International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 06, Issue 05, May 2017, ISSN: 2278 -7798

Classification of ECG Beats based on Fuzzy Inference System

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***Abstract*–ECG based diagnosis of heart condition and defects play a major role in medical field. Most of the ECG diagnosis uses the shape and features of ECG signal to determine the presence of one or more types of heart problems. This paper focus on classification of heart beats based on Fuzzy Inference System. Different ECG waves from standard database are applied to the FIS made for classification and each beat is classified as either normal beat or an arrhythmic beat based on rule base of Mamdani type of Fuzzy Inference system. The ECG waves are taken from standard database MIT-BIH available on physionet website. Total 5 datasets are taken for test and the results are compared for sensitivity and accuracy.**

***Keywords*–ECG based diagnosis, FIS for ECG based diagnosis, fuzzy logic application in ECG diagnosis**

I. Introduction

The heart in human body serves as a pump to drive blood and thereby providing necessary energy and oxygen to different parts of body through blood. The heart pumps blood into human body continuously by following a rhythmic activity called “Cardiac Cycle”. One complete cardiac cycle is responsible for pumping a specific amount of blood into arteries. The cardiac cycle is repeated continuously and we get a gross blood flow pumped into different parts of the body.

Electrical activities of heart are described by a signal called Electrocardiogram (ECG). It is the waveform of the cyclic voltage generated for depolarization and repolarization of heart muscles. ECG contains various waves and durations which are related to different parts of a cardiac cycle. Various waves contained in ECG are as shown in figure 1 below. ECG contains five waves viz. R wave, P wave, Q wave, S wave and T wave, along with durations viz. QRS complex, PR interval, ST interval, PR segment, RR interval and QT interval which has diagnostic significance in medical field.

***Manuscript received May 2017*.**
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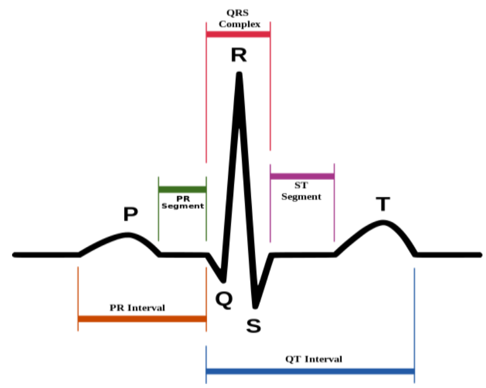

Figure 1: Normal ECG wave

If any of the wave is not present or the shape of ECG segments and their duration plus the peak values are different compared to the ideal values, the condition is said to be arrhythmia.

The method suggested here process an ECG signal in three different steps: (1) ECG preprocessing (2) Applying various algorithms for feature extraction of ECG. (3) Fuzzy logic based Classification system for the given ECG signal. The ECG data are taken from MIT BIH database [11]. The database of MIT BIH is used for taking sample ECG data for normal as well as arrhythmic ECG beats. The database contains the annotations for comparison of feature extraction purpose.The test results for different algorithms are compared for Sensitivity (Se) Positive Prediction accuracy (+P).

II.ECG PRE-PROCESSING

DWT based noise removal technique suggested by hanine*et al.*[2] in his paper is used here for BW and PLI removal from the ECG wave. DWT is a popular technique for timescale analysis and thus the noise removal from a signal with time varying morphology like ECG is done effectively DWT.

(A) Baseline Wander removal:

The given ECG signal is first processed by DWT based high pass filter. The mother wavelet used here is daubechies ‘db45’ wavelet. The level of decomposition is up to level 8 and the signal is reconstructed after removal of approximate coefficients.

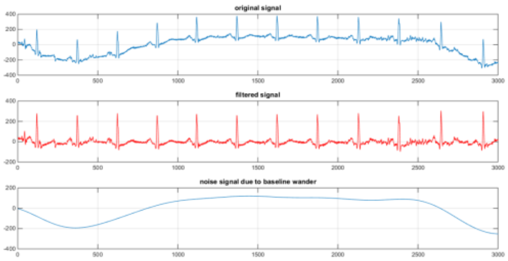

Figure 2: BW removal

The highest frequency component in ECG is of the order of 130 Hz. For removal of baseline wandering, the signal is decomposed by daubechies wavelet 'db45' up to level 8 which gives set of approximate and detailed coefficients corresponding to frequency as shown in table 1 below.

Table 1: Range of frequency for wavelet coefficients

DWT coefficient	**Range of frequency**
d1	130 Hz to 65 Hz
d2	65 Hz to 32.5 Hz
d3	32.5 Hz to 16.25 Hz
d4	16.25 Hz to 8.125 Hz
d5	8.125Hz to 4.062Hz
d6	4.062 Hz to 2.031 Hz
d7	2.031 Hz to 1.015 Hz
d8	1.015 Hz to 0.507 Hz
c8	0 Hz to 0.507 Hz

BW can be considered as low frequency noise of less than 1 Hz. So from above table if approximate coefficients are removed and the signal is reconstructed from detailed coefficients only, it will be free from low frequency noise mainly due to BW. Figure 2 shows the ECG signal filtered by DWT and the noise removed by the method suggested here.

(B) Powerline Interference removal:

The effect of power line interference (PLI) is addition of 50 hz or 60 hz noise component to the original ECG signal. To remove PLI from the ECG signal, wavelet decomposition is used. In this case, the outputs of both the filters (high and low pass) are down sampled and decomposed in next level. This will result in wavelet coefficients for corresponding frequencies as shown in tables 2 and 3 below.

Table 2 Wavelet Coefficients for PLI removal

Level	**Coefficients**							
1	C1				D1			
2	C20		D21		D22		D23	
3	C30	D31	D32	D33	D34	D35	D36	D37

Table 3 Coefficients and corresponding frequency

DWT coefficient	**Range of frequency**
C30	0 to 16.25 Hz
D31	16.25 to 32.5 Hz
D32	32.5 to 48.75 Hz
D33	48.75 Hz to 65 Hz
D34	65 Hz to 81.25 Hz
D35	81.25 Hz to 97.5 Hz
D36	97.5 Hz to 113.75 Hz
D37	113.75 Hz to 130 Hz

As it can be seen from table 3, if the signal is reconstructed discarding set of coefficient D33 corresponding to 48.75 to 65 Hz, will remove the component of 50 Hz and 60 Hz from the signal. Figure.3 shows the result of powerline interference removal from the ECG signal.

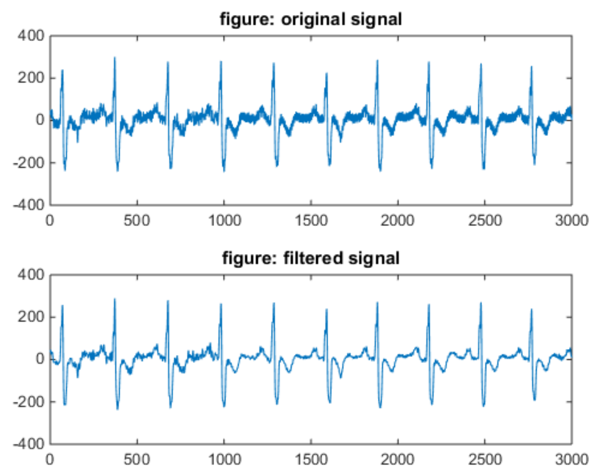

Figure 3 Power line interference removal

III. ECG FEATURE EXTRACTION TECHNIQUES

After removing noise from the ECG signal, next step is detection of ECG features in the signal. As R peak is the highest peak in ECG wave, it is first determined in feature extraction. Based on R peak instances one can easily locate the other peaks and valleys in the signal. Bayasi et.al.[1] in her work suggested a technique of R peak detection based on Pan and Tompkin's algorithm. The algorithm is slightly modified in their work to reduce the memory requirement in the processor they suggested. The algorithm gives good results even for the ECG affected by arrhythmia.

(a) R peak detection using Pan and Tompkin's algorithm

Pan and Tompkin's (PAT) algorithm is a popular technique for detection of QRS complex in ECG. It uses the amplitude thresholding technique and high slope detection for locating R peak accurately in ECG. The algorithm divides into four steps.

First the differentiation of the sampled version of the ECG signal will detect the high slopes of R wave. Differentiation of signal is done by taking difference between current sample and previous sample. After differentiation, next step is point to point square of the ECG samples. This will convert negative slope values to positive and enhance the difference between low and high slope values. Further the signal is processed by mean filtering using a small window so as to collect the peak points of the squared signal. Finally the signal peak values are collected using amplitude thresholding [3]. The algorithm will result in a signal with all the R peak and their instance in the given signal.

(b) QRS complex detection

After detection of R peak, the immediate valley point in forward and backward direction will decide the S and Q valley points respectively.

Once Q and S valleys are available, the QRS on time and QRS off time are determined by the points where there is a sudden change in slope of the signal.

(c) P and T wave detection

The P wave and T wave has characteristics of relatively low slope compared to R wave and relative amplitude of signal is also low.

So to determine the T wave and P wave the process of search based on amplitude thresholding is applied. The T wave is searched in the window of length 2/3 of previous RR interval is used and for P wave a window of length 1/3 of previous RR interval is used. T wave window starts at QRS off time point and P wave window starts at QRS on time point in the signal.

The result of feature extraction is as shown in figure below:

Figure 4 QRS detection results

IV. FIS FOR ECG BEAT CLASSIFICATION

The normal rhythm of ECG is defined as presence of all the waves with specific amplitude and durations between the waves are also standard. The values of various ECG features are not described by thin, sharp or strict boundaries. Rather they are separated based on linguistic rules and have gray area near minimum and maximum values. In this section a classification system which classifies the given signal beats as normal beat or arrhythmic beat based on fuzzy inference system is discussed.

The fuzzy inference system is structured in GUI given in MATLAB for fuzzy inference system. The system is based on Mamdani type of fuzzy inference system. The data for normal and abnormal ECG beats are taken from the MIT BIH database available online at physionetwebsite[2]

The proposed structure of FIS is as shown in figure 5 below.

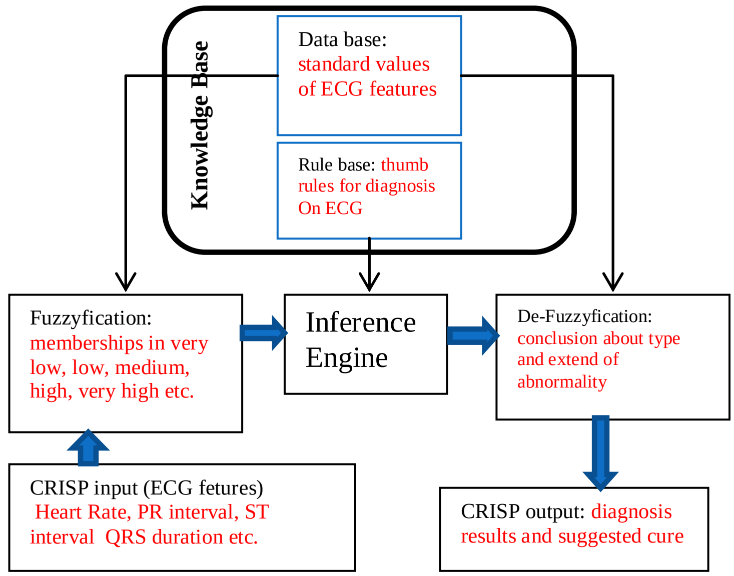

Figure 5: structure of Expert system for ECG diagnosis

MATLAB is a powerful tool to build fuzzy inference system for customized application and test the system using sample inputs. The GUI tool of MATLAB is equipped with flexible and user friendly support for testing the algorithm based on fuzzy inference system. The GUI includes the support for all the steps of fuzzy decision making system by providing a graphical structure in which user can use the different membership functions, if then rules and defuzzyfication blocks as per application requirements. User can also implement the customized membership functions and make changes to fuzzyfication block according to the input range and linguistic terms.

The structure of FIS in this application is implemented on MATLAB FIS editor.It utilizes the standard values and the thumb rules to classify ECG signal as normal and arrhythmic. The classification is based on features of ECG like:RR duration (ms) or inverse of RR that is heart rate (bpm), QRS width (ms), PQ duration (ms), QT duration (ms), P wave height (mv).

The fuzzyfication of all the inputs listed above is done by various fuzzy sets according to standard values of the ECG features which describe them as either normal or abnormal beats. The overall structure of the FIS system is as shown in figure 6 below followed by Rule viewer in figure 7 below.

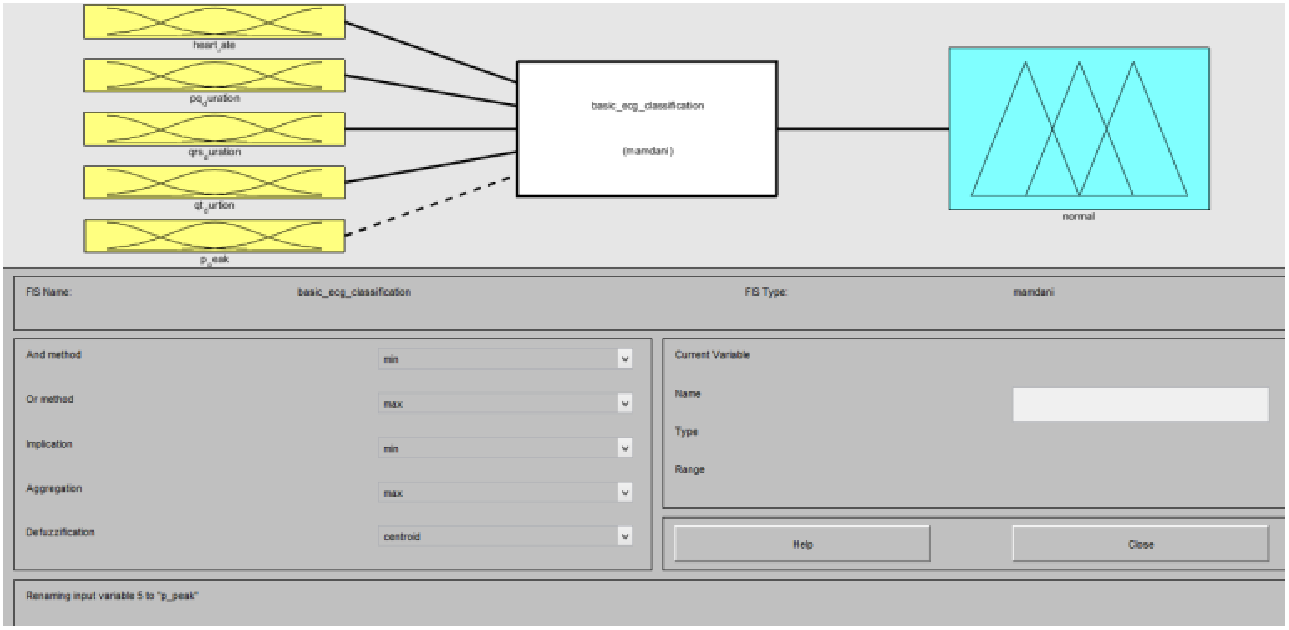

Figure 6 FIS structure for ECG classification

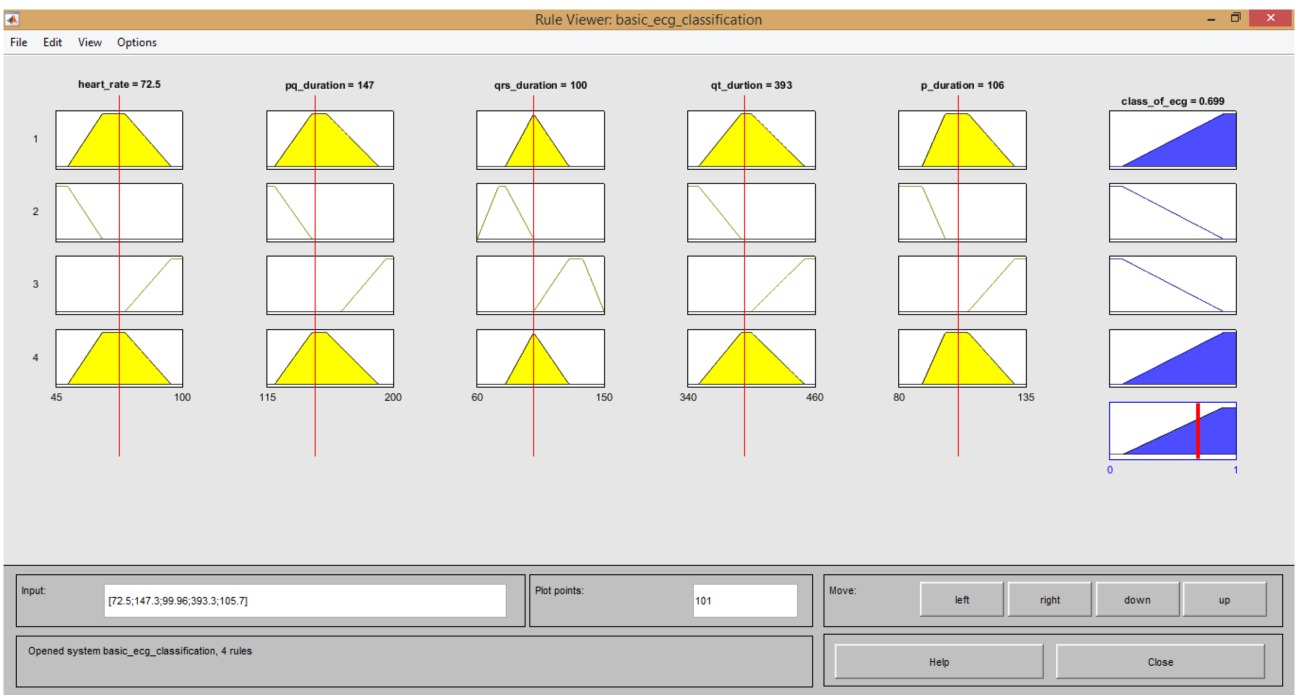

Figure 7Rule viewer of ECG classifier

IV.STANDARD ECG DATA

The MIT BIH is a popular resource of database for ECG analysis. The collection of varieties of ECG datasets in a classified database makes it easier to take the appropriate set for checking various algorithms. In our work we have taken MIT BIH arrhythmia dataset, MIT BIH ST change dataset and MIT BIH noise stress dataset for the purpose of testing our algorithm and the FIS system quality in classification capability.

V. COMPARISON AND RESULTS

The algorithms are tested on ECG records found on physionet.org.

The quality measures for algorithm are taken as Sensitivity (Se), Positive Prediction Accuracy (+P) and Detection Accuracy (DA). Each one can be defined by following equations.

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

Where, TP = number of correctly detected events
FN= number of missed events

Positive Prediction Accuracy
$$+P(\%) = \frac{TP}{TP+FP}\%$$
Where, FP = number of falsely detected events

Detection Accuracy $$DA(\%)= \frac{DP}{T}\%$$

Where DP = number of Detected WPW waves
T = number of Total WPW waves in record

Table 4 and 5 below shows the result of different algorithms applied on some ECG records from MIT BIH. Table 4 shows values of sensitivity (Se) and Table 5 shows result of Positive Prediction accuracy (+P) for various ECG records.

Table 4sensitivity %

RECORD NUMBER	SAMPLING FREQUENCY	NUMBER OF BEATS TESTED	SENSITIVITY OF CLASSIFICATION %
303M	360 HZ	81	88.8
118E00M	360 HZ	69	99
100M	360 HZ	70	92.86
101M	360 HZ	67	95.52
115M	360 HZ	59	80.1

TABLE 5positive prediction accuracy %

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VI CONCLUSION

From the results analysis it can be concluded that the feature extraction method and the fuzzy logic based analysis of the ECG suggested here are capable of generating good results for classification of ECG beats.

The R peak detection by PAT algorithm is an accurate tool showing almost complete agreement with the visual result. The detection of rest of the waves are then becomes easy task referenced to R peak.

The FIS made for the classification of arrhythmic beat and normal beat shows good results. The rule base made for the said classification plays an important role as far as the accuracy is concerned. The system can be used as a part of patient monitoring system to generate alarms when arrhythmia occurs in the ECG of the subject.

VI FUTURE SCOPE

The system can be improved by additions of more number of modules which detect the common abnormalities in the heart, like blockages, Coronary disease, fibrillation and different types of arrhythmia.

The proposed work under this research activity is concerned with detection of heart abnormalities. In this work the ECG signal is processed for diagnosis purpose for a regular heart patient out of hospital environment. The detection suggested is limited to some of the abnormal rhythm which may lead to medically critical conditions. However, there are some more features that can be added to improve performance of the overall system.

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