

Comparison of Wavelet and Filtering Techniques for Denoising ECG Signal

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Abstract— A proper processing of biomedical signals enhances their physiological and clinical information because they carry vital information about the behaviour of the living systems under study. With the analysis of the Electrocardiogram (ECG) signal it may be possible to predict heart problems and play an important role in diagnosis process or monitor patient recovery after a heart intervention. The quality of this signal is degraded mainly by many sources of noise such as power line interference (PLI), baseline drift, muscle contraction noise etc. Present work deals with the design of filter banks based on the discrete wavelet transform (DWT) as well as design of low pass Chebyshev Type I and Butterworth filters using FDA tool in MATLAB environment. De-noised ECG signal is compared with original signal using Mean Square Error (MSE). Results show that denoising schemes involving wavelet domains are able to reduce noise from ECG signals more accurately and consistently with mse of 0.0012 in comparison to noise reduction algorithms in filtering technique which has mse of 0.0799 and 0.1814 for Chebyshev and Butterworth filters respectively.

Keywords— ECG, DWT, Butterworth, Chebyshev, MSE

I. INTRODUCTION

Among the main causes of death in the world nowadays are cardiac diseases and cardiac failure. Therefore a need in the development of

methods and systems for monitoring its functionality is very high. One of the most powerful diagnostic tools in medical application that is commonly used for the assessment of the functionality of the heart is Electrocardiography (ECG). The ECG is nothing but the recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders (Guyton and Hall, 2006).

It is very important to detect and diagnose as early as possible and accurately these cardiac arrhythmias since they usually cause sudden cardiac death. Therefore, the usage of computer software to automatically detect the ECG beats and diagnose the ECG classes is widely used as a reliable technique for the diagnosis of those diseases. However, recording of ECG signal in a clinical environment is normally corrupted with two major noises generated by biological and environmental resources. (Rangaraj, 2002) The first group includes muscle contraction or electromyographic (EMG) interface, baseline drift, ECG amplitude modulation due to respiration and motion artifacts caused by changes in electrode skin impedance with electrode motion. The second group includes power line interference, electrode contact noise, instrumentation noise generated by electronic devices used in signal processing, electrosurgical noise and radio frequency. Different types of interferences are listed in figure 1.



Fig. 1. Interferences in the ECG signal

For the correct evaluation and interpretation of ECG signal it is necessary to suppress these artifacts from the original signal. Therefore, there are several studies proposed in the literature on the development of methods for noise reduction and enhancement. One of the most widely used methods is the least mean square adaptive algorithm (LMS). But this algorithm is not able to track the rapidly varying nonstationary signal such as ECG signal within each heart beat. (Almenar and Albiol, 2005) Presented some of these algorithms which use LMS such as the time- sequence adaptive filter (TSAF), adaptive impulse correlated filter (AICF), and the signal-input adaptive filter (SIF). The TSAF is not robust to noise, and has null output if the beat period increases (makes it have no effect). The disadvantages of AICF are being not very robust to noise, and it's repetitive, it means that for example amplitude R or P is the same in each beat. The SIF is the best, it's not repetitive and it's robust to noise, but it slightly smoothes the mean parameters like R or P amplitudes. Many researchers work on signal noise removing by different filtering method and algorithms which include a method using high pass filter to removes very low frequency component from ECG recording as presented in (Jacek et al., 1999). Linear filtering is also performed for removing baseline wander from ECG signals in the frequency range of 0.5Hz (Van Alste and Schilder, 1985). Adaptive filtering proposed by Windrow can also be used to remove baseline wander. Reference signal is needed in this method, which adds to complexity of hardware and software adaptive filter etc (Jane et al., 1992; Laguna et al., 1992; Meyer and Keiser 1977). Removal of baseline wander and PLI by digital IIR filter (Meyer and Keiser 1977). Santpal Singh Dhillon and Saswat Chakrabarti have used a simplified lattice based adaptive IIR Notch filter to remove power line interference (Singh and Chakrabarti, 2001). Also, comparison of different of different ECG Denoising Techniques Based on PRD & Mean Parameters was presented in (Parsad et al., 2014).

The earlier method of ECG signal analysis was based on time domain method. But this is not always sufficient to study all the features of ECG signals. So, the frequency representation of a signal is required. Among the various time frequency transformations the wavelet transformation is found to be simple and more valuable. Some of the works presented in literature using wavelet includes work by Donoho and Johnstone who proposed several wavelet shrinkage approaches [Donoho and Johnstone, 1994; Beheshti et al., 2008]. (Ustündağ et al., 2013) Presents Performance comparison of wavelet thresholding techniques on weak ECG signal denoising, Denoising ECG signal using Undecimated wavelet transform was carried out in (Gayal and Shaikh, 2014). Therefore, this paper presents a comparison analysis of classical filtering techniques using Butterworth and Chebyshev filters with discrete wavelet transform method. After a brief introduction of electrocardiography in section 2, ECG filtering was presented in section 3; the wavelets will be summarized at Section 4. Work methodology and results and discussion were presented in section 5 and 6 respectively. Finally, conclusion of the work will be given.

II. ELECTROCARDIOGRAPHY

ECG signal is a bioelectrical signal which depicts the cardiac activity of the heart and it is a technique used primarily as a diagnostic tool for various cardiac diseases because of its simplicity. By attaching electrodes at different outer surface of the human skin, electrical cardiac signals can be recorded by an external device. These currents cause the contractions and relaxations of heart by stimulating cardiac muscle (Guyton and Hall, 2006; Acharya, 2012) and travel as electrical signals through the electrodes to the ECG device, which records them as characteristic waves. Different waves and fiducial points of ECG reflect the activity of different parts of the heart which generate the respective flow of electrical currents (Texas, 2012). Figure 2 below shows a schematic representation of a normal ECG and its various waves.

The most important features include the information lying in the P, Q, R, S, and T waves of the ECG signal, ECG beats should be classified based on these features in order to detect different types of cardiovascular diseases. The length of a normal QRS wave is between 80 to 120ms (Martis et al., 2012).

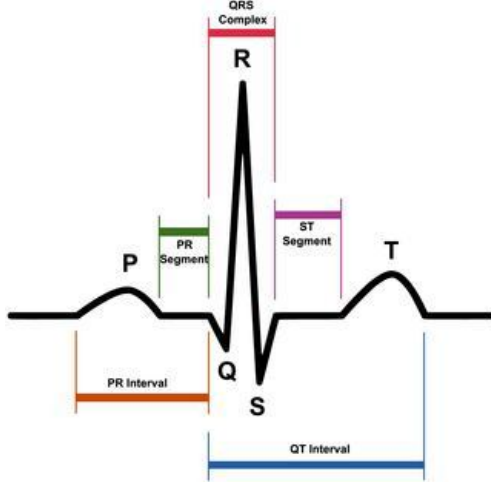


Fig. 2. Normal ECG wave (Murugavel, 2005)

III. ECG FILTERING

A. Butterworth Filter

Butterworth filters are having a property of maximally flat frequency response and no ripples in the pass band. It rolls off towards zero in the stop band. Its response slopes off linearly towards negative infinity on logarithmic Bode plot. Like other filter types which have non-monotonic ripple in the passband or stopband, these filters are having a monotonically changing magnitude function with ω . Butterworth filter has a slower roll off when compared with chebyshev type I/type II filter or an elliptic filter. Hence for implementing a particular stopband specification it will require a higher order. We notice that its pass band is accompanied with a more linear phase response in comparison to chebyshev type I/type II and elliptic filter.

B. Chebyshev filters

Chebyshev type I filters are analog or digital filters having the property of more pass band ripple and type II filters are having more stopband ripple. These filters have a steeper roll off than Butterworth filters. Chebyshev filters reduce the error between idealized and actual filter

characteristics over the range of filter but drawback they face is the ripples in the passband (Sonal et al., 2012).

IV. WAVELET ANALYSIS

The wavelet transformation is based on a set of analyzing wavelets allowing the decomposition of ECG signal in a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG components in this time segment and frequency band.

The continuous wavelet transform (CWT) has been developed as a method to obtain simultaneous, high resolution time and frequency information about a signal. The CWT unlike Short Time Fourier Transform (STFT) uses a variable sized window region. Since the wavelet may be dilated or compressed; different features of the signal are extracted. While a narrow wavelet extracts high frequency components, a stretched wavelet picks up the lower frequency components of the signal (Addison, 2002).

The CWT is computed by correlating the signal $s(t)$ with families of time-frequency atoms $\Psi(t)$, it produce a set of coefficients $C(a,b)$ given by :

$$C(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t) \Psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where b is the time location(translation parameter), a is called scale factor and it is inversely proportional to the frequency ($a>0$), $*$ denotes a complex conjugate and $\Psi(t)$ is the analysing wavelet (mother wavelet).

The Discrete Wavelet Transform (DWT) is a time-scale representation of the digital signal and is obtained using digital filtering techniques. It is found to yield a fast computation of wavelet transform, easy to implement and adopts dyadic scales and translations in order to reduce the amount of computation time, which results in better efficiency of calculation. DWT can be obtained by

$$C_{mn} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t) \Psi_{mn}(t) dt \quad (2)$$

where the dyadic scaled and translated wavelet is defined as

$$\Psi_{mn}(t) = 2^{-m/2}\Psi(2^{-m}t - n) \quad (3)$$

The most common wavelets providing the orthogonality properties are Daubechies, Symlets, Coiflets and Discrete Meyer in order to provide reconstruction using the fast algorithms (Addison, 2002).

The successive low-pass and high-pass filters calculating three levels of DWT is shown in Figure 3.

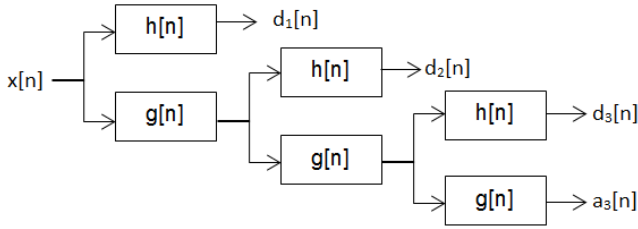


Fig. 3. Three level Wavelet decomposition tree

Each stage consists of two digital filters and two downsamplers by 2 to produce the digitized signal. The low pass filter is denoted by $g[n]$ while the high pass filter is denoted by $h[n]$. At each level, the high pass filter produces detail information; $d[n]$, while the low pass filter associated with scaling function produces coarse approximations, $a[n]$. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. Only the last level of approximation is save among all levels of details, which provides sufficient data. The filter coefficients can be obtained from mother wavelet and scaling functions (Addison, 2002).

V. METHODOLOGY

A. In the first step different filters were designed with the help of FDA tool in Matlab software. FDA tool parameters were chosen with sampling frequency of 1000Hz, cut off frequency of 10Hz and different filter order were tested. Figure 4 shows the general block diagram of filtering method.

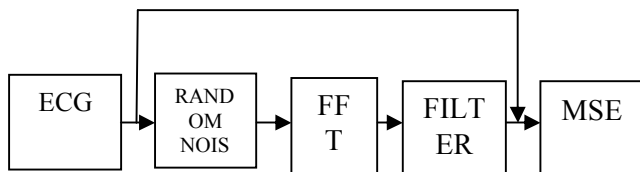


Fig. 4. Filtering Technique

B. The proposed method is based on decomposing the signal into three levels of wavelet transform by using different wavelet families and determining a threshold through a loop to find the value where minimum error is achieved between the detailed coefficients of thresholded noisy signal and the original.

The method can be divided into the following steps:

1- Noise Generation and addition: A random noise is generated and added to the original signal. Mathematically defined:

$$S(n) + X(n) = Xs(n)$$

where $S(n)$ is the random high pass noise, $X(n)$ is free of noise ECG and $Xs(n)$ is the noisy ECG signal.

2. Decomposing of the noisy and original signals using wavelet transform:

The noisy and original signals are decomposed into three levels by discrete wavelet transform using the different wavelet family.

3. Choosing and applying threshold value: 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.

4. Reconstruction:

The original signal is reconstructed using Inverse Discrete Wavelet Transform IDWR (Figure 5).

Thresholding of wavelet coefficients affects greatly the quality of ECG morphology, thus, threshold determination is very essential issue in this case. Two concepts are presented in study to accomplish high quality ECG signal reconstruction; threshold determination using above method and the idea of not to threshold the approximation coefficients of ECG signal. The approximation coefficients contain the low frequency of the original signal where most energy exists. Finally,

the root mean square error (MSE) is calculated to verify the improvement in the reconstructed signal.

Figure 5 below is the scheme for wavelet signal denoising:

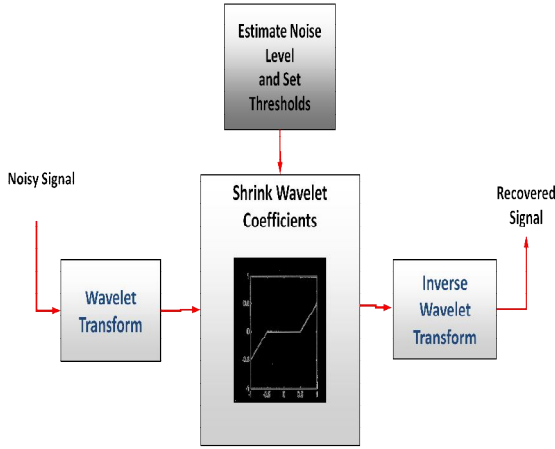


Fig. 5. Wavelet denoising scheme

VI. RESULTS AND DISCUSSION

In the proposed de-noising scheme, the ECG signal was created using a matlab function `ecg(512)`, after replicating the signal to obtain more data, noise was added to the clean signal. Filtering technique using butterworth and chebyshev type I was carried out. Thereafter, the decomposition of ECG signal was carried out using different wavelet families in order to find the effective and robust ECG denoising scheme, also reconstruction of the original signal was carried out. The effectiveness of proposed scheme was determined by the MSE. The result of each method was presented as shown in A to C.

A. Performance Analysis of Filtering Technique

Several numbers of filter orders were experimented with cut off frequency of 10Hz and sampling frequency of 1000Hz. The experiment was carried out using FDA tool in Matlab 2013 environment. Table 1 and 2 below gives the performance measure for Butterworth and Chebyshev filter type I with MSE as an estimation parameter.

Table I

Performance measure for Butterworth filter

S/N	ORDER(N)	MSE
1	2	0.2077
2	4	0.2401
3	6	0.2012
4	8	0.1814
5	10	0.1968
6	12	0.2117

Table II

Performance measure for Chebyshev filter

S/N	ORDER(N)	MSE
1	2	0.0799
2	4	0.3214
3	6	0.4031
4	8	0.3359
5	10	0.2971
6	12	0.3029

From the result above, Chebyshev type I filter performs better than Butterworth filter with MSE of 0.0799 against 0.1814 respectively.

B. Comparison on Wavelet Families for DWT Technique

As another experiment, different wavelet families are compared in terms of MSE. Table 3 gives the results of this comparison. According to the table, Bior2.6 and db10 outperforms other wavelets.

Table III

The performance comparison of wavelet families

Wavelet Name	MSE
Db2	0.0020
Db4	0.0014
Db7	0.0016
Db10	0.0013
Bior1.5	0.0037
Bior2.6	0.0012
Bior3.7	0.0016
Bior6.8	0.0014
Coif2	0.0014
Coif5	0.0015
Sym5	0.0015
Sym8	0.0014

C. Comparison of Filtering and DWT Techniques

Table 4 below shows the performance of ECG denoising using filtering technique and DWT technique. From the result, it was clearly seen

that DWT denoised ECG signal better and clear and shows good performance compared to digital filters.

Table IV

Performance measure for Filtering and DWT technique

S/N	METHOD	MSE
1	Butterworth	0.1814
2	Chebyshev	0.0799
3	DWT	0.0012

Figure 6 below shows the ECG signal before and after applying wavelet ECG denoising scheme.

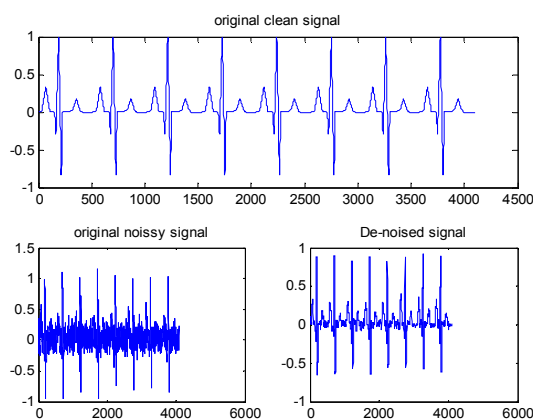


Fig. 6. ECG signal before and after denoising using DWT

VII. CONCLUSION

In this work the design and performance analysis of denoising ECG signal techniques was carried out for the reduction of noise in order to make the ECG signal cleaner and better interpretable by human or machine observer using digital filters and DWT technique. From the results presented wavelet prove itself as a powerful transform for denoising signals in which the mean square error of 0.0012 was found as compared to 0.0799 and 0.1814 for Chebyshev and Butterworth filters respectively. Therefore, Wavelet transform is more suitable for analyzing the pseudo periodic, non stationary ECG signal. Still there is lot of scope of Wavelet transform to be used for analyzing ECG signal. The suitability of Wavelet transform in denoising ECG signal depends upon the proper selection of mother

wavelet. It is my hope that this work will be helpful especially for beginners who are interested to work in biomedical signal analysis.

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