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Different Techniques of Baseline Wandering Removal - A Review

Sonali[1], Payal Patial[2]
Electronics and Communication Engineering, Lovely Professional University, India

Abstract: Electrocardiogram (ECG) signal is a very important measure to know the Heart actual conditions. Thus a proper analysis of this ECG signal is must. The ECG signal is mainly contained with PQRST waves among which QRS complex is the high frequency 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 noises Baseline Wandering is a low frequency noise and can mask some important features of the ECG signal; mainly while analyzing ST segment. Hence it is desirable to remove this noise for proper analysis of the ECG signal. This paper presents various approaches for baseline noise removal in the electrocardiogram (ECG) signal which include methods based on median filtering, adaptive filtering, wavelet adaptive filtering, zero phase filtering, use of project pursuit gradient ascent, cubic spline curve fitting, linear spline curve fitting, high pass filtering, moving average approach, Savitzky-Golay Polynomial approach and empirical mode decomposition.

Keywords: Adaptive Approach, Baseline Wandering, Cubic Spline, ECG, Empirical Mode Decomposition Projection Pursuit, Wavelets.

I. INTRODUCTION

Electrocardiogram is the measure of the electrical activity of the Heart and is measured through potential electrodes placing on the body surface at some specified positions. During the acquisition few conditions such as movement of the patient, respiration, and interaction between the electrodes and skin cause baseline wandering of the ECG signal. Many methods of removing the artifacts in ECG signals have been proposed. In general these methods can be categorized into non-adaptive and adaptive filtering approach. The non-adaptive filtering approaches mainly include IIR filter, FIR filter and notch filter. The high pass filter with 0.5Hz cut-off frequency can be used to remove the baseline wander, which can filter out signal component with frequency below 0.5Hz while frequency above 0.5Hz are preserved; the filter can be implemented recursively and non recursively (IIR and FIR). It has been noticed that the baseline wander is a low frequency noise and has a frequency less than 0.5 Hz. The other methods based on baseline wander estimation are also used, which involves estimating the baseline with polynomial or cubic spline and subtracting it from the disturbed signal; the performance of this method depends on the knots determination accuracy. Wavelet and EMD approach has also been discussed here for the baseline removal.

II. VARIOUS TECHNIQUES

2.1 Through Median Filtering Approach

Chouhan et al. [1] 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.

2.2 Through Adaptive Filtering (AF) Approach

In [7] Adaptive filtering approach has been used for baseline wander removal from the ECG signal using the architecture shown as in figure 1.For adaptive filtering of baseline wandering used here, only one weight is needed and the reference input is a constant with a value of one. The optimal weight w is determined using the Least Mean Squares (LMS) algorithm which is given in (1) as follows:

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

This filter has a zero at 0Hz and consequently it creates a notch with a bandwidth of f_s where f_s 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 f_s =250Hz). This approach produces severe distortion in the ECG signal, especially in the ST segment area [4].

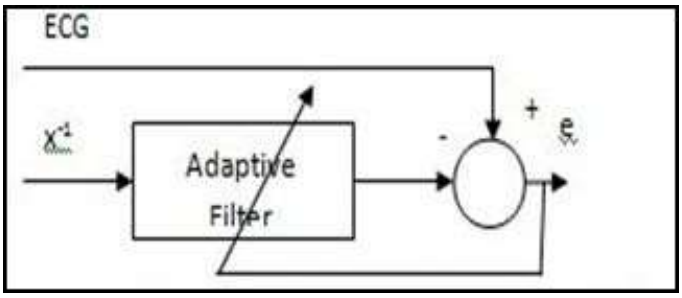

Figure 1: Adaptive filtering for ECG Baseline Removal [7]

2.3 Through Wavelet Adaptive Filtering (WAF) Approach

Park et al. [4] 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 wavelet having orthogonal characteristics. The 7^{th} 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 not require 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.

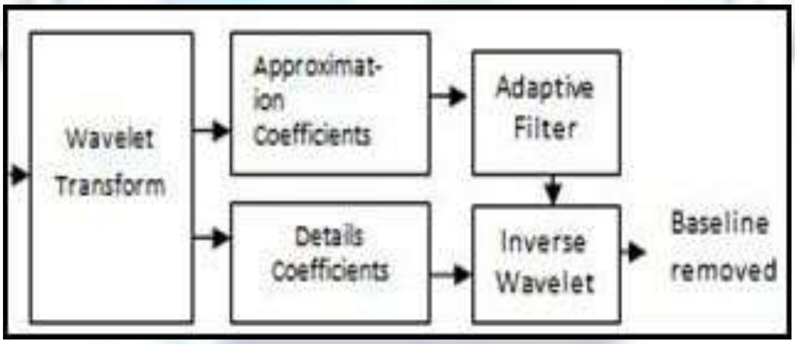

Figure 2 : Baseline removal using WAF [8]

2.4 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 [26] .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 [10]. 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 [27]:

$$y[n] = a_0 x[n] + a_1 x[n+1] + a_2 x[n+2] + a_3 x[n+3] + \cdots + b_1 y[n-1] + b_2 y[n-2] + b_3 y[n+3] \quad (2)$$

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

$$y[n] = a_0 x[n] + a_1 x[n-1] + a_2 x[n-2] + a_3 x[n-3] + \cdots + b_1 y[n-1] + b_2 y[n-2] + b_3 y[n-3] \quad (3)$$

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 Moving Average Approach

A moving average filter smooth the data by replacing each data point by the average of its neighbouring data points which are defined within the span. This process is equivalent to low pass filtering having the response of the smoothing which is given by the following difference equation (4),

$$Ys(i) = \frac{1}{2N+1}(Y(i+N) + Y(i+N-1) + \cdots + Y(i-N)) \quad (4)$$

Where Ys(i) is the smoothed value for the i^{th} data point, and N is the number of neighbouring data points on either side of Ys(i), whereas 2N+1 is the span which is defined for the smoothing [20]. The data equivalent to high pass filtering can be achieved by subtracting the output of this filter from original data. The moving average smoothing method used by Curve Fitting Toolbox follows these rules [20]:

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

2.6 Through Projection Pursuit Gradient Ascent Method

For this method, the source signals must have non Gaussian probability density functions and they must be statistically independent [5]. As the mixture signals tends toward gaussianity which can be seen from central limit theorem. In this paper each source signal is extracted from a set of mixture signal by calculating inner product which gives an orthogonal projection of the signal mixtures. In projection pursuit one signal is extracted at a time in such a way that it will be near to non Gaussian. This method does not need to extract all signals from mixture signals. Any number of possible mixing signals can be extracted [2]. In the case of two signals one is ECG signal and other one is baseline noise signal. If ECG signals are denoted by s_1 and baseline noise by s_2, then the mixture signal can be represented as

$$p_i = a_i s_1 + b_i s_2 \quad (5)$$

Where pi are the mixtures, a_i and bi are some real coefficients. In real life problems we have only pi, that is mixing signals s_1 and s_2 are always unknown. The basic idea behind this is to separate the component signals s_1 and s_2 from the mixture signals pi. Here Kurtosis was used as a measure of non gaussianity to separate the component signals from the mixture. Kurtosis has no information about the Gaussian random variable. It has a positive value for peaked activity distribution and negative value for flat activity distribution. Kurtosis for a unit variance variable can be calculated by the following equation:

$$kurt(y) = E\{(y^4)\} - 3 \quad (6)$$

2.7 Through Cubic Spline Curve Fitting Approach

This method [3] is among the most commonly used approaches for the removal of baseline wandering in the ECG signal. In this approach [3] isoelectric fiducial points are found in the ECG signal with baseline variation for each beat using an approach which is identical to the one discussed earlier and a third order cubic spline is fitted on these points to obtain an estimate for the baseline wander which is then subtracted from the original ECG signal. This Cubic spline interpolation based baseline removal and other interpolation based techniques are adaptive in accordance to the heart rate, as there are more reference points available with increase in heart rate. However, in the absence of any baseline variation in an ECG segment, an error in the calculation of the isoelectric reference point is found that is corresponding to the undesired distortion in the ECG. Hence an accurate definition of the isoelectric reference point is must for proper functioning which can become difficult in the presence of noise in the ECG signal. Due to this reason this approach needs to define the appropriate isoelectric reference point.

2.8 Through Linear Spline Curve Fitting Method

Papaloukas et al. [8] have introduced a simple and effective approach for the removal of baseline wandering from the ECG signal. This method first includes the ECG signal s[n] for a single cardiac cycle starting 60ms before the P-wave and ending 60ms after the T-wave then its mean is taken and subtracted from it to give y[n].Now a first order polynomial p[n] is fitted on y[n]. The sample values of the QRS complex for each cardiac cycle in y[n] are replaced by the corresponding values of p[n] that give y*[n].This replacement of QRS removes for the shift in p[n] towards main QRS polarity due to the high peaks in the QRS complexes. Then, a first order polynomial curve is fitted to y*[n] which is then subtracted from the corresponding region of y[n] which gives the baseline removed signal. This method is very well suited for the use in diagnosis procedures that involves ST segment analysis because it does not affect the ST segment when no baseline variation is present. However, this method may produce discontinuities in the resulting signal at the end points of a cardiac cycle therefore reliable detection of the start and end points of the cardiac Cycle along with accurate QRS delineation is must and which leads this approach a dependent one.

2.9 Through High Pass Filter Approach

Baseline Wandering in Respiratory signals lies between 0.15Hz and 0.5Hz frequencies [19]. 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)

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

$$\sum_{m=0}^{M} a_m\, y[n-m] = \sum_{K=0}^{N} b_k\, x[n-k] \tag{7}$$

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

In the (7), the right side depends only on the inputs x[n] so it is called as feed-forward where as the left side of equation depends on the previous outputs y[n] so it is called as feed-back. As FIR Filters have only feed-forward components, so they can be calculated non-recursively on the other hand IIR Filters have feed-back components also, and they are calculated recursively [23].

2.9.1 IIR Filtering

High pass filters are not all pole filters and in the given by (8), 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:

$$|\,H(f = f_c)\,| = \frac{1}{\sqrt{2}} \tag{8}$$

where, f_c is cut-off frequency.

The transfer function for a second-order Butterworth high-pass filter is given by (9),

$$H(s) = \frac{A_{hp}\, bs^2}{s^2 + \frac{a}{b} w_c s + \frac{w_c^2}{b}} \tag{9}$$

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 [24]. But it has to non-linear phase response, and due to that waveform gets distorted.

2.9.2 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, Hanning Window, Hamming Window and Blackman Window, it has been found that there is a trade off 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) [25]:

$$\begin{aligned} w_k &= \frac{I_0\left[\alpha\sqrt{1-\left[\frac{2n}{N-1}\right]^2}\right]}{I_0(\alpha)} \\ &= 0 \text{ otherwise} \end{aligned} \tag{10}$$

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

2.10 Savitzky-Golay Filtering

Generalized moving average is given by Savitzky-Golay filtering. The filter coefficients can be derived by performing unweighted linear least- squares fit which is performed by using a polynomial of an appropriate degree. Savitzky-Golay filter is also called a digital smoothing polynomial filter or a least-squares smoothing filter [20]. It helps to preserve the peaks and valleys of the ECG signals better than a standard FIR filter.

2.11 Polynomial Fitting

Polynomial fitting is a method to remove baseline by fitting polynomials to representative points in the ECG signal. In each and every beat, a representative sample is defined and called knot. The method used to remove higher-frequency baseline noise and to preserve low-frequency heart information, the order of the polynomial is increased and selecting one knot per beat through which the baseline estimation must pass. With the use of higher-order polynomials the likelihood of producing an accurate baseline estimate increases, but it is linked to an increased computational complexity. The fitting of polynomial is done in such a way that, one subtracted to the original signal, these knots have a value of 0 [29].

2.12 Through Empirical Mode Decomposition (EMD) Method

Empirical Mode Decomposition was developed by Huang et al. [9] 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 extrema 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 [10] 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.

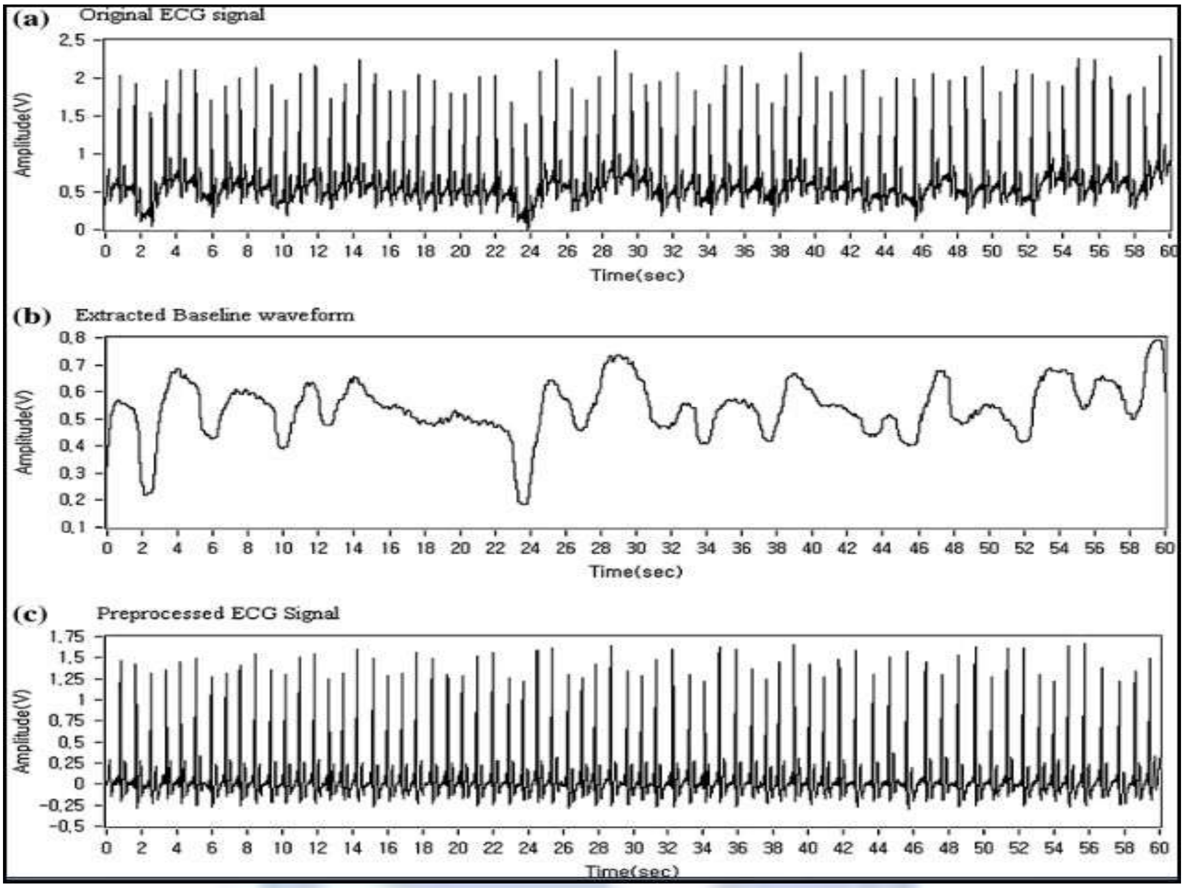

Figure 3 : Removal of Baseline Wandering from ECG Signal

III. CONCLUSIONS

Median Filtering also offers the advantage that the signal is not distorted in the absence of baseline variation and is computationally efficient too. Adaptive Filtering approach produces severe distortion in the ECG signal, especially in the ST segment area. Zero-phase filtering minimizes start-up and ending transients by matching initial conditions. It helps in preserving the features. Baseline Wandering Removal from Human Electrocardiogram Signal using Projection pursuit is an efficient way of separating signals from a mixture where mixing signals are non Gaussian and independent. But one disadvantage of this algorithm is that it extracts one signal at a time. In Cubic spline accurate definition of the isoelectric reference point is mandatory for proper functioning which can become a difficult task in the presence of noise in the ECG signal. Linear Spline Curve Fitting is very well suited for use in diagnosis procedures involving ST segment analysis because it does not affect the ST segment when no baseline variation is present. However, this method may produce discontinuities in the resulting signal at the end points of a cardiac cycle hence reliable detection of the start and end points of the cardiac cycle along with the accurate QRS delineation is must. FIR Filters have only feed-forward components, so they can be calculated non-recursively on the other hand IIR Filters have feed-back components also, and they are calculated recursively. A moving average filter smooth the data by replacing each data point with the average of the neighboring data points which are defined within the span. Savitzky-Golay Filtering helps to preserve the peaks and valleys of the ECG signals better than a standard FIR filter. In polynomial fitting the use of higher-order polynomials the likelihood of producing an accurate baseline estimate increases. Empirical Mode Decomposition also offers a justifiable approach for the removal of baseline variations from the ECG signal. However it is computationally very demanding in comparison to other approaches. Wavelet adaptive filter is the recommended approach for baseline removal for the analysis of ST segment deviations in the ECG signal as it gives comparative better result with less computation. Many researchers are still working on baseline wandering removal for better and distortion less results.

REFERENCES

[1]. 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.
[2]. Friedman, JH, & JW, Turkey, "A projection pursuit algorithm for exploratory data analysis," IEEE transaction on computers, vol 29, pp 881-890, 1974.
[3]. C. R. Meyer and H. N. Keiser, "Electrocardiogram baseline noise estimation and removal using cubic splines and state-space computation techniques," Comput. Biomed. Res., vol. 10, pp. 459-470, 1977.
[4]. 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.
[5]. Hyva¨rinen, E. Oja, "Independent component analysis: algorithms and applications", Neural Networks, vol. 13, pp. 411-430, 2000.
[6]. J. G. Proakis and M. D. G., Digital Signal Processing: Principles, Algorithms, and Applications: Prentice- Hall, 1999.
[7]. P. Laguna, R. Jane, and P. Caminal, "Adaptive Filtering of ECG Baseline Wander," presented at Engineering in Medicine and Biology Society, 1992. Vol.14. Proceedings of the Annual International Conference of the IEEE, 1992.
[8]. C. Papaloukas, D. I. Fotiadis, A. Likas, A. Liavas, and L. Michalis, "Acknowledge -based Technique for the Detection of Ischemic Episodes in Long Duration ECGs," Medical and Biological Engineering and Computing, vol. 39, pp. 105-112, 2001.
[9]. 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.
[10].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.
[11].Gulrajani, Ramesh M., "Bioelectricty and Biomagnetism'', John Wiley and Sons Publishing Company, 1998.
[12].http://en.wikipedia.org/wiki/File:SinusRhythmLabels.svg.
[13].Yunfeng Wu, Rangaraj M. Rangayyan , Yachao Zhou, Sin-Chun Ng, 'Filtering electrocardiographic signals using an unbiased and normalized adaptive noise reduction system', Medical Engineering & Physics 31 (2009) 17–26.
[14].Behzad Mozaffary Mohammad A. Tinati, 'ECG Baseline Wander Elimination using Wavelet Packets', World Academy of Science, Engineering and Technology 3 2005,pp 14-16.
[15].Zahoor-uddin, 'Baseline Wandering Removal from Human, Electrocardiogram Signal using Projection Pursuit Gradient Ascent Algorithm', International Journal of Electrical & Computer Sciences IJECS/IJENS Vol: 9 No: 9, pp 11-13.
[16].Mahesh S. Chavan, R.A.Agarwala, M.D.Uplane, Comparative Study of Chebyshev I and Chebyshev II Filter used For Noise Reduction in ECG Signal, International Journal Of Circuits, Systems And Signal Processing Issue 1, Volume 2, 2008,pp1-17.
[17].Mahesh S. Chavan, R.A.Aggarwala, M.D.Uplane, 'Suppression Of Baseline Wander And Power Line Interference in ECG Using Digital IIR Filter', International Journal of Circuits, Systems And Signal Processing, Issue 2, Volume 2, 2008,pp-356-65.
[18].Fayyaz A. Afsar, M. S. Riaz and M. Arif, 'A Comparison of Baseline Removal Algorithms for Electrocardiogram (ECG) based Automated Diagnosis of Coronory Heart Disease' 3rd International Conference on Bioinformatics & Biomedical Engineering (iCBBE-2009), Beijing, PR of China, June 11-13, 2009.
[19].V. S. Chouhan and S. S. Mehta, "Total Removal of Baseline Drift from ECG Signal, Computing: Theory and Applications-ICCTA '07, 0-7695-2770-1/07.
[20].Matlab help, MATLAB MATHWORKS, http://www.mathworks.com.
[21].Leif Sornmo, & Pablo Laguna, 'Electrocardiogram (ECG) Signal Processing'. Wiley Encyclopedia of Biomedical Engineering, 2006 John Wiley & Sons, Inc., pp-1-16.
[22].Matti Aksela, 'ECG Filtering' T-61.181 Biomedical Signal Processing Presentation 11.11.2004.
[23].Technikum Wien, 'Microprocessor based Design for Biomedical Applications', MBE 3 – MDBA VII: Digital Signal Processing Basics & Applications. embsys.technikum-wien.at/staff/veigl/MDBA/.../I-Introduction.ppt
[24].Filters II – Filter Design with MATLAB', Experiment 3, pp 4-5.,www.cas.mcmaster.ca/~lawford/.
[25].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).
[26].Lisette P. Harting et al., 'On Baseline drift Suppressing In ECG-Recordings', Proceedings of the 2004 IEEE Benelux Signal Processing Symposium, pp133-136.
[27].Steven W. smith, 'The Scientist & Engineer's guide to digital signal processing', second edition 1999, California Technical Publishing, San Diego, California,pp320-330.
[28].Ratnakar Madan et al, 'Signal Filtering Using Discrete Wavelet Transform', International Journal of Recent Trends in Engineering, Vol 2, No. 3, November 2009,pp 96-98.
[29].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.