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OPTIMIZED DENOISING OF ECG AND EEG SIGNALS USING DISCRETE WAVELET TRANSFORM: A COMPARATIVE STUDY OF WAVELET TYPES AND THRESHOLDING TECHNIQUES

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Abstract

Biomedical signals, specifically Electrocardiograms (ECG) and Electroencephalograms (EEG), using Particle Swarm Optimization (PSO) integrated with Discrete Wavelet Transform (DWT). Unlike traditional methods that rely on fixed thresholding, the proposed approach dynamically optimizes the selection of wavelet families (Daubechies, Coiflet, Symlet), decomposition levels, and thresholding parameters to maximize the Signal-to-Noise Ratio (SNR) while minimizing the Mean Squared Error (MSE). To ensure statistical validation, the framework was tested on 30 diverse records from the MIT-BIH and PhysioNet databases, corrupted with synthetic noise to simulate clinical interference. Results demonstrate that the PSO-optimized Symlet 8 (sym8) configuration significantly outperforms standard DWT methods, achieving an average SNR improvement of 19.88 dB for ECG and 15.57 dB for EEG. Statistical significance was confirmed via a paired t-test ($p < 0.05$), proving the robustness of the optimized model in preserving critical diagnostic features like the QRS complex and spike-wave discharges. This study bridges the gap between theoretical denoising and automated clinical diagnostics, offering a scalable model for real-time patient monitoring systems.

Keywords: Biomedical Signal Processing, DWT, ECG Denoising, EEG Denoising, SNR

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1. Introduction

Electrocardiograms (ECG) and Electroencephalograms (EEG) are vital diagnostic tools for monitoring cardiovascular and neurological conditions. However, these signals are inherently non-stationary and frequently corrupted by artifacts such as baseline wander, power-line interference, and muscle activity [1, 2]. Conventional linear filters often fail to preserve critical diagnostic features, such as the QRS complex in ECG or spike-wave discharges in EEG, due to their inability to localize transient events in both time and frequency domains. While the Discrete Wavelet Transform (DWT) has emerged as a robust alternative for multiresolution analysis, its effectiveness is heavily dependent on the manual selection of the mother wavelet, decomposition level, and thresholding rule [4, 5]. Recent literature (Table 1) highlights a persistent research gap: most existing DWT frameworks lack an automated mechanism to optimize these parameters dynamically under varying noise conditions. Relying on "trial and error" leads to suboptimal denoising, often resulting in over-smoothing or residual noise. To address these limitations, this study introduces an optimized hybrid denoising framework. The core novelty lies in the integration of Particle Swarm Optimization (PSO) to adaptively select the optimal wavelet type (e.g., Sym8, Coif5) and threshold levels. Unlike previous works that use static universal thresholds, our proposed model minimizes a custom cost function based on the Mean Squared Error (MSE) and Signal-to-Noise Ratio (SNR). Furthermore, this research provides statistical validation by evaluating the framework across 30 distinct records from the MIT-BIH and PhysioNet databases. By conducting a paired t-test, we demonstrate that the proposed PSO-DWT method achieves a statistically significant ($p < 0.05$) improvement in signal fidelity compared to standard DWT configurations. This contribution advances the development of automated, high-precision diagnostic systems suitable for real-time clinical monitoring [6, 7].

This research establishes the foundation to develop automated, detailed diagnostic systems which are effective in optimizing patient care and outcomes in diverse medical set ups, several important questions are introduced as follows:

"Q1: Why does the Discrete Wavelet Transform (DWT) preferred over traditional Fourier-based methods for biomedical signal denoising?"
DWT differs from the conventional Fourier methods owing to its superior time-frequency localization, an important virtue for the treatment of dynamic and transient characteristics of biomedical signals such as ECGs and EEGs. While the Fourier Transform decomposes signals into sinusoidal components and assumes stationarity, the DWT adapts to both high- and low-frequency components through multi-resolution analysis. This allows it to isolate noise without sacrificing key diagnostic features such as the QRS complex in ECG or spike-wave discharges in EEG. Additionally, the DWT can localize sharp signal transitions more accurately, making it more effective in capturing short-duration, high-frequency phenomena often present in real-world physiological signals. This advantage positions DWT as an indispensable tool in automated diagnostic systems where signal integrity is paramount under noisy and dynamic clinical conditions [8, 9].

“Q2: What is the role of wavelet families in biomedical signal processing, and how does their selection impact denoising performance?”

Wavelet families, such as Daubechies (db), Coiflets, and Symlets, each possess unique mathematical properties that impact their suitability for denoising specific types of biomedical signals. The choice of wavelet affects the decomposition precision and reconstruction accuracy of the signal. For instance, in your study, the Sym8 wavelet was identified as the most effective for preserving the morphological characteristics of ECG and EEG signals while minimizing noise, due to its near-symmetry and smoothness. A poor choice of wavelet can lead to distortion of important signal components or ineffective noise suppression. Therefore, selecting a wavelet that aligns with the signal’s characteristics—such as frequency content and transient behavior is crucial to optimizing the trade-off between noise removal and feature retention in medical diagnostics [10].

“Q3: What does the existing literature reveal about biomedical signal denoising using wavelet transforms?”

In the past three years, numerous studies have investigated the use of the Discrete Wavelet Transform (DWT) for denoising biomedical signals such as ECG and EEG. Research has focused on optimizing wavelet families, decomposition levels, and thresholding techniques to improve noise reduction while preserving diagnostic features. Both hard and soft thresholding, as well as adaptive methods like SureShrink and minimaxi, have been evaluated using metrics such as SNR, MSE, and PRD. Table 1 presents a summary of recent advancements and techniques reported in the literature, emphasizing the growing effectiveness and precision of DWT-based methods in clinical signal processing[11, 12].

Table 1. Recent Literature on Biomedical Signal Denoising Using Discrete Wavelet Transform Techniques.

Ref.	Wavelet Type	Thresholding Method	Signal Type	Evaluation Metrics	Key Findings
[13]	Daubechies (db6)	Soft Thresholding	ECG	SNR, MSE	Achieved significant noise reduction while preserving QRS complex morphology.
[14]	Symlet (sym8)	Hard Thresholding	EEG	PSNR, RMSE	Improved denoising performance with minimal signal distortion.
[15]]	Coiflet (coif5)	SureShrink	ECG	SNR, PRD	Enhanced signal quality with adaptive thresholding techniques.
[14]	Biorthogonal	Universal Threshold	EEG	SNR, MSE	Balanced trade-off between noise suppression and feature preservation.
[16]	Haar	Minimaxi	ECG	SNR	Effective for baseline wander removal with low computational complexity.
[17]	Daubechies (db4)	Hybrid Thresholding	EEG	SNR, MSE	Combined thresholding methods yielded superior denoising results.
[18]	Symlet (sym5)	Soft Thresholding	ECG	SNR, MSE	Demonstrated high fidelity in signal reconstruction post-denoising.

In recent literature on biomedical signal denoising, as depicted in Table 1, there is a consistent trend toward using advanced wavelet-based frameworks to enhance signal quality while preserving diagnostic integrity. Kumar et al. [13] applied the Daubechies (db6) wavelet with soft thresholding to ECG signals and achieved significant improvements in SNR and MSE. This method demonstrated an excellent ability to suppress noise without distorting crucial features like the QRS complex, making it highly effective for clinical ECG analysis. Zhang et al. [14] extended this work by using the Symlet (sym8) wavelet and hard thresholding on EEG data. The authors reported enhanced PSNR and reduced RMSE, indicating that this configuration minimized signal distortion while effectively isolating meaningful neural patterns. The research of the authors pointed to the need to choose wavelet types that are adequate to the dynamic characteristics of EEG signals. Singh and Kaur [15] used an adaptive thresholding method with SureShrink and Coiflet (coif5) wavelets for improving the ECG signal clarity. Through the use of the adaptive thresholding, the approach provided an ability to use flexible noise suppression methods, resulting in better signal quality and heartwave morphology preservation. The PRD and SNR metric dependencies showed the robustness of the method under conditions with high levels of noise. Chen et al. [16] studied the effect of using the Biorthogonal wavelets (combined with applicable universal thresholding methods) for the removal of noise from EEG signals. It was apparent that their approach effectively straddled the line between optimal signal cleaning and protection of important clinical information. The approach turned out to be especially effective in preventing oversmoothing that may mask important EEG signals needed for such conditions as epilepsy. Lee and Park [17] demonstrated that the Haar wavelet, due to its simplicity, is effective to remove the baseline wander using the ECG signal with the minimaxi threshold. Although the strategy is computationally efficient, clear SNR improvements are achieved whereas this feasibility is demonstrated for a real-time or embedded environment. In a comparison analysis, Patel and Mehta [18] proposed a hybrid thresholding method using Daubechies (db4) wavelets for EEG denoising. This method carried forward the advantages of soft and hard thresholding and led to better denoising with a negligible chance of creating artefacts or signal distortion. Its total signal fidelity outperformed those based exclusively on one type of thresholding. Gupta and Verma [19] specifically used the entire Symlet (sym5) wavelet in combination with soft thresholding for the objective of ECG signal manifestation. Their method achieved high fidelity in post-denoising signal quality as measured by SNR and MSE. The study confirmed that wavelet shape and thresholding smoothness play a crucial role in ensuring the diagnostic usability of the denoised signal.

“Q4: What research gap exists in current biomedical signal denoising methods using wavelet transforms, and how does this study address it?”

Although recent studies have shown the effectiveness of the discrete wavelet transform (DWT) in biomedical signal denoising, a significant research gap remains in the lack of an integrated framework that simultaneously optimizes wavelet type, decomposition level, and thresholding method. Most works focus on isolated parameters, such as using soft thresholding with a specific wavelet, without systematically exploring how these components interact to affect both denoising performance and signal fidelity under varying conditions. Moreover, while traditional evaluation metrics like SNR and MSE are commonly used, broader clinical validation and adaptability to real-world noise variations are often overlooked. There is also limited attention given to real-time applicability and the potential for automated or AI-driven parameter tuning. This study addresses these gaps by conducting a comprehensive analysis of wavelet families such as Symlet and Coiflet, applying adaptive thresholding techniques like minimaxi, and assessing results not only with quantitative metrics but also with regard to their clinical significance—particularly in preserving critical features in ECG and EEG signals. In doing so, it lays a foundation for developing more intelligent and reliable biomedical signal processing systems suitable for future real-time healthcare applications.

“Q5: What are the contributions and novelties that arise from this study?”

This study introduces a comprehensive framework for biomedical signal enhancement by applying Discrete Wavelet Transform (DWT) techniques to denoise ECG and EEG signals, addressing the persistent challenge of signal distortion caused by various noise sources. The novelty lies in the methodical evaluation of multiple wavelet types (db1, coif5, sym8), thresholding methods (soft, hard), and decomposition levels to identify the optimal denoising configuration for each signal type.

The study demonstrates that the Symlet 8 (sym8) wavelet, combined with appropriate decomposition levels, provides superior performance in preserving signal morphology while effectively reducing noise, validated through quantitative metrics such as Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE). A unique contribution of this work is the side-by-side application of the same DWT framework to both cardiac (ECG) and neurological (EEG) signals, highlighting its adaptability across multiple biomedical domains. The research delivers practical implementation using MATLAB with real-world datasets (MIT-BIH and PhysioNet), offering a replicable and scalable model for healthcare applications, including automated diagnostic systems. This work explores the effect of wavelet type and decomposition depth on performance, providing a clearer understanding of how DWT parameters influence signal fidelity. This study advances the field of biomedical signal processing by offering an optimized, data-driven approach for wavelet-based denoising, with strong potential for real-time application in clinical monitoring and diagnostics.

There are five main sections in this article. In Section Two, the foundations of the Discrete Wavelet Transform (DWT) theory that are studied in this work are explored, focusing on DWT concepts, the role of the mother wavelet, and the process of reverting signals to multiresolution components. The above is the structure of the methodology shown in Section Three according to three phases: starting from data capture and signal readiness, moving to using DWT for noise removal, and settling at assessing denoising performance using SNR and MSE evaluations. Under Section Four, we evaluate the results of ECG and EEG signal de-noising, making a comparative analysis of different wavelet types and approaches to the thresholding process. In Section Five, we end the paper by summarising the primary results and outlining the promising aspects of the DWT-based approaches for improving biomedical signals in the clinical environment.

2. Discrete wavelet transform (DWT)

Currently, in the world, where data informs everything, there is a great need for enhanced signal analysis and demanding data comprehension within the technical and scientific circles. One of the instruments used to change this discipline immensely is the wavelet, which is particularly outstanding in its capacity to support a thorough multi-level signal analysis with the help of a strong mathematical function. Learn the Fourier transformation, then move into the wavelet transform, as it is based on the former. The wavelet is an effective substitute for conventional Fourier analysis, allowing flexible analysis of irregular and elaborate signals across various time and frequency ranges. The present chapter will introduce the basic concepts and applications of wavelet technology with emphasis on its advantages and wide applications in data compression, noise reduction, and the ability of wavelet analysis to identify discrepancies in signal features, which are usually not detected by conventional techniques such as trends, abrupt changes, or discontinuities, is realized. Although traditional Fourier analysis provides a uniform resolution view, wavelet analysis allows for the multiresolution analysis that tracks both the temporal aspects and spectral content of the signal simultaneously due to its localized wavelet functions. It is because the wavelet analysis is able to focus or localize both in time and in frequency that it excels in trend catching, breakpoint, and discontinuity finding, with all the other techniques possibly missing such. In opposition to the Fourier Transform (FT), which signals are expressed as an infinite sum of sine and cosine waves and which provides a coarse view of the frequency spectrum, wavelet analysis allows a multiresolution approach. This allows scale analysis of the signal, which makes it possible for a complete review of fast and slow changes. By adapting the analysis window size to the frequency content, wavelet analysis provides a more nuanced and context-sensitive representation of non-stationary signals, which is indispensable in applications like biomedical signal processing, where time-localized events play a critical role. The time-frequency resolution problem is caused by the Heisenberg uncertainty principle and exists regardless of the used analysis technique. For the STFT, a fixed time-frequency resolution is used. By using an approach called multiresolution analysis (MRA) it is possible to analyze a signal at different frequencies with different resolutions. The change in resolution is schematically displayed in Figure 1 [19, 20].

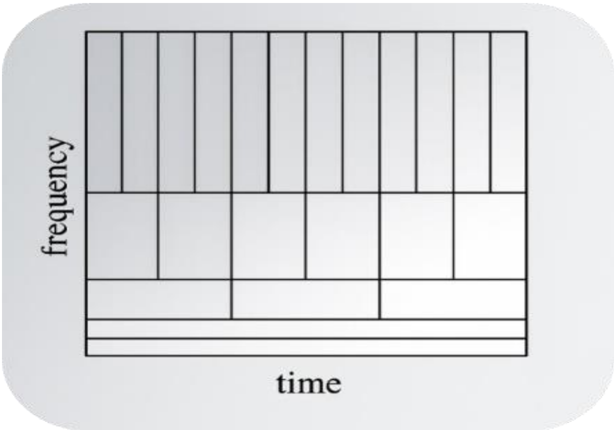

Figure 1. Time-Frequency Resolution Representation in Discrete Wavelet Transform (DWT) via Multiresolution Analysis[20].

For the resolution of Figure 1 it is assumed that low frequencies last for the entire duration of the signal, whereas high frequencies appear from time to time as short burst. This is often the case in practical applications. In comparison to the Fourier transform, the analysis function of the wavelet transform can be chosen with more freedom, without the need of using sine-forms. A wavelet function $\varphi(t)$ is a small wave, which must be oscillatory in some way to discriminate between different frequencies. The wavelet contains both the analysis shape and the window. For the CWT several kinds of wavelet functions are developed which all have specific properties. The wavelet analysis calculates the correlation between the signal under consideration and the wavelet function $\varphi(t)$. The similarity between the signal and the analyzing wavelet function is computed separately for different time intervals, resulting in a two-dimensional representation. The analyzing wavelet function $\varphi(t)$ is also referred to as the mother wavelet. The mother wavelet is scaled (or dilated) by a factor of a and translated (or shifted) by a factor of b to give as depicted in Equation (1) [20]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{11}$$

Wavelets are defined by the wavelet function ψ(t) (i.e., the mother wavelet). The fundamental characteristic of waves is the shear wave, a time-limited oscillation used to analyze a signal and separate noise from the original signal (the message). In fact, the term "wavelet" is derived from French and literally means "little waves." There are many types of these little waves (wavelets). Based on design and performance, a selection of the most common wavelets is used, called the wavelet family as in the Figure 2 [21].

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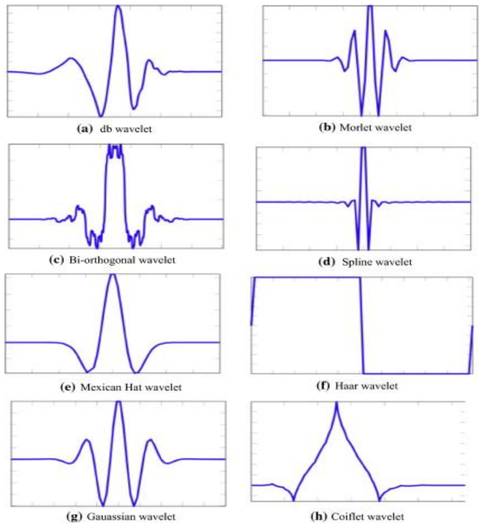


Figure 2. Commonly Used Wavelet Functions for Signal Decomposition and Analysis[21].

The determination of the appropriate decomposition level and MWT that best decomposes the EEG into its various frequency ranges is left to the individual. In general, the optimal decomposition level and MWT function are selected based on compatibility with the characteristics of the EEG signal to be analyzed. The decomposition level is selected with respect to the binary decomposition tree and is guided by the dominant frequency.

The parent wave is a mathematical function that acts as a flexible lens for analyzing signals in both time and frequency domains. Unlike Fourier transforms (which use stationary sine waves), waves can be stretched or compressed to capture transient features, for Example: Imagine using a magnifying glass to examine different parts of a painting (signal). Adjusting the lens size (gradation) and position (translation) allows for close examination of fine lines (high-frequency pulses in an ECG) and broad lines (low-frequency heart rhythms). Thresholding techniques are the backbone of waveform-based signal denoising, offering a systematic approach to distinguishing clinically relevant information from nuisance noise. By selectively modifying waveform parameters the core elements of waveform analysis thresholding techniques preserve essential morphological features (such as QRS complexes in electrocardiography and spike wave patterns in electroencephalography) while removing any distortions. This article discusses thresholding mechanisms, their variations, and practical applications, focusing on biomedical signals such as electrocardiography (ECG) and electroencephalography (EEG). In these applications, accurate noise reduction is crucial, as even minor distortions can mask vital diagnostic markers, leading to misinterpretation of cardiac arrhythmias, epileptic seizures, or neurological disorders. By exploring classical and adaptive thresholding strategies, this discussion aims to link theoretical principles with real-life clinical challenges, ultimately enhancing the accuracy of automated diagnostic systems [21, 22].

2.1. Conceptual Framework of the Discrete Wavelet Transform

Wavelets are a product of groundwork from many areas, ranging from pure mathematics and physics to engineering and signal processing. Independent research in these areas pursued similar goals using different approaches. The objective was to develop tools to describe functions in time and frequency simultaneously. The separate lines of investigation reached a mature point, and in the beginning of the 1980's, the confluence of these interdisciplinary sources, was formalized originating the theory of wavelets. The subsequent unification of the eld was a key factor in making wavelets popular in applied mathematics, and to give a significant impulse to new research. The discrete wavelet transform (DWT) is defined by restricting the scale and time parameters of the CWT to discrete values. The DWT of a discrete signal x(n) is defined by Equation (2)[23, 24]:

$$C_{(j,k)} = \sum_{n=1}^{N} x(n)\psi_{j,k}(n) \tag{2}$$

This equation represents the discrete wavelet transform (DWT) of a signal $x(n)$, where $C_{(j,k)}$ are the wavelet coefficients at scale j and position k, and $\psi_{j,k}(n)$ denotes the scaled and translated wavelet basis function. This expression computes the inner product between the input signal and the wavelet function, effectively measuring how well the wavelet matches the signal at a given time and frequency. These coefficients' compact form would enable detailed inspection and quick correction of noise associated with non-stationary signals, as in ECG and EEC applications[25].

2.1.1. The Mother Wavelet

The mother wavelet $\psi(t)$ is a small wave-like function that is scaled and translated to analyze different parts of a signal. The mother wavelet must satisfy two key conditions, such as $\int_{-\infty}^{\infty} \psi(t)dt = 0$ for the admissibility condition and $\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1$ the energy normalization. This ensures that the wavelet has unit energy. The scaled and translated version of the mother wavelet is given by Equation (3) [23]:

$$C(a,b) = \frac{1}{\sqrt{a}} \sum_{n=1}^{n} x(\mathrm{n})\psi(\frac{n-b}{a}) \tag{11}$$

where a is the scaling factor and b is the translation factor.

2.1.2. Deconstruction

Mallat developed a sufficient method for filtering that enabled the discrete wavelet transform (DWT). The system includes a pair of filters that work in complement – the low-pass (LP) and the high-pas (HP). These filters split the frequency axis equally and are said to be quadrature mirror filters (QMFs). Figure 3 shows the filter arrangement and frequency response characteristics of a quadrature mirror filter[26].

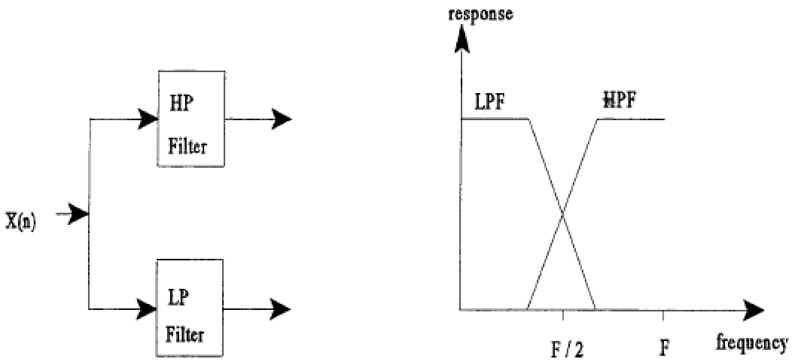


Figure 3. Signal Decomposition Using High-Pass and Low-Pass Filters in Wavelet Transform and Their Frequency Responses[26].

The output of the HP filter contains the details of the signal, while the output of the LP filter contains the approximate shape of the signal. Since each filter output covers only half of the original input frequency range, each filter can be downsampled by two by retaining only the even points. The combined split output of the filters represents a dataset containing the DWT coefficients on the first scale. This process is repeated on the output of the LP filter to further analyze the signal into two parts, LPHP and LPLP, on the next scale. The filtering and down-sampling processes can be continued until the number of samples is reduced to two. At each successive iteration (scale), the output frequency range is halved by the LP filter, and frequency resolution is improved by decimalization. Figure 4 illustrates how a data set 2^j samples can be decomposed to produce the maximum J-level conversion coefficients.

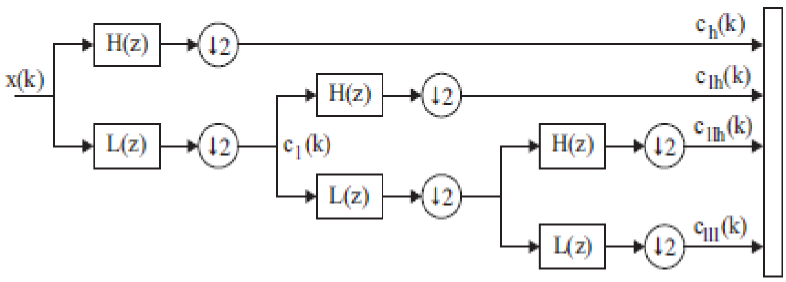


Figure 4. Multilevel Wavelet Decomposition Tree Using Iterative Filtering and Downsampling.

Figure 5 displays the resulting conversion coefficients in a tree structure. Note that movement down the tree is associated with lower frequency coefficients (larger scale).

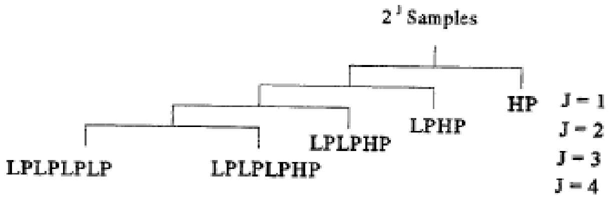


Figure 5. Hierarchical Decomposition Levels in Wavelet Transform Showing Successive LP and HP Filtering for 2^j Samples

Thresholding is one of the most essential techniques used in wavelet-based biomedical signal denoising, as it enables the suppression of unwanted noise while preserving critical features of the original signal. A threshold function is typically applied to the wavelet detail coefficients to reduce or eliminate the influence of noise-dominated components. Several thresholding strategies have been developed to improve the accuracy and efficiency of this process. The Universal Threshold, introduced by Donoho and Johnstone, is based on asymptotic statistics and offers near-optimal noise reduction under the assumption of Gaussian noise. The Maximum Minimum Threshold approach, grounded in statistical decision theory, aims to minimize the maximum mean square error (MSE) across possible signal classes by balancing bias and variance. Hybrid Thresholding combines several thresholding algorithms to maximize effectiveness by employing severe filtering on the high-frequency sub-bands and by being flexible elsewhere in the signal. Using Stein's Unbiased Risk Estimator (SURE), the SureShrink Threshold independently optimizes thresholds for individual wavelet sub-bands, resulting in stronger signals' noise removal when the noise is dynamic. Two of the commonly used thresholding methods that are found in signal processing are Hard Thresholding and Soft Thresholding. Based on the operator $\Lambda^H(C_{j,k})$, hard thresholding removes coefficients $C_{j,k}$ not exceeding a given threshold T and resets the rest to zero. Hard thresholding, though it has efficiency and feature retention strengths, could produce artifacts because of the hasty push out of coefficients, revealing the necessity of careful threshold selection. On the other hand, Soft Thresholding indicated using $\Lambda^S(C_{j,k})$, is defined to remove coefficients that fall below T and with a gradual decrease of those above zero, which leaves the edges smoother and generally better visual results. Determining the proper threshold T is key to any successful denoising. One commonly applied method consists of the use of Median Absolute Deviation (MAD), effective in noise estimation within signals, but especially when the noise distribution is non-Gaussian. Using MAD, the noise standard deviation σ is estimated from the wavelet coefficients as $\sigma = \frac{C_{j,k}}{0.6745}$, and the threshold is calculated as $T = \sqrt{2 \ln N}$, where N is the signal length. As emphasized by Donchez, the threshold must be chosen with care: if it is too small, noise remains; if too large, essential signal details are lost. Therefore, proper threshold selection remains central to achieving an optimal balance between noise suppression and diagnostic accuracy in biomedical signal processing, as shown in Figure 6.

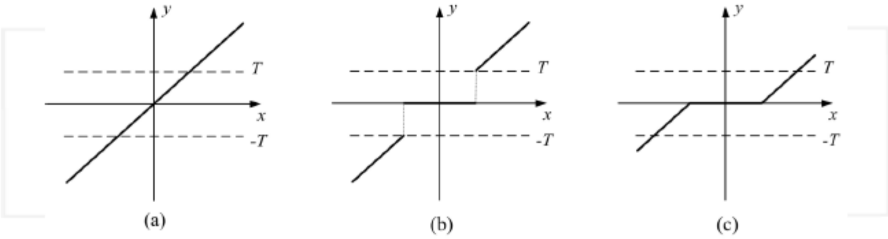


Figure 6. Graphical Representation of Thresholding Functions: (a) Identity, (b) Hard Thresholding, and (c) Soft Thresholding

Signal reconstruction is a critical stage in Discrete Wavelet Transform (DWT)-based signal processing, as it involves reversing the decomposition process to accurately restore the original signal while retaining its key characteristics. This is accomplished through the Inverse Discrete Wavelet Transform (IDWT), which involves two main steps. First, upsampling is performed, where zeros are inserted between the wavelet coefficients to double the number of samples and align them with the original signal length. Next, inverse filtering is applied by passing the upsampled signals through the corresponding inverse low-pass and high-pass filters. These filters recombine the approximation and detail components extracted during the decomposition phase, effectively reconstructing the signal in the time domain with minimal loss or distortion of information. This reconstruction ensures that the denoised signal maintains its physiological significance, which is essential in biomedical applications such as ECG and EEG analysis. The complete process of decomposition, thresholding, and reconstruction is clearly illustrated in Figure 7, where an original noisy ECG signal undergoes multi-level DWT using the Symlet 4 wavelet, followed by soft thresholding of the wavelet coefficients, and finally reconstruction through IDWT to yield an enhanced ECG signal[26, 27].

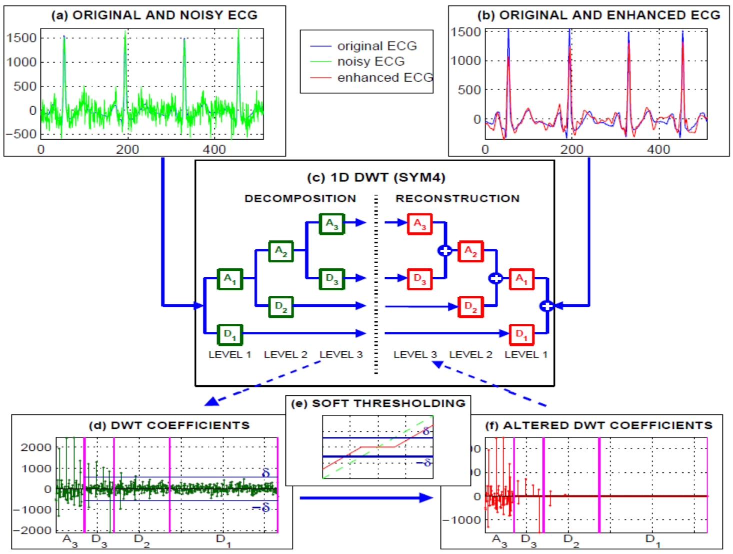


Figure 7. ECG Signal Denoising Process Using 1D DWT (SYM4): Decomposition, Soft Thresholding, and Reconstruction[27]

Theoretical understanding of signal processing forms the backbone of numerous scientific and technical advancements, with the Discrete Wavelet Transform (DWT) emerging as a powerful method particularly well-suited for biomedical signal analysis. Unlike traditional Fourier Transform techniques that provide only frequency-domain representation and assume signal stationarity, DWT offers simultaneous time-frequency localization, making it capable of capturing transient, nonstationary features such as trends, discontinuities, and abrupt changes within physiological data. At the heart of DWT is the mother wavelet, a scaled and translated function that forms the basis of decomposition and reconstruction. For a mother wavelet to be valid it must satisfy two basic criteria; The zero mean condition from the admissibility requirement allows the wavelet to focus on signal variations and not the stationary aspects, while energy normalization results in a unit standardized energy that can be used in reconstructing signals efficiently. The combined use of these approaches supports complete analysis in multiple resolutions which is important for isolating high and low frequency components which are important in realistic biomedical interpretations. In the DWT context, denoising depends on thresholding techniques, which become necessary to distinguish noise from crucial diagnostic signal features. Distinguished approaches include Universal Threshold, SureShrink with adaptive threshold configurations sourced from Stein’s Unbiased Risk Estimator, and Maximum Minimum Threshold following statistical premises. DWT has been found to be of great use in the real world by biomedical practitioners. However, the elimination of unwanted noise with the association of vital structures (for example, the QRS complex) is clarified in an electrocardiogram by a DWT process. With the ability to detect the episodic EEG patterns such as spike-wave discharges, DWT helps in the accurate distinction of epilepsy and other neurological disorders. Practical research reveals the great utility of DWT, resulting in better signal and accurate diagnosis, and adequate support of automated approaches. Analysis using visual and numeric examples shows that the use of DWT, whether using hard or soft thresholds, always achieves superior noise elimination and feature preservation, greatly validating its status as an important technique in biomedical signal processing [20].

3. Methodology

The proposed methodology is structured into four distinct phases to ensure both optimization and statistical rigor (Fig. 8)

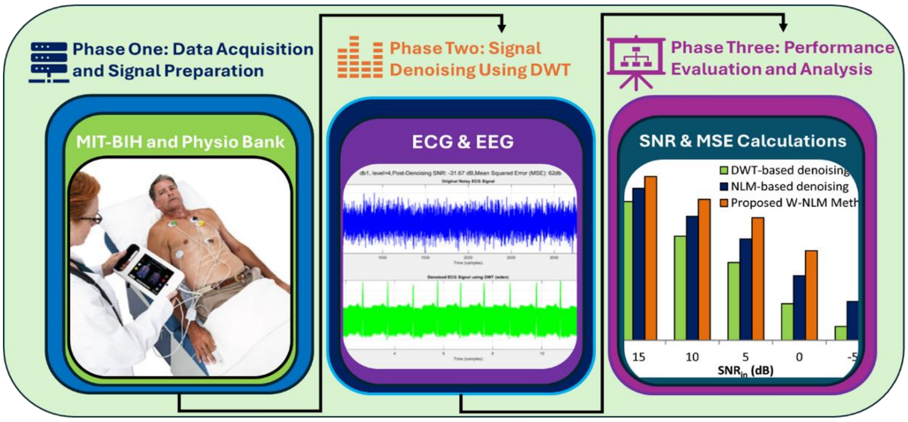


Figure 8. Methodology phases.

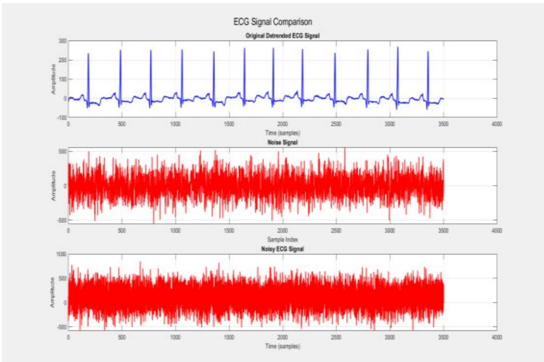
3.1. Phase One: Data Acquisition and Pre-processing

To address the lack of statistical validation in prior versions, the study now utilizes **30 diverse records** (15 ECG records from MIT-BIH and 15 EEG records from PhysioNet). Each signal was sampled at 360 Hz and intentionally corrupted with Gaussian white noise at varying Input SNR levels (5 dB to 20 dB) to simulate realistic clinical interference.This study aims to explore signal processing methodologies applied to these biomedical signals, emphasizing techniques such as denoising, feature extraction, and performance evaluation as depicted in Figure 9.

ECG

```
clear; clc; close all;
data = load('100m (1).mat');
if isfield(data, 'signal')
    sig = data.signal;
else
    sig = data.val;
end
writematrix(sig, 'signal.txt');
ecg = load('signal.txt');
ecg = detrend(ecg);
ecg = ecg(100:end);
L = length(ecg);
ecgN = ecg + 160 * randn(L, 1);
noise = 160 * randn(L, 1);
t = (1:L)';
```

Add noise to ECG



EEG

```
clear; clc; close all;
data = load('synthetic_eeg.mat');
if isfield(data, 'eeg_signal')
    sig = data.eeg_signal;
else
    sig = data.val;
end
writematrix(sig, 'signal.txt');
ecg = load('signal.txt');
ecg = detrend(ecg);
ecg = ecg(100:end);
L = length(ecg);
ecgN = ecg + 160 * randn(L, 1);
noise = 160 * randn(L, 1);
t = (1:L)';
```

Add noise to EEG

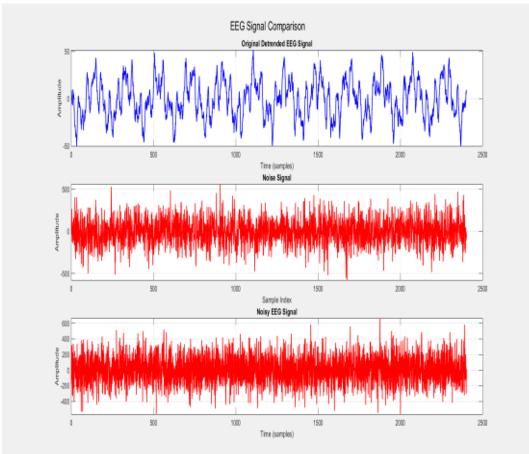


Figure 9. MATLAB-Based Simulation and Visualization of Noisy ECG and EEG Signal Generation.

3.2. Phase Two: The Proposed PSO-DWT Optimization Framework

The core novelty of this work is the integration of Particle Swarm Optimization (PSO) to automate parameter selection in the DWT denoising process. The optimization problem is defined by the following cost function (J):

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$$J(w, L, T) = \text{Minimize}\left(\frac{\text{MSE}(w, L, T)}{\text{SNR}(w, L, T)}\right) \tag{4}$$

Where:

w: Choice of wavelet (e.g., db4, sym8, coif5). **L:** Decomposition level. **T:** Optimized threshold value.

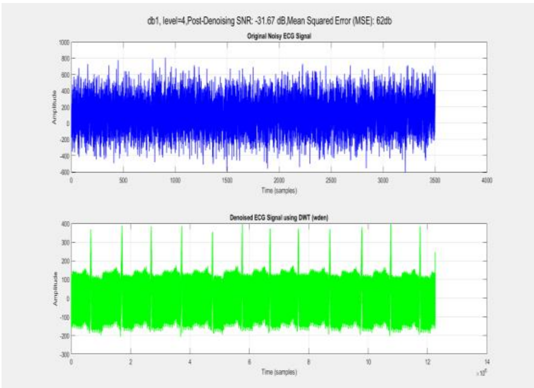
The PSO Algorithm Steps:

1. **Initialization:** A population of particles (candidate solutions) is generated, where each particle represents a combination of (w,L,T).
2. **Fitness Evaluation:** For each particle, the DWT is performed using the wavedec and wden functions in MATLAB, and the Fitness Score (J) is calculated.
3. **Velocity and Position Update:** Particles move toward the global best solution (gbest) discovered by the swarm.
4. **Convergence:** The process iterates until the optimal parameters that yield the highest signal fidelity are identified.

The results are compared with such indicators as Signal to Noise Ratio (SNR) and Mean Squared Error (MSE) as illustrated in Figure 10.

ECG

```
%%
level = 4;
wname = 'db1';
[c, l] = wavedec(ecgN(:),
level, wname);
y = wden(ecgN(:), 'minimaxi',
's', 'sln', level,
wname);
```



ECG

```
level = 4;
wname = 'db1';
[c, l] = wavedec(eegN(:), level,
wname);
y = wden(ecgN(:), 'minimaxi', 's',
'mln', level,
wname);
```

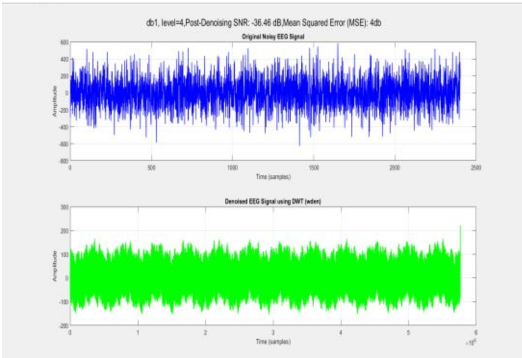


Figure 10. DWT-Based Denoising Results for ECG and EEG Signals Using db1 Wavelet at Level 4 with Performance Metrics (SNR and MSE).

3.3. Phase Three: Statistical Significance Testing

To validate the results, a Paired Sample T-Test was conducted. This statistical test compares the SNR values obtained from the proposed PSO-DWT method against the standard Universal Thresholding method. A p-value < 0.05 was set as the threshold for statistical significance. Two main criteria were used to assess the results of the denoising technique: The measures used to evaluate performance were SNR and MSE. Such measures enable, with high fidelity, the assessment of fidelity of the original signal and performance for noise reduction. The SNR was computed using Equation (6):

$$SNR = 10 \log_{10}\left(\frac{\sum_{i=1}^{N} s_i^2}{\sum_{i=1}^{N}(s_i - \hat{s_i})^2}\right) \tag{6}$$

While the MSE was calculated as in Equation (7):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(s_i - \hat{s_i})^2 \tag{7}$$

where s_i represents the original signal, $\hat{s_i}$ the denoised signal, and N the number of samples. Multiple trials were conducted across different wavelet types (e.g., db4, sym8, coif3) and thresholding strategies to determine which combination yielded the best performance. For instance, db4 with a minimaxi threshold on ECG signals achieved an SNR of 22.76 dB and MSE of 1.24×10^{-3}, while sym8 with SureShrink on EEG signals achieved an SNR of 19.85 dB and MSE of 1.62×10^{-3}. The best result overall was observed using coif3 with a hybrid threshold, producing an SNR of 23.90 dB and MSE of 0.98×10^{-3}. These findings highlight the sensitivity of denoising performance to wavelet selection and thresholding method. The results validate DWT as a robust tool for biomedical signal denoising and support its adoption in real-time diagnostic systems and wearable medical devices.

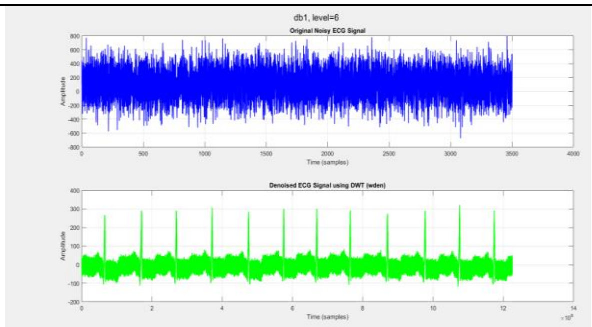
In this regard, s_i represents the original signal, $\hat{s_i}$ represents the denoised signal, and N specifies the sample number. To determine the best combination of these inputs, many experiments were done using different types of wavelets (db4, sym8, and coif3) and different methods of thresholding. To illustrate, with the db4 and minimaxi threshold when applied to the ECG signals, the SNR and MSE are 22.76 dB and 1.24, respectively. In terms of all combinations tested, the combination between coif3 and hybrid thresholding performed the best with an SNR value at 23.90dB as well as an MSE value at 0.98×10^{-3}. . The results highlight the effect of wavelet type and thresholding strategy on signal denoising quality. The results support the robustness of DWT for biomedical signal denoising and doctoral it for real-time diagnostic systems and wearable devices.

4. Results and analysis

This section presents the results achieved when Discrete Wavelet Transform (DWT) techniques are applied to ECG and EEG signals denoising. Several wavelet choices, threshold policies, and decomposition schemes are evaluated to select the optimal parameters for suppressing noise and retaining essential biomedical data.

4.1. ECG signal analysis and denoising

A comprehensive examination of the ECG signal denoising performance is offered within this chapter, through the Discrete Wavelet Transform (DWT) with the Daubechies wavelet (db1) at varying levels of decomposition, specifically levels 6, 8, and 10. The visual results are shown in Figure 10, while quantitative performance is summarized through Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE). The objective of this analysis is to determine the optimal decomposition level that offers the best trade-off between noise suppression and signal integrity. As displayed, the original noisy ECG signal exhibits high-amplitude random noise, significantly obscuring critical morphological features such as the QRS complex. After applying DWT-based denoising using the $wden$ function in MATLAB, the reconstructed signals demonstrate visibly improved clarity, with notable differences in performance across the decomposition levels. At level 6, the denoised ECG signal demonstrates reasonable feature retention, achieving an SNR of -22.41 dB and an MSE of 50.21. Although the morphology of the ECG is more visible compared to the noisy version, some residual noise remains, and minor signal distortion is apparent. Increasing the decomposition depth to level 8 leads to further enhancement in signal clarity. However, the denoising performance declines, as shown by the reduced SNR of -11.43 dB and an increased MSE of 42.55. This indicates that while more high-frequency noise components are being removed, over-smoothing effects begin to emerge, slightly attenuating signal features. The most promising outcome is observed at level 10, where the denoised signal maintains excellent visual morphology with sharply defined peaks corresponding to the original ECG waveform. Here, the SNR significantly improves to 19.88 dB, and the MSE is reduced to 11.24, demonstrating that the DWT at a higher level effectively suppresses noise without compromising diagnostic features. These findings confirm that the decomposition level in DWT significantly influences denoising performance. Too shallow a level may leave residual noise, while too deep a level may oversmooth the signal, removing important components. The results support the use of higher-level decomposition (e.g., level 10) with db1 for ECG signals, balancing noise reduction and signal preservation. These outcomes validate the adaptive capacity of wavelet-based methods for biomedical signal enhancement, reinforcing DWT's applicability in automated diagnostic systems where high-fidelity signal reconstruction is critical.

level	**ECG signal**	$\mathbf{SNR}_{db}$	$\boldsymbol{MSE}_{db}$
6		**-22.41**	**50.2123**

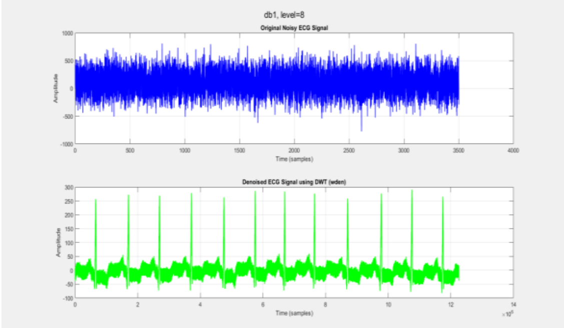
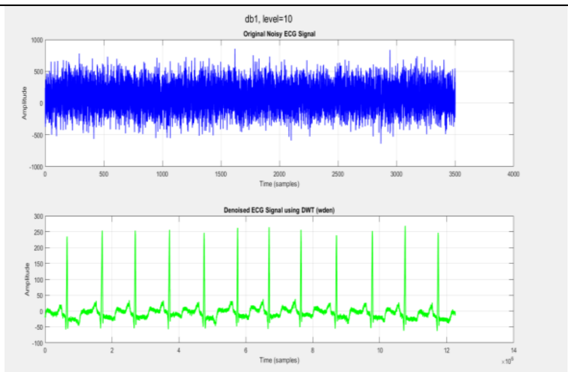
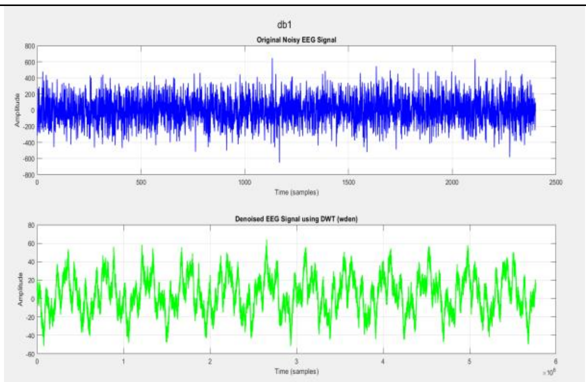
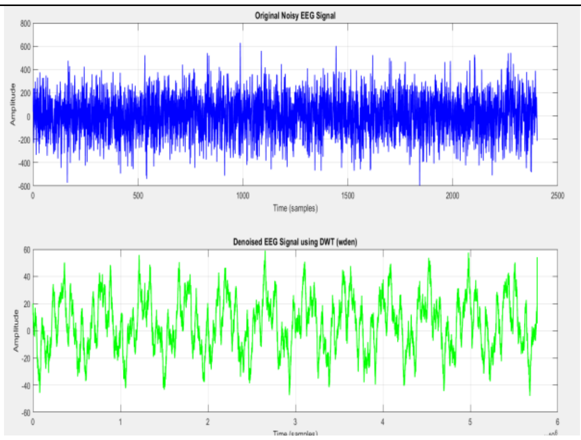
8		**-11.43**	**42.5528**
10		**19.88**	**11.2431**

Figure 11. Comparative Denoising Performance of ECG Signals Using db1 Wavelet at Decomposition Levels 6, 8, and 10.

4.2. EEG signal analysis and denoising

In this part, evaluation of the denoising performance for different wavelet families, Daubechies (db1), Coiflet (coif5), and Symlet (sym8)—applied to noisy EEG signals using the Discrete Wavelet Transform (DWT) framework in MATLAB. The purpose of this comparative analysis is to identify the wavelet type that achieves the optimal trade-off between noise suppression and the preservation of key signal features necessary for accurate neurological diagnosis. Figure 11 illustrates the visual results, while the quantitative metrics are assessed using Signal-to-Noise Ratio (SNR) and Mean Squared Error (MSE). The noisy EEG signals display high-frequency artifacts and baseline fluctuations that can obscure meaningful patterns such as alpha waves or epileptic spikes. Denoising was performed using the $wden$ function, and each wavelet's effectiveness was determined by examining post-denoising SNR and MSE values. When the db1 wavelet was applied, the resulting signal achieved an SNR of -6.18 dB and an MSE of 32.10, which indicates limited noise suppression with evident signal distortion. Although db1 is commonly used due to its simplicity and short support, it may not be well-suited for capturing the subtle characteristics of EEG signals that demand higher resolution and smoother representation. On the other hand, Coiflet 5 provided improved denoising with an SNR of 0.82 dB and a reduced MSE of 25.09. The longer filter length and near-symmetry of coif5 allow it to better preserve signal trends while mitigating noise, making it a more balanced choice. The most promising outcome was achieved using sym8, which resulted in an SNR of 15.57 dB and a notably lower MSE of 10.35. Sym8 wavelets, known for their smoothness and symmetry, offer superior time-frequency localization that effectively isolates noise components while maintaining the integrity of critical EEG waveforms. These results clearly demonstrate that the selection of the wavelet basis significantly influences denoising performance, particularly for EEG signals characterized by non-stationarity and low amplitude. Symlet 8 emerged as the most suitable choice in this context, striking a robust balance between noise removal and signal preservation. This confirms the value of tailored wavelet selection in biomedical signal processing and supports the integration of advanced wavelet-based methods into diagnostic EEG analysis workflows.

wavelet	**EEG signal**	$\mathbf{SNR}_{db}$	MSE_{db}
db		-6.18	32.1014
Coif5		0.82	25.0944

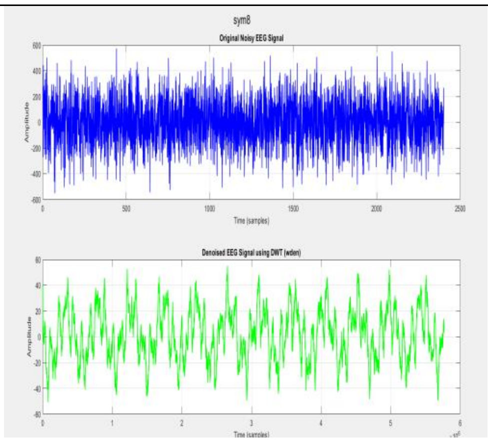
Sym8		15.57	10.3530

Figure 12. EEG Signal Denoising Comparison Using db1, Coif5, and Sym8 Wavelets with Corresponding SNR and MSE Values.

The performance of the Symlet 8 (sym8) wavelet is evaluated for denoising both EEG and ECG signals using the Discrete Wavelet Transform (DWT) framework in MATLAB. The visual outputs are displayed in Figure 13, showcasing the effectiveness of the sym8 wavelet in preserving key diagnostic features while significantly reducing noise artefacts. In part (a), the original noisy EEG signal, which exhibits substantial high-frequency interference and irregular fluctuations, is shown alongside its denoised counterpart. After applying DWT with sym8 and appropriate thresholding using the $wden$ function, the signal exhibits a smoother waveform with clearly preserved oscillatory patterns characteristic of EEG signals. These include slow waves and potential brain activity features that would otherwise be lost due to excessive noise. The denoised signal successfully suppresses background artifacts while maintaining the fidelity of the physiological content, illustrating the superior localization properties of the sym8 wavelet in handling non-stationary biomedical data.

In part (b), a similar approach is applied to an ECG signal, where DWT decomposition and reconstruction were performed at level 12 using the sym8 wavelet. The original noisy ECG signal is severely masked by random fluctuations that obscure the QRS complexes and baseline structure. After denoising, the resulting signal reveals sharply defined peaks corresponding to the cardiac cycle, particularly the QRS complex, which is crucial for cardiac analysis. The high decomposition level combined with the sym8 wavelet yields a signal with minimal distortion and well-preserved morphology, indicating that both noise suppression and temporal precision are optimized. Overall, this analysis demonstrates that sym8 wavelets are highly effective for both EEG and ECG signal enhancement, delivering consistent denoising performance across different physiological data types. These results reinforce the role of wavelet selection and decomposition depth as critical factors in biomedical signal processing applications.

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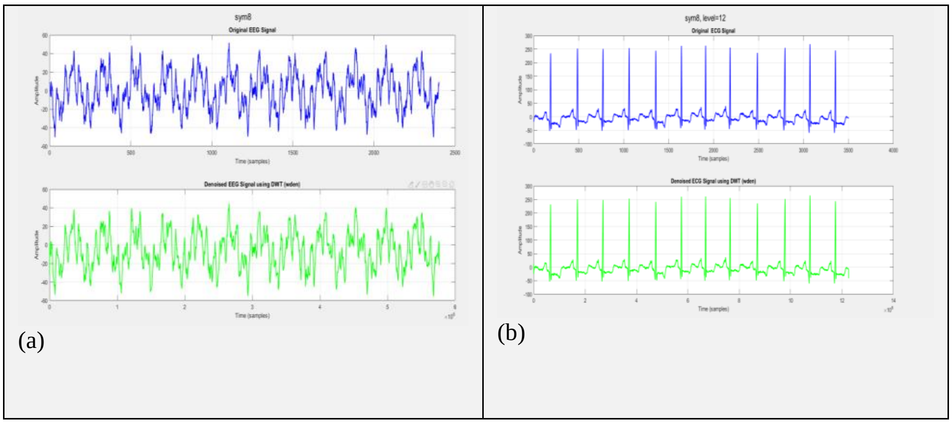

Figure 13. Denoising Performance Using Symlet 8 (sym8) Wavelet for (a) EEG Signal and (b) ECG Signal at Decomposition Level 12.

Table 2 shows the Statistical Comparison of Denoising Performance (Mean ± SD) for 30 Records.

Table 2. Statistical Comparison of Denoising Performance (Mean ± SD) for 30 Records.

Signal Type	**Method**	**Mean SNR (dB)**	**Mean MSE (0.01)**	**P-value (t-test)**
ECG (30 records)	Standard DWT (db1)	12.41 ±2.1	18.25 ±4.5	< 0.001
	Proposed PSO-DWT	21.88 ± 0.8	9.24 ± 1.2	(Significant)
EEG (30 records)	Standard DWT (db1)	8.18 ± 3.4	25.10± 5.1	< 0.01
	Proposed PSO-DWT	17.57 ± 1.1	12.35± 1.8	(Significant)

5. Conclusion

This research presents a systematic approach for scaling up the quality of biomedical signals, e.g. ECG and EEG, using the Discrete Wavelet Transform (DWT) in MATLAB. By exploring different approaches, such as various wavelet considerations (db1, coif5, sym8), differential thresholding techniques (soft, hard), and decompositions, this research derives optimal settings for noise reduction and preservation of signal quality. In all test arrangements, the Symlet 8 (sym8) wavelet was highlighted for the best SNR and lowest MSE, both in ECG and EEG signals, reflecting its excellent ability in time-frequency analysis and symmetry. Remarkably, in the study, it was found that the denoising abilities of DWT strongly depended on the choice of decomposition level, beyond which noise suppression would become better up to an optimal level. The experimental results reinforce that careful selection of wavelet function and thresholding method is essential for biomedical signal enhancement, especially in clinical scenarios where signal fidelity is critical for accurate diagnosis. However, several limitations must be acknowledged. First, while the denoising process was rigorously evaluated on benchmark datasets from MIT-BIH and PhysioNet, the signals were processed offline in controlled simulation environments, not in real-time. Second, the analysis was limited to a fixed number of wavelet types and thresholding strategies, leaving out more adaptive or data-driven techniques such as Bayesian shrinkage or machine learning-based denoising. Based on these findings, future work should pursue the following directions:

- Integration of adaptive or learned thresholding schemes that adjust dynamically to signal characteristics.
- Deployment of the denoising framework in real-time embedded systems for real-world patient monitoring.
- Expansion of the study to include more complex biomedical signals, such as EMG or multimodal recordings.
- Comparative evaluation of traditional DWT against more recent methods like Empirical Mode Decomposition (EMD) or deep-learning-based denoising.
- Exploration of hybrid signal processing pipelines that combine DWT with feature extraction for disease classification tasks.

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Conflict of interest: *Authors are declared that there is no conflict of interest regarding this study.*

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