© 2018 IJSRST | Volume 4 | Issue 5| Print ISSN: 2395-6011 | Online ISSN: 2395-602X
Themed Section: Scienceand Technology

Feasible Route Search on RoadNetworks by Using Clues

M. SandhyaRani[1] ,Dr. R. Muragadoss[2]

[1]PG Scholar, Department of MCA, St.Ann's College of Engineering&Technology, Chirala, Andhra Pradesh,India

[2]Professor, Department of MCA, St.Ann's College of Engineering& Technology, Chirala ,Andhra Pradesh, India

ABSTRACT

The booming industry of location based services is accumulated many collection of users location trajectories of driving, cycling, hiking. We find the problem of discovering the Most Popular Route (MPR) between two locations by taking the traveling behaviors of many backend users. To determining the waiting time every parking vertex to achieve the minimal on-road time becomes a big challenge which further breaks FIFO property. We propose two efficient algorithms using minimum on-road travel cost function to answer the query. This paper focuses on the highly developed solution is using ACO algorithm. It also applied the method considering flow, distance, cost, and emergency. Given a query location and a set of candidate objects in a road network the kNN search finds the k nearest objects to the query location. We propose balanced search tree index, called G tree. The G tree is road network andconstructed by recursively partitioning the road network into sub-networks and each G-tree node corresponds to a sub-network. Propose a class of routing schemes is finding the nodes of highest utility for routing improving the delay and delivery ratio. Additionally proposed an analytical framework based on fluid models is used to analyze the performance of many opportunistic routing strategies, in heterogeneous settings.

Keywords: Social Routing, Social Metrics, Road network, spatial databases, events, geo streaming, mustier solution, traffic analytics.

I. INTRODUCTION

The iniquitousness of mobile devices has given rise to a new spectrum of location based services which are becoming increasingly popular today [1]. On Google maps is easily enjoy the convenience of location based services such as asking directions, planning driving routes, finding restaurants [2]. In a time dependent road network is cost associated with road segment to change over time the existing path planning problem makes use of an important observation known as the FIFO property is vehicle enters a road segment first will also reach the end of road segment first in spite of the time dependent nature [3]. We advocate for a real time evaluation of vehicle traces over road networks and their collective representation as traffic data streams. Similar platforms have emerged lately as vehicle positions and derived statistics are inherently fluctuating, potentially intermittent, and ever more voluminous to be hosted by a traditional DBMS [4]. The authors introduce new Ant Traffic Control System algorithm is derived from the existing class of Ant Colony Optimization (ACO) algorithms. For transporting capacity of the highways is insufficient [5]. Our goal is to design an elegant index which supports efficient kNN search on large road networks. Inspired by the classical R-tree on Euclidean space we design our index on road networks by considering two core features. The first one is a balance tree structure, and we propose a balanced search tree index, called G-tree[6]. Leveraging the node mobility and opportunistic relay for packet delivery is a common technique developed for Delay Tolerant Networks (DTNs) or mobile opportunistic networks [7]. In these delay tolerant networks, the end-to-end path does not exist all the time from the current node to the destination node due to the frequent network partitions [8].

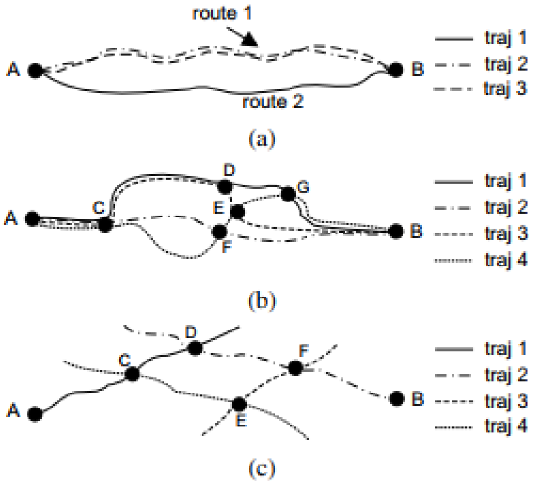


Figure 1. Discovering Popular Routes

II. RELATED WORK

The search of popular routes in light of past movements is highly relevant to trajectory processing including pattern mining trajectory clustering hot route discovery trajectory prediction none of them addresses the problem of discovering the most popular route from one given location to another [9]. Our work is mainly regarding route planning issues while the vast majority of existing work is dealing with a general mining problem. It is essentially a trajectory clustering algorithm based on traffic density which shares the same idea with cluster trajectories by line segment density [10]. Most of the recent path planning algorithms on road network shares a common assumption that the travel along a road follows FIFO property which means a vehicle starting earlier is destination later regardless of the time cost of edges [11]. Diamonds represent processing tasks applied against incoming data according to specific captions rules, and parameterization depicted with ovals [12]. The kNN search involves shortest path computation the key point of kNN search is to quickly find those promising top-k objects rather than to calculate the shortest path from the query location to all candidate objects then rank is feasible to apply them to handle the kNN search on road networks effectively [13]. We propose a novel approach to a new application personalized landmark recommendation based on user's geo tagged photos. Author formulates the landmark recommendation system is collaborative filtering problem. We propose new category regularized matrix factorization method that integrates both user-landmark preference and category-based landmark [14].

III. SYSTEM MODEL

This pre processing stage attempts to associate vehicle locations with road segments of the underlying network. As already mentioned, tracking data from moving vehicles has limited positional accuracy. We integrate spatial access methods for indexing and fast retrieval of road entities since identification of relevant segments must be performed for every incoming position [15]. In Euclidean space tree structured indices R-tree, have salient features to support kNN search. We would like to incorporate two of these features in our G-tree to support kNN search on road networks [16]. The first feature is the balanced tree structure that can help to prune sub trees. Flooding is a fundamental communication primitive for wireless sensor networks. Flooding is used for disseminating code updates and parameter changes, affecting the operation of all nodes in the network flooding occurs each node, typically broadcasts the flooding packet once [17].

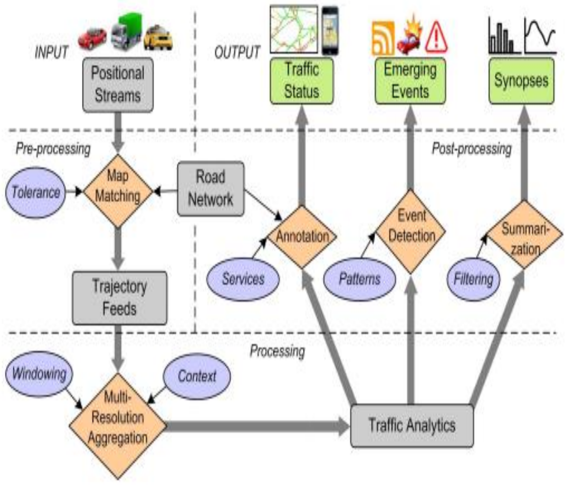
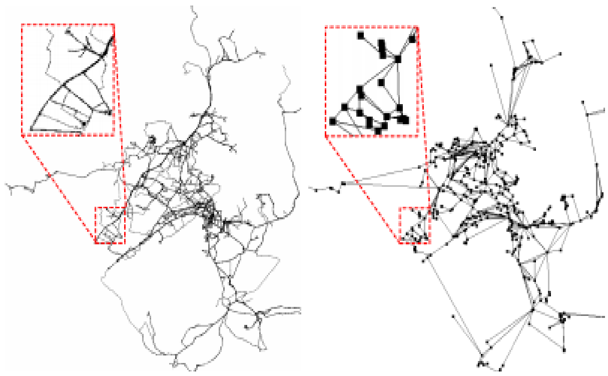


Figure 2. Data flow diagram.

IV. MINING TRANSFER NETWORK

In order to systematically analyze the users traveling behaviors through GPS trajectories first we establish a transfer network from raw trajectories [18]. The transfer network is in effect a directional graph (*N*,) indicating the movements between locations. Here *N* is a set of transfer nodes, which can be an intersection of trajectories or just the end locations of a trajectory [19]. We find out the transfer network by map-matching trajectories to attempt to make this work compatible with both constraint and un-constraint trajectories. Typically traces of hiking, boating, walking, and many out-door activities is constrained by a road network and most maps that people think of as free actually have legal or technical restrictions on their use which hold back people from using them in creating new applications [20]. To calculate the social metric (SM) value of a node a social graph is generated from historical contacts to describe the social relationships among nodes. To generate the social graph a threshold is set on contact frequency to judge whether there is a close relationship between two nodes in the network [21].



(a) Distribution of Trajectory Points (b) Transfer Network

Figure 3. Mining Transfer Network

A.

B. Algorithm Outline

Given a time-dependent graph G(V, E) and a MORT query QMORT (vs, vd, ts1, ts2, td), the proposed algorithm generates the minimal on road time Rp∗sd and the corresponding route with traveling schedule p ∗ sd. The whole process can be divided into three parts as below [22]:

1. Active Time Interval Profiling (ATI) computes the active time interval Ti for each vertex vi, which is bounded by a pair of earliest arrival time vat EA and latest departure time vital.
2. Path Expansion finds the path with minimum on road travel time in a Dijkstra way and produces the Minimum Cost Functions of the visited vertices [23].
3. Route Retrieval returns the actual route schedule with user specified arrival time. Given the proposed speed profile, the earliest arrival time of each vertex is computed by performing SSFP from vs at ts1 as for the latest departure time [24].

B. Vehicle Traffic Routing Algorithm

The authors developed the notion of virtual pheromone inspired by the chemical markers used by ants and termites for communication and coordination. It is implemented by messages relayed from central traffic control to Sensor with Voice Synthesizer [25].

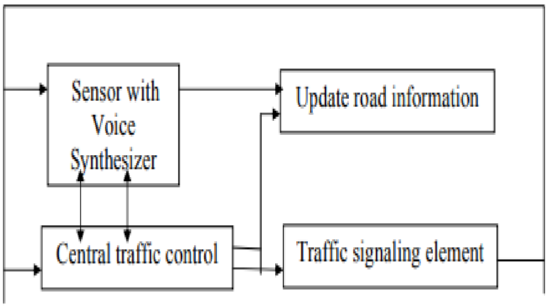


Figure 4. Pictorial representation of ant based traffic control.

The VRT algorithm consists of two crucial parts
(1) Sensing element or Sensor with Voice Synthesizer,
(2) Central traffic control (CTC). Every car includes Sensor with Voice Synthesizer which is connected to CTC from which update information may be achieved. Each Sensor with Voice Synthesizer can process and store data. A distinct server provides supporting element to its central control [26].

V. DTN HIERARCHICAL ROUTING (DHR) ALGORITHM

Find the lowest level k where the source s and the destination d have a common cluster. Define the intermediate source s0 and the intermediate destination d0, which are the level k clusters of s and d respectively [27]. Use the optimal time space algorithm to find the next hop n0 on the shortest path from s0 to d0 based on the level k topology information of s. if k = 0, n0 is the forwarding decision of s, otherwise go back to step 3 with a new k = kj 1, a new d0 being the remote gateway from s0 to n0, and a new s0 being

Step: 1 The Node ad-hoc network creation and view the network

Step: 2 Deployment of Road Side Unit (RSU) with private and public key

Step: 3Analyze the network coverage area with specified distance

Step: 4 Initialization of Road Side Unit

Step: 5 Create Trajectory between one Road Side Unit (RSU) and neighbor RSU with distance

A. Assembly-based Method:

We have an observation that many shortest paths share common sub-paths, and we do not need to store shortest-path distances for all pairs between vertices and borders. Instead we only materialize some pairs and assemble these pairs to implement the Sadist function. The two paths share one of the common sub-path v2v6v7v8 which is the shortest path from border v2 to border v8. This common path can be used to compute the shortest path from v4 to v8 and the shortest path from v5 to v8. This implies us to only store the shortest-path distances of pairs between borders ((v2, v8)) within one G-tree node [28].

(1) Initially, for each leaf node, we use the Dijkstra algorithm to compute the shortest-path distance between any two borders in the leaf node.

(2) We remove all non-border vertices in the leaf node and add shortcuts between any two borders of the leaf node.

(3) We move to the parent of leaf nodes and use the Dijkstra algorithm to compute the shortest-path distance between any two borders in the parent based on the updated graph [29].

(4) We repeat steps 2 and 3 and terminate the algorithm if we have processed the root node.

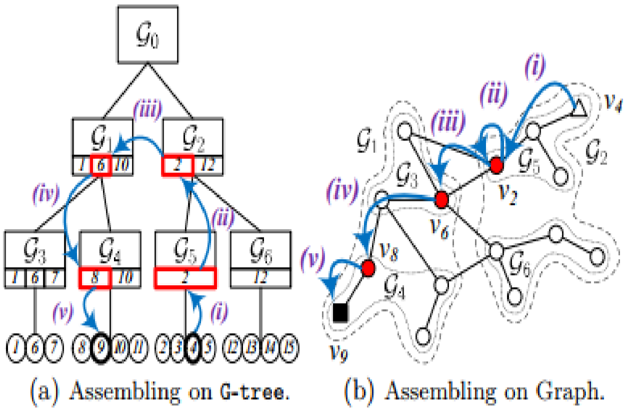


Figure 5. An Assembly-based Method.

VI. EXPERIMENTS RESULTS

We present the results of a comprehensive performance study on one real-world road networks and a small-world graph with different speed profiles, to demonstrate the effectiveness and efficiency of our algorithms. On the one hand larger fan outs will generate larger numbers of borders to partition a sub graph. On the other hand, larger fan outs will reduce the height of G-tree and the number of nodes that need to be partitioned. We divide the dataset into groups with different numbers of trajectory points, and both the clustering time and R-tree node access increase linearly as the number of trajectory points Maximum Probability Product algorithm and compare the results with the corresponding shortest paths using two example queries, and study the average performance of the algorithms.

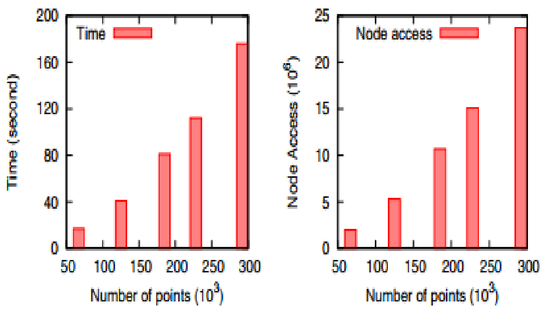


Figure 6. Performance of the Coherence Expanding Algorithm

VII. CONCLUSIONS

We propose a Coherence Expanding algorithm for mining a transfer network from trajectories and develop a reasonable popularity indicator for measuring the popularity of transfer nodes designated destination the Maximum Probability Product algorithm is presented for searching the most popular route. The authors also introduce four factor effecting function cost, distance, flow, emergency which are value added parameter to reduce traffic shortest Spath. We proposed a balanced search tree structure G-tree and devised an efficient best-first search algorithm on the basis of the assembly-based method. Experimental results show that G-tree significantly outperforms state-of-the-arts in terms of both efficiency and index sizes. Our study general framework can be easily applied to any existing social-based routing methods which use social metric per node for relay selection. Simulation results over real-life data traces demonstrate the efficiency of our proposed method.

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About Authors:

M.SANDHYA RANI is currently pursuing her MCA in MCA Department, St.Ann's College Of Engineering and Technology,Chirala, A.P. She received her Bachelor of science from ANU.

Dr. R. MURUGADOSS, MCA., M.E (CSE), Ph.D (CSE), MCSI, MISTE., is currently working Technology as a Professor in MCA Department ,St.Ann's College of Engineering & Technology College, CHIRALA-523187.

His research includes networking and data mining.