Generating Strokes of Road Networks Based on Pattern Recognition

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Key words: Pattern recognition; road network; perceptual grouping; dual carriageways; road junction

1. Introduction and related work

In road networks, road segments that are continuous at intersections are prone to be regarded as naturally long lines of roads, which is called strokes (Thomson and Richardson, 1999) or continuity lines (Figueiredo and Amorim, 2004). Strokes make up natural functional units of a network, and reflect lines of flow or movement within the network (Thomson, 2006). A stroke arises from the aggregation of road sections, in axial maps, or line strings between junctions, in standard road-centre line data. The process of generalization is known in cartography (Thomson and Brooks, 2002) and the rules for aggregating line segments can be based in a number of different properties, such as street names (Jiang and Claramunt, 2004; Rosvall et al, 2005; Tomko et al., 2008) or the angle between two line segments (Figueiredo and Amorim, 2004; Thom, 2005; Thomson, 2006; Porta et al., 2006a, 2006b). However, in some high level-of-detailed road networks, a road section may be presented by dual lines and a road junction may be constituted with many road intersections. Road properties (road names, road type/function etc.) are widely used in road networks generalization. They can indicate the relative importance of roads in networks, and are quite useful in map generalization. For example, roads may be cataloged by different function classes. Those properties can be used conveniently to select important roads. However, because of incompleteness of street network databases, one can not guarantee that every street segment has available properties. Therefore, geometry and topology of road networks are important to help extract these road properties. Mackaness and Mackechnie (1999) proposed a hierarchy clustering method for detecting junctions in road networks. But the method sometimes detects fake junctions and has difficulties to remove those fake junctions. Thom (2005) proposed a method for detecting and collapsing dual carriageways in Ordnance Survey Integrated Transport Network™. Each road section is attributed with a “nature of road” in the initial data, which indicates whether a road section is a dual carriageway. And his strategy is to mark those parallel dual carriageway roads are parts of the same pair However, it relies much on non-geometry attributes in OS ITN format and has difficulties to detect dual carriageways in other datasets with different formats of attributes or even have no attributes. Zhang (2009) presented an exploring procedure to recognize dual carriageways. It uses angular, length, maximal chord etc. to determine the similarity of to road lines, which is independent of any semantic information. But the method has difficulties to extract dual carriageways with other road lines such as with interchanges or ramps.

There are often a lot of complex road patterns existing in high level-of-detailed road networks, for example, dual carriageways and complex road junctions. The previous methods have difficulties to generate strokes from road networks with complex road patterns. For example, dual carriageways may be separated into two strokes, and strokes may be split or deflected at complex road junctions. Hence, dual carriageways and complex road junctions have to be identified to generate correct strokes.

To overcome these shortcomings, this paper focuses on generating strokes from road networks with dual carriageways and complex road junctions. Following the introduction part, the method for generating strokes in road networks is proposed, which encompasses identification of dual carriageways and complex road junctions and generation of strokes. Before conclusions are drawn at the end of this paper, experiments were undertaken to evaluate the feasibilities of the proposed method.

2. Method for generating strokes in road networks

The proposed method encompasses the following key steps

- detect and track dual carriageways in road networks;
- group strokes from dual carriageways as a stroke pair;
- generate single-line strokes in road networks;
- detect complex road junctions based on a density-based clustering method; and
- connect strokes across complex road junctions

The above steps are described as follows, respectively.

2.1. Dual carriageways identification

Our method firstly identifies potential dual carriageways pair based on a buffer growing method and stores the results as a set. Then, it refines the initial results set according to a tracking method. Finally, our method groups the refined dual carriageways in a perception principle.

2.1.1. Detecting initial dual carriageways

The initial dual carriageways pair can be identified according to the buffer growing method (Walter and Fritsch, 1999). In the matching process, one of the road networks is termed as ‘reference’ and the other is ‘target’. Firstly, the buffer of a reference road segment is generated, and then similarity parameters such as distance, angle and position between the reference segment and target segments contained in the buffer are computed. Separated segments with small distance and smooth angle will be regarded as matched pairs of dual carriageways. Secondly, matched target segments on the same side of the reference segment will be connected into one road polyline with no branches. Thirdly, the buffer growing algorithm will merge matched target polylines along the continuity of reference road segments. Fig.1 is an example of buffer growing for pairing dual carriageways. Suppose that target road segment t1 intersects the buffer of the reference segment r1, as illustrated in Fig.1-a, no dual carriageways pair is identified. But the buffer is growing along r1 and t1 and t2 contained in the buffer are matched polylines of r1 and r2, as illustrated in Fig.1-b. If there is no target segment located in the buffer of reference segment, the buffer stops growing, and one initial dual carriageways pair (r2 r3 r4 and t1 t2 t3) is identified. The initial dual carriageways pair will be further extended by a tracking method.

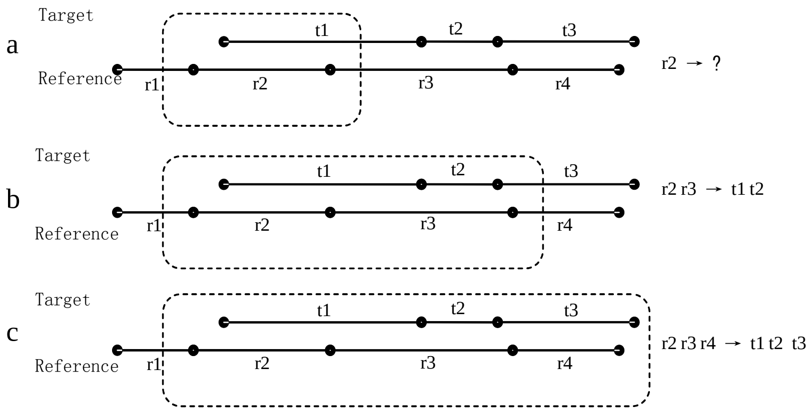


Fig.1 Buffer growing for detecting pair of dual carriageways

2.1.2. Tracking dual carriageways

A heuristic searching method was implemented to track all initial dual carriageways pairs and find the most possible pair as the final dual carriageways. The heuristic search method begins with one dual carriageways pair and connects to initial dual carriageways pair according to the principle of perception grouping. The tracking procedure will stop when there are no initial dual carriageways pairs. In order to store the tracking results, a tree data structure is created as follows.

treeSegment < Id, parentSeg, childSeg, friendSeg, parentNode, childNode, treeType >

The tree data structure treeSegment stores the associated 'Id' of a road segment, which relates to the geometry shape. Moreover, variables 'parentSeg', 'childSeg' and 'friengSeg' are used to store the parent, child and friend segment associated with one segment respectively when tracking dual roads and building tree-like routes. The 'parentNode' and 'childNode' in the data structure of treeSegment are used to mark the end nodes of a segment. One of them connects to parent segment, and the other one connects to the child. The 'treeType' variable indicates which tree a segment belonging to, and its value is 'A' or 'B', and each of them indicate one tree route of dual roads.

The tracking algorithm traverses the detected initial dual carriageways pairs and starts with end nodes of the initial dual carriageways, and mark the end segments of the detected initial dual carriageways pairs as the roots of tracking trees 'A' and 'B', respectively. Then it searches leaf segments of one tree (A e.g.), looks for the target segments which the distance and angle are smaller than thresholds, and insert them into the other tree (B e.g.). There are two criterions when building the trees, which are 1) one child-segment have only one parent-segment in a tree, and 2) the segment belongs only one of the two trees. Suppose there are two or more segments have a common child node in a tree, the algorithm will backtrack from the conflicted point to the root of the tree, and preserve the shortest route from root to the conflicted point. Furthermore, suppose a new segment in one tree (B e.g.) connecting to the other tree (A e.g.), it is hard to determine which tree will be the subsequent child-segments connecting to the conflicted point belong to. Hence, both two cases are considered in the tracking algorithm. The two possible routes are both stored and tracked as follow-up routes, respectively. The longest tracking result at the end of the algorithm will be regarded as the final detected dual carriageways. There are two kinds of end of the algorithm, which are 1) leaves of tree A and B are intersected and there are no other branches to track, and 2) all leaf-segments of tree A and B are father than threshold or their angle is too large, so there is no matched pair to track.

2.2. Generating strokes in road networks

Once all the dual carriageways pairs are identified in the road network. The strokes can be generated based on the principle of perception grouping. Road segments that are not dual carriageways are connected by their angles at the intersections. If a single road segment connects to the end of two parts of dual carriageways, as illustrated in Fig.2, the angle between them is modified to the angle between the bisector of the dual carriageways and the single road segment.

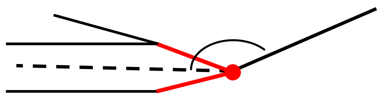


Fig.2 Angle between dual carriageways and single road

2.3. Complex road junctions pattern recognition

The strokes generated in previous step may discontinue across the complex junctions, as illustrated in Figure 3. To overcome the drawback, this paper uses a density-based clustering method (DBSCAN) (Ester et al., 1996) to detect junctions in road networks. And it considers the lengths of strokes connecting to intersections.

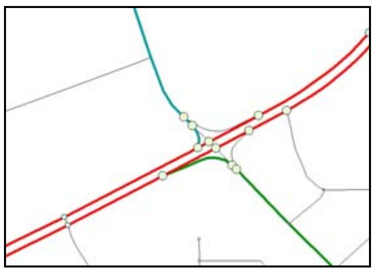


Fig.3 strokes become discontinuous across complex junctions

The proposed density-based clustering method searches for clusters by checking the ε-neighborhood of each intersection in the road network. The neighborhood within a radius ε of a given intersections is called the ε-neighborhood of the intersection. The ε-neighborhood is defined as network distance, rather than Euclidean. The radius of ε-neighborhood varies directly as the length of strokes connecting to the intersections. However, it is hard to create a function about the length of strokes connecting to a intersection and the radius of the intersection. This paper simply sets a threshold of length of strokes. The radius ε will be set to 30m if the length of strokes is longer than threshold, and set to 0 if shorter than threshold. If the ε-neighborhood of an intersection p contains more than the number of the minimal intersections, a new cluster with p as a core object is created. Then it iteratively collects directly density-reachable intersections from these core objects, which may involve the merge of a few density-reachable clusters. The process terminates when no new point can be added to the cluster. Fig.4 shows the detection results of road junctions. The bigger sizes of symbols indicate more complicated junctions.

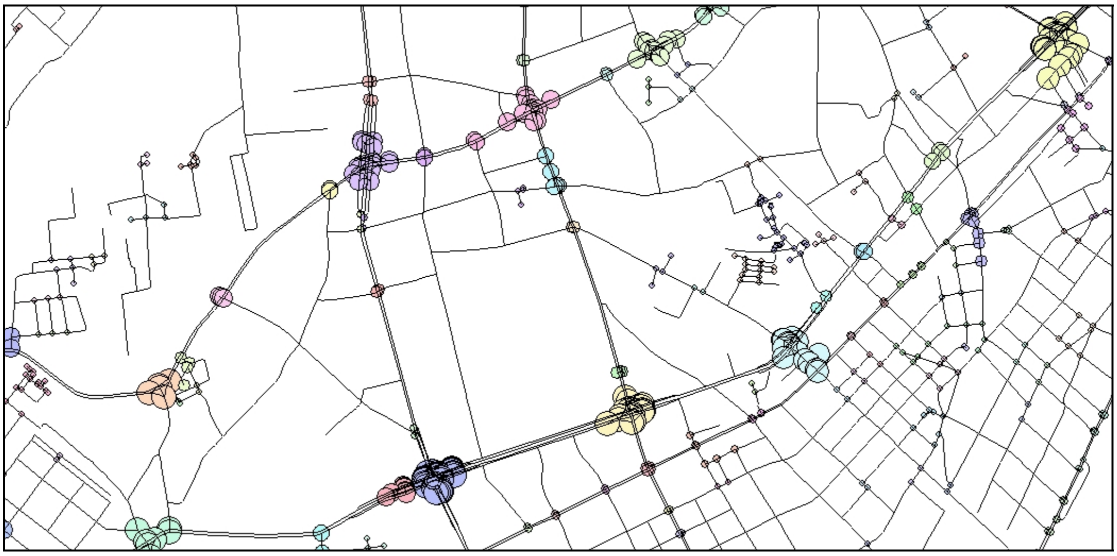
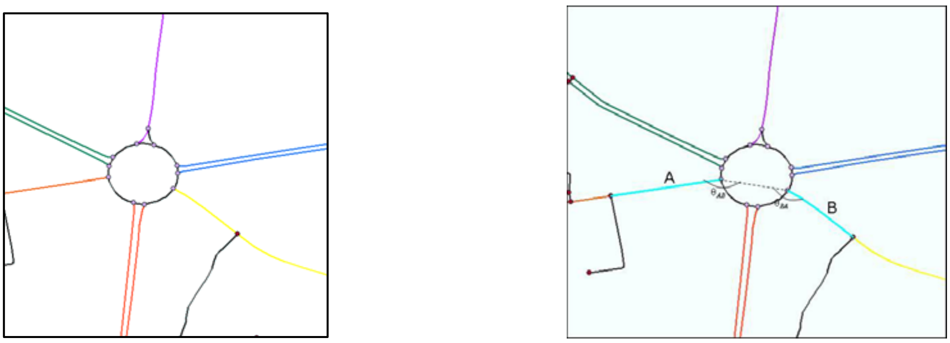


Fig.4 Identification results of complex road junctions

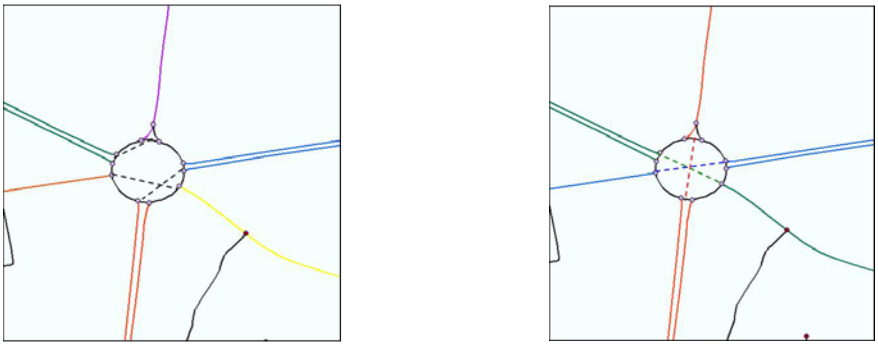
2.4. Grouping strokes across complex road junctions

Once complex road junctions are identified, the strokes connect to a complex road junction should keep continuity according to the principle of perception grouping.This paper developed a method connecting the road through the junction clusters directly to keep the continuity of strokes. As illustrated in Fig.5-a, six strokes connecting to the same detected road junction are discontinuous. In order to satisfy the perceptual grouping concept, the six strokes should be connected as fluent as possible and have no branches. The rule for aggregating discontinuous strokes is based on the angle between them. As illustrated in Fig.5-b, the angle of two strokes is calculated as the mean value of θ_{AB} and θ_{BA}, which are angles between the strokes and the dashed line that connecting the two strokes. For each pairs of strokes, a mean value of angles will be calculated. And there are series of result of strokes grouping across a complex road junction (Fig.5-c). In these results, the best aggregated strokes should have the maximum value of the sum of angles in total. As illustrated in Fig.5-d, the three angles of paired strokes are all near 180 degree and the sum of them is the max value in all kinds of possible pairs. According to the rule of the maximum angle, the generated strokes are able to keep continuity across complex junctions.



(a) Strokes discontinuation cross junctions

(b) Angles between strokes



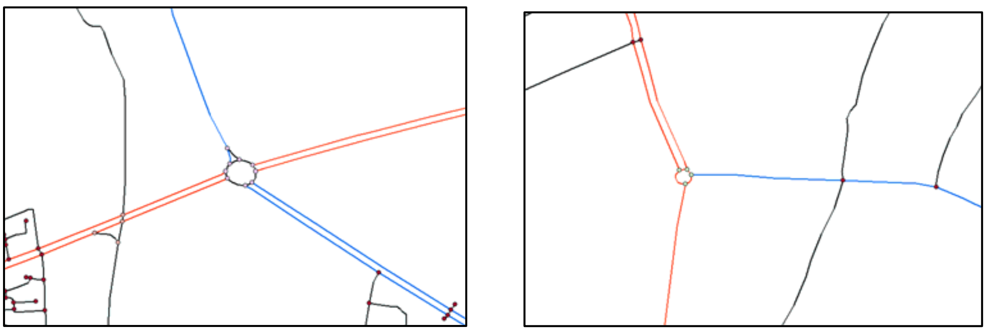
(c) A possible strokes grouping result (d) The final grouping result

Fig.5 Grouping strokes across complex junction

3. Experimental studies

The navigation map datasets of Wuhan city, China was selected to test the feasibilities of the proposed method in this paper. There are 11598 road sections in total in the Whuan datasets. Some roads are represented as dual carriageways and some road junctions are complicated. The proposed method firstly identifies dual carriageways and complex junctions. Then, it generates strokes by aggregating dual carriageways and strokes connecting to complex road junctions. Fig.6 shows some detection results of dual carriageways tracking. And some experimental results of strokes grouping across complex road junctions are shown in Fig.7. It can be seen from the experiment that the generated strokes can satisfy the principle of perception grouping.

Fig.6 Dual carrigeways tracking results



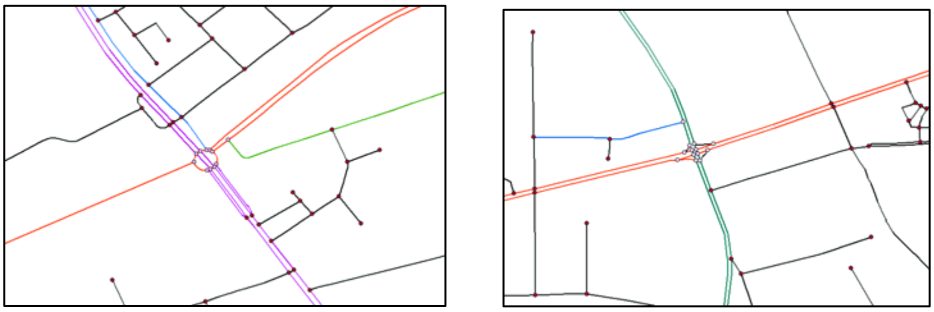


Fig.7 Generating strokes according to the principle of perception grouping

Furthermore, in order to show the continuous effect in the whole perspective, some high grade strokes in the dataset are chosen by the measure of betweenness centrality given by Freeman (Freeman, 1978), which is defined as the following formula, where n_{jk} is the number of shortest paths from stroke j to k, and $n_{jk}(i)$ is the number of shortest paths from stroke j to k, which cross stroke i.

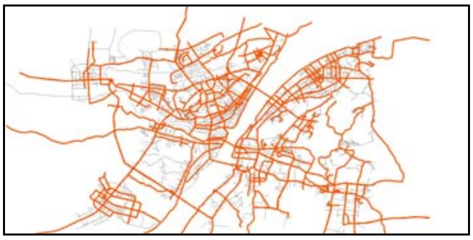
$$C_i^B = \sum_{j \neq k \neq i}^{n} n_{jk}(i) / n_{jk}$$

Betweenness centrality measure is effective to show the whole structure of the urban road network (Jiang and Harrie, 2004; Touya, 2007; Tomko, 2007). Fig.8 shows the results with different numbers of strokes selected by betweenness centrality measure. It can be seen that the strokes are fluent according the perceptual grouping concept.

(a) 40 strokes

(b) 80 strokes

(a) 120 strokes



(b) 160 strokes

Fig.8 Results of strokes selection based on between centrality

The strokes generated can be used for urban road networks analysis and integrated to a generalization system for the generalization of road networks.

4. Conclusions

This paper proposes an automated method for generating strokes from road networks. The proposed method is different from the previous methods. It is able to deal with the road networks with dual carriageways and complex junctions and to keep the continuity of strokes generated. A navigation map dataset was selected to test the advantageous of the proposed method. The experimental results show that the proposed method is capable of automated identifying dual carriageways and complex junctions. Thus, it generates strokes correctly and keeps the continuity. The proposed method also shows a potential function for the generalization of road networks.

5. Acknowledgements

This research is financed by China National Science Foundation (40871185), National High-Technology Research and Development Foundation (2007AA12Z241 and 2007AA12Z212), Key Project of Chinese Ministry of Education Foundation (108085), and Key Laboratory of Precise Engineer and Industry Surveying, State Bureau of Surveying and Mapping Open Foundation (PF2009-19).

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