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An enhanced weight-based topological map matching algorithm for intricate urban road network

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Abstract

Map-matching (MM) algorithms integrate positioning data with spatial road network data to identify the correct link on which a vehicle is travelling and determine the location of a vehicle on a link. There are four classes of MM algorithms, including geometric, topological, probabilistic and advanced. The topological map-matching (tMM) algorithms are relatively simple, easy and quick. Due to considering information of heading, proximity, link connectivity and turn-restriction weights, weight-based tMM algorithms are most robust and widely used tMM algorithms. As is known to all, a metropolis usually has intricate road network. And the urban road density has various performances in different parts of a metropolis' urban area, which makes the weight scores used in tMM algorithm different. As a result, it can affect the accuracy of matched results. In this paper, the authors develop an enhanced weight-based tMM algorithm considering the urban road density. This algorithm was verified using actual taxi GPS data collected in the urban area of Harbin, China, about 600 positioning points and a 1:80,000 scale digital map of Harbin. The results show that this enhanced weight-based tMM algorithm outperforms the base algorithm and has potential to support many applications of Intelligent Transport System (ITS) service.

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Keywords: Weight-based Topological Map-Matching algorithm; GPS; urban road density; ITS

1. Introduction

Map-matching (MM) techniques which integrate positioning data with spatial road network data have been developed in order to provide the real-time, accurate and reliable positioning information required by many ITS services such as route guidance, fleet management and accident and emergency response (Chen et al., 2003; Kim et al., 1996; Phuyal, 2002; Li and Chen, 2005; Li and Fu, 2003; Ochieng et al., 2004; White et al., 2000; Yin and

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Wolfson, 2004; Zhao et al., 2003; Nagendra et al., 2009). An MM algorithm makes use of a range of data including position, heading, speed, and road network topology to identify the correct road segment on which a vehicle is traveling and the vehicle's location on that road segment (Quddus, Ochieng, & Noland, 2007; Smaili Najjar, & Charpillet, 2008; Xu, Liu, Tan, & Bao, 2010). There are four classifications of MM algorithms, including geometric, topological, probabilistic and advanced, and each has its advantages and disadvantages. MM algorithms may be improved by including historical data (such as the previously matched road segment), vehicle speed and topological information on the spatial road network (such as link connectivity) (Nagendra et al., 2009). A MM algorithm that uses such additional information is called a topological MM (tMM) algorithm (Greenfeld, 2002;Li et al., 2005; Marchal et al., 2005; Quddus et al., 2003, 2007). Considering four weights (including heading, proximity, link connectivity and turn restriction), Weight-based tMM algorithms were proved to be high accuracy and could be widely used in real-time applications of ITS services by industry (Nagendra et al., 2009,2012).

As is known to all, lots of metropolises' road density is complex and various, and most current MM algorithms categorize the whole metropolis area as urban, suburban and rural area. However, in the urban area of a metropolis road network is quite intricate and its density performs various, and most existing MM algorithms barely consider this. Therefore, in this paper the authors attempt to develop an enhanced weight-based tMM algorithm in order to involve this situation and assess its performance using real-world field data. This process includes:

- the classification of urban area by urban road density,
- the derivation of four weights(including heading, proximity, link connectivity and turn restriction) in different areas through an optimization process,
- the different performances of the algorithm before and after enhancement using a real positioning data set,

The paper is organized as follow: The next section is an outline of the data including the map and the positioning data. This is followed by describing the base algorithm and map matching errors. And then describes the development of an enhanced weight-based tMM algorithm: including the process of dividing the urban area and optimization technique. The process of evaluating the performance of the enhanced weight-based tMM algorithm using a real positioning data set is then explained. The paper ends with conclusions.

2. Data

2.1. Map data

The map data used in this paper is a 1:80,000 scale of digital map of Harbin, China, which is shown in Figure 1. Road network data used in this study covers the 16.7 km × 14.6 km area around Harbin and consists of expressway, arterial road, secondary trunk road and branch road. Fig. 1 shows the whole network used in this study while Table 1 summarizes the 4 types road lengths and percentages.

2.2. Positioning data

The positioning data used in this paper is the taxicab GPS data in Harbin urban area, which was collected from 500 taxicabs in 2011. This study uses low frequency data with 30 seconds interval. More information is shown in Table 2.

Fig. 1 Urban road network of Harbin

Table 1 The types of Urban road network in Harbin

Road types	Length (km)	Percentage (%)
Expressway	194.52	8.43
Arterial road	514.33	22.29
Second trunk road	884.62	38.34
Branch road	713.81	30.94
total	2307.28	100

Table 2 Positioning data used in this study

Data set no.	Data	Time	Interval	Size
1	2011/4/20	9:00-11:00	30s	333
2	2011/6/4	13:00-15:00	30s	351
3	2011/10/2	20:00-22:00	30s	370

3. Review of base algorithm

This section first describes the base algorithm. This is followed by map matching errors of the base algorithm.

3.1. Base algorithm

The base algorithm, which is outlined below, is almost the same as the algorithm proposed by (Nagendra et al. 2009) and can be executed using a very simple procedure.

The whole process is divided into three key stages: (a) initial MM, (b) MM on a link and (c) MM at a junction.

Process (a):
- Step 1: Identify a set of the candidate links
- Step 2: Identify the correct link from the set of the candidate links
- Step 3: Determinate vehicle position on the identified link
- Step 4: If the vehicle speed is 0, go to Process (b) Step 1.
- Step 5: If the next positioning fix is not near to a junction, go to Process (b) Step 1. Otherwise, go to Process (c) Step 3.

Process (b):
- Step 1: Choose the previously selected link as the correct link.
- Step 2: Determinate vehicle position on the identified link.
- Step 3: Go to Process (a) Step 1.

Process (c):
- Step 1: Identify a set of the candidate links.
- Step 2: Identify the correct link from the set of the candidate links.
- Step 3: Determinate vehicle position on the identified link.
- Step 4: Go to Process (a) Step 1.

There are four weights in this base algorithm: heading, proximity, link connectivity and turn restriction. The heading weight is a cosine function of angle between the vehicle movement direction and link direction (Greenfeld, 2002) and shown in Eq. (1). Where $f(\theta) = \cos(\theta)$.

$$W_h = H_w f(\theta) \tag{1}$$

The weight for proximity is based on the perpendicular distance (D) from the positioning point to the link (Nagendra et al., 2009) and shown in Eq. (2). Where $f(D) = [\frac{(80 - D)}{80}]$.

$$W_p = D_w f(D) \tag{2}$$

When the vehicle is at a junction, two more weights will be necessary including the link connectivity and turn restriction (Nagendra et al., 2009), which are shown in Eq. (3) and Eq. (4).

$$W_c = C_w X \tag{3}$$

$$W_t = T_w Y \tag{4}$$

And where Y={1,-1}, X={1,-1}.The Total Weight Score (TWS) for a link at a junction is the sum of four weights as given below:

$$TWS = H_w \cos(\theta) + D_w[\frac{(80 - D)}{80}] + C_w X + T_w Y \tag{5}$$

The H_w, D_w, C_w and T_w are the weight coefficients for heading, proximity, link connectivity and turn restriction respectively. These coefficients represent the relative importance of different factors in calculating the TWS (Nagendra et al., 2009).

3.2. Map matching errors of the base algorithm

The values of the four weight coefficients (H_w, D_w, C_w and T_w) can be estimated from a series of controlled experiments in a post-processing way (Nagendra et al., 2009). Without considering the difference of the road density in different parts of a city's urban area, the base algorithm can lead to some obvious errors (i.e. location points matched to the wrong road segment). E.g. in dense area, the heading weight is more important than proximity weight, which lead to correct results shown in Fig. 2. However, in sparse area, the same values of these two weights results in incorrect outcomes, which is shown in Fig. 3.

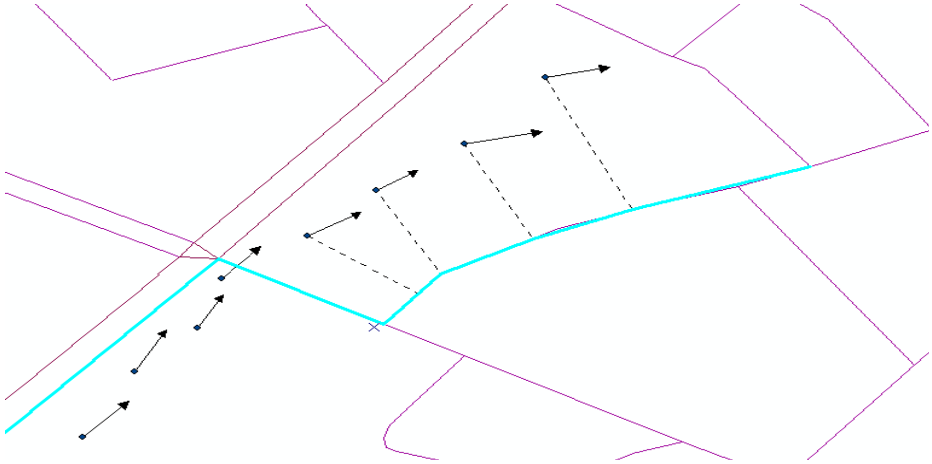

Fig. 2 Correct map matching results in dense area

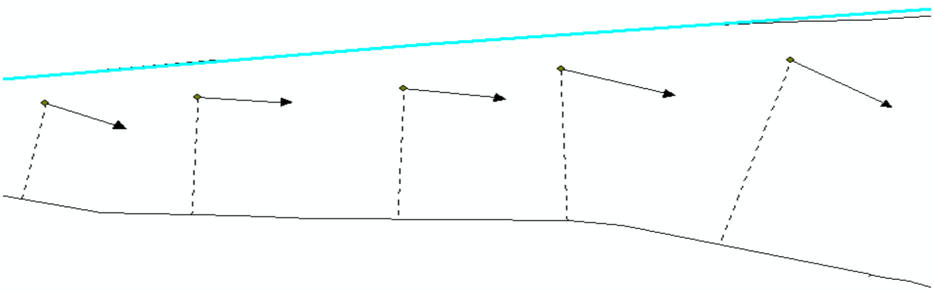

Fig. 3 Incorrect map matching results in sparse area

4. Improvements of the base algorithm

This section is describing the improvements, which consists of the process of dividing urban area, new process added into the base algorithm and calculating the optimal weight scores.

4.1. The process of dividing urban area

In order to solve the mis-matching problems result from barely considering the road density in urban area, the authors attempt to divide the urban area into different parts. The process of dividing is outlined below.

The restriction of classing the urban area is urban road density. Urban road density is the ratio of the length of the urban area's total road network to the urban land area. The road network includes all roads in city: expressway, arterial road, secondary trunk road, and branch way. In Harbin, the urban road network is quite intricate, and the urban area could be divided into 3 types including dense area, common area and sparse area according to urban road density. There are five restrictions:

- road density (km/km^2) = total road length (km) / total area(km^2)
- total road length is the length of express, arterial road, secondary trunk and branch way
- try to make the expressway or arterial road as boundaries
- try to keep the administrative division complete
- the dense area's road density is more than 15 km/km^2, the sparse area's is less than 5 km/km^2 and the rest parts are common areas.

Accordingly, the whole urban area of Harbin is divided into 9 different parts consisting of 2 dense areas, 6 common areas and the rest areas as sparse ones, which is shown in Fig. 4 and table 3.

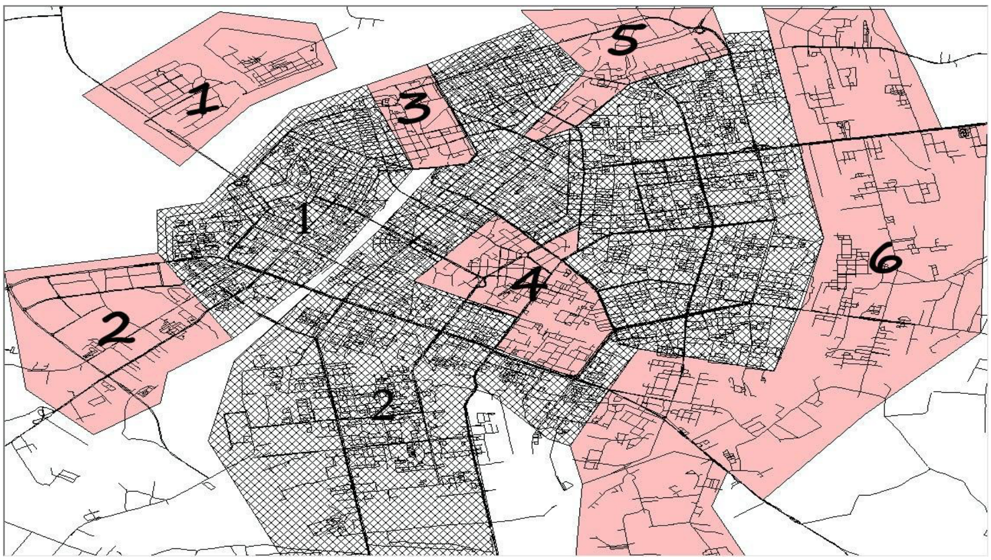

Fig. 4 Result of classification (6 shaded areas are common ones, 2 crosshatched areas are dense ones and the rest areas are sparse ones)

Table 3 Road density of different parts in urban area

Types	no.	Total length of road (km)	Total area (km^2)	Road density (km/km^2)
Dense areas	1	273.82	15.03	18.22
	2	1287.85	79.19	16.26
	total	1561.67	94.22	16.57
Common areas	1	50.43	8.98	5.62
	2	82.28	12.03	6.84
	3	33.83	2.90	11.67
	4	98.32	7.37	13.34
	5	60.95	6.15	9.91
	6	252.91	45.76	5.53
	total	578.71	83.19	6.96
Sparse areas	/	166.90	67.82	1.58
Total areas	/	2307.28	245.23	9.41

Table 4 Weight matrix

Weighs	Dense area	Sparse area	Common area
H_w	42.56	32.59	39.24
D_w	12.37	67.41	48.55
T_w	20.28	1	5.99
C_w	24.79	1	6.22

Table 5 Experimental results

		Base algorithm	Enhanced			
Data set no.		Whole area	Dense area	Common area	Sparse area	total
2	number	351	134	113	104	351
	ARR	92.02	97.01	96.46	99.04	97.44
3	number	370	168	121	81	370
	ARR	90.54	97.02	97.52	100	97.84

4.2. New process added into the base algorithm

The enhanced algorithm first checks three criteria for matching every point to the correct link:

- whether the vehicle is traveling in dense area,
- whether the vehicle is traveling in sparse area,
- whether the vehicle is traveling in common area,

And then the corresponding weights from the weight matrix (Table 4) suitable for that environment. are selected. Previously, a gradient search method was used to determine the optimal values of weight scores used in the map-matching process (Velaga et al., 2009). In this research, the authors using a GA-based optimization algorithm to determine the relative importance of different weights as Nagendra et al. did. Data set no.1 was used for this process.

4.3. Algorithm performance

The most commonly used index for expressing map matching accuracy is the ratio of positioning points correctly matched to links (Tomio et al., 2012). In this paper, the authors use ARP index (accuracy ratio of matched), which is defined as follow:

ARR=number of correctly matched points/total number of experiment points

Note that ARR is 100% if all the points are matched to correct links, and it is 0% if all the points are matched incorrectly. The experimental data is data set no. 2 and 3. Data considered adequate for the purposes of this study was selected and manually matched to actual (true) links.
Because the whole urban area has the same road density with the common area, the authors first experimented on the whole urban area with the common area's weight scores. Then, the authors tested on the dense area, common area and sparse area respectively, and calculated the total value. The results are shown in Table 5.

5. Conclusions

In this study, the authors have developed an enhanced weight-based topological MM algorithm that can be applied in some cities which have intricate road network. The algorithm has been tested using real-world field data collected in different parts of Harbin. The key contributions of this research are:

- dividing Harbin's urban area into different parts according to road density,
- deriving the relative importance of weights using data collected in different areas and
- outperforming the base algorithm.

The enhanced tMM algorithm has the potential to be applied in a range ITS services with a low polling frequency positioning data. This enhanced tMM algorithm is fast, simple and very efficient and therefore, has the good potential to be implemented by industry, especially in city with intricate road network.

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