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Estimation of Baseline Wander Characteristics in ECG Signals Using Adaptive Transversal Filter and Lomb's Periodogram Analysis

Abstract. *A new technique is proposed to estimate the frequency and amplitude of baseline wander in ECG signals. The estimation has been performed in two stages. In the first stage, a QRS detector detects R peaks and signal samples between consecutive R peaks are passed through a weighted average adaptive filter. The cut-off frequency and order of the filter depends upon the time domain characteristics of the input samples and is automatically updated for each RR interval. In the second stage, Lomb's periodogram is utilized to analyse the frequency response of the resultant unevenly sampled time series for estimating the baseline frequencies. These frequencies are then used to demodulate the signal for estimation of respective amplitudes. Results have been obtained using synthetic ECG signals with artificially introduced baseline wander containing single or multiple frequencies. The performance of the technique is evaluated by extracting baseline wander through three standard techniques and comparing the estimation errors.*

Streszczenie. *W artykule opisano propozycje estymatora częstotliwości i amplitudy wahań osi podstawy dla sygnałów w badaniu EKG. Estymacja przebiega w dwóch etapach. Najpierw detektor QRS wykrywa impulsy R, a próbki sygnałów poddawane są filtracji w filtrze adaptacyjnym. W drugim kroku, korzystając z periodogramu Lomb'a, analizowana jest odpowiedź częstotliwościowa, będąca w postaci nierównomiernie pobieranych próbek. Tym sposobem uzyskuje się estymację częstotliwości odniesienia. Działanie algorytmu poddano weryfikacji na bazie symulowanych sygnałów EKG i porównano z trzema standardowymi technikami.* ***(Estymacja charakterystyki przemieszczenia osi podstawy dla sygnałów EKG z wykorzystaniem filtru adaptacyjnego poprzecznego i analizy periodogramem Lomb'a)****.*

Keywords: Electrocardiogram, baseline wander, ECG preprocessing, estimation
Słowa kluczowe: elektrokardiogram, wędrowanie osi podstawy, EKG, przetwarzanie wstępne, estymacja.

Introduction

Elimination of baseline wander is a classical problem in ECG preprocessing. Baseline serves as a reference isoelectric level, corresponding to resting potential of cardiac cells before a new heartbeat is initiated by SA node. Drift in this level can be caused by respiration, loose electrode contact or body movement during ECG acquisition. Consequently, artefactual data is introduced into actual cardiac activity measurements. Both amplitude and wave duration of ECG signal gets considerably effected by baseline variation; former being a measurement of potential with respect to this isoelectric level and latter being a difference between time instants at which a particular wave crosses the baseline.

The spectral components of clinical information and baseline wander overlap and there is no ideal consensus regarding exact frequency content of baseline wander. It is generally understood to be below 0.5 Hz [1, 2]. High frequency baseline wander makes it difficult to differentiate between atrial depolarization (P-wave) and ventricular repolarization (T-wave). Low frequency baseline variations especially affect ST segment analysis which is important for ischemia diagnosis [3]. The amplitude of the baseline wander may go up to 1 V [4].

The methods for eliminating baseline wander always target the problem indirectly without estimating the actual frequency and amplitude of baseline variation trend. Among filtering techniques, conventional FIR and IIR filters [5, 6, 7], time-variant filters [8] and adaptive filters [9, 10] have been utilized. All these techniques make use of low-frequency filtering guidelines issued by AHA [2].

The other commonly employed method besides filtering is third order polynomial interpolation [11]. The accuracy of this method totally depends upon the estimation of PR intervals. The technique is not particularly useful for real time implementations. Moreover, the accuracy degrades for lower heart rates when knots become distant.

In this paper, we propose a new technique to estimate the exact frequency and amplitude of baseline wander. Synthetic ECG signals have been utilized with baseline wander modelled as a function of respiratory frequency [13]. The technique is implemented in two stages. In first stage, a QRS detector detects R peaks in the signal and samples between consecutive R peaks are passed through a linear filter with adaptive characteristics, i.e., cut-off frequency, weights and order of the filter are continuously updated for each RR interval. In second stage, Lomb's method is utilized for spectral analysis of the filtered unevenly sampled time series. The frequency content of baseline wander is estimated from the spectrum of this series. The estimated frequency is then used to demodulate the ECG signal for estimating the amplitude of the baseline wander trend. We briefly present the system model and details of the experimental method in next section. Section 3 includes validation tests, results achieved and related discussions regarding limitations of the technique as well as suggested improvements for future work.

Experimental Model

Synthetic ECG signal for the experiment has been generated using the open source software [12] based on the proposed dynamical model by [13]. Parameters for the signal which were modified are listed in table 1. The only minor modification in the model is to remove the already introduced baseline wander to avoid duplication of coupling. For this experiment, baseline wander is modelled as a sinusoidal function β(t), i.e.,

$$\beta(t) = A\sin(2\pi f_B t) \tag{1}$$

where A and f_B are the amplitude and frequency of the baseline wander trend, respectively. This trend is added to the ECG signal $\psi(t)$. The resultant signal $s(t)$ is represented (figure 1) as

$$s(t) = \psi(t) + A\sin(2\pi f_B t) \tag{2}$$

Table 1. Parameters for ECG signal and baseline model

Parameter	Value
Sampling frequency (f_S)	256 Hz
Number of beats (N)	256
Mean heart rate	80 bpm
Heart rate standard deviation	1 bpm
LF / HF ratio	0.5
Baseline frequency (f_B)	0.25 Hz
Baseline amplitude (A)	0.15 mV

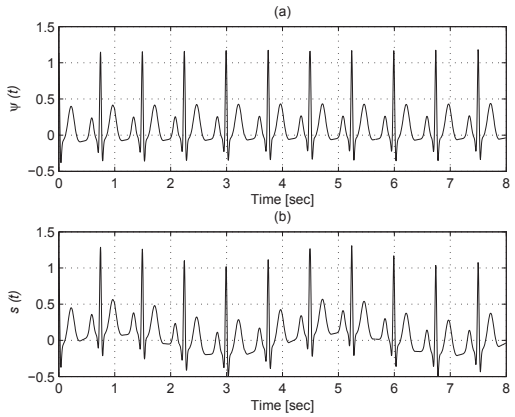

Fig. 1. (a) 8 second excerpt of the synthetically generated ECG signal without baseline wander. (b) Same signal with baseline line added; f_B= 0.25 Hz, A = 0.15 mV.

Stage I: Linear Adaptive Filter

The block diagram of the system is shown in figure 2. First stage consists of a QRS detector which is implemented using algorithm developed by Pan and Tompkins [14]. The output from the detector is fed as a primary input to an adaptive transversal linear filter. The secondary input to filter comes through a counter which counts the signal samples between consecutive R peaks. The order of the filter, coefficients and cut-off frequency depend upon the time domain characteristics of signal samples lying within each RR interval.

To analyse behaviour of the filter, we assume the primary input $u\left(n\right)$ to be a sequence of L samples between first two R peaks of model ECG signal. The order of the filter will therefore be automatically set to L. The output $y\left(n\right)$ can be expressed as:

$$y\left(n\right)=\sum_{k=0}^{L-1}u\left(n-k\right)w_k \tag{3}$$

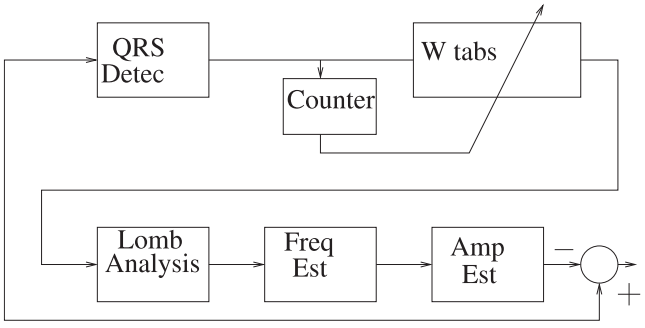

Fig. 2. System block diagram: Stage 1 consists of a QRS detector and the adaptive transversal filter; Stage 2 includes frequency and amplitude estimators.

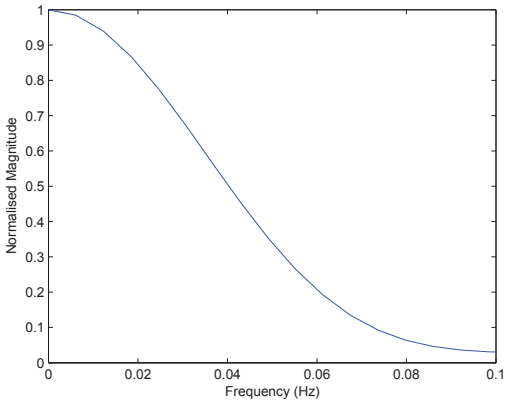

Fig. 3. Transfer function of the adaptive filter for first two consecutive R peaks.

We propose the filter coefficients w_k to be equal to

$$w\left(k\right)=g_1\left(k\right)g_2\left(k\right) \tag{4}$$

where $g_1\left(k\right)$is defined as

$$g_1\left(k\right)=0.5\left[1-\cos\left[\frac{2\pi\left(k-1\right)}{L-1}\right]\right];k=1,\cdots,L-1 \tag{5}$$

and $g_2\left(k\right)$ is defined separately for even and odd L. For L odd:

$$g_2\left(k\right)=\begin{cases}\frac{2k}{L+1} & 1\leq k\leq\frac{L+1}{2}\\ \frac{2(L-k+1)}{L+1} & \frac{L+1}{2}\leq k\leq L\end{cases} \tag{6}$$

For L even:

$$g_2\left(k\right)=\begin{cases}\frac{2k-1}{L} & 1\leq k\leq\frac{L}{2}\\ \frac{2(L-k)+1}{L} & \frac{L}{2}+1\leq k\leq L\end{cases} \tag{7}$$

A weighting factor μ is further introduced in order to control the convergence characteristics of coefficient vector w_k. Therefore (4) can be re-written as:

$$w\left(k\right)=\mu g_1\left(k\right)g_2\left(k\right) \tag{8}$$

The transfer function of the resulting filter is plotted in figure 3. The cut-off frequency f_c at -3 dB depends upon the number of samples L between two consecutive R peaks. This means that the filter coefficients will be updated for each RR interval. The frequency response indicates that the filter can be understood as a low pass filter blocking high fundamental frequencies such as P-QRS-T complexes and power line interference etc, leaving behind very low frequencies including baseline wander and motion artefacts.

Stage II: Frequency Estimation of Baseline Wander

The output from the QRS detector and adaptive filter for 256 beats is plotted in figure 4. It is obvious from (3) – (8) that the filter output $\xi\left(k\right)$ depends upon the the number of samples L that occur during each RR interval. As each R peak occurs at non-uniform intervals, number of samples will also be uneven. Classical FFT based spectral analysis assumes uniform sampling rates of target time series. Therefore, $\xi\left(k\right)$ must be re-sampled at uniform sampling rate to perform FFT

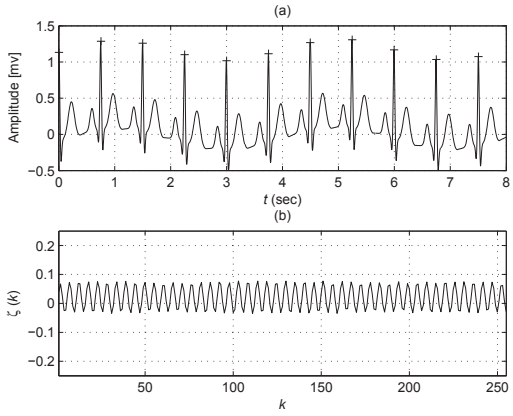

Fig. 4. (a) 8 second excerpt of the output of QRS detector; R peak is marked with '+' sign. (b) Output of the adaptive filter for 256 beats (μ=$\frac{1}{L}$).

analysis. Re-sampling, in case of up-sampling, is generally carried out by interpolating the data on missing points which would add extraneous information into the process. Moreover, for the data with large gaps - like a missing beat or an occasionally long PR interval - interpolation may add spurious power peaks at lower frequencies. Down-sampling, on the contrary, may incur loss of important clinical information.

Lomb's method has already been proposed for spectral analysis of unevenly sampled data as a powerful alternative to re-sampling [15, 16]. In cardiac signal processing, the method has been successfully applied to carry out spectral analysis of heart rate variability [17]. We have utilized here the standard Lomb algorithm [18] to carry out spectral analysis of $\xi(k)$ series. In first step, first and second moment of the series are calculated as

$$\overline{\xi(k)} = \frac{1}{N-1}\sum_{k=1}^{N-1}\xi(k) \tag{9}$$

$$\sigma^2_{\mu_{RR}} = \frac{1}{N-2}\sum_{k=1}^{N-1}\left[\xi(k) - \overline{\xi(k)}\right]^2 \tag{10}$$

Then Lomb normalized periodogram for frequency ω is given by

$$P(\omega) = \frac{1}{2\sigma_\xi^2}\left\{\frac{\left[\sum_k\left(\xi(k)-\overline{\xi(k)}\right)\cos\omega(t_k-\tau)\right]^2}{\sum_k\cos^2\omega(t_k-\tau)}\right\} + \frac{1}{2\sigma_\xi^2}\left\{\frac{\left[\sum_k\left(\xi(k)-\overline{\xi(k)}\right)\sin\omega(t_k-\tau)\right]^2}{\sum_k\sin^2\omega(t_k-\tau)}\right\} \tag{11}$$

$$\tau = \frac{1}{2\omega}\arctan\left(\frac{\sum_k\sin 2\omega t_k}{\sum_k\cos 2\omega t_k}\right) \tag{12}$$

The periodogram evaluates the spectral components only at measured time points t_k rather than the intervals. The relation τ in (12) is the offset that makes the spectral density independent of the constant shift in time interval t_k. Figure 5 shows the comparison between the power spectral density of $\xi(k)$ series computed from FFT method and Lomb method.

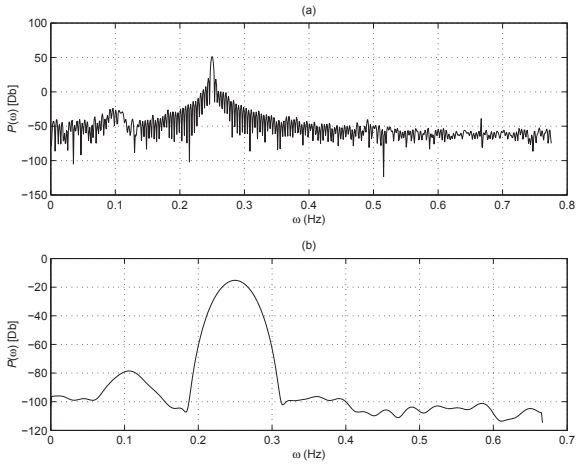

Fig. 5. Comparison between (a) power spectral density using Lomb's method and; the peak is at 0.25 Hz (b) Power spectral density using 1024 point FFT; peak is at 0.2495 Hz.

Table 2. Comparison of actual and estimated baseline wander

f_B (Hz)	$\hat{f_B}$ (Hz)	A (mV)	$\widehat{A}$ (mV)
0.05	0.05	0.20	0.2059
0.15	0.15	0.10	0.1025
0.60	0.60	0.15	0.1507

It can be observed that Lomb's method enhances spectral resolution as well as accuracy of estimation. The estimated frequency $\hat{f_B}$ is exactly equal to the actual baseline frequency f_B, i.e., 0.25 Hz.

Stage II: Amplitude Estimation of Baseline Wander

The estimated frequency $\hat{f_B}$ from last step is next used to estimate the amplitude of introduced baseline in (2). Let $\varepsilon(t)$ be the estimated baseline trend such that

$$\varepsilon(t) = B\sin\left(2\pi\hat{f_B}t\right) \tag{13}$$

where B is any constant. By using (1) and (13), amplitude of original baseline can be estimated by

$$\hat{A} = \frac{\int_0^\infty s(t)\,\varepsilon(t)\,dt}{\int_0^\infty \varepsilon(t)^2\,dt} \tag{14}$$

The estimated amplitude $\widehat{A}$ comes out to be 0.1465 mV which is approximately equal to the actual amplitude of 0.15 mV.

Estimation Using Multi-component Baseline Wander

The technique has been rigorously tested by introducing single and multi-component baseline trends with varying amplitudes. Frequency estimation of a three component baseline trend is depicted in figure 6. The trend is introduced into the same ECG signal (see table 1). The comparison between actual and estimated frequencies and amplitudes is given in table 2. The estimated peaks are exactly equal to the actual frequency components of baseline wander. The estimated amplitude is not exactly equal; however, the estimation error remains well below 10 μV which is clinically insignificant for common pathologies.

Validation Tests and Analysis

The strength of the technique has been validated by implementing three other common methods of baseline wander

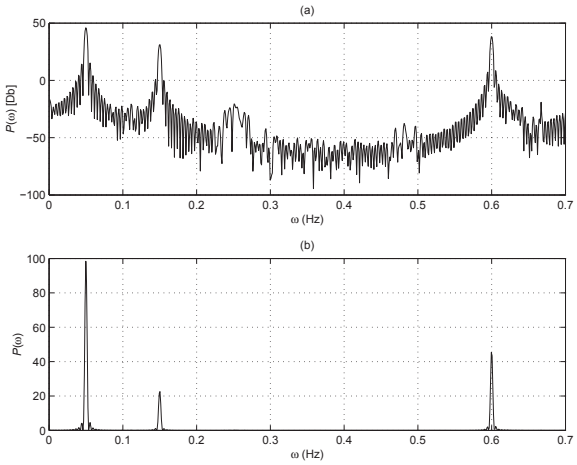

Fig. 6. Two different views of frequency estimation of an ECG signal with baseline trend of three components at 0.05 Hz, 0.15 Hz and 0.6 Hz.

Table 3. Comparison of various validation techniques

Technique	Mean Square Error
Cubic Spline Interpolation	0.001042
Median Filtering	0.002447
Moving Average	0.186217
Proposed Technique	0.000010

removal. These are moving average, median filtering and cubic spline interpolation. For the sake of simplicity, single tone baseline wander of f_B= 0.25 Hz and f_B= 0.15 mV was introduced into the ECG signal. Comparison of these validation techniques is shown in figure 7. Corresponding mean square errors have been listed in table 3.

It is observed that the purposed technique performs better as compared to other three techniques. Cubic spline interpolation works well but it is dependent on accurate estimation of PR interval. Median filtering flattens the ECG waveform and may loose important clinical information while extracting the baseline wander trend. Moving average considerably distorts the waveform by extracting voltage levels which are approximately double than the actual amplitude introduced, i.e., 0.15 mV. Our technique performs best as it targets the estimation of actual characteristics of baseline wander rather than improving the quality of ECG signal itself.

Conclusion

A new technique for estimation of frequency and amplitude of baseline wander in ECG signals has been proposed. The method was demonstrated using synthetic ECG signals with single or multiple tones of baseline wander. Contrary to other conventional methods, this technique proposes to solve the problem through targeted estimation. Comparison was drawn with median filter, moving average and cubic spline interpolation and it is shown that targeted estimation yields the least mean square error.

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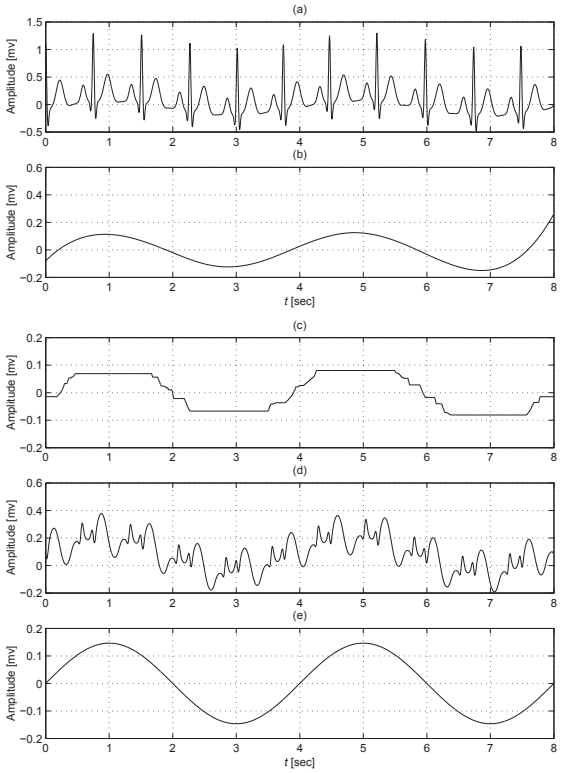

Fig. 7. Comparison of extracted baseline wander trend from various methods. (a) ECG signal with single tone baseline wander with f_B = 0.25 Hz and A = 0.15 mV; (b) Trend extracted by cubic spline interpolation; (c) Trend extracted by median filtering; (d) Trend extracted by moving average method; (e) Trend extracted by our technique.

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