Journal of Advances in Computer Research
Quarterly pISSN: 2345-606x eISSN: 2345-6078
Sari Branch, Islamic Azad University, Sari, I.R.Iran
(Vol. 7, No. 1, February 2016), Pages: 35-48
www.jacr.iausari.ac.ir

A Low Complexity ANFIS Approach for Premature Ventricular Contraction Detection Based on Backward Elimination

Zahra Sadeghi✉[1], Hamid Jazayeriy[2], Soheil Fateri[3]

1) Department of Computer Engineering, Babol Branch, Islamic Azad University, Babol, Iran
2) Faculty of Electrical and Computer Engineering, Noshirvani University of Technology, Babol, Iran
3) Faculty of Computer Engineering, Babol Branch, Islamic Azad University, Babol, Iran

sadeghi.computerco@yahoo.com; jhamid@nit.ac.ir; fateri@baboliau.ac.ir

Received: 2015/02/16; Accepted: 2015/07/25

Abstract

Premature ventricular contraction (PVC) is one of the common cardiac arrhythmias. The occurrence of PVC is dangerous in people who have recently undergone heart. A PVC beat can easily be diagnosed by a doctor based on the shape of the electrocardiogram signal. But in automatic detection, extracting several important features from each beat is required. In this paper, a method for automatic detection of PVC using adaptive neuro-fuzzy inference systems (ANFIS) is presented. In the proposed model first feature selection has been done using backward elimination algorithm, and then an ANFIS has been trained with selected attributes. The performance of the proposed method has been compared with two other methods. Simulation results show that the proposed algorithm, in addition to maintaining the classification accuracy compared to existing methods uses fewer features and requires less computing time, which is suitable for implementation on hardware with limited processing capability.

Keywords: *PVC, Neural Networks, Fuzzy Networks, ANFIS, Feature Selection.*

1. Introduction

The electrocardiogram (ECG) is the record of activities of the heart, which is characterized by these waves: P, QRS complex and T. The QRS complex is the most important wave which characterizes the ventricular contractions. RR interval, which is defined as the distance between QRS complexes, is influenced by emotions and physical activities [1].

The normal electrical conduction in the heart allows the impulse that is generated by the sinoatrial (SA) node of the heart to be propagated to (and stimulate) the cardiac muscle (myocardium). In heart conduction disorders, ventricular excitation originates from other ectopic centers in the myocardium instead of originating from SA node. This leads to a premature ventricular contraction (PVC) also called extra-systole or ectopic beat. RR intervals in PVCs are typically irregular and generate a variety of QRS waveforms, quite differing from the normal ones [1].

Counting the PVCs is of particular importance to predict ventricular tachycardia and to evaluate the regularity of the ventricle depolarization. For example, the risk of ventricular fibrillation (VF) is higher with an increased occurrence of PVCs. As it is mentioned above, the automatic detection of the PVC is a subject of long-term studies [1] .

Several methods have been proposed for detection and classification of heartbeats. Classical techniques extract descriptive features, such as QRS morphology [1], [2], [3] and R–R intervals [1], [2], [4]. Other features rely on QRS frequency components [3,4] or matching pursuits for extraction of time–frequency beat descriptor [3]. Some authors use QRS template matching procedures [5], wavelet and principal component analysis [1], [4], [6] and higher order statistics [7], [8].

For ECG beat classification purpose, several tools have been used, such as artificial neural networks [1], [2] or probabilistic neural networks [9]. K-nearest neighbors (KNN) algorithm [3], [7] and genetic algorithms [9] are also used to classify or optimize the classification accuracy.

In the article by Ebrahimzadeh et al. [10], wavelet transform and multi-layer perceptron (MLP) network are applied for processing and classifying ECG signals taken from MIT-BIH arrhythmia data base [11]. The results of this paper have been also investigated by the authors, in terms of the time required for training the network. However, it should be noted that in online algorithms, the time needed for extracting features is more important than the time needed for network training, since network is trained off-line only once, and training procedure is not required anymore, but feature extraction must be performed on-line and constantly. Therefore, the efficiency of the above algorithm regarding calculations needed for feature extraction have not been studied.

In another study conducted by Rai et al. [12], wavelet transform and neural network were used to separate normal and abnormal beats. A total of 64 features were extracted from the signals of MIT-BIH arrhythmia data base for classification. Extracting this large number of features needs a high computational time and makes on line use of this algorithm impossible .

The data used in the method proposed by Zidelmal et al. [1] was also from MIT-BIH arrhythmia data base. They used 13 features and achieved higher accuracies using a support vector machine (SVM) classifier. However, the required computational time was not discussed in their paper, and their method has not been studied from this perspective. Homaeinezhad et al. [13] proposed an ECG arrhythmia detection algorithm based on neuro-SVM−KNN hybrid classifier with an accuracy of 98%.

In another study by Thomas et al. [14], dual tree complex wavelet transform (DTCWT) based feature extraction technique was used for automatic classification of cardiac arrhythmias. The feature set comprised complex wavelet coefficients extracted from the fourth and fifth scale DTCWT decomposition of a QRS complex signal in conjunction with four other features extracted from the QRS complex signal. The feature set was classified using multi-layer back propagation neural network. Although the experimental results indicated that the method classified ECG beats with an overall sensitivity of 94.64%, the computational time needed for feature extraction is too long.

In a paper by Chen et al. [15], a healthcare management system, named CardiaGuard, which is an expert system designed based on the hybrid classifier, was implemented using SVM and Random Tree (RT) classification algorithm. A comprehensive performance evaluation showed that their hybrid classification engine was able to detect six types of cardiac disorders with higher accuracy rate than the SVM-based classifier is able to do alone.

In this paper, a low complexity algorithm for automatic detection of PVC is presented. Since the method introduced in [1] is one of the newest and most efficient methods in PVC classification, we use the same feature extraction procedure described in [1], and then try to reduce the computational time using feature selection. We also use MLP neural network and adaptive neuro-fuzzy inference systems (ANFIS) for classifying purpose. The proposed method needs less computational time and has high accuracy. The results of reduced complexity algorithm are compared with original method in [1] in sense of classification accuracy and computational time. For further comparison, the results of method in [12] are also presented. In the proposed model first 13 features described in [1], were calculated. Next, feature selection has been done using backward elimination algorithm, which reduced computational time needed for feature extraction. Then ANFIS and MLP network have been trained with selected attributes. The performance of the trained networks has been evaluated using test dataset. The outline of this paper is as follows. In section 2 the main steps of proposed algorithm is introduced. In section 3 a brief description about ANFIS is presented. Section 4 discusses the main steps of feature selection method. In section 5, the results of classification with ANFIS and MLP are presented and in section 6 the experimental results are discussed. Section 7 is for conclusion and discussion.

2. The proposed method

2.1 Data

In this paper, the data is taken from MIT-BIH arrhythmia database [11]. This database has 48 records. Each record has a length of 30 minutes with a sampling frequency of 360 Hz. Data was recorded on two channels; but in the present paper just the first channel is used. These signals contain various waves, artifacts, and arrhythmias and abnormalities. Every record is along with an annotation txt file that provides user with information of every beat existing in that record, including the time point of its occurrence and also its type in terms of being normal or arrhythmia. These interpretations are used to create classifiers and test their performance. In this paper only the signals with the following names that contain a lot of PVCs (according to annotation txt file) have been used:
105m, 106m, 107m, 109m, 114m, 116m, 119m, 124m, 200m, 201m, 203m, 205m, 207m, 208m, 210m, 213m, 214m, 215m, 219m, 221m, 223m, 228m.

Figure 1 shows the occurrence of PVC in the record 114m. According to shape of PVC in various cases, it is found that this arrhythmia appears in different forms and may be quite different for each patient. For this reason, several features have to be used to be able to cover this extensive range of PVC shapes should.

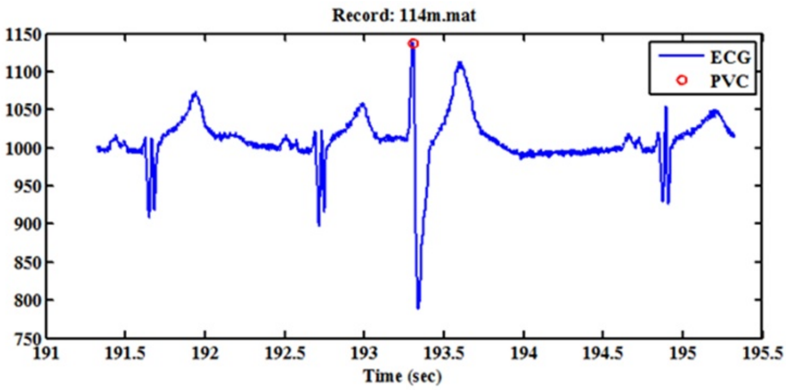

Figure 1. Occurrence of PVC in the record 114

2.2 Filtering signals

Usually two important noises ruin ECG signals. The first noise is a high frequency noise imposed on electronic equipment and the other one is low frequency noise resulting from bioelectric activity of the body, which is called baseline wander. For these two noises, high-pass and low-pass filters with appropriate cutoff frequencies are designed and used. More details can be found in [1].

2.3 Fragmenting ECG

In the present paper, Pan-Tompkins method [16] is used to detect QRS complexes in ECG. Figure 2 shows the result of the algorithm in each segment of record 109m. As it can be seen, the algorithm has found corresponding points in signal with high accuracy.

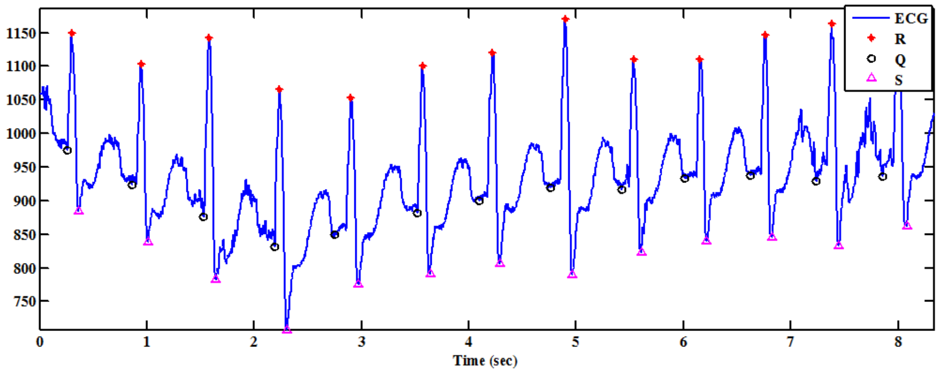

Figure 2. Q, R and S detection, in record 109m

2.4 Feature extraction

QRS complex in ECG changes with any changes to the electrical source and conduction route in the heart. When the activation pulse starts from the SA node and is conducted through its normal route, the QRS complex has a sharp and narrow deflection and contains high frequency components. In case of problems in heart conduction system, the QRS complex becomes wider and its high frequency components are weakened.

We use features that clearly describe quality of a heart beat like RR intervals, QRS morphology and frequency components to classify a heartbeat.

2.4.1 R-R interval

RR intervals provide useful information for clinical diagnosis and detection of arrhythmia [2]. Here we use $RR_i = R_i - R_{i-1}$ as a feature, which means the distance between the current R and the previous R.

2.4.2 Morphological descriptors

QRS duration varies with the place of origination and conduction path of the activation pulse in the heart. So, it is a fundamental feature used for classifying beats. In this work, the QRS duration is calculated by the time interval between the two peaks Q and S.

The morphology of the beat is captured by a four linear predictive coding (LPC) coefficients. The basic idea of this technique is that future values of a discrete signal are estimated as a linear function of previous samples. The most common representation is [1]:

$$\hat{y}_n = \sum_{k=1}^{p} a_k y_{n-k} \tag{1}$$

where a_k is the kth coefficient of linear predictor, p is the order of predictor, $\hat{y}_n$ is the predicted sample and y_{n-k} is the kth sample before the sample y_n.

2.4.3 Frequency features

Frequency feature is another feature used to diagnose heart diseasees. In every heart period, first due to discontinuities in the signal, the beat is filtered by a Blackman window with length of 180ms, then its spectrum is calculated and its power in frequencies 10 Hz, 12.5 Hz, 15 Hz, 17.5 Hz, and 20 Hz is extracted from the spectrum as 6 new features [1].

2.4.4 Power of QS

For completing frequency information, detail coefficients of the wavelet transform at levels 4 and 5 are determined. At these levels, the power of each QS segment is calculated and is used as a feature. In each sub-band, signal variance shows averaged power in that band as follows:

$$\sigma_x^2 = \frac{1}{N} \sum_{n=1}^{N} (x(n) - \bar{x})^2 \tag{2}$$

where $\bar{x}$ is temporal mean of $x(n)$ and N is the number of samples.

2.4.5 Classifying Features

Since the aim of this paper is to separate heart beats into PVC and non-PVC classes, there is a binary classification problem in which Class 1 is related to a PVC heartbeats and class 0 corresponds to a non-PVC beat. Therefore, for each set of 13 features extracted in the previous section, a value of 1 or 0 is derived from annotation file of that signal and placed beside the feature vector, to represent its class.

It should be noted that the number of normal beats is selected equal to the number of PVC beats (some of the normal beats are eliminated) in order to prevent the classifier from biasing toward the class with more samples. Since there were about 3200 PVC beats (Class 1) in the signals introduced in section 2.1, we randomly chose 3200 non-PVC beats (Class 0) from these signals. In this way, there will be a total of 6400 data from both classes. Table 1 summarizes the information of the data

Table 1. Description of the extracted features in the 6400 existing data

Explanation	Feature number
coefficients of the linear detector with relation $\hat{y}_n = \sum_{k=1}^{p} a_k y_{n-k}$	1-4
R-R Interval (current R from previous R)	5
Power of beat at frequencies from 10 to 20 Hz	6-10
Details of level 4 and 5 in wavelet transform of the QRS complex of beat	11-12
QS length in beat	13

3. Sugeno Inference System and Adaptive Neuro-Fuzzy

One of the advantages of fuzzy systems is simplicity and intelligibility (unlike neural networks that are black-box models) that makes them very easy to use and understand. By combining neural networks with fuzzy systems, learning capability is also added to fuzzy systems. For this study the Sugeno fuzzy model [17] has been used to generate fuzzy rules from a set of input and output data. A typical fuzzy rule in the Sugeno fuzzy model is shown in Equation (3):

If x is equal to A and y is equal to B, then:

$$z = f(x, y) \tag{3}$$

where A and B are sets of fuzzy antecedents, and z is the crisp consecutive function.

ANFIS is a class of adaptive networks whose functionality is equivalent to a fuzzy inference system (FIS), which generates a fuzzy rule base and membership functions (MF) automatically. The output of this system can be described by the Equation (4) [18]:

$$\gamma = \sum_{i=1}^{L} \left\{ \frac{(\Pi_{j=1}^{n} MF_j^i(x_j))(z^i)}{\sum_{i=1}^{L} (\Pi_{j=1}^{n} MF_j^i(x_j))} \right\} \tag{4}$$

where MF is the membership function, $x_j (j = 1, 2, ..., n)$ is the jth input and z^j is the output of jth fuzzy rule. ANFIS adapts the parameters of Sugeno type inference system using the neural networks.

Typically the ANFIS network topology consists of connected nodes that depend on parameters that change according to certain learning rules that minimize the error. The learning technique most commonly used is the gradient method, however Jang [17] proposed hybrid learning rule which includes the Least Square or simply LSE Estimator. Considering a fuzzy system with three inputs x, y and z, one output v and a fuzzy inference Sugeno model, one possible set of rules is as shown below:

Rule 1: if x is equal to A_1, y is equal to B_1, and z is equal to C_1, then $f_1=p_1x+q_1y+r_1z+s_1$
Rule 2: if x is equal to A_2, y is equal to B_2, and z is equal to C_2, then $f_2=p_2x+q_2y+r_2z+s_2$

As an example, Figure 3(a) illustrates the reasoning procedure for the Sugeno inference model [18]. The equivalent ANFIS architecture is presented in Figure 3(b). The first layer of Figure 3(b) is represented by adaptive nodes i whose functions are determined by Equations (5–7) [18]:

$$o_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1,2 \tag{5}$$

$$o_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for } i = 3,4 \tag{6}$$

$$o_{1,i} = \mu_{C_{i-4}}(z), \quad \text{for } i = 5,6 \tag{7}$$

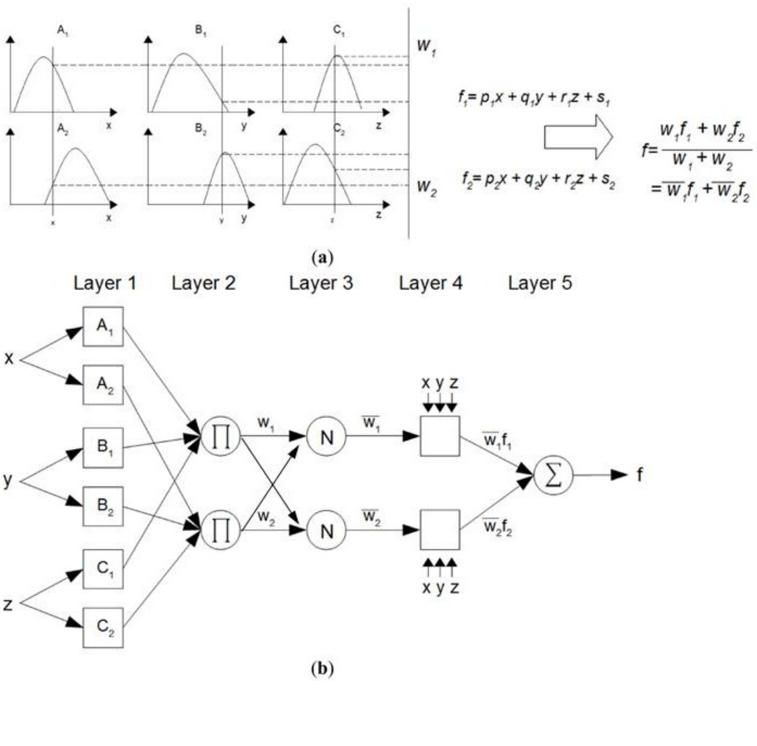

Figure 3. (a) Example of a Sugeno Inference Model with three inputs and two rules and (b) The equivalent ANFIS architecture [18]

where A_i, B_{i-2} and C_{i-4} are fuzzy sets associated with x, y, and z respectively. Thus, $o_{1,i}$ represents the pertinence degree to the fuzzy set $A\,(A_1, A_2, B_1, B_2, C_1 \text{ or } C_2)$ and specifies the degree to each input x, y or z satisfies the fuzzy set A. The membership function μ can be any of the membership functions, including: triangular membership function, Gaussian-membership function, Bell membership function, etc. When the values (called the premise parameters) of the membership function are changed, the function varies. The layer 2 has fixed nodes indicated by Π with outputs that represents the input signals product, as indicated in Equation (8). The output nodes represent the firing strength of a given rule [18]:

$$o_{2,1} = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y)\mu_{C_i}(z),\ i = 1,2 \tag{8}$$

In layer 3 the fixed nodes are referred to N. The ith node calculates the firing strength of rule ith to the sum of all firing strength of rules, given by Equation (9), the nodes in layer 3 are generally known as normalized firing strength [18]:

$$o_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2},\ i = 1,2 \tag{9}$$

In layer 4, the ith node is adaptive with the function given by Equation (10):

$$o_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i(p_i x + q_i y + r_i z + s_i) \tag{10}$$

where $\bar{\omega}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i, s_i\}$ is the set of parameters (called consequence parameters) of this node. The last layer of the Figure 3(b) has only one fixed node called Σ that determines the final output as the sum of all signals represented by Equation (11) [18]:

$$\textit{final output} = o_{5,1} = \sum_i \bar{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{11}$$

For training fuzzy system, ANFIS employs a hybrid method consisting of back-propagation scheme for the parameters associated with the input membership functions and least mean square estimation for the parameters associated with the output layer.

4. Feature selection

One of the problems in using fuzzy system is the dimension of input, since the fuzzy rules increase exponentially relative to the dimension of input. Increasing the number of rules not only increases computational complexity but also makes interpretability of fuzzy systems difficult. Therefore, some procedures are needed to reduce the number of features and determine more effective features. These procedures are generally called feature selection.

For feature selection, backward elimination method is used [19]. In this method, first modeling is performed by eliminating a particular feature and keeping other features, and accuracy of classification is calculated for test data. Then the feature by whose elimination the model will achieve the highest accuracy is selected and considered as the first eliminated feature. Afterward, similar operations are performed for the remaining features and the next feature is eliminated. This process will continue until the number of features reaches the desired number. In order to evaluate performance of networks, accuracy measure with the following formula is used:

$$\text{Accuracy} = \frac{\text{the number of properly classified samples}}{\text{total number of samples}} \times 100 \tag{12}$$

For modeling stage in the elimination process, any model can be used. Since the total number of features is 13 which is too large for an ANFIS, an elimination algorithm with MLP network is used. For this purpose, 40% of the data is used for training, 40% for testing, and 20% for validation. For implementing the network, neural network toolbox in MATLAB 7.14.0.739 (R2012a) was used.

The largest number of features that is computationally feasible for ANFIS is 5 features. Therefore, 8 steps of backward elimination should be done, so that the number of features decreases from 13 to 5. After implementing the algorithm using an MLP network with an appropriate number of neurons, features 1, 3, 4, 5 and 6 remained as the most important features, at the end of elimination algorithm.

5. Classification

At this stage, the number of features is reduced and classification is performed using ANFIS model. For this purpose, Fuzzy Logic Toolbox in MATLAB 7.14.0.739 (R2012a) is used and an ANFIS is trained. The proportion of training, testing, and validation data, are 40%, 40% and 20%, respectively, the same as before. Table 2 shows the information of the trained network as well as the accuracies of various data. In order to reduce the random nature of networks, the accuracies reported here are the results of averaging over 50 runs. As it can be seen, not only has the accuracy of classification not decreased compared to the neural network with 13 features, but there has been also a slight improvement. For better comparison, classification with these 5 features is performed by MLP network. Table 3 shows the results of the classification with this network. As it can be seen, classification accuracy in MLP network has dropped about 3 percent by reduction of the number of features, but accuracy of ANFIS network with the same number of features has improved, making this network superior in classification.

A block diagram of proposed method is shown in Figure 4. As can be seen, the proposed method has two stages: first 13 features in [1] are extracted and then features selected using backward elimination method, are used to train a classifier (ANFIS or MLP). In the second stage the selected features of new beats are extracted and then are fed to the trained classifier to be classified as PVC or normal.

6. Experimental results

In this section we investigate computational time required for extraction of each feature. Table 4 shows the time required for the extraction of features for each beat in one of the records (the record 105m). As it can be seen, the time required for the extraction of all 13 features is about 22.79 seconds. By eliminating the features during elimination process, the computational time is reduced (white part of the table). In the 8th step, by eliminating the 8th feature, computational time decreases from 22 seconds to about 16 seconds; that shows 6 seconds improvement in computing time.

As it can be seen, elimination of features related to linear detector has reduced the computational time about 4 seconds and elimination of calculations related to power has reduced required time to about 12 seconds.

Considering the above mentioned fact, it is reasonable to ignore calculating power at frequency 10 Hz (feature 6), although this would cause a slight error. So all the features related to power calculation can be removed. Thus, this time classification is done by ANFIS and MLP with four features 1, 3, 4 and 5.

Table 2. Specifications of ANFIS network with 5 features 1, 3, 4, 5 and 6 as well as the classification accuracy of various data by this network

Type of network	Number of membership functions for each input	Number of iterations	Type of membership functions	Accuracy (training)	Accuracy (test)	Accuracy (validation)
ANFIS	2	30	Bell shaped	96.25	93.32	93.35

Table 3. Specifications of MLP network with 5 features 1, 3, 4, 5 and 6, as well as the classification accuracy of various data by this network

Type of network	Number of hidden layer neurons	Type of Activation functions of the layers	Accuracy (training)	Accuracy (test)	Accuracy (validation)
MLP	10	sigmoid - sigmoid	91.21	90.62	90.09

Table 5 and 6 show the results of classification by these two networks. As it can be seen, by eliminating the 6th feature, no significant change is observed in the accuracy of classification, but the decrease in the computational time is significant, so that the calculation time has decreased from 16 seconds to about 5 seconds. In other words, there has been an 11-seconds improvement in speed. Also by considering 13 features, computational time decreases from 22 seconds to 5 seconds that shows about 17-seconds improvement in speed.

Figure 5 compares computational time and accuracy in ANFIS and MLP with 4 features (ANFIS-4 and MLP-4) and 5 features (ANFIS-5 and MLP-5) with the results of methods in [1] and [12]. Accuracies and time values are normalized in order to be comparable. As it can be seen, the accuracies of methods of Zidelmal and Rai are very high. Nevertheless, the computational times are also extremely long which makes them inefficient in online applications. The accuracies of the methods introduced in this paper are a little lower compared to the other two methods, but the computing time is drastically reduced. Among the networks of this paper, ANFIS-4 not only has higher accuracy, but also requires shorter computational time that clearly shows its superiority to MLP clearly.

Table 4. Computational time in extracting features during the process of backward elimination

Step	Eliminated Feature(s)	Computational Time (sec)	Step	Eliminated Feature(s)	Computational Time (sec)
0	-	22.79	6	Details of level 5 in wavelet transform	16.68
1	Power at a frequency of 20 Hz	22.51	7	Length of Q wave in beat	16.61
2	Details of level 4 in wavelet transform	22.386	8	Power at a frequency of 12.5 Hz	16.61
3	Second coefficient of linear detector	21.36	9	The features related to linear detector	12.65
4	Power at a frequency of 15 Hz	21.34	10	The features related to power calculation	0.537
5	Power at a frequency of 17.5 Hz	21.32	11	RR	0

Table 5. Specifications of ANFIS network with features 1, 3, 4 and 5 as well as accuracy of classification of various data by this network

Type of network	Number of MFs for each input	Iterations	Type of MFs	Accuracy (training)	Accuracy (test)	Accuracy (validation)	Required time(second)
ANFIS	2	30	Bell	95.43	93.59	93.82	5.37

Table 6. Specifications of MLP network with 4 features: 1, 3, 4 and 5 as well as accuracy of classification of various data by this network

Type of network	Number of hidden layer neurons	Type of Activation functions of the layers	Accuracy (training)	Accuracy (test)	Accuracy (validation)	Required time(second)
MLP	10	Linear - sigmoid	90.70	89.76	89.92	5.537

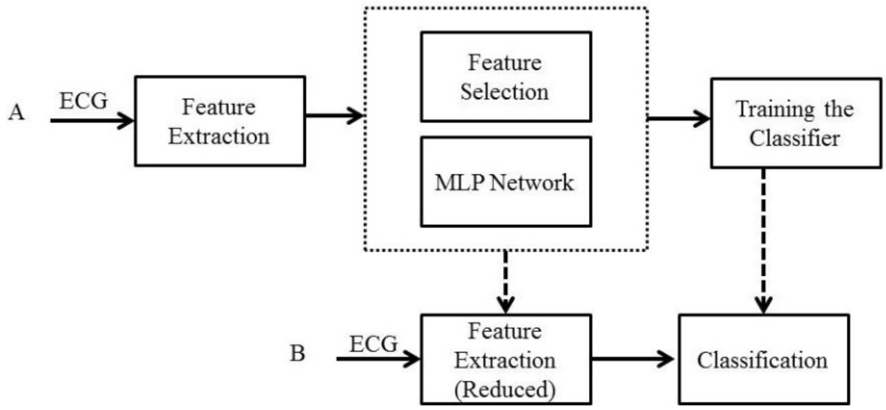

Figure 4. Block diagram of proposed method. A: the feature selection and training procedure. B: classification of new beats with the trained network

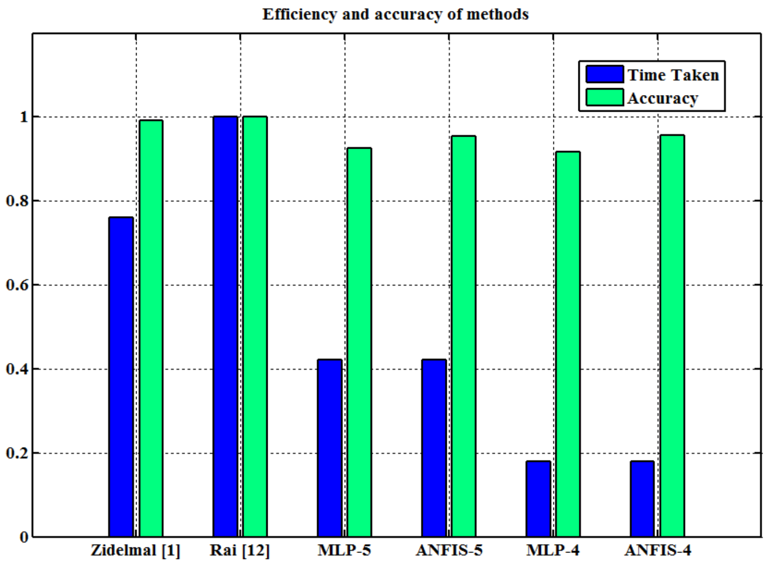

Figure 5. A comparison between computational times and accuracies (both normalized to 1) in different methods

Considering the importance of preprocessing of data before extracting features, it is necessary that newer algorithms are used in this phase of the method. For example, in this paper Pan-Tompkins method was used to detect QRS complexes which had multiple errors. Using algorithms that have already been presented in this field can reduce these errors.

In the proposed method only PVC beats were separated from other beats, but considering the variety of arrhythmias, occurrence of other beats (like ventricular fibrillation) can also be detected.

The feature selection method used in this work is the backward elimination method, which is an easy method but may have some errors in eliminating features, because it does not investigate all the features at once. In order to avoid these errors, newer and more reliable methods can be used such as genetic algorithms, and important features can be selected during some iteration.

7. Discussion and Conclusions

In the present paper, a method was proposed for automatic detection of PVC by ECG signals. In the proposed method, first, 13 important features of a heart beat were extracted. Then, due to the limitation of ANFIS in dimension of input, a method was used for selecting the most important features to feed ANFIS was used. Considering the various methods proposed for feature selection, one of the easiest and most efficient methods called backward elimination was used and 5 important features were selected. By comparing accuracy of ANFIS (in classification with these 5 features) with that of MLP (in classification with all 13 features), it can be seen that the accuracy has not changed much, while the computational time has decreased about 30% , that shows high ability of feature selection algorithm and ANFIS.

Afterward, by further investigation about the time required for extracting each feature, it was found that a great portion of the calculation time is related to only one feature from the remaining 5 features, and by eliminating this feature, computational time will greatly decreased. Thus classification was done by eliminating this feature and it was observed that the accuracy has not dropped much, while the computational time has decreased by 75%, compared to classification with 13 features. For a comparison between the MLP and ANFIS, some simulations with 4 and 5 features were performed using both networks. In both cases, ANFIS outperformed MLP in terms of classification accuracy. The results of these networks were compared with the results of the methods in [1] and [12] and it showed that the introduced method had a little decrease in accuracy, but the computational time had greatly decreased.

References

[1] Z. Zidelmal, A. Amirou, D. Ould-Abdeslam, and J. Merckle, "ECG beat classification using a cost sensitive classifier," computer methods and programs in biomedicine, 2013.

[2] P. De-Chazal, and R. Reilly, "A patient adapting heartbeat classifier using ECG morphology and heartbeat interval features, " IEEE Transactions on Biomedical Engineering, 2006.

[3] I. Christov, G. Gomez-Herrero, V. Krasteva, I. Jecova, and A. Gotchev, "Comparative study of morphological and time–frequency ECG descriptors for heartbeat classification," Medical Engineering and Physics, 2006.

[4] S. N. Yu, and Y.H. Chen, "Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network," Pattern Recognition Letters, 2007.

[5] V. Krasteva, and I. Jecova, "QRS template matching for recognition of ventricular ectopic beats," Annals of Biomedical Engineering, 2007.

[6] C. P. Shen, W.C. Kao, Y.Y. Yang, M.C. Hsu, Y.T. Wu, and F. Lai, "Detection of cardiac arrhythmia in electrocardiograms using adaptive feature extraction and modified support vector machines," Expert System with applications, 2012.

[7] Y. Kutlu, and D. Kuntalp, "Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients," Computer Methods and Programs in Biomedicine, 2012.

[8] F. Melgani, and Y. Bazi, "Classification of electrocardiogram signals with support vector machines and particle swarm optimization," IEEE. Transactions on Information Technology in Biomedicine, 2008.

[9] A. Khazaee, and A. Ebrahimzadeh, "Classification of electrocardiogram signals with support vector machines and genetic algorithms using power spectral features," Biomedical Signal Processing and Control, 2010.

[10] A. Ebrahimzadeh, and A. Khazaee, "Detection of premature ventricular contractions using MLP neural networks: A comparative study, " Measurement, 2010.

[11] R.Mark, and G. Moody, MIT-BIH arrhythmia database http://www.physionet.org/physiobank/database/mitdb/.

[12] H. M. Rai, A. Trivedi, S. Shukla, "ECG signal processing for abnormalities detection using multi-resolution wavelet transform and Artificial Neural Network classifier," Measurement, 2013.

[13] M.R. Homaeinezhad, S.A. Atyabi, E. Tavakkoli, H.N. Toosi, A. Ghaffari, and R. Ebrahimpour, "ECG arrhythmia recognition via a neuro-SVM–KNN hybrid classifier with virtual QRS image-based geometrical features," Expert Systems with Applications (39), 2012.

[14] M. Thomas, M. K. Das, and S. Ari, "Automatic ECG arrhythmia classification using dual tree complex wavelet based features," Int. J. Electron. Commun. (69), 2015.

[15] H. Chen, B. C. Cheng, G. T. Liao, and T.C. Kuo, "Hybrid classification engine for cardiac arrhythmia cloud service in elderly healthcare management," Journal of Visual Languages & Computing (25), 2014.

[16] J. Pan, and W.J. Tompkins, "A real-time QRS detection algorithm," IEEE Transactions on Biomedical Engineering, 1985.

[17] J. S. Jang, "ANFIS: adaptive-network-based fuzzy inference system," IEEE Transactions on Systems, Man and Cybernetics, 1993.

[18] A. Balbinot and G. Favieiro, "A Neuro-Fuzzy System for Characterization of Arm Movements," Sensors (Basel). 2013.

[19] T. E. Azadi, and F. Almasganj, "Using backward elimination with a new model order reduction algorithm to select best double mixture model for document clustering," Expert Systems with Applications, 2009.