뉴로-퍼지 모델을 이용한 항공다중분광주사기 영상의 지표면 분류

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요 약

이 논문에서는 항공다중분광주사기로부터 원격탐사된 영상을 이용하여 영상분류를 수행하기위한 새로운 분류방법을 제안하고, 적용하고자 한다. 이 논문에서 제안된 뉴로-퍼지 영상분류기는 3층 퍼지 퍼셉트론의 일반적 모델로부터 파생된 것으로 지표면 분류를 위한 영상분류시스템으로 구현되었다. 그리고 현재 일반적으로 사용되고 있는 통계적기반의 최대우도 분류기와 성능을 비교하였다. 분류 성능면에서 제안된 방법이 최대우도 방법보다 더 정확하게 분류한다는 것을 알 수 있었는데, 전반적인 분류 정확도에서 7.96%의 차이가 나타났다. 대상별 분류 정확도에 있어 "건물"과 "소나무림"에서는 뉴로-퍼지 분류방법이 보다 큰 차이로 높은 정확도를 보였다. 하지만, "황토지"에서 우도비 분류방법이 더 정확하게 분류되는 경우도 있었다.

Land Surface Classification With Airborne Multi-spectral Scanner Image Using A Neuro-Fuzzy Model

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ABSTRACT

In this paper, we propose and apply new classification method to the remotely sensed image acquired from airborne multi-spectral scanner. This is a neuro-fuzzy image classifier derived from the generic model of a 3-layer fuzzy perceptron. We implement a classification software system with the proposed method for land cover image classification. Comparisons with the proposed and maximum-likelihood classifiers are also presented. The results show that the neuro-fuzzy classification method classifies more accurately than the maximum likelihood method. In comparing the maximum-likelihood classification map with the neuro-fuzzy classification map, it is apparent that there is more different as amount as 7.96% in the overall accuracy. Most of the differences are in the "Building" and "Pine tree", for which the neuro-fuzzy classifier was considerably more accurate. However, the "Bare soil" is classified more correctly with the maximum-likelihood classifier rather than the neuro-fuzzy classifier.

키워드 : 원격탐사(Remote sensing), 뉴로-퍼지(Neuro-fuzzy), 지표면 분류(Land cover classification), 최대우도(Maximum-likelihood)

1. 서 론

Remote sensing data includes reflectional and radiational characteristics of naturally occurring features found on Earth. The classification of multi-spectral image data obtained from airborne or satellite has become an important tool for generating ground cover maps. Of the many classification techniques available, there have been conventional statistical algorithms such as discriminant analysis and the maximum-likelihood classification that allocate each image pixel to a land cover class to which it has the highest probability of membership [2]. The application of a conventional statistical classification 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 have 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.

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In this paper, we present a neuro-fuzzy classification method. The proposed system has a three-layer feed- forward architecture that is derived from a generic fuzzy perceptron [8], and is implemented and applied to the image acquired with the AMS. We also evaluate and compare this system with the maximum-likelihood classifier for land cover classification of remotely sensed data.

This paper is organized as follows : Section 2 provides a brief overview of the neuro-fuzzy and maximum-likelihood classification algorithms. In Section 3, The data used in this paper and the data processing results are described, and the proposed neuro-fuzzy model is compared with the maximum-likelihood algorithm. Finally, Section 4 is the conclusion and discussion.

2. Classification Techniques

2.1 Maximum-Likelihood method

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

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

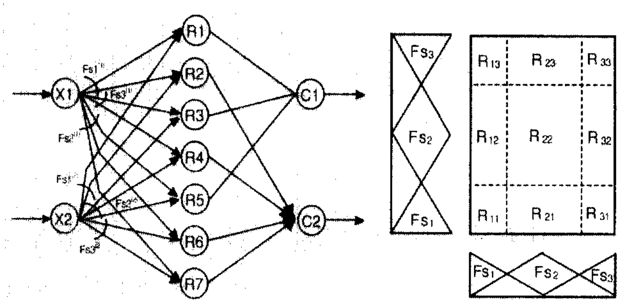
where n is the number of bands, X is the data vector, M_i is the mean vector of class i, and Σ_i is the covariance matrix of class i,

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

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 [9].

2.2 Neuro-Fuzzy method

A general concept of using multilayer neuro-fuzzy as a 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. (Figure 1) (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.



(Figure 1) (a) A three layer feed-forward architecture of the neuro-fuzzy model. (b) fuzzy rules indicated in the corresponding fuzzy subspaces

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 associated with the 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. (Figure 1) (b) shows fuzzy rules indicated in the corresponding fuzzy subspaces.

The learning algorithm of the neuro-fuzzy classification system to adapt its fuzzy sets performs repeatedly 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 $a_R > 0$

$$\delta_R = a_R(1-a_R) \sum_{c \in u_3} W(R, c)\, \delta_c$$

ⓐ Determine the delta value

ⓑ 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 $\sigma > 0$:

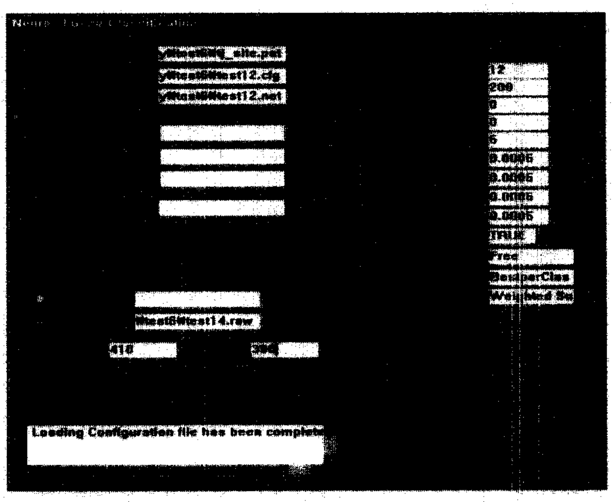
$$\delta_b = \sigma \cdot \delta_R \cdot (c - a) \cdot sgn(a_{x'} - b),$$

$$\delta_a = -\sigma \cdot \delta_R \cdot (c - a) + \delta_b,$$

$$\delta_c = \sigma \cdot \delta_R \cdot (c - a) + \delta_b$$

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

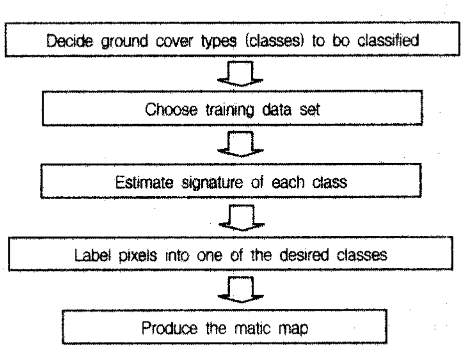
(4) If an epoch was completed, and the end criterion is met, then stop ; otherwise proceed with step (1).



(Figure 2) Neuro-fuzzy classification system

3. Image Classification Procedure

Land cover classification has the procedure most often used for quantitative analysis of remote sensing image data. It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types. The steps for land cover classification are as follows (Figure 3).



(Figure 3) Procedure of image classification

Step 1 : Decide the set of ground cover types into which the image is to be classified. These are the information classes and could, for example, be water, grass, soil, etc.

Step 2 : Choose representative or prototype pixels from each of the desired set of classes. These pixels are said to form training data. Training sets for each class can be established using site visits, maps, air photographs or even photo-interpretation of a color composite product formed from the image data.

Step 3 : Use the training data to estimate the parameters of the particular classifier algorithm to be used ; these parameters will be the properties of the probability model used or will be equations that define partitions in the multispectral space. The set of parameters for given class is sometimes called the signature of that class.

Step 4 : Using the trained classifier, label or classify every pixel in the image into one of the desired ground cover types.

Step 5 : Produce thematic (class) maps which summarizes the results of the classification.

4. Experiments and Result Analysis

The digital image used in our research was acquired with the AMS (Figure 4). It is imaged over Daeduk Science Complex Town, Daejeon, Korea, and selected for the primary comparison between the neuro-fuzzy and maximum-likelihood classification methods. Familiarity with this area is allowed for accurate class training and test site identification. The image used consists of 280 lines, with 280 pixels per line, a pixel size of about 3×3 m spatial resolution, and the three visible and the one near-infrared band. The spectral ranges of AMS are listed in <Table 1>, and the images of band 1, 2, 3, and band 5 used in this research show in (Figure 4).

First, we develop a classification software based on the neuro-fuzzy model, and then apply to this system (Figure 2). For the comparison of accuracy, the same training sites are used by both the neuro-fuzzy and maximum-likelihood classifier. We determine that eight classes covered the majority of land cover feature in the test image. (Figure 5) shows training sites for getting training data set. A set of similar-sized training regions are defined by visual interpretation of the image. Ground field survey data such as land use map compiled by geographer and also used for calculation of classification accuracy.

It is difficult to evaluate classification accuracies. Therefore, we calculate the overall accuracy evaluation function p_o which is defined as follows :

$$P_o = \frac{\sum_{i=1}^{m} C_{ii}}{\sum_{i=1}^{m}\sum_{j=1}^{m} C_{ij}}$$

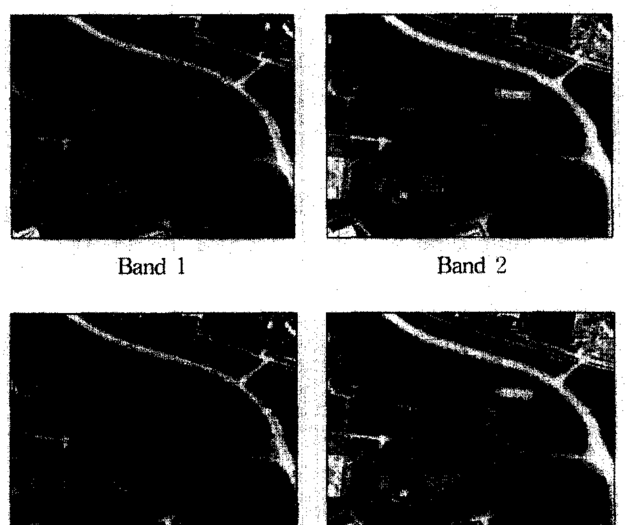
Where C_{ij} is the number of pixels classified w_i into w_j.

The maximum-likelihood classification is applied to the AMS image, and the land cover classification map is generated as (Figure 6) (a). The overall accuracy of the maximum-likelihood classification method is 63.22% and Kappa coefficient 0.46889 (Table 4) (a). There are some major errors in the overall classification. The Cement road and Shadow class is more misclassified than it should be. Also, the mixed class consisting of Building, Water and Pine tree was classified poorly.

In (Figure 6) (b), the classification map shows the result of the neuro-fuzzy model algorithm applied to the AMS image. For the neuro-fuzzy learning process the patterns of training sets are ordered alternatively within the training sets to classify the image. The domains of the four input bands were initially each partitioned by 12 equally distributed fuzzy sets.

〈Table 1〉 Spectral range of AMS

BAND No.	SPECTRAL RANGE	BAND No.	SPECTRAL RANGE
[illegible]	[illegible]	6	0.69 μm~0.75 μm
[illegible]	[illegible]	7	0.76 μm~0.90 μm
[illegible]	[illegible]	8	0.91 μm~1.05 μm
4	0.60 μm~0.62 μm	9	3.00 μm~5.50 μm
[illegible]	[illegible]	10	5.50 μm~14.0 μm

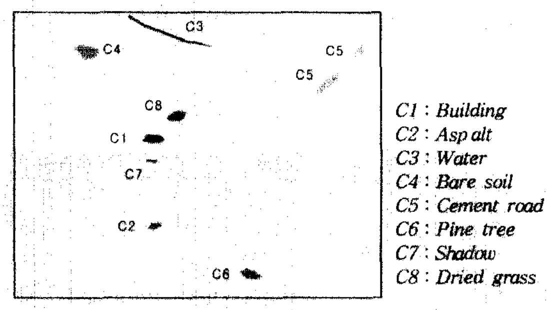


Band 1 Band 2

Band 3 Band 5

(Figure 4) AMS images used in this study

The neuro-fuzzy classifier selected 12 fuzzy sets and 117 fuzzy rules produced to classify the test image from the training sets. Fuzzy sets learning stopped after 418 epochs, because the error was not decreased for 400 epochs. The overall accuracy of the neuro-fuzzy classification method is 71.8% and Kappa coefficient 0.61716 (Table 4) (b). There are some major errors in the overall classification. The "Water" class is more misclassified than it should be. Also, the mixed class consisting of "Building", "Cement road", "Shadow" and "Dried grass" was classified poorly.



(Figure 5) Training sites

〈Table 3〉 Fuzzy rules generated by neuro-fuzzy system

```
#Rule 1:
IF   I1 IS -1 AND I2 IS 1 AND
     I3 IS 1 AND I4 IS -1
THEN C1

#Rule 2:
IF   I1 IS -1 AND I2 IS -1 AND
     I3 IS 1 AND I4 IS -1
THEN C1

#Rule 3:
IF   I1 IS -2 AND I2 IS -1 AND
     I3 IS 1 AND I4 IS -2
THEN C1

#Rule 4:
IF   I1 IS -2 AND I2 IS -1 AND
     I3 IS 1 AND I4 IS -1
THEN C1

      .
      .
      .

#Rule 114:
IF   I1 IS -5 AND I2 IS -4 AND
     I3 IS -4 AND I4 IS -2
THEN C8

#Rule 115:
IF   I1 IS -5 AND I2 IS -4 AND
     I3 IS -3 AND I4 IS 1
THEN C8

#Rule 116:
IF   I1 IS -4 AND I2 IS -4 AND
     I3 IS -4 AND I4 IS 1
THEN C8

#Rule 117:
IF   I1 IS -6 AND I2 IS -6 AND
     I3 IS -5 AND I4 IS -4
THEN C8
```

〈Table 4〉 Classification results using the maximum likelihood (a) and neuro-fuzzy (b) methods

(a) Confusion matrix of maximum likelihood method

	Output								
Input	c1	c2	c3	c4	c5	c6	c7	c8	Total(%)
c1	29.24	17.90	23.22	5.64	10.09	0.00	6.63	7.28	100.0
c2	6.14	75.71	0.00	0.00	18.14	0.00	0.00	0.00	100.0
c3	19.66	0.45	11.45	66.91	0.43	0.38	0.00	0.73	100.0
c4	11.97	0.11	0.00	78.94	0.00	0.00	0.00	8.98	100.0
c5	0.00	4.50	0.00	0.00	95.50	0.00	0.00	0.00	100.0
c6	0.02	0.00	0.00	24.32	0.00	39.15	0.25	36.26	100.0
c7	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.0
c8	0.13	0.00	0.00	20.36	0.00	1.34	2.39	75.78	100.0

Overall accuracy = 63.22

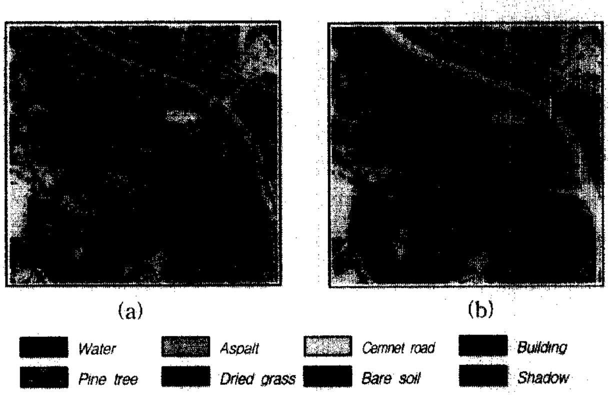
KAPPA COEFFICIENT = 0.46889 Standard Deviation = 0.00241

(b) Confusion matrix of neuro-fuzzy method

	Output								
Input	c1	c2	c3	c4	c5	c6	c7	c8	Total(%)
c1	94.53	0.00	0.00	0.00	2.00	0.00	[illegible]	0.52	100.00
c2	24.44	75.56	0.00	0.00	0.00	0.00	0.00	0.00	100.00
c3	70.00	0.00	29.95	0.00	0.03	0.00	0.00	0.03	100.00
c4	30.45	0.00	0.00	69.51	0.00	0.00	0.00	0.04	100.00
c5	1.80	0.00	0.00	0.00	98.20	0.00	0.00	0.00	100.00
c6	21.49	0.00	0.00	0.00	0.00	77.34	0.00	1.17	100.00
c7	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	100.00
c8	18.30	0.00	0.00	0.00	0.00	0.27	0.07	81.37	100.00

Overall accuracy = 71.18

KAPPA COEFFICIENT = 0.61716 Standard Deviation = 0.00220



(Figure 6) Land cover classification map using the maximum-likelihood (a), and the neuro-fuzzy model (b)

In comparing the maximum-likelihood classification map with the neuro-fuzzy classification map, it is apparent that there is more different as amount as 7.96% difference in the accuracy. Most of the differences are in the "Building" and "Pine tree", for which the neuro-fuzzy classifier was considerably more accurate. However, the "Bare soil" is classified more correctly with the maximum-likelihood classifier rather than the neuro-fuzzy classifier.

5. Conclusion and Discussion

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

The proposed classifier was compared with the maximum-likelihood classifier, a widely-used standard classifier that yields minimum total classification error for Gaussian class distributions. The results show that the "Building", and "Pine tree", for which the neuro-fuzzy classifier was considerably more accurate, however, the "Bare soil" classified more correctly with the maximum-likelihood classifier than the neuro-fuzzy classifier. In comparing the maximum-likelihood classification map with the neuro-fuzzy classification map, it is apparent that there is more different as amount as 7.96% difference in the accuracy. The classified information of the land cover will be used importantly when the results of the classification are to be integrated to a GIS (Geographical Information System). As a further work, a refinement of the classification algorithms as a whole system is needed.

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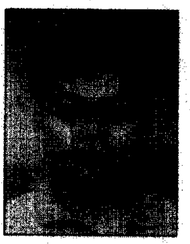

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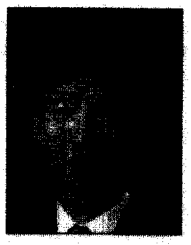

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