NON-PARAMETRIC TEXTURE ANALYSIS USING NEURAL NETWORK

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ABSTRACT:

A method using a neural network was applied for utilizing spatial information. The adopted model of neural network has 3 layered architecture, and the training method of network is the back-propagation algorithm. Co-occurrence matrix that is generated from original image data was used for input pattern to the neural network in order to tolerate variations of patterns like rotation or displacement.

To evaluate this method, classification was executed with this method over the city area and sand area of SPOT HRV panchromatic image data, which cannot be separated with the conventional pixel-wise maximum likelihood method based on spectral information. Obtained classification accuracy using neural network was better than 80%.

KEY WORDS: neural network, spatial feature, texture analysis, landcover classification, co-occurrence matrix.

1. 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 studies have shown that classification accuracies using these sensors are not so high as expected when a pixel-wise supervised maximum likelihood classifier using only spectral information is applied. One of the solutions of this problem is to use spatial information like texture.

In this paper, a method using a neural network was applied for the purpose of utilizing spatial information. To evaluate this method, a case study over the city area and sand area of SPOT HRV panchromatic image data was executed. This area cannot be separated by the conventional method mentioned above. Three kinds of classifier, i.e. the proposed method, a conventional pixel-wise method and a second order statistical texture method proposed by Haralick(Haralick, 1979), were applied.

2. PROPOSED METHOD

The neural network model used in this study is a feedforward multilayered network. 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.

For training the neural network, a back-propagation algorithm was adopted(Rumelhart, 1986). Co-occurrence matrices that had been converted from original image data were used as input patterns to the neural network in order to tolerate variations of patterns like rotation or displacement.

3. EVALUATION OF PROPOSED METHOD

In order to evaluate the 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. This area includes the test site data which is already investigated and categorized to 52 categories. It is easy to evaluate the accuracies of landcover classifications using this data set. Fig. 1 shows the target image data and Fig. 2 shows the test site data.

For the classification target categories, city and sand categories were selected from the 52 categories, because these two categories have very similar spectral characteristics, hence, it is difficult to classify with conventional pixel-wise maximum likelihood method using only spectral information.

Experiment of evaluation was executed by 3 steps as follows.

(1) Preparation of Input Patterns

For the input patterns, city region and sand region, corresponding to that category of the test site data, were extracted. Each region is composed of 9 X 9 pixels. The extracted regions were converted to co-occurrence matrices. The maximum size of the co-occurrence matrix is 256 X 256, since the HRV image data has 256 gray levels. However, the neural network simulator used in this experiment has the limitation of number of neurons in each layer(maximum 1024)(NEC, 1989). 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 were calculated from the 100% and 80% occupation rate of concerned category in extracted regions, were considered for training patterns. For .pa
each kind of training patterns, 26 samples were randomly selected from extracted regions.

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 3000 times on each kind of input patterns and the time needed for training were 78, 48 and 43 minutes for 32 X 32, 16 X 16 and 8 X 8 co-occurrence matrices, respectively.

Fig. 3 shows the convergence of error with the number of times for training. In the case of 32 X 32 and 16 X 16 co-occurrence matrix, the error converged after several tens of times of trainings, but in the case of 8 X 8 co-occurrence matrix, the error didn't converge after 3000 times of trainings. This result suggests that the classification of city area and sand area is difficult with only 8 gray levels.

(3) Classification

Classification test was executed using the prepared input patterns. The number of test patterns was about 17000. 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 experiment.

4. COMPARISON WITH OTHER METHODS

(1) PIXEL-WISE MAXIMUM LIKELIHOOD METHOD

A pixel-wise maximum likelihood classification was performed over the city area and sand area of SPOT HRV panchromatic image data as a typical example of conventional method. Table 1 shows the classification accuracies obtained by this method.

(2) TEXTURE FEATURES METHOD

Another classification method using texture features was examined. In this method, following 4 features(Haralick, 1979), 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 obtained by this method.

5. RESULTS

From 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 regardless of the occupation rate(100% or 80% in city area/sand area), but it was about 63%-99% in the case of texture features method.

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

(3) The classification accuracies were higher in both methods when 80% occupation rate training patterns were used. It can be thought that this result was caused by the wide immunity of target patterns. Thus, from this experiment, it is not clear that the same result can be obtained in the case of multi-categories.

(4) In the case of texture features method, the classification accuracy has been 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 accuracy was very stable. Furthermore, In the case of texture features method, the classification accuracy of test patterns was 85%(average classification accuracy) at the maximum.

(5) With the conventional pixel-wise maximum likelihood method, obtained average classification accuracy was 68.6%. However, with the neural network method, high classification accuracy of 99% was obtained for the target patterns having 91-100% occupation rate, regardless of the training patterns and the size of co-occurrence matrices.

6. 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 for neural network method than for texture features method. Also, the classification accuracy was very stable and high for this method compared with the conventional pixel-wise maximum likelihood method.

REFERENCES

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Rumelhart, D., McClelland, J. and PDP Research Group, 1986. PARALLEL DISTRIBUTED PROCESSING. MIT Press, Vol.1, pp.318-362.

Fig. 2 SPOT HRV Image Data

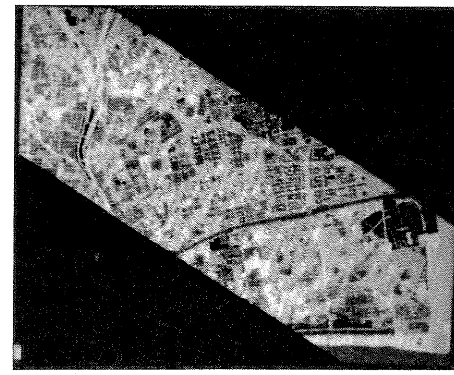
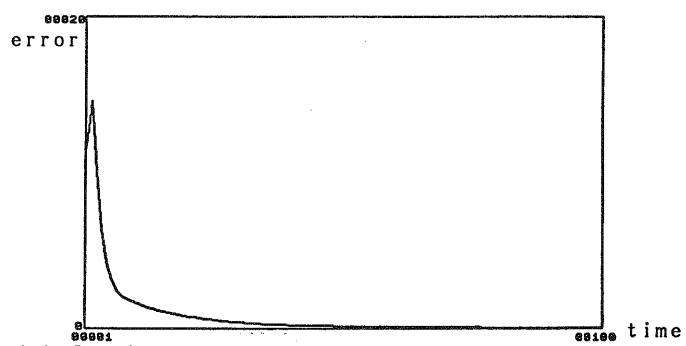
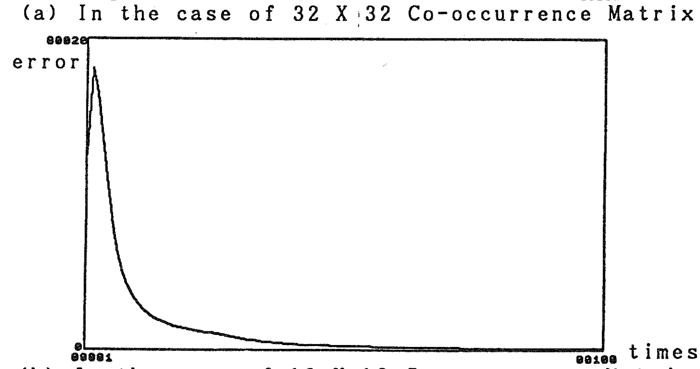


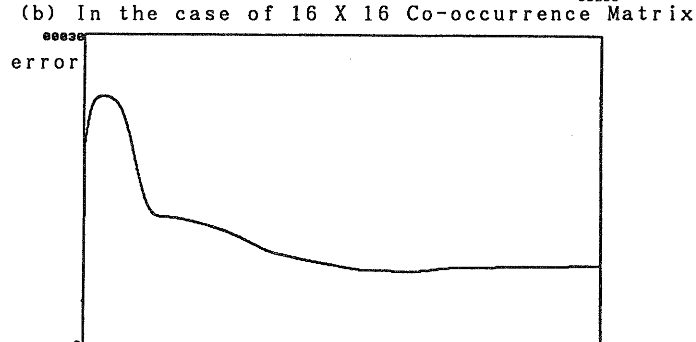
Fig. 3 Test Site Data



(a) In the case of 32 X 32 Co-occurrence Matrix



(b) In the case of 16 X 16 Co-occurrence Matrix



(c) In the case of 8 X 8 Co-occurrence Matrix

Fig. 3 Convergence of Error with the Number of Times for Training

Table 1 Classification Accuracies by Pixel-wise Maximum Likelihood Method

city area	sand area	average
71.9%	65.2%	68.2%

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 Neural Network 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