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Ecological land systems classification using multisource data and neural networks

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Abstract

Under the Canada-Manitoba Partnership Agreement in Forestry Program, a project was initiated to apply artificial neural network technology in ecological land systems classification. Using digital elevation, its derivatives and forest cover data as input, a neural network was constructed for the classification of 27 land-system classes at Duck Mountain, Manitoba, Canada. In this study, we report some efforts made towards the characterization of ecological land- system classes. In particular, we briefly introduce the neural network algorithm used, the data preparation method and some initial training and test results.

Keywords: ecological classification, neural network

Introduction

A land system is a unit of land that is mappable at 1:50,000 and distinguishable based on surface form, materials and hydrology (Pedocan Land Evaluation Ltd., 1988). Classifying an area into various ecological land systems is usually done using airphoto interpretation and ground observations. It is time-consuming and requires a great amount of expert knowledge to derive land system classes based on data from multisources such as terrain and land cover. Efforts have therefore been made to improve the efficiency of land classification using computer-based digital analysis techniques. For example, forest ecosystem classification has been attempted using a knowledge-based approach (Mulder and Corns, 1993). This technique has been applied to Duck Mountain, Manitoba, in the Naia Manitoba project. In that project, expert knowledge must be explicitly acquired and represented in a knowledge base. However, not only is expert knowledge acquisition time-consuming, but the computer representation of expert knowledge is also difficult because expert knowledge is often ambiguous and imprecise.

Artificial neural network technology offers an alternative to constructing a computer system for ecological land systems classification. In such a system, only a set of example data containing the input data and the output classes determined by experts is required (Chen *et al.*, 1993). Expert knowledge does not need to be explicitly acquired. With the learning and adaptive capability of a neural network algorithm, empirical relations between land systems classes and input data from multisources can be automatically established. It is then possible to use these relations to conduct land systems classification of areas with similar input to the example data set. Empirical relations themselves can be used for constructing a basis for expert knowledge. They can also be examined for constructing expert knowledge basis. Therefore, neural networks may be used either as a stand alone tool for land systems classification or a complementary tool for knowledge acquisition when expert knowledge is ambiguous and structurally unclear.

The general objectives of this project are: (i) to characterize empirical relationships between land systems classes and spatial data from multisources using neural network technology; and (ii) to test the feasibility of neural networks for the purpose of land systems classification. In this paper, we present the progress achieved so far towards these goals. We emphasize the neural network design, data preparation, and present some preliminary results.

Neural networks

The process of classification and pattern recognition involves use of a set of discriminant variables, called features, and a list of classes or patterns. Discriminant analyses are employed to partition the feature space and associate each partitioned portion to a specific class or pattern. In natural resource assessment and planning, commonly used discriminant analysis methods are linear discriminant analysis and minimum Euclidian-distance classification (MED) (Wang, 1980; Liu and Burrough, 1986). Recently, artificial neural network (ANN) techniques have received a large amount of research attention in the field of classification and pattern recognition (Pao, 1989; Benediktsson, *et al.*, 1990, Yin and Xu, 1992).

A three-layer back-propagation neural net model is shown in Figure 1. Each neuron, called a node, is represented by a circle. Two nodes between successive layers are interconnected by an arrow and a weight is associated

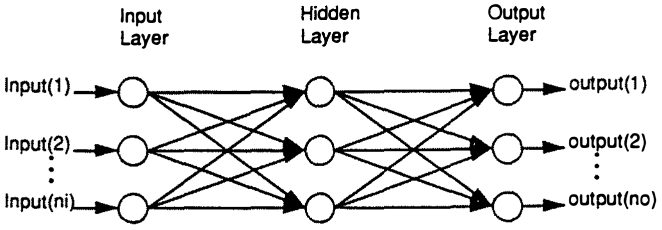

Figure 1: *The structure of a back-propagation neural network model.*

with each interconnection. In this system architecture, each input node accepts a single value. Each node generates an output value. Except the nodes on the output layer, the output from a node is used as the input for all nodes in the next layer.

For ecological land classification, forest cover types, crown closure, and topographic parameters such as slope, aspect and elevation, are input to the network. All the input data are treated in parallel by each neuron of the subsequent layer. For each neuron of the hidden layer a set of weights is determined with each weight corresponding to a neuron of the input layer. Therefore, a weighted sum can be obtained for each neuron of the hidden layer. The output of each neuron on the hidden layer is determined by a non-linear function of the weighted sum as long as the function is continuous and possesses a derivative at all points. The same type of input- output relationship is established between the hidden layer and the output layer. On the output layer, each neuron corresponding to an ecological land class generates a value ranging from 0 to 1 for that class. The greater the output value the greater is the possibility of an input set of data belonging to that ecological land class.

Training the neural network

The most critical step in the use of a neural network is how to set up the net. This involves determining the number of layers, the number of nodes on the hidden layer, the weights and thresholds associated with each node. There can be more than one hidden layer, but one is usually sufficient for characterizing any complicated pattern (Lippmann, 1987). On the other hand, difficult learning tasks can sometimes be simplified by increasing the number of internal layers. The number of nodes on the input layer is the number of input parameters while the number of the nodes on the output layer is the number of classes. The number of nodes on the hidden layer is usually determined empirically.

The neural network uses expert knowledge indirectly. The classification results carried out by experts can be used to train the network such that expert knowledge is implicitly encoded in the net through weights and thresholds. This process is called supervised training. In the training phase, each set of input data and the output class with a desired value (a number close to 1) determined by the experts are presented to the neural network. The net adjusts the weights and thresholds in the net according to the pattern presented using a back-propagation algorithm, an iterative gradient algorithm designed to minimize the mean square error between the actual output and the predetermined (or desired) output values. After all the input data and the output values are presented to the net, a new iteration is initiated and the iteration process is terminated until either the number of iterations is reached or the mean square error is below a preset small value (e.g., 0.01). With either termination scheme, the training results are preserved through writing the weights and thresholds into two files. Training can be continued by loading back the weight and threshold files. During the training, the convergence rate is controlled by two parameters: a gain factor and a momentum coefficient.

After the training process, a set of final weights and thresholds for each node in the hidden layer and the output layer will be obtained. With each set of input features, a feed-forward calculation can then be used to obtain the final output values for all nodes each of which corresponds to a specific ecological land class. Details about the back-propagation algorithm are found in Rumelhart, *et al.* (1986), Eberhart and Dobbins (1990), or Pao (1989).

Study site and data preparation

The study site for this project is located partly inside and partly outside the Duck Mountain Provincial Forest, Manitoba, Canada. Ecological land classification of the same area was conducted using airphoto analysis and ground truthing by Pedocan Land Evaluation Ltd. (1988) under a land system mapping project. Twenty seven ecological land systems classes were mapped (Table 1). There exist a large tract of farmland and some water bodies on the map which were excluded from the classification in this study. A portion (< 10%) of the Pedocan classification map in digital form was used as expert classification results. Two digital data sources, a digital elevation model (DEM) and a forest cover map were available as input. The DEM was digitized based on contour lines of 50 feet interval from 1:50,000 scale National Topographic Series topographic maps. The DEM, forest map, and the land classification map of the Duck Mountain study area were provided by the Manitoba District Office, Canadian Forest Service in Arc/Info data format.

Within Arc/Info, elevation unit was converted from feet to meters for the DEM. The contour lines were then interpolated into 50-meter interval since an interval of 50 feet is too detailed for subsequent analysis. Triangular Irregular Network (TIN) was established based on the interpolated DEM. From the TIN, the slope and aspect information were created for each triangle. The slope has been classified into 10 classes which correspond to 0°, 0° - 1°, 1° - 3°, 3° - 5°, 5° - 7°, 7° - 9°, 9° - 11°, 11° - 15°, 15° -20°, 20° - 25°, respectively. Less than 80 polygons have slopes steeper than 25°. They were set to the last slope class. The average for each slope range was taken as the slope for a particular polygon. The aspect has been categorized into northeast (NE), southeast (SE), southwest (SW), northwest (NW), and flat (FL). The DEM was converted into one Arc/Info coverage in order for the elevation data to be combined with other information. An overlay procedure was made to combine the elevation, slope, aspect, forest cover, and the ecological land classification map. This resulted in one polygon layer and one table summarizing all the attribute information. The table was then exported into an ASCII file containing all the attribute information indexed by a polygon ID number in the overlaid layer (Table 2). The total number of polygons resulted from the overlay was 36107.

Table 2 illustrates the ASCII file structure for the overlaid layer using some real example data. For each polygon in the overlaid layer, a list of variables were exported including Elevation, Slope and Aspect, 3 tree species (Sp1, Sp2, and Sp3) and their corresponding percentage crown closures (P1, P2 and P3), a 5-digit type aggregate (Cover), and the expert derived ecological land system class (Land System). The first column in the table is the polygon ID number. It can be used as a reference for importing the classification results back to the Arc/Info format. The elevation is in meters ranging from 400 - 850 m. Slope is in degrees as mentioned above. For each polygon there are at most three tree species. They are dominant species in a forest stand recorded with their crown closures in the original forest cover maps. Nine tree species in Duck Mountain area are found as dominant species in various forest stands (Table 3). The 5 digits in Cover represent the cover type, subtype, site, cutting class and crown closure of a polygon area, respectively (Manitoba Forestry Branch, undated).

In this study, the idea was to use the Land System as the output for training and validating a network while the rest of the variables as input to the net. However, the Arc/Info export file cannot be used directly by the neural network program. Some preprocessing of these data was made.

Encoding the input and output parameters for use of neural network

A neural net works better if data with a range between 0 and 1 are used. This requires that some of the numerical data (e.g., Elevation in Table 2) be normalized while the thematic data such as aspect be encoded in a numerical range between 0 and 1. During the training process of the neural network, each node on the output layer has to have a value. This can be done by assigning 1 to the node corresponding to the land class and 0s to the rest of the nodes. Because it is harder for a neural net to learn to generate binary outputs, we replaced 1 by a decimal number close to 1, say 0.99,and assigned the rest of the nodes with a small positive number close to 0.

For the input layer, we represented the aspect using 4 nodes (Table 4). As can be seen from Table 4, the encoding method allows more aspects such as N, E, S, and W to be represented. The slopes were represented by their average degrees and normalized to the range between 0 and 1. The elevation was directly normalized to range from 0 to 1. For the forest cover, instead of using the six parameters on species and percentages directly, we represented all the 9 species by 9 separate nodes on the input layer. The percentage of each species in a polygon was used as the input value to its corre-

Table 1: *The Ecological Land Systems Classification scheme.*

General Class	Subclass Code	No. of Training Samples	Accuracy %	No. of Testing Samples	Accuracy %
Morainal	M1	107	61.7	1425	33.7
Morainal-Lacustrine	ML1	98	31.6	5012	9.6
	ML2	97	41.2	2281	13.6
	ML3	92	64.1	794	40.3
Lacustrine-Morainal	LM1	105	55.2	695	29.9
	LM2	100	50.0	828	25.6
	LM3	104	44.2	1075	25.3
Stream Channels	SA	104	43.3	1931	26.4
	SB	104	33.3	2823	8.9
	SI	118	48.3	3472	22.6
Glaciofluvial Ridged Outwash & Beaches	FR1	94	54.3	443	26.1
	FR2	115	77.4	372	63.7
	FB1	109	52.3	690	33.4
	FB2	89	65.2	264	56.4
Fluvial Fans	F1	85	62.3	2185	21.5
	F2	102	68.6	655	43.2
	F3	84	53.6	533	30.9
Bogs	B1	97	46.4	990	17.9
	B2	102	64.7	632	41.7
	B3	86	38.4	913	12.9
	B4	104	55.8	223	39.9
Fluvial-Duned	FD1	142	63.4	142	63.4
	FD2	90	52.2	215	48.3
Fluvial Morainal	FM1	98	30.6	4324	13.3
	FM2	128	57.0	561	38.5
	FM3	103	56.3	1981	41.2
	FM4	83	56.7	648	28.0

Table 2: *Information structure of the Arc/Info export data.*

INPUT											OUTPUT
ID	Aspect	Elevation	Slope	Sp1	P1	Sp2	P2	Sp3	P3	Cover	Land System
217	FL	450	.00	BS	70	TL	20	TA	10	16133	B4
1335	NE	450	.50		0		0		0	44200	FB1
1520	NE	450	.50	BS	40	JP	30	TA	20	14134	FR2
1542	FL	450	.00	BS	40	JP	30	TA	20	14134	FR1

Table 3: *Major forest species in the Duck Mountain study site.*

Species	Code
Black Spruce	BS
White Spruce	WS
Jack Pine	JP
Balsam Fir	BF
Balsam Poplar	BA
Trembling Aspen	TA
Tamarack Larch	TL
Willow	W
White Birch	WB

Table 4: *Encoding the aspects.*

	N	E	S	W
NE	1	1	0	0
SE	0	1	1	0
SW	0	0	1	1
NW	1	0	0	1
FL	0	0	0	0

sponding node. Since there are only three species determined for each polygon, a maximum of three of these nodes will have non- zero values each time. For the site aggregate, the 5 digits were split and assigned to five nodes. All the values corresponding to each node were then normalized. As a result, we had a total of 20 nodes on the input layer. Since there were 27 ecological land systems classes (Pedocan Land Evaluation Ltd., 1988), we had 27 nodes on the output layer.

Some preliminary results

From the total of 36 107 polygon records, 2 740 samples were selected randomly from each ecological land systems class. These 2 740 samples were randomly mixed to form the training samples. A single hidden layer was used. Two nets were constructed with 60 and 100 nodes on their hidden layers, respectively. The weights and thresholds were randomly selected at the beginning of the training of each net. A net was set to terminate when the mean square error became less than 0.01. At every 100th iteration, the mean square errors were calculated for the 2 740 training samples and all 3 6107 samples for testing purposes. For each net, two confusion matrices with 27 X 27 elements were calculated for every 1000 iterations. The two nets are being tested on a SUN Sparc -10 workstation. The net with 100 nodes on the hidden layer converges faster than that with 60-node hidden layer (measured by the mean square errors). Figure 2 shows the error patterns for the training and testing samples we have achieved so far. The convergence rates have been

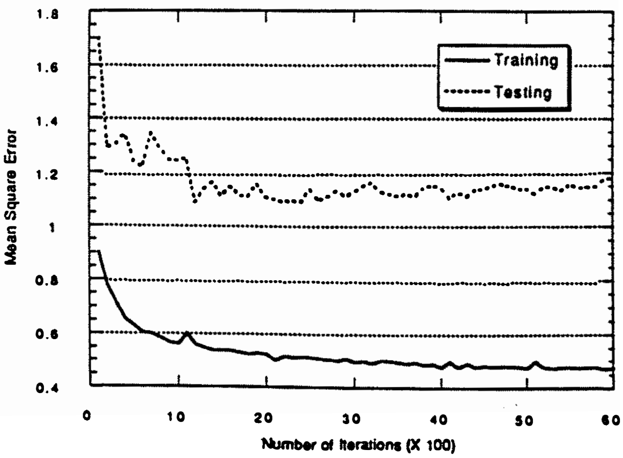

Figure 2: *The training and testing errors obtained by a net with a single hidden layer of 100 nodes.*

very slow after 2 000 iterations. Our previous experiences with other applications such as geological mapping indicated that when mean square errors for training and testing samples were smaller than 0.2, greater than 80% classification accuracies were achievable. As can be seen from Figure 2, the level of errors are greater than 0.4, much larger than the desired error level of 0.01, indicating further training is needed.

After 6 000 times of iteration, the classification accuracies achieved by the net with a 100-node hidden layer were still very poor (Table 1). For the training samples, the accuracy for each individual class varied from 31.6% (ML1) to 77.4% (FR2). The second and third highest accuracies were 68.6% for class F2 and 65.2% for B2. When the entire data set was used as the testing samples, the accuracy of an individual class ranged between 8.9% (SB) and 63.7% (FR2). The second and third highest accuracies were 63.4% (FD1) and 56.4% (FB2). It should be noted that class FD1 is rather small (see Table 1). Therefore, all samples in the class were used in both training and testing.

The training of the neural network requires a tremendous amount of computation. From Figure 2, it seems that the convergence (to approach a smaller mean square error) is difficult to achieve with this particular neural network. We are currently continuing the test.

Ongoing work

To improve the convergence rate and reduce the mean square errors of the neural network for this particular ecological land systems classification problem, four approaches may be considered:

i) weighting each of the input variables. Some variables may have less contribution than others in the classification of land systems;

ii) dropping some input variables with little contribution towards the classification;

iii) adding new variables such as soil data, remote sensing data, etc.

iv) changing the network structure such as increasing the number of hidden layers, increasing the number of nodes on the hidden layer(s) and/or adjusting the gaining factor and momentum coefficient.

For this project, no additional source of information is available. Therefore, strategy 3 cannot be tested. Further analysis of the input data and the level of detail of the classification scheme will be made. It is possible that the amount of information inherent in the available data simply does not support the large number of classes at a sufficiently high level of accuracy. For strategies 1 and 2, some procedures are needed to assess the contribution level for each input variable. We are currently testing a measure called mutual information from information theory for assessing the weight of input variables.

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References

Benediktsson, J.A., P.H. Swain, O.K. Ersoy, 1990. Neural network approaches versus statistical methods in classification of multisource remote sensing data. IEEE Transactions on Geoscience and Remote Sensing. 28(4):540-552.

Chen, J., P. Gong, J. Nie, and J.A.R. Blais, 1993. Application of neural networks in forest ecological classification. ASPRS Technical Papers, Annual Convention of ACSM/ASPRS, New Orleans, Louisiana, February, 1993. Vol. 3, pp.65-71.

Eberhart, R. C., and R. W. Dobbins, ed., 1990. Neural Network PC Tools, A Practical Guide. Toronto:Academic Press, Inc., pp.35-49.

Lippmann, R.P., 1987. An introduction to computing with neural nets. IEEE ASSP Magazine, 4-24.

Liu, C. and P.A. Burrough, 1987. Fuzzy reasoning: a new quantitative aid for land evaluation. Soil Survey and Land Evaluation. 17(2):69- 80.

Manitoba Forestry Branch, undated. Guide for Use of Forest Inventory Maps. Forest Inventory, Forestry Branch, Department of Natural Resources, Province of Manitoba. 21p.

Mulder, J.A., and I.G.W. Corns, 1993. A decision support system for predicting and consolidating ecosystems from existing map data. Proceedings of GIS'93. Vancouver, B.C., Feb. 1993. pp. 153-159.

Pao, 1989. Adaptive Pattern Recognition and Neural Networks. Addison-Wesley:New York.

Pedocan Land Evaluation Ltd. (Edmonton), 1988. Forest ecosystem classification and land system mapping pilot project Duck Mountain, Manitoba, Canadian Forestry Services, Manitoba District Office, Winnipeg, Manitoba, 129p.

Rumelhart, D.E., G.E. Hinton, and R.J. Williams, 1987. Learning internal representations by error propagation. In Parallel Distributed Processing - Explorations in the Microstructure of Cognition, Vol. 1: Eds. by Rumelhart, J.L. McClelland, and PDP Research Group. The MIT Press:Massachusetts. pp.318-362.

Wang, P., 1980. Fuzzy set theory and its applications. Shanghai Science and Technology Press: Shanghai.

Yin, Y., and X. Xu, 1991. Applying neural net technology for multi- objective land use planning. Journal of Environmental Management, 32:349-356.

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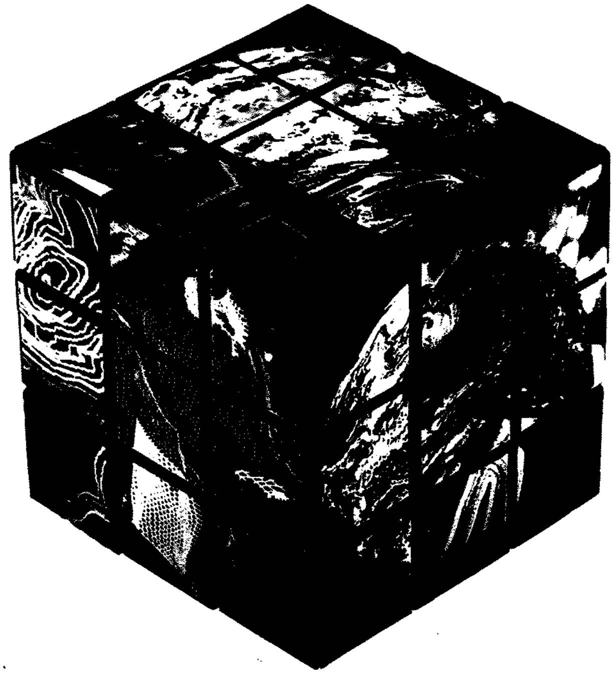

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