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Electrocardiogram Signals Identification for Cardiac Arrhythmias Using Prony's Method and Neural Network

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Abstract—**A new method is presented to identify Electrocardiogram (ECG) signals for abnormal heartbeats based on Prony's modeling algorithm and neural network. Hence, the ECG signals can be written as a finite sum of exponential depending on poles. Neural network is used to identify the ECG signal from the calculated poles. Algorithm classification including a multi-layer feed forward neural network using back propagation is proposed as a classifying model to categorize the beats into one of five types including normal sinus rhythm (NSR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF).**

I. Introduction

THE electrocardiogram (ECG) is an electrical recording of the heart activity that is used as a diagnosis tool by physicians and doctors to check the status of the heart [1]. It provides valuable information about the functional aspects of the heart and the cardiovascular system. The state of cardiac health is generally reflected in the shape of electrocardiogram waveform and heart rate. Early detection of heart diseases can prolong life and enhance the quality of living through appropriate treatment. Since the ECG signals are non stationary signals, this reflection may occur at random of the time scale. In this situation, the disease signs may not show at all times, but would appear at certain irregular intervals during the day.

ECG signal analysis is the main process for the cardiovascular diagnosis. The analysis and identification of ECG signal is divided into two stages: features extraction and classification. In recent year, numerous research and algorithm have been developed to extract the features. Chazal *et al.* [2], presented an automatic classification of heartbeats based on the shape and morphological properties of the P, QRS and T waves.

Alexakis *et al.* [3], introduced a feature extraction method based on both the morphological and time interval features of ECG signal. It also had a problem to describe cardiac patterns having no clear P and T waves. Therefore, it is not suitable for describing some types of heartbeat. Romero *et al.* [4], showed other ECG features extraction based on frequency domain, where the mean, variance and power spectrum of the frequency were taken as a feature of the ECG signal for classification. The based features frequency domain can reveal more important characteristic of the signal. However, it lacks the robustness of noise, and poor performance in classifying heartbeats compared to other techniques. Abadi *et al.* [5], proposed ECG feature extraction system based on the multi-resolution wavelet transform, the feature set was derived from the coefficients of the discrete wavelet transform by detecting QRS complexes.

Ge *et al.* [6] used an autoregressive (AR) analysis to model ECG signals for classifying cardiac arrhythmias based on AR coefficients. SW Chen [7], 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. Owis *et al.* [8] developed another feature extraction technique using the correlation dimension and largest Lyapunov exponent, which were used to model the chaotic nature of five different classes of ECG signals.

Other investigators reported some techniques to classify ECG patterns. Chazal *et al.* [2] 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.* [9], presented support vector machines as a classifier to delineate QRS and non QRS regions. Zadeh *et al.* [10] used a neural network classifier to automatic classification of cardiac arrhythmias into five heartbeat types. Lagerholm *et al.* [11] have applied self-organizing maps for classifying ECG beats.

This paper introduces a new extraction feature method based on Prony's approximation technique and neural network as a classifier model. The verification and the validation of the presented method are accomplished using five types of arrhythmias chosen from MIT-BIH database [12], normal sinus rhythm (NSR), ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF).

II. Removal Of Noise In Ecg Signal Recording

The ECG signal recording usually suffers from unwanted noise. The source of this noise is from muscles noise, base line drift noise, and power line interference noise. A band pass Butterworth filter of band width from 0.5 to 40 Hz [13] is designed to remove those types of noise.

III. Detection Of ECG Signal Poles

Prony introduced a technique for modelling sampled data as a linear combination of damped exponentials [14]-[18]. This method has been applied to various areas, notably electromagnetic scattering, antenna problems signal processing, and radar target identification.

Starting with the basic derivation of Prony's method it is desired to determine an approximation of the form,

$$f(t_i) \cong \sum_{\alpha=1}^{P} R_\alpha \exp(s_\alpha t_i), \qquad \alpha = 1,2,3,\ldots,P, \qquad i = 0,1,2,3,\ldots,D-1, \tag{1}$$

Where $f(t_i)$ is the ECG signal defined at D sampling points $t_0, t_1, t_2, \ldots, t_{D-1}$, s_α is the αth pole, R_α is the αth residue's amplitude.

It is useful to express the equation (1) in discrete sampled data form as normally found in practice, thus,

$$f(t_i) = \sum_{\alpha=1}^{P} R_\alpha \exp(s_\alpha i \delta t) = \sum_{\alpha=1}^{P} R_\alpha (X_\alpha)^i \qquad \alpha = 1,2,3,\ldots,P. \quad i = 0,1,2,3,\ldots,D-1. \tag{2}$$

Where $X_\alpha = \exp(s_\alpha \delta t)$, and the size of the sampling interval is defined as δt.

The above set of nonlinear equations (2) have both two sets of unknowns $X_\alpha 's$ and $R_\alpha 's$.

If the constants $X_\alpha 's$ were known, this set would comprise D linear equations in the P unknowns $R_\alpha 's$ and could be solved exactly if $D = P$ or approximately, by using least square method if $D > P$. However, if the $X_\alpha 's$ are to be determined, at least $2P$ equations are needed.

Using Prony's method procedure, one can define a polynomial $A(M)$ of order P in the variable M, having the same α roots appearing in equations (1) to (2), thus,

$$A(M) = a_0 + a_1 M + a_2 M^2 + \ldots + a_P M^P \tag{3}$$

Equation (3) can be written in terms of its roots as,

$$A(M) = (M - X_1)(M - X_2)\ldots(M - X_P) = 0 \tag{4}$$

Where $X's$ are the roots of the above equation.

In order to determine the coefficients $a_0, a_1, a_2, \ldots, a_P$ in equation (3), the first equation in (2) will be multiplied by a_0, the second equation by a_1,…, the Pth equation by a_P, the result will give the following set of equations,

$$\left.\begin{aligned}
a_0 f_0 &= a_0 R_1 + a_0 R_2 + \ldots + a_0 R_P \\
a_1 f_1 &= a_1 R_1 X_1 + a_1 R_2 X_2 + \ldots + a_1 R_P X_P \\
a_2 f_2 &= a_2 R_1 (X_1)^2 + a_2 R_2 (X_2)^2 + \ldots + a_2 R_P (X_P)^2 \\
\ldots \quad & \ldots \quad \ldots \quad \ldots \quad \ldots \\
a_P f_P &= a_P R_1 (X_1)^P + a_P R_2 (X_2)^P + \ldots + a_P R_P (X_P)^P
\end{aligned}\right\} \tag{5}$$

Adding the above set of equations (5), yields,

$$A(X_1) + A(X_2) \ldots + A(X_P) = f_0 a_0 + f_1 a_1 \ldots + f_P a_P \tag{6}$$

Where $A(X_\alpha)$ is defined in equation (4), X_α is the roots of A, thus, equation (6) yields,

$$f_0 a_0 + f_1 a_1 + \ldots + f_P a_P = 0 \tag{7}$$

A set of $D - P - 1$ additional equation can be obtained similar in a way by repeating the steps explained above. starting from f_1 to $f_{(D-P-1)}$, giving the following set of equations,

$$\left.\begin{aligned}
f_0 a_0 + f_1 a_1 + \ldots + f_P a_P &= 0 \\
f_1 a_0 + f_2 a_1 + \ldots + f_{P+1} a_P &= 0 \\
\ldots \quad \ldots \quad \ldots \quad \ldots \quad & \ldots \\
f_{D-P-1} a_0 + f_{D-P} a_1 + \ldots + f_{D-1} a_P &= 0
\end{aligned}\right\} \tag{8}$$

Since the ordinates f_i are known, and by taking $a_P = 1$ (linear predictor constraint), equation (8) generally can be solved directly for the a if $D = 2P$, or solved approximately by using the least square method if $D > 2P$.

After computing $a's$ coefficients, the $X's$ can be calculated as the root of equation (3). Equation (2) then becomes a set of linear equations in R. Thus, R can be founded from the first P equations (2) or by applying the least square techniques to the entire set.

The poles (s_α) of the ECG signal can be directly calculated as,

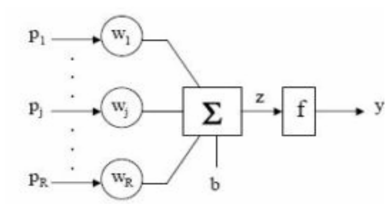
$$s_\alpha = \frac{1}{\delta} \log (X_\alpha) \tag{9}$$

IV. Neural Network

The purpose of classification is to assign an object to a certain class. Many classification methods have been described [2,9,10,11]. Artificial Neural Networks (ANNs) is one of these methods that are used to classify the ECG arrhythmias.

In an ANNs structure, many simple, nonlinear processing elements, called neurons are interconnected via weighted synapses to form a network. The function of each neuron is to compute a weight sum of all synapse inputs, and subtract the sum from the predefined bias, and pass the result through a function whose output ranges between 0 and 1. Figure 1 shows the functional description of single neuron. Where P, w, b, z, f, y are the input, weight, bias, net function, transfer function and the output of neuron respectively.

Multilayer Perceptron (MLP) is the most popular and extensive model of ANN, and is made up of several layers of neurons. Each layer is fully connected to the next one. Usually, ANN consists of two phases: training phase and testing phase. During the training phase, the features are applied at the input and the corresponding desired classes at the output of MLP classifier. A training algorithm is executed to adjust the weights and biases until the actual output of MLP matches the desired output. This training phase continues till the satisfying performance is reached. In the test phase, a set of test features, which are not part of training features, are applied to the trained MLP classifier to test whether it is able to classify unknown features or not.



. Fig. 1. Functional description of single neuron

The classification accuracy, sensitivity and specificity are computed for all the classes by,

$$Accuracy = \frac{(TN + TP)}{TE} \tag{10}$$

$$Sensitivity = \frac{(TE - FN)}{TE} \tag{11}$$

$$Specificity = \frac{(TE - FP)}{TE} \tag{12}$$

Where TN represents normal beats classified as normal, TP represents abnormal beats classified in their respective classes, TE represents the total number of beats, FN represents abnormal beats classified as normal, and FP represents normal beats classified as abnormal [1],[6].

V. Experimental Results

The ECG signal was obtained from the MIT-BIH Arrhythmia Database [12]. The data set used for this work was composed of 5 different 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 was employed.

Using Prony's method that was explained in section (III), the poles from each three second of heartbeat are extracted. As shown in figure 2, the ECG signal is reconstructed using the poles lying on the original signal without any difference. Those poles are divided into two parts, one for the training phase and the other for testing phase.

The MLP classifier model architecture is made up of three layers, the neurons at the input layer is equal to the poles number, 30 neurons at the hidden layer and 5 neurons at the output layer, one for each class. One step secant back propagations training function is used to update the weight and the bias of the network. The Tan-Sigmoid function is used as a transfer function in the first layer, and pure line function is used as transfer function in the output layer. The Mean Square Error (MSE) is used to perform the network classifier error; where the error is the difference between the target and actual network output.

In the training phase of the classifier model, the first part of poles patterns and the corresponding arrhythmias types are adopted as the inputs and the targets. After training, we could get appropriate weights to map the inputs to the desired outputs. In the testing phase, the second part of poles patterns are used to test the performance of MLP classifier model.

Table I and II, show the number of signal used in training and testing phases for all heartbeat classes where the classification results of classifier model for all classes are explained. The accuracy, sensitivity, and the specificity of the classifier model reach 100%.

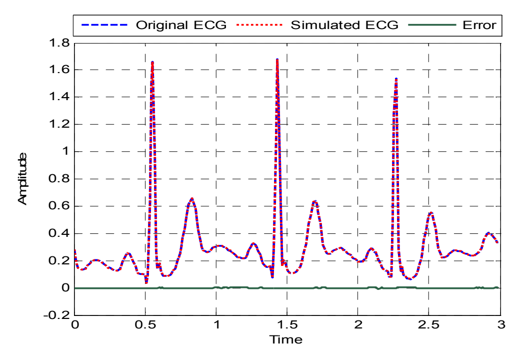


Fig. 2. A patient ECG and simulated ECG

Figure 3 shows the accuracy of classification stages; during the training phase, the accuracy begins from 67.44% to 91.63% and reaches to 100% of the classification. Moreover, in the testing phase, the accuracy begins from 61.90% to 85.71% and reaches to 99.05%, after that it returns to 98.10% and finally reaches to 100%.

TABLE I

CLASSIFICATION RESULTS USING MLP FOR TRAINING DATA

	Training Data size	TN	TP	FN	FP
NR	43	43	-	-	-
VC	43	-	43	-	-
VT	43	-	43	-	-
VB	43	-	43	-	-
VF	43	-	43	-	-
	215	43	172	-	-

TABLE II

CLASSIFICATION RESULTS USING MLP FOR TESTING DATA

	Training Data size	TN	TP	FN	FP
NR	21	21	-	-	-
VC	21	-	21	-	-
VT	21	-	21	-	-
VB	21	-	21	-	-
VF	21	-	21	-	-
	105	21	84	-	-

VI. CONCLUSION

The proposed Prony's method and neural network for poles classification have been shown to be effective in the classification of cardiac arrhythmias in critically ill patients and aid in the diagnosis of heart diseases. Both the newly implemented Prony's method and the neural network used are suitable for real time implementation and can be used as a diagnostic tool.

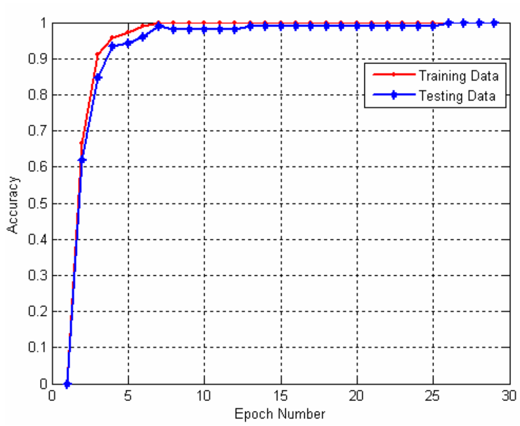


Fig. 3. Accuracy of classification Method

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