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Automatic Road Feature Extraction from WorldView-2 Panchromatic Satellite Images

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Abstract— Road network of Sri Lanka, especially in the sub urban conditions, is frequently upgrading and changing due to the rapid infrastructure development in the country during past several years. For planning and management of other related developments and resources, updated road data base is very much essential. The application of spatial future extraction form high resolution satellite images creates new and fast feasibilities for automatic road feature extraction to overcome the limitations of conventional methods of upgrading excising road maps. In this research two automatic systems were developed by using Artificial Neural Network (ANN), one system for extracting gravel road and another for extracting tar roads. Pixel spectral (DN) values were used to obtain training data set for ANN. NDVI threshold values based on area of road, morphological operations like filling holes, smoothing, thinning were used to distinguish road features from other related features. Finally, two subset of gravel roads and three subsets of tar roads were simulated to check the developed systems which provide overall completeness, correctness, quality, redundancy and RMS 0.996, 0.989, 0.986, 0.008 and 0 respectively. Most importantly, the gaps caused by obstacles like trees and buildings were filled and continuous road features were extracted in this research.

Index Terms— GIS, Remote Sensing, Road Feature, ANN, WorldView-2, Automatic feature extraction, Map updation

1 Introduction

ROADS are one of the most important man-made features and they play significant role in number of geospatial applications such as infrastructure planning, satellite based navigation, automated route planning, transportation system modeling and traffic management, etc [7], [6], [3]. Before the invention of sea, air and rail travel, roads were the solitary means of transporting goods and people from one location to another. Even in today's modern society, roads are the more frequently used mode of transport [6], [3]. Sri Lanka is now on a rapid infrastructure development, after the three decades of civil war. It has been noted that many road development and expansion projects are going on especially in sub urban areas. Due to these improvements the nature and the size of the roads are changing frequently. Therefore, reliable updating of existing road networks is essential to support many decision making applications of further developing activities.

For updating of GIS data bases and maps, the changed road futures are commonly extracted by using field surveying techniques. However, this traditional approach is comparatively time consuming and expansive to perform than the use of satellite and aerial images [5]. Feature extraction techniques based on satellite or aerial images reduces the cost considerably and performs in quick time as manually, semi automatically and fully automatically [4]. The simplest operation is the manual method; however, the accuracy of extracted road features are depending on operator and it also time consuming considerably. However, if there is a unique method to extract road features automatically and accurately it is very useful for updating GIS database and maps frequently and timely manner. Presently, with the advances of satellite technology, high spatial resolution satellite images are available, for instance WorldView II and Quick Bird, for accurate and frequent feature extraction projects. Although automatic road feature extraction is long term research topic in computer vision, remote sensing, photogrammetry and GIS communities, but until now it is a challenging research topic due to complex surrounding environment such as vehicle and shadow caused by trees and buildings [3].

Humans can easily identify roads in remote sensing images, but this has turned out to be a difficult task for computers [2]. ANN is an information processing system that has certain performance characteristics in common with biological neural network. Feature extraction also a kid of pattern recognition, so neural network can be used for automatic feature extraction [1]. Since road features have its own spectral characteristic, road features can be distinguished from other features present in a satellite image. As well as such spectral characteristics can be used to train artificial neural network in order to identify road features automatically.

2 Research Methodology

The road feature extraction was implemented using Learning Vector Quantification in Artificial Neural Network by using MATLAB software. LVQ is a supervised variant of the self-organizing map algorithm (SOM) that can be used for labeled input data. It is a method for training competitive layers in a supervised manner.

For this study a panchromatic image with 0.5m spatial resolution worldview II satellite was used. Two subset images were taken, one for tar road extraction and another for gravel road and they were used as input vector for LVQ network. Then target classes were created by using the said subset images based on pixel spectral information as road class and non-road class and then those were used as target vectors for

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LVQ network. New LVQ networks in ANN were defined in MATLAB software using 'newlvq' function; one for tar road extraction and another for gravel.

lvqnet = newlvq(PR,S1,PC,LR,LF)

where; PR- R-by-2 matrix of minimum and maximum values for R input elements, S1- the number of first layer hidden neurons, PC- S2 element vector of typical class percentages, LR- learning rate and LF - learning function, are the parameters for LVQ network.

Based on which, the defined LVQ networks were trained to classify road features while checking training confusion matrix to a know total correct classification percentage. Accordingly, if TCCP > 90% that network was accepted otherwise training was done again and again by changing neural network defined parameters and neural network training parameters. Then that trained networks were simulated by using another large subset images taken from original panchromatic image. In the case of tar road extraction, NDVI value was used to remove all vegetation area from extracted tar road patches.

However, the remaining noise patches were identified and removed by using simple threshold value based on area condition. In this research, the threshold value was changed gradually until all unwanted patches were removed. The missing patches caused by center line and gap caused by obstacles like trees and building should be filled in order to obtain continues road features. For, extracted roads filtering, smoothing and thinning presses were applied in order to obtain the center line of road using morphological operation provided by MATLAB toolbox. Then continues road features were obtained. The resulting binary images were in raster format and they should be converted into vector format. In this research, techniques in ArcGIS was used to produce respective vector layers.

2.1 Validation of developed LVQ networks

Validation of developed automatic system is essential to check the accuracy of the system. First extracted road vector layers were geo-referenced by using coordinate of original panchromatic image. Then reference road layers were created by digitizing roads in original image manually. Since road is linear feature, all data can be used for accuracy assessment instead of selected sample point.

Wiedemann et al (1998) proposed several quality measures to evaluate the quality of extracted roads, and that was used to perform the accuracy assessment. Accordingly, a buffer was created for the extracted road layer and for reference road layer. For the tar road, the road width and for gravel road, the average road width was selected as buffer width. Figure 2.1 and 2.2 represent the matched extraction and matched reference respectively.

Accordingly, following equations were modeled and used to validate the automatic system,

$$Completeness = \frac{length\ of\ matched\ reference}{length\ of\ reference} \approx \frac{TP}{TP+FN} \quad (for\ low\ redundency)$$

$$Correctness = \frac{length\ of\ matched\ extraction}{length\ of extraction} = \frac{TP}{TP+FP}$$

$$Quality = \frac{length\ of\ matched\ extraction}{length\ of extraction + length\ of\ unmatched\ reference} = \frac{TP}{TP+FP+FN}$$

$$Rudendency = \frac{length\ of\ matched\ extraction - length\ of\ matched\ reference}{length\ of\ matched\ extraction}$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{l}(d(extr_i;ref)^2)}{l}}$$

Where:
L: Number of pieces of matched extraction,

$(d(extr_i;ref)$: Shortest distance between the i[th] piece of the matched extraction and the reference network.

TP: True Positive and FN: False Negative

If the overall accuracy is greater than 90% then those extracted road layers were used to update the GIS data base. Updating of GIS data base was performed using extracted road layers by using techniques in ArcGIS.

3 Results and Discussion

Two LVQ networks in ANN were developed to build automatic systems for road extraction from World View II high resolution satellite image; one system for gravel road extraction and another for tar road extraction. The developed automatic systems were simulated using two subsets of gravel road and one subset of tar road. The resulted automatics extractions for two gravel and one tar road are presented in figure 3.1, 3.2 and 3.3 respectively.

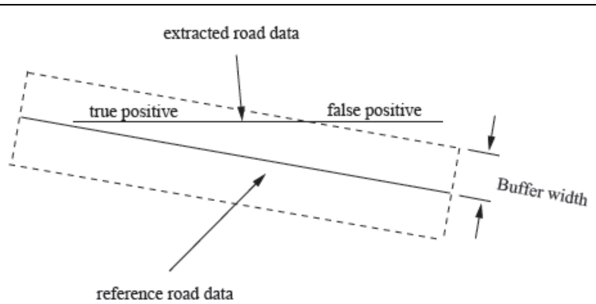

Figure 2.1 Matched Extraction

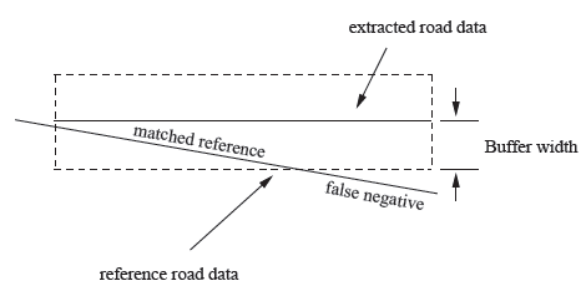

Figure 2.2 Matched Reference

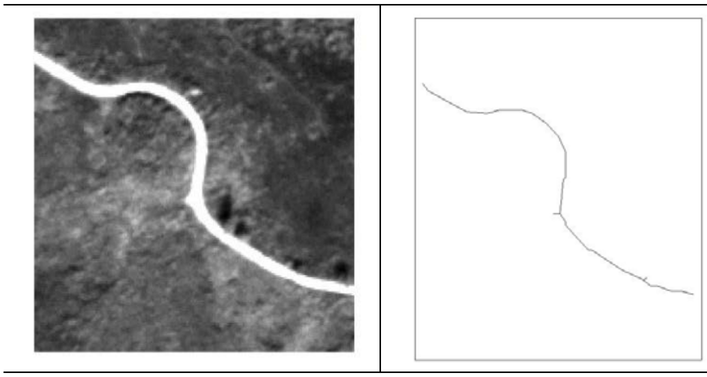

Figure 3.1 Input image and output extraction by the system for gravel road (subset 1). Scale 1: 600

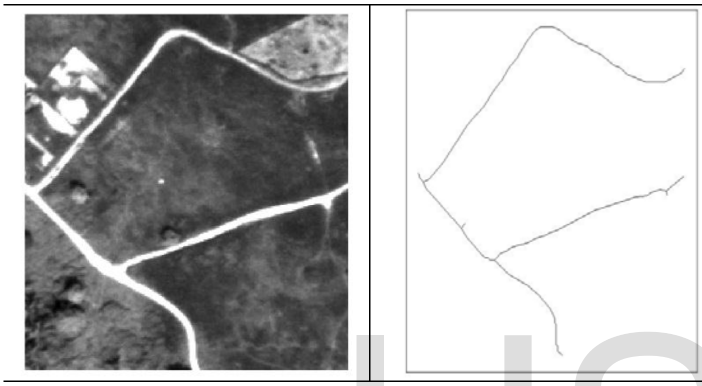

Figure 3.2 Input image and output extraction by the system for gravel road (subset 2). Scale 1: 600

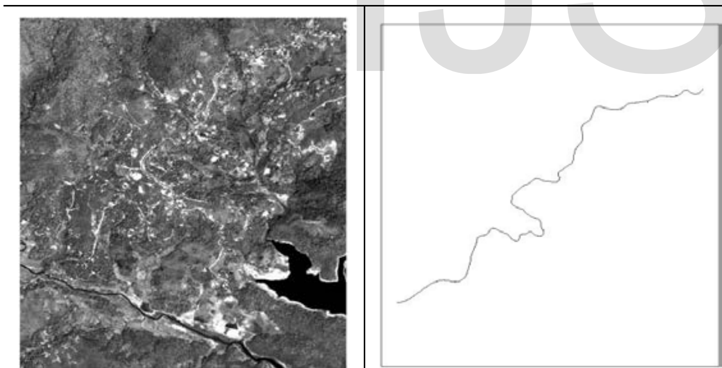

Figure 3.3 Input image and output extraction by the system for tar road (subset 1). Scale 1: 15,000

Accuracy assessment of these extracted road features was performed according to the proposed methodology. Accordingly the quality measures were obtained as listed in table 01. For the accuracy assessment the average road width was selected as buffer width of gravel road because road width in gravel roads were not uniform. Further, the calculated RMS values were equal to zero; due to shortest distance between pieces of the matched extraction and the reference network were equal to zero for all pieces because they overlapped in many places.

Table 01: Accuracy assessment of extracted road features

Measures	Gravel road subset 1	Gravel road subset 2	Tar road subset 1
Completeness	1	1	0.983
Correctness	0.991	0.9899	0.972
Quality	0.991	0.9899	0.956
Redundancy	0.015	0.0067	0.0132
RMS[m]	0	0	0

For accurate feature extraction, it is important to check the accuracy of training process that can be done using training confusion matrix. For the development of automatic systems for road feature extraction using ANN, only the accurately classified input vectors need to be utilized. Figure 3.4 shows the 1st results obtained from the second subset image, which is evident that the system was not correctly trained. If total correct classification percentage (TCCP) in training confusion is closer to 100% that network can be considered as correctly trained network. The accuracy of training process can be increased by changing ANN designed parameters and/or training parameters. Hence, the LVQ network was trained again and again by changing ANN designed parameters and training parameters until TCCP was closer to 100 %. When numbers of hidden neurons were changed as 8 and learning rate was changed as 0.001% and other parameters were remained as constant, it was able to obtained TCCP as 100%. By simulating that network with the same second subset of gravel road, reliable result was obtained as shown in figure 3.5.

However, in this research the results obtained from both approaches were compared and identified that each and every pixel's DN value similar to gravel road. Therefore, those pixels were classified as gravel road features. In that way this research has obtained most reliable result for gravel road extraction. The resulted road feature after applying the threshold value is presented in figure 3.6.

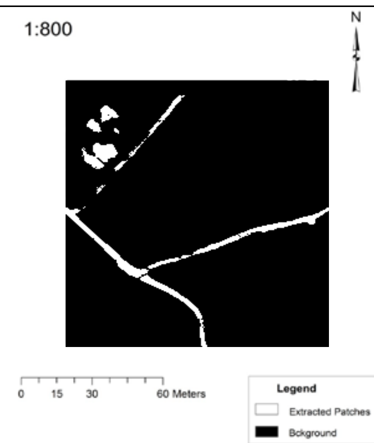

Figure 3.4: 1st results obtained through second subset

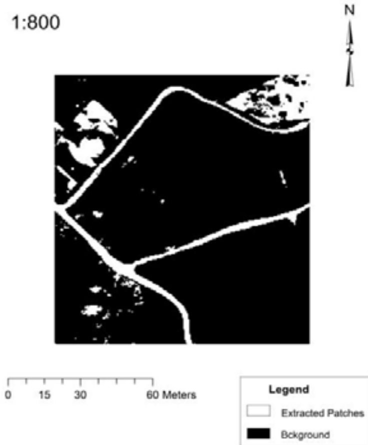

Figure 3.5: Results obtained through second subset with TCCP as 100%

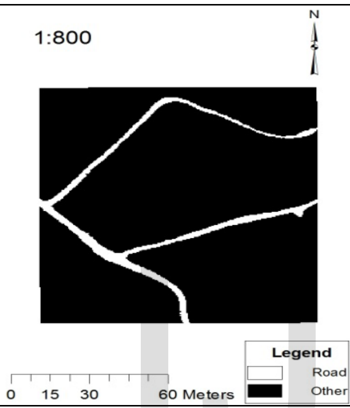

Figure 3.6: Extracted gravel road patches

When simulating the trained network using subsets of original image, other pixels that has similar DN values to tar road were classified as tar road features. However, most of those pixels were vegetation areas, because DN value of vegetation areas are more similar to tar road DN value in panchromatic image. Therefore, removing vegetation areas from extracted patches were essential in the case of tar road extraction. NDVI values were used to remove vegetation areas from the extracted patches and the resulted tar road is shown in figure 3.7 and 3.8 respectively.

Figure 3.7: Extracted tar road patches

Figure 3:8: Extracted patches of tar road after removing vegetation areas

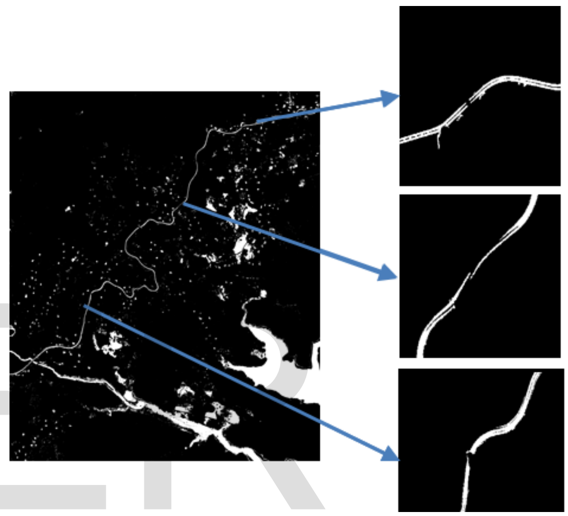

Figure 3.9: The gaps of extracted road

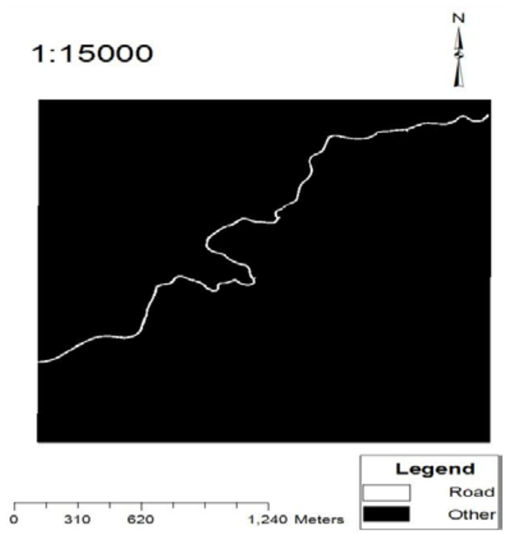

Figure 3.10: Extracted tar roads

The extracted road feature shown in figure 3.8 is not continuous due to gaps and missing data caused by obstacles as shown in figures 3.9. These gaps were filled and continuous road feature was obtained by applying morphological techniques. The resulted final road feature is shown in figure 3.10.

4 Conclusion and Recommendations

The research proves that learning vector quantification in ANN is a good tool for feature extraction from high resolution panchromatic satellite images. However, when training ANN the accuracy of training process should be considered because it is only possible to obtain accurate results from correctly trained network. The design parameter and training parameter are responsible for accuracy of training process; therefore, by changing parameters an accurate trained network can be achieved. In the case of tar road extraction, the NDVI image is essential to remove vegetation areas from extracted patches. Applying threshold value based on area condition is very beneficial to remove unwanted areas from extracted patches for both gravel and tar road. Noises due to similar pixels can be removed and road features can be extracted accurately. However applying threshold value based on area condition is enough for gravel road extraction.

The developed systems has shown overall completeness, correctness, quality, redundancy and RMS of 0.996, 0.989, 0.986, 0.008 and 0 respectively. These quality measures prove that ANN can be used for developing an automatic systems to extract road feature from WorldView II high resolution satellite images.

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