Classification of Renal Failure Using Simplified Fuzzy Adaptive Resonance Theory Map

Venkatesan P† and Suresh M L††

†Department of Statistics, Tuberculosis Research Centre, ICMR, Chennai, India
††Research Scholar, Sathyabama University, Chennai, India

Abstract

Simplified Fuzzy Adaptive Resonance Theory Map (SFAM) is a family of neural networks that performs incremental supervised learning of recognition categories and multidimensional maps of both binary and analog patterns. SFAM is fast, interactive, incremental and stable and it is being applied to prediction in many areas. Medical diagnoses present many challenges in classifying patients based on symptoms. One of the major problems in medical diagnosis is the subjectivity involved in classification of diseases like renal failure. This paper discusses the usefulness of SFAM in classifying renal failure. A database containing 1200 renal failure cases are used in this work and the network model resulted in about 90% correct classification.

Key words:

Simplified Fuzzy ART Map, Medical Diagnosis

1. Introduction

There are many areas in medicine in which classification and recognition of data patterns is vital [1]. There is substantial research work in progress to solve the pattern classification problems [2]. Artificial Neural networks (ANN) are preferred to solve these problems, because of their parallel processing capabilities, as well as decision making abilities. ANN have been applied for various medical classification tasks such as predicting prognosis and survival rates[3], choosing therapy for peptic ulcers [4], diagnosing breast cancer[4], interpreting tissue sections and blood chemistry[5], diagnosing dementia[5], interpreting electrocardiograms[5],diagnosing myocardial infarction[5-6],diagnosing epilepsy[7], diagnosing of low back disorder[8], classification of thyroid disorders[9],identification of Alzheimer's diseased tissue[10],diagnosing diabetes[11] and so on. ANNs are used as information analysis tools, which provide valuable aid for pattern classification. The Simplified Fuzzy ARTMAP Network has also been applied for the solution of various pattern classification problems [12-18].

Adaptive Resonance Theory (ART) neural networks were originally proposed by researchers from Boston University [19-20], for pattern classification. ART is a new type of neural network designed by Grossberg in 1976 to solve stability-plasticity dilemma [21]. ART1 was developed in 1983 allowing unsupervised classification of binary inputs. Then ART2 was developed allowing unsupervised classification of analog inputs. In 1987, ARTMAP was developed allowing supervised classification of analog inputs. Carpenter et-al refined the system to a general one by incorporating Fuzzy ART dynamics and termed it Fuzzy ARTMAP and it used supervised learning and classification of analog patterns [22-24]. Kasuba propounded the Simplified Fuzzy ARTMAP (SFAM) system, which is a simplification of Fuzzy ARTMAP. The SFAM network is a step ahead of Fuzzy ARTMAP, in reducing the computational overhead and architectural redundancy of Fuzzy ARTMAP. We have used a simplified version of fuzzy ARTMAP proposed by Kasuba [25]. This network, like other fuzzy ARTMAP networks uses normalized and complemented inputs. This paper summarizes the experiments with Simplified Fuzzy ARTMAP network applied to renal failure data.

2. Simplified Fuzzy ARTMAP

SFAM is a fast, online/interactive, incremental, supervised learning system for analog inputs. SFAM uses simple fuzzy learning rules like max and min for activation and selection of neurons. The fuzzy rules minimize the computation required for learning and it learns every pattern with very few iterations. But training back propagation network is time consuming and it takes thousands of epochs for the network to reach the equilibrium. And it is also not guaranteed to reach the global minimum. The network starts with no connection weights, grows in size to suit the problem, uses simple learning equations, and has only user-selectable parameter known as vigilance parameter. The fast learning capability is made possible by a series of processing stages: input creation, input formatting output node activation, pattern matching, and categorical mapping.

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SFAM contains two layers: an input and an output layer. A block diagram of the SFAM network highlighting the main architecture is shown in fig.1. Input into the network must be normalized to a value from 0 to1. Hence a suitable normalization value must be chosen so that no input will fall outside the valid range. A compliment coder normalizes the input and also provides the fuzzy compliment for each value. This expanded input (I) is then passed to the input layer. Weights (w) from each output node sample the input layer, making the weights top-down. Training begins with just one hidden node whose weights are set equal to the first record and prediction is set equal to the class of the first record. Similarly, whenever a new class is encountered a new node is created. The node, whose weights best match the current input, supplies the prediction provided, the degree of the match exceeds the vigilance threshold value. If this prediction is correct, the weights of this winning node are adjusted towards this input. If the prediction is wrong or vigilance threshold is not achieved, a new node is created with weights and prediction equal to this record.

Network is said to be in a state of resonance, if the Network function value exceeds vigilance parameter. Network is said to be in a state of mismatch reset, if vigilance parameter exceeds match function value. Once the network is trained, by passing input pattern into complement coder and then input layer, all the output nodes compute activation function with respect to input. The winner, which is the node with the highest activation function, is chosen. The category of the input is found by assigning it the category of the most highly activated node max (T_j). The category layer merely holds the names of the (m) categories that the network is expected to classify.

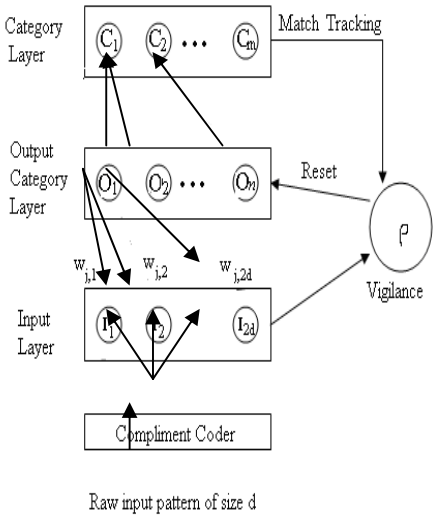

Fig. 1 Block diagram of SFAM network

The training algorithm is now described for completeness. For a given input vector a of d features, the compliment vector $\bar{a}$ represents the absence of each feature

$$\bar{a} = 1 - a \tag{1}$$

The internal compliment coded input vector I is then of dimension 2d.

$$I = (a, \bar{a}) = (a_1, a_2, .. a_d, \bar{a}_1, \bar{a}_2, .. \bar{a}_d) \tag{2}$$

The activation and matching functions are defined as

$$T_j = \frac{|I \wedge W_j|}{\alpha + |W_j|} \tag{3}$$

$$M = \frac{|I \wedge W_j|}{|I|} \tag{4}$$

where Wj are current values of templates a (weight vector) associated with output nodes j and α is a small value close to zero. The updates of templates that belong to resonant domain are represented as an assignment statement.

$$W_j = (1 - \beta) W_j + \beta |I \wedge W_j| \tag{5}$$

where β is the learning rate, $0 \leq \beta \leq 1$. The operator $|I \wedge W_j| = \sum \min (I, W_j)$ used in (4) and (5) defines "fuzzy AND "which assumes positive, normalized values of the inputs.

2.1. Renal failure

The kidneys are the body's filtering system. They remove waste materials from the blood. They also help to maintain the body's balance of chemicals, like sodium and potassium and produce hormones and vitamin D. There are many risk factors that lead to renal failure. Some of them are diabetes, inflammation, high blood pressure, blockage, and infection in blood stream, certain medicines, polycyclic kidney disease, poor heart function, irregular flow of blood to kidneys, severe bleeding, low blood volume, bladder obstruction and so on[26-27]. Acute renal failure is the sudden loss of kidney's ability to perform functions like elimination of excess fluid and waste material from the blood. Acute renal failure is most common in people who are already hospitalized, or it tends to occur after a complicated surgery, a severe injury or when blood flow to the kidney is affected. Loss of renal function may also develop gradually over time, with few symptoms in early stages, referred as chronic renal failure. High blood pressure and diabetes are the most common causes of chronic renal failure. About 30% of patients with diabetes develop renal failure [28-30].

2.2. Database

A total of 1200 renal failure data were collected from Government General Hospital, Chennai over a period of 7 years from the year 1999 to 2006.Information of patients demographic and disease characteristic were collected. A total of 17 covariates were considered for the network. Further details on the database are given in [31].

2.3. Performance Measures of SFAM

A common tool for classification analysis is the confusion matrix [32], a matrix of size n × n, where n denotes the number of possible classes. The validity measures used to assess the network are sensitivity (called as recall), specificity, and positive prediction (called as precision) [33].

2.4. SFAM Model for Renal Failure Data

The network model for the renal failure data has 17 inputs and 17 complementary inputs. Each node of the hidden layer predicts a class and the output contains 3 nodes, which are shown in fig.2. The commonly used 2/3 and 1/3 partitions were adopted for the training and testing [34]. The training data was used to train the model, and the test data was used to measure the performance of the trained network. There were 126 acute, 778 chronic and 296 diabetic renal failure cases respectively. The disease and demographic characteristics are given in table 1 and 2. Out of the 1200 renal failure patients 847 (70.6%) were men and the mean age was 48 years. The frequencies of different disease conditions are given for the three categories conditions are given for the three categories.

Table 1: Mean (SD) of the continuous covariates

Variable	Acute(126) Mean (SD)	Chronic(778) Mean (SD)	Diabetic(296) Mean (SD)	Total(1200) Mean (SD)
Age	44.54(14.07)	46.49(14.1)	53.8(9.7)	48(14)
Cholesterol	184.75(57.08)	168.75(26.3)	175.2(19.2)	172(30)
Hemoglobin	10.8(2.5)	8.4(2.3)	8.9(2.3)	8.7(2.4)
PCR	0.87(0.91)	1.99(1.47)	2.87(1.59)	2.09(1.56)

Table 2: Distribution of demographic and disease Characteristics

Variable	A(126)	C(778)	D(296)	T(1200)
<5 years	8.7	14 .0	15.9	13.9
Diabetic	0.8	2.2	39.5	11.3
5<x<10years				
>10years	2.3	.13	44.6	11.3
Edema (present)	46.03	89.3	86.8	84.2
Family History (present)	2.4	0.9	1.0	1.1
Hesitancy (present)	3.2	3.1	0.7	2.5
<5years	44.4	79.4	70.3	73.5
Hypertension	0	3.6	17.2	6.6
5<x<10years	0.8	2.4	6.1	3.2
>10years				
Nocturia (present)	3.2	9.4	8.8	8.6
Obstruction (present)	4.8	4.2	2.7	3.9
Oliguria (present)	50	72.6	63.5	68.0
Polyuria (present)	4.0	1.8	2.4	2.2
Puffiness of face (present)	38.1	87.7	82.8	81.3
Sex (male)	65.1	71.7	70.0	70.6
Tobacco (yes)	27.8	38.1	32.4	35.6
Urgency (yes)	1.6	1.0	1.0	1.1

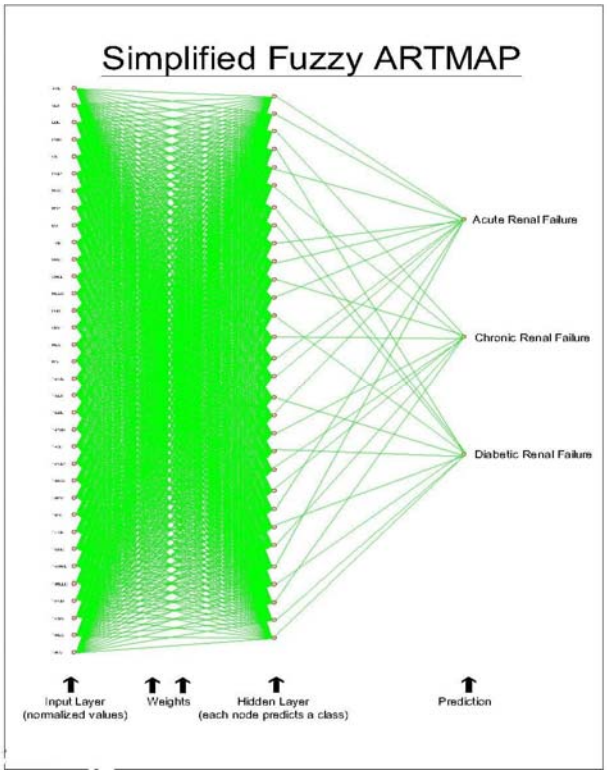

Fig.2 SFAM for renal failure data

3. Results: Tables 3-5, give the prediction error associated with SFAM, using a pair wise classification. The overall classifications of all the 3 categories are given in table 6. The most important parameter for SFAM is vigilance parameter "ρ". The test was done for different values of "ρ", $0 \leq \rho \leq 1$ with an increment step of 0.1. The acute vs chronic classification has about 87% correct classification with vigilance parameter.51.The correct classification ranged from 70.67% to 94.08% for various vigilance parameters. Diabetes and acute category had correct classification of 94.37%with vigilance parameter .59. Diabetic and chronic category had correct classification of 93.30% with vigilance parameter.43. Also the correct classification ranged from 78.57% to 97.56% for acute and diabetic categories for different vigilance parameters. Similarly the correct classification ranged from 87.43% to 93.30% for chronic and diabetic categories. The overall correct classification for all the 3 categories is 85.7% with vigilance parameter.53. The correct classification for all the categories ranged from 60.25% to 85.75% for various vigilance parameters.

Table 3: Confusion Matrix (Acute vs Chronic)

Actual/Predicted	Acute	Chronic	Total	Prediction Error%
Acute	22	22	44	50.0
Chronic	17	240	257	6.6
Total	39	262	301	13.0
Actual Error%	43.6	8.4	13.0	

From table 3, Out of the 44 acute cases, the network correctly predicts as acute in 22(50%) of the cases and out of 257 chronic cases 240(93.4%) were correctly predicted. The overall correct classification is 87%. From table 4, out of 252 chronic cases, the network correctly predicts as chronic in 246(97.6%) cases and out of 106 diabetic cases the network predicts 88 as diabetic (83%), and the overall correct classifications is 93.3%. From table6, the network predicts 9 as acute out of 26(34.6%) and 259 chronic cases were predicted correctly out of 287 (91.27%) and 75 cases as diabetic out of 87(86.2%). The overall correct classification in all the categories is 85.7%. On the whole overall classification for pair wise and all the categories the network prediction is 90.15%.

Table 4: Confusion Matrix (Chronic vs Diabetic)

Actual/Predicted	Chronic	Diabetic	Total	Prediction Error %
Chronic	246	06	252	2.4
Diabetic	18	88	106	17.0
Total	264	94	358	6.7
Actual Error%	6.8	6.4	6.7	

Table 5: Confusion matrix (Acute vs diabetic)

Actual/Predicted	Acute	Diabetic	Total	Prediction Error%
Acute	47	05	52	9.6
Diabetic	03	87	90	3.3
Total	50	92	142	5.6
Actual Error%	6.0	5.4	5.6	

Table 6: Confusion Matrix (All Categories)

Actual/Predicted	Acute	Chronic	Diabetic	Total	Prediction Error %
Acute	9	17	0	26	65.4
Chronic	11	259	17	287	9.8
Diabetic	0	12	75	87	13.8
Total	20	288	92	400	14.3
Actual Error%	55.0	10.1	18.5	14.3	

4. Summary and Conclusion

SFAM network model gives high accurate classification of the 3 categories, where the classification between categories contains a lot of redundancy, particularly between acute and chronic. 11 out of the 17 input variables were binary in nature. SFAM is sensitive to the order of the inputs. To overcome this problem data were spread uniformly in both testing and training. Also to increase the classification percentage, multiple SFAM networks can be utilized with a voting scheme. A variant of fuzzy ARTMAP, known as fusion ARTMAP and a hybrid Neural Network system for pattern classification are useful to handle the missing data. Most of the input

variables are fuzzy in nature and the target variables of 3 renal classifications are achieved with high level of accuracy. As a future work modification in activation function and matching function may improve the prediction accuracy. A major limitation of SFAM for medical decision-support applications is, it has no provision for missing data items when generating predictions. The prediction may be improved using other fuzzification and defuzzification rules. Further studies are needed to demonstrate SFAM's usefulness in disease conditions like renal failure which has often fuzzy data.

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Received the M.Sc.,M.Phil. and Ph.D Degrees, from Madras Univ. in 1975, 1980 and 1990 respectively. After working as Asst.statistician (from 1982), Research Officer (from 1991), Senior Research Officer (from 1995), Assistant Director (from 2001), and Deputy Director (from 2006) in the Department of Statistics, Tuberculosis Research Centre (TRC), Indian Council of Medical Research (ICMR), Chennai. He is now working as a Scientist at TRC, ICMR since 2008. His research interest includes machine learning, computational biology, survival analysis, disease modeling, hidden Markov models and MCMC. He is the fellow of ISMS, India. He is a member of IBS, IABMS, ISPS, and IASP

Received the M.Sc. and M.Phil from Madurai Kamaraj University in 1984 and 1990 respectively. After working as Lecturer (from 1984), Assistant professor (from 1996) in Sathyabama University, in the Department of Mathematics, he is now working in Easwari Engineering College, as Assistant professor and doing his research activities under the guidance of Dr.Venkatesan. His areas of interest are neural network and fuzzy logic.