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A Novel Method for ECG Signal Discrimination of Cardiac Arrhythmias Based on Pade's Approximation Technique

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Abstract

This paper presents an electrocardiogram (ECG) beat classification scheme based on Pade's approximation technique and neural networks for discriminating five ECG beat types. These are normal rhythm (NR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF). ECG signal samples from MIT-BIH arrhythmia database are used to evaluate the proposed method. The ECG signal is modeled as a rational function of two polynomials of unknown coefficients using Pade's approximation technique, where the model coefficients, poles of the denominator, are used as a feature for the ECG signals. The classification is performed using a multilayered perceptron (MLP) neural network. The experimental results demonstrate the efficiency of the proposed techniques for modeling and classifying the ECG beat types using Pade's approximation technique and MLP neural network.

1. Introduction

Cardiovascular diseases (CVDs) are the main cause of death globally, where more people die annually from CVDs than from any other cause. Approximately 17.5 million people died from CVDs in 2005, representing 30% of all global deaths according to the world health organization (WHO) report. By 2015, almost 20 million people will die from CVDs [1]. Some of the CVDs causing death are due to ventricular arrhythmias, valve disease, and coronary artery disease. Since the detection of these diseases in the initial stages are of great importance in the treatment and prolonging life of patients. Electrocardiogram (ECG) is the most important tools used by cardiologists for diagnostic purposes [2]. It provides valuable information about the functional aspects of the heart and the cardiovascular system. This information when extracted and analyzed, leads to useful interpretation.

Feature extraction from ECG signal has been found very helpful for detecting and identifying various cardiac arrhythmias. In recent years, numerous research and algorithm have been developed for extract features. SW Chen [3], presented a total least squares based Prony modeling algorithm to discriminate three types of heartbeat (VF, VT, and SVT). Two features, energy fractional factor (EFF) and predominant frequency (PF) were derived from the total least squares based Prony model. Classification accuracy reaches 95.24%, 96.00% and 97.78% for SVT, VF and VT respectively.

Owis M. *et al.* [4] developed another feature extraction technique using the correlation dimension and largest Lyapunov exponent, to model the chaotic nature of five different classes of ECG signals. The analysis of the indicated features differed significantly among different arrhythmia types and hence could be useful in ECG signal classification. Dingfei Ge *et al.* [5, 6] used an autoregressive (AR) and multivariate AR models to extract the features from ECG signals for classifying cardiac arrhythmias based on AR coefficients.

Chazal *et al.* [7] presented an automatic classification of heartbeats based on the shape and morphological properties of the P, QRS and T waves. However, morphological features of P and T waves were often difficult to detect because their amplitudes were relatively low, and they were occasionally included in noise. Therefore, the feature extraction methods may have missing value problem, and thus may cause bad result in the automatic diagnosis. Inan O.T. *et al.* [8] presented a proficient classification algorithm for PVC beats which combines wavelet transform, timing interval features and neural network classification. The wavelet transform was used to extract morphological information from the ECG data. A neural network classifier was designed, trained and tested to discriminate heartbeats using the feature sets.

Ahmad R. N. *et al*. [9] proposed an electrocardiogram classification technique based on multiple signal classification (MUSIC) algorithm, morphological descriptors, and neural networks for classifying ECG signal. MUSIC algorithm is used to calculate pseudo spectrum of ECG signals. The low-frequency samples of the pseudo spectrum with variance of peak values and times are combined as feature vector and then served as input for the neural network classifier. The experimental results achieved a promising accuracy of 99.03% for classifying the beat types using multilayer perceptron neural network. Turker Ince *et al.* [10] proposed an automated patient-specific ECG heartbeat classifier, which is based on an efficient formation of morphological wavelet transform features and temporal features from the ECG data.

Other investigators reported some techniques to classify ECG signals. Chazal *et al.* [7] introduced classification model based on linear discriminant analysis. It was shown that it was effective for quantifying the classification of ECG abnormalities. Mehta *et al.* [11] presented support vector machines as a classifier to delineate QRS and non QRS regions. Zadeh *et al.* [12] and B. Anuradha *et al.* [13] used a neural network classifier to automatic classification of cardiac arrhythmias types. The results showed that the proposed method is effective for classification of cardiac arrhythmias, with an acceptable high accuracy. Lagerholm *et al.* [14] presented a method for clustering of QRS complexes which includes Hermite function representation and self organizing maps.

The main objective of the present study is to apply Pade's approximation (PA) as a new technique to model the ECG signal and classify certain cardiac arrhythmias based on PA coefficients. Most of the techniques involve significant amounts of computation and processing time for extraction of features and classification. The other disadvantage is the small number of arrhythmias classified using a given technique with most techniques being used to classify two to three arrhythmias. There is a need for extending a particular technique for a larger number of arrhythmias. In addition, the proposed technique should be amenable to real-time implementation so that it can be used in intensive care units (ICU).

The poles or resonant frequencies of a signal can be used as a signature and useful features of that signal to discriminate it from others for the purpose of signal identification [15]. It has been used in many areas, radar target identification [16], speech recognition [17], antenna application [18], and classifying the underwater source for passive sonar [19]. Many methods have been proposed to extract the poles or resonant frequencies of a signal, such as: Prony's method [20], and Pade's approximation technique [21].

In this study, the ECG signals were modeled using Pade's approximation technique for classifying cardiac arrhythmias. The advantage of modeling is its simplicity and is suitable for real time classification at the ICU or ambulatory monitoring. PA modeling is adapted for extracting good features from ECG signals, thus enabling the discrimination of certain ECG arrhythmias. In the current study, the PA coefficients computed from the ECG signals were classified using a multilayered perceptron neural network. Various arrhythmias including normal rhythm (NR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF) were classified. The verification and the validation of the presented method are accomplished using these types of arrhythmias chosen from MIT-BIH database [22].

The reset of the paper is organized as follows: Section II outlines the methodology of the proposed algorithm for heartbeat classification schema. In section III, ECG signal pre-processing is briefly described. In section IV the new feature extraction model is introduced. In section V the classifier model is presented and the experimental result and the conclusion are presented in section VI and VII respectively.

2. Methodology

Figure 1 depicts the stages of the proposed algorithm for heartbeat classification schema. It consists of three stages: a preprocessing stage, Pade's approximation technique in the feature extraction stage, and neural networks in the classification stage. First, the ECG signals are preprocessed by filtering to remove baseline wander, power line interference, and high frequency noise, enhance signal quality, and omit equipment and environment effects. Next, Pade's approximation technique is applied to model ECG signals, where the poles calculated from PA technique are used as feature set. Finally, a neural network, including a multilayered perceptron, is employed. The experimental results demonstrate the effectiveness and efficiency of the proposed feature set and MLP neural network for ECG beat recognition.

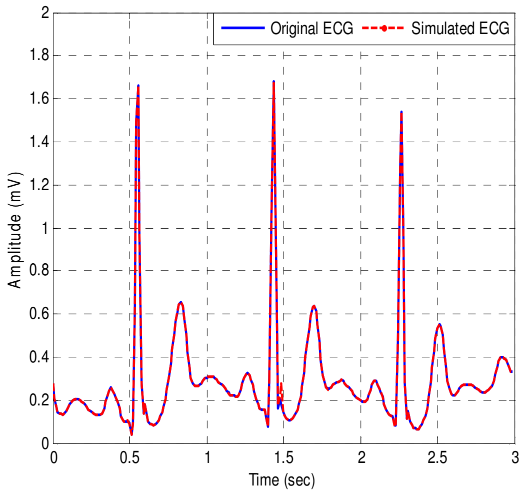

Figure 2.a. A patient ECG and simulated ECG with normal rhythm.

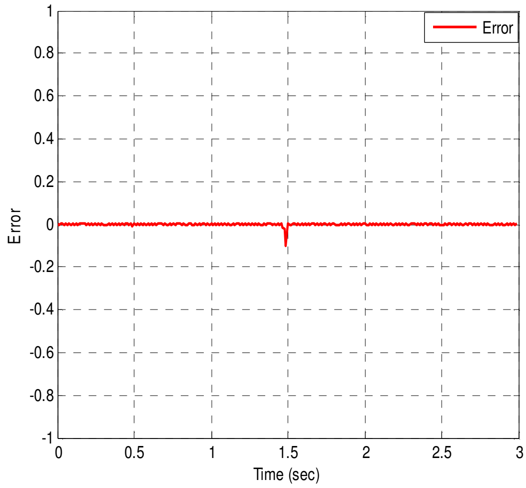

Figure 2.b. Difference between patient ECG and simulated ECG amplitude against time

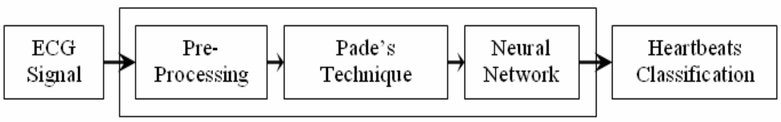

Figure 1. Block diagram of proposed algorithm

3. Preprocessing

The objectives of preprocessing stage are the omission of high frequency noise and the enhancement of ECG signal quality to obtain appropriate features. Furthermore, we should remove equipment and environment influences on recorded signals. The ECG signal was obtained from the MIT-BIH database where it may be affected by different noise types, baseline wander, artifact, and power line interference. Hence, the presence of several noise sources in the signal may impair ECG signal analysis accuracy. A band pass Butterworth filter of band width from 0.5 to 40 Hz [23] is designed to remove those types of noise.

4. Review on pade's approximation technique

The Padé approximation is a rational function [21] that can be thought of as a generalization of a Taylor series polynomial. A rational function is the ratio of two polynomials [24]-[28]. Because these functions only use the elementary arithmetic operations, they are very easy to evaluate numerically. The polynomial in the denominator allows us to approximate functions that have singularities.

More precisely, a Padé approximation of order n, d to an analytic function $f(x)$ at a regular point or pole x_0 is the rational function $P(x)/Q(x)$ where $P(x)$ is a polynomial of degree n, $Q(x)$ is a polynomial of degree d. If d is equal to n, the approximation is called a diagonal Padé approximation of order n. Let $f(x)$ be the ECG signal, it can be written as rational function as,

$$f(x) \cong \frac{P_n(x)}{Q_d(x)} \tag{1}$$

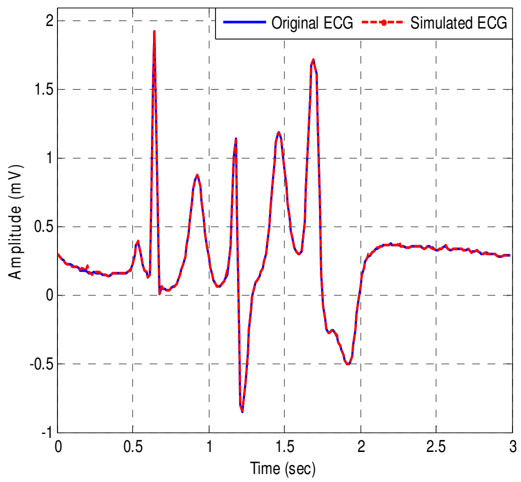

Figure 3.a. A patient ECG and simulated ECG with ventricular couplet.

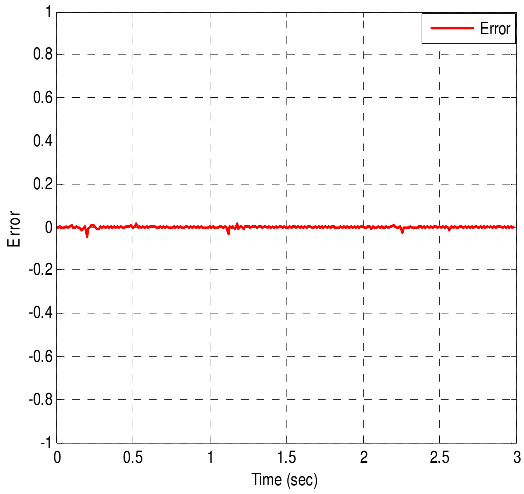

Figure 3.b. Difference between patient ECG and simulated ECG amplitude against time

This ECG signal is known and can be sampled at D points, $i = 0,1,2,...,D-1$,

$$f(x_i) \cong \frac{P_n(x_i)}{Q_d(x_i)} \tag{2}$$

Where,

$$P_n(x_i) = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha \tag{3}$$

$$Q_d(x_i) = \sum_{\beta=0}^{d} b_\beta x_i^\beta \tag{4}$$

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

$$f(x_i).\sum_{\beta=0}^{d} b_\beta x_i^\beta = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha \tag{5}$$

Let $b_0 = 1$ (linear predictor constrain). Equation (5) can be rewritten as,

$$f(x_i) = \sum_{\alpha=0}^{n} a_\alpha x_i^\alpha - \sum_{\beta=1}^{d} f(x_i) b_\beta x_i^\beta \tag{6}$$

Repeated application of equation (6) at the different sampling points from 0 *to* $D-1$, we can have D equations written in matrix form,

$$[F] = [X].[A] \tag{7}$$

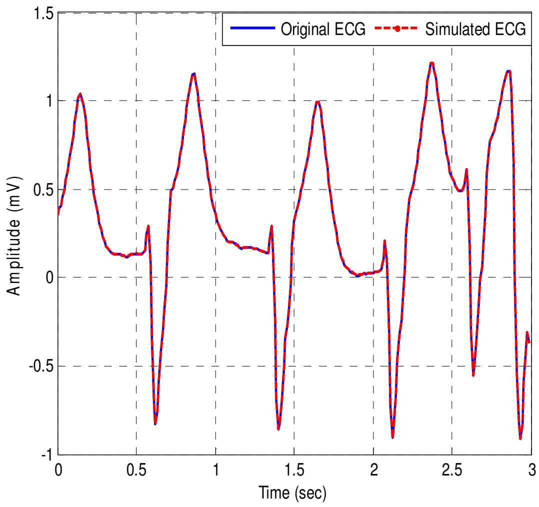

Figure 4.a. A patient ECG and simulated ECG with ventricular tachycardia.

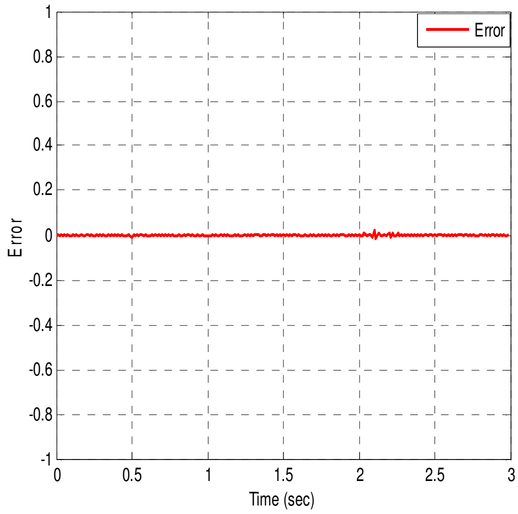

Figure 4.b. Difference between patient ECG and simulated ECG amplitude against time

Where,

$$[F]=[f_0,f_1,f_2,...,f_{D-1}]^T \tag{8}$$

$$[A]=[a_0,a_1,a_2,...,a_n,b_1,b_2,...,b_d]^T \tag{9}$$

$$[X]=\begin{bmatrix} 1 & x_0 & \cdots & x_0^n & -f_0x_0 & -f_0x_0^2 & \cdots & -f_0x_0^d \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_i & \cdots & x_i^n & -f_ix_i & -f_ix_i^2 & \cdots & -f_ix_i^d \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_{D-1} & \cdots & x_{D-1}^n & -f_{D-1}x_{D-1} & -f_{D-1}x_{D-1}^2 & \cdots & -f_{D-1}x_{D-1}^d \end{bmatrix} \tag{10}$$

The unknown coefficients $[a_0,a_1,...,a_n,b_1,...,b_d]$ can be calculated using Gauss Jordan method for $D=n+d+1$, or using the least squares method for $D>n+d+1$.

Finally, the denominator polynomial zeros are calculated, which it is the poles of the function $f(x)$, will be feature set of the ECG signal, fed to the neural network classifier model to detect cardiac arrhythmias and make the diagnostic decision.

5. Classifier model

Classifier model based on artificial neural networks (ANNs) was utilized throughout this study. ANNs are biologically inspired networks that are useful in application areas such as pattern recognition, classification etc [9]. The decision making process of the ANNs is holistic, based on the features of input patterns, and is suitable for classification of biomedical data. ANNS involves a network of simple processing nodes (neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and

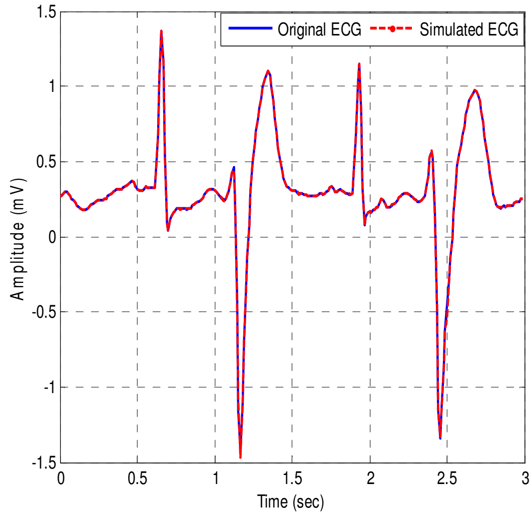

Figure 5.a. A patient ECG and simulated ECG with ventricular bigeminy.

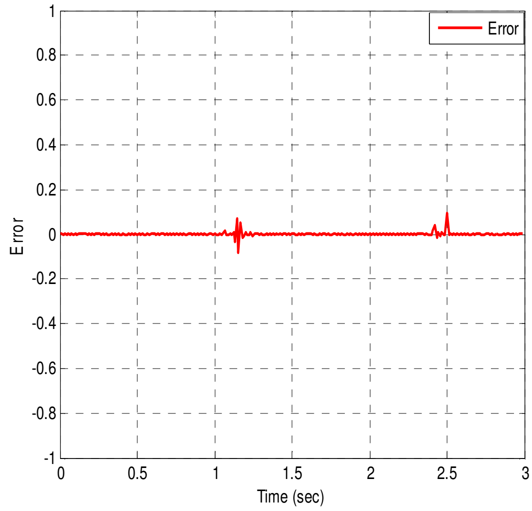

Figure 5.b. Difference between patient ECG and simulated ECG amplitude against time

element parameters. Figure 7 shows the functional description of single neuron, where x, w, u, f, y are the input, weight, net function, transfer function and the output of neuron respectively.

A multilayer feedforward network is an important class of neural networks. Usually, the network is comprised of a set of source nodes that form the input layer. It also includes one or more hidden layers of computation nodes and an output layer of computation nodes as shown in figure 8. Throughout the neural network, the input feature propagates in a forward direction and on a layer by layer basis. These neural networks also called multilayer perceptrons (MLPs).

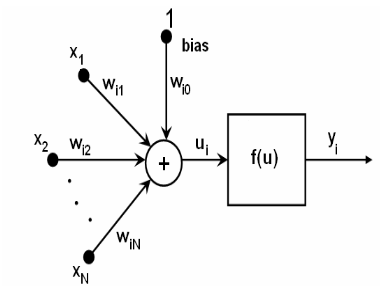

Figure 7. Functional description of single neuron.

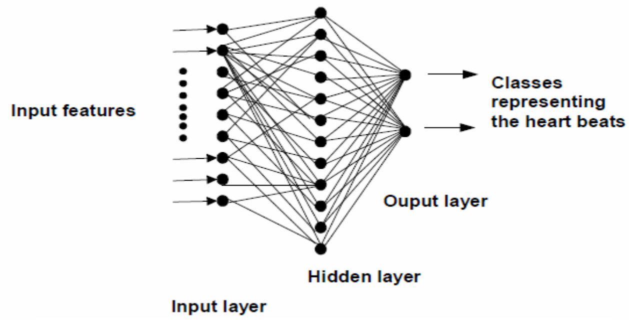

Figure 8. Multilayer perceptrons architecture

Multilayer perceptrons are trained in a supervised manner algorithm with error back propagation algorithm whose basis is on the error correction learning rule. Error back propagation learning is a two-path transmission through the layers of the networks. The paths are forward and backward. In the forward path, following the application of an input vector to the source nodes, its effect propagates through the network layer by layer with the result of production of a set of outputs as the actual response of the network. During the forward path, the synaptic weights of the networks are fixed. However, during the backward path, an error-correction rule is used to adjust the synaptic weights. A major part is to compute the error by subtraction the actual response from a desired (target) response. By the backward propagation of this error against the direction of synaptic connection, error back propagation is done. An Adjustment of the synaptic weights is done to move the actual response of the network closer to the desired response in a statistical way. The classification accuracy, sensitivity and specificity are computed for all the classes by,

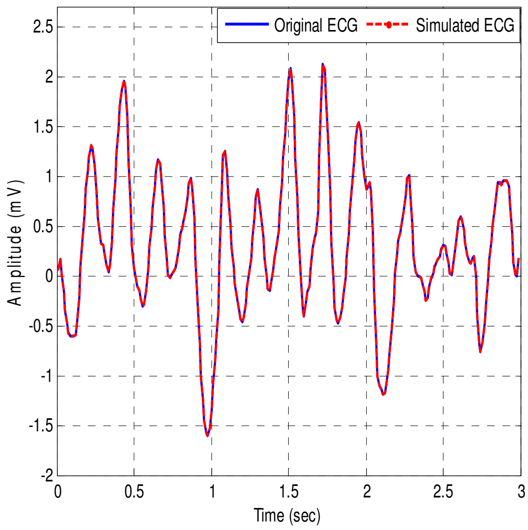

Figure 6.a. A patient ECG and simulated ECG with Ventricular Fibrillation.

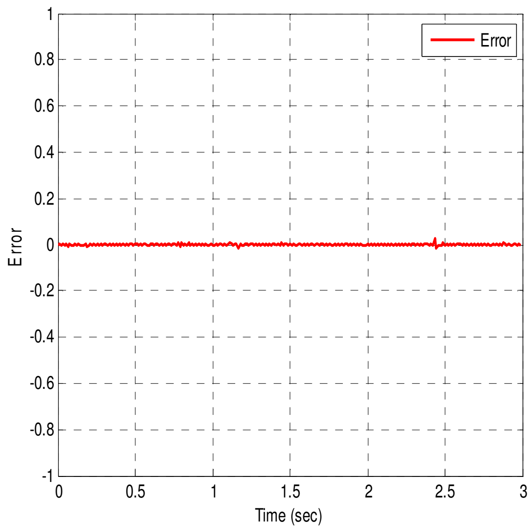

Figure 6.b Difference between patient ECG and simulated ECG Amplitude against time.

$$Accuracy = \frac{(TN + TP)}{TE} \tag{11}$$

$$Sensitivity = \frac{(TE - FN)}{TE} \tag{12}$$

$$Specificity = \frac{(TE - FP)}{TE} \tag{13}$$

where TP, TN, FP, FN, and TE stand for true positive, true negative, false positive, false negative, and total number of beats, respectively [2],[5].

6. Experimental result

The Pade approximation model was applied to five different types of ECG signals from the MIT-BIH database and was taken from lead number two, these types including normal (NR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF). Each type was represented by 64 different patients signal having duration of three seconds long. The VF signals were sampled at 250 sample/sec, while the others were sampled at 360 sample/sec. Resembling adjustment is employed. And the classification was performed using MLP.

The poles from each three second of ECG signal are extracted using Pade's approximation technique. These set of poles are fed to the back propagation neural network to classify the arrhythmias. As shown in figure 2, 3, 4, 5, and 6, the ECG signal can be reconstructed using the computed poles with percentage error tending to zero.

The architecture of MLP was made from three layers, input layer, hidden layer, and output layer. The number of neurons selected at input layer is equal to the number of poles, and 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 as transfer function 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.

To validate the proposed technique, 64 ECG signal from MIT-BIH are used, divided into two subset to train and test the classifier model for all cardiac arrhythmias. As shown in Table 1 and 2, all ECG signal types are classified correctly in their classes. The results demonstrate the efficiency of the proposed method for classifying ECG signal types. The accuracy, sensitivity, and the specificity of the classifier model are computed according to equations (11), (12) and (13) which reach 100% for all ECG signal types.

Table 1. Classification result using MLP for training data

Classes	NR	VC	VT	VB	VF	
NR	43	-	-	-	-	
VC	-	43	-	-	-	
VT	-	-	43	-	-	
VB	-	-	-	43	-	
VF	-	-	-	-	43	
						215

Table 2. Classification result using MLP for testing data

Classes	NR	VC	VT	VB	VF	
NR	21	-	-	-	-	
VC	-	21	-	-	-	
VT	-	-	21	-	-	
VB	-	-	-	21	-	
VF	-	-	-	-	21	
						105

7. Conclusion

A new features extraction technique of ECG signal is presented based on Pade approximation techniques, according to the experimental result, Pade approximation proved its ability to detect and extract the poles from ECG signal, which has been used as feature set of the ECG signal. And MLP has been introduced as a classifier model to classify the ECG heartbeats based on the poles that extracted from the ECG signal. The experimental result shows the ability and the efficiency of this method for detecting the poles and identifying the ECG signal with high accuracy.

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