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Road Extraction from High Resolution Remote Sensing Images based on Multi-features and Multi-stages

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Abstract. *Road extraction from high resolution remote sensing imagery is very important for many applications such as GIS data updating, transportation management and city planning. In this paper we propose a semi-automatic multi-stage method to extract roads from high resolution remote sensing imagery based on multi-features. The proposed method contains two main steps, i.e. segmenting original image with radiometric features put to use and deleting non-road information by use of geometric features. First the input image is segmented into road and non-road regions, in which Directional Texture Signature (DTS) and Geary's C are used to extract road and obtain a rural road map. Next the results of the previous two steps are fused and purer road information can be obtained. Subsequently, extracted non-road objects such as buildings and parking lots with the same consistency of gray value can be removed in terms of the geometric characteristics of road, i.e. large areas as well as long strips. Experimental results demonstrate the effectiveness of the proposed method of extracting roads from high-resolution remote sensing imagery.*

Keywords: High Resolution Remote Sensing Imagery; Road Extraction; Multi-features; Directional Texture Signature; Geary's *C*.

1. **Introduction.** How to quickly and efficiently extract geographic information from remote sensing images has been the research hotspot in recent years and road extraction is an important part of extracting ground object information from remote sensing imagery. Due to the fact that road information falls into the type of the basic geographic information which is crucial, its extraction, identification and precise location for mapping are meaningful in remote sensing, data acquisition, image understanding, cartography and they serve as a reference to other surface features. To date, road extraction from remote sensing images has received a lot of attention and researchers have presented various approaches for extracting road information from remote sensing imagery. A detailed review of road extraction methods can be found in literatures [1-2], in which the techniques include seed point-based [3], object-based, active contours [4], mathematical morphology [5-6], snakes [7], knowledge base method [8] and dynamic programming [9], etc.

In addition, some researchers classified the road extraction methods into fully automatic or semi-automatic methods. Miao *et al.* [10] presented a semi-automatic method for road centerline extraction from high resolution satellite images in which the geodesic method was used to extract the initial road segments and link the foregoing road seed points. Their method can obtain smooth correct road centerlines. Yuan *et al.* [11] proposed an automatic method for road extraction, in which the image was segmented by LEGION (Local Excitatory Globally Inhibitory Oscillator Networks) network and they then extracted medial axis of each segment and selected points located in potential road regions, finally used a LEGION model to group medial axis points. Chaudhuri *et al.* [12] presented a semi-automatic approach for road extraction, which included three main steps-directional morphological enhancement, directional segmentation and thinning. Besides that, Ünsalan and Sirmacek [13] presented an effective automated method for road network detection by using probabilistic and graph theoretical methods. Valero *et al.* [14] presented a method based on advanced directional morphological operators for extracting roads in high resolution remote sensing images, which consists in building a granulometry chain by use of path openings and path closings to construct morphological profiles. Mena *et al.* [15] proposed an automatic method to extract road in rural and semi-urban areas. They sought the GIS update starting from color images and preexisting vectorial information, and they also used Texture Progressive Analysis to segment input images. A Multistage method for road extraction was presented by Xu [16], in which the framework was a combination of multifeature-based mean shift, SVM classifier, and shape feature filter. Hu *et al.* [17] proposed an algorithm using multiple features to detect road centerlines from the remaining ground points after filtering.

In high resolution remote sensing images, roads present as long strips with a certain width and generally roads' radiometric features are different from surrounding environment. Some researchers' methods of extracting roadinformation from high resolution remote sensing images vary from region to region. Generally the first step of these methods is segmenting (or classifying) the original images on the basis of the spectral or radiometric information of the image to obtain the coarse road segments, but it is difficult to obtain satisfactory result by use of radiometric or spectral features only. In order to improve extraction accuracy, the geometric features of road in the image are considered and some researchers combined spectral and spatial information to extract road information [18].

In this paper, we propose a semi-automatic road extraction method from high resolution remote sensing images based on multi-stages and multi-features which are region-based. The remainder of this paper is organized as follows, in Section II road extraction based on multi-features is presented, experiments are conducted on several sets of data and experimental results are reported in Section III and lastly conclusions are drawn in Section IV.

2. **Road Extraction based on Multi-Features.** In order to extract accurate road information, different features of image and road are used, i.e. texture, radiometric and geometric features. Multiple features of road, namely texture, gray value and shape features are used to extract road regions and road networks from satellite images and adopted to improve the accuracy of road extraction by fusing texture, gray and shape features. In this section, the proposed method is described in mainly two steps. First, the original image of the road and non-road regions is segmented by use of roads' radiometric features, in which Directional Texture Signature (DTS) and Geary's C are used to segment images. Next non-road regions are eliminated on basis of data fusion and road's geometric features, then purer road regions is acquired. Fig. 1 shows the flowchart of the proposed method.

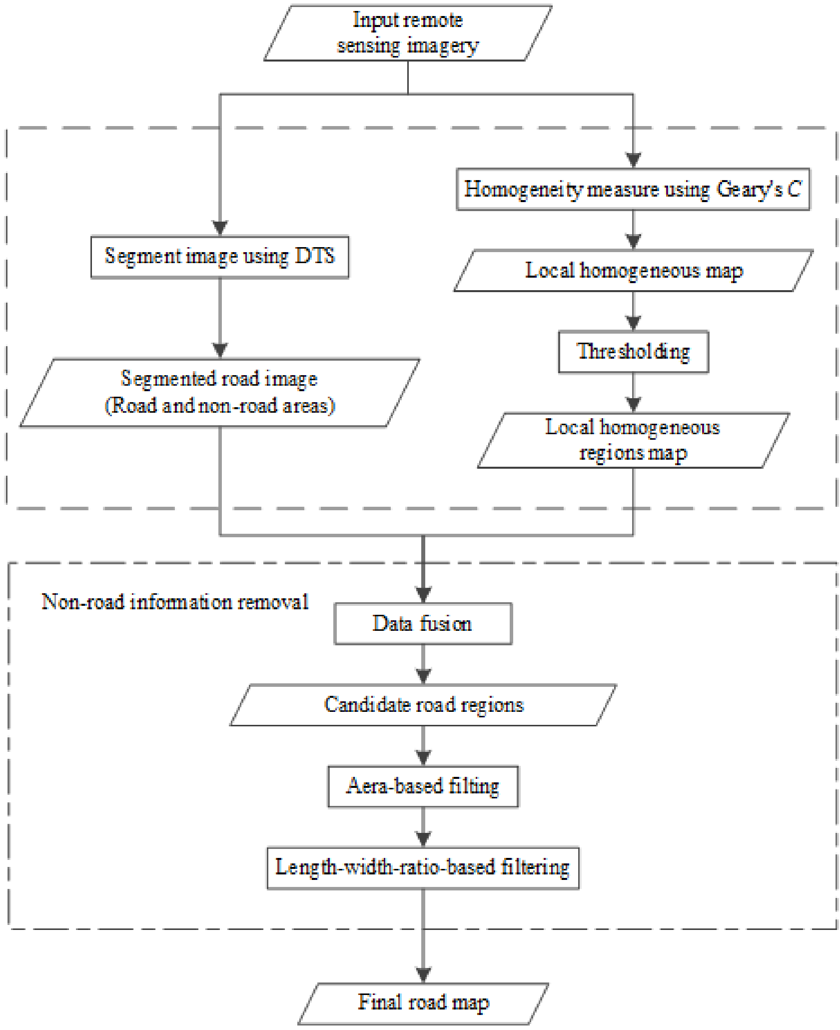


FIGURE 1. Flowchart of the proposed method.

2.1. **Image segmentation into road and non-road regions using DTS.** The aim of this step is to segment the remote sensing imagery into road and non-road using DTS [19]-[21]. DTS is a texture measure as shown in Fig. 2. In order to illustrate the meaning, we select the point p at the center of a crossing. At each pixel p in the image, $T(\alpha, \omega, p)$ is defined as the variance from the mean for a rectangular set of pixel of width ω around the point p whose principal axis lies at an angle of α from horizontal. This measure is computed for a set of angles $\alpha_0, \alpha_1, \cdots, \alpha_n$, Fig. 2 (a) shows the rotating templates for a single point. At the point p, the DTS is defined as the set of values $T(\alpha_0, \omega, p), T(\alpha_1, \omega, p), \cdots, T(\alpha_n, \omega, p)$,.The graph of a DTS for the above single point p is shown in Fig. 2 (b), from which we can see that each variance minimum (valley features) is the direction of road. If there are two obvious characteristics of the valley with the corresponding angle difference of 180 degrees, this pixel is located at consecutive road section. If there are three or four valley characteristics, this pixel is probably located at the road intersection, and valley characteristics can't be found about non-road point. The road can be distinguished from other objects by identifying the shape characteristics of the corresponding DTS graph.

In this paper, we use gray variance to measure the DTS for the image:

$$i' = i + n\sin(\theta) + k\cos(\theta). \tag{1}$$

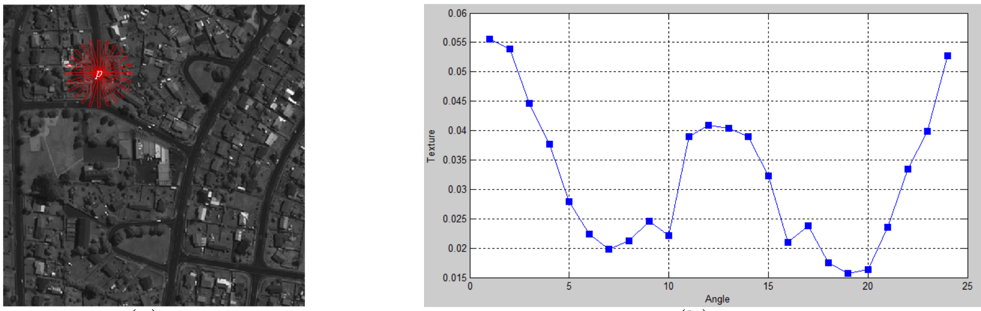
$$j' = i + n\cos(\theta) + k\sin(\theta). \tag{2}$$

$$m(i,j,L,\theta) = \frac{\sum_{n=-r}^{r}\sum_{k=0}^{L} p(i',j')}{(2r+1)\times(L+1)}. \tag{3}$$

$$\sigma^2(i,j,L,\theta) = \frac{\sum_{n=-r}^{r}\sum_{k=0}^{L}(p(i',j') - m(i,j,L,\theta))^2}{(2r+1)\times(L+1)}. \tag{4}$$

where $(2r+1)$ and $(L+1)$ are the length and the width of the rectangle template respectively, (i', j') is the pixel in the template, θ is the directional of the template, $p(i', j')$ is gray value of the (i', j'), $\sigma^2(i,j,L,\theta)$ and $m(i,j,L,\theta)$ are the variance and mean value in the degree θ of the template at the pixel (i, j) respectively.

The result in this step is a road map which is a binary image with road pixels as '1' and other object pixels as '0'.



(a) (b)

FIGURE 2. Directional Texture measurement. (a) how the texture filter is applied to the image over a set rectangular regions about a single pixel p. (b) a graph of the corresponding Directional Texture Signature values, taken at 24 discrete locations over 360 degree for a single pixel p.

2.2. **Obtaining Homogeneous Regions Map using Geary's *C*.** As known to all, roads are continuous and elongated regions with nearly constant width, and the road information has local homogeneity features in aerial and high resolution satellite images [16]. Based on this property, it can be inferred that roads should be located in homogeneous regions. Therefore, the goal of this step is to measure the local homogeneity of gray values of the remote sensing image in order to obtain the potential road information. Local homogeneity measurement is using local spatial statistics [22]. In this paper, local Geary's C is used to measure local homogeneity properties of the remote sensing imagery.

Geary's C is a measure of spatial autocorrelation or an attempt to determine if adjacent observations of the same phenomenon are correlated. Spatial autocorrelation is more complex than autocorrelation because the correlation is multi-dimensional and bi-directional.

Geary's C is defined as [23]:

$$C = \frac{(N-1)\sum_i\sum_j \omega_{ij}(X_i - X_j)^2}{2W\sum_i(X_i - \overline{X})^2}. \tag{5}$$

where N is the number of spatial units indexed by i and j, X is the variable of interest, $\overline{X}$ is the mean of X, ω_{ij} is a matrix of spatial weights, and W is the sum of all ω_{ij}.

In this paper, the formula (6) is used to calculate local Geary's C of the image [24-25].

$$c(x_{ij}) = \frac{\omega^2 \sum_a \sum_b \omega_{ab}(d)(I(x_a - I(x_b))^2}{\sum_a (I(x_a - \overline{I}_\omega(x_{ij}))^2}. \tag{6}$$

where ω is width of the window for which is a square, the window size of local Geary's C is determined by artificial, since small homogeneous regions cannot be correctly measured by local Geary's C with a large size window, the width of the window is set to 2 or 3 pixels.

In equation (6), x_a and x_b denote 2 pixels in the window, $I(x_a)$ and $I(x_b)$ are their corresponding gray values, $\overline{I}_\omega(x_{ij})$ is the mean of all pixels' gray values in the window, d is the distance between x_a and x_b, and $\omega_{ab}(d)$ is the weight at distance d, so that $\omega_{ab}(d) = 1$ if point x_a is within distance d from point x_b or $\omega_{ab}(d) = 0$ if otherwise.

After all the pixels' $c(x_{ij})$ of the input image computed, a local Geary's C map of the original image can be obtained and then the map is segmented by use of a threshold to extract homogeneous regions and roads information in those homogeneous regions. So a binary image can be obtained with homogeneous regions pixels as '1' which consider as 'roads'.

2.3. **Non-road Information Removal.**

1). Data Fusion

The purpose of data fusion is to improve the accuracy of the road extraction results by using different features of road. Hellwich *et al.* [26] presented an approach to the combined extraction of linear as well as surface objects from multisensory image data based on a feature and object level fusion [15].

The idea of data fusion is also used in our approach, in which the original image is segmented into road and non-road regions using DTS, then local homogeneous regions map can be obtained by local Geary's C, and finally the two binary results are combined to generate a purer road map using data fusion. With information fusion, non-road information will be removed and most misclassified and true road regions will be disconnected since misclassified and true roads have different geometrical properties. This is helpful to filter information fusion result with aid of geometric features to further improve road extraction accuracy.

2). Area-based Filtering

According to the geometric characteristics of road, roads do not have small areas, so the regions with small areas can be regarded as non-road and should be deleted to get pure road information.

The criterion for judging whether the region is the road area or not can be expressed as:

$$\text{Regin} = \begin{cases} \text{road} & R_{area} < R_{thr} \\ \text{non-road} & \text{otherwise} \end{cases} \tag{7}$$

where R_{area} is the area of region and R_{thr} is the threshold value to judge whether the region is road or not will be determined by experiment results.

3). Length-width-Ratio-based Filtering

As mentioned above, road is narrow and long regions with obvious linear features. Through the identification of the linear features from the extraction result, it's easy to remove the non-linear features such as point features, planar features, etc., which may be non-road regions. The ratio of length to width index is linear feature index commonly used and the traditional aspect ratio is defined as:

$$R = \frac{L_{mer}}{W_{mer}}. \tag{8}$$

where L_{mer} is the length of the minimum bounding rectangle of homogeneous region and W_{mer} is the width of the rectangle. In the application of the R mentioned in (8) for road extraction, if the road is a curved road and cannot well describe linear features, we can modify the definition to overcome this limitation in the next part: the total number of pixels in the detection region are taken as the area of the external rectangle, with the diagonal of minimal external rectangle as the long side to create a new rectangle, then

$$W = \frac{n}{L}. \tag{9}$$

where W is the width of the new rectangle; n is the pixels of the detection region; L is the length of the new rectangle, and L can be calculated by

$$L = \sqrt{L_{mer}^2 + W_{mer}^2}. \tag{10}$$

so the ratio of length to width can be calculated as

$$R_{mer} = \frac{L}{W} = \frac{L_{mer}^2 + W_{mer}^2}{n}. \tag{11}$$

In terms of road's geometric characteristics, road regions should have large values of R_{mer}, so regions with small values of R_{mer} can be regarded as nonlinear features and should be removed.

3. **Expermental Results and Discussion.** In order to evaluate the performance of the proposed method, we test the approach on several high resolution satellite image sets. Two experiments are presented to extract roads from IKONOS panchromatic image and QuickBird image respectively. Accordingly, the two data sets provide a good sample to test the proposed roads extraction method in complex urban scenes and these data sets contain various types of roads with different intersections, different widths and other objects. Then the proposed method is compared with two other existing road extraction methods.

3.1. **Road Extraction on Real Images by the Proposed Method.** In the first experiment, the proposed method is tested on an IKONOS panchromatic image, while the image of the study area is shown in Fig. 3 (a). It contains 1024×1024 pixels, where some dark roads are featured. It can be seen that this image is complex for the reason that lots of objects have similar geometric features in surrounding environment with roads. Besides that, the image includes some different types of roads, such as annular roads, linear roads and curving roads, etc., and contains different widths of roads. In addition, the test image also contains different types of junctions, so it is difficulty to extract roads from this image. In this experiment, the data set is first preprocessed based on median filter to remove noise for the purpose of producing a smooth image and the filter window size is 3×3. Then DTS algorithm is used to segment image into road and non-road regions where roads show bright features and non-roads show dark features. The result of the segmentation is shown in Fig. 3 (b), in which template rotation angle is set to 20 degrees, and there are 18 templates at each pixel. Next local homogeneity measurement of the original remote sensing image is performed with the use of Geary's C and the result of the homogeneity measurement is shown in Fig. 3 (c), in which the width of the window is set to 2 pixels. Then the homogeneity measurement map is segmented by use of a given threshold, the threshold value of gray difference is obtained by Otsu's method [27] and the segmentation result is shown in Fig. 3 (d). In the next procedure,

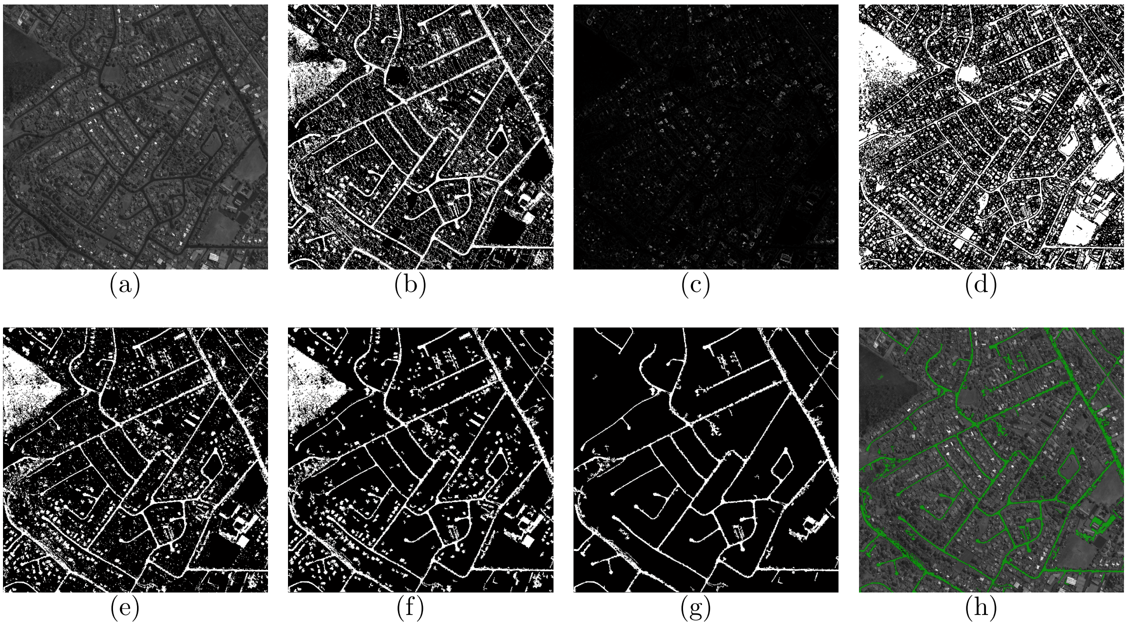


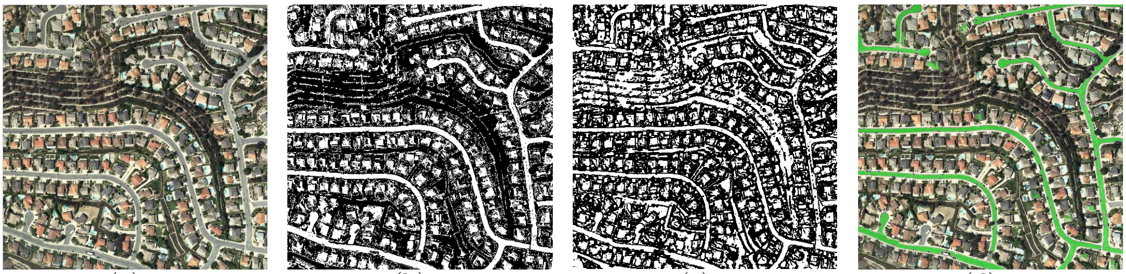
Figure 3. Results of experiment on IKONOS image. (a) Image of the study area. (b) Result of segment using DTS. (c) Local homogeneity measurement using Geary's C. (d) Candidate of the road map. (e) Result of information fusion. (f) Result of removing small area regions. (g) Result of eliminating non-linear features. (h) Result of superposition of the extracted road on the top of the original image.

the results of Fig. 3 (b) and (d) are combined to generate a pure road map, and the result of information fusion is shown in Fig. 3(e). Finally, area threshold and the ratio of length to width threshold are put to use to remove non-road information. The area threshold and the ratio of length to width threshold are 50 and 9, with the results shown in Fig. 3 (f) and (g). The result of extracted road overlap on the original image is shown in Fig. 3 (h).

In order to assess new general and effective method, the second experiment is carried out based on a QuickBird imagery with a spatial size of 512×512 pixels. The image of study area is shown in Fig. 4 (a) and it can be seen that roads have many branches at various orientations in this image. It should be noticed that road regions are similar with surrounding environments and roads in this image show different radiometric features from the IKONOS panchromatic image. In addition, the parameter setting of this experiment is different from the experiment in which IKONOS image is used. In the step of segmenting image by use of DTS of this second experiment, template rotation angle is set to 20 degrees and there are 18 templates at each pixel to calculate texture information. The width of the window is set to 3 pixels in homogeneous measurement process. The results of this experiment are illustrated in Fig. 4 (b)-(d).

In the results from the above two experiments, only a few false alarms remain. The obtained results show how roads regions have been extracted with good precision and good reliability. Through these results it can be seen that the proposed method is effective for the extraction of different road types from different images.

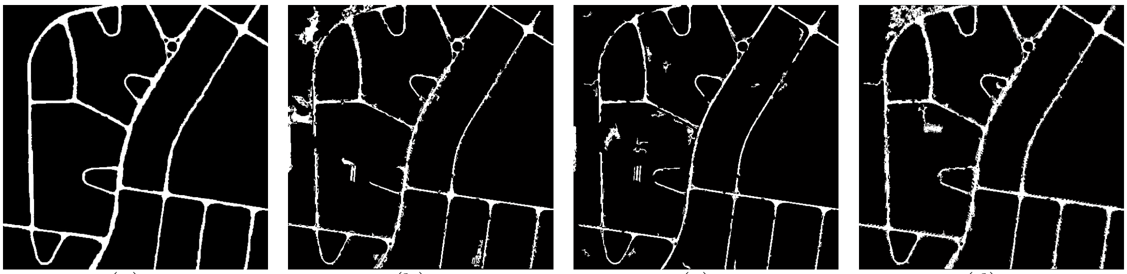
3.2. **Comparisons with Existing Methods.** In order to evaluate performance of the proposed road extraction algorithm, we implemented the method and compared with two other road extraction methods using local gray value consistency [28] and edge-filtering



(a) (b) (c) (d)

FIGURE 4. Results of experiment on QuickBird image. (a) Image of the study area. (b) Result of segment using DTS. (c) Candidate of the road map. (d) Result of superposition of the extracted road on the top of the original image.

method [29]. These two methods are selected because both of the two and the previously proposed method are segmenting image rely on homogeneous measurement. Fig. 5 depicts the comparison results of the mentioned above three methods and it can be found that the proposed method can obtain better extraction results than the other two methods. Fig. 5 (a) presents the road map that is manually digitized from the original image and this road map is used as reference to evaluate the extraction results in this experiment. Fig. 5 (b) is the result of road extraction by use of local gray value consistency method; Fig. 5 (c) shows the result of edge-filtering method and the result of our method is shown in Fig. 5 (d). For quantitative evaluation proposed method, there are five measures of



(a) (b) (c) (d)

FIGURE 5. Comparison of road extraction results. (a) The reference road map. (b) Local gray value consistency. (c) Edge-filtering method. (d) Proposed method.

accuracy used [30].

$$\text{Completeness} = \frac{TP}{TP + FN} \times 100\%. \tag{12}$$

$$\text{Correctness} = \frac{TP}{TP + FP} \times 100\%. \tag{13}$$

$$\text{Quality} = \frac{TP}{TP + FP + FN} \times 100\%. \tag{14}$$

$$\text{Omit} = \frac{FN}{TP + FN} \times 100\%. \tag{15}$$

$$\text{Redundancy} = \frac{FP}{TP + FN} \times 100\%. \tag{16}$$

where TP is the pixels obtained by proposed method which are coinciding with the road reference map, while FP is the extracted pixels which are not in the road reference data and FN is the pixels which are in the reference map but not in the obtained pixels.

Table 1 shows the results of the three methods. From Table 1, it can be seen that the proposed method expresses a better performance in the extraction of roads from high resolution remote sensing imagery compared with the two other methods.

Table 1. Quality of the three methods for road extraction

Methods	Local gray value consistency	Edge-filtering	Proposed method
TP	14794	12275	19528
FP	4664	2499	3196
FN	8167	10686	3433
Completeness	64.43%	53.46%	**85.05%**
Correctness	76.03%	83.09%	**85.94%**
Quality	53.55%	48.21%	**74.66%**
Omit	35.57%	46.54%	**14.95%**
Recundancy	20.31%	**10.88%**	13.92%

4. **Conclusion.** In this paper, a semi-automatic multi-stage method based on multi-features has been proposed to extract road from high resolution remote sensing imagery, in which DTS and Geary's C are applied to separate potential road-segment interesting regions from background. Based on data fusion and geometric features, road segments are extracted. The proposed method is tested by three experiments and the results demonstrate that this method is feasible and effective for road information extraction. In the practice of segmenting image into road and non-road regions by DTS and Geary's C, lots of non-road information is also extracted as a result of the mere consideration of the gray value of the image and this irrelevant information should be further filtered and cut out. Then with the geometric features of road taken into consideration, shape features are used in the proposed method which can retain linear features and most nonlinear features can be eliminated. While on the other hand the thresholds of shape features are set by the trial, therefore to avoid the threshold selection problem, road shape features will be used as the key measures of structural information to extract road information in the future research.

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