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Removal of baseline wander from ECG signal based on a statistical weighted moving average filter*

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Abstract: Baseline wander is a common noise in electrocardiogram (ECG) results. To effectively correct the baseline and to preserve more underlying components of an ECG signal, we propose a simple and novel filtering method based on a statistical weighted moving average filter. Supposed a and b are the minimum and maximum of all sample values within a moving window, respectively. First, the whole region $[a, b]$ is divided into M equal sub-regions without overlap. Second, three sub-regions with the largest sample distribution probabilities are chosen (except M<3) and incorporated into one region, denoted as $[a_0, b_0]$ for simplicity. Third, for every sample point in the moving window, its weight is set to 1 if its value falls in $[a_0, b_0]$; otherwise, its weight is 0. Last, all sample points with weight 1 are averaged to estimate the baseline. The algorithm was tested by simulated ECG signal and real ECG signal from www.physionet.org. The results showed that the proposed filter could more effectively extract baseline wander from ECG signal and affect the morphological feature of ECG signal considerably less than both the traditional moving average filter and wavelet package translation did.

Key words: ECG signal, Baseline wander, Morphological feature, Moving average filter, Wavelet package translation
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1 Introduction

Electrocardiogram (ECG) signals are usually contaminated by baseline wander (BW), which is commonly caused by electrode-skin impedance changes due to perspiration, patient movement, and respiration (Momot, 2009). Observing ECG signal with BW, a cardiologist's eyes become easily fatigued, which may inadvertently cause an inaccurate interpretation. In addition, BW severely influences computer-based processing. Therefore, it is necessary to reduce noise such as BW and power interference before the ECG signal is automatically analyzed by a computer and finally interpreted by a cardiologist (Hu *et al*., 2010). In recent years, two methods have often been applied to remove BW: polynomial fitting and high-pass filtering. The first approach uses a polynomial interpolation to estimate the baseline (BL). BL is fitted from some fiducial points that are determined from P-R intervals (Boucheham *et al*., 2005), whereas these fiducial points are difficult to accurately locate before noise is removed from the ECG signal. As a result, this approach is ineffective (Burattini *et al*., 2006) if the ECG signal is contaminated by noise. A high-pass filter could be used to avoid this particular disadvantage. A moving average filter (Leski and Henzel, 2005) and wavelet translation (Xu *et al*., 2007) were often used to construct a high-pass filter. However, a high-pass filter would unavoidably introduce distortions in various parts of the ECG signal, especially in the ST segment due to the spectra of the ST segment that overlaps the spectra of BW (Chen *et al*., 2006; Shi *et al*., 2008).

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The ECG signal is a quasi-periodic signal with some special characteristics, i.e., impulse-like nature, non-stationarity, and non-symmetry, with respect to the baseline (Fig. 1). On the other hand: (1) the impulse-like part such as QRS complex has a short duration; (2) BW, as a low-frequency disturbance, is not synchronized with QRS complex. Thus, a high-pass filter based on a moving average is a very simple and frequently used method to remove BW. However, the traditional moving average always distorts the morphological features of the ECG signal due to its impulse-like component. Therefore, in this paper we propose a simple and reliable high-pass filter based on a statistical weighted moving average.

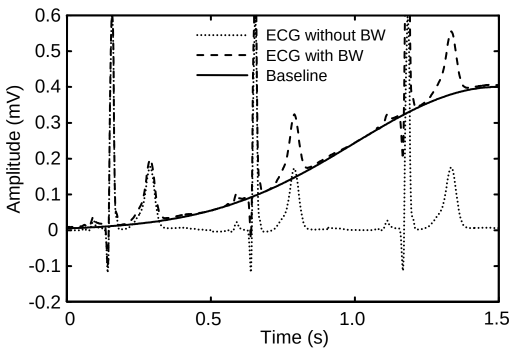

Fig. 1 ECG signal without baseline wander (BW), ECG signal with BW, and the baseline
A baseline without wander is a baseline at the isoelectric level

2 ECG signals and methods

2.1 Standard ECG signal and simulated baseline wander

To assess the performance of a baseline correction algorithm, one would need to acquire a 'clean' ECG signal (standard ECG signal) without BW, a baseline with known BW, and a 'real' ECG signal mixed by both.

2.1.1 Standard and real ECG signals

The PhysioNet website provides a public service of the PhysioNet Resource funded by the National Institutes of Health, the National Institute of Biomedical Imaging and Bioengineering, and the National Institute of General Medical Sciences (NIBIB and NIGMS, 1999). In cooperation with the annual computing in cardiology conference, PhysioNet hosts a series of cardiology challenges, in which researchers and students address unsolved problems of clinical or basic scientific interest using data and software provided by PhysioNet. These databases include the T-wave alternans challenge database, which contains 100 multichannel ECG records sampled at 500 Hz with 16-bit resolution over a ±32 mV range. In most cases, each record contains the standard 12 diagnostic ECG signals, but a few contain only two or three signals. Table 1 lists this channel information provided by the header file (*.hea) of every record.

Table 1 Channel information provided by the header file (*.hea) of every record

Channel number	Channel name
12	I, II, III, aVR, aVL, aVF, V1–V6
3	E-S, A-S, A-I
2	ECG1, ECG2

From the T-wave alternans challenge database (www.physionet.org/pn3/twadb/), twa18 and twa34 are chosen for experiments. Because ECG signal of the twa34 channel I has an almost (perceptually) isoelectric level baseline, a standard ECG signal is replaced by a segment of an ECG signal from the twa34 channel I. The chosen standard ECG signal lasts 6 s and holds 11 ECG cycles (Fig. 2a). The ECG signal of the twa18 channel III is severely contaminated by BW. Thus, the ECG signal of the twa18 channel III is used as a real contaminated ECG signal to verify the performance of the proposed method.

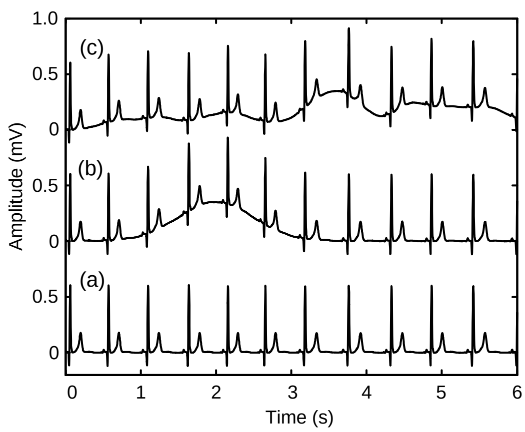

Fig. 2 Standard ECG signal (a), synthesized ECG signal with baseline wander (BW)-like amplitude modulation (b), and synthesized ECG signal with BW-like sinusoid (c)

2.1.2 Simulated baseline wander like amplitude modulation

Both the patient's movement and the perspiration between electrode and skin unavoidably cause an electrode-skin impedance change. As a result, similar to the amplitude modulation in communication, the amplitude of ECG signal, which is acquired through the electrode, varies with the changing impedance. This kind of BW is simulated from the Gaussian model (Boucheham *et al*., 2005):

$$\mathrm{bl}(i) = A \cdot \exp\left(-s(i-p)^2\right), \tag{1}$$

where bl(i) is the ith BL value, A is the BL peak with an appropriate peak time p, and s is the amplitude change rate of BL. Fig. 2b shows the synthesized ECG signal with BW-like amplitude modulation. In this experiment, A, p, and s were set as 3.5 mV, 2 s, and 2.0, respectively.

2.1.3 Simulated baseline wander like sinusoid

Obviously the patient's respiration may lead to the periodic change of the BL curve. Boucheham *et al*. (2005) simulated this using a sinusoidal model:

$$\mathrm{bl}(i) = A \cdot \sin(2\pi f i). \tag{2}$$

The bl simulated by Eq. (2) is a determinate signal. In fact, due to much random interference, bl should not be a sinusoid. To gain this 'real' BW-like sinusoid, two methods are used. One method involves normal distribution noise (Sörnmo, 1993) and the other is Gaussian white noise (Boucheham *et al*., 2005). The former involves normal distribution noise filtered by a fifth-order Butterworth low-pass filter. The latter involves white Gaussian noise filtered by means of an eigenfilter with the following characteristics: passband frequency F_p=0.5 Hz, maximum passband ripples R_p=0.1 dB, stopband frequency F_s=1 Hz, and maximum stopband ripples R_s=15 dB. These two kinds of noise represent the real BW presented in ECG signals much better than Eq. (2) models the BW. In this experiment, normal distribution noise was used to simulate a BW-like sinusoid. The mean and variance of the normal distribution were 0.6 and 0.1, respectively. Fig. 2c illustrates the synthesized ECG signal with BW-like sinusoid.

2.2 Traditional high-pass filter

There have been many means to constitute linear or nonlinear high-pass filters (Clifford *et al*., 2006), such as infinite-impulse response (IIR) and finite-impulse response (FIR). The performance of IIR filters is generally unacceptable due to a nonlinear phase response, which introduces distortion into an ECG signal. Though sampling rate decimation could drastically reduce FIR complexity, the time delay introduced by an FIR filter is still unacceptable, especially when FIR is applied in short-lasting signals. Therefore, both the moving average filter and wavelet package translation are discussed here.

2.2.1 Moving average filter

A moving average filter can be expressed as

$$y(n) = \frac{1}{2N+1}\sum_{i=-N}^{N} x(n+i), \tag{3}$$

where $x(n)$ and $y(n)$ are input signal and output signal of the moving average respectively, and N specifies the observation window length equal to $2N$+1. BL can be estimated using Eq. (3). Based on Eq. (3), a high-pass filter is formed:

$$z(n)=x(n)-y(n), \tag{4}$$

where $z(n)$ is the output signal of the high-pass filter. The high-pass filter based on moving average is called MA in this paper.

From Fig. 1, it is obvious that the BL values estimated from the P-R segment (between 0.3 s and 0.6 s) are very close to real baseline values, while the BL values estimated from segments including QRS complex and T wave are far away from the real baseline. Therefore, if an observation window covers some sample points with extreme amplitudes, an ECG signal would be distorted after the ECG signal is filtered using Eqs. (3) and (4).

2.2.2 Wavelet packet transform

Wavelet package translation (WPT) was introduced by Coifman and Wickerhauser (1992) as a generalized family of multiresolution orthogonal or biorthogonal bases (Hu *et al*., 2009). Unlike wavelet transformation, which is realized only by a low-pass filter bank, WPT possesses a basic two-channel filter bank and is iterated over a low- or high-pass branch. As a result, WPT can obtain some finer frequency bands than wavelet transformation. Therefore, WPT has been widely used in biomedical signal analysis (Xu *et al.*, 2007; Hu *et al.*, 2009).

Given a finite energy signal with scaling space U_0^0, WPT might decompose U_0^0 into small subspaces U_j^n in a dichotomous way (Fig. 3). U_j^{n-1} shows the nth subspace at the jth resolution level. The dichotomous way is realized using the following recursive scheme:

$$U_{j+1}^n = U_j^{2n} \oplus U_j^{2n+1}, \quad n = 0,1,...,2^{-j}-1, \tag{5}$$

where j (j=−1, −2, −3, …) is the resolution level and '⊕' denotes orthogonal decomposition. U_{j+1}^n, U_j^{2n}, and U_j^{2n+1} are three close spaces corresponding to $u_n(t)$, $u_{2n}(t)$, and $u_{2n+1}(t)$, respectively. $u_n(t)$ satisfies

$$\begin{cases} u_{2n}(t) = \sqrt{2}\sum_{k\in\mathbb{Z}} h(k)u_n(2t-k), \\ u_{2n+1}(t) = \sqrt{2}\sum_{k\in\mathbb{Z}} g(k)u_n(2t-k), \end{cases} \tag{6}$$

where $u_0(t)$ is identified with the scaling function φ and $u_1(t)$ with the mother wavelet ψ. $h(k)$ and $g(k)$ are the coefficients of the low- and high-pass filter, respectively. The sequence of functions $\{u_n\}$ (n=0, 1, 2, …) generated from a given function u_0 by Eq. (6) is called the wavelet packet basis function (db6 in this study).

<table>
<tr><td colspan="8">U_0^0 (0, f_s/2) Hz</td></tr>
<tr><td colspan="4">U_{-1}^0 (0, $f_s/2^2$) Hz</td><td colspan="4">U_{-1}^1 ($f_s/2^2$, f_s/2) Hz</td></tr>
<tr><td colspan="2">U_{-2}^0</td><td colspan="2">U_{-2}^1</td><td colspan="2">U_{-2}^2</td><td colspan="2">U_{-2}^3</td></tr>
<tr><td>U_{-3}^0</td><td>U_{-3}^1</td><td>U_{-3}^2</td><td>U_{-3}^3</td><td>U_{-3}^4</td><td>U_{-3}^5</td><td>U_{-3}^6</td><td>U_{-3}^7</td></tr>
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Fig. 3 The tree structure of wavelet package translation (WPT) to the third resolution level
(0, f_s/2) Hz is the frequency band of a scaling space, and f_s is the sample frequency

The ECG signal with BW is decomposed to the eighth resolution level (j=−8) by WPT. The whole scaling space, with frequencies in the interval (0, $2^{-1}f_s$), is divided into 256 subspaces with frequencies correspondingly in the interval ((n−1)$2^{j-1}f_s$, $n2^{j-1}f_s$). Here, n=1, 2, ..., 256, and f_s is the sampling frequency of the ECG signal (f_s=500 Hz in this study). The frequency interval at the first subspace, U_{-8}^0, is [0, 0.98] Hz, and BW's spectrum is usually below 1 Hz. Thus, to reduce BW, the wavelet packet coefficients at the first subspace are set to zero, and the coefficients in other subspaces remain unchanged. The ECG signal is then reconstructed from all processed wavelet packet coefficients.

2.3 High-pass filter based on statistical weighted moving average

Although the sample values at the PR and ST segments often change, they usually distribute near the real baseline. These sample points belonging to PR and ST segments are distributed closer to the baseline than the samples from the QRS complex. In other words, within the observing window there is a smaller value bound covering most sample points belonging to the baseline. Thus, it is more reasonable that the mean value in the smaller bound is considered as the BL value of the moving window when compared to that of the whole bound. Therefore, Eq. (4) can be modified as

$$y(n) = \sum_{i=-N}^{N} w(n+i)x(n+i) \Big/ \sum_{i=-N}^{N} w(n+i), \tag{7}$$

where $w(n+i)\in[0, 1]$ are the weight values. Suppose that $x(1)$, $x(2)$, …, $x(2N+1)$ is an ECG signal series within one moving average window, and that a and b are the minimum and maximum of the ECG signal series, respectively. For every sample point in the moving window, its weight value is calculated according to the following steps.

First, the whole value bound $[a, b]$ is divided into M sub-bounds (or sub-regions) with equal width and without overlap:

$$[a, a_1], [a_1, a_2], …, [a_{m-1}, a_m], …, [a_{M-1}, b]. \tag{8}$$

If there are K sample points whose values are within the mth sub-bound $[a_{m-1}, a_m]$, the sample distribution probability of the mth sub-bound, $[a_{m-1}, a_m]$, is calculated by

$$p(m)=K/(2N+1). \tag{9}$$

Then, M sub-bounds are queued in descending order according to their distribution probability $p(m)$. If in the preceding k ($k \le M$) sub-regions there are two or more sub-regions with the same probability, these sub-regions with the same probability are incorporated into one sub-region. New sub-bounds are queued again according to a new probability in the same manner.

At last, these value bounds of the preceding k sub-regions with the largest distribution probability are chosen to incorporate into one region and the region is symbolized as $[a_0, b_0]$ for simplicity.

Thus, the sample weights are achieved according to the following formula:

$$w(n+i)=\begin{cases}1, & x(n+i)\in[a_0,b_0],\\ 0, & x(n+i)\notin[a_0,b_0].\end{cases} \tag{10}$$

The algorithm in which Eqs. (4) and (7)–(10) are applied altogether is called a high-pass filter based on a statistical weighted moving average (SMA for short). If $M \le 3$, SMA is obviously the same as the traditionally used MA.

3 Experimental results

For numerical evaluation of the performance of the proposed algorithm, normalized root mean square error (NRMSE) and maximum error (ME) are used to measure the distortion and error introduced into the filtered ECG signal:

$$\mathrm{NRMSE}=\sqrt{\frac{\sum_{i=1}^{L}\left(\mathrm{ecg_{in}}(i)-\mathrm{ecg_{out}}(i)\right)^2}{\sum_{i=1}^{L}\left(\mathrm{ecg_{in}}(i)\right)^2}}, \tag{11}$$

$$\mathrm{ME}=\max_{i=1,2,\ldots,L}\left(|\mathrm{ecg_{in}}(i)-\mathrm{ecg_{out}}(i)|\right), \tag{12}$$

where $\mathrm{ecg_{in}}$ and $\mathrm{ecg_{out}}$ are the original signal and the filtered signal, respectively, and L is the length of ECG signal.

Fig. 4 shows the NRMSE and ME for WPT, MA, and SMA. The horizontal axis represents the moving window width $2N+1$ changing from 51 to 151. M is the number of sub-bounds after the whole value bound $[a, b]$ is divided using Eq. (8). Both NRMSE and ME were calculated between the standard ECG signal and its ECG signal filtered from the synthesized ECG signal plotted in Fig. 2c, because the BW of the synthesized ECG signal is similar to both sinusoidal and amplitude modulation. NRMSE and ME caused by WPT were constant, 0.3967 μV and 104 μV, respectively.

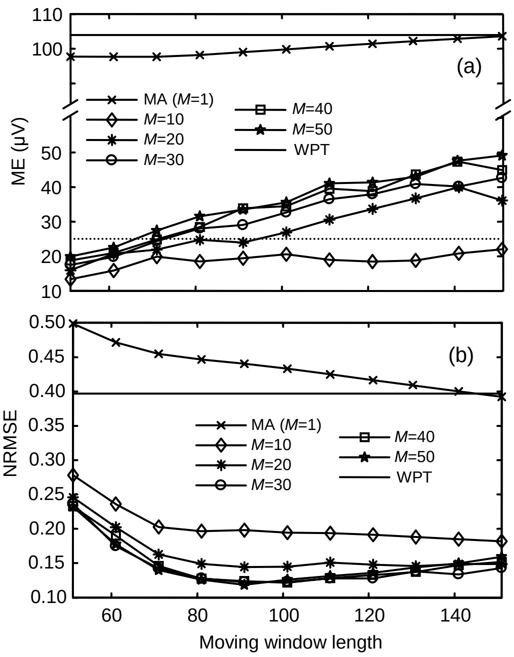

Fig. 4 Relation between distortion and moving window length for wavelet package translation (WPT), traditionally used MA, and our proposed high-pass filter based on a statistical weighted moving average (SMA)
(a) Maximum error (ME) vs. moving window length; (b) Normalized root mean square error (NRMSE) vs. moving window length. M is the number of sub-bounds. SMA is the same as MA when M=1

Though NRMSE and especially ME did not necessarily decrease with the increase of the moving average window length, it is obvious that the distortion resulting from SMA was much less than the distortion from traditional MA and WPT, no matter how long the window width was. In general, one error accounts for only local distortion, but NRMSE reflects the whole distortion degree in terms of the morphology of the ECG signal. On the other hand, local distortion does not seriously hamper the accurate analysis of the whole ECG signal, and the local error is random in a certain extent. Therefore, NRMSE is better for measuring distortion than ME.

Fig. 4 interprets this viewpoint. When $2N+1=131$, these NRMSEs were almost equal for $M=20$, 30, 40, and 50; in contrast, their corresponding MEs were much different.

Fig. 4 shows that NRMSE decreased with the increase of the number of regions, M. When $M\geq30$, NRMSE decreased very slowly. Another phenomenon is that, the NRMSE when $2N+1=91$ and $M=20$ was very small and its corresponding ME was below 25 μV. In many research experiments for ECG signals, 25 μV is a maximum error level that could be allowed. Thus, $2N+1=91$ and $M=20$ were applied in all the following SMA experiments.

Fig. 5 illustrates the whole BW-reduced effect of the three methods. The original ECG signal was the synthesized ECG signal plotted in Fig. 2c. Obviously, SMA could more effectively reduce BW than MA and WPT. All NRMSEs and MEs shown in Fig. 4 were calculated from the filtered ECG signal between 0.5 s and 5.5 s as shown in Fig. 5. Due to the edge effect of the moving window, the filtered ECG signals before 0.5 s and after 5.5 s were not used. Globally, the performance of WPT was better than that of MA. However, locally the maximum error caused by WPT was larger than that of MA. This is the reason why the NRMSE of WPT was lower than that of MA, and why the ME of WPT was higher than that of MA in this experiment.

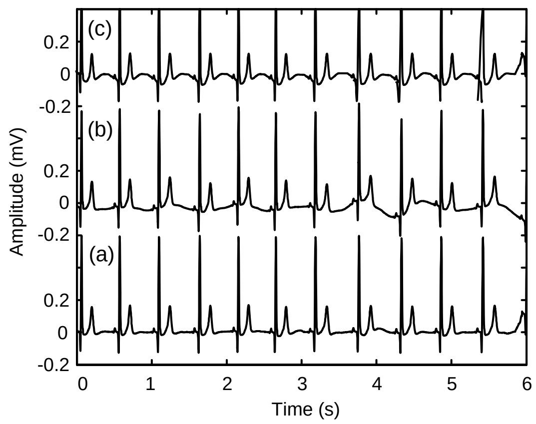

Fig. 5 The whole baseline wander reduced effect of our proposed high-pass filter based on a statistical weighted moving average (SMA) (a), wavelet package translation (WPT) (b), and traditionally used MA (c) on the same original ECG signal

The original ECG signal was the synthesized ECG signal plotted in Fig. 2c

Visual inspection of the three BW-removed signals in Fig. 5 demonstrates that: (1) the ECG signal filtered by SMA is closer to the original standard ECG signal obtained by the other two methods; (2) both MA and WPT result in much distortion at QRS complex, ST segment, and R wave. Fig. 6 presents some local details of the filtered signal. Obviously, after the ECG signal with BW was filtered by MA, SMA, and WPT, the morphology of the original ECG signal was more or less destroyed. SMA introduced the least distortion among the three methods.

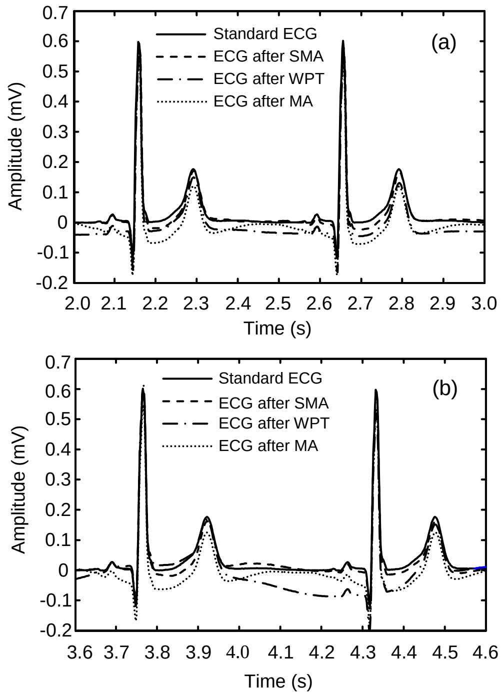

Fig. 6 Comparison of morphological distortion caused by our proposed high-pass filter based on a statistical weighted moving average (SMA), wavelet package translation (WPT), and traditionally used MA

(a) Filtered results of the synthesized ECG signal in Fig. 2b; (b) Filtered results of the synthesized ECG signal in Fig. 2c

Fig. 7 shows the results of SMA applied to a real ECG signal. The real ECG signal was obviously contaminated by high-frequency noise and BW (Fig. 7a). To extract the baseline from the ECG signal, a low-pass filter was first used to reduce high frequency noise. In this experiment, the cut-off frequency was 50 Hz. The baseline was then extracted from the filtered ECG signal. The extracted baseline is depicted in Fig. 7b. Fig. 7 shows that SMA performs well when applied to a real ECG signal.

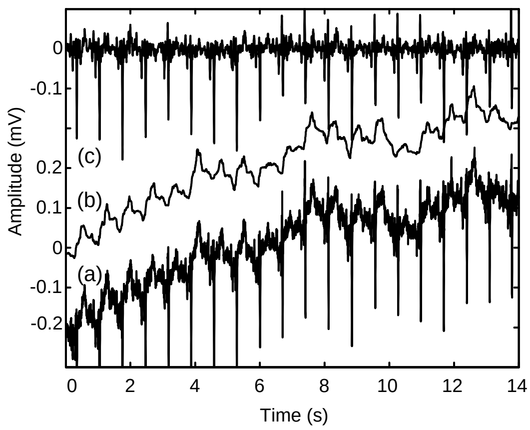

Fig. 7 An example of our proposed high-pass filter based on a statistical weighted moving average (SMA) applied to a real ECG signal

(a) Raw ECG signal; (b) Baseline extracted from raw ECG signal by SMA; (c) ECG signal whose baseline was removed by SMA. For clear display, the extracted baseline was increased by 0.2 mV

4 Conclusions

Baseline correction has always been a necessary preprocessing in the biomedical signal acquiring and analyzing system. The proposed high-pass filter based on a statistical weighted moving average (SMA) is able to adaptively estimate baseline with wander. Compared with MA and WPT, SMA caused the least distortion in every whole-beat cycle, especially for the waves or the segments with much clinical usefulness, such as QRS complex, ST segment, and T wave, whose morphological features should be more effectively preserved during the preprocessing process. Less distortion is beneficial to further analysis of the ECG signal (Jeong *et al*., 2010). In addition, SMA uses a shorter moving average window to extract BW-like sinusoid and BW-like important amplitude modulation; thus, the baseline correction procedure takes less time than those in MA and WPT. Therefore, the proposed algorithm is an effective means of removing BW from ECG signals and its application to other biomedical signals should be considered.

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