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Accurate urban road centerline extraction from VHR imagery via multiscale segmentation and tensor voting

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ABSTRACT

Accurate road centerline extraction from very-high-resolution (VHR) remote sensing imagery has various applications, such as road map generation and updating etc. There are three shortcomings of existing methods: (a) due to noise and occlusions, most road extraction methods bring in heterogeneous classification results; (b) morphological thinning is a fast and widely used algorithm to extract road centerline, while it produces small spurs; (c) many methods are ineffective to extract centerline around the road intersections. To address the above three issues, we propose a novel road centerline extraction method via three techniques: fused multiscale collaborative representation (FMCR) & graph cuts (GC), tensor voting (TV) & non-maximum suppression (NMS), and fitting based centerline connection. Specifically, FMCR-GC is developed to segment the road region from the image by incorporating multiple features and multiscale fusion. In this way, homogenous road segmentation can be achieved. Then, TV-NMS is introduced to generate a road centerline network. It not only extracts smooth road centerline, but also connects the discontinuous ones together. Finally, a fitting based algorithm is proposed to overcome the ineffectiveness of existing methods in the road intersections. Extensive experiments on two datasets demonstrate that our method achieves higher quantitative results, as well as more satisfactory visual performances by comparing with state-of-the-art methods.

1. Introduction

Accurate road extraction from remote sensing images is an essential preprocessing step for various applications, such as vehicle navigation [1], geographic information system (GIS) update [2] and intelligent transportation system [3] etc. However, it is time-consuming, costly and tedious to manually label the road area from the image. Thus, it is desired to find ways to automatically extract road areas from images. Although, recent researches on road extraction [4–7] have been proposed to address this challenging task, they are far from mature.

Due to recent advances in remote sensors, a large amount of high-resolution images become available, which exhibit more details about the earth surface. Various state-of-the-art approaches [8–12] have been proposed to tackle the object extraction task from the high-resolution remote sensing images. Yao et al. [8] proposed a coarse-to-fine model to detect the airport area from remote sensing images using target-oriented visual saliency and CRF. To extract man-made objects from high spatial resolution remote sensing images, Li et al. [9] introduced a fast level set evolution based approach. An SVM vector machine approach [10] was introduced to detect the cloud area in the remote sensing image. Yuan et al. [11] introduced an image segmentation algorithm for the remote sensing images by combining spectral and textual features. A new building extraction approach was introduced in [12], which fused the knowledge of shadow and urban area information.

Like various extraction tasks above, it is also an urgent task to extract road from high-resolution images for various applications. Although many existing methods (e.g. dynamic programming and snake based algorithm [13], template matching based algorithm [14] and hough transform based algorithm [15]) have achieved satisfactory performance for the low-resolution images. They are failed to extract road region from the high-resolution images. Compared with road extraction from low-resolution images, there are a number of difficulties to extract the road area from high-resolution remote sensing imagery. First, small objects can be observed and the images tend to be affected by noise. Thus the spectral signatures of road become more heterogeneous. Second, complex backgrounds and contextual objects, such as trees, buildings and vehicles on the roads, usually

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appear in the high-resolution images. Finally, there are some road-like objects, such as buildings, rivers and parking lots, that may be misclassified as roads.

Most road area extraction methods [16,17] are developed to segment road region in pixel level. Due to noise and occlusions under vehicles and trees, these methods may bring in heterogeneous segmentation. For the task of road centerline extraction, many researchers [17–19] applied the morphological thinning algorithm. Although thinning-based approaches are fast and easy to perform, they may produce small spurs around the centerline. This will largely affect the construction of road network. Later, some regression based methods [20,21] are developed to alleviate this shortcoming. However, they are ineffective to extract the centerline around the road intersections.

To overcome the above shortcomings in the existing methods, we propose a novel three-stage based method to extract smooth and complete road centerline from very-high-resolution (VHR) remote sensing images: (1) Homogeneous road area segmentation; (2) Smooth and accurate road centerline extraction; 3) Centerline connection around the road intersections. The proposed method integrates three techniques, that is, fused multiscale collaborative representation (FMCR) & graph cuts (GC), tensor voting (TV) & non-maximum suppression (NMS), and fitting based centerline connection. Specifically, to obtain a homogeneous road area segmentation result, a FMCR-GC based road segmentation algorithm is proposed, which incorporates multiple features and multiscale fusion. Then, to gain smooth and accurate centerline network, a TV-NMS based centerline extraction algorithm is put forward. Finally, to well connect the centerline in the road intersections, a fitting based centerline connection algorithm is introduced.

The main contributions of the proposed approach are highlighted as follows:

- FMCR and GC are combined to obtain a homogenous road segmentation result. In FMCR, a novel road based feature is firstly proposed, which integrates spectral, structural and contextual road characteristics. This feature is in line with the human perception of road recognition.
- A new TV-NMS based centerline extraction method is introduced to extract the road network. It can not only extract smooth and accurate road centerline, but also connect the nearby discontinuous centerline due to unconnected regions in the segmentation result.
- To overcome the ineffectiveness of the existing centerline extraction methods in the intersection areas, a fitting based centerline connection algorithm is proposed to complete the unconnected centerline around the road intersections.
- A new and challenging road centerline extraction dataset is publicly available for further studies. It contains 30 VHR remote sensing images together with the corresponding centerline reference maps.

The remainder of this paper is arranged as follows. The related road extraction work is systematically reviewed in Section 2. In Section 3, the details of the proposed road area extraction and centerline extraction method are introduced. Experimental evaluations as well as detailed comparisons between our method and state-of-the-art methods are provided in Section 4. Finally, the conclusions will be outlined in Section 5.

2. Previous work

For VHR images, according to the extracted road results, the existing road extraction approaches can be classified into two classes: (1) *road area extraction* methods, (2) *road centerline extraction* methods. Road area extraction methods mainly depend on image classification and segmentation. Zhang et al. [16] proposed an integrated approach that combines *k*-means, fuzzy logical classifier and shape descriptors of angular texture signature. It can separate the roads from the parking lots that have been misclassified as roads. A new method for extracting roads based on advanced directional morphological operators was proposed in [22], in which Path Openings and Path Closings were introduced to extract structural pixel information. Yuan et al. [23] presented an automatic road extraction method for remote sensing images based on locally excitatory globally inhibitory oscillator networks. A multistage framework to extract roads from the high-resolution multispectral satellite image was introduced by Das et al. [6]. In this method, probabilistic support vector machines and salient features were used.

Recently, a convolutional neural network based algorithm was introduced to learn features from noisy labels in [24], in which the training labels were generated by applying an algorithm trained on a general image dataset. Mnih et al. [25] proposed a deep neural network method to extract urban road network from high-resolution images. In this method, unsupervised pretraining and supervised post-processing were introduced to improve the performance of the road detector substantially. A higher-order conditional random field (CRF) model was applied for road network extraction by Wegner et al. [26], in which the road prior was represented by higher-order cliques that connect sets of superpixels along straight line segments, and the road likelihood was amplified for thin chains of superpixels.

Most popular and successful road centerline extraction methods consist of one or two processing steps: (1) classification and (2) centerline extraction. Zhu et al. [27] proposed a road centerline extraction approach, which was based on the binary-greyscale mathematical morphology and a line segment match algorithm. An accurate centerline detection and line width estimation method via radon transform was introduced in [28]. Gamba et al. [29] extracted the road centerline with the help of adaptive filtering and perceptual grouping. A novel road centerline extraction method was proposed in [17] by integrating multiscale spectral-structural features, support vector machines (SVMs) and morphological thinning algorithm. In recent years, Poullis and You [30] proposed a novel vision-based system for automatic road centerline extraction. This system integrated Gabor filtering, tensor voting and global optimization using graph-cuts into a unified framework. A novel system [31] was introduced to extract road centerline from high resolution images, in which probabilistic road center detection, road shape extraction, and graph-theory-based road network were utilized. Chaudhuri et al. [18] presented a semi-automatic road centerline extraction algorithm. To achieve this, directional morphological enhancement and directional segmentation were used to extract the road area, then thinning method was applied to extract the road network. An automatic road centerline extraction method was introduced by Miao et al. [21], in which potential road segments were obtained based on shape features and spectral features, followed by multivariate adaptive regression splines to extract road centerline.

Shi et al. [19] presented a two-step method for urban road extraction. First, spectral-spatial classification and shape features were employed to obtain road segmentation results. Then morphological thinning algorithm was used to extract centerline. An integrated urban main-road centerline detection method was introduced in [20]. Road extraction result was obtained by fusing the result of spectral-spatial classification and local Geary's C method. Then, to extract smooth road centerline, local linear kernel smoothing regression algorithm was introduced. It relieves the shortcoming of thinning algorithm, while it can't