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Filter Bank Approach to Critical Cardiac Abnormalities Detection using ECG data under Fuzzy Classification

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Abstract—*Electrocardiogram (ECG) based health diagnosis of cardiac diseases has been a saturated area of research and almost any known heart-condition can be detected and diagnosed by doctors in the hospital setting. However, these approaches fall extremely short when attempting to design an automatic detection system to do the same. The situation becomes even more difficult when the measurement system is being designed for a ubiquitous application in which the patient is not confined to the hospital and the device is attached to him/her externally while the person is involved in daily chores. This paper presents the classification technique for one such system which is being built by the same team [1]. Hence the presented work covers the initial findings related to some of the cardiac conditions that can be monitored in this setting 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 systems, the detection and classification techniques have to be extremely simple in order to be stored in the small memory of the microcontroller of the ubiquitous system. The paper presents one such technique that is a combination of digital filters and Fuzzy classifications implemented at look-up table level in order to preserve the simplicity of the system.*

Keywords- Fuzzy Classifier, Finite Impulse Response (FIR) filters, Electrocardiogram (ECG), Ubiquitous computing, Atrio- Ventricular Block, Premature Ventricular Contraction, Fibrillation.

I. INTRODUCTION

Due to increasing numbers of people with illnesses and high costs associated with managing and treating them, two mission-critical schemes can be enforced in order to ensure that low-cost and qualitative health services can be delivered. Firstly, the usual hospital-based healthcare should be transformed to personal-based healthcare, which can lead to the prevention of illnesses or early prediction of diseases. Secondly, cutting-edge technologies have to be developed with the aim of reducing medical costs in the following aspects:

1. Innovative & low-cost medical device without professional involvements;
2. Precise and reliable automatic diagnosis system to avoid unnecessary clinical visits and medical tests;
3. Telecommunication technologies to support caregivers in remote accessing and diagnosing the patients' status.

One such solution is a wearable heartbeat monitor. While a number of such gadgets are available in the market today and are successfully used by athletes as well as for simpler fitness workouts, the main objective of these devices is to get the heartbeat count only. The other solutions comprise of wearable and (Wireless Body Area Networks) WBAN-based health monitoring systems that combine automatic diagnosis system and wireless application protocol (WAP) into ubiquitous telemedicine system [1]-[9]. The importance of such systems can be understood by their significant contribution to healthcare and to patients' lifestyles.

A. Clinical significance:

- Sudden cardiac death is a global health concern. This can occur both in the hospital and out-of-hospital. Early recognition and initiation of treatment has an important effect on outcomes and survival, especially cardio-pulmonary resuscitation (CPR) and defibrillation. Therefore, early identification of patients at high risk of cardiac arrest becomes extremely important.
- Monitoring systems by themselves are only useful if treatment recommendations can be interpreted from them. Therefore, the proposed automatic and real-time symptoms classification becomes essentially important, especially for the cardiac patients at different stages. The timely classification results will provide the doctors more information to cater to more preferable treatment for the patients.

- Security issue in telemedicine is always a big concern. Using a novel biometrics method, sensitive medical information will be secured and protected to prevent unauthorized use. Meanwhile, the interference between WSNs of different patients can also be avoided.

II. OVERVIEW OF THE SYSTEM

A new system for this purpose is being built by the authors and their team to alleviate the existing system from the limitations related to the mode of on-board processing, range of access to the healthcare facilities, and correct diagnosis. This paper presents one of the techniques in this context that has been implemented for detecting healthy vs. diseased heartbeats. Specifically, three conditions are selected for this initial development of the algorithm; 2[nd] degree Atrio-Ventricular block (AV2BLK), Premature Ventricular Contraction (PVC), and Ventricular Fibrillation (VFIB). One specific reason for selecting only these for the time being is the fact that when the first two conditions appear, the patient has a good chance of reaching the hospital or other healthcare facilities since the system can predict the condition in time. The third condition is usually very serious and the patients have only a few minutes before it could become fatal. However, nowadays many public places such as malls, airports, etc. have de-fibrillators available for such emergencies. If the VFIB condition is detected then the proper instrument can be quickly attached in order to save the life of the patient.

Figure 1 shows the block diagram of operation of the test hardware for this system. Essentially, the data will come to the data acquisition system ADS1198-ECGFE-PDK Data Acquisition Module [10] from Texas Instruments, USA. This device has an eight-channel, 24-bit, low-power, integrated analog front-end (AFE) designed for patient monitoring and portable and high-end electrocardiogram (ECG) applications and for prototyping. After many experimental observations, the system utilizes only the first chest lead from the standard ECG monitoring protocol and still provides sufficient information in the signal. However, before using real patients' data, a test bed was developed using CARDIOSIM-II, an ECG Arrhythmia Simulator (Biometric Cables). The Cardiosim-II [11] generates 11 Arrhythmia Waveforms listed below:

1. AFIB (Atrial fibrillation)
2. AV2BLK1 (second degree block type 1)
3. RBBB (Right bundle branch block)
4. PAC (Premature atrial contraction)
5. PVC(Premature ventricular contraction)
6. PVC R ON T (PVC R wave on T wave)
7. MFPVC (Multi focal PVC)
8. BIGEMINY (Normal beats repeated)
9. RUN 5 PVC (5PVCs+36 normal beats, Repeated)
10. VTACH (Ventricular tachycardia)
11. VFIB (Ventricular fibrillation)

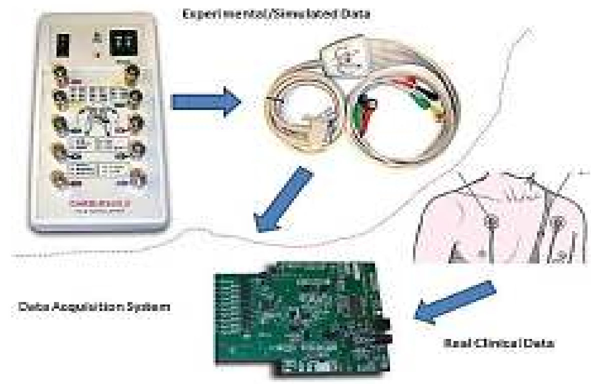


Figure 1. Overview of the system's test hardware.

III. EXPERIMENTAL SYSTEM

The intension of this experimental setup is to generate the waveform of ECG using an ECG simulator to simulate waveforms of different arrhythmia related conditions and analyzing the waveform before trying it in the real human subject. Figure 2 shows the actual experimental setup used in this work to obtain the ECG data for various healthy as well as diseased cases.

Although the interface software is capable of obtaining 10-lead data from this setup, but the actual wearable system will only have one channel of data and hence the acquired data from this experimental system was also restricted to the 1[st] channel only.

Figure 2. Experimental setup used in this work. Inset shows top view of connections for the simulator and the data acquisition modules.

IV. THE CARDIOSIM ECG SIGNALS

The simulator produces 10 different healthy ECG signals with different rates in order to mimic various physical situations such as walking, running, lying down, etc. .One of these, sitting posture waveform, has been used as the reference healthy signal in the presented work. This and Three other signals used in developing the classification system are shown in Figures 3-6.

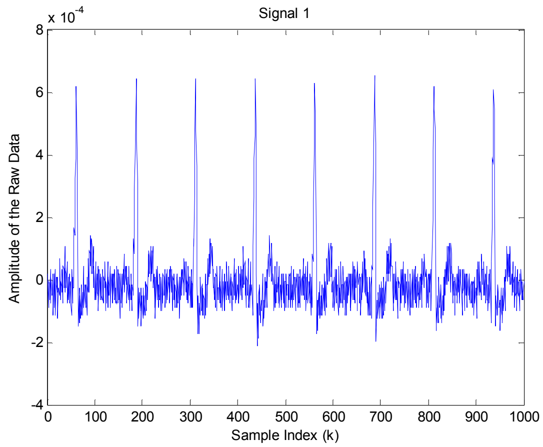


Figure 3. ECG signal of a healthy person in sitting posture.

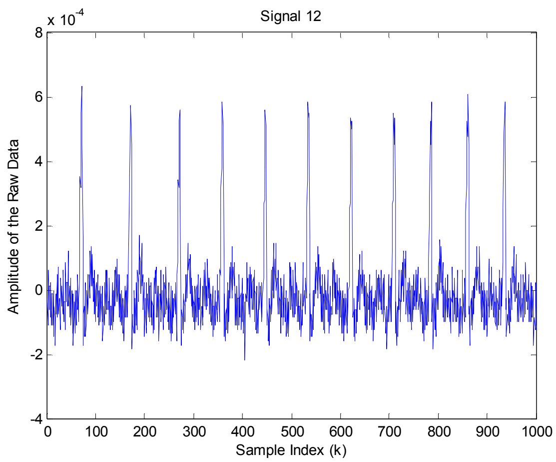


Figure 4. ECG signal for a 2nd degree Atrio-ventricular block.

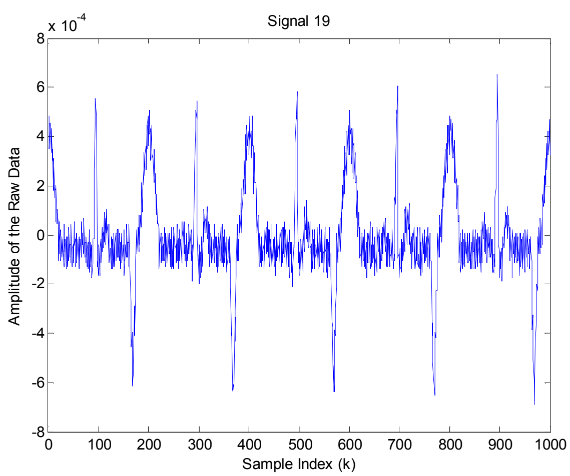


Figure 5. ECG signal for Premature Ventricular Contraction (R5PVC).

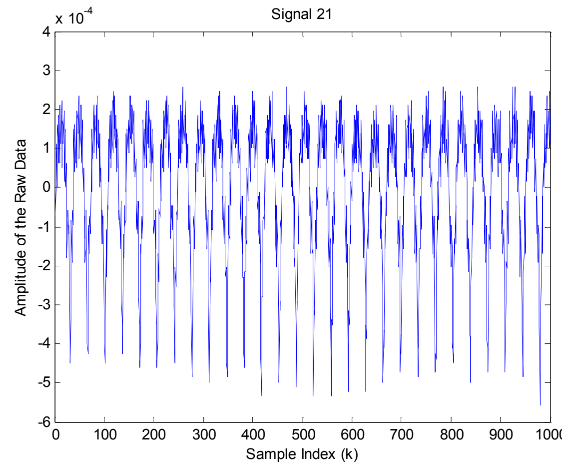


Figure 6. ECG signal for a Ventricular Fibrillation (VFIB) scenario.

The high amount of noise indicates the electronic sampling and other such noise sources and the waveforms represent very raw form of the ECG dataset without any processing. The three disease cases selected for this study are briefly described in the following:

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. Electrocardiographically, some P waves are not followed by a QRS complex. There is progressive lengthening of the PR interval and then failure of conduction of an atrial beat. This is followed by a conducted beat with a short PR interval and then the cycle repeats itself. This occurs commonly after an inferior myocardial infarction, and tends to be self-limiting.

B. *5 PVCs +36 Normal Beats, repeated (RUN 5 PVC):*

It gives a waveform of five PVCs and then 36 normal beats. This is repeated. (Definition from other patient simulator).

C. *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.

V. ALGORITHM

Figure 7 shows various components of the main algorithm presented in this paper for type classification for the ECG signals shown in Figures 3-6.

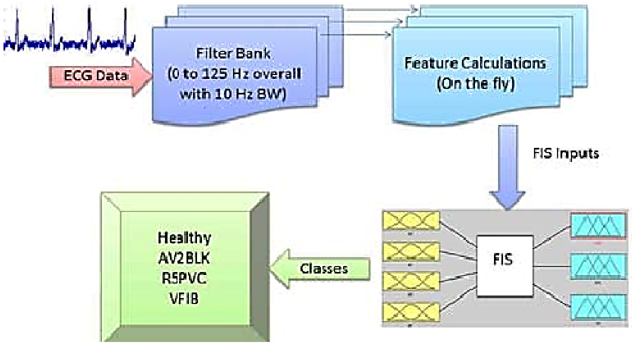


Figure 7. Overall block diagram of the classification system.

The raw ECG signals are first normalized and de-trended as a standard procedure. Hence mean of the sampled window of data is calculated at this point. The main idea behind this algorithm 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.

A. 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. The first of these filters is shown in Figure 8.

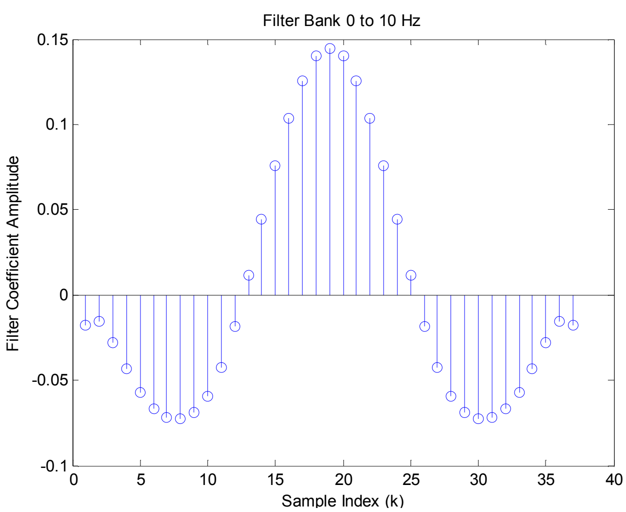


Figure 8. The first of the six FIR filters used in this work.

The resulting signals for the four classes of Figures 3-6 are shown in Figures 9-12.

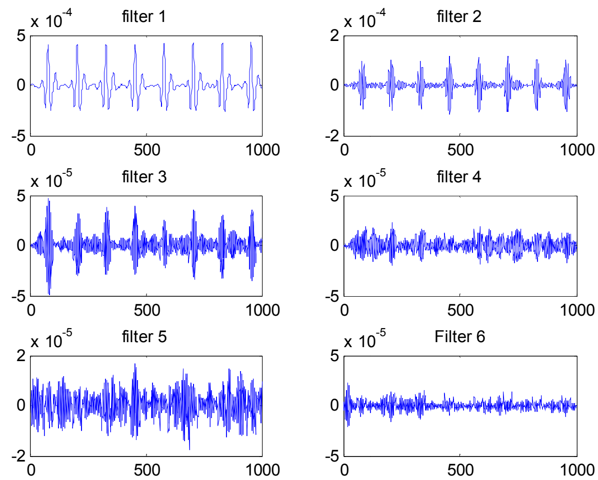


Figure 9. Filter outputs for the signal in Figure 3.

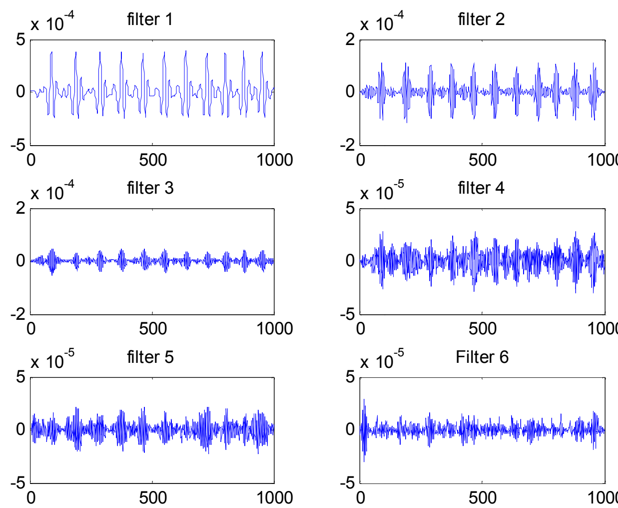


Figure 10. Filter outputs for the signal in Figure 4.

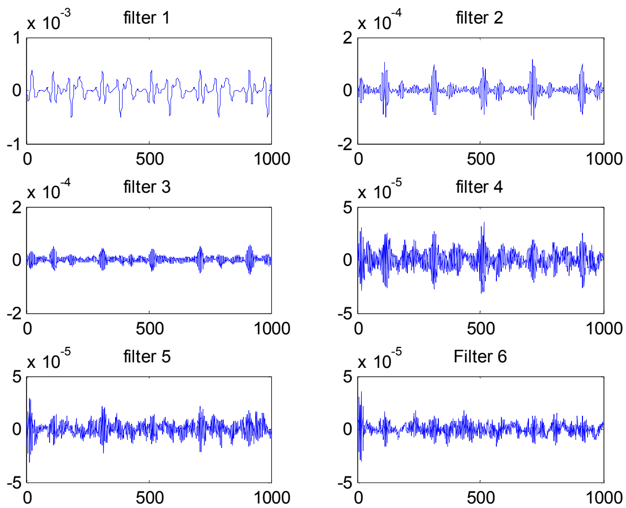


Figure 11. Filter outputs for the signal in Figure 5.

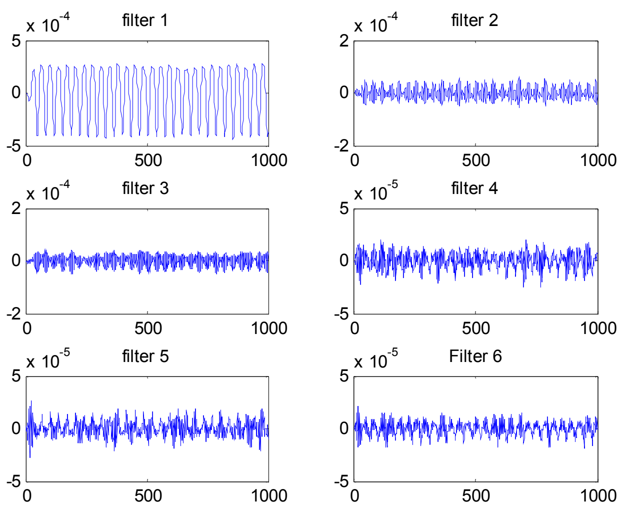


Figure 12. Filter outputs for the signal in Figure 6.

Looking at the various resulting signals, it can be easily concluded that the main component results from the first filter bank. Others are too similar and are too small in magnitude as well compared with the first filter output. This observation enabled us to discard the other filters from the filter bank (at least for the selected type of signals) and thus using a smaller set of signals for further processing.

VI. FUZZY INFERENCE SYSTEM (FIS)

Fuzzy logic [12] 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 [13]. Fuzzy Logic may be considered an extension of binary logic theory that does not require crisp definitions and distinctions. Hence, the developed FIS is not only innovative in terms of its structure and functionality and its application in clinical practices, but also very powerful since it translates the heuristics from human experts into tangible quantitative data and consequently into useful estimates.

A. *Feature Selection*

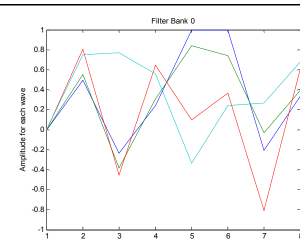
Since the ultimate technique's usage is in wearable monitoring system, hence, there is a need for measures or Features that can be calculated quite quickly and recursively. This led to the decision to use the statistical measures only instead of geometrical measures as used by most of the automated detection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

1. Mean
2. Standard Deviation
3. Median
4. Energy(sum-squared values)
5. Skewness
6. Kurtosis
7. Harmonic Mean
8. Mean Deviation

Figure 13 shows the values of various waveforms from the filter bank. Based on the selectivity of various measures, it can be seen from Figure 13 that certain measures are good in classifying the four signals. These can be summarized in the form of a table, as shown below:

Signal	**Features**
Original	2, 3, 5, 6, 7
Filtered from Bank 1	1, 6, 7
Filtered from Bank 2	6, 7
Filtered from Bank 3	5, 6, 7
Filtered from Bank 4	5, 6, 7
Filtered from Bank 5	6, 7
Filtered from Bank 6	5, 6, 7

Table 1. Feature selection: Left column lists the signals being studied, and the Right column lists the prominent features that provide sufficient degree of separation in terms of the feature value.



(a)

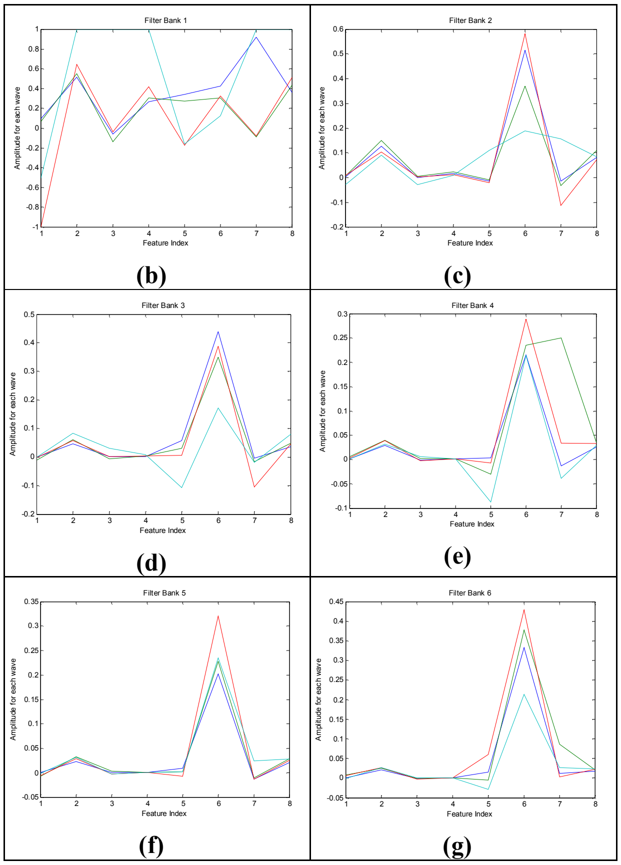


Figure 13. Feature selection strategy. Various plots of the feature values for (a) Original signal, and (b) through (g) filtered outputs from Filter Bank 1 through Filter Bank 6.

As can be seen that the features 6, and 7 occur most frequently and hence were used for the feature space. Also, for the selected four classes of the outputs, it was found that only the original signal and the first filter bank output would be sufficient for the required classification.

The proposed FIS is shown in Figure 14, and is composed 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 set of 5 rules that represents the heuristical combination of the membership functions with historical understanding of the human user in the domain under study.

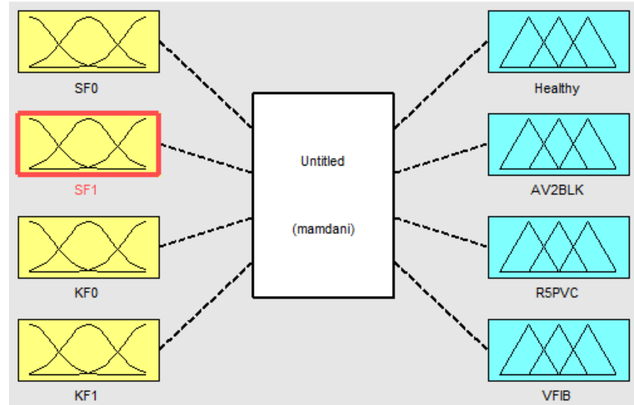
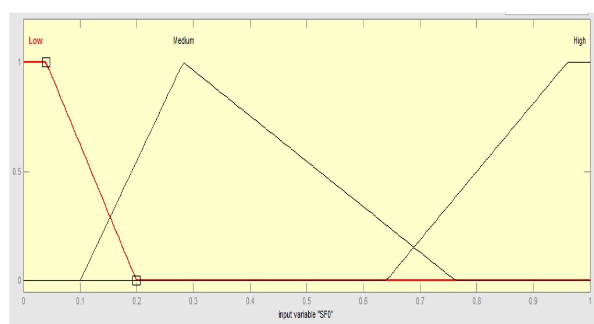
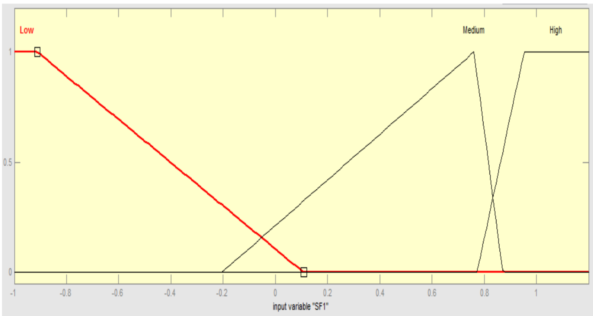


Figure 14. The FIS structure for the ECG classifier.

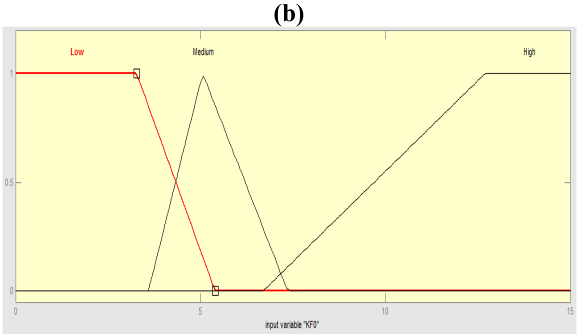
Figure 15 represents the input membership functions with individual grouping. First of all the data from the training signals was collected under each category of the Four features. Then a Fuzzy c-mean clustering algorithm [13] was applied to find feasible boundaries between these classes. These boundary values are then used in each class of input as AV,R5, and VF memberships so that forming rules can be 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 16) 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. The x-axis in all of the curves shown in Figures 13 and 14 represents the input values for each input membership function. The y-axis is from 0 to 1 representing the overall probabilistic space.



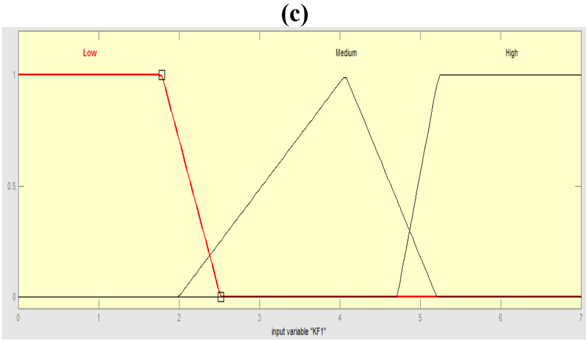
(a)



(b)



(c)



(d)

Figure 15. Input Membership functions; (a) SF0, (b) SF1, (c) KF0, and (d) KF1.

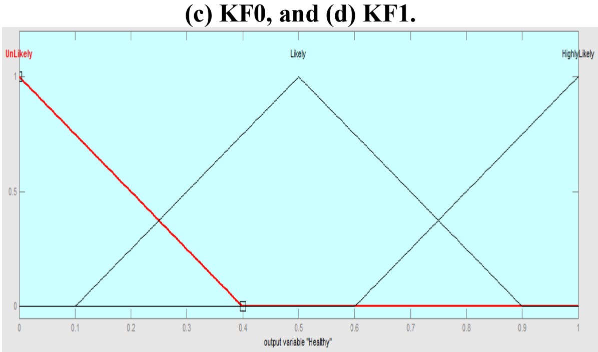


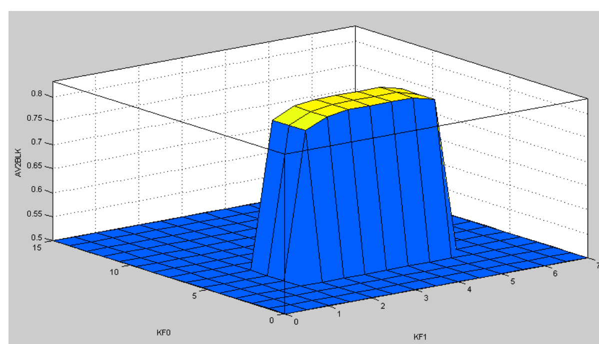
Figure 16. Output Membership function for the class "Healthy". Other three classes are also the same in structure.

B. Rule Base

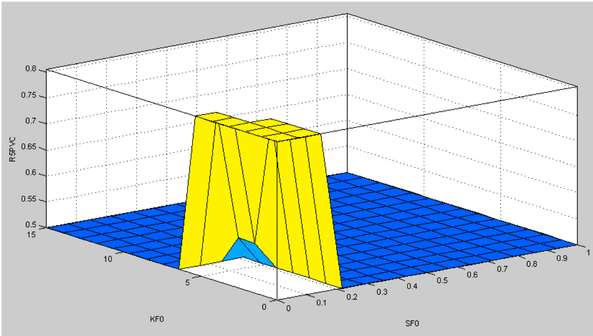
A set of 5 rules was formed based on typical visual heuristics. This rule-base utilizes the membership degrees and their underlying values mapped from the membership functions to perform Boolean Logical inference for a particular set of inputs. For each rule, a decision bar is generated which, when combined with the other rules in a similar way, constitutes a decision surface. This set of rules is 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 rules are shown below:

1. If (SF0 is High) and (SF1 is High) and (KF0 is High) and (KF1 is High) then (Healthy is HighlyLikely)
2. If (SF0 is Medium) and (SF1 is Medium) and (KF0 is Medium) and (KF1 is Medium) then (AV2BLK is HighlyLikely)
3. If (SF0 is Low) and (SF1 is Low) and (KF0 is Low) and (KF1 is Medium) then (R5PVC is HighlyLikely)
4. If (SF0 is Low) and (SF1 is Low) and (KF0 is Low) and (KF1 is Low) then (VFIB is HighlyLikely)
5. 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 output characterizations but were not exhaustively tested as part of the presented work. Once these rule-base implications are 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 17.



(a)



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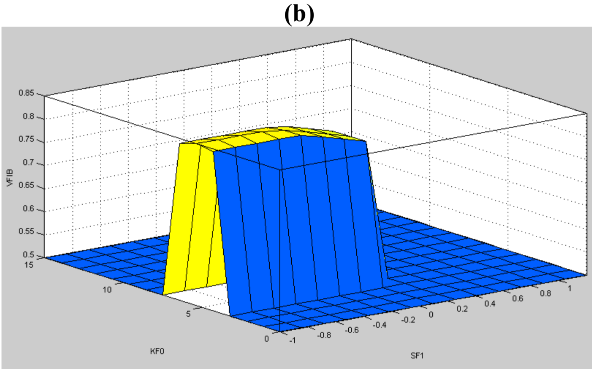

(c)

Figure 17. Decision surface for (a) AV2BLK between “KF0” and “KF1”, (b) R5PVC between “KF0” and “SF0”, and (c) VFIB between “KF0” and “SF1”.

The results have shown almost 100% correct detection for the three diseased cases. Other cases can be similarly incorporated in the rule base and hence into the whole classification system.

VII. CONCLUSION

In this paper, an innovative strategy is presented to perform computationally low cost classification for the ECG signals. This technique can be used in near real-time classification from the ECG data as it arrives. Hence the system can be used as classifier as well as a predictor for certain heart conditions.

Actual hardware implementation of this system is underway for a small form factor which will make it feasible for wearable health monitoring system. While all the constituent modules are not really new, however, the overall strategy presented here is quite unique and has shown results which are very interesting and showing the usefulness of the technique. Detecting the heart conditions (for certain targeted diseases) on the fly (i.e., as the data samples arrive) is an extremely on the fly (i.e., as the data samples arrive) is an extremely embedded design. However, with the presented strategy, one can isolate the most useful part of the signal can be indirectly detected and hence it can be further exploited for predicting the successive conditions based on the current data.

VIII. ACKNOWLEDGMENT

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