Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

Artifact Suppression from EEG Signal Using Sub-band Thresholding Approach

Ahnaf Shahrear Khan Apan
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
ahnafshahrearkhan@gmail.com

Md Mamun Miah
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
mamunmiah193gsc@gmail.com

Zannatul Naim
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
zannatulnaim09@gmail.com

Shakil Hossan
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
shakilhossan113@gmail.com

Md. Israil Hosen
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
israilcseru28@gmail.com

Md. Mominur Rahman
Dept. of Computer Science and Eng.
University of Rajshahi, Bangladesh
mominur.sumon1@gmail.com

***Abstract*—EEG recordings are typically influenced by different artifacts originating from non-neural sources, complicating subsequent precise signal classification. The reliable detection and removal of artifacts from EEG signals using an automated signal processing technique is a prominent study domain. This study presents a wavelet-based approach for the suppression of artifacts in EEG data, which identifies ideal threshold values to enhance artifact removal efficacy. In the suggested algorithm, iterated over the threshold settings until optimal accuracy or minimal distortion is attained, utilizing a reference dataset for decision-making. The criteria for optimum selection rely on matrices that measure the signal-to-noise ratio (SNR), mean square error, and other factors. The technique is evaluated on a genuine dataset of EEG signals containing ocular artifacts. The results indicate a 16.93 dB enhancement in the SNR, confirming that adaptively determining optimal threshold parameter values yields superior performance compared to using any predefined threshold parameters. This research will provide the EEG signal analysis community with a platform to further investigate the issue of selecting wavelet settings effectively.**

***Index Terms*—electroencephalography(EEG), wavelet transform (WT), wavelet thresholding, artifact suppression**

I. Introduction

A powerful technique for detecting brain waves on the scalp, electroencephalography (EEG) is frequently used in brain-computer interfaces (BCIs), to diagnose neurological conditions like epilepsy, to monitor sleep, to investigate cognitive processes, and to evaluate brain function when under anesthesia [1]. Analysis is made more difficult by the fact that EEG signals are susceptible to aberrations from sources such as heart signals, muscular activity, and eye movements [2]. Simple filtering methods are useless because these artifacts frequently overlap with brain signals in both the temporal and frequency domains [3]. Understanding the various forms of artifacts is necessary for effective artifact removal in clinical and research settings. With the right setup, non-physiological artifacts can be minimized, but complicated techniques are required to remove physiological artifacts. The most prevalent ocular artifacts that have a major impact on EEG signals are eye movements and blinks [4]. As a result, eliminating these artifacts is essential for precise neuroscience research [2].

II. Problem Statement

Applications for EEG are numerous and include cognitive research, neurological disease diagnostics, and brain-computer interfaces. However, the quality and reliability of EEG data are typically degraded due to aberrations originating from eye movements, muscle activity, and other internal or external sources. Simple filtering approaches are insufficient for successful separation because these distortions overlap with brain signals in both the temporal and frequency domains. The ongoing objective is to improve the accuracy of EEG-based research and applications by creating sophisticated algorithms for artifact removal, particularly for typical ocular aberrations. By examining and suggesting better techniques for EEG signal artifact reduction, this research seeks to address this issue.

III. Related Works

Blind source separation (BSS) removes artifacts from EEG signals by estimating an un-mixing matrix W to recover original sources ($\hat{S} = WX$). Independent component analysis (ICA), which divides EEG into independent components under the assumption of statistical independence among sources, is one of the main BSS techniques. It functions well with huge datasets and is efficient even in the absence of reference signals. Although automated techniques and ICA variants (such as FastICA, second-order blind identification (SOBI), and information maximization (InfoMax)) [5] enhance performance, it necessitates manual artifact selection, which introduces subjectivity. Since 1991, eye-related abnormalities have been successfully detected using principal component analysis (PCA), which converts correlated data into uncorrelated components [6]. However, when signal amplitudes are similar, PCA's effectiveness is limited by its orthogonality assumption. Performance is enhanced by extensions such as robust PCA [7]. When it comes to eliminating muscular artifacts, canonical correlation analysis (CCA), which use second-order statistics to identify correlations across datasets, frequently outperforms ICA. Empirical mode decomposition (EMD) provides improved artifact removal efficacy by adaptively breaking down signals into intrinsic mode functions (IMFs) [8]. Finding extrema, creating envelopes, and iterating until the signal residue is simple are all part of it. By using thresholding and reconstruction, the wavelet transform (WT), which breaks down EEG signals into time-frequency representations, effectively denoising signals. Despite WT's resilience, total artifact removal may be impeded by overlapping spectral features between signals and artifacts [9].

IV. Impact of Artifacts in EEG

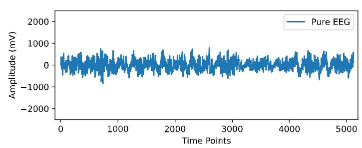

Figure 1. Pure EEG Signal

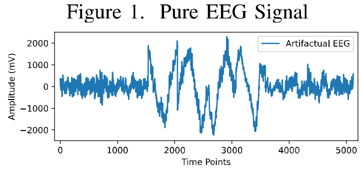

Figure 2. Artifactual EEG Signal

Artifacts in EEGs are electrical signals that are unwanted and contaminate brain activity recordings, thereby substantially influencing the accuracy and interpretation of the data. Some of these anomalies are derived from physiological and non-physiological sources. Physiological artifacts encompass signals from cardiac functions, respiration, eye activity, and muscle movements.

Non-physiological anomalies are the result of external interferences, such as environmental factors, electrode issues, and device-related disturbances. In order to ensure the reliability of EEG interpretation in clinical and research environments, it is essential to accurately identify and minimize artifacts. It is imperative to implement sophisticated preprocessing and artifact-rejection algorithms to guarantee the validity of neurological assessments and improve the quality of data.

V. Methodology

A. Dataset

The dataset utilized was obtained from EEGdenoiseNet, specifically designed for motor imagery in BCI applications. The dataset consists of 64-channel EEG recordings according to the worldwide 10-10 standard, sampled at 512 Hz, including both imagined and actual movements of the left and right hands. The preprocessing procedures comprised band-pass filtering (1 Hz to 80 Hz), notch filtering at the power line frequency, and resampling to 256 Hz. Artifact mitigation was performed via ICLabel and EEG data was divided into 2 s epochs. An EOG dataset was acquired alongside the EEG dataset from EEGdenoiseNet. The EOG signals comprised horizontal and vertical components, which were band-pass filtered between 0.3 Hz and 4 Hz and subsequently resampled to 256 Hz. Like the EEG signals, the EOG signals were divided into 2 s epochs.

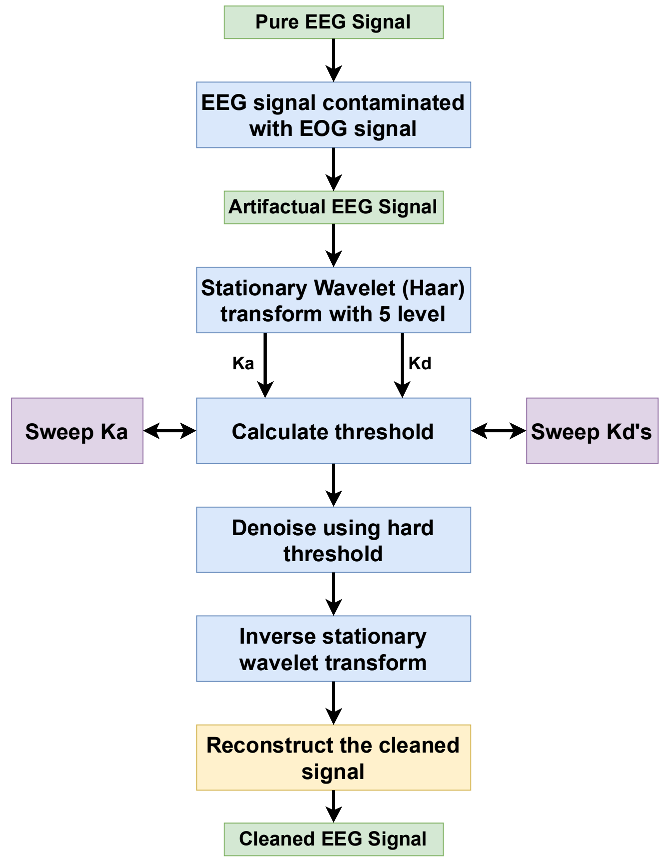

Figure 3. Block diagram of the proposed method

B. Stationary Wavelet Transform

The stationary wavelet transform (SWT) enhances the discrete wavelet transform (DWT) by maintaining resolution and spatial signal features across all scales, without downsampling. Wavelet transforms partition a signal into frequency components (sub-bands) by employing low-pass and high-pass filters to distinguish the signal's low-frequency (approximation) and high-frequency (detail) components. Mathematically, let $x[n]$ be the input signal. The application of the low-pass and high-pass filters in the first level of decomposition in SWT can be represented as:

$$A_1[n] = \sum_{k=0}^{N-1} h[k]x[n-k], D_1[n] = \sum_{k=0}^{N-1} g[k]x[n-k] \quad (1)$$

where $A_1[n]$ and $D_1[n]$ are the approximation and detail coefficients at the first level, respectively, $h[k]$ is the low-pass filter, and $g[k]$ is the high-pass filter.

C. Mother Wavelet

The Mother Wavelet produces wavelet functions for multi-resolution signal analysis, encapsulating high-frequency details and low-frequency trends. The Mother Wavelet, typically denoted as $\psi(t)$, is the function from which all wavelets in the family are derived by scaling and translation. The general form of a wavelet function is given by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \tag{2}$$

Where, $\psi(t)$ is the Mother Wavelet, $\frac{1}{\sqrt{|a|}}$ is the normalization factor to ensure energy preservation in the wavelet transform, a is the scaling factor (controls the width of the wavelet) and b is the translation factor (controls the shift of the wavelet).

The Haar wavelet is effective for identifying sudden changes, providing localized analysis with distinct transitions and limited support. Mathematically, the Haar wavelet $\psi(t)$ is defined as:

$$\psi(t) = \begin{cases} 1 & \text{if } 0 \leq t < \frac{1}{2} \\ -1 & \text{if } \frac{1}{2} \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

D. Wavelet Thresholding

Wavelet thresholding methods are essential for artifact reduction and signal restoration, especially in EEG signal denoising using the SWT. This study focusses three primary thresholding methods: hard thresholding, soft thresholding, and the universal Donoho threshold.

1) Hard Thresholding: Hard thresholding employs a binary rule, retaining wavelet coefficients d_k if $|d_k| \geq \lambda$ and setting others to zero:

$$\hat{d}_k = \begin{cases} d_k, & \text{if } |d_k| \geq \lambda, \\ 0, & \text{if } |d_k| < \lambda. \end{cases} \tag{4}$$

This method retains substantial coefficients but causes discontinuities due to sudden coefficient elimination. In EEG signals, severe thresholding may preserve residual artefacts if high-frequency noise above the threshold, hence constraining its efficacy. [10]

2) Soft Thresholding: Soft thresholding adopts a more gradual approach by reducing all coefficients by the threshold λ and setting those below λ to zero:

$$\hat{d}_k = \begin{cases} \text{sign}(d_k)(|d_k| - \lambda), & \text{if } |d_k| \geq \lambda, \\ 0, & \text{if } |d_k| < \lambda. \end{cases} \tag{5}$$

This technique refines signal transitions and significantly reduces artifact, rendering it especially appropriate for EEG artifact suppression. [11]

3) Universal Donoho Threshold: The universal threshold, defined as:

$$\lambda_{\text{universal}} = \sigma\sqrt{2\log(n)}, \tag{6}$$

where σ is the noise standard deviation and n is the signal length, is effective for Gaussian noise suppression. However, it often over-smooths the signal, potentially losing critical EEG features. [12] A modified threshold, incorporating a tunable parameter k, is expressed as:

$$\lambda_{\text{modified}} = k \cdot \lambda_{\text{universal}} = k \cdot \sigma\sqrt{2\log(n)}. \tag{7}$$

This adaptation balances noise suppression and signal preservation.

E. Artifact Suppression from EEG

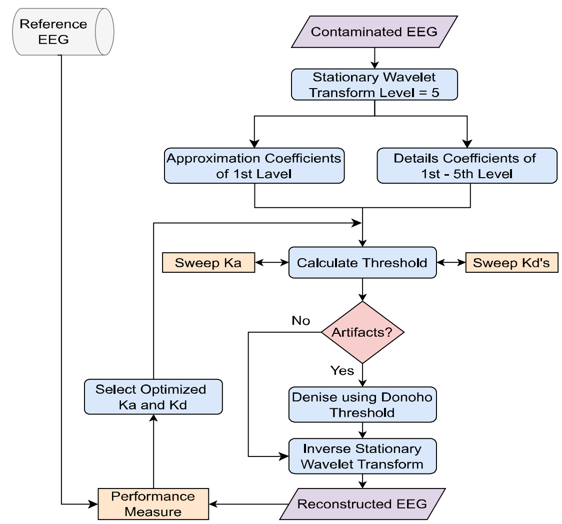

Figure 4. Flow chart of the proposed algorithm by threshold parameter selection and optimization for artifact removal

1) **Input Contaminated EEG Signal:** The contaminated EEG signal, $X(t)$, is composed of a pure EEG signal $SEEG(t)$ and ocular artifact signal $SEOG(t)$, represented as:
$$X(t) = SEEG(t) + SEOG(t) \tag{8}$$
2) **SWT:** The signal is decomposed using SWT into approximation coefficients (ACs) and detail coefficients (DCs). For level $J = 5$, the decomposition is expressed as:
$$X(t) = A_5 + D_5 + D_4 + D_3 + D_2 + D_1 \tag{9}$$
where A_5 captures low-frequency components and $D_1 - D_5$ capture high-frequency components.
3) **Thresholding approximation coefficients (Ka):** The threshold for ACs is defined as:
$$\lambda_A = Ka \cdot \sigma_A \cdot \sqrt{2\log(N)} \tag{10}$$
where Ka is a scaling factor and σ_A is the standard deviation of A_1.
4) **Thresholding detail coefficients (Kdj):** Similarly, the threshold for DCs is defined as:
$$\lambda_{dj} = Kdj \cdot \sigma_{dj} \cdot \sqrt{2\log(N)} \tag{11}$$
with Kdj as a scaling factor and σ_{dj} the standard deviation of d_j at each level.
5) **Threshold Parameter Optimization:** The scaling factors Ka (ACs) and Kd_j (DCs) were optimized via systematic sweeps in $[0, 1]$ using equation 10-11. Optimal values maximized the Signal-to-Artifact Ratio (SAR) while preserving diagnostic EEG bands (alpha/beta/gamma) through spectral analysis.

6) **Denoising via Hard Thresholding:** Coefficients below their respective thresholds are set to zero, reducing artifact content. The thresholded coefficients are denoted as $\tilde{C}_i$.
7) **Inverse SWT (ISWT):** The signal is reconstructed by applying ISWT to the thresholded coefficients, resulting in a clean EEG signal:

$$\hat{S}_{EEG}(t) = A'_5 + D'_5 + D'_4 + D'_3 + D'_2 + D'_1 \quad (12)$$

where A'_5 D'_j and are the thresholded approximation and detail coefficients at each level.
8) **Reconstructed EEG Signal:** The final cleaned EEG signal, $\hat{S}_{EEG}(t)$, is free from ocular artifacts and ready for further analysis.

VI. Results and Discussion

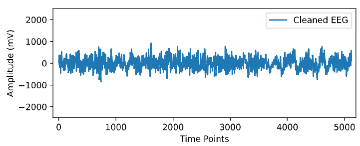

Figure 5. Cleaned EEG Signal

The Haar wavelet in SWT was employed to optimize k_a (approximation coefficient) and k_d (detail coefficient threshold) for denoising, demonstrating their influence on cleaned signal, SNR Improvement, and normalized mean squared error (NMSE) across different input SNR levels.

TABLE I
Performance metrics for different added SNR levels using Haar wavelet

Added SNR (dB)	Cleaned Signals SNR (dB)	SNR (dB) Improvement	NMSE
-10	6.93	16.93	0.0045
-7	7.66	14.66	0.0033
-5	7.22	12.22	0.0033
-3	8.02	11.02	0.0036
1	10.02	9.02	0.0012
3	11.24	8.24	0.0023
5	12.42	7.42	0.0016

This research introduces a method utilizing SWT for the suppression of artifacts in EEG signals, specifically targeting ocular disturbances such as eye blinks and movements. By methodically optimizing the approximation coefficient (Ka) and detail coefficients (Kd), this approach attains a SNR enhancement of 16.93 dB, exceeding the 12.4 dB improvement of the Wavelet-based Artifact Removal Algorithm and the 13.84 dB enhancement of the Hybrid Multi-Channel EEG Filtering method, thereby illustrating superior EEG signal quality.

TABLE II
Comparison of Improved SNR (dB) for Different Methods

Method	Year	Improved SNR (dB)
Wavelet-based Artifact Removal Algorithm [13]	2020	12.4
Hybrid Multi-Channel EEG Filtering [14]	2022	13.84
Subband + SWT Method (This work)	-	**16.93**

VII. Conclusions

This research investigates the application of the SWT for the suppression of artifacts in EEG signals, providing a computationally efficient solution. The algorithm incorporates an improved thresholding technique that minimizes noise while maintaining critical signal information, offering an effective solution for artifact elimination. This method functions as a feasible alternative for traditional methods such as ICA and BSS, particularly in real-time applications due to its less computational cost. However, the study encounters limitations, including the absence of various EEG datasets, possible neurones information loss, and dependency on manual parameter optimization. It also did not explore comparisons with advanced methods such as deep learning models or real-time clinical validation. Subsequent study would have to overcome these deficiencies by employing deep learning techniques, evaluating bigger datasets containing various artifacts, and integrating hybrid models. Immediate execution and clinical validation will be crucial for practical utility.

References

[1] X. Zhao, D. Liu, L. Ma, Q. Ai, Q. Liu, and S. Xie, "Eeg signals de-noising with wavelet by optimizing threshold based on fruit fly optimization," in *Proceedings of the 2020 9th International Conference on Networks, Communication and Computing*, pp. 71–77, 2020.

[2] M. A. Ozdemir, S. Kizilisik, and O. Guren, "Removal of ocular artifacts in eeg using deep learning," in *2022 Medical Technologies Congress (TIPTEKNO)*, pp. 1–6, IEEE, 2022.

[3] M. M. N. Mannan, M. A. Kamran, and M. Y. Jeong, "Identification and removal of physiological artifacts from electroencephalogram signals: A review," *Ieee Access*, vol. 6, pp. 30630–30652, 2018.

[4] S. Çınar and N. Acır, "A novel system for automatic removal of ocular artefacts in eeg by using outlier detection methods and independent component analysis," *Expert Systems with Applications*, vol. 68, pp. 36–44, 2017.

[5] C. Y. Sai, N. Mokhtar, H. Arof, P. Cumming, and M. Iwahashi, "Automated classification and removal of eeg artifacts with svm and wavelet-ica," *IEEE journal of biomedical and health informatics*, vol. 22, no. 3, pp. 664–670, 2017.

[6] P. Berg and M. Scherg, "Dipole modelling of eye activity and its application to the removal of eye artefacts from the eeg and meg," *Clinical Physics and Physiological Measurement*, vol. 12, no. A, p. 49, 1991.

[7] A. R. Teixeira, A. M. Tomé, E. W. Lang, P. Gruber, and A. M. Da Silva, "Automatic removal of high-amplitude artefacts from single-channel electroencephalograms," *Computer methods and programs in biomedicine*, vol. 83, no. 2, pp. 125–138, 2006.

[8] M. K. I. Molla, M. R. Islam, T. Tanaka, and T. M. Rutkowski, "Artifact suppression from eeg signals using data adaptive time domain filtering," *Neurocomputing*, vol. 97, pp. 297–308, 2012.

[9] D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, A. Biraben, F. Wendling, L. Senhadji, and I. Merlet, "Removal of muscle artifact from eeg data: comparison between stochastic (ica and cca) and deterministic (emd and wavelet-based) approaches," *EURASIP Journal on Advances in Signal Processing*, vol. 2012, pp. 1–15, 2012.

[10] S. Foucart, "Hard thresholding pursuit: An algorithm for compressive sensing," *SIAM Journal on Numerical Analysis*, vol. 49, pp. 2543–2563, 2011.

[11] D. L. Donoho, "De-noising by soft-thresholding," *IEEE Transactions on Information Theory*, vol. 41, pp. 613–627, 1995.

[12] J. V. K. Vaishali Sangle, Archana K. Chaudhari, "Ocular artifact detection in eeg using wavelet analysis," in *IEEE International Conference on Recent Trends in Electronics, Information Communication Technology (RTEICT)*, pp. 1271–1275, 2018.

[13] M. K. Islam and A. Rastegarnia, "Wavelet-based artifact removal algorithm for eeg data by optimizing mother wavelet and threshold parameters," in *2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)*, pp. 1–6, IEEE, 2020.

[14] M. S. Hossain, M. B. I. Reaz, M. E. Chowdhury, S. H. Ali, A. A. A. Bakar, S. Kiranyaz, A. Khandakar, M. Alhatou, and R. Habib, "Motion artifacts correction from eeg and fnirs signals using novel multiresolution analysis," *IEEE Access*, vol. 10, pp. 29760–29777, 2022.