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AUTOMATIC ROAD EXTRACTION FROM HIGH RESOLUTION SATELLITE IMAGES USING NEURAL NETWORKS, TEXTURE ANALYSIS, FUZZY CLUSTERING AND GENETIC ALGORITHMS

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KEY WORDS: Road Extraction, Neural Networks, Co-occurrence Texture Analysis, Fuzzy Clustering, Vectorization

ABSTRACT:

In this article, a new method for road extraction from high resolution Quick Bird and IKONOS pan-sharpened satellite images is presented. The proposed methodology consists of two separate stages of road detection and road vectorization. Neural networks are applied on high resolution IKONOS and Quick-Bird images for road detection. This paper has endeavoured to optimize neural networks' functionality, using a variety of texture parameters. These texture parameters had different window sizes and grey level numbers, not only from source but also from pre-classified image. Road vectorization is based on the idea of road raster map clustering obtained from the previous road detection stage. In this step, despite of genetically guided clustering, a new flexible clustering methodology is proposed for road key point identification. The last step of road key point connecting is carried out based on the obtained information from a fuzzy shell based clustering. The accuracy assessment of the obtained vectorized road network proved the ability of the proposed method in sub-pixel road extraction.

1. INTRODUCTION

1.1 Road Extraction

The presence of high resolution satellite images and their potential to be used in wide variety of applications such as preparing and updating maps have made the automatic extraction of object, especially roads and buildings, a new challenge in remote sensing.

Traditionally, road extraction from aerial and satellite images has been performed manually by the operator. Considering the fact that this method was costly and time consuming the efficiency was by no means very high.

Automatic road extraction provides means for creation, maintaining, and updating transportation network. It also provides data bases for traffic management, automated vehicle navigation and guidance.

Vigorous methods have been proposed for automatic and semi-automatic extraction of road networks from satellite images. Recently, these methods are more focused on high resolution satellite images due to their outstanding characteristics in mapping from space.

1.2 Related Researches Review

A comprehensive review on the proposed methods for road extraction is found in (Mena, 2003) where these methods are categorized from different aspects. A comprehensive reference list is also accessible.

(Mohammadzadeh et al. 2006) proposed a new fuzzy segmentation method for road detection in high resolution satellite images with only a few number of road samples. Afterward by using an advanced mathematical morphological operator, road centrelines were extracted.

A road detection strategy based on the neural network classifiers was introduced by (Mokhtarzade and Valadan, 2007) where a variety of input spectral parameters were tested on the functionality of the neural network for both road and background detection.

The idea of geometrical and topological analysis of high resolution binary images for automatic vectorization of segmented road networks was presented in (Mena, 2006). Robust polynomial adjustment was used for geometrical analysis while mathematical morphological operators were applied in topological adjustment.

Recently, many researchers have tested the idea of using contextual information for improving segmentation process of road regions.

The research presented by (Mena and Malpica, 2005) is a good example for exploiting texture information in road extraction. In his paper, Mena and Malpica, performed a GIS updating using the pre-existing vectorial information and the RGB bands of high resolution satellite or aerial images. The binary segmentation performed in his research was based on Texture Progressive Analysis – the three level of texture statistical evaluation – being developed based on evidence theory framework. Finally, through skeleton extraction and

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morphological operators, the obtained binary image was vectorized.

Furthermore, (Zhang and Couloigner 2006) evaluated the effectiveness of angular texture signature to discriminate among parking lots and roads using high resolution satellite images. In their research, spectral and textural information were used separately for detection of roads and for eliminating of non-road pixels respectively.

In this research, a two stages road extraction methodology is presented consisted of road detection and a vectorization processes.

Road detection is performed on high-resolution pan-sharpened RGB Quick Bird and IKONOS satellite images, using texture parameters in artificial neural network algorithms.

The vectorization procedure is made up of two steps of road key point identification and generating road connections. Road key point identification is performed using c-means clustering on road raster map. For this reason, at first the possibility of genetically guided clustering is evaluated. Then a novel methodology for flexible road key point determination, called increasing ellipse, is proposed.

When road key points as the centre of different adjacent road patches are determined, a fuzzy shell clustering provides the clues for establishment of road segments.

In section 2, the proposed methodology for both steps of road detection and vectorization are described. Section 3 presents the obtained practical results and accuracy assessment parameters.

2. METHODOLOGY

Road networks in high resolution satellite and aerial images are presented as elongated homogeneous areas having a distinct brightness differences from the background.

Therefore, the common practice of automatic road extraction from high resolution satellite images, as it is implemented in this research, consists of two main steps entitled as "Road Detection" and "Road Vectorization".

Figure 1 shows the diagram of the implemented methodology of road extraction in this research.

The first step of road detection concentrates on discriminating between road and background pixels. It is considered as an image segmentation process where a meaningful value is assigned to each image pixel that can be used as the criterion to distinguish between road and non-road pixels.

In this research, neural networks are applied for road detection where different spectral and texture parameters are uses as their input parameters. The result of road detection is a binary image, representing all detected road pixels which is called "road rater map".

The vectorization step aims at extracting the road network centreline and its sides from the previously produced road raster map.
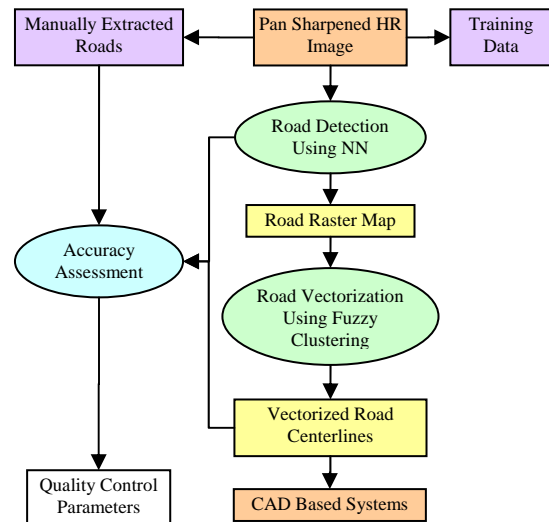

Figure 1. The methodology of road extraction

In this research, a novel method of road raster map clustering is developed to identify road key points, where a fuzzy shell clustering provides the required information to generate vectorized road networks.

It should be mentioned that the vectorization step can be implemented independently from the road detection step. Hence, it could be applied on any road raster map generated from different road detection methodologies.

In the following, the detailed methodologies for each of these two main steps are explained in different sections.

2.1 Road detection

In this research, the most common back propagation neural networks are used as the image classifiers for road detection. Figure 2 shows the designed neural network structure for this reason.
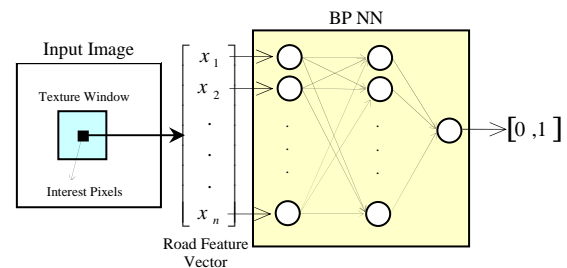

Figure 2. Road detection using neural networks

As shown in figure 2, the input layer consists of neurons the same number as road feature vector dimension where each input neuron is in charge of receiving one normalized input parameter. Only one hidden layer is designed in the neural network while the number of neurons in this layer can be varied.

The output layer has only one neuron, expressing the neural network's response in the range of [0, 1] as the road association value for the interest pixel.

After applying the trained neural network on the entire input image, the road raster map can be produced assuming a threshold on the road association value of input image pixels.

A detailed survey on road detection using artificial neural networks can be found in (Mokhtarzade and Valadan, 2007).

Beside spectral values, textural behaviour of road pixels as being homogeneous areas is the most outstanding road pixel property in the high resolution satellite images. Hence, incorporating spectral and textural parameters for road feature vector generation is going to be implemented in this research.

The input image was converted to different levels of intensity values and a variety of co-occurrence texture parameters, consisting of Energy, Entropy, Contrast, Homogeneity, were extracted from different window sizes.

Except the source satellite image, the preliminary road raster map generated from a simple neural network (trained only with spectral information) was also used as the input image for texture analysis.

Different combinations of texture and spectral parameters were put in the road feature vector and the functionality of the neural network was evaluated comparing the road raster map and the reference manually determined road pixels.

It was determined that using all four texture parameters, extracted from the preliminary road raster map, accompanied by the spectral information of the source image can make the optimum road feature vector. This road feature vector could improve both road and background detection ability of neural network.
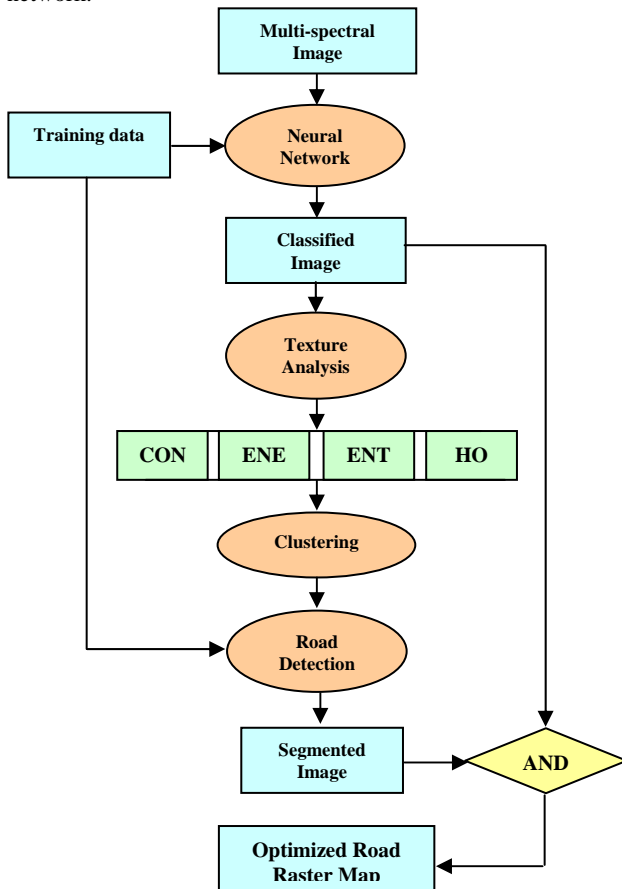

Figure 3. Road detection using texture parameters of preliminary road raster map

Figure 3 shows the diagram of the proposed methodology for road detection using texture parameters in neural networks.

The detailed explanation about this subject can be found in (Mokhtarzade, et al, 2007).

2.2 Road vectorization

The vectorization methodology implemented in this research is based on the idea of road raster map clustering, first introduced by (Doucette et al., 2001). This process can be divided into two main steps as "road key point identification" and "road key point connection".

2.2.1 Road Key Point Identification

In the first step of road key point identification, the road raster map, obtained from the road detection process, is segmented into different adjacent road patches based on image space clustering algorithm. When the clustering is performed, the centroid of each road patch is regarded as a road key point.

In (Doucette et al., 2001), a K-mean crisp clustering algorithm with user defined cluster number was applied on high resolution road raster map using a uniform distribution of cluster centres. This traditional method can produce acceptable results provided that the available roads in the raster map share rather the same distribution in the image and have similar widths. Furthermore, the initial number of clusters, determined by trial and error, has a major influence on the success of this method.

In order to overcome the mentioned shortcomings of the traditional method, especially the influence of initial cluster number, a genetically guided clustering with a variable length chromosome introduced in (Malay K. et al., 2005) was developed.

Considering the elongation property of road patches, an ellipse was used to represent clusters shape. In this manner, the chromosome structure was designed as five-gene blocks where each block represents an ellipse position (x, y), shape (a, b) and orientation parameters. Figure 4 shows the structure of the designed chromosome for the case of having M clusters.
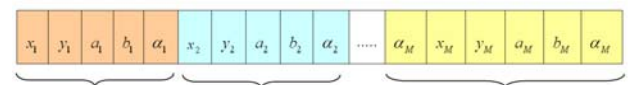

Figure 4. Chromosome structure for genetically guided ellipse clustering

The proposed genetic fitness function used in this research is shown in equation 1.

$$Fitness\_Function = \frac{\sum_{i=1}^{M} FP_i}{M^2} \qquad (1)$$

Where FP_i shows the filled percent of ith ellipse computed as below:

$$FP_i = \frac{N_i}{4a_i b_i} \qquad (2)$$

Where N_i represents the number of road pixels assigned to i^{th} cluster (road patch).

Beside genetically guided road key point identification, the idea of ellipse clustering was developed to another novel method called "increasing ellipse". In this method, for each road patch representative ellipse, the following parameters are determined:

$$Area_i = 4.a_i.b_i$$
$$Diff\%_i = \frac{Area_i - N_i}{Area_i} \qquad (3)$$
$$Sample\%_i = \frac{N_i M}{N}$$

In this equation $Diff\%_i$ shows the percent of the ith ellipse area difference with the area covered by its associated road pixels. Also $Sample\%_i$ is a measure of the expected assigned road pixels to the ith road patch. Based on the above introduced ellipse parameters, road patches are categorized as Noise, Coincide and Under-Evaluation patches. Noise patches are those clusters having the following conditions:

$$(Diff\% \rangle Mean_{Diff\%}\% + 2.5\sigma_{Diff\%})AND(Sample\%\langle 0.5)$$
$$Sample\%\langle 0.1 \qquad (4)$$
$$b\langle 2$$

In equation 5, $Mean_{Diff\%}$ and $\sigma_{Diff\%}$ are the mean and standard deviation of $Diff\%_i$ values of all M clusters.

Coincide patches are those clusters satisfying the conditions expressed in equation 5.

The patch is not markes as Noise patch
$$Diff\%\langle Threshold \qquad (5)$$
$$a < 4b$$

Under-Evaluation patches are the rest of clusters not marked as noise nor as coincide patches. Figure 5 shows the methodology of the invented increasing ellipse clustering. The termination condition of this procedure is to have no ender-evaluation patches while all of them are categorized as coincide or noise patches
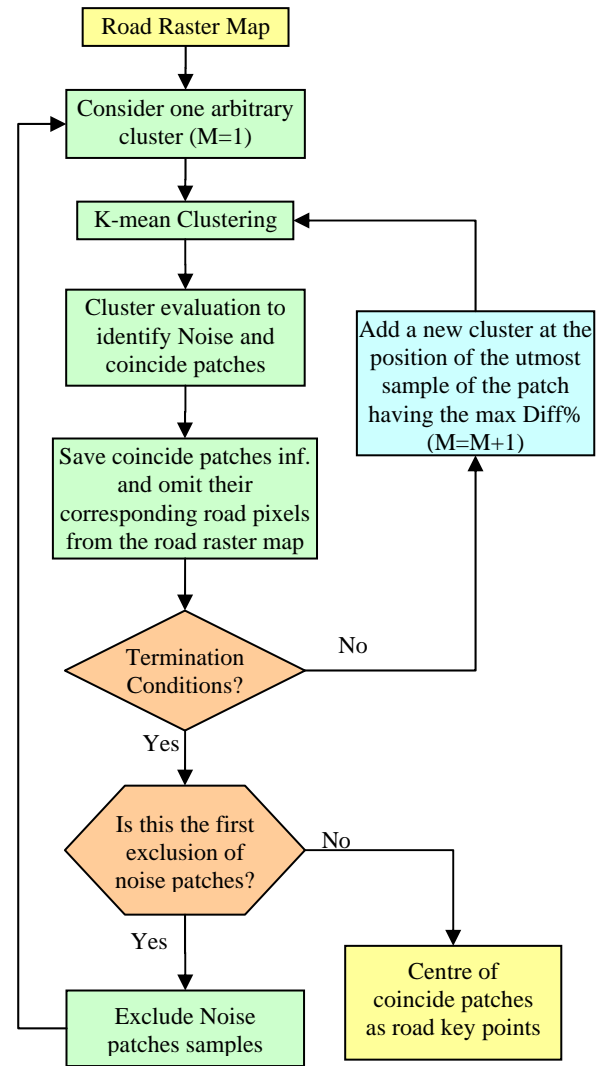

Figure 5. Increasing ellipse road vectorization

The termination condition of this procedure is to have no ender-evaluation patches while all of them are categorized as coincide or noise patches.

2.2.2   Road Key Point Connection: In order to make correct connections between the identified road key points, the presence of common road pixels between adjacent road patches were used as the connection guide.

For this reason, a fuzzy shell clustering was implemented on the pre-determined ellipse, representative of coincide patches. Vague samples, which are road pixels belonging to more than one road patch with rather the same membership values, were determined based on the obtained membership matrix. Using the centroid of vague road pixels as the middle point of key points, the corresponding connections were generated.

3.   PRACTICAL RESULTS

In order to evaluate the functionality of the road extraction method proposed in this research, two sub-samples of pan-sharpened Quick Birds and IKONOS images from Bushehr harbor and Kish Island in Iran were used as case study. Figures 6 and 7 show the source input images with their manually

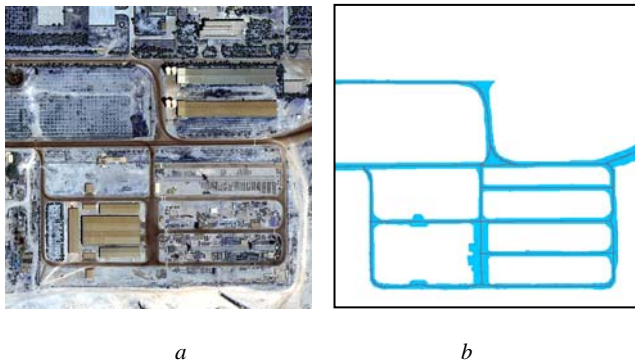produced reference images applied in accuracy assessment procedure.

<center>*a*   *b*</center>

Figure 6. Pan-sharpened Quick Bird image of Bushehr harbor and its manually produced reference image
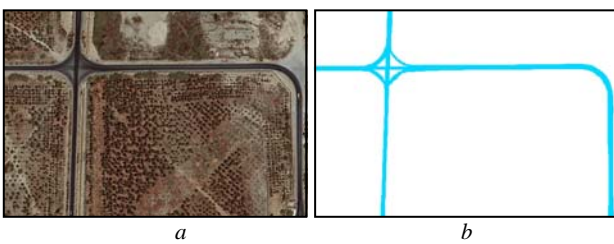

<center>*a*   *b*</center>

Figure 7. Pan-sharpened IKONOS image of Kish Island and its manually produced reference image

In the following sections, the practical results of different step of road extraction are presented accentuating on practical aspects of the implementation.

3.1 Implementation Results of Road Detection

Road detection was performed using an artificial neural network consisting of 7 neuron in its input layer in charge of receiving 3 spectral values (R, G, B) and 4 textural parameters as explained in section 2.1. The hidden layer was made up of 10 neurons and the output layer, having only one neuron, was designed to show the response of neural network.

	Sample #1			Sample #2		
	RCC	BCC	RMSE	RCC	BCC	RMSE
No Texture Parameter	82.36	93.53	0.172	77.05	90.86	0.259
Using Texture Parameters	93.54	96.31	0.106	80.77	96.15	0.196

Table1. Accuracy assessment of road detection procedure

About 500 road and 500 background pixels were selected from each input image to be used in neural network training stage.

An adaptive strategy was applied for learning rate and momentum parameters to stabilize the training stage of the neural network.

In order to evaluate the performance of the road detection procedure, three quality control parameters, RCC, BCC and RMSE were used.

RCC and BCC, stand for "Road/Background Detection Correctness Coefficient" respectively, are the average of correct neural network response for road and background detection by comparison the manually produced reference image (Figures 6-b and 7b). Regarding the difference between the neural network response and its true expected response (0 for background and 1 for road pixels) as the error values, the Root Mean Square Error (RMSE) can be computed as the third accuracy assessment parameter.

Figure 8 show the neural network road detection results for input pan-sharpened images of Figures 6a and 7a. These gray scale images are produced by multiplying the normalized neural network output by 255.

<center>*a*   *b*</center>
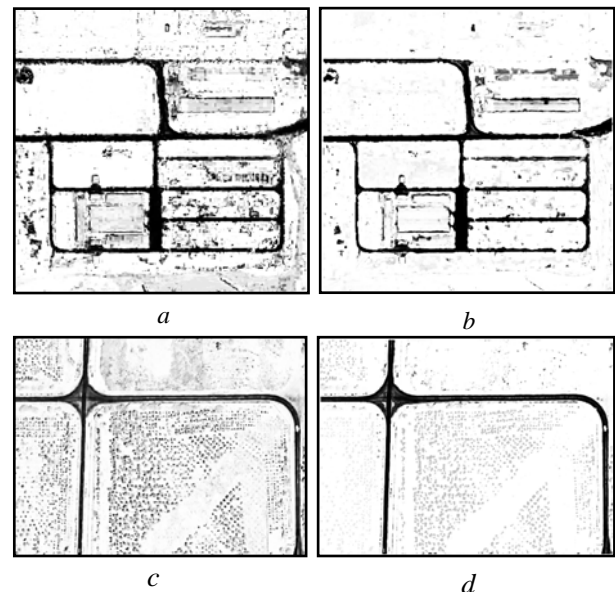
<center>*c*   *d*</center>

Figure 8. Neural network road detection results

In Figure 8, the left side images (8a and 8d) show the obtained result of simple neural network where no texture parameter is used. Right side images of Figure 8 (8b and 8d) depicts the output of the proposed neural network structure where texture parameters of the preliminary road raster maps (Figures 8a and 8c) are used beside spectral information for neural network input parameters set generation.

Table 1 show the obtained accuracy assessment parameters for both cases where the input source image of Figures 6a and 7a are called sample#1 and Sample#2.

The presented accuracy assessment parameters in Table 1 show that both road and background detection ability of the textural improved neural network are improved and thus the efficiency of the proposed road detection methodology in this research is approved.

3.2 Implementation Results of Road Vectorization

The obtained results of improved neural networks (Figures 8b and 8d) were converted to road raster map putting a threshold on the grey scale values. The obtained road raster maps were used in the road vectorization process described in section 2.2.
At the first attempt, genetically guided road key point determination was performed on a simulated road raster map. Although the obtained result was acceptable, the computation time, even for the small size simulated road raster map, was

high. The computation time problem reduced the practical attractiveness of this method and the alternative method pf increasing ellipse was followed.

The threshold value for coincide path determination was chosen to be 0.2. It should be mentioned that this value is selected based on the S/N ratio of the input road raster map. Figures 9 and 10 show the obtained result of road key point identification for two input images of Figures 6a and 7a. in this images, each road patch with its representative ellipse is presented in a separate colours.
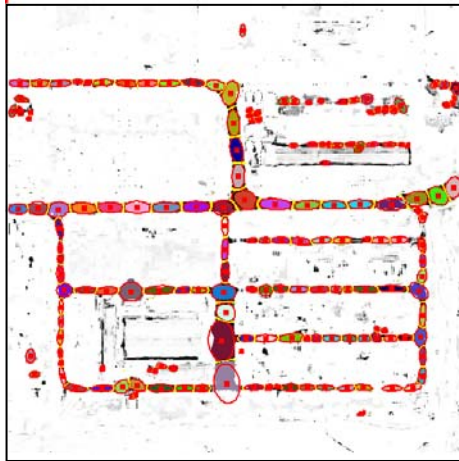

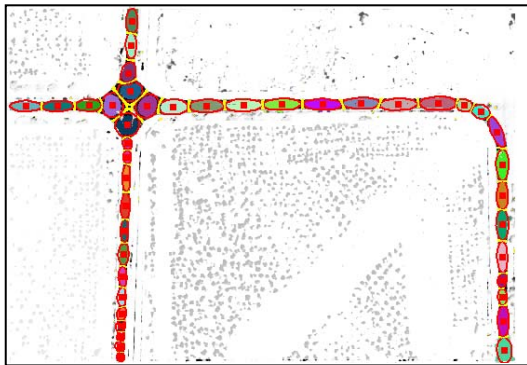Figure 9. Road key point identification of input image 6a

Figure 10. Road key point identification of input image 7a

A fuzzy shell clustering was performed based on the predetermined coincide road patches and vague road pixels were determined. These pixels are shown in Figures 9 and 10 with yellow colour.Finally, considering the centroid of vague road pixels, the road connections were generated as shown in Figures 11 and 12 for input source images of Figures 6a and 7q respectively.
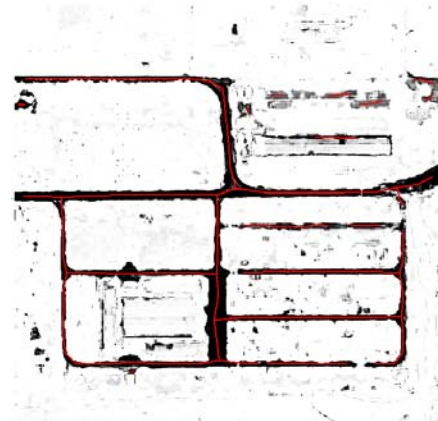

Figure 11. Road vectorization of input image 6a

Figure 12. Road vectorization of input image 7a

In order to evaluate the performance of road vectorization procedure, three accuracy assessment parameters were designed and computed which are called "Mean Deviation", "Completeness" and RMSE.

Mean deviation is computed as follows:

$$\text{Mean Deviation} = \frac{\text{Deviation Area}}{\text{Road Legth}} \qquad (6)$$

Where, deviation area is the area between the identified road centerline and the manually reference extracted road vector map. Completeness, as the second vectorization accuracy assessment parameter, represents the length percent of the extracted road network in the input image.

Table 2 shows the obtained accuracy assessment parameters for both sample#1 and Sample #2.

	Mean Deviation	Max. Deviation	Completeness	RMSE
Sample #1	0.53	2.00	88%	0.55
Sample #2	0.38	1.41	84%	0.49

Table 2. Accuracy assessment parameters of road vectorization procedure

4. CONCLUSIONS

In this article, a road extraction methodology from high resolution satellite images is proposed.

The first step called road detection was performed based on NN classifiers. It was discovered that using texture parameters of a binerized pre-determined road raster map integrated with spectral information of individual pixels can improve both road and background detection ability of neural networks.

In the second step of road vectorization, genetic algorithms did not show enough attractiveness as they are quite time consuming for image clustering.

A novel clustering algorithm was proposed for road key point identification wich is based on shape interpretation of road patches. Then the obtained road key points were connected considering the adjacency information obtained form a fuzzy clustering.

The designed methodology was performed on different pan-sharpened IKONOS and Quick Bird sample images and the road extraction ability the proposed method was approved.

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