LETTER

A New Self-Organization Classification Algorithm for Remote-Sensing Images

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SUMMARY This paper presents a new self-organization classification algorithm for remote-sensing images. Kohonen and other scholars have proposed self-organization algorithms. Kohonen's model easily converges to the local minimum by tuning the elaborate parameters. In addition to others, S.C. Amatur and Y. Takefuji have also proposed self-organization algorithm model. In their algorithm, the maximum neuron model (winner-take-all neuron model) is used where the parameter-tuning is not needed. The algorithm is able to shorten the computation time without a burden on the parameter-tuning. However, their model has a tendency to converge to the local minimum easily. To remove these obstacles produced by the two algorithms, we have proposed a new self-organization algorithm where these two algorithms are fused such that the advantages of the two algorithms are combined. The number of required neurons is the number of pixels multiplied by the number of clusters. The algorithm is composed of two stages: in the first stage we use the maximum self-organization algorithm until the state of the system converges to the local-minimum, then, the Kohonen self-organization algorithm is used in the last stage in order to improve the solution quality by escaping from the local minimum of the first stage. We have simulated a LANDSAT-TM image data with 500 pixel × 100 pixel image and 8-bit gray scaled. The results justifies all our claims to the proposed algorithm.

key words: *neural network, self-organization, remote-sensing, classification*

1. Introduction

Remote sensing images of the earth surface taken from a satellite contain various useful information. One approach to analyze remote sensing images is clustering. Clustering remote-sensing images is to force each pixel based on images of different p-type bands in one of several clusters according to the similarity of the p-dimensional feature vector.

Some well-known hierarchical clustering methods include the Ward algorithm and the Centroid algorithm. Other clustering methods such as self-organization clustering algorithms, proposed by Kohonen [1] and Takefuji [6], use unsupervised-neural-network-learning model. The hierarchical clustering methods have a serious problem when the state of the system converges to a local minimum and they require a long computation time. The self-organization models proposed by Kohonen and Takefuji are able to resolve the problem. However, their methods have much rooms to be improved [2]–[6].

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Generally, image classification problems take enormous computation time due to large amount of data. (There are M^N possible ways when we classify N pixels into M clusters.) Therefore, our objective is to present a high-speed classification algorithm.

In this paper, we propose a new self-organization algorithm where two self-organization algorithms including the feature map model proposed by Kohonen and the maximum neuron model proposed by Takefuji are fused. We compare our algorithm with the best existing self-organization algorithms using real remote-sensing images.

2. Three Algorithms

2.1 Maximum Neuron Model (MNM)

In classifying P-dimensional N pixels into M clusters, M×N neurons are required. U_{nm} is the input to the nmth neuron, and V_{nm} is the output. $V_{nm} = 1$ if the pixel n is assigned to cluster m, and $V_{nm} = 0$ otherwise. x_{sk} is the density of pixel k in the sth image file, X_k the feature vector of pixel k, and $\overline{X_l}$ the feature vector of the centroid of cluster l in the following equation. nl is the number of pixels classified into cluster l.

$$X_k = (x_{1k}, x_{2k}, \ldots, x_{Pk}),\ \overline{X_l} = (\sum_{k=1}^{N} X_k V_{kl})/nl \quad (1)$$

The distance between pixel k and cluster l based on the square of Euclidean measure is given as R_{kl} in the following equation.

$$R_{kl} = (X_k - \overline{X_l})^2 \quad (2)$$

The objective function is determined by the mean square root when each pixel is classified into suitable clusters as follows:

$$E = \sum_{k=1}^{N} \sum_{l=1}^{M} R_{kl} V_{kl} \quad (3)$$

Generally speaking, the lower the value of E, the better the result of image clustering. The purpose of this clustering problem is to reduce the value of E. In order to converge to the optimum solution by reducing the value of E, the derivatives of input U with respect to time t are given by:

$$\Delta U_{kl} = -R_{kl} \quad (4)$$

The output V of the maximum neuron is determined by:

$$V_{km}(t+1) = 1 \quad if\ U_{km} = \max[\ U_{kl}(t); \forall : l\ ], \quad (5)$$
$$0 \quad \text{otherwise}$$

Algorithm of MNM

1 Initialize the input of neurons U with uniform-random values.

2 Use the input-output function of Eq. (5) to update the new output values.

3 In each clustering, compute the centroid (or cluster means) $\overline{X_l}$ using Eq. (1).

4 For each neuron, compute the value of R of Eq. (2) and derivatives of Eq. (4).

5 For each neuron, update input U using the first order Euler's method:

$$U_{kl}(t+1) = U_{kl}(t) + \Delta U_{kl} \quad (6)$$

6 Go to step 2 until the value of E does not change.

2.2 Kohonen's Feature Map Model

The Kohonen's feature map clustering algorithm is described as follows. In classifying P-dimensional N pixels into M clusters, P-dimensional weight vectors W_1, $W_2, \ldots, W_M$ are required ($W_l = (w_{1l}, w_{2l}, \ldots, w_{Pl})$).

Algorithm of Kohonen's model

1 Initialize W with uniform-random values.

2 For each pixel, compute the distance between the pixel and the M weight vectors based on the mean square root.

$$(X_k - W_l)^2 \quad (l = 1, 2, \ldots M) \quad (7)$$

Then, select a vector W_z such that W_z satisfies Eq. (8), and update W_z using Eq. (9) as shown in Fig. 1.

$$(X_k - W_z)^2 = \min(X_k - W_l)^2 \quad (8)$$
$$(l = 1, 2, \ldots M)$$
$$W_z(t+1) = W_z(t) + \alpha(X_k - W_z) \quad (9)$$
$$(0 < \alpha < 1)$$

3 Go to step 2 until $W_l \approx \overline{X_l}(l = 1, 2, \ldots, m)$. (In the early learning stage, α is set at about 0.8. As the learning progresses, α gradually becomes closer to 0.)

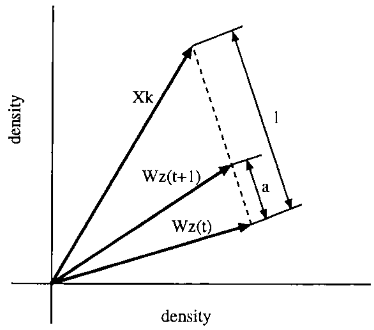

Fig. 1 P-dimensional vector space.

Table 1 LANDSAT-D sensor.

band	frequency(μm)
1	0.45~0.52
2	0.52~0.60
3	0.63~0.69
4	0.76~0.90
5	1.55~1.75
6	10.40~12.60
7	2.08~2.35

2.3 The Proposed Algorithm

1 First, use the MNM until the value of E does not change anymore.

2 Then, use the Kohonen's model until the state of the system converges to a solution.

3. Tested Data

The remote-sensing images of Yokohama taken by the LANDSAT-D with TM (Thematic Mapper) are used. The resolution is 30×30 m, and the data size is 500 pixel $\times$ 100 pixel. The image data are taken by seven frequency bands as shown in Table 1, and the density is 8-bit gray scaled as shown in Fig. 2.

4. Tested Results

Figure 3 shows the tested results using three methods (MNM, Kohonen's model, and the proposed algorithm) where the number of clusters is seven as shown in Table 2. Figure 4 shows the relationship between E and the number of iteration steps. Figure 4 shows that it takes more than 70 iteration steps to converge in MNM and Kohonen's model, while about 20 iteration steps in the proposed algorithm.

Table 3 and Figs. 5–8 show the statistical result of three methods where each method was simulated by 200 runs, and 5-clustering, 7-clustering, 9-clustering, and 11-clustering were experimented respectively. Table 3 and Figs. 5–8 show that the proposed algorithm

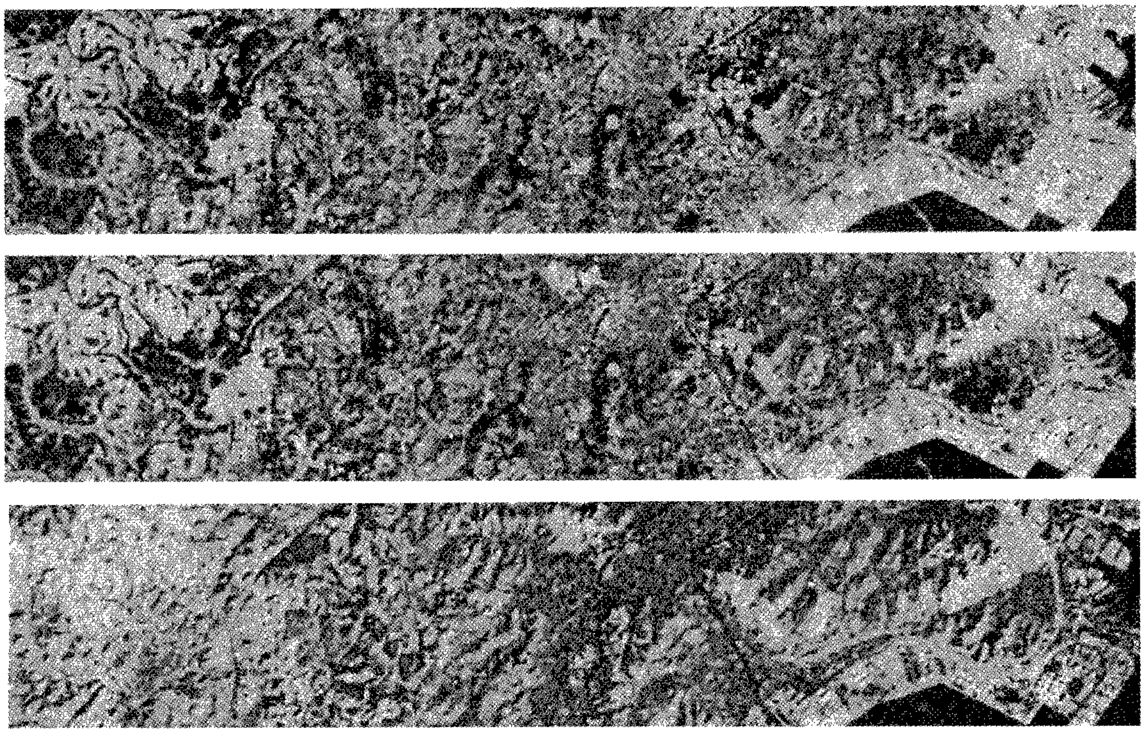

Fig. 2 Remote-sensing images of band2, band3, and band4.

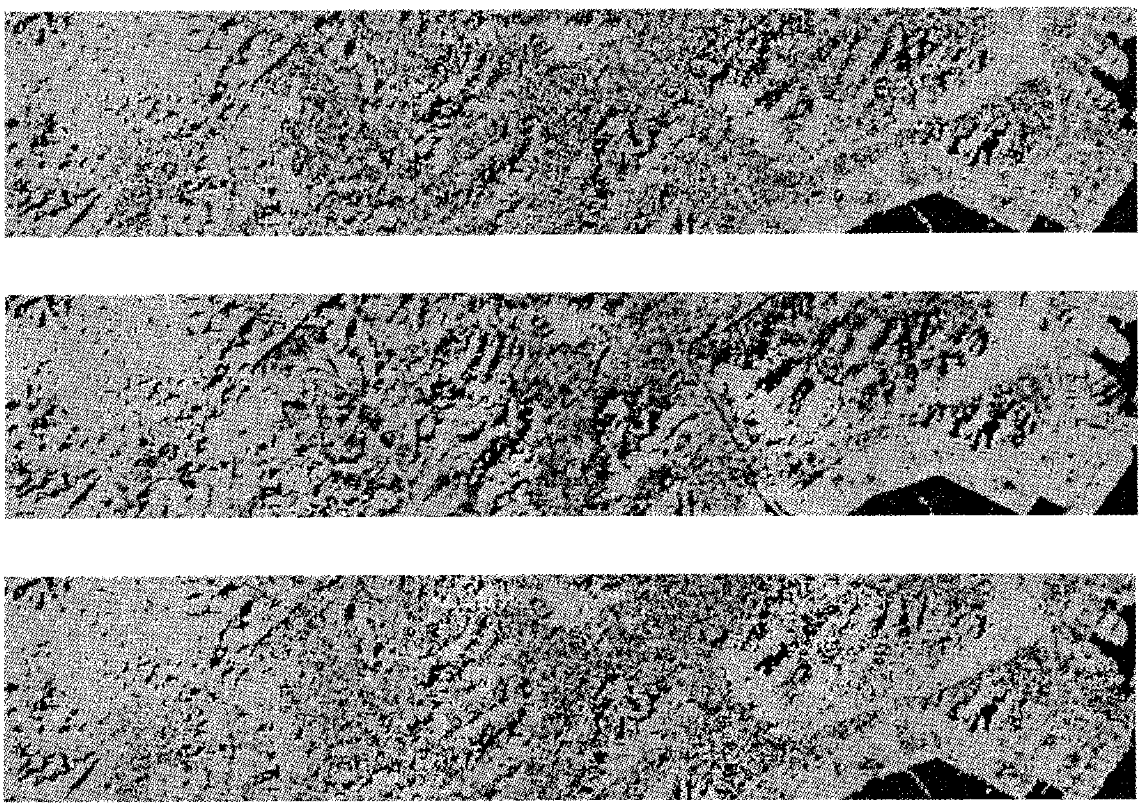

Fig. 3 7-clustering of three methods. (a), (b), (c) show the result of the MNM, that of Kohonen's model, and that of the proposed method respectively.

is superior to MNM and Kohonen's model in terms of the solution quality. For example, the average cost of E by 200 7-clustering simulation runs is 8.73×10^7 in the MNM, 9.37×10^7 in the Kohonen's model, and 8.35×10^7 in the proposed algorithm. The simulation result describes that the proposed algorithm converges to the best solution among three methods. The standard deviation cost of E by 200 7-clustering simulation runs is 3.27×10^6 in the MNM, 1.15×10^7 in the Kohonen's model, and 1.88×10^6 in the proposed algorithm. The simulation result concludes that the proposed algorithm provides the best solution quality among three methods. We have obtained the same result in the experiments of 5-clustering, 9-clustering, and 11-clustering.

Table 2 Seven clusters.

cluster	color
sea	blue
city	red
vegetation	green
road	brown
forest	yellow
building	gray
artificial green	pink

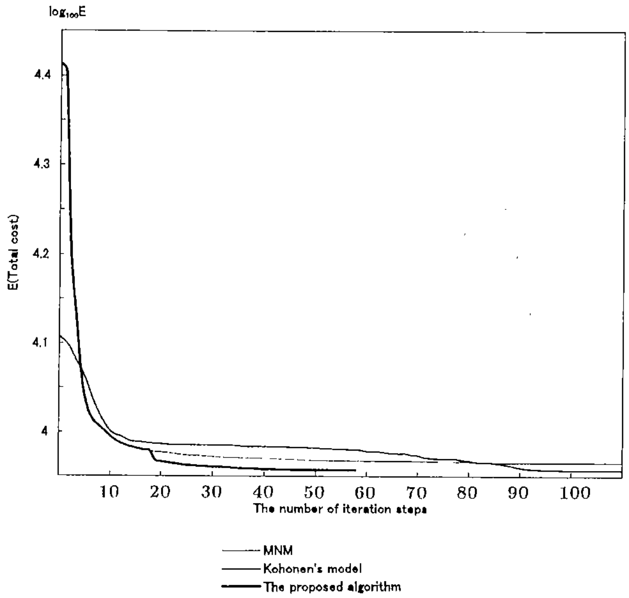

Fig. 4 The relationship between E and the number of iteration steps.

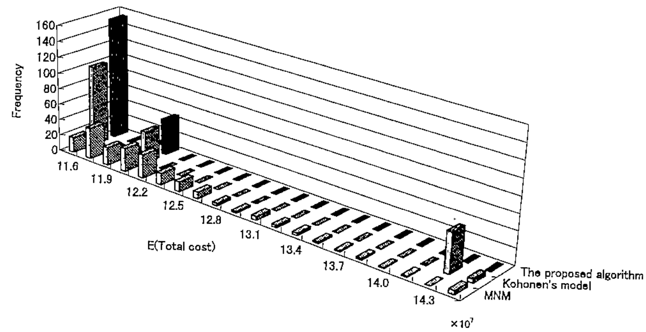

Fig. 5 5-clustering by 200 simulation runs.

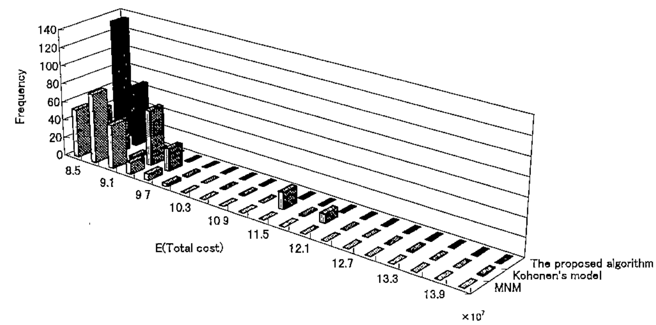

Fig. 6 7-clustering by 200 simulation runs.

Table 3 Statistical analysis.

The average cost of E by 200 simulation runs.

The number of clusters	MNM	Kohonen's model	The proposed algorithm
5	1.25×10^8	1.21×10^8	1.15×10^8
7	8.73×10^7	9.37×10^7	8.35×10^7
9	7.17×10^7	7.95×10^7	6.88×10^7
11	6.12×10^7	6.94×10^7	5.82×10^7

The standard deviation cost of E by 200 simulation runs.

The number of clusters	MNM	Kohonen's model	The proposed algorithm
5	1.85×10^7	6.71×10^6	1.69×10^6
7	3.27×10^6	1.15×10^7	1.88×10^6
9	1.76×10^6	7.67×10^6	7.13×10^5
11	1.48×10^6	7.37×10^6	8.98×10^5

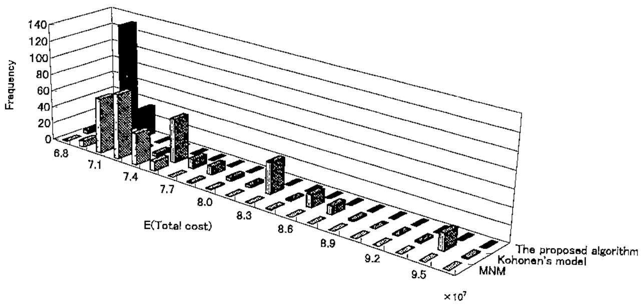

Fig. 7 9-clustering by 200 simulation runs.

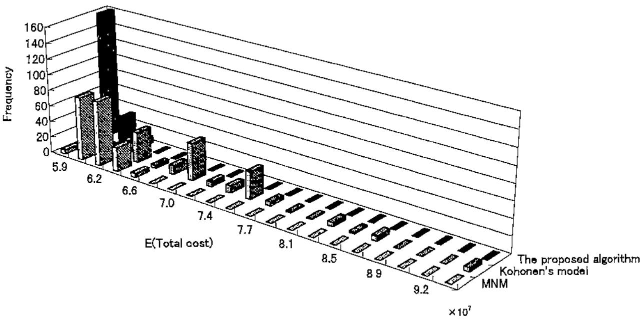

Fig. 8 11-clustering by 200 simulation runs.

5. Conclusion

Figure 4 shows that the number of iteration steps of the proposed method to converge to a solution is the smallest among three methods. In other words, our new method shows the fastest solution convergence. Table 3 and Figs. 5–8 show the superiority of the solution quality in the proposed method. In our experiments, the advantages of our method were partly justified in terms of the solution quality and the computation time.

By using binary neuron model, the fluctuated converging process provided and produced by MNM has been dynamic. However, MNM easily converges to the oscilliation state of local minimum because of the limitation of its ability. In the Kohonen's model it takes longer computation time to converge than MNM does. Moreover, the solution quality of the Kohonen's model depends on the initial state. To resolve these problems in Kohonen's model one of well known method is to make a time chart for the parameter tuning. Generally, the optimal parameter tuning is a time-consuming task based on empirical knowledge. The proposed algorithm simply resolves these problems by using MNM as a pre-processing of Kohonen's model.

References

[1] T. Kohonen, "Physiological interpretation of the self-organizing map algorithm," Neural Networks, vol.6, pp.895–905, 1993.
[2] G. Yiping and B.C. Forster, "Unsupervised classification of high spectral resolution images using the Kohonen self-organization neural network," Chinese Journal of Infrared and Millimeter Waves, vol.13, no.6, pp.457–465, 1994.
[3] L.O. Hall, A.M. Bensaid, L.P. Clarke, R.P. Velthuizen, M.S. Silbiger, and J.C. Bezdek, "A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain," IEEE Trans. Neural Networks, vol.3, no.5, pp.672–682, 1992.
[4] N.M. Allinson and M.J. Johnson, "Self-organising N-tuple feature maps," Neural Network World, 5, pp.503–510, 1993.
[5] T. Li, L. Fang, and K.Q-Q. Li, "Hierarchical classification and vector quantization with neural trees," Neurocomputing, 5, pp.119–139, 1993.
[6] S.C. Amartur, D. Piranio, and Y. Takefuji, "Optimization neural networks for the segmentation of magnetic resonance images," IEEE Trans. Medical Imaging, vol.11, no.2, pp.215–220, 1992.
[7] Y. Takefuji, K.-C. Lee, and H. Aiso, "An artificial maximum neural network: A winner-take-all neuron model forcing the state of the system in a solution domain," Biological Cybernetics, vol.67, pp.243–251, 1992.