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CLASSIFICATION IN A NEURAL NETWORK ENVIRONMENT**

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NONLINEAR ASPECTS OF DATA INTEGRATION FOR LAND-COVER
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ABSTRACT

Some results of exploring nonlinear aspects of a neural network methodology to provide land-cover in satellite imagery are presented. All required images are used in a Back-Error Propagation (BEP) network which is a nonlinear data integrator for spatial patterns classification. The network is trained to give the basic categories: grass, moisted soil, bare soil, forest, water and built-up areas. The results of a partial classification are used in a posterior analysis which is done to get the final classification in more detailed classes of land use. The performance results show how powerful is a neural-network based methodology for satellite imagery integration and classification.

INTRODUCTION

Land-cover classification can be considered as a conventional classification process whose goal is to separate data into discrete groups of known identity.

Usually in this process techniques of classification are used to generate land-cover classes and sub-classes from satellite imagery. Much of the earliest conventional classification techniques were based on the probability density function of data belonging to each class /1/. The main problem is to find an efficient classification algorithm which could define boundaries among classes which are often not well separated. In addition, a classification algorithm has to take into account the existence of different textures within each class.

In order to get the maximum information from the multivariate data, the classification algorithm should be isotropic, in the sense that each weighted source data is equally accounted.

For practical results, the classification algorithm has to be robust to the data variability, generating correct pixel classification under noisy data.

Statistical classification methods usually assign the most likely class to the observed data. Although optimal theoretical results are obtained for the assumption about probability density functions, in real situations the true probability density functions are different from their theoretical models.

The main advantage of the neural network approach for

classification tasks is its distribution free characteristics, besides its potential to weight each data /2/. So, neural networks seem to be a compromise between classification techniques based on statistical methods and heuristics procedures. The learning capabilities of neural network provide a mechanism to assimilate the statistical information of the observed data. On the other hand, the neural network topology could be considered as a synthetic composition of the observed data /3/.

In this paper we present some results in land-cover classification experiments using two neural network Back-Propagation models. One of them is based on a "Monolithic" architecture in which all integrated data are used for a exclusive class activation, and the other is based on "class-distributed" architecture where each neural network is trained to recognize only one class characteristic.

DEFINITIONS

A neural network consists of nodes called neurons, and weighted links between these neurons simulating synaptic activities. Mathematically speaking, a neural network maps the values of inputs neurons to output neurons. In a formal model the output value is typically computed as some nonlinear bounded function of a weighted sum of activities of the neuron inputs. These inputs are the output values of other neurons.

One of the most known neural network model is the Back-Propagation that has been under experiment in land-cover classification problems. The Back-Propagation neural network has three or more processing layers: an input layer, one or more hidden layers and an output layer.

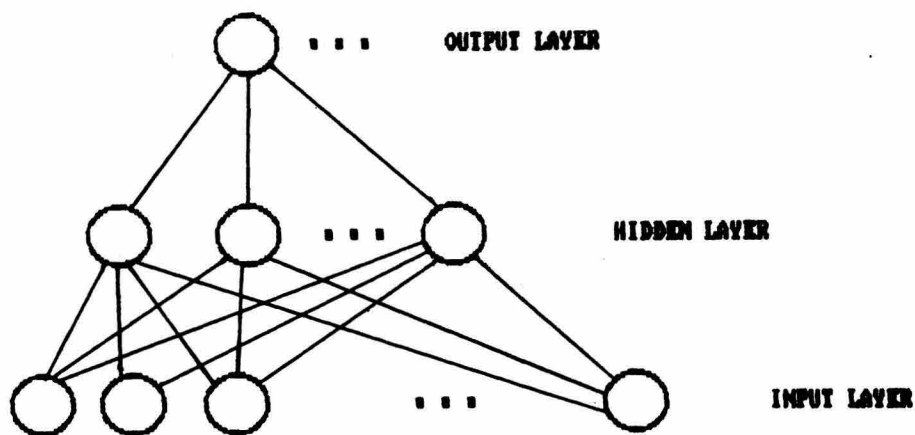


Fig. 1. Back-error Propagation Model

Each node has an activity represented by the following equation:

$$o_j = f(\sum_i w_{ij} x_i - l_j) \quad (1)$$

where:

o_j is the output value of the node j ;

f is a nonlinear function, such as a sigmoid:

$$f = 1 / (1 + e^{-x}) \quad (2)$$

w_{ij} are the weights between the nodes of two layers linked, i and j ;

x_j is the input value of the node i ;

l_j is a threshold.

In the learning phase of the Back-Propagation algorithm the way of adjust the weights is according to the following

equation:

$$\Delta w_{ij} = \eta \delta f' \quad (3)$$

where η is a learning rate, δ is the difference between the desired output of neuron j and its actual output, and f' is the partial derivative of the sigmoid function $f(\cdot)$.

For classification, usually a neural network operates as a class identifier which receives a set of input vectors and produces responses at each output unit associated to each class.

Monolithic classifier.

Back-Propagation networks can form arbitrarily complex decision boundaries to separate very meshed classes /4/. The Monolithic classifier, as shown in figure 2, is a Back-Propagation neural network whose output nodes are associated to each class.

An output node is activated every time the input x of the network belongs to the associated class. The output nodes have as activities a weighted function of the same hidden node activities in the previous layer. The decision rule is to select that class corresponding to the output node with the largest output.

The supervised learning algorithm specifies, for each possible input, an associated output vector. The function of the learning algorithm is to choose the best values of the weights so the output units give the correct class indication when it is in the classification procedure. In the learning procedure the algorithm consider an exclusive class labeling. This means all classes are considered in the learning process, but each class is labeled one at a time, and the

same weight set has to adapt itself to all classes characteristics. Often that limits the neural network performance.

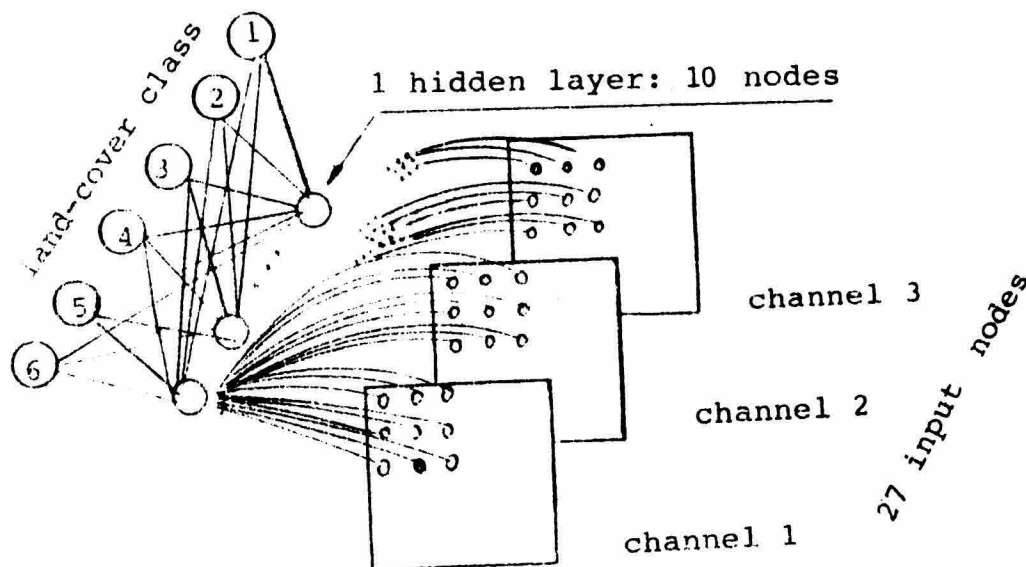


Fig. 2. Monolithic Classifier

Class-distributed classifier.

As shown in the figure 3, this type of classifier consists of a set of networks. Each network is specialized in classifying one kind of class. The decision rule is also to select that class corresponding to the output node, or network output, with the largest output. Differently to the Monolithic approach the boundaries to be determined by this classifier are a competition of individual boundaries defined by each network. A class-distributed architecture permits the use of the simplest neural networks for each class learning. It makes easier the learning task, because there is no interference among networks during the learning procedure.

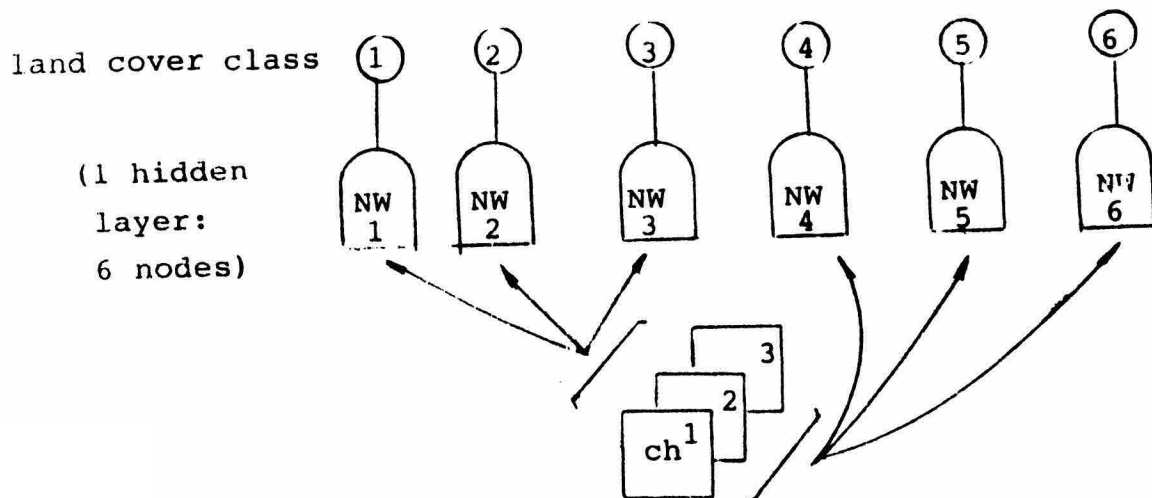


Fig. 3. Class- distributed classifier

EXPERIMENTS

The research discussed in this paper concerns the determination of the most appropriate approach to land-cover classification tasks, when there are more than two classes to be identified, in between the previously described.

Relative performance was estimated by comparing classification results of the Monolithic approach to the class-distributed, using the same imagery, same learning sites and a learning window of (3 x 3) pixels. This size permitted a fine consideration of texture details in both the training and classification procedures.

Both approaches were used to classify a data set consisting

of a Landsat Thematic Mapper imagery (channels 3, 4 and 5). Channels 3, 5 and 7 have been indicated as good information sources for sites visualization when seen separately. In case those sources are considered superposed channels RGB TM 435 are better for urban studies .

Each channel comprises an image of (512 x 512) pixels. The area used for classification is Sao Jose dos Campos, Sao Paulo State/Brazil. Only six basic classes were considered: grass, moisted soil, bare soil, forest, water and built-up areas.



Fig. 4. Landsat image (Channel 5) with the training areas considered.

The picture shown in the figure 4 corresponds to the channel 5 of the considered Landsat image.

The neural networks in the two approaches had the following architectures:

- Monolithic: 27 input nodes (three input layers each containing (3x3) input nodes); one hidden layer with 10 nodes and an output layer with 6 nodes, one for each class.

- Class-distributed: Six identical architectures each consisting of 27 input nodes (three input layers each containing (3x3) input nodes); one hidden layer with 6 nodes and an output layer with one node.

RESULTS

The training procedure for the monolithic approach stopped at 1500 epochs (each epoch corresponds to a training set). For the class-disstributed approach different numbers of epochs were established for the stopping error condition to each network. In this case, 250 epochs were used for water and bare soil networks; 500 epochs for forest and 2000 epochs for the others landcover classes.

The Back-Propagation learning parameters were: learning rate = 0.8 and momentum = 0. Experimentally we have observed that after those epochs, usually the error is less than 25 % of the initial error.

The classification performance was measured comparing the networks results to the true class indication which was provided by an expert in the domain, by maps and aerial photographs.

In the figure 5 results of Monolithic approach for all the land-cover classes are shown, and in figure 6, the class-distributed approach

CONCLUSIONS

The land-cover classification results demonstrate that the Monolithic approach adequately retrieve classes' type better than the class-distributed one. However both of the two approaches are robust in land-cover discrimination, combining spatial and spectral information.

In the class-distributed approach the decision process is based on a competition between all the six class-distributed networks. Some classifying distortions were observed due to different network sensitivity. In addition it was noted that for small number of hidden nodes misclassifications occurred in the class-distributed approach.

Although observing each class-distributed network activation it is noted a good performance, as shown in the figure 7 for the network specialized for the water class.

It was also observed that both monolithic and class-distributed networks are sensitive to the quality and number of data samples. It implies a special care in the data sample for the learning phase.

Finally it was identified that neural networks seem to be an efficient tool for incremental learning in different scenarios where a multitude of classes characteristics can be assimilated.

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Fig. 5 - Results of monolithic approach.

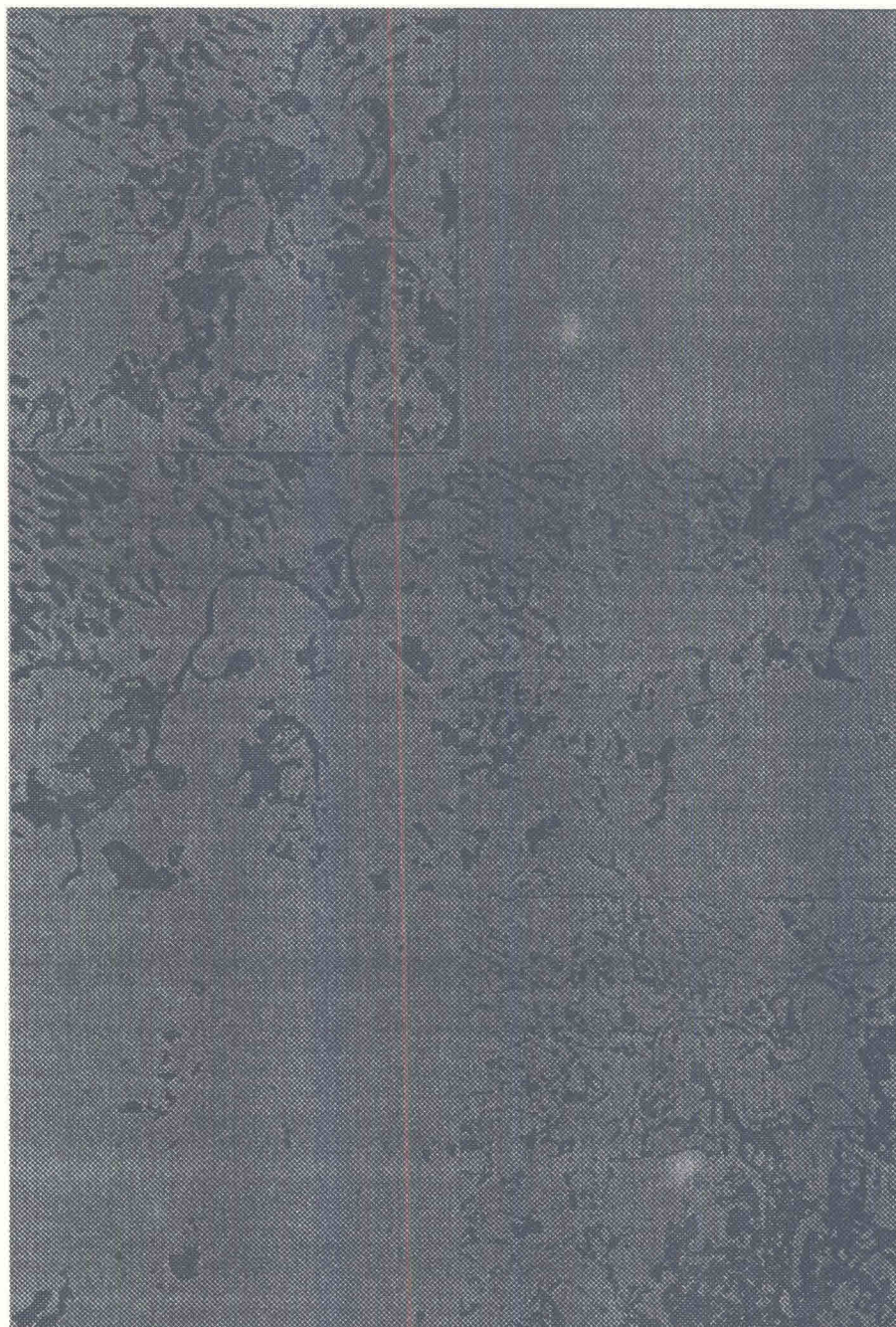


Fig. 6. Results of class-distributed approach.

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6. REFERENCES

1. J. Lee; R.C.Weger; S.K.Sengupta and R.M Welch, "A Neural Network approach to cloud classification," **IEEE Trans.on GRS**, Vol.28 No.5, pp. 846-855, Sept. 1990.
2. J. A. Benediktsson; P.H. Swain and O.K. Ersoy, "Neural Network approaches versus statistical methods in classification of multisource remote sensing data," **IEEE Trans. on GRS**, Vol. 28, No. 4, July 1990, pp. 540-552.
3. R. Hecht-Nielsen, **Neurocomputing.** Addison-Wesley Publishing Co.,1990.
4. G. F. Hepner; T. Logan; N. Ritter, and N. Bryant, "Artificial Neural Network classification using a minimal training set: comparison to conventional supervised classification," **Photogrammetric Engineering and Remote Sensing**, Vol. 56, no. 4, pp. 469-473, April 1990.