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PATIENT FACING SYSTEMS

A Wavelet Transform Based Feature Extraction and Classification of Cardiac Disorder

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Abstract This paper approaches an intellectual diagnosis system using hybrid approach of Adaptive Neuro-Fuzzy Inference System (ANFIS) model for classification of Electrocardiogram (ECG) signals. This method is based on using Symlet Wavelet Transform for analyzing the ECG signals and extracting the parameters related to dangerous cardiac arrhythmias. In these particular parameters were used as input of ANFIS classifier, five most important types of ECG signals they are Normal Sinus Rhythm (NSR), Atrial Fibrillation (AF), Pre-Ventricular Contraction (PVC), Ventricular Fibrillation (VF), and Ventricular Flutter (VFLU) Myocardial Ischemia. The inclusion of ANFIS in the complex investigating algorithms yields very interesting recognition and classification capabilities across a broad spectrum of biomedical engineering. The performance of the ANFIS model was evaluated in terms of training performance and classification accuracies. The results give importance to that the proposed ANFIS model illustrates potential advantage in classifying the ECG signals. The classification accuracy of 98.24 % is achieved.

Keywords ECG · Symlet wavelet transform · Five cardiac arrhythmias · Myocardial ischemia · ANFIS

Introduction

CardioVascular Disease (CVD), including heart disease and stroke, accounts for approximately 17 million deaths each year across the globe. According to World Health Organization (WHO) calculate approximately, in 2003, 16.7 million people around the globe die of CVD every year. By 2020 heart disease and stroke will become the leading cause of both death and disability in global, with the number of sufferers projected to increase to more than 20 million a year and to more than 24 million a year by 2030 (Atlas of Heart Disease and Stroke, WHO 2004). The major percentage increase will occur in the Eastern Mediterranean Region. The prevalent increase in number of deaths will occur in the South-East Asia Region. According to the most recent figures published by the Australian Bureau of Statistics and the Department of Health, cardiovascular or heart disease remains the leading cause of death in Australia, accounting for around 38 % of all deaths in 2002 (Cardiovascular Health 2002, Australian Institute of Health and Welfare 2004) and 34 % of all deaths in 2006. It is the leading cause of death in the USA with almost 2,000 Americans dying each day i.e. 1 death every 43 s.

Heart attacks occur when the blood flow is blocked owing to the presence of a blood clot in the coronary artery while strokes are due to the result of blocked or burst of blood vessels in the brain. Heart defects and a range of other malfunctions, occur due to improper pumping of blood. These cause long term problems and even death. The ECG can be employed to detect heart disease, heart attack, abnormal heart rhythms and an enlarged heart condition that may cause heart failure throughout the day. Physicians first locate fiducial points such as Q, R, S in the ECG from which they locate P waves, QRS complex, T waves and U waves. Recognition of the fiducial points and calculations of the many useful parameters such as the heart rate variations, arterial/ventricular arrhythmias and ST-segment deviations, are the most general information used to evaluate the symptomatic patients. The patients who have had myocardial infraction offer a tedious routine for the physicians; approximately 100,000 cardiac cycles are recorded per patient in a day with an ECG device. The physicians have to interpret this

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large amount of ECG data to search for only a few abnormal cardiac beats in the ECG. Physicians may overlook some abnormal cycles because they have to interpret such a large amount of data. Therefore, there is an urgent need for an automatic ECG interpreting system to help to reduce the burden of ECG interpretation.

The interpretation of the ECG signal is an application of pattern recognition. The purpose of pattern recognition is to automatically categorize a system into one of a number of different classes has been pointed out by Saxena [1], Bhyri [2]. An experienced cardiologist can easily diagnose various heart diseases just by looking at the ECG waveforms printout. The use of computerized analysis of easily obtainable ECG waveforms can considerably reduce the doctor's workload. Some analyzers assist doctor by producing a diagnosis; others provide a limited number of parameters by which the doctor can make his diagnosis by soroor Behbahani [3]. xdAfter the analysis, the ECG is either interpreted as "Normal" or "Abnormal". The recognition and analyzing of ECG signal is difficult because the size and form may change eventually and there can be considerable amount of noise in the signal. Hence, the processing of ECG is very important step in the examination of ECG by physicians.

In this paper, a new approach based on Adaptive Neuro Fuzzy Inference Systems (ANFIS) is being attempted and presented for classification of the various cardiac disorders and data analysis of the ECG and by using Wavelet Transform (WT) techniques. This approach is to be a very effective for the pattern recognition.

ECG signal

The ElectroCardioGraph (ECG) is the graphical representation of the electrical voltages generated during the cardiac cardiac action. Since it reflects the rhythmic electrical depolarization and repolarization of the atria and ventricles, its shape, time interval and amplitude give much more information about the current state of the heart. Every One cardiac cycle of ECG shown in Fig. 1. consists of P wave, QRS complex, T wave, small U wave. This is frequently visible in 50 to 75 % of ECG. These signals are an essential tool for the diagnosis of cardiac abnormalities. A better performance of an automatic ECG analyzing system highly depends upon the accurate and reliable detection of the QRS complex. The QRS complex is the most critical step in automatic electrocardiogram analysis such as arrhythmia detection and classification of ECG diagnosis and heart rate variability studies. The QRS detection affords the fundamentals for almost all automated ECG analysis algorithm. Perfect detection of QRS is an important issue in many clinical conditions. The feature extraction of the ECG signal, consisting of various characteristic points, can detect the cardiac abnormalities. Consequently, the ECG signal was decomposed into time frequency

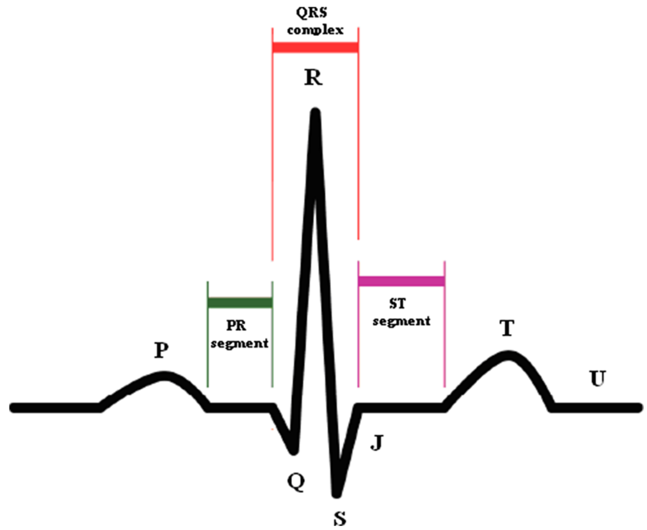


Fig. 1 Typical Normal ECG Waveform

representations using discrete wavelet transform. A several number of techniques have been devised by the researchers to detect QRS complex. The QRS complexes originally developed by Pan and Tompkins [4] in assembly language for implementation on a Z80 microprocessor, but it takes less time and are implemented easily. The major drawback of this algorithm is that frequency variation in QRS complexes adversely affects their performance characteristics. Therefore a real time QRS detection algorithm in the C language was developed by Hamilton and Tompkins [5]. The researchers Cuiwei Li et al. use the wavelet transform. It is easily to characterize the ECG waves and the QRS complex [6]. Several automated ECG classifier systems employing different techniques for feature extraction from ECG signals and for classification of ECG patterns have been proposed by several researchers. Various solutions to ECG classification problem based on support vector machine [7], linear discriminant analysis [8], artificial neural network [9, 10], filter banks [11], self organizing maps [12], and wavelet transform [13, 14], have been presented in the literature. Fuzzy set plays an important role in dealing with uncertainty when making decisions in medical applications. Hence, fuzzy sets have attracted the attention and interest in modern information technology [15–18]. In this work, a new approach based on ANFIS is presented for classification of the ECG signals.

Wavelet transform

The ECG signals are considered as representative signals of cardiac physiology, which are helpful in diagnosing cardiac disorders. The absolute way to display this information is to perform spectral analysis. The Wavelet Transform (WT) gives very general techniques, which can be implemented to many tasks in signal processing. The ECG signal, consisting of many characteristic points, can be compressed into a few points. These points characterize the behaviour of the ECG signal. This feature of using a lesser number of parameters to represent the ECG signal is particularly important for recognition and diagnostic functions. The WT can be thought of as an extension of the classic Fourier transform, but instead of working on a single scale (time or frequency), it works on a multiple-scale basis. This multiple-scale feature of the WT allows the decomposition of a signal into a number of scales, every scale representing a particular coarseness of the signal. The procedure of multiresolution decomposition of a signal $x[n]$ is schematically shown in Fig. 2. Every stage of this scheme consists of two digital filters and two down samplers by 2. The initial filter, the discrete mother wavelet is g[n], high pass in nature, and the second, h[n] is its reflect version, low-pass in nature. The down sampled outputs of first high pass and low-pass filters give the detail, $d1$ and the approximation, $a1$, respectively. The first approximation, $a1$ is more decomposed and this process is continued as shown in Fig. 2 [19, 20].

Adaptive neuro fuzzy model

Adaptive Neuro Fuzzy Inference Systems (ANFIS) is one of hybrid Neuro-Fuzzy inference expert systems. Both Neural Network (NN) and Fuzzy Logic (FL) are universal estimators. They can estimate any function to any prescribed accuracy, provided that enough hidden neurons and fuzzy rules are presented. The ANFIS is a FIS implemented in the framework of an adaptive fuzzy neural network shown in Fig. 3. It combines the clear representation of a Fuzzy Inference System (FIS) with the learning power of Artificial Neural Networks (ANN) [10, 21, 22]. The advantage of a fuzzy set is the depiction of prior knowledge into a set of constraints to reduce the optimization research space is consumed. The adaptation of back propagation to structured network to automate fuzzy control parametric tuning is utilized from neural network. For specific parameters that define membership functions, ANFIS uses the gradient descent algorithm to fine-tune them. For succeeding parameters that define the coefficients of every equation, ANFIS uses the least-squares method to recognize them. This approach is thus called hybrid learning method since it combines gradient descent algorithm and least-squares method. There are no constrains on the node

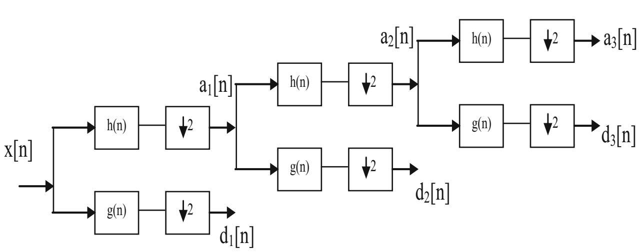


Fig. 2 Three level wavelet decomposition tree

functions of an adaptive network except for the requirement of piecewise differentiability. Hybrid systems are increasing research area in medical applications. This system overcomes some of the main drawbacks of conventional expert systems such as the consultation with human experts for knowledge acquisition. A Neuro Fuzzy contains three major components, which are fuzzification stage, rule base and the defuzzification stage. In the first layer is the direct input layer. Every node represents one ECG feature and sends these input variables from the features extraction to next layer directly. Next, the second layer is the fuzzification layer. In this particular layer, each extracted ECG feature is fed to fuzzy nodes. The third layer is the fuzzy rules stage. Every node in this layer represents one fuzzy represents one fuzzy if-then rule. The last layer is the neural network linking layer.

ECG database

PhysioBank database is a large and growing archive of well-characterized digital recordings of physiological signals and related data for use by the biomedical research community. The databases of MIT-BIH Arrhythmia Database, MIT-BIH Atrial Arrythmia Database and Malignant Ventricular Arrhythmia Database were used for the analysis. The VT episodes are taken from the MIT-BIH Arrhythmia Database and VF and VFL episodes from the MIT-BIH Malignant Ventricular ArrhythmiaDatabase. The data pertaining to heart rhythms of eight patients experiencing spontaneous arrhythmia are recorded [23].

Material and methods

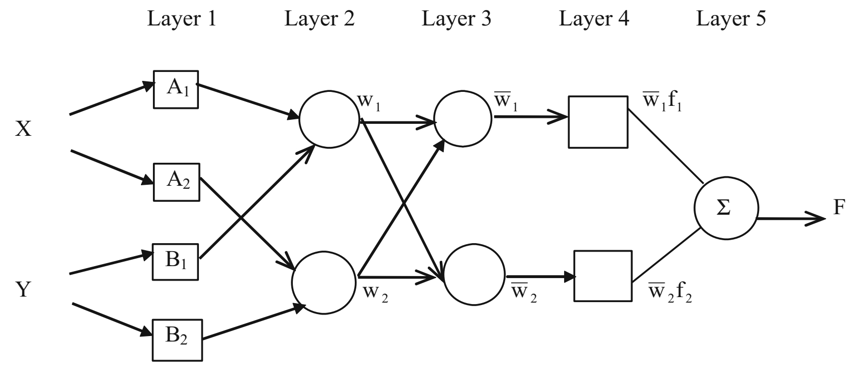
The block diagram of the proposed method for ECG beat classification shown in Fig. 4. This method is separated into three steps: (1) preprocessing (2) ECG Preprocessing and (3) classification by ANFIS.

Pre-processing

Clinical ECG recordings undergo several stages of filtering in an attempt to decrease the noise. Each noise source resides in a characteristic frequency band. Poor conductance between skin and electrode creates slowly varying potentials which manifests as baseline wander in the ECG. The output function of this WT will be our filtered signal. Ψ (t) given in the Eq. (1). The parameters of this filtering are the attenuation factor β, and the basic frequency f.

$$\Psi\,(t) = \exp\left(\frac{t^2}{\beta^2}\right)\cos\left(2\Pi ft\right) - \lambda \tag{1}$$

Fig. 3 ANFIS architecture for a two rule sugeno system



β - Attenuation factor, f - base frequency, Ψ (t) - WaveletTransform, λ - DC factor eliminator

Our goal is to find those parameter values and contribute the most to a good QRS detection ratio. The value of these parameters will be chosen so that it assures all the significant parts of the sum defined in Eq. (1), but it eliminates all additional calculations for the attenuated part of the signal, that hardly influences the result. Elimination of this low and high frequency components from the signal using the filters is the concrete effect of the wavelet filtering shown in Figs. 5 and 6.

The scale towards the right comprises of various colours depicting the range of energy available in the particular sector of waveform after the elimination of baseline shown in Fig. 7. The Sensitivity presents the percentage of the beats that were correctly detected by the algorithm.

$$\text{Sensitivity}\ (\%) \ = \frac{TP}{TP+FN} \tag{2}$$

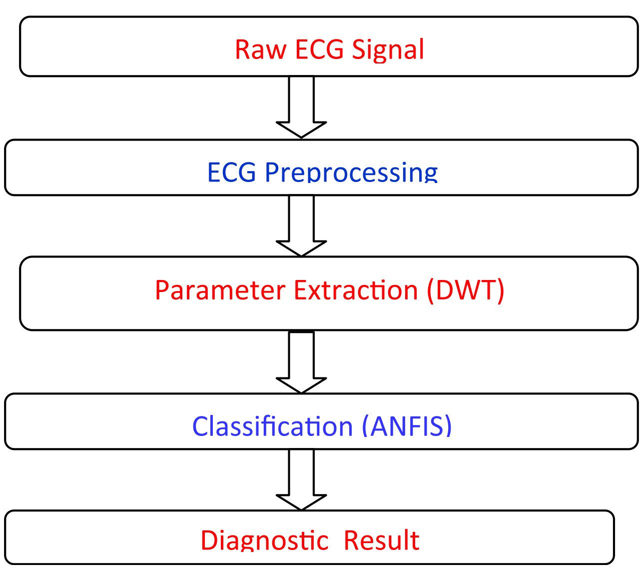


Fig. 4 Proposed method for ECG beat classification

Where TP is True Positive (Correctly detected)

FN is False Negative (No. of missed detection)

The Positive Predictivity reports the percentage of beat detections which were true beats.

$$\text{Positive Predictivity}(\%) \ = \frac{TP}{TP+FP} \tag{3}$$

FP is False Positive (No. of extra detection) in QRS complex

Table 1 shows the results of the Symlet Spline Wavelet based QRS detection algorithm for the MIT-BIH Database. The average sensitivity of this QRS detection algorithm is 99.56 % and its Positive Predictivity is 99.52 %.

The FN and FP values tend to dropdown abruptly to lower value for records corresponding to (104, 203 and 207). The ECG waveforms in the above records are characterized by high complexity which leads to internal difficulties in detecting the QRS complex.

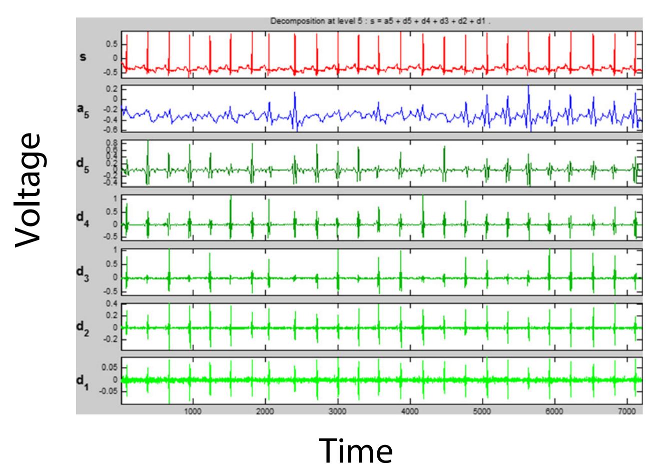


Fig. 5 Decomposition of symlet Wavelet – Original Signal

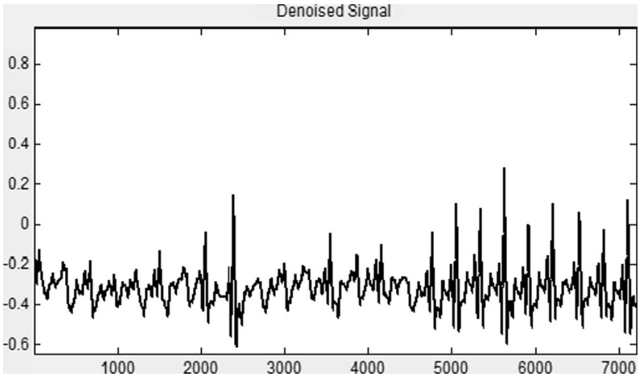


Fig. 6 Denoised Signal

Classification of life- Threatening arrhythmia using ANFIS

Generalized BELL membership function

The classification of cardiac arrhythmia using ANFIS utilizes the GBELLMF. GBELLMF (x, parameters) returns a matrix, which is the universal bell membership function calculated at x. Parameters are a 3-element vector that determines the shape and position of this Membership Function. The specified Generalized BELL membership function is shown in Fig. 8. It depends on three parameters a, b, and c as given by the Eq. (4)

$$f(x,a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{4}$$

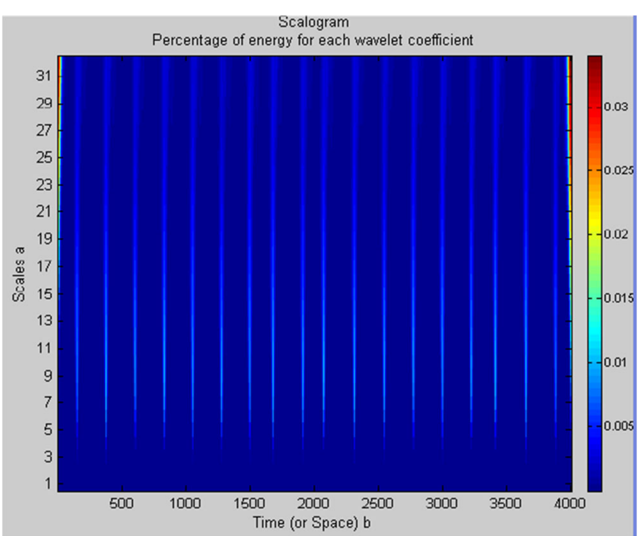


Fig. 7 Scalogram from a clinical ECG recording using Symlet Wavelet

Table 1 Results of the symlet wavelet based qrs detection algorithm for the mit-bih database

Record	TP	FN	FP	Sensitivity (%)	Positive Predictivity (%)
100	2,261	11	0	99.51	100
101	1,856	7	4	99.62	99.78
102	2,185	1	0	99.95	100
103	2,079	3	0	99.85	100
104	2,215	15	43	99.32	98.92
105	2,543	11	4	99.56	99.84
109	2,526	4	3	99.84	99.88
111	2,126	1	0	99.95	100.00
113	1,794	0	1	100.00	99.94
114	1,878	1	3	99.95	99.84
115	1,941	5	1	99.74	99.94
116	2,403	14	6	99.42	99.75
117	1,538	0	1	100.00	99.93
118	2,269	8	1	99.64	99.95
119	1,986	5	0	99.74	100.00
121	1,863	4	1	99.78	99.94
122	2,476	0	1	100.00	99.95
123	1,518	1	0	99.93	100.00
200	2,598	4	3	99.84	99.84
201	1,963	18	6	99.09	99.69
202	2,095	7	1	99.66	99.95
203	2,963	14	75	99.52	98.62
205	2,256	17	1	99.36	99.96
207	2,950	86	121	96.31	94.89
Total	52,282	237	277	99.56	99.52

Hybrid learning algorithm

ANFIS employs an efficient hybrid learning method that combines gradient decent and the least-square method. Each epoch of hybrid learning algorithm include a forward pass and a backward pass. In the forward pass, this premise parameters are fixed, functional signals go forward till layer 4 and the

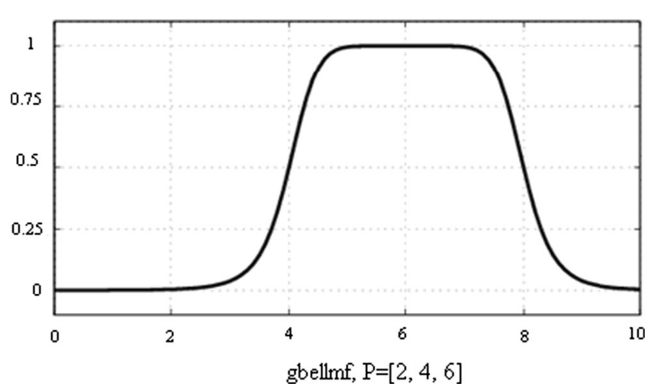


Fig. 8 Generalized BELL membership function

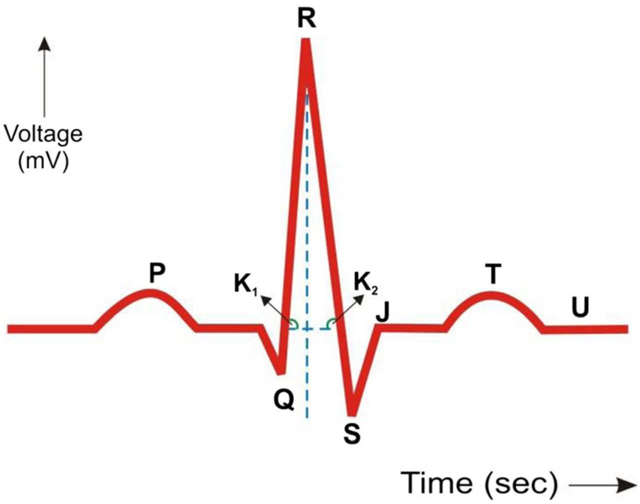


Fig. 9 Detection of QRS complex slope

consequent parameters are identified by the least square estimate, then the signals go forward to layer 5. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent which is used in Backpropogation Algorithm. Hybrid learning rule can grant us the overall optimization of the consequence parameters for the given premise parameters. In this way, we can, not only reduce the number of dimensions used in the gradient descent algorithm, but also accelerate the rate of convergence of the parameters.

Input seletion

In order to diagnose heart disease successfully, it is important to select the appropriate inputs of an ANFIS model of ECG. They must contain the useful information of ECG and have a close relationship with the characteristic points of ECG. In this thesis, we extracted the feature points of the ECG such as point R, point S, point P and point T of the wave using Wavelet Transform. And then we fitted the data between the QRS complex beginning and midpoint, the midpoint and the endpoint by a straight line, whose slope values are recorded as K_1 and K_2 respectively as shown in Fig. 9.

The extracted results of four different shapes of QRS segment are:

- Ventricular Tachycardia
- Ventricular Fibrillation
- Ventricular Flutter

At the opinions of physicians, five variables were selected as input feature sets: Point Q, Point R, Point S, K_1 and K_2.

Training system

The whole process is to identity the shapes of P wave and QRS complex. First, we train five SUB-ANFIS models as

Fig. 10 Architecture of the Training System

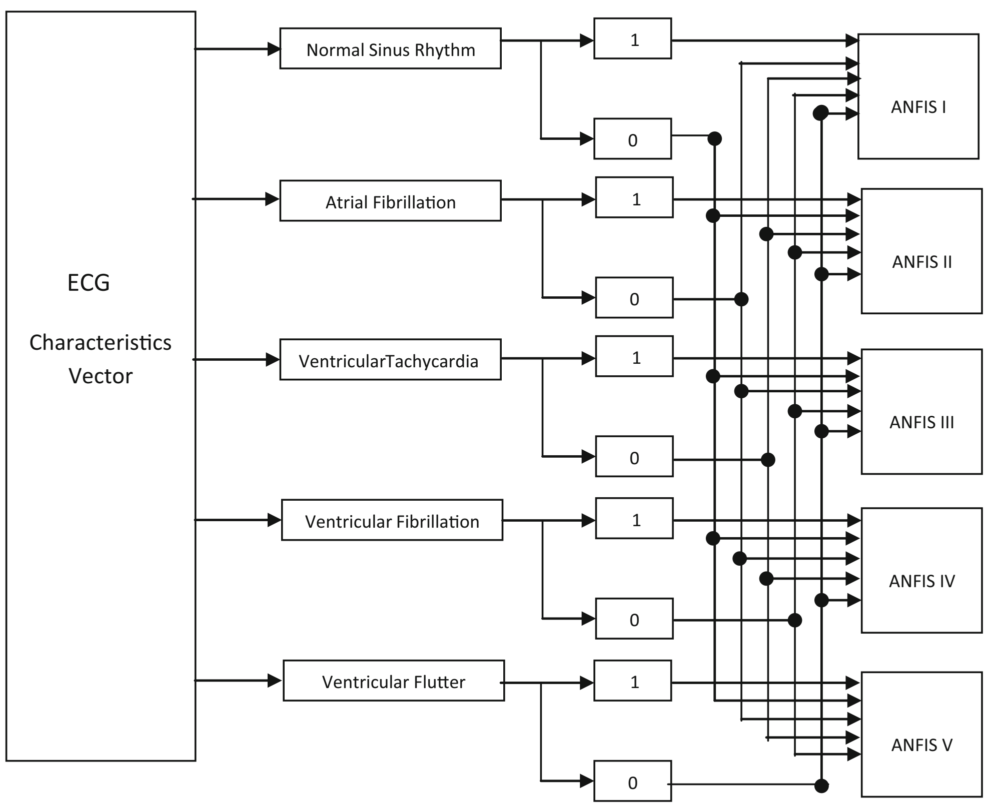


Table 2 Relationship between sub-anfis and the shape of ECG segment

SUB-ANFIS	ANFIS 1	ANFIS 2	ANFIS 3	ANFIS 4	ANFIS 5
The shape of the ECG Segment	NSR	AF	VF	VT	VFLU

shown in Fig. 10. The Relationship between SUB-ANFIS and the shape of ECG segments showed in Table 2.

We collected data type of the shapes of P wave and QRS complex and divide them into two subsets. One is called as training data and the other as test data. The data is further subdivided as output=1 and output=0. This forms the training data. In the system, the five SUB-ANFIS models are trained at the same time. The processing of training is terminated when it reaches the designated value or when the error of training reach the predictive error. During the training process, if the error diminishes four times, then we should increase the step length. If the error vibrates twice consecutively, then we should shorten the step length. After the training, the error in each pattern should be less than the order of magnitude of 10^{-5}.

The recognizing strategy

After training, we obtained five SUB-ANFIS models. They are corresponding to the P wave and three shapes of QRS, as shown in Table 2. The test samples are inputted into these models to calculate the errors, $e_i = \left|1-\hat{y}_i\right|$ (i denote the type of SUB-ANFIS models), where $\hat{y}_i$ is the output of the i^{th} SUB-ANFIS model. Then let e_k=min$\{e_1,e_2,e_3,e_4,e_5\}$ where k is related with one of five SUB-ANFIS models, the shapes of the P wave, QRS complex are corresponding to the model. The Structure of the Diagnostic system is shown in Fig. 11.

Results and discussions

The classification of the arrhythmia is carried out using a ANFIS whose input is the energy level calculated by the wavelet transform. To achieve clustering of the ECG waveforms into five different classes, the no of output layer should be five in Table 3. The output target vector was arranged as the desired output vector for each class. It is a set of Boolean value vectors. In addition to each record in the MIT-BIH Database there is an annotation file in which each heartbeat has been identified by expert cardiologist. This annotated information can be used for designing the target vector and evaluating the classifier performance.

The data used for training and testing in this research is obtained from the MIT-BIH Database and was extracted by the feature extraction method. ECG signal classifier becomes, more critical as the number of signal abnormalities increase. To overcome this, a feature vector containing the following features was employed as the input vector for the classifier. A total of eight features were extracted. The extracted features are obtained by applying existing feature extraction algorithms to the selected signals from the MIT-BIH Database.

This research focuses on the ECG classification, through which determination of a suitable ANFIS for the classification. The five ANFIS classifiers were trained with the back propagation gradient descent method in combination with the least squares method when five features (dimension of the extracted feature vectors) representing the ECG signals were

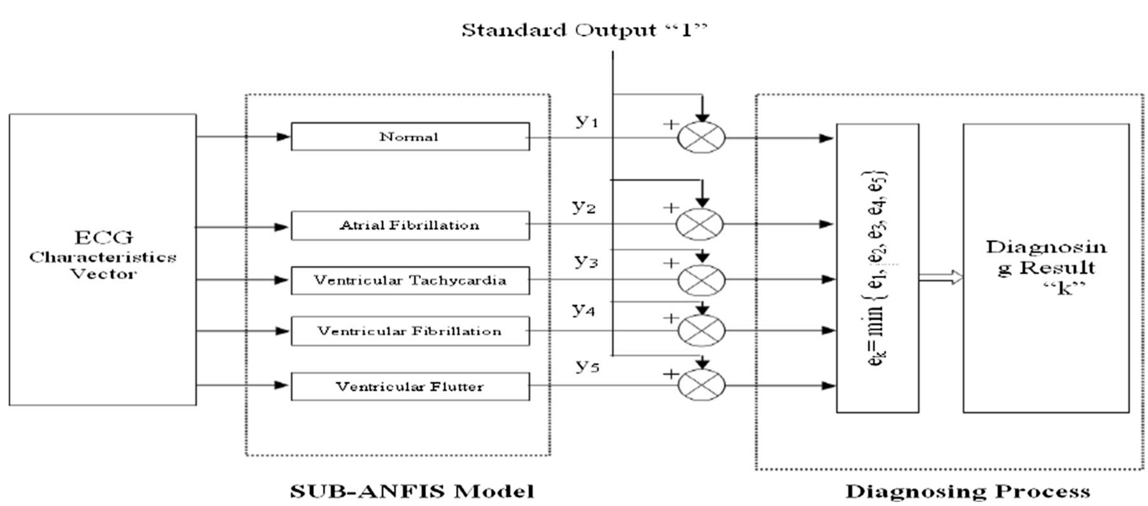


Fig. 11 Structure of the Diagnostic System

Table 3 The 5 output target vector

Signal	Vector	Heart Condition
NSR	[1 0 0 0 0]	Normal Sinus Rhythm
AF	[0 1 0 0 0]	Arial Fibrillation
VT	[0 0 1 0 0]	Ventricular Tachycardia
VF	[0 0 0 1 0]	Ventricular Fibrillation
VFL	[0 0 0 0 1]	Ventricular Flutter

used as inputs. To improve the classification accuracy, the sixth ANFIS classifier (combining ANFIS) was trained using the outputs of the five ANFIS classifiers as input data. The ECG signals were divided into two separate data sets—the training data set and the testing data set. The adequate functioning of the ANFIS depends on the sizes of the training set and the test set.

In this study, 70 % of data set was to be training and 30 % of data set was to be testing. The highest accuracy was obtained by dividing the data for training and testing. The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the four classes of ECG signals.

Each ANFIS used 430 training data in 840 training epochs and the step size for parameter adaptation had an initial value of 7.5038×10^{-5}. The step size is decreased (by multiplying it with the component of the training option corresponding to the step size decrease rate) if the error measure undergoes two consecutive combinations of an increase followed by a decrease shown in Fig. 12. The step size is increased (by multiplying it with the increase rate) if the error measure undergoes four consecutive dips. At the end of 850 training epochs, the network error (mean square error) convergence curve of each ANFIS was derived as shown in Fig. 13. From the curve, the final convergence value is 2.3509×10^{-4}. Feature saliency provides a means for choosing the features, which are best for classification. Therefore, in this study changes of the final (after training) membershipfunctions with

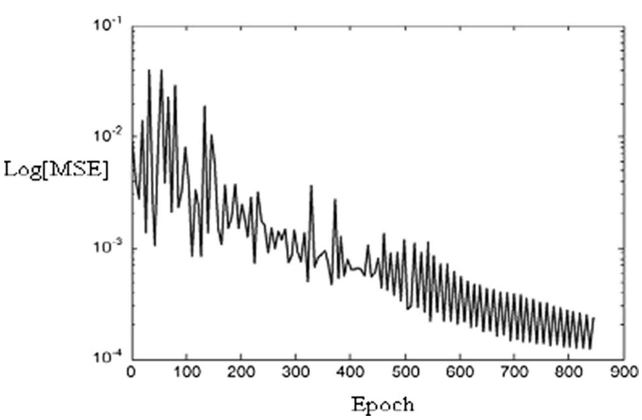


Fig. 12 Adaptation of parameter steps of each ANFIS

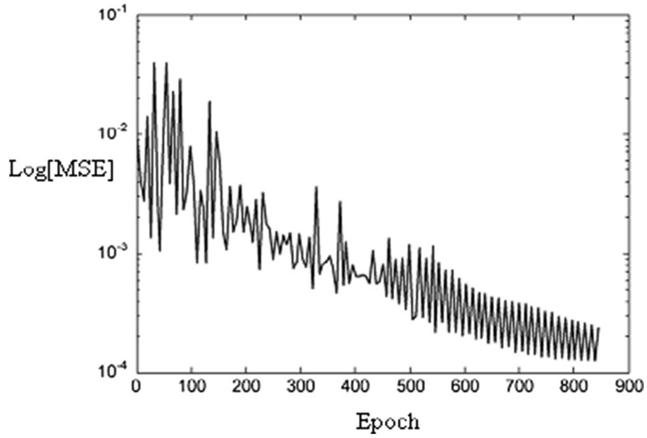


Fig. 13 The curve of network error convergence

respect to the initial (before training) membership functions of the input parameters were examined. Membership function of each input parameter was divided into three regions, namely, small, medium, and large. After training, 185 testing data were used to validate the accuracy of the ANFIS model for classification of the ECG signals.

Higher accuracy was obtained by dividing the data into two equal parts for training and testing Data. The test performance of the classifiers can be determined by the computation of total classification accuracy of each type of beat using the following Eq. (5).

$$\text{Classification Accuracy} = \frac{\text{Number of beats correctly classified}}{\text{Total number of beats}} \tag{5}$$

The performance results of the ANFIS used for classification of the ECG signals is given in Table 4.

The presented ANFIS model combined the neural network adaptive capabilities and the fuzzy logic quantitative method. Some performance concerning the salient features on classification of the ECG signals were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS model. The total classification accuracy of the ANFIS model was 98.24 % presented

Table 4 Performance results of ANFIS

Type of Arrhythmia	Training Data	Testing Data	Mis classification	Classification Accuracy (%)
NSR	95	45	0	100.00
AF	80	35	1	97.14
VT	75	30	1	94.33
VF	95	40	1	97.00
VFLU	85	35	1	94.11
Total	430	185	7	98.24

Table 5 Clinical dataset for eight patients

Patient	NSR	AF	VT	VF	VFLU
1.	27	14	13	-	-
2.	-	-	2	6	12
3.	35	-	-	32	-
4.	-	-	3	15	8
5.	39	-	3	17	12
6.	34	-	-	25	5
7.	10	13	9	8	13
8.	34	-	12	6	5

in Table 4. The results obtained of the proposed ANFIS model can be used in classifying the ECG signals by taking into consideration the misclassification rates.

Real time implementation

Simulations recordings of surface leads II and VI of a normal 12 lead ECG were obtained from eight patients using electrophysiological recorders. These patients exhibit sustained Normal Sinus Rhythm, Ventricular Tachycardia Atrial Fibrillation, Ventricular Fibrillation, Ventricular Flutter and any combination of these rhythms during electrophysiological testing and Automatic Implantable Cardioverter Defibrillator (AICD) implantation. Three independent observers classified the ECG recordings as one of the following rhythms: NSR, AF, VT, VF, and VFL.

Eight patients comprised the study population. The heart rhythms exhibited by the eight patients can be seen in Table 5. Eight of the patients exhibited different combinations of two or three types of rhythms. The seventh patient exhibited all four types of rhythms.

Three independent observers performed the original rhythm classification. Number of rhythm was countered for a patient during an interval of 4.5 s. The intervals were selected at random from rhythms by the three observers.

Data were analyzed using Cubic Spline Wavelet filtered with a cutoff frequency of 200 Hz and subsequently digitized at 1,200 Hz. Up to 60 s of continuous data were digitized for each rhythm. In this work, the data was divided into 4.5 s contiguous intervals of NSR, AF, VT, VF, VFL rhythms.

For each patient, classifiers were created for each rhythm interval. The ANFIS in the classifiers were able to learn the training data within approximately 20 epochs. For training data, the overall average accuracy for each patient's classifier is listed in Table 6. Each classifier had four possible outputs:

- Correctly Classified :4.5 s rhythm interval was classified correctly.
- Undetermined : 4.5 s rhythm interval was (two classification) classified as two rhythms.
- Undetermined : 4.5 s rhythm interval was not (no classification) classified
- In correctly Classified : 4.5 s rhythm interval was classified as a different rhythm

The presented ANFIS model combined the neural network adaptive capabilities and the fuzzy logic quantitative method. Some performance concerning the salient features on classification of the ECG signals were obtained through analysis of the ANFIS. The classification results and statistical measures were used for cslculating the ANFIS. The total classification accuracy of the ANFIS model was 98.24 % as presented in Table 5.

Detection of myocardial ischemia

Myocardial Ischemia (MI) is the most common cardiac disorder and its early diagnosis is of great importance. It is defined by a reduced blood flow to parts of the myocardium which causes alterations in the ECG signal, such as deviations in the ST segment and changes in the T wave. MI is considered to be a major complication of the cardiac function and a prime cause for the occurrence of cardiac infarction and dangerous cardiac arrhythmias.

Table 6 Performance results of the Intra- Patient classification accuracy

Patient	Correctly Classified	Incorrectly Classified	Undetermined (no classification)	Undetermined (two classification)	Accuracy (%)
1	51	0	1	2	94.11
2	16	0	1	1	87.50
3	62	3	1	1	91.93
4	24	0	1	1	91.66
5	69	0	2	3	92.75
6	58	1	2	3	89.65
7	47	2	1	3	84.61
8	49	1	3	4	83.67

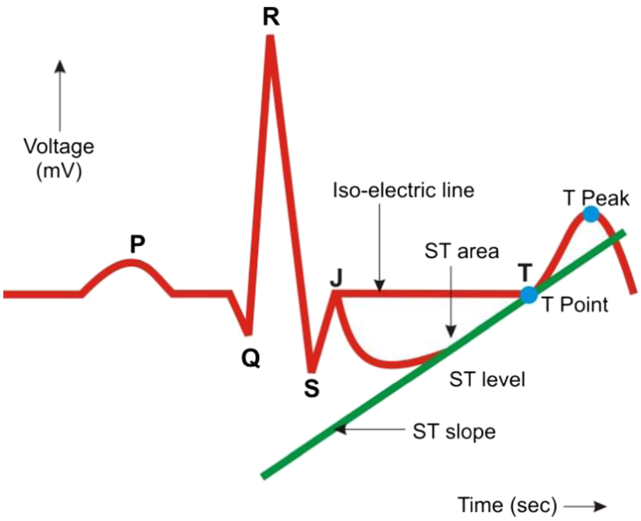


Fig. 14 The relevant ST segment points in ECG signal

A typical ST segment is comprised of the following fiducial points: S, J, ST area, T point, T peak, and ST segment level measurement. Figure 14 shows the relevant ST segment points in ECG signal. In order to identify these fiducial points, we use the WT method. WT has been successfully applied to the digital processing of ECG signals for its ability to localize the signals in both time and frequencies. The ST level change episodes lasting several seconds or sometimes some minutes, is an important indication in the diagnosis of myocardial ischemia.

A QRS complex is classified as non-premature complex, its duration is greater than 85 % of the mean QRS duration and less than 110 % of the mean QRS duration, and its difference area value is greater than 85 % when is compared with the non-PVC pattem. The baseline is very important to measure the STsegment deviation because it is the reference. Baseline is estimated like the mean value of the onset for the last three non-PVC complexes; this process is made for each lead. The middle point of the ST segment is set according to a relation between the mean RR interval and the distance since the J-point to the sample where to measure the ST segment deviation. It is made to avoid a measurement over the first branch of the T wave. The ST segment deviation is computed for leads II, V1 and V5 and the module of the ST vector. The classification of each beat as normal or ischemic based on a set of rules used by cardiologist for locating ST episodes to diagnose ischemia. The two rules are framed based on ST deviation being measured relative to ST deviation in the reference template which has been constructed from the first 30s of each record. The extractive results of six different shapes of ST segment: normal, downsloping depression, horizontal depression, upsloping depression, concave and convex elevation. The first rule refers to negative ST deviation, in which ST deviation is more than 0.08 mV below the isoelectric line and has an angle larger than 65° measured from vertical line, it is considered as negative ST deviation or ST depression sown in Table 7.

Table 7 ST Episode sensitivity and positive predictivity matrix

Algorithm Reference	ST Episode	Not Episode
ST Episode	TP	FN
Not Episode	FP	TN

Table 8 Performance of the episode detection method for 8 recordings of the ESC ST database

Record	Healthy Beat Number	Ischemia Beat Number (TP)	FN	FP	Positive Sensitivity (%)	Positive Predictivity (%)
e0103	7221	15	1	0	93.75	100.00
e0104	6598	9	2	1	81.81	90.00
e0105	6628	30	4	0	88.24	100.00
e0106	6759	21	1	0	95.45	100.00
e0107	7085	11	1	1	91.66	91.66
e0108	8567	34	6	0	85.00	100.00
e0111	7486	12	1	0	92.30	100.00
e0113	8911	35	5	6	87.50	85.36
Total	89.32	95.23				

Table 8 shows the results of applying our method toeachrecord. For each ECG recording, the sensitivity and positive predictivity values are given in terms of percentages

When aggregate gross statistics was used, we obtained 89.32 % and 95.23 % for episode sensitivity and positive predictivity. The time needed for the processing of each ECG recording was $455s\pm91s$.

Conclusion

This paper presented a effective, noise tolerance QRS detection algorithm based on symlet wavelet transform and found to be more suitable for this application because it reduces the probability of error in the detection of the QRS complex. The usefulness of the properties of the wavelet transform for QRS detection has been studied in this paper and a new QRS complex detector has been proposed. The extracted features, devised method to detect and classify the ECG signal abnormalities automatically. The advantage of the ANFIS classifier using the proposed feature vector is its simplicity and it can be easily implemented. The presented ANFIS model is combined with the neural network adaptive capabilities and the fuzzy logic qualitative approach. Classification results and statistical measures are used for evaluating the ANFIS. The total classification accuracy of the ANFIS model is 98.24 %. The attempt to classify the ECG signal has been successfully achieved.

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