Object Oriented Road Extraction from Remote Sensing Images Using Improved Watershed Segmentation

LIU Dawei¹*, GAO Shujing¹
¹Information Engineering College, Engineering University of PAP, Xi'an, Shaanxi, China
* LIU Dawei: wjmicheal@163.com

Abstract. A novel object oriented road extraction method is presented for the road extraction from remote sensing images. Firstly, an improved watershed algorithm is adopted for image segmentation, and the spectral, texture and geometric features of the image are fully considered in the segmentation process so as to improve the segmentation accuracy. Then road knowledge base is built and various features of the road are added into the base. Finally, the road extraction purpose is reached by calculating the features of the objects and comparing them with the knowledge base. Experiment results show that the method can achieve higher accuracy and quality in road extraction.

1. Introduction
As one of the basic data of topographic map and geographic information system, road extraction research has important theoretical and practical significance. Traditional pixel oriented road extraction methods, such as template matching method¹⁻², snake model method³, dynamic programming method⁴, have achieved certain results in some cases, but the extraction process mainly depends on the gray information of pixels. The factors considered are mainly the neighborhood relationship and statistical characteristics of pixels, but the shape, topology and texture of roads can not be considered, Therefore, it is difficult to overcome the phenomenon of "different objects with the same spectrum" in image extraction, and the extraction accuracy is greatly limited. The object-oriented processing method takes the polygonal region which is composed of pixels with the same or similar attributes after image segmentation as the basic processing unit in road extraction. Because the processing object is a determined continuous region, this method can comprehensively consider the spectrum, shape, texture and other characteristics of the road, and make full use of the image context information, so it breaks through the limitation of traditional pixel oriented extraction method.

Based on this, this paper proposes an object-oriented road extraction method. Firstly, the improved watershed algorithm is used to segment the image. In order to improve the segmentation accuracy, the geometric, spectral and texture features of the segmented region are considered comprehensively; then, the road knowledge base is constructed, and the road spectrum, geometry, texture and other features are included in the knowledge base; finally, by calculating the object features and comparing with the road feature set in the knowledge base, the purpose of road extraction is achieved. Experimental results show that this method can achieve high accuracy and extraction quality in road extraction.

2. Improved watershed segmentation algorithm
Watershed segmentation is an image segmentation algorithm based on geographical morphology. This algorithm has strong ability to suppress noise, and can obtain single pixel wide, accurate positioning,
continuous and closed segmentation edge \cite{5}. In this paper, it is applied to the segmentation of high-resolution image. However, this algorithm is prone to over segmentation, so an improved algorithm is proposed in this paper. Based on the traditional watershed transform, the algorithm uses the method of region merging to solve the problem of over segmentation. The flow of the algorithm is as follows:

1. Firstly, the gradient image of the original image is obtained, and then the gradient image is smoothed by Lee filter. The reason for smoothing operation is that as the input of watershed transform, there are local extremum caused by noise, quantization errors and some fine textures in gradient image, which is one of the factors leading to the over segmentation phenomenon of watershed transform \cite{6}, and smoothing operation can suppress the over segmentation phenomenon to a certain extent. (2) Watershed segmentation is applied to the processed gradient image \cite{7}. (3) After the initial segmentation of the image, the two-step region merging is applied to get the final segmentation result.

The two-step region merging divides the merging process into two steps. After the initial segmentation of image, the segmentation objects have the characteristics of small area and large number. Where the image gradient changes sharply, the initial segmentation objects often have only a few pixel sizes, and their gray characteristics are obvious, but the texture or shape attributes have little reference significance. At the same time, due to the large number of initial segmentation regions, if the texture and other attributes of each small region are calculated at the beginning of merging, the amount of computation is very large. Therefore, in the first step, only the most significant gray information of region attributes is considered, and the region area threshold is used as the termination condition. When the region is merged to a certain area and has obvious texture attributes, the second step of merging is carried out, and the texture information of the region is added into the merging criteria to improve the accuracy of region merging.

The algorithm flow of two-step region merging is shown in Fig. 1. In the first step of merging, the area threshold $s$ is set to determine whether the segmented region is a minimal region. If the area is less than $s$, it is a minimal region, otherwise it is a non-minimal region. The similarity calculation formula of adjacent regions $A$ and $B$ is as follows:

$$ g_{AB} = \| g_A - g_B \|_2^2 $$

In formula (1), $g_A$ and $g_B$ are gray mean vectors of CIE ($L^*a^*b^*$) space of region A and B respectively.

![Algorithm diagram of two step region merging](image)

Fig. 1. Algorithm diagram of two step region merging

The merging rule of the first step is: for the current area, merge the most similar area calculated according to formula (1) in its neighborhoods. After the first step of merging, the number of divided regions is greatly reduced, while the area of the divided regions increases and is more practical. At this time, the second merging step is performed, and the texture attributes of the regions are added to the merging criteria.

In the second merging step, the algorithm uses gray level co-occurrence matrix (GLCM) to calculate the texture features of the object. In this step, the similarity measure of adjacent regions $A$
and B includes gray similarity and texture similarity. For the calculation of gray similarity, see formula (1). The texture similarity is \( v_{AB} = |v_A - v_B| \), where \( v_A \) and \( v_B \) are the texture features of regions A and B respectively. According to GLCM, a variety of texture feature operators can be obtained. In this paper, we use the dissimilarity operator, which has strong discrimination for texture. The calculation formula of dissimilarity can be found in reference [9]. The merging rule of the second step is: for any region A, there is a neighborhood B, so that \( v_{AB} < v \) and \( g_{AB} < g \), where \( v \) and \( g \) are the texture similarity and gray similarity thresholds, respectively.

3. Construction of the road knowledge base

After image segmentation, we need to calculate the various features of the objects and compare them with the known features of the geo-objects to achieve the purpose of object extraction. The known features of geo-objects come from the knowledge base, which is a collection of features of ground geo-objects. In this paper, the description of road features includes geometric features, spectral features and texture features.

The geometric features include the aspect ratios of the roads and the area ratios to the minimum circumscribed rectangles. Because the roads are generally slender, their aspect ratios are greater than a certain threshold, and their area ratios to the minimum circumscribed rectangles are less than a certain threshold.

Spectral features refer to the brightness value of the roads. Due to the high radiations of the roads, the brightness value is generally high, which is greater than a certain threshold.

Texture features refer to the dissimilarity of road objects. Because the internal gray level of the road objects is uniform after segmentation, it shows local consistency, so the dissimilarity value of the roads should be less than a threshold.

4. Object feature calculation

For the feature set in the road knowledge base, it is necessary to calculate the corresponding features of the segmented objects. The brightness value and GLCM characteristic value of the object have been calculated in the process of region merging. The brightness value of an object is the first element value of the gray mean vector in its CIE(L*a*b*) space, that is, the L value. The GLCM value of the object is also calculated in the second step of region merging. The following describes the calculation method of the geometric characteristics of the object.

The geometric features of the object include the area ratio \( f \) between the object and its minimum circumscribed rectangle and the aspect ratio \( a \) of the object. Object minimum circumscribed rectangle refers to the rectangle whose boundary is determined according to the maximum abscissa \( X_{max} \), minimum abscissa \( X_{min} \), maximum ordinate \( Y_{max} \) and minimum ordinate \( Y_{min} \) of each vertex of the object. The calculation formula of area ratio \( f \) is as follows:

\[
f = A / ((X_{max} - X_{min}) * (Y_{max} - Y_{min}))
\]

In formula (2), \( A \) is the area of the object, which is represented by the number of pixels here, and the coordinates of the object are represented by the row and column number of the image where it is located.

When calculating the length width ratio of roads, the roads are divided into two forms. The first form is relatively curved roads, as shown in Figure 2(a), which is called type I road; the second form is that the roads are relatively straight, as shown in Figure 2 (b), which is called type II road.

![Fig.2. Two road types](image-url)
For two different types of roads, the calculation method of aspect ratio is also different. For type I road, we need to use the statistical method to calculate. Assuming that the segmentation object is expressed as O, we need to first construct the covariance matrix \( S \) of O coordinate:

\[
S = \begin{pmatrix}
\text{Var}(X) & \text{Cov}(XY) \\
\text{Cov}(XY) & \text{Var}(Y)
\end{pmatrix}
\]

(3)

where

\[
\text{Var}(X) = \frac{1}{A_o} \sum_{x \in O} x_i^2 - \left( \frac{1}{A_o} \sum_{x \in O} x_i \right)^2
\]

(4)

\[
\text{Var}(Y) = \frac{1}{A_o} \sum_{y \in O} y_i^2 - \left( \frac{1}{A_o} \sum_{y \in O} y_i \right)^2
\]

(5)

\[
\text{Cov}(X,Y) = \frac{1}{A_o} \sum_{x,y \in O} x_i y_i - \left( \frac{1}{A_o} \sum_{x \in O} x_i \right)\left( \frac{1}{A_o} \sum_{y \in O} y_i \right)
\]

(6)

In formula (3)-(6), \( X \) represents the set of all \( x \) coordinates of object O, \( Y \) represents the set of all \( y \) coordinates of object O, and \( A \) represents the area of object O.

Suppose the two eigenvalues of \( S \) are \( \lambda_1 \) and \( \lambda_2 \) respectively, and assuming that \( \lambda_1 \geq \lambda_2 \), let

\[
a_1 = \frac{\lambda_1}{\lambda_2}
\]

(7)

Then for type I road O, its final aspect ratio is \( a_1 \).

If O is a type II road, its aspect ratio is:

\[
a_2 = \max\left(\frac{w^2 + ((1 - f)h)^2}{A}, \frac{h^2 + ((1 - f)w)^2}{A}\right)
\]

(8)

In formula (8), \( \max(\cdot) \) represents the operation of taking a larger value, \( w \) and \( h \) are the length and width of the circumscribing rectangle of object O, \( A \) is the area of object O, and the calculation of \( f \) is in formula (2).

For type I roads, the calculation result is more accurate when formula (7) is used, but when formula (8) is used, the result will be larger than the actual result; for type II roads, the calculation result of formula (8) is closer to reality. The calculation result of formula (7) is larger than the actual result. In actual operation, it is difficult to determine whether the road belongs to Type I or Type II. Therefore, in this calculation, for the object O, formulas (7) and (8) are used to calculate its aspect ratio, and finally the smaller value of the two is selected. That is: \( a = \min(a_1, a_2) \).

5. Experimental results and analysis

A Resturs DK1 multi-spectral remote sensing image is used for the experiment, as shown in Figure 3. The experimental data is a residential area in the north of Atlanta, Georgia, USA, covering a range of \( 84^\circ 32' 28" - 84^\circ 32' 43" \) W, \( 34^\circ 6' 39" - 34^\circ 6' 49" \) N, the spatial resolution of the image is 1.25 meters, the size is 483 rows and 569 columns, the imaging time is November 2019, and the display bands are green, red, and near-infrared. The types of features in this area mainly include houses, roads, trees, open spaces, grasslands, etc. The effectiveness of this method is illustrated by extracting road features in the image. The implementation language of the method in this paper is Java, JDK version 1.8, and the operating system is Windows 10.

Fig.3. Experiment image
Fig. 4. Segmentation result of the image

Firstly, the image is segmented by the method in this paper. The segmentation parameters are $s=300, g=70, v=10.5$. The segmentation results are shown in Figure 4. Through visual observation, it can be found that the edges of the segmented geo-objects are relatively clear and accurate, and different geo-objects are well distinguished, which shows the effectiveness of the method in this paper. After the segmentation, the road knowledge base is constructed. According to the characteristics of the image, the brightness threshold $g_f$, texture contrast threshold $v_f$, the area ratio threshold $f_f$ between the object and the minimum bounding rectangle, and the aspect ratio threshold $a_f$ are set in the road knowledge base. The four threshold parameters were $g_f=75, v_f=8.4, f_f=0.09, a_f=1.5$; finally, the object features are calculated. For the object $O$ in the segmented image, if it belongs to the road, its features must meet the threshold range of the road knowledge base of the image:

1. $g_o > g_f$
2. $v_o < v_f$
3. $f_o < f_f$
4. $a_o > a_f$

where $g_o, v_o, f_o$ and $a_o$ are the brightness value, texture contrast value, area ratio and aspect ratio of the object $o$ respectively. By calculating the features of all the segmented objects and comparing with the knowledge base, the final road extraction result is obtained, as shown in Figure 5.

Fig. 5. Road extraction result

After the road extraction, this paper uses the complete rate $c_m$, the correct rate $c_r$ and the extraction quality $q_l$ proposed by Wiedemann[8] to evaluate the extraction results, where

$$c_m = l_r / l_{t}$$
$$c_r = l_r / l_i$$
$$q_l = l_r / (l_t + l_n)$$

In equations (9) to (11), $l_r$ is the correct road length extracted, $l_t$ is the actual road length, $l_i$ is the total road length extracted, and $l_n$ is the road length not extracted. The value range of the three indexes all belong to $[0,1]$. The higher the value, the better the calculation effect. Through the calculation, the three index values of this experiment are $c_m=0.90, c_r=0.93, q_l=0.85$, and the three index values are higher, which shows the effectiveness and accuracy of the algorithm.
6. Conclusion
Aiming at the problem of road extraction in remote sensing images, this paper proposes a novel object-oriented extraction algorithm, which aims to overcome the shortcomings of traditional pixel road extraction methods and improve the accuracy of road extraction. The algorithm realizes the image segmentation through the improved watershed segmentation, and constructs the road knowledge base including spectrum, geometry, texture and other features. By calculating the object features and comparing with the knowledge base, the purpose of road extraction is achieved. The experimental results show that the algorithm can achieve high accuracy and extraction quality in road extraction.

Acknowledgments
This work is supported in part by the Fundamental Research Funds of Engineering University of People’s Armed Police under Grant WJY202102, and in part by the Military Theory Research Project of Engineering University of People’s Armed Police under Grant JLY2021052.

References
[1] Kim T, Park S, Kim M, et al. Tracking Road Centerlines from High Resolution Remote Sensing Images by Least Squares Correlation Matching [J]. Photogrammetric Engineering & Remote Sensing, 2004, 70(12):1417-1422.
[2] Chen G, Sui H, Tu J, et al. Semi-automatic Road Extraction Method from High Resolution Remote Sensing Images Based on P-N Learning[J]. Geomatics and Information Science of Wuhan University, 2017, 42(6):775-781.
[3] Kumar P, McElhinney C P, Lewis P, et al. An automated algorithm for extracting road edges from terrestrial mobile LiDAR data[J]. Isprs Journal of Photogrammetry & Remote Sensing, 2013, 85(11):44-55.
[4] Li Y, Hu X, Zhang J, et al. Automatic Road Extraction In Complex Scenes Based on Information Fusion From LiDAR and Remote Sensing Imagery[J]. Acta Geodaetica et Cartographica Sinica, 2012, 41(6):870-876.
[5] A M H, A J G, A Y D, et al. A novel FMH model for road extraction from high-resolution remote sensing images in urban areas[J]. Procedia Computer Science, 2019, 147:49-55.
[6] Li Y, Peng B, He L, et al. Road Extraction from Unmanned Aerial Vehicle Remote Sensing Images Based on Improved Neural Networks[J]. Sensors, 2019, 19(19):4115.
[7] Wei Y, K Zhang, Ji S. Simultaneous Road Surface and Centerline Extraction From Large-Scale Remote Sensing Images Using CNN-Based Segmentation and Tracing[J]. IEEE Transactions on Geoscience and Remote Sensing, 2020, PP (99):1-13.
[8] Wiedemann C, Heipke C. Empirical evaluation of automatically extracted road axes [C]. CVPR Workshop on Empirical Evaluation Methods in Computer Vision, 1998:172-187.table 3.