Personalized Trajectory Reconstruction Problem with Low-Sampling Data

Edison Ospina, Francisco Moreno
Departamento de Ciencias de la Computación y la Decisión
Universidad Nacional de Colombia. Facultad de Minas.
Medellin, Colombia
e-mail: ecospinaa@unal.edu.co; fjmoreno@unal.edu.co

***Abstract*—A huge amount of trajectory data can be derived from GPS equipped devices and location based services. However, the trajectory data are low-sampled (i.e., have a low and irregular sampling rate). In this paper, the problem of Personalized Route/Trajectory Reconstruction is reviewed when low-sampling data are considered or user criteria are incorporated in the reconstruction. Research work in route planning systems and the most used routing algorithms are also analyzed in order to suggest research directions that include the level of personalization or uncertainty management as a way to predict/complete a low-sampling trajectory.**

Keywords-Personalized Route Planning Systems; Location-Based Services; Trajectory Reconstruction; Uncertainty.

I. INTRODUCTION

Being able to choose the most convenient route to travel from one place to another is a desirable possibility when planning activities. For example, tourists usually ask for the best routes for visiting attractive places. Fields such as logistic, traffic control, and advertising also demand solutions in this regard in order to meet a variety of requirements, such as quality of road, cost of fuel, route availability, and user preferences, among others [1][2][3]. Several authors have recently been focused on the incorporation of user preferences and multi-criteria decision making aspects in light of the route personalization [3]. Other approaches have used GPS data representing historical movements of users based on individual [5] or collective behavior [6]. The resulting routes are usually closer to the typical ones actually followed by users than those suggested by route planners as optimal (the shortest and fastest) [7][8].

According to the literature reviewed, the terms *Route Finding Problem* and *Path Finding Problem* are used interchangeably. Other term related to the Route Finding Problem (RFP) is *Routing* (or Route) *Planning Systems* (RPS). The request for a route to travel from one place to another in the RFP is considered the pair for finding a trajectory between low-sampled points. Therefore, the reviewed research works are analyzed in relation to the RFP, paying special attention to those taking into account *user criteria* or *low-sampling-rate data* (i.e., when the time interval between consecutive GPS points of some trajectories is higher than a given threshold) [1]. When low-sampling-rate data is present, the reconstruction of trajectories may be needed, i.e., the description of the movement of the object between the two points where no data points are available to know where the object is while travelling.

The rest of this paper is organized as follows: Section II describes routing planning systems; Section III describes personalization, i.e., incorporation of user preference criteria as a way to deal with the trajectory reconstruction problem; Section IV addresses the reconstruction of trajectories under low-sampling-rate data, and Section V concludes the paper and proposes future work.

II. ROUTING PLANNING SYSTEMS

RPS are commonly recognized as decision support systems [9][10]. These systems sometimes are referred to as geo-related decision support tools [10]. In Table I, some variations of the term referring to RPS are presented. Conventional solutions to RFP are limited because the routing is based on just one dimension (criterion): the cost [11][12][13]. Many definitions include, explicitly or implicitly, the notion of personalization, suggesting that user interaction is required. Recent researches have been carried out to improve these models through their personalization and the incorporation of multi-criteria decision making including preference models [3][4].

TABLE I. COMMON TERMS REFERRING TO ROUTING PLANNING SYSTEMS.

Author	Term	Comment
[4]	Routing systems	Routing systems aim to help users on finding the optimal path to their destination regarding travel distance, travel time, among other criteria.
[10]	Personalized user-centric route finding	A personalized user-centric route finding application incorporates user preferences and the environmental features around a user. User preferences and environmental features are the key elements to assess a route.
[3]	Personalized route planning systems	A personalized route planning system provides a route based on minimizing a combination of user defined criteria such as travel distance, travel time, the number of traffic lights, and road types.
[11]	Route guidance systems	Route guidance systems refer to all the factors considered before and during a trip to choose or adjust a route. Route guidance systems are recognized as a fundamental component of intelligent transportation systems.

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A brief schema review of the RFP in RPS is shown in Figure 1. The RPS are supported by *Routing Planning Algorithms*. When the personalization is included, incorporating preferences or decision strategies originates the concept of *Personalized Routing Planning Systems*.

The classical algorithm for RFP based on the shortest path issue was proposed by Dijkstra [14] and it has been used widely to find the shortest path between an origin vertex and a destination vertex in a weighted graph, exploring the entire graph to determine the lowest cost route. Similarly, the A* algorithm (a modification of Dijkstra's algorithm) finds the optimal path using an appropriate heuristic that defines which is the best node to be visited next (it avoids explore the entire graph) based in the lowest heuristic cost [15], e.g., some of the Minkowski metrics [16]. All of these early approaches are based on algorithms that use an *edge cost*, i.e., they performed a one-dimensional analysis. For this reason, these algorithms are inadequate or incomplete since users generally have different purposes and they do not share the same movement behavior, highlighting the need to *personalize* and allow the user to interact with RPS.

III. PERSONALIZATION

The technology-based definition of personalization provided by the Personalization Consortium (2005) is "the use of the technology and customer information to tailor electronic commerce interactions between a business and each individual customer". An experiment conducted by Golledge [17] showed that the criteria used by humans to deal with path selection problems may be a complex task that covers a wide spectrum of choices. The routes were determined using criteria selection such as shortest distance and fewest turns. Variables such as orientation and the possibility of retracing the route (i.e., interchange the origin and the destination) were also studied to determine the change of the user route criteria selection when traveling in one direction or the other. To illustrate the above problem, two possible routes between an origin O and a destination D are shown in Figure 2. The route O-C-D is usually suggested by common RPS without considering the probability of a traffic jam or local restrictions for moving between streets.

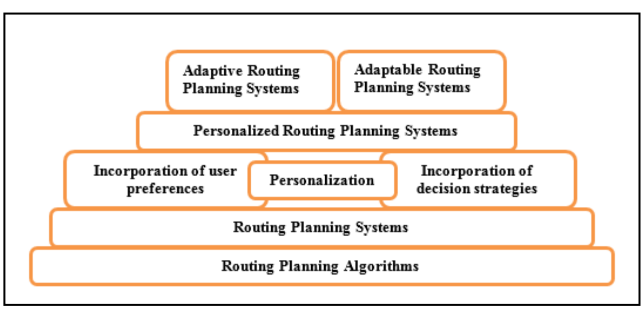

Figure 1. Schema review of the RFP according to personalization in RPS.

However, most users would select the route O-A-B-D even though path O-C-D has the minimum distance, because more points of interest (POI) can be found along it (supermarkets, parks, or gasoline stations). This is evidenced by Duckham and Kulik [18], showing how a *simple path* solution offers considerable advantages over shortest paths in terms of ease of description and execution. Several researchers have stated the importance of the personalization when solving routing planning tasks [3][5][9].

The goal of personalization is the automatic adaptation of an information service in response to the *implicit* or *explicit* needs of a specific user [9]. That is, the automatic identification of preferences from the user movement behavior history [7][8] or explicit requests of the user [3][10]. Also, Fischer [19] stated that personalization can be described by *adaptable* and *adaptive* methods, and Oppermann [20] gives the following definition to those terms: in adaptable systems the user controls the adaptation process whereas in adaptive systems the process is automatic, i.e., without user intervention. Nadi and Delavar [3] define adaptable and adaptive personalized route guidance systems in the context of RPS. Examples of adaptable [3][10] and adaptive [21][22] RPS can be widely found in the literature.

In [13], static and dynamic systems, deterministic and stochastic systems, reactive and predictive systems, and centralized and decentralized systems are distinguished. In [11], descriptive and prescriptive guidance and static and dynamic guidance are reviewed. In [12], route guidance systems are classified as infrastructure-based and infrastructure-less systems. Infrastructure-based systems are based on two components: i) hardware devices deployed in streets/roads and ii) computer systems installed in moving objects (e.g., a GPS). Infrastructure-less systems require only the second component. Personalization can also be defined in terms of user route choice criteria.

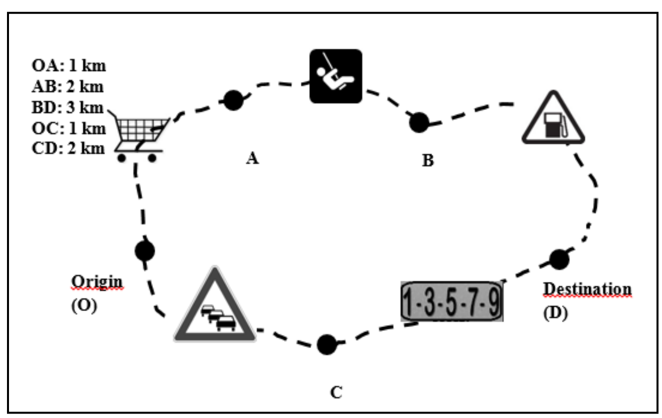

Figure 2. Problem of route finding in a road network.

A special issue of the personalization in RPS is the characterization and incorporation of several criteria, e.g., route length or travel time. Table II shows some of them classified as quantitative (they are measured from a map or any other source) and qualitative (they are no-numeric criteria that are ranked according to the impact on the user). Previous research [3][4][23] found that route selection criteria can be grouped into four general criteria: speed (time, distance), safeness, simplicity, and attractiveness (POIs-based scenic path):

A. Speed: Distance

Distance is normally considered the most important criterion for route choosing. Even without route planning systems, the path with the shortest distance is intuitively chosen with a minimum previous knowledge of the RN structure (however, the presence of known POIs may lengthen the road trip. See *attractiveness*).

B. Speed: Time

Time is a variable that depends of several factors such as length (time is directly proportional to the length of road), average speed (higher in main avenues than in small streets), quality of roads, and weather conditions (e.g. when it rains, travel time is higher due to traffic conditions derived from it) or quality of traffic as described in [4].

C. Safeness

It groups a series of criteria based on characteristics (bike lane availability, area safeness, night lighting, traffic level), possibilities (lack of busy intersections, public transport, and roundabouts), and features of the road (presence or lack of pavement, slope angle) [23].

D. Simplicity

The simplest path is based on the idea that the turns imply reductions of velocity and unnecessary maneuvers. Thus, the path is "better" if it has fewer turns [4]. Moreover, the description of the path is easier when a simplest path approach is followed, as the explanation, depiction, understanding, memorizing, and/or execution of it [18], which is useful for users who are navigating through an unfamiliar geographic environment.

TABLE II. QUANTITATIVE AND QUALITATIVE CRITERIA OF RFP.

Author	Criteria	Quantitative	Qualitative
[3][4]	Distance, Travel Time	x	
[4][8][23]	Traffic	x	
[3][4][18]	Costs of Turns/ Simplest Paths	x	
[24][25]	Number of Scenic Landscapes / POIs	x	
[3]	Number of Junctions, Travel Reliability, Directness, Road Width, Number of Stop Signs	x	
[3]	Quality of Road, Type of Road		x

E. Attractiveness

Variables such as distance, time, or turns are common route criteria for navigating a street network, but computation of the most scenic route is a special issue [26]. The scenic-path notion is defined from the touristic perspective. The main idea is to travel from A to B trying to visit as much touristic places as possible and minimizing route length at the same time. The cost is the number of touristic attractions between the two points (for instance, the streets with a considerable number of POIs have the lowest cost). A modification of the cost is required before the execution of a shortest path algorithm if the goal is to find a route that traverses as much POIs as possible and, at the same time, the shortest route between two POIs.

Figure 3 exhibits a section of Guarne, a small town in Colombia, with a route between two points using the shortest path algorithm. Figure 3(a) shows the minimum distance between point A and B. Figure 3(b) shows the route with the minimum travel time between point A and point B. Figure 3(c) shows the route between the two points using the simplest path approach. The turns in the path are less in the latter, even though the whole path may be longer. Figure 3(d) shows the route using the scenic path approach: the route is draw along the street nearest to the town river where touristic attractions are present (restaurants, beach games, etc.).

Figure 3 shows how a path may vary when different criteria are considered. Users not always choose the shortest route. This set of exercises provides evidence that route selection is a process that requires support of decision strategies and preference models to back personalization.

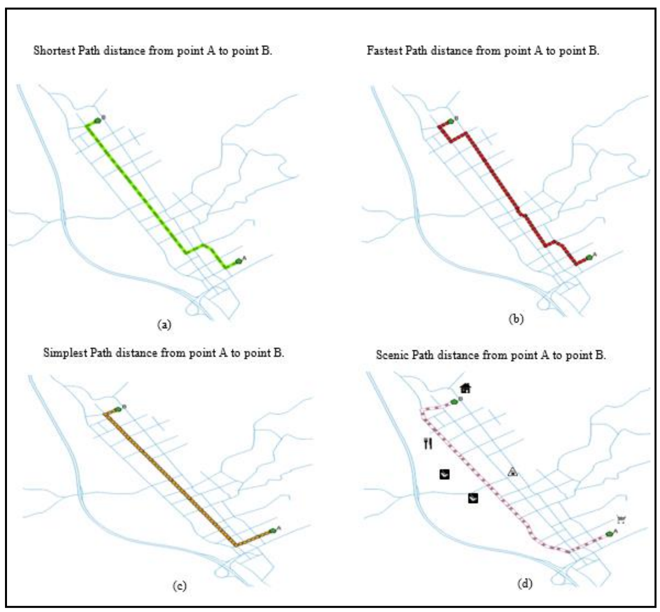

Figure 3. Different route finding criteria from point A to point B.

IV. Personalized Route Finding Based on Trajectories

The RFP reviewed here is the reconstruction of low-sampling trajectories. To solve this problem, pattern-based and greedy searches approaches has been considered (Preference-based Greedy search, NaïVe Greedy search, Pattern+Greedy search) [27]. Pattern-based approaches allow *offline* processing of historical trajectory data to discover mining patterns and infer routing information [1], while greedy search approaches make optimal local choices at every decision stage, providing a dynamic/*online* recommendation on the best immediate location to be visited [27]. Most of these procedures deal with a general mining/prediction problem over historical trajectories [6][8][27][28]. In the reviewed works, the personalization is based on the trajectory history data of a particular user.

A. *Route Planning based on GPS trajectories*

In [29], the problem of searching the *k-Best Connected Trajectories* (*k*-BCT) is addressed. A small set of locations (queried points) is given as an input to an incremental k-NN (K-Nearest Neighbor) based algorithm, which progressively retrieves trajectories nearest to each location, using best-first and depth-first k-NN algorithms. The quality of the connection between locations provided by the discovered trajectories is given by a similarity measure. A dataset of Beijing collected by the Microsoft GeoLife Project was used to analyze the efficiency of the KNN algorithm, showing a better search performance if the best-first k-NN algorithm is chosen. In [6], the problem of discovering the *most popular* route between two given locations using historical user trajectories is addressed. A *Coherence Expanding Algorithm* is proposed for mining users movements together with a popularity indicator. Then, an algorithm for searching the most popular route given two locations is applied. Considering 276 truck trajectories used in Athens and applying the proposed algorithm, the most popular routes were identified. Then, these findings were compared against those obtained with the shortest path approach. In [5], a *Pattern-aware Personalized routing framework* (PPT) is proposed using a two-step method to compute personalized routes. First, a set of frequent road segments is derived from a user historical trajectories database to construct a familiar RN followed by a specific user. Then, while a route is computed between a specific source and a destination, a second algorithm is proposed to discover the top-k personalized routes connecting some of the segments that a user has previously traveled. The algorithms were tested using a real trajectory dataset from one user in Kaohsiung, Taiwan. The algorithms derived the top-k personalized routes that approximate the real top-k personalized routes. In [8], smart driving directions are mined from taxi drivers' experience. A routing algorithm is proposed to provide the fastest route from a given origin to a given destination. Thus, a time-dependent graph is built where nodes are recognized as landmarks, i.e., road segments traversed by a significant number of taxis and edges represent taxi routes between landmark roads. This demonstrates that about 16% of time can be saved with this method compared to speed-constraint and real time traffic-based methods. In [7], fast routes are mined from taxi traces and are customized for a particular driver behavior. A mobile device learns about the user driving behavior thanks to the user driving routes and finds the fastest route. This model outperforms the previous work [8]. In [27], the construction of a preferred route using location check-in data are done based in the popularity of a certain route and the preferences ranked by a set of users. The goal is to build a trajectory where the reconstruction meets the preferred locations to be visited by a *group of persons* using Gowalla check-in data and a Pattern+Greedy method (this combination of Pattern and Greedy route search outperforms both methods when used separately). Similarly, in [28], the top-k Trajectories are extracted from interesting regions with higher scores (attractiveness) mined from historical GPS trajectories. A framework for trajectory search called Pattern-Aware Trajectory Search (PATS) is developed, which includes an off-line pattern discovery module and an online pattern-aware trajectory search module. This framework only searches for the top-k maximal trajectories with higher scores according to the number of interesting regions and does not infer new routes.

B. *Uncertainty in Trajectories*

When a trajectory is reconstructed, its uncertainty should be considered. Uncertainty from different sources is evidenced by Kuijpers and Moelans [30]: i) Accuracy of the GPS observation and ii) the uncertainty derived from low sampled points of a trajectory. Those are also referred as measurement and sampling errors [31]. Previous works [5][6][8][29] relied on high-sampled trajectories; however, the effectiveness of inferred routes is poor due to its inadequate management of low-sampling trajectories where uncertainty is reflected. The causes for *low-sampling* trajectories include the lack of users sharing their position or taking geo-tagged photos from every place and every second. This is due to the privacy concerns publishing personal location data to potentially untrustworthy service providers may pose [32]. Research works has been carried out to preserve publishing data of a moving object to a third party for data analysis purposes [33][34]. Privacy-preserving techniques has been studied based on false location [35], space transformations [36], or spatial cloaking [37]. However, those works are not aimed to reduce low-sampling directly. Instead, they provide privacy-preserving techniques to promote location, sharing information.

The main features of the trajectories regarding to uncertainty are highlighted in [38]:

1) *Spatial Biases:* The locations of data points in two trajectories are different, i.e., two similar trajectories can be depicted by means of different location data points.

2) *Temporal Biases:* The occurrence time of two trajectories are different, i.e., two similar trajectories visiting the same POIs could be done in two different time periods.

3) *Silent Durations:* The time periods when no data points are available to describe the movements of the users.

Relevant data are missing during silent durations. User movement criteria can fulfill partially those silent durations. For the best of our knowledge, the low-sampling-rate trajectory reconstruction problem has not considered the user preferences. We strongly believe this is a rich research area with application in several domains. For example, for location-based advertising, it might mean the possibility of advertising strategies based on data about routes followed by users from a POI A to a POI B.

Several studies [27][39][40] infer routes from a sequence of POIs but a detailed route between two consecutive POIs is not specified. The underlying assumptions of these works are that the user movement is free. However, the infrastructure, e.g., buildings, may be considered to obtain a reduced overall uncertainty and inaccuracy in the data. In [2], a Route Inference framework based on Collective Knowledge (RICK) is developed. Given a set of locations and a time span, a two-step method is followed: first, a "routable graph" is built and, then, the top-k routes according to the route inference algorithm are constructed. Two real dataset are used: registers of Foursquare check-in application used in Manhattan and trajectories used in Beijing. The aim is to demonstrate the effectiveness and efficiency of RICK. In [1], the problem of reducing uncertainty for a given low-sampling-rate trajectory is addressed. Historical data are used to discover popular routes as an estimation of low-sampling trajectories. A real trajectory dataset generated by taxis in Beijing in a period of three months is used to validate the effectiveness of their proposal and shows higher accuracy than the existing map matching [41].

V. CONCLUSIONS AND FUTURE WORK

The trajectory reconstruction problem is still an open research issue, especially what is related to uncertainty due to low-sampling data and incorporation of user preferences. Simple linear interpolation, as a method of reconstruction, does not represent users real movement because they move according to a certain criteria such as time or the amount of touristic/scenic places. Indeed, the reconstruction of trajectories using user preferences is expressed as a need in recent research works [38][42]. As far as we know, there are no works that involve several criteria as a way to reconstruct low-sampling trajectories. This approach can be enhanced by the restriction of the movement in a RN [43] and methods to predict the location of moving objects in a RN [44]. Moreover, the current availability of GPS loggers gathered from mobile devices are useful in a variety of ways to make driving better [45], but effective usage of the huge amount of data is still a challenge [46]. Considering the different possibilities of user criteria reconstruction of trajectory and the huge amount of low-sampling data, data analysis tasks related to these possibilities of reconstruction can be conducted. Therefore, analytic results over reconstructed trajectories can vary if different criteria of reconstruction are used. For example, if a trajectory is reconstructed based on the criterion of minimize turns, the main avenues might be interesting for analysis tasks because those are the longest without deviations, but if the amount of POIs are used as a criterion of reconstruction, then the avenues nearest to tourist attractions might be the interesting ones.

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