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Attention-Based Noise Reduction for Surface-Electromyography: A Novel Method for Enhanced Signal Quality in Clinical Diagnostics

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ABSTRACT— Surface Electromyography (Semg) Signals Are An Important Tool For Monitoring And Measuring Muscle Activity, Rehabilitation, Human-Computer Interaction (Hci) Systems, And Diagnosis Of Neurological Disorders. However, These Signals Are Often Affected By Various Sources Of Noise And Disturbance During Recording, Which Reduces The Integrity, Quality Of The Signal And Increases The Error Of Diagnostic Applications. Traditional Denoising Techniques, Such As Filters And Decomposition Methods, Often Fail To Handle The Non-Stationary Nature Of Semg, Resulting In A Loss Of Essential Information. This Study Introduces A Novel Denoising Technique, Generalized Successive Variable Mode Decomposition (Gsvmd), Which Integrates Successive Variational Mode Decomposition (Svmd), Soft Interval Thresholding (Sit), And Attention Mechanisms To Enhance Signal Clarity. The Proposed Method Was Evaluated Using Data From Twelve Healthy Subjects And Twenty-Four Stroke Patients, Demonstrating A Higher Signal-To-Noise Ratio (Snr) And Lower R-Squared (R^2) Values Compared To Conventional Denoising Techniques. Moreover, Statistical Tests, Including Paired T-Tests And Analysis Of Variance (Anova), Confirmed The Significant Enhancements Achieved By The Method, With P-Values Less Than 0.001 And $P < 0.05$, Thereby Validating Its Effectiveness And Robustness. Gsvmd Utilizes Data Mining To Dynamically Adjust Signal Components, Ensuring Robust Denoising Without Losing Critical Information. Its Reduced Dependency On Hyperparameters And High Computational Efficiency Make It Suitable For Real-Time Clinical Applications, Providing Enhanced Accuracy And Reliability For Neuromuscular Assessments.

Keywords— Attention Mechanism, Clinical Diagnostics, Data Mining, Surface Electromyography, Successive Variational Mode Decomposition.

Introduction

surface Electromyography (sEMG) is a widely used non-invasive technique for measuring the electrical activity of muscles during voluntary and involuntary movements. By capturing the summation of electrical signals from multiple active motor units, sEMG provides valuable insights into neuromuscular activity and is extensively applied in various domains, including the diagnosis of neuromuscular disorders, rehabilitation engineering, and Human-Computer Interaction (HCI) systems [1, 2]. Despite its widespread use, sEMG signals are highly susceptible to a range of noise sources, such as powerline interference, electronic equipment noise, motion artifacts, baseline shifts, and physiological interferences like Electrocardiogram (ECG) signals. These unwanted disturbances can obscure true muscle activation patterns and degrade signal quality, thereby complicating analysis and interpretation in clinical and engineering applications [3]. To address these challenges, various denoising techniques have been developed over the past decades, each targeting the unique characteristics of sEMG signals. Traditional methods, such as Impulse Response (IR) filters, including notch and band-pass filters, have been effective in mitigating specific noise frequencies like powerline interference [4] . However, these approaches may inadvertently suppress important signal components when the noise spectrum overlaps with the frequency band of interest, thereby reducing the diagnostic accuracy. More sophisticated methods, such as adaptive filtering techniques like Kalman and Wiener filters, offer the ability to dynamically adapt to changing noise conditions. While these methods provide improved noise attenuation, they are computationally intensive and highly sensitive to parameter selection, limiting their practicality in real-time applications [5]. Principal Component Analysis (PCA) and its extension, MultiScale PCA (MSPCA), are effective in eliminating noise but

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are computationally demanding and may struggle to capture subtle signal variations. Similarly, methods like Multiple Signal Classification (MUSIC), Single Spectrum Analysis (SSA), and Blind Source Separation (BSS) show potential but encounter significant challenges in real-time implementation and maintaining signal fidelity [6]. Signal decomposition techniques, such as Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and their variants, have gained prominence due to their ability to handle the non-stationary and nonlinear nature of sEMG signals [7, 8]. Although these methods demonstrate superior noise separation capabilities, they often suffer from challenges such as mode mixing and sensitivity to noise variations, requiring careful parameter tuning to achieve optimal performance [9]. To address these limitations, Variational Mode Decomposition (VMD) was introduced as an enhanced method for isolating signal components into distinct frequency bands, thereby providing better noise separation [10]. However, VMD is computationally demanding and requires a pre-defined number of modes, which can hinder its application in dynamic environments. Sparse representation techniques and dictionary learning methods, such as Bayesian Sparse Dictionary Learning (BSDL), have also demonstrated potential in retaining critical signal features while efficiently modeling noise, yet they remain limited by high computational costs and implementation complexity [11]. Furthermore, generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) have been explored for sEMG signal reconstruction, although their performance in generalizing to unseen data remains suboptimal [12, 13].

Despite significant advancements, the development of a universally robust and efficient method for real-time sEMG denoising, particularly for clinical applications, remains a challenging problem. This study aims to provide a comprehensive evaluation of existing denoising methods, focusing on their strengths, limitations, and suitability for various sEMG applications. Furthermore, we introduce a novel denoising approach, Generalized Successive Variable Mode Decomposition (GSVMD), which integrates adaptive mode decomposition with attention mechanisms to achieve superior noise separation and signal preservation. Through a detailed comparative analysis, this work seeks to establish GSVMD as a viable alternative for enhancing the quality and reliability of sEMG signals, thereby enabling more accurate neuromuscular assessments in clinical diagnostics and functional evaluations.

Methods and Materials

Experimental Setup and Data Collection

This study involved two groups of participants: twelve healthy individuals (8 men, 4 women, aged 24–70 years) and twenty-four patients (11 men, 13 women, aged 32–83 years) diagnosed with Arterial Ischemic Stroke (AIS) of the Middle Cerebral Artery (MCA). The healthy participants were recruited from the Islamic Azad University of Mashhad, while stroke patients were selected in collaboration with the neurology department of Bou Ali Sina Hospital. The experimental setup followed ethical guidelines, and all participants provided informed consent. The experimental setup is shown in Fig. 1.

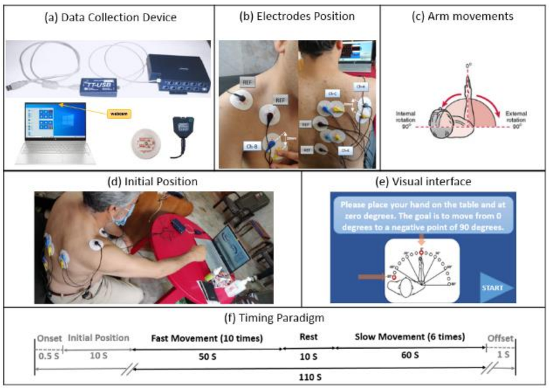

Fig. 1. a) The instrumentation for data collection. b) Positioning of electrodes on PD, PM, MT, and LT muscles. c) Illustration of arm movements. d) Initial setup posture of participants for recording. e) Visual interface utilized. f) Timing paradigm employed [14].

GSVMD Algorithm Implementation

Based on Fig. 2, The raw sEMG signals are often contaminated by various types of noise, including power line interference, motion artifacts, and baseline drift. To ensure that the subsequent analysis focuses on the true muscle activity, the signals undergo several preprocessing steps:

1. *Filtering:* Bandpass filtering is applied to retain the frequency components most relevant to sEMG signals, typically between 20 and 500 Hz. This step removes low-frequency noise and high-frequency artifacts that are not related to muscle activity.
2. *Normalization:* The amplitude of sEMG signals can vary significantly between participants due to differences in skin

impedance and muscle mass. Normalization is used to scale the signals to a consistent range, facilitating comparison across different trials and participants.

3. *Segmentation:* Each gesture trial is segmented into smaller time windows. This step is critical for analyzing the temporal dynamics of the signals and for training machine learning models that rely on time-series data.

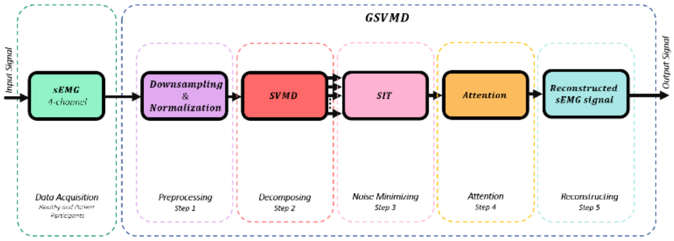

Fig. 2. The overall diagram shows the GSVMD method in simple blocks.

The GSVMD is designed to decompose the sEMG signal into multiple sub-components or modes, each representing a distinct frequency band within the original signal. Unlike traditional decomposition methods such as EMD, GSVMD incorporates sparsity constraints and variational optimization to enhance the separation of signal components and reduce noise. The SVMD method first decomposes the sEMG signal into narrow-band components, known as Intrinsic Mode Functions (IMFs). Each IMF captures a unique frequency component of the original signal, allowing for a detailed analysis of the signal's structure. After decomposing the signal, the SIT method is applied to each IMF to suppress noise and enhance the meaningful signal content. This process involves setting a threshold that dynamically adjusts to the noise level in each IMF, ensuring that only significant signal features are preserved. An attention mechanism is incorporated to assign weights to the IMFs based on their importance. Fig. 3 shows the block diagram of the proposed attention mechanism. This mechanism evaluates each IMF's relevance to the original sEMG signal using criteria such as amplitude, frequency content, and correlation. By assigning higher weights to the most relevant IMFs, the algorithm can focus on the components that carry the most critical information. The final step involves reconstructing the denoised sEMG signal by combining the weighted IMFs. The result is a clean version of the original signal, with most of the noise removed while retaining the essential features.

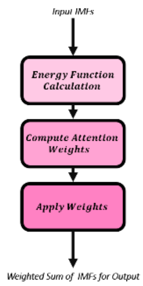

Fig. 3. The general block diagram of the proposed attention mechanism.

Results

This study evaluates the effectiveness of the proposed GSVMD method for sEMG signal denoising against traditional methods, including Band-Pass Filter combined with Notch Filter (BPF-NF), WT, EMD, VMD, and VMD-SIT. The experiments were conducted on a system equipped with an Intel i3-1215U processor, 16GB of RAM, and MATLAB R2023a, operating on a 64-bit version of Windows 10. The Signal-to-Noise Ratio (SNR) and R-square (R^2) were used to measure the performance of each method. Higher SNR values indicate better denoising capability, whereas lower R^2 values suggest reduced noise impact on signal quality. The computational complexity of each method was assessed by measuring the time required to process a 192448-sample segment of sEMG data, corresponding to a duration of approximately 187.9375 seconds. This ensures that the results are hardware-dependent and reflect the processing efficiency under the defined conditions. The statistical significance of performance differences between the GSVMD and other methods was established using paired t-tests and Analysis of Variance (ANOVA) followed by Tukey's Honestly Significant Difference (HSD) test. The raw sEMG signals from healthy and stroke participants were collected and pre-processed. Downsampling and normalization were key steps in this process, resulting in a standardized dataset for further analysis. The GSVMD method was then applied to decompose the signals into multiple modes (Mode 1 to Mode 12). This decomposition enabled effective noise removal and facilitated the evaluation of computational complexity and accuracy.

In Fig. 4 and Fig. 5, the GSVMD method's decomposition process for a healthy participant is depicted, showing distinct frequency spectra for each mode.

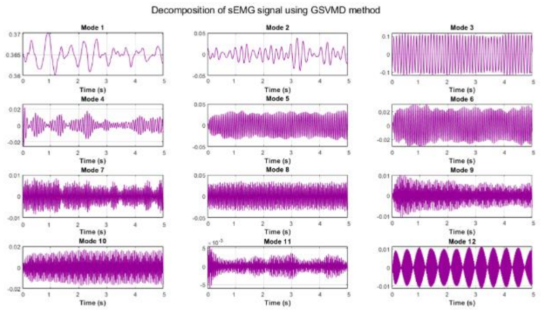

Fig. 4. The decomposition of the sEMG signal using the GSVMD method to give Mode 1~ Mode 12 for channel 1 of healthy participant (AZ).

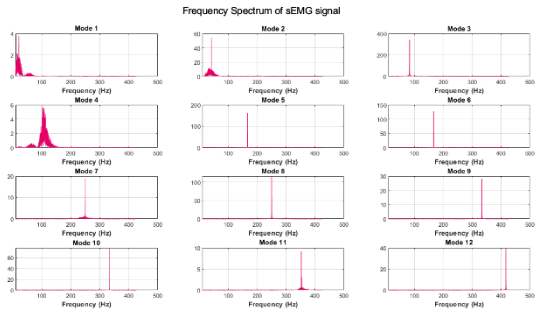

Fig. 5. The frequency spectrum of Mode 1~ Mode 12 for channel 1 of healthy participant (AZ).

The GSVMD method's denoising performance was compared to BPF-NF, WT, EMD, VMD, and VMD-SIT using both healthy and stroke participant data, as shown in Fig. 6 and Fig. 7, and detailed in TABLE I and TABLE II Results indicate that GSVMD consistently produced higher SNR values and lower R^2 values, confirming its superior noise removal capability. Although the BPF-NF method was faster, it compromised signal integrity by removing vital information in the 50-60 Hz frequency range, where muscle activities and firing rates are often observed [15].

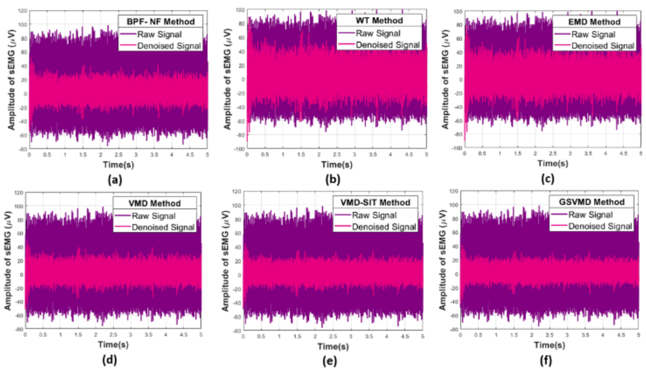

Fig. 6. The sEMG signal healthy participants denoising using: (a) BPF-NF method, (b) WT method, (c) EMD method, (d) VMD method, (e) VMD-SIT method, (f) GSVMD method (for channel 1 of healthy participant (AZ)).

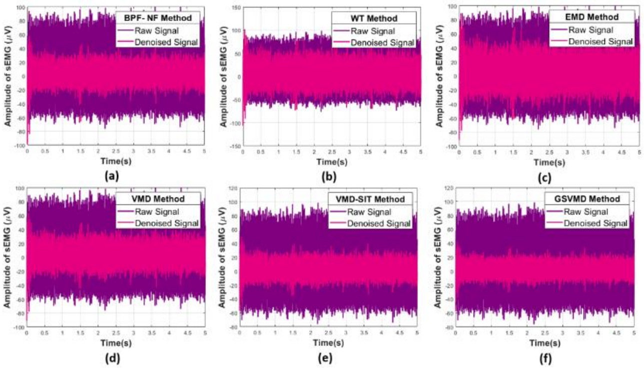

Fig. 7. The sEMG signal patient participants denoising using: (a) BPF-NF method, (b) WT method, (c) EMD method, (d) VMD method, (e) VMD-SIT method, (f) GSVMD method (for channel 1 of patient participant (ST)).

TABLE I. The statistical results of performance evaluation of different methods for healthy participants.

Method	SNR *(mean±SD)*	R-Square *(mean±SD)*	Computation Time *(mean±SD)*	Paired t-test *(SNR p-value)*	Paired t-test *(R^2) p-value)*
BPF-NF	5.6688 ± 0.0901	0.5233 ± 0.0365	0.0027 ± 0.031	< 0.001	< 0.001
WT	3.6329 ± 0.0994	0.9591 ± 0.0256	0.0084 ± 0.056	< 0.001	< 0.001
EMD	3.8456 ± 0.0597	0.8047 ± 0.0554	0.0252 ± 0.054	< 0.001	< 0.001
VMD	5.6114 ± 0.0842	0.5122 ± 0.0450	0.0296 ± 0.051	< 0.001	< 0.001
VMD-SIT	5.9023 ± 0.0884	0.5066 ± 0.0415	0.0328 ± 0.022	< 0.001	< 0.001
GSVMD	6.1457 ± 0.0566	0.4885 ± 0.0213	0.0145 ± 0.007	N/A	N/A

a. N/A: Not Applicated.

TABLE II. The statistical results of performance evaluation of different methods for PATIENT participants.

Method	SNR *(mean±SD)*	R-Square *(mean±SD)*	Computation Time *(mean±SD)*	Paired t-test *(SNR p-value)*	Paired t-test *(R^2) p-value)*
BPF-NF	5.3842 ± 0.0868	0.5589 ± 0.0287	0.0027 ± 0.055	< 0.001	< 0.001
WT	3.4078 ± 0.0755	0.9644 ± 0.0266	0.0085 ± 0.023	< 0.001	< 0.001
EMD	3.3935 ± 0.0748	0.8492 ± 0.0331	0.0253 ± 0.065	< 0.001	< 0.001
VMD	5.3227 ± 0.0551	0.5421 ± 0.0468	0.0298 ± 0.021	< 0.001	< 0.001
VMD-SIT	5.6188 ± 0.0698	0.5273 ± 0.0237	0.0331 ± 0.029	< 0.001	< 0.001
GSVMD	5.8772 ± 0.0755	0.5017 ± 0.0098	0.0146 ± 0.011	N/A	N/A

a. N/A: Not Applicated.

Due to the inherent variability and non-stationarity of sEMG signals, multivariate methods are less effective in addressing channel-specific noise profiles. Therefore, univariate methods like GSVMD are more suitable for sEMG denoising, as they can better handle signal artifacts and variability on a per-channel basis. Additionally, univariate processing reduces computational overhead, enhancing real-time application feasibility.

Discussion

This research emphasizes the importance of clean sEMG signals in clinical diagnostics and Muscle Computer Interface (MCI) systems, highlighting the need for effective denoising techniques to maintain signal integrity. Various types of noise, such as white Gaussian noise, colored noises, and power line interference, can hinder accurate sEMG interpretation, especially in clinical and rehabilitation settings. To address this, the study introduces a novel method called GSVMD and compares it to five traditional denoising methods (BPF-NF, WT, EMD, VMD, and VMD-SIT). GSVMD demonstrates superior noise removal and signal preservation, particularly for stroke patients, achieving higher SNR and lower R2 values. It also exhibits better computational efficiency, making it ideal for real-time applications. Unlike VMD and VMD-SIT, which require predefined mode numbers, GSVMD adaptively decomposes signals without prior knowledge, making it more versatile. Although GSVMD performs well, it has limitations, such as difficulty eliminating certain noise types (e.g., white and colors noise) and higher standard deviations in some tests due to limited iterations. Future research should focus on integrating preprocessing steps, exploring hardware solutions, and optimizing GSVMD for real-time applications, potentially enhancing its utility in clinical diagnostics and rehabilitation contexts.

Conclusion

This study introduces the GSVMD as an optimal denoising method for sEMG signals, emphasizing its effectiveness in preserving data integrity and crucial information for clinical applications. The proposed GSVMD method was evaluated against five traditional techniques (BPF-NF, WT, EMD, VMD, and VMD-SIT) and demonstrated superior noise removal capabilities, higher SNR, and lower R2 values, particularly for stroke patients. Statistical analyses, including paired t-tests and ANOVA, confirmed GSVMD's significant improvement over other methods ($p < 0.001$). The technique ensures smooth and continuous denoised signals, making it ideal for disease diagnosis, rehabilitation system development, and muscle synergy analysis. Unlike methods like BPF-NF, which may remove essential information, GSVMD maintains signal fidelity while efficiently removing noise. This makes it particularly valuable for clinical diagnostics, where accurate and timely interpretation of muscle activity is crucial for effective treatment planning and neuromuscular rehabilitation. Overall, GSVMD offers a reliable solution for enhancing the quality and usability of sEMG data in both research and clinical settings.

Ethical Approval

This study was approved by the Ethics Committee of Mazandaran University of Medical Sciences (IR.MAZUMS.REC.1398.902) and registered with the Iranian Registry of Clinical Trials (IRCT20200914048720N1). Written informed consent was obtained from all participants before their involvement in the research.

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