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Road Extraction from Satellite Map ImageryBased on MGA of Detector Responses

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Abstract

A road network grouping algorithm for satellite map image is proposed by exploiting multiscale geometric analysis of detector responses. Before running the algorithm, a response map made up of responses, which is binerized, skeletonized, and vectorized to generate road candidates, is obtained by applying a local detector to a satellite map image. Then the proposed method identifies real road segments among the candidates and fills gaps between them. It works in three steps.1) Guidance segments are extracted at different street image from the response map using multiscale techniques and merged to get more appropriate approximation 2) Segments are labeled “road” or “noise” using relaxation labeling techniques,among which road ones or grouped as they may lie on differentroads.

3) Connection points between candidates are acquired by mapping candidates to grouped “road” guidance segments. Those connection points are linked with straight lines are curvilinear segments after a segmentation process. The experiments on Open Street Map (OSM) images from the satellite map image show the effectiveness of this new method.

Keywords: Multiscale geometric analysis, relaxation labeling,road network extraction.

I. Introduction

ROAD network extraction from Satellite Map Images is difficult tasks due to: 1) The variety of roads with different features like width, curvature and intersection in the same image 2) Variable features along road segments 3) The dependence of geometric shape of roads on image resolution 4)The multiplicative signal dependent noise known as speckle. In past 30 years to developed extract roads from satellite images a road network grouping process. Linear target detection operator and classification are combined into extract roads in high resolution satellite map image. A road network grouping algorithm for satellite map images is proposed by exploiting multiscale geometric analysis of detector responses. The proposed method identifies real road segments among the candidates and fills gaps between them. Many road network grouping methods take only the candidates as a posteriori probability. We present a grouping method, instead, exploiting both the responses of local detectors and candidates in this paper.

It is well accepted by now that vision is an inherently multiscale phenomenon and the visual task is to represent and interpret intensity fields replete with singularities. Moreover, it has been suggested that an efficient representation might be the key to many image processing tasks, including compression, denoising, and feature extraction. Wavelets provide a robust representation for one dimensional piecewise smooth signal, but they are poorly adapted for higher dimensional phenomena such as edges and contours. A multiscale image analysis framework named beamlet analysis in which line segments play a role analogous to the role player by points in wavelet analysis. Beamlets provide a multiscale structure to represent linear and curvilinear features. The speed of the algorithm is also considered as an important index, so recently an algorithm for rapid detection of roads is proposed. Owing to the simple road extraction operator of only two direction and structure optimization algorithm, the algorithm can be realized rapidly. During the optimization of algorithm, the connection method via comparing gradient is used to process after the segments are extracted via beamlet. The gradient connection method can produce better details and maintain the continuity of the roads.

In this paper, a road network grouping algorithm named road network grouping based on Multiscale Geometric Analysis of Detector Responses (RGMGAR), is designed by exploiting multiscale geometric analysis frameworks. The main idea is to acquire pairs of connection points between road candidates according to the guidance segments which are obtained with Multiscale Geometric Analysis.

II. Related Work

A. Road Detector

Road detectors output large responses for points lying on road like structures. Taking into account the statistical properties of speckle, the ratio road detector performs a good detection of linear features in Satellite Map images. In this paper, we employ this detector to generate response map. Dark linear targets as well as bright ones are treated as roads according to the detector described above. In this paper, only the case of dark targets is considered, so we need to make a slight change of the detector. A necessary step for edge detection methods using local detectors is the closing stage; starting from local information, a more global one must be deduced by a grouping process. MRF is widely used in the grouping of poor local detection. Let S_d denote the set of detected segments during the local process. All possible connections between any two segments in S_d make up S'_d. Then $S=S_d \cup S'_d$ is endowed with a graph structure, each segment *i* being a node, and two nodes *i* and *j* being linked by an arc if they share a common endpoint. Road detection is assigning labels ("road" or "others") to each node by maximizing the posterior probability distribution of labels $L= \{l_1, l_2, \ldots, l_N\}$ (l_i is either "road" or "others") given the observation $D= \{d_1, d_2, \ldots, d_N\}$ (d_i is response obtained from the detector) , $p(L \mid D)$. According to MRF model, the maximization above is equivalentto minimize the global

$$U(l|d) = \sum_{i=1}^{N} V(d_i|l_i) + \sum_{c \in C} V_c(l)$$

energy function

Where V (d_i | l_i) is the potential of the likelihood andV $_c$ (l) is the potential of a priori.

B. Multiscale Geometric Analysis and Beamlet

Multiscale geometric analysis (MGA) provides effective ways to detect, organize, represent, and manipulate data which nominally span a high-dimensional space. Among the various MGA frameworks, beamlets offer optimally sparse representation of smooth curves embedded in an image. Beamlet analysis provides opportunity to develop global optimization algorithms based on the neighboringness of beamlets coefficients in the beamlet graph. Beamlet gives sparse representation for tiny curve within the plane and whichis considered to be the optimal representation to some extent. A beamlets is a line segments with its endpoints on the boundary of a dyadic square, the sidelength of which determines the beamlet's scale, as shown in Fig.1 (a).when defining points at pixel level, we get a discrete beamlet, see Fig.1(b), and its length is the number of pixels on it. In this paper only discrete beamlets are involved. Let f(x1, x2) be a continuous function over a square, beamlets transform is defined as

$$T(b) = \int_b f(x(l))dl$$

Where $x(l)$ traces out the beamlet b along a unit speed path.

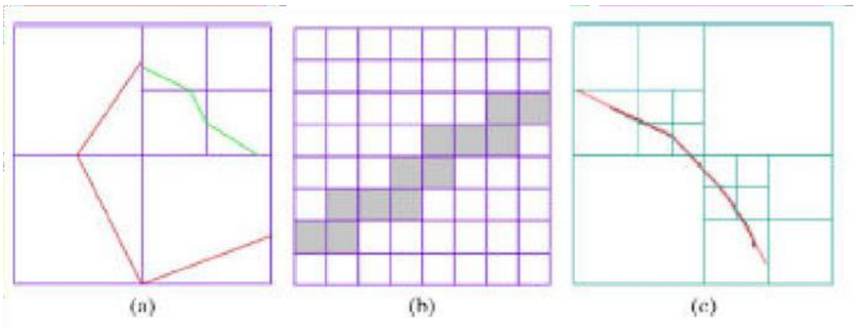


Fig.1. Beamlets and beamlet decomposition. (a)Beamlets at twodifferent scales. (b) A discrete beamlet. (c) A simple example ofbeamlet decomposition,the dark segment is input data and the red ones are beamlets.

Let gray level be the gray level value of a pixel, the discrete version of beamlet transform can be written as

$$T(b) = \sum_{p \in b} \text{graylevel}(p).$$

Where *l*(*b*) the length of beamlet *b*, beamlet decomposition is to find the optimal partition.

C. Relational Constraints

We list several relational constraints used in this paper which are important to group straight line segments or curves as follows.

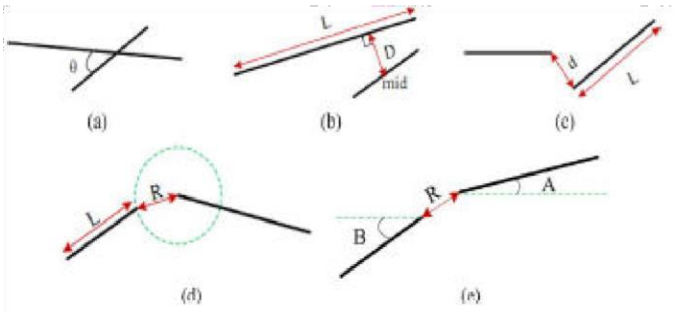


Fig. 2. Relational constraints. (a) Angular distance. (b) Lateral distance. (c) Endpoints distance. (d) Proximity. (e) Continuity.

• **Angular distance:** This measure is determined by the angle between two lines as shown in Fig.2(a).Angular distance is defined as

$$D_a = \min(|\theta_1 - \theta_2|, \pi - |\theta_1 - \theta_2|)$$

• **Lateral distance:** Lines in the same group must be close in lateral direction as measured by distance of midpoint of the shorter segment perpendicular to the longer segments. With L and D denoting the length of the longer segment and the perpendicular distance respectively, the lateral distance can be written as

$$D_l = \frac{D}{L}.$$

• **Endpoint distance:** The endpoint distance is defined as

$$D_e = \frac{d}{L}.$$

• **Proximity:** The proximity of two base segments reflects the perceptual significance that they project close together, see Fig.2(d).Let L and R be the minimum distance between them at their endpoints respectively. The proximity is formulated by

$$P = \frac{L^2}{2\pi R^2}.$$

• **Continuity:** Continuity is the structural relationship by which segments are grouped into smooth curves. It is calculated according to

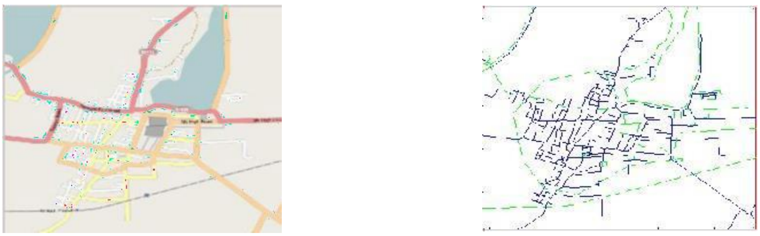
$$C = \frac{1}{(A^2 + B^2)(\alpha + \beta R)}$$

Here A and B are tangent angles of segments at joined endpoints. Parameters α and β controls the departure from co linearity of the joined segments and the sensitivity to the length of gap. α and β are used to judge which connection style to select: connect closer distance or connect smaller angle. The greater α is, the more likely to connected two segments with similar angle. The greater β is the more likely to connected two segments with smaller distance.

III. Guidance Segments

In this section, such a process exploiting beamlets is detailed. It aims at generating guidance segments to group road candidates and is accomplished in three steps:

Merging, Labeling and Grouping. First, beamlets are extracted at different resolutions from the response map and are merged to get rid of noise segments. This process takes advantage of *a posteriori* probability. Then, beamlets are labeled "road" or "noise" based on knowledge about road structures.



a) b)

Fig.3. Extract the Street Map images. a) Satellite map image, b) Response image.

Beamlets extracted from response image contain much noise as well as much detail in the decomposition at a fine resolution. An explanation to why beamlet analysis has a better performance on response image than the original data is that the detector accomplishes a denoising process when detecting target pixels, which results in a reduction of background pixels with low gray levels. To approximate the roads more appropriately, we decompose the response image at two different resolutions and remove the noise segments in the finer resolution based on the clues provided in the coarser resolution. Three main components in labeling, *neighborhood definition*, *constraint relation* and *update function* are detailed in remain of this part. The labeling process picks "road" beamlets out of the whole beamlet sets. They are grouped into different sequences since they may belong to different roads in the image considering perceptual grouping factors such as *proximity* and *continuity*. The procedure is as follows. Let a beamlet be the reference segment. Other beamlets with larger proximities than the threshold are located around the two endpoints of the reference segment. Among these, a beamlet having the largest continuity, which is larger than the threshold, is determined.

IV. Linking Segments

a. Mapping

In this part, we aim at getting connection points as well as discarding redundant candidates by mapping candidates to GSs. It accomplished in three steps :(1) There are more than onecandidates mapped to a same guidance. (2) The order of GS in agroup and the order of candidates mapped to each GS. (3) Candidates appear pair by pair in the sequence. The nearest twoend points of two different neighbor candidates then make up a pair of connection points.

b. Linking Segments Based On Mean shift

We explain how to generate curvilinear segments between connection points. To generate linking segments by combining edges acquired from the segmentation algorithm. We find two nearest nodes in the graph and trace the path between them using the depth limited graph traversal algorithm. There may be no feasible path between two nodes and then a straight line segment is taken. The speckles in SAR images have an impact on the image quality, for example, the outlines are blurred. Therefore, the edges of Satellite map image segmentation may not stick to the roads.

As we can see, the number of edges in a path is restricted to "Max" (depth limited). It avoids searching the graph widely and generating useless paths. When the length of a path is much larger than the distance between two connection points, it is discarded. Taking into account the length and the count of edges, we evaluate a path by

$$s(p) = \omega \times length(p) + (1 - \omega) \times count(p)$$

Where $length(p)$ and $count(p)$ are the length and the count of edges respectively. is a coefficient in the interval [0, 1]. The optimal path has the smallest $s(p)$. Observe that there may be no feasible path between two nodes, and then a straight line segment is taken.

V. Experiments and Analysis

During the experiments, the ratio road detector is first applied to the original Satellite images and provides response images. Beamlets are extracted from the response image at different resolutions. After merging, labeling and grouping those beamlets, we get straight line segments representing the mainroads, as shown in Figs. 3(b).

Comparing the results of proposed method and MRF based method, we can see that the RG-MGAR extracts more actual roads. It is mainly because the MRF based method prefers to link long candidates and neglect short ones by rewarding a longer length. Whereas the RG-MGAR maps all candidates to guidance segments and link them based on the mapping order regardless of their lengths. We also note that, the method fails to extract roads in dense urban areas where roads are always short and interrupted or blurred by buildings. The curvilinear linking generation procedure seems not to make much improvement in Fig.4.1 as there are almost straight roads. These factors lead the proposed method to a higher rate of false detection than the MRF based method. Another road extraction method is proposed in, Class-Aided Feature-Level Fusion is realized by combining two road extractors which are respectively designed for urban and rural areas from very high resolution Satellite map image scenes and fuse the above results. Junction-Aware Extraction, proposedby M. Negri, is an algorithm based on multiscale detection of street candidates and MRF optimization to extract urban road network, the results are shown in Figs.4.3.

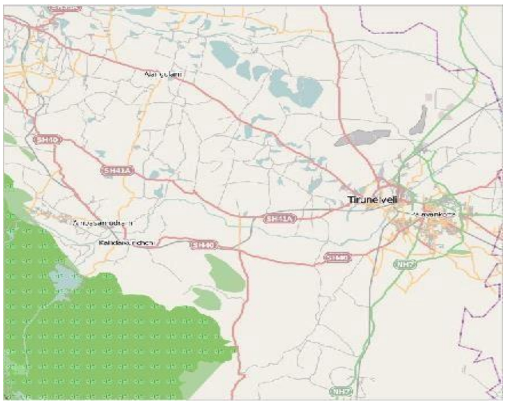


Fig: 4.1. Input Image Open Street Map

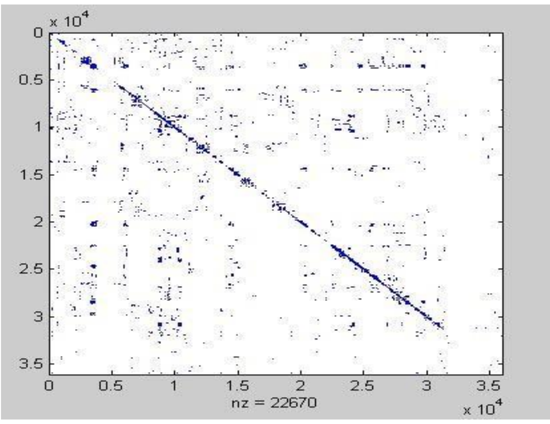


Fig.4.2. Processing Image

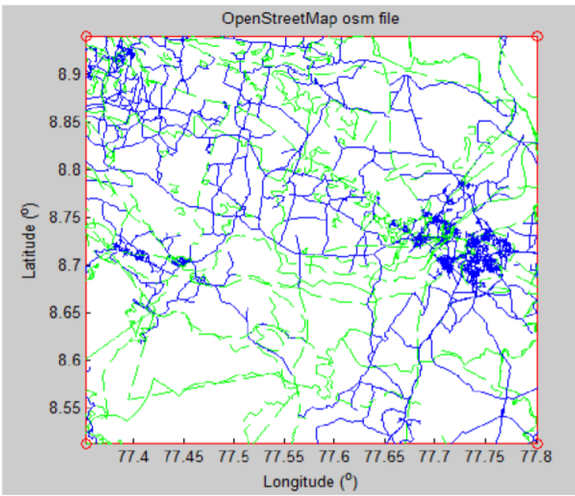


Fig.4.3. Response Image

The ratio road detector is first applied to the original Satellite Map images and provides response images. Connection points of road candidates are obtained by mapping candidates to guidance segments. Roads extracted by *markov* random field (MFR) based method are also presented. The future work includes introducing features of urban buildings in the grouping algorithm to reduce the rate of false detection. The curvilinear linking generation procedure seems not to make much improvement. There are almost straight roads. These factors lead the proposed method to a higher rate of false detection than the MRF based method. Another road extraction method is proposed, Class-Aided Feature-Level Fusion is realized by combining two road extractors which are respectively designed for urban and rural areas from very high resolution in the satellite map scenes.

VI. Conclusion

In this paper, a two-step road extraction approach for MAP images is presented. Our main contribution is introducing multiscale geometric analysis techniques to the road network grouping algorithm. Adopting the multiscale thinking in beamlet analysis, we represent the response image that contains roads with guidance segments at different locations. Furthermore, those segments locating on the main roads are picked out by the relaxation labeling techniques and grouped into different series. Taking into account of both the orientations of guidance segments and the locating accuracy of road candidates, we get pairs of connection points and link them with curvilinear segments that generated after a segmentation of the response image. Experiment results show that the proposed method has higher completeness and quality indexes than the MRF based method.

VII. Future Enhancement

The RG-MGAR (Road networks grouping based on multiscale geometric analysis of detectors responses) has the largest completeness. The new method has a poorer correctness. This is false detection in the building area. The future work includes introducing features of urban buildings in the grouping algorithm to reduce the rate of false detection. Time cost is another measurement of an algorithm, which is closely related to the segments and optimization algorithms and there have different results for different images. The time cost of ouralgorithm is on the same scale with MRF, but we will be more complicated.

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