CLASSIFICATION OF SPATIAL DATA USING A HYBRID NEURAL NETWORK-EXPERT SYSTEM

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ABSTRACT

A hybrid neural network/expert system has been developed to map land cover such as forest soil or vegetation overstorey from digital spatial data (that may include remotely sensed imagery, elevation data, and terrain features derived from the elevation data). The method is different because the hybrid system exhibits the inherent advantages of both neural network and expert system models. Firstly, the hybrid system may acquire (or learn) geographic and forest management knowledge from the spatial data, using homogeneous training areas. Secondly, it is possible to record and interrogate "experience" using a knowledge base linked to the neural network, and to use the knowledge to assist in the classification of land cover. The expert system and neural network components of the hybrid system operate as a fully integrated system; in other words, the expert system does not simply process the output of the neural network.

Key words: Artificial Intelligence, Expert Systems, Neural Networks, Renewable Resources, Classification

INTRODUCTION

Expert systems have been devised to perform various functions with respect to digital spatial data including predicting fire behaviour in the Northern Territory of Australia (Davis and Nanninga, 1985; Davis et al., 1986); the identification of objects from remotely sensed digital data (such as training areas [Goodenough et al., 1987]); interpreting airports from (digital) maps and aerial photographs (McKeown, 1987); planning helicopter routes (Garvey, 1987); updating forestry maps by using remotely sensed data for change detection (Goldberg et al., 1985); dispatch of forest fire control resources (Kourtz, 1987); selection and scheduling of cultural practices in forests (Rauscher and Cooney, 1987); and aiding forest managers by linking rules about aspen silviculture and management (White and Morse, 1987). Gray and Stokoe (1988) and Robinson and Frank (1987) provide summaries of other expert systems that have been applied to environmental assessment and management problems. Forsyth (1984) discussed general concepts in Bayesian (statistical) updating of probabilities. Lee *et al.* (1987) combined the two visible Landsat MSS bands with the two MSS infrared bands using Bayesian updating. They obtained similar results by using evidential calculus (Shafer, 1979). Expert systems have been developed to integrate knowledge with remotely sensed and digital terrain model data, and have been shown to improve mapping accuracy compared with using remotely sensed data alone (Skidmore, 1989a).

There are a number of problems with using expert systems for analysing spatial data. Firstly, expert systems have limitations when learning knowledge (ie. inducing rules) (Forsyth, 1989, page 197-221). In addition, the rules may be correlated and therefore contravene the assumption of independence in the inferencing engine (Skidmore, 1989a). If rules are missing or incorrect, or the set of independent variables (eg. GIS data layers) are incomplete, derived maps and images may be erroneous (Skidmore, 1989a).

An alternative method is neural networking. Limited work has been undertaken in applying this technology to spatial data. Hepner *et al.* (1990) claimed promising results by using a neural network to train remotely sensed data, and then inverting the model to classify unknown image pixels.

Critics of neural networks have identified problems with the technology. Neural networks do not use structured representations of knowledge. In other words, there is no explicit consideration of formal semantics and logic in the network model (Davis, 1980). In contrast to expert systems, the knowledge is not incorporated into the networks as rules. Another criticism of the neural network approach is that constants are often used to weight connections, with some researchers asserting that these constants represent 'fudge factors' (Pinker and Prince, 1988).

Forsyth (1989) states that '...connectionist (neural networks) techniques will prove to be better for some tasks (perception) while symbolist techniques (expert systems) will prove superior for other tasks (mostly intellectual)'. In this study, these two, as yet disparate, techniques have been combined into a single hybrid system for the analysis of digital spatial data and the storage of knowledge. The proposed method is examined using the soil landscape unit data set, obtained from an area of native eucalypt forest in south east Australia (Skidmore *et al.*, 1991).

METHODS

Database construction

Certain data sets are readily available over forested regions of Australia. For example, forest overstorey vegetation types may be classified from remotely sensed data (Skidmore and Turner, 1988), while terrain parameters such as gradient, topographic position and aspect may be derived from digital elevation models (DEMs) (Skidmore, 1989b and 1990). A raster data base comprising soil wetness, gradient and vegetation overstorey may be generated from these sources. In turn, these data sets may be used to predict the occurrence of forest resource parameters; in this case forest soil landscape units.

Two main sources of information exist for predicting the occurrence of forest soils. One is prior expert knowledge of the occurrence of the forest soils, as used by Skidmore *et al.* (1991). For example, it is known that the Residual Crest (RC) soil landscape unit occurs on dry ridges. A second source of information are "training areas"; in other words, homogeneous areas of soil may be identified in the field or on aerial photographs. (Note that when delineating training areas, an analyst will usually have no understanding of the underlying ecological relationships between the class being mapped and environmental parameters such as aspect or gradient). In this study, both sources of knowledge are used to assist in classifying the correct soil landscape units.

Outline of method

In the first phase of the classification process, a neural network is constructed to classify the forest soil landscape units, based on training area data available to the analyst. In this phase, the classification process "learns" about the ecological position of forest soils, based on the training areas supplied by the analyst. Any unknown grid cells are then classified by the neural network. If there is an unambiguous solution (ie. only one soil landscape unit may represent the cell), then the process steps to the next cell to be classified. However, if more than one soil landscape unit exists at the grid cell, then the algorithm turns to the knowledge base created from the knowledge of human expert(s).

A convenient method for formally storing expert knowledge is in a prior probability table (eg. Skidmore *et al.*, 1991). The proposed algorithm uses a modified neural network learning rule, based on the *Widrow-Hoff rule* or *delta rule* (Sutton and Barto, 1981; Rumelhart and McClelland, 1986), to access the knowledge base. The learning rule is used to decide which of the possible soil landscape units, identified during the previous processing stage, should best represent the cell.

Detailed methodology

The neural network is based on a modified delta rule (also known as the Widrow-Hoff rule) (Sutton and Barto, 1981). In this implementation of the delta rule, homogeneous areas are

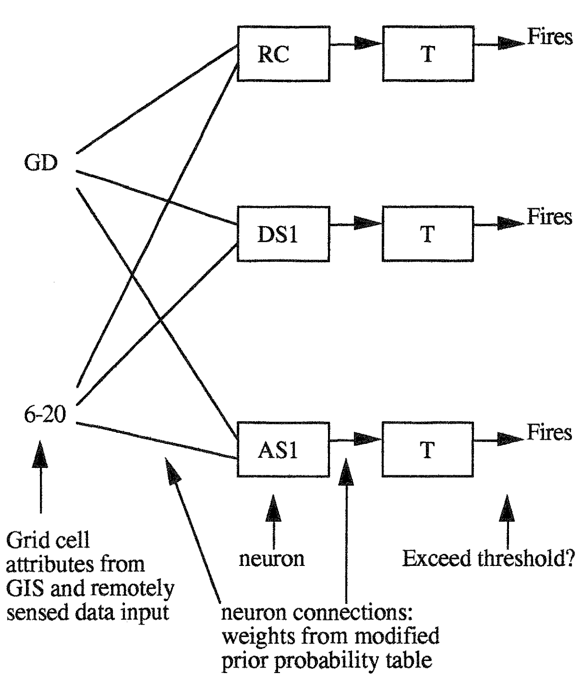

Figure 1: Diagram showing the structure of the hybrid model

delineated by the analyst and provide training area data that link the environmental attributes in the raster GIS, to the soil landscape units. For example, a typical grid cell is shown in Figure 1. There are two environmental attributes which describe this cell *viz.* GD (ie. a Gully which is Dry) and 6-20 (ie. gradient is between 6° and 20°). (Note that another grid cell may have different attributes). Assume that the grid cell may be described as one of the following soil landscape unit classes *viz.* RC (ie. Residual Crest), DS1 (ie. Degrading Slope 1) or AS1 (ie. Aggrading Slope 1).

There are four possible conditions for the cell attributes *viz.* 'GD' and '6-20' both occur, 'GD' occurs, '6-20' occurs, or neither attribute occurs. Let '1' represent that an attribute occurs over the cell, whilst '0' represents that an attribute does not occur. If the training area information indicates that a soil class (eg. RC) exists when GD and 6-20 occur over the cell, then indicate that a 'neuron' will fire. This is stated formally in Table 1.

Table 1: Cell attribute conditions that cause a neuron to fire, thereby indicating that soil class RC exists.

GD	1	1	0	0
6-20	1	0	1	0
Fires?	1	1	1	0

Now, assume that the neuron fires only if a threshold 'T' is exceeded. For example, the 'GD' and '6-20' attributes occur together as in column 1 of Table 1, and cause the neuron to fire because the threshold 'T' is exceeded. Also assume that the attributes 'GD' and '6-20' which connect to the neuron have some weight W_i. For example, if the threshold T = 0.6, then the combined weight of the GD and 6-20 attributes must be greater than 0.6, in order for the neuron to fire. It therefore follows that Table 1 may be re-expressed as a series of inequalities, as shown below in Table 2.

Table 2: Series of inequalities expressing whether the neuron will fire, based on the weight of the attributes connected to the neuron

$$
\begin{array}{ll}
W_1 + W_2 & > T \\
W_1 & > T \\
W_2 & > T \\
0 & > T
\end{array}
$$

From the inequalities, it can be seen that T is negative. It can also be seen that if W_1 and W_2 are negative, then T will correlate with W_1 and W_2. In other words, as W1 or W2 becomes smaller, the value of T will also decrease. Stated formally,

Let W_1 and $W_2 < 0$.
Note that $T < 0$.
Therefore, as $W_1 \text{---> } -1, T < W_1$;
as $W_2 \text{---> } -1, T < W_2$;
as $W_1 + W_2 \text{---> } -1, T < W_1 + W_2$.
Therefore as $W_1, W_2 \text{---> } -1$;
$T \text{---> } < W_1, W_2$

To ensure that this relationship is true, the weights W_1 and W_2 should be expressed in a negative range; that is, W_1 and W_2 should range between -1 and 0. The initial weights for 'GD' and '6-20' may be derived from a modification of the expert knowledge prior probability table, as developed by Skidmore (1989a).

The prior probability table contains the probability that a soil landscape unit occurs, given an environmental condition. For example, the probability that the Residual Crest soil landscape unit occurs on a dry gully is 0.3. It is easy to re-express this probability value to range between -1 and 0, ie. -1 + 0.3 yields -0.7. All initial weights provided by the expert system prior probability table are similarly re-expressed to range between -1 and 0.

For each of the three soil types being considered here (ie. RC, DS1 and AS1), the delta rule is used to train a neuron, and a threshold T is calculated. The algorithm used follows the Widrow-Hoff rule, as outlined by Sutton and Barto (1981). Firstly, the reinforcement signal is calculated, which is the signal that determines the change in the connection weights between neurones:

$$r_i(t) = [z(t) - y(t)]\, x_i(t)$$

where z(t) is a specialised signal which is used to converge the weights towards the desired solution, and $x_i(t)$ is the stimulus pattern of synapse i at time t, for i = 1,...,n synapses. Note that $y(t) = \sum\{w_i(t)x_i(t)\}$, summed over i = 1,...,n synapses. A synaptic weight increases or decreases in proportion to the reinforcement signal $r_i(t)$:

$$w_i(t+1) = w_i(t) + cr_i(t),$$

where c = positive learning rate constant, and $w_i(t)$ = weight of synapse i at time t. It is this weight which determines whether a neuron fires

The most likely soil type to represent a cell is determined by the neuron with the highest threshold. In other words, the neuron with the highest T, which fires in response to the input GIS data cell, is chosen to represent the cell.

It is possible to deduce from the first column of Table (1) that the following sentence is true:

RC occurs on GD and RC occurs on 6-20

The 'rule of elimination' in formal logic (Graham, 1989, page 63) allows us to infer that both of the following sentences are also true:

RC occurs on GD
RC occurs on 6-20

Thus, where only one of the cell attributes (such as GD) are present in Table 1, RC will also occur (that is the neuron will fire). The rule of *modus tollens* allows us to conclude that if GD and 6-20 do not occur, RC is not present (Graham, 1989, page 64). In this case the neuron will not fire, as shown in column 4 of Table 1.

EXAMPLE

A simple worked example follows. Assume there are three layers in a GIS comprising remotely sensed data, gradient and combined topographic position-soil wetness. In addition, it is assumed that there are three soil landscape units to be classified by the hybrid neural network-expert system *viz.* residual crest, degrading soil and aggrading soil. If each neuron calculates the threshold for a soil-landscape unit, then there will be three neurones (one for each soil-landscape unit), with each neuron having 2^3 (ie. 8) possible combinations of GIS layer values.

A typical neuron being trained from a homogeneous field training area is shown in Figure 1 for two attributes. In this example, three attributes connect to the neuron from the GIS grid cell *viz.* DG (dry gully), 6-20 (gradient of 6-20 degrees) and STA (ie. the remotely sensed data is classified to vegetation type silvertop ash). The eight possible combinations of cell attributes are shown in Table 3. Associated with the attributes is information about whether the neuron fires (or does not fire) for the RC, DS1 and AS1 soil types. This information is obtained from the training areas. For example, consider the first column in Table 3a below. A cell may occur over a dry gully, with a gradient of less than 6 degrees, and an overstorey of STA. Using training area information, it is known that the cell contains the RC soil type. Thus the column indicates that where GD, 6-20 and STA are present (indicated by a '1'), RC is also known to occur, and therefore the neuron will fire (also indicated by a '1'). The above argument holds for DS1 and AS1 soil types (see Tables (3b) ad (3c)).

Table 3(a): Cell attributes causing the neuron to fire, thereby indicating soil class RC exists.

RC								
GD	1	1	1	0	0	0	1	0
6-20	1	1	0	1	0	1	0	0
STA	1	0	0	1	1	0	1	0
Fires?	1	1	1	1	1	1	1	0

Table 3(b): Cell attributes causing the neuron to fire, thereby indicating soil class DS1 exists.

DS1								
GD	1	1	1	0	0	0	1	0
6-20	1	1	0	1	0	1	0	0
STA	1	0	0	1	1	0	1	0
Fires?	1	1	1	1	1	1	1	0

Table 3(c): Cell attributes causing the neuron to fire, thereby indicating soil class AS1 exists.

AS1								
GD	1	1	1	0	0	0	1	0
6-20	1	1	0	1	0	1	0	0
STA	1	0	0	1	1	0	1	0
Fires?	1	1	1	1	1	1	1	0

As explained above, a set of inequalities may be generated to describe the behaviour of each neuron. Thus for RC, the set of inequalities are:

$$
\begin{array}{lllll}
W_1 + & W_2 + & W_3 & > & T \\
W_1 + & W_2 & & > & T \\
W_1 & & & > & T \\
 & W_2 + & W_3 & > & T \\
 & & W_3 & > & T \\
 & W_2 & & > & T \\
W_1 & + & W_3 & > & T \\
 & & 0 & > & T
\end{array}
$$

The weights to be applied to each neuron synapse are obtained from the expert system probability matrix (Skidmore *et al.*, 1991), which are then re-expressed into the range -1 ---> 0 (Table 4).

Table 4: Prior probability of an environmental variable occurring given a soil landscape unit.

Environmental variable	Soil Landscape Unit RC	DS1	AS1
STA	-0.5	-0.5	-0.3
6-20	-0.7	-0.4	-0.5
GD	-0.7	-0.5	-0.4

These values were input to neurones of a neural network and the following results obtained:

Table 4: Threshold values for each soil landscape unit

Soil landscape unit	Threshold
RC	-1.47
DS1	-0.94
AS1	-0.76

The highest threshold value becomes the cover class which represents the cell; in this case soil landscape unit AS1. An alternative approach to decide the cover type to represent the cell, is to sum the threshold outputs listed in Table 4, and to distinguish between the cover types based on a majority function, using the concept of the perceptron (Hubel and Wiesel, 1962).

If only one cover type exists over the particular combination of cell attributes being considered, then there is no need to test for the most likely cover type using the neural network.

DISCUSSION

The hybrid neural network/expert system has advantages inherited from both models. Firstly, it is possible to input training areas to the hybrid system via the neural network component. The training areas are relatively homogeneous regions representative of a land cover type (such as a soil landscape unit). The neural network uses this information to automatically associate cover types with particular combinations of cell attributes. This process is equivalent to an aerial photograph interpreter learning features on an aerial photograph by association with known ground cover types.

The second advantage of the hybrid approach is an ability to formalise prior knowledge about the cover types, and to incorporate this knowledge into the classification process. In other words, an analyst may know that a particular soil landscape unit has a high possibility of occurring on a specific environmental position (eg. RC occurs on dry ridges). This a priori knowledge may be 'hardwired' into the probability matrix, and used to decide the most likely class to represent the cell.

In this paper, a simple soil landscape mapping exercise has been cited, using three cell attributes. Clearly it would be possible to generalise the hybrid system, by using many cell attributes and mapping many classes.

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