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Fuzzy ARTMAP supervised classification of multi-spectral remotely-sensed images

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Abstract. The fuzzy ARTMAP has been applied to the supervised classification of multi-spectral remotely-sensed images. This method is found to be more efficient, in terms of classification accuracy, compared to the conventional maximum likelihood classifier and also multi-layer perceptron with back propagation learning. The results have been discussed.

1. Introduction

During the past three decades, probabilistic, evidential and syntactic methods have been successfully applied to remotely-sensed data analysis. The major problem encountered in these statistical approaches is that it is sometimes difficult accurately to model the underlying probability density function of each class of remotely-sensed object using the available training set. Recently, artificial neural networks have been used extensively in multi-spectral image classification. Notable amongst these are multi-layer perceptron (MLP) with error back propagation and Kohonen's Self Organizing Maps. The back propagation approach is by far the most popular strategy employed for object classification in the remotely-sensed images. (Benediktsson *et al.* 1990, Bischof *et al.* 1992, Hermann and Khazenie 1992).

2. Fuzzy methods in remote sensing

The demarcation between two object classes in a remotely-sensed image is usually not crisp but imprecise. Therefore, an alternate strategy of pattern classification based on fuzzy logic has been applied for classification (Palubinskas 1995, Foody 1996). In the classification of remotely-sensed images, it is difficult to distinguish precisely between some pairs of landcover types, such as sparse grassland and soil, shallow and deep water bodies. To deal with the classification more accurately, an alternate philosophy of assigning fuzzy membership function to each class has been proposed (Wang 1990, Foody 1994). Neural networks incorporating fuzzy learning have been used for pattern classification in the recent past (Kosko 1992). Buckley and Hayashi (1994) have presented an excellent survey of various fuzzy neural networks and their applications.

3. Fuzzy ARTMAP

Adaptive Resonance Theory (ART) based neural networks have evolved from the biological theory of cognitive information processing and have been proposed for pattern classification (Grossberg 1976). An ART map using two ART modules

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to perform the mapping of input-output relations has been used for supervised classification of binary input patterns (Carpenter *et al.* 1991). A generalized version of ARTMAP has been proposed by Carpenter *et al.* (1992) for classification of analogue patterns. This architecture, called fuzzy ARTMAP, achieves a synthesis of fuzzy logic and ART networks. In this Letter, we apply fuzzy ARTMAP to the classification of multi-spectral images obtained from the LISS-II sensor of IRS-1B satellite. The results have been compared with conventional maximum likelihood classifier (MLC) and MLP with back propagation learning. The observed advantages are faster learning and better classification accuracy.

3.1. *Architecture*

Fuzzy ARTMAP architecture, modified to suit the classification of multi-spectral remotely-sensed data is depicted in figure 1. There are four layers of neurons in this ARTMAP, viz., input layer, category layer, mapfield layer and output layer. The input layer consists of $2n$ neurons to take care of the complement coded input feature vector of dimension n. The category layer starts with a single neuron and dynamically grows in number as the learning proceeds. The output and mapfield layers consist of m neurons each, where m is the output class dimension. There exists a one-to-one

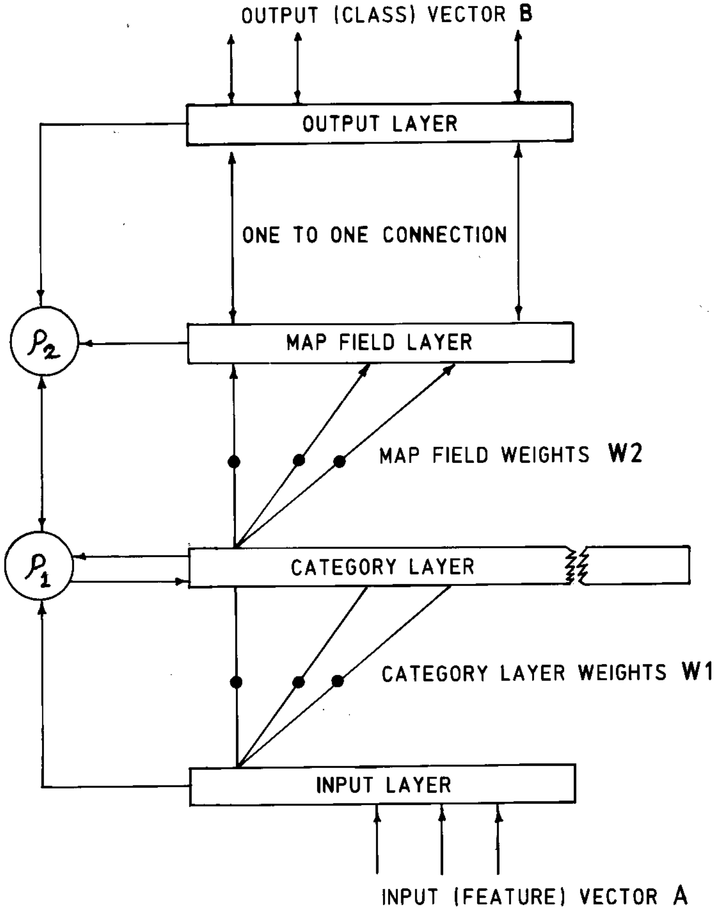

Figure 1. Fuzzy ARTMAP architecture.

connection between these two layers. Two vigilance parameters ρ_1 and ρ_2 control the operation during learning and operational phases of the network. The mapfield weights and category layer weights are learnt adaptively during the process known as 'resonance'.

3.2. *Variables and parameters*

The following parameters have been chosen for the training of fuzzy ARTMAP:

(*i*) Choice parameter α : A small positive constant, $\alpha \cong 0$.
(*ii*) Weight learning constants β_1 and β_2 : For fast learning, $\beta = 1{\cdot}0$.
For slow learning, $0 \leqslant \beta \leqslant 1{\cdot}0$.
(*iii*) Vigilance parameters ρ_1 and ρ_2 : Normally set very close to 1·0.

The other variables which have been used are,

(*i*) Input feature vector : $\mathbf{A}$
(*ii*) Output class vector : $\mathbf{B}$
(*iii*) Weight vector between input layer to a node in category layer : $\mathbf{W}_1$
(*iv*) Weight vector between a chosen node of category layer to mapfield layer : $\mathbf{W}_2^*$

3.3. *Equations employed in fuzzy ARTMAP*

(*i*) Norm of vector $\mathbf{P}$, $|\mathbf{P}| = \Sigma\, p_i$ where p_i are the components.
(*ii*) Fuzzy **AND** Operation between two vectors of the same dimension
$$\mathbf{P} \wedge \mathbf{Q} = \min(p_i, q_i) \text{ for all components}$$
(*iii*) Category choice
$$S = \frac{|\mathbf{A} \wedge \mathbf{W}_1|}{\alpha + |\mathbf{W}_1|}$$
(*iv*) Match ratio at mapfield
$$R_m = \frac{|\mathbf{B} \wedge \mathbf{W}_2^*|}{|\mathbf{B}|}$$
(*v*) Match ratio at category layer
$$R_c = \frac{|\mathbf{A} \wedge \mathbf{W}_1|}{|\mathbf{A}|}$$
(*vi*) Weight learning (also known as resonance)
(a) $\mathbf{W}_1^{(\mathrm{new})} = \beta_1(\mathbf{A} \wedge \mathbf{W}_1^{(\mathrm{old})}) + (1 - \beta_1)\, \mathbf{W}_1^{(\mathrm{old})}$
(b) $\mathbf{W}_2^{(\mathrm{new})} = \beta_2(\mathbf{B} \wedge \mathbf{W}_2^{(\mathrm{old})}) + (1 - \beta_2)\, \mathbf{W}_2^{(\mathrm{old})}$

4. Proposed algorithm

The fuzzy ARTMAP based algorithm from classification of remotely-sensed data is presented below:

4.1. *Learning phase*

(*i*) Present the complement coded input and desired output. The first input sample will commit the first node of the category layer. Go for resonance.
(*ii*) Present next input-output pair. Set $\rho_1 = 0$.
(*iii*) Calculate category choice score (S) for each committed node of category layer.
(*iv*) Choose the node with maximum S.
(*v*) Calculate the match ratio at map field (R_m) for the corresponding node.

(*vi*) If $R_m \geqslant \rho_2$ (Vigilance Test), then go for resonance and go to (*ii*) Else do the following:
  (*a*) Set $\rho_1 = R_c$ of current input.
  (*b*) Choose all nodes in category layer such that $R_c \geqslant \rho_1$.
  (*c*) Check selected node for $R_m \geqslant \rho_2$.
  (*d*) If a node is found, then go for resonance and go to (*ii*).
  (*e*) If all the selected nodes are exhausted, commit a new node and go for resonance.

(*vii*) Go to step (*ii*). Repeat until all the training samples are exhausted.

(*viii*) Go to step (*ii*) and iterate with the same samples until either the category layer nodes stop growing, or number of iterations exceeds T, an appropriately chosen positive constant.

4.2. *Operational phase*

(*i*) Present the input.
(*ii*) Calculate score S for each of the committed node.
(*iii*) Choose the node with maximum score.
(*iv*) Get the output vector corresponding to the chosen node, which will indicate the category of the input pixel.

4.3. *Discussion on the selection of parameters*

The parameter α is a tie-breaking constant and it can be chosen around 0·01. Weight learning constants β_1 and β_2 can be set to 1·0 in the beginning of learning phase and set to a smaller value in the subsequent trials. Both parameters α and β have a direct bearing on the proliferation of hidden layer nodes. Vigilance parameters ρ_1 and ρ_2 are set to 1·0 for getting the most accurate results.

5. Application in remotely-sensed image classification

We present a new approach to multi-spectral remote sensing data classification using fuzzy ARTMAP. Six multi-spectral images of four bands and of 512 by 512 size, acquired by Linear Imaging Self-scanning Sensor (LISS-II) camera of Indian Remote Sensing Satellite (IRS-1B) have been selected for our experiment. The resolution of the images is 36·5 m. The number of classes vary from 6 to 13 in each scene of different regions.

The training samples were selected by visual interpretation of the scenes by domain experts. In the training phase, 40 per cent of the samples were used and the remaining 60 per cent were applied in the operational phase to assess the accuracy. The training samples were neither subjected to any statistical analysis nor pruned on some intuitive basis keeping the realities of imprecision and overlapping classes in the data intact. In order to preserve their relative values, the grey levels have been normalized between 0 and 1.

The four band pixel grey values and their complements i.e., 8-dimensional input vectors were presented to the network. In the output binary vector, the bit of that particular class to which the input belongs was set to 1 and the remaining bits were set to 0. All weights were initially set to 1, and they monotonically decrease as the learning progresses. The classes were presented in an absolutely random sequence. The category layer nodes were allowed to grow freely in a fixed number of iterations.

6. Results

The classified image data have been obtained using three methods viz., fuzzy ARTMAP, MLC and MLP. The original image and the corresponding classified output image using fuzzy ARTMAP are shown in figures 2 and 3. The errors of omission and commission in the form of error matrix are shown in table 1. The

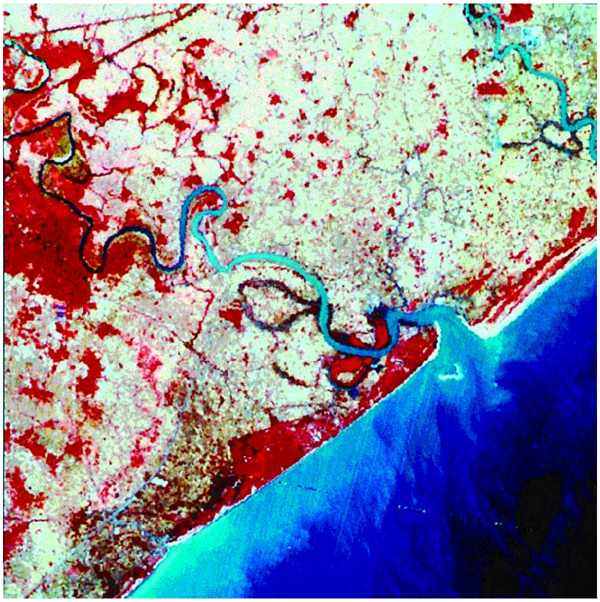

Figure 2. FCC of the original image.

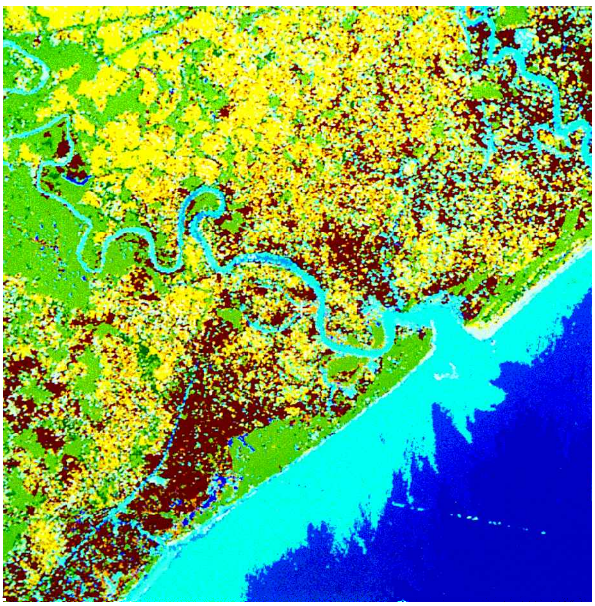

Figure 3. Classified output using fuzzy ARTMAP.

Table 1. Error of omission and commission.

	1	2	3	4	5	6	7	8	9	10	11	12	13	Total
1	1569													1569
2		584												584
3			391		1						1		52	445
4				457										457
5			2		174	24							10	210
6			3		15	2012						3	3	2036
7			4				471	1			17			493
8							1	292	1	12	1	2		309
9						1		2	49			1		53
10							1	17	11	205			26	260
11			9				9	1		1	221		7	248
12						5	3	6		23		506		543
13			99		11	5					6		552	673
Total	1569	584	508	457	201	2047	485	319	61	241	246	512	650	7880

Total no of correctly classified pixels = 7483
Total no of misclassified pixels = 397

name of the classes against their numbers as appear in table 1 are shown in table 2. The accuracy of classification in each method is shown in table 3.

It is observed that there is an advantage (about 5 per cent in the overall classi-

Table 2. Types of classes arranged as per their sequence on table 1.

Class No	Name of the class
1	Deep water I
2	Deep water
3	Sand
4	Shore water
5	Sparse vegetation
6	Inland vegetation
7	River water I
8	River water II
9	Tanks
10	Oxbow (Vegetation)
11	Shore-clear water
12	Wet agricultural land
13	Dry agricultural land

Table 3. Comparison of accuracy of classification.

Data set No.	Fuzzy ARTMAP	MLP	MLC
1	94·96	88·18	89·69
2	77·05	71·65	72·22
3	88·66	83·80	84·31
4	81·93	77·86	77·43
5	74·55	70·39	71·94
6	91·12	87·58	86·27

fication accuracy) of using fuzzy ARTMAP compared to the other two methods. The results of MLC and MLP are comparable. The training time of fuzzy ARTMAP is substantially less (about 1 per cent in each case) compared to MLP and found to be slightly less compared to MLC.

7. Conclusion

An application of fuzzy ARTMAP to the classification of multi-spectral remotely-sensed images have been demonstrated here. The results have been compared with MLP and MLC. With the VLSI implementation of fuzzy ARTMAP, it will be possible to get near real-time classification of images. Fuzzy ARTMAP is stable, easy to use and it is many times faster than MLP. Above all, fuzzy ARTMAP has a smaller number of parameters to manage. Problem specific choice of initial weights are not required to be selected. The learning as well as operational phases of fuzzy ARTMAP are also very stable.

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