AUTOMATIC ROAD EXTRACTION OF URBAN AREA FROM HIGH SPATIAL RESOLUTION REMOTELY SENSED IMAGERY

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ABSTRACT:

For the significance of road information to the city management, urban roads are subjects of great concern to be extracted from remotely sensed images. With the availability of high spatial resolution images from new generation commercial sensors, how to extract roads quickly, accurately and automatically has been a cutting-edge problem in remote sensing related fields. Present main approaches of automatic road extraction cannot fully exploit the spectral information of roads in the imagery and get the required accuracy. Considering the road knowledge, we develop a new approach to extract roads accurately and automatically, in which spectral and geometric features of roads are both considered and represented. The approach contains three steps: rough classification, which enhances the full exploitation of spectral contents and ensures the continuity of roads for the following steps; road connection algorithm, which extracts road skeletons roughly; and result grooming, which includes connecting, smoothing, linking and produces the final result. We take Beijing City as a study case and use QUICKBIRD image to implement the approach. As results turn out, the approach achieved a satisfactory accuracy of 96.7% on main roads while 74.3% on secondary roads and proves to be of high practical value.

1. INTRODUCTION

Roads, as one of the most important man-made objects, are of great significance in landscape and transportation. Urban road information extraction plays a critical role in GIS data update, image matching, object detections and finite element analysis, etc. With the rapid growth of road related services, such as navigation systems, telematics, and location-based services, the efficient extraction of road information is in urgent need nowadays.

Conventional methods for creating and updating road information rely heavily on manual work and therefore are very expensive and time consuming. With the development of remote sensing technology, especially the commercialization of high spatial resolution remote sensing data, people now can obtain accurate and real time road network information from remotely sensed images, which is essentially important in the fields of transportation management, urban planning, automatic car navigation system, and emergency management (Gong, 2006).

For the complexity of urban road system, using remotely sensed images to recognize and extract road network has been a cutting-edge problem in remote sensing and related fields (Shi, 2001;Gong, 2006). Many researches have done on the topic and achieved abundant results. However, existed road extraction methods still have problems in popularization and application: the extraction accuracy cannot satisfy the needs of engineering application; the automation is in a relatively low level; the performance is limited by either road materials or complex road networks.

Shi and Mena had reviewed some of these approaches (Shi, 2001; Mena, 2003). Present main approaches are those like dynamic programming (Gruen, 1995), texture analysis applied to a single layer, Snakes (Trinder, 1995), mathematical morphology based on geometric shape (An, 2003; Zhu, 2004). All these models or algorithms are mainly based on radiometric characteristics and geometric constraints of road information in the imagery thus do not exploit fully the spectral information of roads. Besides, few of them focus on the extraction of complex urban road-network and the automation is in a relatively low level. Especially, when applying these methods to highly dense urban central regions, unlike to countryside or suburban area, most of these methods will probably lose their efficacy and accuracy considering the numerous ground details and diverse composition of land cover types found in the urban central regions. For one thing, abundant ground targets within or beside roads cause too many non-road speckles or mixed pixels, and the road targets are correspondingly broken and inconsistent to a large extent, which render the pre-process of these methods hard to reach a satisfactory accuracy, let alone the further process; for another thing, these methods fails to take a frequently-seen phenomenon of shadows on roads into account, thus they are unable to extract roads covered by shadows.

This paper presents a novel road extraction approach focusing on extracting the road network in urban central area accurately and automatically. The approach makes full use of spectral and

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geometric properties of roads in the imagery, and proposes a new algorithm named "road connection algorithm" to ensure the continuity of roads, thus successfully overcomes the problems mentioned in the above paragraphs. The approach includes three steps in a clear logic: rough classification, road connection algorithm, and result grooming.

In this paper, we take Beijing city as a study case and the data we utilize is multi-band QUICKBIRD image. In order to evaluate the result, we define an assessment system according to information in the imagery and achieved a satisfactory result. The approach has proved to be simple, quick, automatic and efficient.

The remainder of this paper is organized as follows. The automatic road extraction framework which includes the rough classification, road connection and result grooming is introduced in section 2. In section 3, we utilize this method to extract road from QUICKBIRD image and give the accuracy assessment. At last, conclusions are presented in section 4.

2. METHODOLOGICAL FRAMEWORK

The approach includes both spectral and geometric constraints about roads network in urban areas. The methodological framework contains three steps: rough classification, road connection, and result grooming.

2.1 Road Feature Analysis

In high spatial resolution remotely sensed images, urban roads have following properties:

Stability of spectral property: The spectral properties of uncovered roads are stable to a certain degree. Because urban roads are mainly constructed by asphalt or cement, especially asphalt dominates a large part; spectral properties of roads are limited to a fixed range which corresponds to the spectral range of road materials. However, in the imagery, objects on roadsides like zebra crossings, cars and people cause noises due to the huge spectral difference to roads.

Continuity of roads: Normally roads in reality are continuous and regular in geometry, while in the imagery, trees and shadows of high buildings by roads interrupt the continuity of roads to a large degree. But on the whole, roads in the imagery still have impressive connection and regularity.

Straightness: On high spatial resolution images, urban roads are straight and smooth with no small wiggles thus can be recognized as combinations of straight road segments.

Topological property: Road segments are always connected with each other constituting road networks, and impossible to be broken suddenly.

2.2 Rough Classification

The first step is rough classification, which enhances the exploitation potential of spectral content for automated road extraction.

Firstly, after atmospheric and geometric correction, we need to pre-process images to eliminate noises in the imagery. For high spatial resolution satellite images, there are primarily three types of noises: the first is called white noise that is formed during the imaging stage; the second is produced in re-sampling or compressing process; the last is determinant, referring to noises that are caused by the difference of extracted features to non-extracted features. So, we should smooth the image by smoothing filter, which could reduce the former two kinds of noises and make different physical feature in accordance with different gray distribution region, thus facilitate the feature discrimination and extraction. In this paper, we utilize median filter to achieve the goal. Through repetitive tests, 3×3 template proves to be effective in eliminating small vehicles on roadsides in the imagery. At the meantime, this method is simple, quick and automatic, hence the advantage of applying to high spatial resolution images of huge volumes.

Then, clustering algorithm is used to identify road classes. The key parameter is the number of spectral clusters K into which a scene is classified. Many researches have done on the selection of K value, while in this paper, we adopt automatic K-mean Clustering algorithm to classify the image simply into two classes, one of which contains road information. Advantages of such clustering method are obvious: the method is higher in automation, less sensitive to initial conditions, and costs less computational expenses. Most importantly, as shadows on roads are classified into the class containing road information, the method ensures the road continuity. For non-road speckles or patches within the road class, they can be eliminated commendably in the next stage.

2.3 Road Connection Algorithm

In order to extract roadside in spite of heavy shadows on roads, we bring forward a new algorithm named "road connection algorithm". This is the key procedure of the whole frame work, in which spectral and geometric features of roads are represented in two rules: (1) spectral feature: for each pixel, only when its three radiometric properties are similar to those of roads, it can be identified as road candidates. (2) geometric feature: on high resolution image, roads are usually smooth with no small wiggles. Thus in an appropriate distance, road segments, including smooth curves, can be recognized as straight line segments.

According to road geometrical properties mentioned above, for each pixel on the image, search in specific direction in a straight line at fixed step. If the proportion of road candidate pixels (refers to pixels whose spectral property satisfies the road) to all pixels on the line exceeds a threshold value S that we give in advance, all pixels on the line L could be identified as road pixels. After that, we convert original non-road pixels to road pixels.

Assume the image after rough classification as I, and the result after road connection algorithm as RI, and the value of number 1 marks road. Then the pseudo codes are as follows:

```
Pro Road Extract (I, L, R)
W = image width, H = image height
For i = 1 to H do begin
  For i = 1 to W do begin
    For θ = 0 to 180 by 15 do begin
      DL → pixels on the line segments starting from (i,j) in θ
direction with length L
      RN→ number of pixels in DL in image RI whose value
equal 1
      If RN ⩾ 1 then continue
      End if
```

```
      N→ number of pixels in DL in image I whose value equal 1
      N1→ number of pixels in DL in image I
      If N1/N ⩽ R then
        RI (DL) = 0
      End if
      If N1/N ⩾ R then
        RI (DL) = 1
      End if
    End for
  End for
End for
```

Compared with other methods, this method is more efficient, and makes full use of road knowledge. K-mean clustering classifier done previously quickens the search speed without the need to compare spectral values of pixels with those of the standard. Meanwhile, the algorithm can deal well with discontinuous roads which are occluded by shadows and other geo-types. After that, a rude result image is produced on which roads are extracted as sets of straight segments.

2.4 Result Grooming

The rude result image derived from the last procedure is groomed using mathematical morphology in this stage. The grooming stage relies on four basic steps: connecting, smoothing, thinning and linking.

The connecting joins discrete road segments using morphological dilation. The smoothing, which combines morphological opening and closing operator, reduces the roughness of road edges significantly. The thinning erodes the road segment into one-pixel width. To achieve the goal, the thinning process is improved by introducing regions corresponding to more local information. The image is split into equally sized regions and in each region, morphological thinning operators are selected automatically according to local road width information. The linking, the last step of grooming stage, concentrates on correct connection of one-pixel wide road segments and final elimination of non-road information from the image. Geometrical features such as size, connectivity and distance between road segments are considered to achieve the purpose. Single or too short segments would be eliminated from the image.
After this final step, we acquire the result image which contains road network information extracted from original remotely sensed imageries.

3. IMPLEMENTATION OF THE AUTOMATIC ROAD EXTRACTION APPROACH

In this section, we take Beijing City as a study case to implement the proposed approach. The data we choose is QUICKBIRD multi-band image.

3.1 The Data of Study Area

We take QUICKBIRD image for example, and the image was graphed in Nov. 2002. There are four multi spectral band data and a panchromatic data. The resolution of 4-multi spectral bands is 2.44meters, which is Blue band (450-520nm), Green band (520-600nm), Red band (630-690nm) and NIR band (760-900nm). The resolution of panchromatic band is 0.61meters, but there is only one band and the image is monochrome lack in spectrum information. So we choose 4 multi-spectral bands as a study image to extract road.

The study area, with the size of 1000×500 pixels in the imagery, covers an area of nearly 3 km^2 in Beijing city. The image contains large volumes of detailed information, including roads, buildings, vehicles, trees, shadows, zebra crossings and other geo-types. And the image is seriously affected by shadows as other areas in the original image.

Firstly, we do some pretreatment before classification. Geometrical correction, atmosphere correction and rational correction are done. Then we adopt the median filtering as mentioned above and can get the image as Figure 1 after correction.

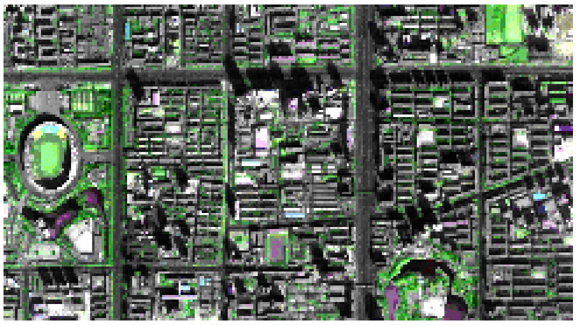

Figure 1. The image of study area. It is shown using red, green and blue bands, which are real colors. And the image has been corrected primarily.

3.2 Automatic Road Extraction

Then we use the proposed approach to extract roads from the image. The method in this paper is demonstrated in figure 2. After atmosphere and geometric correction, we classify the whole image through K-mean clustering into two classes. Assigning the number of classification as two, spectral properties of roadsides and shadows on roads are similar in this wide spectral range; so, darker objects like roads and shadows are classified into the same class while other lighter objects are classified into the other. So on the acquired binary image, roads and shadows on roads are classified into the same class thus ensures the continuity of roads. The rough classification result can be found in figure 3.

Next, the road connection algorithm we invented in this paper is applied to the binary image to extract the road skeletons roughly. Because of the algorithm based on road knowledge including continuity, shape, topology of urban roads, we can get a satisfactory result of road network connection. The connected results are quite good. As shown in figure 4, we can see clearly that main roads are generally extracted while some of the sub-roads are extracted too.

After that, we adopt morphological algorithms to process discrete road segments, smooth road edges and erode roads to one-pixel width. Morphological dilation is firstly used and discrete road segments are connected together while the roads are also widened. Then morphological opening and closing operators are used to smooth the road edges; as a result, roughness of road edges is reduced significantly, which is beneficial for thinning in the next step. Morphological erosion is widely used to thin linear features and here we introduce the concept of regions. The image is split into equally sized regions; so, in each region, morphological thinning operator is selected automatically according to local road width information. The linking, the last step of grooming, uses comprehensive road features. Size, connectivity and distance between road segments are considered to link road segments and eliminate tiny single wrong road segments. Through steps mentioned above, the rough result of road network is groomed and final result turns out, which only contains connecting and continuous road networks and without any noise information.

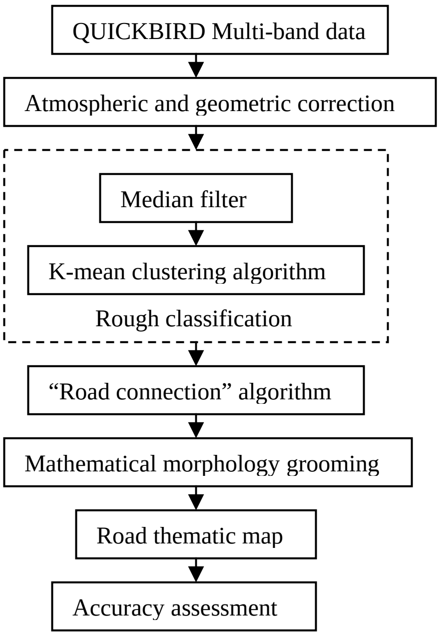

Figure 2. Road information extraction flowchart. It mainly contains three steps: rough classification using K-mean cluster, road connection based on road knowledge and mathematical morphology grooming.

Figure 3. Rough classification image using K-mean cluster algorithm. It is a binary image. The darker objects are roads and shadows, and other geo-types are classified into lighter in the image.

Figure 4. Result of road connection algorithm. The algorithm is based on road knowledge including continuity, shape, and topology of urban roads. The road features are obvious in the imagery.

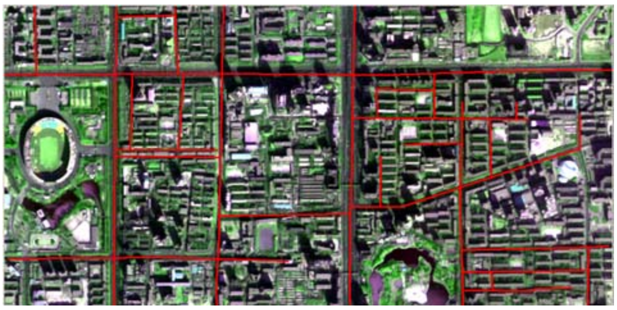

Figure 5. Compared image overlap road thematic image with the original image. It clearly shows the extraction result

3.3 Accuracy Assessment

In order to simplify the evaluation of the result, we define main road as those with the width larger than 10 pixels or the length more than 300 pixels, and the sub-road as those with the width less than 10 pixels and the length between 100 and 300 pixels. Road segment which is also defined to evaluate the result refers to the segment between intersections of roads of the same level. Accuracy is given at last in table 1. As results turn out, 86.7% main road segments and 65.7% sub-road segments are extracted correctly, while 10.0% main road segments and 8.6% sub-road segments are recognized partially. Only 3.33% main road segments are failed to be extracted, while that proportion of sub road segments is 15.7%.

	Main roads	**Sub-roads**
Complete	86.7%	65.7%
Incomplete	10.0%	8.6%
Missing	3.33%	25.7%
Manual Ref.	30	35
Result	30	37
Wrong	0	2/37=5.4%

Table 1. Road information extraction accuracy assessment

4. CONCLUSION

The proposed approach of automatic road extraction from high spatial resolution images can improve the accuracy of road extraction and reduce the effects of occlusions on roads such as shadows. Through tests, the method proves to be simple, accurate, and highly automatic, applying well to road extraction from high spatial resolution images of huge volumes. The unsupervised classification is used first to convert the image with huge detailed information into a binary image, which facilitates the road searching process without the need to judge the spectral property of pixels one by one. Then set the clustering number as two, and this can avoid the road interruption caused by shadows on roads. Secondly, according to the continuity of roads, we define a fixed step to search in the image and identify road pixels by the proportion of road pixel numbers on the step. This procedure significantly ensures the continuity of roads, reducing the road occlusions caused by other unrelated objects. Besides, if the pixel on a direction has been searched, the next pixel will be searched immediately, which avoids the repetitive search and improves the efficiency significantly. Thirdly, we process the rude result image through morphological operators to connect discrete line segments and smooth the lines. So, the subjects of morphological process are roads, excluding non-road objects, and will not cause errors on non-road region, which acquires higher accuracy compared to simply morphological process in the whole image. After connecting and smoothing, we introduce the concept of region to erode roads according to local road width information to get the skeleton of roads, and the result is one-pixel road width image. Considering the topological and geometric properties of roads, we can eliminate single and too short line segment further. The result image could be converted to vectors for potential use.

However, the approach needs to be improved further to extract secondary roads that are covered by wayside trees or shadows. One possible solution is to recognize continuous and rectangular shaped trees as roads through training. Meanwhile, better methods of eliminating shadows in high spatial resolution images are expected.

To sum up, the approach in this paper could extract urban road network from high spatial resolution image accurately and automatically and is of satisfactory practical value.

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