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Application of artificial neural networks to identify the premature ventricular contraction (PVC) beats

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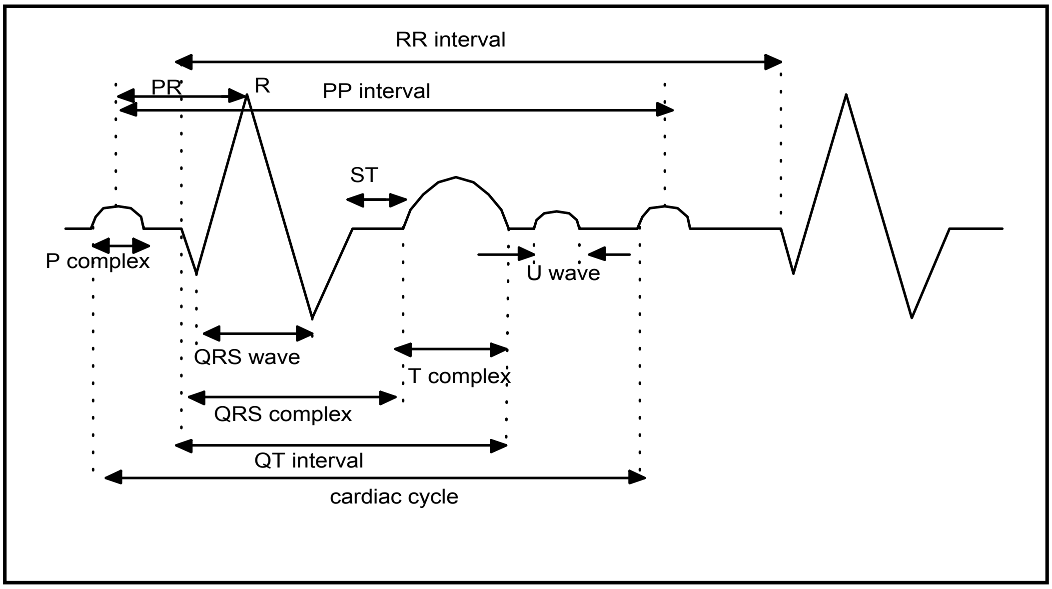
Premature ventricular contraction (PVC) is a cardiac arrhythmia that can result in sudden death. Understanding and treatment of this disorder would be improved if patterns of electrical activation could be accurately identified and studied during its occurrence. In this paper, we shall review three feature extractions algorithms of the electrocardiogram (ECG) signal, Fourier transform, linear prediction coding (LPC) technique and principal component analysis (PCA) method, with aim of generating the most appropriate input vector for a neural classifier. The performance measures of the classifier rate, sensitivity and specificity of these algorithms will also be presented using as training and testing data sets from the MIT-BIH (Massachusetts Institute Technology – Beth Israel Hospital) database.

Keywords: ECG signal, linear prediction coding, principal component analysis, Fourier transform, neural networks, premature ventricular contraction, MIT-BIH arrhythmia database

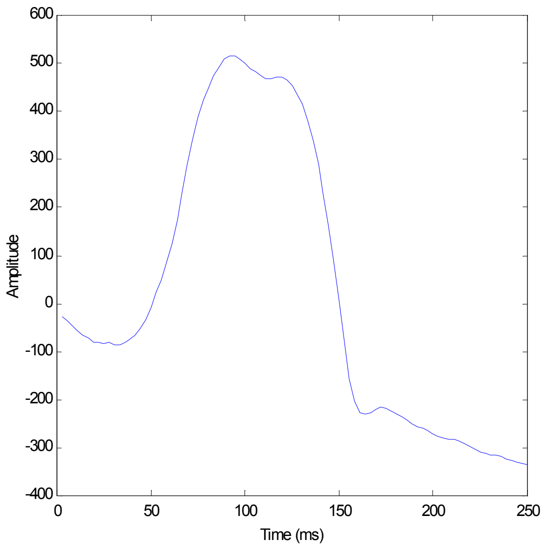
INTRODUCTION

Premature Ventricular Contraction (PVC) is an ectopic cardiac pacemaker located in the ventricle. PVCs are characterized by the premature occurrence of bizarre shaped QRS complexes, with the electrocardiographic wave (QRS) usually greater than 120 ms. These complexes are not preceded by a P wave, and the P wave is usually large and opposite in direction to the major deflection of the QRS. PVCs occurring early in the cardiac cycle R-on-T phenomenon) are associated with increased mortality rates and subsequent arrhythmic events. Patients with frequent PVCs or bigeminy may report syncope, this is due to inadequate stroke volume or to decreased cardiac output caused by effectively halving the rate. Long runs of PVCs also can result in hypotension. The waveforms of normal and abnormal PVC beats are shown in Fig. 1.

(a)



(b)



(c)

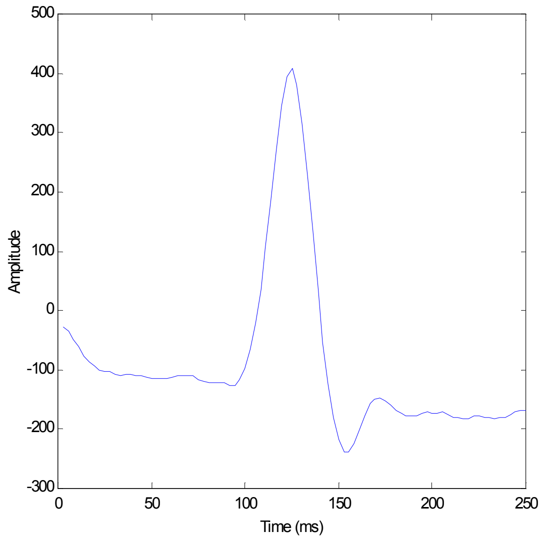


Fig. 1. The waveforms of normal and abnormal PVC beats
a — ECG cardiac cycle, b — QRS of normal beat, c — QRS of PVC beat

The correct classification of heart beats is fundamental to ECG monitoring systems, such as an intensive care, automated analysis of long-term recordings, arrhythmia monitor and cardiac defibrillators. Counting the occurrence of ectopic beats is of particular interest to support the detection of ventricular tachycardia and to evaluate the regularity of the depolarization of the ventricles. For example, the risk sudden death for patients with a structural heart disease is higher with an increased occurrence of premature ventricular complex (PVCs) [1].

Since a large amounts of data often must be analyzed and stored when examining cardiac signals, computers are used to automate signal processing. Artificial neural networks (ANNs) provide one computational tool that is being applied to problems in cardiovascular medicine. ANNs are modeled after biological neural networks. Implemented as computer programs, ANNs consist of multiple, interconnected neurons arranged in different layers. Although substantially simpler than biological neural networks, the goal in using ANNs is to build computer systems that have learning, generalized processing, and adaptive capabilities resembling those seen in biological neural networks. ANNs can learn to recognize certain inputs and to generate a particular output for a given input.

ANNs offer advantages over conventional methods for the analysis of cardiac signals since they are reliable for pattern identification and classification and can detect patterns and make distinctions between different patterns that may not be apparent to human analysis [2]. ANNs perform well for the analysis of signals, such as cardiac arrhythmia signals, that are complex and may contain high levels of noise. With many interconnected neurons. ANNs are massively parallel and thus are suitable for real-time applications.

The purpose of the present work is to derive better parameters for reducing the size of the neural network classifier while maintaining good classification accuracy. A prerequisite to this goal is to find parameters that represent each condition with acceptable discrimination capability. Therefore the QRS template is reduced using Fourier transform, LPC, and PCA methods. A three temporal parameters such as the instantaneous RR interval and its average over the previous ten beats, the mean-square value, which can be thought of as the average signal power of the QRS complex segment, are used along with the reduced QRS templates to provide a three feature vectors of each ANN classifier.

1. METHODS

1.1. Data preparation

In this work, we concentrate on the classification of normal and abnormal PVC beats. ECG records of nine patients were selected from the MIT-BIH arrhythmia database [3, 4] shown in table 1. The sampling frequency of the ECG signals in this database is 360 Hz.

Table 1. Evaluation data taken from the MIT-BIH arrhythmia database

Records number	Number of normal beats	Number of PVC beats
106	1507	520
116	2302	109
119	1543	444
203	2529	444
208	1586	992
213	2641	220
215	3196	164
221	2031	396
228	1688	362

1.2. Band-pass filtering

With the advent of low-cost microcomputers and data-acquisition systems, digital filters are fast replacing their analogue counterparts. The electrocardiogram (ECG) obtained from body electrodes have the following unwanted noise components:

a. baseline wander; which may be caused due to a number of factors arising from biological or instrument sources such as electrode skin resistance, respiration and amplifier thermal drift;

b. 60 Hz power-line interference;

c. 100 Hz interference from fluorescence lights.

Several integer coefficient recursive FIR filters have been reported in the past [5, 6, 7, 8]. The proposed integer coefficient band-pass filter achieves the elimination of both 60 and 100 Hz interferences along with the low-frequency baseline wander [9].

Its transfer function is given by

$$H(z) = (1 - z^{-360})(1 + z^{-150}) / (1 - z^{-6}) .$$

1.3. Extraction of the QRS complex

In this study, we concentrate on the classification of normal and abnormal PVC beats. The five records selected from MIT-BIH ECG arrhythmia database are used for the development and evaluation of the three classifiers. The availability of annotated MIT-BIH database has enabled the evaluation of performance for each ANN classifiers. The QRS segments are obtained as 30 point templates. The position of annotation labels is used to identify the peak of the R wave, and with 15 points on one side and the remaining on the other side with respect of the R peak were picked up to form the template.

1.4. Diagnostics feature selection

It is basically impossible to apply any classification method directly to the ECG samples, because of the large amount and the high dimension of the examples necessary to describe such a big variety of clinical situations.

A set of algorithms from signal conditioning to measurements of average wave amplitudes, durations, and areas, is usually adopted to perform a quantitative description of the signal and a parameter extraction [10]. On this set of extracted ECG parameters, several techniques for medical diagnostic classification are then applied, such as probabilistic approaches, heuristic models, and knowledge-based systems [11]. In the last years the connectionist approach was also applied with satisfactory results [12, 13].

The aim of this work was to determine suitable input feature vectors which would discriminate between the normal and abnormal PVC beats. The principle effects of this technique results in the generation of a smaller descriptive feature vector and hence subsequently reducing the architecture of the network itself and increasing its generalization ability [14]. In this study, three sets of features were tested:

(1) The QRS complex in ECG signal varies with origination and conduction path of the activation pulse in the heart. When the activation pulse originates in the atrium and travels through the normal conduction path, the QRS complex has a sharp and narrow deflection, and the spectrum contains high frequency components. When the activation pulse originates in the ventricle and does not travel through the normal conduction path, the QRS complex becomes wide, and the high frequency components of the spectrum are attenuated. Centred on the peak of the R wave, the QRS complex is extracted by applying a window of 250 ms. This window duration was chosen so as to extract the QRS complex portion only and to exclude the P wave and T wave. In general P-R and R-T intervals have duration higher than 100 ms due to the atrioventricular conduction time and the absolute refractory period of the ventricular muscle respectively. Each QRS complex is Fourier transformed and then the power spectrum is calculated [15, 16]. Before computing the Fourier transform, a Hamming window is applied to completely supress discontinuities due to the adjacent T-wave and P-wave. Since the length of the QRS window is 250 ms and the sampling frequency is 360 Hz, then nine spectral components shown in Fig. 2 with central frequencies at 4, 8, 12, 16, 20, 24, 28, 32, 36 Hz in addition to the temporal parameters constitute the twelve features vector fed into the first neural classifier. Fig. 2 shows typical normalized power spectra of two QRS complexes with maximum amplitude between 4–36 Hz.

(a)

(b)

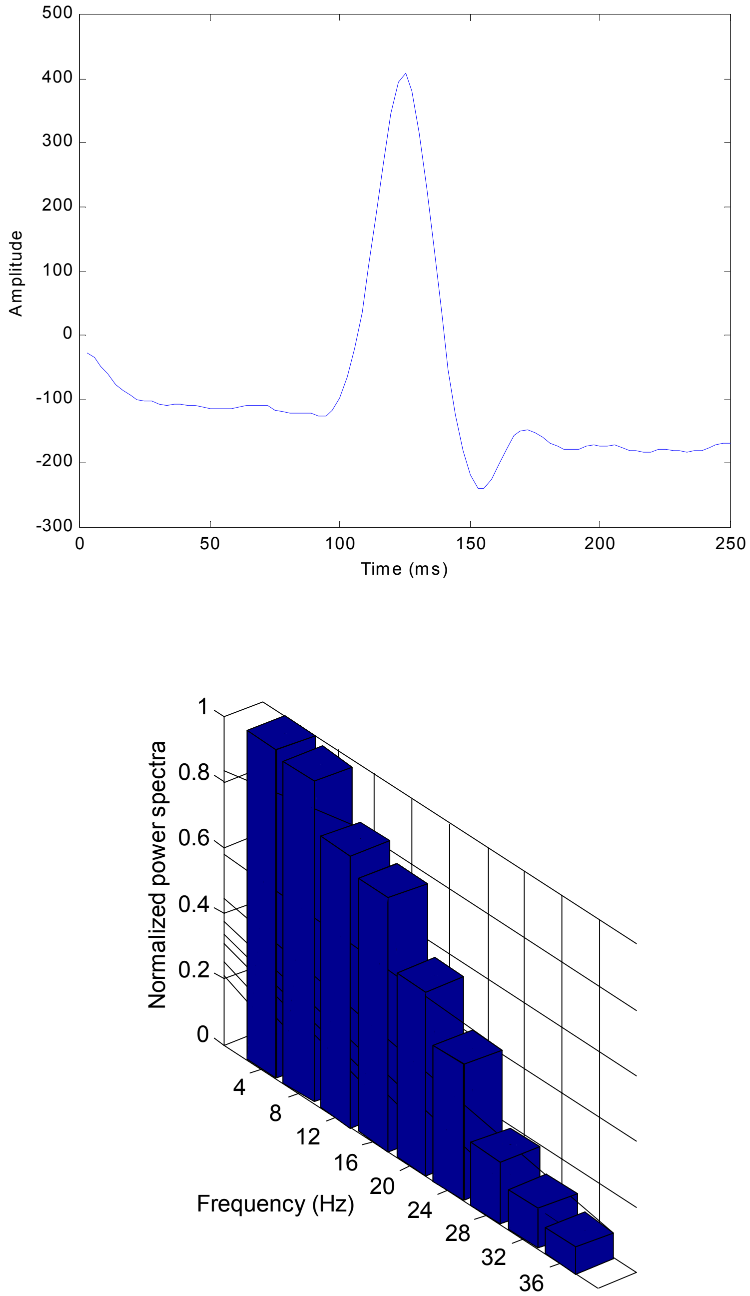
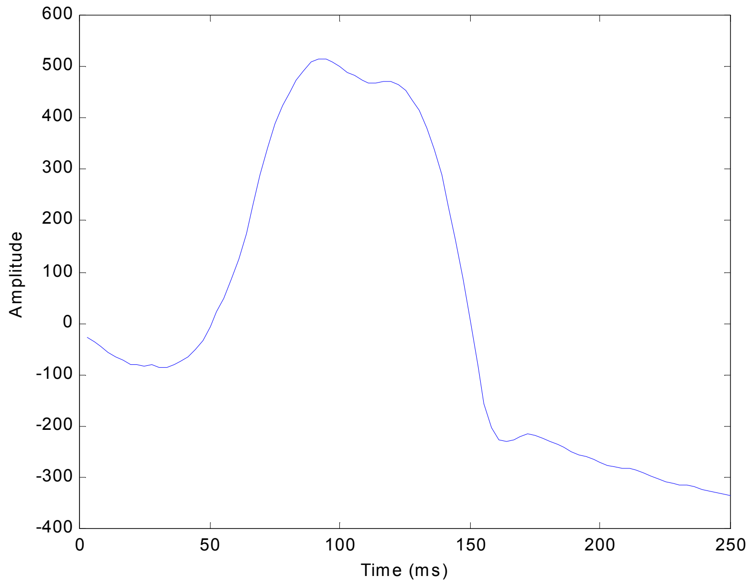


Fig. 2 (a) and (b). QRS pattern (a) and QRS spectra (b) of a normal beat

(c)



(d)

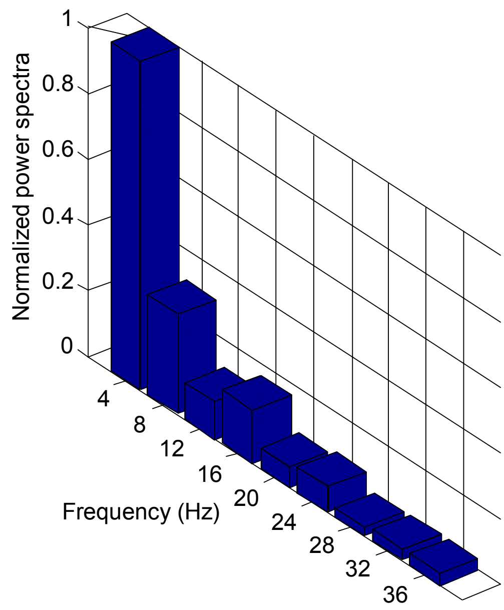


Fig. 2 (c) and (d). QRS pattern (c) and QRS spectra (d) of a PVC beat

(2) The information of each beat is represented by a 10-element vector, knowing that the 30-dimensional QRS template is reduced to a seven-dimensional vector using PCA. It is designed such that the data set may be represented by a reduced number of "effective" features and yet retain most of the intrinsic information content of the data. We may reduce the number of features needed for effective data representation by discarding those linear combinations that have small variances and retain only those terms that have large variances [17, 18]. The data vector is then approximated with the largest eigenvalues of the correlation matrix, introducing an approximating error.

(3) The last beat information is represented by a five-element vector, by using LPC method. The basic idea of this technique is that sampled QRS segment can be approximated as a linear combination of the past QRS samples. The optimal prediction of the present sample y_n is simply given by:

$$y_n = \sum_{i=1}^{p} a_i y_{n-i} ,$$

Where a_i is the i^{th} linear prediction coefficient, and p is the order of the predictor.

There exist a number of different methods to extract the LPC coefficients, i.e. the a_i. The approach used in this work is based on Burg's method, which minimizes the sum-squared of both the forward and the backward prediction errors, which is also known as the maximum entropy method. We pointed out that increasing the prediction order would not reduce the prediction error [19, 20], which means the linear prediction order does not need to be greater than two for fast cardiac arrhythmia detection. The two LPC coefficients $\{a_1, a_2\}$, plus the three other features of ECG beat presented above constitute the input vector of the third classifier.

1.5. Neural network classifier architecture

Our experiments were performed using the neural network tool box in Matlab 5.3. During our experiment the limitations encountered with the use of the back-propagation algorithm are related to the lack of criteria for determining the optimum network structure, learning coefficient and momentum. These parameters depend on the nature, distribution and complexity of the input data. In the present study, they were determined by a trial-and-error approach. The number of neurons in the input layer was fixed by the number of elements in the input feature vector. Therefore the input layer had 12 neurons for the first ANN classifier, 10 neurons for the second, and 5 neurons for the third one using respectively Fourier transform, PCA and LPC methods. The output layer was determined by the number of classes desired. In our study, the unique neuron of the output layer corresponds to the normal and PVC beats. In practice, the number of neurons in the hidden layer varies according to the specific recognition task and is determined by the complexity and amount of training data available. If too many neurons are used in the hidden layer, the network will tend to memorize the data instead of discovering the features. This will result in failing to classify new input data. Using a trial-and-error method, we tested hidden layers varying between two and 20 neurons. The optimum number of neurons in the hidden layer was found to be five for the first

ANN classifier, three for the second and two for the last one. Consequently, we used one network structure of twelve -five-one (i.e. twelve neurons at the input layer, five at the hidden layer and one at the output layer), and the two other structures respectively of ten-three-one and five-two-one.

With large values of the learning coefficient and momentum, a network may go through large oscillations during training and may never converge. Smaller learning coefficient and momentum tend to create a more stable network but require a long training time. For a good compromise between training speed and network stability, the learning coefficient and momentum were selected in such a way that their values decreased with the increase of the training epoch. To generate an efficient network, different learning coefficients and momenta were selected for different layers. In the present work, the normalized root-mean-square (RMS) error of the output layer was used as a criterion to select these parameters. The selected learning coefficients and momenta correspond to the deepest slope of the normalized RMS error. Fig. 3 shows the change in the RMS error during a training process.

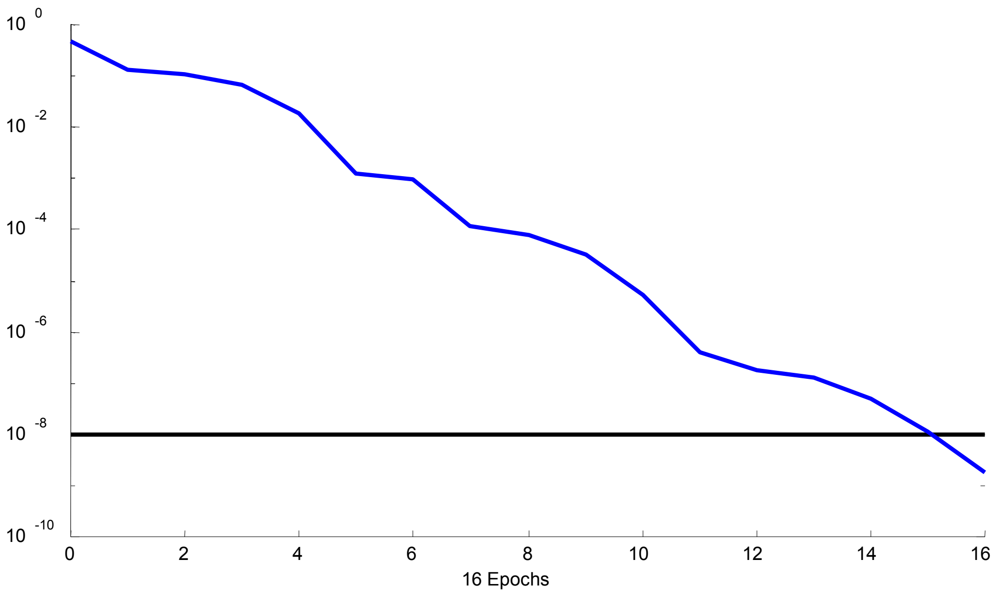


Fig. 3. RMS error of the first classifier during the training process

Using the hyperbolic tangent sigmoid as the neural transfer function, the input feature vectors were scaled to the range from –1 to +1 to fit into the dynamic range of this function. Before the training process was started, all the weights were initialized to small random numbers. This ensured that the classifier network was not saturated by large values of the weights. The threshold of convergence was set at 10^{-8} of the normalized RMS error. Training was stopped when the convergence threshold was reached or when the 2000th epoch was encountered. In this experiment, training set was formed by choosing 100 normal beats and 100 PVC beats obtained from the following records number: 106, 203, 215, 228 of MIT-BIH database. In order to enhance the generalization capability of the neural network, the training and the test sets are formed by data obtained from different patients. It is observed that for some beat types, there are waveform variations among the vectors belonging to the same class.

2. PERFORMANCE MEASURE INDICES

The performance of the neural classifiers was evaluated by computing the percentages of sensitivity (SE), specificity (SP) and correct classification (CC), the respective definitions are as follows:

- Sensitivity: [SE = 100×TP/(TP+FN)] is the fraction of real events that are correctly detected among all real events.
- Specificity: [SP = 100×TN/(TN+FP)] is the fraction of nonevents that has been correctly rejected.
- Correct classification: [CC = 100×(TP+TN)/(TN+TP+FN+FP)] is the classification rate.

In these formulas TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of false positives. Since we are interested in estimating the performance of the classifier based on the recognition of PVC beats, the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are defined appropriately as shown below:

– TP: classifies PVC as PVC;
– FP: classifies normal as PVC;
– TN: classifies normal as normal;
– FN: classifies PVC as normal.

The results of the evaluation of the neural classifier in terms of correct classification sensitivity and specificity are summarized in table 2 (actual number of beats) and table 3 (percentage).

Table 2. Beat-by-beat, record by record testing result of the experiment (1^{st} ANN classifier)

Records	TP	FP	FN	TN
116	99	15	10	2287
119	442	49	2	1494
208	987	65	5	1521
213	102	522	118	2119
221	384	3	12	2028

Table 3. Beat-by-beat, record by record testing result of the experiment (2^{nd} ANN classifier)

Records	TP	FP	FN	TN
116	95	62	14	2240
119	439	101	5	1442
208	903	88	89	1498
213	97	631	123	2010
221	373	34	23	1997

Table 4. Beat-by-beat, record by record testing result of the experiment (3^{d} ANN classifier)

Records	TP	FP	FN	TN
116	81	92	28	2210
119	417	123	27	1420
208	896	203	96	1383
213	68	735	152	1906
221	362	53	34	1978

Table 5. Performances of the 1st neural classifier

Records	Correct classification, %	Sensitivity, %	Specificity, %
116	98.96	90.82	99.34
119	97.43	99.54	96.82
208	97.28	99.49	95.90
213	81.12	46.36	80.23
221	99.38	96.96	99.85
Avr.	94.83	86.63	94.42

Table 6. Performances of the 2nd neural classifier

Records	Correct classification, %	Sensitivity, %	Specificity, %
116	96.84	87.15	97.30
119	94.66	93.91	93.45
208	93.93	90.32	94.45
213	73.64	44.09	76.10
221	97.65	91.19	98.32
Avr.	91.34	81.33	91.92

Table 7. Performances of the 3d neural classifier

Records	Correct classification, %	Sensitivity, %	Specificity, %
116	95.02	74.31	96
119	92.45	93.91	92.02
208	88.40	90.32	87.20
213	68.99	30.90	72.16
221	96.41	91.41	97.39
Avr.	88.25	76.17	88.95

Tables 5, 6, 7 show the classification results (correct classification, sensitivity, and specificity indices) for PVC beat detection applied on the files of the MIT-BIH database for three methods (Fourier transform, PCA, and LPC).

We noticed that the record 213 presents the worst results due to the noise altered the signal during the acquisition phase.

Our result is better than those reported in literature [21, 22, 23].

3. DISCUSSION AND CONCLUSION

In this study we decided to investigate the effect of reducing the number of features on the accuracy of the classifiers. The performance indices of all PVC beat detection techniques are analogous to each other when MIT-BIH data-base is used for evaluation. This work comparatively evaluates the performances of three neural classifiers. The best performance was achieved by the first ANN classifier using Fourier transform method with 98.54% correct classification , 98.30% specificity and 99.93% sensitivity. This performance was achieved because we did not need to filter the ECG signal which may have altered it. We were only interested on the QRS spectra (4 Hz – 32 Hz). This spectra is far from the power-line interference (60 Hz) and the baseline wandering (<1 Hz).These results demonstrate that non-linear classification models, such as neural networks, offer significant advantages over classical approaches in ECG beat classification. With a good feature selection, it is possible to get robust neural classifier for a larger class of cardiac arrhythmias. Such neural network classifier can be hardware implemented and used in intensive care units.

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