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An Optimal Wavelet Approach for ECG Noise Cancellation

Supriya Goel*, Pradeep Tomar, Gurjit Kaur

School of Information and Communication Technology
Gautam Buddha University, India
goel.supriya03@gmail.com, parry.tomar@gmail.com
,gurjeet_kaur@rediffmail.com

Abstract

Electrocardiogram (ECG) is a vital biomedical signal for diagnosing heart diseases, but now it has many other applications like stress recognition, biometric recognition, etc. But ECG signal gets noisy from various sources like as muscle noise, electrode artifacts, baseline drift noise and respiration. As wavelet transforms shows a good performance in denoising the ECG signal however, the selection of appropriate mother wavelet functions and number of wavelet decomposition level is still an issue to remove the various kinds of noises from the input signal. It is essential to denoise the ECG signal to get appropriate features of ECG signal.This research work analyze and compare the removal of noise and distortion in ECG signal using five wavelets (Daubechies, Coiflet, Haar, Biorthogonal and Symmlet) with four thresholding rules (SURE, Hybrid, Universal and Minimax) and various decomposition levels of Undecimated Wavelet Transform (UWT) and Discrete Wavelet Transform (DWT).

Keywords: *ECG, DWT, SNR, MSE, PSD, SURE, UWT*

1. Introduction

Cardiac pathology ECG has been widely used to detect heart disease. ECG is the measurement of the electrical activity of cardiac muscle. In the time domain the ECG signal is categorized by different waves viz., P, Q, R, S, T and U as shown in Figure 1.

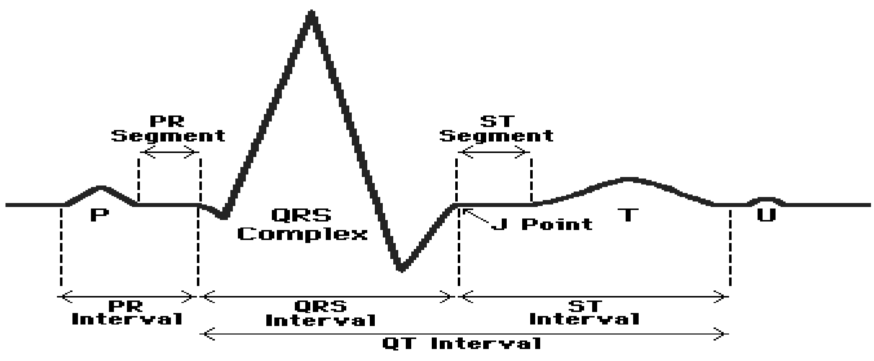

Figure 1. ECG Waveform

The P wave represents atrial depolarization. The Q, R & S waves together make up QRS complex, which represents ventricular depolarization whereas T wave characterizes the ventricular repolarisation. The interval between S wave and the beginning of the T wave is called the ST segment. In some ECG an extra wave can be seen at the end of the T wave, called as U wave [1]. In frequency domain ECG signal varies from 0.05 Hz to

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100Hz whereas the associated amplitude values vary from 0.02 mV to 5 mV. The amplitude values of the human body bioelectrical signals are measured in micro volts (MV) [2].ECG analysis and processing is used to extract the characteristic features of the ECG. This signal gets corrupted by different kinds of artifacts such as muscle noise, electrode artifacts, baseline drift noise and respiration. These artifacts, affects the ST segment, reduces the signal quality as well as frequency resolution that produces large amplitude signals in ECG which resembles PQRST waveforms and hides very small features that may be vital for diagnosis and clinical monitoring. The goal of ECG signal enhancement is to separate the valid signal components from the noise, so to create an ECG signal that facilitates an easy and accurate interpretation[3]. There are many methods for denoising of ECG signals like digital filters, adaptive filters, Empirical Mode Decomposition (EMD) and Wavelets. Digital filters and adaptive methods can be applied to the signal whose statistical characteristics are stationary in many cases. ECG signal is one of the signal that is considered as a non-stationary signal which needs hard work for denoising [4]. An efficient method for processing such a non-stationary signal is the wavelet transform. It supersedes the problem of nonlinear phase and time delay caused by filters. Furthermore, it decomposes the signal into a frequency time scale which makes it appropriate to be used for non-stationary signals, like ECG [5]. An effective de-noising technique should minimize the noise content in the signal and also ensure that the important details in the signal are not lost or altered. The basic aim is to improve the Signal to Noise Ratio (SNR) ratio of the signal,minimize the (Mean Square Error) MSE using various practices [6].

Wavelet Transform is a signal processing technique which uses a fully scalable modulated window to solve the signal-cutting problem by shifting the window along with the signal and for every position of the spectrum [7]. By virtue of its multi-resolution representation capability, the wavelet transform has been used effectively in vital applications such as transient signal analysis [8], numerical analysis [9], computer vision [10], and image compression [11], along with many other audiovisual applications. A wavelet is basically a small wave which has energy concentrated in time as shown in figure 2.

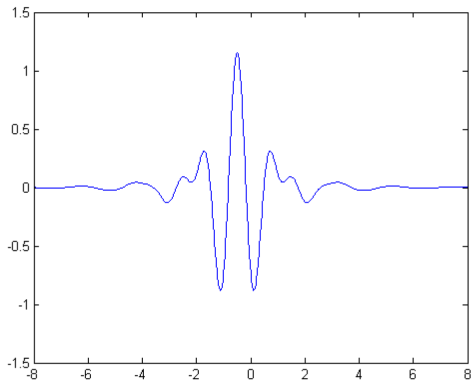

Figure 2. Wavelet Function

Scaled and shifted copies of the main pattern, so-called the “mother wavelet”, are known as wavelets. The mother wavelet function Ψ{s,T(t)} is defined by equation (1), where T is translation parameter and, s as scale parameter.

$$\Psi\{s,T(t)\}= 1/\frac{1}{\sqrt{s}}\,\Psi(t-T/s) \quad (1)$$

Mother wavelet Ψ(t) is a function of zero.

$$\int \Psi\,(t)dt = 0 \quad (2)$$

Continuous Wavelet Transform of signal f(t) is calculated as

$$W(s,T)=1/\sqrt{s} \int f(t)\ \Psi(t\text{-}T/s)dt \quad (3)$$

After denoising, the original signal is then reconstructed using inverse discrete wavelet transform which is defined as:

$$f(t)=\iint W(s,t)\Psi s,T\,(t)dTds \quad (4)$$

Discrete version of continuous wavelet transform is known as the discrete wavelet transform and is obtained by using discrete steps j of scale factor s,and discrete steps k of translation factor T.Discrete mother wavelet is defined as

$$\Psi j,k(t)=1\frac{1}{\sqrt{sj}}\,\mathcal{E}f(n)\ \Psi(s\text{-}jn\text{-}kt) \quad (5)$$

For removal of noise the coefficients obtained from the wavelet decompositions are further processed using threshold selection techniques. The selection of suitable Thresholding rule is a significant point which must be considered whenever any wavelet function is being used. Wavelet thresholding is the signal estimation practice to meet the capabilities of signal denoising. Standard wavelet thresholding rules, consists of hard thresholding and soft thresholding functions [12]. The signal if the threshold value is too large or too small cannot be estimated precisely.

$$Wht=\begin{cases} W, & W \le t \\ 0, & W > 0 \end{cases} \quad (6)$$

$$Wst=\begin{cases} [sign(w)(|w|-t)], & |W| \ge t \\ 0, & W > 0 \end{cases} \quad (7)$$

where W is wavelet coefficient,t is value of threshold which is applied on wavelet coefficients. In this research work thresholding rules used are SURE, hybrid, universal and minimax.Sure thresholding is used in the soft threshold estimator,to estimate the risk for a particular threshold value and gives a decision accordingly [13].

$$Sure\ (x,T)=\sum_{m=0}^{n-1}(x_b[m]) \quad (8)$$

With

$$C(u)=\begin{cases} \mu^2-\sigma^2, & u \le T \\ \sigma^2-T^2, & u > T \end{cases} \quad (9)$$

$$T = agr_t \min\ Sure(X,T) \quad (10)$$

Minimax Scheduling uses fixed threshold and it gives performance for Mean Square Error (MSE) against an ideal events. The extreme value estimator can apprehend minimized of maximum mean square error for a given function.

$$Wtm=\begin{cases} o.3936+0.1829*(\log n)/(\log 2) & |n| > 32 \\ 0 & |n| \le 0 \end{cases} \quad (11)$$

In this method, the threshold value will be selected by obtaining a minimum error between wavelet coefficient of noise signal and original signal. Universal thresholdingcan be used as an alternative to the useof minimax threshold. It is bigger in magnitude than the minimaxthreshold[14] . The value of the threshold is calculated as:

$$T=sqrt(2*log(length(X)) \tag{12}$$

Where, T is the threshold value and X is noisy signal. The Hybrid thresholding is a combination of SURE and global thresholding method. If the signal-to noise ratio of the signal is very small, then the SURE method approximation will have more amount of noise. In this kind of situation, the fixed form threshold is selected by means of global thresholding rule is used.

Wavelets used in this research paper are Daubechies, Haar, Coiflet, Symmlet and Biorthogonal.Here Daubechies Wavelet is a family of orthogonal wavelets defining a discrete wavelet transformand categorized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (called the father wavelet) which generates an orthogonal multiresolution analysis[15] .

$$\phi(x)=\sqrt{2}\sum_{k=0}^{L-1} h_k\, \phi(2x-k) \tag{13}$$

where $\phi(x)$ is normalized
$\int_{-\infty}^{\infty} \phi(x)dx = o$ and wavelet $\Psi(x)$is defined in terms of scaling function

$$\Psi(x) = \sqrt{2}\sum_{k=0}^{L-1} g_k \phi(2k\text{-}x) \tag{14}$$

Where $\phi(x)$ is the scaling function.,$\Psi(x)$ is the wavelet.In this wavelet, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal. This slight change, however, provides a marvelous improvement in the proficiencies of these new transforms. The Haar Waveletis a sequence of rescaled "square-shaped" functions which combine form a wavelet family [16]. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines [17].For every pair n, k of integers in Z, the Haar function $\psi n, k$ is defined on the real line R by the formula:

$$\Psi_{n,k}(t) = 2^{\frac{n}{2}}\Psi(2^n t - k) \qquad t \in R \tag{15}$$

The Haar wavelet's mother wavelet function$\Psi(t)$ can be described as:

$$\Psi(t) = \begin{cases} 1 & 0 \le t < 1 \\ -1 & 0.5 \le t < 1 \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

Its scaling function $\phi(t)$ can be described as:

$$\phi(t)=\begin{cases} 1 & 0 \le t < 1 \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

In Coiflet Wavelets both the scaling function (low-pass filter) and the wavelet function (High-Pass Filter) must be normalized by a factor $1/\sqrt{2}$.Its scaling function $\phi(t)$ can be described as$\phi(t)=2\sum_{k\epsilon Z} h_k\ \phi(2\text{-}k)$. Biorthogonal Wavelets are families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function[18][19].

$$\Psi_{j,k}(x) = 2^{-\frac{j}{2}}\Psi\left(2^{-j}x^{-k}\right) \qquad j,k \in Z \tag{18}$$

The amended version of Daubechies wavelet with increased symmetryand have similar properties are known as symmlet wavelets. There are 7 different Symlet functions from sym2 to sym8.

To achieve optimum performance in the preprocessing stage of the ECG signal, it is very crucial to select the best wavelet function for the given ECG and also the related features like threshold selection rule, decomposition level, *etc*.In the previous researches author worked on wavelet functions like daubechies, coiflet, symmlet on very few decomposition levels with very less thresholding rules.[19] P. Karthikeyan et. Al.(2012) [20] considered the DWT for denoising using three wavelet functions ("db4", "coif5" and "sym7") and four different Thresholding rule were used to denoise the ECG signals. The experimental result shows the significant reduction of above considered noises and it retains the ECG signal morphology effectively. Results shows that the "coif5" wavelet and “rigrsure” thresholding rule is optimal for better SNR ratio for the real time ECG signals.JS Sørensen (2011) [21] compares the ability to preserve information and noise reduction of the ECG for five wavelets. Computation times and SNR improvements for different noise coverages were calculated and compared. In a clinical setting where the amount of noise is unknown, IIR filters appears to be preferred for consistent performance. Oscar Hernández (2009) [22] uses Undecimated Wavelet Transform (UWT) with db06 wavelet for ECG noise removal. This research paper aims to select the optimal wavelet function and related features to attain the best noise free signal. In addition to previous research we further included Haar, biorthogonal wavelet with hybrid, minimax and universal thresholding rules with more decomposition levels. The results are also compared for UWT and DWT wavelet transforms. Four different performance measures were considered for analysis i.e. SNR,MSE, variance and periodogram of Power Spectral Density (PSD).

2. System Implementation

In this work, we employed different types of wavelet thresholding rules to remove noises from the ECG signal. Previous researchers have used: "db4", "coif5" and "sym7" wavelet function for genetic algorithm based denoising in ECG signal [23]. We extended the work by including more thresholding rules, decomposition levels for latest wavelet functions. The soft thresholding method is investigated with four different thresholding rules (Sure,Hybrid, Universal and minimax). All the noises are having certain frequency characteristics and ranges i.e. power line noise (50 Hz or 60 Hz), baseline wander (>1Hz), and high frequency noises (>100). Therefore, the effect of noises in the frequency spectrum of ECG lies in between (0-500) Hz. Figure 3 shows the procedure of wavelet decomposition on the input ECG signals. On each level of wavelet decomposition, the value of threshold has been calculated by applying the threshold selection rules and the wavelet coefficient (soft thresholding). In general, the value of ECG signal frequency above 100 Hz does not have any useful information [6].In addition, the effect of baseline wandering is usually lies in the frequency range of less than 1 Hz. After applying threshold on each level of the original signal, the effects of noises on the ECG signals were removed and then the signal is reconstructed on each level by using Inverse Discrete Wavelet Transform (IDWT). The process of the analysis is represented in figure 3.

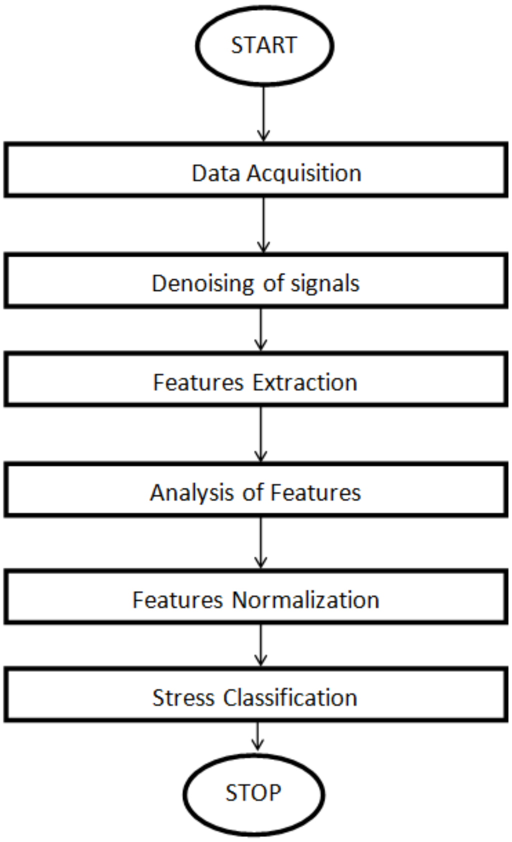

Figure 3. Process of Wavelet Denoising

3. Results and Simulation

There are five wavelet functions and four threshold rules which areconsidered in analyzing the performance of denoising the ECG signals using soft thresholding method. DWT and UWT basedthresholding has been tested over the ECG datasets and each with duration of (~10 min).

3.1. Analysis of ECG noise removal in terms of S/I ratio :

In this research work SNR of wavelets with different decomposition levels has been calculated for UWT & DWT as shown in Figure 4 and 5.

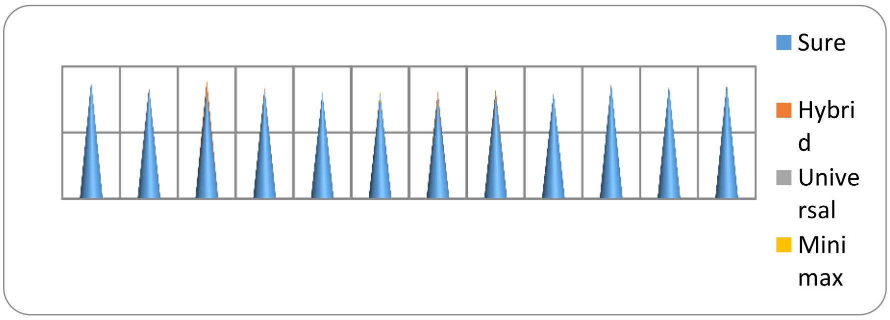

Figure 4. SIR of Different Wavelets with Undecimated Wavelet Transform (UWT)

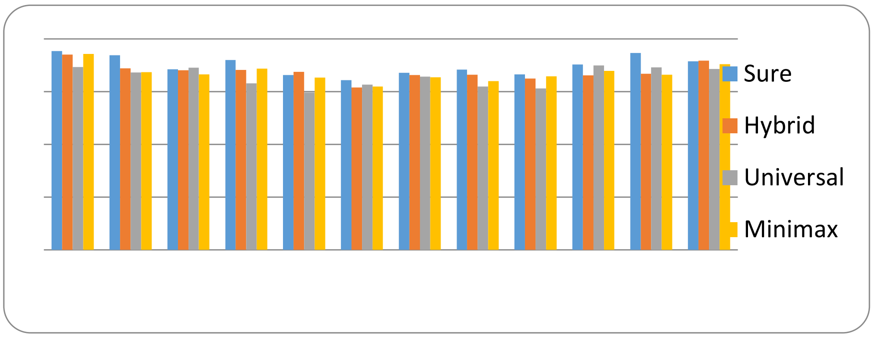

Figure 5. SIR of Different Wavelets with Discrete Wavelet Transform (DWT)

Here SNR is the ratio of amplitude of ECG signals before noise removal to the amplitude of noise removed through waveletdenoising.

$$R=\sum_{1}^{N-1} X_i \text{raw signal}/Xi \text{ noisy signal}$$

While calculating SNR of different wavelets, It is foundthat db06 wavelet(UWT type) and db02 (DWT type) gives maximum value. Among all the 12 wavelets in UWT type, db02 gives higher SNR value i.e. 1.781126 where as in DWT type,bior 3_3 gives higher value i.e 1.8864 for sure thresholding while coiflet 5 gives the worst results. Sure thresholding gives the most appropriate results as compare to other thresholding rules.

3.2. Analysis of ECG Noise Removal in Terms of Mean Square Error :

Table 1 and 2 shows mean square error of different wavelets with UWT and DWT type. In this research work MSE of wavelets with different decomposition levels has been calculated for UWT & DWT. Here MSE is calculated between denoised ECG signal and noisy ECG signal.

$$MSE=1/n \sum_{i=1}^{n}(x_{i(\text{denoised signal})} - x_{i}\ (\text{noisy signal}))$$

From the analysis of mean square error, it is found that it has minimum value i.e .00384for db06 waveletof UWT type and 0.00259 for db02 of DWT typeat minimax thresholding.Bior 3_3 is giving minimum MSE with UWT type and db02 gives minimum value for the discrete type while symmlet wavelet gives the worst results. Sure thresholding gives the most appropriate results as compare to other thresholding rules.

Table 1. Mean Square Error of Different Wavelets (Undecimated Type) According to Different Threshold Rules

Wavelet Type	DAUBECHIES			HAAR	COIFLET		SYMMLET			BIORTHOGONAL		
Thresholding	Db02	Db04	Db06	Haar	Coif 3	Coif 5	Sym 3	Sym 5	Sym 8	Bior 1_3	Bior 2_6	Bior 3_3
SURE	.00430	.00409	.00434	.00347	.00430	.00525	.00544	.00556	.00667	.00421	.00300	.00391
HYBRID	.00457	.00438	.00458	.00474	.00585	.00979	.00499	.00416	.00424	.00376	.00390	.00401
UNIVERSAL	.00509	.00365	.00473	.00425	.00634	.00585	.00615	.00681	.00638	.00413	.00428	.00474
MINIMAX	.00396	.00329	.00259	.00378	.00582	.00523	.00559	.00521	.00546	.00361	.00346	.00381

Table 2. Mean Square Error of different Wavelets (Discrete Type) according to different Threshold Method

Wavelet Type	DAUBECHIES			HAAR	COIFLET		SYMMLET			BIORTHOGONAL		
Thresholding	Db02	Db04	Db06	Haar	Coif 3	Coif 5	Sym 3	Sym 5	Sym 8	Bior 1_3	Bior 2_6	Bior 3_3
SURE	.002019	.001806	.003163	.003672	.003479	.003616	.00277	.00342	.00508	.00277	.003567	.001929
HYBRID	.002034	.00219	.003029	.003585	.004439	.003757	.00323	.00427	.00492	.00192	.003858	.003296
UNIVERSAL	.002216	.001834	.0027	.00372	.003986	.00413	.00378	.003668	.003633	.002102	.003732	.001908
MINIMAX	.001732	.00168	.00259	.004056	.00457	.00523	.002774	.003517	.00399	.003081	.003591	.002472

3.3. Analysis of ECG noise removal in terms of Variance :

Table 1 and 2 shows variance of different wavelets with UWT and DWT type.Variance measures how far each number in the set is from the mean. Variance is calculated by taking the differences between each number in the set and the mean, squaring the differences (to make them positive) and dividing the sum of the squares by the number of values in the set.

Table 3. Variance of Different Wavelets (Undecimated Type) According to Different Threshold Method

Wavelet Type	DAUBECHIES			HAAR	COIFLET		SYMMLET			BIORTHOGONAL		
Thresholding	Db02	Db04	Db06	Haar	Coif 3	Coif 5	Sym 3	Sym 5	Sym 8	Bior 1_3	Bior 2_6	Bior 3_3
SURE	.04799	.04511	.0.0434	.0446	.0452	.04280	.0408	.0412	.04319	.04875	.04774	.049046
HYBRID	.04576	.0438	.0458	.0490	.04078	.04257	.04365	.0440	.0404	.0449	.04437	.04545
UNIVERSAL	.04837	.0438	.04956	.0442	.04222	.03988	.041936	.0437	.0412	.04318	.04677	.04600
MINIMAX	.045917	.04744	.04763	.0432	.041079	.0428	.04753	.0460	.0395	.05388	.04564	.04969

Table 4.Variance of Different Wavelets (Discrete Type) According to Different Threshold Methods

Wavelet Type	DAUBECHIES			HAAR	COIFLET		SYMMLET			BIORTHOGONAL		
Thresholding	Db02	Db04	Db06	Haar	Coif 3	Coif 5	Sym 3	Sym 5	Sym 8	Bior 1_3	Bior 2_6	Bior 3_3
SURE	.0478	.0453	.0463	.050177	.0461	.044933	.4443	.0446	.04748	.0464	.04795	.0479
HYBRID	.04508	.0446	.0456	.04287	.0448	.041002	.04572	.0435	.04175	.0434	.04284	.0495
UNIVERSAL	.04482	.0450	.045329	.04432	.0411	.042977	.04061	.04537	.0424	.0502	.0484	.0483
MINIMAX	.050014	.0441	.04324	.04670	.0425	.04202	.04585	.03857	.04704	.0448	.0478	.0454

From above analysis it is analyzed that variance is maximum for bio 3_3 minimax i.e. .04969 for UWT type and Haar Surei.e .050177 for DWT type.It is also analyzed that it is maximum with biorthogonal wavelet for UWT type and also for Discrete type. Sure

Thresholding gives the most appropriatevalue results as compare to other thresholding rules.

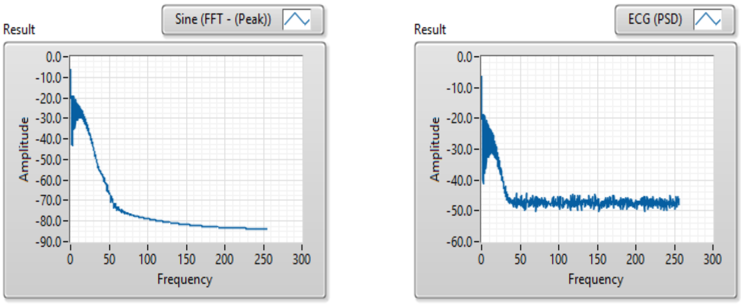

Figure 6. PSD of (a) Clean ECG Signal (b) Noisy ECG Signal

3.4. Analysis of ECG noise removal in terms of PSD:

PSD shows the strength of the deviations(energy) as a function of frequency. In other words, it shows at which frequencies deviations are resilient and at which frequencies variations are fragile.Figure 6 shows PSD of clean signal and noisy signal. The unit of PSD is energy per frequency(width) and you can obtain energy within a specific frequency range by integrating PSD within that frequency range. Computation of PSD is done directly by the method called FFT or computing autocorrelation function and then transforming it.Figure 6 shows PSD of clean ECG signal and Noisy ECG signal.Figure 7 and 8 shows PSD of UWT and DWT for different wavelets (a) Daubechies (b) Haar (c) Coiflet (d) Symmlet (E) Biorthogonal.

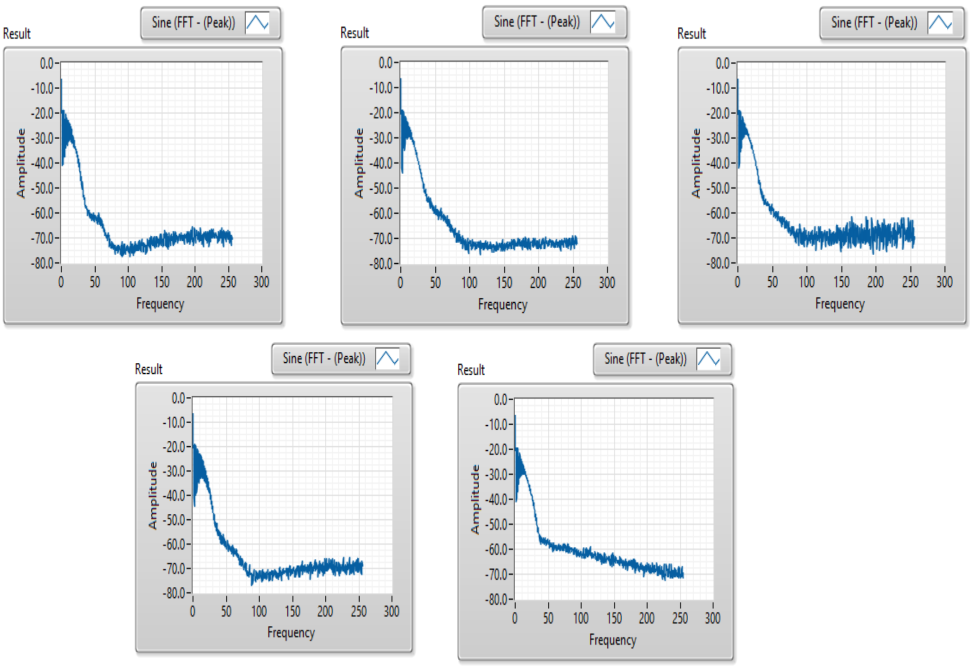

Figure 7. Power Spectral Density of Wavelets for UWT (a) Daubechies (b) Haar (c) Coiflet (d) Symmlet (e) Biorthogonal

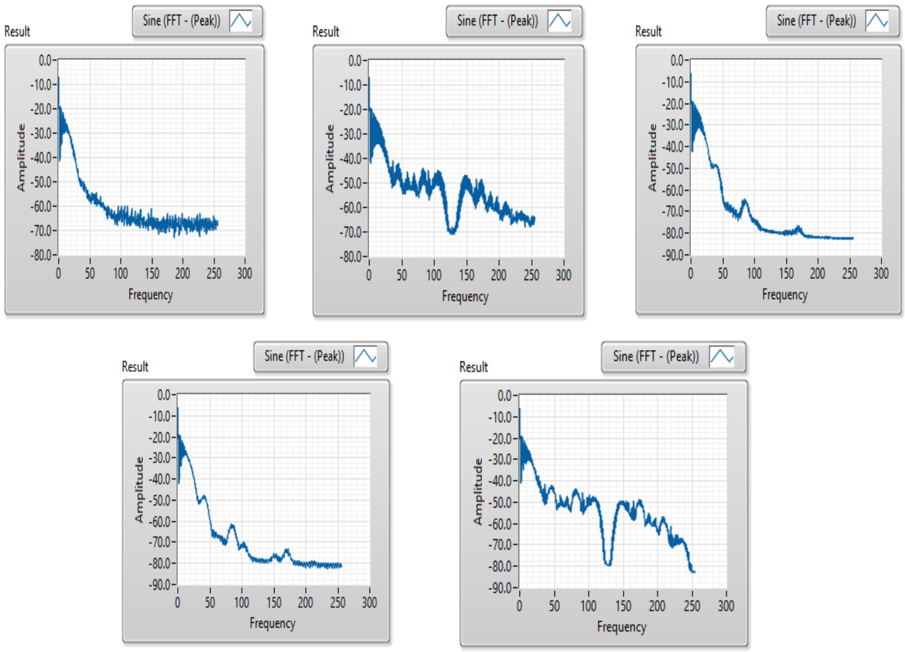

Figure 8. Power Spectral Density of Waelets for DWT (a) Daubechies (b) Haar (c) Coiflet (d) Symmlet (e) Biorthogonal

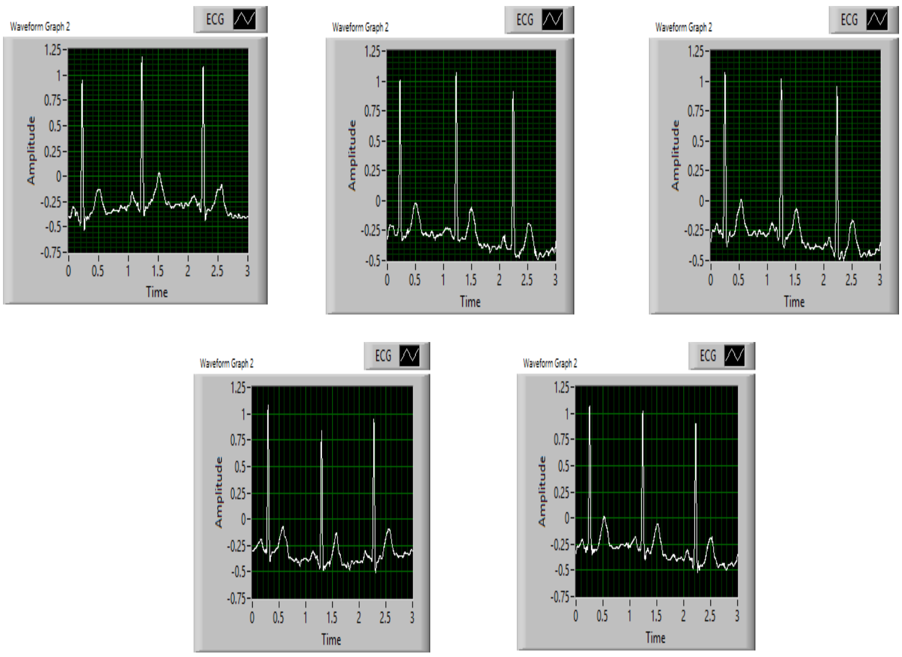

Figure 10. ECG signal after Noise Removal for Wavelets (UWT) (a) Daubechies (b) Haar (c) Coiflet (d) Symmlet (E) Biorthogonal

3.5. ECG Morphology after Noise removal

Figure 9 shows morphology of clean and noisy ECG signal.In clean ECG signal P wave is at 0.24 mV,QRS is at 1.125 mV and T is at 0.05 mV. Figure 10 and 11 shows morphology of ECG signal of different wavelets. From the study of ECG morphology, it is concluded that in biorthogonal wavelet of UWT as well as DWT type P wave is at 0.23 mV, QRS is at 1.1 mV and T is at -0.02 mV which is nearest to the values of clean ECG signal. Although biorthogonal wavelet gives nearest values in DWT, it also distorts the signal.Haar wavelet in DWT type gives less nearest values as compare to biorthogonal wavelet but signal remain distortionless.

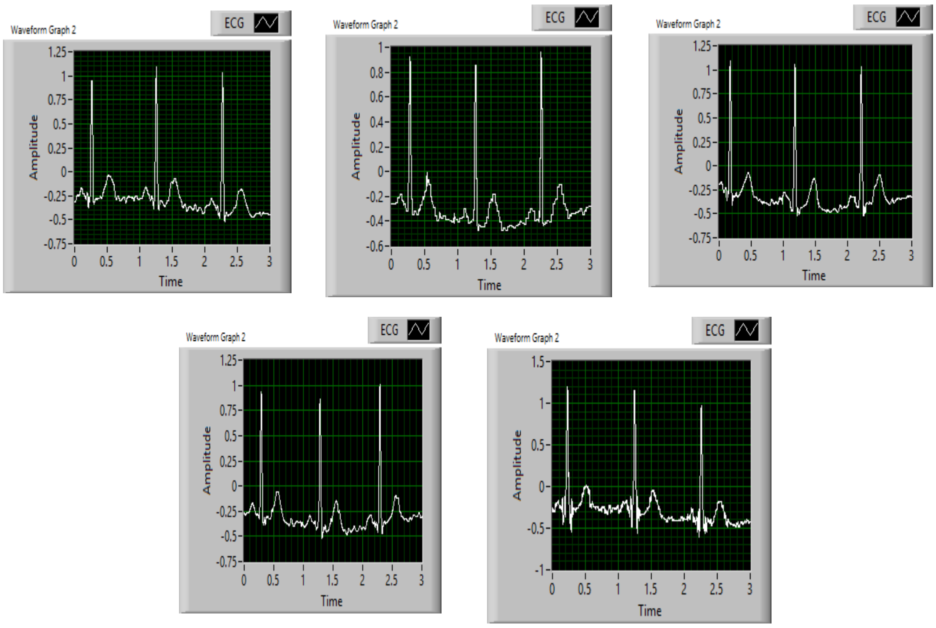

Figure 11. ECG Signal after Noise Removal for Wavelets(DWT) (a) Daubechies (b) Haar (c) Coiflet (d) Symmlet (e) Biorthogonal

4. Conclusion

In this research work five wavelets (Daubechies,Coiflet,Haar,Biorthogonal and Symmlet) with four thresholding rules(SURE,Hybrid,Universal and Minimax) and various decomposition levels are taken.Results are analyzed with SNR ratio,MSE,Variance, PSD and morphology of output ECG signal.Results shows that in SNR and MSE db06 in UWT type and db02 in DWT type gives best results.Biorthogonal and Haar wavelet in UWT and DWT gives best results in terms of variance and PSD. From the simulation results it is analyzed that Sure Thresholding is best thresholding rule for denoising the ECG.From the outputof ECG waveform, it is analyzed that Biorthogonal wavelet for UWT and Haar wavelet for DWT gives best denoising results.

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Authors

Supriya Goel, She is working as a research scholar in the School of Information and Communication Technology, Gautam Buddha University, Greater Noida, U.P., INDIA since 2013. Supriya Goel earned her M.Tech from Department of Electronics and Communication Engineering, D.C.R.U.S.T University Murthal, Haryana, INDIA. Supriya Goel has good teaching, research and software development experience. Apart from teaching, her major current research interest is Biomedical Signal Processing. She has also contributed more than 10 papers/articles in national/international journals and conferences. She is also UGC net qualified.

Pradeep Tomar, He is working as Assistant Professor in the School of Information and Communication Technology, Gautam Buddha University, Greater Noida, U.P., INDIA since 2009. Dr. Tomar has good teaching, research and software development experience. Dr. Tomar has qualified the National Eligibility Test (NET) for Lecturership in Computer Applications in 2003, Microsoft Certified Professional (MCP) in 2008, SUN Certified JAVA Programmer (SCJP) for the JAVA platform, standard edition 5.0 in 2008 and qualified the IBM Certified Database Associate - DB2 9 Fundamentals in 2010. Dr. Tomar has been awarded with Bharat Jyoti Award by India International Friendship Society in the field of Technology in 2012. He has been awarded for the Best Computer Faculty award by Govt. of Pondicherry and ASDF society. His biography is published in Who's Who Reference Asia, Volume II. Several technical sessions in national and international conferences had been chaired by Dr. Tomar and he delivered expert talks in FDP, workshops, national and international conferences. His major current research interest is in Component-Based Software Engineering. Two books "Teaching of Mathematics" and "Communication and Information Technology" at national levels have been authored by Dr. Tomar. He has also contributed more than 80 papers/articles in national/international journals and conferences. He served as member of editorial board and reviewer for various Journals and national/international conferences.

Gurjit Kaur, She is working as an Assistant Professor in the School of Information and Communication Technology, Gautam Buddha University, Greater Noida, U.P., India. She earned her Ph.D. degree in the area of Optical Communication from Panjab Univeristy, Chandigarh and her M. Tech from PEC University of Technology, Chandigarh with distinction. Dr. Kaur has also qualified MCSE and Microsoft Certified Professional (MCP). She has authored a book named Optical Communication at national level and contributed a book chapter entitled WiMAX Technology for Broadband Wireless Communication in Handbook of WiMAX "WiMAX Standards and Applications" (Volume III) of Florida Atlantic University Boca Raton, Florida published by CRC Press. Dr. Kaur is having distinction of receiving a Gold medal by former president of India Late Dr. A. P. J. Abdul Kalam for being overall topper of the Punjab Technical University, Jalandhar. Apart from teaching, she is guiding various research scholars in the areas of wireless and optical communication. She has also contributed more than 60 papers/articles in national/international journals and conferences.

