Journal of Engineering Science and Technology
Vol. 15, No. 1 (2020) 636 - 654
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A HYBRID IMPROVEMENT APPROACH FOR ECG SIGNAL ENHANCEMENT

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Abstract

The electrocardiogram records the cardiovascular action, is widely utilized for diagnosing heart diseases. Thus, the ECG turned into a normal piece of any complete medical evaluation. Moreover, the ECG became a basic device that allows observing a patient who is at home. R-peak is the basis peak for reliable health condition observing. The ECG has been treated as one of the least difficult techniques for automatic detection of the QRS complex. Nevertheless, the ECG signal transmission is often accompanied by noise due to poor channel conditions. This paper aims to remove the noise from the ECG signal to present a signal that makes a visual interpretation easier. Numerous techniques launched to improve the ECG signal. Accordingly, we address the ECG signal through three techniques: Empirical Mode Decomposition, Ensemble Empirical Mode Decomposition, and Complementary Ensemble Empirical Mode Decomposition. Moreover, we will make some improvements to the ECG signal using the Butterworth filter and Wavelet filter. Finally, this research provides a comparison of the result obtained from all models based on four different types of classification algorithms: K-Nearest Neighbors, Support Vector Machine, Naive Bayes, and Random Forest. Consequently, we are investigating various tests to evaluate the performance of the proposed approach to discover the best steps to address the ECG signals.

Keywords: Butterworth filter, CEEMD, EEMD, EMD, Wavelet filter.

1. Introduction

The ECG signal is the process of recording the electrical activity that results from a heartbeat within a certain time frame. The ECG device uses to document information about the heart structure that emerges from the heart muscle depolarization with every heartbeat. This device consists of electrodes placed in different places on the patient's body skin. The ECG signal uses broadly for detection of heart illness, which is characterized as six peaks and valleys. Peaks and valleys are usually labelled with *P*, *Q*, *R*, *S*, *T*, and *U* symbols as shown in Fig. 1.

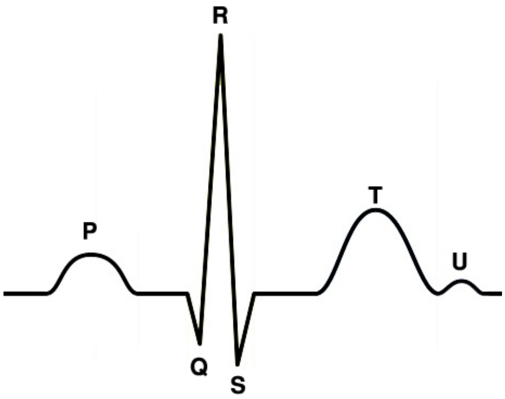


Fig. 1. ECG signal.

The ECG signal is a non-stationary bio-electrical signal, which including valuable clinical information. Ordinarily, clinical information reveals about measure rate and rhythm of heartbeats, size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, effects of cardiac drugs, and function of an implanted pacemaker [1]. It is necessary to carefully examine the ECG signal by specialized cardiologists to diagnose life-threatening arrhythmias. Moreover, the automatic classification of cardiac disorders through computerized analysis can provide objective diagnostic results and would save both time and effort to cardiologists. Nevertheless, these pieces of information exposed to damage by several types of noise, which cause a wandering baseline. Consequently, the wandering baseline causes repetition of an improper pattern on the screen. This wandering baseline occurs due to electrode malfunction such as bad electrodes, improper electrode site preparation, patient movement, electromagnetic interference from other electronic devices, and noise coupled from other electronic devices, which is usually high frequencies [2].

The ECG signals will contain noise-changing waveforms that making the clinical observation inaccurate and misleading. Accordingly, we need to utilize denoising algorithms for obtaining a clear ECG signal, which ought to improve the signal-to-noise ratio. Consequently, it is recommended to use the processing algorithms to improve the quality of the ECG signal. There are many methods of ECG denoising for both linear and nonlinear systems such as advanced averaging, median filter, adaptive filtering, Fourier transforms, and wavelet transform.

The ECG denoising methods have some downsides. Because it not only eliminates noise but also removes the high-frequency components of the non-stationary signal that are crucial in the waveform detection [3]. Accordingly, the best method should produce a clear and readily observable signal with preserving original characteristic waveform without distorting. The EMD was recently introduced as a technique for processing the non-linear and non-stationary signal. Also, The EMD serves as an alternative to those methods [4].

This research describes the effective computational methods for analysis, enhance, and as well as provide a clear ECG signal. The Information sources consist of two sets of ECG signal data: training dataset and testing dataset. The ECG signal data sets are downloaded from databases, which available on the website (www.physionet.org). Ordinarily, these data sets include valuable information about the ECG signal, which used for further processing by using workspace in Matlab. The second section briefly reviews the literature reviews related to learning-based methods for ECG detecting arrhythmias.

The third section focuses on the methodology and explains the proposed methods in detail. The EMD, EEMD, and CEEMD methods will apply to the whole recordings of the ECG signal. Accordingly, we explain how can we obtain correspondence Intrinsic Mode Functions (IMFs)? In order to have a clear ECG signal, and how the IMFs are pooling again without the residual signal. Moreover, we discuss the effectiveness of the Butterworth filter and Wavelet filter on pre-processed signals in the proposed methods. Addition to, we review the classification algorithms, which use for comparison.

The fourth section highlights and examines the experimental results by comparing the data sets based on four different types of classification algorithms. The classification algorithms reported in this review, are a strong asset to discover the best steps to address the ECG signal. Finally, this research outlines the challenges of ECG signal analysis and provides a critical assessment of the presented methods.

2. Literature Reviews

Various studies have been presented by researchers for the purpose of studying and classification the ECG signals. These studies are revolving around pre-processing techniques, various feature extraction techniques, filtering techniques, and classifiers.

Suchetha et al. [5] presented a comparative analysis study of EMD-based filtering methods. They proposed three different denoising methods: EMD based partial reconstruction, EMD based adaptive filtering technique, and EMD based adaptive filtering by extracting the interference. These novel techniques aim to noise cancellation in the ECG signal under frequency (48-51) Hz according to varying noise amplitudes. Moreover, these techniques clearly summarize the enlargement of the EMD method, which follow the property of signal dependency and are adaptive. Consequently, this study showed enhanced performance in order to reduce wavelet noise. This enhanced performance is often coupled by two conditions: a) the Signal-to-Noise Ratio (SNR) is low; b) there is no restriction that signal magnitude should be higher than the noisy signal.

El Bouny et al. [6] proposed a novel method for ECG signal enhancement. This method based on Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Higher-Order Statistics (HOS) with a Hybrid Interval Thresholding (HIT) function. Consequently, the ECG signal decomposes into a set of IMF components using the EMD method. The IMFs obtained are subdivided into three groups: Higher Frequency Noisy (HFN) IMFs, Lower Frequency Noisy (LFN) IMFs and Noiseless Relevants (NR) IMFs. These groups classify on the basis of the Fourth Order Cumulant (FOC), which is a novel criterion derived from the HOS. Thus, the ECG signal is reconstructed by combining the thresholded IMFs and the retained unprocessed lower frequency relevant IMFs.

Kabir and Shahnaz [7] proposed a novel ECG denoising approach based on EMD algorithms and Discrete Wavelet Transform (DWT) domains. They proposed a perform windowing in the domain of EMD to reduce the noise generated by the initial IMFs instead of completely eliminating it's. Moreover, the ECG signal obtained is transformed in the DWT domain using adaptive soft thresholding to reduce the noise. Consequently, the ECG signal is reconstructed at a better time resolution in view of useful properties of the DWT compared to the EMD method in energy conservation with the presence of noise. Thus, this study aims to maintain the QRS complex to give a relatively cleaner ECG signal.

Chang and Liu [8] used the EEMD method to improve the noise filtering performance based on the mode-mixing reduction between near IMFs scales. Moreover, they presented a study to develop an ECG filtering approach based on the low IMF scales that contain high-frequency parts and conversely. Notwithstanding, the low-pass filter performance with EMD and EEMD method, is highlighted in this study. Nevertheless, the Wiener filter, which uses to compare the filtering performance with EEMD, is another noise filtering approach used in this study. In this paper, we proposed a hybrid improvement approach for the ECG signal enhancement. In this approach, the ECG signal will pass through several phases of noise reduction and optimization to obtain an enhanced ECG signal as shown in Fig. 2.

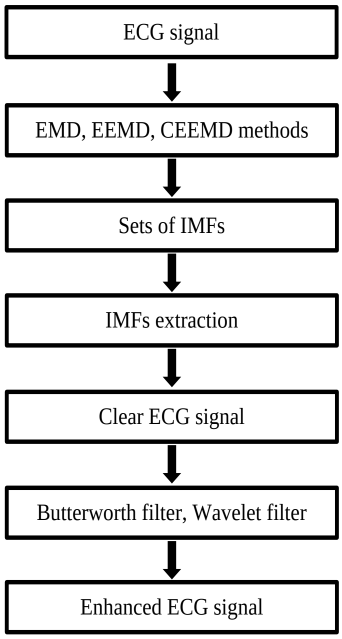


Fig. 2. General schematic of ECG signal enhancement.

3. Methodology

3.1. ECG denoising techniques

During the acquisition of the ECG signal, it may get corrupted by different types of noises, as we explained before. Thus, there are various denoising methods used to remove the noise, which presents in the ECG signal. Some of these methods we will use and discuss in this paper are EMD, EEMD and CEEMD.

3.1.1. Empirical mode decomposition

Huang et al. [9] introduced the EMD, in which, is a method to analyse the non-linear and non-stationary signal. The EMD is a technique of high-frequency denoising that happens due to a wandering baseline pattern. It breaks down the signal into several components of IMF as shown in Fig. 3. Subsequently, The IMFs is prepared for partial signal reconstruction. The IMF components should satisfy the two following conditions [10-12]:

- The number of extrema and zero crossings must be equal to each other or at least one uneven, in the whole data set.
- The mean value of the local maxima and local minima of the envelope is constantly zero, at any point.

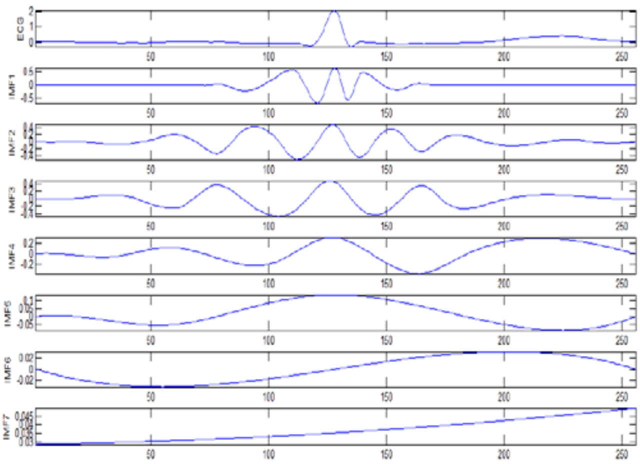


Fig. 3. Decomposition the ECG signal into a set of IMF components.

The sifting process is the systematic algorithm adapted for decomposing the ECG signal into a set of IMF components. The sifting process is described in the following sequential steps:

- Transfer the original signal $X(t)$ to $H(t)$.
- Identify all the maxima and minima points of signal $H(t)$. The maxima and minima points are called the local extrema points.
- Connect all the local extrema points by a cubic spline curve to obtain the upper and lower envelopes $e_{Max}(t)$ and $e_{Min}(t)$.
- Calculate the mean value between the upper and lower envelopes.

$$M1(t) = [e_{Max}(t) + e_{Min}(t)]/2 \quad (1)$$

- Subtract the mean value from the H(t) signal to compute the first component.

$$H2(t) = H1(t) - M1(t) \quad (2)$$

- Repeat the steps 2 to 5 to get the $H_K(t)$ signals that satisfy IMFs conditions. The stopping criterion for producing an IMF is calculating the Standard Deviation. The SD is defined as:

$$SD = \sum_{t=0}^{T} \frac{|h_{k-1}(t) - h_k(t)|^2}{h_{k-1}^2(t)} \quad (3)$$

- Subtract the extracted IMFs from the signal. Iterate all steps until extract all IMFs with consideration of the remaining signal as the original signal.

$$R1(t) = X(t) - IMF1(t) \quad (4)$$

- The sifting process finally terminates when the residue Rn becomes either constant, monotonic slope or function with only one local extrema. The original signal is calculated as:

$$X(t) = \sum_{j=1}^{n} IMF_j(t) + R_n(t) \quad (5)$$

3.1.2. Ensemble empirical mode decomposition

The EEMD is a remarkable improvement of the EMD method. Wu and Huang have proposed the EEMD method [13] following a study of the statistical characteristics of white noise [14]. The EEMD is considered a new approach to the sifting process, which addresses the mode mixing problem of the conventional EMD method [13]. The sifting process of the two methods: EMD and EEMD, is operating very similarly. Nevertheless, the new sifting process relies on the addition of white noise with finite amplitude to process the signal repeatedly before applying the EMD algorithm. Accordingly, the white noise added in each experiment will resolve the mode mixing problem. Moreover, this process provides a uniform statistical characteristic frame in the time-frequency domain. The EEMD method can be portrayed as:

- Add white noise to the targeted signal.

$$X_i(t) = X(t) + W_i(t), \ i=1, 2 \ldots N \quad (6)$$

- Apply the EMD method for decomposing the signal with the addition of different white noise each time into the IMFs and residue.

$$X_i(t) = \sum_{j=1}^{n} IMF_{ij}(t) + R_{in}(t), \ i=1, 2 \ldots N \quad (7)$$

- Each IMF fund obtained by decomposing the targeted signal can be represented as follows:

$$IMF_j(t) = \frac{1}{N} \sum_{i=1}^{N} IMF_{ij}(t) \quad (8)$$

- The original signal can be calculated as:

$$X(t) = \frac{1}{N} \sum_{j=1}^{n} \sum_{i=1}^{N} IMF_{ij}(t) + \frac{1}{N} \sum_{i=1}^{N} R_{in}(t) \quad (9)$$

3.1.3. Complementary ensemble empirical mode decomposition

The CEEMD method has enhanced and raised the EEMD method efficiency [15]. The CEEMD method eliminates the white noise residual, which is added to the IMFs in the EEMD method. Accordingly, this new approach adds the white noise twice to the original signal: once negatively and once positively. The final IMFs are the ensemble of both the IMFs with positive and negative noise after processing by the EEMD method [16]. The three steps of the CEEMD method can be portrayed as:

- Add white noise to the original signal.

$$\begin{bmatrix} X_i^+(t) \\ X_i^-(t) \end{bmatrix} = \begin{bmatrix} X(t) + W_i(t) \\ X(t) - W_i(t) \end{bmatrix},\ i=1,\ 2 \ldots N \tag{10}$$

- Apply EEMD method.
- The original signal can be calculated as:

$$X(t) = \frac{1}{2N} \sum_{j=1}^{n} \sum_{i=1}^{N} \left(IMF^{+}{}_{ij}(t) + IMF^{-}{}_{ij}(t)\right) + \frac{1}{2N} \sum_{i=1}^{N} \left(R^{+}{}_{in}(t) + R^{-}{}_{in}(t)\right) \tag{11}$$

3.2. ECG enhancement techniques

Many techniques have been discussed in the field of noise removal from the ECG signal. This paper discusses and provides a comparative analysis of the performance of two types of filters: Butterworth filter and Wavelet filter. Filtration techniques are used primarily in signal processing and are implemented in various ECG signal analysis systems. However, in this research, filtration techniques are used to enhance the ECG signals, which are processed and implemented by EMD, EEMD and CEEMD methods. Notwithstanding, we used three methods to remove the noise present in the ECG signals. However, some intrinsic noise remains agglutinant in the ECG signals could not be removed by the proposed methods. Consequently, the ECG signals filtering is considered a contextual. It can be implemented when the desired information remains ambiguous and requires further processing. Moreover, the filtering process remains an important issue where data should be filtered or disposed-off.

3.2.1. Butterworth filter

Butterworth filter was first designed by Butterworth [17], which sensitivity is uniform in the pass region. Butterworth filter is an electronic filter, which is characterized by various filters: low pass filter, high pass filter, multistage filter, bandpass filter, and bandstop filter [17].

Butterworth filter has a monotonic frequency amplitude response and non-monotonic ripples in the bandpass filter or bandstop filter. Consequently, it will require higher orders to implement a particular specification in the band pass filter and bandstop filter.

We will be dealing with the low pass Butterworth filter, which is the best in the time domain and removes high-frequency noises [18-20]. Because the low pass filter completely eliminates the signal above the cut-off frequency and exactly passes the signal below the cut-off frequency [21]. In this paper, we will create a Matlab function to design a low pass Butterworth filter of any order. Here is the algorithm function call for a 2^{nd} order filter is illustrated in Fig. 4.

1: **input:** CSig = Clear ECG Signal
2: **input:** *n* = 2 // *n* is the filter order
3: **input:** *Wn* = 0.09 // *Wn* is the cut-off frequency
4: **input:** ftype = 'low' // ftype is the filter type
5: [*b*, *a*] = butter (*n*, *Wn*, ftype) // a, *b* is the transfer function coefficients
6: **output**: Enhanced ECG Signal=filter (*b*, *a*, CSig)

Fig. 4. Algorithm 1: Low pass Butterworth filter.

3.2.2. Wavelet filter

The wavelet transforms are a mathematical tool for decomposing a signal into a set of oscillatory waveforms to reveal many signal properties [22-24]. The earliest work in the wavelet transforms dates back to the 1980s by some researchers interested in the wavelet field. However, Daubechies [25] drew the attention of the largest applied mathematics communities in signal processing, statistics and numerical analysis. The wavelet transforms satisfy certain mathematical requirements and used to represent data that shows signal details and trends to study each component with a resolution matched to its scale. This representation characterized by reducing noise, compress data and perform many other operations.

The wavelet transforms similar to the Fourier transform [22-24]. Consequentially, the idea of wavelet transforms began with Joseph Fourier's theories of frequency analysis since the early 1800s. The main benefits of wavelet methods over traditional Fourier methods are measuring the utilization of localized basis functions and therefore, the faster computation speed. As with Fourier analysis, there are three basic steps to filtering signals using wavelets:

- Decompose the signal using the wavelet transforms.
- Filter the signal in the wavelet space using a threshold.
- Invert the filtered signal to reconstruct the original using the inverse wavelet transforms.

In signal processing, wavelets have been widely investigated for use to filtering the ECG signal, among numerous different applications [26-28]. We will be dealing with the soft thresholding Wavelet transforms. The soft thresholding is more suitable for reducing signal noise, especially with EMD, EEMD, and CEEMD methods, to contain wavelet coefficients on both signal and white noise used [29, 30]. Accordingly, Matlab function that designed to perform the Wavelet transforms is illustrated in Fig. 5.

1: **input:** CSig = Clear ECG Signal
2: **input:** opt = '*gbl*' // opt is the thresholding option
3: **input:** Wname= ' sym4' // Wname is the wavelet name
4: **input:** *N* = 4 // *N* is the level of wavelet decomposition
5: **input:** *thr* = 5.9 // *thr* is threshold to apply wavelet coefficients
6: **input:** *sorh* = 's' // sorh is the type of thresholding
7: **input:** keepapp = 1 // keepapp is threshold approximation setting
8: **output:** Enhanced ECG Signal = wdencmp (opt, CSig, Wname, *N*, *thr*, *sorh*, keepapp)

Fig. 5. Algorithm 2: Wavelet transforms.

3.3. Classifiers comparative study

Classification algorithms map input data to a specific category in which, ideas and objects are recognized, differentiated and understood [31]. It is noted, the classification plays a key role in computer programming [32] to draw some conclusions from input values provided for training. Moreover, classification is essential in the prediction, decision-making, inference, and in all types of environmental interaction. Here are the steps to build a classification model:

- Initialize the classifier to be used.
- Train the classifier using training data *X* and train label *y*.
- Prediction of target data by giving an unlabelled observation *X*, prediction (*X*) returns the expected label *y*.
- Evaluate the classifier model.

3.3.1. K-Nearest neighbors' algorithm

The K-NN algorithm is a simple non-parametric method used to pattern recognition based on classification and regression [33]. For both classification and regression, a useful method can be used to assign weights to neighbors' contributions, so that close neighbors contribute more on average than distant bridges. The K-NN classification is a type of instance-based learning [34]. Therefore, this type of classification is considered lazy learning, but effective if training data is large [35]. The reason is obvious because it simply stores examples of training data without creating a generic internal model.

The K-NN algorithm is the simplest types of classifications, which implemented in this paper. Classification is computed from a simple majority vote of the k nearest neighbours of each point as well as the distance metric applied [36]. There are many types of distance metric such as Cityblock, Chebychev, Cosine, Minkowski, and Euclidean distance. However, the common distance metric used to measure continuous variables is the Euclidean distance [36]. The Euclidean distance is the default setting used to calculate the nearest distance.

3.3.2. Support vector machine algorithm

The SVM algorithm is a classification and regression supervised learning model, which can be used to training rules from data. The SVM algorithm constructs depend on the concept of separating the training data set as points in different hyperplanes mapped to a very high-dimensional space [37]. The origin of the SVM algorithm dates back to the 1960s by inventors Vapnik and Lerner [38]. Then in the 1990s, there was a proposal from Boser et al. [39] to create nonlinear classifiers by applying the kernel trick on hyperplanes with a maximum-margin. Consequently, Cortes and Vapnik [37] proposed the current standard of the SVM algorithm in 1995.

The SVM algorithm refers to prior knowledge of decision planes that determine hyperplanes. Hyperplanes are decision boundaries that classify data points distinctly into a set of objects that have different class memberships. Moreover, the hyperplanes depend on the number of features to draw the multidimensional space. Data points that fall on either side of the hyperplane can be attributed to different classes. A better separation is achieved by the hyperplane with the largest distance to the nearest training data point for any class [40, 41].

3.3.3. Naive bayes algorithm

The NB algorithm is a simple and effective classifier in machine learning for constructing classifiers. The NB algorithm has been studied in the early 1960s [42]. It is a probabilistic classifier based on applying Bayes' theorem. Bayes' theorem assumes strong independence among the features to predict the class of the unknown data set. Accordingly, the NB classifier relies on the premise that the presence of a particular feature in a class is independent of the presence of any other feature.

In this study, we used two types of Naive Bayes model distribution: Gaussian distribution and Kernel distribution. Gaussian distribution is suitable for predictors in case the distribution in each class is normal. In this case, the NB classifier computes the mean and standard deviation of the training data in that class. Kernel distribution is appropriate for predictors that assume the features follow a continuous distribution. It is used in cases where the distribution of a predictor may be skewed or have multiple peaks or modes. In these cases, the NB classifier computes the smoothing density estimate for each class based on the training data in that class. It requires more computing time and memory than Gaussian distribution. Kernel distribution is applied in automatic medical diagnosis for predicting the possible disease [43].

3.3.4. Random forest algorithm

The RF algorithm is an ensemble learning classifier that fits a number of decision trees on various subsets of the training data set [44, 45]. Random decision forests correct for decision trees' habit of overfitting to their training data set [46]. The sub-sample size is always the same as the sample size of the original input, but samples are drawn with the replacement. An average RF algorithm is used to improve the predictive accuracy of the model and the output of the class that is, the classes' mode, or the mean prediction of individual trees [44, 45].

Ho [44] proposed the general method of random decision forests in 1995. His subsequent work concluded in the same vein [45] to other splitting methods that behave similarly. As long as, it forced randomly to be insensitive to some features dimensions. Nevertheless, the tree forests splitting with oblique hyperplanes can gain accuracy while growing without suffering from overtraining.

The RF algorithm inputs consist of a training data set and labels, and the outputs will be a set of a decision tree with an N tree. The surrogate splitting is used based on missing predictors, to assign a case that having a missing value for the variable, which uses a surrogate split for a node. Classification and Regression Tree (CART) algorithm uses the best surrogate split among those variables not missing in the case. The surrogate splitting ensures every case can be classified, whether the case has missing values or not.

4. Experimental Results

In this section, we discuss the experimental results to evaluate the proposed hybrid improvement approach for the ECG signal enhancement. The purpose of this research is discovering the best steps to address the ECG signals.

Therefore, we apply four commonly classification algorithms: K-Nearest Neighbors, Support Vector Machine, Naive Bayes, and Random Forest, to find out, which one gives the best result. The implementation of these algorithms will include all the samples in the data sets. Each algorithm follows a specific pattern to classify the ECG signals.

Experimental results depend on the comparison between the original signals and the enhanced outcomes of the three methods: EMD, EEMD, and CEEMD. Accordingly, Experimental results indicated that the proposed algorithms could effectively detect the enhanced ECG signal. Nevertheless, the performance measures will implement in comparison with some recent methods to confirm the proposed approach.

The EMD is a fully data-based approach, which has the property of adaptive and signal-dependency [9]. The EMD is able to break down the original signal into several components of IMF without necessitating any preselected basis function. Consequently, this method is quite suitable for processing non-linear and non-stationary signals, especially with respect to the restoration of the QRS complex. Moreover, we enhanced the ECG signals using the Butterworth filter and Wavelet filter to try to remove residual noise. Butterworth filters have a magnitude response that is maximally flat in the bandpass and monotonic overall.

Accordingly, Butterworth filters suitable for remove high-frequency noises. Wavelet filter characterized by reducing noise, compress data, and faster computation speed depending on the localized basis functions. Consequently, we use the Wavelet filter with soft thresholding for reducing signal noise.

As mentioned in this study, we use the MIT-BIH arrhythmia database for analysing and denoising of the ECG signals. MIT-BIH database is downloaded from PhysioBank databases, which is available on the website (www.physionet.org). The ECG signals subdivided into two data sets: training dataset and testing dataset. Each dataset consists of 1200 ECG sample distributed over 6 categories.

In Fig. 6, we reviewed some samples for the ECG signals. These samples were taken from the raw data for the ECG signals, as well as represent the ECG signals after were processed using EMD, EEMD, and CEEMD methods. Whatever the improvement in the ECG signals, it is difficult to quantify or to be seen by the human eye. On the contrary, we can see the marked improvement in the ECG signals, in Fig 7. In Fig. 7, we have mentioned the methods that have shown significant improvement on the ECG signals. The performance superiority of a hybrid approach that consists of EEMD method and Butterworth filter can be seen from Fig. 7.

Although, it is possible to see how the enhanced ECG signals are. However, it is necessary to carry out the classification in order to ascertain the accuracy of the proposed approach in improving the ECG signals. Automatic classification of the heartbeats is one of the most important steps towards the identification of pathology using ECG.

The correct choice of classification algorithm and features representing heartbeats is crucial for successful classification. Classification of the ECG signals plays an important role in diagnoses of heart diseases. An accurate ECG classification is a challenging problem.

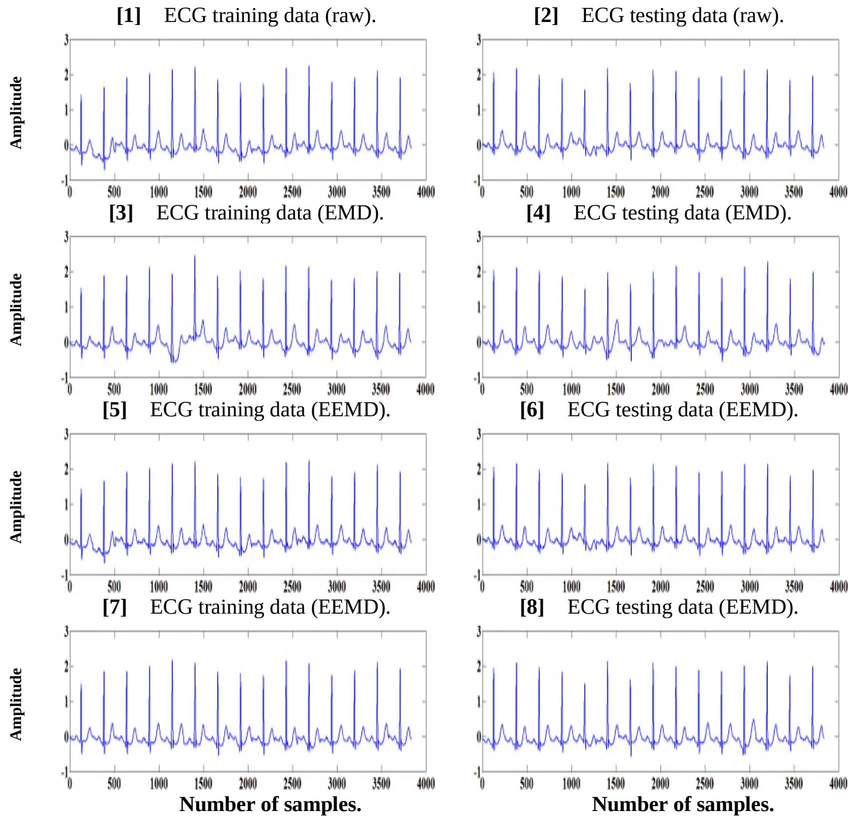
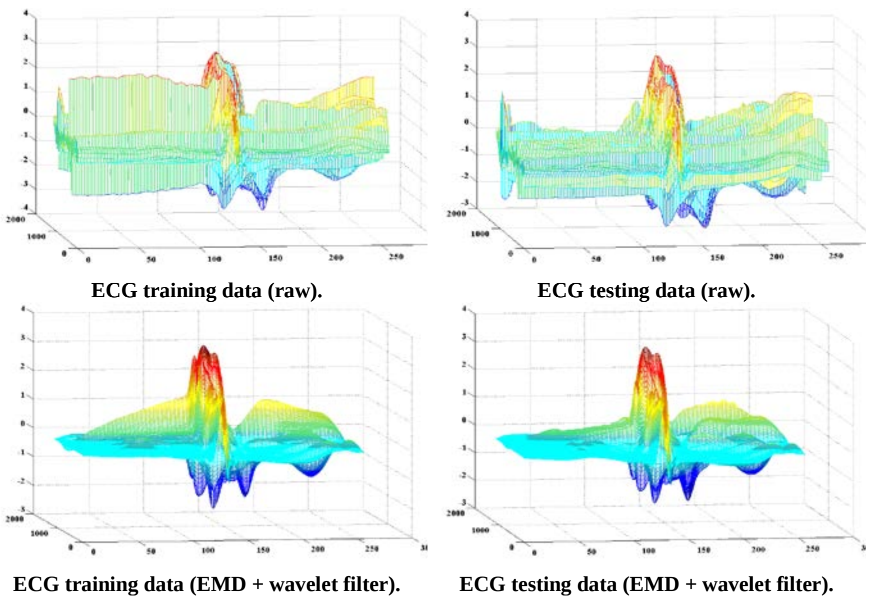
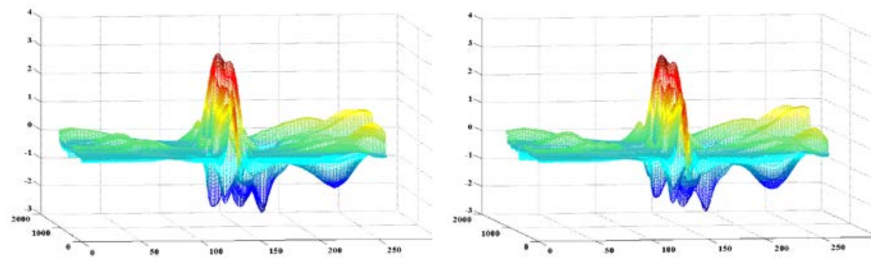
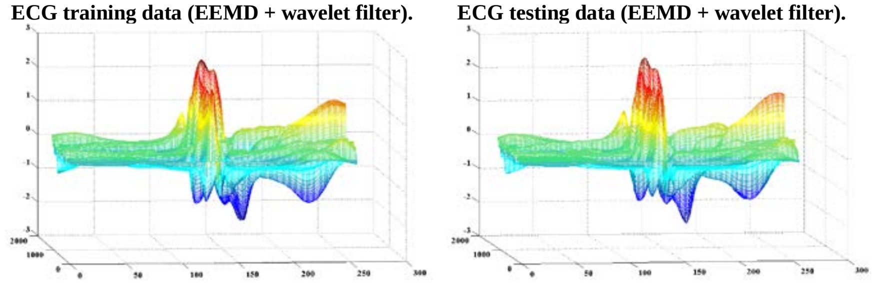


Fig. 6. Samples of ECG signals obtained after EMD, EEMD, and CEEMD methods.





ECG training data (EEMD + wavelet filter). **ECG testing data (EEMD + wavelet filter).**



ECG training data (CEEMD + butterworth filter). **ECG testing data (CEEMD + butterworth filter).**

Fig. 7. MATLAB Simulation for the enhanced ECG signals.

We used the default settings for the four different types of classification algorithms implemented in Table 1. As shown in Table 1, the EEMD and CEEMD algorithms showed an excellent response with the proposed filters. Consequently, we obtained a better degree of accuracy using a hybrid improvement approach that consists of EEMD method and wavelet filter through the following classifications: NB with Gaussian distribution, NB with Kernel distribution, SVM, and KNN. The accuracy up to 85.5%, 95%, 94.5%, and 99.7% with correction rate up to 28%, 16%, 5%, and 1.3% respectively. Moreover, a hybrid improvement approach that consists of EEMD method and Butterworth filter provides a better degree of accuracy through the following classifications: NB with Gaussian distribution, NB with Kernel distribution, and SVM. This accuracy up to 82.75%, 95.25%, and 92.75% with correction rate up to 24%, 17%, and 3% respectively.

In contrast, the CEEMD method results showed a good degree of accuracy when we used Butterworth filter through the following classifications: NB with Gaussian distribution, NB with Kernel distribution, and SVM. The accuracy up to 81.34%, 92.75%, and 95.25% with correction rate up to 22%, 14%, and 6% respectively. Moreover, a hybrid improvement approach that consists of CEEMD method and Wavelet filter provide a good degree of accuracy through the following classifications: NB with Gaussian distribution, NB with Kernel distribution, SVM, and KNN. This accuracy up to 80.67%, 92.34%, 93%, and 99.5% with correction rate up to 21%, 13%, 3% and 1.2% respectively. Although, the EMD method showed an improvement in the ECG signals, less than the two methods mentioned above. Accordingly, the results indicated that the EEMD and CEEMD are effective methods for the ECG signal enhancement with filters. Although many methods have been reported, their direct comparison is questionable due to their differences in types of heartbeats being classified, ECG features, variability in ECG waveforms of patients, and classification algorithms. Nevertheless, we compared the results of our approach with other research [47, 48] to validate it as shown in Fig. 8.

Table 1. Experimental results of ECG signal.

Original signal		**KNN classification with *K***				
		1	3	5	7	9
		98.333	98.333	98.333	98	97.833
		SVM classification				
		90.25				
		Naive Bayes classification				
		Gaussian			**Kernel**	
		66.84			81.59	
		Random forests classification				
		Without surrogate			**With surrogate**	
		94.4167			94.8333	
EMD		**KNN classification with *K***				
		1	3	5	7	9
	Without filter	96.833	95.916	94.916	94.583	94.25
	Butterworth filter	97.167	97.583	98.166	97.5	97
	Wavelet filter	**98.833**	**98.75**	**98.666**	**98.583**	**98.416**
		SVM classification				
	Without filter	88.6667				
	Butterworth filter	**90.9167**				
	Wavelet filter	**91.333**				
		Naive Bayes classification				
		Gaussian			**Kernel**	
	Without filter	63.42			72.92	
	Butterworth filter	**77.75**			**86.5**	
	Wavelet filter	**79.42**			**83.75**	
		Random Forests classification				
		Without surrogate			**With surrogate**	
	Without filter	93.5833			93.6667	
	Butterworth filter	85.3333			85.75	
	Wavelet filter	80.75			79.75	
EEMD		**KNN classification with *K***				
		1	3	5	7	9
	Without filter	**99**	**98.583**	**98.416**	**98.25**	**97.916**
	Butterworth filter	97.833	97.666	97.666	97.416	97.25
	Wavelet filter	**99.666**	**99.666**	**99.583**	**99.25**	**99.083**
		SVM classification				
	Without filter	89.4167				
	Butterworth filter	**92.75**				
	Wavelet filter	**94.4167**				
		Naive Bayes classification				
		Gaussian			**Kernel**	
	Without filter	**68.17**			**84.17**	
	Butterworth filter	**82.75**			**95.25**	
	Wavelet filter	**85.5**			**95**	
		Random Forests classification				
		Without surrogate			**With surrogate**	
	Without filter	**94.5833**			94.8333	
	Butterworth filter	92.0833			93	
	Wavelet filter	89.8333			90.1667	
CEEMD		**KNN classification with *K***				
		1	**3**	**5**	**7**	**9**
	Without filter	**99.166**	**99.083**	**98.916**	**98.916**	**98.833**
	Butterworth filter	98.166	98.083	98.166	97.916	97.833
	Wavelet filter	**99.5**	**99.5**	**99.333**	**99.083**	**98.833**
		SVM classification				
	Without filter	89.4167				
	Butterworth filter	**95.25**				
	Wavelet filter	**93**				
		Naive Bayes classification				
		Gaussian			**Kernel**	
	Without filter	**74.75**			**91.59**	
	Butterworth filter	**81.34**			**92.75**	
	Wavelet filter	**80.67**			**92.34**	
		Random Forests classification				
		Without surrogate			**With surrogate**	
	Without filter	**96.5**			**96.4167**	
	Butterworth filter	90			89.9167	
	Wavelet filter	91.0833			91.1667	

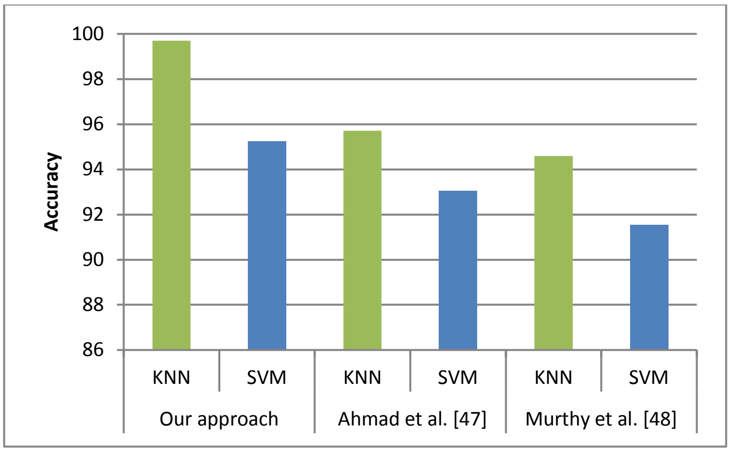


Fig. 8. Comparison of accuracy obtained from our approach with some researches.

5. Conclusions

In this paper, we improved the EMD methods using the Butterworth filter and Wavelet filter to enhance the ECG signal. Three methods are applied: EMD, EEMD, and CEEMD, all of it rely on the signal breakdown into various components called the IMFs.

The experimental results showed performance excellence using a hybrid improvement approach that consists of the EEMD method and Wavelet filter. This hybrid improvement approach, which classifies by Naive Bayes classification contributed to improving the ECG signals by up to 85.5%, and correction rate up to 28% based on Gaussian distribution. Although, we obtained the best improvement percentage of the ECG signals by combining the EEMD method with Wavelet filter by up to 99.7% using KNN classification, the correction rate up to 1.3%. Moreover, the EEMD method has proved superior in most classifications, when the ECG signals are filtered by a Wavelet filter. Nevertheless, the hybrid improvement approach that consists of the EEMD method and Butterworth filter achieved the second-best improvement by up to 82.75% and correction rate up to 24% using Gaussian distribution of NB classification. Also, the performance superiority of the CEEMD method without any filter in all classifications. Accordingly, the results proved that the enhanced ECG signal using Wavelet filter has a better balance between smoothness and accuracy than the Butterworth filter.

In addition, we aim to develop this work using different processing algorithms to improve the quality of the ECG signals. Also, we would like to conduct a broader study that includes other filtering techniques.

Nomenclatures

e_{Max}	Upper envelopes
e_{Min}	Lower envelopes
H	Transferred signal
M	Mean value

R	Remaining signal
t	Number of signals
W	White noise
X	Original signal

Abbreviations

CEEMD	Complementary Ensemble Empirical Mode Decomposition
DWT	Discrete Wavelet Transform
ECG	ElectroCardioGram
EEMD	Ensemble Empirical Mode Decomposition
EMD	Empirical Mode Decomposition
IMFs	Intrinsic Mode Functions
K-NN	K-Nearest Neighbors
NB	Naive Bayes
QRS	A pattern seen in ECG trace that refers to activity in heartbeats
RF	Random Forest
SD	Standard Deviation
SVM	Support Vector Machine

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