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DWT OPTIMAL FILTER FOR NOISE FILTRATION IN ECG

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Abstract

The condition of the heart is determined by the electrocardiogram. Unwanted signals are called noise that is presented around hospitals. This distorts the ECG signal during the patient's measurement. Error free diagnosis of electrocardiogram requires filtering of the unwanted signal. Wavelet transform based filter is used for removal of such noise from ECG. Comparison of different types of wavelet has been made for the selection of optimal wavelet. Improved SNR is obtained by Meyer and Symlet wavelet. Selection of appropriate thresholds helps in improvement of result. Comparative analysis of different thresholds is also presented in the paper. The record from the arrhythmia database of the MIT - BIH is used for the testing of the algorithm.

1. Introduction

World Health Organization's reports show that 30% death occurs due to cardiac abnormalities [1]. In India approximate 30 million heart patients are present and 0.2 million heart medical procedures played out each year. Almost 17.3 million individuals are passing in India because of heart maladies. Hence, investigation of Electrocardiogram assumes a crucial job [2]. For saving the time and work of cardiologist automatic processing of ECG is necessary. The first step for the signal processing is denoising.

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1. 1 ECG

The ECG represents electrical activity of the heart. The deviations in the shape of typical ECG demonstrate different cardiovascular issue. In the typical state Cardiac cells are electrically polarized. By depolarization and re-polarization process of cardiac cell electric current starts flow over the heart muscle and it can be sensed by the electrodes placed on the surface of the body. Figure 1 shows the cardiac waveform of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys [3]. ECG gives the information for the identification of heart disease like arrhythmia, Tachycardia, abnormal beats, fibrillation etceteras [4].

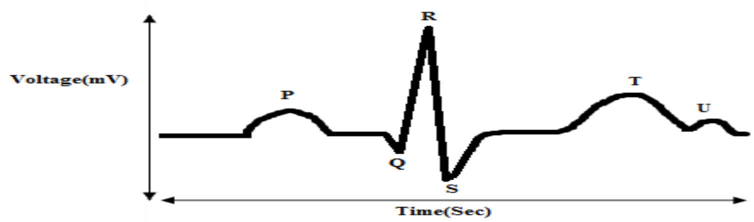

Figure 1. Electrocardiogram.

0.05-100 Hz is the frequency range of an ECG signal and its dynamic range of one to ten mV. An ECG cycle representing a single heartbeat is generally composed of different waves named by the letters P, Q, R, S and T. U wave is also present in some cases [5]-[7]. P-wave represents the propagation of the Sinoatrial (SA) Node action potential through the atria [8]. During the period of ventricular contraction, the QRS complex produces. Re-polarization of the ventricles generates T wave [9].

1.2 NOISE

Noise is unwanted or undesirable signal which introduces in signal by several ways. It contaminates the signal and changes its structure. To suppress this noise from the signal denoising process required. ECG includes noise such as baseline drift, high-frequency noise and power line interference etcetera.

1.2.1 Baseline Wander (BLW)

Whenever the impedance between electrodes and patient's skin changes a noise generates in the system known as base line drift or base line wander.

The responsible factors for BLW are respiration and body movements, moving cables, loose contacts of electrodes and offset voltages in electrodes. Baseline drift affects the low frequency components (ST segment) of ECG signal because its frequency range is below 0.5 Hz [10]-[11].

1.2.2 High Frequency Noise (HFN)

Muscular activity other than heart creates this noise. It is also called as Electromyography noise or muscle artifacts. The frequency range of this noise is more than 100 Hz [12].

1.2.3 Power Line Interference (PLI)

Power cables and equipment placed near the ECG device generate electromagnetic fields. Due to improper shielding between patient and recorder, these fields create interference with the electrocardiogram known as power line interference. It decreases the quality of signal which disturbs the clinical diagnosis. The frequency of this noise is 50 Hz or 60Hz [13].

1.3 WAVELET

A wavelet generates oscillation waves which increases from zero, rises to maximum value and then falls back to zero. The wavelets are scaled and translated copies (known as “daughter wavelets”) of a finite-length or fast-decaying oscillating waveform (known as the “mother wavelet”). Time duration, time location and frequency band are different for every analyzing wavelet. Therefore, the coefficient of wavelet resulting from the wavelet transformation corresponds to a measurement of the ECG elements in this frequency band and time segment [14]-[17].

Wavelet analysis consist continuous and discrete type wavelet transform. The popular wavelets used over here are shown in table 1.

Table 1. Wavelet Family.

Wavelets	Abbreviation	Wavelets	Abbreviation
Daubechies	db	Discrete approximation of Meyer	dmey
Biorthogonal	bior	Symlets	sym
Haar	haar	Coiflets	coif

Wavelet Threshold helps for further processing of the signal. Four kinds of threshold available in wavelet transform. Rigrsure and Sqtwolog are used for one dimensional data. Heursure threshold is used for low signal to noise ratio signal. Minimaxi is used for the fixed threshold.

1.4 Mit-Bih Database

Boston's Beth Israel Hospital develops the database of ECG record and at MIT has started research into arrhythmia analysis. Now it is freely available for the researcher on the website [18].

1.5 Signal TO Noise Ratio

The performance analyzes using the following parameters:-

$$\text{SNR output} = 20 \times \log 10\left(\frac{\text{ECG output}}{\text{ECG output} - \text{ECG output}}\right) \tag{1}$$

Various methods have been proposed by researchers for ECG denoising. A. Fedotov proposed a technique based on orthogonal wavelet decomposition for the study of impact of wavelet transform parameters on ECG distortion level [19]. Shing, et al. presented a method grey spectral noise cancellation for ECG denoising [20]. Diptangshu, et al. compared the different types and level of Daubechies wavelets for noise reduction [21]. Rakshit described empirical mode decomposition for denoising [22]. Lei Wang et al. studied about the effect of denoising by adaptive wavelet threshold [23]. Monisha and Shreya used Band Pass and Savitzky-Golay Filters for noise suppression of ECG [24]. Tanuj and Rajesh suggested an algorithm for the choice of soft and hard thresholding of wavelet transform for ECG denoising [25].

Section 2 explains wavelet transforms based methods for denoising of different noise in ECG. Types of noise, noisy ECG and denoised ECG by this method shown in the figure of this section. Section 3 consist comparison tables of mother wavelet and threshold. Section 4 represents final conclusion of this paper.

2. Methodology

In this research denoising of ECG has done by different mother wavelets and thresholds. The block diagram of the work is shown in figure 2.

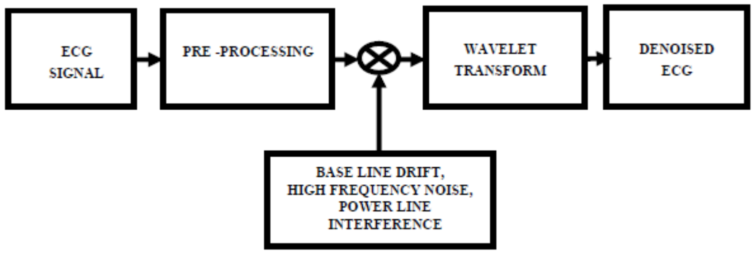

Figure 2. Block diagram of Noise Filtration.

2.1 ECG Signal

In first step ECG record has taken in matlab executable format from MIT-BIH arrhythmia database. The duration of this file is one minute for this research work. Figure 3 shows the original ECG which is the record number 113m of MIT-BIH database.

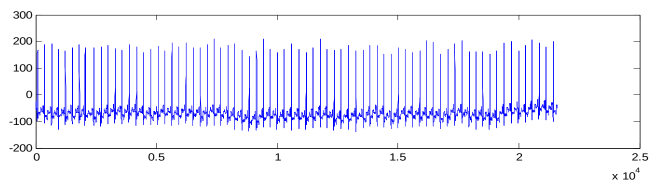

Figure 3. Original ECG (113m).

2.2 Preprocessing

Normalization and base line correction have done in preprocessing the stage. The Base line sometimes cause by variations in electrode impedance, excessive body movements or respiration [12]. Equation 1 [6] used for base line correction:

$$ECGsingle = ECGsingle - mean(ECGsingle) \qquad (2)$$

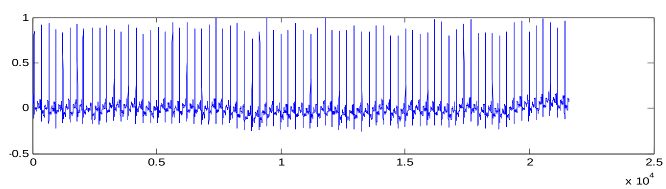

Figure 4. ECG Record 113m after Preprocessing.

The base line in figure 3 deviates from the reference point while it starts from zero or reference line in vertical axis of figure 4 due to preprocessing.

2.3 Noise

2.3.1 Base Line Wander

It creates problems for the identification of R peaks of the ECG. This noise changes the isoelectric line of T wave therefore it appears as higher than the R-peak. ST segment is highly affected by BLW. Figure 5 indicated the plot of BLW.

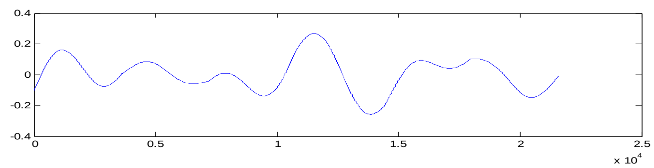

Figure 5. Base Line Wander.

2.3.2 High Frequency Noise

It mainly overlaps with QRS complex and creates the problem in its detection as described in figure 6.

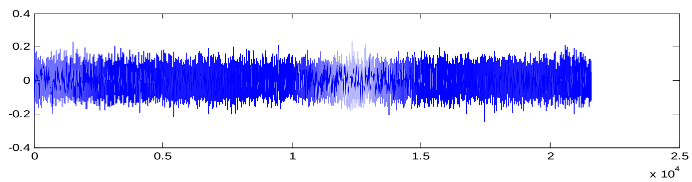

Figure 6. High Frequency Noise.

2.3.3 Power Line Interference

It changes the amplitude of the noise varies up to 50% of the ECG amplitude peak [18]. PLI cause issue in interpreting small amplitude waves because it adds unreliable and fictitious waveforms. The plot of PLI on Matlab is shown in figure 7.

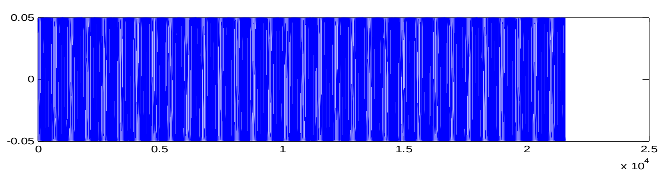

Figure 7. Power Line Interference.

2.4 Wavelet Transforms

Wavelet transforms are a mathematical means for performing signal analysis when signal frequency varies over time Wavelet denoising performs following functions [4]:

1. Denoising

2. Decomposition

3. Threshold

4. Reconstruction

Base line drift removes by decomposing the signal up to level nine. By the use of reconstruction coefficient regenerate the signal and subtract it from the noisy signal gives the denoised ECG. Table 2 shows the frequency at different decomposition level of detail coefficient.

Table 2. Decomposition level and frequency ranges.

Level of Decomposition	Range of Frequency (Hz)	Level of Decomposition	Range of Frequency
D1	250–125	D6	7.81–3.90
D2	125–62.5	D7	3.90–1.95
D3	62.5–31.25	D8	1.95–0.98
D4	31.25–15.63	D9	0.98–0.49
D5	15.63–7.81	D10	0.49-0.25

The denoised ECG form base line drift shown in figure 8 for ECG record 100.m.

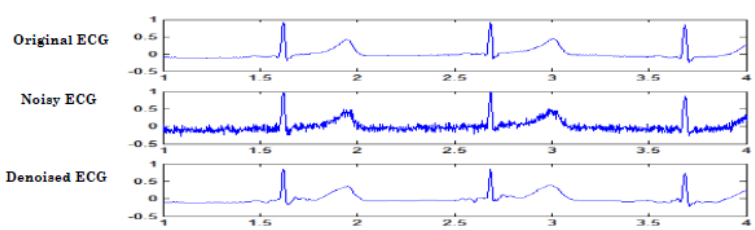

Figure 8. Denoising of Base Line Drift.

For high frequency reduction wavelet decomposition of the noisy signal at level 5 is sufficient. Wavelet denoising is applied in this decomposed signal which gives a signal free from high-frequency noise. Figure 9 shows for record 100.m denoised ECG.

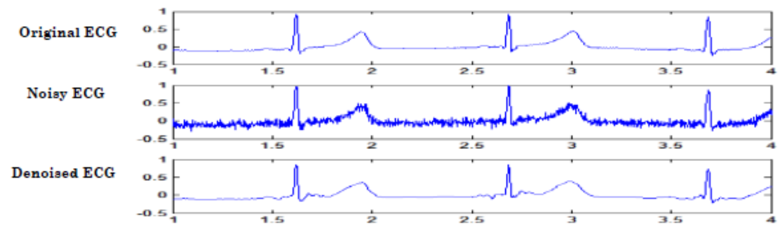

Figure 9. Denoising of High Frequency Noise.

In case of Power line interference wavelet denoising is applied on the signal after the third level decomposition of the noisy signal. The output shows in figure 10.

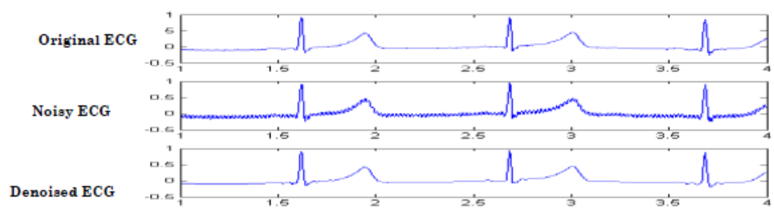

Figure 10. Denoising of Power Line Interference.

3. Results and Discussions

The ECG record has taken from the MIT-BIH arrhythmia database. The analyzing functions for the suppression of base line drift, high-frequency noise and power line interference by Haar, Symlet, Meyer, Biorthogonal, Daubechies. Results obtained from the testing of an algorithm shown satisfying noise elimination. Algorithm has tested on all forty eight ECG records of MIT –BIH database. The average of Signal to Noise ratio obtained by different wavelets for denoising of Base Line Drift are shown in table 3.

Table 3. Comparison of Different Wavelet for the Denoising of Base Line Drift.

Sr. No.	Wavelet	Input SNR	Output SNR
1	haar	3.5823	9.9769
2	db4	3.5823	11.2790
3	bior 3.5	3.5823	11.1316
4	rbio4.4	3.5823	11.2263
5	coif 4	3.5823	11.2476
6	sym8	3.5823	11.2514
7	sym4	3.5823	11.2561
8	db6	3.5823	11.2572
9	sym20	3.5823	11.5526
10	dmey	3.5823	11.7435

Table 3 indicates that the Meyer and symlet wavelet gives higher signal to noise ratio. For removal of high-frequency noise and power line interference all signal of the database have applied on the algorithm and the values of signal to noise ratio is tabulated on table 4.

Table 4. Comparison of Different Wavelet for the Denoising of High Frequency Noise and Power Line Interference.

Sr. No.	Wavelet	HFN		PLI	
		Input SNR	Output SNR	Input SNR	Output SNR
1	haar	8.8243	12.6120	13.6453	13.6558
2	dmey	8.8243	12.3894	13.6453	21.8962
3	sym20	8.8243	13.2913	13.6453	20.3598
4	db6	8.8243	14.0507	13.6453	18.1311
5	bior3.5	8.8243	14.0569	13.6453	14.2698

6	coif4	8.8243	14.3434	13.6453	18.8933
7	rbio4.4	8.8243	14.3930	13.6453	18.6456
8	db4	8.8243	14.4341	13.6453	17.5037
9	sym8	8.8243	14.5460	13.6453	18.5675
10	sym4	8.8243	14.6678	13.6453	17.8360

The assessment of table 4 shows the higher performance is given by symlet (sym4, sym8) wavelet for removal of HFN noise while PLI has efficiently removed by Meyer and symlet wavelet transform. Heursure, Rigrsure, Minimaxi, Sqtwolog are the different types of threshold in wavelet transform, so, it is requisite to find out which threshold provides higher output [4]. Therefore different threshold applied on the algorithm for the testing of each signal. The result is tabulated on table 5.

Table 5. Comparison of different Wavelet Threshold for the denoising of High Frequency Noise and of Power Line Interference.

Sr. No.	Thresholds	HFN		PLI	
		Input	Output	Input	Output
1	sqtwolog	8.8243	6.4351	13.6453	17.4684
2	minimaxi	8.8243	8.67934	13.6453	19.0664
3	heursure	8.8243	14.6678	13.6453	21.6981
4	rigrsure	8.8243	14.7642	13.6453	22.2253

The comparative chart of the different threshold for denoising is presented in figure 11.

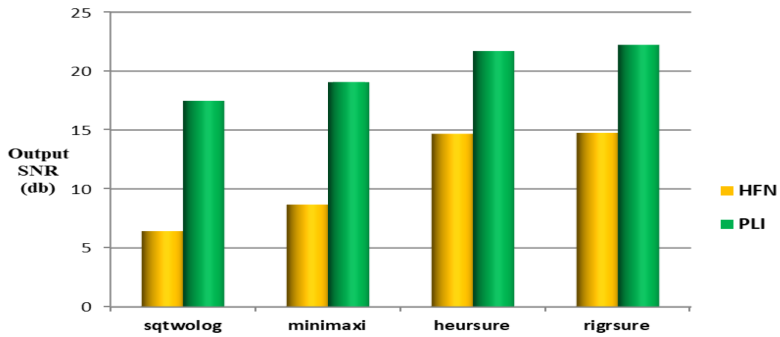

Figure 11. Comparison of Wavelet Thresholds for Noise.

It has been observed from figure 11 rigrsure and heursure thresholds gives improved result.

4. Conclusion

The impression of denoising in ECG plays significant role in the recognition of the component and disease classification. Presented work pointed that Meyer wavelet provides best response in the removal of power line interference and base line wander. For reduction of high-frequency noise, Symlet gives higher output in terms of SNR. The response of Symlet is also satisfactory in the filtration of power line interference and base line wandering noise as demonstrated in figure 12.

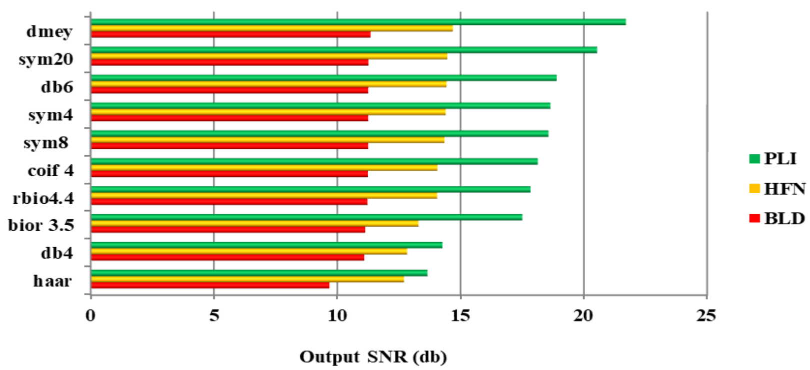

Figure 12. Comparison of Wavelets for BLD, HFN and PLI noise.

It has been noticed that the value of SNR changes with changing the type of threshold. Different thresholds applied on the algorithm and found higher result by rigrsure threshold in the removal of all types of noise. Therefore, the optimal filter for denoising can be designed by Meyer or Symlet wavelet using a rigrsure threshold. The presented investigation may be also useful for other biological signal such as Electromyogram, Phonocardiogram etceteras.

References

[1] V. Fuster and B. B. Kelly, Promoting Cardiovascular Health in the Developing World, Institute of Medicine (US) Committee on Preventing the Global Epidemic of Cardiovascular Disease: Meeting the Challenges in Developing Countries, Washington (DC): National Academies Press (US), 2010.

[2] V. Singh and N. Rashmi, ECG Denoising using Wavelet Transform and Filters IEEE WiSPNET Conference (2017), 2395-2400.

[3] L. Cromwell, F. J. Weibell and E. A. Pfeiffer, Biomedical Instrumentation and Measurements Prentice Hall of India, New Delhi, 2005.

[4] S. S. Rathore and N. Tripathi, Detection of QRS complex in ECG signal using wavelet transform and thresholding technique, International Journal on Future Revolution in Computer Science and Communication Engineering 4(2) (2018), 465-467.

[5] R. Protik and Md. Nafiur, Analyzing QRS complex, ST segment and QT interval of ECG signal to determine the effect of having energy drinks on hypercalcaemia, IEEE 16th International Conference on Computer and Information Technology, 2014.

[6] N. K. Dewangan and S. P. Shukla, ECG Arrhythmia classification using discrete wavelet transform and artificial neural, Network IEEE, International Conference on Recent Trends in Electronics Information Communication Technology (2016), 1946-1950.

[7] K. V. L. Narayana, Wavelet based QRS detection in ECG using MATLAB, Innovative Systems Design and Engineering 2(7) (2011), 60-68.

[8] A. H. Kashou and H. E. Kashou, Physiology, Sinoatrial Node (SA Node) Treasure Island (FL), Stat Pearls Publishing, 2019.

[9] R. G. Carroll, The Heart Elsevier's Integrated Physiology (2007), 65-75.

[10] V. S. Chouhan and S. S. Mehta, Total removal of baseline drift from ECG signal, IEEE International Conference on Computing: Theory and Applications, 2007.

[11] A. Feher, Denoising ECG Signals by applying discrete wavelet transform, IEEE International Conference on Optimization of Electrical and Electronic Equipment, 2017.

[12] M. A. Awal and M. Ahmad, Wavelet Based Distortion Measurement and Enhancement of ECG signal IEEE International Conference on Biomedical Engineering, Penang, Malaysia (2012), 373-378.

[13] Y. D. Lin and Y. H. Hu Power-line interference detection and suppression in ECG signal processing In Biomedical Engineering, IEEE Transactions 55(1) (2008), 354-357.

[14] I. Daubechies, Ten Lectures on Wavelets CBMS-NSF Lecture Notes number 61, SIAM, Philadelphia, 1992.

[15] A. Graps, An Introduction to Wavelets IEEE proceeding, Computational Science and Engineering 2(2) (1995), 50-61.

[16] O. Singh and R. K. Sunkaria, The utility of wavelet packet transform in QRS complex detection - A comparative study of different mother wavelets, IEEE, 2nd International Conference on Computing for Sustainable Global Development (2015), 1942-1947.

[17] http://www.physionet.org/mitdb.

[18] S. Thalkar, Various techniques for removal of power line interference from ECG signal International Journal of Science and Engineering 4 April (2016), 12-23.

[19] A. A. Fedotov, Myographic Interference Filtering from ECG Signals Using Multiresolution Wavelet Transform Biomedical Engineering 52(5) (2019), 344-347.

[20] S. H. Liu, C. H. Hsieh and Wenxi Chen, ECG Noise cancellation based on grey spectral noise estimation MDPI Sensors, February 2019.

[21] D. Pandit, L. Zhang, C. Liu and N. Aslam, Noise Reduction in ECG Signals Using Wavelet Transform and Dynamic Thresholding Springer Emerging Trends in Neuro Engineering and Neural Computation, Series in Bio Engineering, Singapore, 2017.

[22] M. Rakshit and S. Das, An efficient ECG denoising methodology using empirical mode decomposition and adaptive switching mean filter, Biomedical Signal Processing and Control 40 (2018), 140-148.

[23] L. Wang, W. Sun and Y. Chen, Wavelet transform based ECG denoising using adaptive thresholding, ICBBS, Shenzhen, China (2018), 35-40.

[24] M. Chakraborty and S. Das, Determination of Signal to Noise Ratio of Electrocardiograms Filtered by Band Pass and Savitzky-Golay Filters, Elsevier Procedia Technology 4 (2012), 830-833.

[25] T. Yadav and R. Mehra, Denoising and SNR improvement of ECG signals using wavelet based techniques, IEEE Second International Conference on Next Generation Computing Technologies, Dehradun, India, October (2016), 14-16.