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# Advanced Noise Removal Technique for ECG Signal Using Improvised Adaptive Algorithm

[1]Senthil Kumar K, [2]Dr.M.Malleswaran
[1]Research Scholar, [2]Department of electronics and Communication Engineering,
University College of Engineering Kanchipuram, Tamil Nadu, India.
[1]senthilkumar.k@ritchennai.edu.in, [2]malleshaut@gmail.com

**Abstract**— Statistics suggest that on a global level, Cardio vascular disease (CVD) accounts for 31% of all deaths. The estimated cost of CVD will be $1,044 billion by 2030. These CVD will be easily identified by using ECG signal. An electrocardiogram or ECG, is a graphical record delivered by an electrocardiograph which records the electrical action of the heart over a period of time. The signal is acquired by measuring electrical potentials between different locations of the body. The calculation of heart rate is very easy and simple with modern ECG machines. The denoising of ECG signal is a main concern to get the absolute results for better and corrective diagnosis of heart problems. The adaptive thresholding techniques are used for denoising of ECG signals with the help of Wavelet Transform.

**Index Terms** — Cardio Vascular Diseases(CVD); ECG-Denoising; thresholding technique, adaptive algorithm, Wavelet Transform(WT),Mean Square Error(MSE), Signal to Noise Ratio (SNR).

## 1 INTRODUCTION

ECG (Electrocardiogram) is the process of recording the electrical activity of the heart by combining a series of waves and deflections. This is done by using many pairs of leads placed at different positions of the body [1]. An ECG cycle consists of three parts: P wave, QRS complex and T wave [2]. This cycle represents the process of depolarization of the heart that occurs during each heartbeat. Cardiologists use ECG to detect abnormal heart rhythms (arrhythmias) and to discover pathologies [3]. However, since the ECG signal can be in the order of hundreds of microvolts up to 1 millivolt, it can be combined with artifactual signals of similar frequency and often of larger amplitude. These signals are so called artifacts and they are classified mainly in: i) baseline wonder noise due to heavy respiratory activity of the patient, ii) power line interference caused by electrical devices, which is also referred to as AC (Alternating Current) interference, iii) muscle contraction interference due to electrical activity of muscle contractions, and vi) motion artifact due to the physical movement of the patient. Continuously monitoring ECG signals overhours combined with activity status is very important to prevent cardiovascular diseases and to detect symptomatic signs for patients with unusual events [4]. Wearable ECG systems are designed with the aim to read patient's vital signs and transmit this information to the clinicians over a period of time. However, wearable systems suffer from motion induced and muscle artifacts which are the most difficult to eliminate because their spectrum overlap with the spectrum of the ECG signal. While many researches have been conducted to remove ECG artifacts, motion and muscle artifacts still remains unsolved problem [5].

Recently, wavelet transform (WT) was extensively used in various applications including the processing of non-stationary signals [6]. Unlike Fourier transform, WT provides more information about frequency and time representation of the signal. However, Discrete Wavelet Transform (DWT) is more popular among researchers due to of the usage of computers.

In this paper, wavelet-based techniques are presented and applied for ECG denoising with an evaluation of their performances.

The remainder of the paper is organized as follows:

Section 2 consist of denoising of ECG signal using wavelet are reported; Section 3, consist of details of the selected algorithms presented; Section 4 consist of results and discussion; finally, Section 5 consist of conclusions.

## 2 EXISTING METHODS

In the year 2017, Satria Mandala [8], proposed a comprehensive simulation and analysis to measure the effectiveness of several wavelet-based denoising techniques. In this experiment, Adaptive White Gaussian Noise (AWGN) is added to the ECG signal prior to the

denoising process. These three thresholding methods hard thresholding, soft thresholding and Adaptive Thresholding (Visu Shrink thresholding) will be compared and applied to the Noisy ECG signal. From the result obtained it can be seen that hard thresholding technique has the best performance. Meanwhile, the worst performance is in visu shrink method with MSE is 0.033762867 and SNR is 10.54400367 db.

In the year 2016, Saif Eddine Hadji, Proposed a Wavelet based technique for denoising the ECG signal. In this paper, two wavelet-based techniques wavelet shrinkage denoising and multi-resolution thresholding using stationary wavelet transformation (SWT) has been used. The proposed combination between the two former methods improves the smoothness of the signal but it doesn't solve the motion artifacts problem.

The objective of this paper is to present a systematic evaluation of several commonly used wavelet-based denoising techniques. In particular, we conduct numerical experiments in Matlab to test the methods and the performance of each method is evaluated by measuring its Signal to Noise Ratio (SNR) and Mean Square Error (MSE) values.

## 3 METHODOLOGY

Basically, the procedure of wavelet thresholding denoising includes three main steps: decomposing the noisy signal into sub-bands by wavelet transform, filtering noise through removing coefficients which are smaller than the thresholds, reconstructing the signal without noise components. Hence, the choice of thresholding functions and threshold values plays an important role in the global performance of a wavelet processor for noise reduction.

### 3.1 WaveletTransform

The wavelet transform decomposes the non-stationary signal into a number of scales having different frequency component and analyses each scale with a certain resolution for getting accurate features of the signal. The sum of overall time of the signal multiplied by a scaled and shifted version of the wavelet function is given as:

$$H(a,b) = \int_{-\infty}^{\infty} x(t)\varphi_{a,b}(t)dt \qquad (1)$$

The Discrete Wavelet Transform (DWT) is chosen mostly in practical application for accurate reconstruction of the signal due to its low computational complexity over FFT. Hence DWT is defined mathematically as;

$$H(a,b) = p(j,l) = \sum_{n\in z} x(n)\varphi_{j,l}(n) \qquad (2)$$

### 3.2 Thresholding

Thresholding method is a technique of filtering the signal using an estimation that exploits the characteristics of the denoising signal [7]. This method can reduce the noise by setting the coefficient lower than the threshold value [9]. Basically, wavelet thresholding is categorized into two thresholding methods, namely, hard thresholding and soft thresholding method.In 1994, Donoho proposed a universal thresholding to determine the thresholding value in soft thresholding method and Visu Shrink thresholding method also utilizes the universal thresholding to determine the thresholding value. These three thresholding methods (hard thresholding, soft thresholding and Visu Shrink thresholding) are the most widely used by researchers for denoising signal [10][11].

### 3.3 Types of Thresholding

Hard Thresholding - Hard thresholding is a procedure to remove or maintain the signal noise based on specific predefined criteria [11]. This technique adjusts the component of noise subspace to zero. In practice, the wavelet coefficients are set to zero if they are smaller than the threshold (Th).This method is expressed as [9]:

$$\omega_{\eta\tau} = \begin{cases} w, \text{if } |w| \geq TH \\ 0, \text{ Otherwise} \end{cases} \qquad (3)$$

Soft Thresholding - Similar to the hard thresholding, soft thresholding utilizes mathematical formulation to remove or maintain the signal noise. This method is performed according to the following formula [9]:

$$\omega_{\eta\tau} = \begin{cases} [\text{sign}(w)](|w| - t), \text{if } |w| \geq TH \\ 0, \text{ Otherwise} \end{cases} \qquad (4)$$

Adaptive Thresholding - Visu shrink thresholding is introduced in [12] by implementing universal thresholding method according to the following formula [13]:

$$TH = \sigma\sqrt{(2\log_{\varepsilon}(\nu))} \qquad (5)$$

Where n is the signal length and ı is the standard deviation calculated by σ = Mean Absolute Deviation (MAD)/ 0.6746.

### 3.4 Evaluation paramters

In this work, the performance of wavelet thresholding on denoising ECG signal will be analyzed using Signal

to Noise Ratio (SNR) and Mean Square Error (MSE). These two metrics are common used to analyze the performance of denoising ECG signal.

Signal to Noise Ratio (SNR): Signal to Noise Ratio (SNR) is a measurement for determining the quality of a signal containing noise. SNR is calculated according to the following formula [9]:

$$\mathrm{SNR} = 10\log_{10}\sum_{n-0}^{N-1} s(n)^2/(s(n)-\sim s(n))^2 \qquad (6)$$

The value s(n) denotes the clean signal and ~s(n) signifies the signal after denoising process. The SNR indicates the ratio of signal power to noise power. Higher value of SNR shows that denoising signal performing well.Mean Square Error (MSE): Mean Square Error (MSE) is an alternative method to evaluate the difference between actual and predicted data. MSE is computed using the following formula [9]:

$$\mathrm{MSE} = \frac{1}{N}\sum_{n-0}^{N-1}(s(n) - \sim s(n)) \qquad (7)$$

Similar to the SNR, the value s(n) denotes the noiseless signal and ~s(n) signifies the signal after denoising process.The MSE value performs the difference between clean ECG signals with denoised signal.

### 3.5 Flow Chart

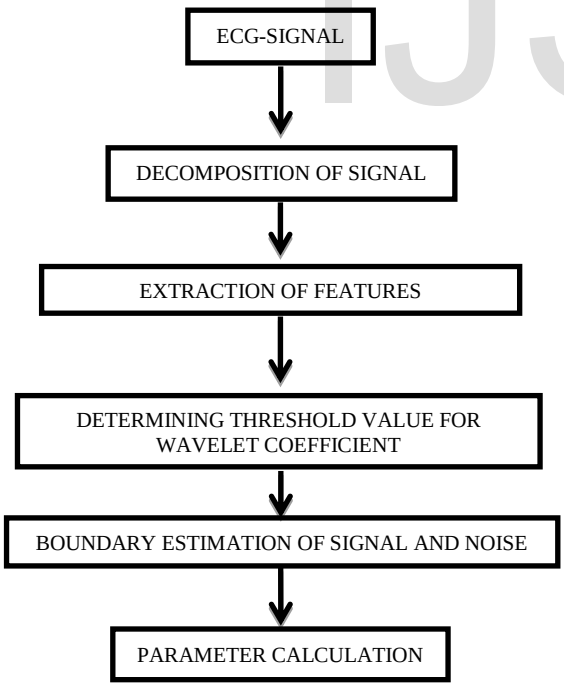


Fig 1. Algorithm process for denoising the ECG signal

## 4 RESULTS AND DISCUSSIONS

We performed rigorous experiments for measuring the SNR and MSE values using the common simulation parameters. The results of our experiment are summarized in Table I. From Table I, it can be seen that Adaptive thresholding technique has the best performance. The technique has the lowest average of MSE and the highest SNR value compared to others.

### 4.1 Simulating denoising techniques in Matlab

The template is the simulations of denoising techniques are performed by conducting following steps:

i) Signal decomposition: Each of the signals is decomposed into parts using wavelet basis Daubechies in several level of decomposition, namely level 4, 8, and 12.

ii) Setting thresholding value: Our research considers thresholding techniques, these thresholding techniques are carried out using specific parameters.

iii) Signal reconstruction: In this process the reconstruction of the original (i.e., noiseless signal) is performed. The reconstruction results are then compared with the original signals to measure the effectiveness of the denoising techniques.

### 4.2 Simulation results

Fig. 1 to Fig. 4 shows the conditions of ECG signals, i.e., ECG with noise and denoised ECG signal, ECG peak detection. As indicated in previous paragraph in this section, Adaptive thresholding perform better in denoising ECG signal compared with other wavelet techniques. The result of denoising based on Adaptive thresholding is shown in Fig. 2.

### 4.3 Figures and Tables

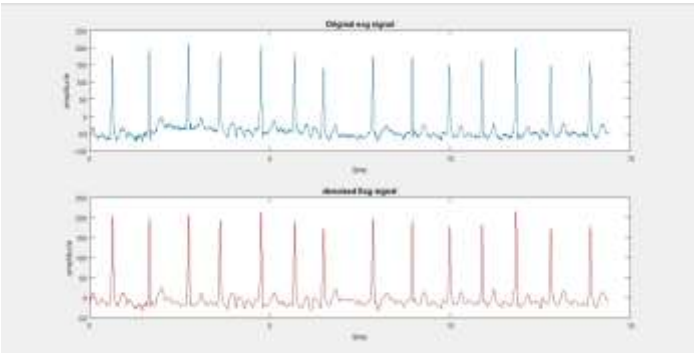

Fig.2. Original and denoised signal

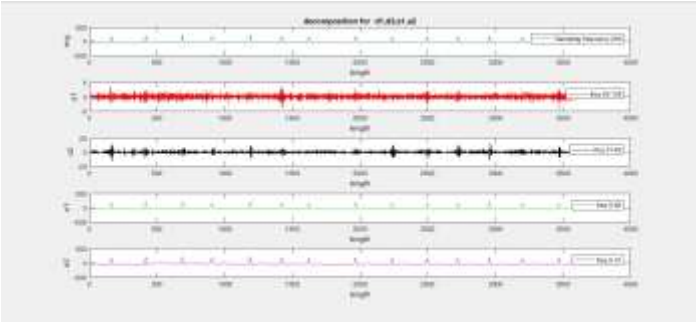

Fig.3. Decomposition of signal

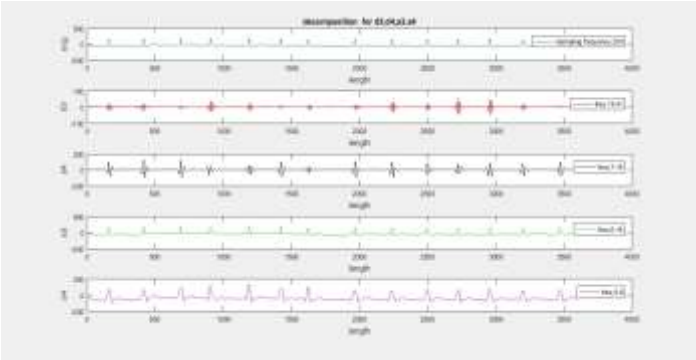

Fig.4. Decomposition of signal

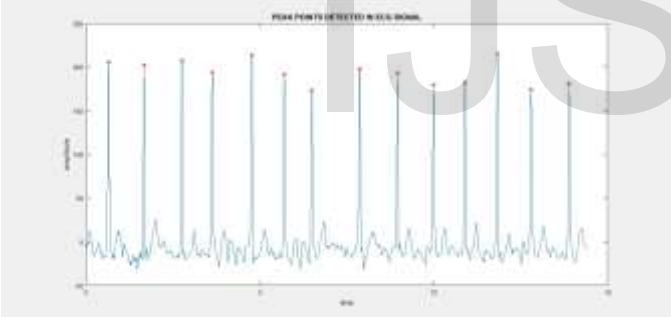

Fig.5. ECG peak detection

Table 1. Performance analysis for different datasets

| ECG data sets | SIGNAL TO NOISE RATIO-(SNR) | MEAN SQUARE ERROR -(MSE) | MEAN ABSOLUTE ERROR-(MAE) | CROSS-CORRELATION (CC) |
|---|---|---|---|---|
| 200 | 43.745 | 0.3398 | 0.0097 | 0.9775 |
| 201 | 29.365 | 0.4609 | 0.0113 | 0.9583 |
| 210 | 28.503 | 0.4810 | 0.0115 | 0.9634 |
| 215 | 21.212 | 0.0749 | 0.0045 | 0.9255 |
| 228 | 15.617 | 0.4606 | 0.0113 | 0.9494 |
| 234 | 32.026 | 0.4618 | 0.0113 | 0.9123 |

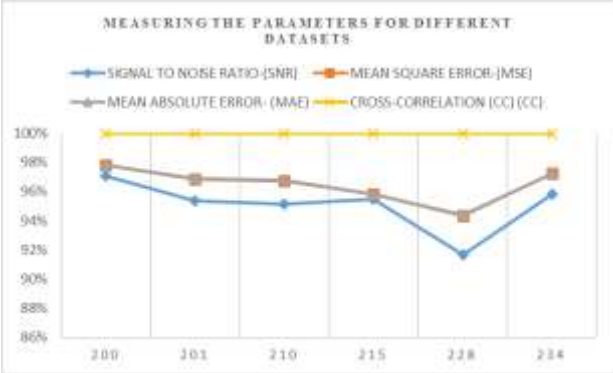


Fig.6. Performance analysis for different datasets

## 5 CONCLUSION

In this paper a new improvised adaptive threshold has been proposed. The new thresholding technique has been experimentally tested for Different ECG signals from MIT-BIH Arrhythmia ECG Database. The obtained results of SNR and MSE shows that the experimented thresholding technique is more suitable when compared to Donoho's thresholding technique to denoise for the detection of early stage abnormalities in ECG signals.

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