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Research Article

A Study of Chosen an Optimum Type of Wavelet Filter for De-Noising an ECG signal

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Abstract

Among various biological signals for the diagnosing of cardiac arrhythmia, Electrocardiographic (ECG) signal is the most significant one. The interesting challenge is an accurate analysis of the noisy ECG signal. Prior to accurate analysis, these signals need for de-noising to remove these unwanted noises in the signal to get an accurate diagnosis. In order to get the best de-noising results, it should have an accurate decision about the filters that we deal with for de-noising the signals. So, in this paper we present a study for choosing the optimum wavelet filter for de-noising the electrocardiograph (ECG) signal. Signals were stored as a one-dimensional matrix and series of procedure were performed to reduce the noise. The wavelets filters were chosen that very close to the original signal after applied a random-noises to the ECG signals to get familiar with the possible noise that can the signal affected with it. Also, estimation the most standard wavelet families namely Symlets, Coiflet, and Daubechies with different methods of threshold and decomposition levels were done. The purposes of this study to conclude the convenient wavelet functions in decomposition, the de-noising and the reconstruction, the method of the threshold, and the optimal decomposition level of the wavelet.

Keywords: *ECG, wavelet function, filters, WGN, de-noising.*

1. Introduction

The electrical activity of explaining cardiac muscle action is the Electrocardiogram signal. It is interfering easily with differs noises whilst collecting and registration. Instability of electrode skin effect, the Electromyogram (EMG) signal, baseline wandering, and 50 / 60 Hz power line interference are the noisiest sources troublesome. These noises are hard to take off by steps of a typical filter. The high-frequency component EMG signal generates according to the random muscles shrinking, whilst the sudden transients are according to the unexpected body motion. A low-frequency component baseline wandering is according to the rhythmic exhalation and inhalation through breathing. (Reddy, 2009)

The ECG signal is one of the vital signals which are treated as a non-stationary signal and requirement a difficult work for de-noising (Łski J, 1991; Shrouf A, 1994). One of the most serious issues is the ways to remove or minimize the impact of noises. Electrode-skin contact instability (Power line interference) can be tacked off by utilized typical filter steps but the white Gaussian noise (WGN) interference is complicated to take off utilizing previous procedures (Phinyomark, 2009).

For reducing the ECG signal noises a lot of mechanisms are found such as adaptive method, digital filters, and wavelet transforms thresholding methods. An effective mechanism for an ECG (non-stationary) signal treatment is the wavelet transform. The wavelet transform can be utilized as signal decomposition in the scale time-frequency plane (Alfaouri, 2008). An advanced signal processing Wavelet denoising algorithms have received considerable attention in the removal of white Gaussian noise (Phinyomark, 2009). That wavelet transformation is based on an analytical wavelets group that permitting the ECG signal decomposition in coefficients set. Each analytical wavelet has its own frequency band, time duration, and time location. The Discrete Wavelet Transform is accomplished with a filter bank that decomposes the signal by utilizing sequential low and high pass procedures' filtering (Elbuni, 2009).

This paper presents the performance of different types of wavelet types by applying three algorithms at different levels to artificial and real signals. The remainder of the paper is ECG and wavelet backgrounds found in Section 2. Section 3 includes details of the usage data and the methodology. Sections 4 the related work. Section5 the results of de-noising signals and discussion and finally, the conclusion is represented in section 6.

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2. Back grounds

In this section, we show a Brief background about our ECG and wavelet filter.

2.1 ECG over view

The electrocardiograph's output is ECG signals; ECG signals measures the heart's electrical voltage. For a heart specialist, ECG signal present a lot of information about the heart case of the patient, making ECG a significant scope in recent medicine. There is a large requirement for automation of the observing process since ECG signals are continued data plots. This performs a whole scope in algorithm theory; DSP (Digital Signal Processing) and peaks' detecting of ECG signals. The major sources for the noise are:

A. From the power mains, (50–60) Hz pickup and harmonics which is known as power-line interference.
B. A variable connection between the skin and the electrode, cause baseline drift, known as Electrode connection noise.
C. The changing in the electrode-skin impedance caused shifts in the baseline which is Motion artifacts.
D. Electromyogram (EMG) signals are produced and mixed with the ECG signals breathing, cause drifting in the baseline called as Muscle contraction.

2.2 Wavelet Filter

Wavelet transform is an athletic tool that permits to us viewing the information of time for the signal and its frequency content. This means that it charts a one-dimensional signal of time into a tow dimensional signal of time and frequency (Elbuni, 2009). Wavelet transforms include performed a generic function in terms of easy, constant structure blocks in diverse scales and situations. The structure blocks are created from a single constant function called mother wavelet via translation (the process of moving something from one place to another) and expansion process (Rosas-Orea, 2005). The wavelet function's selection is the first and the more important step. It is significant to select the right filter because it defines the ideal reconstruction (Abbas, 2015). Furthermore, wavelets are designed adaptable and alterable in order to be suitable for individual applications (Mallat, 1999).

3. Materials and Methodology

In this section, the materials that are used and the ways that used to filter it.

3.1 Materials

In order to get the purpose of this paper, its needed to extend the range of data that applied the various types of filter on it for getting wide results which are led to the best choice of filter, so it is used the ECG real-time system (which is collected and registered by heart rate monitoring system with AD8232 ECG sensor and Arduino microcontroller from healthy person) and MIT-BIH Arrhythmia Database monitoring.

3.2 Methodology

One of the widely mathematical techniques used in signal processing is the discrete wavelet transform (DWT). The purpose of this transform is to decompose a signal into differs resolutions utilizing high pass filter and low pass filter. Several high and low pass coefficients have been developed for a large choice among different scales and translations in order to obtain different sorts of signal analysis, e.g. Debauchies coefficients, Coiflets coefficients, and Symlets coefficient regarding the equations of the decomposition.

The aim of de-noising algorithm of the wavelet is to remove the noise from the signal ECG (t) by rejected the noise n(t) and to retrieve the interesting signal S(t). The model form performed in equation (1) (Z. Qingju, 2006).

$$S\,(t) = ECG\,(t) + n\,(t) \tag{1}$$

The generic wavelet-based de noising steps are set in three steps :

4. The Decomposition

The first significant step is the chosen of a wavelet function and decomposition level J; count the wavelet decomposition of the ECG signal at the J level .The right filter is important to select because it counts the good reconstruction.

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right) \tag{2}$$

Where $a, \tau \in R; a > 0$

a is the factor's scaling,
τ is the factor's shifting, and the function ψ(t) is the basal wavelet function depending on a and τ.

The second step is the chosen number of the decomposition levels of the signal. DWT gets high-frequency components when utilizes high pass filter such named details (D) and gets low-frequency components when utilizes a low-pass filter such named approximations (A). The noise-reducing steps are based on minimizing the noise in high-frequency signal's details. The decomposition levels divers from the first decomposition level to J level.

Where

$$J = \log_2 N \tag{3}$$

and N is the length of the signal (in samples) of the time-domain (K. Englehart, 2003).

4.1 The De-noising Wavelet Detail Coefficients

Chooses a threshold value and apply thresholding to the coefficients' detail for each level .Several threshold estimation methods are found such as sure threshold, minimax, universal threshold, and hybrid threshold. After threshold values are determined, thresholding can be completed by utilizing the soft and hard transformation.

4.2 The Hard Thresholding

It can be characterized such as the usual operation for making all detail coefficient thresholds zero and then keeping the other detail coefficients. This can show like (C. F. Jiang, 2007):

$$\boldsymbol{C_k} = \begin{Bmatrix} \boldsymbol{C_k} & \boldsymbol{if}\ |\boldsymbol{C_k}| \geq \boldsymbol{\delta} \\ \boldsymbol{0} & \boldsymbol{other\ wise} \end{Bmatrix} \tag{4}$$

4.3 The Soft Thresholding

It is an expansion of the hard thresholding. In the beginning, the whole coefficients' detail, that the absolute values are minimal than the threshold value is zeroed and then the other coefficients' detail are shrunk towards zero. It can be described like as:

$$\boldsymbol{C_k} = \begin{Bmatrix} \boldsymbol{sgn(C_k)(C_k - \delta)} & \boldsymbol{if}\ |\boldsymbol{C_k}| \geq \boldsymbol{\delta} \\ \boldsymbol{0} & \boldsymbol{other\ wise} \end{Bmatrix} \tag{5}$$

in the biomedical signal's processing field like as ECG and EMG signals, it is found that the soft thresholding performs better results than the hard thresholding. In this study, it is utilized the soft thresholding to get an optimal wavelet function for the de-noising ECG signals.

4.4 The Minimax Thresholding

It was presented in (D. Donoho, 1993). Minimax threshold consists of an optimal threshold that is obtained from reducing the fixed term in an upper bound of the noise involved in the respect of the function.

4.5 Sure threshold

The Rigorous SURE threshold described a schema that utilized a threshold value in each resolution -4 levels of the wavelet coefficients which was presented in (D. Donoho, 1993). Also, it is known as Sure Shrink.

4.6 Universal threshold

This de-noising algorithm is also known as VisuShrink which was presented in (Agante, 1999). It is an alternative to the minimax threshold.

After choosing the thresholds, then detecting the types of wavelets that are the closest wavelet's types to the ECG signal that in order to get the best results.

1) The Reconstruction: count the reconstruction based on the J level main approximation coefficients and the modified detail coefficients of levels from 1 to J.

For achieving and optimizing the three steps above, four points should be managed, namely chosen of the convenient wavelet function, decomposition level, the estimation of the threshold, and the transformation of the threshold. After choosing the thresholds, then detecting the types of wavelets that is the closest wavelet's types to the ECG signal that in order to get the best results.

Related Works

Many types of research have been achieved in the scope of removing of ECG noises and their analysis. Various methods are utilized for this target such as undecimated wavelet transform (Agante, 1999) wavelet transform (D.L. Donoho, 1994, 1995), digital filter (IIR or FIR) (D.L. Donoho,, 1995; Guoxiang, 2001) and other. Poornachandra S set an adaptive universal threshold of the wavelet, to the ECG signals which were utilized for the signal corrupted with the Gaussian noise. Alfieri M and Daqrouq K offered the wavelet thresholding schedule utilized the Daubechies (dB) wavelet for the ECG signal. Eddy GU et al. (Reddy, 2009) prepared an electrocardiogram de-noising technique utilizing the promoted thresholding Wavelet transform. M. C. E. Rosas-Orea and the others showed a related simulation survey with three wavelet-based denoising algorithms applied for real signals and synthetic signals. The signal analysis was completed by applying the soft and the hard thresholds to signals with a diverse size of the sample. The minimax threshold, the rigorous SURE threshold, and the universal threshold were utilized for removing the Gaussian noise from the real and the synthetic signals. The results showed that a hard threshold with the SURE algorithm got good showing than of the other algorithms in synthetic signals. At the other side, a soft threshold with a Universal threshold algorithm showed that the good showing in the real signals while utilizing Daubechies wavelet with 5 vanishing moments (Rosas-Orea, 2005).

5. Calculations, Results and Discussion

This section presented the calculations that used in the results and the result.

5.1 Calculations

This de-noised study is done by the parameters signal to noise ratio (SNR) value and mean square error (MSE). These parameters are computed between the original ECG signal and the de-noised ECG signal. The good suitable wavelet function is completed get by the lower MSE and higher SNR values between the original and the de-noised ECG signal. Where X1(i) is the original signal, X2(i) is the de-noised signal N is the sampling rate. The MSE and SNR are given by equations (6) and (7) respectively (Jenkal, 2016)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x(i) - \hat{x}(i))^2 \quad (6)$$

$$SNR = 10\ log(\frac{\sum_{i=1}^{N} x^2}{\sum_{i=1}^{N}(x(i)-\hat{x}(i))^2}) \quad (7)$$

5.2 Results and Discussion

These results are obtained by using two signals: signal from MIT-BIH data base and a real signal from heart rate monitor system. The most common types of noises that the ECG signals are affected with it are power line interface, EMG noise, and the synthetic SNR. Appling these three noises on the signals and getting a lot of results that don't have space to offer all it here. So, the most important one which is the WGN case is present.

5.2.1 ECG Signal from MIT-BIH Data Base

MIT-BIH (100m) database is used to apply the WGN represent the synthetic SNR on it and get the results. The results of filtering the noisy signal are shown in Tables (1, 2, 3, and 4).

Table 1 shows ECG signal (MIT-BIH data base 100) noised with white Gaussian noise which is present the synthetic SNR WGN with 15 db, and filtered by sym4 wavelet type at (1, 2, 3, 4, 5, 6, 7, 8, 9, 10 &11) decomposing levels, soft threshold, and sure method, Minimax method and universal method.

Table 1: ECG Signal Noised with WGN, Filtered by Sym4, Soft Threshold, and Three Threshold Methods

Sym4 sure method 15	SNR	MSE	Sym4 Minimax method	SNR	MSE	Sym4 Universal method	SNR	MSE
Level 1	32.6149	0.0155	Level 1	32.6121	0.0155	Level 1	32.6149	0.0155
Level 2	35.2905	0.0084	Level 2	35.2944	0.0084	Level 2	35.2839	0.0084
Level 3	37.5933	0.0049	Level 3	37.1221	0.0055	Level 3	36.5910	0.0062
Level 4	38.4471	0.0041	Level 4	36.9376	0.0057	Level 4	35.6292	0.0078
Level 5	38.3028	0.0042	Level 5	36.3736	0.0065	Level 5	34.8426	0.0093
Level 6	37.7156	0.0048	Level 6	35.8863	0.0073	Level 6	34.4915	0.0101
Level 7	37.3860	0.0052	Level 7	35.2063	0.0085	Level 7	33.9487	0.0114
Level 8	36.6984	0.0061	Level 8	34.7713	0.0095	Level 8	33.6194	0.0123
Level 9	36.3938	0.0065	Level 9	34.5686	0.0099	Level 9	33.4633	0.0128
Level 10	36.3625	0.0066	Level 10	34.4835	0.0101	Level 10	33.3861	0.0130
Level 11	36.2882	0.0067	Level 11	34.2743	0.0106	Level 11	33.2227	0.0135

Table 2 shows ECG signal (MIT-BIH data base 100) noised with white Gaussian noise which is present the synthetic SNR WGN, and filtered by db4 wavelet type at (1, 2, 3, 4, 5, 6, 7, 8, 9, 10 &11) decomposing levels, soft threshold, and sure method, Minimax method and universal method.

Table 2: ECG Signal Noised with WGN, Filtered by Db4, Soft Threshold, and Three Threshold Methods

db4 sure method 15	SNR	MSE	db4 Minimax method	SNR	MSE	db4 Universal method	SNR	MSE
Level 1	32.6500	0.0154	Level 1	35.3390	0.0083	Level 1	32.6523	0.0154
Level 2	35.3491	0.0083	Level 2	37.3373	0.0052	Level 2	35.3544	0.0083
Level 3	37.5475	0.0050	Level 3	37.3373	0.0052	Level 3	36.9856	0.0057
Level 4	38.9386	0.0036	Level 4	37.8174	0.0047	Level 4	36.3701	0.0065
Level 5	38.6179	0.0039	Level 5	37.0472	0.0056	Level 5	35.5855	0.0078
Level 6	37.2505	0.0053	Level 6	36.0509	0.0070	Level 6	34.8513	0.0093
Level 7	36.6924	0.0061	Level 7	35.2452	0.0085	Level 7	34.2269	0.0107
Level 8	36.1545	0.0069	Level 8	34.8529	0.0093	Level 8	33.9137	0.0115
Level 9	35.8044	0.0074	Level 9	34.5904	0.0099	Level 9	33.7012	0.0121
Level 10	35.6594	0.0077	Level 10	34.4816	0.0101	Level 10	33.6124	0.0123
Level 11	35.4920	0.0080	Level 11	34.3524	0.0104	Level 11	33.5064	0.0126

Table 3 shows ECG signal (MIT-BIH data base 100) noised with white Gaussian noise which is present the synthetic SNR WGN, and filtered by coif2 wavelet type at (1, 2, 3, 4, 5, 6, 7, 8, 9, 10 &11) decomposing levels, soft threshold, and sure method, Minimax method and universal method.

Table 3: ECG Signal Noised with WGN, Filtered by Coif2, Soft Threshold, and Three Threshold Methods.

Coif2 sure method	SNR	MSE	Coif2 Minimax method	SNR	MSE	Coif2 Universal method	SNR	MSE
Level 1	32.3937	0.0163	Level 1	32.4089	0.0163	Level 1	32.4156	0.0163
Level 2	35.0871	0.0088	Level 2	35.143	0.0087	Level 2	35.1626	0.0086
Level 3	37.0818	0.0056	Level 3	36.8736	0.0058	Level 3	36.4081	0.0065
Level 4	38.2498	0.0042	Level 4	36.8750	0.0058	Level 4	35.6343	0.0077
Level 5	38.412	0.0041	Level 5	36.0408	0.0071	Level 5	34.8599	0.0093
Level 6	37.9136	0.0046	Level 6	35.6870	0.0077	Level 6	34.4052	0.0103
Level 7	37.6819	0.0048	Level 7	35.3437	0.0083	Level 7	33.9753	0.0114
Level 8	37.5430	0.0050	Level 8	35.2988	0.0084	Level 8	33.8883	0.0116
Level 9	37.587	0.0049	Level 9	35.3185	0.0083	Level 9	33.8883	0.0116
Level 10	37.578	0.0050	Level 10	35.3226	0.0083	Level 10	33.8799	0.0116
Level 11	37.5522	0.0050	Level 11	35.2422	0.0085	Level 11	33.7844	0.0119

Table 4 shows ECG signal (MIT-BIH data base 100) noised with white Gaussian noise which is present the synthetic SNR WGN with15 db, and filtered by coif5 wavelet type at (1, 2, 3, 4, 5, 6, 7, 8, 9, 10 &11) decomposing levels, soft threshold, and sure method, Minimax method and universal method.

Table 4: ECG Signal Noised with WGN, Filtered by Coif5, Soft Threshold, and Three Threshold Methods

Coif5 sure method	SNR	MSE	Coif5 Minimax method	SNR	MSE	Coif5 Universal method	SNR	MSE
Level 1	32.3471	0.0165	Level 1	32.3687	0.0164	Level 1	32.3795	0.0164
Level 2	35.2738	0.0084	Level 2	35.3464	0.0083	Level 2	35.3608	0.0083
Level 3	36.9135	0.0058	Level 3	36.7263	0.0060	Level 3	36.4711	0.0064
Level 4	37.9478	0.0045	Level 4	36.7382	0.0060	Level 4	35.5035	0.0080
Level 5	37.3121	0.0053	Level 5	35.7356	0.0076	Level 5	34.5616	0.0099
Level 6	37.3038	0.0053	Level 6	35.2202	0.0085	Level 6	34.0987	0.0110
Level 7	37.3070	0.0053	Level 7	34.9538	0.0091	Level 7	33.7318	0.0120
Level 8	37.3088	0.0053	Level 8	34.9237	0.0091	Level 8	33.6666	0.0122
Level 9	37.3338	0.0052	Level 9	34.9091	0.0092	Level 9	33.6294	0.0123
Level 10	37.3338	0.0052	Level 10	34.9131	0.0091	Level 10	33.6203	0.0123
Level 11	37.3437	0.0052	Level 11	34.8910	0.0092	Level 11	33.5698	0.0125

As a conclusion from the results in the Tables above that the best threshold is sure threshold. So, a comparing the four types of wavelets (sym4, db4, coif2, and coif5) with sure method and 11 levels shown in Figure (1), where the X axis represent the levels and the Y axis represents the values of the MES in (A), and X axis represent the levels and the Y axis represents the values of the SNR in (B).

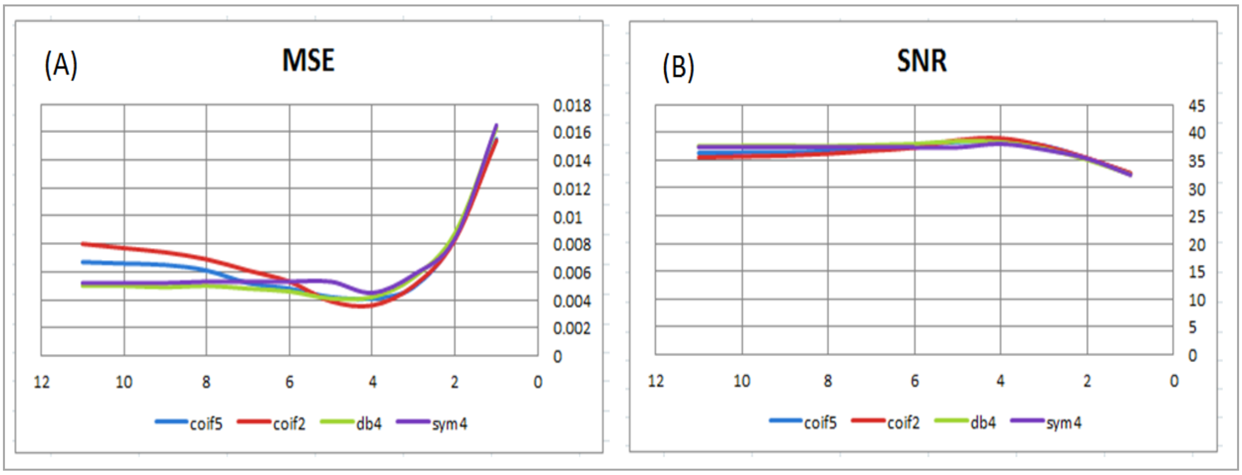

Figure 1: SNR and MSE of the Four Types of Wavelet, (A) MSE Representation, (B) SNR Representation.

As illustrated previously, the result of getting from the four tables that the db4 type is optimum for de-noising the WGN from the signal with MSE value (0.0036) and SNR value (38.9). While in the cases of power line interface and EMG noise, the optimum type for de-noising is also db4 with MSE value (0.0011) and SNR value (44.35) for power line interface and MSE value (0.0010) and SNR value (44.35) for EMG noise.

Figure 2 shows the ECG signal, the noisy signal, and the de-noised signal which is de-noised by db4 level four and sure method. Where the X axis represents the samples and the Y axis represent the Amplitude in mvolt.

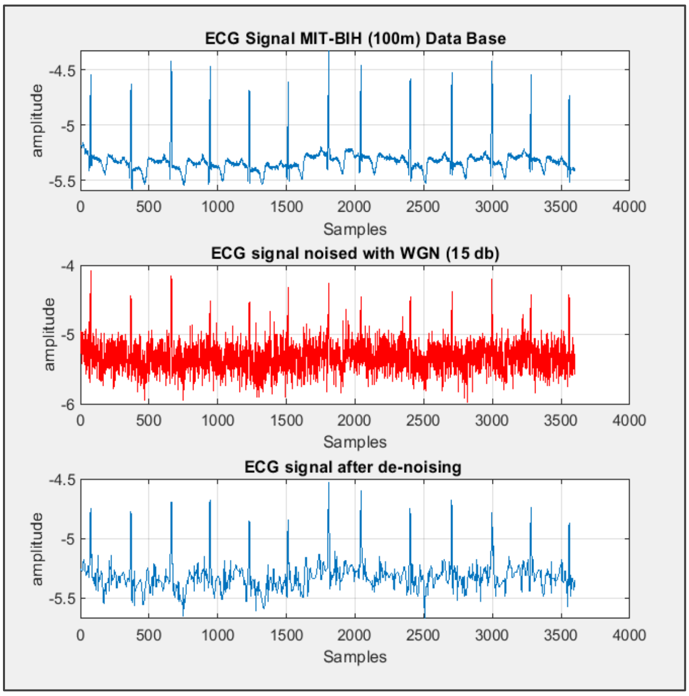

Figure 2: Represent the ECG Signal, the Noisy Signal, and the Denoise Signal.

5.2.2 ECG Signal from the Transmitter of Heart Rate Monitoring System

According to the getting results which is presented in section 5.2.1, it is concluded that the sure threshold is the best one, so it is used it in the ECG signal from the heart rate monitoring. This signal is collected by using ECG sensor with its electrodes and Arduino, connected to a healthy person with the age of 31 years old. ECG signal is noised with WGN (15 dB). Table (5) shows the result of filtering the signal by sym4 and db4 types, while Table (6) shows the results of filtering the signal by coif2 and coif5.

Table 5: ECG Signal Noised with WGN (15db), and Filtered by Sym4 and Db4 Wavelet Types at (1 to 9) Decomposing Levels, Soft Threshold, and Sure Method

Sure method Sym4	SNR	MSE	Sure method Db4	SNR	MSE
Level 1	23.9481	0.0254	Level 1	23.6834	0.0270
Level 2	24.3376	0.0232	Level 2	23.3478	0.0292
Level 3	23.7852	0.0264	Level 3	22.8013	0.0331
Level 4	23.1027	0.0309	Level 4	22.1639	0.0383
Level 5	23.2200	0.0301	Level 5	22.2224	0.0378
Level 6	23.2618	0.0298	Level 6	22.2355	0.0377
Level 7	23.3041	0.0295	Level 7	22.1069	0.0388
Level 8	23.3021	0.0295	Level 8	22.1069	0.0388
Level 9	23.2880	0.0296	Level 9	22.1107	0.0388

Table 6: ECG Signal Noised with WGN (15db), and Filtered by Coif2 and Coif5 Wavelet Types at (1 to 9) Decomposing Levels, Soft Threshold, and Sure Method

Sure method Coif2	SNR	MSE	Sure method Coif5	SNR	MSE
Level 1	23.3875	0.0289	Level 1	23.1826	0.0303
Level 2	23.6752	0.0271	Level 2	23.1341	0.0307
Level 3	23.4132	0.0288	Level 3	22.8461	0.0328
Level 4	22.6806	0.0340	Level 4	22.1862	0.0381
Level 5	22.7804	0.0333	Level 5	22.3203	0.0370
Level 6	22.8126	0.0330	Level 6	22.3584	0.0367
Level 7	22.8438	0.0328	Level 7	22.3874	0.0364
Level 8	22.7890	0.0332	Level 8	22.3899	0.0364
Level 9	22.7998	0.0331	Level 9	22.3954	0.0363

From Table (5) and Table (6) it shown that the sym4 is the optimum filter type with level two that has MSE (0.0232) and SNR (24.33) which are lower MSE and higher SNR comparing to the db4, coif5, and coif2. So, this filter applied to the noisy signal and getting the de-noised signal. Figure (7) show the ECG signal, the noisy signal, and the de-noised signal.

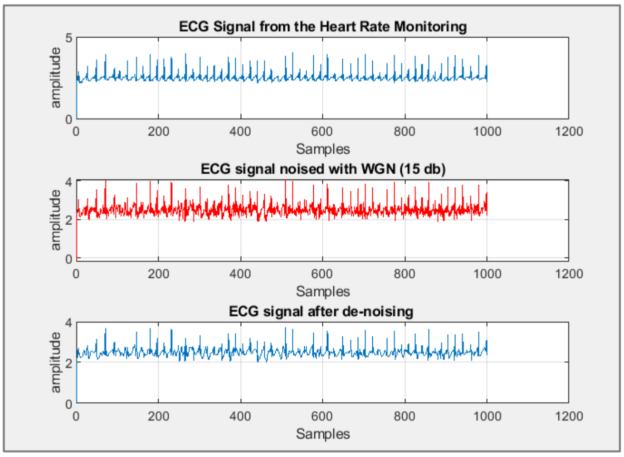

Figure 7: Represents the ECG Signal, the Noisy Signal, and the De-noise Signal with Sym4 Level 2, where the X axis is Samples and the y axis amplitude in m volt.

Conclusion

After getting the result from ECG signal de-noising by using the wavelet filter with different types, thresholds, and levels its conclude that the wavelet filter is a good filter to choose it because it has multi choices that suitable for many signals and applications. The important thing that must give it a big attention is the choosing of wavelet filter type that is similar to the signal in shape or close to its shape. According to signals used in this study, the optimum type of the wavelet is the four level of Daubitches (db4) type for MIT-BIH data base and the level two of sym4 for ECG signal from monitoring system since it performed good results in the MSE which is lower and SNR which is higher according to what its desired. This study is compared to other studies in the used parameters, the applied noised types, and the type of signal. The comparison is done in Table (9).

Table 9

Ref	ECG signals	Threshold rule	Threshold method	Noised removed	Evaluate performance parameters	Wavelet type	Result
[7] 2005	Real and synthetic	Soft and Hard	Minimax Sure Universal	Gaussian noise	MSE	Db4	Hard and SURE in synthetic Soft, with a Universal in real
[22] 2010	One ECG	Hard Soft	Rigrsure Heursure	Gaussian Salt and pepper speckle	RMSE and SNR	Db4 and Haar	Haar optimum level was level 10 whilst Db4 optimum level was level 8.
[23] 2010	MIT-BIH database	Hard and soft	Heursure Minimax Sure Universal	Electrode motion, Muscle artifact, Baseline wandering, And Composite noise	SNRi and SNRo	Db1, Db4, Db8, Sym1, Sym4, Sym8, Sym 9 and Sym10	Sym9 wavelet, level5, and minimax threshold give better denoising results for the ECG signals.
[24] 2012	ECG signals obtained from ten female	Hard and soft	Rigrsure Heursure Minimax Global	baseline wandering, high-frequency, and power line interference noises	noise power, SIR, PSD, PRD	db4, coif5, and sym7	The final experimental results showed that the sure thresholding method and coif5 wavelet given better results to denoise the ECG signal.
[25] 2016	ECG datasets	Hard and soft	SURE, Hybrid, Universal and Minimax	Muscle noise, electrode artifacts, baseline drift noise and respiration	Variance, PSD, SNR, MSE and ECG morphology.	Coiflet, Daubechies, Biorthogonal, Symmlet, and Haar	Haar and Biorthogonal perform better results in PSD and variance. Sure Thresholding was the best thresholding method to denoise the ECG signal
[26] 2016	Offline-RAW ECG signal	----	------	Canceling noises from ECG	Compression between ECG signal in different types	Meyer, coiflet, and sym	Symmlet
Paper study 2020	**MIT-BIH database and real time ECG system.**	**Soft**	**Sure Minimax and Universal**	**Power line interface, MEG noise, and WGN**	**MSE SNR**	**Sym4 Db4 Coif5 Coif2**	**Sure thresholding is better for the two types and db4 for MIT-BIH signal, and sym4 for ECG real time.**

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