CLASSIFICATION OF REMOTE SENSING IMAGERY USING AN UNSUPERVISED NEURAL NETWORK

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ABSTRACT

This paper presents an unsupervised method for classification of remotely sensed imagery. The main body of the method is an unsupervised artificial neural network model called the adaptive resonance theory 2 (ART2). The primary use of the model is to produce a fine classification from multispectral data. Since ART2 is able to learn and classify by self-organization without the help of the training data, it is therefore used to generate numerous spectral classes. Then the spectral classes are regrouped using a hierarchical clustering technique. The main objective of the clustering is simply to regroup all the relevant spectral classes to the appropriate information classes. The proposed method is tested using an artificial image and a Spot image. The results indicate that the method can provide a successful and fine discrimination between different spectral classes and the final regrouping accuracy can reach a satisfied level. It appears that the proposed method is feasible and useful for classifying remotely sensed data.

1. INTRODUCTION

Information of land-cover/land-use extracted from remotely sensed imagery has represented a very important data for natural resource planning. Recently, the use of neural network for image classification has received a great deal of interests. For instance, the neural network has been applied to Landsat TM (Bischof and et al., 1992), Spot (Dreyer 1993), and radar image (Hara, 1994). All these studies have demonstrated the usefulness of neural networks in various remote sensing data. However, most effort of these studies has put in the use of supervised neural network. The supervised approach normally requires training set to classify the image into useful categories. The selection of training set ordinarily needs the aids from the user, such as the prior knowledge about the region to be classified, the manual identification of appropriate training region, and intensive analysis of the training data. As a result, the supervised classification is a highly user-dependent process (Lillesand, 1995). It is obvious that the accuracy of the unsupervised classification is highly dependent on the training data selected. Unsupervised neural network has been successfully applied to recognize the characters, speech, and patterns (Kosko, 1990), but very few has been applied to remotely sensed image.

This study proposes an unsupervised neural network classification for remote sensing image. Two stages are included in the proposed algorithm. At first stage, we use an unsupervised neural network, called Adaptive Resonance Theory 2 (ART2) (Carpenter and Grossberg, 1988), to perform an initial multispectral classification. The main objective of this stage is to obtain spectral classes as fine as possible. The resultant classes is then re-grouped by a hierarchical clustering algorithm (Jain, 1988) to attain a small set of information classes at second stage. In this paper, the fundamental idea of ART2 and hierarchical clustering are addressed in section 2. The following section 3 and 4 present the test data used in this study and their results and discussion. Finally, conclusion remarks are given in section 5.

2. METHODS

2.1 ART2 Neural Classifier

Many neural network models tend to forget old information if they attempt to learn new information. The adaptive resonance theory (ART) neural network can learn many things without necessarily forgetting things learned in the past. In addition, the network is able to self-adapt configurations in real time for retaining codes of categories in response to input pattern, that can be presented in any order. They are several available types of the ART neural networks. In this study, the ART2 network is employed for the classification because of its potential in dealing with gray scale images. Figure 1 depicts the ART2 architecture which consists of two major modules: the attentional and orienting modules. The attentional module is further divided into two fields: an input representation field F1 and a category representation field F2. There are six layers, w, x, v, u, p, and q, on the F1 field within which bottom-up input patterns and top-down predicted prototypes are matched. The activities of these layers can be found in the figure. When the input pattern reaches a stable state in field F1, a bottom-up signal is transmitted to the F2 field. The neurons on the field then compete with one another for the signal. If one of the neuron wins, its corresponding prototype encoded in the top-down connections is initiated. The prototype and the bottom-up pattern are then matched to each other within the F1 field. If the goodness of the match is satisfied with certain criterion, the input pattern is regarded as being in the category represented by the F2 neuron. If the match is poor, the competition process proceeds until all the neurons in F2 field are inspected. If no neuron wins in the competition, a new neuron is created to represent the new prototype (or new category).

2.2 Hierarchical Clustering

The spectral classes obtained at ART2 stage are regrouped using hierarchical clustering method at this stage. The spectral distance between two classes is calculated for all classes, then regroups two classes that has the minimum distance into one class. The regrouping process continues between the classes until the class numbers reach the desired numbers. As a result, the final product will provide the information classes.

3. DATA

The data used in this study includes a simulated image and a Spot High Resolution Visible image. The simulated image is used to test the performance of the proposed classification algorithm, while Spot image is employed to demonstrate the practical applications of the method. The simulated image is designed to know both gray values and the corresponding class of each pixel in order to evaluate the classification accuracy more easily. It is generated first by applying an unsupervised ISODATA clustering algorithm to a subimage (512 x 512 pixels) selected from an arbitrary Spot image. Seven classes are produced in this case. Next, the statistical parameters such as the mean and standard deviation are calculated for each class in all three bands. Then the simulated image is formed by specifying the gray value of each pixel in each band according to its class and the statistical parameters. In this study, each gray value is randomly chosen using its corresponding mean and up to three times of the standard deviation. The resulting simulated image is shown in Figure 2. It appears that the image is rather complex and could be a challenge for testing any classification performance. The real test image of size 512x512 pixels is selected from a Spot image. The image was acquired on September 19, 1994 and its corresponding test site is located at Chung-li area of northern Taiwan. The site mainly is a land-use mixture of agriculture and urban. The major land-cover/land-use types can be identified as rice paddy, grass, barren land, lake, and built-up land. Figure 3 shows the test image.

4. RESULT and DISCUSSION

The performance of the proposed method is tested firstly by using the simulated image. At first, 40 spectral classes are generated by ART2. The relatively small standard deviation of gray values (below 3.5) of each class indicates that the classes generated by ART2 are rather pure and homogeneous, an indication of fine classification of ART2. These 40 classes are then re-grouped to 7 classes. Figure 4 shows the classified simulated image. In addition, the accuracy analysis is performed by comparing with original class image. The overall accuracy of 99% demonstrates the excellent performance of the proposed method.

The land-use mixture of agriculture and urban features in the test site basically forms a rather complicated image. The spectral responses in this area can be separated into a lot of different spectral classes which may represent significant or insignificant information classes. It is obvious that the conventional classification approach will have difficulty to perform a fine separation of this sort of surface features. The proposed ART2 approach, in fact, accomplishes a delicate and fine classification by separating the test Spot image into 51 spectral classes. . By inspecting the topographic maps and the ground truth, it is obvious that the dominant surface appearance in the test site can be categorized into six major land-cover/land-use classes: lake, grass, rice paddy, barren land, highly-reflective roof, and built-up land. Therefore, 51 spectral classes obtained from ART2 are re-grouped into 6 classes using the hierarchical clustering method. Figure 5 illustrates the classified Spot image. The accuracy analysis, based on a random process carried out on the topographic maps and the classified image, indicates that an overall accuracy of 95% can be reached for the test Spot image.

5. CONCLUSION

An unsupervised neural network classification for remotely sensed imagery is proposed in this study. Firstly, the adaptive resonance theory 2 (ART2) neural network is employed to perform a fine classification. The main objective of ART2 is to produce the spectral classes as fine as possible from multispectral remote sensing data. Then the hierarchical clustering method is used to re-group the spectral classes to form the significant information classes. The proposed method is tested by using a simulated image and a Spot image. The analysis demonstrates that the proposed approach needs only few user-specified parameters to perform unsupervised classification while still keeps an overall accuracy above 95% for both simulated and Spot images. The test results indicates that the proposed method is very promising for the practical application of remotely sensed image.

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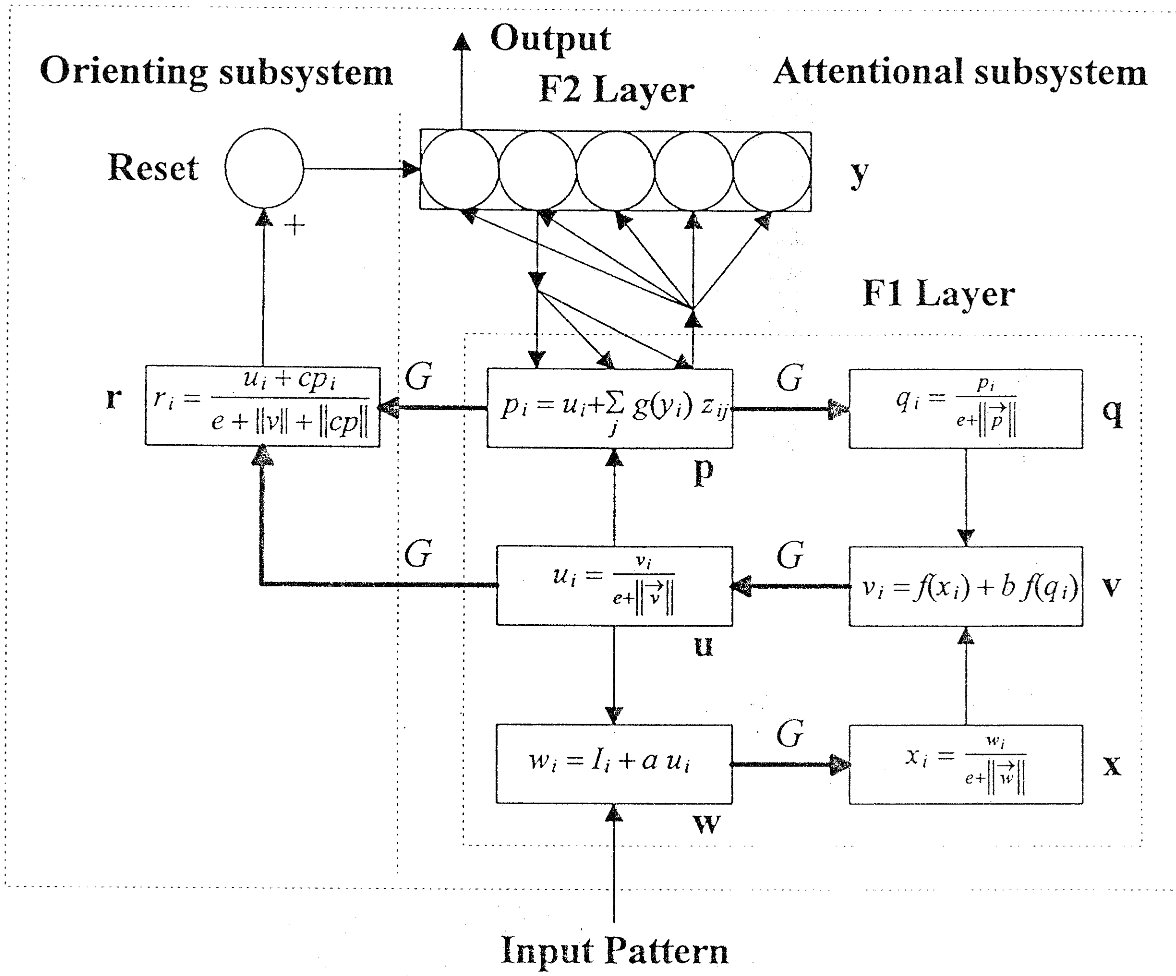

Figure 1 Structure of ART2 Neural Network

$$w_i = I_i + a\, u_i \qquad x_i = \frac{w_i}{e+\left\|\vec{w}\right\|}$$

$$v_i = f(x_i) + b\, f(q_i) \qquad u_i = \frac{v_i}{e+\left\|\vec{v}\right\|}$$

$$p_i = u_i + \sum_j g(y_i)\, z_{ij} \qquad q_i = \frac{p_i}{e+\left\|\vec{p}\right\|}$$

$$r_i = \frac{u_i + cp_i}{e + \|v\| + \|cp\|}$$

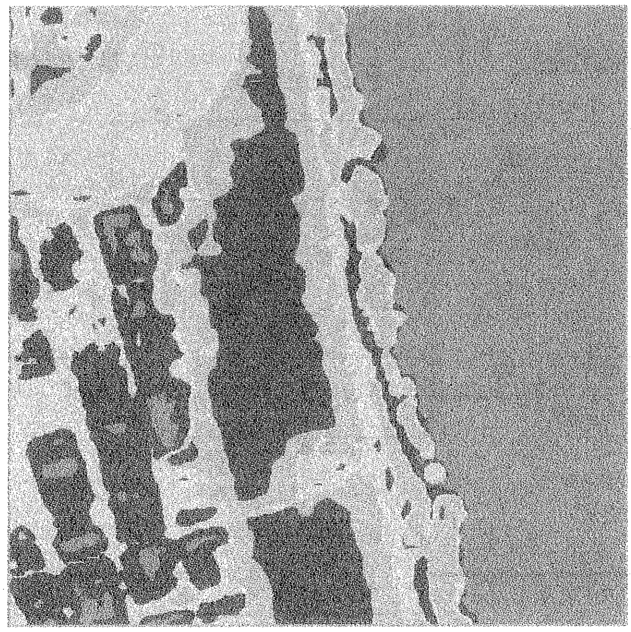

Figure 2 Simulated Image

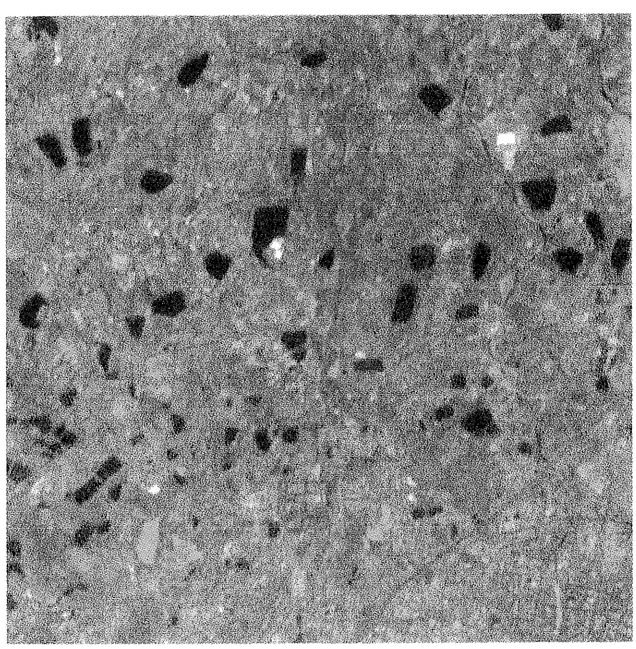

Figure 3 SPOT Image(Copyright CNES)

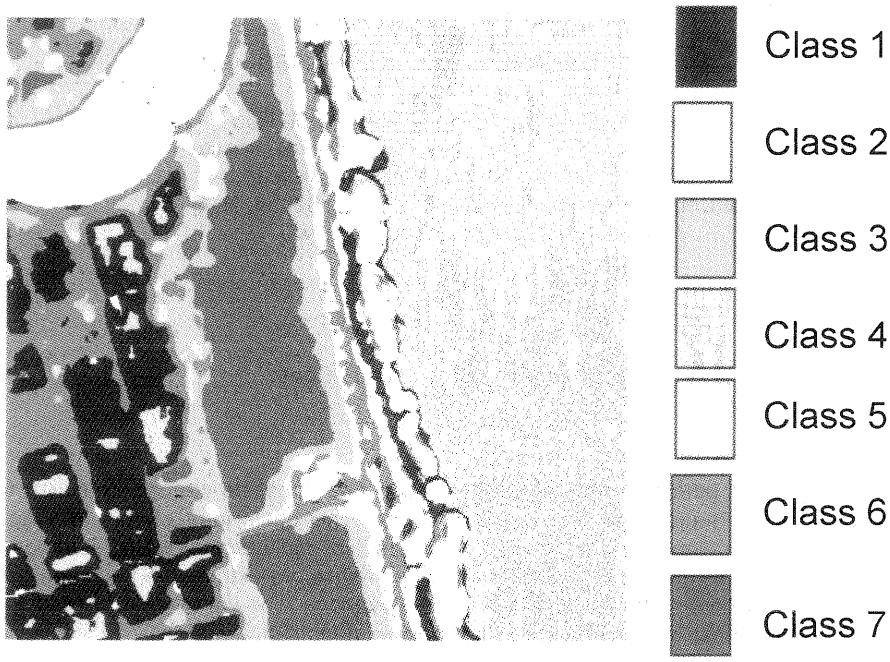

Figure 4 Classified Simulated Image

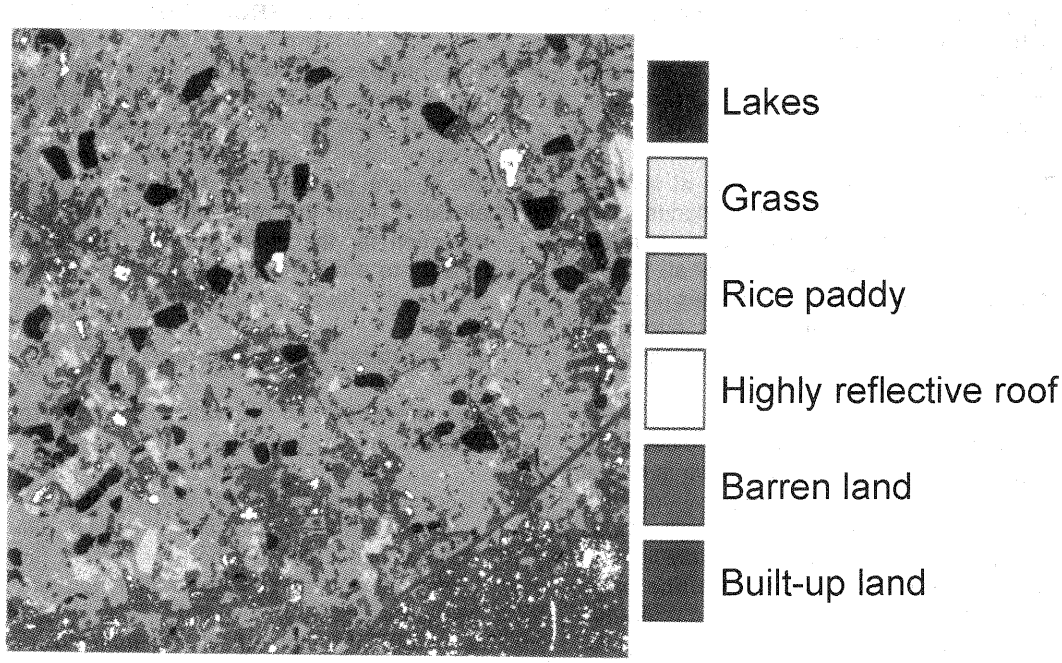

Figure 5 Classified SPOT Image