# Classification and Prediction of Critical Cardiac Arrhythmias Using Filter Bank and Fuzzy Classification Approach

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***Abstract*— This paper presents a method of automatic processing of the Electrocardiogram (ECG) signal for the classification of heart arrhythmias. ECG based health diagnosis of cardiac problems has been a saturated area of research. Almost, any known heart-condition can be detected and diagnosed by doctors in the hospital but these approaches mostly fail when attempting to design an automatic detection system to do the same. Hence the presented work covers the initial findings related to some of the cardiac conditions that can be monitored and the detection system can produce warning signals that can be conveyed to the concerned healthcare persons if signs of such conditions begin to show. Due to the compact nature of such kind of systems, the detection and classification techniques have to be extremely simple in order to be face some real time constraints. Data were obtained from 48 records of the MIT-BIH arrhythmia database [9] (only one lead). Three types of arrhythmic beats were classified using this method, namely Second Degree block type I (AV2BLK),5 PVCs +36 Normal Beats, repeated (RUN 5 PVC),Ventricular Fibrillation(VFIB), in addition to the Normal Beat (NB). A learning dataset for the fuzzy network was obtained from a record set available in MIT-BIH Arrhythmia Database Directory and documentation. Feature set was based on ECG morphology and time intervals.**

***Keywords— Atrio-VentricularBlock, Electrocardiogram (ECG), Fibrillation, Fuzzy Classifier, MIT-BIH Arrhythmia Database,Premature ventricular Contraction, Ubiquitous computing.***

## I.INTRODUCTION

Each year, arrhythmia disease claims approximately 400.000 lives, and costs up to $ 30 billion in combined health care spending in France, Germany, Italy, Spain, and in the United Kingdom.
Heart arrhythmia results from any disturbance in the rate, regularity, site of origin, or conduction of the cardiac electric impulse.
Arrhythmias can be divided into two groups. The first one is a life threatening and require immediate therapy, like as the ventricle fibrillation. Detection of these arrhythmias is well researched, and successful detectors have been designed. The second one which is investigated in this study, includes arrhythmias that are not imminently life-threatening, but may require therapy to prevent future problems.
In this work we consider three types of arrhythmic beats:

*A.Second Degree block type I (AV2BLK)*
Refers to a disorder of the cardiac conduction system in which some atrial impulses are not conducted to the ventricles. In his case, some P waves are not followed by ideal QRS complex. There is progressive lengthening of the PR interval and then failure of conduction of an atrial beat. This is followed by a beat with a short PR interval and then the cycle repeats itself. This occurs commonly after an inferior myocardial infarction.

*a.5 PVCs +36 Normal Beats, repeated (RUN 5 PVC)*
It gives a waveform of five PVCs and then 36 normal beats. This is repeated.

*B.Ventricular Fibrillation (VFIB)*
VF is the result of highly irritable ventricle(s), which begin to send out rapid electrical stimuli. The stimuli are chaotic resulting in no organized ventricular depolarization. The ventricles do not contract because they never depolarize. Because the ventricles are fibrillating and never contracting, the patient does not have a pulse, cardiac output, or blood pressure.
The main aim of this work is to realize a robust classifier able to identify all the above cited types of ectopic beats by using fuzzy network.

## II. METHODOLOGY

This chapter summarizing our methods is subdivided into four sections: MIT/BIH arrhythmia database, signal processing for feature extraction, fuzzy classifier and performance metrics. The first outlines the ECG data used in this study and provides a brief description of the MIT/BIH arrhythmia database. The second contains a relevant introduction to wavelet transform theory and a description of the various feature sets used in training and classification. The third section details the design, training, and testing of the fuzzy classifier. Finally, the last section,

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performance metrics, elucidates the measures used to evaluate the performance of our classifier.

*A.MIT/BIH Arrhythmia Database*

In this paper, ECG data from the MIT/BIH arrhythmia database were used . The database was created in 1980 as a reference standard for arrhythmia detectors. Its inception allowed developers of arrhythmia analyzers an objective measure of accuracy, specificity, and sensitivity. The primary goal of providing this metric was to spur the automated arrhythmia detection and classification technology. Moody and Mark report that since 1980 it has been used worldwide in over 500 sites for this purpose.

The database is comprised of 48 files, each containing 30-min ECG segments selected from 24-hr. Recordings of 47 different patients. Of the 48 files, 23 were randomly chosen and 25 were selected to include uncommon, threatening, arrhythmic heart-beat samples [16]. Each file contains two leads, with modi-fied-lead II available in 45 files, V1 in 40 files, and II, V2, V4 and V5 distributed among 11 files. Data are bandpass-filtered at 0.1–100 Hz and sampled at 360 Hz. We used a total of 40 records from the database, focusing on modified-lead II signals except in two files (102 and 104), in which lead V5 was substituted since modified-lead II was not available.

*B . ALGORITHM*

The main idea behind the algorithm presented in this paper is to have the signal decomposed into various frequency components that ultimately correspond to various features of the ECG signal, hence, making it possible to classify them. Each module in this algorithmic view is described below and Figure 1 shows these various components.

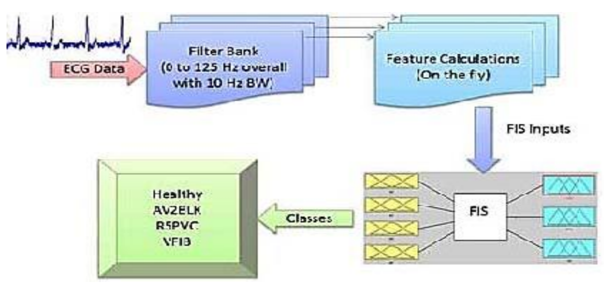


FIG 1-Overall block diagram of the classification system.

*Filter Bank:*
The main filters are designed as FIR filters of order 36, i.e., requiring at least 36 samples before being able to approximate the last sample as filtered one. Since the sampling frequency being used is 125 Hz, we have up to 62.5 Hz of frequencies available for this analysis step. Hence, 6 filters were constructed each with a bandwidth of 10 Hz. The ranges these filters covered are: 0-10 Hz, 11-20 Hz, 21-30 Hz, 31-40 Hz, 41-50 Hz, and 51-62.5 Hz.

*Fuzzy inference system (FIS):*

Fuzzy logic [8] is probably the most suitable tool for the purpose of quantifying the human perception according to the general understanding of the information present in the measurements by the physician or surgeon, thus obtaining a better classification. A Fuzzy Inference System (FIS) has been developed in this work using MATLAB's Fuzzy Logic tool box. Fuzzy Logic may be considered an extension of binary logic theory that does not require crisp definitions and distinctions. Hence, the developed FIS has not only compact structure and functionality, but also very innovative since it translates the heuristics from human experts into tangible quantitative data and consequently into useful estimates.

a. *Feature Selection:*
Since the ultimate technique's usage is in wearable monitoring system, hence, there is a need for measures or Features that can be calculated quite quickly and recursively. This led to the decision to use the statistical measures only instead of geometrical measures as used by most of the automated detection algorithms. A set of 8 different features were tried out with various waveforms obtained from the filter banks. The features used are: Mean,median,mode,standarddeviation,skewness,kurtosis,energy,harmonic mean.

The proposed FIS(shown in Figure 2) consists of the following:

- Four input membership descriptors (representing the feature space; SF0, SF1, KF0, and KF1). Here SF0 and KF0 represent the Skewness and Kurtosis of the original signal, and SF1 and KF1 are the same for the first.
- Three output membership descriptors for the diseased cases (AV2BLK, R5PVC, and VFIB), and
- A group of 5 rules that represents the heuristical combination of the membership functions with historical understanding of the human user in the domain under study.

Figure 2 represents the input membership functions with individual grouping. First, the data from the training signals was collected under each category of the Four features. Then a Fuzzy c-mean clustering algorithm was applied to find feasible boundaries between these classes. These boundary values are then used in each class of input as AV,R5, and VF memberships so that forming rules can be output characterizations but were not exhaustively tested as part of the presented work. Once these rule-base implications are accomplished easily. In each membership distribution, the boundary value represents the middle of the trapezoidal function with 10% gradient fall on either side. Hence, each of these degrees can now be represented by a mathematical function that will map the input value of the feature with its functional weights to produce the fuzzified version of the input data. The Output variable of the FIS (Figure 2) corresponds to the three degrees of membership representing three conditions of the disease. Each one of these memberships is evenly distributed triangular distributions corresponding to "Un-likely", "Likely", and "Highly-likely" degrees.

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*Rule Base:*

A set of 5 rules was formed based on typical visual heuristics. This rule-base utilizes the membership degrees and their underlying values mapped from the membership functions to perform Boolean Logical inference for a particular set of inputs. For each rule, a decision bar is generated which, when combined with the other rules in a similar way, constitutes a decision surface. These rules are an intuitive collection of antecedents and their consequents which most physicians will agree with. Each rule represents a collection of possible heuristics combined together using AND operation. None of the rules actually utilize any form of statistical or algebraic decision boundary. These group of rules are shown below:

If (SF0 is High) and (SF1 is High) and (KF0 is High) and (KF1 is High) then (Healthy is HighlyLikely)

If (SF0 is Medium) and (SF1 is Medium) and (KF0 is Medium) and (KF1 is Medium) then (AV2BLK is HighlyLikely)

If (SF0 is Low) and (SF1 is Low) and (KF0 is Low) and (KF1 is Medium) then (R5PVC is HighlyLikely)

If (SF0 is Low) and (SF1 is Low) and (KF0 is Low) and (KF1 is Low) then (VFIB is HighlyLikely)

If (SF0 is Medium) and (SF1 is Low) and (KF0 is Medium) and (KF1 is Medium) then (R5PVC is Likely)(VFIB is HighlyLikely)

Obviously, there can be other possibilities or other combinations of these memberships for other

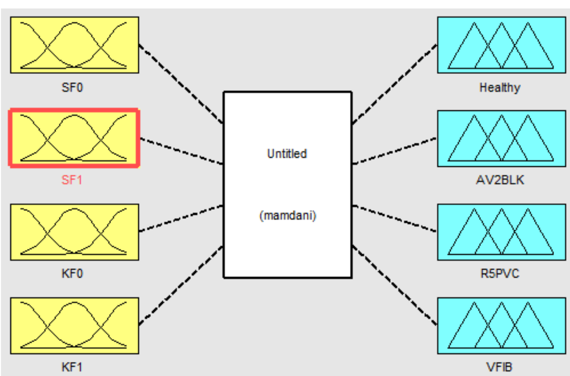
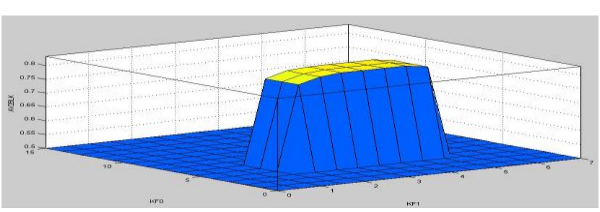
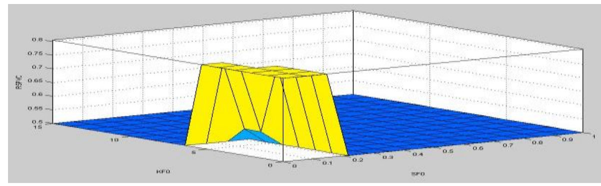



Figure 2. The FIS structure for the ECG Classifier

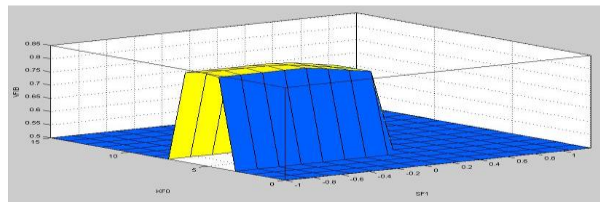
established, an overall decision surface is pre-calculated. For each set of input values, the centroid is calculated for the area of this decision surface that overlaps with the decision rules applicable to the input memberships. The centroid value is an indicator of the degree to which the inputs correspond to the rule-base and consequently provide a number that depicts the degree of output. The resulting decision surfaces are multidimensional and cannot be displayed as one hyper surface. However, some subset decision surfaces can be plotted and are shown in Figure 3.



**(a)**



**(b)**



**(c)**

Figure 3.Decision surface for (a) AV2BLK between "KF0" and "KF1", (b) R5PVC between "KF0" and "SF0", and (c) VFIB between "KF0" and "SF1".



## III.PERFORMANCE METRICS

We quantified our classifier performance using the most common metrics found in literature which are accuracy, sensitivity, and positive predictivity. The former expresses the overall system performance over all types of beats while the two latter quantities are specific to each class of beat. The methods used to quantify the performance of our classifier in each of these three areas are discussed below.

*Accuracy, Sensitivity, and Positive Predictivity*

The most crucial metric for determining overall system performance is usually accuracy. We defined the overall accuracy of the classifier for each file as follows:

$$A=100(1-N_e/N_b)$$

In this equation, $A$ is the accuracy, and the variables, $N_e$ and $N_b$, represent the total number of classification errors and beats in the file, respectively. In addition to accuracy, two other measures of classifier performance are sensitivity ($Se$) and positive predictivity($Pp$)

$$Se=TP/(TP+FN)$$
$$Pp=TP/(TP+FP)$$

In these equations, TP, FP, and FN denote true positives, false positives and false negatives. True positives are beats which have been correctly assigned to a certain class whereas false positives are beats which have been incorrectly assigned to that same class. A false negative occurs when a beat should have been assigned to that class

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but was missed and assigned to another class. Consequently, sensitivity measures how successfully a classifier recognizes beats of a certain class without missing them whereas positive predictivity measures how exclusively it classifies beats of a certain type.

*Weighted Average Sensitivity and Positive Predictivity*

We determined that average sensitivity and positive predictivity were not useful measures of overall performance because of the tremendous variation among files in number of normal, PVC, and unknown beats. The sensitivity for a file with only one PVC beat, for example, is much less relevant to overall system PVC sensitivity than the result from a file with 500 PVC beats. Consequently, we weighted the averages according to the number of beats of each class.

## IV. CONCLUSION

In this paper, an automatic classification for arrhythmia detection is presented, and its performance is evaluated by measuring the system sensitivity, specificity and error after the all MIT-BIH positive and negative cases have been normalized. The system errors are caused by two main reasons: 1-The pre-processing and filtering processes in some cases, are not enough to remove all type of noise affecting the ECG signal, and sometimes they cause a signal distortion, so the QRS detection and the feature extraction procedure don't perform as well as they are supposed to do; 2- Other types of arrhythmia are rarely present in some records; thus we haven't sufficient cases to be inserted in the dataset and they resulted as unrecognized patterns from our system.

The future work will focus on developing our ECG filtering method to reduce the first cause of system error, and we will try to find more data containing different cases of arrhythmia to overcome the second one. We hope this system can be further developed, in order to realize a low-cost, high performance, simple to use and portable equipment for ECG signal monitoring.

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