MULTISPECTRAL IMAGE SEGMENTATION USING ART1/ART2 NEURAL NETWORKS

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ABSTRACT: In this research, remote-sensing multispectral images are analyzed and interpreted by means of a neural network approach. In particular, the advantages found by using Adaptive Resonance Theory network of the data are shown and commented. We used the ART1 and ART2 structures that accept binary data and continuous-value data, so that each input can be for each pixel directly the vector of the gray level values at each band. This choice is due to the attempt to simplify algorithm as much as possible. Experiments carried out with ADEOS and LANDSAT-5 images are given.

1. INTRODUCTION

For the classification of the satellite-image data by visual perception, the image interpretations are depended upon the experts in decoding, classifying and comparing the color signals of each data package from multiple bands of satellite images. Classifying satellite images by this means can be done easily if the colors and appearance of each data package can be obviously seen. On the contrary, it is hard for the data looking alike in colors and appearance to be decided what types of data package they should be classified into. This requires the experts' skill in interpreting the images of each area. This research aimed at realizing the importance of accurate classifications of the satellite-image data. It was interested in two models of basic networks based on adaptive resonance theory (ART). ART possessed the qualifications of satellite-image classifications by unsupervised-clustering network scheme. That is, this paradigm of classifications had the network scheme trained by unsupervised-learning rules. So the network scheme could be adapted by means of weight modifying and accurate-result verifying which are based on the input patterns only. In this study, satellite multispectral image segmentation was performed by comparing between two most popular forms of ART, named ART1 and ART2.

2. ADAPTIVE RESONANCE THEORY

Adaptive resonance theory was developed by Carpenter and Grossberg (Fausett, 1994). One form, ART1, is designed for clustering binary vectors; another, ART2, accepts continuous-valued vectors. These nets cluster inputs by using unsupervised learning. Input patterns may be presented in any order. Each time a pattern is presented, an appropriate cluster unit is chosen and that cluster's weights are adjusted to let the cluster unit learn the pattern. As is often the case in clustering nets, the weights on a cluster unit may be considered to be an example for the patterns placed on that cluster.

2.1 ART1 algorithm

ART1 (Carpenter 1987a) is designed to cluster binary input vectors. The architecture of an ART1 net consists of two fields of units, the F_1 units and the F_2 (cluster) units, together with a reset unit to control the degree of similarity of patterns placed on the same cluster unit. This main portion of the ART1 architecture is illustrated in Figure 1. The F_1 interface unit X_i is connected to the F_2 cluster unit Y_j by bottom-up weight b_{ij}. Similarly, unit Y_j is connected to unit X_i by top-down weights t_{ji}. The F_1 and F_2 layers are connected by two sets of weighted pathways. In addition, several supplemental units are included in the net to provide for neural control of the learning process. It is designed so that it is not required either that patterns be presented in a fixed order or that the number of patterns to be clustered be known in advance. Updates for both the bottom-up and top-down weights are controlled by differential equations.

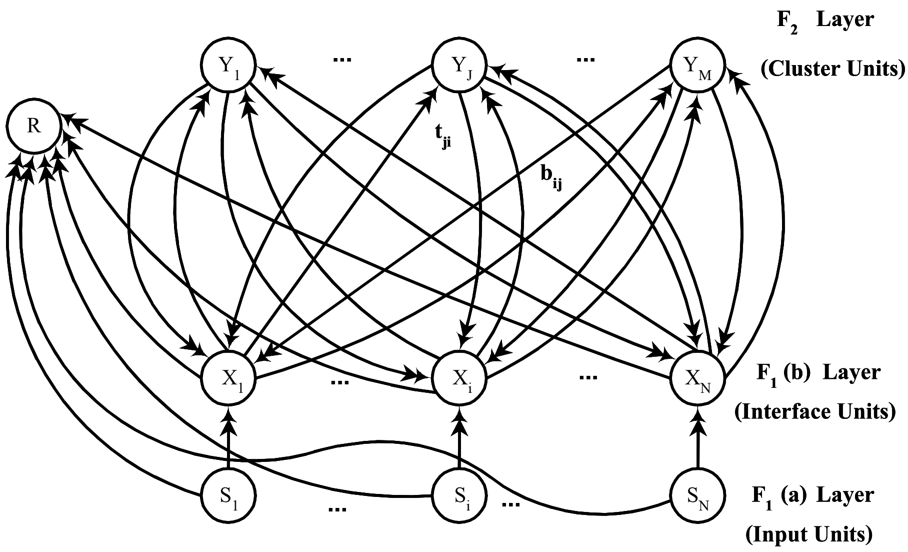


Figure 1: Typical ART1 architecture.

2.2 ART2 algorithm

ART2 (Carpenter 1987b) is designed to perform for continuous-valued input vectors the same type of tasks as ART1 does for binary-valued input vectors. A typical ART2 architecture is illustrated in Figure 2. The F_1 layer consists of six types of units (W, X, U, V, P, and Q units). There are *n* units of each of these types, where *n* is the dimension of an input vector. The F_2 field contains only one layer, which is denoted by Y and serves as a competitive layer. There are top-down and bottom-up full connections between F_1 and F_2 pattern prototypes are to be preserved on these connections. The input signal is $S = (S_1, ..., S_i, ..., S_n)$ continues to be sent while all of the sections to be described are performed. At the beginning of a learning trail, all activation is set to zero. The computation within the F_1 layer can be thought of as originating with the computation of the activation of unit U_i (the activation of unit V_i normalized to approximately unit length). Next, a signal is sent from each unit U_i to its associated units W_i and P_i. The activation of units Wi and Pi are then computed. Unit W_i sums the signal it received from U_i and the input signal S_i. P_i sum the signal it receives from U_i and the top-down signal it receives if there is an active F_2 unit. The activation of X_i and Q_i are normalized version of the signal at W_i and P_i. An activation function is applied at each of units before the signal is sent to V_i. V_i then sums the signals if receives concurrently from X_i and Q_i. This completes one cycle of updating the F_1 layer.

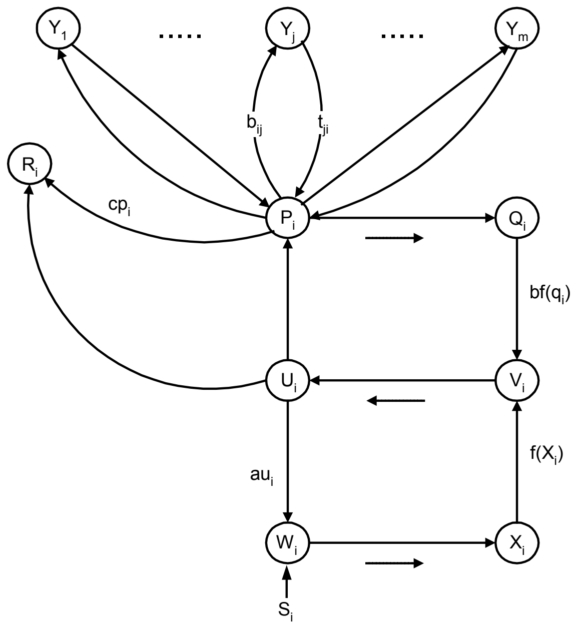


Figure 2: Typical ART2 architecture.

After the activation of the F_1 units have reached equilibrium, the P_i units sent their signals to the F_2 layer, where the winner-take-all competition chooses the candidate cluster unit to learn the input pattern. The units U_i and P_i in the F_l layer also send signal to the corresponding reset unit R_i. The reset mechanism can check for a reset each time it receives signal from P_i and U_i, which aggregates the activities of P_i and U_i and transmits the result to the vigilance parameter. Vigilance parameter then decides whether or not a reset signal is emitted to the layer y in field F_2. There are also gain control units in the network. They normalize activity patterns over layers.

3. APPLICATION TO MULTISPECTRAL IMAGE SEGMENTATION

The multispectral images provided by ADEOS and LANDSAT-5 satellites are generally represented in 8 bits/pixel image format. Each pixel, constituted by (*n* x 8 bit) data where *n* is the number of bands, could be considered as two different data types: either 8*n* binary values or *n* continuous values, as illustrated in Figure 3. Therefore, the ART1 can be applied when the pixel is arranged as binary-valued input vector, while the ART2 can accept the pixel arranged as continuous-valued input vector.

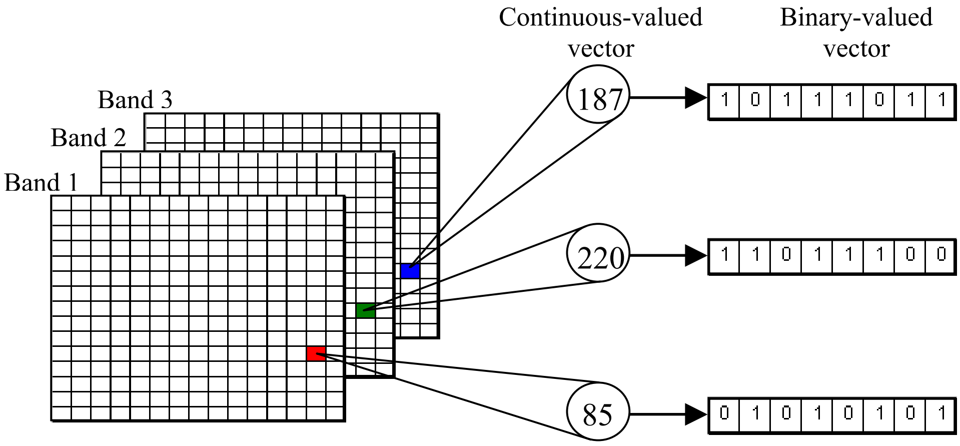
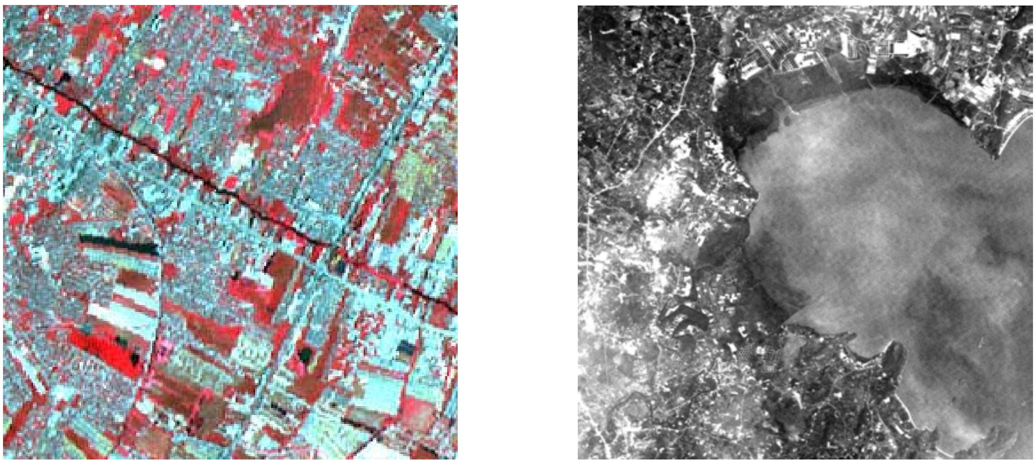


Figure 3: Illustration of pixel values arranged as binary and continuous values.

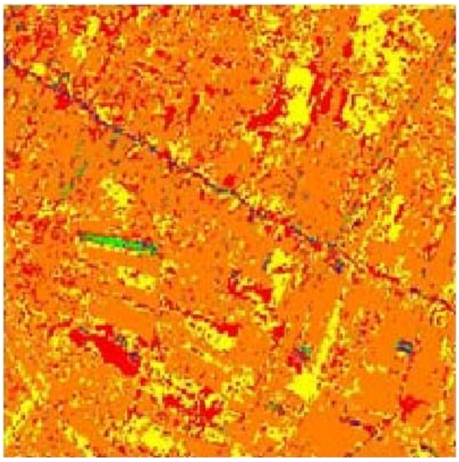
4. EXPERIMENTAL RESULTS

Figure 4 displays two tested images used for comparison between ART1 and ART2 algorithm. The image sizes are both 256 x 256 pixels. Figure 4(a) is three-band image of Bangkok area from ADEOS satellite, and Figure 4(b) is four-band image of Chumporn area from LANSAT-5 satellite.

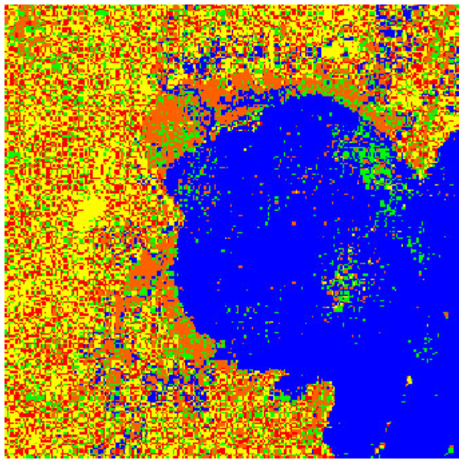


(a) (b)

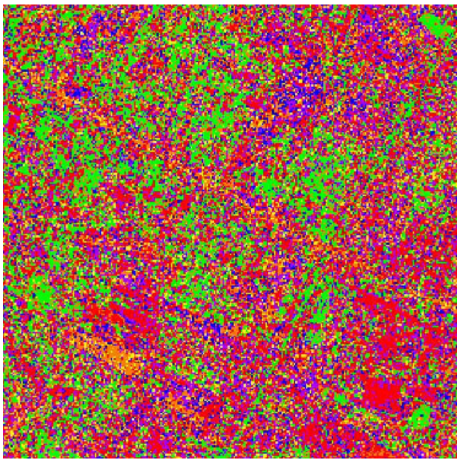
Figure 4: Tested images. (a) ADEOS image of Bangkok area. (b) LANDSAT-5 image of Chomporn area.



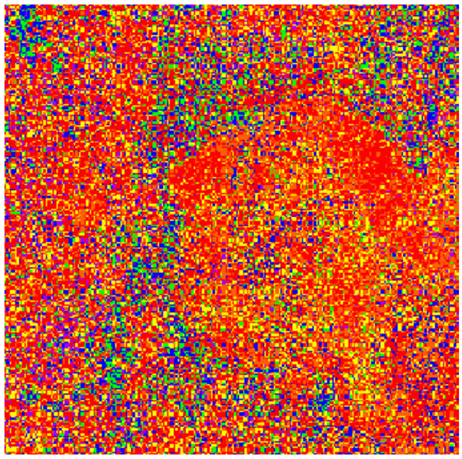
(a)



(b)



(c)



(d)

Figure 5: Segmentation images resulted by ART1 algorithm. (a-b) 5 clusters. (c-d) 7 clusters.

The segmentation results of the images in Figure 4 by using ART1 and ART2 algorithm are shown in Figure 5 and 6 respectively. For the results of ART1, in Figure 5(a) and (b), there were five clusters. In Figure 5(c) and (d), the number of clusters was increased to seven. It was shown that the number of clusters could be increased or controlled, but the more clusters the ART1 has the more hardly to see the images. For the results of ART2, in Figure 6(a) and (b), there were four clusters. In Figure 6(c) and (d), the number of clusters was increased to seven. Increasing the number of clusters is not useful because the visibility stayed the same. Thus, ART1 structure could classify the obscurity of satellite images better than ART2 structure. But ART2 could classify the area scope much better than ART1.

5. CONCLUSIONS

We have presented a comparative study of using two popular models of ART neural networks for segmentation of satellite multispectral images. ART1 needs input as binary data, but ART2 requires continuous-value data. The results of this study are as follows. ART1 structure could classify the obscurity of satellite images better than ART2 structure because the input binary data are different in value. ART2 could classify the area scope much better than ART1.

6. ACKNOWLEDGEMENT

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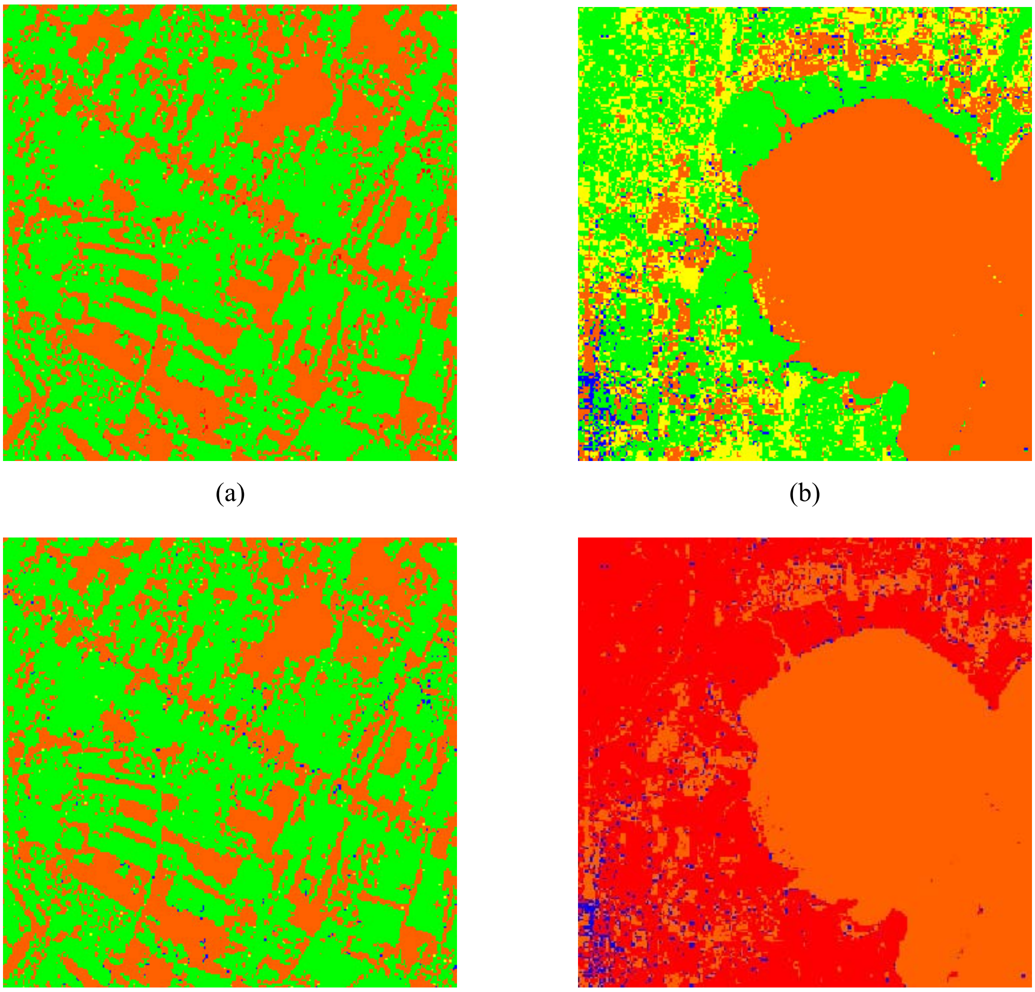

Figure 6: Segmentation images resulted by ART2 algorithm. (a-b) 5 clusters. (c-d) 7 clusters.

7. REFERECNES

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