

Enhancing the Precision of ECG Baseline Correction: Selective Filtering and Removal of Residual Error¹

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Reemergence of the problem of baseline correction is related to recent advancements in the electrocardiographic (ECG) analysis of beat-to-beat repolarization changes which play an important role in risk assessment and the prediction of sudden cardiac death. These alterations often have an amplitude of a few microvolts and duration of several milliseconds and their detection requires special accuracy of baseline estimation. Using detailed analysis of various types of residual errors we designed a two-step procedure for selective filtering of ECG and removal of residual error with minimal distortion of cardiac complexes and tested this approach on 100 simulated and 210 real ECG signals. Application of this procedure provided a twofold reduction in the error of baseline estimation and T-wave amplitude measurements compared to high-pass filtering. Selective application of this approach to the segments with low baseline drift allowed analysis of low-amplitude, beat-to-beat changes in repolarization during more than 70% of the recording time. © 2000 Academic Press

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INTRODUCTION

Estimation and correction of the baseline wander (BW) constitutes the first step in the ECG analysis (1). Removal of BW, which includes motion and respiratory artifacts, from the long-term ECG recordings can be difficult because the spectrum of noise often overlaps with the spectrum of cardiac signal (2). A variety of filters and correction techniques have been developed for estimation of baseline at rest, during ambulatory monitoring, and for exercise testing (1–13). Due to the changing frequency of BW which often overlaps with the low-frequency elements of the cardiac complexes, none of the methods provide a general solution to the problem but several adequately detect and track the major changes in the P and QRS complexes.

Reemergence of the problem of baseline correction is related to recent advancements in the electrocardiographic (ECG) analysis of beat-to-beat repolarization changes which

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play important role in risk assessment and prediction of sudden cardiac death. These alterations often have amplitude of a few microvolts and duration of several milliseconds and their detection requires special accuracy of baseline estimation (14–16). Rapidly growing computational power of microprocessors provides a basis for the implementation of potentially more accurate but computationally expensive techniques. Several commercial Holter ECG and body surface potential mapping systems allow recording with a higher than 1- μ V resolution and greater than 1000-Hz sampling frequency.

Ambulatory ECG recordings are contaminated by highly variable noise across the entire spectrum of frequency components. Obviously, a highly accurate analysis of minute changes in repolarization cannot be performed in the segments that have a high noise. However, our results demonstrate that ambulatory recordings do not contain high baseline noise more than 70% of the time and thus can be used for analysis of beat-to-beat repolarization changes. We sought, therefore, to develop a method for classifying the segments of ECGs into those with high and low BW and to correct BW with minimal distortion of cardiac complexes.

Baseline artifact contains a broad spectrum of frequency components that can change from moment to moment. Since Wilson in 1931 defined the baseline as the potential at a time when the heart is producing no electrical current, several investigators emphasized practical difficulties in finding this interval on the ECG (17). The potential confounding factors can be related to cardiac or extracardiac sources. The cardiac sources include reduction or disappearance of the isoelectric interval due to the fast heart rate, prolonged repolarization, or atrial flutter. The extracardiac sources include patient movement, changes in the electrode position, respiration, and muscle contraction. BW due to any one or a combination of these sources can cause substantial problems in tracking the changes in ST segment, T-wave amplitude, or QT interval. However, removal of low-frequency elements from BW is especially difficult in the context of analysis of repolarization changes because spectrum of repolarization lies in the low-frequency range as well. Therefore, in this study we focus on the low-frequency elements in BW and do not consider high-frequency artifacts.

In previous studies, the objective for the BW filter was defined as the suppression of BW more effectively than the standard 0.05-Hz single-pole high-pass filter, and reproduction of the ECG signal without visible distortion of cardiac complexes (7). We assumed that the optimal correction must satisfy the following two requirements: (1) remove the low-frequency elements that are not related to the cardiac electrical activity; and (2) preserve the shape and amplitude of the PQRST complexes. The first condition was assessed by the signal to noise ratio (SNR) and the root mean square (RMS) error of residual BW in simulated signals. Although the second condition is more difficult for tracking, it can be estimated by the RMS error of T-wave amplitude, a sensitive and diagnostically important parameter of cardiac repolarization. Since the amplitude and frequency of BW and cardiac complexes vary among individual subjects and even in the same subject over time, the correction must adapt to the behavior of BW. We sought to develop an adaptive procedure that can be adjusted to the magnitude and frequency of BW in each time interval, preserving the cardiac complexes from distortion and accurately removing BW. Using detailed analysis of various types of residual errors, we designed a two-step procedure for selective filtering of ECG and removal of residual error

and tested this approach on simulated and real ECG signals. This approach enabled us to achieve a twofold reduction in the error of baseline and T-wave amplitude estimation compared to high-pass filtering and to identify large portions of ambulatory ECGs that do not require BW filtering, thus saving the original signal from unnecessary filtering.

METHODS

It has been repeatedly emphasized that any filtering of the ECG signal causes certain distortion of the cardiac complexes (3, 9). Thus, an ideal filter for BW correction must identify the periods that have minimal or no BW and avoid filtering of these portions.

To illustrate this idea and to demonstrate a distortion caused by unnecessary filtering, we consider a 20-s ECG shown in Fig. 1. The signal was constructed by concatenating a single PQRST complex recorded at 1000 Hz sampling frequency. Then it was filtered by a low-pass, second-order Butterworth filter with a cutoff frequency 0.6 Hz in the forward/backward direction that yields a fourth-order null phase filter. The filtered signal represents the estimated baseline shown by the solid line in Fig. 1. Subtracting this baseline from the original signal is equivalent to high-pass filtering with the same cutoff frequency. This filter meets the AHA recommendations which require the cutoff frequency for filtering the ECG signals to be less than or equal to 0.67 Hz (11). However, the filter causes a downward displacement of baseline and, in addition, introduces a nonlinear distortion with larger effect on the ST-T segment than the PR part of the cardiac complexes (Fig. 1). Figure 2 shows the spectrum of the same ECG which has an accurate, zero-level baseline. There are two major peaks in the power spectrum. The first peak is close to 0 Hz and represents the positive mean level of the ECG signal due to the predominantly positive content of the PQRST complexes. The second peak is approximately at 0.8 Hz and corresponds to the frequency of heart rate. The spectrum of the estimated baseline obtained by the above-described low-pass filtering has the same peaks. Thus, high-pass filtering of BW, which is equivalent to subtracting the estimated baseline from the original ECG, introduces two significant spectral distortions at 0 and 0.8 Hz. Although the cut-off frequency of the filter was 0.6 Hz, it nevertheless affected the spectral component at 0.8 Hz because of the nonideal nature of the filter. Slower heart rates will thus result in larger distortion of the cardiac complexes.

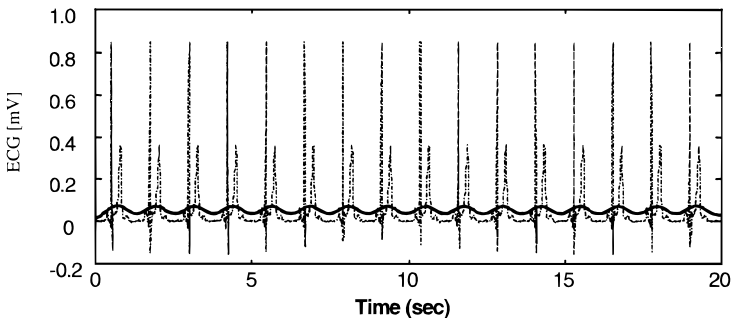


FIG. 1. Clean ECG signal (dashed line), the estimated baseline from the 0.5-Hz low-pass filter (solid line).

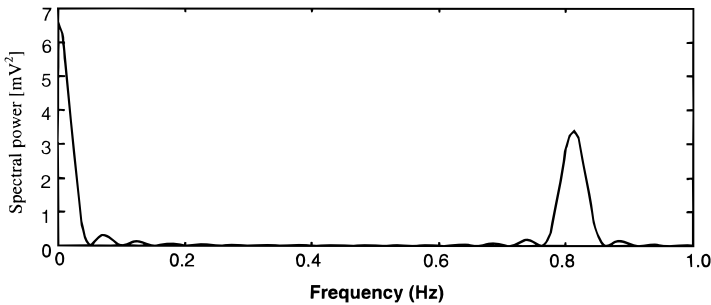


FIG. 2. Spectrum of the clean ECG signal in Fig. 1 has two components: at 0.05 and 0.8 Hz. The first, dc component, is required for estimation of the correct zero level. The second component represents the frequency of heart rate.

This example demonstrates the problems associated with high-pass filtering and allows us to formulate the properties of the ideal BW correction. (1) Noise-free portions of the signal should not be filtered. (2) The cutoff frequency of BW filters should be sufficiently high for the removal of BW but lower than the frequency of heart rhythm to avoid the distortion of cardiac complexes. (3) Displacement of baseline and distortions of the high-pass filtering require additional correction to obtain an accurate isoelectric line.

We developed a two-step correction procedure (TSC). (1) At the first step, portions of ECG that contain a large BW are identified and the frequency of BW is determined. These portions are filtered using high-pass filters with cutoff frequency adjusted to the frequency of BW. Infinite impulse response (IIR) filters are applied in a forward/backward direction to avoid phase distortion. The transfer function of the bidirectional filter is then the square of the original one. The squared transfer function has a steeper slope and the cutoff frequency is effectively shifted resulting in a smaller passband. Considering this effect, the transfer functions were calculated for both the original and bidirectional filters. As a result of this step, the major BW is filtered out from the signal without unnecessary filtering of BW-free portions. The processed signal is used as an input to the second step of the procedure (Fig. 3). (2) At this stage the ECG is free from any large BW, and the QRS complexes can be detected using a simple algorithm. Following these procedures, a fine BW correction is performed bringing the baseline to the exact zero level.

Detailed Description of the Algorithm

Consider a noisy ECG signal $x(nT)$ with baseline drift $b(nT)$. We can write $x(nT)$ as

$$x(nT) = \tilde{x}(nT) + b(nT), \quad [1]$$

where T is the sampling interval, $\tilde{x}(nT)$ is the clean ECG signal, and $b(nT)$ is BW which can be divided into the large drift $b_1(nT)$ and smaller variations, $b_2(nT)$, i.e., $b(nT) = b_1(nT) + b_2(nT)$, where $b_2(nT)$ is at least an order of magnitude smaller than $b_1(nT)$. The sampling interval T was included into the formulations to describe modifications in this parameter during the processing.

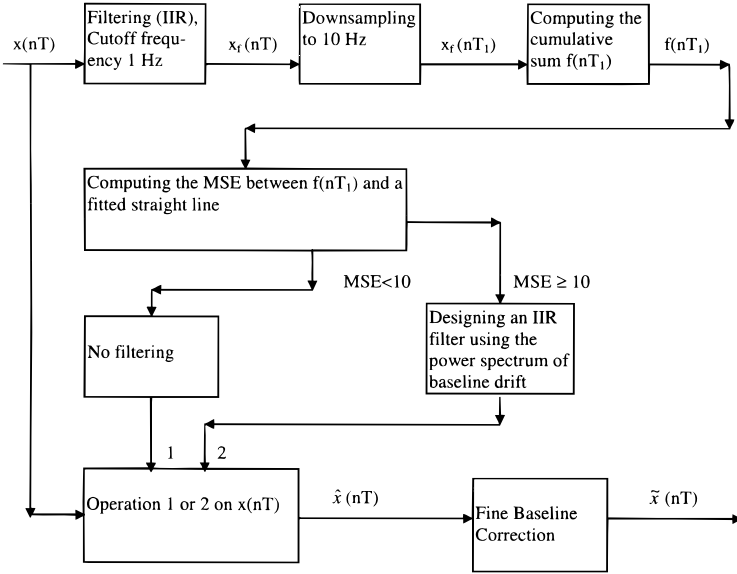


FIG. 3. Block diagram of the TSC method.

The procedure of accurate estimation of $b(nT)$ and its removal from the ECG signal $x(nT)$ to obtain the clean ECG signal $\tilde{x}(nT)$ has been divided into the following steps. The purpose of the first step is to estimate $b_1(nT)$, the largest component of BW, which provides an approximation of $b(nT)$. The process of BW correction is governed by the magnitude and frequency of $b_1(nT)$ in each time interval. If $b_1(nT)$ in a portion of the signal is larger than a preselected threshold, then a high-pass filter with a cutoff frequency related to that of $b_1(nT)$ is applied. If the BW is small, then the signal is not filtered at the first step and the BW is corrected using the second step only. Identification of the portions with small BW is carried out to avoid the negative effects of high-pass filtering illustrated in Fig. 1. At the second step, referred to as the fine baseline correction, we use the signal constructed from the portions with (1) filtered-out large $b_1(nT)$ and (2) unfiltered small $b_1(nT)$ to correct the residual part of BW, $b_2(nT)$.

Step I: Determining the Magnitude of Baseline Drift

To determine the magnitude of $BW \approx b_1(nT)$, a second-order low-pass IIR filter with 1-Hz cutoff frequency is applied to each 20-s segment in forward and backward directions. The filter also serves as an antialiasing filter, and the data are downsampled to 10 Hz, resulting in a short, 200-point signal $x_f(nT_1)$, where T_1 is the new sampling interval. The downsampling is applied to reduce the processing time and the number of computations. The signal $x_f(nT_1)$ provides an estimate of BW, but it can have some components of P-wave and QRST complexes in it. To estimate the magnitude of BW in this signal we compute

the cumulative sum

$$f(nT_1) = \sum_{i=0}^n x_f^2(nT_1). \quad [2]$$

The mean squared error (MSE) between the function $f(nT_1)$ and a fitted line $p(nT_1)$ yields the estimated magnitude of BW

$$\text{MSE} = 100 \sum_{n=0}^{N-1} |p(nT_1) - f(nT_1)|^2. \quad [3]$$

We used this criterion instead of the energy of the signal $x_f(nT_1)$ because it is less sensitive to the alterations in R- and T-wave amplitudes.

From the extensive experimentation (see Results), it was observed that the $\text{MSE} = 10$ was the best dividing value between the high and low BW. As an example, consider an ECG signal with small baseline drift (Fig. 4a). In Fig. 4b the solid line shows the function $f(nT_1)$, and the dashed line shows the fitted function $p(nT_1)$. The MSE in this case was found to be small (0.0096). In Fig. 5 the same variables are shown for high base drift ($\text{MSE} = 4703$).

If MSE is equal or larger than 10 in a 20-s portion of the signal, we design a high-pass filter as discussed in the next section and remove the major component of BW ($b_1(nT)$). For segments with a small baseline drift ($\text{MSE} < 10$) we do not perform high-pass filtering and apply the procedures described in the following sections.

Filter Design

As described in the previous section, the filter is applied only to those segments of the signal that have high baseline drift. To find the cutoff frequency, we use the signal $x_f(nT_1)$, the low-pass-filtered and downsampled version of the original signal. This is accomplished by computing the power spectrum of $x_f(nT_1)$ of each 20-s portion of the signal.

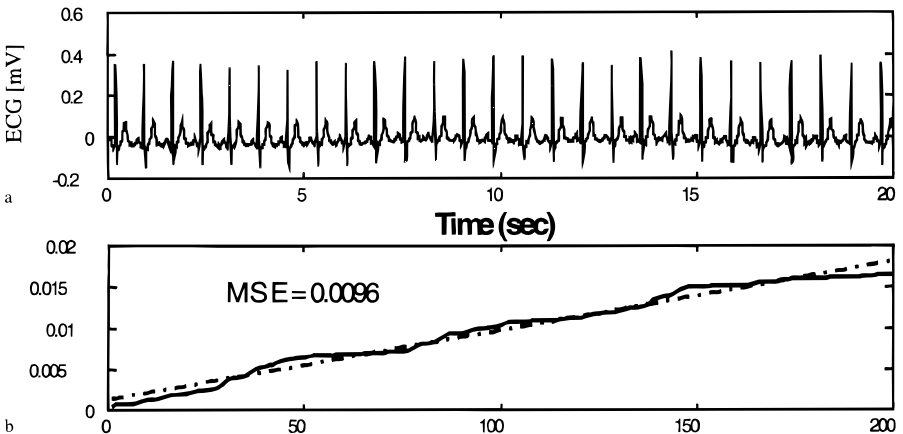


FIG. 4. Real ECG signal with small baseline drift (a) which is indicated by a small MSE (b). In b, Function $f(nT_1)$ is plotted as solid line, the fitted function $p(nT_1)$ is plotted as dashed line.

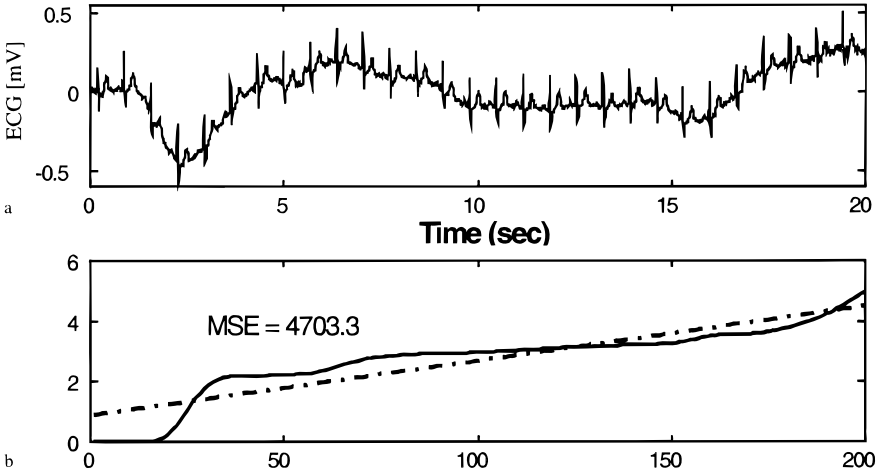


FIG. 5. Real ECG signal with large baseline drift (a) which is indicated by a high value of MSE (b). In b, function $f(nT_1)$ is plotted as solid line, fitted function $p(nT_1)$ is plotted as dashed line.

The lowest frequency components of the cardiac complexes in more than 99% of adults, 99% of the time are greater than 0.67 Hz (11). Therefore, spectral energy E_{b_1} in the range 0–0.67 Hz is assumed to represent the total energy of BW. The cutoff frequency f_{c_1} for high-pass filtering is taken as the higher border of the frequency range that contains 99% of the total energy E_{b_1}

$$E_{f_{c_1}} = 0.99 E_{b_1} \quad [4]$$

Using this cutoff, the second-order high-pass IIR filters are designed and applied to the segments of the ECG signal that have large BW. We thus obtain a signal that is free of major baseline drift $\hat{b}_1(n)$ and can be written as

$$\hat{x}(n) = x(n) - \hat{b}_1(n) \quad [5]$$

The signal $\hat{x}(n)$ has a small BW and the R-waves can be detected using simple R-wave detection algorithms that are, otherwise, sensitive to the large baseline drifts (18). Although the residual BW in this signal is relatively small ($\leq 100 \mu\text{V}$), this accuracy is not sufficient for the precise measurements of T-wave amplitude or assessment of body surface potential recordings (5, 14–16). For these tasks we propose the second step of the algorithm, referred to as the fine baseline correction (FBC), which removes the minor, residual baseline drifts $b_2(n)$. This procedure is discussed in the next section.

Step II: Fine Baseline Correction

For the second step of the correction we use the signal $\hat{x}(n)$ obtained from the previous stage. We use the fine baseline correction to bring the baseline to zero in the portions of ECG in which large BWs were filtered out and in the portions in which small BWs did not require high-pass filtering. As was already mentioned earlier, the fine baseline

correction is performed after the R-waves have been identified. The primary objective for finding the accurate baseline level is to determine the PQ and TP intervals and to interpolate the data points between them. Since the magnitude of BW is small after the first step, linear interpolation works accurately, whereas cubic spline interpolation can introduce extraneous frequency components and distort the original signal (2–4).

To find the PQ and TP segments we use local windows W_Q and W_T in the vicinity of Q-wave onset and T-wave offset, respectively, where W_Q and W_T are adjusted according to the average heart rate and estimated Bazett-corrected QT interval.

We then define a threshold for each window. If $x(n)$ is the ECG signal, then

$$\text{Thresh}_Q = \frac{\sum_{n=Q_0-W_Q}^{n=Q_0+W_Q} |x(n+1) - x(n)|}{N}$$

$$\text{Thresh}_T = \frac{\sum_{n=T_0-W_T}^{n=T_0+W_T} |x(n+1) - x(n)|}{N},$$

where N is the length of the window W_Q and W_T , respectively.

In each window, the longest continuous segments whose discrete-time derivatives are below the threshold values are assigned as PQ and TP segments, respectively. The rest of the values for the fine baseline estimation, $\hat{b}_2(n)$, is found by linear interpolation between the PQ and TP segments. The starting point for the interpolation is the last point of the PQ segment, and the end point is the first point of the TP segment. Finally, the baseline-corrected signal $\tilde{x}(n)$ is obtained as

$$\tilde{x}(n) = \hat{x}(n) - \hat{b}_2(n)$$

RESULTS

The proposed method was tested on signals with simulated and real baseline drifts.

Signals with Simulated Baseline Drift

We first construct a 20-s “clean” ECG signal with baseline at zero level by concatenating 1-s segments of ECG which consist of PQRST complex and short portions before P-wave and after T-wave. The resulting 20-s ECG signal has 20 PQRST complexes and a 60 bpm heart rate. Changes in heart rates were reproduced by addition or removal of data points before and after PQRST complexes. A simulated, three-component baseline drift was added to the clean ECG. The first component was a sine wave with a 0.2-Hz frequency and a 400- μ V peak amplitude, and the second component was a cosine wave with a 0.45-Hz frequency and a 300- μ V peak amplitude. These two components result in a BW that was simulated in previous studies to span typical respiratory frequencies (8, 9). In addition, a low-frequency random component was also added to the BW. This component was generated by filtering white noise (700 μ V peak amplitude) through a bidirectional fourth-order IIR filter with 0.3-Hz cutoff frequency. Thus, if we consider the clean ECG signal as $x_c(n)$, the test signal can be written as

$$x(n) = x_c(n) + \sin(2\pi 0.2n) + \cos(2\pi 0.45n) + \eta(n), \quad [6]$$

where $\eta(n)$ is the low-frequency random component of the simulated baseline drift. We tested the algorithm by generating the baseline drift 100 times, each time with a different $\eta(n)$. The magnitude of the simulated BW was high, and the MSE given by Eq. [3] was higher than 10 in all 100 simulations, requiring application of high-pass filtering (Step I) and fine baseline correction (Step II). This procedure improved the SNR by approximately 24 dB and reduced the RMS error of baseline estimation by 95.5%. The cutoff frequency of the filters was 0.5269 ± 0.0072 Hz (range: 0.495–0.570 Hz). If the time-invariant high-pass filtering alone was applied, the resulting SNR was almost 2 times lower and the RMS error was more than two times larger than after TSC (Table 1).

The TSC is less influenced by the changes in heart rate than the time-invariant filtering. In additional 200 simulations at different heart rates, the range of the RMS errors in baseline estimation using filtering with 1-Hz cutoff frequency was 1.7 times larger than for TSC (33 and 56 μV , respectively). The range of the RMS errors in T-wave amplitude estimation was 2.4 times larger for the filtering than for TSC (82 and 34 μV , respectively).

A representative example of the simulated baseline drift is shown in Fig. 6. The clean ECG was constructed as described at the beginning of this section (Fig. 6a). Figure 6b shows the same signal with simulated, three-component BW. Note the large magnitude of the baseline drift also represented by low SNR (−3.33 dB). Since the MSE given by the Eq. [3] was higher than 10, the signal was high-pass filtered with 0.525-Hz cutoff frequency which was found as described in the previous section. The SNR of the filtered ECG signal is 8.57 dB (Fig. 6c). At the next step, the R-waves were detected and the fine baseline correction was applied improving the SNR to 21.06 dB (Fig. 6d).

To illustrate the effect of the filter cutoff, we consider a baseline drift that consists of the two sinusoids given in Eq. [6]. We added this BW to the clean ECG signal, filtered it, and estimated the error between the filtered signal and the clean ECG at different cutoffs. The relationships between the cutoff frequency of the filters, the error of the estimated baseline, and the distortion of PQRST complexes are shown in Fig. 7. The cutoff frequency that gives the minimum RMS error of the estimated baseline differs from the frequency that gives the minimum RMS error of the T-wave amplitude measurement (Fig. 7a). If the cutoff frequency is lower than the optimal one, a residual BW introduces errors in the measurements of T-wave amplitude. If the cutoff frequency is higher than

TABLE 1

Performance of Time-Invariant Filtering and TSC on 100 Simulated Baseline Drifts

Estimate	Raw signal	Time-invariant filtering, cutoffs		TSC	Average cutoff frequency of the optimal filter (Hz)
		0.6 Hz	1 Hz		
SNR (dB)	-3.05 ± 0.138	11.29 ± 0.036	13.78 ± 0.054	22.11 ± 0.58	0.5269 ± 0.0072
Range	−3.38 to −2.69	11.17 to 11.39	13.65 to 13.90	19.91 to 25.2	0.495 to 0.57
RMS error (μV)	433.1 ± 4.78	61.22 ± 0.25	46.00 ± 0.29	19.58 ± 1.28	Same as above
Range	421.9 to 444.7	60.56 to 62.05	45.31 to 46.67	13.58 to 25.16	

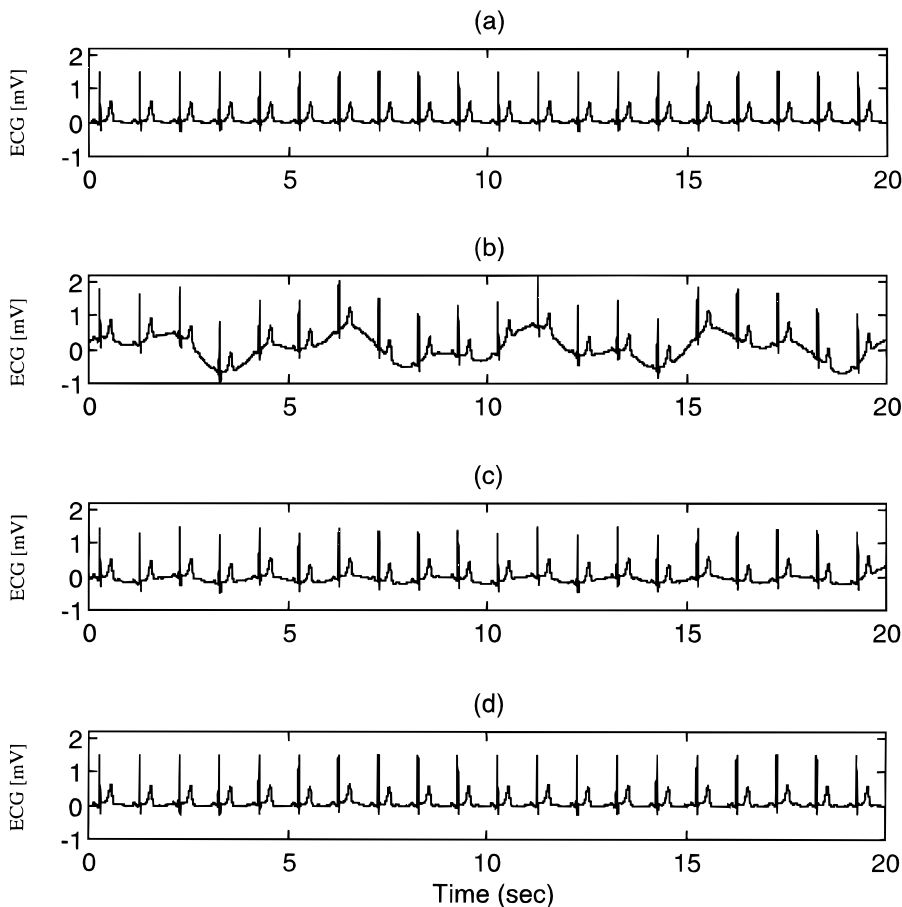


FIG. 6. Clean ECG signal (a), the signal with simulated baseline drift (b), the same signal after high-pass filtering (cutoff frequency: 0.525 Hz) (c), and the signal after the fine baseline correction (d).

the optimal one, extraneous frequency elements are introduced into the signal and components of the T-waves are filtered out. Furthermore, the optimal cutoffs shift when the heart rate changes (Fig. 7b). The advantage of the proposed method is related to avoiding excessively high cutoffs by adaptive filtering and removing the residual BW after the filtering.

Signals with Real Baseline Drift

We applied the proposed method to 110 Holter ECGs recorded during 24 h at 400-Hz sampling rate, 12-bit resolution, and bandpass frequency 0.05–85 Hz. The signals were obtained from patients with structural heart disease and control subjects without a history of cardiovascular disease. ECGs from patients with structural heart disease had variable

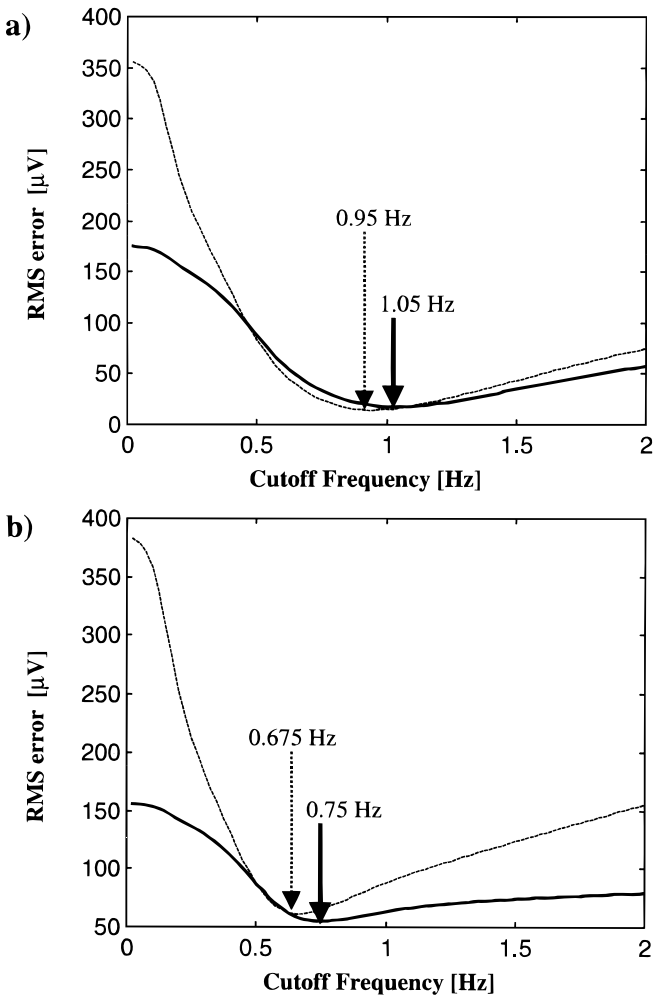


FIG. 7. Changes in the RMS error of baseline estimation (solid line) and the RMS error of T-wave amplitude estimation (dashed line) as functions of filters' cutoff frequency at different heart rates. Minimum RMS errors are indicated by arrows. (a) HR = 96 bpm, minimum RMS of T-wave amplitude 14.54 μV at 0.95 Hz, minimum RMS of baseline 17.35 μV at 1.05 Hz. (b) HR = 42 bpm, minimum RMS of T-wave amplitude 61.5 μV at 0.675 Hz, minimum RMS of baseline 55.15 μV at 0.75 Hz.

amount of ventricular ectopy (5–25%). Five patients had complex ventricular ectopy that included bigeminy and trigeminy; two patients had nonsustained (<30 s) runs of ventricular tachycardia. Most of the patients with structural heart disease had morphological changes in the repolarization segments including flat, inverted, or biphasic T-wave, and depressed or elevated ST segment. Each file had 4320 segments of 20-s duration which yielded a total of 475,200 segments. In addition, the TSC method was also tested on 100 segments of 20-s duration obtained from the 32-channel body surface potential map-

ping ECGs (BSPM) recorded at 1-kHz sampling frequency and 12-bit resolution. Two experienced observers reviewed the accuracy of BW correction in all the BSPM files and in 2 h, randomly chosen segments of each 24-h recording.

To estimate the proportion of the ECG signals that have a small BW and do not require high-pass filtering (Step 1), we calculated the number of segments that had the $MSE < 10$. The filters' cutoff frequency for each data segment was also recorded. The results are summarized in Table 2. Almost 75% of the Holter data files did not have large BW and thus did not require high-pass filtering. The average cutoff frequency of the filters for the Holter ECGs was 0.560 ± 0.076 Hz (range: 0.162 to 0.662 Hz). In the BSPM data set, 87% of the recordings did not require filtering. The cutoff frequency of the filters in this data set was lower because the data were obtained under controlled conditions (0.363 ± 0.076 Hz, range: 0.245 to 0.480 Hz).

An example of a real signal with BW corrected by the TSC method is demonstrated in Fig. 8. The magnitude of BW is high ($MSE > 10$), requiring the high-pass filtering with 0.47-Hz cutoff frequency (Step 1). The filtered signal is shown in Fig. 8b. At the next step, residual baseline wander was eliminated using the fine baseline correction (Step II) which results in an accurate isoelectric line (Fig 8c).

DISCUSSION

We analyzed the methods for correction of baseline in the ECG signals and developed a two-step approach that might be useful for analysis of minute beat-to-beat changes in cardiac repolarization. The method consists of the following elements. (1) The magnitude of BW is determined for each segment of the ECG recording, and the segments are classified into those with small and large baseline drift. (2) The frequency of BW is determined in the segments with large BW. These segments are high-pass filtered with a cutoff that depends on the frequency of BW, thus providing a good separation between the baseline and cardiac complexes. (3) The majority of segments (75 and 87% of Holter ECGs and body surface mapping recordings, respectively) have small BW. These segments are not subjected to high-pass filtering which results, as we have demonstrated, in unnecessary distortion of the cardiac complexes. (4) The residual BW that remains after filtering out large baseline drifts is corrected using linear interpolation.

TABLE 2

Proportion of Data Requiring High-Pass Filtering (Step I of the Optimal Correction)

Type of Recording	Number of files	Duration of each file	Required high-pass filtering (%)	Saving (%)	Average cutoff frequency of the filter (Hz)
Ambulatory ECG	110	24 h	25.08	74.92	0.56 ± 0.0759 Range: 0.1625 to 0.6625
32-lead body surface mapping	100	20 s	13	87	0.3631 ± 0.0757 Range: 0.245 to 0.48

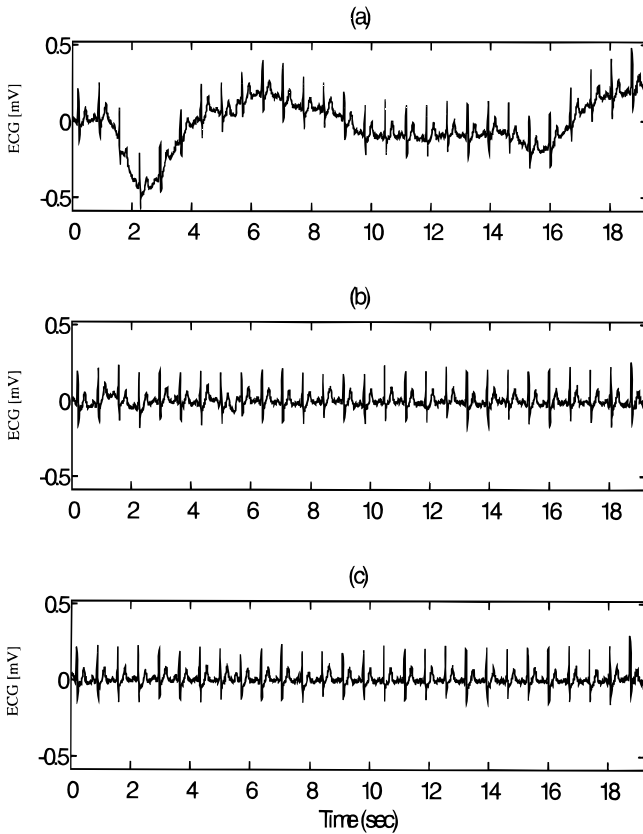


FIG. 8. Real Holter ECG signal with a large baseline drift (a) The signal after high-pass filtering (b), and the signal after the fine baseline correction (c).

Comparison with Previous Methods

Time-invariant filtering of the entire recording is a simple and frequently used method of baseline correction (3, 6–9, 19, 20). Both finite impulse response (FIR) and infinite impulse response (IIR) filters have been used to eliminate the baseline drift. Because of the adverse nonlinear effects on the low-frequency elements, such as the STT segment, only the filters with linear phase are recommended by the American Heart Association (11). The IIR filters generally have a nonlinear phase which can be corrected by several techniques. A bidirectional, forward/backward filter which can be implemented off-line or on-line with a small time delay gives null phase (9, 10, 21). Using IIR filters with optimized equ-ripple linear phase approximation, one can also achieve an almost linear phase response (7). The FIR filters with linear phase are rarely used because they have a long impulse response, thus requiring many multiplications (4). There have been attempts to design FIR filters with shorter impulse responses and nearly linear phase in the passband (6, 13).

These types of filtering eliminate the major part of baseline drift but, as Fig. 7 shows, do not return the baseline exactly to zero level and cause distortions in the low-frequency elements of the cardiac complexes. The difference between the effect of filtering on T-wave amplitude and baseline wander adds to the complexity of the problem. The optimal cutoff frequency evidently depends on the frequency of BW but other factors including heart rate also influence the cutoff, as Fig. 7 demonstrates. This diminishes the accuracy of time-invariant approach in general, while the types of residual errors depend on the specific cutoff. In Fig. 7, the 0.5-Hz cutoff leaves the residual BW in the signal, whereas the 1-Hz cutoff introduces extraneous frequency components and partially filters out the T-waves. Although the 0.67-Hz cutoff proposed by the AHA recommendations gives a relatively small error, the performance of the method depends on the frequency of BW and heart rate (11). Thus, the accuracy of time-invariant filtering of the same ECG varies following the changes in heart rate (Fig. 7). Filtering with 1-Hz cutoff frequency gave small RMS error in previous studies; however, as Fig. 7 demonstrates, this was achieved at the cost of a relatively large distortion of cardiac complexes (8, 9). The same figure shows that the distortion of QRST complexes quickly increases above the 0.7-Hz cutoff. In fact, any given cutoff frequency gives residual RMS which can vary between 16 and 98 μV and can heavily bias the measurements of the low-amplitude changes in repolarization (14–16). Our approach of classifying the segments of ECG into those with large and small BW according to the Eq. [3] provides a tool for selecting an acceptable noise level for each parameter to be measured. Thus, portions with large BW can be discarded from the analysis that requires precise estimation of very small repolarization changes.

In our study, a cutoff frequency of the optimal filter depended on the frequency of BW but not on the heart rate. Therefore, the upper limit for the cutoff frequency was 0.67 Hz in accordance with the AHA recommendations (11). Since the lowest frequency components of the cardiac complexes correspond to the longest RR interval and in more than 99% of adults a mean resting heart rate is greater than 40 bpm corresponding to 0.67 Hz frequency, we assumed that the energy below 0.67 Hz represents pure BW (11). Thus, the cutoff frequency was adjusted to the frequency of BW by spanning the range that contains 99% of the energy in each time window. The distortion and extraneous frequencies introduced into the cardiac complexes by the filtering cannot be corrected afterward and, therefore, should be avoided by choosing the cutoff frequency of filtering below that of heart rate (Fig. 7). Further improvement of the accuracy can be achieved by using the frequency of heart rate for adjustment of the cutoff frequency (13).

It is important to note that the second step of BW correction is required after the filtering regardless of the filter's characteristics. Filtering the signal produces a zero-mean signal, but its zero level rarely corresponds to the real baseline. The correct baseline can be restored only if the BW consists of periodic components. Since real baseline drifts have nonperiodic components with nonzero mean value, it is impossible to find the accurate baseline of these signals using high-pass filtering alone. Thus, the second step is required for the accurate BW correction. Removal of residual, low-magnitude BW is effectively achieved by simple linear interpolation which cannot be performed on the raw signal with high baseline drift.

Comparing TSC and the time-invariant filtering we found that the former method gives two times lower RMS error and distortion of the T-wave. In our simulations we

used two deterministic components reproducing respiratory frequencies of BW (9). In addition, the nonperiodic variations of BW existing in real signals were simulated by the low-pass-filtered random noise. The performance of TSC was not affected by the complexity of BW, demonstrating the reliability of our method for correcting various BWs that appear in real signals.

Adaptive filtering. Different techniques based on the idea to adapt the filter cutoff frequency to the characteristics of BW have been developed. The simplest solution to correct the baseline is ensemble averaging of the ECG signal. However, this procedure requires a large number of complexes to be recorded (22). There have been attempts to design adaptive FIR filters using a dc signal as a reference input for adjusting the cutoff frequency to the amount of baseline drift (2, 3). Since the adaptation is delayed, this method causes some distortion of the QRST complexes which makes it inappropriate for the accurate analysis of beat-to-beat changes in the cardiac waveforms (2). Another approach has been selecting the cutoff frequency according to the amount of BW from several constant values between 0.5 and 1.5 Hz and letting the cutoff frequency be controlled by the low-frequency properties of BW which is similar to the first step of TSC method. The error between the output of the selected filter and that of the filter with the highest cutoff frequency is used recursively for selecting the appropriate filter (3). However, if no BW is present, the signal still will be filtered with the lowest cutoff frequency, whereas TSC does not filter the segments with small BW. This difference becomes significant when minute changes in repolarization are studied, since application of TSC to Holter recordings and BSPMs did not require filtering in more than 70% of the segments. The second difference is the removal of residual noise at the second step of TSC.

Cubic spline interpolation. This method may produce inaccurate results if the signal has ectopic beats, slow heart rate, or a high baseline drift (4). The accuracy of the method is inferior compared to time-invariant or time-varying high-pass filtering (3). When the magnitude of BW is small, it is better approximated by linear functions, whereas fitting a cubic spline can introduce extraneous frequency components. Therefore, we chose linear interpolation at the second step of TSC when large BW is already removed from the signal.

Linear interpolation for removing residual baseline drift. Linear interpolation applied to the signal with large BW causes distortions of the cardiac complexes due to the multiple frequency elements in the baseline drift. However, linear interpolation works accurately on low-amplitude and frequency baseline drifts (1). Our results demonstrate that in this case linear interpolation provides a two- to threefold improvement in the SNR and reduces RMS in the estimation of BW.

Limitations

The computational approach is relatively intensive; it requires forward/backward filtering, frequency estimation, and least-squares line fitting for each 20 s of data. This limits the technique to retrospective applications on high-end Holter ECG, body surface potential mapping, and stress-test systems. At this time, this approach is too expensive computationally for implantable cardiac devices. Recent advancements in microprocessor technology make it possible to apply TSC in event and other types of monitors including bedside systems.

The described approach may not be effective for the correction of BW which has a frequency higher than 0.675 Hz and a large magnitude. However, some components of BW above 0.675 Hz will still be removed due to the nonideal nature of the filter. This will allow detecting the PR and TP segments and implementing linear interpolation for the removal of residual BW. Although BWs consisting of such high frequencies are theoretically possible, they can rarely be seen in real ECG signals. Among the 475,200 segments of ambulatory and body surface mapping recordings that we studied, the frequency of BW was always lower than 0.675 Hz. Furthermore, estimation of the MSE according to Eq. [3] can be used for identifying the segments with large BW in which the detailed analysis of P-wave and QRST complex might not be accurate.

A potential threshold effect may occur when the Step I filtering is performed only in some ECG segments. This may create a discontinuity between the filtered and unfiltered sections of the signal. This effect can be avoided by local smoothing in the vicinity of the border between the filtered and unfiltered sections.

The method was not affected by various forms and disturbances of cardiac complexes provided that R-waves and baseline segments were correctly identified. Indeed, the test set of real Holter ECGs and BSPM recordings included those with different arrhythmias, conduction abnormalities, and morphological changes in the ST segment and T-wave. There were no visible biases introduced by the differences in cardiac complexes.

CONCLUSIONS

Analysis of minute beat-to-beat repolarization changes can be performed in Holter ECG and body surface mapping recordings by selecting the segments that have a relatively small BW and applying a two-step adaptive filtering and removal of residual error. Applying this procedure can allow accurate BW correction and analysis of low-amplitude, beat-to-beat changes in repolarization during more than 70% of the recording time which, in turn, might be important for risk stratification and prediction of malignant arrhythmias and sudden death (14–16).

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