Raziq et al., Geoinfor Geostat: An Overview 2016, 4:4
DOI: 10.4172/2327-4581.1000159

Geoinformatics & Geostatistics: An Overview

Research Article

A SCITECHNOL JOURNAL

Extraction of Urban Road Network from Multispectral Images Using Multivariate Kernel Statistics and Segmentation Method

Abdur Raziq*, Aigong Xu*, Yu Li and Xuemei Zhao

Abstract

Extraction of the urban road from multispectral images has been a challenging task in the remote sensing communities, from the last few decades. The common problems currently encountered in the extraction of urban road network are the scene covered by trees shadows and similar spectral objects, whilst, the roads has different widths and surface material. In this paper automatic road extraction algorithm is proposed. The proposed methodology is combining the ISODATA classification and the kernel statistics techniques to extract the urban road network from the remote sensing satellite images. The proposed methodology has three main steps; the first step is to perform classification of the color image, then these color classify images are converted into binary segmented images using the proposed algorithm. Secondly, the proposed algorithm is tested on the overlay color images (red line image) to detect the road network as binary images. Some filtering techniques are used to remove the redundant objects and connect the disconnected segment of the road such as segments reconstruction and region filling. Finally, post-processing techniques are employed to extract the centerline of the urban road, such, as the thinning algorithm is used. The intended procedures are implemented on various multispectral datasets such as IKONOS and QuickBird images which contribute accurate evaluation. The methodology can extract linear features such as road network in urban environment efficiently which is useful for recognizing some of other linear features. Experimental results yield that suggested methodology is computationally robust and effective.

Keywords:

Urban road extraction, Multispectral images, ISODATA classification, kernel statistics, Binary image, Post-processing, Thinning algorithm.

Introduction

The automatic extraction of linear information such as road networks is important data source in updating GIS database for traffic monitoring, intelligent transportation system, vehicle navigation, urban transportation mapping, city planning, land management, industrial development, tourism, cartographic feature extraction, geomorphologic, topographic mapping, disaster management, emergency handling, fault detection and son on For example, In case of traffic monitoring periodically images are required. Whilst in disaster management accessibility of information is needed on urgent basis. The author Hu et al. [1] point out that linear feature mathematically can be described by straight lines or arbitrary curves, for instance in digital mapping and GIS, road centerline, stream, shoreline, are normally analyzed is a vector data. Remote sensing imagery has been regarded the ancillary data source for topographic mapping by Heipke et al. [2].

With the revolution of remote sensing technology and the availability of high-resolution satellite imagery stimulate the development of new image processing algorithms for feature extraction in the urban area. In urban environment, roads and buildings are the major features for urban planning and land management. Remote sensing is a cost-efficient way to recognize the position of roads, highway, street, bridges and other ground transportation features to determine the road traffic conditions substantially [3]. And also economic life of urban occupants [4]. In addition daily life activities of the residents depend on the road network, the efficiency and security of every planned activity are critically bonded to how updated the knowledge about the position and condition of the road. For an update of road map such as field, survey are found costly and time-consuming procedures, remotely sensed and more specifically high-resolution satellite imagery is taken into consideration to provide highly accurate and timely information about urban roads network to detect changes and update map [5,6]. Road extraction has been the great concern since the first effort in satellite imaging [7] and along with the progressive technology and the day by day advances in imaging and data acquisition system the whole concepts and techniques of road extraction have been developing with time. For instance autonomous agents and ant colony optimization (ACO) algorithms develop for road map updating solution by Jin et al. [3,8] developed road feature extraction from high-resolution aerial images based on multi-resolution image analysis and used Gabor filters technique [8,9] developed an automatic method of extracting roads based on ISODATA segmentation and shadow detection from large-scale aerial images [10]. Presented road and roadside feature extraction using imagery and LIDAR data for transportation operation [11]. Proposed method for extraction of roads from a large scale dense point cloud merged from multiple aerial and terrestrial source scans of an urban environment. A detailed inspection of the road extraction methods can be looked at [12]. Also, Mena [13] examined some of the ideas. For instance, a simple classification can be easily performed dividing road detection methods into automatic or semi-automatic methods.

In addition many researcher have developed and employed automatic methods for extraction of hypotheses for road segments through line and edges detections and from a connection reconstruction between road segments and from a construction between road segments and from road network [14,15,16]. The methods estimate the road network as a set of straight lines, from this restricted assumption the accuracy of the road as suffers. By mainly focusing on geometrical shape criteria, operators derived from mathematical morphology [17]. Also Geman and Jedynak

***Corresponding author:** Aigong Xu, Liaoning Technical University, Institute for Remote Sensing Science and Application, School of Geomatics, Fuxin, Liaoning123000, China, Tel: +86 418 3350478; Fax: +86 418 3350478; E-mail: xu_ag@126.com

Abdur Raziq, Liaoning Technical University, Institute for Remote Sensing Science and Application, School of Geomatics, Fuxin, Liaoning123000, China, Tel: +86 418 3350478; E-mail: arraziqgis013@gmail.com

Received: October 05, 2016 **Accepted:** November 08, 2016 **Published:** November 14, 2016

doi: 10.4172/2327-4581.1000159

[18] developed another statistical model to track roads through hypothesis testing; morphological methods developed by Serra are a set theory. This method is sensitive to the geometry of features and uses set operations such as union, intersection, complementation, dilation, erosion and thinning to identify geometrical characteristics of objects [19,20] proposed a granulometry analysis based on mathematical morphology for detecting roads. In road extraction methodologies, the morphological filtering is used to remove the speckle and unwanted features preserving road segments as much possible. However, the use of a morphological filter in road detection suffers some limitations. An efficient morphological operators using paths as structuring elements proposed by Talbot and Appleton [21]. Paths as families of narrow, elongated, yet not necessarily perfectly straight structuring elements. These path operators constitute a useful alternative to operators using only straight lines. Mathematical morphology operations are also used to find the line skeletons in a binary image [21]. Also Karathanassi et al. [22] have used the concepts of mathematical morphology for extracting urban features from remotely sensed data. Daryal and Kumar [23] presented path opening and closing technique and used advanced directional mathematical morphology for the detection of the road network in very high-resolution remote sensing images.

A multi scale extraction for urban road intersection in high-resolution panchromatic imagery presented in Cai et al. [24]. A numbers of researcher used a non-parametric multivariate density estimation technique based on statistics [25,26,27]. Whilst, Hwang et al. [28] proposed a non-parametric histogram based thresholding methods for weld defect detection in radiography [29]. Submitted also a new approach of optimal thresholding, while fast scheme for optimal thresholding using genetic algorithms proposed by Snyder et al. [30] another important contribution by Yin [31] for color thresholding method for image segmentation of natural images. Kulkarni [32] Presented edge extraction using entropy operator. Shiozaki [33] used entropy a new definition and its applications [34] introduced potential functions algorithms for color image edge enhancement. Sindoukas [35] put an estimation of probability density function mode. Parzen [36] presented automatic isotropic color edge detection scheme.

Unfortunately, a very little research on road network extraction from multispectral imagery has been published including some work of Fan et al. and Doucette et al. [37,38]. The growing technology of remote sensing, high quality and fine spatial resolution satellite images have become available from different platforms. For instance, IKONOS satellite imagery has a spatial resolution of 1m in panchromatic mode and 4m resolutions in multispectral mode and QuickBird with 0.6m panchromatic and 2.4m multispectral mode are available. These images enable the extraction of even minor objects in urban areas. They have raised a renewed possibility of timely and efficiently updating changed road networks in urban areas. A numbers of problems have been investigated by scientist for the extraction of road from low to high-resolution satellite imagery in urban environment, for instance automatic extraction of roads from satellite images faces various challenges, because the image appearance of roads depends upon the spatial resolution of the satellite images, image degradation or presences of non-road linear feature in the image. In addition, the extraction is hidden by noise on satellite images. Although considerable attention has been given on the development of automatic road extraction techniques, but still it remains a challenging task due to the widespread variations of roads in the urban area and the complexities of their environments. For instance occlusions due to cars, trees, buildings, shadow [39]. Actually the multi-spectral data includes an NIR band that is suitable of vegetation and artifact in the urban area. This could be very helpful in a road identification step [40] now the research is developed in the direction of data fusion technique, for extraction of road networks from pan-sharpened MSI in urban areas [41] still; many problems are needed to be researched in the extraction of road networks from MSI, especially from high-resolution MSI. For example, most of the existing road extraction methods for MSI rely on an automated and reliable classification of road surfaces [37,38,42] used supervised or an unsupervised classification method are not satisfied the accuracy of road extraction. The main difficulty lies in the high misclassification between roads and other spectrally similar objects, for instance, parking lots, buildings or crop fields etc. Another issue involves the extraction of road centerlines, i.e. how can we accurately and robustly extract road centerlines from classified imagery. Some representative work in extracting road networks from MSI has been conducted by Song and Civco [37,38,43] present a novel methodology for fully automated road centerline extraction that exploits the spectral content from high-resolution multi-spectral images. Preliminary detection of candidate road centerline components is performed with anti-parallel-edge centerline extraction (ACE). This is followed by constructing a road vector topology with a fuzzy grouping model that links nodes from a self-organized mapping of the ACE components [39]. For example, Doucette et al. [39] used a spatial filter to refine the road class resulting from an image classification of their input IKONOS MS images. The refinement was achieved by removing noisy pixels, such as the building pixels, using the spatial filter based on the assumption that all of the small size components are not actual road pixels. The road segments are then joined and thinned to form a road network. Similarly, Doucette in [44] the coarse road class is obtained by thresholding the original panchromatic image. Zhang [42] used two shape measures, namely smoothness and compactness, to further reduce the misclassification between roads and other spectrally similar objects from a support vector machine (SVM) classifier. For road centerline extraction from classified imagery [38,37] presented a self-organizing road map (SORM) approach to road centerline delineation from classified imagery. The SORM is essentially a spatial clustering technique adapted to identify and link elongated regions. This technique is independent of a conventional edge definition and can meaningfully exploit multi-spectral imagery. The application of the proposed algorithm and procedure is to extract urban road from high- resolution images such is IKONOS and QuickBird, and creating a binary image to reduce the misclassification of the objects with other similar spectral object in the image, also to extract the centerline of road. In this Paper, the proposed methodology is combining the ISODATA classification and the kernel statistics techniques to extract the urban road network from the multispectral images. The rest of the paper is organized as follows: Section 2 describes the detail of algorithm developed in this paper. In Section 3, the proposed algorithm is tested on various MS images i.e., IKONOS, QuickBird, for urban road network extraction. Finally, Section 4 contains the conclusion and further research work.

Description of the Proposed Algorithm

Given a multispectral image $x = \{xi: i = 1, \ldots, N\}$, where i is the index of pixels, $xi = (xid: d = 1, \ldots, D)\ T$ is spectral measurement vector of pixel i, D is the dimension of the vector, $xid \in \{1, \ldots, j, \ldots, J\}$ is the components of xi, J is the maximum intensity taken by the components, N is the number of the pixels, T is transposition operation. In statistics based image processing, the image x can be

doi: 10.4172/2327-4581.1000159

viewed as the configuration of a random vector field $X = \{Xi: i = 1, \ldots, N\}$, where $Xi = (Xid: d = 1, \ldots, D)\ T$ is the random vector defined corresponding to pixel *i*, and *xi* is the configuration of the random vector *Xi*.

Let $XNi = \{Xi': i' \in Ni\}$ be the set of spectral measurement vectors for the neighbors of pixel *i*, where *Ni* is the set of neighbors of pixel *i*. The probability density function (*pdf*) of *Xi* is defined to the sum of multivariate Gaussian distributions with means Xi' and covariance $\Sigma i'$.

$$p(\boldsymbol{X}_i) = \frac{1}{2\pi^{-D/2}\left|\boldsymbol{\Sigma}_{i'}\right|^{-1/2}} \exp\left\{-\frac{1}{2}(\boldsymbol{X}_i - \boldsymbol{X}_{i'})^T \boldsymbol{\Sigma}_{i'}^{-1}(\boldsymbol{X}_i - \boldsymbol{X}_{i'})\right\} \quad (1)$$

$$\boldsymbol{\Sigma}_{i'} = (\boldsymbol{X}_{i'} - \bar{\boldsymbol{X}}_i)^T(\boldsymbol{X}_{i'} - \bar{\boldsymbol{X}}_i) \quad (2)$$

$$\bar{\boldsymbol{X}}_i = \frac{1}{\# N_i}\sum_{i' \in N_i} \boldsymbol{X}_{i'} \quad (3)$$

Where # *Ni* is the number of elements within the set *Ni*. By using the above *pdf*, road strength can be calculated as $y = \{y_i = p(xi): i = 1, \ldots, N\}$. Normalize y_i*'s* from 0 to 255 and take their integer parts,

$$y_i = \left\lfloor \frac{y_i - y_{\min}}{y_{\max} - y_i} \times 255 \right\rfloor \quad (4)$$

where $y_{min} = min\{y_i: i = 1, \ldots, N\}$, $y_{max} = max\{y_i: i = 1, \ldots, N\}$, $\lfloor\cdot\rfloor$ is rounding operator. As a result, $y = \{y_i: i = 1,\ldots, N\}$ can be considered as a road strength image. The above road strength image can be classified as two clusters, road and background, according to a threshold *T*. Given a threshold *T*, the probability for road pixels can be defined as

$$p_r(j) = \frac{c_j}{\sum_{j'=0}^{T} c_{j'}}, \quad 0 \le j \le T \quad (5)$$

where $cj = \#\{yi = j: i = 1,\ldots, N\}$, the probability for road pixels as

$$p_b(j) = \frac{c_j}{\sum_{j'=T+1}^{J} c_{j'}}, \quad T+1 \le j \le J \quad (6)$$

The corresponding entropies of the pixel clusters, road, and background, are respectively given by

$$H_r(T) = -\sum_{i=0}^{T} p_r(j)\log p_r(j) \quad (7)$$

$$H_b(T) = -\sum_{i=T+1}^{M} p_b(j)\log p_b(j) \quad (8)$$

The optimal threshold for performing the road and background pixel classification can be obtained

$$T = \arg\max_{T'}\{H_r(T') + H_b(T')\} \quad (9)$$

Based on the threshold T, the binary image of extracted road $z = \{zi: i = 1,\ldots, N\}$ can be calculated as follows

$$Z_i = \begin{cases} 255, & \text{if } y_i \le T \\ 0, & \text{if } y_i > T \end{cases} \quad (10)$$

Experiments and Results

To evaluate the proposed algorithm for extracting urban road, the first experiments are performed on two different datasets of high-resolution remote sensing images, including QuickBird and IKONOS images. In this paper, the result of road extraction is illustrated. The main reason for this choice is that they have an urban complex scene and irregular road shapes in the images. The test images have a size of 250 × 250 pixels and a 1 m resolution see Figures 1 and 2 shows the complete procedure of the proposed method for road extraction stepwise.

The pseudo-color segmented images generated from the test images are given in Figure 3 which is obtained by ISODATA image classification. It can be observed from the segmented images that the objects in Figure 3 (a1) and (a2) are catalogued into four classes where the road network is shown in purple color, while the objects in Figure 3 (a2) road is corrupted in some parts of the image; this is due to the effect of shadow trees along the roadside, trees is indicated in red color. Figure 3 (a1) and (a2) some misclassification, can be observed is due to similar spectral objects. In order to overcome these problems of misclassification the segmented pseudo-color images are converted into binary images using the proposed algorithm.

Figure 4 shows the binary images of the road network extracted from the segmentation images shown in Figure 3. It can be observed from Figure 4 that the extracted roads are corrupted by other objects with similar spectral objects. In addition, the proposed algorithm reduces the classes from Figure 3 into two classes such as black and white are shown in Figure 4 It is assumed that the white color having the value is 0 represented background while in contrast black color having value 1shown road network. It can be observed in Figure 4 (a1). QuickBird image is less contaminated than IKONOS image Figure 4 (a2). This is due to the shadow of trees and open field in the image. However, sometime due to the presence of cars and shadow of buildings may affect the efficiency of road extraction.

The parameter used in these experiments of the proposed algorithm is the value of thresholding is T-133 for the binary images

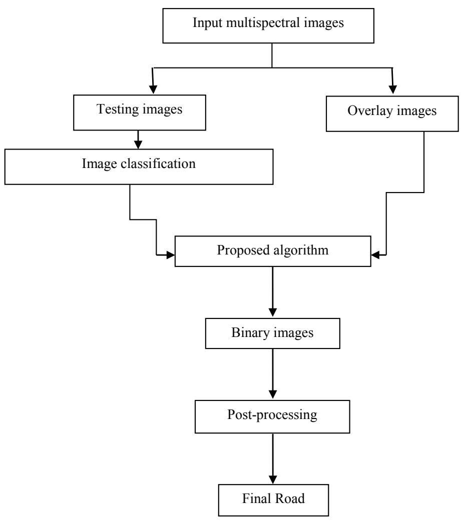

Figure 1: Flowchart of the proposed procedure.

(a1) (a2)

Figure 2: Testing images (a1) QuickBird and (a2) are IKONOS images.

doi: 10.4172/2327-4581.1000159

see in Figure 4. In addition, the value of entropy is 0.01 and the dimension D is equal to 3, also used the mean of neighborhood relationship with 3 x 3 sizes.

The second experiment is performed on the four datasets of high-resolution remote sensing images (Figure 5). In this case, the main aim of the proposed algorithm is directly detects the red line of the road represented the centerlines of the road; It can be observed that the proposed algorithm perfectly extracted the road red segments (Figure 6). However, it can be discovered that the algorithm directly converted the overlay and testing images as binary images and detect road correctly shown in Figure 6. Road segments are not correctly

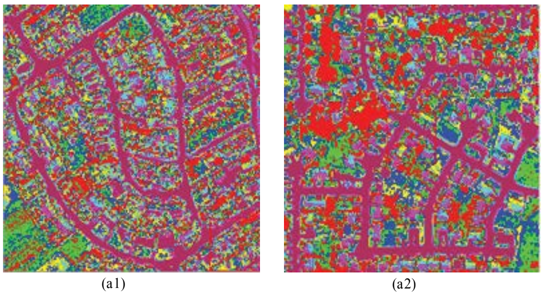

Figure 3: Result of ISODATA segmented images.

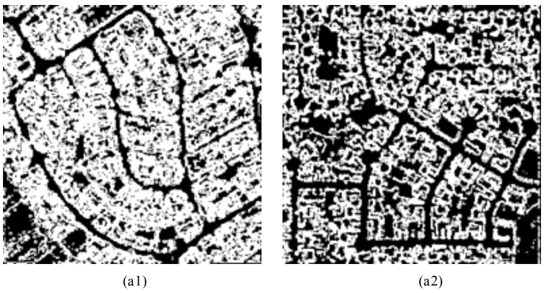

Figure 4: Binary images result of the proposed algorithm.

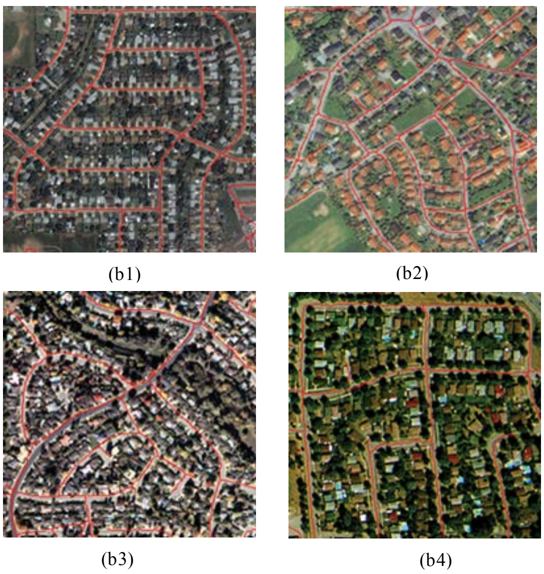

Figure 5: Overlay and testing images (b1)-(b3) are IKONOS, (b2)-(b4) are QuickBird.

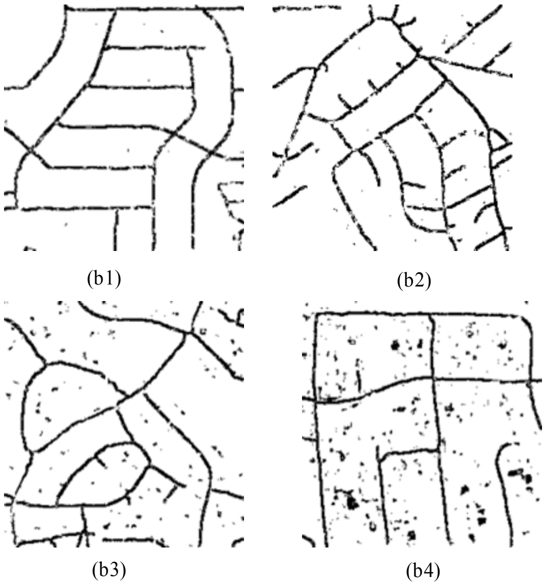

Figure 6: Binary images results of the proposed algorithm (Case.2.).

linked, and some small redundant objects are also detected in the output results mainly visible in Figure 6 (b3) and (b4).

Post-Processing Approaches

The Post-processing approaches involve filtering, for instance, lines or segments reconstruction, region filling and thinning of roads centerlines extraction.

Due to the complexity of the scene in remote sensing images, the extracted objects are contaminated by other objects. For example, the shapes of the road can be affected by cars, shadow of buildings and trees on the roads. However, some non-road objects having similar color features with road can also are misclassified as the roads see Figure 6. In order to overcome these problems of misclassification and extraction of road correctly, some filtering techniques are necessary to end this issues. For this purposes line or segment reconstruction and region filling techniques are used to eliminate the effect brought by cars and shadow of trees and buildings shown in Figure 7. And region filling is used to clean off the misclassified non-road features having non-linear shapes.

Finally, the thinning algorithm procedure is carried out developed by Tarku et al. [45] to extract the centerline of the road. The road centerlines are accurately detected illustrated in Figure 8.

The application of the intended algorithm are to convert the segmented color images into binary images in creating two classes black and white color which representing the foreground pixel (road pixel) and background pixel (non-road pixel) and also the direct extraction of an urban road from overlay and testing images accurately see Figures 4 and 6. The proposed methodology give much better results and can reduce the issue of similar features and misclassification spectral object problems and detect the centerline of road efficiently, pointed out in the researches [37,20,42]. To compare the result of the proposed filters in this experiment is more excellent such as line or segment reconstruction of road and region filling to remove the undesired nonlinear objects, as equate with the result of mathematical morphology operations used by Amini et al. [20,46]. These researchers used mathematical morphology operation to find

doi: 10.4172/2327-4581.1000159

the line skeletons in binary images. This proposed methodology is more efficiently and precisely detects the urban road network. Experimental results have confirmed that this proposed procedure can provide more reasonable result demonstrated in Figures 2-8.

Evaluation and Conclusions

Automatic urban road network extractions are presented from high-resolution satellite remote sensing images, i.e. IKONOS and QuickBird. In this paper, a series of algorithm and procedure are employed, firstly, the ISODATA classification techniques are applied for testing QuickBird and IKONOS images to provide a basis for the proposed algorithm see Figures 3 and 4 for further details. The major and practical merits of this approach are introducing the kernel statistics and some filters followed by the post-processing procedure. The intended algorithm is capable of converting the already segmented images to binary images shown in Figure 4. Where the road network is illustrated in linear and irregular shapes in black color. While the white color is represented as a background.

The proposed algorithm have the ability to reduces the classes of the segmented images and misclassification of the road and other similar spectral features i.e. shadow of trees along the roads and occlusion of the car on the road etc. it can be observed that the road is accurately classified in Figure 4 extracted from the segmented color image. Experimental results indicated possible use of the algorithm in extracting the road network from high-resolution satellite images in a reliable way. In some patches grassy field, open and parking area is classified as roads.

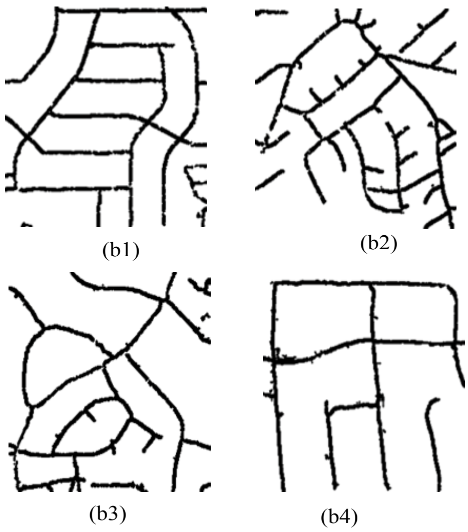

Figure 7: Result of segment reconstruction and filled region images.

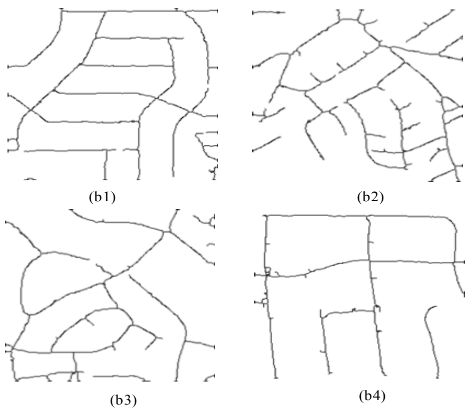

Figure 8: Result of the thinning algorithm.

Secondly, the proposed algorithm is tested on the overlay color testing images see in Figure 5 as four datasets. In this case, the road segments parts are correctly detected without any other spectral similar objects in Figure 6 particularly in Figure 6 (b1), (b2). Nevertheless, Figure 6 (b3), (b4) non-linear features are observed. In order to overcome these issues, some post-processing filters are implemented to remove the undesired objects, for example, segments reconstruction to link the road segments and region filling techniques to remove the redundant non-road objects (Figure 7). But still it remains a challenging task to link the disconnected segment roads.

In future to deal with these problems, classical post-processing technique should be used to a fully connected graph using higher level representation by Tupin et al. and Wang et al. [14,15]. It is recommended to remove the small nonlinear features morphological method should be used such as dilation, erosion, opened and closed operation to identify geometrical characteristics of objects by Li et al. [47].

Finally, thinning algorithm is carried out in the experiment developed by Zhang and Suen [46] to extract the centerline of urban roads (Figure 8). The proposed methodology demonstrated the efficiency of the intended procedures to extract urban road network correctly from high-resolution satellite remote sensing images such as IKONOS and QuickBird.

Acknowledgments

The authors would like to acknowledge the support they have received by the National Key Research and Development Program of China (2016YFC0803102) and the Liaoning Province University Innovation Team Program of China (LT2015013).

References

1. Hu XZ, Zhang, Li J (2009) Linear feature extraction using adaptive least squares template matching and a scalable slope edge model. International Journal of Remote Sensing 30: 3393-3407.
2. Heipke C, Pakzad K, Willrich F, Peled A (2004) Theme issue integration of geodata and imagery for automated refinement and updating of spatial databases (Editorial) ISPRS Journal of Photogrammetry & Remote Sensing 58: 127-128.
3. Zarrinpanjeh N, Samadzadegan F, Schenk T (2013) A new ant based distributed framework for urban road map updating from high resolution satellite imagery. Computers & Geosciences 54: 337-350.
4. Samadzadegan F, Zarrinpanjeh N (2008) Earthquake destruction assessment of urban roads network using satellite imagery and fuzzy inference systems. The International Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences 37: 409-414.
5. Das S, Mirnalinee T, Varghese K (2011) Use of salient features for the design of a multistage framework to extract roads from high-resolution multispectral satellite images. Geoscience and Remote Sensing IEEE Transactions 49: 3906-3931.
6. Movaghati S, Moghaddamjoo A, Tavakoli A (2010) Road extraction from satellite images using particle filtering and extended Kalman filtering Geoscience and Remote Sensing. IEEE Transactions on 48: 2807-2817.
7. Bajcsy R, Tavakoli M (1976) Computer recognition of roads from satellite pictures Systems, Man, and Cybernetics, IEEE Transactions 623-637.
8. Jin H, Miska M, Chung E, Li M, Feng Y (2012) Road Feature Extraction from High- Resolution Aerial Images Upon Rural Regions Based on Multi-Resolution Image Analysis and Gabor Filters. Remote Sensing Advanced Techniques and Platforms 387.

9. Jin H, Feng Y (2010) Towards an automatic road lane marks extraction based on Isodata segmentation and shadow detection from large-scale aerial images.
10. Urala S, Shana J, Romeroa M, Tarkoa A (2015) Road and Roadside Feature Extraction Using Imagery and LIDAR Data for Transportation Operation. ISPRS Annals of Photogrammetry. Remote Sensing and Spatial Information Sciences 1: 239-246.
11. Boyko A, Funkhouser T (2011) Extracting roads from dense point clouds in the large-scale urban environment ISPRS Journal of Photogrammetry and Remote Sensing 66: S2-S12.
12. Mena JB (2003) State of the art on automatic road extraction for GIS update: a novel classification. Pattern Recognition Letters 24: 3037-3058.
13. Mena JB, Malpica JA (2005) An automatic method for road extraction in rural and semi-urban areas starting from high-resolution satellite imagery. Pattern Recognition Letters 26: 1201-1220.
14. Tupin F, Maitre H, Mangin JF, Nicolas JM, Pechersky E (1998) Detection of linear features in SAR images: application to road network extraction Geoscience and Remote Sensing, IEEE Transactions on 36: 434-453.
15. Wang JP, Treitz M, Howarth PJ (1992) Road network detection from SPOT imagery for updating geographical information systems in the rural-urban fringe. International Journal of Geographical Information Systems 6: 141-157.
16. Zhou G, Cui Y, Chen Y, Yang J, Rashvand H, et al. (2011) Linear feature detection in polarimetric SAR images. Geoscience and Remote Sensing, IEEE Transactions on 49: 1453-1463.
17. Serra J, Vincent L (1992) An overview of morphological filtering. Circuits, Systems and Signal Processing 11: 47-108.
18. Geman D, Jedynak B (1996) An active testing model for tracking roads in satellite images. Pattern Analysis and Machine Intelligence. IEEE Transactions 18: 1-14.
19. Zhang C, Murai S, Baltsavias EP (1999) Road network detection by mathematical morphology. Citeseer.
20. Amini J, Saradjian M, Blais J, Lucas C, Azizi A (2002) Automatic road-side extraction from large- scale image maps. International Journal of Applied Earth Observation and Geoinformation 4l: 95-107.
21. Talbot H, Appleton B (2007) Efficient complete and incomplete path openings and closings. Image and Vision Computing 25: 416-425.
22. Karathanassi V, Iossifidis C, Rokos D (1999) A thinning-based method for recognizing and extracting peri-urban road networks from SPOT panchromatic images. International Journal of Remote Sensing, 20: 153-168.
23. Daryal MN, Kumar V (2010) Linear Extraction of Satellite Imageries using Mathematical Morphology. International Journal of Computer Applications 3.
24. Valero S, Chanussot J, Benediktsson JA, Talbot H, Waske B (2010a) Advanced directional mathematical morphology for the detection of the road network in very high resolution remote sensing images. Pattern Recognition Letters 31: 1120-1127.
25. Cai H, Yao G, Li M (2015) A multi-scale extraction for urban road intersection in high-resolution panchromatic imagery Multimedia Technology IV 91.
26. Economou G, Fotinos A, Makrogiannis S, Fotopoulos S (2001) Color image edge detection based on nonparametric density estimation. In Image Processing, Proceedings International Conference 922-925 IEEE.
27. Hu Y, Lou JG, Chen H, Li J (2007b) Distributed density estimation using non-parametric statistics. In Distributed Computing Systems, ICDCS'07, 27th International Conference on, 28-28 IEEE.
28. Hwang JN, Lay SR, Lippman A (1994) Nonparametric multivariate density estimation: a comparative study. Signal Processing. IEEE Transactions 42: 2795-2810.
29. Nacereddine N, Hamami L, Oucief N (2005) Non-parametric histogram-based thresholding methods for weld defect detection in radiography. World Acad. Sci. Eng. Technol 9: 213-217.
30. Snyder W, Bilbro G, Logenthiran A, Rajala S (1990) Optimal thresholding a new approach. Pattern Recognition Letters 11: 803-809.
31. Yin PY (1999) A fast scheme for optimal thresholding using genetic algorithms. Signal processing 72: 85-95.
32. Kulkarni N (2012) Color thresholding method for image segmentation of natural images. International Journal of Image, Graphics and Signal Processing (IJIGSP) 4: 28.
33. Shiozaki A (1986) Edge extraction using entropy operator. Computer Vision, Graphics, and Image Processing 36: 1-9.
34. Pal NR, Pal SK (1991) Entropy: a new definition and its applications. Systems, Man and Cybernetics, IEEE Transactions 21: 1260-1270.
35. Sindoukas D, Laskaris N, Fotopoulos S (1997) Algorithms for color image edge enhancement using potential functions. Signal Processing Letters IEEE 4: 269-272.
36. Parzen E (1962) On estimation of a probability density function and mode the annals of mathematical statistics 1065-1076.
37. Fan J, Aref WG, Hacid MS, Elmagarmid AK (2001) An improved automatic isotropic color edge detection technique. Pattern Recognition Letters 22: 1419-1429.
38. Doucette P, Agouris P, Musavi M, Stefanidis A (1999) Automated extraction of linear features from aerial imagery using Kohonen learning and GIS data in Integrated Spatial Databases 20-33 Springer.
39. Doucette P, Agouris P, Stefanidis A, Musavi M (2001) Self-organised clustering for road extraction in classified imagery. ISPRS Journal of Photogrammetry and Remote Sensing 55: 347-358.
40. Gao J, Wu L (2004) Automatic Extraction of road networks in urban areas from Ikonos imagery based on spatial reasoning. In Proceedings of ISPRS XXth Congress 12-23.
41. Zhang Q, Couloigner I (2006) Benefit of the angular texture signature for the separation of parking lots and roads on high resolution multi-spectral imagery. Pattern Recognition Letters 27: 937-946.
42. Zhang C (2004) Towards an operational system for automated updating of road databases by integration of imagery and geodata. ISPRS Journal of Photogrammetry and Remote Sensing 58:166-186.
43. Song M, Civco D (2004) Road extraction using SVM and image segmentation. Photogrammetric Engineering & Remote Sensing 70: 1365-1371.
44. Doucette P, Agouris PP, Stefanidis A (2004) Automated road extraction from high- resolution multispectral imagery. Photogrammetric Engineering & Remote Sensing 70: 1405-1416.
45. Tarku K, Bretschneider T, Leedham C (2004) Unsupervised detection of roads in high- resolution panchromatic satellite images. In Proceedings of the International Workshop Advanced Image Technology (IWAIT-2004) 15-19.
46. Zhang TY, Suen CY (1984) A fats parallel algorithm for thinning digital patterns. Communications of the ACM 27: 236-239.
47. Li J, Li Y, Dong H (2002) Automated extraction of urban road networks from IKONOS imagery using a fuzzy mathematical morphology approach, International Archives of Photogrammetry. Remote Sensing and Spatial Information Sciences 34: 259-263.

Author Affiliation

Top

Liaoning Technical University, Institute for Remote Sensing Science and Application, School of Geomatics, Fuxin, Liaoning 123000, China