A REGION-BASED APPROACH TO LAND-USE CLASSIFICATION OF REMOTELY-SENSED IMAGE DATA USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Conventional pixel-by-pixel techniques like the maximum-likelihood method often achieve insufficient results for the classification of intra-urban areas or complex landscape patterns on high-resolution remote sensing imagery. This is especially due to the fact, that pixel-wise classifiers do not take into account the possible relations or similarities that may exist between one pixel and its neighbours. In this paper, a method using modified co-occurrence matrices combined with a neural network was applied for the purpose of utilizing spatial information. Instead of counting gray level co-occurrences, boundary lengths of adjacent regions were computed. The neural network type used in this study is ATL (Adaptive Threshold Learning). ATL is a supervised feedforward network which differs significantly in concept from the widely used backpropagation paradigm. The presented method was tested using Landsat TM data obtained over the city of Santos/Brazil. It is shown that this approach produces promising land-use classification results in terms of classification accuracy. In particular, the obtained land-use classes are more realistic and noiseless compared with a conventional Bayesian method.

1. INTRODUCTION

The overall objective of image classification procedures is to automatically categorize all pixels in an image into land-cover classes (Lillesand and Kiefer, 1994). This is relatively easy with conventional pixel-wise classifiers because land cover is directly related to the pixel values on an image (Gong and Howarth, 1992b).

For the classification of intra-urban areas, however, conventional pixel-by-pixel techniques like the maximum-likelihood method often achieve insufficient results. This is due to two facts. First, distinct urban areas represent different types of land use. In contrast to land cover, land use is a cultural concept. Whereas land cover is defined as the physical evidence on the surface of the earth, the term land use relates to man's activities or economic functions associated with a specific piece of land (Lillesand and Kiefer, 1994). What we see on remote sensing imagery is only the physical evidence of land use as represented by combinations of various land-cover types (Driscoll, 1985).

Second, conventional classifiers employ only spectral information on a pixel-by-pixel basis (Gong and Howarth, 1992a). This strategy does not take into account the possible relations or similarities that may exist between one pixel and its neighbours (Gonzáles and Lopez, 1992). A large amount of spatial information is thus ignored. Therefore, accurate land-use maps cannot be obtained through a direct transformation from remotely-sensed data to land-use categories; they require information from both spectral and spatial contexts to characterize the land use (Gong and Howarth, 1992b).

There are several types of classification which make use of additional information, as well as the multispectral information from a classification unit (see, for example, Mohn et al., 1987, and Kartikeyan et al., 1994). In this paper, a method using modified co-occurrence matrices in combination with a feedforward neural network called ATL was applied for the purpose of utilizing spatial information.

2. METHODOLOGY

2.1 A Region-Based Co-Occurrence Matrix

One of the most popular methods to measure spatial dependencies involves the use of the gray-level co-occurrence matrix. This matrix contains the relative frequencies P_{ij} with which two neighbouring pixels separated by distance d and angle α occurs on the (sub-)image, one with gray level i and the other with gray level j. In this study, the gray-level values were replaced by land-cover classes derived from a pixel-specific unsupervised classification of multispectral imagery using the ISODATA method (Hall and Ball, 1965). Furthermore, the total length of the boundary between region i' and j' on the image or within a subimage defined from a buffer zone around a region substitutes the relative frequencies P_{ij}. For example, the modified co-occurrence matrix of the pattern in Figure 1 is

$$\begin{pmatrix} 0 & 4 & 26 \\ 4 & 0 & 8 \\ 26 & 8 & 0 \end{pmatrix}.$$

Several statistical measures, such as homogeneity, contrast, and entropy can be computed from a co-occurrence matrix to describe specific textural characteristics of an image (Haralick et al., 1973). But these scalar parameters contain only a part of texture information. It is more advisable to employ the co-occurrence matrix itself. However, it is difficult to treat two-dimensional arrays in conventional statistical classifiers like the maximum likelihood method. On the other hand, it is easy to handle two-dimensional data in neural networks. Therefore, classification using co-occurrence matrices can be carried out simply by using a neural network (Inoue et al., 1993).

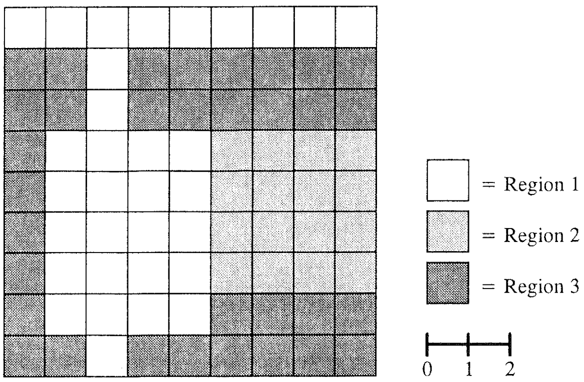

Figure 1: Landscape pattern of three regions

2.2 Neural Network Methods for Pattern Recognition

A neural network is a directed graph consisting of neurons or nodes arranged in layers with interconnecting links (Haykin, 1994). These structures represent systems composed of many simple processing elements operating in parallel, whose function is determined by network structure, connection weights, and node function (Hara et al., 1994).

Recently, neural networks have been applied to a number of image classification problems due to the following characteristics of neural networks (e. g., Chen et al., 1993): (1) they have an intrinsic ability to generalize; (2) they make weaker *a priori* assumptions about the statistical distribution of the classes in the dataset than a parametric Bayes classifier; and (3) they are capable of forming highly non-linear decision boundaries in the feature space. Therefore, a neural network has the potential of outperforming a parametric Bayes classifier when a feature statistics deviate significantly from the assumed Gaussian normal distribution. Indeed, the results of Benediktsson et al. (1990), Bischof et al. (1992), and Heermann and Khazenie (1992) indicate that a neural network can classify imagery better than a conventional supervised classification procedure using identical training sites.

Several neural network models have been proposed since Rosenblatt (1958) introduced the perceptron. The most common network type is the multilayer feed-forward neural network with connections only between nodes in neighbouring layers. The connection weights are iteratively adjusted in order to minimize an error criterion function. One of the most popular and widely investigated supervised learning paradigms is backpropagation (Rumelhart et al., 1986). It uses a gradient descent technique to minimize a cost function equal to the mean square difference between the desired and actual net outputs. The backpropagation method is an efficient algorithm and can solve problems of non-linear decision. However, it suffers from the weakness of very slow convergence during training. Very often the learning dynamics stop at a local minima rather than the global minima. Another procedure is introduced for this reason here which stands out due to its extremely fast learning ability.

2.3 The ATL Network Model

ATL (Adaptive Threshold Learning) is a supervised feedforward network, but one that differs significantly in concept from backpropagation. ATL is a proprietary paradigm belonging to Neurotec, Inc. The ATL algorithm is similar to RCE (Restricted Coulomb Energy) which is patented by Nestor, Inc. RCE got its name from the way it models attractor basins, analogous to the Coulomb law of attraction between particles of opposite electrical charge. ATL is based on a similar concept.

Figure 2 shows the architecture of an ATL network. Input nodes are fully connected to the internal nodes, and the internal nodes are selectively connected to the output nodes. An output node operates as an OR gate. If any of its inputs are active it produces an output - otherwise it does not (Chester, 1993).

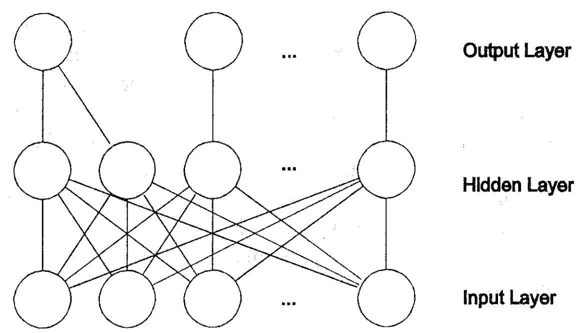

Figure 2: Three-layer topology of an ATL network

The ATL training algorithm attempts to create basins of attraction which cover each decision region. Figure 3 shows a simple two-dimensional case. The circles in the diagram are the attractor basins, whose center are located by the synaptic weight vector, **w**, of the internal node. The radius θ_i of the ith basin corresponds to the node's threshold. If an input vector, **i**, falls within an attractor basin, then the internal node associated with that attractor basin is activated.

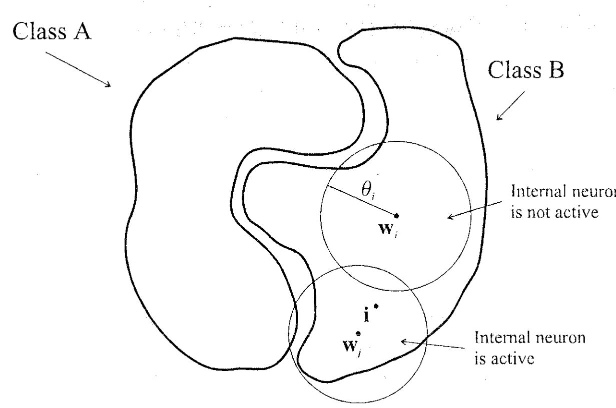

Figure 3: Two-dimensional decision regions with training vectors and basins of attraction.

The training process starts with no basins of attraction; the system creates them as a result of actions taken when training vectors are presented sequentially. The following two rules, applied to each training vector in turn, suffice to produce these basins (Wasserman, 1994):

1. If a training vector is applied that does not lie within a basin of attraction of the same class as that of the training vector, a basin of radius θ_{new} is created, centred at that training vector. The radius is chosen to be less than the distance to the center of the nearest basin of any other class (Fig. 4).

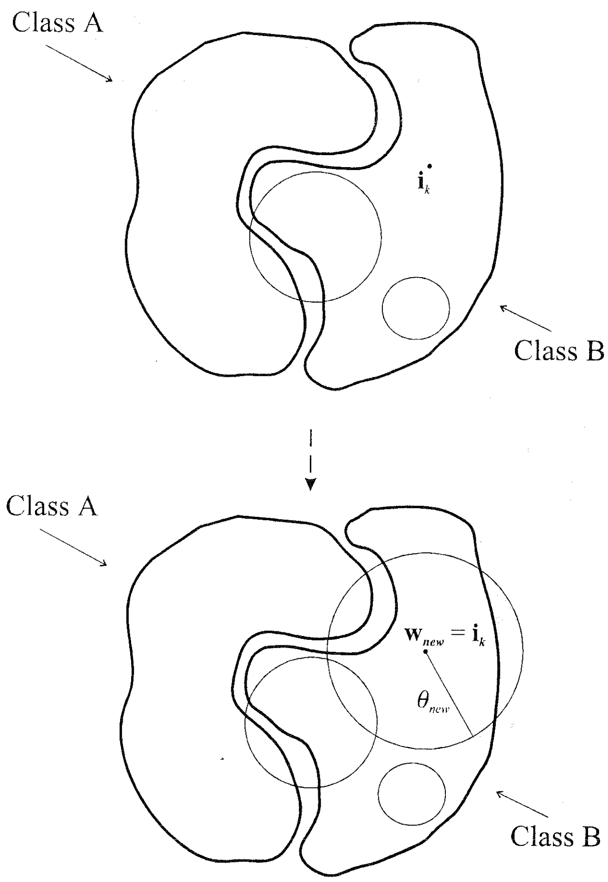

Figure 4: Insertion of a new basin of attraction

2. If an applied training vector falls in the basin of attraction of a different class, the radius of that basin is reduced until the training vector lies just outside of the basin (Fig. 5).

Following these steps, training vectors generate multiple basins approximating contours of underlying classes A and B (Fig. 6).

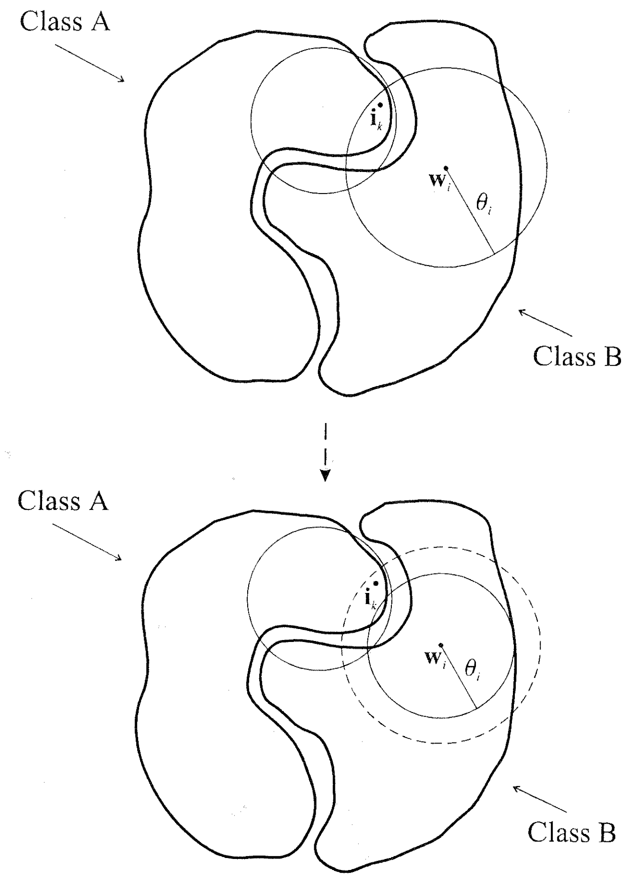

Figure 5: Contraction of a basin of attraction

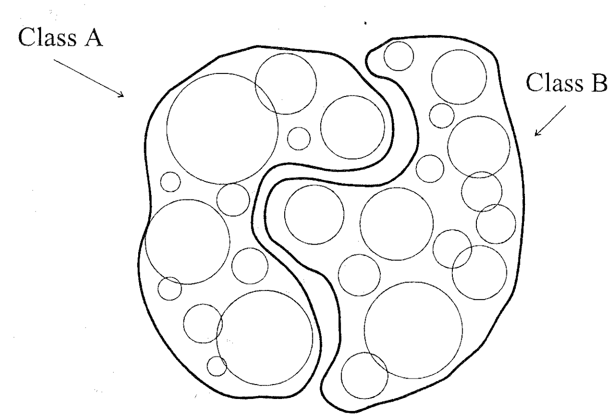

Figure 6: Approximated decision regions

3. EXPERIMENTS

The area selected for study is the city of Santos/Brazil; the input data used in this study is a geocoded 7-channel Landsat TM image acquired on 16 April 1992. A subscene of 384 by 384 pixels which covers a large portion of the harbour of Santos (approximately 9.6 km by 9.6 km) was selected for the classification tests. A black-and-white reproduction of a natural false-color composite covering the subscene is shown in Figure 7.

The objective of the study is the discrimination between the intra-urban land-use classes 'Residential Area', 'Industrial Area', 'Docks', and 'Other Areas'. The training stage of the classification procedure is given by the following steps:

Step 1: An unsupervised ISODATA classification was executed on the 7-channel TM-subscene. The resulting land-cover map consists of 20 classes.

Step 2: Representative training samples for each land-use class were selected.

Step 3: Modified co-occurrence matrices based on a buffer distance of 100 m were generated for each region of the training samples. The elements beneath the main diagonal of the region-based co-occurrence matrix form an input vector for the ATL network. The output layer consists of four neurons, one neuron for each land-use class.

During the classification phase, a region-based co-occurrence matrix is computed on each region of the image respectively. Figure 8 shows the results of the neural network classification. They are more realistic and noiseless compared with a conventional Bayesian method (Fig. 9). Table 10 and 11 show the classification accuracy achieved by a maximum-likelihood classification and the neural network approach. The results indicate that a neural network approach based on region-based co-occurrence matrices can outperform a conventional maximum-likelihood method, especially when land-use maps instead of land-cover maps are generated.

4. CONCLUSION

The classification tests show that region-based co-occurrence matrices combined with an ATL network have potential for discriminating several intra-urban land-use classes with high accuracy. The proposed method produces more realistic and noiseless land-use classes compared with a conventional Bayesian classifier. The neural network approach exceeds the overall classification accuracy achieved by the maximum-likelihood method by 14%. Because of its fast convergence during training and its ability to approximate arbitrarily complicated decision regions, the ATL algorithm used in this study is an appropriate alternative to backpropagation.

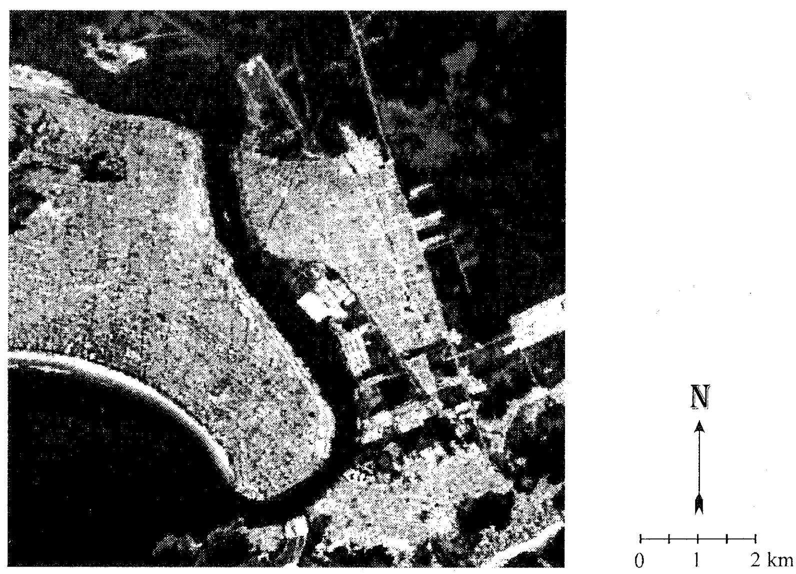

Figure 7: Black-and-white reproduction of a natural false-color composite covering Santos/Brazil

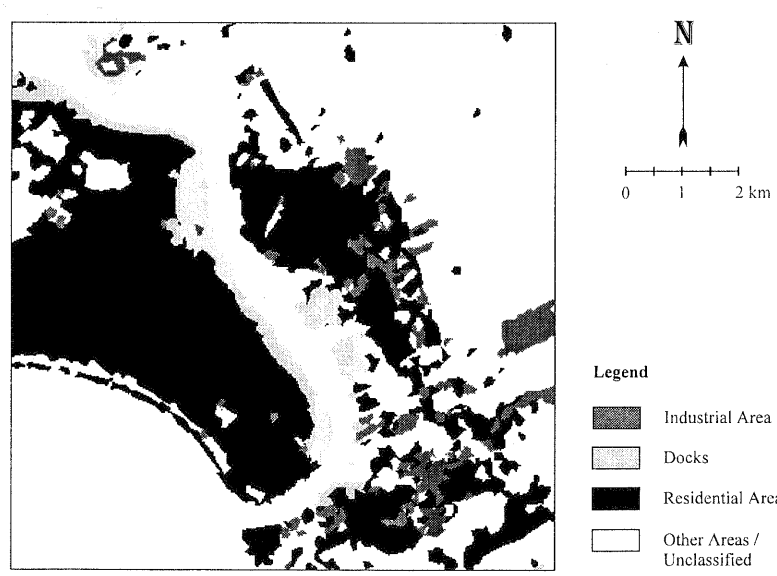

Figure 8: Result of ATL classification based on modified co-occurrence matrices

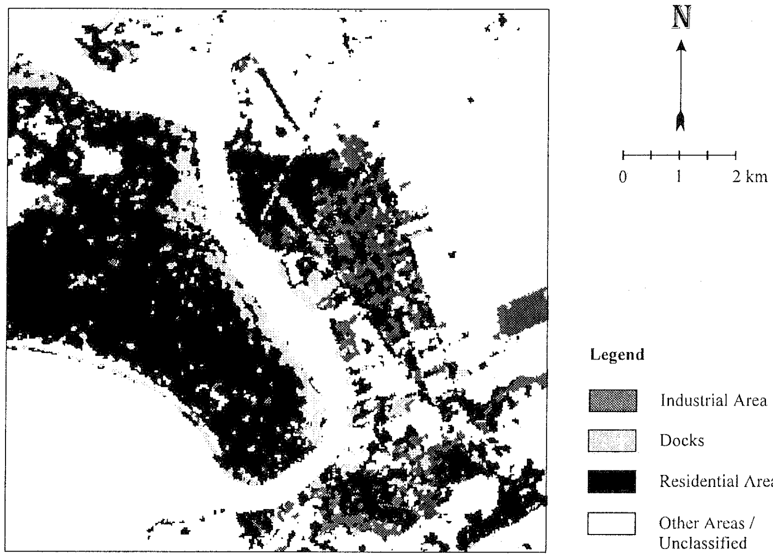

Figure 9: Result of maximum-likelihood classification

Land-Use Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Residential Area	120	72	66	55.0 %	91.7%
Docks	24	38	16	66.7%	42.1%
Industrial Area	12	39	12	100.0%	30.7%
Other Areas	100	107	97	97.0%	90.7%
	Σ 256	Σ 256	Σ 191		

Overall Classification Accuracy = 74.6% $= \frac{191}{256}$

Table 10: Accuracy report for maximum-likelihood classification

Land-Use Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Residential Area	90	72	70	77.8 %	97.2%
Docks	34	38	30	88.2%	79.0%
Industrial Area	26	39	24	92.3%	61.5%
Other Areas	106	107	103	97.2%	96.3%
	Σ 256	Σ 256	Σ 227		

Overall Classification Accuracy = 88.7% $= \frac{227}{256}$

Table 11: Accuracy report for the neural network classification using region-based co-occurrence matrices

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