

## 7. STATISTICAL RESEARCH

### Ongoing Study:

#### **Classification using Simplified Fuzzy Adaptive Resonance Theory Map**

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 has been applied for 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.

Artificial Neural networks (ANN) are preferred for solving these problems because of their parallel processing capabilities as well as decision making abilities. ANNs have been applied for various medical classification tasks such as predicting prognosis and survival rates. ANN is used as an information analysis tool, which provides valuable aid for pattern classification. The Neuro-Fuzzy systems have also been applied for the solution of various pattern classification problems.

Adaptive Resonance Theory (ART) neural networks were originally proposed by researchers for pattern classification. ART1 was developed allowing unsupervised classification of binary inputs and ART2 was developed allowing unsupervised classification of analog inputs. This network uses normalized and complemented inputs and summarizes the experiments with Simplified Fuzzy ARTMAP network applied to renal failure data.

SFAM is a fast, online/interactive, incremental, supervised learning system for analog signals. It is essentially a two-layer network that is specialized for pattern recognition, capable of learning every training pattern with very little iteration. This translates the processing time measured in seconds rather than days or weeks to run 1000s of epochs in conventional back-propagation neural networks. The network starts with no connection weights, grows in size to suit the problem, uses simple learning equations, and has only user-selectable parameter. SFAM surpasses the performance of many other machine learning techniques in many

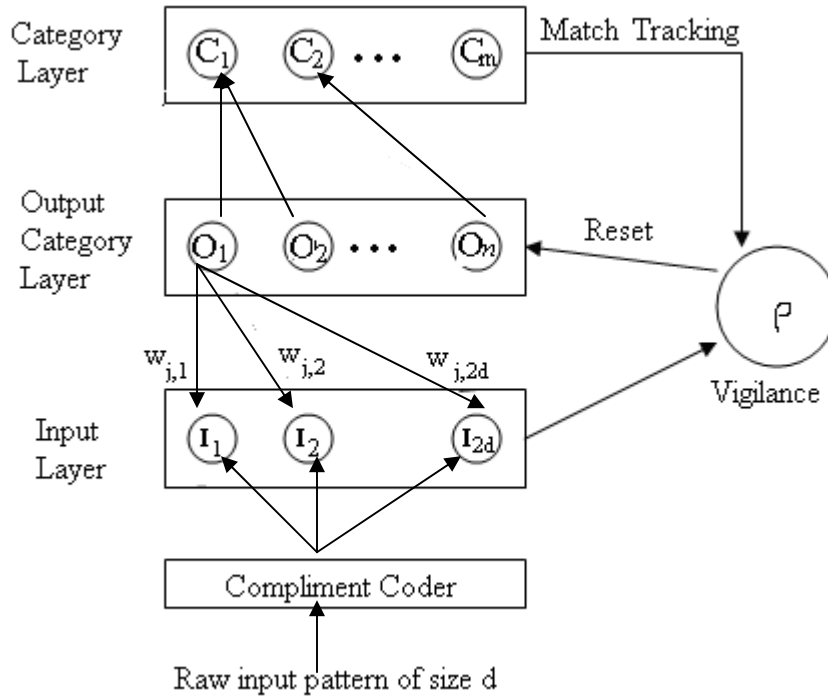
benchmark problems. This fast learning capability is made possible by a series of processing stages: input creation, input formatting output node activation, pattern matching, and categorical mapping.

SFAM contains two layers: an input and an output layer. A block diagram of the SFAM network showing the main architecture is given in Fig.7.1. 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 toward 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 state of resonance if the network function value exceeds vigilance parameter. Network is said to be in state of mismatch reset if vigilance parameter exceeds match function value. Once the network has been 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.

Input into the network must be normalized to a value from 0 to 1, hence a suitable normalization value must be chosen so that no input will fall outside of 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 weighting top-down. The category layer merely holds the names of the ( $m$ ) categories that the network is expected to classify.

**Fig. 7.1:** 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

$$\bar{a} = 1 - a \quad (1)$$

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

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

The activation and matching functions were defined as

$$T_j = \frac{|I \wedge W_j|}{\alpha + |W_j|} \quad (3)$$

$$M = \frac{|I \wedge W_j|}{|I|} \quad (4)$$

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

$$W_j = (1 - \beta)W_j + \beta|I \wedge W_j| \quad (5)$$

Where  $\beta$  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 ANN” which assumes positive, normalized values of the inputs.

Once SFAM has been trained, a ‘feed-forward’ pass through the compliment-coder and into the input layer classifies an unknown pattern. The output node activation is evaluated for each output node in the network. The category of the input is found by assigning it the category of the most highly activated node  $\max(T_j)$ .

**Application to renal failure classification:** The kidneys are the body’s filtering system. There are many risk factors for renal failure. 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. The renal failure data were collected from Government General Hospital, Chennai which comprises of 1200 cases over a period of six years. There were 126 acute, 778 chronic and 296 diabetic renal failure cases respectively. The network model consists of 17 input nodes. The commonly used 2/3 and 1/3 partitions were adopted for the training and testing. The training data was used to train the model, test data was used to measure the performance of the trained network. Out of the 1200 renal failure patients 847 (70.6%) were men and mean age was 48 years. Using the 17 covariates, the aim is to classify the cases into pair wise categories.

## Results:

The overall classification of chronic and diabetic categories is given in table 7.1.

**Table 7.1:** Confusion Matrix (Chronic vs Diabetic)

↓ <b>Actual/Predicted</b> →	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%	

The neural networks will prove useful in renal failure prediction with selected important covariates as inputs. Moreover, SFAM is sensitive to the order of the inputs. To overcome this problem and to increase the classification percentage, we can utilize multiple SFAM networks with a voting scheme. Another limitation of SFAM for medical decision-support applications is it has no provision for missing data items when generating predictions. A variant of fuzzy ARTMAP, known as fusion ARTMAP, has a solution for this problem. The results show that SFAM has superior performance compared to Multilayer perception. A comparative study of SFAM with other techniques like Radial Basis Function, Recurrent networks are in progress.

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