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Artificial Neural Networks Paddy Field Classifier using Spatiotemporal Remote Sensing Data

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Abstract: Monitoring changes in paddy field area is important since rice is staple food, and paddy agriculture is a major cropping system in Asia. For monitoring change in land surface, various applications using different satellites were researched in the field of remote sensing. However monitoring paddy field area with remote sensing is difficult due to the temporal change in land surface, and difference of spatiotemporal characteristics in countries and regions. In this paper, we applied artificial neural network to classify paddy field areas using moderate resolution sensor data that includes spatiotemporal information. Our aim is to automatically generate a paddy field classifier in order to create localized classifiers for each country and region.

Keywords: artificial neural network, classification, Remote sensing, MODIS.

I. INTRODUCTION

Monitoring changes in paddy field area is important since rice is staple food and paddy agriculture is a major cropping system in Asia. For monitoring change in land surface, many satellites were launched and its applications were researched in the field of remote sensing.

Monitoring paddy field area with remote sensing is difficult because a paddy has an annual cycle that can be classified into three main periods [1]: (1) the flooding and rice transplanting period, when the land surface is observed as water; (2) the growing period, when increasing vegetation index was observed; (3) the fallow period, when land surface is observed as soil. For monitoring change in land cover, moderate resolution remote sensing is effective because of the high frequency of these satellites to scan the same area.

In the past research for paddy field area estimation using remote sensing, decision trees or stochastic analysis based methods using spatiotemporal information were proposed [1] [2]. On the other hand, it is difficult to apply the same models for different countries and regions. In this paper we applied artificial neural network to classify paddy field area using moderate resolution remote sensing data in order to automatically generate the classifier.

II. METHOD

Multi-Layered Perceptron

Multi-layered perceptron (MLP) is a type of artificial neural network (ANN) that can approximate complex function by machine learning. In this research, we used MLP shown as Fig. 1 in order to learn a classification function of paddy field area from the MODIS data set.

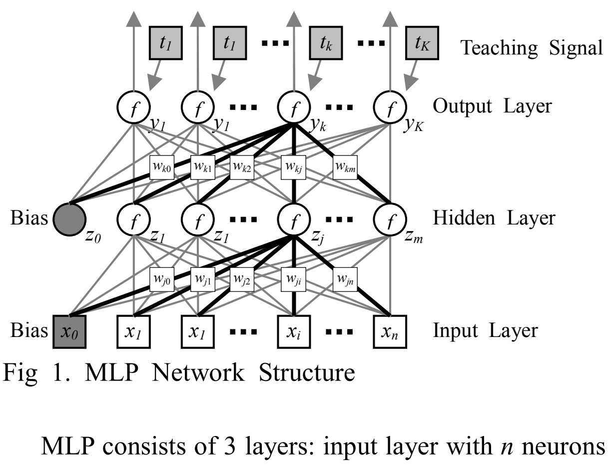

Fig 1. MLP Network Structure

MLP consists of 3 layers: input layer with n neurons and a bias neuron, hidden layer with m neurons and a bias neuron, and output layer with K neurons. Each neuron is connected with every neuron in the next layer, and each connection has a weight value. When an input signal $x = \{x_1, x_2, \ldots x_n\}$ is given, jth output signal z_j of hidden layer's neuron and kth output signal y_k of output layer's neuron are calculated by following expressions:

$$z_j = f\left(\sum_{i=0}^{n} w_{ji} x_i\right), \quad (1)$$

$$y_k = f\left(\sum_{j=0}^{m} w_{kj} z_j\right), \quad (2)$$

where $i = 0, 1, 2 \ldots, n$; $j = 0, 1, 2 \ldots, m$; $k = 0, 1, 2 \ldots, K$; f is the activation function, and z_0 and x_0 are bias neurons. Bias neuron always output 1.0 to next layer's neurons. For activation function, Sigmoid function was used.

MLP modifies each weight value using back propagation (BP) training [3]. Let be $x^p = \{x_1^p, x_2^p, \ldots x_n^p\}$, $p = 1, 2, \ldots, N$ is pth input signal, and $t^p = \{t_1^p, t_2^p, \ldots t_K^p\}$ is pth teaching signal. The teaching signal is true output signal that correspond to pth input signal x^p where projection function can be defined as follow

$$t_p = g(x_p). \quad (3)$$

When pth training pattern $\{x^p, t^p\}$ is given, BP training modifies weights for minimizing mean square error E defined as following expression

$$E = \frac{1}{N}\sum_{p=1}^{N}\left\|t^p - y^p\right\|^2. \quad (4)$$

At the training step in BP training, the weight modification $\Delta w_{ji}(s)$ and $\Delta w_{kj}(s)$ are defined as follows:

$$\Delta w_{ji}(s) = -\lambda \cdot \frac{\partial E}{\partial w_{ji}} + \mu \cdot \Delta w_{ji}(s-1), \quad (5),$$

$$\Delta w_{kj}(s) = -\lambda \frac{\partial E}{\partial w_{kj}} + \mu \cdot \Delta w_{kj}(s-1), \quad (6)$$

where λ is a learning rate, and μ is a momentum rate. Each weight is commonly initialized by random value. As a result of training, MLP learns a function $g(x)$ by modifying weight values.

In this research, MLP was used as 2 class classifier such that classifies positive or negative (1 or 0) for paddy field class. However MLP output is continuous value, so that it is necessary to decide positive or negative from the continuous output value. In this experiment, pth final output was defined by following function.

$$Output^p = \begin{cases} positive & if \quad y^p > \theta \\ negative & otherwize \end{cases}. \quad (7)$$

where θ is predefined threshold value.

MLP learning result is unstable from the initialization problem that MLP learning falls into different local minima by the initial weight values. For resolving unstableness, combination with ensemble learning and MLP is commonly used. Ensemble Learning is a method for improving the stability of machine learning algorithms by using multiple learners. For ensemble method, bagging method was used [4]. bagging is a typical ensemble method that aggregates multiple training results. For aggregating, voting was used, as this is commonly used in bagging for classifier. Let $L(x)$ be an aggregated learner, $L_s(x)$ be a multiple weak learner where $s = 1, 2, \ldots, r$; and $c = 1, 2, \ldots, C$ be class label. A robust learner $L(x)$ is defined by following expression.

$$L(x) = \arg\max_c \left|\{s; L_s(x) = c\}\right|. \quad (8)$$

Each learner is trained by using bootstrap samples [5]. Let T be training data set, training data subset $T_s \in T$ for sth learner is constructed by using random sample.

III. EXPERIMENT

1. Paddy Field Area Estimation using Moderate Resolution Remote Sensing

For this paper, we used MODIS (Moderate Resolution Imaging Spectoradiometer) data collected at Tokyo University of Information Sciences TUIS, Japan. TUIS receives satellite MODIS data over eastern Asia, and provides this data for open research use.

Fig. 2 shows NDVI (Normalized Difference Vegetation Index) maps for north region of Kyushu, Japan in 3 different months (A, January; B, June; C, September) derived from 1-month composite MODIS sensor data. NDVI is a vegetation index defined by bands 1 and 2 (visible red and near infra-red).

D of Fig. 2 shows the land-truth data provided by the Japanese Ministry of Land, Infrastructure, Transport and Tourism (JMLIT). The red colored pixels show that the paddy area ratio is larger than other land-use types in the corresponding 500m x 500m area. The land-truth data is provided in vector data format, so the data was converted into raster format of 500m scale pixel data (1 pixel = 500m x 500m resolution) in order to use the data as the solution set.

From these maps, it can be seen that paddy field areas' vegetation changes in period of time. However, it is difficult to extract a generalized rule for paddy classification from this spatiotemporal information. Because annual cycle of a paddy is different in each countries and region, the changes in spatiotemporal information are different in each region. Our aim is to automatically generate a paddy classifier using artificial neural network and spatiotemporal MODIS sensor data shown as D of Fig. 2.

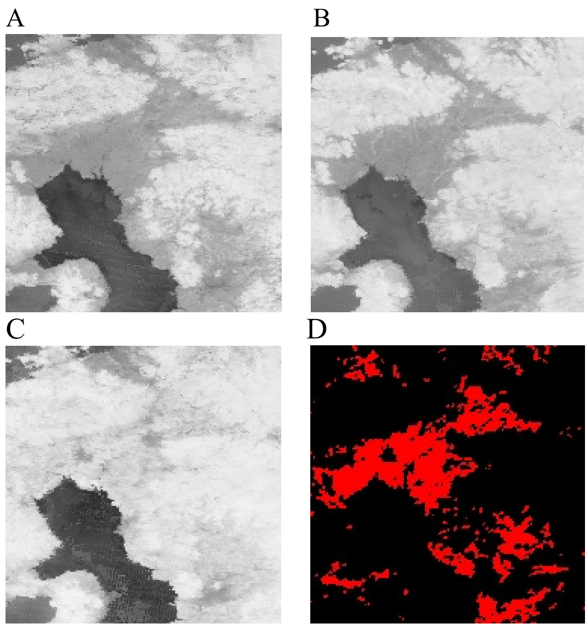

Fig 2 NDVI maps and land-truth data for north region of Kyushu, Japan

2. MLP Paddy Field Classifier

In previous our research, we evaluate MLP paddy field classifier using spatiotemporal MODIS band 1 and band 2 (red and infra red) data [6]. From this result, proposed MLP paddy field classifier could not yield sufficient accuracy for practical use. For improving classification accuracy, we investigate using 3 bands as input signals.

In the paddy field annual cycle, the features of paddy fields are vegetation, soil and water index. For vegetation index, NDVI was commonly used. NDVI is defined as follow.

$$NDVI = (RED - NIR)/(RED + NIR)\,, \tag{9}$$

where *RED* is visible red reflectance, and *NIR* is near infra-red reflectance.

Similarly, for indices of soil and water, NDSI (Normalized Difference Soil Index) and NDWI (Normalized Difference Water Index) was proposed by W. Takeuchi and Y. Yasuoka [7]. NDSI and NDWI are defined as follows

$$NDSI = (SWIR - NIR)/(SWIR + NIR)\,, \tag{10}$$

$$NDWI = (RED - SWIR)/(RED + SWIR)\,, \tag{11}$$

where *SWIR* is short wave infra-red reflectance. Short wave infra-red reflectance is corresponds to band 6 data in MODIS data set. Considering NDSI and NDWI, we additionally used band 6 data.

In this paper, we prepared 4 different MLP Paddy field Classifier model shown in Table 1 for the evaluating improvement of accuracy using band 6 data. The differences of each model are input size n and hidden size m.

In 3 bands models, 1 month part of input signals consists of band 1, band 2, and band 6. In 2 bands models, 1 month part of input signals consists of band 1 and band 2. In 3 months models, input signals consist of bands data of January, June and September (2 or 3 x 3 inputs). This 3 months correspond to 3 periods of the paddy annual cycle. In 11 months models, input signals consist of bands data of January to November per 1-month (2 or 3 x 11 inputs). The band data of each month was derived from 1-month composite MODIS sensor data of 500m resolution.

For teaching signal, land-truth data was used. This value is paddy or non-paddy (1 or 0), it were derived from digital national land information provided by the JMLIT. The parameters of MLP were defined by prior experiment.

Table 1. MLP parameters for the paddy classifier using MODIS sensor data.

	Parameters					
	n	m	K	λ	μ	θ
3 bands 3 months	9	9	1	0.25	0.05	0.3
3 bands 11 months	33	33	1	0.25	0.05	0.3
2 bands 3 months	6	6	1	0.25	0.05	0.3
2 bands 11 months	22	22	1	0.25	0.05	0.3

n: input size, m: hidden size, K: output size,
λ: learning rate, μ: momentum rate, θ: output threshold

3. Experimental Result

In this experiment, we evaluated classification accuracy by using proposed paddy classifier. For evaluating classification accuracy, MODIS data was divided into 2 disjoint sub set, training data set and test data set, by using random sampling from the north region of Kyushu, Japan shown in Fig. 1. The number of test data set was 10% of the number of training data set. Table 2 shows classification accuracy of the proposed paddy classifier.

Table 2 shows the comparison of classification accuracy. It can be confirmed that 3 bands 11 month model yielded best total classification rate. In addition, 3 bands models yielded better result compared with 2 bands models in total and paddy classification rate. This result shows the effectiveness of using band 6 data in MLP paddy field classifier.

On the other hand, in the classification rate for paddy field, 3 months models were tend to yield better result than 11 months models. This tendency was similar to previous our research. It is expected that this accuracy reduction was caused by increasing input size. Considering automatically generating paddy classifier, it is necessary to investigate feature selection methods because the annual cycle changes when the target region is changed.

Table 2. The comparison of classification accuracy in proposed paddy classifier.

	Correctly Classification Rate		
	Total	Paddy	Non-Paddy
3 bands 3 months	0.879	0.746	0.908
3 bands 11 months	0.908	0.714	0.953
2 bands 3 months	0.873	0.719	0.908
2 bands 11 months	0.876	0.707	0.915

IV. CONCLUSION

In this paper, we proposed MLP paddy field classifier using spatiotemporal MODIS band 1, band 2 and band 6 data in order to automatically generate a classifier. From the computer simulation, we confirmed that the improvement of classification accuracy by additionally using band 6 data. This result shows the effectiveness of using band 6 data in MLP paddy field classifier. In addition the proposed paddy field classifier yielded 0.908 classification rate. Considering that 0.95 or more accuracy is necessity for practical use, it can be concluded that proposed MLP paddy field classifier yields good result.

In this experiment, we confirmed that error was occurred when convert into raster format from vector format for create land-truth data. It is expected that accuracy can be improved by the reducing this error. In addition, we plan to compare with other paddy classifier based on decision tree method, and other machine learning methods.

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