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ECG Denoising Based on the Empirical Mode Decomposition

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Abstract— **The electrocardiogram (ECG) has been widely used for diagnosis purposes of heart diseases. Good quality ECG are utilized by the physicians for interpretation and identification of physiological and pathological phenomena. However, in real situations, ECG recordings are often corrupted by artifacts. One prominent artifact is the high frequency noise caused by electromyogram induced noise, power line interferences, or mechanical forces acting on the electrodes. Noise severely limits the utility of the recorded ECG and thus need to be removed for better clinical evaluation. Several methods have been developed for ECG denoising. In this paper, we proposed a new ECG denoising method based on the recently developed Empirical Mode Decomposition (EMD). The proposed EMD-based method is able to remove high frequency noise with minimum signal distortion. The method is validated through experiments on the MIT-BIH database. Both quantitative and qualitative results are given. The results show that the proposed method provides very good results for denoising.**

I. Introduction

The electrocardiogram (ECG) is the recording of the cardiac activity and it is extensively used for the diagnosis of heart diseases. In the data recording process, noise often appears as a result of recording error, which is particularly significant during a stress test. In this situation, noise is usually caused by the electromyographic (EMG) noise during the recording, instrument amplifiers, ambient EM signals by the cables, and power-line interferences. Moreover, with the recent telemedical applications involving transmission and storage of ECG, noise also appears due to poor channel conditions. A noisy ECG may hinder the physician's correct evaluations on patients. Therefore, ECG denoising is important for clinical purposes.

Many approaches have been reported in the literature to address ECG enhancement, e.g., [1], [2], [3], [4], [5]. Among them, the wavelet-based method [2] is a very typical tool for denoising since the wavelet-based method is very suitable for denoising of Gaussian type noise in various areas.

In this paper, we propose a new method for ECG denoising based on the Empirical Mode Decomposition (EMD). The EMD was recently introduced in [6] as a technique for processing nonlinear and nonstationary signals and also as an alternative to the current available methods such as the wavelet analysis, the Wigner–Ville distribution and the short–time Fourier transform. The EMD has been applied to several biomedical engineering problems [7], [8]. As these contributions demonstrate, the EMD is a good tool for artifact reduction. This motivates us to develop a method for ECG denoising based on the EMD.

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Denoising by the EMD is in general carried out by partial signal reconstruction based on the fact that noise components tend to lie in the first several Intrinsic Mode Functions (IMF). This strategy works well for those signals whose frequency content is clearly distinguished from that of noise and is successfully applied in [8]. However, this assumption cannot be made in the ECG case because the QRS complex spreads over the first several IMFs that contain significant noise. In this paper, we propose an ECG denoising method based on the EMD using an information preserving partial reconstruction.

The performances of our algorithm are demonstrated through various experiments performed over several records from the MIT-BIH Arrhythmia Database. Both quantitative and qualitative results are presented. The experimental studies show that the proposed EMD–based method is a good tool for ECG denoising.

II. Empirical Mode Decomposition

The EMD relies on a fully data-driven mechanism that does not require any *a priori* known basis. The aim of the EMD is to decompose the signal into a sum of IMFs. 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. An IMF represents a simple oscillatory mode as a counterpart to the simple harmonic function used in Fourier analysis.

Given a signal $x(t)$, the starting point of the EMD is the identification of all the local maxima and minima. All the local maxima are then connected by a cubic spline curve as the upper envelop $e_u(t)$. Similarly, all the local minima are connected by a spline curve as the lower envelop $e_l(t)$. The mean of the two envelops is denoted as $m_1(t) = [e_u(t) + e_l(t)]/2$ and is subtracted from the signal. Thus the first proto-IMF $h_1(t)$ is obtained as

$$h_1(t) = x(t) - m_1(t). \tag{1}$$

The above procedure to extract the IMF is called the *sifting* process. Since $h_1(t)$ still contains multiple extrema in between zero crossings, the sifting process is performed again on $h_1(t)$. This process is applied repetitively to the proto-IMF $h_k(t)$ until the first IMF $c_1(t)$, which satisfies the IMF condition, is obtained. Some stopping criteria are used to terminate the sifting process. A commonly used criterion is the Sum of Difference (SD)

$$SD = \sum_{t=0}^{T} \frac{|h_{k-1}(t) - h_k(t)|^2}{h_{k-1}^2}. \tag{2}$$

When the SD is smaller than a threshold, the first IMF $c_1(t)$ is obtained, which is written as

$$x(t) - c_1(t) = r_1(t). \tag{3}$$

Note that the residue $r_1(t)$ still contains some useful information. We can therefore treat the residue as a new signal and apply the above procedure to obtain

$$r_{i-1}(t) - c_i(t) = r_i(t) \quad i = 1, \ldots, N. \tag{4}$$

The whole procedure terminates when the residue $r_N(t)$ is either a constant, a monotonic slope, or a function with only one extremum. Combining the equations in (3) and (4) yields the EMD of the original signal,

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t). \tag{5}$$

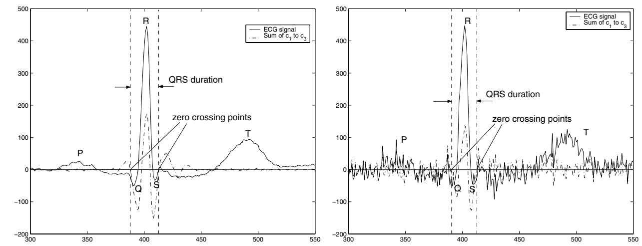
The result of the EMD produces N IMFs and a residue signal. For convenience, we refer to $c_n(t)$ as the nth-order IMF. By this convention, lower order IMFs capture fast oscillation modes while higher order IMFs typically represent slow oscillation modes. If we interpret the EMD as a time-scale analysis method, lower order IMFs and higher order IMFs correspond to the fine and coarse scales, respectively.

III. ECG Denoising Using EMD

Denoising in the EMD domain is usually done by discarding lower-order IMFs with the assumption that the signal and noise are well-separated in frequency bands. However, for ECG, although most signal power is concentrated in lower frequencies, the QRS complex spreads across the mid to high frequency bands. This complicates ECG denoising since removing lower order IMFs will introduce severe QRS complex distortion, e.g., R-wave amplitude attenuation. A more sophisticated strategy must be utilized to preserve the useful information.

An analysis of the EMD on clean and noisy ECG indicates that the QRS complex is associated with oscillatory patterns typically presented in the first three IMFs. Therefore, it is possible to filter the noise and at the same time preserve the QRS complex by temporal processing in the EMD domain. The following four steps constitute the denoising procedure:

A) Delineate and separate the QRS complex.
B) Use proper windowing to preserve the QRS complex.
C) Use statistical tests to determine the number of IMFs contributing to the noise.
D) Filter the noise by partial reconstruction.



(a) (b)

Fig. 1. Delineation of the QRS complex in the EMD domain. The solid line is the ECG signal and 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.

A. 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. In these two figures, the ECG signal is plotted in solid line and the dash-dotted line is the sum of the first three IMFs: $d(t) = c_1(t) + c_2(t) + c_3(t)$. A close examination on Fig. 1(a) reveals that the QRS complex is bounded by the two zero crossing points of $d(t)$. One zero-crossing point is on the left hand side of the local minimum near the fiducial point (R-wave) and the other is on the right hand side of the local minimum near the fiducial point, as shown in Fig. 1(a). 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.

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 on the left hand side of the left minimum and on the right hand side of the right minimum. These two points are identified as boundaries of the QRS complex.

Here, and in the remainder of the paper, we assume that the fiducial points are either known (for example, by annotation) or can be determined by some other methods. In step 3), a window must be established such that the desired minimum points fall inside the window. The window size can be chosen based on *a priori* knowledge. For example, it is known that, given a QRS complex, there is a 200 ms refractory period before the next one comes [9], which corresponds to 72 samples if the sampling frequency is 360 samples/s. In this case, a window centered at the fiducial point with a span of 30 samples on each side can be utilized.

B. Windowing to preserve the QRS complex

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.

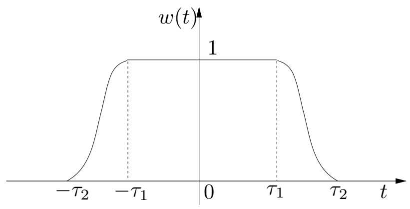


Fig. 2. Tukey window (tapered cosine) function

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 (tapered cosine window)

$$w(t) = \begin{cases} \frac{1}{2}\left[1+\cos\left(\pi\frac{|t|-\tau_1}{\tau_2-\tau_1}\right)\right], & \tau_1 \leq |t| \leq \tau_2 \\ 1, & |t| < \tau_1 \\ 0, & |t| > \tau_2 \end{cases} \tag{6}$$

where τ_1 is the flat region limit and τ_2 is the transition region limit. The graphical representation of the Turkey window is shown in Fig. 2.

When using (6), the flat region width $2\tau_1$ is chosen such that it equals the QRS complex boundary determined by the method in Section III-A. The transition region is set to avoid abrupt "cutoff" of the window and reduce the distortions. The spread of the oscillatory pattern around the QRS complex increases with the IMF order. Consequently, a variable width transition region in (6) is adopted to cope with the spreading effect of the various IMFs. We define the ratio between the one-sided transition region length $|\tau_1 - \tau_2|$ and the flat region length $2\tau_1$ as

$$\beta = \frac{|\tau_1 - \tau_2|}{2\tau_1}, \tag{7}$$

where β is a free parameter. For example, for the first IMF, β can be set to be 30%. Likewise, for the jth IMF, β is chosen as $30 \times j\%$, which indicates that the window itself spreads as the QRS complex spreads with increasing order of IMF.

C. Determination of noise order by statistical test

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. An example of such a test is the t-test, which is also used in [8] to identify the noise-contributing IMFs.

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:

$$\begin{aligned} H_0: &\quad \text{mean}(c_{PS}^M(t)) \neq 0 \\ H_1: &\quad \text{mean}(c_{PS}^M(t)) = 0 \end{aligned} \tag{8}$$

where c_{PS}^M is the Mth order partial sum of the IMFs

$$c_{PS}^M(t) = \sum_{i=1}^{M} c_i(t). \tag{9}$$

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 role of the noise order in the EMD-based method is similar to the cutoff frequency in frequency domain filtering, which 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

$$P = \min(P_t, 5), \tag{10}$$

where P_t is the noise order obtained from the t-test. The rationale of (10) 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.

D. Denoising by partial reconstruction

Having establish 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:

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t) c_i(t) + \sum_{i=P+1}^{N} c_i(t) + r_N(t), \tag{11}$$

where $\psi_i(t)$ is the window function for the i-th IMF which is constructed by concatenating the window functions (6), each of which is centered at the QRS complex. Note that the window function $\psi_i(t)$ consist of variable size windows that are calculated in Section III-B, and the noise index P is determined in Section III-C.

IV. EXPERIMENTAL STUDIES

Several different simulations are carried out to evaluate the performance of the proposed EMD-based method. In the first experiment, qualitative results are shown while the second experiment gives the quantitative evaluation. In the following examples, all the ECG signals used in the simulations are

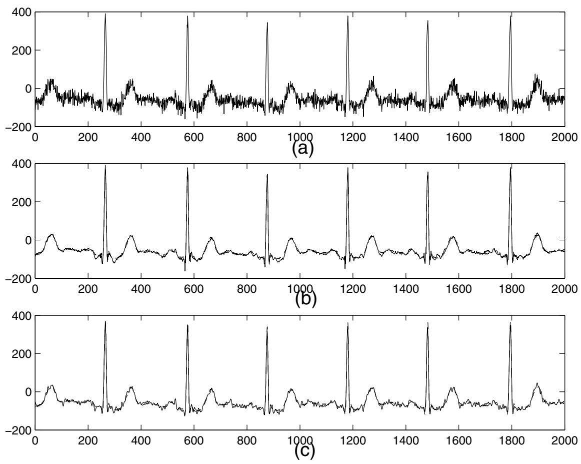


Fig. 3. Results for Gaussian noise. (a) noisy signal; (b) EMD result; (c) Butterworth LPF result. Enhanced (solid) vs. original signals (dashed)

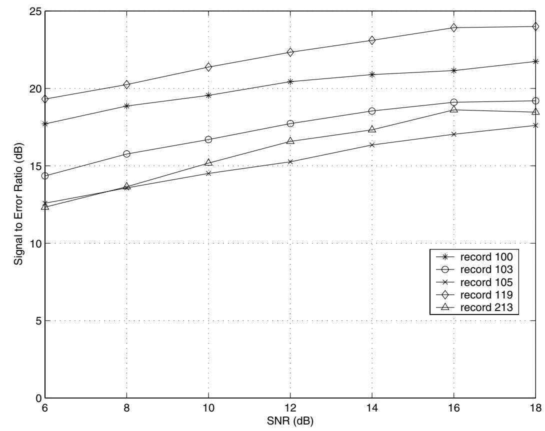


Fig. 4. SER (dB) vs. SNR (dB) for five signal records: 100,103,105,119, and 213 in Gaussian noise case.

from the MIT-BIH Arrhythmia Database. 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), $\mathrm{SER} = \sum_{n=0}^{L-1} x^2(n) / \sum_{n=0}^{L-1} [x(n) - \hat{x}(n)]^2$, where $x(n)$ and $\hat{x}(n)$ are the original and the enhanced signals, respectively.

A. *Qualitative Results*

The signal under test is the record 103 from the MIT-BIH Arrhythmia Database with additive Gaussian noise that makes the SNR 10 dB. The IMFs of the noisy signal are obtained after the EMD is applied. Based on the relationship of the QRS complex and the oscillatory patterns revealed in Section III-A, the QRS complex is delineated. In the statistical t-test, the significant level α is set to be 0.01. Thus, the noise order P is determined to be 4 since at this moment $p = 0.0019 < \alpha$. The transition parameter β in the window function is set to be 30%. Figure 3 shows the noisy, original, and enhanced signals. The proposed method is compared with the widely used Butterworth lowpass filtering method and demonstrates better results in terms of visual quality. In addition, the SER of the EMD-based method is calculated to be 18.31 dB, which is greater than 17.45 dB achieved by the LPF method.

B. *Quantitative Evaluation*

Next, we study the behavior of the method quantitatively by taking different signals from the database and using multiple realizations of noise at different SNR.

We arbitrarily choose five records from the MIT-BIH database, 100,103,105,119, and 213. For each record, the SNR is changed from 6 to 18 dB. At each SNR, 100 Monte Carlo runs are performed to get an averaged SER value. The results are shown in Fig. 4. The horizontal axis corresponds to the SNR and the vertical axis shows the average SER for the 100 runs. It shows that the SER improves when increasing the SNR.

V. Conclusions

A novel method based on the EMD for ECG denoising is presented. The denoising problem is approached by a new technique-the empirical mode decomposition. The technique developed in this work considers that both useful information and noise components are embedded in the IMFs. Thus, window functions are designed to preserve the QRS complex and partial IMF reconstruction is then applied. The method achieves both denoising and QRS complex preservation. The effectiveness of the EMD in ECG denoising is shown through simulations from standard database. The technique used here can be applied in practical stress ECG tests and Holter monitoring as in these cases strong noise is prominent which may interfere correct diagnosis.

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