International Journal of Science, Engineering and Technology Research (IJSETR)
Volume 06, Issue 04, April 2017, ISSN: 2278 -7798

Fuzzy Inference System based Detection of Wolff Parkinson's White Syndrome

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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. In this paper a fuzzy logic based expert system is suggested for detection of a type of heart blockage known as Wolff Parkinson's White (WPW) Syndrome. Fuzzy logic is an expert tool for decision making. A Fuzzy Inference System is made for classification of ECG signal using if then rules. The database for ECG is taken from physiobank. The suggested system is tested for 10 different signals with and without WPW presence. The system gives almost complete agreement with the visual results.**

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

I. Introduction

WPW is a syndrome related to ventricular block and disturbed pacing rhythm due to blockage of electrical path between SA node and AV node in heart. It is a type of disorder in activation sequence of ECG wave originating in the SA node of natural pacemaker of heart

The figure below shows an ideal ECG wave with all its components present and in a predefined sequence.

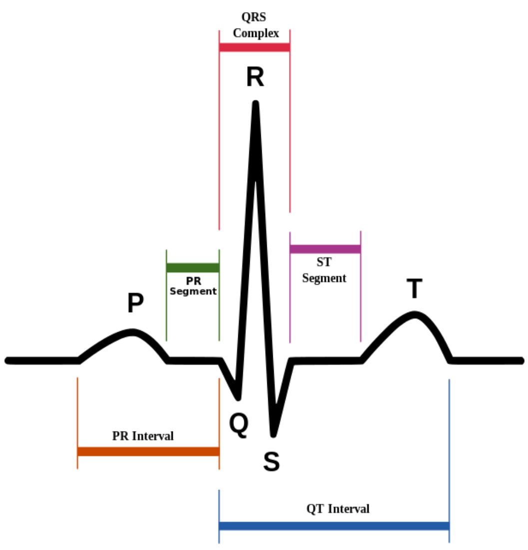

Figure 1: Normal ECG wave

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. Out of number of reasons for arrhythmia, some are under the class of arrhythmia due to a blockage in natural pacemaker of heart.

There are three basic types of heart blockage namely first degree AV block, second degree AV block and third degree AV block. All above are related to disturbed rhythm between SA node and AV node. In addition, there are some blockages related to disturbed activation of lower chambers of heart known as ventricular blockages. These include Right Bundle Branch Block, Left Bundle Branch Block and the condition of Wolff Parkinson's White Syndrome.

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 physionet website [11]. The ECG datasets of PTBDB from physionet website are used as row ECG data which are available on physionet website. The test results for different algorithms are compared for Sensitivity (Se) Positive Prediction accuracy (+P).

II.ECG PRE-PROCESSING

In this paper, DWT based noise removal technique suggested by hanine*et al.*[2] in his paper is used for BW and PLI elimination from the ECG wave.

(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.

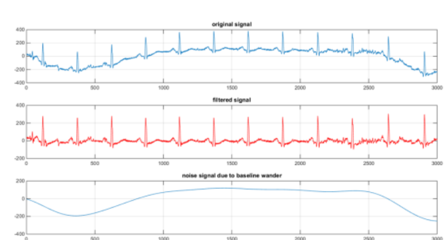

Figure 2: BW removal

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 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

<table>
<tr><th>Level</th><th colspan="8">Coefficients</th></tr>
<tr><td>1</td><td colspan="4">C1</td><td colspan="4">D1</td></tr>
<tr><td>2</td><td colspan="2">C20</td><td colspan="2">D21</td><td colspan="2">D22</td><td colspan="2">D23</td></tr>
<tr><td>3</td><td>C30</td><td>D31</td><td>D32</td><td>D33</td><td>D34</td><td>D35</td><td>D36</td><td>D37</td></tr>
</table>

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.

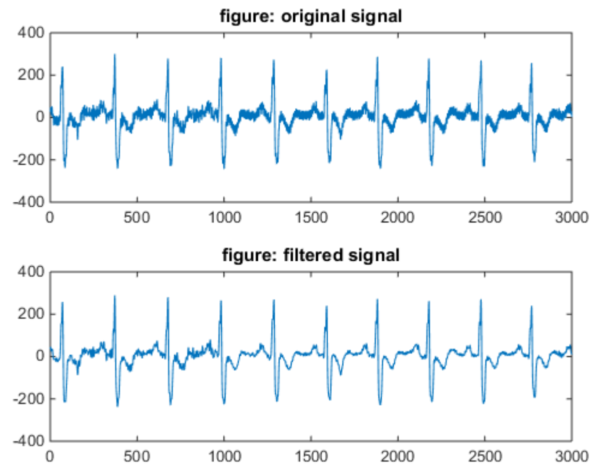

Figure 3 Power line interference removal

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:

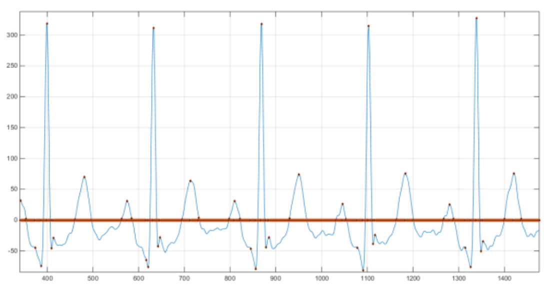

Figure 4 QRS detection results

IV. FIS FOR WPW SYNDROME

In recent years, the number and variety of applications of fuzzy logic have increased significantly. The applications range from consumer products such as cameras, camcorders, washing machines, and microwave ovens to industrial process control, medical instrumentation, decision-support systems, and portfolio selection. It is a theory which relates to classes of objects with unsharp boundaries in which membership is a matter of degree.

The ECG analysis is a problem of classification based on one or more features extracted from ECG. The values of various ECG features, viz. RR interval. ST interval and values, PR interval, QT interval, QRS width and many more, are directly relate to heart functioning. The abnormal heart functioning can be detected based on the ECG features and their variations.

The proposed structure of FIS for heart abnormality detection, or classification, can be as given in figure 5 below.

The WPW is a condition described by following changes in ECG pattern:

1. Short PR interval
2. Prolonged QRS interval
3. The presence of the delta wave in the QRS complex.

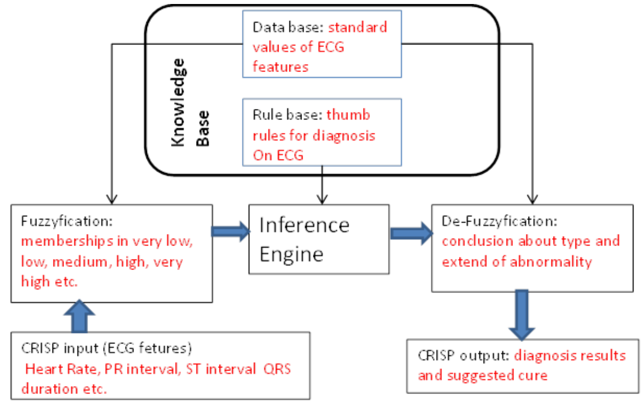

Figure 5 FIS for ecg analysis

4. Tachycardia.

The inputs are fuzzyfied by bell shaped membership functions based on standard range of values of all the intervals stated above. The input to the system are PR interval, QRS width, the area of the delta wave and the heart rate of the signal.

The following figure 6 shows the FIS proposed for WPW syndrome implemented on MATLAB GUI for FIS.

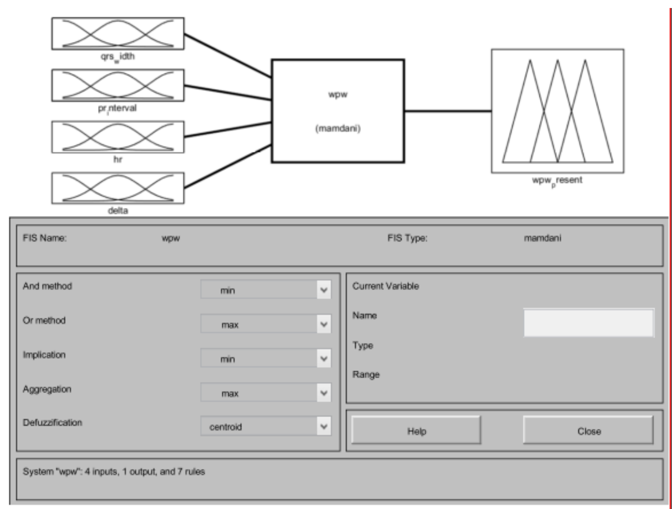

Figure 6 FIS for WPW on MATLAB GUI

The rule base used for classification of WPW waves and non WPW waves is based on following linguistic rules. The dependency of WPW on PR interval and QRS interval is included using if then rules in rule base. The delta wave area is combined for presence or absence of delta. The heart rate is used to measure tachycardia conditions.

The output is mapped between 0 to 1 depending on input conditions and the level of 0.5 indicates boundary for presence of WPW. Means if the output is more than 0.5, the WPW is present and if below 0.5, the WPW is absent.

Following figure shows the rule base used in the FIS for decision making.

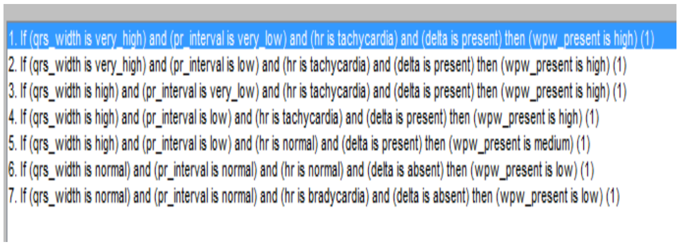

Figure 7 rule base for WPW classification

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IV.STANDARD ECG DATA

The ECG data are taken from MIT BIH database available on the website physionet.org. The dataset of PTBdiagnostic ECG database are used for testing various algorithms. The results are compared for sensitivity and accuracy for more than 100 beats of various datasets. The results obtained are compared with visual results on graph.

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

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

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

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

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

Table 5.1 shows the result of different algorithms applied on some ECG records from MIT BIH. Table 5.1(a) shows values of sensitivity (Se). Table 5.1(b) shows result of Positive Prediction accuracy (+P) and table 5.1(c) shows the result of Detection accuracy (DA) for various ECG records.

Table 4Results %

Record (PTBDB database) 100 beats	Detection accuracy	Sensitivity	Positive prediction accuracy
Patient002/s0015	93	98	99
Patient010/s0036	94	96	99
Patient013/s0045	86	93	97
Patient014/s0046	95	99	98
Patient019/s0058	91	90	96
Average of all records	91.8	95.2	97.8

VI CONCLUSION

From the results obtained above, it can be concluded that the FIS is a powerful tool for classification of ECG waves based on its features. The ability of fuzzy logic to analyze the linguistic values based on its closeness to the ideal value makes it a suitable tool for such applications. The ECG based diagnosis depends highly on decision making which often has linguist terms to be interpreted based on experience. Hence the fuzzy logic based classifications give good result in application for ECG analysis.

VI FUTURE SCOPE

Further this system can be extended to applications in different heart disease like myocardial infarction, ischemia and other defects in heart cycle. Most of the applications requires classification based on linguistic terms and hence it is suitable to apply fuzzy logic to classify heart beats. Moreover these logic tools can be used to develop a local or remote patient monitoring systems.

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