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ECG Signal Analysis for Abnormality Detection in the Heart beat

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Abstract

Automatic recognition of cardiac arrhythmias is important for diagnosis of cardiac abnormalities. Detection of various abnormalities in the heart to identify various heart diseases can be made through an Adaptive Neuro-Fuzzy Inference System (ANFIS) preprocessed by subtractive clustering. Some recordings of the MIT-BIH database has been used for training and testing our neural network based classifier. Six types of heartbeats are classified: normal sinus rhythm, premature ventricular contraction (PVC), atrial premature contraction (APC), left bundle branch block (LBBB), right bundle branch block (RBBB), and paced beats. Our goal is to detect important characteristics of an ECG signal to determine if the heartbeat is normal or irregular. Therefore, in this paper, an expert system for Electrocardiogram (ECG) classification is analyzed. DWT is used in preprocessing for filtering ECG recordings, and extraction of some features performs the classification task.
Keywords- ANFIS, Arrhythmias, ECG, MIT-BIH, Subtractive Clustering

I. INTRODUCTION

The Electrocardiogram (ECG) signal is an important signal among all bioelectrical signals used in the diagnosis of many cardiac disorders. It can be recorded from the wave passage of the depolarization and repolarization processes in the heart. The voltage in the heart tissues is conducted to the body surface where it is measured using electrodes. The current is diffused around the surface of the body. An ECG is generated by a nerve impulse stimulus to the heart. The current at the body surface will build a voltage drop, with an impulse variation. This is very small amplitude of impulse, which requires a thousand times of amplification. A typical ECG tracing of a normal heart rate (or cardiac cycle) shown in figure 1.1 consists of a P wave, QRS complex and a T wave. A small U wave is normally visible in most of the ECGs. The baseline voltage of ECG is known as isoelectric line. Typically, the isoelectric line is measured as the portion of tracing, following the T wave and preceding the next P wave. The P wave represents atrial depolarization, the QRS complex represents the ventricular depolarization and T wave represents the repolarization of ventricle [1].The most important part of the ECG signal analysis is the shape of QRS complex. The ECG signal may differ for the same person such that they are different from each other and at the same time similar for different types of heartbeats [2]. The purpose of this study is to help the cardiologist in diagnosis through neuro fuzzy model classifiers. The rules of neuro fuzzy model classifiers allow for an increase in the feasibility of the diagnosis. A physician can easily check a fuzzy model classifier for acceptance, and can verify why a certain classification result was obtained for a certain heartbeat by checking the degree of fulfillment of the individual fuzzy rules [3]. Electrical activity of the heart can be recorded at the surface of the body using an electrocardiogram. Therefore, the electro-cardio-gram (EKG) is referred to a voltmeter that uses up to 12 different leads (electrodes) placed on designated areas of the body. The electrical activity of the heart is generally sensed by monitoring electrodes placed on the skin surface. The electrical signal is very small (0.0001 to 0.003). These signals are within frequency range of 0.05 to 100Hz.In ECG signal processing, instrumentation amplifier plays major role since signal generated by human body are very low in amplitude. High gain must be obtained with high common-mode rejection ratio (CMRR).

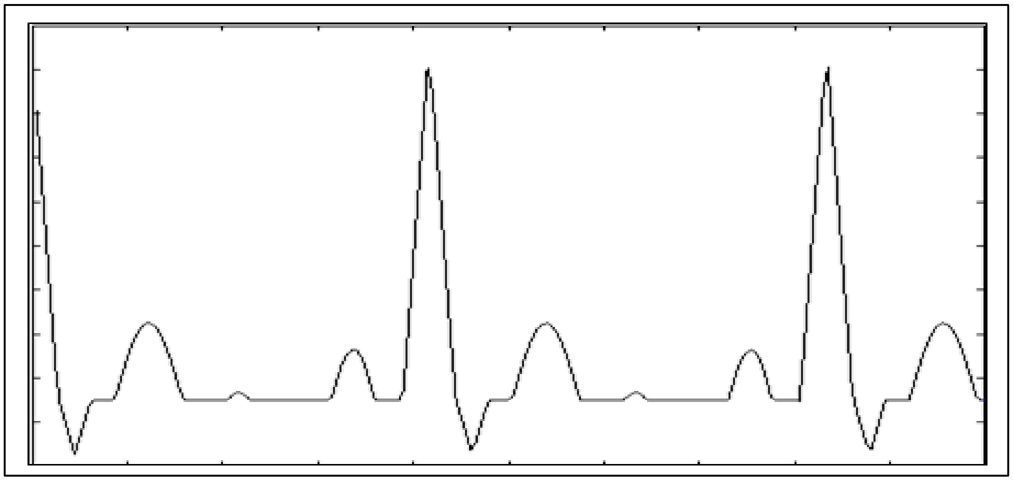

Fig. 1.1: Typical ECG signal of normal heart rate

MATLAB was used to test and adjust a digital filter [4] , in order to obtain a good QRS complex noise free, which represents the ventricular depolarization in the ECGs, i.e., it shows the electrical impulse of the heart as it passes through the ventricles. The shape of ECG conveys very important hidden information in its structure. The amplitude and duration of each wave in ECG signals are often used for the manual analysis. Thus, the volume of the data being enormous and the manual analysis is tedious and very time-consuming task. Naturally, the possibility for the doctors of missing vital information is high. Therefore, medical diagnostics can be performed using computer-based analysis and classification techniques [5] Besides the fact that the ECG record can be noisy, the main problem in computer-based classification is the wide variety in the shape of beats belonging to the same class and beats of similar shape belonging to different classes [6-7]. Computer-based diagnosis algorithms generally have three steps, namely: EGC signal detection, extraction of useful features from the signal and classification.

The Artificial Neural Network (ANN) is a tool, used to model human cognition or neural biology using mathematical operations. ANN has certain performance characteristics in common with biological neural networks. A neural network is characterized by its pattern of connections between the neurons (called its architecture), its algorithm of determining the weights on the connections (called its training, or learning algorithm), and its activation function [8].

II. CLASSIFICATION APPROACH

A. Data Collection

MIT–BIH arrhythmia database consists of 48 ECG signal records. Each record comprises several files, the signals, the annotations and specifications of signal attributes. Each record of the MIT–BIH database is 30 minutes selected from 24 hours. The sampling frequency of the ECG signals in this database is 360Hz, and records are annotated throughout; by this we mean that each beat is described by a label called an annotation. Typically an annotation file for an MIT– BIH record contains about 2000 beat annotations, and smaller numbers of rhythm and signal quality annotations. In previous studies, 10-12 records from this database were used and 500 samples were selected from each record.

B. Flow of the complete classification

Figure 2.1 shows typical flow chart of the complete classification of ECG signals.

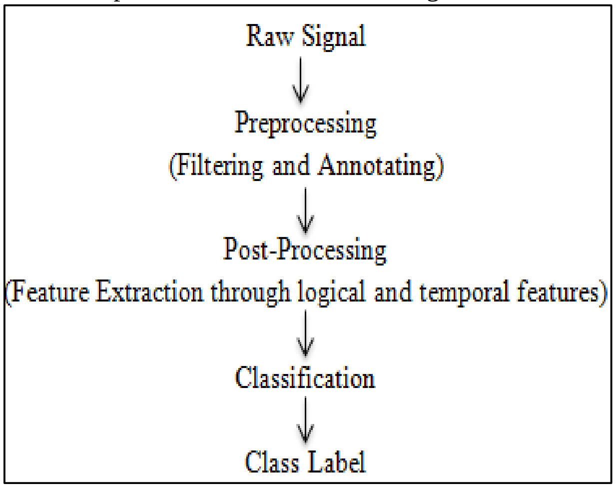

Fig. 2.1: Flowchart for complete classification of ECG signals

Before classification, the database signals need to be pre-processed for observation and training. Pre-processing includes low pass filtering the signal to remove 60Hz power noise. The low pass filtered signal has a base line shift and would not represent the true amplitude. Hence high pass filtering is used to make the signal shift back to the dc base line level to obtain the amplitude information from signal.

The annotations of each heart beat for each signal are read from the downloadable MATLAB package from the online database. A premade algorithm is applied for detecting the various parts of signal to complete the annotations. ANFIS is used to classify each heartbeat of the signal into normal and abnormal beats. It is a binary classifier and hence has one output to the network. The annotations of each signal are allowed as an input to the classifier to be trained. These inputs are different characteristics (usually temporal intervals and amplitudes of various parts) of the signal. The inputs are then passed through an ANFIS for classification.

A MATLAB toolbox, called the Physionet Waveform Database (WFDB) toolbox, is specially used for analysing the ECG signals. It can be downloaded from the Physionet website. This toolbox consists of functions that annotate the signal and specialized algorithms for detecting various points of an ECG signal. One of the annotation functions allow for classifying each heartbeat as normal or abnormal as determined by two cardiologists. Several records could not be simulated under the toolbox. Table 2.1 shows the MIT-BIH records and the number of corresponding heartbeat types. Another function that uses an algorithm for detecting the QRS complex onset and offset of an ECG signal is called the Pan-Tompkins algorithm. The same function detects the P wave onset and offset as well as the T wave onset and offset [9].

Figure 2.2 shows eight input temporal features of an ECG signal. Figure 2.3 shows the amplitudes of the P, Q, R, S, and T waves.

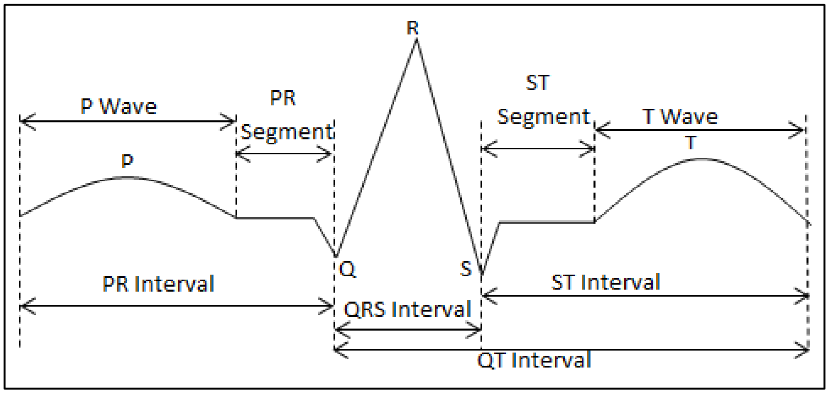

Fig. 2.2: Several temporal features of an ECG Signal

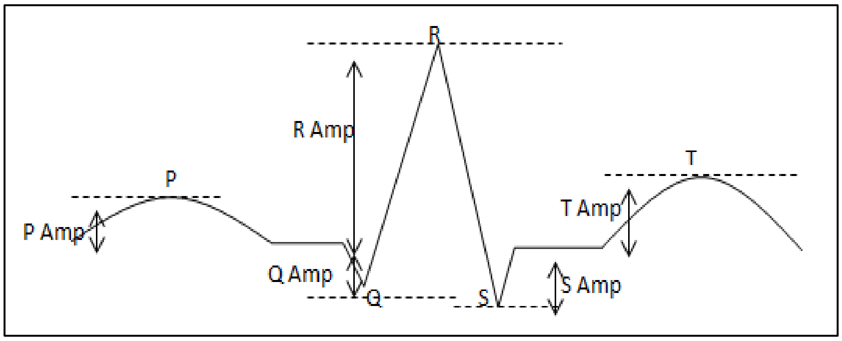

Fig. 2.3: Amplitude input features

The 7 input features that vary as per the heart rate are R amplitude (mV), RRp interval (sec), RRs interval (sec), RRs/RRp, PR interval (m sec), QRS interval (m sec) and ST interval (m sec).

Table 2.1: MIT-BIH records and corresponding heartbeat types: 'N' being normal, 'V' being PVC, 'A' being APC, 'L' being LBBB, 'R' being RBBB, and 'P' being paced beats

Record	N	V	A	L	R	P
100	2239	1	33	0	0	0
101	1860	0	3	0	0	0
102	99	4	0	0	0	2028
103	2082	0	2	0	0	0
104	163	2	0	0	0	1380
105	2526	41	0	0	0	0
106	1507	520	0	0	0	0
107	0	9	0	0	0	2078

Since the ANFIS is a binary classifier, and hence one output, six ANFIS' were trained, validated, and tested. A threshold was used at the output of each ANFIS to classify a heartbeat as either a specific heartbeat (denoted as '1') or a heartbeat without the specific heartbeat (denoted as '0'). Let N represent normal heartbeats and represent all the heartbeats without the normal heartbeats, V represent PVC heartbeats and represent all heartbeats without PVC heartbeats, A represent APC heartbeats and represent all the heartbeats without the APC heartbeats, L represent LBBB heartbeats and represent all the heartbeats without the LBBB heartbeats, R represent RBBB heartbeats and represent all the heartbeats without the RBBB heartbeats, P represent paced heartbeats and represent all heartbeats without the paced heartbeats. The method of classifying is illustrated in Figure 2.4.

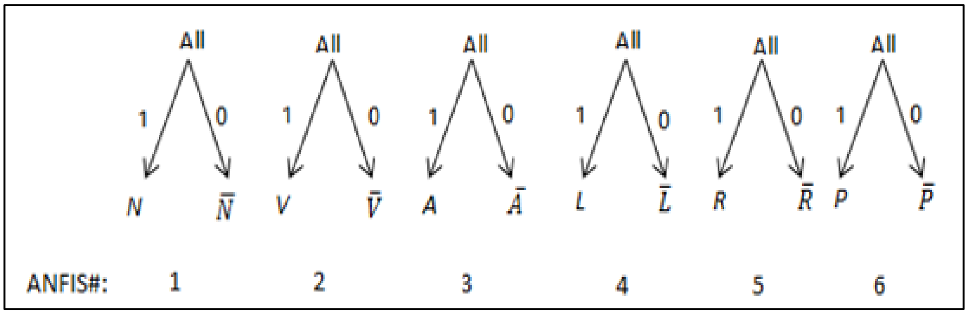

Fig. 2.4: Method of classification with ANFIS

A threshold after each ANFIS determines if the heartbeat is the specific heartbeat denoted as a target of '1' or all heartbeats without the specific heartbeat denoted as a target of '0'. Let f and fth represent the output of an ANFIS and the value of the output after a threshold respectively, either '0' or '1'. The threshold is as follows: If f < 0.5, then fth= 0; Else fth = 1.

Figure 2.4 shows each ANFIS structure. This diagram represents internal functionality of the system. The method used here is ANFIS under subtractive clustering. Each input feature is passed through k clusters for the case of subtractive clustering. 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 k.n nodes. For the second, third, and fourth layers, the number of nodes was calculated to be k nodes. It is necessary to annotate the signal to extract the features. The MIT-BIH website holds multiple tools for analyzing and annotating various heart signals. This ECG classification is based off the Arrhythmia Database [9].

First, a DC drift and normalization is performed. The signal is subtracted by the overall mean of the signal and then normalized at each sample. This straightens out the signal along the zero volt base-line. A digital BPF consisting of a cascade of a LPF and a HPF with a pass band from 5-15 Hz is then applied to the signal. This reduces the influence of noise, 60 Hz interference, base-line wander, and T-wave interference. A derivative filter is then applied to provide the QRS complex slope information. A squaring function is applied to make all data points positive and does nonlinear amplification of the output of the derivative selecting the higher frequencies (ECG frequencies). The squaring is done by squaring the signal point by point. Moving-window integration is performed to obtain waveform feature information in addition to the slope of the R wave. Let T represent the sampling period and N represent the number of samples in the width of the integration window. For our case of 360 samples per second, the window is 30 samples wide. A lower set of thresholds is then placed based on the band pass filtered ECG signal. An upper set of thresholds is placed based on the moving-window integration. The higher of the two thresholds in each of the two sets is used for the first analysis of the signal. The lower threshold is used if no QRS is detected in a certain time interval so that a search-back technique is necessary to look back in time for the QRS complex. Thresholds of a signal and noise peak detect the QRS complex. They are expressed in equations (12-20) referenced in the paper [10]. Two RR intervals averages are calculated and maintained in [10]. The reason for maintaining the RR intervals is to be able to adapt to quickly changing or irregular heart rates. When an RR interval is less than 360 ms, a judgment is made to determine whether a QRS complex or a T wave is identified. If the maximal slope that occurs during this waveform is less than half of the QRS waveform that preceded it, it is identified to be a T wave; otherwise, it is a QRS complex.

III. RESULTS

Since the ANFIS classifies between only two classes, six ANFIS were created for classification method based on Figure2.4. The heartbeat types are normal, PVC, APC, LBBB, RBBB, and paced. The records chosen to train, validate and test were the second modified limb leads (MLII) randomly selected for each specific heartbeat. The heartbeat types extracted from the records were normal, PVC, APC, LBBB, RBBB, and paced. Each heartbeat type was divided into 55% training, 10% checking, and 35% testing data. Starting with the first ANFIS from Figure 2.4, a classification was made between normal heartbeats and all six heartbeat types without the specific normal heartbeats denoted as$\bar{N}$. By setting the radius r_a to 0.45 for subtractive clustering three clusters were generated for each input.

Table 7 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 $\bar{N}, \bar{V}, \bar{A}, \bar{L}, \bar{R}$ and $\bar{P}$ in Figure 2.4.

Table 3.1: claasification 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

Results are obtained based on the performance measurement parameters to evaluate the effectiveness of the classifier. These parameters include accuracy, sensitivity and specificity. All three measurements include heartbeats that define true positive, true negative, false positive, and false negative. Let TP, TN, FP and FN represent true positive, true negative, false positive and false negative heartbeat classified respectively. Then the measurement parameters can be defined as

$$\text{Accuracy (\%)} = \frac{TP+TN}{N} \text{ x } 100\ \%,$$

$$\text{Sensitivity (\%)} = \frac{TP}{TP+FN} \text{ x } 100\% \text{ and}$$

Specificity (%) = $\frac{TN}{TN+FP}$ x 100% [11]. Measurement parameters are found to be according to the table 3.2.

Table 3.2: Measurement parameters for ANFIS under subtractive clustering

Accuracy (%)	Sensitivity (%)	Specificity (%)
98.1	94.22	99.31

IV. CONCLUSION AND FUTURE SCOPE

The recordings were collected from MIT-BIH database for training and testing our neural network based classifier and it was found that ANFIS based classifier is giving the efficient and improved results by increasing the convergence speed as compared to gradient descent ANN. The ANFIS had the advantage of integrating the best features of fuzzy systems and neural networks in ECG classification. ANFIS under subtractive clustering has a higher performance in terms of average accuracy, average sensitivity, and average specificity. The ANFIS under subtractive clustering converged faster than the gradient descent ANN. The Accuracy, sensitivity and specificity of the method used in classification i.e. ANFIS classifier under subtractive clustering is found to be 98.1, 94.22 and 99.31 respectively. ANFIS has strong computational complexity restrictions. One way to reduce the complexity is integrating “don’t care” values in rules. This means an elimination of a connection is done between the fuzzification layer and the rule layer.

Future work on improving the ANFIS classifier could be done by analysing the rules. Having an advantage of tuning rules over black box systems such as ANNs, the user could measure the degree of fulfilment for several rules. This could bring about a more effective FIS for evaluating test data. Another possible future work is expanding the range of input features.

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