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Analysis of Butterworth and Chebyshev Filters for ECG Denoising Using Wavelets

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Abstract: *A wide area of research has been done in the field of noise removal in Electrocardiogram signals.. Electrocardiograms (ECG) play an important role in diagnosis process and providing information regarding heart diseases. In this paper, we propose a new method for removing the baseline wander interferences, based on discrete wavelet transform and Butterworth/Chebyshev filtering. The ECG data is taken from non-invasive fetal electrocardiogram database, while noise signal is generated and added to the original signal using instructions in MATLAB environment. Our proposed method is a hybrid technique, which combines Daubechies wavelet decomposition and different thresholding techniques with Butterworth or Chebyshev filter. DWT has good ability to decompose the signal and wavelet thresholding is good in removing noise from decomposed signal. Filtering is done for improved denoising performence. Here quantitative study of result evaluation has been done between Butterworth and Chebyshev filters based on minimum mean squared error (MSE), higher values of signal to interference ratio and peak signal to noise ratio in MATLAB environment using wavelet and signal processing toolbox. The results proved that the denoised signal using Butterworth filter has a better balance between smoothness and accuracy than the Chebvshev filter.*

Keywords*: Electrocardiogram, Discrete Wavelet transform, Baseline Wandering, Thresholding, Butterworth, Chebyshev*

I. Introduction

ECG signals are produced from human heart activities. Potential difference between two points on the body surface, versus time is represented graphically with the help of ECG. While recording ECG in a clinical environment it is usually contaminated by baseline wandering due to respiration, power line interference, poor-electrode contact, muscle contraction noise and patient movement. So removal of these noises is necessary in ECG analysis for correct diagnosis.

The main aim of this paper is to remove common noise caused by baseline wandering. Patient movement, bad electrodes and improper electrode site preparation etc. are the main causes of baseline wandering. Baseline wander's range is usually below 0.5Hz which is similar to the ST segment frequency range. The assessment of ST deviation becomes difficult due to baseline wander. A normal ECG can be decomposed in to various components, named P, Q, R, S and T waves. Each of mentioned components has its own typical behavior. A typical one-cycle ECG tracing is shown in Fig.1.

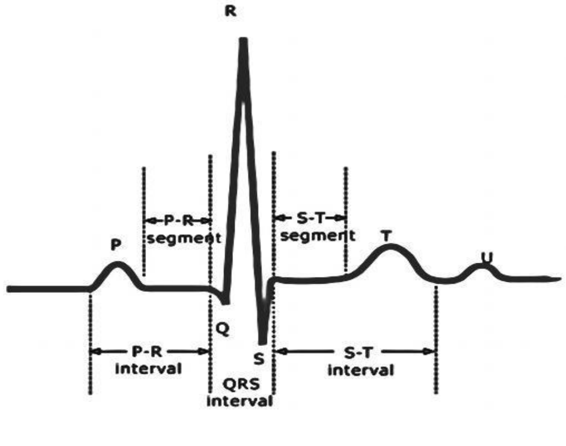

Figure.1 ECG Waveform [1]

Up to now many methods of removing the baseline wander are proposed. A classical method using high pass filter removes very low frequency component from ECG recording [2]. Linear filtering is also performed for removing baseline wander from ECG signals in the frequency range of 0.5Hz [3]. A ringing effect (Gibbs phenomenon) is introduced by this method on the ECG signal analysis [4]. In order to overcome this limitation, polynomial fitting (PF) or cubic spline filter came in to existence. This method includes cubic spline approximation and subtraction technique, which consists off baseline estimation with polynomial or cubic spline and then subtracting it from disturbed signal. [5]. 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 [6-7]. In this work DWT based denoising is performed . Daubechies wavelet function (db4) and four thresholding rules are considered along with Butterworth or Chebyshev filters to analyse the efficiency of noise removal from ECG signals.

II. WAVELET TRANSFORM

A multiresolution property is associated with wavelet transform to give both time and frequency domain information in a simultaneous manner through variable size window. The DWT of a signal "x" is calculated by passing it through a series of filters i.e low pass and high pass filters. The inner product of the signal $x(t)$ and the wavelet function $\psi_{m,k}$ provides a set of coefficients $X_{DWT}(m,k)$ for m and k by applying DWT on signal $x(t)$. DWT can be considered as one of the multi-rate signal processing systems that use multiple sampling rates in the processing of discrete time signals. The DWT of a signal x(t) is given by [8]:

$$X_{DWT_K} = \int_{-\infty}^{\infty} x(t) 2^{m/2} \psi(2^m t - k) dt \qquad \text{...(1)}$$

$$X_{IDWT}(t) = \int_{-\infty}^{\infty} \sum_{m=-\infty}^{m=\infty} \sum_{k=-\infty}^{k=\infty} X_k^m 2^{m/2} \psi(2^m t - k) dt \qquad \text{...................................... (2)}$$

Where $\psi_{m,k}$ is the wavelet function. The discrete wavelet transform of a signal $x(t)$ is calculated by passing it through a series of filters namely low pass filter (LPF) and high pass filter (HPF). The coefficients associated with low pass filter is called approximation coefficients and high pass filtered coefficients are called detailed coefficients. Further the approximation coefficients are divided in to new detail and approximation coefficients. This decomposition process is carried out until the required frequency response is achieved from the given input signal. Fig.2 represents the multilevel decomposition.

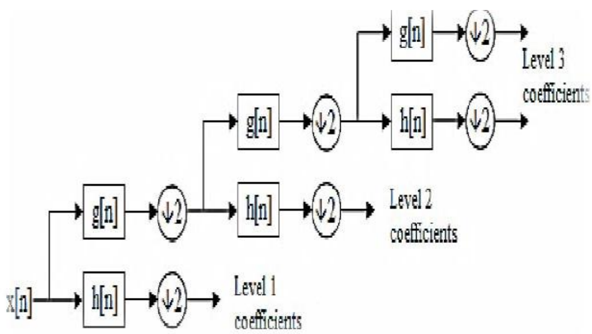

Figure.2 DWT multilevel decomposition[1]

2.1 Wavelet Thresholding

2.1.1 Hard and Soft Thresholding

A kind of signal estimation technique called wavelet thresholding have signal denoising capabilities. Wavelet shrinkage operation is categorized in to two thresholding methods Hard and soft. Performance of thresholding purely depends on the type of thresholding method and the thresholding rule used for the given application. In hard thresholding the coefficients smaller than the threshold are vanished and the other ones are kept unchanged. However, the soft thresholding makes a continuous distribution of the remaining coefficients centered on zero by scaling them. The hard threshold function wht is unstable (sensitive even small changes in the signal) and soft thresholding function wst is stable as shown in eq (3) and (4):

$$w_{ht} = \begin{cases} w & |w| > t \\ 0 & |w| < t \end{cases} \qquad \text{...(3)}$$

$$w_{st} = \begin{cases} [sign(w)](|w| - t), & |w| \geq t \\ 0 & |w| < t \end{cases} \quad \text{……………………(4)}$$

However, the stability of soft thresholding function is much better than the hard thresholding and it tends to have a bigger bias due to the shrinkage of larger wavelet coefficients.

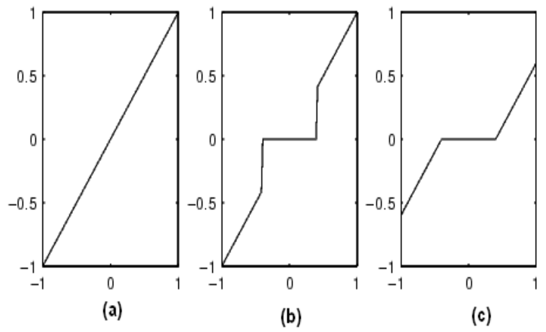

Figure.3 (a) original signal (b) Hard Threshold signal (c) soft threshold signal[9]

2.1.2 Thresholding Rules

Donoho has initially proposed denoising of signals and images based on fixed thresholding [10]. Here, the value of threshold (t) is computed as:

$$t = \sigma\sqrt{2\log(n)/n} \quad \text{……………………………………..(5)}$$

Where $\sigma = \frac{MAD}{,6745}$

MAD represents the median of wavelet coefficients and n is the total number of wavelet coefficients. There are four types of thresholding rules mostly used by different researchers on denoising applications [11].

Global Thresholding

This can be considered a type of fixed threshold or global thresholding method and it is computed as:

$$wt_q = \sqrt{2\log n} \quad \text{…………………………………………………………..(6)}$$

Where n represents the total no of wavelet coefficients. In this method log value of the length of wavelet coefficients provides a minmax performance.

.**Rigrsure Thresholding**

It depends on the Stein's unbiased estimate of risk. In this rulee risk estimation for a particular threshold value is done. It is an adaptive thresholding method which is proposed by Donoho and Jonstone and It is based on Stein's unbiased likelihood estimation principle [12].

Heursure Thresholding

When SURE AND global thresholding methods are combined together, a new rule is formed named as Heursure threshold rule. SURE estimation method becomes worthless if the signal-to noise ratio of the signal is very poor, then it will show more noises. In this kind of situation, the fixed form threshold is selected by means of global thresholding method.

Minimax Thresholding

Minimax threshold yields minmax performance for Mean Square Error (MSE) against ideal procedures. Minmax threshold also behaves as fixed threshold. This method does the job of obtaining a minimum error between original signal and wavelet coefficients of noise signal and depending on it selects a threshold value.

III. ECG FILTERING

3.1 Butterworth Filter

Butterworth filters are having a property of maximally flat frequency response and no ripples in the pass band. It rolls of towards zero in the stop band. It's 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 comparing 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 it's pass band is accompanied with a more linear phase response in comparison to chebyshevtype I/type II and elliptic filter.

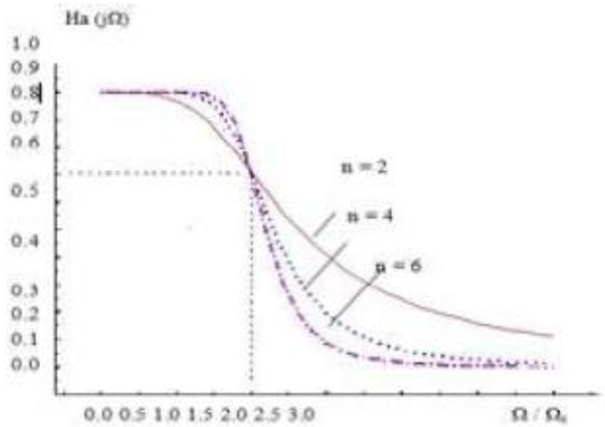

Figure.4 Frequency response of Butterworth filter

3.2 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 reduces the error between idealized and actual filter characteristics over the range of fllter but drawback they face is the ripples in the passband[13].

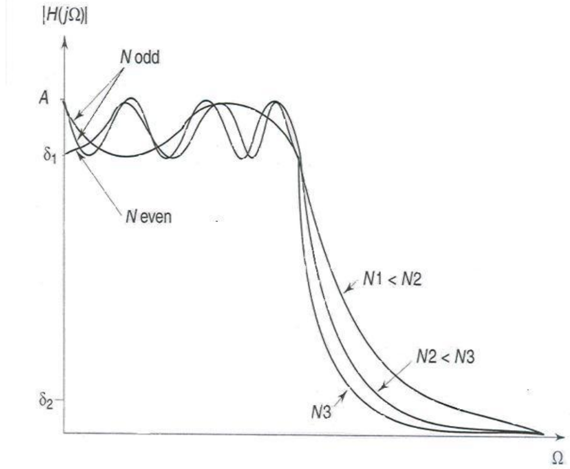

Figure.5 Magnitude response of a low pass Chebyshev TypeI filter

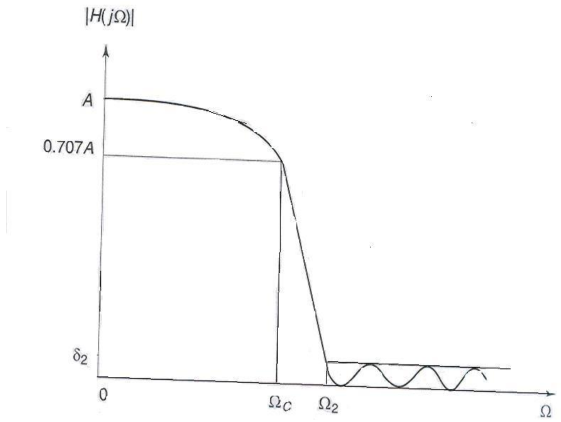

Figure.6 Magnitude response of a low pass Chebyshev Type II filter

IV. PROPOSED DENOISING METHODS AND RESULTS

In this paper Daubechies wavelet (db4) with a decomposition tree of level 4 is used because it can provide a well orthogonality to high frequency noise with a given number of vanishing moments. Record no.

300 from non-invasive fetel electrocardiogram database (nifecgdb) has been taken, which is sampled at a rate of 1 kHz with 16 bits resolution. The noise signal of 0.2 Hz frequency has been generated in MATLAB environment and then added to original ECG database to make a noisy signal. The simulated noise corrupted signal has been implemented using wavelet for proper feature extraction.

To do this job firstly we decompose the signal at level 4. For each level from 1 to 4, a threshold rule is selected and soft or hard technique is applied to detailed coefficients. Signal reconstruction is done based on the original approximation coefficients of level 4 and modified detailed coefficients of levels from1 to 4. Noisy signal is also denoised automatically by MATLAB function wden. Now further getting improved performance of automatically and manually denoised signals, filtering is performed. Butterworth and Chebyshev filters are applied for comparison. For butterworth filtering initially a high pass butterworth filter of order 1 and normalized cut off frequency 0.3 is taken and applied to automatically and manually denoised signals. Then again a butterworth low pass filter of same order and normalized cut off frequency 0.15 has been designed and applied to high pass filtered manually and automatically denoised signals.

Similarly for comparison a chebyshev high pass filter of order 1 and normalized cut off frequency 0.6 is designed and applied to automatically and manually denoised signals. Again a achebyshev low pass filter of order 1 and normalized cut off frequency 0.15 is designed and applied to high pass filtered manually and automatically denoised signals.

Different statistical tools like signal to interference ratio (SIR), mean square error (MSE) and peak signal to noise ratio (PSNR) are used to evaluate the performance of denoising. Table 1 shows the result of denoising using Chebyshev filter. Here after wavelet decomposition, thresholding is performed on detailed coefficients. For this a thresholding rule is selected from heursure, rigrsure, minimaxi and sqtwolog and hard or soft technique is applied for automatic or manually denoised signals. Table shows the result of denoising using Daubechies and Butterworth/Chebyshev filters.

V. MATLAB BASED SIMULATIONS

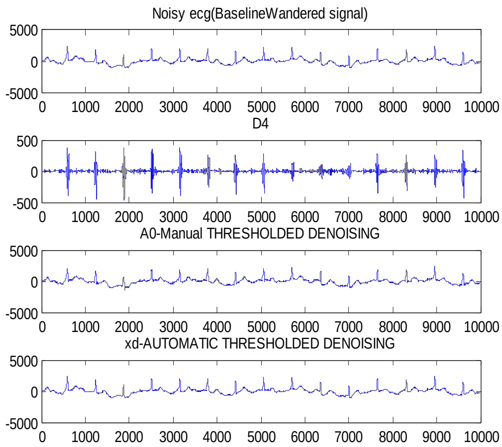

Figure.7 Rigrsure, soft thresholded denoised signal

Fig.7 represents the waveforms for baseline wandered noisy signal and automatically/manually thresholded denoised ECG signals by selecting rigrsure rule and soft thresholding method.

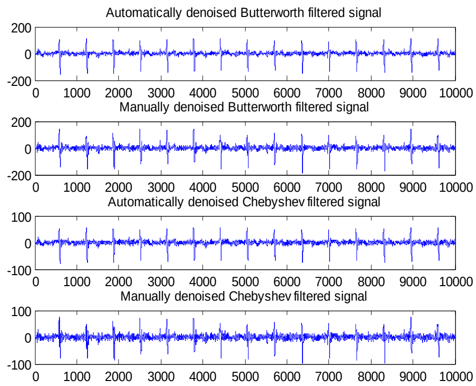

Figure.8 Rigrsure, soft thresholded and filtered signal

Fig.8 represents the simulated waveforms after filtering. This filtering is done after performing the wavelet thresholded denoising. Butterworth and Chebyshev filters are used for this denoising.

We observe from above waveforms that after filtering baseline-wander are removed and ECG signal comes to its original baseline.

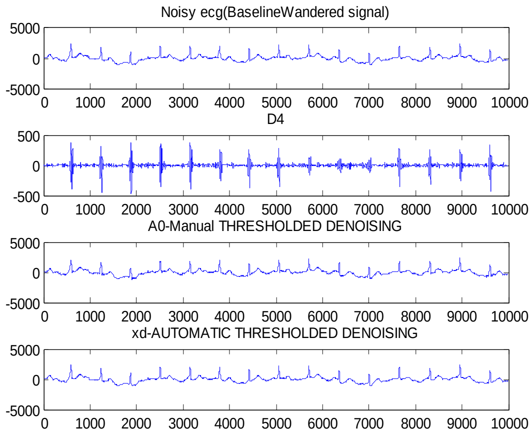

Figure.9 Minimax soft thresholded signal

Fig. 9 also indicates the noisy ECG and manually/automatically thresholded denoised ECG signals by selecting minimax rule and soft thresholding method. Fig. 10 indicates the Butterworth and Chebyshev filtered signal after wavelet thresholded denoising using minimax rule.

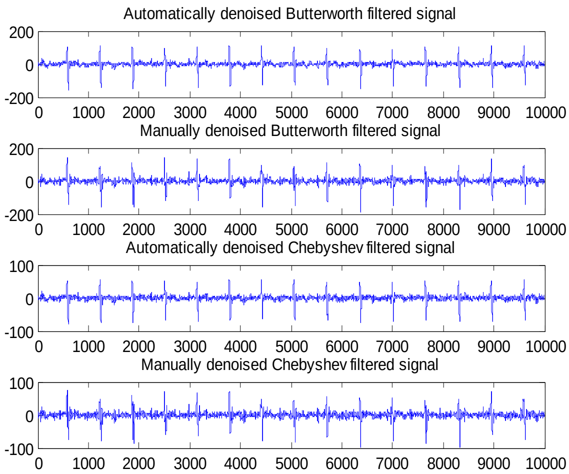

Figure.10 Minimax soft thresholded and filtered signal

VI. PERFORMANCE ESTIMATION PARAMETERS

6.1 Mean square error:

It is a performance function of a network. It is given as:

$$MSE = \sum \frac{(I_1 - I_2)^2}{m \times n} \quad \ldots\ldots (7)$$

Where I_1 is the raw data before denoising and I_2 is the denoised data.

6.2 Peak signal to noise ratio:

$$PSNR = 10 \log_{10} \frac{R^2}{MSE} \quad \ldots\ldots (8)$$

Where R is the maximum fluctuation in the raw input signal.

6.3 Signal to interference ratio:

It is ratio of amplitude of input signal before denoising and amplitude of noise removed through denoising.

Table. 1 Denoising using DWT and Chebyshev/Butterworth Filters

FILTER TYPE			CHEBYSHEV			BUTTERWORTH		
			MSE	**PSNR(db)**	**SIR**	**MSE**	**PSNR(db)**	**SIR**
Heursure	**Soft Threshold**	**Auto**	14.7526	55.6905	1.0012	14.7363	55.6953	1.0029
		Manual	14.7525	55.6905	1.0011	14.7362	55.6953	1.0025
	Hard Threshold	**Auto**	14.7265	55.6905	1.0012	14.7363	55.6953	1.0029
		Manual	14.7525	55.6905	1.0011	14.7362	55.6953	1.0025
Rigrsure	**Soft Threshold**	**Auto**	14.7526	55.6905	10012	14.7363	55.6953	1.0029
		Manual	14.7525	55.6905	1.0011	14.7362	55.6953	1.0025
	Hard Threshold	**Auto**	14.7526	55.6905	1.0012	14.7363	55.6953	1.0029
		Manual	14.7525	55.6905	1.0011	14.7362	55.6953	1.0025
Minimaxi	**Soft Threshold**	**Auto**	14.7525	55.6905	1.0012	**14.7361**	**55.6953**	**1.0029**
		Manual	14.7523	55.6905	1.0010	14.7361	55.6953	1.0024
	Hard Threshold	**Auto**	14.7526	55.6905	1.0012	14.7363	55.6953	1.0029
		Manual	14.7525	55.6905	1.0011	14.7363	55.6953	1.0025
Sqtwolog	**Soft Threshold**	**Auto**	14.7524	55.6905	1.0012	14.736	55.6953	1.0028
		Manual	14.7523	55.6906	1.0010	14.7361	55.6953	1.0024
	Hard Threshold	**Auto**	14.7526	55.6905	1.0012	14.7362	55.6953	1.0029
		Manual	14.7525	55.6905	1.0010	14.7363	55.6953	1.0025

Table 1 shows the result of denoising using Daubechies wavelet and Chebyshev/butterworth filters. In this table the bold values show the lower value of MSE and slightly higher values of SIR and PSNR. But there is not significant improvement in results. Both are giving almost similar results.

VII. Conclusion

In this paper Electrocardiogram denoising is performed using hybrid technique which is a wavelet thresholded denoising followed by butterworth or chebyshev filtering. This hybrid technique removes baseline wander noise and has good denoising capability. Results reveal that denoising performance of both butterworth and chebyshev filters are almost same. There is no significant difference between butterworth and chebyshev filters in terms of denoising, and denoising performance further can be enhanced by some other combination of hybrid techniques like wavelet transform and Savitzky-golay filter.

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