Comparison of different approaches for removal of Baseline wander from ECG signal

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Manpreet kaur Aneja
Sant Longowal Institute of Engineering and Technology

Birmohan Singh
Sant Longowal Institute of Engineering and Technology

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Manpreet Kaur
Associate Professor
Department of EIE
SLIET Longowal

Birmohan Singh
Associate Professor
Department of CSE
SLIET Longowal

Seema
Department of ECE
SLIET Longowal

ABSTRACT
Baseline wandering can mask some important features of the Electrocardiogram (ECG) signal hence it is desirable to remove this noise for proper analysis and display of the ECG signal. This paper presents the implementation and evaluation of different methods to remove this noise. The parameters i.e. Power Spectral density (PSD), average Power & Signal to noise ratio (SNR) are calculated of signals to compare the performance of different filtering methods. IIR zero phase filtering has been proved efficient method for the removal of Baseline wander from ECG signal. The results have been concluded using Matlab software and MIT-BIH arrhythmia database.

Categories and Subject Descriptors
I 5.4 [**Pattern Recognition**]: Applications – Signal Processing, Waveform Analysis

General Terms
ECG, MIT-BIH, Noise, ECG Filtering, Power Spectral Density, Baseline wander, QRS, Drifting

Keywords
Baseline wander, Filtering, wavelet, Polynomial fitting, PSD.

1. INTRODUCTION

Cardiac failure and cardiac diseases are among the main causes of death in the world. Therefore, it is necessary to have proper methods to determine the cardiac condition of the patient. Electrocardiography (ECG) is a tool that is widely used to understand the condition of the heart [1]. The electrocardiographic signal is the electrical representation of the heart's activity. Computerized ECG analysis is widely used as a reliable technique for the diagnosis of cardiovascular diseases. However, ambulatory ECG recordings obtained by placing electrodes on the subject's chest are inevitably contaminated by several different types of artifacts [3]. Commonly encountered artifacts include : Powerline interference, Electrode contact noise, Motion artifacts, Baseline Drift, Instrumentation noise generated by electronic devices, Electrosurgical Noise. Baseline wander elimination is considered as a classical problem. It is considered as an artifact which produces atrifactual data when measuring the ECG parameters, especially the ST segment measures are strongly affected by this wandering. In most of the ECG recordings the respiration, electrode impedance change due to perspiration and increased body movements are the main causes of the baseline wandering [4].

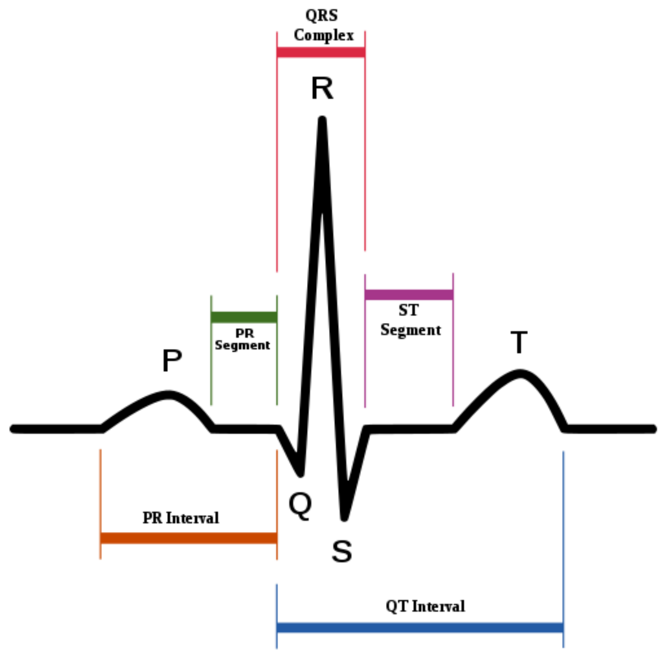

Fig1: Nornal ECG [2]

The baseline wander noise makes the analysis of ECG data difficult. Therefore it is necessary to suppress this noise for correct evaluation of ECG. Many researchers have worked on development of methods for reduction of baseline wander noise. Zahoor-uddin, presented Baseline Wandering Removal from Human Electrocardiogram Signal using Projection Pursuit Gradient Ascent Algorithm & shows the comparative study of the results of different algorithms like Kalman filter, cubic spline and moving average algorithms [5]. Mahesh S. Chavan *et al* has presented the Comparative Study of Chebyshev I and Chebyshev II Filter for noise reduction in ECG Signal [6]. Mahesh S. Chavan *et al* also compared the results of Butterwoth filter and Elliptic filter for the suppression of Baseline and Powerline interferences [7]. Fayyaz A. Afsar et al. compared different approaches which include linear Digital filters, Adaptive filters, Multiresolution analysis and Curve fitting for the removal of baseline drift [8]. V.S. Chouhan and S.P. Mehta developed an algorithm for total removal of Baseline drift from ECG signal & deploy least square error correction & median based correction [9].

2. IMPLETATION TECHNIQUES

2.1 High Pass Filter

Respiratory signal wanders between 0.15Hz and 0.5Hz frequencies [9]. The design of a linear, time-invariant, highpass filter for removal of baseline wander involves several considerations, of which the most crucial are the choice of filter cut-off frequency and phase response characteristic. The cut-off frequency should be chosen so that the clinical information in the ECG signals remains undistorted while as much as possible of the baseline wander is removed. Hence, it is essential to find the lowest frequency component of the ECG spectrum. In general, the slowest heart rate is considered to define this particular frequency component; the PQRST waveform is attributed to higher frequencies. If too high a cut-off frequency is employed, the output of the high pass filter contains an unwanted, oscillatory component that is strongly correlated to the heart rate [11]. On the basis of Impulse Response, there are generally two types of digital Filters:

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

Digital Filters can be described by the generalized discrete differential equation:

$$\sum_{m=0}^{M} a_m . y[n-m] = \sum_{k=0}^{N} b_k x[n-k]$$

a, b : filter coefficients, x[n] : input signal
y[n] : output signal, M,N : filter order

The right side of above equation depends only on the inputs x[n] so it is called feed-forward & the left side depends on the previous outputs y[n] i.e. called feed-back. FIR Filters have only feed-forward components, they can be calculated non-recursively. IIR Filters have feed-back components also, they are calculated recursively [13]. This paper presents the design & implementation of high pass FIR filter of order 400 using Kaiser Window & IIR Butterworth filter of order 2 with cut-off frequency 0.5Hz.

2.2 IIR Filtering

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

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

where Ahp is high pass gain

It should be noted that high pass filters are not all pole filters as it contains two‘s’ in numerator. It shows two zeroes at origin. The frequency response of this filter decreases monotonically with frequency and

$|H(f = fc)| = 1/\sqrt{2}$ where f_c is cut-off frequency.

The decrease is very slow in the passband and quick in the stopband. In a design problem where no ripple is acceptable in passband and stopband, Butterworth filter is a good choice [14]. But due to no-linear phase response, the waveform gets distorted. The Magnitude Response & Phase Response of Butterworth filter is shown in Fig2.

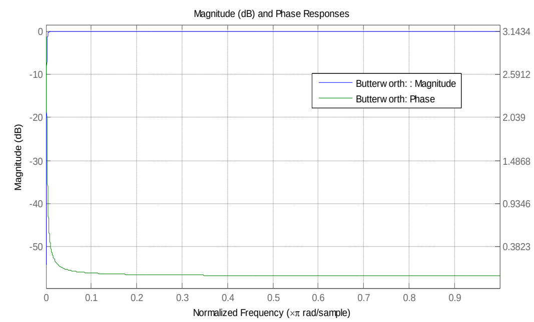

Fig2: Magnitude Response & Phase Response of Butterworth filter

2.3 FIR Filtering

The high pass FIR filter is designed by using Kaiser window. The basic principle of the window design method is to truncate the ideal response with a finite length window. In the filters design using windows like Rectangular, Bartlett, Hanning, Hamming and Blackman it has been found that a trade off exists between the main lobe width and the side lobe amplitude. 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. However, for the minimum stop band attenuation and pass band ripple, the designer must find a window with an appropriate side lobe level and then choose order to achieve the prescribed transition width. In this process, the designer may often have to settle for a window with undesirable design specifications. To overcome this problem Kaiser has chosen a class of windows based the portable Speriodal functions. The Kaiser window is given by following equation [15]:

$$w_k = \frac{I_0[\alpha\sqrt{1-[\frac{2n}{N-1}]^2}]}{I_0(\alpha)} \quad for\ |n| \le \frac{N-1}{2}$$

= 0 otherwise

The order of filter designed here is 400 and sampling frequency 360Hz. The magnitude response and phase response are shown in Fig 3.

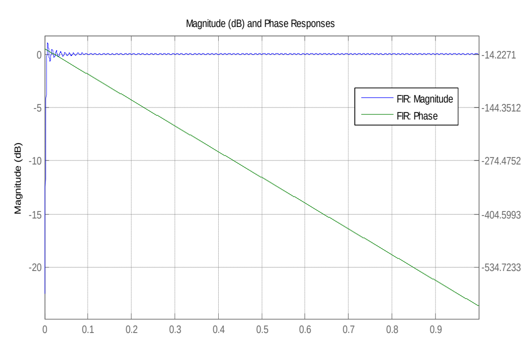

Fig 3: Magnitude Response & Phase Response of FIR filter using Kaiser window

2.4 Zero Phase Filtering

The output of the FIR filter is combined with a group delay. As the filter order increases, the complexity of the filter increases. However, if the filter order is selected to be low, then the noise suppression performance of the filter will decrease. Infinite impulse response (IIR) filters, on the other hand, can achieve a sharp transition region with a small number of coefficients. However, an IIR filter that has a cutoff frequency high enough to remove baseline wander has a nonlinear phase response which distorts 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 selected so that the filter could be used for real time purposes. This way, the delay of each frequency component is applied forwards and backwards in time and is therefore cancelled [16] .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 & helps in preserving features in the filtered time waveform exactly where those features occur in the unfiltered waveform [10]. By using the coefficients of above 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 [17]:

$$y[n] = a_0x[n] + a_1x[n+1] + a_2x[n+2] + a_3x[n+3] + \cdots$$
$$+b_1y[n+1] + b_2y[n+2] + b_3y[n+3]$$

The above equation is of recursive filter implemented in forward direction.

$$y[n] = a_0x[n] + a_1x[n-1] + a_2x[n-2] + a_3x[n-3] + \cdots$$
$$+b_1y[n-1] + b_2y[n-2] + b_3y[n-3]$$

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

2.5 Wavelet Approach

A wavelet transform decomposes a signal into basis functions which are known as wavelets. Wavelet transform is calculated separately for different segments of the time-domain signal at different frequencies resulting in Multi-resolution analysis. It is designed in such a way that the product of time resolution and frequency resolution is constant. Therefore it gives good time resolution and poor frequency resolution at high frequencies whereas good frequency resolution and poor time resolution at low frequencies. This feature of multi resolution analysis makes it excellent for signals having high frequency components for short durations and low frequency components for long duration [18]. Wavelet analysis consists of decomposing a signal into a hierarchical set of approximations and details. The words approximation and detail are justified by the fact that approximations taking into account the low frequencies whereas the detail corresponds to the high frequency correction [10]. As baseline wandering occurs at low frequencies so it is due to approximations. In this method the ECG signal is decomposed into eight levels using Daubchies6 wavelet. When all the details are superimposed, it results the waveform that eliminate the baseline drift. Different compositions were also tried using approximations, but the inclusion of every approximation introduces the baseline drift.

2.6 Moving Average Approach

A moving average filter smooth data by replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low pass filtering with the response of the smoothing given by the difference equation by the difference equation

$$Ys(i) = \frac{1}{2N+1}(Y(i+N) + Y(i+N-1) + \cdots + Y(i-N))$$

where $Y_s(i)$ is the smoothed value for the ith data point, N is the number of neighboring data points on either side of $Y_s(i)$, and $2N+1$ is the span [10]. By subtracting the output of this filter from original data, the data equivalent to high pass filtering can be achieved as shown in Fig 8. The moving average smoothing method used by Curve Fitting Toolbox follows these rules [10]:

- The span must be odd.
- The data point to be smoothed must be at the center of the span.
- The span is adjusted for data points that cannot accommodate the specified number of neighbors on either side.
- The end points are not smoothed because a span cannot be defined.

2.7 Savitzky-Golay Filtering

Savitzky-Golay filtering can be thought of as a generalized moving average. The filter coefficients can be derived by performing unweighted linear least- squares fit using a polynomial of an appropriate degree. For this reason, a Savitzky-Golay filter is also called a digital smoothing polynomial filter or a least-squares smoothing filter [10]. It helps to preserve the peaks and valleys of the ECG signals better than a standard FIR filter.

2.8 Polynomial Fitting

Polynomial fitting is a method to remove basline by fitting polynomials to representative points in the ECG signal. In each beat, a representative sample is defined and called knot. Increasing the order of the polynomial and selecting one knot per beat through which the baseline estimation must pass is the method used to remove higher-frequency baseline noise and preserve low-frequency heart information, which is useful for other processes to apply after the baseline wander removal. By using higher-order polynomials the likelihood of producing an accurate baseline estimate increases, although it is obviously linked to an increased computational complexity. The polynomial is fitted in such a way that, one subtracted to the original signal, these knots have a value of 0 [19]. In this paper the polynomial of degree 6 is used to fit the ECG waveform.

3. Resulting waveforms

The original ECG waveform having baseline drift is shown in Fig 4.. Firstly when conventional IIR ans FIR high pass filters are implemented , the ECG waveform has been distorted to large extent. Large ringing effect can be seen at the starting of the waveforms(figs 5 &6). To overcome this effect, zero-phase digital filtering is performed and the waveforms shown in Figs (7,8). The waveforms obtained after other filtering approaches are shown in Figs (9, 10, 11, & 12). To compare their performances, some parameters are calculated.

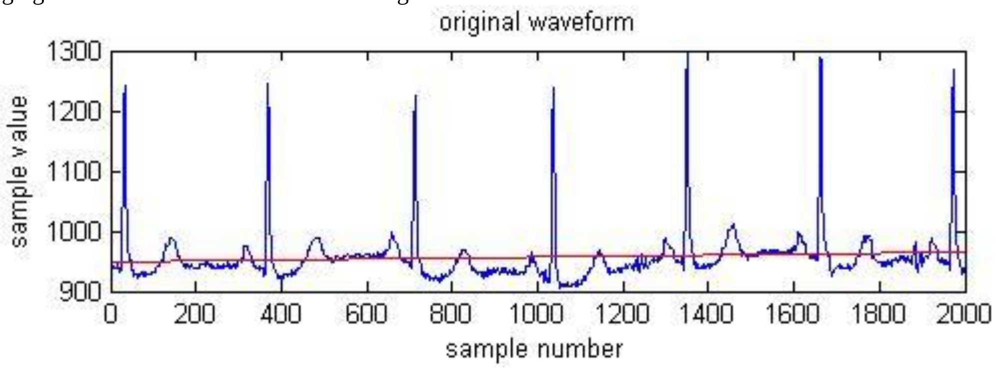

Fig 4:Original Waveform

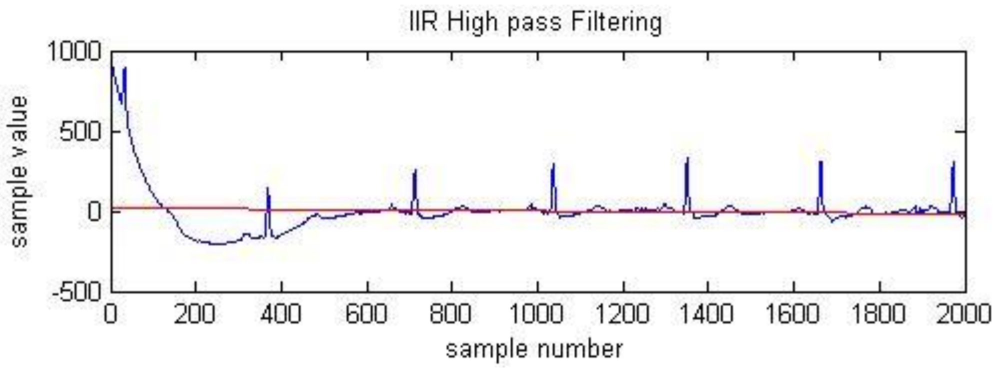

Fig5:After IIR High Pass Filtering

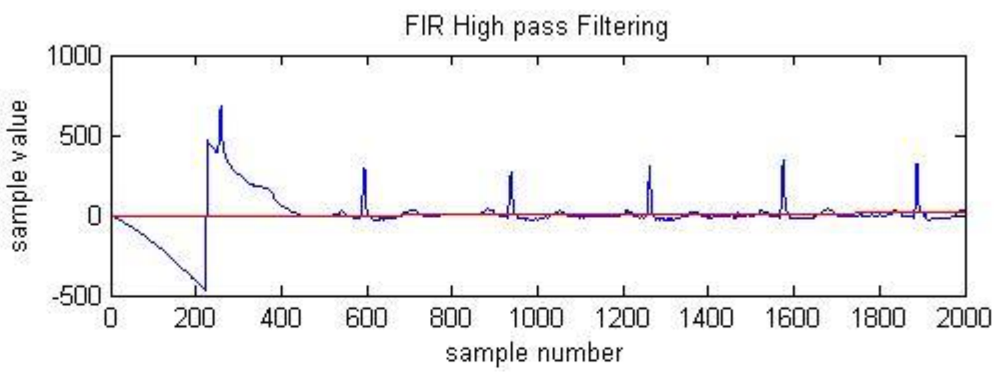

Fig 6: After FIR High Pass filtering

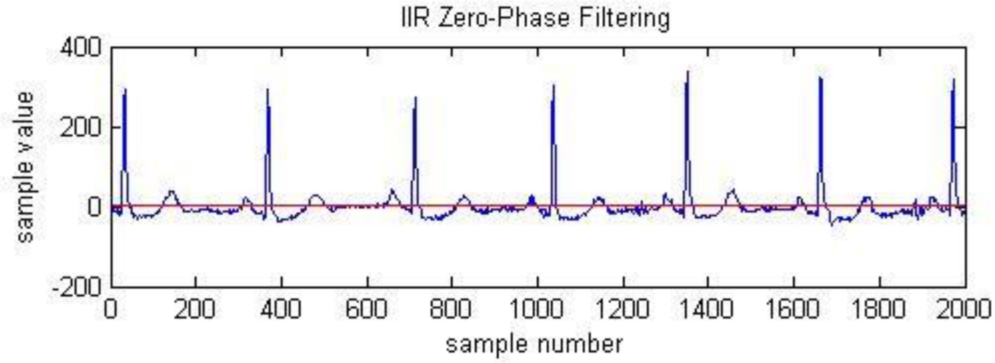

Fig 7: after IIR Zero-Phase filtering

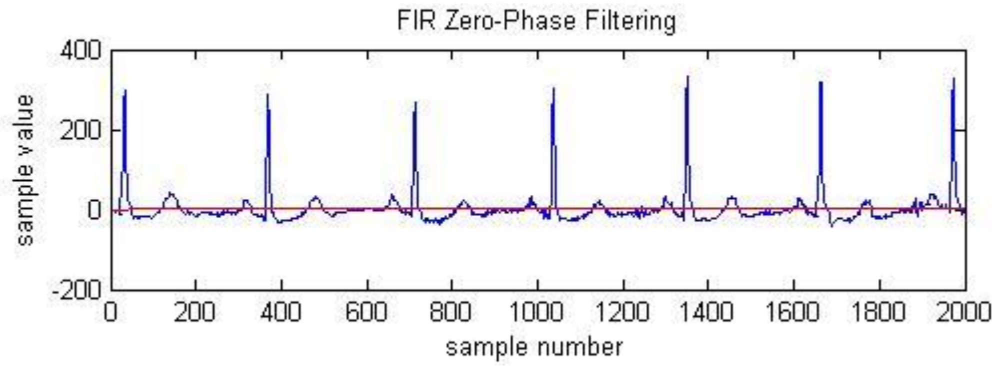

Fig 8: After FIR-Zero Phase Filtering

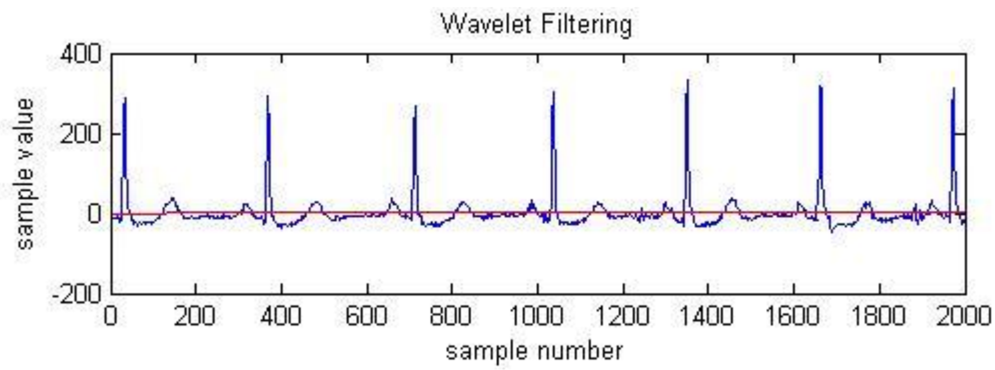

Fig 9: After wavelet approach

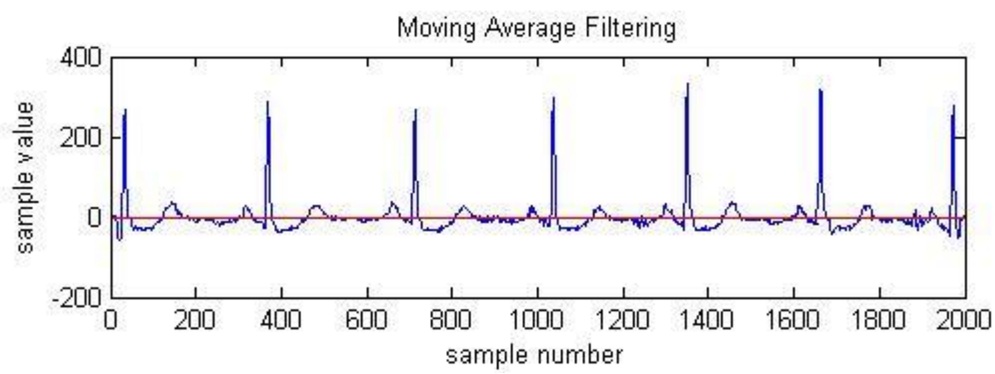

Fig 10: After moving Average filtering

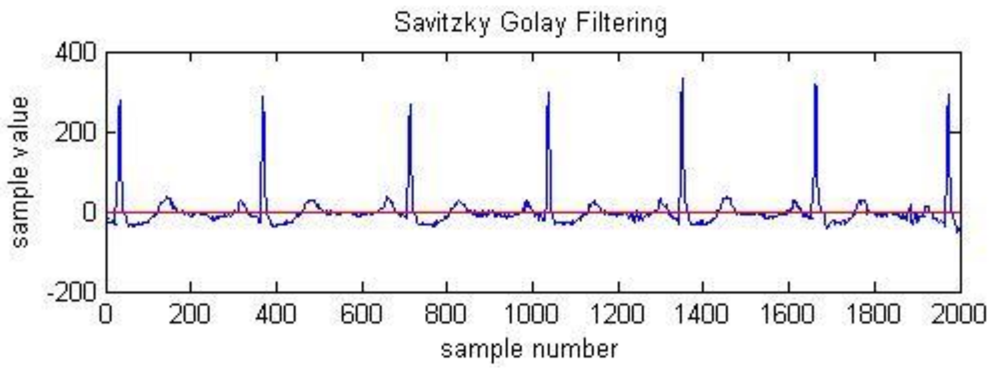

Fig 11: After Savitzky Golay Filtering

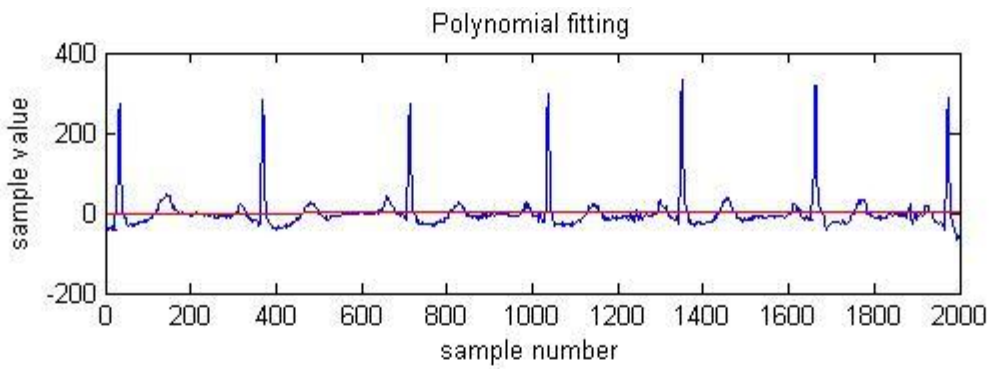

Fig 12: After Polynomial Fitting

4. CALCULATION PARAMETERS

4.1 Power Spectral Density (PSD)

The periodogram power spectrum estimate represents the distribution of the signal power over frequency. From the spectrum the frequency content of the signal can be estimated directly. Power spectral density (PSD) of ECG signal is calculated as follows:

$$S(f) = \frac{1}{FsN}\left|\sum_{n=1}^{N} x(n)e^{-j(2\pi f/Fs)n}\right|$$

where Fs is sampling frequency.

The periodogram is an estimate of the PSD of the signal defined by the sequence $[x_{1,...,}\, x_N]$. Periodogram uses an nfft-point FFT to compute the power spectral density [10].

4.2 Signal to Noise Ratio (SNR)

SNR is a parameter used to quantify and compare the performance of algorithms and also determine the noise level in an ECG beats. The expression used to calculate SNR is as follows:

SNR= 10 log10 (variance (S0) / variance (S0-Sf))
where S0= original Signal Sf= filtered signal

4.3 Average Power

The area under the PSD curve is the measure of the average power [10]. This parameter is used to compare the average power of the signal after filtering with different approaches.

Table1 : Comparison of parameters of all filtering approaches

Filtration Method	PSD at 0.35Hz (dB/Hz) Before filtration	PSD at 0.35Hz (dB/Hz) After filtration	SNR (dB)	Average Power of signal (dB)	Waveform Modification
IIR HP	36.31	38.29	-9.834	43.11	Modified
IIR Zero Phase	36.31	-5.33	12.708	32.64	Not Modified
FIR HP	36.31	32.72	-9.834	42.11	Modified
FIR Zero Phase	36.31	12.61	11.679	32.58	Not Modified
Wavelet	36.31	7.674	11.689	32.49	Not Modified
Moving Average	36.31	3.008	10.989	32.31	Not Modified
Savitzky-Golay	36.31	3.986	11.65	32.42	Not Modified
Polynomial Fitting	36.31	-1.312	11.16	32.42	Not Modified

5. CONCLUSIONS

Table 1 show that ECG waveform has been modified when filtered using conventional IIR high pass filter & FIR high pass filter. It can also be seen visually from figs [5 & 6]. From the remaining approaches, IIR zero phase filtering shows better results. The value of PSD has been reduced from 36.31 dB/Hz to -5.33dB/ Hz. Graphically it is shown below in fig 13. This reduction in PSD value shows that Baseline drift has been reduced effectively. The average Power & SNR are also greater as compared to others. The order of filter required in this case is also very low. So the complexity and computational load is far less as compared to others. This proves that IIR zero phase filtering is best method among the various proposed techniques in this paper.

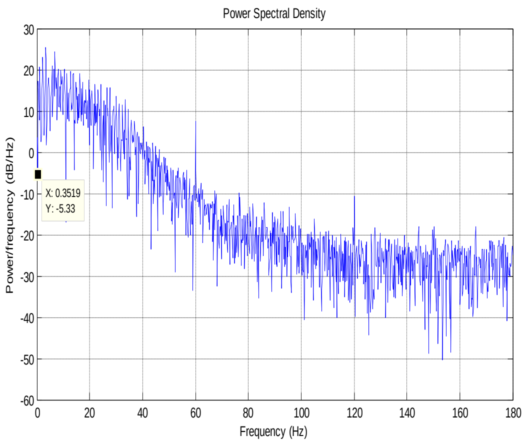

Fig13: PSD of IIR Zero- Phase filtered data

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