AN ADAPTIVE BACKPROPAGATION NEURAL NETWORK FOR ARRHYTHMIA CLASSIFICATION USING R-R INTERVAL SIGNAL

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Abstract: Automatic detection and classification of cardiac arrhythmias with high accuracy and by using as little information as possible is highly useful in Holter monitoring of the high risk patients and in telemedicine applications where the amount of information which must be transmitted is an important issue. To this end, we have used an adaptive-learning-rate neural network for automatic classification of four types of cardiac arrhythmia. In doing so, we have employed a mix of linear, nonlinear, and chaotic features of the R-R interval signal to significantly reduce the required information needed for analysis, and substantially improve the accuracy, as compared to existing systems (both ECG-based and R-R interval-based). For normal sinus rhythm (NSR), premature ventricular contraction (PVC), ventricular fibrillation (VF), and atrial fibrillation (AF), the discrimination accuracies of 99.59%, 99.32%, 99.73%, and 98.69% were obtained, respectively on the MIT-BIH database, which are superior to all existing classifiers.

1. Introduction

Arrhythmia is an abnormality in the heart's rhythm, or heartbeat pattern. During an arrhythmia, heart may beat too slow, too fast, or with an irregular rhythm. Some types of arrhythmia, such as ventricular fibrillation, are serious and even life-threatening. In many countries, arrhythmia is the primary cause of sudden cardiac

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death. As such, development of new methods for detecting heart's abnormalities is an active research area.

A relatively new approach for assessing heart activities and discriminating different cardiac abnormalities is to analyze the heart rate variability (HRV) signal. The aim in HRV analysis is to examine the sinus rhythm modulated by the autonomic nervous system. To do so, one should detect the occurrence of the SA-node action potentials. This is, however, practically impossible and, thus, the fiducial points for the heart beat are usually determined from ECG recordings.

The nearest observable activity in ECG compared to SA-node firings is the P-wave, emanating from arterial depolarization. Thus, the heart beat period is generally defined as the time difference between two successive P-waves. The signal-to-noise ratio of P-wave is, however, clearly lower than that of the strong QRS complex that emanates primarily from ventricular depolarization. Therefore, the heart beat period is commonly evaluated as the time difference between the easily detectable QRS complexes, i.e. the R-R interval signal.

R-R interval signal is a nonlinear and nonstationary signal that reflects the interaction between the autonomic nervous system and the cardiovascular system. As such, measurement and mathematical analysis of R-R interval signal has been an active research area, which can provide adequate insight into existing or potential heart deficiencies in patients.

Various techniques have been used in the literature for automatic arrhythmia feature extraction and classification. Examples include threshold-crossing intervals [8], artificial neural networks [3, 5, 14, 16, 21, 27, 30, 36, 38], wavelet transform [17], wavelet analysis combined with radial basis function neural networks [4], support vector machines [6, 28], Bayesian classifiers [23], fuzzy logic with the Markov models [32], fuzzy equivalence relations [2], rule-based algorithms [31], and fuzzy expert systems [10]. Most studies use the analysis of the ECG signal itself [4, 8, 17, 21, 27, 28, 36, 38]. However, they are sensitive to noise and require many time-consuming processes.

An alternative approach is to use R-R interval signal, which can be obtained by measuring R-R time intervals (time intervals between successive R peaks). As such, R-R interval-based arrhythmia detectors can detect certain types of arrhythmia that cause variations in R-R intervals.

Different methods for detection and classification of cardiac arrhythmias using R-R interval signals were introduced in the past. Tsipouras *et al.* [30] proposed an algorithm based on both time and time-frequency analysis of R-R interval signal using a set of neural networks. Their method classifies the ECG segments as normal or arrhythmic segments but cannot identify the type of arrhythmia. Acharya *et al.* [2] employed a multilayer perceptron (MLP) together with a fuzzy classifier for arrhythmia classification using R-R interval signal. They classified the input ECG segments into one of the four different arrhythmia classes. In [31], Tsipouras *et al.* proposed a knowledge-based method for classifying arrhythmia into four different categories. Also, in [33], a fuzzy expert system is presented for classifying arrhythmic beats into four classes.

Although numerous very accurate algorithms exist for detecting and classifying arrhythmic beats and episodes, they have generally been applied to relatively small data sets [8, 16, 27]. Besides, training and testing are overlapped in some existing

classifiers. For example, in [33], where the best results for R-R interval-based arrhythmia classification are reported, the 2° heart block (BII) is present only in record 231 of the MIT-BIH arrhythmia database, i.e. training and testing for BII are done on one subject. The same is true for VF in record 207.

A highly irregular heart rate is a prime indicator of some important cardiac arrhythmia such as AF. As R-R interval signal contains variations in heart rate, it is a good candidate for detecting irregular rhythms. In this paper, we analyze R-R interval signal for classifying cardiac arrhythmias into four classes, namely, normal sinus rhythm (NSR), premature ventricular contraction (PVC), ventricular fibrillation (VF), and atrial fibrillation (AF). In doing so, we note that linear measures in R-R interval signal are inadequate for classification of multiple rhythm changes. We explore nonlinear dynamics of R-R interval signal to quantify some of the more complex structures in the heart-rate time-series. Fig. 1 represents the phase space plots for the NSR, PVC, AF, and VF arrhythmia. As seen, the phase space patterns are completely different for different arrhythmia. For NSR, the phase space plot looks like a cluster of points with the mean 60-80 beats per minute. In the PVC, there would be a sudden impulsive jump in the heart rate due to a pre-ventricular beat in the ECG signal. This may be indicated as a sudden spike in the phase space plot. In VF, the heart rate and its variation are high and hence, the phase space plot is randomly distributed in the upper right corner of the phase space plot. Finally, in the AF, heart rate signal records highly erratic variability depicted as scattering of points in the phase space plot. As such, we use a combination of linear, nonlinear, and chaotic features, and apply them as inputs to a back-propagation neural network, whose learning-rate is adapted throughout the training period to classify each episode into one of the four arrhythmia classes. We only need to detect the QRS complex and extract the R-R intervals. This is in contrast to other approaches that need to detect the P wave or the T wave, which are time-consuming and complicated. Noisy data can be efficiently analyzed because existing QRS detection algorithms perform well. To evaluate our proposed method, we explore a large data set obtained from the MIT-BIH arrhythmia database and the MIT-BIH malignant ventricular arrhythmia database, and use different subjects for training and for testing the classifier.

The rest of this paper is organized as follows. Our developments and proposed algorithm are presented in Section 2. Section 3 contains the results of applying our proposed scheme to the arrhythmia database. The advantages of the proposed method as well as a comparison with existing methods are discussed in Section 4. Finally, concluding remarks are given in Section 5.

2. Materials And Methods

2.1 Database

The data set for R-R interval signal in this paper is generated from ECG signals provided by the MIT-BIH arrhythmia database and the MIT-BIH malignant ventricular arrhythmia database [20]. The MIT-BIH arrhythmia database was created in 1980 as a reference standard for serving all those who conduct research on the cardiac arrhythmia detection and classification problem [22]. This database in-
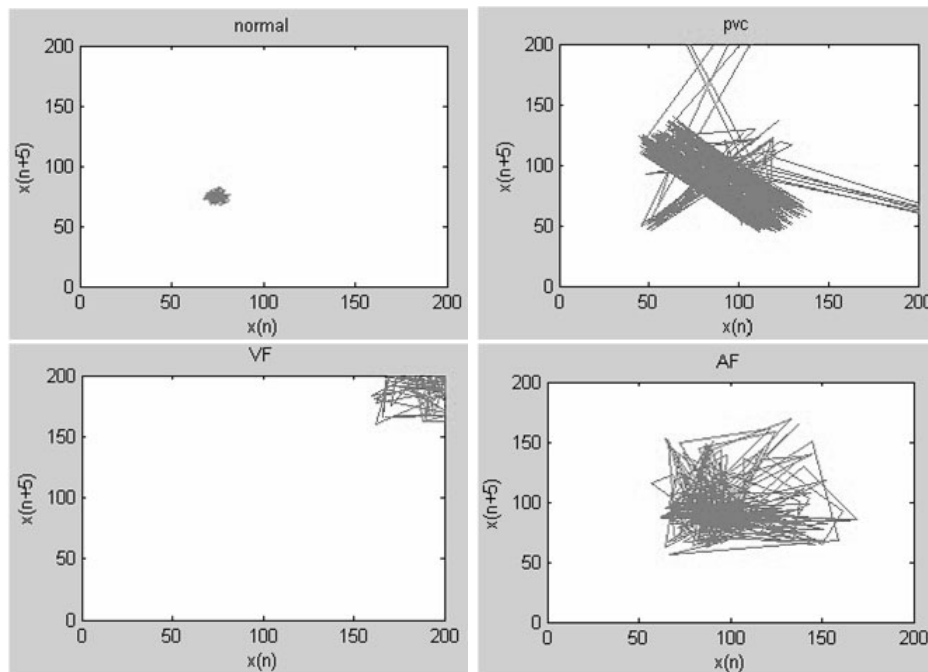
Fig. 1 *Phase space plots for the Normal sinus rhythm (NSR), PVC, VF, and AF arrhythmia.*

cludes 48 ECG recordings each for 30 minutes with a total of about 109000 R-R intervals. The ECG signals were bandpass-filtered in the frequency range of 0.1 to 100 Hz and were sampled at the rate of 360 samples per second. Each of the about 109000 beats was manually annotated by at least two cardiologists working independently. Their annotations were compared, consensus on disagreements was obtained, and the reference annotation files were prepared [22]. The reference annotation files include beat, rhythm, and signal quality annotations.

Due to inadequate PVC and VF instances in the MIT-BIH arrhythmia database, we also used the MIT-BIH malignant ventricular arrhythmia database after resampling its ECG recordings at the rate of 360 samples per second. This database includes 22 half-hour ECG recordings of subjects who experienced episodes of sustained ventricular flutter and ventricular fibrillation, and contains only rhythm labels (no beat labels).

A total of 2009 ECG segments each with 32 R-R intervals were selected from the above mentioned databases, which contains all four different arrhythmia classes considered in this study. The specialists' rhythm annotations for each segment were also considered along with the segments.

2.2 Proposed scheme

Our analysis is carried out in three stages, as shown in Fig. 2. The preprocessing part extracts R-R intervals from ECG. Then, linear and nonlinear features are
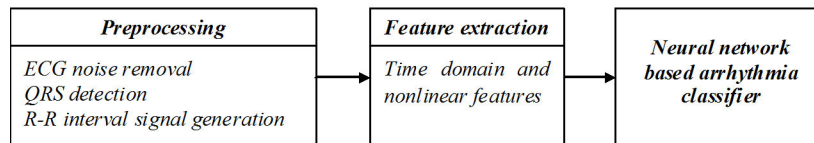
Fig. 2 *Block diagram of the proposed arrhythmia classifier.*

obtained. Finally, the extracted features are used for training a neural network for classification. In what follows, we describe each part in detail.

2.2.1   Preprocessing

ECG signals are usually contaminated with several types of noise, including power line interference (A/C), electromyogram (EMG) noise, and baseline wandering (BW), which affect the detection of QRS and hence the quality of the resulting R-R interval signal. We remove such contaminations by using a 5 to 15 Hz band-pass filter [24] prior to any further processing. Then R-R intervals are extracted from the filtered ECG as follows. Initially, a point in the QRS complex is detected (QRS point), using Pan-Tompkins algorithm [24]. Afterwards, the R wave in the QRS complex is identified within the time window [QRS−280 ms, QRS+120 ms] by locating the maximum absolute value of the signal. Now, the R-R interval signal is constructed by measuring the time interval between consecutive R waves, is segmented into small episodes each containing 32 R-R intervals, and labeled using the database rhythm annotations.

2.2.2   Feature extraction

Different linear and nonlinear parameters are defined to describe the R-R interval signal. We use linear features specified in the special report of the Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology in 1996 [29], as well as certain nonlinear features, as described below.

Linear Analysis – Time Domain Features   Time domain features include changes in the heart rate over time or in the intervals between successive normal cardiac cycles [18]. We use the following time domain features:

Mean: Mean of all R-R intervals in each segment;

RMSSD: Root mean square of successive interval differences in each segment;

SDNN: Standard deviation of R-R intervals in each segment;

SDSD: Standard deviation of differences between adjacent R-R intervals in each segment;

pNN50: Number of pairs of adjacent R-R intervals differing by more than 50 ms divided by the total number of all R-R intervals in that segment.

Nonlinear Analysis Recent studies indicate that nonlinear analysis is more efficient in detecting abnormal patterns and R-R fluctuations as compared to using the standard HRV measurements [19]. We use the following nonlinear features of the R-R interval signal:

SD1, SD2, SD1/SD2: A relatively new tool for R-R interval signal analysis is the Poincaré plot, which does not require the R-R interval signal to be stationary [7]. Poincaré plot is a graphical representation of the correlation between successive R-R intervals, i.e. a plot of $RR(n+1)$ as a function of $RR(n)$. This plot can be quantitatively analyzed by calculating the standard deviations of the distances of $RR(i)$ from the lines $y = x$ and $y = -x + 2 \times RR_m$, where RR_m is the mean of all $RR(i)$. These standard deviations are denoted by SD_1 and SD_2, respectively, where SD_1 is related to the fast beat-to-beat variability in the data, and SD_2 describes the longer-term variability of $RR(i)$. The ratio SD_1/SD_2 is usually used to describe the relation between the two components [34].

ApEn: The approximate entropy (ApEn) is a measure of unpredictability of fluctuations in a time series, and reflects the likelihood that similar patterns will not be sequential. A time series containing many repetitive patterns has a relatively small ApEn, while a less predictable (i.e. more complex) process has a large ApEn [12]. We use the method proposed in [25] to calculate ApEn for each segment in the R-R interval signal by setting pattern length $m = 2$ and the measure of similarity $r = 20\%$ of the standard deviation of the segment, as in [26].

LLE: The Lyapunov exponent is a measure of how fast two nearby points on a trajectory will diverge from each other as the system evolves, and indicates the system's dependency on initial conditions [9]. A positive Lyapunov exponent is a strong indicator of chaos [15, 37]. Even though an m dimensional system has m Lyapunov exponents, in most applications it is sufficient to obtain only the largest Lyapunov exponent (LLE). In practice, usually the average LLE is used. To calculate the average LLE, a starting point is selected in the reconstructed phase space, and all the points within a predetermined distance from the starting point are found. Then, as the system evolves, the average distances between the trajectory of the initial point and the trajectories of the neighboring points are calculated. The slope of the line of the logarithms of these average values in time is the average LLE for the selected initial points. The procedure is repeated for different starting points to obtain the average LLE for all starting points [35].

DFA: The detrended fluctuation analysis (DFA) can quantify the fractal scaling properties of short R-R intervals. This technique is a modification of the root-mean-square analysis of random walks applied to nonstationary signals [13]. The root-mean-square fluctuation of an integrated and detrended time series is measured in different observation windows and plotted against the size of the observation window on a log-log scale [1]. To apply to R-R interval signal, the integrated R-R time series (of the total length N) is obtained by

$$y(k) = \sum_{i=1}^{k} (RR(i) - RR_{avg}), \tag{1}$$

where $y(k)$ is the kth value of the integrated series, $RR(i)$ is the ith inter-beat interval, and RR_{avg} is the average inter-beat interval over the entire series. The

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integrated time series is divided into windows of equal length n. In each window, a least-squares line is fitted to the R-R interval data (representing the trend in that window). The y coordinate of the straight line segments is denoted by $y_n(k)$. We detrend the integrated time series in each window. The root-mean-square fluctuation of this integrated and detrended series is then calculated by

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_n(k)]^2}. \qquad (2)$$

This computation is repeated over all window sizes to obtain the relationship between $F(n)$ and window size n representing the number of beats in that window. Typically, $F(n)$ increases with window size. Fluctuations in small windows can be characterized by a scaling exponent (self similarity factor) α that is the slope of the line relating $\log(F(n))$ to $\log(n)$ [1]. We computed the short-term DFA by setting the window size in the range of $4 \leq n \leq 16$.

STA: The sequential trend analysis (STA) of the R-R interval signal evaluates the sympathetic-parasympathetic balance by providing the spectral analysis of the signal without requiring the signal to be stationary. To perform the STA, we plot $\Delta RR(n)$ against $\Delta RR(n+1)$ and divide the plane into four quadrants. The points located in the +/+ quadrant indicate two consecutive interval increments, meaning that the heart rate is decreasing, and the ones in the -/- quadrant indicate two consecutive interval decrements, meaning that the heart rate is increasing. We use the density of the points within the -/- and +/+ quadrants as the two features that measure the sympathetic and parasympathetic activities, respectively [7].

2.2.3   Neural network arrhythmia classifier

Artificial neural networks (ANNs) are biologically inspired networks that are useful for pattern recognition, classification, etc. The decision-making process of ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data. Typically, a multilayer feedforward neural network can be trained as a nonlinear classifier using the generalized back-propagation algorithm [11].

In this paper, the features extracted from linear and nonlinear analysis are used for training a back-propagation neural network. We employ a three-layered network that includes 13 inputs, one hidden layer consisting of 20 neurons with the standard sigmoid activation functions, and 4 outputs with real values in the interval [0, 1]. The output neuron with the maximum value indicates the class to which the applied input belongs. To improve the performance of the classifier and to reduce the sensitivity to learning rate, we use adaptive-learning-rate back-propagation and momentum training methods.

In the conventional steepest descent back-propagation algorithm, the learning rate is held constant throughout the training. The performance of the algorithm is very sensitive to the learning rate. If the learning rate is set too high, the algorithm may oscillate, and becomes unstable. If the learning rate is too small, the algorithm will take too long to converge. The optimal learning rate may change during the training process, as the algorithm moves across the performance surface. The performance can be improved if we allow the learning rate to adapt during

the training process. An adaptive learning rate will attempt to keep the learning step-size as large as possible while keeping the learning stable, and is a function of the complexity of the local error surface [10].

In the learning process, we combine adaptive-learning-rate with momentum training. The momentum allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low-pass filter, the momentum allows the network to ignore small disturbances in the error surface, without which a network may get stuck in a shallow local minimum. Momentum is added to back-propagation learning by making weight changes equal to the sum of a fraction of the last weight change and the new change suggested by the back-propagation rule [10]. In brief, the weights are updated by

$$\Delta \mathbf{x} = m_c \times (\Delta \mathbf{x})_{prev} + l_r \times m_c \times \frac{\partial(\mathit{perf})}{\partial \mathbf{x}}, \tag{3}$$

where $(\Delta \mathbf{x})_{prev}$ is the previous change to the weights, the bias variables $\mathbf{x}$ and the learning rate l_r are adapted at each epoch, and m_c is the momentum constant. The back-propagation rule is used for calculating derivatives of the performance perf with respect to weights and bias variables $\mathbf{x}$. Each variable is adjusted according to the gradient descent with momentum.

The training of the neural network ends if the sum of the squared errors for all segments is less than 0.001, or 2000 training epochs is reached, or the performance gradient falls below the minimum gradient. The initial learning rate, the learning rate increment factor, and the momentum factor are set to 0.05, 1.05, and 0.9, respectively. The number of data sets for training and testing of the neural network classifier, and the results for each class are listed in Tabs. I and II, respectively. Also, the training curve of the proposed neural network classifier is shown in Fig. 3. As can be seen, the performance goal was met in 345 epochs.

3. Results

A total number of 2009 segments, consisting of 1136 NSR segments, 71 PVC segments, 459 VF segments, and 343 AF segments were used for training and testing. Note that the percentage of NSR segments in the data set is high, which is in agreement with the fact that ECG recordings usually have a high percentage of normal beats. The R-R interval signals in each class are randomly divided into training sets and testing sets in an approximate ratio of 3/5 and 2/5, respectively, in such a way that patients in the training set are different from patients in the testing set. Training and testing are repeated 10 times, and the averaged results are presented.

Performance of the classifier is analyzed in terms of sensitivity, specificity, and accuracy, defined as

$$\mathrm{Sensitivity}(\%) = \frac{TP}{TP + FN} \times 100, \tag{4}$$

$$\mathrm{Specificity}(\%) = \frac{TN}{TN + FP} \times 100, \tag{5}$$

Database Annotation	Classification Results			
	NSR	PVC	VF	AF
NSR	520.8	0	0.2	2
PVC	0	25.8	0	2.2
VF	0	0	206.8	1.2
AF	1.4	3.8	1	118.8

Tab. I *Correct Classification of Testing Set in Each Class by the Proposed Algorithm and the Spread of Erroneous Classifications.*

Arrhythmia Classes	Number of Training and Test Segments	Proposed ABP Classifier			CLBP Classifier		
		Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
NSR	613,523	99.58	99.61	99.59	97.67	93.52	95.97
PVC	43,28	92.14	99.56	99.32	40.71	99.91	98.03
VF	251,208	99.42	99.82	99.73	95.38	97.66	97.13
AF	218,125	95.04	99.29	98.69	75.84	96.23	93.35
Average		96.55	99.57	99.33	70.40	96.83	96.12

Tab. II *Performances Analysis of the Proposed Adaptive-Learning-Rate Back-Propagation (ABP) and Constant-Learning-Rate Back-Propagation (CLBP) Classifiers.*
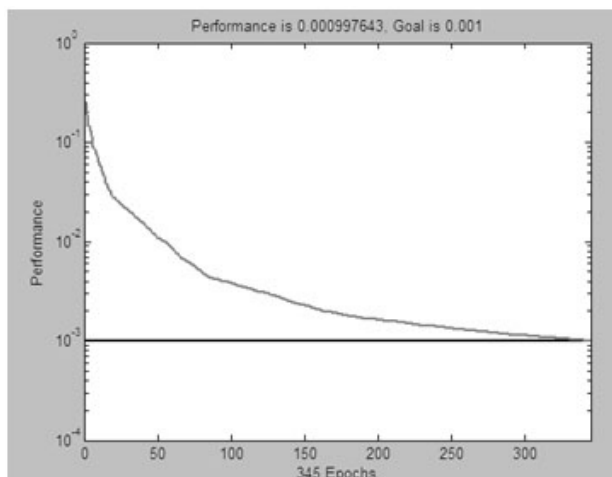
Fig. 3 *Training curve of the proposed NN.*

$$\text{Accuracy}(\%) = \frac{TP + TN}{TP + FN + TN + FP} \times 100, \tag{6}$$

where TP, TN, FP, and FN stand for the number of true-positive, the number of true-negative, the number of false-positive, and the number of false-negative events, respectively. A segment of R-R interval signal with VF classified as VF is TP-classified. A non-VF segment classified as non-VF is TN-classified. A non-VF segment classified as VF is FP-classified, and a VF segment classified as non-VF is FN-classified.

The average correct classification results over 10 runs on the testing set for each class together with the spread of erroneous classifications are shown in Tab. I. As can be seen, for NSR, on average, 2 segments are misclassified as AF (0.38%) and 0.2 segments as VF (0.04%). For PVC, on average, only 2.2 segments are misclassified as AF (7.86%). For VF, on average, only 1.2 segments are misclassified as AF (0.58%). For AF, on average, 3.8 segments are misclassified as PVC (3.04%), 1.4 segments as NSR (1.12%), and 1 segment as VF (0.8%). This classifier can discriminate NSR with an average accuracy of 99.59%, PVC with 99.32%, VF with 99.73%, and AF with 98.69%. These results demonstrate the effectiveness of the proposed arrhythmia classification algorithm in discriminating the four different types of arrhythmia.

The performance measuring parameters are also calculated for the conventional back-propagation neural network classifier. The learning method and its parameters in this classifier are the same as those of the adaptive back-propagation, the only difference being that the learning rate is constant. Tab. II shows the average values of performance measures for both conventional and adaptive-learning-rate back-propagation classifiers. As can be seen, the overall sensitivity, specificity, and accuracy of the proposed method, i.e. 96.55%, 99.57% and 99.33%, respectively, are significantly higher than those of the non-adaptive classifier.

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4.   Discussion

Detection and classification of arrhythmia episodes is the final application the algorithm is intended for. Because of the high accuracy and using only the R-R interval information, which needs only detecting the R peaks and saving their occurrence time from various amounts of information included in the ECG signal, our proposed method can be applicable in long-term monitoring of the patients and also because of using little information to detect arrhythmias, it can be suitable for telemedicine applications where the amount of information which must be transmitted is an important issue. However, our proposed method is limited to detection of 4 arrhythmia classes and it must be verified by other types of arrhythmia and on a larger database.

Existing schemes for arrhythmia detection and classification either directly utilize ECG or analyze heart rate signal. Some (i.e [8, 16, 27, 38]) focus on detecting only a single arrhythmia type (mostly VF and AF). In [16], a classification rate of 100% for AF in a small data set is reported. In [30], ECG segments are classified into normal or arrhythmic by using neural networks. In [2], different heart rhythms are detected and classified into two or three arrhythmia types using a knowledge-based system. A neural network-based method that uses wavelet transform is developed in [14] for detecting only NSR and PVC. Compared to existing methods, our proposed R-R interval-based scheme is more accurate for a wider range of different arrhythmia types (four types).

Our results show that a combination of linear, nonlinear, and chaotic features extracted from the R-R interval signal applied to an adaptive-learning-rate backpropagation neural network with momentum training can accurately and efficiently discriminate different types of cardiac arrhythmia. Obtaining the R-R interval signal only needs detecting R peaks in ECG, which can be done highly accurately using the existing QRS detection algorithms that are robust against interference. The exclusive use of R-R intervals substantially reduces the processing complexity, as compared with other methods.

Tab. II shows that our adaptive-learning-rate back-propagation classifier (ABP) outperforms the widely used constant-learning-rate back-propagation classifier (CLBP) in [3, 5, 14, 16, 21, 27, 30, 36, 38]. In particular, ABP improves the discrimination of PVC and AF by an average sensitivity of 51.43% and 19.20%, respectively. On average, sensitivity, specificity, and accuracy of the proposed classifier are 26.15%, 2.74%, and 3.21% higher compared to CLBP, respectively. This demonstrates the effectiveness of ABP for arrhythmia classification. Moreover, because of using the adaptive-learning-rate scheme in our approach, it converged in 345 epochs on average, as compared to CLBP which does not converge even in 2000 epochs.

5.   Conclusions

A robust and effective neural-network-based arrhythmia classifier is developed and presented, which can be used as an efficient tool for diagnosing cardiac arrhythmias. The neural network classifier utilizes a combination of linear and nonlinear parameters derived from the R-R interval signal. For a faster convergence, an adap-

tive learning-rate neural network with momentum training was used. The proposed classifier demonstrates satisfactory performance in discriminating the four common types of cardiac arrhythmia. The discrimination accuracy for NSR, PVC, VF, and AF are 99.59%, 99.32%, 99.73%, and 98.69%, respectively. These results show the usefulness of the proposed classification algorithm.

We proposed an approach based on R-R interval signal for arrhythmia classification, which uses only the R-peaks information and showed that using nonlinear dynamics of R-R interval signal is an effective approach in accurately discriminating the different types of arrhythmia. Our proposed classifier is superior to existing classifiers in terms of the overall sensitivity, specificity, and accuracy. Its main advantage is that it is completely based on R-R intervals that can be obtained quite accurately even for noisy or complicated ECG recordings. In addition, the exclusive use of R-R intervals substantially reduces the required information needed for analysis and processing time, as compared to other direct ECG-based methods. Because of its low complexity and high accuracy, our proposed method can be used as a real-time arrhythmia classifier for reliable clinical monitoring of patients.

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