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ANALYSIS OF SAVITZKY-GOLAY FILTER FOR BASELINE WANDER CANCELLATION IN ECG USING WAVELETS

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ABSTRACT

Electrocardiogram (ECG) has always been the most basic useful and low cost tool for diagnosis. Various kinds of noises can contaminate the ECG signals which lead to incorrect diagnosis. In this paper a new method is developed for removal of baseline wander based on Daubechies wavelet decomposition using adaptive thresholding techniques and Savitzky-Golay filtering. Here ECG records are taken from non-invasive fetal electrocardiogram database, noise is generated using MATLAB instructions and added to original ECG signal. In fact DWT has the quality of better signal decomposition and thresholding has the ability of removing noise from decomposed signal. If we apply Savitzky-Golay filter further then preserving the peak it can smooth out the signal without much destroying its original property. In this paper we have done a comparative study between our proposed method and conventional wavelet method consisting only Daubechies wavelet decomposition along with thresholding techniques. This comparison is done by evaluating different statistical parameters like mean square error (MSE), signal to interference ratio (SIR) and peak signal to noise ratio (PSNR).

KEYWORDS: *Electrocardiogram, baseline-wander, Savitzy-Golay filter, Thresholding, Wavelet Transform*

I. INTRODUCTION

During recording of electrocardiogram signal, baseline wander is the main classical problem which comes in to existence. It mainly occurs due to patient movement. Baseline wander usually has low frequency range which is below 0.5 Hz and very similar to ST segment frequency range. Up to now various methods of baseline wander removal from ECG have been developed. Infinite Impulse Response (IIR) is proposed by many of the researchers to remove the effects of baseline wander form ECG signals [1,2]. However IIR filter design is simple but they are not suitable to filter highly non-linear signals in the entire ECG range because they require increased memory and high filtering time. Other methods like adaptive filtering methods are also used for suppression of power line interference and other noises from ECG signals [3,4,5]. This method has the advantage of small residual errors and fast filtering response [6]. The drawback of this method is that it requires either signal or noise characteristics information as a reference signal. Temporal averaging filtering is a new technique for efficient noise removal but large numbers of time frames are required for it. Removing noise from physiological signals, Independent component analysis is also preferred but ICA does not need prior information about the signal [7]. Linear filtering is used by most researchers for baseline wander removal but Gibbs phenomenon is introduced on ECG signal by this method[8]. Further polynomial fitting or cubic spline filter is proposed for baseline wander removal and to overcome the above mentioned problem. Recently wavelet transform has been proven to be a useful tool for non-stationary signal analysis [9,10]. Plain FIR average filter impose limits on their use for removing noise. A high degree of noiseless signal can be achieved on the condition of requiring large filter length so that filter's pass band becomes smaller than the signal bandwidth. By doing this useful high frequencies from the desired signal are removed. If we consider ECG, s(n)= x(n)+v(n),where x(n) is the actual ECG signal and v(n) is the noise. If noise signal v(n) is attempted to smooth out, the filter begins to smooth out the desired signal x(n) to an undesirable scale. Another category of filter which are generalizations of FIR filter can preserve better the high-frequency content of the desired signal and known as polynomial smoothing, or least-squares smoothing filters[11]. If this polynomial smoothing filter called Savitzky-Golay filter is combined with Discrete wavelet decomposition then high degree of denoising performance can be achieved.

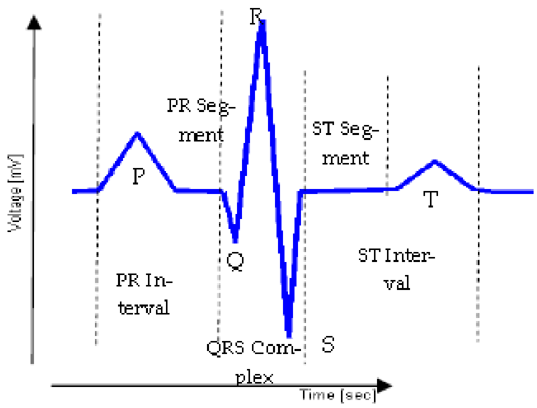

Figure1. An idealized ECG waveform [12]

II. WAVELET TRANSFORM

The Fast Fourier Transforms (FFT) decomposes the signal into an infinite length of sine and cosine functions. However, the time-domain information is lost and only spectral information in the frequency domain is provided and vice-versa. This drawback can be overcome by Short Time Fourier Transform (STFT) as it represents the signal in both time and frequency domains using moving window function. A constant size window is preferred for this method and therefore it does not give multi resolution information of the signal. However, both time and frequency domain information through variable size window is provided by wavelet transform in a simultaneous manner as the wavelet transform holds the property of multi resolution. Scaled and shifted version of mother wavelet (a signal with tiny oscillations) gives the wavelet transform. The mother wavelet DWT is expressed by [13]:

$$\psi_{ab}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{a}\right) a,\ b \in R,\ a>0, \qquad (1)$$

Where, 'a' is the scaling and 'b' is the shifting factor. R is the wavelet space. The mother wavelet must satisfy the condition of admissibility as sown in eqn.2.

$$C_\psi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)^2|}{\omega} d\omega \le \infty \qquad (2)$$

Where, ψ (ω) is the Fourier transform of the mother wavelet function $\psi_{a,b}$ (t).

In this paper Daubechies wavelet is used for decomposition of a signal in time-frequency scale plan. Daubechies wavelets, discrete wavelet transform come under a family of orthogonal wavelets and having the characteristics of maximal number of vanishing moments.

Denoising using wavelets involves decomposition of a signal at level N by selecting a particular wavelet function. Then a denoised version of input signal is obtained by thresholding the detailed coefficients for each level from 1 to N using a threshold rule and applying hard or soft thresholding methods.

In hard thresholding the coefficients having absolute value lower than the threshold tent to zero. In this thresholding signal value is x if x>thr, and is 0 if x<=thr. Soft thresholding has nice mathematical properties and it is an extension of hard thresholding, Soft thresholding makes the coefficients zero whose absolute values are lower than the threshold, and then shrinks coefficients having non-zero value towards 0. The soft threshold signal is sign(x)(x-thr) if x>thr and is 0 if x<=thr. There are various types of thresholding rules mentioned as below.

2.1 Thresholding Rules

2.1.1 Rigorous Sure Threshold (RST):

By this rule estimate of the risk for a particular threshold value t is achieved and it is based on Stein's unbiased risk estimation. A threshold value is selected by minimizing the risks in t.

2.1.2 Universal Threshold(UT):

This is proposed by Donoho and it is used as an alternative to minimax threshold. It's value is proportional to a small factor multiplied by the log (length(x) [14]. {Wavelet distortion measurement}

$$Th = \sigma\sqrt{2 * \log(length(x))}$$

Where Th is the threshold value, σ is the median absolute deviation with respect to time and x is the noisy signal.

2.1.3 Heuristic Sure threshold:

'heursure' is a synthesis. If we get a very small value of signal to noise ratio then SURE estimate becomes noisy and give bad results. If this type of situation exists then fixed form threshold is used.

2.1.4 Min-max threshold:

'Mnimaxi' yields a minmax performance for a mean square error against an ideal procedure using a fixed threshold. In statistics for designing estimators minmax principle is frequently used. Minimum of the maximum mean square error obtained for the worst function in a given set is obtained by the minmax estimator.

III. BASELINE WANDER CANCELLATION USING SAVITZKY-GOLAY FILTER

Baseline wander is a common phenomenon in biomedical electric recordings. In baseline wander, baseline drifts from its original position with respiration representing a sinusoidal component at the frequency of respiration, which is added to the ECG signal. Respiration also varies the amplitude of ECG signal by about 15 percent. By performing amplitude modulation of the ECG by sinusoidal component added to the ECG signal this variation could be reproduced. Fig. 2 shows an example of baseline wandering effect on ECG signal. Usually during normal breathing condition the range of baseline wander has an upper limit less than 1 Hz. However, the upper limit may be larger when any kind of exercise is being performed by patient. The transient baseline also changes with patient movements showing a resemblance with one cycle of a sine wave having duration of 100 to 500ms and a frequency range from 2 to 10 Hz.

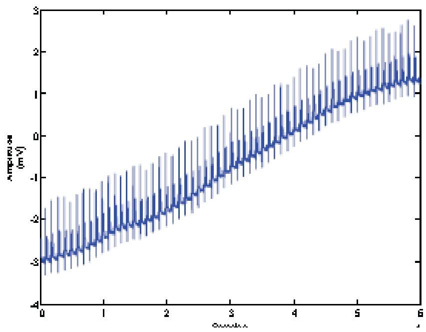

Figure 2. A recorded ECG signal distorted by baseline wandering [15]

S-G filters does the job of smoothening the noisy data by performing a least square fitting of a frame of data to a polynomial of given degree. The degree indicates the order of a polynomial up to which fitting of each frame of data is done and the number of samples used to perform the smoothing for each data point is represented by frame size. A noisy signal whose frequency span without noise is large is usually smoothed by S-Golay filters. In this type of application, standard averaging filter can't perform much better because they have the tendency to filter out a significant portion of the signal's high frequency content along with the noise. Thus S-Golay filters are preferred in such type of applications. The peak preservation property of S-Golay filters has found attractive application in electrocardiogram processing. Standard averaging filters are more powerful at rejecting noise in comparison to S-Golay filters. In Fig. 3 a numerical experiment is performed using a 33 point smoothing filter, that is, $n_L = n_R = 16$. The first waveform represents a test function, which have six "bumps" of varying widths and all of height 8 units. The dotted curve is the underlying function used to generate the synthetic data. Gaussian white noise of unit variance is added to this function to make it noisy. The middle waveform of Figure 3 shows the smoothed waveform by a moving window average. The window extends 16 points leftward and rightward, for a total of 33 points. We see that the broadest bump is nicely smoothed by window of width 33 but at the cost of loss of height and increase of width of the narrower bumps. In the lower waveform smoothening is done with a Savitzky-Golay using the same 33 points width and degree M = 4. We observe that heights and widths are nicely preserved but at the cost of badly smoothing the broadest bump. This occurs due to the fact that the central positive lobe of the Savitzky-Golay filter coefficients fills only a fraction of the full 33 point width.

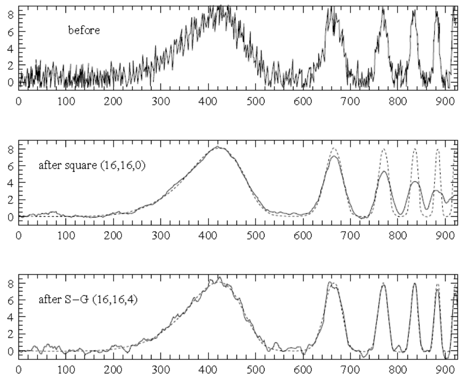

Figure.3 smoothening by moving average FIR and Savitzky- Golay filter [16]

In Fig.4 a numerical experiment is performed using a 65 point smoothing filter, that is, $n_L = n_R = 32$. Here smoothing is performed on the same noisy "data" using broader Savitzky-Golay filters of 3 different.

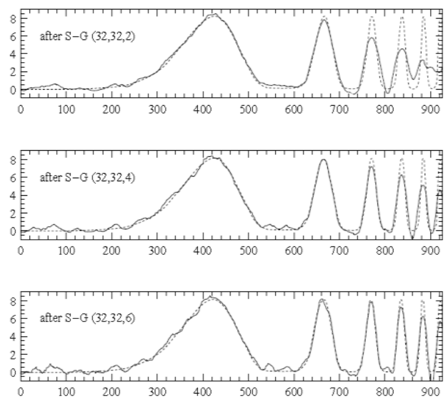

Figure 4. Smoothening by wider 65 point Savitzky-Golay filter of three different orders. M=2,4,6[16]

Orders M = 2, 4, 6. We observe that higher order filters perform best at preserving features heights and widths but at the cost of less smoothing on broader features. Savitzky-Golay filtering manages the job of smoothing without loss of resolution but within limits. It performs this task by considering some redundancy of distant data points that can be used to reduce the level of noise.

IV. PROPOSED DENOISING METHOD

In this work 20 ECG records are taken by non-invasive fetal electrocardiogram signal and sampled at a rate of 1 kHz with 16 bits of resolution. The noise signal of 0.2Hz frequency is generated in MATLAB environment and added to the original ECG database to make a noisy ECG signal. After that Savitzky-Golay FIR smoothing filter having polynomial order of 0 and frame size 15 is applied to noisy data. Then a smooth function (using MATLAB) is applied on filtered signal. It smoothes the data using moving average filter with a span of 230. Then best smooth signal is obtained by subtracting the earlier smoothed signal from S-Golay filtered signal. This smooth ECG signal is decomposed by Daubechies (db4) wavelet up to level 8 and denoised manually. To do this job first we decompose the signal at level 8. A threshold rule is selected and soft or hard technique is applied to detailed coefficients. Signal is reconstructed based on the original approximation coefficients of level 8 and modified detailed coefficients of levels from 1 to 8. Automatic denoising is also performed here. In this process detcoef (MATLAB function) is used which extracts the detailed coefficients at level 8 from wavelet decomposition structure. Then ddencmp (MATLAB function) is used by which default values are obtained for the general procedure related to denoising of smoothed ECG signal using wavelets. These values further can be used for wdencmp. Thus we are left with the denoised version of smoothed ECG signal obtained by wavelet coefficients thresholding using global positive threshold. This is our clean ECG signal.

In order to evaluate our method using Savitzky-Golay filter and comparing it with conventional wavelet method using db4 wavelet decomposition along with different thresholding rules, we have calculated peak signal to noise ratio(PSNR), signal to interference ratio(SIR) and mean square error (MSE). For better denoising performance PSNR and SIR values should be high and MSE value should be small. After denoising with proposed method these parameters are estimated as-

4.1 Parameters Estimation

4.1.1 MSE (Mean square error)

The squared norm of the difference between a signal s and it's approximation $\hat{s}$ divided by the number of elements in the signal give a measure of mean square error [17].

$$MSE=\frac{\|s-\hat{s}\|^2}{k} \tag{3}$$

4.1.2 PSNR (Peak Signal to Noise Ratio)

PSNR is the peak signal-to-noise ratio is measured in decibels (dB).The PSNR is only meaningful and can be defined for data encoded in terms of bits per pixel, or bits per sample. For example, an image with 8 bits per pixel contains integers from 0 to 255.

$$PSNR = 20\log_{10}\left(\frac{2^B-1}{\sqrt{MSE}}\right) \tag{4}$$

Where B represents bits per sample.

4.1.3 SIR(Signal to Interference ratio)

$$SIR = \sum_{i=1}^{n}\left(\frac{x(i)_{rawsignal}}{x(i)_{noisesignal}}\right) \tag{5}$$

Where, $x(i)_{rawsignal}$ represents amplitude of the input signal before denoising and $x(i)_{noisesignal}$ indicates amplitude of noise removed through denoising

V. RESULTS AND DISCUSSIONS

In this paper for ECG denoising we have compared our proposed method using Daubechies wavelet decompositin and S-Golay filter with the conventional wavelet method which includes only

Daubechies wavelet decomposition along with different thresholding techniques. A table showing SIR is manipulated for comparison purpose.

Table1. shows a comparison between SIR values obtained through conventional wavelet method and our proposed method. For conventional wavelet method SIR is tested on 20 real ECG signals sampled at a rate of 1 kHz and for our proposed method we have taken the ECG records from non-invasive fetal electrocardiogram database whose properties are similar to the earlier one.

By comparing the values of SIR for both methods we observe that there is an average allover significant improvement in the value of SIR using our proposed method.

Table 1. SIR table for comparison between conventional wavelet method and our proposed method

Data Set (Sample)	**Signal to Interference Ratio (SIR)**				**SIR by proposed method using automatic denoising**
	Db4[6]				
	Rigrsure	**Heursure**	**Sqtwolog**	**Minimaxi**	
1	1.91	2.3	2.29	2.2	1.2499
2	0.77	0.6	0.56	0.6	1.4269
3	0.95	0.9	0.82	0.9	1.9096
4	0.71	0.7	0.59	0.6	1.4716
5	0.87	0.9	0.7	0.8	1.5042
6	0.86	0.8	0.67	0.7	1.5529
7	0.8	0.8	0.69	0.8	1.8777
8	0.89	0.8	0.72	0.8	1.7878
9	1.22	1.3	1.52	1.4	1.2668
10	0.9	0.8	0.75	0.8	1.8268
11	1.2	1.3	1.5	1.4	1.7274
12	1.29	1.3	1.52	1.4	2.0141
13	0.8	0.6	0.54	0.6	2.0425
14	0.95	0.9	0.81	0.9	1.2244
15	0.72	0.7	0.58	0.6	1.0130
16	0.85	0.9	0.7	0.8	1.3586
17	0.83	0.7	0.58	0.7	2.0442
18	0.78	0.7	0.59	0.7	1.6086
19	0.91	0.8	0.71	0.8	1.4438
20	0.86	0.8	0.75	0.8	1.1465

Table2. shows the other parameters like mean square error(MSE) and peak signal to noise ratio (PSNR) for our proposed method using Daubechies wavelet decomposition along with Savitzky-golay filter. Bold values indicate highest values of SIR and PSNR and lowest values of MSE which is the required criterion for improved denoising performance.

Table 2. SIR ,PSNR and MSE table for proposed method (db4 wavelet decomposition with S-Golay filter)

Database file	**SIR**	**MSE**	**PSNR**
ecgca102_edfm..mat	1.2499	40.3585	49.8366
ecgac115_edfm.mat	1.4269	88.0791	70.8599
ecgca127_edfm.mat	1.9096	116.149	68.7969
ecgca154_edfm.mat	1.4716	29.5704	49.131
ecgca192_edfm.mat	1.5042	8.8005	56.3405
ecgca244_edfm.mat	1.5529	398.8643	64.2644
ecgca252_edfm.mat	1.8777	214.5697	66.8151
ecgca274_edfm.mat	1.7878	**0.1752**	77.7216

ecgca290_edfm.mat	1.5944	263.2262	63.6378
ecgca300_edfm.mat	1.2668	15.8942	54.5895
ecgca308_edfm.mat	1.8268	71.6286	70.197
ecgca323_edfm.mat	1.7274	74.2282	67.8506
ecgca368_edfm.mat	2.0141	3.6711	**84.3898**
ecgca384_edfm.mat	2.0425	37.1647	72.837
ecgca392_edfm.mat	1.2244	195.038	62.0274
ecgca410_edfm.mat	1.013	256.18	48.2757
ecgca416_edfm.mat	1.3586	100.5436	70.0188
ecgca436_edfm.mat	**2.0442**	66.5328	71.6837
ecgca444_edfm.mat	1.6086	578.8492	60.4863
ecgca445_edfm.mat	1.4438	21.9237	51.3595
ecgca473_edfm.mat	1.1465	672.2441	62.0337

VI. SIMULATED WAVEFORMS

Here we have used MATLAB 7.9.0.529 (R2009b) for simulation purpose. Figure 5 shows the simulated waveforms for record no.115. First waveform shows the original ECG record. Second waveform shows the noisy ECG record when baseline wandering of 0.2 Hz is added to original ECG record. Third waveform shows the result of automatic wavelet thresholded denoising using S-Golay filter. Fourth waveform shows the result of custom or manual denoising using savitzky-Golay filter and daubechies wavelet decomposition selecting soft threshold method and Rigrsure threshold rule.

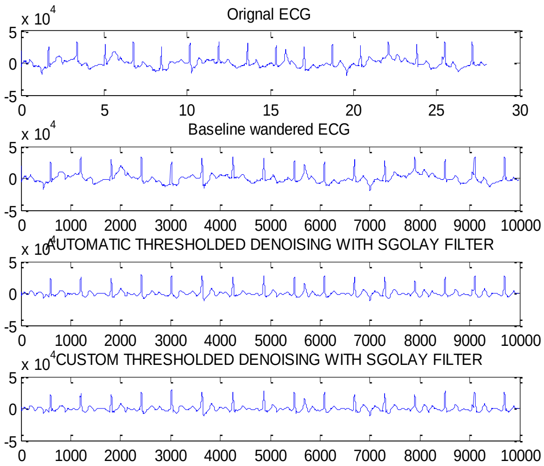

Figure 5 Simulated waveforms for Record 115

Figure.6 also shows the similar result for record no. 154. From these waveforms we have observed that our proposed method removes the baseline wander and baseline is shifted to its original position. Here manual denoising is done using Daubechies wavelet decomposition and Savitzky-Golay filter selecting soft thresolding method and heursure rule.

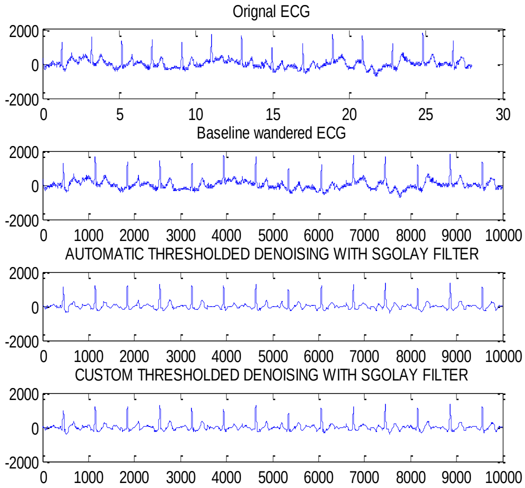

Figure 6 Simulated waveform for record 154

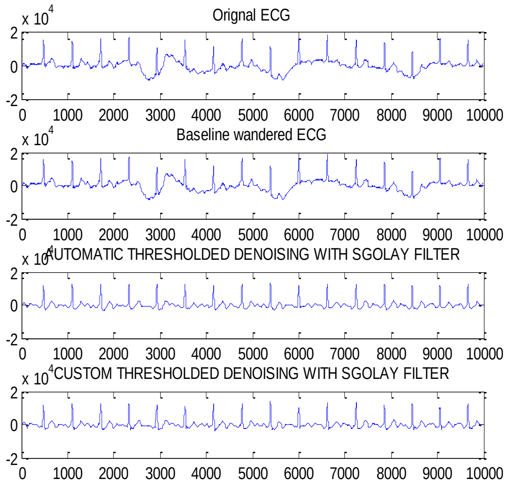

Figure 7 Simulated waveform for Record 392

VII. CONCLUSION

In this paper we have shown that a straightforward application of S-Golay filter along with wavelet denoising gives significant SIR improvements competitive with conventional wavelet denoising while causing noticeably less signal distortion. The proposed technique removes baseline wandering, while preserving the clinical information and the morphology of the ECG record. Unlike other baseline schemes our proposed method is an automatic method and there is no parameter needed to set before the starting of the method. Also the components of all wandering classes that are not correlated to ECG are removed by this method.

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