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INTEGRATION NEURAL NETWORKS AND GIS IN MODELING LANDSCAPE CHANGES

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ABSTRACT

Geographical information system is very powerful tool to manage and analyses land use data. The integration of Geographic Information Systems and Artificial Neural Networks offers a mechanism to lower the cost of analysis of landscape change by reducing the amount of time spent interpreting data. Artificial Neural Networks (ANNs) have been proven to be useful in the interpretation of natural resource information. Back-Propagation Neural Networks are one of the most common and widely used architectures. Many architectures and types of ANNs have been developed, and many of them are PC-based. Change prediction is based on the analysis of the Markov chain. This process determines the condition of the system on the basis of its previous condition and likelihood of changes which have occurred between them. Models of change serve as useful tools for exploring the various mechanisms by which land use change occurs actual projecting and potential future environmental and evaluating the impact.

Keywords: Land use change, Artificial neural networks, Geographic information systems

INTRODUCTION

Changes in land use result from the complex interaction of many factors including policy, management, economics, culture, human behaviour, and the environment [5], [11]. An understanding of how land use changes occur is critical since these anthropogenic processes can have broad impacts on the environment, altering hydrologic cycles and biogeochemical dynamics [15], size and arrangements of natural habitats such as forests [5] and species diversity [4]. Changes to land use can also effect local and regional economies [3]. Geographic information system (GIS) is a powerful tool for working with the landscape data and modelling.

ANNs are powerful tools that use a machine learning approach to quantify and model complex behaviour and patterns. ANNs are used for pattern recognition in a variety of disciplines, such as landscape classification [11], image analysis and pattern classification [13], climate forecasting [6], mechanical engineering and remote sensing [1]. The use of neural networks has increased substantially over the last several years because of the advances in computing performance [14] and the increased availability of powerful and flexible ANN software.

ARTIFICIAL NEURAL NETWORKS

An artificial neural network (ANN) is a computational model based on the behaviour of neural networks of living organisms [9]. An artificial neural network differs from other forms of computer intelligence in that it is not rule- based, as in an expert system. An ANN is trained to recognize and generalize the relationship between a set of inputs and outputs.

Early artificial neural networks were inspired by perceptions of how the human brain operates. In recent years the developments in ANN technology have made it more of an applied mathematical technique that has some similarities to the human brain. Artificial neural networks retain as primary features two characteristics of the brain: the ability to „learn“ and to generalize from limited information [10].

Neural Networks, both biological and artificial, employ massive, interconnected simple processing elements, or neurons. Simplified, it functions as follows: each neuron consists of the body, dendrites, and an axon – a long dendrite connecting the other neurons. The axon uses synapses to attach itself to another neuron and sends out signals to the other neuron. Each neuron receives signals from more neurons. Once the complete signal (of all the neurons) exceeds a certain limit, the neuron becomes active and begins to send out a signal. The composition of artificial neural networks is similar to biological neuron (Fig. 1).

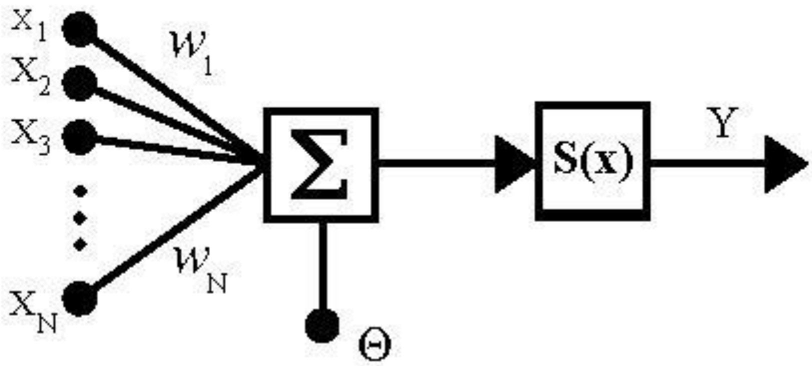

Fig. 1 Artificial neuron.

A neuron is acted upon by input signals X1, ..., Xn, each with a different weight W1, ..., Wn. The sum of weights Σ is compared with the threshold value Θ and this value is exceeded, the neuron is activated and sends the signal further on using the trigger function S(x) (or transfer function). There are more types of trigger functions. The simplest one is the leap function, the most commonly used one is the sigmoid function or the RBF (Radial Basis Function).

A neural network contains a number of neurons, which may be stored in one or more layers. Figure 2 shows a general scheme of a network with a set of inputs, one layer of neurons and a set of outputs. In artificial neural networks, the knowledge stored as the strength of the interconnection weights (a numeric parameter) is modified through a process called learning, using a learning algorithm. This algorithmic function, in conjunction with a learning rule, (i.e., back-propagation) is used to modify the weights in the network in an orderly fashion. The weights, with which the individual inputs act upon the neurons and the neurons act further upon the other layers of neurons, and the outputs, can be calculated using the iterative algorithm. The network is learning [14].

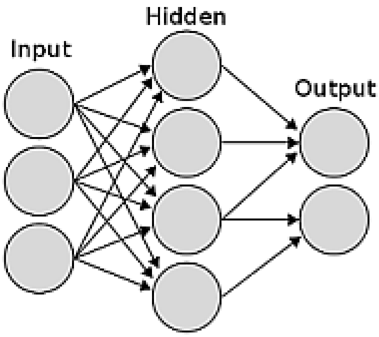

Fig. 2 Neural network with one hidden layer.

Unlike most computer applications, an ANN is not “programmed”, rather it is “taught” to give an acceptable answer to a particular problem. Input and output values are sent to the ANN, initial weights to the connections in the architecture of the ANN are assigned, and the ANN repeatedly adjusts those interconnection weights until the ANN can successfully produce output values that match the original values. This weighted matrix of interconnections allows the neural network to learn and remember [14].

The first step in utilizing an ANN to solve a problem is to train the ANN to “learn” the relationship between the input and outputs. This is accomplished by presenting the network with examples of known inputs and outputs, in conjunction with a learning rule. The ANN maps the relationship between the inputs and outputs and then modifies its internal functions to determine the best relationship that can be represented by the ANN.

The inner workings and processing of an ANN are often thought of as a “black box” with inputs and outputs. One useful analogy that helps in the understanding of the mechanism occurring inside the “black box” is to consider the neural network as a super-form of multiple regression [10]. Just as in linear regression, which finds the relationship such that {y} = f{x}, the neural network finds some function f{x} when trained. However, the neural network is not limited to linear functions. It finds its own best function as best it can, given the complexity used in the network, and without the constraint of linearity [10]. At first, the weights are random, the calculation is carried out and an analysis whether the network estimated a correct result follows. If this is not the case, the weights are modified until the correct result is achieved. This course of study is elaborated in detail in many resources.

BACK-PROPAGATION ARTIFICIAL NEURAL NETWORKS

The basic structure of an ANN, including the back-propagation ANN, consists of layers of neurons or processing elements. These layers are the input layer, output layer, and hidden layer. Hidden layers are so named because they have no connections external to the network. Generally, for most applications, one hidden layer is sufficient. More than one hidden layer greatly increases the amount of time required for training and testing without noticeable improvement in performance. While figure 2 shows a relatively simple neural network, increasingly more complex networks can be developed by employing more hidden layers and more intra-layer connections.

The input layer of a neural network presents the input data to the processing neurons of the network. Data patterns, which are created by the translation of data from vector to raster form and then to a 1-dimensional column vector, are simultaneously passed forward from the input layer to a processing layer. A pattern consists of the value for each input (if training the output is also needed) for a given location. The number of inputs depends on the type of problem to be solved. The input data can be either binary or continuous.

The hidden layers receive the data from the input layer. Each connection in the hidden layer has a weight, or strength, of connection associated with it. Each neuron of the input layer is connected to each neuron in the hidden layer. In the same fashion, each neuron of the hidden layer is connected to each neuron on the next layer. The next layer may be another hidden layer or the output layer. In a feed-forward type of network the data flow is from the input layer to the output layer, through the hidden layer or layers. In a back-propagation ANN the feed-forward pass is followed by a backward pass during which the interconnection weights between neurons are modified based on error values.

The output layer produces the final results of processing by the ANN. During the training phase, these output results are compared with the known output, error calculated and interconnection weights adjusted. After training is completed, the output layer produces the values that are returned to the GIS.

ARTIFICIAL NEURAL NETWORKS AND GIS

Geographical information system (GIS) is a technological field that incorporates geographical features with tabular data in order to map, analyse, and assess real-world problems. The key word to this technology is Geography – this means that the data (or at least some portion of the data) is spatial, in other words, data that is in some way referenced to locations on the earth. Coupled with this data is usually tabular data known as attribute data. Attribute data can be generally defined as additional information about each of the spatial features. An example of this would be schools. The actual location of the schools is the spatial data. Additional data such as the school name, level of education taught, student capacity would make up the attribute data. It is the partnership of these two data types that enables GIS to be such an effective problem solving tool through spatial analysis [2].

GIS operates on many levels. On the most basic level, GIS is used as computer cartography, i.e. mapping. The real power in GIS is through using spatial and statistical methods to analyse attribute and geographic information. The end result of the analysis can be derivative information, interpolated information or prioritized information [12].

LAND CHANGE MODELER (LCM)

The Land Change Modeler is revolutionary land cover change analysis and prediction software which also incorporates tools to analyse, measure and project the impacts on habitat and biodiversity [8]. Land Change Modeler includes a suite of intelligent tools that address the complexities of change analysis, resource management and habitat assessment while maintaining a simple and automated workflow. The LCM analyses the layers with the resulting: i) a text file containing a table with change likelihood, ii) a text file carrying the information of the number of cells (a table of area changes, which could change from one type to another for each type of overlay, iii) a raster containing the information about the likelihood of the occurrence of each type of surface on a given spot in a given time period. The Land Change Modeler interface includes five tabs. The Land Change Modeler is included within the IDRISI GIS and Image Processing software and is available as a software extension for use with ESRI's ArcGIS product, which is oriented to the pressing problem of accelerated land conversion and the very specific needs of biodiversity conservation [8].

ARTIFICIAL NEURAL NETWORKS IN LCM

IDRISI in its actual version uses three implementations of ANNs to its interface [8]:

Multi Layer Perceptron - one of the most commonly used models of neural networks and its structure corresponds with the one (fig. 3)4. There are several layers of neurons that serve as predictors of values in the output layer. The manner of learning is the so-called learning with a teacher, which means that the algorithm is learnt from training data. This algorithm has been successfully applied in IDRISI in the MLP module and it can be used for classification purposes, for example aerial photographs or satellite images of land use.

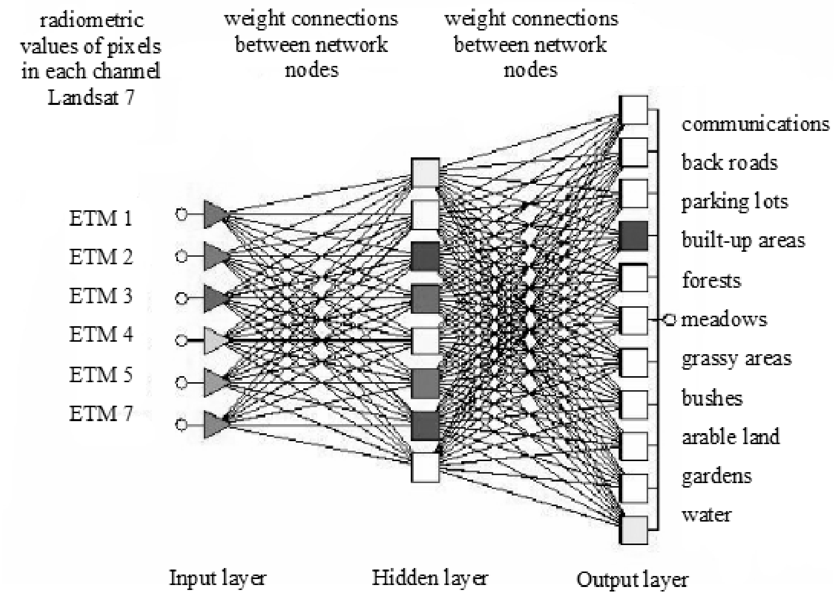

Fig. 3: MLP network for land use identification.

Fig. 3 shows a model network. The darker shade of red in the hidden layer identifies a higher weight of neurons per result. The resultant classification of the type of land use is accomplished based on the rule "the strongest takes it all" – the type of land use, which was rated as the top one in the output layer, as matched with a given pixel. However, neural networks can be used to predict a continuous variable. In practice, they are used to predict the sequence of time lines, to ascertain machinery settings, etc.

Self Organising Maps (SOM) - This algorithm is an example of learning without a teacher. It has become very popular mainly thank to the fact, that no training data are necessary. The network model consists of one layer of neurons arranged in the shape of a raster. The principle is to arrange the neuron raster so that the data topology is maintained while the whole space is covered. The algorithm results in a trained network, which can match objects with individual neurons while maintaining the distance in the original space (regardless of its dimension). It has been proved that the results resemble greatly the results obtained using the k-means method (cluster analysis). The algorithm may be used to search similar images – they will appear close to each other in the neural raster.

An SOM advantage is the fact that it keeps learning, thus not only specification of the raster through time occurs, but the algorithm is capable of reaction and adjustment to slow changes. The SOM algorithm has been again implemented in IDRISI in the packet of the same name, however, in an adjusted form, so it is possible (or necessary) to input training areas, therefore this concerns learning with a teacher.

The third algorithm implemented in IDRISI is the Fuzzy ARTMAP. It also offers to classify areas from aerial photographs and satellite images.

CONCLUSION

The integration of Geographic Information Systems and Artificial Neural Networks offers a mechanism to lower the cost of analysis of landscape change by reducing the amount of time spent interpreting data. This integration allows the interpretive result from a small area to be transferred to a larger, naturally similar area [7]. One of the most cumbersome aspects of this type of application is the data transfer from the GIS to the ANN and back. Landscape data used to produce an interpretive result is most efficiently managed in vector form. However, one of the most widely used ANNs, a Back-Propagation Neural Network, requires data in raster form that is arranged in one-dimensional column vectors. As with all GIS projects, the first step is the conversion of all information into digital form. For a natural resource application, the information will tend to consist of maps of landscape change. This information is usually polygonal and includes themes such as types of land use. The other common type of input for natural resource applications are surfaces. This type of data can be store as arcs with the elevation or thickness as an arc attribute. However, for analytic purposes, surfaces are best stored as grids or lattices [2]. For an ANN to be used as a tool to interpret change and their prediction, the map information must be converted into patterns. These patterns consist of a value for each input theme at a given location. ANNs were used to learn the patterns of development in the region and test the predictive capacity of the model, while GIS were used to develop the spatial, predictor drivers and perform spatial analysis on the results. During the training of the ANN, the patterns must also contain the value of the accepted output value for each location. Once the trained ANN has produced an interpretive result, the result must be converted back into GIS (generally as a polygon coverage) for the production of an output map. This map, showing the interpretive result, can be evaluated to see if further training is needed.

The ANN can be considered as a very useful tool for land use changes predictions. IDRISI tools are one of the best current GIS software that can be easily applied to whole process of land use prediction in different areas. Because of variety of input data and different parameters, all results have to be evaluated very carefully.

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