T.C.
SAKARYA UNIVERSITY OF APPLIED SCIENCES
GRADUATE EDUCATION INSTITUTE

THE EFFECT OF EMG-BASED ATTENTIONAL FOCUS ON HUMAN MACHINE INTERFACE APPLICATIONS

Ph.D. THESIS

Ayse Nur AY

Institute Department : MECHATRONICS ENGINEERING

Supervisor : Assoc. Prof. Dr. Mustafa Zahid YILDIZ

April 2021

T.C.
SAKARYA UNIVERSITY OF APPLIED SCIENCES
GRADUATE EDUCATION INSTITUTE

THE EFFECT OF EMG-BASED ATTENTIONAL FOCUS ON HUMAN MACHINE INTERFACE APPLICATIONS

Ph.D. THESIS

Ayse Nur AY

Institute Department : MECHATRONICS ENGINEERING

This thesis has been accepted unanimously of votes by the examination committee on 02/ 04/ 2021.

JURY	SUCCESS STATUS
Head of Jury: Assoc. Prof. Dr. Mustafa Zahid YILDIZ	Successfully completed
Jury Member: Prof. Dr. Ali Fuat BOZ	Successfully completed
Jury Member: Prof. Dr. Rasit KOKER	Successfully completed
Jury Member: Assoc. Prof. Dr. Adil Deniz DURU	Successfully completed
Jury Member: Assist. Prof. Dr. Mehmet KOCATURK	Successfully completed

DECLERATION

I declare that all the data in this thesis was obtained by myself in academic rules, all visual and written information and results were presented in accordance with academic and ethical rules, there is no distortion in the present data, in case of utilizing other people's works they were refereed properly to scientific normas, the data presented in this thesis has not been used in any other thesis in this university or in any other university.

Ayse Nur Ay

17/ 03/ 2021

ACKNOWLEDGEMENTS

I would like to extend to my acknowledgement and my sincere gratitude to all people who helped me to complete this Ph.D. study.

Firstly, I would like to express my deepest appreciation to my supervisor Assoc. Prof. Dr. Mustafa Zahid YILDIZ from Sakarya University of Applied Sciences for encouraging me and for providing me all facilities to complete this thesis. His guidance and valuable suggestions helped me a lot during my research.

Secondly, I would like to express my gratitude to my thesis committee: Prof. Dr. Ali Fuat BOZ and Prof. Dr. Rasit KOKER from Sakarya University of Applied Sciences for their helpful comments and suggestions during my thesis progress.

Thirdly, I would like to give my special thanks to Prof. Dr. Osman ELDOGAN and Assist. Prof. Dr. Kasım SERBEST for providing me the EMG measurement device that made it possible for me to perform all my experiments for this thesis. I want to also thank to my labmate Baris DOLUKAN for being voluntary to my all preliminary measurements and for his moral support during Ph. D study period. Furthermore, I appreciate the help from all my volunteer students for their contribution to the experiments.

Finally, I am grateful the most to my family for being my source of strength, for their support in achieving my academic goals and always on my side in every condition.

TABLE OF CONTENTS

LIST OF ABBREVIATONS

ANN	: Artificial Neural Network
BF	: Biceps Femoris
BPA	: Backpropagation Algorithm
CWT	: Continuous Wavelet Transform
DNN	: Deep Neural Network
DWT	: Discrete Wavelet Transform
EMG	: Electromyography
FFT	: Fast Fourier Transform
HMI	: Human Machine Interface
IEMG	: Integrated Electromyography
KNN	: K-nearest-neighbors
MAV	: Mean Absolute Value
MUAPTs	: Motor Unit Action Potentials
MUs	: Motor Units
MVC	: Maximum Voluntary Contraction
PCA	: Principal component Analysis
RELU	: Rectified Lieer Unit
RMS	: Root Mean Square
SD	: Standart Deviation
SE	: Standart Error
SM	: Semimembranosus
ST	: Semitendinosus
SVM	: Support Vector Machine
WT	: Wavelet Transform

SYMBOLS

cm	: Centimeter
f	: frequency
kg	: kilogram
kHz	: Kilohertz
mV	: Milivolt
N	: Length of the signal
p	: Significance level
y	: year (age)
Xn	: the signal
µV	: Microvolt

LIST OF TABLES

LIST OF FIGURES

THE EFFECT OF EMG-BASED ATTENTIONAL FOCUS ON HUMAN MACHINE INTERFACE APPLICATIONS

SUMMARY

It is well known that attentional focus instructions affect motor skills and learning of performers. These instructions are divided into two groups: internal focus and external focus. Many studies showed that external focus of attention enhances motor performance and learning but reduces muscular activity whereas, internal focus of attention increases it. The low muscular activity results in more efficient movements especially in case of sport performances. Nevertheless, low muscular activity is not always preferred in engineering field such as prosthetics, EMG-based robotics, Human Machine Interface applications.

In this thesis, three different approaches, based on the effects of attentional focus strategies on muscular activity, are proposed.

In the first step, several EMG mesurements were conducted. During the experiments, the participants performed weight-lifting (2 kg dumbbell) under control, no instuctions were given, internal, focusing on the active muscle and external, focusing on the dumbbell, focus of attentions. The EMG records via biceps brachii muscle of the participants were analysed statistically. The Wilcoxon Sign-Ranks tests results showed that, for RMS, MAV, IEMG and Integrated FFT parameters there was a significant difference ($p = 0.05$) between external and internal focus groups and internal focus enabled higher EMG activity. In addition, the main effect of attentional focus between control and external groups was also significant. However, there was no statistical difference between control and internal data.

The second approach was based on classification of the EMG signals according to participants' attentional focus preferences. For this purpose, six statistical features, namely, maximum, minimum, mean, standard deviation, RMS and variance of recorded EMG signals were extracted from both time and frequency domains. These feautures were used as inputs for Artificial Neural Network (ANN) classifiers. The classification rates of ANNs were found to be 87.54% for time-domain and 82.69% for frequency domain. These findings suggest that even though the origin of the signal belongs to same healthy person, just by changing the attentional focus preferences, EMG activity differed remarkably.

Although these results were promising in the field of engineering, in case of EMG-based control mechanisms, the classifier performances would expected to be in very high accuracy. Consequently, the signals were classified using Deep Neural Networks (DNN) which can enable higher accuracy. Here, DNNs were designed using coefficients, 4^{th} level, of DB4 and HAAR wavelets as inputs. The classification rates were found to be 99.07% and 99.54%, respectively. Since these DNNs the attentional focusing types were

classified in a very high accuracy, here it was hypothesized that attentional focus preferences would be used as alternate inputs to HMIs.

The third approach investigated the impacts of attentional focus strategies on hamstring muscles which are responsible for hip and knee movements in many sports. The experiment was designed to examine the EMG activity of hamstring muscles, the semitendinosus, the semimembranosus and the biceps femoris on amateur football players during leg curl exercises. The results of the experiments showed that while the EMG activity response of semitendinosus and semimembranosus were in line with literature in case of attentional focus preferences, the biceps femoris shows no significant response regarding change between attentional instructions. Since hamstring muscle injuries are the most common sports injury, these findings can help trainers for planning their exercise programs. Besides, these results also provides a better understanding of mind-muscle connection phenomena and highlights the outlier amongst the common acceptance.

In summary, the findings of this thesis show that one's focus of attention could be predicted using neural networks, during the performance. Hence, attentional focusing might be an important strategy not only for performance improvement to human movement but also for advancing the EMG-based control applications. Besides, it is also highlighted here that positive effect of verbal instructions via internal focus might also be useful for physicians to plan effective muscular rehabilitation treatment for patients who suffered a stroke or a disorder of lower or upper limb extremities. Furthermore, the results of attentional focus effects were not limited to only control mechanisms, but also in sport fields.

Keywords: Attentional focus, Electromyography, EMG-based classification, HMI.

DİKKATLE ODAKLANMANIN EMG-TEMELLİ İNSAN MAKİNE ARAYÜZÜ UYGULAMALARINA ETKİSİ

ÖZET

Dikkatle odaklanma direktiflerinin motor becerilerini ve kişilerin öğrenmesini etkilediği iyi bilinmektedir. Bu direktifler genel olarak iki gruba ayrılır: iç odaklanma ve dış odaklanma. Birçok araştırma, hareketin etkisine odaklanan dış odaklanmanın, motor performansı ve öğrenmeyi artırdığını ancak bunun yanında kas aktivitesini azalttığını gösterirken, iç odaklamanın bunu artırdığını göstermiştir. Düşük kas aktivitesi, özellikle spor performanslarında daha verimli hareketler sağlasa da bunun yanısıra, özellikle protez çalışmaları, EMG tabanlı robotik, İnsan Makine Arayüzü uygulamaları gibi mühendislik alanlarında düşük kas aktivitesi her zaman tercih edilmemektedir.

Bu tezde, dikkatle odaklanma stratejilerinin kas aktivitesi üzerindeki etkilerine dayanan üç farklı yaklaşım önerilmiştir.

İlk adım olarak, birtakım EMG ölçümleri yapılmıştır. Deneylerde, katılımcılara kontrol (hiçbir talimatın verilmediği), iç odaklanma (aktif kasa odaklanma) ve dış odaklanma (dambıla odaklanma) durumları altında 2 kg' lık dambıl kaldırma hareketleri yaptırılmıştır. Katılımcıların biseps brachii kasları üzerinden EMG kayıtları istatistiksel olarak analiz edilmiştir. Wilcoxon Sign-Ranks test sonuçları, RMS, MAV, IEMG ve Integrated FFT parametreleri için dış ve iç odak grupları arasında önemli bir fark olduğunu ($p = 0.05$) ve iç odaklamanın daha yüksek EMG aktivitesini sağladığını göstermiştir. Ek olarak, kontrol ve dış odaklanma grupları arasındaki dikkatle odaklanmanın ana etkisi de istatistiksel olarak önemli bulunmuştur. Bununla birlikte, kontrol ve iç odaklanma verileri arasında istatistiksel bir fark görülmemiştir.

İkinci yaklaşım, katılımcıların dikkatle odaklanma tercihlerine göre EMG sinyallerinin sınıflandırılmasına dayandırılmıştır. Bu amaçla, kaydedilen EMG sinyallerinin maksimum, minimum, ortalama, standart sapma, RMS ve varyansı olmak üzere altı farklı istatistiksel özellikleri hem zaman hem de frekans alanlarından çıkarılmıştır. Bu özellikler, Yapay Sinir Ağı (YSA) sınıflandırıcıları için girdi olarak kullanılmıştır. YSA sınıflandırma oranları sırasıyla zaman alanı için % 87,54 ve frekans alanı için% 82,69 olarak bulunmuştur. Bu bulgular, sinyalin kaynağı aynı sağlıklı kişiye ait olsa bile, kişilerin sadece dikkatle odaklanma tercihlerini değiştirerek, EMG aktivitelerinin önemli ölçüde farklı olabileceğini göstermiştir.

Bu sonuçlar mühendislik alanı için ümit verici olsa da, yine de EMG tabanlı kontrol mekanizmaları düşünüldüğünde, sınıflandırıcı performanslarının çok yüksek doğrulukta olması beklenir. Bu nedenle, bir sonraki aşama olarak sinyaller, daha yüksek doğruluk sağlayabilen Derin Sinir Ağları (DNN) kullanılarak sınıflandırılmıştır. Burada DNN'ler, giriş olarak DB4 ve HAAR ana waveletlerin 4. seviye katsayıları kullanılarak tasarlanmıştır. Sınıflandırma başarı oranları sırasıyla DB4 için % 99,07 ve HAAR için % 99,54 olarak bulunmuştur. Bu DNN'ler dikkatle odaklanma çeşitlerini çok yüksek bir

doğrulukla sınıflandırıldığından, burada kişilerin dikkatle odaklanma tercihlerinin İnsan-Makine Arayüzlerine alternatif girdiler olarak kullanılabileceği varsayılmıştır.

Üçüncü yaklaşım olarak, birçok spor alanında kalça ve diz hareketlerinden sorumlu olan hamstring kasları üzerindeki dikkatle odaklanma stratejilerinin etkileri araştırılmıştır. Deneyler, amatör futbolcuların semitendinosus, semimembranosus ve biseps femoris hamstring kaslarının EMG aktivitelerini bacak kıvırma egzersizleri sırasında incelemek için tasarlanmıştır. Bu deneylerin sonuçları incelendiğinde, semitendinosus ve semimembranosus'un dikkatle odaklanma tercihleri durumlarındaki EMG aktivitelerinin literatürle uyumlu olduğu görülmüştür. Bunun yanısıra, biseps femoris kaslarının dikkatle odaklanma talimatlarına istatistiksel olarak önemli bir yanıt vermediğini tespit edilmiştir. Hamstring kasları yaralanmaları en yaygın spor yaralanmaları olduğundan, bu bulgular antrenörlerin egzersiz programlarını planlamalarına yardımcı olabilir. Ayrıca, bu sonuçlar aynı zamanda zihin-kas bağlantısı fenomeninin daha iyi anlaşılmasını sağlamış olup, ortak kabul edilmiş düşünceler içerisindeki aykırı yaklaşımı vurgulamıştır.

Anahtar Kelimeler: Dikkatle odaklanma, Elektromiyografi, EMG tabanlı sınıflandırma, HMI.

CHAPTER 1. INTRODUCTION

This chapter of the thesis is prepared for better understanding and easier following of the studies. The introduction of an attentional focus and detailing the relation of attentional focus with electromyography are the main purpose of this chapter. Additionally, summary information about Human Machine Interface and the recognition of research gaps are given here. Moreover, the methods and results of the earlier studies were investigated here. Finally, the aim of this thesis and hypothesis are also clarified in this section.

1.1. Attentional Focus

Attentional focus is defined as the focus of a person's attention at a specific moment. First studies about attentional focus have been demonstrated that verbal instructions and feedback through an individual's focus of attention have an important influence on performance and learning of motor skills.

Salmoni et al., conducted several experiments using a probe technique and movement types. Their results showed that the longer movements were less attention demanding than the shorter movements. They also concluded that movement time had no effect on the results (Salmoni et al., 1976).

Newell and Hoshizaki studied attention, movement duration and velocity. Their experimental results showed that attention demands of movement can change according to movement velocity (Newell & Hoshizaki, 1980).

Wulf et al., presented that if instructions or a feedback is given to a learner while he or she is performing, their learning may be enhanced. Besides, they also showed that the time needed to complete the performance can be reduced (Gabriele Wulf et al., 1998).

Shea and Wulf investigated the effects of attentional focus instructions and feedback on motor learning. They concluded that type of instructions is a criteria for enhancing motor skill learning (Shea & Wulf, 1999).

Wulf et al., studied the effects of attentional focus in sport skill. Their experiments were based on practicing pitch shots in golf. Participants had no experience in playing golf. Their results showed that type of instructions had effects on the performance of the participants (Gabriele Wulf et al., 1999).

As known, attentional instructions are given during or before the performance and contain information about the way of performing the skill. Besides, they may be related to the learning of difficult skills. For example, in case of sports, a learner's focus of attention must be directed on the relevant features of the task. In order to achieve that kind of focus of attention, a learner is generally directed with information about the right placement of different body parts, dynamics or timing of the movements. However, a researcher must know what kind of information should be given to the performer.

In order to provide better understanding about learning process, the effectiveness of different types of attentional focus instructions were investigated experimentally by Wulf et al. (Gabriele Wulf et al., 1998). Their results showed that the impact of attentional instructions is influenced by the way in which they are presented to the learner. Therefore, atttentional focus strategies were divided into two types: external and internal focus of attention.

1.1.1. Internal focus vs. external focus

An internal instruction directs a performer's focus on body movements or the action itself whereas, an external instruction directs her/ his focus on apparatus, environment or the effect of the action. These definitions can be understood better with a dart throwing example (Lohse et al., 2014). If a performer focuses on her/his arm position or body orientation before throwing the dart, it is considered as an internal focus whereas, if she or he focuses on the target board itself, it is called an external focus.

Wulf et al. demonstrated that attentional focus instructions might be more helpful for learning if they direct it to the learner's attention to the effects of her or his movements (external focus) (Gabriele Wulf et al., 1998). In the following studies that were designed to compare the effectiveness of an internal and an external focus of attention on learner's performance such as in golf, balance-based tasks, volleyball, etc. the significant differences were found between external and internal focus. Besides, external focus found to be more effective and seemed to enhance learning skills (G. Wulf et al., 2002; Gabriele Wulf et al., 2001).

In 2001, Wulf et al. explained the difference between external and internal focusing with "*Constrained-Action Hypothesis*" (Gabriele Wulf et al., 2001). According to this hypothesis, when a subject focuses externally during a performance, the subject's motor system will be more natural and self-organized, whereas an internal focus may actually constrain automatic control processes that would normally regulate the movement. In order to test this hypothesis, they used a dynamic balance task in which the participants were directed to focus their attention either internally or externally. Consistent with the hypothesis, smaller balance errors were found in external focus group compare to internal focus group. Subsequent studies also supported this hypothesis by comparing the impact of effect-related (external) as opposed to movement-related (internal) focus of attention. For example Wulf et al., investigated the effectiveness of external focus feedback on learning. Their experimental results indicated that effect-related feedback (external) was more effective than movement-related (internal) on learning (G. Wulf et al., 2002). Mc Nevin et al., enlarged the research area by suggesting increasing the distance of an external focus. Their results demonstrated that more distance resulted more natural control of motor system (McNevin et al., 2003). Additionally, Wulf and Su investigated whether external focusing affects both beginners and experts in golf shot. Their experimental results showed that external focus enhanced the performance of experts as well (Gabriele Wulf & Su, 2007).

The performance tasks can be evaluated under two categories. Movement effectiveness and movement efficiency (Gabriele Wulf, 2013). Movement effectiveness can be associated with reliability, balance, accuracy and consistency in achieving the goal of the movement. However, movement efficiency is linked with speed, endurance, movement kinematics, maximum force production and muscular activity.

In this thesis, experimental tasks were based on examining movement efficiency. Here, attentional focus was investigated associated with muscular activity of performers during a movement.

1.1.2. Electromyography

Electromyography (EMG) is a technique deals with recording and analysis of myoelectric signals which are produced in response to the nerve stimulation in muscles. The EMG signal is composed of the action potentials, which is resulted from depolarization and repolarization processes at muscle fiber membrane, from muscle fiber groups structured into motor units (MUs). In other words, the EMG signal is simply the summation of the Motor Unit Action Potentials (MUAPTs) of all recruited motor units as presented in Figure 1.1 (Stashuk, 2001).

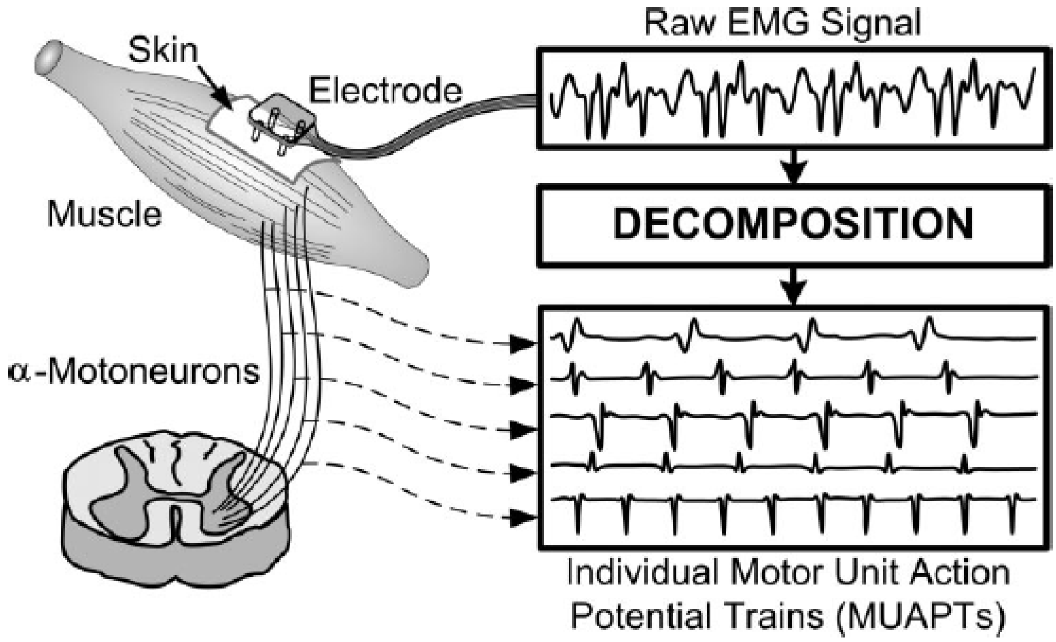


Figure 2.1 : Decomposition of the surface EMG signal.

EMG signals can be measured by electrodes attached to the skin on top of the surface muscles. However, in order to detect maximum signal, the orientation of the electrodes must be perpendicular to the muscle fibers. Besides, the EMG sensor itself should be placed in the center of the muscle belly. Therefore, it will far away from the edge of the muscles and tendons as well. In Figure 1.2 a representation of EMG sensor orientation is displayed (Delsys, 2011).

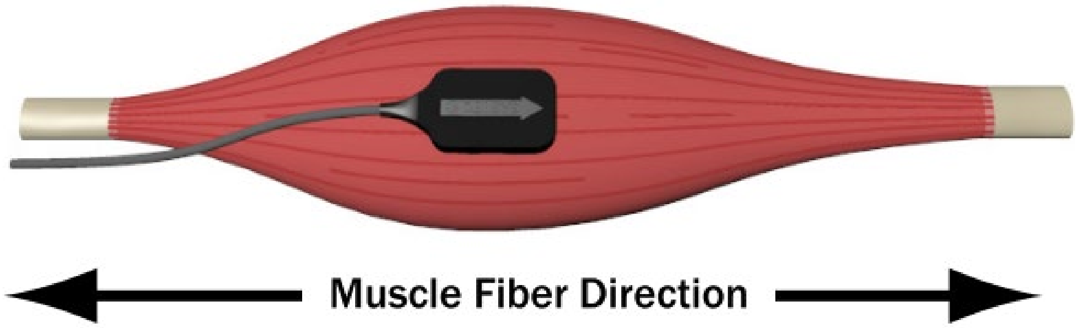


Figure 2.2 : EMG sensor orientaion with respect to the muscle fibers.

The voltage range for EMG signals is between μV to mV and they contain noise. Therefore, some filtering techniques are performed to the raw signals for processing EMGs. In addition, instrumentation amplifiers are used for noise reduction and signal amplification. A simple block diagram of surface EMG acquisition is given in Figure 1.3 (Cavalcanti Garcia & Vieria, 2011).

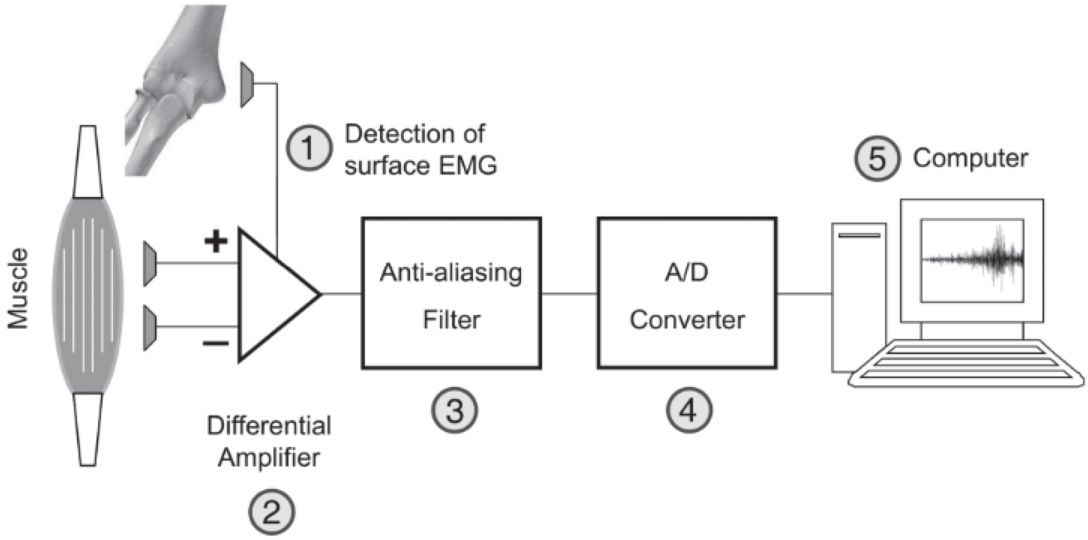


Figure 2.3 : Block diagram of surface EMG acquisition.

In Figure 1.3, number 1 represents the detection of EMG signals and a reference electrode. Number 2 is amplification step whereas, number 3 is preprocessing phase which is analog filtering. Sampling of the signal into digital voltage values is done in number 4 and finally monitoring and storing the signal is displayed in number 5.

When the EMG signals are filtered and processed as required, then feature extraction can perform on the signals. In this way, valuable information presents in signals can be determined.

In this thesis, EMG acquisition, EMG signal processing, monitoring and recording of the signals and feature extraction from EMG signals are explained step by step in Chapter 2. The relation between the muscular activity and attentional focus strategies is explained in the following section.

1.1.3. EMG-based attention

In order to learn whether the impact of attentional focusing type differences would also be established at neuromuscular level, electromyography (EMG) was used by Vance et al., for the first time (Vance et al., 2004). In their study, two experiments were conducted. In both experiments, participants were asked to perform biceps curl under various attentional focus instructions. Results of the first experiment showed that movements were performed faster under external focus condition compared to internal focus and Integrated EMG (IEMG) activity was also reduced when performers adopted externally. In the second experiment, movement time was controlled using a metronome and the results also showed that external focus reduced the EMG activity. Their findings may also be useful in sports in which maxiumum forces have to be producted. Therefore, the positive effect of external focus may be generalized to maximum force production tasks. Since external focus provides more automatic control processes, their results were in line with constrained-action hypothesis as well.

Zachry et al., confirmed and extended previous findings by demonstrating focusing externally not only reduces EMG activity but also increases movement accuracy (Zachry et al., 2005).

Marchant et al., added a control condition to their experiments to obtain maximum voluntary contraction (MVC) data and their results also showed that force production was higher and muscular activity was lower under external focus condition (Marchant et al., 2009).

Wulf et al., investigated neurophysiological mechanisms of external focus effect by using EMG on a jump and reach task. They measured muscular activity of anterior tibialis, biceps femoris, vastus lateralis, rectus femoris and gastrocnemius muscles during jumps. They found that with an external focus, EMG activity was reduced in majority of the muscles. They concluded that external focusing led to an efficient and effective movement pattern production (Gabriele Wulf et al., 2010).

Lohse et al., studied the effects of attentional focusing strategies on a force production task and they compare the agonist and antagonist muscles. Their results showed that EMG activity was lower in the antagonist (tibialis anterior) muscle. However, there was no effect of attention on the agonist (soleus) muscle (Lohse et al., 2011).

Ardakani et al., conducted an experiment with older men (mean of age 70.7 + 2.6) in order to determine the influence of attentional focus and somato-sensory manipulation on postural control and muscular activity. Their results also showed that external focus reduced EMG activity (Ardakani et al., 2015).

Ashraf et al., yielded similar results on effects of external focus with 20 children (8-10 years old). They concluded that external focus improve both efficiency and effectiveness of children's movement in a maximum force production task (Ashraf et al., 2017).

Ay et al., conducted an experiment based on weight-lifting. Their results showed that the EMG activity was also was reduced when performers focused externally which was also in line with constrain-action hypothesis (Ay et al., 2019).

Although the positive effect of external focus in movement effectiveness and efficiency appeared to be clear and consistent, still some questions remain in literature. Because, all these results underscore the performances and achievements of people with an external focus.

This thesis brings a new perspective to the studies on the effects of attentional focusing strategies. Thus, here the impacts of attentional focus preferences on EMG-based Human Machine Interface applications are elaborated which is going to be a novel approach.

1.2. EMG-Based Human Machine Interface

Although EMGs are generally used for identification of neuromuscular diseases, the EMG activity and the resulting movement has also investigated in many research by analyzing the duration, magnitude and amplitude of the signals (Sharma & Dubey, 2012; Shobhitha et al., 2013).

With the developed technology, it is also very common now to use EMGs as control signals in Human Machine Interface (HMI) interactions. An HMI is known as a component of a software application or device that allows humans to interact with machines. The main purpose of EMG-based control of HMIs is translating the user's aim (as EMG signals) into relevant computer commands. There are many HMI applications that use EMG signals to control mechanisms such as smart wheelchairs, artificial hands and prosthetics (Naseer et al., 2018; Pan et al., 2019; Rafiee et al., 2011). Such EMG-based control is possible with proper signal processing, feature extraction and accurate signal classification which is the most important part of designing EMG-based interfaces.

Ibrahimy et al., designed an Artificial Neural Network (ANN) trained by Levenberg-Marquardt algorithm for hand motion detection. Their network could classify the hand motions (left, right, up and down) from the EMG signal features with 88.4% accuracy. Therefore, they concluded that the classification efficiency would increase with enriched signals. (Ibrahimy et al., 2013).

Ahmad et al., proposed a Deep Neural Network (DNN) classifier using EMG signals for finger pattern recognition. The purpose of their study was improving classification success rate for prosthetics control. The results showed that the designed DNN was able to classify five fingers pattern with 99.3% of accuracy rate (Ahmad et al., 2018).

Naseer et al., provided improved control of individual fingers, which are the thumb, index, middle, ring and little finger of robotic hand using EMGs. A Deep Neural Network (DNN) was designed as a classifier. The success rate of the classifier was found to be 95%. They concluded that their work could be useful for hand rehabilitation as well (Naseer et al., 2018).

Shi et al., presented a bionic hand which is controlled by hand gesture recognition based on EMG signal classification. In their study, they designed a prototype for hand posture recognition with the purpose of controlling the bionic hand using EMG signals. They preferred mean absolute value, slope sign change, zero crossing, and waveform length in their algorithm for extracting features and k-nearest-neighbors (KNN) as the classifier to achieve hand-posture recognition. Their results showed that hand postures were recognized with a 94% accuracy of the classifier (Shi et al., 2018).

Tavakoli et al., offered a support vector machine (SVM) classifier using EMG signals for hand gesture recognition. Their results showed that the system recognized hand closing and opening, wrist flexion, extention and double flexion gestures with the classifier accuracy of 95 -100% (Tavakoli et al., 2018).

Nazmi et al., provided a classification system based on walking gait event detection especially in the stance and swing phases using EMGs. Their obtained results showed that the classifier with Levenberg-Marquardt algorithm performed with 87.4% accuracy (Nazmi et al., 2019).

Although recent studies within the area of EMG-based HMI, robotic control and prosthetics seem to be advanced, most of the studies do not give enough importance to the environmental, physical or mental condition of a person during the measurements.

This thesis has bridged the gap between attentional focus strategies during EMG measurements and EMG-based classifiers.

1.3. Aim of the thesis

This thesis is based on implementing attentional focusing strategies into EMG measurements in order to get comparable muscular activities and classifying performers' EMG signals according to his/her focus of attention preferences. Therefore, the classification results could be used as alternate inputs for EMG-based mechanism. With this new point of view, the useful inputs for the HMI applications would be doubled by type of attentional focus which is going to be a novel approach.

It is well-known that Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) are generally preferred for classification purposes. In this thesis, different experiments were designed for EMG measurements. The acquired EMG signals were processed and useful features were extracted out of the signals for classification purposes. As known, attentional focus is the ability of performers to select relevant stimuli while ignoring other stimuli in the environment. Since user status such as attention affects performance of control mechanism, with these proposed ANN and DNN models, attentional focus-based EMG signals could be differentiated in very high accuracy.

In literature, the importance of verbal instructions during performances are well established. As it was clarified in the previous sections, verbal instructions through external focus have shown a positive effect on movement outcomes of performers. Besides, low EMG activity, resulted external focus of attention, has many advantages such as enhancing the performer's motor skills and learning. However, in case of performance of HMI mechanisms, high EMG activity, resulted internal focus, can also have several advantages such as better signal quality which has great benefit when these signals are used as inputs for EMG-based control mechanisms.

Hypothetically, internal focusing might also have advantages especially when it is used by a therapist during a rehabilitation session. Since internal focus constrain the movement automaticity, the patient would generate more muscular activity to complete the movement. As high EMG activity is required for better control mechanisms and variation in attention can modulate EMG signals both in time and frequency domain, an internal focus could also be beneficial particularly during a robot-assisted musculoskeletal rehabilitation. Therefore, when a patient, who has suffered a stroke or has a disorder in the upper extremities, can be instructed internally by a physical therapist during a rehabilitation session, the patient could perform the movement more successfully and accurately with the help of robot-assisted mechanism controlled by the patient's EMG signals.

In this thesis, in order to compare the effects of attentional focusing strategies, EMG activities of different muscles were compared. The first two experiments were designed according to performance of biceps brachii muscles whereas, the last experiment was based on muscular activities of hamstrings.

As known, semitendinosus, semimembranosus and biceps femoris muscles are three major components of hamstrings. It is also hypothesized in this thesis that EMG response of hamstrings to attentional verbal instructions may be a distinctive feature between semitendinosus, semimembranosus and biceps femoris muscles. Therefore, sporting professionals and trainers can exploit the results to improve their training protocols. This thesis also provides a deeper insight on the dynamics of hamstrings by exploring mind-muscle connection one-step ahead which is also novelty of this thesis.

Overall, this thesis opens up the avenue for further research on the usage of EMG activities of various muscles subjected to attentional focus on the engineering field.

CHAPTER 2. MATERIALS AND METHODS

In this chapter, the steps of designing process of the experiments are enlightened. For this thesis, three different experiments were performed. The first one was based on weigh-lifting via biceps brachii muscles and the second one was basically extended version of the first experiment. The last one was based on leg curl exercices via hamstring muscles. The entire measurement process of each trial is explained in detail in the following sections.

2.1. Preliminary Experiment: Biceps Brachii Muscles

The biceps brachii is one of the main muscles that is located on the front of the upper arm which acts on both the elbow joint and the shoulder joint. The biceps brachii on the muscle map is displayed in Figure 2.1 (*EMGworks Acquisiton*, 2010).

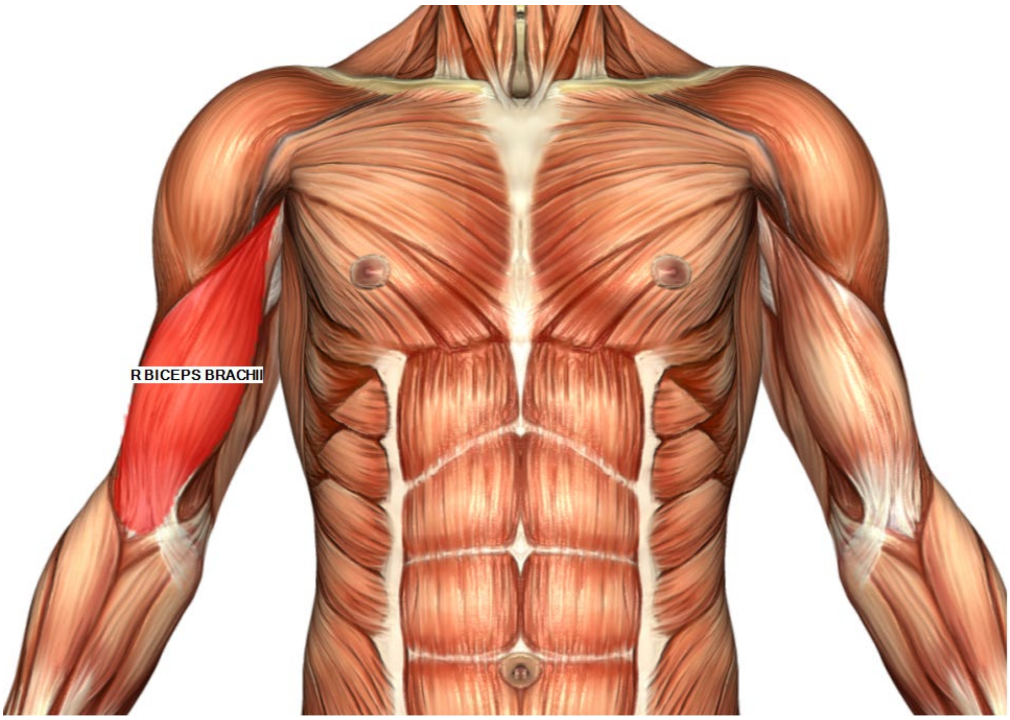


Figure 2.1 : The right biceps brachii muscle on the muscle map.

The function of biceps is that it flexes the forearm (Scanlon & Sanders, 2007). During flexion, the opposing parts of the short and long heads of the biceps brachii muscle help stabilize the shoulder (Cael, 2010).

Biceps curl is general name for a series strength exercises using dumbbell, resistance bands, etc. These exercises mainly target the biceps brachii muscles. There are many studies that used bicep curl tasks to determine muscular activity under different attentional focus conditions. In a study by Vance et al., directing performers to focus on their arms (internal) as opposed to the weight bar (external) resulted in higher muscular activity in biceps brachii muscles (Vance et al., 2004). In another study, it was also established that with an internal focus, the EMG activity was higher (Marchant et al., 2009).

In this thesis, the first experiment was designed to yield similar EMG activity results with literature based on attentional focusing strategies. With the purpose of getting comparable results, healthy participants were performed weight-lifting using a dumbbell and their EMG signals were measured via biceps brachii muscles under various attentional focus conditions.

2.1.1. Participants

8 healthy female and 8 healthy male university students (age = 22 ± 1.5 years, height = 171 ± 7 cm, weight = 69 ± 14 kg) volunteered for the trials. They were naive to the experimental task and none of them were aware of specific purpose of the study. Informed consent was obtained from all participants before the experiments, in compliance with the university's Institutional Review Board.

2.1.2. Experimental procedure

In order to measure EMG signals from the participants' biceps brachii muscles, Delsys Bagnoli^{TM} EMG System was used. Besides, for acquiring, monitoring, processing and recording the signal via LabVIEW, NI-DAQmx card was connected.

The performances were conducted in a quiet room. Each participant was requested to sit on a chair during the trials. For the experiment, they were asked to lift 2 kg dumbbell with their dominant hand. They were instructed to perform up-hold-down exercises. Each position took 5 seconds and repeated 3 times for various attentional focus conditions. The representation of up-hold-down procedure of a participant was displayed in Figure 2.2.

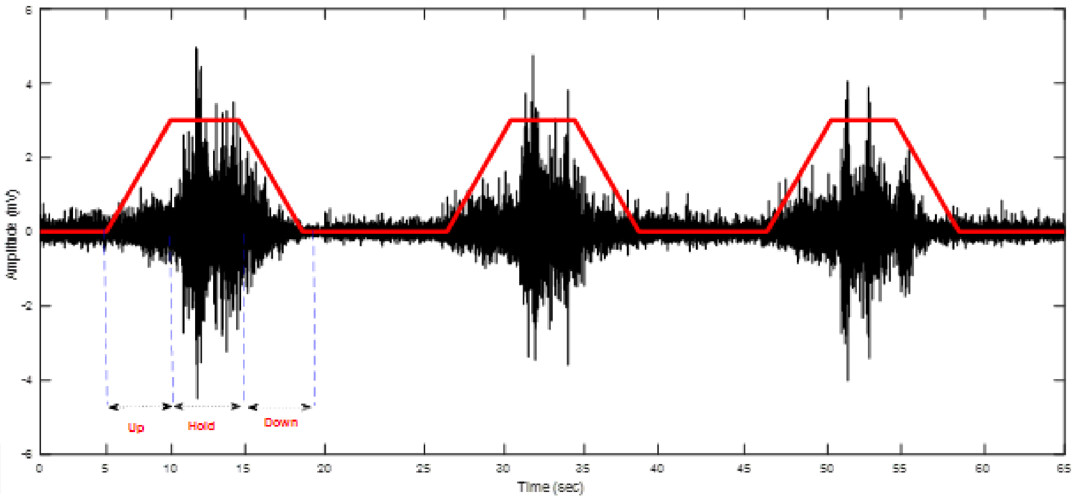


Figure 2.2 : The representation of up-hold-down procedure of a participant.

The first measurements were performed as control condition. Under the control condition, the participants have performed weight-lifting without any instructions. The verbal instructions at the beginning of each measurements for internal focus were “In this trial, I would like you to focus only the contraction of your biceps muscles where the electrodes are placed” whereas, “In this trial, I would like you to focus only the dumbbell during all period” for external focus.

In order to prevent fatiguing effects, participants rested for approximately 2-3 minutes between measurements (McAllister et al., 2014). One of a participant’s EMG measurement is displayed in Figure 2.3.

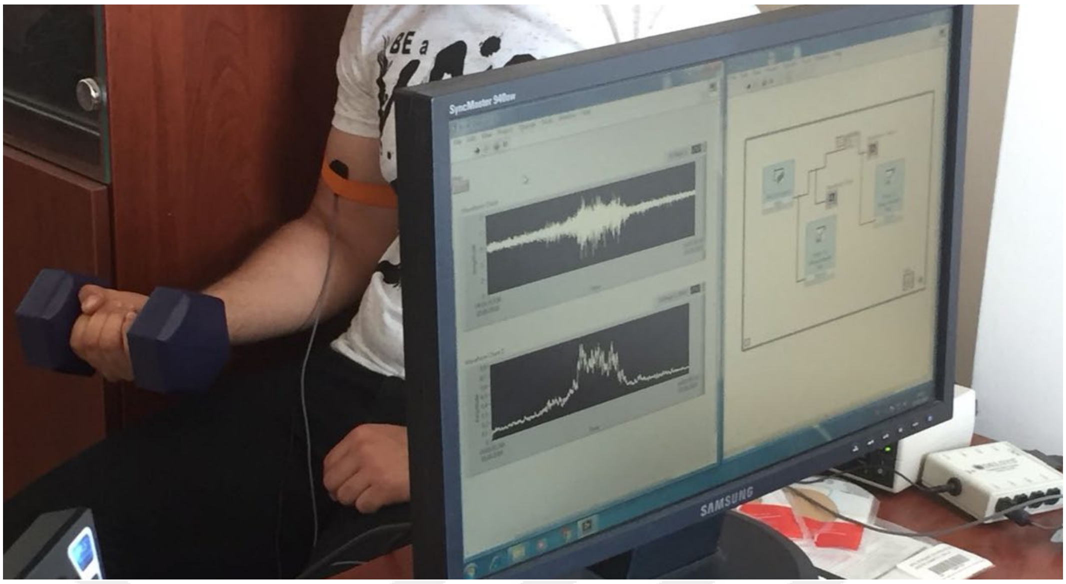


Figure 2.3 : One of a participant's EMG measurement.

In these experiments, the criteria for success was based on performing the exercises as regular as possible according to time intervals. Since all performers were individual, all analysis were based on within subject analysis.

After acquiring the data from all participants, a developed algorithm was implemented to LabVIEW for preprocessing the signals.

2.1.3. Preprocessing of EMG signals and data analysis

Firstly, a Butterworth band pass filter which is a combination of low pass and high pass filter was used. Here, lower cutoff frequency was set to be 20 Hz to remove environmental noise whereas, higher cutoff frequency was set to be 500 Hz to attenuate DC offset noise voltage (Politti et al., 2016).

As it is known, the Root Mean Square (RMS) value of a continuous time waveform is the square root of arithmetic mean of the squares of the original values. In this study, the RMS values of eact data sets were calculated with the help of simple RMS function in LabVIEW and their results were used for data analysis. Preprocessing of EMG signals and RMS calculation in LabVIEW is given in Figure 2.4 (Ay et al., 2019).

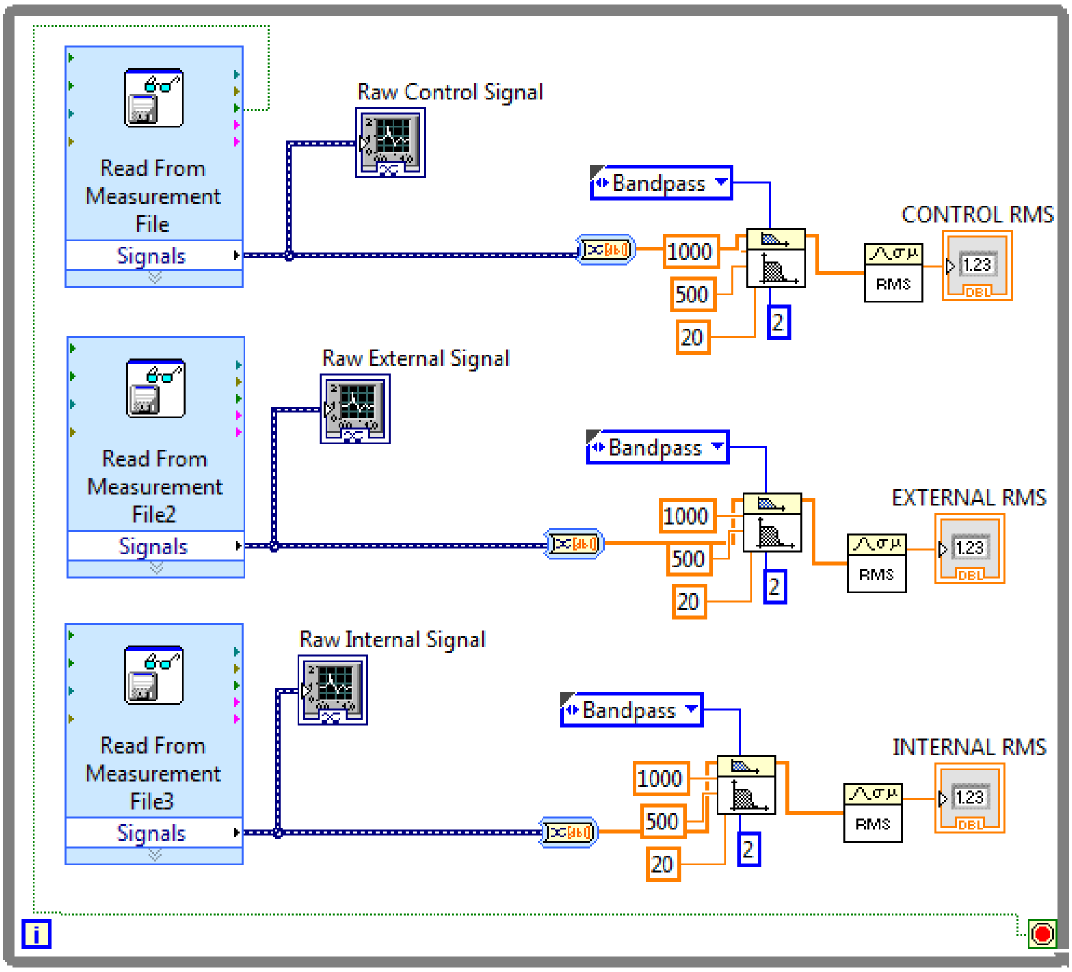


Figure 2.4 : Preprocessing of EMG signals and RMS calculation in LabVIEW.

After getting comparable results with limited number of participants (results are given in Chapter 3), in agreement with literature, it was decided to extend the first experiments for further analysis.

2.2. Experiment 1

The preliminary experiment was completed with 16 (8 female, 8 male) volunteers. After getting promising results from the first measurement, 19 (5 female, 14 male) new students also participated in the trials.

2.2.1. Participants

In total, 35 healty participants (age 21 ± 2 years, height = 172 ± 6 cm, weight = 69 ± 12 kg) were involed in the study [dataset] (Ay & Yildiz, 2020). They were also naive to the experimental task and none of them were aware of specific purpose of the study. Informed consent was also obtained from all participants before the experiments, in compliance with the university's Institutional Review Board.

2.2.2. Procedure

The whole procedure was repeated exactly in the same way with the previous one. First trials were completed under control condition. The second trials were under internal focus condition with same instructions given and the last trials were under external focus as well. The block diagram of the experimental procedure and the data analysis are displayed in Figure 2.5.

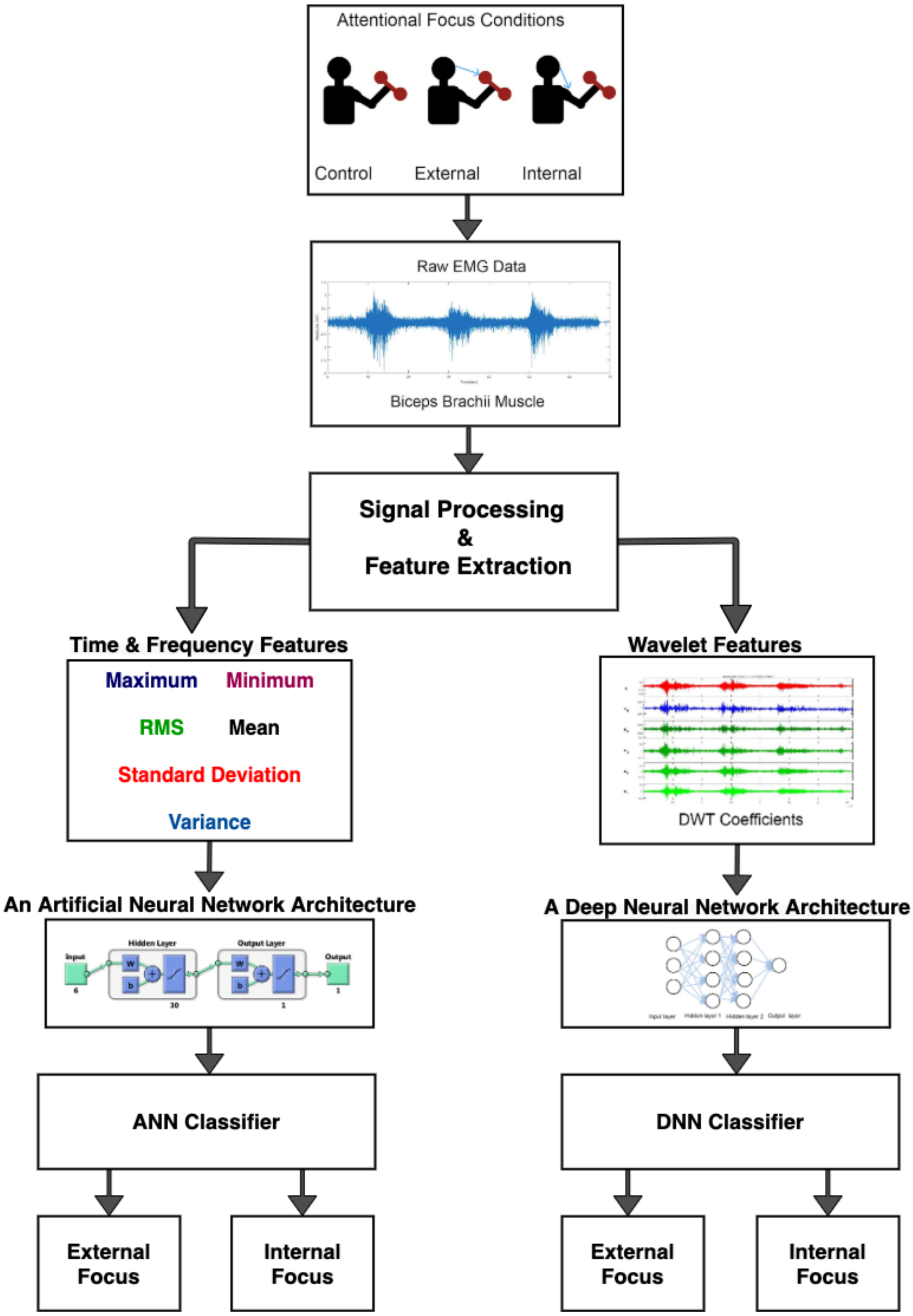


Figure 2.5 : The block diagram of the experimental procedure and data analysis.

2.2.3. Data Analysis

After acquiring the data, time and frequency-domain analyses were performed. In order to extract time-domain features, the root-mean-square (RMS), mean absolute values (MAV) and Integrated EMG (IEMG) values of the data were calculated for each data sets on LabVIEW and the results were recorded for statistical analysis (Singh, 2013). The following equations give RMS (2.1), MAV (2.2) and IEMG (2.3) values for ‘n’ samples where Xn represents the signal in a segment and N represents length of the signal.

$$\text{Vrms} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{2.1}$$

$$\text{MAV} = \frac{1}{N}\sum_{n=1}^{N} |x_n| \tag{2.2}$$

$$\text{IEMG} = \sum_{n=1}^{N} |x_n| \tag{2.3}$$

With the purpose of analyzing the data in frequency domain, Fast Fourier Transform (FFT) were performed on the EMG signals of each performers. From the signal, integrated FFT values were taken for statistical analysis. Figure 2.6 depicts the EMG signal in frequency domain of a single subject.

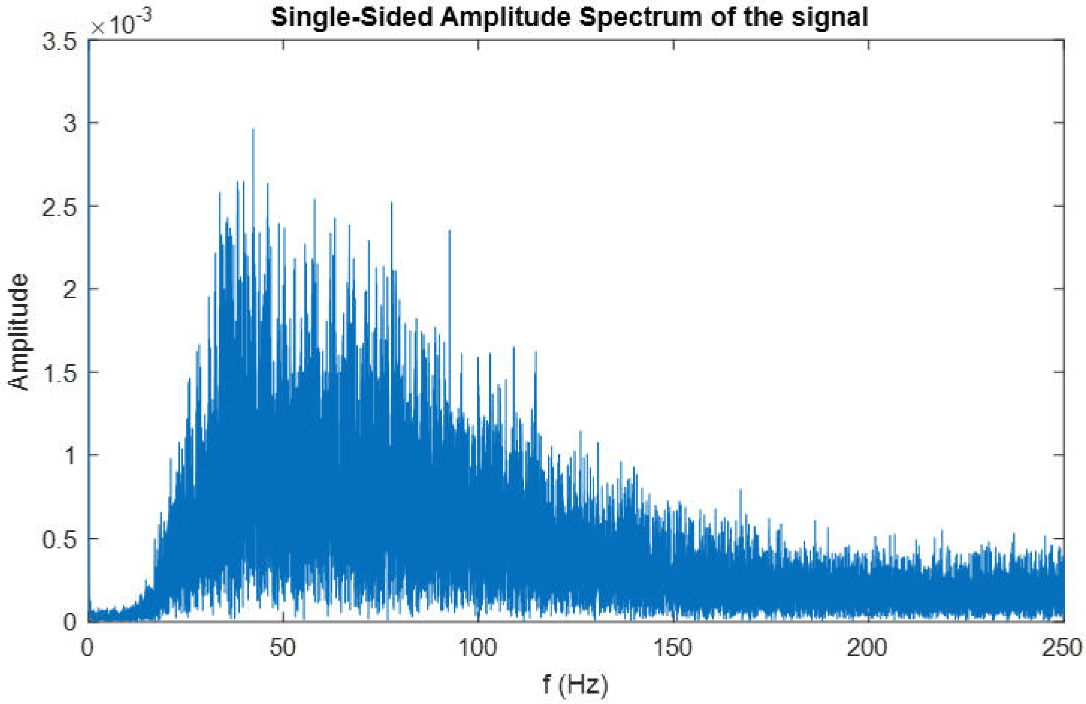


Figure 2.6 : One of the participant' EMG signal in frequency domain during one trial.

Both time and frequency data sets were checked for normality adopting Shapiro-Wilks and Kologorov-Shimirnov tests (Tremolada et al., 2019). In both tests, the data were not found to be normally distributed. Therefore, a non-parametric Friedman test was applied to RMS, MAV, IEMG and Integrated FFT values for each group to compare conditions and Wilcoxon Signed-Ranks test ($p = 0.05$) were computed post-hoc to test specific differences between the conditions (Couvillion & Fairbrother, 2018; Schücker & Parrington, 2019).

2.2.4. Feature Extraction

2.2.4.1. Features for artificial neural network classifiers

In total, 3 focusing type x 35 participants (105 data files) were collected with 36000 samples length for each dataset. Feature extraction was performed on MATLAB. Control, external and internal datasets were created for 35 participants. Since under control condition, it is unclear whether participants focused externally or internally due to their individual preferences, the control data was not used for signal classification. Therefore, 70 different data sets were available to differentiate the attentional focusing type from another. The maximum, minimum, average RMS, mean, variance and standard deviation were extracted from the data sets to be used as inputs to a neural network classifier (Daud et al., 2013; Nazmi et al., 2016; Phinyomark et al., 2017).

In this thesis, two different Artificial Neural Networks (ANNs) were designed. Six statistical features, namely, maximum, minimum, RMS, mean, variance and standard deviation were delivered from time and frequency domain data, for ANN 1 and ANN 2, correspondingly.

Firstly, topology of the network was identified and then training algorithm and neuron activation functions (Al-Timemy et al., 2008; Ibrahimy et al., 2013) were determined. Our ANNs were feedforward trained by Levenberg-Marquardt algorithm and the output layer corresponds to the internal (Class 1) and external (Class 0) focus of attention. The data was separated into three phases, namely, training (70%), validation (15%) and testing (15%) for both ANN1 and ANN2. The sigmoid function was chosen as neural activation function (Oweis et al., 2014). It is known that the number of neurons in hidden layers affect the performance of neural network. However, there is no specific rule to choose the number of hidden neurons for a reliable classification. Thus, in order to get the best classification results, different number of hidden neurons were tried from 10 to 50 in ANNs in this thesis.

The performance results of the ANNs are given in Chapter 3.

2.2.4.2. Features for deep neural network classifiers

The superposition of multiple motor unit activities known as EMG signals. In order to use these signals for nerve and muscle control, EMG signals decomposition is one of the key points. Wavelet analysis is commonly used for signal decomposition (Amanpreet, 2019; Reaz et al., 2006). Wavelet Transform (WT) is generally used for analyzing non-stationary and fast transient signals. Besides, WT represents a very suitable method for EMG signal classification as well. There are two types of wavelet transforms: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT).

In thesis, in order to classify the signals according to subjects' attentional focus conditions, Discrete Wavelet Transform (DWT) coefficients of the participants' EMG signals were chosen to be used as input feature vectors to a Deep Neural Network (DNN).

Haar and Db4 wavelets were chosen as mother wavelets (Ghofrani Jahromi et al., 2017). DWT coefficients were extracted using MATLAB Wavelet Analyzer Toolbox. The EMG signals were decomposed up to the 4th level and the coefficients were cd1, cd2, cd3, cd4 and ca4. Coefficient cd4 represents the highest frequency components whereas, ca4 represents the lowest one. The representation of signal decomposition up to the 4^{th} level is given in Figure 2.7.

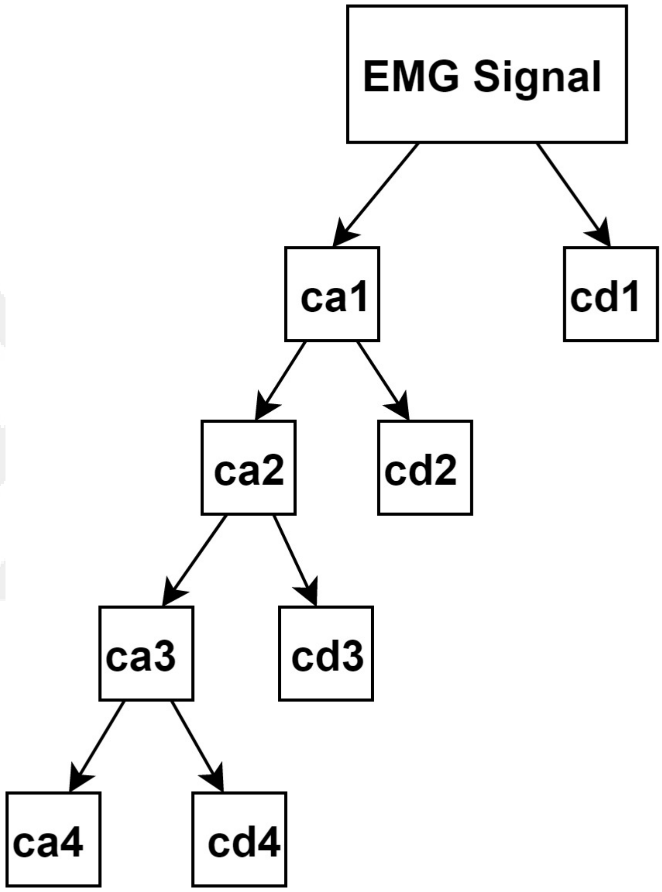


Figure 2.7 : The EMG signal decomposition up to the 4^{th} level.

In this thesis, each cd4 having length of 2250 coefficients for the Haar and Db4 wavelets were generated. In order to prevent missing information on the signal, the data of 2 participants were removed from the analysis and control condition data was not used as well. Thus, the decomposition procedure was done for the signals belonging to 33 participants for both external and internal condition data. The feature vectors from Haar and Db4 wavelets decomposition were used as an input to the designed DNN classifier.

A deep neural network topology consists of inputs, hidden layers and outputs. A DNN is usually designed with two or more hidden layers. The number of neurons in each hidden layer can be differ for the best classification performances. Each hidden and output layers have an activation function. One of the activation functions that is commonly used in a deep learning known as the rectified linear unit (ReLU). This function is applied to hidden layers for both training and classifying the data. Another commonly used activation function is called sigmoid function which is a nonlinear function and used for output layers in many deep learning classifiers (Shrestha & Mahmood, 2019).

In the model, designed for this study, two hidden layers each having 32 neurons were preferred. 33 x 2250 data for internal and 33 x 2250 data for external were used. 33 x 100 data out of 33 x 4500 was separated for testing. 70% of the data (33 x 3080) were assigned as training and the remaining 30% of data (33 x 1080) set as the test data. Keras library was chosen and the success rate of the designed neural network was calculated. ReLU was used as activation function for each hidden layer and sigmoid function was used for the output layer. Different epoch numbers were tried for the best classification success rate. Since it is unclear whether participants focused externally or internally under control condition, here the control data were also not used as inputs for signal classification.

The performance results of the DNNs are given in Chapter 3.

2.3. Experiment 2: Leg Curl Exercises

After getting reliable results form the previous experiments, another experiment was designed to obtain the effects of attentional focusing strategies on multiple muscles.

First two experiments were based on biceps brachii muscle activities while weight-lifting. Here, this experiment was based on hamstring muscles. In order to investigate the effect of attentional focus instructions on the hamstring muscle group during a leg curl exercise, muscular activity of semitendinosus, semimembranosus and biceps femoris were compared.

The hamstrings are a group of muscles that include semitendinosus (ST), semimembranosus (SM) and biceps femoris (BF) (Herman, 2006). These muscles are responsible for actions at the hip and knee and they are known as powerful hip extensors (McAllister et al., 2014). The activation level of these muscles is critical for performing many different sports, for instance football and sprint. Besides, strengthening these muscles play an important role to prevent hamstring injuries (Ebben et al., 2009; Woods et al., 2004). Therefore, it is critical for trainers, athletes and physiotherapists to improve strength training programs that could target the hamstrings in an effective way to gain strength and reduce potential hamstring strain injuries (Tillaar et al., 2017).

The leg curl is one of the exercise that commonly used for improving flexibility and strengthening muscles in hamstrings (Wright et al., 1999). The exercise includes basically bending both legs at the same time and trying to reach gluteal muscles with the heels and returning back to the initial position with a controlled movements (Delavier, 1998) and IEMG is one of a standard tools to obtain total muscular activity of targeted muscle during exercises. Therefore, in this experiment, the participants performed leg curls following attentional focus instruction while the muscular activity was recorded via IEMG.

Many research on attentional focusing especially in sports has constantly showed that external focus increases motor performance, learning skills and reduces muscular activity (e.g., sports, athletic training) relative to internal focus (Ille et al., 2013; Pascua et al., 2015; Gabriele Wulf, 2013).

To our knowledge, there are no studies indicating that the impact of verbal instructions on the activity of semitendinosus, semimembranosus and biceps femoris muscles during leg curl exercises. Thus, the aim is to investigate EMG activity of hamstrings when subjects are instructed to perform leg curl exercises.

In this thesis, it is hypothesized that EMG response of hamstrings to attentional verbal instructions may be a distinctive feature between semitendinosus, semimembranosus and biceps femoris muscles. This study opens up the avenue for further research on the muscular activity of hamstrings subjected to attentional focus. Sporting professionals and trainers can exploit the results to improve their training protocols. The EMG results enable modern prosthetics to simulate the hamstrings more realistically. In summary, this study provides a deeper insight on the dynamics of hamstrings by exploring mind-muscle connection one-step ahead.

2.3.1. Participants for experiment 2

20 male amateur football players with mean age of 18.0 (± 0.5) volunteered to take part in the trials. Descriptive characteristics of the participants are given in Table 2.1.

Table 2.1: Descriptive characteristics of the participants (N = 20, mean ± SD)

Age (y)	Height (cm)	Weight (kg)	Sport Experience (y)	Lifted Weight for MVC (kg)
18.0 ± 0.5	177.8 ± 6.0	69.0 ± 7.9	7.8 ± 2.9	40.6 ± 5.2

The average weights to be lifted were calculated according to their body segments parameters including head, trunk, both upper arms, both forearms and hands values (Clauser et al., 1969). Subjects were naive to the purpose of the study. However, a week before testing day, each of them had a familiarization session with leg curl exercises.

In the measurement day, all participants were informed of the procedures involved in the experiment and they were asked to answer physical activity and medical history questionnaires. The methodology was approved at the Institutional level, and informed consent was obtained before participation.

2.3.2. Experimental procedure

All data collection was conducted in sport and exercise laboratory of Faculty of Sport Sciences in the university. A day before the measurements, participants were asked to shave their hamstring area of both right and left legs. On a single test day, before the measurements, each participant was asked to complete 15 minutes standardized football-specific dynamic warm-up (Hammami et al., 2018). Following to warm-up, the subjects were allowed to rest for 5 minutes. During this rest, hamstring area was cleaned with alcohol and electrodes were placed over ST, SM and BF muscles. The placement of electrodes on hamstrings are displayed in Figure 2.8 (*EMGworks Acquisiton*, 2010).

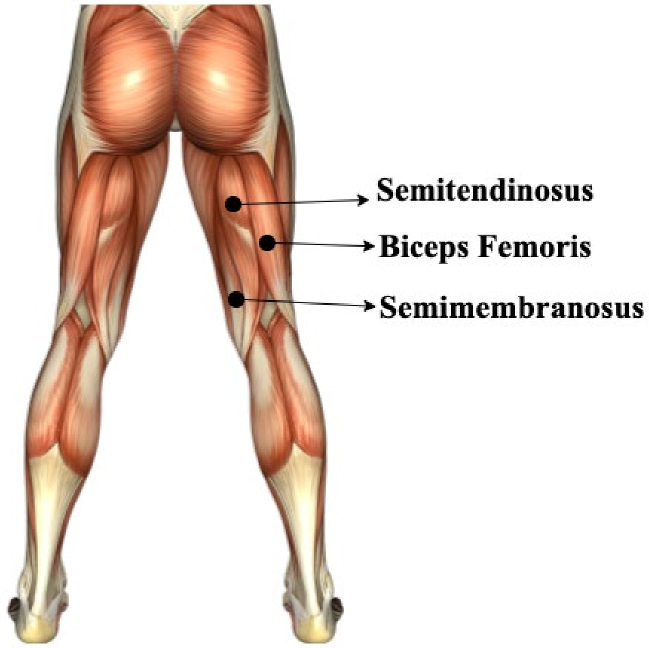


Figure 2.8 : The electrodes placement on hamstring muscles.

Participants first completed 3 repetitions of maximum voluntary contractions (MVCs) during a leg curl exercise for normalization (Halperin et al., 2014). One of a participant's MVC measurements are shown in Figure 2.9.

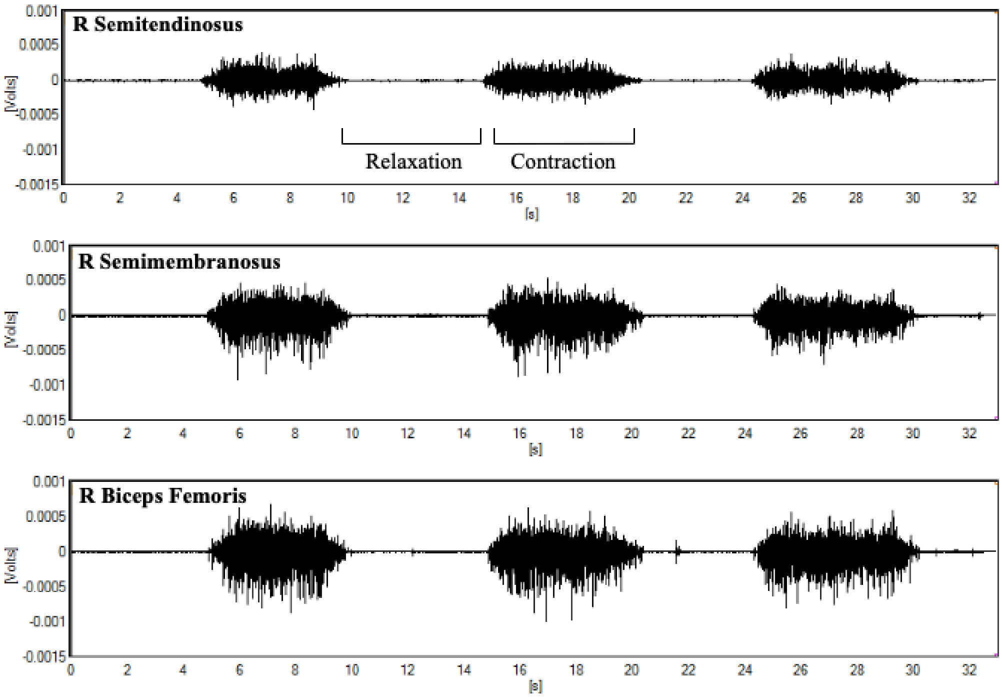


Figure 2.9 : One of a subject's MVC measurements of ST, SM and BF muscles.

No specific attentional instructions were given in MVC measurements. Following the MVC trial, participants completed control, internal and external attentional focusing trials with 6 repetitions for each movement.

Subjects rested for approximately 2-3 minutes between attentional focus trials to avoid fatiguing effects (McAllister et al., 2014). Prior to beginning of each trial, participants were given their allocated instructions verbally by the researcher. For the control trials, no instructions were given. For the internal trials, as it is a body part oriented, participants were instructed to "Focus upon the muscles that the electrodes are attached to and concentrate on contracting these muscles at maximum level" while for the external focus trials, as it is a target/object oriented, participants were instructed to "Focus upon the weight and concentrate on lifting that weight accurately." The verbal instructions were in line with previous studies (Gokeler et al., 2015; Marchant, 2011). In order to prevent possible influence of visual or auditory feedbacks, the computer was positioned in such way that the participant could not see any of his results presented on monitor. In addition, foot position of the participants was not standardized in the experiments because the researchers felt that the subjects' experience would allow foot position to be habitual. Besides, there was no audience, but researchers were present in the laboratory. Therefore, the participants could concentrate on mentally focusing upon the emphasis of the instructions given.

2.3.3. Measurements

EMG was used to quantify muscle activity during leg curl exercises. The 8-channel model Delsys Bagnoli™ EMG System was also used for these experiments. The DE 2.1 Single Differential Surface EMG Sensor was used to subtract EMG potentials. EMGworks Acquisition software was used to acquire and monitor the data and EMGworks Analysis software was used for filtering and processing the data. In order to determine muscular activity during trials, surface electrodes were placed along the targeted both left and right leg hamstring muscles (Figure 2.8). The experimental setup is represented in Figure 2.10.

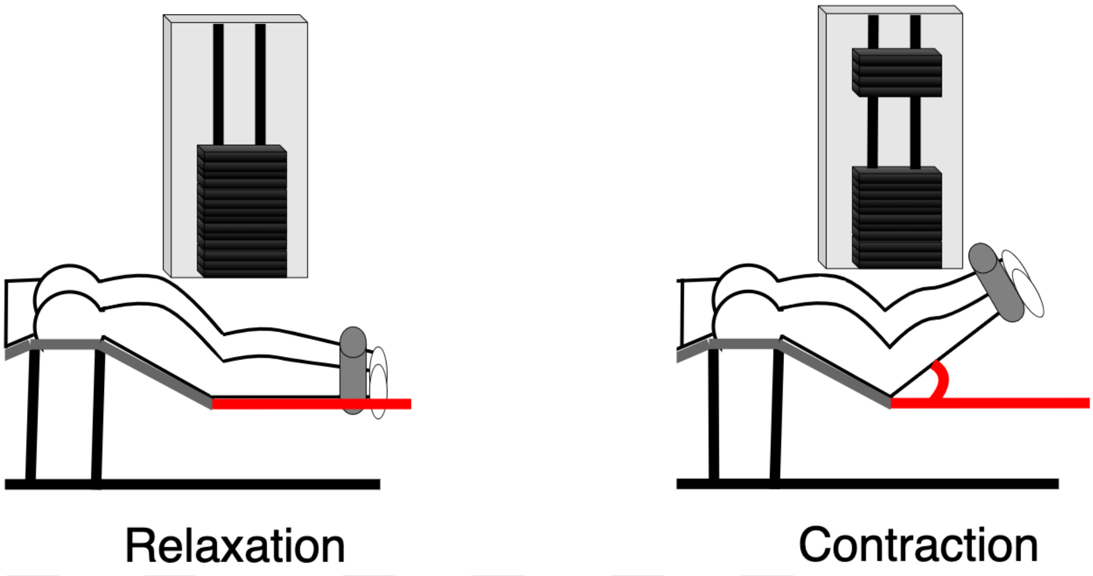


Figure 2.10 : Experimental task on a leg curl machine.

Measurements were taken from both legs of the participants but only dominant legs EMGs were used for analysis. The representation of one of the participants measured EMG signals were displayed in Figure 2.11.

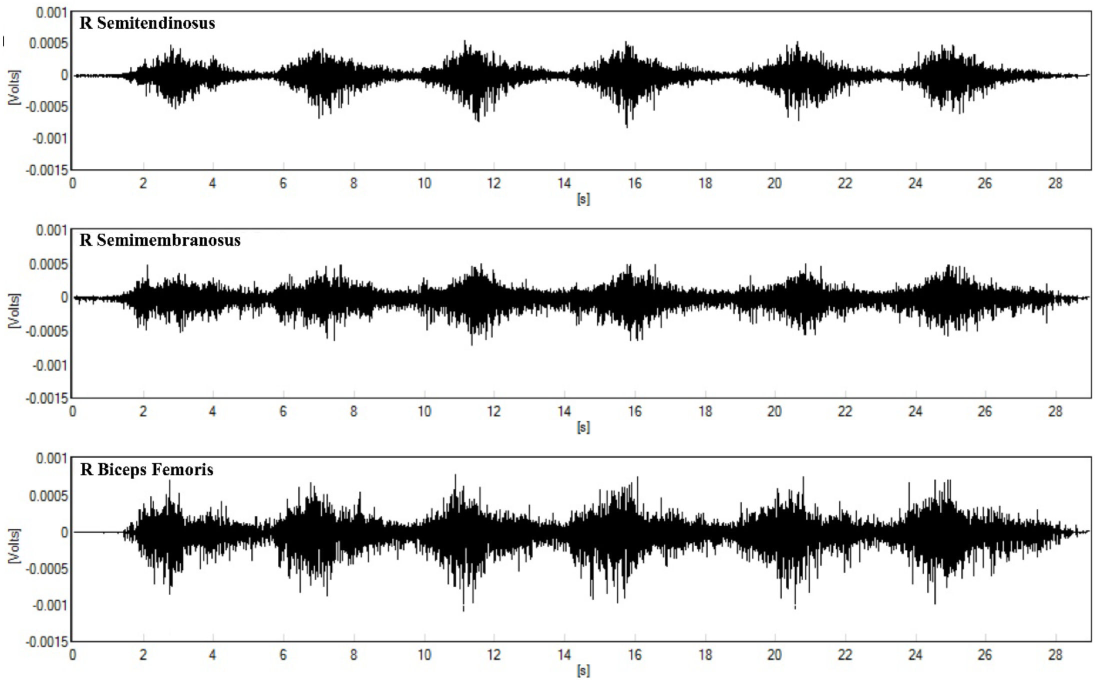


Figure 2.11 : A participant' s raw EMG measurements of ST, SM and BF

The raw EMG signals were sampled at 2 kHz. Maximum root mean square (RMS) values of recordings were used to normalize the data. The output of normalization was displayed as a percentage of MVC value (Vance et al., 2004). Therefore, it can be used to create a common ground when comparing the data between participants.

2.3.4. Data analysis

In order to measure muscle activities of the participants, Integrated EMG (IEMG) was calculated on the data's MVC values. Each data sets were checked for normality adopting Kolmogorov-Shimirnov and Shapiro-Wilks tests (Tremolada et al., 2019). The data were found to be normally distributed. Therefore, paired sampled t test ($p \leq 0.05$) was performed on the average IEMG values to determine if there is a significant difference between participants' muscles activities under various attentional focus conditions (Marchant et al., 2009; Zachry et al., 2005). The results are given in the following chapter.

CHAPTER 3. RESULTS AND DISCUSSION

In this chapter, the results of each experiments are given. Firstly, the results of the first trials (with 16 subject) are presented and the discussion of these results are also given. Secondly, results of ANN (with 35 subjects) and DNN (with 33 subjects) classifiers are specified. Discussion of all the results is also available in detail in the following sections. Finaly, the results of the last experiments (with 20 football player) are explained and evaluation of these results are also given. Since results of the experiments are not comparable, here all results and their discussions are given under different headings.

3.1. Preliminary Experiment

In order to obtain the differences between attentional focus condition groups, the data sets were checked for normality adopting Kolmogorov-Smirnov test (Tremolada et al., 2019). The data were found to be normally distributed. Therefore, paired t-test ($p = 0.05$) was applied to the data. The p value was found to be less than 0.05. Consequently, the results showed that there was a significant difference between external and internal focus conditions in their EMG activity level which is in line with previous attentional focus related studies. Besides, the muscular activity was lower when participants were instructed to focus on the dumbbell (external) instead of focus on their biceps brachii muscles (internal). These findings were also in line with constrain-action hypothesis (Gabriele Wulf et al., 2001). Moreover, these results also suggest that performers would achive experimental tasks such as grasping, weight-lifting or force production with less EMG activity resulted external focus of attention.

3.2. Experiment 1

3.2.1. Statistical results of experiment 1

A non-parametric Friedman test results showed that there was a significant difference between attentional focus conditions for RMS, MAV, IEMG and Integrated FFT values. The statistical results are presented in Table 3.1.

Table 3.1 : A non-parametric Friedman test results of different parameters.

Statistical Parameter	P value ($p = 0.05$)	Chi-square (2) N = 35
RMS	0.0032	11.4857
MAV	0.0053	10.4714
IEMG	0.0003	15.8286
Integrated FFT	0.0037	11.2100

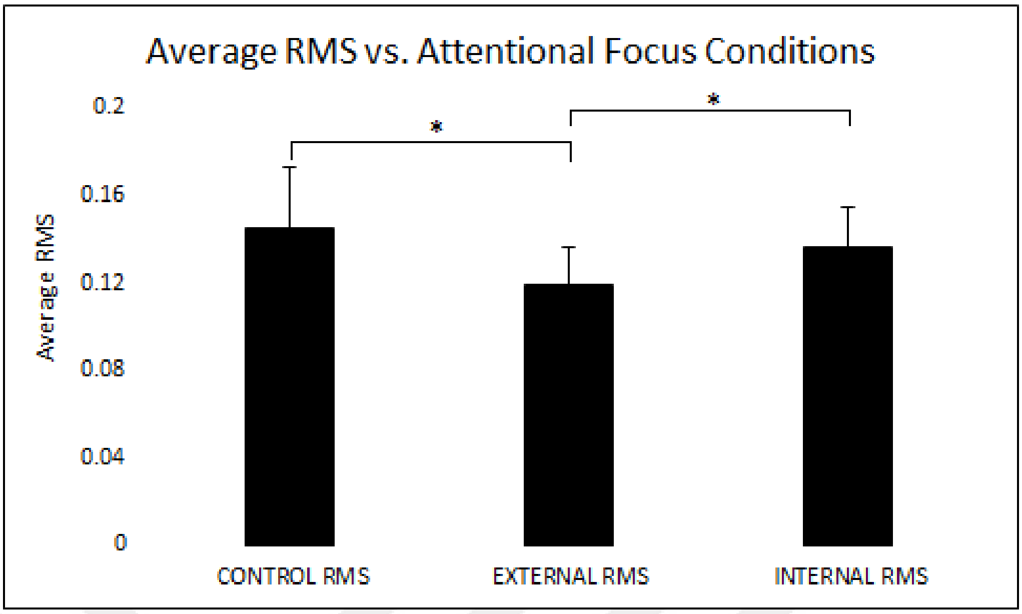
After obtaining the statistical difference between the data sets, in order to determine specific differences between attentional conditions, Wilcoxon Signed-Ranks tests (p = 0.05) were applied. The Wilcoxon Sign-Ranks tests results are given in Table 3.2.

Table 3.2 : Statistical Wilcoxon Signed-Ranks tests results of different parameters for all data.

Statistical Parameter	P value (Control – External)	P value (Control – Internal)	P value (External – Internal)
RMS	0.0069	0.1538	0.0012
MAV	0.0034	0.2709	0.0001
IEMG	0.0187	0.4207	0.0001
Integrated FFT	0.0079	0.1468	0.0001

The results of Wilcoxon Signed-Ranks test, post-hoc, for RMS, MAV, IEMG and Integrated FFT parameters showed that the main effect of attentional focus between external and internal was highly significant ($p < 0.001$). Besides, there was a statistical difference between control and external condition ($p < 0.05$) as well. However, no statistical difference was found between control and internal data.

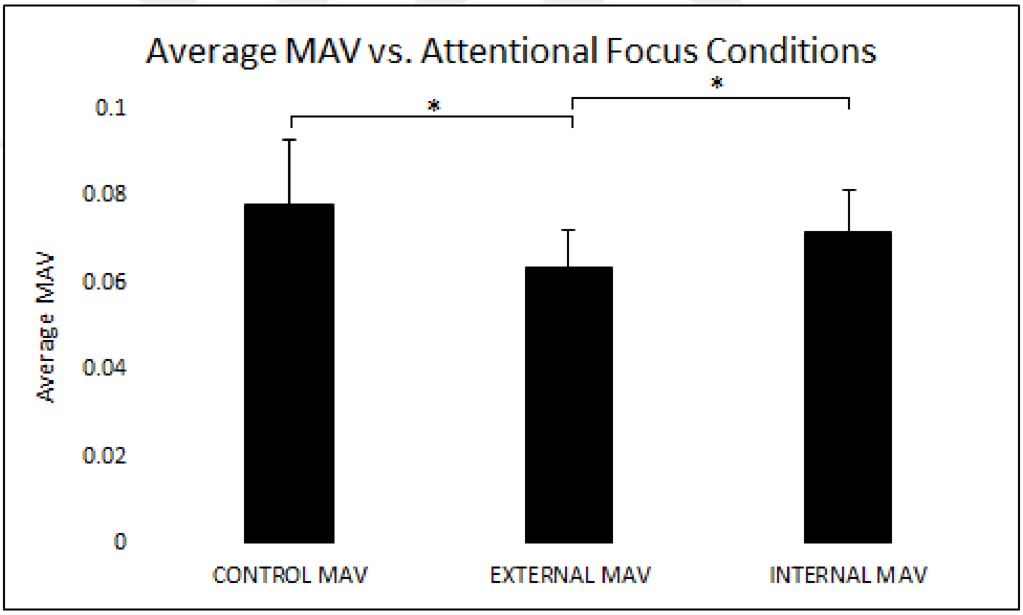
The graphical representation of average RMS is displayed in Figure 3.1.



*Indicates a significant difference between the groups and error bars refer to Standard Error (SE).

Figure 3.1 : Average RMS results of all data for each conditions.

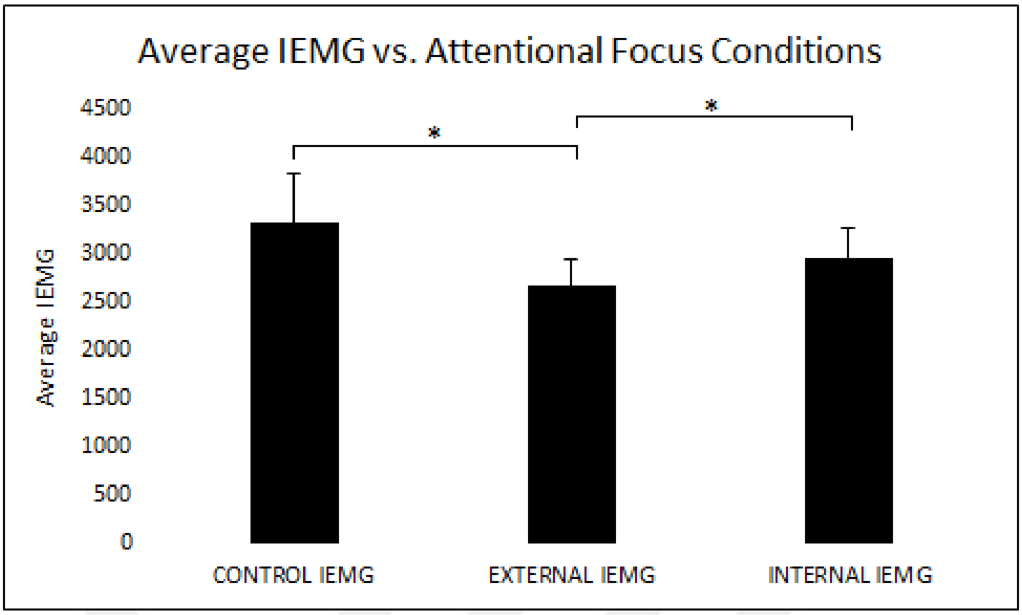
The graphical representation of average MAV is showed in Figure 3.2.



*Indicates a significant difference between the groups and error bars refer to Standard Error (SE).

Figure 3.2 : Average MAV results of all data for each conditions.

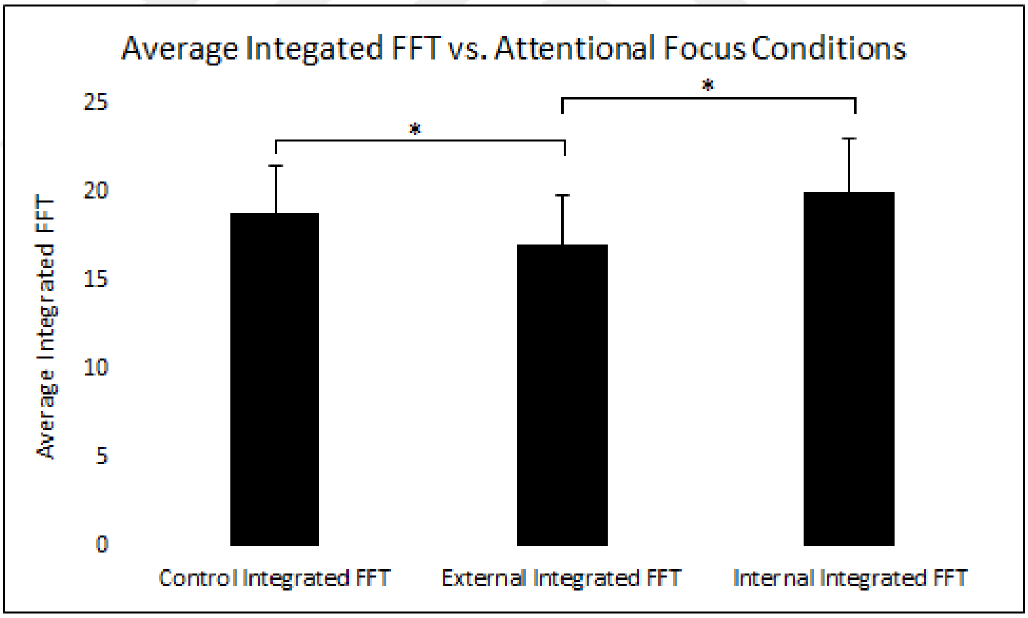
The graphical representation of average IEMG is presented in Figure 3.3.



*Indicates a significant difference between the groups and error bars refer to Standard Error (SE).

Figure 3.3 : Average IEMG results of all data for each conditions.

The graphical representation of average Integrated FFT is presented in Figure 3.4.



*Indicates a significant difference between the groups and error bars refer to Standard Error (SE).

Figure 3.4 : Average Integrated FFT results of all data for each conditions. Results of ANN classifiers

The performances of ANN1 (time-domain) and ANN2 (frequency-domain) were compared by obtaining average results of training (70%), validation (15%) and test (15%) data. In order to keep the consistency between classification rate calculations, the results were calculated 3 times and their average results were evaluated. The summary of the EMG classification performances is displayed in Table 3.3.

Table 3.3 : Performance comparison of Neural Network for EMG classification.

Neural Networks	Training	Validation	Test	Overall	Hidden Layer
ANN1	64.77	70.72	75.94	67.5	10
	81.62	82.56	92.31	83.39	20
	86.87	87.67	90.32	87.54	30
	80.14	81.57	78.79	80.13	40
	75.38	83.42	78.29	77.09	50
ANN2	62.54	64.31	65.4	63.21	10
	80.42	79.48	77.46	79.73	20
	81.46	88.21	83.16	82.69	30
	72.64	68.65	77.85	73.31	40
	75.12	70.68	67.58	73.15	50

It was concluded from Table 3.3 that the neural network with 30 neurons achieved the best classification rate which is 87.54% with ANN1. In case of ANN2, the best results were also obtained with 30 neurons. However, the success rate was lower compare to ANN1 which is 82.69%. The evaluation of classification performances of ANN1 and ANN2 is given in the following section.

3.2.2. Discussion of the ANN results

The results of the experiments showed that EMG activity was reduced under external focus condition, in agreement with previous studies, compare to control and internal one. Earlier studies that used EMG as a measurement parameter and run the experiments under various attentional focus conditions are given in Table 3. 4.

Table 3.4 : Studies related to attentional focusing.

Experimental Task	Parameters	Results
Bicep curls (Vance et al., 2004)	IEMG activity	External< Internal
Basketball free throws (Zachry et al., 2005)	EMG activity	External< Internal
Isokinetic elbow flexion (Marchant et al., 2009)	EMG activity	External< Internal
Jump and Reach (Gabriele Wulf et al., 2010)	EMG Activity	External< Internal
Dart throwing (Lohse et al., 2010)	EMG Activity	External< Internal
Isometric Force Production. (Lohse et al., 2011)	EMG Activity	External< Internal
Balance task (Ardakani et al., 2015)	EMG Activity	External< Internal
Vertical Jump Task (Ashraf et al., 2012)	EMG RMSE	External< Internal
Current study	EMG activity	External< Internal

The results of the present study confirm and extend previous findings. Even though, in many former studies, external focus was found to result in more effective movement outcomes than internal focus, the present study was the first investigation of whether the influence of an individual's attentional focus would also be seen in his/her EMGs to be used as control signals in robotics. Even though these results were not desired in case of previous studies, in term of HMI applications, the higher EMG activity means the better signal quality thereby the signal can be classified in such way that it can be used for controlling robotic mechanisms.

In this experimental study, the EMG classification results for different attentional focusing types were presented. The results indicate that the designed algorithms ANN1 and ANN2 were successfully classified the signals and the average rates were 87.54% and 82.69%, respectively. These results that are in line with previous studies are shown in Table 3.5.

Table 3.5 : Comparison of classification results with related studies.

Researcher	Method	Classification Rate
(Al-Timemy et al., 2008)	ANN with BPA	88% and 91%
(Ibrahimy et al., 2013)	ANN with trainlm	88.4%
(Mane et al., 2015)	ANN	93.25 %
(Duan et al., 2016)	ANN	93.2 %
(Kehri et al., 2017)	ANN with PCA	92.4 %
(Oleinikov et al., 2018)	ANN	91 %
Current Study	ANN	87.54 % and 82.69%

In the research by Al-Timemy et al., they classified the EMG signals as they represent either myopathy or neuropathy. In the other studies, they used ANNs for hand motion detection applications (Duan et al., 2016; Mane et al., 2015; Oleinikov et al., 2018) and Kehri and his colleagues used the signals to classify neuromuscular diseases (Kehri et al., 2017). In this present study, the signal classification was succeeded by means of time and frequency domain features extracted according to participants' attentional focus preferences and the results were found to be 87.54% and 82.69%, for ANN1 and ANN2 respectively.

The main difference between our study and the former ones is that our origin of the signal has not changed. In other words, this research is not relied on classifying EMG diseases which includes abnormal signals due to a patient's fitness. Our results were based on same performers' EMG signals. Additionally, the hand motion detection studies are also not difficult to classify according to their different signal outputs. However, in our study, the only difference that make the results significant was the individual's focus of attention preferences. Even though they are all healthy and performed exactly same procedure in the experiments, just by changing their attentional focusing type, the results were changed, remarkably. Another point of view to this study is that one's focus of attention type would be predicted from his/her EMG activity which can also be useful in control mechanisms.

3.2.3. Results of DNN classifiers

The results of 33 students were evaluated in this part of the study. The data from two students out of 35 were not found to be suitable for deep neural network classifier. Therefore, they were removed from the analysis.

Figure 3.5 shows the EMG activity of a single participant, represented as a function of external versus internal focus.

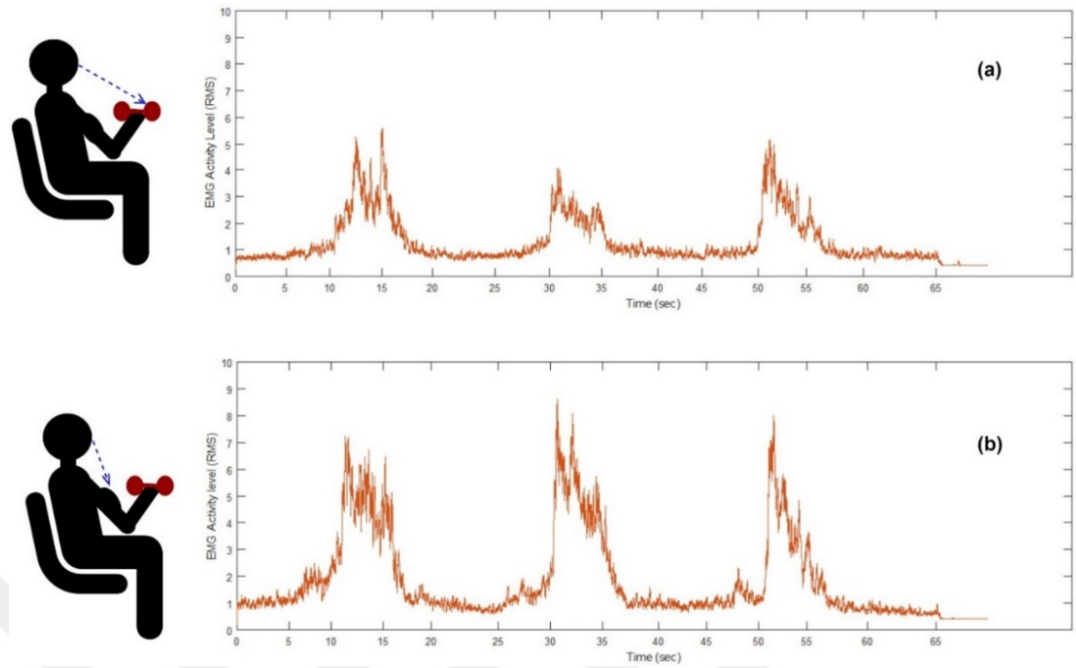


Figure 3.5 : A participant's EMG activity under external and internal focus conditions. (a) External condition (a participant focuses on the dumbbell during performance) - (b) Internal condition (a participant focuses on biceps brachii muscle during performance).

After getting significant difference between EMG activities under external and internal focus and obtaining classification results for ANNs, a deep neural network model was developed for the classification of the attentional focusing strategies of a participant based on wavelet coefficients of his/her EMG signal. The deep neural network model was compiled and the results of performance comparison of deep neural network for EMG classification with different epoch numbers are given in Table 3.6.

Table 3.6 : Performance comparison of DNN for EMG classification with different epoch numbers

Wavelet Coefficients	**Training (70%)**	**Test (30%)**	**Overall**	**Epoch Number**
DB4 (4^{th} level)	89.94	90.83	90.39	100
	96.66	97.65	97.16	200
	98.21	99.92	99.07	300
	96.33	99.7	98.02	400
HAAR (4^{th} level)	90.23	91.36	90.8	100
	95.42	97.88	96.65	200
	99.22	99.85	99.54	300
	98.28	99.1	98.69	400

The best classification success rate of the model was obtained with 300 epochs for both DB4 and Haar wavelets. The classification rate was found to be 99.07% for DB4 coefficients whereas, 99.54% for Haar coefficients.

3.2.4. Discussion of DNN results

It is known that most of the HMI studies (Pan et al., 2019) based on using a subject's EMG signals to control such as artificial prosthetic arms, wheel chairs (Abbaspour et al., 2020; Amanpreet, 2019; Shi et al., 2018). In all these EMG-based control studies, the useful signal features must be extracted in order to classify the signals.

In our study, DWT coefficients of subjects' signals were extracted as features under external and internal focus of attention to be used as inputs for a deep neural network. Although the signals seemed to be similar (Figure 3.2), the classification rates for designed DNN were pretty high.

The overall rate of the classification was found to be 99.07% for DB4 whereas, 99.54% for Haar methods. It can clearly be understood that with both preferred mother wavelets for EMG signals (Baspinar et al., 2015) , the results were promising.

Another point of view to this study is that the results would be used for musculoskeletal rehabilitaiton. Recent studies have proved that verbal instructions could have a powerful influence on motor performance and learning by directing a subject's focus externally rather than internally (Gokeler et al., 2015; Welling et al., 2016).

Hunt et al. confirmed and extended previous studies by suggesting the use of attentional focusing strategies by physical therapists during rehabilitation sessions (Hunt et al., 2017). Instructions given by a physical therapist are a key consideration in teaching motor skills and directing a patient's attention of focus. Hence, in order to perform effective movement outcomes for the patients during rehabilitation physical therapists could have a great advantage by promoting an external focus of attention through verbal instructions.

Although verbal instructions through external focus have shown a positive effect on movement outcomes, it has been hypotheised in this thesis that internal focusing might also have several benefits. For example, in case of musculoskeletal rehabilitation internal focusing might enhance the effectiveness of the therapy. As known, internal focus constrains the automaticity of movement which causes more muscular activity to be generated. Since higher EMG activity means better EMG-based control, internal focus culd be useful especially during a robot-assisted musculoskeletal rehabilitation. Therefore, when a physical therapist instructs her or his patients internally, the patient, who has upper extremity disorders, could perform the required movements more successfully with the help of EMG-based robot-assisted mechanism. Since appropriate instructions are critical to effective guidance of movements, these results might be useful for physicians to plan their treatment as well. If this suggestion is considered by physical therapists, the advantages of internal focusing might be seen on the outcome of the treatments.

Overall, unlike previous attentional focus related studies, this part of the thesis emphasizes the advantages of focusing internally. This opposite point of view is based on comparison of EMG activities of performers and presenting the possible benefits of internal focusing on HMIs, robotics, prosthetics and in robot-assisted musculoskeletal rehabilitation. The methodology is given here has also proved that the EMG signals could be classified according to attentional focusing type for the first time with quite high success rates (99.07% and 99.54%) which means when this model is applied for real-time control mechanisms, the system might work in such way that the mechanism can be controlled accurately. Just by changing attentional focusing type the patients can control their movement with the help of EMG based systems. With the ability to predict type of attention, this novel approach might also be useful for physicians to plan effective treatment for their patients.

3.3. Experiment 2

3.3.1. Results of experiment 2

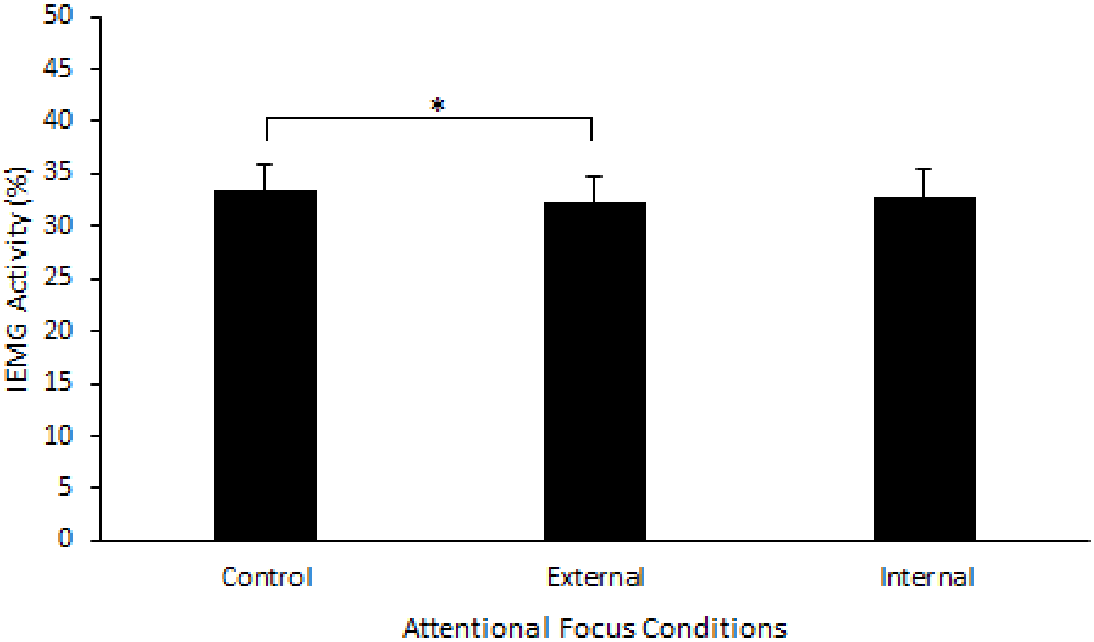
IEMG activity of 20 participants were calculated and the results were analyzed. Table 3.7 shows the paired t-test results ($p < 0.05$) of normalized IEMG activity of ST, SM and BF muscles, respectively during 3 attentional focus conditions.

Table 3.7 : Paired t-test results of hamstring muscles under various attentional focus conditions

Muscle (dominant)	Control – External (p value)	Control – Internal (p value)	External – Internal (p value)
Semitendinosus	0.0355*	0.0610	0.1844
Semimembranosus	0.0124*	0.0008*	0.2865
Biceps femoris	0.2584	0.0823	0.3847

* Denotes significant difference between the groups

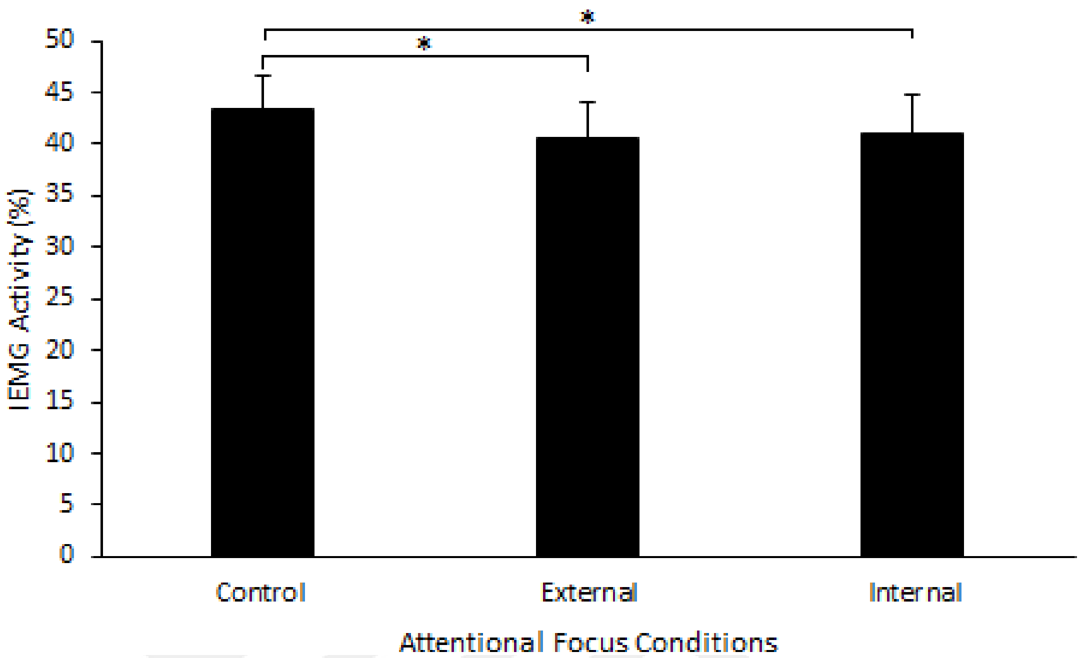
A significant main effect of the verbal attentional focusing instructions were observed in IEMG of ST (*p = 0.0355*) with the external condition exhibiting a lower mean IEMG (32.24 ± 10.7 %IEMG) than the control condition (33.58 ± 11.81 %IEMG). However, internal verbal instructions (32.69 ± 10.73%IEMG) had no significant effect (*p > 0.05*) on ST. The graphical representation of IEMG activity for Semitendinosus is displayed in Figure 3.6.



*Indicates a significant difference between IEMG activities under these focusing conditions (paired t-test, $p < 0.05$) and error bars refer to Standard Error (SE).

Figure 3.6 : Average IEMG activity of ST under control, external and internal focus of attention.

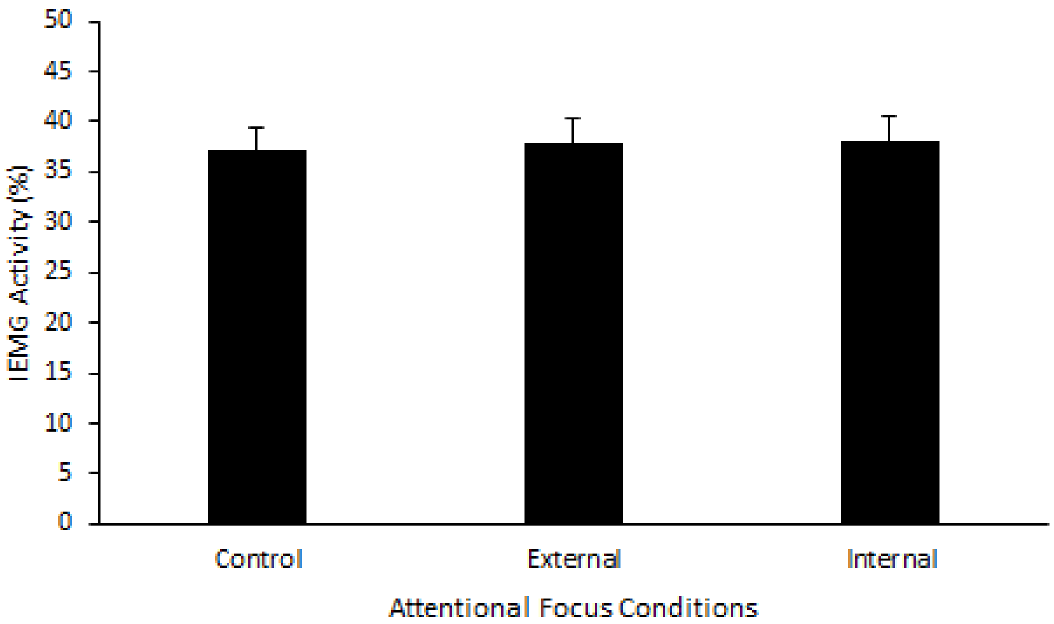
The main effect of attentional focusing instructions on IEMG of SM during the task was significant (p = 0.0124) with the external condition exhibiting a lower mean IEMG (40.56 ± 15.17 %IEMG) than the control condition (43.31 ± 17.13 %IEMG). There was also significant difference (p = 0.0008) between control and internal (40.99 ± 16.14 %IEMG) conditions in SM muscle. However, the difference between external an internal was not found to be significant ($p > 0.05$). The graphical representation of IEMG activity for Semimembranosus is displayed in Figure 3.7.



*Indicates a significant difference between IEMG activities under these focusing conditions (paired t-test, $p < 0.05$) and error bars refer to Standard Error (SE).

Figure 3.7 : Average IEMG activity of SM under control, external and internal focus of attention.

In case of Biceps Femoris, no significant changes were found between any attentional focusing conditions. The graphical representation of IEMG activity for Biceps Femoris is displayed in Figure 3.5.



*Indicates a significant difference between IEMG activities under these focusing conditions (paired t-test, $p < 0.05$) and error bars refer to Standard Error (SE).

Figure 3.8 : Average IEMG activity of BF under control, external and internal focus of attention. There was no significant difference between attentional focusing conditions (paired t-test, $p > 0.05$).

The results showed that the different verbal attentional focus instructions resulted in comparable IEMG activity for the ST, SM and BF muscles during leg curl exercises.

3.3.2. Discussion of experiment 2

The main findings of this study demonstrate that there are significant differences in activation between muscles under various attentional focusing strategies.

Lewis and Sahrmann already showed that the EMG activity of hamstrings were reduced when women were instructed as follows "use your gluteal muscles to lift your leg while keeping your hamstrings muscles relaxed" (Lewis & Sahrmann, 2009). Their results were based on comparing the effects of instructing the participants to contract gluteal muscles and afterwards the hamstring muscles. However, here we compared the effect of verbal instructions on IEMG activity of each hamstring muscles.

In our study, as the leg curl exercise is directly targeting hamstring muscle group, it was expected that the effect of attentional focus instructions on hamstrings during leg curl exercises could be clearly observed. One of the key findings of our results that external focusing showed the lowest EMG activity in all muscles which is in line with “constrained-action hypothesis” (Vance et al., 2004; Gabriele Wulf et al., 2001). Our results revealed that when considering the IEMG activity of the ST, SM and BF, the significant decrease with external focus could only be seen in ST and SM which are the medial hamstrings. No significant changes were found for BF under any attentional focus conditions.

Semimembranosus showed the highest muscle activation under all conditions and both external and internal focusing resulted significant decrease compare to the control condition. As expected, external focusing reduced the EMG activity. However here, interestingly muscular activity was also reduced with internal focusing which is in contradiction with the Schoenfeld and Contreras study (Brad J Schoenfeld & Contreras, 2016). They suggest using internal focus via mind-muscle connection would provide great advantage to maximize muscular development which is especially important to the fitness professionals. As mind-muscle connection related studies showed that internal focusing would enhancemuscle hypertrophy (Paoli et al., 2019; Brad Jon Schoenfeld et al., 2018), here the results of the experiments demonstrated that internal focusing had no positive effect on the hamstring muscles.

For semitendinosus, the EMG activity was significantly different between control and external conditions. Similar to BF, there was no significant difference between control and internal conditions. Marchant showed that if there is no specific instructions under control conditions, the subjects appear to direct their attention toward the control of movements which is similar to internal focus condition (Marchant, 2011). Therefore, based on our results, it may be possible that majority of our participants focused internally as habitual practice during control condition.

Kellis et al. explained architectural differences and similarities between hamstring muscles in detail and they came to the conclusion that intra-muscular differences have an effect on the function of the hamstrings as a muscle group. They also suggested that additional factors would be required for estimation of whole muscle architecture (Kellis et al., 2012). Since our study showed that different muscles correspond to different responses due to the attentional instructions at EMG activity level, the ability of the muscle to be focused amongst hamstring muscles demands a separate study.

The results of the present study indicate that among the hamstring muscles the EMG activity of both semitendinosus and semimembranosus was reduced under external focus condition. Contrary the the conventional effect belief, the biceps femoris muscles showed no significant change of EMG activity while being subjected to different attentional focus conditions. As leg curl exercise gives us an insight specifically into the hamstrings, this study allows improved efficiency on planning for training that involves hamstring muscles which eventually protects sport professionals from potential injuries.

CHAPTER 4. GENERAL CONCLUSION

There are several important findings in this thesis. Firstly, the EMG activity of biceps brachii muscle was reduced when the performers focused externally during weight-lifting which was in line with the literature. Therefore, it is clear that external focus enhances motor skills and learning of people but reduces EMG activity. Nevertheless, this thesis emphasizes the positive effects of internal focus.

In order to use the EMG signals in engineering field such as in HMIs, high EMG activity is preferred for better signal quality so that it can be used as useful inputs for robotic control purposes. Since the internal focus increases the EMG activity, one can say that, focusing internally would create more useful inputs for control-based mechanisms.

Furthermore, with this study, the performer’s EMG signals could be classified according to his/her attentional focus preferences. The ANN and DNN classifiers, feeded with different features, showed that even though the origin of the signals belongs to the same healthy people with the same experimental task, just by changing focus of attention type the signals could be classified with a very high accuracy. Therefore, one’s focus of attention type would be predicted from his/her EMG activity which may make a notable difference when these signals are used for EMG-based control mechanisms. When this model is applied for real-time control mechanisms, the system might work in such way that the mechanism can be controlled accurately.

Additionally, it might be also possible that just by changing attentional focusing type, instructed by a physician, patients, who has suffered a stroke or upper extremity disorders, can improve the efficiency of their movement with the help of EMG based robot-assisted systems. This novel approach might also be helpful for physicians to plan effective treatment for their patients.

Morever, these results were not limited to only biceps brachiie muscles. The results of leg curl exercise experiment also showed that the effects of attentional focusing type can differ from one muscle to another. The results indicated that among the hamstring muscles the EMG activity of both semitendinosus and semimembranosus was reduced under external focus condition. Contrary to the conventional effect belief, the biceps femoris muscles showed no significant change of EMG activity when subjected to different attentional focus conditions. Besides, as opposed to mind-muscle connection phenomena, in this study, internal focusing had no positive effect on hamstring muscle activities.

This thesis implements attentional focusing strategies into the engineering field. By classifying the EMG signal according to performers' attentional preferences with high accuracy, it has been concluded here that the output of the classifiers can be used as alternate inputs for HMI applications. Therefore, number of useful inputs would be doubled which is a novel approach.

As a result, this thesis suggested that attentional focusing strategies may have several advantages in engineering fields such as HMI, robotics, EMG-based control and it also gives a new perspective to the studies in the field of attentional focus.

REFERENCES

Abbaspour, S., Lindén, M., Gholamhosseini, H., Naber, A., & Ortiz-Catalan, M. (2020). Evaluation of surface EMG-based recognition algorithms for decoding hand movements. *Medical and Biological Engineering and Computing*, *58*(1), 83–100. https://doi.org/10.1007/s11517-019-02073-z

Ahmad, J., Butt, A. M., Hussain, M., Akbar, M. A., & Rehman, W. U. (2018). The Deep Neural Network Based Classification of Fingers Pattern Using Electromyography. *Proceedings of 2018 2nd IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference, IMCEC 2018*, *Imcec*, 455–461. https://doi.org/10.1109/IMCEC.2018.8469534

Al-Timemy, A. H. A., Ghaeb, N. H., & Khalaf, T. Y. (2008). Wavelet Neural Network Based Emg Signal Classifier. *The 1st Regional Conference of Eng. Sci. NUCEJ*, *11*(1), 137–144.

Amanpreet, K. (2019). Machine learning-based novel approach to classify the shoulder motion of upper limb amputees. *Biocybernetics and Biomedical Engineering*, *39*(3), 857–867. https://doi.org/10.1016/j.bbe.2019.07.007

Ardakani, Z. P., Abdoli, B., Farsi, A., & Ahmadi, A. (2015). The Effect of Attentional Focus and Manipulation of Somatosensory on EMG of Selected Balance Muscles in Elderly. *Indian Journal of Fundamental and Applied Life Sciences*, *5*(1), 5522,5528.

Ashraf, R., Aghdasi, M. T., Sayyah, M., & Taghibiglo, N. (2012). The effects of internal and external focus of attention on children`s performance in vertical jump task. *International Journal of Basic Sciences & Applied Research*, *1*(1), 1–5.

Ashraf, R., Sayyah, M., & Services, H. (2017). The effect of attentional focus strategies on children performance and their EMG activities in maximum a force production task. *Turkish Journal of Kinesiology*, *3*(2), 26–30.

Ay, A. N., Dolukan, Y. B., & Yildiz, M. Z. (2019). The Effect of Attentional Focus Conditions on Performer's EMG Activity. *Academic Perspective Procedia*, *1*(1), 240–247. https://doi.org/10.33793/acperpro.01.01.45

Ay, A. N., & Yildiz, M. Z. (2020). *Mendeley Data - Data of EMG-Based Attentional Focus Experiments*. Mendeley Data. https://doi.org/10.17632/grmzmpvt4c.2

Baspinar, U., Senyürek, V. Y., Dogan, B., & Varol, H. S. (2015). Comparative study of denoising sEMG signals. *Turkish Journal of Electrical Engineering and Computer Sciences*, *23*(4), 931–944. https://doi.org/10.3906/elk-1210-4

Cael, C. (2010). *Functional Anatomy*.

Cavalcanti Garcia, M. ., & Vieria, T. M. . (2011). Medicina del deporte. *Revista Andaluza de Medicina Del Deporte*, *4*(1), 17–28. https://doi.org/10.36104/amc.2018.1400

Clauser, C. E., McConville, J. T., & Young, J. W. (1969). Weight, Volume, and Center of Mass of Segments of the Human Body. *National Technical Information Service*.

Couvillion, K. F., & Fairbrother, J. T. (2018). Expert and novice performers respond differently to attentional focus cues for speed jump roping. *Frontiers in Psychology*, *9*(NOV), 1–9. https://doi.org/10.3389/fpsyg.2018.02370

Daud, W. M. B. W., Yahya, A. B., Horng, C. S., Sulaima, M. F., & Sudirman, R. (2013). Features Extraction of Electromyography Signals in Time Domain on Biceps Brachii Muscle. *International Journal of Modeling and Optimization*, *3*(6), 515–519. https://doi.org/10.7763/ijmo.2013.v3.332

Delavier, F. (1998). *Strength Training Anatomy* (Second Edi). Human Kinetics.

Delsys. (2011). *EMG System User's Guide*. https://delsys.com/downloads/USERSGUIDE/bagnoli-emg-system.pdf

Duan, F., Dai, L., Chang, W., Chen, Z., Zhu, C., & Li, W. (2016). SEMG-Based Identification of Hand Motion Commands Using Wavelet Neural Network Combined with Discrete Wavelet Transform. *IEEE Transactions on Industrial Electronics*, *63*(3), 1923–1934. https://doi.org/10.1109/TIE.2015.2497212

Ebben, W. P., Feldmann, C. R., Dayne, A., Mitsche, D., Alexander, P., & Knetzger, K. J. (2009). Muscle activation during lower body resistance training. *International Journal of Sports Medicine*, *30*(1), 1–8. https://doi.org/10.1055/s-2008-1038785

EMGworks Acquisiton (4.3). (2010). Delsys. https://delsys.com/emgworks/acquisition/

Ghofrani Jahromi, M., Parsaei, H., Zamani, A., & Dehbozorgi, M. (2017). Comparative analysis of wavelet-based feature extraction for intramuscular EMG signal decomposition. *Journal of Biomedical Physics and Engineering*, *7*(4), 365–378. https://doi.org/10.22086/jbpe.v0i0.538

Gokeler, A., Benjaminse, A., Welling, W., Alferink, M., Eppinga, P., & Otten, B. (2015). The effects of attentional focus on jump performance and knee joint kinematics in patients after ACL reconstruction. *Physical Therapy in Sport*, *16*(2), 114–120. https://doi.org/10.1016/j.ptsp.2014.06.002

Halperin, I., Aboodarda, S. J., Basset, F. A., & Behm, D. G. (2014). Knowledge of repetitions range affects force production in trained females. *Journal of Sports Science and Medicine*, *13*(4), 736–741.

Hammami, A., Zois, J., Slimani, M., Russel, M., & Bouhlel, E. (2018). The efficacy and characteristics of warm-up and re-warm-up practices in soccer players: A systematic review. *Journal of Sports Medicine and Physical Fitness*, *58*(1–2), 135–149. https://doi.org/10.23736/S0022-4707.16.06806-7

Herman, I. P. (2006). *Physics of the Human Body*. Springer.

Hunt, C., Paez, A., & Folmar, E. (2017). the Impact of Attentional Focus on the Treatment of Musculoskeletal and Movement Disorders. *International Journal of Sports Physical Therapy*, *12*(6), 901–907. https://doi.org/10.26603/ijspt20170901

Ibrahimy, M. I., Ahsan, M. R., & Khalifa, O. O. (2013). Design and performance analysis of artificial neural network for hand motion detection from EMG signals. *World Applied Sciences Journal*, *23*(6), 751–758. https://doi.org/10.5829/idosi.wasj.2013.23.06.117

Ille, A., Selin, I., Do, M. C., & Thon, B. (2013). Attentional focus effects on sprint start performance as a function of skill level. *Journal of Sports Sciences*, *31*(15), 1705–1712. https://doi.org/10.1080/02640414.2013.797097

Kehri, V., Ingle, R., Awale, R., & Oimbe, S. (2017). Techniques of EMG signal analysis and classification of neuromuscular diseases. *Advances in Intelligent Systems Research*, *137*, 485–491. https://doi.org/10.2991/iccasp-16.2017.71

Kellis, E., Galanis, N., Kapetanos, G., & Natsis, K. (2012). Architectural differences between the hamstring muscles. *Journal of Electromyography and Kinesiology*, *22*(4), 520–526. https://doi.org/10.1016/j.jelekin.2012.03.012

Lewis, C. L., & Sahrmann, S. A. (2009). Muscle activation and movement patterns during prone hip extension exercise in women. *Journal of Athletic Training*, *44*(3), 238–248. https://doi.org/10.4085/1062-6050-44.3.238

Lohse, K. R., Sherwood, D. E., & Healy, A. F. (2010). How changing the focus of attention affects performance, kinematics, and electromyography in dart throwing. *Human Movement Science*, *29*(4), 542–555. https://doi.org/10.1016/j.humov.2010.05.001

Lohse, K. R., Sherwood, D. E., & Healy, A. F. (2011). Neuromuscular effects of shifting the focus of attention in a simple force production task. *Journal of Motor Behavior*, *43*(2), 173–184. https://doi.org/10.1080/00222895.2011.555436

Lohse, K. R., Sherwood, D. E., & Healy, A. F. (2014). On the advantage of an external focus of attention: A benefit to learning or performance? *Human Movement Science*, *33*(1), 120–134. https://doi.org/10.1016/j.humov.2013.07.022

Mane, S. M., Kambli, R. A., Kazi, F. S., & Singh, N. M. (2015). Hand motion recognition from single channel surface EMG using wavelet & artificial neural network. *Procedia Computer Science*, *49*(1), 58–65. https://doi.org/10.1016/j.procs.2015.04.227

Marchant, D. C. (2011). Attentional focusing instructions and force production. *Frontiers in Psychology*, *1*(JAN), 1–9. https://doi.org/10.3389/fpsyg.2010.00210

Marchant, D. C., Greig, M., & Scott, C. (2009). Attentional focusing instructions influence force production and muscular activity during isokinetic elbow flexions. *Journal of Strength and Conditioning Research*, *23*(20), 2358–2366.

McAllister, M. J., Hammond, K. G., Schilling, B. K., Ferreria, L. C., Reed, J. P., & Weiss, L. W. (2014). Muscle activation during various hamstring exercises. *Journal of Strength and Conditioning Research*, *28*(6), 1573–1580.

https://doi.org/10.1519/JSC.0000000000000302

McNevin, N. H., Shea, C. H., & Wulf, G. (2003). Increasing the distance of an external focus of attention enhances learning. *Psychological Research*, *67*(1), 22–29. https://doi.org/10.1007/s00426-002-0093-6

Naseer, N., Ali, F., Ahmed, S., Iftikhar, S., Khan, R. A., & Nazeer, H. (2018). EMG Based Control of Individual Fingers of Robotic Hand. *3rd International Conference on Sustainable Information Engineering and Technology, SIET 2018 - Proceedings*, 6–9. https://doi.org/10.1109/SIET.2018.8693177

Nazmi, N., Abdul Rahman, M. A., Yamamoto, S. I., & Ahmad, S. A. (2019). Walking gait event detection based on electromyography signals using artificial neural network. *Biomedical Signal Processing and Control*, *47*, 334–343. https://doi.org/10.1016/j.bspc.2018.08.030

Nazmi, N., Rahman, M. A. A., Yamamoto, S. I., Ahmad, S. A., Zamzuri, H., & Mazlan, S. A. (2016). A review of classification techniques of EMG signals during isotonic and isometric contractions. *Sensors (Switzerland)*, *16*(8), 1–28. https://doi.org/10.3390/s16081304

Newell, K. M., & Hoshizaki, L. E. F. (1980). Attention demands of movements as a function of their duration and velocity. *Acta Psychologica*, *44*(1), 59–69. https://doi.org/10.1016/0001-6918(80)90076-1

Oleinikov, A., Abibullaev, B., Shintemirov, A., & Folgheraiter, M. (2018). Feature extraction and real-time recognition of hand motion intentions from EMGs via artificial neural networks. *2018 6th International Conference on Brain-Computer Interface*, 1–5. https://doi.org/10.1109/IWW-BCI.2018.8311527

Oweis, R. J., Rihani, R., & Alkhawaja, A. (2014). ANN-based EMG classification for myoelectric control. *International Journal of Medical Engineering and Informatics*, *6*(4), 365. https://doi.org/10.1504/ijmei.2014.065442

Pan, L., Crouch, D. L., & Huang, H. (2019). Comparing EMG-based human-machine interfaces for estimating continuous, coordinated movements. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(10), 2145–2154. https://doi.org/10.1109/TNSRE.2019.2937929

Paoli, A., Mancin, L., Saoncella, M., Grigoletto, D., Pacelli, F. Q., Zamparo, P., Schoenfeld, B. J., & Marcolin, G. (2019). Mind-muscle connection: effects of verbal instructions on muscle activity during bench press exercise. *European Journal of Translational Myology*, *29*(2), 106–111. https://doi.org/10.4081/ejtm.2019.8250

Pascua, L. A. M., Wulf, G., & Lewthwaite, R. (2015). Additive benefits of external focus and enhanced performance expectancy for motor learning. *Journal of Sports Sciences*, *33*(1), 58–66. https://doi.org/10.1080/02640414.2014.922693

Phinyomark, A., Khushaba, R. N., Ibáñez-Marcelo, E., Patania, A., Scheme, E., & Petri, G. (2017). Navigating features: A topologically informed chart of electromyographic features space. *Journal of the Royal Society Interface*, *14*(137). https://doi.org/10.1098/rsif.2017.0734

Politti, F., Casellato, C., Kalytczak, M. M., Garcia, M. B. S., & Biasotto-Gonzalez, D. A. (2016). Characteristics of EMG frequency bands in temporomandibullar disoders patients. *Journal of Electromyography and Kinesiology*, *31*, 119–125. https://doi.org/10.1016/j.jelekin.2016.10.006

Rafiee, J., Rafiee, M. A., Yavari, F., & Schoen, M. P. (2011). Feature extraction of forearm EMG signals for prosthetics. *Expert Systems with Applications*, *38*(4), 4058–4067. https://doi.org/10.1016/j.eswa.2010.09.068

Reaz, M. B. I., Hussain, M. S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: Detection, processing, classification and applications. *Biological Procedures Online*, *8*(1), 11–35. https://doi.org/10.1251/bpo115

Salmoni, A. W., Sullivan, S. J., & Starkes, J. L. (1976). The attention demands of movements: A critique of the probe technique. *Journal of Motor Behavior*, *8*(3), 161–169. https://doi.org/10.1080/00222895.1976.10735068

Scanlon, V. C., & Sanders, T. (2007). *Essentials of Anatomy and Physiology* (fifth).

Schoenfeld, Brad J, & Contreras, B. (2016). Attentional Focus for Maximizing Muscle Development: The Mind-Muscle Connection. *Strength & Conditioning Journal*, *38*(1), 27–29.

Schoenfeld, Brad Jon, Vigotsky, A., Contreras, B., Golden, S., Alto, A., Larson, R., Winkelman, N., & Paoli, A. (2018). Differential effects of attentional focus strategies during long-term resistance training. *European Journal of Sport Science*, *18*(5), 705–712. https://doi.org/10.1080/17461391.2018.1447020

Schücker, L., & Parrington, L. (2019). Thinking about your running movement makes you less efficient: attentional focus effects on running economy and kinematics. *Journal of Sports Sciences*, *37*(6), 638–646. https://doi.org/10.1080/02640414.2018.1522697

Sharma, S., & Dubey, A. K. (2012). Movement control of robot in real time using EMG signal. *ICPCES 2012 - 2012 2nd International Conference on Power, Control and Embedded Systems*, 1–4. https://doi.org/10.1109/ICPCES.2012.6508060

Shea, C. H., & Wulf, G. (1999). Enhancing motor learning through external-focus instructions and feedback. *Human Movement Science*, *18*(4), 553–571. https://doi.org/10.1016/S0167-9457(99)00031-7

Shi, W. T., Lyu, Z. J., Tang, S. T., Chia, T. L., & Yang, C. Y. (2018). A bionic hand controlled by hand gesture recognition based on surface EMG signals: A preliminary study. *Biocybernetics and Biomedical Engineering*, *38*(1), 126–135. https://doi.org/10.1016/j.bbe.2017.11.001

Shobhitha, A. J., Jegan, R., & Melwin, A. C. (2013). OWI-535 EDGE Robotic Arm Control Using ElectroMyoGram (EMG) Signals. *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, *2*(6), 282–286.

Shrestha, A., & Mahmood, A. (2019). Review of deep learning algorithms and architectures. *IEEE Access*, *7*(c), 53040–53065. https://doi.org/10.1109/ACCESS.2019.2912200

Singh, Y. (2013). *Analaysis and Classification of EMG Signal Using LabVIEW with Different Weights*. Thapar University, India.

Stashuk, D. (2001). EMG signal decomposition: How can it be accomplished and used? *Journal of Electromyography and Kinesiology*, *11*(3), 151–173. https://doi.org/10.1016/S1050-6411(00)00050-X

Tavakoli, M., Benussi, C., Alhais Lopes, P., Osorio, L. B., & de Almeida, A. T. (2018). Robust hand gesture recognition with a double channel surface EMG wearable armband and SVM classifier. *Biomedical Signal Processing and Control*, *46*, 121–130. https://doi.org/10.1016/j.bspc.2018.07.010

Tillaar, R. Van Den, Asmund, J., & Solheim, B. (2017). Comparison of Hamstring Muscle Activation During High-Speed Running and Various Hamstring Strengthening Exercises. *International Journal of Sports Physical Therapy*, *12*(5), 718–727. https://doi.org/10.16603/ijspt20170718

Tremolada, M., Taverna, L., & Bonichini, S. (2019). Which factors influence attentional functions? Attention assessed by KITAP in 105 6-to-10-year-old children. *Behavioral Sciences*, *9*(1). https://doi.org/10.3390/bs9010007

Vance, J., Wulf, G., Töllner, T., McNevin, N., & Mercer, J. (2004). EMG activity as a function of the performer's focus of attention. *Journal of Motor Behavior*, *36*(4), 450–459. https://doi.org/10.3200/JMBR.36.4.450-459

Welling, W., Benjaminse, A., Gokeler, A., & Otten, B. (2016). Enhanced retention of drop vertical jump landing technique: A randomized controlled trial. *Human Movement Science*, *45*, 84–95. https://doi.org/10.1016/j.humov.2015.11.008

Woods, C., Hawkins, R. D., Maltby, S., Hulse, M., Thomas, A., & Hodson, A. (2004). The Football Association Medical Research Programme: An audit of injuries in professional football - Analysis of hamstring injuries. *British Journal of Sports Medicine*, *38*(1), 36–41. https://doi.org/10.1136/bjsm.2002.002352

Wright, G. A., Delong, T. H., & Gehlsen, G. (1999). Electromyographic Activity of the Hamstrings during Performance of the Leg Curl, Stiff-Leg Deadlift, and Back Squat Movements. *Journal of Strength and Conditioning Research*, *13*(2), 168–174. https://doi.org/10.1519/1533-4287(1999)013<0168:EAOTHD>2.0.CO;2

Wulf, G., McConnel, N., Gartner, M., & Schwarz, A. (2002). Enhancing the learning of sport skills through external-focus feedback. *Journal of Motor Behavior*, *34*(2), 171–182. https://doi.org/10.1080/00222890209601939

Wulf, Gabriele. (2013). Attentional focus and motor learning: A review of 15 years. *International Review of Sport and Exercise Psychology*, *6*(1), 77–104. https://doi.org/10.1080/1750984X.2012.723728

Wulf, Gabriele, Dufek, J. S., Lozano, L., & Pettigrew, C. (2010). Increased jump height and reduced EMG activity with an external focus. *Human Movement Science*, *29*(3), 440–448. https://doi.org/10.1016/j.humov.2009.11.008

Wulf, Gabriele, Höß, M., & Prinz, W. (1998). Instructions for motor learning: Differential effects of internal versus external focus of attention. *Journal of Motor*

Behavior, *30*(2), 169–179. https://doi.org/10.1080/00222899809601334

Wulf, Gabriele, Lauterbach, B., & Toole, T. (1999). The learning advantages of an external focus of attention in golf. *Research Quarterly for Exercise and Sport*, *70*(2), 120–126. https://doi.org/10.1080/02701367.1999.10608029

Wulf, Gabriele, McNevin, N., & Shea, C. H. (2001). The automaticity of complex motor skill learning as a function of attentional focus. *Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology*, *54*(4), 1143–1154. https://doi.org/10.1080/713756012

Wulf, Gabriele, & Su, J. (2007). An external focus of attention enhances golf shot accuracy in beginners and experts. *Research Quarterly for Exercise and Sport*, *78*(4), 384–389. https://doi.org/10.1080/02701367.2007.10599436

Zachry, T., Wulf, G., Mercer, J., & Bezodis, N. (2005). Increased movement accuracy and reduced EMG activity as the result of adopting an external focus of attention. *Brain Research Bulletin*, *67*(4), 304–309. https://doi.org/10.1016/j.brainresbull.2005.06.035

RESUME

Name- Surname : **Ayşe Nur AY**

Date of birth and place : [redacted]

E-mail : [redacted]

EDUCATION:

- **Bachelor degree :** 2013, Erciyes University, Faculty of Enginnering, Biomedical Engineering.
- **Master degree :** 2016, Anhalt University of Applied Sciences (Köthen) & Martin Luther Universitat Halle-Wittenberg / GERMANY, Master of Engineering in Biomedical Engineering.

PROFESSIONAL EXPERIENCE AND AWARDS:

- 2013-2014, Volunteer work, ST Anne’s Court Residential Care Home Bournemouth/ United Kingdom.
- 2014, Volunteer work, Energy Kids Club/ English teaching, Antalya / Turkey
- 2016-2018, Research Assistant in Deparment of Mechatronics Engineering at Sakarya University
- 2018-2021, Research Assistant in Deparment of Mechatronics Engineering at Sakarya University of Applied Sciences.
- 2021, Graduated from Sakarya University of Applied Sciences with doctoral diploma.

PUBLICATIONS, PRESENTATIONS AND PATENTS DRAWED FROM THE DOCTORAL THESIS:

- **Ay, A. N., Dolukan, Y. B., & Yildiz, M. Z. , 2018.** The Effect of Attentional Focus Conditions on Performer's EMG Activity. *,* 09-11 November 2018, Antalya, Turkey.

- **Ay, A. N., Dolukan, Y. B., & Yildiz, M. Z. , 2019.** The Effect of Attentional Focus Conditions on Performer's EMG Activity. *Academic Perspective Procedia*, 1(1), 240–247. https://doi.org/10.33793/acperpro.01.01.45.

- **Ay, Ayse Nur and Yildiz, Mustafa Zahid., 2020.** The effect of attentional focusing strategies on EMG-based classification. *Biomedical Engineering / Biomedizinische Technik*. https://doi.org/10.1515/bmt-2020-0082.