Detecting Musculoskeletal Co-contraction for Ankle Rehabilitation through Variational Mode Decomposition in sEMG

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I certify that this research work titled ***"Detecting Musculoskeletal Co-contraction for Ankle Rehabilitation through Variational Mode Decomposition in sEMG"*** is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged/referred.

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Copyright Statement

Acknowledgments

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 set up 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.

My parents raised me, when I was not capable of walking. I am profusely thankful to my mother. Everything I am today, every achievement I've earned, I owe to my angelic mother. Her unwavering love and support has been the cornerstone of my success. I am thankful to my beloved father who always continued to support me throughout in every department of my life.

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Dedicated

To my angelic mother (Farzana), whose love lights my way,

To my hard-working father (Muhammad Amir), my rock every day,

To my dearest brothers (Usman & Mansoor), whose bonds I'll cherish, come what may.

To my loving husband (Danish), my heart's truest stay.

Abstract

The ankle joint plays important role in performing fundamental activities such as walking and other essential daily tasks. Muscular co-contraction improves joint quality as impaired ankle joint causes gait issues, induces pain and sometimes inflammation. The need is to characterize the ankle muscle co-contraction in sEMG signal by using an efficient technique i.e. Variational Mode Decomposition (VMD) to make sure that it could be a non-pharmacological treatment for persons having ankle joint issues. VMD approach analyzes surface electromyographic signals from antagonist muscles of the lower limb during walking of 20 healthy individuals and assesses muscular co-contraction using the coscalogram function. In this research, the novel combination of the scalogram visualization technique with Variational Mode Decomposition (VMD) is employed for the first time. The present study compares VMD with the Continuous Wavelet Transform (CWT) approach and shows that VMD outperforms CWT in terms of both SNR and RMSE. On average, the increase in SNR in case of VMD (-17.65 ± 8.1dB to 2.98 ±2.2dB, $p<0.05$) was greater than that of CWT (-17.65 ±3.7dB to 1.34±1.5dB). Similarly, the reduction in RMSE with VMD (0.023 ±0.0029 to 0.017 ±0.0015, $p<0.05$) surpassed that achieved with CWT (0.023±0.0027to 0.020±0.0025). This study aims to introduce a method that would be helpful for clinical and rehabilitation purposes to improve joint quality by identifying ankle muscle co-contraction.

Key Words:

Variational mode decomposition, Scalogram, sEMG, co-contraction, Continuous wavelet transform, ankle rehabilitation

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CHAPTER 1

1 INTRODUCTION

1.1 Background of the study

Nowadays, there has been a notable increase in the prevalence of joint disorders, encompassing a range of conditions and injuries that affect the joint articulations within the human body. These disorders can arise from a multitude of factors, including overuse, traumatic incidents, and underlying medical conditions. The ankle joint plays a crucial role in enhancing various aspects of human performance, notably improving physical capabilities in work environments. Its optimal functionality is vital for fundamental activities such as walking and other essential daily tasks. Including ankle-strengthening exercises in your daily routine can help prevent accidents and improve your mobility. Life-changing events are directly linked with lower limb performance. Some researchers suggest that co-contraction exercises may help in the rehabilitation of injured joints for their focus on improved joint working.

Figure 1: Ankle joint injury [1]

Among the intricate network of joints, the ankle joint emerges as a linchpin in bolstering various facets of human performance. Its optimal functionality is paramount for executing fundamental activities, most notably the art of ambulation, and a plethora of other indispensable daily tasks. A robust and agile ankle joint is indispensable, not only for maintaining an individual's independence in routine activities but also for enhancing productivity in occupational environments.

Even though these exercises sound promising, we're still not completely sure how well they work for making joints healthier. There are different ways to measure how muscles work together, but there isn't one perfect way that everyone agrees on. This means we need to take a close look at the research that's been done and see if these exercises really do help. Muscular co-contraction is hypothesized to be a good application for clinical purposes. However, the efficacy of ankle muscle co-contraction to be helpful for joint health remains unclear. Different techniques exist for assessing muscular co-contraction; however, a gold standard has not been established. Researchers have designed various studies, but due to poor decomposition performance, instability, and other issues, the evidence of ankle muscle co-contraction being advantageous for rehabilitation purposes required improvement.

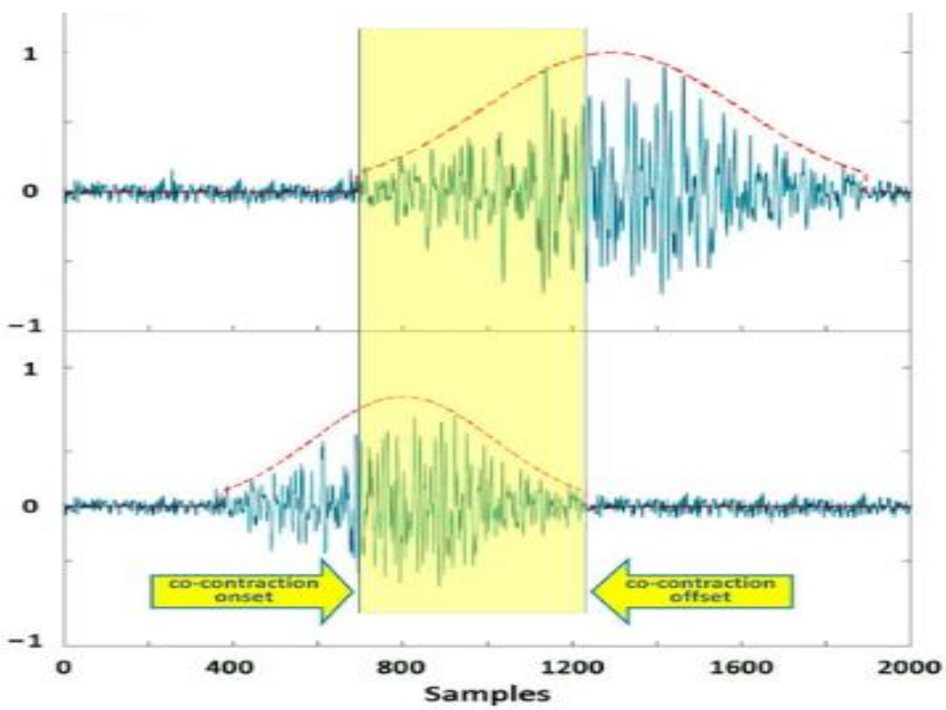

Figure 2: Two simulated sEMG signals that are appropriate for detecting co-contraction. [2]

Scientists have done a bunch of studies to figure out if these exercises are beneficial for joint health. But there have been some challenges, like problems with how they measure muscle activity and other factors that can make the results unclear. So, we need to keep studying to understand if these exercises are as helpful as they seem.

Muscular co-contraction is when different muscles around a joint work together at the same time to help stabilize it and make movements more precise. This is an important way our body controls movement. It helps us stay balanced and move smoothly. Co-contraction happens when we do all sorts of activities, from everyday tasks to sports. It's a normal way our body works to do things effectively. Studying co-contraction helps us understand how our muscles and nerves work together.

In the medical field, looking at co-contraction patterns can tell us about certain muscle and movement problems. Fig 2 shows the co-contraction pattern in muscle. It helps diagnose conditions like cerebral palsy, issues from strokes, and injuries to our muscles and bones. Knowing about co-contraction also helps plan treatments that focus on improving specific muscle movements. In lower limbs, co-contraction is especially important. It helps us stay steady when we stand, walk, or do any kind of active movement. It's like a key factor in supporting our weight and keeping us balanced, especially when we're on bumpy ground or carrying heavy things.

In the past, scientists have used different methods to study how muscles work together in the upper arm. They use things like the co-contraction index (CCI) and coactivation ratio to measure this. They also use techniques like the Double threshold statistical algorithm (DT) and Rudolph's index (RI). But there hasn't been as much research on how muscles work together in the lower legs while walking

Recently, a group of researchers took a close look at how muscles in the thigh and ankle work together. They also looked at joint torque, which helps give an idea of how much co-contraction is happening. This kind of research helps us understand how our muscles cooperate, especially when we're moving around. Scientists have conducted different studies, but because of poor decomposition performance, problems with stability, and issues with background noise, we still don't know for sure if ankle muscles working together is really good for joint health. We also need to improve the evidence that shows if it's helpful for rehabilitation.

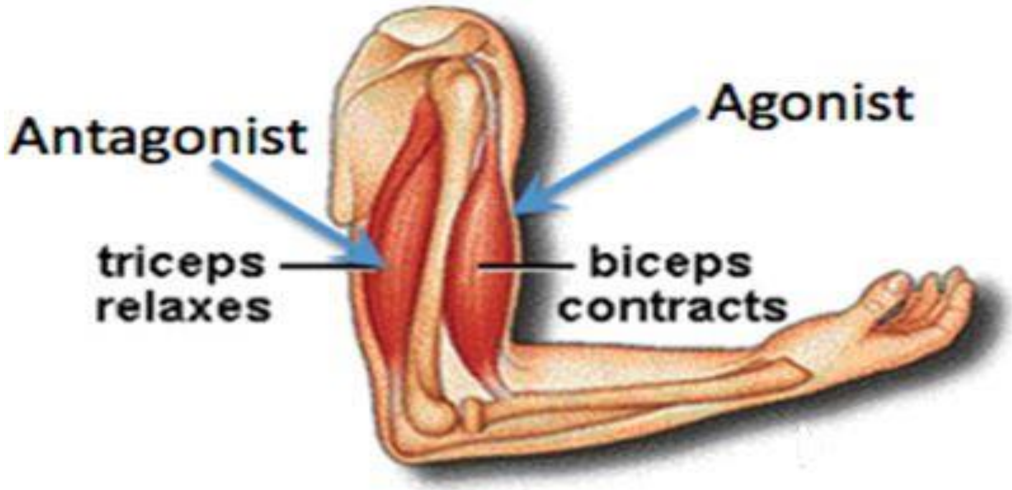

Figure 3: Antagonist muscles cooperating with each other [3]

This thesis reports the findings of a thorough study of a method that would be helpful for clinical and rehabilitation purposes to improve joint quality by quantifying ankle muscle co-contraction.

1.2 Problem Statement

In literature, previous studies have demonstrated that various techniques have been adopted for the analysis of muscle co-contraction of sEMG signals taken from the upper limb i.e., Co-contraction Index (CCI), Double threshold statistical algorithm (DT), Rudolph's index (RI) etc. However, there is a notable deficiency of data on the topic of muscle co-contraction in the lower limbs while walking. Recently, a group of researchers presented a comprehensive analysis of thigh muscle and ankle muscle co-contraction. Researchers have designed various studies, but due to poor decomposition performance, instability, modal aliasing effect, and low noise resistance, the efficacy of ankle muscle co-contraction to be helpful for joint health remains unclear, along with the evidence of ankle muscle co-contraction to be advantageous for rehabilitation purpose required improvement. To recognize the role of muscular co-contraction for clinical and rehabilitation purposes, there is a need to characterize the ankle muscle co-contraction by using some efficient technique i.e. Variational Mode Decomposition to make sure that it could be a non-pharmacological treatment for persons having ankle joint issues.

1.3 Objectives of the study

- To identify co-contraction in lower limb antagonist muscles
- To quantify ankle muscle co-contraction in sEMG signal by using variational mode decomposition technique
- To assess how co-contraction be helpful for clinical and rehabilitation purposes

CHAPTER 2

2 LITERATURE REVIEW

2.1 Introduction

In the past few decades, surface electromyography (sEMG) signals have emerged as a valuable tool in the fields of clinical research, biomedical engineering, and human movement analysis. These signals provide a window into the intricate interactions between muscles and the nervous system during voluntary movements, offering essential insights into the functioning of the neuromuscular system. EMG records the electrical activity of muscles to evaluate their response to nerve signals from the brain. EMG signals play an important role in clinical/medical and engineering fields. They are of two types: surface EMG (sEMG) and intramuscular EMG [4]. Both differ from each other by electrodes i.e., non-invasive and invasive electrodes [5]. Surface electromyography (sEMG) signals have revolutionized our understanding of human movement, offering a unique window into the dynamic interplay between muscles and the nervous system.

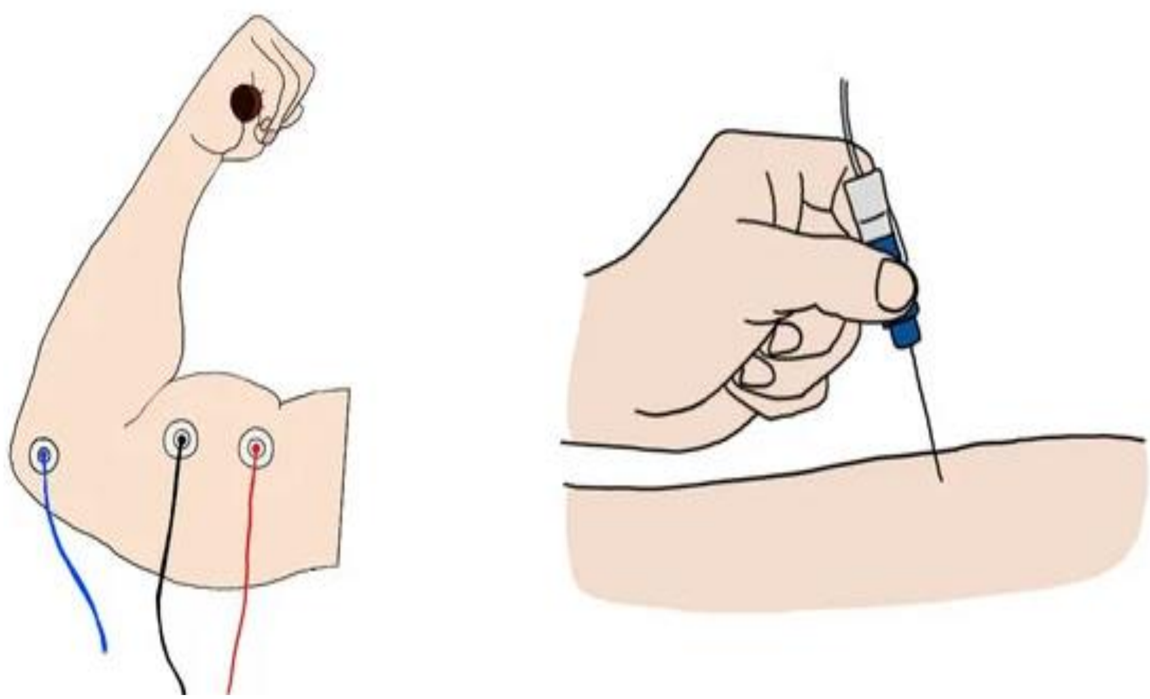

Figure 4: Surface EMG and Intramuscular EMG [6]

Unlike invasive methods that require needles, sEMG involves placing electrodes on the skin surface to non-invasively capture the electrical activity generated by contracting muscles. This technique has gained prominence due to its accessibility, safety, and capacity to provide valuable insights into various physiological and functional aspects of muscle activity. sEMG is preferably used nowadays to extract information about muscle activation [7]. sEMG signals are instrumental in a wide range of disciplines, spanning both clinical and engineering domains. In the realm of clinical medicine, sEMG serves as a diagnostic tool to assess muscle health, detect neuromuscular disorders, and monitor the progress of rehabilitation programs. It offers clinicians the ability to uncover abnormalities in muscle activation, identify nerve damage, and evaluate muscle coordination patterns. In parallel, the engineering field harnesses sEMG for the design and development of prosthetics, exoskeletons, and assistive devices, enabling individuals with mobility impairments to regain lost functions. Moreover, sEMG is indispensable in sports and ergonomics research, facilitating the optimization of athletic performance, injury prevention, and the enhancement of workplace safety. Surface electromyography (sEMG) stands as a pivotal tool in the fields of clinical research, biomedical engineering, and human movement analysis. Its non-invasive nature allows for the detailed examination of the neuromuscular system during voluntary movements, offering a unique window into the intricate interactions between muscles and the nervous system. Unlike invasive methods that necessitate the use of needles, sEMG involves the placement of electrodes on the skin surface to capture the electrical activity generated by contracting muscles. This accessibility, coupled with its safety, has propelled sEMG to the forefront of physiological and functional assessments of muscle activity. It plays a fundamental role in both clinical and engineering domains. In the clinical realm, sEMG serves as a diagnostic tool, assessing muscle health, detecting neuromuscular disorders, and monitoring rehabilitation progress. This capability empowers clinicians to uncover abnormalities in muscle activation, identify nerve damage, and evaluate muscle coordination patterns, contributing to more accurate diagnoses and tailored treatment plans. EMG signals can be used to diagnose nerve damage, muscle dysfunction, etc. Furthermore, they can be used for rapid torque development [8], gait analysis, and recording muscle movements e.g. muscle co-contraction [9]. For this purpose, the acquisition of an accurate EMG signal is essential [10].

Functioning of the ankle joint is related to multiple valued performances in human life including improved physical performance at work. It is a key requirement for gait and other activities of living. Including ankle-strengthening exercises in your daily routine can help prevent accidents and improve your mobility. The functioning of the ankle joint holds paramount significance in daily life across a multitude of dimensions. It serves as a linchpin for mobility and ambulation, underpinning activities like walking, running, and various movements that hinge on stability and balance.

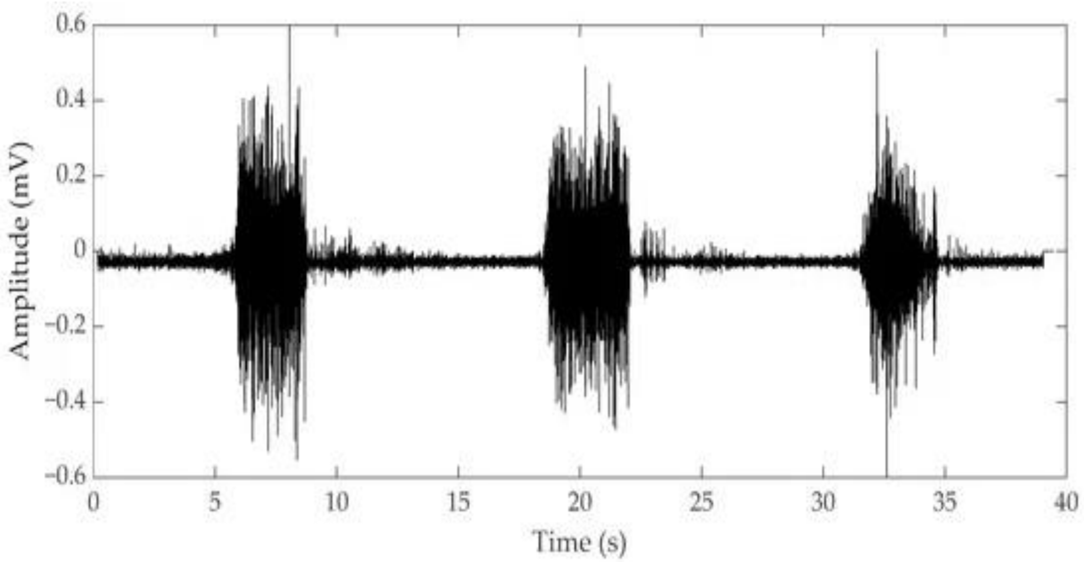

Figure 5: EMG data during muscle contraction and relaxation [6]

Additionally, the ankle joint assumes a pivotal role in sustaining upright posture, thereby distributing body weight evenly and averting potential falls or missteps. Negotiating diverse terrains, including uneven ground, stairs, slopes, and obstacles, heavily relies on the proper functioning of the ankle joint, which facilitates adjustments in foot position to accommodate changes in the environment. Furthermore, an array of routine tasks, from rising from a chair to ascending stairs and maintaining equilibrium while executing chores, hinges on the ankle's integrity. In the realm of sports and recreation, its flexibility, strength, and stability are instrumental, enabling activities like jogging, sports participation, dancing, and cycling. The ankle joint's capacity for flexion, extension, inversion, and eversion is indispensable for pursuits ranging from driving to playing musical instruments and engaging in various physical endeavors. It shoulders a significant portion of the body's weight during standing, walking, and running, efficiently distributing this load to mitigate stress on other joints. A well-functioning ankle joint not only reduces the likelihood of injuries but also exerts a positive influence on overall health, as dysfunction can lead to compensatory movements, potentially causing issues in other joints or muscles. Ultimately, the quality of life is directly influenced by the state of the ankle joint, as its health is intrinsic to independence, social engagement, occupational pursuits, and recreational activities, making it an indispensable cornerstone of daily living. However, poor-quality ankle causes gait issues and induces pain and sometimes inflammation. The consequences of ankle injuries extend beyond pain and disability from the incident, potentially affecting physical, psychological, and social well-being in the long term. Muscular co-contraction may improve a person's joint quality.

Muscle co-contraction refers to the simultaneous activation of antagonist muscles around a joint. Muscular co-contraction is a fundamental phenomenon in human motor control that underscores the intricate coordination of muscles around a joint during movement. It involves the simultaneous activation of antagonist muscles to stabilize joints and fine-tune movements. This sophisticated motor control strategy serves as a mechanism for enhancing joint stability, maintaining balance, and refining movement precision. While co-contraction is considered a normal physiological response, its precise coordination plays a critical role in a diverse array of activities, from basic functional tasks to complex athletic maneuvers. It is a normal motor control strategy used to perform various functional tasks effectively. The study and quantification of muscular co-contraction have widespread implications across multiple fields, contributing to a deeper understanding of neuromuscular function and its applications. In the clinical realm, assessing co-contraction patterns provides insights into neuromuscular pathologies and movement disorders. It aids in diagnosing conditions such as cerebral palsy, stroke-related impairments, and musculoskeletal injuries. Furthermore, co-contraction analysis informs rehabilitation strategies, enabling tailored interventions that target specific muscle interactions to restore optimal movement patterns. Cocontraction in the lower limb constitutes a fundamental mechanism with far-reaching implications for human movement and functional capabilities. Its significance is prominently underscored by its pivotal role in bolstering joint stability and support, serving as a linchpin for weight-bearing activities like walking and dynamic motions. Moreover, cocontraction assumes a critical function in preserving posture and balance, particularly in scenarios where the body's equilibrium is challenged, such as when navigating uneven terrain or carrying heavy loads. The precision and control of movements, including fine motor tasks like writing or intricate manipulations, owe much to the coordinated action of cocontracting muscles. This mechanism is particularly invaluable in swiftly changing situations or rapid movements, thwarting potential joint displacement. Furthermore, cocontraction steps in as a compensatory mechanism, lending support to weaker or fatigued muscle groups, and contributes significantly to proprioception, fortifying spatial awareness and coordination. In cases of joint instability stemming from pathological conditions, cocontraction offers a safeguard, mitigating excessive motion. It additionally optimizes movement efficiency, ensuring that muscle forces are channeled effectively, and plays a pivotal role in rehabilitation efforts, aiding in the recovery from injuries and reducing the likelihood of future occurrences. Altogether, cocontraction in the lower limb emerges as a cornerstone of human movement, influencing everything from basic postural control to complex athletic maneuvers, underlining its critical relevance in daily life and functional performance. During limb movement, co-contraction of muscle results in stiffness of joints, hence enhancing the accuracy and stability of joints [11]. Walking at various speeds and over greater distances/durations would increase muscle co-contraction recruitment and subject variability [12]. While elevated co-contraction levels can lead to adverse outcomes. Excessive co-contraction is a major contributing factor to walking impairments [13], causes fatigue [14], leads to higher energy consumption, and may obstruct movement [15].

2.2 Quantification Techniques

Muscular co-contraction is hypothesized to be a good application for clinical purposes. Assessing muscular co-contractions is crucial in understanding the intricate coordination of muscles around a joint during movement. Over the years, various quantification techniques have been developed to analyze and measure co-contractions, providing valuable insights into neuromuscular function. These techniques have evolved to encompass a range of methodologies, each offering unique advantages and considerations. One widely employed method is surface electromyography (sEMG) paired with cross-correlation analysis. This approach involves recording the electrical activity of muscles using surface electrodes and then cross-correlating the signals from pairs of muscles around a joint. By calculating the degree of similarity or synchronization between muscle activity patterns, researchers can quantify the level of co-contraction. This technique has been utilized in studies focusing on activities such as gait, posture, and isometric contractions. Additionally, sEMG-based cross-correlation analysis enables the assessment of co-contraction patterns in both healthy individuals and those with neuromuscular disorders, providing valuable diagnostic and rehabilitative information. Another prominent technique involves the use of biomechanical modeling and simulation. This approach integrates musculoskeletal models with experimental data to estimate muscle forces and joint moments during movement. By applying optimization algorithms, researchers can infer the co-contraction levels of specific muscle pairs around a joint. This technique provides a comprehensive understanding of the forces acting on a joint and the corresponding muscular contributions. Moreover, it allows for the investigation of co-contraction strategies across a range of tasks, aiding in the development of tailored rehabilitation programs for individuals with movement impairments. However, it is important to note that this method requires precise anatomical and biomechanical data, which may pose challenges in some clinical settings. Different techniques exist for assessing muscular co-contraction; however, a gold standard has not been established. Previous studies have demonstrated that various techniques have been adopted for the analysis of muscle co-contraction of sEMG signals taken from the upper limb i.e. to quantify co-contraction, researchers use indexes such as the co-contraction index (CCI) and the coactivation ratio [16], double threshold statistical algorithm (DT) [17], Rudolph's index (RI) [18]. However, there is a notable deficiency of data on the topic of muscle co-contraction in the lower limbs [19] while walking. Recently, a group of researchers presented a comprehensive analysis of thigh muscle [20] and ankle muscle co-contraction [21]. Measuring joint torque provides an indirect measure of co-contraction. Changes in joint torque can indicate how opposing muscles are contributing to joint stability. Dynamic joint torque analysis during tasks like walking or squatting can reveal co-contraction patterns [22]. Co-contraction can be assessed by analyzing joint angles and muscle activation patterns during specific tasks. Three-dimensional motion analysis provides insights into how antagonist muscles stabilize the joint [23]. Computational models simulate muscle forces and joint movements. These models can predict co-contraction patterns and muscle contributions to joint stability during various tasks. Normalized mutual information (NMI) measures the statistical dependency between EMG signals of antagonist muscles. It quantifies the similarity of patterns in EMG signals, with higher NMI values representing stronger co-contraction [24]. Frequency domain techniques such as coherence and phase synchronization quantify the coordination between antagonist muscles' frequency components. Higher coherence values suggest synchronized co-contraction [25].

Continuous Wavelet Transform (CWT) is another previously used technique for quantifying muscular co-contraction in sEMG signals. The Continuous Wavelet Transform is indeed a valuable method for analyzing signal dynamics across both time and frequency domains. It can be utilized to assess co-contraction patterns in sEMG signals by examining how the frequency components of antagonist muscle activations interact over time [26]. Researchers have designed various studies, but due to poor decomposition performance, instability, modal aliasing effect, and low noise resistance, the efficacy of ankle muscle co-contraction to be helpful for joint health remains unclear, along with the evidence of ankle muscle co-contraction to be advantageous for rehabilitation purpose required improvement.

2.3 Denoising Techniques

In the field of signal processing, a variety of denoising techniques have been employed to enhance the quality of signals contaminated with noise. These techniques serve as pivotal tools in extracting meaningful information from noisy data. The Moving Average (MA) filter, for instance, is a straightforward method that smoothens data by replacing each point with the average of its neighboring values. However, it may lead to a loss of sharp features in the signal. The Median filter, on the other hand, is adept at mitigating the impact of outliers and impulse noise by substituting data points with the median value of nearby points. Yet, it may not be as effective in scenarios where noise is distributed uniformly. Wavelet thresholding, a more advanced technique, leverages the wavelet transform to decompose signals into distinct frequency components, subsequently applying thresholding to suppress noise. However, the choice of the threshold can be critical and may require tuning for optimal results. Kalman filtering, a recursive algorithm, is widely utilized for estimating the state of dynamic systems in the presence of noise, making it invaluable in control systems and navigation. Nevertheless, it assumes a linear and Gaussian model for the system and noise, which may not always hold true in real-world scenarios. The Savitzky-Golay filter employs polynomial regression to achieve noise reduction while preserving essential features of the signal. However, it may struggle with signals that exhibit rapid, high-frequency changes. Empirical Mode Decomposition (EMD) is a data-driven approach that decomposes signals into Intrinsic Mode Functions (IMFs) representing oscillatory components, proving particularly effective for non-stationary and nonlinear signals. However, the method may suffer from mode mixing, where the IMFs may not always represent distinct oscillatory modes. Total Variation Denoising minimizes the total variation of a signal while retaining crucial features, making it well-suited for piecewise smooth signals. Yet, it can potentially oversmooth the signal, leading to a loss of finer details. Non-local Means (NLM) leverages the similarity between patches of a signal to reduce noise, proving especially effective for images and signals with spatially correlated noise. However, it can be computationally intensive, particularly for large datasets. Principal Component Analysis (PCA) projects data onto orthogonal components to reduce noise, serving as a versatile tool for dimensionality reduction and noise reduction in various applications. However, it assumes that the noise is uncorrelated with the signal, which may not always hold true in practice. These denoising techniques collectively play a crucial role in enhancing the fidelity and utility of signals in diverse fields of study and application, although they may exhibit specific limitations in certain scenarios.

Nowadays, a significant number of individuals experience joint disorders, which encompass a range of conditions and injuries that impact the joints. Such disorders can arise from factors such as excessive joint usage or other underlying causes. The consequences of ankle injuries extend beyond pain and disability from the incident, potentially affecting physical, psychological, and social well-being in the long term. Muscular co-contraction may improve a person's joint quality. The need is to characterize the ankle muscle co-contraction in sEMG signal by using an efficient technique i.e., Variational Mode Decomposition to make sure that it could be a non-pharmacological treatment for persons having ankle joint issues. This study aims to present a method that would be helpful for clinical and rehabilitation purposes to improve joint quality by quantifying ankle muscle co-contraction.

2.3.1 Variational Mode Decomposition (VMD)

Variational Mode Decomposition (VMD) is a relatively recent signal processing technique that has garnered significant attention due to its effectiveness in decomposing non-stationary and nonlinear signals into their constituent modes. Since its introduction, VMD has found applications in various fields, ranging from biomedical signal processing to image analysis and beyond. Variational mode decomposition is a process that decomposes input signals into a discrete number of sub-signals (modes), each with limited bandwidth. The VMD method is an effective way of separating harmonic signals of close frequency range. Unlike other methods, it is not affected by the sampling frequency, thus avoiding mode mixing. VMD is a generalized form of the Wiener filter that divides the signal into multiple adaptive bands [18]. The model estimate, along with its associated center frequency, undergoes regular updates, resulting in a dynamic model estimation. Following each estimation, the model is converted into the time domain through the inverse Fourier transform. VMD then breaks down the initial signal into distinct sub-signals referred to as Intrinsic Mode Functions (IMFs). By iteratively decomposing a signal into a finite number of modes and associated frequency components, VMD enhances our capacity to unveil hidden structures, recognize hidden patterns, and identify temporal and spectral variations within signals that might otherwise remain obscured. With applications spanning diverse fields, from biomedical signal analysis to environmental monitoring and beyond, VMD holds the potential to reshape the way we glean insights from intricate data, fostering breakthroughs across scientific and engineering disciplines. Once a signal has been decomposed, it is necessary to select specific IMFs to reconstruct the desired signal. Hilbert transformation can be employed to determine each IMF's frequency, taking into account its center frequency and limited bandwidth frequency. Based on these frequencies, the necessary IMFs for each signal reconstruction are then selected. VMD has found diverse utility in fields like image processing and environmental data analysis. In image analysis, VMD has been employed for tasks such as denoising, texture analysis, and image fusion. By decomposing images into intrinsic modes, VMD facilitates the extraction of relevant information while suppressing noise and unwanted artifacts. Additionally, in environmental monitoring, VMD has been used to analyze complex datasets related to geophysical phenomena, such as seismic signals and oceanographic data. The adaptability of VMD to different types of signals and its ability to uncover underlying structures have contributed to its wide-ranging applicability across various scientific domains.

Variational Mode Decomposition has proven to be a powerful tool in the analysis of non-stationary and nonlinear signals across various scientific disciplines. Its effectiveness in decomposing complex signals into interpretable intrinsic modes has led to significant advancements in fields such as biomedical signal processing, image analysis, and environmental monitoring. Variational Mode Decomposition (VMD) has found noteworthy application in the domain of electromyography (EMG) signal processing, offering a novel approach to disentangling the complex dynamics of muscle activation. The Variational Mode Decomposition (VMD) technique has garnered significant attention as an effective denoising tool in signal processing applications. In recent years, a multitude of studies have demonstrated its efficacy across various domains. In the field of in telecommunications, VMD has been employed to mitigate noise in communication channels, leading to improved signal quality and robustness in data transmission. Its versatility extends to environmental signal processing, where it has facilitated the extraction of meaningful information from noisy data in fields such as seismology and environmental monitoring. The adaptability and success of VMD in denoising a wide range of signals underscores its promise as a versatile and potent tool in signal processing applications. However, it is important to note that while VMD offers substantial advantages, challenges such as parameter selection and computational complexity persist, necessitating ongoing research efforts to refine and optimize its implementation. The growing body of literature on VMD attests to its increasing recognition and adoption as a valuable denoising technique with broad applicability across diverse scientific and engineering disciplines. Researchers have recognized the potential of VMD to effectively analyze and extract meaningful information from EMG signals, aiding in the understanding of muscle coordination, fatigue, and co-contraction patterns. The novelty of this research is that it’s the first time that VMD is being used for quantification of muscular co-contraction. It has been not used yet for this purpose.

CHAPTER 3

3 METHODOLOGY

3.1 Introduction:

The approach taken in this research is completely based on the technique used for quantification of muscular co-contraction. As explained earlier there are many methods of signal quantification, Variational Mode Decomposition is the technique that has been chosen for this research work. In this research, the novel combination of the scalogram visualization technique with Variational Mode Decomposition (VMD) is employed for the first time. This integration proves pivotal in gaining profound insights into the time-frequency characteristics of the EMG signal's intrinsic mode function. Given below are the steps that describe the whole research process.

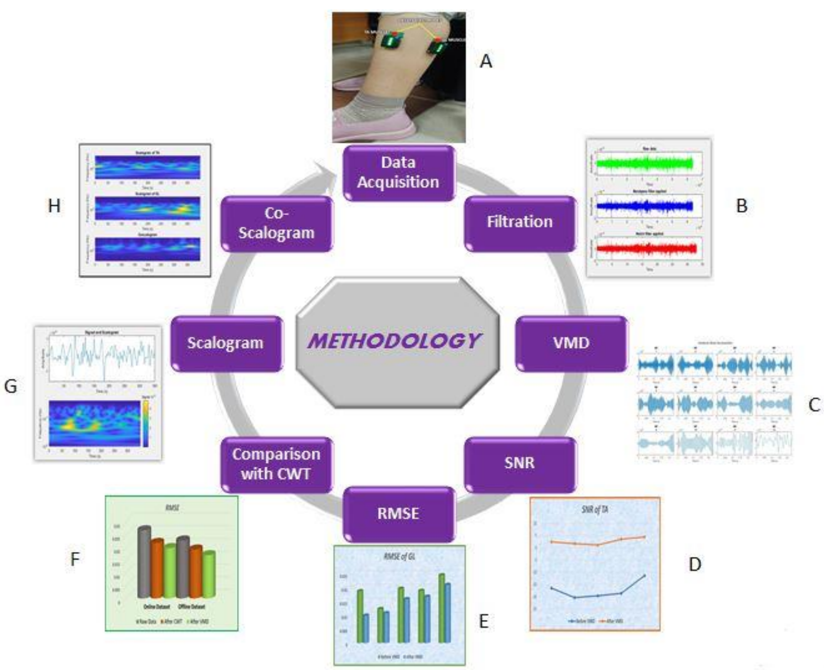

Figure 6: Methodology A. Acquire the raw data through Delsys trigno wireless EMG sensors B. Apply a filtration process to remove unwanted noise or interference from the acquired data C. Utilize Variational Mode Decomposition (VMD) to decompose the signal into its constituent components D. Evaluate the Signal-to-Noise Ratio (SNR) to quantify the quality of the decomposed components E. Calculate the Root Mean Square Error (RMSE) to assess the accuracy of the decomposition process F. Conduct a comparative analysis between Variational Mode Decomposition (VMD) and Continuous Wavelet Transform (CWT) for signal decomposition G. Generate a scalogram to visualize the time-

frequency representation of the signal H. Create a coscalogram to display the co-contraction of TA-GL muscles

3.2 Data Collection:

3.2.1 Subjects

The dataset contains sEMG signals collected during the walking of 20 adults in good health (10 males and 10 females). The mean (± Standard Deviation, SD) characteristics are: age 24 ± 2 years; height 172 ± 10cm; weight 61 ± 8kg; Body mass index (BMI) 21.5 ± 2.1kg/m^2. Exclusion criteria include abnormal gait, pathological or chronic joint pain, surgical intervention, and BMI ≥ 25. Informed consent was obtained, before the experiment onset, from all subjects involved in this study. The other (online) walking dataset of 5 healthy subjects is taken from UCI Machine Learning Repository [27].

3.2.2 Experimental setup

Delsys Trigno Wireless EMG Sensors were used for data collection from lower limb muscles. Firstly, the muscles were cleaned with an alcohol swab, and excess hair was shaved. Before electrode placement, make sure that the skin surface above the muscles is clean for proper electrode-skin contact. sEMG electrodes were placed perpendicular to muscle fibers on the skin surface above the muscle belly. The shin muscles used for data collection were Tibialis Anterior (TA) and Gastrocnemius Lateralis (GL) as they were selected as representative muscles of the ankle. Approval no.: ref#NUST/SMME-BME/ REC/000142/20012023 was granted by the local ethical committee of the National University of Science and Technology, Islamabad, Pakistan for data recording.

To capture muscle activity, two (2) wireless surface EMG sensors (Trigno Wireless EMG system, Delsys, Boston, MA, USA) were positioned on ankle muscles according to SENIUM recommendations [28]. sEMG signals were measured during 30 seconds of ground walking. The experimental setup is shown in Fig. 7. Subjects were instructed to perform a 30-second overground walk at their natural pace. Selecting a natural pace is based on the premise that walking comfortably enhances the consistency of EMG data, as opposed to an increase in variability that occurs when subjects are instructed to walk unnaturally [29].

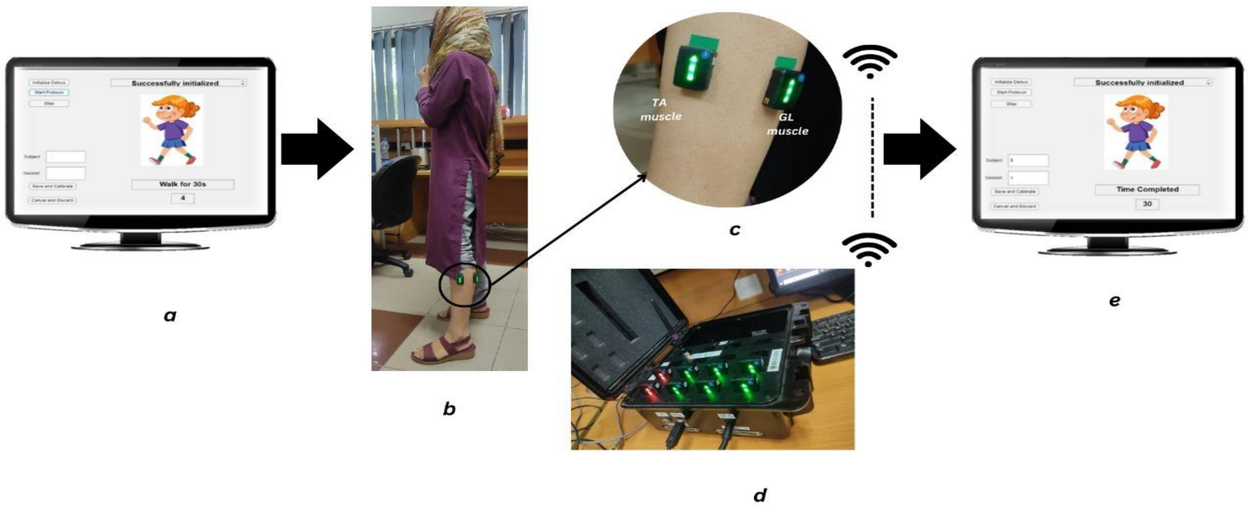

Figure 7: Experimental Setup (a) Data protocol starts, as Delsys successfully initiated (b) Subject providing data (c) Electrode placement on Tibialis Anterior (TA) and Gastrocnemious Lateralis (GL) muscles of lower limb (d) sEMG acquisition system (e) Protocol ends after data collection

3.3 Filtration:

Filtration of raw electromyographic (EMG) signals is necessary for several reasons related to signal quality, interpretation, and analysis. EMG signals are generated by the electrical activity of muscles and can be influenced by various physiological and environmental factors.

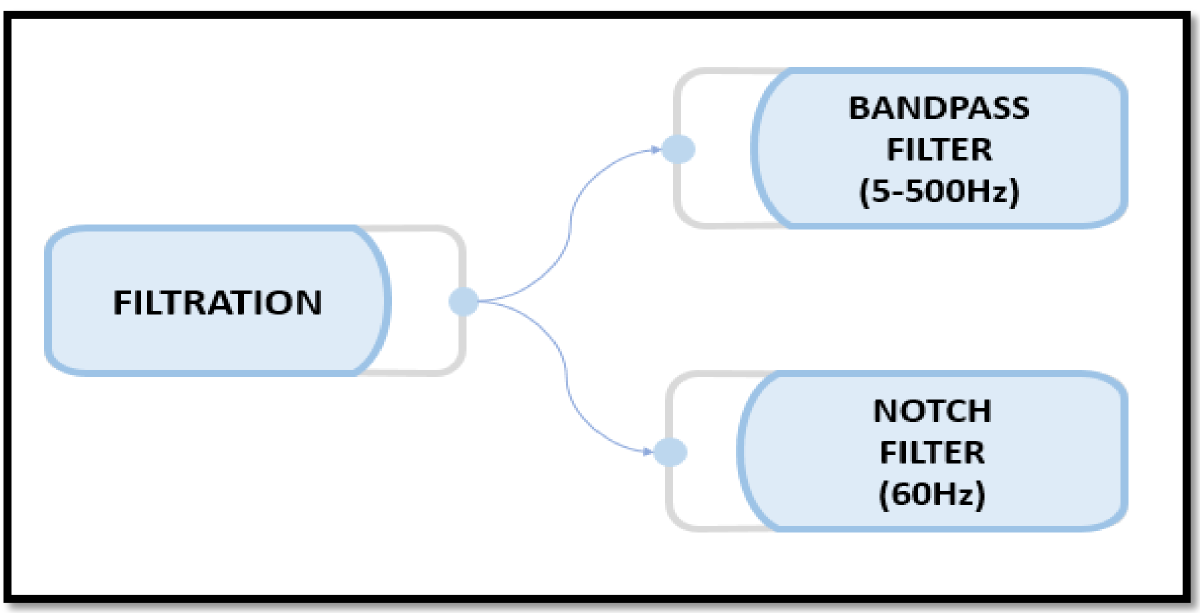

Figure 8: Filtration

Filtering helps enhance the accuracy and reliability of these signals for further analysis and interpretation.

EMG signals are susceptible to various sources of noise, such as electrical interference, movement artifacts, and ambient electromagnetic signals. Filtering can help reduce these unwanted components, improving the signal-to-noise ratio and making it easier to identify and analyze the actual muscle activity. EMG signals contain a wide range of frequencies, including those from muscle contractions as well as noise. Depending on the specific application, certain frequency bands that correspond to muscle action are required. Filtering allows us to isolate and focus on the frequency range relevant to analysis, which can make interpretation and feature extraction more accurate. During muscle contractions, there can be abrupt changes in the signal due to sudden movements or electrode placement changes. These artifacts can obscure the underlying EMG activity. Filtering can help remove or reduce such artifacts, making the signal more consistent and interpretable.

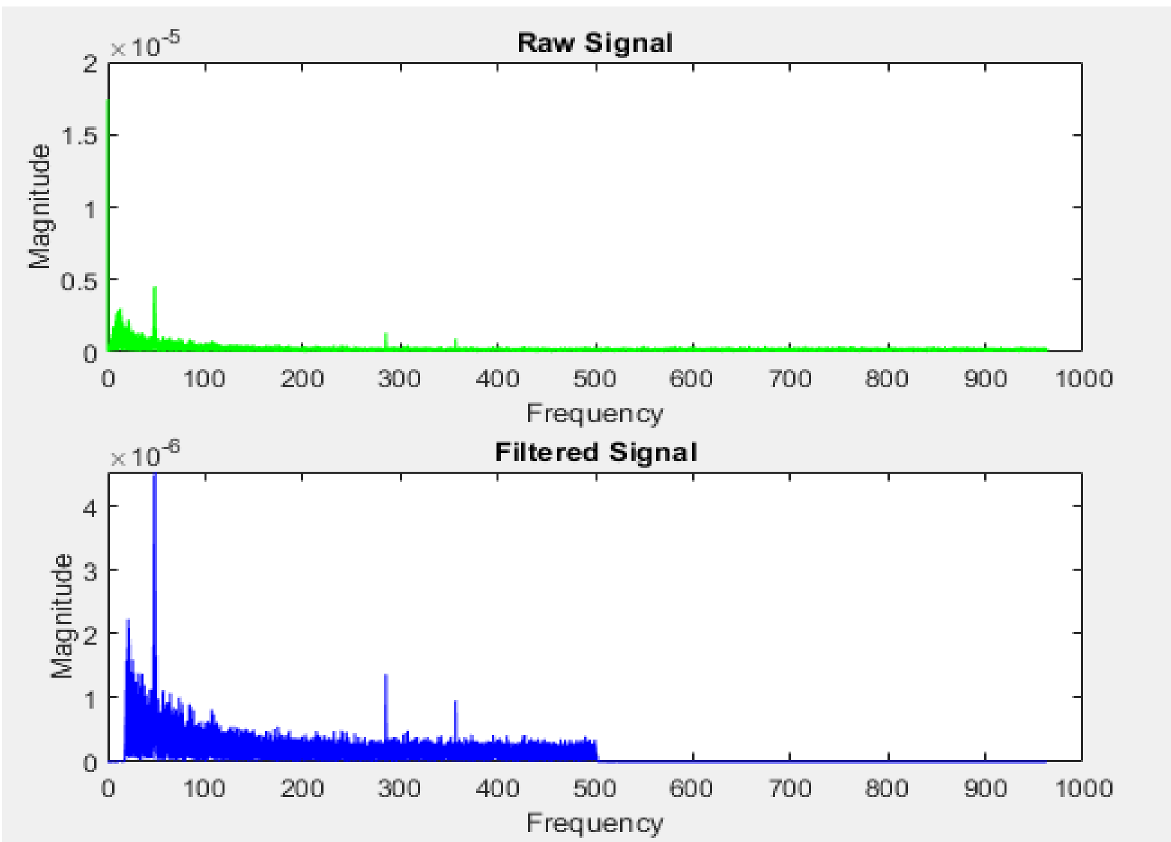

Figure 9: Pre-Bandpass and Post-Bandpass Filtration

EMG signals can include unwanted physiological components such as cardiac activity (EMG from the heart) or movement-related artifacts. Filtering can help remove or minimize these components to isolate the muscle-specific activity. By reducing noise and isolating the relevant frequency components, filtered EMG signals are easier to interpret and analyze. This is especially important in clinical applications where accurate diagnosis and treatment decisions rely on the quality of the EMG data.

Many analyses and applications involve extracting specific features from EMG signals, such as amplitude, frequency, and duration of muscle contractions. Filtering can enhance the accuracy of feature extraction algorithms by providing cleaner and more reliable input data.

Hence, It is essential to remove artifacts and noise from EMG data for accurate quantitative signal processing as EMG signals are used in a variety of fields, including biomechanics, sports science, rehabilitation, and neurology. In these applications, accurate and filtered EMG signals are essential for making informed decisions and drawing valid conclusions.

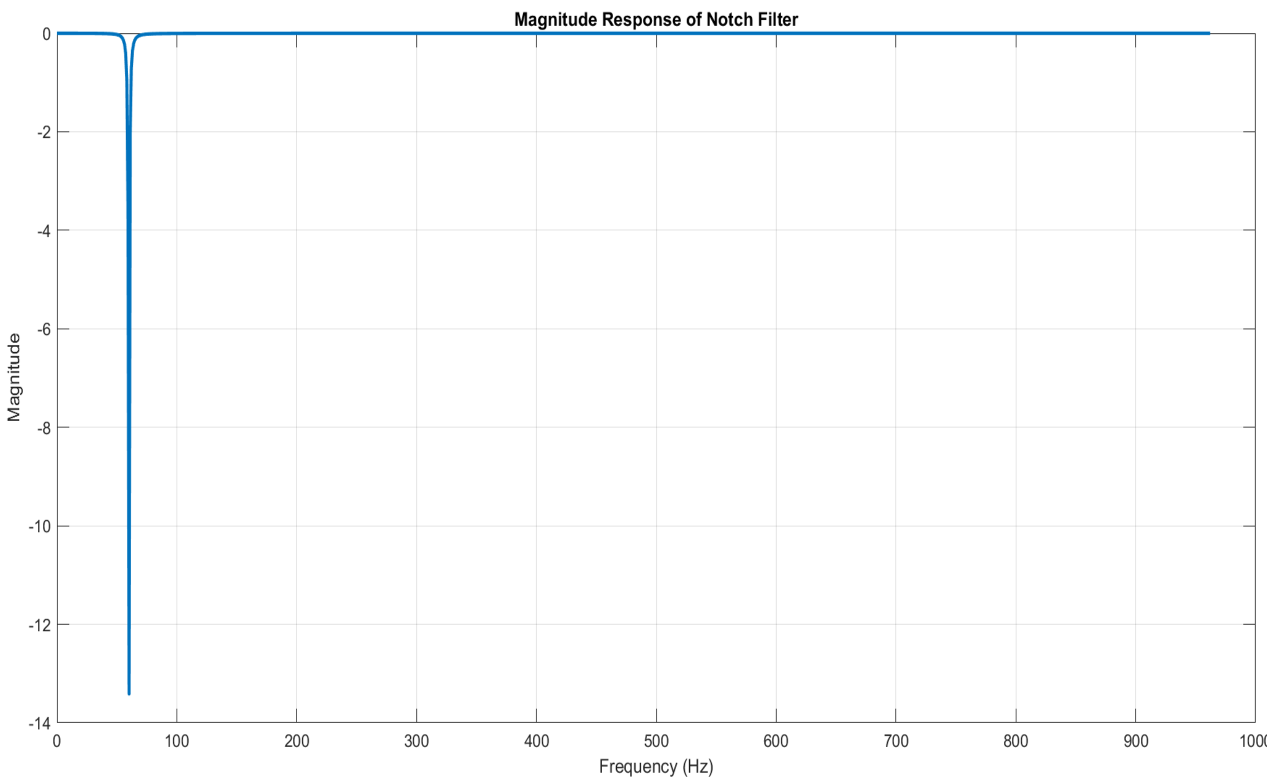

Figure 10: Magnitude response of Notch Filter

Recorded data from sEMG signals were filtered by applying a Butterworth 4th order bandpass filter, with lower and upper cut-off frequencies 20Hz and 500Hz respectively, to remove any undesired frequency content. To reduce power line interference, the sEMG signals were filtered using a notch filter at 60Hz as shown in Fig. 10. Fig. 9 shows the frequency spectrum of the sEMG signal before and after applying the bandpass filter.

3.4 Variational Mode Decomposition:

After that, Variational Mode Decomposition (VMD) was adopted to efficiently denoise the signal. The VMD method is an effective way of separating harmonic signals of close frequency range. Unlike other methods, it is not affected by the sampling frequency, thus avoiding mode mixing. VMD is a generalized form of the Wiener filter that divides the signal into multiple adaptive bands [30]. The process of VMD is illustrated in Fig. 11. The model estimate, along with its associated center frequency, undergoes regular updates, resulting in a dynamic model estimation. Following each estimation, the model is converted into the time domain through the inverse Fourier transform.

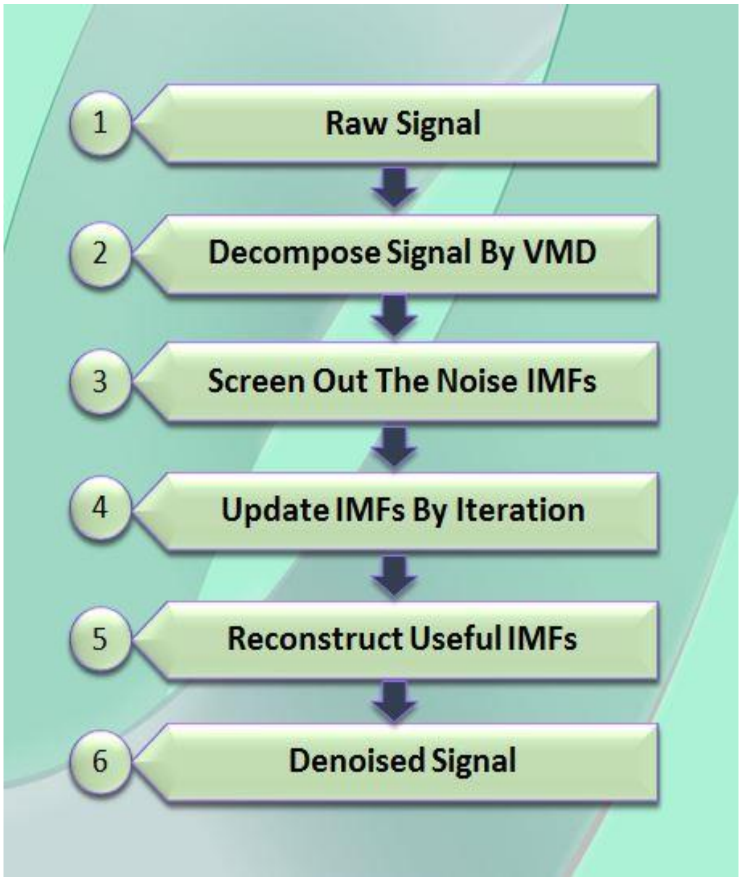

Figure 11: VMD process 1.Capture the original unprocessed data stream 2. Employ Variational Mode Decomposition (VMD) to break down the signal into its constituent components 3. Filter out the unwanted Intrinsic Mode Functions (IMFs) containing noise 4. Continuously refine the IMFs through an iterative process 5. Reconstruct the relevant IMFs to reconstruct the signal of interest 6. Obtain the denoised final signal by combining the refined IMFs.

3.4.1 Signal Decomposition

The VMD procedure entails discretely partitioning the original signal into distinct sub-signals, commonly referred to as Intrinsic Mode Functions (IMFs).this is given by:

$$f = \sum_{k=1}^{M} \mu^{k} \qquad (1)$$

"f" denotes the original signal with "μk" as its sub-signal, where "M" stands for the total number of modes. The function μk(t) is defined as

$$\mu^{k}(t) = a^{k}(t) \bullet \cos(\varphi^{k}(t)) \qquad (2)$$

" $\varphi^{k}(t)$ " signifies the phase of the signal, while " $a^{k}(t)$" represents the signal's envelope

To determine the bandwidth, we begin by generating an analytic signal representation that exhibits a one-sided frequency. Next, we adjust the resulting one-sided spectrum by employing harmonic mixing with a complex frequency exponential. Ultimately, we evaluate the squared norm of the signal's gradient. Considering these procedures, the associated optimization problem transforms into:

$$min_{\{uk\},\{wk\}} \left| \{ \sum_{k}\| \partial t [(\delta(t) + \frac{j}{\pi t}) * u_{k}(t)] e^{-j\omega \mathrm{k} t} \|_{2} \} \right. \qquad (3)$$

The operator "L2" corresponds to the squared norm of the expression, whereas "(δ(t) + j/(πt)) * u_k(t)" represents the Hilbert transform of u_k(t), thereby converting it into an analytic signal. This transformation aims to obtain a frequency spectrum that only contains positive frequencies. By incorporating a quadratic penalty factor and introducing the exponential Lagrangian multiplier, the problem is effectively converted from one with constraints to one without. [31].

The quadratic penalty factor serves to guarantee the accuracy of the reconstructed signal, while the Lagrangian multiplier enforces the constraint with precision. The optimization problem as a whole is tackled using the alternate direction method of multipliers (ADMM). This strategy entails solving a sequence of sub-optimization problems iteratively, as outlined in equation (4) below. These sub-problems aim to progressively minimize the cost function related to the parameter of interest [32].

$$u_k^{\,n+1} = \arg min_{\,uk\in X}\ \{\ \alpha \| \, \partial t\,[(\ \delta(t) + \frac{j}{\pi t})\ * u_k(t)\ ]\ e^{ij\omega \mathrm{k}t}\|_2\ \} + \|\ f(t) - \sum_i ui(t)\ + \frac{\lambda(t)}{2} \|_2\ \} \qquad (4)$$

Equation (4) above can be converted from the time domain to the frequency domain using the Parseval/Plancherel Fourier Isometry method.

$$u_k^{\ n+1}\ (w) = \frac{f\ (w) - \sum_{i\neq k} \hat{u}i(w) + \frac{\hat{\lambda}(w)}{2}}{1 + 2\alpha(w - wk)2} \qquad (5)$$

In order to halt the iterations, it is necessary to set a specific criterion. This criterion is considered met when the aforementioned equation is satisfied within a designated level of discrimination accuracy. Once this condition is met, we can acquire K narrow-band Intrinsic Mode Function (IMF) components. The flowchart for the Variational Mode Decomposition Algorithm is illustrated in Figure 13.

$$\frac{\sum_k \ \ \| \, uk\ n{+}1 - uk\ n\|2}{uk\ n\|2} < \varepsilon. \qquad (6)$$

In order to generate a new approximation of a noisy signal, the coefficients of the initial Intrinsic Mode Function (IMF) are randomly reorganized in the subsequent approximation. The resulting reorganized IMFs are then combined with the decomposed IMFs that remain unaltered to produce the updated approximation. This iterative process is repeated until the desired number of approximations is reached.

Each mode signifies a unique component or pattern within the EMG signal. These patterns, depicted in Figure 12, can represent information related to muscle activity (relevant) or extraneous information like noise or artifacts (irrelevant). These modes undergo iterative refinement by updating their parameters in each iteration [33].

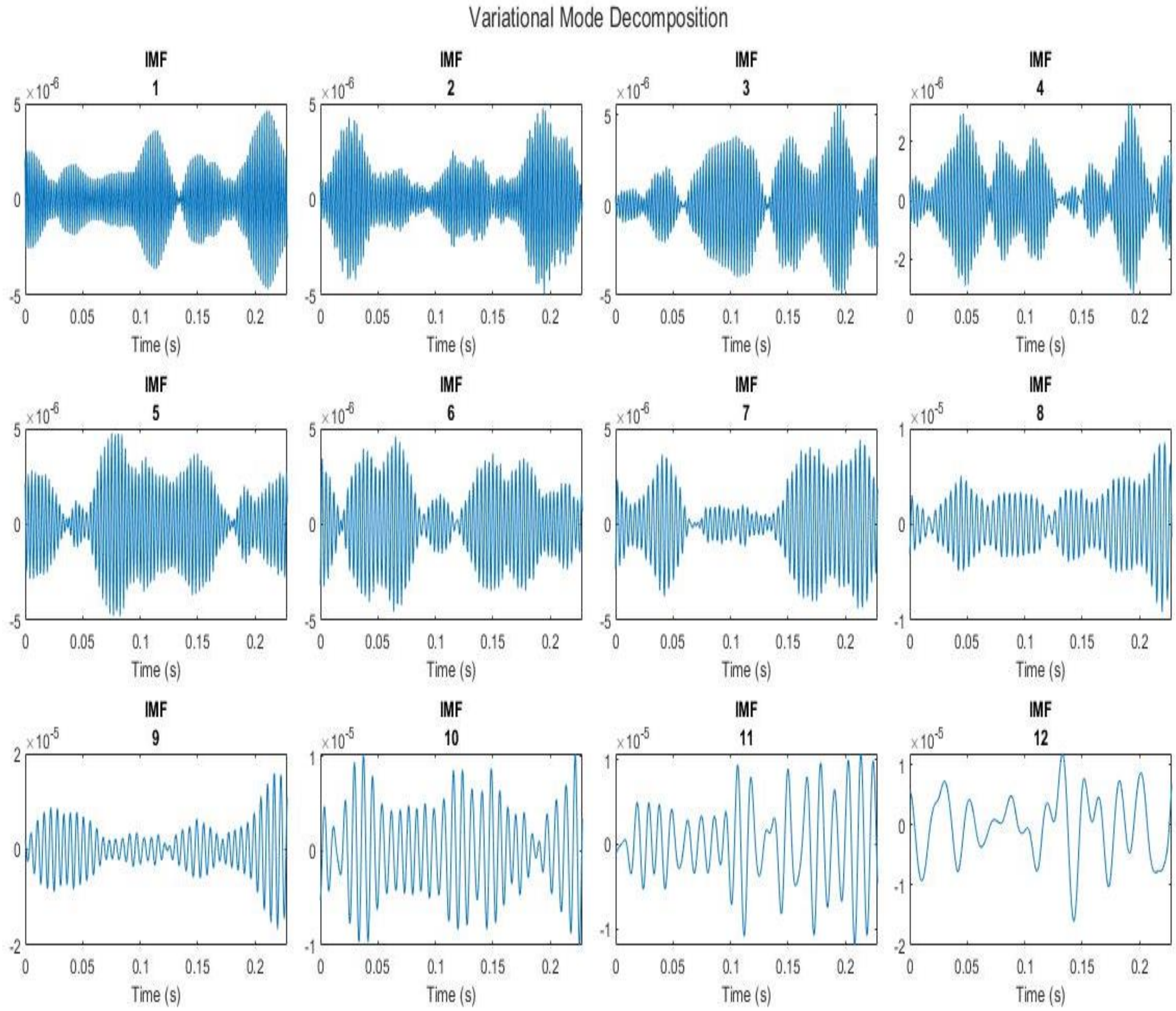

Figure 12: Decomposition of sEMG signal using VMD

This refinement process involves two steps: initially, in the frequency domain, the modes are adjusted by modifying their central frequencies according to the signal's spectral characteristics. Subsequently, in the time domain, the modes are further refined by minimizing interference between them.

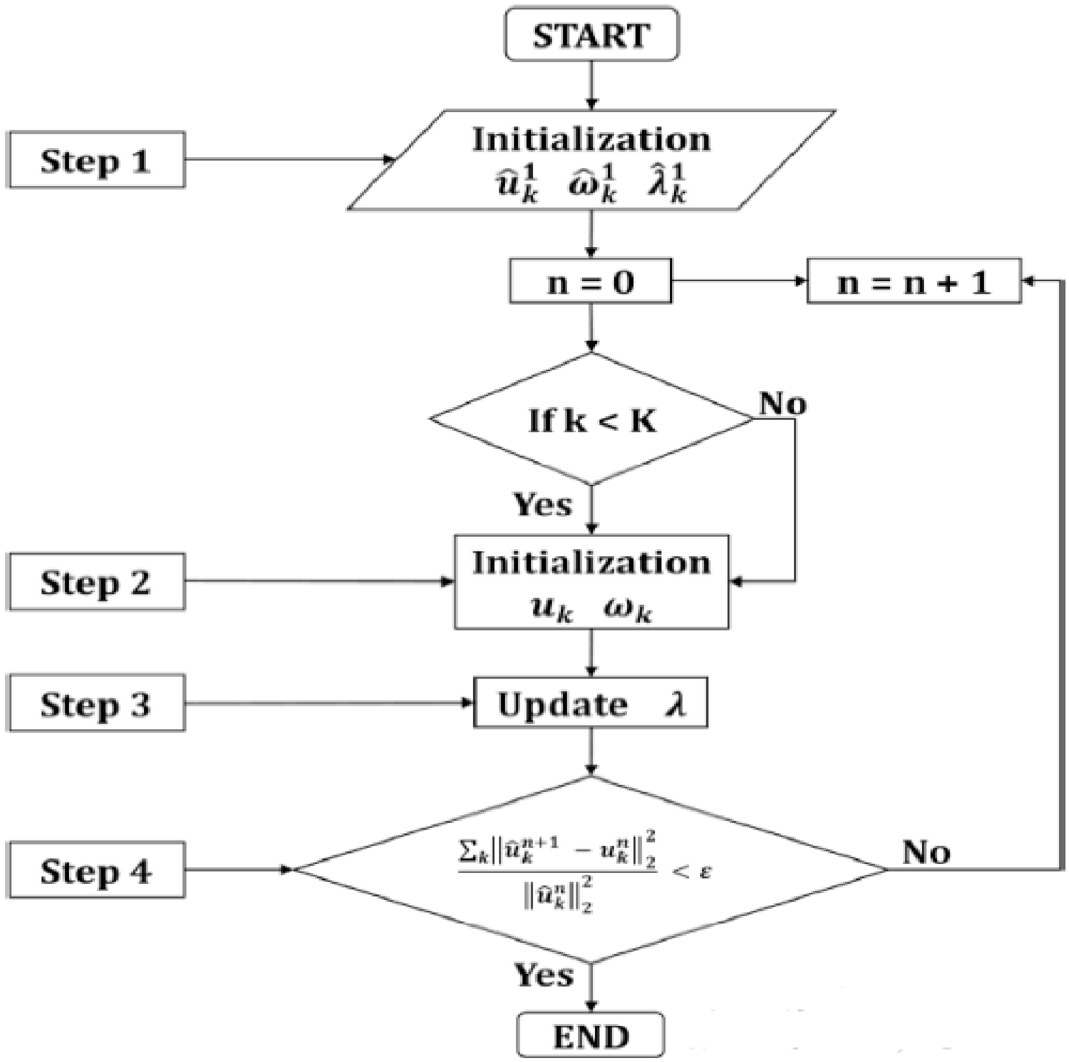

Figure 13: Flowchart for Variational Mode Decomposition Algorithm.

The frequency spectrum shows that each IMF contains a narrow frequency and a central frequency band [34] as illustrated in Fig.14. The frequency spectrum of Intrinsic Mode Functions (IMFs) obtained by Variational Mode Decomposition (VMD) represents the distribution of frequency components present within each IMF. Each IMF corresponds to a specific oscillatory mode or pattern in the signal. The frequency spectrum provides information about the dominant frequencies and their respective amplitudes within each mode. This can be valuable for analyzing and understanding the underlying frequency content and dynamics of the signal, which can be useful in various applications such as signal processing, feature extraction, and pattern recognition. Finally, based on the signal's frequency domain characteristics, IMF components were extracted with narrow bands. Additionally, an efficient and adaptable segmentation of the frequency band was executed, which effectively prevented mode aliasing [35]. Each IMF is updated with every iteration. Thus, minimizing noise iteratively. This study focuses on elucidating the distinct advantages of VMD, specifically in its utilization of iterative processes within the intrinsic mode functions (IMFs), resulting in more effective noise reduction compared to the conventional CWT. CWT lacks this intrinsic property of iterative refinement of IMFs.

3.4.2 Signal Reconstruction

In each IMF, there is a collection of frequencies that exist within the original signal. These decomposed models containing significant data are combined to reconstruct the original signal.

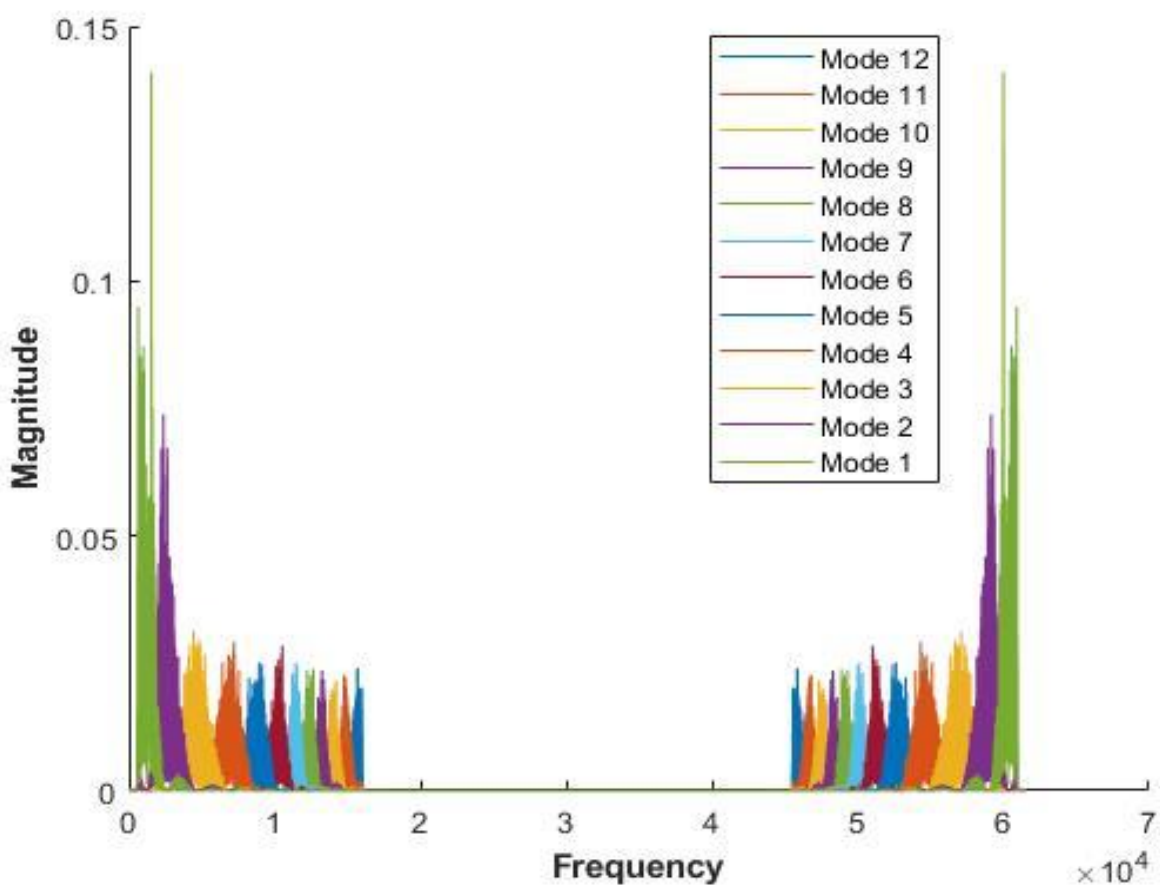

Figure 14: Frequency spectrum of IMFs obtained by VMD

The reconstructed signal represents the essential features of muscle activity while minimizing noise and artifacts. The frequency spectrum shows that each IMF contains a narrow frequency and a central frequency band. The first Intrinsic Mode Function (IMF) contains the highest frequency range and therefore has the highest amount of noise. The lower frequencies can be observed in the higher IMFs, which have a lower amount of noise. This can be seen in the Fig 12. As the order of IMFs increases, the frequency bands converge. The narrower frequency bands found in the IMFs are advantageous for subsequent signal-filtering procedures. These decomposed models can then be utilized to reconstruct the initial signal with enhanced precision [36].

3.5 Segmentation:

Segmentation in signal processing refers to the process of dividing a longer signal into smaller, manageable sections or segments. Each segment typically contains a finite number of samples. The purpose of segmentation is to enable more localized analysis, processing, and manipulation of signals, especially when dealing with signals that are non-stationary or when specific features are of interest. In signal processing, this technique is used to reduce the artifacts and distortions that can occur when applying mathematical operations, such as the Fourier Transform, to a finite segment of a longer signal. The purpose of windowing is to mitigate the effects of spectral leakage and improve the accuracy of analyzing and processing signals.

Segmentation allows to focus analysis on specific portions of a signal that are relevant to analysis goals. This is particularly important when dealing with signals that have varying characteristics over time, such as speech, biomedical signals, and seismic data. Signals often contain important features that carry meaningful information. By segmenting the signal, features can be extracted from each segment separately, allowing us to analyze and compare these features more effectively. Some signals exhibit time-varying frequency components. Segmentation allows to perform time-frequency analysis techniques (such as the Short-Time Fourier Transform or the Wavelet Transform) on localized segments of the signal, revealing how the frequency content changes over time. For very long signals, processing the entire signal at once can be computationally intensive. Segmentation helps to work with smaller chunks of data, potentially reducing the computational complexity of algorithms. In this research, the whole 30-second sEMG signal is divided into 400 segments for simplicity and to extract relevant information from the data.

In essence, segmentation in signal processing provides a way to analyze and process signals in a more focused and localized manner, helping to extract relevant information, detect events, and perform various types of analysis tailored to the characteristics of each segment.

3.6 Scalogram:

After that, the scalogram function was employed to evaluate muscular activation. A scalogram is a graphical representation used in signal processing and time-frequency analysis to visualize how the frequency content of a signal changes over time. It is often used to analyze non-stationary signals, which are signals that change their frequency components over time. Time-frequency analysis is used to study how the frequency content of a signal evolves over time. Traditional Fourier analysis gives information about the frequency components of a signal, but it doesn't provide any insight into when these components occur. Time-frequency analysis techniques, like the wavelet transform, and variational mode decomposition help to observe the changing frequency components over time.

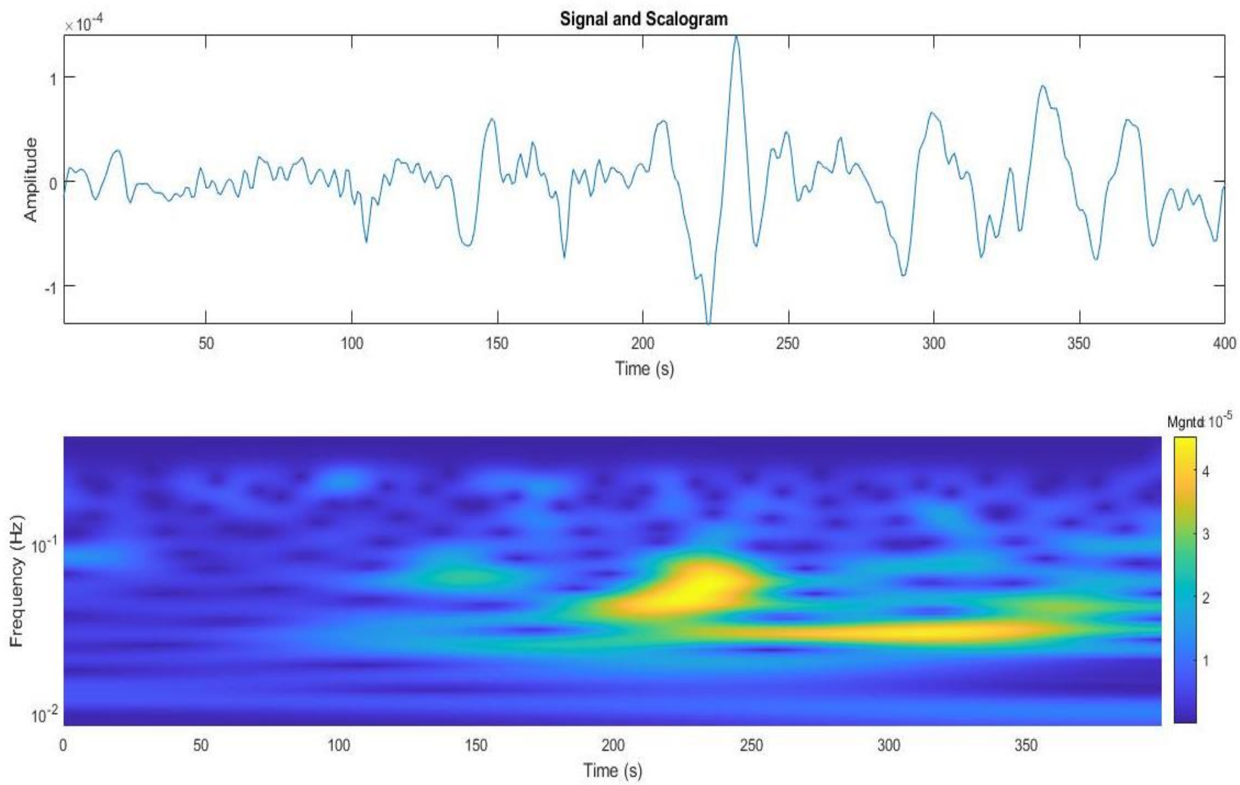

Figure 15: sEMG signal and its Scalogram

The scalogram has been widely used in electromyography (EMG) signal research to analyze and interpret the time-frequency characteristics of muscle activity. A scalogram is a graphical representation of the coefficients. It is usually displayed as a 2D plot, with time on one axis and frequency on the other axis. The color or shading used in the scalogram indicates the amplitude or energy of the corresponding frequency component in the signal. Darker regions typically represent stronger or more dominant frequency components, while lighter regions indicate weaker or less dominant components. When analyzing a scalogram, it can be observed how different frequency components of the signal become more prominent or fade away over time. This is particularly useful when studying signals that change their underlying dynamics.

In previous studies, researchers have used scalograms for multiple purposes. i.e., time-frequency analysis, motor unit action potential, EMG signals analysis in the context of hand gesture recognition, muscular fatigue detection etc. Scalogram visualization techniques have always been used with wavelet transform in the past. In this research, it's being used with variational mode decomposition (VMD) for the first time. VMD presents an alternate approach to decompose time-varying signals into Intrinsic Mode Functions (IMFs) that have distinct frequency characteristics. Similarly, to the wavelet transform, VMD can be used to analyze the time-frequency content of signals [37]. Using the Scalogram visualization technique with VMD can help gain insights into the time-frequency characteristics of the signal's intrinsic mode functions. This approach could be particularly useful when one is interested in understanding the dynamic changes in the frequency content of non-stationary signals, such as biomedical signals like EMG. Fig. 15 shows the scalogram of sEMG signal.

Scalogram method effectively locates events in time and frequency domains. It is useful for detecting short and long-duration events with high precision. Scalogram techniques can be applied in various business and academic settings where event detection and localization are critical.

In summary, a scalogram is a visual tool that allows one to explore the changing frequency content of a signal over time, providing insights into the signal's time-varying spectral characteristics. It's commonly used in fields like signal processing, neuroscience, audio analysis, and geophysics to analyze and interpret non-stationary signals.

3.7 Coscalogram:

A coscalogram typically refers to a type of coherency scalogram, where coherency quantifies the degree of linear association between two signals within the frequency domain. It's often used to analyze the synchronization or coordination between two signals, such as the activity of antagonistic muscles in EMG signals.

When it comes to analyzing EMG signals to detect co-contraction of antagonistic muscles, a coscalogram can provide valuable insights. Co-contraction describes the simultaneous activation of muscles that have opposing functions around a joint, like flexor and extensor muscles. This can be an important indicator of motor control and stability in various activities. A coscalogram is a powerful tool to reveal the coordination and synchronization between these muscle activities. It helps to uncover the underlying patterns of co-contraction and provides insights into the functional interactions between these muscles.

A coscalogram visually represents the coherency values across time and frequency. Regions of high coherency on the coscalogram correspond to periods when the antagonistic muscle signals are synchronized. These regions are indicative of co-contraction, where the muscles are working together to stabilize a joint or perform a task. Analyzing the frequency distribution of high coherency values on the coscalogram helps to determine the specific frequency bands in which co-contraction is occurring. This information can be important for understanding the motor control strategies being employed. Different frequency bands might correspond to different types of movements or tasks. In this research, only one task i.e. normal walking is being carried out.

Co-contraction of antagonistic muscles is a crucial aspect of motor control and joint stability. It allows for precise control of movements and helps to maintain joint integrity. Detecting and understanding co-contraction patterns using coscalograms can provide valuable information about the underlying motor strategies employed by the neuromuscular system. In clinical settings, coscalograms can be used to assess muscle coordination patterns in patients with neuromuscular disorders, joint injuries, or rehabilitation needs. Changes in co-contraction patterns can indicate impairments or adaptations in motor control.

Co-contractions of ankle muscles play a pivotal role in maintaining joint stability during weight-bearing activities, such as walking, running, and standing. Analyzing coscalograms can provide insights into how different muscle groups work together to stabilize the ankle joint and ensure proper movement control.

A coscalogram complements the information provided by individual scalograms of antagonistic muscle signals. It highlights periods of coordinated muscle activity, indicating co-contraction, and provides a visual representation of the temporal and frequency-specific aspects of this coordination. This information is essential for understanding motor control, joint stability, and functional interactions between muscles in various contexts, from clinical assessments to sports performance analysis.

Coscalogram offers a quantitative approach to assessing muscle coordination. This data-driven analysis provides objective information that complements subjective clinical assessments, enabling a more comprehensive understanding of muscle interactions. Ankle injuries, such as sprains, strains, and fractures, are common in sports and daily activities. The coscalogram function applied to denoised sEMG signals provides a quantitative method for evaluating muscle co-contraction [38]. The onset and offset of co-contraction activity were determined by pinpointing the initiation and termination points of energy zones within the coscalogram.

3.8 Performance Evaluation:

For evaluating the performance of the implemented method, we chose two commonly used metrics - signal-to-noise ratio (SNR) and root mean squared error (RMSE). These metrics find broad application in the assessment of signal filtering techniques' efficacy.

3.8.1 Signal-to-noise Ratio (SNR)

The signal-to-noise ratio (SNR) stands as a fundamental concept in signal processing, providing a measure of the relationship between the magnitude of a target signal and the magnitude of the ambient background noise within a given signal. It is often used to describe the quality of a signal, indicating how much the signal stands out from the noise. SNR is an important metric in various fields, including telecommunications, audio processing, image processing, and more. SNR serves as a valuable tool for evaluating signal quality and noise interference in signal processing.

Mathematically, the SNR is the ratio between the power (or energy) of the noise and the power (or energy) of the signal:

$$\text{SNR}= \frac{Power\ of\ Signal}{Power\ of\ Noise} \qquad (7)$$

In decibels (dB), which is a more commonly used unit to express ratios, the SNR is calculated as:

$$\text{SNR}_{\text{dB}} = 10 \cdot \log_{10}(\text{SNR}) \qquad (8)$$

To make a fair comparison, the signal-to-noise ratio was calculated for the original raw signal and filtered denoised signal as:

$$SNR = 10 \bullet \log_{10} \frac{\Sigma(f\ (t)2)}{\Sigma(\ (\hat{f}\ (t) - f\ (t))2\ )} \qquad (9)$$

where $f(t)$ is the original signal and $\bar{f}(t)$ is the denoised signal.

A higher SNR value indicates that the signal is stronger relative to the noise, leading to a clearer and more reliable representation of the underlying information in the signal. Conversely, a lower SNR value indicates that the noise is more dominant, which can make it challenging to accurately extract meaningful information from the signal.

In practice, achieving a high SNR is desirable, as it allows for better signal quality and easier detection of patterns or features within the signal. Engineers and researchers often employ various signal processing techniques, such as filtering, modulation, and error correction, to improve the SNR of signals to enhance their usability and accuracy.

3.8.2 Root Mean Squared Error (RMSE)

Root Mean Square Error (RMSE) is a metric used in signal processing to quantify the accuracy of predictive models or processing techniques by measuring the average magnitude of differences between predicted or processed values and actual observed values in a dataset. It is calculated by taking the square root of the mean of squared differences between predictions and observations. In signal processing, RMSE serves as a crucial tool to evaluate the quality of signal reconstruction, noise reduction, and predictive modeling, helping to guide the optimization of algorithms and techniques to achieve accurate and reliable results.

Mathematically, Root Mean Squared Error (RMSE) was calculated for the original raw signal and filtered denoised signal as:

$$\text{RMSE}= \sqrt{\frac{1}{L}\Sigma(\, f\ (t) - \hat{f}\ (t)\ )2\ )} \qquad (10)$$

where $f(t)$ is the original signal and $\bar{f}(t)$ is the denoised signal. L is the length of the signal.

The RMSE allows calculating the amount of error by which the denoised signal varies from the raw noisy signal. RMSE provides a single numerical value that quantifies the average magnitude of the differences between processed values and actual values. This makes it a concise and informative way to understand how well a processing technique is performing. In signal processing, accuracy is crucial. RMSE helps assess how closely the processed signal matches the true signal. It provides insights into how well the processing algorithm is capturing the underlying characteristics of the signal, such as amplitude, frequency, and timing. RMSE helps quantify how well the processing method mitigates or amplifies noise and artifacts. A lower RMSE indicates better noise reduction while preserving important signal features.

CHAPTER 4

4 RESULTS:

After applying the VMD technique on sEMG data collected from 20 subjects, the signal is decomposed into various IMFs as shown in Fig.12. Each IMF contains a central frequency and a narrow frequency band in the original signal's range of frequencies as illustrated in Fig.14. The first Intrinsic Mode Function (IMF) contains the highest frequency range and therefore has the highest amount of noise [39]. The lower frequencies can be observed in the higher IMFs, which have a lower amount of noise, as evident from Fig.12. As the number of IMFs increases, frequency bands converge. The narrower IMFs are beneficial for signal filtering.

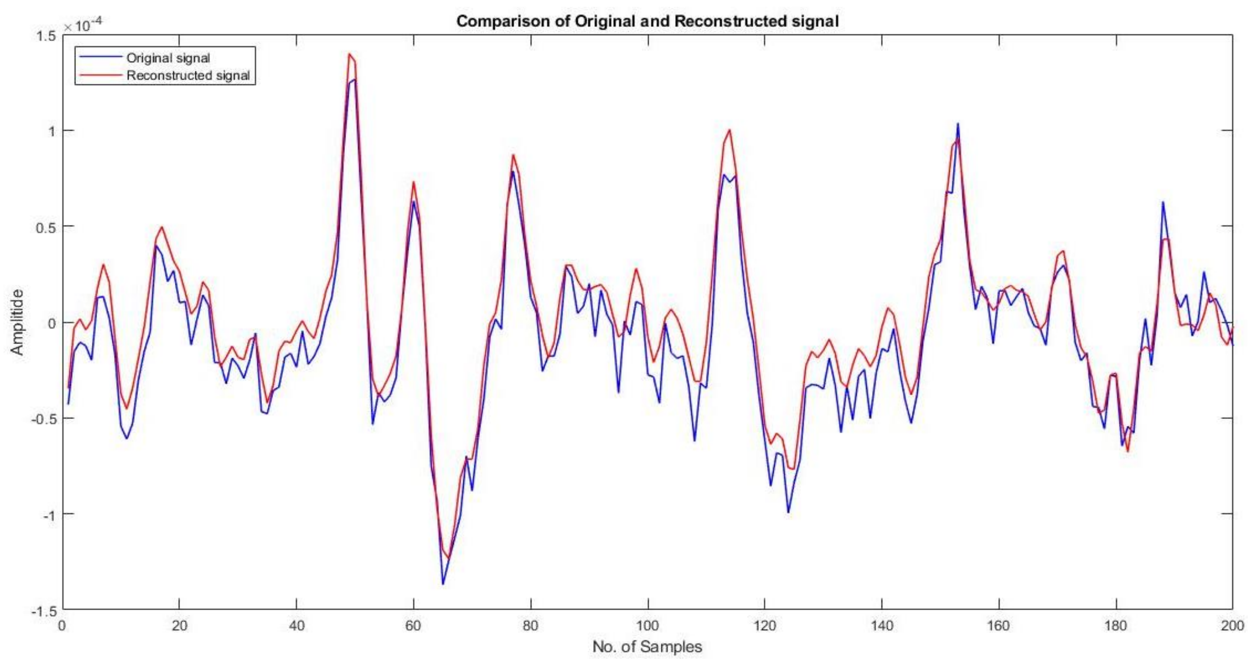

Figure 16: Comparison between the original signal and the signal after denoising

The significant data in the decomposed models are merged to reconstruct the original signal. In Fig. 16, a comparison between the original signal and the signal after denoising can be seen. The signal has retained its original characteristics while minimizing the noise and artifacts.

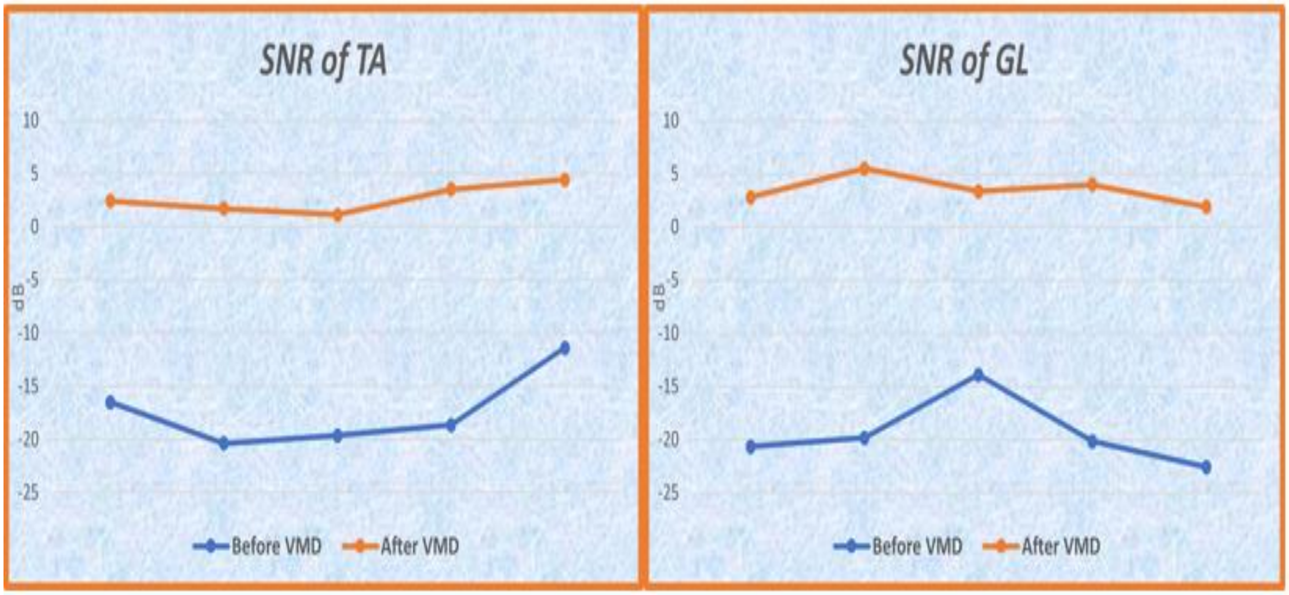

Figure 17: SNR of TA and GL muscles before and after application of VMD

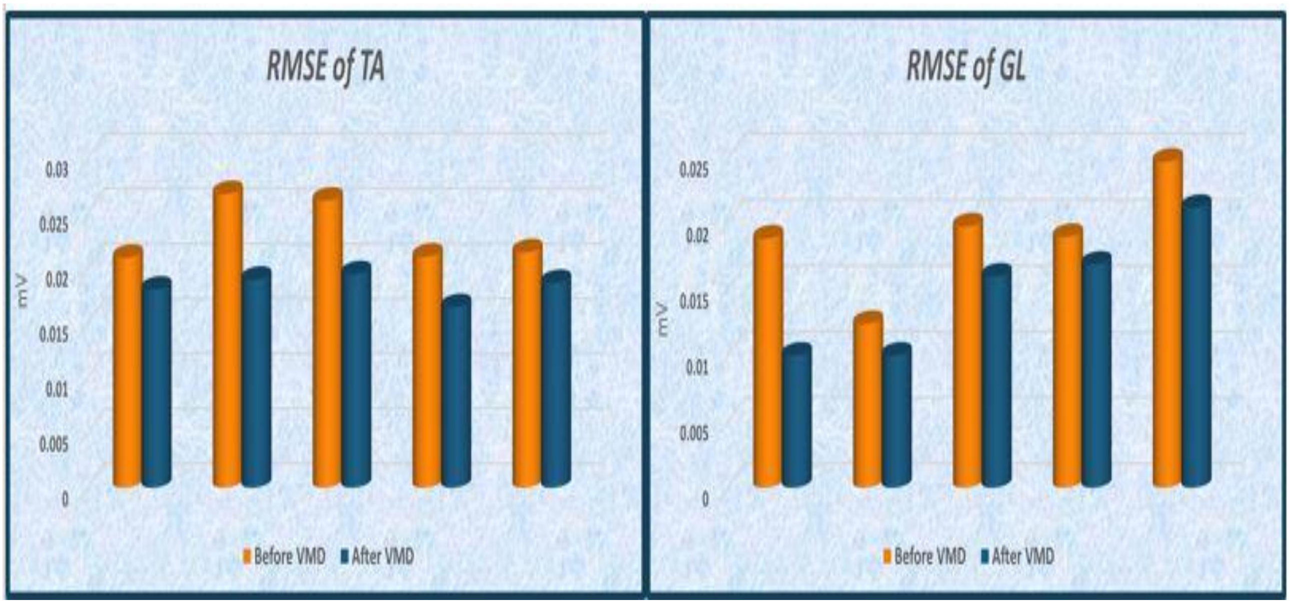

Figure 18: RMSE of TA and GL muscles before and after application of VMD

The results illustrated in Fig.17 and Fig.18 demonstrate a notable enhancement of SNR and a significant reduction in RMSE respectively, of TA and GL muscles after applying VMD. These outcomes strongly indicate the efficacy and suitability of the VMD technique. A higher SNR and lower RMSE indicate better noise reduction while preserving important signal features [34].

Figure 19: Comparison of VMD and CWT in terms of SNR

Figure 20: Comparison of VMD and CWT in terms of RMSE

After obtaining promising outcomes through the implication of the Variational Mode Decomposition (VMD), a comparative assessment was conducted with the Continuous Wavelet Transform (CWT) technique to discern their relative effectiveness. SNR results displayed in Fig.19, and RMSE results in Fig.20 showed a noticeable discrepancy between VMD and CWT in terms of their noise reduction capabilities.

The iterative nature of VMD in generating Intrinsic Mode Functions (IMFs) demonstrated a marked reduction in noise levels [40], underscoring its superiority over CWT. The absence of an iterative process in CWT hindered its ability to achieve comparable levels of noise reduction.

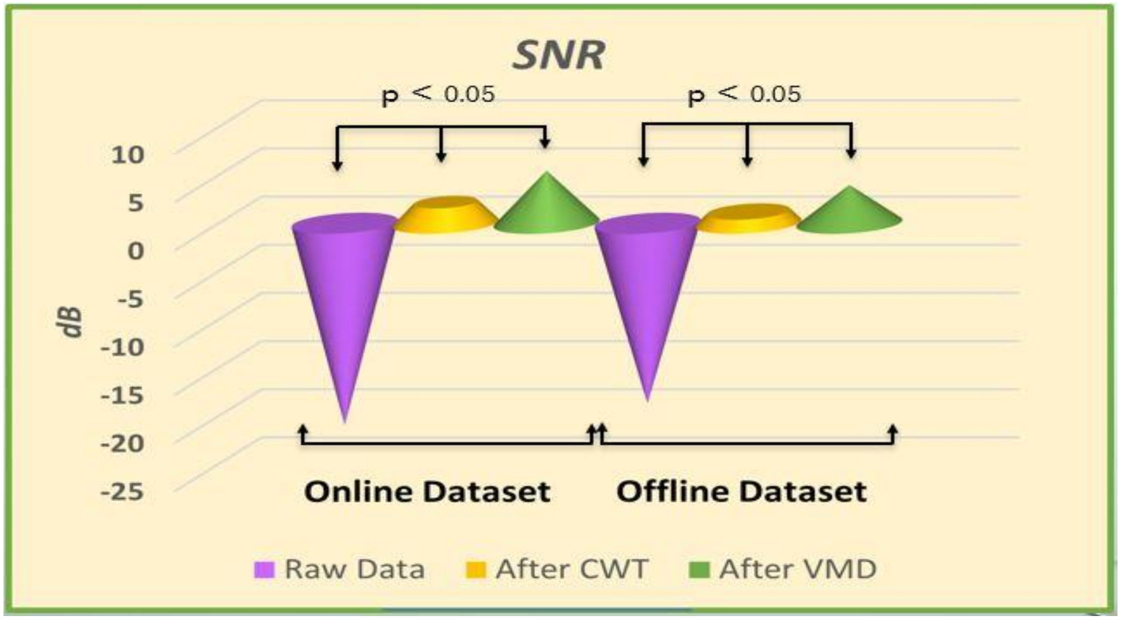

Figure 21: Comparison of CWT and VMD using both online and offline datasets in terms of SNR

To further reinforce the findings, the process was repeated using online data. This extended evaluation consistently affirmed VMD's superior performance over CWT.

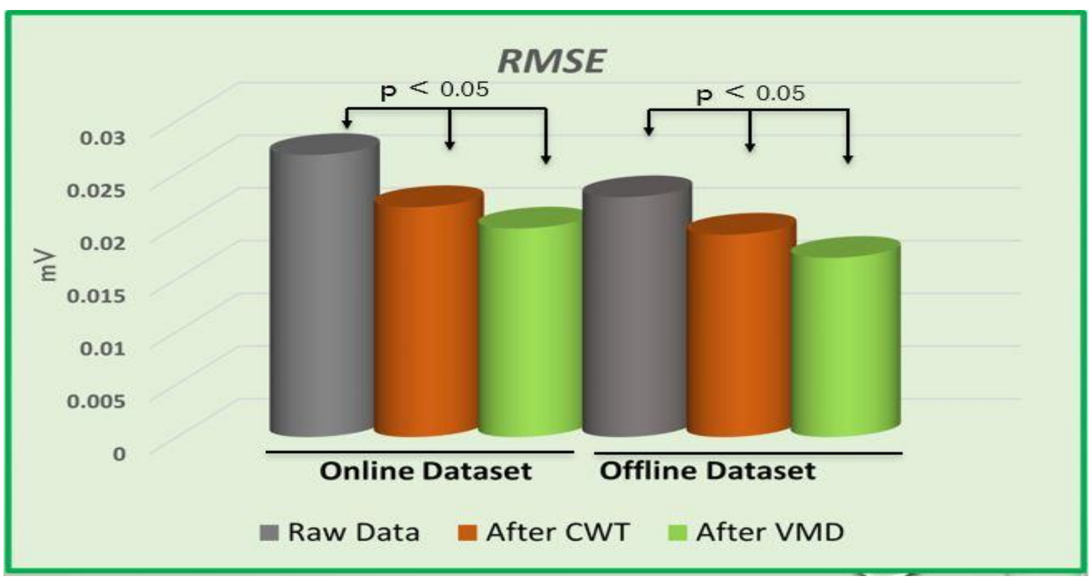

Figure 22: Comparison of CWT and VMD using both online and offline datasets in terms of RMSE

The comparison of results obtained after applying CWT and VMD on online data as well as offline data illustrated improvement in SNR in Fig.21 and minimization in RMSE in Fig.22. The results demonstrate that VMD outperforms CWT in terms of both SNR and RMSE.

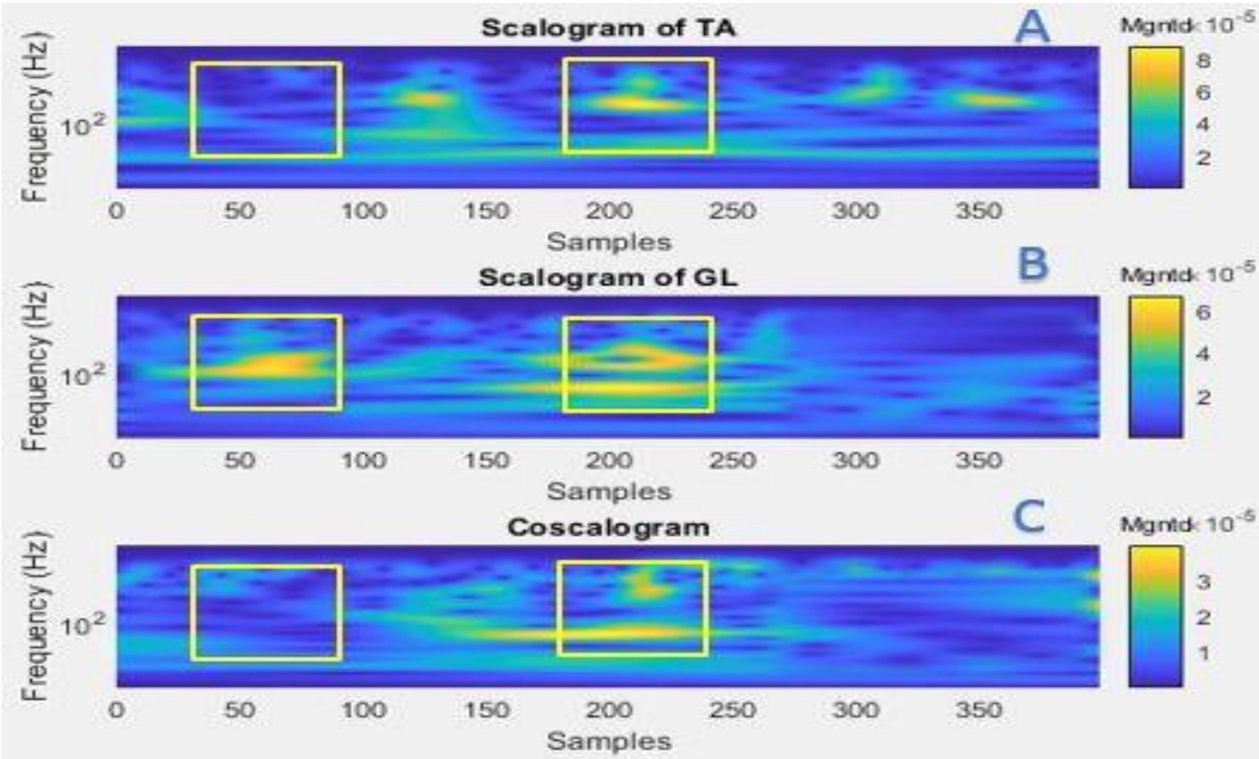

Figure 23: Panel A: TA sEMG Scalogram, Panel B: GL sEMG Scalogram, Panel C: TA-GL Coscalogram. Coscalogram obtained by offline data

The application of VMD denoising yields more reliable ankle-muscle sEMG signal enhancing the accuracy of subsequent co-contraction quantification. The novel combination of the Scalogram visualization technique with VMD is employed to gain insights into the time-frequency characteristics of the signal's intrinsic mode functions. The co-scalogram results from Fig.23 highlight periods of coordinated muscle activity, indicating co-contraction between antagonist muscles, and providing a visual representation of the temporal and frequency-specific aspects of this coordination. A coscalogram complements the information provided by individual scalograms of antagonistic muscle signals. Panel A and B of Fig.23 show the scalogram function of the sEMG signal, after VMD denoising, of the antagonist's muscles i.e. tibialis anterior (TA) and gastrocnemius lateralis (GL) respectively. Panel C displays a time-frequency coscalogram representing the cross-energy density between the denoised TA and GL signals. Fig 23 displays the coscalogram obtained by offline data while Fig. 19 illustrates the coscalogram obtained by online data.

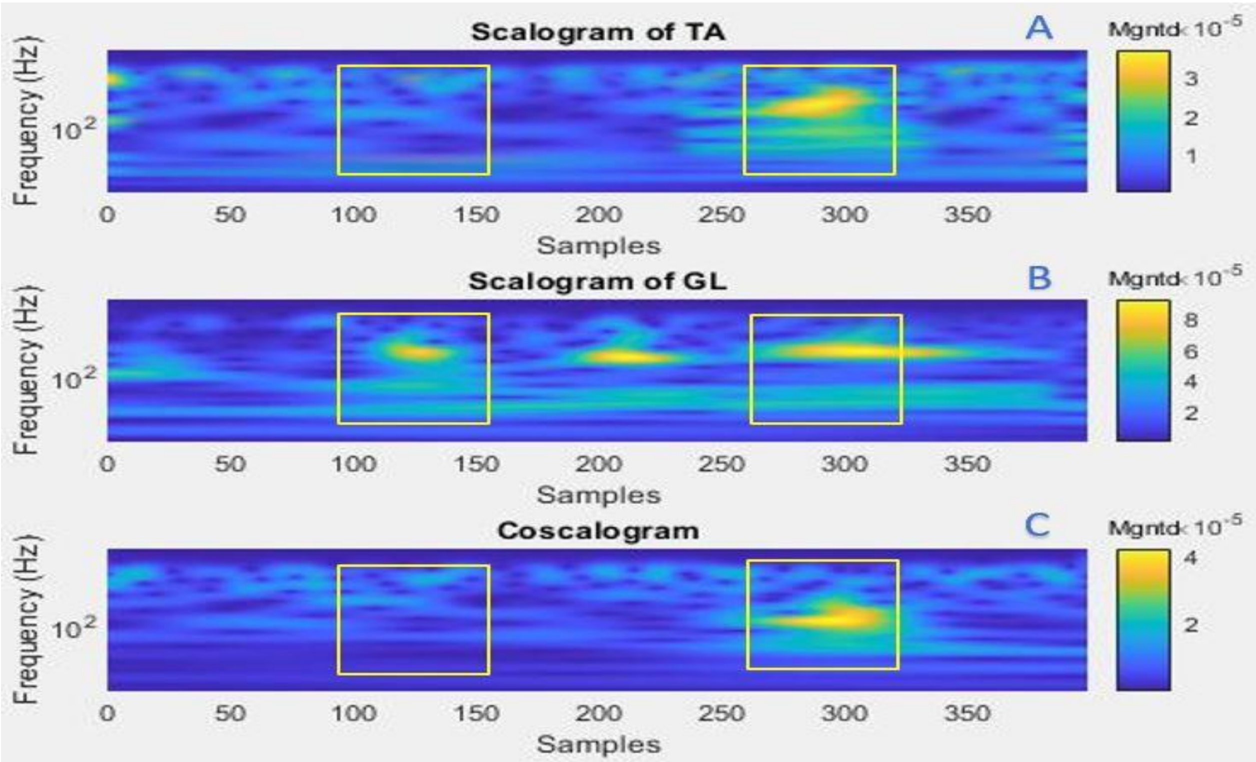

Figure 24: Panel A: TA sEMG Scalogram, Panel B: GL sEMG Scalogram, Panel C: TA-GL Coscalogram. Coscalogram obtained by online data

4.1 Statistical Analysis:

The results obtained were validated by comparing the SNR and RMSE of all three groups (raw data, CWT-processed data, VMD-processed data) collectively using the ANOVA test. A significant difference ($p<0.05$) was determined through the ANOVA one-way testing.

CHAPTER 5

5 DISCUSSION AND CONCLUSION:

This research proposes a Variational Mode Decomposition (VMD) method to characterize ankle muscle co-contraction in sEMG signal. To gain insights into the time-frequency characteristics of sEMG signals' intrinsic mode functions (IMFs), a novel combination of Scalogram visualization techniques is employed with VMD. The study focuses on the efficient denoising of the sEMG signal as a better-denoised signal will give a clear result of co-contraction that would be useful for the treatment of patients having ankle joint issues.

Although CWT quantifies ankle muscles very finely as mentioned in [38], when VMD was compared with CWT by using online as well as offline data, the proposed method (VMD) offers better results than the previously proposed method (CWT) as evident from Fig. 21 and Fig.22. In the study, it was observed that, on average, the increase in SNR with VMD (from -17.65 ± 8.1dB to 2.98 ± 2.2dB, $p<0.05$) exceeded that achieved with CWT (from -17.65 ± 3.7dB to 1.34 ± 1.5dB). Likewise, it was found that the reduction in RMSE using VMD (from 0.023 ± 0.0029 to 0.017 ± 0.0015, $p<0.05$) outperformed CWT's performance (from 0.023 ± 0.0027 to 0.020 ± 0.0025). VMD, characterized by its iterative refinement of IMFs [41], shows superiority over CWT. The single-pass nature of CWT limited its adaptability to complex signal environments, thereby rendering it less effective in achieving comparable levels of noise reduction.

Fig.16 clearly shows that denoising has been done effectively as the reconstructed signal maintains the attributes of the original signal. The reliability of the proposed method is proved by an increase in SNR in Fig.17 and a decrease in RMSE in Fig.18.

Fig. 23 and Fig. 24 shows that co-contraction of TA-GL will appear only on the coscalogram if both muscles contract at the same time. The left yellow box in panel C shows no co-contraction because the TA muscle is not activated, although GL shows activation. The right yellow box shows activation in panels A and B, so it also shows co-contraction in panel C.

Analyzing coscalograms provides insights into how different muscle groups work together to stabilize the ankle joint and ensure proper movement control, as co-contractions of ankle muscles play a pivotal role in maintaining joint stability. A coscalogram may help in assessing muscle coordination changes after injury and throughout the rehabilitation process. It aids clinicians and therapists in designing targeted exercises to restore optimal muscle co-contractions and joint stability. Muscular co-contraction plays a pivotal role in ankle rehabilitation, offering a valuable strategy to enhance joint stability, functional recovery, and overall mobility. During the rehabilitation process, targeted exercises that promote controlled co-contraction of muscles around the ankle joint can have profound benefits.

The study aimed to characterize the ankle muscle co-contraction in sEMG signal for ankle rehabilitation purposes. The study proposes an efficient technique i.e., VMD to analyze surface electromyographic signals from TA-GL muscles of 20 healthy individuals and assess muscular co-contraction by using coscalogram function. This method (VMD) was compared with the previously used method (CWT) and the results prove that VMD provides better performance than CWT in terms of SNR and RMSE.

5.1 Future Work and Recommendation:

In the future, investigation on the potential of incorporating machine learning techniques, such as deep learning or reinforcement learning, can be carried out to enhance the accuracy and real-time applicability of muscle co-contraction analysis in ankle rehabilitation.

Exploring the integration of VMD analysis with virtual reality environments for immersive rehabilitation experiences. This could involve real-time feedback and visualizations of muscle co-contraction patterns to enhance patient engagement and motivation during rehabilitation exercises.

Investigation of the feasibility of implementing real-time VMD-based feedback systems in clinical settings could be done in the future.

5.2 Limitations of the study

Factors like muscle fatigue and individual variability in muscle activation patterns can influence muscle co-contraction levels. These factors can cause fluctuations in co-contraction measurements, making it challenging to generalize findings across different subjects or over extended periods of time.

VMD is a sophisticated signal processing technique that requires careful parameter selection and validation. The accuracy of VMD's decomposition and its ability to accurately extract underlying muscle activity patterns depend on these parameters. Incorrect parameter choices can lead to inaccurate results.

Focusing on only two muscles (tibialis anterior and gastrocnemius lateralis) might not provide a comprehensive understanding of the entire ankle complex and how different muscle combinations contribute to co-contraction during various movements.

People have unique muscle activation patterns due to differences in anatomy, movement strategies, and training history. The results might vary across individuals, limiting the generalizability of findings.

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