Extraction of Rice-planted Area Using a Self-organizing Feature Map

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Abstract: We introduce a neural network of self-organizing feature map (SOM) to classify remote-sensing data, including microwave and optical sensors, for the estimation of areas of planted rice. This method is an unsupervised neural network which has the capability of nonlinear discrimination, and the classification function is determined by learning. The satellite data are observed before and after rice planting in 1999. Three sets of RADARSAT and one set of SPOT/HRV data were used in Higashi–Hiroshima, Japan. The RADARSAT image has only one band of data and it is difficult to extract the rice-planted area. However, the SAR back-scattering intensity in a rice-planted area decreases from April to May and increases from May to June. Therefore, three RADARSAT images from April to June were used in this study. The SOM classification was applied the RADARSAT and SPOT data to evaluate the rice-planted area estimation. It is shown that the SOM is useful for the classification of satellite data.

Keywords: Remote sensing, Synthetic aperture radar, Self-organizing feature map.

I. INTRODUCTION

Rice is the most important agricultural product in Japan, and is planted in a wide area, but it is still difficult to estimate the rice-planted areas every year. Therefore, the development of a system for monitoring the rice crop will be welcome. Remote-sensing satellite images by optical sensors like LANDSAT/TM or SPOT/HRV have been used to estimate rice-planted areas. However, these optical sensors have sometimes been unable to get the necessary data at a suitable time because it is often cloudy and rainy during the rice-planting season in Japan.

On the other hand, space-borne synthetic aperture radar (SAR) penetrates through the cloud cover. Hence, SAR observes the land surface in all weather conditions. Suga et al [1] show that the back-scattering intensity of C-band SAR images, such as RADARSAT or ERS-1/SAR, changes greatly from noncultivated bare soil conditions before rice-planting to water-inundated conditions just after rice-planting. In addition, Ribbes et al [2] and Liew et al [3] show that RADARSAT images are rather sensitive to changes in the rice biomass in the growing period of the rice. Therefore, rice-area estimation has to be achieved at an early stage. Suga et al [4] attempted to estimate the rice-planted area using RADARSAT fine-mode data at an early stage. The accuracy of estimating the rice-planted area by the maximum likelihood method (MLH) was approximately 40% of the estimated area found by SPOT multispectral data. In this study, the authors attempt to estimate the rice-planted area from RADARSAT data using SOM, i.e., unsupervised classification.

II. TEST SITE AND DATA

The test area was about 7.5 × 5.5 km in Higashi-Hiroshima, Japan. This site is located in the eastern part of Hiroshima, Japan. Three multi-temporal RADARSAT fine-mode (F1F) images, taken on April 8, May 26, and June 19, 1999, were used as the test data. SPOT/HRV multispectral data, taken on June 21, 1999, were used to generate a reference image for rice-planted area estimation.

The three merged RADARSAT images and one SPOT image described above, in part of the test site, are shown in Figures 1 and 2. The land surface conditions in the rice-planted area on April 8 was noncultivated bare soil before rice-planting, with a rather rough soil surface. The surface conditions on May 26 were an almost smooth water surface just after rice-planting, and that of June 19 was a mixture of growing rice and water surface. It was found that the rice-planted areas were shown as a dark tone in the RADARSAT images.

The RADARSAT raw data were processed using a Vexcel SAR processor (VSARP), and single-look power images with 6.25 m ground resolution were generated. Then the images were filtered using a median filter with a 7 × 7 moving window. All RADARSAT and SPOT images were overlaid onto a topographic map with a 1 : 25,000 scale. As RADARSAT images are much distorted by foreshortening due to topography, a digital elevation model (DEM) with 50 m spatial resolution, issued by the Geographical Survey Institute (GSI) of Japan, was used to correct the foreshortening of the RADARSAT images.

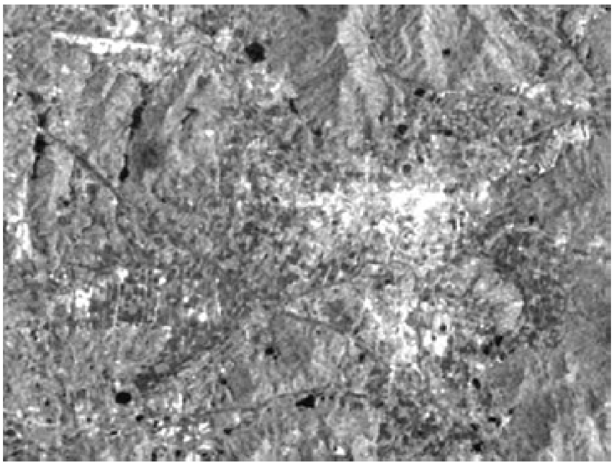

Fig. 1. RADARSAT image in the test site
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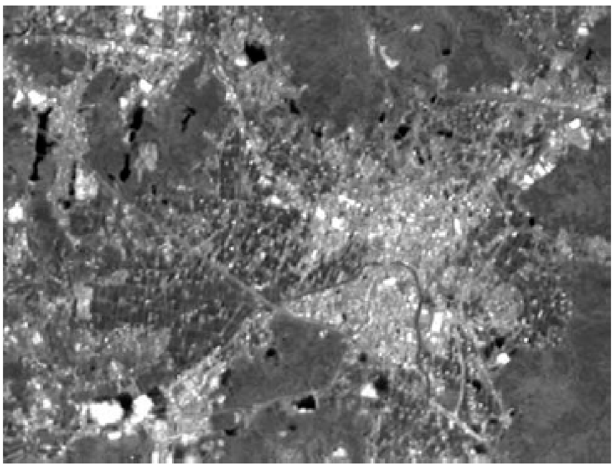

Fig. 2. SPOT-2/HRV image in the test site
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III. SOM ALGORITHM

We now briefly summarize the algorithm for the SOM. The structure of the SOM consists of two layers.

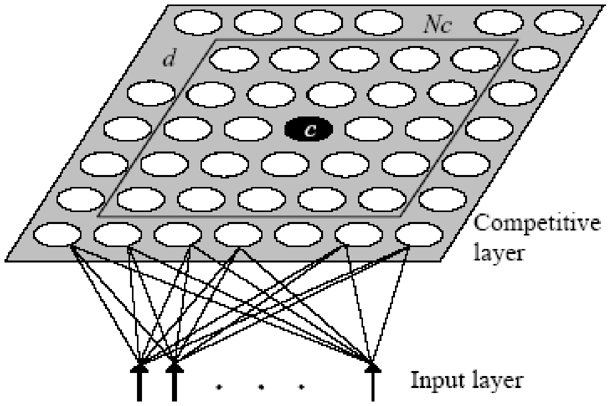

Fig.3. SOM structure of the neural network

One is an input layer, and the other is a competitive layer. The total input net_j of the neuron j is modeled by the following equation:

$$net_j = \sum_i w_{ji} x_i = (w_{j1} w_{j2} \dots w_{jn})(x_1 x_2 \dots x_n)^t = W_j x^t$$
$$W_j = (w_{j1} w_{j2} \dots w_{jn}),\ \ x = (x_1 x_2 \dots x_n),\ \ \|W_j\| = 1,\ \ \|x\| = 1 \tag{1}$$

where w_{ji} denotes the weighting function from neuron i to neuron j, and x_i is the input to the neuron i. Here, the superscript t denotes the transpose and $\| \ \|$ is the Euclidean norm.

When an input vector $\mathbf{x}$ is applied to the input layer, we will find the nearest neighboring weight vector W_c to the input vector $\mathbf{x}$ such that

$$\|W_c - \mathbf{x}\| = \min_j \|W_j - \mathbf{x}\| \tag{2}$$

The neuron c corresponding to the weight vector W_c is called the winner neuron. We select the neighborhood neurons within the distance d, which are shown in Figure 3, and a set of indices for neurons located in the neighborhood of c is denoted by N_c.

Then the weighting vectors of the neurons contained in N_c are changed such that those weighting vectors would become as similar as possible to the input vector $\mathbf{x}$. In other words, the weighting vectors are adjusted as follows:

$$\Delta W_j = \eta(t)(W_j - \mathbf{x}) \qquad \text{for} \quad j \in N_c \tag{3}$$
$$\Delta W_j = 0 \qquad \text{for} \quad j \notin N_c \tag{4}$$

where

$$\Delta W_j = W_j(new) - W_j(old) \tag{5}$$
$$\eta(t) = \eta_0 (1 - \frac{t}{T}),\ \ d(t) = d_0 (1 - \frac{t}{T}) \tag{6}$$

Here, t is the iteration number, T denotes the total iteration number, and $\eta_0 > 0$, $d_0 > 0$ are initial values of $\eta(t)$, $d(t)$, respectively, where $d(t)$ denotes the distance from the neuron c.

IV. CLASSIFICATION

The rice-planted area was extracted using SOM methods from three temporal RADARSAT images and one SPOT image. Kohonen's SOM is a classification method based on competitive neural networks.

The SOM was applied by the parameters, as shown in the Table 1. RADARSAT and SPOT images were classified into 16 categories by the SOM. We then labeled the categories into rice-planted area, forest area, and urban area.

Table 1. The parameters of SOM

Neurons	Learning iterations	$\eta(t)$	$d(t)$
4×4	1,080,000	0.03	2

V. EXPERIMENTAL RESULTS AND DISCUSSION

In order to make the proposed method effective, we classified the satellite image data by the SOM method. Figure 4 shows the classification image by SPOT, and Figure 5 shows the classification image by RADARSAT. Comparing Figure 5 with Figure 4, the rice-planted area by RADARSAT was extracted less than that by SPOT.

The speckling noise could still be seen in the image of the rice-planted area, and the majority filter with a 7 × 7 window was applied to the extracted rice images by RADARSAT and SPOT. For an evaluation of the rice-planted area extraction, we defined two indices, true production rate (TPR) and false production rate (FPR). The TPR and FPR are calculated by

$$TPR = \frac{\alpha}{\alpha + \beta} \times 100 \quad (7)$$

$$FPR = \frac{\gamma}{\alpha + \gamma} \times 100 \quad (8)$$

where α means the number of relevant rice-planted areas extracted, β means the number of relevant rice-planted areas not extracted, and γ means the number of irrelevant rice-planted areas extracted. The extracted rice-planted areas in the SPOT image by supervised the MLH was used as the reference rice-planted area image.

Table 2 shows the results for the TPR and FPR by the SOM classification. Figures 6 and 7 show the extraction result of the rice-planted area by SPOT and RADARSAT, respectively. In the comparison between SPOT MLH and SPOT SOM, the result shows that the TPR is about 89% and the FPR is about 32%. The result with RADARSAT shows that the TPR is about 44% and the FPR is 27%. The results of the rice-planted areas by RADARSAT images did not give such a high coincidence rate as those by SPOT in the quantitative evaluation. However, about 44% of the relevant rice-planted area was obtained by the SOM method, which was the unsupervised classification. The SOM classification is especially effective when the field survey is in a difficult situation, such as an investigation in a foreign country.

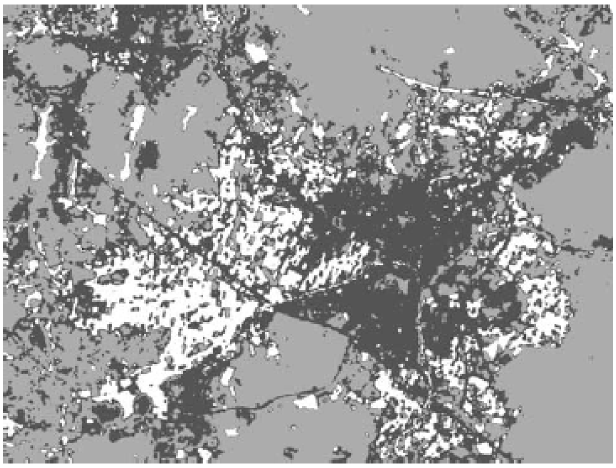

Fig. 4. Classification result of SPOT image by SOM (White: rice, Light gray: forest, Dark gray: urban)

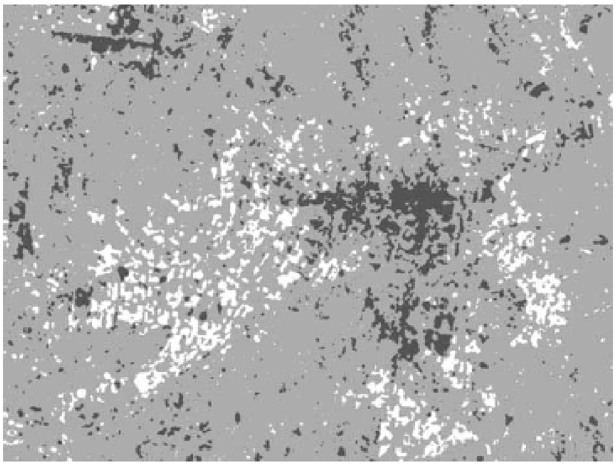

Fig. 5. Classification result of RADARSAT image by SOM (White: rice, Light gray: forest, Dark gray: urban)

Table 2. The results of TPR and FPR for rice-planted area evaluation

Comparison data	TPR (%)	FPR (%)
SPOT MLH vs SPOT SOM	88.58	31.96
SPOT MLH vs RADARSAT SOM	43.75	27.12

VI. CONCLUSION

Rice-planted area extraction was attempted using multitemporal RADARSAT data taken at an early stage of the rice-growing season by SOM classifications. The SOM is an unsupervised classification with a shorter computational time than the supervised classification methods like MLH or LVQ.

In a future study, we will apply this and other neural network methods to other SAR data on the extraction of rice-planted areas.

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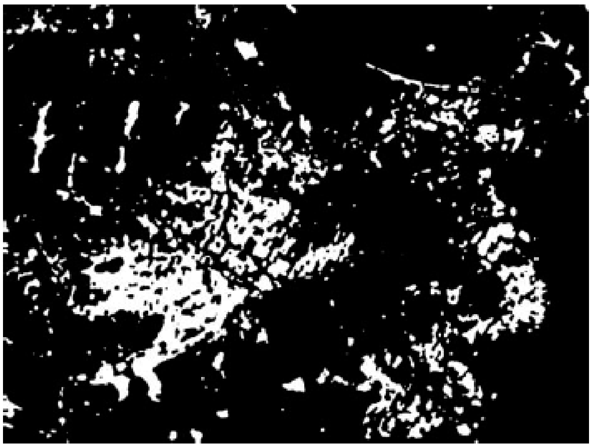

Fig.6. Extraction result of rice-planted area by SPOT data

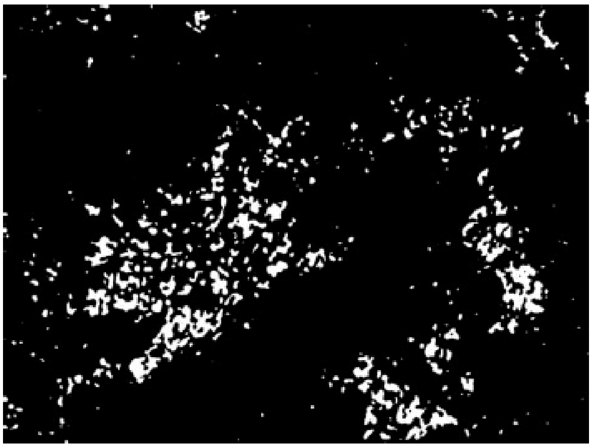

Fig.7. Extraction result of rice-planted area by multi temporal RADARSAT data