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A Study of ECG Signal Classification using Fuzzy Logic Control

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Abstract: ***I in ECG signals, there are significant variations of waveforms in both normal and abnormal beats. In this study, we have three stages preprocessing, feature extraction (using wavelet transform) and classification (using fuzzy logic control). Signal processing techniques to detect abnormalities in ECG signals were investigated using the MIT-BIH Arrhythmia Database. The aim of developing methodology is to distinguish between normal beats and abnormal beats in an ECG signal. ECG signals were first decomposed using wavelet transform. The feature vectors were then extracted from these decomposed signals as normalized energy and entropy using wavelet analysis. To improve the classification of the feature vectors of normal and abnormal beat. The combination of wavelet decomposition and the classification using feature vectors of the beats in ECG signals separate abnormal beats from normal beats using fuzzy logic control. Evaluating the proposed algorithm, resulting in sensitivity 100% for all except AF 90%, specificity 100% and total classification accuracy 97%.***

Keywords: fuzzy logic control, wavelet transform, energy and entropy

1. Introduction

The ECG is a bioelectric signal, which records the heart's electrical activity versus time; therefore it is an important diagnostic tool for assessing heart function. The electrical current due to the depolarization of the Sinus Atria (SA) node stimulates the surrounding myocardium and spreads into the heart tissues. A small proportion of the electrical current flow to the body surface .By applying electrodes on the skin at the selected points, the electrical potential generated by this current can be recorded as an ECG signal. The interpretation of the ECG signal is an application of pattern recognition. The purpose of pattern recognition is to automatically categories a system into one of a number of different classes. An experienced cardiologist can easily diagnose various heart diseases just by looking at the ECG waveforms printout. In some specific cases, sophisticated ECG analyzers achieve a higher degree of accuracy than that of cardiologist, but at present there remains a group of ECG waveforms that are too difficult to identify by computers [1].

2. Methodology

This study has three stages, preprocessing, feature extraction and classification.

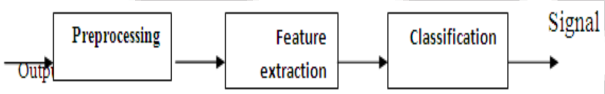

Figure 1: System design stages

2.1 Pre-processing

Digital signal processing (DSP) technology and its advancements have dramatically impacted our modern society everywhere. Without DSP, we would not have digital/Internet audio or video; digital recording; CD, DVD, and MP3 players; digital cameras; digital and cellular telephones; digital satellite and TV; or wire and wireless networks. Medical instruments would be less efficient or unable to provide useful information for precise diagnoses if there were no digital electrocardiography (ECG) analyzers or digital x-rays and medical image systems [2].

2.2 The common sources of ECG noise

- Power line interference.
- Muscle contraction noise.
- Electrode contact noise.
- Patient movement.
- Baseline wondering and ECG amplitude due to respiration
- Instrumentation noise
- Electrosurgical noise. and other less significant noise source

2.3 Filters

To extract non-noise signal from ECG data coming from a variety of sources, Filters suitable for that task. A filter alters or removes unwanted components from signals. Depending on the frequency range that the filters either pass or attenuate, filters can be classified into;

- Low-pass filter which passes low frequencies but attenuates high frequencies
- High-pass filter which passes high frequencies but attenuates low frequencies
- Band pass filter which passes a certain band of frequencies
- Band-stop filter which attenuates a certain band of frequencies

2.4 Infinite Impulse Response Filters

Designing an IIR filter usually means that: If we are given the input–output sequence, it is easy to find the transfer function H(z) as the ratio of the z transform of the output to the z transform of the input[3].

$$H(z) = \frac{\sum_{k=0}^{M} b(k) z^{-k}}{\sum_{k=0}^{N} a(k) z^{-k}}; \quad a(0) = 1 \tag{1}$$

2.5 Finite Impulse Response Filters

It has also been known by other names such as the transversal filter, non-recursive filter, moving-average filter, and tapped delay filter [3]. The transfer function of an FIR filter is given by:

$$H(z^{-1}) = b_0 + b(1)z^{-1} + b(2)z^{-2} + \cdots + b(M)z^{-M} \tag{2}$$

2.6 QRS Detection

QRS detection provides the fundamentals for almost all automated ECG analysis algorithms. Due to its characteristic shape (see Fig.2) it serves as the basis for the automated determination of the heart rate, as an entry point for classification schemes of the cardiac cycle, and often it is also used in ECG data compression algorithms[4].

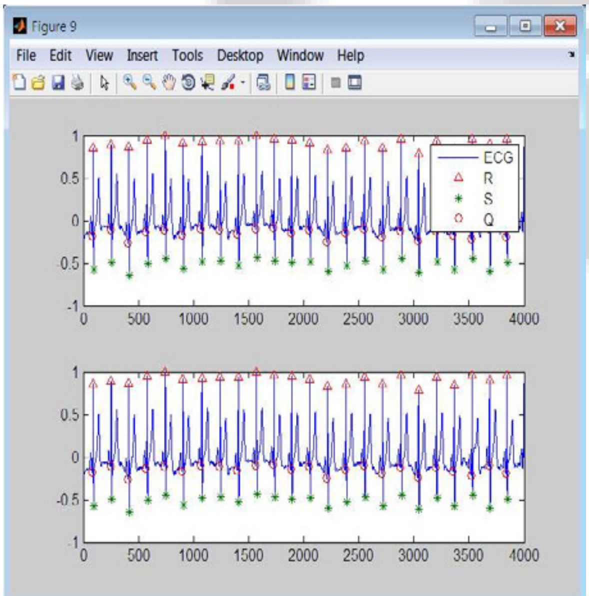

Figure 2: QRS Detection

2.6 ECG feature extraction

After pre-processing, the second stage towards classification is to extract features from the signals. The features, which represent the classification information contained in the signals. The goal of the feature extraction stage is to find the smallest set of features that enables acceptable classification rates to be achieved. Fourier analysis provides frequency-domain information but it does have limitations. One important limitation is that a Fourier coefficient represents a component that lasts for all time. This makes Fourier analysis less suitable for non stationary signals. Wavelet analysis, which provides both time and frequency information, can overcome this limitation. The wavelet transform has a fully scalable window, which allows a more accurate local description and separation of signal characteristics. Another advantage of the wavelet transform is its adaptability. Because there is not just one wavelet, wavelets can be chosen to fit individual applications. Wavelet theory has been applied to the wide range of ECG analyses: feature extraction, noise reduction, data compression, and QRS detection. The features of the signals, such as energy and entropy, were then extracted from these decomposed signals as feature vectors.

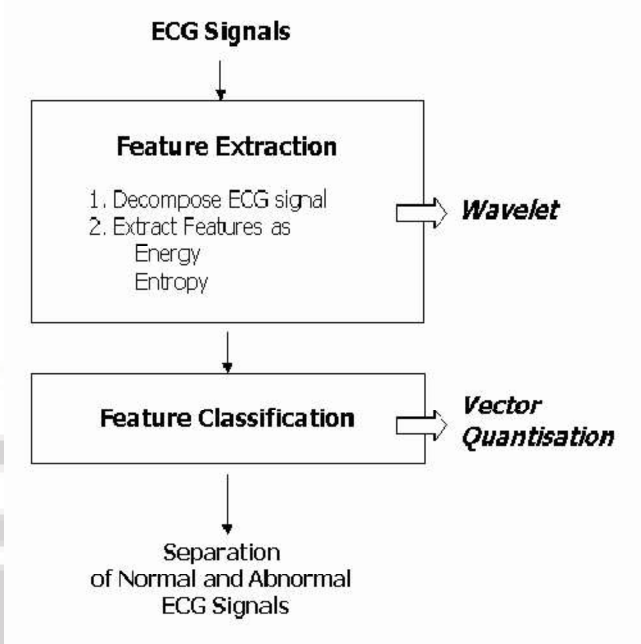

Figure 3: ECG Analysis Flow [5]

2.7 Classification

2.7.1 Fuzzy logic

Fuzzy logic was first introduced in 1965 by Lotfi A. Zadeh with the concept of fuzzy sets as an extension of the classical set theory formed by crisp sets. Later he defined a whole algebra, fuzzy logic, which uses fuzzy sets to compute with words as an extension of the proper operations of classical logic [6].

In most cases a fuzzy logic system is, in fact, a nonlinear mapping of an input data vector into a scalar output where this relation is defined by linguistic expressions which are obviously computed with numbers. Thus a fuzzy logic system is unique in that it is able to handle numerical data and linguistic knowledge. The richness of this logic is that there are many possibilities which lead to many different mappings [7].

Why Use Fuzzy Logic?

Here is a list of general observations about fuzzy logic:

- Fuzzy logic is conceptually easy to understand.
- Fuzzy logic is flexible.
- Fuzzy logic is tolerant of imprecise data.
- Fuzzy logic can model nonlinear functions of arbitrary complexity.
- Fuzzy logic can be built on top of the experience of experts.

- Fuzzy logic can be blended with conventional control techniques.
- Fuzzy systems don't necessarily replace conventional control methods. In many cases fuzzy systems augment them and simplify their implementation.
- Fuzzy logic is based on natural language.

2.7.2 Fuzzy Sets

In classical set theory, participation of an element in a set is either all or nothing. Hence the characteristic function maps an element into either 0 (not in the set) or 1 (in the set) [8]:

2.7.3 Membership Functions

A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept.

Each membership function is defined by a name called a label. For example, an input variable such as in this study "Energy" might have three membership functions labeled as low, mid and high.

The selected membership function types are:

- Triangle: The Triangular membership function name is trimf. It collects more than three points to form a triangle.
- Trapezoidal: The Trapezoidal membership function name is trapmf. It has a flat top and a truncated triangle curve [9].

2.7.4 Linguistic Variables

Linguistic variables are the input or output variables of the system whose values are words or sentences from a natural language, instead of numerical values. A linguistic variable is generally decomposed into a set of linguistic terms, here we have energy and entropy.

2.7.5 Universe of discourse

Elements of a fuzzy set are taken from a Universe of discourse_ or Universe for short. The universe contains all elements that can come into consideration. Even the universe depends on the context [10].

If-Then Rules

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. These if-then rule statements are used to formulate the conditional statements that comprise fuzzy logic.

A single fuzzy if-then rule assumes the form

If x is A then y is B

Where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourse) X and Y, respectively. The if-part of the rule "x is A" is called the antecedent or premise, while the then-part of the rule "y is B" is called the consequent or conclusion.

3. Results

All my signals are from MIT-BIH Arrhythmia Database. The ECG signals in this database have been annotated by cardiologists; they're all at signal.dat" because they have actual information". We can't deal with them easy, after we safe them; we use a software called rdsign212 to open them as a binary matrix under matlab. For each beat the energy and entropy have been identified and abnormal beats have been classified.

Preprocessing Results

After Preprocessing stage we have the results as we see below;

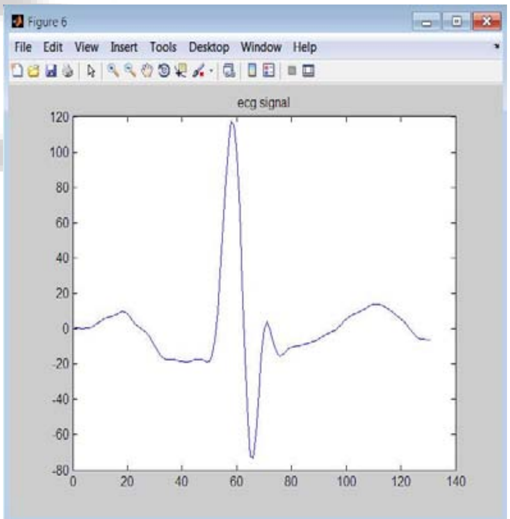

Figure 4: Normal ECG signal after filtering

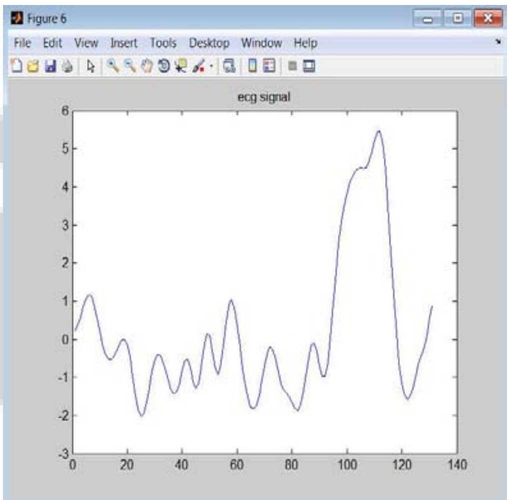

Figure 5: Abnormal ECG signal (Af) after filtering

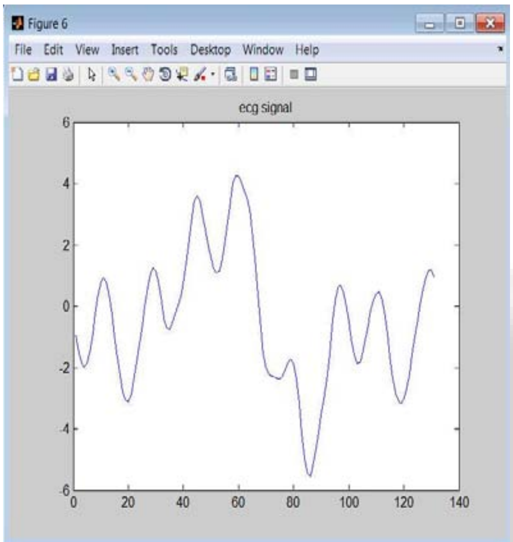

Figure 6: Abnormal ECG signal (Malignant) after filtering

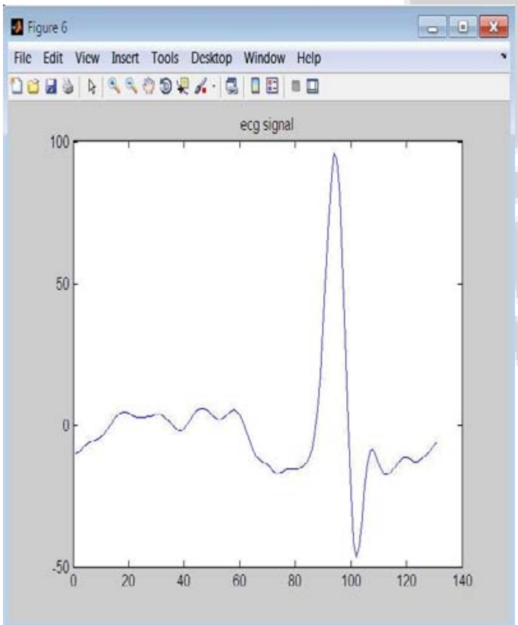

Figure 7: Rarely normal ECG signal energy

The variance was employed as the energy of each beat of decomposed signals.

$$E(j)n \frac{1}{N-1} \sum_{i=1}^{N} (xi - m)^{2} \qquad (3)$$

(j: beat number, N: number of samples in one beat, i: sample number, n: decomposition level, m: sample mean).

The energy was then normalized across the levels, which allows comparison between the decomposed signals in different levels.

The normalized energy is defined as:

$$E(j)_{\,norm\_n} = \frac{E(j)n}{\sqrt{E(j)1^{2} + E(j)2^{2} + \cdots E(j)n^{2}}} \qquad (4)$$

(j: beat number, n: decomposition level).

• Entropy:

Another feature vector used was entropy. The entropy of signal is a measure of the randomness of the signal. The entropy of each beat was first calculated with two commonly used types of the entropy, Shannon entropy and log-energy entropy.

$$Ent^{shannon}\ beat(j) = -\sum_{i=1}^{N} x_i^{\,2} \log(x_i^{\,2}) \qquad (5)$$

$$Ent^{\log}\ beat(j) = \sum_{i=1}^{N} \log(x_i^{\,2}) \qquad (6)$$

(j: beat number, n: decomposition level, N: sample size, i: sample number)

The entropy of the beat j at decomposition level n was obtained as follows.

$$Ent\ (j)_{\log\ \_n} = \sum_{i=1}^{N} \log(x_i^{\,2}) \qquad (7)$$

(j: beat number, n: decomposition level, N: sample size, i:sample number)

Direct comparison can be made between the entropy of the different levels, because entropy is an average measure; therefore normalization is not required [11].

3.1Classification Results

FIS consists of four modules, Fuzzification module, Knowledge base module, Inference engine module and Defuzzification module. Fuzzy inference methods are classified as direct methods and indirect methods. Direct methods, such as Mamdani's and Sugeno's, are the most commonly used. Indirect methods are more complex. Mamdani method is most commonly used fuzzy inference technique. Mamdani model is a knowledge driven predictive model, it works with inputs of crisp data and also with intervals and or linguistic terms. The major advantage of this model is it provides a measure of confidence for predicting future value when the actual value is unknown.

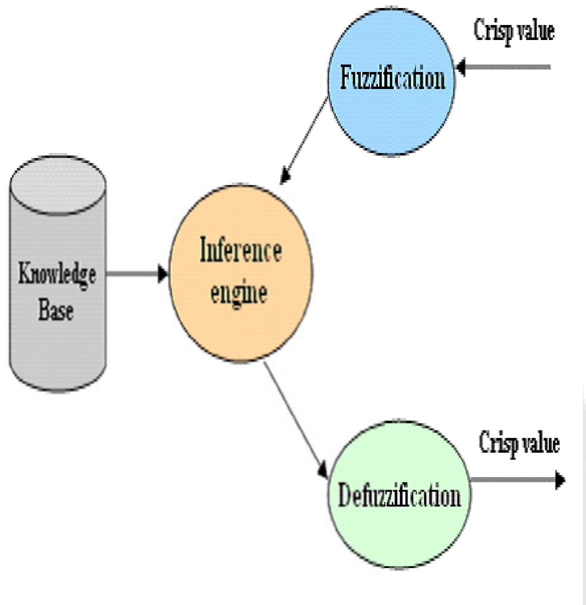

Figure 8: Structure of fuzzy inference system [9]

3.2 Fuzzy Rules

Fuzzy rules are linguistic IF-THEN- constructions that have the general form "IF A THEN B" where A and B are Number of Fuzzy Rules is dependent on number of input variables and their membership functions. In Fuzzy Rule Based Selection model has 2 variables and 3 membership functions = 3^2 = 9 rules has shown in Fig (9)

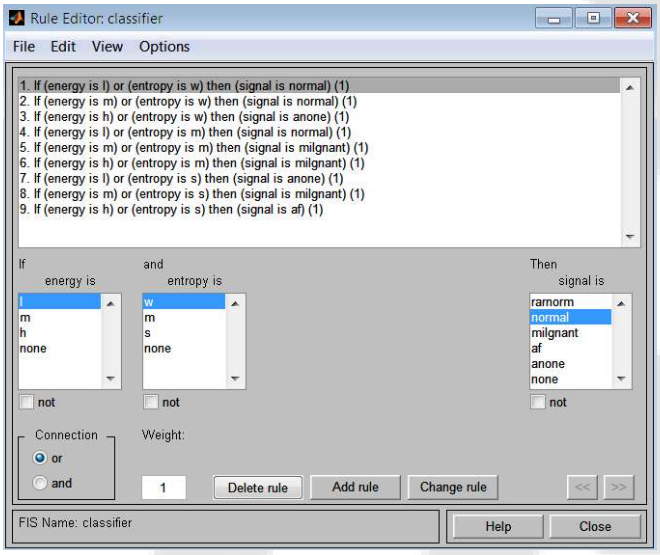

Figure 9: Rule Editor

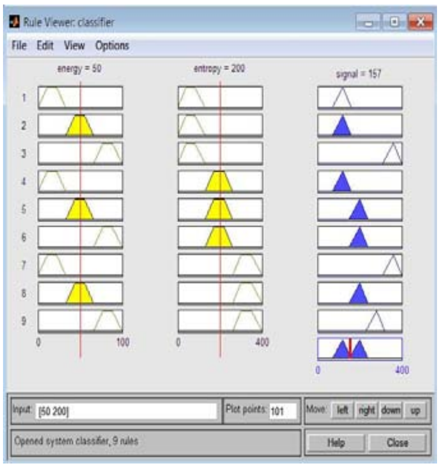

Figure 10: Fuzzy Rule Based Selection Process

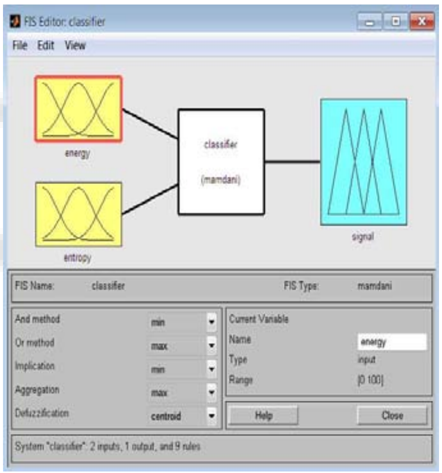

Figure 11: Fuzzy Rule Based Model

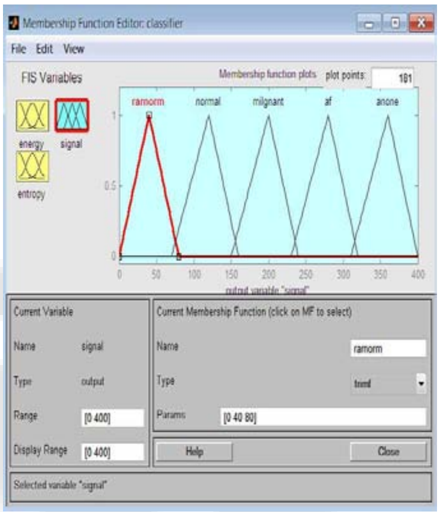

Figure 12: Membership Function for Output Classifier

Table 1

Signal	*Ea*	*Entropy*	*Class*
16272	14.7	251.6	Normal
16420	20.7	223.3	Normal
16539	10.7	242.4	Normal
16786	55.2	185	Normal
16795	96.2	261.9	Normal
17052	11.3	212.1	Normal
17453	12.5	205.5	Normal
17683	30.1	163.7	Normal
19140	63.6	250.2	Normal
18177	55.6	247.1	Normal
Normal	30.1	163.7	Normal
Rarnorm			
18184	29.5	112.2	Rarnorm
16773	45.8	99.8	Rarnorm
16483	88	148.1	Rarnorm
16273	50.4	58.2	Rarnorm
Malignant			
418	75.5	311.5	Malignant
419	97	279.7	Malignant
420	75.6	318.5	Malignant
421	77.7	190.5	Malignant
422	93.2	277.3	Malignant
423	56.8	313.1	Malignant
424	96.6	215.1	Malignant
425	73.2	300.7	Malignant
426	90.5	255.8	Malignant
427	71	261.9	Malignant
AF			
04015	46.5	114.7	Rarnorm
04126	98.6	395.7	AF
04746	72.8	401	AF
05091	53.3	353.4	AF
06995	93.6	349.9	AF
07910	74	335.8	AF
08215	97.1	347.1	AF
8405	9.2	346.9	AF
040043	88	372.7	AF
050091	53.3	353.4	AF

The test performance of the classifiers can be determined by the computation of sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined as:

- Sensitivity: number of true positive decisions/number of actually positive cases.
- Specificity: number of true negative decisions/number of actually negative cases.
- Total classification accuracy: number of correct decisions/ total number of cases [12].

The values of the statistical parameters (sensitivity, specificity and total classification accuracy) are given in Table2.

$$Sei = \frac{TPi}{\mathrm{TPi + FNi}} \quad (8)$$

$$Spi = \frac{TNi}{TNi + FPi} \quad (9)$$

$$PPVi = \frac{TPi}{TPi + FPi} \quad (10)$$

$$\mathrm{NPVi} = \frac{TNi}{\mathrm{TNi + FNi}} \quad (11)$$

$$TCA = \sum_{i=1}^{5} \frac{\mathrm{TPi}}{\mathrm{Tr}} \quad (12)$$

where TPi (true positives) denotes the number of heartbeats of the ith class that are correctly classified (that is, NORM classified as NORM, see Table 1); FNi (false negatives) represents the number of heartbeats of class i but that are misclassified (that is, NORM not classified as NORM); TNi (true negatives) is the number of heartbeats not belonging to the number of the ith class and not classified in the ith class (that is, Rarnorm, Malignant Ventricular, and Af not classified as NORM); FPi (false positives) denotes the number of heartbeats classified erroneously in the ith class (that is, Rarnorm, Malignant Ventricular, and Af classified as NORM); and Tr represents the total number of heartbeats listed in table 1.

- Table 2 Results

Table 2

Arrhythmia classes	*Sensitivity*	*Specificity*	*TCA*
Normal	100%	100%	97%
Rarnorm	100%	100%	97%
Malignant	100%	100%	97%
AF	90%	100%	97%

4. Conclusion

My goal is to classify ECG signals normal and abnormal; this study contains three stage, preprocessing, feature extraction and classification. IIR filters are used to prepare signals; feature vectors were then extracted from these decomposed signals as normalized energy and entropy using wavelet analysis. To improve the classification of the feature vectors of normal and abnormal beats. The combination of wavelet decomposition and the classification using feature vectors of the beats in ECG signals separate abnormal beats from normal beats using fuzzy logic control. Evaluating the proposed algorithm, resulted in sensitivity 100% for all except AF 90%, specificity 100% and total classification accuracy 97%.

5. Recommendations

I faced some problem from the beginning like "how to open signal.dat "but I try , try and try again till I reach the software "rdsign212".

For future work I recommended the researchers to deal with fuzzy logic control because it is very easy to understand and work.

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