AUTOMATIC LINEAR FEATURE EXTRACTION OF IRANIAN ROADS FROM HIGH RESOLUTION MULTI-SPECTRAL SATELLITE IMAGERY

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ABSTRACT:

Attaining geospatial information is a challenge for many scientific practitioners. Such information is a necessary tool for spatial decision making. Remote Sensing (RS) is the leading art/science providing the data for many global or local applications such as: green house effect, pollution, military, urban and land use. Graphical elements of geospatial information can be divided into: points, lines, and planimetric features. The most prominent linear topographic features are roads, rivers, railways and vegetation boundaries. Roads are important large-network man-made structures. All the elements can be derived from RS images. Many efforts have been performed to extract proper information efficiently. They can be classified into: manual and automatic feature extraction. Manual techniques are fading away as they are inefficient and inaccurate. Automatic extraction of geospatial phenomena has been the subject of extensive research for the past decade. Feature extraction approaches are diverse especially for linear features whose major methodologies are: fusion-based, fuzzy-based, mathematical morphology, model-based approach, dynamic programming and multi-scale grouping. In this paper, an approach based on fuzzy and mathematical morphology is introduced. In the developed fuzzy process, each pixel is transformed into a matrix of membership degrees representing the fuzzy inputs. A minimum-reasoning rule is, then, applied to infer the fuzzy outputs. Finally, a defuzzification step is applied to extract features. Advanced morphological concepts: 'trivial opening', 'granulometry' and 'skeleton' are applied to remove small objects, narrow paths and noises automatically. In addition, shadows of trees and buildings that cause partially covered roads are recovered. This object of this paper is to illustrate an applied method for automatic extraction of Iranian roads from pan-sharpened IKONOS images. The method is successfully executed on different regions including urban, suburban and rural areas. It is concluded that extracted road centrelines are so accurate and precise. The results are more promising at the crosses and curved segments. The extracted road centreline is easily inserted in a *GIS*. For future work, authors intend to introduce the fuzzy classification method into an artificial neural network program. In addition, the illustrated method can be used for the purpose of change detection in the road network system of a city from high resolution satellite images.

1. INTRODUCTION

For the development of a large number of countries topographic mapping from space must be regarded as a necessity (Konecny and Schiewe, 1996). Today many suitable and operational sensors exhibiting various spatial, spectral and temporal resolutions and continuously delivering raw imagery are in orbit, and more are to come. Thus, the time and cost intensive manual procedure necessary for turning these images into useful geographic information constitutes the main bottleneck, which needs to be overcome. The solution is an increase in automation in order to improve the efficiency of satellite topographic mapping. The major types of linear topographic objects are roads, rivers, railways and vegetation boundaries. The major linear features of interest right now are roads. Automatic extraction of roads from digital images has been an active research subject for a decade. This field is quite young and the major approaches are not settled. Research in feature extraction is still very diverse and object extraction is a fundamental computer vision operator.

There are different methodologies for feature extraction, especially for linear features such as image fusion for feature extraction (Pigeon et al., 2001), fuzzy-based approach (Agouris et al., 1998), mathematical morphology (Zhang, 1999), model-based approach (Buckner, 1998), dynamic programming (Gruen et al., 1995), multi-scale grouping and context (Mayer et al., 1997), and kalman filtering (Vosselman et al., 1995).

2. METHODOLOGY

2.1 Stage 1: Developed Fuzzy System

In the first step, we have developed a fuzzy method used by Melgani et al. (2000). In this approach multispectral remote sensing images are segmented in two classes: road and non-road. By sampling from road surface, mean value of the road in each band will be obtained. We have defined 5 membership functions (MFs) with special means and standard deviations in each band. Then, a fuzzification step is applied for obtaining an estimation of the class contributions in each band assuming a Gaussian distribution of the classes. After a MIN and a MAX operation on these fuzzy inputs results to the fuzzy classification of the scene. Then a hard classification can be deduced in the defuzzification step in order to achieve to the segmented image. This method is successfully applied on IKONOS Pan-sharpened image. Figure 1 shows defined hypothetic MFs for bands one and two. There are 5*5=25 classes for two bands and 5*5*5=125 classes for three bands. Figure 2 shows implementation flowchart used in the fuzzy step.

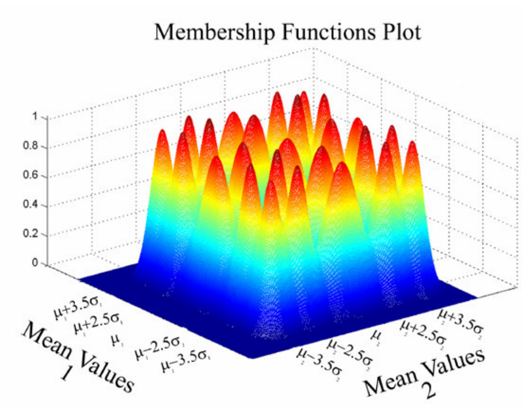

Figure 1. Defined classes using MFs of bands 1 and 2

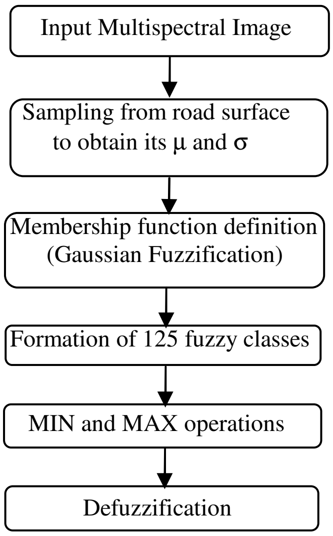

Figure 2. Implementation flowchart in fuzzy step

A fuzzy class c in band b is defined by $f_{b,c}(x_b)$ where x_b is the grey level of the pixel in band b. $\mu_{b,c}$ is the mean value of class c in band b. $\sigma_{b,c}$ is the standard deviation of class c in band b. The pixel vector X in the B-dimensional space is (Melghani et al., 2000):

$$X = [x_1, x_2, \ldots, x_b, \ldots, x_B]$$

$$f_{b,c}(x_b) = \exp\left(-\frac{(x_b - \mu_{b,c})^2}{2 * \sigma_{b,c}^2}\right) \Rightarrow f = [f_{b,c}] \qquad (1)$$

$$\forall x_b \in [0,255] \quad \sum_{i=1}^{255} f_{b,i}(x_b) = 1$$

For the hard classification, first a MIN operation is applied on each column of the matrix *f*. Then a MAX operation will be performed on these elements to obtain the element with the highest value (fuzzy output) and the corresponding class of that element will be considered as associated fuzzy class to that pixel. As mentioned before, there are 125 hypothetic classes. Among these classes, only 64th class is road (this depends on the order of the classes in the matrix *f*). Other classes will be considered as non-road. In this manner, the image is segmented into road and non-road segment.

2.2 Stage2: Mathematical Morphology

Line based methods for automatic road network extraction from high resolution images involves edge-line detection, threshold selection, grouping and road linking. The difficulties arise when threshold selection and linking based on conditions such as proximity, orientation and geometrical constraints. With the complexity in the image due to the occlusions and difference of materials on both sides of road, these conditions normally are not satisfied specially for Iranian roads. This makes line based methods less effective for high resolution images. The approach used in the second stage is shown in figure 3 which is nearly close to the approach used by Zhang et al., (1999).

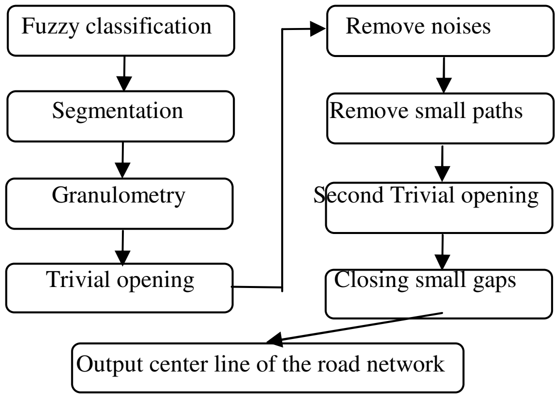

Figure 3. Block diagram used in morphology approach

Trivial opening is defined by Serra and Vincent (1993). It provides a practical mean of object detection and identification. It does not affect the shape and size of the objects of interest. Let *X* be a collection of connected pixels of objects where *Xi* is an object in *X*. Then, with a criterion *T*:

$$Trivial\ Opening = \begin{cases} X(i), \ if \ X(i) \ satisfies \ criterian \ T \\ \varphi, \quad Otherwise \end{cases}$$

$$\delta_{Xi}^{1} = (Y \oplus H) \bigcap Xi \qquad (2)$$

$$recon_{Xi}(Y) = \bigcup_{n \geq 1} \underbrace{\delta_{Xi}^{1} \delta_{Xi}^{1} \delta_{Xi}^{1} \delta_{Xi}^{1} \ldots \delta_{Xi}^{1}}_{n \ \ times}(Y)$$

$recon_{Xi}(Y)$ is the geodesic dilation of order n and δ_{Xi}^{1} is the elementary geodesic dilation. Assuming a pixel *Y* is in *Xi* then *Xi* is reconstructed from *Y* by iterating the elementary geodesic dilation until the whole object is covered. Figure 4 demonstrates the reconstruction of an object by morphological reconstruction.

The above mentioned trivial opening can be used to measure the size and shape of objects in an image. The opened images are compared with the original image to generate measures with respect to different size of structure element but with same shape. These measures can be used as shape and size signature of the original image (Granulometry) and can be plotted as a pattern spectrum.

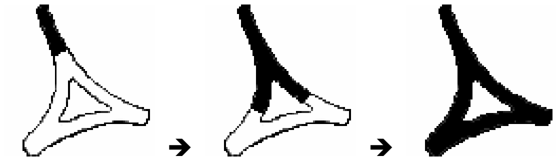

Figure 4. Morphological reconstruction

2.3 Implementation and Results

The methodology is applied to pan-sharpened IKONOS images of a rural area of *Kish Island* (Persian Gulf) and an urban area of *Rasht* (a city in northern Iran) as demonstrated in figures 5 and 6 respectively. Each figure consists of (a) the original image, (b) the fuzzy classified image, (c) segmented image, (d) result of trivial opening on segmented image, (e) initially identified road surface, (f) result of opening operation, (g) applying second trivial opening to remove narrow paths, (h) effect of closing to fill the small gaps, (i) extracted road center line, and (j) final extracted road centerline which is superimposed on the original image. Please note that there are extreme radiometric variations on the road surface of the *Rasht* city image and also its road sides. These variations have affected the result of the classification extremely. Meanwhile the result of the morphology process seems to be more satisfactory.

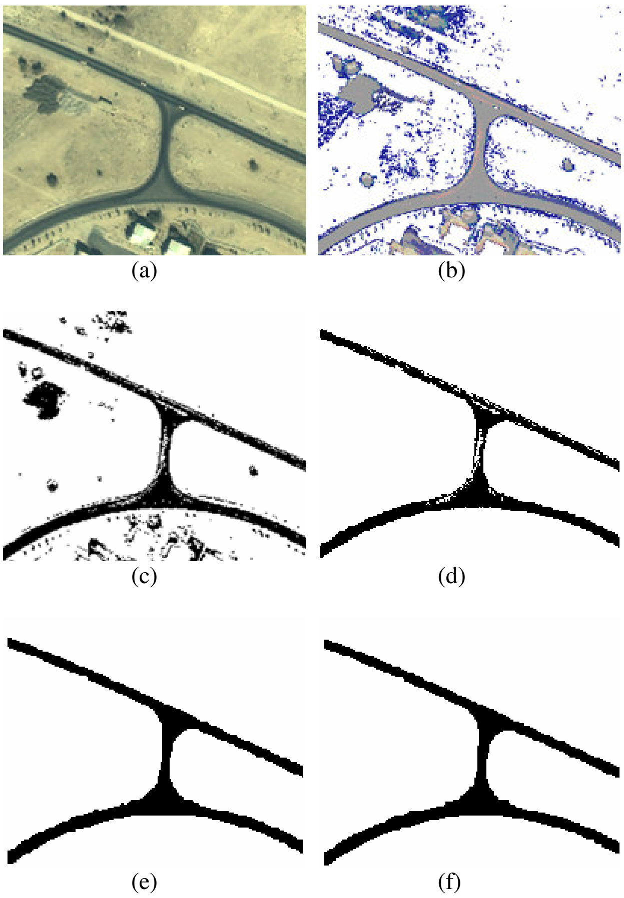

Figure 5. Road extraction from pan-sharpened IKONOS image of a rural area of *Kish* island: (a) original image, (b) fuzzy classified image, (c) segmented image, (d) result of trivial opening, (e) initially identified road surface, (f) result of opening operation

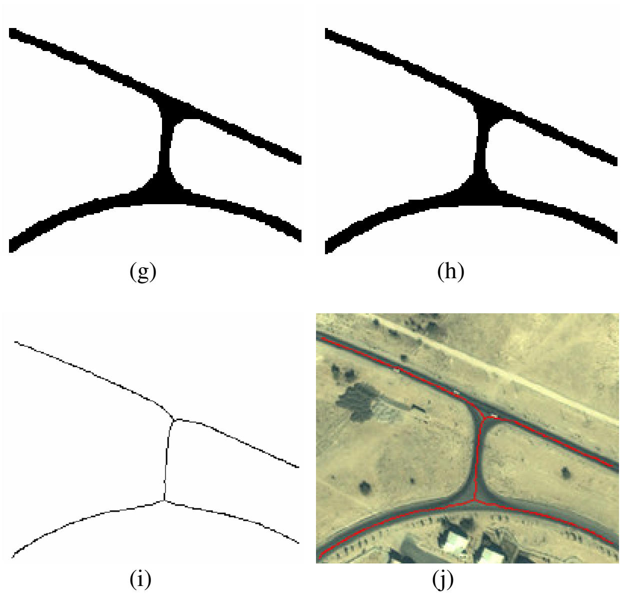

Figure 5. (g) applying second trivial opening, (h) effect of closing, (i) extracted road center line, and (j) extracted road centerline in red which is superimposed on the original image

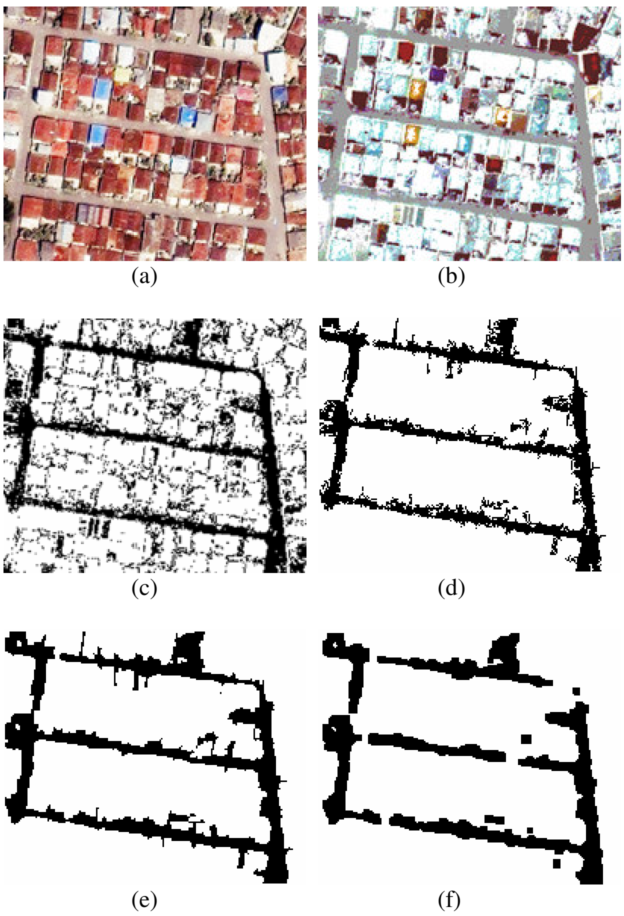

Figure 6. Road extraction from pa-sharpened IKONOS image of a rural area of *Kish* island: (a) original image, (b) fuzzy classified image, (c) segmented image, (d) result of trivial opening, (e) initially identified road surface, (f) result of opening operation

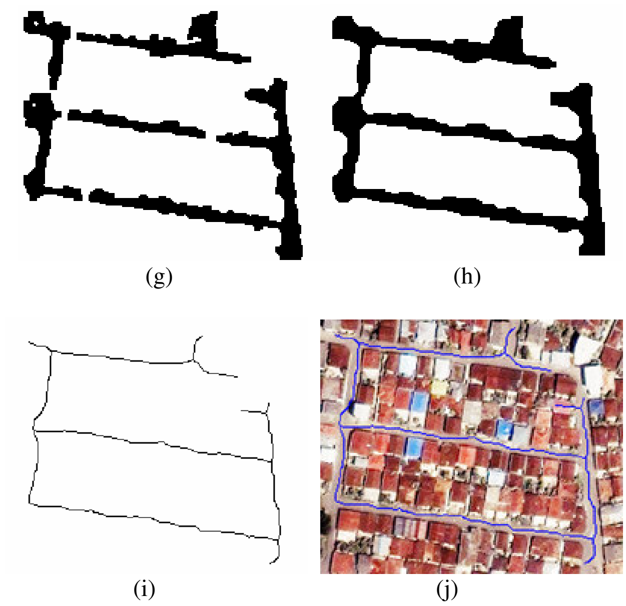

Figure 6. (g) applying second trivial opening, (h) effect of closing, (i) extracted road center line, and (j) extracted road centerline in blue which is superimposed on the original image

3. CONCLUSIONS

In this paper, an approach to detect road network from high resolution image using combination of a developed fuzzy system and mathematical morphology is proposed. In the fuzzy stage, only mean value and standard deviation of road is enough to classify the input image. The methodology has high performance for hyper spectral images that different image bands can be easily inserted or removed. Also it is tested that the mentioned fuzzy approach is much faster than maximum likelihood classification. Another advantage of this fuzzy classification method is its ease in introducing on artificial neural networks.

The algorithm in the mathematical morphology stage is based on the assumption that road network forms an elongated area which can be extracted as the connected components with certain criteria. Trivial opening preserves the whole road network and filter out the noises. Granulometry analysis was performed with trivial opening to provide size information of objects in the image. The results show that this approach provides sufficient information from successive steps for automatic road extraction and has satisfactory results for updating of road databases and change detection issues.

4. REFERENCE

Agouris, P., Gyftakis, S., and Stefanidis, A., 1998. Using a fuzzy supervisor for object extraction within an integrated geospatial environment. In: *International Archives of Photogrammetry and Remote Sensing,* Vol. 32, Part III/1, pp. 191-195.

Buckner, J., 1998. Model based road extraction for the registration and interpretation of remote sensing data. In: *International Archives of Photogrammetry and Remote Sensing*, Stuttgart, Germany, Vol. 32, Part 4/1, pp. 85-90.

Gruen, A. and Li, H., 1995. Semi-automatic road extraction by dynamic programming, *ISPRS Journal of Photogrammetry and Remote Sensing,* 50(4), pp. 11-20.

Konecny, G., and Schiewe, J., 1996. Mapping from digital image data with specific reference to MOMS_02. *ISPRS Journal of photogrammetry and remote sensing,* 51, pp. 173-181.

Mayer, H., Laptev, I., and Baumgartner, A., 1997. Automatic extraction based on Multi-Scale modeling, context and snakes. In: *International Archives of Photogrammetry and Remote Sensing*, Vol. 32, Part 3-2W3, pp. 106-113.

Melgani, F., Hashemy, B., and Taha, S.M.R., 2000. An explicit fuzzy supervised classification method for multispectral remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing,* 38(1) 287-295.

Pigeon, L., Solaiman, B., and Toutin, T., 2001. Linear planimetric feature domains modelling for multi-sensors fusion in remote sensing. In: *Proceedings of SPIE AeroSense - International Symposium on Aerospace/Defence Sensing, Simulation, and Controls, Orlando,* Vol. 4051, 8 p.

Vincent, L., 1993. Morphological greyscale reconstruction in image analysis: Applications and efficient algorithms. *IEEE Transaction on Image Processing*, 2(2): 176-201.

Zhang, C., Murai, S. and Baltsavias, E., 1999. Road network detection by mathematical morphology. In: *Proceedings of ISPRS Workshop on 3D Geospatial Data Production: Meeting Application Requirements*, Paris, France, Pages: 185-200.