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ECG signal conditioning by morphological filtering

Yan Sun *, Kap Luk Chan, Shankar Muthu Krishnan

Biomedical Engineering Research Center, School of Electrical and Electronic Engineering, Nanyang Technological University, Nanyang Avenue, 639798 Singapore

Abstract

Clinically obtained electrocardiographic (ECG) signals are often contaminated with different types of noise and baseline drifting commonly occurs. In order to facilitate automated ECG analysis, signal conditioning is undoubtedly a necessity. In this paper, a modified morphological filtering (MMF) technique is used for signal conditioning in order to accomplish baseline correction and noise suppression with minimum signal distortion. Compared with existing methods for ECG signal conditioning, MMF performs well in terms of the filtering characteristics, low signal distortion ratio, low computational burden as well as good noise suppression ratio and baseline correction ratio.

Keywords: ECG; Signal conditioning; Baseline correction; Noise suppression; Morphological filtering

1. Introduction

Electrocardiographic (ECG) signals are often contaminated by noise from diverse resources and forms: 50/60 Hz power line interference, motion artifact from the electrode–skin interface, muscle activities [1,2]. In addition, baseline drift caused by the respiration, radio frequency surgical noise and motion of the subject [3] degrades ECG signals significantly. Therefore, signal conditioning for baseline correction and noise suppression is typically the first step in the analysis of ECG signals. The objective of ECG signal conditioning is to produce an output that can facilitate the subsequent processing, such as ECG episode characterization for life-threatening arrhythmia recognition, or the characteristic wave detection for non-life-threatening ECG signals. It is important to minimize the distortion of the ECG signal caused by signal conditioning algorithms so that analysis on the conditioned signal can be performed to give reliable results.

* Corresponding author. Tel.: +1-65-7906324; fax: +1-65-7912274.
E-mail address: eysun@ntu.edu.sg (Y. Sun).

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Conventionally used techniques for noise suppression are often based on band-pass filtering [4–6]. However, band-pass type of linear filtering techniques have a fixed cut-off frequency which distorts the ST segment as well as the QRS complex significantly. It is also not adaptive and hence cannot track the changing characteristics of the time-varying ECG signals, which tend to vary quasiperiodically, with each period corresponding to one heart beat. Recently, adaptive filtering techniques have been developed for the purpose of noise suppression in ECG signals. Most adaptive noise-removal methods [7–9] are based on the least mean squares principle or on the recursive least squares principle. They gradually reduce the mean squared error between the input signal and some reference signal. However, in some cases, these techniques experience the difficulty of not being able to obtain a suitable reference signal, which limits the wide application of this kind of approach. Wavelet transform, being a very promising technique for joint time–frequency analysis, provides an interesting solution to ECG signal conditioning [10,11]. By decomposing signals into transform domains, a number of coefficients at different scales can be obtained. By selecting suitable scales and disregarding the coefficients below predefined thresholds, additive noise and baseline drift can be separated from the ECG signal components. However, in this kind of techniques, the scales and the thresholds for the non-stationary baseline correction and noise suppression cannot be selected adaptively.

Morphological operators have been widely used in the signal- and image-processing fields because of their robust and adaptive performance in extracting the shape information in addition to their simple and quick sets computation [12–15]. Chu and Delp used the combined opening and closing operators for baseline correction and noise suppression of ECG signals and good filtering performance was obtained [16]. However, their morphological filtering (MF) algorithm distorts the characteristic points in ECG signal. This makes it difficult for the subsequent processing to reliably detect the significant ECG components or intervals. In this paper, a modified morphological filtering (MMF) algorithm is proposed for baseline correction and noise suppression of ECG signals. For baseline correction, the same operators are used in the MF algorithm and the MMF algorithm. For noise suppression, modified morphological operators are used in the MMF algorithm. Better signal conditioning performance has been obtained.

This paper is organized as follows. Mathematical background on morphological operators is introduced in Section 2. The proposed MMF algorithm for ECG signal conditioning is described in Section 3. Section 4 covers the experimental results and discussions. Lastly, a conclusion of this paper is given in Section 5.

2. Mathematical morphology operators

Mathematical morphology (MM), which is based on sets operations, provides an approach to the development of non-linear signal processing methods, in which the shape information of a signal is incorporated [17]. In MM operations, the result of a set transformed by another set depends on the shapes of the two sets involved. The shape information of a signal can be extracted by using a structuring element to operate on the signal. A specific structuring element has to be designed depending on the shape characteristics of the signal that is to be extracted.

There are two basic morphological operators: erosion ($\ominus$) and dilation ($\oplus$). Opening ($\circ$) and closing ($\bullet$) are derived operators defined in terms of erosion and dilation. These operators are described in detail below with corresponding mathematical expressions. Throughout this paper $f(n)$, $\{n = 0, 1, \ldots, N-1\}$, denotes a discrete signal consisting. N points, and $B(m)$, $\{m = 0, 1, \ldots, M-1\}$, is a symmetric structuring element of M points:

$$\text{erosion}: (f \ominus B)(n) = \min_{m=0,\ldots,M-1} \left\{ f\left(n - \frac{M-1}{2} + m\right) - B(m) \right\}$$

$$\text{for } n = \left\{ \frac{M-1}{2}, \ldots, N - \frac{M+1}{2} \right\}. \tag{1}$$

Erosion is a 'shrinking' operator in which the values of $f \ominus B$ are always less than those of f.

$$\text{dilation}: (f \oplus B)(n) = \max_{m=0,\ldots,M-1} \left\{ f\left(n - \frac{M-1}{2} + m\right) + B(m) \right\}$$

$$\text{for } n = \left\{ \frac{M-1}{2}, \ldots, N - \frac{M+1}{2} \right\}. \tag{2}$$

The dilation operation is an 'expansion' operation in which the values of $f \oplus B$ are always greater than those of f:

$$\text{opening}: f \circ B = f \ominus B \oplus B, \tag{3}$$

$$\text{closing}: f \bullet B = f \oplus B \ominus B, \tag{4}$$

The opening of a data sequence can be interpreted as sliding a structuring element along the data sequence from beneath and the result is the highest points reached by any part of the structuring element. Similarly, the closing of a data sequence can be interpreted as sliding a 'flipped-over' version of the structuring element along the data sequence from above and the result is the set of lowest points reached by any part of the structuring element. In most applications, opening is used to suppress peaks, while closing is used to suppress pits.

In Chu's MF algorithm [16], the baseline correction and noise suppression are performed as follows:

$$f_b = f_o \circ B_o \bullet B_c,$$

$$f = \tfrac{1}{2}[(f - f_b) \circ B \bullet B + (f - f_b) \bullet B \circ B], \tag{5}$$

where f_o is the original ECG signal, f_b is the detected baseline drift, and f is the resultant signal after signal conditioning. B_o and B_c are structuring elements for opening and closing, respectively. B is another structuring element for opening and closing in noise suppression.

3. Proposed MMF algorithm for ECG signal conditioning

The proposed MMF algorithm, viz., the MF algorithm with modified opening and closing operators, for baseline correction and noise suppression in the conditioning of the ECG signal, is shown in Fig. 1.

ECG signal is conditioned through a sequence of opening and closing operations. Based on the different characteristics of the baseline drift and the noise contamination in the ECG signals,

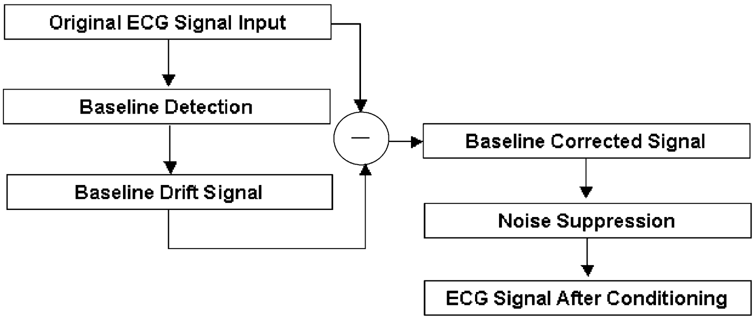

Fig. 1. Block diagrams for the proposed MMF ECG signal conditioning algorithm.

different structuring elements and different morphological operators are used. For baseline correction, an opening operator followed by a closing operator is defined; for noise suppression, modified opening and closing operators are used. They are described in detail in the following subsections.

3.1. Baseline correction

The correction of baseline is performed by removing the drift in background from the original ECG signal. It follows Chu's method. The signal is first opened by a structuring element B_o for removing peaks in the signal. Then the resultant waveforms with pits are removed by a closing operation using the other structuring element B_c. B_o and B_c are selected as two horizontal line segments of zero amplitude, but with different lengths. The final result is then an estimate of the baseline drift f_b. The correction of the baseline is then done by subtracting f_b from the original signal f_o.

The reasons for using different lengths in B_c and B_o are as follows. The baseline drift signal is estimated by removing the ECG signal from the test signal. Hence, the construction of the structuring element for baseline correction depends on the duration (or width) of the characteristic wave and the sample frequency (F_sHz) of the ECG signal. If the width of a characteristic wave is T_w (s), the number of samples of the wave is T_wF_s. In order to extract the characteristic wave, the structuring element B_o should have a length larger than T_wF_s. Since the subsequent closing operation is used to remove the pit left by the opening operation, the length of the structuring element B_c must be longer than the length of B_o. The width of the characteristic wave in the ECG signal, such as the P wave, the T wave, and the QRS complex, is generally less than 0.2 s. Hence, L_o, the length of B_o, is selected as $0.2F_s$, and L_c, the length of B_c, is typically selected to be longer than B_o, at about $1.5L_o$.

3.2. Noise suppression

After baseline correction, noise suppression is performed by processing the data through an opening and a closing operation concurrently, and then the results are averaged. In this study, the opening and closing operations for noise suppression use a structuring element pair, B_{pair}, not a single structuring element as in Chu's MF algorithm shown in Eq. (5). B_{pair} is defined as $B_{pair} = \{B_1, B_2\}$, where $B_1 \neq B_2$, i.e., different in shape but the same in length. The sequence of B_1 and B_2 corresponds to the order of dilation and erosion in the opening and closing operations. The process of signal conditioning is described by the following equation:

$$\begin{aligned} f &= \tfrac{1}{2}(f_{bc} \bullet B_{pair} + f_{bc} \circ B_{pair}) \\ &= \tfrac{1}{2}(f_{bc} \oplus B_1 \ominus B_2 + f_{bc} \ominus B_1 \oplus B_2), \end{aligned} \tag{6}$$

where f is the resultant signal after noise suppression, and f_{bc} is the signal after baseline correction. The B_{pair} is selected by considering the purpose of analysis and the morphological properties of the ECG signal. B_1 is selected to be a triangular shape and B_2 is a line segment. A triangular structuring element is used to retain the peaks and valleys of the characteristic waves, such as the QRS complex, the P and T waves, while a short line segment structuring element is used for removing noise in the ECG signal. In order to minimize the distortion to the ECG signal, the length of B_1 is selected to be the same as that of the B_2. Since the processing is discrete, the selection of the structuring element length is related to the bandwidth of ECG signal, and the sampling rate. Given that the sampling frequency is fixed, a shorter structuring element can be used to reduce the distortion of the waveform. Based on the sample frequency F_s, the lengths of B_1 and B_2 are selected as 5 sample units each, with values of $B_1 = (0,\ 1,\ 5,\ 1,\ 0)$, $B_2 = (0,\ 0,\ 0,\ 0,\ 0)$.

Using the proposed structuring element pair, noise can be suppressed while reducing the smoothing of the significant peaks and valleys in the ECG signal, which are essential characteristic singularities for the subsequent reliable detection of the characteristic waves.

3.3. Performance evaluation of signal conditioning

The performance of signal conditioning is judged by the level of noise reduction it achieves and on the signal distortion it causes. In this study, three parameters are used for algorithm evaluation: the baseline-correction ratio (BCR), the noise-suppression ratio (NSR), and the signal-distortion ratio (SDR), which are defined as follows:

$$\begin{aligned} \mathrm{BCR} &= \frac{\sum_{t=1}^{T} \|b(t)\|}{\sum_{t=1}^{T} \|b_o(t)\|}, \\ \mathrm{NSR} &= \frac{\sum_{t=1}^{T} \|n(t)\|}{\sum_{t=1}^{T} \|n_o(t)\|}, \\ \mathrm{SDR} &= \frac{\sum_{t=1}^{T} \|d_o(t) - \mathrm{d}(t)\|}{\sum_{t=1}^{T} \|\mathrm{d}(t)\|}, \end{aligned} \tag{7}$$

where $b_o(t)$ is the baseline component in the original input signal $f_o(t)$, $t \in [1, T]$, $b(t)$ is the detected baseline drift using one of the filtering algorithms, $n_o(t)$ is the noise component in the original input signal, $n(t)$ is the suppressed noise, $d_o(t)$ is the clean signal component in the input signal and d is the filtered signal. BCR is defined for measuring the degree of baseline being corrected; NSR is defined for measuring the degree of noise being suppressed, and SDR is defined for measuring the degree of signal being distorted after the conditioning. The larger the value of BCR and NSR, or the smaller the value of SDR, the better is the performance of signal conditioning.

3.4. Computational complexity analysis

The computational burden for the WF algorithm is $O(N \log_2 N)$ while for the MMF algorithm it is $O(MN)$, where N is the length of the test signal and M is the length of the structuring element. Usually, M is far shorter than N. For baseline correction, M is larger than $\log_2 N$; hence, the computational burden of the WF algorithm is less than that of the MMF algorithm. For noise suppression, M is much smaller than $\log_2 N$; hence, the computational burden of the WF algorithm is larger than that of the MMF algorithm. Because of this the WF algorithm is not compared with the MMF algorithm in the following test of noise suppression and the difficulty of setting empirical thresholds.

4. Experimental results and discussions

In order to evaluate the proposed algorithm, a number of experiments were performed using simulated data and known MIT–BIH arrhythmia database. Experimental results for noise and baseline drift suppression using the proposed MM operators are presented and discussed in this section. In addition, they are compared with those obtained using the WF method [18] for baseline correction and compared with the MF algorithm for noise suppression. For noise suppression, the WF algorithm is not compared because there are some parameters need to be selected empirically, making a fair comparison difficult.

4.1. Algorithm testing using simulated data

Experiments using simulated data were performed so that the proposed algorithms could be tested in an absolutely controlled environment. The performance of the algorithms could be evaluated by starting with a known signal, corrupting it by adding noise and baseline drift, performing signal conditioning operations, obtaining the recovered signals and comparing the recovered signal with the known signal. Then, BDR is used for evaluating the performance of baseline correction by the MMF and WF algorithms. NDR and SDR are computed for evaluating the performance of noise suppression by the MMF and MF algorithms.

A noisy ECG signal can be modeled as

$$S(n) = I(n) + N(n) + B(n), \tag{8}$$

where $S(n)$ is the corrupted ECG signal (a discrete time series), $I(n)$ is the clean ECG signal generated from the simulator, $N(n)$ is the noise component and $B(n)$ is the baseline drift.

In this study, clean ECG signal is generated from a *PROPAQ encore* ECG simulator manufactured by Welch Allyn Protocol System Inc. Company.

Noise is modeled by a mixture of Gaussian noise according to [16], which has a probability distribution function of

$$N(n) = (1-\varepsilon)G_1\left(\frac{n}{\sigma_1}\right) + \varepsilon G_2\left(\frac{n}{\sigma_2}\right), \tag{9}$$

where G_1 and G_2 are the probability distribution functions of Gaussian random variable. σ_1 and σ_2 are standard deviations of G_1 and G_2. σ_2 is typically much larger than σ_1. As σ_1 and σ_2 increase,

Table 1
BCR, NSR and SDR for performance evaluation of signal conditioning

	BCR		NSR		SDR	
Data set	WF	MMF/MF	MF	MMF	MF	MMF
1	0.8370	0.9836	0.7970	0.7856	0.1132	0.0612
2	0.8860	0.9899	0.7964	0.7903	0.1065	0.0584

the noise amplitude increases. ε is a weight, which controls the distribution of G_1 and G_2, the background noise and the impulsive noise, respectively.

Baseline drift is simulated by adding a slanted line to a sinusoidal signal [16]:

$$B(n) = B + mn + A\cos\left(2\pi\frac{n}{N} + \phi\right). \tag{10}$$

The period of the sinusoid N controls the severity of the baseline roll. m controls the slope of the baseline drift, which can be represented as $m = \tan(\theta)$, θ is the angle of slope. A controls the amplitude of upward or downward drift. Using different values for ϕ allows different baseline drift sequences to be generated with similar characteristics. The bias term B is set so that the sequence values do not get out of range.

4.1.1. *Data set 1*

As shown in Fig. 2, the top four plots are the generated test data, which include the following:

- clean signal: normal ECG time series generated from the simulator;
- noise: $\varepsilon = 0.2$, $\sigma_1 = 0.1$ and $\sigma_2 = 1$;
- baseline drift: $m = 0.01$, $B = -0.6$ mV and $A = 0.2$ mV;
- corrupted signal: clean signal corrupted with baseline drift and noise.

4.1.2. *Data set 2*

As shown in Fig. 3, the test data set includes the following:

- clean signal: ECG time series with abnormal beats generated from the simulator;
- ε mixture noise: $\varepsilon = 0.1$, $\sigma_1 = 0.15$ and $\sigma_2 = 1.8$;
- baseline drift: $m = 0.02$, $B = 0.0$ mV and $A = 0.8$ mV;
- corrupted signal: clean signal corrupted with baseline drift and noise.

Based on the test results of data sets 1 and 2 shown in Figs. 2 and 3, the values of BCR for the WF and MMF algorithms, the NSR and SDR for the MF and MMF algorithms, are computed and listed in Table 1 for comparison.

Table 1 shows that the BCR values obtained using the MMF algorithm are larger than those obtained using the WF algorithm, and both the NSR and SDR values obtained using the proposed MMF algorithm are lower than those obtained using the MF algorithm. Hence, for baseline correction, the MMF algorithm has better performance than the WF algorithm; for noise suppression, the MMF algorithm achieves lower SDR by compromising on the noise-reduction ratio.

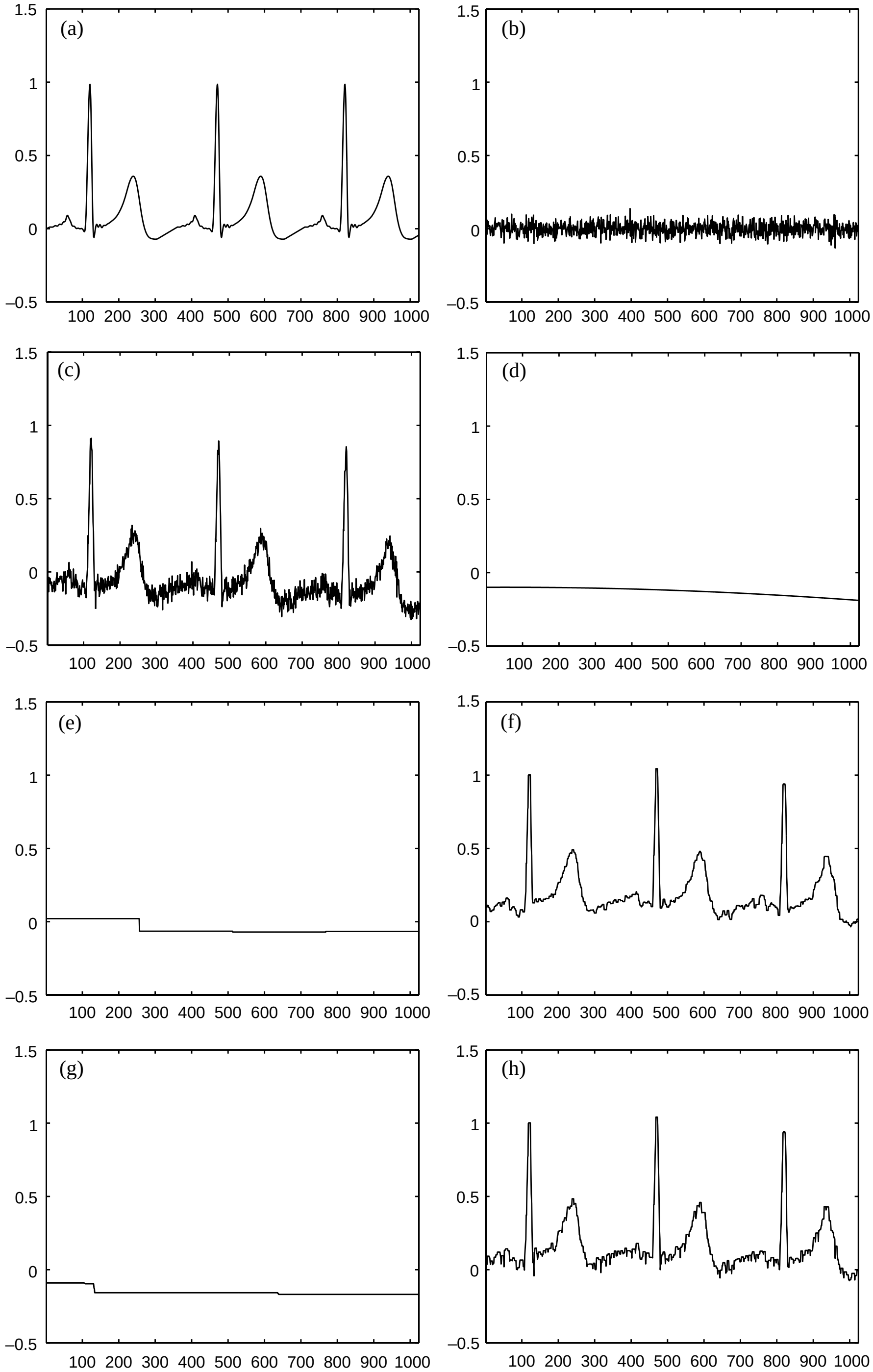

Fig. 2. Results of data set 1: (a) simulated clean ECG signal; (b) simulated noise signal; (c) simulated baseline drift signal; (d) simulated contaminated ECG signal; (e) detected baseline drift by the WF algorithm; (f) denoised signal by the MF algorithm; (g) detected baseline drift by the MMF algorithm; (h) denoised signal by the MMF algorithm.

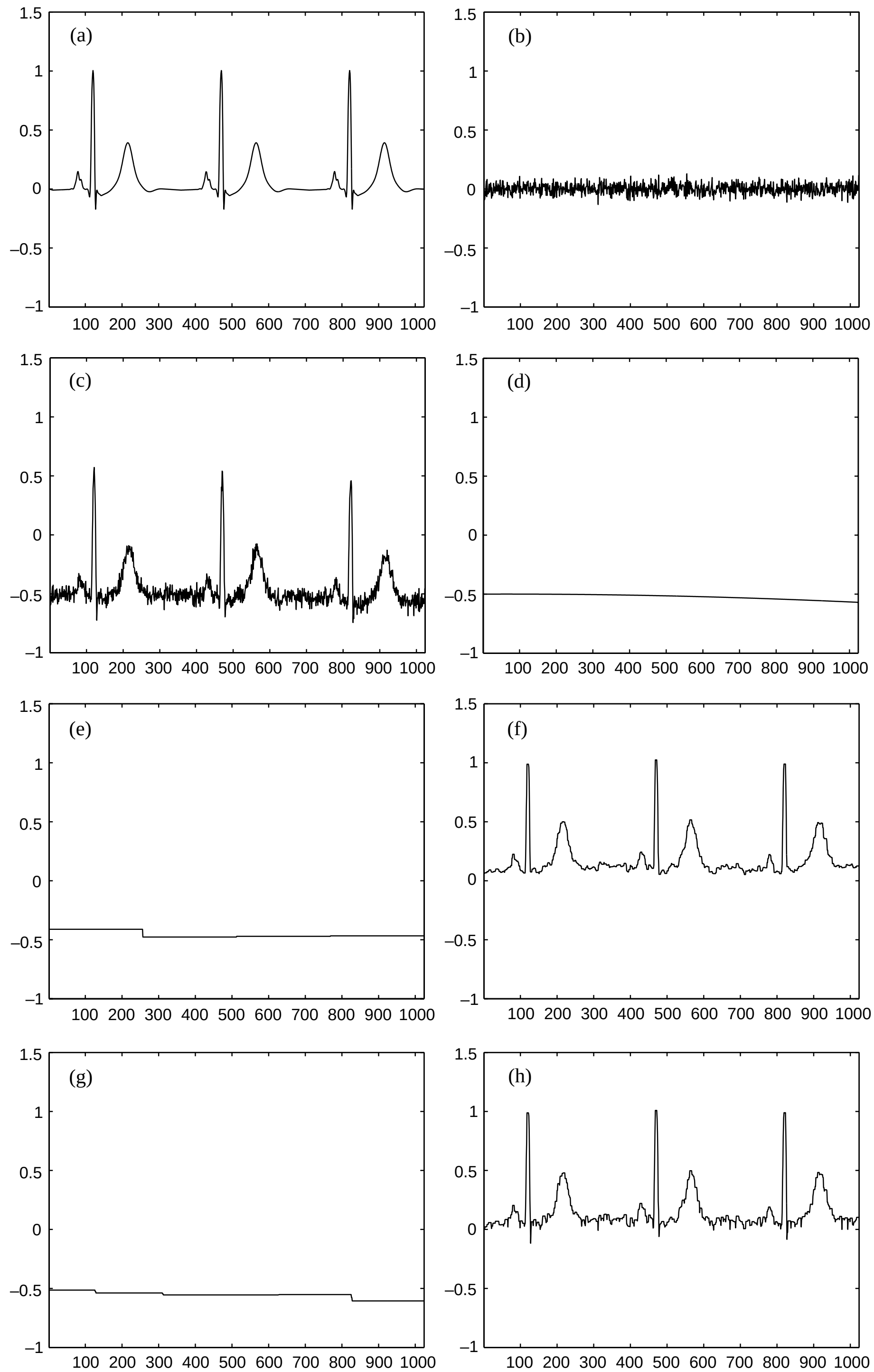

Fig. 3. Results of data set 2: (a) simulated clean ECG signal; (b) simulated noise signal; (c) simulated baseline drift signal; (d) simulated contaminated ECG signal; (e) detected baseline drift by the WF algorithm; (f) denoised signal by the MF algorithm; (g) detected baseline drift by the MMF algorithm; (h) denoised signal by the MMF algorithm.

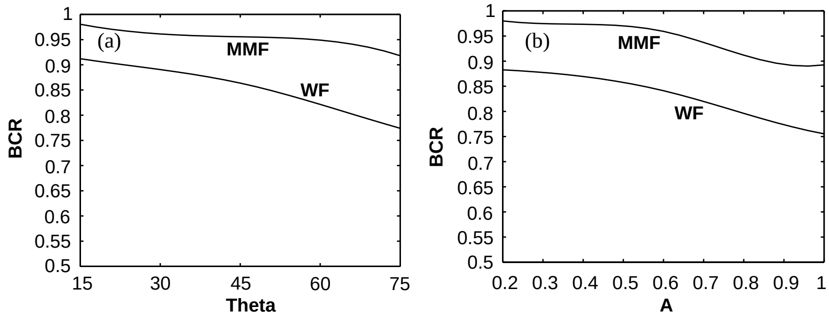

Fig. 4. Comparison of BCR values for the WF and MMF algorithms with the variation of (a) θ and (b) A.

In the simulated signal, two components are included, i.e., the baseline drift described by Eq. (10) and the noise described by Eq. (9).

Simulations were conducted for different parameters in the signal. For baseline correction, fixing $\theta = 0$, the BCR values for the WF and MMF algorithms, as A varies from 0.2 to 1, are plotted in Fig. 4(b). Fixing $A = 0$, the BCR values, as θ varied from 15 to 75, are plotted in Fig. 4(a).

The results shown in Fig. 4 are consistent with the results obtained in data sets 1 and 2. The BCR values for the MMF algorithm are higher than those for the WF algorithm. Hence, better performance of baseline correction can be achieved by the proposed MMF algorithm than by the WF algorithm.

For noise suppression, defining $K = \sigma_2/\sigma_1$, fixing $K = 10$, $\sigma_1 = 0.1$, and allowing ε to vary from 0.1 to 0.5, the NSR values obtained by the MF and the MMF algorithms are shown in Fig. 5(a). The SDR values obtained by the MF and MMF algorithms are shown in Fig. 5(c). Fixing $\varepsilon = 0.2$, $\sigma_1 = 0.1$, as K varies from 5 to 25, the NSR values obtained by the MF and MMF algorithms are shown in Fig. 5(b), the SDR values obtained by the MF and MMF algorithms are shown in Fig. 5(d).

The results shown in Fig. 5 are also consistent with those obtained in the first two cases (data sets 1 and 2). The NSR values for the MMF algorithm are slightly lower than those for the MF algorithm. However, the SDR values obtained by the MMF algorithm are lower than those obtained by the MF algorithm. The MMF algorithm achieves lower SDR by compromising on the noise-reduction ratio.

From Table 1, and Figs. 4 and 5, the following conclusions can be drawn:

(1) For baseline correction, the MMF algorithm works better than the WF algorithm.
(2) For noise suppression, the MF algorithm is a little better than the MMF algorithm. However, the MF algorithm distorts the clean ECG signal more than the MMF algorithm does. The MMF algorithm retains the significant singular points by compromising on the noise-reduction ratio. Since the significant singular points are very important in the subsequent ECG analysis steps, the MMF algorithm is preferred.

4.2. *Algorithm testing using MIT-BIH arrhythmia database*

Selected ECG data from MIT-BIH arrhythmia database were used to evaluate the performance of the proposed algorithm. Comparative results using MF and MMF algorithms are given. Each set

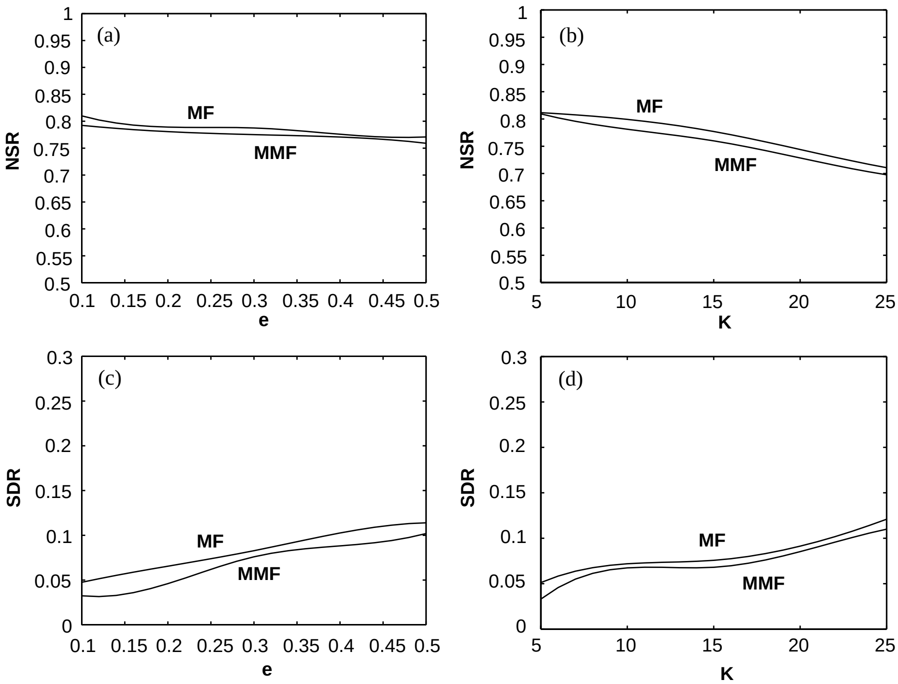

Fig. 5. Comparison of NSR and SDR values for the MF and MMF algorithms with the variation of ε (a) and (c) and K (b) and (d).

of data was digitized at 360 Hz from a single patient using "lead II". Fig. 6(a) shows a signal exhibiting bursts of baseline wander (record 31).

The signal conditioning results of record 31 are shown in Figs. 6(b)–(d). The plot (b) shows the signal after baseline correction; (c) is the denoised signal obtained by MF algorithm; and (d) is the denoised signal obtained by the proposed MMF algorithm. Fig. 7 shows another example of ECG signal conditioning.

As shown in Figs. 6 and 7, good performance of baseline correction can be observed. The characteristic waves in the ECG signal are shown to be more smoothed in (c), the plot of the noise-suppression results obtained by the MF algorithm, than in (d), the plot of the result obtained by the MMF algorithm.

Selected ECG time series with over 5000 QRS complexes were tested for detecting the QRS complex using a peak-valley-extractor defined using MM operators proposed in [19]. The correct detection rate (CDR) of the QRS complexes is used to evaluate the performance of different conditioning techniques. The values of CDR for the original signal without conditioning, the signals conditioned using Chu's MF algorithm and the proposed MMF algorithm were computed, respectively, and compared. The comparative results are reported in Table 2.

Compared with the MF algorithm, better detection performance using the proposed MMF algorithm has been observed as shown in Table 2. Therefore, as an ECG conditioning algorithm, MMF is preferable.

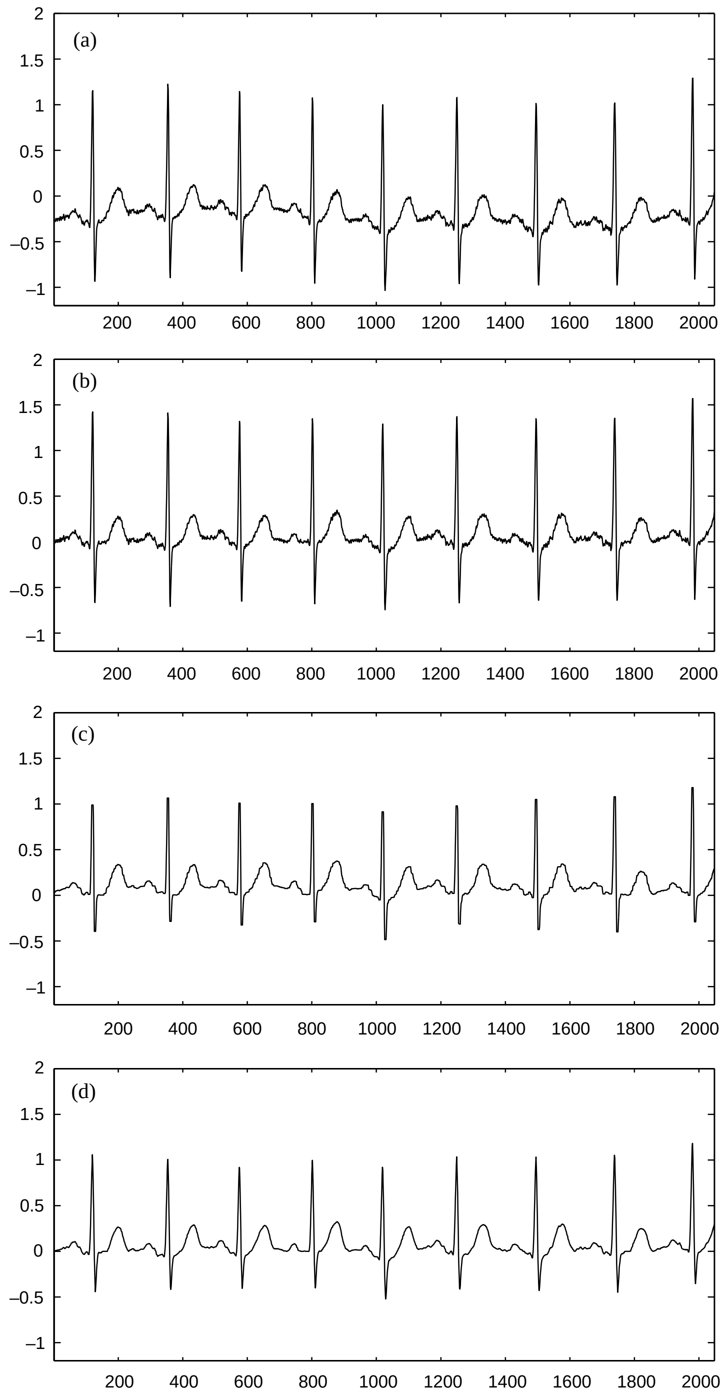

Fig. 6. Conditioning results of record 31: (a) original ECG signal; (b) signal after baseline correction; (c) denoised signal obtained by MF algorithm; (d) denoised signal obtained by the proposed MMF algorithm.

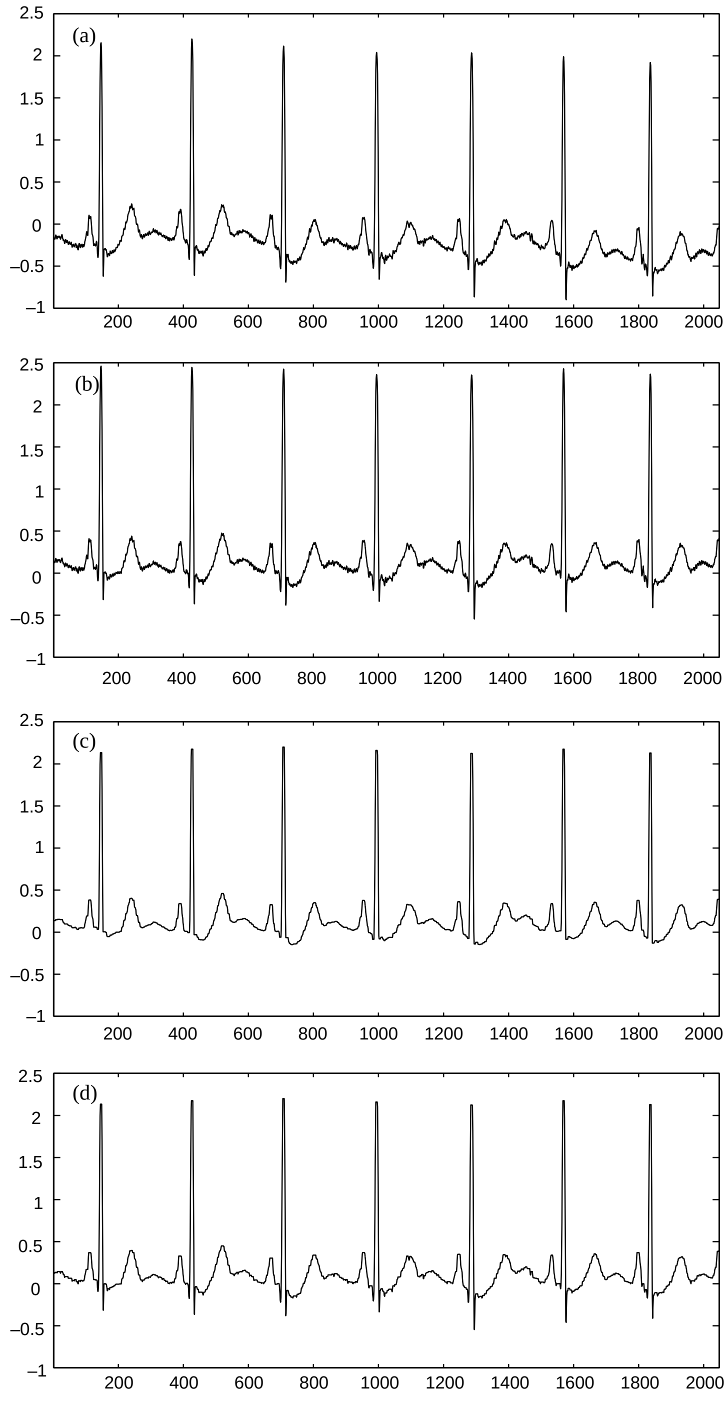

Fig. 7. Conditioning results of record 37: (a) original ECG signal; (b) signal after baseline correction; (c) denoised signal obtained by MMF algorithm; (d) denoised signal obtained by the proposed MF algorithm.

Table 2
The comparison of CDR for three algorithms

	Without conditioning	With conditioning	
		MF	MMF
CDR	96.7%	98.9%	99.4%

5. Conclusions

In conclusion, a morphological filtering algorithm using modified morphological operators, called the MMF, is proposed for baseline correction and noise suppression in ECG signals. By using a structuring element pair in closing and opening operations, signal distortion rate in ECG signal can be decreased by sacrificing the noise suppression rate a little and the corresponding computational burden is lessened. The MMF algorithm can retain the significant characteristic waves and intervals in the ECG signal, which is more important for subsequent processing, such as the ECG characteristic wave or interval detection, or arrhythmia recognition. The performance of the proposed algorithm for signal conditioning was evaluated by using simulated signals and clinically acquired ECG data from a standard set. Results were compared with those obtained by other ECG conditioning techniques. In addition, a comparison of the QRS complexes detecting from the original signal, from the signal after conditioning using Chu's morphological filtering algorithm as well as using the proposed MMF algorithm, was performed. The results show that the proposed MMF algorithm is more suitable for the conditioning of the ECG signal, in view of the subsequent processing.

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Yan Sun is pursuing her Ph.D. degree in BioMedical Engineering Research Center, School of Electronic and Electrical Engineering, Nanyang Technological University, Singapore. She got her master's degree in biophysics in 1998 from Academia Sinica, China. Her research interests are signal processing, pattern recognition, and medical informatics. Ms. Sun is a student member of the IEEE and the EMBS.

Kap Luk Chan (M'92) obtained his Ph.D. degree in Robot Vision from Imperial College of Science, Technology and Medicine, University of London, London, UK in 1991. He is now an associate professor in the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. His research interests are in image analysis and computer vision, particularly in texture analysis, statistical image analysis and perceptual grouping, image and video retrieval, machine learning in computer vision, and biomedical signal and image analysis. He has also been a consultant to local and multinational companies in Singapore. He is a member of the IEEE and an associate member of IEE.

Shankar Muthu Krishnan is presently the director of Biomedical Engineering Research Center and an associate professor in the School of EEE, Nanyang Technological University, Singapore. He got his Ph.D. degree from the University of Rhode Island and has worked in the academia, healthcare industry and hospitals in USA. His research interests are medical instrumentation, image processing, telemedicine, bio-optics and medical robotics. Dr. Krishnan serves as a member of the National Medical Research Council of Singapore and is also actively involved in IEEE EMBS and the Biomedical Engineering Society of Singapore. He is also a consultant on several medical projects.