Automatic Detection of Premature Complexes in ECG Using Wavelet Features and Fuzzy Hybrid Neural Network

F. Farrokhi, M. H. Moradi, and R. Miri

***Abstract*—This paper will purpose a beat recognition algorithm using discrete wavelet coefficients and fuzzy hybrid neural network. Cardiac beats have been detected from differential of compressed wavelet coefficients by Linear Approximation Data Transfer (LADT) algorithm and adaptive thresholds. The variance and sum of the squared wavelet coefficients and the R-R ratio of successive beats have been applied to the self organizing subnetwork connected in cascade with a multi layer perceptron as final classifier. The c-means and Gustafson-Kessel algorithms have been applied for the self-organizing layer. Potential of the method was examined using MIT_BIH arrhythmia database. Results show high detection (99.43%) and high sensitivity (99.65%) on 59864 detected beats and 100% sensitivity and specificity on premature beat recognition.**

***Index Terms*—Premature ventricular complex, premature atrial complex, ECG beat detection, ECG beat recognition, neuro fuzzy classifier, discrete wavelet transform.**

I. Introduction

ECG has become the most common diagnostic tool for monitoring the patients believed to suffer from cardiac disease. The long term recorded ECG allows physicians to analyze a patient's heart function up to 24 hours continuously. These ECG signals provide information that can be used to detect the transient arrhythmias, which may not be presented during the regular or exercise ECG tests in hospitals. Many useful parameters, such as the heart rate variations, atrial/ventricular arrhythmias, and ST-segment deviations are the most general information used to evaluate the symptomatic patients and those who have had myocardial infarction.

Premature ventricular contractions (PVC) are the most common ventricular arrhythmias. PVC may occur as an isolated single extra cardiac beat or in sequence with another to cause serious arrhythmias such as ventricular tachycardia (VT). The detection of PVC's in the analysis of electro cardiogram (ECG) may prognosticate ventricular fibrillation (VF), which is preceded by runs of PVC's or ventricular tachycardia [1]. Although one should remember that the major problem in detection of PVC's is their shape variations.

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F. Farrokhi is with the Department of Biomedical Engineering, Azad University, Science and Research Campus, Tehran 1477753183, Iran (e-mail: fardad@teacher.com).

M. H. Moradi is with the Department of Biomedical Engineering, Amirkabir University of Technology, Tehran, Iran.

R. Miri is with the Department of Medical Science, Shahid Beheshti University, Tehran, Iran.

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According to the past experiences, premature beat diagnosis methods have been classified into three groups. The first method of detection is based on comparing beats, in which a template has been compared to other beats [2]. Since PVC's are very different in shapes, classification of PVC's was not accurate enough. The second method however is based on time domain features of beats such as duration and area, waveform and R-R interval relations [3]. In this method just PVC's with an evident peak are considered, therefore if the occurred PVC has R' peak, it has not been classified correctly. The last method uses parametric models [4], [5]. The most common problem, like the previous two, is the shape variations of premature beats especially premature ventricular complexes, causing frequent errors in classification. Therefore the solution to this problem should contain optimized features and an intelligent classifier which can solve the problem of shape variations.

In most feature extraction methods for ECG classification there are two ways of analyzing ECGs; one is to use information taken from a single beat and the other is to use an algorithm, which selects time intervals containing more beats. There is no evidence that using either method produces better results. Cardiologists also use both beat features and heart rate in diagnosing a patient's disease. Since the wavelet transformation provides a description of the signal in the time scale domain and permits the representation of temporal characteristics, in this paper discrete wavelet coefficients and their statistical parameters have been used as classification features and continuous wavelet coefficients for general beat detection algorithm. Wavelet based features are used as beat features in this work. To complete features information, heart rate information has also been used along with them to detect premature beats.

The combined features are used as inputs to a fuzzy hybrid neural network, which is composed of a self-organizing layer in cascade with a multi-layer perceptron. The fuzzy self-organizing layer preclassified input vectors by different membership values. These values are applied to the MLP subnetwork for final classification.

Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. The complexity and limitation of previous mechanisms are largely due to the lack of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases. On the contrary, fuzzy classification assumes the boundary between two neighboring classes as a continuous, overlapping area within which an object has partial membership in each class. Self-organizing layer in a fuzzy hybrid neural network helps to minimize overlapping of classes.

The results presented here will help for a better recognition of premature beats from normal ones. Therefore a combination of beat information by rhythm, and using a fuzzy hybrid neural network as a classifier will lead to a better result.

II. Theory and Methods

A. Beat Detection Algorithm

The first step for beat classification is detection of heart beats. The major problem in detection process is the variations of the heart beat shape. In this section we will present an algorithm that gives a presentation of a heart beat which is not affected by beat shapes.

So far the following methods have been used for beat detection:

1. Simple mathematical relations [6]-[10].

Algorithms based on amplitude and slope are most immune to EMG noise. These algorithms are sensitive to changes in baseline which can be corrected by high pass filtering. Filtering of EMG noise is more difficult due to the frequency spectrum overlap with the QRS complex. Consequently algorithms which are insensitive to baseline changes but sensitive to high frequency noise show less potential than the amplitude –slope algorithms or reliable performance in a clinical setting.

2. Parametric models [11], [12].

The ability of the algorithms is to recognize different forms of normal or abnormal QRS complexes or to ignore large peaked T-waves. Even by using more than one channel in parametric model based algorithms, the problems of misdetection persist.

3. Statistical methods [13].

In such methods, the statistical behavior of ECG was used for its beat detection as well as checking detection validity. Presented results show that this method has no adequate results.

4. Algorithms, which were based on Neural networks [14], [15].

The ECG is a non-linear signal, so it cannot be whitened effectively by a linear filter. Since artificial neural networks are inherently non-linear models, ANN-based filtering is potentially useful. The problems with neural network based algorithms are

a) Learning is too time consuming
b) They have a closed structure and improving the ability of network due to new information requires network training.

Neuro fuzzy methods are presented to solve such problems in ANN(s).

5. Fuzzy methods (Fuzzy rule based & Neuro Fuzzy Methods) [14], [16].

By using fuzzy techniques in neural network structure we gained:

a) Rapid learning from a large amount of data;
b) Adapting in a real time and in an online mode;
c) Open structures where new features can be introduced at a later stage of the system operation.

Although some questions remain, for instance; how should we find rules? Is it better to find features by fuzzy neural network or to use such network as a classifier for the time, frequency and time-frequency features?

6. Algorithms based on signal transforms (Fourier Transform, Hilbert Transform, Wavelet Transform, etc…) [17]-[20].

These algorithms were based on representing beat appearance in ECG by patterns, which can be detected easier than the original signal. In the present and the following section, we will demonstrate some advantages in this feature domain. We also suggest that this may be an open field for further investigations even if presented results in the references have not been desirable.

Our study shows that none of the above methods is accurate enough for beat detection, in the way they have been used before and they should be revised and even combined together. Numerous of false-positives occurred by using methods for PVC and VF beat detection. However some of the methods such as wavelet based ones, have good results for normal beat detection in the high signal to noise ratios [21]-[23].

Here by considering the time-scale abilities of wavelet Transform, an algorithm is presented which has wonderful results in detecting normal and abnormal ECG beats. The mentioned algorithm is very important for the beat classification algorithms and any classification algorithms which need the beats occurring time intervals.

If we choose the derivative of a lowpass function as a prototype in the continuous wavelet integral, the transformed signal, is proportional to the derivative of the signal once lowpass filtered at a given scale. Consequently the transformed signal shows zeros at different scales in the positions where original signal shows local maxima or minima. Whenever signal has abrupt changes the transform shows positive maxima or negative minima [24].

In this paper the selected prototype wavelet was the Mexican hat, which has required properties.

By studying the transformed signal, it is cleared that when the beat takes place in wavelet transform there is an evident wavelet template, but detecting the presence of the prototype needs some consideration. Through trial and error the algorithm was obtained. The algorithm steps are as follows:

1. The selected ECG record, which is one of the MIT_BIH arrhythmia database records, is filtered by a bandpass (1 to 35 HZ) zero phase filter.
2. Filtered signal is averaged in a moving 10-point window (sampling frequency is 360 HZ).
3. The continuous wavelet transform of the preceded step was computed. The wavelet prototype is Mexican hat and the scale is five.
4. The transformed signal is compressed by Linear Approximation Data Transfer (LADT) algorithm [25], which approximates the curve by lines. The distance for discarding points is five, and the points which their distance of them is less than five are kept.
5. In this step two thresholds are determined, if we consider the result of step 4 in a matrix called C (linear approximated data);

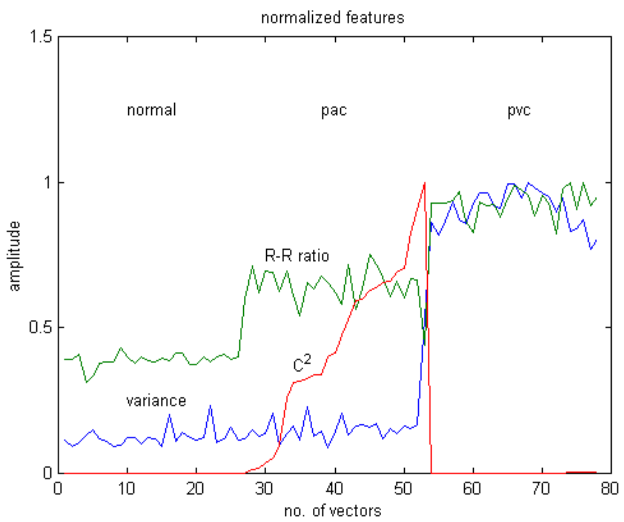

Fig. 1. Normalized features (R-R ratio, variance and square of the wavelet coefficient).

$$CP = C > 0 \quad (1)$$

$$CN = -1 \times C < 0 \quad (2)$$

$$BP = \text{Mean } (CP) \text{ in a 3 second window} \quad (3)$$

$$BN = \text{Mean } (CN) \text{ in a 3 second window} \quad (4)$$

Then the positive and negative thresholds are:

$$THP = 1/3(BP + \text{Max } (CP)) \quad (5)$$

$$THN = 1/3(BN + \text{Max } (CN)) \quad (6)$$

6. The derivatives (difference of samples) of CP and CN are simply calculated.
7. If for any of points in the result of the preceding step the amplitude is grater than BP or less than BN then from 50 points before to 50 points after the detected point is searched. If there is any point, which is greater than the previous, and the next point, this point is written in the temporary detected beat matrix.
8. By consideration of low amplitude fast VF waves as beats; the heart needs at least 200msec to beat again. If the time interval of any of the following points was less than 200 msec, then the detected beat is discarded.

B. Premature Beat Detection Algorithm

This algorithm consists of the following steps:
1. The selected ECG record which is one of the MIT_BIH arrhythmia database records is filtered by a bandpass (1 to 35 Hz) zero phase filter and is averaged in a moving 10 point window.
2. In this step ECG beats are detect by the algorithm of the previous subsection.
3. The detected beats are centered in a 200msec window and then the isopotential value (the mean) is subtracted and the window multiplied with a Hanning window to ensure the end points are zero, thus eliminating possible edge effects.
4. A 6-level discrete wavelet transform decomposition of each characteristic beat is achieved using a 10th order Daubechies wavelet. The wavelet type and decomposition level were chosen after some initial trials but they remain an area of the research requiring further investigation.

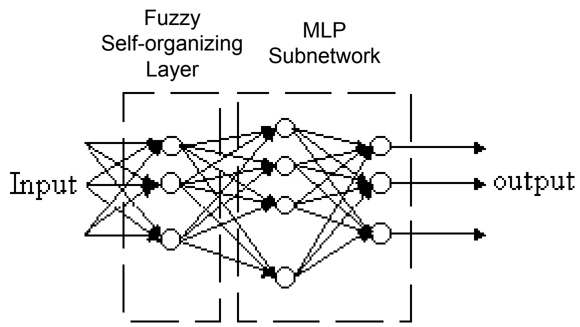

Fig. 2. The structure of the fuzzy hybrid neural network.

By analyzing the result and considering the advantages of combined features, the selected features are as follows:
1. The variance of the wavelet coefficients.
2. The energy of the wavelet coefficients (sum of squared coefficients).
3. The R-R ratio for the consecutive beats

The characteristics of the features are shown in Fig. 1, and indicate that they are distinct enough to be classified by an intelligent classifier.

C. Fuzzy Hybrid Neural Network

In order to classify features, we applied a fuzzy hybrid neural network, which composed of two subnetworks connecting in cascade. The network structure is shown in Fig. 2. The first network is a fuzzy self-organizing layer, which performs a preclassification task and is responsible for managing the data in a way that makes the data of a class more similar by using different membership values.

Assume the vector representing the features under classification is denoted by $\mathbf{x}_k$ for $k = 1,2,...,p$, where $\mathbf{x}_k = [x_{k1}, x_{k2},..., x_{kN}]^T \in R^N$. Let these vectors be partitioned into the C cluster, each represented by the center vector $\mathbf{c}_i = [c_{i1}, c_{i2},..., c_{iN}]^T$. The membership degree of each data vector $x_j (j = 1,2,..., p)$ into i-th cluster $(i = 1,2,...,c)$ called μ_{ij} is in a matrix denoted by $\mu \in R^{c \times p}$. The clustering algorithm determines the membership matrix in a way, which minimizes the objective function E:

$$E = \sum_{i=1}^{c} \sum_{j=1}^{p} \mu_{ij}^m d^2(\mathbf{x}_j, \mathbf{c}_i) \quad (7)$$

subject to

$$\sum_{i=1}^{c} \mu_{ij} = 1 . \quad (8)$$

The parameter m controls the fuzziness of clustering (typically $m = 1.2$). The function $d(x_j, c_i)$ measures the distance between the data vector x_j and the cluster center c_i.

The Gustafson and Kessel (GK) method is an extension of fuzzy C-means Method (FCM) [26]. Different distributions and cluster sizes usually load to sub optimal results with FCM. In order to adapt to different structures in data, GK used the covariance matrix to capture ellipsoidal properties of clusters. Gustafson and Kessel (1979) have extended the fuzzy C-Means algorithm for an inner-product metric norm:

$$d^2(\mathbf{x}_j, c_i) = (\mathbf{x}_j - c_i)^T \mathbf{M}_i (\mathbf{x}_j - c_i) \quad (9)$$

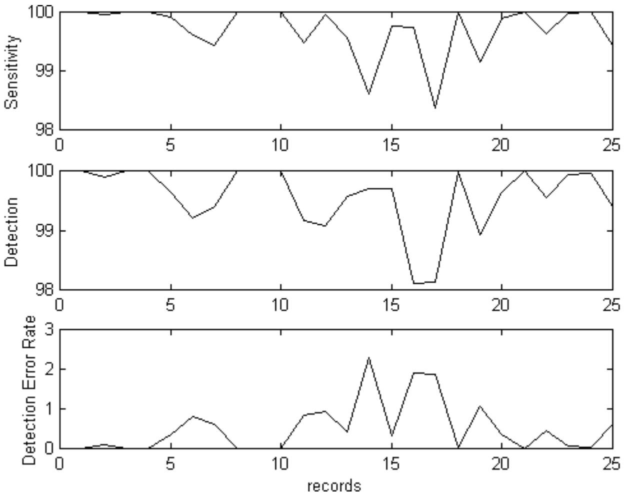

Fig. 3. Sensitivity, detection and detection error rate for 25 records of MIT_BIH arrhythmia database.

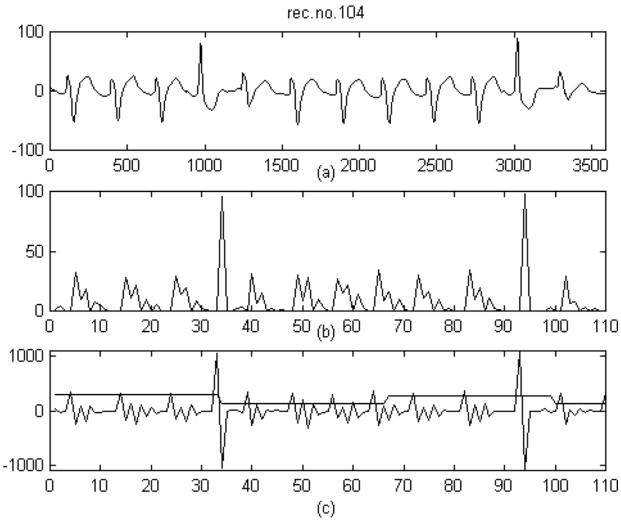

Fig. 4. (a) ECG samples of record No.104, (b) compressed continuous wavelet transform of signal, and (c) differential of compressed wavelet coefficient with adaptive thresholds.

where $\mathbf{M}_i$ is a positive definite matrix adopted according into the actual shapes of the individual clusters described approximately by the cluster covariance matrices $\mathbf{F}_i$. $\mathbf{M}_i$ and $\mathbf{F}_i$ are as follows:

$$\mathbf{F}_i = \frac{\sum_{j=1}^{p} \mu_{ij}(\mathbf{x}_j - c_i)(\mathbf{x}_j - c_i)^T}{\sum_{j=1}^{p} \mu_{ij}^m} \tag{10}$$

$$\mathbf{M}_i = \sqrt[N]{\det(\mathbf{F}_i)}\mathbf{F}_i^{-1}. \tag{11}$$

The Gustafson-Kessel algorithm can be presented in the following way. At a given dataset $\mathbf{x}_k \in \mathrm{R}^N$, choose the number of clusters $1 < c < N$, the weighting exponent $m > 1$ and the termination tolerance $\varepsilon > 0$. Initialize the fuzzy partition matrix $\boldsymbol{\mu}$ randomly in a way that

$$\sum_{i=1}^{c} \mu_{ij} = 1 \tag{12}$$

is satisfied. Then iterate through the following steps.

1) Compute the cluster prototypes (centers) $\mathbf{c}_i (i = 1,2,...,c)$

$$\mathbf{c}_i = \frac{\sum_{j=1}^{p} \mu_{ij}^m \mathbf{x}_j}{\sum_{j=1}^{p} \mu_{ij}^m} \tag{13}$$

2) Calculate the cluster covariance matrix $\mathbf{F}_i (i = 1,2,...,c)$ according to (10).

3) Compute the distances between the input vector $\mathbf{x}_j$ and the cluster center $\mathbf{c}_i$ using (9) and (11).

4) Update the fuzzy partition matrix

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij} / d_{kj})^{2/(m-1)}} \tag{14}$$

If $d_{ij} = 0$ for some $i = I$, take $\mu_{Ij} = 1$ and $\mu_{ij} = 0$ for $i \neq I$. Iterations continued until for two succeeding iterations $\left\| U^l = U^{l-1} \right\| \leq \varepsilon$.

After training the fuzzy self-organizing layer, the MLP subnetwork has been trained by use of membership coefficient matrix $\boldsymbol{\mu}$ as input.

The input vectors into the MLP subnetwork are the membership degrees determined by the fuzzy self-organizing layer. Thus, the number of input nodes equals the self-organizing neurons and the output neurons are equal to the number of classes. Number of neurons in the hidden layer is very important and in this work has been selected through some trial and errors.

The MLP has been trained by back propagation algorithm.

III. Results

The potential of our beat detection method was examined using MIT_BIH arrhythmia database as shown in Figs. 3 and 4. The results are depicted in Table I (results for each files) and Table II (average performance). Sensitivity and specificity are calculated according to (15) and (16)

$$Se = \frac{TP}{TP + FN}, \tag{15}$$

$$Sp = \frac{TP}{TP + FP}. \tag{16}$$

where TP stands for number of true positives, FN for false negatives and FP for False positives.

In classification section, the information of the ECG beats through the discrete wavelet transform coefficients are applied to the fuzzy hybrid neural network. The inputs are the R-R ratio of the succeeding beats and the variances and the square of the wavelet coefficients.

To test the beat recognition ability, we select 1000 beats randomly by uniform distribution from any of the classes (Premature Ventricular Complexes, Premature Atrial Complexes and Normal, for a total population of 3000 beats) from MIT_BIH arrhythmia database for training and 3000 different beats for testing. The tolerance for self-organizing layer training is selected $1e-6$.

TABLE I
RESULTS FOR BEAT DETECTION ALGORITHM

Rec. No	FP	FN	Total True QRSs	Detection (%)	Detection Error Rate	Sensitivity
100	0	0	2270	100	0	100
101	1	1	1866	99.89	0.107	99.95
102	0	0	2407	100	0	100
103	0	0	2083	100	0	100
104	6	2	2203	99.64	0.363	99.91
105	10	10	2514	99.20	0.797	99.60
106	1	11	1979	99.39	0.606	99.44
107	0	0	2036	100	0	100
118	0	0	2227	100	0	100
119	0	0	1976	100	0	100
200	8	13	2518	99.17	0.833	99.48
201	16	1	1827	99.07	0.930	99.95
202	0	9	2079	99.57	0.432	99.57
203	27	40	2912	99.70	2.30	98.61
205	2	6	2586	99.70	0.309	99.77
207	36	6	2226	98.11	1.89	99.73
208	7	47	2876	98.12	1.88	98.36
209	1	0	2937	99.97	0.034	100
210	6	22	2620	98.93	1.06	99.16
212	7	3	2731	99.64	0.366	99.89
213	0	0	3205	100	0	100
214	2	8	2223	99.55	0.450	99.64
215	1	1	3278	99.94	0.061	99.97
217	1	0	2168	99.95	0.046	100
219	1	12	2117	99.39	0.614	99.43

TABLE II
AVERAGE PERFORMANCE

Rec. No	FP	FN	Total True QRSs	Detection (%)	Detection Error Rate	Sensitivity
100-219	133	211	59864	99.43	0.5746	99.65

After training the self-organizing layer, the vectors of membership degrees are applied to a $N_{3,10,20,3}$ MLP, which is trained by back propagation algorithm. The training error has been selected 1e-8.

To test the whole network performance like training sets of data, we select 3000 beats (1000 from each class). The results are depicted in Table III.

IV. CONCLUSION

We purposed a beat detection algorithm based on the derivative of the compressed continuous wavelet coefficients and adaptive thresholds, which shows good detection (99.43%) and sensitivity (99.65%) on 59864 beats of database. Presented algorithm have better sensitivity in 18 records among 25 selected MIT_BIH Arrhythmia database records compared to [27] and have better average sensitivity totally in comparison with [27] ($Se = 99.59\%$) and [12] ($Se = 98.68\%$). These results show that the purposed algorithms are accurate enough to be used for detecting beats in classification algorithm.

A new Premature beat classification that applies the discrete wavelet coefficients as beat features in combination with R-R Ratio as rhythm feature and self-organizing fuzzy hybrid neural network has been purposed in this paper.

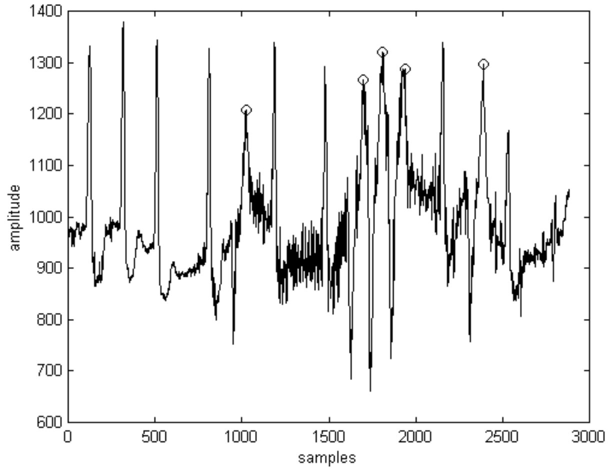

Fig. 5. Examples of detected PVCs (marked by ‘o’) in high signal to noise ratio; MIT_BIH Arrhythmia database, record No. 203.

TABLE III
RESULTS FOR PREMATURE BEAT RECOGNITION ALGORITHM

Total beats No.	Misclassification	Sensitivity (%)	Specificity (%)
3000	0	100	100

The features used for classification are managed by G-K algorithm and classified by a MLP neural network shows good efficiency and the best results.

These investigations show that using the abilities of continuous wavelet for abrupt change detection and abilities of discrete wavelet transform for details detection in combined features along with fuzzy hybrid learning process can reach outstanding accuracy (100%) and sensitivity (100%) even in difficult cases such as Fig. 5 and may have find practical applications in recognition of different types of ECG beats. These are the subjects of further studies.

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Fardad Farrokhi was born in Kermanshah, in 1972. He received the B.Sc. degree in Electronic Engineering from University of Khaje Nasir Addin Toosi in 1996 and M.Sc. degree in Electronic Engineering from South Tehran Campus of the Islamic Azad University in 1998. He received his Ph.D. degree in Bioelectric Engineering from Islamic Azad University Science and Research Campus in 2004. The title of his thesis is Arrhythmia Classification by Fuzzy Networks. His research interests include Fuzzy Networks, Feature selection methods & Pattern recognition.

Since 2001 he has been an academic member of Electronic Department of Islamic Azad University Central Campus.

Mohammad H. Moradi received the B.Sc. and M.Sc. degrees in electronic engineering from Tehran University in 1988 and 1990, respectively, and the Ph.D. degree from the University of Tarbiat Modarres, Tehran, Iran in 1995.

Since 1995, he has been with the School of Biomedical Engineering, AmirKabir University of Technology, where he is currently an Associate Professor and Director of Higher education.

His primary research and teaching interests involve the theory and application of medical instrumentation, biomedical signal processing and fuzzy neural systems. He has published over 70 technical papers in international conferences and journals and translated one book.

Reza Miri received his M.D. degree in 1981 from University of Mashad and specialty of Cardiology in 1993 from the University of Shahid Beheshti.

From 1993 to 1994, he was employed as an Assistant Professor at Semnan University. In 1994, he joined the Department of Cardiology at Shahid Beheshti University as an Assistant Professor.

Dr. Miri is a member of Iranian Heart Association (I.H.A).