Arrhythmia Detection on ECG Signals by Using Empirical Mode Decomposition

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***Abstract* — One of the main causes of sudden deaths is heart disease. Early detection and treatment of cardiac arrhythmias prevent the problem from reaching sudden deaths. The purpose of this study is to develop an arrhythmia detection algorithm based on Empirical Mode Decomposition (EMD). This algorithm consists of four steps: Preprocessing, Empirical Mode Decomposition, feature extraction and classification. Six arrhythmia types were used for differentiate normal and arrhythmic signals obtained from the MIT-BIH Arrhythmia database. These are normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), paced beat and atrial premature beats (APB). Three different classifiers were used to classify ECG signals. The method achieves better result with accuracy of 87% using linear discriminant analysis (LDA) classifier for detection of normal and arrhythmic signals.**

Keywords* — *ECG Signal; Arrhythmia; Empirical Mode Decomposition; Feature Extraction; ECG Signal Classification

I. Introduction

Heart is a muscle that its working principle similar a pump which is constantly working. Electrocardiogram is an electrical activity of the heart that its represent the electrical movement during a heartbeat. Under the healthy conditions, heart rate for a person ranges from 60 to 100 beats a minute and a cardiac cycle take place 0.8 sec [1]. If the heart rate increases above 100 beats per minute, this is called tachycardia and if the heart rate decreases below 60 beats this is called bradycardia. Arrhythmia is any irregularity of the heart rate that cause an abnormality in your heart rhythm [2]. There are many different arrhythmia types according to their location, speed or rhythm in the heart. Early detection and treatment of cardiac arrhythmias prevents the problem from reaching sudden deaths. There are many scientific studies using engineering methods and medical devices for the diagnosis of cardiac arrhythmias. Some examples are time-domain analysis [3], sequential hypothesis testing algorithm [4], artificial neural networks [5, 6], time-frequency analysis [7], multiway sequential hypothesis testing [8], wavelet analysis [9], multifractal analysis [10], wavelet analysis combined with radial basis function neural networks [11] and non-linear dynamical modelling [12].

In 1998, Huang et al. [13] proposed a new signal analysis technique called the empirical mode decomposition (EMD) that decomposes an ECG signal into levels of intrinsic mode functions (IMFs). This technique is useful for analyzing nonlinear and nonstationary time series signals such as ECG signal [14]. The principle of EMD is to separate a signal into several elements with higher to lower frequencies. The purpose of this study is develop an efficient arrhythmia detection algorithm based on EMD. ECG signals are non-stationary and non-linear signals that it can be easily analyze with using EMD [18].

II. Methods

The main purpose of this study is develop an efficient arrhythmia detection algorithm based on EMD. Proposed algorithm consists of four steps: Preprocessing, EMD, feature extraction and classification. In preprocessing step, ECG signals were filtered for removing contaminants. Filtered signals were decomposed into IMFs using EMD. Power spectral density (PS) and variances of PS were extracted from the signals in feature extraction step. These steps were applied IMFs of the signals from IMF 1 to IMF 7. Features of original signal, IMF 1 and IMF 2 of the signal were selected after all IMFs were tested for accurate classification. Finally, classification was applied for differentiate normal and arrhythmic signals.

27 records were selected from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database [15]. Each record contain two-channel ECG signals and each ECG signal duration is 30-min. These channels are the modified limb lead II (MLII) and one of the modified leads V1, V2 or V5. The frequency of the each ECG data is 360 Hz and band pass filtered at 0.1–100 Hz. The sampling rate is 360 samples per second with a reading made over a 10 mV range. Because of the mismatch in the position of the second channel, MLII lead recordings were used [16]. Six arrhythmia types were classified: Normal, PVC, APB, LBBB, RBBB and paced beats. Due to duration of each record is 30-min, 6 different parts were taken from the record with each part include 20 sec. Method of study was applied all parts of the signal and the signals were classified according to their arrhythmia type.

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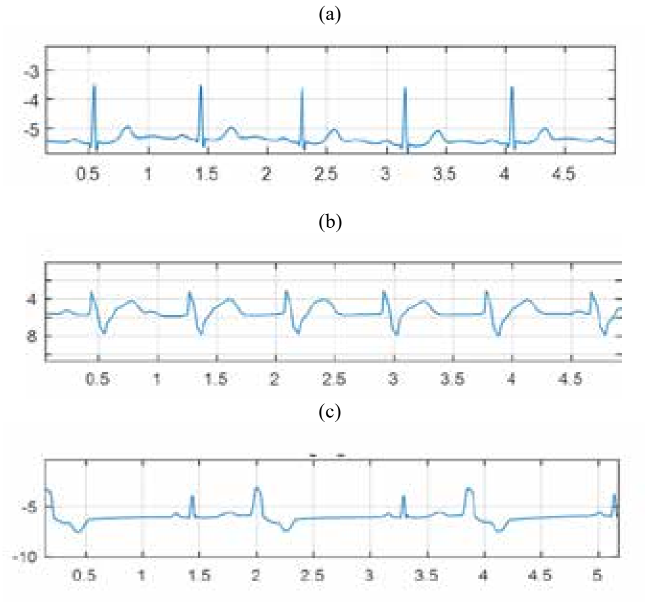

Fig. 1. (a) Normal ECG rhythm (103 of MIT-BIH database); (b) ECG rhythm of Paced beats (107 of MIT-BIH database); (c) ECG rhythm of PVC (119 of MIT-BIH database)

A. *Preprocessing*

Baseline wandering and power line interference are most affected on the ECG signal that they can effect ECG signal analysis when extract useful information. These noise types may disrupt the ECG signal and make the feature extraction and classification steps less accurate. Baseline wandering frequency is generally bellows 0.5 Hz. Power line interference frequency is generally 60 or 50 Hz [17]. In this study, 10th order Butterworth low pass filter with 53 Hz cut-off frequency and 3rd order Butterworth high pass filter with 0.75 Hz cut-off frequency were used for removing contaminants from the ECG signals.

B. *Empirical Mode Decomposition*

EMD is a method that decompose a signal without leaving the time domain. EMD has different property from Fourier transform or wavelet transform because the basic functions of EMD is directly derived from the original signal. It is decomposition of any complex signal into several IMFs which are elementary AM-FM-type components as shown in Fig. 2. When the signal is decomposed, the IMFs are created by an iterative procedure called a sifting process. A sifting process is called an IMF if two conditions are provided [19]:

1) In the signal, the number of local extrema and that of zero crossings must be equal to each other or different by at most one.

2) The mean value of the envelope defined by the local maxima and local minima is zero at any time point.

When the decomposition occur, original signal is separated IMF and residual. This procedure is represented as in (1).

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

where $c_i(t)$ is the number of IMFs and $r(t)$ is the final residual. The result of the EMD produces IMFs and a residue signal. The number of IMFs can't be determined and it depends on the volume of the oscillatory activity. The steps of the EMD process are represented as [20]:

1) Find the local maxima and local minima of original signal x(t).

2) Generate the upper and lower envelope by a cubic spline interpolation of the extrema points.

3) Calculate the average of the upper and lower envelope,

$$m(t) = [e_{min}(t) + e_{\max}(t)]/2\,. \qquad (2)$$

4) Subtract this average from the original signal,

$$h(t) = x(t) - m(t). \qquad (3)$$

5) Check if the result $h(t)$ is an IMF. If $h(t)$ does not satisfy IMF properties, repeat the procedure. If $h(t)$ has IMF properties, then IMF1 is formed as $c_1(t)$.

6) Subtract IMF1 from the original signal *x(t)* to find residual,

$$r_1(t) = x(t) - c_1(t). \qquad (4)$$

Then repeat the procedure by replacing IMF1 instead of $x(t)$ to obtain IMF 2. This procedure is repeated to create other IMFs until the final residue signal is a monotonic function.

The EMD decomposes signals into narrow-band components with decreasing frequency. Therefore first IMFs carry high frequency components of the original signal $x(t)$ and as the order of IMFs increases, their frequency decreases [21]. In this study, EMD was used for arrhythmia detection to extract the high-frequency components and to keep the useful information of ECG signal.

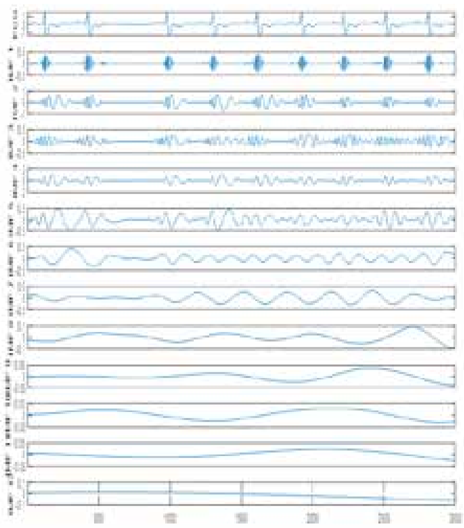

Fig. 2. Example of decomposing ECG signal into IMFs by using EMD (118 of MIT-BIH database)

C. *Feature Extraction*

Feature extraction is a process of obtaining the information which is required to correctly describe a large set of data. If extracted features are enough for detection, classification process can easily classify the data. In our study, after EMD process is applied, two features were extracted from the signal and its IMFs. These are Power Spectrum (PS) and variance of PS. PS is used because it detects unexpected changes in the frequency content [22]. Variance is used because it gives the information about how much the spectrum spreads from the mean frequency [23].

PS is the signal power distribution over the frequency. In our study periodogram estimation of the PS is achieved by using the Fast Fourier Transform (FFT) [22]. PS periodogram estimate gives us the frequency spectral content of the input signal which is utilized for the detection of unexpected changes such as irregular beats in the frequency spectrum. Hence, PS gives the information about at which frequency ranges are dominant and that useful for further analysis. Variance gives an idea about the spread of the spectrum around the mean frequency. It calculates the power of fluctuations which represents how far the signal fluctuates from the mean [23].

D. *Classification*

The purpose of classification is to accurately estimate the target class for each case in the data. Scientists use different machine learning algorithms to exactly predict the target class. These algorithms can be classified into two groups based on the applying learn algorithm for make predictions: supervised and unsupervised learning. Supervised learning is a process that based on possible outputs are previously known and that the data used to train the algorithm is labeled with correct answers. The training data include a set of training examples. Unsupervised learning is a process that trying to find hidden information in unlabeled data [24]. There are different classification techniques for ECG arrhythmia classification. In this study SVM, Naive Bayesian and LDA classification techniques were used for differentiate normal and arrhythmic signals. These techniques include supervised learning algorithm that estimate set of function from labeled training data. Before classification was applied, efficient features were extracted from original signal, IMF1, IMF2 and feature vector was created.

III. RESULTS

Three parameters were used to compare classification results: accuracy, sensitivity and specificity. Sensitivity is representing how well the test predicts which signals have a given arrhythmia. Specificity is representing how well the test predicts which signals do not have a given arrhythmia. Accuracy is how well the test classified arrhythmia types through all arrhythmias [21]. These parameters are calculated as in (5), (6) and (7).

$$ACC = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$SEN = \frac{TP}{TP+FP} \tag{6}$$

$$SPE = \frac{TN}{TN+FP} \tag{7}$$

Where TP is true positive, TN is true negative, FP is false positive and FN is false negative. Classification performance of LDA classifier is shown in Table I.

TABLE I. Classification performance of LDA

LDA							
	FN	FP	TN	TP	ACC	SEN	SPE
NORMAL	6	6	120	30	0,92	0,83	0,95
LBBB	4	26	112	20	0,81	0,83	0,81
RBBB	10	11	127	14	0,87	0,58	0,92
PACED BEAT	18	0	138	6	0,88	0,25	1
PVC	16	12	114	20	0,82	0,55	0,9
APB	6	5	139	12	0,92	0,66	0,96

TABLE II. Average of performance measures

	N-BAYESIAN	LDA	SVM
Average of accuracy	0.85	0.87	0.85
Average of sensitivity	0.59	0.60	0.54
Average of specificity	0.92	0.92	0.91

Features were extracted from IMF1 to IMF7, but used only IMF1 and IMF because of frequency is decrease when the number of IMF increase. Due to decreasing frequency, the quality of the features is also decrease. ECG signals were classified into six different part according to their arrhythmia type. Average of accuracy, sensitivity and specificity are presented in Table II. As shown in Table II, LDA algorithm provides better result than SVM and Naive Bayesian algorithms. Accuracy of normal signal classification is 92% and accuracy of LBBB signal classification is 81% with using LDA as shown Table I.

IV. CONCLUSIONS

This study provides an algorithm for accurate detection of normal and arrhythmic ECG signals. In the classification step, SVM, LDA and N-Bayes algorithms were used to classify the extracted features. The algorithm predicted similar results to differentiate normal and arrhythmic signals. Their results demonstrate that the normal signal classification is more successful than the arrhythmic signal classification. Among the arrhythmic signals, LBBB arrhythmia type was more dominant than the others. Because of this, most arrhythmic signals were classified as LBBB signals. LDA provided better results than SVM and N-Bayes while comparing average of performance measures. The detection performance on the MIT-BIH arrhythmia database obtained by our study and others published methods are presented in Table III. Advantage of EMD approach as compared to other methods is that signals are processed in the time domain and thus it is easier to evaluate the analysis. EMD removes the high-frequency components and keeps the useful information of ECG signals to extract efficient features [21]. This study is based on appropriate choice of IMFs for accurate detection of normal and arrhythmic ECG signals. The proposed method might be improved by increasing tested ECG recordings or selecting different features.

TABLE III. Performance comparison of previously arrhythmia detection algorithms

Literature	Features	Classifier	Accuracy
F. A. Elhaj [25]	linear and non-linear	Neural Network	98.91
S. Shadmand [26]	Hermit function coefficient and temporal	BBNN	97
Chazal and Reilly [27]	Morpholog+heart beat interval	LDA	85.9
Kamath [28]	Teager energy function features	Neural Network	95
Proposed Method	EMD	LDA	87

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