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Analysis of Wavelet Families for Baseline Wander Removal in ECG signals

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Abstract: Electrocardiograph (ECG) is the most effective method in detection of cardiac arrhythmias. The PQRST properties from the recorded ECG are used to analyze the type of arrhythmia. For accurate clinical interpretations, ECG signals are subjected to noise removal. Baseline wandering is a major source of noise which can be efficiently removed using wavelet based approach. In this paper, twelve different ECG samples from MIT BIH Arrhythmia database are analyzed using six mother wavelet functions- haar, db8, sym5, coif5, bior4.4 and rbio4.4. The wavelets are evaluated using three different performance measures such as Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), and Mean Absolute Error (MAE). The experimental results show that coif5 wavelet is efficient in significantly reducing the baseline wandering in the ECG signals.

Keywords: ECG, Baseline Wander, Wavelets.

I. INTRODUCTION

The Electrocardiogram ECG describes the electrical activity of the heart. ECG is characterized by a recurrent sequence of a five principal waves, denoted by P,Q,R,S and T each one showing some beat by beat variability. The ECG record is used today in a wide variety of clinical applications. Its importance has been strengthened thanks to the discoveries of subtle variability patterns which are present in rhythm or wave morphology [1]. It is obtained by placing electrodes on the chest, arms and legs. With every heartbeat, an impulse travels through the heart, which determines its rhythm and rate and causes the heart muscle to contract and pump blood. The electrodes used for ECG recording are positioned so that the spatiotemporal variations of the cardiac electrical field are sufficiently well-reflected. The difference in voltage between a pair of electrodes is referred to as a lead. The ECG is typically recorded with a multiple-lead configuration. The electrode wires are connected to a differential amplifier specially designed for bioelectrical signals. The voltage variations measured by the electrodes are cause by the action potentials of the excitable cardiac cells, as they make the cells contract. The ECG is characterized by a series of waves whose morphology and timing provide information used for diagnosing diseases reflected by disturbances of the electrical activity of the heart. The time pattern that characterizes the occurrence of successive heartbeats is also very important.

The ECG ranges from a few microvolts to about 1V in magnitude. Whereas the characteristic waves of an ECG have a maximal magnitude of only few millivolts, a wandering baseline in the ECG due to variations in electrode-skin impedance may reach 1V. Some noises can corrupt ECG signal significantly. Considerable ECG noises are power-line noise, Electro Myo Gram (EMG) noise and baseline noise [1]. These noises can mask some important features of the ECG signal hence it is desirable to remove them for proper analysis and display of the ECG signal. Power-line noise consists of interference in the ECG by nearby AC power supplies and power lines. This affects the ECG as sinusoidal waves which are of the same frequency as the base and harmonic frequencies of 50 or 60 Hz of the power supply. EMG noise is caused by the contraction of other muscles besides the heart. When other muscles contract, they generate depolarization and repolarization waves that can also be detected by the ECG.

Various approaches are given in the literature for the task of denoising [2], which can be roughly divided into two categories: denoising in the original signal domain (e.g., time or space) and denoising in the transform domain (e.g., Fourier or wavelet transform). For the removal of such noise an advanced signal processing method, such as Discrete Wavelet Transform (DWT) denoising technique may be used. The development of wavelet transforms over the last two decades revolutionized modern signal and image processing, especially in the field of ECG signal denoising. Wavelet transform can be used to extract the relevant time-amplitude information from a signal. But the wavelet should be chosen such that it is able to characterize well the signal [3]. There are fifteen different families with their own member wavelets. In order for selecting the suitable wavelet, Peak Signal to Noise Ratio, Mean Square Error, and Mean Absolute Error between the noisy and noise free signals are evaluated to choose the effective wavelet for denoising the ECG signals.

II. PROBLEM DEFINITION

The ECG signals were pre- processed by filtering it to remove the baseline wander, the power line interference, and the high frequency noise, hence enhancing the signal quality, and omitting the equipment and the environmental effects. As for pre-processing of the ECG signal, noise cancellation requires different strategies for different noise sources. The noise reduction using an adaptive filter with constant or unity reference input was performed, which was used to cancel baseline wander. However, this filter is not reliable for applications that require diagnostic ECG analysis. The baseline wandering and the power-line interference are the most substantial noises and can strongly affect the ECG signal analysis [4].

Low frequency artifacts and baseline drift may be caused in the chest lead ECG signals by coughing or breathing, with large movements of the chest, or when an arm or leg is moved during the ECG data acquisition. Poor contact of the electrodes and perspiration of the patient under the electrodes may affect the electrode impedance which causes low frequency artifacts. Baseline drift may sometimes be caused by variations in temperature and bias in the instrumentation and amplifiers as well. This type of noise is undesired and needs to be removed before any further signal processing, for proper analysis and display of the ECG signal.

Clinicians measure slopes and time intervals in ST, RR and QT segments to predict any abnormalities in the cardiac activity [5]. Therefore, the slope of the baseline should be zero for clean ECG data. When there is baseline wandering noise in the ECG signal, the slope deviates from zero, and this causes difficulties in the evaluation of ECG recordings. For example, baseline drift makes analysis of isoelectric part of the ST segment difficult especially when there is an ST segment elevation or depression, where the slope of the interval is significant. If there is baseline wandering noise, it would be hard to differentiate noise related slope from the slope of the ST segment. Also, a large baseline drift may cause the positive or negative parts in the ECG to be clipped or badly detected by the analog to digital converter or the other hardware.

The baseline wander is an extraneous, low-frequency activity in the ECG which may interfere with the signal analysis, making the clinical interpretation inaccurate. When baseline wander takes place, ECG measurements related to the isoelectric line cannot be computed since it is not well-defined. Baseline wander is often exercise-induced and may have its origin in a variety of sources, including perspiration, respiration, body movements and poor electrode contact. The spectral content of the baseline wander is usually in the range between 0,05-1Hz [6] but, during strenuous exercise, it may contain higher frequencies and thus it is interpreted as a noise.

III. WAVELET TRANSFORM

Fourier transform based spectral analysis is the dominant analytical tool for frequency domain analysis. However, Fourier transform cannot provide any information of the spectrum changes with respect to time. The Fast Fourier Transforms (FFT) produces the signal into an infinite length of sine and cosine functions [7]. 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 [8]. 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 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:

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

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.

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

Where, ψ (ω) is the Fourier transform of the mother wavelet function *(ψa,b (t))*. 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[9]. 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.

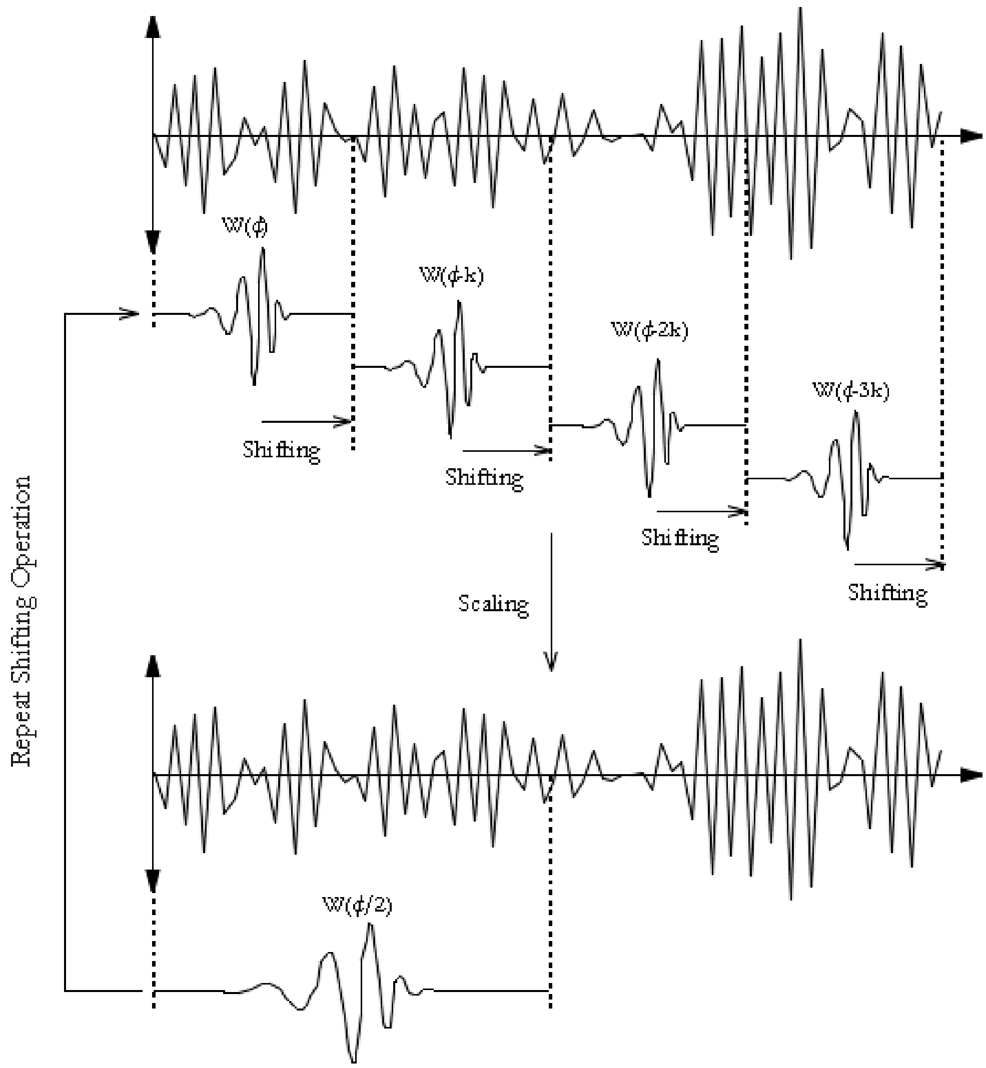

Figure 1: The scaling and shifting process of DWT

IV. Analysis of Basic mother Wavelets and its type

Wavelet families vary in terms of several important properties like support of the wavelet in time and frequency and rate of decay, symmetry or antisymmetry of the wavelet, the accompanying perfect reconstruction filters have linear phase, number of vanishing moments, wavelets with increasing numbers of vanishing moments result in sparse representations for a large class of signals and images, regularity of the wavelet, smoother wavelets provide sharper frequency resolution, additionally, iterative algorithms for wavelet construction converge faster and the Existence of a scaling function [10].

Following are the basic types of mother wavelets:

1. Crude wavelets – Gaussian, Morlet, Mexican hat.
2. Infinitely irregular wavelets – Meyer, Dmeyer.
3. Orthogonal and Compactly supported wavelets – Daubechies, Symlet, Coiflets.
4. Biorthogonal and Compactly supported wavelet pairs – Biorthogonal , Reverse biorthogonal.
5. Complex wavelets – Complex Gaussian, Complex Morlet, Complex Shannon, Complex frequency B-spline.

Properties of the wavelets:

- Haar

Compactly supported orthogonal, symmetry, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm and explicit expression.

- Daubechies

Arbitrary regularity, compactly supported orthogonal, asymmetry, arbitrary number of vanishing moments, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm.

- Coiflets

Arbitrary regularity, compactly supported orthogonal, near symmetry, number of vanishing moments, vanishing moments for scaling function, existence of scaling function, orthogonal analysis, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm.

- Biorthogonal

Arbitrary regularity, compactly supported biorthogonal, symmetry, arbitrary number of vanishing moments, existence of scaling function, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform.

- Reverse Biorthogonal

Arbitrary regularity, compactly supported biorthogonal, symmetry, arbitrary number of vanishing moments, existence of scaling function, biorthogonal analysis, exact reconstruction, FIR filters, continuous transform, discrete transform, fast algorithm.

V. PERFORMANCE MEASURES

A. PSNR

Signal-to-noise ratio is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels[11]. A ratio higher than 1:1 (greater than 0 dB) indicates more signal than noise. While SNR is commonly quoted for electrical signals, it can be applied to any form of signal. PSNR is defined as

PSNR is defined as

$$PSNR = 10.\log_{10}\left(\frac{MAX^2{}_I}{MSE}\right) \quad (3)$$

$$= 20.\log_{10}\left(\frac{MAX^2{}_I}{\sqrt{MSE}}\right) \quad (4)$$

$$= 20.\log_{10}(MAX_I) - 10.\,\mathrm{Log}_{10}(MSE) \quad (5)$$

The higher the PSNR value, the higher the reconstruction of the image [22].

B. Mean Square Error

Mean Squared Error of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss [11]. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated, MSE is defined as,

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2. \quad (6)$$

C. Mean Absolute Error

Mean Absolute Error is a quantity used to measure how close forecasts or predictions are to the eventual outcomes [11]. The mean absolute error is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|. \quad (7)$$

As the name suggests, the mean absolute error is an average of the absolute errors $e_i = |f_i - y_i|$, where f_i is the prediction and y_i the true value.

VI. RESULTS AND DISCUSSION

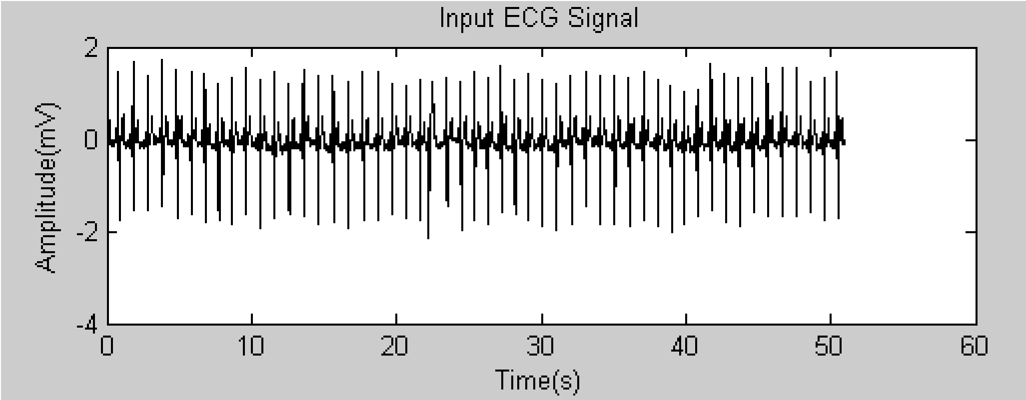

Figure 2: Raw input ECG signal

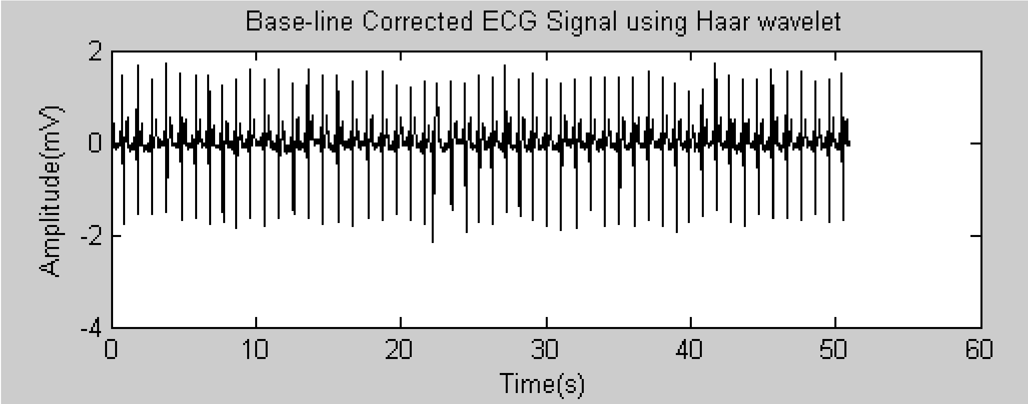

Figure 3: Baseline corrected ECG signal using Haar wavaelet

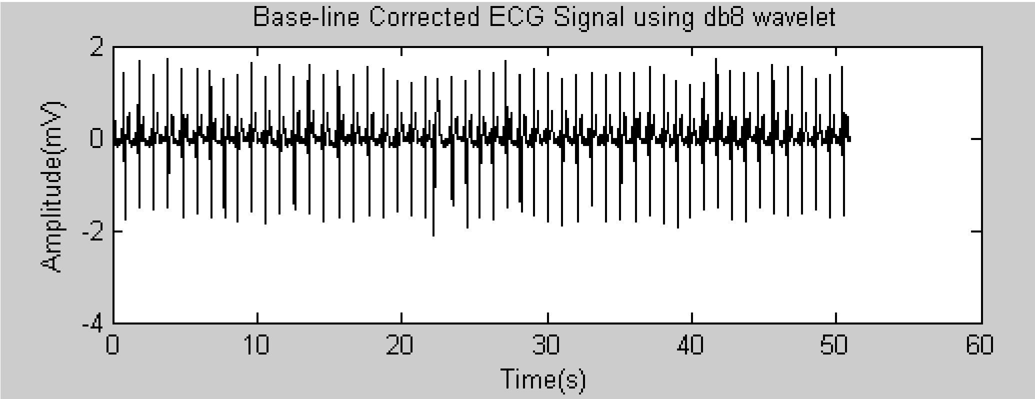

Figure 4: Baseline corrected ECG signal using db8 wavelet

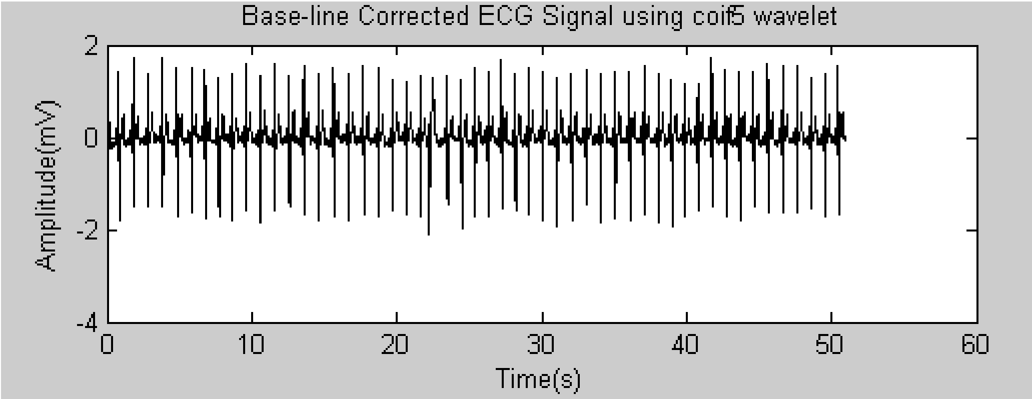

Figure 5: Baseline corrected ECG signal using coif5 wavelet

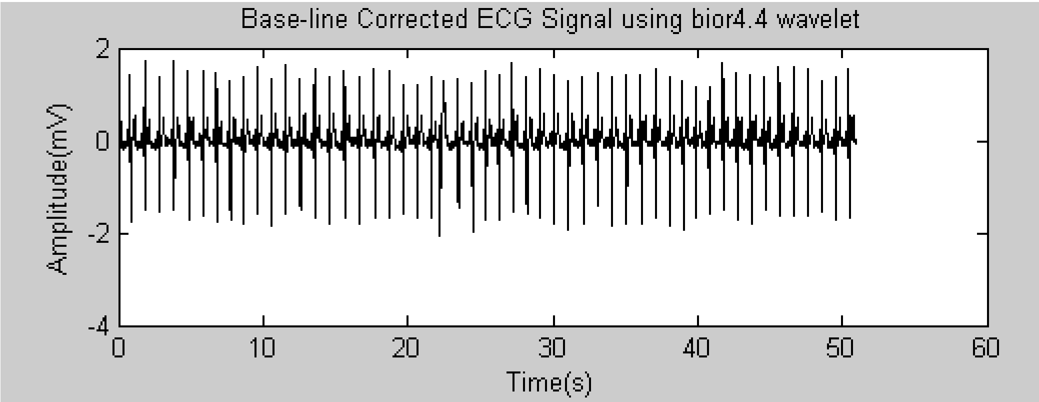

Figure 6: Baseline corrected ECG signal using bior4.4 wavelet

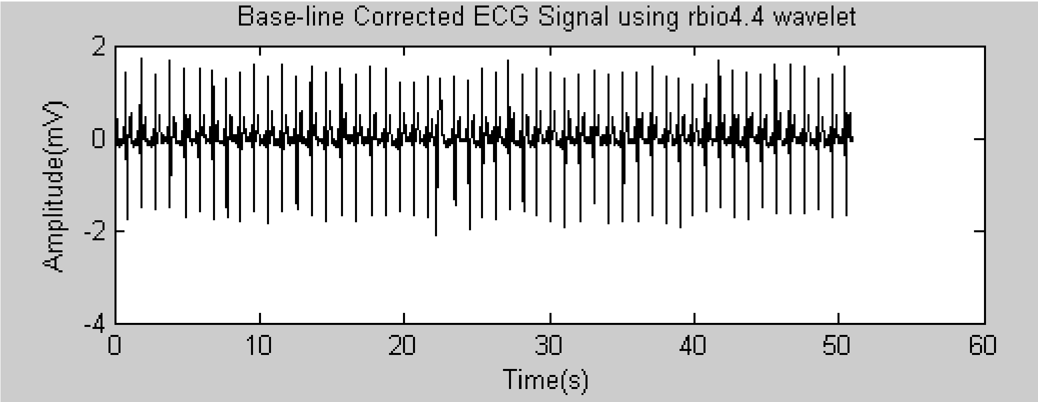

Figure 7: Baseline corrected ECG signal using rbio4.4 wavelet

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
haar	PSNR in dB	63.03	65.39	68.71	68.51	71.86	77.03	62.54	70.86	55.81	55.62	66.18	75.00
	MSE	0.03	0.18	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.17	0.01	0.002
	MAE	0.17	0.08	0.08	0.09	0.005	0.02	0.18	0.06	0.36	0.41	0.12	0.03

Table 1: Performance of Haar wavelet on twelve samples of ECG signals

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
db8	PSNR in dB	63.30	67.93	69.06	68.56	71.59	76.30	62.59	71.16	55.71	55.61	66.07	76.94
	MSE	0.03	0.01	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.17	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.001

Table 2: Performance of db8 wavelet on twelve samples of ECG signals

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
coif5	PSNR in dB	63.36	68.98	69.10	68.57	71.38	76.46	62.59	71.13	55.77	55.60	65.96	77.35
	MSE	0.03	0.008	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.05	0.03	0.18	0.06	0.36	0.41	0.12	0.02

Table 3: Performance of coif5 wavelet on twelve samples of ECG signals

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
bior4.4	PSNR in dB	63.25	68.18	68.99	68.57	71.45	76.76	62.60	71.14	55.81	55.51	65.92	76.39
	MSE	0.03	0.009	0.008	0.009	0.004	0.001	0.03	0.005	0.17	0.18	0.01	0.005

	MAE	0.17	0.07	0.08	0.09	0.05	0.02	0.18	0.06	0.36	0.41	0.12	0.03

Table 4: Performance of bior4.4 wavelet on twelve samples of ECG signals

Mother Wavelet	Parameter	Dataset (samples)											
		1	2	3	4	5	6	7	8	9	10	11	12
rbio4.4	PSNR in dB	63.20	67.89	69.09	68.57	71.46	76.60	62.60	71.14	55.79	55.55	65.93	77.13
	MSE	0.03	0.01	0.008	0.009	0.004	0.001	0.03	0.05	0.17	0.18	0.01	0.001
	MAE	0.17	0.07	0.08	0.09	0.05	0.03	0.18	0.06	0.36	0.41	0.12	0.02

Table 5: Performance of rbio4.4 wavelet on twelve samples of ECG signals

VII. Conclusion

In this paper five different mother wavelets –haar, db8, coif5, bior4.4, rbio4.4 are analysed for baseline wander removal in ECG using its PSNR, MSE and MAE values as the performance measure. Wavelets are analysed for correcting the baseline wandering by altering the low frequency components of the raw ECG signal. Out of the five coif5 wavelet gives the higher PSNR value and reduced MSE and MAE. Table 1,2,3,4 and 5 describes the PSNR, MSE and MAE values for all the wavelets analysed. In future further more wavelets can be compared.

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