Efficient Use of Biorthogonal Wavelet Transform for Caridac Signals

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Summary
The ECG finds its importance in the detection of cardiac abnormalities. ECG signal processing in an embedded platform is a challenge which has to deal with several issues. Noise reduction in ECG signal is an Important task of biomedical science. ECG signals are very low frequency signals of about 0.5Hz-100Hz. There are various artifacts which get added in these signals and change the original signal, therefore there is a need of removal of these artifacts from the original signal. The noises that commonly disturb the basic electrocardiogram are power line interference, electrode contact noise, motion artifacts, electromyography (EMG) noise, and instrumentation noise. These noises can be classified according to their frequency content. In this paper, the discrete wavelet transform (DWT) at level 8 was applied to the ECG signals and decomposition of the ECG signals was performed.
In this paper we have used bi-orthogonal wavelet transform for denoising ECG signal and also showed that it gives maximum efficient idea for noise removing process. The simulation is done in MATLAB environment. The experiments are carried out on MIT-BIH database. Performance analysis was performed by evaluating Mean Square Error (MSE), Signal-to-noise ratio (SNR), Peak Signal-to-noise ratio (PSNR), and visua inspection over the denoised signal from each algorithm.

Key words:
ECG, Wavelet Transform , discrete wavelet transform, PSNR, MSE

1. INTRODUCTION

One of the main problems in biomedical data processing like electrocardiography is the separation of the wanted signal from noises caused by powerline interference, high frequency interference, extern electromagnetic fields and random body movements and respiration [1]. Different types of digital filters are used to remove signal components from unwanted frequency ranges. It is difficult to apply filters with fixed coefficients to reduce random noises, because hum behavior is not exact known depending on the time. Adaptive filter technique is required to overcome this problem. Electrocardiogram (ECG) is one of the most important parameters for heart activity monitoring. A doctor can detect different types of deflections by the full form analysis of the ECG signal. Fig. 1 shows the standard ECG Signal.

In many applications for biomedical signal processing the useful signals are superposed by different components.Interference may have technical sources, for example, power supply harmonic 50 Hz, high frequency noises and electromagnetic fields from other electronic devices, and biological sources, such as muscular reaction, respiratory movements and changing parameters of the direct contact between electrodes and the skin [1]. So, extraction and analysis of the information-bearing signal are complicated, caused by distortions from interference. Using advanced digital signal processing this task can be shifted from the analogue to the digital domain [2]. Usually two types of digital filters are used for data processing: frequency-selective filters with fixed coefficients and filters with variable coefficients. Various adaptive and non-adaptive methods are there for ECG signals enhancement[3]-[7].For non stationary signals it is not adequate to use Digital filters or Adaptive method because of loss of information. In this study, the discrete wavelet transform was utilized to decompose the ECG and then the Noise frequency components related to the ECG were removed. Wavelet thresholding de-noising methods deals with wavelet coefficients using a suitable chosen threshold value in advance.

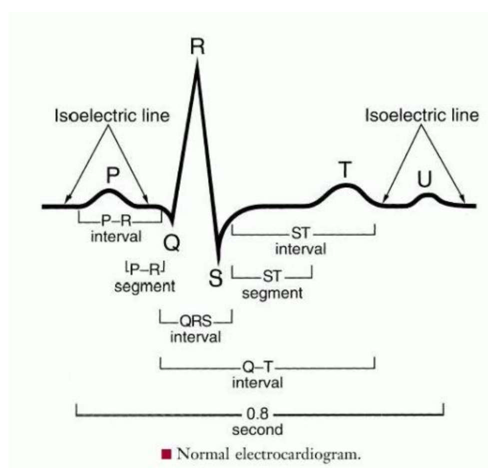

Fig. 1 An standard ECG waveform

Manuscript received February 5, 2015
Manuscript revised February 20, 2015

The wavelet coefficients at different scales could be obtained by taking DWT of the noisy signal. Normally, those wavelet coefficients with smaller magnitudes than the preset threshold are caused by the noise and are replaced by zero, and the others with larger magnitudes than the preset threshold are caused by original signal mainly and kept (hard-thresholding case) or shrunk (the soft-thresholding case). Then the denoised signal could be reconstructed from the resulting wavelet coefficients. In recent years wavelet transform (WT) has become favorable technique in the field of signal processing. Donoho et al [9][10] proposed the denoising method called "wavelet shrinkage"; it has three steps: forward wavelet transform, wavelet coefficients shrinkage at different levels and the inverse wavelet transform, which work in denoising the signals such as Universal threshold, SureShrink, Minimax.

2. METHODOLOGY

For biomedical signals, most of the statistical characteristics of these signals are non-stationary. In particular, the analysis of biological signals should exhibit good resolution in both time domain and frequency domain. Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high frequency information. One major advantage afforded by wavelets is the ability to perform local analysis, that is, to analyze a localized area of a larger signal.

A wavelet is a waveform of effectively limited duration that has an average value of zero. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. The fact that wavelet transform is a multiresolution analysis makes it very suitable for analysis of non-stationary signals such as the ECG signal.[11].

In wavelet transform, a signal x(t) which belongs to the square integrable subspace L2(R) is expressed in terms of scaling function $\Phi j,k(t)$ and mother wavelet function $\Psi j,k(t)$. Here j is the parameter of dilation or the visibility in frequency and k is the parameter of the position.

$$x(t) = \sum_{k} a_{jo,k} \varphi_{jo,k}(t) + \sum_{j=j_0}^{\infty} \sum_{k} b_{j,k} \psi_{j,k}(t) \qquad \ldots(1)$$

where a, b are the coefficients associated with $\varphi j,k(t)$ and $\psi j,k(t)$ respectively.

Discrete Wavelet Transform :-The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets. The scaling function $\varphi j,k(n)$ and the mother wavelet function $\psi j,k(n)$ in discrete domain are

$$\varphi_{j,k}(n) = 2^{j/2} \varphi(2^j n - k) \qquad \ldots(2)$$

$$\psi_{j,k}(n) = 2^{j/2} \psi(2^j n - k) \qquad \ldots(3)$$

ECG Denoising Using Wavelet Transform :- In this proposed method, the corrupted ECG signal x(n) is denoised by taking the DWT of raw and noisy ECG signal. A family of the mother wavelet is available having the energy spectrum concentrated around the low frequencies like the ECG signal as well as better resembling the QRS complex of the ECG signal. We have used Bior wavelet, which resembles the ECG wave.

In discrete wavelet transform (DWT), the low and high frequency components in x(n) is analyzed by passing it through a series of low-pass and high-pass filters with different cut-off frequencies. This process results in a set of approximate coefficients (cA) and detail coefficients (cD). To remove the power line interference and the high frequency noise, the DWT is computed to level 8 using bior mother wavelet function and scaling function. Then the approximate coefficients at level 8 (cA8) are set to zero. After that, inverse wavelet transform (IDWT) of the modified coefficients are taken to obtain the approximate noise of the ECG signal. The residue of the raw signal and the approximate noise is obtained to get noise free ECG signal.Fig 2 shows the complete process for noise removal.

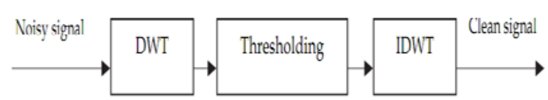

Fig. 2 Wavelet Transform Based Noise Removal

Biorthogonal Wavelet Transform:- This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and the other for reconstruction instead of the same single one, interesting properties are derived.We have following biorthogonal wavelet filter:-
bior1.1 bior1.3 bior1.5 bior2.2 bior2.4 bior2.6 bior2.8 bior3.1 bior3.3 bior3.5 bior3.7 bior3.9 bior4.4 bior5.5 bior6.8

3. RESULTS

The ECG signals used are MIT BIH arrhythmia database ECG recording [8].In this project both base line wander (nonstationary noise) and power line interference (stationary noise) have been considered. This MIT BIH arrhythmia database consists of two channel ECG recording. The sampling rate of the recording is 360 samples per second. To demonstrate power line interference (PLI) cancellation we have chosen MIT-BIH record number 100. The input to the filter is ECG signal corresponds to the data 100 corrupted with synthetic PLI with frequency 60Hz. Wavelet transform was realized with support of Matlab and Wavelet Toolbox. MSE, PSNR and SNR improvement are measured and compared.We have performed denoising using various wavelets of biorthogonal wavelet filter. We have also compared biorthogonal wavelet with other wavelets. But we found that biorthogonal wavelet bior3.9 is most suitable for ECG denoising. Various figures and table are as follows:

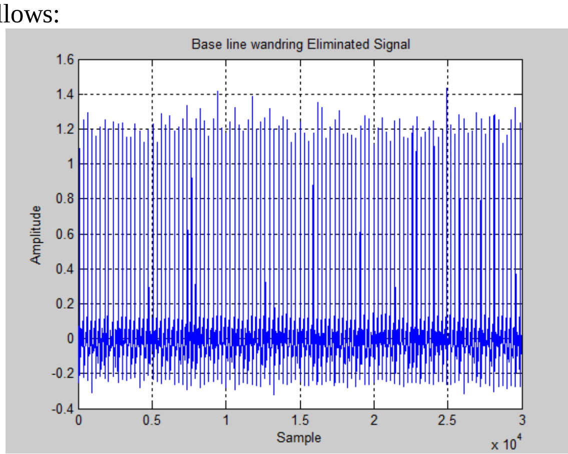

Fig. 3 Noisy ECG Signal

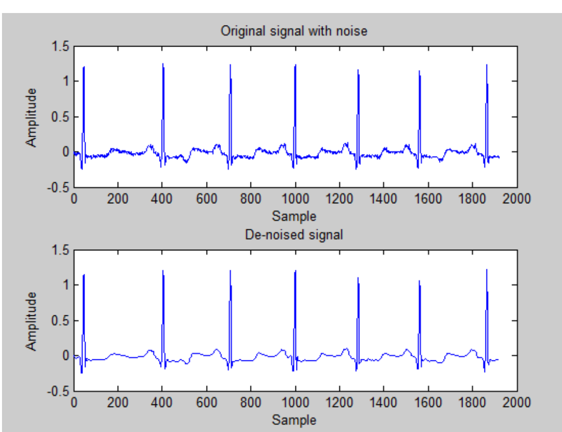

Fig. 4 Denoised ECG Signal(MIT-BIH 100.dat)

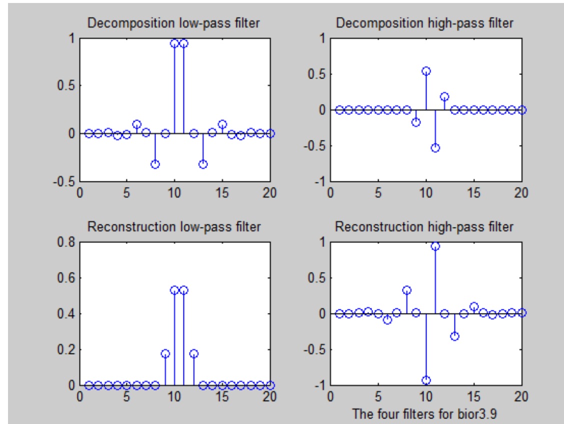

Fig.5 Bior3.9 Biorthogonal Four Filters

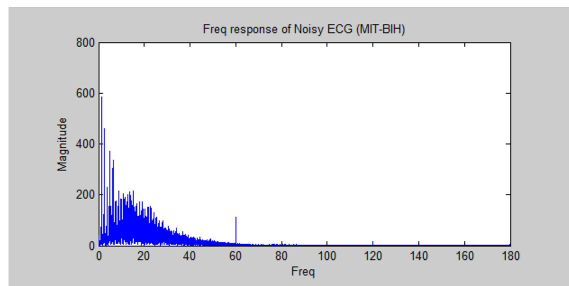

Fig.6 Freq Response of Noisy ECG Signal

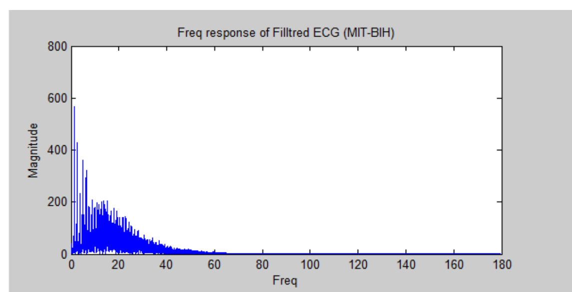

Fig. 7 Freq Response of Denoised ECG

TABLE 1 Performance of Various Wavelet

TYPE OF WAVELET	MSE (In DB)	PSNR (In DB)	SNR (In DB)
Haar	4.1085e-004	36.9974	17.9362
DB4	3.5226e-004	37.6656	18.6242
Sym 6	3.4186e-004	37.7957	18.7704
Coif 2	3.4542e-004	37.7507	18.7346
Bior3.9	2.3774e-004	39.3732	20.5785
Dmey	3.9868e-004	37.1279	18.0214

4. CONCLUSION

Filtration was applied for many ECG signals in several papers, but the wavelet Transform denoising is much better then filters.The reason is that spectrum of the noise interfere with spectrum of the ECG signal. By wavelet filtering are filtrated some frequency levels independent each other, whereas by classical filtration isn't possible to separate the signal and noise.Therefore is using wavelet denoising more useful then filtering. Bior (bior3.9) wavelet transform is the best method to de-noise the noisy ECG signals.We have compared several type of wavelet denoising, but we found that Bior3.9 gives max SNR and PSNR values. It also gives lowest MSE.

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Arpit Sharma has completed his B.Tech from Jaipur Engineering College, Jaipur, India in Electronics and Communication. Right now he is pursuing his M.tech from Kautilya Institute of Tech. and Engg., Jaipur, India. His Field of interest is to make a noice free signal by using filters and to increase the accuracy.