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Improved ECG signal denoising by using an EMD-based algorithm

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Abstract

Good quality ECG facilitates the physician in better interpretation of the physiological or pathological status of the heart. However, in practical situations, the ECG signals often get corrupted by various noises including 1) power line interferences (PLI) and 2) Baseline wander. Such noises need to be removed for improved clinical analysis. Although some methods have been developed for enhancing ECG quality, they have limitations and hence, in the present work, we proposed a new EMD-based method to effectively remove both high frequency noise as well as baseline wander (BW) with minimum signal distortion. Studies were conducted on the databases of MIT-BIH, and the results are explained. Our studies demonstrate that the proposed EMD method provides superior results for denoising and removal of BW and PLI.

Key words: Butterworth, ECG, EMD, IMF, Wavelet.

Introduction

ECG is recorded with the help of electrodes attached to the skin of arms, legs and chest of our body through a device kept external to the body and the recordings are displayed on a paper or monitor. In practical situations, quite often, the ECG signals get corrupted with various noises [1]. Hence, denoising of ECG signals is very important to avoid wrong interpretations and to ensure good diagnosis and treatment. Moreover, In recent years in the wake of growing importance for telemedicine, clear and noise free ECG is an important tool to deal with patients [2]-[3]. The two main artifacts that often contaminate ECG signals are 1) Base line wander (BW) caused by respiration and other movements and 2) High frequency noise such as electromyographic noise due to muscle activity. Many techniques have been reported in the literature for denoising of ECG signal such as wavelet transform [4]-[5], advanced averaging technique [6], singular value analysis [7] and adaptive filtering [8]. However, they have some limitations (only provide point estimate, less robust to different levels of noise, cannot distinguish between high frequency noise and QRS information etc.). Therefore, in the present study we aimed to use a novel method based on EMD for ECG signal enhancement.

Originally, EMD was introduced by Huang et al [9] for analyzing data from non stationary and nonlinear processes. It is an adaptive and data driven technique that has received more attention to enhance signal quality. One of the important applications of EMD in biomedical engineering can be found wherever blood pressure is analysed (10). During ECG signal analysis, EMD helps understand chaotic nature, analyze heart rate visibility (HRV) [1], [11], reduce interference by gastric signals and gastro esophagul reflux disease (GERD) [12].

Proposed Method

In the present work by using EMD, the noisy ECG signal was decomposed in to IMFs, the powerline interference was almost concentrated in the first IMFs. The noise dominated IMFs, referred as noise rank was established. The base line wander was almost set in the last IMFs [1]. Then the noisy IMFs were filtered using Butterworth lowpass filter, wavelet transform methods and EMD methods to remove BW and PLI.

A) Empirical mode decomposition

EMD is an important adaptive technique which decomposes any complicated signal in to finite, small number of intrinsic mode functions (IMFs) that may represent zero mean amplitude and frequency modulated components. While other data analysis methods like Fourier and wavelet-based methods depend on some pre defined basis functions to represent a signal, EMD does not need any a priori defined basis system [13]-[15]. Moreover, EMD also fulfils the perfect reconstruction property, i.e. superimposing all extracted IMFs together with the residual slow trend reconstructs the original signal without information loss or distortion. EMD utilizes sifting process on the signal to extract IMFs. At any point, the mean value of envelope defined by local maxima and envelope defined by local minima is zero. An IMF symbolized a simple oscillatory mode as a counterpart to the simple harmonic function used in fourier analysis.

At a given sign x (t), the beginning point of the EMD is the identification of all the native maxima and minima. All the native maxima are then connected by a cubical spline curve as the upper envelope $e_u(t)$. In the same manner, all the native minima are connected by a spline curve as the lower envelope $e_l(t)$.
The mean of the two envelopes is indicated as

$$m_1(t) = \frac{[e_u(t)+e_l(t)]}{2} \qquad (1)$$

and is subtracted from the signal. Thus, the primary proto-IMF $h_1(t)$ is obtained as

$$h_1(t) = x(t) - m_1(t) \qquad (2).$$

B) ECG denoising using EMD

High-frequency denoising by the EMD method is generally done by partial signal reconstruction, which is premised on the fact that noise components fall in the first several IMFs. This strategy goes well for such signals whose frequency content is clearly distinguished from that of noise and is successfully applied in [12]-[13]. The proposal is to determine the index of the IMFs, beginning from fine to coarse scale which includes most of the noise components. Based on the index, the IMFs corresponding to the noise are removed and the original signal could be reconstructed by summing up the remaining IMFs. Nevertheless, in the case of ECG this approach is not appropriate because the QRS complex spreads across lower-to high-frequency bands making ECG denoising more complicated. Therefore, while processing ECG, EMD-based denoising requires a different approach.

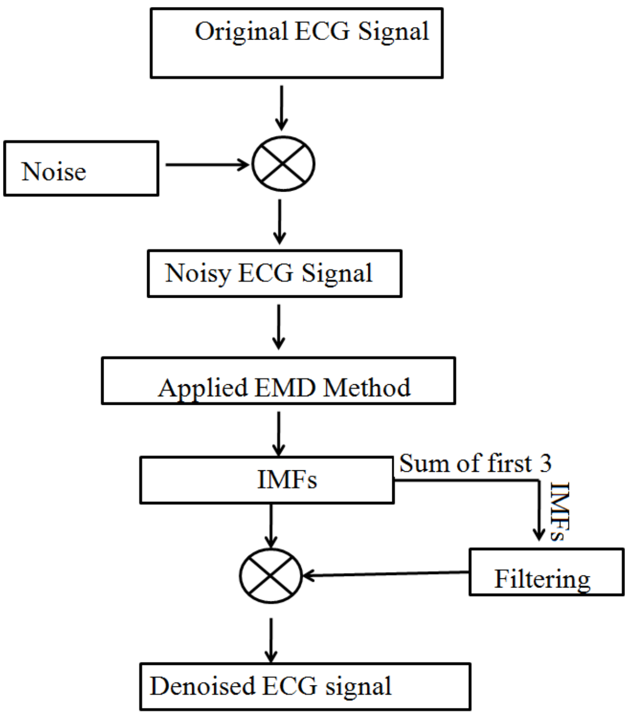

Fig.1. Denoising of ECG signal.

The EMD decomposes the signal into IMFs with falling frequency content. The EMD of clean and noisy ECG records are exemplified below (fig.2), which expresses the specific patterns associated with the QRS complex and noise in the EMD domain.
A noisy signal is represented which was obtained by adding Gaussian noise to the clean signal as showed in Fig. 2, and the resulting expression as well as IMFs of the noisy signal are shown in Fig. 3. It is observed that the frequency content of every single IMF decreases as the order of IMF increases. It may be noted that the oscillatory patterns determined in the initial three IMFs are mainly due to the QRS complex, that has robust high-frequency parts. This observation is used to delineate the QRS advanced [1]. Compared to the clean signal case, the primary IMF of the noisy signal contains robust noise parts. The oscillatory patterns of the QRS complex become more apparent starting from the second IMF. Analysis of EMD on clean and corrupted ECG indicates that it is possible to filter the noise and at the same time conserve the QRS complex by temporal processing in the EMD domain. Multiple evaluations show these characteristics for all EMD decompositions of ECG graph signals.
The following four steps show the projected denoising procedure.

(1) Demarcate and separate the QRS complex.
(2) Correct windowing is used to preserve the QRS complex.
(3) Applied math tests are used to work out the quantity of IMFs causative to the noise.
(4) Then, filter the noise by partial reconstruction.

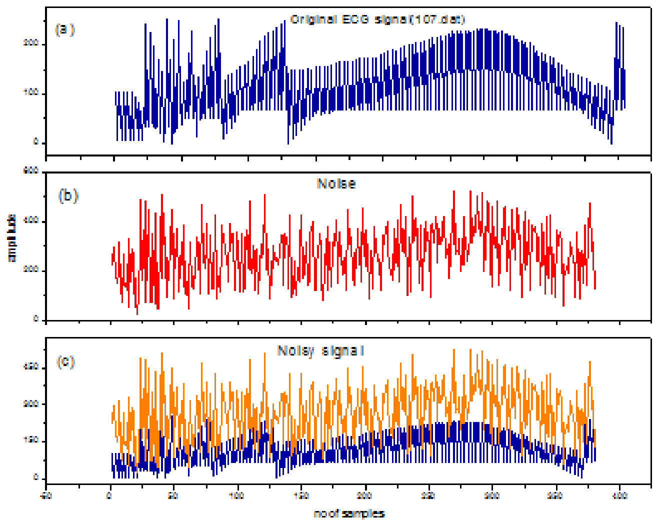

Fig.2. (a) Clean ECG signal and (b) noise (c) noisy signal.

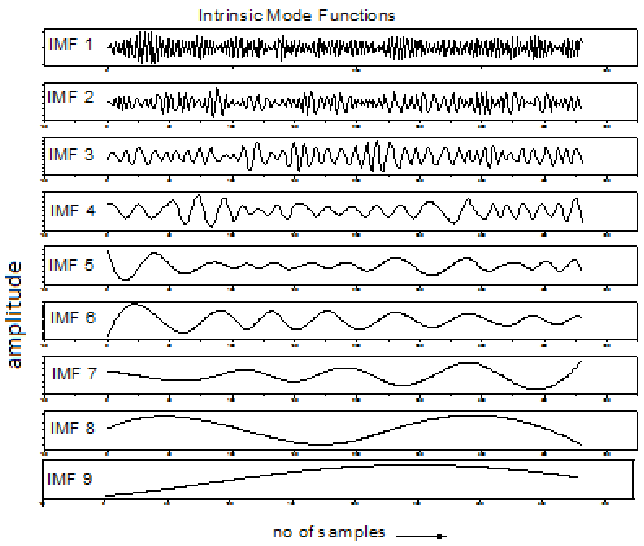

Fig. 3. Intrinsic Mode Functions (1–9), from top to bottom: Vertical axes of subplots are not in the same scale.

B (1) Demarcate and separate the QRS complex

The first several IMFs may be jointly used to delineate the QRS complex. Given the total of the primary 3 IMFs d(t), we delineate the QRS complex through the subsequent procedure:

(1) Establish the fiducial points.

(2) Employ the EMD to the noisy ECG signal, sum the initial three IMFs to get d (t).

(3) Realize the 2 nearest local minima on both sides of the fiducial.

(4) Find the 2 nearest zero-crossing points on the left hand side of the left minimum and on the right-hand side of the proper minimum. These 2 points are recognized as boundaries of the QRS complex.

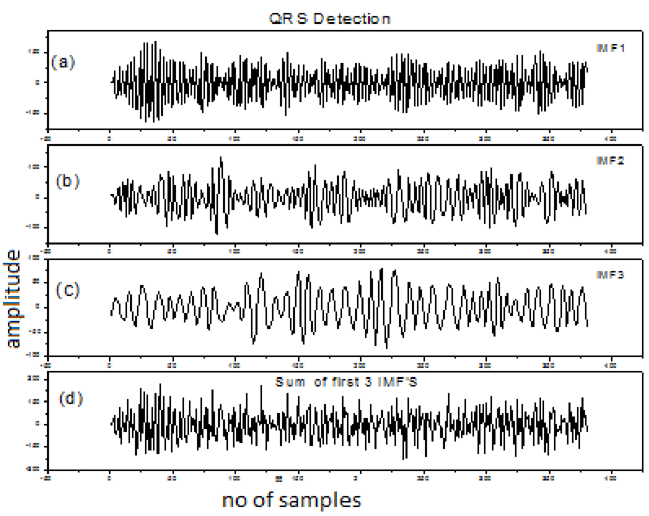

Fig. 4. QRS Detection: Sum of the first three IMFs.

In this work, we assume that the fiducial points are either known (for instance, by annotation) or can be found out by other methods.

B (2) Use correct windowing to preserve the QRS complex

The window function is a time domain window applied to the initial several IMFs corresponding to the noise. Since the window size is set by the delineation results in the initial step, these window functions alter their sizes as per the QRS duration. We used Tukey window here for typical window function (tapered cosine window):

$$w(t) = \begin{cases} \frac{1}{2}\left[1+\cos\left(\pi\frac{|t|-\tau_1}{\tau_2-\tau_1}\right)\right] & \tau_1 \le |t| \le \tau_2 \\ 1 & |t| < \tau_1, \\ 0 & |t| > \tau_2, \end{cases} \quad (3)$$

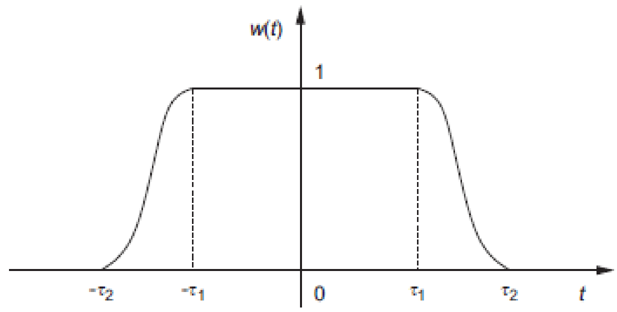

Fig. 5. Tukey window (tapered cosine) function.

Where τ_1 denotes the flat region limit and τ_2 represents the transition region limit. Fig 5 depicts the graphical representation of the Tukey window.

The transition region is set to avoid sudden "cutoff" of the window and decrease the distortions. As shown in Fig. 3, with increase in IMF order the spread of the oscillatory pattern around the QRS complex enhances. We define the ratio between the one-sided transition region length $\tau_1 - \tau_2$ and the flat region length $2\tau_1$ as

$$\beta = \frac{|\tau_1 - \tau_2|}{2\tau_1} \quad (4)$$

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 j × 30%, revealing that the window itself spreads as the QRS complex spreads with increasing order of IMF.

B (3) Use applied math tests to work out the quantity of IMFs causative to the noise

When ECG signal is considered, the contaminating noise is zero mean while the signal is non zero mean, which enables the noise and signal to be separated in ECG domain. The t -test is able to establish if the mean of the IMF deviates from zero. In the t -test, we performed the following hypothesis testing:

$$H_0: mean\left(c_{PS}^M(t)\right) = 0, H_1: mean\left(c_{PS}^M(t)\right) \ne 0,$$

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

$$c_{PS}^M(t) = \sum_{i=1}^{M} c_i(t) \quad (5)$$

The IMF order Pt at the termination point denotes that there are Pt IMFs that majorly contribute 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, and indicates how many IMFs should be removed.

B (4) Filtering the noise by partial reconstruction

After establishing a method to find out the noise order, we could filter the noise by partial IMF reconstruction. The window functions are applied to the P IMFs which are considered to be noise components so as to preserve the QRS complex. For the ith IMF, a window function $\psi_I(t)$ is constructed by concatenating the window functions, each of which centered at the QRS complex is applied. In Mathematical terms,

$$\psi_i(t) = \sum_{j=1}^{N_r} w_{ij}(t), \tag{6}$$

Where Nr stands for the number of QRS complex and wij (t) represents the variable size window for the jth QRS complex in the ith IMF. The aim of the window functions $\psi_I(t)$ was to remove the noise and retain the QRS complex. To reduce the distortion further, we defined the complementary window function which is given by,

$$\bar{\psi_i}(t) = 1 - \psi_i(t), \forall t \tag{7}$$

Obviously, $\bar{\psi}_i(t)$ suppresses the QRS complex and retains some noise information. Its effect is contrary to that of $\psi_I(t)$. Here, $\bar{\psi}_i(t)$ is applied to the first P IMFs in conjunction with$\psi_I(t)$. The main reason of using the complementary window function is to avoid abrupt alterations to the QRS complex by allowing a negligible amount of noise components in the lower-order IMFs. The sum of the P windowed IMFs, the remaining N –P IMFs, and the residue forms the reconstructed signal:

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t) c_i(t) + \sum_{i=1}^{P} a_i\, \bar{\psi}_i(t) c_i(t) + \sum_{i=P+1}^{N} c_i(t) + r_N(t), \tag{8}$$

Where, 0 $< a_i <$1 is the attenuation coefficient. Typically a_i can be set between 0.1 and 0.3.

C) ECG BW removal by applying EMD

Base line wander is a low frequency phenomenon mostly located in the last higher order IMFs except some residue. Therefore, just eliminating the last IMFs may lead to significant distortions. Hence, the BW has to be separated from the desired components in the last several IMFs and BW order has to be established. In order to remove the BW, first and foremost a BW estimate was obtained via a "multiband" filtering approach. The estimated BW was then subtracted from the signal, giving the reconstructed signal. A bank of lowpass filters was applied to the last several IMFs. The sum of the output of this filter bank functions as the BW estimate. Presume the signal with BW is x(t), after performing the EMD, we obtained all the IMFs:

$$x(t) = \sum_{i=1}^{N+1} c_i(t), \tag{9}$$

We designed a bank of low pass filters $h_i(t)$, i = 1, 2,..., Q, and then filtered the IMFs starting from the last, $c_{N+1}(t)$, by these lowpass filters. The cutoff frequencies of the low pass filters are chosen as follows. The cut off frequency of the first low pass filter $h_1(t)$ was set to be w_0. The cutoff frequency of the kth filter was set as

$$\omega_k = \frac{\omega_0}{M^{k-1}}, \tag{10}$$

Where M >1 is a frequency folding number. The cut off frequencies are related in this fashion due to the fact that, with decrease in IMF order, fewer BW components, but more signal components, are present in the IMF. This multiband filtering scheme treats each IMF as a sub band of the signal and performs filtering on each sub band.

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

$$var\{b_i(t)\} = \frac{1}{L-1} \sum_{t=0}^{L-1} [b_i(t) - \mu_{bi}]\, 2 \tag{11}$$

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

$$b^\wedge(t) = \sum_{i=1}^{Q} b_i(t) \tag{12}$$

Finally, by removing the BW reconstructed signal was obtained

$$\bar{x}(t) = x(t) - \hat{b}(t) \tag{13}$$

Generally, ECG signals are contaminated by both high-frequency noise and BW. The denoising method used above for removing BW can be used here also to remove both alterations. Because 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. Therefore, the reconstructed signal after removing both high-frequency noise and BW could be

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t) c_i(t) + \sum_{i=1}^{P} a_i\, \bar{\psi}_i(t) c_i(t) + \sum_{i=P+1}^{N} c_i(t) - \sum_{j=1}^{Q} h_j(t) * c_{N-j+2}(t), \tag{14}$$

Where the residue $r_N(t)$ in (13) is rewritten as $c_{N+1}(t)$.

Results

To evaluate the proposed EMD based method performance, simulations were carried out for several different cases. A noisy signal s(t)=x(t)+n(t) was processed to obtain an enhanced reconstructed version x^(t). The corrupted signal s (t) consists of an original clean and noise free signal x (t), and a noise component realization n (t), that may be synthetic or real. Two sets of experiments for ECG signals are presented here. The first simulation experiment was executed over synthetic noise and BW, and in the second experiment we examined the real noise. All the ECG signals used were taken from the MIT–BIH arrhythmia database. Every file in the database consists of two lead recordings sampled at 360 Hz with 11 bits per sample of resolution. The quantitative evaluation is done by the signal-to-error ratio (SER):

$$SER = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1} [x(t) - x^\wedge(t)]^2}, \tag{15}$$

Where x(t) is the original clean signal and x^(t) is the reconstructed signal.The amount of noise in s(t) is assessed by the signal to noise ratio(SNR):

$$SNR = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1} n^2(t)}, \tag{16}$$

Where n(t) is the noise realization.

A) Synthetic noise and BW

Synthetic noise and BW were added to the signal from the first lead of record 107 from the MIT–BIH arrhythmia database. The reason for choosing the signal is, it captures normal sinus rhythms and is reasonably free of noise. The experiments cover three cases: Gaussian noise alone, BW only, and both Gaussian noise and BW.

A (1) Testing with Gaussian noise

To the original clean signal, Gaussian noise was added to yield a 10 dB SNR. The IMFs of the noisy signal were obtained by applying the EMD method. Finally, the reconstructed signal was obtained. Based on the relationship of the QRS complex and the oscillatory patterns explained above, the QRS complex was delineated.

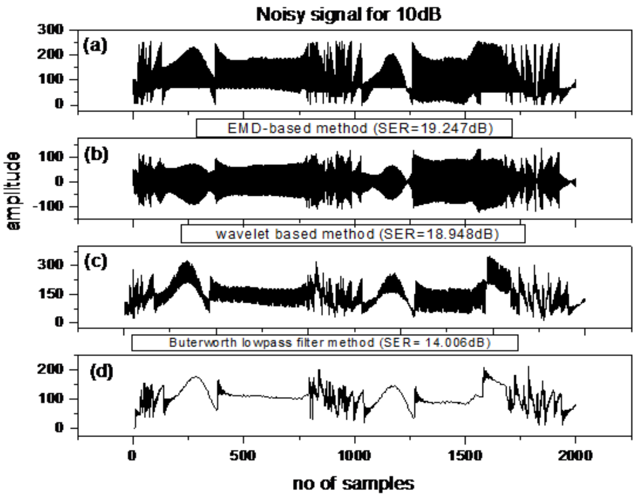

Fig.6.ECG denoising for Gaussian noise (a)Depicts noisy signal for 10dB, (b)Using EMD method(SER=19.24dB), (C)Using wavelet based method(SER=18.94), (d)Butterworth lowpass filtering method (SER=14dB).

In the low pass filtering method, the cutoff frequency was set to be 30 Hz, which was experimentally chosen to attain best denoising quality as shown in fig.6. It is observed that the proposed method achieved performance similar to that of wavelet-based method. This is true only when synthetic noise is used. In the case of real noise, the proposed EMD method outperforms the wavelet-based method.

A (2) Testing with Baseline wander (BW)

To produce the synthetic BW, a Gaussian signal with variance on the order of the power of the original ECG signal was first generated. Addition of BW to the original ECG results in a signal with BW. Then the resulting signal was passed through a lowpass filter. Then, we compared the proposed method with the Butterworth highpass filtering method. The cutoff frequency of highpass filter was experimentally set to be 0.09 Hz, which achieves best BW removal quality. The reconstructed signals by the proposed EMD-dependent method and the highpass filtering method are shown in Fig.8. Similar kind of reports were earlier made with a modified EMD method to remove BW in fetal signal denoising [11]

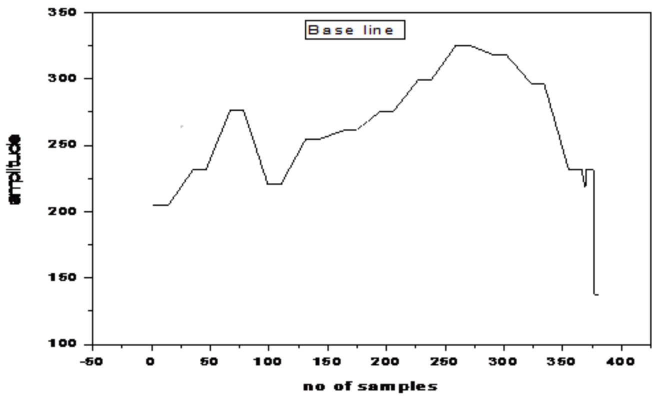

Fig.7. Base line

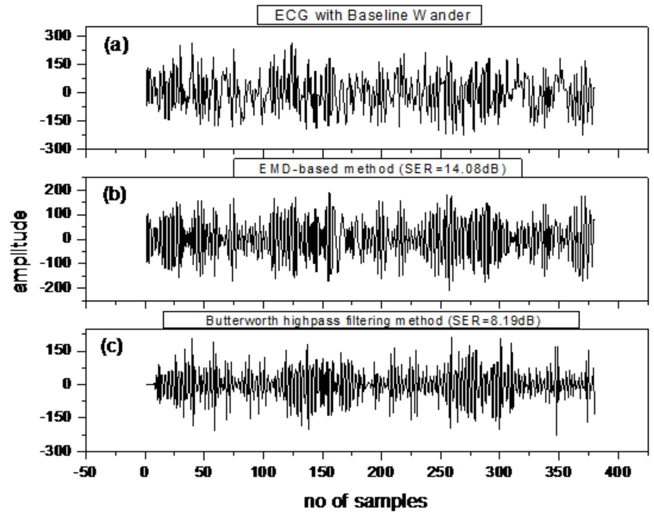

Fig.8. ECG signal with Baseline Wander (a) Using EMD based method (SER = 14.08 dB), (b) Using Butterworth highpass filtering method (SER=8.19dB).

A (3) Testing with Gaussian noise and BW

Here, both Gaussian noise and BW were added to the original ECG. For comparison, the Butterworth bandpass filtering method was implemented to remove both types of artifacts. The two cutoff frequencies of the bandpass filter are the cutoff frequencies of the lowpass and highpass filters used in the previous two experiments. The noisy and the reconstructed signals are depicted in Fig.9, from which we can demonstrate that the performance of the EMD-based method is almost identical as that of individual cases.

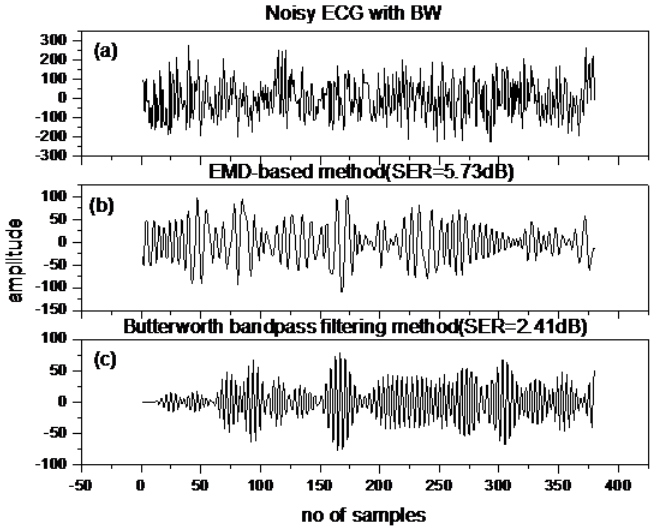

Fig. 9. ECG enhancement for Gaussian noise and BW (a) noisy ECG with BW, (b)Emd-based method(SER=5.73dB), (c)Butterworth bandpass filtering method(SER=2.41dB).

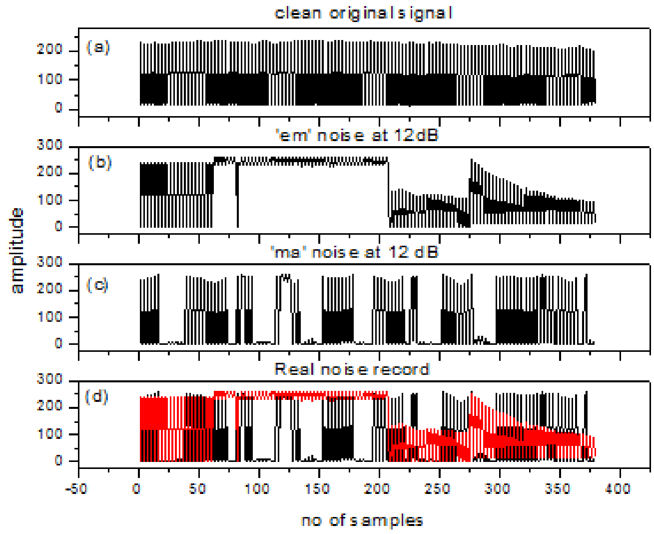

Fig.10. Real noise added to clean signal,(a) Original signal,(b)using 'em'noise at 12dB,(c)'ma' noise at 12dB,(d) shows Real noise

B) Testing with real noise

The second simulation experiment was carried out to demonstrate how the proposed new method works when a signal is processed under real conditions. In this, the first 1,000 samples from an MIT BIH noise free signal were used. The noisy signals were split into consecutive blocks to continuously process the long-term records (except in the lowpass filtering method). Fig. 10 depicts the 1,000-samples noise free record from the MIT BIH database (record 107). The noisy signal was obtained by adding the noise record in Fig. 10(a) attaining an SNR of 10 dB. The noise signal was obtained as the contribution of "muscle artifact" and "electromyogram" noise in Fig. 10(b) and (c), respectively, at an SNR of 12 dB in both cases. The total noise is corrupt the original signal x (t) is obtained as

$n(t) = k_1 n_{ma}(t) + k_2 n_{em}(t)$, So that $k_i, i = 1, 2,$ with the same SNR

$$SNR_0 = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1} [k_1 n_{ma}(t)]^2} = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1} [k_2 n_{em}(t)]^2}, \quad (17)$$

The resulted SNR is assessed with (16)

In Fig.11, the original signal, noisy signal, and reconstructed signals from the EMD–based method, the Butterworth lowpass filtering and the wavelet-based methods are displayed in the range of samples from 1,000 to 1,500, which has been arbitrarily chosen. However, both lowpass filtering and wavelet-based methods failed to remove the real noise adequately. The calculated SERs reveal that EMD method is better than wavelet method which is better than butterworth filter method, when applied to the real noise. In the EMD dependent method, the signal is processed in consecutive blocks of 1000 samples as seen in Fig.11. (b), the method does not introduce any distortion at the borders of consecutive segments. Finally, the long-term test is repeated under the same conditions with the records 100,103,105,107,119 and 213 at different SNRs, as represented in table 1. It is clear that, the wavelet-based method shows less ability to deal with real noise than the EMD-based method. We can see the behaviour of the wavelet-based method in Fig.11. (d) where only few noise components are smoothed (see also Fig.11. (b) to compare), but it is unable to remove the strong noise components. These results further substantiate that the proposed EMD-method is applicable to synthetic noise cases as well as for real noise cases.

As shown in Fig.12, six records are selected from the MIT-BIH database. The input SNR values are plotted on the horizontal axis and the vertical axis shows the average SERs of reconstructed signal. It can be observed that SER improves as the SNR is increased.

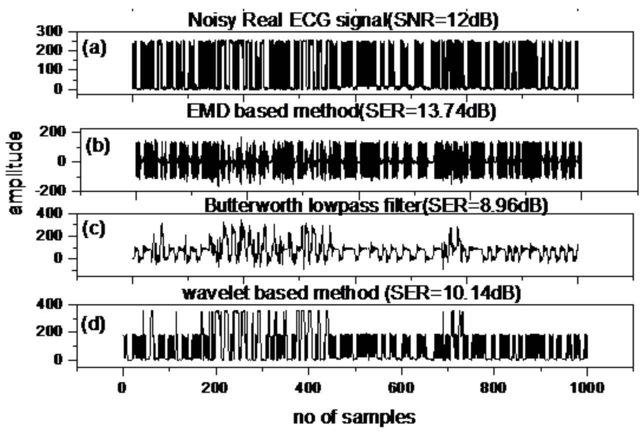

Fig.11.ECG denoising for real noise.From top to bottom:(a) noisy Real ECG signal, (b) EMD based method,(SER=13.74dB), (c) Butterworth lowpass filtering method,(SER=8.96dB),(d)wavelet–based method,(SER=10.14dB).

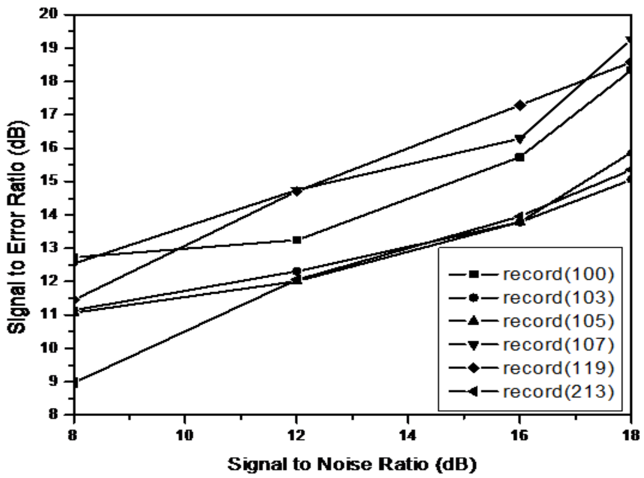

Fig.12. SNR(dB) vs SER(dB) for six signal records:100, 103, 105, 107, 119, 213 in Gaussian noise case.

TABLE 1. Real time performence with several records from MIT-BIH database. (a) SER value for the EMD-based method, (b) SER value for the Butterworth lowpass filtering method, (c) SER value for the wavelet-based method.

Signals	8dB			12dB			16dB			20dB		
	EMD_{ser}^{a}	$BLPF_{ser}^{b}$	WT_{ser}^{c}	EMD_{ser}^{a}	$BLPF_{ser}^{b}$	WT_{wt}^{c}	EMD_{ser}^{a}	$BLPF_{ser}^{b}$	WT_{ser}^{c}	EMD_{ser}^{a}	$BLPF_{ser}^{b}$	WT_{ser}^{c}
100	12.73	3.38	10.44	13.24	3.97	11.13	15.73	4.52	13.78	18.34	4.94	14.20
103	11.14	2.07	9.14	12.31	2.94	6.05	12.78	3.06	12.03	14.06	4.26	12.78
105	11.87	1.88	6.61	12.01	3.96	7.21	13.79	5.94	10.71	15.87	6.34	11.06
107	12.54	5.64	6.91	13.74	8.96	10.14	16.29	9.23	13.18	19.26	9.98	13.98
119	11.45	6.25	6.54	14.71	9.36	10.24	17.45	8.65	12.04	19.25	8.31	11.27
213	8.78	4.12	6.14	11.02	10.32	6.35	13.56	6.49	10.51	16.24	7.54	10.01

Conclusion

A new EMD-based technique is used for ECG signal enhancement. The developed denoising technique is not based on the simple partial summation of IMFs, but different IMFs were chosen and processed. Real and synthetic noises and BW were worked on to show the efficiency of the EMD method in ECG signal denoising. The simulation results demonstrate that the proposed EMD-based method effectively removes the BW and PLI to achieve ECG signal enhancement. In fact, our results demonstrated that, the new EMD based method outperforms both wavelet and Butterworth filtering techniques. In conclusion, we suggest that the proposed technique can be well used in practical stress ECG tests to enhance signal quality.

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