Research Journal of Applied Sciences 9 (7): 429-435, 2014
ISSN: 1815-932X

Efficient Use of Bi-Orthogonal Wavelet Transform for Caridac Signals

Arpit Sharma
Department of Electronics and Communication,
Kautilya Institute of Technology and Engineering, Jaipur, India

Abstract: 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 0.5-100 Hz. 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 study, these we have used wavelet transform based approach for removing these noise. In this study, the Discrete Wavelet Transform (DWT) at level 8 was applied to the ECG signals and decomposition of the ECG signals was performed. After removal of noise component using thresholding technique, decomposed signal is again constructed using Inverse Discrete Wavelet Transform (IDWT). Here for de-noising the ECG signal, bi-orthogonal wavelet transform is used and the most efficient idea for noise removal process is concluded with this wavelet transform. The simulation has been 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 visual inspection over the de-noised signal from each algorithm.

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

INTRODUCTION

One of the main problems in biomedical data processing like electrocardiography is the separation of the wanted signal from noises caused by power line interference, high frequency interference, external electromagnetic fields and random body movements and respiration (AAMI, 1991). 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. Figure 1 shows the standard ECG signal.

Different types of digital filters are used to get the main signal components and to remove 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.

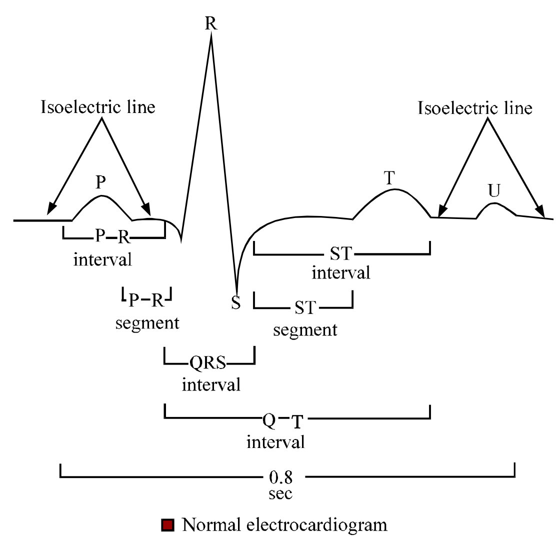

Fig. 1: A standard ECG waveform

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, 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 (AAMI, 1991). 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 (Ifeachor and Jervis, 2002). Usually two types of digital filters are used for data processing:

- Frequency-selective filters with fixed coefficient
- Filters with variable coefficients

Various adaptive and non-adaptive methods are there for ECG signals enhancement or other biomedical signal improvements (Lin and Hu, 2008; Thakor and Zhu, 1991; Chavan *et al*., 2005; Leski and Henzel, 2005; Mihov and Dotsinsky, 2008). For non stationary signals, it is not adequate to use digital filters or adaptive method because of loss of information and low value of SNR. The discrete wavelet transform has become a powerful technique in biomedical signal processing (Natwong *et al*., 2006; Sierra *et al*., 1996; Boutaa *et al*., 2008). In this study, the discrete wavelet transform was utilized to decompose the ECG and then the noisy frequency components related to the ECG were removed. Wavelet threshold de-noising methods deals with wavelet coefficients using a suitable chosen threshold value in advance.

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 de-noised 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 proposed the De-Noising Method called "wavelet shrinkage", it has three steps:

- Forward wavelet transform
- Wavelet coefficients shrinkage at different levels
- The inverse wavelet transform which work in de-noising the signals such as universal threshold, SureShrink, Minimax (Donoho and Johnstone, 1994; Donoho, 1995).

MATERIALS AND METHODS

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 researchers 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 multi-resolution analysis makes it very suitable for analysis of non-stationary signals such as the ECG signal (Mahmoodabadi *et al*., 2005).

In wavelet transform, a signal x(t) which belongs to the square integral subspace $L^2(R)$ 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:

$$x(t) = \sum_k a_{j_o,k}\varphi_{j_o,k}(t) + \sum_{j=j_o}^{\infty}\sum_k b_{j,k}\psi_{j,k}(t) \tag{1}$$

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:

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

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

The DWT has the capability of decomposing a signal of interest into an approximation and detail information. It can thus analyze the signal at different frequency ranges with different resolutions. The DWT is implemented by means of a pair of digital filter banks where the signal is successively decomposed. The two filters are a high pass filter and a low pass filter. Scaling function and wavelet function are associated with low pass and high pass filters, respectively and they are used in the DWT algorithm. These filters provide the decomposition of the signal with different frequency bands by recursively applying filters to the signal. The signal is then split equally into its high and low frequency components, called details and approximations, respectively. In the DWT algorithm, the input signal x(t) is first passed through the high pass filter and low pass filter and subsequently the outputs of both filters are decimated by a factor of two. The input signal to the filters is the ECG. The high pass filtered data set is the detail coefficients at level 1 and the low pass filtered data set is the approximation coefficients at level 1. This process can continue for further decomposition at level 2-4 until the limit of data length is reached. In addition, it is possible to reconstruct the original signal from the approximation and detail coefficients.

ECG de-noising using wavelet transform: In this proposed method, the corrupted ECG signal x(n) is de-noised 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. Researchers 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. Figure 2 shows the complete process for noise removal.

Thresholding Method: In discrete wavelet transform, threshold is applied to the signal after passing through the DWT and then IDWT is taken. Global threshold value is given as:

$$T = \sigma\sqrt{2 \text{Log}\, N} \tag{4}$$

Where:

T = The threshold
N = No. of samples
σ = The standard deviation of noise for white Gaussian noise

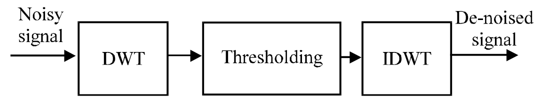

Fig. 2: Wavelet transform based noise removal

Two thresholding methods are used namely Hard Threshold and Soft Threshold.

Bi-orthogonal 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. Researchers have following bi-orthogonal 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.

RESULTS AND DISCUSSION

The ECG signals used are MIT BIH arrhythmia database ECG recording (www.physionet.org/physiobank/database/#ecg.). Here, both base line wander (non-stationary 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, researchers 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 60 Hz. Wavelet transform was realized with support of MATLAB and Wavelet Toolbox. The ECG signals were decomposed by the DWT at level 8. It can be observed that the activity of baseline wandering was found in the A8, since the baseline wandering is low frequency activity. In order to remove the baseline wandering from the ECG signals, the synthesis process of the inverse DWT was performed.

In this study, the original signal was reconstructed with-out the A8 information. MSE, PSNR and SNR improvement are measured and compared. Researchers have performed de-noising using various wavelets of Bi-orthogonal wavelet filter. Researchers have also compared Bi-orthogonal wavelet with other wavelets like Daubechies, Haar, Symlet and Coif. But, researchers found that Bi-orthogonal wavelet bior3.9 is most suitable for ECG de-noising. Figure 3 shows the noisy signal and the noise are removed with Bior3.9 wavelet from the original signal as depicted in Fig. 4.

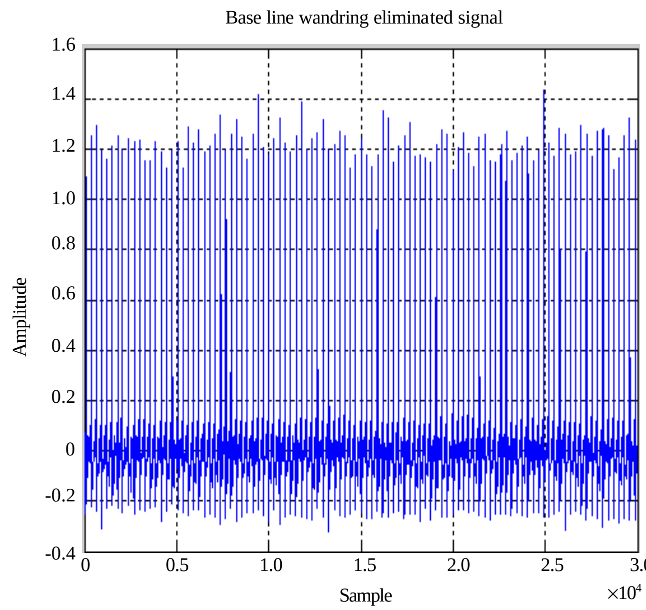

Fig. 3: Noisy ECG signal

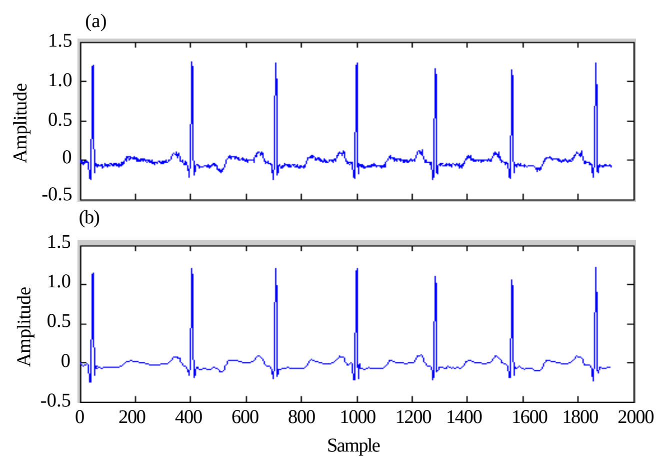

Fig. 4: De-noised ECG signal (with Bior3.9); a) Original signal with noise; b) De-noised signal

Table 1: Performance analysis table for various wavelets

Types of wavelets	MSE	PSNR (DB)	SNR (DB)
Haar	4.1085e-004	36.9974	17.9362
Dmey	3.9868e-004	37.1279	18.0214
DB4	3.5226e-004	37.6656	18.6242
Coif 2	3.4542e-004	37.7507	18.7346
Sym 6	3.4186e-004	37.7957	18.7704
Bior2.8	2.8113e-004	38.6452	19.7645
Bior3.7	2.5705e-004	39.0340	20.2263
Bior3.9	2.3774e-004	39.3732	20.5785

Figure 5 shows the four filters of Bior3.9 by which all the filtrations are done. Figure 6 and 7 show the frequency response of noisy ECG signal and de-noised ECG signal, respectively. Table 1 represents the calculations of signal to noise ratio with different wavelets. Figure 8 is showing wavelet and scaling

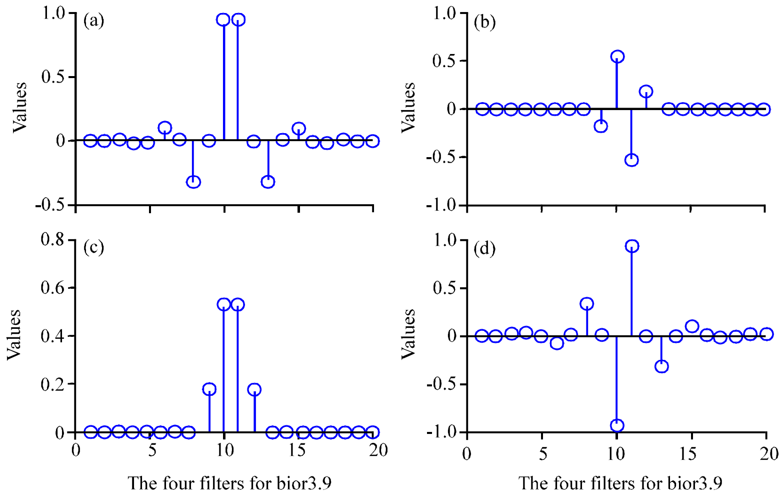

Fig. 5: Bior3.9 bi-orthogonal four filters; a) decomposition low-pass filter; b) decomposition high-pass filter; c) reconstruction low-pass filter and d) reconstruction high-pass filter

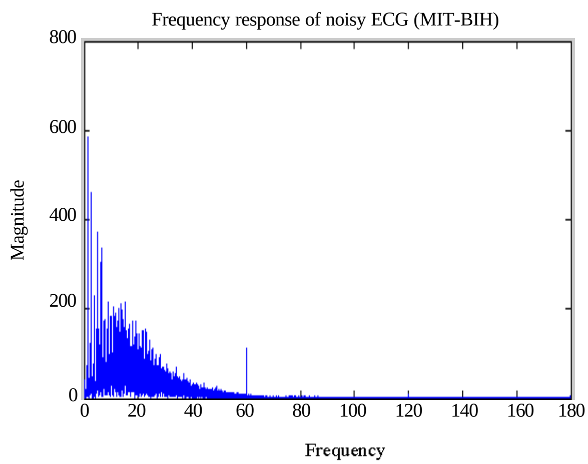

Fig. 6: Frequency response of noisy ECG signal

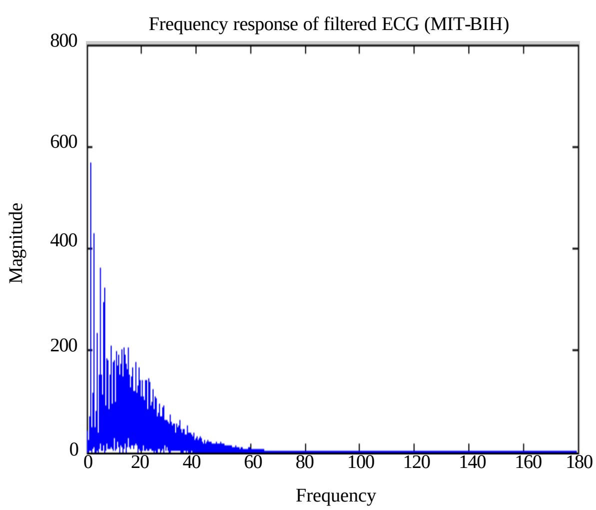

Fig. 7: Frequency response of de-noised ECG (with Bior3.9)

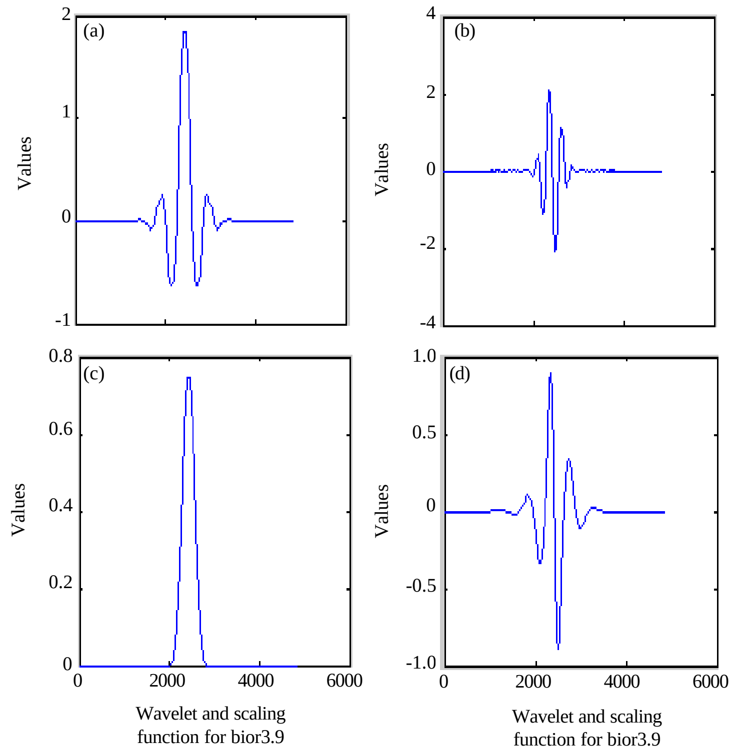

Fig. 8: Wavelet and scaling function for Bior3.9; a) decomposition scaling function PHI; b) decomposition wavelet function PSI; c) reconstruction scaling function PHI and d) reconstruction wavelet function PSI

function for Bior 3.9. In Fig. 8, two figures are showing the decomposing scaling function and decomposition wavelet function while below two are for reconstruction.

CONCLUSION

Filtration was applied for many noisy ECG signals in several papers but the wavelet transform de-noising is much better then such type of filtration. The reason is that spectrum of the noise interfere with spectrum of the ECG signal. By wavelet filtering noisy ECG signals are filtrated at some frequency levels, independent each other whereas by classical filtration isn't possible to separate the signal and noise.

Therefore, is using wavelet de-noising more useful then filtering. Bior (bior3.9) wavelet transform is the best method to de-noise the noisy ECG signals. As from Table 1, researchers found that wavelet de-noising using bior 3.9 wavelet gives lowest value of MSE and highest value of PSNR. So, wavelet de-noising using bior 3.9 wavelet is most efficient method.

REFERENCES

AAMI, 1991. Diagnostic Electrocardiographic Devices. Association for the Advancement of Medical Instrumentation, California, ISBN: 9780910275682, Pages: 39.

Boutaa, M., F. Bereksi-Reguig and S.M.A. Debbal, 2008. ECG signal processing using multiresolution analysis. J. Med. Eng. Technol., 32: 466-478.

Chavan, M.S., R.A. Agarwala and M.D. Uplane, 2005. Digital elliptic filter application for noise reduction in ECG signal. Proceedings of the 4th WSEAS International Conference on Electronics, Control and Signal Processing, November 17-19, 2005, Florida, USA., pp: 58-63.

Donoho, D.L. and I.M. Johnstone, 1994. Ideal spatial adaptation by wavelet shrinkage. Biometrika, 81: 425-455.

Donoho, D.L., 1995. De-noising by soft-thresholding. IEEE Trans. Inform. Theor., 41: 613-627.

Ifeachor, E.C. and B.W. Jervis, 2002. Digital Signal Processing: A Practical Approach. Prentice Hall, UK., ISBN-13: 9780201596199, Pages: 933.

Leski, J.M. and N. Henzel, 2005. ECG baseline wander and powerline interference reduction using nonlinear filter bank. Signal Process., 85: 781-793.

Lin, Y.D. and Y.H. Hu, 2008. Power-line interference detection and suppression in ECG signal processing. IEEE Trans. Biomed. Eng., 55: 354-357.

Mahmoodabadi, S.Z., A. Ahmadian, M.D. Abolhasani, M. Eslami and J.H. Bidgoli, 2005. ECG feature extraction based on multiresolution wavelet transform. Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society, January 17-18, 2006, Shanghai, pp: 3902-3905.

Mihov, G. and I. Dotsinsky, 2008. Power-line interference elimination from ECG in case of non-multiplicity between the sampling rate and the power-line frequency. Biomed. Signal Process. Control, 3: 334-340.

Natwong, B., P. Sooraksa, C. Pintavirooj, S. Bunluechokchai and W. Ussawawongaraya, 2006. Wavelet entropy analysis of the high resolution ECG. Proceedings of the IEEE Conference on Industrial Electronics and Applications, May 24-26, 2006, Singapore, pp: 1-4.

Sierra, G., T. Fetsch, L. Reinhardt, A. Martinez-Rubio and M. Makijarvi *et al*., 1996. Multiresolution decomposition of the signal-averaged ECG using the Mallat approach for prediction of arrhythmic events after myocardial infarction. J. Electrocardiol., 29: 223-234.

Thakor, N.N. and Y.S. Zhu, 1991. Application of adaptive filtering to ECG analysis: Noise cancellation and arrhythmia detection. IEEE Trans. Biomed. Eng., 38: 785-794.