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An ECG Beat Classification Using Adaptive Neuro-Fuzzy Inference System

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***Abstract*— *Electrocardiography (ECG or EKG) uses electrodes to measure an electrical activity of heart. These heart signal allows comprehensive analysis of the heart condition. Acquisition of ECG signal from the human body is a non-invasive process that opens the door to new possibilities for the application of advanced signal processing and data analysis techniques in the diagnosis of heart diseases. With the availability and help of large database of ECG signal, a computationally intelligent system can be built and can take place of a cardiologist. The various abnormalities in the patient heart can be detected to identify various cardiac disease by use of Adaptive Neuro-Fuzzy Inference System (ANFIS) preprocessed by subtractive clustering. In this paper, six types of heartbeats are classified: Normal sinus rhythm, premature ventricular contraction (PVC), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Premature Contraction (APC) and paced beats. The research aimed at detecting important characteristics (features of an ECG signal to determine whether the patient heartbeat is normal or irregular. The results from three different trials indicate an average accuracy of 98.43 %, average sensitivity of 95.3% and average specificity of 98.6%. These results are comparable to two artificial neural network (ANN) algorithms: gradient descent and Lavenberg Marquardt, as well as ANFIS preprocessed by grid partitioning*.

***Keywords*— *ECG, Clustering, ANFIS, ANN, Grid Partitioning*.

I. INTRODUCTION

ECG signal allows detection of various conditions and abnormalities of patient's heart. The ECG characteristics may include abnormalities, size and position of chambers, cardiac pathologies, heart rate, damage to tissues, blockages in veins etc. The major problem with today's ECG signal instruments is their inability to characterize the signals without a doctor's complete evaluation and diagnosis. This problem is now solved by the research in the field of Computational Intelligence (CI) which gives promising research results. An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of Neuro-Fuzzy classifier and is one of the most important area of study in Computational Intelligence. The main objective of the research is to explore various areas of ANFIS to classify ECG heartbeats which are common and compare the results of ANFIS with artificial neural networks.

Research Importance

Now a days cardiac arrhythmias are one of the reason for high mortality rate. The study of ECG signal pattern and variability in the heart rate in terms of computer based analysis and classification of diseases can be helpful in diagnostics [15]. Applying computational intelligence to medical diagnosis have shown to be successful in the past and thus important to classify heart signal.

The goal of this research is to facilitate the cardiologist through Neuro-Fuzzy model classifier. The algorithms of the classifier model allow for increase in interpretability and understandability of the diagnosis and the physician can easily check the model for plausibility and verify the classification results obtained for a specific heartbeat by checking the degree of fulfillment.

Brief Approach

For ECG analysis and classification, MIT-BIH Arrhythmia database is used to observe and extract features. It consists of 48 half hour excerpts of two channel ambulatory ECG records which were obtained from 47 subjects. Sampling rate of the recordings is 360 samples per second. The bit resolution is 11 bits and the amplitude range is 10 mV peak to peak. The annotations are important for learning in the Neuro-Fuzzy classifier.

The database of ECG signals are first preprocessed for observation and training. Preprocessing stage includes removal of 50 Hz power line interference accomplished by passing the signal through low pass filter. The signal may be distorted with a baseline wander and may not represent the true amplitude of the signal, hence a high pass filter is used to detrend the ECG signal to baseline level in order to obtain the true amplitude information. The annotation of each heartbeat is read from a downloadable MATLAB package from MIT-BIH database. A proposed algorithm for detecting various segments of an ECG signal is then applied to complete the annotation.

ANFIS is a binary classifier used to classify between normal and abnormal heartbeats and has one output to the network. The annotation of each ECG is an input to the classifier model to be trained. These annotations acts as different feature input to the model. These features are generally temporal, interval and amplitudes of various segments.

The limitations of ANFIS with traditional method is the convergence speed. It is shown that the ANFIS has a faster convergence spped than a typical artificial neural network which is due to smaller fan-out for back-propagation and the network's first three layers are not fully connected. The smoothness of the model is guaranteed by interpolation. The limitations are computational complexity which is due to the exponential complexity of the number of rules for grid partitioning.

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II. Classification Approach

Figure 1 shows an overall approach to classification of hearbeat. The raw ECG signal is first preprocessed. This means the signal is filtered to remove various artifacts present in the signal and it is annotated. Filtering involves both a low pass and high pass filter. Then the true amplitude information of various parts of ECG signal is extracted.

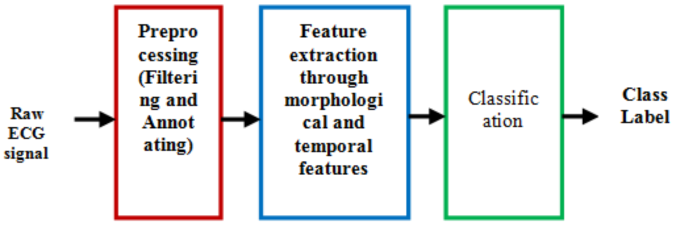

Fig. 1. Classification approach of heartbeats.

The inputs of the system consists of features of the signal. Features can be either annotated or calculated. The dominant features input to the classifier consists of both temporal and amplitude information of an ECG heartbeat.

Let n and m represent the number of input features and number of heartbeats to classify respectively. The input features to the classifier is specified in table I below. The inputs vary according to the heart rate. A normal heart rate or normal sinus rhythm is in between 60-100 beats per minute. The table I below shows the seven feature inputs chosen based on three sources and are inputs to the ANFIS classifier model. 'NF' indicates there is no feature information to identify specific particular heartbeat. The leftmost coloumn indicates six types of heartbeats to be classified. The ration RRs/ RRp is used as an input because it gives an indication of variation in heart rate.

TABLE I. Input features of an ECG signal.

	R Amplitude (mV)	RRp Interval (Sec)	RRs Interval (sec)	RRs/RRp
Normal	1.5 – 2.0	0.6 – 1.2	0.6 – 1.2	1
PVC	< 2	< 0.6	>1.2	>1
APC	>2	< 0.6	>1.2	>1
LBBB	NF	NF	NF	NF
RBBB	NF	NF	NF	NF
Paced	>2	NF	NF	NF

	RR Interval (msec)	QRS Interval (msec)	ST Segment (msec)
Normal	120-200	80-100	80-120
PVC	NF	>120	NF
APC	NF	< 80	NF
LBBB	NF	>120	NF
RBBB	NF	>120	>120
Paced	>280	>120	NF

Figure 2 shows the general block diagram for Classifying ECG signal.

ANFIS is a binary classifier and hence one output, six ANFIS are trained, validated and tested. A threshold is used at the output for each ANFIS for classification of heartbeat as either a specific heartbeat denoted as '1' or non-specific heartbeat denoted as '0'.

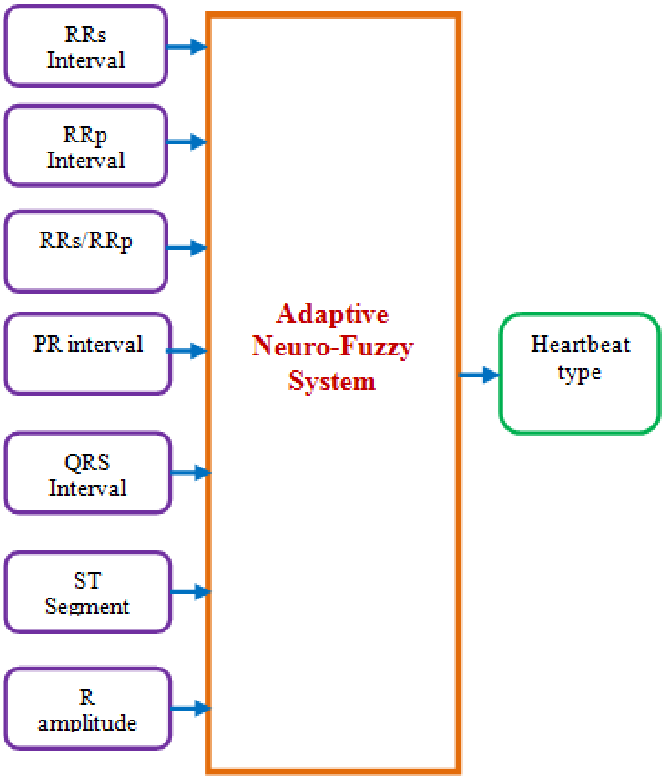

Fig. 2. General block diagram for classification.

Let N be the normal heartbeats, V be the PVC heartbeats, L be the LBBB heartbeats, R be the RBBB heartbeats, A be the APC heartbeats and P be the paced heartbeats.

The specific heartbeat determination correctly is done after deciding a threshold after each ANFIS and denoted as a target '1' and for non-specific heartbeat is denoted as target '0'. Let f be the output of an ANFIS and f_{Th} be the value of the output after a threshold either '0' or '1'. The threshold can be defined as follows:

$$\text{If } f < 0.5 \text{ then } f_{Th} = 0;$$
$$\text{Else } f_{Th} = 1.$$

Figure 3 shows the internal functionality of the ANFIS structure. First each input feature is passed through two membership functions for the case of grid partitioning or K clusters for the ease of subtractive clustering. Two membership functions, for example, would capture the *'high'* and *'low'* linguistic information for each input feature. Three membership functions would capture the *'high'*, *'medium'* and *'low'* linguistic information for each input feature. For more membership functions, linguistic information would encompass more ranges for each input feature. Since the number of input features is seven, the number of nodes for each layer can be calculated. For the first layer, the number of nodes was calculated to be 14 nodes (grid partitioning) and $K.n$ nodes (subtractive clustering). The number of nodes calculated is 128 for the second, third and forth layer using grid partition and K nodes using subtractive clustering.

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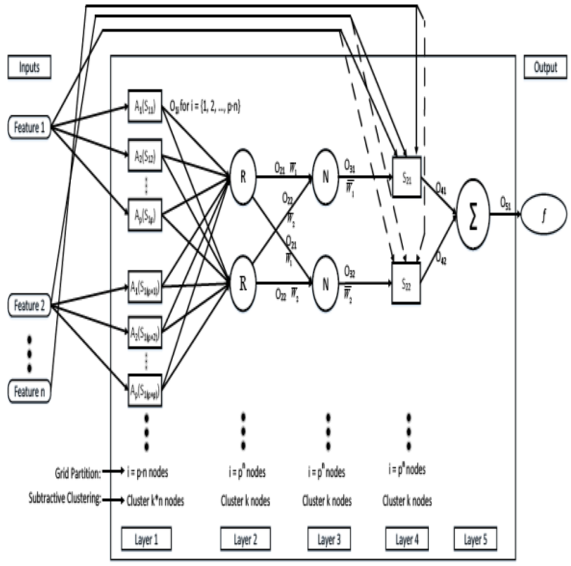

Fig. 3. General ANFIS structure.

III. Program Flow

Figure 4 below shows flowchart for classification of ECG heartbeats. The flow starts with choosing the ECG signal for classification. Normalization of the input features from the ECG signals was done through the subtractive clustering algorithm. The signal was then detrend and cleased of noise through a high and low pass filter for preprocessing. Seven features are extracted. Since the ANFIS has one output, the output vector is created. For each index of the vector is assigned to a specific heartbeat type. For example, normal heartbeats would be defined as '1' and other heartbeat types (five other heartbeats) would be defined as '0'. An input data matrix of features was generated and concatenated with an output vector. The matrix was divided for each heartbeat type into training data (55% of the input data) , checking data for validation (10% of the input data) and testing data (45% of the input data). 100 random heartbeats were selected from six specific heartbeat records with more than 100 heartbeats of the specific type were selected.

Classification begins by choosing the number and type of membership functions for the ANFIS. More number of membership functions needs to be taken in consideration for generation of fuzzy rules. The MATLAB function 'anfis' only supports 256 fuzzy rules. Since there are 7 inputs and number of fuzzu rules is equivalent to number of membership functions p to the power of the number of inputs n for grid partitioning , three membership function is not supported. For this reason, two membership functions are chosen for grid partitioning: representing linguistically 'high' and 'low' partitions of each input feature. The number of antecedent and consequent parameters can then be calculated for grid partitioning. They were calculated as 42 and 1024 respectively. The rule layer was chosen to be an AND function. This means the output of the rule layer is a minimum of two membership functions as opposed to the maximum through the OR function.

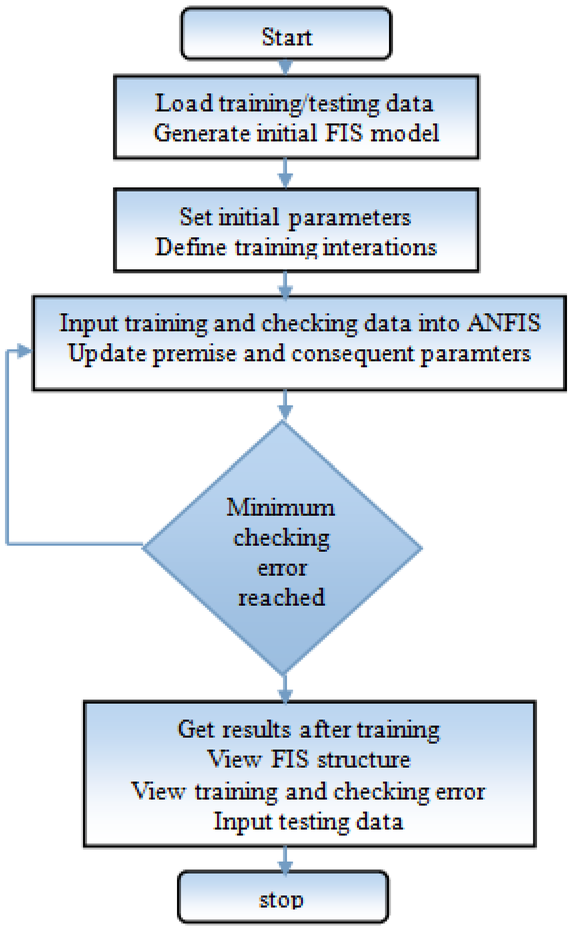

Fig. 4. Classification program flowchart.

The ANFIS algorithm generates an output FIS for training, validating and testing data. Training and checking (also called validation) RMSE (root-mean-square error) is calculated for each data sample i.

The root mean square error compares the actual output of the Fuzzy inference system with the desired output value. Consider t be the number of heartbeats used for training. The RMSE for training can be expressed as:

$$RMSE = \sqrt{\frac{1}{t}\sum_{i=1}^{t}(y_i - y'_i)^2}$$

The RMSE gives more accurate value of the error between a model (output of FIS) and observed data (training/validation data output value). There are statistical properties such as variance and standard deviation that makes RMSE a desirable measurement. It is desirable to have a RMSE decrease or converge as the number of iterations increase. The RMSE of the checking data is used to prevent overfitting. If the RMSE of the checking data increases, overfitting occurs which is a result of fitting the fuzzy systems to the training data so well that it no longer fits the testing data effectively? This leads to decrease in generality. The ANFIS algorithm chooses novel parameters associated with the minimum checking error before overfitting. Once RMSE of the training data attempts to decrease as the number of iterations increases and overfitting is eliminated. In evaluating the ANFIS, the trained FIS is used to evaluate the test data. The output is a result of classification. A threshold, on training, checking and testing output vectors is used to convert fractional numerical assignments for each heartbeat to integers, either '0' or '1'.

IV. PERFORMANCE EVALUATION METHOD

Accuracy, sensitivity and specificity can be used as performance measurements to evaluate the effectiveness of a classifier The measurement includes heartbeats that defines true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Let *N* be the total number of heartbeats classified. The three performance parameters can then be expressed as:

$$Accuracy\ (\%) = \frac{TP + TN}{N}\ X\ 100\ \%$$

$$Sensitivity\ (\%) = \frac{TP}{TP + FN}\ X\ 100\ \%$$

$$Specificity\ (\%) = \frac{TN}{TN + FP}\ X\ 100\ \%$$

V. SIMULATION RESULTS

From experimentation in generating six ANFIS, it is observed that ANFIS number 1 and 5 represents a convergence when training RMSE curve flattens and when checking RMSE continues to decrease. The remaining RNFIS number 2,3,4 and 6 represents convergence when the checking RMSE reaches a minimum before overfitting. Oscillations is observed in ANFIS 3,4, and 6 which can be removed by decreasing the initial step size. Table II shows the training and checking results for the six ANFIS'.

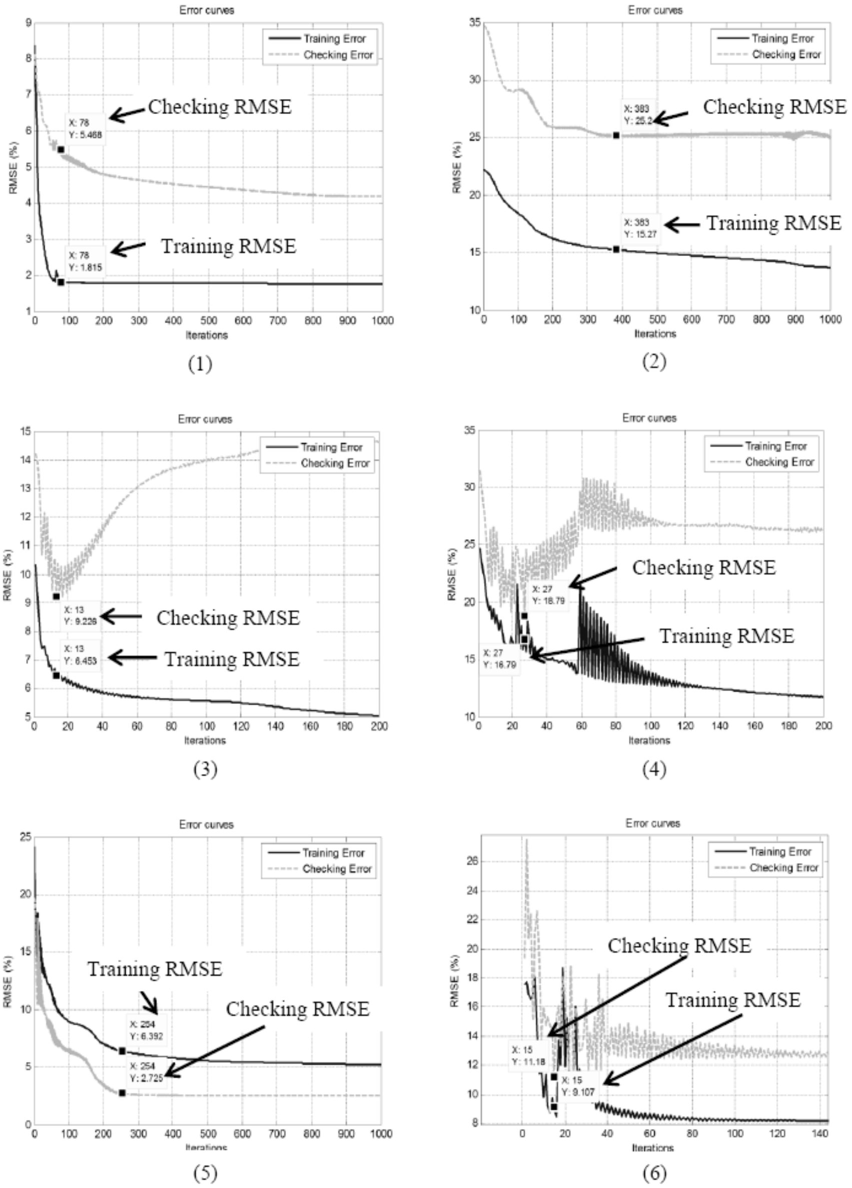

Fig. 5. Trial 1 RMSE training and checking curves for the six ANFIS.

TABLE II. Trail 1 training and checking results for the six ANFIS'.

ANFIS	r_a	Initial Step size	Training iterations	Training RMSE (%)	Checking RMSE (%)
1	0.45	0.001	77	1.82	5.47
2	0.45	0.001	383	15.27	25.20
3	0.45	0.01	13	6.45	9.23
4	0.45	0.02	27	16.79	18.79
5	0.60	0.01	254	2.73	6.39
6	0.40	0.13	15	9.11	11.18

Table III shows the classification results for the six ANFIS'. Classifications of the true positive specific heartbeats are denoted by TP. These heartbeats represent the normal (N), PVC (V), APC (A), LBBB (L), RBBB (R) and paced (P) heartbeats. Classification of the true negative heartbeats without the specific heartbeat is denoted as TN. These beats are represented by *N', V', A', L', R'* and *P'*.

TABLE III. Trail 1 classification results for the six ANFIS'.

ANFIS	TP	TN	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	35	175	100	100	100
2	32	158	90.48	65.31	98.14
3	34	175	99.52	100	99.43
4	34	175	99.52	100	99.43
5	34	175	99.52	100	99.43
6	34	175	99.52	100	99.43

The results in table III shows the ANFIS classifier is effective at detecting specific heartbeats. The ANFIS numbered 2 is poor in classification between PVC heartbeats and other hearbeats without PVC. This is observed from poor sensitivity value of 65.31%.

VI. CONCLUSION

The ANFIS has the advantage of integrating the best features of fuzzy systems and neural networks in ECG classification. The fuzzy system was able to represent prior knowledge into a set of constraints to reduce the optimization search space. Moreover the fuzzy systems has the ability to provide smoothness as compared to interpolation among the rules. The Neural network adapts the weights of neurons through back propagation to automate the fuzzy parametric tuning. Table IV shows the classification results of the four algorithms performed for three trials under the same data used to train, validate and test for randomized ECG record selection and randomized heartbeats. ANFIS using Subtractive clustering method has better performance in terms of accuracy, sensitivity and specificity.

TABLE IV. Average accuracy, sensitivity and specificity results for 3 trials for several algorithms.

Algorithm	Average Accuracy (%)	Average Sensitivity (%)	Average Specificity (%)
ANFIS under subtractive clustering	98.10	94.99	98.87
Gradient Descent ANN	95.61	87.69	97.80
Lavengerg-Marquardt ANN	97.98	94.09	98.81
ANFIS under grid partitioning	94.59	82.64	97.90

The ANFIS under subtractive clustering converged faster than the gradient descent ANN. However the Lavenberg-Marquardt ANN convergence was much faster even though the computational requirements are much higher per iteration. The higher convergence speed was because the algorithm is comprised of both the Gauss-Newton method and gradient descent. Gradient descent assures convergence through proper selection of the step size parameter but convergence is slow.

The average run-time for the ANFIS using subtractive clustering method is reasonable as compared to the ANN algorithms: Subtractive clustering and ANFIS. Both made use of LSE while the ANFIS performed an additional algorithm being the gradient descent. It is found that the ANFIS ultilizing grid partitioning is inferior in terms of convergence speed. ANFIS has better computational complexity restrictions.

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