Migration Letters

Volume: 21, No: S5 (2024), pp. 523-530

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Solution For Vehicle Routing Problem (VRP) Using Travel Pattern

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Abstract

Vehicle routing problem (VRP) is a well established optimization the field of location based applications like route planning, recommendation system for transportation and logistics in supply chain etc. It deals with delivering goods and shipments located at a source location to the remote locations, with overall objective of reduction of cost of distribution. Since fifties, when it was first proposed this problem exists in many different variations like VRPPD, LIFO, VRPTW, and CVRP. Many mathematical solutions evolved since then. These algorithms assign some weight to edges of digitized road network. Weights may be dependent on other factors like shortest distance, traffic condition etc., individually or a combination of these factors. Almost all the solutions use this road network graph to compute the shortest path and then do the optimization for minimizing the distribution cost. But it's not necessary that the shortest path selected by this weighing scheme be the best path. Many factors influence the determination of the best path between any two given places. For example, security, lighting conditions, condition of the road etc. These are known by local drivers and local residents and so mostly these people drive through most optimal and best paths. We propose a framework in which spatial data mining is performed on location data captured from location devices for finding the frequently traveled paths between each pair source and destinations and are used while scheduling the vehicle trips.

Index Terms—*Data Mining, VRP, GPS, Graph, Optimization, Road Network.*

INTRODUCTION

Transportation system comes with one of the challenging problem in real world related to transportation of goods, shipments and people commonly known as routing problem. Organizations dealing with such proble[1]ms need to optimize transportation plan. Transportation will become even more important in the future with expansion of world economy [2]. Vehicle routing problem (VRP) is one important optimization fields of route planning logistics [4]. The Vehicle Routing Problem (VRP) deals with optimization problem of optimizing routes for transportation involving multiple destinations considering constraints [3].

Since fifties, when it was first proposed, this problem exists in many different variations like VRPPD, LIFO, VRPTW and CVRP etc. Solution to Vehicle Routing Problem with Pickup and Delivery (VRPPD) deals with a large number of logistics need to be transported from various source locations to multiple destinations following optimal routes with constraints. The objective is to compute optimal routes for a fleet of vehicles to pickup and drop-off locations whereas, Vehicle Routing Problem with (LIFO) solves same issue with considering additional constraint on the loading of the vehicles at source and delivery of the most recent item picked up. VRP with Time Windows (VRPTW) deals with constraint on delivery destinations have pre-defined time window for delivery. Capacitated

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Vehicle Routing Problem (CVRPTW) considers the constraint of limited capacity for carriage when scheduling delivery route [4].

Fleet of vehicles with limited capacity needs to be planned route in order to visit set of destinations at a minimum cost which is objective of Vehicle Routing Problem (VRP) [16]. All algorithmic solutions uses road Network Graph. These algorithms assign some weight to edges of Road network graph. Weights may be dependent on factors like shortest distance, traffic condition etc., individually or a combination of these factors. The solutions in the literature can be categorized as Static and Dynamic. In the static Vehicle Routing Problem, all the contributing factors are known a priori [1]. Dynamic Vehicle Routing Problems (DVRP) deals with unseen scenarios which have arisen like road blocks, water logging etc. obtained by using communication and information technologies and processed in real time. Static solutions are quick in computation but less practical in dealing with surprising situations for e.g., road blocks, while dynamic solutions are harder in computation time but are more practical in handling unseen situations. Almost all the solutions use this road network graph to compute the shortest path [18] and then do the optimization for minimizing the distribution cost. But it's not necessary that the shortest path selected by this weighing scheme be the best path. Many factors influence the determination of the best path between any two given places. For example, security, lighting conditions, condition of the road etc. These are known by local drivers and local residents and so mostly these people drive through most optimal and best paths for e.g., taxi drivers follow the best and optimized paths to maximize their income [17].

In this paper we formulate a framework which is based on spatial data mining. Proposed solution depends upon the mining of location traces received from location device installed on the vehicles. From which, frequency of paths between each source and destination is extracted [6]. Then Given a set of destinations to be scheduled, current existing TSP strategy is used but while selecting the edges to be travelled on between any two points is selected from most frequently followed path.

FINDING TRAVEL PATTERN BEHAVIOR

GPS devices log the positional information in log files. Example GPS traces stored in database is as shown in Figure 1.

Fig 1. GPS traces stored in database

Decomposing these data into smaller units of trips is known as Trip segmentation [5].

GPS devices log the continuous positional information in log files. Decomposing these data into smaller units of trips is known as Trip segmentation [5, 7]. For example a user travel log contains continuous location ordered sequence $p_1, p_2 \ldots\ldots p_1, p_{i+1} \ldots\ldots p_n$ representing user has traveled from $p_1, p_2 \ldots\ldots p_i$ and halts there for some time and then travels $p_i, p_{i+1} \ldots\ldots p_n$ then this represents two trips. One realistic scenario representing this is user travels to office in morning and end of day goes to a restaurant is two trips. Further user goes back home after dining then that will be considered as another trip. An example of trip calculated after trip segmentation is as shown in Figure 2.

Fig 2. Trip calculated after trip segmentation

MAP MATCHING

Research on Map Matching started in 90’s and today, Algorithms with high accuracy and efficiency are available. Map Matching deals mapping location traces information to digitized road network [6]. Sample road network stored in database is as shown in Figure 3.

Fig 3. Road network stored in database

Map matching is a well-established in literature which deals with locating user’s location on the road network and has many use cases in different applications which depends on moving object data like route recommendation, traffic prediction, route prediction etc. [10, 11, 12]. When user travels on a road network the GPS location captured may have some inaccuracies which may be because of various factors like error in reading obtained from satellite, hardware limitation of receiving device and in many cases error in digitization of road network. This makes difficult to locate exact position of user on road network and many a times introduces ambiguity in determination process. Map matching process make use of GPS location data and digitized road network and maps user’s exact position on road network [5, 6]. In this work, user trips represented by sequence of GPS data points are converted to sequence of road network edges using Map Matching. Fig. 8 shows GPS points in Fig 7 mapped to network and Fig. 9 edges of road network for mapped locations.

Map matching algorithms can be an offline or online process. Offline matching process finds the overall route of the vehicle after the completion of trip by user whereas the online matching process determines user exact location of user on road network in real time. In case of online matching the look-ahead are not available and the algorithm is bound to use only current and previously obtained positional data. While in earlier case look ahead is available [5]. We also adopt offline matching strategy.

Approaches for matching of location data found in literature can be categorized into three groups geometric, Topological and advanced [10]. A Geometric map matching algorithm considers only geometry of road network for mapping a given location coordinate (latitude-longitude) to edges of road network. These algorithms are unaware of topology of road edge segments and only are based on shape of road segment geometry [13, 14]. Map matching algorithms which utilizes geometry of the road segments as well as connectivity relationships of the links is known as topological map matching [14]. Advanced Map matching algorithms uses more complex logic in addition to geometrical and topological information. Some algorithms uses look ahead information, some uses fuzzy logic and some algorithms are developed for handling various kind of uncertainties.

A raw trip composed of GPS location traces is as shown in Figure 4 and resultant data when trip is mapped to road network is as shown in Figure 5.

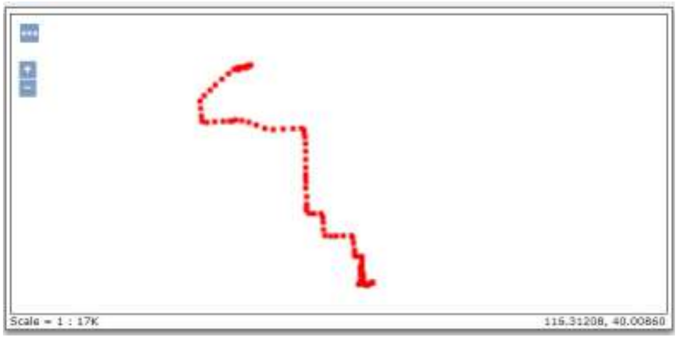

Fig 4. Trip as sequence of GPS coordinates

. Fig 5. Trip converted to sequence of network edges using map matching

FREQUENT TRAVELLED PATHS: MAP MATCHING BASED APPROACH

Each Trip is now a set of edges, and hence trip can be represented as string (composed of edge id‘s of the constituent edges). We use Leveinstein’s distance for calculating inter trip distance as opposed to approach in [8]. This approach does the exact comparison and not the approximation based. Unlike approach in [15], where the trips are expressed as strings but strings are composed of names of places and not the path followed between those places. If between two places more than one path is available, it cannot be distinguished as which path is followed between the two places. In our work the strings represents the segments of the path followed and hence it can distinguish between the different paths followed between the two places even if multiple paths are available.

Definition: Two Trips T1<ex1,ex2,……exn> and T2<ey1,ey2,……eyn> are said to be similar if
ST(T1,T2)≥ d threshold where,

$$ST(X,Y)=\max(\text{length}(X),\text{length}(Y))-LD(X,Y)$$

Where LD is Levenshtein's Distance [6].

Then frequently occurring paths occurring between each destination are stored in spatial enabled database. Given any two location pair (nodes on the graph of Road network source's' and destination 'd') the frequently traveled edges can be retrieved by firing SQL in the trip database. For example,

SELECT trip_{id} COUNT(trip_{id})FROM trip_table
WHERE source='s' and Destination='d'
GROUP BY trip_{id} ORDER BY trip_{id}

One example trips with frequency can be as shown in Table 1.

Id	Trip	Frequency
1	d_1, d_2, d_3, d_4, d_1	1110k
2	d_1, d_2, d_4, d_3, d_1	350k
3	d_1, d_3, d_2, d_4, d_1	750k
4	d_1, d_3, d_4, d_2, d_1	900k
5	d_1, d_4, d_2, d_3, d_1	1200k
6	d_1, d_4, d_3, d_2, d_1	100k

Table 1. Trips with frequency of traversal

FREQUENTLY TRAVELLED PATHS BASED SOLUTION TO VEHICLE ROUTING PROBLEM (VRP)

Given is the set of destinations to be visited $d_1, d_2 \ldots . d_n$ find the optimized travel order for the vehicle. Approach now is to select between each pair of location points the set of edges and their combined length. For example to find the cost of traveling between d_1 and d_2, first SQL needs to be fired is:

SELECT trip_{id} , SUM ($\text{edge}_{\text{costs}}$in trip))
FROM trip_table WHERE source= d_1 and Destination= d_2
GROUP BY trip_{id}
ORDER BY trip_{id}

Output is the set of edge ids of the frequently traveled paths $e_1, e_2 \ldots . e_k$
Cost of Path between the $d_1, d_2$is calculated as

$$= \sum_{i=1}^{n} d_i$$

d_i is the weight of e_1 in standard solutions.

In this way, for all of locations a combined weight matrix is obtained. For example, if four locations are to be covered d_1, d_2, d_3, d_4 corresponding resultant matrix obtained can be as in Table 2.

	d_1	d_2	d_3	d_4
d_1	0	2	5	7
d_2	2	0	8	3
d_3	5	8	0	1

d_4	7	3	1	0

Table 2: Weight matrix for VRP

The traveling salesman problem (TSP) is all about finding the shortest tour through number of destinations. For this instance of TSP, exhaustive search is applied to generate all combinations of routes for a source and destination for a problem [9].

Id	Trip	Cost	Frequency
1	d_1, d_2, d_3, d_4, d_1	18	1110k
2	d_1, d_2, d_4, d_3, d_1	11	350k
3	d_1, d_3, d_2, d_4, d_1	23	750k
4	d_1, d_3, d_4, d_2, d_1	11	900k
5	d_1, d_4, d_2, d_3, d_1	23	1200k
6	d_1, d_4, d_3, d_2, d_1	23	100k

A threshold is defined for cutoff of the routes for minimum number of frequency is required. In this example if threshold is set to 500k then Trip with Ids 2 and 6 are removed. From remaining candidates Trip with Id 4 has the minimum cost and hence is the recommended route for VRP.

IMPLEMENTATION

Proposed framework has two phases, in first phase give an source and all required destinations to be covered. It requires road network data in digital form. Road network data is sourced from Open Street Map (OSM). OSM is open platform from where digital data like road network, land usage, water bodies, national and international boundaries can be downloaded. In this work road network data from India and China is used. Data is stored in geo-Spatial enabled data relation base. For this purpose Postgres database with PostGis data layer enabled for handling geometrical data types. Road network data is preprocessed in Sql format and imported in data base. On this road network data shortest path algorithm is run to calculate the distances between source and destinations. Second phase is to construct travel pattern model. It requires Road network data and historical travel data. Road network data is same which is used in previous phase. Figure 6 shows a sample road network data stored in database.

Historical location traces are sequence of GPS traces collected from users. This data for evaluation is sourced from Microsoft's Geolife Project [19, 20, 21]. This corpus has millions of historical GPS data collected over time and released for research purpose. Location traces are decomposed in smaller units and stored in PostGis database which was used for storage of road network data as well. Figure 7 shows sample GPS data sourced and loaded in database. All implementation is done on real datasets.

Fig 6. Sample road network

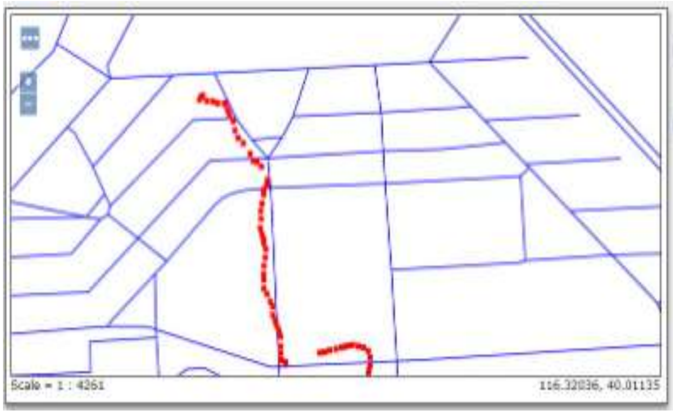

Fig 7. Shows sample GPS data

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