A COMPARISON OF NEURAL NETWORK AND EXPERT SYSTEM METHODS FOR ANALYSIS OF REMOTELY-SENSED IMAGERY

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ABSTRACT

This paper describes an experimental comparison which has been made between two alternative methods of image classification: one based on a neural network and the other on a rule-based expert system. Both methods were applied to the same image data. The results show that both methods give useful performance improvements in comparison with more traditional parametric classifiers. It was also found that the performance level attained by the two approaches was approximately the same. The neural network was, however, faster to develop although the expert system was much more transparent and easier for a user to understand.

INTRODUCTION

There has been much interest recently in the development of methods for analysis of remotely-sensed imagery based on expert or knowledge-based systems and on neural networks. Both techniques are currently yielding interesting results and are useful in the integration of information from geographical information systems in the image understanding process. At the Joint Research Centre both techniques have been exploited in image classification primarily for discrimination of land cover and crop classes. Initially these two techniques were implemented independently. However, in view of the fact that they were being applied to similar problems it was decided to carry out an inter-comparison. This was done using a common dataset with an identical remote sensing problem. The purpose of this exercise was firstly to assess how the two methods compared in terms of actual performance and secondly to see how they compared in terms of ease of use. Clearly in remote sensing the development effort needed for a particular analysis method can be as important as the actual performance level attained. Expert or knowledge-based methods differ quite considerably from neural networks even though they are often grouped together as 'artificial intelligence' techniques.

TEST DATA SET

In order to carry out the comparison between the two methods an experiment was performed using single date and two date multispectral SPOT imagery. A test area was chosen of approximately 10 x 14 km. in the Département Loir-et-Cher in central France. This is primarily an agricultural area with a considerable amount of cereal production, although there are also some extensive areas of forestry and some small lakes.

Altogether a classification scheme of seven different land cover classes was chosen for the experiment. These classes were: (1) wheat, barley and oats, (2) maize and sunflower, (3) rape seed, (4) alfalfa and pasture, (5) forest, (6) water, and (7) other -this class includes urban pixels. The classification was done on a pixel-by-pixel basis without the use of any segmentation procedures. The reason for using single and two-date imagery instead of longer multitemporal series is that one of the main uses of such imagery is in the rapid estimation of crop yields which require fast regular products. Generally at this latitude it is very difficult to get frequent clear sky coverage of the same site over a period of 2 - 3 months (Kontoes and Stakenborg 1990). Single date or two date products generally have to be used.

NEURAL NETWORK METHOD

The neural network approach that has been adopted is based on the multilayer perceptron model trained by the backpropagation algorithm. Such networks consist of an input layer of neuron nodes, an output layer and one or two 'hidden' layers in between. The nodes are linked with connections which carry 'weights'.

At the JRC networks with two hidden layers and as many as 100 nodes have been successfully implemented to classify as many as 20 separate land cover classes (Kanellopoulos et al. 1991). However for the expert system comparison experiment it was necessary to classify only seven classes for which single hidden layer networks were found to be sufficient. The network architectures for the seven class problem are shown in figure 1. In each case there are seven output nodes -one per class. The input layer had three nodes for single date imagery and six nodes for two-date imagery. In each case one input node corresponds to one spectral channel of the image data. The hidden layer contained 15 nodes for the single date imagery and 21 nodes for the two date imagery. In all cases we used fully connected networks. The approximate size of the architecture is deduced using heuristic geometrical arguments as found in Lippmann (1987). More nodes are required in the hidden layer for the two date case because of the extra dimensionality of the input data requiring more complex discrimination surfaces.

The backpropagation training procedure for the networks is a sequential process which requires typically several hundred passes

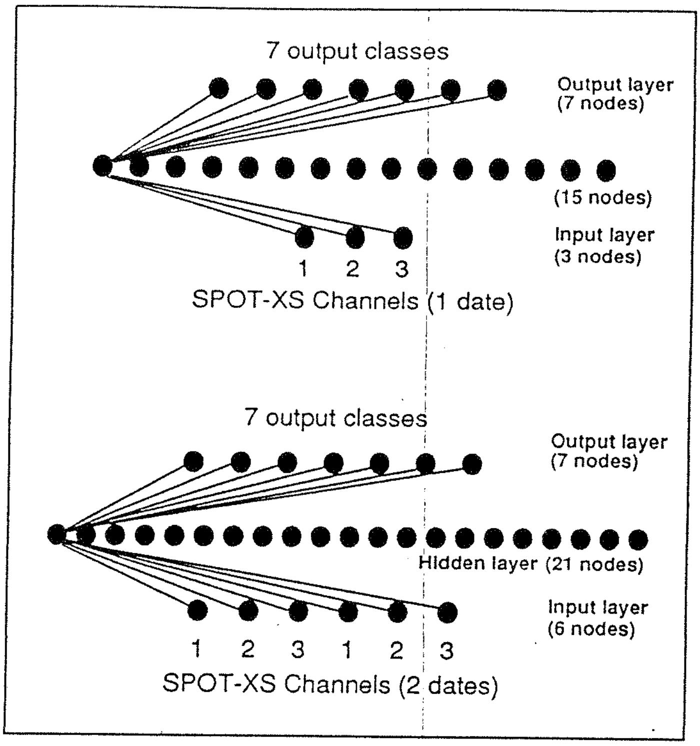

Figure 1. Neural Network Architectures for One and Two Date Experiments.

through a training dataset. In our experiments a training set of 6700 pixels was used. In order to reach a good classification performance approximately 600 iterations through the training set were required. Each time the weights in the network were adjusted until the network error reduced acceptably so that when a verification dataset was presented to the network a good classification performance was achieved.

EXPERT SYSTEM METHOD

The expert system involved a rule-based approach to class recognition in the SPOT imagery. In our approach the expert system was used as a post-classification refinement tool -i.e. an initial class product was derived from the imagery by a standard algorithm (e.g. maximum likelihood) and then the rules were applied in an attempt to modify and improve that product -see figure 2. In our experiments both image context rules and geographic context rules were used. The former were concerned with enforcing spatial simplicity and spatial consistency in the image using local neighbourhood information in the image; the latter were concerned with exploiting background geographic knowledge to correct likely class errors i.e. where the geographical situation of a particular pixel was inconsistent with the class label initially assigned to it. The geographic context information came from two data layers in a GIS -these were 'soil type' and 'road proximity' -both of which were obtained from digitised maps stored as coverages in an ARC/INFO system (they were then co-registered with the available imagery and converted into raster form).

A rule base was then built to exploit these data layers in the post-classification process. The soil rules could be used to eliminate some of the errors in crop classification and the road proximity information was useful in helping to distinguish the agricultural classes from the more natural vegetation classes which were generally found further from the communication routes. Altogether a total of 52 rules were used in the final system.

In general these rules did not give definite YES/NO answers about classes -they gave indications of tendencies towards favouring or disfavouring certain class labels. Each rule therefore had a class 'support value' attached to it (in the range 0 -> 1) which indicated how strongly it confirmed or disconfirmed a particular class or set of classes in our classification scheme. For most pixels more than one rule applied and all the individual pieces of 'evidence' in the form of class support values had to be combined. For this purpose we used the Dempster-Shafer model of evidence combination. Further details of this approach can be found in Wilkinson and Mégier (1990).

COMPARISON OF CLASSIFICATION RESULTS

Both the neural network and the expert system methods were applied separately to the Loir-et-Cher test area imagery and the final classification results were evaluated using ground data from selected mapped segments. Overall an average classification accuracy figure was calculated for the seven classes. The results are shown below in Table 1.

Classifier Type	Av. performance (single date image)	Av. performance (2 date imagery)
Maximum-likelihood	68.6%	78.5%
Maximum-likelihood + Expert System	81.2%	81.3%
Neural Network	82.3%	82.5%

Table 1. Comparison of Results

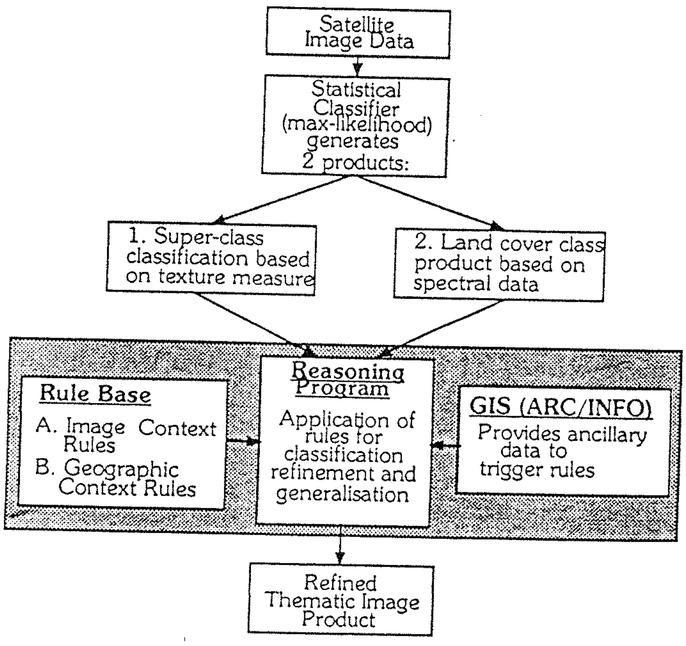

Figure 2. Expert System for Classification Refinement

COMPARATIVE BENEFITS/DISADVANTAGES

The results in table 1 indicate that both the expert system and the neural network method gave a useful accuracy improvement compared with the use of a standard parametric classifier alone. The improvement was more significant with single date imagery than with two-date imagery indicating that the extra information in a second image helps to correct some of the uncertainties in the single date image that were corrected either by the neural network or the expert system. However even with the two date imagery the use of the expert system or neural network is justified by the extra 3 - 4% accuracy improvement. Interestingly the results from the neural network and the expert system are very similar, and also there appears to be a limit to the accuracy level attainable at about 82-83%. This apparent limit may come either from an absolute limit to the information content of the satellite data or from error in the actual ground data. It is perhaps most likely that both factors are playing an important role in limiting the maximum accuracy attainable by whichever method is employed.

It is also useful to make a general appraisal of how these two approaches compare in more general terms. Firstly the neural network method gave the most accurate results, but only by a very small amount (~1%). It is also possible that the expert system would have yielded a better result if a more extensive rule base were to be used, but it is not possible to know this. Also the neural network was trained to classify only with the image data and not with any of the ancillary map data used in the expert system. It is therefore possible that the use of this extra information as an input to the neural network could have yielded better results as well. The neural network method was computationally tedious since it required of the order of 4 hours on a Sparcstation-2 to learn how to classify accurately by the back-propagation algorithm. However, against this we must consider the rule base development time for the expert system which was of the order of several weeks. The actual classification process takes only a few minutes by either method. It terms of user understanding, the expert system approach wins to a considerable degree since the actual procedure for improving the classification is written down in English-like rules -with the neural network the procedure is hidden inside a set of automatically learned network weights. The expert system method is therefore more useful where users need to understand what factors are most important in separating the classes.

CONCLUSION

As a resu't of these experiments we can say that both the neural network and the expert system method have important roles in classifying remotely-sensed image data. We have demonstrated that both methods give useful improvements in accuracy compared to other methods. Overall in terms of speed of development and actual final classification accuracy achieved the neural network method seems to be better. However for user comprehension and transparency the expert system method appears to be best.

Perhaps the best conclusion to reach from this is that both approaches have a place in the tool-kit of the remote sensing specialist, and that they can have complementary roles. It is also possible that an expert system could be used in combination with a neural network in some circumstances to explain to the user how the neural network has weighted various input parameters -i.e. to make it more understandable. Such a concept of integrated neural and expert systems has already been suggested outside of the remote sensing field (Caudill 1990).

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