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Original Article

Elimination of Noise from Ambulatory ECG Signal using DWT

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***Abstract** - The proposed work presents an efficient Wavelet Transform for noise removal from ambulatory cardiac signals and finds the R-R intervals making the signal ready for diagnosis. Noise affects cardiac analysis by creating some outliers. ECG signals can get corrupted by power line interference; direct current (DC) offset noise. These noises need to be filtered using moving average, wiener filter, etc. Some additional outlier bands might be attached to the ECG signal upon filtering. These signals can be removed using IIR (Infinite Impulse Response) and FIR (Finite Impulse Response) filters. Discrete Wavelet Transform (DWT) based technique designed using Python software is implemented in de-noising the Electrocardiograph (ECG) signal. The performance of de-noising is based on parameters like the selection of the wavelet (mother) function, the threshold method selected, the threshold value chosen, and the level of decomposition. Standard ECG signals available in the Physionet database, specifically the Arrhythmia Database MIT-BIH and PTB Database, are used to implement the proposed DWT method. Daubechies 8 (db8) is employed for high amplitude R wave detection. R waves are reference waves used in detecting the other waves by searching maxima and minima using windows. The same method also gives other features of R-R interval, QRS complex, P-R interval, ST deviation, and heart rate. SNR (Signal-to-Noise Ratio), MSE (Mean Square Error), RSME (Root Mean Square Error), and PSNR (Peak Signal-to-Noise Ratio) for soft and hard threshold techniques using Bayes Shrink and Visu Shrink methods were also estimated. The proposed approach gives maximum PSNR, average normalized MSE of 0.96, and SNR of 74%. The method proposed exhibits considerable noise elimination from ECG signals, and the de-noised signal obtained is suitable for ambulatory diagnosis.*

***Keywords** - Discrete Wavelet Transform (DWT), cardiac signal, threshold method, SNR, MSE, R interval.*

1. Introduction

ECG signals record the bio-electrical impulses of the heart. In the acquisition process, the ECG signal is a Cardiac signal that is easily overwhelmed by different noises. Affected by various noises, which can degrade the signal quality. The proposed noise removal algorithm is inspired by Johnstone and Donoho [1]. Threshold determination is an important issue since the quality of ECG morphology is affected by shrinkage. Noise reduction from the signal using wavelet coefficients shrinkage is a well-known method that uses threshold calculations. It is intended to find an optimum wavelet function and threshold for de-noising the noisy signal. Once noise is removed, the signal is segmented, and regions of interest are obtained. These regions of interest help calculate the heart rate and evaluate using thresholding and windowing.

P_Q_R_S_T waves, as shown in Fig.1, are seen in the ECG signal, heart electrical activity in the signal Depolarization, of atria, is shown by a P wave, Depolarization of ventricular is shown by QRS complex wave and repolarization of the ventricle is shown by T waves [1], ECG signal has a bandwidth of 0.5 to 100 Hz. Analysis of signal is done in four steps perform. The first step is Acquiring signals from the leads. The signal is the voltage difference between the leads. The noise contaminates the ECG signal due to baseline wander and interference due to power lines. In the next step, noise removal becomes necessary, so the second steps become the de-noising step. From the clean, the ECG signal's important features are extracted. Features extraction becomes the third step. Based on the features extracted, the ECG signal is classified for different diseases[2]. The time-domain analysis cannot extract all the features from the ECG scenario. Hence frequency domain analysis of ECG signal has been performed by the researchers recently[3]. A typical ECG signal is shown in Fig.1. Accurate rate levels of Q, R, and S find can be detected in noise-free signals accurately [4]

The objective is to formulate an algorithm for de-noising the ECG signal with DWT and reconstructed signal. The MSE, RMSE, SNR, and PSNR are estimated. The proposed method is applied to 117.dat MIT BIH record and comparatively studied to find the best basic wavelet and decomposition level.

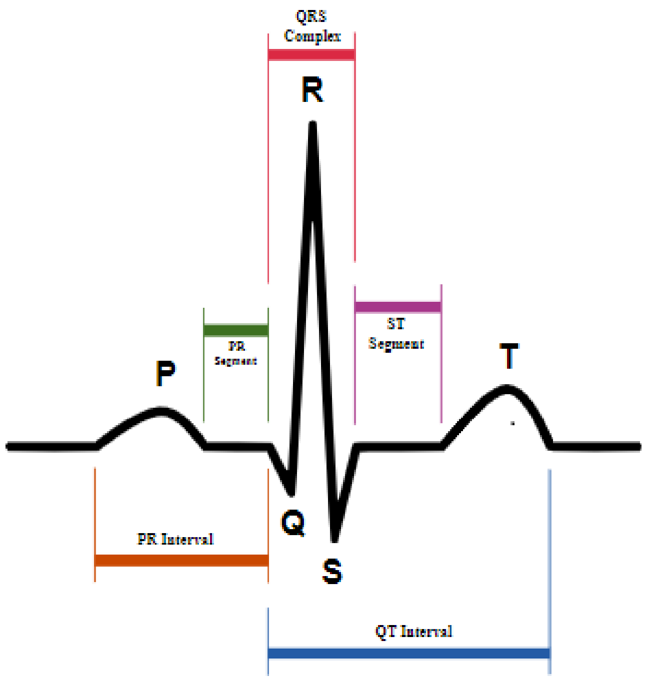

Fig. 1 Typical ECG Waveform

Table 1. Represents different waves and specifications [5]

Types of Waves	Amplitude (mV)	Interval	Duration (sec)
P	0.25	PR	0.12 to 0.2
Q	25% of R	QRS	0.09
R	1.6	RR	0.6 to 1.0
T	0.1 to 0.5	ST	0.05 to 0.15

Table 2 shows the different frequency ranges and noise types which mainly lie in the in-band (0.05-150Hz) frequency range of the ECG signal. The frequency ranges of different noise overlap with different segments of the ECG signal [3]. Due to the overlap, traditional noise filtering techniques (IIR, FIR) are not sufficient. Many methods have been suggested to eliminate the noise.

Table.2 Primary Noises in ECG Signal [2]

Type of Artifact/ Noise	Power Line Interference (PLI)	Baseline Drift (BD)	Electromyogram (EMG)interference	Motion Artefact (MA)
P-P Magnitude/ Amplitude	50% of p-p ECG amplitude	15% of p-p ECG amplitude	10% of p-p ECG amplitude	10% of p-p ECG amplitude
Frequency Spectrum span	50/60Hz	0.15 – 0.3 Hz	(DC to 10,000 Hz) (119)	1 – 100 Hz
Full-Scale Deflection over Frequency Range	Narrowband with less than 1Hz	0.15Hz-0.3Hz	0.01Hz-100 Hz	DC and 1KHz
Source of noise	Capacitive and Inductive coupling	Respiration	Contraction of any muscle other than cardiac muscle.	Charge distribution variation at the skin and electrodes interface. (Muscle-movement)
Effect on the ECG signal	P-wave change	ST-Segment change	Low amplitude distorts the ECG signal	The time interval between consecutive R peaks and QRS complex.
Probable condition	Atrial Arrhythmia Fibrillation, Atrial Enlargement	Myocardial infarction, Brugada syndrome	Numerous/ Many ECG Arrhythmias	Bradycardia

In section two, existing methods related to the de-noise techniques are discussed. In section three, implementation for the removal of noise is proposed. In an implementation, results are shown in section four. The result analysis is presented in the fifth section. In the sixth section, conclusions are discussed.

2. Existing Methods

DWT using a mother wavelet with various thresholds was applied to get a better SNR for de-noising cardiac signals. Noisy cardiac signals are filtered using Gorden Cornelia and Reiz Romulus [5]. Independent Component Analysis is done by Liu *et at.* for de-noising and DWT [6]. Weidonz Zhou and Jean Gotman cleaned the noise using the threshold method and independent component analysis [7]. Lin *et at.* have used sym5 mother wavelet and soft thresholding for reducing the noises [8] H.T. Patil and Holambe have suggested DWT-based Biorthogonal 2.4 with a soft threshold suppressing noise in the ECG signal [9]. Li *et al.* have used Coiflets5 mother wavelet and eliminated high-frequency interference and noise due to power line proximity [10]. Time-varying morphology of the physiological signal conditions of ECG is used for the diagnosis, but the detection is difficult due to noise. The methods for de-noising the signal using different techniques have been discussed by Paul Addison [11]. In the preprocessing, step Hilbert Transform is employed to filter and enhance QRS detection in the transform domain [12]. An efficient R peak location obtained using local maxima derived from consecutive wavelets scales is presented by Li *et al.* [13]. Non-stationary signals are analyzed using Nonlinear Empirical Mode Decomposition [14]. Bounty has discussed real-time QRS detection and suggested using adaptive weighted total variation de-noising [15]. IoT based healthcare application using cloud computing is capable of providing a solution for de-noising the signal and arrhythmia detection [16]

3. Proposed De-noise Method

Wavelet-Transform is the widely accepted signal de-noising technique, specifically for signal processing of ambulatory waves. Wavelet Transform (W Traf) is used for de-noising [3,7,10]. Wavelet-based approaches are mostly used to analyze the time-frequency domain because of the high performance and low complexity observed. A DWT method is used for de-noising the signal. The threshold value selection, wavelet (mother) function, and decomposition level are the steps performed for the de-noising process. The mother wavelet functions Daubechies (Db4) and (Db8), Symlet (Sym4) and (Sym8), Biorthogonal (Bior5.5) and (Bior6.8) are studied and also tested hard, and soft thresholding is considered. Experimenting with 1 to10 levels, the best level of wavelet de-noising to suppress the White Gaussian Noise (WGN) is decided in the proposed work. The de-nosing process was developed based on noise free signal added with WGN making a noisy signal and compared with noise free signal. Data for reference is collected from the online Database MIT BIH, PTB, and 117.dat records are considered [17] and sampled at 360 Hz frequency

3.1. *Discretise Wavelet-Transform (DWT)*

Continuous Wavelet-Transform (CWT), Stationary Wavelet-Transform (SWT), and DWT are different types of Wavelet-Transforms. Donoho's DWT approach was applied in this proposed study. The definition of DWT is as follows [18, 19]

$$DWT(s,l) = 2^{-s}\sum_n x[n]\,(2^{-s}n - l) \quad \ldots \quad (1)$$

Where *l represents* the location parameter, and *s* represents the dilation parameter [19], n =1, 2, ---- *N and* the total number of samples N and Complex Conjugate of analyzing wavelet function ψ^*.

The mathematical equation for DWT is given in equation (1). DWT decomposes and is used as signals at different frequency slots. DWT is perceived by taking the signal through filters (high-pass and low-pass) [19]. The signal is decomposed by DWT in low-frequency elements as Approximation Coefficients A_ϕ given by equation (2) and high-frequency elements as Detailed Coefficients D_ψ is given by equation (3), thereby analyzing input signal at different frequency slots with different resolutions.

$$A_{\Phi(s_0,l)} = \frac{1}{\sqrt{N}}\sum_n x[n]\,\Phi_{s_0,l}[n] \quad \ldots\ldots \quad (2)$$

$$D_{\psi(s,l)} = \frac{1}{\sqrt{N}}\sum_n x[n]\,\psi_{s,l}[n] \quad \ldots.. \quad (3)$$

Where $s_0 = 0$, $N=2^S$; s=1,2,3, …., S; n=1,2,3 …. N; *l*= 1, 2, 3, …. 2^s-1, n = Number of samples, S determines the width of $D_{\psi(s,l)}[n]$, $2^{s/2}$ is the amplitude of the function, *l* is the position vector of $\psi_{(s,\ l)}$ [n] and ψ is the wavelet coefficient.

Discrete input signal x [n] is the input given to two levels of DWT. Here the number of samples is n, as presented in Fig.1. In proposed work levels, up to ten are used. A low-pass filter h[*n*] blocked the low-frequency part and passed the high-frequency part of the input signal. g[n] a high-pass filter, block the high-frequency part and pass the low-frequency part. ↓ represents a down-sampling filter.

For DWT analysis, the x [n] input signal is filtered through h[*n*] (low-pass) and g[*n*] (high-pass) filter sequence. The coarse coefficients of approximation are generated by the h[*n*] filter, and coefficients detail is generated by the g[*n*] filter at each level of analysis. The h[*n*] filter and g[*n*] filter satisfy the orthogonal condition given by equation (4).

$$|A_\phi|^2 + |D_\psi|^2 = 1 \ldots \quad (4)$$

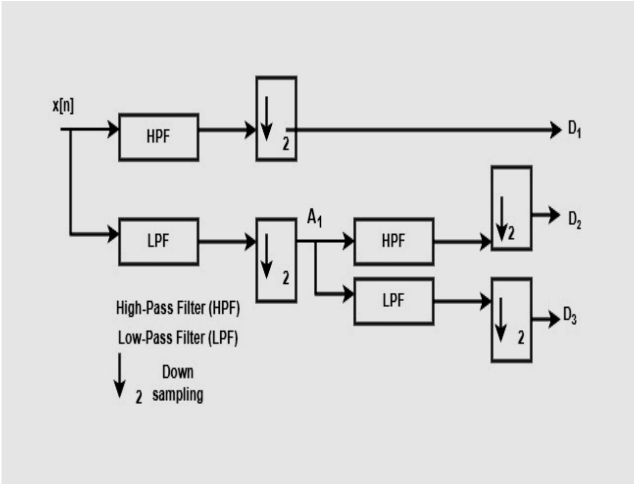

Fig.1 Two-level DWT decomposition filter model

3.2. Inverse Discrete Wavelet Transform (IDWT)

$$\hat{x}[n] = \frac{1}{\sqrt{N}} \sum_l A_{\phi(s_0,l)} \psi_{(s_0,l)}[n] + \frac{1}{\sqrt{N}} \sum_{s=s_0}^{\infty} \sum_l D_{\psi(s,l)} \psi_{(s,l)}[n] \quad \ldots (5)$$

$\hat{x}[n]$ is the reconstructed IDWT signal. After eliminating noise, the de-noised signal can be reconstructed using the estimated detailed coefficients of DWT. The updated detail coefficients are used with thresholding to get the reconstructed signal. The implementation of two levels of IDWT is presented in Fig.2. Where $\hat{x}[n]$is discretized wavelet reconstruction?

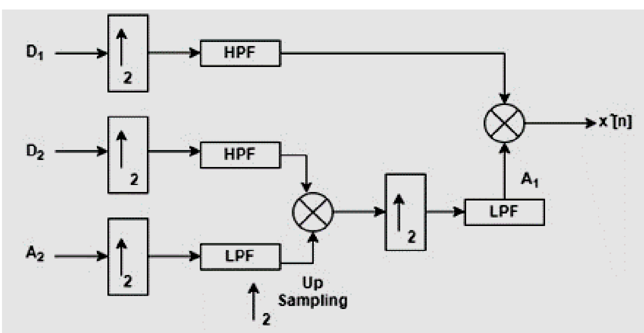

Fig. 2 Two-level Inverse Discrete Wavelet Transform

Donohoe and Johnston proposed reducing the noise by shrinking functions and involving threshold selection [16]. The wavelet shrinkage core is the selection of the threshold. Bayes Shrink's de-noising method is used in the proposed work.

Bayes Shrink: Bayesian mathematical framework is used in the Bayes Shrink rule. In each detail of the sub-band, the generalized Gaussian distribution of wavelet coefficients minimizes the noise in the signal. Where the threshold value is as stated in equation (6), $\psi_{(s,l)}$ is the Detail coefficient that forms the finest decomposition level.

$$\lambda = median \frac{|\psi_{(s,l)}|}{0.6745} \ldots (6)$$

The hard threshold function is as given in equation (7), where the magnitude of the decomposition coefficient is made zero if less than a specific(threshold) value λ. When the magnitude $\widetilde{\psi_l}$is greater than the specific given threshold value, decomposition coefficients remain unchanged.

$$\widetilde{\psi_l} = \begin{cases} \psi_l, & if\ |\psi_l| > \lambda \\ 0, & if\ |\psi_l| \le \lambda \end{cases} \ldots (7)$$

The local properties of the signal do not change by the hard threshold method, but as there is a discontinuity, some fluctuations in the reconstruction are observed. The soft threshold and the original signal [16] as shown in Fig. 3.
The soft threshold function is as given in equation (8), where the magnitude of $\widetilde{\psi_l}$the decomposition coefficient. Is less than a specific threshold value λ, it is chosen as zero. When $\widetilde{\psi_l}$magnitude is greater than the specific given threshold value, then coefficients of decomposition are the same as the magnitude of the threshold function minus the threshold value.

$$\widetilde{\psi_l} = \begin{cases} sign(\psi_l)(\psi_l - \lambda), & if\ |\psi_l| > \lambda \\ 0, & if\ \ |\psi_l| \le \lambda \end{cases} \quad \ldots (8)$$

Where $\widetilde{\psi_l}$are the estimated decomposition coefficients, and *sign* ($\widetilde{\psi_l}$) is the signum function?
As there is no discontinuity, the reconstruction has no fluctuation, as shown in Fig.4. For illustrating the concept of hard and soft thresholds in Fig.3 and Fig. 4, the threshold λ is taken as 0.5, and the magnitude of the threshold function is taken as $-4 \le \psi_l \le 4$.

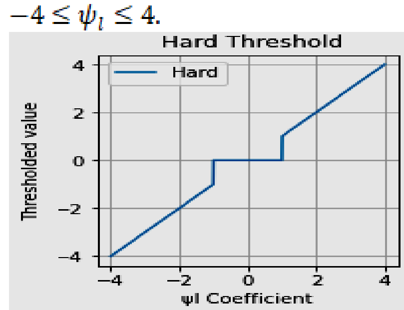

Fig. 3 Hard Threshold

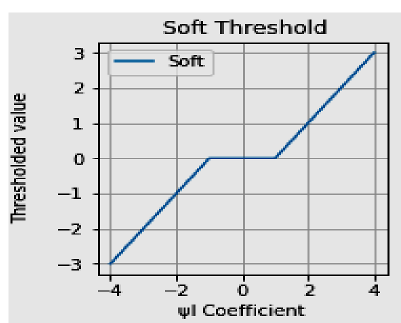

Fig. 4 Soft Threshold

3.3 De-noising Algorithm for ECG signal

- Input: 117.dat original ECG signal
- Add the White Gaussian Noise (WGN) at 0.08 Hz frequency
- Select the mother wavelet (Db8)
- Apply DWT using nine-level decomposition input
- Apply soft thresholding
- Calculate A_φ and D_ψ for each level, with downsampling by 2 decompositions
- Reconstruct the signal with Inverse Discrete Wavelet Transform (IDWT), using upsampling by 2 with the help of Detail coefficients (D_ψ) obtained while shrinking Approximate coefficient (A_φ) to zero.
- Calculate De-noising parameters like SNR Before de-noising, SNR After de-noising, MSE, PSNR, and RMSE.
- Output: De-noised ECG signal.
- Repeat the above process for 117 noisy signals.

4. Result and Analysis

In the proposed work, 117 ECG signal is the original signal without noise, and 117 ECG noisy signals is the noisy ECG signal obtained by adding 20Hz. WGN to the original 117 ECG signal. By applying the Soft and Hard threshold and using six different mother wavelets at all ten levels, both the signals are filtered, and the parameters are calculated. Fig. (5) shows the maximum SNR values for 6 to 10 levels for soft and hard thresholds and six mother wavelet functions. The maximum SNR value is obtained for the soft threshold and at the ninth level. Table 2 shows precise SNR values obtain for different wavelet functions at 1 to 10 levels. The output of the R Peak, based on maxima obtained from the proposed DWT transform, determines the R peak. ECG signal indicates R peak position overlaid by the masks of the red line.

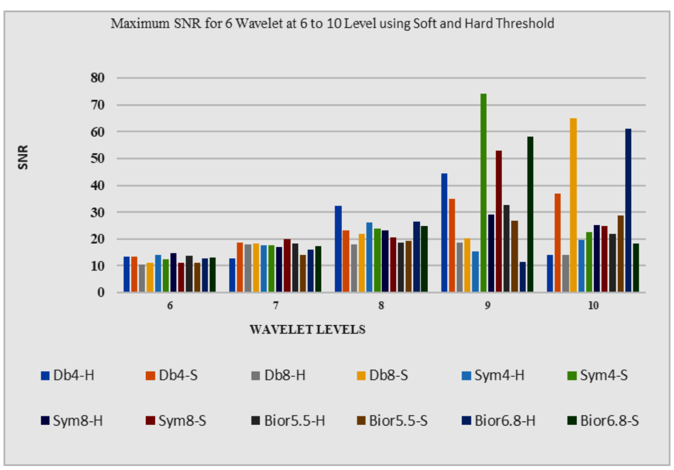

Fig. 5 Maximum SNR for 12 mother wavelets at 6 to 10 levels using Soft and Hard threshold

Fig.5 the SNR for SNR for 12 mother wavelets at 6 to 10 levels using Soft and Hard thresholds. In this study, Daubechies Wavelet shows similarity with ECG signal. The 117 ECG noisy signals after filtering (filtered signal) have been sampled at a 360 Hz frequency. Using Daubechies (Db4 and Db8), Symlets (Sym4 and Sym8), and Biorthogonal (Bior5.5 and Bior6.8) mother wavelets, the signal is decomposed up to 10 levels. After decomposing, de-noising parameters like SNR, MSE, RMSE, and PSNR are calculated.

Table 2. Precise MSE values obtain for different wavelet functions at 1 to 10 levels

Level	Db4	Db8	Sym4	Sym8	Bior5.5	Bior6.8
1	1.18	1.18	1.02	1.14	1.19	1.16
2	1.12	1.09	1.07	1.06	1.09	1.09
3	1.04	1.06	1.02	1.04	0.99	1.05
4	1.01	1.05	1.02	1.04	1.01	1.05
5	1.03	1.02	1.02	0.98	0.98	1.02
6	0.99	0.99	0.99	1	0.99	1
7	0.97	1	1	1.03	1.02	0.97
8	0.98	0.97	1	1.02	1.03	1.04
9	1.01	0.96	1	0.99	0.99	1.01
10	1.02	1	0.99	0.98	1.01	0.98

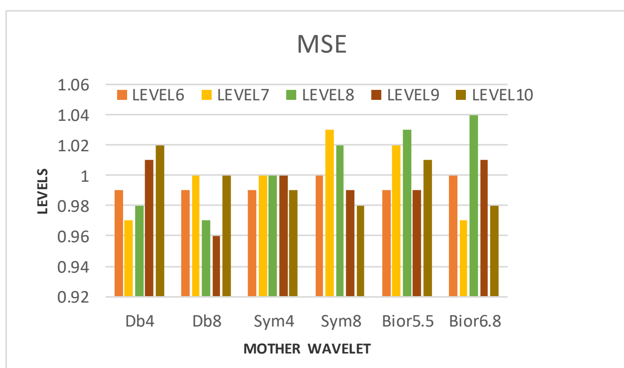

Fig. 6 MSE using a soft threshold for different mother wavelets

Table2 shows that wavelet functions Db8 gives the minimum MSE compared to the other mother wavelet functions at level 9. for Db8, the level 9 MSE value is observed to be minimum in Fig.6.

SNR for decomposition at all levels is presented in Fig.7, and SNR values are compared for the six mother wavelets, and the trend is observed. SNR value for Db8, Sym4, and Bior6.8 is found to be maximum.

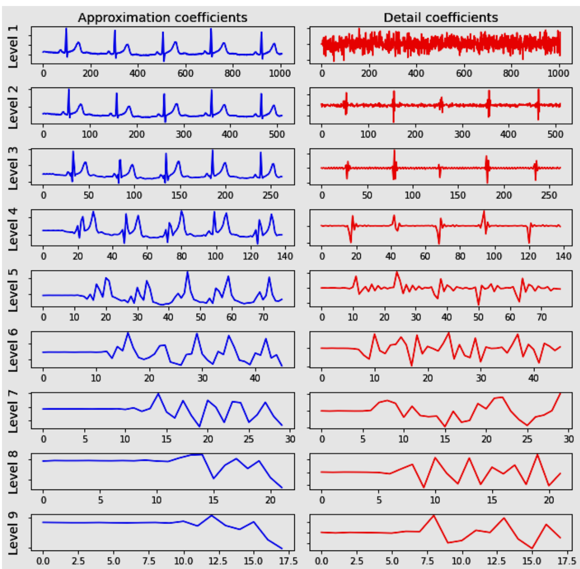

Fig. 7(a) Original Signal Decomposition

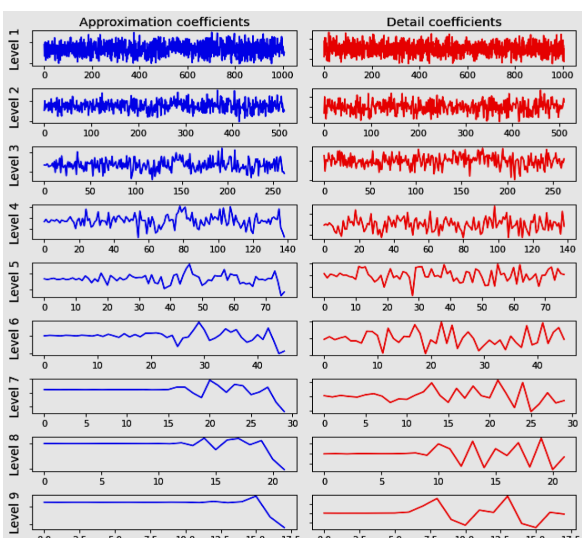

Fig. 7(b) Noisy Signal Decomposition

By decomposition using the Db8 mother wavelet and applying a soft threshold for 9 levels, the approximate and detailed coefficients are obtained for the original signal and are represented in Fig.7 (a). Similarly, approximate and detailed coefficients for noisy signals are represented in Fig.7 (b).

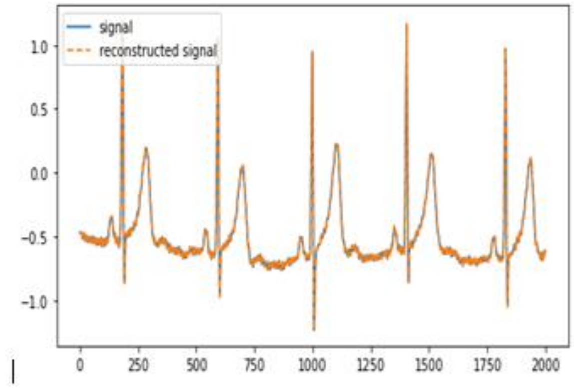

Fig.7 (c) ECG Signal Reconstruction

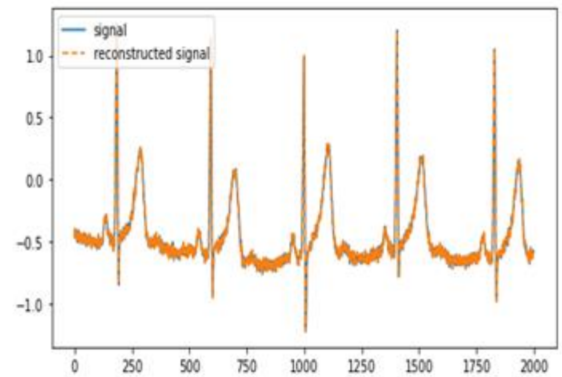

Fig.7 (d) ECG Noisy Signal Reconstruction

The original signal and the noisy signal are reconstructed using IDWT and are represented respectively in Fig 7 (c) and Fig 7 (d). The high-frequency component of the noise is eliminated at this step. De-noising parameters MSE, RSME, PSNR, SNR before, and SNR after filtering for ECG signal are presented in Table3.

Table3 Parameters of De-noising using Db8 Wavelet

LEVEL	MSE	RMSE	PSNR	SNR Before filtering)	SNR (After filtering)
1	1.18	1.08	23.71	1.66	2.36
2	1.09	1.04	23.87	1.62	3.23
3	1.05	1.03	23.90	1.65	4.41
4	1.05	1.03	23.95	1.67	6.49
5	1.02	1.02	24.02	1.64	9.23
6	0.99	0.99	24.08	1.61	11.04
7	1.01	1.00	24.05	1.64	18.29
8	0.97	0.98	24.12	1.59	21.74
9	0.96	0.98	24.13	1.61	65.08
10	1.01	1.01	24.04	1.64	20.38

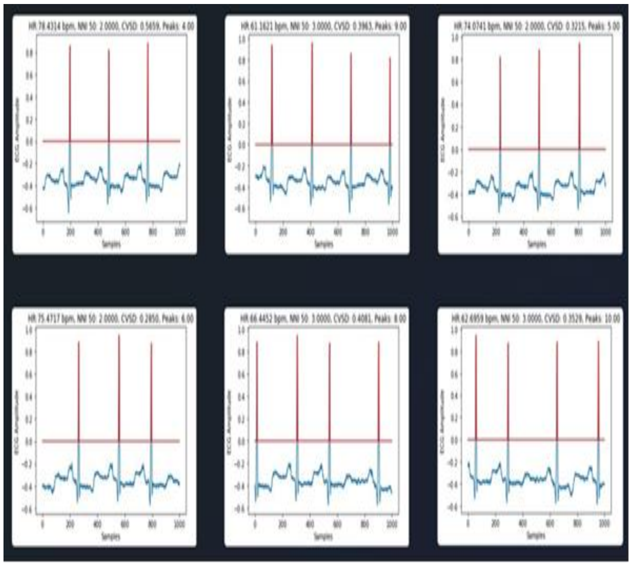

Fig. 8 Detection of R-R Interval

In the proposed system, six mother wavelet functions are studied with soft and hard threshold functions up to 10 levels. It is observed that Db8, Sym4, and Bior6.8 give satisfactory results for DWT filtering with a soft threshold at level 9. But comparatively Db8 mother wavelet performs better when MSE is considered. Therefore, at level 9 maximum SNR value (74%) and minimum MSE value (0.96) are obtained for the soft threshold. The RMSE value is also minimum. The lower the value of RMSE, the better the signal recovered after filtering. PSNR, obtained at level 9 with soft thresholding and DB8 mother wavelet, is maximum. Db4 and Db8-based wavelets are more appropriate for overcoming PLI (low-frequency) noise, and Sym4 and Sym8 are appropriate for suppressing the Electromyogram (high-frequency) interference. Fig .8 shows the simulation result of R Peak detection. De-noising and extracting the feature of the cardiac signal.

4. Conclusion

In the proposed work ECG signal de-noising algorithm is formulated. The noisy signal is analyzed, and detailed and approximate coefficients are estimated using the DWT method. The signal is reconstructed using these coefficients and soft thresholding. Two consecutive R-R (N-N) intervals are located and used to obtain the heart rate for various arrhythmia conditions. The SNR, MSE, RMSE, and PSNR are obtained. The proposed algorithm is applied to study and find the comparatively best basic wavelet and decomposition level by using the thresholding technique. The proposed method selects an optimal mother wavelet for de-noising the signal. This selection is decided on the values obtained for MSE and SNR of the filtered signal. The proposed method gives Db8 and Sym4 the optimal wavelet functions with soft thresholding at level 9 and maximum output SNR and minimum MSE. Appropriate wavelet function for ECG de-noising is found to be wavelet function Db8 and Sym4, which gives more effective removal of WGN. The future scope is to design a hybrid model developed based on a combination of DWT and CNN to classify the heart conditions. It can also be achieved by using ensemble classification with Deep-learning. Researchers can try and test different combinations of the most effective models and evaluate the best possible ensemble system for high accuracy and low power ECG processing scenarios.

Conflicts of Interest

"The authors declare that there is no conflict of interest regarding the publication of this paper.

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