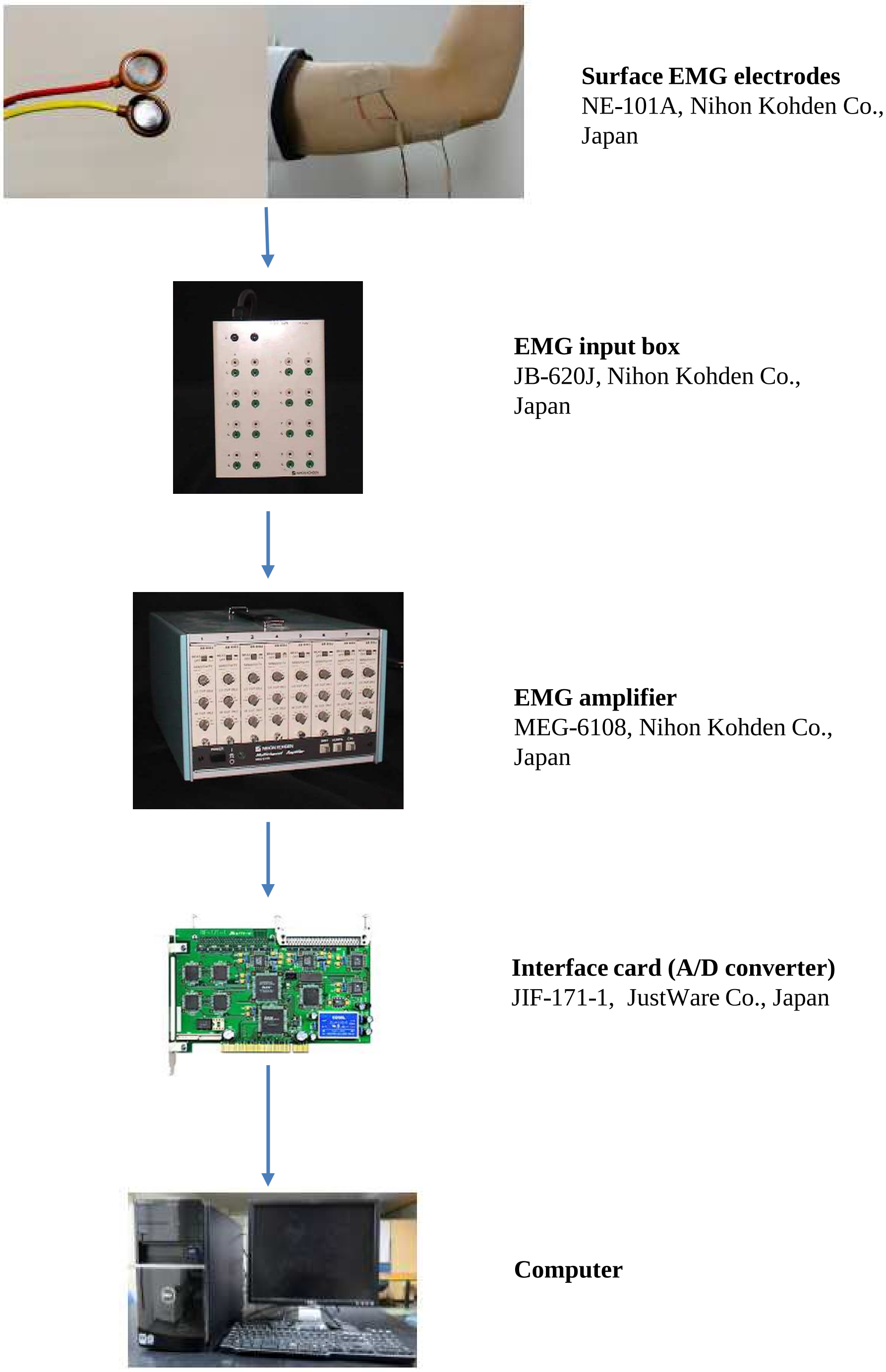


Figure 3.1: EMG signal acquisition setup

detection method is selected and it is discussed in this subsection. The same method is used for the detection of EMG signals in all the experiments and studies in this thesis. A typical measuring procedure of surface EMG signals is depicted in Fig. 3.1. First step of the EMG signal detection procedure is to attach the surface electrodes [NE-101A, Nihon Kohden Co., Japan] over the skin surface of the interested muscles. Before attaching, EMG electrodes and the skin are cleaned well using an alcoholic liquid such as ethanol. Then, a conductive ionic paste is used between the skin and the electrode to reduce the static electric insulation cause by the dry skin. In all studies demonstrate in this thesis, EEG paste [Z-181JE, Nihon Kohden Co., Japan] is used as the conductive paste. In order to measure the EMG signal of a particular muscle, a pair of surface EMG electrodes is attached over the skin surface of the muscle with a separation around 1-1.5 cm. Moreover it is necessary to have a reference EMG electrode for the system and that reference electrode is attached on an electrically unrelated tissue. The EMG signals are then send to an input box which consists of input channels for several electrodes and the reference electrode. The input box [JB-620J, Nihon Kohden Co., Japan] used in this study consists of eight input channels for eight electrodes and another one for the reference electrode. Then, the signals from the input box are passed to a multi-channel amplifier [MEG-6108, Nihon Kohden Co., Japan]. The gain of the multi-channel amplifier is set to 50 V/V. Amplified EMG signals are then send to a computer through an interface card [JIF-171-1, JustWare Co., Japan] by converting analog signals to digital signals.

3.4 A study on effects of muscle fatigue on EMG signals and EMG-based control

As highlighted in the section 3.2, to get a better understanding about the effects of muscle fatigue on EMG-based control, a study was conducted based on set of muscle fatiguing experiments. This section details about that conducted study which was basically a analysis of EMG signal variations in set of upper-limb muscles during muscle fatigue exercises. Two EMG features which consist of EMG amplitude and spectral features were calculated from the raw EMG signals of four muscles of human upper-limb namely biceps, deltoid-anterior, deltoid-posterior and supinator. Those muscles are often used in EMG-based control of human upper-limb power-assist exoskeletons. The two features interested in this study were EMG Root Mean Square (RMS) and EMG Mean Power Frequency (MPF). In this study, subjects were asked to perform four basic motions of upper-limb namely shoulder abduction/adduction, shoulder vertical flexion/extension, elbow flexion/extension and forearm pronation/supination at the beginning of the experiments. Then, in order to gain the muscle fatigue conditions, a set of muscle fatiguing exercises were conducted. Finally, immediately after the fatiguing exercises, the same motions which conducted before the muscle fatiguing exercises were performed again to measure and compare the effect of muscle fatigue on each of the EMG features in each different motions of the upper-limb.

3.4.1 Method

In order to understand the EMG changes due to muscle fatigue, the EMG signals of the upper limb muscles were monitored using the setup explained in the section 3.3. The EMG signals of the biceps, deltoid-anterior, deltoid-posterior and supinator of the right upper-limb were measured during the experiments. Locations of the EMG electrodes placed on the upper-limb muscles are shown in Fig 3.2. Then, two 3-axis accelerometers attached over the shoulder and forearm using adhesive tapes were used to measure the shoulder and forearm angles respectively. A rotary encoder attached to the elbow joint using two rigid links was used to record the elbow joint angle (refer Fig. 3.3).

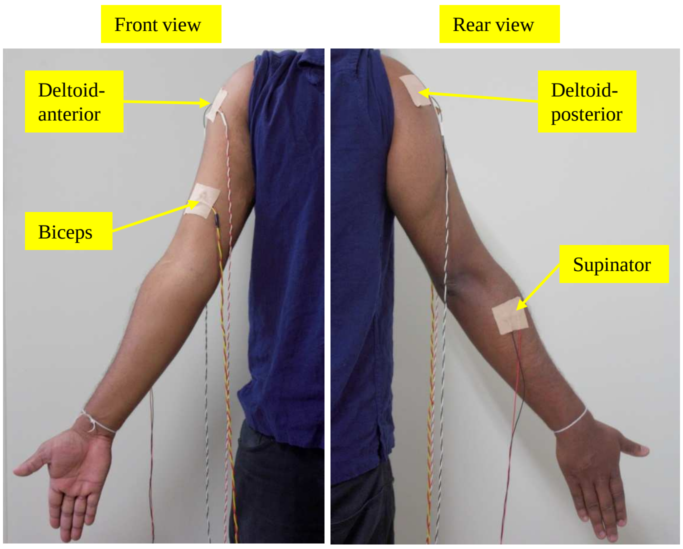


Figure 3.2: Locations of the upper-limb muscles monitored in this study

Three healthy young men (age: 24-27) who did not have any history of previous

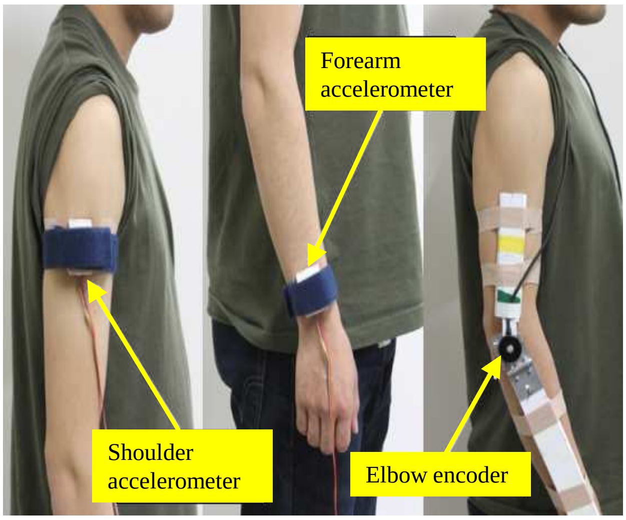
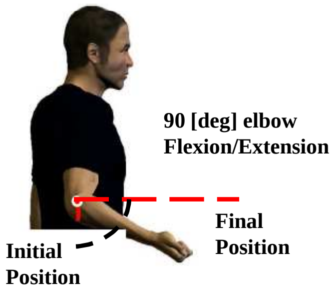
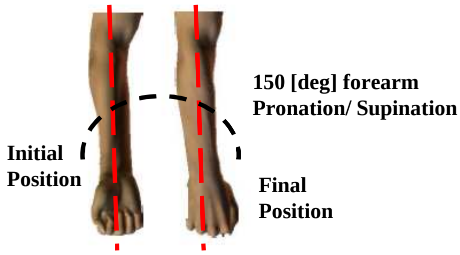


Figure 3.3: Placement of angular measurement sensors

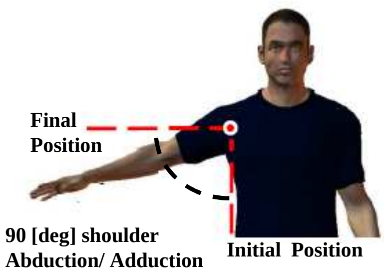


(a)

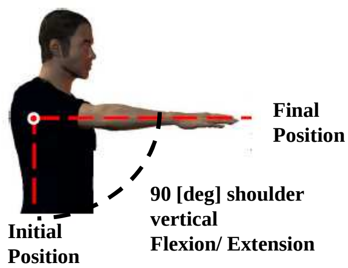


(b)

Figure 3.4: Range of (a) elbow flexion/extension (b) forearm pronation/supination movements



(a)



(b)

Figure 3.5: Range of (a)shoulder abduction/adduction (b) shoulder vertical flexion/extension movements

muscle disorders of upper limb participated in this study. Each subject was provided with full instructions about the experimental procedure before the experiments commence. The subjects were asked to perform four different upper limb motions; shoulder abduction/adduction, shoulder vertical flexion/extension, elbow flexion/extension and forearm pronation/ supination. The initial positions and motion ranges of elbow flexion/extension and forearm supination/pronation movements are shown in the Fig. 3.4 (a) and (b) respectively. The initial positions and motion ranges of shoulder shoulder abduction/adduction and vertical movements are shown in Fig. 3.5 (a) and (b) respectively.

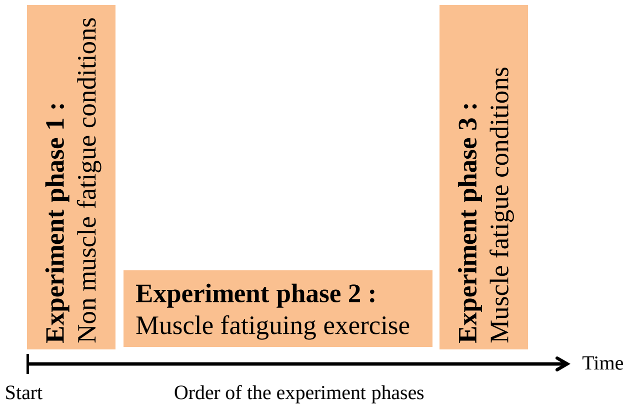


Figure 3.6: Order of the experiment phases

The experiments carried out in three phases as shown in fig. 3.6. The experimental procedure for only the elbow flexion/extension movements is described here for the simplicity and other movement experiments were conducted in similar routines. At the first phase of the elbow motion experiment, the subjects were asked to perform three repetitions of elbow flexion/extension motion with holding a 2 kg weight in hand. The elbow motion range was around 0-70 [deg]. Moreover, a software metronome was used in order to maintain a regular speed motions. This first phase of the experiment was carried out to measure the EMG changes before the muscle fatiguing exercise/conditions. Then, one minute rest time was given before the start of the second phase of the experiment. At the second phase of the experiment, a muscle fatiguing exercise was carried out. In this phase, the subjects were asked to carry out repetition elbow flexion/extension motions (range of motion was around 0-90 degrees) with a 4 kg weight in hand and in line with the software metronome for maximum two minutes. In the meantime, verbal encouragement were given to motivate the subjects during this phase. However, before end of the two minutes if the subjects felt they could not complete the full two minutes, they were asked to stop. Nevertheless, immediately after finishing the second phase, the subjects were asked to repeat the motions similar to the first phase of the experiment again in the third phase in order to measure the EMG changes after the muscle fatiguing exercise. For shoulder abduction/adduction, shoulder vertical flexion/extension and forearm pronation/supination same procedure was followed. Around five minutes of rest times were given between the each motion experiments.

In the next step, a set of EMG features was calculated from raw EMG signals in real time. The EMG RMS was calculated using raw EMG signals as the first feature because, EMG RMS is often used as a primary control signal in real time EMG-based control methods. The EMG RMS is a time domain feature and it was calculated as follows.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} v_i^2} \tag{3.1}$$

where v_i is the voltage value of EMG channel at i_{th} sampling and $N$is the number of the samples in a segment. N was set to 400 and the EMG sampling rate was set to 2 [kHz] in this study.

In order to analysis the effects of muscle fatigue conditions using EMG signals, in addition to the time domain features, spectral or frequency domain features has often been used. Main mechanism behind the muscle fatigue manifestation is when the muscle fatigue occurs power spectrum density of the EMG signal is shifting towards the lower frequencies. However in order to use this frequency spectrum shift in a useful manner as a measurement or as an input, it is necessary to calculate it as a single indicator. Among such indicators of muscle fatigue, EMG mean power frequency (MPF) and median power frequencies have been recognized as the gold standard measures of muscle fatigue in not only engineering studies but also in clinical studies. On the other hand, those two EMG features have commonly been used in most of the previous studies as muscle fatigue indicators. Many studies have reported that amplitude features often increase and spectral frequency features such as

MPF and median power frequency usually decrease with fatigue conditions [95–97]. Even though the median power frequency has usually been considered as less sensitive to noise, on the other hand the MPF has been suggested as a more reliable measure of fatigue in practice. Especially, the MPF is a more reliable measure of spectral shift mainly because of its lower standard deviation. Moreover, the MPF feature has shown a relatively better performance in class separation than the median power frequency feature in few studies. Therefore in this study, the EMG MPF was decided to use as the frequency domain feature. The MPF is the frequency of EMG signal at which the average power within the segment/window is reached. The MPF was calculated based on the following equation.

$$\mathrm{MPF} = \frac{\sum_{i=1}^{M} f_i PSD_i}{\sum_{i=1}^{M} PSD_i} \tag{3.2}$$

where PSD_i is i_{th} line of the EMG power spectrum density , f_i is the center frequency value of the frequency bin i and M is the length of the power spectrum density ($M = 512$). The power spectrum density was calculated using Fast Fourier Transformation (FFT) algorithm with 512 data point window and at every 128 data points of overlapping window. During the 128 data points (approximately 50 ms) same value for MPF was kept for 128 times until a new value was calculated in order to synchronous with the EMG sample rate.

3.4.2 Results and discussion

Figure. 3.7 (a) and (b) depicts how the EMG RMS of biceps and deltoid-posterior muscles of subject A were changed with the time during the muscle fatiguing exercise respectively. The EMG RMS was increased with respect to time in each contraction. Similar results were observed for other muscles and other subjects. Though it shows a clear increment in the plots, it was difficult find a clear linear trend in EMG RMS patterns. Different patterns of increment were found across the different muscles and the subjects. On the other hand, the EMG MPF features of all interested muscles showed a decrement along with the number of contractions. However as similar to the EMG RMS, the patterns of decrement were different across the muscles and the subjects. Figure. 3.8 (a) and (b) show the variations of

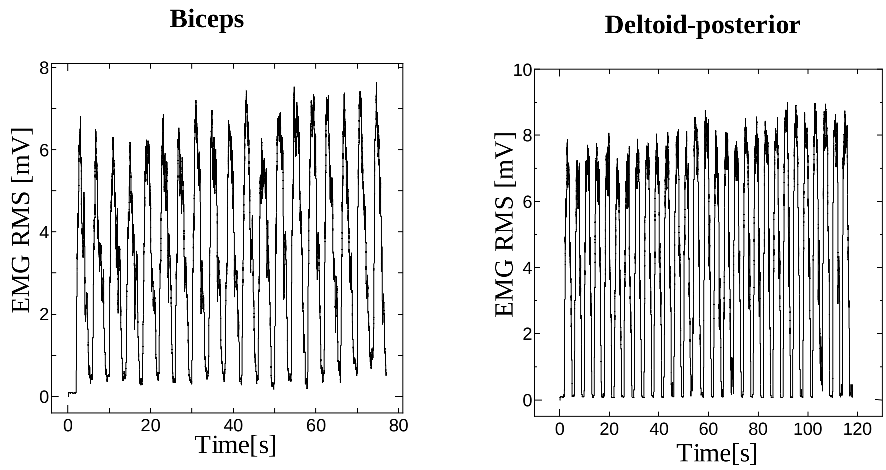


Figure 3.7: EMG RMS patterns of biceps and deltoid-posterior during the fatiguing exercise of subject A

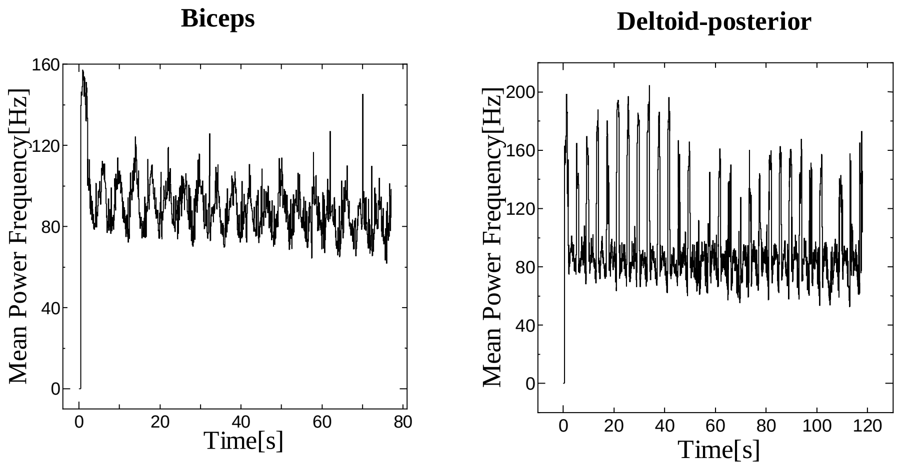


Figure 3.8: EMG MPF patterns of biceps and deltoid-posterior during the fatiguing exercise of subject A

the EMG MPF in each contraction for the biceps and deltoid-posterior muscles during the relevant muscle fatigue exercises respectively.

On the other hand, fig. 3.9 (a) and (b) illustrate the variations of the EMG RMS feature of biceps muscle during single elbow flexion/extension cycle of subject B, before and after the muscle fatiguing exercise respectively. It appears that approximately for the same motions, respective EMG RMS value has been increased after the muscle fatiguing exercise. Therefore, these results show the effects of muscle fatigue on EMG signals. However in

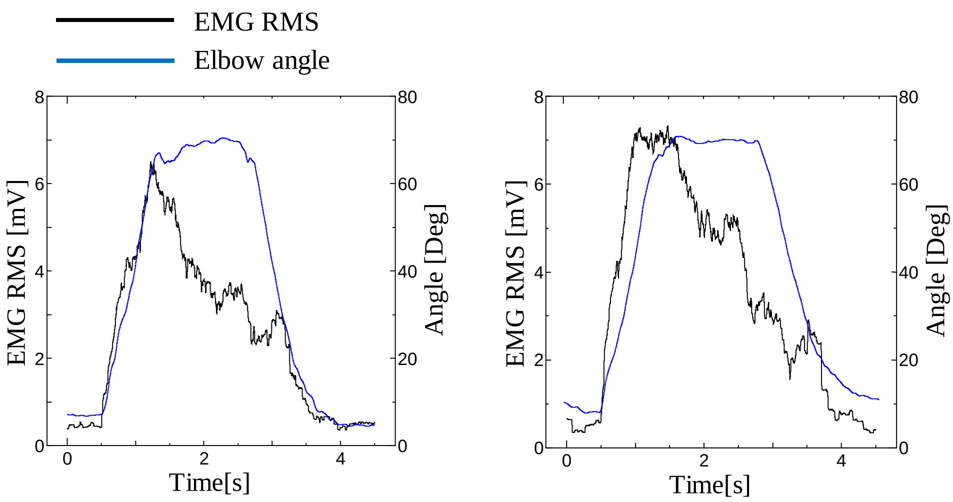


Figure 3.9: Comparison of EMG RMS of biceps muscle during the workout,(a) before and (b) after the fatiguing exercise of subject B

order to further understand the effects of muscle fatigue on EMG features, a quantitative analysis was carried out. To do that, percentage variation of an EMG feature of a particular muscle after fatiguing exercises with respect to the initial conditions was calculated as follows:

$$\text{Percentage variation } = \left(\frac{AVG_{af} - AVG_{bf}}{AVG_{bf}}\right).100\% \tag{3.3}$$

where AVG_{bf} and AVG_{af} is the average of an EMG feature of a particular muscle across the three successive contraction cycles before and after muscle fatiguing exercise respectively. Calculated percentage variations are shown in Table. 3.1, Table. 3.2 and Table. 3.3 for subject A, subject B and subject C respectively.

It may reasonable to argue that these changes on each EMG features were due to muscles fatiguing conditions, as all other conditions prior and posterior the fatiguing experiment were approximately maintained same. The results clearly show that EMG RMS feature has been affected by the muscle fatigue. Therefore these results urge the need of focusing on muscle fatigue conditions whenever EMG RMS signals are used in controlling

Table 3.1: Percentage variations of each EMG feature in subject A

EMG Feature	Biceps	Deltoid-posterior	Deltoid-anterior	Supinator
RMS	+26%	+28%	+27%	+19%
MPF	-16%	-22%	-19%	-12%

Table 3.2: Percentage variations of each EMG feature in subject B

EMG Feature	Biceps	Deltoid-posterior	Deltoid-anterior	Supinator
RMS	+28%	+26%	+26%	+20%
MPF	-15%	-18%	-17%	-11%

Table 3.3: Percentage variations of each EMG feature in subject C

EMG Feature	Biceps	Deltoid-posterior	Deltoid-anterior	Supinator
RMS	+18%	+21%	+19%	+18%
MPF	-18%	-20%	-21%	-15%

exoskeletons and other similar applications. For an example, in fig. 3.9 (a) represents the relationship with EMG RMS feature and the elbow angle before muscle fatiguing exercise was conducted. Let there is a controller which has trained for estimating the EMG-based elbow joint torque and control a robot using EMG RMS changes with respect to relationship between elbow angle during before the muscle fatiguing conditions. This controller may not be able to effectively estimate the elbow joint torque and control the robot due to different relationship between EMG RMS and the elbow angle (eg. as shown in fig. 3.9 (b)) after the muscle fatiguing exercises.

Therefore it might not be effective to use the EMG RMS alone as the input feature in EMG-based control approaches, as exoskeleton users can be suffered by muscle fatigue due to long term use and physical exhaustion. Moreover, this urges the necessity of a modification method to EMG-based control approaches during muscle fatigue condition in order to compensate the effects of muscle fatigue and achieve a long term use of exoskeletons or similar robot systems.

On the other hand, the above results can be used to support a claim that additional frequency domain features such as the EMG MPF can be used to recognize the muscle fatigue conditions. Therefore these results suggest that, a combination of these two features might be a good option to be used as input features to EMG-based control approaches in order to more effectively deal with muscle fatigue conditions when using upper-limb exoskeletons or similar robot systems.

3.5 Compensation of the effects of muscle fatigue on EMG-based control

In the case of EMG-based control, one of the EMG amplitude features; the EMG RMS is usually being used as the primary input signal to the controller. It is because, the EMG RMS feature can be mapped in to the motion intention of the user and it can be calculated in real-time (It is an important requirement for EMG-based control methods). However as discussed in the section 3.4 the results showed that, the amount of EMG RMS signal can be changed when the muscle get fatigued in addition to the level of contraction. This effect may induce problems with the expected functioning of the exoskeletons or similar robots. Therefore, this shows the importance of making necessary adjustment to the EMG-based control methods to compensate for the effects of muscle fatigue on the overall EMG-based control approaches to get an effective outcome during muscle fatigue conditions.

In this context, this section presents a novel method of using fuzzy-neuro modifiers to compensate the effects of muscle fatigue on EMG-based control to be used in upper-limb power-assist exoskeletons. Design and implementation of the proposed methods, experimental procedures and validations of the proposed methods are detailed within next subsections.

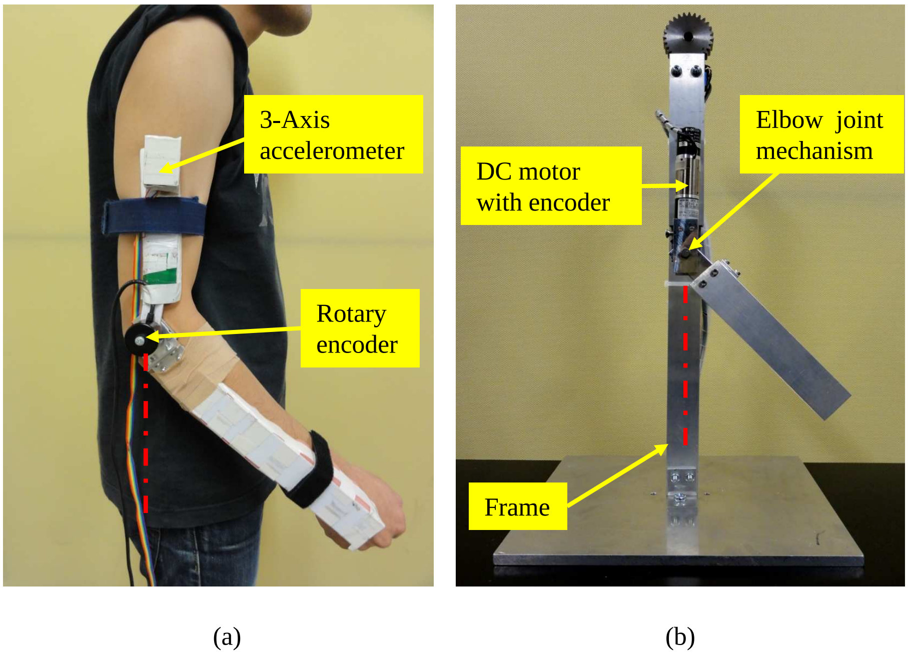


Figure 3.10: (a) Placement of the motion sensors (b) Robot arm used in the study

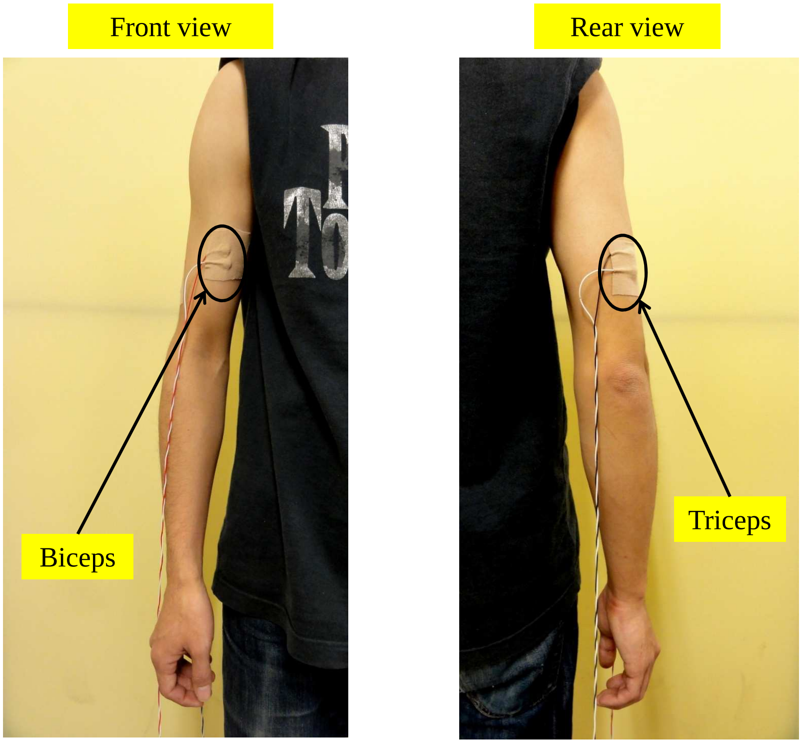


Figure 3.11: locations of the EMG electrodes placed over the biceps and triceps of the upper-limb

3.5.1 Experimental setup

In order to implement and validate the method going to propose here, certain muscles or prominent muscles of upper-limb should be selected. The biceps and triceps are identified as the most active muscles for the elbow flexion/extension motions which are involved in the most of the daily motions. Moreover, biceps and triceps are bi-articular muscles that are involved in the shoulder motion as well. Thus, the EMG signals of biceps and triceps were monitored to control a robot arm similar to elbow joint based on the motion intention of the user during muscle fatigue situation in this study. The robot used in this study is shown in fig. 3.10 (b). It consists of two rotational joints which can simulate shoulder and elbow joint motions in parallel to sagittal plane of the human body. Basically, these two joints (i.e. shoulder and elbow) are controlled by two DC motors with in-built encoders. However, as this study targeting on the elbow joint motions, the shoulder joint was remained lock during the experiments. The robot was therefore used as an external robot arm which was required to move according to the elbow flexion/extension motion of the user based on EMG signals of biceps and triceps muscles. The effects and validations of the proposed method can clearly interpret using this type of robot arm due to the possibility of measuring desired elbow motions of the user and motions of the robot generated by the EMG-based controller independently.

The EMG signals of the biceps and the triceps muscles were measured using surface EMG electrodes with bipolar montage using the setup illustrated in the section 3.3. The EMG sample rate was set to 2 kHz in this study. Additionally, elbow angle and shoulder angles were measured at a rate of 2 kHz using a rotary encoder attached to elbow (using two links and adhesive tapes) and a 3-axis accelerometer respectively. Moreover, the robot's elbow joint angle was measured using the in-built encoder of the motor at a rate of 2 kHz. The motion sensors attachment and the locations of the EMG electrodes over biceps and triceps are shown in fig. 3.10 (a) and fig. 3.11 respectively.

3.5.2 Estimation of EMG-based joint torque using EMG signals

The EMG RMS has often been used as the primary input signal in many EMG-based control methods since it reflect the motion intention of user more effectively during non-muscle fatigue conditions. Therefore at first, the EMG RMS of biceps and triceps muscles were calculated based on the equation 3.1 in real time. In this study, N was set to 100. Basically, all joint torques of upper-limb can be estimated based on the EMG RMS of relevant muscles. According this rationale, the EMG-based joint torque for controlling the elbow joint of the robot can be written as in equation 3.4. In fact this equation can be considered as a simplified version of the muscle-matrix-model which was used in previous studies (see the Background chapter for more details) to control the upper-limb power-assist exoskeleton [77, 106].

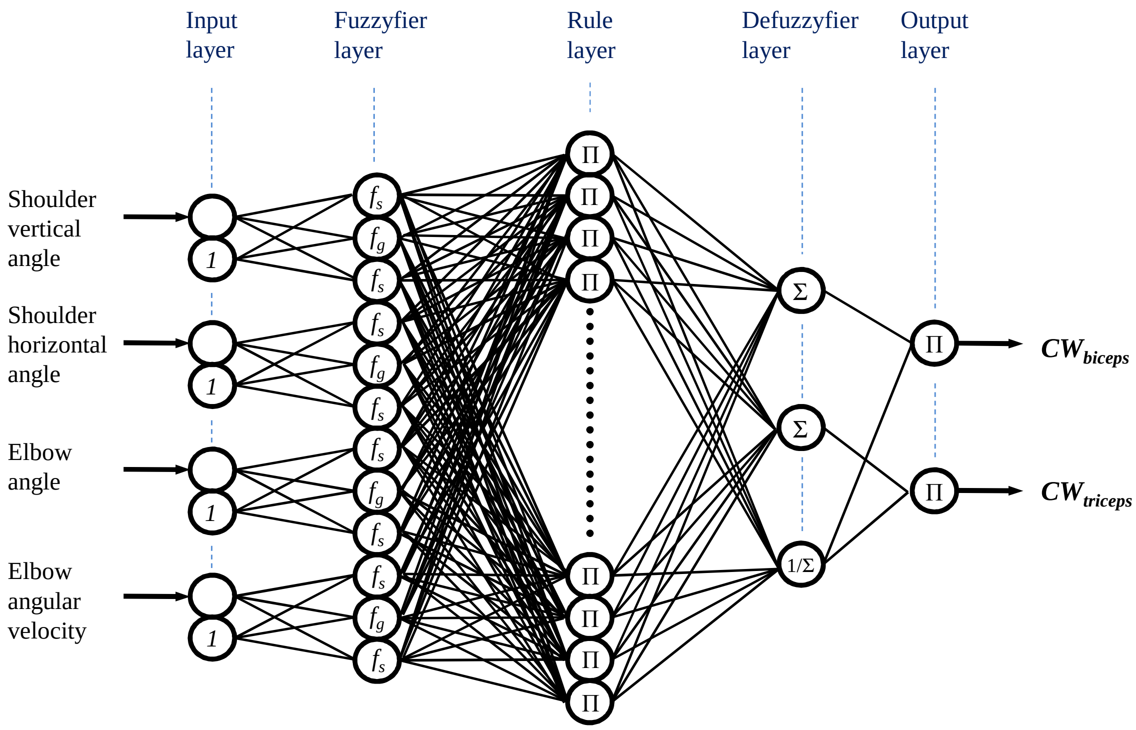


Figure 3.12: Structure of the fuzzy-neuro modifier used to estimate the coefficients, CW_{biceps} and $CW_{triceps}$

$$\tau_{\text{elbow}} = \begin{bmatrix} w_{elbow.biceps} & w_{elbow.triceps} \end{bmatrix} \begin{bmatrix} ch_{\text{biceps}} \\ ch_{\text{triceps}} \end{bmatrix} \tag{3.4}$$

where τ_{elbow}, ch_{biceps} and ch_{triceps} are EMG-base elbow joint torque, EMG RMS of the biceps muscle and EMG RMS of the triceps muscle, respectively. The weights $w_{elbow.biceps}$ and $w_{elbow.triceps}$ are the corresponding weights related to the elbow joint torque, biceps and triceps muscles which were estimated by a fuzzy-neuro modifier according to the variations of upper-limb posture in real-time in order to adjust the influences of the changes of the EMG signals. The structure of this fuzzy-neuro modifier is shown in fig. 3.12. Shoulder vertical and horizontal angles, elbow joint angle and angular velocity (calculated using time differentiation of the elbow joint angle) were fed into the fuzzy-neuro modifier in real time. Those four input features were calculated using the motion sensors attach to the user as illustrated in section 3.5.1.

The structure of the fuzzy-neuro modifier is basically similar to a common fuzzy-neural network. This fuzzy-neuro modifier consists of five layers (input, fuzzyfier, rule, defuzzifier, and output layers), as shown in fig. 3.12. In the input layer, the joint angles and velocities of the user's upper limb were acquired. These input information were then fuzzified in the fuzzifier layer. Three fuzzy linguistic variables namely zero (ZO), positive small (PS) and positive big (PB) were prepared for each joint angle and velocity variables in the fuzzifier layer. Sigmoid functions (f_S) and Gaussian functions (f_G) were used as the membership functions in the fuzzifier layer. The fuzzy membership functions for joint angles and velocities in the fuzzyfier layer are shown in Fig. 3.13. Generally, f_S and f_G were expressed as follows:

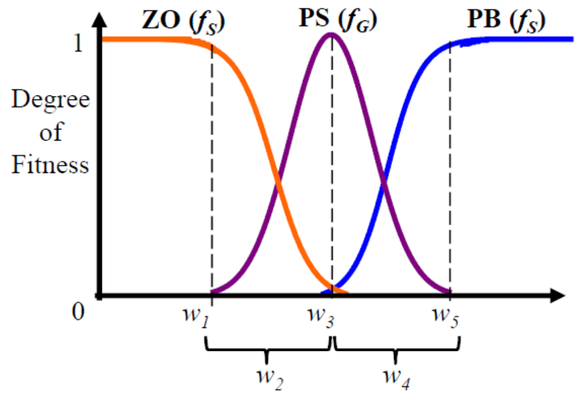


Figure 3.13: Membership functions of the fuzzy linguistic variables of joint angles and velocities

$$f_S(u_S) = \frac{1}{1+e^{-u_S}} \tag{3.5}$$

$$u_S(x) = w_o + w_i x \tag{3.6}$$

$$f_G(u_G) = e^{-u_G^2} \tag{3.7}$$

$$u_G(x) = \frac{w_o + x}{w_i} \tag{3.8}$$

where w_o is a threshold value, w_i is a weight value, and x is the input value (i.e: in this case the joint angles/velocities). The weight value, w_i and threshold value, w_o for the PB membership function that relates to the sigmoid function were calculated as follows.

$$w_{i(\text{PB})} = \log\left[\frac{1/H.rate - 1}{1/L.rate - 1}\right] / (w_3 - w_5) \tag{3.9}$$

$$w_{o(\text{PB})} = (-1)\log\left[1/H.rate - 1\right] - w_5 w_{i(\text{PB})} \tag{3.10}$$

The weight value and the threshold value for the PS membership function that relates to the gaussian function were calculated as:

$$w_{i(\mathrm{PS})} = \sqrt{\frac{[(-)w_3 + (w_3 + w_4)/2]^2}{\log[1/M.rate - 1]}} \tag{3.11}$$

$$w_{o(\mathrm{PS})} = (-)w_3 \tag{3.12}$$

For the ZO membership function, weight value and threshold value (relates to the Sigmoid function) were calculated as:

$$w_{i(\mathrm{ZO})} = \log\left[\frac{1/H.rate - 1}{1/L.rate - 1}\right] / (w_3 - w_1) \tag{3.13}$$

$$w_{o(\mathrm{ZO})} = (-1)\log[1/H.rate - 1] - w_1 w_{i(\mathrm{ZO})} \tag{3.14}$$

$H.rate$, $M.rate$ and $L.rate$ are parameters which define the sigmoid and gaussian functions. Basically, those parameters are responsible for the shape of the respective functions. In this study, the values were set to $H.rate = 0.98$, $L.rate = 0.02$ and $M.rate$ were selected depending on the particular feature variations. Parameters w_1, w_3 and w_5 were decided considering the variations of upper-limb joint angles and velocities during upper-limb motions. Next in the rule layer, defined fuzzy IF-THEN rules were applied. In the rule layer, π is the multiplicand of the fuzzified inputs. One can notice that, there are two outputs from each neuron in the rule layer(see fig. 3.12). One of them was multiplied by the relevant weights and summed in the next defuzzyfier layer. The other was just summed and then inverted in the defuzzyfier layer. The multiplied value of these outputs was used as the output of the final/output layer. Therefore, generally an output (e.g: CW_{biceps}) of the fuzzy-neuro modifier can be mathematically expressed as follows.

$$\mathrm{Output} = \frac{\sum_{i=1}^{N} w_{ri} y_{ki}}{\sum_{i=1}^{N} y_{ki}} \tag{3.15}$$

where, y_{ki} is the degree of fitness of $i\mathrm{th}$ rule, w_{ri} is the weight for $i\mathrm{th}$ rule, N is the number of rules in the fuzzy-neuro modifier. Eventually, the two weights in equation 3.4 were obtained by the product of initial weight values and the final outputs of the fuzzy-neuro modifier as shown in the following equations.

$$w_{elbow.biceps} = w_{0.bicpes} \times CW_{biceps} \tag{3.16}$$

$$w_{elbow.triceps} = w_{0.tricpes} \times CW_{triceps} \tag{3.17}$$

where $w_{0.bicpes}$ and $w_{0.tricpes}$ are initial weight values which were set to 1 and -1 respectively.

3.5.3 Proposed fuzzy-neuro modifiers for compensation of the effects of muscle fatigue on EMG-based control

Even though the estimated EMG-based elbow joint torque using only EMG RMS of biceps and triceps as in equation 3.4 may effective during non muscle fatigued conditions, it may not that effective if the muscles are fatigued. This is because as mentioned earlier, the EMG RMS signals can be affected during the muscle fatiguing situations other than the contraction level. Therefore, in order to compensate for the effects of muscle fatigue on EMG-based control, a method of using another fuzzy-neuro modifiers which suppose to consider the influences of muscle fatigue is proposed in this section.

As the first step of this method, the EMG-based elbow joint torque estimation equation 3.4 was modified. Two new coefficients were introduced to equation 3.3 and therefore in the modified version; the EMG-based elbow joint torque was estimated as follows.

$$\tau_{\text{elbow.FC}} = \begin{bmatrix} w_{elbow.biceps}.\boldsymbol{w_{BFC}} & w_{elbow.triceps}.\boldsymbol{w_{TFC}} \end{bmatrix} \begin{bmatrix} ch_{\text{biceps}} \\ ch_{\text{triceps}} \end{bmatrix} \tag{3.18}$$

where $\tau_{\text{elbow.FC}}$ is the estimated EMG-based elbow joint torque with muscle fatigue compensation. w_{BFC} and w_{TFC} are the two new weights introduced and they are supposed to be changed according to another two fuzzy-neuro modifiers proposed for compensation of the effects of muscle fatigue. The architectures of the fuzzy-neuro modifiers for compensation of the muscle fatigue effects of the biceps and the triceps muscles are shown in

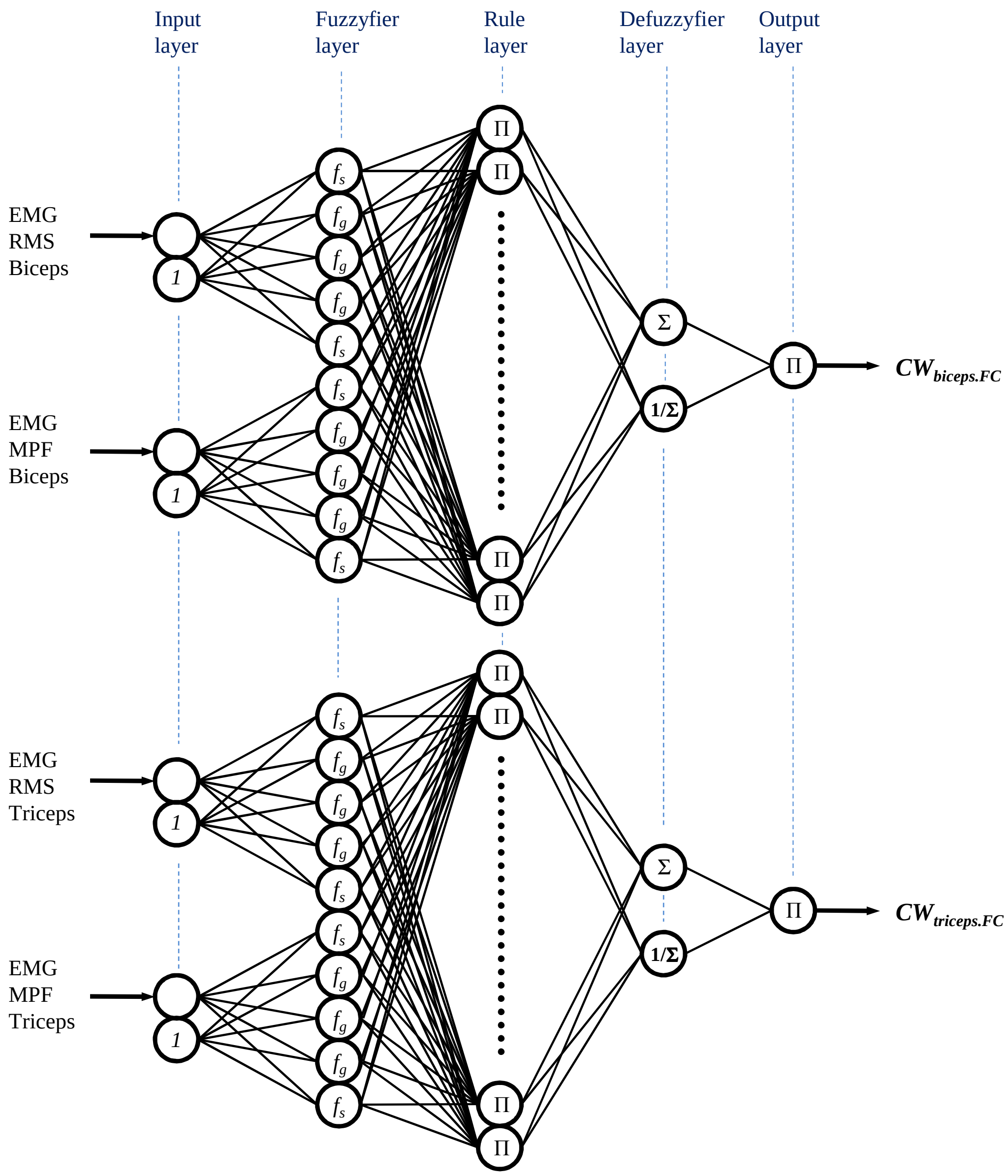


Figure 3.14: Proposed fuzzy-neuro modifiers for compensation of the effects of muscle fatigue in biceps (Top) and triceps (bottom)

fig. 3.14. The structure of each fuzzy-neuro modifier is almost similar to what was detailed in section 3.5.2. In these fuzzy-neuro modifiers in addition to the EMG RMS, the EMG MPF was used as an input feature. The EMG RMS and EMG MPF were calculated using equation 3.1 and 3.2 respectively as introduced in section 3.4.1. Here N=100, M=1024

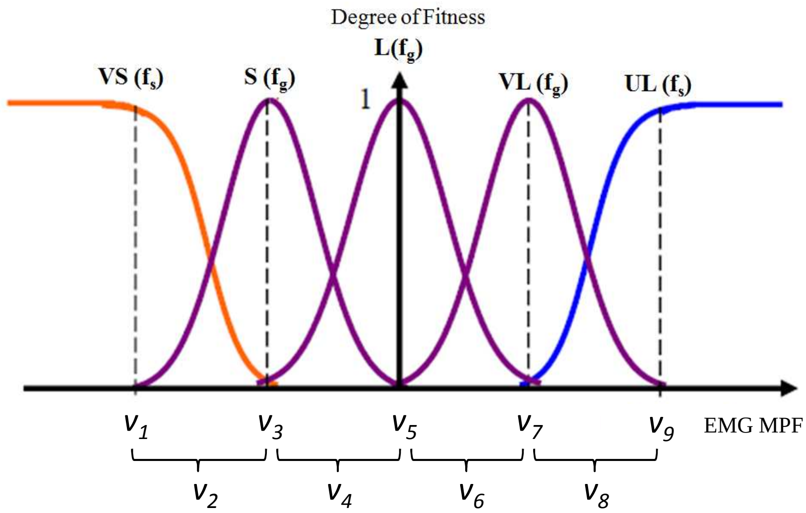


Figure 3.15: Membership functions of the fuzzy linguistic variables of EMG MPF

and sample rate was 2 kHz. The EMG RMS and MPF features were divided into five regions/five linguistic variables as very small (VS), small(S), large (L), very large(VL) and ultra large(UL) in the fuzzifier layer where the input information is fuzzyfied. As similar to the method discussed in section 3.5.2, two nonlinear functions (i.e. Gaussian function (f_G) and sigmoid function(f_S)) were used to express the membership functions. For an example, the membership functions for the EMG MPF feature is shown in fig. 3.15. Here, for VS and UL the sigmoid functions were used whereas S, L, VL regions were represented by Gaussian functions. The same membership function arrangement was used for the EMG RMS feature as well. The functions f_S and f_G were calculated using the equations mentioned in section 3.5.2 where input values were EMG RMS and EMG MPF in this case. However, in order to calculate the respective w_o and w_i for each membership function, following set of equations were used.

$$w_{i(\mathrm{UL})} = \log\left[\frac{1/H.rate - 1}{1/L.rate - 1}\right] / (v_7 - v_9) \tag{3.19}$$

$$w_{o(\mathrm{UL})} = (-1)\log\left[1/H.rate - 1\right] - v_9 w_{i(\mathrm{UL})} \tag{3.20}$$

$$w_{i(\mathrm{VL})} = \sqrt{\frac{[(-)v_7 + (v_7 + v_8)/2]^2}{\log[1/M.rate - 1]}} \tag{3.21}$$

$$w_{o(\mathrm{VL})} = (-)v_7 \tag{3.22}$$

$$w_{i(\mathrm{L})} = \sqrt{\frac{[(-)v_5 + (v_5 + v_6)/2]^2}{\log[1/M.rate - 1]}} \tag{3.23}$$

$$w_{o(\mathrm{L})} = (-1)v_5 \tag{3.24}$$

$$w_{i(\mathrm{S})} = \sqrt{\frac{[(-)v_3 + (v_3 + v_4)/2]^2}{\log[1/M.rate - 1]}} \tag{3.25}$$

$$w_{o(\mathrm{S})} = (-)v_3 \tag{3.26}$$

$$w_{i(\mathrm{VS})} = \log\left[\frac{1/H.rate - 1}{1/L.rate - 1}\right] / (v_3 - v_1) \tag{3.27}$$

$$w_{o(\mathrm{VS})} = (-1)\log[1/H.rate - 1] - v_1 w_{i(\mathrm{VS})} \tag{3.28}$$

The parameters v_1, v_3, v_5, v_7 and v_9 were selected considering the variations of EMG MPF and EMG RMS features of biceps and triceps individually. Then in the rule layer, the coefficient for each weight was reasoned in any combination of EMG RMS and EMG MPF variations. There are two outputs form each neuron in the rule layer. One of them was multiplied by the weight and summed in the next layer. The other was just summed and then inverted in the defuzzyfier layer. The multiplied value of these outputs was the output of the final/output layer. Finally, the outputs from these two fuzzy-neuro modifiers were used to calculate the w_{BFC} and w_{TFC} in equation 3.18 as follows.

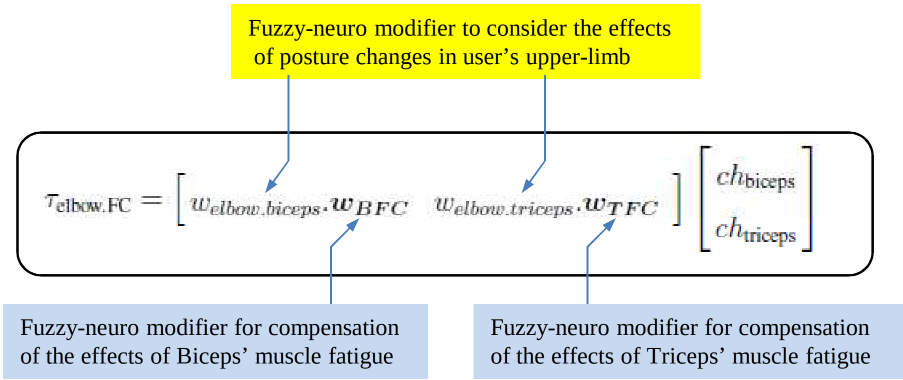


Figure 3.16: Estimation of weights in EMG-based elbow joint torque calculation equation 3.18 using the fuzzy-neuro modifier for influencing the upper-limb posture changes and newly proposed fuzzy-neuro modifiers for muscle fatigue effects compensation

$$w_{BFC} = w_{0.bicpes.FC} \times CW_{biceps.FC} \tag{3.29}$$

$$w_{TFC} = w_{0.tricpes.FC} \times CW_{triceps.FC} \tag{3.30}$$

where $w_{0.bicpes.FC}$ and $w_{0.tricpes.FC}$ are the initial weight values. Finally, it should be noted that three fuzzy-neuro modifiers were employed in estimating the final EMG-based elbow joint torque in the proposed method for compensation of the effects of muscle fatigue. For better visualization, a graphical interpretation of the estimated final EMG-based torque as in equation 3.18 is shown in fig. 3.16.

In order to drive the robot arm, the desired elbow angular acceleration of the elbow motion was then calculated using the EMG-based elbow joint torque as follows.

$$\tau_{\text{elbow.FC.avg}} = \frac{1}{N_f} \sum_{k=1}^{N_f} \tau_{\text{elbow.FC}}(k) \tag{3.31}$$

$$\ddot{\theta}_d = M^{-1} \tau_{\text{elbow.FC.avg}} \tag{3.32}$$

where $\tau_{elbow.FC.avg}$ is the average of $\tau_{elbow.FC}$ in N_f number of samples, $\ddot{\theta}_d$ is the desired elbow angular acceleration and M is the moment of inertia of the part below elbow joint of the robot arm. Then in order to control the robot arm based on the desired motion intention of the user, the following torque was generated by the robot.

$$\tau_{\text{motor}} = M\ddot{\theta}_d + k_v(\dot{\theta}_d - \dot{\theta}_r) + k_p(\theta_d - \theta_r) + G(\theta_r) + F_{fri}(\dot{\theta}_r) \tag{3.33}$$

where τ_{motor} is the elbow joint motor torque command generated. k_v and k_p are the control gains. $\dot{\theta}_d$ and θ_d are desired elbow angular velocity and angle, which were calculated based on the equation 3.32 respectively. Then $\dot{\theta}_r$ and θ_r are the joint angular velocity and angle of the robot arm respectively. $G(\theta_r)$ and $F_{fri}(\dot{\theta}_r)$ represent the gravity and the robot joint friction functions respectively.

3.5.4 Adaptation of fuzzy-neuro modifiers

Adaptation of the each fuzzy-neuro modifier itself to each user is necessary. Each fuzzy-neuro modifier is trained to adapt itself to each user based on the information of the user's elbow joint angle and the robot's joint angle. In other words, an error-back propagation learning algorithm was employed to minimize the squared error function (E) as shown below:

$$E = \frac{1}{2}(\theta_h - \theta_r)^2 \tag{3.34}$$

where θ_h is the angle measured from the user's elbow joint using the rotary encoder. As there are three fuzzy-neuro modifiers that need to be trained for each user, following method was introduced in the training procedure. At first, each user was asked to train the robot without the two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue in effect. This was achieved by maintaining the two coefficients, w_{BFC} and w_{TFC} to 1 during training. In other words, the training loop of the two fuzzy-neuro modifiers related to muscle fatigue compensation were turned off (This was achieved by setting learning rates of the fuzzy-neuro modifiers for fatigue compensation to zero). Nevertheless during this training period, the users were asked to avoid their muscles getting fatigued. Therefore, several short time training periods were carried out by providing proper rest times in between the training sessions. After the sufficient level of control accuracy of the robot arm was reached, the first stage of training was stopped. Then the adaptation of two fuzzy-neuro modifiers for compensation of effects of muscle fatigue was started. However during this training period, the learning of the fuzzy-neuro modifier for influencing the posture changes in the upper-limb was set to zero and allowed two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue to learn. In this case, the users were asked to perform the elbow flexion/extension motions while allowing the two coefficients (i.e: w_{BFC} and w_{TFC}) to change according to the variation of the EMG MPF and RMS signals of the two muscles until they felt muscle fatigue. This second step was conducted for several times for each user in order to properly adapt the two fuzzy-neuro modifiers for variations of the muscle fatigue effects by minimizing the error between the desired and measured angles. In this study, all the training procedures were carried out in real-time and the number of data used in the training was depended on the duration of the training time and the sample frequency. In this study, the sample frequency was set at 2 kHz as mentioned before and for all three fuzzy-neuro modifiers, learning rates were set to 0.0001.

3.6 Evaluation of the proposed methods

3.6.1 Experiments

Experiments were carried out in order to validate the proposed fuzzy-neuro modifiers for compensation of the effects of muscle fatigue on EMG based control. Since, the effectiveness of the fuzzy-neuro modifier which takes the effects of postural changes was verified already in the previous studies [77, 106], the effectiveness of the proposed method against the muscle fatigue was evaluated in this study. Three healthy men (subject A (age-27), subject B (age 25), subject C (age 23)) who did not have records of previous upper-limb muscle disorders participated in the experiments. Complete instructions about the experimental procedure were given to each subject before the study commence.

As first, teaching processes for three fuzzy-neuro modifiers were conducted for each subject as illustrated in the section 3.5.5 in order to adapt the EMG-based controller to each user. The subjects were asked to hold a 2 kg weight in their hands while doing the elbow flexion/extension motions. After the training sessions, the subjects were asked to perform the testing experiments to evaluate the performance of the proposed method. In the testing sessions, the subjects performed the elbow flexion/extension motions until they felt fatigued and unable to continue the motions while holding the 2 kg weight. In the testing, the subjects were instructed to perform the elbow motions with slow and fast phases during separate sessions. A software metronome was used to guide the slow or fast motions. The subjects were instructed to follow the metronome beat (which was set to beat at 1Hz) and performed the elbow motions along with the metronome beats. All subjects were provided with a time to practice in following the metronome sound prior to the testing phase. In the slow motion testing, each elbow flexion/extension cycle was spanned around 5 [s] periods (5 beats) and for the fast motion it was approximately 1 [s] period (1 beat). Sufficient rest times were given to the subjects between the testing sessions.

It is important to clear that the robot was controlled by the elbow joint EMG-based torque estimated under the all three fuzzy-neuro modifiers are in effect (i.e.: EMG-based elbow joint torque estimation using equation 3.18) during these experiments. But in order to evaluate the effectiveness of the proposed methods, it is important to compare the performance of the robot without employing the proposed two fuzzy-neuro modifiers for compensation of the effects of the muscle fatigue (i.e.: estimation of the EMG-based elbow joint torque using equation 3.4). Moreover, it is important to compare the methods with and without muscle fatigue compensation with respect to the similar input conditions. Therefore, EMG RAW signals and human motions data were recorded for each and every session during the testing experiments. Therefore in order to test the EMG-based controller performance without the muscle fatigue compensation, the recorded data were fed into the program in real time and allowed the robot to perform according to the generated EMG-based joint torque using equation 3.4.

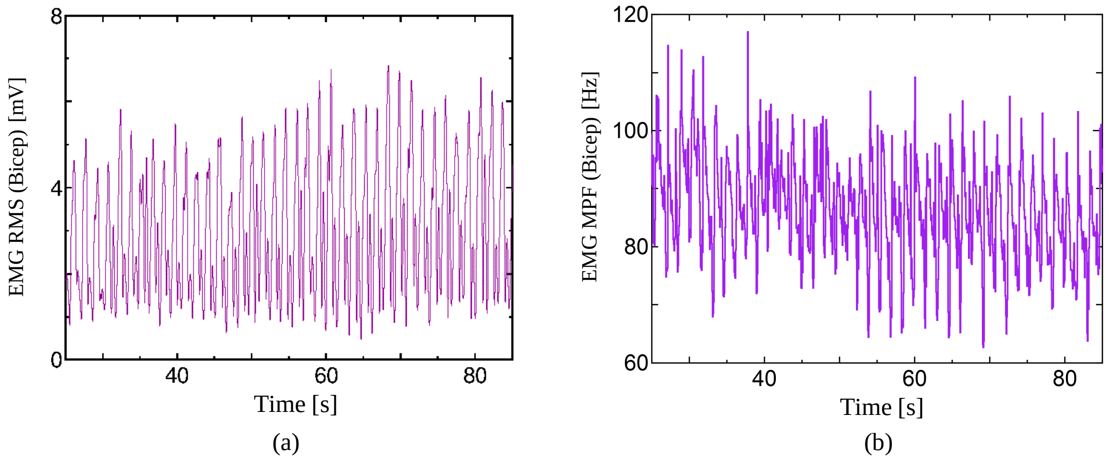


Figure 3.17: (a) EMG RMS [mV] of the biceps (b) Mean Power Frequency (MPF) [Hz] of the biceps variations of Subject A during a sample period of a fast elbow flexion/extension experiment

3.6.2 Results and discussion

In order to evaluate the effectiveness of the proposed method, the experimental results were analyzed. Figure 3.17 depicts variations of (a) EMG RMS and (b) MPF features of the bicep muscles of subject A during a fast elbow flexion/extension motion. It can be observed that the EMG RMS is increasing and the EMG MPF is decreasing towards lower frequencies (The EMG MPF feature variation using 2 [s] moving average window is shown in the plot only for aiding the better visualization)with respect to time or number of contractions. As discussed in previous sections, these results suggest an indication of muscle fatiguing conditions. Similar variations were obtained for the subject B and C as well. However, the EMG features of triceps did not show much variations with respect to the biceps during most of the testing experiments. This may probably due the nature of the experiments where the activity level of the biceps was prominent throughout the experiments. Though with different variations of the EMG RMS and EMG MPF during different levels of the muscle fatigue conditions of the biceps and the triceps muscles across the each subject, the proposed two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue should be able to adapt to those changes through proper learning. Therefore, if the proposed method effectively able to estimate the EMG-based elbow joint torque according to the motion intention of the subject during the muscle fatigue conditions, the measured motion of the robot should follow closely to the subject's desired elbow motion.

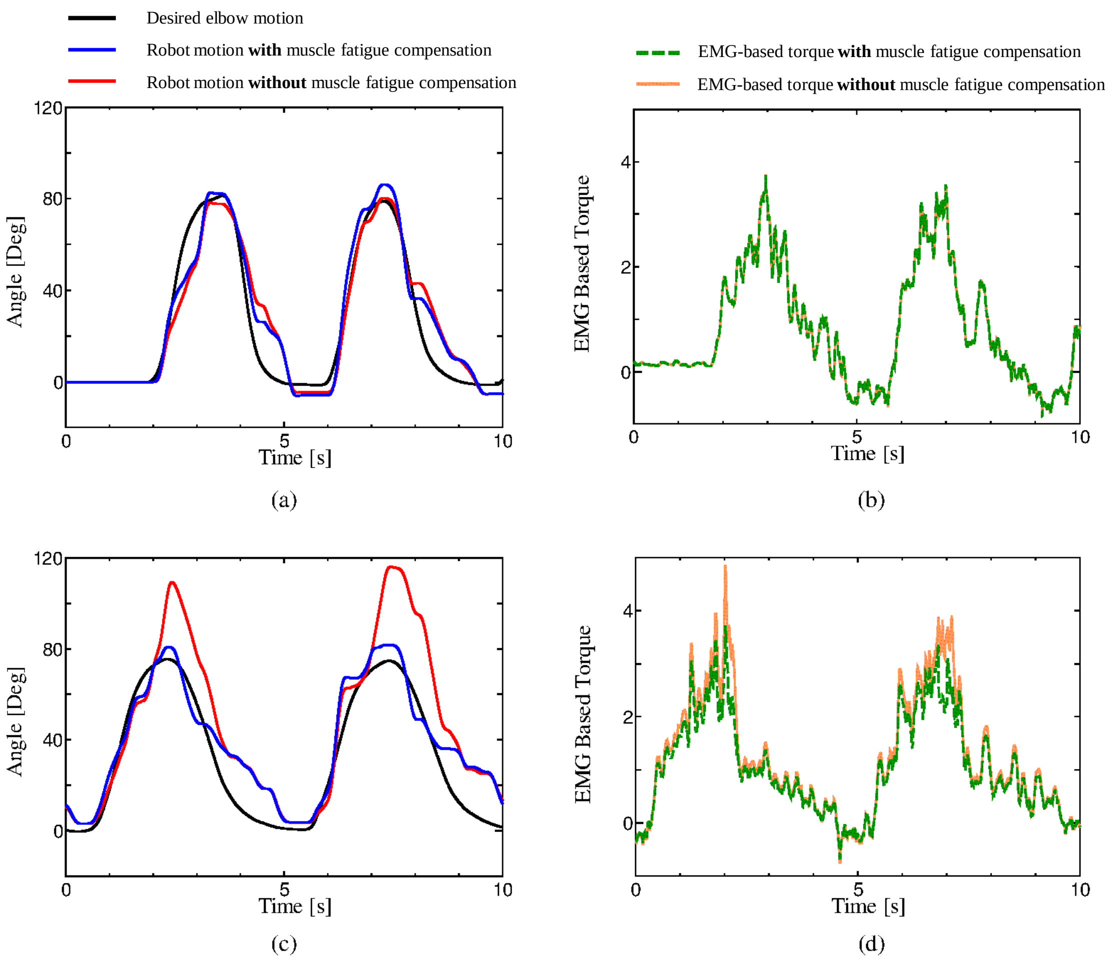


Figure 3.18: (a) Elbow and robot angle variations and (b) EMG based torque variations during two consecutive elbow flexion/extension cycles near to the start of a slow elbow motion experiment, (c) Elbow and robot angle variations and (d) EMG based torque variations during two consecutive elbow flexion/extension cycles near to the end of a slow motion experiment, of Subject A

Experimental results of the subject A during a slow elbow flexion/extension testing session are shown in fig. 3.18. Figure. 3.18 (a) represents the variations of the user's elbow angle and robot's joint angle during two successive elbow flexion/extension cycles near to the start of the experiment with and without the two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue in effect. As the fig. 3.18 (a) represents a starting phase of the experiment, it can be considered as a non-fatigue conditions of the two muscles. From the results of fig. 3.18 (a), one can see that the robot has been able to move closely to the desired elbow motions in both with and without the muscle fatigue compensation method. Nevertheless in order to compare the effectiveness, the average peak angle difference between desired elbow motion and the robot's motion is calculated as follows:

$$\text{Average peak angle difference} = \frac{\sum_{i=1}^{cycle} |peak\ angle_{robot}(i) - peak\ angle_{elbow}(i)|}{cycle} \tag{3.35}$$

where $peak\ angle_{robot}$ and $peak\ angle_{elbow}$ are the peak angle of robot's motion and desired elbow motion during single elbow flexion/extension cycle respectively. $cycle$ is the number of elbow flexion/extension cycles and in this case two successive elbow flexion/extension cycles ($cycle = 2$) such as appear in the fig 3.18 (a) are considered. The calculated average peak angle difference for the results shown in the fig 3.18 (a) are 4 [deg] and 3 [deg] with respect to the approaches with and without the proposed fuzzy-neruo modifiers for fatigue effect compensation respectively.

On the other hand, fig. 3.18 (c) shows two successive elbow flexion/extension cycles during an ending phase of the same experiment session. Such an ending phase of the experiment can be considered as the time period where the subject's muscles in fatigued conditions. As expected, a clear overshoot can be seen in the robot motion without the proposed two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue. The reason for this overshoot of the robot's angle during muscle fatigue conditions is the increment of the EMG RMS which ultimately causes increment to the EMG-based elbow joint torque estimation. However if the proposed method was effective, the robot's motion should be much closer to the desired elbow motion of the subject even during the muscle fatigue conditions. The robot's motion with the proposed fuzzy-neuro modifiers for compensation of the effects of muscle fatigue is shown in blue color curve in the fig 3.18 (c). Clearly one can observe that, the robot's motion with the muscle fatigue compensation is closely following

Table 3.4: Average peak angle differences during two successive elbow flexion/extension cycles near to the end (which reflect the muscle fatiguing conditions) of slow motion experiments for each subject with and without the proposed two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue

Subject	with fatigue compensation	without fatigue compensation
A	5 [deg]	37 [deg]
B	8 [deg]	37 [deg]
C	2 [deg]	15 [deg]

the desired elbow motion than the robot's motion without the muscle fatigue compensation. Therefore, this result shows the effectiveness of the proposed method.

Even though only the results of the subject A being analyzed here, similar results were observed for subject B and C as well. Table 3.4 includes the average peak angle difference (during two successive elbow flexion/extension cycles) for with and without the proposed method for muscle fatigue compensation during ending phases of slow elbow motion experiments for each subject. Results of the table 3.4 further suggest that the proposed method with the two fuzzy-neuro modifiers has been able to compensate the effects of muscle fatigue on EMG-based control so that the average peak angle difference between desired and the robot's motion is reduced.

Furthermore, the estimated EMG-based elbow joint torques related to the conditions in (a) and (c) are shown in fig. 3.18 (b) and (d) respectively. Even though no significant difference can be seen in the case of non-fatigue conditions (as in (b)) between with and without the muscle fatigue compensation, one can observe that during the muscle fatigue conditions (as in (d)) the estimated EMG-based torque based on the proposed method for compensation of the muscle fatigue appears to be lower with respect to the estimated EMG-based torque without the muscle fatigue compensation. Anyhow, in order to get a quantitative idea on the reduction of torque due to proposed method for compensation of the effects of muscle fatigue, percentage reduction of the average torque was calculated as the ratio between difference (with and without the muscle fatigue compensation) of average torques to average torque without the muscle fatigue compensation. The average torque reduction during the two successive elbow flexion/extension motions near to end of the experiments for the subject A, B and C were 9%, 10% and 8% respectively. Therefore, these result also support that the proposed method is effective during muscle fatigue conditions to control the robot.

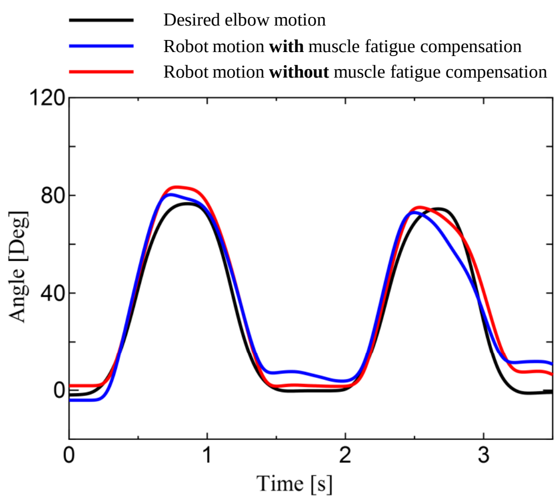


Figure 3.19: Desired elbow motion and respective robot's motion during two consecutive elbow flexion/extension cycles near to the start of a fast elbow motion experiment of the subject B

Figure 3.19 shows the results of two successive elbow flexion/extension cycles near to the start of a fast elbow motion experiments of subject B. In this conditions, it can be considered that subject's muscles in non fatigued conditions. Similar to the results of slow motion experiments, during the starting phase of the experiment, both approaches (i.e: with and without two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue)appear to estimate the desired elbow motions of the subject effectively as shown in fig. 3.19. For the results shown in 3.19, the average peak angle difference between desired elbow motion and the robot's motion with and without the two fuzzy-neuro modifiers for muscle fatigue compensation are 3 [deg] and 4 [deg] respectively.

On the other hand, fig 3.20 depicts the results for two successive elbow flexion/extension cycles during the ending period of relatively fast elbow motion experiments of subject A, B and C. It appears that for all the subjects, the EMG-based controller without the proposed

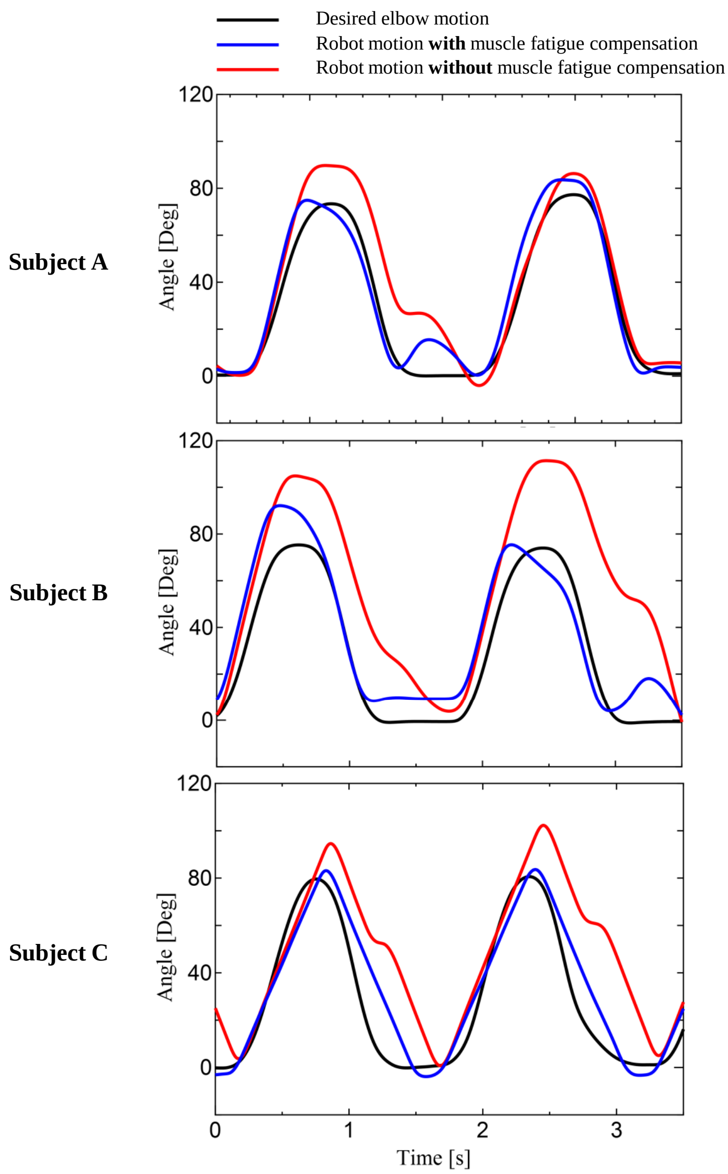


Figure 3.20: Desired elbow motions and respective robot's motions during two consecutive elbow flexion/extension cycles near to the ending phases of the fast elbow motion experiments of subject A, B and C

two fuzzy-neuro modifiers for muscle fatigue compensation have not able to effectively estimate the desired motion of the subjects. This can be recognized by the overshoots appear in the red colored curves of 3.20. Beside, it can be observed that the blue colored curves

Table 3.5: Average peak angle differences during two successive elbow flexion/extension cycles near to the end of the fast elbow motion experiments (which reflect the muscle fatiguing conditions) for each subject with and without the proposed two fuzzy-neuro modifiers for compensation of the effects of muscle fatigue

Subject	with fatigue compensation	without fatigue compensation
A	4 [deg]	12 [deg]
B	10 [deg]	34 [deg]
C	6 [deg]	19 [deg]

appear to be closer to the desired elbow motions curves. The blue colored curves represent the robot's motion with muscle fatigue compensation. Therefore, these results suggest that the EMG-based controller with the proposed muscle fatigue compensation method has been able to effectively estimate the subject's elbow motion so that the difference between the desired elbow motion and the robot's motion has been reduced.

Table 3.5 reports the average peak angle difference between the desired elbow motion and the robot's motion, with and without the fatigue compensation with relevant to the results shown in fig 3.20. Furthermore, as similar to the slow motion experiments, the percentage reduction of the average torque during the two successive elbow flexion/extension motions near to the ending phase of fast motion experiments were calculated and those values were 9%, 18% and 12% for subject A, B and C respectively. Therefore, these results also suggest the effectiveness of the proposed methods. Nevertheless, it was observed that sometimes the effectiveness of the proposed method during the fast elbow motion with respect to the slow elbow motion has been slightly deteriorated. One of the possible reasons for causing this may be the variations of the accuracy of the MPF feature estimation using the FFT algorithm during the fast elbow motions.

When a particular subject is not in the biceps or triceps muscles fatigue conditions, variations of the EMG RMS and the EMG MPF should be normal. However as the subject proceed with the muscle fatigue conditions, the EMG RMS and the EMG MPF features are changed and this variations are influenced on EMG-based control. But, the proposed fuzzy-neuro modifiers for compensation of the effects of muscle fatigue are adapted to

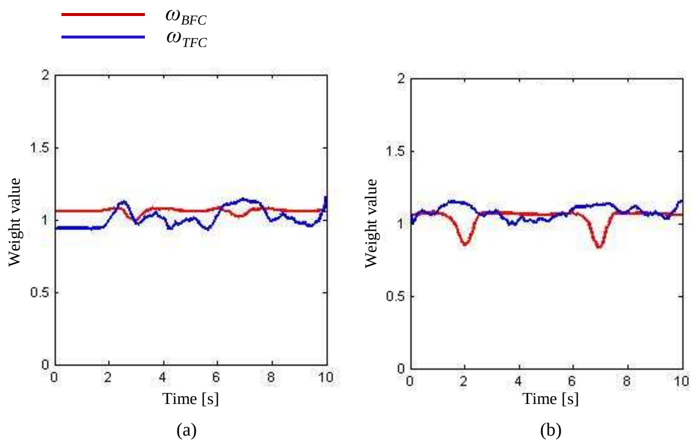


Figure 3.21: Example variations of w_{BFC} and w_{TFC} weights during (a) 10 [s] near to the start of the slow elbow motion experiment (b) 10 [s] near to the end of the slow elbow motion experiment , of the Subject A

these changes in real-time. As a result, the outputs of these fuzzy-neuro modifiers; the two coefficients w_{BFC} and w_{TFC} are modified according to the muscle fatigued conditions. For an example fig. 3.21 (a) and (b) show the filtered variations of w_{BFC} and w_{TFC} coefficients during two successive elbow flexion/extension cycles in the start (results related to fig 3.18 (a) and (b)) and ending (results related to fig 3.18 (c) and (d)) phase of the slow elbow motion experiment of the Subject A, respectively. It can be observed that, the w_{BFC} coefficient has been decreased during the muscle fatigue situation (as in fig. 3.21 (b)) with respect to the non fatigue situation (as in fig. 3.21 (a)). On the other hand, the w_{TFC} coefficient has not showed a considerable difference in between these two conditions which may due the nature of the experiment where the activity level of the biceps muscle was prominent over the triceps muscle. Nevertheless, these results also backup the effectiveness of the proposed method during muscle fatigue.

Therefore from the overall analysis, it turns out that the proposed method based on the multiple fuzzy-neuro modifiers with the EMG RMS and the EMG MPF features as inputs could be beneficial for compensation the effects of muscle fatigue on EMG-based control.

3.7 Summery

This chapter presented a study which mainly focused on one of the issues in EMG-based control methods: muscle fatigue. At first, this chapter illustrated about a study which was carried out to find out the effects of muscle fatigue on EMG based control in upper-limb power-assist. The results of that study suggested that the importance of using EMG frequency domain features in addition to time domain features as the inputs for EMG-based control methods during muscle fatigue conditions. Then, a novel fuzzy-neuro modifiers based method for compensation of the effects of muscle fatigue on EMG-based control of human upper-limb power-assist was proposed. Effectiveness of the proposed method for compensation of the effects of muscle fatigue on EMG-based control was experimentally evaluated with providing a detailed discussion. The results of that evaluation suggested that the proposed method can be applied to compensate the effects of muscle fatigue on EMG-based control. With increasing number of EMG-based control approaches for assistive robots such as upper-limb exoskeletons, the proposed method can be beneficial in order to deal with the problem of muscle fatigue on EMG-based control.

Chapter 4

Investigating the Feasibility of EEG Signals for Evaluation of Perception-Assist Control in Upper-Limb Exoskeletons

This chapter presents a research that aims to investigate the feasibility of EEG signals for evaluation of the perception-assist control in upper-limb exoskeletons. The perception-assist control has been introduced to upper-limb exoskeletons in addition to power-assist control in order to safely interact with surrounding environment for the users with deteriorated perception abilities. In the perception-assist control, the exoskeletons generate additional motion modification to the user's motions based on information of environment monitoring sensors to ensure the safety of the user. As it is difficult for the exoskeleton to plan all proper perception-assist for each and every task, tool, and environment, basically exoskeletons are required to learn the proper perception-assist by its own. In this learning process, it is necessary to judge the correctness or incorrectness of the perception-assist performed by the exoskeleton. At the beginning, this chapter investigates the use of EMG signals to judge performed perception-assist. Results of that analysis show that EMG signals are sometimes not adequately changed for the judgments and that could lead to eventually jeopardize the learning of process of perception-assist. Therefore in addition to EMG signals, this chapter investigates the possibility of utilizing EEG signals measured from brain of the user to judge the performed perception-assist in upper-limb exoskeletons. Moreover, this chapter highlights the potential abilities and benefits of using EEG signal alone instead of EMG signals for the evaluation of perception-assist to be used in learning process of perception-assist in upper-limb exoskeletons.

4.1 Perception-assist control for upper-limb exoskeletons

Even though with a lot of promising results, most of the existing power-assist exoskeleton robots assume the proper environment perception abilities of the users. However in the case of physically weak persons, the perception ability is also deteriorated sometimes. For an example, with advancing the age; vision, environment perception ability and reaction time may decline as well for the physically weak people. In such situations, a user might do some unintended actions unconsciously and the exoskeleton robot might assist the user to be involved in an unexpected accident. Therefore, it is important to assist the sensing ability of such persons with the help of additional sensors of the robotic exoskeleton to avoid those situations. In this context, the concept of perception-assist has been introduced in some of the exoskeleton designs in addition to the power-assist capabilities [111–113] to prevent such unexpected accidents.

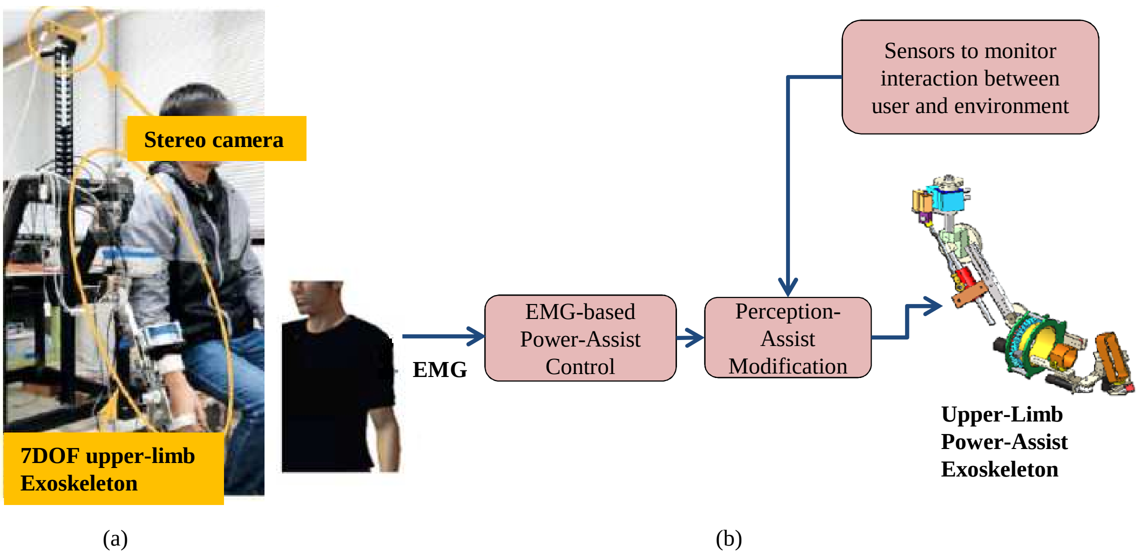


Figure 4.1: (a) 7-DOF upper-limb power-assist exoskeleton with the capability of perception-assist control [113] (b) Basic structure of the perception-assist control with EMG-based power-assist control

In the perception assist control, the exoskeleton robot modifies the user's motion automatically by generating perception-assist torque in addition to the power-assist torque if the exoskeleton robot locates any troubles in the user's motion. General idea of this concept can be graphically represented as in fig 4.1(b). In order to recognize such issues in the user's motion, the exoskeleton robots are equipped with different environment monitoring sensors such as cameras, ultrasonic sensors and laser range finders. As an example, fig 4.1 (a) shows the setup uses for the perception-assist control of the Saga University 7DOF upper-limb exoskeleton. In this setup, a stereo camera is used to monitor the interaction between user and environment. With this proposed perception-assist control method, the upper-limb exoskeleton can assist not only the motion of the user but also the perception of the user intelligently, when he/she is going to interact with the environment. Based on the environmental information acquired from the sensors of the exoskeleton robot, the motion of the exoskeleton user is modified if there are any disturbances in the motion trajectory of the user's hand when the user tries to interact with the environment.

For an example, imagine a situation where a exoskeleton user tries to move his/her hand towards an object, grab it and return it to an initial position. If the user is performing this task with a correct hand trajectory, the perception-assist control system recognizes it with the information gained from the environment sensors and allows the correct motion. In other words, no perception-assist is introduced if the system identify the hand trajectory of the user as a correct one. However, if the user is going to grab the object with a wrong hand trajectory, then the exoskeleton automatically corrects the trajectory of the user's hand motion to grab the object by assisting the perception of the user. This is realized by introducing a perception-assist torque in addition to the power-assist torque in the upper-limb exoskeleton control method.

There could be various situations where perception-assist might be required based on a task performed by the user, a tool he/she is using or specific environment. However practically, it is difficult to prepare perception-assist for each and every situation. Therefore, the perception-assist is carried out in pre-estimated situations and basically the exoskeleton robot is required to learn the perception-assist in non-estimated condition [113]. In this learning process, evaluation of the performed perception-assist modification is necessary. Because, the ability of recognizing errors made by the exoskeleton during perception-assist is crucial for improving the performance of the perception-assist control method.

4.2 Evaluation of the perception-assist: Towards identifying EMG and EEG as potentials signals

One of the possibilities of evaluating a performed perception-assist control task by the exoskeleton is the analysis of EMG signals. If the perception-assist control of the exoskeleton is correct, respective EMG signals should become smaller as the user recognizes the risk of his own motion and follows the motion modification. Conversely the EMG signals should become larger, if the performed perception-assist control of the exoskeleton robot is incorrect as the user tries to act according to his/her own motion intention and resists the erroneous motion modification. However, the respective EMG signals should be become larger enough during the incorrect perception-assist in order to identify the difference between correct and incorrect instances. If the EMG signals do not change adequately for a judgment during an incorrect perception-assist, the learning process might not be successful.

On the other hand, if the exoskeleton make a mistake in the perception-assist control and tries to assist the user in a wrong way, he/she should be able to feel something goes wrong and he/she can recognize it as well. This recognition is a part of the brain process of the particular exoskeleton user. Brain signals related to feeling of error has been explored in recent studies and suggested the existence of error-related potentials in the EEG recorded just after the occurrence of an error event [114]. Moreover, several studies [115, 116] have reported that similar erroneous related brain signals/potentials are usually originated in the brain region of anterior cingulate cortex (ACC). Also several recent studies [117–119] have reported the conducted studies on utilizing the EEG error related potentials in brain machine interfaces and similar applications. Therefore in light of these background, the EEG signals make another potential candidate for identifying the correctness or incorrectness of the perception-assist.

In this context, the objective of the research work presents in this chapter is to study about the variations of EMG signals during perception-assist control and investigate the

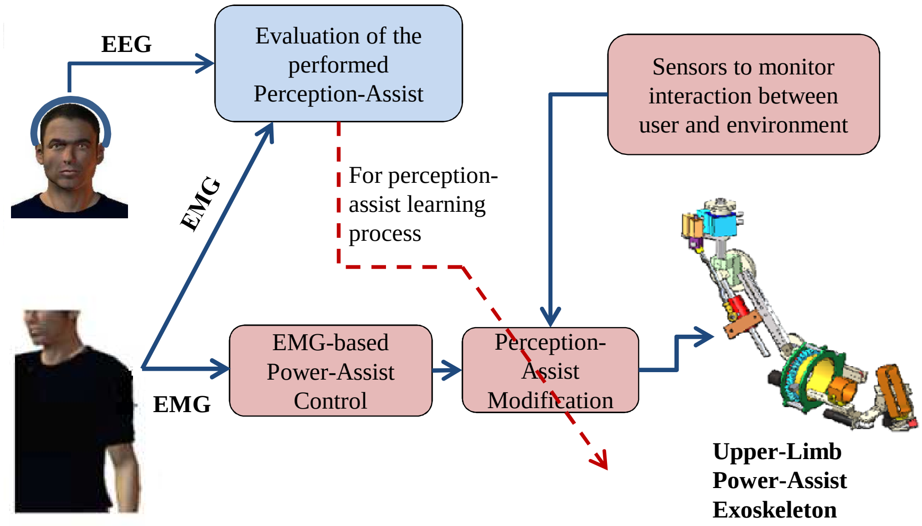


Figure 4.2: A graphical interpretation of the concept highlights in this research

feasibility of EEG signals to judge the correctness or incorrectness of the perception-assist to be used in learning process of perception-assist control in upper-limb exoskeletons. A graphical interpretation of the concept which is highlighted in this research is shown in fig. 4.2.

4.3 Experimental setup

Overall experimental setup use in this research is shown in fig 4.3. This setup mainly consists of a wrist assist exoskeleton, an EMG acquisition system, an EEG acquisition system and a personal computer. Specific details of each part are illustrated in following subsections.

4.3.1 Wrist assist exoskeleton

In this research, a wrist assist exoskeleton is used for the experiments. During the experiments, EEG signals generate from the user's brain are monitored. However, it is a known that the EEG signals can sometimes suffer with body movements artifacts. Especially, in the case of upper-limb exoskeletons, EEG signals can be in affected by the motions of the shoulder or elbow as they are closer to the head (i.e. the EEG sensor net). In this context, the use of a wrist assist exoskeleton in this research is more reasonable as it may provide the

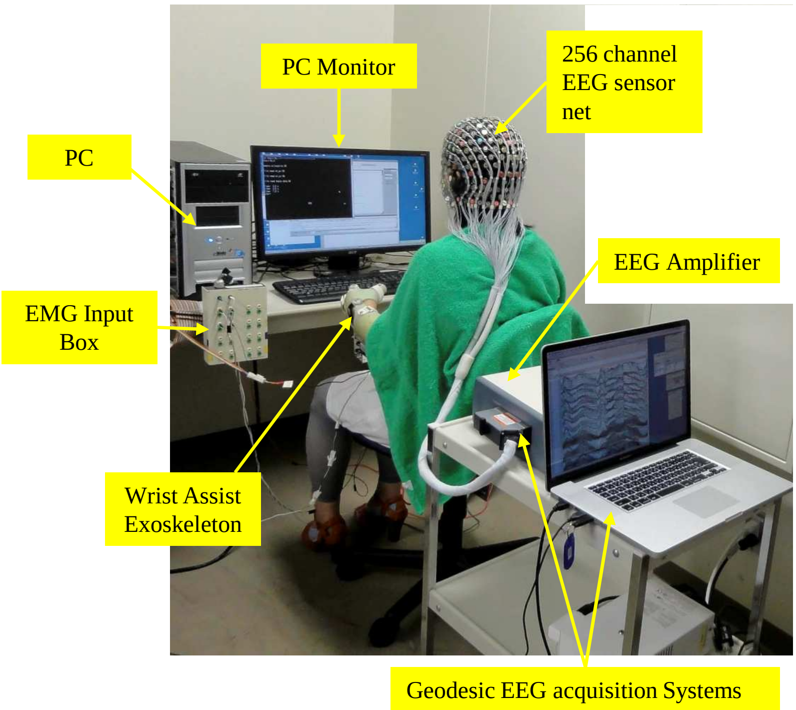


Figure 4.3: Overall experiment setup

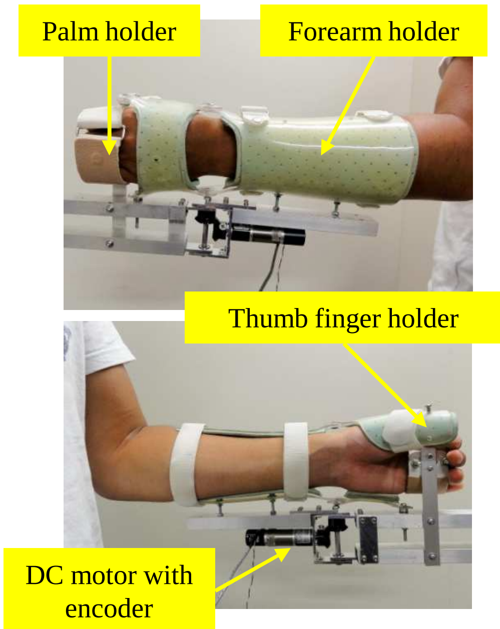


Figure 4.4: Wrist assist exoskeleton

EEG signals with less motion artifacts during the experimental period. Fig. 4.4 shows the wrist assist exoskeleton robot that used in this study. It can assist the wrist flexion/extension motions of the user. The wrist assist exoskeleton is attached to the user with the help of a forearm sleeve, a palm holder and a thumb finger holder.

4.3.2 EMG-based power-assist

EMG signals directly reflect the muscle activations and so the motion intention of the user. Therefore skin surface EMG signals were used to control the power-assist wrist exoskeleton. The EMG signals of flexor carpi radialis and extensor carpi ulnaris muscles were identified as the responsible muscles for wrist flexion/extension motions and so, they were used as the input signals to EMG-based power-assist controller of the wrist exoskeleton robot. The EMG signals were measured using the same arrangement that was explained in section 3.3. In this study, the EMG signal acquisition rate was set to 2 kHz. Moreover, the power-assist control method use for controlling this wrist assist exoskeleton was similar to the method described in chapter 2, section 2.3.5.

4.3.3 EEG signal acquisition

This section introduces the system that used for acquisition of EEG signals in this research. The EEG signals were measured using Geodesic EEG acquisition System (Electrical Geodesics Inc.). Hardware system of this EEG acquisition system mainly consists of a sensor array and an amplifier. An application software called Net Station [109] provided with the system is used for controlling various parameter during the EEG signal acquisition, real time signal visualization and recording of the EEG signals. Moreover, facilities to use custom made programs instead of relying of Net Station application for EEG signal acquisition are also supported by the system. Fig. 4.5 shows the overall hardware system.

Several steps must be followed for preparation of the EEG system before using it. The EEG array consists of 256 non-dry type electrodes. Prior to the experiments, all electrodes are prepared by soaking the EEG sensor array in a mixer of granular or powdered potassium chloride (KCl), a drop of baby shampoo and water. Normally, the soaking is needed for at least 5 minutes to ensure adequate wetting of the sponges of the EEG electrodes. An

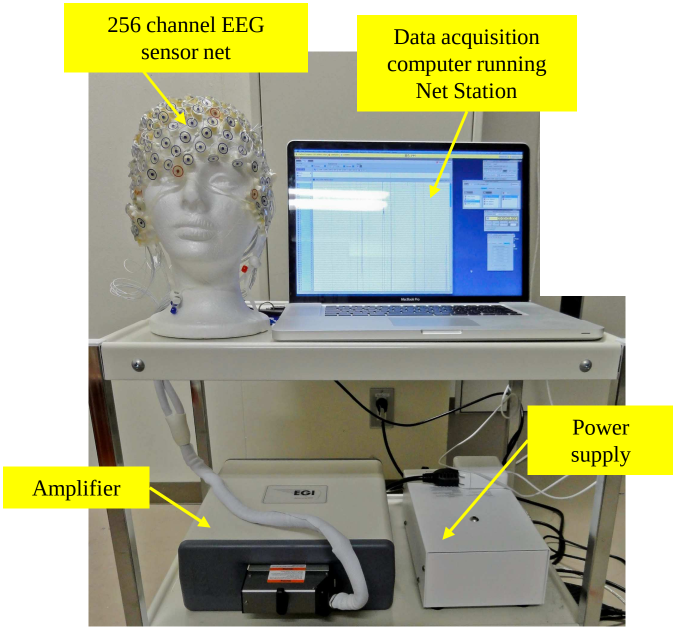


Figure 4.5: Hardware setup of the Geodesic EEG acquisition system (Electrical Geodesics Inc.)

example set up of this process is shown in fig. 4.6.

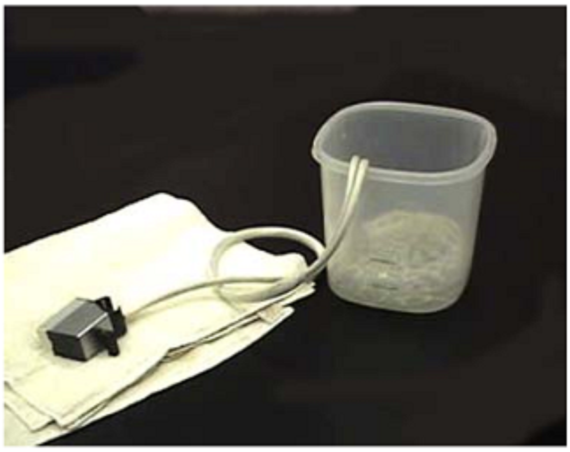


Figure 4.6: Soaking arrangement of the sensor array in the electrolyte bucket

Before applying the Geodesic Sensor Net over a subject's head, several head measurements are needed to ensure the correct use of the sensor net. Therefore, the first step is to calculate the proper net size. This can be done by measuring the largest part of the head

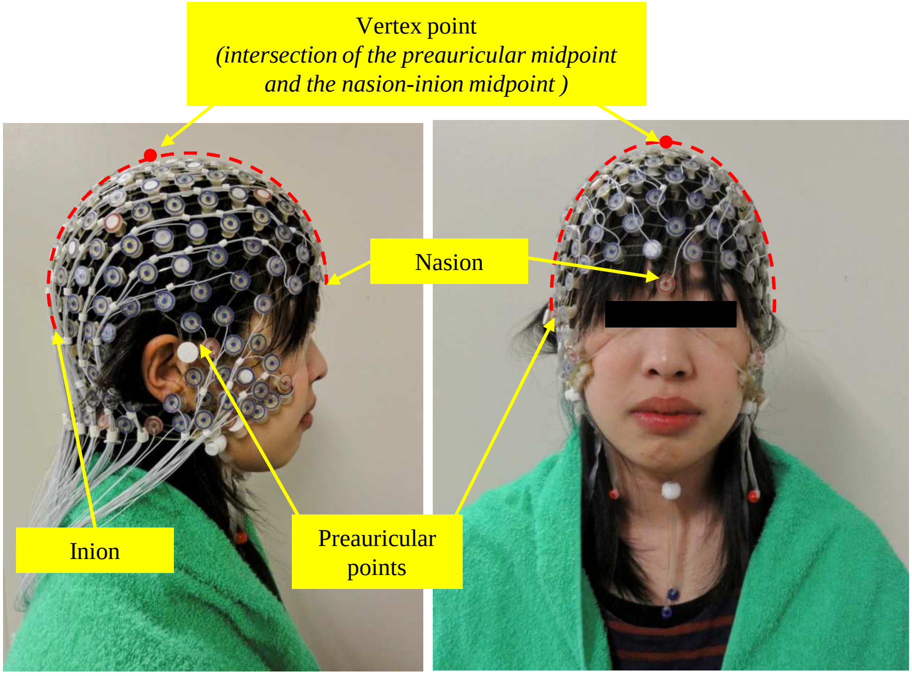


Figure 4.7: A subject who wearing the EEG sensor net during this study. (Land marks use for measuring circumference of the head and determine the vertex point are marked in the figure) [110]

circumference with a measuring tape and select the appropriate net size using the given manual. Then, in order to correctly place the sensor net over the subject's head, a vertex point is determined. The vertex; on the top of the head, is the midpoint between the nasion (the indented area where the bridge of the nose meets the skull) and inion, centered between the preauricular points (the indented area in front of each ear flap, where the jaw meets the skull). Figure. 4.7 shows these land marks positions. In the experiments, it is important to place the sensor net as precisely as possible in order to compliance with the standards. More details about this process can be found in Geodesic sensor net technical manual [110].

The vertex point of this EEG system as mentioned above is also represented by the Cz electrode position in the international 10-20 EEG electrode referencing system. More information about the 10-20 system are presented in the chapter 2, section 2.4.3. In the Geodesic sensor net, the electrode positions related to 10-20 system have been marked already by the manufacturer and fig. 4.8 shows the respective electrode positions map.

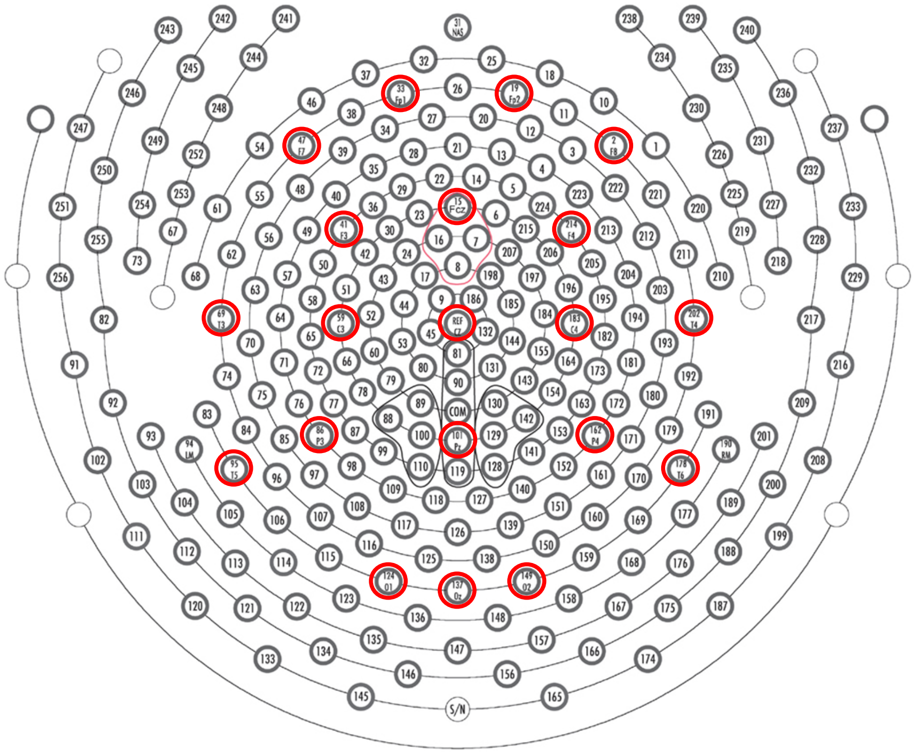


Figure 4.8: Location map of 256 EEG electrodes (10-20 electrodes are circled in red color)

4.4 Experiment protocol for introducing virtual perception-assist control

In the experiments, subjects sat on a chair in front of a PC monitor as shown in fig 4.3. Then the subjects were asked to wear the wrist assist exoskeleton and do the wrist motions according to the commands visible on the PC monitor. Each command visible on the monitor were displayed based on a timing diagram. Timing diagram of a single trial is shown in fig. 4.9.

Each trial began with a ready symbol. At the start of 3 [s], left or right command was displayed on the monitor and subjects were asked to operate the wrist exoskeleton with power-assist according to the showing direction. Then at 3.5 [s], the exoskeleton robot

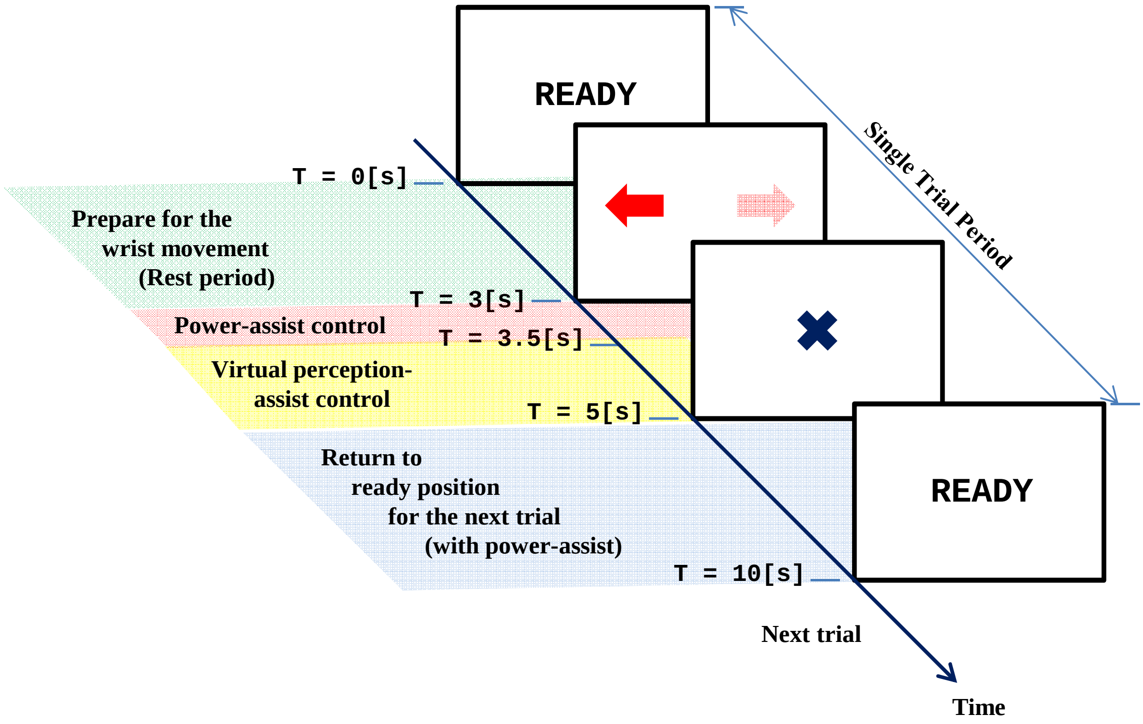


Figure 4.9: Timing diagram of a single trial

randomly introduced an additional wrist joint torque for a 1.5 [s] period either in the same or opposite directions to the subject's intended motion (It should be noted that, during this action no symbols on the PC monitor were indicated). Basically, this added torque could be considered as a virtual perception-assist torque during the power-assist control of the exoskeleton robot. If the introduced virtual perception-assist torque was generated in the subject's indented direction, the subject simply followed the modified motion by judging it as a correct perception assist. On the other hand, if the added torque was acting against the subject's motion intention, it was judged as a wrong perception-assist where subject tried to resist the modified motion of the exoskeleton robot. Nevertheless in the next 5 [s], subjects were instructed to return their hand to the original position and prepare for the next trial. Therefore, a single trial was spanned with 10 [s] and an experiment session was consisted of such 10 single trials. Those ten trails were distributed with error/correct perception-assist trial ratio of either 5/5, 6/4 or 4/6. However as mentioned previously, the order of the correct or wrong perception-assist was randomly maintained.

4.5 Experiments

In the experiments, three healthy young subjects participated. Details of the subjects are reported in table 4.1. Complete information and instructions about the experimental procedure were given to all the subjects prior to the experiments. The subjects were instructed to follow the aforementioned experiment protocol during this study. For each subject, 10 sessions were carried out. Therefore, total number of perception-assist trials per subject were 100 (50 trials related to error perception-assist and 50 trials related to correct perception-assist). A sufficient rest time was given to all subjects in between each session in order to prevent any fatigue conditions during the experiments.

Table 4.1: Details of the subjects participated for recording of the data

Subject	Gender	Age [Years]
Ta	Female	24
Th	Male	28
Ha	Male	30

4.6 Results of the analysis of EMG signals during perception-assist

In order to identify the variations of the EMG signals during perception-assist, an analysis of EMG signals was conducted. Top plot of the fig. 4.10 show the results of EMG RMS of the two muscles; flexor carpi radialis and extensor carpi ulnaris along with the wrist joint torque during a correct perception-assist trial of the subject **Ta**. In this trial, the subject was instructed at 3.0 [s] the command appeared in the monitor to move the wrist to the right side (i.e: to perform flexion motion of the left wrist). As the subject moved her wrist to the right side, at 3.5 [s] the virtual perception-assist torque was added to the wrist joint torque so that the resulted direction of the motion modification of the exoskeleton was also to the right side. As this modification was agreed with the initial motion intention, this trial can be considered as a correct perception-assist trial. The shaded areas in blue color in the plots represent the time periods where the perception assist torques were added. As it can

Correct
perception-assist
trial

Error
perception-assist
trial
(High EMG variations)

Error
perception-assist
trial
(Low EMG variations)

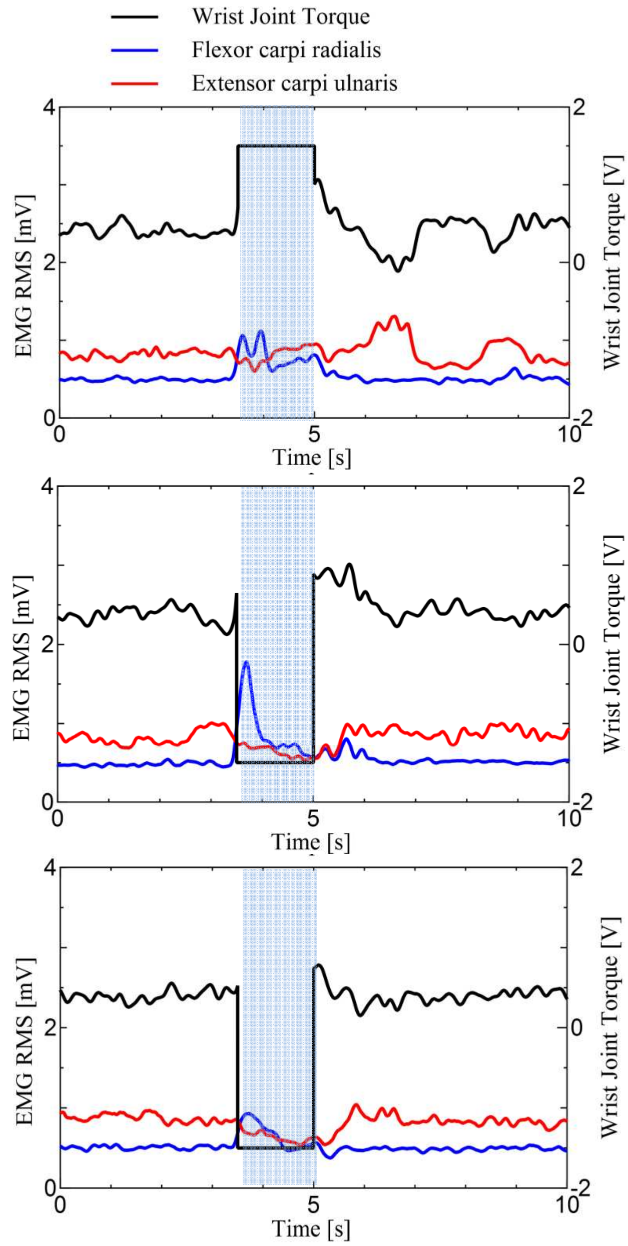


Figure 4.10: Variations of EMG and torque signals during perception-assist trials of subject **Ta**. *Top*: a correct perception-assist trial, *Center*: an error perception-assist trial showing high EMG variations. *Bottom*: an error perception-assist trial showing low EMG variations. (Shaded area in blue color represents the time period where the perception assist torque was introduced)

be seen from the figure, the EMG signals became smaller during the perception-assist (over the shaded area) because, the subject recognized the correct perception-assist added by the

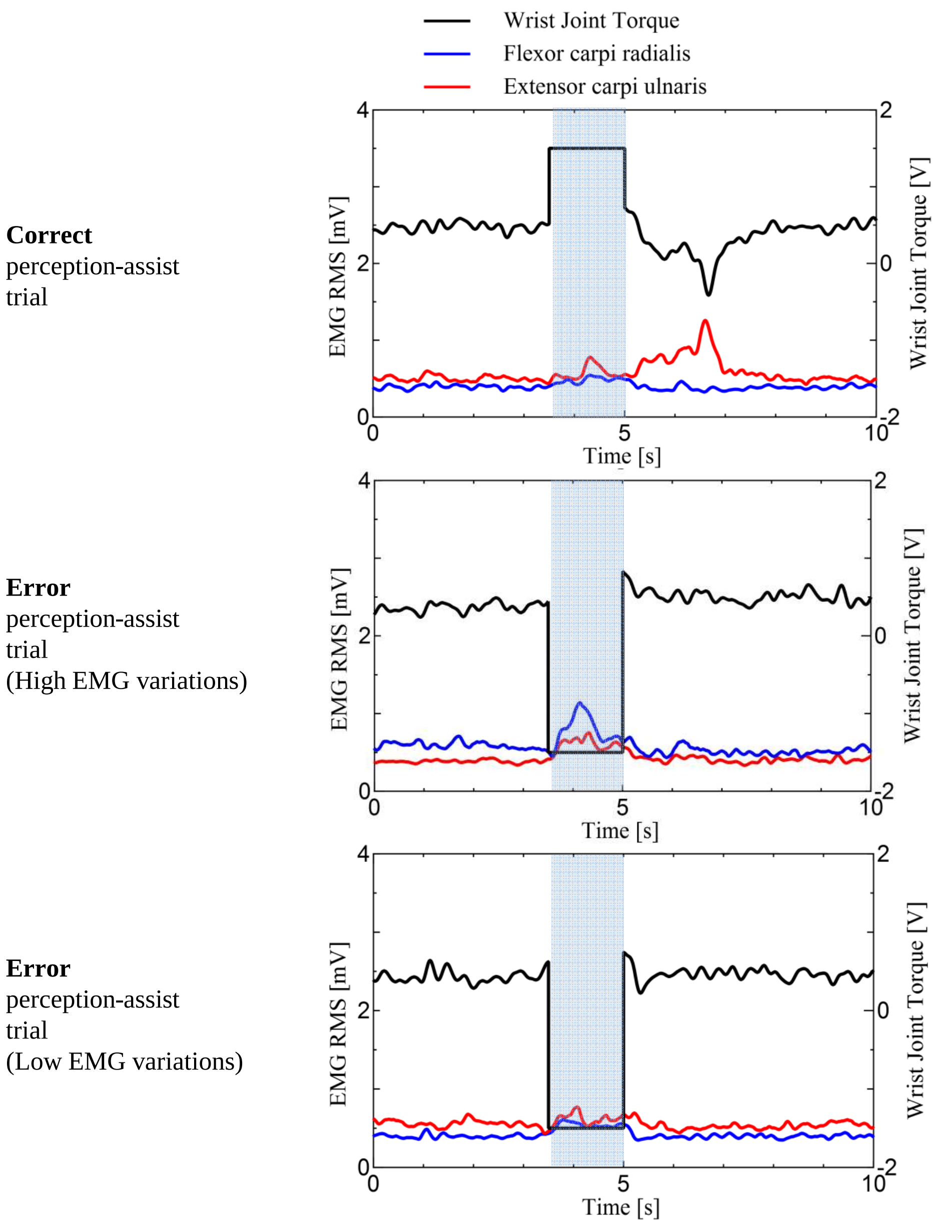


Figure 4.11: Variations of EMG and torque signals during perception-assist trials of subject **Th**. *Top*: a correct perception-assist trial, *Center*: an error perception-assist trial showing high EMG variations. *Bottom*: an error perception-assist trial showing low EMG variations. (Shaded area in blue color represents the time period where the perception assist torque was introduced)

exoskeleton and followed the motion modification. Moreover, observed EMG variations for subjects **Th** and **Ha** during correct perception-assist trials are shown in the top plots of

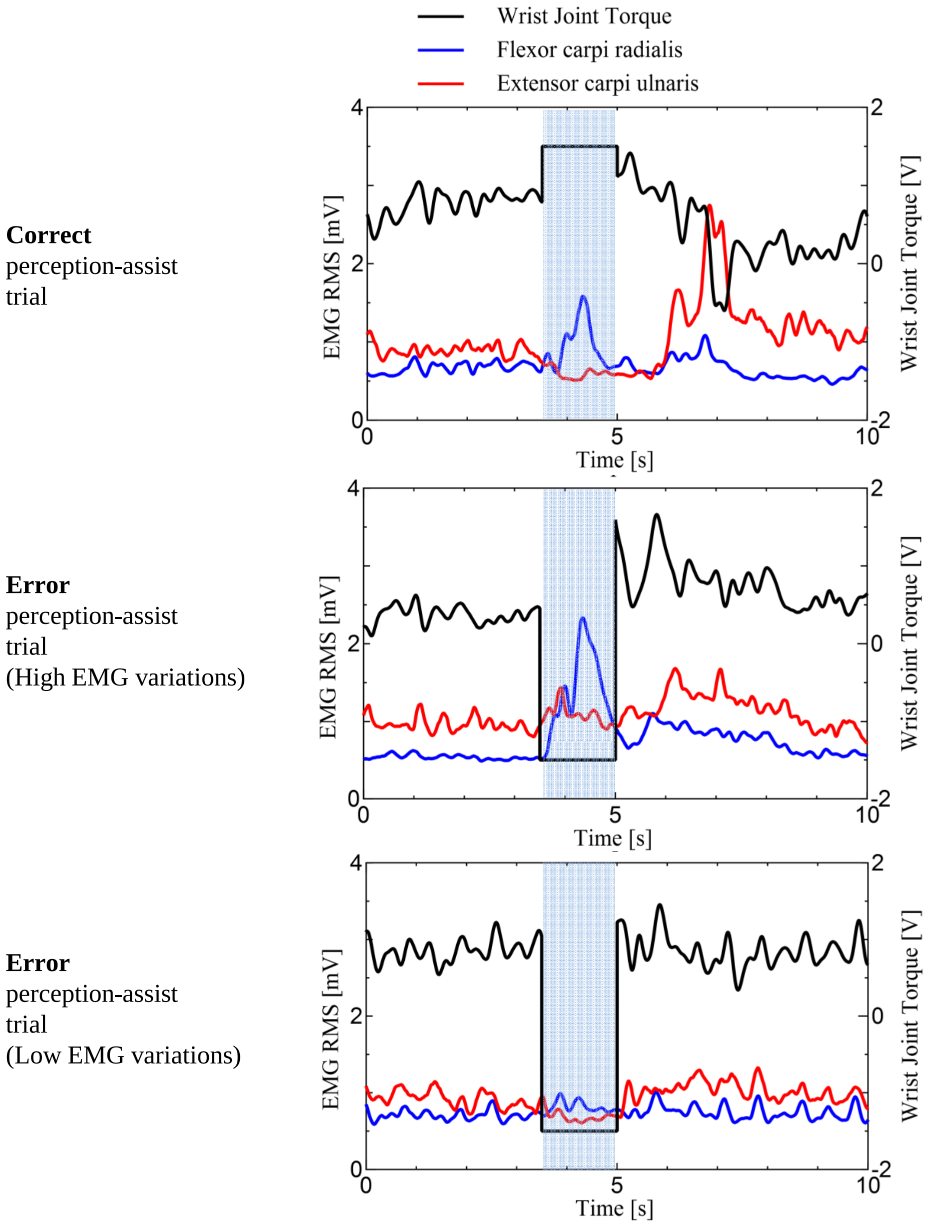


Figure 4.12: Variations of EMG and torque signals during perception-assist trials of subject **Ha**. *Top*: a correct perception-assist trial, *Center*: an error perception-assist trial showing high EMG variations. *Bottom*: an error perception-assist trial showing low EMG variations. (Shaded area in blue color represents the time period where the perception assist torque was introduced)

fig. 4.11 and fig. 4.12 respectively.

On the other hand, the EMG signals should become larger if the performed perception-assist by the exoskeleton robot is incorrect, as the user tries to act according to her own motion intention and resist the erroneous motion modification. Center plot of the fig. 4.10 depicts the EMG signals and the torque signals variations during a wrong perception-assist trial of subject **Ta**. In this trial, the subject was instructed at 3.0 [s] by the command appeared in the monitor to move the wrist to the right side. However, at 3.5 [s] the virtual perception-assist torque was added to the wrist joint torque so that the resulted direction of the motion modifications of the exoskeleton was to the left side (i.e: extension motion of the left wrist). As this modification was against the motion intention, this can be considered as a wrong perception-assist trial. As it appears in the figure, the EMG signals have been increased with compare to the correct perception-assist trial (i.e top plot of the fig. 4.10) in the shaded area where the virtual perception-assist torque was introduced. The reason for the increment of the EMG signals in this case was the subject tried to resist the erroneous modified motions of the exoskeleton. Furthermore, center plots of fig. 4.11 and fig. 4.12 show the similar increment of EMG signals during error perception-assist trials with compare to respective correct perception-assist trials of subject **Th** and **Ha** respectively. If similar EMG signals increments can be obtained for each and every time for any subject, EMG signals could have been used easily for judging the performed perception-assist.

Bottom plot of fig. 4.10 shows the EMG signals and the torque signals variations during a wrong perception-assist trial of subject **Ta**. The experimental scenario was same with the previously described error perception-assist trial. However, in this case it can be observed that the EMG signals have not increased even with the resistive intension of the subject. Bottom plots of fig. 4.11 and fig. 4.12 also depict such low levels of EMG signal variations during error perception-assist trials with compare to respective center plots. When such low EMG signals occur during error perception-assist trails as shown in those bottom plots, it is difficult to distinguish such error perception-assist trials from the correct perception-assist trials.

Therefore, these results yield that sometimes EMG signals do not change enough even if the subject tries to resist the erroneous perception-assist motion which may eventually lead the evaluation of the performed perception-assist based on EMG signals is difficult. Moreover, some muscles of the upper-limb are difficult to be monitored as they are placed more deep inside the limb. In those instances, monitoring proper EMG signals might be difficult. Also in some cases, for a particular user such as paralyzed person, some of the muscles may not available for measuring the EMG signals. Therefore in light of these facts, it is encouraged to utilize other input signals such as EEG as discussed previously for the evaluation of the perception-assist control of upper-limb exoskeletons.

4.7 Support Vector Machines (SVM)

As from the results appeared in the previous subsection, it is reasonable to think that a simple threshold based method on EMG signals might not provide a better recognition between the correct or incorrect perception-assist trials performed by the exoskeleton. The differences between users and the differences between EMG output ranges of muscles make it difficult to use such simple EMG signal threshold level based method for judging the perception-assist. On the other hand, this problem can be taken as a two class (i.e: correct vs error perception-assist) classification problem. There are different methods reported for realizing of such two class classification problems [108]. However among those methods, Support Vector Machine (SVM) is identified as one of the established methods especially for two class classifications.

The SVM is a classification technique originally introduced by Vapnik [121]. The SVM has known to perform well in a number of real world problems which including EEG signals classification studies as well [122]. In the case of two class classification problem, a set of labeled patterns can be represented as $\{(x_1, y_1), (x_2, y_2), ..., (x_p, y_p)\}$ where patterns $x_p \in \Re^d$ and labels $y_p \in \{-1, 1\}$ which referring to two different classes. The SVM algorithm basically tries to separate the data of the two classes by finding a hyperplane yielding the largest possible margin. Here, the margin is the distance between nearest data points of different classes, as presented in fig. 4.13. Such a SVM classification using linear decision boundaries is known as a linear SVM. A parameter called regularization parameter (C) is used in the linear SVM and value of the C is responsible for dealing with outliers and

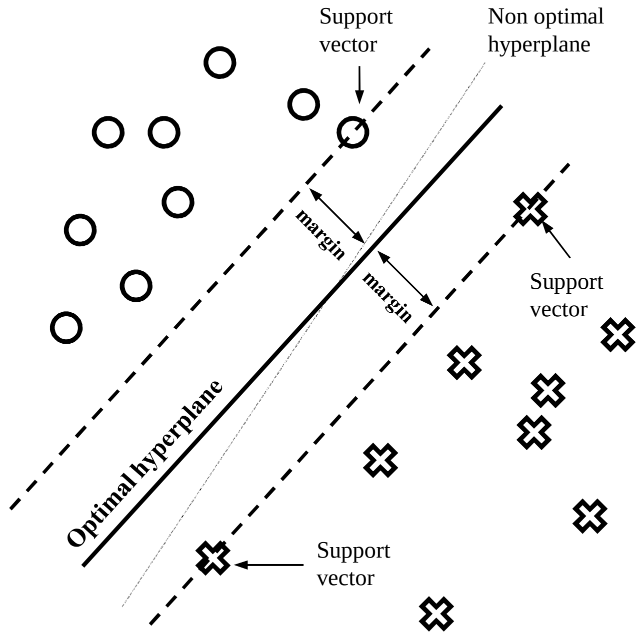


Figure 4.13: A graphical illustration of linear SVM

allowing errors on the training set. Therefore, finding a suitable value for C is an essential part of the model selection process. If no prior knowledge is available for choosing C, it has to be estimated based on training data using techniques such as cross validation.

On the other hand, it is possible to build nonlinear decision boundaries without highly enhancing the classifier's complexity, using a technique called kernel trick. The kernel trick deals with implicitly mapping of the data to another space (usually of much higher dimensionality) using a kernel function. Some of the common kernel functions are Gaussian radial basis function, polynomial function, etc.

Due to several advantages, the SVM has became one of the popular methods among two class classification algorithms. The SVM is known to have good generalization properties [123, 124] and known to be insensitive to over-training [124] as well. Moreover, it known be resistant to curse of dimensionality [123]. On the other hand, the SVM has only few hyper parameters that need to be defined such as the regularization parameter C in the linear SVMs. Therefore in this research work, it was decided to use the SVM for classification between correct and incorrect perception-assist trials.

4.8 Evaluation of the perception-assist using EMG and EEG signals

As highlighted in the section 4.2, EEG might be a potential signal that can be used to harness the information about the correctness or incorrectness of the performed perception-assist. Therefore, this section aims to investigate the feasibility of EEG signals for evaluation of the perception-assist in addition to the EMG signals. This section details the attempted approaches for evaluation of perception-assist control using EMG and EEG signals during this research work.

4.8.1 Evaluation of the perception-assist with multiple SVM based method

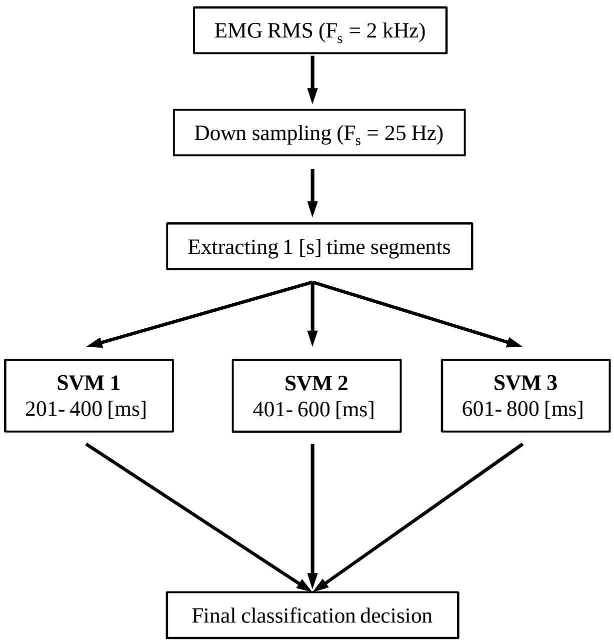


Figure 4.14: Flow chart of the method that used EMG alone. Here F_s is the sample rate.

In this approach, a multiple SVM based method for evaluation of the correctness or incorrectness of the perception-assist using EMG and EEG signals was proposed. In order to compare the effectiveness of this approach that used both the EMG and EEG signals for perception-assist judgment, it was compared with a method that used only the EMG signals.

The method that utilized only the EMG signals is illustrated with a flow chart as shown in fig. 4.14. First the EMG RMS signals were down sampled from 2 kHz to 25 Hz in order to reduce the high dimensionality. As described in the experiment protocol, the perception-assist was introduced during 3.5[s] to 5[s]. Therefore, the EMG or EEG feature extraction should be done within this time period. In this research, therefore 1[s] time segments that counted from the instant where the perception-assist torque started as shown in fig. 4.15 were extracted from all the trials. This made data set of 100 one second time segments for the analysis.

Instead of using one SVM classifier, multiple SVM classifiers were employed in this approach. The main idea behind using several classifiers was to reduce the dimensionality of the input feature vector to a particular SVM classifier. Furthermore, there is a possibility that several classifiers could jointly outperform a single classifier if they appropriately combined. In this study, EMG temporal signals data were used as the input features. A time window of 200-800 [ms] from the 1 [s] time segment was selected for EMG temporal feature extraction. The selection of this time window was decided based on preliminary analyze of recorded EMG signals. In the proposed method for only using EMG signals, three independent SVM classifiers were implemented. The EMG temporal data from the time windows of 201-400 [ms], 401-600 [ms] and 601-800 [ms] were fed to those three SVM classifiers as the input vectors. Therefore, 10 data points (from the two EMG channels) were produced as the feature vector to each SVM classifier. Eventually, to get the final classification decision, the outputs of the three SVM classifiers were combined with the majority vote method.

A 10-fold cross validation method was used to verify the performance of the classification results of each subject. In this method, in a particular fold, testing of the classifier was carried out using one of the experiment sessions (10% of all data) where data of the other nine sessions (90% of all data) were used to train the SVM classifiers. Same process was followed other nine folds. Moreover, in each fold it was ensured that the tested data was unseen to the SVMs during SVM training.

On the other hand, fig. 4.16 shows a graphical representation of the method that was proposed in combine EMG-EEG approach for the evaluation of the perception-assist. In

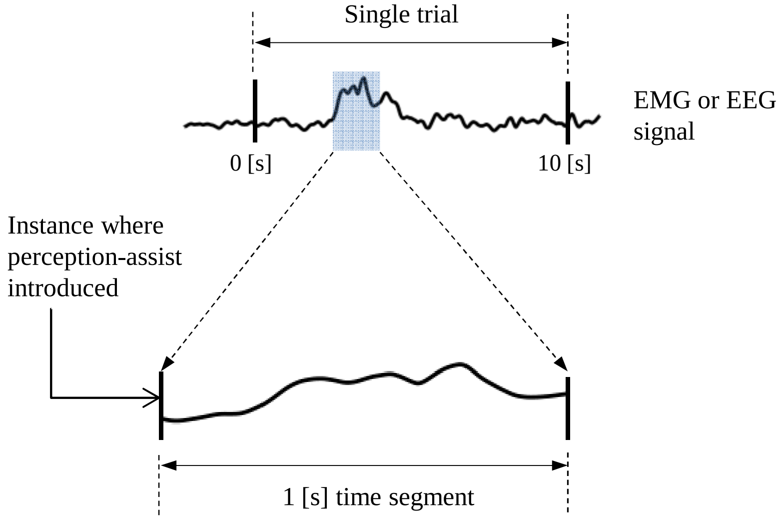


Figure 4.15: 1[s] time segment extracted from a single trial

this approach, the first step was to use a common average reference (CAR) as the spatial filter [120] for raw EEG signals. As such error related EEG signal is known to be a relatively slow cortical potential, the EEG signals were band pass filtered between 1-10 Hz in the next step. Then, in order to reduce the high dimensionality of data, the EEG signals were down sampled from 250 Hz to 25 Hz. In the next step, the EEG signals during 1[s] time windows related to each single trial were extracted from all EEG channels as illustrates in 4.16.

Even though, the EEG signals were recorded using the 256 EEG electrodes sensor net, not all those channels may carry the relevant information. Therefore, it is important to select the relevant EEG channels. In previous studies such as in [84], a sum of cosine angle based selection algorithm was proposed for selecting the EEG channels. In that study, the selected channels were varied based on the subject and the task he/she performed. However, such selection of sensors using preliminary experiments is a time consuming task and may be a tedious work for the subjects to perform over many experiments.

On the other hand, similar error related brain signals/potentials are believed to be originated from Anterior Cingulate Cortex (ACC) of the brain. Several studies [115, 116] have researched this in details. The relevant region (ACC) of brain is located near to the frontal

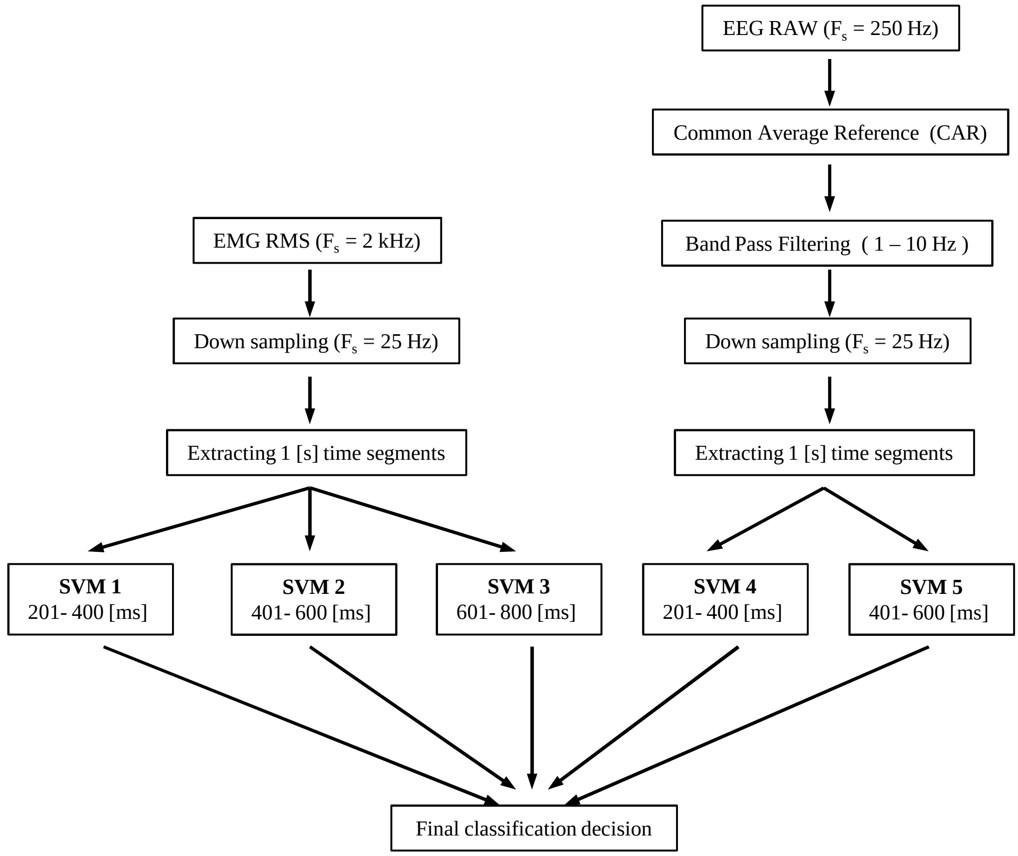


Figure 4.16: Flow chart of the method that used combine EMG-EEG. Here F_s is the sample rate.

lobes and along with the walls which divide the left and right hemisphere. Furthermore, several studies have reported that electrode positions FCz and Cz (based on the international 10-20 standard) can be used to monitor such error related EEG signals effectively. In fact, these two EEG channels are placed basically above the location of the ACC. On the other hand, more number of EEG electrodes will cause a high dimensional input feature vector. However, it is usually advantageous to reduce the number of input features or reduce the dimension of the input vector to a classifier in order to have a better predictive results and a less computationally intensive approach. When a large input feature vector is supplied to a classifier, usually it needs a large number of training data in order to avoid over fitting of the classifier as well. Furthermore, recording such a large number of training data from subjects especially in this type of applications might not be practical. On the other hand, if it is possible to use common and generally available EEG channels for the

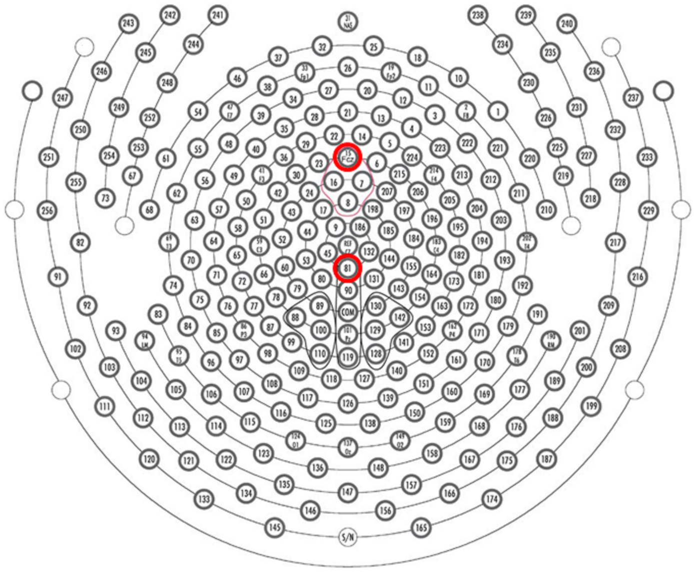


Figure 4.17: Selected EEG channels (ch 15 and ch 81) for feature extraction

EEG signal feature extraction that might be useful as well. Therefore after considering all these reasons, it was decided to use the EEG channel FCz and Cz (as shown in fig. 4.17) for the EEG feature extraction in this study. However as Cz is the reference electrode of this EEG acquisition systems, channel 81 was used instead of Cz (which is the nearest channel to Cz). Moreover, channel 15 represents the FCz position of the sensor array.

Basically there are two ways of fusion of EEG signals with the EMG signal based SVM classifiers. One way is using EEG features as the input features to those EMG signal based SVM classifiers. This can be considered as input or feature level fusion. The second possibility is to use separate SVM classifiers for the EEG signals and then final decision is calculated based on combine decision of all EMG and EEG classifiers. This can be considered as decision level fusion. However, the mentioned first approach will further increase the size of the input vector to SVM classifiers. Moreover, the time window for feature extraction of EEG signals may differ from the time window used for extracting the EMG features. Due to these reasons, the second approach was utilized in this study. As similar to the method described for the EMG signal based method, temporal data of the selected two channels were prepared as the inputs features to the SVMs. Based on the average EEG signal variations across all three subject and across two EEG channels results, the time window for EEG feature extraction was selected as 200-600 [ms]. Two independent SVM classifiers were used for classification based on EEG features. Thus, 10 data points (from the two EEG channels) were prepared as the feature vector to each SVM classifier. Finally, decisions from the three SVM classifiers based on EMG signals and decisions from the two SVM classifiers based on EEG signals were fused using the majority vote scheme to estimate the final recognition output as shown in fig. 4.16. As same as the EMG only approach, a 10-fold cross validation method was employed to evaluate the performance.

4.8.2 Results and Discussion

In order to analysis the performance of the proposed methods, recognition rates for error and correct perception-assist were calculated based on following performance matrix as shown in fig. 4.18.

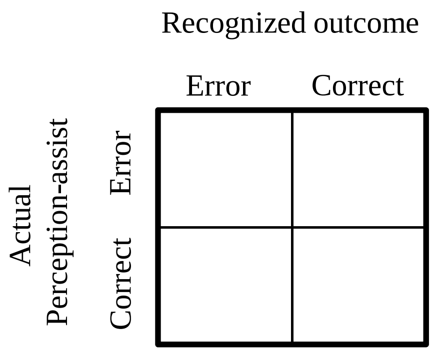


Figure 4.18: Performance matrix

Figure 4.19 reports the recognition rates (calculated by averaging the accuracy rates of 10-fold cross validation) of all the subjects based on the approach that used only EMG signals to judge the correctness or incorrectness of the performed perception-assist. Only using EMG signals, it was able to correctly recognize the error perception-assist trials with a overall accuracy of 80.5% across all subjects. In learning process of the perception-assist, it is required to accurately identify the erroneous perception-assist as much as possible and use that results to learn accordingly. On the other hand, there was an average 64.4% probability of recognizing the correct perception-assist trials correctly across all subjects.

More importantly, both the correct and error perception-assist recognition rates should be increased together for better overall accuracy of the perception-assist evaluation. If the classifier mistakenly recognizes an error perception-assist trial as a correct one, it will not much influence on the learning process of the perception-assist. It will only be a missed chance (miss hit) in the learning process. However much more damage may be done to the learning process, if the classifier mistakenly judge a correct perception-assist trial as an error perception-assist trial (false alarm). Therefore, not only improving the accurate identification of error perception-assist trials, but also decreasing the miss classification of correct perception-assist trials as the error perception-assist trials is vital for the learning.

Subject **Ta**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	76.6%	23.4%
Correct	29.0%	71.0%

Subject **Th**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	85.6%	14.4%
Correct	40.9%	59.1%

Subject **Ha**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	79.3%	20.7%
Correct	36.9%	63.1%

Figure 4.19: Performance matrix for EMG only approach

On the other hand, fig. 4.20 shows the accuracy rates for the combine approach that used both the EMG and EEG signals to judge the performed perception-assist. For all the subjects, accuracy rates for correctly identifying the erroneous perception-assist have been improved for the case of using both the EMG and EEG signals in comparison to the case of using only EMG signals. Using both the EMG and EEG signals, it was able to correctly judge the erroneous perception-assist with a overall accuracy of 84.53% across all the subjects. As shown in fig. 4.20, the recognition rates of the correct perception-assist in respective subjects have also become increased with the relevant values in fig. 4.19. On average a 68.6% accuracy rate has shown for the recognition of the correctly performed perception-assist trials. Although the improvements when the method that used both the EMG and EEG signals are varied with each person, the recognition of the correctness or incorrectness of the perception-assist performed by the exoskeleton using both EMG and

EEG is effective from these experimental results.

Subject **Ta**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	79.3%	20.7%
Correct	26.0%	74.0%

Subject **Th**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	88.8%	11.2%
Correct	32.1%	67.9%

Subject **Ha**

Actual Perception-assist	Recognized outcome: Error	Recognized outcome: Correct
Error	85.5%	14.5%
Correct	36.1%	63.9%

Figure 4.20: Performance matrix for combine EMG and EEG approach

Therefore, the overall experimental results show that the recognition of error perception assist by using both EMG and EEG signals is relatively higher than that of using EMG signals alone. Moreover, the classification rate of correctly recognizing a correct perception-assist trial is also increased with the combine approach of using EMG and EEG signals. Therefore, these results show that EEG signals can be used to improve the recognition of the correctness or incorrectness of the perception-assist in upper-limb exoskeletons.

4.9 A study of investigating the possibility of using only EEG signals for evaluation of the perception-assist

The primary objective of this study was to explore whether can EEG signals alone be used to judge the correctness or incorrectness of perception-assist. Even with adequate levels of changes in EMG signals, it is required to recognize EMG signals of which muscle/muscles is/are changed during perception-assist in order to properly recognize the perception-assist. In other words, for different perception-assist tasks different muscle or combinations of muscles have to be monitored. But, due to the complexity of the upper limb motions during day to day life activities, this might not be a straightforward task. On the other hand it may possible to argue that, the user may experience the similar feeling about any error perception-assist irrespective of different types of perception-assist tasks or motions. Therefore, if it is possible to judge the correctness or incorrectness of the perception-assist solely based on EEG signals, definitely it will be an advantage.

In this study, all the analyses and methods for evaluating the perception-assist were carried out based on the experimental sessions described in section 4.5. Pre-processing of EEG signals was almost similar to the steps followed in the previously explained approach. As the first step, raw EEG signals were spatially filtered using common average reference method. Then such error related EEG signals are known to be relatively slow cortical potentials, the EEG signals were band pass filtered between 1-10 Hz. In order to reduce the higher dimensionality of the EEG data, it was then sub sampled to 25 Hz. Then as mentioned in previously, 1[s] time segments were extracted from every single trials. Therefore, data set of 100, 1[s] time segments were prepared.

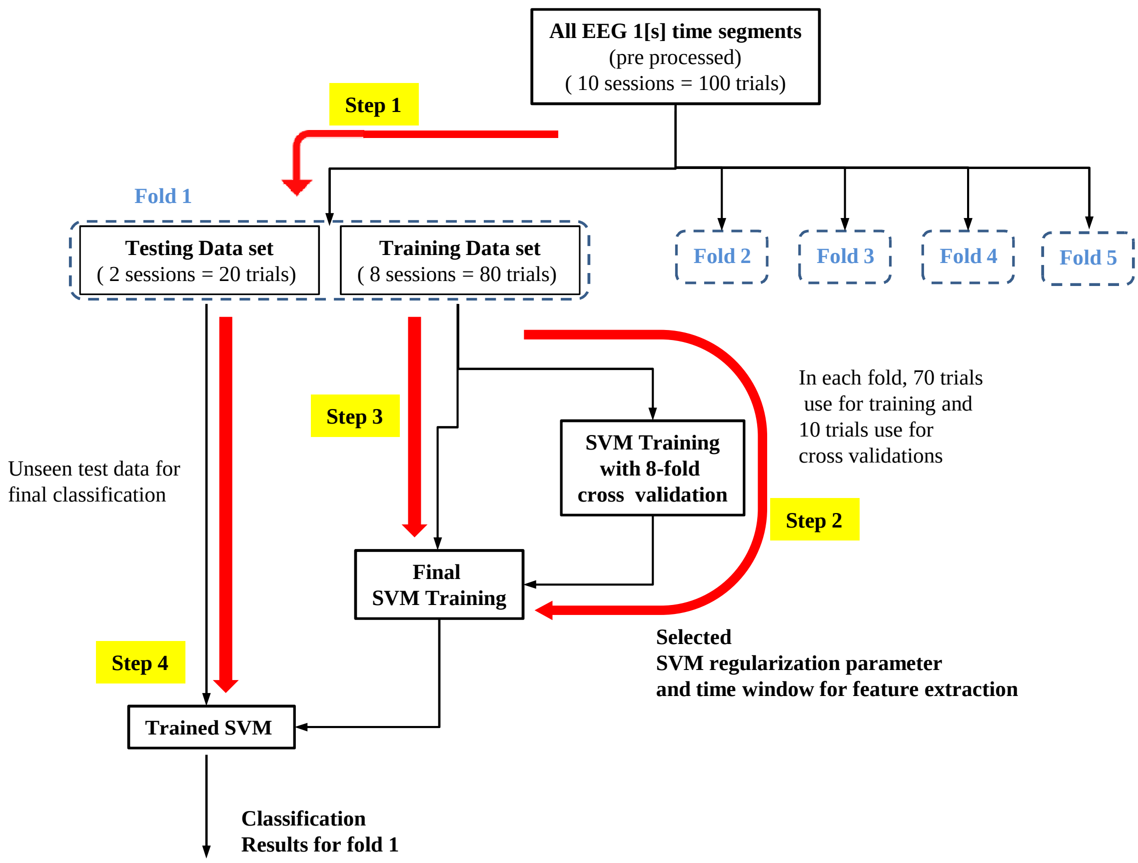


Figure 4.21: Flow chart of the steps used for SVM training, cross validation and testing for EEG data

Similar to the previous study, it was decided to use SVM as the classifier to judge whether the performed perception-assist is correct or incorrect in this study. In the previous approach, the time window for extracting the temporal input features of EMG and EEG signals was fixed for all the subjects. However due to the variations of EEG signals across the subjects, it is important to select a suitable EEG feature extraction time window for each subject respectively. Therefore in this study, a method was prepared to select the appropriate time window for EEG feature extraction in each subject during SVM training phase.

Flow chart of the method that proposed in this study is illustrated in fig. 4.21. For any kind of classifier, it is required to have a training based on training data. After that, the trained classifier is applied to classify the test data in order to verify the effectiveness. More importantly, those test data must be completely unseen data set for the classifier. In other words, the test data set must not be used by any means for the classifier training. Therefore considering these points, it was decided to use 80% of the all recorded data for training the SVM classifier and use rest of the 20% data for testing the classifier. It is basically using of data sets of 8 sessions to train the classifier and test the effectiveness of the classifier based on rest of the 2 sessions. Nevertheless, as the total data set consisted of relatively a low number of single trials (i.e: 100 data set of 1[s] time segments), it was decided to evaluate the classifier based on a 5 fold training-testing process. This is the first step of this method as marked in fig. 4.21. Moreover, column 2 and 3 of the table 4.2 report the sessions used for training and testing data sets in this process for each fold, respectively. Main intention of this 5 fold training-testing process was to get a relatively better generalized performance of the classifier rather than based on single training-testing process.

Table 4.2: Training and testing data set partition

Fold	Sessions used for Training	Sessions used for Testing
1	1 to 8	9 and 10
2	1 to 6, 9 and 10	7 and 8
3	1 to 4, 7 to 10	5 and 6
4	1 and 2, 5 to 10	3 and 4
5	3 to 10	1 and 2

At each fold, the SVM classifier was required to learn based on the available training data. For any classifier, it makes the output result based on the input features. Therefore, the selection of a set of relevant input features is important issue in most of the classifiers. Pre-feature selection methods are usually employed and the basic idea behind the feature variable selection is to pick the most relevant set of features that can result in acceptable predictive performance. Thus based on the reasons mentioned in the previous approach, two EEG channels namely; channel 15 and 81 were selected for EEG feature extraction in this study.

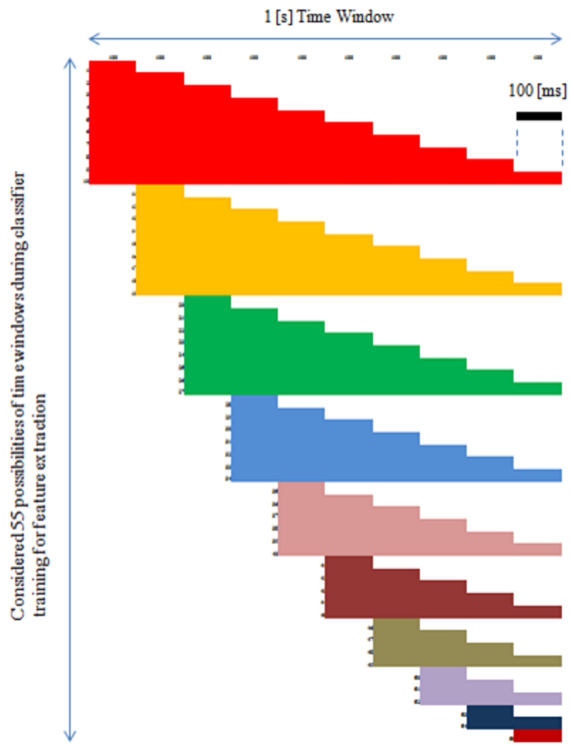


Figure 4.22: 55 possibilities of time window considered for classification during classifier training. (1 [s] time window starting from 3.5 [s] in single trial)

The second step of the flow chart in fig. 4.21 is to train the SVM with a cross validation method to find the SVM model parameters and appropriate time window for EEG feature extraction. Classification must be done for each and every perception-assist task during each trial. As the perception-assist task started after 3.5 [s] in each trial, it is reasonable to think that if any variation of EEG signals related to perception-assist should be existed after 3.5 [s]. Length of the time window (which start from 3.5 [s]) for EEG feature extraction were selected independently per subject based on the classification performance of the classifier over the training data set. In this selection process, 55 possibilities of time windows were considered for classification as shown in fig. 4.22. The smallest time window length was considered as 100 [ms] and the largest was 1000 [ms] (which the total length of the 1[s] time segments). Thus, the selection of the appropriate time window for EEG feature extraction and SVM hyper parameter selection (In this case, the linear kernel was used as the kernel function of the SVM and therefore only one hyper parameter was needed to find) were required to carry out based on the training data. In order to realize this, a 8-fold cross-validation method was used. In this cross-validation method, in each fold, the validation of the classifier was done based on one of the experiment sessions (validation data set) and data of the other 7 sessions were used to train the SVM classifiers. Then, the hyper parameter and the time window with highest cross-validation accuracy were selected to model the final SVM classifier based on whole training data set (trained using all 8 sessions) and this step is illustrated as step 3 in the fig. 4.21. Finally, the effectiveness of this trained classifier was evaluated based on the respective data of two sessions used for testing as shown in table 4.2 (unseen 20 data). This step is marked as step 4 in the fig. 4.21.

4.9.1 Results

The variations of EEG signals across subjects and along the time are not consistent. Due to high variability of EEG signals, it is sometime difficult to spot the straightforward differences between error and correct perception-assist related EEG signals during a single trial. However if there are any differences between EEG signals of error versus correct perception-assist trials, the trained classifiers will be able to make use of them.

In this study, a SVM based method was used for recognition of the correctness or incorrectness of the perception-assist trials and the results for the subjects are reported in fig. 4.23. It shows the recognition rates (as calculated based fig. 4.18) for the correct and error perception-assist trials for each subject based on average classification performance over the 5 folds as mentioned in table 4.2. In this study, the correctly performed perception-assist trials were able to recognize at an average rate of 57.4% across all three subjects

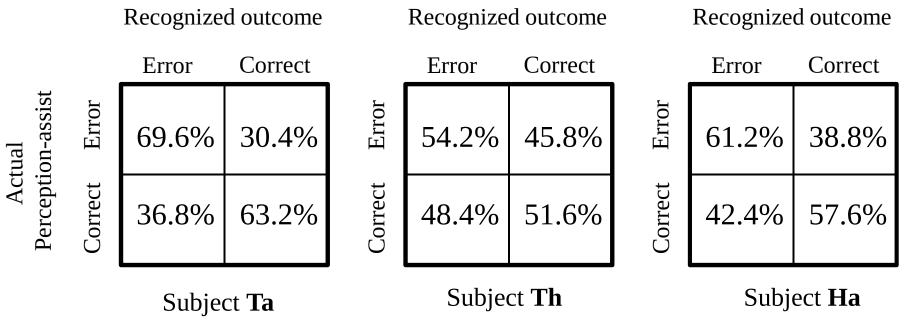


Figure 4.23: Performance matrix for EEG only approach (average over 5 folds)

whereas, the error perception-assist trials were able to identify with a 61.6% rate.

Table 4.3: Selected time windows during 5 folds of testing for all subjects

Fold	Subject **Ta**	Subject **Ha**	Subject **Th**
1	100-800 [ms]	300-800 [ms]	100-800 [ms]
2	200-800 [ms]	300-900 [ms]	300-800 [ms]
3	100-1000 [ms]	1-900 [ms]	300-800 [ms]
4	200-800 [ms]	200-900 [ms]	1-800 [ms]
5	200-800 [ms]	1-900 [ms]	400-700 [ms]

Moreover, table 4.3 reports the selected time windows for classification during 5 folds of training-testing for all the subjects. For the subject **Ta**, results across five folds showed a relatively higher consistency of selected time window periods whereas, for the subject **Ha** and **Th** selected time window across 5 folds were not relatively consistent. Furthermore, the classification results signify that inter-subject differences have stronger influence on the classification performance.

Even though the recognition rates are not highly encouraging in comparison to the results obtained for the EMG only or EMG-EMG combine approaches, the recognition rates are grater than the chance level. Thus, these moderate recognition rates suggest that the feasibility of using EEG signals to recognize the correctness or incorrectness of the performed perception-assist in upper-limb exoskeletons. Depending on the situation and condition of the subject either EMG, EEG or combination of EME-EEG can be switched in between to judge the correctness or incorrectness of the perception-assist. Especially, in the case of an exoskeleton user who does not have required muscles to measure the EMG signals or simply difficult to measure the EMG signals, the EEG signals based evaluation might be useful. As mentioned previously, even with adequate variations in EMG signals, it is required to recognize EMG signals of which muscle/muscles is/are changed during perception-assist in order to properly judge it. Therefore, for different perception-assist tasks different muscle or combinations of muscles have to be monitored. However, due to the complexity of the upper limb motions during daily life activities, this might be a difficult task. On the other hand, the brain response to the error situations in the context of this application might be same about any error perception-assist irrespective of different perception-assist tasks or motions. In such situations, the evaluation of perception-assist based on only EEG signals might be beneficial. Nevertheless, this investigation can be used to back the possibility of using EEG signals to judge the correctness or incorrectness of the performed-perception assist in upper-limb exoskeletons. However, further research effort is needed to improve the effectiveness.

4.10 Summery

This chapter investigated the feasibility of EEG signals for evaluation of the perception-assist control performed by the upper-limb exoskeletons. Based on existing knowledge and previous studies, EMG and EEG signals were identified as potential candidates for evaluation of the perception-assist control. Three healthy subjects carried out experiments using a wrist assist exoskeleton with perception-assist while monitoring EMG and EEG signals. Results of the analysis of EMG signals during perception-assist yielded that the EMG signals are sometimes not adequately changed for the judgments of the perception-assist. Therefore in addition to EMG signals, this chapter investigated the possibility of using EEG signals for this purpose. In that case, the correctness or incorrectness of the perception-assist was judged using a combination of EMG-EEG signals based on multiple SVM based method and the results showed a relatively higher accuracy compared to the approach based on only EMG signals. Later on the study, an attempt was made to judge the perception-assist based on only EEG signals. However, the accuracy of the recognition was not that encouraging even though it was above the chance level. On the other hand, it was lower than that of the EMG only or EMG-EEG combine approaches. Therefore, it was suggested that to use both EMG and EEG signals in combination for a higher recognition accuracy of the perception-assist. Furthermore, it was highlighted that depending on the situation and condition of the user either EMG, EEG or combination of EMG-EEG can be switched in between to evaluate the correctness or incorrectness of the perception-assist.

Chapter 5

Conclusions and Future Work

An upper-limb exoskeleton robot is one of the most effective assistive robots that can be used to assist or rehabilitate the motions of upper-limbs of a physically weak individual. Controlling upper-limb exoskeletons however, requires sophisticated technologies, as they always interact with human users. It is necessary to control the upper-limb exoskeletons based on the motion intention of the user. EMG and EEG signals have been identified as potential input signals to the control methods of upper-limb exoskeletons since EMG and EEG signals reflect the motion intention of the user. Even though there has been remarkable progress in the recent past in control methods for upper-limb exoskeletons based on EMG and EEG signals, there are several problems which need further research effort. Therefore, the objective of this thesis was to address issues related to the control of upper-limb exoskeletons using EMG and EEG signals. More specifically, this thesis focused on the issue of muscle fatigue in EMG-based control and investigating the feasibility of EEG signals for evaluation of the perception-assist in upper-limb exoskeletons.

The structure of the thesis consists of five chapters where the first chapter was used to explain the motivation behind the work of this thesis with a brief introduction. Second chapter basically presented the background on upper-limb exoskeleton control methods based on EMG and EEG signals. Notably, challenges and gaps to be filled in existing EMG and EEG control methods that have been proposed for upper-limb exoskeletons were identified and discussed in the second chapter. Major contributions of this thesis are two fold and they were presented in chapters three and four.

The first half of the thesis addressed the problem of muscle fatigue on EMG-based control and the relevant research work is reported in chapter three. Muscle fatigue can considerably modify the EMG to EMG-based torque relationship as muscle fatigue has an influence on variations of the EMG amplitude. At the beginning, experiments were carried out with three healthy young subjects to find out the effects of muscle fatigue on EMG signals and EMG-based control in human upper-limb power-assist. The results of these experiments signified that an EMG amplitude feature such as EMG Root mean square (RMS) only is not adequate as an input signal for an effective EMG-based control during the muscle fatigue conditions. Therefore, the necessity of using frequency domain EMG features as additional input features to recognize the muscle fatigue conditions and utilize in EMG-based control was highlighted.

In order to compensate for the effects of muscle fatigue on EMG-based control, this thesis proposed a novel method based on multiple fuzzy-neuro modifiers which used EMG MPF in addition to EMG RMS as an input to identify the muscle fatigue conditions. During the experiments three healthy young subjects were asked to perform repeated elbow flexion/extension motions to control a robot arm using EMG-based control. Results were analyzed and it was observed that the robot is over shooting without muscle fatigue compensation method as a result of increasing EMG RMS during muscle fatigue conditions. On the other hand, the proposed method for the compensation of the effects of muscle fatigue was able to effectively reduce the overshoots of the robot motions. Therefore from the overall analysis it turned out that the proposed method based on multiple fuzzy-neuro modifiers with EMG RMS and MPF features as inputs can be effectively used to compensate for the effects of muscle fatigue on EMG-based control. With an increasing number of EMG-based control approaches for assistive robots, the proposed method is beneficial to deal with the problem of muscle fatigue.

The second half of the thesis investigated the feasibility of EEG signals for evaluation of the perception-assist control performed by the upper-limb exoskeletons. This research work was presented in chapter four. Perception-assist has been introduced apart from the power-assist for upper-limb exoskeletons to avoid the undesired motion intentions by the users with deteriorated perception abilities. Perception-assist needs to be learned by the exoskeleton itself and in this learning process, it is required to judge the correctness or incorrectness of the perception-assist performed by the exoskeleton.

In this research work, EMG and EEG signals were identified as potential candidates for evaluation of the perception-assist control. Experiments were carried out with three healthy young subjects to control a wrist assist exoskeleton with perception-assist while monitoring EMG and EEG signals. Results of the analysis of EMG signals which were acquired from two muscles, flexor carpi radialis and extensor carpi ulnaris during perception-assist suggested that EMG signals sometimes do not adequately change according to the judgments of the perception-assist. Moreover, for a particular user, it might be difficult to measure the EMG signals or required muscles may simply be unavailable. For these reasons, in addition to EMG signals, this thesis suggested to explore the possibility of utilizing EEG signals.

In this context, correctness or incorrectness of the perception-assist was judged using a combination of EMG-EEG signals. Multiple SVM based methods were applied to classify the error vs correct perception-assist trials. Temporal data of EMG RMS of the aforementioned muscles and pre-processed temporal data of EEG channels 15 (FCz) and 81 (an electrode near to Cz) during pre-selected time window from where the perception-assist was introduced in each trial were used as the input features to multiple SVMs. Results of the method that used a combination of EMG and EEG signals showed a relatively higher accuracy compared to the method that used only EMG signals to judge the perception-assist. Moreover, an attempt was made to judge the perception-assist based on only EEG signals. In that attempt, pre-processed temporal data of EEG channels 15 and 81 during a time window that was selected based on SVM training stage was used to extract the input features. Even though the accuracy of the recognition between correct vs incorrect perception-assist trials was above the chance level in this attempt, it was lower than that of EMG only or EMG-EEG approaches. Therefore, this research work suggested that, a combination of EMG and EEG signals can be used to realize higher judgment accuracy of the perception-assist. Moreover, this thesis highlighted that depending on the situation and condition of the user either EMG, EEG or combination of EMG-EEG can be switched in between to judge the correctness or incorrectness of the perception-assist.

5.1 Future Work

Although the results presented in this thesis have demonstrated the effectiveness of the proposed methods and approaches, they could be further improved in a number ways. As presented in the first half of this thesis, the proposed method based on multiple fuzzy-neuro modifiers with EMG RMS and MPF features as inputs was able to effectively compensate the effects of muscle fatigue on EMG-based control. Basically the effectiveness of the this method relies on input features to the fuzzy-neruro modifiers and better estimation of those features during dynamic experiments or real life situations. Therefore, other measures of muscle fatigue in addition to EMG MPF and EMG RMS can be tested as the input features to the proposed multiple fuzzy-neuro modifiers based method in future studies to investigate whether the effectiveness can be further enhanced. Moreover, robust methods for estimating frequency domain EMG features during dynamic conditions can be further studied.

In this thesis, the method proposed for compensation of the effects of muscle fatigue on EMG-based control was only evaluated with three healthy and young subjects. However, real end users of these assistive robotic systems such as upper-limb exoskeletons may considerably differ from those young subjects. Therefore in future studies, it is important to evaluate and improve the proposed methods with a larger pool of subjects including at least a few end users such as physically weak or old.

On the other hand, the research work on investigating the feasibility of EEG signals for evaluations of the perception-assist presented in the second half of this thesis opens up many future work. Results presented in chapter four have shown the feasibility of using EEG signals to evaluate the correctness or incorrectness of the perception-assist in upper-limb exoskeletons. Even though, the recognition accuracy was increased to a certain extent with the combined approach of EMG and EEG signals in comparison to the EMG only approach, the results of the EEG only approach was not that encouraging. Therefore, it is important for future studies to work on improving EEG based recognitions. That will enable to improve the combined EMG-EEG based approach as well. On the other hand, in this research work, only two EEG channels over the brain ACC area were used for the feature extractions as those two electrodes were known to be suitable for error related brain activity monitoring. However, it will be interesting to find out other EEG channels that could be used to enhance the recognition of error related brain activities. Nevertheless, the number of EEG channels used for feature extraction should be considered carefully as the dimension of the input vector to classifier will depend on that as well. Especially, in real conditions it may be difficult to perform many training sessions for a user to record more data for training of the classifiers. Therefore, future studies should focus on classifier training with less number of training trials. Moreover, from this investigation it was made clear that time window for feature extraction varies across subjects and even between sessions of the same subject as well. Therefore, more adaptive techniques for the selection of the time window for EEG feature extraction could lead to better recognition rates.

In this investigation, perception-assist experiments were limited to only wrist movements and the experiment was synchronized with time (using signal trial protocol). However, the actual scenario could be a person wearing a 7-DOF upper-limb exoskeleton and performing self paced movements (without time driven protocol using the images shown in the monitor). Therefore, in future studies the experiment protocol should be modified in order to test the approaches in real life conditions. On the other hand, in the case of 7-DOF upper-limb exoskeletons in more dynamic conditions, relatively higher level of movements are inevitable and those movement will affect the EEG signals as well. Therefore, suitable EEG artifact removal or filtering methods must be used for EEG signals.

Finally, the research work related to perception-assist evaluation presented in the thesis was carried out with only three healthy young subjects. Future studies could extend to experiment with more subjects including at least a few end users such as physically weak or old people to evaluate and improve the effectiveness of the methods.

Publications

Refereed Journals

1. Thilina Dulantha Lalitharatne, Kenbu Teramoto, Yoshiaki Hayashi, Thrishantha Nanayakkara, Kazuo Kiguchi, ”Evaluation of Fuzzy-Neuro Modifiers for Compensation of the Effects of Muscle Fatigue on EMG-Based Control to be Used in Upper-Limb Power-Assist Exoskeletons”, ***Journal of Advanced Mechanical Design, Systems, and Manufacturing***, vol.7, no.4, 2013, pp. 736-751

2. Thilina Dulantha Lalitharatne, Kenbu Teramoto, Yoshiaki Hayashi, Kazuo Kiguchi, ”Towards Hybrid EEG-EMG-Based Control Approaches to be Used in Bio-robotics Applications: Current Status, Challenges and Future Directions”, ***Paladyn, Journal of Behavioral Robotics***,vol.4, no.2, 2013, pp. 147-154

3. Kazuo Kiguchi, Thilina Dulantha Lalitharatne, Yoshiaki Hayashi, ”Estimation of Forearm Supination/Pronation Motion Based on EEG Signals to Control an Artificial Arm”, ***Journal of Advanced Mechanical Design, Systems, and Manufacturing***, vol.7, no.1, 2013, pp. 74-81

International Conferences/Symposiums

1. Thilina Dulantha Lalitharatne, Kenbu Teramoto, Yoshiaki Hayashi, Kazuo Kiguchi, ”EEG-based evaluation for perception-assist in upper-limb power-assist exoskeletons”, ***World Automation Congress 2014 (WAC 2014)***, Kona, Hawaii

2. Thilina Dulantha Lalitharatne, Kenbu Teramoto, Yoshiaki Hayashi, Kazuo Kiguchi, ”Evaluation of Perception Assist with an Upper-Limb Power-Assist Exoskeleton using EMG and EEG Signals”, ***Proc. of 11th IEEE International Conference on Networking, Sensing and Control (ICNSC 2014)*** , 2014, pp. 524 - 529

3. Thilina Dulantha Lalitharatne, Yoshiaki Hayashi, Kenbu Teramoto, Kazuo Kiguchi, ”Compensation of the effects of muscle fatigue on EMG-based control using fuzzy rules based scheme”, ***Proc. of 35th Annual International Conference on the IEEE Engineering in Medicine and Biology Society (EMBC2013)***, 2013, pp. 6949 - 6952

4. Thilina Dulantha Lalitharatne, Yoshiaki Hayashi, Kenbu Teramoto, Kazuo Kiguchi, ”A study on effects of muscle fatigue on EMG-based control for human upper-limb power-assist”, ***Proc. of IEEE 6th International Conference on Information and Automation for Sustainability (ICIAfS 2012)***, 2012, pp. 124 - 128

5. Thilina Dulantha Lalitharatne, Akihiro Yoshino, Yoshiaki Hayashi, Kenbu Teramoto, Kazuo Kiguchi, ”Toward EEG control of upper limb power-assist exoskeletons: A preliminary study of decoding elbow joint velocities using EEG signals”, ***Proc. of 2012 International Symposium on Micro-NanoMechatronics and Human Science (MHS 2012)***, 2012, pp. 422 - 425

6. Kazuo Kiguchi, Thilina Dulantha Lalitharatne, Akihiro Yoshino, Yoshiaki Hayashi, ”Control of Forearm Supination/Pronation Motion of an Artificial Arm Based on EEG Signals”, ***Proc. of 2012 ASME-ISPS / JSME-IIP Joint International Conference on Micromechatronics for Information and Precision Equipment (MIPE 2012)***, 2012, pp. 222 - 224

7. Kazuo Kiguchi, Thilina Dulantha Lalitharatne, Yoshiaki Hayashi, ”Control of Lower-Limb Power-Assist Robot Based on EEG signals”, ***Proc. of The 2nd IFToMM Asian Conference on Mechanism and Machine Science (Asian-MMS 2012)***, 2012, pp. 110

References

[1] Population Division, DESA, United Nations. Magnitude and Speed of Population Ageing. *World Population Ageing 1950-2050*. [Online]. Available: www.un.org/esa/population/publications/worldageing19502050/

[2] Population Division, DESA, United Nations. Demographic Determinants of Population Ageing. *World Population Ageing 1950-2050*. [Online]. Available: www.un.org/esa/population/publications/worldageing19502050/

[3] Chih-Wei Chen, Chou-Ching K.Lin , Ming-Shaung Ju, "Hand Orthosis Controlled Using Brain-Computer Interface", *Journal of Medical and Biological Engineeing*, vol. 29, no.5 , 2009, pp. 234-241

[4] Christine E. King, Po T. Wang, Masato Mizuta, David J. Reinkensmeyer, An H. Do, Shunji Moromugi, Zoran Nenadic, "Noninvasive Brain-Computer Interface Driven Hand Orthosis", *Proc. of Annual International Conf. of The IEEE Engineering in Medicine and Biology Society*, 2011, pp. 5786-5789

[5] C.J. Yang, J.F Zhang, Y.Chen, Y.M.Dong, and Y. Zhang, A review of exoskeleton-type systems and their key technologies, *Proc. IMechE, Journal of Mechanical Engineering Science: Part C*, vol. 222, no. 8, 2008, pp. 1599-1612

[6] J.L Pones, "Wearable Robots: biomechatronic exoskeletons", West Sussex, England, Wiley,ISBN: 978-0-470-51294-4, 2008, pp. 1-64

[7] J.C. Perry, J. Rosen, and S. Burns, Upper-Limb Powered Exoskeleton Design, *IEEE/ASME Trans. on Mechatronics*, vol. 12, no. 4, 2007, pp. 408-417

[8] H. Kazerooni, J.L. Racine, Lihua Huang, R.Steger, "On the Control of the Berkeley Lower Extremity Exoskeleton (BLEEX)", *Proc. of the 2005 IEEE International Conf. on Robotics and Automation, (ICRA 2005)*, 2005, pp. 4353-4360

[9] http://www.cyberdyne.jp/english/robotsuithal/

[10] K. Kiguchi, M.H. Rahman, M. Sasaki, K. Teramoto, Development of a 3DoF mobile exoskeleton robot for human upper-limb motion assist, *Proc. Robotics and Autonomous Systems*, 2008, pp. 678-691

[11] J. Rosen, N. Brand, M.B. Fuchs, M. Arcan, A Myosignal-Based Powered Exoskeleton System, *IEEE Trans. on Systems, Man, and Cybernetics*, Part A, vol. 31, no. 3,

2001, pp. 210-222

[12] K. Kiguchi, T. Tanaka, K. Watanabe, T. Fukuda, An Exoskeleton for Human Elbow and Forearm Motion Assist, *Proc. of IEEE Int. Conf. on Robotics and Automation*, 2003, pp. 3600-3605

[13] B. Hudgins, P. Parker, R.N. Scott, ”A new strategy for multifunction myoelectric control”, *IEEE Trans. on Biomedical Engineering*, vol. 40, no. 1, 1993, pp. 82-94

[14] D. Farina, R. Merletti, ”Comparison of algorithms for estimation of EMG variables during voluntary isometric contractions”, *Journal of Electromyography and Kinesiology*, vol.10, no. 5, 2000, pp. 337-49

[15] S. Gregory Rash, Electromyography fundamentals, 1999, Online: www.ac.wwu.edu/chalmers/EMGfundamentals.pdf.

[16] C.D. Luca, Surface electromyography: Detection and recording, 2002

[17] NIHON KOHDEN, http://www.nihonkohden.com/

[18] Surface EMG Systems and Sensors, http://www.delsys.com/

[19] Biosemi EEG/ECG/EMG/BSPM/NEURO amplifier electrodes, http://www.biosemi.com/

[20] CED Products, http://www.ced.co.uk/pru.shtml

[21] R.A.R.C. Gopura, D.S.V. Bandara, J.M.P. Gunasekara, T.S.S. Jayawardan, ”Recent Trends in EMG-Based Control Methods for Assistive Robots”, *Electrodiagnosis in New Frontiers of Clinical Research*, DOI: 10.5772/56174

[22] M.A. Oskoei, H. Hu, ”Myoelectric control systems: A survey”, *Biomedical Signal Processing and Control*, vol.2, no. 4, 2007, pp. 275-294

[23] EJ Rechy-ramirez, H. Hu, ”Stages for Developing Control Systems using EMG and EEG Signals: A survey”, 2011

[24] T. Lenzi, SMM. De Rossi, N. Vitiello, MC. Carrozza, ”Proportional EMG control for upper- limb powered exoskeletons”, *Proc. of conf. of IEEE Enginering Medical and Biology Society*, 2011, pp. 628-631

[25] R.A.R.C Gopura, K. Kiguchi, ”Electromyography (EMG)-signal based fuzzy-neuro control of a 3 degrees of freedom (3DOF) exoskeleton robot for human upper-limb motion assist”, *Journal of the National Science Foundation of Sri Lanka*, [Internet]2009 Dec 31 [cited 2013 Mar 10], Available from: http://www.sljol.info/index.php/JNSFSL/article/view/1470, vol. 37, no. 4

[26] K. Kiguchi, T. Tanaka, T. Fukuda, ”Neuro-fuzzy control of a robotic exoskeleton with EMG signals”, *IEEE Trans. on Fuzzy Systems*, vol.12, no. 4, pp. 481-490

[27] L. Lucas, M. DiCicco, Y. Matsuoka, ”An EMG-Controlled Hand Exoskeleton for Natural Pinching”, *Journal of Robotics and Mechatronics*, vol. 16, no. 5, 2004, pp. 482-488

[28] D.S. Andreasen, S.K. Allen, D.A. Backus, , ”Exoskeleton with EMG Based Active Assistance for Rehabilitation”, *Proc. of International Conf. on Rehabilitation Robotics*, 2005, pp. 333-336

[29] A.V. Hill, ”The heat of shortening and the dynamic constants of muscle”, *Proc. of the Royal Society of London. Series B, Biological Sciences*, vol. 126, no.843, 1938, pp. 136-195

[30] http://biorobotics.eng.uci.edu/

[31] T. Nef, M. Mihelj, G. Colombo, R. Riener, ”ARMin-Robot for Rehabilitation of the Upper Extremities”, *Proc. of IEEE International Conf. on Robotics and Automation*, Orlando, USA, 2006, pp. 3152-3157

[32] R. Martini, ”Aging and the muscular system”, Chapter 10: Muscle Tissue, *Fundamentals of Anatomy and Physiology*, 5th Edition, Benjamin-Cummings Publishing Company, 2000

[33] E. Niedermeyer, F. H. Lopes da Silva, Electroencephalography: Basic principles, clinical applications and related fields, 3rd edition, Lippincott, Williams & Wilkins, Philadelphia, 1993

[34] M. Teplan, Fundamentals of EEG measurement, *Measurement Science Review*, 2, 2002, pp. 1-11

[35] H. L. Atwood, W. A. MacKay, Essentials of neurophysiology, B.C.Decker, Hamilton, Canada, 1989

[36] www.medical.toshiba.com

[37] www.elekta.com

[38] Gerwin Schalk, Eric C. Leuthardt, ”Brain-Computer Interfaces Using Electrocorticographic Signals”, *IEEE Reviews In Biomedical Engineering*, vol. 4, 2011, pp. 140-154

[39] www.shimadzu.com

[40] K. Kiguchi, M.L iyanage, Y. Kose, Y. Hayashi, D.Jeon, ”3D Perception-Assist for an Upper-Limb Power-Assist Exoskeleton” , *Proc. of the 14th IASTED International Conf. on Robotics and Applications*, 2009, pp. 60-66

[41] Kazuo Kiguchi, Manoj Liyanage, Yasunori Kose, ”Perception Assist with an Active Stereo Camera for an Upper-Limb Power-Assist Exoskeleton”, *International Journal*

of Robotics and Mechatronics, vol. 21, no. 5, 2009, pp. 614-620

[42] K. Kiguchi, Y. Kose, Y. Hayashi, ”An Upper-Limb Power- AssistExoskeleton Robot with Task-Oriented Perception-Assist”, P*roc.of IEEE/RAS-EMBS International Conf. on Biomedical Robotics and Biomechatronics*, 2010, pp. 88-93

[43] K. Kiguchi, Y. Hayashi, ”Adaptive Perception-Assist to Various Tasks for an Upper-Limb Power-Assist Exoskeleton Robot”, *Proc. of IEEE International Conf. on Systems, Man and Cybernetics*, 2011, pp. 717-721

[44] J.L. Pons, et al., ”Upper-Limb Robotic Rehabilitation Exoskeleton: Tremor Suppression, Rehabilitation Robotics”, edited by S. S. Kommu, 2007, pp. 453-470

[45] Kazuo Kiguchi, Yoshiaki Hayashi, ”Upper-Limb Tremor Suppression with a 7DOF Exoskeleton Power-Assist Robot” , *Proc. of 35th Annual International Conf.on the IEEE Engineering in Medicine and Biology Society (EMBC2013)*, 2013

[46] Kazuo Kiguchi, Yoshiaki Hayashi, Toyoko Asami, ”An Upper- Limb Power-Assist Robot with Tremor Suppression Control”, *Proc. of IEEE International Conf. on Rehabilitation Robotics (ICORR2011)*, pp. 440-443

[47] http://www.emotiv.com

[48] http://www.gtec.at

[49] http://www.quasarusa.com

[50] http://neurosky.com

[51] http://www.egi.com/

[52] Jaakko Malmivuo, Robert Plonsey, Bioelectromagnetism, Oxford University Press, New York, 1995, ISBN 0-19-505823-2

[53] H.H. Jasper, ”The ten-twenty electrode system of the International Federation”, *Electroencephalography and Clinical Neurophysiology*, 1958, pp. 371-375

[54] F. Sharbrough , G.E. Chatrian, RP. Lesser, H. Lders, M.Nuwer, TW.Picton, ”American Electroencephalographic Society Guidelines for Standard Electrode Position Nomenclature”, *Journal of Clinical Neurophysiology*, vol. 8, 1991, pp. 200-202

[55] D.W. Klass, ”The Continuing Challenge of Artifacts in the EEG”, *American Journal of EEG Technology*, vol.35, 1995, pp. 239-269

[56] Tzyy Ping Jung, Scott Makeig, Colin Humphries, Te-Won Lee, Martin J. Mckeown, Vicente Iragui, Terrence J. Sejnowski, ”Removing electroencephalographic artifacts by blind source separation”, *Psychophysiology*, 37, 2000, pp. 163-178

[57] R.J. Croft, R.J. Barry, ”Removal of ocular artifact from the EEG: a review”, *Clinical*

Neurophysiology, vol. 30, no. 1, 2000, pp. 5-19

[58] S. Fok , R. Schwartz, M.W Ronkiewicz, C. Holmes, J. Zhang, T. Somers, D.Bundy, E.Leuthardt , "An EEG-based brain computer interface for rehabilitation and restoration of hand control following stroke using ipsilateral cortical physiology", 3*3rd Annual International Conf. of the IEEE EMBS*, Boston, Massachusetts USA, 2011

[59] Martin Lotze , Ulrike Halsband, "Motor imagery", *Journal of Physiology* , Paris, vol.99, 2006, pp. 386-395

[60] G. Onose, C. Grozea, A. Anghelescu, C. Daia , C.J. Sinescu, A.V. Ciurea, et al, "On the feasibility of using motor imagery EEG-based brain-computer interface in chronic tetraplegics for assistive robotic arm control: a clinical test and long-term post-trial follow-up", *Spinal Cord*, vol. 50, 2012, pp. 599-608

[61] A. Ramos-Murguialday, M. Schrholz, V. Caggiano, M. Wildgruber, A.Caria, et al. "Proprioceptive Feedback and Brain Computer Interface (BCI) Based Neuroprostheses", *PLoS ONE* , vol. 7, no. 10, 2012, e47048, doi:10.1371/journal.pone.0047048

[62] A.A. Frolov et al, "Principles of Neurorehabilitation Based on the Brain Computer Interface and Biologically Adequate Control of the Exoskeleton", *Human Physiology*, vol. 39, no. 2, 2013, pp. 196-208

[63] F. Lotte, M. Congedo, A. Lsecuyer, F. Lamarche, B. Arnaldi, "A Review of Classication Algorithms for EEG-based Brain-Computer Interfaces", *Journal of Neural Engineering*, vol. 4, no. 2, 2007

[64] G. Pfurtscheller, F.H. Lopes da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles", *Clinical Neurophysiology*, vol. 110, no. 11, 1999, pp. 1842-1857

[65] D. Regan, Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine, New York, NY, Elsevier, 1989

[66] Guangyu Bin, Xiaorong Gao, Yijun Wang, Bo Hong, Shangkai Gao, "VEP-Based Brain-Computer Interfaces: Time, Frequency, and Code Modulations [Research Frontier]", *IEEE Computational Intellegence Magazine*, vol. 4, 2009, pp. 22-26

[67] Luis Fernando Nicolas-Alonso, Jaime Gomez-Gil, "Brain Computer Interfaces, a Review", *Sensors*, vol.12, no. 2, 2012, pp. 1211-1279, doi:10.3390/s120201211

[68] Takeshi Sakurada, Toshihiro Kawase, Kouji Takano, Tomoaki Komatsu, Kenji Kansaku, "A BMI-based occupational therapy assist suit: asynchronous control by SSVEP", *Frontiers in Neuroscience*, vol. 7, 2013

[69] Chih Wei Chen. Chou Ching K, "Hand Orthosis Controlled Using Brain computer Interface", *Journal of Medical and Biological Engineering*, vol. 29, no. 5, 2009, pp. 234-241.

[70] Rupert Ortner, Brendan Z. Allison, Gerd Korisek, Herbert Gaggl, Gert Pfurtscheller, ”An SSVEP BCI to Control a Hand Orthosis for Persons With Tetraplegia”, *IEEE Trans. On Neural Systems and Rehabilitation Engineering*, vol. 19, no. 1, 2011

[71] Gert Pfurtscheller, Teodoro Solis-Escalante, Rupert Ortner, Patricia Linortner, Gernot R Mller-Putz, ”Self-paced operation of an SSVEP-Based orthosis with and without an imagery-based ”brain switch:” a feasibility study towards a hybrid BCI”, *IEEE Trans. on neural systems and rehabilitation engineering*, vol. 18, no. 4, 2010, pp. 409-414

[72] Guillaume Clauzel, Christa Neuper and Gernot Mller-Putz, ”Offline Decoding of Hand Movement Directions from Non-Invasive EEG”, *International Journal of Bioelectromagnetism*, vol. 13, no. 2, 2011, pp. 90-91

[73] Trent J. Bradberry, Rodolphe J. Gentili, Jose L. Contreras-Vidal, ”Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals”, *The Journal of Neuroscience*, vol. 30, no. 9, 2010, pp. 3432-3437

[74] T.D. Lalitharatne, A. Yoshino, Y. Hayashi, K. Teramoto, K. Kiguchi, ”Toward EEG control of upper limb power-assist exoskeletons: A preliminary study of decoding elbow joint velocities using EEG signals”, *Proc. of International Symposium on Micro-NanoMechatronics and Human Science (MHS)*, 2012, pp. 421-424

[75] S. Moubarak, M.T. Pham, T. Pajdla, T. Redarce, ”Design and modeling of an upper extremity exoskeleton”, *Proc. 11th International Congress of the IUPESM : medical physics and biomedical engineering world congress*, 2009, pp. 476-479

[76] N. Jarrass, M. Tagliabue, J.V.G. Robertson, A. Maiza, V. Crocher, A. Roby-Brami, G. Morel, ”A Methodology to quantify alterations in human upper limb movement during comanipulation with an exoskeleton”, *IEEE Trans. on neural systems and Rehabilitation Engineering*, vol. 18, no. 4, 2010, pp. 389-397

[77] K. Kiguchi, Y. Hayashi, ”An EMG Based Control for an Upper-Limb Power-Assist Exoskeleton Robot”, *IEEE Trans. on Systems, Man and Cybernetics-Part B*, vol. 42, no. 4, 2012, pp. 1064-1071

[78] G.R. Muller-Putz, G. Pfurtscheller, ”Control of an electrical prosthesis with an SSVEP based BCI”, *IEEE Trans. on Biomedical Engineering*, vol. 55, no. 1, 2008, pp. 361-364

[79] Jonathan R. Wolpaw, Niels Birbaumer, Dennis J. McFarlanda, Gert Pfurtschellere, Theresa M. Vaughan , ”Brain-computer interfaces for communication and control”, *Clinical Neurophysiology*, vol. 113, no. 6, 2002, pp. 767-791

[80] R. Martini, ”Aging and the muscular system, Chapter 10: Muscle Tissue”, In 5th Edition, *Fundamentals of Anatomy and Physiology*, Benjamin-Cummings Publishing Company, 2000

[81] R. Leeb, H. Sagha, R. Chavarriaga, Jdel R. Millan, ”A hybrid brain-computer interface based on the fusion of electroencephalographic and electromyographic activities”, *Journal of Neural Engineering*, vol. 8, no. 2, 2011, doi: 10.1088/1741-2560/8/2/025011

[82] R. Leeb, H. Sagha, R. Chavarriaga , Jdel R. Millan, ”Multimodal Fusion of Muscle and Brain Signals for a Hybrid-BCI”, *Proc. of Annual International Confernece of The IEEE Engineering in Medicine and Biology Society*, 2010, pp. 4343-4346

[83] E. Rocon, J.A. Gallego, L. Barrios, A.R. Victoria, J. Ibanez, D. Farina, F. Negro, J.L. Dideriksen, S. Conforto T.D Alessio, G. Severini, J.M. Belda-Lois, L.Z. Popovic, G. Grimaldi, M. Manto, J.L. Pons, ”Multimodal BCI-mediated FES suppression of pathological tremor”, *Proc. of Annual International Confernece of The IEEE Engineering in Medicine and Biology Society*, 2010, pp. 3337-3340

[84] Kazuo Kiguchi, Yoshiaki Hayashi, ”A Study of EMG and EEG during Perception-Assist with an Upper-Limb Power-Assist Robot”, *Proc. of IEEE International Conference on Robotics and Automation*, 2012, pp. 2711-2716

[85] Subrata Kumar Kundu, Kazuo Kiguchi, Etsuo Horikawa, ”Design and Control Strategy for a 5 DOF Above-Elbow Prosthetic Arm”, *International Journal of Assistive Robotics and Mechatronics*, vol. 9, 2008, pp. 79-93

[86] Kazuo Kiguchi, Thilina Dulantha Lalitharatne, Yoshiaki Hayashi, ”Estimation of Forearm Supination/Pronation Motion Based on EEG Signals to Control an Artificial Arm”, *Journal of Advanced Mechanical Design, Systems, and Manufacturing*, vol. 7, 2013, pp. 74-81

[87] S.K. Kundu, K. Kiguchi, ”Development of a 5-DOF Prosthetic Arm for Above Elbow Amputees”, *Proc. of IEEE International Conference on Mechatronics and Automation*, 2008, pp. 207-212

[88] F. Cincotti, F. Pichiorri, P. Arico, F. Aloise,F. Leotta, F. de Vico Fallani, Jdel R. Milln , M. Molinari, D. Mattia, ”EEG-based Brain- Computer Interface to support post-stroke motor rehabilitation of the upper limb”, *Proc. of Annual International Confernece of The IEEE Engineering in Medicine and Biology Society*, 2012, pp. 4112-4115

[89] G.R. Muller-Putz, C. Breitwieser, Michael Tangermann, Martijn Schreuder, M. Tavella, R. Leeb, F. Cincotti, F. Leotta, C. Neuper, ”Tobi hybrid BCI: principle of a new assistive method”, *International Journal of Bioelectromagnetism*, vol. 13, 2011, pp. 144-145

[90] Gernot R. Muller-Putz, Christian Breitwieser, Febo Cincotti, Robert Leeb, Martijn Schreuder, Francesco Leotta, Michele Tavella, Luigi Bianchi , Alex Kreilinger, Andrew Ramsay, Martin Rohm, Max Sagebaum, Luca Tonin, Christa Neuper,

Josedel.R.Millan, ”Tools for brain-computer interaction: a genaral concept for a hybrid BCI”, *Frontiers in Neuroinformatics*, 2011, doi: 10.3389/fninf.2011.00030

[91] J.R. Wolpaw, D.J. McFarland, T.M. Vaughan, ”BrainComputer Interface Research at the Wadsworth Center”, *IEEE Trans. on Rehabilitation Engineering*, vol. 8, no. 2, 2000, pp. 222-226

[92] Theresa M. Vaughan, Jonathan R. Wolpaw, Emanuel Donchin, ”EEG-Based Communication: Prospects and Problems”, *IEEE Trans. on Rehabilitation Engineering*, vol. 4, no.4, 1996, pp. 425-430

[93] Muscle faitgue, Wikipedia, http://en.wikipedia.org/wiki/Muscle_fatigue

[94] Roger.M. Enoka, Jacques Duchateau, ”Muscle fatigue: what, why and how it influences muscle function”, *Journal of Physiology*, vol. 586, no. 1, 2008, pp. 11-23

[95] T. Sadoyama, T. Masuda, H. Miyano, ”Relationship between muscle fiber conduction velocity and frequency parameters of surface EMG during sustained contraction” , *European Journal of Applied Physiology*, vol. 51, 1983, pp. 247-256

[96] M. Hagberg, ”Electromyographic Signs of Shoulder Muscular Fatigue in Two Elevated Arm Positions”, *American Journal of Physical Medicine*, vol. 60, 1981, pp. 111-121

[97] R. Merletti, L.R. Lo Conte, ”Surface EMG signal processing during isometric contractions”, Journal of Electromyography and Kinesiology, vol.7, no.4, 1997, pp. 241-250

[98] F. Stulen, C.J. De Luca, ”Frequency parameters of the myoelectric signals as a measure of muscle conduction velocity”, *IEEE Trans. on Biomedical Engineering*, vol.28, no.7, 1981, pp 515-523

[99] J.R. Potvin, ”Effects of muscle kinematics on surface EMG amplitude and frequency during fatiguing dynamic contractions”, *Journal of Applied Physiology*, vol.82, no.1, 1997, pp. 144-151

[100] M.A. Nussbaum, ”Static and dynamic myoelectric measures of shoulder muscle fatigue during intermittent dynamic exertions of low to moderate intensity”, *European Journal of Applied Physiology*, vol.85, no.3-4, 2001, pp. 299-309

[101] J.R. Potvin, L.R. Bent, ”A validation of techniques using surface EMG signals from dynamic contractions to quantify muscle fatigue during repetitive tasks”, *Journal of Electromyography and Kinesiology*, vol.7, no.2, 1997, pp. 131-139

[102] A.Luttmann, M. Jager, W. Laurig, ”Electromyographical indication of muscular fatigue in occupational field studies”, *International Journal of Industrial Ergonomics*, vol.25, no.6, 2000, pp. 645-660

[103] D.T. MacIsaac, P.A. Parker, K.B. Englehart, D.R. Rogers, ”Fatigue estimation with a multivariable myoelectric mapping function”, *IEEE Trans. on Biomed Engineering*, vol.53, 2006, pp. 694-700

[104] M. Gonzalez-Izal, D. Falla, M. Izquierdo, D. Farina, ”Predicting force loss during dynamic fatiguing exercises from non-linear mapping of features of the surface electromyogram”, *Journal of Neuroscience Methods*, vol.190, 2010, pp. 271-278

[105] Ruwan Gopura, PhD Thesis, Department of Advanced Technology Fusion, Saga University, 2009

[106] K. Kiguchi, Q. Quan, ”Muscle-Model-Oriented EMG-Based Control of an Upper-Limb Power-Assist Exoskeleton with a Neuro-Fuzzy Adjuster”, *Proc. of IEEE World Congress of Computational Intelligence*, 2008, pp. 1179-1184

[107] R.A.R.C. Gopura, K. Kiguchi, ”SUEFUL-7: A 7 DOF Upper-Limb Exoskeleton Robot with Muscle-Model-Oriented EMG-Based Control”, *Proc. of IEEE/RSJ Int.Conf. on Intelligent Robots and Systems*, 2009, pp. 1126-1131

[108] F. Lotte, M. Congedo, A. Lcuyer, F. Lamarche , B. Arnaldi, ”A review of classification algorithms for EEG-based brain-computer interfaces”, *Journal of Neural Engineering*, vol. 4, no. 2, 2007

[109] Net Station Acquisition Technical Manual, Electrical Geodesics, Inc.

[110] Geodesic Sensor Net Technical Manual, Electrical Geodesics, Inc.

[111] K. Kiguchi, M. Liyanage, ”A Study on a 4DOF Upper-Limb Power- Assist Exoskeleton with Perception-Assist”, *Proc. of International Conf. on Biomedical Electronics and Devices*, 2008, pp. 164-169

[112] K. Kiguchi, Y. Kose, Y. Hayashi, ”An Upper-Limb Power-Assist Exoskeleton Robot with Task-Oriented Perception-Assist”, *Proc. of IEEE/RAS-EMBS International Conf. on Biomedical Robotics and Biomechatronics*, 2010, pp. 88-93

[113] K. Kiguchi, Y. Hayashi, ”Adaptive Perception-Assist to Various Tasks for an Upper-Limb Power-Assist Exoskeleton Robot”, *Proc. of IEEE International Conf. on Systems, Man and Cybernetics*, 2011, pp. 717-721

[114] M. Falkenstein, J. Hoormann, S. Christ, J. Hohnsbein, ”ERP components on reaction errors and their functional significance: A tutorial”, *Biological Psychology*, vol. 51, 2000, pp. 87-107

[115] D.H. Mathalon, S.L. Whitfield, J.M. Ford, ”Anatomy of an error: ERP and fMRI”, *Biological Psychology*, vol.64, no. 12, 2003, pp. 119-141

[116] Matthew M. Botvinick, Jonathan D. Cohen, Cameron S. Carter, ”Confict monitoring and anterior cingulate cortex: an update”, *Trends in Cognitive Seciences*, vol.8,

no.12, 2004, pp. 529-546

[117] P.W. Ferrez, J.d.R. Milln, ”You are wrong!Automatic detection of interaction errors from brain waves”,*19th International Joint Conf. Artificial Intelligence*, Edinburgh, U.K., Aug 2005

[118] E. Lopez-Larraz, I. Iturrate, L. Montesano, J. Minguez, ”Real-time recognition of feedback error-related potentials during a time-estimation task”, *Proc. of the Annual International Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2010, pp. 2670-2673

[119] I. Iturrate, L. Montesano, J. Minguez, ”Robot Reinforcement Learning using EEG-based reward signals”, *2010 IEEE International Conf. on Robotics and Automation*, Anchorage, USA, 2010

[120] D.J.McFarland, L.M.McCane, S.V.David, J.R.Wolpaw, ”Spatial filter selection for EEG-based communication”, *Electoencephalography and clinical neurophysiology*, vol. 103, no. 3, 1997, pp. 386-394

[121] V. Vapnik, Statistical learning theory, Wiley, 1998

[122] B. Blankertz, G. Curio, K.Muller, ”Classifying single trial EEG: Towards brain computer interfacing”, *Advances in Neural Information Processing Systems*, vol. 14, 2002, pp. 157-164

[123] K.P. Bennett, C. Campbell ”Support vector machines: hype or hallelujah?”, *ACM SIGKDD Explorations Newsletter*, vol. 2, no. 2, 2000, pp. 1-13

[124] A.K. Jain, R.P.W. Duin, J. Mao, ”Statistical pattern recognition: A review”, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 22, no. 1, 2000, pp. 4-37

[125] K. Kiguchi, Y. Imada, and M. Liyanage, ”EMG-based neuro-fuzzy control of a 4DOF upper-limb power-assist exoskeleton”, *Proc. IEEE Int. Conf. Eng. Med. Biol. Soc.*, 2007, pp. 3040-3043.