IJSRD - International Journal for Scientific Research & Development| Vol. 3, Issue 02, 2015 | ISSN (online): 2321-0613

Analysis of Removing Baseline Wander Noise from Electrocardiogram Signal by using Deferent Techniques

Sanjeev Kumar Pathak[1] Girraj Prasad Rathor[2]
[1,2]Department of Electronics & Communication Engineering
[1,2]Technocrats Institute of Technology, Bhopal, India

Abstract— Electrocardiogram (ECG) is the most significant digital signal for the diagnosis of Heart Diseases. The condition of heart is observed by QRS wave of ECG signal. The observation of working of heart may affect if the ECG signal gets affected by noises. Baseline wander noise is one of the most significant noises which affects the ECG base position and defects the QRS positions in ECG wave. It is very important to remove this noise to perfect diagnosis of heart condition. There are many techniques which have been developed to remove the baseline wander noise. This paper analysis these techniques and produces a compression between them to obtain the most effective technique for removal of baseline wander effects from ECG Signal.

Key words: Electrocardiogram, Baseline Wander Noise, FIR Filter, IIR Filter, Independent Component Analysis
General Terms: ECG, ECG De-noising, Baseline Wader Noise, PSD, SNR

I. INTRODUCTION

The electrocardiogram (ECG) is the recording of the electrical movement of heart which express the state of heart is broadly utilitarian for analytic of heart sicknesses. Instructing regarding ECG is a non-obtrusive system which for the most part utilized as an issue analytic instrument for cardiovascular ailments. Because of weak non-stationary nature of ECG signal effectively meddle by noise. To acquire noise free Electrocardiogram signal denoising is the system to detached the licit signal segment from undesired signals [1]. A noise free Electrocardiogram signal gives data about the electrophysiology of the heart affliction and ischemic changes that may happen [2]. For the most part ECG signals frequency range is 0.05-100 Hz and element range of ECG signal is 1-10mv. Fundamentally ECG signal is described by five valleys and crests focuses by the P, Q, R, S, and T. also its waveform is tedious and have different knocks and parts of the waveform are assigned as the P-wave, QRS-complex and T-wave, PR-portion, ST-fragment, PR-interval and QT-interval as given in Fig. 1. Baseline wander is the low frequency movement in ECG signal as shown in Fig. 2. Because of this noise estimation of ECG parameters produce right data is unwind a dreary occupation. Pattern wander can be affected by electrode changes because of sweat, development and breath. Uprooting the standard float in ECG signal is most fundamental, in the event that it not appropriately evacuated than some essential data will be defiled or lost. The frequency range of standard wander is by and large underneath 0.5 Hz which is indistinguishable as the frequency range of ST-section [3]-[4].

Diverse strategies utilized for assessing evacuation standard wander. The high pass filter utilized with the 0.5 Hz cut–off frequency .This cut-off frequency is fundamental for uprooting standard wander and it ought to be favored so that the clinical data in ECG signals remains not mutilated [5]. Advanced filters are for the most part utilized to evacuation benchmark wander noise. The Cut-off frequency and phase reaction are two most paramount elements considered in computerized filter plans. The use of straight phase filters keeps the issue of phase bending and evaluating the gauge wander [6]. Limited drive reaction (FIR) filters having bolster forward components and its generally executed utilizing non-recursive structures. It can have a careful direct phase. Endless motivation reaction (IIR) filters are having input components and IIR filters are utilizing recursive structure. Unending motivation reaction (IIR) zero phase filtering additionally utilized uprooting of benchmark wander [7]-[8]. These techniques are use cut-off frequency for evacuating pattern wander and give undistorted ECG signal.

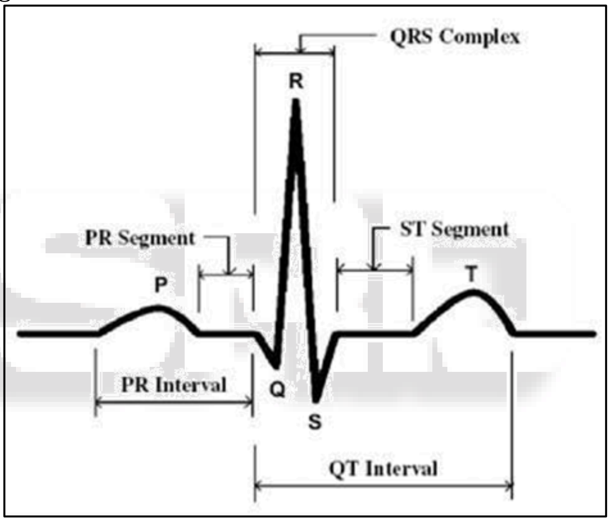

Fig. 1: The Basic ECG signal

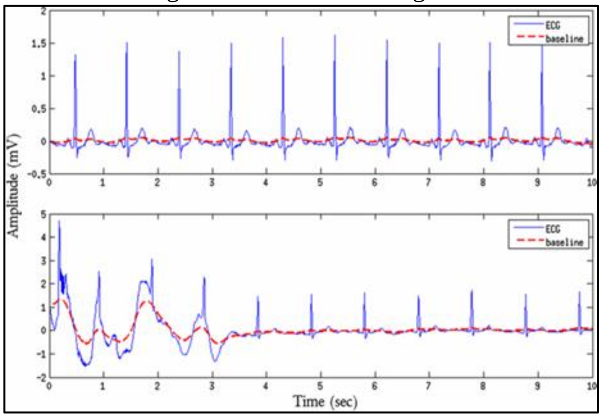

Fig. 2: ECG Signal with Noise of Baseline Drift

Cubic spline bend fitting and linear spline bend fitting are the diverse filtering methods which uproot baseline wander by taking reference focuses. Cubic spline is characterized as the isoelectric references focuses are obligatory for legitimate execution in light of the fact that it can make challenges in vicinity of noise in ECG signals. Linear spline bend fitting system is accomplish the ECG sub-signal for a solitary heart cycle which beginning 60ms preceding the P-wave and completion 60ms after the T-wave and afterward subtracting mean of sub-signal. It is most suitable for utilization in finding strategy including ST section examination in light of the fact that if baseline float is not introduce it doesn't influence the ST Segment [9]-[10]. Wavelet changes and Empirical mode decomposition (EMD) strategies are additionally used for evacuation baseline wander. Wavelet versatile filters utilized for baseline expulsion from ECG signals to decrease contortion of ST-portion. It comprises with two steps. To begin with is wavelet change disintegrates ECG signals into seven frequency groups, and second is versatile filter [11]. Observational mode decomposition (EMD) likewise offers a guaranteeing methodology for baseline wanders evacuation [12].

Versatile filtering is the methodology for evacuating baseline wander. It fundamentally utilized for evacuate DC component of ECG signal. It is additionally delivering some bending in ECG signal essentially in the ST- portion zone [13]-[14]. Autonomous component analysis (ICA) is an alternate decision of baseline wander evacuation [15]. It used to independent commonly autonomous component from blended signals. This methodology is nearly identified with blind source separation (BSS). Presently days ICA is broadly utilized for dividing biomedical signals from blended signal furthermore bioimage [16]-[18]. Quick ICA is an alternate calculation which is focused around negentropy and least probability estimation [19]-[20].

The overall paper structure as follows: Section 2 describes the deferent implementation techniques for ECG baseline wander removal. Section 3 shows the deferent performance parameters and in Section 4 paper will concluded the research.

II. IMPLEMENTATION TECHNIQUE

A. *High Pass Filter:*

Respiratory signal wanders somewhere around 0.15hz and 0.5hz frequencies. The outline of a linear, time-invariant, high pass filter for evacuation of baseline wander includes a few contemplations, of which the most pivotal are the decision of filter cut-off frequency and phase reaction trademark. The cut-off frequency ought to be picked so that the clinical data in the ECG signals stays undistorted while however much as could be expected of the baseline wander is evacuated. Consequently, it is fundamental to discover the most reduced frequency component of the ECG spectrum. By and large, the slowest heart rate is considered to characterize this specific frequency component; the PQRST waveform is credited to higher frequencies. On the off chance that excessively high a cut-off frequency is utilized, the yield of the high pass filter contains an undesirable, oscillatory component that is unequivocally related to the heart rate [3]-[6]. On the premise of Impulse Response, there are for the most part two sorts of computerized Filters:

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

We can realize Digital Filters by the generalized discrete differential equation:

$$\sum_{m=0}^{M} a_m . y[n-m] = \sum_{k=0}^{N} b_k . x[n-k] \qquad (1)$$

Where an and b are filter coefficients, x[n] is info signal, y[n] is yield signal and M, N are filter order. The right half of above comparison depends just on the inputs x[n] so it is called feed-forward & the left side relies on upon the past yields y[n] i.e. called feed-back. FIR Filters have just feed forward components; they can be figured non-recursively. IIR Filters have feed-back components likewise; they are figured recursively. This paper displays the configuration & execution of high pass FIR filter of order 400 utilizing Kaiser Window & IIR Butterworth filter of order 2 with cut-off frequency 0.5Hz.

B. *IIR Filtering:*

The equation given billow shows transfer function for a second-order Butterworth high-pass filter:

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

Where A_{hp} is high pass gain. High pass filters are not all pole filters as it contains two‘s’ in numerator and shows two zeroes at origin. The frequency response of this filter decreases monotonically with frequency:

$$|H(f = f_c)| = \frac{1}{\sqrt{2}} \qquad (3)$$

Where cut-off frequency is represented by f_c. The decrement is very slow in the pass band and quick in the stop band. Butterworth filter is a superior choice in design trouble, where no ripple is adequate in pass band and stop band [7] But due to no-linear phase response, the waveform becomes distorted.

C. *FIR Filtering:*

The high pass FIR filter is outlined by utilizing Kaiser window. The fundamental rule of the window outline strategy is to truncate the perfect reaction with a limited length window. In the filters outline utilizing windows like Rectangular, Bartlett, Hanning, Hamming and Blackman it has been observed that an exchange off exists between the principle lobe width and the side lobe amplitude. The fundamental lobe width is conversely relative to the N order of the filter. An increment in the window length diminishes the move band of the filter. Nonetheless, for the base stop band constriction and pass band swell, the fashioner must discover a window with a fitting side lobe level and after that pick order to accomplish the recommended move width. In this process, the planner might regularly need to settle for a window with undesirable outline details. To beat this issue Kaiser has picked a class of windows based the versatile Speriodal capacities. The Kaiser window is given by taking after comparison [8]:

$$w(n) = \begin{cases} \dfrac{I_0\left(\pi\alpha\sqrt{1-\left(\frac{2n}{N-1}-1\right)^2}\right)}{I_0(\pi\alpha)}, & 0 \le n \le N-1 \\ 0, & Otherwisw \end{cases} \qquad (4)$$

D. *Wavelet Filtering:*

A wavelet transform decays a signal into premise capacities which are known as wavelets. Wavelet change is computed independently for diverse sections of the time-space signal at distinctive frequencies bringing about Multi-determination analysis. It is planned in such a path, to the point that the result of time determination and frequency determination is consistent. Subsequently it gives great time determination and poor frequency determination at high frequencies though great frequency determination and poor time determination at low frequencies. This gimmick of multi determination analysis makes it superb for signals having high frequency components for brief times and low frequency components for long length of time [18]. Wavelet analysis comprises of decaying a signal into a various leveled set of close estimations and points of interest. The words rough guess and subtle element are supported by the way that estimates considering the low frequencies while the point of interest relates to the high frequency redress [10]. As baseline wandering happens at low frequencies so it is because of rough guesses. In this technique the ECG signal is disintegrated into eight levels utilizing Daubchies6 wavelet. At the point when all the subtle elements are superimposed, it comes about the waveform that wipes out the baseline float. Diverse structures were additionally taken a stab at utilizing rough guesses, yet the consideration of each close estimation presents the baseline float.

E. Polynomial Fitting:

Polynomial fitting is a system to evacuate baseline by fitting polynomials to delegate focuses in the ECG signal. In each one beat, an agent specimen is characterized and called bunch. Expanding the order of the polynomial and selecting one bunch every pulsated through which the baseline estimation must pass is the strategy used to uproot higher-frequency baseline noise and protect low frequency heart data, which is helpful for different techniques to apply after the baseline wander evacuation. By utilizing higher-order polynomials the probability of creating exact baseline evaluation increments, despite the fact that it is clearly connected to an expanded computational multifaceted nature. The polynomial is fitted in such a route, to the point that, one subtracted to the first signal, these bunches have an estimation of 0 [19].

F. Independent Component Analysis (ICA):

The calculations for Independent component analysis (ICA) were created in the most recent ten years, so it is very much new field of exploration. It can be formulated as Eq. (5), x1(t) and x2(t) are linear combinations of the sources s1 (t) and s2 (t).

$$x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) \quad (5)$$
$$x_2(t) = a_{21}s_1(t) + a_{22}s_2(t)$$

The objective of the problem is to recover the unknown signal s1 (t) and s2 (t), from the mixed signal x1(t) and x2(t) without the known information mixing process coefficients a11, a12, a21 and a22. Where unknown signal s1 (t) and s2 (t) are statistically independent. The formal definitions of the ICA can be formulated as in Eq. (6) for multiple sources and signals [20].

$$x_i(t) = a_{i1}s_1(t) + a_{i2}s_2(t) + \cdots + a_{in}s_n(t) \quad i \in [1, n] \quad (6)$$

Where n is the number of sources and mixture sources. This formula can also be expressed in matrix form as in Eq. (7)

$$X = A_{n\times n} \cdot S \quad (7)$$

Where X and S is the column matrices of mixture signal and sources respectively, and $A_{n\times n}$ is the mixture coefficients matrix. The solution of ICA can be achieved when distribution of the sources diverges from Gaussianity. The deviation from Gaussianity can be determined using measures such as Negentropy. Nongaussianity can be measured by the approximation to negentropy as in Eq. (8)

$$J(y) \ \alpha \ (E\{G(y)\} - E\{G(v)\})^2 \quad (8)$$

Where α represents proportionality, v is a Gaussian variable with zero mean and unit variance, due to this E{G(v)} is a constant. The non-quadratic function G(y) usually depends on the problem. The commonly used functions are expressed in Eq. (9)

$$G_1(y) = \frac{1}{a_1}\log(\cos(a_1 y))$$
$$G_2(y) = -e^{(-1/2 y^2)}$$
$$G_3(y) = y^4 \quad (9)$$

Where a1 ϵ [1; 2]

Some preprocessing is necessary before applying ICA in input signal. These processes are centering and whitening, the obtained signals ought to be centered by subtracting their mean value and then they are whitened by linearly transformed to make components uncorrelated and have unit variance. Whitening can be performed by using eigenvalue decomposition to the covariance matrix shown in Eq. (10)

$$E[y.y^T] = D.V.D^T \quad (10)$$

Where, D and V are the orthogonal matrix of eigenvectors and diagonal matrix of eigenvalues respectively. Now a new variable Z can be represent affecter whitening by Eq. (11) and Eq. (12)

$$Z = D.V^{1/2}.D^T.y \quad (11)$$
$$Z = D.V^{1/2}.D^T.Ps = \widetilde{P}s \quad (12)$$

The Fast and fixes point ICA is the direct extension of standard ICA. The functionality of fast and fixed point ICA is to find a way, which can maximize non-gaussianity $w^T x$. The stapes of ICA algorithm are.

- Initialize *w* as a one direction weight vector.
- Weight vectors updating according to the Eq. (13)

$$w^* = E\{xg(w^T x)\} - E\{xg'(w^T x)\}w \quad (13)$$

and weight normalization is as Eq. (14)

$$w = w^*/\|w^*\| \quad (14)$$

- Repeat above step if the weights have not converged, where *w*, is the weight vector to calculate latent source $s = w^T x$.

III. PERFORMANCE PARAMETERS

A. Signal to Noise Ratio (SNR):

SNR is the power ratio among a signal and noise. It is uttered as in terms of the logarithmic decibel scale as in Eq. (15)

$$SNR = 10\log_{10}\left(\frac{E_S}{E_N}\right)^2 \quad (15)$$

Where, Es = average signal amplitude
E_N = average noise amplitude

B. Signal to Interference Ratio (SIR):

SIR is a amount to indicate the quantity of extraction. The equation for SIR as in Eq. (16)

$$SIR = \frac{\|Y_i - S_i\|^2}{\|S_i\|^2} \quad (16)$$

Where, Y= extracted signal
S= input signal

C. Power Spectral Density (PSD):

The periodogram power spectrum estimate shows the allocation of the signal power over frequency. From the band the frequency content of the signal can be estimated directly. Power spectral density (PSD) of ECG signal is intended as follows as in Eq. (17):

$$s(f) = \frac{1}{F_s N}\left|\sum_{N=1}^{N} x(n)e^{-j\left(\frac{2\pi f}{F_s}\right)n}\right| \qquad (17)$$

Where F_s is sampling frequency. The periodogram is an approximation 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].

D. Average Power:

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

IV. CONCLUSIONS

This paper reviews deferent ECG baseline wander removal techniques developed in last decade. Table 1. Show comparison of estimation parameters for deferent filtering approaches. Results are obtained for IIR HP, FIR HP, wavelet transform, moving average, savitzky golay, polynomial fitting and ICA. Results are shown while taking initial PSD as 35.60 for all approaches. It is observed that output PSD for ICA approach is 0.847dB/Hz, output SNR is 12.45 dB and average power is 32.45 dB. Which is much better than other approaches. It is observed that ICA approach is much better approach rather than other approaches for baseline removal. These results may more improved by implementing fast ICA with multiple adjustments.

V. ACKNOWLEDGMENT

The author would like to express their sincere thanks to Dr. Shivendra Singh, Head of the Department of Electronics and Communication, all authors the reference for this research, All faculty members of the department and of all the persons who have supported in any way for this survey.

Filtering Method	PSD at 0.35Hz (dB/Hz) Before filtration	PSD at 0.35Hz (dB/Hz) After filtration	SNR (dB)	Average Power of signal (dB)
IIR HP	35.60	37.19	-9.758	42.10
FIR HP	35.60	31.74	-9.32	41.12
Wavelet	35.60	7.356	11.689	31.56
Moving Average	35.60	3.018	10.358	31.21
Savitzky-Golay	35.60	3.896	11.64	31.34
Polynomial Fitting	35.60	-1.312	10.15	31.42
ICA	35.60	0.847	12.45	32.45

Table 1: Comparison between deferent ECG baseline wander filtering approaches

REFERENCES

[1] Joshi, S. L., Vatti R. A., and Tornekar, R. V. 2013. A Survey on ECG Signal Denoising Techniques. International Conference on Communication Systems and Network Technologies. 60-64.

[2] Das, M.K., and Ari, S. 2013. Analysis of ECG signal denoising method based on S-transform. IRBM. Vol. 34. Issue 6. 362–37.

[3] Gurumurthy, S., and Valarmozhi. 2013. System Design for Baseline Wander Removal of ECG Signals with Empirical Mode Decomposition Using Matlab. International Journal of Soft Computing and Engineering (IJSCE). Vol. 3. Issue 3.

[4] Jane, R., Laguna, P., Thakor, N.V., and Caminal, P. 1992. Adaptive baseline wander removal in the ECG: comparative analysis with cubic spline technique. Proceedings of Computers in Cardiology, Durham, NC. 143-146.

[5] Chouhan, V. S., and Mehta, S. S. 2007. Total removal of baseline drift from ECG signal. in Proceedings of International Conference on Computing: Theory and Applications (ICCTA '07). 512–515.

[6] Van Alst´e, J. A., Van Eck, W., and Herrmann, O. E. 1986. ECG baseline wander reduction using linear phase filters. Computers and Biomedical Research. Vol. 19. No. 5. 417–427.

[7] Kaur, M. and Seema. 2011. Comparisons of Different Approaches for Removal of Baseline Wander from ECG Signal. International Journal of Computer Applications (IJCA). Vol.5. 30-34.

[8] Harting, L. P., Fedotov, N. M., and Slump, C. H. 2004. On baseline drift suppressing in ECG-recordings. in Proceedings of the IEEE Benelux Signal Processing Symposium. 133–136.

[9] Rinen, H., and Oja, E. 2000. Independent component analysis: algorithms and applications. Neural Networks. Vol.13. 411-430.

[10] Meyer, C. R., and Keiser, H. N. 1977. Electrocardiogram baseline noise estimation and removal using cubic splines and state-space computation techniques. Computers and Biomedical Research. Vol. 10. No. 5. 459–470.

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

[12] Blanco-Velasco, M., Weng, B., and Barner, K. E. 2008. ECG signal denoising and baseline wander correction based on the empirical mode decomposition. Computers in Biology and Medicine. Vol. 38. 1-13.

[13] Kabir, Md. A., and Shahnaz, C. 2012. Denoising of ECG signals based on noise reduction algorithms in EMD and wavelet domains. Biomedical Signal Processing and Control. Vol.7. 481– 489.

[14] Laguna, P., Jane, R., and Caminal, P. 1992. Adaptive Filtering of ECG Baseline Wander. Engineering in Medicine and Biology Society, International Conference of the IEEE. Vol.14.

[15] Widrow, B., Glover, J. R., and McCool, J. M. 1975. Adaptive noise cancelling: principles and applications. Proceedings of the IEEE. Vol. 63. No. 12. 1692–1716.

[16] Barati, Z., and Ayatollahi, A. 2006. Baseline wandering removal by using independent

component analysis to single-channel ECG data. Proceedings of International Conference on Biomedical and Pharmaceutical Engineering (ICBPE ’06). 152–156.
[17] Nimitha, U. and Supriya, P. 2011. Independent Component Approach for the Analysis of ECG Signals. Proceedings of the IEEE. 1-5.
[18] Hyvärinen, A., and Oja, E. 2000. Independent Component Analysis: Algorithms and Applications. Neural Network. Vol. 13. Issues 4–5. 411–430.
[19] Milanesi, M., Vanello, N. and Positano, V. 2005. Frequency domain approach to blind source separation in ECG monitoring by wearable system. in Proceedings of Computers in Cardiology. 767–770.
[20] Luo, Y., Hargraves, R. H., Belle, A., Bai, O., Qi, X., Ward, K. R., Pfaffenberger, M. P., and Najarian, K. 2013. A hierarchical method for removal of baseline drift from biomedical signals: application in ECG analysis. The Scientific World Journal. 1-10.
[21] Hyvarinen. Fast and robust fixed-point algorithms for independent component analysis. IEEE Transactions on Neural Networks. Vol. 10. No. 3. 626–634.
[22] US Patent, ’’US5318036’’, Hewlett Packard.