ICIC Express Letters
Part B: Applications
Volume **7**, Number **12**, December **2016**

pp. **2671–2676**

A HIERARCHICAL OBJECT-BASED METHOD FOR SUBURBAN ROAD EXTRACTION FROM REMOTE SENSING IMAGE

Rui Xu[1,2,3]

[1]College of Information Science and Engineering
[2]Fujian Provincial Key Laboratory of Big Data Mining and Applications
Fujian University of Technology
No. 3, Xueyuan Road, University Town, Fuzhou 350118, P. R. China

[3]Key Lab of Spatial Data Mining & Information Sharing of Ministry of Education
Spatial Information Research Center of Fujian Province
Fuzhou University
No. 523, Gongye Road, Fuzhou 350002, P. R. China
dr.xurui@126.com

Received May 2016; accepted August 2016

Abstract. *Road extraction from remote sensing image is a very popular topic. There are many methods dealing with this problem, but few of them focus on suburban roads. This paper presents a hierarchical object-based method for suburban road extraction. First, the image is preprocessed by the Normalized Difference Vegetation Index (NDVI) and the Hue-Saturation-Intensity (HSI) Index. Vegetation regions, shadows and water areas are then removed. Second, texture features are applied to classifying the preprocessed image into two categories: road and non-road. Homogeneous property is combined to remove false classification so as to generate initial road skeleton. Third, the road skeleton is refined by using a series of morphology operations and shape features. Fourth, the curvilinear feature of road skeleton is detected by a set of multiple filtering detectors. Finally, a regression method is performed to extract smooth and accurate road centerlines. The experimental results indicate that the proposed method is suitable for suburban road extraction.*
Keywords: Road extraction, Object-based method, Classification, Centerline, Remote sensing image

1. **Introduction.** Road extraction from remote sensing image has been an active research subject in recent years. The extracted road network has diverse important applications, such as Geographic Information System (GIS) database update, urban mapping and planning, vehicle navigation, change detection, and image registration. However, it is time-consuming and tedious to manually label the road area from the image. With the help of computers, it is possible to reduce a lot of labor and time.

Various approaches have been proposed for this field and almost all the existing work shares similar processing pipeline. Poullis and You [1] classified road extraction methods into three categories: 1) pixel-based method; 2) region-based method; and 3) knowledge-based method. However, few of the existing methods have focused on the extraction of suburban roads. We briefly highlight the representative work for suburban roads extraction in the following. Grote et al. [2,3] proposed a region-based approach to extract suburban roads. The road candidates were detected by the normalized cuts algorithm, and were then connected to form road skeleton by the grouping algorithm. Mirnalinee et al. [4] designed a multistage framework based on region and edge integration to extract road networks. Experimental results on suburban scenes show this multistage framework is suitable for suburban road extraction. Koutaki et al. [5] provided a method for suburban road extraction. Their method first detected intersections of suburban roads. The road network was then extracted by the connecting rule based on the detected intersections.

Impressive results have been made by the above-mentioned literature. However, due to the lack of fully considering the features of suburban roads, most of the existing methods perform well only for one particular type of scene. To overcome this shortcoming, we present a new hierarchical object-based framework for extracting suburban roads. In this hierarchical framework, we firstly remove vegetation regions, shadows and water areas by the Normalized Difference Vegetation Index (NDVI) and the Hue-Saturation-Intensity (HSI) Index. Then the image is classified into road class and non-road class by texture features. By removing the non-road class we get the initial road skeleton. Next, homogeneous property, morphology operations and shape features are used respectively to refine the road skeleton. We finally extract road centerlines based on the curvilinear structure of road skeleton. Experiments show that the proposed method is able to achieve a good performance in road centerline extraction.

The remainder of this paper is organized as follows. The proposed approach is presented in Section 2. Experimental results are presented in Section 3. Conclusions are provided in Section 4.

2. **Methodology.** The workflow of the proposed method is presented in this section. The organization of this method is shown in Figure 1. The details of each step are introduced as follows.

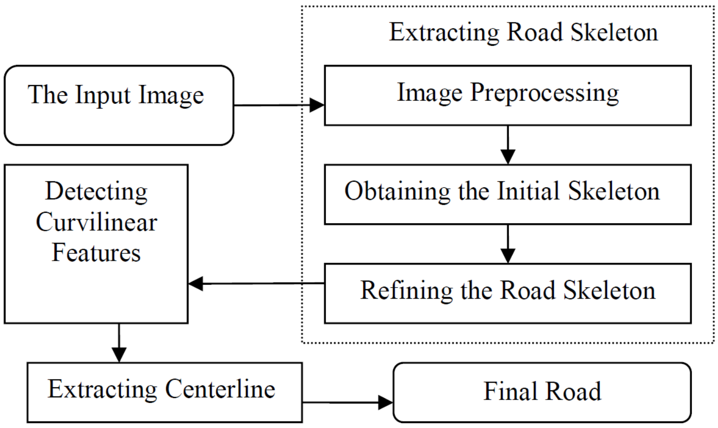

FIGURE 1. Flowchart of the proposed method

2.1. **Road skeleton extraction.**

2.1.1. *Image preprocessing.* To improve the efficiency of our method, first, image is preprocessed to remove noises such as vegetation, shadows, and water areas. We calculate the vegetation regions based on the NDVI which is obtained from the Red and Near-Infrared (NIR) by the following formula: $NDVI = (NIR - Red)/(NIR + Red)$ [6]. Next, an HSI color space is converted from a Near-Infrared-Red-Green false color space, and then shadow regions and water areas are detected by the HSI index which is calculated by the following formula: $HIS\ index = (Saturation - Intensity)/(Saturation + Intensity)$. Finally the noises are removed by Otsu's threshold.

2.1.2. *Obtaining the initial road skeleton.* The Gabor filters [7] have received considerable attention, because the characteristics of certain cells in the visual cortex of some mammals can be approximated by these filters. In addition, these filters have been shown to possess optimal localization properties in both spatial and frequency domain, and thus are well suited for texture classification problems.

In this paper, Gabor filter is applied to extracting texture feature of the image. After determining m scales and n orientations of Gabor filter, the mean μ_{mn} and standard deviation σ_{mn} can be calculated. The texture feature vector is defined as follows.

$$f_1 = [\mu_{00}\sigma_{00}, \mu_{01}\sigma_{01}, \ldots, \mu_{m-1,n-1}\sigma_{m-1,n-1}] \tag{1}$$

When the image is preprocessed in Subsection 2.1.1, the vegetation, shadows, and water areas are removed. By using the Gabor texture feature vector, the classification of SVM is applied to classifying the preprocessed image into two classes: the road class and the non-road class.

Due to the complexity of remote sensing image, it is difficult to extract roads accurately by using classification alone. To overcome this problem, more properties should be used and integrated with classification. Road surface usually has homogeneous property which reflects region consistency, with occasional variations. Gradient values of the image are often used to measure image homogeneous property. After the computation of the gradient values of the image, the image is thresholded into two classes: the homogeneous region and non-homogeneous region. If a pixel x is categorized into the road class and the homogeneous region at the same time, it is defined as road pixel; otherwise, it is defined as non-road pixel. The fusion of the road class region and the homogeneous region generates initial road skeleton.

2.1.3. *Refining the road skeleton.* Although the algorithm of obtaining the road region is able to remove most false road regions, misclassified roads still exist. Further processing is needed to improve the reliability of road extraction. First, a series of morphology operations such as corrosion and open operation is used to refine the initial skeleton. Second, road shape features are used to filter false segments. These features can be measured by area, compactness, slenderness and length-width ratio. Then the road skeleton is refined by the multistage postprocessing.

2.2. **Curvilinear structure detection.** By previous steps, the refined road skeleton is produced. However, the produced skeleton contains a few irregular shapes. In order to extract correct and smooth road centerlines, the curvilinear feature of road skeleton should be detected and enhanced. In this paper, we follow the method of Panagiotakis et al. [8].

Let $F(a, w)$ be a zero mean polynomial filter of orientation angle a and width w. The convolution of I_d with the $F(a, w)$ for different angles a and widths w is computed, yielding the image $I_f(a, w)$

$$I_f(a, w) = |I_d * F(a, w)| \tag{2}$$

Image $I_f(a, w)$ hosts an enhancement of the curvilinear structures of orientation a and width w. Eighteen different angles and three different widths were employed. The resulting image I_m is provided by getting the maximum of the corresponding pixel values of image $I_f(a, w)$

$$I_m = \max_{a,w} I_f(a, w) \tag{3}$$

In the resulting image, the maximum-response score map can be obtained. The curvilinear structures under any orientation and width are enhanced. [8] provided the details of each step about this method. As a high response score indicates a higher possibility for the road structure, road skeleton is well identified and smoothened.

2.3. **Extracting centerline.** The process of road centerline extraction can be approximately equivalent to determine the quantitative relationship between x and y directions from the discrete points. The quantitative relationship can be determined on the x and y directions by regression methods.

Multivariate Adaptive Regression Splines (MARS) is a nonlinear and nonparametric regression technique which was first proposed by Friedman [9]. MARS has been increasingly used in recent years in road centerline extraction as Miao et al. [10] have shown that this method is effective in extracting centerlines from road skeleton.

MARS builds models from two sided truncated functions of the *predictors* (x) of the form:

$$(x-t)_+ = \left\{ \begin{array}{ll} x-t & x>t \\ 0 & otherwise \end{array} \right\} \tag{4}$$

This paper uses MARS to extract road centerlines from the enhanced curvilinear skeleton. It is worth mentioning that extracting centerline by MARS directly from the road skeleton cannot get satisfactory results. The curvilinear structures of road skeleton need to be enhanced first.

3. **Experiment.** In this experiment, the study area is a part of suburb image which was recorded by the PLEIADES optical sensor. The study area has a spatial dimension of 800*800 pixels. The spatial resolution is 0.5m per pixel. Figure 2(a) shows the study area of this experiment. After preprocessing, we classify the image into road class and non-road class, and the initial skeleton is obtained. Next, we use homogeneous property, morphology operations and shape features respectively to refine the skeleton. The refined skeleton is shown in Figure 2(c). Figure 2(b) shows the result of Grote's method [2]. Compared with our method, Grote's method has two drawbacks: (1) most false road regions are not removed, (2) greenbelt cannot be detected and the two-way road is identified as a one-way road. In order to extract accurate and smooth road centerline, the curvilinear feature of road skeleton is enhanced, with the result shown in Figure 2(d). Finally, road centerlines are extracted from the curvilinear structures by MARS method, with the result shown in Figure 2(f). Figure 2(e) shows the result of the morphological thinning algorithm [11]. It can be seen from this experiment that the proposed method shows good performance, while the morphological thinning algorithm produced many undesired spurs and branches.

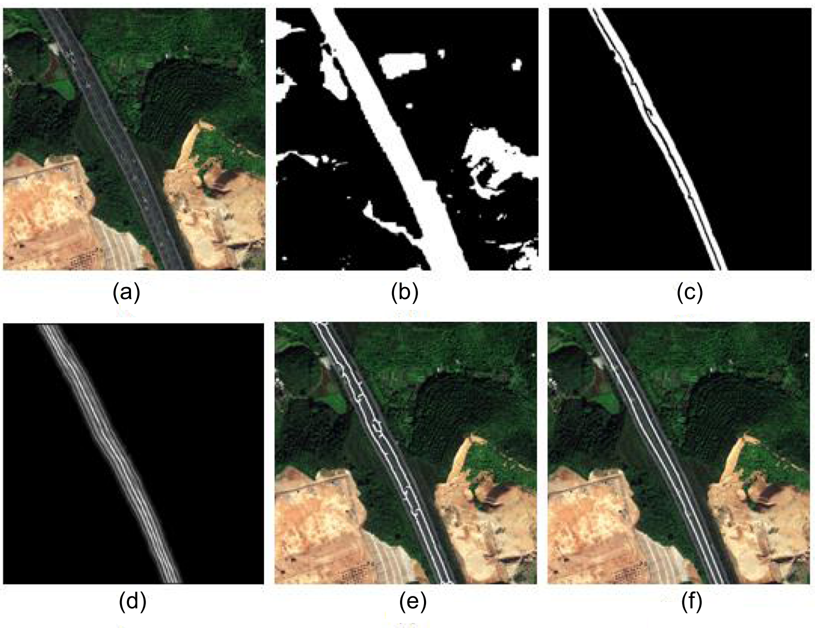

FIGURE 2. (a) Original image, (b) result of the skeleton by Grote's method [2], (c) result of the refined skeleton, (d) result of the curvilinear, (e) result of the morphological thinning algorithm [11] shown in white, (f) result of the proposed method shown in white

To quantify the performance of the proposed method, three accuracy measures [12] are used to evaluate it. These measures are: 1) $completeness = TP/(TP + FN)$; 2) $correctness = TP/(TP + FP)$; and 3) $quality = TP/(TP + FP + FN)$. The variables TP, FN, and FP denote true positive, false negative, and false positive, respectively.

We make comparisons between our method and Grote's method in completeness, correctness and quality with the result shown in Table 1. It is indicated that though Grote's method achieves high completeness, our method achieves higher accuracy in correctness and quality. It can be concluded that the proposed method provides a practical solution for suburban road extraction with comparatively high efficiency.

Table 1. Comparison of the two different road skeleton extraction methods

Methods	Completeness	Correctness	Quality
Grote's method	100%	51%	51%
Proposed method	89%	96%	86%

4. **Conclusions.** This study presents a hierarchical object-based method for suburban road extraction from remote sensing image. The experimental result shows that the proposed method is effective. There are three advantages about our method described as follows. Firstly, taking account of the features of suburban roads, the proposed method reduces non-road noises by removing vegetation regions, shadows and water areas. Secondly, the proposed method improves the accuracy of classification by integrating homogeneous property. Thirdly, the proposed method improves the smoothness and accuracy of extracting road centerlines by detecting the curvilinear feature of road skeleton through a set of multiple filtering detectors.

However, the proposed method is semi-automatic and many parameters need to be set by users. Future work will therefore focus on an objective and automatic threshold and parameter determination method.

Acknowledgment. This work is supported by the Project of Science and Technology of Fujian Province (2016H0001), the Project of Fuzhou Municipal Science and Technology Bureau (2015-G-53), and the Key Project of Science And Technology of Fujian Province (2014H6006). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

REFERENCES

[1] C. Poullis and S. You, Delineation and geometric modeling of road networks, *ISPRS Journal of Photogrammetry and Remote Sensing*, vol.65, no.2, pp.165-181, 2010.

[2] A. Grote, C. Heipke, F. Rottensteiner and H. Meyer, Road extraction in suburban areas by region based road subgraph extraction and evaluation, *Proc. of Urban Remote Sensing Joint Event*, Shanghai, 2009.

[3] A. Grote, C. Heipke and F. Rottensteiner, Road network extraction in suburban areas, *Photogrammetric Record*, vol.27, no.137, pp.8-28, 2012.

[4] T. T. Mirnalinee, S. Das and K. Varghese, An integrated multistage framework for automatic road extraction from high resolution satellite imagery, *Journal of Indian Society of Remote Sensing*, vol.39, no.1, pp.1-25, 2011.

[5] G. Koutaki, K. Uchimura and Z. Hu, Automatic road extraction based on intersection detection in suburban areas, *Journal of Imaging Science & Technology*, vol.49, no.2, pp.163-169, 2005.

[6] B. N. Holben, Characteristics of maximum-value composite images from temporal AVHRR data, *International Journal of Remote Sensing*, vol.7, no.11, pp.1417-1434, 1986.

[7] I. Fogel and D. Sagi, Gabor filters as texture discriminator, *Biological Cybernetics*, vol.61, no.2, pp.103-113, 1989.

[8] C. Panagiotakis, E. Kokinou and A. Sarris, Curvilinear structure enhancement and detection in geophysical images, *IEEE Trans. Geoscience and Remote Sensing*, vol.49, no.6, pp.2040-2048, 2011.

[9] J. H. Friedman, Multivariate adaptive regression splines, *The Annals of Statistics*, vol.19, no.1, pp.1-67, 1991.

[10] Z. Miao, W. Shi, H. Zhang and X. Wang, Road centerline extraction from high-resolution imagery based on shape features and multivariate adaptive regression splines, *IEEE Geoscience and Remote Sensing Letters*, vol.10, no.3, pp.583-587, 2013.

[11] M. Song and D. Civco, Road extraction using SVM and image segmentation, *Engineering and Remote Sensing*, vol.70, no.12, pp.1365-1372, 2004.

[12] C. Wiedemann, C. Heipke and H. Mayer, Empirical evaluation of automatically extracted road axes, *Proc. of the CVPR Workshop on Empirical Evaluation Methods in Computer Vision*, Los Alamitos, CA, pp.172-187, 1998.