International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 15, No.1 (Mar-24)

http://dx.doi.org/10.12785/ijcds/150196

A Novel Approach for Denoising ECG Signals Corrupted with White Gaussian Noise Using Wavelet Packet Transform and Soft-Thresholding

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Received 16 May 2023, Revised 24 Jan. 2024, Accepted 7 Feb. 2024, Published 10 Mar. 2024

Abstract: The electrocardiogram (ECG) is a vital tool for detecting heart abnormalities, However, noise frequently disrupts the signals during recording, reducing diagnostic precision. During wireless recording and portable heart monitoring, one major source of noise is called additive white Gaussian noise (AWGN). Therefore, clean ECG signals are really important to diagnose cardic disorders. To address this concern , a novel approach is introduced that employs the Wavelet Packet Transform (WPT) for effective ECG signal denoising. WPT provides a comprehensive signal analysis, using the Symlets 8 mother wavelet function, decomposing ECG data into high and low frequency components over two levels. Subsequent to this, a soft thresholding (ST) technique is implemented to attenuate noise. Moreover, the universal threshold technique is incorporated, dynamically determining threshold values. Proposed method efficiently reduces noise through thresholding, addressing both low and high frequency noise components at each level. The retained coefficients are then utilized in the inverse WPT to reconstruct the denoised ECG signal. Comprehensive analysis highlights the robustness of our approach, demonstrating better performance compared to established denoising techniques on the MIT-BIH database. Performance metrics including Signal-to-Noise Ratio (SNR), SNR Improvement (SNRimp), correlation coefficient (CC) , Percentage Root Mean Square Difference (PRD) and Mean Squared Error (MSE) are employed. Proposed WPT approach, tailored through suitable decomposition levels and mother wavelet selection, represents a substantial improvement in ECG signal denoising beyond conventional techniques. The proposed method showcases substantial improvements over EMD-DWT, with 28.32% lower RMSE, 34.99% higher SNR, and 0.25% enhanced CC.

Keywords: Wavelet Transform (WT); electrocardiogram (ECG); Noise reduction; denoising; Discrete Wavelet Transform (DWT); Additive white Gaussian noise (AWGN); Wavelet Packet Transform (WPT); Soft thresholding (ST); Hard thresholding (HT)

1. Introduction

Heart failure (HF) is a serious social, economic, and public health concern across the world and its incidence and prevalence are rising [1]. The electrical impulses that are generated by the heart manifest as ECG patterns.It gathers a wealth of knowledge on the health of human hearts [2]. Early identification of cardiac arrhythmias and various other cardiovascular disorders is critical for accurate diagnosis and intervention [3]. Recent technological developments have sparked the innovation of methods for online tracking of patient's ECGs and in fact, the status of the heart [4-5]. The inclusion of noise as they are being recorded and sent in ECG signals is the first issue that develops in such systems [6,7]. The ECG signal's morphological structure is distorted by various noises, including AWGN, electromyographic noise (EMG), baseline wander (BLW) and powerline interference (PLI).

The existence of these noises interferes with the appropriate detection of cardiac disorders. When ambulatory patient monitoring and wireless recording are used, AWGN is one of the several noises that severely contaminates the ECG signal [8,9]. Since it is now possible to monitor a patient's heart status remotely, it is crucial to denoize the ECG signal as little as possible without distorting its morphological structure [10]. Many different methods have been suggested throughout the years to denoise the ECG signal. Those methods often depend on the nature and characteristics of the noise.

The most advanced techniques include FIR filtering [11, 12], neural networks [13], adaptive filtering [14], principal component analysis (PCA) [15], nonlocal means (NLM) [16], discrete wavelet transform (DWT) decomposition [17,18]. In [19] majority of the ECG noise was reduced using DWT, and the remaining noise was reduced using a deep neural network. [20, 21] used adaptive, soft and hard thresholding approaches for ECG signal denoising

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employing DWT. Improved wavelet thresholding assisted in the noise reduction of ECG signals (NIWT) [22]. A novel noise variation estimate using a genetic algorithm was used to reduce a new noise fluctuation, amidst the noisy background of the ECG signal together with the DWT (GAMNVE) [23].

A real-time noise reduction method is empirical mode decomposition (EMD) [24]. It breaks down a non-stationary signal into its constituent intrinsic mode function (IMFs). ECG signals with AWGN were successfully denoised using hybrid models integrating DWT and EMD [25,26]. The ECG was successfully denoised using a variational mode decomposition (VMD)-based approach [27].[47] highlights an innovative ECG denoising method, combining variational mode decomposition and empirical wavelet transform. This approach effectively mitigates noise issues in clinical ECG data, demonstrating superior performance .

An innovative adjustable window function designed for FIR filter optimization, demonstrating superior performance in terms of side-lobe suppression and ripple reduction compared to Gaussian and Kaiser windows. Notably, this method substantially enhances noise reduction in distorted ECG signals, showcasing its practical utility, particularly in eliminating of AWGN noise [41]. [42] presents a two-stage algorithm for denoising ECG signals contaminated by AWGN. It models the signal as a combination of spike-like and smooth components, using majorization-minimization and modified singular spectrum analysis methods. The approach demonstrates effective denoising, outperforming existing approaches. Potential challenges may arise in accurately differentiating between spike-like and smooth components, particularly in more intricate noise environments.

The research outlined in [43] presents a novel approach for noise and artifact detection in ECG signals. It employs time series clustering by extracting unique features from the signal and grouping samples through agglomerative clustering. Moreover, the approach's efficacy might be hindered by its susceptibility to variations in noise characteristics and its potential limitations in effectively addressing intricate and diverse noise patterns.

The research documented in [44] tackles the issue of precise QRS complex identification within noisy ECG signals, proposing a novel denoising method employing variable frequency complex demodulation (VFCDM). The method exhibits superior performance in denoising compared to established approaches, highlighting its potential for improved ECG signal quality assessment and arrhythmia detection. This approach encounters difficulties due to increased complexity and parameter tuning, sensitivity to noise variations, potential overfitting, trade-off between denoising and signal preservation. In [45] an innovative hybrid approach integrating NLM and modified EMD (M-EMD) is introduced, illustrating improved denoising performance and computational efficiency when contrasted with conventional techniques. Yet challenges include algorithm complexity, parameter sensitivity, denoising-preservation trade-off, and computational demands.

[28] introduces a novel approach for ECG denoising combining VMD and digital filtering techniques. By generating narrow-band variational mode functions (VMFs) to design variable notch filters, PLI was effectively eliminated, thereby enhancing signal quality for accurate cardiovascular diagnosis.

Although numerous approaches have shown potential denoising performance, each has its benefits and drawbacks. By resolving the flaws of the aforementioned advanced denoising techniques, noise's harmful impact on ECG signal may be minimized more drastically. Certainly, due to its ability to capture information across a broad range of frequencies, the WPT can be exceptionally efficacious in addressing AWGN from ECG signals.

As AWGN exhibits a uniform distribution of energy across all frequencies, the WPT's ability to analyze both low and high-frequency components simultaneously aligns well with the AWGN characteristics.

By iteratively applying wavelet transformations to scaling and wavelet coefficients, the WPT can adeptly segregate and eliminate noise while preserving essential features of the ECG signal. This renders the WPT a robust choice for this denoising task. Unlike previous methods that combined various techniques, WPT offers an independent solution, simplifying the denoising process. WPT's adaptive thresholding, multiresolution analysis, and localized processing techniques allow it to tackle noise effectively. This iterative approach selectively isolates noise while maintaining ECG characteristics, making WPT a robust choice for enhancing ECG signal quality by eradicating AWGN noise.

Using two-level WPD decomposition, the ECG signal and AWGN are first split into their respective detail and approximation coefficients in the proposed study. The denoising process using the WPD is applied exclusively to coefficients extracted from the approximation of lower frequencies at Level 2.

Because the detail coefficients contain high-frequency disturbances as well as certain signal details, the process of soft-thresholding is applied to denoise them [29]. In this study, the level 2 approximation coefficients closely resemble the envelope corresponding to the lower frequencies of the ECG signal. That only a two-level wavelet decomposition is utilized.

The efficiency of WPD will be decreased by higher-order decomposition since it will provide approximation coefficients with distorted envelopes. On the database of MIT-BIH arrhythmia, studies conducted demonstrate that the suggested technique denoises the ECG with a significant enhancement in SNR value and significant decreases in

MSE values. In comparison to prior suggested approaches like NLM, NLWT and Hybrid EMD-wavelet.

The paper is organized into nine sections. Materials and methods are covered in Section 2. Section 2.1 discusses Denoising Using WPT, The principle of thresholding is discussed in Section 3, in Section 3.1 Threshold value selection is explained, suggested denoising approach is discussed Within Section 4, The selection of the parameter is covered in Section 5, Section 5.1 Metrics for quantitative performance evaluation is discussed, Databases for recording ECG signals and noise are shown in Section 6. Section 7 explores the obtained results. Section 8 contains a discussion of the proposed Method. Section 9 concludes by presenting findings.

2. MATERIALS AND METHODS

Since its introduction, the WT has evolved into the most potent tool for signal analysis across a variety of disciplines, including the study of non-stationary signals. WT offers a time-frequency analysis that, in contrast to the conventional Fourier transform (FT), can identify transient, local or intermittent components in the signal being analyzed. The process is a linear transform that uses a scaled besides shifted variant derived from the mother wavelet to refine a signal into a multi-resolution representation. Mallat [30] has presented an effective and reliable approach, the data being analysed in the DWT are transmitted via two high-pass and low-pass filters, respectively, followed by down sampling to produce the signal's high-frequency contents (details) and low-frequency contents (approximations). The approximations are once more sent employing the identical pair of lowpass and high-pass filters within the following level, yielding a new set of details and approximations. As shown in figure 1, this procedure is carried out recursively prior to the desired breakdown level is reached.

The two-level 1D IDWT synthesis filter model shown in figure 2, reconstructs the original signal by applying the inverse process, merging detail and approximation coefficients via upsampling and filtering to achieve signal reconstruction. These procedures form the basis in signal analysis, compression, and denoising. Denoising with DWT approach employs the DWT to analyze the signal being studied, producing a number of coefficients. By preserving the coefficients related to the signal and thresholding out the noise-related ones, one may accomplish noise rejection.

Three stages are typically included in wavelet thresholding. First, DWT [31] is used to decompose the signal (for example, the ECG signal). The outcome involves decomposition of the signal into low-high, high-high, high-low and low-low sub-bands. Subsequently, a non-linear thresholding is applied to each DWT sub-band coefficient. whenever the DWT coefficient falls below the defined threshold, the coefficient values are made zero. Alternatively, it is preserved. Lastly, to retrieve the denoised signal, an inverse DWT is performed. A method for choosing the ideal threshold value was put out by Donoho and Johnstone [32].

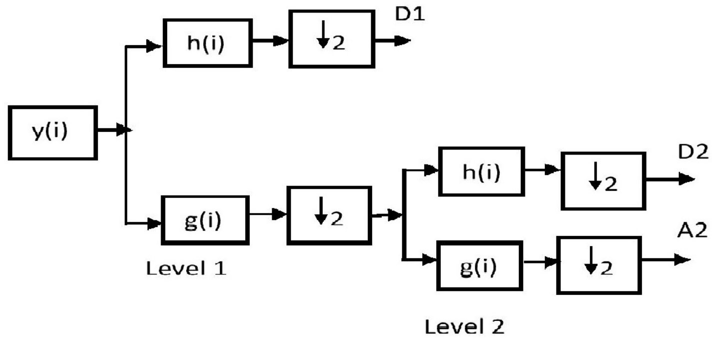


Figure 1. Signal analysis two-level 1D DWT Decomposition filter model

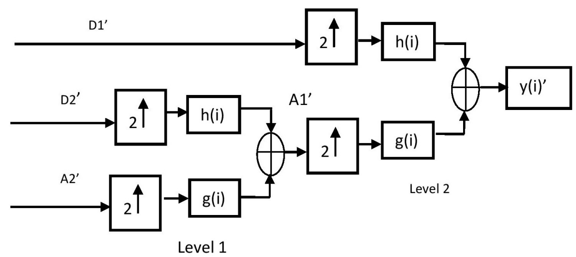


Figure 2. Signal synthesis two-level 1D IDWT Decomposition filter model

As denoted in figure 1 and figure 2 high pass filter $h(i)$, Low pass filter $g(i)$, A contains approximation coefficients and D Detail coefficients, ['] denotes denoised output.

Coifman, Meyer, and Wickenhauser introduced the WPT [33–34]. It enables a deeper signal analysis and is a further development of the wavelet decomposition shown in figure 3. To analyze the frequency components of a signal from time domain, a level-by-level transformation is offered. This feature provides improved frequency resolution. The WPT, a variant of the commonly used DWT, employs the decomposition scheme to each level's approximations as well as its details, yielding a full binary tree.

where A1 denotes approximation component, X(n) being the original signal, D1 signifies the detail component, AA2 is the approximation component of A1, DA2 is the detail component of the A1, AD2 is the approximation component of D1, DD2 is the detail component of D1. WPT serves as a natural extension of the DWT, that provides, more localized time-frequency information than DWT, while maintaining increased adaptability. In contrast to the DWT's iterative application solely to scaling coefficients in the low-pass filter band, WPT allows for more intricate investigations by facilitating the subdivision of both details and approximations into more specific sub-components.

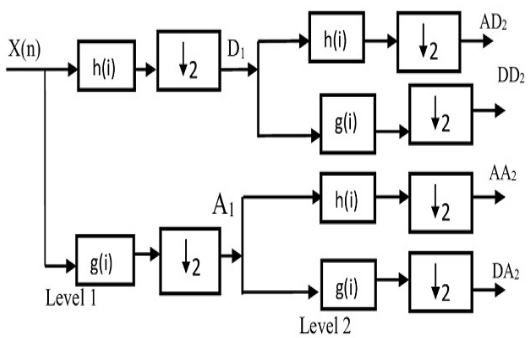


Figure 3. Two level decomposition, using WPT

This versatility proves particularly advantageous for tasks that rely on careful and detailed examination of frequencies.

A. Denoising Using WPT

The WPT produces a full binary tree by applying the decomposition to both the details and the approximations on each level [35]. WPT is a better choice for signal analysis if noise is present in both high- and low-frequency sub-bands.

WT is applied iteratively via WPT to the high- and low-frequency components. WPT employs wavelet packets (WPs) as its fundamental building blocks, which are produced by a linear operation of wavelet functions, with the WPs acquiring attributes of their associated wavelet functions. Consequently, the level-by-level analysis of a signal into a series of WPs is known as the WPT process.

Figure 4 illustrates the block diagram of the real-time two-level wavelet packet architecture for reconstruction and decomposition. The Real-time WPT architecture depicted in Figure 4 incorporates a two-level decomposition process that utilizes both upsampling and downsampling operations. In it, a signal is divided into approximate and detailed coefficients.

Then, the second-level coefficients for approximation and details are derived from the corresponding coefficients at the initial level. The noisy ECG signal is decomposed into frequency subbands using high-pass and low-pass filtering followed by downsampling. Subbands are processed using ST to minimize noise while retaining vital features.

After sub-subband ST, the processed subbands undergo upsampling at second-level decomposition, yielding sub-subbands capturing finer details. The denoised signal output is generated through reconstruction. Upsampling and down-sampling enhance subband processing, allowing effective noise reduction while preserving signal characteristics.

3. THRESHOLDING PRINCIPLE

A signal-estimation technique is wavelet thresholding that takes advantage of WT's capabilities for signal de-noising. A modest threshold can produce an output that is near to the input however, it may still exhibit noticeable noise. While a big threshold creates a signal containing a significant amount of zero coefficients. As a consequence, a smoother signal is generated, but the details are lost. Two different thresholding methods exist, HT and ST. At more detailed scales, the wavelet coefficients are likely to encompass the dominant portion of the noise. These coefficients are set to zero using the HT approach, which would lead to naturally occurring scale-based noise filtering. However, such scale coefficients also frequently encompass crucial edge information from the signal. These coefficients are additionally strained out in the HT technique. However, wavelet coefficients are suppressed by a threshold value rather than being eliminated in the ST method approach. Consequently, the signal examined experiences alleviated distortion.

Therefore, in this study, we employ Donoho and Johnstone's wavelet ST method to denoise the chosen signal. Donoho and Johnstone [36] defined the ST

$$\tilde{D}_j = \begin{cases} sign(D_j)(D_j - \lambda) & if\ |D_j| > \lambda \\ 0 & if\ |D_j| \leq \lambda \end{cases} \tag{1}$$

Where $\tilde{D}_J$ are the updated detail coefficients, D_j is the noisy signal's WPT decomposition's detail coefficients and λ is the threshold where $\lambda \geq 0$.

A. Threshold value selection

The threshold value is one of the crucial factors that determine how well noise is suppressed. Depending on whether the threshold value is too little or too big, the de-noised ECG signal may either uphold specific interferences or exhibit some discontinuities and distortion, depending on the chosen value.

In our pursuit of an optimal denoising methodology, the Sqtwolog (Sqrtlog or Universal Thresholding) technique is employed [36]. Unlike traditional methods that depend on predefined thresholds or complex estimations, Sqtwolog utilizes automated, data-driven threshold determination. This process entails determining the threshold using the square root of the logarithm of coefficients at each decomposition level, aligning it with the signal's complexity and addressing the challenge of selecting appropriate threshold values. Through dynamically adjusting thresholds based on the characteristics of the signal, it ensures consistent tailoring to input properties. This automated adaptation eradicates threshold ambiguity, thereby enhancing reproducibility of denoising outcomes.

$$\lambda = \sigma \sqrt{2 \ln(N)} \tag{2}$$

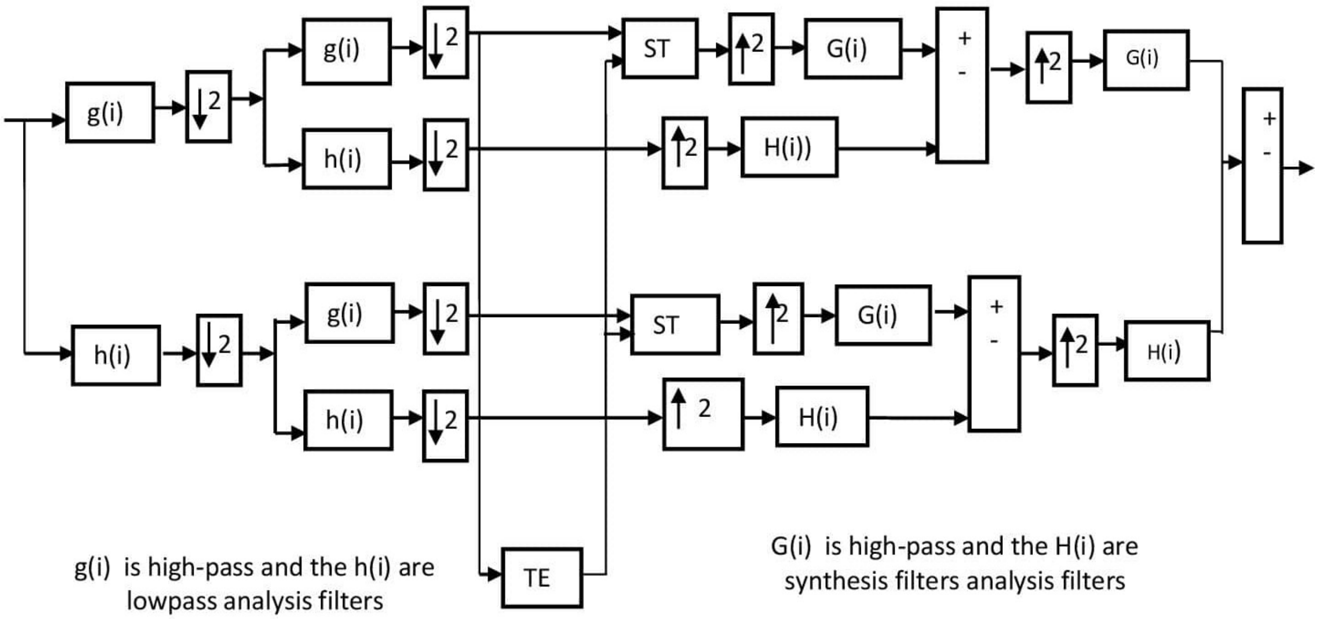


Figure 4. Real-time WPT architecture block diagram for signal denoising

where σ is the noise deviation, N Indicates the sample size in a noisy signal and λ signifies the appropriate estimate of noise energy under the assumption that noise is Gaussian distributed.

$$\sigma = \frac{MAD}{0.6745} \tag{3}$$

where MAD, calculated using the first-level coefficients, is the median absolute deviation

$$MAD = median\left(|w - median(w)|\right) \tag{4}$$

w being the wavelet coefficient.

4. PROPOSED DENOISING TECHNIQUE

When wireless ECG signal recording is performed, it is distorted by AWGN. It is vital to eradicate AWGN from ECG signals for proper diagnosis since it influences the diagnostic characteristics. Denoising is an inverse issue that tackles restoration of a clean signal, while utilizing information about the noise characteristics from noisy observation. To represent channel noise, AWGN is often utilized. Given an AWGN-contaminated ECG signal, The observed ECG signal is expressed as

$$Y_n[z] = x[z] + q[z] \tag{5}$$

where $Y_n[z]$ represents the noisy signal, $x[z]$ represents a clear ECG signal and the zero-mean AWGN with variance σ^2 is denoted by $q[z]$.

Our paper presents a comprehensive approach to ECG signal analysis using WPT with the Symlets 8 mother wavelet function. ECG data is decomposed into low- and high-frequency components across two levels. Subsequently, a two-noise attenuation strategy is employed. Initially, a ST technique is applied to subdue noise, followed by the integration of the universal threshold technique to dynamically set threshold values.

The steps listed below are suggested in work as a means of achieving a noise-free signal. The flow chart figure 6 also illustrates the processes that are utilized to process the noisy ECG signal. By evaluating the denoised outputs using various performance metrics, the study seeks to determine the most suitable mother wavelet for effectively suppressing noise while retaining important signal details. The selected denoised ECG output is anticipated to offer valuable insights into improving the accuracy of ECG signal analysis and diagnosis.

1 Database of MIT-BIH arrhythmia is utilized to acquire the ECG signals.
2 To introduce noise into the ECG signals, AWGN is combined with the original ECG with varying the signal-to-noise ratio (SNR)
3 Distortions around ECG features caused by AWGN are identified in the signal (refer to figure 7).

4 WPT is applied, employing a carefully chosen Mother Wavelet (MW), at a second decomposition level. This results in cA (approximation) and cD (detail) coefficients.
5 At the second level, minimize the cA and cD coefficients obtained from the WPT.
6 Soft thresholding is employed on the coefficients obtained at the second level to effectively suppress the AWGN while retaining important signal features.
7 Apply the IWPT to get the denoised signal $X_d[n]$.
8 Utilize metrics to assess and quantify the outcomes of the denoising process.
9 Compile the denoised signals, threshold values, chosen wavelets, and evaluation metrics into a comprehensive table.
10 Select the best denoising outcomes based on the compiled data, considering signal quality and associated metrics.

The graphical depiction in figure 7 offers a detailed insight into the denoising performance variation among various mother wavelet functions (MWF) when applied to ECG signals. Notably, Symlets and Coiflets MWFs exhibit superior noise reduction capabilities in comparison to the Daubechies MWF. This assertion finds additional validation through the analysis of spectrograms, which conclusively verifies the effective removal of high-frequency noise components.

Moreover, the main emphasis of this study involves the utilization of distinct wavelet functions, including Symlets (sym), Daubechies (db), and Coiflets (coif). These wavelet functions are employed to perform an extensive comparative assessment of their effectiveness in terms of denoising performance within the context of ECG signal processing.

In figure 5, a clear visual comparison is presented among the original noisy ECG and denoised ECG signal obtained via suggested denoising approach based on WPT. This graphical representation enables a direct and insightful evaluation of the effectiveness of the denoising process.

5. Parameter selection

The efficacy of the intended denoising strategy is determined on a few important factors. Various parameters were improved throughout analysis utilizing ECG records via standard MIT-BIH arrhythmia database [37]. Different recordings are utilized for parameter selection and performance evaluation. The next sections address the process of selection of different characteristics and the performance metrics employed to compare the proposed technique with current techniques.

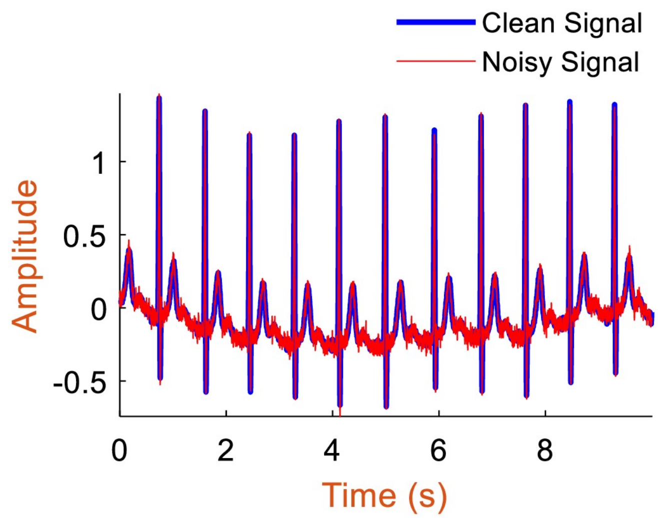


Figure 5. Comparison of the original noisy ECG signal with the processed denoised ECG signal acquired by employing the proposed Wavelet Packet Transform-based denoising approach.

A. Quantitative Performance Assessment Metrics

In this paper, a quantitative investigation were conducted utilizing several performance metrics, which encompassed SNR_{out} , SNR_{imp}, PRD, CC and MSE. The following are the criteria

$$SNR_{out} = 10\log_{10}\left(\frac{\frac{1}{N}\sum_{h=0}^{N-1}|\hat{x}(h)|^2}{\frac{1}{N}\sum_{h=0}^{N-1}|x(h)-\hat{x}(h)|^2}\right) \tag{6}$$

$$PNR = \sqrt{\frac{\sum_{h=1}^{N}(\hat{x}(h)-x(h))^2}{\sum_{h=1}^{N}(x(h))^2}} \tag{7}$$

$$MSE = \sum_{h=1}^{N}(\hat{x}(h)-x(h))^2 \tag{8}$$

$$SNR_{imp} = 10\log_{10}\left(\frac{\sum_{h=0}^{N-1}|y(h)-x(h)|^2}{\sum_{h=0}^{N-1}|x(h)-\hat{x}(h)|^2}\right) \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{h=1}^{N}(\hat{x}(h)-x(h))^2}{N}} \tag{10}$$

$$CC = \frac{E\left((x-\mu_x)(\hat{x}-\mu_{\hat{x}})\right)}{\sigma_x \times \sigma_{\hat{x}}} \tag{11}$$

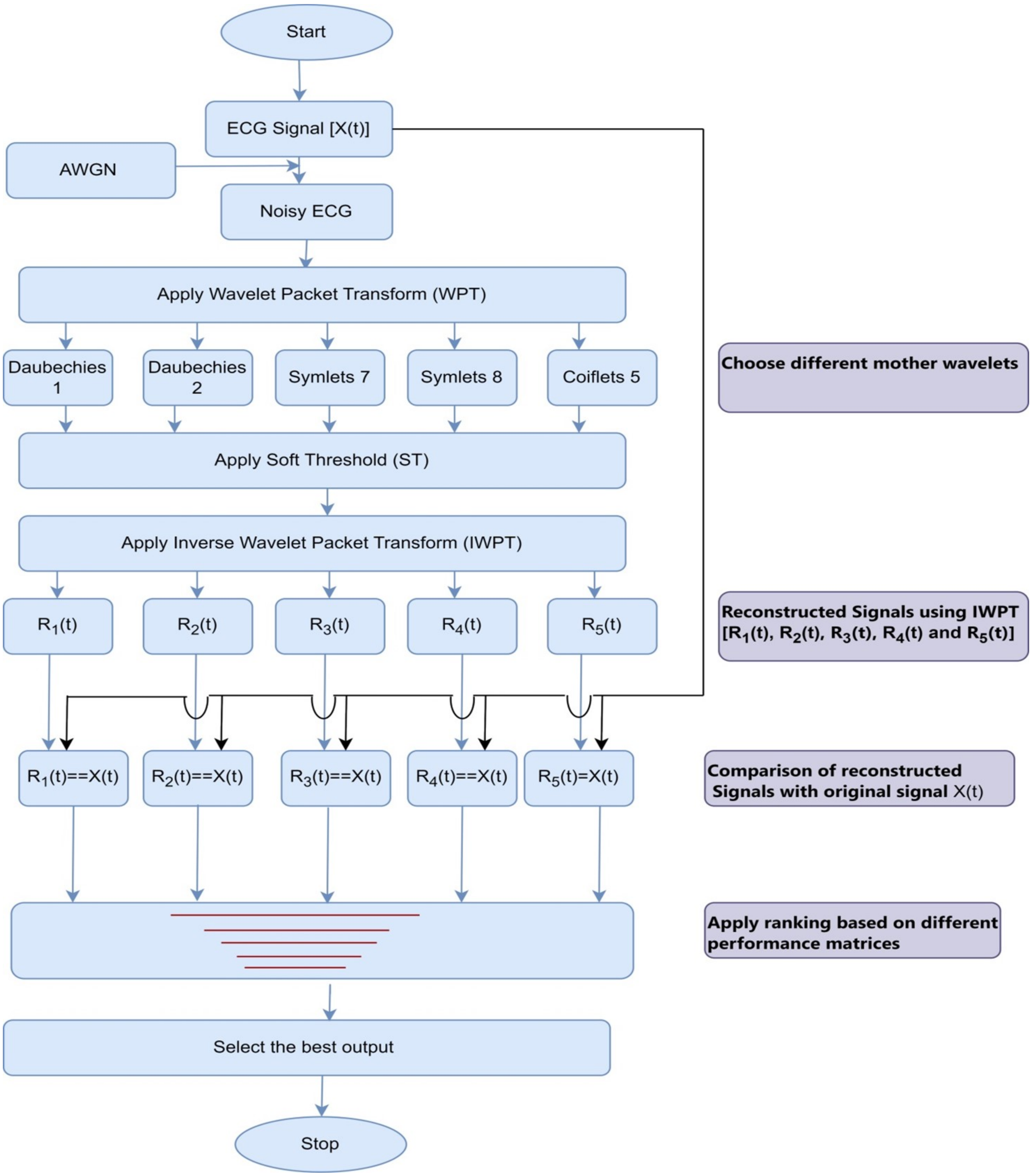
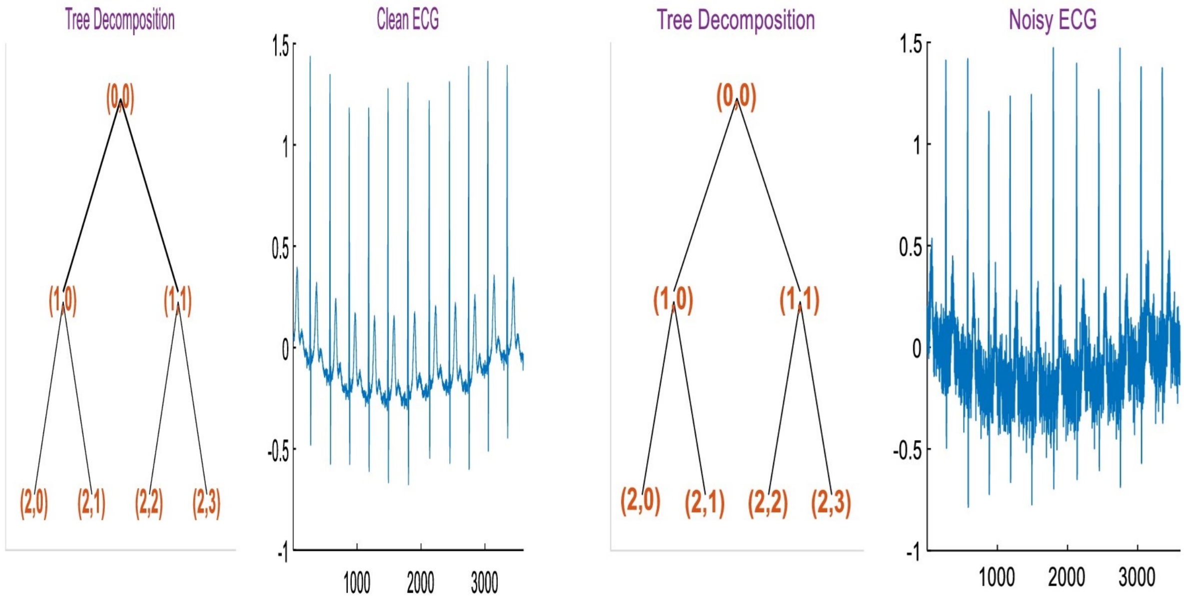


Figure 6. Flowchart depicting the proposed technique for eradicating AWGN from ECG signals.


Tree Decomposition
(0,0)
(1,0)
(1,1)
(2,0)
(2,1)
(2,2)
(2,3)
Clean ECG
Tree Decomposition
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(2,1)
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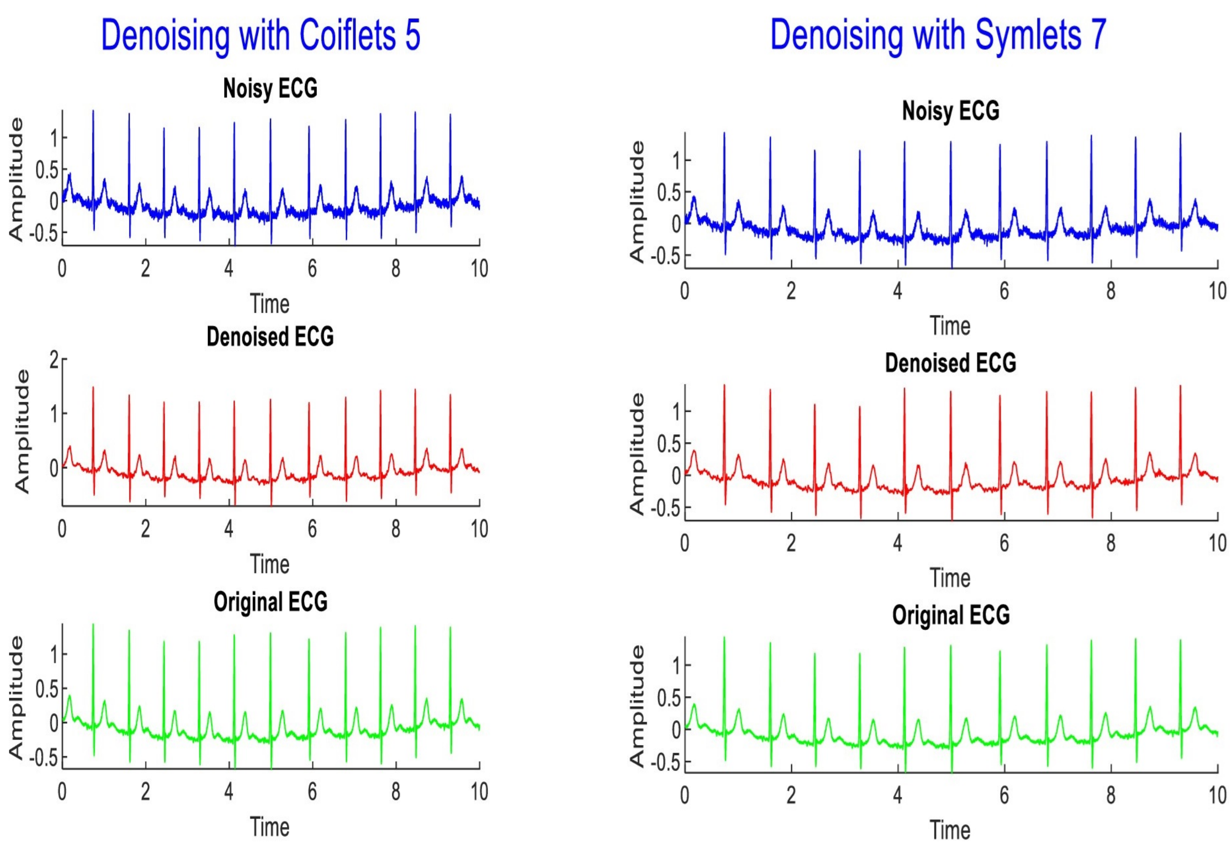
(2,3)
Noisy ECG


Denoising with Coiflets 5
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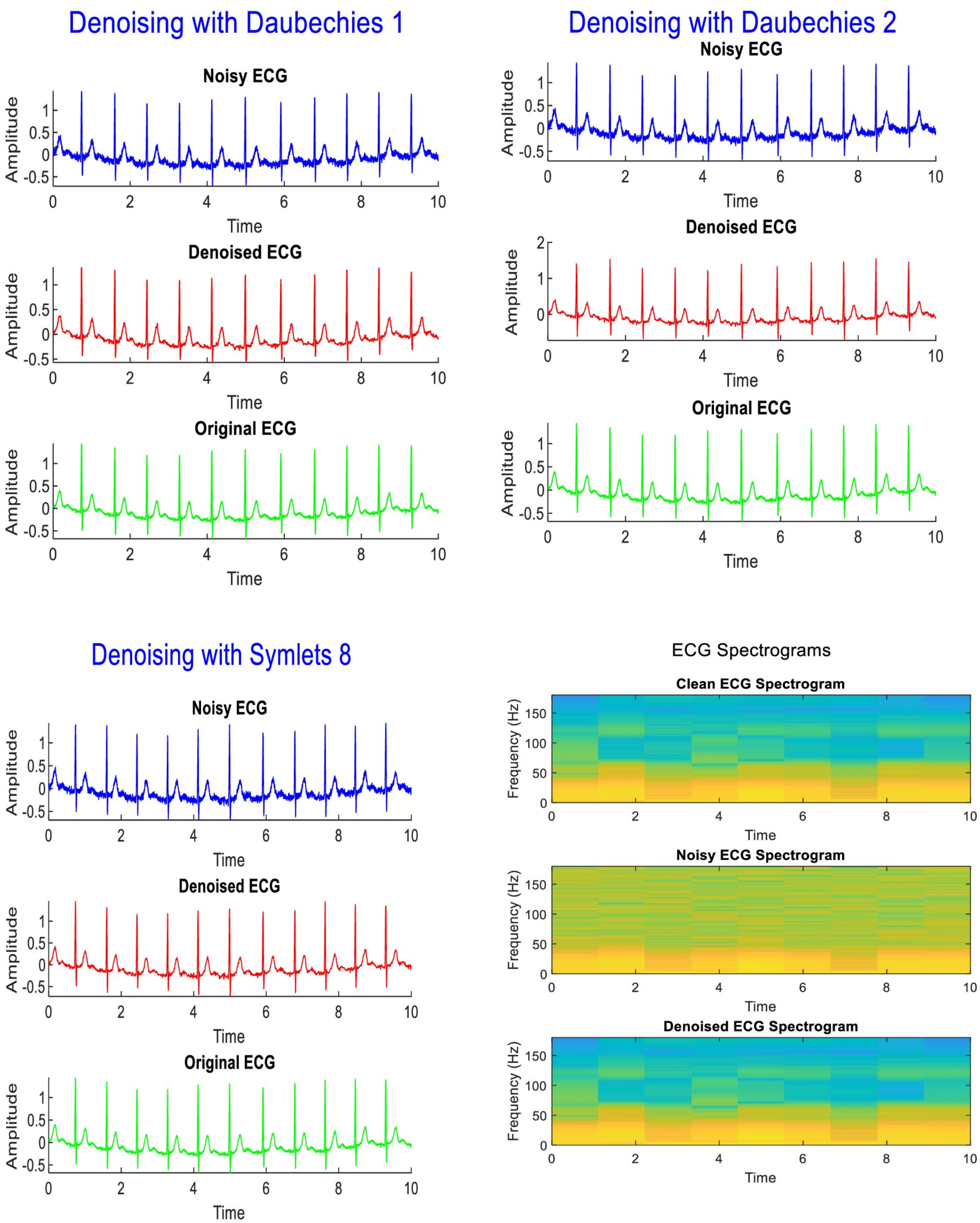

Figure 7. Displays the denoising performance of different mother wavelet functions (MWF) for ECG signals. Symlets and Coiflets MWFs outperform Daubechies MWF in terms of noise reduction, with spectrogram analysis confirming the elimination of high-frequency noise components.

N being the overall quantity of samples of the pure ECG signal, $\hat{x}(h)$ denotes the approximated clean ECG signal acquired by the denoising approach, $y(h)$ signifies the signal following the addition of noise, and $x(h)$ signifies the unadulterated ECG signal, where E denotes the expectation operator, μ_x, $\mu_{\hat{x}}$ are the mean values and σ_x, $\sigma_{\hat{x}}$ denotes standard deviation of $x(h)$ and $\hat{x}(h)$ respectively.

Each of the aforementioned metrics has a particular relevance such as SNR_{imp} compares output and input signal to examine the increase in SNR, between the denoised output and noisy input, MSE calculates the mean square error, whereas PRD identifies the level of distortion found within the denoised output. The CC is often employed to evaluate the similarity between two signals.

6. Databases for noise and ECG signals

The suggested study makes use of Real ECG records. To compute the performance for the filtering process, distortion-free data are required. MIT-BIH Physionet database, with a 360 Hz sampling rate, was used in this investigation[37]. Realistic ECG recordings (Record No: 100, 103, 104, 105, 106, 115,119,208 and 215) are taken into consideration from the MIT-BIH arrhythmia database to analyze the suggested approach and gauge its performance on a qualitative level.

Figure 8 presents our algorithm's denoising effectiveness on MIT-BIH Record 106. Utilizing a 20 dB input SNR, the algorithm preserves key cardiac features while reducing noise within the ECG signal.

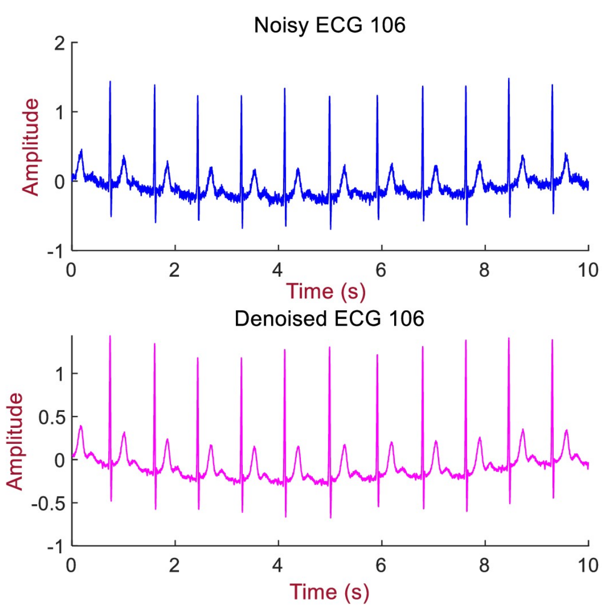

Figure 8. Denoising Performance of Proposed Algorithm on Record 106 from MIT-BIH Database at 20 dB Input SNR

The noisy ECG signals used in the studies were produced artificially by adding AWGN at predetermined SNR levels applied to Unprocessed signals acquired from the database. The cardiac signals within the PTB diagnostic database, includes several ECG signals that have recognized pathologies and are also employed with a sampling frequency of 1000 Hz. Five diseases are chosen from among those, and one signal for each disease is examined for performance evaluation.

7. Results

The effectiveness of different wavelet functions employing various performance parameters in Table I, averaged across all 10 records taken into consideration for parameter selection at input SNR levels of 15dB, 10dB, 5dB, and 0dB. The results indicate SNR_{imp}, SNR_{out} *and* PRD at various SNR levels corresponding to each wavelet function.

Significantly, wavelet functions exhibit varying performance across different SNR levels, highlighting the importance of considering parameter selection. The assessment encompasses wavelet functions such as Daubechies 1, Daubechies 2, Symlets 7, Symlets 8, and Coiflets 5. For all of the examined test ECG recordings, PRD values for different denoising approaches are compared to the suggested approach in figure 9. The PRDs for studied methodologies on distinct input SNR levels illustrates the efficacy of the devised approach can be seen from the bar plot, Depicting a substantial improvement surpassing the current state-of-the-art methods.

TABLE I. Wavelet function comparison using different performance metrics averaged across all 10 recordings examined for parameter selection at 15dB, 10dB, 5 dB, and 0 dB input SNR levels

Input SNR	Param.	Daub. 1	Daub. 2	Symlets 7	Symlets 8	Coiflets 5
0	SNR_{out}	7.35	7.19	7.24	7.90	7.38
	SNR_{imp}	6.17	5.97	6.02	6.82	6.20
	PRD	22.32	22.42	20.14	19.03	19.16
5	SNR_{out}	11.16	11.16	11.17	11.94	11.24
	SNR_{imp}	5.90	5.88	5.89	5.98	5.97
	PRD	18.31	18.36	17.34	17.06	17.08
10	SNR_{out}	16.16	16.38	16.29	16.84	16.35
	SNR_{imp}	5.97	6.19	6.09	6.86	6.15
	PRD	9.78	9.39	8.56	7.46	7.46
15	SNR_{out}	20.33	21.09	21.33	21.74	21.13
	SNR_{imp}	5.20	5.95	6.19	6.19	5.99
	PRD	7.70	7.89	6.65	5.84	5.85

Where Param. means Parameters and Daub. means Daubechies. The quantitative analysis is based on performance parameters, including SNRimp, PRD, and MSE. Experiments are carried out using ECG signals contaminated with noise, that are created synthetically by adding AWGN at various SNR levels.

The suggested method plus a few contemporary approaches are then used to denoise the noisy ECG data. The experimental performance employing signals numbers 100, 103, 104, 105, 106, 115, and 215 is provided to compare the findings with the approaches in [38,39,40]. MSE metric is used to determine how much information is lost or altered during the denoising process of ECG signal.

The MSE number should be negligibly low, and ideally, it should be zero. figure 9 presents the quantitative assessment of MSE for different techniques. For all input SNR levels taken into consideration, the MSE value for the suggested technique is the lowest. Figure 9's area plot for MSE comparison emphasizes the superiority of the proposed approach over current ones. The level of distortion is quantified by measuring PRD, The emphasis is on maintaining a distortion value that is as minimal as possible. Figure 10 illustrates a visual representation of the step-by-step denoising process applied to ECG signals employing WPT. It outlines the sequential phases within the proposed denoising method , offering a graphical overview of the signal processing approach for effectively eliminating noise from ECG data using WPT.

The suggested approach yields lowest PRD across all levels of SNR for each test record. At varied input SNR levels applied to a specific ECG record, the suggested technique's SNRimp is much greater than that of other current approaches.

The NLM [40] and non-local wavelet transform domain filtering [38] approaches are utilized for comparison. In [40], it has previously been demonstrated that these methods outperform conventional wavelet thresholding and the various approaches derived from it. The outcomes of the hybrid-EMD and NLM methods are taken directly from [38]. Table II provides the results of the various approaches on various signals at a 20 dB noise level. This table presents a performance evaluation comparing the proposed method with NLM[40] and NLWT[38] on disordered ECG signals obtained from the PTB diagnostic data repository. Significant results reveal the competitive performance of the proposed method in terms of MSE, PRD and SNR improvement metrics across different cardiac conditions such as myocardial infarction, myocarditis, bundle branch block, ventricular hypertrophy and cardiac dysrhythmia. Figure 7 likely demonstrates the efficacy of the suggested Wavelet Packet Transform-based denoising approach for the ECG signal. It should be noted that the proposed technique performs Superior to the existing approaches across all SNR levels for all three performance criteria. Among these metrics, the suggested method's increase in SNR is notably significant.

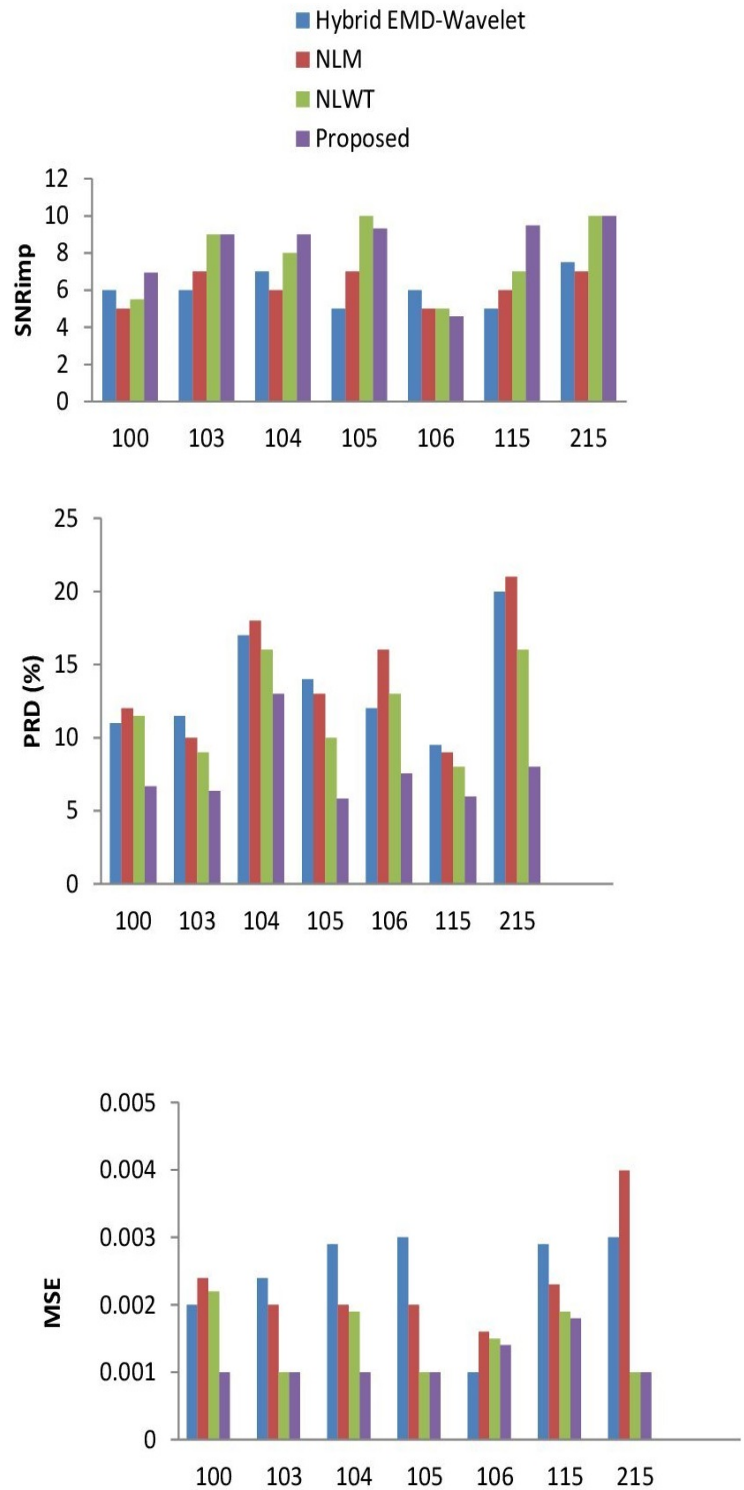

Figure 9. Denoising Performance Proposed Algorithm on different Records from MIT-BIH Database at 20 dB SNR

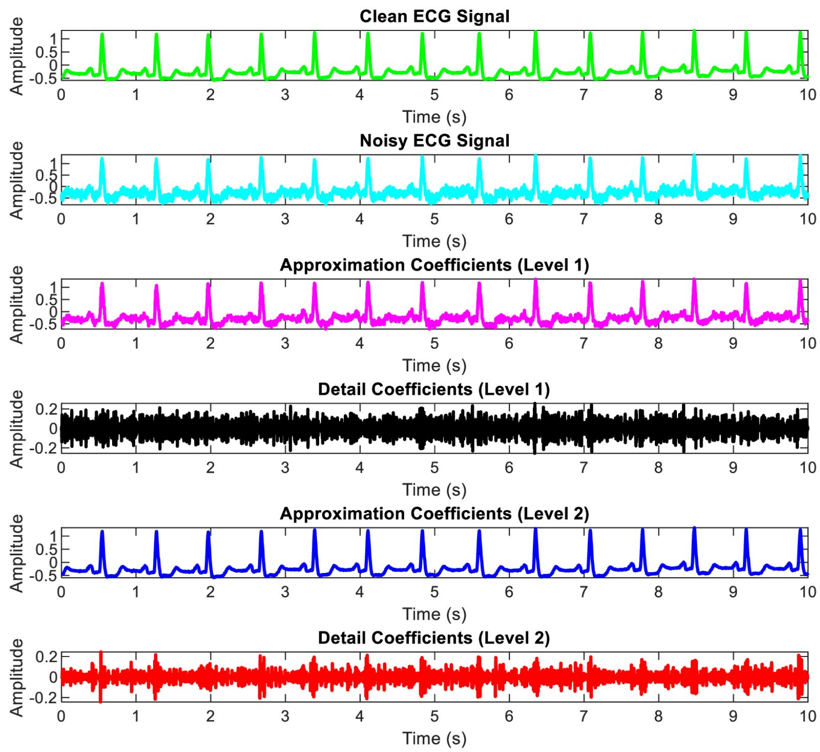

Figure 10. Steps involved in Denoising of Proposed Algorithm on Record 105 from MIT-BIH Database

TABLE II. Performance comparison of the suggested method with the NLM and NLWT approaches on various disordered ECG signals acquired through the PTB diagnostic data repository

Cardiac diseases	Record ID	NLM [40]			NLWT [38]			Proposed Method		
		PRD %	MSE	SNR_{imp}, dB	PRD %	MSE	SNR_{imp}, dB	PRD %	MSE	SNR_{imp}, dB
cardiac dysrhythmia	s0032_rem	23.50	0.0015	17.38	19.10	0.0010	19.18	0.0010	15.62	19.69
Myocarditis	s0508_rem	28.14	0.0015	15.43	18.82	0.0006	18.92	0.0005	16.09	19.93
bundle branch block	s0430_rem	20.32	0.0011	18.38	16.81	0.0007	20.03	0.0006	16.15	20.98
myocardial infraction	s0354l_rem	24.75	0.0011	16.38	20.20	0.0007	18.15	0.0006	19.14	21.19
ventricular hypertrophy	s0432_rem	20.55	0.0008	18.18	17.05	0.0006	19.81	0.0004	16.81	22.49

TABLE III. Analyzing and comparing the proposed method with DWT ('sqtwolog') and EMD-DWT ('sqtwolog') Approaches for ECG Signals using MIT-BIH Arrhythmia Database.

Signal	DWT using 'sqtwolog' [46]			EMD-DWT using 'sqtwolog' [46]			Proposed Method		
Signal	RMSE	SNR	CC	RMSE	SNR	CC	RMSE	SNR	CC
104m	0.1314	5.6048	0.9541	0.0738	8.1122	0.9855	0.0528	10.9671	0.9880
105m	0.1602	6.5769	0.9636	0.0343	13.2633	0.9983	0.0215	14.8677	0.9988
119m	0.2398	9.7109	0.9835	0.0509	16.4371	0.9991	0.0494	17.9722	0.9994
208m	0.1227	7.2262	0.9829	0.0652	9.9725	0.9948	0.0507	10.9311	0.9968
Average	0.1635	7.2797	0.9710	0.05605	11.9462	0.9944	0.0436	13.6845	0.9957

In the comparative analysis of signal processing techniques for analyzing ECG signals using the MIT-BIH Arrhythmia Database, significant performance metrics were observed , as presented in table III. The DWT approach utilizing 'sqtwolog' [46] exhibited an average RMSE of 0.1635, an average correlation coefficient of 0.9710 and an average SNR of 7.2797. Meanwhile, employing the EMD-DWT technique with 'sqtwolog'[46] showcased an average RMSE of 0.05605, an average CC coefficient of 0.9944 and an average SNR of 11.9462.However, the proposed method, demonstrated promising outcomes, with an average RMSE of 0.0436, an average CC coefficient of 0.9957 and an average SNR of 13.6845. These results highlight the efficacy of the suggested method in comparison to the well-established DWT and EMD-DWT methods using utilizing 'sqtwolog'[46]. These findings imply that the proposed method may offers improved accuracy and noise reduction capabilities for ECG signal analysis, this significance is particularly vital in medical diagnostic applications. The comparative analysis reinforces the potential of the proposed approach for enhancing ECG signal processing techniques.

8. Discussion

The proposed approach's thresholding of detail coefficients DD2 and DA2 successfully eliminates the presence of high-frequency artifacts existing in the ECG data. The noise components present in the low-frequency range are reduced by thresholding of the approximation coefficients AD2 and AA2 while keeping the ECG signal's morphological structure. In contrast to previous DWT strategies that required higher decomposition levels to accurately eliminate noise emanating from low-frequency components with precision.

The proposed denoising procedure uses only two levels of decomposition. Furthermore, soft-thresholding of the approximation and detail coefficients is possible simultaneously. Consequently, the total computational expense of the procedure is greatly decreased. The coefficient of approximation at Level 2 accurately represents the ECG signal's envelope, while ST efficiently removes noise components. This work employs ST because of the importance of the morphological structure of ECG. However, there is considerable likelihood of throwing crucial ECG signal information while HD.

9. Conclusion

AWGN is a prevalent issue that can interfere with electrocardiogram (ECG) signals, making them difficult to analyse and understand. In this article, we suggest a method for eliminating AWGN from ECG data using the WPT. By using the right mother wavelet and decomposition levels, this proposed method developed a unique WPT approach for ECG signal denoising. When compared to the five approaches, nonlocal wavelet transform domain filtering [38], hybrid-EMD [39], the NLM method [40], DWT using 'sqtwolog'[46] and EMD-DWT using 'sqtwolog'[46]. Experimental findings have demonstrated that the proposed technique is highly effective in removing AWGN from ECG signals while preserving the underlying ECG features. The suggested method outperforms the others on number of performance parameters.

The ability of the suggested approach to maintain the diagnostic elements in the signal is significantly superior than the current techniques is also highlighted. Wavelet function performs well at signal denoising while preserving ECG signal's morphological structure due to its tight support and orthogonality. The experimental findings demonstrate that the suggested approach can greatly enhance the ECG signal's quality and the denoising outcomes have greater SNR, lower MSE, greater CC and lower PRD. Overall, the suggested method offers a highly promising approach for AWGN removal in ECG signals, which could facilitate more accurate diagnosis and analysis of cardiovascular diseases. Future research might concentrate on adapting the suggested approach to handle different forms of noise and testing its effectiveness in more sophisticated ECG signal processing applications. As we reflect on our findings, numerous promising avenues emerge for future exploration. Primarily, adapting this approach to effectively tackle various types of noise, including BLW, PLI and other artifacts, could enhance its robustness in real-world applications. Combining this approach with other sophisticated signal processing techniques offers the potential to further improve its efficacy. The efficacy of WPT can be leveraged, as it presents a valuable tool for extracting significant features from the signal that may reveal various cardiac conditions and abnormalities.

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