A Comparative Analysis of Different Features for EMG Signal Classification

By

Zainab Ikram

(Registration No: 00000362310)

Department of Biomedical Engineering & Sciences

School of Mechanical and Manufacturing Engineering

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

(2024)

A Comparative Analysis of Different Features for EMG Signal Classification

By

Zainab Ikram

(Registration No: 00000362310)

A thesis submitted to the National University of Sciences and Technology, Islamabad,

in partial fulfillment of the requirements for the degree of

Master of Science in

Biomedical Sciences

Supervisor: Dr. Muhammad Asim Waris

School of Mechanical and Manufacturing Engineering

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

(2024)

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS/MPhil thesis written by **Regn No. 00000362310 Zainab Ikram** of **School of Mechanical & Manufacturing Engineering (SMME)** has been vetted by undersigned, found complete in all respects as per NUST Statues/Regulations, is free of plagiarism, errors, and mistakes and is accepted as partial fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis titled. **A Comparative Analysis of Different Features for EMG Signal Classification**

Signature:

Name (Supervisor): Muhammad Asim Waris

Date: 05 - Jul - 2024

Signature (HOD):

Date: 05 - Jul - 2024

Signature (DEAN):

Date: 05 - Jul - 2024

Form TH-4

National University of Sciences & Technology (NUST)

MASTER'S THESIS WORK

We hereby recommend that the dissertation prepared under our supervision by: Zainab Ikram (00000362310)
Titled: A Comparative Analysis of Different Features for EMG Signal Classification be accepted in partial fulfillment of the requirements for the award of MS in Biomedical Sciences degree.

Examination Committee Members

1. Name: Adeeb Shehzad Signature:

2. Name: Aneeqa Noor Signature:

Supervisor: Muhammad Asim Waris Signature:

Date: 05 - Jul - 2024

Head of Department

05 - Jul - 2024
Date

COUNTERSINGED

05 - Jul - 2024
Date

Dean/Principal

CERTIFICATE OF APPROVAL

This is to certify that the research work presented in this thesis, entitled "A Comparative Analysis of Different Features for EMG Signal Classification" was conducted by Ms Zainab Ikram under the supervision of Dr. Muhammad Asim Waris.

No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the Department of Biomedical Engineering & Sciences in partial fulfillment of the requirements for the degree of Master of Science in Field of Biomedical Engineering & Sciences.

Department of Biomedical Engineering & Sciences National University of Sciences and Technology, Islamabad.

Student Name: Zainab Ikram Signature: Zainab

Supervisor Name: Dr. Muhammad Asim Waris Signature: ______

Name of Dean/HOD: Dr. Muhammad Asim Waris Signature: ______

AUTHOR'S DECLARATION

I Zainab Ikram hereby state that my MS thesis titled "A Comparative Analysis of Different Features for EMG Signal Classification" " is my own work and has not been submitted previously by me for taking any degree from National University of Sciences and Technology, Islamabad or anywhere else in the country/ world.

At any time if my statement is found to be incorrect even after I graduate, the university has the right to withdraw my MS degree.

Name of Student: Zainab Ikram

Date: 22-July-2024

PLAGIARISM UNDERTAKING

I solemnly declare that research work presented in the thesis titled "A Comparative Analysis of Different Features for EMG Signal Classification" is solely my research work with no significant contribution from any other person. Small contribution/ help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and National University of Sciences and Technology (NUST), Islamabad towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS degree, the University reserves the rights to withdraw/revoke my MS degree and that HEC and NUST, Islamabad has the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized thesis.

Student Signature: Zainab

Name: Zainab Ikram

To my loving family, for your unwavering support, encouragement, and belief in me throughout this journey. Your love, understanding, and sacrifices have been my constant source of strength and inspiration. This accomplishment is as much yours as it is mine.

ACKNOWLEDGEMENTS

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You setup in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout in every department of my life.

I would also like to express my deepest gratitude to my husband whose love and support have been a constant source of strength and motivation in completing this thesis.

I would also like to express special thanks to my supervisor Dr. Muhammad Asim Waris for his help throughout my thesis and also for Signals in Biomedical Sciences and Clinical Biostatistics courses which he has taught me.

I would also like to pay special thanks to Urwah Imran and Maham Nayab for their tremendous support and cooperation. Each time I got stuck in something; they came up with the solution. Without their help I wouldn't have been able to complete my thesis. I appreciate their patience and guidance throughout the whole thesis.

I would also like to thank Dr. Adeeb Shehzad and Dr. Aneeqa Noor for being on my thesis guidance and evaluation committee

Lastly, I would like to express my gratitude to all the individuals who have rendered valuable assistance to my study.

TABLE OF CONTENTS

LIST OF TABLES

Page No.

LIST OF FIGURES

Page No.

LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

EMG	Electromyography
sEMG	Surface Electromyography
MPR	Myoelectric Pattern Recognition
MUAP	Motor Unit Action Potentials
ANS	Autonomic Nervous System
MES	Myoelectric Signals
MEC	Myoelectric Control
SVM	Support Vector Machine
CARD	Cardinality
MAV	Mean Absolute Value
BP	Band power

ABSTRACT

Electromyography (EMG) signals serve as vital tools in neurological and neuromuscular conditions diagnosis. Various features are used as inputs for pattern recognition algorithms. This project intends to increase the precision and efficacy of prosthetic limb control, with the goal of boosting the quality of life for individuals with limb amputations, using a Linear Support Vector Machine technique. Specifically, we intend to analyze the usefulness of the distinctive feature known as Cardinality within diverse combinations of time-domain and frequency-domain features. In order to improve signal quality, the raw EMG signal is filtered and segmented. The time-domain and frequency-domain features are then retrieved from overlapping segments, and the most relevant ones are retained using exhaustive feature selection. An SVM classifier is then used to examine the possible impact of Cardinality on prosthetic control and rehabilitation outcomes. The research findings show that the efficiency of Cardinality is dependent on the precision of the units used. Cardinality performed best when seven decimal points are used. MAV stands out among time-domain features, as it generated a high number of combinations with Cardinality, enhancing its performance in myoelectric pattern recognition and BP emerges as the top-performing frequency-domain feature when integrated with Cardinality, surpassing other frequency-domain features and forming the most numerous combinations. The SVM classifier achieved classification accuracy of 85.58% of M1, 70.49% of M2, 77.32% of M3, 77.24% of M4, 80.82% of M5, 77.52% of M6, 82.94% of M7, 84.34% of M8, 84.75% of M9, 86.92% of M10 for the combination of Cardinality with MAV and BP. As advancements in prosthetics and rehabilitation technologies continue, the insights gained from this study can play a pivotal role in refining the precision and efficiency of Myoelectric Control systems, ultimately benefiting individuals with limb loss or motor impairments.

Keywords: Electromyography Signals (EMG)**,** Myoelectric Pattern Recognition (MPR), Support Vector Machine (SVM) classifier, Cardinality (Card), Mean Absolute Value (MAV), Band Power (BP).

CHAPTER: 1

1.1 INTRODUCTUTION

Electromyographic signals, or EMG signals, are the electrical impulses produced by the contraction of human skeletal muscle (Ashraf et al., 2020). EMG signals can be obtained via the electromyography technique, which includes placing electrodes on the skin's surface or directly into muscular tissue. The non-invasive technique involves indirectly recording muscle movement by placing electrodes on the skin surface, whereas the invasive technique involves directly recording muscle movement by inserting electrodes into the muscle tissue.

Various factors influence the properties of an electromyogram (EMG), including its amplitude and spectral aspects. These characteristics include skin thickness and temperature, the quantity of fat between the muscle and the skin, the rate of blood circulation, and sensor placement. Furthermore, tiredness, the ageing process, and neuromuscular diseases can all have a negative impact on muscle performance and EMG patterns (Kundu & Subarram Naidu, 2021).

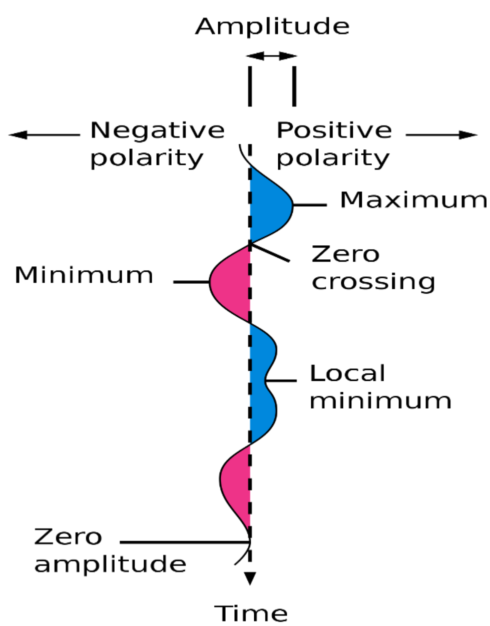


Figure 1.1 provides an illustration of a seismic waveform.

Electromyography (EMG) signals have a variety of roles in medical, scientific, and clinical settings. These signals help professionals diagnose neurological and neuromuscular disorders, evaluate walking patterns in gait laboratories, and assist specialists with biofeedback and ergonomic assessments. Furthermore, EMG is a great resource in research laboratories, allowing for the investigation of many aspects of muscle function. It also plays an important role in guiding rehabilitation therapy, allowing for patient-specific interventions. This includes research into biomechanics, motor control, neuromuscular physiology, analysis of movement problems, posture evaluation, and the development of successful physical therapy regimens. (Raez et al., 2006).

In rehabilitation therapies, the primary objective of limb prothesis is to emulate optimal performance. These prostheses are designed to not only reinstate functional capabilities but also replicate the visual characteristics of a missing limb for individuals who have experienced limb loss due to accidents or congenital limb deficiency. Such individuals are frequently susceptible to the potential onset of psychological distress, stemming from societal marginalization and their constrained ability to perform activities of daily living. According to estimations, it has been noted that in 2005, approximately 664,000 individuals in the United States had experienced limb amputations, and about 900,000 had suffered minor limb losses ("Standards for Reporting EMG Data," 2014). Furthermore, it is anticipated that these statistics will undergo a twofold increase by the year 2050 (Hubbard & Berkoff, 1993). Global estimations have indicated a substantial surge in amputations due to multifactorial influences, encompassing factors such as weapon-related violence, accidents, population growth, acts of terrorism, natural calamities like earthquakes and tsunamis, and certain pathological conditions including diabetes and vascular ailments (Budzynski et al., 1973). It has been documented that from 1988 to 1996, approximately 1 out of every 200 individuals in the USA encountered issues associated with amputations. Furthermore, hospitals carried out an average of approximately 130,000 amputation procedures annually (Woods & Bigland-Ritchie, 1983).

During the seismic event that occurred in Pakistan in 2005, there were approximately 19,700 reported injuries directly associated with the limbs. Among this cohort, a substantial 78% of cases necessitated limb amputations as a result of the trauma sustained (ALKNER et al., 2000). Within the specific geographical context of Sindh, a total of 1115 limb amputations were documented, with the causal factors encompassing traffic accidents, acts of terrorism, agricultural mishaps, underlying medical conditions, incidents of gun violence, and industrial accidents (Jobe et al., 1984). A gender-based analysis revealed that males exhibited a significantly higher susceptibility to limb injuries, with a striking ratio of 7:1 when compared to females. This predilection towards male subjects can be attributed, in part, to their greater participation in labour-intensive, mechanized work environments (Yao et al., 2000).

This study is motivated by a desire to advance our scientific understanding and technological capabilities in the realm of EMG signal analysis. This research aims to augment the precision and efficacy of prosthetic limb control, enhancing the quality of life for amputees. Beyond practical applications, the study contributes to the scientific knowledge base concerning neuromuscular systems, fostering technological innovation in the domain of wearable devices and sensors. Ultimately, these endeavors aim to foster societal inclusivity and propel the frontier of scientific inquiry in biomechanics and rehabilitation science. The anticipation of motion utilizing EMG signal is particularly significant in the context of governing prosthetic limbs and exoskeletons. Employing pattern recognition algorithms driven by EMG features facilitates the intuitive control of multiple robotic or virtual joints for individuals who have experienced amputation (Farina et al., 2014), stroke (Lee et al., 2011), or spinal cord injuries (Liu & Zhou, 2013). The effectiveness of this control mechanism hinges on the capabilities of EMG features to more accurately characterize patterns of muscular activity, underscoring their essential role in this application.

In contrast to features commonly found in existing literature, cardinality consistently demonstrates superior accuracy in pattern recognition-based Myoelectric Control (MEC), even amidst variations in sampling frequency, time window length, contraction dynamics, the number and type of movements (individual or simultaneous), and different pattern recognition algorithms. Therefore, cardinality is advocated as a more effective feature for MEC in predicting motion volition. Cardinality, denoted as card(A) or #A, delineates the numerical count of distinct elements within a set. Unlike amplitude-sensitive metrics such as mean absolute value, zero crossings, and root mean square, cardinality remains impervious to direct current offsets induced by electrode impedance mismatches. This property aligns cardinality with features akin to wavelength and the quantification of slope changes. It is imperative to acknowledge that the precision of cardinality is contingent upon the specific units employed, such as byte, word, double, etc. (Ortiz-Catalan, 2015). In the context of this investigation, a superior feature was carefully selected to form a comprehensive collection of characteristics for the segmented signal. This feature ensemble combines one time-domain and one frequency-domain feature, as well as cardinality. The goal of this feature selection is to improve the accuracy and effectiveness of muscle pattern identification. This upgrade has far-reaching consequences, particularly in terms of enhancing the control interface for devices such as prosthetics, which will provide practical benefits to amputees and people with motor disability.

The selective selection of a time-domain feature and a frequency-domain feature, combined with cardinality, is intended to capture a comprehensive picture of the segmented signal's characteristics. The recognition of complicated muscle patterns becomes more strong and subtle as features from multiple domains are integrated. This, in turn, contributes to refining the control algorithms for assistive devices, ensuring a more natural and responsive interface between users and prosthetic limbs. The ultimate goal is to use these advanced features to help people who have difficulty moving around. The study aims to improve prosthetic device functioning and adaptability by optimising muscle pattern recognition. This equates to enhanced control, increased user satisfaction, and a significant improvement in quality of life for people who have had limbs amputated or have motor impairments. As a result, the research not only enhances scientific knowledge but also has a direct and positive impact on the creation of assistive devices, accelerating progress in the field of rehabilitation engineering.

1.2 HISTORY

The history of electromyography (EMG) dates back to the 17th century when Francesco Redi documented that the electric rays had specialized muscles capable of generating electricity. By the 18th century, scientists like Walsh observed that the muscles of eel fish could produce sparks of electricity. In the late 18th century, Galvani showed that electricity could make muscles contract (Kleissen et al., 1998). In the mid-19th century, Dubois-Raymond discovered that you could record electrical activity during muscle contractions. The term "electromyography" was introduced by Marey in 1890 when he made the first recordings of this electrical muscle activity. In 1922, Gasser and Erlanger used an oscilloscope to display muscle electrical signals. However, due to the unpredictable nature of these signals, they could only provide limited information. From the 1930s to the 1950s, researchers improved their ability to detect electromyographic signals and started using better electrodes to study muscles (Shahid et al., 2005). Clinical use of surface EMG began in the 1960s, and in the early 1980s, Cram and Steger introduced a method for scanning various muscles using EMG devices (Cram & Kasman GS Holtz J., n.d.).

It wasn't until the mid-1980s that electrode integration techniques advanced enough to allow mass production of small and lightweight EMG equipment. Today, there are many commercially available amplifiers for EMG signals. In the early 1980s, cables were developed that could capture the tiny electrical signals of interest without interference (Nikias & Raghuveer, 1987). Over the past 15 years, research has improved our understanding of how to record surface EMG effectively. Nowadays, surface electromyography is commonly used in clinical settings to monitor superficial muscles, while intramuscular electrodes are reserved for deep muscles (Kleissen et al., 1998). Among the earliest applications of electromyography (EMG), a pivotal role emerged with the extraction of EMG signals, acting as a fundamental input source for power-guided upper limb prostheses. Termed "myoelectric control," this concept finds its origins in the 1940s and experienced notable progress from the 1960s to the 1980s (Lundberg et al., 1994). In the 21st century, the landscape has evolved further, with a particular focus on designing and developing a varied array of powered prostheses. Contemporary research is distinguished by a strong emphasis on recognition-based controllers that take advantage of the complexities of EMG patterns.

This area of investigation within the broader field of electromyography not only examines the historical evolution of myoelectric control but also highlights the contemporary focus on advancing prosthetic significantly to the complex study and understanding of muscle activity and hold potential applications in diverse medical and research contexts technologies. The use of EMG patterns as a foundation for recognition-based controllers is a well-established and well explored aspect of EMG research, significantly contributing to the continuous efforts to improve the functioning and usability of powered prostheses. This ongoing research holds promise for new innovations in technological assistance, particularly in the field of upper limb prosthetic control (Mathiassen et al., 1995). One of the two categories of electromyography (EMG) is Needle EMG, which involves using needles for the recording of muscle electrical activity. True to its name, this technique is designed to capture the EMG signal arising from the activation of Motor Unit Action Potentials (MUAP) in the immediate vicinity of the needle, covering a very small area. This method proves beneficial for obtaining highly concentrated information from both deep and superficial muscles. The second category, known as surface electromyography (sEMG), operates on a different principle. This approach involves the detection of action potentials from motor units across a more extensive surface area of the muscle. Its utility lies in providing a holistic understanding of muscular contractions on a global scale. Surface electromyography is predominantly employed to discern MUAPs in superficial muscles. Contemporary applications of surface EMG incorporate specialized electrodes, such as 2D electrode grids or linear electrode arrays (Hiraiwa et al., n.d.). These advancements not only facilitate the implementation of filters, including spatial filters but also empower an in-depth analysis of various parameters of individual MUAPs. As a result, both Needle EMG and surface electromyography contribute.

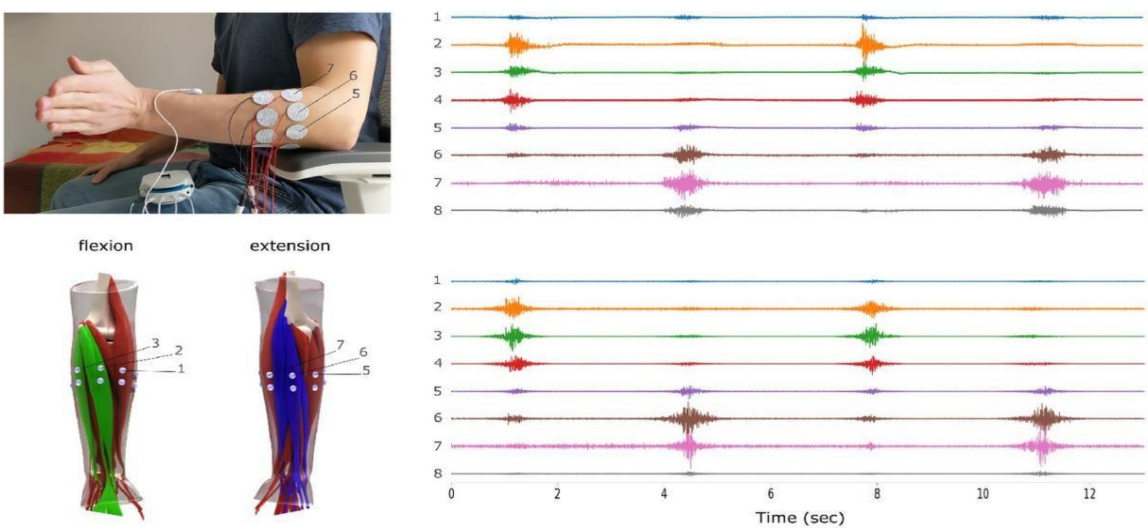


Figure 1.2 demonstrates the arrangement of surface electrodes on the forearm, positioned to capture EMG signals during both flexion and extension movements.

The close proximity of muscles to surrounding tissues poses a significant challenge in the domain of electromyography (EMG) signal recording. This challenge is particularly pronounced when employing surface electromyography (sEMG), where interference from neighbouring tissues has the potential to obscure crucial information. This stands in contrast to the more direct needle EMG method. Despite this inherent challenge, the popularity of sEMG has soared, thanks to its user-friendly features that enable convenient signal recording and its non-invasive nature. The interference from surrounding tissues, while a notable drawback, has not deterred the widespread adoption of sEMG. The non-invasiveness and ease of use make sEMG an attractive option for a broad spectrum of users. This includes not only seasoned researchers but also extends to amateur operators and individuals engaged in non-medical research settings.

The preference for sEMG can be attributed to its practical advantages, as it allows for a more accessible and comfortable recording experience compared to needle EMG. This democratization of signal recording technology has broadened the scope of EMG applications beyond traditional medical research, reaching fields such as sports science, human-computer interaction, and ergonomics. The versatility and convenience of sEMG contribute to its increasing relevance in various domains, making it a valuable tool for both professionals and enthusiasts alike. Despite the challenges posed by tissue interference, the widespread adoption of sEMG underscores its pivotal role in advancing our understanding of muscle activity and enhancing the applicability of EMG technology in diverse contexts. The widespread adoption of sEMG in various applications, such as fatigue assessment, biofeedback systems, and movement analysis, signifies its versatility. However, this versatility has brought about operational challenges. The absence of standardized guidelines for the use of sEMG has led to compromised reliability in the collected EMG signal data. This issue is underscored by the presence of conflicting results and factual discrepancies in research papers spanning the last two decades, causing a degree of perplexity among contemporary researchers (Day et al., 1989). In light of these challenges, there are growing concerns regarding the dependability of surface electromyography across different applications. While modern EMG techniques have certainly simplified the process of recording signals, the interpretative phase remains intricate due to the operational complexities associated with sEMG. Consequently, potential inconsistencies in findings related to EMG patterns, modalities, timing, and muscle activation rates raise questions about the overall reliability of sEMG in contemporary research and application.

Contemporary electromyography (EMG) encompasses both needle EMG and surface EMG techniques, serving as integrated and interdependent tools for EMG signal processing. These two methods operate as interconnected instruments, mutually dependent in the intricate process of EMG signal processing. Their collective significance is particularly pronounced in investigations that delve into various physiological parameters. Needle EMG, with its precise capabilities, holds a central role in diagnostic practices, providing detailed insights into muscular activity. Conversely, surface EMG is notably prevalent in fields such as ergonomics, motion analysis, sports medicine, occupational medicine, prosthetic control devices, and biofeedback. What distinguishes surface EMG is its non-invasive nature, allowing for painless and frequent examinations of the neuromuscular system's functionality. This characteristic makes it an invaluable tool for understanding and assessing muscle activity in a variety of practical applications. Despite the substantial role played by surface electromyography, it is observed that its uses and applications are often overlooked and not comprehensively covered in academic circles. Consequently, there is a growing focus on emphasizing the non-invasive nature of surface EMG, highlighting its significance and potential across various disciplines (Hallett et al., 1975). This concerted effort aims to underscore the importance of surface electromyography in the contemporary understanding and utilization of EMG techniques, fostering a more holistic approach to its application in diverse fields.

1.3 MOTIVATION

This research is motivated by a keen interest in advancing our scientific comprehension and technological capabilities within the domain of Electromyography (EMG) signal analysis. The primary objective is to elevate the precision and effectiveness of prosthetic limb control, with the ultimate goal of enhancing the overall quality of life for individuals with limb amputations. Moreover, the study aspires to fortify the healthcare field by enabling more accurate diagnosis and monitoring of neuromuscular disorders, potentially facilitating early intervention and leading to improved patient outcomes. The implications of this study extend beyond the realms of prosthetics and healthcare. It holds significant promise for influencing human-computer interaction, ergonomics, and occupational health. By offering refined assessments of muscle fatigue and ergonomic stress, the research could contribute to creating healthier and more sustainable work environments. This has the potential to positively impact occupational practices and overall well-being. In addition to its practical applications, the study contributes to the scientific understanding of neuromuscular systems, laying the groundwork for technological innovation in wearable devices and sensors. Insights gained from this research may fuel advancements in the design and implementation of technologies that seamlessly integrate with the human body, enhancing the capabilities of assistive devices and health monitoring systems. Ultimately, the overarching goal of these research endeavors is to foster societal inclusivity by addressing the unique needs of individuals with limb amputations and neuromuscular disorders. Simultaneously, the study seeks to push the frontier of scientific inquiry in the interdisciplinary fields of biomechanics and rehabilitation science, aiming to unlock new possibilities for enhancing human mobility, well-being, and overall quality of life.

1.4 OBJECTIVE

The study aims to conduct a comprehensive comparative analysis of various EMG features commonly utilized in EMG signal classification. Specifically, it seeks to explore the impact of a time-domain feature, Cardinality, on classification accuracy using an SVM classifier. Cardinality's performance depends on the precision of the units used. In this study, Cardinality performs best with seven decimal points. Features play a pivotal role in characterizing the unique patterns within EMG signals that are indicative of different muscle activities. In the context of this investigation, a standout feature is meticulously chosen to constitute a set of features for the segmented signal. This set encompasses not only a time-domain feature but also a frequency-domain feature, complemented by the consideration of cardinality. The primary objective of this feature selection is to amplify the precision in recognizing intricate muscle patterns. The overarching aim is to provide substantial benefits to amputees and individuals facing motor impairments, facilitating more seamless and intuitive control over advanced devices, particularly prosthetics. This research holds the potential to significantly advance the field, fostering advancements in assistive technology and ultimately improving the quality of life for those with limb loss or motor challenges.

1.5 STRUCTURE OF THESIS

The thesis is thoughtfully structured into four insightful chapters, each contributing to a comprehensive understanding of electromyography (EMG) signals. In the inaugural chapter, a retrospective examination of the history of EMG signals sets the stage, providing valuable context for the subsequent exploration. Additionally, the chapter outlines the overarching objectives of the thesis work, offering a roadmap for the ensuing research journey.

Chapter 2 serves as the cornerstone, offering an in-depth exploration of fundamental concepts essential for grasping the intricacies of electromyography signal generation. Commencing with an exploration of the contraction mechanism of smooth muscles and the integral role of motor units within, Cerebellum, the neuromuscular system responsible for orchestrating muscle movements, this chapter lays the groundwork for the thesis's primary focus. The discussion shifts towards the development of power-based prostheses, highlighting the significance of surface myoelectric signals derived from surface electromyography (sEMG) as a substantial and efficient input system. Within this context, the technical application known as myoelectric control takes centre stage, with a detailed examination of its principles. Furthermore, the chapter delves into the technical aspects of EMG signal filtration, segmentation into disjoint and overlapping segments, and the critical aspects of feature extraction and selection—a core subject of the thesis.

Chapter 3 unveils the methodology employed in the thesis, providing insights into the process of obtaining datasets, the application of filters to remove unwanted signals from the EMG signal, the intricacies of signal segmentation, and the extraction of time-domain and frequency-domain features from both disjoint and overlapping segments of the EMG signal. A noteworthy feature of this chapter is the application of an exhaustive feature selection technique, exploring all conceivable combinations of Cardinality with the 10 time-domain features and 5 frequency-domain features.

The conclusive chapter, Chapter 4, serves as the culmination of the research endeavour, where all findings are systematically summarized, presented, and discussed. This final section offers a platform for synthesizing the results, reflecting on their implications, and engaging in a comprehensive discussion. Through this structured approach, the thesis not only contributes to the existing body of knowledge but also lays the groundwork for potential future research avenues in the dynamic field of electromyography. In summarizing the chapter’s findings, it is evident that the Mean Absolute Value extracted from the time-domain feature demonstrated a notable propensity for forming diverse combinations with Cardinality. Simultaneously, within the realm of frequency-domain features, Band Power emerged as a key player, showcasing a substantial association with Cardinality. The synergy of these three features in combination yielded favorable outcomes, underscoring their synergistic impact on the overall result.

CHAPTER: 2

2.1 FUNDAMENTAL CONCEPTS

Electromyography (EMG) involves recording the electrical activity generated by muscle contractions. This is valuable because EMG is closely linked to torque, making it a useful tool for assessing muscle tension in various physical examinations (Viitasalo & Komi, 1977). EMG signals have a complex nature. For better understanding of the EMG signals, it is essential to gain insights into the origin and characteristics of the EMG signal. The neuromuscular component plays a pivotal role in facilitating voluntary bodily movements, wherein the contraction and relaxation of muscles are initiated through the orchestrated functioning of specialized nervous system cells known as neurons.

Neurons are responsible for generating a minute electrical potential difference at the surface of muscle cells, serving as the trigger for the initiation of the muscle contraction process. This electrical alteration subsequently triggers the activation of motor neurons, which are specialized nerve cells with the responsibility of regulating muscle activity. This activation leads to a specific electric pattern denoted as depolarization, signifying a modification in the electric charge within the neuron. The waveform generated in the course of this process is then conveyed to the terminus of the neuron, which is identified as the Postsynaptic Neuron, called Action Potential or sometimes simply abbreviated as AP. The term "Postsynaptic Neuron" designates the neuron that receives and responds to these electrical signals, ultimately culminating in the initiation of muscle contraction. An action potential is initiated within a muscle fiber when its internal membrane potential increases by approximately 40 mV from its resting level, typically around -90 mV relative to the surrounding extracellular fluid. This initiation can occur either at the neuromuscular junction, when the muscle is stimulated by a motor nerve fiber, or at the point opposite to the cathode when direct electrical stimulation is applied. The resulting action potential then propagates bidirectionally along the muscle fiber, a process that shares fundamental similarities with the mechanisms observed in nerve fibers, the process of action potential propagation in muscle fibers closely resembles that observed in nerve fibers although there are some subtle distinctions (Huxley, 1974).

2.1.1 THE CONTRACTILE MECHANISM

The physiological dynamics of muscle contraction hinge on the interplay between two fundamental variables: length and tension. Within the realm of physiology, it is crucial to distinguish between muscle shortening and contraction, as tension can be generated within a muscle without any concomitant change in its length. This phenomenon is exemplified when one holds a stationary dumbbell or cradles a peacefully sleeping child. Upon the cessation of muscle contraction, a subsequent phase of muscle relaxation ensues, characterized by the return of muscle fibers to a low-tension state. The muscular system in mammals encompasses three distinct types of muscles: skeletal, cardiac, and smooth. Skeletal muscles, firmly attached to bones, confer structural integrity and strength to the body. The cardiac muscles form the walls of the heart, facilitating the rhythmic pumping of blood through the vasculature. Smooth muscles, found in diverse anatomical locations such as blood vessels, the gastrointestinal tract, bronchioles, uterus, and bladder, play a pivotal role in various physiological functions.

To further dissect the complexity of muscle contraction within the human body, it is instructive to consider the specialization of muscle subtypes. Broadly speaking, muscle fibers fall into two major categories: striated muscle fibers and smooth muscle fibers. Striated muscle fibers, distinguished by the presence of actin and myosin filaments orchestrating contraction, exhibit an organized structure with repeating sarcomeres, resulting in a distinctive striated microscopic appearance. Cardiac muscle tissue, an involuntary striated muscle fiber, falls under the intricate control of the autonomic nervous system (ANS). In contrast, skeletal muscle tissue, a voluntary striated muscle fiber, is subject to conscious control. Smooth muscle fibers, in contrast, lack the characteristic sarcomeric organization but utilize actin and myosin contraction to achieve functions such as the constriction of blood vessels and the propulsion of contents within hollow organs. These fibers operate involuntarily, responding to reflexes and the regulatory signals of the body's autonomic nervous system (ANS). The intricate and specialized nature of muscle contraction thus underscores the multifaceted orchestration of physiological processes within the human body (Gash et al., 2023).

In our bodies, the contraction of smooth muscle cells is mainly controlled by two things: receptors and mechanical stretching, which activate the proteins responsible for muscle contraction. Another way to trigger contraction is by changing the electrical charge on the cell's surface. This can happen when the cells receive signals or when they get stretched. For the muscle to contract, a special enzyme called myosin light chain kinase (MLC kinase) has to add a phosphate group to a part of the myosin protein. This phosphorylation process is like a switch that allows myosin to connect with another protein called actin, initiating the contraction. All of this requires energy, which comes from a molecule called ATP that cells use for various activities. So, the main factor that determines the activity of smooth muscle is whether the myosin protein is phosphorylated or not. This phosphorylation is a highly regulated process, meaning it's carefully controlled by the body (Webb, 2003). Interestingly, some smooth muscle cells can maintain a low level of myosin phosphorylation even when there are no external signals telling them to contract. This low-level activity keeps the muscles in a state of partial contraction, known as smooth muscle tone. The intensity of this tone can be adjusted as needed by changing the level of myosin phosphorylation. This ability to fine-tune muscle tone is important for various functions in our bodies (Webb, 2003).

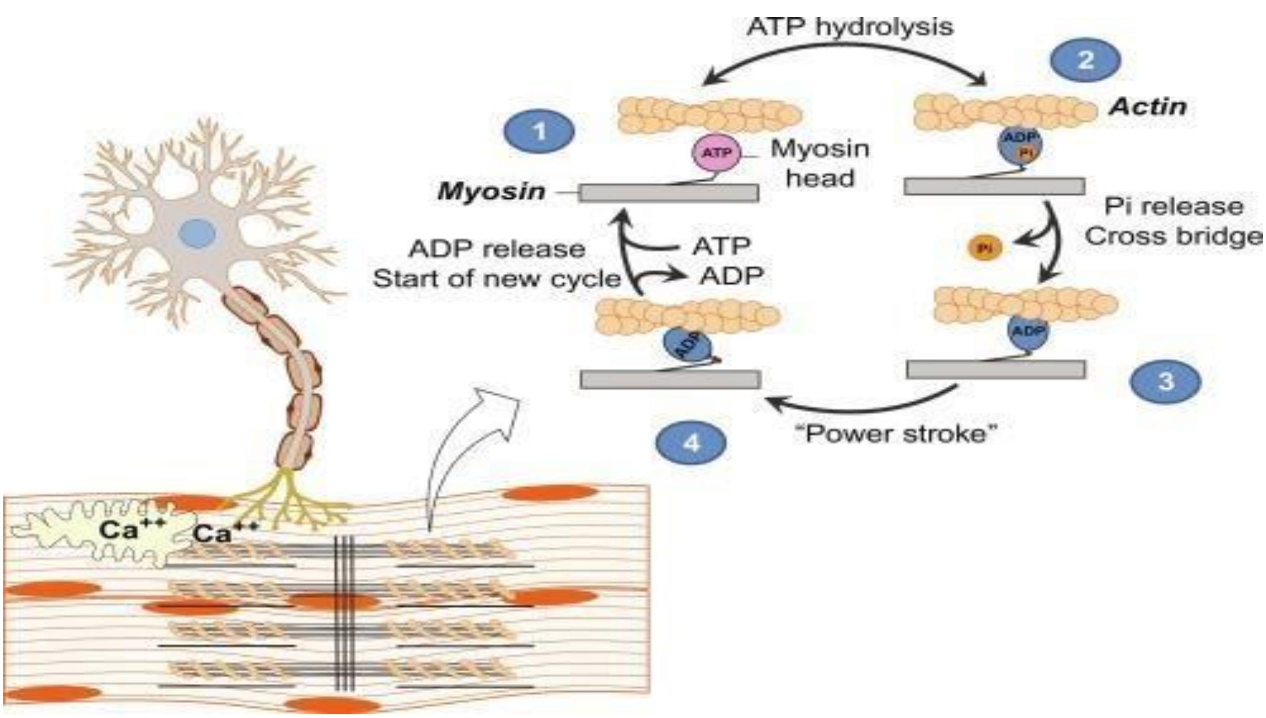


Figure 2.1.1 depicts the physiological processes involved in the muscle's contractile mechanism.

2.1.2 *MYOFILAMENTS*

Myofilaments are the individual proteins responsible for initiating muscle contraction. Within the intricate architecture of muscle fibers, sarcomeres emerge as the contractile structures formed by the overlapping presence of actin and myosin myofilaments. The myosin filaments, characterized by their thickness and straight alignment, are arranged in parallel, featuring a central shaft and globular heads at each end. On the other hand, actin, the thinner filaments composed of two elongated protein strands, is positioned between myosin filaments and connected at the Z line of sarcomeres. The regulatory components governing the interaction between actin and myosin include tropomyosin, a rope-like protein covering myosin-binding sites on actin, and troponin, a complex with three subunits: Troponin C (TnC), which binds calcium ions (Ca2+), Troponin I (TnI), inhibiting actin and myosin binding, and Troponin T (TnT), connecting other troponins to tropomyosin. This intricate molecular arrangement underscores the sophisticated control mechanisms underlying muscle contraction.

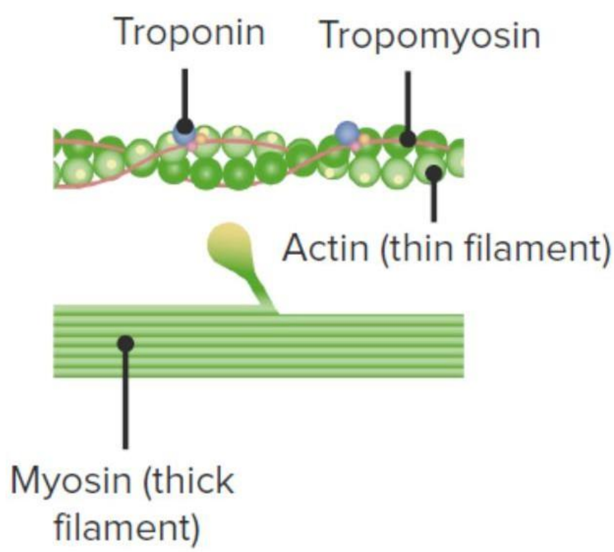


Figure 2.1.2 shows the structure of the thin filament, actin, and the thick filament, myosin, is notable for the presence of a globular head on myosin. The actin filament features yellow dots representing myosin-binding sites, which are normally covered by tropomyosin in a state of rest. Troponins, housing calcium-binding sites, play a crucial role. In the presence of calcium, troponins induce a conformational change in the troponin–tropomyosin complex, uncovering the myosin-binding sites on actin. This exposure allows myosin to bind to actin, and when coupled with the presence of ATP energy, initiates muscle contraction.

2.1.3 EMG SIGNAL GENERATION

The electromyography signal is the electrical output generated by an active muscle and is detectable by placing an electrode or electrodes on the skin above the targeted muscle. When a muscle contracts, ions move across the muscle fiber membrane, constituting an electrical current (I) measured in Amperes (electric charge per second). These electrical currents modify the electrical potential in the surrounding tissue. The voltage, representing the difference in electrical potential between two points, is measured in Volts (V). The voltage detected on the skin surface is influenced by the resistance or impedance, measured in Ohms (Ω), posed by the surrounding muscle, subcutaneous tissue, and skin to the electric current flow. The time-varying distribution of voltage on the skin surface due to the muscle's electrical activity is termed the surface electromyography (sEMG) signal. This signal offers insights into muscle contraction. Importantly, it's essential to recognize that measuring the electrical activity via sEMG doesn't equate to gauging the tension developed within the muscle, as the EMG signal precedes mechanical muscle activity. Moreover, it's plausible for electrical and mechanical muscle activities to unfold independently of each other (McManus et al., 2020). Electricity is fundamentally centered around the concept of charge and its movement. The notion of charge originated from experimental observations, notably from Benjamin Franklin's investigation. Franklin's experiment involved rubbing a glass rod with silk, leading to the observation that the rod attracted the silk. Upon rubbing a second glass rod with silk, these rods exhibited repulsion. Franklin, seeking to explain this phenomenon, arbitrarily designated the charge on the glass rod as positive and the charge on the silk as negative. The introduction of the electric field concept aimed to elucidate the force between these charged objects. The flow of charges corresponds to the concept of current, measured in amperes or amps. Current is defined as the amount of charge, measured in coulombs, moving per unit of time (seconds). Positive charges moving from silk to rod are combined with negative charges flowing in the opposite direction, from rod to silk, to determine the total current flow. Although current has a direction, it can be defined as either the net rate of flow of negative charges or the net rate of flow of positive charges. The convention, however, designates current as the net rate of flow of positive charges, explaining the representation of diagrams with current flowing from positive leads to negative leads. While it may seem counterintuitive given that electrons, the usual charge carriers, are negative, the convention remains consistent for circuit design purposes. In the example of the rod-silk interaction, the convention implies that current flowed from silk to rod, whereas in physical reality, electrons moved from rod to silk. Despite this potential for confusion, the convention remains irrelevant for the practical aspects of circuit design (Barry, 1991).

In the neuromuscular system, each muscle is controlled by a group of motor neurons that initiate muscle contractions. When an electrical signal, known as an action potential (AP), travels along the axon of motor neuron and reaches the connection point between the nerve and muscle, called the neuromuscular junction, it triggers the generation of an action potential in each muscle fiber connected to that motor neuron. In the neuromuscular system, each muscle is controlled by a group of motor neurons that initiate muscle contractions. When an electrical signal, known as an action potential (AP), travels along the motor neuron's axon and reaches the connection point between the nerve and muscle, called the neuromuscular junction, it triggers the generation of an action potential in each muscle fiber connected to that motor neuron (Farina & Holobar, 2016). The genesis of electromyography (EMG) signals is rooted in the intricate orchestration of the neuromuscular system, beginning with the activation of motor neurons. These specialized nerve cells, originating from the central nervous system, transmit signals that prompt muscle movement. At neuromuscular junctions, the meeting point between motor neurons and muscle fibres, neurotransmitters are released, initiating a cascade of events that set the stage for muscle contraction. The activation of muscle fibers follows the release of neurotransmitters, setting off a sequence of electrical events. The initiation of an action potential propagates along the sarcolemma, the muscle fibre’s membrane, triggering the release of Ca^{+2} ions from the sarcoplasmic reticulum. This influx of Ca^{+2} ions is pivotal for the interaction between actin and myosin filaments, the molecular machinery responsible for muscle contraction. As these filaments slide past each other, muscle fibres contract, and the associated electrical activity intensifies. At the core of EMG signal generation is the concept of motor units, comprising a motor neuron and the muscle fibres it controls. When a motor neuron is activated, all the muscle fibres within its motor unit contract in unison. This collective activation generates an electrical field, and electrodes placed on the skin's surface or inserted into muscle tissue following a specific protocol, capture this electrical activity. The resulting EMG signal is a graphical representation of the summation of individual muscle fibre action potentials, reflecting the overall muscle activation during a specific task or movement. The utilization of EMG signals extends into both clinical and research domains. Clinicians employ EMG to diagnose neuromuscular disorders, assess muscle function, and monitor rehabilitation progress. In research, EMG serves as a valuable tool to delve into biomechanics, study muscle coordination, and unravel the complexities of motor control. The waveform of the EMG signal provides researchers and healthcare professionals with a dynamic insight into the real-time interplay between the nervous system and skeletal muscles during voluntary movements, offering a nuanced understanding of muscle activity and function.

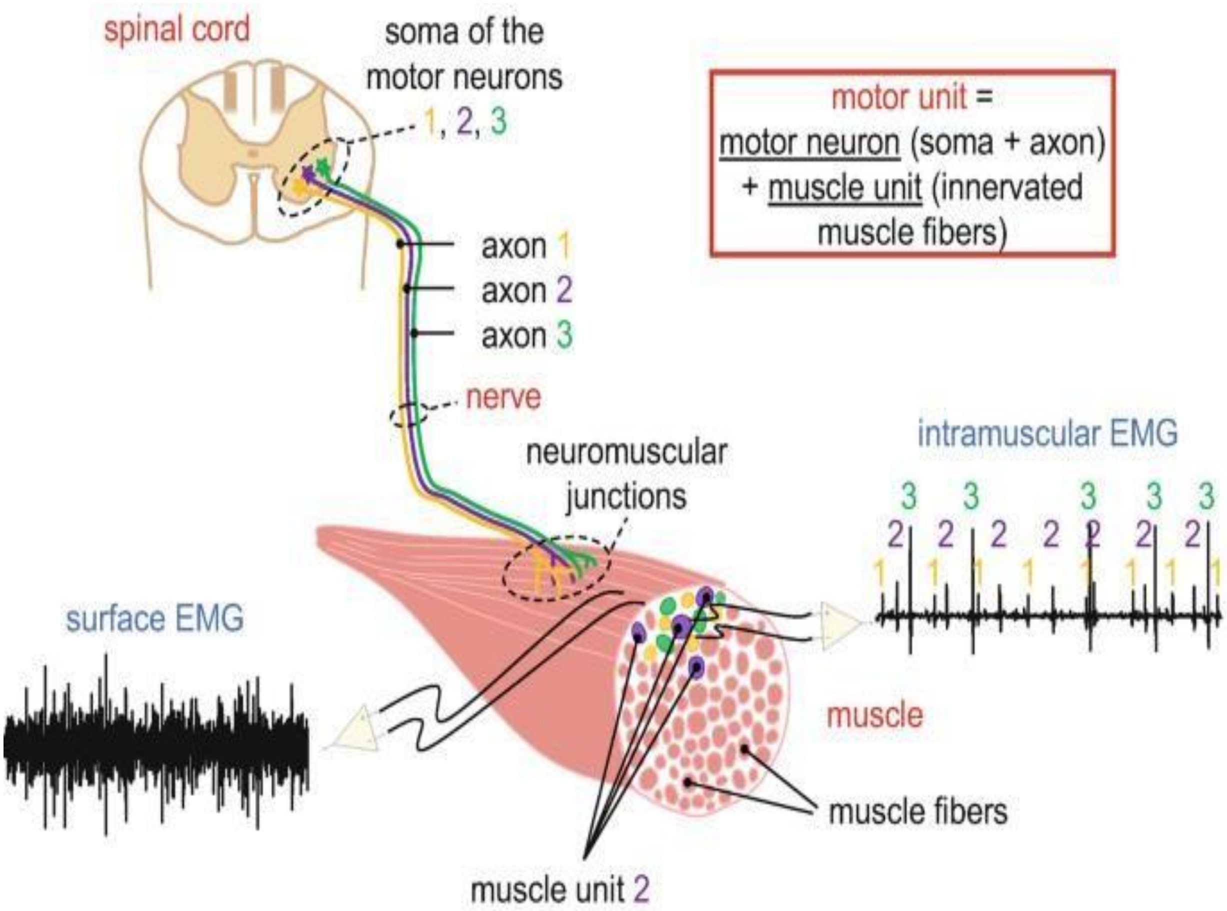


Figure 2.1.3 depicts the process of generation of EMG signals.

2.1.4 MOTOR UNIT

A motor unit is comprised of a single α-motor neuron and all the muscle fibers it innervates. The innervation ratio, representing the number of muscle fibers innervated by a single motor unit, can vary significantly depending on the muscle's function. Activation of a motor unit leads to the contraction of all its associated muscle fibers. Physiologically and biochemically, there are three types of motor units: (1) Slow fatigue-resistant motor units (type I) contract slowly, generate relatively small forces, and rely on oxidative metabolism; (2) Fast fatigable motor units (type IIb) contract rapidly, produce the greatest force, and rely on anaerobic glycolysis; (3) Fast fatigue-resistant motor units (type IIa) exhibit properties between the other two. While most muscles contain all three types of motor units, the proportions vary according to the muscle's specific function. The size principle dictates that smaller motor units with lower thresholds are typically recruited first within a muscle, producing the smallest increment in force. Various disorders can arise from damage or dysfunction of motor units due to genetic or acquired factors such as toxicity, trauma, or infections. Conditions primarily affecting the motor neuron or its axon fall under the category of neurogenic diseases, while those predominantly impacting the muscle fibers are termed myopathic diseases, including conditions like muscular dystrophies (Weinberger & Dostrovsky, 2010).

A motor unit is the smallest functional unit in the neuromuscular system and consists of two essential components: a motor neuron and the muscle fibres it commands. Motor units exhibit distinctiveness in their ability to be consciously activated by the brain when there is a desire to move a specific muscle. The reliability of the connection between the motor neuron and muscle fibre at the neuromuscular junction is crucial. It ensures that every time an action potential travels down the motor neuron's nerve fibre (motor neuron AP) and reaches the neuromuscular junction, it consistently triggers an action potential in the muscle fibre it's linked to, resulting in what's called a Motor Unit Action Potential (MUAP). This one-to-one relationship between motor neuron APs and MUAPs essentially means that muscle units act as natural signal amplifiers. The relatively weak neural signal from the brain is effectively magnified within the muscle fibre due to the dependable transmission at the neuromuscular junction. As a result, even small neural signals can generate significant muscle contractions, allowing us to control our muscles with precision and strength (Farina & Holobar, 2016).

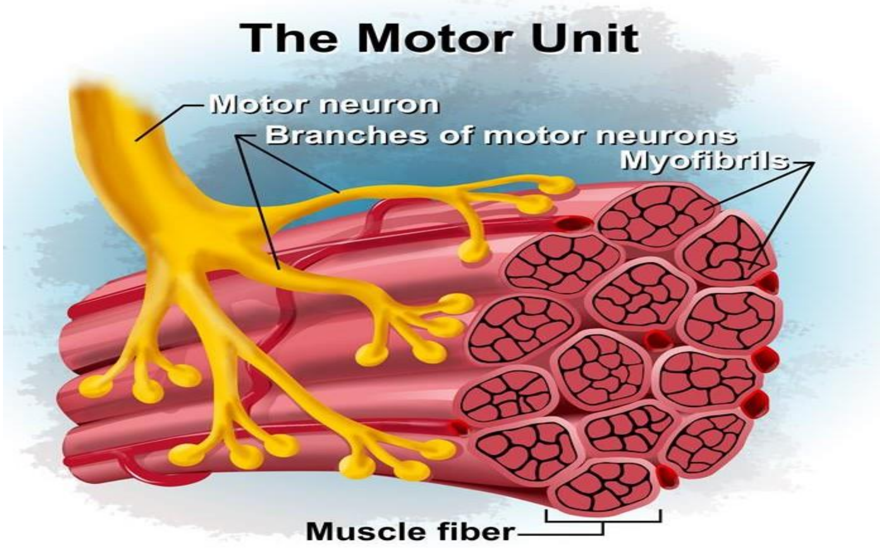


Figure 2.1.4 visualizes the motor units within the human nervous system.

2.2 EMG CHARACTERISTICS

In signal analysis, when capturing the electrical contractions of muscles through needle electromyography, the recorded signals may exhibit either sporadic or pseudo-stochastic characteristics (Berardelli et al., 1986). To examine sporadic signals, various determining variables are employed to characterize isolated motor unit action potentials (MUAPs) and other waves (Ferraccioli et al., 1987). This allows for the observation of signal shape, time characteristics, and amplitude. In contrast, pseudo-stochastic signals can be derived by employing diverse statistical models. When capturing the electrical activity of muscles, the signal's frequency is influenced by multiple factors. Initially, during the recording process, the signal is impacted by the intramuscular electrical activity of the tissues, thus affecting volume conduction (Petrofsky & Lind, 1980). In this context, the attenuation of high-frequency components in the signals becomes more pronounced in comparison to the diminishing effect on low-frequency components. This attenuation corresponds to the increased distance of action potential generators from the surface of the electrode. Notably, it has been observed that active electrodes characterized by smaller surface areas and higher input resistance or impedance tend to manifest more delicate and nuanced high-frequency responses, whereas the opposite holds true for electrodes with contrasting characteristics (Mambrito & De Luca, 1984). When employing sEMG to capture electrical activity, it's noteworthy that the signal's frequency components consistently register below 500 Hz (TESCH et al., 1990). In contrast, a single-fibre EMG electrode boasts a maximum frequency of 10 kHz, while for Compound Nerve Electrodes (CNE), this upper limit is set at 2 kHz (Hakkinen et al., 1998). This nuanced awareness of frequency characteristics proves to be invaluable in the realm of physiological studies.

The focal point of frequency analysis primarily revolves around the exploration of muscular fatigue, predominantly leveraging sEMG data. Nevertheless, it's important to acknowledge that comparable insights can be gleaned from needle EMG studies. Furthermore, in the context of needle EMG investigations, the examination of chronic neurogenic states tends to unveil a predilection towards lower frequency components. Conversely, myopathies in these studies often exhibit a deviation towards the higher frequency spectrum. This comprehensive understanding of frequency dynamics not only enhances our grasp of muscular fatigue through sEMG analysis but also provides valuable insights into the distinctive frequency signatures associated with neurogenic conditions and myopathies, as observed in needle EMG studies (Chan et al., 2000). The amplitude of an EMG signal is influenced by factors similar to those affecting frequency. Key determinants include electrode size, the spacing between electrodes, and the location of the action potential (AP) generator (Reimers-Neils et al., 1994). In the case of measuring the amplitude of a single Motor Unit Action Potential (MUAP) with a single-fibre EMG electrode, the recorded values typically range between 0.3 mV and 10 mV (Bø & Stien, 1994). It's noteworthy that the strength of the fibres acting as potent electrical generators has minimal impact in this context. Consequently, it can be stated that depending on action potential (AP) amplitude for a single muscle fibre is not a reliable diagnostic criterion for single-fibre electromyography (EMG). On the contrary, the employment of concentric needle electrodes shows more promising outcomes in capturing motor unit action potential (MUAP) amplitude. This is attributed to the minimal changes in distance within this electrode configuration. Moreover, concerning macro-EMG, the reliance on distance is notably diminished compared to the previously mentioned factors. Consequently, it is judicious to infer that the amplitude of the macro-MUAP serves as an indicator of the strength of the action potential generator. The inadequacy of relying on AP amplitude for single-muscle fibres in single-fibre EMG underscores the need for more robust diagnostic criteria. The use of concentric needle electrodes is favoured due to its ability to provide more reliable assessments of MUAP amplitude, facilitated by the inherent advantages of minimal distance variations in this electrode arrangement. Furthermore, the diminished influence of distance in macro-EMG emphasizes the significance of considering other factors when evaluating the amplitude of macro-MUAP. This nuanced understanding contributes to a more comprehensive interpretation of EMG data, enhancing diagnostic accuracy in assessing the strength and characteristics of the underlying action potential generator (VRANA, 1993).

2.3 MYOELECTRIC CONTROL

The development of power-based prostheses relies significantly on surface myoelectric signals derived from surface electromyography (EMG), serving as a crucial and effective input system. In technical terms, this control application is referred to as myoelectric control. It has gained widespread popularity, particularly among individuals born with congenital upper limb amputation or those who have undergone amputation due to injuries or accidents. This system is intricately designed to enable voluntary control over the selection and adjustment of multi-dimensional prosthetics. The underlying concept hinges on harnessing the voluntary control capabilities inherent in various parameters of myoelectrical signals obtained from either muscular groups or individual muscles. The origin of control signals for myoelectric controllers typically involves the presence of viable residual muscle in individuals with amputations or the available muscle in cases of congenital limb deficiencies. In instances where there is a significant superficial muscle and a closely spaced bipolar electrode pair on the surface, it becomes feasible to capture myoelectric signals solely from this muscle, creating a single muscle control channel (Cholewicki & McGill, 1994). Alternatively, with a fine wire intramuscular bipolar electrode, it is possible to isolate a specific muscle segment and utilize the action potential trains of motor units as sources for control signals. However, from a clinical perspective, the latter signal source is not considered practical due to the invasive nature of transcutaneous electrodes (Calancie et al., 1994). For surface electrodes, limitations associated with a single muscle source include the necessity for a superficial muscle, a requirement for small interelectrode spacing, and, in the case of congenital amputees, uncertainties related to the positioning of the muscle.

In contrast to the aforementioned single muscle myoelectric channel, a strategically positioned widely spaced electrode pair on the limb can capture signals from an entire muscle group. This multi-muscle control signal source involves the temporal and spatial summation of the electrical activity produced by the muscles within the group. Due to the practical challenges associated with obtaining a single muscle source, the use of a multi-muscle source has become the more prevalent method for control. It is more straightforward to place a widely spaced electrode pair on the limb and utilize all available signals rather than seeking specific positions on individual muscles. From a control information perspective, the temporal and spatial summation of signals from a muscle group offers certain advantages over a single muscle source (Ng et al., 1998). This stems from the observation that each muscle's contribution to the sum is contingent on the intended action of the limb. Consequently, the contribution pattern can be voluntarily controlled and employed for control purposes.

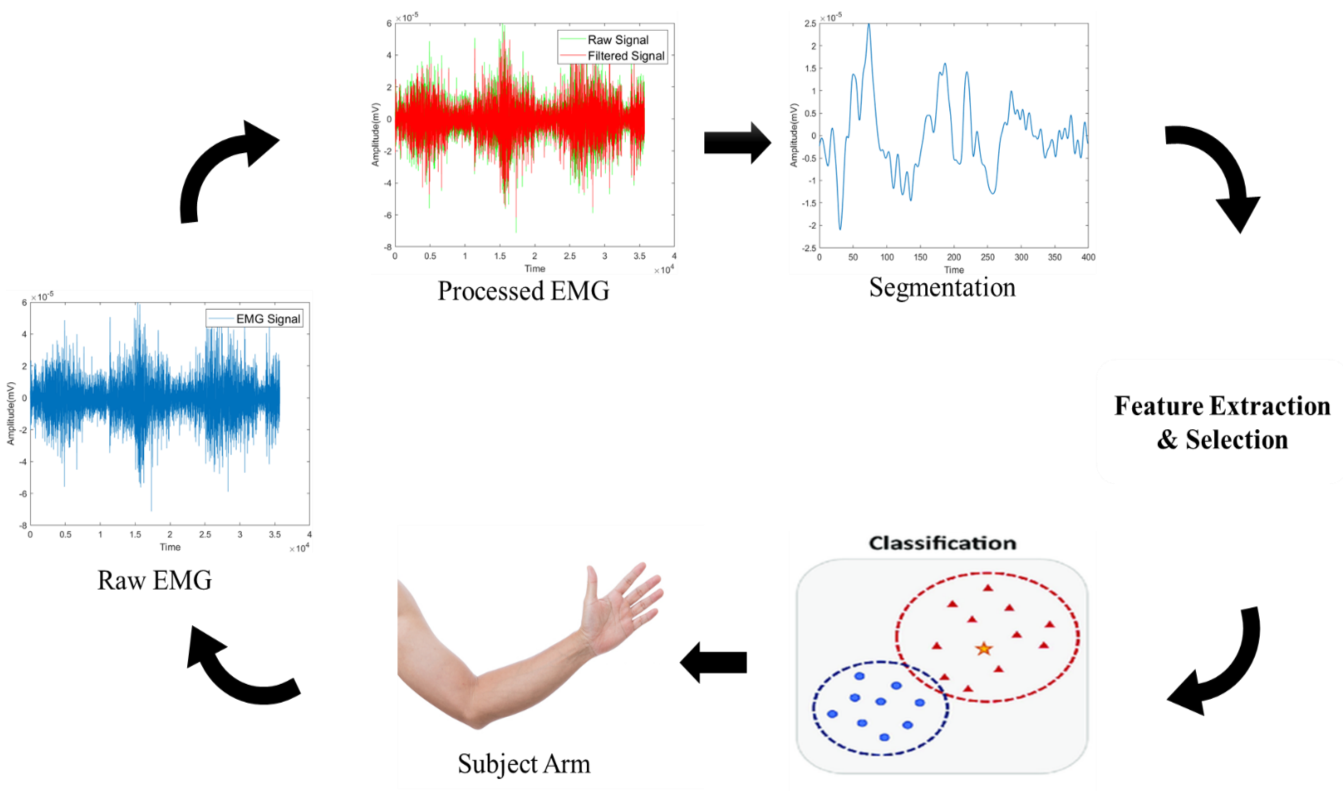


Figure 2.3 illustrates the pattern recognition-based myoelectric control system.

2.4 CONTROL SYSTEM BASED ON PATTERN RECOGNITION

In order to enhance the hierarchy of devices for optimizing the control of myoelectric signals, it is essential to develop a more advanced strategy capable of discerning the diverse motion states of the specific muscle being targeted. The above figure 7 illustrates a myoelectric control system based on pattern recognition. This can be achieved through two distinct approaches (Sang-Hui Park & Seok-Pil Lee, 1998).

Initially, it is desirable for the system to gather additional information regarding muscular activity in its active state. This can be accomplished through either or both of the following approaches:

i. To acquire exclusive information about the targeted muscular groups, the system should utilize various MES channels.
ii. Another approach involves developing sets of features capable of extracting maximum information from input signals, enabling differentiation between distinct motion categories.

Finally, it is essential to construct a classifier with the capability to effectively utilize the extracted information. This classifier plays a crucial role in assimilating input information and determining its respective class of origin.

2.5 APPROACHES FOR MEASURING MYOELECTRIC SIGNALS

When employing the surface myoelectric signal, the main consideration related to the positioning of recording electrodes is to capture the maximum novel information regarding muscle activity. To achieve this goal, when situating electrodes on the upper limb, two options are available. In the technique employed by Hudgins, a singular bipolar channel is utilized, featuring widely spaced bipolar electrodes (Nummela et al., 1994). This configuration involves the strategic placement of one electrode on the biceps and another on the triceps. The objective of this method is to capture the comprehensive activity across a substantial muscle volume, amalgamating the signals into a unified myoelectric channel.

Despite its advantages, this approach comes with a notable drawback. The absence of spatial discrimination in monitoring the activities of distinct muscles is a limitation. Consequently, the potential arises for novel information originating from different muscles to undergo destructive interference within this singular channel configuration. This limitation poses challenges to the precise extraction and differentiation of unique muscular signals, highlighting the need for alternative strategies that offer improved spatial resolution in myoelectric signal monitoring. The other is using multiple bipolar channels, each featuring closely spaced electrode pairs, becomes imperative due to the more localized pickup region under such pairs. This approach demands the deployment of several channels to effectively capture the activities of diverse muscle groups. The advantages of employing multiple channels address the shortcomings associated with a single channel (Murray et al., 1984) (Hogan, 1976). Now, spatial discrimination becomes achievable, allowing for a more nuanced understanding of the distinct activities of various muscles. Additionally, the risk of destructive cancellation is mitigated, ensuring that valuable information from different muscle sources can be discerned without interference.

Numerous studies have convincingly demonstrated that the utilization of multiple MES channels offers significantly enhanced discrimination capabilities among various control states, surpassing the performance of single-channel systems. The myoelectric signal, with its inherent characteristics, has the potential to exert influence over and guide the control signal in terms of its competencies. It's crucial to emphasize that the research methodologies devised by previous scientists predominantly involved recording contractile MES or myoelectric signals within a constant or steady-state environment (Akazawa et al., 1983). This controlled setting aimed to capture the myoelectric activity during contractions. Notably, when subjected to statistical analysis, the resulting output often manifests as a randomly generated signal, as previously discussed. Analysing the properties of these myoelectric signals reveals a noteworthy aspect: the specified patterns of neuronal firing responsible for executing contractions, coupled with the active modification of recruited motor units, collectively contribute to a myoelectric signal that exhibits minimal temporal or time-dependent structure during the steady-state phase. This temporal characteristic underscores the dynamic and adaptive nature of myoelectric signals, prompting a nuanced understanding for devising effective control strategies in diverse applications.

Hudgins and colleagues extensively investigated the impact of myoelectric signals concurrent with the initiation of active muscle contraction. Their research revealed a notable presence of transient patterns within the waveform structure, as depicted in Figure 7. This figure illustrates localized behavioural patterns corresponding to both pronation and supination orientations of the forearms, along with the observable elbow flexion and extension. Furthermore, the data presented in the figure was derived from the muscular activity of the biceps and triceps in the arm. To record these activities, a single pair of bipolar electrodes was strategically placed on these muscle groups. The intention was to encompass a significant portion of these musculoskeletal regions for enhanced efficiency and a more comprehensive understanding of the myoelectric responses during various movements.

The insights gained from this research contribute to a deeper understanding of the dynamic interplay between myoelectric signals and muscle contractions, particularly in the specified musculoskeletal contexts. The detailed observations of local behavioural patterns provide valuable information for refining strategies in myoelectric control systems, with potential implications for applications in prosthetics, rehabilitation, and other related fields. Upon analysis in the time domain, these waves exhibited distinct contrasts in the considered patterns. Simultaneously, an examination of pattern groups obtained at specific contraction rates revealed that their respective structures were sufficiently distinct, allowing for visual differentiation across varying rates of contractions. Several other researchers have also noted the existence of this visible arrangement, indicating a systematic integration of neuronal units in the brain known as motor units (Solomonow et al., 1994).

This ordered assimilation of motor units may arise from a "motor plan" situated within the central nervous system (CNS), the absence of sensory feedback pathways during rapid bursts of activity, or a combination of both factors. Elaborating on this, the systematic patterns observed in myoelectric signals during different contraction rates underscore the intricate coordination within the CNS. The discernible variations in patterns not only highlight the complexity of motor unit integration but also suggest potential factors influencing this organization, such as pre-established motor plans or the dynamic interplay of sensory feedback pathways. This nuanced understanding contributes to the broader knowledge of neurophysiology and has implications for the design and optimization of myoelectric control systems in applications ranging from prosthetics to neuromuscular rehabilitation.

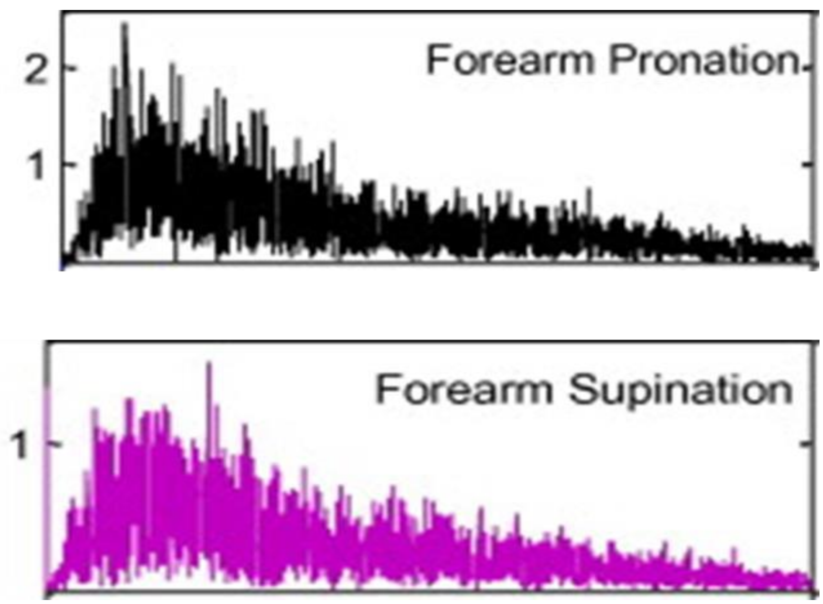


Figure 2.5(a) depicts the forearm pronation EMG signal. Figure 2.5(b) depicts the forearm supination EMG signal.

The indication of determinism in the transient myoelectric signals (MES) occurring during the initiation of muscle contractions implies that these data could serve as a potent tool for distinguishing MES patterns associated with various types of movements. This capability has been illustrated by Hudgins et al. in the context of a prosthetic control system, as elaborated below, and by Farry et al., who applied it to teleoperation of a robotic hand. Expanding on this notion, the recognition of determinism in transient MES not only suggests a valuable discriminative feature for different movement types but also underscores the potential applicability of such findings in advanced control systems. The work by Hudgins and colleagues, along with the research conducted by Farry and team, highlights practical implementations in prosthetics and teleoperation of robotic systems. These applications showcase the real-world utility of understanding and leveraging determinism in MES patterns, opening avenues for enhanced control precision and functionality in diverse technological domains (Turton et al., 1996) (PETROFSKY et al., 1982).

2.6 SIGNAL FILTRATION

The amplitude of the electromyographic (EMG) signal is generally acknowledged to fall within the microvolt to low millivolt range, typically ranging from 0 to 6 mV peak-to-peak or 0 to 1.5 mV RMS. In the frequency domain, the energetic distribution of the EMG signal primarily occurs within the 0 to 500 Hz range, with dominant components concentrated in the 50 to 150 Hz range. Beyond the 0-500 Hz frequency range, signals with energy levels lower than electrical noise become impractical for use (J. Wang et al., 2013). Several key sources contribute to the noise encountered during the acquisition of EMG signals. Firstly, inherent noise from electronic components within the signal detection and recording instrument is a notable factor. Additionally, ambient noise stemming from electromagnetic radiation in the surrounding environment contributes to the overall noise profile. Motion artifacts represent another source, introducing electrical signals mainly within the 0-20 Hz range due to factors such as electrode-skin interface disturbances and movement of the cable connecting the electrode to the amplifier. Lastly, the inherent instability of the EMG signal adds another layer of complexity, with unstable components in the 0-20 Hz range attributed to the quasi-random nature of the firing rate of muscular motor units. Overall, understanding and managing these various sources of noise is crucial for accurate and reliable EMG signal acquisition and interpretation (De Luca & C. J., 2002).

In the circuitry for amplification and filtering, both high-pass and low-pass filters are implemented following the initial and secondary amplification stages. This choice is made to address the simultaneous amplification of both unwanted noise and the electromyographic (EMG) signals, as this is unfavourable for subsequent processing. When designing a filter, key parameters such as the corner frequency, roll-off rate, and circuit topology must be carefully selected. The corner frequency, roll-off rate, and circuit topology are critical considerations in filter design. The corner frequency determines the point at which the filter begins to attenuate signals, the roll-off rate indicates the slope of the filter's frequency response curve, and the circuit topology defines the arrangement of components within the filter. The filter order dictates the roll-off rate, representing the rate at which the filter response attenuates signals. For instance, a first-order filter exhibits a roll-off rate of -6 dB/octave, while a second-order filter has a steeper -12 dB/octave roll-off rate. This implies that the roll-off rate is proportional to the order of the filter, and higher-order filters are typically constructed by cascading first- and second-order blocks. This approach allows for effective control over the frequency response and ensures that the filter adequately addresses the specific requirements of amplifying and filtering EMG signals while minimizing unwanted noise (J. Wang et al., 2013). Furthermore, the multifaceted nature of electromyography (EMG) signals is not only influenced by the anatomical and physiological aspects of muscles and the regulatory mechanisms of the nervous system but is also intricately tied to a myriad of technical considerations. Expanding on this, the specific timing and intensity of muscle contractions are crucial determinants, as they directly impact the characteristic features of EMG waveforms.

The distance between the electrode and the target muscle is another critical factor, influencing signal amplitude and morphology. Additionally, the presence of adipose tissue between the skin and muscle introduces a layer of complexity, as it can attenuate or distort the recorded signals. In the realm of instrumentation, the properties of both the electrode and the amplifier wield significant influence. The choice of electrode material, size, and configuration, as well as the amplifier's specifications, can collectively shape the overall quality of the recorded EMG signals. Moreover, the efficacy of signal acquisition is highly dependent on the intimate contact between the skin and the electrode, making skin preparation and electrode placement pivotal considerations in ensuring accurate and reliable measurements.

Different types of filters are employed in signal filtration, each designed to target particular frequency ranges. A low-pass filter allows frequencies below a certain cutoff point to pass through while attenuating higher frequencies. This type of filter is commonly used to eliminate high-frequency noise or unwanted components, allowing the smoother representation of the signal's low-frequency content. On the other hand, a high-pass filter permits frequencies above a designated cutoff to pass, effectively removing low-frequency components from the signal. Band-pass filters are designed to selectively pass a specific range of frequencies while attenuating those outside the desired band. This type of filtration is valuable when focusing on isolating signals within a particular frequency range of interest, as seen in applications like EEG signal processing or vibration analysis. Conversely, a band-stop filter also known as notch filter does the opposite, attenuating a specific frequency range while allowing others to pass through.

Notch filters are often employed to remove unwanted interference, such as powerline noise at 50 or 60 Hz.

2.7 SIGNAL SEGMENTATION

The analysis of biological signals, such as ECG, relies on the valuable insights provided by individual peaks, leading to the segmentation of these signals based on their distinctive shapes. However, when dealing with EMG signals, the intricacies of muscle activity demand a more nuanced approach. Individual peaks, while informative, may not furnish adequate details for effective PR-based MEC. Given the non-stationary nature of EMG signals—where statistical features fluctuate over time—researchers opt to study these signals in segments of varying durations.

The segmentation strategy serves a dual purpose. Firstly, each segment, functioning as a snapshot in a particular time slot, assists in predicting the overarching features and attributes of the continuous signal stream. Secondly, it acknowledges the non-uniformity in the behaviour of muscles over time, ensuring a more comprehensive analysis. Yet, as with any analytical method, there are trade-offs to consider. The length of the signal segment emerges as a critical factor. Longer segments inherently encapsulate more information about the original signal, contributing to a richer understanding of muscle activity. However, this advantage comes at the cost of increased hardware complexity in the context of practical PR-based MEC (Tangel et al., 1991).

The delicate balance between segment length and processing considerations introduces a trade-off, forcing a compromise between the speed of data processing and the precision of section descriptions. In this delicate interplay, shorter segments become more susceptible to challenges such as volatility, extraction bias, and noise due to their limited temporal scope. As researchers grapple with optimizing this balance, they aim to discern the ideal segment length that simultaneously captures the intricacies of EMG signals while maintaining a manageable level of hardware complexity. This ongoing exploration reflects the dynamic nature of signal processing, where methodological choices impact the depth and accuracy of our understanding of muscle activity in real-world contexts. A segment duration of less than 200ms proves inadequate in accurately representing the original signal (Yang & Winter, 1985). To ensure a more faithful reproduction of the original signal in both real-time Muscle Effort Classification (MEC) scenarios and offline analyses, it is recommended that a segment surpasses the 200ms threshold. Striking a balance between real-time responsiveness and signal fidelity, real-time MEC typically imposes a limit of 300ms on segment size for seamless operation.

The segmentation process, as illustrated in Figure 9, involves two distinct approaches. In the case of a disjoint segment, its length is determined solely by its span. On the other hand, an overlapped segment's length is influenced by both its duration and a threshold value (adjustment). The temporal dynamics of sequential segments, characterized by leaps or gaps, are smaller than their respective lengths but exceed the processing time required for MEC. To elaborate further, the choice of segment duration becomes a critical factor in achieving a balance between capturing meaningful signal information and ensuring computational efficiency. Segments that fall below the 200ms threshold may lack the necessary detail, impacting the fidelity of the signal reproduction. Conversely, exceeding the 300ms limit, as imposed by real-time constraints, may compromise the timeliness of MEC operations (Hazlett & Hazlett, 1999). The segmentation process, whether disjoint or overlapped, involves a thoughtful consideration of both temporal span and threshold values, influencing the overall effectiveness of signal analysis for muscle effort classification. Thus, the intricacies of segment length and its implications underscore the challenges in optimizing MEC methodologies for both real-time applications and comprehensive offline analyses.

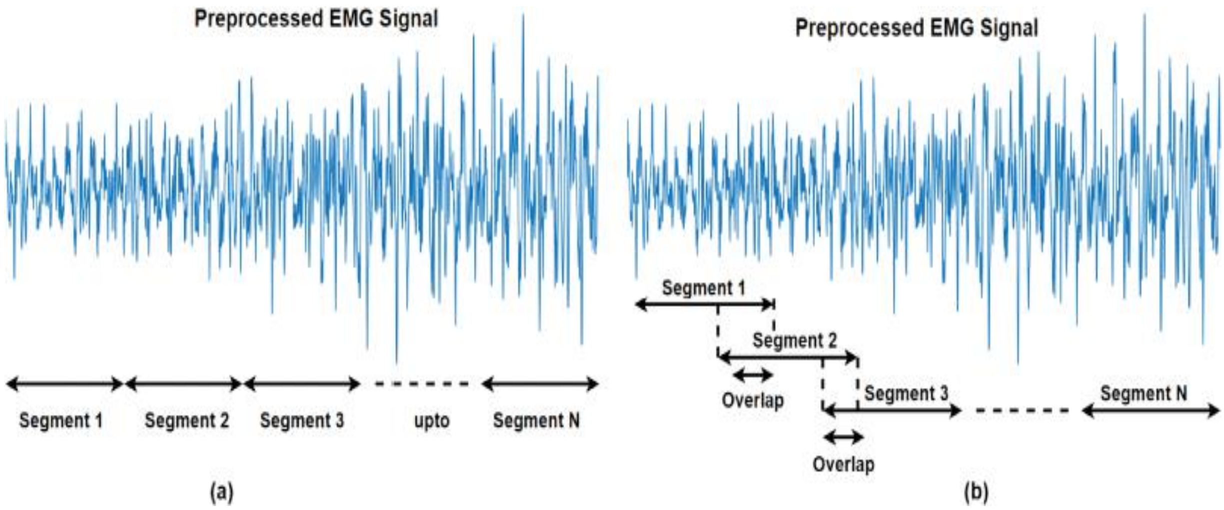


Figure 2.7(a) employs a disjoint segmentation technique, dividing the pre-processed EMG signal into non-overlapping segments of equal length. Figure 2.7(b) illustrates overlap segmentation, featuring segments with overlapping portions, fostering continuity between successive segments

Feature extraction is then performed on each window to characterize muscle activity effectively. Mean absolute value, root mean square, and waveform length are among the common features extracted. These features serve as descriptors that represent the essential characteristics of the muscle activity within each segment. The criteria for segmentation are established based on the goals of the analysis. This could involve identifying specific events, such as the onset or offset of a movement, or recognizing patterns within the signal. The segmentation process itself entails applying these criteria to delineate distinct phases or activities within the EMG signal, marking the start and end points of each segment. Post-processing steps may include smoothing the segmented signal to reduce abrupt changes and enhance interpretability. It is essential to validate the segmentation results through visual inspection or quantitative analysis, ensuring the accuracy and reliability of the segmented data. Ultimately, the segmented EMG signal is subjected to in-depth analysis and interpretation. Researchers analyse each segment to extract valuable insights into muscle activity, fatigue, or other relevant parameters. The interpretation of segmented data contributes to a comprehensive understanding of the physiological and biomechanical aspects captured by the EMG signal, fostering advancements in fields such as sports science, rehabilitation, and human-computer interaction.

2.8 FEATURE EXTRACTION

Feature extraction is a fundamental process in signal processing and pattern recognition that involves distilling relevant information from raw data to create a set of features better suited for analysis. This technique is widely applied in various domains, including machine learning, image processing, and physiological signal analysis. In the context of physiological signals like electromyography (EMG), feature extraction aims to identify and quantify key attributes or patterns within the signal that are pertinent to the specific analysis or application at hand. Feature extraction in the analysis of electromyography (EMG) signals commonly initiates post-segmentation. This crucial process involves selecting pertinent features by identifying attributes that capture essential aspects of the signal, aligning with the specific objectives of the study. The careful selection of these features is pivotal in shaping the subsequent analysis and interpretation of the EMG data. These selected features may undergo mathematical transformations to enhance their discriminatory power or suitability for a particular analysis. Additionally, normalization techniques may be employed to ensure consistency and comparability of feature values across different datasets or conditions. The actual extraction of features involves computing or deriving the chosen attributes from the signal using predefined algorithms or mathematical operations. The extracted features serve as inputs for subsequent analysis, such as classification, clustering, or trend analysis, depending on the goals of the study. In machine learning applications, these features contribute to the learning process, aiding algorithms in identifying patterns and relationships within the data. Effective feature extraction is paramount for improving the performance of machine learning models, as it helps reduce dimensionality, mitigate the curse of dimensionality, and focus on the most relevant information within the dataset.

The predominant and widely adopted feature for characterizing the MES is the index of gross activity, typically represented by measures like variance, mean absolute value, or similar metrics. Additionally, there have been successful presentations and utilization of multivariate feature sets aimed at providing supplementary insights into the MES within each channel (Komi et al., 2000). In the early stages, the features extracted from electromyography (EMG) signals were constrained by the computational capabilities of the era. These features predominantly relied on time-domain statistics, encompassing metrics such as variance, zero crossings, and the "length" of the waveform locus. However, as computational power advanced, there was a paradigm shift towards more sophisticated systems. With increased computational resources, new feature extraction systems emerged, incorporating techniques like autocorrelation time series models, spectral measurements, and coefficients. These approaches allowed for a more comprehensive analysis of EMG signals, capturing intricate details of muscle activity. The evolution of feature extraction methods continued with the integration of advanced techniques such as short-time high-order spectrum analysis, wavelet transforms, and wavelet packet transforms. In contemporary applications, Fourier transform has also played a crucial role in extracting features from EMG signals. Current methodologies aim to exploit the temporal structure of MES patterns, offering a more nuanced understanding of muscle activity. These advancements in feature extraction techniques not only enhance the accuracy and sensitivity of EMG signal analysis but also pave the way for a deeper exploration of the underlying physiological processes associated with muscle function (Granata & Marras, 1995).

2.9 CLASSIFICATION

EMG signal classification involves categorizing electromyography (EMG) signals into different groups or classes based on their patterns and characteristics. This process typically employs machine learning algorithms or signal processing techniques to analyze the electrical activity recorded from muscles and distinguish between different muscle actions or conditions. The goal is to identify and classify specific patterns in the EMG signals that correspond to different muscle activities, such as contraction, relaxation, or specific movements. Researchers and clinicians use EMG signal classification for various applications, including diagnosing neuromuscular disorders, controlling prosthetic devices, and understanding muscle function in rehabilitation settings. By training algorithms to recognize distinct patterns in EMG signals, it becomes possible to infer the intended movement or action of a user, facilitating the development of advanced prosthetics, assistive devices, or biofeedback systems.

Hence, in this context, pattern classification encompasses three fundamental categories of practical approaches. Traditionally, the statistical and syntactic methods have stood out as the two most prevalent and frequently employed approaches in the field. Over time, these approaches have played pivotal roles in shaping the landscape of pattern classification, providing frameworks for understanding and categorizing data based on statistical characteristics and syntactic structures. As technology and methodologies advance, new paradigms within these categories and emerging hybrid approaches continue to contribute to the evolution of pattern classification techniques (Visser et al., 1999). The category of learning, or neural, techniques represent the latest development in pattern classification, evolving from the foundational concepts of perceptrons and adaptive linear components into the extensive realm of artificial neural networks. This evolution has significantly broadened the scope of capabilities in understanding and classifying complex patterns. Examining the application of classifiers in MES control systems reveals a historical reliance on statistical classifiers until the mid-1980s. It was during this period that the pioneering applications of artificial neural networks emerged, signifying a transformative shift in classification methodologies. The subsequent exploration of artificial neural networks for MES pattern recognition has been marked by a diverse range of architectures and learning algorithms.

Within this framework, investigations have delved into structures such as simple feed-forward multilayer perceptrons, dynamic networks, and self-organizing feature maps. The research landscape has further expanded with recent inquiries into the utilization of advanced techniques like genetic algorithms and fuzzy logic classifiers. A recurring observation from these studies underscores the intrinsic importance of the feature set in the overall performance of MES classification. While potent classifiers may contribute marginally to improving the accuracy of MES classification, the consensus points to the paramount significance of selecting and defining a robust feature set. This recognition emphasizes the pivotal role that thoughtful feature engineering plays in optimizing the efficiency and effectiveness of MES classification, further advancing the field and its applications in diverse domains. In this study, the utilization of Linear Support Vector Machine (Linear SVM) is noteworthy. Let's delve into a brief overview of Linear SVM to better comprehend its role in the research. A Linear Support Vector Machine (Linear SVM) is a classification algorithm specifically designed for binary classification tasks. The term "linear" signifies its focus on identifying a linear decision boundary, often termed a hyperplane, to separate data points of different classes in a feature space. The primary objective of a linear SVM is to optimize the margin, representing the distance between the hyperplane and the nearest data points (support vectors) of each class. The hyperplane is strategically positioned to achieve the optimal separation between classes. Linear SVMs find applications in diverse domains such as histogram-based image classification, spam categorization, financial time series forecasting, face membership authentication, and general data analysis and classification (Dagher, 2008). Linear SVMs prove particularly effective when the relationship between input features and classes exhibits linearity. However, in cases of more intricate, non-linear relationships, kernelized SVMs come into play. Kernelized SVMs transform input features into a higher-dimensional space, enabling a more effective separation of classes.

CHAPTER: 3

3.1 METHODOLOGY

The schematic diagram delineates the methodological framework employed in this study. Initially, the raw signal undergoes a filtration process to enhance its signal quality. Subsequently, the signal is subjected to a systematic segmentation process. Following segmentation, time-domain and frequency-domain features are extracted from overlapping segments. Feature selection is then meticulously performed using an exhaustive technique, ensuring the retention of only the most relevant and discriminative features. The classification accuracy is subsequently evaluated using a Support Vector Machine (SVM) classifier, known for its robust performance in classification tasks. This structured methodology aims to systematically analyse the dynamic properties of the signal and derive meaningful insights from the data.

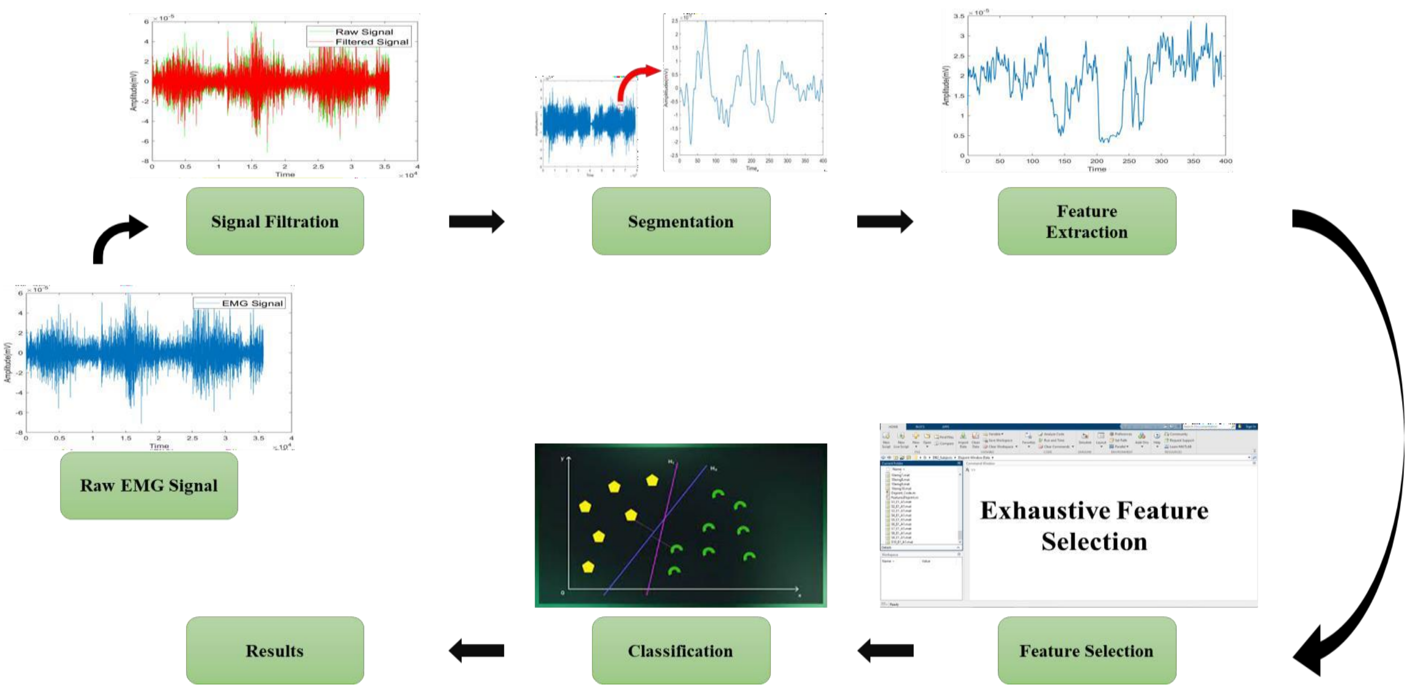


Figure 3.1 illustrates the flowchart depicting the sequential process for exploring the Cardinality as a feature.

3.2 Dataset

The dataset under investigation in this study has been sourced from the Ninapro database, with a specific focus on the Ninapro DB2 dataset. This dataset is curated to encompass the motor activities of 10 distinct hand movements performed by 10 intact subjects. Each set of data corresponds to 17 hand movements, specifically centered around exercise number 1, with a meticulous examination of 10 specific hand movements. The temporal structure of the dataset is characterized by each hand movement lasting for 5 seconds, followed by a 3-second interval. The 10 hand movements featured in the dataset include the following actions: thumbs raised, index finger extended while others are flexed, ring and little fingers flexed while others are extended, thumb opposing the base of the little finger, all fingers spreading apart, fingers curled into a fist, index finger pointing outward, extended fingers brought together, wrist turned outward with the middle finger as the axis, wrist turned inward with the middle finger as the axis, along with the resting position of the hand.

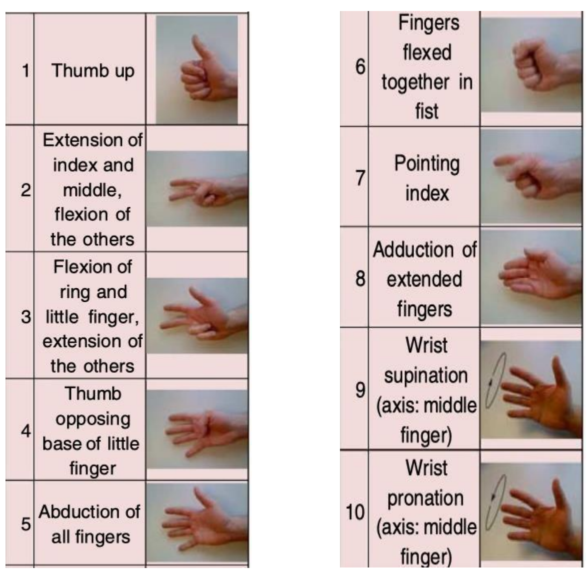


Figure 3.2 shows the different hand movements used in this study.

The acquisition of muscle activity data is facilitated by the implementation of a Delsys Trigno Wireless EMG system equipped with 12 active double differential wireless electrodes. These electrodes, operating at a sampling frequency of 2000 Hz, are strategically positioned for comprehensive data collection. Eight of them are evenly distributed around the forearm near the radio-humeral joint, two are placed on key locations of the flexor digitorum and extensor digitorum, and the remaining two are situated on crucial areas of the biceps and triceps. This meticulous arrangement is designed to achieve a thorough sampling approach while ensuring precise anatomical positioning. In essence, the dataset's detailed composition, along with the sophisticated instrumentation employed, underscores the methodological rigor applied in collecting muscle activity data for the study's analytical purposes.

3.3 Preprocessing

The electromyographic (EMG) signal, encompassing a spectral range from 10 Hz to 500 Hz, is susceptible to various undesired elements during recording, such as line interference and motion artifacts, which can compromise the integrity of the original signal. Consequently, a meticulous pre-processing regimen was applied to the dataset to address these concerns. The pre-processing involved the application of a notch filter at 50 Hz to attenuate electrical interferences and a fourth-order digital Butterworth high-pass filter spanning the range of 20 Hz to 500 Hz, effectively minimizing motion artifacts.

Expressed in mathematical terms, a one-dimensional signal with noise is often characterized as follows:

$$s(i) = f(i) + \sigma.e(i),\ i = 1, 2, \dots n - 1$$

In this equation, $f(i)$ represents the actual signal, $e(i)$ represents the noise, and $s(i)$ encapsulates the signal contaminated with noise. This formulation succinctly captures the interplay between the genuine signal and the noise component within the EMG signal.

It is noteworthy that valuable signals tend to exhibit low-frequency or gradual variations, while noise signals typically manifest as high-frequency variations (M. Wang et al., 2019). This observation underscores the importance of differentiating between the signal and noise components, especially in the context of EMG data analysis, where the preservation of meaningful signals is paramount. The utilization of notch and high-pass filters in the pre-processing stage aligns with best practices to ensure the fidelity of the EMG signal for subsequent analysis.

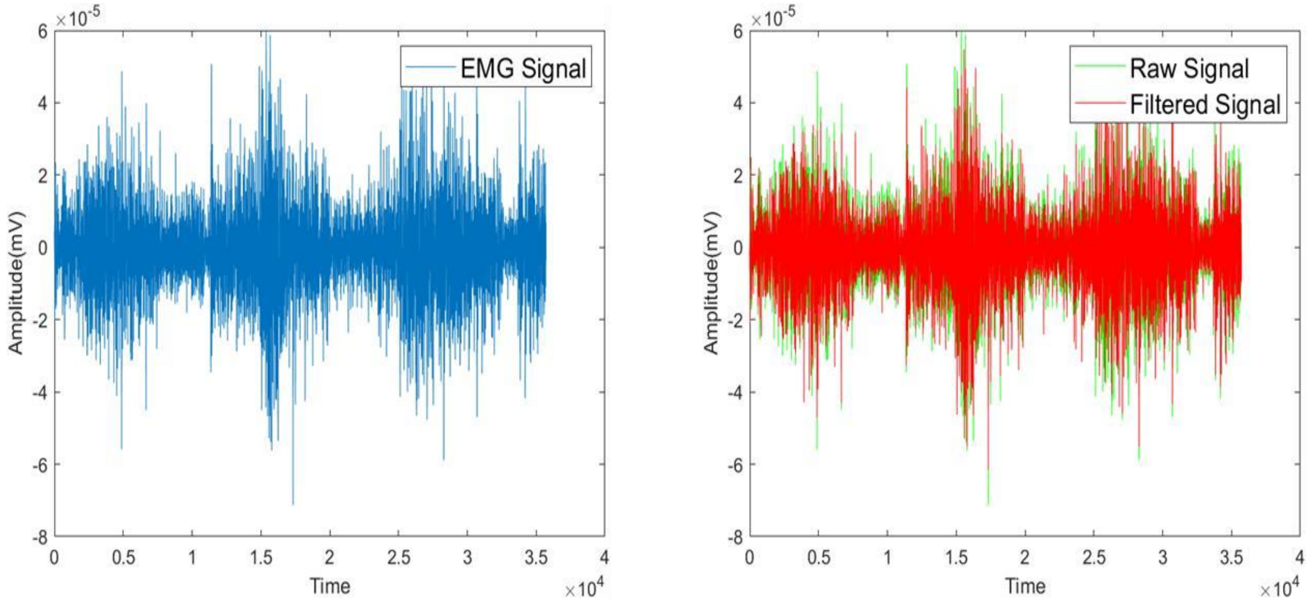


Figure 3.3(a) visualizes the raw EMG signal. Figure 3.3(b) visualizes the filtered EMG signal.

3.4 Segmentation

Segmentation, within the realm of signal processing, constitutes a fundamental procedure aimed at breaking down a continuous data stream or sequence into discernible and meaningful segments or sections. The primary objective of segmentation is to pinpoint and isolate specific patterns, features, or events embedded within the data, thereby facilitating a more structured and manageable framework for subsequent analysis. The overarching categorization of segmentation encompasses two principal types: Disjoint Segmentation and Overlapping Segmentation. Disjoint segmentation involves the partitioning of a continuous data stream or sequence into distinct and non-overlapping segments or intervals. Each segment operates as an independent unit, devoid of any temporal overlap with its adjacent counterparts. The hallmark of disjoint segmentation lies in the clearly defined boundaries demarcating consecutive segments, contributing to a modular and compartmentalized representation of the data. Conversely, overlapping segmentation adopts an approach wherein a continuous data stream or sequence is divided into segments that share a certain degree of temporal overlap. In this method, each segment encompasses a portion of the time span covered by its neighbouring segments. The degree of overlap is governed by a designated step size or overlap parameter, dictating the extent of temporal convergence between consecutive segments. Overlapping segmentation proves advantageous in capturing more comprehensive information and context within sequential data analysis, offering a broader perspective on the intricate dynamics embedded in the signal. In essence, segmentation serves as a pivotal preprocessing step, introducing a structured framework for the analysis of continuous data streams by delineating distinct segments, each holding valuable insights into the underlying patterns and features of the signal. The choice between disjoint and overlapping segmentation hinges on the analytical objectives and the nature of the information sought within the data.

Biomedical signals, such as Electrocardiogram (ECG) signals, are conventionally segmented based on the distinctive shapes of individual peaks, where each peak encapsulates valuable information about the original signal. However, the segmentation approach for Electromyography (EMG) signals, particularly in the context of Myoelectric Control (MEC) based on pattern recognition, requires a more nuanced strategy than relying solely on a single peak. Moreover, EMG signals present a challenge due to their non-stationarity, indicating fluctuations in statistical characteristics across temporal intervals. This inherent variability necessitates the analysis of EMG signals in segments of varying time durations. Each segment, representing a specific time interval within the signal, plays a pivotal role in estimating the overall characteristics of the complete signal. The choice of segment duration involves a delicate balance between obtaining sufficient information about the original signal and managing computational burden, especially in the context of real-time Myoelectric Control. Longer segments offer a more comprehensive representation of the signal but may incur higher computational costs. Striking the right balance is crucial for optimizing the precision of signal representation within a segment while maintaining computational efficiency. On the other hand, shorter segments, particularly those shorter than 200ms, are more prone to variance, bias in feature extraction, and susceptibility to noise interference. Therefore, a segment duration exceeding 200ms is deemed critical for ensuring precise signal representation in both offline and real-time Myoelectric Control applications. This consideration addresses the need for a pragmatic approach in segmenting EMG signals, accounting for the trade-off between computational efficiency and the accuracy of signal representation, a crucial aspect in the successful implementation of Myoelectric Control systems (Ortiz-Catalan et al., 2013) (Valls-Solé et al., 1999).

Maintaining a careful balance is essential, especially when considering the processing time constraints inherent in Myoelectric Control (MEC). The step size must be configured to be shorter than the segment length but still within the acceptable processing time for real-time MEC applications. This meticulous consideration aims to optimize the temporal alignment between overlapping segments while accommodating the computational demands of MEC systems. In the pursuit of achieving an equilibrium between the benefits of longer segments for enhanced pattern recognition in MEC and the constraints of processing time, the study employs an overlap segmentation approach. This technique allows for the utilization of segments longer than 200ms, contributing to improved pattern recognition capabilities in MEC applications (Ashraf et al., 2020). In the specific context of this study, both disjoint and overlap segmentation techniques are thoroughly investigated across the dataset. The analysis involving disjoint segments adopts a fixed length of 400 milliseconds, providing a basis for comparison. On the other hand, the analysis of overlapping segments incorporates a step size equivalent to 50% of the length of the disjoint segments. This approach ensures a substantial overlap between consecutive segments, facilitating a comprehensive exploration of the dataset and enabling a robust evaluation of the efficacy of both segmentation techniques.

3.5 Feature Extraction

Feature selection constitutes a pivotal facet within the domain of pattern recognition-based Myoelectric Control (MEC). The exploration of this area has witnessed extensive research efforts, resulting in the proposal and comparative analysis of diverse time-domain and frequency-domain features. In the realm of classification, the present study delves into a total of sixteen features including Card, other are comprising of ten time-domain features and five frequency-domain features. These features encompass a rich set of descriptors, including mean absolute value (MAV), average energy (AE), standard deviation (STD), waveform length (WL), root mean square (RMS), zero crossings (ZC), myopulse percentage rate (MYOP), integrated EMG (IEMG), skewness (SK), kurtosis (KUR), cardinality (CARD), mean frequency (FreqMn), median frequency (FreqMd), frequency ratio (FreqRatio), band power (BP) and power bandwidth (BW). These features play a central role in the training and testing phases of the pattern recognition-based MEC system. Notably, the time-domain feature "Cardinality" undergoes meticulous scrutiny to validate its authenticity. This involves a comprehensive evaluation achieved by systematically combining both time-domain and frequency-domain features. Employing an exhaustive feature selection technique, the study generates every conceivable combination of time-domain and frequency-domain features independently. Each combination comprises two distinct features, alongside the constant feature, Cardinality. This thorough exploration and assessment of feature combinations not only contribute to enhancing the understanding of the interplay between different features but also underscore the significance of the "Cardinality" feature within the broader context of pattern recognition in Myoelectric Control systems. Because Cardinality is affected by the precision of the units employed, in this study, the best results were obtained when expressing Cardinality up to seven decimal points, aligning with the precision required by the utilized signal.

3.6 Classification

To comprehensively evaluate classification accuracies across various feature sets, exhaustive combinations were meticulously formed for both time-domain and frequency-domain features independently. Specifically, 45 combinations per subject were generated for time-domain features, while 10 combinations were produced from frequency-domain features. Within the realm of time-domain features, the optimal outcome materialized when integrating Cardinality (Card) with Mean Absolute Value (MAV). In contrast, among frequency-domain features, the highest classification performance was achieved through the synergistic combination of Cardinality with Band Power (BP). In this study, a Linear Support Vector Machine (Linear SVM) served as the classification algorithm to discern the optimal combination of time-domain and frequency-domain features. This optimal combination, when paired with Cardinality, demonstrated superior classification accuracy. A Linear SVM is specifically designed for binary classification problems, seeking to establish a linear decision boundary, or hyperplane, that efficiently separates data points from different classes in a feature space. The algorithm focuses on optimizing the margin, defined as the distance between the hyperplane and the nearest data points (support vectors) of each class. The Linear SVM classifier employed in this study was trained with a linear kernel and a box constraint of 1. The dataset underwent a randomization process, with 70% allocated for training and 30% for testing. The subsequent evaluation and presentation of results exclusively considered the testing data. MATLAB R2022a was the chosen platform for data analysis and processing. Remarkably, the SVM classifier achieved classification accuracy of 85.58% of M1, 70.49% of M2, 77.32% of M3, 77.24% of M4, 80.82% of M5, 77.52% of M6, 82.94% of M7, 84.34% of M8, 84.75% of M9, 86.92% of M10 for the combination of Cardinality with MAV and BP.

The meticulous exploration of feature combinations and the subsequent utilization of a Linear SVM yielded noteworthy results in terms of classification accuracy. Specifically, among the ten hand movements studied, Movement number 10 demonstrated exceptional effectiveness, showcasing superior performance in terms of classification accuracy of 86.92% when compared to the remaining nine movements. Statistical analysis was conducted to assess potential differences between these movements. The results indicated a significant distinction between Movement number 2 and Movement number 10, with a p-value of 0.001. A p-value equal to or less than 0.05 suggests a notable difference between datasets. Conversely, no statistically significant difference was observed among the other hand movements, as evidenced by p-values greater than 0.05. These findings underscore the significance of feature selection and the thoughtful integration of complementary features in enhancing the overall performance of Myoelectric Control (MEC) systems. The use of a Linear SVM, with its capacity for binary classification based on linear decision boundaries, showcased its efficacy in accurately distinguishing between different classes within the dataset. The algorithm's ability to optimize the margin, crucial for effective separation between classes, contributed to its success in achieving perfect classification accuracy for the optimal feature combinations. The adoption of a linear kernel in the SVM training process, coupled with a box constraint of 1, reflected a deliberate choice in favor of simplicity and interpretability, especially when dealing with feature sets that exhibit approximately linear relationships. This pragmatic approach aligns with the inherent characteristics of the dataset and contributes to the algorithm's robust performance. The results obtained not only validate the effectiveness of the chosen features but also emphasize the importance of the interplay between feature selection and classification algorithm in the realm of

Myoelectric Control. This study contributes valuable insights into the optimization of feature sets for improved pattern recognition, a critical aspect in advancing the precision and efficiency of Myoelectric Control systems.

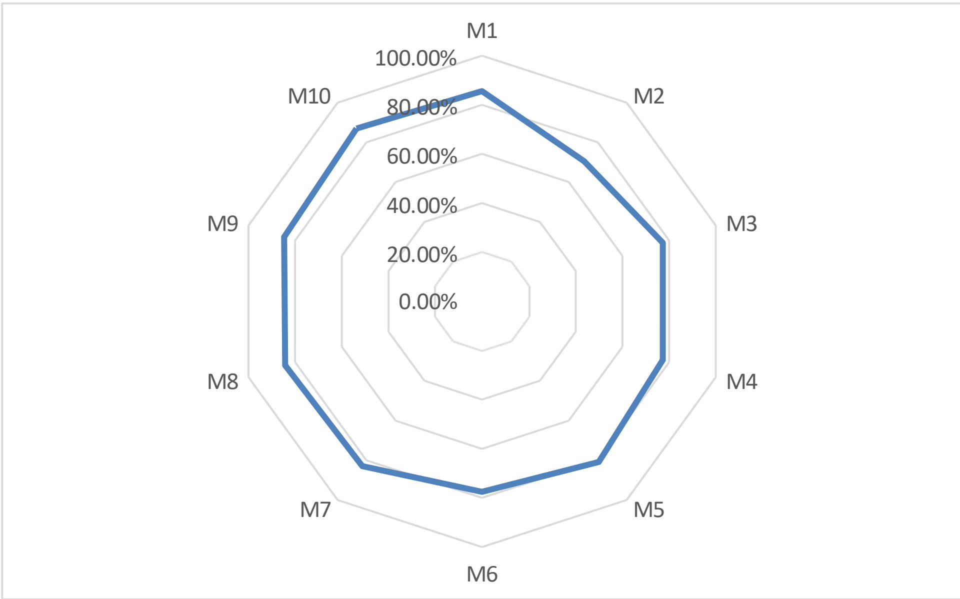
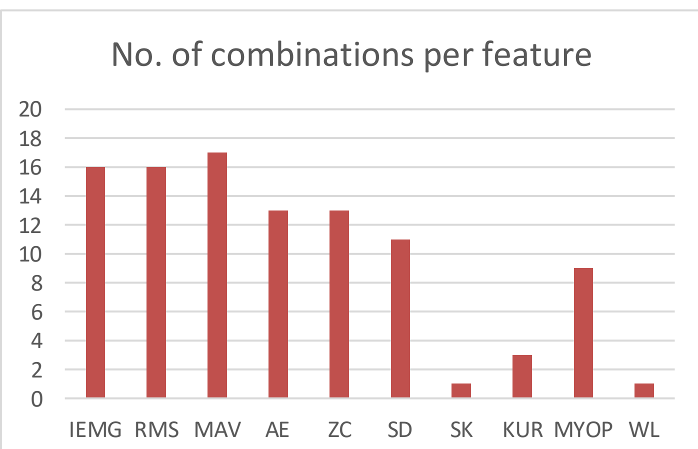


Figure 3.6 illustrates the MAV, CARD, BP combination radar chart classification accuracy of all ten hand movements.

CHAPTER: 4

4.1 RESULTS

The research findings underscore significant distinctions in the classification accuracy of time-domain and frequency-domain features when integrated with the pivotal feature Cardinality, particularly. Among the time-domain features, the standout performer is Mean Absolute Value (MAV), surpassing other features in terms of its efficacy when paired with Cardinality. This superiority can be attributed to MAV's ability to generate the highest number of combinations, contributing to its robust performance in the myoelectric pattern recognition task. Similarly, within the realm of frequency-domain features, Band Power (BP) emerges as the top performer when combined with Cardinality, outperforming other frequency-domain features and forming the most numerous combinations.



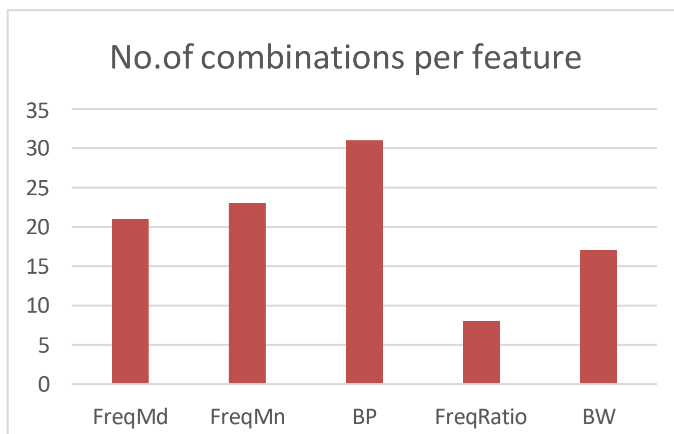


Figure 4.1(a) visualizes the time-domain features. Figure 4.1(b) visualizes the frequency-domain features.

The optimal feature set that consistently outperforms other time-domain and frequency-domain features in the domain of myoelectric pattern recognition is composed of MAV, Cardinality, and BP. This triad of features achieves a remarkable classification accuracy when employed in conjunction with SVM classifier. These findings not only highlight the pivotal role of feature selection in enhancing pattern recognition but also provide a concrete and effective feature set for optimizing the precision and efficacy of myoelectric control systems.

No. of Movement	Classifications Accuracy
M1	85.58%
M2	70.49%
M3	77.32%
M4	77.24%
M5	80.82%
M6	77.52%
M7	82.94%
M8	84.34%
M9	84.75%
M10	86.92%

Table 4.1 illustrates the combination of MAV, CARD, BP classification accuracy of all ten hand movements.

In the examination of ten distinct hand movements, Movement number 10 emerged as particularly noteworthy, showcasing an exceptional classification accuracy of 86.92%. This performance surpassed that of the remaining nine movements. Moreover, Movement number 1 demonstrated commendable accuracy, achieving a noteworthy 85.58%. To explore potential distinctions between specific movements, statistical analyses were conducted. Firstly, an examination of Movement-1 and Movement-10 was carried out. The results of this analysis revealed no significant difference between the two, as indicated by a p-value of 0.75. In statistical terms, a p-value greater than 0.05 suggests a lack of noteworthy difference between datasets. Conversely, the Movement number 2 achieved the lowest classification accuracy of 70.49% than other movements. When comparing Movement-2 and Movement-10, a distinctive contrast emerged, supported by a statistically significant p-value of 0.001. This result implies a notable difference in characteristics between these two movements. The meticulous statistical analyses thus provide valuable insights into the varying effectiveness of different hand movements in the context of classification accuracy. The outcomes not only confirm the efficacy of the selected features but also underscore the significance of the synergy between feature selection, classification algorithms in Myoelectric Control. This research provides valuable insights into enhancing pattern recognition by optimizing feature sets, a crucial factor in elevating the accuracy and efficiency of Myoelectric Control systems.

4.2 DISCUSSION AND CONCLUSION

This study aims to evaluate the effectiveness of a unique feature, Cardinality, in prosthetic control and rehabilitation applications. The effectiveness of Cardinality is contingent upon the accuracy of the units employed. In this research, Cardinality demonstrates optimal performance when utilizing seven decimal points. The approach involves testing various combinations of features through exhaustive feature selection technique to assess the distinctive qualities of Cardinality. The results emphasize the interplay between feature selection and classification algorithms in MEC. The optimal feature set, comprising MAV, Card, and BP, achieved remarkable classification accuracy. This set not only validates the effectiveness of chosen features but also provides a concrete foundation for enhancing pattern recognition in myoelectric control.

In conclusion, this study contributes valuable insights into the design and optimization of Myoelectric Control systems. The methodological rigor, from signal acquisition to feature selection and classification, reflects a systematic approach to address the challenges posed by EMG signal analysis. The identified optimal feature set, including MAV, Cardinality, and BP, represents a robust foundation for myoelectric pattern recognition. These features, when integrated into a Linear SVM classifier, demonstrate the accuracy of 85.58% of M1, 70.49% of

M2, 77.32% of M3, 77.24% of M4, 80.82% of M5, 77.52% of M6, 82.94% of M7, 84.34% of M8, 84.75% of M9, 86.92% of M10 for the combination of Card with MAV and BP, setting a benchmark for future studies in the field. As advancements in prosthetics and rehabilitation technologies continue, the insights gained from this study can play a pivotal role in refining the precision and efficiency of Myoelectric Control systems, ultimately benefiting individuals with limb loss or motor impairments.

In summary, this study provides valuable insights into the practical application of EMG-based pattern recognition models. While acknowledging certain limitations, such as the necessity for additional research on EMG signals with different and broader features sets and broader investigations involving diverse demographics, the study establishes a groundwork for future research pursuits. By addressing these limitations and exploring novel research avenues, researchers can further refine and optimize EMG-based Pattern recognition models, thereby augmenting their efficacy and relevance in clinical settings and the development of assistive devices.

REFRENCES

1. Akazawa, K., Milner, T. E., & Stein, R. B. (1983). Modulation of reflex EMG and stiffness in response to stretch of human finger muscle. Journal of Neurophysiology, 49(1), pp.16–27.
2. ALKNER, B. A., TESCH, P. A., & BERG, H. E. (2000). Quadriceps EMG/force relationship in knee extension and leg press. Medicine & Science in Sports & Exercise, 32(2), 459. https://doi.org/10.1097/00005768-200002000-00030
3. Ashraf, H., Waris, A., Jamil, M., Gilani, S. O., Niazi, I. K., Kamavuako, E. N., & Gilani, S. H. N. (2020). Determination of Optimum Segmentation Schemes for Pattern Recognition-Based Myoelectric Control: A Multi-Dataset Investigation. IEEE Access, 8, 90862–90877. https://doi.org/10.1109/ACCESS.2020.2994829
4. Barry, D. T. (1991). AAEM minimonograph #36: Basic concepts of electricity and electronics in clinical electromyography. Muscle & Nerve, 14(10), 937–946. https://doi.org/10.1002/mus.880141003
5. Berardelli, A., Dick, J. P., Rothwell, J. C., Day, B. L., & Marsden, C. D. (1986). Scaling of the size of the first agonist EMG burst during rapid wrist movements in patients with Parkinson's disease. Journal of Neurology, Neurosurgery & Psychiatry, 49(11), 1273–1279. https://doi.org/10.1136/jnnp.49.11.1273
6. Bø, K., & Stien, R. (1994). Needle emg registration of striated urethral wall and pelvic floor muscle activity patterns during cough, valsalva, abdominal, hip adductor, and gluteal muscle contractions in nulliparous healthy females. Neurourology and Urodynamics, 13(1), 35–41. https://doi.org/10.1002/nau.1930130106

7. Budzynski, T. H., Stoyva, J. M., Adler, C. S., & Mullaney, D. J. (1973). EMG Biofeedback and Tension Headache: A Controlled Outcome Study. Psychosomatic Medicine, 35(6), 484–496. https://doi.org/10.1097/00006842-197311000-00004
8. Calancie, B., Madsen, P., & Lebwohl, N. (1994). Stimulus-Evoked EMG Monitoring During Transpedicular Lumbosacral Spine Instrumentation. SPINE, 19(24), 2780–2785. https://doi.org/10.1097/00007632-199412150-00008
9. Chan, F. H. Y., Yong-Sheng Yang, Lam, F. K., Yuan-Ting Zhang, & Parker, P. A. (2000). Fuzzy EMG classification for prosthesis control. IEEE Transactions on Rehabilitation Engineering, 8(3), 305–311. https://doi.org/10.1109/86.867872
10. Cholewicki, J., & McGill, S. M. (1994). EMG assisted optimization: A hybrid approach for estimating muscle forces in an indeterminate biomechanical model. Journal of Biomechanics, 27(10), 1287–1289. https://doi.org/10.1016/0021-9290(94)90282-8
11. Cram, J. R. (1998)., & Kasman GS Holtz J. (n.d.). Introduction to Surface Electromyography.
12. Dagher, I. (2008). Quadratic kernel-free non-linear support vector machine. Journal of Global Optimization, 41(1), 15–30. https://doi.org/10.1007/s10898-007-9162-0
13. Day, B. L., Dressler, D., Maertens de Noordhout, A., Marsden, C. D., Nakashima, K., Rothwell, J. C., & Thompson, P. D. (1989). Electric and magnetic stimulation of human motor cortex: surface EMG and single motor unit responses. The Journal of Physiology, 412(1), 449–473. https://doi.org/10.1113/jphysiol.1989.sp017626
14. De Luca, & C. J. (2002). Surface electromyography: Detection and recording. DelSys Incorporated, 10(2), 1–10.

15. Farina, D., & Holobar, A. (2016). Characterization of Human Motor Units From Surface EMG Decomposition. Proceedings of the IEEE, 104(2), 353–373. https://doi.org/10.1109/JPROC.2015.2498665

16. Farina, D., Jiang, N., Rehbaum, H., Holobar, A., Graimann, B., Dietl, H., & Aszmann, O. C. (2014). The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 22(4), 797–809. https://doi.org/10.1109/TNSRE.2014.2305111

17. Ferraccioli, G., Ghirelli, L., Scita, F., Nolli, M., Mozzani, M., Fontana, S., Scorsonelli, M., Tridenti, A., & De Risio, C. (1987). EMG-biofeedback training in fibromyalgia syndrome. The Journal of Rheumatology, 14(4), 820–825.

18. Gash, M. C., Kandle, P. F., Murray, I. V., & Varacallo, M. (2023). Physiology, Muscle Contraction.

19. Granata, K. P., & Marras, W. S. (1995). An EMG-assisted model of trunk loading during free-dynamic lifting. Journal of Biomechanics, 28(11), 1309–1317. https://doi.org/10.1016/0021-9290(95)00003-Z

20. Hakkinen, K., Kallinen, M., Izquierdo, M., Jokelainen, K., Lassila, H., Malkia, E., Kraemer, W. J., Newton, R. U., & Alen, M. (1998). Changes in agonist-antagonist EMG, muscle CSA, and force during strength training in middle-aged and older people. Journal of Applied Physiology, 84(4), pp.1341–1349.

21. Hallett, M., Shahani, B. T., & Young, R. R. (1975). EMG analysis of stereotyped voluntary movements in man. Journal of Neurology, Neurosurgery & Psychiatry, 38(12), 1154–1162. https://doi.org/10.1136/jnnp.38.12.1154

22. Hazlett, R. L., & Hazlett, S. Y. (1999). Emotional response to television commercials: Facial EMG vs. self-report. Journal of Advertising Research, 39(2) (pp.7-7).

23. Hiraiwa, A., Shimohara, K., & Tokunaga, Y. (n.d.). EMG pattern analysis and classification by neural network. Conference Proceedings., IEEE International Conference on Systems, Man and Cybernetics, 1113–1115. https://doi.org/10.1109/ICSMC.1989.71472

24. Hogan, N. (1976). A review of the methods of processing EMG for use as a proportional control signal. Biomedical Engineering, 11(3), 81–86.

25. Hubbard, D. R., & Berkoff, G. M. (1993). Myofascial Trigger Points Show Spontaneous Needle EMG Activity. Spine, 18(13), 1803–1807. https://doi.org/10.1097/00007632-199310000-00015

26. Huxley, A. F. (1974). Muscular contraction. The Journal of Physiology, 243(1), 1–43.

27. Jobe, F. W., Moynes, D. R., Tibone, J. E., & Perry, J. (1984). An EMG analysis of the shoulder in pitching. The American Journal of Sports Medicine, 12(3), 218–220. https://doi.org/10.1177/036354658401200310

28. Kleissen, R. F. M., Buurke, J. H., Harlaar, J., & Zilvold, G. (1998). Electromyography in the biomechanical analysis of human movement and its clinical application. Gait & Posture, 8(2), 143–158. https://doi.org/10.1016/S0966-6362(98)00025-3

29. Komi, P. V., Linnamo, V. E. S. A., Silventoinen, P. E. R. T. T. I., & Sillanpaa, M. (2000). Force and EMG power spectrum during eccentric and concentric actions. Medicine and Science in Sports and Exercise, 32(10) (pp.1757-1762).

30. Kundu, B., & Subarram Naidu, D. (2021). Classification and Feature Extraction of Different Hand Movements from EMG Signal using Machine Leaning based Algorithms. 2021

International Conference on Electrical, Communication, and Computer Engineering (ICECCE), 1–5. https://doi.org/10.1109/ICECCE52056.2021.9514134

31. Lee, S. W., Wilson, K. M., Lock, B. A., & Kamper, D. G. (2011). Subject-Specific Myoelectric Pattern Classification of Functional Hand Movements for Stroke Survivors. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 19(5), 558–566. https://doi.org/10.1109/TNSRE.2010.2079334
32. Liu, J., & Zhou, P. (2013). A Novel Myoelectric Pattern Recognition Strategy for Hand Function Restoration After Incomplete Cervical Spinal Cord Injury. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(1), 96–103. https://doi.org/10.1109/TNSRE.2012.2218832
33. Lundberg, U., Kadefors, R., Melin, B., Palmerud, G., Hassmén, P., Engström, M., & Elfsberg Dohns, I. (1994). Psychophysiological stress and emg activity of the trapezius muscle. International Journal of Behavioral Medicine, 1(4), 354–370. https://doi.org/10.1207/s15327558ijbm0104_5
34. Mambrito, B., & De Luca, C. J. (1984). A technique for the detection, decomposition and analysis of the EMG signal. Electroencephalography and Clinical Neurophysiology, 58(2), 175–188. https://doi.org/10.1016/0013-4694(84)90031-2
35. Mathiassen, S. E., Winkel, J., & Hägg, G. M. (1995). Normalization of surface EMG amplitude from the upper trapezius muscle in ergonomic studies — A review. Journal of Electromyography and Kinesiology, 5(4), 197–226. https://doi.org/10.1016/1050-6411(94)00014-X
36. McManus, L., De Vito, G., & Lowery, M. M. (2020). Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With

Rehabilitation Engineers. Frontiers in Neurology, 11. https://doi.org/10.3389/fneur.2020.576729

37. Murray, M. P., Mollinger, L. A., Gardner, G. M., & Sepic, S. B. (1984). Kinematic and EMG patterns during slow, free, and fast walking. Journal of Orthopaedic Research, 2(3), 272–280. https://doi.org/10.1002/jor.1100020309
38. Ng, J. K., Kippers, V., & Richardson, C. A. (1998). Muscle fibre orientation of abdominal muscles and suggested surface EMG electrode positions. Electromyography and Clinical Neurophysiology, 38(1), 51–58.
39. Nikias, C. L., & Raghuveer, M. R. (1987). Bispectrum estimation: A digital signal processing framework. Proceedings of the IEEE, 75(7), 869–891. https://doi.org/10.1109/PROC.1987.13824
40. Nummela, A., Rusko, H., & Mero, A. (1994). EMG activities and ground reaction forces during fatigued and nonfatigued sprinting. Medicine and Science in Sports and Exercise, 26(5), 605–609.
41. Ortiz-Catalan, M. (2015). Cardinality as a highly descriptive feature in myoelectric pattern recognition for decoding motor volition. Frontiers in Neuroscience, 9. https://doi.org/10.3389/fnins.2015.00416
42. Ortiz-Catalan, M., Brånemark, R., & Håkansson, B. (2013). BioPatRec: A modular research platform for the control of artificial limbs based on pattern recognition algorithms. Source Code for Biology and Medicine, 8(1), 11. https://doi.org/10.1186/1751-0473-8-11
43. PETROFSKY, J. S., GLASER, R. M., PHILLIPS, C. A., LIND, A. R., & WILLIAMS, C. (1982). Evaluation of the amplitude and frequency components of the surface EMG as an

index of muscle fatigue. Ergonomics, 25(3), 213–223. https://doi.org/10.1080/00140138208924942

44. Petrofsky, J. S., & Lind, A. R. (1980). The influence of temperature on the amplitude and frequency components of the EMG during brief and sustained isometric contractions. European Journal of Applied Physiology and Occupational Physiology, 44(2), 189–200. https://doi.org/10.1007/BF00421098
45. Raez, M. B. I., Hussain, M. S., & Mohd-Yasin, F. (2006). Techniques of EMG signal analysis: detection, processing, classification and applications. Biological Procedures Online, 8, 11–35. https://doi.org/10.1251/bpo115
46. Reimers-Neils, L., Logemann, J., & Larson, C. (1994). Viscosity effects on EMG activity in normal swallow. Dysphagia, 9(2), 101–106. https://doi.org/10.1007/BF00714596
47. Sang-Hui Park, & Seok-Pil Lee. (1998). EMG pattern recognition based on artificial intelligence techniques. IEEE Transactions on Rehabilitation Engineering, 6(4), 400–405. https://doi.org/10.1109/86.736154
48. Shahid, S., Walker, J., Lyons, G. M., Byrne, C. A., & Nene, A. V. (2005). Application of Higher Order Statistics Techniques to EMG Signals to Characterize the Motor Unit Action Potential. IEEE Transactions on Biomedical Engineering, 52(7), 1195–1209. https://doi.org/10.1109/TBME.2005.847525
49. Solomonow, M., Baratta, R., Bernardi, M., Zhou, B., Lu, Y., Zhu, M., & Acierno, S. (1994). Surface and wire EMG crosstalk in neighbouring muscles. Journal of Electromyography and Kinesiology, 4(3), 131–142. https://doi.org/10.1016/1050-6411(94)90014-0
50. Standards for Reporting EMG Data. (2014). Journal of Electromyography and Kinesiology, 24(2), I–II. https://doi.org/10.1016/S1050-6411(14)00042-X

51. Tangel, D. J., Mezzanotte, W. S., & White, D. P. (1991). Influence of sleep on tensor palatini EMG and upper airway resistance in normal men. . . Journal of Applied Physiology, 70(6) (pp.2574-2581).

52. TESCH, P. A., DUDLEY, G. A., DUVOISIN, M. R., HATHER, B. M., & HARRIS, R. T. (1990). Force and EMG signal patterns during repeated bouts of concentric or eccentric muscle actions. Acta Physiologica Scandinavica, 138(3), 263–271. https://doi.org/10.1111/j.1748-1716.1990.tb08846.x

53. Turton, A., Wroe, S., Trepte, N., Fraser, C., & Lemon, R. N. (1996). Contralateral and ipsilateral EMG responses to transcranial magnetic stimulation during recovery of arm and hand function after stroke. Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control, 101(4), 316–328. https://doi.org/10.1016/0924-980X(96)95560-5

54. Valls-Solé, J., Rothwell, J. C., Goulart, F., Cossu, G., & Muñoz, E. (1999). Patterned ballistic movements triggered by a startle in healthy humans. The Journal of Physiology, 516(3), 931–938. https://doi.org/10.1111/j.1469-7793.1999.0931u.x

55. Viitasalo, J. H. T., & Komi, P. V. (1977). Signal characteristics of EMG during fatigue. European Journal of Applied Physiology and Occupational Physiology, 37(2), 111–121. https://doi.org/10.1007/BF00421697

56. Visser, C. P. J., Coene, L. N. J. E. M., Brand, R., & Tavy, D. L. J. (1999). The incidence of nerve injury in anterior dislocation of the shoulder and its influence on functional recovery. The Journal of Bone and Joint Surgery. British Volume, 81-B (4), 679–685. https://doi.org/10.1302/0301-620X.81B4.0810679

57. VRANA, S. R. (1993). The psychophysiology of disgust: Differentiating negative emotional contexts with facial EMG. Psychophysiology, 30(3), 279–286. https://doi.org/10.1111/j.1469-8986.1993.tb03354.x
58. Wang, J., Tang, L., & E Bronlund, J. (2013). Surface EMG Signal Amplification and Filtering. International Journal of Computer Applications, 82(1), 15–22. https://doi.org/10.5120/14079-2073
59. Wang, M., Wang, X., Peng, C., Zhang, S., Fan, Z., & Liu, Z. (2019). Research on EMG segmentation algorithm and walking analysis based on signal envelope and integral electrical signal. Photonic Network Communications, 37(2), 195–203. https://doi.org/10.1007/s11107-018-0809-1
60. Webb, R. C. (2003). Smooth muscle contraction and relaxation. Advances in Physiology Education, 27(1–4), 201–206. https://doi.org/10.1152/advan.00025.2003
61. Weinberger, M., & Dostrovsky, J. O. (2010). Motor Unit. In Encyclopedia of Movement Disorders (pp. 204–206). Elsevier. https://doi.org/10.1016/B978-0-12-374105-9.00486-X
62. Woods, J. J., & Bigland-Ritchie, B. (1983). Linear and non-linear surface EMG/force relationships in human muscles. An anatomical/functional argument for the existence of both. American Journal of Physical Medicine, 62(6), 287–299.
63. Yang, J. F., & Winter, D. A. (1985). Surface EMG profiles during different walking cadences in humans. Electroencephalography and Clinical Neurophysiology, 60(6), 485–491. https://doi.org/10.1016/0013-4694(85)91108-3
64. Yao, W., Fuglevand, R. J., & Enoka, R. M. (2000). Motor-Unit Synchronization Increases EMG Amplitude and Decreases Force Steadiness of Simulated Contractions. Journal of Neurophysiology, 83(1), 441–452. https://doi.org/10.1152/jn.2000.83.1.441