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Noise Removal from ECG Signal and Performance Analysis Using Different Filter

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Abstract: *This paper presents removal of noise from the ECG signal by using Digital filters designed with FIR and IIR technique. The analysis of ECG signal has great importance in the detection of cardiac abnormalities. The ECG signal is preserve of the electrical performance of heart versus time. ECG signal of a normal heart beat consists of a three parts P wave, QRS complex and T wave. The P wave reflect the activation of the right and left atria. The QRS complex shows depolarization of the activation of right and left ventricles. Results are obtained for the given order of the filter using windowing technique for the FIR filter. The wavelet transform is used to reduce the effect of noise to get refined signal. The power spectral density and average power, before and after filtration using different window techniques and wavelet utilization at 4 and 6 dB are compared. Order of the filter is also different. Filter with the Kaiser window shows the best result.*

Keywords: *ECG, FIR Filter, Windowing Technique, Wavelet Transform, power spectral density and average power*

1. Introduction

Interference occurs in ECG signal is very common and serious problems. Digital filter are designed to remove this limitation. FIR with different windowing method is used. The results are obtained at low order . The input signals are taken from ECG database which includes the normal and abnormal waveforms. FDA tool is used in MATLAB to design these filters [1]. Many times when ECG signal is recorded from surface electrode that are connected to the chest of patient, the surface electrode are not tightly in contact with the skin as the patient breath the chest expand and contract producing a relative motion between skin and electrode. This results in shifting of baseline which is also known as low frequency baseline wander. The fundamental frequency of baseline wander is same as that of respiration frequency. It is required that baseline wander is removed from the ECG before extraction of any meaningful feature.

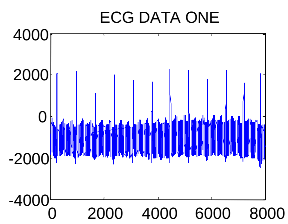

Fig1. *ECG data with 8000 samples on the conference website.*

Baseline wander makes it difficult to analyze ECG, especially in the detection of ST-segment deviations.

2. Filter Design Methods

2.1. Window Use in Designing

FIR filters can also be designed using the windowing method. The ideal filter have infinite number of samples in time domain given in equation 3. Windows are performed in order to have finite number of samples in time domain for reliable filter design.

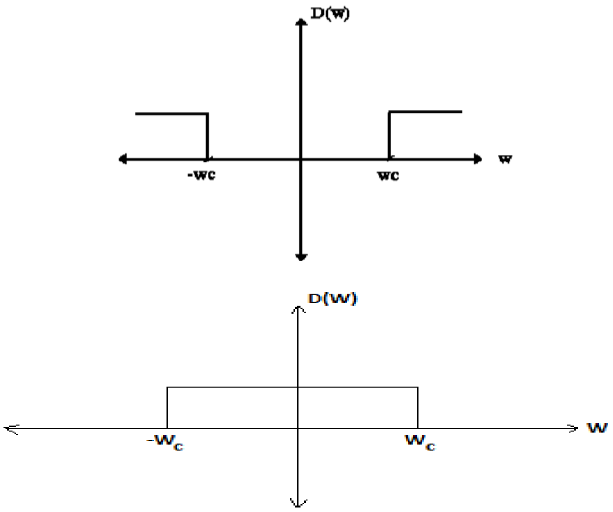

Fig4. *Magnitude response of an ideal window.*

A window function from –wc to wc is employed to show the windowing effect [15].

There are different windowing functions. The important window functions are rectangular window, Hamming, Hanning, Blackman windows[15].

2.1.1. Rectangular Window

The filter is required to have finite number of values within a certain interval, from -M to M. This is equivalent to multiplying d (k) by a rectangular function given by

$$w(n) = \begin{cases} 1, if|n| < M \\ 0, otherwise \end{cases} \tag{4}$$

2.1.2. Hamming Window

Discontinuties in the time function cause ringing in the frequency domain. The rectangular window is replaced by a window function ending smoothly at both ends which will cause reduction in ripples. The hamming window is an important window function. The hamming window is defined as:

$$w(n) = .54 - .46\cos\left(\frac{2\pi n}{N-1}\right), \quad n = 1,2,3,4......N+1 \tag{5}$$

Where N is the order of the filter and M is the window length. This equation defines the window samples as already shifted (indices from 0 to ‘N-1‘). So the impulse response of the FIR low pass filter designed using the hamming window is[15]:

$$h(n) = w(n).d(n-M) \qquad h(n) = \left(.54 - .46\cos\left(\frac{2\pi n}{N-1}\right)\right)\frac{\sin((n-M).wn)}{(n-M).\pi} \tag{6}$$

The ripples that occur in rectangular windowing in both the pass band and the stop band are virtually eliminated. Thus, the filtered data will have a wider transition width.

The Hamming window is defined mathematically as:

$$w(n) = .5 - .5\cos\left(\frac{2\pi n}{N-1}\right) \quad n = 0,1,2,3,4......N-1 \tag{7}$$

The difference of Hamming window is performed window function. This function is quite similar to the Hamming window.

2.1.3. Blackman Window

The Blackman window exhibits a lower maximum stop band ripple in the resulting FIR filter than the Hamming window. It is defined mathematically as:

$$w(n) = 0.45 + 0.5\cos\left(\frac{2\pi n}{N-1}\right) + 0.08\cos\left(\frac{4\pi n}{N-1}\right) \tag{8}$$

The width of the main lobe in the magnitude response is wider than that of the Hamming window.

2.1.4. High Pass Filter Design

The amplitude response of a low pass filter is shown in Fig. 5. Low pass filter is first applied, and with simple transformations the high pass filter can then be easily performed.

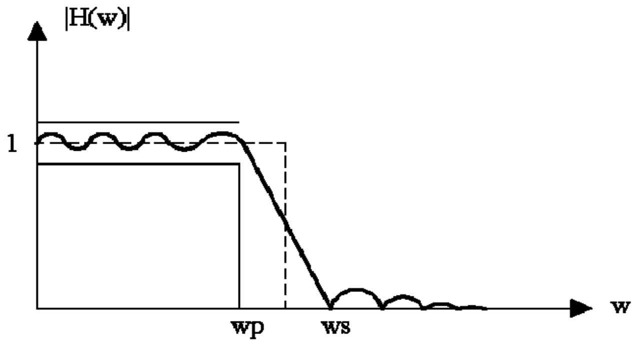

Fig5. *Magnitude response of a low pass filter.*

Pass-band and stop-band regions are illustrated with equation 9 and equation 10.

The derivation of the transformation is specified with the following equations:

$$wp = \frac{2\pi f_{pass}}{f_s}, ws = \frac{2\pi f_{stop}}{f_s} \quad \& \quad wc = \frac{2\pi f_c}{f_c} \tag{9}$$

The ideal cut off frequency, fc, is at the midpoint between the pass band and stop band edge frequencies set in equation 10 $f_c = \frac{f_{pass} + f_{stop}}{2}$ (10)

The transition width is defined as:

$$\Delta f = f_{stop} - f_{pass} \tag{11}$$

Since the role of f_{pass} and f_{stop} are interchanged in order to design high pass filter. The ideal high pass impulse response is obtained from the inverse Fourier transform of the ideal high pass frequency response. It is specified by equation 12:

$$d(k) = \delta(k) - \sin\left(wc.k\right)/\pi k \tag{12}$$

The windowed filter impulse response is:

$$h(n) = w(n)\left[\delta(n-M) - \frac{\sin[(n-M).w_c]}{(n-M)}\right]$$

$$h(n) = \delta(n-M) - w(n)\frac{\sin[(n-M).w_c]}{(n-M)\pi} \tag{13}$$

2.2. IIR Filter Design

An IIR filter is one whose impulse response theoretically continues for ever because the recursive terms feedback energy into the filter input and keep it as specified in the following equation:

$$y(n) = \left[\sum_{k=1}^{N} a(k).y(n-k) + \sum_{k=0}^{M} b(k).x(n-k) \right]$$

$$H(z) = \frac{\sum_{k=0}^{M} b(k) z^{-k}}{\sum_{k=0}^{N} a(k) z^{-k}} \tag{14}$$

The theory of Butterworth function is explained here but, the order of the filter should be high and implementing a filter of that order is not easy to perform. In addition to this difficulty, solving these high order equations is not straightforward.

2.3. Wavelet

A wavelet [11] is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

As wavelets are a mathematical tool they can be used to extract information from many different kinds of data, including - but certainly not limited to – audio signals and images. Sets of wavelets are generally needed to analyze data fully.

3. Results and Conclusion

In this paper various noise removal techniques are applied to ECG signals[10], ECG database data sample, and the performance of these approaches are studied on the basis of spectral density and average power of signal. In the first step, the most simple approach which is linear trend or a piecewise linear trend to remove baseline drift is applied after that various digital filters are applied to the noisy ECG data having Baseline noise as shown in fig 4.1 then the wavelet approach is used for overall denoising of ECG signal and finally the digital filter is applied on the sample ECG signal to remove Power line noise. All of the above steps are performed using MATLAB software

3.1. Calculation of Parameters

The two important parameters to check the suppression of Baseline noises are spectral density and average power of signal [6].

3.2. Power spectral density

Table1. *Comparison of various filters for Removal of noise at ECG sample input 1.*

Filter	Filter Order	Spectral Density before Filtration	Spectral Density after Filtration	Wavelet output at 4dB	Wavelet output at 6dB
Hanning	450	61.0009	55.9501	55.9431	55.9465
Kaiser	450	61.0009	53.3143	53.3014	53.3075
Rectangular	450	61.0009	53.3131	53.3002	53.3063
Chebyshev	2	61.0009	52.6343	52.6217	52.6286
Eleptic	2	61.0009	52.6402	52.6276	52.6345

Table1 and 2 shows the comparison of different filters. The trade-off between spectral density and average power is best among all the filters.

Spectral density of data 1 using different filters is shown as follows:

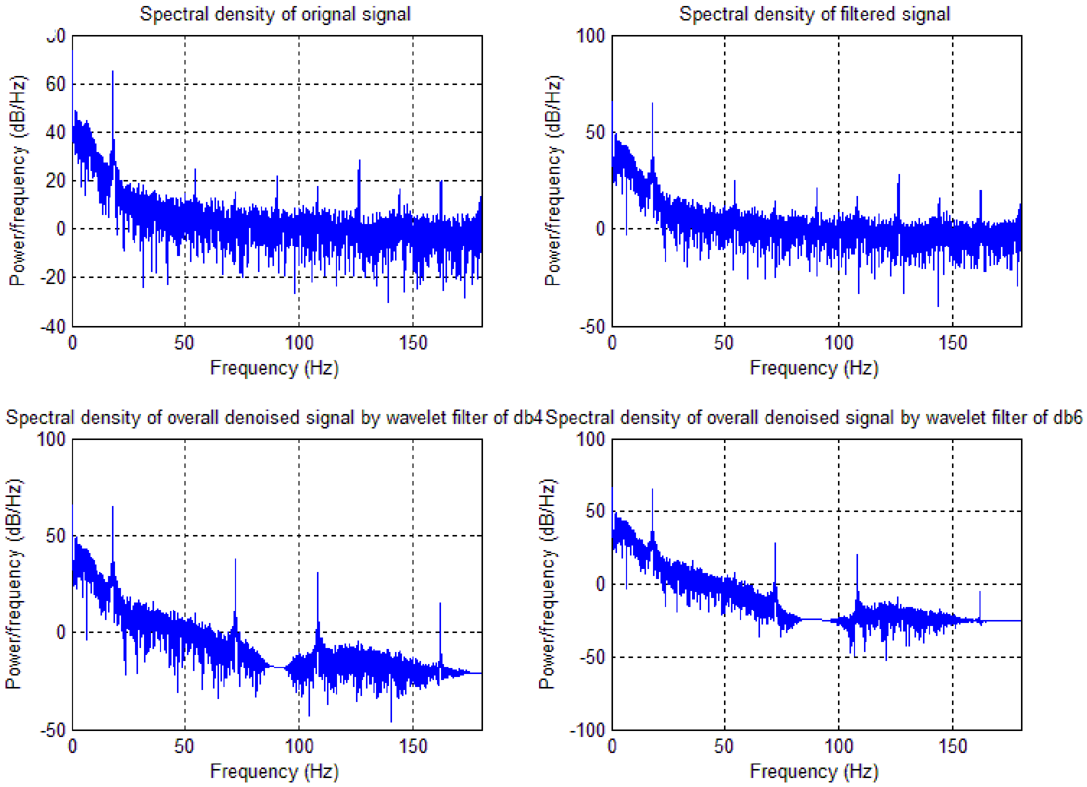

Fig6. *Spectral Density using Hanning filter Fig.6 Spectral Density using Hanning filter*

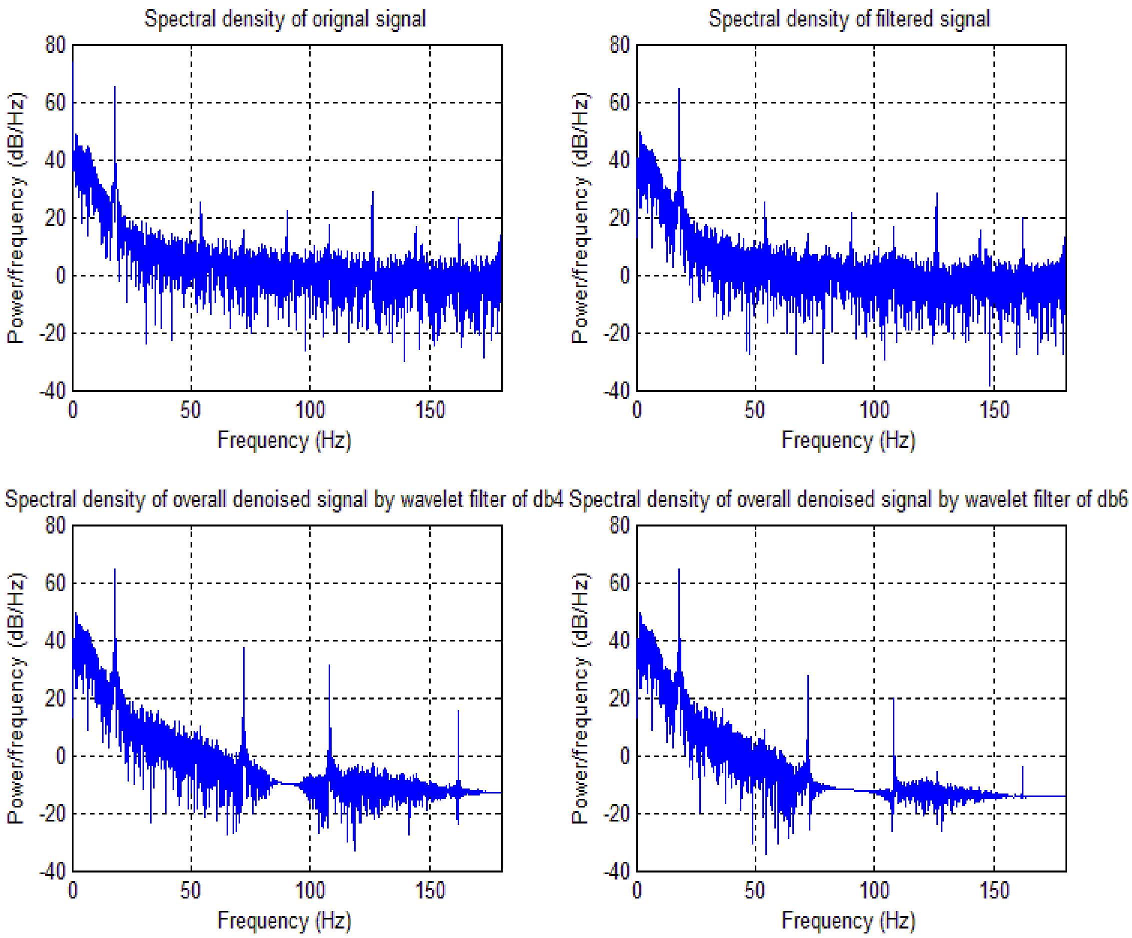

Fig7. *Spectral Density using Kaiser Filter*

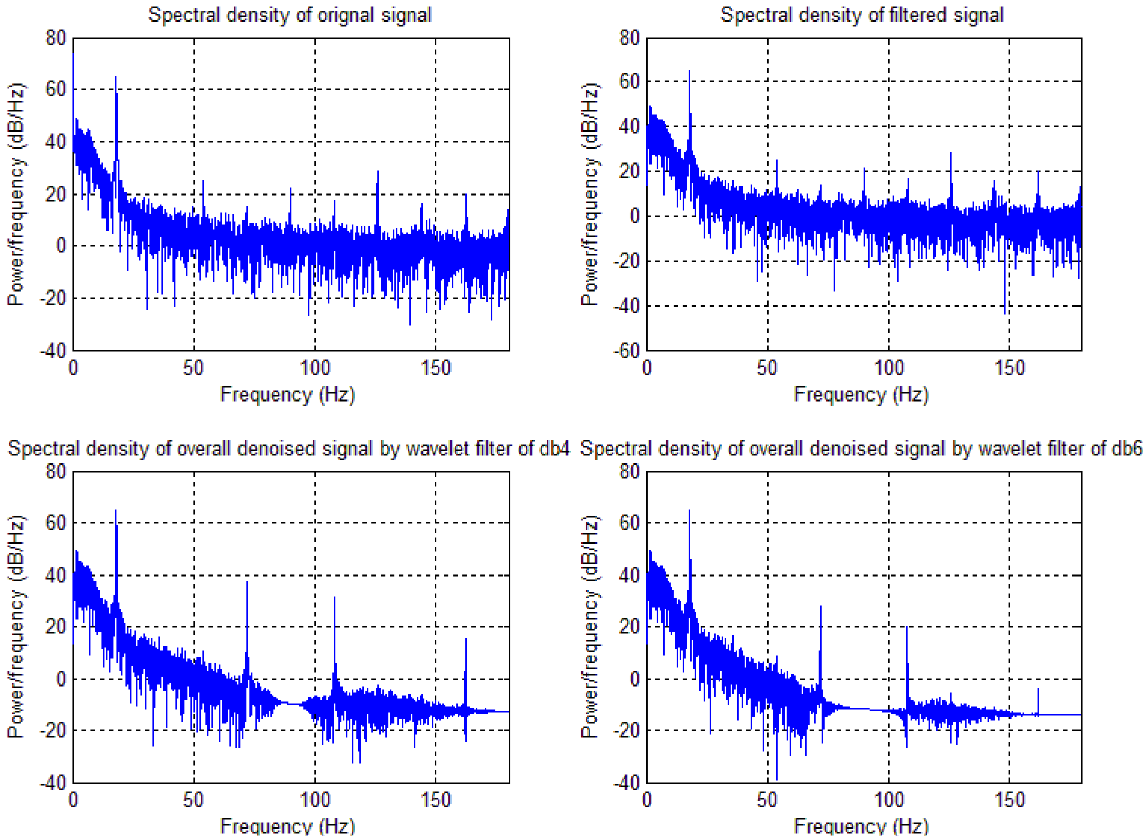

Fig8. *Spectral Density using Rectangular filter*

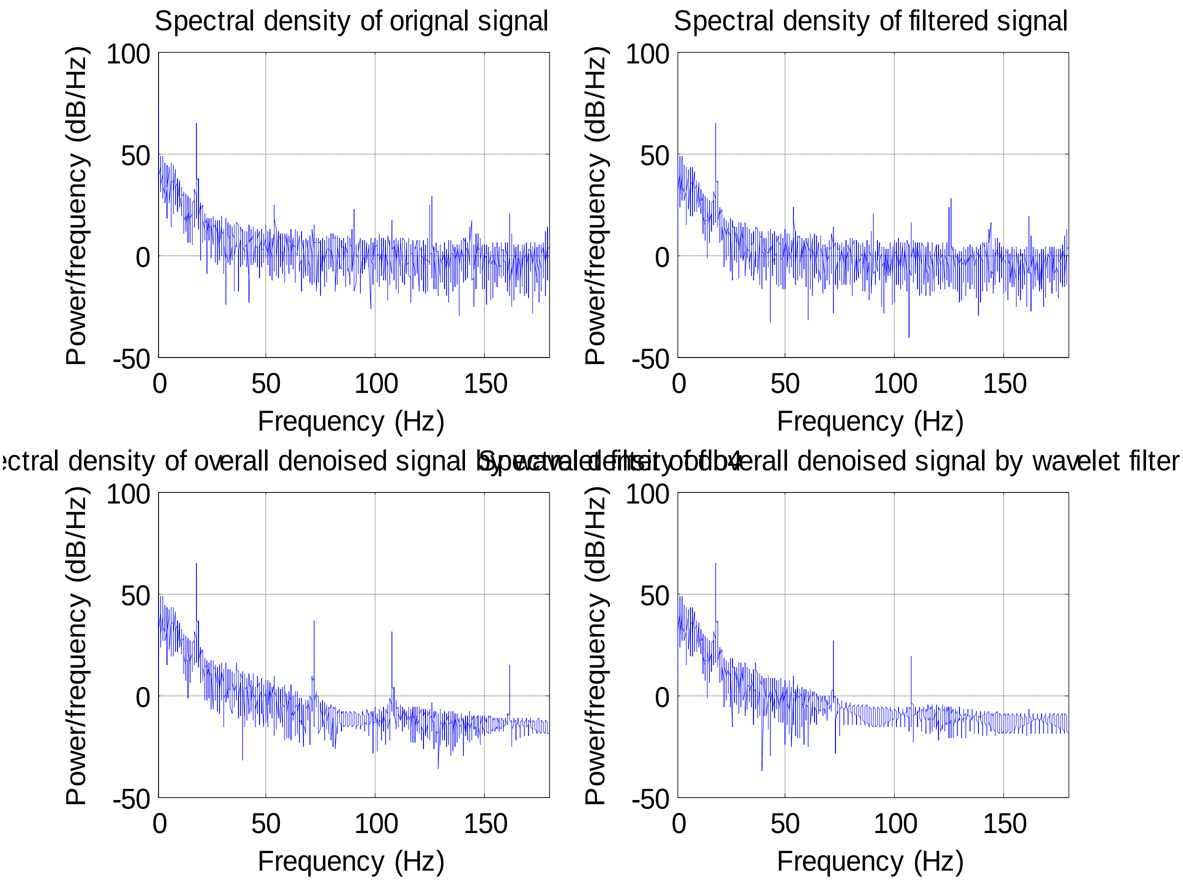

Fig9. *Spectral Density using chebyshev filter*

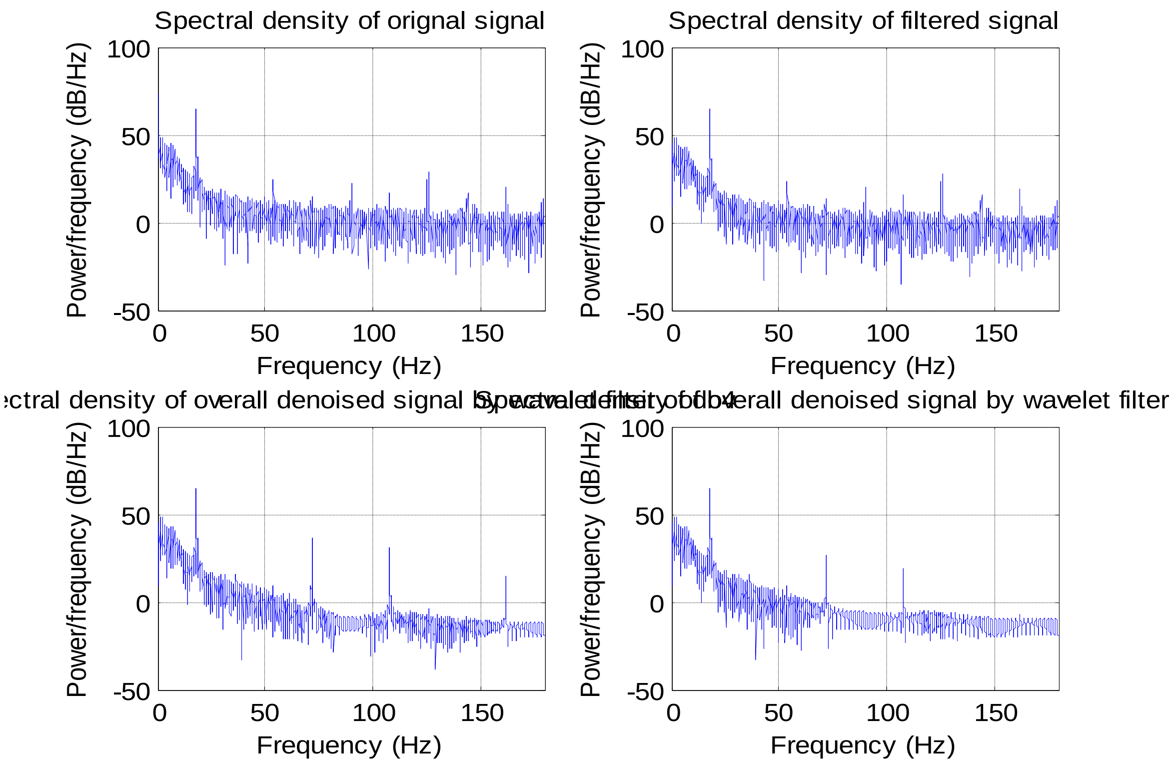

Fig10. *Spectral Density using Eleptic filter*

But it can also visualize that the waveform got distorted to some extend in case of rectangular window. The Kaiser Window and rectangular window is also showing better results at the expense of some more computational load as the order of the filter is large. But in case of remaining windows i.e. Hamming and Blackman windows, the order of filter easily grow very much high. It increases the number of filter coefficients which increases the large memory requirement and problems in hardware implementation. So, the Kaiser Window filter can be best choice for the removal of Baseline wandering among filters [2].

Average power Comparison of various filters for Removal of noise at ECG sample input 1 in Table 2

4. Conclusion

This paper concludes the work in this thesis; digital FIR and IIR filter with wavelet for removal of Baseline noise were implemented in MATLAB. It is observed that the choice of the cut-off frequency is very important, a lower than required cut-off frequency does not filter the actual ECG signal component, however some of the noise successfully, but the ECG signal is distorted in the process. Cut-off frequency varies corresponding to heart rate and baseline noise spectra. Thus, constant cut-off frequency is not always appropriate for baseline noise suppression; it should be selected after a careful examination of the signal spectrum.

Table2. *Average power Comparison of various filters for Removal of noise at ECG sample input 1*

Filter	**Filter Order**	**Average Power before Filtration**	**Average power after Filtration**	**Wavelet output at 4dB**	**Wavelet output at 6dB**
Hamming	450	61.7562	57.882	57.873	57.877
Kaiser	450	61.7562	56.3233	56.3104	56.3165
Rectangular	450	61.7562	56.3209	56.3080	56.3141
Chebyshev	2	61.7562	55.6436	55.6309	55.6378
Elliptic	2	61.7562	55.6456	55.6329	55.6398

When FIR filter with wavelet is applied on signal it can be observe that the combination of Kaiser and wavelet yield the smallest phase delay among all the FIR filters combination. It can remove the Baseline noises without distorting the waveform. But the order of filter is 450.However, high filter orders are required to obtain this satisfactory result and this increases the computational complexity of the filter. Furthermore, there is significant delay in the filter result, thus this combination can be applied to long data window. Therefore, this combination is appropriate only for offline application, but for real time application, in which short intervals of data is filtered and fast implementation is important, FIR is not an appropriate filtering method.IIR and wavelet combination is more appropriate for real time filtering application due to its lower computational complexity, and its better trade-off between average power and spectral density. It completely eliminates the oscillations produced at the starting of the waveform called ringing effect. For performance analysis we use different baseline noise removal methods for the purpose of comparison. The results are presented in the tabulation form. From the table it can conclude that it outperform the other method.

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