A practical route guidance approach based on historical and real-time traffic effects

LU Feng
State Key Laboratory of Resources and Environmental Information System, IGSNRR, Chinese Academy of Sciences
Beijing, P. R. China
luf@lreis.ac.cn

DUAN Yingying ZHENG Nianbo
State Key Laboratory of Resources and Environmental Information System, IGSNRR, Chinese Academy of Sciences
Beijing, P. R. China
duanyy@lreis.ac.cn, zhengnb@lreis.ac.cn

Abstract—**Implementing convenient traveling information service is a crucial task for deploying intelligent transportation system applications and location-based services. Traditional traveling information service systems, such as car navigation systems or web maps, only provide relatively static information which doesn't truly reflect the dynamic changes of traffic situation, and result in very limited practical use. Although there have emerged some car navigation products and other applications involving dynamic traffic information, considering the rapid change of city traffic situation, these applications still face practical difficulties for all the information received real-timely will get outdated within a few minutes, which makes the so called dynamic applications basically time-slice limited static ones. Aiming at such a problem, a short-term traffic prediction approach and a consequent real-time route guidance process are presented in this paper which integrates historical traffic based statistical reasoning, real-time traffic and events processing, with a BP neural network based analytical model, to forecast the situation and evaluate the influence of traffic during the traveling process. Then a collaboration working framework is set forward to implement dynamic route guidance, with the combination of a GIS server, a traffic forecasting server and a database management system. The traffic forecasting server, integrating with historical statistics reckoning continuously receives real-time traffic information obtained from floating vehicles, traffic events described in natural language, and achieves short-term forecasting results for the whole road networks, then fed the results back into the database management system and GIS server, so that a time-dependant optimal routing can be conducted through a dynamic least traveling time algorithm developed in this study. A prototype navigation system fulfilling the above aspects has been developed and the dynamic route choice approach demonstrated on road networks in the downtown area of Beijing city. The approach presented in this paper is argued to provide a practical solution for real-time public traveling information service and dynamic web maps.**

Keywords-traffic forecasting; traffic simulatio; BP neural networ;, natural language processing; dynamic route guidance

I. BACKGROUND

City traffic is an urgent problem nowadays, but no better solution is found so far. To mitigate the city traffic problems, it has got commonly understood that not only transportation infrastructure construction, but also traffic management and controlling must achieve great progress with modern information and communication technologies (ICT) and GIS technologies [Goodchild 2000].

Over the past decades, GIS has found many successful applications in different fields, including intelligent transportation system (ITS) and location-based services (LBS). It can be used to manage road network concerned data efficiently and to assist with transportation planning and controlling [Miller and Shaw 2001]. Moreover, GIS can also be integrated with other technologies to establish real-time traffic information service system to collect, process, release and utilize real-time traffic information, so as to offer effective technical support for traffic management, intelligent navigation, transport dispatch and public traveling service.

The integration of various application models into GIS has enabled users to surpass the data inventory and management stage and conduct sophisticated modeling, analysis and visualization for spatial decision-making [Fletcher 2000]. However, in the transportation related applications, most GIS tools are based on a static view of road network, and this mismatching with real-time circumstance renders GIS inadequate to cope with network dynamics [Huang and Jiang 2002]. Presently, most of the vehicle navigation systems, logistics dispatch systems and web maps are static map data based applications. Although there have been some successful applications involving real-time traffic information, such as the famous VICS in Japan, RDS-TMC in Europe, ATIS and ADVANCE system in US, they mainly provides current traffic information to the users and ignore the possible traffic change in several minutes. The online Google Map applications surely provides short-term traffic forecasting capability, but it is based on the historical traffic data reasoning, which acts as an experienced driver who knows the general trend of traffic all the road network in different time. In general, how to make reliable short-term traffic forecasting and provide practical and accurate solution for real-time public traveling information service is still at the beginning of the industry. With the development of traffic collection and communication technologies, processing dynamic traffic information and conducting short-term traffic forecasting on road network, and providing dynamic traffic information service, have been a crux for vehicle navigation system and public traveling information services.

This research is supported by the Hi-Tech Research and Development Program of China under grant No 2006AA12Z209, 2007AA12Z24; NSFC project under grant No (40871184) and Knowledge Innovation Key Program of CAS (KZCX2-YW-308). Their supports are gratefully acknowledged.

In this paper, we set forward a practical short-term traffic forecasting approach which integrates historical traffic data statistics, real-time traffic events processing, with a BP neural network based analytical model, to forecast the situation and evaluate the influence of traffic during the traveling process, and developed a collaboration working framework to implement dynamic route guidance.

The remainder of this paper is organized as follows. Section 2 introduces the classical short-term traffic forecasting approaches. Section 3 proposes our approach on short-term traffic forecasting in detail. A collaboration working environment is developed in Section 4. Then a case study is conducted in Section 5 with a real road network and traffic information. Lastly Section 6 draws a conclusion.

II. CLASSICAL SHORT-TERM TRAFFIC FORECASTING

A. *Mathematical models*

Short-term traffic forecasting must be developed with the collected real-time traffic information to guide the public traveling. In the past decades, many researches have been conducted and a lot of models or approaches have been presented including moving average model (MA), Autoregressive model (AR), Autoregressive Integrated Moving Average model (ARIMA) models, Kalman filter models, benchmark function-exponential smoothing model, spectrum analysis, multi-dimensional and fractal approaches, wavelet analysis approaches, neural network approaches, cellular automata and agent based models, kernel machine methods, to name a few (Yin et al. 2002; Shi and Zheng 2004; Pan et al. 2006).

Most of the classical short-term traffic forecasting approaches are statistics based approaches which establish subjective models on data series. Unfortunately, traffic system is a complicated system involving people participation and changing frequently, whose non-linearity and uncertainty makes it difficult to achieve reliable forecasting results. Currently released traffic forecasting products mainly probe the general rules of the changing traffic flow in road networks with data mining on historical datasets. Such an approach seems to be practical and gets some applications, such as the Google Maps.

Furthermore, considering the social characteristics of traffic system, the participators of the system are also the interveners for the system. With the wide applications of real-time traffic and forecasting information, the inconsistency of the traffic forecasting will emerge inevitably, i.e., the releasing of the traffic forecasting result will change the forecasting result itself, so as to make the result won't accord with the travelers' practical experience. The Discrete choice methods presented in computational economy provides a possible approach dealing with such a dilemma, which aims to probe the response and behavior process of the travelers on real-time traffic information [Train 2003]. However, this approach is still on the stage of theoretical research, and has a long distance to practical applications.

B. *Microscopic traffic simulation*

Microscopic traffic simulation is a hot research topic which describes in detail the production, movement, disappearance of traffic related entities (vehicles, pedestrians, etc.) and the interactions between them. Due to its ability to capture the full dynamics of time-dependent traffic phenomena and its capacity to deal with behavioral models of the reactions of drivers exposed to ITS systems, microscopic traffic simulation has become a popular tool for examining the feasibility and assessing the impact of an ITS project [Jayakrishnan and Sahraoui 2001]. Many microscopic traffic simulation approaches and models have been presented in decades, and some have got utilized in commercial systems.

Most of the microscopic traffic simulation systems only build logical network to represent the road networks. It makes the information exchange between the vehicles and road networks difficult. Moreover, the logical network can't meet the requirement of the simulation model kernel on the dedicate parameters describing the road networks. Besides, most simulation systems behave weak in building, processing and visualizing road networks. Therefore, integrating traffic simulation system and GIS has attracted much attention. The resultant system is argued to have complementary strengths of both [You and Kim 2000]. Actually, some microscopic traffic simulation platforms, such as Paramics and TransModeler provide abundant GIS capability and can be regarded as extended GIS platform for specific applications.

However, the main purpose of microscopic traffic simulation systems is supporting transportation planning, but not for traffic forecasting. Almost all of the microscopic traffic simulation software pose limitations on inputted road network scale, and require many parameters such as the number of lanes, the data of signal timing and phasing, origin-destination (OD) statistics and information on the demarcation of traffic zones, the traffic composition of different vehicles. These preconditions and required data are difficult to get satisfied or obtained. This unfortunate situation argues microscopic traffic simulation platforms may take no effects for the dynamic travel information service. To inspect it, in our research, the microscopic traffic simulation software CorSim is compared with the presented approach characterized with historical traffic statistics combined with BP neural network model, in conducting short-term traffic forecasting.

III. INTEGRATED SHORT-TERM TRAFFIC FORECASTING

A. *Inspection of microscopic traffic simulation*

Parameters relating to the network entities that CorSim requires can be edited with an interactive tool embedded in CorSim. Once invoked, CorSim dynamically accesses the real-time traffic information, simulates the traffic flows and average driving speeds for each roadway segments in different time periods, and transfers the results to GIS.

However, according to our practice of traffic simulation in China cities, even though those parameters used to describe the traffic systems and driver behaviors have be calibrated carefully, the whole road network has been divided into several overlapped sub-networks and forecasting are conducted simultaneously in the sub networks and afterwards t combined, the traffic simulation based on a historical traffic flow dataset of one month (15 minutes periodically) still couldn't get satisfactory results due to the complicated multi-modal domestic traffic situation, and the lack of some necessary factors. The experiment result showed that the CorSim simulation software only achieved a 56.8% average accuracy for traffic flow forecasting. The historical traffic statistics, comparably achieved a 78.0% average accuracy. It means that if the traffic flow is smooth enough, using the CorSim to forecast the short-term traffic flow is not reliable enough. The author argues that other microscopic traffic software may behave similarly awful for the short-term traffic forecasting, unless all the impossible precondition and factors can get satisfied and obtained accurately (almost impossible). In other words, using microscopic traffic simulation to conduct short-term traffic forecasting for a whole road network is impractical.

B. Historical traffic data statistics

Complex city traffic holds some inherent principles or trends. For example, an experienced taxi driver, relying on his knowledge about the traffic change in different time, can more easily find out more suitable paths than the common drivers in the dynamic city traffic environment. Jiang (2007) and Jiang et al. (2008) proved that city streets are hierarchically organized and can be characterized by the 80/20 principle (Zipf law), i.e., a minority of streets accounts for a majority of traffic flow; more accurately, the 20% of top streets accommodate 80% of traffic flow (20/80), and the 1% of top streets account for more than 20% of traffic flow (1/20). Such regular laws can undoubtedly be used to determine the spatial-temporal distribution pattern, and at least, under most circumstance, can tell us the possible traffic change, yet provide relatively reliable results. Based on such cognition, the statistical analysis on historical traffic data takes an important role in short-term traffic forecasting. For the modern cities, there have been many measures to collect the historical traffic data including magnetic loops, microwave probing, video processing, floating vehicles (e.g., taxis equipped with GPS receivers) [Tong 2006], cellular phone signal mining [Bar-Gera 2007]. Long-term and complete historical traffic data offers very valuable data source for traffic prediction.

In this paper, with the historical datasets of the driving speed changes every 5 minutes on roadways, a simple arithmetic average is taken as the general traffic situation for every roadway. Average relative errors are shown in table 1.

TAB 1 RESULTS OF HISTORICAL TRAFFIC DATA STATISTICS

Weekday	Average relative error
Monday	0.136
Tuesday	0.207
Wednesday	0.295
Thursday	0.098
Friday	0.108
Saturday	0.136
Sunday	0.103
Average	**0.155**

C. BP neural network based forecasting approach

The historical traffic statistics can only get the general patterns for traffic change, and lacks the consideration of real-time traffic and events. But it provides a good foundation for traffic forecasting in real-time traffic environment.

A real-time traffic forecasting approach based on BP (Back Propagation) neural network is utilized in our study. It takes both the advantage of historical and real-time traffic information. The historical average driving speed for each roadway is taken to reflect its historical traffic characteristics. All of the historical data is organized in a DBMS as a series of data tables shown in table 2, where the historical data in Monday is highlighted as an example.

TAB 2 INPUT VALUES FOR BPNN

Weekday	**Time**				
	7:00~7:05	**7:06~7:10**	**7:11~7:15**	**..**	**20:56~21:00**
1th Monday	21.573	21.365	20.574	..	21.365
2th Monday	20.962	20.200	20.766	..	23.389
…	…	…	…	..	…
12th Monday	22.673	17.776	19.322	..	19.664
13th Monday	21.162	20.200	20.385	..	22.000

The BP neural networks are trained with the datasets including historical driving speed for each roadway that is collected at the same time structure (the same column in table 2) as well as the real-time driving speed for each roadway in current time period. Inputted values were normalized between 0 and 1. Since the traffic in current time period t has more distinct influence on forecasting the driving speed in time period t+1 than the historical data in time period t+1, the driving speed in current time period t was endued with a heavier initial weight than the historical data in the time period t+1. The networks were trained using a gradient decent back propagation algorithm and finished for 10,000 iterations or until the error reached the desired limit. The error measure used in this study is the averaged relative error over the testing data set, and is defined as:

$$PE_i = \frac{\sum_{i=1}^{n} \frac{|P_i - D_i|}{D_i}}{N} \qquad (1)$$

Where:

P_i = forecasted output value from the network for the i^{th} exemplar

D_i = desired output value for the i^{th} exemplar

N = number of exemplars in the test data set

After well trained, the driving speed for each roadway in time period t+1 is derived as the forecasted data and gets outputted. As illustrated in figure 1, n refers to the n^{th} weekday, t refers to the t^{th} time period, and X_{nt} refers to the average driving speed in the time period t on the n^{th} weekday.

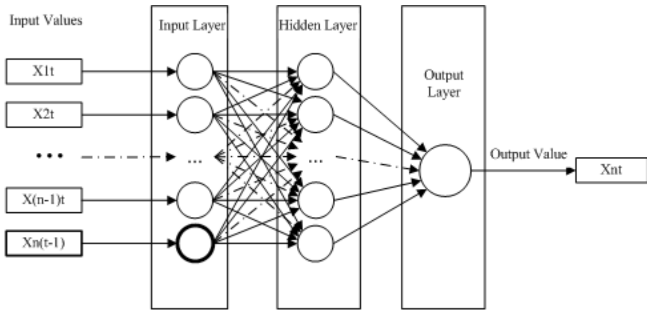

Fig 1 Schematic illustrating on BPNN topology

A major advantage of BP neural network approach is that the network will learn to ignore any inputs that don't contribute to the output during the training process. This means when some gross errors exist in the collected traffic data, the network can still converge on a reliable solution. The BP neural network based forecasting approach is tested by real traffic information collected in Beijing city. Table 3 shows the results of the forecasting models.

TAB3 RESULTS OF TRAFFIC FORECASTING APPROACH WITH BPNN

Weekday	Average relative error
Monday	0.095
Tuesday	0.094
Wednesday	0.217
Thursday	0.094
Friday	0.082
Saturday	0.119
Sunday	0.102
Average	**0.115**

D. Traffic events collection and processing

Neither of the magnetic loops, float vehicle or cellular phone signal analysis technologies can obtain the abrupt traffic events on spots or road cross turns. Once the abrupt traffic events happen, the traffic policemen, onlookers or people concerned will report the events and resulted influence (on the spot or monitor viewing) to the information center via cellular phones, short messages or other instant message systems. It is argued the most popular manner for collecting abrupt traffic events such as car crushes, accidents or traffic jams. Other events such as temporary traffic regulation, road construction are also real-timely reported to the information center presently. Real-time traffic event message is an effective supplement to the automatic traffic sensors. However, most of this kind of information is described in natural language and requires artificial translation to form the valuable information suitable for applications. It has been a time consuming task. Taking Beijing as an example, there are over 8000 traffic messages in natural Chinese sent to the information center artificially and only less than one tenth can be processed in time. The bottleneck focuses on understanding the natural language describing traffic and matching understood traffic information in LRS forms with the underlying road network spatial dataset, including the matching of address with the geometrical information, matching of multi-source LRS, and LRS and GIS positioning manner.

Understanding natural language consists of natural language segmentation and semantic understanding. Figure 2 shows the flow of understanding the traffic information described in natural language.

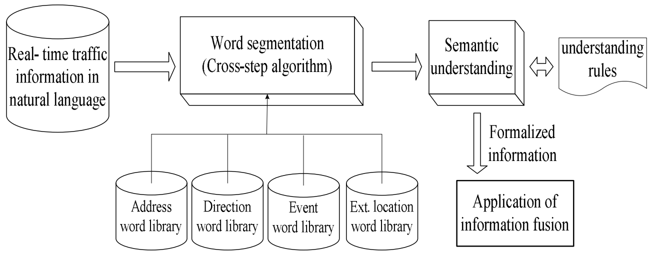

Fig.2 Technical flow for understanding

Understanding the traffic information only concerns how to rapidly and accurately process the key words representing addresses, directions and events.

The classical or improved maximum matching (MM thereafter) algorithms make the pointer move on the whole sentence to deal with every Chinese character one by one, and match with the libraries continuously. It doesn't utilize the rule of record length distribution, and doesn't process the complete words. So a novel cross-step word segmentation algorithm is set forward to process real-time traffic information represented in natural Chinese. This algorithm sets corresponding steps of word segmentation for address, direction and event libraries, and improves the one step running of the string pointer in classical Chinese word segmentation to flexible multiple steps running, so as to aggregate possible Chinese words efficiently. The proposed algorithm runs 10 times faster than an improved MM algorithm, while keeps similar accuracy and robustness.

The influence that the traffic events brings is reflected through the possible driving speed lost on underlying roadways, which is argued to be correlative with the event types and degrees.

The real-time traffic and events undoubtedly pose important influence on the turn costing. In our study, the famous HCM is utilized to model the influence of the real-time driving speed on the turn costing, with a precondition that the driving speed has a positive relation with the traffic flow.

IV. COOPERATIVE WORKING ENVIRONMENT

A. Framework

The author designed a framework of the cooperative working platform which consists of short-term traffic forecasting server, GIS application server, and online database management system server, as shown in figure 3.

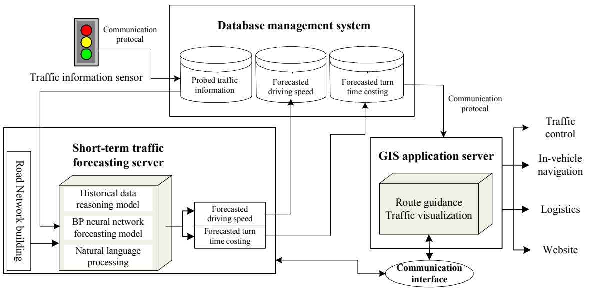

Fig 3 Framework of the cooperative working

The traffic information was collected by different sensors, including traffic flow, driving speed and events in natural Chinese language, and real-timely transferred to the central server, and then stored in an Oracle 9i database. The short-term traffic forecasting server periodically accesses the collected traffic information and provides the forecasted driving speed for each road segments of the whole road network using the integrated traffic forecasting approach. The forecasted results are stored back into the database system. Then the GIS server will be notified, so as to access the forecasted information to guide the dynamic navigation.

With multithread and Socket communication method, the authors designed a communication interface between the traffic forecasting server and GIS application server, to facilitate the three servers work collaboratively. The communication interface works as follows:

1) A timer is set up in the traffic forecasting server coinciding with the period of traffic information collecting, to invoke the traffic forecasting periodically;

2) Once the forecasting completed and the results stored back into the database server, a notice is sent to the GIS application server. Then the GIS application server immediately updates the average driving speed for each road segment and the estimated time cost at turns by accessing the database server, and uses the real-time information to implement the time-dependant route guidance;

3) After the GIS server finishes the information updating, it sends a notice to the traffic forecasting server, so as to prepare a new cycle of traffic forecasting.

V. CASE STUDY

Firstly the road network topology was built and stored in the database system. Once the GIS application server initiates, it accesses the forecasted traffic flow periodically from the database system and updates the topology of the road network. When the client sends a request to the GIS application server for dynamic path querying, the server applies a time-dependant least traveling time algorithm to get the optimal path based on the forecasting traffic information, and send the result to the client.

A time-dependant least traveling time algorithm was implemented based on an improved Dijkstra's algorithm with a quad-heap priority queue. The forecasted average driving speed and turn costing stored in the database system are used in the algorithm to accomplish the dynamic route guidance. If the travel couldn't be completed in one forecasting time period, the forecasting would be invoked midway to adaptively conduct the path scheduling again.

A prototype fulfilling the short-term traffic forecasting and dynamic route guidance has been developed and validated with a real city road network and real-time driving speed dataset collected with over 10000 taxis equipped with GPS receivers, and over 500 traffic event reports in natural Chinese language. The database server is built on Oracle 9i.

The traffic data used involves the driving speed of over 2000 major roadways collected every five minutes in Beijing from July 1st to September 30th, 2007， as shown in table 4.

TAB4 COLLECTED DRIVING SPEED DATA IN THE STUDY

Roadway ID	**Length**	**Travel time**	**Congestion level**
23	796	65	1
200	770	103	1
201	305	79	2
217	88	23	3
320	241	64	2
368	197	29	1
…	…	…	…
1143	564	253	3

The traffic events are collected from Beijing Traffic Radio in Chinese nature language firstly (as shown in figure 4), and then be syncopated and parsed into segmented words with semantic rules. The segmented words are translated into address, direction, event and location libraries using a cross-step word segmentation algorithm. Then the resulted traffic influence is matched with road network maps for further applications

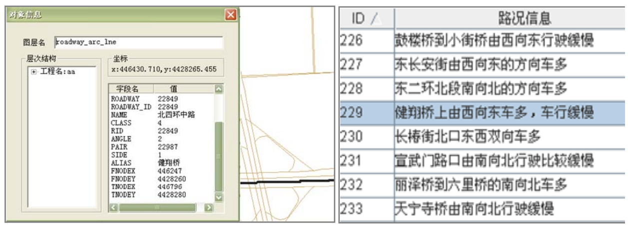

Fig.4 Traffic events described in natural language

When the BP neural network based traffic forecasting server receives the real-time traffic and events information, the forecasted driving speed in next 5 minutes for every roadways is obtained from the well trained network, and the network is adjusted at the same time. Then the traffic forecasting server sends a notice to the GIS application server.

The GIS application server provides least travel time paths under dynamic traffic circumstances by using a quad-heap priority queue based Dijkstra's algorithm [Lu et al., 2000]. When a request is send to the GIS server from the client, the

GIS server will provide time-dependant optimal travel routes with forecasted traffic, and sends the results to the clients. If the travel time is longer than the forecasting time cycle, the routes would be recalculated momentarily and adaptively. Figure 5 shows the dynamic route guidance results for the same origin and destination at different time with forecasted traffic data. The figure 5(a) shows the shortest route. The figure 5(b) shows the least travel time route at 3 am. The figure5(c) shows the least travel time route at 8 am. The figure 5(d) shows the least travel time route at 1 pm.

Fig.5 Dynamic optimal routes based on forecasted traffic data

VI. CONCLUSION

The lack of accurate short-term traffic forecasting approaches makes dynamic route guidance a difficult task. This paper presents a short-term traffic forecasting approach integrating historical traffic data statistics, BP neural network based forecasting model and natural language understanding for representing traffic events, and develops a framework of combining GIS, traffic forecasting server and database management system to implement dynamic route guidance. With experimental analysis, the presented approach is proved accurate and is argued to be a practical solution for dynamic public traveling information service.

REFERENCES

[1] Goodchild M F. GIS and transportation: status and challenges. Geoinformatica, 2000, 4(2): 127-139.

[2] Miller H. J., and Shaw, S. L. Geographic Information Systems for Transportation: Principles and Applications. Oxford University Press, New York, 2001.

[3] Fletcher D. Geographic information systems for transportation: a look forward: In Transportation in the new Millennium: State of the Art and Future Directions. Transportation Research Board, National Research Council, Washington, D.C., 2000.

[4] Huang B. and Jiang B. AVTOP: a Full Integration of TOPMODEL into GIS. Environmental Modelling & Software, 2002, 17(3): 261-268.

[5] Shi Q. X. and Zheng W. Z. Short-term traffic flow prediction methods comparison of road networks. Journal of Traffic and Transportation Engineering, 2004, 4(4): 68-71. (in Chinese)

[6] Yin H., Wong S., Xu J. Urban traffic flow prediction using a fuzzy-neural approach. Transportation Research Part C, 2002, 10(2): 85-98.

[7] Pan M. Y., Yan F., Xie H. Y. Intelligent traffic simulation based on agent and cellular automata. Journal of Traffic and Transportation Engineering, 2006, 6(2): 70-74. (in Chinese)

[8] Jayakrishnan, R., J. S. Oh, and A. Sahraoui. Calibration and Path Dynamics Issues in Microscopic Simulation for Advanced Traffic Management and Information Systems. TRB Paper #01-3437, National Research Council, Washington D. C., 2001.

[9] You, J., and Kim, T. J. Development and evaluation of a hybrid travel time forecasting model. Transportation Research Part C, 2000, 8:231- 256.

[10] JIANG, B., A topological pattern of urban street networks: universality and peculiarity. Physica A, 2007, 384:647–655.

[11] Jiang B., Street hierarchies: a minority of streets account for a majority of traffic flow. International Journal of Geographical Information Science, 2008: 1~16. DOI: 10.1080/13658810802004648.

[12] Tong D. Traffic information deriving using GPS probe vehicle data integrated with GIS. In: Proceedings of GIS-T'2006 Symposium[C], Columbus, Ohio, USA, 2006: 27-29.

[13] Bar-Gera H. Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: A case study from Israel. Transportation Research Part C, 2007, 15(6): 380-391.

[14] Lu F., Zhou C. H, Wan Q., 2000, An improved Dijkstra's shortest path algorithm based on quad heap priority queue and MBR searching method, Proceedings of the 9th Spatial Data Handling Symposium, 2000,6b:3-13