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Different Techniques to Remove Baseline Wander from ECG Signal

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Abstract-

Baseline wandering noise can mask some important features of the ECG signal; hence it is desirable to remove this noise for proper analysis of the ECG signal. This paper presents different approaches for performing baseline noise removal in the electrocardiogram (ECG) signal which include methods based on use of project pursuit gradient ascent, cubic spline curve fitting, linear spline curve fitting, median filters, digital filters, adaptive filters, wavelet adaptive filters and empirical mode decomposition.

Keywords-ECG, Baseline Removal, Projection Pursuit, Wavelets, Cubic Spline, Empirical Mode Decomposition

I. INTRODUCTION

ECG measures electrical potentials on the body surface via contact electrodes. Conditions such as movement of the patient, breathing, and interaction between the electrodes and skin cause baseline wandering of the ECG signal. Many methods of removing the artifacts in ECG signals were proposed in last twenty years. In general these methods can be categorized into non-adaptive and adaptive filtering. 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 interference of 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).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.

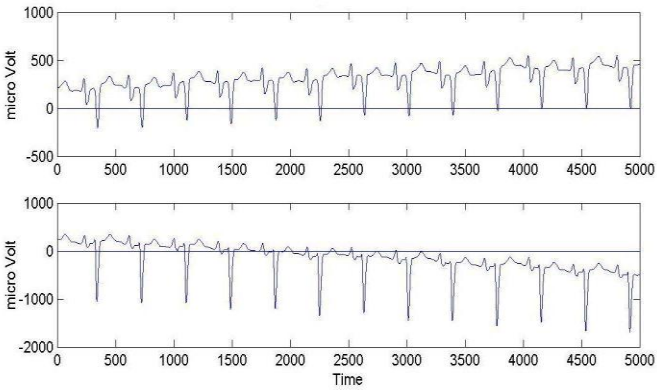

Figure 1. ECG signals with baseline drift [5]

II. DIFFERENT TECHNIQUE

A) Projection Pursuit Gradient Ascent

The source signals must have non Gaussian probability density functions and they must be statistically independent [1]. Mixture signals tends toward gaussianity which can be seen from central limit theorem. Here each source signal is extracted from a set of mixtures signal by calculating inner product which gives an orthogonal projection of the signal mixtures. Now the key point is this that how such a weight vector can calculate such a weight. In projection pursuit one signal is extracted at a time which will be as non Gaussian as possible. This method does not need to extract all signals from mixture signals. Any number of possible mixing signals can extracted [2]. In case of two signals one is ECG signal and other one is baseline noise signal. Let ECG signal is denoted by s_1 and baseline noise by s_2 , now the mixture signal can be represented as,

$$p_2 = a_1 s_1 + b_1 s_1 \quad (1)$$

Where p_i are the mixtures, a_i and b_i are some real coefficients. In real life problems we have only p_i , mixing signals s_1 and s_2 are always unknown. The basic job is to separate the component signals s_1 and s_2 from the mixture signals p_i . 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,

$$\text{Kurt}(y) = E\{(y4)\} - 3 \qquad (2)$$

B) Use of Cubic Spline Curve Fitting

In this approach [3] isoelectric fiducial points are found in the ECG signal with baseline variation for each beat using an approach identical to the one discussed earlier and a third order cubic spline is fitted on these points to obtain an estimate of the baseline which is then subtracted from the original ECG signal. This method is among the most commonly used approaches for removal of ECG baseline variation. Cubic spline interpolation based baseline removal and other interpolation based techniques adapt themselves automatically to the heart rate as more reference points become 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 or the corresponding level causes undesired distortion in the ECG. Therefore accurate definition of the isoelectric reference point is mandatory for proper functioning which can become difficult in the presence of noise in the ECG signal.

C) Use of Linear Spline Curve Fitting

Papaloukas et al. [4] have proposed a simple and effective approach for the removal of baseline from the ECG signal. This method takes the ECG signal s[n] for a single cardiac cycle starting 60ms before the P-wave and ending 60msafter the T-wave and subtracts its mean from it to give y[n].Next 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] to give y*[n].This replacement removes for the shift in p[n] towards main QRS polarity due to the high peaks in the QRS complex. Thereafter, a first order polynomial curve is fitted to y*[n] which is then subtracted from the corresponding region of y[n] to obtain the baseline removed signal. This method 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 therefore reliable detection of the start and end points of the cardiac Cycle along with accurate QRS delineation is required.

D) Median Filtering

Chouhan et al. [5] give a technique for baseline removal using median filtering on the electrocardiogram. In this procedure, firstly the median of the ECG signal is 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 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.

E) FIR High Pass Filtering (FIR HPF)

Since the baseline signal is a low frequency signal therefore Finite Impulse Response (FIR) high pass zero phase forward-backward filtering [6] with a cut-off frequency of 0.5Hz to estimate and remove the baseline in the ECG signal can be used. The order of the high pass filter is taken to be 700. This approach does not require the detection of any reference points in the ECG signal. However, due to the high filter order, this approach presents a high computational load. Moreover to nullify any phase distortions, zero-phase forward backward filtering have to be used which cannot be implemented in real-time.

F) Adaptive Filtering (AF)

Adaptive filtering has been used for baseline removal from the ECG in [7] using the architecture shown in figure 3.

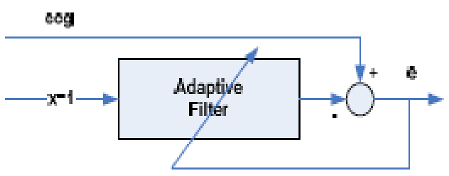

Figure 2. Adaptive Filtering for ECG Baseline Removal [7]

For adaptive filtering of baseline wandering, 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 as follows,

$$W(k+1) = w(k) + 2\mu e(k)\, x(k) \quad (3)$$

This filter has a zero at 0Hz and consequently it creates a notch with a bandwidth of $(\mu/\pi)f_s$ where fs is the sampling frequency. Because AHA recommends cut-off frequencies 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 [8].

G) Wavelet Adaptive Filtering (WAF)
Park et al. [8] (see fig. 4) have proposed a wavelet adaptive filter for baseline removal from the ECG to minimize distortion of the ST Segment. In this method the ECG signal with baseline is decomposed up to 7 levels using Wavelet Transform with Vaidyanathan-Hoang wavelet having orthogonal characteristics. The 7th level approximation coefficients have frequency components in the range of 0- 1.4Hz. These coefficients are then subjected to the adaptive filter with a cut off frequency of 0.8Hz. The filtered output and the details coefficients are used for reconstruction using inverse wavelet transform to produce the baseline removed signal.

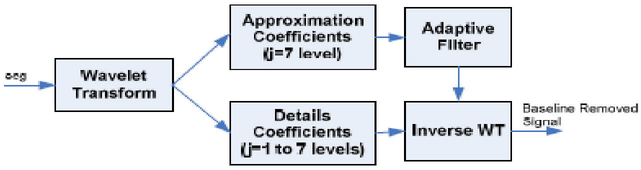

Figure 3. Baseline Removal using WAF [8]

This approach presents a very effective approach for baseline removal as it does not require the calculation of any reference points and the use of wavelet transform for the analysis of the inherently non-stationary ECG signal.

H) Use of Empirical Mode Decomposition (EMD)
Empirical Mode Decomposition [9] is a fully data-driven technique for analysis of non-stationary signals in which no a priori known basis is required. In EMD the input signal is decomposed into a sum of intrinsic mode functions (IMFs). 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 from the IMF obtained by the decomposition of the input ECG signal is used. This is done in a way to remove low frequency components from the ECG signal which results in the removal of baseline variation. For further details refer to [10]. This method also offers a promising approach for removal of baseline variations from the ECG signal. However it is computationally very demanding in comparison to other approaches.

III. DISCUSSION AND CONCLUSION

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. 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 difficult 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 therefore reliable detection of the start and end points of the cardiac Cycle along with accurate QRS delineation is required. Median Filtering also offers the advantage that the signal is not distorted in the absence of baseline variation and is computationally efficient. Adaptive Filtering approach produces severe distortion in the ECG signal, especially in the ST segment area. Empirical Mode Decomposition also offers a promising approach for 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. Many researchers are still working on base line noice reduction for better results without distorting the waveform.

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