Short Communication

Model-based parameter estimation applied on electrocardiogram signal

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An Electrocardiogram (ECG) feature extraction system was developed based on the calculation of the poles employing Pade's approximation techniques. Pade's approximation was applied on five different classes of ECG signals' arrhythmia. Each signal was represented as a rational function of two polynomials of unknown coefficients. Poles were calculated for this rational function for each ECG signals' arrhythmia and were evaluated for a large number of signal windows for each arrhythmia. The ECG signals of lead II (ML II) were taken from MIT-BIH database for five different types. These were the ventricular couplet, ventricular tachycardia, ventricular bigeminy, and ventricular fibrillation and the normal. ECG signal was divided into multiple windows, where the poles were calculated for each window, and was compared with the poles computed from the different arrhythmias. This novel method can be extended to any number of arrhythmias. Different classification techniques were tried using neural networks, K nearest neighbor, linear discriminate analysis and multi-class support vector machine.

Key words: Arrhythmias analysis, electrocardiogram, feature extraction, statistical classifiers.

INTRODUCTION

Cardiovascular diseases are the main cause of death globally, where more people die annually from cardiovascular diseases compared to other causes. Approximately 17.5 million people died from cardiovascular diseases in 2005, representing at least 30% of all global deaths according to the World Health Organization report. By 2015, almost 20 million people will die from cardiovascular diseases. The electrocardiogram (ECG) signal is one of the most important tools in clinical practice to assess the cardiac status of patients. This signal represents the potential difference between two points on the body surface, versus time, Rajendra et al. (2007). Extracting the features from this signal has been found very helpful in explaining and identifying various cardiac arrhythmias.

This could be difficult, when the size of the data of the ECG is huge and the existence of different noise types may be contained in the ECG signals. Furthermore, manual analysis is considered time consuming and is prone to errors; hence arises the importance of automatic recognition of the extraction of the features ECG signals.

Many tools and algorithms have been proposed to extract feature from ECG signals such as, total least squares based Prony modeling algorithm (Chen, 2000) Chaos theory (Owis et al., 2001), autoregressive and multivariate autoregressive models (Dingfei et al., 2002; 2007), heartbeat interval and ECG morphology (Chazal et al., 2004), wavelet transform (Inan et al., 2006), and multiple signal classification algorithm (Ahmad et al., 2008). Most of the aforementioned techniques, involve significant amounts of computation and processing time for features extraction and classification. Another disadvantage is the small number of arrhythmias that can be classified to two or three arrhythmias. Therefore, there is a need for a new technique to classify a larger number of arrhythmias. In addition, the proposed technique can be amenable to real time implementation so it can be used in intensive care units or ECG signal collected.

The objective of the present work is to apply Pade's approximation technique to represent the ECG signal as a rational function of two polynomials of unknown coefficients in order to classify cardiac arrhythmias based on the calculation of poles. These poles of the ECG signal can be used as a signature and a useful feature for

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signal discrimination and identification.

MATERIALS AND METHODS

The proposed method for heartbeat classification schema consists of three stages: the preprocessing stage, the feature extraction stage, and the classification stage. First, the ECG signals were pre-processed by filtering it to remove the baseline wander, the power line interference, and the high frequency noise, hence enhancing the signal quality, and omitting the equipment and the environ-mental effects. Next Pade's approximation technique was applied to model ECG signals, where the poles calculated were used as feature set. Finally, different classifier models were employed to evaluate the proposed method.

The ECG signal may be affected by the different noise types, the baseline wander, the artifact, and the power line interference. Generally, the presence of several noise sources in the signal may corrupt the ECG signal, and make the feature extraction and classification less accurate. To minimize the negative effects of the noise, a Butterworth Band Pass Filter was designed to perform noise reduction. The cutoff frequencies of the band pass filter were selected to be from 0.5 to 40 Hz.

Pade introduced a technique for modelling sampled data as a rational function of two polynomials, Liao et al. (1992), Monsoon et al. (1996), Fatma (1996), Jozef et al. (2001), Van Assche et al. (2006). This method has been applied to various areas, notably electromagnetic scattering, antenna problems signal processing, and radar target identification, Berni (1975).

Let $f(t)$ represent the ECG signal for a certain time interval T and is sampled at D sampling points. Hence it can be written as a rational function of two polynomials $P_n(t)$, $Q_m(t)$ as follows:

$$f(t) \cong \frac{P_n(t_i)}{Q_m(t_i)} \cong \sum_{\alpha=0}^{n} a_\alpha t_i^\alpha \Bigg/ \sum_{\beta=0}^{m} b_\beta t_i^\beta \qquad (1)$$

Where a, b are the unknown coefficients to be determined. Equation (1) can be written in the following form,

$$f(t).\sum_{\beta=0}^{m} b_\beta t^\beta = \sum_{\alpha=0}^{n} a_\alpha t^\alpha \qquad (2)$$

Where b_0 can be taken equal one for linear predictor constrain. Thus, Equation (2) can be rewritten as,

$$f(t) = \sum_{\alpha=0}^{n} a_\alpha t^\alpha - \sum_{\beta=1}^{m} f(t) b_\beta t^\beta \qquad (3)$$

Equation (3) has $n+m+1$ unknowns ($a's$, $b's$). Those unknown coefficients can be calculated using Gauss Jordan method if $D = n+m+1$, or using the least squares method if $D > n+m+1$. Finally, the denominator polynomial m zeros are calculated, which are the poles P_β of the ECG signal $f(t)$, defined by the real and imaginary pars as follows:

$$P_\beta = \varphi_\beta + j\omega_\beta \quad , \beta = 1,2,3,...,m \qquad (4)$$

Where $\omega_\beta = 2\pi f_\beta$, and f_β are the β resonance complex frequency or its inverse is the β pole of the ECG signal's window interval T, Fatma (1996).

The proposed algorithm for heartbeat classification schema was tested on the MIT-BIH Arrhythmia database (www.physionet.org). The data set used for this work comprises five different types including normal, ventricular couplet, ventricular tachycardia, ventricular bigeminy, and ventricular fibrillation. Each type is represented by 64 different patients signal having duration of three seconds long, they are taken from lead number two (MLII). The signal duration can be divided into multiple windows each of 3 s, then the process of calculation the poles P_β or f_β is applied on each window consecutively.

In order to investigate the validity of the proposed method, four classifiers model are employed. Neural networks, K nearest neighbor, linear discriminate analysis and multi-class support vector machine. All classifier models are designed trained and tested using the poles sets extracted from ECG signals (43 for training and 21 for testing). All features sets are divided into independent training and testing sets using n-fold cross validation method. This scheme randomly divides the available data into n approximately equal size and mutually exclusive folds. For an n-fold cross validation run, the classifiers are trained with a different n fold used each time as the testing set, while the other $n-1$ folds are used for the training data. In this study three fold cross validation are employed.

A feed forward Multilayer Perceptron (MLP) neural network with three layers is implemented, input layer, hidden layer, and output layer. The number of neurons selected at input layer is equal to the number of poles and the accompanied complex frequencies. The neurons at the output layer are selected according to the number of classes. One step secant back propagations training function is used to update the weight. The Tan-Sigmoid function is used as the transfer function in the first and second layers, and pure line function is used in the output layer. An error-correction rule is used to adjust the synaptic weights; where the error is the difference between the target and actual network output.

The distance function applied for K nearest neighbor technique is the Euclidean distance to match the test examples with training examples and for different values of k where k is taken to be 1, 3 and 5. One versus the rest MC-SVM technique with linear training algorithm is employed in this work.

Following the guidelines proposed by the Association for the Advancement of Medical Instrumentation, AAMI (1987), three benchmark parameters were used to assess the algorithm performance: accuracy, specificity, sensitivity defined in the followings Equations (5-7) and is tabulated in Table 1.

$$Accuracy = \frac{(TN + TP)}{\Sigma} \qquad (5)$$

$$Sensitivity = \frac{TP}{TP + FN} \qquad (6)$$

$$Specificity = \frac{TN}{TN + FP} \qquad (7)$$

Where, TP, TN, FP, and FN stand for true positives, true negatives, false positives, and false negatives respectively.

True positives represent abnormal beats classified in their respec-tive classes whereas true negative represents normal beats classi-fied as normal. False positives represent normal beats classified as abnormal and false negatives represent abnormal beats classified

Table 1. The performance measures used in this study.

		nr	vc	vt	vb	vf	sum
				Algorithm label			
	NR	*NRnr*	*NRvc*	*NRvt*	*NRvb*	*NRvf*	*ΣNR*
	VC	*VCnr*	*VCvc*	*VCvt*	*VCvb*	*VCvf*	*ΣVC*
Reference label	VT	*VTnr*	*VTvc*	*VTvt*	*VTb*	*VTvf*	*ΣVT*
	VB	*VBnr*	*VBvc*	*VBvt*	*VBvb*	*VBvf*	*ΣVB*
	VF	*VFnr*	*VFvc*	*VBvt*	*VFvb*	*VFvf*	*ΣVF*
							Σ

TN = NRnr; TP = VCvc + VTvt + VBvb + VFvf; FP = NRvc + NRvt + NRvb + NRvf; FN = VCnr + VTnr + VBnr + VFnr. NR: normal rhythm. VC: ventricular couplet. VT: ventricular tachycardia. VB: ventricular bigeminy. VF: ventricular fibrillation
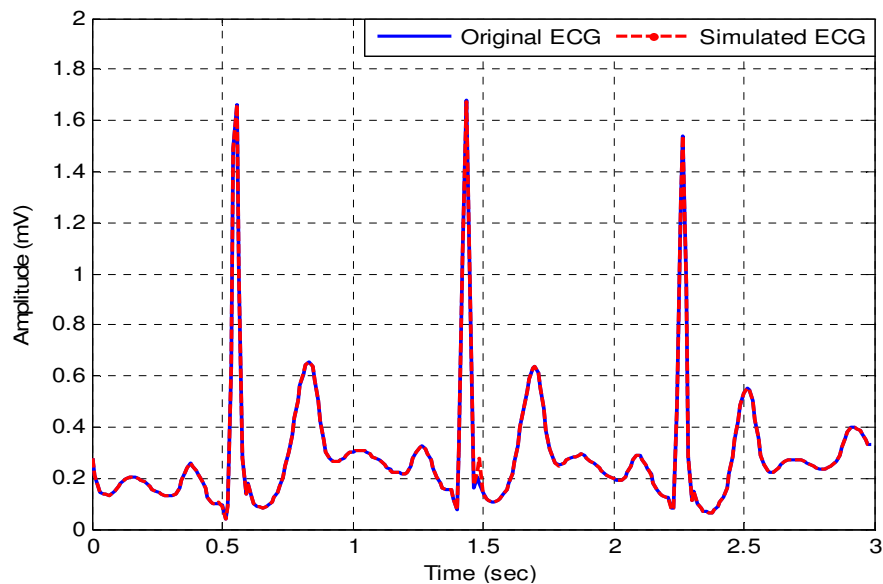

Figure 1. A patient ECG (blue line) and simulated ECG (red line) with normal rhythm using Pade's approximation technique.

beats classified as normal.

RESULTS AND DISCUSSION

Initially, ECG signals are filtered using a Butterworth band pass filter with cutoff frequencies of 0.5 to 40 Hz to reduce the noise. Then, Pade's approximation technique is employed for all the filtered ECG signals to extract the poles. A reconstruction of all these ECG signals using the previous calculated poles, complex natural frequency resonances, proves the exactness of the method employed. This is shown in Figures 1. Both the original filtered ECG signal and the constructed ECG signal from Pade's approximation technique coincide on each other.

Application of various classifier models to test those features is the final stage of the proposed schema. The Artificial Neural Network and K nearest neighbor gave the best results, where the accuracy and specificity and sensitivity reached to 100%. The accuracy for multi-class support vector machine and linear discriminate analysis reaches to 98.10%, where two signals are classified in-correctly. But, the specificity and sensitivity for multi-class support vector machine is reached to 100% and reached for linear discriminate analysis to 99.05%. This mean, the multi-class support vector machine is better than linear discriminate analysis to classify normal beat as normal.

Table 2 shows a comparison between the proposed technique with other method introduced by Owis et al. (2001) and Kafieh et al. (2007). Owis et al. (2001) developed a feature extraction technique using the correlation dimension and the largest Lyapunov exponent, to model the chaotic nature of five different classes of ECG signals. Kafieh et al. (2007) presented a method to

Table 2. Comparison between presented and other techniques.

Feature extraction technique	Classifier model	Specificity (%)	Sensitivity (%)
Owis et al. (2001)	K nearest neighbor	40.63	80.45
Kefieh et al. (2007)	Learning vector quantization	88	98
Proposed Method	Neural network	100	100

Kafieh et al. (2007) presented a method to discriminate the ECG rhythms using their roots location in auto regressive (AR) model. It can be seen from Table 2, the author presented method achieves higher specificity and sensitivity than other techniques. On other hand, three seconds of data were necessary to discriminate the rhythms in the proposed method by Owis et al. (2001). Although two seconds can be implemented to apply the proposed method and even less in this study, three seconds were used to compare with Owis et al. (2001).

Heartbeat classification schema based on poles of the ECG signal windows using Pade's approximation technique is presented. Also, neural network and K nearest neighbor gave more accuracy than other techniques to classify the ECG heartbeats based on the calculated poles extracted. The experimental results show the ability and the efficiency of this proposed schema for detecting the poles and identifying the ECG signal features with high accuracy.

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