ROAD WIDTH MEASUREMENT FROM REMOTE SENSING IMAGES

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ABSTRACT

In this paper, we propose a novel approach for road width measurement from high resolution satellite or aerial images. The proposed approach has three main steps. First, we extract line segments and road center lines on the given remote sensing images. Second, we could obtain many pairs of parallel lines with width information by computing the positional relationship between each other. Then K-means is performed to cluster these parallel lines into several clusters by the width information of them. Finally, an energy function is introduced to assign the width range of a cluster to each pixel on road center lines, the width range is viewed as the width of the corresponding road segment. Attribute to parallel lines extraction, parallel lines clustering and our energy function, the proposed road width measurement method is able to provide high quality results on road width measurement.

Index Terms—road width measurement, K-means, road network extraction, satellite images

1. INTRODUCTION

Road information extraction from satellite images is a challenging problem in remote sensing image processing. Effective road information extraction approach make it possible for automatic transportation data acquisition which is significant for providing many convenient services. For instance, road information extraction can plan path for unmanned aerial vehicles automatically and provide valuable prior knowledge for vehicles detection.

Road information extraction has gained considerable attention in recent years. Many scholars proposed various effective methods to extract road information from given remote sensing images. Gamba *et al.* [1] extracted linear features from optical images by multiple directional filters in their method. Perceptual grouping were applied to detect road segments with these features. Yang and Wang [2] presented a novel algorithm to detect main roads in remote sensing images. They detected road primitives such as homogenous and line segments firstly. Then they linked these primitives as road. Wiedemann and Ebner [3] developed a method to connect roads in completely extracted road networks. Roads were linked by a link hypothesis based on the road network characteristics. A semi-automated road detection method was proposed by Chaudhuri *et al.* [4]. The method includes directional segmentation, directional morphological enhancement and thinning. Zhang and Couloginer [5] presented a method based on Radon transform to extract centerlines from classified road imagery. The method has a great performance in dealing with straight road segments. A centerline extraction method based Hough transform was proposed by Poullis and You [6]. First, they use a set of Gaussian-based filters to compute the magnitude at each road pixel. Then Hough Transform is iteratively applied to extract road centerlines. Yuan *et al.* [7] proposed an automatic road extraction method based on locally excitatory globally inhibitory oscillator networks. A framework for road centerline extraction was proposed by Shi *et al.* [8]. The framework incorporates local Geary's C, spectral-spatial classification, shape features, locally weighted regression and tenser voting. Ünsalan *et al.* [9] extracted rough road primitives with the spectral, shape and gradient features of road at first, then proposed topology analysis scheme was applied to refine the road map. An ADSM algorithm based on spectral character and contrast was presented by Zang *et al.* [10]. Road like structures could be detected by ADSM algorithm, then a mask was constructed to denote potential road regions. Zang *et al.* [11] also developed joint enhancing filtering framework to facilitate extracting road network from satellite images.

However, these works focus on road network extraction but pay less attention on the road width estimation. In this paper, we propose a robust method to measure road width attribute. We extract line segments at first. With the detected road center line, we match these line segments each other and obtain many pairs of parallel lines. K-means is then applied to cluster parallel lines into several clusters by their width. Finally, we introduce an energy function to assign the width range of a cluster to each pixel on extracted road center lines.

2. METHODOLOGY

Firstly, LSD (Line Segment Detector) [12] and ADSM algorithm [10] are applied to extract linear features and road center lines from given remote sensing images respectively. Therefore, we could obtain many pairs of parallel lines by using plane geometry knowledge. Distance, overlap ratio and the difference of slope are computed between every two line segments. Two line segments will be considered as a pair of parallel lines if their slope difference and distance are both small, and the overlap ratio is large enough. After that, K-means algorithm is used to cluster these parallel lines into several clusters by their width, and give each cluster a cluster label. At last, we construct an energy function and assign a cluster label to each pixel on road center lines by minimizing the energy function.

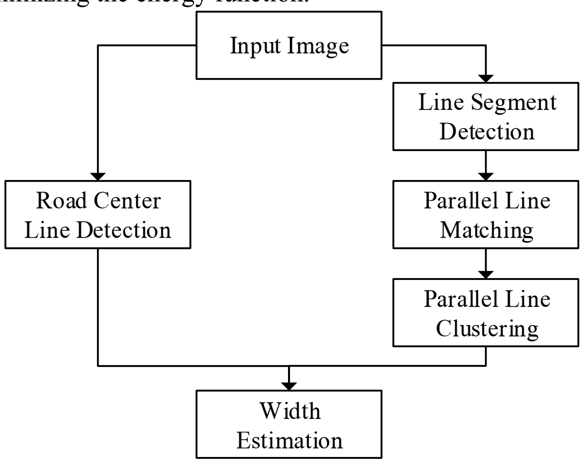


Fig.1: algorithm flow chart

2.1. Parallel lines matching and clustering

By observing the characteristics of road, it is obvious that the road width is define by the distance between the two edges of road. In order to extract road edges, LSD is applied to extract line segments from given remote sensing images in advance. And road center lines are also needed in computing road width. Road center lines are extracted by ADSM algorithm [10] beforehand.

Line segments extraction leads to parallel lines matching and parallel lines width computing. Obviously, the distance between two parallel edges could be considered as the width of a road. After line segment detection, the edges of some road segments are extracted. Here we are interested in searching for parallel edges of roads. For this purpose, detected line segments should be matched to produce pairs of parallel lines. Firstly, the slope of every line segment is computed. For each line segment, we then search some line segments which have the same slope up to a certain tolerance 3 degrees as parallel lines candidates. Furthermore, the overlap ratio also should be taken into account. Overlap ratio indicates the overlap ratio between two line segments in the principal parallel line direction.

In the case of target line segment M and its candidate N, the overlap ratio from M to N could computed as follows. Firstly, line segment M is sampled at fixed step sizes to produce a sample point set P_M. Let L_N be the line where line segment N located in. Secondly, we draw lines perpendicular to line L_N over each sample point in P_M. Let n be the total number of vertical points which are located in line segment N. The overlap ratio from M to N is defined as

$$R_{MN} = \frac{n}{|P_M|}$$

where $|P_M|$ is the size of P_M. Accordingly, R_{NM} could be computed in the same way. Let $p(x_0, y_0)$ be a point, and let $Ax + By + C = 0$ be the line L. We draw a line perpendicular to line L over point p. The vertical point $q(x_1, y_1)$ is define as

$$x_1 = \frac{B^2x_0 - ABy_0 - AC}{A^2 + B^2}$$

$$y_1 = \frac{A^2x_0 - ABx_0 - BC}{A^2 + B^2}$$

If both of the overlap ratio from line segment M to candidate N R_{MN} and the overlap ratio from candidate N to M R_{NM} are smaller than 0.2, the candidate line segment must be discarded.

At last, we compute the distance between target line segment and its candidates, and cast off those candidates which the distance between them and target line segment is smaller than a fix value. The fix value is chosen depends on the statistical information of road width, and it is set to 20 in our experiments. For a pair of parallel line segments M and N, if line segment M is shorter than line segment N, their distance could be computed by computing the distance from the midpoint of M to line segment N. The result of parallel lines matching is shown in Figure 2(a). Here we obtain 8 pairs of parallel lines. Every pair of parallel lines are marked by a random color.

After previous work, we obtain numerous pairs of parallel lines. The appearance of roads shows that the width of a road changes a litter. Therefore, it is logical to infer that the width of a road segment is similar to that of other road segments which are adjacent to it. In other words, a road segment may has a same cluster label with other road segments which are adjacent to it when these road segments have been clustered by their width.

Here we apply K-means to partition these parallel lines into several clusters by their width. We choose the width of parallel lines as the input data. With regard to the total number of clusters k, we try it from 2 to a fix number, such as 10. Then Davies–Bouldin index [13] is used to find the best k value. Let C_i be a cluster of data points. Let X be a sample point in cluster C_i. The scatter within the cluster could be defined as follows:

$$S_i = \frac{1}{|C_i|}\sum_{X \in C_i} \|X - Z_i\|$$

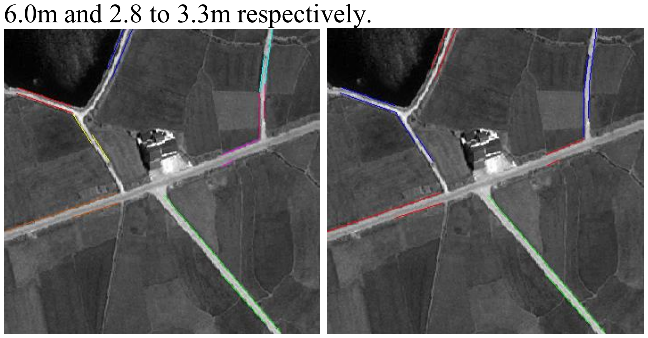
where Z_i is the centroid of C_i and $|C_i|$ is the size of the cluster i.

$$d_{ij} = \|Z_i - Z_j\|$$

where d_{ij} is a measure of separation between cluster C_i and cluster C_j.The DB Index is defined as follows:

$$DB_k = \frac{1}{k}\sum_{i=1}^{k} R_i$$

where $R_i = \max_{j=1,\dots,k,j\neq i} \frac{s_i+s_j}{d_{ij}}$, k is the total number of clusters. A smaller DB Index means that the clustering is better, and the corresponding k value is better. In this way, we could find a best k value and cluster these parallel lines into k clusters. Parallel lines in a same cluster has similar widths. As can be seen in Figure 2(b), parallel lines are clustered into three clusters which are labeled by red color, blue color and green color respectively, and parallel lines which belong to a same cluster are labeled by a same color. The widths of those parallel lines labeled by red color, green color and blue color are within the range of 7.5m to 8.1m, 5.7m to 6.0m and 2.8 to 3.3m respectively.



(a) (b)

Fig.2: (a) parallel lines extracted. (b) K-means result

2.2. Road width estimation

In this paper, our objective is to give a width range to every road segment. And every pixel on road center lines has a corresponding road segment. Therefore, we will give every pixel a width range of the corresponding road segment. In previous work, we cluster parallel lines into some clusters by their width and give each cluster a cluster label. Every cluster contains several pairs of parallel lines with similar width, so a cluster represent a width range. Our approach is to give a cluster label to each pixel on road centerlines. Then the width range of the cluster indicates the width of corresponding road segment of the pixel.

For this purpose, every pixel on road centerlines should be assigned a cluster label to denote which width range the corresponding road segment belongs to. A simple way to label a pixel with a cluster label is to find a pair of parallel lines which are nearest to the pixel, then the cluster label of the nearest parallel lines is assigned to the pixel. In consideration of that the width of a road is changeless, it is desired that the labeling process refers not only to the pixel's own position but also to the region consistency. For instance, with regard to a pixel p, if all of the pixels neighboring to p get a cluster label k, the cluster label of p is most likely to be k. In addition, in order to satisfy different preferences, it is necessary to allow the user to specify emphasis on pixel's own position or the region consistency.

Therefore, for each pixel p on extracted road centerline L, our aim is to find a cluster label lab_p, such that the sum of the distance from p to cluster lab_p and the cost of label difference between p and its neighboring pixels get minimum. Let lab_p be the cluster label p gets. Formally, our aim can be written as:

$$\arg\min_{lab_p}(D(p, lab_p) + \varepsilon \cdot S(lab_p, lab_q))$$

where $D(p, lab_p)$ is the data term, $S(lab_p, lab_q)$ is the smooth term, and $\varepsilon \in [0,1]$ is a balancing factor which determines how the smooth term affects the results.

$D(p, lab_p)$ indicates the minimal distance from pixel p to one pair of parallel lines which belongs to cluster lab_p, it is defined as

$$D(p, lab_p) = \min_{l\in PL_{lab_p}}(Dis(p, l))$$

where PL_{lab_p} includes all of parallel lines which belongs to cluster lab_p, l is a line segment belongs to PL_{lab_p}, $Dis(p, l)$ indicates the distance from pixel p to line segment l.

$S(lab_p, lab_q)$ indicates the influence from neighboring pixels. It is defined as

$$S(lab_p, lab_q) = \sum_{q\in N_p} sign(lab_p, lab_q) \cdot \left\| C_{lab_p} - C_{lab_q} \right\|$$

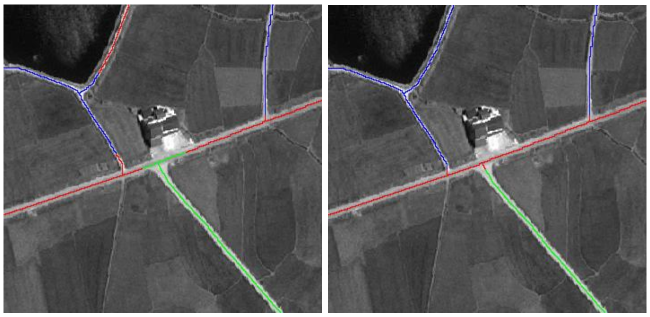
where N_p is the neighborhood of pixel p which includes those neighboring pixels located in road centerlines, here N_p is set as 12 pixels which are nearest to p. C_{lab_p} is the centroid of cluster lab_p . $\left\| C_{lab_p} - C_{lab_q} \right\|$ indicates the distance between the centroid of cluster lab_p and the centroid of cluster lab_q. The sign function $sign(lab_p, lab_q)$ equals 0 if $lab_p = lab_q$ and equals 1 otherwise.

At last, the classic graph cut algorithm is implemented to find the optimal labeling scheme which minimizes the total cost of all pixels. Every pixel located in road centerlines get a cluster label, the width range of the cluster indicates the width of the corresponding road segment.

3. RESULTS AND ANALYSIS

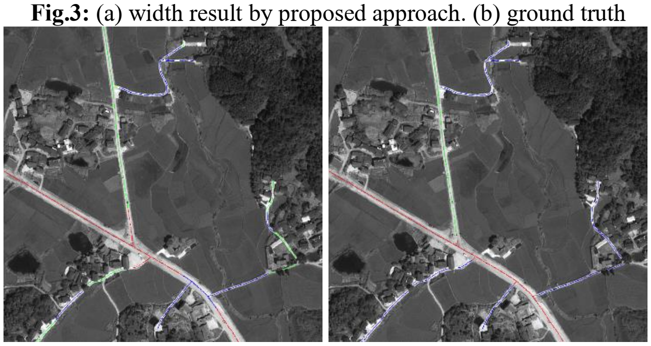
Several experiments are designed to assess the performance of our approach proposed in this paper. Here we mainly test the approach with some satellite images of rural area, from Pleiades-1A satellite. For demonstration purposes, road segments in same width range are marked with same color. We'll compare the results to ground truths which are manually generated, and compute the correctness of the results.

The resolutions of these remote sensing images are 0.5 m. In Figure 3, road segments with the width from 7.5m to 8.1m are marked with red lines, road segments with the width from 5.7m to 6.0m are marked with green lines, and road segments with the width from 2.8m to 3.3m are marked with blue lines. The correctness is 71.15%. In Figure 4, road segments with the width from 12.3m to 13.0m are marked with red lines, road segments with the width from 5.8m to 6.2m are marked with green lines, and road segments with the width from 3.1m to 3.5m are marked with blue lines. The correctness is 72.43%. As can be seen in Figure 3 and Figure 4, most of the road segments get a correct width range. But there are also some errors happen when our algorithm be interfered by some objects near to roads, such as lakes, rivers and buildings. This is also what we are going to research next.



(a) (b)

Fig.3: (a) width result by proposed approach. (b) ground truth



(a) (b)

Fig.4: (a) width result by proposed approach. (b) ground truth

We also tested our approach largely on the remote sensing image of Shaoshan City recorded by Pleiades-1A satellite with resolution 0.5m. The size of the satellite image is 28648*37929 pixels. In order to facilitate the test, we divided the satellite image into patches. The experiment are applied in each image patch. The correctness of the synthesized result is 68.34%. Buildings beside of roads in urban area reduced the correctness of the approach.

4. Conclusions

In this paper, a framework for accurate and stable road width measurement from remote sensing images has been presented. The framework is an integrated approach which incorporates line segment extraction, parallel lines matching method, K-means algorithm, and an energy function. By using line segment extraction and parallel lines matching method, our approach could extract most of the parallel edges of road segments. Then the energy function combined with K-means give accurate width range to road segments. In our next research, we will try to introduce some effective algorithms which could eliminate the interference produced by objects nearby at roads, to achieve a greater performance.

5. ACKNOWLEDGMENT

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REFERENCES

[1] P. Gamba, F. Dell'Acqua, and G. Lisini, "Improving Urban Road Extraction in High-resolution Images Exploiting Directional Filtering, Perceptual Grouping, and Simple Topological Concepts," *IEEE Geosci. Remote Sens. Lett.*, vol. 3, no. 3, pp. 387–391, Jul. 2006.

[2] J. Yang and R. S. Wang, "Classified Road Detection from Satellite Images based on Perceptual Organization," *Int. J. Remote Sens.*, vol. 28, no. 20, pp. 4653–4669, Oct. 2007.

[3] C. Wiedemann and H. Ebner, "Automatic Completion and Evaluation of Road Networks," *Int. Archives Photogramm., Remote Sens., Spatial Inf. Sci.*, vol. 33, no. B3/2, pp. 979–986, 2000.

[4] D. Chaudhuri, N. K. Kushwaha, and A. Samal, "Semi-automated Road Detection from High Resolution Satellite Image by Directional Morphological Enhancement and Segmentation Techniques," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 5, no. 5, pp. 1538–1544, Oct. 2012.

[5] Q. Zhang and I. Couloigner, "Accurate Centerline Detection and Line width Estimation of Thick Lines Using The Radon Transform," *IEEE Trans. Image Process.*, vol. 16, no. 2, pp. 310–316, Feb. 2007.

[6] C. Poullis and S. You, "Delineation and Geometric Modeling of Road Networks," *ISPRS J. Photogramm. Remote Sens.*, vol. 65, no. 2, pp. 165–181, Mar. 2010.

[7] J. Yuan, D. Wang, B. Wu, L. Yan, and R. Li, "LEGION-based Automatic Road Extraction from Satellite Imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 11, pp. 4528–4538, Nov. 2011.

[8] W. Z. Shi, Z. L. Miao, and J. Debayle, "An Integrated Method for Urban Main-Road Centerline Extraction from Optical Remotely Sensed Imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 6, pp. 3359–3372, 2014.

[9] C. Ünsalan and B. Sirmacek, "Road Network Detection Using Probabilistic and Graph Theoretical Methods," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 11, pp. 4441 – 4453, 2012.

[10] Y. Zang, C. Wang, L. Cao, Y. Yu, J. Li, "Road Network Extraction via Aperiodic Directional Structure Measurement," *IEEE Trans. Geosci. Remote Sens.*, 2016, DOI: 10.1109/TGRS.2016.25-14602 6.

[11] Y. Zang, C. Wang, Y. Yu, L. Luo, K. Yang, J. Li, "Joint Enhancing Filtering for Road Network Extraction," *IEEE Trans. Geosci. Remote Sens.*, pp. 1-15, Dec. 2016.

[12] Rafael Grompone von Gioi, Jérémie Jakubowicz, Jean-Michel Morel, Gregory Randall, "LSD: A Fast Line Segment Detector with a False Detection Control," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 4, pp. 722-732, Apr. 2010.

[13] David L. Davies, Donald W. Bouldin, "A Cluster Separation Measure," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. pami-1, no. 2, Apr. 1979.