System Design for Baseline Wander Removal of ECG Signals with Empirical Mode Decomposition using Matlab

Sasikumar Gurumurthy, Valarmozhi

Abstract— The electrocardiogram (ECG) records the cardiac activity and it is extensively used for diagnosis of heart diseases. It is also an essential tool to allow monitoring patient sat home, thereby advancing telemedical applications. Even though these contributions are for different projects, the issue common to each is the use of ECG for remote monitoring and assistance under different telecommunication platforms. The transmission of ECG often introduces noise due to poor channel conditions. In this paper, we propose a new method for removing the baseline wander interferences based on Empirical Mode Decomposition (EMD). EMD is a relatively new, data-driven adaptive technique used to decompose ECG signals into a series of Intrinsic Mode Functions (IMFs).The baseline wander is mainly involved in special lower frequency IMFs. To evaluate the performance of the method, Clinic ECG signals are used. Results indicate that the method is powerful and useful in removing the baseline wander in ECG signal and does not distort the ECG signals.

Index Terms— Baseline Wander, Empirical mode decomposition, Electro cardio Gram, Intrinsic Mode Functions

I. INTRODUCTION

One of the first applications of Empirical Mode decomposition (EMD) is in the field of Biomedical Engineering, where blood pressure is studied. Some other applications of EMD are in ECG signal processing for investigating its chaotic nature, analysis of heart rate visibility (HRV), artifact reduction in gastric signals and extraction of lower esophageal sphincter pressure in the gastro esophageal reflux disease. EMD is an emerging new technique for adaptively decomposing nonstationary signal in a sum of local oscillatory components (IMFs). It is local in time, fully data-driven, and does not require any prior knowledge on the nature and the number of IMF components embedded in the data[1]. This technique has already been applied with success in biology and medicine. The idea of EMD is applied to develop strategies to automatically identify the relevant IMFs that contribute to the slow-varying trend in the data and presented its application on the extraction of the LES pressure in GERD. Through both computer simulations and actual data that the method is able to successfully extract the LES pressure signal and compares favorably to the conventional low-pass filer.

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A. Motivation

Electrocardiogram (ECG) has been used extensively for detection of heart disease. A classical problem in recording the ECG signal is that the measured signal is corrupted by baseline wander. The baseline wander is a interference may severely corrupt an ECG recording. Removing the baseline interference in ECG signal is usually the necessary preprocessing step to enhance the signal characteristics for diagnosis. Problems with patient movement, bad electrodes and improper electrode site preparation etc can cause baseline wander. The frequency range of baseline wander is usually below 0.5Hz, which is similar as the frequency range of ST segments. Baseline wander makes interpretation ECG recordings difficult, especially the assessment of ST deviation. So before analyzing the ECG signal, removing the baseline wander is necessary.

B. Problem Description

The main goal of this work is to separate the valid ECG from the undesired artifacts so as to present a signal that allows easy visual interpretation. Many approaches have been reported in the literature to address ECG enhancement. Some recent relevant contributions have proposed solutions using a wide range of different techniques, such as perfect reconstruction maximally decimated filter banks and nonlinear filter banks, advanced averaging, the wavelet transform, adaptive filtering, singular value decomposition, and independent component analysis.

C. Related Work

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In this paper, we propose a new method for ECG enhancement based on the empirical mode decomposition (EMD). The EMD was recently introduced in as a technique for processing nonlinear and no stationary signals. It also serves as an alternative to methods such as the wavelet analysis, Wigner–Ville distribution, and the short-time Fourier transform. It is proposed as a preprocessing stage to efficiently compute the instantaneous frequency through the Hilbert transform, although it can be applied independently as well.

It is reported in that EMD behaves as a "wavelet-like" dyadic filter bank for fractional Gaussian noise. This conclusion has been applied in a detruding and denoising example in.

The present work is one of the first applications of EMD in biomedical engineering, where signals are studied. Regarding ECG signal processing, one of the first EMD-based contributions is, which investigates the chaotic nature of ECG. Also related to the cardiac system, the EMD is utilized in the analysis of heart rate variability (HRV). The EMD is also used for artifact reduction in gastric signals. Finally in, the EMD is utilized to extract the lower esophageal sphincter pressure in the gastro esophageal reflux disease.

As the brief review above demonstrates, the EMD is a good tool for artifact reduction applications. This motivates the proposed use of the EMD for ECG enhancement. In this work, we address both denoising and BW removal based on the EMD.

The contributions of this work lie in two aspects. First, we introduce the use of the EMD in ECG enhancement. Second, noting that both high-frequency noise and BW components are mixed with ECG signal component in the EMD domain, we develop novel methods to remove both types of artifacts.

The performance of the proposed algorithm is demonstrated through various experiments performed over several records from the MIT–BIH arrhythmia database. Quantitative and qualitative experiments are carried out for synthetic and real noise cases. The experimental studies show that the proposed EMD-based method is a good tool for ECG denoising and BW removal, especially for the important real noise cases.

II. OVERVIEW OF PROPOSED SYSTEM

A. Introduction of Problem and its Related Concepts

The electrocardiogram (ECG) is the recording of the cardiac activity and it is extensively used for diagnosis of heart diseases. It is also an essential tool to allow monitoring patient sat home, thereby advancing telemedical applications. Recent contributions in this topic are reported in. Even though these contributions are for different projects, the issue common to each is the use of ECG for remote monitoring and assistance under different telecommunication platforms. The transmission of ECG often introduces noise due to poor channel conditions. Moreover, there are other types of noise inherent in the data collection process. These artifacts are particularly significant during a stress test. The main sources of such artifacts are: (1) the baseline wander (BW) mainly caused by respiration, and (2) high-frequency noise such as the electromyography (EMG)noise caused by the muscle activity. Moreover, the motion of the patient or the leads affects both types of artifacts. 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.

Many approaches have been reported in the literature to address ECG enhancement. Some recent relevant contributions have proposed solutions using a wide range of different techniques, such as perfect reconstruction maximally decimated filter banks and nonlinear filter banks, advanced averaging, the wavelet transform, adaptive filtering, singular value decomposition, and independent component analysis.

In this paper, we propose a new method for ECG enhancement based on the empirical mode decomposition (EMD). The EMD was recently introduced in as a technique for processing nonlinear and no stationary signals. It also serves as an alternative to methods such as the wavelet analysis, Wigner–Ville distribution, and the short-time Fourier transform. It is proposed as a preprocessing stage to efficiently compute the instantaneous frequency through the Hilbert transform, although it can be applied independently as well.

B. Gaps Identified from Existing System

Up to now, many methods of removing the baseline wander in ECG signal are proposed. Highpass filter is the classical method which removes very low frequency component from ECG recording. The component with frequencies below 0.5Hz is filtered out, while frequencies above are completely preserved in both amplitude and phase. Unfortunately, because the spectra of baseline wander and the ECG signal are very close, and in some cases may overlap, it is difficult to eliminate the wander and leave the ECG signal undistorted. Other methods for removal of baseline wander include cubic spline approximation and subtraction technique, which involves estimating the baseline with polynomial or cubic spline and subtracting it from the disturbed signal; the performance of this method depends on the knots determination accuracy. Adaptive filtering can also be used to remove baseline wander, which was first proposed by Widrow [9] [10]. The method does not disturb the ECG frequency spectrum but it requires reference signal, which adds to the complexity of hardware and software adaptive filter etc.

C. Proposed Solution

We propose a new method for ECG enhancement based on the empirical mode decomposition (EMD). The EMD was recently introduced in as a technique for processing nonlinear and nonstationary signals. It also serves as an alternative to methods such as the wavelet analysis, the Wigner–Ville distribution, and the short-time Fourier transform. It is proposed as a preprocessing stage to efficiently compute the instantaneous frequency through the Hilbert transform, although it can be applied independently as well. It is reported in that EMD behaves as a "wavelet-like" dyadic filter bank for fractional Gaussian noise. This conclusion has been applied in a detrending and denoising example the work in presents one of the first applications of EMD in biomedical engineering, where blood pressure is studied. Regarding ECG signal processing, one of the first EMD-based contributions, which investigates the chaotic nature of ECG. Also related to the cardiac system, the EMD is utilized in the analysis of heart rate variability (HRV). The EMD is also used for artifact reduction in gastric signals. Finally, in the EMD is utilized to extract the lower esophageal sphincters pressure in the gastro esophageal reflux disease. As the brief review above demonstrates, the EMD is a good tool for artifact reduction applications. This motivates the proposed use of the EMD for ECG enhancement. In this work, we address both denoising and BW removal based on the EMD. The contributions of this work lie in two aspects. First, we introduce the use of the EMD in ECG enhancement. Second, noting that both high-frequency noise and BW components are mixed with ECG signal component in the EMD domain, we develop novel methods to remove both types of artifacts.

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The performance of the proposed algorithm is demonstrated through various experiments performed over several records from the MIT–BIH arrhythmia database. Quantitative and qualitative experiments are carried out for synthetic and real noise cases. The experimental studies show that the proposed EMD-based method is a good tool for ECG denoising and BW removal, especially for the important real noise cases.

III. OVERALL DESIGN

The design of the system consists of a brief review of the EMD is presented. The algorithms for denoising and baseline removal are explained. Next section presents the experimental studies that demonstrate the performances of the proposed method. Finally, conclusions are given at the end.

A. System Architecture Design

The system is designed in an efficient way to provide a clean ECG signal. The signal inputs are obtained, the corresponding maxima and minima points are identified, the correspondence IMFs are obtained and finally the first three IMFs are added together in order to get a clear ECG signal.

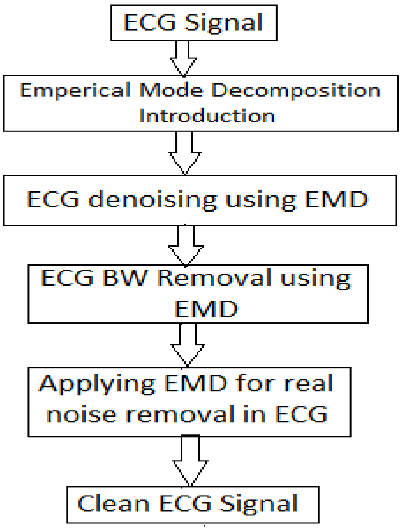

Fig. 1. System Architecture Design.

B. Empirical Mode Decomposition

The EMD was recently proposed by Huang et al. as a tool to adaptively decompose a signal into a collection of AM–FM components. Traditional data analysis methods, like Fourier and wavelet-based methods require some predefined basis functions to represent a signal. The EMD relies on a fully data-driven mechanism that does not require any *a priori* known basis. It is especially well suited for nonlinear and nonstationary signals, such as biomedical signals. The aim of the EMD is to decompose the signal into a sum of intrinsic mode functions (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 envelope *eu(t)*. Similarly, all the local minima are connected by a spline curve as the lower envelope *el(t)*. The mean of the two envelopes 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

$$h_1(t) = x(t) - m_1(t) \qquad (1)$$

The above procedure to extract the IMF is referred to as 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):

$$\sum_{t=0}^{T} \frac{[h_{k-1}(t) - h_k(t)]^2}{h_{k-1}^2(t)} \qquad (2)$$

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

$$r_1(t) = x(t) - c_1(t) \qquad (3)$$

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

$$\begin{aligned} &r_1(t) - c_2(t) = r_2(t), \\ &\ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \\ &r_{n-1}(t) - c_n(t) = r_n(t). \end{aligned} \qquad (4)$$

The whole procedure terminates when the residue $r_{N(t)}$ is either a constant, a monotonic slope, or a function with only one extreme um. Combining the equations in (3) and (4) yields the EMD of the original signal:

$$x(t) = \sum c_n(t) + r_{N(t)} \qquad (5)$$

The result of the EMD produces *N* IMFs and a residue signal. For convenience, we refer to $c_n(t)$ as the *n*th-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.

Huang's data-driven EMD method was initially proposed for the study of ocean waves, and found immediate applications in biomedical engineering. The major advantage of EMD is that the basis functions are derived directly from the signal itself. Hence the analysis is adaptive, in contrast to Fourier analysis, where the basis functions are fixed sine and cosine waves.

The central idea of this method is an iterative sifting process that decomposes a given signal into a sum of IMFs, those basic building blocks that make up data complex time series. A signal must satisfy two criteria to be an IMF: (1) the number of extrema and the number of zero crossings are either equal or differ at most by one; and (2) the mean of its upper and lower envelopes equals zero.

The first criterion is similar to the narrow-band requirement. The second criterion modifies a global requirement to a local one, and is necessary to ensure that the instantaneous frequency will not have unwanted fluctuations as induced by asymmetric waveforms.

To make use of EMD, the signal must have at least two extreme one maximum and one minimum to be successfully decomposed into IMFs. Given these two definitive requirements of an IMF, the sifting process for extracting an IMF from a given signal x(t) is described as follows:

1. Two smooth splines are constructed connecting all the maxima and minima of x(t) to get its upper envelope, $x_{up}(t)$, and its lower envelope, $x_{low}(t)$; The extreme can be simply found by determining the change of sign of the derivative of the signal. Once the extreme are identified, all the maxima are connected by a cubic spline line as the upper envelope. The procedure is repeated for the local minima to produce the lower envelope. All the data points should be covered by the upper and lower envelopes.

2. The mean of the two envelopes is subtracted from the data to get their difference

$$d(t) = [x_{low}(t) + x_{up}(t)]/2$$

3. The process is repeated for d(t) until the resulting signal, $c_1(t)$, the first IMF, satisfies the criteria of an intrinsic mode function. The residue $r_1(t) = x(t) - c_1(t)$ is then treated as new data subject to the sifting process as described above, yielding the second IMF from $r_1(t)$. The procedure continues until either the recovered IMF or the residual data are too small, in the sense that the integrals of their absolute values or the residual data have no turning points. Once all of the wavelike IMFs are subtracted from the data, the final residual component represents the overall trend of the data. At the end of this process, the signal x(t) satisfies (5), where N is the number of IMFs, r_N denotes the final residue (signal trend), and $c_j(t)$ are nearly orthogonal to each other, and all have zero means. Due to this iterative procedure, none of the sifted IMFs is derived in closed analytical form. In practice, after a certain number of iterations, the resulting signals do not carry significant physical information, because, if sifting is carried on to an extreme, it could result in a pure frequency modulated signal of constant amplitude.

To avoid this, we can stop the sifting process by limiting the standard deviation, computed from two consecutive sifting results, which is usually set between 0.2 and 0.3. By construction, the number of extrema is decreased when going from one residual to the next, and the whole decomposition is guaranteed to be completed with a finite number of modes. By the sifting process, the data are represented by intrinsic mode functions, to which the Hilbert transform can be applied. The Hilbert spectrum enables us to represent the amplitude and the instantaneous frequency as functions of time in a three-dimensional plot.

The resulting time–frequency distribution of the amplitude is called the Hilbert amplitude spectrum. The two-step procedure, EMD and its subsequent Hilbert spectral analysis, is called the Hilbert–Huang transform (HHT). The HHT method provides not only a more precise definition of particular events in time–frequency space than wavelet analysis, but also more physically meaningful interpretations of the underlying dynamic processes.

1) ECG Denoising using EMD: High-frequency denoising by the EMD is in general carried out by partial signal reconstruction, which is premised on the fact that noise components lie in the first several IMFs. This strategy works well for those signals whose frequency content is clearly distinguished from that of noise and is successfully applied in. The basic idea is to statistically determine the index of the IMFs that contain most of the noise components, beginning from fine to coarse scale. Given the index, the IMFs corresponding to the noise are removed and the reconstruction of the original signal is obtained by summing up the remaining IMFs.

However, this approach cannot be assumed in the ECG case because the QRS complex spreads over the lower-order IMFs. Therefore, in the ECG case, EMD-based denoising requires a different strategy. Noise encountered in ECG applications is usually located in the high-frequency band. Although most ECG signal power is concentrated in lower frequencies, the QRS complex spreads across the mid- to high-frequency bands.

This complicates ECG denoising since lowpass filtering or simply removing lower order IMFs will introduce severe QRS complex distortion, e.g., R-wave amplitude attenuation. As Section 2 illustrates, the EMD decomposes a signal into IMFs with decreasing frequency content.

The EMD of clean and noisy ECG records are illustrated in the following two examples, thus revealing specific patterns associated with the QRS complex and noise in the EMD domain. Consider first a clean ECG signal (first lead of record 103) from the MIT–BIH arrhythmia database decomposed by the EMD as shown in Fig. 2.

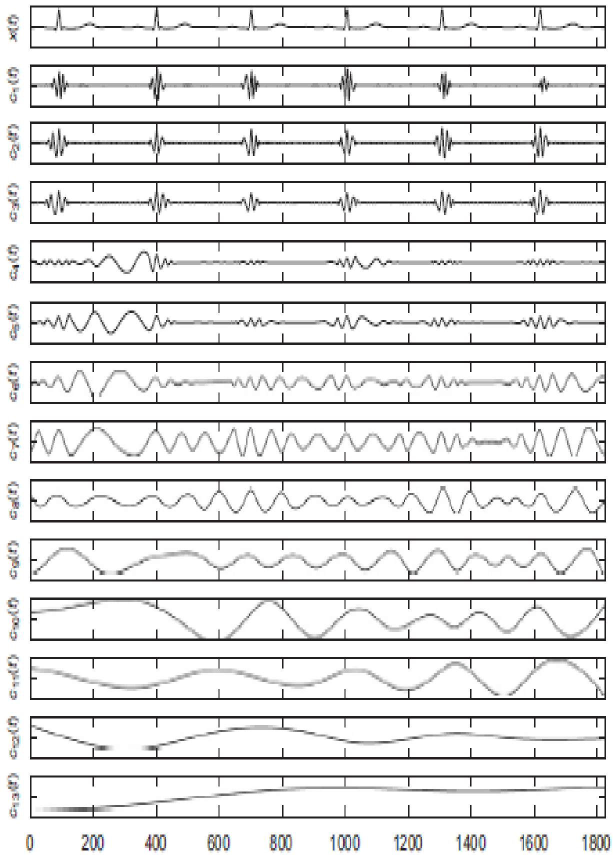

Fig. 2. EMD of Clean ECG, from top to bottom: clean ECG and resulting IMF 1- 13. Vertical axes subplot are not in the same scale.

The top plot shows the original ECG, and the remaining show all the IMFs from low to high orders. Consider next the EMD of a noisy ECG. A representative noisy signal is obtained by adding Gaussian noise to the clean signal in Fig. 2, the result of which is shown in the top graph of Fig. 3. The IMFs of the noisy signal are also shown in Fig. 3.

Compared to the clean signal case, the first IMF of the noisy signal contains strong noise components. The oscillatory patterns of the QRS complex become more apparent starting from the second IMF. An analysis of EMD on clean and noisy ECG indicates that it is possible to filter the noise and at the same time preserve the QRS complex by temporal processing in the EMD domain. Multiple evaluations show these characteristics for all EMD decompositions of ECG signals.

Therefore, the following four steps constitute the proposed denoising procedure:

STEP 1: Delineate and separate the QRS complex.

STEP 2: Use proper windowing to preserve the QRS complex.

STEP 3: Use statistical tests to determine the number of IMFs contributing to the noise.

STEP 4: Filter the noise by partial reconstruction

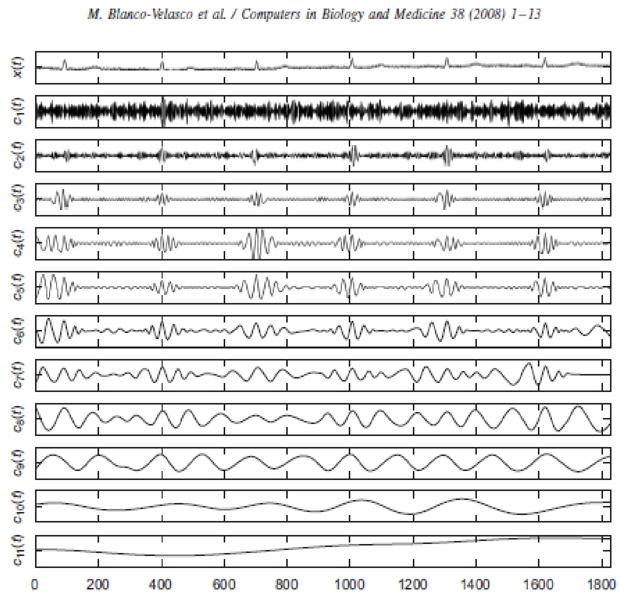

Fig. 3. EMD of a Noisy ECG, from top to bottom: Noisy ECG and resulting IMF 1- 11. Vertical axes subplot are not in the same scale.

2) ECG BW Removal with EMD: Since BW is a low-frequency phenomenon, it is expected that the major BW components are located in the higher-order IMFs. The residue, which can also be regarded as the last IMF, may not correspond to the BW because the BW may have multiple extrema and zero crossings, which violates the residue definition. Indeed, the BW spreads over the last several IMFs. Simply removing the last several IMFs may introduce significant distortions.

Thus, the BW must be separated from the desired components in the last several IMFs. Moreover, as in the denoising case, the number of IMFs that contribute to the BW must be established. This number is referred to as BW *order*.

To remove the BW, 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 filter bank serves as the BW estimate. Suppose the signal with BW is *x(t)*.

After performing the EMD, we obtain all the IMFs:

$$x(t) = \sum_{i=1}^{N+1} c_i(t) \qquad (14)$$

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 $h_i(t)$, $i = 1, 2... Q$, and then filter the IMFs starting from the last, $c_{N+1}(t)$, by these lowpass filters. The outputs of these filters are

$$\begin{aligned} b_1(t) &= h_1(t) * c_{N+1}(t), \\ b_2(t) &= h_2(t) * c_N(t), \\ &\ldots\ldots \quad \ldots. \quad \ldots.. \\ b_Q(t) &= h_Q(t) * c_{N-Q+2}(t), \end{aligned} \qquad (15)$$

where $*$ denotes the convolution. The cutoff frequencies of the lowpass filters are chosen as follows. Set the cutoff frequency of the first lowpass filter $h_1(t)$ to be 0. The cutoff frequency of the k^th filter is set as

$$\omega_k = \frac{\omega_0}{M_k - 1}, \qquad (16)$$

where *Mk*-1 is a frequency-folding number. The cutoff frequencies are related in this fashion due to the fact that, as the IMF order decreases, fewer BW components, but more signal components, are present in the IMF.

This multiband filtering scheme considers each IMF as a subband of the signal and performs filtering on each subband. 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

$$\text{var}\{b_i(t)\} = \frac{1}{L-1}\sum_{t=0}^{L-1}[b_i(t) - \mu b_i]^2, \qquad (17)$$

where b_i is the mean value of b_i *(t)*. Starting from the last IMF, we choose *Q* such that $\text{var}\{b_{Q+1}(t)\}$ and $\text{var}\{b_Q(t)\}$, where is an appropriate established threshold.

The selection of the parameters *can* be based on *a priori* knowledge or can be experimentally tuned according to the BW behavior. In the later simulations, some typical values are given for these parameters.

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

$$b(t) = \sum_{i=1}^{Q} b_i(t) \qquad (18)$$

Finally, removing the BW yields the reconstructed signal

$$x(t) = \sum_{j=1}^{N} c_j(t) + r_N(t), \qquad (19)$$

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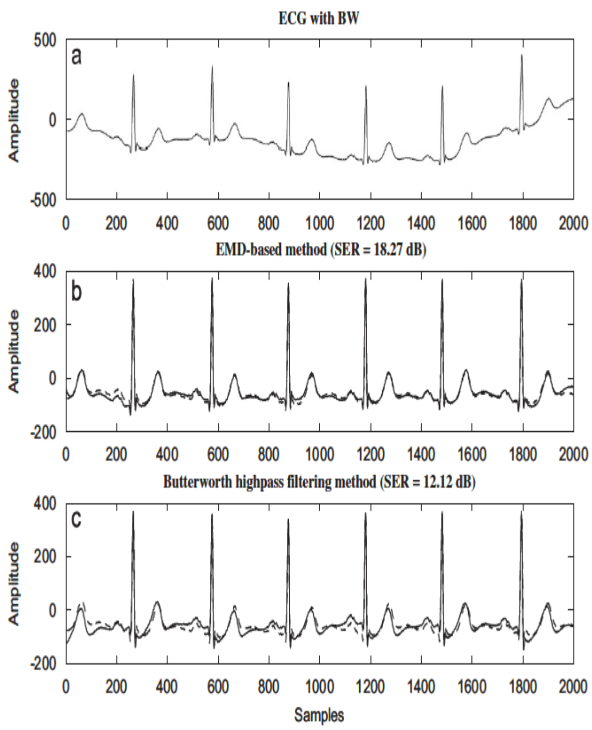

Fig. 4. Example for set of Signals

In the most general case, ECG signals are contaminated by both high-frequency noise and BW. The method of denoising in and the method of removing BW in can be combined to remove both artifacts. 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. Consequently, the reconstructed signal after removing both high-frequency noise and BW is

$$x(t)=\sum_{i=1}^{P}\varphi_i(t)c_i(t)+\sum_{i=1}^{P}a_i\varphi_i(t)c_i(t)+\sum_{i=P+1}^{N+1}c_i(t)-\sum_{j=1}^{Q}h_j(t)*c_{N-j+2}(t)$$

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

3) Real Noise Removal: In this experiment, we consider the ECG case corrupted by real noise. Here, the denoising is considered since the wavelet based method is targeted for denoising. Two real noise records are taken from the MIT–BIH noise stress test database [25], the muscle artifact "ma" record and the electrode motion "em" record. The BWin each record is eliminated by lowpass filtering in order to provide quantitative results with (21). Let *n*ma*(t)* and *n*em*(t)* be the "ma" and "em" BW free noise records, respectively. The total noise utilized to corrupt the original clean signal *x(t)* is obtained as *n(t)* = *k*1*n*ma*(t)* + *k*2*n*em*(t)*, so that *ki*, *i* = 1, 2, is chosen to contribute with the same SNR0:

$$\text{SNR0} = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1}[k1\ n\text{ma}(t)]^2} = \frac{\sum_{t=0}^{L-1} x^2(t)}{\sum_{t=0}^{L-1}[k2\ n\text{ma}(t)]^2}$$

A long-term experiment is carried out to show how the proposed method works when a signal is processed under real conditions. The first 46,000 samples (corresponding to a bit more than 2 min) from an MIT noise free signal are used. The noisy signals are split into consecutive blocks to continuously process the long-term records (except in the lowpass filtering method).

Figure.4 shows an example of the set of signals involved in this experiment. In (a), the 46,000-samples long noise free record from the MIT database is depicted (record 103).The noisy signal is obtained by adding the noise record in (d) attaining an SNR of 9.01 dB. The noise signal is obtained as the contribution of "ma" and "em" noise in (b) and (c), respectively, at an SNR0 of 12 dB in both cases. In the original, noisy, and reconstructed signals from the EMD-based, the Butterworth lowpass filtering, and the wavelet-based methods are displayed in the range of samples from 10,000 to 15,000, which has been arbitrarily chosen.

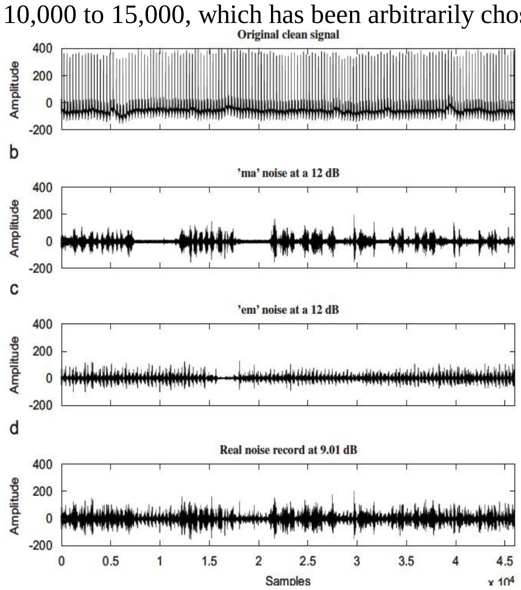

Fig. 5. Set of Signals

The figure 5 shows that the significant noise components are eliminated by the proposed method. However, both lowpass filtering and wavelet-based methods fail to remove the real noise satisfactorily. In addition, the SERs for the EMD based, the Butterworth filtering, and the wavelet-based methods are calculated to be 12.27, 4.65, and 9.15 dB, respectively, which again confirm the superior performance of the proposed method when applied to the real noise. In the EMD based method, the signal is processed in consecutive blocks of 2000 samples, and, as it can be seen in (c), the method does not introduce any distortion at the borders of consecutive segments. Finally, the long-term test is repeated under the same circumstances with the records 100, 103, 105, 119, and 213 at different SNRs. The results are presented in Table 1 in terms of SER for the corresponding methods. As can be observed here once again, the wavelet-based method shows less ability to deal with real noise than the EMD-based method. We can see the behavior of the wavelet-based method in (e) where only few noise components are smoothed (see also (b) to compare), but it is unable to remove the strong noise components. These results further demonstrate that the proposed method is not only applicable to synthetic noise cases, but also suitable for real noise cases.

IV. IMPLEMENTATION

The performance of the existing method is tested with actual ECG signals. Results indicate that the method is powerful and useful and the baseline interference can be eliminated from the ECG signal and does not distort the ECG signal. Performance of the new method is implemented on the actual ECG signal corrupted by baseline interferences. Finally, conclusions are drawn in section 5.

A. Tools Used

We used MATLAB for the process of registering images. MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran. MATLAB is specialized for image processing and digital signal processing.

B. User Interface Design

The user interface consists of options for choosing image files as input to the system. The preview of the images is made available in the same window as soon as the image files are selected using the 'browse' button. Once the previews are shown, the user is expected to click on the 'execute' button. As the button is clicked the system starts processing and carries out all the steps involved. When the processing is done, intermediate results are shown in separate windows and the final output image is shown in the same GUI window.

C. Screen Images

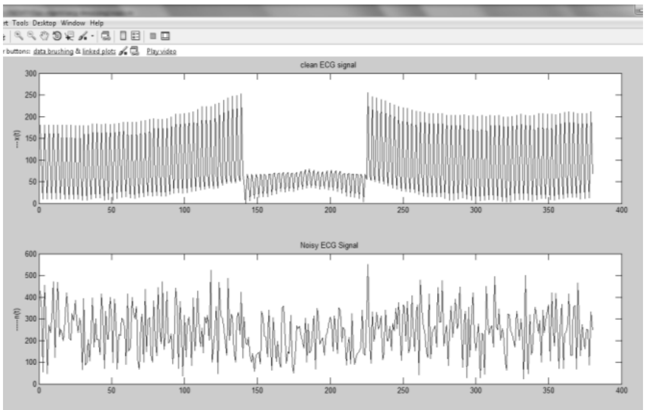

Fig. 6. Clean ECG Signal and Noisy Signal

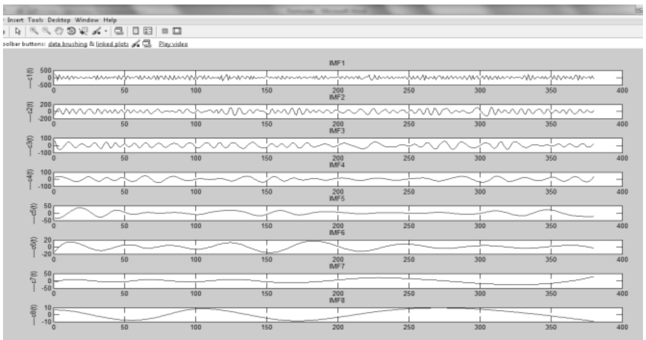

Fig. 7. Calculation of IMF

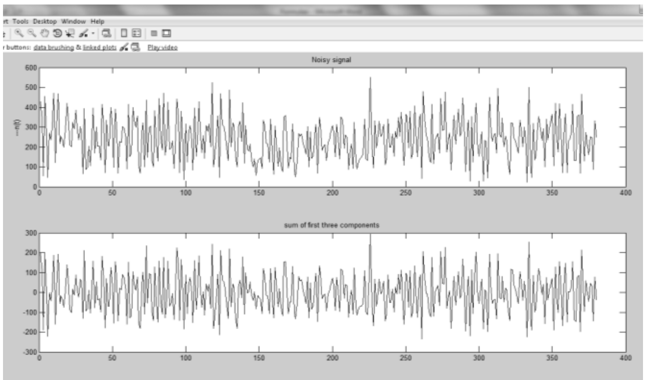

Fig. 8. Sum of three components of IMF

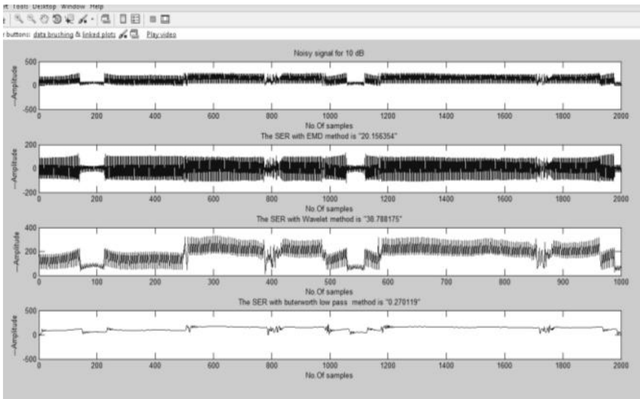

Fig. 9. Removal of Synthetic Noise using EMD

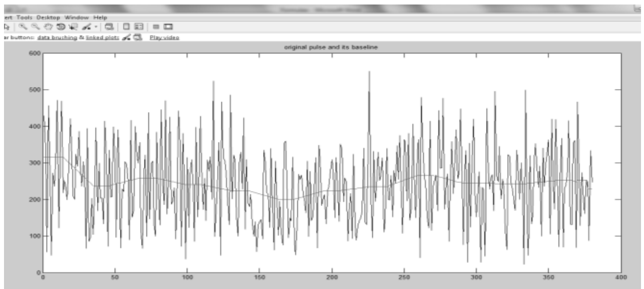

Fig. 10. Adding Baseline Wander for original Signal

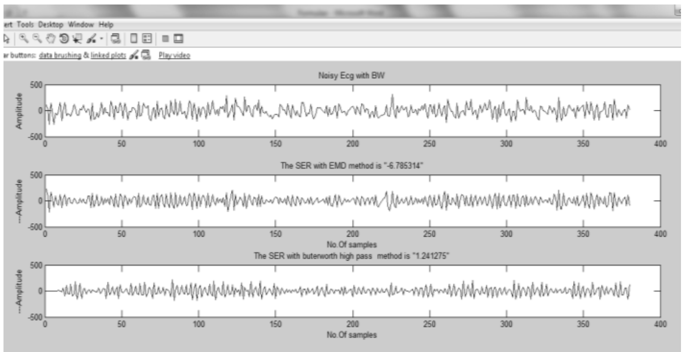

Fig. 11. Removal Baseline Wander with EMD

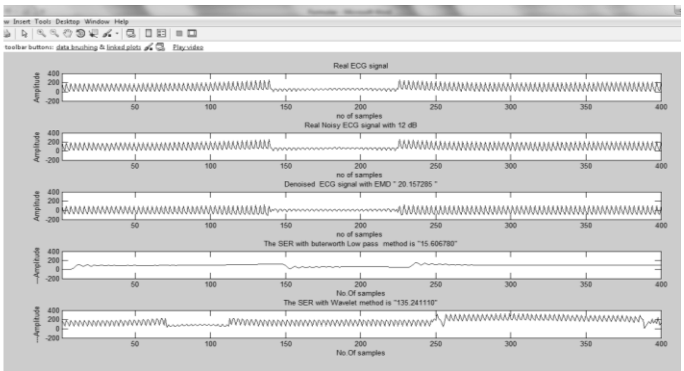

Fig. 12. Removal of Real Noise using EMD

D. Result and Discussion

The effectiveness of the EMD in ECG enhancement is shown through several experiments that consider real and synthetic noise and BW. Results indicate that the EMD is an effective enhancement tool, especially for real noise and BW.

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The techniques used here can be applied in practical stress ECG tests and long-term Holter monitoring as in these cases strong noise and BW components are present in the recorded ECG. Results further demonstrate that the proposed method is not only applicable to synthetic noise cases, but also suitable for real noise case.

V. CONCLUSION

A novel method for ECG enhancement based on the EMD is presented. Both high-frequency noise and BW removal are addressed. Enhancement is achieved through the development of two EMD-based methods to address each type of artifact. The techniques developed are not based on simple partial summation of IMFs, as in previous work. Rather, different IMFs are chosen and processed to successfully achieve the denoising and BW removal. The effectiveness of the EMD in ECG enhancement is shown through several experiments that consider real and synthetic noise and BW. Results indicate that the EMD is an effective enhancement tool, especially for real noise and BW. The techniques used here can be applied in practical stress ECG tests and long-term Holter monitoring as in these cases strong noise and BW components are present in the recorded ECG.

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