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**SATELLITE IMAGERY AND EXOGENOUS DATA INTEGRATION BY NEURAL
NETWORK IN AUTOMATIC LAND-COVER CLASSIFICATION**

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PALAVRAS-CHAVE: Neural Network; Land-Cover Classification;
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Satellite imagery and exogenous data integration
by neural network in automatic land-cover classification

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ABSTRACT

Certainly data integration for land-cover classification requires a non-linear system to associate satellite imagery with exogenous imagery. In this study we present some results of a Neural Network based methodology to provide land-cover classifications. Two approaches are investigated: a) The Monolithic integration: all required registred images are the inputs of only one Back-Error Propagation (BEP) network. The network is trained on purpose to get the final classification. b) The class-distributed integration: for each class a specific network learns from all sattelite imageries its class characteristics. In both approachs, topographic mapping is taken into account as exogenous data.

1. INTRODUCTION

Various heuristic and problem-specific methods have been proposed to classify multisource data. Most of them are statistical-based approaches which are not convenient multivariate statistical models because the data are multitype and their sources may not be equally reliable¹. This implies that the data sources need to be weighted according to their reliability and relative information content.

Neural Network models for classification of multivariate remotely sensed and geographic data have been already used². The main advantage of the Neural Network approach for classification tasks is its distribution free characteristic, besides its potential to weighred each data.

One of the most known neural network model is the Back-Propagation that has been under experiment in land-cover classification problems³.

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 data are integrated, and the other is based on "class-distributed" architecture where each neural network is trained to recognize only one class characteristics. It is discussed also how exogenous data are integrated and how these two training/classifying approaches affect the correct classification accuracy.

2. CLASS LEARNING USING NEURAL NETWORKS

A neural network consists of nodes called neurons, and weighted links between these neurons simulating synaptic activities. 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.

The Back-Propagation Neural Network has three or more processing layers: an input layer, one or more hidden layers and an output layer. Each node has an activity represented by the following equation:

$$o = f \left(\sum_j w_j x_j - \theta \right)$$

where f is a nonlinear function, w_j are the weights and θ is a threshold.

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.

2.1 Monolithic classifier

Back-Propagation networks can form arbitrarily complex decision boundaries to separate very meshed classes⁴. The Monolithic classifier, as shown in figure 1 is a Back-Propagation neural network whose output nodes are associated to each class.

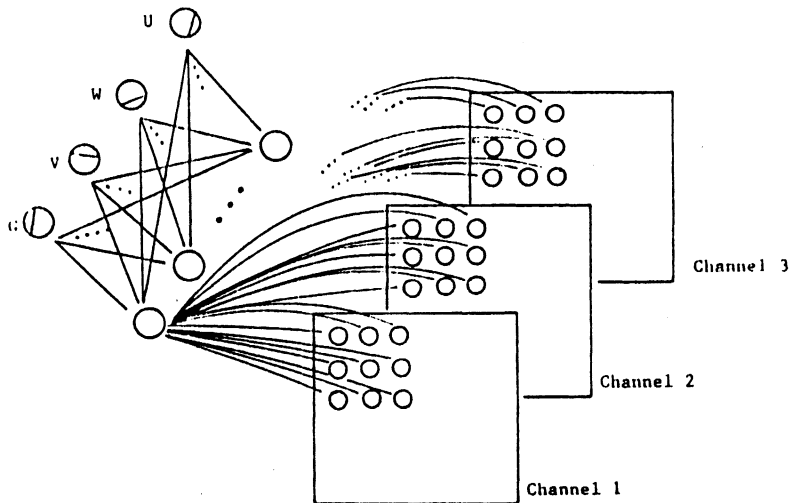


Figure 1 - Monolithic Neural Network Approach.

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 on at a time, and the same weight set has to adapt itself to all classes characteristics. Often that limits the neural network performance.

2.2. Class-distributed classifier

As shown in the figure 2., this type of classifier consists of a set of networks. Each network is specialized to classify 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.

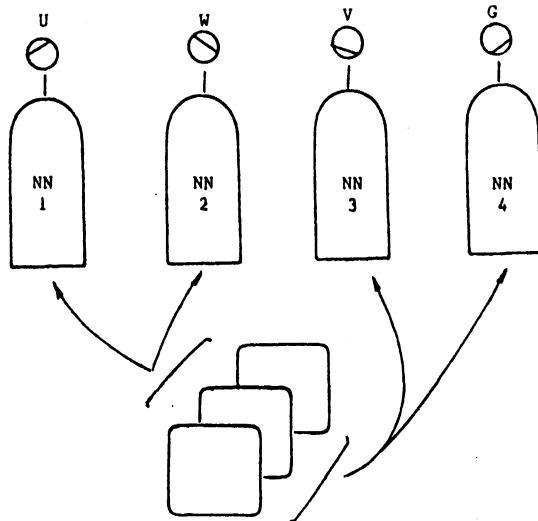


Figure 2 - Class-Distributed Neural Network Approach.

3. EXPERIMENTAL RESULTS

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 the following four data sources:

- Landsat Thematic Mapper imagery (channels: 3,4, 5);

- Topographic map

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 given a better visualization.

The exogenous data as a filled contour line map offers evident separation between the plateau where the down town is located and the tilled plain.

Each channel comprises an image of (512 x 512) pixels. The area used for classification is Sao Jose dos Campos, a area in Sao Paulo/Brazil. Only four basic classes were considered: urban, water, grass and vegetation.

Relating all data sources we notice that there is variation in the topographic data sources for classes vegetation and urban and for classes water and grass.

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

- Monolithic: 36 input nodes (four input layers each containing (3x3) input nodes); one hidden layer with 9 nodes and an output layer with 4 nodes, one for each class;

- Class-distributed: Four identical architectures each consisting of 36 input nodes (four input layers each containing (3x3) input nodes); one hidden layer with 3 nodes and an output layer with one node.

The training procedures of the neural network approaches were said to converge after 400 epochs (each epoch corresponds to a training set). 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.

Considering the non-homogeneity of data more training areas were used for classes where the data present high variability. As example: urban class (8 areas), water (3 areas), grass (3 areas) and vegetation (5 areas). However the overall quality parameters as homogeneity and connectivity and sharp transition boundaries of two approaches was been observed but not measured.

In the figure 4 we can see results of Monolithic approach given that the image to be classified is the one shown in figure 4a (channel 5) and in 4b is the same image classified. In figures 4c,4d,4e and 4f it is shown the urban, water, vegetation and grass classes, respectively.

4. CONCLUSIONS

The land-cover classification results demonstrate that the Monolithic approach do not adequately retrieve classes' type as reliably as the Class-distributed one.

However both of the two approaches are robust in land-cover discrimination, combining spatial and spectral information.

Also the exogenous data integration as an image format biases the classification process because of topographic class intensity dependency. So the intensity codification of topographic information has to be carefully chosen.

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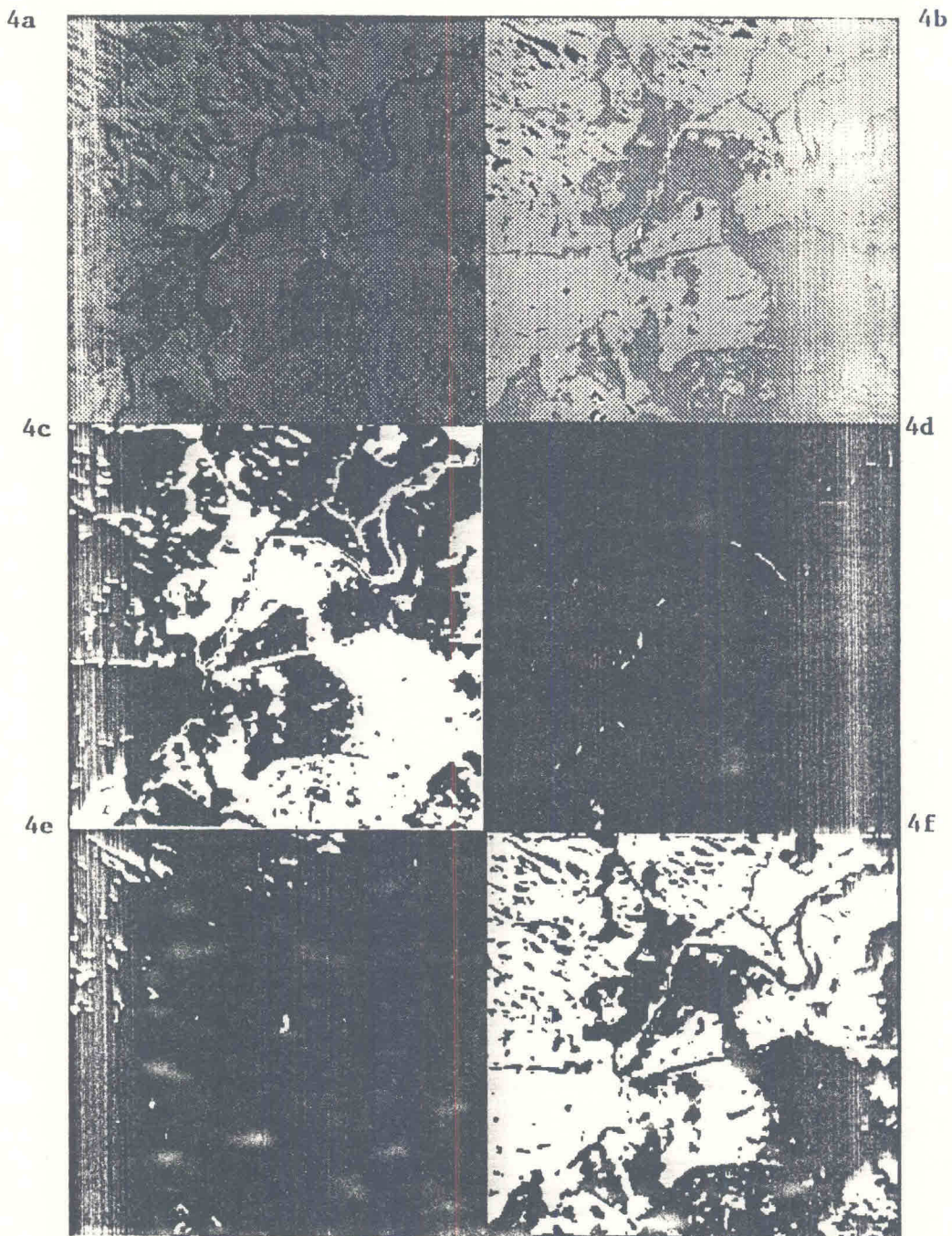


Figure 4 - Monolithic Approach Classification Results

4a) Original Image - Channel 5

4b) Classified Image with all four class codified by intensities

Classified Images white pixels: 4c) Urban; 4d) Water;

4e) Vegetation; 4f) Grass.