MOBILE BASED GIS FOR TRANSPORTATION USING MULTILAYER FEEDFORWARD NEURAL NETWORK

Priya Iyer K.B.[1] **Shanthi V.**[2] **Prashanth Papanasam S.**[3]

[1]Research Scholar, Sathyabama University
[2]Professor, St. Joseph College of Engineering
[3]B.Tech.(IT), Eswari Engg, College, Chennai, India
Email: [1]priya_balu_2002@yahoo.co.in, [2]drvshanthi@yahoo.co.in

Abstract

The technological evolution which occurred in Communication, GIS and GPS systems favored the novel techniques in building the intelligent transportation systems. The Advanced Traveler Information Systems (ATIS) which is part of ITS assist the travelers with travel scheduling and route information to improve the convenience and efficient travel. Existing ATIS applications focuses only on traffic aware trip planning based on user point of interest. In this paper, we present a new ATIS System called Mobile enabled Geographic Information system for Transportation (MGIS-T) which provides travel information based on user preferences such as mode of travel(like car, bike, walk etc) and keyword based point of interest. For the first time, the trip is planned according working hours of point of interest categories. New algorithms were developed which provides route information as well as shortest path to reach POI based on travel time as metric. The CPU time and I/O cost incurred by the proposed algorithm were shown experimentally. As a result, the MGIS-T system provides the user with effective routes according to the user's query preferences efficiently.

Keywords: Intelligent Transportation System, Trip Planning, Spatial Queries, GIS, Location based services, GPS.

I. INTRODUCTION

The advancements in communication technologies help in building new Intelligent Transportation Systems (ITS). The most popular applications are Route Guidance system, Traffic Management System, Congestion Management, Parking assist units, Lane keeping assistance etc. The widespread adoption of modern technologies (GPS and GIS) in smart phones made mobile users geo-savvy providing location based services 24/7 around the clock. In modern geographic information systems, trip planning represents an important class in ATIS. For example, a tourist who wishes to visit a set of keyword based point of interest of different categories within the working hours of POI and on a specific vehicle type represents a new MGIS-T query.

All the existing studies gives the route planning trips based on network distances, travel time but not based on the mode of travel, working hours of POI and keyword (sub-category of POI). Thus this paper helps to find the set of data objects by considering different categories of keyword based POI with their visiting hours to user specified location on a future journey schedule based on travel time and mode of travel. Travel time information is derived based on historical data by considering day significance and time. However travel time is affected by a number of factors such as road conditions, climatic conditions, driver attitude and country's cultural habits etc.

To sum up we make the following contributions:

1. Finds nearest data objects for MGIS-T queries for future Trip by taking traffic travel time as metric.
2. Travel time prediction on specified route is computed by using historical traffic data where significance of day and time is considered.
3. The trip planning is based on user travel mode and keyword based point of interest category.
4. The objects are visited by ordering the POI categories based on the working hours of the POI.
5. Designing efficient algorithm for finding data objects thru four phases namely Query Initiator and Object Prioritizer (QOP), Travel Time Forecaster (FTF), Neural Network Perceptor (NNP), TripFinalizer and Optimizer (TFO).
6. The algorithm further gives route information for entire trip and shortest path to reach the all POI.

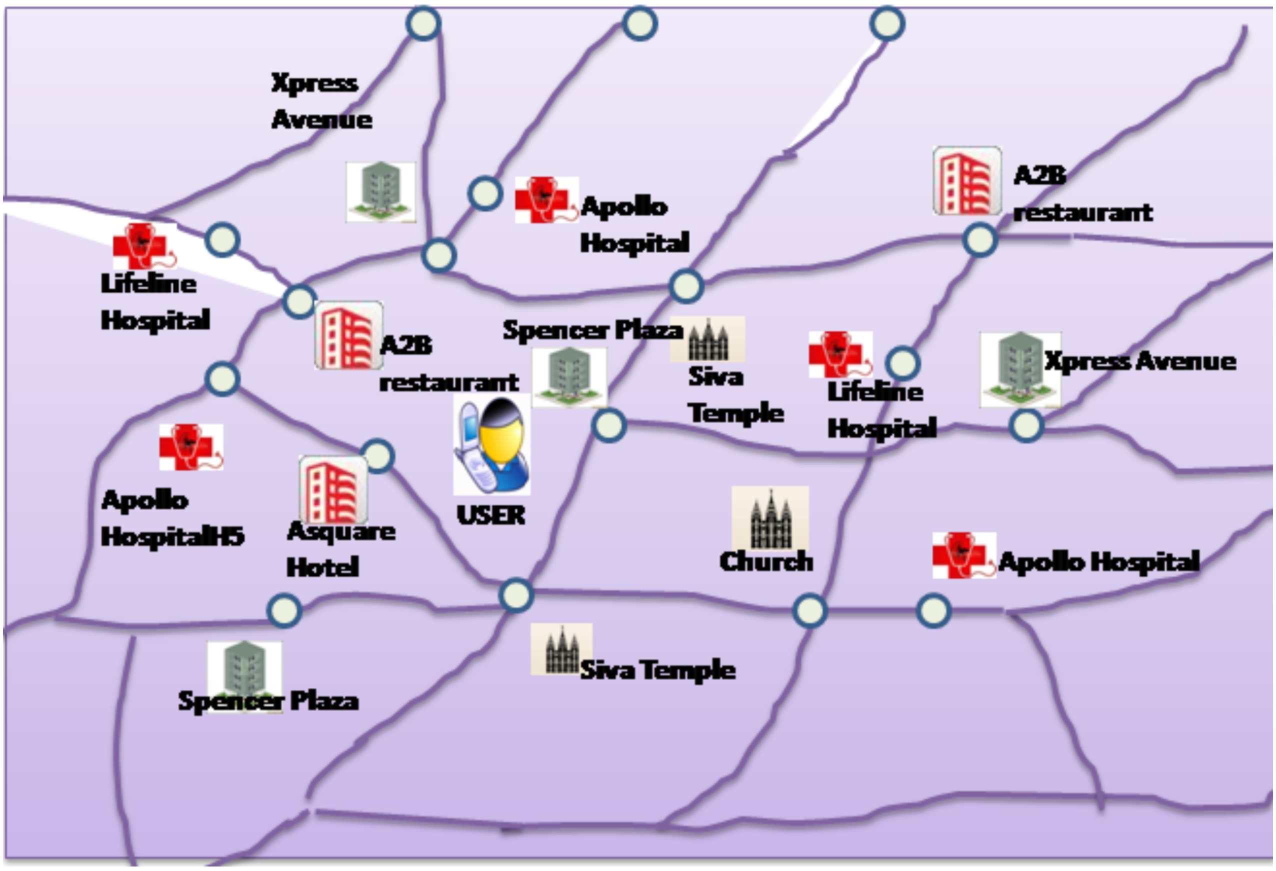

Fig. 1. Road Network

The reminder of this paper is organized as follows. In section 2, we review the related work on both trip planning queries and developing intelligent transportation System. In section 3, we formally defined MGIS-T query in Road Networks. In section 4, we introduce Multi-Layer Feedforward Neural Network based approach for retrieving data objects in road networks. Section 5 presents the results of our experimental evaluation of our proposed approaches with a variety of Spatial Network with large number of data and query objects. Finally section 6 concludes the paper with future research.

II. RELATED WORK

2.1 Trip Planning Queries

Trip planning queries helps users to find optimal route that minimizes the travel time. In [13], an optimal sequenced route is defined that retrieves the route that starts from a source and passes through a number of locations in particular order of POI types. In [14], a Multitype NN query is introduced which finds the shortest path for the query point such that only one type is visited during the journey. In [2], a trip planning queries which visits each POI without order is introduced. In [16], a collective spatial keyword search where a group of objects that are close to a query point and collectively cover a set of a set of query keywords are returned as the result.

In [17], keyword-aware optimal route query, is defined to find an optimal route such that it covers a set of user-specified point of interest with a specified budget constraint and objective score of the route is optimized. In [9], a three phases fuzzy inference system (FIS) proposed to map social and demographic variables to total number of trips between origin-destination (OD) pairs. In [12], an method which incrementally retrieves data objects according to their distances to the destination and computes kMDO results for a subset of nodes in the network. In [5], a MRPSR query with three fast approximation algorithms to efficiently compute routes which can fulfill all the traveling rules with a near-optimal travel distance based on the underlying road networks is introduced.

In [11], a novel system, CompRec-Trip, which can automatically generate composite recommendations that allows flexible package configuration and incorporates users' cost budgets on both time and money. In [7], introduces the problem of modeling urban transportation where certain aspects of the data such as multiple modes (e.g., automobile, bus, train, pedestrian) that the user can alternate between are probabilistic in nature. In [4], trip planning is defined as laborious job requiring interaction with a combination of services such as travel guides, personal travel blogs, map services and public transportation.

2.2 Travel time Studies

From the travelers' perspective, accurate travel time predictions reduce the uncertainty in decision making about departure time and route choice, which in turn reduce travelers' stress and anxiety. From the operators' point of view, travel time prediction models may be used to determine the reliability of a transportation system. Consequently, travel time prediction methods are central to Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) [15][1]. Mean-variance estimation method was also used in [10] to predict bus travel time variability. Travel Time Prediction Using floating Car Data Applied to Logistics Planning by taking into account that routes of long-range trips are not completely given in advance but are rather unknown and subject to change[16]. short-term prediction of highway travel times, which represent an accurate estimation of the expected travel time for a driver commencing on a particular route based on the fusion of different types of data that come from different sources (inductive loop detectors and toll tickets) and from different calculation algorithms[4]. Car following model using a fuzzy inference system (FIS) to simulate and predict the future behavior of a Driver-Vehicle- Unit (DVU) based on a new idea for estimating the instantaneous reaction of DVU, as an input of fuzzy model [6].

In summary, previous studies on trip planning are limited to either Euclidean space or metric space for a specific application. In contrast, our work focuses on the travel time as a metric for poi search and working hours of the keyword based POI which play a vital role in building ATIS. Travel time prediction is based on previous traffic data considering factors such as time slice of the day, day significance etc. The route information and shortest path to reach all POI is based on neural network.

III. SYSTEM MODEL

In this section, we describe the road network and system model; define the MGIS-T trip planning query search in spatial networks. We assume a spatial network [California Road Network], containing set of static data objects as well as query objects searching their objects along with their visiting hours and based on keyword. We assume all road maps and daily traffic data, visiting hours schedule are maintained by cloud server.

3.1 Road Network

We model the underlying road network as a weighted undirected graph $G = (V, E)$ where E is an Edge set of road segments in the road network, V is the Vertex set of intersection points of the road segment and each edge is given travel time of its corresponding road segment as weights.

We consider our system with a mobile environment in which mobile user is able to communicate with the service provider through wireless communication infrastructure e.g.: Wi-Fi.

3.2 Definition

A MGIS-T trip planning query is based on travel time, where data objects are returned in the relative to the user location and travel time is predicted from historical data. The PSQ is useful in following situations:

Example1: if a user wants to visit a HDFC Bank, Siva Temple and A2B Restaurant. Here the working hours of bank are 10am to 2pm. The temple will be opened from 6am to 12pm and the restaurant timings are 8am to 3pm. Then basing on the priority of POI schedule and travel mode, the POI objects are visited.

IV. ALGORITHM

4.1 Phase I: Query Initiator and Prioritizer

The algorithm first finds the nearest vertex of the query origin. The user location is given by GPS / Wi-Fi or any location specified by the user. The GetVertex function returns the nearest neighboring road node "u" of the user location. Harvesian Formula is used in finding the distance between two locations. The nodes in database are sorted in descending order of their

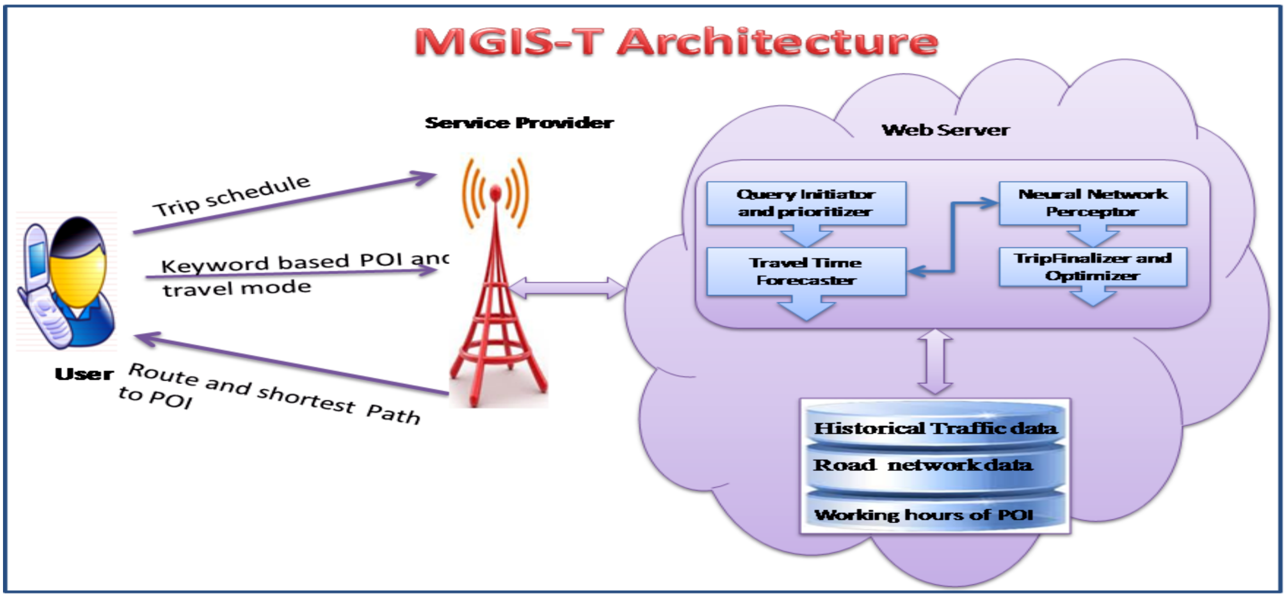

Fig. 2. Architecture – MGIS-T

distances from user location "u" where the top most nodes gives the nearest neighbour of "u". Basing on the working hours of POI the POI are prioritized.

4.2 Phase II: Travel Time Forecaster (FTF)

During this phase, the travel time for future journey date is predicted. The travel schedule includes both date of journey and time of journey. We know traffic depends on various factors like day of travel, time, weather condition etc. we assume travel time depends on day significance, time of journey only. We design a Fuzzy Travel Time Forecaster inference engine in MATALB. The Day significance is categorized

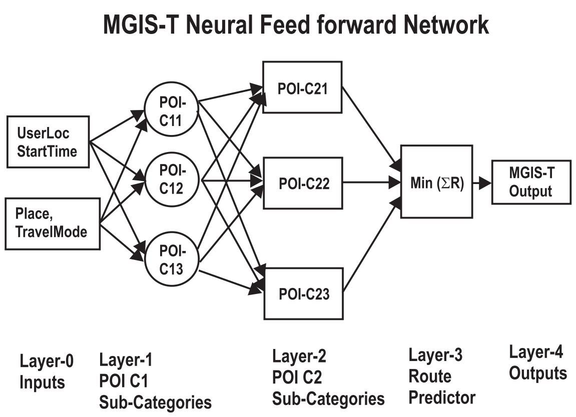

Fig. 3. Neural NetworkArchitecture – MGIS-T

as HOLIDAY, MONDAY, MID-WEEKDAY, FRIDAY, WEEKEND-SATURDAY, WEEKEND-SUNDAY.

The function DateSignificance returns the datem apkey basing on the journey date significance(holiday or weekday or weekend etc). The function TraveltimeMap returns the slice of travel time from inference rules.

4.3 Phase III: Neural network Perceptor

From the nearest node, all adjacent nodes are traversed to find the list of first user preferred query point. While searching the query points, the query checks for only the Keyword based Poi and filters out the unwanted data points that are out of range of user preferences. The algorithm proceeds by applying the other query preferences on the list of candidate data objects. All the candidate objects are refined by considering the minimum travel time and other factors. At the end, the algorithm returns the goal object relative to user location.

4.4 Phase IV: Trip Finalizer and Optimizer

On receiving the several routes this phase decides the minimum route trip. Optimization is achieved by computing the travel times to selected hotels which have the potential to participate in the ?nal query answer instead of all hotels. This approach would enhance the query processing by avoiding redundant extensive computations. Aggregations for secondary query points are done before applying retrieval. This helps in further reduction of query computation.

4.5 Algorithm

Algorithm 1 :

MGIS-T (uloc,pref[],A[],journeyschedule)

/* upos: query origin (latitude,ongitude) , pref[], an array consisting of user query preferences Q1,Q2,..Qn and A[], an array of their corresponding attributes a1,a2,..an, journey schedule: date and travel time of journey */

1. Find the nearest vertex for the query origin uloc

u → Getvertex(uloc/loc)

2. C[i]={0} /*set the initial candidate objects as zero */
3. PQ → Prioritize(pref[], A[])
4. While(1)
5. Begin
6. Subcat[] → RetrievePoi[PQ[], region)
7. For each Subcat[]
8. begin
9. SR[i] → Find Shortest Route (Subcat[],CPOI) * retrieves the shortest path to reach POI*/
10. For end
11. CPOI=PQ[i]
12. While End
13. R[]=CalSumRoute()
14. if (CheckMin(R[])) then
15. DispTripPlan() /* display keyword POI object */
16. end if

Table 1: Travel Time

Stort Node	End Node	Travel Time 1	Travel Time 2
9793	9794	0.0001977	0.0001977
9794	9795	0.0000955	0.0000955
9795	9796	0.00008	0.00008
9796	9819	0.0002068	0.0002068
978	1455	0.0002525	0.0002525
9796	9889	0.0001676	0.0001676
9796	9949	0.0002568	0.0002568
9797	9798	0.0001577	0.0001577
9798	9799	0.0003163	0.0003163
9799	9800	0.0001934	0.0001934
9800	9801	0.0002384	0.0002384
9801	9802	0.0003809	0.0003809

Table 2: Working Hours POI

Date	Time	Key Value	Category	Description
20.02.2011	04.00A.M - 08.00A.M.	1	WEEKDAY	NIL
02.01.2011	15.00P.M - 20.00P.M.	10	WEEKEND	NIL
17.01.2011	15.00P.M - 20.00P.M.	100	WEEKDAY	NIL
17.01.2011	22.00 P.M - 04.00 A.M.	102	WEEKDAY	NIL
18.01.2011	04.00A.M - 08.00A.M.	103	WEEKDAY	NIL
18.01.2011	08.00A.M - 11.00A.M.	104	WEEKDAY	NIL
18.01.2011	11.00 A.M - 15.00 A.M.	105	WEEKDAY	NIL
18.01.2011	15.00 P.M - 20.00 P.M.	106	WEEKDAY	NIL
18.01.2011	20.00P.M - 22.00P.M.	107	WEEKDAY	NIL
18.01.2011	22.00P.M - 04.00A.M.	108	WEEKDAY	NIL
19.01.2011	04.00A.M - 08.00A.M.	109	WEEKDAY	NIL

V. EXPERIMENTAL EVALUATION

5.1 Experimental Setup

We conducted experiments on California road network which contains 21,050 nodes and 21693 edges. The algorithm is implemented in Java and tested on Windows Platform with Intel Core 2 CPU and 80GB memory1. The main metric we adopt is CPU time that reflects how much time the algorithm takes in processing a query. The input map is extracted from Tiger/Line files that are publicly available [18].

5.2 Results

(i) Travel time prediction for Query route Q1

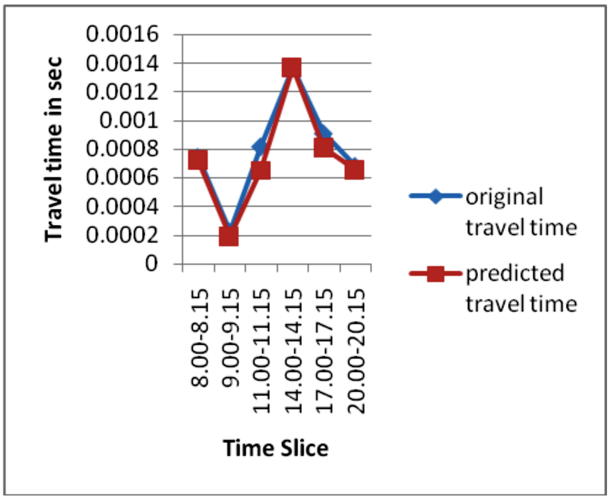

Fig. 4. Travel time comparision

With this experiment in Fig 4, we show the travel time of original and predicted values for Query Q1.

(ii) Travel time prediction for Node n1

In Fig. 5, we show the travel time taken for any one node during the varying time slices.

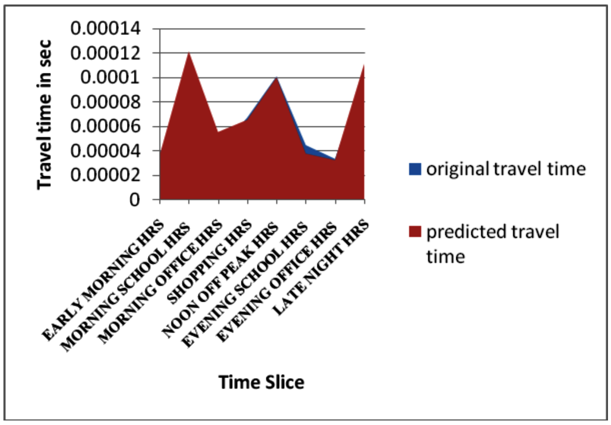

Fig. 5. Travel time prediction

(iii) Impact of query optimization on dominant objects

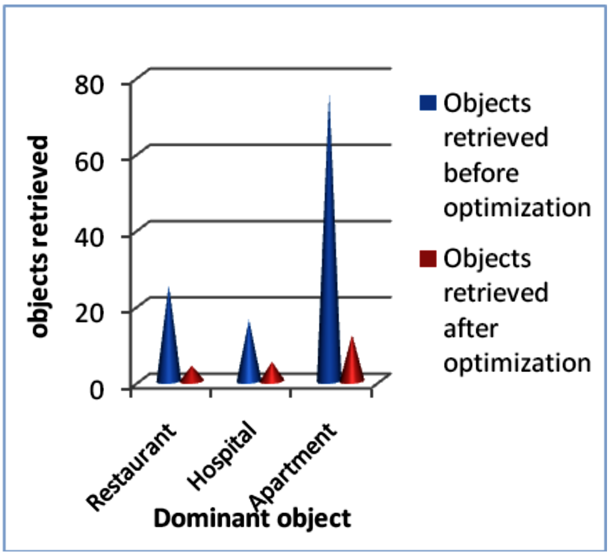

Fig. 6. Object retrieved before and after optimization

In Fig. 6, we show the impact of query optimization in object retrieval from database.

VI. CONCLUSION

In this paper, we propose a MGIS-T queries on travel time dependent road networks. This algorithm efficiently searches and computes the data object to query origin with user preferences like travel mode, keyword based POI categories. The travel time is predicted using historical data based on significance of Day and Time. The POI are visited based on the visiting hours of the POI. The algorithm also provides the shortest path to reach the POI.

Additional future works includes query for moving objects, multimodal transports, road types etc and taking weather conditions, day light for travel time prediction.

REFERENCES

[1] B. Bartin and K. Ozbay. Determining the optimal configuration of highway routes for real-time traffic information: A case study. IEEE Transactions on Intelligent Transportation Systems, vol. 11, no. 1, pp. 225–231, 2010.

[2] F. Li, D. Cheng, M. Hadjieleftheriou, G. Kollios, and S.-H. Teng. On trip planning queries in spatial databases. In SSTD, pages 273–290, 2005.

[3] Z. Chen, H. T. Shen, and X. Zhou. Discovering popular routes from trajectories. In ICDE, pages 900–911, 2011.

[4] Gang Chen, Chen Liu , Meiyu Lu , Beng Chin Ooi, Shanshan Ying , Anthony K. H. Tung , Dongxiang Zhang , Meihui Zhang. A Cross-Service Travel Engine for Trip Planning, 2012.

[5] Haiquan Chen • Wei-Shinn Ku•Min-Te Sun • Roger Zimmermann. The partial sequenced route query with traveling rules in road networks. Geoinformatica (2011) 15:541–569.

[6] J.Jassbi1, P.Makvandi1*, M. Ataei2 and Pedro A. C. Sousa3. Soft system modeling in transportation planning: Modeling trip flows based on the fuzzy inference system approach. African Journal of Business Management Vol. 5(2), pp. 505-514, 18 January, 2011.

[7] Joel Booth, Prasad Sistla, Ouri Wolfsony, Isabel F. Cruzz . A Data Model for Trip Planning in Multimodal Transportation Systems. EDBT 2009, March 24–26, 2009,

[8] T. Kurashima, T. Iwata, G. Irie, and K. Fujimura. Travel route recommendation using geotags in photo sharing sites. In CIKM, pages 579–588, 2010.

[9] Khodayari A, Kazemi R, Ghaffari A,Braunstingl R. Design of an improved fuzzy logic based model for prediction of car following behavior. IEEE International Conference on Mechatronics (ICM), 2011, On Page(s): 200 – 205.

[10] E. Mazloumi, G. Rose, G. Currie, and S. Moridpour. Prediction intervals to account for uncertainties in neural network predictions: Methodology and application in bus travel time prediction, Engineering Applications of Artificial Intelligence, 2010.

[11] Min Xie y, Laks V.S. Lakshmanan y, Peter T. Wood z . CompRec-Trip: a Composite Recommendation System for Travel Planning. ICDE Conference 2011, IEEE

[12] Sarana Nutanong, Egemen Tanin, Jie Shao, Rui Zhang, Kotagiri Ramamohanarao . Continuous Detour Queries in Spatial Networks. IEEE Transactions on Knowledge and Data Engineering, **Volume:** 24 , July 2012, **Page(s):** 1201 – 1215.

[13] M. Sharifzadeh, M. R. Kolahdouzan, and C. Shahabi. The optimal sequenced route query. VLDB Journal, 17(4):765–787, 2008.

[14] Shuo Shang, Bo Yuan, Ke Deng Kexin Xie, Kai, Xiaofang Zhou. PNN Query Processing on Compressed Trajectories, 2011.

[15] F. Soriguera F. Robusté. Highway travel time accurate measurement and short-term prediction using multiple data sources. Transportmetrica, Volume 7, Issue 1, 2011 , pages 85-109.

[16] Xin. Cao, G. Cong, C. S. Jensen, and B. C. Ooi. Collective spatial keyword querying. In SIGMOD, pages 373–384, 2011.

[17] Xin Cao Lisi Chen Gao Cong Xiaokui Xiao. Keyword Aware Optimal Route Search. August 27th 31st 2012, Istanbul, Turkey. Proceedings of the VLDB Endowment, Vol. 5, No. 11.

[18] Tiger/Line: ww.census.gov/geo/www/tiger/.