Identification of Cardiac Arrhythmia Using ECG Signal Based ANFIS Classifier

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Abstract

Heart disease is the 2nd largest and dangerous disease in the world. The proposed Adaptive Neuro Fuzzy Inference System (ANFIS) modeling used to classify Bradycardia, Tachycardia, Bundle Branch Block which is very dangerous to human. Wavelet Transform gives the time, frequency localization of the ECG signal and used to diagnose and extract features for the classification process. Based on these statistics features and its membership function; 243 rules have been framed to design the FIS architecture. With the Multi-Layer Perceptron Neural Network (MLP NN) the error value has been computed during the forward pass, then derivation of the error value has been calculated, with this the weight value has been updated. To train the network 2,00,000 samples are used and 1,00,000 samples used for testing and validation. The subtractive clustering and Grid partitioning techniques are used and compared, to validate the performance of the classification process. 100% sensitivity is achieved in classification of the Normal and Bundle Branch Block using subtractive clustering. 96% sensitivity is achieved in detecting Bradycardia using Grid Partitioning, Showing better performance of the classification of heart arrhythmias.

Keywords: *ECG, Cardiac Arrhythmia, Discrete Wavelet Transform, ANFIS Classifier*

1. Introduction

The impact of High Blood pressure, Diabetes, inactivity, High cholesterol, and smoking cause of the CardioVascular Disease (CVD) [1]. There are many types of cardiac arrhythmias, such as Premature Ventricular Contraction, Atrial Fibrillation, Supraventricular Ectopy, Paced beat, Myocardial Infarction, Ventricular Tachycardia, Atrial Fibrillation etc.

Electro Cardiogram (ECG) signal shows the electrical activities like depolarization and repolarization of the heart muscle. Any abnormality in the heart muscle and valve can be identified with changes in duration, shape of the ECG signal. This paper focuses the differences in the QRS wave component of the ECG signal. The classification of ECG signal is necessary for the detection of different cardiac Arrhythmias. Consequently, ECG signal recognition and classification play a vital role in saving human life. ECG waveform detection should be reliable and accurate, otherwise the patient may lose the chance of treatment [2]. Therefore, precise time, frequency localized Wavelet Transforms algorithm has been developed, which is more efficient and accurate than Discrete Fourier Transform (DFT) [3].

Finite Impulse Response (FIR) and Adaptive filtering techniques [10], are used to filter out the noise component from the original signal with any reference signal (noise or original signal).

Filter output is only depending on the present input, there is no feedback connection with it, so it will give only lesser accuracy in removing the 50 Hz power line interference noises from the ECG signals. In the Fourier Analysis, the exact time location of the frequency signal will not be achieved. The Wavelet Transform (WT) Technique overcome these limitations because most of the signal components of the ECG signal are in low frequency nature (for longer duration) than the High frequency components (of shorter duration).

It is very difficult to frame mathematical (Hard Computing) model for the classification of the Cardiac arrhythmia signal because it is very complex in nature, which leads to the analysis in the soft computing domain [4]. The new era of Artificial Intelligence (AI) centered on the concepts, theoretical dimensions, and algorithm design techniques gleaned from nature such as Artificial Neural Network and Bioinspired computing. The new trend is to combine different algorithms to take advantage of built-in functionality to build a hybrid algorithm [5].

Different Artificial Intelligence (AI) techniques are used to classify cardiac arrhythmias, this paper explores with the Adaptive Neuro fuzzy Inference System (ANFIS) classifier. [6] – [7] Shows how to view the neuro-fuzzy process as a set of fuzzy rules. In the same way as fuzzy rules, this model can be created entirely from the input, output data or initialized with the a priori knowledge. The resulting model has the benefits of learning by patterns and the simple understanding of its working by fusing fuzzy structures and neural networks.

2. Materials and Methods

The heart functionality is analysed by fetching the ECG signal from the Human body. Physionet [8] MIT/BIH (Massachusetts Institute of Technology / Beth Isrel Hospital) Databases are used for the analysis of various Cardiac Arrhythmia. MATLAB software is used for fetching and processing of the ECG signal. Single ECG signal is represented by following three different file formats namely header file, data file and annotation file. In this header file contains sample number, sampling frequency, ECG signal format, patient history, detailed clinical information, ECG lead type and ECG lead number. The ECG signal was sampled with a resolution of 11-bit over 10 mV at 360 samples per second for each channel. ECG signal is stored in 212 format binary datafile, number of leads times 12 bits to be stored as a the number of samples, and the binary annotation file comprises of beat annotations. The data acquisition, pre-processing and feature extraction of raw ECG signal is a very important and time taking process for the successful classification of the neuro-fuzzy architectures. The Feature Extraction workflow is shown in the figure 1.

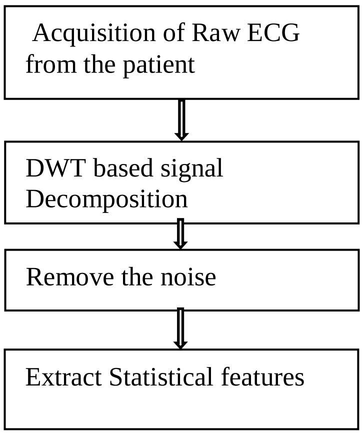

Figure 1. Feature Extraction Techniques

2.1. Denoising

In the data acquisition process the ECG signal can interfere with these noises: Power line interference, electrode touch noise, baseline drift, motion irregularities, chest wall, Electro MyocardioGram (EMG), instrument noise, electrosurgical noise. The Wavelet Transforms [9] enables the multi-resolution processing of the ECG signal, which decomposes the original signal into sub-signals. It significantly helps to remove the distortion in the lower and in higher frequency band.

In this work Discrete Wavelet Transform (DWT) is used, which are discretely sampled to correct the baseline of the ECG signal. First, the raw ECG signal is decomposed into four number of the detail coefficients (D1-D4) and one approximation coefficient A4 using Daubechies wavelet of order 4 (db4), and then reconstructed coefficients are calculated using decomposition structure and wavelet function. The shape similarity of the ECG signal and the Db wave is more, which gives better recognition. To eliminate base line drift, wandering and other noises the reconstructed coefficients are subtract from the ECG signal.

2 Feature extraction

After the Denoising process it is necessary to detect the feature which is having a higher correlation with the class information. This can be done with the Feature extraction process [11]. The wavelet transform uses multi-determination strategy which breaks down various frequencies with different resolutions. It is equipped for speaking to signals in various resolutions by enlarging and compacting in premise capacities. The premise work in wavelet investigation is characterized by two parameters which are scaled and interpreted. For a wavelet of request N, the premise capacity can be written as:

$$\varphi(n) = \sum_{j=0}^{N-1} (-1)^j c_j (2n + j - N + 1) \qquad (1)$$

A quick calculation of Wavelet Transform is found to yield the Discrete Wavelet Transform (DWT), which is a period scale representation of the computerized signal acquired using advanced moving methods. It is anything but difficult to actualize and receives dyadic scales and interpretations keeping in mind the end goal to decrease the measure of calculation time, which brings about a better proficiency of computation. Factual highlights are removed. The pre-processes ECG signal is deteriorated utilizing Daubechies wavelet which is shown in figure 2. The wavelet filter with scaling capacity resembles the ECG signal gives a better detection of low frequencies of the ECG signal is approximated by precluding the signs high reappearance parts. The 4th level of detailed wavelet coefficient reflects the energy level information of the ECG signal and other varying parameters. The fourth and eight level of decomposed wavelet coefficients are shown in figure 3.

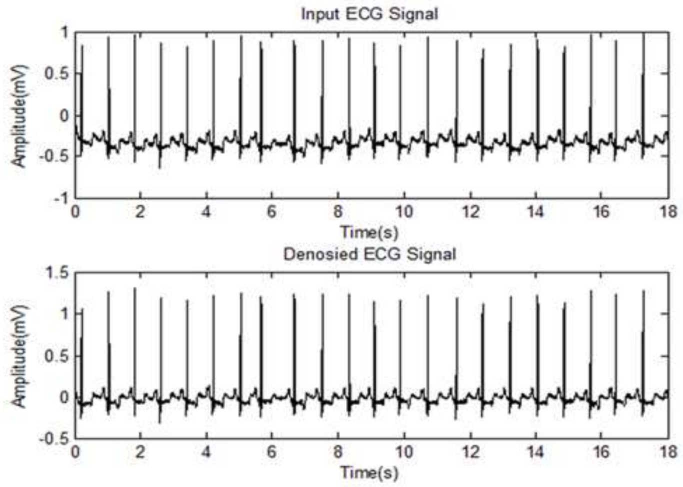

Figure 2. Base-line corrected signal

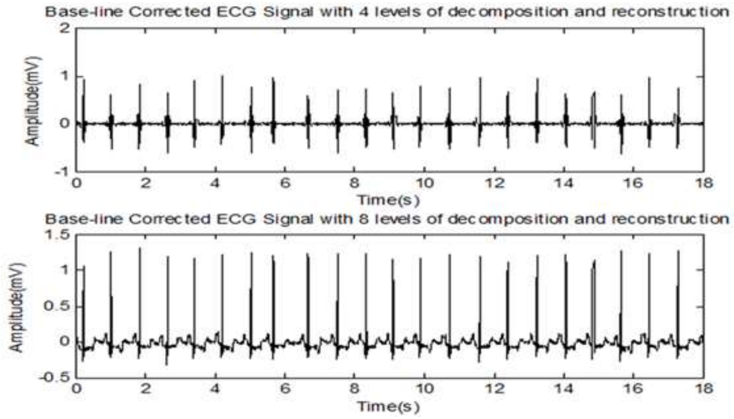

Figure 3. DWT Decomposition

The calculated coefficients of the wavelet provide a compact representation that displays the time and frequency energy distribution of the signal. Consequently, the ECG signal's calculated information and wavelet approximation coefficients were used as the function vector representing the signals. Five standard statistical parameters are extracted from the ECG signals. A signal of 3,00,000 discrete data was selected as considered ECG signal data. For each ECG signal, the detail wavelet coefficients of fourth level (3,00,000) were computed. From the approximation coefficients, various morphological features are extracted.

First, an accurate time center for each QRS complex should be obtained to measure features from the detected QRS complexes either regular or arrhythmic via the proposed method. Thus, find this point, the absolute maximum and absolute minimum DWT dyadic scale 2^4 indices are calculated using the start-offset positions of the corresponding QRS series. The best time center of each QRS complex detected is the mean of the excerpted DWT zero-crossing locations.

The derived statistical features are listed below:
1. Energy
2. Maximum
3. Minimum

4. Mean
5. Standard deviation

3. Classification

A fuzzy neural network or neuro-fuzzy system is a learning machine that utilizes estimate techniques from neural networks to find the parameters of a fuzzy system (i.e., fuzzy sets, fuzzy rules). Neural network will learn from scratch, with the examples observed. With this network, Fuzzy used to bring the relationship between these parameters to target function in the form of linguistic rules. If the information derived from the neural network is not sufficient, Fuzzy system needs to modify it. The information tuning is done in a heuristic way, and it will get back end support form neural network. In non-linearly interconnected and complex systems, Fuzzy logic uses simple mathematical functions in the form of rules. The optimum number of fuzzy rules is formulated with the knowledge of neural networks. The higher learning ability of neural networks allows the precious interpretation of parameters of membership functions.

ANFIS bridge the advantages of Artificial Neural Network (ANN) and Fuzzy Inference System (FIS), this hybrid-learning rule used to optimize the fuzzy system parameters of a first-order Sugeno system. ANFIS is a fuzzy Sugeno model of coordination where the last fuzzy deduction framework is upgraded through the ANNs with the back propagation gradient descent strategies. ANFIS be a class of versatile systems which are practically identical to the fuzzy deduction framework. It maps contributions through information participation work and related parameters, and after that through yield enrollment capacity to yield. The Sugeno method's advantages are computationally efficient, and work well with linear techniques, optimization, and adaptive techniques. It has ensured stability of the surface of the output, even an untrained input if fed as input. First use of the Sugeno Fuzzy Inference System (FIS) is planned for the Framework. There are two kinds of FIS, Subtractive Clustering and Grid Partition.

3.1 Grid partitioning

The ANFIS Grid segment requires the quantity of participation capacities for each information. This framework utilizes the gbell formed participation capacity to portray the fuzzy sets information and Sugeno yield enrollment works as straight sets. [12] shows how the hybridization of the Fuzzy Inference system with Artificial Neural Network improves the performance of the classification process. In view of the participation capacities, at that point the fuzzy IF-THEN decides that have a fuzzy predecessor and consistent result are built. The governing base is made concurring the mastering learning utilizing MATLAB administer base manager. In light of the three enrollment work (little, medium, substantial) that being utilized, for the 5 input features of energy, mean, minimum, maximum and standard deviation, of the quantity of administering base made are given by 3^5= 243 rules are generated.

3.2 Subtractive clustering

A Data clustering [13] is a procedure of putting comparable information into gatherings. A clustering calculation segments an informational index into a few gatherings to such an extent that the difference inside a gathering is bigger than among gatherings. Grouping methods are utilized as a part of a conjunction with outspread premise work systems or fuzzy displaying basically to decide the introductory area for spiral premise capacities or fuzzy if-then guidelines. There is distinctive clustering method is available for grouping the data, such as, k-implies clustering, fuzzy c-implies grouping, mountain grouping and subtractive grouping.

On the off chance that there is no evident thought what number of bunches there ought to be for a given arrangement of information, subtractive grouping is a quick, one-pass calculation for evaluating the quantity of groups and the group focuses in an arrangement of information. Consider an accumulation of n information focuses on a m-dimensional space. Without loss of sweeping statement, the information indicates are accepted have been standardized inside a hypercube. Since every datum point is a possibility for bunch focuses, a thickness measure at the information point x_i is characterized as:

$$D_j = \sum_{j=1}^{n} exp\left(\frac{-\left(\|x_i - x_j\|^2\right)}{\left(\frac{r_a}{2}\right)^2}\right) \qquad (2)$$

r_a is the radius of a neighborhood
x_{c1} is the first cluster center
D_{c1} is the highest density measure
Next the density measure for each data point x_i is revised by the formula (3)

$$D_i = D_i - D_{cl} exp\left(\frac{-\left(\|x_i - x_{cl}\|^2\right)}{\left(\frac{r_b}{2}\right)^2}\right) \qquad (3)$$

The constant r_b defines a neighborhood that has measurable reductions in density measure [14].

The constant r_b is normally larger than r_a to prevent closely spaced cluster centers. ($r_b = 1.5 \ r_a$).

After the density calculation is revised for each data point, the next x_{c2} cluster center is chosen, and all data point density measurements are revised. The process is repeated until the output of a sufficient number of cluster centers. It should be noticed that several parameters such as types of activation functions, range of control, squash factor, accept ratio and reject ratio were assessed. Based on trying-and-error method the suitable ranges and types were chosen for these parameters. The Subtractive clustering method finds cluster number of the specified input and it assigns membership functions equal to the number of clusters. Gbell membership function is used, and 14 rules are generated using 5 inputs,1 output.

4. Results and Discussions

This work demonstrates that with the Wavelet Transformed ECG signal is denoised and the Statistical features are extracted. The ANFIS trained classifier used to classify four different Cardiac Arrhythmias. The results and analysis of various features that are extracted are discussed as follows.

4.1. Data fetching and pre-processing

The ECG signal is fetched from the MIT-BIH database, and then pre-processed using Discrete Wavelet Transform. Using DWT, baseline wandering, and other noises are removed in the first 4 scales.

4.2. Feature Extraction

DWT decomposes the pre-processed signal into approximation and detail coefficients. From the fourth level of detail coefficients statistical features are calculated. The DWT decomposition is performed using db4 wavelet. Table 1 shows the extracted features Mean, Energy, Standard Deviation, Minimum and Maximum Magnitude from the ECG signal record nos: 100,102,104,106.

Table 1. Statistical Features Extracted with Wavelet Transform

S No	ECG Signal Record No	*Mean (mV)*	*Standard Deviation (mV)*	*Minimum Magnitude (mV)*	*Maximum Magnitude (mV)*	*Energy (J/s)*
1	100	*0.0124*	*0.4282*	*-1.6537*	*2.4337*	*0.1832*
2	102	*-0.0594*	*0.8091*	*-3.5554*	*4.6291*	*0.6570*
3	104	*-0.0133*	*0.6419*	*-3.0113*	*3.9431*	*0.4114*
4	106	*-0.0023*	*0.3646*	*-2.6533*	*1.2688*	*0.1327*

4.3. Classification

The features are classified using ANFIS toolbox. All the neuro-fuzzy architectures [15] use the gradient descent techniques for the learning its internal parameters shown in figure 4. There are five inputs (Mean, Standard Deviation, Minimum, Maximum and Energy) to the system, and one output. To the classifier, these input patterns are assigned, the output is restricted to lie in the range between 1 to 4, so that they can represent the probability of class membership. In the classification process for each specific class each specific feature is assigned, according to the characteristic of the ECG signal statistical features. For generating fuzzy inference system [16], the parameters of subtractive clustering are set as follows: Range of influence=0.5, Squash factor=0.55, Accept ratio=0.5, Reject ratio=0.15. With these parameters, 14 fuzzy rules are obtained. Five statistical features are selected, and three membership functions are used with normalized range.

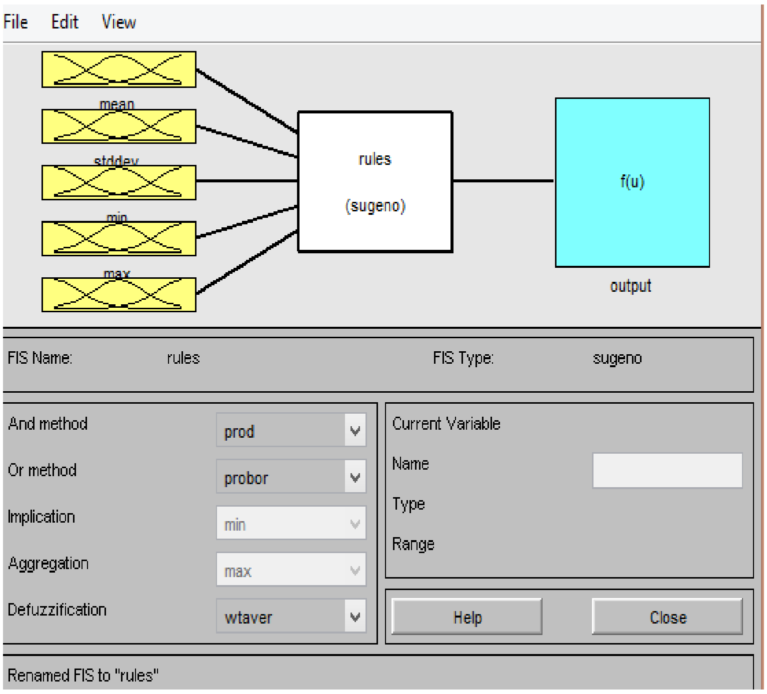

Figure 4. Sugeno type ANFIS system

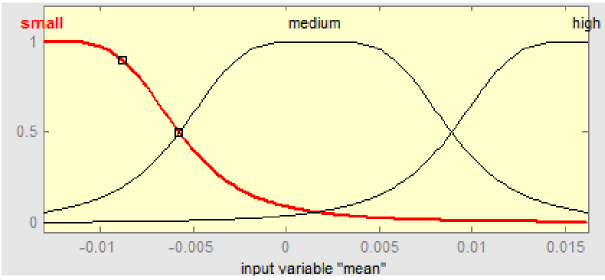

Figure 5 (a)Mean Membership function

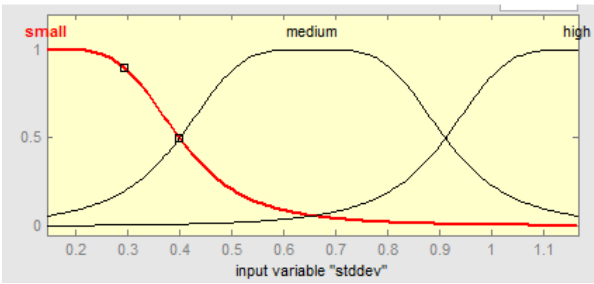

Figure 5 (b) Standard Deviation Membership function

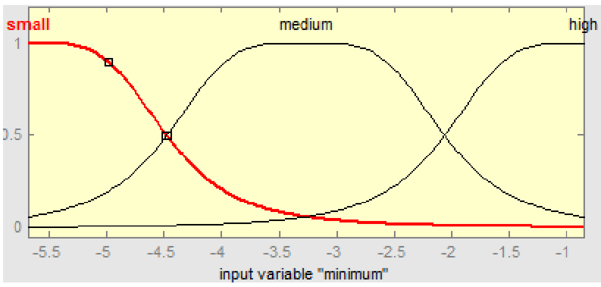

Figure 5 (c) Minimum Magnitude Membership function

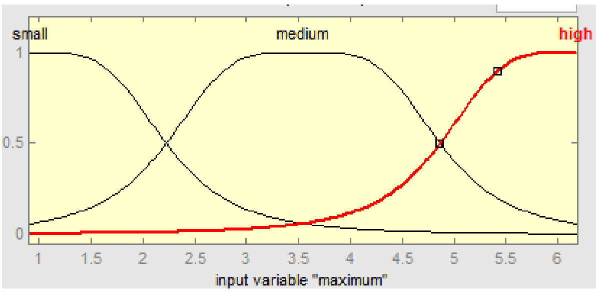

Figure 5 (d) Maximum Magnitude Membership function

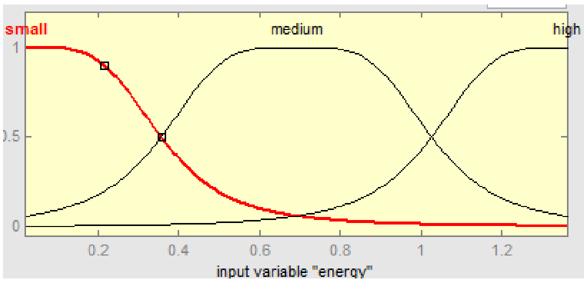

Figure 5 (e) Energy Membership function

Figure 5 Membership functions of Grid Partitioning

The three membership functions are named small, medium, high. The membership functions before training are shown in Figure 5, for 5 different statistical features from 5(a) to 5(e). Classification of the statistical features using grid partitioning is shown in figure 6(a) to 6(e). Compared with the initial membership function the final membership functions are updated in all features. From that totally 243 rules generated using ANFIS using Grid partitioning method. There are five inputs and single output. The final output is the weighted average of five inputs each rule has. Three different sets of 32 ECG record taken for training, testing, and validation.

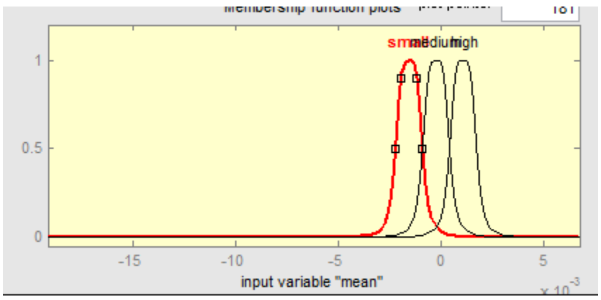

Figure 6 (a) Mean Membership function

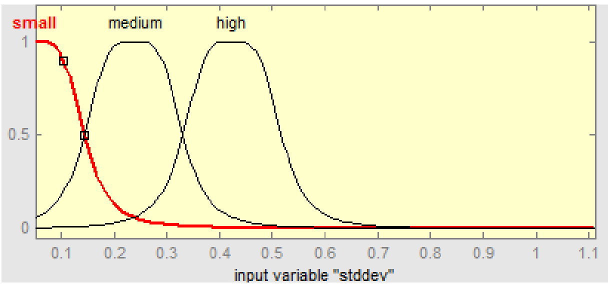

Figure 6 (b) Standard deviation Membership function

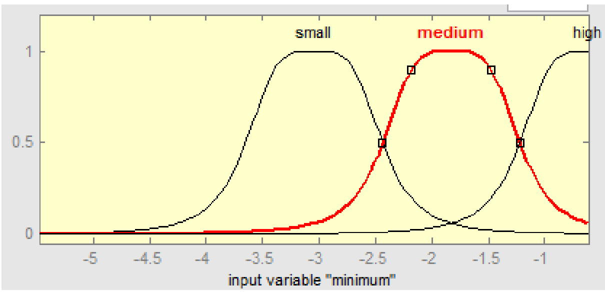

Figure 6(c) Minimum Magnitude Membership function

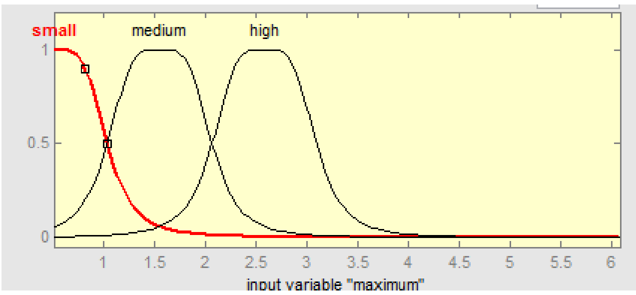

Figure 6 (d) Maximum Magnitude Membership function

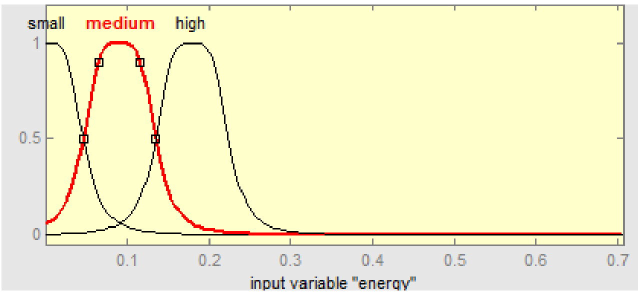

Figure 6 (e) Energy Membership function

Figure 6 Membership functions of Subtractive Clustering

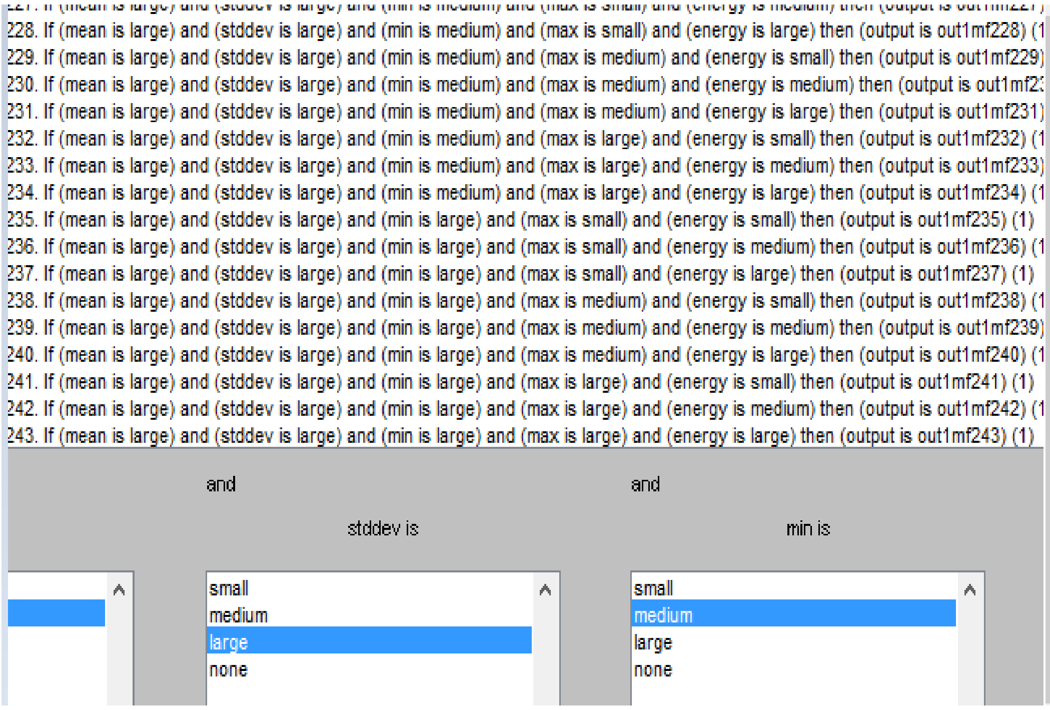

Figure 7 Rules generated using grid partitioning

Figure 7 shows, 243 rules generated using ANFIS using Grid partitioning method. There are five inputs and single output. The Figure 8 (a) shows ANFIS Classifier plot for Statistical Features using Grid partitioning, that the ANFIS output in red marks is correctly classified into four classes and achieved 100% training accuracy. The figure 8 (b) shows the testing data, with blue mark represents the target, and the red mark denotes the FIS output. The figure 8(c)checking data validation model some samples are moving away from the targeted region.

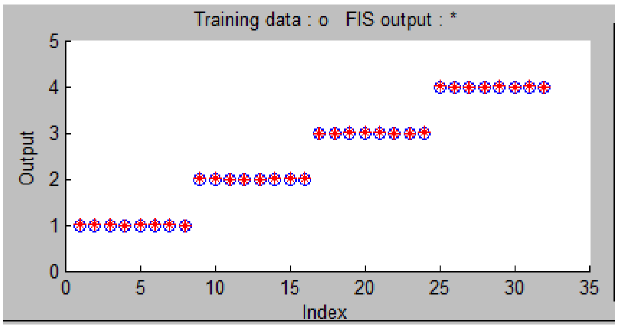

Figure 8 (a) Training data using Grid partitioning

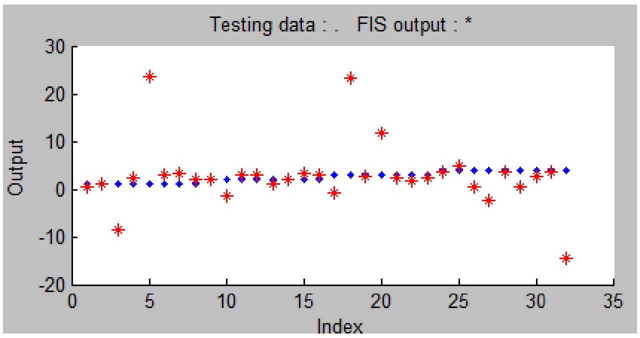

Figure 8 (b) Testing data using Grid partitioning

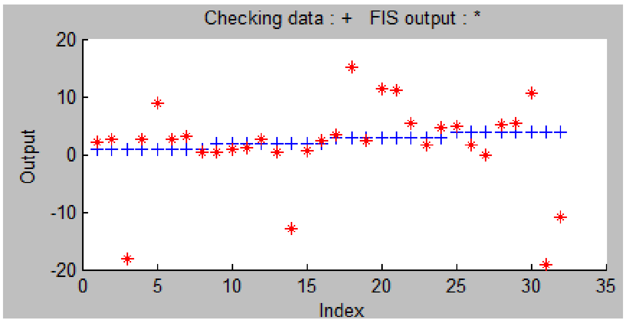

Figure 8(c) Checking data using Grid partitioning

Wavelet Transform based Hidden Markov Model (HMM)[17] gives 80% of beat detection performance and Support Vector Machine (SVM) classifier [18] gives 80 % of accuracy, the proposed approach gives higher accuracy than those previously derived techniques. The Figure 9 shows ANFIS Classifier plot for Statistical Features using subtractive clustering, the outputs are represented in red marks, are correctly classified into four classes with 99% of training accuracy.

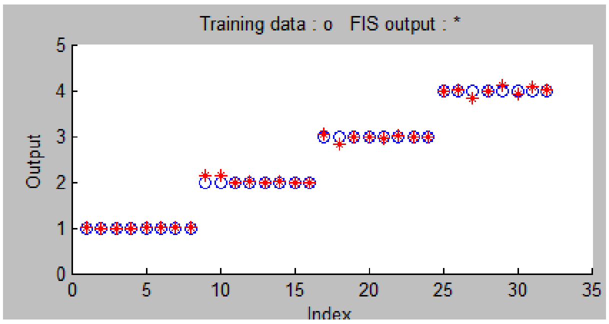

Figure 9(a) Training data using subtractive clustering

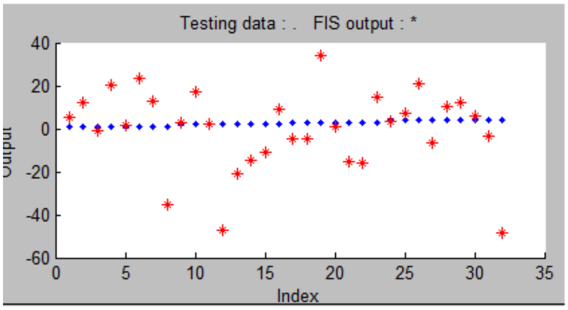

Figure 9(b) Testing data using subtractive clustering

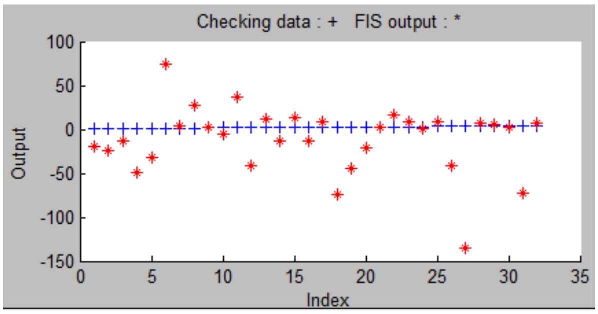

Figure 9 (c) Checking data using subtractive clustering

The subtractive clustering technique generates clusters and depending on the that the number of membership functions. Figure 9(a) shows the target of classes 1,2,3,4 and the ANFIS output. For testing 1,00,000 samples are taken which are tested using subtractive clustering shown in figure 9 (b) and (c). The checking data given by red mark, denotes the ANFIS output, that gives the result of classification.

Table 2 Performance measures using Grid partitioning algorithm

Classes	Class Category	Sensitivity(%)	Specificity(%)	Overall Accuracy(%)
1	Normal	75	92	80
2	Bradycardia	57	96	
3	Tachycardia	88	88	
4	Bundle Branch Block	62	85	

Table 3 Performance measures using subtractive clustering algorithm

Classes	Class Category	Sensitivity (%)	Specificity (%)	Overall Accuracy (%)
1	Normal	100	88	82
2	Bradycardia	77	86	
3	Tachycardia	80	90	
4	Bundle Branch Block	100	90	

Table 2 & 3 shows the performance measure of ANFIS classifier using Grid partitioning and subtractive clustering. 100% sensitivity is achieved in classifying

Normal and Bundle Branch Block using subtractive clustering. 96% Sensitivity of Bradycardia using Grid Partitioning. [2] gives the sensitivity of 87.5% and 89.5% and Specificity 96%; our approach gives higher performance measures in Sensitivity and Specificity on Normal 1st and Bundle Branch Block 4th class.

Sugeno Type ANFIS classifier is designed and tested for statistical features of ECG signals. An accuracy of 82% is obtained using Grid partitioning, which is higher than subtractive clustering. The sensitivity of the classifier using statistical features for the classifying Normal (class 1), Bundle Branch Block (class 4) is improved compared with the previous approaches. ANFIS classifier successfully classifies the four classes Normal, Bradycardia, Tachycardia, Bundle Branch Block into class 1 to 4, and gives class 0 when the unknown input is given.

CONCLUSION AND FUTURE WORK

ANFIS system used to classify the cardiac arrhythmia based on the wavelet transform based extracted statistical feature. The behavior of the ECG signal is represented in the form of membership functions.The network is initially trained with the back propagation gradient descent algorithm, fuzzy system used to overcome the uncertainties in the data patterns. ANFIS model presented in this work proves that it gives higher classification accuracy, specificity and sensitivity.

In the future work, both statistical and morphological features are fused and can be given as input to the classifier. Mamdani model can be used for classifying the various kinds of features and the performance measures can also be compared. By using other hybrid algorithms to test the selected features that are appropriate for many forms of heart disease detection, the characteristics of the wave features for the ECG analysis can be generalized to another method. It is also possible to improve the diagnostic reliability of the ANFIS system, which incorporates the adaptive capabilities of the neural network and the fuzzy analytical approach of the logic.

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