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Automatic intersection and traffic rule detection by mining motor-vehicle GPS trajectories

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ABSTRACT

The generation of road networks from ubiquitous motor-vehicle GPS trajectories has recently gained wide interest. However, few attempts have been made to automatically extract road network properties such as intersections and traffic rules to facilitate the production of high-quality routable maps. For urban street networks, the vehicle trajectory logged by a GPS receiver tends to be straight on streets and curved at intersections although the local deviation exists due to vehicle paths deviating from road centrelines and GPS positioning errors. This paper uses large curved trajectories at traffic intersections and presents novel algorithms for automatically detecting road intersections and traffic rules. Two inherent issues related to GPS trajectories have been resolved using the proposed approach. First, the serious fluctuations of vehicle trajectories due to multipath reflectivity from high-rise buildings have been eliminated, thereby enabling the effective detection of real curved trajectories occurring at traffic intersections. Second, the heterogeneity of traffic density has been considered when using the curved trajectories to automatically detect road intersections. The proposed algorithm was implemented using open-source software libraries and tested using large taxi trajectories collected in Suzhou City, China. A total of 285 at-grade intersections were detected automatically, and dynamic traffic rules were elucidated for each intersection. Compared with the manually interpreted results, the detection results were high quality and provided detailed information for the construction of a routable map.

1. Introduction

Digital road maps include the location and traffic rules, which are clearly important for both consumers and businesses. At present, remote sensing interpretations may be used to obtain the locations of road maps but cannot capture traffic rules as an instantaneous imaging method. The commercial maps are created by companies fielding fleets of specialized vehicles equipped with high precision GPS to drive the roads and record data, and the difficult is to obtain the traffic rules by approaching each turning path, e.g. 12 turning paths for a crossing. These processes are expensive, time-costly, and not up-to-date. An emerging alternative is to use GPS data from regular vehicles driving their regular routes for map generation.

Public vehicles are extensively equipped with single-frequency global positioning system (GPS) data loggers for location tracking at regular intervals. The tracking data can be treated as low-cost sensors to probe the dynamics of city traffic status with all day and full coverage. Comparing to remote sensing interpretation and cartographic, it reduces production cost and enhances the present situation to build a high-quality road network based on GPS trajectories. The challenge is to detect the location and traffic rules of intersection traversed by the vehicles from the time-series trajectories.

In a routable network, intersections are essential junctions that connect different roadways. Algorithms for generating intersections from vehicle trajectories can be grouped into two basic types. One type directly extracts intersections using either the geometric characteristics of trajectories at intersections or the spatial relationships between multiple trajectories at intersections. For example, Fathi and Krumm (2010) identified intersections for the first time using an advanced shape descriptor to analyse the specific patterns of the heading changes in tracking points. Lassarre, Bonnet, Bodin, et al. (2012) obtained the locations of crossings by intersecting two pedestrian trips. Wu, Zhu, Tao, and Wang (2013) sought converging points to recognise the locations of dense turning points as intersections. Wang et al. (2015) detected intersections by analysing the densities of large-angle intersection points among neighbouring vehicle trajectories. Zhou, Fang, Thill, Li, and Li (2015) characterized the intersection features of an urban transportation network with good connectivity, a high density of trajectories and multiple traversing trajectory patterns to detect intersection locations. The other type of algorithm detects roadways from trajectories and

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produces intersections by simply connecting these roadways. For example, the typical incremental method for generating road maps developed by Bruntrup, Edelkamp, Jabbar, and Scholz (2005) and Li, Qin, Xie, and Zhao (2012) added a single trajectory to a graph by considering the relationship between the input points from the trajectory and the existing graph and by determining whether a new node and edge must be created. Clustering trajectories to generate road centrelines is another important approach (Edelkamp & Schrödl, 2003; Yanagisawa, Akahani, & Satoh, 2003; Schroedl, Wagstaff, Rogers, Langley, & Wilson, 2004; Hwang, Kang, & Li, 2005; Liu, Zhu, Wang, et al., 2012). Centrelines are computed by spatially clustering nearby trajectories, and intersections are recognised as the locations where centrelines meet.

Most of the above algorithms treat intersections as points at which roadways are connected, and the connectivity that guides approaching vehicles is not specified explicitly. However, an intersection represents a compact junction for which a set of turning paths and forbidden turning times are fundamental for the schedule of approaching vehicles. Even to adapt to changes in urban traffic flow, the layout of turning paths and traffic rules at intersections may be adjusted dynamically, i.e., left turn banned from during rush hour. So these approaches are insufficient for meeting the requirements of the generation of a high-quality routable road map for an intelligent transportation system. To provide detailed information regarding the structure and traffic rules of intersections for more efficient or optimal routing, this paper developed a comprehensive approach focusing on the detection of both locations and turning paths, including the forbidden turning time, of intersections using a large number of vehicle GPS trajectories.

2. Methods

An intersection is a road junction where two or more roadways either meet or cross. Various road markings, traffic lights and traffic signs schedule the approaches of vehicles to the intersection at appropriate speeds and prevent vehicle crashes. In this study, we propose modelling intersections as simple circular areas in which the structure and traffic rules are illustrated as follows.

Fig. 1a is an intersection diagram to allow for a visual understanding of our approach. To provide clear navigation information for routing, the intersection is represented as a network graph (Fig. 1b). In such a model, the location of an intersection and its traffic rules can be easily modelled by considering the spatio-temporal characteristics of the vehicle GPS trajectories near the intersection using the following scheme.

Considering that intersections are strongly correlated to the curved parts of vehicle GPS trajectories (henceforth referred to as *turns*), it can be assumed that *turns* generally occur at intersections rather than on roadways. Based on this assumption, a comprehensive approach for detecting intersections and extracting traffic rules was developed, as shown in Fig. 2, where three essential steps are illustrated. First, a density grid of *turns* is generated. The value of a cell represents the number of *turns* passing over the cell. Next, the locations and extensions of the intersections are detected using density analysis. Finally, the traffic rules of the intersections are determined by clustering the time series dataset of the tracking points.

2.1. Density grid generation

2.1.1. Extracting turns from trajectories

Cities generally have gridiron street plans; that is, the roads in cities are often straight and intersect at right angles. Observed vehicle GPS trajectories consist of the actual vehicle path and the local deviation that results from GPS positioning errors. Although vehicle paths are generally straight on streets and curved at intersections, *turns* occasionally occur in roadways. The local deviation is randomly distributed around the positioned points on the path due to multipath reflectivity effects.

We propose a specific heading-difference analysis method for extracting *turns* from GPS trajectories as follows. Based on the above understanding of GPS trajectories, the changes of the headings of tracking points have two components: a high frequency portion from the ubiquitous impacts of multipath reflectivity and a low frequency portion from vehicles turning at intersections.

We established a linear reference system along a trajectory, in which the *x*-axis is the linear distance from the starting point and the *y*-axis is the heading of the tracking point along the trajectory. As shown by the blue line in Fig. 3, the headings of the tracing points fluctuate largely. A distance-weighted average heading filter was proposed to remove high frequencies and keep only the changes of headings caused by turning behaviours. The smoothed heading ($\overline{h_i}$) was calculated as follows:

$$\bar{h_i} = \sum h_k w_k, \qquad k \in set(V) \tag{1}$$

$$h_k = f(P_{k-1}, P_{k+1}) \tag{2}$$

$$w_k = \frac{d_{k-1,k} + d_{k,k+1}}{2}, \qquad d_{k-1,k} = |P_k - P_{k-1}| \tag{3}$$

where $\overline{h_i}$ is the weighted average of the heading at point *i*, *V* is a point set in the window centred at point *i*, the heading h_k at point *k* is determined by two neighbour points $k-1$ and $k+1$, w_k is the weight, and $d_{k-1,k}$is the distance between points $k-1$ and *k*.

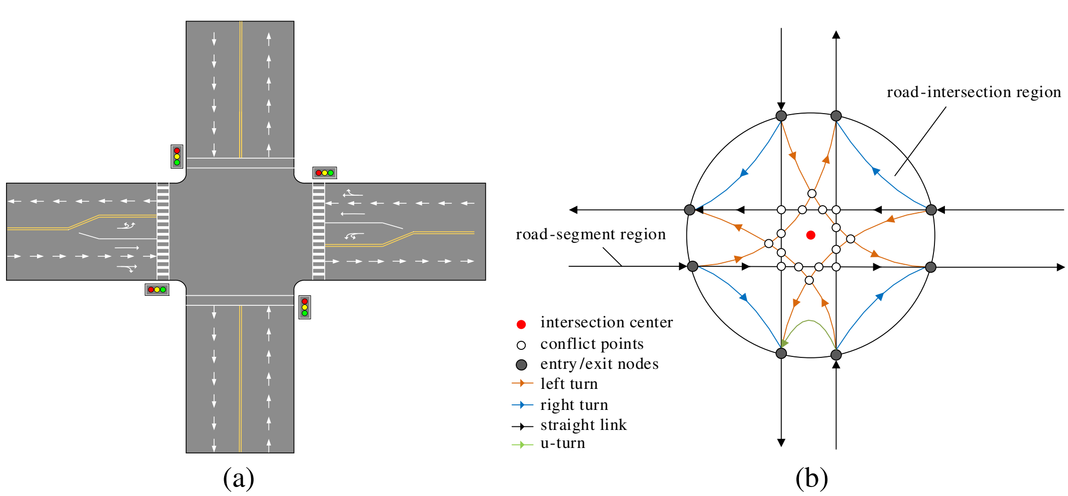

Fig. 1. The structure and turning paths of an intersection. (a) Diagram of an at-grade intersection, (b) Simplified intersection model.