EMG Signal Evaluation by Graph Signal Processing & Total Variation Denoising

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Supervisor: Dr. Muhammad Asim Waris

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Dedicated to my beloved parents, whose boundless love and encouragement have been the cornerstone of my academic journey. Besides, I extend my heartfelt appreciation to my dear friend, whose unwavering support, guidance, and belief in my potential have been invaluable. This accomplishment is a witness to the love and support of my parents and the friendship I have been fortunate to receive. This achievement is as much theirs as it is mine.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

AF	Abduction of all fingers
CWT	Continuous Wavelet Transformation
EMG	Electromyography
FF	Flexion of all fingers
GSP	Graph Signal Processing
RMSE	Root Mean Square Error
sEMG	Surface Electromyography
SNR	Signal to Noise Ratio
VMD	Variational Mode Decomposition
VG	Visibility Graph
WE	Wrist extension
WRD	Wrist radial deviation
WUD	Wrist ulnar deviation

ABSTRACT

Electromyography (EMG) serves as a vital diagnostic tool in medical and clinical research, enabling the monitoring and analysis of muscle electrical activity. In medical diagnostics, EMG aids in identifying and assessing neuromuscular syndromes, i.e. amyotrophic lateral sclerosis (ALS). However, EMG signals are prone to various forms of noise and interference, posing challenges to accurate data interpretation. Thus, the development of robust denoising techniques is crucial for enhancing EMG signal quality and addressing practical challenges in clinical diagnostics, rehabilitation, and neuromuscular research. This research introduces an innovative methodology integrating Variational Mode Decomposition (VMD) and Graph Signal Processing (GSP) to improve EMG signal quality. Unlike conventional approaches like Continuous Wavelet Transform (CWT), this study explores the untapped potential of VMD with Intrinsic Mode Functions (IMFs) 16 and GSP in EMG signal analysis. sEMG data collected from 10 subjects using the EMG-USB (OT Bioelettronica) underwent denoising techniques, specifically CWT, VMD, and GSP. Evaluation of noise reduction performance reveals compelling results, with GSP demonstrating superior noise reduction capabilities compared to VMD and CWT. Specifically, GSP increases the SNR by 259.15 meanwhile decreases the RMSE by 0.07. In comparison, VMD upturns SNR with 111.56 and declines RMSE of 0.15. While both VMD and GSP outperform CWT, which exhibits SNR enhancements of 90.46 and RMSE reductions by 0.15. Statistical analysis validates the significant improvements ($p < 0.05$) provided by VMD and GSP over CWT across varying noise levels. Notably, VMD and GSP collectively exhibit substantial enhancements in both SNR and RMSE metrics, underscoring their efficacy in preserving signal fidelity while minimizing noise and artifacts.

Keywords: EMG, Variational Mode Decomposition, Graph Signal Processing, Continuous Wavelet Transform, SNR, RMSE, Denoising Techniques.

CHAPTER 1: INTRODUCTION

1.1 Background and Significance

Human body is a complex network of muscles, nerves, and intricate neuromuscular connections that allow for a wide range of motor functions. Electromyography (EMG) serves as a fundamental tool in exploring this complexity by capturing and interpreting the electrical activity generated by muscle contractions.

In the realm of medical diagnostics, EMG aids in the identification and valuation of disorders like of neuromuscular, i.e. amyotrophic lateral sclerosis (ALS), and peripheral neuropathy etc. It provides essential information for physicians to make accurate diagnoses, assess disease progression, and devise appropriate treatment plans. Moreover, EMG is instrumental in monitoring the effectiveness of treatments and interventions aimed at improving the neuromuscular system's health and function. Electromyography (EMG) is a valuable diagnostic tool widely used in medical and clinical research to monitor and analyze the electrical activity of muscles. EMG signals provide essential understandings hooked on the working of the neuromuscular arrangement that helps in the identification and handling of various neuromuscular disorders and enhancing the understanding of motor control mechanisms. However, EMG signals are inherently susceptible to various forms of noise and interference, which can hinder the accurate interpretation of the information. Therefore, the development of robust denoising techniques is essential to enrich the quality of EMG signals and improve their diagnostic and analytical capabilities.

Beyond diagnostics, EMG plays a pivotal role in clinical research. Researchers use EMG data to delve into the intricacies of muscle activity, investigate motor control mechanisms, and gain a deeper understanding of the neuromuscular system's functionality. In fields like rehabilitation and biomechanics, EMG signals are harnessed to design and evaluate prosthetic devices, assess the effectiveness of physical therapy, and optimize ergonomic design for various applications, including sports and ergonomics that necessitate the quality improvement of these muscle signals. While EMG signals offer a wealth of information, they are not without their challenges. EMG recordings often feature noise and interference originating from various sources. Electrical artifacts, such as 50/60 Hz power line interference and equipment-related noise, can corrupt the signals. Additionally, EMG data may be affected by movement artifacts resulting from the repositioning of electrodes or the patient's movements during data acquisition. Biological factors like sweating and skin impedance variations can introduce further distortions. The presence of noise and interference in EMG signals poses significant obstacles. It complicates the analysis of these signals, making it challenging to extract accurate information about muscle activity and motor control. Misinterpretation of EMG data can lead to incorrect diagnoses and hinder the progress of clinical research and treatment strategies.

Recognizing the crucial role of EMG in medical diagnostics, clinical research, and various interdisciplinary domains, it is imperative to develop effective denoising techniques that can enhance the quality of EMG signals. The aim is to abstract the underlying physiological information from the signals though minimizing the impact of noise and interference. By improving the fidelity of EMG data, clinicians, researchers, and engineers can make more accurate assessments, diagnoses, and decisions.

This thesis embarks on a journey to address the challenge of denoising EMG signals by exploring the integration of two promising denoising techniques: Variational Mode Decomposition (VMD) and Graph Signal Processing (GSP) and compared the results with well-known denoising method Continuous Wavelet Transformation (CWT).

1.2 Problem Statement

The persistent challenge of noise and interference within electromyography (EMG) signals presents a formidable barrier, hindering the precise analysis essential for extracting crucial information regarding muscle activity and motor control. The intricate evaluation of these signals not only compromises diagnostic accuracy but also impedes advancements in clinical research and the formulation of effective treatment strategies for neuromuscular disorders. This pervasive issue underscores an urgent need for innovative denoising techniques within EMG signal processing. By addressing the complexities posed by noise and interference, these techniques aim to enhance the reliability and utility of EMG data, facilitating more accurate interpretation and enabling significant progress in understanding and managing neuromuscular conditions. Thus, the proposed study seeks to contribute novel methodologies capable of mitigating noise effects and optimizing the usability of EMG signals for clinical and research applications.

1.3 Motivation

This master's thesis is motivated by the pressing need to enhance the quality of EMG signals and augment the accuracy of their analysis by addressing the pervasive issue of noise and interference. The essential objective of this study is to assess the performance of a novel denoising methodology that compares two powerful signal noise reduction techniques that are “Variational Mode Decomposition (VMD)” and “Graph Signal Processing (GSP)”. The integration of GSP, which takes into account spatial dependencies in the data, and VMD, known for its effectiveness in noise reduction while preserving essential signal features, opens a promising avenue for mitigating noise in EMG signals.

1.4 Objectives

The aims of this research encompass a multifaceted exploration of EMG signal filtration. First and foremost, this study aims to assess the effectiveness of “Variational Mode Decomposition (VMD)” and “Graph Signal Processing (GSP)” in the setting of EMG signal handling. The goal is to leverage these techniques to reduce noise and interference, thereby improving the overall quality of EMG signals.

Moreover, a key aspect of this research involves conducting a complete comparative analysis. Specifically, intended to evaluate the performance of the projected techniques of “Variational Mode Decomposition (VMD)” and “Graph Signal Processing (GSP)” methodology in comparison toward the well-known denoising method of “Continuous Wavelet Transformation (CWT)”. This evaluation primarily revolve around the quantification of performance using essential performance metrics of “Signal to Noise Ratio” and “Root Mean Square Error”. Beyond methodological investigation and comparative analysis, this research aspires to contribute to the broader ground of EMG signal processing. The ultimate goal is to increase the state of the art in this domain, by a particular focus on enhancing the accuracy of clinical diagnoses, facilitating more precise biomedical research, and expanding the horizons of applications that rely on the fidelity of EMG data. In doing so, the aim is to bridge the gap between current denoising techniques and the specific requirements of EMG signal processing, thereby paving the way for more reliable and insightful analysis of muscle activity and neuromuscular functions.

1.5 Overview of the Thesis

To achieve these research objectives, this thesis is organized into several chapters, each dedicated to addressing specific aspects of the proposed approach. The pipeline of this research study is outlined by means of the chapter 1 that enlightens the background and significance, motivation for the study of this thesis, research objectives and structure of thesis. Chapter 2 deliberates literature work as of thorough review of the existing literature on EMG signal processing techniques, including Continuous Wavelet Transformation, Variational Mode Decomposition and Graph Signal Processing. The chapter address the limitations and challenges associated with current methods for EMG signal denoising. Chapter 3 elucidate the proposed methodology that integrates Variational Mode Decomposition and Graph Signal Processing in comparison with Continuous Wavelet Transformation to improve EMG signal quality. The chapter provide insights into filtration, processing, segmentation, performance evaluation and classification. In chapter 4, the results of the denoising techniques are presented, along with a comparative analysis of the Variational Mode Decomposition and Graph Signal Processing with Continuous Wavelet Transformation. The findings are discussed comprehensively, shedding light on their implications for EMG signal processing and their potential impact on biomedical applications. The final chapter 5 of conclusion and discussion provide a summary of the research findings and their significance that outlines the potential directions for further development of EMG signal denoising techniques and their submission in the broader field of biomedical engineering and healthcare.

CHAPTER 2: LITERATURE REVIEW

This chapter contains significant sum of work that has already been done on EMG Signal Evaluation using different techniques i.e. “continuous wavelet transformation (CWT)”, “variational mode decomposition (VMD)” and “graph signal processing (GSP)”. The majority of previous research on “Graph Signal Processing” has primarily focused on EEG signals, with limited attention given to EMG signals. There is a noticeable scarcity of literature applying this technique to EMG signals, however, “variational mode decomposition” focused on EMG signals but there is a notable lack of attention given to EMG signals when employing VMD with IMFs above 12. To have a better understanding of this study, most of the preexisting work has been studied and reviewed to acquire a survey on preexisting procedures and their accuracies to get better results.

EMG signals play an essential part in medical analysis and biomedical performances. As for the complexity of EMG signals, influenced by anatomical and physiological muscle properties, necessitates progressive methods for recognition, decomposition, processing, and classification. In 2011, the study elucidate that the Wavelet Transform emphasizes the necessity for sophisticated signal processing methods and draws attention to the shortcomings of the nonlinearities that are currently present in surface electromyography (EMG) signals [1]. Wavelet analysis is introduced as a more efficient alternative to Fourier analysis. The study explores the application of Wavelet Transform (WT) for denoising Electromyography (EMG) signals, specifically those acquired from forearm muscles. The historical background of EMG development is discussed, emphasizing its clinical significance and applications in studying neuromuscular disorders. The study illustrates how denoising can retain signal energy while removing noise by contrasting manual thresholding with compression techniques for threshold selection. The study concludes that, for the analysis of EMG signals, wavelet denoising can be a potent addition to conventional filtering methods [1]. In 2015, the study introduced a novel approach to denoise surface electromyography (sEMG) signals contaminated by powerline interfering noise, baseline wandering, and white Gaussian noise [2]. Unlike existing filters that target individual noise types, the proposed method uses “Variational mode decomposition

(VMD)” to break the signal into band-limited modes. Each noise category is identified within specific modes and removed separately. WGN is suppressed through a threshold that adapts to the noise level. The efficacy of this filter is assessed using simulations and real world signals, comparing it to traditional filters corresponding infinite impulse response, empirical mode decomposition, and ensemble empirical mode decomposition etc. The results indicate that the VMD-based filter excels in removing BW and WGN, and is effective in reducing PLI noise, particularly at low signal to noise ratios. The denoising performance is assessed using such metrics of root mean square error by decrease, improvement in signal to noise ratio, and measurement decline in the association coefficient (η). The proposed method outperforms other filters, achieving an 18.6 dB, 19.2 dB, and 8.0 dB improvement in SNR for PLI, BW, and WGN, respectively, at -6 dB SNR [2]. Investigational results demonstrate complete noise removal from relaxing conditions, with noticeable spikes illustrious in moving conditions. The study discovers the unique physiognomies of VMD and establishes the possibility by means of it for EMG signal denoising. The proposed filter's efficiency in removing three categories of noise makes it suitable for various applications requiring cleaning of EMG signals in preprocessing stages, likewise for recognition of different gestures as well as for decomposition of EMG signals. The study contributes to advancing the field of EMG signal processing and opens avenues for further research and applications. Furthermore, in 2020, the study proposed a method of graph signal processing. EEG signals have been the main focus of earlier work on “Graph Signal Processing”. The method of graph signal processing employed a step of Graph Discrete Fourier Transform by projecting EEG signals data onto the Eigen space of the matrix of Laplace for a weighted visibility graph [3]. The weights determined using a Gaussian kernel function, enhancing the representation of sudden fluctuations during seizures. The methodology involved by mapping time series EEG signals into a Gaussian kernel weighted visibility graph, applying GDFT to obtain feature vectors, and using Power Spectral Density (PSD) for classification. The classifier based on crisp rule with a predefined threshold distinguished between healthy and ictal (epileptic) classes. Simulation results on an EEG database demonstrated a remarkable 100% accuracy in detecting epileptic seizures [3]. The study emphasized the significance of Graph Signal Processing in analyzing irregularly sampled signals, particularly in the context of brain signals that highlighted the superiority of GDFT-based features over traditional entropy-based methods for epilepsy detection. The proposed Gaussian weighted visibility graph approach outperformed existing methods, showcasing its potential for accurate and efficient seizure detection. The study concluded by discussing future avenues, including the extension of the proposed method to detect further brain syndromes and its application of brain signals as for diffusion modeling. Overall, the studies pointed to improved performance when compared to wavelet approaches, highlighting the technique's potential to raise the caliber of signal analysis in medical applications.

CHAPTER 3: METHODOLOGY

3.1 Introduction

To improve the quality of EMG signals, this research employs a distinctive approach that integrates Variational Mode Decomposition (VMD) and Graph Signal Processing, drawing comparisons with Continuous Wavelet Transformation. The foremost consideration of this research study is the introduction of a novel methodology involving VMD with Intrinsic Mode Functions (IMFs) 16 and Graph Signal Processing, a groundbreaking integration up till now unexplored in the setting of EMG signal analysis. The utilization of VMD with IMFs 16 and the Graph Signal Processing, represents an innovative paradigm shift in the exploration of time-frequency characteristics inherent in EMG signals. This integration serves as a crucial framework for gaining profound insights into the quality of the signal.

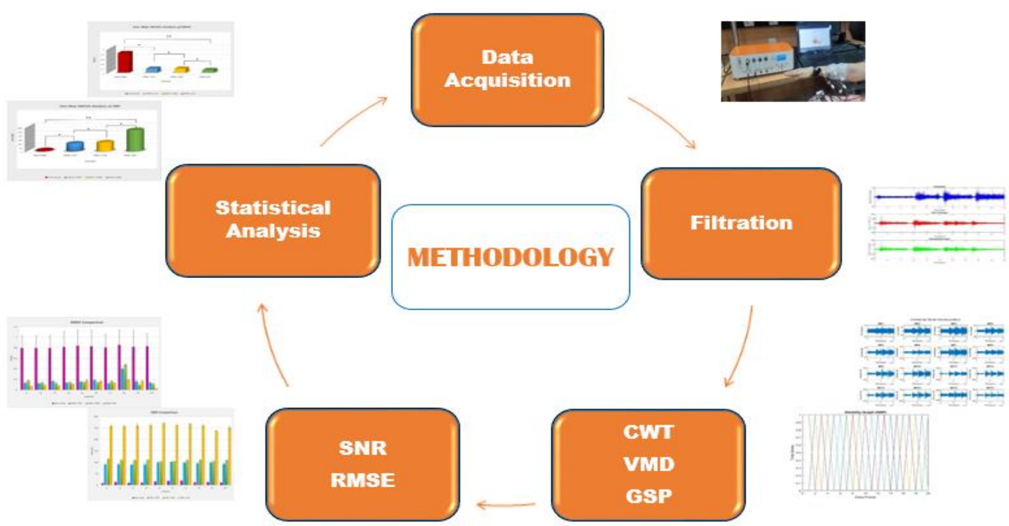

Figure 3.1: Methodology

A comprehensive elucidation of the research methodology unfolds in Figure 3.1 by encapsulating a systematic series of steps meticulously designed to address the overarching objective of improving EMG signal quality by removing noise and interference.

3.2 Data Collection

3.2.1 Subjects

The dataset comprised a set of 10 subjects aged between 18 and 50, all of whom were healthy individuals with no history of neuromuscular disorders or related conditions. None of the subjects had undergone any form of surgery. Ethical approval was obtained prior to data collection, and all participants were thoroughly informed about the entire procedure. Subsequently, each individual willingly agreed and formally provided consent by signing a consent form, thereby granting permission for the data collection procedure.

3.2.2 Data Acquisition Procedure

Subjects were comfortably seated in a controlled environment to minimize external interference. Prior to the experimental session, the skin over the electrode placement sites was cleaned to reduce impedance. EMG-USB (OT Bioelettronica) system was employed for real-time data acquisition, ensuring precise synchronization with the subjects' movements. Subjects were given verbal cues to execute the prescribed movements accurately.

The acquired dataset, characterized by its high sampling rate and comprehensive electrode placement, forms the foundation for subsequent analyses aimed at extracting meaningful insights into muscle activity patterns during the specified movements. The rigorous experimental setup ensures the reliability and validity of the obtained data, contributing to the robustness of the study's findings.

3.2.3 Experimental Setup

Electromyographic (EMG) data was acquired using EMG-USB (OT Bioelettronica), employing a high sampling rate of 2048 Hz and 11 pairs of differential electrodes, with 8 pairs strategically located at an equal space below the radiohumeral joint. Among these, 1 pair was positioned at the “biceps brachii muscle”, whereas 2 pairs were situated on the “flexor digitorum” and “extensor digitorum muscles”. The selection of electrode placement aimed to capture comprehensive muscle activity associated with the performed movements. Subjects were instructed to perform six distinct movements, each designed to elicit specific muscle activations. All the six movements included, “Abduction of all fingers (AF)”, “Flexion of all fingers (FF)”, “Wrist extension (WE)”, “Wrist radial deviation (WRD)”, “Wrist ulnar deviation (WUD)” and “Wrist extension with a closed hand (WE)”. Each movement was repeated four times, and each repetition lasted for a standardized duration of five seconds. A three-second rest period separated consecutive repetitions. This design was implemented to ensure sufficient data points for analysis while allowing for patient recovery and minimizing fatigue effects.

Figure 3.2: EMG-USB (OT Bioelettronica)

3.3 Filtration

Filtering of raw EMG signals are imperative for multiple reasons, encompassing signal quality, interpretation, and analysis. The genesis of EMG signals lies in the electrical activity of muscles, a process susceptible to diverse physiological and environmental factors. The application of filtering is instrumental in augmenting the accuracy and dependability of these signals, preparing them for subsequent analysis and interpretation.

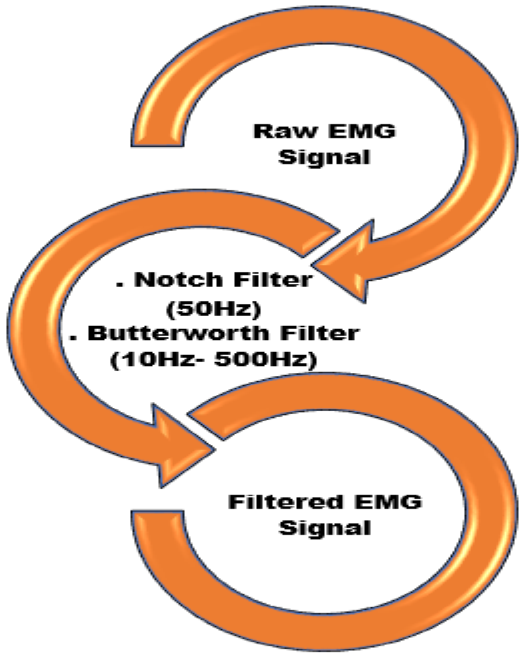

Figure 3.3: Filtration Process

EMG signals are inherently vulnerable to various sources of interference, including electrical disturbances, movement artifacts, and ambient electromagnetic signals. Filtering plays a crucial role in mitigating these unwanted components, thereby enhancing the SNR ratio. This improvement facilitates the identification and analysis of authentic muscle activity. Given that EMG signals encompass a broad spectrum of frequencies, including those from muscle contractions and noise, tailored filtering becomes essential. Depending on the specific context, isolating frequency bands relevant to muscle action becomes necessary. Filtering enables the concentration on the pertinent frequency range, thereby refining the accuracy of interpretation and feature extraction. During muscle contractions, sudden movements or changes in electrode placement can induce abrupt changes in the signal, leading to artifacts that obscure the underlying EMG activity. Filtering serves as a valuable tool in eliminating these artifacts, rendering the signal more consistent and interpretable. EMG signals typically contain frequency components ranging from a few hertz to several hundred hertz, due to which filtering of specific frequencies required.

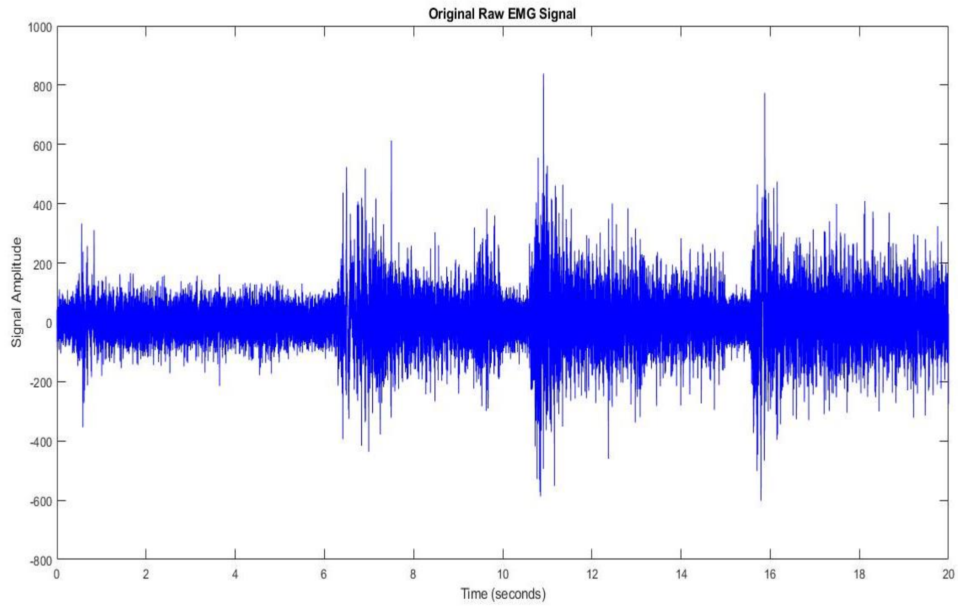

Figure 3.4: Raw EMG Signal

EMG signals encompass undesirable physiological elements, including cardiac activity and artifacts associated with movement. The application of filtering is instrumental in eliminating these components, thereby isolating muscle-specific activity. Through the reduction of noise and isolation of pertinent frequency components, filtered EMG signals become more accessible for interpretation and analysis. This assumes particular significance in clinical contexts where precise diagnosis and treatment decisions hinge on the quality of EMG data. Here Fig. 3.4 illustrates the unprocessed electromyography (EMG) signal in its raw form. EMG signals typically contain frequency components ranging from a few hertz to several hundred hertz. Bandpass filtering is used to separate the concerned frequency bands, which parallels to the distinctive frequency assortment of muscle activity. The bandpass filter attenuates frequencies outside this range, including movement artifacts by low frequency and electrical noise by high-frequency. In addition to the muscle activity frequency array, EMG signals can also be contaminated by interference from powerline noise with 50 Hz and its harmonics. Notch filtering is employed to selectively remove these specific frequency components, reducing powerline interference and improving the signal quality.

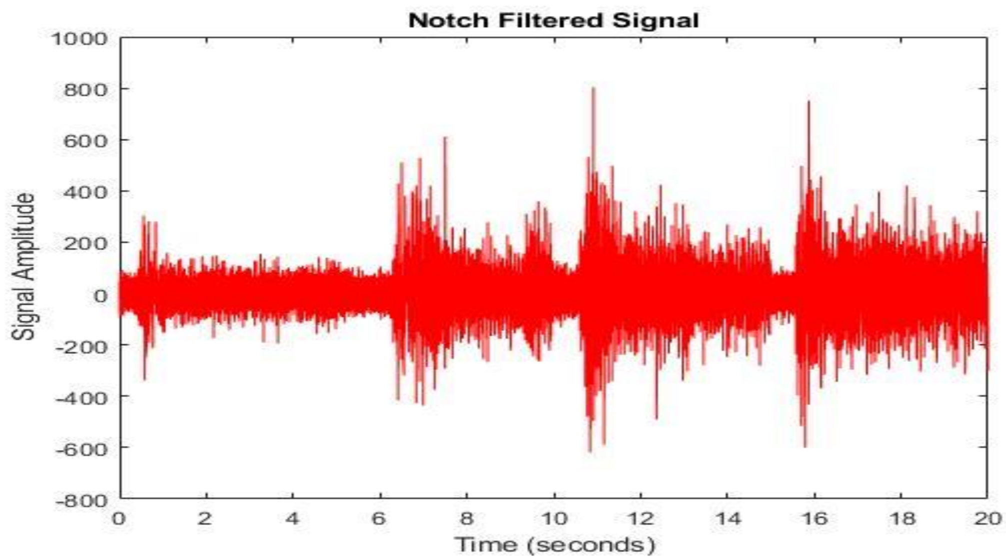

Figure 3.5: Notch Filtered Signal

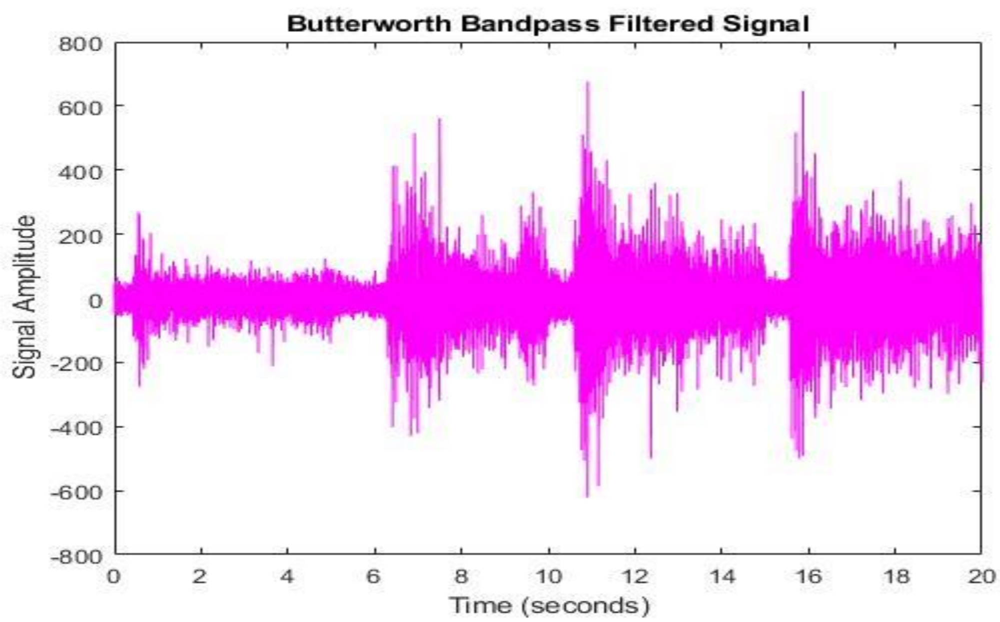

Figure 3.6: Butterworth Bandpass Filtered Signal

The EMG signals underwent a filtration process, commencing with the application of a 50Hz Notch filter to eliminate powerline interference from the raw EMG data, as depicted in Fig.3.5.

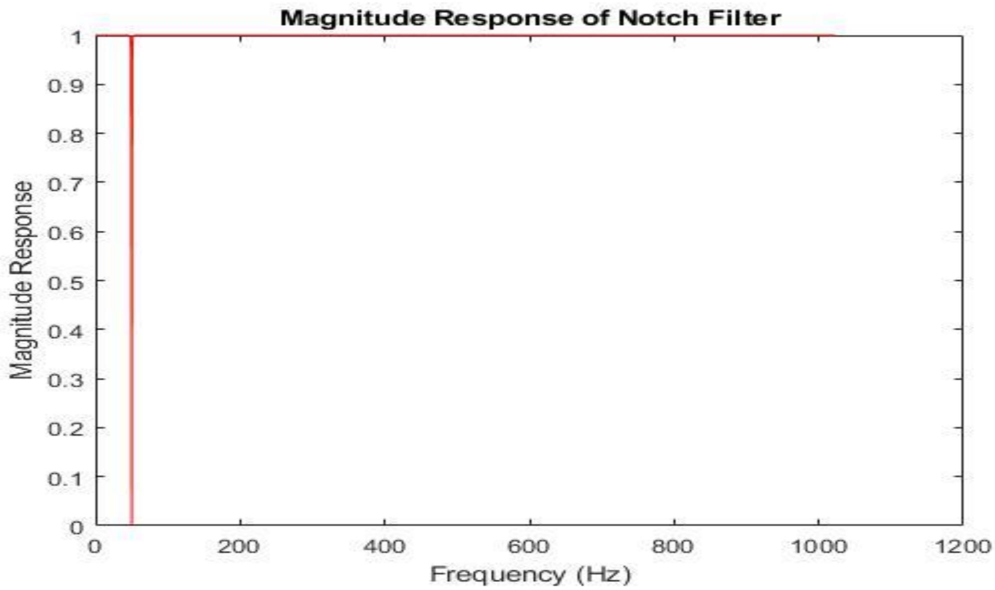

Figure 3.7: Magnitude response of Notch Filter

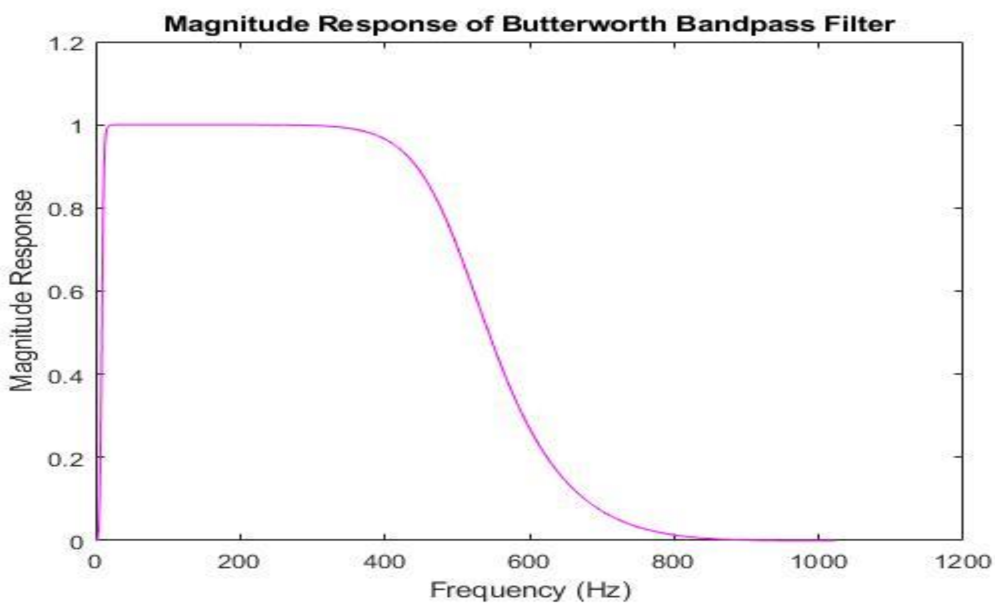

Figure 3.8: Magnitude response of Butterworth Bandpass Filter

Afterwards, a Butterworth filter within the 10 Hz of cutoff frequency as of high pass and of 500 Hz applied as of for low pass within the filter, displayed in Fig.3.6. The magnitude response for notch filter is shown in Fig.3.7. Subsequently, a Butterworth filter, characterized by a linear phase response in the passband, was employed to eliminate undesirable low and high frequencies. The resulting signal exhibited a smooth roll-off, representing a good compromise between steepness and smoothness. Specifically, a 4th order Butterworth filter was utilized, featuring a high pass and a low pass as illustrated its magnitude response in Fig.3.8.

EMG signals encompass undesirable physiological elements, including cardiac activity and artifacts associated with movement. The application of filtering is instrumental in eliminating these components, thereby isolating muscle-specific activity. Through the reduction of noise and isolation of pertinent frequency components, filtered EMG signals become more accessible for interpretation and analysis. This assumes particular significance in clinical contexts where precise diagnosis and treatment decisions hinge on the quality of EMG data.

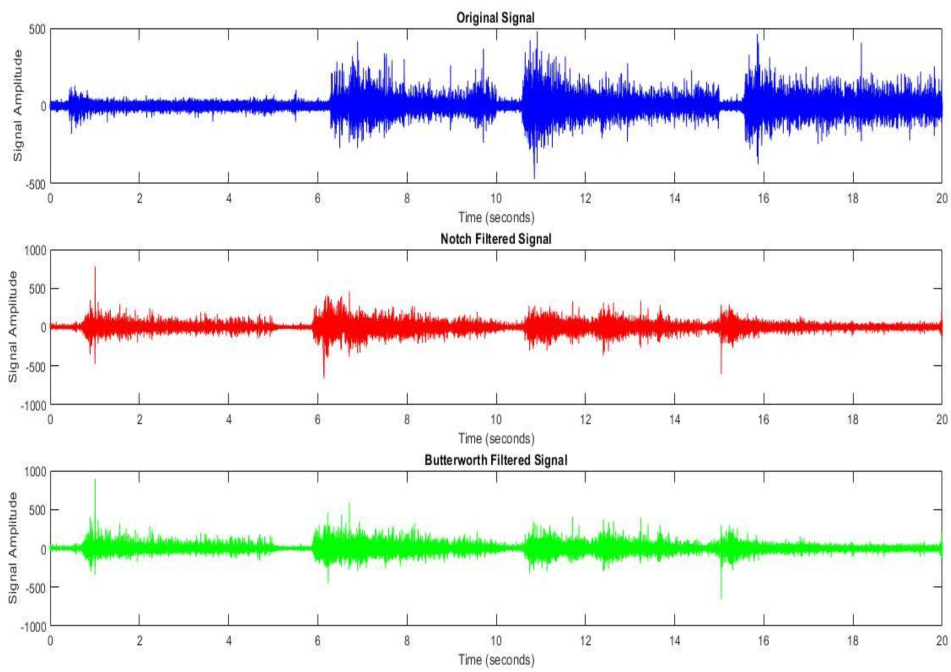

Figure 3.9: Original Raw EMG Signal and Filtered Signals

Fig. 3.9 presents a visual representation of the raw signal alongside the filtered signal subsequent to the presentation of the Notch filter and Butterworth filter. This comparative display serves to elucidate the efficacy of the filtration process in attenuating unwanted frequencies and enhancing the overall quality of the EMG signal.

Numerous analyses and applications necessitate the drawing out of specific features from EMG signals as of amplitude, frequency, and duration of muscle contractions. Filtering contributes to refining the accuracy of feature extraction algorithms by providing input data that is cleaner and more dependable. Consequently, the removal of artifacts and noise from EMG data is imperative for precise quantitative signal processing, given the widespread use of EMG signals in diverse fields, including biomechanics, sports science, rehabilitation, and neurology. In these applications, the indispensability of accurate and filtered EMG signals is underscored, as they serve as foundational elements for making well-informed decisions and drawing valid conclusions.

3.4 Denoising Techniques

The goal of the study is to integrate “Variational Mode Decomposition (VMD)” and “Graph Signal Processing (GSP)”, drawing comparisons with “Continuous Wavelet Transformation”, to augment the overall quality of EMG signals by decreasing noise and interference. The primary focus lies in quantifying the efficacy of these approaches by evaluating of as “Signal-to-Noise Ratio” and “Root Mean Square Error”. Improving the quality of EMG signals is pertinent to addressing practical challenges and devising effective solutions, with potential implications in clinical diagnostics, rehabilitation, and neuromuscular research endeavors.

3.4.1 Variational Mode Decomposition (VMD)

The Variational Mode Decomposition (VMD) method implemented for efficient signal denoising. Illustrated in the accompanying Fig.3.10 are the procedural steps involved in the proposed VMD-based filtering approach. Initially, employing VMD, the raw EMG signal, denoted as f(t), undergoes decomposition into K individual Intrinsic Mode Functions (IMFs), represented as $u^k(t)$. The determination of the appropriate quantity of IMFs is contingent upon the complexity of the signal, with a reduction in the number of IMFs potentially leading to a decrease in the signal's dimensionality. However, an excessive allocation of IMFs may result in overfitting of noise and artifacts, thereby yielding inaccurate decomposition outcomes. Each IMF is characterized by a bandwidth constrained by its respective center frequency, denoted as ω^k. Subsequently, specific types of noise are identified within distinct IMFs. The number of IMFs selected can be influenced by the signal's SNR. A higher SNR may necessitate a smaller number of IMFs, whereas a lower SNR may require a greater number of IMFs to ensure a detailed representation. This decomposition process, which focuses on center frequencies, renders VMD an effective technique for noise reduction and feature extraction in various applications such as motion classification, fatigue evaluation, and other EMG signal processing tasks.

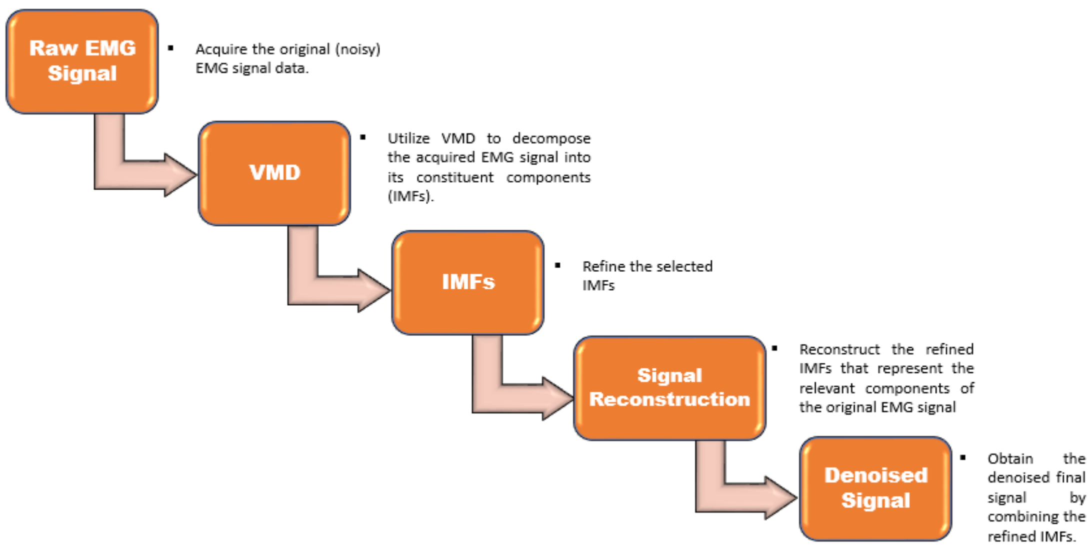

Figure 3.10: Steps of Variational Mode Decomposition (VMD) process

Variational Mode Decomposition (VMD) method proves to be highly efficient in segregating harmonic signals within a close frequency range. Unlike alternative techniques, it remains unaffected by the sampling frequency, thereby mitigating the occurrence of mode mixing. VMD serves as a comprehensive version of the Wiener filter, partitioning the signal into numerous adaptive bands. The operational procedure of VMD is delineated in Figure 3.10. Through regular updates, the model estimate, coupled with its corresponding center frequency, undergoes refinement, resulting in a dynamic model estimation [4]. Subsequent to each approximation, the model is transformed back keen on to the time domain by using the inverse Fourier transform. VMD operates as a non-recursive signal decomposition method, breaking down an input signal into a collection of modes, distinct sub-signals commonly stated as Intrinsic Mode Functions (IMFs), as expressed by the following equation [4]:

$$\sum_{k=1}^{K} \mu^{k} = f \tag{3.1}$$

"f" represents the original signal, comprising sub-signals denoted as "μ^{k}", where "k" indicates the total number of modes. The expression $\sum_{k=1}^{K} \mu^{k}$ signifies the summation over all modes. Intrinsic Mode Functions are characterized as amplitude-modulated-frequency-modulated (AM-FM) signals, expressed as follows [5]:

$$\mu^{k}(\mathrm{t}) = \mathrm{a}^{k}(\mathrm{t}) \bullet \cos(\varphi^{k}(t)) \tag{3.2}$$

Where "$a^{k}(t)$" represents the instantaneous amplitude, while "$\varphi^{k}(t)$" denotes the instantaneous phase. It is notable that both "$a^{k}(t)$" and the instantaneous frequency "$w^{k}(t) = \varphi^{k\prime}(t)$" (expressed as the derivative of $\varphi^{k}(t)$) exhibit considerably slower variations compared to the phase $\varphi^{k}(t)$".

The resolution of VMD is to decompose an input signal into a predefined number of sub modes, denoted as μ^{k}, possessing distinct sparsity characteristics while accurately replicating the input signal. In this context, the sparsity attribute of each sub mode is determined by its frequency domain bandwidth. Essentially, it is hypothesized that each mode "k" is primarily focused around a central pulsation "w^{k}", a charateristic determined alongside with the breakdown process.

The proposed approach involves generating the associated analytic signal for each mode u^{k}, to consider the bandwidth of a mode, using the Hilbert transform to get a unilateral frequency spectrum. Subsequently, the frequency spectrum of each mode is shifted to the baseband by adjusting it with an exponential tuned to the projected center frequency. The expected bandwidth is then determined through the Gaussian smoothness of the demodulated signal, quantified by the squared L2-norm of the gradient. The resultant controlled Variational problem is outlined as follows [10]: Where $\{\mu_{k}\} := \{\mu_{1}, \ldots, \mu_{K}\}$ and

$\{\omega_k\} := \{ \omega_1, \ldots, \omega_K\}$ serve as concise representations for all modes set and their respective center frequencies. The symbol ∂t denotes the gradient function, while δ(t) represents the Dirac distribution.

$$\min_{\{\mu_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * \mu_k(t) \right] e^{-j\omega k t} \right\|_2^2 \right\} \tag{3.3}$$

$$\text{s.t.} \quad \sum_{k=1}^{K} \mu_k = f$$

However, the expression "(δ(t) + j/(πt)) * u_k(t)" is recognized as the impulse response of the Hilbert transform, which is applicable to the mode u(t) and the original signal f(t). The Hilbert transform facilitates the conversion of the signal into the frequency domain, but to retain it in the time domain, it is convolved with the signal (it is noted that multiplication in the frequency domain match up to convolution in the time domain) [4]. This transformation is aimed at yielding a frequency spectrum containing solely positive frequencies. The re-establishment restraint problem incorporates a quadratic penalty function and the Lagrange multiplier operator. The quadratic penalty function serves to convert the constrained optimization problem into an unconstrained optimization problem, ensuring precise reconstruction. Meanwhile, through the application of the Lagrange multiplier, the inhibited variational problem transitions into an unrestricted one. This process is encapsulated by the augmented Lagrangian method, as described below [6].

As "α" signifies the balancing parameter, while "λ" indicates the Lagrangian multiplier. The optimization problem in its entirety is addressed utilizing the alternate direction method of multipliers (ADMM) [4]. This approach involves iteratively solving a

$$L(\{u_k\},\{\omega_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \tag{3.4}$$

series of sub-optimization problems. Leveraging the Parseval/Plancherel Fourier isometry within the L2 norm, this problem can be resolved in the frequency domain by transitioning from the time domain [10]. The update process for each estimated mode "u_k" and its corresponding center frequency "ω_k" proceeds as follows:

$$\hat{u}_k{}^{n+1}(\omega) = \frac{f(\omega) - \sum_{i\neq k}\hat{u}i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega k)2} \tag{3.5}$$

$$\omega_k{}^{n+1} = \frac{\int_0^\infty \omega \left| \hat{u}k(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}k(\omega) \right|^2 d\omega} \tag{3.6}$$

In this context, "n" represents the iterative numbers, and the Lagrange algorithm's operator is λ. Based on the mode iteration "u_k" and center frequency "ω_k," the ADMM algorithm is employed to directly optimize in the frequency domain following Fourier transform [11]. To conclude the iterations, it becomes imperative to establish a specific criterion. This criterion is deemed fulfilled when the following equation attains a predetermined level of discrimination accuracy. Upon satisfying this condition, we can obtain K narrow-band Intrinsic Mode Function (IMF) components.

$$\frac{\sum_k \left\| \hat{u}_k^{n+1} - \hat{u}_k^{n} \right\|^2}{\hat{u}_k^{n}\|_2^2} < \varepsilon \tag{3.7}$$

To create a revised approximation of a noisy signal, the coefficients of the initial Intrinsic Mode Functions (IMFs) undergo random reformation in each subsequent approximation. The resultant reorganized IMFs generated are then integrated with the decomposed IMFs that remain unchanged to form the refined approximation. This iterative procedure continues until the desired number of approximations are achieved.

Each mode represents a distinct component or pattern within the Electromyography (EMG) signal. These patterns, as illustrated in the Figure 3.11, can convey relevant information pertaining to muscle activity or irrelevant information such as noise or artifacts. These modes undergo iterative refinement by updating their parameters in each iteration [12]. This refinement process comprises two steps: initially, in the frequency domain, the modes are adjusted by modifying their central frequencies based on the signal's spectral characteristics. Subsequently, in the time domain, the modes are further refined to minimize interference between them. This refinement process is instrumental in analyzing and comprehending the signal's underlying frequency content and dynamics, which is valuable for various applications including signal processing, feature extraction, and pattern recognition [22].

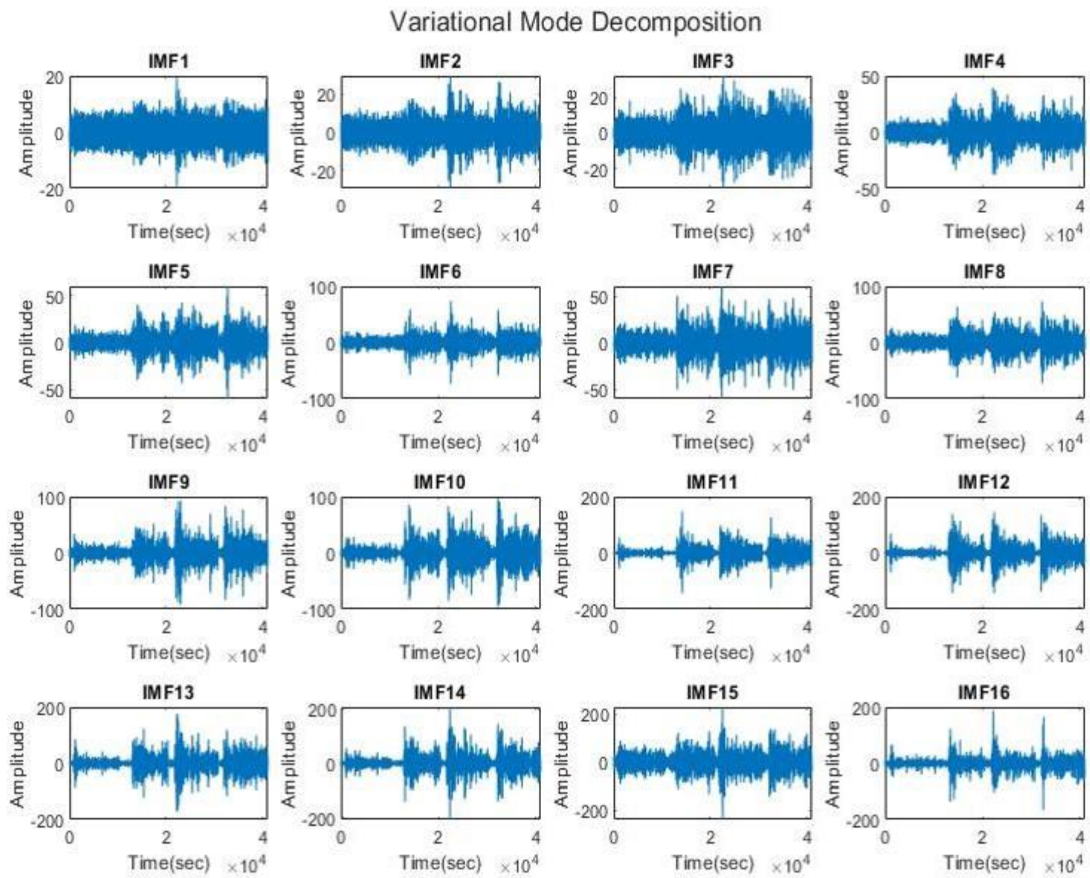

Figure 3.11: Decomposition of EMG signal using VMD

Moreover, IMF components are extracted with narrow bands based on the signal's frequency domain characteristics. An efficient and adaptable segmentation of the frequency band is executed to effectively prevent mode aliasing. Each IMF is updated with every iteration, thereby iteratively minimizing noise, as these modes endure iterative refinement by updating their parameters in each iteration. This study aims to highlight the distinct advantages of VMD, particularly its utilization of iterative processes within the intrinsic mode functions (IMFs), leading to more effective noise reduction compared to the conventional method of Continuous Wavelet Transform (CWT). Unlike the traditional process of this CWT, VMD possesses this intrinsic property of iterative refinement of IMFs.

3.4.2 Graph Signal Processing (GSP)

A developing focus that expands on conventional signal processing methods is called graph signal processing. Graph Signal Processing (GSP) examines signals with irregular domains that are present on graph nodes rather than regular intervals like grids [3].

In various practical scenarios, the domain of signals does not conform to equidistant time intervals or regular spatial grids. Instead, the sensing domain of data may be irregular and, in certain instances, unrelated to time or space. In order to efficiently encode the structural information within such data, novel tools are under development within the field of Graph Signal Processing (GSP). GSP focuses on analyzing signals whose domains are irregular and are situated on the nodes of a graph, as opposed to being distributed along regular intervals like grids. In these belongings, the data field is defined by a graph, comprising vertices (nodes) where there are defined data values, and edges that connects them, are their relationships [3]. Graphs are leveraged to exploit the inherent relationships amongst the data centered on its pertinent properties. The handling of signals whose domains are determined by graphs has directed to the appearance of graph data processing as a significant field within big data signal dealing out nowadays.

Graph Signal Processing (GSP) entails the application of signal treating techniques on graphs. Unlike other classical signal processing, which operates on signals arranged along a defined axis, graph signals lack such ordering. While data often exhibit structure, it is imperative to consider the underlying structure when processing graph signals. Graphs serve as effective tools for this purpose, enabling the representation of structured data through graph signals. This representation encapsulates both the structural aspects (edges) and the data values at vertices, offering a concise format for encoding structural information within the data [23].

The extension of classical signal processing methodologies to accommodate graph signals can greatly enhance the analysis of such data. The applications of graph signal processing span various domains including biomedical research, social network analysis, and transportation, among others.

Graph Signal Processing (GSP) constitutes a computational framework employed to analyze signals that are defined on graphs. Within the realm of biomedical signal processing, GSP presents a promising approach for addressing issues associated with noise reduction in electromyography (EMG) signals. EMG signals are depicted as graphs, where electrodes are mapped to nodes, and connections between electrodes signify signal correlations [24]. The process of filtering facilitates the transformation of raw EMG data into graph representations.

Fundamental Concept of Graph Signal

A graph *G* can be represented as a set comprising vertices *v* and edges *E*, linking these vertices, that is signified as,

$$G = \{v, E\} \tag{3.8}$$

In this representation, vertices are depicted as points (nodes), whereas boundaries as of edges are depicted as lines (connections) between these nodes. An edge (*v*) among vertices *i* and *j* implies that $(i, j) \in v$. Consider each node *i* to have a signal, $g(i)$, which yields a real number as output.

$$g\ (i) : v \rightarrow \mathbb{R} \tag{3.9}$$

In the meantime there are *N* vertices, there exist *N* distinct values for *i* within $g\ (i)$. The graph signal can be defined as the collection of the these *N* distinct signals as follows.

$$G = [g(1), g(2),\ldots..,g(N)]^T \tag{3.10}$$

Graphs can exist in two forms: undirected and directed [23]. In an undirected graphs, it is assumed that an edge connecting vertex *i* to vertex *j* also connects vertex *i* to vertex *j*. Thus, if $(i, j) \in v$, then $(j, i) \in v$. However, this bidirectional belongings does not generally hold for directed graphs. Undirected graphs can be regarded as a distinct case of directed graphs.

Given a set of vertices and edges, a graph can be signified by an adjacency matrix, denoted as A. This matrix describes the connectivity between vertices, with A being an N

× N matrix for N vertices. Elements Aij of the adjacency matrix assume values in $\{0, 1\}$ i.e. $A_{ij} \in \{0, 1\}$, where $Aij = 0$ signifies no connection between vertices i and j, and $Aij = 1$ indicates a connection.

$$A_{ij} = \begin{cases} 1 & if\ (i,j) \in v \\ 0 & if\ (i,j) \notin v \end{cases} \tag{3.11}$$

As for an undirected graphs, the adjacency matrix is symmetric, i.e. $A = A^T$.

A graph is uniquely characterized by its adjacency matrix for the given set of nodes. Altering the numbering of vertices leads to corresponding adjustments in the adjacency matrix. Though, such renumbering does not alter the graph itself, as these graphs are said to be isomorphic. The relationship between the adjacency matrices of the original and renumbered graphs is expressed using a permutation matrix P as $A_2 = P\ _{A1}P^T$.

Edges in graphs can possess weights. When weights are assigned to edges, a weighted graph is formed. The set of weights, denoted as W, corresponds to the set of edges v. A weighted graph encompasses a broader spectrum than an unweighted graph. Typically, edge weights are assumed to be nonnegative real numbers. By associating weight 0 with non-existent edges, the graph can be characterized using a weight matrix W similar to the adjacency matrix A. A nonzero element Wij describes an edge between vertices i and j along with the associated weight, whereas $Wij = 0$ indicates the absence of an edge between vertices i and *j [23]*.

On behalf of undirected graphs, the weighting matrix is symmetric, i.e. $W = W^T$. On the other hand, for directed graphs, this symmetry does not necessarily hold.

Graph Laplacian

The graph Laplacian plays a pivotal role in graph signal processing as it provides the foundation for frequency domain analysis of graph signals through its eigenvectors and eigenvalues [3]. The graph Laplacian matrix, denoted as L, is given by:

$$L = D - W \tag{3.12}$$

Where, W represents the weight matrix and D signifies the degree matrix of the graph

The weight matrix stores the different weights associated with edges, allowing for varying edge weights within the graph.

The degree matrix (D) is a matrix where each diagonal element signifies the total edge weights connected to a particular node [12]. Specifically, the i^{th} diagonal element, denoted as di, weight sums of all edges connected to the i^{th} vertex. A degree matrix of an undirected graph, denoted by D, is a diagonal matrix where the diagonal elements D_{ij} are equal to the sum of weights of all edges connected with the vertex j.

$$D_{ij} = \sum_{j=1}^{N} W_{ij} \tag{3.13}$$

Meanwhile for an unweighted and undirected graph, the value of D_{ij} is equals the number of edges connected to the j^{th} vertex.

For undirected graphs, the Laplacian matrix is symmetric i.e. $L = L^T$, with non-positive off-diagonal entries and rows summing up to zero.

The normalized Laplacian, denoted as L_{norm} , is well-defined as:

$$L_{norm} = D^{-1/2} (D - W) D^{-1/2} \tag{3.14}$$

<u>Eigenvectors and Eigenvalues of Graph Laplacian</u>

Furthermore, the eigenvectors and eigenvalues of the Graph Laplacian can be obtained by the following equation:

$$(A - \lambda I) v = 0 \tag{3.15}$$

Here, A represents the matrix of interest, λ denotes the eigenvalue, I stands as the identity matrix, and v remains the zero vector. The solutions for λ yield the eigenvalues (λ_k), while solutions for v correspond to the eigenvectors (u_k, where coefficient of the eigenvectors are $k = 0, 1. . . N - 1$). The Graph Laplacian, L, possesses a complete set of orthonormal eigenvectors, with eigenvalues typically sorted in increasing order that offers the foundation for frequency domain analysis of signals in the weighted graphs.

Eigen values:

$$\lambda_k = \lambda_0 < \lambda_1 \leq . . . \leq \lambda_{N-1} \qquad (3.16)$$

Eigen vectors:

$$u_k = u_0, u_1, . . . ,u_{N-1} \qquad (3.17)$$

Eigenvectors associated with smaller eigenvalues exhibit less rapid variation along the edges.

Graph Wavelet Transform

Graph signals can be represented spectrally using either the adjacency matrix or Laplacian frequency decomposition. By leveraging the eigenvalues and eigenvectors of the graph Laplacian in conjunction with the graph signal g, the graph wavelet transform can be formulated as follows [23]:

$$X = U^{-1} g \qquad (3.18)$$

Wherever U is a matrix containing the eigenvectors of the adjacency matrix in its columns. The elements of vector X are denoted as $X(k)$ for $k = 0 , 1 , . . . , N-1$. When $U^{-1} = U$, the element $X(k)$ serves as a estimate of the analyzed signal onto the k^{th} eigenvector, acting as a basis function for decomposing graph signals, can be defined as:

$$X(k) = \sum_{i=0}^{N-1} g(i)u_k(n) \qquad (3.19)$$

Thus, the graph wavelet transform can be interpreted as a decomposition of the signal onto the set of eigenvectors serving as orthonormal basis functions. The inverse graph wavelet transform is given by:

$$g = U X \tag{3.20}$$

this can be expressed as:

$$g(i) = \sum_{k=o}^{N-1} X(k) u_k(n) \tag{3.21}$$

This inverse wavelet signifies a development of the original graph signal g in terms of eigenvectors and eigenvalues.

Visibility Graph (VG)

An algorithm known as the visibility algorithm is employed to convert time series data into graphs. This method establishes connections between data points based on their visibility, generating a graph that retains characteristics of the original series. Regular series yield regular graphs whereas random series produces random graphs, in addition fractal series yield scale-free networks [3].

EMG time series data is transformed into a visibility graph, where a graph comprised by a set of nodes interconnected by edges. Each data point in the EMG time series is treated as an vertex, and edges between nodes are determined using the visibility graph methodology.

In the visibility graph (VG), each data point parallels to a node in the graph. An edge exists between nodes x_i and x_j if there are no other nodes between them in terms of visibility. Specifically, an edge can be present between time instants t_i and t_j with data points x_i and x_j, based on the following criterion for the intermediate node x_k at t_k:

$$X(t_k) < X(t_i) + (X(t_j) - X(t_i)) \frac{tk-ti}{tj-tk} \text{ ; } i< k<j \tag{3.22}$$

This proposed technique is implemented using MATLAB. The Figure 3.12 signifies the result of the visibility graph of the EMG signal of data points from the dataset. The visibility graph is calculated based on the first 20 elements of the segmented signal and their corresponding time indices. The Visibility Graph (VG) illustrates connections among nodes (data points) within the signal. Each node typically corresponds to a specific data point in temporal instance. The x-axis signifies the position of data points along the time series. The y-axis signifies the values of the time series.

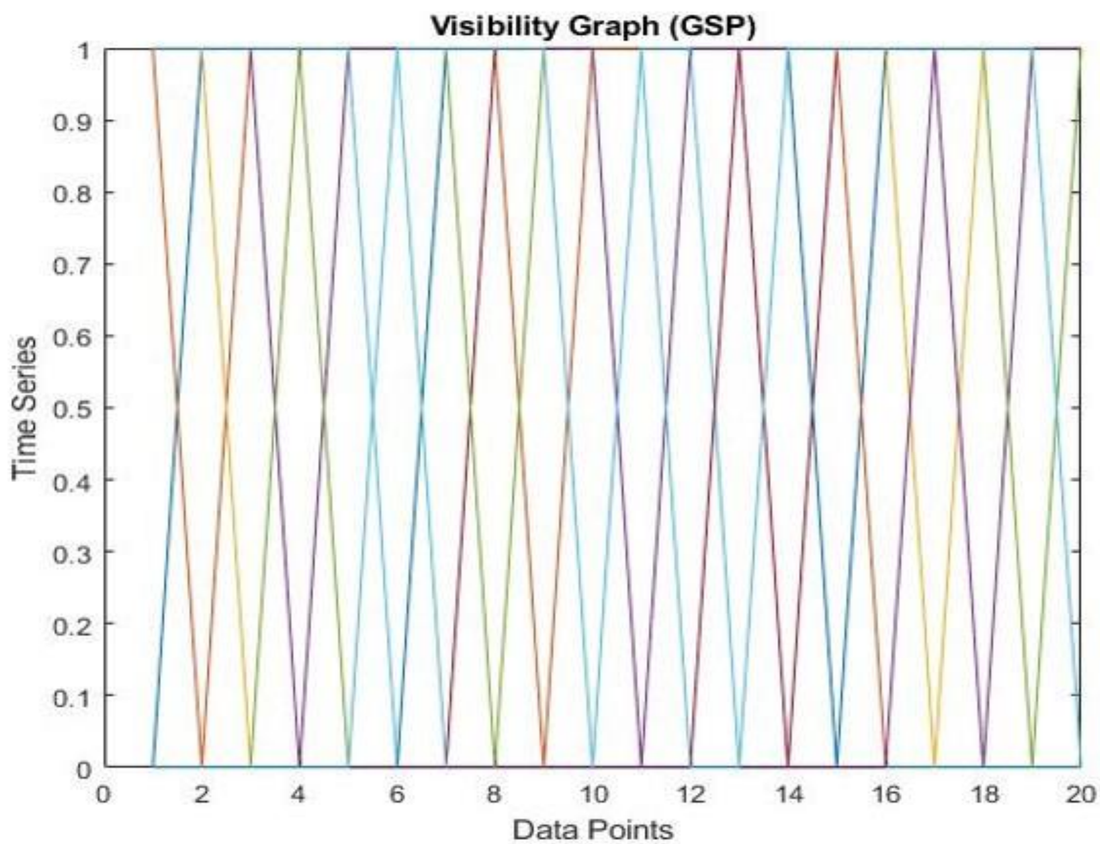

Figure 3.12: Visibility Graph of EMG Signal

The visibility graph in the Fig. 3.12 that is extracted from a time series EMG dataset exhibits the following characteristics[23]:

- Connected: Each node perceives at least its nearest neighbors (to the left and right).
- Undirected: The algorithm is structured in a way that does not define directionality in the links.
- Unweighted: Weighting is necessary when the signal is attenuated, as is the case with EMG signal filtering, it is not attenuated so not required here.
- Additionally, the EMG signal is non-periodic where Boundary periodicity=0, further obviating the need for weights.

This analysis reveal patterns of connectivity and interactions within the EMG signal by representing graph from the time series signal.

3.4.3 Continuous Wavelet Transformation (CWT)

In comparison with VMD and GSP the study delve into the methodology of applying Continuous Wavelet Transformation (CWT) on electromyography (EMG) signals. CWT is a powerful tool for time-frequency analysis, allowing the investigation of signal characteristics across for together in time and frequency domains simultaneously. The application of CWT on EMG signals provides insights into the temporal and spectral features of muscle activity, offering valuable information for various applications including gesture recognition, prosthetic control, and neuromuscular disorder diagnosis.

Continuous Wavelet Transformation (CWT) is a mathematical tool used for analyzing non-stationary signals. Unlike Fourier Transform, which represents signals solely in the frequency domain, CWT decomposes signals into time-frequency representations, enabling the analysis of signal dynamics over time and across different frequency components simultaneously. The CWT of a signal is obtained by convolving the signal with a scaled and translated version of a mother wavelet function [1].

Choosing an appropriate mother wavelet is crucial for CWT analysis as it determines the resolution and sensitivity of the time-frequency representation. In the context of EMG signal analysis, commonly used mother wavelets include Morlet, Daubechies, and Symlets. The choice of the mother wavelet depends on the specific characteristics of the EMG signal under investigation, such as its frequency content, temporal dynamics, and noise characteristics [28].

Before applying CWT, preprocessing steps are often employed to enhance the quality of EMG signals and mitigate potential artifacts. Preprocessing techniques include baseline removal, filtering (e.g., bandpass filtering to remove noise and motion artifacts), and normalization to account for variations in signal amplitude across different trials or subjects. Proper preprocessing ensures that the EMG signals are appropriately prepared for CWT analysis, facilitating accurate interpretation of the results.

Though, careful deliberation of signal preprocessing, wavelet selection, and result interpretation is essential to ensure the reliability and validity of CWT EMG analyses.

Continuous 1-D Wavelet Transform:

The implementation of CWT involves convolving the preprocessed EMG signals with the chosen mother wavelet at multiple scales and time points. This results in a time-frequency representation of the EMG signals, with each point in the CWT matrix corresponding to the energy or power of the signal at a specific time and frequency. The CWT coefficients can be visualized using spectrograms or contour plots, providing insights into the frequency content and temporal dynamics of muscle activity.

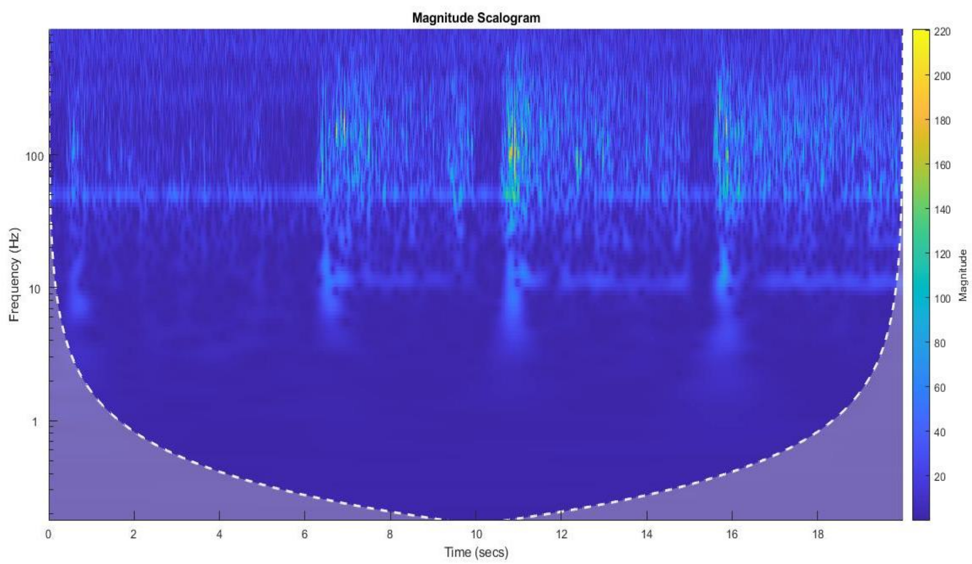

Figure 3.13: Magnitude Scalogram

The application of Continuous Wavelet Transformation (CWT) on electromyography (EMG) signals, utilizing MATLAB as the primary tool for analysis. The process involves signal preprocessing, CWT computation, denoising using soft thresholding, segment extraction, and evaluation of the denoised signal's quality.

The EMG signals loaded first from the obtained EMG dataset. The signal then extracted and plotted to visualize its temporal dynamics and amplitude variations over time.

The Continuous 1-D Wavelet Transform (CWT) computed on the EMG signal using inbuilt cwt function. This transformation generated a time-frequency representation of the signal, highlighting its frequency content and temporal evolution. The resulting scalogram in Fig.3.13 provides insights into how signal energy is distributed across different frequency bands at various time points.

Denoising using Soft Thresholding:

Soft thresholding is a method commonly used in signal processing and particularly in denoising applications. It is a form of shrinkage operation applied to the coefficients obtained from a signal's transformation, such as the wavelet transform. The goal of soft thresholding is to suppress small coefficients while preserving the significant ones, effectively reducing noise in the signal. The process of soft thresholding involves two main steps: the first is thresholding in which each coefficient obtained from the signal transformation is compared against a predetermined threshold value. And the other one is Shrinkage where coefficients with magnitudes smaller than the threshold are set to zero, while those larger than the threshold are adjusted by subtracting or adding the threshold value, depending on their sign.

To diminish noise and enhance the signal-to-noise ratio (SNR), the soft thresholding applied to the wavelet coefficients obtained from the CWT. A threshold value is determined based on a fraction of the maximum coefficient magnitude, and coefficients below this threshold are suppressed. The denoised signal is then reconstructed using the inverse CWT (icwt) function. Soft thresholding is effective in denoising signals because it exploits the assumption that the noise in the signal typically consists of small amplitude fluctuations, while the signal contains larger amplitude components itself. By selectively removing small coefficients, soft thresholding can effectively suppress noise while preserving the essential features of the signal. However, choosing an appropriate threshold value is important, as it directly influences the balance between noise reduction and signal distortion. Common methods for selecting the threshold include using a fixed fraction of the maximum coefficient magnitude or employing statistical techniques.

Mathematically, the soft thresholding operation for a coefficient *x* with threshold λ is given by:

$$\text{soft\_thresh}(x,\lambda) = \begin{cases} x - \lambda & \text{if } x > \lambda \\ 0 & \text{if } |x| \leq \lambda \\ x + \lambda & \text{if } x < -\lambda \end{cases} \tag{3.22}$$

Here, λ signifies the threshold value, and |x| means the absolute value of the coefficient.

At that point, soft thresholding applied to the wavelet coefficients wt. The threshold value calculated as 10% of the maximum absolute value of all wavelet coefficients. Then, soft thresholding is performed element-wise on the wavelet coefficients using the following formula:

$$\text{soft\_thresh}(x,\lambda)=\text{sign}(x)\cdot\max(|x|-\lambda,0) \tag{3.23}$$

Wherever x represents each wavelet coefficient, λ is the threshold value, and sign(x) returns the sign of x. lastly, the denoised signal is reconstructed from the denoised wavelet coefficients "wt_denoised" using MATLAB's icwt function. This reconstructed signal, stored in the variable signal_denoised, represents the original EMG signal with noise reduced through soft thresholding of the wavelet coefficients.

In short, soft thresholding in this technique here involves calculating a threshold based on a fraction of the maximum absolute wavelet coefficient magnitude and then applying soft thresholding to suppress small coefficients while preserving significant ones. The denoised signal is reconstructed from the modified wavelet coefficients for further analysis.

Afterwards a 20-second segment of the EMG signal is used for further analysis. This segment is visualized along with the corresponding denoised signal to observe the effects.

The EMG signal segment envisioned the corresponding denoised signal to observe the effects of noise reduction and signal fidelity preservation.

3.5 Performance Evaluation

To assess the effectiveness of the implemented techniques, two widely used metrics: "signal to noise ratio" and "root mean square error" were utilized. These metrics are extensively employed in evaluating the effectiveness of signal filtering techniques.

3.5.1 Signal-to-noise Ratio (SNR)

The "Signal-to-Noise Ratio" plays a vital role in assessing the effectiveness of the projected method by quantifying the quality of a signal comparative to the background noise existing in the signal. A higher SNR indicates a stronger, clearer signal comparative to the noise, thereby facilitating more accurate and reliable signal detection and interpretation. SNR holds significance across various domains including signal processing, sensor networks and telecommunications by achieving a high SNR that is fundamental for ensuring the robustness and efficacy of the system. Mathematically, the SNR represents the proportion of the influence of the signal of interest to the influence of the background noise.

$$SNR = \frac{Power\ of\ Signal}{Power\ of\ Noise} \tag{3.24}$$

SNR is often expressed in decibels (dB) and computed using the formula:

$$SNR_{dB} = 10 \bullet \log_{10}(SNR) \tag{3.25}$$

To ensure an equitable comparison for this study, the signal-to-noise ratio was computed for the original raw signal and filtered denoised signal as follows:

$$SNR = 10 \bullet \log_{10} \frac{\sum (f\ (t)\ )^2}{\sum \left(\hat{f}\ (t) - f\ (t)\ \right)^2} \tag{3.26}$$

Here f (t) denotes the original signal and $\hat{f}(t)$ represent the denoised signal.

In practical terms, attaining a high SNR is preferable, as it facilitates improved signal quality and simplifies the detection of patterns or features within the signal. A greater SNR value signifies a stronger signal compared to the noise, resulting in a clearer and more dependable portrayal of the underlying information within the signal. Conversely, a lower SNR value implies a greater dominance of noise, creating it challenging to precisely extract significant information from the signal.

3.5.2 Root Mean Square Error (RMSE)

Root Mean Square Error utilized as a performance evaluation metric to measure the accuracy of processing technique. This metric holds significant importance in measuring the average magnitude of differences between observed values (original signal) and predicted values (denoised signal) within a dataset. Its computation involves deriving the mean square root of the squared discrepancies between estimates and observations. Generally, lower RMSE values are indicative of better model performance, while higher values suggest a greater degree of prediction error. Within signal processing, RMSE assumes a pivotal role in assessing the efficacy of signal reconstruction, noise mitigation, and predictive modeling endeavors. Consequently, it aids in directing the refinement of algorithms and techniques to attain precise and dependable outcomes. A lower RMSE signifies improved noise reduction while preserving essential signal attributes.

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

$$\text{RMSE}= \sqrt{\frac{1}{L}\Sigma\left(f\ (t) - \hat{f}\ (t)\ \right)^2\ )} \qquad (3.27)$$

Where f(t) signifies the original signal and $\hat{f}(t)$ represents the denoised signal and L denotes the length of the signal.

A smaller RMSE value signifies closer agreement between observed and predicted values, indicating superior model performance. The RMSE facilitates the assessment of the discrepancy amongst the denoised signal and the original noisy signal. It offers a single numerical measure that captures the average magnitude of disparities amongst processed and actual values, thus serving as a succinct and informative indicator of processing technique performance. Accuracy holds paramount importance in signal processing, and RMSE shows a vital part in evaluating the alignment between the processed and true signals. It offers insights into the extent to which the processing algorithm accurately captures the inherent features of the signal, encompassing parameters such as amplitude, frequency, and timing. RMSE aids in quantifying the efficiency of the processing method in attenuating the noise and artifacts.

CHAPTER 4: EXPERIMENTAL OUTPUTS

4.1 Denoising Results

The sEMG data collected from 10 subjects using the EMG-USB (OT Bioelettronica) underwent initial notch filtering at 50Hz, followed by bandpass filtering using butterworth filter with cutoff frequencies of 10Hz and 500Hz, as Fig.4.1 displays the frequency spectrum of original and butterworth bandpass filter. Subsequently denoising techniques were applied, specifically “Continuous Wavelet Transform (CWT)”, “Variational Mode Decomposition (VMD)”, and “Graph Signal Processing (GSP)”. The application of these techniques resulted in significant reduction of noise and artifact minimization while preserving the innovative characteristics of the signal.

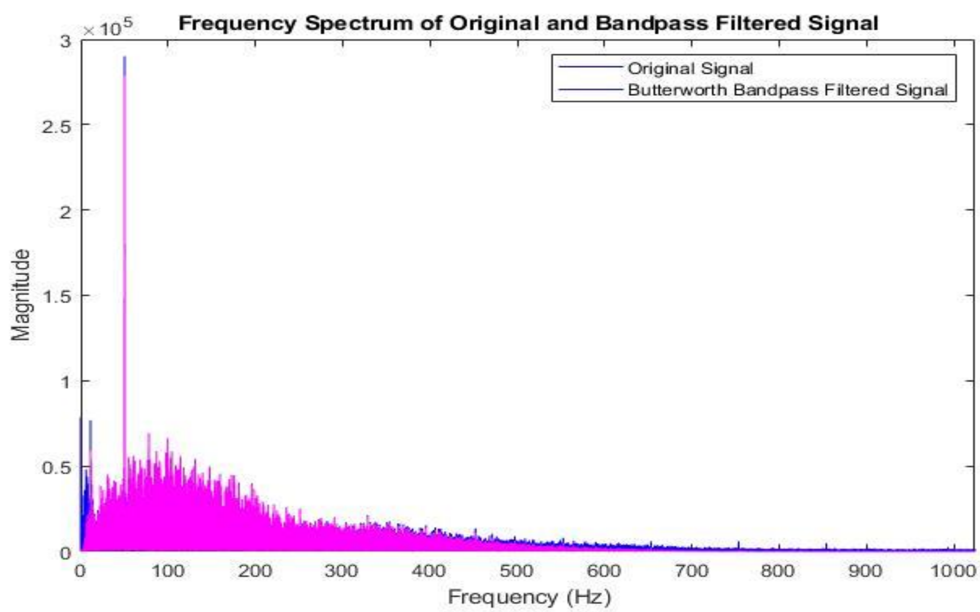

Figure 4.1: Frequency Spectrum of Original and Butterworth Bandpass Filter

In Fig. 4.2, an evaluation amid the real EMG signal and the denoised signal using the CWT technique is presented. Similarly, Fig. 4.3 displays the assessment among the original signal and the denoised signal obtained through the VMD technique, while Figure 4.4 depicts the comparison for the GSP technique. The application of these denoising methods yielded reliable results.

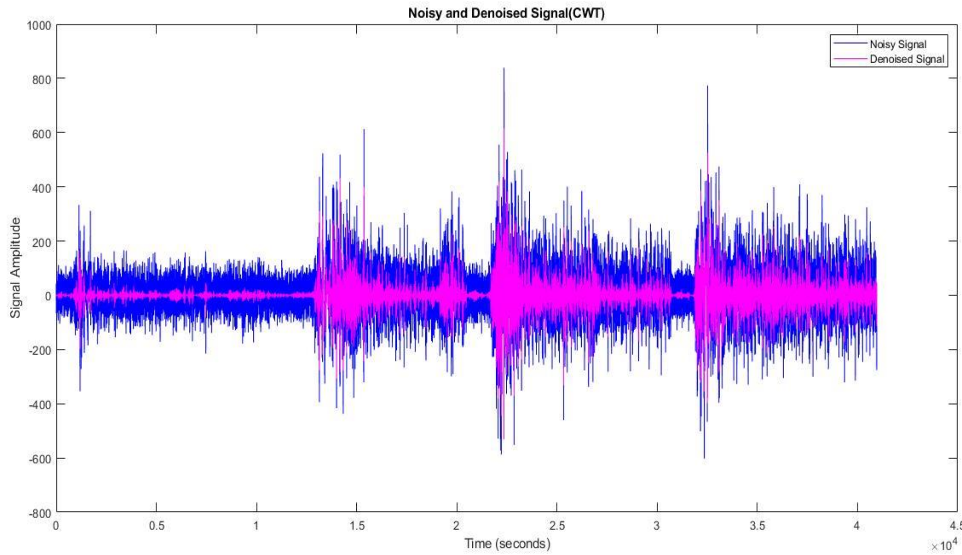

Figure 4.2: Reconstructed Signal for CWT

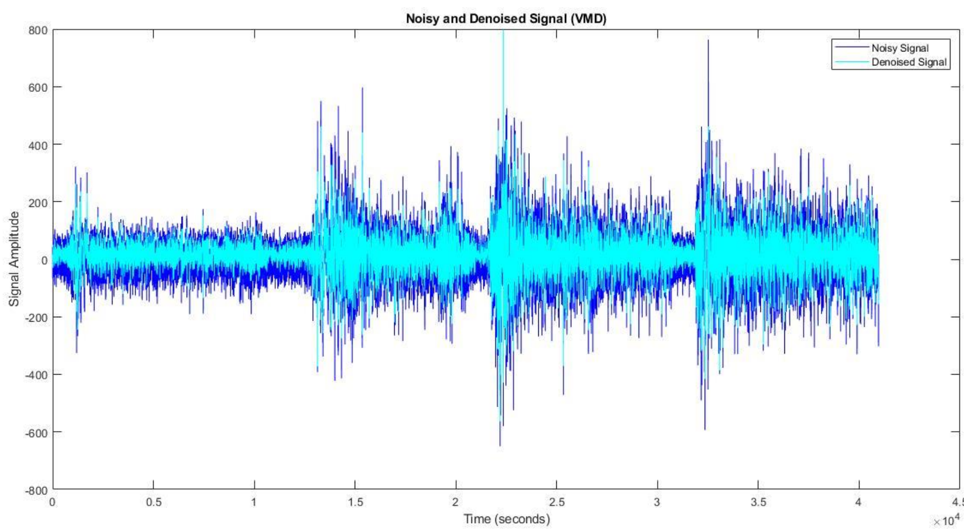

Figure 4.3: Reconstructed Signal for VMD

From these figures, it is evident that the denoised signals closely resemble the original EMG signals, indicating successful noise reduction without significant distortion by preserving original characteristics that is significant for accurate analysis.

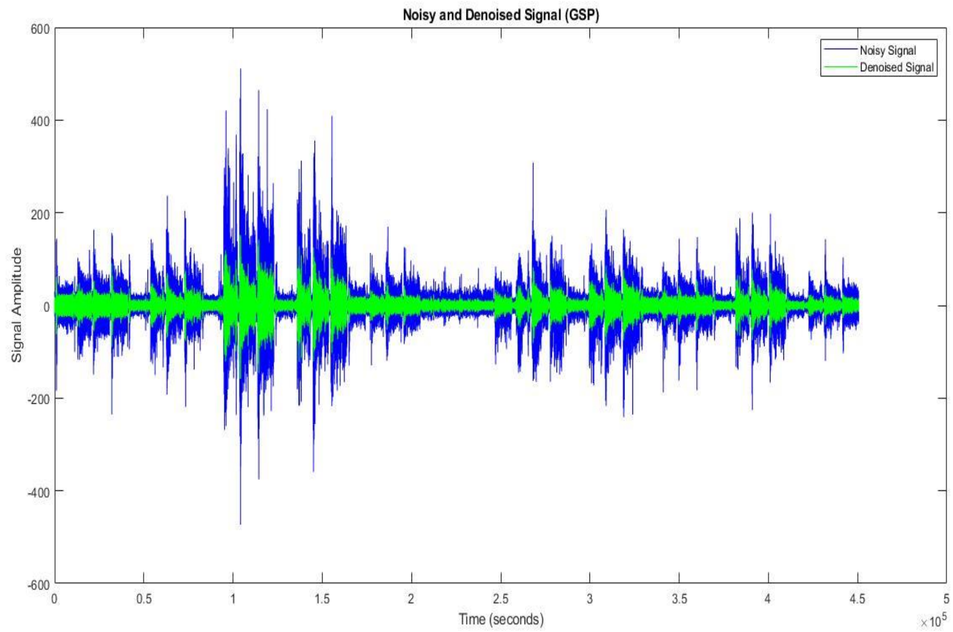

Figure 4.4: Reconstructed Signal for GSP

By visually predicting these figures for all cases, it is obvious that these methods worked well by demonstrating effective denoised reduction. This preservation of original characteristics is significant for accurate analysis and interpretation of the underlying physiological processes.

4.2 Comparison

Two denoising techniques, called “Variational Mode Decomposition (VMD)” and “Graph Signal Processing (GSP)” were tested to assess the performance by using “Signal to Noise Ratio” and “Root Mean Square Error”. The signal has retained its original characteristics while minimizing the noise and artifacts. The outcomes, demonstrated in Fig. 4.5 and Fig. 4.6, exhibit a notable enhancement of SNR and a significant reduction in RMSE after applying VMD. Similarly, the results, shown in Fig. 4.7 and Fig. 4.8, exhibit a notable enhancement of SNR and a significant reduction in RMSE after applying GSP. Likewise, Fig. 4.9 and Fig. 4.10, shows the results of SNR and RMSE after applying CWT. A higher SNR and lower RMSE indicate better noise reduction while preserving important signal features.

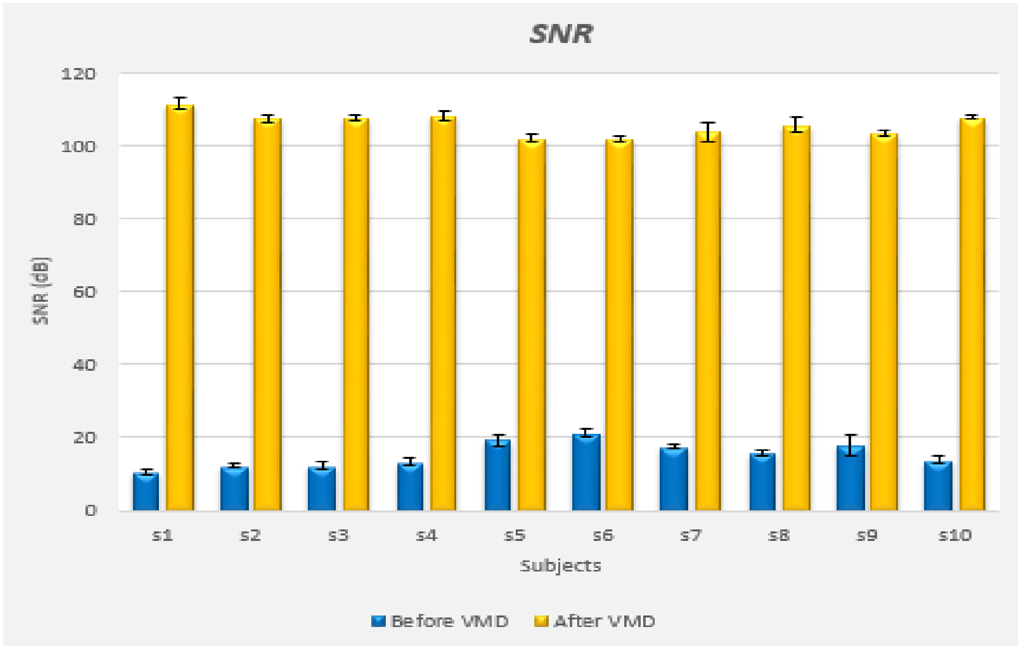

Figure 4.5: SNR of EMG before and after applying VMD

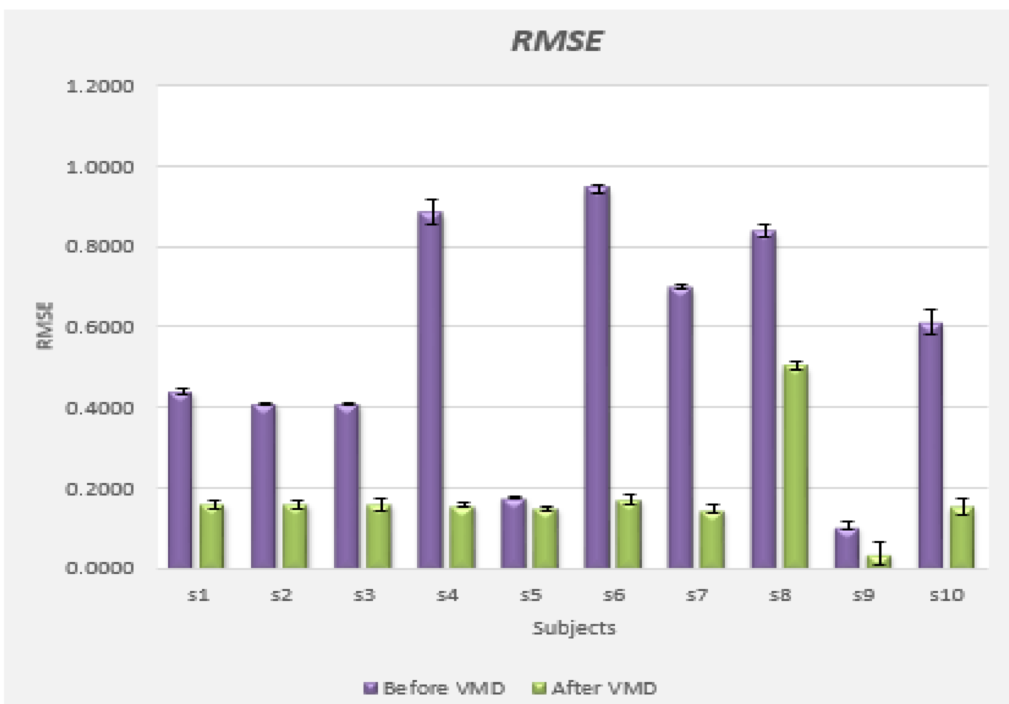

Figure 4.6: RMSE of EMG before and after applying VMD

By foreseeing the results, in Fig. 4.5 and Fig. 4.6, reveal a notable enhancement of SNR and a significant reduction in RMSE after applying VMD, respectively.

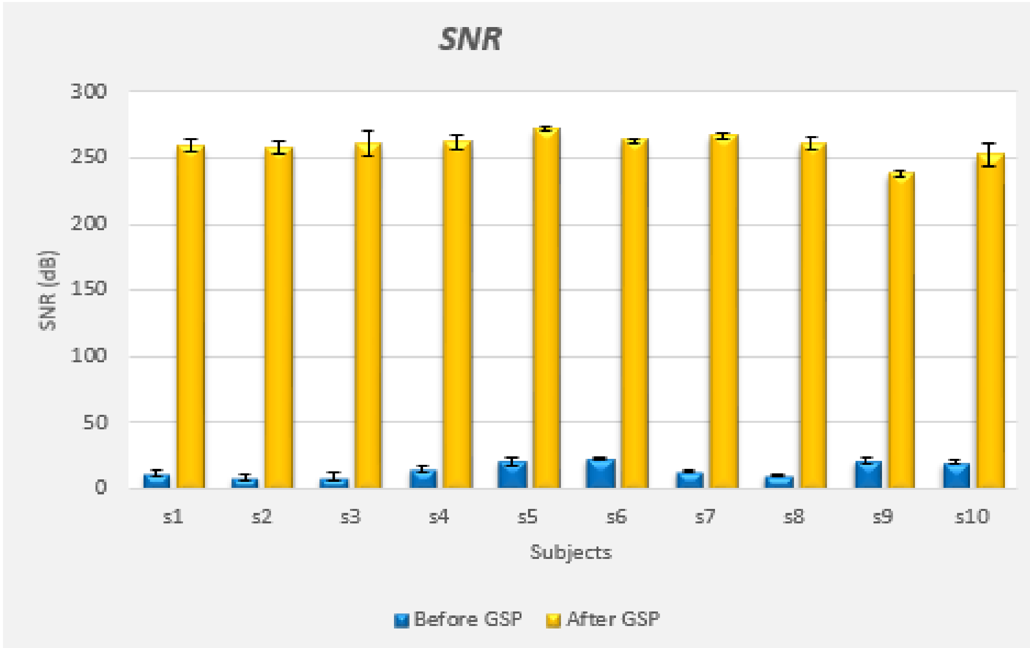

Figure 4.7: SNR of EMG before and after applying GSP

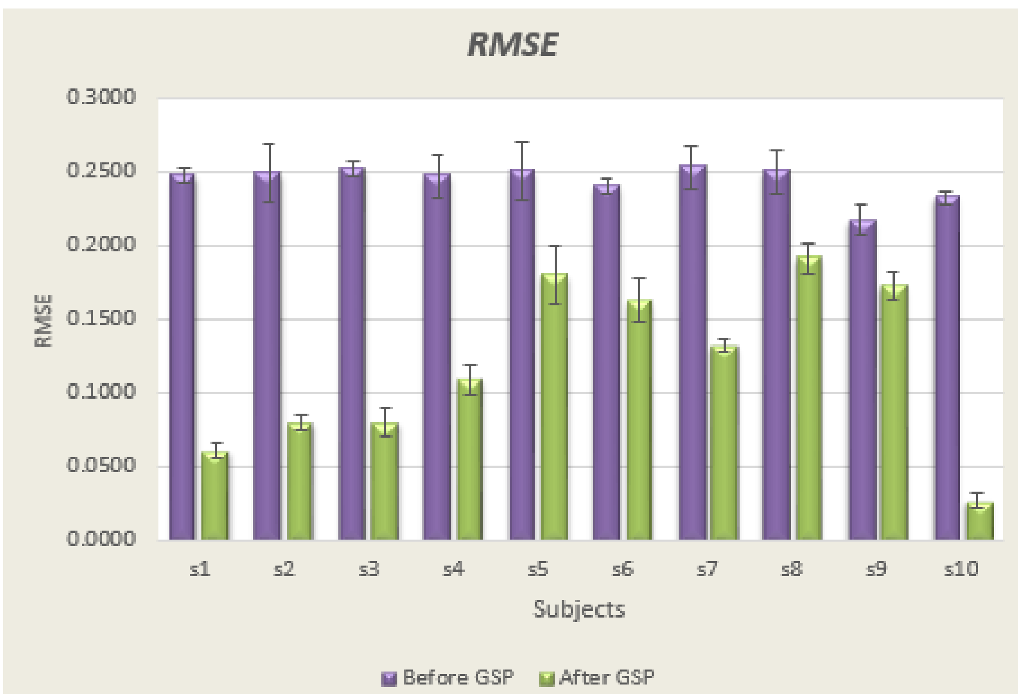

Figure 4.8: RMSE of EMG before and after applying GSP

The outcomes, validated in Fig. 4.7 and Fig. 4.8, exhibit a notable enhancement of SNR and a significant reduction in RMSE after applying GSP, respectively.

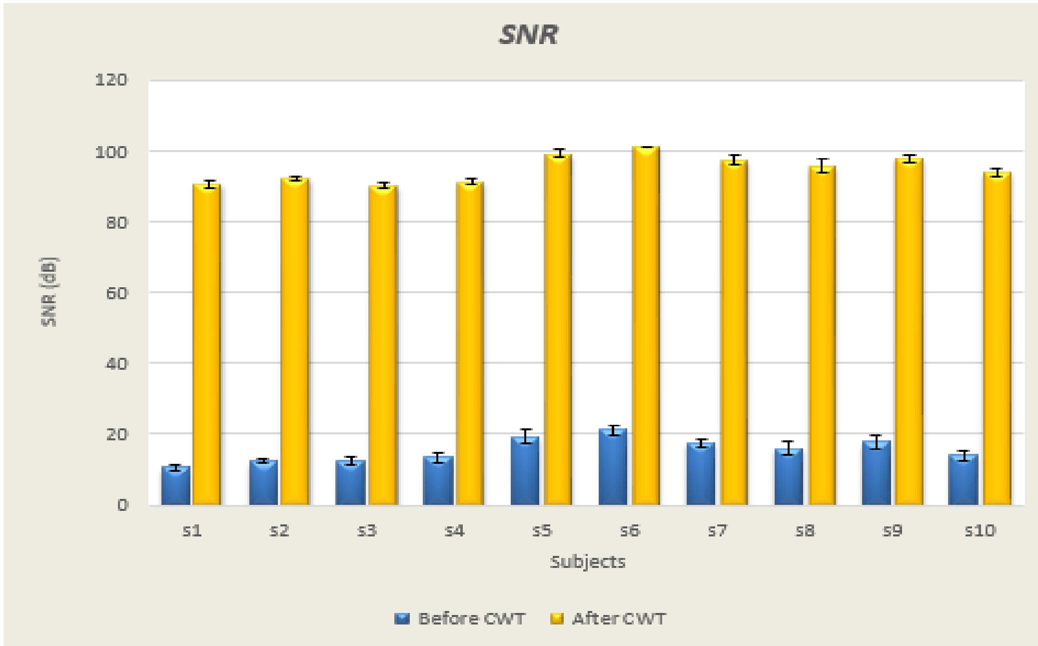

Figure 4.9: SNR of EMG before and after applying CWT

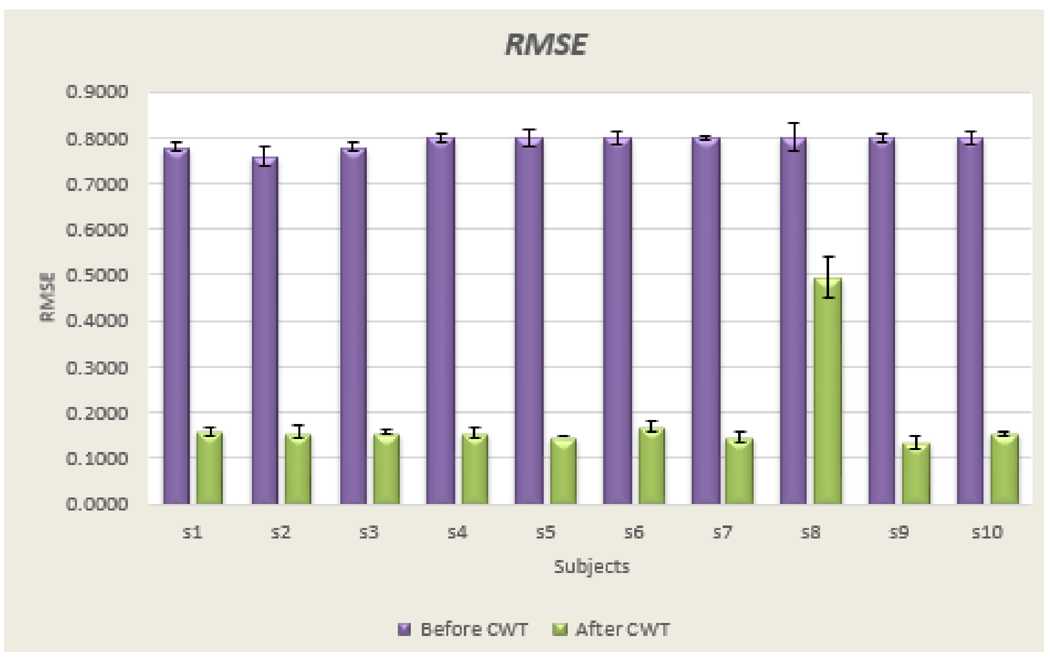

Figure 4.10: RMSE of EMG before and after applying CWT

Likewise, the outcomes after applying CWT are portrayed in Fig. 4.9 and Fig. 4.10 as of SNR and RMSE, respectively. As it is indicated that higher SNR and lower RMSE point toward better noise reduction while preserving important signal features.

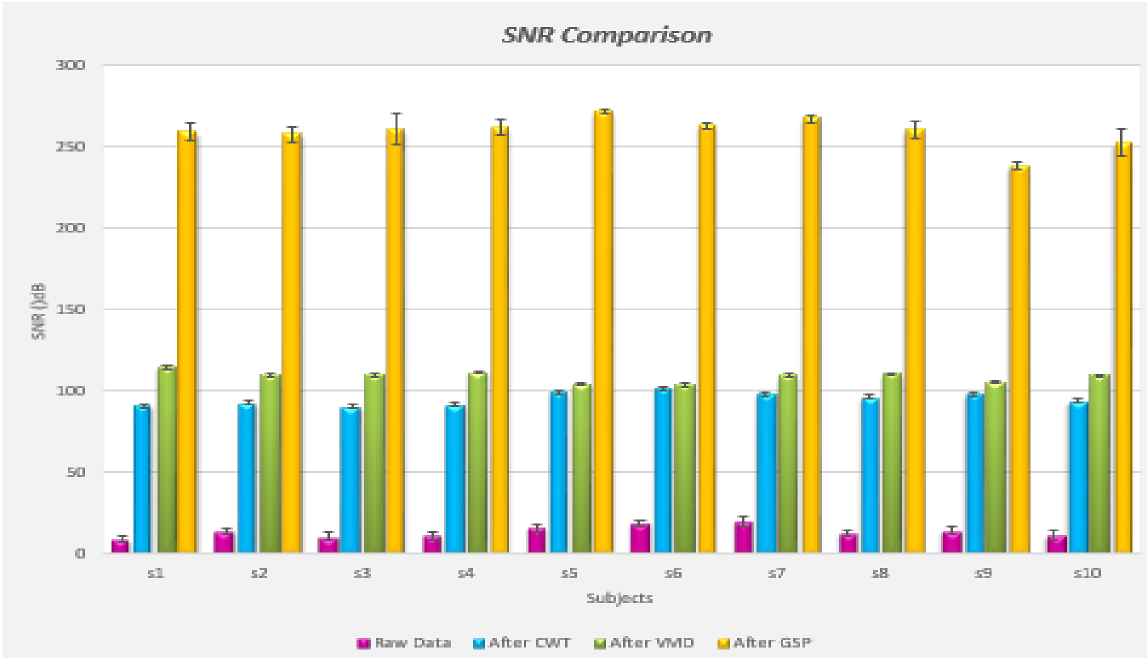

Figure 4.11: Comparison of VMD, GSP and CWT in terms of SNR

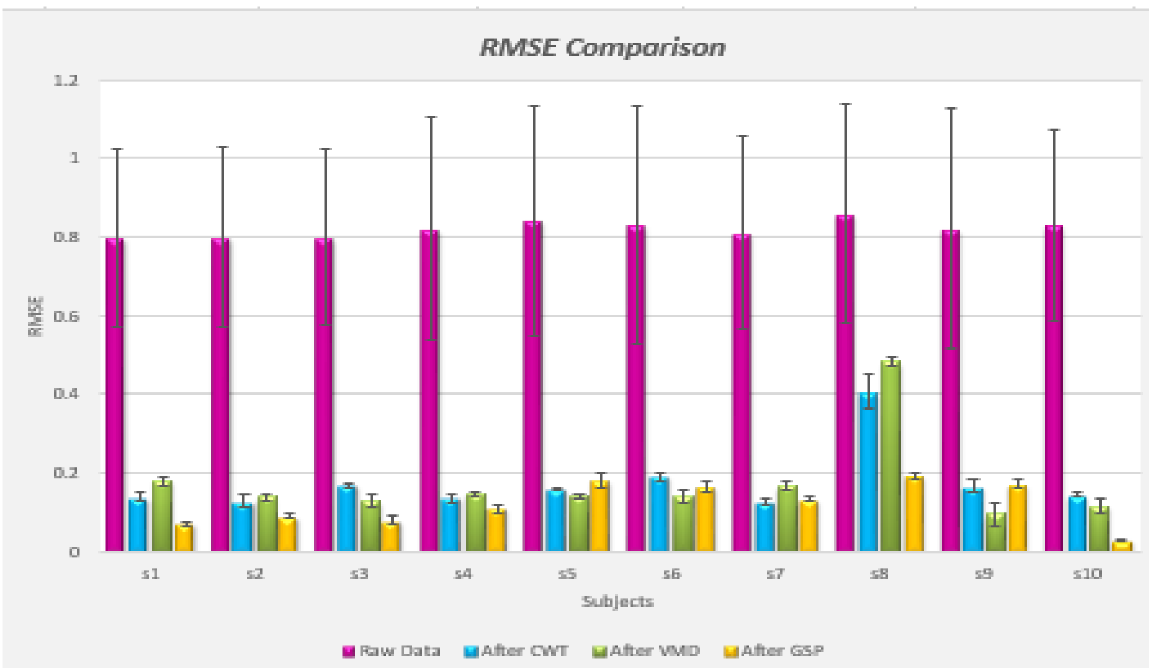

Figure 4.12: Comparison of VMD, GSP and CWT in terms of RMSE

After obtaining promising outcomes through the implication of the "Variational Mode Decomposition (VMD)" and "Graph Signal Processing (GSP)", a comparative assessment was conducted with the "Continuous Wavelet Transform (CWT)" technique to discern their relative effectiveness. The comparison was made, where SNR results displayed in Fig.4.10, and RMSE results in Fig.4.11 showed a noticeable difference between VMD, GSP and CWT in terms of their noise reduction capabilities.

4.3 Statistical Analysis:

The obtained results were validated by comparing the SNR and RMSE of all four groups (raw data, CWT-processed data, VMD-processed data and GSP-processed data) collectively by means of the One-Way ANOVA test.

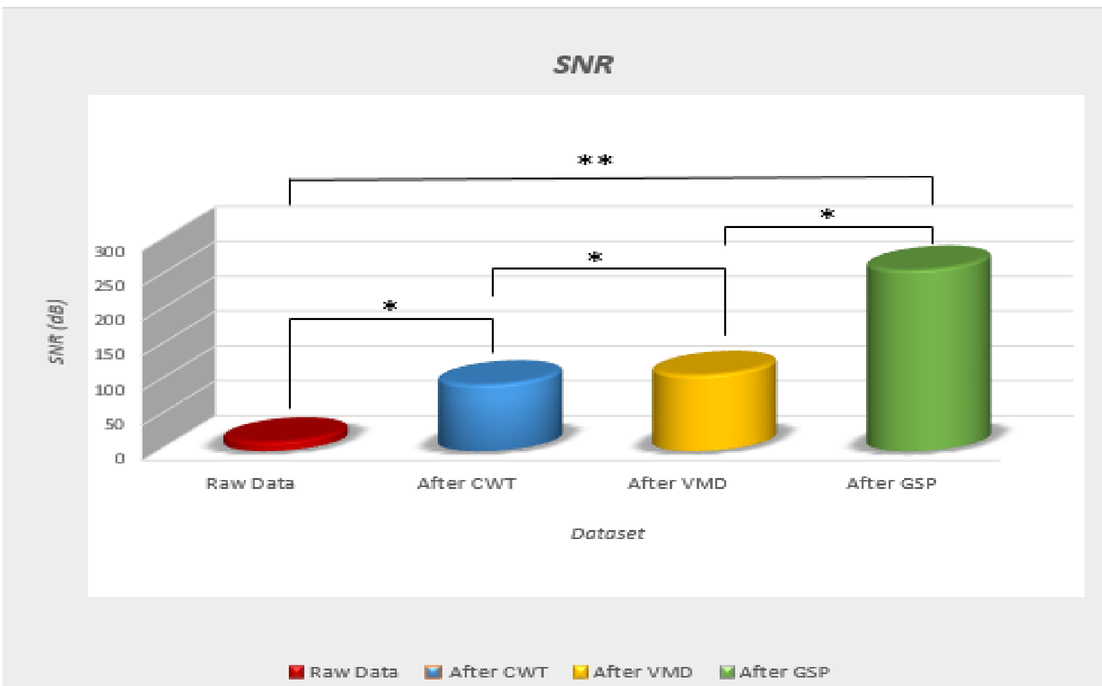

Figure 4.13: SNR Results '∗' specifies significant differences with a level of $p < 0.05$ and '∗∗' indicates significant differences with a level of $p < 0.01$

A significant difference $p < 0.05$ and $p < 0.01$ was determined through the One-Way ANOVA testing. As Figure 4.13 shows Statistical Analysis of SNR where'∗' specifies significant differences with a level of $p < 0.05$ and '∗∗' shows significant differences with a level of $p < 0.01$, however Figure 4.14 shows Statistical Analysis of RMSE where'∗'

designates significant differences with a level of $p < 0.05$ and '∗∗' directs significant differences with a level of $p < 0.01$.

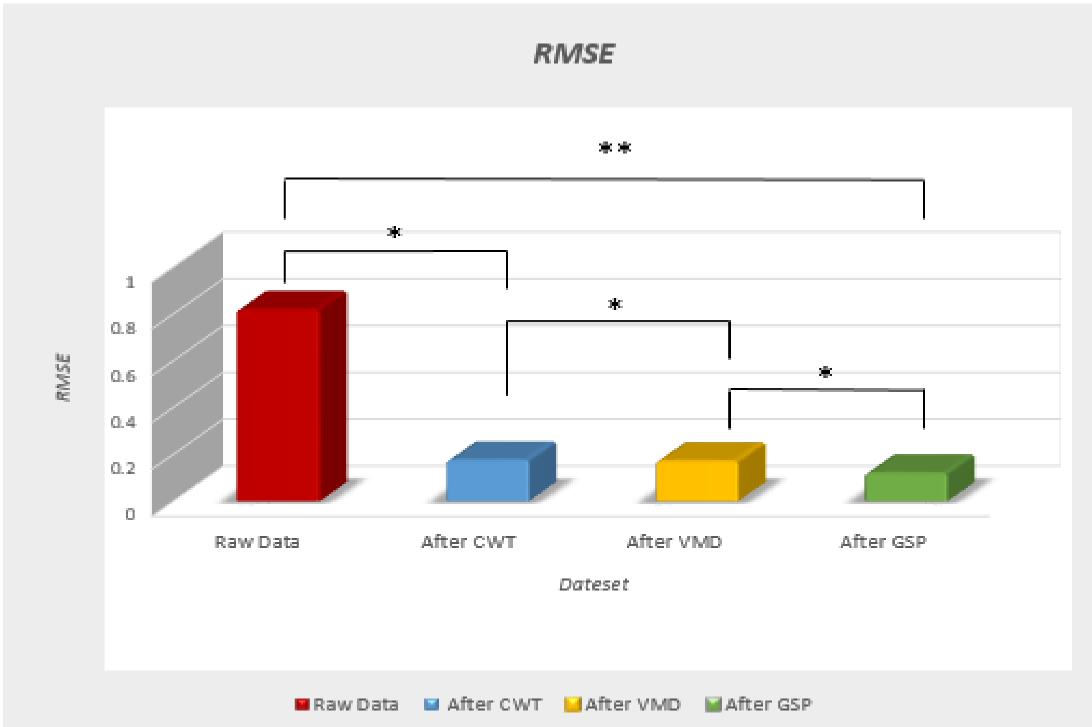

Figure 4.14: RMSE Results '∗' shows significant differences with a level of $p < 0.05$ and '∗∗' indicates significant differences with a level of $p < 0.01$

Remarkably, "Variational Mode Decomposition" and "Graph Signal Processing" yielded better results than "Continuous Wavelet Transform" in removing noise from EMG signals, regardless of the noise level.

CHAPTER 5: DISCUSSION AND CONCLUSION

The study aimed to address the existing gap in literature, particularly focusing on the underexplored areas of EMG signal processing. While prior research predominantly concentrated on various signals using “Continuous Wavelet Transformation (CWT)” and “Variational Mode Decomposition (VMD)”, there was a noticeable lack of attention given to EMG signals when employing VMD with IMFs above 12. Additionally, although “Graph Signal Processing (GSP)” had been previously explored in signals such as EEG, its application to EMG signals remained notably understudied. To fill this void, we utilized VMD with 16 IMFs and applied GSP on EMG signals, resulting in improved outcomes.

A comprehensive comparative analysis was showed to assess the performance of the offered VMD and GSP algorithms in comparison to the established denoising method, CWT. This evaluation was centered on essential performance metrics of as “Signal to Noise Ratio” and “Root Mean Square Error”. The obtained results were validated by comparing the Signal to Noise Ratio and Root Mean Square Error of all four groups (raw data, CWT-processed data, VMD-processed data, and GSP-processed data) collectively using the One-Way ANOVA test. Remarkably, “Variational Mode Decomposition” and “Graph Signal Processing” consistently outperformed “Continuous Wavelet Transform” in removing noise from EMG signals across all noise levels.

Beyond methodological investigation and comparative analysis, the research aimed to contribute to the broader field of EMG signal processing. By enhancing the accuracy of clinical diagnoses, facilitating more precise biomedical research, and broadening the applications relying on the fidelity of EMG data, we aimed to progress the state of the art in this area.

All the results demonstrated that denoising has been done effectively as the recreated signal maintains the attributes of the raw signal. The reliability of the projected method by comparison all the techniques is proved by an increase in SNR as depicted in Figure 4.11 and a decrease in RMSE as shown in Figure 4.12.

However, the statistical testing determined the significant differences. As Figure 4.13 illustrates the results of the SNR, revealing significant differences of $p < 0.05$ among the raw data and CWT data, between CWT data and VMD data, and amongst VMD data and GSP data. Additionally, there are significant differences of $p < 0.01$ observed among all four groups, including raw data, CWT data, VMD data, and GSP data, collectively.

Similarly, the results for RMSE, as depicted in Figure 4.14, shows significant differences of $p < 0.5$ between the raw data and CWT-processed data, between CWT data and VMD data, and between VMD data and GSP data. Furthermore, there are significant differences of $p < 0.01$ among all four groups, including raw data, CWT-processed data, VMD-processed data, and GSP-processed data, collectively.

Through a multifaceted exploration, this study demonstrated the efficiency of "Variational Mode Decomposition" and "Graph Signal Processing" in improving EMG signal quality. By addressing the identified literature gap, conducting a comprehensive comparative analysis, and advancing EMG signal processing techniques, the research has laid a foundation for more reliable and insightful analysis of muscle activity and neuromuscular functions.

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