A Neuro-Fuzzy Model Approach for the Land Cover Classification

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Absract : **This paper presents the neuro-fuzzy classifier derived from the generic model of a 3-layer fuzzy perceptron and developed the classification software based on the neuro-fuzzy model. Also, a comparison of the neuro-fuzzy and maximum-likelihood classifiers is presented in this paper. The Airborne Multispectral Scanner(AMS) imagery of Tae-Duk Science Complex Town were used for this comparison. The neuro-fuzzy classifier was more considerably accurate in the mixed composition area like "bare soil" , "dried grass" and "coniferous tree", however, the "cement road" and "asphalt road" classified more correctly with the maximum-likelihood classifier than the neuro-fuzzy classifier. Thus, the neuro-fuzzy model can be used to classify the mixed composition area like the natural environment of korea peninsula. From this research we conclude that the neuro-fuzzy classifier was superior in suppression of mixed pixel classification errors , and more robust to training site heterogeneity and the use of class labels for land use that are mixtures of land cover signatures.**

Ⅰ. INTROUDUCTION

The classification of multispectral image data obtained from aircrafts or satellites has become an important tool for generating ground cover maps. Classification techniques available the most widely used are conventional statistical algorithm such as discriminant analysis and the maximum-likelihood classification. The application of a conventional statistical classification allocates each image pixel to a land cover class with which it has the highest probability of membership [2]. Problems with this type of classification, particularly in relation to normal distribution assumptions and the integration of ancillary data, particularly if incomplete or acquired at a low level of measurement precision, prompted the development of alternative classification approach [3][4]. Recently, researchers has turned to approaches such as artificial intelligence, for example, fuzzy c-means and neural networks [5][6]. Although there are many instances when the conventional and alternative classification techniques have been used successfully in the accurate mapping of land cover, they are not always appropriate for land cover mapping applications.

The neuro-fuzzy classification method presents in this paper. The proposed neuro-fuzzy classification system has a three layer feed-forward architecture that is derived from a generic fuzzy perceptron [8], and has been developed and applied to the image acquired with the airborne multispectral scanner(AMS). Also, we evaluate the performance of a neuro-fuzzy against a maximum-likelihood classifier for the land cover classification of remotely sensed data.

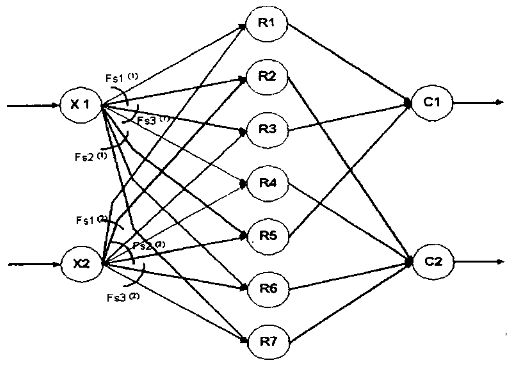
This paper is organized as follows: Section Ⅱ provides a brief overview of the neuro-fuzzy model and the maximum-likelihood classification algorithms. In Section Ⅲ, The data used in this paper and the data processing result is described, and the proposed neuro-fuzzy model is compared with the maximum-likelihood algorithm. Finally, Section Ⅳ is the conclusion and discussion.

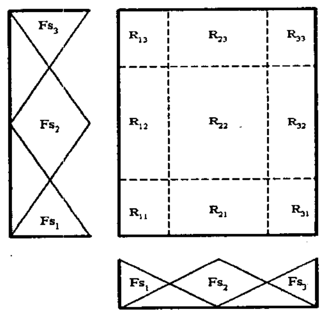
Ⅱ. ANALYSIS OF ALGORITHMS

A. Neuro-fuzzy classifier

A general concept of using mutilayer neuro-fuzzy as pattern classification is to create fuzzy subsets of the pattern space in the hidden layer and then aggregate the subsets to form a final decision in the output layer. The proposed neuro-fuzzy classification system has a three layer feed-forward architecture that is derived from a generic fuzzy perceptron. The Fig. Ⅰ (a) represents the structure of the neuro-fuzzy system. The first layer contains the input units representing the pattern feature, the hidden layer holds rule units representing the fuzzy rules, and the third layer consists of output units, one for each class.

A fuzzy perceptron can be viewed as a usual three layer perceptron that is fuzzified to a certain extent. Only the weights, the net inputs, and the activations of the output units are modeled as fuzzy sets. A fuzzy perceptron is like a usual perceptron used for function approximation. The advantage lies within the interpretation of its structure in the form of linguistic rules, because the fuzzy weights can be





(a) (b)

Fig. Ⅰ . (a) A three layer feed-forward architecture of the neuro-fuzzy model. (b) fuzzy rules indicated in corresponding fuzzy subspaces

associated with linguistic terms. The network can also be created partly, or in the whole, out of linguistic (fuzzy IF-THEN) rules. The neuro-fuzzy classifier considered here is based on the technique of distributed fuzzy IF-THEN rules, where grid-type fuzzy partitions on the pattern space are used. The Fig. Ⅰ (b) shows fuzzy rules indicated in corresponding fuzzy subspaces.

The learning algorithm of neuro-fuzzy classification system to adapt its fuzzy sets performs repeatly through the learning set Γ_s by repeating the following steps until a given end criterion is reached.

(1) Select the next pattern from the learning set R_s and propagate it .

(2) Determine the delta value $\delta_{ci} = t_i - a_{ci}$

(3) For each rule unit R with $a_R > 0$

ⓐ Determine the delta value

$$\delta_R = a_R(1-a_R)\sum_{c\in U_3} W(R,c)\delta_c$$

ⓑ Find x' such that

$$W(x',R)(a_{x'}) = \min_{x\in U_1}\{W(x,R)(a_x)\}$$

ⓒ For the fuzzy set $W(x',R)$ determine the delta values for its parameter a, b, c using the learning rate $\sigma > 0$:

$$\delta_b = \sigma \cdot \delta_R \cdot (c - a) \cdot sgn(a_{x'} - b),$$
$$\delta_a = - \sigma \cdot \delta_R \cdot (c - a) + \delta_b,$$
$$\delta_c = \sigma \cdot \delta_R \cdot (c - a) + \delta_b$$

and apply the chages to $W(x',R)$

(4) If an epoch was completed, and the end criterion is met, then stop; otherwise proceed with step (1).

B. Maximum-Likelihood classifier

The maximum-likelihood classifier is a parametric classifier that relies on the second-order statistics of a Gaussian probability density function model for each class. The class probability density functions usually are assumed to be normal, then the discriminant functions become

$$\begin{aligned} g^i &= p(X \mid w_i)p(w_i) \\ &= p_i(2\pi)^{-n/2} \mid \Sigma_i \mid^{-1/2} \bullet \exp\left\{ -\frac{1}{2}(X - M_i)' \Sigma_i^{-1} (X - M_i) \right\} \end{aligned}$$

where n is the number of bands, X is the data vector, M_I is the mean vector of class i, and Σ_i is the covariance matrix of class i,

$$X = \begin{bmatrix} x_i \\ x_i \\ x_i \\ \vdots \\ x_i \end{bmatrix} \qquad M_i = \begin{bmatrix} \mu_{i1} \\ \mu_{i2} \\ \mu_{i3} \\ \vdots \\ \mu_{in} \end{bmatrix} \qquad \Sigma_i = \begin{bmatrix} \sigma_{i11} & \sigma_{i12} & \sigma_{i13} & \cdots & \sigma_{i1n} \\ \sigma_{i21} & \sigma_{i22} & \sigma_{i23} & \cdots & \sigma_{i2n} \\ \sigma_{i31} & \sigma_{i32} & \sigma_{i33} & \cdots & \sigma_{i3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{in1} & \sigma_{in2} & \sigma_{in3} & \cdots & \sigma_{inn} \end{bmatrix}$$

In the maximum-likelihood classification, pixels are allocated to their most likely class of membership. Given equal *a priori* probabilities, this can be achieved by allocating each case to the class with the highest probability density function, or equivalently, by allocating each pixel to the class with which it has the highest *a posteriori* probability of membership. For equal *a priori* probabilities, the *a posteriori* probabilities are assessed as the probability density of a case relative to the sum of the densities.

Ⅲ. DATA PROCESSING AND RESULTS

The digital image used in our study was acquired with the airborne multispectral scanner(AMS) on March. 10, 1992. It was imaged over Tae-Duk Science Complex Town, Korea, and selected for the primary comparison between the neuro-fuzzy and maximum-likelihood classification methods. Familiarity with the area allowed for accurate class training and test site identification. The image used consists of 390 lines, with 410 pixels per line, a pixel size of about 3 x 3 m, and the three visible and the one near-infrared bands. The spectral range of AMS listed in Table Ⅰ , and the false color image of band 5, 3 and 2 , and band 7, 5 and 3 used in this study shows in FigureⅡ(a) and FigureⅡ(b) respectively.

First, we developed the classification software based on the neuro-fuzzy model, and then applied to this study. For the comparison of accuracy, the same training sites were used by both the neuro-fuzzy and the maximum-likelihood classifier. We determined that eight classes covered the majority of land cover feature in the test image(Table Ⅱ). Table Ⅱ shows the mean and standard deviation of each class as defined by training samples. First a set of similar-sized training regions were defined by visual interpretation of the image.

The maximum-likelihood classification applied to the four band image, generating the land cover classification map in the Figure Ⅲ(b). The accuracy of the training regions was 95.8% and the accuracy of the test regions was 88.7%. Although the test site accuracy of the maximum-likelihood method is high, there are some major errors in the overall classification. The "water" class is much more extensive than it should be. Also, the mixed class consisting of "bare soil", "dried grass" and "coniferous tree" was classified poorly , however, the "cement road" and "asphalt road" classified clearly as shows in the Figure Ⅲ(b).

In the Figure Ⅲ(a) , the classification map shows the result of the neuro-fuzzy model algorithm applied to the test image. For the neuro-fuzzy learning process the patterns of training sets ordered alternatively within the training sets and classify the image. The domains of the four input bands were initially each partitioned by 12 equally distributed fuzzy sets. The neuro-fuzzy classifier selected 12 fuzzy sets and 104 fuzzy rules out of 778 fuzzy rules produced to classify the test image from the training sets. Fuzzy sets learning stopped after 327 epochs, because the error was not decreased for 200 epochs. After learning, 21 out of 778 patterns from the training set were classified wrongly(97.30% correct). Considering all 159900 patterns from the test image the neuro-fuzzy classifier performed well with 93.23% correct classifications.

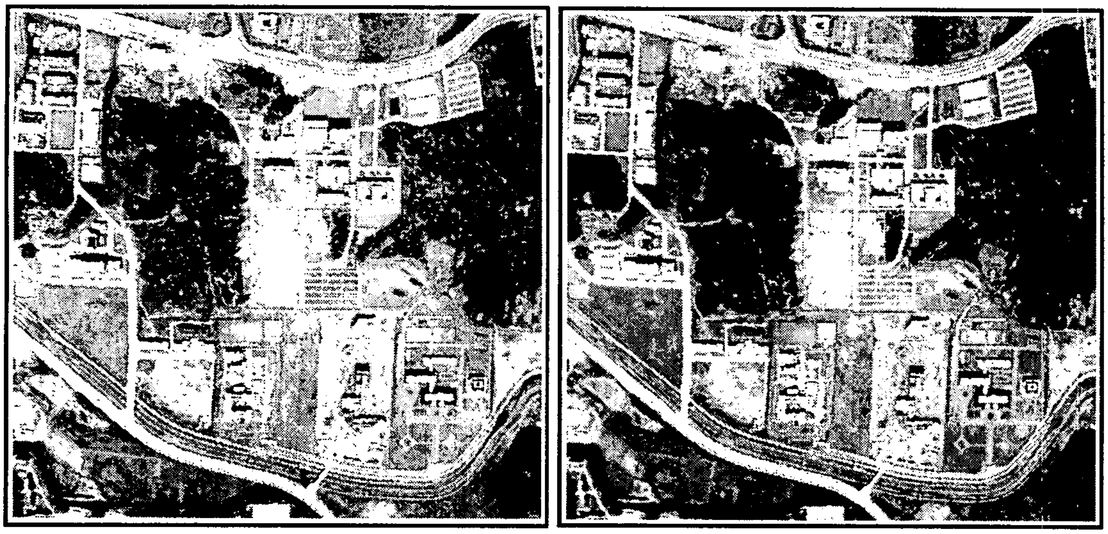
In comparing the maximum-likelihood classification map(Figure Ⅲ(b)) with the neuro-fuzzy classification map(Figure Ⅲ(a)), it is apparent that there is more difference than the 8% difference in test image accuracy indicates. Most of the differences are in the "water" and the mixed composition area like "bare soil", "dried grass" and "coniferous tree", for which the neuro-fuzzy classifier was considerably more accurate. However, the "cement road" and "asphalt road" classified more correctly with the maximum-likelihood classifier than the neuro-fuzzy classifier.

Table Ⅰ . Spectral range of AMS

BAND No.	SPECTRAL RANGE	BAND No.	SPECTRAL RANGE
1	0.42 μm ~ 0.45 μm	6	0.69 μm ~ 0.75 μm
2	0.45 μm ~ 0.52 μm	7	0.76 μm ~ 0.90 μm
3	0.52 μm ~ 0.60 μm	8	0.91 μm ~ 1.05 μm
4	0.60 μm ~ 0.62 μm	9	3.00 μm ~ 5.50 μm
5	0.63 μm ~ 0.69 μm	10	5.50 μm ~ 14.0 μm

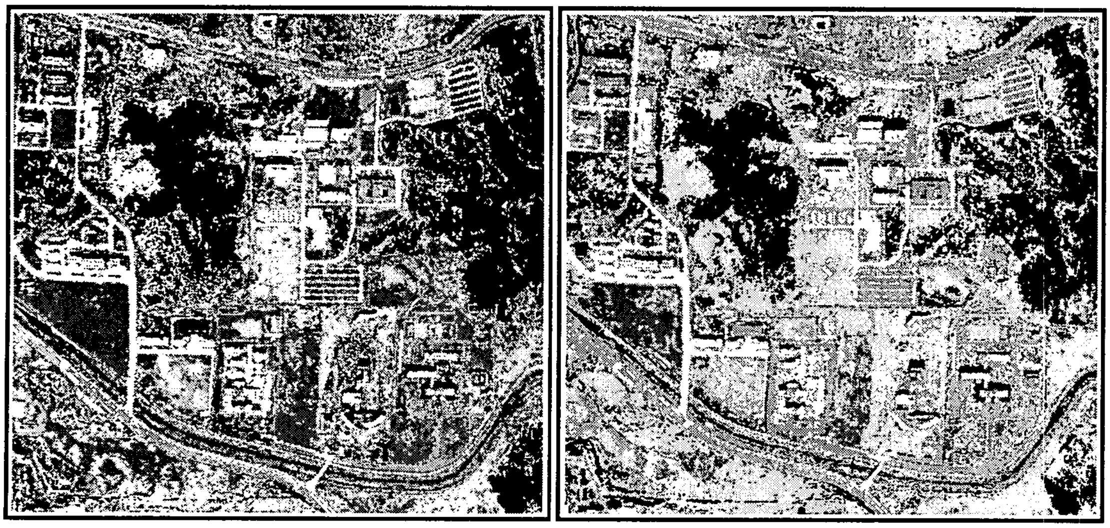
Table Ⅱ. The means and standard deviation of the defined by the training data.

	Class Means				Class Standard Deviation			
Class	Band 2	Band 3	Band 5	Band 7	Band 2	Band 3	Band 5	Band 7
oniferous tre	79.21	83.45	72.52	165.18	2.82	6.23	5.6	33.46
eciduous tre	111.17	117.33	126.85	161.33	13.19	15.79	16.87	12.71
Water	145.167	170.94	153.44	99.62	20.35	33.17	38.31	38.6
Asphalt road	212.42	225.87	223.95	215.23	30.14	28.74	29.57	27.91
Cement road	232.38	239.14	242.14	243.76	38.84	28.66	23.45	20.29
Shadow	94.9	93.75	89.2	89.35	13.64	20.79	26.6	35.23
Bare soil	189.48	227.04	237.76	243.512	21.67	29.07	28.66	21.69
Dried grass	144.56	159.73	166.19	184.16	4.43	6.35	5.74	6.3



(a) (b)

Figure Ⅱ. The false color image of (a) band 5, 3 and 2 and (b) band 7, 5 and 3



(a) (b)

Figure Ⅲ. Land cover classification map using the neuro-fuzzy model (a) and the maximum-likelihood (b)

Figure Ⅳ. Index of classes

Ⅳ. CONCLUSION AND DISCUSSION

In this paper, we have presented the neuro-fuzzy model approach and developed the software for the land cover classification. The neuro-fuzzy classifier was derived from the generic model of a 3-layer fuzzy perceptron. The neuro-fuzzy classifier can be initialized by prior knowledge using fuzzy if-then rules and it can also be interpreted after the learning process, and creates fuzzy rules learning it's fuzzy sets by adapting parameters of the membership functions.

The proposed neuro-fuzzy classifier was compared with the maximum-likelihood classifier, a widely-used "standards' classifier that yields minimum total classification error for Gaussian class ditributions. The result shows that the mixed composition area like "bare soil", "dried grass" and "coniferous tree", for which the neuro-fuzzy classifier was considerably more accurate, however, the "cement road" and "asphalt road" classified more correctly with the maximum-likelihood classifier than the neuro-fuzzy classifier. Thus, the neuro-fuzzy model can be used to classify the mixed composition area like the natural environment of korea peninsula. From this research we conclude that the neuro-fuzzy classifier was superior in suppression of mixed pixel classification errors , and more robust to training site heterogeneity and the use of class labels for land use that are mixtures of land cover signatures.

REFERENCES

[1] Maselli, F., C. Conese, G. Zipoli, and M. A. Pittau, 1990. Use of Error Probabilities to Improve Area Estimates Based on Maximum Likelihood Classification. *Rem. Sensing of Environment*, 31,155-160

[2] Mather, P. M., 1987, *Computer processing of Remotely Sensed Images*(Chichester: Wiley).

[3] Moon, W. M., 1993, On mathematical representation and integration of multiple spatial geoscience datasets. *Canadian Journal of Remote Sensing*, 19, 63-67.

[4] Peddle, D. R., 1993, An empirical comparison of evidential reasoning, linear discrimant analysis and maximum likelihood algorithms for land cover classification. *Canadian Journal of Remote Sensing*, 19, 31-44.

[5] Cannon, R. L., Dave, J. V., Bezdek, J. C., and Trivedi, M. M., 1986, Segmentation of a thematic mapper image using the fuzzy c-means clustering algorithm. *I.E.E.E. Transactions on Geoscience and remote Sensing*, 24, 400-408.

[6] N. D. Ritter and G. F. Hepner, 1990, "Application of an artificial neural network to land cover classification of thematic mapper imagery', *Computer Geosci.*, 16, 873-880.

[7] H Ishibuchi, K Nozaki, and H Tanaka, 1992, Distributed representation of fuzzy rules and its application to pattern classification. *Fuzzy Sets and System.*, 52, 21-32.

[8] S. K. Halgamuge and M. Glesner., 1994, Neural networks in designing fuzzy systems for real world applications. *Fuzzy Sets and Systems*, 65, 1-12.