Classification of TM image Using a Competitive Learning Neural Network

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Abstract

Recent progress in Artificial Neural Networks (ANNs) research has demonstrated the usefulness of ANNs in variety of applications. In remote sensing community, a supervised learning network paradigm, Back Propagation (BP), has been successful applied to land-cover classification of satellite images. Two of the major problems associated with BP network for land-cover classification are that its convergence time is usually very long, and it does need a suitable training data set. This paper describes applying an unsupervised learning network paradigm, Competitive Learning (CL), to land-cover classification of TM image on a Winner-Take-All (WTA) basis. The final results showed that CL of WTA still needs to improvement for satisfying the requirements of land-cover classification.

1. Introduction

The renewed interest in Artificial Neural Networks (ANNs) is mainly due to the development of multi-layer learning algorithms ([17]), which enable the ANNs to learn using a more complex structure to solve the problems in the book Perceptrons ([16]). Another important reason is that more internal dynamics of the network is revealed through insights into the fundamental laws governing the convergence of the group behavior of interacting physical elements. Parallel ANNs of the type described by Hopfield, Kohonen, and Grossberg have been shown to be well suited to the task of pattern recognition and classification ([4] [14]). Generally it involves setting up a network architecture, and then training the network through a set of training data. The result network is then found to be capable of classify subsequent testing data in terms of a set of training data.

In remote sensing community, a number of researchers have demonstrated the use of ANNs techniques. Back Propagation (BP), a supervised learning paradigm of ANNs, has been shown to be useful in classification of satellite images. For examples, a number of researchers ([3]

[8] [15]) have used BP for land-cover classification, and Lee et al. (1990) used BP to classify cloud segmentation. But, there are some inhibit problems when use BP network for land-cover classification. For examples, given a large training data sets required to form an adequate representation of the input vector space in land-cover classification, the BP training algorithms appear infeasible using exist computer technology because its convergence is time consuming. Also, changes in the band or scene selection means that a classifier under one condition is inappropriate for use in another condition. Under these circumstances (both for handling large training data sets and changing band/scene conditions), it may appropriate to work with unsupervised learning networks.

In unsupervised learning, a network is expected to self-organize to a state the reflects the distribution of input patterns while a desired response is not given in an explicit form. Therefore, unsupervised learning has a possibility of discovering unknown relationships among input patterns and can be a model of rule finding or concept formation. In this paper a Competitive Learning (CL) network was applied to land-cover classification of TM image on a Winner-Take-All (WTA) basis.

2. Methods

Competitive Learning (CL) Networks

The basic competitive learning network is a two-layer, fully connected, feedforward network.

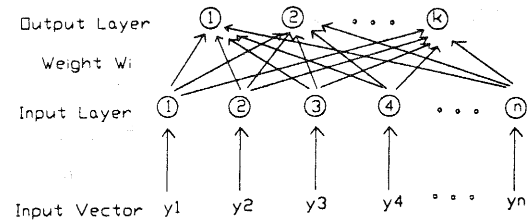

Figure 1. A Competitive Learning Network

The two layers of competitive learning network such as the first layer consists of n input neurons, and the second layer includes k output neurons (Fig. 1). The weight (synaptic) connection between the input and output neurons is denoted by Wi (i=1,2 ...k). The learning of the network is carried out by changing the weight (synaptic) connection Wi between the neurons in the input and output layers. For details, further references and applications see [7] [11] [17].

Competitive Learning with Winner-Take-All(WTA) Activation

Competitive learning can take a variety of forms depending on the precise update rule used and the method for implementing competitive activation mechanisms. There exist in the literature numerous suggestions that Winner-Take-All (WTA) property is based on technical as well as biological principles ([6]). Therefore, one of the most common methods is to activate the most "excited" neuron and then allow that neuron to modify its weight vector using a standard linear update rule. The WTA activation rules are usually used instead of fixed threshold tests, and will activate the single neuron whose excitation level is the greatest. In practice, unsupervised CL network amount to centroid estimation and nearest-neighbor classification when using WTA property.

Summary Competitive Learning Algorithm

(1) Initialize weight vectors (Wi, i=1,2,...,k) for the k output neurons to either small random values or small uniform values because sample-dependent initialization avoids many pathologies that can distort nearest-neighbor learning.

(2) Present random input vector, Y. Find the closest or "winning" weight vector (Wj) by using excitation function E.

$$Ej = E(\| Y - Wj \|) = \min_{I} \| Wi - Y \|$$

where $\| Y \|^2 = Y_1^2 + Y_2^2 + Y_3^2 \ldots + Yn^2$, which defines the squared Euclidean vector norm of Y.

(3) Update the winning weight vector (Wj*) by the following learning rule:

$$Wj^* = Wj + \eta (Y - Wj)$$

where η is an learning rate, and $0 < \eta < 1$.

(4) Present next random input vector.

Typical a set of random input vectors will cycle through the network a number of times until a stable clustering gas evolved. Besides, in the majority of cases the distance Ej are calculated using the Euclidean distance function although frequently the Manhattan ("city block") or some kind of statistical distances (variance) are used as well.

3. Data Source and Experimental

In this research, Landsat-7 Thematic Mapper (TM) image is used as input to a competitive learning neural network. The TM 7-band imagery of the region was obtained in Columbus, Ohio, 1988 (Dr. Merry, personal communication, 1995). The network is unsupervised training to associate the spectral data of each pixel with one of 10, 15, and 30 possible land cover categories. There are a total of 270,000 pixels (with band 3, 4, 5) and 630,000 pixels (from band 1 to 7) of testing datasets. These pixels are contained within a 300 x 300 pixel region within the area which is about 5 miles north of Columbus, Ohio. The ground truths of land cover data (road and water) for the region were obtained by topographic map (from Engineering Department of Franklin County, Ohio) at scale about 1:4748 that was cover the area on 1987.

Compared using TM bands 3, 4, and 5 with TM bands 1~7, the visual viewing results are not great difference. However, the final performance of the CL is measured by the proportion of the total pixels assigned to the correct land cover category, and the overall percentage correctly characterized (PCC). The PCC for each category type is calculated. A minimum classification accuracy of 85% has been suggested for remote sensing data. This level of performance is not expected at this research stage. The results are far below than suggested accuracy, and one of the output results is in the Appendix.

4. Discussion and Conclusion

As noted by Grossberg, Rumelhart and Zipser, and among others, one problem with the standard unsupervised competitive learning update scheme is that some neurons may never win the competition as never learn. A phenomenon of monopoly is a common problem. A monopoly is defined as a state in which a small number of output cells respond to all the input patterns and the other remaining cells never respond to any of the input patterns.

To avoid the state of monopoly, some networks set the initial synaptic connection to be random ([18]). Other modifications, monopoly can be avoided in several ways by using two other unsupervised learning paradigms, Kohonen learning and conscience learning. Kohonen learning is that the weights of all neurons in a neighborhood of the winning neuron are updated and the size of this neighborhood is gradually decreased over time. Conscience learning is that a conscience is added to frequently winning neurons to feel "guilty" and reduce their winning rate.

Numerous ANNs studies have been performed with discrete, class-separable data. Classification of remote sensing satellite data in high dimension is a challenge for using ANNs technique because most researches have been performed on low-dimensional statistical data, and a few researches have been performed on high-dimensional artificial or reality data. Although the study of neural network techniques for classifying multispectral and multisource satellite data is in the beginning stage and this level of performance of competitive learning network is not expected at this research stage, neural network appears some advantages as inherently parallel, self-organization, good generalization to be feasible classifier for every large multichannel images, and it can be an alternative method for land-cover classification by improving its learning capability.

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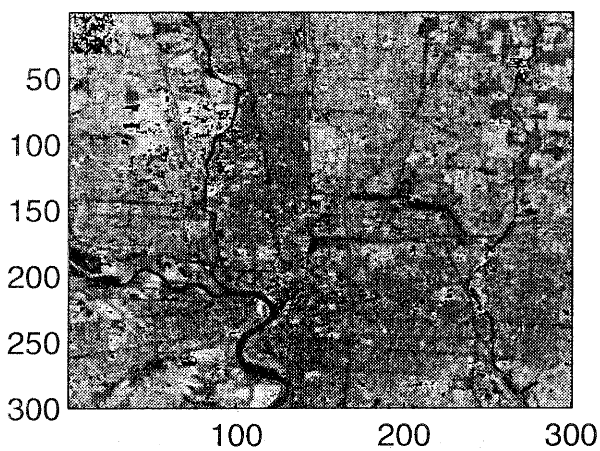
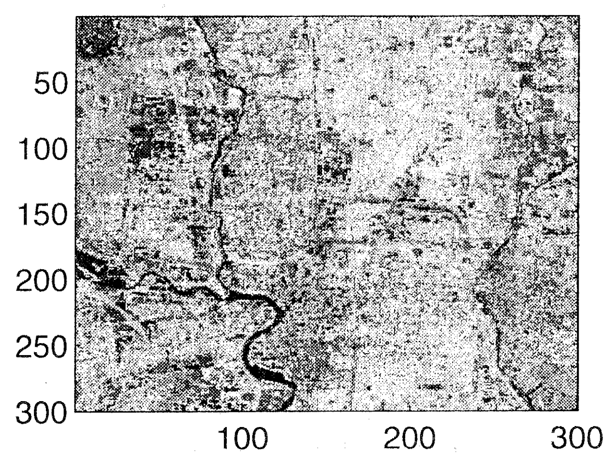
Appendix

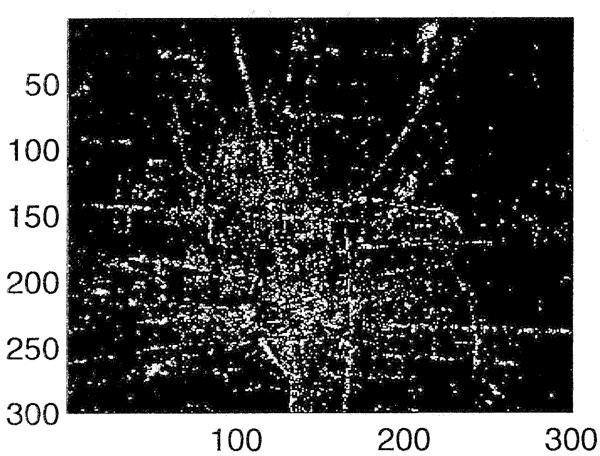
TM band 4: Columbus, OH



15 categories of TM band 3,4,5 with WTA



Land use: Road



Land cover: Water