

AR Modeling for Cardiac Arrhythmia Classification using MLP Neural Networks

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ABSTRACT

In this paper, we propose a three stage technique for cardiac arrhythmia classification. This method includes a de-noising module, a feature extraction module and a classification module. In the first module we investigate the application of a FIR least squares filter for noise reduction of the electrocardiogram (ECG) signals. The feature extraction module explores the ability of autoregressive model (AR) to extract relevant features from one-lead electrocardiogram signals in order to classify certain cardiac arrhythmias. Then a number of multilayer perceptron (MLP) neural networks with different number of layers and seven training algorithms are designed. The performances of the networks for speed of convergence and accuracy classifications are evaluated for various ECG data types including normal sinus rhythm, atrial premature contraction, premature ventricular contraction, ventricular tachycardia, ventricular fibrillation and Supraventricular tachycardia obtained from the MIT-BIH database. Among the different training algorithms, the resilient back-propagation (RP) algorithm illustrated the best convergence rate and the Levenberg–Marquardt (LM) algorithm achieved the best overall detection accuracy. The classification accuracies of the six types of arrhythmia were 98.7% to 100% which is a significant improvement.

Keywords

Autoregressive model, cardiac arrhythmia, ECG features, ECG classification, MLP, RP algorithm, LM algorithm, neural networks, MIT-BIH database.

1. INTRODUCTION

The ECG is the most important biosignal used by cardiologists for diagnostic purposes. The ECG signal provides key information about the electrical activity of the heart. The early detection of the cardiac arrhythmias can prolong life and enhance the quality of living through appreciate treatment. Therefore, we need many techniques that analyze the ECG signal to detect the heart diseases. In this paper, the following arrhythmia categories have been considered: Normal sinus rhythm (NSR), Pre-ventricular contraction (PVC), Ventricular tachycardia (VT), Ventricular fibrillation (VF), Supra ventricular tachycardia (SVT) and Atrial premature contraction (APC). Among those threatening arrhythmias, VT and VF are most dangerous because they produce the hemodynamic deterioration. Sudden death accounts for approximately half of all deaths from cardiovascular disease and is generally caused by VT and VF. Other arrhythmias such PVC, APC etc, are not so lethal, but are also important for diagnosis. PVC arrhythmia, result from the existence of ectopic centers in the ventricular area of the

heart that changes the path propagation of the activation front and leads to generation of premature contractions of the ventricles that are independent of the pace set by the sinoatrial node[1]. Many studies have shown that PVC can be linked to increased mortality when it is associated with myocardial infarction. So is the case with other arrhythmias. Consequently, their immediate detection and treatment is essential for patients with heart disease. Continuous ECG monitoring permits observation of cardiac variations over an extended period of time, either at the bedside or when patients are ambulatory, providing more information to physicians. Thus, continuous monitoring increases the understanding of patients' circumstances and allows more reliable diagnosis of cardiac abnormalities. Due to the large number of patients in intensive care units and the huge amounts of ECG data, several methods for automated arrhythmia classification have been developed in the past few decades to simplify the monitoring task. In the literature, several methods have been proposed for the automatic classification of ECG signals. Among the most recently published works are those presented in [2–7]. In [2], the authors used a MLP neural network classifier and achieved an accuracy of 88.3% in their testing set. In [3], the authors used morphological information as the features and a neural network classifier for differentiating the ECG beats. In [4], the author used independent components analysis (ICA) for ECG detection. In [5, 6], the authors used the power spectral density (PSD) of ECG signals. In [7], the authors have modeled the ECG signals using the MME (modified mixture of experts) network structure with diverse features. Generally, the performance of ECG pattern classification strongly depends on the characterization power of the features extracted from the ECG data and the design of the classifier. Autoregressive modeling (AR) has been used in various applications, including classification of physiological signals like ECG, EEG, heart rate etc. The advantage of AR modeling is its simplicity and is suitable for real-time classification at the ICU or ambulatory monitoring. AR models are popular due to the linear form of the system, simultaneous equations involving the unknown AR model parameters and the availability of efficient algorithms for computing the solution. AR modeling has been used extensively to model heart rate variability (HRV) and for power spectrum estimation of ECG and HRV signals [8–12]. Several researchers have previously used the AR Modeling coefficients in different ways as parametric features rather than the original signal time series and achieved good

classification performance [13,14]. Accordingly, in the current work we exploit the capability of AR modeling parameters to classify six types of cardiac arrhythmias namely NSR, APC, PVC, SVT, VT and VF. In the classification stage, we have used the Multilayer Perceptron Neural Network. Three hundred sample patterns each from the six classes were selected for classification. In this paper, we propose an automated method for cardiac arrhythmia classification. In the preprocessing module, a FIR least squares filter is used to provide an informative representation that is both robust to noise and tuned to the morphological characteristics of the waveform features. For the feature extraction module we have used a suitable set of features that consist of six coefficients resulting from autoregressive modeling of the three components of the ECG signal (P, QRS, T waves). Then we investigated several MLP neural networks by varying number of hidden layers and neurons for each layer. Multiple algorithms were employed for training of neural networks. The performance of these algorithms was compared in several experiments. The paper is organized as follows. Section 2 describes the preprocessing module. Section 3 explains the feature extraction. Section 4 presents the classifier. Section 5 describes the database and performance metrics. Section 6 shows some simulation results. Section 7 discusses the results and finally Section 8 concludes the paper.

2. ECG DATA PROCESSING

2.1 Preparing Data for AR Modeling

The data in the analysis was obtained from the MIT-BIH Arrhythmia Database (MITDB), Creighton University Ventricular Tachyarrhythmia Database (CUDB), and MITBIH Supraventricular Arrhythmia Database (SVDB). The NSR, PVC and APC were sampled at 360Hz, the VT and VF were sampled at 250Hz, and the SVT was sampled at 128Hz.

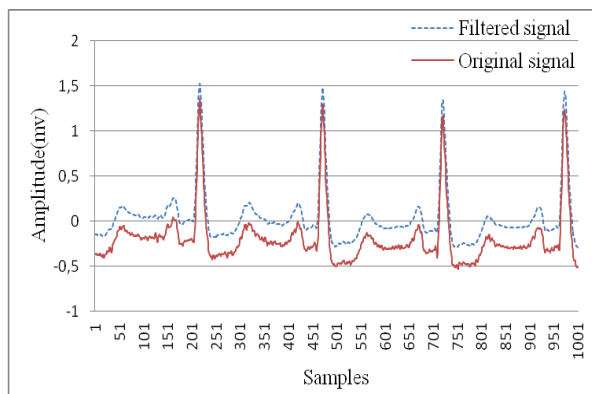


Fig. 1 Suppression of noise from ECG record No105

The data including VT, VF, and SVT were resampled in order that all the ECG signals in the analysis had a sampling frequency of 360Hz. ECG recordings are very often contaminated by residual power-line (PL) interference, base-line drift, artifacts and EMG disturbances due to involuntary muscle contractions (tremor) of the patient. The base-line drift resulting from electrochemical processes at the electrode-to-skin barrier is a typical low-frequency noise that distorts the

susceptible ST segment. All ECG data have been filtered by a FIR least squares filter with a pass band [0 40] Hz to remove the DC drift and the other types of noise (Fig. 1).

The QRS complexes used in this context were extracted from the filtered signals based on the arrhythmia database annotations. A normal ECG refers to the usual case in the health adults where the heart rate is 60~100 beats per minute, RR intervals in APC are shorter than NSR, the RR intervals in VF and VT are much shorter than normal. In the current study, the sample size of the various segments was cycle varying, it is dynamically estimated according to the cardiac rhythm; 34% of RR interval samples before R peak and 66% of RR interval samples after R peak were picked for modeling. It is adequate to capture most of the information from a particular cardiac cycle (P, QRS, and T). Finally the following types of ECG data were ready for AR modeling and feature extraction, a brief description is given for each class [15].

2.1.1 Normal Sinus Rhythm

Heart rate is 60 to 100 beats per minute, P waves are rounds, smoothes and uprights in lead 2. Every QRS complex is preceded by a P wave. Each P wave is the same distance from the QRS complex less than 0.20 seconds. All QRS complexes are similar in size and shape and point in the same direction. Each QRS has the same distance from the T waves and the QRS duration is 0.10 seconds or less. Refer Fig.2.

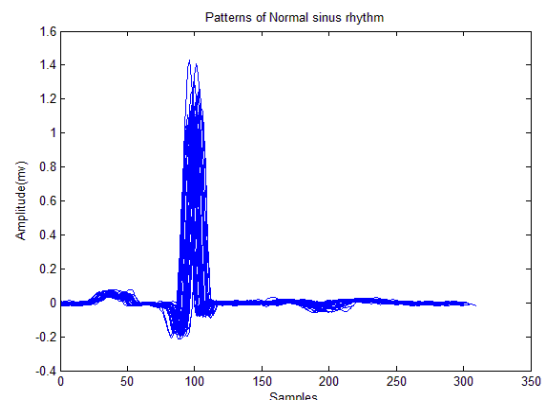


Fig.2 Patterns of NSR (record 100 of MIT-BIH database)

2.1.2 Ventricular Tachycardia

VT is a rapid heartbeat that originates in one of the lower chambers (the ventricles) of the heart. To be classified as tachycardia, the heart rate is usually at least 100 beats per minute. There are widened QRS complexes. The rhythm is usually regular, but on occasion it may be modestly irregular. Rapid ventricular rhythms are more serious than rapid atrial rhythms because they make the heart extremely inefficient. Refer Fig.3.

2.1.3 Supra Ventricular Tachycardia

SVT is any tachyarrhythmia that originates above the ventricles; it requires only atrial and/or atrioventricular (AV) nodal tissue for its initiation and maintenance. It is usually a narrow-complex tachycardia that has a regular, rapid rhythm.

Aberrant conduction during SVT results in a wide complex tachycardia. The P waves are frequently buried in preceding T waves and difficult to see due to the fast rhythm of this arrhythmia. Refer Fig.4.

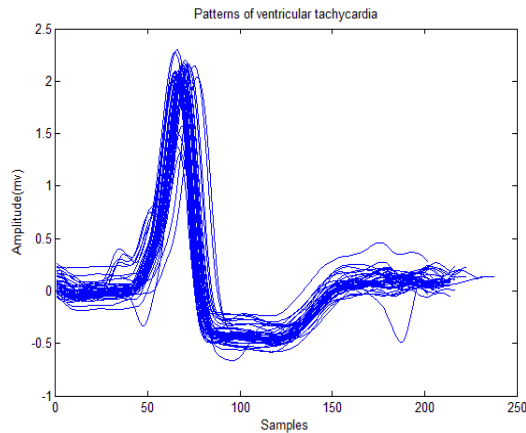


Fig.3 Patterns of VT (record cu13 of CUDB database)

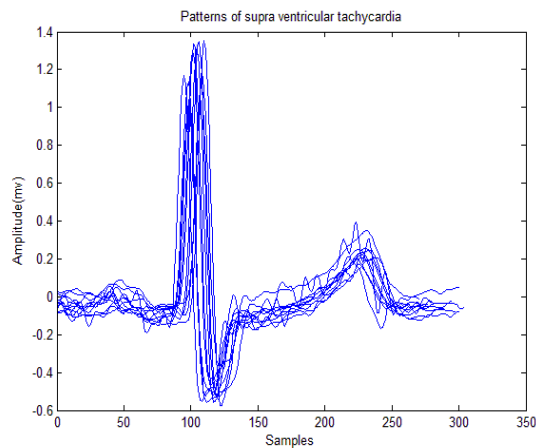


Fig. 4 Patterns of SVT (record 800 of MIT-BIH database)

2.1.4 Premature Ventricular Contraction

PVCs result from any disruption of the normal electrolyte shifts during depolarization and repolarization, they are caused by the existence of an irritable ventricular focus. It may be uniform or multiform. Usually PVC is followed by a full compensatory pause because the sinus node timing is not interrupted. PVC may be followed by a non compensatory pause if the PVC enters the sinus node and resets its timing; this enables the following sinus P wave to appear earlier than expected. Characteristics Complex is early Wide QRS (>0.12 seconds), Often has a compensatory pause, not preceded by P wave and T wave has an opposite deflection. Usually rhythm is irregular. Refer Fig. 5.

2.1.5 Atrial Premature Contraction

During APC, P Waves may have a different shape. PR Interval normally varies in a normal range of (0.12–0.20 sec). QRS interval is Normal (0.06–0.10 sec). After the APC, sinus rhythm usually resumes. Rhythm is irregular whenever APC occurs. Refer Fig. 6.

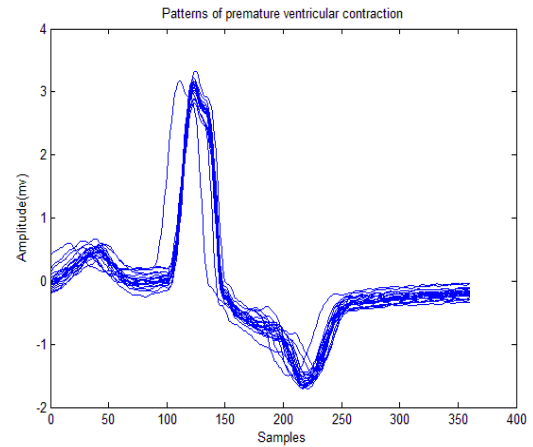


Fig. 5 Patterns of PVC (record 119 of MIT-BIH database)

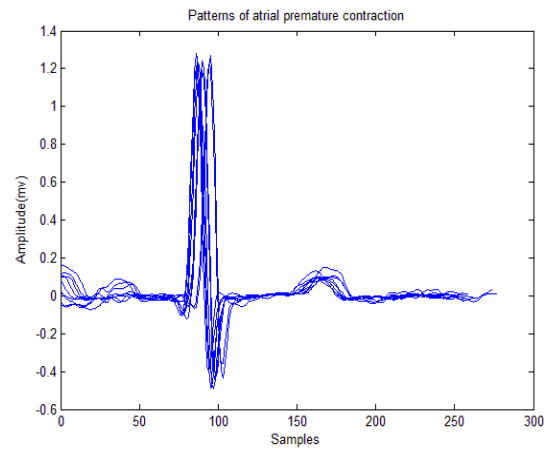


Fig. 6 Patterns of APC (record 209 of MIT-BIH database)

2.1.6 Ventricular Fibrillation

VF is defined as chaotic asynchronous fractionated activity of the heart that occurs with no ventricular depolarization or contraction. No P waves, no QRS interval and no PR interval. The amplitude and frequency of the oscillatory activity can be used to define the type of fibrillation as coarse, medium, or fine. Small baseline undulations are considered fine; large ones are coarse. Refer Fig. 7.

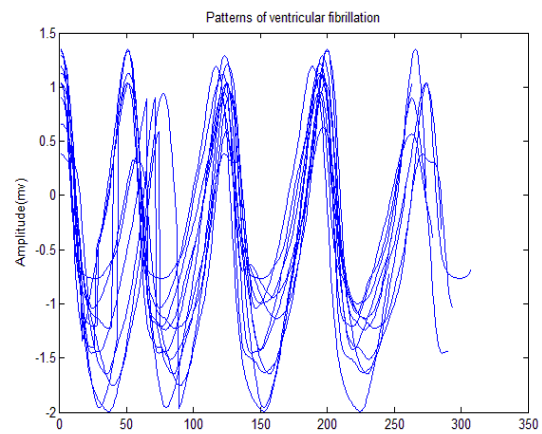


Fig. 7 Patterns of VF (record cu01 of CUDB database)

2.2 Autoregressive Modeling

The six classes of ECG signals with a sampling frequency of 360Hz were utilized for AR modeling after filtering. A general AR model of order P can be expressed as

$$y(n) = \sum_i^P a_i(n) y(n-i) + e(n)$$

Where $y(n)$ represents ECG signal, $e(n)$ represents unknown, zero mean white noise, which is called modeling error, $a_i(n)$ represents the AR model coefficients.

The model order P means that P past samples are needed to predict the present value of the data. The model was estimated from the points of data from each cardiac cycle of the six types of ECG signals. The model order selection was performed on the six types of the ECG signals, various model orders were preselected to choose the more adequate for best classification, an order of 2 appears sufficient to model ECG signal for the purpose of classification. Burg's algorithm was used to compute the AR coefficients.

3. ECG FEATURES EXTRACTION

Physiological signals are frequently characterized by a non stationary time behavior; the ECG signal is highly non stationary within each beat. The AR model coefficients $a_i(n)$ are time-varying. In this section a new method of feature extraction for purpose of cardiac arrhythmia classification is presented. The classifier based on the MLP neural networks uses new features extracted from the morphology of each part of the ECG data. The ECG data segments were extracted according to the arrhythmia database annotations. Each segment contains R_i samples (number of samples between two successive R peaks), R_i/3 before R_i peak and 2/3*R_i after R_i peak, the QRS complex were presented by a segment of R_i/6 samples centered on R_i peak as shown in Fig. 8.

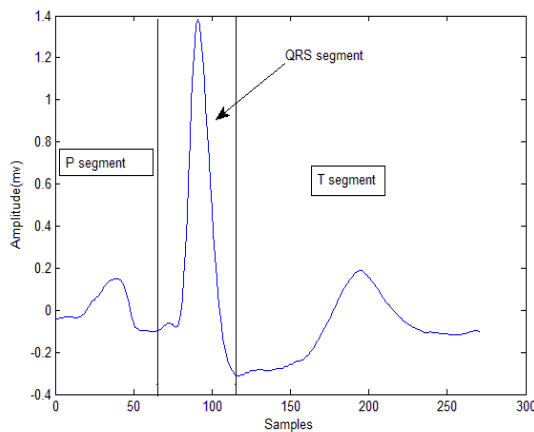


Fig 8: Extraction of the three part of a particular cardiac cycle

Finally AR modeling was performed on every segment of the cardiac cycle and coefficients were estimated by Burg's algorithm, a feature vector of six elements was produced for each data patterns. Table 1 show a sample of these feature vectors for the six considered cardiac arrhythmia.

Table 1: Samples of features vectors of the six ECG types

APC	-1.8873	0.9735	-1.9244	0.9263	-1.9263	0.9333
NSR	-1.9060	0.9595	-1.9499	0.9504	-1.9398	0.9399
SVT	-1.9485	0.9841	-1.8979	0.9126	-1.9459	0.9541
VF	-1.9584	0.9792	-1.9748	0.9920	-1.9761	0.9925
VT	-1.9733	0.9871	-1.9520	0.9689	-1.9778	0.9808
PVC	-1.9768	0.9872	-1.9778	0.9781	-1.9844	0.9846

4. DATABASE AND PERFORMANCE METRICS

4.1 Performance Metrics

One of the significant issues in ECG beat classification is how to appropriately evaluate the performance of a proposed method. In this study, we have considered three statistical indices:

$$Accuracy \% = \frac{Number\ of\ total\ tested\ beats - FP - FN}{Number\ of\ total\ tested\ beats} \times 100$$

$$Specificity \% = \frac{Number\ of\ total\ tested\ beats - FP}{Number\ of\ total\ tested\ beats} \times 100$$

$$Sensitivity \% = \frac{Number\ of\ total\ tested\ beats - FN}{Number\ of\ total\ tested\ beats} \times 100$$

Where FP stands for the words false positive and FN stands for the words false negative. Sensitivity measures how successfully a classifier recognizes beats of a certain class without missing them, whereas specificity measures how exclusively it classifies beats of a certain type.

4.2 ECG Database

The data used in this study was obtained from the MIT-BIH databases. We used the MIT-BIH Arrhythmia Database (MITDB) [16], Creighton University Ventricular Tachyarrhythmia Database (CUDB) [17], and the MIT-BIH Supraventricular Arrhythmia Database (SVDB) [18] to evaluate the performance of our proposed algorithm. The MITDB contains 48 half-hour excerpts of two-channel ambulatory ECG recording, obtained from 47 subjects studied between 1975 and 1979, continuous ECG signals are band pass-filtered at 0.1-100 Hz and then digitized at 360 HZ. The CUDB contains 35 files, 1 channel per file, and each channel 508 seconds long. The SVDB database contains 78 files, 2 channels per file, each channel 1800 seconds long. In this work, we have used a total of 10 records marked as: 100, 101, 105, 200, 209, 119, 800, cu01, cu02 and cu13.

5. RESULTS

5.1 Features Extraction results

The ECG features were extracted by applying AR modeling of order 2 to the ECG signals. This resulted in six AR coefficients to represent an ECG segment. Each beat is featured only with six parameters, two from each beat segment (P, QRS, and T). VTs are characterized by widened QRSs which are less widened in SVTs, P waves are often buried in preceding T waves in SVT beats, then information extracted from the three segments may discriminates them effectively. Fig. 9 shows that there is a very good class separation between VT and SVT. In Fig 10 this discrepancy is less obvious but the class separation will be better when the four other features will be taken in consideration. Then we can conclude that the six features give a good power to classify the different classes of ECG signals.

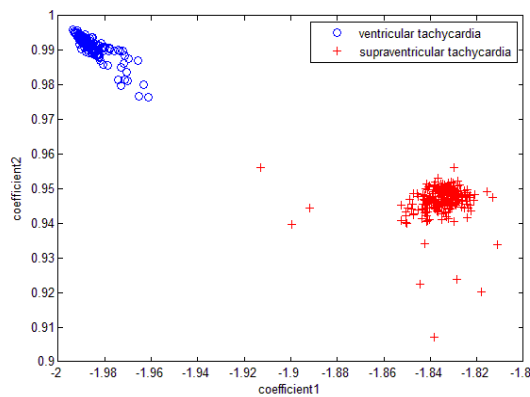


Fig 9: Discrepancy of VT and SVT

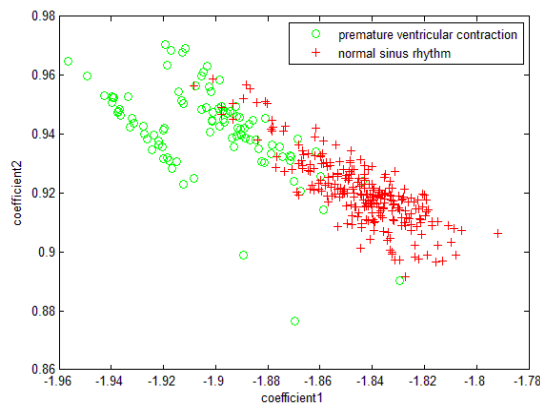


Fig 10: Discrepancy of PVC and NSR

In this research, six types of ECG signals namely, NSR, APC, PVC, VF, VT and SVT were considered for classification which was performed using a number of multilayer perceptron neural networks with different number of layers and seven training algorithms. One hundred and fifty cases each from the six classes were selected at random in training phase, and the remaining cases were used for testing in testing phase. The sensitivity, specificity and accuracy values were computed for all the ECG classes.

5.2 MLP Neural Network Architectures and Training Algorithms

Various network architectures were evaluated to find an optimum solution for ECG signal diagnosis problem. In order to evaluate system performance, the number of hidden layers as well as the number of neurons in the hidden layers was varied in different experiments. The output (target) vector is defined with a combination of 1s or 0s to represent each of the classes being recognized. To assign the ECG waveforms into one of six different classes, the number of neurons in the output layer is set to be six. Table 2 shows the ECG classes and representation of the desired neural network outputs.

Table 2: ECG classes and representation of desired neural network outputs

No	ECG description	Neural network outputs					
1	Normal sinus rhythm	1	0	0	0	0	0
2	Pre-ventricular contraction	0	1	0	0	0	0
3	Atrial premature contraction	0	0	1	0	0	0
4	Ventricular fibrillation	0	0	0	1	0	0
5	Ventricular tachycardia	0	0	0	0	1	0
6	Supra ventricular tachycardia	0	0	0	0	0	1

We investigated four architectures of neural networks. Two architectures, NET1 and NET2 have a single hidden layer with X neurons which was set to 30 and 20, respectively, and we propose two other network architectures NET3 and NET4 with two hidden layer. NET3 and NET4 also have 6 neurons at the input layer and 6 neurons in output layer. Hidden layers of NET3 have both 15 neurons, and these values for NET4 are 15 and 12 neurons. Other parameters for these four architectures are the same. In order to facilitate the performance comparison of different training algorithms, we have used their acronyms. Table 3 shows these training algorithms and their acronyms.

In order to compare the convergence speed and total accuracy of different training algorithms, the classifiers were trained for a predetermined value of mean-squared error (MSE). The number of training iterations, the total accuracies and the time required to achieve the mentioned value of error were recorded. MSE was set to 0.00001. In order to evaluate the recognition accuracies (Acc) of the classifiers with different training algorithms and structures, the classifiers were trained for a predefined number of iterations set at 1000. Three previously defined performance metrics were used for each neural network. For example it can be seen that for NET3 (which has 2 hidden layers with 15 neurons in each layer) the best test accuracy and the fewest epoch numbers are obtained with the LM training algorithm but the best training time was obtained with the RP algorithm. The results are shown in Table 4. In order to simplify the comparison among the different results, we have highlighted in bold type the best results for each of the network structures.

It is clear that the best overall accuracy is reached with the NET3 (which has 2 hidden layers with 15 neurons in each layer) and where the Levenberg–Marquardt algorithm is used for training phase. The Levenberg–Marquardt training algorithm gives the best accuracy for all considered architectures.

Table 3: Nine different training algorithms used for training of MLP neural networks

Acronym	Algorithm
RP	Resilient backpropagation
SCG	Scaled conjugate gradient
CGB	Conjugate gradient with Powell–Beale restarts
CGP	Polak–Ribière conjugate gradient
BFGS	Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton backpropagation
OSS	One-step secant quasi-Newton
LM	Levenberg–Marquardt

Table 4: Comparative results for total accuracy and speed convergence of different training algorithms

Network hidden layers	Training function	Accuracy in test (%)	Training time (s)	Number of epochs
15*15	RP	98.0	2	72
15*12		98.2	6	201
30		98.3	5	197
20		97.3	3	124
15*15	CGP	94.6	2	35
15*12		81.7	3	48
30		97.9	5	67
20		98.2	4	74
15*15	CGB	94.8	3	40
15*12		81.9	3	51
30		82.9	6	90
20		97.7	3	55
15*15	BFGS	98.6	17	71
15*12		81.8	10	69
30		80.8	13	75

20		80.9	7	77
15*15	OSS	97.4	5	80
15*12		82.0	4	64
30		97.7	8	129
20		98.4	8	132
15*15	LM	99.6	20	38
15*12		98.8	18	46
30		99.0	40	94
20		99.0	9	31
15*15	SCG	99.4	6	117
15*12		82.4	4	74
30		97.8	3	75
20		98.8	5	107

5.3 Classification Results

The ECG features were extracted by applying autoregressive modeling of order 2 to the ECG signals. This resulted in six AR coefficients to represent an ECG segment in this research. Six types of ECG signals namely, NSR, APC, PVC, VF, VT and SVT were considered for classification. Classification was performed using multilayer perceptron neural networks. One hundred and fifty cases each from the six classes were selected at random in training phase, and the remaining cases were used for testing in testing phase. The sensitivity and specificity values were computed for all the ECG classes. The results of the MLP based classification are shown in Tables 5 and 6. The results for a sample training set are shown in Table 5 and the classification sensitivity and specificity for various classes are shown in Table 6. The accuracy of detecting NSR, APC, PVC, SVT, VT and VF were 99.3%, 98.7%, 100%, 99.3%, 100%, and 99.3% respectively, the overall accuracy is 99.6%.

Table 5: Classification results based on AR coefficients for sample training set

classes	NSR	PVC	APC	VF	VT	SVT
NSR	149	0	1	0	0	0
PVC	0	150	0	0	0	0
APC	1	0	148	1	0	0
VF	0	0	0	150	0	0
VT	0	0	0	0	150	0
SVT	0	0	1	0	0	149

Table 6: Performance of the classification based on AR coefficients

Classes	NSR	PVC	APC	VF	VT	SVT
Sensitivity	99.3%	100%	98.7 %	100%	100%	99.3%
Specificity	99.3%	100%	98.7%	99.3%	100%	100%

6. DISCUSSION

The arrhythmias classification by neural network classifier requires generation of the input vectors which should include features that represent properly the rhythm and the morphology of the arrhythmia. The main objective of this study was to explore the ability of autoregressive modeling (AR) to extract relevant features from one-lead electrocardiogram signals in order to classify certain cardiac arrhythmias. The modeling results showed that the AR order of 2 was sufficient to model ECG signals for the purpose of the classification, the same order was considered in [19] where two AR coefficients and the mean-square value of QRS complex segment were utilized as features for classifying PVC and NSR using a fuzzy ARTMAP classifier, sensitivity of 97% and specificity of 99% were achieved. In the current study a variable sample size based on R-R intervals was considered to extract the relevant information from a particular cardiac cycle then better features were extracted from modeling process, in [14 and 20] a fixed sample size of 1.2 seconds and 0.9 seconds respectively had been used, which lack of exactitude due to the heart variability rhythm (APC and VT samples are much shorter than SNR). The use of variable sample size enhance considerably the classification accuracy by producing better features.

Physiological signals are frequently characterized by a non stationary time behavior, the ECG signal is highly non stationary within each beat; the AR model coefficients $a_i(n)$ are time-varying. In [13, 14, and 20] these AR coefficients were considered constants over the whole pattern samples; the non stationary nature of the ECG signal is omitted. In our study we divide a cardiac cycle into three part (P, QRS, and T segments), AR coefficients were estimated for each segment separately, which pick some information about the non stationary nature of the ECG signal. Considering the non stationary nature of ECG signals give us better features that enhance the classification performance.

The classification results show that AR modeling can be used to discriminate between different arrhythmias. The classification results achieved using AR modeling is comparable to the recently published results on the classification of cardiac arrhythmias. Normal and abnormal PVC conditions have been classified using the QRS power spectrum and self-organizing maps with sensitivity of 82.71% and specificity of 88.06% [21]. Accuracy of 93% and 96% has been reported for VT and VF respectively using a modified sequential probability ratio test algorithm [11]. An overall accuracy of 93% to 99% was achieved with decimated ECG data and artificial neural networks [22]. The total least squares-based Prony modeling technique produced an

accuracy of 95.24%, 96% and 97.78% for SVT, VT and VF respectively [23].

The current study classifies six types of ECG arrhythmias, the same set of arrhythmias was considered for classification in [13 and 24]. In [13] the accuracy of detecting the same types of arrhythmia were 93.2% to 100% using AR modeling and a generalized linear model based algorithm. The accuracy of discrimination of NSR, APC, SVT, PVC, VT and VF were 99.307%, 99.274%, 99.854%, 98.344%, 99.441% and 99.883%, respectively with a support vector machine (SVM) based classifier [24], the results of our proposed method were 98.7% to 100%.

As our experimental results indicate the classification performance of the MLP neural networks convergence according to speed and accuracy. Generally, it is a difficult problem to determine which training algorithm is the fastest for a given task since many factors are at play. These factors include: the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). To compare the speed of the training methods, consider Table 4. As shown, most of the algorithms have good convergence, but the RP algorithm shows the highest speed of convergence. To compare training algorithms for the classification of the ECG signals, accuracy was calculated for each class. In terms of the recognition accuracy, it can be seen that the LM algorithm achieved the best performance for all the four MLP neural networks considered in this study.

7. CONCLUSIONS

We have proposed a number of efficient methods to accurately classify six types of cardiac arrhythmia. These methods include three modules: an efficient preprocessing module, a feature extraction module and a classifier. We used a FIR least squares filter to de-noise ECG signals in the preprocessing module. In the feature extraction module we extracted 6 coefficients of AR modeling as the effective features for differentiating normal beats, and other beats. Then a number of MLP neural networks with different number of layers and different training algorithms were designed. Classification abilities of these algorithms were compared for six different classes of ECG signals. Four architectures with one hidden or two hidden layers were chosen for this investigation. These networks were trained with seven different training algorithms. An overall classification accuracy of 99.6% for testing dataset was achieved over various ECG signals from the MIT-BIH database. Simulation results show that the RP algorithm possessed the best convergence rate. The LM algorithm achieved a smaller number of iterations and the best accuracy but did poorly on convergence speed. The RP algorithm was the optimum choice since it had the best convergence speed as well as very good accuracy levels. However, these results are not general and they vary to a large extent over multiple classification problems.

Autoregressive modeling of the three part of the cardiac cycle give efficient features that characterize separately the three important part of the cardiac cycle; the most relevant information is stored in the QRS complexes.

It should be noted that in addition to selection of classifier type and architecture, feature set selection might also have a vital role in classification results. Further examination of other feature sets with more relevant information about the non linear and non stationary nature of the ECG signal may be warranted in future studies. Other classifiers with higher overall recognition accuracies may also be studied.

In this study, we have used a scalar AR model to extract relevant information from one lead ECG signals. Further work is in progress to use multivariate AR modeling to process and extract relevant features from two lead ECG signals, the preliminary results show a considerable improvement of the classification accuracy. We project also to apply our method to Electroencephalogram (EEG) and other biomedical signals.

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