# Non-Parametric Texture Extraction using Neural Network

# 신경 회로망을 사용한 비 파라메테 텍스춰 추출

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## 요 약

본 연구에서는 화상에 있어서 패턴의 공간적인 특징을 추출하기위한 목적으로 신경회로망을 적용하는 방법을 제안하였다. 적용한 신경회로망은 3층의 구조를 가지며, 그 학습방법으로는 back-propagation 알고리즘을 사용하였다. 또한 이동이나 회전과 같은 패턴의 변위에 대응하기 위하여, 화상으로부터 co-occurrence matrix를 구하여, 신경회로망의 입력패턴으로 사용하였다. 제안한 방법을 평가하기 위하여 종래의 대표적방법인 화소의 spectral 정보를 이용한 최대유도법(maximum likelihood method)으로는 식별이 곤란한 시가지지역과 모래자역을 선정하여, 본 방법과 Haralick에 의하여 제안된 texture features를 이용하여 분류한 결과, texture features를 이용한 방법으로는 67%~89%의 식별률을 얻었음에 반하여, 본 연구에서 제안한 신경회로망을 사용한 방법으로는 80%~98%의 안정되고 높은 식별률을 얻었다.

## Abstract

In this paper, a method using a neural network was applied for the purpose of utilizing spatial features. The adopted model of neural network the three-layered architecture, and the training algorithm is the back propagation algorithm. Co-occurrence matrix which is generated from original imge was used for input pattern to the neural network in order to tolerate variations of patterns like rotation or displacement. Co-occurrence matrix is explained in appendix. To evaluate this method, classification was executed with this method and texture features method over the city area and sand area, which cannot be sepaiated with the conventional method mentioned aboved. In the results of this method and texture features proposed by Haralick, the method using texture features was separation rate of 67%-89%. On the contrary, the method using neural network proposed in this reserach was stable and high separation rate of 80%-98%.

## Ⅰ. Introduction

With the launch of the second generation high resolution sensors like LANDSAT TM and SPOT HRV, many kinds of researches have been done to certificate the capability of these sensors for landcover classification. Most of the results of these sensors are not so high as expected when conventional supervised maximum likelihood classifier[1] using only spectral informaton is applied. One of the solutions of this problem is to use additional information, and among the additional informations, spatial features like textures are considered as useful.

In this paper, a method using a neural network

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was applied for the purpose of utilizing spatial features. The adopted model of neural network has three layered architecture, and the training algorithm is the back-propagation algorithm. Co occurrence matrix which is generated from original image was used for input pattern to the neural network in order to tolerate variations of patterns like rotation or displacement. Co-occurrence matrix is explained in appendix.

To evaluate this method, classification was executed with this method and texture features method over the city area and sand area of SPOT HRV panchromatic image data, which cannot be separated with the conventional method mentioned above.

## II. A Classification Method using Neural Network

### 2.1 Configuration of Neural Network and Training Algorithm

The neural network model used in this study is a feed-forward multi-layered network. Training method adopted is the back-propagation algorithm[2]. That is, the network is composed of three layer which are an input layer, a hidden layer and an output layer, Each layer has multiple neurons which are completely connected with the neurons of neighboring layer. When a pattern is inputed to the input layer of the network, the output value is computed by the forward pass which computes the activity levels in the previous layer. Training is performed by modifying the strengh of each connection(weight, threshold) to minimize the squares of the difference between the actual and desired output value. Fig. 1 illustrates the multi-layered network, and the flow of input pattern and error propagation when the network is trained by the back-propagation algorithm. In the experiments, the numbers of neurons of the input layer, the hidden layer and the output layer were 1024(at the maximum), 4, and 2, respectively.

### 2.2 Experiments with Proposed Method

In order to evaluate proposed method described above, SPOT HRV panchromatic image data was classified using the proposed method. The Sagami river basin in Japan was selected for the target area(Fig. 2) This area includes the test site data which is already investigated and categorized in 52 categories. Fig. 3 shows the test site data.

For the classification target categories, city and sand were selected from the 52 categories, because it is difficult to classify with conventional pixel-wised maximum likelihood method using only spectral information.

For the computing machine, NEC's neural net-

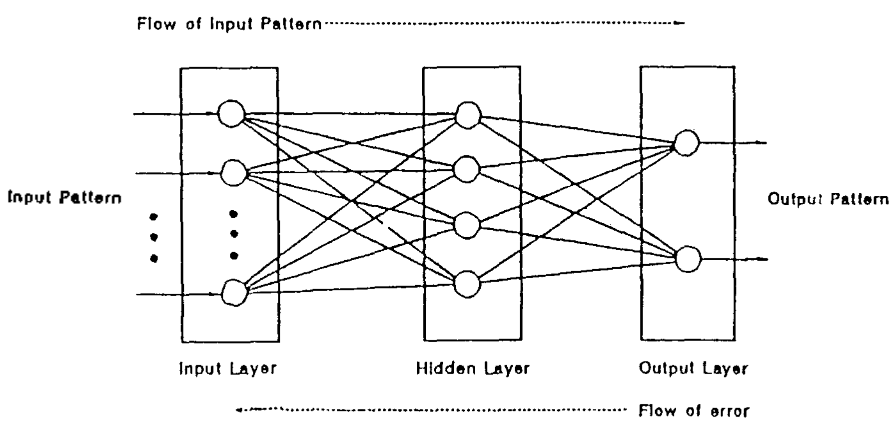


Fig. 1 Configuration of Neural Network used in the Experiment

work simulator board, named Personal Neuron Computer NEURO 07, was used. The main processor of this board is special data flow type processor names IMPP, and the speed is about 170,000 connections per second.

Experiment of evaluation was executed by 3 steps as follows.

Fig. 2 SPOT HRV Image Data

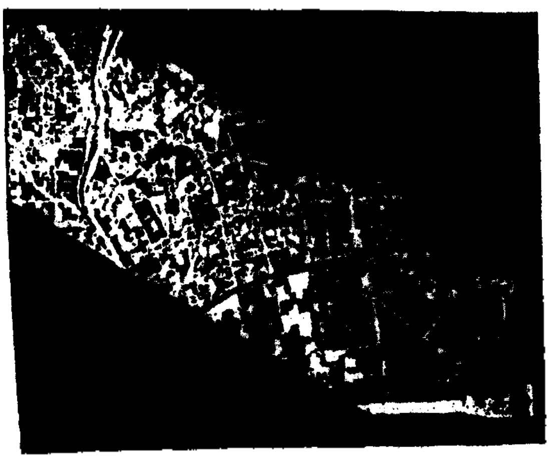

Fig. 3 Test Site Data

(1) Making of Input Patterns

For the input patterns, city area and sand area, corresponding to that category of the test site data, were extracted. Each pattern is composed of 9 X 9 pixels. The extracted data were converted to co-occurrence matrix is 256 X 256, since the HRV image data has 256 gray levels. However, neural network simulator used in the experiment has the limitation of number of neurons in each layer(maximum 1024)[3]. From this reason, the size of co-occurrence matrix was compacted to 32 X 32, 16 X 16 and 8 X 8, respectively. That is, the gray level of target image data which has 256 gray levels, was linearly converted to 32 levels, 16 levels and 8 levels, respectively.

(2) Training of the Network

A part of input patterns, which have the 100% and 80% occupation rate(the ratio of pixels with concerned category and pixels in given area) of concerned category in that area, were considered for training patterns. Since input patterns were composed of 3 kinds of co occurrence matrix for each category(city area and sand area), training patterns consisted 12 kinds pattern((2 kinds of categories) X (2 kinds of occupation rate) X (3 kinds of co-occurrence matrix)). For each kind of training patterns, 100 samples were used for training patterns. Therefore, the total number of training patterns was 1200.

Training was performed by the back-propagation method using these training patterns and teaching patterns which are the desired output values of network for the two kinds of categories. Training was performed 1000 times on each kind of input patterns and the time needed for training were 28, 17 and 15 minutes for 32 X 32, 16 X 16 and 8 X 8 co-occurrence matrices, respectively.

Fig. 4 shows the convergence of error with the number of times for training. In Fig. 4, x-coordinate represents the number of training times and y-coordinate represents the number of error in the neural network. In the case of 32 X 32 and 16 X 16 co-occurrence matrix, the error converged after several tens of times of training, but in the case of 8 X 8 co-occurrence matrix, the error didn't converge after 1000 times of trainings. This result suggests that the classification of city area and sand area is difficult with only 8 gray levels.

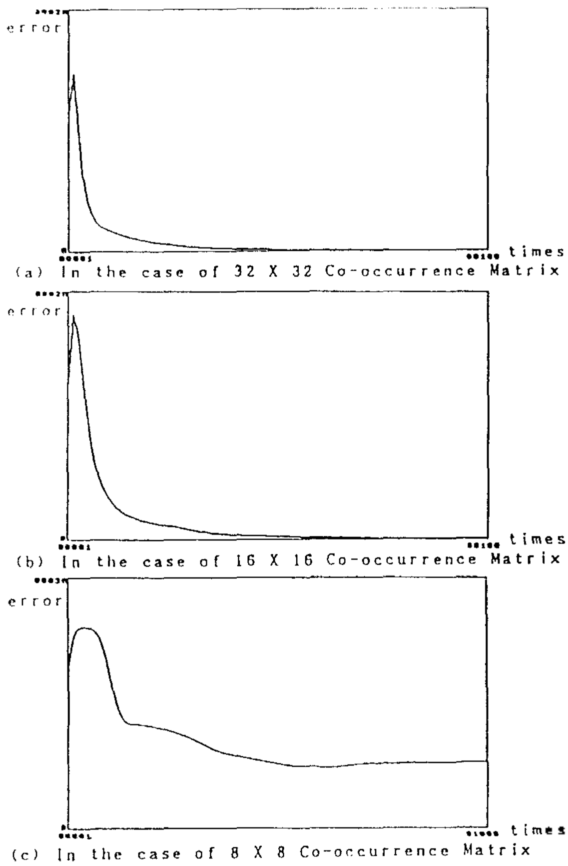


Fig. 4 Convergence Error with the number of times for trainig

(3) Classification

Classification test was executed using the prepared input patterns except for training patterns. The number of test patterns were about 8400 samples. In the case of 8 X 8 co-occurrence matrix, classification test was not executed because the error didn't converge. Table 3 shows the classification accuracies obtained by the experiments.

## Ⅲ. Comparison with Other Methods

### 3.1 Pixel-wised Maximum Likelihood Method

A pixel-wised maximum likelihood classification was performed over the city area and sand area of SPOT HRV panchromatic image data as a comparison to a typical conventional method. Table 1 shows the classification accuracy.

Table 1. Classification Accuracies by Pixel-wise Maximum Like Likelihood Method

| city area | sand area | average |
|---|---|---|
| 71.9% | 65.2% | 68.2% |

### 3.2 Texture Features Method

In order to examine the proposed method using a neural network, another classification method were considered. Since the co-occurrence matrix which was used for input pattern of neural network has non-parametric characteristics, texture features method, which has non-parametric characteristics, was considered. In this method, following 4 texture features[4], which had been calculated from the co-occurrence matrix, were used.

1) Contrast
2) Inverse different moment
3) Angular second moment
4) Entropy

As a classifier, maximum likelihood classifier was used. Table 2 shows the classification accuracies by this method.

## Ⅳ. Results

Form the table 1, 2 and 3, following results were obtained.

(1) The classification accuracy of the training patterns was 100% in the case of neural network method regardless of the occupation rate (100% or 80% in city area and sand area), but it was about 63-99% in the case of texture features method.

(2) The classification accuracy was higher when using 80% occupation rate training patterns in both methods. It can be thought that this result was caused by the wide immunity of target patterns. It is not clear that the same result can be obtained in the case of multi-categories only from this experiment.

(3) In the case of texture features method, the classification accuracy was higher with 32 X 32 co-occurrence matrix.

**Table 2.** Classification Accuracies by Texture Features Method unit : %

| occupation rate | occupation rate of concerned category in 9X9 region | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 100% | | | | | | 80% | | | | | |
| | size of co-occurrence matrix | | | | | | size of co-occurrence matrix | | | | | |
| | 32 × 32 | | | 16 × 16 | | | 32 × 32 | | | 16 × 16 | | |
| | city | sand | avg. | city | sand | avg. | city | sand | avg | city | sand | avg. |
| training patrn | 85.4 | 92.8 | 89.1 | 98.9 | 63.5 | 81.2 | 94.4 | 86.2 | 90.3 | 96.6 | 62.6 | 79.6 |
| 91% ~ 100% | 61.6 | 90.9 | 76.3 | 77.8 | 60.3 | 69.1 | 88.1 | 82.8 | 85.5 | 88.0 | 61.1 | 74.6 |
| 81% ~ 90% | 68.6 | 81.8 | 75.2 | 85.2 | 48.6 | 66.9 | 92.5 | 71.2 | 81.8 | 88.1 | 50.7 | 69.4 |
| 71% ~ 80% | 65.6 | 84.2 | 74.9 | 84.9 | 54.7 | 69.8 | 93.3 | 74.7 | 84.0 | 87.3 | 57.5 | 72.4 |
| 61% ~ 70% | 64.8 | 86.3 | 75.6 | 83.6 | 58.6 | 71.1 | 92.7 | 77.7 | 85.2 | 87.5 | 60.1 | 73.8 |
| 51% ~ 60% | 63.7 | 91.2 | 77.5 | 82.2 | 67.8 | 75.0 | 90.0 | 75.8 | 82.9 | 87.4 | 66.7 | 77.1 |

**Table 3.** Classification Accuracies by Texture Features Method unit : %

| occupation rate | occupation rate of concerned category in 9X9 region | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 100% | | | | | | 80% | | | | | |
| | size of co-occurrence matrix | | | | | | size of co-occurrence matrix | | | | | |
| | 32 × 32 | | | 16 × 16 | | | 32 × 32 | | | 16 × 16 | | |
| | city | sand | avg. | city | sand | avg. | city | sand | avg. | city | sand | avg. |
| training patrn | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 91% ~ 100% | 98.9 | 96.3 | 97.6 | 99.3 | 98.2 | 98.8 | 98.0 | 95.9 | 97.0 | 99.7 | 96.5 | 98.1 |
| 81% ~ 90% | 94.6 | 83.9 | 89.3 | 93.9 | 86.3 | 90.2 | 98.0 | 97.9 | 98.0 | 96.1 | 94.5 | 95.3 |
| 71% ~ 80% | 93.0 | 81.8 | 87.4 | 92.5 | 99.8 | 96.2 | 97.2 | 97.2 | 97.2 | 94.6 | 98.6 | 96.6 |
| 61% ~ 70% | 86.5 | 79.1 | 82.8 | 88.3 | 70.5 | 79.4 | 93.0 | 98.9 | 96.0 | 89.3 | 99.3 | 94.3 |
| 51% ~ 60% | 84.2 | 89.4 | 86.8 | 87.4 | 71.1 | 79.3 | 92.0 | 100 | 96.0 | 87.2 | 100 | 93.6 |

(4) In the case of texture features method, the classification accuracy changed according to the size of co-occurrence matrix or the occupation rate. On the contrary, in the case of neural network method, obtained classification accuracies were very stable. Futhermore, in the case of texture features method, the classification accuracies of training patterns were 63% ~ 99%, however, in the case of neural network method, the classification of accuracies of training patterns were 100%.

(5) Generally speaking, neural network method showed more stable and higher classification accuracy than texture features method. Especially, it is remarkable that the classification is stable even if the target patterns are slightly different from training patterns.

(6) With the conventional pixel-wised maximum likelihood method, obtained average classification accuracy was 68%. However, with the neural network method, high classification accuracy of 98% was obtained for the target patterns having 91-100% occupation rate, regardless of the training patterns and size of co-occurrence matrices. This result strongly suggests the robustness of neural network method.

## V. Conclusion

In this paper, a method using a neural network was proposed to utilize spatial information of image data. In order to evaluate the proposed method, SPOT HRV image data was classified by this method and texture features method.

Through the experiments, the obtained classification accuracy was higher using neural network method than using texture features method. Also, the classification accuracy was stable and high for this method compared with the conventional pixel-wised maximum likelihood method.

## Appendix

Co-occurrence matrix is defined as follows. The co-occurrence matrix is the square matrix obtained by calculating from digital image, that is, each element of i-th column and j-th row represents the probability of occurrence that gray levels of pixels are different(one is i and the other is j), and the displacement of pixels is $(r, \theta)$. Fig. 5 shows the displacement between pixels, and Fig. 6 shows the example of co-occurrence matrix. Co-occurrence matrix has statistical characeristics f texture, independant on rotation or movement of image.

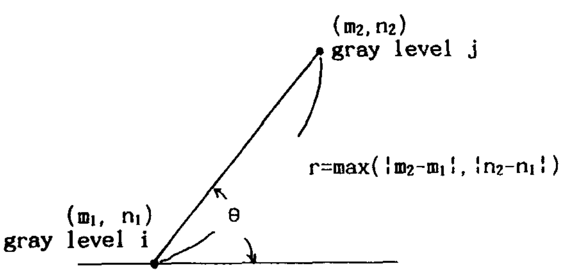


Fig. 5 displacement $(r, \theta)$

| | | | |
|---|---|---|---|
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 2 | 2 | 2 |
| 2 | 2 | 3 | 3 |

(a) given image

$$\begin{array}{c|c} & \rightarrow j \\ & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ i \downarrow 3 \end{matrix} & \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix} \end{array}$$

(b) $(r, \theta)=(1, 0^{\circ})$

$$\begin{array}{c|c} & \rightarrow j \\ & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ i \downarrow 3 \end{matrix} & \begin{bmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix} \end{array}$$

(c) $(r, \theta)=(1, 90^{\circ})$

$$\begin{array}{c|c} & \rightarrow j \\ & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ i \downarrow 3 \end{matrix} & \begin{bmatrix} 2 & 1 & 3 & 0 \\ 1 & 2 & 1 & 0 \\ 3 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix} \end{array}$$

(c) $(r, \theta)=(1, 135^{\circ})$

$$\begin{array}{c|c} & \rightarrow j \\ & \begin{matrix} 0 & 1 & 2 & 3 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ i \downarrow 3 \end{matrix} & \begin{bmatrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$

(d) $(r, \theta)=(1, 45^{\circ})$

Fig. 6 Example of Co-occurrence matrix

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