ECG Signal Denoising Using Wavelet Thresholding Techniques in Human Stress Assessment

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Abstract: In recent years, Electrocardiogram (ECG) plays an imperative role in heart disease diagnostics, Human Computer Interface (HCI), stress and emotional states assessment, etc. In general, ECG signals affected by noises such as baseline wandering, power line interference, electromagnetic interference, and high frequency noises during data acquisition. In order to retain the ECG signal morphology, several researches have adopted using different preprocessing methods. In this work, the stroop color word test based mental stress inducement have done and ECG signals are acquired from 10 female subjects in the age range of 20 years to 25 years. We have considered the Discrete Wavelet Transform (DWT) based wavelet denoising have incorporated using different thresholding techniques to remove three major sources of noises from the acquired ECG signals namely, power line interference, baseline wandering, and high frequency noises. Three wavelet functions ("*db4*", "*coif5*" and "*sym7*") and four different thresholding methods are used to denoise the noise in ECG signals. The experimental result shows the significant reduction of above considered noises and it retains the ECG signal morphology effectively. Four different performance measures were considered to select the appropriate wavelet function and thresholding rule for efficient noise removal methods such as, Signal to Interference Ratio (SIR), noise power, Percentage Root Mean Square Difference (PRD) and finally periodogramof Power Spectral Density (PSD). The experimental result shows the "*coif5*" wavelet andrigrsurethresholding rule is optimal for unknown Signal to Noise Ratio (SNR) in the real time ECG signals.

Keywords: Electrocardiogram, Discrete Wavelet Transform, Thresholding, Baseline Wandering, Power Line Interference.

1. Introduction

Electrocardiogram (ECG) signal is a graphical representation of cardiac activity and it uses the primary measure for identifying various heart diseases and heart abnormalities. In general, ECG signals have unique morphological characteristics (P-QRS-T complex) and it is highly significant than other biological signals. It is possible to diagnose many cardiac diseases by analyzing the variations of this morphology visually. However, the presence of noises in ECG signals will severely affect the visual diagnosis and feature extraction of various applications (stress measurement, emotion estimation and human computer interfaces, etc.). In order eliminate the noises and to extract the efficient morphology of ECG signals, several preprocessing methods have been proposed over past few decades [1-5]. Many of the researchers have used digital Infinite Impulse Response (IIR) filter to remove the effects of power line interference and baseline wander from ECG signals [4, 6]. Because, the design of IIR filter is simple, on other hand, higher order IIR filters are performing well to remove the noises from the signals. However, it has the drawback of increased filtering time, memory and incapable to filter the highly non-linear signals in the entire ECG range. Recent years, adaptive

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filtering methods used for removing the power line interference and other noises from ECG signals [5, 7,8]. This method is more well-known due to its faster filtering response and smaller residual errors[9]. However, this method requires reference signal (either signal or noise characteristics) information for the effective filtering process.

In [10], the temporal averaging filter is adopted for noise removal and it requires a large number of time frames for effective noise reduction. Independent Component Analysis (ICA) is for removing the noises from physiological signals in [9]. But, the ICA does not allow the prior information about the signals for efficient filtering [10]. On other hand, the linear filtering is also adopted for removing the baseline wander from ECG signals in the frequency range of 0.5 Hz [11]. This method introduces the ringing effect (Gibbs phenomenon) on the ECG signal analysis. In order to rectify this limitation, polynomial fitting (PF) or namely cubic spline filter was introduced for noise removal from ECG signals. In recent years, discrete wavelet transforms based thresholding is used to resolve the limitations on efficient noise removal from ECG signals using above mentioned filtering methods [11]. This method does not introduce any artificial information to the original signal and it independently generates the threshold value based on the signal attributes [12]. However, selection of appropriate wavelet function, thresholding methods and thresholding rule play an important role in signal denoising[11]. There are several types of wavelet functions are available to denoise the signals and to extract the efficient statistical and geometrical features for further applications. Some of the researchers considered to select the mother wavelet function based on: (i) eyeball inspection, (ii) correlation between the signal of interest and original signal, and (iii) based on the cumulative energy [13] . Genetic algorithm based mother wavelet and thresholding selection also considered to denoise the signal and it is the complex algorithm for the mother wavelet selection and may require more computation time that not included in detail [11].

In this work, the DWT based denoising was performed to remove the three different noises from ECG signal. Three different wavelet functions and four thresholding rules were considered to analyze the efficiency on noise removal from ECG signals. The organization of this paper is given as follows: section 2 describes the implementation of DWT based denoising of ECG signals using thresholding methods, section 3 discusses the research methodology, section 4 presents the computational performance measure, section 5 discusses the results of this work and finally conclusion is given in section 5.

2. Wavelet Transform

The Fast Fourier Transforms (FFT) produces the signal into an infinite length of sine and cosine functions. However, the transform losses the information is about time domain and gives only spectral information in the frequency domain and vice versa. In order to overcome this problem, Short Time Fourier Transform (STFT) was proposed and it represents the signal in both time and frequency domains using moving window function [14]. In this method, the window should always have a constant size, and thereby it does not give multi resolution information on the signal. However, the wavelet transform holds the property of multi resolution to give both and time and frequency domain information in a simultaneous manner through variable window size. The wavelet transform is scaled and shifted version of the time mother wavelet (a signal with tiny oscillations).The mother wavelet DWT is expressed by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{a}\right) a,\ b \in R,\ a>0, \quad (1)$$

where, 'a' and 'b' are the scaling and the shifting factor, respectively and R is the wavelet space. The mother wavelet must satisfy the condition (admissibility) in Eqn.2.

$$C_\psi = \int_{\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty \quad (2)$$

where, ψ (ω) is the Fourier transform of the mother wavelet function $(\psi_{a,b}\ (t))$.

A. Wavelet Filters

The time-frequency representation of DWT is performed by repeated filtering of the input signal with a pair of filters namely, low pass filter (LPF) and high pass filter (HPF), and its cutoff frequency is the middle of input signal frequency. The coefficient corresponding to the low pass filter is called as Approximation Coefficients (CA) and similarly, high pass filtered coefficients are called as Detailed Coefficients (CD) is shown in Figure 1. Furthermore, the CA is consequently divided into new approximation and detailed coefficients. This decomposition process is carried out until the required frequency response is achieved from the given input signal.

B. Wavelet Thresholding

*B.1. Hard Thresholding and Soft Thresholdin*g

Wavelet thresholding is the signal estimation technique that exploits the capabilities of signal denoising. Thresholding methodis categorized into two types such as hard thresholding and soft thresholding. The Figure 2 shows the soft and hard thresholding of the original signals. Performance of thresholding is purely depends on the type of thresholding method and thresholding rule used for the given application. The hard threshold function (w_{ht})tends to have bigger variance and it is unstable (sensitive even small changes in the signal) shown in Eqn. 3. However, soft thresholding function (w_{st}) is much stable than hard thresholding and it tends to have a bigger bias due to the shrinkage of larger wavelet coefficients descrbed in Eqn.3. In addition to these methods, the hyper-trim shrinkage with α- trim thresholding is proposed for signal denoising [15]. In general, most of the researchers have proved that, the soft thresholding method gives the best results with other methods on denoising the ECG signal [11, 15].

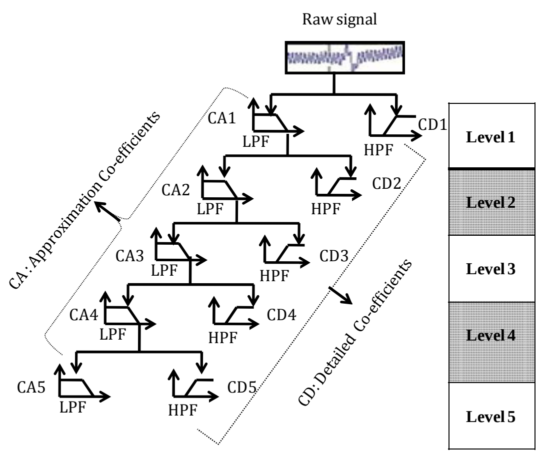

Figure 1. Filter bank structure for implementing DWT

$$w_{ht} = \begin{cases} w & |w| \geq t \\ 0 & |w| < t \end{cases} \quad (3)$$

$$w_{st} = \begin{cases} [sign(w)](|w| - t), & |w| \geq t \\ 0, & |w| < t \end{cases} \quad (4)$$

where *w* is a wavelet coefficient; *t* is a value of threshold which is applied on the wavelet coefficients

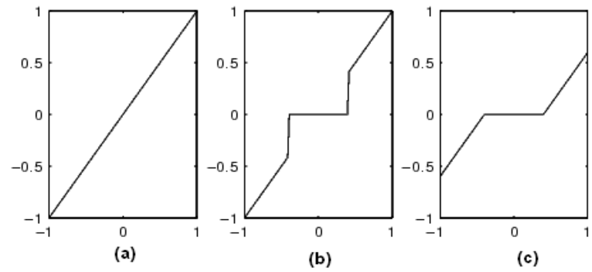

Figure 2.(a) Original signal; (b) Hard threshold signal; (c) Soft threshold signal [16]

B.2 Thresholding Rules

Donoho's has initially proposed the fixed thresholding based denoising of signals and images [15]. Here, the value of threshold (t) is computed as:

$$t = \sigma\sqrt{2\,log(n)/\,n} \tag{5}$$

where$\sigma = \frac{\text{MAD}}{0.6745}$, MAD is the median of wavelet coefficients and *n* is the total number of wavelet coefficients. There are four types of thresholding rules mostly used by different researchers on denoising applications [11].

B.2.1 Global Thresholding (wt_q)

This is a fixed threshold or global thresholding method and it is computed as:

$$wt_q = \sqrt{2\,log(n)} \tag{6}$$

where n is the total number of wavelet coefficients

This method yields the minmax performance is multiplied by the log value of the length of the wavelet coefficients.

B.2.2 Rigrsure(wt_{su})

Steins unbiased risk estimator (SURE) or rigrsure is an adaptive thresholding method which is proposed by Donoho and Jonstone and it is based on Stein's unbiased likelihood estimation principle [17]. This method computes is likelihood estimation first using the given threshold *t*, and then minimize the non-likehood *t*, so the threshold has been obtained.

B.2.3 Heursure (w_{th})

Heursure threshold 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 estimation will have more amounts of noises. In this kind of situation, the fixed form threshold is selected by means of global thresholding method. *2.2.2.4 Minimax (w_{tm})*

Minimax threshold is also used fixed threshold and it yields minmax performance for Mean Square Error (MSE) against an ideal procedures. Because the signal requiredthe denoising can be seen similar to the estimation of unknown regression function, this extreme value estimator can realize minimized of maximum mean square error for a given function.

$$w_{tm} = \begin{Bmatrix} 0.3936 + 0.1829*(log(n)/log(2)), & |n|>32 \\ 0 & |n|\leq 0 \end{Bmatrix} \tag{7}$$

In this method, the threshold value will be selected by obtaining a minimum error between wavelet coefficient of noise signal and original signal.

C. Wavelet Denoising Algorithm

In practice, the raw signal acquired using data acquisition system is expressed by $X\ (n)$,

$$X\ (n)\ =\ s\ (n)\ +\ u\ (n) \tag{8}$$

In assumption, the raw signals are usually contaminated with noise as shown in equation 8, where$s\ (n)$ is the useful signal and u (n) is the noise information, which includes all (power line interference, baseline wandering, high frequency noises, etc) sources of noises. In order separate noises in the (u(n)), the denoising algorithm is given below

- Initially, decompose the input signal using DWT: Choose a wavelet and determine the decomposition level of a wavelet transform *N*, then implement *N* layers wavelet decomposition of signal *S*.
- Select the thresholding method and thresholding rule for quantization of wavelet coefficients. Apply the thresholding on each level of wavelet decomposition and this thresholding value removes the wavelet coefficients above the threshold value (soft thresholding).
- Finally, the denoised signals reconstructed without affecting any features of signal interest. The reconstruction was done by performing the Inverse Discrete Wavelet Transform (IDWT) of various wavelet coefficients for each decomposition level.

The above three steps, the most critical is to select the proper threshold. Because, it directly reflects the quality of the de-noising [18].

3. Methods

A. Subjects and Data Acquisition

In this work, ECG signals are acquired by using 3 electrodes using AD Instruments and each one electrode is placed on th noises (baseline wanders). Figure 3 shows the 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 above the value of threshold has been removed (soft thresholding). In general, the value of ECG signal frequency above 100 Hz does not have any useful information [6]. Hence, the corresponding wavelet coefficients on CD1, CA1, and CA2 are changed into zero. In addition, the effect of baseline wandering is usually lies in the frequency range of less than 1 Hz. Therefore, the wavelet coefficients corresponding to this frequency range is removed from our analysis. After applying threshold on each level of the original signal, the effects of noises on the ECG signals were removed. Finally, we have reconstructed the signal on each level by using Inverse Discrete Wavelet Transform (IDWT) to obtain noise free ECG signals.

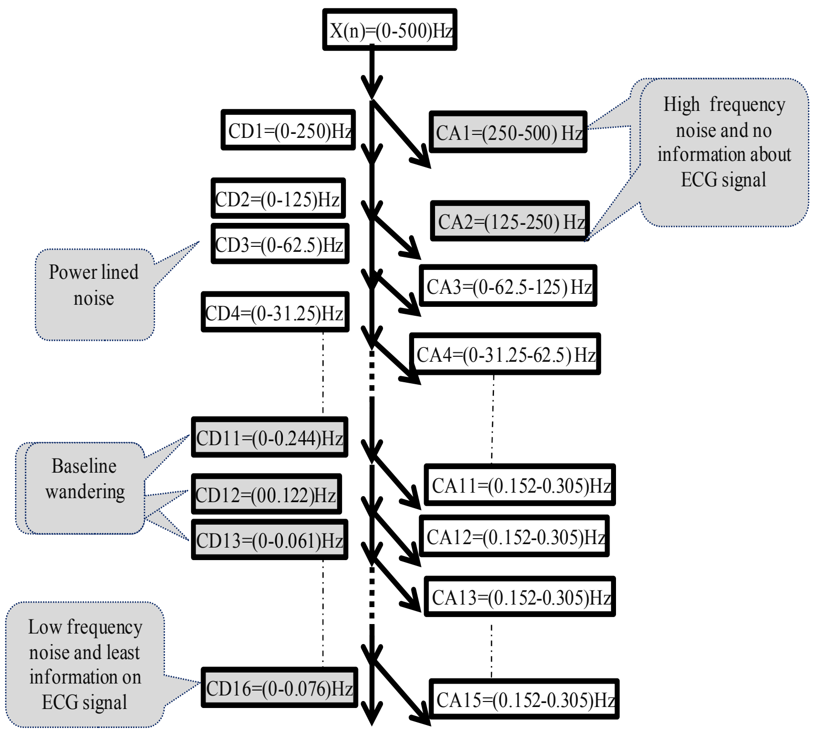

Figure 3. DWT filter structure with relevant noises

4. Performance Estimation

In this work, the performance of different wavelet thresholding on denoising the ECG signals have been measured using four measures such as Signal to Interference Ratio (SIR), Percentage Root.

Mean Square Difference (PRD), Power Spectral Density (PSD) and Noise Power (Pn). However, in this case SNR of acquired signal is unknown and all of the above estimates are analyzed. The significance preprocessing of a signal is measured by means of getting the higher value of SIR and PRD.

A. Signals to Inference Ratio (SIR)

The SIR is expressed as in Eqn 9:

$$R = \sum_{i=1}^{n} \left(\frac{x(i)_{\, raw\, signal}}{x(i)_{\, noise\, signal}} \right) \tag{9}$$

where, $x(i)_{raw\, signal}$ is amplitude of the input signal before denoising and $x(i)_{noise\, signal}$ is amplitude of noise removed through denoising. The performance of SIR of three-wavelet function over four different wavelet threshold rule is given in Table 1.

B. Percentage Root Mean Square Difference (PRD)

The value of PRD is computed by using Eqn.10.

$$PRD = 100 * \sqrt{\frac{\sum_{i=1}^{n} \left[x(i)_{raw\, signal} - x_{(i)denoised\, signal} \right]^2}{\sum_{i=1}^{n} \left[x(i)_{raw\ \ signal} \right]^2}} \tag{10}$$

where, $x_{(i)denoised\, signal}$ is amplitude of denoised signal. Table.2 shows the PRD value for the different wavelet and thresholding rule.

C. Noise power $(\boldsymbol{Pn})$

The noise power $(Pn)$is obtained by subtracting the signal power before denoising to the denoised signal. The minimum noise power and perfect morphology show the excellent denoising performance. The noise power is expressed as:

$$P(n) = x(i)_{\, raw\, signal}{}^{2} - x(i)_{\, denoised\ \ signal}{}^{2} \tag{11}$$

D. Power Spectral Density $(\boldsymbol{PSD})$

The Power spectral density function (PSD) shows the strength of the variations (energy) as a function of frequency and it shows at which frequency variations are strong and at which frequencies variations are weak. The PSD have calculated using Fast Fourier Transform (FFT). Figure 4 shows the PSD of signal before and after preprocessing.

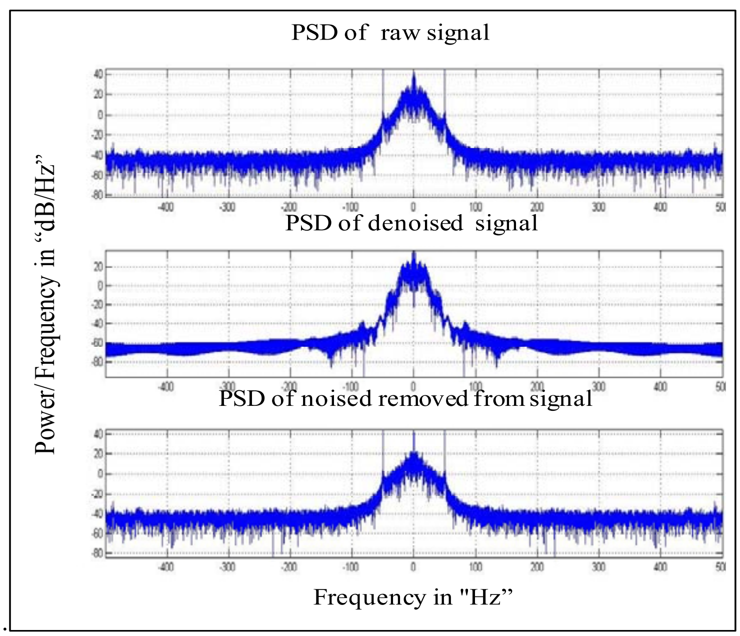

Figure 4. PSD of the signal before and after denoising

5. Results and Discussion

There are three wavelet functions and four threshold rules have considered in analyzing the performance of denoising the ECG signals using soft thresholding method. From the literature, we found that, wavelet transform shows a good performance on 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. In this work, DWT based thresholding has been tested over the 20 ECG datasets and each with duration of (~13 min) from the stress assessment experiment. In practice, the value of Signal to Noise Ratio (SNR) is unknown due to the acquisition of signal under real time applications.

Table 1. Selection of suitable wavelet function and thresholding rule for denoising the ECG signals using SIR

Data Set (Sample)	Signal to Interference Ratio (SIR)											
	Db4				Coif 5				Sym 7			
	Rigrsure	Heursure	Sqtwolog	Minimaxi	Rigrsure	Heursure	Sqtwolog	Minimaxi	Rigrsure	Heursure	Sqtwolog	Minimaxi
1	1.91	2.3	2.29	2.2	1.81	2	2.2	2.1	1.8	2.2	2.45	2.2
2	0.77	0.6	0.56	0.6	0.72	0.7	0.56	0.6	0.74	0.6	0.55	0.6
3	0.95	0.9	0.82	0.9	0.95	0.9	0.8	0.9	0.94	0.9	0.78	0.8
4	0.71	0.7	0.59	0.6	0.75	0.7	0.59	0.7	0.73	0.7	0.56	0.6
5	0.87	0.9	0.7	0.8	0.9	0.8	0.66	0.8	0.86	0.8	0.6	0.7
6	0.86	0.8	0.67	0.7	0.83	0.8	0.56	0.7	0.78	0.7	0.56	0.6
7	0.8	0.8	0.69	0.8	0.81	0.8	0.7	0.7	0.81	0.8	0.69	0.7
8	0.89	0.8	0.72	0.8	0.93	0.9	0.72	0.8	0.9	0.9	0.71	0.8
9	1.22	1.3	1.52	1.4	1.2	1.3	1.51	1.4	1.18	1.3	1.53	1.4
10	0.9	0.8	0.75	0.8	0.99	1	0.77	0.8	0.93	0.9	0.74	0.8
11	1.2	1.3	1.5	1.4	1.18	1.3	1.49	1.4	1.2	1.3	1.5	1.4
12	1.29	1.3	1.52	1.4	1.24	1.3	1.49	1.4	1.26	1.3	1.52	1.4
13	0.8	0.6	0.54	0.6	0.77	0.7	0.6	0.7	0.75	0.7	0.58	0.6
14	0.95	0.9	0.81	0.9	0.95	0.9	0.8	0.9	0.94	0.9	0.79	0.8
15	0.72	0.7	0.58	0.6	0.74	0.7	0.57	0.6	0.74	0.7	0.56	0.6
16	0.85	0.9	0.7	0.8	0.86	0.9	0.67	0.8	0.84	0.8	0.6	0.7
17	0.83	0.7	0.58	0.7	0.8	0.8	0.55	0.6	0.76	0.7	0.57	0.7
18	0.78	0.7	0.59	0.7	0.82	0.8	0.65	0.7	0.78	0.8	0.6	0.7
19	0.91	0.8	0.71	0.8	0.92	0.9	0.74	0.8	0.92	0.9	0.72	0.8
20	0.86	0.8	0.75	0.8	0.89	0.9	0.74	0.8	0.88	0.9	0.74	0.8
Hit ratio between in between thresholding rules in numbers (%)	16 (80%)	-	4 (20%)	-	17 (85%)	-	3 (15%)	-	16 (80%)	-	4 (20%)	-
Overall hit ratio between wavelets in numbers (%)	5 (25%)	-	2 (10%)	-	11 (55%)	-	-	-	-	-	2 (10%)	-

*Bold letters-indicates the best value between threshodling rules of single wavelet
*Bold letters with shade indicates the best value in between all wavelets

Because of noises are mainly from unknown and uneven sources. It is unable to eliminate all the noises during the data collection. In this work, the acquired stress ECG data contains various noises that inconsistently spread over the various ECG records. It was identified visually and these noises are the main reason for less accuracy of stress level assessment and classification research. The Figure 5 shows one of the subject data during the stress assessment and concurrently the Figure 5 shows the reduction of baseline wander even the signal has power line interference.

The SIR performance on denoising ECG signals is given in Table 1 and it allows finding out the better thresholding rules (rigrsure and sqwtlog) which is performing well over other thresholding rules. Indeed, "coif5" wavelet function gives the better SIR rate while comparing with other three-wavelet functions.

Table 2 shows the performance of PRD on denoising the ECG signal. Here, the rigrsure and sqwtlog are performing better over other thresholding rules. The rigrsure gives the maximum performance on all three wavelet functions. However, the sqwtlog is also gives the best results in "*coif5*" and *"sym7"* wavelets. Based on the PRD value rigrsure of *"coif5"* wavelet and sqwtlog of "*sym7*" is better.

According to the noise power estimation, the rigrsurethresholding rule is more significantly perform over other thresholding rules. Figure 6 shows the performance of noise power over different wavelet functions and thresholding rules. From Figure 6, "*coif 5"*rigrsure combinations shows that, the noise power is very less compared to all other thresholding rules and wavelet functions. Similarly, the hit ratio in Table 3 of noise also supported the above finding.The overall best performed thresholding rule of three wavelets were shown in Figure 7.

Table 2. Selection of wavelet function and thresholding rule for denoising the ECG signals using PRD

Data Set (Sample)	**Percentage Root Mean Square Difference (PRD)**											
	Db4				**Coif5**				**Sym7**			
	Rigrsure	**Heursure**	**Sqtwolog**	**Minimax i**	**Rigrsure**	**Heursure**	**Sqtwolog**	**Minimax i**	**Rigrsure**	**Heursure**	**Sqtwolog**	**Minimax i**
1	36782	36907	36914	36891	36623	36655	36832	36749	36864	36982	36994	36967
2	2313	2306	2308	2306	2583	2582	2459	2522	2409	2316	2301	2357
3	2045	2037	1977	2022	2117	2069	1997	2055	2115	2098	2009	2069
4	592	780	792	807	556	549	710	625	699	827	850	772
5	890	930	934	920	63	273	681	353	586	931	943	910
6	4657	2893	2452	3100	3385	3279	2786	3041	3367	3183	2399	2928
7	3237	3543	3522	3436	2648	2835	3204	2952	2889	3310	3459	3257
8	5153	5064	5050	5088	5447	5224	5072	5270	5241	5182	5101	5180
9	3714	3434	3454	3431	4524	4474	4193	4338	3659	3502	3459	3565
10	4379	3937	3894	4084	3844	3892	3846	3877	3769	3776	3865	3818
11	3729	3748	3824	3770	3751	3756	3777	3762	3940	3883	3894	3881
12	4113	3866	3868	3912	4811	4420	4035	4346	4318	3964	3911	4054
13	3116	2525	2453	2699	3310	3250	2839	3057	2969	2452	2357	2603
14	1962	218	657	183	176	197	358	241	698	248	645	118
15	111	295	337	194	122	135	303	217	135	365	375	344
16	2526	2780	2795	2742	2204	2228	2468	2342	2666	2802	2826	2748
17	1993	1848	1847	1864	1936	1876	1881	1908	1842	1834	1841	1837
18	3243	3089	3032	3044	3281	3256	3093	3183	2955	2950	2959	2957
19	3315	4020	4086	3802	3914	3934	3948	3936	3637	4078	4146	3909
20	2622	3258	3269	3174	1891	2035	2420	2207	2701	3238	3297	3177

*Bold letters-indicates the best value between thresholding rules of single wavelet
*Bold letters with shade indicates the best value in between all wavelets

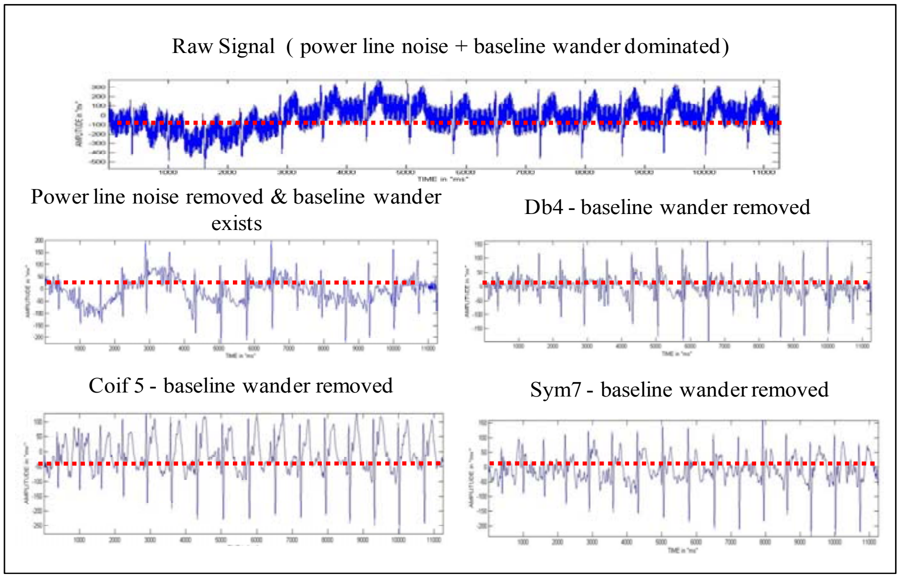

Figure 5. ECG signal before and after baseline wander removal

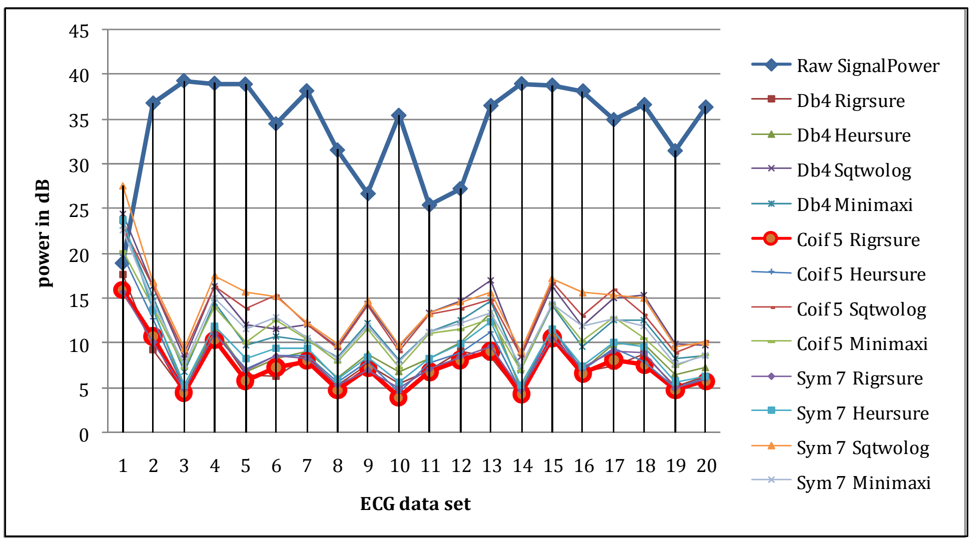

Figure 6. Selection of suitable wavelet function and thresholding rule for denoising the ECG signals using noise power

Table 3. Power of noise in various wavelet and threshold rule

Performance	Noise Power											
	Db4				Coif 5				Sym 7			
	Rigrsure	Heursure	Sqtwolog	Minimaxi	Rigrsure	Heursure	Sqtwolog	Minimaxi	Rigrsure	Heursure	Sqtwolog	Minimaxi
Hit ratio between in between thresholding rules in numbers (%)	20 (100%)	-	-	-	20 (100%)	-	-	-	20 (100%)	-	-	-
Overall hit ratio between wavelets in numbers (%)	5 (25%)	-	-	-	14 (70%)	-	-	-	1(5%)	-	-	-

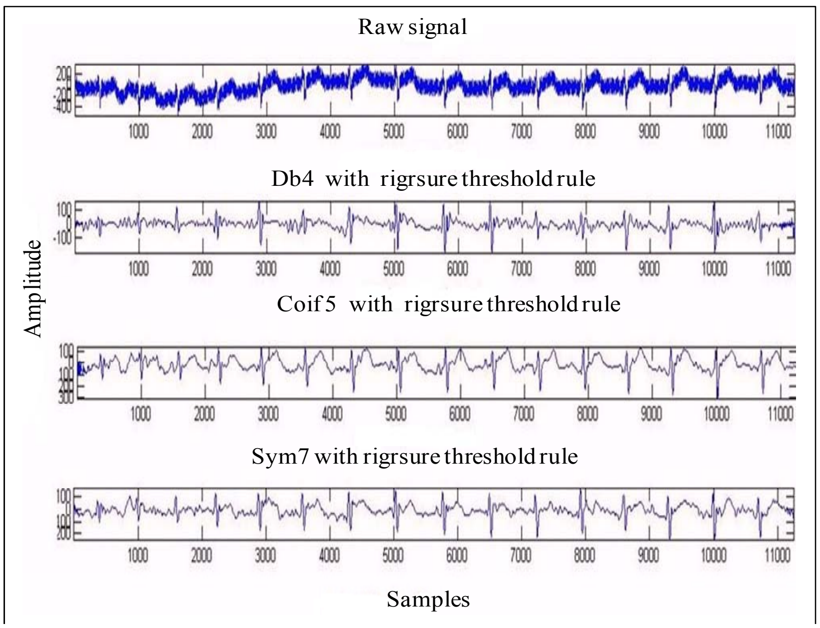

Figure 7. Comparison between ECG morphologies of three wavelet functions (dataset15)

Compared all other thresholding techniques, rigrsure based thresholding gives the results of noise free ECG as similar to its morphology. However, overall ECG morphology based analysis shows "*coif5*" wavelet function and rigrsure combination performing excellent morphological characteristics rather than other combination types.

6. Conclusion

In this paper, to extract the quality ECG signal from the raw noisy ECG signal DWT based denoising were employed by using three wavelet function and four thresholding rules. In order to identify the performance of denoising, four simple measures were investigated and results are discussed. The morphology of ECG signals not deviates as well in all three wavelets. However, the morphology "*db4"*and *"sym7"* wavelets based ECG signals areinfinitesimally differencefromthe actual PQRST in all thresholding rules and the "*coif5"* wavelet function holds the excellent morphology in rigrsure threshold rule rather than other three rules. The "*db4"* wavelet gives the more suppressed "T" wave and "*sym7"* gives the disturbed ECG pattern. The overall performance of "*coif5*" is better than other wavelet based on morphological characteristics preservation and four performance measures. The "*coif5"* based wavelet transform produces the excellent ECG signal even though the signal contaminates power line noise, baseline wander, and low and high frequency noises. The paper concludes that the "c*oif5"* wavelet and rigrsure threshold rule gives the best result for ECG signal denoising. This method is very simple compared to other denoising approach like genetic algorithm. The measure based wavelet function and thresholding method suitable for other biological signals denoising even the signal is unknown SNR.

7. Acknowledgments

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