ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR CLASSIFICATION OF ECG SIGNALS

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ABSTRACT

This paper, presents an intelligent diagnosis system using hybrid approach of adaptive neuro-fuzzy inference system (ANFIS) model for classification of Electrocardiogram (ECG) signals. Feature extraction using Independent Component Analysis (ICA) and Power spectrum, together with the RR interval then serve as input feature vector, this feature were used as input of ANFIS classifiers. six types of ECG signals they are normal sinus rhythm (NSR), premature ventricular contraction (PVC), atrial premature contraction (APC), Ventricular Tachycardia(VT), Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT). The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy inference system. The results indicate a high level of efficient of tools used with an accuracy level of more than 97%.

Keywords: *ANFIS, adaptive neuro, fuzzy inference system, ECG, ICA, Power Spectral, RR-interval.*

1. INTRODUCTION

For several years, the automatic classification of ECG signals has received great attention from the biomedical engineering community. This is mainly due to the fact that ECG provides cardiologists with useful information about the rhythm and functioning of the heart. Therefore, its analysis represents an efficient way to detect and treat different kinds of cardiac diseases. A standard scalar ECG is shown in fig.1. It consists of P-wave, PR-interval, PR-segment, QRS complex, ST-segment, and T-wave. The QRS complex is a very important signal that is useful in the diagnosis of Arrhythmias diseases. In this paper, we use the QRS complex to achieve ECG beat classification[1]-[2]. In general, the normal ECG rhythm means that there is a regular rhythm and waveform. However, the ECG rhythm of the patient with arrhythmia will not be regular in certain QRS complex [3].

Several researchers have addressed the problem of automatic detection and classification of cardiac rhythms, such as: In [4] used the blind source separation techniques for feature extraction, The features were be classified by distance classifier, Bayes minimum error classifier, and K-Nearest neighbour classifier. In [5] used wavelet transform for ECG feature extraction, using Fuzzy classifier. In [6] used fuzzy hybrid neural network composed of two sub-networks connected the fuzzy self-organizing layer performing the pre-classification task and the

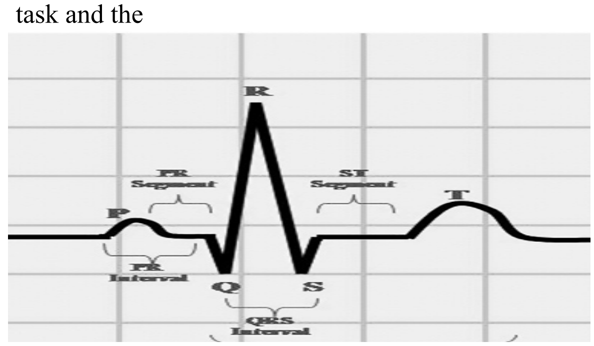

Figure 1. Standard scalar electrocardiogram

following multilayer perceptron (MLP) working as the final classifier. In [7] used largest Lyapunov exponent, spectral entropy and Poincare geometry for ECG feature extraction. adaptive neuro-fuzzy inference system (ANFIS) was presented for classification of the ECG signals. In [8] used wavelet transform for ECG feature extraction, There are two classifiers that used Analytical classifier and ANFIS classifier. In [9] used Lyapunov exponents for ECG feature extraction, adaptive neuro-fuzzy inference system (ANFIS) was presented for classification of the ECG signals. In [10] used three different techniques to extract features from ECG signal which are Fast Fourier Transform, Autoregressive Modeling, and Principal Component Analysis. The features were be classified by using three different classifiers which are ANN, and two types of statistical classifiers which are minimum distance classifier, Bayes minimum distance classifier.

This paper proposes a new method for the classification of the cardiac rhythms. Feature extraction using Independent Component Analysis (ICA) and Power spectrum, together with the RR interval then serve as input feature vector, this feature were used as input of ANFIS classifiers.

2. INDEPENDENT COMPONENT ANALYSIS (ICA)

Is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. What distinguishes ICA from other methods is that it looks for components that are both statistically independent, and nongaussian. and has been successfully applied to numerous signal processing problems in areas as biomedicine, communications, finance, and remote sensing[11]-[12].

In ICA , the observed data are typically expressed as a linear combination of independent latent variables such that:

$$v = A\,s \qquad (1)$$

where v = [v1, v2, . . . , vN] is the vector of observed random variables, s = [s1, s2, . . . , sN] is the vector of statistically independent variables called the independent components, and A is the unknown mixing matrix. If we denote the columns of matrix A by aj the model can be written as:

$$X = \sum_{i=1}^{n} a_i\, s_i \qquad (2)$$

In this model the only vector known is x and both A and s are estimated.

2.1 The Algorithm of ICA

There are several ICA algorithms in use. Such as Fast-ICA algorithm, it developed by [13] , also called a fast-fixed point algorithm.

2.2 Fast Fixed-Point Algorithm

The Fast-ICA algorithm[14] is a computationally highly efficient method for performing the estimation of ICA. It uses a fixed-point iteration scheme that has been found in independent experiments to be 10-100 times faster than conventional methods for ICA. Another advantage of the Fast-ICA algorithm is that it can be used to perform projection pursuit as well, thus providing a general-purpose data analysis method that can be used both in an exploratory fashion and for estimation of independent components (or sources).

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

ANFIS is one of hybrid neuro-fuzzy inference expert systems and it works in Takagi-Sugeno-type fuzzy inference system, which was developed by Jang[15]. ANFIS has a similar structure to a multilayer feed forward neural network but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights are associated with the links.

3.1 ANFIS Structure

ANFIS architecture consists of five layers of nodes. Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist of fixed nodes. The adaptive nodes are associated with their respective parameters, get duly updated with each subsequent iterations while the fixed nodes are devoid of any parameters[16]-[17]-[18].

Rule 1: If (x is A1) and (y is B1) then (f1 = p1x + q1y + r1)
Rule 2: If (x is A2) and (y is B2) then (f2 = p2x + q2y + r2)

where x and y are the inputs, Ai and Bi are the fuzzy sets, fi are the outputs within the fuzzy region specified by the fuzzy rule, pi, qi and ri are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Fig. 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

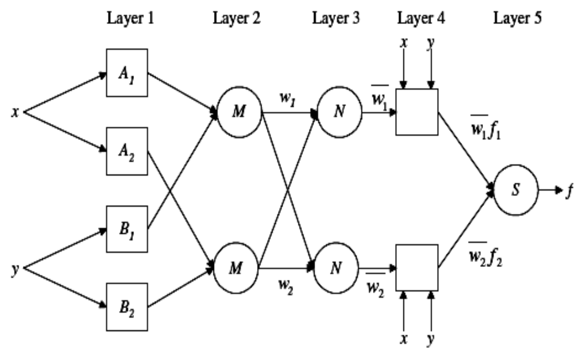

Figure 2. ANFIS architecture

Layer 1: fuzzification layer Every node I in the layer 1 is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{Ai}(x), \quad \text{For i=1,2} \qquad (3)$$

$$O_i^1 = \mu_{Bi-2}(y), \quad \text{For i=3,4} \qquad (4)$$

where x and y is the inputs to node i, where A is a linguistic label (small, large) and where μAi (x), μBi-2 (y) can adopt any fuzzy membership function. Usually we choose μAi (x) to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_{Ai}(x) = 1 / 1 + \{(x - c_i / a_i)^2\}^{b} \qquad (5)$$

where (ai, bi and ci) are the parameters of the membership function. Parameters are referred to as premise parameters.

Layer 2: rule layer a fixed node labeled M whose output is the
product of all the incoming signals, The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{Ai}(x)\, \mu_{Bi}(y) \quad i=1,2 \qquad (6)$$

Layer 3: normalization layer are also fixed node is a circle node labeled N.

$$O_i^3 = \bar{w}_i = w_i / (w_1 + w_2) \quad i=1,2 \qquad (7)$$

Layer 4: defuzzification layer an adaptive node with a node The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial.

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad i=1,2 \qquad (8)$$

Layer5: summation neuron a fixed node which computes the overall output as the summation of all incoming signals.

$$O_i^5 = \sum^{2} \bar{w}_i f_i = \sum_{i=1}^{2} w_i f_i / (w_1 + w_2) \qquad (9)$$

3.2 Hybrid Learning of an ANFIS

ANFIS using a strategy of hybrid training algorithm to tune all parameters. It takes a given input/output data set and constructs a fuzzy inference system whose membership function parameters are tuned, or adjusted, using either a backpropagation algorithm in combination with a least squares type of method.

4. DATA DESCRIPTION

The ECG signals are obtained from the MIT-BIH arrhythmia database for recognition. all samples at a sampling frequency of 360 Hz.

5. PROPOSED METHODS

The block diagram of the proposed method for ECG beat classification is depicted in Fig. 3. The method is divided into three steps: (1) preprocessing (2) calculation of feature vector and (3) classification by ANFIS.

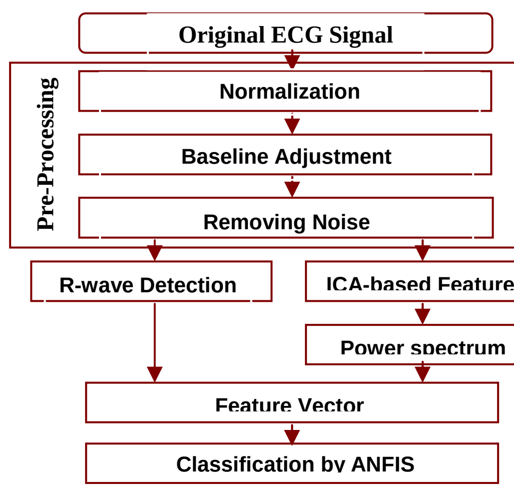

Figure 3. Block diagram of the proposed scheme for ECG beat classification.

5.1 Pre-processing

Each sample is pre processed by normalization process which necessary to standardize all the features to the same level[19]. After that the signal baseline may be shifted from zero line due to unexpected conditions such as patient movements, so that the baseline of the ECG signal was adjusted at zero line by subtracting the median of the ECG signal[20]. ECG signals can be contaminated with several types of noise, so we want to filtering the signal. the unwanted noise of the signal must be removing. ECG were filtered using Low pass filter ,High pass filter and Notch filter[21].

5.2 Calculation of feature vector

There are several algorithms for performing ICA. In this paper, a fast fixed-point algorithm was used to estimate the independent components is show in Fig. 4. [13]-[14]. The ICA features are then built into the Power Spectral to extract important feature, together with the RR interval then serve as input feature vector. There are five power spectrum features were extracted from the ECG signal at (4, 8, 12, 16 and 20 Hz) is show in Fig. 5. the term power spectrum means the amount of power per unit (density) of frequency (spectral) as a function of the frequency [22].

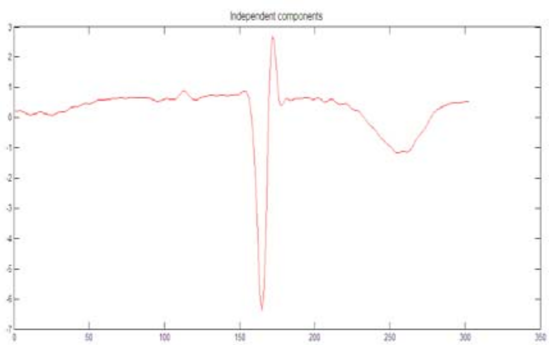

Figure 4. independent components

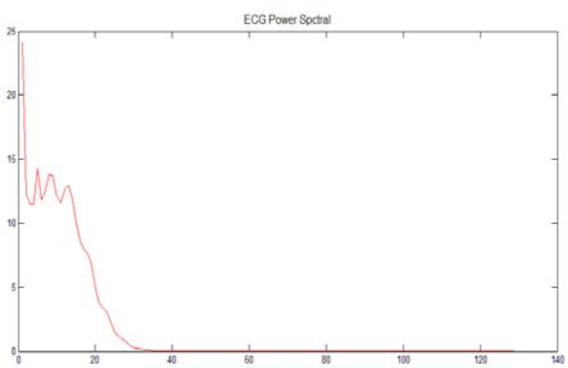

Figure 5. power spectrum features were extracted from the ECG signal.

The RR interval between successive QRS peaks is considered as another important feature for recognizing many ECG arrhythmias. The RR interval is calculated as the time difference between the R points of the present and previous beat. There are several algorithms to Detect R-wave, we used Pan-Tompkins algorithm [23] .

5.3 Classification using ANFIS

An ANFIS based classifier is presented as a diagnostic tool to aid physicians in the classification of heart diseases. ANFIS using a strategy of hybrid approach of adaptive neuro-fuzzy inference system, we compose these two intelligent approaches, it will be achieve good reasoning in quality and quantity. In other words we have fuzzy reasoning and network calculation. The objective of classification is to classifier six types of ECG signals, the feature vectors were applied as the input to an ANFIS classifier. the ANFIS network has a total of 128 fuzzy rules and one output, The classification by ANFIS was performed using MATLAB.

6. RESULTS AND DISCUSSION

We get our bet classifier on the MIT-BIH arrhythmia database. A total of 420 datasets for six classes, out of which 280 datasets were used for training, and 140 datasets used for testing. And we do not intend to detect the R-waves but use the information of R-waves provided in the MIT-BIH database which were manually verified by specialists. The six types of ECG signals they are normal sinus rhythm(NSR), premature ventricular contraction (PVC), atrial premature contraction (APC), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT).

Training results of the ANFIS is show in Table1

Classes	Training Set	NSR	PVC	APC	VF	VT	SV
NSR	50	50	0	0	0	0	0
PVC	50	0	50	0	0	0	0
APC	50	0	0	50	0	0	0
VF	50	0	0	0	50	0	0
VT	50	0	0	0	0	50	0
SV	30	0	0	0	0	0	30

Table1 show Training results of the ANFIS

Testing results of the ANFIS is show in Table2

Two Ventricular Fibrillation was classified incorrectly as Ventricular Tachycardia. One Ventricular Tachycardia was classified incorrectly as Ventricular Fibrillation, and one Supraventricular Tachycardia was classified incorrectly as Ventricular Tachycardia.

Table2 show Testing results of the ANFIS

Classes	Testing Set	NSR	PVC	APC	VF	VT	SV
NSR	25	25	0	0	0	0	0
PVC	25	0	25	0	0	0	0
APC	25	0	0	25	0	0	0
VF	25	0	0	0	23	2	0
VT	25	0	0	0	1	24	0
SV	15	0	0	0	0	1	14

After training association rules in the form of IF then rules are generated and extracted. an example of initial and final (after rule extraction) decision surfaces are given in Fig. 6.

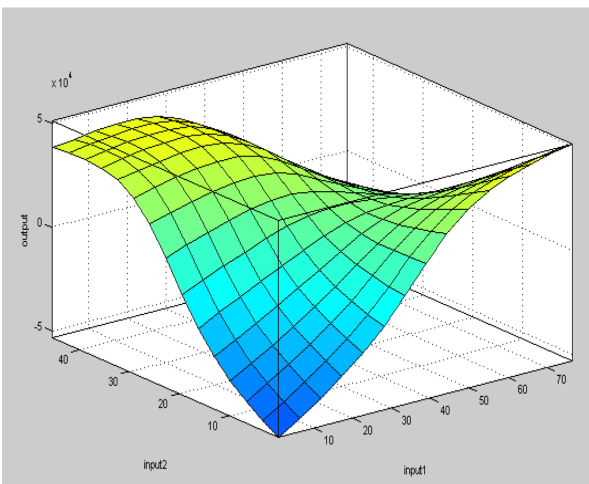

Figure 6.Final decision surface for input 1 and input 2

Table3 summarizes the comparative results of these methods, in which the first row of the table is the result of the method ICA, Power Spectral and ANFIS proposed in this paper. Among the seven methods, the proposed method outperforms the other methods with an impressive accuracy of 97.1 % to discriminate six ECG beat types. Although this comparison may not be completely fair because of the different numbers and types of ECG beats tested, the propose scheme reveals to be a powerful tool in the computer-aided diagnosis of heart diseases based on ECG.

Reference	Method	Number of beat types	Accuracy (%)
Proposed method	ANFIS-ICA	6	97.1 %
[9]	ANFIS	4	96.39%
[6]	FNN	6	96%
[7]	ANFIS	8	94%
[8]	ANFIS-DWT	8	94%
[5]	Fuzzy-DWT	8	93.13%
[10]	FFT-PCA-AR	3	92.7
[4]	BSS-Fourier	5	85.04%a

Table3 Comparative results of different methods
a Calculated from the results in the paper.

7. CONCLUSION

We propose a method that uses combine independent component analysis (ICA), Power spectrum to extract important feature, together with the RR interval and ANFIS classifiers for ECG beat classification. six types of ECG samples were selected from the MIT-BIH arrhythmia database for experiments. ANFIS classifier demonstrated high classification accuracies of over 97%.

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