Neuro-ANFIS Architecture for ECG Rhythm-Type Recognition Using Different QRS Geometrical-Based Features

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Abstract: The paper addresses a new QRS complex geometrical feature extraction technique as well as its application for electrocardiogram (ECG) supervised hybrid (fusion) beat-type classification. To this end, after detection and delineation of the major events of ECG signal via a robust algorithm, each QRS region and also its corresponding discrete wavelet transform (DWT) are supposed as virtual images and each of them is divided into eight polar sectors. Then, the curve length of each excerpted segment is calculated and is used as the element of the feature space. To increase the robustness of the proposed classification algorithm versus noise, artifacts and arrhythmic outliers, a fusion structure consisting of three Multi Layer Perceptron-Back Propagation (MLP-BP) neural networks with different topologies and one Adaptive Network Fuzzy Inference System (ANFIS) were designed and implemented. To show the merit of the new proposed algorithm, it was applied to all MIT-BIH Arrhythmia Database records and the discrimination power of the classifier in isolation of different beat types of each record was assessed and as the result, the average accuracy value Acc=98.27% was obtained. Also, the proposed method was applied to 8 number of arrhythmias (Normal, LBBB, RBBB, PVC, APB, VE, PB, VF) belonging to 19 number of the aforementioned database and the average value of Acc=98.08% was achieved. To evaluate performance quality of the new proposed hybrid learning machine, the obtained results were compared with similar peer-reviewed studies in this area.

Keywords: Feature Extraction, Curve Length Method, Multi Layer Perceptron, Adaptive Network Fuzzy Inference System, Fusion (Hybrid) Classification, Arrhythmia Classification, Supervised Learning Machine.

1 Introduction

Heart is a special myogenic muscle which its constitutive cells (myocytes) possess two important characteristics namely as nervous (electrical) excitability and mechanical tension with force feedback. The heart's rhythm of contraction is controlled by the sino-atrial node (SA node) called the heart pacemaker. This node is the part of the heart's intrinsic conduction system, made up of specialized myocardial (nodal) cells. Each beat of the heart is set in motion by an electrical signal from the SA node located in the heart's right atrium. The automatic nature of the heartbeat is referred to as automaticity which is due to the spontaneous electrical activity of the SA node. The superposition of all myocytes electrical activity on the skin surface causes a detectable potential difference which its detection and registration together is called electrocardiography [1]. However the heart's electrical system controls all the events occurring when heart pumps blood. So if according to any happening, the electro-mechanical function of a region of myocytes encounters a failure, the corresponding abnormal effects will appear in the electrocardiogram (ECG) which is an important part of the preliminary evaluation of a patient suspected to have a heart-related problem. Based on a comprehensive literature survey among many documented works, it is seen that several features and extraction (selection) methods have been created and implemented by authors. For example, original ECG signal [17], preprocessed ECG signal via appropriately defined and implemented transformations such as

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discrete wavelet transform (DWT), continuous wavelet transform (CWT) [21], Hilbert transform (HT) [64], fast Fourier transform(FFT) [48-49], short time Fourier transform (STFT) [10], power spectral density (PSD) [51-52], higher order spectral methods [46-47], statistical moments [24], nonlinear transformations such as Liapunov exponents and fractals [43-45] have been used as appropriate sources for feature extraction. In order to extract feature(s) from a selected source, various methodologies and techniques have been introduced. To meet this end, the first step is segmentation and excerption of specific parts of the preprocessed trend (for example, in the area of the heart arrhythmia classification, ventricular depolarization regions are the most used segments). Afterwards, appropriate and efficient features can be calculated from excerpted segments via a useful method. Up to now, various techniques have been proposed for the computation of feature(s). For example mean, standard deviation, maximum value to minimum value ratio, maximum-minimum slopes, summation of point to point difference, area, duration of events, correlation coefficient with a pre-defined waveform template, statistical moments of the auto (cross) correlation functions with a reference waveform [32], bi-spectrum [46], differential entropy [37], mutual information [39], nonlinear integral transforms and some other more complicated structures [33-45] may be used as an instrument for calculation of features.

After generation of the feature source, segmentation, feature selection and extraction (calculation), the resulted feature vectors should be divided into two groups "train" and "test" to tune an appropriate classifier such as a neural network, support vector machine or ANFIS, [30-40]. As previous researches show, occurrence of arrhythmia(s) affects RR-tachogram and Heart Rate Variability (HRV) in such a way that these quantities can be used as good features to classify several rhythms. Using RR-tachogram or HRV analysis in feature extraction and via simple if-then or other parametric or nonparametric classification rules [7-9], artificial neural networks, fuzzy or ANFIS networks [10-14], support vector machines [15] and probabilistic frameworks such as Bayesian hypotheses tests [16], the arrhythmia classification would be fulfilled with acceptable accuracies. Heretofore, the main concentration of the arrhythmia classification schemes has been on morphology assessment and/or geometrical parameters of the ECG events. Traditionally, in the studies based on the morphology and the wave geometry, first, during a preprocessing stage, some corrections such as baseline wander removal; noise-artifact rejection and a suitable scaling are applied. Then, using an appropriate mapping for instance, filter banks, discrete or continuous wavelet transform in different spatial resolutions and etc., more information is derived from the original signal for further processing and analyses. In some researches, original and/or preprocessed signal are used as appropriate features and using artificial neural network or fuzzy classifiers [17-25], parametric and probabilistic classifiers [26-28], the discrimination goals are followed. Although, in such classification approaches, acceptable results may be achieved, however, due to the implementation of the original samples as components of the feature vector, computational cost and burden especially in high sampling frequencies will be very high and the algorithm may take a long time to be trained for a given database. In some other researches, geometrical parameters of QRS complexes such as maximum value to minimum value ratio, area under the segment, maximum slope, summation (absolute value) of point to point difference, ST-segment, PR and QT intervals, statistical parameters such as correlation coefficient of a assumed segment with a template waveform, first and second moments of original or preprocessed signal and etc. are used as effective features [29-35]. The main definition origin of these features is based on practical observations and a priori heuristic knowledge whilst conducted researches have shown that by using these features, convincing results may be reached. On the other hand, some of studies in the literature focus on the ways of choosing and calculating efficient features to create skillfully an efficient classification strategy [36-39]. In the area of nonlinear systems theory, some ECG arrhythmia classification methods on the basis of fractal theory [40, 41], state-space, trajectory space, phase space, Liapunov exponents [42-44] and nonlinear models [45] have been innovated by researchers. Amongst other classification schemes, structures based on higher order statistics in which to analyze features, a two or more dimensional frequency space is constructed can be mentioned [46, 47]. According to the concept that upon appearance of changes in the morphology of ECG signal caused by arrhythmia, corresponding changes are seen in the frequency domain, therefore, some arrhythmia classifiers have been designed based on the appropriate features obtained from signal fast Fourier transform (FFT), short-time Fourier transform (STFT), auto regressive (AR) models and power spectral density (PSD), [48-53]. Finally, using some polynomials such as Hermite function which has specific characteristics, effective features have been extracted to classify some arrhythmias [54, 55]. The general block diagram of the proposed heart arrhythmia recognition-classification algorithm including two stages train and test is shown in Fig. 1. According to this figure, first, the events of the ECG signal are detected and delineated using a robust wavelet-based algorithm [62-63]. Then, each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space and to increase the robustness of the proposed classification algorithm versus noise, artifacts

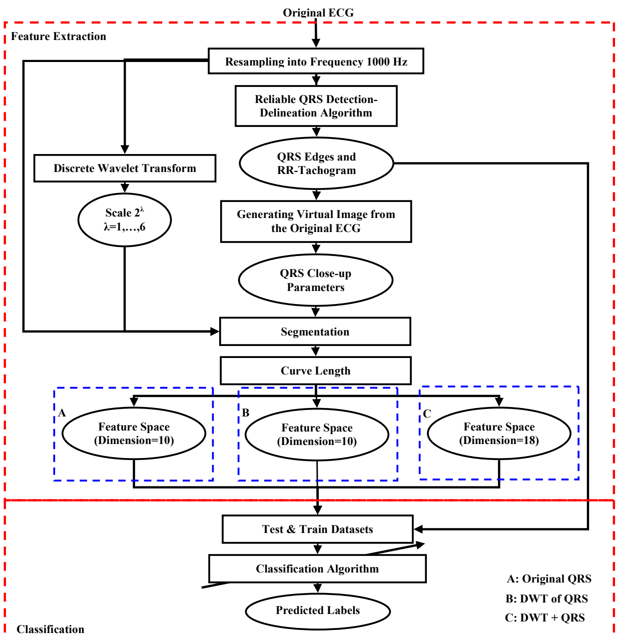

Fig. 1 The general block diagram of an ECG beat type recognition algorithm supplied with the virtual image-based geometrical features.

and arrhythmic outliers, a fusion structure consisting of three MLP-BP neural networks with different topologies and one ANFIS were designed and implemented. The new proposed algorithm was applied to all 48 records of the MIT-BIH Arrhythmia Database (MITDB) and the average value of Acc=98.27% was obtained. Also, the proposed hybrid classifier was applied to 8 number of arrhythmias (Normal, LBBB, RBBB, PVC, APB, VE, PB, VF) belonging to 19 number of the MITDB and the average value of Acc=98.08% was achieved. To compare the outcomes with previous peer-reviewed studies and to show the generalization power of the proposed classification algorithm, 4,011 and 4,068 samples have been selected for training and for testing groups, respectively.

The List of Abbreviations is as follows:

ANFIS:	Adaptive Network Fuzzy Inference System
MF:	Membership Function
ECG:	Electrocardiogram
DWT:	Discrete Wavelet Transforms
SNR:	Signal to Noise Ratio
ANN:	Artificial Neural Network
MEN:	Maximum Epochs Number
NHLN:	Number of Hidden Layer Neurons
RBF:	Radial Basis Function
MLP-BP:	Multi-Layer Perceptron Back Propagation
LR:	Learning Rate
FP:	False Positive
FN:	False Negative
TP:	True Positive
P+:	Positive Predictivity (%)
Se:	Sensitivity (%)
CPUT:	CPU Time
MITDB:	MIT-BIH Arrhythmia Database
SMF:	Smoothing Function
FIR:	Finite-duration Impulse Response
LBBB:	Left Bundle Branch Block
RBBB:	Right Bundle Branch Block
PVC:	Premature Ventricular Contraction
APB:	Atrial Premature Beat
VE:	Ventricular Escape Beat
PB:	Paced Beat
VF:	Ventricular Flutter Wave

2 Materials and Methods

2.1 Discrete Wavelet Transform using à Trous Method

Generally, it can be stated that the wavelet transform is a quasi-convolution of the hypothetical signal $x(t)$ and the wavelet function $\psi(t)$ with the dilation parameter "a" and translation parameter "b", as the following integration.

$$W_{a^x}(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\big((t-b)/a\big)dt, \quad a > 0 \tag{1}$$

The parameter a can be used to adjust the wideness of the basis function and therefore the transform can be adjusted in several temporal resolutions. In Eq. 1, for dilation parameter "a" and the translation parameter "b", the values $a = q^k$ and $b = q^k lT$ can be used in which q is the discretization parameter, l is a positive constant, k is the discrete scale power and T is the sampling period. By substituting the new values of the parameters "a" and "b" into the wavelet function $\psi(t)$, the following result is obtained.

$$\psi_{k,l}(t) = q^{-k/2}\psi(q^{-k}t - lT);\ k,l \in Z^+ \tag{2}$$

The scale index k determines the width of wavelet function, while the parameter l provides translation of the wavelet function.

If the scale factor a and the translation parameter b are chosen as q=2 i.e., $a = 2^k$ and $b = 2^k l$, the dyadic wavelet with the following basis function will be resulted [76],

$$\psi_{k,l}(t) = 2^{-k/2}\psi(2^{-k}t - lT);\ k,l \in Z^+ \tag{3}$$

To implement the à trous wavelet transform algorithm, filters $H(z)$ and $G(z)$ should be used according to the block diagram represented in Fig. 2-a, [76]. According to this block diagram, each smoothing function (SMF) is obtained by sequential low-pass filtering (convolving with $G(z)$ filters), while after high-pass filtering of a SMF (convolving with $H(z)$ filters), the corresponding DWT at appropriate scale is generated. In order to decompose the input signal $x(t)$ into different frequency passbands, according to the block diagram of Fig. 2-b, sequential high-pass low-pass filtering including down-sampling should be implemented. The filter outputs $x_H(t)$ and $x_L(t)$ can be obtained by convolving the input signal $x(t)$ with corresponding high-pass and low-pass finite-duration impulse responses (FIRs) and contributing the down-sampling as

$$\begin{cases} x_L(t) = \sum_{k=-\infty}^{k=+\infty} g(k)\,x(2t-k) \\ x_H(t) = \sum_{k=-\infty}^{k=+\infty} h(k)\,x(2t-k) \end{cases} \tag{4}$$
$t = 0, 1, \ldots, N-1$

On the other hand, to reconstruct the transformed signal, the obtained signals $x_H(t)$ and $x_L(t)$ should be first be up-sampled by following simple operation

$$\begin{cases} x_L^*(2t) = x_L(t) \quad , \quad x_L^*(2t+1) = 0 \\ x_H^*(2t) = x_H(t) \quad , \quad x_H^*(2t+1) = 0 \end{cases} \tag{5}$$
$t = 0, 1, \ldots, N-1$

If the FIR lengths of the H(z) and G(z) filters are represented by L_H and L_G, respectively, then the reconstructing high-pass and low-pass filters are obtained as

$$\begin{cases} g^*(t) = g(L_G - 1 - t) \\ h^*(t) = h(L_H - 1 - t) \end{cases} \tag{6}$$

Then the reconstructed signal $x_R(t)$ is obtained by superposition of the up-sampled signals convolution with their appropriately flipped FIR filters as follow

$$x_R(t) = \sum_{k=-\infty}^{k=+\infty} h^*(k)\,x_H^*(t-k) + \sum_{k=-\infty}^{k=+\infty} g^*(k)\,x_G^*(t-k) \tag{7}$$

For a prototype wavelet $\psi(t)$ with the following quadratic spline Fourier transform,

$$\mathbf{\Psi}(\Omega) = j\Omega\left(\frac{\sin(\Omega/4)}{\Omega/4}\right)^4 \tag{8}$$

the transfer functions $H(z)$ and $G(z)$ can be obtained from the following equation

$$\begin{aligned} H(e^{j\omega}) &= e^{j\omega/2}\left(\cos(\omega/2)\right)^3 \\ G(e^{j\omega}) &= 4je^{j\omega/2}\left(\sin(\omega/2)\right) \end{aligned} \tag{9}$$

and therefore,

$$\begin{aligned} h[n] &= \\ (1/8)&\{\delta[n+2] + 3\delta[n+1] + 3\delta[n] + \delta[n-1]\} \\ g[n] &= 2\,\{\delta[n+1] - \delta[n]\} \end{aligned} \tag{10}$$

It should be noted that for frequency contents of up to 50 Hz, the à trous algorithm can be used in different sampling frequencies. Therefore, one of the most prominent advantages of the à trous algorithm is the approximate independency of its results from sampling frequency. This is because of the main frequency contents of the ECG signal concentrate on the range less than 20 Hz [62-63]. After examination of various databases with different sampling frequencies (range between 136 to 10 kHz), it has been concluded that in low sampling frequencies (less than 750 Hz), scales 2^λ (λ=1, 2, …, 5) are usable while for sampling frequencies more than 1000 Hz, scales 2^λ (λ=1, 2, …, 8) contain profitable information that can be used for the purpose of wave detection, delineation and classification.

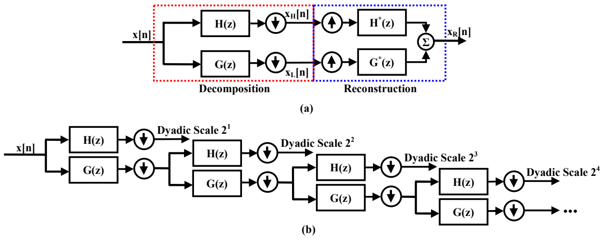

Fig. 2 FIR filter-bank implementation to generate discrete wavelet dyadic scales and smoothing functions transform based on à trous algorithm. (a) one-step generation of detail coefficient scales and reconstruction of the input signal. (b) four-step implementation of DWT for extraction of dyadic scales.

2.2 ANFIS Classification Strategy

ANFIS is a fuzzy Sugeno model of integration where the final fuzzy inference system is optimized via the ANNs training. ANFIS can be viewed as a class of adaptive networks which are functionally equivalent to fuzzy inference system. It maps inputs through input membership function and associated parameters, and then through output membership function to outputs. ANFIS uses back-propagation or a combination of least square estimation and back-propagation for membership function parameter estimation. The most important point in data classification by ANFIS is designing of fuzzy rules. To solve this problem, several clustering techniques such as fuzzy c-means (FCM), K-means clustering (KMC) and histogram adaptive smoothing (HAS) can be utilized. In this study, subtractive clustering is used in which each cluster represents one independent rule, (Jang, 1993 [71]).

2.2.1 Subtractive Clustering

A Data clustering is a process of putting similar data into groups. A clustering algorithm partitions a data set into several groups such that the similarity within a group is larger than among groups. Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction. Clustering techniques are used in conjunction with radial basis function networks or fuzzy modeling primarily to determine initial location for radial basis functions or fuzzy if-then rules. There are different clustering technique such as k-means clustering, fuzzy c-means clustering, mountain clustering and subtractive clustering. If there is no clear

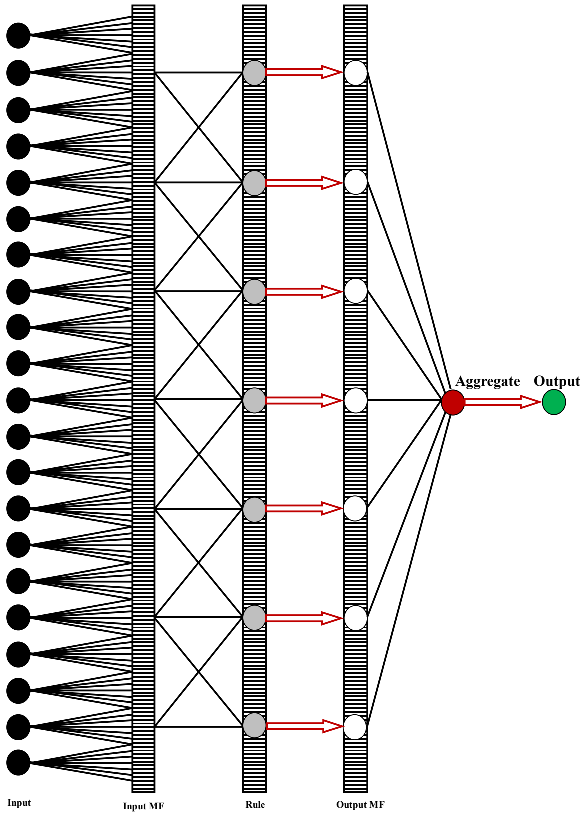

Fig. 3 The general of ANFIS used for heart rhythm classification.

idea how many clusters there should be for a given set of data, subtractive clustering is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. Consider a collection of n data points in an m-dimensional space. Without loss of generality, the data points are assumed to have been normalized within a hypercube. Since each data point is a candidate for cluster centers, a density measure at data point $\mathbf{x}_i$ is defined as:

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{(r_a/2)^2} \right) \tag{11}$$

where r_a is a positive constant. Hence a data point will have a high density value if it has many neighboring data points. The radius r_a defines a neighborhood; data points outside this radius contribute only slightly to the density measure. After the density measure of each data point has been calculated, the data point with the highest density measure is selected as the first cluster center. Let x_{c1} be the point selected and D_{c1} its density measure. Next the density measure for each data point x_i is revised by the formula

$$D_i = D_i - D_{c1} \exp\left(-\frac{\|\mathbf{x}_i - \mathbf{x}_{c1}\|^2}{(r_b/2)^2} \right) \tag{12}$$

where r_b is a positive constant. Therefore, the data points near the first cluster center x_{c1} will have significantly reduced density measures, thereby making the points unlikely to be selected as the next cluster center. The constant r_b defines a neighborhood that has measurable reductions in density measure. The constant r_b is normally larger than ro to prevent closely spaced cluster centers; generally r_b is equal to 1.5 r_a. After the density measure for each data point is revised, the next cluster center x_{c2} is selected and all of the density measures for data points are revised again. This process is repeated until a sufficient number of cluster centers are generated.

When applying subtractive clustering to a set of input-output data, each of the cluster centers represents a prototype that exhibits certain characteristics of the system to be modeled. These cluster centers would be reasonably used as the centers for the fuzzy rules' premise in a zero-order Sugeno fuzzy model, or radial basis functions in a Radial Basis Function Network (RBFN). For instance, assume that the center for the i-th cluster is c_i in an M dimension. The c_i can be decomposed into two component vectors p_i and q_i, where p_i is the input part and it contains the first N element of c_i; q_i is the output part and it contains the last M - N elements of c_i. Then given an input vector x, the degree to which fuzzy rule i is fulfilled is defined by

$$\mu_i = \exp\left(-\frac{\|\mathbf{x} - \mathbf{p}_i\|^2}{(r_a/2)^2} \right) \tag{13}$$

This is also the definition of the i-th radial basis function if we adopt the perspective of modeling using RBFNs. Once the premise part (or the radial basis functions) has been determined, the consequent part (or the weights for output unit in an RBFN) can be estimated by the least-squares method. After these procedures are completed, more accuracy can be gained by using gradient descent or other advanced derivative-based optimization schemes for further refinement, (Jang, 1993 [71]).

3 The Neuro-ANFIS Fusion Classification Algorithm: Design, Implementation and Performance Evaluation

3.1 QRS Geometrical Features Extraction

3.1.1 ECG Events Detection and Delineation

In this step, QRS complexes are detected and delineated. Today reliable QRS detectors based on Hilbert [64, 65] and Wavelet [62, 63] transforms can be found in literature. In this study, an ECG detection-delineation method with the sensitivity and positive predictivity Se = 99.95% and P+ = 99.94% and the average maximum delineation error of 6.1 msec, 4.1 msec and 6.5 msec for P-wave, QRS complex and T-wave, respectively is implemented [62]. By application of this method, detecting the major characteristic locations of each QRS complex i.e., fiducial, R and J locations, becomes possible.

3.1.2 Detected QRS Complex Geometrical Features Extraction [77]

In order to compute features from the detected QRS complexes either normal or arrhythmic via the proposed method, first a reliable time center should be obtained for each QRS complex. To find this point, the absolute maximum and the absolute minimum indices of the excerpted DWT dyadic scale 2^4 using the onset-offset locations of the corresponding QRS complex, are determined. It should be noted that according to comprehensive studies fulfilled in this research, the best time center of each detected QRS complex is the mean of zero-crossing locations of the excerpted DWT (see Fig. 4)

To make a virtual close-up from each detected QRS complex, a rectangle is built on the complex with following specifications:

- The left-side mid-span of the rectangle is the fiducial location of the QRS complex.
- The Absolute distance of the complex from the fiducial point is the half of the rectangle height.
- The center of rectangle is the time-center of the QRS complex.
- The right-hand abscissa of the rectangle is the distance between QRS time center and its J-location.

Afterwards, Each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the elements of the feature space, (therefore, for each detected QRS complex, 16 features are computed). The quantity curve-length of a hypothetical time series x(t) in a window with length W_L samples can be estimates as

$$M_{CL}(k) \approx \frac{1}{F_s} \sum_{t=k}^{k+W_L-1} \sqrt{1+\left[\left(x(t+1)-x(t)\right)F_s\right]^2} \qquad (14)$$

where, F_s is sampling frequency of the time series x(t).

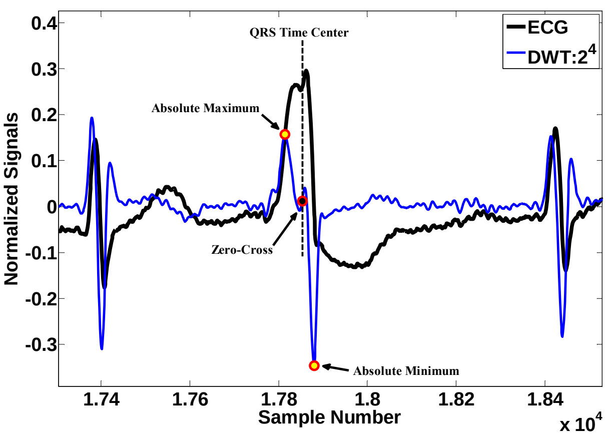

Fig. 4 Determination of the time center of a detected QRS complex using excerpted DWT scale 2^4. The vertical axis unit is arbitrary.

The curve length is suitable to measure the duration of the signal $x(t)$ events, either being strong or weak. Generally, the M_{CL} measure indicates the extent of flatness (smoothness or impulsive peaks) of samples in the analysis window. This measure allows the detection of sharp ascending/descending regimes occurred in the excerpted segment [63].

In Fig. 1, the general block diagram of the ECG beats annotation algorithm with the proposed QRS geometrical feature space is illustrated. A generic example of a holter ECG and its corresponding 2^4 DWT dyadic scale with the virtual images of the complexes provided for feature extraction as well as two quantities obtained from the RR-tachogram are shown in Fig. 5.

3.2 Design of the Hybrid (Fusion) Neuro-ANFIS Classification Algorithm

3.2.1 Design of the Particle Classifiers

In the heart-beat classification context, due to differences existing in the theory and the structure of the several types of classifiers such as Artificial Neural Network (ANN) and ANFIS reasonably, achieving exactly similar result from them given a common train and test feature spaces, can't be expected. Assessments confirm that in the arrhythmia classification of the MITDB, even if the average discrimination power of an appropriately designed classifier is superior to another rival classifier, however, existence of some records in which exceptionally higher generated accuracies obtained from the rival classifier may be possible. In order to increase the total accuracy of the proposed classification algorithm, one way is to synthesize the output of several classification algorithms with different inherent structures to achieve the best accuracy as much as possible leading to higher robustness against uncertainties and probable arrhythmia or outliers. In this study, to build a fusion (hybrid) classification scheme, three MLP-BP with different topologies and one ANFIS are properly regulated using the train dataset. The specifications of each classification algorithm are described below.

MLP-BP1. The first MLP-BP classifier includes one hidden layer with number of hidden layer neurons (NHLN) equal to 11 and tangent sigmoid and the logarithmic sigmoid as the activation functions of the hidden layer and output layer, respectively. Also, for this ANN, MEN is chosen to be 200.

MLP-BP2. This classifier possesses one hidden layer with NHLN=12. The tangent sigmoid was chosen as the activation function for both hidden and output layers, respectively. For this ANN, MEN = 150 was assigned.

MLP-BP3. The third MLP-BP classifier includes one hidden layer with logarithmic sigmoid as the activation function for both hidden and output layers, respectively. For this ANN, MEN = 300 and NHLN=14 was assigned.

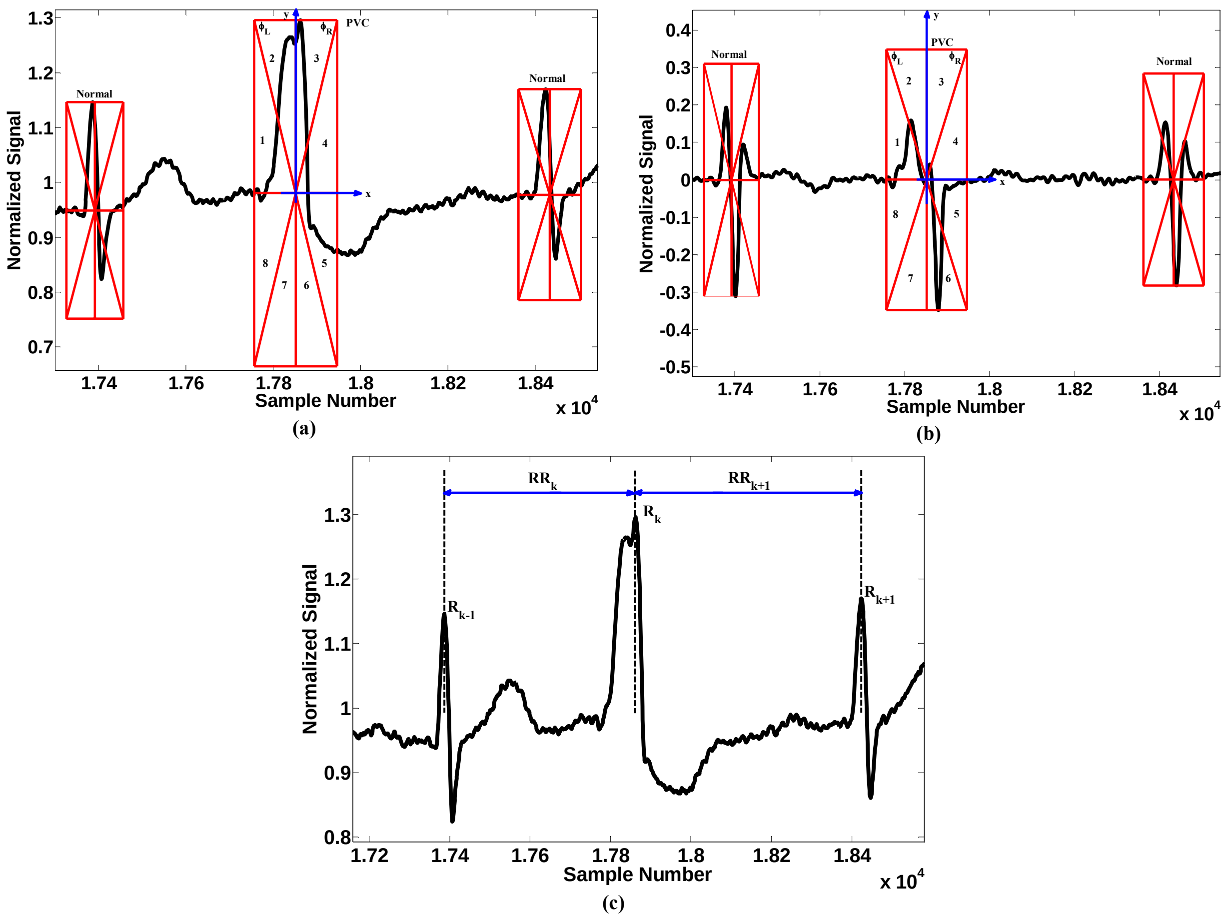

Fig. 5 Extraction of the geometrical features from a delineated QRS complex via segmentation of each complex into 8 polar sectors by generating of a virtual image from the complex. (a) original ECG, (b) DWT of the original ECG and (c) RR-interval. The vertical axis unit is arbitrary.

ANFIS. for generating fuzzy inference system, the parameters of subtractive clustering is set as follow: Range of influence=0.5, Squash factor=0.55, Accept ratio=0.5, Reject ratio=0.15. With these parameters, 7 fuzzy rules are obtained.

It should be noticed that several parameters such as types of activation functions and several values for NHLN, MEN, Range of influence, Squash factor ,Accept ratio and Reject ratio were examined and were altered based on trying-and-error method and suitable ranges and types were chosen for these parameters.

3.2.2 The Neuro-ANFIS Fusion Classification Scheme

To design a fusion classification algorithm, after appropriate training of three MLP-BP classifiers, ANFIS is regulated to merge results of all particle classifiers. To train this classifier, obtained outputs of each MLP-BP are set as the train feature vector for ANFIS.

In Fig. 6, the block diagram of the proposed fusion classification algorithm including different classifiers in the train and test stages is illustrated.

To evaluate performance of the proposed feature extraction method and the fusion classification algorithm, the following steps are pursued.

- Evaluation of the discriminate power of the selected features.
- Design of the particle classifiers and their implementation to all MITDB records.
- Design of the fusion classifier for each MITDB record and comparing the obtained results with each particle classifier.
- Selection of some rhythms from the MITDB records and designing of the particle and fusion classifiers.
- Comparison of the obtained final results with previous similar peer-reviewed studies.

3.3 Results and Discussion

In Table 1, the numeric codes of the 23 MITDB rhythms and their corresponding annotations are illustrated. After implementation of the three MLP-BP neural networks and ANFIS classifier and the corresponding fusion classifier to all 48 MITDB records and calculation of the accuracy, the obtained

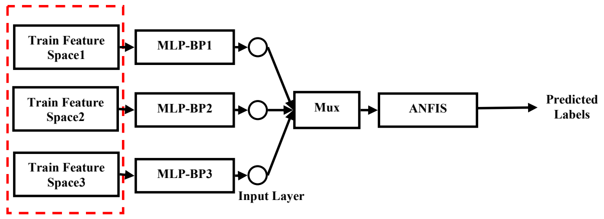

Fig. 6 Design of the fusion classification algorithm via merging the outpur of several pre-trained particle classifiers in ANFIS.

Table 1 The different rhythm types and the corresponding equivalent ASCII code integer numbers.

Numeric Code	Rhythm	Numeric Code	Rhythm
33	Ventricular Flutter Wave	83	Supraventricular Premature or Ectopic Beat
34	Comment Annotation	86	Premature Ventricular Contraction
43	Rhythm Change	91	Start of Ventricular Flutter/Fibrillation
47	Paced Beat	93	End of Ventricular Flutter/Fibrillation
65	Atrial Premature Beat	97	Aberrated Atrial Premature Beat
69	Ventricular Escape Beat	101	Atrial Escape Beat
70	Fusion of Ventricular and Normal Beat	102	Fusion of Paced and Normal Beat
74	Nodal (junctional) premature Beat	106	Nodal (junctional) Escape Beat
76	Left Bundle Branch Block Beat	120	Non-Conducted P-wave (Blocked APC)
78	Normal Beat	124	Isolated QRS-Like Artifact
81	Unclassifiable Beat	126	Change in Signal Quality
82	Right Bundle Branch Block Beat		

Table 2 Performance of the fusion classification algorithm for all MIT-BIH records.

MIT Rec	Total # of Beats	Rhythm Codes	# of Beats of Each Annotated Rhythm	# class	1st Neural Net	2nd Neural Net	3rd Neural Net	ANFIS
100	2274	[43,78,65,86]	[1,2239,33,1]	2	99.84	99.79	100	100
101	1874	[43,78,126,124,81,65]	[1,1860,4,4,2,3]	3	99.8660	100	100	100
102	2192	[43,47,102,78,86]	[5,2028,56,99,4]	5	99.5126	99.04	99.61	99.91
103	2091	[43,78,126,65]	[1,2082,6,2]	2	99.7605	100	100	100
104	2311	[43,47,102,126,81,78,86]	[45,1380,666,37,18,163,2]	6	91.6304	91.41	92.11	93.61
105	2691	[43,78,86,126,124,81]	[1,2526,41,88,30,5]	5	97.8177	97.16	97.95	98.53
106	2098	[126,43,78,86]	[30,41,1507,520]	4	96.2963	95.94	96.77	97.44
107	2140	[43,47,86,126]	[1,2078,59,2]	2	100	100	100	100
108	1824	[43,78,86,120,126,65,124,70,106]	[1,1740,16,11,41,4,8,2,1]	6	98.8044	98.49	98.94	99.51
109	2535	[43,76,70,86,126]	[1,2492,2,38,2]	2	100	100	100	100
111	2133	[43,76,126,86]	[1,2123,8,1]	2	99.7479	99.65	99.81	99.88
112	2550	[43,78,126,65]	[1,2537,10,2]	2	99.8071	99.79	99.8125	100
113	1796	[43,78,97]	[1,1789,6]	2	100	99.54	100	100
114	1890	[43,78,86,74,70,124,126,65]	[3,1820,43,2,4,1,7,10]	5	99.7679	99.53	99.84	99.94
115	1962	[43,78,126,124]	[1,1953,2,6]	2	99.8169	99.46	99.842	99.91
116	2421	[43,78,86,65,126]	[1,2302,109,1,8]	3	99.8824	99.66	99.9452	100
117	1539	[43,78,126,65]	[1,1534,3,1]	1	100	100	100	100
118	2301	[43,82,86,65,120,126]	[1,2166,16,96,10,12]	5	98.4552	98.16	98.6314	99.45
119	2094	[43,78,86,126]	[103,1543,444,4]	4	99.564	97.28	99.64	100
121	1876	[43,78,126,65,86]	[1,1861,12,1,1]	2	100	100	100	100
122	2479	[43,78,124]	[1,2476,2]	1	100	100	100	100
123	1519	[43,78,86]	[1,1515,3]	1	100	100	100	100
124	1634	[43,82,74,86,70,65,126,106]	[13,1531,29,47,5,2,2,5]	6	95.2160	94.67	95.74	96.95
200	2792	[43,86,78,65,126,70]	[148,826,1743,30,43,2]	5	93.4412	92.44	94.11	95.84
201	2039	[43,78,97,106,86,120,65,74,126,70]	[35,1625,97,10,198,37,30,1,4,2]	8	91.4598	92.71	92.86	93.74
202	2146	[43,78,86,65,124,97,70]	[8,2061,19,36,2,19,1]	5	98.65	97.36	98.85	98.98
203	3107	[43,126,78,86,97,124,81,70]	[45,57,2529,444,2,25,4,1]	6	96.25	95.36	96.74	97.02
205	2672	[43,78,86,65,70,126,124]	[13,2571,71,3,11,2,1]	4	99.57	98.25	99.41	99.91
207	2385	[43,82,86,76,91,33,93,126,124,69,65]	[24,86,105,1457,6,472,6,15,2,105,107]	10	95.58	94.58	95.86	96.23
208	3040	[43,70,86,78,126,124,83,81]	[53,373,992,1586,24,8,2,2]	6	96.454	95.54	96.84	96.98
209	3052	[43,78,65,124,126,86]	[21,2621,383,7,19,1]	5	97.7	97.47	97.62	98.53
210	2685	[43,78,86,70,126,97,124,69]	[17,2423,194,10,17,22,1,1]	6	97.36	97.29	97.651	97.89
212	2763	[43,82,78,126,124]	[1,1825,923,13,1]	3	98.92	98.65	99.02	99.46
213	3294	[43,78,70,65,86,97]	[43,2641,362,25,220,3]	5	94.46	92.97	95.12	95.79
214	2297	[43,76,86,126,124,81,34,70]	[25,2003,256,4,5,2,1,1]	5	99.38	98.45	99.63	99.81
215	3400	[43,78,86,126,65,34,70]	[5,3195,164,30,3,2,1]	4	99.1882	99.14	99.32	99.55
217	2280	[43,47,102,86,78,126,124]	[67,1542,260,162,244,4,1]	6	86.578	85.66	88.15	88.87
219	2312	[43,78,86,70,34,65,120]	[21,2082,64,1,4,7,133]	6	97.7941	97.61	97.87	97.94
220	2069	[43,78,65,126]	[17,1954,94,4]	4	99.7576	98.54	99.82	99.91
221	2462	[43,78,86,126]	[23,2031,396,12]	4	98.8654	97.78	98.92	99.31
222	2634	[43,78,126,65,106,74]	[136,2062,15,208,212,1]	5	86.4762	85.33	87.12	88.05
223	2643	[43,78,86,65,101,70,126,97]	[28,2029,473,72,16,14,10,1]	7	95.0570	92.49	95.41	95.78
228	2141	[43,78,124,86,126,65,34]	[41,1688,24,362,20,3,3]	5	96.4757	95.53	96.83	96.98
230	2466	[43,78,126,124,86]	[207,2255,2,1,1]	2	100	99.85	100	100
231	2011	[43,82,34,78,120,65,86]	[11,1254,427,314,2,1,2]	4	97.7500	99	99.12	99.89
232	1816	[43,82,65,126,106]	[1,397,1382,35,1]	3	96.2707	94.89	96.54	96.74
233	3152	[43,86,78,65,70,124]	[71,831,2230,7,11,2]	5	98.2951	97.57	98.51	98.84
234	2764	[43,78,126,74,86]	[3,2700,8,50,3]	3	99.8278	99.72	99.88	99.97
Total # of Subjects		48	Average Accuracy (%)	98.27375				
Total # of Complexes		112,646						

results are shown in Table 2. According to this table, the ANFIS classifier yielded the average accuracy of Acc=98.27% given all data and all rhythms of the MITDB records. As it can be seen in this table, the overall performance quality associated with the ANFIS is superior rather than the each MLP classifier. In order to be able for comparing the obtained results of this study with the outcomes of the previous researches ([46,72-75]), utilizing exactly the same train and test databases is mandatory. To this end, records 100, 102, 104, 105, 106, 107, 109, 111, 114, 116, 118, 119, 124, 200, 207, 209, 212, 214 and 217 are selected from the MITDB records and the rhythms Normal, left bundle branch block (LBBB), right bundle branch block

Table 3 The name of selected MITDB records with their rhythm types contents for the aim of performance evaluation and comparison with other studies.

	Normal		LBBB		RBBB		PVC		APB		VE		PB	
record	train	test	train	test	train	test	train	test	train	test	train	test	train	test
100	146	158	0	0	0	0	0	0	18	15	0	0	0	0
102	0	0	0	0	0	0	0	0	0	0	0	0	100	100
104	0	0	0	0	0	0	0	0	0	0	0	0	100	100
105	165	179	0	0	0	0	12	12	0	0	0	0	0	0
106	100	107	0	0	0	0	150	150	0	0	0	0	0	0
107	0	0	0	0	0	0	0	0	0	0	0	0	100	100
109	0	0	185	201	0	0	11	11	0	0	0	0	0	0
111	0	0	158	171	0	0	0	0	0	0	0	0	0	0
114	119	129	0	0	0	0	12	12	5	5	0	0	0	0
116	150	163	0	0	0	0	31	31	0	0	0	0	0	0
118	0	0	0	0	193	212	5	5	53	43	0	0	0	0
119	101	109	0	0	0	0	127	127	0	0	0	0	0	0
124	0	0	0	0	136	150	13	13	0	0	0	0	0	0
200	114	123	0	0	0	0	236	236	16	14	0	0	0	0
207	0	0	108	117	8	8	30	30	58	49	55	50	0	0
209	171	185	0	0	0	0	0	0	208	174	0	0	0	0
212	60	65	0	0	163	180	0	0	0	0	0	0	0	0
214	0	0	149	161	0	0	73	73	0	0	0	0	0	0
217	0	0	0	0	0	0	0	0	0	0	0	0	100	100
Total	1126	1218	600	650	500	550	700	700	358	300	55	50	400	400

(RBBB), premature ventricular contraction (PVC), atrial premature beat (APB) , ventricular escape beat (VE) , paced beat (PB) and ventricular flutter wave (VF) are extracted according to the MITDB annotation files. In Table 3, the name of the MITDB records as well as the selected rhythm types and their corresponding beat numbers are presented.

3.3.1 Error Analysis

It should be noted that if some diversely designed classification algorithms show error rate diversity relative to each other for a given common database, then the utilization of them in a fusion classification structure is justified. In Fig. 7, the error rate diversity of structural classifiers including three MLP-BP and ANFIS classifier is demonstrated. In Table 4, the performance of the fusion classification algorithm has been described by the obtained confusion matrix. For instance, the fifth row of this table shows that 2, 3, 1, 4, 0, 1 and 0 beat numbers were falsely classified into the Normal, LBBB, RBBB, APB, VE, PB and VF categories, respectively. In this way the number of fusion classifier false negative (FN) detections for the PVC class equals to 11.

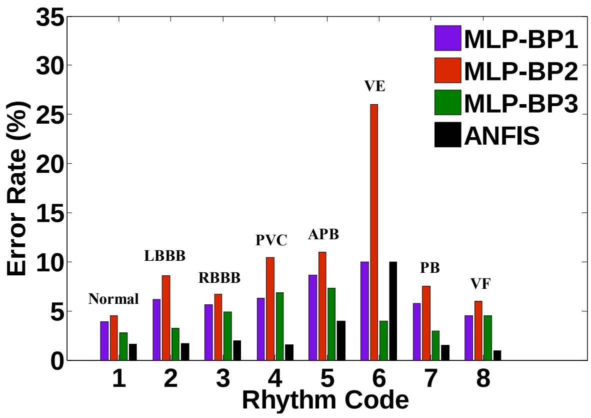

Fig. 7 Error-rate diversity analysis for justification of the fusion of Three MLP-BP and ANFIS classifiers.

Table 4 Performance evaluation of the presented classification algorithm for the selected MITDB records the confusion matrix.

	Normal	LBBB	RBBB	PVC	APB	VE	PB	VF
Normal	1198	10	2	2	2	1	3	0
LBBB	5	639	1	3	1	0	0	1
RBBB	2	4	539	1	3	0	1	0
PVC	2	3	1	689	4	0	1	0
APB	1	0	1	7	288	2	1	0
VE	0	1	1	0	3	45	0	0
PB	2	0	1	1	0	2	394	0
VF	0	0	0	2	0	0	0	198

On the other hand, for instance,the third column of this table illustrates that 10, 4, 3, 0, 1,0 and 0 beat numbers from the Normal, RBBB, PVC, APB, VE, PB and VF categories, respectively were falsely classified as LBBB class, i.e., the number of fusion classifier false positive (FP) detections for the LBBB class equals is 18.

3.4 Arrhythmia Classification Performance Comparison with Other Works

In the final step, in order to show the marginal performance improvement of the proposed arrhythmia hybrid classification algorithm, the method is assessed relative to other high-performance recent works. The result of comparison of the proposed method and other works is shown in Table 5.

4 Conclusion

In this study, a new supervised heart arrhythmia hybrid (fusion) classification algorithm based on a new QRS complex geometrical features extraction technique as well as an appropriate choice from each beat RR-tachogram was described. In the proposed method, first, the events of the ECG signal were detected and delineated using a robust wavelet-based algorithm. Then, each QRS region and also its corresponding DWT were supposed as virtual images and each of them was divided into eight polar sectors. Next, the curve length of each excerpted segment was calculated and is used as the element of the feature space.

Table 5 Performance evaluation of the presented fusion classification algorithm.
(a) Results obtained from several classification algorithms implemented in this study including three MLP and ANFIS classifiers.
(b) summary of previous studies.

(a)

Classifier	sensitivity								Total Accuracy (%)
	Normal	LBBB	RBBB	PVC	APB	VE	PB	VF	
MLP-BP1	96.06	93.85	94.37	93.72	91.34	90	94.25	95.5	94.45
MLP-BP2	95.49	91.39	93.28	89.58	89	74	92.5	94	92.45
MLP-BP3	97.2	96.77	95.1	93.143	92.67	96	97	95.5	95.7
ANFIS	98.36	98.31	98	98.43	96	90	98.51	99	98.08

(b)

Authors	Method	Signal	Dataset	Accuracy
Linh and Osowski [78]	Feature extraction: Hermite Coefficients Classification: anfis	ECG	7279 beats from MIT-BIH; 3611 training-3668 testing; [Normal: 2344, LBBB: 1250, RBBB: 1050, PVC:1400, APB:658,VE:105, VF: 472]	96
N.Kannathal and C.M. Lim [14]	Feature extraction: Largest Lyapunov exponent, Spectral entropy, Poincare geometry Classification: anfis	RR interval	600 dataset from MIT-BIH; 320 training-280testing; 10 classes	94
Osowski and Linh [73]	Feature extraction: cumulants of the second, third and fourth order Classification: fuzzy hybrid neural network	ECG	7185 beats from MIT-BIH; 4035 training—3150 testing [Normal: 2250, APB: 658, LBBB: 1200, PVC: 1500, RBBB: 1000, VF: 472, VE: 105]	96.06
Dokur and Olmez [67]	Feature extraction: discrete wavelet transform Classification: intersecting spheres network	ECG	3000 beats from MIT-BIH; Normal, LBBB, RBBB, P, p, a, VE, PVC, F, f: 300 from each category; 1500 training—1500 testing	95.7
S. N. Yu and Y. H. Chen[46]	Feature extraction: higher order statistics of subband components Classification: feedforward neural network	ECG	7185 beats from MIT-BIH; 4035 training—3150 testing [Normal: 2250, APB: 658, LBBB: 1200, PVC: 1500, RBBB: 1000, VF: 472, VE: 105]	97.53
Hu et al. [74]	Feature extraction: PCA in 29 points from QRS, instantaneous and average RR-interval, QRS complex width Classification: mixture of experts (SOM, LVQ)	ECG	25 min from each record in MIT-BIH 200 series excluding records 212, 217, 220, 222 and 232 [Normal: 43897, PVC: 5363]	95.52
Tsipouras et al. [30]	Feature extraction: RR-interval Classification: knowledge-based system	RRinterval signal	30000 beats from MIT-BIH [N, P, f, P, Q, LBBB, RBBB: 25188, PVC, F: 2950, APB, a, J, S: 1213, e, j, n, VE: 265, VF: 384]	95.85
This study	Feature extraction: Geometrical properties obtained from segmentation of each detected-delineated QRS complex virtual image as well as RR-tachogram Classification: A fusion structure consisting of three MLP and ANFIS classifiers	ECG	8079 beats from MIT-BIH; 4011 training—4068 testing [Normal: 2344, LBBB: 1250, RBBB: 1050, PVC:1400 , APB:658,VE:105 ,PB:800, VF: 472]	98.08

To increase the robustness of the proposed classification algorithm versus noise, artifacts and arrhythmic outliers, a fusion structure consisting of different classifiers namely three MLP-BP neural networks with different topologies and one ANFIS were designed. To show the merit of the new proposed algorithm, it was applied to all 48 MITDB records and the discrimination power of the classifier in isolation of different beat types of each record was assessed and as the result, the average value of Acc=98.27% was obtained as the accuracy. Also, the proposed method was applied to 8 number of arrhythmias namely as Normal, LBBB, RBBB, PVC, APB, VE, PB, VF belonging to 19 number of the MITDB and the average value of Acc=98. 08% was achieved showing marginal improvement in the area of the heart arrhythmia classification. To evaluate performance quality of the new proposed hybrid learning machine, the obtained results were compared with several similar studies.

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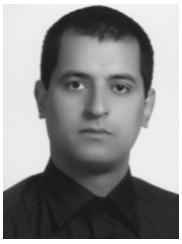

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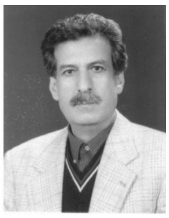

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