FUZZY SUPERVISED CLASSIFICATION OF REMOTELY SENSED DATA USING ARTIFICIAL NEURAL NETWORK

by

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CERTIFICATE

This is to certify that the thesis entitled, **Fuzzy Supervised Classification of Remotely Sensed Data Using Artificial Neural Network**, being submitted by **Manoranjan Kalita** for the award of degree of **Doctor of Philosophy**, is a record of bonafide research work carried out by him. He has worked under my guidance and supervision for submission of this thesis, which to my knowledge, has reached the requisite standard. This thesis, or any part thereof, has not been submitted to any other University or Institute for the award of any degree or diploma.

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ABSTRACT

Classification is the key step of a remote sensing image analysis system as it derives the final output, that is, a thematic map. A major unresolved issue in classification is the classification of mixed pixels.

Conventional crisp concept of one-pixel-one-class fails in the classification of mixed pixels due to the expressive inadequacy of these techniques. Fuzzy set theory, put forward by L.A. Zadeh in 1965 has the theoretical basis required to address this issue. Additionally, conventional popular classifiers like maximum likelihood technique also fail to derive high accuracy when data does not conform to normal distribution. The combination of fuzzy set theory and technique of neural network is seen to be versatile enough to handle nonlinear problems in diverse fields.

The present study aims to evolve a methodology for fuzzy classification of remote sensing image using neural network – popularly termed as a neurofuzzy approach to classification.

Experiments are carried out initially with synthetic image created from a real satellite image for better control on the investigations. The synthetic pixels are generated using the concept of Linear Mixture Model (LMM) which is well accepted in the domain of spectral unmixing. The series of experiments help to identify the best performing neural network configuration. Trials are confined to the feed-forward neural networks. Correspondingly, the most widely accepted back-propagation algorithm is used as the starting point. For fine tuning of the technique, series of experiments are conducted with

different combinations of activation functions, three modes of back-propagation algorithm, that is, gradient descent, Levenberg-Marquardt and Elman algorithm. And lastly, comparative assessment is made between the best of back-propagation (LMBP) and radial basis function (RBF). In all the cases, comparative performance is evaluated in terms of error estimates derived from the outputs of an independent set of synthetic test pixels. The neural network configuration so evolved is the best amongst the tested ones, and is tested on real scenes. Another series of experiments are carried out on neural network outputs of real scenes in order to frame rules for final neurofuzzy classification. Finally, the framed rules are further tested with the classification of a relatively 'simple' scene. On getting encouraging results in terms of correlation between the predicted and the known membership values, the same rules are validated in the classification of a 'heterogeneous' scene with three combinations of defined classes.

Results show the possibility of qualitative gradation of the pixels in a scene from ideal pure, ideal mixed, real pure, real mixed and undefined based on a scale of 'Deviation Index'. Additionally, fuzzy classification of the ideal pixels, both pure and mixed, are straight-forward. Moreover, implementation of membership functions designed for each class extracts additional information on real pixels and their mixtures. The correlation achieved is of the order of 0.75 in the case of the simple scene and of the order of 0.6 to 0.7 for a heterogeneous scene.

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