"An Approach for Devanagari Handwritten character recognition using HMM and Fuzzy ARTMAP"

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ABSTRACT:
In this paper focus is on recognition of handwritten characters of Devanagari script. Recognition of Devanagari handwritten alphabets is important because of its applicability to a number of problems like many commercial forms, mythological records recognition in archeology department and offline document recognition generated by the expanding technological society. Though various new trends and technologies emerged in these days, still handwriting is playing an important role. To recognize handwritten data there are different strategies like Hidden Markov Models (HMM) and Simplified Fuzzy ARTMAP (SFAM). Our focus is on Fuzzy ARTMAP, which is an updated version of Predictive Adaptive Resonance Theory, works on feedback mechanism. It also has an ability to adjust clusters as per the requirements, which is beneficial to reduce noise.

General Terms
Pattern Recognition, HMM, Simplified Fuzzy ARTMAP etc.

Keywords
Devanagari handwritten character.

1. INTRODUCTION:
Devanagari script was developed to write Sanskrit but was later adapted to write many other languages such as Marathi, Hindi, Konkani and Nepali. However, Sanskrit is an ancient language but written material still existed. After English and Chinese language, Hindi is world's third most commonly used language. Many other Indian languages use close variant of this script (Masica, 1991). Still, Devanagari Handwritten character recognition is an open field of research which has large amount of scope for development. (Bahlmann et al., 2004)

A few models are already applied for the hand written characters recognition system include structure based models(Aparna et al. 2004; Chan and Yeung,1998),stochastic models (Li et al.,1998) ,learning-based models (Manke and Bodenhausen,1994) and support vector machines etc.

To use all the available information carried by both labeled and unlabeled patterns, it is necessary to combine supervised and unsupervised learning in a single training algorithm.

HMM are basically sequence classifiers and are widely used for recognition of handwritten characters [7]. They are stochastic models and can cope with noise and also give variations in handwriting.

An evolutionary approach has been proposed to improve simplified fuzzy ARTMAP neural network performance for character recognition of printed Devanagari characters and handwritten characters as well. Some of Devanagari characters are so similar to each other. Here some fuzzy values are used for similar characters to improve recognition. Fuzzy ARTMAP already gives better performance for Thai and Malayalam characters. [9]

Fuzzy ARTMAP is a class of neural network architecture, which synthesizes fuzzy logic with adaptive resonance theory neural networks [2]. The architecture consists of two ART modules, i.e. ARTα and ARTb that create the steady recognition categories in response to arbitrary sequence of input patterns. ARTα receives a stream of { $\widetilde{a^p}$} of input patterns and ARTb receives a stream of {$\widetilde{b^p}$} from the set of input patterns { $\widetilde{a^p}$, $\widetilde{b^p}$} during the process of supervised learning. These modules linked by associative learning network and internal controller that ensures autonomous system operation in real time. Fab which is the inter-art module that links together ARTα and ARTb modules and known as the map field gets triggered whenever one of the ARTα or ARTb categories is active.

The term fuzzy refers to a flexible sense of membership of elements to a set. In fuzzy sets each element belongs to the membership value (values are between 0 to 1). The membership function is $\mu_A{}^{(x)}$is associated with a fuzzy set a $\tilde{A}$such that the function maps every element of the universe of discourse X.

A fuzzy set can be defined as;

If X is a universe of discourse and x is element of X,then a fuzzy set A can be defined on X may be written as a collection of ordered pairs

A= { (x,$\mu_A{}^{(x)}$), x є X }

There are many ways to define membership functions like Intuition, Inference, Rank ordering, Angular Fuzzy sets, Neuralnetworks, Genetic Algorithms etc. Here the inference technique is used to define membership function.

Various Fuzzy relations can be apply on fuzzy sets. Also there are fuzzy operations like Cartesian product, Union, Intersection and Complement.

2. PROBLEM:
Character recognition is extremely difficult to automate. Human being can recognize various objects and make sense out of large amount of visual information, apparently requiring very little efforts. Simulating the task performed by human to recognize to the extentallowed by physical limitations will be enormously profitable for the system. This necessitates study and simulation of Artificial Neural

Network. The problem contains the dataHandwritten Devanagari Alphabets, where handwritten Devanagari characters are the input for the system, while printed characters will be target output of the system.

Data Collection: A special sheet has to be design for data collection. Data are collected from 100 people from different fields and age. Data acquisition is done manually i.e. The plain paper sheet was provided to the respondent and asked to write the characters from अ to औ for one time. After that documents are scanned using HP-scan jet 5400c at 300 dpi which gives low noise and good quality image. The digitized images are stored in BMP file as follows:

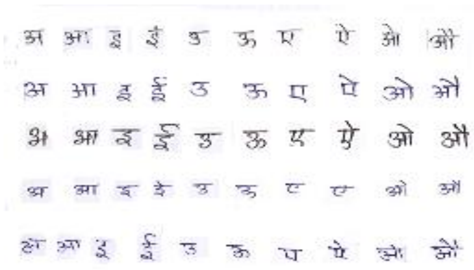

Fig. 1 : Handwritten Alphabets Data Collection

3. PRAPOSED SOLUTION:
Simplified Fuzzy ARTMAP:

The main goal of computer science is to develop an intelligence machine that can perform satisfactorily in unaided fashion in a complex environment. Adaptive Resonance Theory (ART) learns in an unsupervised fashion to fulfill the goal. The ART was introduced by Stephen Grossberg in 1976.The term resonance refers to the so called resonant state of network in which a category prototype vector matches the current input vector so close enough that the orienting system will not generate a reset signal in the other attentional layer. The networks learn only in their resonant states. The architecture of ART is based on the idea of adaptiveresonant feedback between two layers of nodes as developed by Grossberg (1988).

ART allows cluster input by unsupervised learning. One can present input patterns in any order. Each time when a pattern is presented, an appropriate cluster unit is chosen and the cluster's weights are adjusted to let the cluster unit to learn the pattern. The weights on the cluster unit may be considered to be an exemplar for the patterns placed on the cluster.

There is one disadvantage with HMM also that is it takes much training time especially at higher number of states.[7] Also the recognition time is increased as the increase in states.

Many researcher thought that Backpropagation as a solution for the Pattern recognition. [6] But Fuzzy ARTMAP based on Predictive ART (ARTMAP) can also be used for pattern recognition of characters. This network gives best performance on image recognition [2].here it is applied on character recognition too. The network will be more efficient for the recognition of similar characters.

ARTMAP is supervised, self learning, real time, self organizing network which supports slow and fast learning,[1] whereas, Backpropagation is a supervised and supports slow learning. [4] The first ARTMAP system was used to classify the inputs on the set they posses in the form of vector of binary values which gives the presence or absence of feature [2]. The more general Fuzzy ARTMAP system learn to classify the inputs by a set of feature having values zero and one which gives the presence or absence of feature.[8]

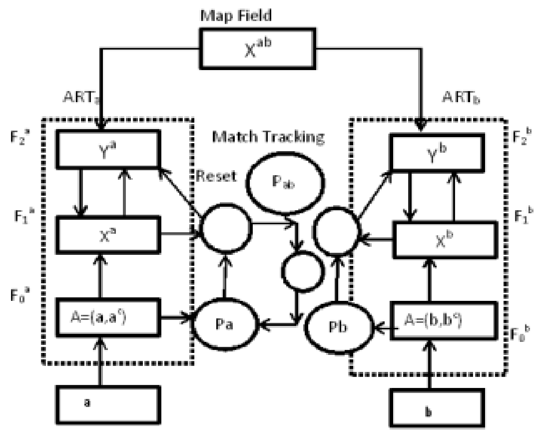

Fig 2: Working Feature of ARTMAP

The main elements of ARTMAP are two modules ARTa and ARTb . Both ARTa and ARTb are self organised and have character grouping on separate input sets.

The communication of ARTa and ARTb map field , which is responsible to control the learning of ARTa association with learing of ARTb This map is associated with the compressed and symbolic presentation of the families exemplars of a and b. The map field is also responsible to control the vigilance parameter of ARTa .

If a mismatched at map filed between ARTa category mapped by the input 'a' and ARTb category mapped by input 'b', then the vigilance at ARTa is increased by very minimum value to search the specific input category.

In Fuzzy ART leaning is always converges as it behaves like monotonically non increasing. The comparison of ART with Fuzzy ART as follows [11]:

ART 1 (BINARY)	FUZZY ART (ANALOG)
CATEGORY CHOICE	
$T_j = \frac{\lvert \mathbf{I} \cap \mathbf{w}_j \rvert}{\alpha + \lvert \mathbf{w}_j \rvert}$	$T_j = \frac{\lvert \mathbf{I} \wedge \mathbf{w}_j \rvert}{\alpha + \lvert \mathbf{w}_j \rvert}$
MATCH CRITERION	
$\frac{\lvert \mathbf{I} \cap \mathbf{w} \rvert}{\lvert \mathbf{I} \rvert} \geq \rho$	$\frac{\lvert \mathbf{I} \wedge \mathbf{w} \rvert}{\lvert \mathbf{I} \rvert} \geq \rho$
FAST LEARNING	
$\mathbf{w}_j^{(\text{new})} = \mathbf{I} \cap \mathbf{w}_j^{(\text{old})}$	$\mathbf{w}_j^{(\text{new})} = \mathbf{I} \wedge \mathbf{w}_j^{(\text{old})}$
$\cap$ = logical AND intersection	$\wedge$ = fuzzy AND minimum

Fig:3 Comparison between ART1 and Fuzzy ART

The fuzzy operations like AND and OR are formed on the basis of choosing minimum and maximum value respectively.

The minimum operator is used to denote the Intersection operation while the maximum gives union.

Without any additional processing stability property can be gain as the Fuzzy ART learning always converges because of all adaptive weights are monotonically non-increasing. The Fuzzy ART is more powerful than ART1 because it can learn input in response to binary as well as analog form, while, ART1 can learn input from binary input vector only.

Kasuba's Simplified Fuzzy ARTMAP(Kasuba,1993) which is a vast simplification of Carpenter and Grossberg's fuzzy ARTMAP has reduced computational overhead and architectural redundancy when compared to its predecessor[5]. Also, the model employs simple learning equations with a single user selectable parameter and can learn single training pattern within small number of training iterations. Fuzzy ARTMAP accomplishes high speed, accuracy in both of recognition like online as well as offline.It has number of parameters and it require no problem specific crafting or choice of initial weights or parameters[11].

Simplified fuzzy ARTMAP is essential a two-layer net containing an input and output layer.[2]

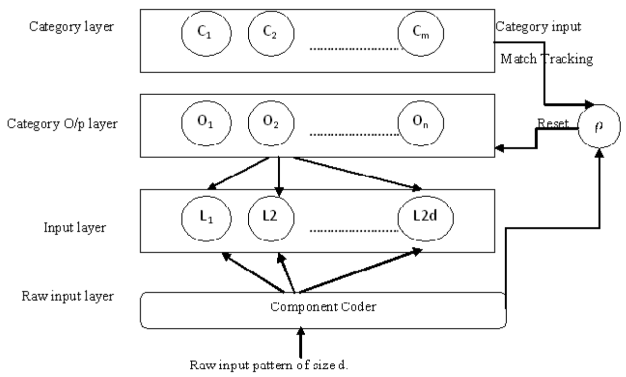

Fig.4 : Simplified Fuzzy ARTMAP

The input to the network flows through the complement coder where the input string is stretched to double the size by adding its complement also. The complement coded input then flows into input layer and remains there. The category layer merely holds the names of the M number of categories that the network has to learn. Vigilance parameter and match tracking are mechanisms of the network architecture which primarily employed for network training.ρ is the vigilance parameter can range from 0 to 1. It controls the granularity of the output node encoding. Because of high vigilance values make the output node much fussier during pattern encoding, low vigilance renders the output node to be liberal during the encoding of patterns.

The match tracking mechanism of the network is responsible for adjustment of vigilance values. When an error occurs in the training phase during the classification of patterns, i.e. when the selected output node does not represent the same output category corresponding to the input pattern presented, match tracking is evoked. Depending upon the situation, match tracking may result in the network adjusting its learning parameter and the network opening new output nodes.

Complement coding is used for input normalization and it represents the presence of particular feature in the input pattern and its absence. For example, if a is the given input pattern vector of d features then $\bar{a}^c$ represents the absence of each feature where a can be given as,

$$\bar{a} = \{a_1, a_2, \ldots, a_d\} \tag{1}$$

$$a^c = \{1-a_1, 1-a_2, \ldots, 1-a_d\} \tag{2}$$

As simplified fuzzy ARTMAP needs input values lie between 0 to 1, normalization process is necessary to adjust the input values. The complement coded input vector I is obtained by concatenating $\bar{a}^c$ with $\bar{a}$ can be given by,

$$I = (\bar{a}, \bar{a}^c) = (a1, a2, \ldots, ad, 1\text{-}a1, 1\text{-}a2, \ldots, 1\text{-}ad\} \tag{3}$$

The learning equations of the architecture call for the computation of $|I|$, can be given as

$$|\rho| = \sum_{i=1}^{d} pI \text{ ,for } \rho = (p1, p2, \ldots, pd) \tag{4}$$

The automatic input vectors can be given by using observed complement vector,

$$|I| = |(\bar{a}, \bar{a}^c)| = \sum_{i=1}^{d} a_i + (d - \sum_{i=1}^{d} a_i) \tag{5}$$

As soon as the simplified fuzzy ARTMAP presents the complement coded form of input patterns, all output nodes become active to verify degrees. This activation process of output nodes is denoted by Tjand referred to as the activation function jth output node, where Wj is the corresponding top-down weight. The Tjcan be given by,

$$Tj(I) = \frac{|I \wedge w_j|}{\alpha + |W_j|} \tag{6}$$

Here consider the value of α close to 0 i.e. usually about 0.0000001. The node having highest activation function is winner.

Winner = max (Tj)
(7)

If no match is encoded from output node then vigilance parameter decide to open new output node. It means that resonance has occurred in network. When match functions exceeds the value of vigilance parameter indicates the output node is not fit enough to learn the input pattern. In this case following weight updating equation has been used,

$$w_j^{new} = \beta (I \wedge w_j^{old}) + (1-\beta) w_j^{old} \tag{8}$$

Where $0 < \beta \le 1$

Once the network has been trained, the inference of patterns, known or unknown, i.e. the categories to which the patterns belong, may be easily computed.

4. WORKING OF FEATURE EXTRACTOR:

The classification of two-dimensional objects from visual image data is an important pattern recognition (PR) task. This task exemplifies many aspects of a typical PR problem,including feature selection,dimensionally reduction and the use of qualitative descriptors.

Moments are the extracted features derived from raw measurements.Where moments are used to achieve Rotation (R), Scaling (S),Translation (T) invariants.

Properties of invariance to R,S,T transforms may be derived using function of moments.The moment transformation of an image function f(x,y) is given by

$$mpq = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p\, y^q\ f(x,y)dx\, dy\ p,q = 0,1,2,\ldots\ldots,\infty \quad (1)$$

However, in the case of a spatially discredited 5×7 (M×N) character denoted by f(i,j) is approximated as,

$$mpq = \sum_{i=0}^{5}\sum_{j=0}^{7} i^p\, j^q f(i,j) \quad (2)$$

Here the value of f(i,j)=0 or 1 depending upon whether the (i,j)th pixel

The term intensity is represented by various aspects like the way of handwriting, ink used for written character i.e. $0 \leq f(i,j) \leq 1$ indicating that the intensity lies between the ends of a spectrum (depends upon ink).

However f(i, j) is constant over any pixel region. Consider it as central moment.

The central moments are given by,

$$\mu_{pq} = \sum_{i=0}^{5}\sum_{j=0}^{7}(i-\hat{i})^p\ (j-\hat{j})^q\ f(i,j) \quad (3)$$

Where

$$\hat{i} = \frac{m_{10}}{m_{00}}\ ,\ \hat{j} = \frac{m_{01}}{m_{00}} \quad (4)$$

The central moments are still sensitive to R and S transformation. The scaling invariant may be obtained by further normalizing µpqas,

$$\eta pq = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q}{2}+1}} \qquad p+q=2,3,\ldots.. \quad (5)$$

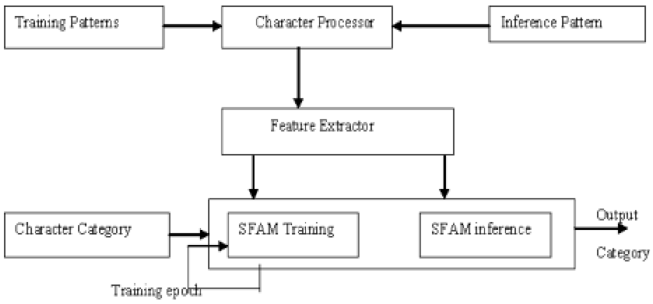

Fig 5 Block dig. Of recognition system

Consider the following figure which gives the binary pixel matrix for Devanagari handwritten character ' '

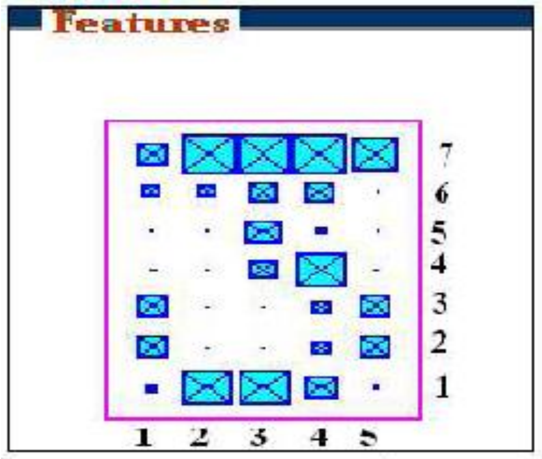

Fig 6: 5×7 Binary pixel representation of Devanagari character' '

Algorithm:

Algorithm SFARTMAP-train (P , A , I)

Step 1: Choose the value of vigilance parameter and small value for α. Set NO_OF_TRAINIGN_EPOCHS to number of epoch you want and COUNT_OF_TRAINING_EPOCHS to 0.

Step 2: I = 1;

COUNT_OF_TRAINING_EPOCHS = COUNT_OF_TRAINING_EPOCHS + 1

While(COUNT_OF_TRAINING_EPOCHS <= NO_OF_TRAINIGN_EPOCHS) Repeat step 3-12

Step 3: Input the pattern vector $I_i = (a_{i1}, a_{i2}\ \ldots\ldots\ldots, a_{id})$ of dimensions d and its category C_i.

Step 4: Compute the augmented input vector

$AI_i = (a_{i1}, a_{i2}, \ldots\ldots\ldots\ldots, a_{id}, 1- a_{i1}, 1- a_{i2}, 1- a_{id})$

Step 5: If AI_i is the first input in the given category C_i set the top down weight vector W_i as AI_i

i.e. $W_i = AI_i$;

Link W_i to category $C_{i;}$

Go to step 12.

Step 6: If AI_i is an existing pattern then compute activation function $T_j (AI_i)$ for each existing top-down weight

Nodes W_j

$$T_j(AI_i) = \frac{|AI_i \wedge w_j|}{\alpha+|W_j|} \quad ;$$

Step 7: choose the node k having highest activation value.

$T_k (AI_i) = \max T_j(AI_i)$

Step 8: Compute the match function $MF_k(AI_i)$ of the winning node k;

If $MF_k(AI_i) > p$ and C_i is same as that category C_k linked to W_k then update weight vector W_k as

$$W_k^{new} = W_k^{old} + (I \wedge W_k^{old})$$

(Here β = 1)

Step 9: If $MF_k(AI_i) > p$ and C_i is not the category C_k linked to W_k then

Undertake match tracking by p to $MF_k(AI_i)$ and increment value of ϵ

$P = MF_k(AI_i) + \epsilon$

If some more top down weight nodes exist

Then next highest winner W_k among the top- down weight nodes should be considered

goto step 8;

Else

goto step 11;

Step 10:

If $MF_k(AI_i) < P$

Then

If some more top_down weight nodes existsThen Consider the next highest winner $W_k$among the top-down weight nodes.

goto step 8;

Else goto Step 11;

Step 11: Create a new top down weight node Wi such that Wi = AI_i and link the node to the category C_i

Step 12: If no more input patterns then goto step 13;

Else

I = I +1

Goto step 3

Step 13: goto step 2;

End SFARTMAP-TRAIN

c) Algorithm SFARTMAP – INF (W,I)

Step 1: Let W_j , j= 1,2, ……. S is the top-down weight vectors obtained after training the network with a given set of training patterns.

Let I_i be the inference pattern set each of whose category is to be inferred by the network;

i= 1

Step 2: Read input I_i;

Step 3: Compute the augmented input AI_i

Step 4: for j = 1 to s

Compute activation function

$$T_j(AI_i) = \frac{|AI_i \wedge w_j|}{\alpha + |W_j|} \quad ;$$

End

Step 5: choose the winner k among the s activation functions

$T_k(AI_i) = \max T_j(AI_i)$

Step 6: output the category C_k linked to $T_k(AI_i)$ as the one to which I_i belongs to.

Step 7: If no more inference pattern vectors then exit

Else

i=i+1

goto step 2;

End SFARTMAP-INF

5. DISCUSSION AND CONCLUSION:

As per the discussion with team members on several algorithms of neural network like Back propagation, ART1, ART2 etc.,the fuzzy ARTMAP is widely used for the image recognition[2]. But as comparative to above mentioned algorithm of Neural Network it will be more efficient because of its self adjusting behavior. Again it gives the better performance on Thai character recognition[9] and Malayalam characters recognition [10] .One can get more recognition rate of Devanagari handwritten characters. And particularly, would like to work on similar type of Devanagari handwritten characters where system get fails to recognize them.

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