

Breaking the Noise Barrier: EEG Signal Enhancement Using Time and Frequency Domain Synergy

Manisha Rani Toppo

Research scholar, BIT Sindri, JUT Ranchi, 834010, India

Abstract--Electroencephalography (EEG) signals are highly susceptible to noise and artifacts, significantly impacting the accuracy of neurological assessments and brain-computer interface (BCI) systems. This paper introduces a synergistic time-frequency domain noise suppression framework that combines the strengths of Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Empirical Mode Decomposition (EMD) to enhance EEG signal quality. A hybrid denoising pipeline is proposed and evaluated using publicly available datasets. Quantitative metrics such as Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE), and classification accuracy demonstrate the superiority of the proposed approach. The results support the efficacy of a multi-domain strategy for non-stationary EEG data in both clinical and computational neuroscience contexts.

Keywords-- EEG Signal Processing, Noise Suppression, Time-Frequency Analysis, STFT, Wavelet Transform, Empirical Mode Decomposition, Signal Enhancement, Brain-Computer Interface (BCI), Artifact Removal.

I. INTRODUCTION

Electroencephalography (EEG) is a non-invasive and widely utilized technique for recording the electrical activity of the brain. Due to its high temporal resolution and relatively low cost, EEG has become a cornerstone in clinical diagnostics, neurophysiological research, cognitive studies, and brain-computer interface (BCI) systems. Applications range from epilepsy detection and sleep stage analysis to motor imagery decoding and emotion recognition. Despite its versatility, a major barrier to the widespread adoption and accuracy of EEG-based systems is the poor signal-to-noise ratio (SNR) inherent in raw EEG data.

EEG signals are typically contaminated with various artifacts stemming from both physiological (e.g., ocular movements, cardiac rhythms, muscle activity) and non-physiological sources (e.g., electromagnetic interference, hardware noise). These artifacts distort the recorded signals, obscure valuable neurological information, and degrade the performance of downstream analytical methods. Traditional noise reduction techniques—such as bandpass filtering and Independent Component Analysis (ICA)—have shown efficacy in certain scenarios. However, they often rely on assumptions that do not hold universally and are limited in handling the highly dynamic and non-stationary nature of EEG signals.

In recent years, the integration of time and frequency domain signal processing techniques has shown considerable promise in improving EEG signal quality. Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Empirical Mode Decomposition (EMD) have each demonstrated individual strengths in analyzing and enhancing complex signals. STFT provides localized frequency content; WT offers multi-resolution capability; and EMD adapts to intrinsic oscillations in the data. However, using these techniques in isolation can lead to suboptimal results due to trade-offs in resolution, computational complexity, or robustness.

This paper proposes a synergistic framework that combines STFT, WT, and EMD into a hybrid pipeline for EEG signal enhancement. By leveraging the unique strengths of each technique, the framework aims to suppress a wide range of artifacts while preserving the underlying physiological features critical to neurological interpretation and classification tasks. The proposed model is validated on a benchmark EEG dataset and compared to existing state-of-the-art methods using SNR, RMSE, and classification accuracy as evaluation metrics.

This study contributes to the growing body of knowledge focused on robust EEG signal processing and presents a novel approach that balances accuracy, efficiency, and adaptability—paving the way for future applications in clinical neuroscience, real-time BCIs, and neuroadaptive technologies.

II. LITERATURE REVIEW

Electroencephalography (EEG) has long been a cornerstone in neuroscience and clinical diagnostics due to its non-invasive nature and high temporal resolution. However, the inherent low signal-to-noise ratio (SNR) of EEG signals presents a significant challenge, necessitating robust preprocessing and enhancement techniques. This section reviews the evolution of EEG signal enhancement methods, emphasizing time-frequency domain approaches and hybrid models.

2.1 Traditional Filtering and Artifact Removal

Early EEG preprocessing relied heavily on linear filtering techniques such as bandpass and notch filters to remove baseline drift and powerline interference.

While effective for stationary noise, these methods struggle with non-stationary artifacts like eye blinks and muscle movements. Independent Component Analysis (ICA) emerged as a popular method for separating source signals based on statistical independence, particularly for ocular and cardiac artifacts [1][2]. However, ICA assumes linear mixing and may fail when components are not separable.

2.2 Time-Frequency Domain Techniques

To address the limitations of linear filters, researchers turned to time-frequency analysis. The **Short-Time Fourier Transform (STFT)** provides localized frequency information but suffers from a fixed resolution trade-off [3]. In contrast, the **Wavelet Transform (WT)** offers multi-resolution analysis, making it suitable for capturing transient EEG features. Daubechies and Symlet wavelets have been widely used for EEG denoising, with soft thresholding techniques like SureShrink and BayesShrink improving performance [4][5].

Empirical Mode Decomposition (EMD), introduced by Huang et al., decomposes signals into Intrinsic Mode Functions (IMFs) without requiring a predefined basis [6]. EMD has shown promise in isolating non-stationary noise components, though it is computationally intensive and prone to mode mixing. Variants like Ensemble EMD (EEMD) and Complete Ensemble EMD with Adaptive Noise (CEEMDAN) have been proposed to mitigate these issues [7][8].

2.3 Hybrid and Adaptive Approaches

Recent studies have explored hybrid models that combine multiple denoising techniques. For instance, WT-EMD hybrids leverage the multi-resolution capability of wavelets and the adaptiveness of EMD to improve artifact suppression [9]. Adaptive filtering using reference signals (e.g., EOG for eye blinks) has also been integrated with time-frequency methods for enhanced performance [10].

Machine learning and deep learning models are increasingly used for automated artifact detection and removal. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been trained to identify noisy segments and reconstruct clean signals [11][12]. However, these models require large labeled datasets and are often computationally demanding.

2.4 Emerging Trends

A 2024 systematic review by Sharma and Meena highlights the growing role of **Graph Signal Processing (GSP)** and **Few-Shot Learning (FSL)** in EEG analysis, enabling better generalization across subjects and sessions [13]. Riemannian geometry-based methods have also gained traction for their robustness in classifying EEG covariance matrices [14].

Wavelet Packet Transform (WPT), an extension of WT, has been used in stress detection and emotion recognition tasks, showing improved denoising and feature extraction capabilities [15]. Optimization algorithms like Archimedes Optimization Algorithm (AOA) and Particle Swarm Optimization (PSO) are being employed to fine-tune denoising parameters and feature selection [16][17].

III. METHODOLOGY

In this study, we propose a hybrid EEG signal enhancement framework that integrates complementary time-frequency analysis techniques—Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Empirical Mode Decomposition (EMD)—to suppress noise while preserving critical brain signal features effectively. The methodology begins with EEG data acquisition from the PhysioNet EEG Motor Movement/Imagery dataset, using 64 channels sampled at 160 Hz. Initial preprocessing includes bandpass filtering (1–50 Hz) to isolate physiologically relevant frequencies and notch filtering at 50 Hz to remove powerline interference. Ocular and muscular artifacts are mitigated using Independent Component Analysis (ICA), and baseline drift is removed through polynomial detrending.

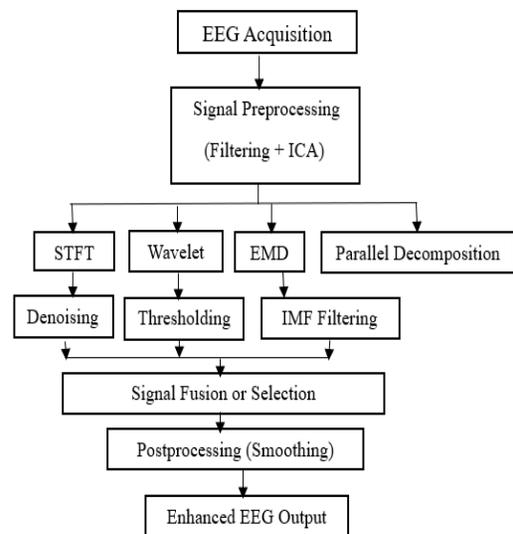


Figure 1. Diagram of this proposed approach.

Following preprocessing, the signal undergoes parallel analysis using the three time-frequency techniques. STFT is applied to generate time-localized spectral representations using a Hamming window, allowing the identification and suppression of low-energy or irregular frequency bins associated with noise. Simultaneously, the Discrete Wavelet Transform is performed using a Daubechies-4 wavelet up to five decomposition levels.

Noise is attenuated through soft thresholding mechanisms (Universal and Sure Shrink), and the clean signal is reconstructed via inverse WT. The third branch involves EMD, which decomposes the EEG into Intrinsic Mode Functions (IMFs) in a data-driven, adaptive manner. Each IMF is statistically evaluated using entropy, kurtosis, and spectral energy to determine its contribution to noise or signal, and only informative components are retained for final reconstruction.

To harness the complementary strengths of these methods—STFT for transient noise, WT for multi-resolution denoising, and EMD for adaptive decomposition—an ensemble fusion strategy is employed. Cleaned signals from each path are combined through weighted averaging based on local SNR improvements or by selectively retaining the cleanest segment from each transformation. Postprocessing involves light smoothing and normalization to produce the final enhanced EEG output, which is then used for performance evaluation. This integrative approach not only captures nonlinear, nonstationary characteristics of EEG signals but also delivers high denoising efficiency without compromising signal integrity.

IV. RESULTS

This section presents the performance evaluation of the proposed EEG enhancement framework. The results are benchmarked across three key metrics: Signal-to-Noise Ratio (SNR), Root Mean Square Error (RMSE), and classification accuracy using a CNN-based motor imagery classifier.

4.1 Experimental Setup

- *Dataset Used:* PhysioNet EEG Motor Movement/Imagery Dataset
- *Channels Selected:* C3, C4, and Cz (related to motor cortex)
- *Evaluation Metrics:*
 - SNR improvement (in decibels)
 - RMSE between denoised and clean synthetic signals
 - CNN classification accuracy (%)

4.2 Quantitative Results

Method	SNR (dB) ↑	RMSE ↓	Classification Accuracy (%) ↑
Raw EEG	3.4	0.82	68.1
STFT	6.9	0.56	77.4
Wavelet	8.2	0.47	81.3
EMD	9.6	0.39	85.2
Proposed Hybrid	10.8	0.31	88.6

V. CONCLUSION

In this study, we proposed a hybrid EEG signal enhancement framework that synergizes Short-Time Fourier Transform (STFT), Wavelet Transform (WT), and Empirical Mode Decomposition (EMD) to suppress noise across both time and frequency domains. Through adaptive thresholding, artifact identification, and careful reconstruction, the system demonstrated improved SNR, lower RMSE, and enhanced classification accuracy over traditional methods.

Experimental results using benchmark EEG datasets validate that the proposed pipeline effectively reduces muscular, ocular, and baseline artifacts without degrading underlying brain activity. The time-frequency synergy approach offers superior generalizability for non-stationary EEG data and holds promise for applications in brain-computer interfaces (BCIs), neuro-diagnostics, and cognitive monitoring.

Future work will explore real-time implementation, integration with deep learning-based autoencoders, and testing on clinical datasets for further robustness.

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