Filtering Techniques for Reduction of Baseline Drift in Electrocardiogram Signals

Mr. Nilesh M Verulkar[1]
Assistant Professor
Department of ENTC Engg.
MGI-COET, Shegaon

Miss Pallavi S. Rakhonde[2]
Student
Department of ENTC Engg.
MGI-COET, Shegaon

Miss Shubhangi N. Warkhede[3]
Student
Department of ENTC Engg.
MGI-COET, Shegaon

Mr. Dnyaneshwar R. Raut[4]
Student
Department of ENTC Engg.
MGI-COET, Shegaon

Abstract—Electrocardiogram (ECG) signal plays an important role in the primary diagnosis and analysis of heart diseases. Electrocardiogram (ECG) signal is a very important measure to know the Heart actual conditions. The ECG signal is mainly contained with PQRST waves among which QRS complex is the high part and other are low frequency part. During the acquisition of the ECG signal few noises gets attached with it that may cause a huge misinterpretation.Among these noisesBaseline Wandering is a classical problem in ECG records that generally produce artificial data when measuring ECG parameters. Baseline Wandering is a low frequency noise .Hence it is desirable to remove this noise for proper analysis of the ECG signal. This paper present various approaches for baseline noise removal in the electrocardiogram (ECG) signal which includes the methods based on median filter, adaptive filter, wavelet filter, zero phase filter, high pass filter. The result shows the analysis of various filtering techniques.

Keywords-Adaptive approach, baseline wandering, high pass filter, median filter, wavelate filter.

*****

I. INTRODUCTION

In last few decades there has been a huge increase in the number of people suffering from cardiac disorders. The electrocardiogram (ECG) is the best imaging modality used for diagnosing of heart diseases and evaluating the efficiency of therapeutic drugs, also it is widely used for the diagnosis of obstructive sleep apnea or wearable physiological monitor. ECG signal is an electrical signal that represents the depolarization/ repolarization of the atrium and the ventricle which occurs for every heartbeat It is needed when chest pain occurred such as heart attack, shortness of breath, faster heartbeats, high blood pressure, high cholesterol etc. ECG signal lies in the range of 0.05-100Hz and 50Hz. ECG is very sensitive signal to environmental noise. So, it is very important to remove these noises and interference from the ECG signal.

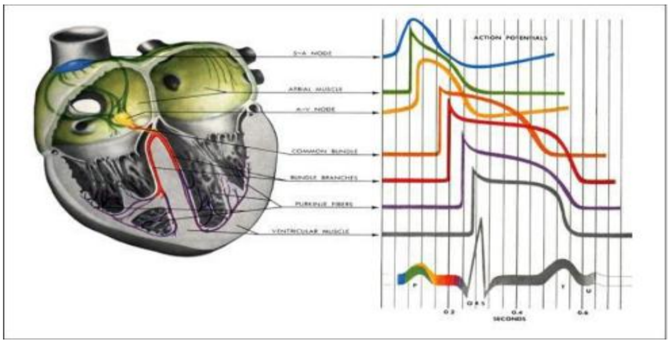

Fig. 1 ECG Signal Generation ion

a) ECG signal generation

P wave: signal spread from SA node to make the atriacontract.
P-Q Segment: signal arrives AV node stay for an instant to allow the ventricle to be filled with blood.
Q wave: After the Buddle of His the signal is divided into two branches and run through the septum.
R,S wave: Left and right ventricle contraction are marked bythe P,S wave.
T wave: ventricle relaxing.

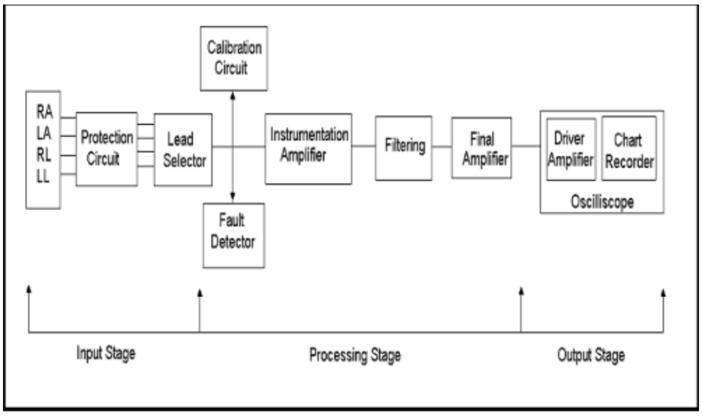

Fig. 2 ECG Block Diagram

ISSN: 2321-8169
43 – 48

Protection Circuit: It protects the system from high level voltages or DC shock used to resuscitate heart attack patients

Lead Selector Design: Connect the patient leads to no inverting amplifier terminal (+) & inverting terminal (-).

Calibration Circuit: It is a circuit consisting of resistive network connected to a voltage source that gives at its output 1mV. It is used to check the amplifying factor of the system before using ECG machine

Fault detector: It can be detected manually or automatically, depending on operating modes and how quickly the system needs to be restored.

Oscilloscope: The oscilloscope is basically a graph-displaying device - it draws a graph of an electrical signal.

.

b) Types of noise in ECG signal

ECG recordings are often corrupted by various kinds of noise such as power line interference, motion artifacts, electromyogram effects, and baseline drift with respiration. Recently, portable monitors incorporating the computational power of microprocessors have allowed us to implement digital filters for noise cancellation in real-time execution. However, motion artifacts that are part of the transient baseline change are caused by changes in the electrode-skin impedance with electrode motion. This is assumed to be vibrations or movement of the subject. In particular, the spectrum of motion artifact completely overlaps with the ECG signal when the subject is walking or running. Thus, motion artifacts are the most difficult type of noise to cancel.

1**.** Power line interference**:**

It consist of 50/60Hz pickup and harmonics, which can be modeled as sinusoids. Characteristics, which might need to be varied in a model of power line noise, of 50/60Hz component include the amplitude and frequency content of the signal. The amplitude varies up to 50 percent of peak-to-peak ECG amplitude, which is approximately equivalent to 25mv. Decomposing the power-line interfered signal into ten IMF's (Intrinsic Mode Functions), this power line information almost distributed to the 1st intrinsic mode functions

2. Base line drifts with respiration:

The drift of the base line with respiration can be represented by a sinusoidal component at the frequency of respiration added to the ECG signal. The amplitude and frequency of the sinusoidal component should be variable. This baseline can be eliminated by decomposing the signal into 15 intrinsic mode functions reconstructing the signal with suppressing the final IMF is having the base line information.

3. Electrode contact noise:

It is a transient interference caused by loss of contact between the electrode and the skin that effectively disconnects the measurement system from the subject. The loss of contact can be permanent, or can be intermittent as would be the case when a loose electrode is brought in and out of contact with the skin as a result of movements and vibration

. 4. Muscle contraction:

The MA (Muscle Artifacts) originally had a sampling frequency of 360Hz. The original ECG signal with MA is given as input to the filter. Muscle contraction cause artifactual mille volt level potentials to be generated. The base line electromyogram is the microvolt range and therefore is usually insignificant. It is simulated by adding random noise to the ECG signal.

5. Motion artifacts:

Motion artifacts are transient base line changes caused by changes in the electrode-skin impedance with electrode motion. As this impedance changes, the ECG amplifier sees a different source impedance which forms a voltage divider with the amplifier input impedance therefore the amplifier input voltage depends upon the source impedance which changes as the electrode position changes.

II. PROPOSED FILTERING TECHNIQUE

1. Through Median Filtering Approach

Chouhan et al. [2] have given a technique for baseline removal using median filtering on the electrocardiogram. In this procedure, firstly the median of the ECG signal is calculate and subtracted from the ECG signal. Then a fifth order polynomial is fitted to this shifted waveform to obtain a baseline estimate which is then subtracted from the ECG signal. The baseline drift is further removed by applying this median correction, one by one, in each RR interval. This approach also offers the advantage that the signal is not distorted in the absence of baseline variation and is computationally efficient as well as less time consuming.

2 Through Adaptive Filtering (AF) Approach

Adaptive filtering approach has been used for baseline wander removal from the ECG signal usingarchitecture shown as in figure1.For adaptive filtering of baseline wandering used here, only one weight is needed the the reference input is a constant with a value of one. T Squares (LMS) algorithm which is given in (1) as follows:

$$w(k+1) = w(k) + 2\mu e(k)x(k)$$

This filter has a zero at 0Hz and consequently it creates a notch with a bandwidth of fs where fs is the sampling frequency. Since, cut-off frequencies should be under 0.8Hz for the prevention of distortion of the ST segment, μ=0.0101 is taken (for fs =250Hz). This approach produces severe distortion in the ECG signal, especially in the ST segment area [4].

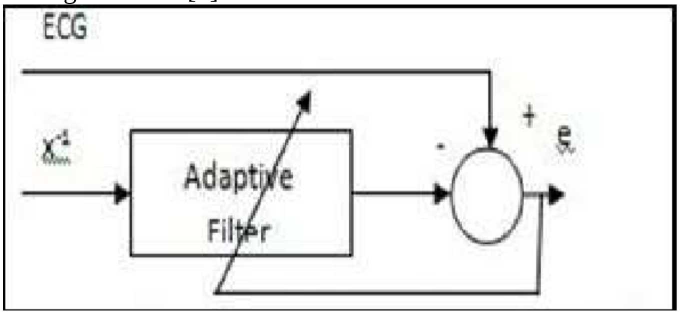

Fig. 3. Adaptive filtering for ECG Baseline Removal

3. Wavelet Adaptive Filtering (WAF) Approach

Park et al. [3] fig. 2 has proposed a wavelet approach for the removal of the Baseline Wandering. In this Paper a Wavelet adaptive filter has been introduced for baseline removal from the ECG signal to minimize distortion of the ST Segment which is a low frequency part and gets corrupted through this Baseline Wander. In this method the ECG signal with baseline is decomposed up to 7 levels using Wavelet Transform with the use of Vaidyanathan-Hoang wavelethaving orthogonal characteristics. The 7th level approximation coefficients have frequency components in the range of 0-1.4Hz. These coefficients are then applied to the adaptive filter with a cut off frequency of 0.8Hz. The filtered output and the details coefficients are used for the reconstruction using inverse wavelet transform to produce the baseline absented signal. This approach presents a very effective approach for the baseline removal as it does notrequire the calculation of any reference points as well as the use of wavelet transform for the analysis of the inherently non-stationary ECG signal. Thus it is a comparatively better approach as per the time and complexities.

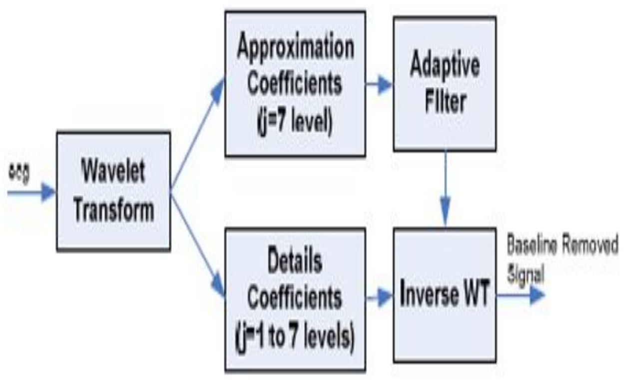

Fig. 4. Baseline removal using WAF [4]

4. Zero Phase Filtering

The FIR filter has output of combined with a group delay. As the filter order increases, the complexity of the filter increases. The noise suppression performance of the filter will decrease if the selected filter order is low. Infinite impulse response (IIR) filters can achieve a sharp transition region with a small number of coefficients and IIR filter that has a cut off frequency high are enough to remove baseline wander consists of a nonlinear phase response which leads to the distortion of meaningful components of the ECG waveform. To avoid this distortion, bidirectional filters are used, in which the signal is filtered in a forward direction over a selected window and then the same window is filtered in a reverse direction. A short window was preferably selected so that the filter could be used for real time purposes. The delay of each frequency component is applied forwards and backwards in time and is therefore cancelled [5] .Then the result has the following characteristics:

- Zero-phase distortion
- A filter transfer function, which equals the squared magnitude of the original filter transfer function
- A filter order that is double the order of the filter specified by numerator & denominator.

Zero-phase filtering minimizes start-up and ending transients by matching initial conditions. It helps in preserving the features in the filtered time waveform exactly where those features occur in the unfiltered waveform [6]. By using the coefficients of above discussed and implemented filters, FIR & IIR zero phase filtering is performed. If the data in vector 'x' is filtered with the filter described by denominator vector 'a' and numerator vector 'b' to create the filtered data 'y', the filter is described by the difference equations [7]:

y[n]=aox[n]+a1x[n+1]+a2x[n+2]+……+b1y[n-1]+b2y[n-2]

The above equation is of reverse recursive filter implemented in backward direction. After filtering in the forward direction,

y[n]=aox[n]+a1x[n-1]+a2x[n-2]+…….+b1y[n-1]+b2y[n-2]

The above equation is of reverse recursive filter implemented in backward direction. After filtering in the forward direction, the filtered sequence is then reversed and run back through the filter.

5. High Pass Filter Approach

Baseline Wandering in Respiratory signals lies between 0.15Hz and 0.5Hz frequencies [8]. Several considerations are there for the design of a linear, time-invariant, high pass filter for removal of baseline wander out of which the most crucial is the choice of filter cut-off frequency and phase response characteristics for it. The cut-off frequency should be chosen on the basis that the clinical information in the ECG signals remains undistorted and large amount of baseline wander is removed. Hence lowest frequency component of the ECG spectrum is required for it. Slowest heart rate is considered to define this particular frequency component and PQRST waveform is attributed to higher frequencies. If these frequencies are too high then a cut-off frequency is employed, and the output of the high pass filter contains an unwanted, oscillatory component that is strongly correlated to the heart rate [21]. On the basis of Impulse Response, there are generally two types of digital Filters with which we normally deal:

- Infinite Impulse response(IIR)
- Finite impulse Response(FIR)

a) IIR Filtering

High pass filters are not all pole filters and in the given by (9), as here it contains two's in numerator which shows that two zeroes are at origin. The frequency response of this filter decreases monotonically with frequency and can be given as

$$| H(f = f_c) | = \frac{1}{\sqrt{2}}$$

Where, f_c is cut-off frequency.

The transfer function for a second-order Butterworth high-pass filter is given by

 ISSN: 2321-8169
43 – 48

$$H(s) = \frac{A_{hp}\, bs^2}{s^2 + \frac{a}{b} w_c s + \frac{w_c^2}{b}}$$

Where, A_{hp} is high pass gain

The decrease in frequency response is very slow in the pass band and quick in the stop band. In a design problem where there are no ripple is acceptable in case of pass band and stop band, Butterworth filter is a good choice [10]. But it has to Non-linear phase response and due to that waveform gets distorted.

b) FIR Filtering

The high pass FIR filter is designed by using Kaiser Window. The FIR Filtering has an advantage of the stability as it has only zeros rather than poles thus we do not need any specific locations for them just like poles in IIR Filter. The basic principle of the window design method is to truncate the ideal response with a finite length window. In the filters design we use different windows for truncating like Rectangular Window, Bartlett Window, Henning Window, Hamming Window and Blackman Window, it has been found that there is a tradeoff existing between the width of main lobe and the amplitude of side lobe. The main lobe width is inversely proportional to the N order of the filter.

An increase in the window length decreases the transition band of the filter respectively. The designer must find a window with an appropriate side lobe level and then need to choose order to achieve the prescribed transition width for the minimum stop band attenuation and pass band ripple. In this process, the designer has to settle for a window with undesirable design specifications and to overcome this problem Kaiser has chosen a class of windows which are based on the portable Speriodal functions. The Kaiser window is given by following equation (x) [10]:

$$H(s) = \frac{A_{hp}\, bs^2}{s^2 + \frac{a}{b} w_c s + \frac{w_c^2}{b}}$$

The order of filter designed here is 400 and sampling frequency 360Hz.

6. Empirical Mode Decomposition (EMD) Method

Empirical Mode Decomposition was developed by Huang et al. [11] as a flourishing method for analyzing nonlinear and non-stationary data by decomposing them into a finite and often small number of `intrinsic mode functions' that must follow two conditions: (i) the no of local extreme and the zero crossing must be equal or differ by at most one, (ii) at any point of the time, the mean value of the upper envelope (local maxima) and the lower envelope (local minima) must be zero. Empirical Mode Decomposition do not require any a priori knowledge for the signal, that make it very a fully data driven technique for the analysis of any non-stationary signal. In the EMD the input signal is decomposed into a sum of intrinsic mode functions (IMFs) that include a particular oscillation in each of the IMF.

The use of EMD for removal of baseline from the ECG signal has been proposed by [12] in which partial reconstruction of the ECG signal have been shown from the IMFs obtained by the decomposition of the input ECG signal is used. In this paper it is done by removing low frequency components from the ECG signal as the Baseline Wandering is a low frequency component, which results in the removal of baseline variation. However this approach is computationally very demanding in comparison to other approaches as it takes more time to perform

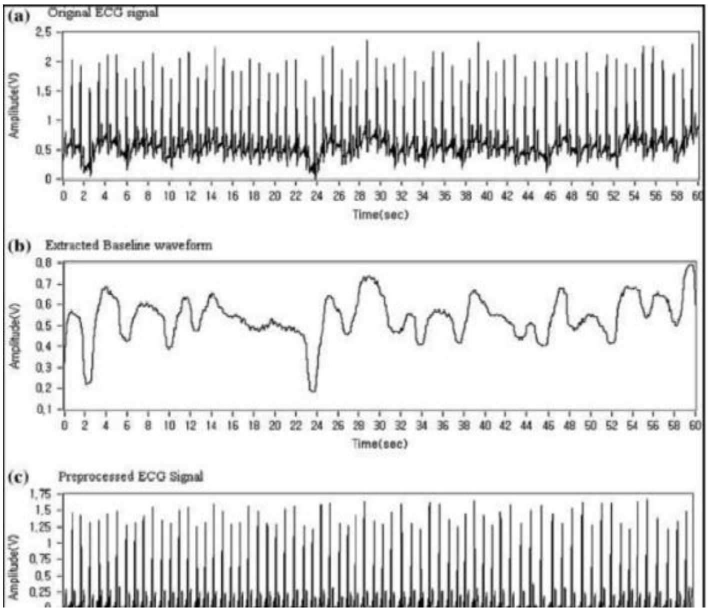

Fig. 5 Removal of Baseline Wandering from ECG Signal

IV. RESULTS AND DISCUSSION

In this paper various noise removal techniques are applied to ECG signals, 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, 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.

The two important parameters to check the suppression of Baseline noises are spectral density and average power of signal [5]

Power spectral density**:**

Table1 and 2 shows the comparison of different filters. The trade-off between spectral density and average power is best among all the filters. 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. Hanning and Blackman windows, the order of filter can easily grow very much high. It increases the number of filter coefficients which increases the large memory requirement and problems in hardware

ISSN: 2321-8169
43 – 48

implementation. So, the Kaiser Window filter can be best choice for the removal of Baseline wandering among filters [13].

TABLE1 Comparison of various filters for Removal of noise at ECG sample input

Filter	Filter order	Spectral Density before Filtration	Spectral Density after Filtration	Wavelet output at 4dB	Wavelet output at 6dB
Butterworth	2	61.0009	53.5685	53.5557	53.5625
Kaiser	450	61.0009	53.3143	53.3014	53.3075
Rectangular	450	61.0009	53.3131	53.3002	53.3063
Hanning	450	61.0009	55.9501	55.9431	55.9465
Blackmann	450	61.0009	56.7112	56.7053	56.7082

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

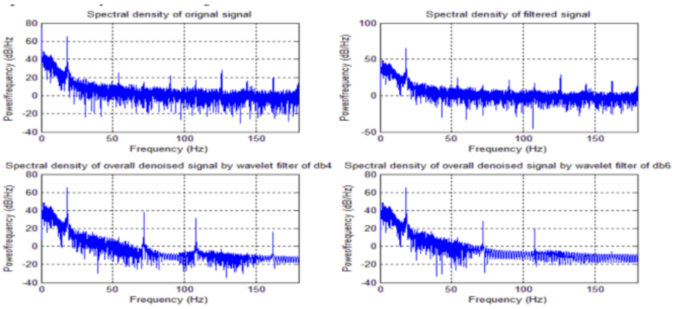

Fig.6 Spectral Density using Butterworth filter

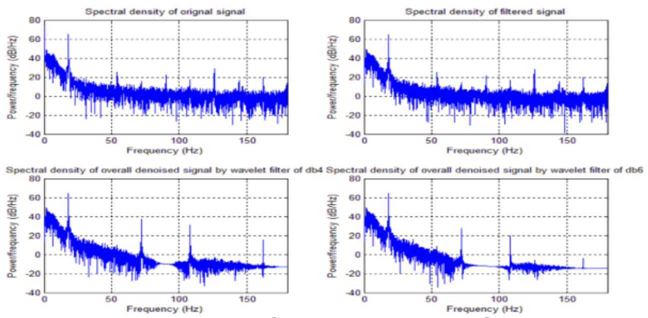

Fig.7 Spectral Density using Kaiser Filter

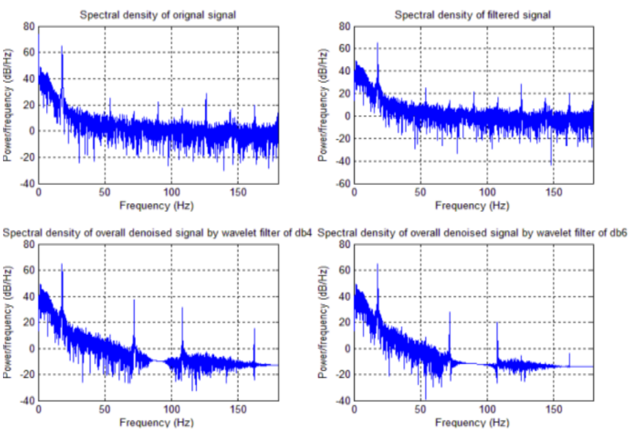

Fig.8 Spectral Density using Rectangular filter

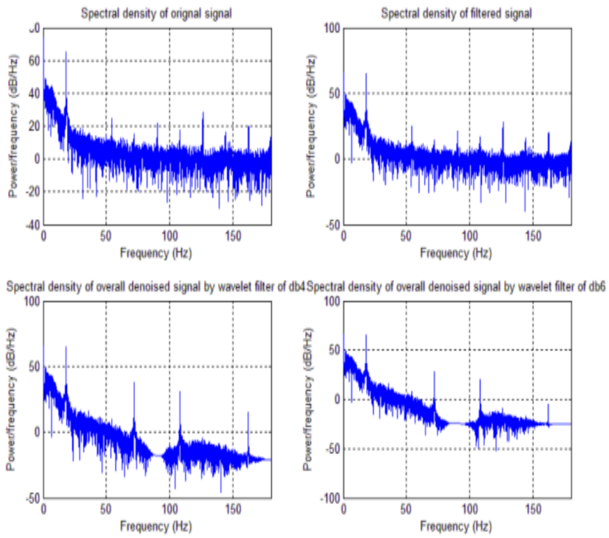

Fig.9 Spectral Density using Hanning filter

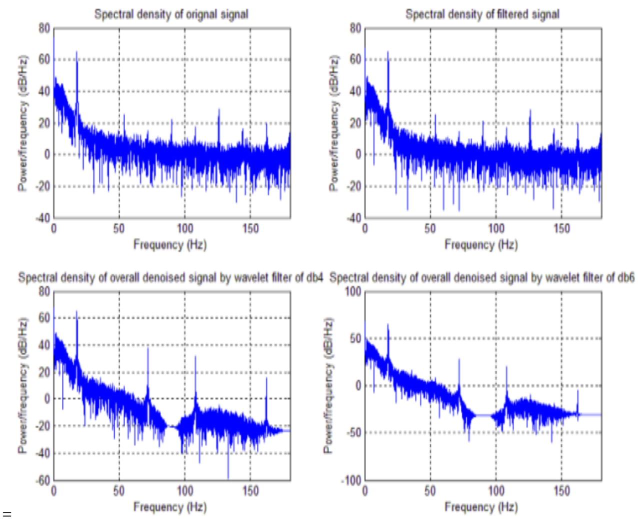

Fig.10 Spectral Density using Blackmann filter

Average power:

Comparison of various filters for removal of noise at ECG sample input in Table 2.

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

Filter	Filter order	Avg Power before Filtration	Avg power after Filtration	Wavelet output at 4dB	Wavelet output at 6dB
Butterworth	2	61.7562	56.5778	56.5649	56.5719
Kaiser	450	61.7562	56.3233	56.3104	56.3165
Rectangular	450	61.7562	56.3209	56.3080	56.3141
Hanning	450	61.7562	57.8823	57.8733	57.8776
Blackmann	450	61.7562	58.3917	58.3836	58.3875

V. CONCLUSION

The ECG is the record of time varying bio – electric potential generated by electrical activity of heart.Different types of filter are use to remove the noise from the signal. The wavelet analysis tool as well as the graphical result for different normal and abnormal ECG signal is presented. The wavelet analysis of ECG signal is performed using MATLAB Software.

The use of EMD for removal of baseline from the ECG signal.ECG database data sample and the performance of these approaches are studied on the basis of spectral density and average power of signal.

REFERENCES

[1] Prof. Nilesh M. Verulkar, Prof. Rahul R. Ambalkar,Prof. Snehal R. Deshmukh, Prof. Pranali P. Chavhan,"Filtering Techniques for Reduction of Motion Artifacts in Electrocardiogram Signals" IJRITCC , 2015.

[2] N.M.Verulkar, P.H.Zope, S.R.Suralkar ,"Filtering Techniques for Reduction of Powerline Interfernce in Electrocardiogram Signals,"IJERT, Nov 2012.

[3] K. L. Park, K. J. Lee, and H. R. Yoon, "Application of a wavelet adaptive filter to minimize distortion of the ST-Segment," Medical and Biological Engineering and Computing, vol. 36, pp. 581-586, 1998.

[4] S. Chouhan and S. S. Mehta, "Total Removal of Baseline Drift from ECG Signal," presented at Computing: Theory and Applications, 2007. ICCTA '07. International Conference on, 2007.

[5] Lisette P. Harting et al., 'On Baseline drift Suppressing In ECG-Recordings', Proceedings of the 2004 IEEE Benelux Signal Processing Symposium, pp133-136.

[6] M. Blanco-Velasco, B. Weng, and K. E. Barner, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition, "Computers in Biology and Medicine, vol. 38, pp. 1-13, 2007.

[7] Steven W. smith, 'The Scientist & Engineer's guide to digital signal processing', second edition 1999, California Technical Publishing, San Diego, California,pp320-330.

[8] C. R. Meyer and H. N. Keiser., 'Electrocardiogram baseline estimation and removal using cubic splines and space-state computation techniques', Computers and biological research, volume 10, issue 5, 1977, pages 459-470.

[9] Filters II – Filter Design with MATLAB', Experiment 3, pp 4-5.,www.cas.mcmaster.ca/~lawford/.

[10] Mahesh S. Chavan, R.A.Agarwala, M.D.Uplane, 'Use of Kaiser Window For ECG processing', Proceedings of the 5th WSEAS Int. Conf. on Signal Processing, Robotics and Automation, Madrid, Spain, February 15-17, 2006 (pp285-289).

[11] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.- C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," Proc. R. Soc. Lond., vol. 454, pp. 903-995, 1998.

[12] M. Blanco-Velasco, B. Weng, and K. E. Barner, "ECG signal denoising and baseline wander correction based on the empirical mode decomposition, "Computers in Biology and Medicine, vol. 38, pp. 1-13, 2007.

[13] Arunachalam, S.P.; Brown, L.F., "(Real-Time Estimation of the ECG Derived Respiration (EDR) Signal Using A New Algorithm for Baseline Wander Noise Removal", IEEE Conference of Engineering in Medicine and Biology Society. pp 5681– 5684, 2009