AUTOMATIC FEATURE EXTRACTION FROM SATELLITE IMAGES USING LVQ NEURAL NETWORK

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ABSTRACT: Feature extraction is the most important application in spatial data management in the manner of automatic updating of GIS databases from enormous satellite imagery. It has been widely done by manual interpretation or automatic classification. Presently many studies have been addressed to extract features in semi-automatic methods. Hence there is a lack of investigation addicted to the successfulness of an automated approach of extracting natural and man-made features from that imagery due to the complexity of the image and that of parameterizing neural network. This paper describes about a neural network image interpretation system which is designed to efficiently extract Land use or Land cover information from high spatial resolution imagery using self-organizing supervised learning Artificial Neural Network (ANN). Learning Vector Quantization (LVQ) approach was employed in this study to classify four main Land use or Land cover feature types; Buildings, water, vegetation and roads. That information segmented into quite homogeneous polygons and digitized according to the feature attribute information in a standard GIS format. These extracted layers could be used to update GIS database. The developed model is trained and tested to scenes of very high resolution images from QuickBird satellite acquired from Colombo urban area. The accuracy was assessed by quality matrices using visual interpretation. Overall accuracy of proposed method was 78%. The result of this study exposed that a successful application of LVQ approach for feature derivation from high resolution remote sensing image. Although this model demonstrated high sensitivity to training sample data, it required filtering to achieve supreme preciseness. Further results showed that remote sensing based feature extraction can be a complex process in urban region and poor or insufficient training data may interactively affect performance of the developed system.

1. INTRODUCTION

At present, satellite and airborne remote sensing systems can provide large volumes of spatial data which is invaluable in monitoring the Earth resources and the influence of human activities on the Earth with finer spatial and spectral resolution and providing more accurate and precisely detailed information. Urban areas are undergoing changes. Hence, there is an urgent requirement of up to date large scale data for numerous purposes. Feature extraction is particularly an important application in map production of many countries. Further there are often no up to date maps and automated methods have been proposed to improve the speed and effectiveness of map production process (Lari and Ebadi, 2007). However, updating process of these data is still in a lethargic state.

There was a great concern in extraction of land use or land cover information from satellite data using digital image processing techniques since late 1960s (Estes and Jensen, 1998; Lulla and Dessinov, 2000). Number of approaches has been reported for feature extraction procedure. Automatic object detection is one of common methods in feature extraction; however, still this method has many issues. The challenge of developing automated line detection algorithms still remains due to the complex structure of remotely sensed imagery. In response, a number of different statistical approaches have been widely used for classifying land use or land cover information (Swain and Davis, 1978; Schowengerdt, 1983). With advancement of satellite sensors, the attention has turned toward the novel robust classification approaches like, Artificial Neural Network (ANN) (Benediktsson et al., 1990; Dam et al., 2008).

Artificial Neural Networks (ANNs) were originally designed as pattern-recognition and data analysis tools that mimic the neural storage and analytical operations of the brain. High spatial resolution remote sensory data are often composed of many heterogeneous patches of terrain and complex nonlinear patterns. Additional superior advantages of ANNs include parallel computation, the ability to estimate the non-linear relationship between input data and desired outputs and fast generalization capability. Many previous studies have proved that ANNs perform better than traditional classification methods such as maximum likelihood classifiers on multispectral images (Bischof et al., 1992; Foody and Arora, 1997) in terms of classification accuracy. Additionally, ANN provides more general solutions to line generalization problems, by avoiding splitting the process into isolated operators, such as simplification, smoothing and enhancement (Werschlein and Weibel, 1994).

Development of automatic, efficient and reliable approaches to extract information from remotely sensed data to update a GIS database is an urgent necessity. In Sri Lanka, such an automated extracted system is not available or very limited. But one study has investigated to extract road features from high resolution panchromatic satellite image (Wijesingha et al., 2013). The objective of this study was to develop a self-organizing supervised learning Artificial Neural Network (ANN) image interpretation system which can efficiently extract Land use or Land cover information from high spatial resolution imagery using Learning Vector Quantization (LVQ) approach.

2. MATERIALS AND METHODS

2.1 Data source

The QuickBird satellite images which were with 0.6 m Panchromatic and 2.4 m Multispectral spatial resolution were used. Training data and testing data, which had an area around 145 × 100 m, as to represent four varieties of major land cover or land use types were selected from Colombo urban region, Sri Lanka. Figure 1 shows the tested panchromatic image for deriving features.

Figure 1: Panchromatic test image

2.2 Methods

In this study, ANN was implemented by Neural Network Toolbox available in the MATLAB software. Figure 2 shows the methodology adopted in this study.

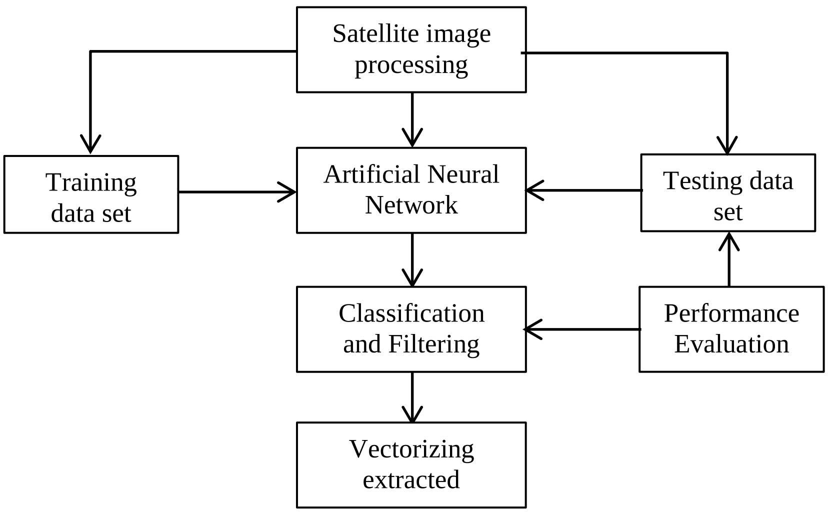


Figure 2: Methodology for the extraction of polygonal features

DN values of the QuickBird images were converted into spectral reflectance using ERDAS IMAGINE 2014 according to the equations given by Keith Krause (2005) for QuickBird images under the image processing segment.

Subset images with known attributes were selected as training data from panchromatic reflectance image for road and building classes. Training data of vegetation and water feature were selected from NIR reflectance image. The spectral data (reflectance value) for each of the feature type is gathered and passed to the input layer of the LVQ neural network. The actual target class value is sent to neurons of the output layer by assigning the neuron representing this class by a value of 1, while all remaining neurons assigned to a value of 0. The trained LVQ network was used to classify the test image. The Neural Networks of building and road features were simulated using a test image obtained from QuickBird panchromatic reflectance image. The remaining two classes were simulated using a test image obtained from NIR reflectance image of the same area of interest.

Under the filtering segment, extracted objects of each category were compared with Tasseled Cap Transformed image space to filter only the corresponding or required objects by removing the group of pixels misclassified within the scene. The Tasseled Cap Transform (TCT) is a practical vegetative index and spectral enhancement. Kauth and Thomas (1976) define the special feature space known as Tasseled Cap space. This special feature space is defined by coordinate axes that are characteristic of physical features within the imagery. The TCT projects spectral space coordinates (i.e. DNband1, DNband2) onto Tasseled Cap space. Traditionally, those three axes were defined as: Brightness, Greenness and Wetness.

In final segment, extracted features were reasonably altered by applying suitable conditions to effectively remove noise and a line simplification technique that proposed by Douglas-Peucker (1978) after vectorization process to eliminate produced zigzag bounding polygons. Finally, the produced vector layers were converted into shape files with attribute information in a standard GIS format to update database.

2.3 Performance Evaluation

In this study, the Quality metrics were generated by comparing the extracted features against an accurate reference set gain by visual interpretation of pan sharpen test image in count of pixels. To evaluate the performance of the model, the following factors are required (McKeown et al., 2000).

- Detection Percentage is a measurement of the percentage of the reference features that has been extracted.

$$\text{Detection Percentage} = \frac{\text{TP} \times 100}{\text{TP+FN}}$$

- Branching factor is a ratio of the correctly and incorrectly identified features.

$$\text{Branching Factor} = \frac{\text{FP}}{\text{TP}}$$

- Quality Percentage is a measurement of the absolute quality of the system.

$$\text{Quality Percentage} = \frac{\text{TP} \times 100}{\text{TP+FN+FP}}$$

Where,
TP - True Positive : the pixel classified as an object by both approaches
TN - True Negative : the pixel classified as a non-object by both approaches
FP - False Positive : the pixel classified as an object by automatic approach but not by a person
FN - False Negative : the pixel classified as a non object by automatic approach but not by a person

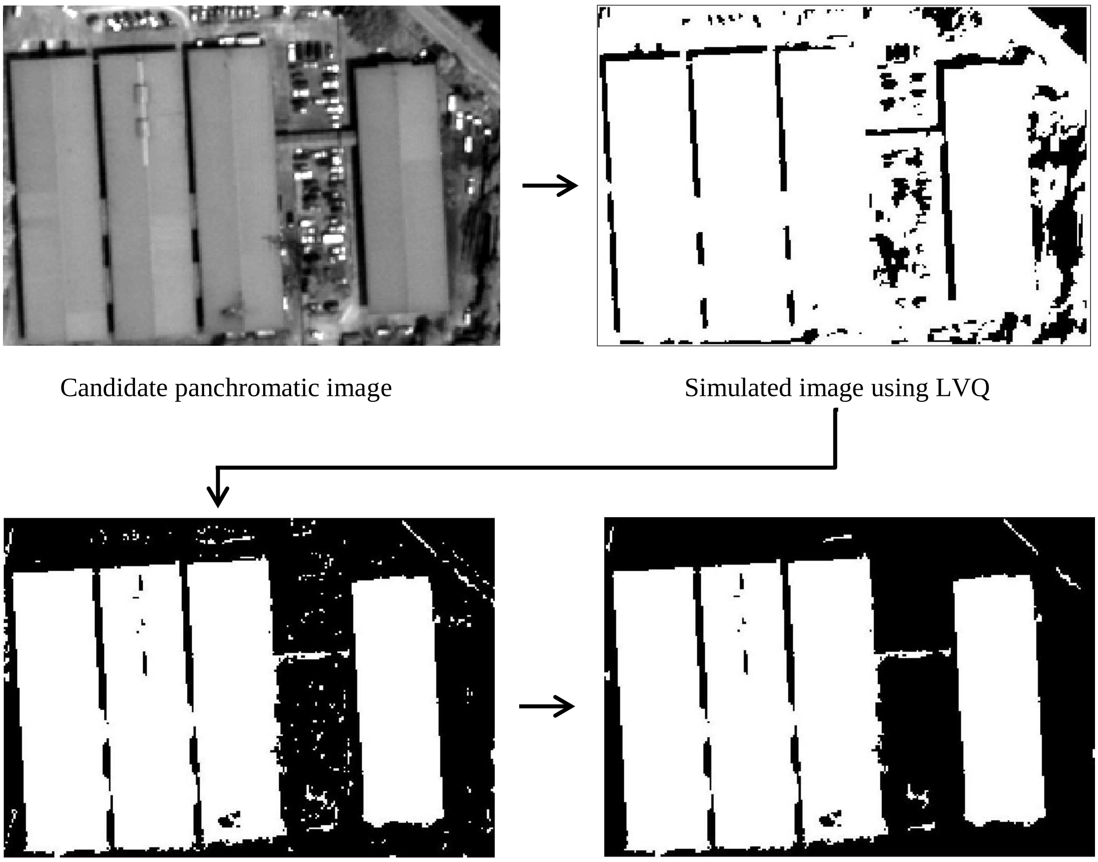
3. RESULTS AND DISCUSSION

After a number of experiments on the ideal training dataset for LVQ net, it was found suitable dataset according to availability of the image that would be sufficient for the neural networks to learn the characteristics of the training data with around more than 95% classification accuracy. The number of training epochs was found to be the optimum as 100, following a series of experiments.

Table 1: Obtained classification accuracy of training dataset

Feature Class	Obtained Classification Accuracy (%)
Vegetation	98.2
Water	98.1
Building	100.0
Road	99.3

The test image was classified and the resulted binary image was filtered using the Tasseled Cap transformed image. Figure 3 illustrates an example of the intermediate result and output obtained during the feature extraction process of buildings.



Candidate panchromatic image

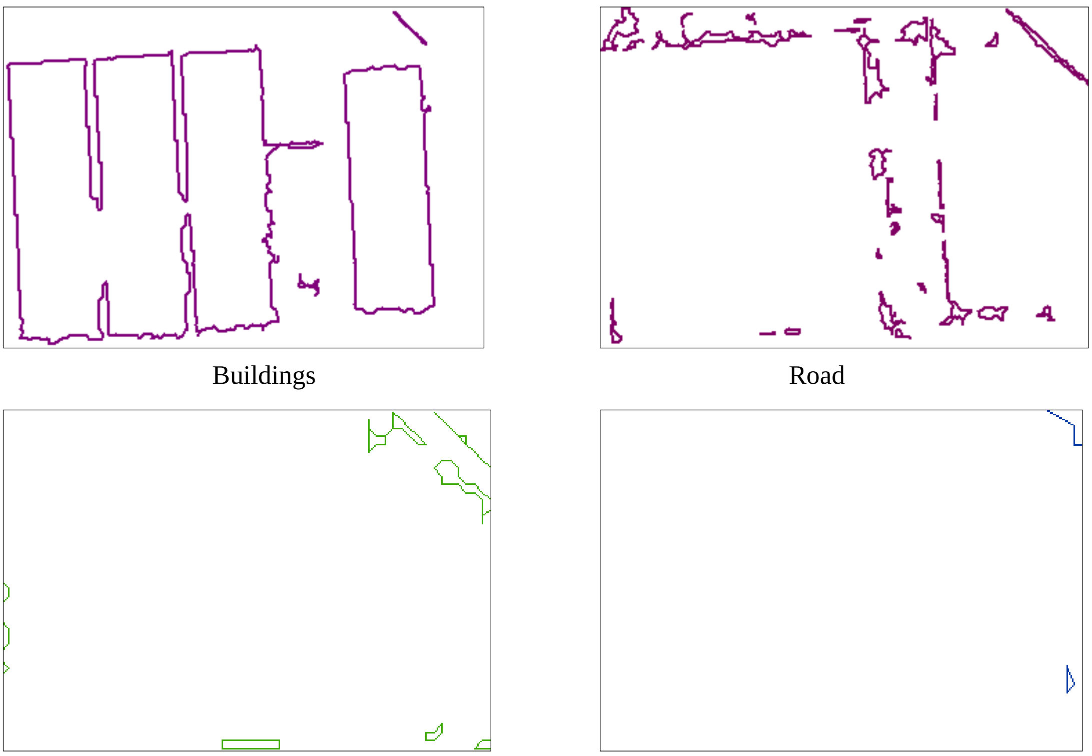
Simulated image using LVQ

Tasseled cap transformed image

Filtered objects

Figure 3: Extraction process of buildings features

The finally extracted Land use or Land cover vector features are shown in Figure 4.



Buildings

Road

Vegetation

Water

Figure 4: Extracted features

The overall performance of the system is shown by Table 2. Hence the extracted feature polygons can be used to update database a GIS database.

Table 2: Performance Evaluation

Extracted Feature Category	Detection Percentage (%)	Branching Factor	Quality Percentage (%)
Vegetation	83.1461	0.0270	81.3187
Water	94.4444	0.2941	73.9130
Road	90.6135	0.5451	60.6528
Building	97.2460	0.0124	96.1030
Over All	**91.3625**	**0.2197**	**77.9969**

By considering imagery, same illumination of contrast material plays a major role of error in object identification and extraction. The quality of training data sets also affects the training process. It was very difficult to find a training data set with homogeneous feature type in the imagery selected. Shadows contributed to un-extracted objects and lead to low detection significantly during extraction process of road and building features. Further practical limitations of building delineation were complex structure and interconnected objects.

4. CONCLUSIONS

This study has shown that a vector map can be produced in a robust manner by a supervised ANN classification by combining remote sensing and geographic information system technologies. Furthermore, it showed a great potential for updating old GIS data with commercial value.

The efficacy of this procedure depends upon the accuracies of the classification and that of filtering. In this study overall accuracy of 78% was achieved, partially as a result of careful design of the ANN. Additionally, complexities of the image could be adversely affecting the performance of the developed system, many factors, such as atmospheric conditions, mixed pixels, complex man-made features, complex biophysical environment and poor or insufficient training data. Neural network approaches are a prospective tool for accurate analysis and interpretation of large volume of spatial data.

5. REFERENCES

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