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CARDIAC HEALTH DIAGNOSIS USING HEART RATE VARIABILITY SIGNALS – A COMPARATIVE STUDY

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ABSTRACT The electrocardiogram (ECG) is a representative signal containing information about the condition of the heart. The shape and size of the P-QRS-T wave, the time intervals between its various peaks etc. may contain useful information about the nature of disease afflicting the heart. However, these subtle details can not be directly monitored by the human observer. Besides, since bio-signals are highly subjective, the symptoms may appear at random in the time scale. Therefore, the signal parameters, extracted and analyzed using computers, are highly useful in diagnostics. This paper deals with the classification of certain diseases using Artificial Neural Network (ANN), Fuzzy relations and statistical classifier. The heart rate variability is used as the base signal from which certain parameters are extracted and presented to the ANN for classification. The same data is also used for Fuzzy classifier and statistical classifiers. The Fuzzy classifier and statistical classifiers are seen to be correct in about 90% of the test cases, and the radial basis classifier yields correct classification in over 95% of the cases.

Key Words: electrocardiograms, Fuzzy classifier, ANN, HRV, Lyapunov exponent

1. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart. Monitored by placing sensors at the limb extremities of the subject, electrocardiogram (ECG) is a record of the origin and propagation of the electric potential through cardiac muscles. It is considered a representative signal of cardiac physiology, useful in diagnosing cardiac disorders. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate [1]. It may contain important pointers to the nature of diseases afflicting the heart.

However, bio-signals are non-stationary signals and hence its reflection may occur at random on the time scale.

That is, the disease symptoms may not show up all the time, but would manifest at certain irregular intervals during the day. Therefore, for effective diagnostics, the study of ECG pattern and heart rate variability signal (instantaneous heart rate against time axis) may have to be carried out over several hours. Heart rate variability (HRV) is a useful signal for understanding the status of the Autonomic nervous system (ANS).

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Past 20 years have witnessed the recognition of the significant relationship between autonomic nervous system and cardiovascular mortality including sudden death due to cardiac arrest [2, 3, 4, 5, 6]. Owing of the significant results obtained in this area a task force was set up by the Board of European Society of Cardiology and was co-sponsored by the North American Society of Pacing and Electrophysiology. Numerous numbers of papers appeared in connection with HRV related cardiological issues [7, 8, 9, 10] reiterates the significance of HRV in assessing the cardiac heath. The interest in the analysis of heart rate variability (HRV), that is, the fluctuations of the heart beating in time, is not new. Furthermore, much progress was achieved in this field with the advent of cheap and massive computational power, which provoked many recent advances.

HRV is a non-invasive measurement of cardiovascular autonomic regulation. Specifically, it is a measurement of the interaction between sympathetic and parasympathetic activity in autonomic functioning. There are two main approaches for analysis: time domain analysis of HRV for standard deviation of normal to normal intervals (SDNN); and frequency domain analysis for power spectrum density (PSD). The latter provides high frequency (parasympathetic activity) and low frequency (sympathetic activity) and total power (sympathetic/parasympathetic balance) values. Spectral analysis is the most popular linear technique used in the analysis of HRV signals [11, 12, 13]. Spectral power in the high – frequency (HF: 0.15-0.5 Hz) band reflects Respiratory Sinus Arrhythmia (RSA) and, thus, cardiac vagal activity. Low-frequency (LF: 0.04-0.15 Hz) power is related baroreceptor control and is mediated by both vagal and sympathetic systems. Very low- frequency (VLF: 0.0033-0.04 Hz) power appears to be related thermoregulatory and vascular mechanisms, and renin-angio tensin systems.

A complex system like cardiovascular system can not be linear in nature and by considering it as a nonlinear system can lead to better understanding of the system dynamics. Recent studies have also stressed the importance of nonlinear techniques to study HRV in both health and disease. The progress made in the field using measures of chaos has attracted scientific community applying these tools in studying physiological systems, and HRV is no exception. There have been several methods of estimating invariants from nonlinear dynamical systems reported in the literature [14, 15, 16, 17]. In this work, three non-linear parameters are used to find the effectiveness of the reflexology on the HRV signal.

2. MATERIALS AND METHOD

For the purpose of the present work, more than 300 subjects – patients suffering from various cardiac diseases as well as those in normal health – have been studied. The data for this work is collected from Kasturba Medical Hospital, Manipal, India. The details of the age, sex and number of subjects in various groups are indicated in Table I. The ECG data is stored in a holter monitor for the duration of 10-15 minutes. Then this data is sampled at a sampling rate of 200 sps with a resolution of 12bits/sample and stored in a random access file. Later, from this file, QRS complex is obtained [18, 19]. The interval between two successive QRS complexes is defined as the R-R interval (t_{r-r} seconds), from which the heart rate (beats per minute) is derived. Thus, the volume of the data being enormous, the study is tedious and time consuming. Naturally, the possibility of the analyst missing (or misreading) vital information is high. Therefore, computer based analysis and classification of diseases can be very helpful in diagnostics R-R interval is then found out. The interval between two successive QRS complexes is defined as the r-r interval (t_{r-r} seconds) and the heart rate (BPM: beats per minute) is given as:

$$HR=60/t_{r-r} \tag{1}$$

For the purpose of this study, the cardiac disorders are classified into five categories namely,

(i) Complete Heart Block (CHB)
(ii) Sick Sinus Syndrome (SSS), Atrial Fibrillation (AF)
(iii) Ischemic/Dilated Cardiomyopathy
(iv) PVC
(v) Normal

In this work, an effort is made to classify five different classes with one normal class and four different cardiac diseases. The classification is done using three different techniques namely neural network, fuzzy inference system and a statistical classifier. A comparative study is performed on the classification results achieved using different techniques.

Table I. Number of subjects in various groups.

TYPE	Number of Male subjects (21-34 yr)	Number of Male subjects (45-70 yr)	Number of Female subjects (21-34 yr)	Number of Female subjects (45-70 yr)	Total
Normal	30	30	30	30	120
Ectopics	11	35	12	31	89
Sick Sinus Syndrome (SSS)	4	13	1	11	29
Atrial Fibrillation (AF)	0	15	7	14	36
Isc./Dilated Cardiomyopathy	4	18	8	12	42
Complete Heart Block (CHB)	3	8	7	9	27

i). **Normal Sinus Rhythm (NSR):** All p waves upright, rounded and similar in size and shape. A p wave exists for every QRS complex. Each P wave is the same distance from the QRS complex – less than 20 seconds. All QRS complexes are the same size and shape and point in the same direction. Each QRS is the same distance from the T waves and the qrs the duration is 10 seconds or less. Heart rate is varying 60-100 beats/minute and is rhythmic.

ii). **Preventricular contraction (PVC):** Problems are formed outside the SA node. QRS complex is widened and not associated with the preceding P wave. T wave is inverted after PVC. It is often followed by a compensatory pause. In couplets, there are two consecutive PVCs exists. In Bigeminy, there is PVC after every other NSR.

iii). **Complete Heart Block (CHB):** The heart rate will be usually between 30-35BPM. P waves are not conducted to the ventricles because of block at the AV node. The P waves are indicated below and show no relation to the QRS complexes. They 'probe' every part of the ventricular cycle but are never conducted. All the impulses generated from the sinus node are not conducted to the ventricle. No impulses are conducted and the ventricular rate becomes dependent on spontaneous ventricular depolarizations. Severe symptomatic bradycardia with HR = 20-40bpm. The ventricles are depolarized by a ventricular escape rhythm.

iv). **Sick Sinus Syndrome & Atrial Fibrillation (SSS & AF):** Sick sinus syndrome is a disturbance of the normal rhythm of the heart. The electrical impulse that drives the heart beat starts in the sinoatrial (SA) node of the heart, and then spreads through specialized conduction pathways, causing orderly depolarization and contraction of the heart muscle. This can be traced on an electrocardiogram. The hear rate is varying between bradycardia and tachycardia rhythmically. In atrial fibrillation, sinus rhythm does not occur. Instead, multiple **"patterns"** of electrical impulses travel randomly through the atria, leading to random activation of different parts of the atria at different times. Because the tissues of the right and left atria are not stimulated to contract in an organized manner, the walls of the atria quiver. Irregular ventricular rhythm. Sometimes on first look the rhythm may appear regular but on closer inspection it is clearly irregular.

v). **Ischemic/Dilated Cardiomyopathy:** Ischemic Cardiomyopathy is ventricular systolic dysfunction caused by atherosclerotic coronary artery disease (CAD). As a result of smoking, hypertension, diabetes mellitus, lipid disorders, chronic inflammation, and genetic susceptibility, atherosclerotic plaque accumulates in the walls of coronary arteries resulting in reduced flow of blood and oxygen to the heart. Irregular heartbeats can be observed under this condition.

3. NEURAL NETWORK CLASSIFIER

Artificial Neural Networks are biologically inspired networks – inspired by the human brain in its organization of neurons and decision making process – which are useful in application areas such as pattern recognition, classification etc [20]. The decision making process of the ANN is more holistic, based on the aggregate of entire input patterns, whereas the conventional computer has to wade through the processing of individual data elements to arrive at a conclusion.

The Neural Networks derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of unknown input data into categories, provided they are previously trained to do so. The accuracy of the classification depends on the efficacy of training, which in turn depends upon the rigor and depth of the training. The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input.

Three issues need to be settled in designing an ANN for a specific application: (i) topology of the network and (ii) training algorithm (iii) neuron activation function. A network may have several 'layers' of neurons and the overall architecture may either be feedback or feed forward structure. If the task is merely to distinguish linearly separable classes, a single layer perceptron classifier is quite adequate. If the class separation boundaries can be piecewise linear approximated, then a two layer perceptron classifier needs to be used. If the class boundaries are more complex, a three layer *feed forward* neural network, with sigmoid activation function is more suitable [21, 22].

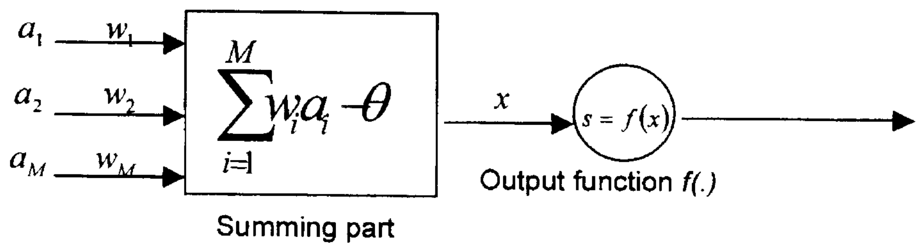

Figure 1. Model of an artificial neuron (processing unit).

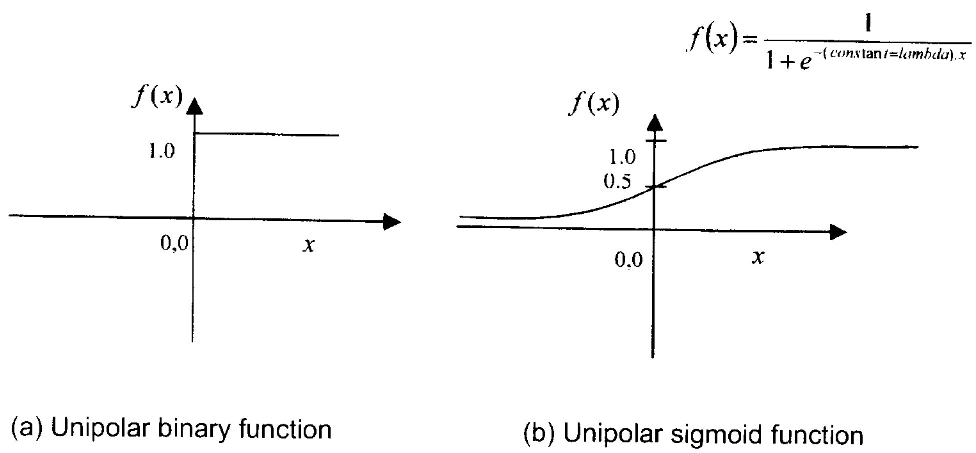

Figure 2. Neuron activation functions.

A neural network classifier is implemented using radial basis functions [23]. The net input to the radial basis transfer function is the vector distance between its weight vector w and the input vector p, multiplied by the bias b. The radial basis function has a maximum of 1 when its input is 0. As the distance between w and p decreases, the output increases. Thus a radial basis neuron acts as a detector, which produces 1 whenever the input p is identical to its weight vector p. Probabilistic neural network, which is a variant of radial basis network is used for the classification purpose. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose element indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output vector probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities and produces a one for that class and a 0 for the other classes. The architecture for this system is shown in Figure 3.

In this implementation we have used D=160 input training vector/target vector pairs. Each target vector has K =5 elements (Table II). One of these elements is one and the rest is zero. Thus each input vector is associated with one of K = 5 classes.

The first layer input weights **w** is set to the transpose of the matrix formed from the D training pairs. As the input feature vector has R=3 inputs, the weight matrix formed is of dimension 3 x 160. When an input x is presented, $\|w - x\|$ is calculated. $\|w - x\|$ Indicates how close the input is to the vectors of the training set. These elements are multiplied, element-by-element, by the bias and sent to the radial basis transfer function. An input vector close to a training vector will be represented by a number close to one in the output vector Q. The second layer weights p are set to the matrix T of target vectors. Each vector has a one only in the row associated with that particular class of input, and zeros elsewhere. The multiplication Qp sums the elements of Q due to each of the K input classes. Finally, the second layer transfer function is complete by finding producing a one corresponding to the largest element and zeros elsewhere. Thus the network has classified the input vector into a specific one of K classes because that class had the maximum probability of being correct.

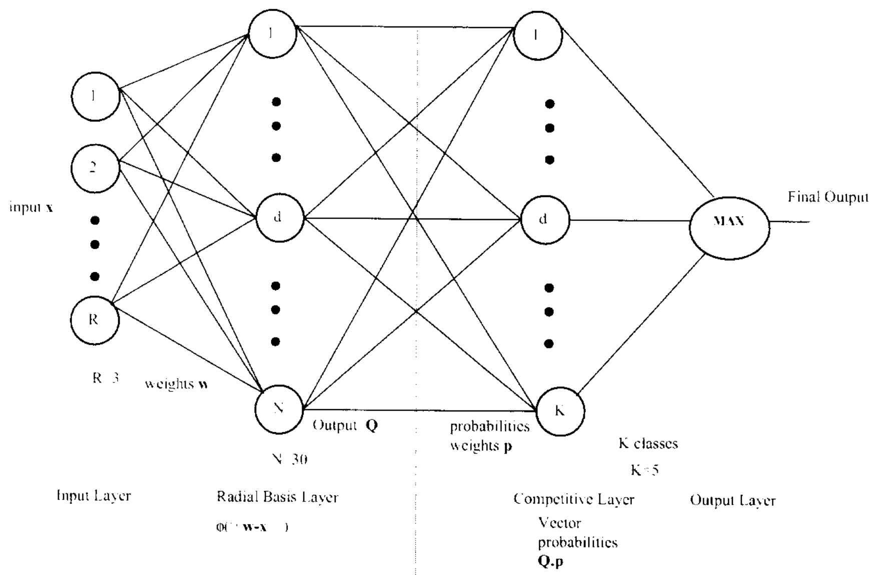

Figure 3. Probabilistic Neural Network Architecture.

Table II. Various types of output classes.

Serial Number	B1	B2	B3	B4	B5	Type of Disease
1	1	0	0	0	0	Complete Heart Block (CHB)
2	0	1	0	0	0	Sick Sinus Syndrome (SSS) & Atrial Fibrillation
3	0	0	1	0	0	Ischemic/ Dilated Cardiomyopathy
4	0	0	0	1	0	Ectopics
5	0	0	0	0	1	Normal

4. DISEASE CLASSIFICATION USING ANN

The ANN classifier is fed by three parameters derived from the heart rate signal:

i). **Average Heart rate (HR_{avg}):** Though the heart rate is a non-stationary signal, the range of heart rate for various disease categories are seen to be different, the average heart rate can serve as a parameter of classification (Table III). The average is evaluated for 10 minutes interval.

ii). **Largest Lyapunov exponent (LLE)**: Lyapunov exponent (λ) is a measure of the rate at which the trajectories separate one from other [24, 25, 26]. A negative exponent implies that the orbits approach a common fixed point. A zero exponent means the orbits maintain their relative positions; they are on a stable attractor. Finally, a positive exponent implies the orbits are on a chaotic attractor. For two points in a space X0 and X0 + Δx0, that are function of time and each of which will generate an orbit in that space using some equations or system of equations, then the separation between the two orbits Δx will also be a function of time. This separation is also a function of the location of the initial value and has the form Δx (X0, t). For chaotic data set, the function Δx (X0, t) will behave erratically. The mean exponential rate of divergence of two initially close orbits is characterized by:

$$\lambda = \lim_{t\to\infty} \frac{1}{t} \ln \frac{|\Delta x_0 (X_{0,} t)|}{|\Delta X_0|} \tag{2}$$

The Lyapunov exponent "λ" is useful for distinguishing various orbits.

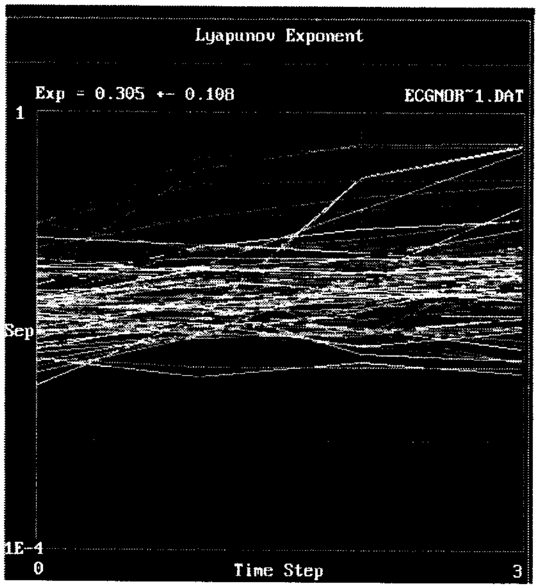

Figure 4. Lyapunov Exponent.

Largest Lyapunov exponent's (LLE) quantify sensitivity of the system to initial conditions and gives a measure of predictability (Figure 4). Presence of positive Lyapunov exponent indicates chaos. Even though a m dimensional system has m Lyapunov exponents, in most applications it is sufficient to compute only largest Lyapunov exponent (LLE). We make use of the method proposed by Rosenstien et al [27], which is robust with data length. This method looks for nearest neighbor of each point in phase-space and tracks their separation over certain time evolution. The LLE is estimated using a least squares fit to "average" line defined by:

$$y(n) = \frac{1}{\Delta t} \langle In(d_i(n)) \rangle \tag{3}$$

Table III. Range of input parameters to ANN classification model

Class	HR_{avg} (bpm) (Average)	LLE	Ener 1
Complete Heart Block	33.80-38.0	0 ± 0.121 - 0.207 ± 0.127	0.05 to 0.32
SSS & AF	67.60-120.10	0.563 ± 0.151 – 0.941 ± 0.083	0.93-1.39
Isc./Dil. Cardiomyopathy	88.94-122.03	0 ± 0.082 – 0.416 ± 0.108	0.06 to 0.60
PVC	65.20-122.03	0.005 ± 0.169 – 0.747 ± 0.058	0.32 to 0.87
Normal	56.56-97.64	0.172 ± 0.105 – 0.488 ± 0.056	0.06 to 0.35

where $d_i(n)$ is the distance between i^{th} phase-space point and its nearest neighbor at n^{th} time step, and $\langle . \rangle$ denotes the average overall phase space points. This last averaging step is the main feature that allows an accurate evaluation of LLE even when we have a short and noisy data.

iii). **Ener 1**: The frequency of heart rate variation for various diseases are seen to be different. The power spectrum of heart rate variability signal shows a marked concentration of energy in different frequency bands [28, 29, 30]. Therefore the ratio of energy content in different frequency bands can be used as parameters of classification. In the present case, two input signals are derived by evaluating the ratio of energy content in two separate frequency bands:

Ener 1 = ([energy content in the band (33.3 – 100) Hz] / [energy content in the band (0 – 33.3) Hz])

5. FUZZY CLASSIFIER

In a fuzzy classification system, pattern space is divided into multiple subspaces, and for each subspace, the relationships between the target patterns and their classes are described by if-then type fuzzy rules. The superb capability of this system is that a nonlinear classification boundary can be easily implemented. Unknown patterns are classified by fuzzy inference, and patterns that belong to an unknown class which was not considered at learning can be easily rejected. Ishibuchi et al proposed methods to acquire a fuzzy classification system automatically by a simple learning procedure and a genetic algorithm [31, 32]. With these methods, however, a pattern space is divided lattice-like. Therefore, many fuzzy rules corresponding to fine subspaces are required to implement a complicated classification boundary.

A fuzzy classifier [33] using subtractive clustering and Sugeno fuzzy inference system is implemented as a classifier as shown in Figure 5. The algorithm for implementation is as follows:

Step 1 - Fuzzify Inputs: The input is fuzzified using symmetric gaussian membership function given by

$$f(x;\sigma,\mu) = \frac{e^{-(x-\mu)^2}}{2\sigma^2} \qquad (4)$$

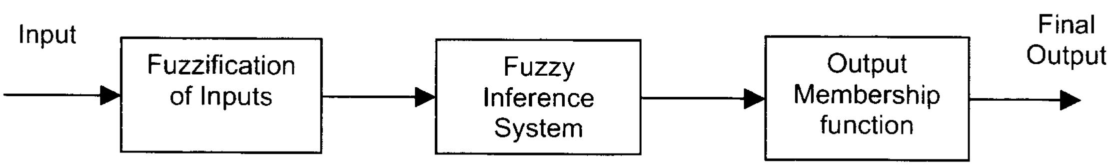

Figure 5. Fuzzy classification System.

where σ and μ are variance and mean respectively

Step 2 - Fuzzy inference: Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic for making decisions. From the fuzzified inputs, the cluster centers are determined using subtractive clustering method. In this method,

- The data point with the highest potential to be the first cluster center is selected
- All data points in the vicinity of the first cluster center (as determined by radii) is removed in order to determine the next data cluster and its center location
- This process is iterated until all of the data is within the radii of a cluster center

Step 3 - Obtaining the output: Final output is obtained using sugeno fuzzy model. The output membership function is linear and is given by $r = ax + by + cz + d$.

The output level r_i of each rule is weighted by the firing strength w_i of the rule. The final output of the system is the weighted average of all rule outputs, computed as

$$\text{Final Output} = \frac{\sum_{i=1}^{N} w_i r_i}{\sum_{i=1}^{N} w_i} \tag{5}$$

6. STATISTICAL CLASSIFIER

A widely used pattern recognition method is calculating the various parameters required for recognition processing from the probabilistic statistical nature of sample patterns, and recognizing unknown patterns based on those calculated parameters. This is generally called "statistical pattern recognition". Since statistical pattern recognition is based on the probability distribution model of target patterns, this method can be applied to any processing target. Statistical pattern recognition can be classified into a parametric method and a non-parametric method. In the case of a parametric method, the probability distribution type of target patterns is defined in advance. With a non-parametric method, on the other hand, recognition equipment can be designed only from sample patterns, without any prior knowledge. In other words, a non-parametric method can process various recognition patterns that have different probabilistic statistical natures simultaneously and easily. This method is expected to be used as a recognition engine in multimedia environments, which will be common in the future.

The statistical classifier [34,35] is implemented using discriminant functions as shown in Figure 7.

A classifier assigns feature vector $\mathbf{x}$ to class ωi if the discriminant function $gi(\mathbf{x}) > gj(\mathbf{x})$ for all $j \neq i$. By Bayes theory, maximum value for discriminant function corresponds to minimum conditional risk,

$$gi(\mathbf{x}) = -R(\alpha i \,|\, \mathbf{x})$$

where $R(\alpha i \mid \mathbf{x}) = \sum C(\alpha i \mid \omega j)\, P(\omega j \mid \mathbf{x})$ is the conditional risk or expected loss and $C(\alpha i \mid \omega j)$ is the loss function incurred for taking action αi . $C(\alpha i \mid \omega j)$ is taken as the symmetrical loss (*zero-one*) function which assigns zero loss to correct decision.

$$C(\alpha_i | \omega_j) = \begin{cases} 1, i \neq j \\ 0, i = j \end{cases} \qquad \text{where } i, j = 1, 2, \dots c$$

Thus, conditional risk is $R(\alpha i \mid \mathbf{x}) = 1 - P(\omega i \mid \mathbf{x})$. A simplification for the above is $gi(x) = P(\omega i \mid \mathbf{x})$, so that maximum discriminant function corresponds to maximum a posteriori probability. Classification remains unchanged if $gi(\mathbf{x})$ is replaced by $f(gi(\mathbf{x}))$ as long as $f(.)$ is a monotonically increasing function. Hence the discriminant is chosen as

$$g_i(x) = \log(p(\mathbf{x} \mid \omega j)) + \log(P(\omega j))$$

Assuming gaussian probability density function for each class, the discriminant function can be represented as

$$g_i(x) = -\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i) - \frac{1}{2}\log|\Sigma_i| + \log P(\omega_i) \tag{6}$$

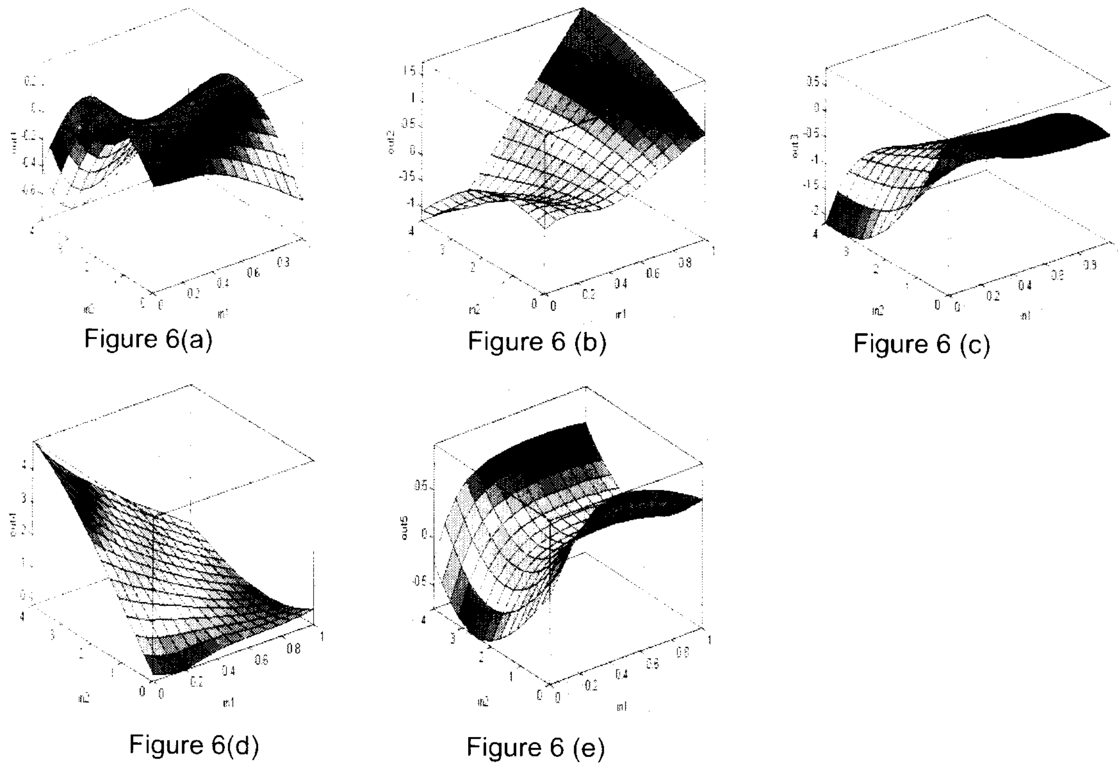

Figure 6. Output Fuzzy Inference Surface for (a) Complete Heart Block (b) Sick Sinus Syndrome (c) Ischemic Cardiomyopathy (d) PVC (e) Normal.

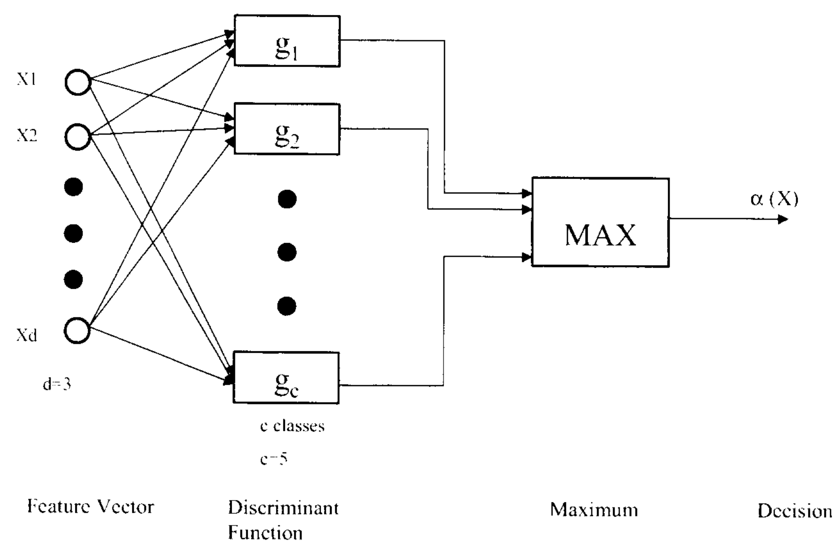

Figure 7. Statistical Classifier.

The classifier is implemented with feature vector having three inputs (d=3) and five output classes(c=5). Five discriminant functions ($gi(x)$ for $1 \leq i \leq 5$) are formed for each of the classes described in section 2.

7. RESULTS

It can be seen from the results that, the statistical classifier and fuzzy classifier gives about 90% correct classification and radial basis classifier gives about 95% correct classification.

Statistical classifiers are less complex, easy to implement. It does not require any training and hence it is fast. Even fuzzy classifiers are easy to implement and also fast. But the radial basis function classifiers do need training and hence takes time to deliver the correct output. This result can further be improved by taking more varied test data.

8. CONCLUSION

Neural Network classifier, Fuzzy relation classifier and statistical classifiers are developed as diagnostic tools to aid the physician. However, these tools generally do not yield results with 100% accuracy. The accuracy of the tools depend on several factors, such as the size and quality of the training set, the rigor of the training imparted, and also parameters chosen to represent the input. However, from the results listed in Table IV, V, and VI, it is evident that the classifiers are effective to the tune of about 90 – 95% accuracy.

Table IV. Neural Network Classifier results

Class	No. of data set used for training	No. of data set used for testing	Percentage of correct classification
Complete Heart Block	20	10	100
AF & SSS	20	10	80
Isc./Dil. Cardiomyopathy	30	20	95
PVC	30	20	100
Normal	60	30	100

Table V. Results of Fuzzy Clustering Classifier

Class	No. of data set used for training	No. of data set used for testing	Percentage (%) of correct classification
Complete Heart Block	20	10	100
SSS, AF	20	10	80
Isc./Dil. Cardiomyopathy	30	20	90
PVC	30	20	100
Normal	60	30	93.33

Table VI. Results of Statistical Classifier

Class	No. of data set used for training	No. of data set used for testing	Percentage (%) of correct classification
Complete Heart Block	20	10	100
SSS, AF	20	10	70
Isc./Dil. Cardiomyopathy	30	20	85
PVC	30	20	90
Normal	60	30	100

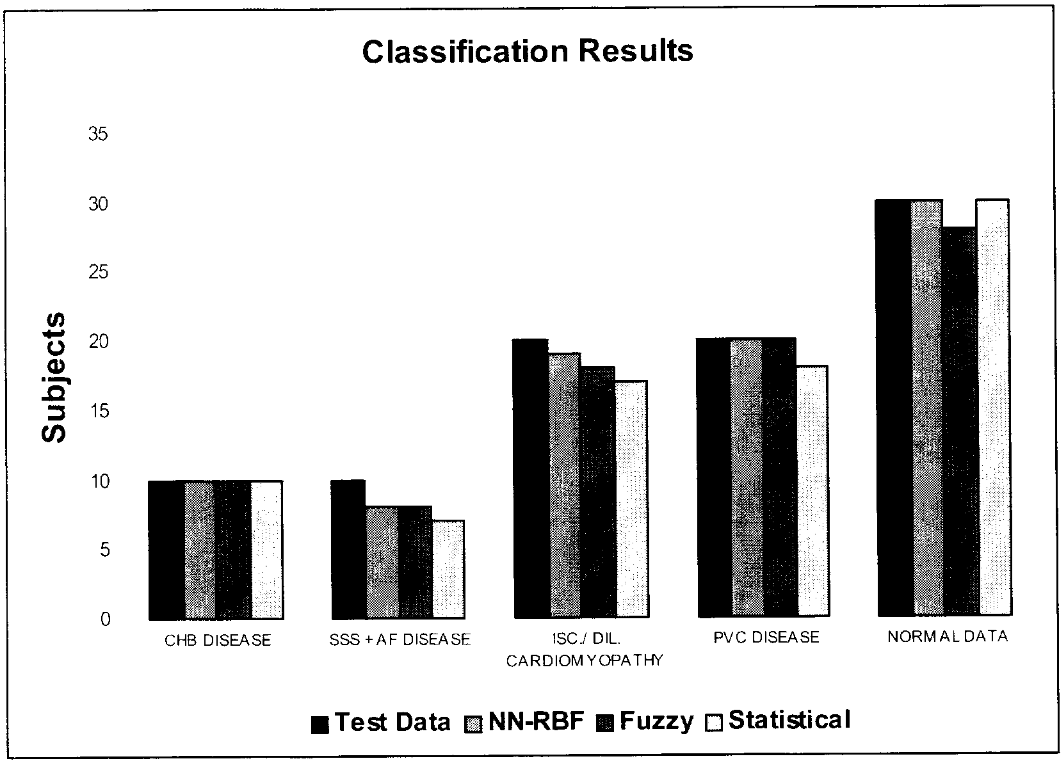

Figure 8. Classification Accuracy of five categories of cardiac health.

Table VII. Overall Results of three classification techniques

Disease	Test Data	Classification Results		
		NN-RBF Classifier	Fuzzy Classifier	Statistical Classifier
CHB DISEASE	10	10	10	10
SSS + AF DISEASE	10	8	8	7
ISC./ DIL. CARDIOMYOPATHY	20	19	18	17
PVC DISEASE	20	20	20	18
NORMAL DATA	30	30	28	30
% Classification Accuracy (Overall)		96.67	93.33	91.11

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FUZZY ROBUST TRACKING FOR A CLASS OF NONLINEAR SYSTEMS-APPLICATION TO THE CHEN'S CHAOTIC ATTRACTOR*

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ABSTRACT—In this paper, the problem of forcing a nonlinear system to track a desired reference in the presence of uncertainties in the system's parameter values is addressed for a class of nonlinear systems which can be described by a Takagi-Sugeno Fuzzy model. This approach is obtained by properly combining the theory of robust regulation and the Takagi-Sugeno modeling. By a suitable design of local robust controllers for each linear subsystem, it is shown that the aggregated controller guarantees asymptotic tracking even in the presence of variations on the parameters of each linear subsystems and in the membership functions.

Key Words: Robust output regulation, Takagi-Sugeno Fuzzy model, Chen Chaotic System

1. INTRODUCTION

A cornerstone problem in control theory is that of controlling it to track, at least asymptotically, a desired reference signal, preserving at the same time some suitable stability property of the closed-loop scheme. Among the different approaches studied, the so-called regulator theory has provided a frame to accomplish such objectives. The regulator problem consists in finding a state or error feedback controller such that the equilibrium point of the closed system with no external signals is asymptotically stable, and the tracking error goes to zero when the system is under the influence of the exosystem. Roughly speaking, the solution to this problem is related to the existence of a steady state behavior of the system on which the tracking error is zeroed. The steady state dynamics may be seen as the dynamics that a stable system undergoes when excited with a stable input. This problem has been studied intensively both in the linear case [3], and recently in the nonlinear setting [6], [5], by showing that the nonlinear regulator problem is solvable by means of the solution of a partial differential equations, named Francis-Isidori-Byrnes (FIB) equations. On the other hand, for nonlinear systems, it has been shown that the inclusion of an internal model in the controller structure was also necessary and sufficient for having robust regulation, i.e., the capability of the controller for maintaining the output tracking error within certain predefined bounds while ensuring the stability of the closed-loop system, despite the presence of parameter perturbations [4]. Following these ideas, in [7], [2] and [1], an error feedback controller which relies on the existence of an internal model is presented. This internal model represents an inclusion of the exosystem dynamics into an observable one, which allows generating, as in the linear case, all the possible steady state inputs for the admissible values of the system parameters. A remarkable feature is that the controller is constructed on the basis of the linear approximation of the nonlinear system and, in the case when the immersion is linear, the controller becomes fully linear. However, since the solvability of this robust solution relies on the existence of a solution of both the FIB equations and the existence of an internal model, for which no solution is guaranteed a priori, then for many complex physical systems, this may become a drawback.

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