Comparative Study of Empirical Mode Decomposition applied in experimental biosignals

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Abstract

Electrocardiogram is a widely used biosignal for diagnosis of pathological situation concerning heart function. Interpretation and analysis of this signal is critical for the selection of the appropriate treatment and this highlights the necessity for clean signals without any kind of artifacts. Several methods have been developed in order to remove artifacts and delineate the characteristics of the ECG that physicians need to evaluate. In this paper, Empirical Mode Decomposition (EMD) is considered and the application of the decomposition method in experimental signals acquired by means of a wireless sensor network is evaluated. The proposed technique is based on the EMD and is studied comparatively to classic techniques of signal processing. Certain metrics are implemented to evaluate the performance of the technique and the results show good results of the EMD based method.

1. Introduction

The electrocardiogram (ECG) is a widely used diagnostic tool for heart physical condition. It can reveal pathological and physiological events related to the heart function and this highlights the importance of analyzing clean ECG signals.

The combination of electrocardiogram and wireless sensor networks expand the possibilities of cardiac activity monitoring and advancing telemedicine applications.

In real situations, ECG recordings are often corrupted by artifacts. This is deteriorated if wireless transmission is considered which adds noise and artifacts at the biosignal apart from those sources of artifacts being added at the acquisition point or the conditioning circuit.

Main sources of artifacts are the baseline wander (BW) due to respiration, high frequency noise caused by muscles motion, electrode contact noise due to poor attachment or movement of the electrode on the skin. Power line interference is a basic source of interference with significant harmonic amplitude up to the fourth harmonic. Instrumentation noise and electrosurgical noise are two kind of noise that processing algorithms have difficulties in compensating and is mainly due to saturation of input amplifiers or noise with frequency range higher than the frequency range of the ECG signal [1].

Many different techniques are reported in the literature to address the ECG corruption by artifacts. Most common techniques employ filter banks [2], wavelet transformation [3], adaptive filtering [4], independent component analysis [5].

In this paper, a technique is proposed for ECG enhancement which is based on the Empirical Mode Decomposition. The EMD method was introduced in [6] as a technique for processing nonlinear and nonstationary signals.

Variables in biology and generally biosignals are considered nonstationarily stochastic [7]. Nonlinear decomposition method for time series which are generated by an underlying dynamical system obeying nonlinear equations is usually a good approach to identify intrinsic oscillatory modes of the signal by its characteristic time scales.

Compared to the wavelet transformation which utilizes fixed basis functions, EMD follows different procedure which will be analyzed further and is possibly matching better to the varying nature of ECG biosignal.

Related literature references suggest that EMD has been applied in heart rate variability (HRV) [8], analysis of respiratory mechanomyographic signals [9], ECG enhancement artifact and Baseline wander correction [10], R-peak detection [11], Crackle sound analysis in lung sounds [12].

The characteristic time scales of the signal are represented in modes called Intrinsic Mode Functions being a complete, orthogonal, local and adaptive decomposition which preserve physical properties [6].

One issue arising from the application of the EMD is the so-called mode mixing which suggest that IMFs consist of oscillations of disparate scales [13]. This causes the IMFs not to have physical meaning by itself, suggesting falsely that there may be different physical process represented in a mode. To overcome the scale separation problem, a noise assisted data analysis method was recently proposed, the Ensemble EMD, which defines the true IMF components as the mean of an ensemble of trials.

2. Empirical Mode Decomposition

The empirical mode decomposition does not require any known basis function and is considered a fully data driven mechanism suited for nonlinear and nonstationary signals. The goal of the procedure is the decomposition of the signal into components with well defined instantaneous frequencies.

Each component extracted (IMF) is defined as a function with equal number of extrema and zero crossings (or at most differed by one) with its envelopes (defined by all the local maxima and minima) being symmetric with respect to zero. This implies that the mean value of each IMF is zero.

Given a signal x(t), the algorithm of the EMD can be summarized as follows :

1. Locate local maxima and minima of $d_0(t)=x(t)$.

2. Interpolate between the maxima and connect them by a cubic spline curve. The same applies for the minima in order to obtain the upper and lower envelopes $e_u(t)$ and $e_l(t)$, respectively.

3. Compute the mean of the envelopes:

$$m(t) = \frac{e_u(t) + e_l(t)}{2} \tag{1}$$

4. Extract the detail $d_1(t)= d_0(t)-m(t)$ (sifting process)

5. Iterate steps 1-4 on the residual until the detail signal $d_k(t)$ can be considered an IMF (satisfy the two conditions): $c_1(t)= d_k(t)$

6. Iterate steps 1-5 on the residual $r_n(t)=x(t)- c_n(t)$ in order to obtain all the IMFs $c_1(t)$,.., $c_N(t)$ of the signal.

The result of the EMD process produces N IMFs ($c_1(t)$, $c_2(t)$,…$c_N(t)$) and a residue signal ($r_N(t)$) :

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \tag{2}$$

In step 5, in order to terminate the sifting process it is commonly used a criterion which is the sum of difference (SD):

$$SD = \sum_{t=0}^{T} \frac{| d_{k-1}(t) - d_k(t) |^2}{d_{k-1}^2(t)} \tag{3}$$

When the SD is smaller than a threshold, the first IMF is obtained and this procedure iterates till all the IMFs are obtained. In this case, the residue is either a constant, or a monotonic slope or a function with only one extremum.

In [14] the sifting process ends (verification whether c_i is an IMF) if the range of m(t) is a very low fraction of that of c_i (< 0,001). Additionally, after all the IMF extractions it is checked if the range of the residue is low with respect to that of the original signal and it is proposed a 10% threshold.

The application of the EMD method results in the production of N IMFs and a residue signal. The first IMFs extracted are the lower order IMFs which captures the fast oscillation modes while the last IMFs produced are the higher order IMFs which represent the slow oscillation modes. The residue reveals the general trend of the time series.

This is summarized in the Fig.2 where EMD is applied in a fraction (length 3000 samples) of experimental ECG signal of total length equal to 16000 samples acquired. Total number of IMFs is 16.

2.1 EMD based Proposed Technique

The proposed technique in this paper, which is based on the Empirical Mode Decomposition, relies on the partial signal reconstruction by appropriate selection of those IMFs that contribute to the signal and exclusion of those IMFs that mainly contribute to the noise contamination of the signal.

Literature references indicate that frequency range of an electrocardiogram and specifically of the QRS complex is mainly at the range of 10Hz to 25Hz [17]. Broadening the frequency range, the proposed technique is consisted of two main criteria. The first criterion, after the spectral density computation of each IMF, sets the frequency limits and the second criterion searches within the frequency range of the first criterion, for significant power components within each IMF.

For a significant percentage of frequency components over the power threshold set by the second criterion, the index of the IMF is considered for partial signal reconstruction. Different power thresholds result in a slightly different set of IMFs and the same applies for different frequency range set by first criterion.

High Frequency denoising by the EMD based technique is carried out by partial signal reconstruction which is based on the fact that noise components are mainly observed at the first several IMFs. Furthermore, for high order IMFs frequency content and power are out of the frequency range and power amplitude set by the two criteria for the ECG signal.

The proposed technique is applied on filtered ECG experimental signals acquired by means of a wireless sensor network. It is also applied on unfiltered signals in order to validate the observation that the lower order IMF mainly contribute to the noise contamination.

The evaluation of the performance of the proposed technique is aided by the computation of certain metrics that will be presented in the chapter of the experimental procedure.

3. Experimental Procedure

Experimental electrocardiogram was acquired at 512 Hz sampling frequency by means of a wireless sensor network. The network consists of wireless nodes (Tmote Sky [15]) which sample the biosignal and transmit it through the network to the sink, the point where processing and analysis of the acquired data is taking place.

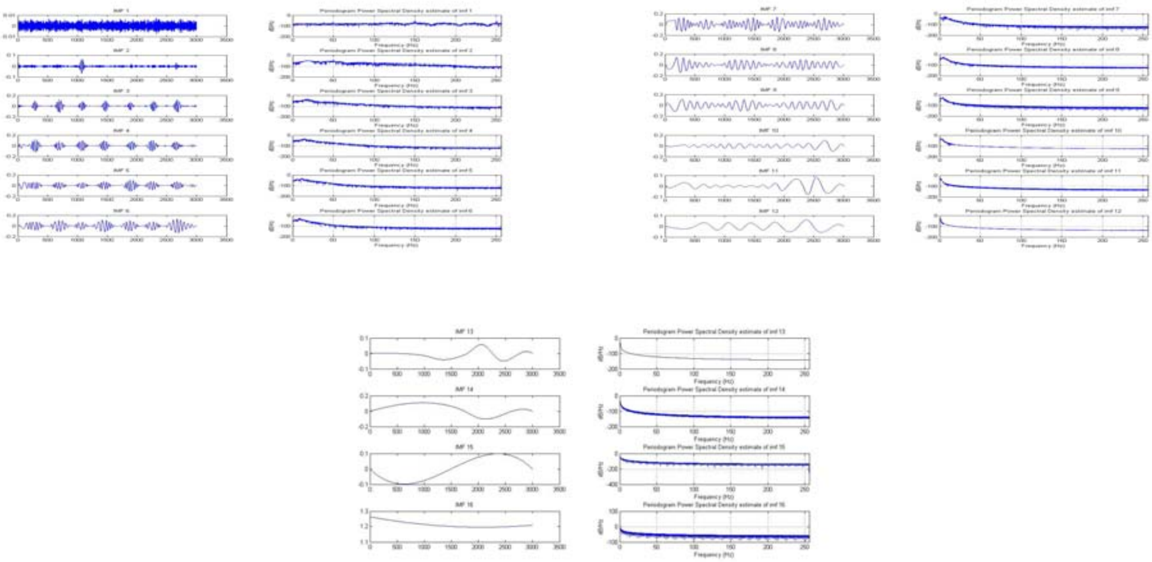


Fig. 2 Example of EMD method application at a 3000 samples experimental ECG signal. At the left side of each plot are the IMFs produced and at the right side their periodograms. Total number of IMFs is 16

The main purpose of the network is to sense, sample and relay the monitored biosignal to the processing unit. The key feature of this layer is the redundancy and the functionality.

Motes interfacing with sensors are part of the network collecting data for the network. The routing is flexible and it establishes automatically a communication link between a new member node, and the sink. Malfunctioning can cause topological changes and the reorganization of the network is required. Redundancy is achieved by multihop communication. In the case of failure of one node relaying information its functionality is overtaken by other nodes within the range of WSN.

Electrocardiogram was recorded using standard electrodes and during the experimental session the subject was comfortably sitting and breathing freely.

Some of the signals acquired were fractioned at signals of several beats, typically 3000 samples, in order to acquire figures demonstrating more details and produce smaller number of IMFs. In this paper, signals that were processed have a total length of 16000 samples.

3.1 Processing Procedure

Signals acquired by means of the wireless sensor network with length of 16000 samples approximately, are stored and classified as noisy signals and processed with the EMD based technique.

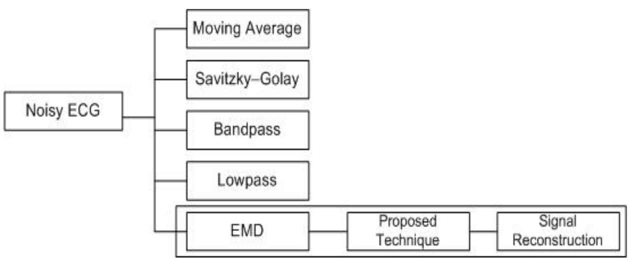
The evaluation of the performance of the whole procedure is accomplished by implementing certain metrics and it is compared to the results of the processing of the same signals with classic techniques.

Noisy signals processed by applying a moving average procedure of window length equal to 15 were obtained and named properly. This is fair trade off window length resulting from the trials of several window lengths and evaluating the performance as well as the distortion to the signal.

The application of Savitzky – Golay smoothing filter [16] reveals the main advantage of this approach that is to preserve features of the signal such as maxima, minima and width, which are usually flattened by other adjacent averaging techniques such as moving average.

Classic techniques are also implemented such as band-pass filtering with bandwidth appropriate for an ECG signal and selected characteristics not to distort or deform the signal.

Finally three low-pass filters were also implemented with different cutoff frequencies. The techniques applied in ECG signals along with the proposed technique are summarized in Img. 1.



Img. 1 Techniques implemented for the evaluation of the proposed technique

Filtered signals with all the methods used to compare and evaluate the performance of EMD are depicted in Fig.3

The input of every processing technique is the signal s(t) which is a version of the electrocardiogram x(t) corrupted by artifacts noise n(t). The noisy signal s(t) = x(t) + n(t) is processed and the output of every processing stage is a filtered or reconstructed version of s(t) ($\hat{s}(t)$) which is a free of noise version of x(t). The n(t) is the representation signal of the noise added to the signal x(t) and for this case is real noise for the experimental electrocardiograms.

The quantitative evaluation is assessed by certain metrics:

Signal to Error Ration (SER):

$$SER = \frac{\sum_{n=0}^{N-1} s^2(t)}{\sum_{n=0}^{N-1}\left[s(t) - \hat{s}(t) \right]^2} \tag{4}$$

where s(t) is the real signal and $\hat{s}(t)$ is the reconstructed or filtered signal.

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{n=0}^{N-1} (s(t) - \hat{s}(t))^2}{N}} \tag{5}$$

Cross Correlation Coefficients:

$$\rho_{xy} = \frac{\sum_{n=0}^{N-1} (x_i - \bar{x})(y_i - \bar{y})}{(N-1)s_x s_y} \tag{6}$$

4. Results

The EMD based technique was applied in filtered signals and compared the results to those obtained by the application to unfiltered signals. Table 1 summarizes results.

Table 1 Total number of IMF after the EMD application on signals.

Signal	Number of IMFs	Spectral Characteristics
lowpass_filtered_filt1	27	45, 50
lowpass_filtered_filt2	26	40, 50
lowpass_filtered_filt3	24	35, 49
sgolay_filtered_noisy	28	-
moving_filtered_noisy	29	-
bandpass_filtered_noisy	25	1-45 (band pass zone)
noisy_ECG	28	-

Results from table 1 reveal that when signal is processed with a filter that may cause changes to the spectral density of data, this is represented in a reduction of IMF produced and subsequently in time computation and resource demands.

Other techniques also applied on the data that do not affect significantly the spectral characteristics produce processed signals that are insensitive to changes of IMF number production through the EMD processing.

Time computation data in Table 2 supports this observation. Time is calculated with the tic toc functionality in MATLAB for every EMD processing.

Table 2 Time computation of EMD processing on filtered signals

EMD processing Time	Time(sec)
lowpass_filtered_filt1	829,42
lowpass_filtered_filt2	629,37
lowpass_filtered_filt3	297,29
sgolay_filtered_noisy	535,68
moving_filtered_noisy	731,63
bandpass_filtered_noisy	574,50

For every signal either noisy original ECG signal or filtered-processed signal the EMD based technique is applied in order to export an index IMF set appropriate for partial signal reconstruction. The performance of the reconstruction process is evaluated by certain metrics that were presented in the processing procedure chapter of the paper.

Examples of the reconstruction process output are presented in Figure 4. The input in the procedure is the filtered-processed or unfiltered signal, in the case of reconstruction process of noisy ECG, and the output is an IMF set which is appropriate according to the frequency range conditions and power thresholds for the partial signal reconstruction. This is achieved by summing the IMFs selected in the set.

The correlation of the reconstructed signal with the original signal is significantly high especially for Savitzky-Golay and moving average processing as their good performance is well based in literature in peaky signals. Results are summarized in table 3.

Correlation achieved and SER for the reconstructed signal with the appropriate selection of IMFs after the EMD based technique application to noisy ECG experimental signal, is significantly high (table 3). This suggests that results after the reconstruction process of noisy signals reveal better performance for the technique in noisy signals rather than lowpass and bandpass filtered ECG signals.

This is due to the fact that lowpass and bandpass filtering distorts at a degree and reduce the power of the ECG signal in higher and lower frequencies. Reconstruction process actually is focused on a frequency range which is parameterized and in this range it considers the power of the frequency components. If these components have significantly reduced power and the IMF is consisted of them this IMF is excluded from the IMF index selection set.

Table 3 Metrics for the reconstruction process evaluation

Signal	Cross Corr	RMSE	SER
lowpass_filtered_filt1	0,844	0,107	5,36
lowpass_filtered_filt2	0,897	0,081	6,97
lowpass_filtered_filt3	0,879	0,086	6,24
sgolay_filtered_noisy	0,983	0,032	14,59
moving_filtered_noisy	0,989	0,021	16,08
bandpass_filtered_noisy	0,960	0,048	10,65
noisy_ECG	0,960	0,050	10,94
noisy_ECG (3000 samples)	0,989	0,023	14,80

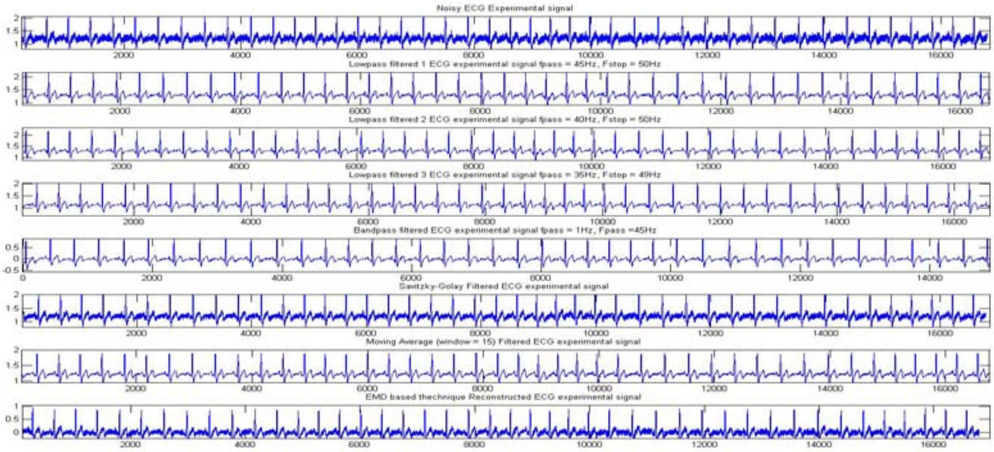


Fig. 3 Filtered ECG experimental signals. At the top plot is depicted the original unfiltered noisy signal and from the second plot to the eighth plot are depicted 3 lowpass filtered signals,1 bandpass filtered,1 Savitzky-Golay filtered, 1 moving average filtered signal and the Reconstructed signal produced by the EMD based tedhnique.

5. Discussion

In this paper it is presented an Empirical Mode Decomposition based technique that utilize double criteria in order to form an IMF set that are considered suitable for partial signal reconstruction.
The double criteria are based on frequency range of the biosignal, in this case experimental ECG signals, and power thresholds. Those IMFs with frequency components that satisfy both of the criteria and constitute a significant percent of the IMF spectral density are included in the IMF index set. The other IMFs are excluded.
Implementation of the described technique revealed that lower order IMFs mainly contribute to the partial signal reconstruction and higher order IMFs are generally excluded from the process.
Mode mixing problem sets difficulties in selecting the suitable IMFs since the mixing of frequencies in more IMFs may interfere with the reconstruction process and distort results. By considering the frequency range at every IMF as well as power threshold is a way to deal with this issue but a more robust and precise way such as Ensemble EMD has been proposed recently [13].
Decomposition of the signal demands a significant computational cost and resources. Results indicate that a preprocessing stage prior to the application of EMD as well as filtering may improve these costs by reducing the number of the produced IMFs without compromising the signal quality and quantity of information in the reconstruction process.
The implementation of the proposed technique in a sensor network node level is under investigation considering the findings summarized in this paper regarding the computational cost, resources as well as the performance of the technique.
There is an ongoing research on the application of the proposed technique on MIT-BIH records and primary data from the processing and the reconstruction process support the results and conclusions of the paper.
Research interest on Empirical Mode Decomposition is growing and literature proposes the use of the method on other fields of biomedical signal processing.

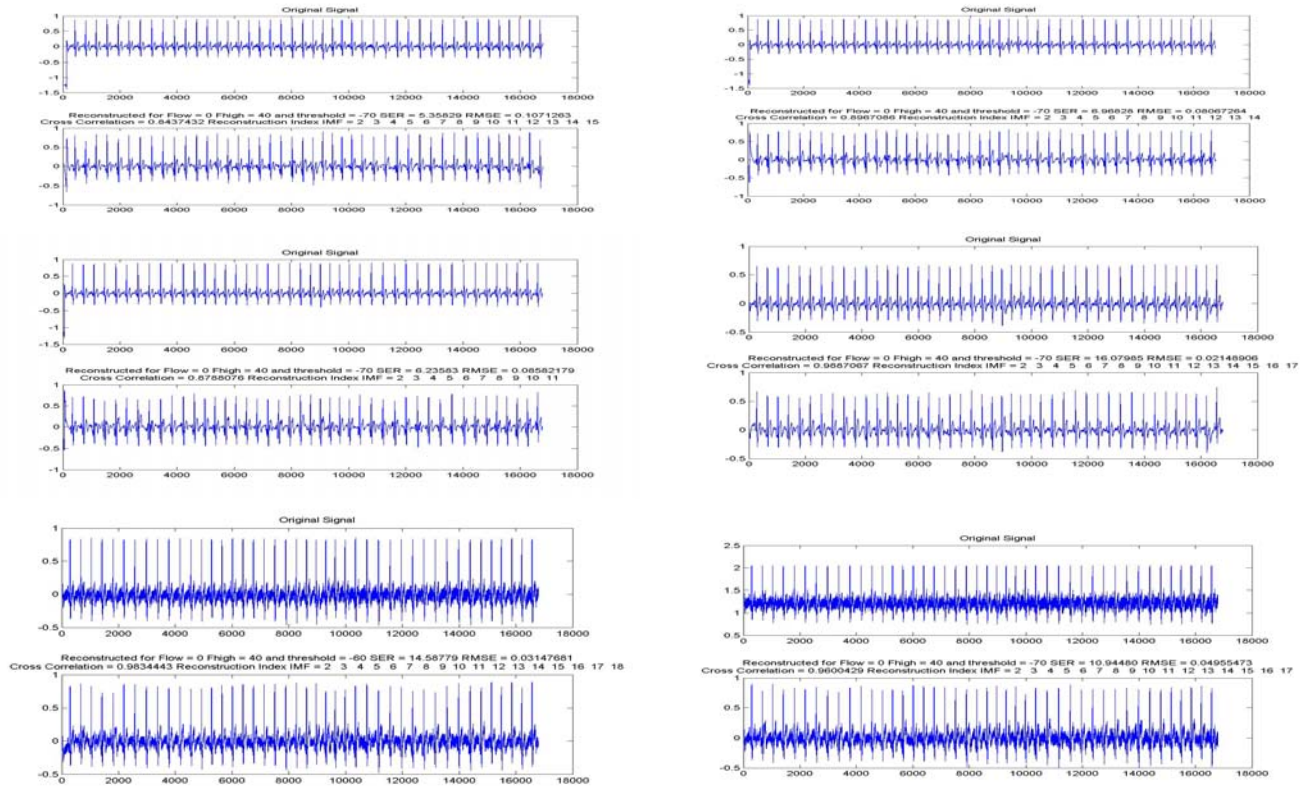


Fig. 4 Reconstruction process after the application of EMD based technique for ECG experimental signals. At the first line plots the left plot depicts the reconstruction of the lowpass ECG signal with filter1, the right plot the reconstruction of the lowpass ECG with filter2 and at the middle line plots the left depicts the reconstruction of the lowpass filter3 ECG signal and the right plot the reconstruction of the moving averaged ECG signal. At the lower plots the left depicts the reconstruction process of an Savitzky-Golay processed ECG experimental signal and the right plot the reconstruction process of the noisy unfiltered signal.

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