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Administrative division based data segmentation for autonomous paddy field classifier modeling

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Abstract: Monitoring changes in paddy area is important since rice is staple food, and paddy agriculture is a major cropping system in Asia. The decision trees or stochastic analysis based methods using spatiotemporal satellite sensor data is effective to monitor paddy area by the remote sensing. On the other hand, it is difficult to apply the same models for different countries and regions. Therefore we applied artificial neural network to classify paddy area in order to automatically generate the classifier. From the computer simulation, the proposed paddy classifier yielded high classification rate in the data subset of north region of Chiba. However, the accuracy was corrupted by the difference of annual cycle pattern. Thus, in this paper, we investigate an administrative division based data segmentation method in order to divide the data set into different groups so that the different patterns of paddy annual cycle is divided to different groups.

Keywords: artificial neural network, classification, remote sensing

1 INTRODUCTION

Monitoring changes in paddy 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. However monitoring paddy area with remote sensing is difficult due to the temporal change in land surface, and difference of spatiotemporal characteristics in countries and regions.

In our past research, we applied artificial neural network to classify paddy areas using moderate resolution sensor data that includes spatiotemporal information. Our aim is to automatically generate a paddy classifier in order to create localized classifiers for each countries and region. From the experiments, proposed paddy field classifier yielded a good result in the classification accuracy. However, the classification accuracy is depends on the set geographical area for the training data sampling. In this paper, we investigate an administrative division based data segmentation method in order to divide the data set into different groups so that the different patterns of paddy annual cycle is divided to different groups.

This classified paddy field data is visualized on a web system that called Satellite Image Data Analysis System (SIDAS). Tokyo University of Information Sciences receives Moderate Resolution Imaging Spectroradiometer (MODIS) data, one of the sensors equipped by NASA's Terra and Aqua satellites, and researches of the analysis on change of environment as part of the academic frontier project. For the information infrastructure of this frontier research, we are developing a SIDAS to support of web system, a parallel distributed system configuration using multiple PC clusters, database for MODIS data to publish the research results and MODIS data for public use. In this research, we develop the sub-systems of satellite image preprocessing, the analysis using satellite image and the map visualization in order to publish the research results.

2 PADDY FIELD CLASSIFIER

2.1 Paddy Field Classifications on Remote Sensing

Monitoring paddy area with remote sensing is difficult because a paddy has an annual cycle that can be classified into three main periods: (1) the flooding and rice transplanting period, when the land surface is observed as water; (2) the growing period, when vegetation index is increased by the vegetative growth; (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 areas estimation using remote sensing, decision trees or stochastic analysis based methods using spatiotemporal information were proposed. 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 area using moderate resolution remote sensing data in order to automatically generate the classifier.

2.2 Multi-Layered Perceptron Classifier

In this paper, Multi-layered perceptron (MLP) was used. MLP is a type of artificial neural network that can approximate complex function by machine learning. MLP is trained by data set that consists of a feature vector and a teaching signal.

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.

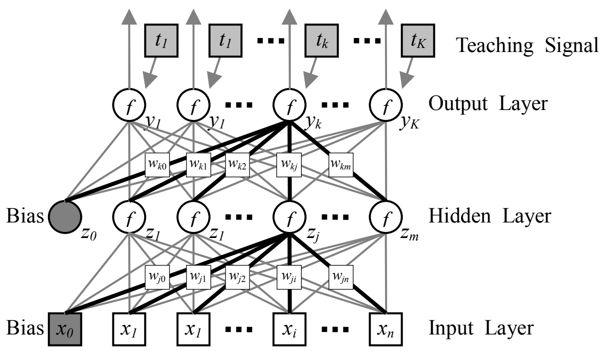

Fig.1. MLP Network Structure

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 $\mathbf{x} = \{x_1,x_2,\ldots x_n\}$ 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:

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

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

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

$$t_p = g(x_p). \tag{3}$$

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

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

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

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

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

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.

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

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.

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

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.

2.3 MLP Paddy Classifier

For the input signals of samples, 1-month composite MODIS sensor data on 1 pixel was used. The input signals consist of red, infra-red and short wave infra-red of January to September per 1-month (36 inputs) in order to learn temporal pattern of paddy area. The band data of each month was derived from 1-month composite MODIS sensor data of 500m resolution. 1-month composite data is the technique that composites multiple satellite image between 1 month into a single satellite image in order to reduce the noise and distortion such as the cloud and the sensor angle. 1-month composite data is a commonly used for the analysis on the remote sensing.

For teaching signal, 1km meshed land use map provided by the Japanese Ministry of Land, Infrastructure, Transport and Tourism (JMLIT) were used. The land use map is converted into the raster image of same pixel size by the liner interpolation because the meshes of land use map are not matched to the pixels of satellite image.

2.4 Training Data Segmentation

From the experiments of our previous research, proposed paddy field classifier yielded a good result in the classification accuracy. However, the classification accuracy is depends on the set geographical area for the training data samples. The paddy annual cycle patterns is diversified when the training data area is increased in size, therefore the large number of hidden layer neurons and the long training iterations are necessity to learn the annual cycle patterns.

Considering that the difference of paddy annual cycle is occurred by the culture, the political decision and the geographical feature, we investigated an administrative division based data segmentation method that the data set is divided by the administrative division. From the viewpoint of the geomorphology, it is expected that the administrative division based segmentation is effective to separate the pattern of paddy annual cycle because the boarder of administrative division is generally decided on the geographical feature such as the river and the mountain.

The samples that consist of the input signal values and a teaching signal value are divided into the groups by the administrative division. For the data of administrative division, the administrative division map provided by JMLIT was used. The maps provided by JMLIT was converted into the raster image because the maps constructed by vector image. The MLP classifier is separately trained for each divided data sets. Therefore the MLP learned the patterns of paddy annual cycle for the target prefecture that derived by the administrative division.

2.5 Visualization System of Paddy Classification

In this research we develop a paddy map visualization system as an application framework of SIDAS in order to publish the latest paddy map by the latest satellite images. Figure 2 shows an overview of paddy map visualization system.

The data set provider has a data divider that divides the samples of MODIS sensor data and land use data for the MLP paddy classifier regard to the administrative division. The divided data is used to train the MLP paddy classifiers and classify the samples by corresponding learned paddy classifiers. The MLP paddy classifier is separately trained by the given data for an area of administrative division. After the training, the samples can be classified into paddy or non-paddy by the learned MLP paddy classifier for each administrative division. Finally, the classification result is visualized as RGB image by the map visualizer for web publishing.

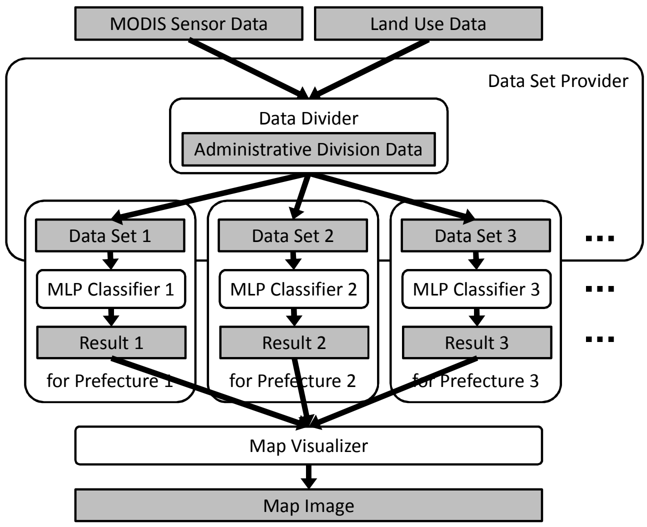

Fig.2. Overview of paddy map visualization system

SIDAS has a database of MODIS sensor data as the raster image format. The land use data and administrative division data also stored in SIDAS database as raster image. The data divider is implemented by using the composite function in SIDAS middleware. SIDAS has a middleware for satellite image analysis such as the image I/O, image composition, image masking, image visualization, and etc. The data division function was implemented as the image masking of MODIS sensor data by the administrative division data. Because the mask image should be consisted by {0, 1} value in SIDAS middleware, the administrative division data was converted into the raster image with {0, 1} value.

The divided data set is provided as the multi-channel RAW image format similar to MODIS sensor data. In this system, MLP classifier is implemented to handle the multi-channel RAW image for input signals. The input channels consist of red, infra-red, short wave infra-red, and land use of January to September per 1-month. The result of classification is also provided as the multi-channel RAW image. The output channel consists of the label of classification.

For the visualization of paddy map, the multi-channel RAW image to RGB image convert functions on SIDAS was used. The SIDAS image convert functions is developed to visualize the maps of visual light, vegetation index and sea surface temperature, and land surface temperature. This convert functions can convert the multi and single channel RAW image into the RGB color image. The RGB color image is used for the web publishing of satellite image.

3 EXPERIMENT

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. The number of test data set was 10% of the number of training data set.

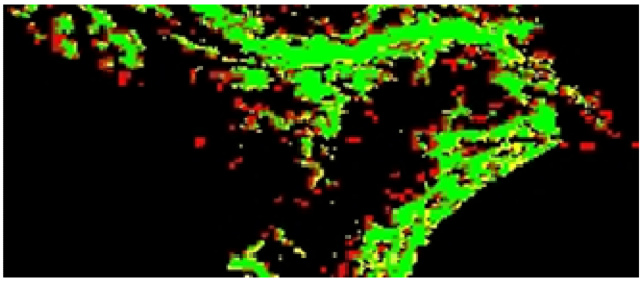

Fig.3. Result of Paddy Map Visualization

From the computer simulation, the proposed paddy classifier yielded 0.851 classification rate in the data subset of Chiba prefecture. Figure 3 is a result of paddy map visualization. Green colored area is correctly classified area as paddy field. Red colored area is incorrectly classified as non-paddy for paddy field and Yellow colored area is incorrectly classified as non-paddy for paddy field. This result shows that the larger area of paddy field can be correctly classified. On the other hand, the small paddy field area and the neighbor of the boarder of paddy area are difficult to classify due to the mixture of different land use in pixel.

4 CONCLUSION

In this paper, we proposed an administrative division based data segmentation method in order to divide the data set into different groups to separate the different pattern of paddy annual cycle by administrative division. Moreover, we develop the SIDAS application framework and implement the proposed method on this framework.

From the result of paddy map visualization, the paddy map generated by proposed paddy classifier is yielded good result in the classification accuracy. On the other hand, it was clarified a problem of the mixture of different land use in pixel for improving accuracy.

For future works, we plan to generate the maps for whole prefecture in Japan. Moreover, we evaluate the accuracy and investigate the effectiveness for the practical use of paddy field monitoring.

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