A NEW URBAN ROAD DETECTION METHOD IN HIGH-RESOLUTION IMAGES BASED ON BAYESIAN NETWORK

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KEY WORDS: High Resolution Image; Road Detection; Bayesian Network; GIS Guidance

ABSTRACT:

In view of the fact that road network detection effect in high-resolution image is not satisfying, an approach for road network detection based on Bayesian Network is put forward in this paper. First, under the guidance of existing GIS data, extract roads from remote-sensing images, and obtain most of the unchanged road edge information and suspected road edge information. Then, making use of the reasoning ability of Bayesian Network, collect strong evidence for identifying road network. Judge and make an inference from road edge information with the method of hypothetical test to extract road network in the remote-sensing image, and change information of the road network can also be obtained.

1. INTRODUCTION

Under GIS guidance, target tracking technology can make good use of the existing information in GIS, so good detection result is often available (Will, 2002). Besides, in high-resolution image, there are many road targets, and detail features of image are very rich. Buildings and vegetation along the roads, automobiles running on the roads, white zebra crossing, and even shadow s of buildings and trees all can be favorable evidences for identifying road network (Wang and Newkirk, 1988). And Bayesian Network can make full use of prior knowledge and sample information for reasoning and verification. Consequently, the method of establishing a buffer area under GIS guidance has been adopted in this paper to extract candidate road information in the new remote-sensing image, including unchanged road information and suspected road information. Then, make a detailed analysis of features of urban road landscape to extract auxiliary information, such as road sign and marking, vehicles, and green belts. At last, taking such auxiliary information as evidence, make an inference from the candidate roads by Bayesian Network to judge whether they are roads, on the basis of which the road network in the remote-sensing image is extracted, and change information is obtained.

Canny operator is used in this paper for edge detection. Then smooth and compress the tracked edges. After finishing registration of high-resolution remote-sensing images and GIS vector and edge detection and tracking, start road tracking under GIS guidance.

Road tracking under GIS guidance is to extract candidate roads from the vector line segments obtained after edge tracking in accordance with existing road vector data. In view of error of coordinates among multi-source image data, guiding and tracking can't be conducted directly by GIS road data. Instead, a tracking and extracting approach based on buffer area shall be adopted. Namely, on the basis of existing road vector, mark buffer area around it. The vector line segments within the buffer area are listed among candidate road sections. Then automatically group road sections or road line segments by the constraint conditions of geometric properties and image attributes (Emmanuel and Jordi, 2007). Road grouping can connect most of road sections, forming basic framework of roads.

2. METHOD

Bayesian Network expresses dependent relationship and incident relationship of variables in the problem domain with visible network model by a directed graphic model based on probabilistic reasoning (Murphy, 2002).

After data pre-processing the candidate road information and selecting the line segments probably being roads, this approach will detect correctness of the roads based on Bayesian Network (Zhang et al., 2006). Judge whether these line segments are edges of roads by evidences. Next, normalize the line segments of roads. Then try to obtain complete roads by checking the result of normalization and judging broken points of roads.

2.1 Processing of Candidate Road Sections

Processing of candidate road sections aims at rejecting the trivial line segments being not roads. In a high-resolution remote-sensing image, characteristic of an urban main road is that it is quite long and has two edges (Nevatia and Babu, 1980; Lindi and Quacken, 2004). Consequently, processing of

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candidate road sections mainly follows two principles: collinear and parallel. Find the line segments being comparatively longer by collinear principle, which are probably being roads. After judging a long line segment, find line segments that are parallel with it around it by parallel principle, and continue to find its collinear line segments and connect them. Repeat such actions until all candidate road sections have been judged.

2.2 Detection of Road Correctness Based on Bayesian Network

Detection of road correctness based on Bayesian Network makes certain whether the information on candidate road sections is real information of roads by analyzing information on candidate road sections, vehicles, and green belts with Bayesian Network model (Jida et al., 2008). The processing flow chart is shown in the following figure:

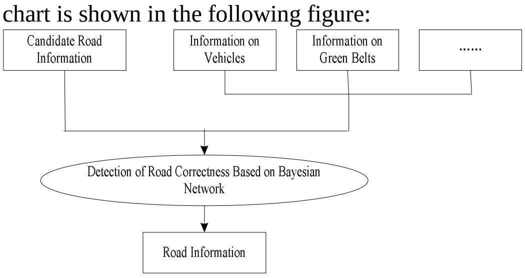


Fig.1 Process of Detecting Road Correctness Based on Bayesian Network

In accordance with the theory of Bayesian Network, Bayesian Network model is established as shown in the following figure:

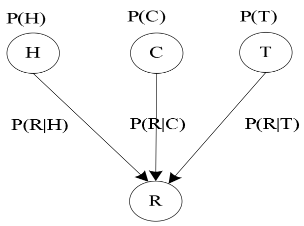


Fig.2 Network Model for Detecting Road Correctness Based on Bayesian Network

In the figure: H stands for candidate road section; C stands for vehicle; T stands for Greenbelts; R stands for road.

It can be known from the figure that this Bayesian Network model includes four nodes, three oriented edges, and six conditional probability tables (among which three are prior probability tables). Values of the three variables H, C, T can be 0 and 1. 0 stands for wrong judgement, and 1stands for right judgement. Prior probability values obtained by collecting statistics from experiments are as follows:

Tab.1 Prior Probability Value of Each Variable

P(X)	P(H)	P(C)	P(T)
P(x_0)	0.75	0.85	0.65
P(x)	0.25	0.15	0.35

As for conditional probability:

（1）P(R|H): Whether a candidate road section is a real road section, length is an important concept. The longer a line segment is, the more likely the candidate road section will be a real road. And assume that P (R|H) is subject to exponential distribution, and then its probability distribution function is:

$$\mathrm{P(R \mid H)} = 1 - e^{-\lambda L} \quad (1)$$

Length of urban main roads is calculated by kilometres. So when λ =1/100, if length of a line segment L=1000, it can be judged to be a road.

（2）P_1(R|C): It is not reliable to judge a line segment to be a road section only by the existence of a vehicle beside it. So quantity of vehicles and their distributing state are considered in this model for road detection.

First, the relationship between a road and M, quantity of vehicles around a candidate road section is: when there are more vehicles, it is more likely to judge a candidate road section to be a road. When the number of vehicles reaches X, it can be confirmed that this candidate road section is a real road. So assume that P_1 (R|C) is subject to piecewise function distribution, and then its probability distribution function is:

$$\mathrm{P_1(R \mid C)} = \begin{cases} \mathrm{M/X} & 0 < M < X \\ 1 & M >= X \end{cases} \quad (2)$$

Next, relationship of a road and vehicle distribution is described by d/D, ratio between maximum length of connecting line of vehicles at two ends of each traffic lane within the length of candidate road and length of the candidate road section . Because value of d/D is random, which is closely related with traffic movement on the road while the image is being generated, assume that P_2(R|C) is subject to piecewise function distribution, then its probability distribution function is:

$$P_2(R \mid C) = \begin{cases} 1/3 & 0 \le d/D < 1/3 \\ 2/3 & 1/3 \le d/D < 2/3 \\ 1 & 2/3 \le d/D < 1 \end{cases} \quad (3)$$

Quantity of vehicles and their distributing state determine P (R|C), probability of road detection correctness. Because P_2(R|C) is quite random, set probability proportion weight between P_1(R|C) and P_2(R|C) is 2：1, then:

$$\mathrm{P(R \mid C) = P_1(R \mid C) * 2/3 + P_2(R \mid C) * 1/3} \quad (4)$$

（3）P(R|T): Generally speaking, in urban image, long and narrow greening zones are closely connected with roads. So relationship between a road and K the length of Greenbelts is established by this model. The longer the green belt is, the more likely it is to judge the candidate road section to be a road. Assume that P (R|T) is subject to exponential distribution, and then its probability distribution function is:

$$\mathrm{P(R \mid T)} = 1 - e^{-\lambda K} \quad (5)$$

According to statistical empirical value, set λ =1/50.

Because information on candidate road section, vehicles and green belts are independent, according to total probability formula, it can be obtained that:

$$\mathrm{P(R) = [P(H)P(R|H) + P(C)P(R|C) + P(T)P(R|T)] * 1/3} \quad (6)$$

Set threshold P, if P(R)>=P, information on candidate road section is road information . Otherwise, it is not road information.

2.3 Detection of Road Integrity

As for detection of road integrity, one task is leak checking, trying to find out undetected information during extraction of candidate road sections (Lee and Park, 2000). And the other task is to detect new roads with existing knowledge during the process of road detection.

The process of detecting road integrity is also a process of finding new road sections. Namely, traverse the two edges of road sections, and one edge of a road section may be broken. Once a road section is found to be broken, the knowledge around it shall be analyzed in detail. There are three possibilities:

One edge is broken, and no new road is found. If there are high buildings or tall trees in line at the side of a road, shadows may be left, which may affect the identification of a road. In such case, the road may be broken. If no evidence can be found showing the existence of a new road, it belongs to leak detection of road section. We only need to connect the two road sections beside the broken point.

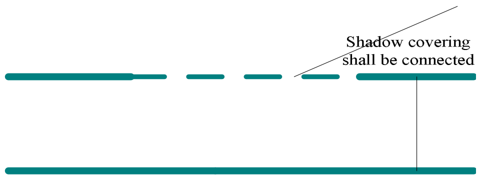


Fig.3 Case One of Road Integrity Detection

a) One edge is broken, and a new road is found. After analysis, if parallel lines, information on vehicles or green belts are found in the direction of broken point, a new road may exist.

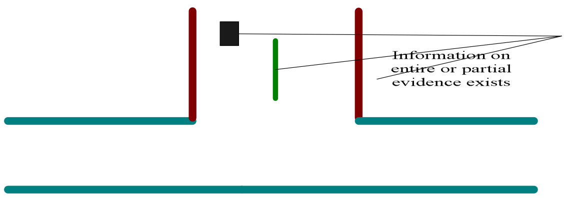


Fig. 4 Case Two of Road Integrity Detection

b) Two edges of the road are broken at the same time, and a new road is found. After analysis, if parallel lines, information on vehicles or green belts are found in the direction of broken points on both sides, a new road crossing the existing road may be found.

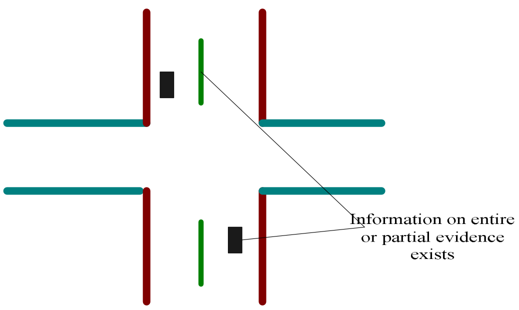


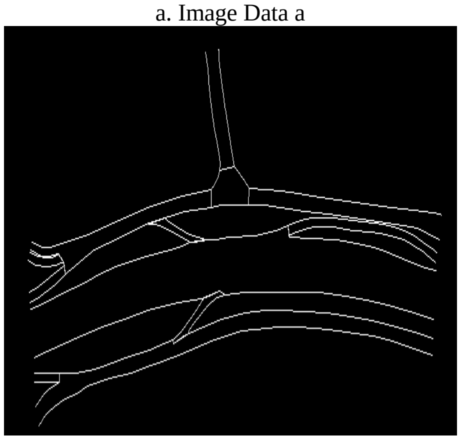
Fig.5 Case Three of Road Integrity Detection

3. EXPERIMENTS AND ANALYSIS

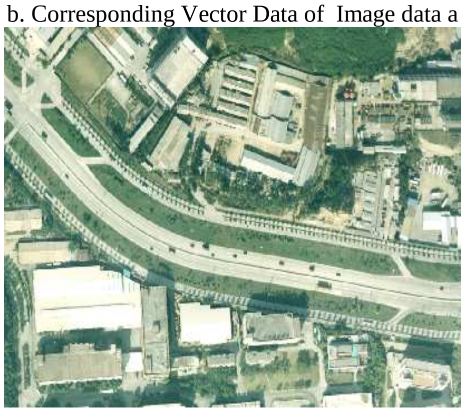
Two principles have been followed during the process of choosing experimental data in this paper: first, experiment with high-resolution remote-sensing image of urban main road network; second, since approach proposed in this paper is based on Bayesian theories, evidences are inevitably involved, so vehicles and green belts in the image are necessary.

The following are two images chosen for experiments:

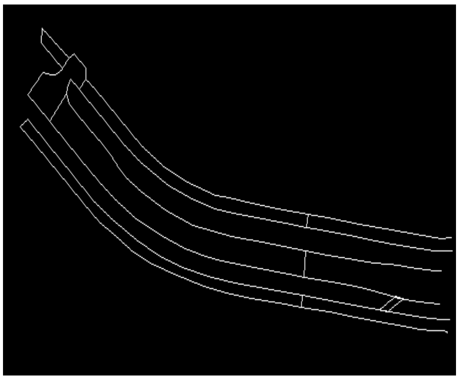
a. Image Data a



b. Corresponding Vector Data of Image data a



c. Image Data b



d. Corresponding Vector Data of Image data b
Fig. 6 Experiment images

Experiment 1：

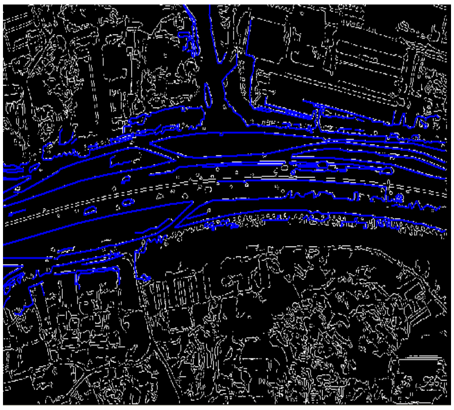


Fig. 7 Result of Road Following under GIS Guidance(Image Data a)

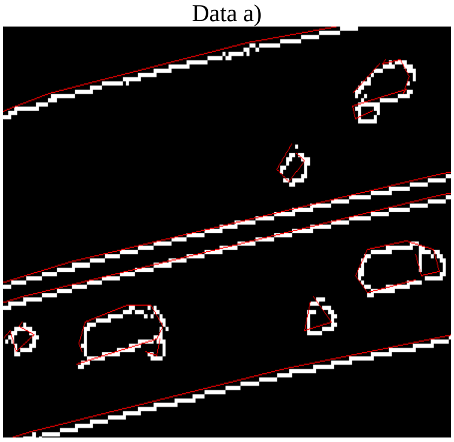


Fig. 8 Vehicle Detection Result of Image data a

Fig.9 Road Detection Result of Image data a

Experiment 2：

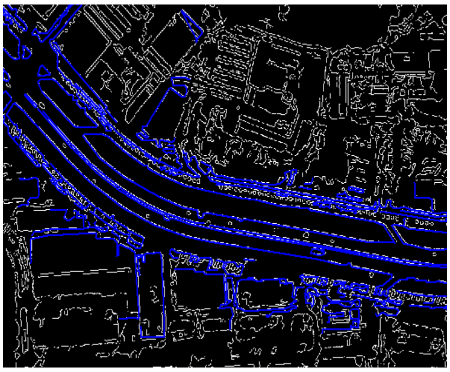


Fig. 10 Result of Road Following under GIS Guidance(Image Data b)

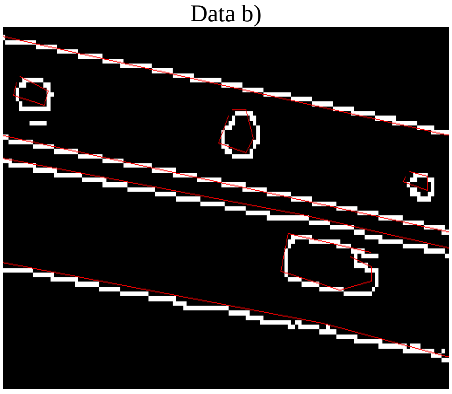


Fig. 11 Vehicle Detection Result of Image data b

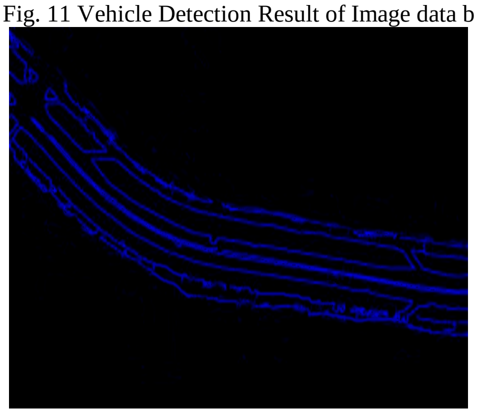


Fig. 12 Road Dection Result of Image data b

There are many ways in which road detection result matches vector data of real roads, among which buffer correlation matching is one of the successfully applied ones. Main idea of this method is as follows: first, break up the fold-lines that stand for roads in the road detection result and vector data of real roads into line segments. Then, taking a vector line segment of one side for reference, establish a buffer area in certain width around the vector line segment. Find line segments in the vector data of the other side. These line segments shall meet the condition that whole or part of the line segment is within the buffer area and collinear directional difference is within certain extent. Segments within the buffer area are called right matching sections, while segments outside the buffer area are called wrong matching sections.

4. CONCLUSION

This paper has designed an approach for extracting candidate road sections under GIS guidance. In order to obtain candidate roads, a series of processes are conducted, such as image registration, edge detection and tracking, road tracking under GIS guidance and road grouping. It has also studied theories on Bayesian Network. Combining information of candidate road sections and information of vehicles and green belts, it establishes a Bayesian Network model for road detection. And road network and change information can be obtained finally.

Since many surface features in high-resolution image can be used as evidence for road detection, and only vehicles and green belts have been selected in this paper, effects of other objects, such as vehicle separating line, central line of road, and zebra crossing need more experiments. During the process of establishing Bayesian Network model, prior knowledge needs to be initialized. These threshold values were obtained by collecting statistics of experimental data in this paper. What kind of mathematical distribution state that these threshold values correspond to need further study.

ACKNOWLEDGMENTS

The work described in this paper was funded by National Natural Fund of China (NSFC) (No.60602013), National Key Fundamental Research Plan of China(973) (No.2006CB701304), National High Technology Research and Development Program of China (863) (No.2007AA120204) and Research Grant of State Key Laboratory of Subtropical Building Science in South China University of Technology (NO.2008KB12).

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