IMAGE CLASSIFICATION BY SPATIAL SHIFT INVARIANT NEURAL NETWORK

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ABSTRACT

I proposed the new method to classify images using artificial neural network technology imitating bio-neural network behind retina and in visual cortex, in order to use spatial information like human interpretation. The method has two important characteristics: to extract both spectral and spatial information simultaneously, and to execute feature extraction and classification in a narrow sense in a step.
Two elementary experiments were done: geological classification using slope gradation map (image) into two categories, and land use classification using aerial photograph into three categories. Ratios of correct answer were 82 % and 93 % for the training samples.

1 INTRODUCTION

Though human easily understands geometric features on aerial photographs or remotely sensed images, computer hardly recognizes them. It comes from difficulty of understanding spatial information by computer. Therefore I tried to introduce computer simulated neural network imitates neural network behind retina and in visual cortex (Zeki, 1993; Muramatsu, 1995) for image classification.

2 METHODOLOGY

A computer simulated neural network for image classification is prepared. The neural network is layered type. A kind of error back propagation learning algorithm (Rumelhart et. al., 1986a, 1986b) is used for the network.

The classification method using the neural network is expected to have two important characteristics comparing to the conventional image classification method including one using neural network technology (Fukue et. al. 1998).

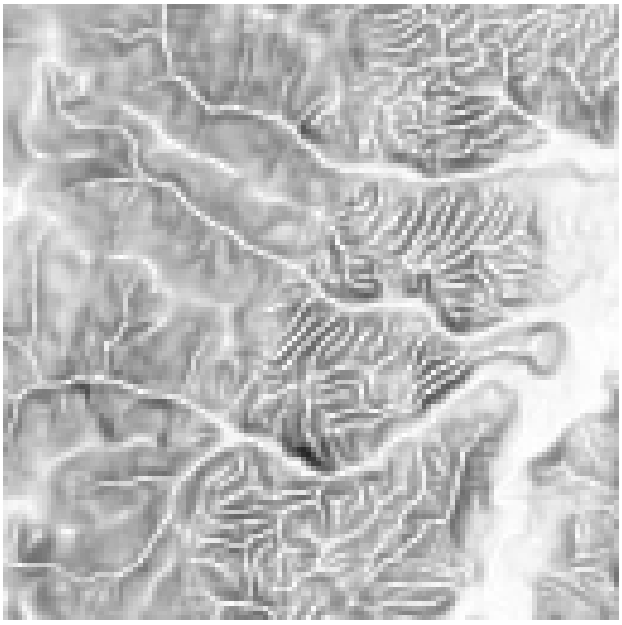
One is that the neural network is designed to extract both spectral and spatial information simultaneously. The conventional method processes them separately.

The other is that the neural network executes feature extraction and classification in a narrow sense. Feature extraction is to calculate feature variables from original image for each pixel (or region). Classification in a narrow sense is to determine each pixel (or region) to a certain class based on statistics using the feature variables. There are standard theories, for example maximum likelihood method, on classification in a narrow sense. There is however no clear criteria on selecting feature variables, especially for spatial feature, on feature extraction.

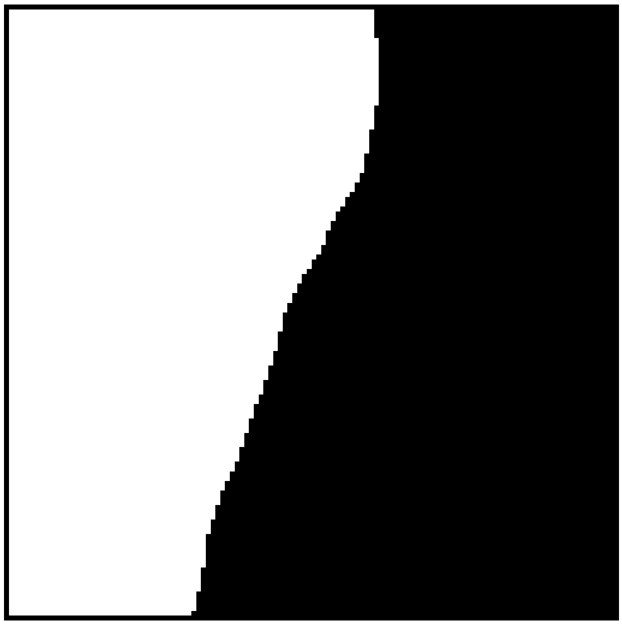
3 EXPERIMENTS

3.1 GEOLOGICAL CLASSIFICATION OF SLOPE GRADATION MAP

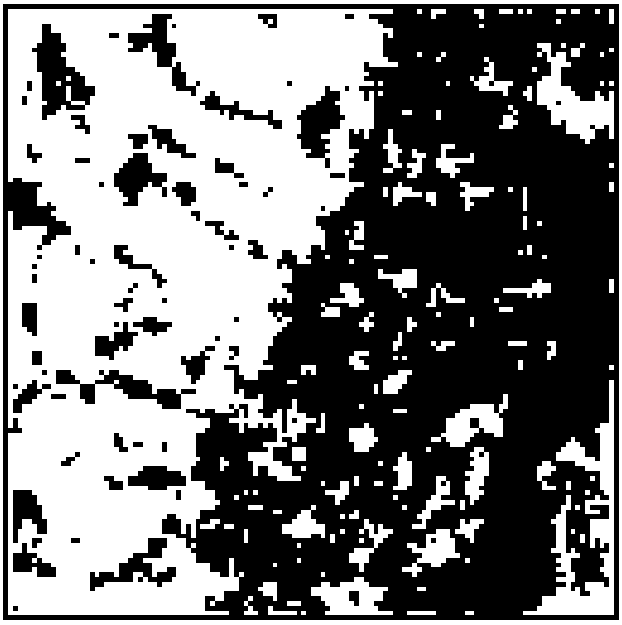
Slope gradation map (Kamiya et. al., 2000) is gray scale image that shows dip (slope) of ground. Geomorphological and geological information is able to extract from the map by interpretation. The image does not show reflectance of ground, but it looks to be simpler example for extraction of spectral and spatial information simultaneously than aerial photographs or remotely sensed images. Figure 1 (a) is an example of slope gradation map calculated from DEM,



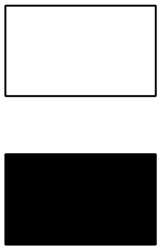
(a) Slope Gradation Map



(b) Classification Result by Interpretation



(c) Classification Result by the Neural Network



All images are size of 128×128 pixels

Figure 1. Geological Classification of Slope Gradation Map

which grid interval is about 50m. Left half of the map is interpreted as mountains with serpentine because of dullness (figure 1 (b)), which means the interpreter uses spatial information.

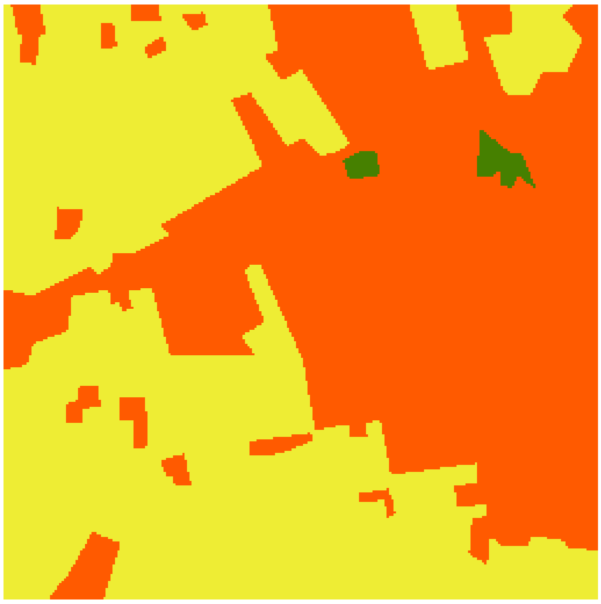
The neural network learned its connection weight 10,000 times using the pair of figure 1 (a) and (b) as a tutor. Figure 1 (c) is a classification result of the tutor (figure 1 (b)). The ratio of correct answer comparing to interpretation result, which is also tutor, was 82 % excluding boundary of the image.

3.2 LAN USE CLASSIFICATION OF AERIAL PHOTOGRAPH

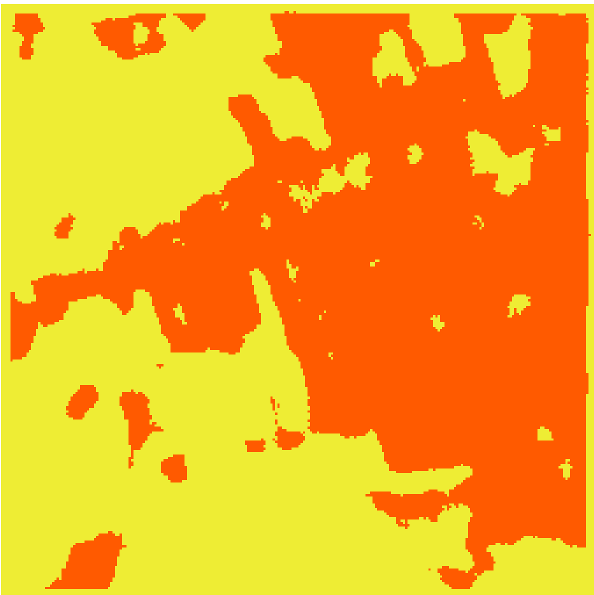
Figure 2 (a) is a 1/25,000 color aerial photograph. The photograph is scanned by 100 DPI. Sampling pitch on the ground is about 6.3 m. The image was classified into 3 categories by interpretation: (1) housing area, (2) agricultural fields, and (3) forest. The housing area includes greenhouses, and bare land and vegetation near houses. Some of the agricultural fields are covered with vegetation and the others are not, some of them is quite similar to the bare land in the housing area.

The neural network learned its connection weight 1,000 times using the pair of figure 2 (a) and (b) as a tutor. Figure 2 (c) is a classification result of the tutor (figure 2 (b)). The ratio of correct answer comparing to interpretation result, which is also tutor, was 93 % excluding boundary of the image.

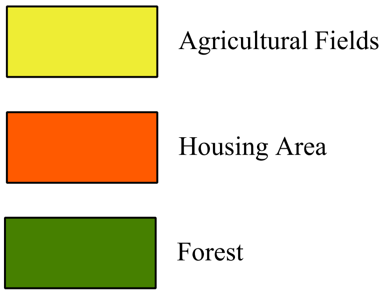
(a) Aerial Photograph



(b) Classification Result by Interpretation



(c) Classification Result by the Neural Network



All images are size of 256×256 pixels

Figure 2. Land Use Classification of Aerial Photograph

4 CONCLUSIONS

I proposed the new method to classify images using neural network technology imitating bio-neural network behind retina and in visual cortex. Elemental classification experiments using the neural network succeeded. The two expected characteristics of the classification were confirmed: to extract both spectral and spatial information simultaneously, and to execute feature extraction and classification in a narrow sense in a step.

REFERENCES

Fukue, K., Simoda, H., Sakata, T., 1998. Neural Network Classifier driven by Co-Occurence Matrix for Land Cover Components, *Proceedings of the 24th Japanese Conference on Remote Sensing,* pp. 155-156 (in Japanese with English Abstract).

Kamiya, I., Kuroki, T., Tanaka, K., 2000. Interpretation of Geomorphology and Geology using Slope Gradation Map, *Geoinformatics,* Vol. 11, No. 1, pp.9-22 (in Japanese with English Abstract).

Muramatsu, M., 1995. Introduction to Neuroscience, Saiensusha, Tokyo. (in Japanese)

Rumelhart, D. E., Hinton, G. E., Williams, R. J., 1986a. Learning Internal Representation by Error Propagation, in Rumelhart, D. E., McClelland, J. L., the PDP Research Group (eds.), *Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol. 1: Foundations,* The MIT Press, Cambridge, pp. 318-362.

Rumelhart, D. E., Hinton, G. E., Williams, R. J., 1986b. Learning Representation by Back-Propagation Errors, *Nature,* Vol. 323, No. 9, pp. 533-536.

Zeki, S., 1993. A Vision of the Brain, Blackwell Scientific Publications, Oxford.