A New ECG Enhancement Algorithm for Stress ECG Tests

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Abstract

In real situations, ECG recordings are often corrupted by artifacts. Two dominant artifacts present in ECG are: 1) High frequency noise caused by electromyogram induced noise, power line interferences, or mechanical forces acting on the electrodes; 2) Baseline wander that may be due to respiration or the motion of the patients or the instruments. These artifacts severely limit the utility of the recorded ECG and thus need to be removed for better clinical evaluation. Several methods have been developed for ECG enhancement. In this paper, we proposed a new ECG enhancement method based on the recently developed Empirical Mode Decomposition (EMD). The proposed EMD-based method is able to remove both high frequency noise and baseline wander with minimum signal distortion. The method is validated through experiments on the MIT-BIH databases.

1. Introduction

The electrocardiogram (ECG) is the recording of the cardiac activity and it is extensively used for the diagnosis of heart diseases. There are basically two types of noise, which are particularly significant during a stress test: the baseline wander and the high frequency noise. In ECG enhancement, the goal is to separate the valid ECG from the undesired artifacts so as to present a signal that allows easy visual interpretation. Several approaches have been reported in the literature to address ECG enhancement [1, 2].

In this paper, we propose a new method for ECG enhancement based on the Empirical Mode Decomposition (EMD) [3]. EMD decomposes a signal into a collection of AM-FM components called Intrinsic Mode Functions (IMF) that do not require any *a priory* known basis. The EMD has been demonstrated as a good tool for artifact reduction in biomedical applications such as [4]. This motivates us to use the EMD for ECG enhancement. So, the contributions of this work lie in two aspects. First, the use of EMD in ECG enhancement. Second, we develop novel methods to remove both types of artifacts. The performances of our algorithm are demonstrated through various experiments performed over several records from the MIT-BIH Arrhythmia Database.

2. Methods

EMD decomposes the signal into a sum of IMFs [3]. An IMF is defined as a function with equal number of extrema and zero crossings (or at most differed by one) with its envelopes, as defined by all the local maxima and minima, being symmetric with respect to zero. So given a signal $x(t)$, it can be expressed as

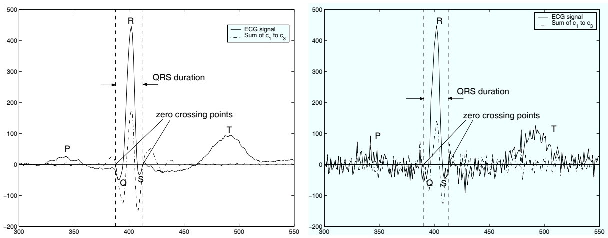
$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t), \tag{1}$$

where $c_n(t)$ is referred as nth-order IMF. By this convention, lower order IMFs capture fast oscillation modes while higher order IMFs typically represent slow oscillation modes. In (1), $r_N(t)$ is called the residue which is a constant, a monotonic slope, or a function with only one extremum. It can also be regarded as the last IMF.

For the denoising case, as the QRS complex spreads over the several first IMFs, it cannot be performed by simply discarding lower-order IMFs. Our method to filter the noise consists of four steps: 1) delineate and separate the QRS complex, 2) use proper windowing to preserve the QRS complex, 3) use statistical tests to determine the number of IMFs contributing to the noise, and 4) filter the noise by partial reconstruction.

2.1. Delineation of the QRS complex

To preserve the QRS complex, we need a delineation of the QRS complex. The QRS complex and the oscillatory patterns in the first three IMFs are illustrated in Fig. 1 for both clean and noisy ECG signals. The ECG signal is plotted in solid line and the dash-dotted line is the sum of the first three IMFs: $d(t) = c_1(t) + c_2(t) + c_3(t)$. Figure 1(a) reveals that the QRS complex is bounded by the two zero crossing points of $d(t)$. Even in the noisy case (Fig. 1(b)), this relation holds, which shows that the usage of the three IMFs is a robust choice in the sense that it is not affected by the noise.



(a) (b)

Figure 1. QRS delineation. The dash-dotted line is the sum of the first three IMFs: $c_1(t) + c_2(t) + c_3(t)$. (a) Clean ECG. (b) Noisy ECG.

Given the sum of the first three IMFs $d(t)$, we can delineate the QRS complex through the following procedure: 1) Identify the fiducial points. 2) Apply the EMD to the noisy ECG signal. Sum the first three IMFs to get $d(t)$. 3) Find the two nearest local minima on both sides of the fiducial point within a window. 4) Detect the two zero-crossing points as boundaries of the QRS complex.

2.1.1. QRS complex windowing

Next, a window function is designed to preserve the QRS complex. The window function is a time domain window applied to the first several IMFs corresponding to the noise. A general design guideline for the QRS preserving window function is that it should be flat over the duration of the QRS complex and decay gradually to zero so that a smooth transition introduces minimal distortion. Since the window size is determined by the delineation results in the first step, these window functions adjust their sizes according to the QRS duration. A typical window function, and that which is used here is the Tukey window

$$w(t) = \begin{cases} \frac{1}{2}\left[1 + \cos\left(\pi \frac{|t| - \tau_1}{\tau_2 - \tau_1}\right)\right], & \tau_1 \leq |t| \leq \tau_2 \\ 1, & |t| < \tau_1 \\ 0, & |t| > \tau_2 \end{cases} \tag{2}$$

where τ_1 is the flat region limit and τ_2 is the transition region limit. When using (2), the flat region width $2\tau_1$ is chosen such that it equals the QRS complex boundary determined by the method in Section 2.1. The transition region is set to avoid abrupt "cutoff" of the window and reduce the distortions.

2.1.2. Determination of noise order

The number of the IMFs that are dominated by noise, referred to as the *noise order*, must be established. For ECG signals, the contaminating noise is usually zero mean while the signal is nonzero mean. This fact enables the noise and signal to be separated in the EMD domain. Since lower order IMFs contain the noise, we perform a statistical test to determine if a particular combination of IMFs has zero mean. The t-test is able to establish if the mean of the IMF deviates from zero. In the t-test, we basically perform the following hypothesis testing:

$$\begin{aligned} H_0: &\quad \mathrm{mean}(\mathrm{c_{PS}^M(t)}) \neq 0 \\ H_1: &\quad \mathrm{mean}(\mathrm{c_{PS}^M(t)}) = 0 \end{aligned} \tag{3}$$

where c_{PS}^M is the Mth order partial sum of the IMFs, $c_{PS}^M(t) = \sum_{i=1}^{M} c_i(t)$.

By selecting a certain significance level α, the null hypothesis H_0 is rejected in favor of the alternative hypothesis H_1 if the p value is less than α. Thus starting from the first IMF, we perform a t-test on the partial sum $c_{PS}^M(t)$ for $M = 1, 2, \ldots$ until we obtain a partial sum $c_{PS}^{P_t}(t)$ that accepts the alternative hypothesis. The IMF order P_t at the termination point indicates that there are P_t IMFs that contribute primarily to the noise, and is thus set as the noise order. The noise order indicates how many IMFs should be removed.

In some cases the ECG itself has a mean close to zero. Using the previous technique to determine the noise order results in oversmoothing or loss of information since the noise order will be very large. To avoid this potential problem, the noise order is set as

$$P = \min(P_t, 5), \tag{4}$$

where P_t is the noise order obtained from the t-test. The rationale of (4) is that IMFs with order higher than 5 typically contain little or no noise. Thus this approach avoids the oversmoothing problem without sacrificing noise removal.

2.1.3. Denoising by partial reconstruction

Having established a method to determine the noise order, we can filter the noise by partial IMF reconstruction. To preserve the QRS complex, the window functions are applied to the P IMFs considered to be noise components, and the sum of these windowed IMFs and the remaining IMFs forms the reconstructed signal:

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t) c_i(t) + \sum_{i=P+1}^{N} c_i(t) + r_N(t), \tag{5}$$

where $\psi_i(t)$ is the window function for the i-th IMF which is constructed by concatenating the window functions (2), each of which is centered at the QRS complex. Note that the window function $\psi_i(t)$ consists of variable size windows that are calculated in Section 2.1.1, and the noise index P is determined in Section 2.1.2.

2.2. Baseline Wander Removal

As the BW spreads over the last several IMFs, it must be separated from the signal components in those IMFs. Moreover, the number of IMFs that contribute to the BW must be established. This number is referred to as the *baseline wander order*.

A BW estimate is first obtained via a "multiband" filtering approach. The estimated BW is then subtracted from the signal, yielding the reconstructed signal. A bank of lowpass filters are applied to the last several IMFs. The sum of the output of this filterbank serves as the BW estimate.

Suppose the signal with BW is $x(t)$. After performing the EMD, we obtain all the IMFs

$$x(t) = \sum_{i=1}^{N+1} c_i(t), \tag{6}$$

where the residue is included in the summation as the last IMF $c_{N+1}(t)$. Denote the BW order as Q. We design a bank of lowpass filters $h_i(t),\ i = 1, 2, \ldots, Q$ and then filter the IMFs starting from the last one $c_{N+1}(t)$ by these lowpass filters. The outputs of these filters are

$$b_i(t) = h_i(t) * c_{N-i+2}(t),\ \ i = 1, 2, \ldots, Q, \tag{7}$$

where $*$ denotes the convolution. Set the cutoff frequency of the first lowpass filter $h_1(t)$ to be ω_0. The cutoff frequency of the kth filter is set as

$$\omega_k = \frac{\omega_0}{M^{k-1}}, \tag{8}$$

where $M > 1$ is a frequency-folding number.

The output $b_i(t)$ extracts the BW component in each IMF. Therefore, it can be used to determine the BW order Q. The variance of each $b_i(t)$ is determined as

$$\mathrm{var}\{\mathrm{b_i(t)}\} = \frac{1}{\mathrm{L}-1} \sum_{\mathrm{t}=0}^{\mathrm{L}-1} [\mathrm{b_i(t)} - \mu_{\mathrm{b_i}}]^2, \tag{9}$$

where μ_{b_i} is the mean value of $b_i(t)$. Starting from the last IMF, we choose Q such that $\mathrm{var}\{\mathrm{b_{Q+1}(t)}\} < \zeta$ and $\mathrm{var}\{\mathrm{b_Q(t)}\} \geq \zeta$, where ζ is an appropriate established threshold. The selection of the parameters ω_0, M, ζ can be based on *a priori* knowledge or can be experimentally tuned according to the BW behavior.

Once the BW order Q is determined, the outputs of all the filters are synthesized to form the estimate

$$\hat{b}(t) = \sum_{i=1}^{Q} b_i(t). \tag{10}$$

Finally, removing the BW yields the reconstructed signal

$$\tilde{x}(t) = x(t) - \hat{b}(t). \tag{11}$$

In the most general case, ECG signals are contaminated by both high frequency noise and BW. As the noise only affects the lower-order IMFs while the BW only affects the higher-order IMFs, the methods do not interfere with each other and can be combined. Consequently, the reconstructed signal after removing both high frequency noise and BW is

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t)c_i(t) + \sum_{i=P+1}^{N+1} c_i(t) - \sum_{j=1}^{Q} h_j(t) * c_{N-j+2}(t), \tag{12}$$

where the residue $r_N(t)$ in (5) is rewritten as $c_{N+1}(t)$.

3. Results

All the ECG signals used are from the MIT-BIH Arrhythmia Database [5]. Every file in the database consists of 2 lead recordings sampled at 360 Hz with 11 bits per sample of resolution. The quantitative evaluation is assessed by the signal-to-error ratio (SER), $SER = \sum_{n=0}^{L-1} x^2(t) / \sum_{n=0}^{L-1} [x(t) - \hat{x}(t)]^2$, where $x(t)$ and $\hat{x}(t)$ are the original and the enhanced signals, respectively.

3.1. Synthetic Noise and Baseline Wander

The first lead of record 103 is chosen because it captures normal sinus rhythms and is reasonably free of noise. The first 2000 samples are taken for the evaluation. Gaussian noise is added to the original clean signal to yield a 10 dB SNR. Then, we follow the procedure in Section 2. In the statistical t-test, the significance level α is set to be 0.01. Thus, the noise order P is determined to be 4 since at this level $p = 0.0019 < \alpha$. We also add synthetic BW. The proposed method in Section 2.2 is then utilized to estimate BW. The parameters ω_0, M, and ζ are experimentally set to be 0.8, 20, and 10, respectively. The noisy signal and the final result of the recovery are shown in Fig. 2 with a SER of 16.76 dB. As can be seen, the proposed method yields good results in terms of visual quality.

Next, a quantitative study is carried out. Records 100,103,105,119, and 213 are arbitrarily chosen. The SNR of each record is ranged from 6 to 18 dB. At each SNR, 100 Monte Carlo runs are performed to obtain an averaged SER value. Results for Gaussian noise and BW are shown in Fig. 3. The horizontal axis in the plot corresponds to the input ECG SNR and the vertical axis shows the average SER. The overall performance is quite good.

3.2. Real noise experiment

We consider the denoising and BW removal of an ECG corrupted by severe real noise. The signal under test is the first 8000 samples of record 232 from the MIT-BIH Arrhythmia Database. The corruption added to the signal

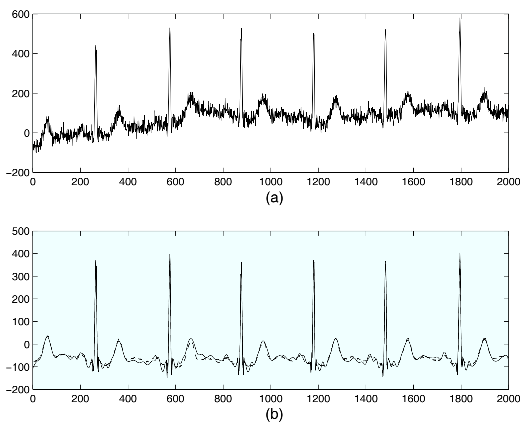


Figure 2. (a) Noisy ECG with BW; (b) enhanced signal (solid) vs. original signal (dashed). SER=16.76 dB.

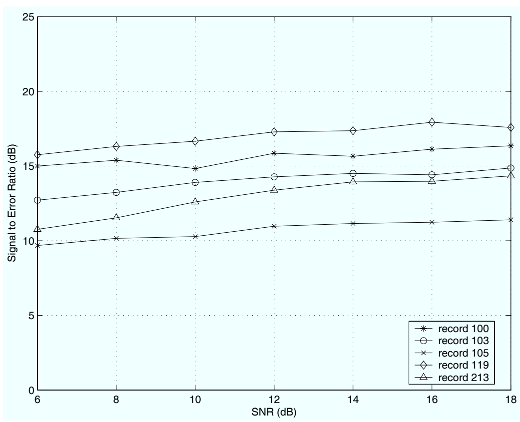


Figure 3. SER (dB) vs. SNR (dB) in both Gaussian noise and BW case.

is the 'ma' noise from the MIT-BIH Noise Stress Test Database [5]. All parameters used in this experiment are the same as those in Section 3.1. The signal is processed by taking consecutive blocks of 2000 samples. The EMD–based enhanced ECG is shown in Fig. 4 (b). The figure shows that the significant noise components are nearly eliminated by the proposed method. Furthermore, the BW exhibited in the noisy record is also corrected in the enhanced ECG. This result further demonstrates that the proposed method is suitable for real noise cases.

4. Conclusions

A novel method for ECG enhancement based on the EMD is presented. Both high frequency noise and baseline wander removal are addressed. Enhancement is achieved through the development of two EMD-based methods to address each type of artifact. Results indicate that the EMD is an effective enhancement tool.

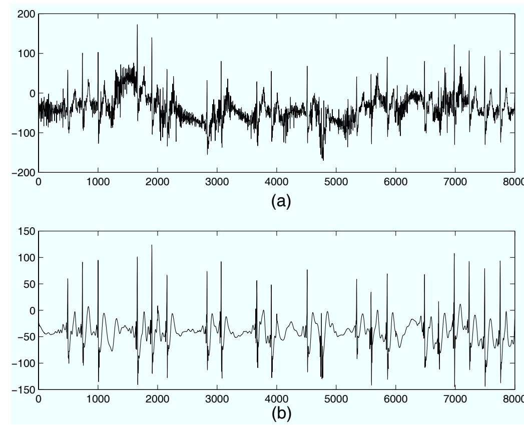


Figure 4. (a) ECG record 232 corrupted by real 'ma' noise; (b) Enhanced ECG.

Acknowledgment

M Blanco–Velasco's work has been supported in part under grants PR–2005–0131 from the Spanish Ministry of Science and Education, PI052277 from the Fondo de Investigación Sanitaria (FIS) and CAM-UAH2005/021 from both the Autonomous Community of Madrid and the University of Alcalá.

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