Adaptive Wavelet Thresholding for Noise reduction in Electrocardiogram (ECG) Signals

Er. Manpreet Kaur [1] and Er. Gagandeep Kaur[2]

[1]M.tech (CSE), RIMT Institute of Engineering & Technology, Mandi Gobindgarh, Punjab, India.
[2]AP. M.Tech (CSE), RIMT Institute of Engineering & Technology, Mandi Gobindgarh, Punjab, India.

Abstract:

In diagnosis of diseases Ultrasonic devices are frequently used by healthcare professionals. The medical imaging devices namely X-ray, CT/MRI and ultrasound are producing abundant images which are used by medical practitioners in the process of diagnosis . The main problem faced by them is the noise introduced due to the consequence of the coherent nature of the wave transmitted. These noises corrupt the image and often lead to incorrect diagnosis. In general, ECG signals affected by noises such as baseline wandering, power line interference, electromagnetic interference and high frequency noises during data acquisition. In the recent paper we have considered the Discrete Wavelet Transform (DWT) based wavelet Denoising have incorporated using different Thresholding techniques to remove major sources of noises from the acquired ECG signals. The experimental results shows the significant reduction of White Gaussian noise and it retains the ECG signal morphology effectively. Different performance measures were considered to select the appropriate wavelet function and Thresholding rule for efficient noise removal methods such as Mean Square Error (MSE),Peak Signal to Noise Ratio (PSNR) and Percentage Root Mean Square Difference (PRD) . The experimental result shows the *db"* wavelet and BayesShrink Thresholding rule is optimal for reducing noise in the real time ECG signals.

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

1. Introduction:

There is an exponential increase in digital data, obtained from various signals specially the biomedical signals such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG) etc. Transmission techniques of these biomedical signals through communication channels is an important issue as it allows experts to make a remote assessment of the information carried by the signals, in a very cost-effective way. Storage of these bio-medical signals leads to a large volume of information. How to transmit or store these signals efficiently becomes the most important issue.

ECG is derived from electro (electrical activity), cardio (heart) and graph (write).It is used for measuring activities of heart so it helps in determining if a person has any problems of the heart. EEG is derived from electron, encephalos (brain) and gram(record). EEG is the equipment used for measuring electrical activities of the brain. EEG is mainly used for diagnosing EMG is done to find diseases that damage muscle tissue, nerves, or the junctions between nerve and

2. Basics of ECG Signal.

Electrocardiogram (ECG) signal is a graphical representation of cardiac activity and it uses the primary measure for identifying various heart diseases and heart abnormalities.

seizure disorders, infections, tumors, degenerative disorders and metabolic disturbances that could affect the brain. ECG determines rate of heartbeats, heart chamber positions and if there is any damage to heart and involves no risk or pain but EEG comes with certain adverse conditions.

Both the ECG and the EEG uses electrodes for determining electric impulses of the heart and the brain. In EEG, the electrodes are attached to the scalp. But for taking ECG, the electrodes are attached to the chest, legs, arms and neck. While about 16 to 20 electrodes are used in EEG testing, about 12 electrodes are used in ECG testing.

While An electromyogram (EMG) measures the electrical activity of muscles at rest and during contraction. Nerve conduction studies measure how well and how fast the nerves can send electrical signals. Nerves control the muscles in the body with electrical signals called impulses. These impulses make the muscles react in specific ways.

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. Figure 1 shows the normal ECG traces which consist of P wave, QRS complex and T wave.

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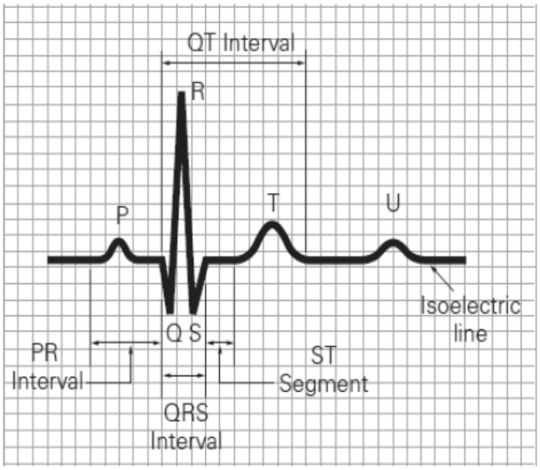


Fig.1. An ECG wave pattern for one cardiac cycle.

P wave: When the electrical impulse is conducted from the SA node towards the AV node and spreads from right to left atrium, the depolarization (contraction) of the atria occurs. The depolarization of atria results the P Wave in the ECG.

QRS complex: The QRS complex consists of three waves, sequentially known as Q, R and S. The rapid depolarization of both the ventricles results this complex. The muscles of the ventricles have large muscle mass than that of atria, hence its amplitude is much larger than that of P wave.

T wave: Ventricular repolarization results the preceding of ST segment and the T wave.

U wave: The origin of U wave is not clear and it is rarely seen. It is probably produced due to the repolarization of the papillary muscles.

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 to eliminate the noises and to extract the efficient morphology of ECG signals, several preprocessing methods have been proposed over past few decades.

In clinical environment during acquisition, the ECG signal encounters various types of artifacts. The ones of primary
compressed into a few features by performing
spectral analysis of the signals with the WT.

3.2 Discrete Wavelet Transform:

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete

interest are power line interference, external electromagnetic field interference, noise due to random body movements and respirational movements, electrode contact noise, electromyography (EMG) noise, and instrumentation noise. These noises degrade the signal quality, frequency resolution and strongly affect the morphology of ECG signal containing important information.

It is essential to reduce disturbances in ECG signal and improve the accuracy and reliability for better diagnosis. Thus, filtering of the ECG signal is a necessary preprocessing step to conserve the useful information and to remove such noises.

The ECG signal provides the following information of a human heart :

- disturbances in heart rhythm and conduction
- abnormalities in the spread of electrical impulse across the heart
- information about a prior heart attack
- sign of coronary artery disease
- abnormal thickening of heart muscle

3. DE-NOISING OF ECG SIGNAL

The Wavelet transform method is used for De-noising of noisy ECG signal:

3.1 Wavelet transform:

For the wavelet transform, the basis functions are more complicated called wavelets, mother wavelets or analyzing wavelets and scaling function. In wavelet analysis, the signal is broken into shifted and scaled versions of the original (or mother) wavelet. The fact that wavelet transform is a multi resolution analysis makes it very suitable for analysis of non-stationary signals such as the ECG signal.

The wavelet transform is capable of representing signals in different resolutions by dilating and compressing its basis functions. The ECG signals which consisting of many data points, can be

set of the wavelet scales and translations obeying some defined rules.

Discrete Wavelet transform is an emerging tool for the de-noising of non-stationary signals like ECG. There are number of wavelet families like Haar, Daubechies (Db), Symlet etc for analysis and synthesis of signal. Proper selection of wavelet basis function plays a vital role in Denoising. The ECG signals were decomposed into time-frequency representations using Discrete Wavelet Transform (DWT).

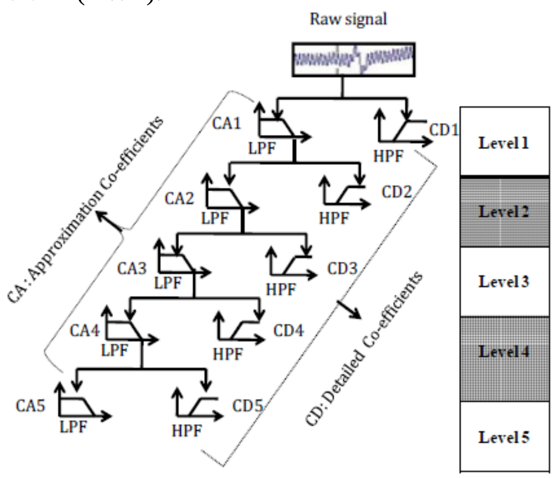


Figure 2. Filter bank structure for implementing DWT

Discrete Wavelet Transform is also referred to as decomposition by wavelet filter banks. This is because DWT uses two filters, a low pass filter (LPF) and a high pass filter (HPF) to decompose the signal into different scales. The output coefficients of the LPF are called approximations while the output coefficients of the HPF are called details.

Because of its great time and frequency localization ability, the DWT can reveal the local characteristics of the input signal. The DWT represents a 1-Decompodition signal s(t) in terms of shifted versions of a low pass scaling function φ(t) and shifted and dilated versions of a prototype band pass wavelet function ψ(t).The major advantage of the DWT is that it provides good time resolution. Good resolution at high frequency and good frequency resolution at low frequency.

4. Implementation:

Since Daubechies (Db) is mostly morphologically similar to the ECG signal, so in present work Db is used in de-noising . For wavelet analysis the MATLAB program, which contains a very good wavelet toolbox is used.

First we perform DWT of the noisy ECG signal i.e. signal was decomposed using a wavelet decomposition. Then threshold is applied to the signal after passing through the

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \varphi \left(\frac{t-b}{a}\right)$$

Where a = scaling parameter and b= shifting parameter.

3.3 Wavelet Denoising Algorithm:

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

X(n)=s(n)+u(n)

In assumption, the raw signals are usually contaminated with noise as shown in above equation,

Where(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.

DWT to remove the coefficients below a certain value, to remove the low amplitude noise or undesired signals and any noise overlap. Threshold is calculated using equation:

$$T=\sigma\sqrt{2\log N}$$

Where T is the threshold, N is no. of samples, σ is the standard deviation of noise.

The Threshold plays an important role in the Denoising process. Finding an optimum threshold is a tedious process. Normally, Hard Thresholding and soft

Thresholding techniques are used for such de-noising process. Hard Thresholding is a keep or kill rule whereas Soft Thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule.

Soft Thresholding has major advantages over Hard Thresholding. Soft Thresholding reduces the abrupt sharp changes and provides an image whose quality is not affected. Due to these advantages, Soft Thresholding is more frequently used .

4.1 BayesShrink Method:

BayesShrink performs soft Thresholding, with the data-driven, sub band dependent threshold. For each level a threshold value is found through a loop, and it is applied for the detailed coefficients of the noisy and original signals.

The optimum threshold is chosen by taking the minimum error between the detailed coefficients of noisy signal and those for original signal. It is used to shrinkage the wavelet detailed coefficients of the noisy signal such that: the output wavelet transform coefficients after and T is the chosen threshold.

$$t_B = \sigma^2/\sigma_s$$

where σ*2* is the noise variance and σ*s*2 is the signal variance without noise. The noise variance σ*2* is estimated from the sub band HH1 by the median estimator.

5. Different Evaluation Measures:

Several experiments are conducted to evaluate the BayesShrink method. The performance metrics used are:

(i) MSE(Mean Square Error)
(ii) Peak Signal to Noise Ratio (PSNR) and
(iii) PRD(Percentage Root Mean square Difference).

(i)MSE-It is estimated between the de-noised ECG signal and original ECG signal given by equation,

$$MSE = \frac{\sum_{M,N} [I_1 (m,n) - I_2 (m,n)]^2}{M * N}$$

where M and N, m and n are number of rows and columns in the input and output image respectively.

(ii)PSNR is a quality measurement between the original and a denoised image. The higher the PSNR, the better is the quality of the compressed or reconstructed image.

$$PSNR = 10 \, log_{10} \left[\frac{R^2}{MSE}\right]$$

(iii)PRD-The distortion resulting from the ECG processing is frequently measured by the percent Root-mean-square difference (*PRD*). It is calculated to verify the improvement in the reconstructed signal.

$$PRD = \sqrt{\frac{\sum_{n=0}^{N} (V(n) - V_R (n))^2}{\sum_{n=0}^{N} V^2 (n)}} * 100\%$$

V (n): original ECG signal.
V_R (n): reconstructed ECG signal.

Experimental Results:

To evaluate our Denoising algorithm we have used ECG data records of 7200 samples with sampling frequency of 0.5 Hz to 100 Hz. Gaussian noise signal is used as the noise sources and embedded in the ECG signal. The db (Daubechies) mother wavelet function is used in the DWT process for this work. We have considered the 3rd level decomposition for this algorithm, it depends on the filtering process.

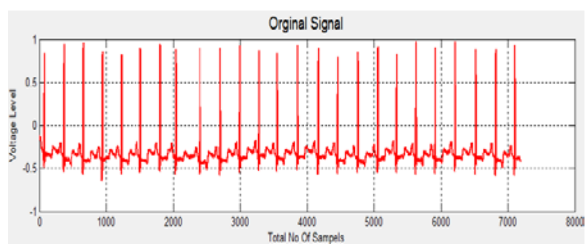


Fig.3(a) Original ECG Signal.

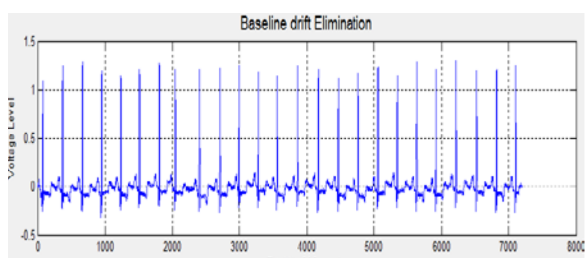


Fig 3(b) Baseline Drift Elimination.

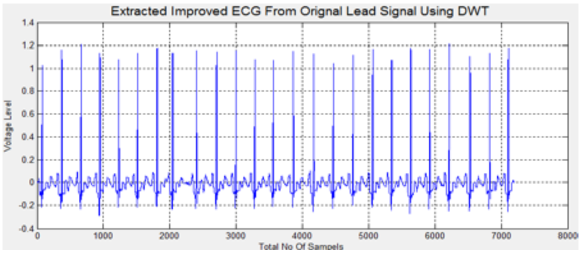
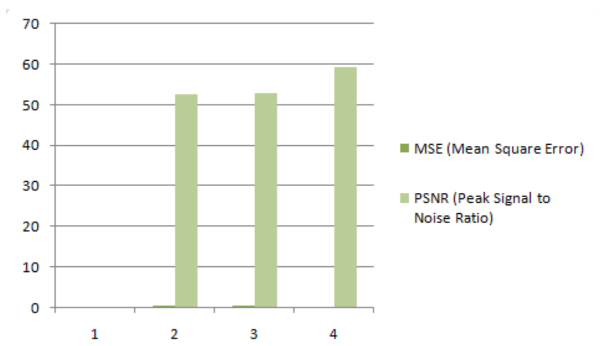


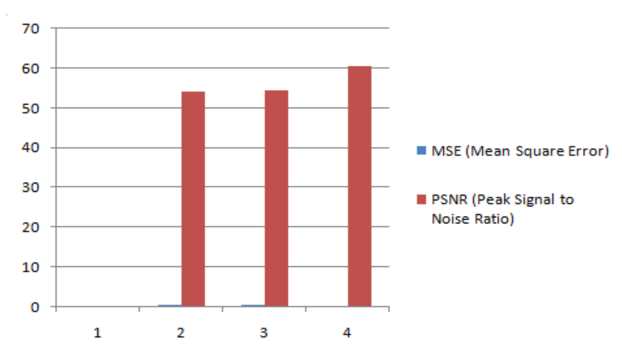
Fig 3(c) Reconstructed ECG Signal.

Figure 1 (a) shows the original ECG signal and the figure(b) separately shows the noisy ECG signal corrupted by WGN and its estimated (Denoised) version is correlated to the original noise free ECG signal and fig (c) shows reconstructed signal for data record of 7200 samples.



Fig(a).Comparison of MSE and PSNR for ECG Sample I.

Different experiments are conducted to evaluate noise free signal. In Table I, it presents db mother wavelet performed wavelet Denoising algorithms with ECG data records of 7200 samples and for a particular threshold value (λ) different parametric values such as (i) Mean square error (MSE) (ii) Peak Signal to Noise Ratio (PSNR) and (iii) PRD are calculated for White Gaussian Noise.



Fig(b).Comparison of MSE and PSNR of ECG Sample II.

Data Type	**Discrete Wavelet Transform(DWT)** Daubechies (db)		
	MSE (Mean Square Error)	**PSNR (Peak Signal to Noise Ratio)**	**Percentage Root Mean Square Difference** (PRD in %)
ECG Sample 1	*0.35*	*52.69*	*0.89*
	0.32	*53.09*	*1.12*
	0.07	*59.46*	*2.20*
ECG Sample 2	*0.26*	*54.04*	*1.10*
	0.24	*54.38*	*0.91*
	0.06	*60.71*	*0.41*

Table .1(a). To Compare the performance of Various Distortion Measuring parameters i.e. MSE, PSNR and PRD for both ECG samples I & II **.**

Using MSE, PSNR and PRD the distortion is measured comparing the original signal with reconstructed signal. PSNR is a quality measurement, this parameter is inversely related to distortion, that is, its numerical value decreases as the distortion in reconstructed signal increases. Therefore, the higher the PSNR, the better is the quality of the compressed or reconstructed signal.

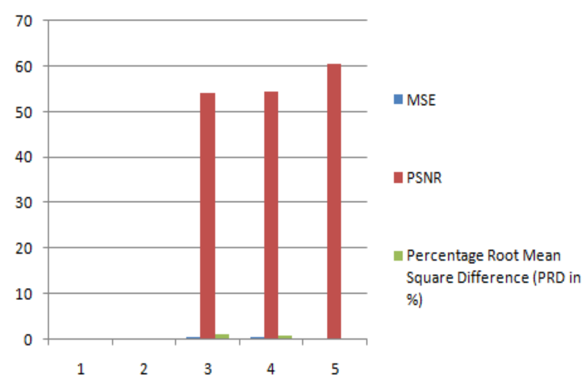


Fig.(c) Comparative results of both ECG samples**.**

Conclusion:

The wavelet transform allows processing non- stationary signals such as ECG signal. So Filtering is an important step in ECG signal processing because the current need of healthcare industries is to preserve useful diagnostic information with minimum noise. Our presents work shows the effect of the wavelet Thresholding on the quality reconstruction of an ECG signal. In our algorithm we have discussed the case that ECG signal has been noised with WGN. In this paper, de-noising of ECG signal using discrete wavelet transform is analyzed. The obtained results of the comparative analysis i.e. by applying Soft BayesShrink Thresholding with Daubechies mother wavelet filtering and consider 3rd level decomposition wavelet Denoising technique we analyzed the improvement in error. Therefore, the experimental results prove that produced signals which are more cleaner and smoother and at the same time kept significant details, resulting in a clearer an appealing vision.

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