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Removal of baseline wandering in ECG signal by improved detrending method

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Abstract. The very first step to process electrocardiogram (ECG) signal is to eliminate baseline wandering interference that is usually caused by electrode-skin impedance mismatch, motion artifacts due to a patient's body moment or respiratory breathing. A new method is thus suggested to remove baseline wandering in ECG by improving the detrending method that was originally proposed for eliminating slow non-stationary trends from heart rate variability (HRV). In our proposed method, a global trend is estimated in terms of baseline wandering by merging the local trend based on an ECG segment that represents a part of the ECG signal. The experimental results show that the improved detrending method can efficiently resolve baseline wandering without distorting any morphological characteristic embedded in the ECG signal in no time delay manner.

Keywords: Electrocardiogram (ECG), baseline wandering, detrending, heart rate variability (HRV), high-pass filter

1. Introduction

A number of studies have been conducted to correct the baseline fluctuations under the assumption that the drift wanders within the low-frequency bandwidth below 1 Hz. Van Alste, et al. [1] designed a Finite Impulse Response filter to remove baseline fluctuation and Ezenwa, et al. [2] also eliminated the interference by chasing an equi-potential surface (iso-electric region) with applying the baseline tracking algorithm that utilizes the characteristics of ECG signal. Laguna [3] and Jane, et al. [4] implemented the cascaded adaptive filter in two phases and Pandit [5] devised an algorithm to correct baseline wandering by applying Short-Time Fourier Transform. Shusterman, et al. [6] suggested a selective filter to nullify the effect of baseline wandering. Dotsinsky, et al. [7] applied bi-directional digital filtering algorithm and Mneimneh, et al. [8] exploited the qualities of Kalman filter using an approximated polynomial function that reflected the features of ECG signal. Mateo, et al. [9] considered Many Adaptive Linear Neurons (MADALINE) artificial neural network model to delete

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ECG baseline wander. Additionally, Zhao, et al. [10, 11] and Blanco-Velasco, et al. [12] tried to remove baseline fluctuation and simultaneously suppress the additive noise including power line interference in ECG signal by applying empirical mode decomposition and adaptive filter. Iliev, et al. [13] proposed a composite filter to delete both powerline interference and baseline wandering. Rahman, et al. [14] removed the artifacts by applying adaptive filter based on error nonlinearity Least Mean Square (LMS) algorithm. Furthermore, the Constrained Stability Least Mean Square (CSLMS) algorithm [15] was applied to decrease mean-square error of LMS algorithm. The wavelet transform was considered to eliminate baseline wandering in ECG by implementing a search algorithm based on computing wavelet packet coefficients [16] and a hierarchical model utilizing Independent Component Analysis (ICA) [17] was proposed to suppress the baseline wandering in the ECG. To reduce baseline wandering for bioelectrical signals, constrained convex optimization problem [18] was solved and the fractal modeling [19] was also considered by interpreting baseline fluctuation as the first order Brownian-motion process. All of the previously suggested digital filters to reduce baseline wandering face a drawback: a certain amount of time delay is required to get the filtered signal. Thus, the meaningful information contained in the initial stage of getting ECG signal can't be resolved or can be lost due to the failure of correcting baseline distortion. Furthermore, the artificial neural network such as MADALINE model requires a proper training stage to approach the desired output signal and it is difficult to handle the persistent non-stationary trend especially in a long-term ECG signal. Therefore, this paper suggested a new method to remove baseline wandering in ECG by improving the detrending method that was originally proposed for eliminating slow non-stationary trends from Heart Rate Variability (HRV).

2. Method

2.1. Detrending with smoothness priors formulation

Detrending procedure estimates the trend of the given signal based on smoothness prior formulation. Tarvai, et al. [20] presented a detrending method and tested its properties to remove the fluctuating level of RR intervals in ECG data before HRV analysis was considered.

Eqs. (1)-(6) show the expressions for estimating the trend by detrending procedure [20].

$$z = z_{stat} + z_{trend} \tag{1}$$

$$z_{trend} = H\theta + v \tag{2}$$

$$\hat{z}_{trend} = H\hat{\theta}_\lambda \tag{3}$$

$$\hat{\theta}_\lambda = \left(H^T H + \lambda^2 H^T {D_d}^T D_d H\right)^{-1} H^T z \tag{4}$$

$$D_d(d=2) = D_2 = \begin{pmatrix} 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{pmatrix} \tag{5}$$

$$\hat{z}_{stat} = z - H\hat{\theta}_\lambda = \left(I - \left(I + \lambda^2 {D_2}^T D_2\right)^{-1}\right) z \tag{6}$$

Where, z is an input signal consisting of the stationary part, z_{stat} and the low-frequency component, z_{trend}. v is an observation error and H is an observation matrix. θ is the regression parameter and λ is a

Table 1

λ and the corresponding cutoff frequency

λ	F_c
1	$0.189 \times F_s$
2	$0.132 \times F_s$
3	$0.093 \times F_s$
10	$0.059 \times F_s$
20	$0.041 \times F_s$
50	$0.025 \times F_s$
300	$0.011 \times F_s$

regularization parameter for estimating $\hat{\theta}_\lambda$ in the least square sense. Thus, $\hat{\theta}_\lambda$ denotes the estimated regression parameter by applying a regularization parameter, λ. D_d indicates the difference matrix approximating d^{th} derivative operator and consequently D_2 denotes the second order difference matrix. The stationary component $\hat{z}_{stat}$ can be estimated by subtracting non-stationary trend, $H\hat{\theta}_\lambda$.

2.2. Improved detrending algorithm

The process for removing the baseline wandering in the ECG signal by detrending method starts from setting the cutoff frequency through the determination of the regularization parameter, λ and then removes the non-stationary trend by applying Eq. (6). The optimal value of λ can be derived by applying the regression analysis to the data points as stated in Table 1 [20].

Eq. (7) shows a curve fitting result by converting an exponential model into a linear one with the logarithmic transformation.

$$F_c = 0.1865\,\lambda^{-0.5022} \cdot F_s \tag{7}$$

where F_c is the cut-off frequency and F_s means the sampling frequency.

In contrast with FIR and IIR digital filter, the entire segment in the input signal is considered during

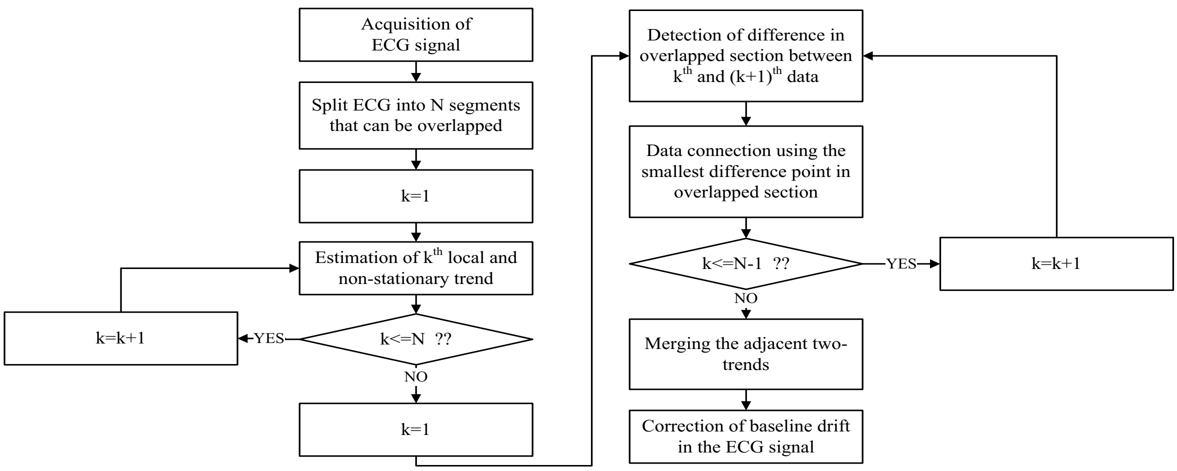


Fig. 1. A block diagram for illustrating our proposed detrending method.

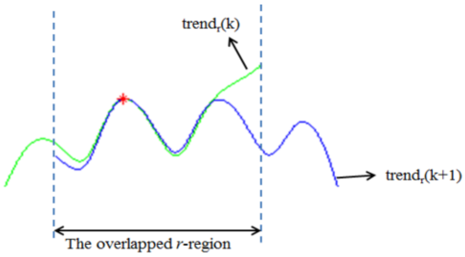


Fig. 2. Merging two-adjacent trends, $trend_r(k)$ and $trend_r\ (k+1)$.

the detrending operation and it has the advantage of no time delay in getting the processed signal. However, due to the requirement of computing the inverse of a matrix, this approach is not applicable to a long-term ECG or a large volume of data. Thus, to overcome this inherent problem for correcting baseline wandering in the ECG signal, a new detrending algorithm is proposed as illustrated in Figure 1.

Eq. (8) describes the process that connects two adjacent-trends.

$$P_c(k) = Min_r\left(abs\big(trend_r(k) - trend_r(k+1)\big)\right) \tag{8}$$

where $P_c(k)$ is k^{th} connecting point, r is the overlapped region and $trend_r(k)$ is the overlapped section of k^{th} trend data. Figure 2 shows the merging process by connecting two-adjacent trends in the overlapped r-region with identifying $P_c(k)$ to guarantee a smooth connection between two trends.

3. Results

To test the proposed detrending algorithm for estimating the baseline wandering in the ECG signal, European ST-T database [21] is used. This data has 250 Hz sampling frequency with the acquisition time in one minute. The value of regularization parameter, λ is chosen to be 2102.7757 in order to set the cut-off frequency with 1 Hz. Figure 3 shows the result of removing the baseline fluctuation in the ECG signal using the improved detrending method. In order to verify the performance of the proposed detrending method, baseline wandering in the ECG signal is also removed using a 4^{th}-order Butterworth high-pass filter (cutoff frequency = 1 Hz) as shown in Figure 4.

Figures 3 and 4 demonstrate that detrending method and Butterworth filter can effectively cancel the baseline wandering. However, unlike the detrending method, a Butterworth high-pass digital filter deforms the morphological characteristic especially in the initial part of the ECG signal. In other words, detrending method is more effective in removing the baseline wandering and simultaneously maintaining the original characteristics in the ECG signal. For the frequency spectrum analysis, Figures 5(a) and 5(b) show the results of applying Discrete Fourier Transform to the trends estimated by the improved detrending method and a Butterworth high-pass digital filter, respectively.

Note that the spectral leakage in the estimated trend occurs less when the detrending method is applied.

4. Conclusion

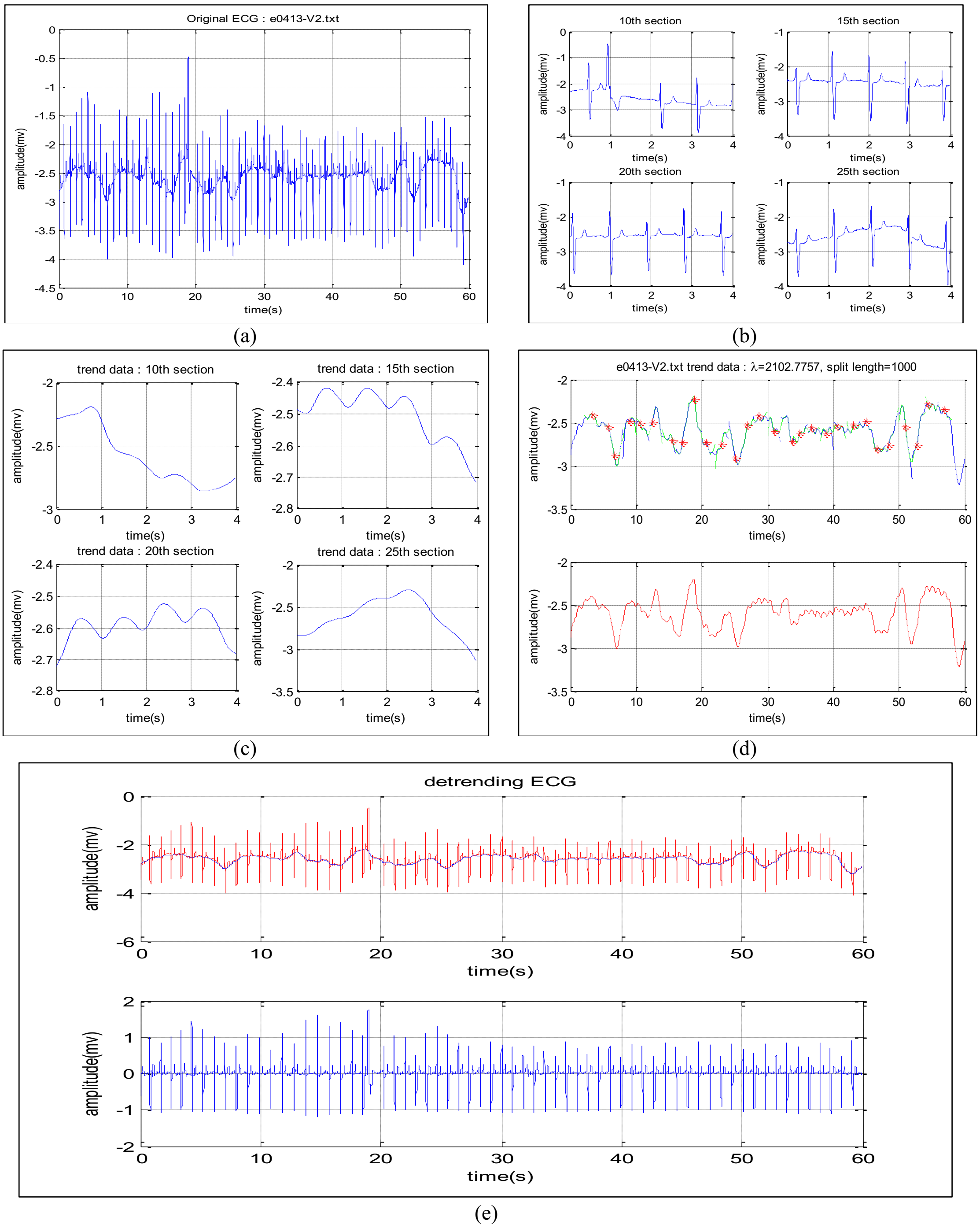


Fig. 3. The result of removing the baseline wandering in the ECG signal using the improved detrending method (a) the original ECG signal (b) the splited ECG-segments (k = 10, 15, 20, 25) (c) the estimated local trends in the segments (k = 10, 15, 20, 25) (d) the merging process of connecting local trends (e) the original ECG signal superimposed with the global trend in terms of baseline wandering (top) and the ECG signal with baseline wandering cancellation (below).

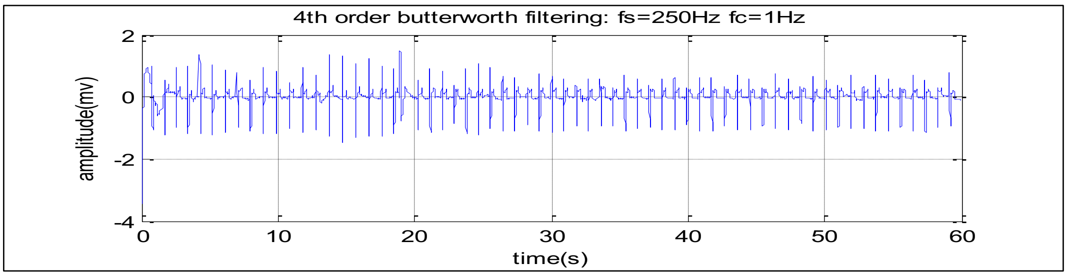
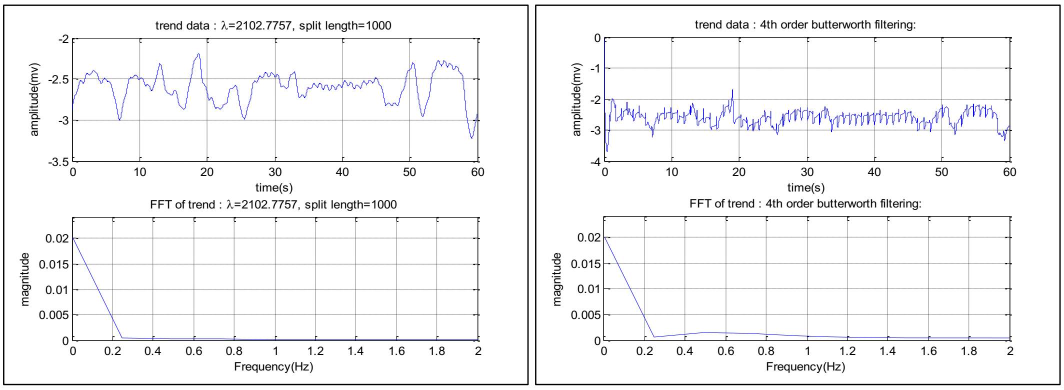


Fig. 4. The filtered ECG signal by 4th-order Butterworth high-pass filter.



(a) (b)

Fig. 5. Frequency spectrum of the trend estimated by (a) improved detrending method (b) the 4th-order Butterworth high-pass filter.

The acquired ECG signal especially measured in a patient centric environment is vulnerable to the baseline wandering interference due to a patient's body moment or respiratory breathing. This low-frequency noise may disturb the clinician in deciding the diagnostic parameters, thus methods are proposed to correct the baseline wandering. One common method is high-pass filtering but it may deform the important morphology of the ECG signal and evoke time delay. It should be also noted that a certain amount of spectral leakage above 1 Hz exists in the trend signal estimated by the conventional Butterworth high-pass filter (see Figure 5) and this leakage might cause the problem of deforming the diagnostic features in the ECG signal. The detrending method can be adopted to extract the global non-stationary trend in the ECG signal but it requires a large amount of matrix-inversion computations. To overcome this difficulty, a new detrending method is suggested by finding the local trends and merging them into a global one. The simulation results show that the proposed method can not only eliminate the baseline wandering but also keep the original waveform characteristics in the ECG signal. Thus, it can be concluded that our improved detrending method can effectively eliminate the baseline wandering without distorting morphological features in the original ECG signal.

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