SUPERVISED AND UNSUPERVISED NEURAL MODELS FOR MULTISPECTRAL IMAGE CLASSIFICATION

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KEY WORDS: Land Cover, Classification, Identification, Algorithms, Artificial_Intelligence, Imagery, Pixel, Multispectral

ABSTRACT:

Competitive learning neural networks have been successfully used as unsupervised training methods. It provides a way to discover the salient general features that can be used to classify a set of patterns in neural networks. Competitive learning models have shown superior training results compared with the K-means or ISODATA algorithms. In this study, the model is extended for image classification. A new layer is added to this one-layer competitive learning to form a two-layer complete classification system. In addition, a modified competitive learning (CL) using simulated annealing is proposed. The preliminary results show that this model for image classification is encouraging. As the backpropogation multilayer perceptron (MLP) neural networks have been used for image analysis, a comparative study is provided for images on these two different models. The models were tested on Landsat TM data.

1. INTRODUCTION

Multispectral image classification is one of the important techniques in the quantitative interpretation of remotely sensed images. Remotely-sensed images usually involve a pixel (picture element) having its characteristics recorded over a number of spectral channels [1]. A pixel can be defined as a point in n-dimensional feature (spectral) space. The thematic information can then be extracted in multispectral image classification. Hence, the output from a multispectral classification system is a thematic map in which each pixel in the original imagery has been classified into one of several spectral classes. Multispectral image classification may be subjected to either supervised or unsupervised analysis, or to a hybrid of the two approaches [2,3].

A hybrid multispectral image classification system for quantitative analysis consists of unsupervised training for defining feature classes and supervised classification for assigning an unknown pixel to one of several feature classes. In the training stage, the objective is to define the optimal number of feature classes and the representative prototype of each feature class. Feature classes are groups of pixels that are uniform with respect to brightness in several spectral, textural, and temporal bands. Unsupervised training is a critical step in the hybrid image classification system. Once feature classes are defined, each pixel in the image is then evaluated and assigned to the class in which it has the highest likelihood of being a member using a classification decision rule in the classification stage.

Artificial neural networks have been employed for many years in many different application areas such as speech recognition and pattern recognition [4,5]. In general, these models are composed of many nonlinear computational elements (neural-nodes) operating in parallel and arranged in patterns reminiscent of biological neural nets. Similar to pattern recognition, there exist two types of modes for neural networks – unsupervised and supervised. The unsupervised type of these networks, which possesses the self-organizing property, is called competitive learning networks [5]. A competitive learning provides a way to discover the salient, general features which can be used to classify a set of patterns [5].

Because of the variations of object characteristics, atmosphere condition, and noise, remotely sensed images may be regarded as samples of random processes. Thus, each pixel in the image can be regarded as a random variable. It is extremely difficult to achieve a high classification accuracy for most per-pixel classification algorithms (classifiers). Photo interpreters have had pre-eminence in the use of context-dependent information for remote sensing mapping.

Neural networks have been recognized as an important tool for constructing membership functions, operations on membership functions, fuzzy inference rules, and other context-dependent entities in fuzzy set theory. On the other hand, attempts have been made to develop alternative neural networks, more attuned to the various procedures of approximate reasoning. These alternative neural networks are usually referred to as fuzzy neural networks. In this study, the competitive learning neural networks and Backpropagation neural networks will be explored for the multispectral classification.

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2. ARTIFICIAL NEURAL NETWORKS FOR MULTISPECTRAL IMAGE CLASSIFIERS

Artificial neural networks (ANNs), a brain-style computation model, have been used for many years in different application areas such as vector quantization, speech recognition and pattern recognition [4,5]. In general, ANN is capable of tolerating the noise, distortion and incompleteness of data taken from the practical applications. Researchers have developed several different paradigms of ANNs [4,5]. These paradigms are capable of detecting various features represented in input signals. An ANN is usually composed of many nonlinear computational elements. These computational elements operate in parallel to simulate the function of human brain. Hence, an ANN is characterized by the topology, activation function, and learning rules. The topology is the architecture of how neurons are connected, the activation function is the characteristics of each neuron, and the learning rule is the strategy for learning [4,5]. ANN is also well suited for parallel implementations because of the simplicity and repetition of the processing elements.

2.1 Unsupervised Models

One type of these networks, which posses the self-organizing property, is called competitive learning networks. Three different competitive learning networks, the simple competitive learning network (SCL), Kohonen's self-organizing feature map (KSFM) and the frequency-sensitive competitive learning (FSCL) network were used as unsupervised training methods in some recognition systems [7]. Similar to statistical clustering algorithms, these competitive learning networks are able to find the natural groupings from the training data set. The topology of the Kohonen self-organizing feature map is represented as a 2-Dimensional, one-layered output neural net. Each input node is connected to each output node. The dimension of the training patterns determines the number of input nodes. Unlike the output nodes in the Kohonen's feature map, there is no particular geometrical relationship between the output nodes in both the simple competitive learning network and the frequency-sensitive competitive learning network. During the process of training, the input patterns are fed into the network sequentially. Output nodes represent the 'trained' classes and the center of each class is stored in the connection weights between input and output nodes.

The following algorithm outlines the operation of the simple competitive learning network as applied to unsupervised training [8]; let L denote the dimension of the input vectors, which for us is the number of spectral bands. We assume that a 2-D (N x N) output layer is defined for the algorithm, where N is chosen so that the expected number of the classes is less than or equal to N^2.

Step 1: Initialize weights $w_{ij}(t)$ ($i= 1, ..., L$ and $j= 1, ..., N \times N$) to small random values.

Steps 2 - 5 are repeated for each pixel in the training data set for each iteration.

Step 2: Present an input pixel $X(t) = (x_1, ..., x_L)$ at time t.

Step 3: Compute the distance d_j between the x_i and each output node using

$$d_j = \Sigma_{i=1,\,L} (x_i - w_{ij}(t))^2$$ where i, j, L, w_{ij} and x_i are similarly defined as in steps 1 and 2.

Step 4: Select an output node j^* which has minimum distance (i.e. the winning node).

Step 5: Update weights of the winning node j^* using

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i - w_{ij}(t)), \quad i=1, ..., L$$

and $1 \le j \le N \times N$, where $\eta(t)$ is a monotonically slowly decreasing function of t and its value is between 0 and 1.

Step 6: Select a subset of these N^2 output nodes as spectral classes.

Competitive learning provides a way to discover the salient general features which can be used to classify a set of patterns. However, there are many problems associated with competitive learning neural networks in the application of remotely sensed data. Among them are: 1) underutilization of some neurons [5], 2) the learning algorithm is very sensitive to the learning rate, $\eta(t)$ in remotely sensed data analysis, and 3) the number of output nodes in the network must be greater than the number of spectral classes embedded in the training set. Ideally, the number of output nodes should be dynamically determined in the training (learning) environment instead of being specified a priori.

For multispectral classification, the simple competitive learning networks are extended to include one more layer which will determine the category to which the input pixel belongs. The new architecture is shown in Figure 1. Each neuron in the category decision layer is calculating the difference between the input pixel value and each category protype, respectively, and a simple logic box which will determine the minimum value among those computed differences and hence the corresponding category.

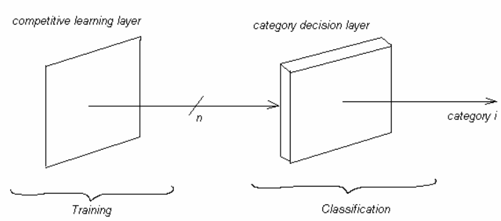

Figure 1. A modified competitive learning neural networks with the extension of a category decision layer.

2.2 Supervised Models

Many adaptive, non-parametric neural-net classifiers have been proposed for real-world problems. These classifiers show that they are capable of achieving higher classification accuracy than conventional pixel-based classifiers [9]; however, few neural-net classifiers which apply spatial information have been proposed. The feed-forward multilayer neural network has been widely used in supervised image classification of remotely sensed data [10, 11]. Arora and Foody [12] concluded that the feed-forward multilayer neural networks would produce the most accurate classification results. A backpropagation Feed-forward multilayer network as shown in Figure 2 is an interconnected network in which neurons are arranged in multilayer and fully connected. There is a value called *weight* associated with each connection. These weights are adjusted using the back-propagation algorithm or its variations, which is called *training* the neural networks. Once the network is well trained, it can be used to perform the image classification.

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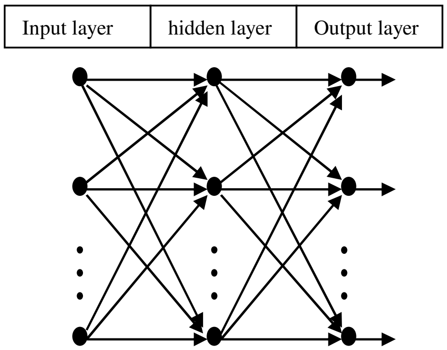

Figure 2. A backpropagation feed-forward multilayer neural networks.

3. SIMULATED ANNEALING

Simulated Annealing (SA) [13, 14] will be used to enhance the simple competitive learning neural networks. SA is an optimization algorithm that is based on the process of annealing metals. When a metal is heated up and slowly cooled down, it is hardened into an optimal state. The analogy behind this is that the algorithm begins the search for the optimal solution by exploring many possible solutions [13, 14]. Slowly, it restricts the search paths to only the most promising solutions as the algorithm is said to be cooling down. The laws of thermodynamics state that at temperature, *t*, the probability of an increase in energy of magnitude, δE, is given by

$$P(\delta E) = \exp(-\delta E / kt)$$

where *k* is a constant known as the Boltzmann's constant.

This equation is directly used in simulated annealing, although it is usual to drop the Bolzmann's constant as this was only introduced into the equation to cope with different materials. Therefore, the probability of accepting a worse state is given by the equation

$$P = \exp(-c/t) > r$$

where

c = the change in the cost function

t = the current temperature

r = a random number between 0 and 1

The probability of accepting a worse move is a function of both the temperature of the system and of the change in the cost function. This approach allows SA to explore solutions that the simple competitive learning networks might reject on its own. Simulated annealing allows for some randomness in its search for the optimal or near optimal solution.

Simulated annealing introduces some randomness into the selection of clusters (categories). This releases the algorithm from being trapped in a local optimum and allows it to venture into a search for the global optimum.

4. EXPERIMENTS

The image shown in Figure 3 is one of tested images using both competitive learning networks and backpropagation feed-forward multilayer networks. The results from applying the simple competitive learning networks, modified competitive learning networks and backpropagation feed-forward multilayer networks to the image, respectively and the results are shown in Figures 4 – 6.

Figure 3. An original TM satellite image.

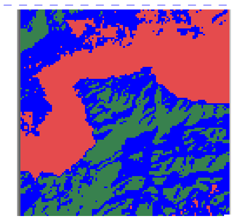

Figure 4. A classified image using the simple competitive learning neural networks.

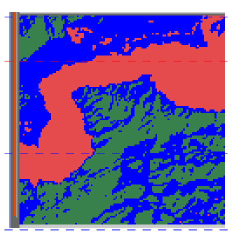

Figure 5. A classified image using the modified competitive learning neural networks.

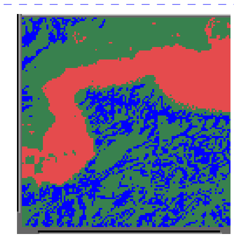

Figure 6. A classified image using feed-forward multilayer neural networks.

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5. CONCLUSIONS

The advantages, stable training results and no requirement of a priori knowledge provided by the simple competitive learning, and optimization for preventing fixation to the local minima provided by simulated annealing, are integrated in this modified model. Like most competitive learning models, this modified model can be applied in different areas such as computer vision, pattern classification, industrial product inspection, etc. In this study, the results of the proposed combined technique are compared with the results of the backpropagation feed-forward neural networks used to classify the same image. The one-hidden layer feed-forward network trained with backpropagation algorithm was developed. The preliminary results showed that the modified competitive learning networks are promising. The time complexity and the overall classification accuracy assessment will be performed in our experiments.

ACKNOWLEDGEMENTS

The authors, Hung and Coleman, wish to acknowledge the support of the Center for Hydrology, Soil Climatology, and Remote Sensing (HSCaRS) staff. Contribution by the HSCaRS Research Center, Department of Plant and Soil Sciences, the Agricultural Experiment Station, Alabama A&M University, Normal, AL 35762. Journal no. 538. Research supported by NAG5-10721 from the National Aeronautics and Space Administration (NASA), Washington, DC, USA. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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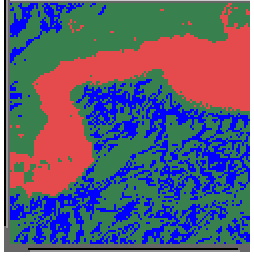

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