Paper presented at the 22nd Asian Conference on Remote Sensing, 5 - 9 November 2001, Singapore.

CONTEXTUAL REFINEMENT OF NEURAL NETWORK CLASSIFICATION USING RELAXATION LABELLING ALGORITHMS

Krishna Mohan BUDDHIRAJU

Senior Research Engineer
Centre of Studies in Resources Engineering
Indian Institute of Technology, Bombay
Powai, Mumbai 400 076
Tel: (91) 22 576 7676 Fax: (91) 22 572 3190
email: bkmohan@csre.iitb.ernet.in
INDIA

KEYWORDS: **Contextual post-processing, artificial neural networks, relaxation labeling, image classification**

Abstract. Neural networks are growing in popularity today as a tool for classification of remotely sensed images. Majority of the neural network applications involve the error backpropagation algorithm for training the network to work as a classifier. While this algorithm has been successfully employed in various image classification problems, the errors associated with per-pixel classifier still persist, even if on a smaller scale than other methods. The contextual information embedded in a pixel's neighbourhood is a powerful mechanism to exploit the local knowledge and correct the errors. In this paper, the neural network output is scaled and input to the contextual classifier based on probabilistic relaxation labeling algorithm. The approach is tested using an IRS image and the results indicate that there is an improvement in classification accuracy over the conventional maximum likelihood method.

1. INTRODUCTION

Remotely sensed images are a valuable source of spatial data for a variety of natural resources management and environmental monitoring tasks. With developments in the sensor and computing technologies, some approaches to data analysis and information extraction, not attempted earlier, become feasible now. Artificial neural networks and contextual classification can be mentioned as examples of beneficiaries of the technological developments. Both are highly computation intensive and amenable to parallel and distributed implementation. It is illustrated in this paper that analysis of remotely sensed images using artificial neural networks, followed by contextual refinement is useful for improving accuracy of image classification.

As seen in Fig. 1 below, the neural net classified image is refined further using contextual information present in a pixel and its immediate local neighbourhood.

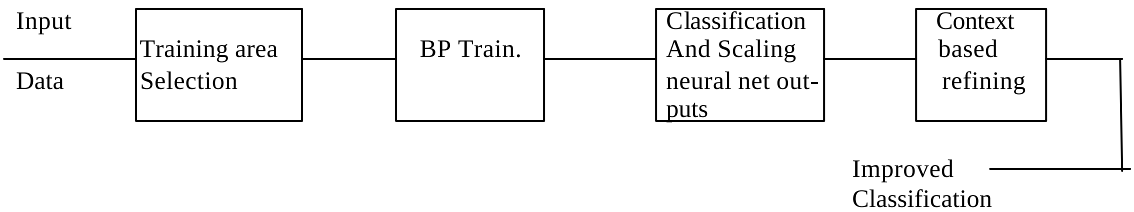

Fig. 1 Schematic Diagram of Proposed Methodology

Details of the standard feedforward neural network training using the backpropagation algorithm are too well known to warrant repetition here. Interested readers are referred to Yegnanarayana (1999) and Haykin (1994) for detailed exposition to this topic.

2. CONTEXTUAL REFINEMENT OF NEURAL CLASSIFICATION

Contextual information is inherently used by the human visual system while inferring the contents of the scene presented to it. In the domain of remote sensing, the context exists in the form of the label or class attached to pixels and their neighbours. It is an important fact that is not taken into consideration in pixel based classifiers that an image is comprised of regions or spatially adjacent groups of pixels where each region has pixels of the same class. The interclass compatibility and incompatibility place constraints on the likely class of a pixel given the class labels of its neighbours. The relaxation labeling framework (Rosenfeld and Kak, 1082) is used for this purpose.

2.1 Probabilistic relaxation labelling algorithms

Relaxation labelling schemes can be explained in four major steps:

1. Initialization of the class probabilities of the pixels
2. Specification of the interclass compatibility matrices
3. Computation of the class probability updates based on contextual support
4. Assessment of the impact of contextual refinement

Relaxation labelling is an iterative approach to image classification which assigns a set of probabilities p_i to every pixel i such that

$$0 \le p_i(\lambda) \le 1; \sum_{\lambda=1}^{L} p_i(\lambda) = 1 \tag{1}$$

L is the total number of classes. $P_i(\lambda)$ is the probability that pixel i belongs to class λ. The classification of the pixels is iteratively updated such that the class assigned to a pixel is consistent with the classes present in the neighbourhood. The class probabilities are iteratively updated by pooling the neighbourhood *support* for every class at each pixel:

$$p_i^{k}(\lambda) = f(p_i^{(k-1)}(\lambda), q_i(\lambda)) \tag{2}$$

$q_i(\lambda)$ is the support received by i from the neighbours for label λ. After a number of iterations, for every pixel i, some label (or class) λ_k will have highest probability (close to 1) compared to other labels and pixel i can be assigned to the class k with little ambiguity.
In natural scenes, very often the presence of a particular class at a pixel necessitates or precludes the occurrence of some other class in the neighbourhood. For example, a pixel of the class building needs another class road in the vicinity. Similarly a class desert precludes the probability of having a class forest in the neighbourhood. These constraints are numerically represented as compatibility coefficients, denoted by $r_{ij}(\lambda,\lambda')$. The notation reads as compatibility of label λ at i with label λ' at neighbouring pixel j. For every pair (i,j) we have an L * L matrix of the compatibility coefficients.

The support any neighbour offers is dependent on its label probabilities and the compatabilities between different label pairs belonging to the pixel under consideration and its neighbour. Stronger the compatibility between the label pair (λ,λ') and higher the label probability $p_j(\lambda')$, more is the support offered by the neighbour j through the particular label λ' to label λ at i. This requirement is satisfied by the form

$$q_{ij}(\lambda) = \frac{1}{L} \sum_{\lambda'} r_{ij}(\lambda,\lambda') p_j(\lambda') \tag{3}$$

where $q_{ij}(\lambda)$ is the average support received from the neighbour j by pixel i for label λ through all labels of j. Since $p_j(\lambda')$s act as nonnegative weights in summing $r_{ij}(\lambda,\lambda')$ over λ', the range of $q_{ij}(\lambda)$ is the same as that of $r_{ij}(\lambda,\lambda')$. The total support received by pixel i for label λ through the entire neighbourhood is obtained by combining all the individual neighbour supports as follows:

$$q_i(\lambda) = \sum_j d_j q_{ij}(\lambda) \tag{4}$$

where $d_j \geq 0$ and $\sum_j d_j = 1$. It is common to use $d_j = 1/|\{N(i)\}|$ where is the set of neighbours of i and |.| denotes the cardinality of the argument set. The second way to combine the supports is

$$q_i(\lambda) = \prod_j q_{ij}(\lambda) \tag{5}$$

Rosenfeld et al. (1976) have combined the neighbour supports and label probabilities $p_i^k(\lambda)$ according to the rule

$$p_i^{(k+1)}(\lambda) = \frac{p_i^k(\lambda) q_i(\lambda)}{\sum_\lambda p_i^k(\lambda') q_i(\lambda')} \tag{6}$$

The denominator acts as a normalising factor such that

$$\sum_\lambda p_i^{k+1}(\lambda) = 1 \quad \text{if} \quad \sum_\lambda p_i^k(\lambda) = 1 \tag{7}$$

Here it is assumed that $0 \leq q_i(\lambda) \leq 1$, which will be true if nonnegative compatibility coefficients are used. It can be seen from this expression that if the neighbour support is strong, then the updated probability will be larger than the prior to updating, and if the neighbour support is weak, then the updated probability will be smaller than that prior to updating. After a number iterations , for pixel i, some label λ_i will have largest probability, significantly higher than that of any other label, which may be taken as the convergence point.

Since the relaxation process is iterative in nature, it needs an initial labelling to start with. The initial probabilities are computed in different ways for different applications. For the problem at hand, the responses of the output nodes of the neural network $d_i(\lambda)$ are used to compute initial probability $p^0(\lambda)$ as

$$p_i^0(l) = \frac{d_i(l)}{\sum_l d_i(l)} \tag{8}$$

Where $d_i(\lambda)$ is the output of the neural network of pixel i for the class λ.

The compatibility coefficients represent the label compatibility information quantitatively. These are defined in various ways, depending on the application. Peleg (1978) have suggested that the compatibilities may be modelled as mutual information between label λ at i and label λ' at j. They also suggested alternatively, correlation coefficients to represent the compatibilities. In our case, using a priori knowledge about relative likelihoods of cooccurrence of different classes, a matrix of compatibilities is prepared, having three types of values - (-1 for extreme incompatibility), (0.5 for modest compatibility) and (1 for full compatibility). Further, these compatibilities are taken to be the same for all neighbour pairs irrespective of their relative positions.

2.2 Issues in contextual refinement by relaxation labelling

The processes taking place during relaxation labeling can be described as a mixture of inter-label competition and co-operation. Compatible labels mutually reinforce each other to occur at neighbouring positions, while competing labels try to suppress the other. One of the drawbacks of such processes is the erosion of object boundaries, particularly when the objects are small in size. The larger and stronger classes tend to overgrow and erode and eventually gobble up small regions in the neighbourhood. This is often the case if relaxation labeling iterations are allowed to run for ten or more iterations.

An obvious remedy for this problem is to protect the boundary pixels of objects. For instance, if certain pixels are identified as boundary pixels, the label updation step can be controlled by

a) entirely leaving out the boundary pixels, allowing them to retain the initial labels
b) scaling the neighbour support by a factor (<1) specified by the user
c) a mixture of both (a) and (b)

In this paper both (a) and (b) are evaluated towards protecting boundary pixels.

The edge pixels in this study are identified using Canny operator (Canny, 1986) to mark edge and non-edge pixels. The hysterisis thresholds are selected in such a way that only the major edges are extracted. It is also possible to determine the boundary pixels on the basis of observing the responses of the output nodes of the neural network: boundary pixels are often mixed pixels having more than one category within its area and more than node would produce significant response. By observing the difference of the significant and next most significant node responses, pixels can be marked as edge pixels where the difference is smaller than a user specified threshold (0.1 – 0.2). The latter criterion was not attempted in this study, and will be pursued in a future study.

3. RESULTS AND DISCUSSION

The above methodology is tested using a subimage from IRS-1A scene covering northern part of Mumbai city. Seven major landuse/landcover classes are identified from the image, viz., Forest, Vegetation, Marshy land, Builtup / Open area, Dense builtup area, Clear water, and Polluted water. The major landmarks in this image are the Thane creek on the right, and the three lakes on the left - Powai, Vihar, and Tulsi.

The overall accuracy is shown in table 1. For comparison purposes, the conventional maximum likelihood classification was also carried out on the data. The scheme proposed here has promise, and is being investigated further, particularly from the point of view of protecting linear features, weak classes etc.

The original image of the area is shown in Figure 2 as a standard false colour composite. The classified image using neural network is shown in Fig. 3a and the post-processed image using relaxation labeling in Fig. 3b. Approximately 4400 pixels are reclassified out of an approximate 181,000 in this process. No particular pattern was identified but generally these pixels tended to be along the class boundaries. Seven iterations of the relaxation labeling algorithm have been run on the neural network output after rescaling it.

Algorithm	**Overall accuracy(%)**
MLC	91.6
RLT	94.7

ACKNOWLEDGEMENTS

The support received from ISRO-IIT(B) Space Technology Cell for carrying out this research is acknowledged. The author also wishes to acknowledge the encouragement received from Head, CSRE and programming work carried out by former project associates Mr. B.V.Koti Reddy, Mr. Mukund Dharwadkar and Ms. Jayshree I. Neeli.

REFERENCES

Adeli, H., and Hung, S., 1995, Machine Learning - Neural Networks, Genetic Algorithms, and Fuzzy Systems, John Wiley.

Benediktsson, J.A., Swain, P.H., and Erosy, O. 1992, Neural Network Approaches versus Statistical Methods in Classification of Multisource Remote Sensing Data, IEEE Trans. Geoscience and Remote Sensing, vol. 28, no. 4, pp. 540-552.

Bose, N.K., and Liang, P., 1996, Neural Network Fundamentals with Graphs, Algorithms, and Applications, Mc-Graw Hill, NY.

Canny, J.F., 1986, Finding edges and lines in images, IEEE Trans. Pattern Analysis and Machine Intelligence

Haykin, S., 1994, Neural Networks: A Comprehensive Foundation, Prentice-Hall, Englewood Cliffs, NJ.

Duda, R.O., and Hart, P.E. 1973, Pattern Classification and Scene Analysis , Wiley, NY.

Heermann, P.D., and Khazenei, N. 1992, Classification of Multispectral Remote Sensing Data using a Backpropagation Neural Network , IEEE Trans. Geoscience and Remote Sensing, vol. 30, pp. 81-88.

Lippmann, R.P. 1991, An Introduction to Computing with Neural Networks, IEEE ASSP Magazine.

Paola. J.D. and Schowengerdt, R.A. 1995, A Review and Analysis of Back Propagation Neural Networks for Classification of Remotely Sensed Multispectral Imagery, International Journal of Remote Sensing, 1995, Vol.16, No.16, pp. 3033-3058.

Rosenfeld, A., and Kak, A.C. 1982, Digital Picture Processing, vol. 2, Acad. Press.

Rumelhart, D., Hinton, G., and Williams, R. 1986, Learning Internal Representations by Error Propagation, in *Parallel Distributed Processing: Exploration in the Microstructure of Cognition*, D.E. Rumelhart, and J.L. McClelland (ed.), vol. 1, pp. 318-362, MIT Press, MA.

Fig. 2. ORIGINAL IRS COLOR COMPOSITE

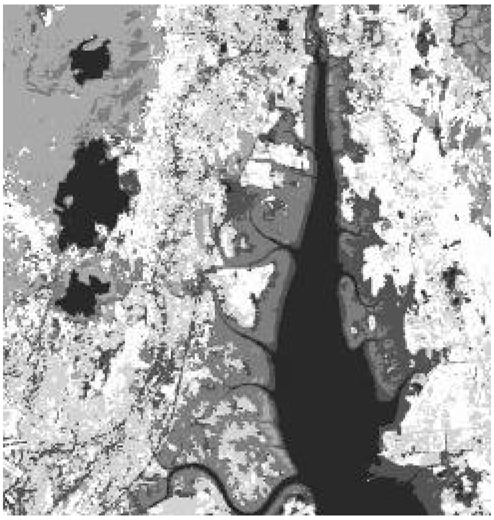

Fig. 3a MLC PER-PIXEL CLASSIFICATION

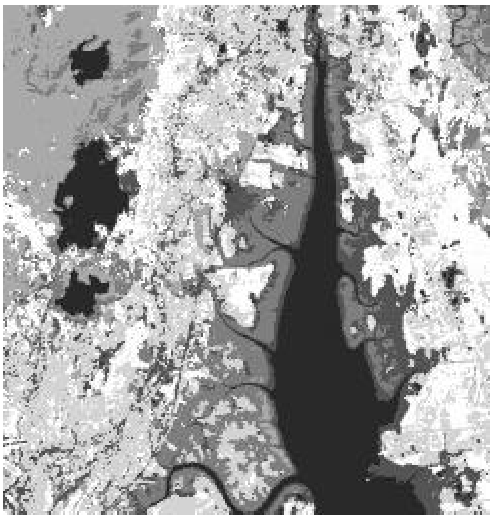

Fig. 3b CLASSIFICATION USING RLP TECHNQUE