J. Vis. Commun. Image R. 40 (2016) 300–311

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Improved road centerlines extraction in high-resolution remote sensing images using shear transform, directional morphological filtering and enhanced broken lines connection ☆

Ruyi Liu [a], Qiguang Miao [a,*], Bormin Huang [b], Jianfeng Song [a], Johan Debayle [c]

[a] School of Computer Science and Technology, Xidian University, Xi'an 710071, Shaanxi, China
[b] The Space Science and Engineering Center, University of Wisconsin-Madison, Madison, USA
[c] Centre Ingnierie et Sant, Ecole Nationale Suprieure des Mines, 42023 Saint-Etienne, France

ARTICLE INFO

Article history:
Received 7 January 2016
Revised 31 May 2016
Accepted 23 June 2016
Available online 6 July 2016

Keywords:
Road centerlines extraction
Shear transform
Multivariate adaptive regression splines (MARS)
Directional segmentation
Tensor voting

ABSTRACT

Road information plays an important role in many civilian and military applications. Road centerlines extraction from high-resolution remote sensing images can be used to update a transportation database. However, it is difficult to extract a complete road network from high-resolution images, especially when the color of road is close to that of background. This paper proposes an improved method for road centerlines extraction, which is based on shear transform, directional segmentation, shape features filtering, directional morphological filtering, tensor voting, multivariate adaptive regression splines (MARS) and enhanced broken lines connection. The proposed method consists of five steps. Firstly, directional segmentation based on spectral information and shear transform is used to segment the images for obtaining the initial road map. Shear transform is introduced to overcome the disadvantage of the loss of the road segment information. Secondly, we perform hole filling to remove the holes due to noise in some road regions. Thirdly, reliable road segments are extracted by road shape features and directional morphological filtering. Directional morphological filtering can separate road from the neighboring non-road objects to ensure the independence of each road target candidate. Fourthly, tensor voting and MARS are exploited to extract smooth road centerlines, which overcome the shortcoming that the road centerlines extracted by the thinning algorithm have many spurs. Finally, we propose an enhanced broken lines connection algorithm to generate a complete road network, in which a new measure function is constructed and spectral similarity is introduced. We evaluate the performance on the high-resolution aerial and QuickBird satellite images. The results demonstrate that the proposed method is promising.

1. Introduction

Road extraction from remote sensing images plays a fundamental role in a variety of applications in recent years, such as map localization, urban planning, resource management, natural disaster analysis and transportation system modeling. As we have entered an era of high-resolution earth observation, the advances in high spatial and spectral remote sensing technology and computer techniques have led to explosive growth and usage of remote sensing data [1]. Wang et al. [2] proposed a compressed sensing method to improve the performance of image reconstruction for multi-source and multi-temporal images. How to extract the road from these high quality remote sensing images is very important. However, it is unrealistic to manually label the road areas from the image. Thus, it is desired to automatically extract road from images. Fortunately, some parallel frameworks on many-core processors [3] [4] can provide support for the enormous computational requirements introduced by massive remote sensing data. Recently a lot of efforts have been made to design various algorithms for road extraction, but some challenging problems remain unsolved due to various conditions in different regions (e.g., urban roads, suburban roads and rural roads) and partial occlusions (e.g., clouds, buildings, shadows, trees and cars) [5], and further studies are needed.

This paper presents an improved method for road centerlines extraction, which is based on shear transform, directional segmentation, shape features filtering, directional morphological filtering, tensor voting, multivariate adaptive regression splines (MARS) and enhanced broken lines connection. The objective of this work is to develop an efficient method for accurate road centerlines

☆ This paper has been recommended for acceptance by Zicheng Liu.

* Corresponding author.
E-mail address: qgmiao@126.com (Q. Miao).

http://dx.doi.org/10.1016/j.jvcir.2016.06.024
1047-3203/

extraction. Our approach includes five steps: (1) obtain the initial road map; (2) fill the holes in some road regions; (3) remove the non-road area; (4) extract smooth road centerlines; and (5) generate a complete road network.

The remainder of the paper is organized as follows: Related work regarding road extraction is reviewed next. In Section 3, the proposed method is described. In Section 4, we compare the experimental results with the state-of-the-art methods, and show that our method yields significantly preferable results. Finally, the concluding remarks are given in Section 5.

2. Related work

The following gives a review of road extraction algorithms. Road extraction methods can be classified into two categories: automatic and semi-automatic [6]. Various road extraction algorithms have been reviewed in [6]. Poullis and You [7] grouped road extraction methods into three categories: pixel-based, region-based, and knowledge-based.

The pixel-based methods depend on the information obtained from the pixels [8]. Gamba et al. [9] extracted the urban road by adaptive directional filtering, perceptual grouping, and simple topological concepts. This method ameliorated the visual understanding and dramatically improved the quality of the extracted road network. However, it was difficult to enumerate all possible road masks. Poullis et al. [7] developed a novel method, which consists of the Gabor filtering, the tensor voting and the graph-cuts, for automatic extraction of the complex road network from various sensor resources. The method performed well except for the cases where the background color and the foreground road color were too similar to discriminate. Probabilistic and graph theoretical methods for road extraction were exploited in [10], which can be used to extract the road network in a reliable manner. However, there were some road segments missing due to the road-like patterns in farms and rural regions.

The region-based methods segment the imagery into regions and then refine the extracted road network by a rule [8]. Yuan et al. [11] presented a new method for road extraction from satellite imagery, which is called "locally excitatory globally inhibitory oscillator networks" (LEGION). It could be used in a wide range of applications where region and boundary information need to be considered. A multistage road extraction method in [12] relied on the features of roads such as nearby linear trajectory and different spectral behavior in high-resolution satellite images. The method could extract major sections of a road network, some junctions, and curved roads from high-resolution multispectral images, but may not work well on a region where the grayscale of road is similar to that of neighboring buildings. Li et al. [13] defined two structural features based on orientation histograms and morphological profiles to guide the region merging of BPT.

The knowledge-based road extraction methods rely on such information as geometric and radiometric properties of roads [8]. Hu et al. [14] proposed a two-step approach for extracting a road network from aerial images. They detected the direction of road and then pruned the branches. Although this approach is useful for understanding road network topologies, it can't generate a complete road network and also need input the seed point manually. Another road extraction method was developed in [15], which was based on perceptual organization and classification in human vision system (HVS). However, it depends on the straight line segments. Mokhtarzade et al. [16] presented an artificial neural network approach for road detection from high-resolution satellite images. This method is more time-consuming in the training and recalling stages. To improve road extraction accuracy, radiometric and geometric features of road have been integrated to extract a road network [17].

Several authors also proposed road extraction methods from different viewpoints. Hu et al. developed a hierarchical approach for grouping or linking the fragmented lines into long collinear features globally and efficiently [18]. Yin et al. proposed a globally optimized method which integrated both object and edge features to extract urban road information from VHR images [19].

The most related approach is the one by Chaudhuri et al. [20]. They developed customized operators to accurately extract the road from high-resolution satellite imagery using directional morphological enhancement, segmentation and thinning. It is used to extract the roads only for high-resolution panchromatic remote sensing imagery. In order to provide a good balance between computational efficiency and accurate extraction of road pixels, a small set of directions were considered in [20]. Due to discrete nature of the image, the directions of road segments are difficult to estimate and may not be in the selected set of directions. Thus, some road segments are not detected. These problems are the underlying motivation of our work. We would like to develop an efficient method that can extract the roads from multispectral images and address the problem of directional limitation. In order to extract roads from multispectral images, the spectral information is used in the directional segmentation. Shear transform [21–26] provides a more favorable treatment of directions and more directions for elongated regions are estimated. So the shear transform is introduced to get more directions for the road segments. In order to remove the regions which are closely linked to the road, we apply the directional morphological filtering. To produce a more correct and complete road network, an enhanced broken lines connection method is proposed.

3. Improved road centerlines extraction

In this section the proposed method is presented, whose flowchart is shown in Fig. 1. The details of each step are presented as follows.

3.1. Directional segmentation based on spectral information and shear transform

3.1.1. Shear transform

Roads are mostly elongated segments with locally linear properties in the image. Road segments have definite directions, but the directions of elongated regions are difficult to estimate. Road segments are lost to some degree in the process of segmentation due to the direction constraint that only a small set of directions are considered, so it is difficult to extract the whole complete road regions. However, looking for pixels in all directions can be computationally complex. Therefore, in order to deal with it, the shear transform [21–26] is introduced here.

Shear transform is an affine transform which is similar to the rotation transform. The rotation transform is a very convenient tool to provide directionality and preserve important geometric information such as length, angles, and parallelism. However, this operator does not preserve the integer lattice, which causes severe problems for digitization. In contrast to this, shear transform with a shear matrix does not only provide directionality, but also preserves the integer lattice when the shear parameter is an integer. Thus, it is conceivable to assume that directionality can be naturally discretized by a shear matrix. If the shear transform is applied on an image, the line segments keep the characteristic of linear features, and the directional information of the line segments would be more.

Let $W_{s,k}$ denote the shear operation, where $s = 0$ or $s = 1, k \in [-2^{ndir}, 2^{ndir}], k \in Z, Z$ denotes the set of integers and $ndir$ is the direction parameter ($ndir \in N$). In our implementation, the