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Generating lane-based intersection maps from crowdsourcing big trace data

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ABSTRACT

Lane-based road information plays a critical role in transportation systems, a lane-based intersection map is the most important component in a detailed road map of the transportation infrastructure. Researchers have developed various algorithms to detect the spatial layout of intersections based on sensor data such as high-definition images/videos, laser point cloud data, and GPS traces, which can recognize intersections and road segments; however, most approaches do not automatically generate Lane-based Intersection Maps (LIMs). The objective of our study is to generate LIMs automatically from crowdsourced big trace data using a multi-hierarchy feature extraction strategy. The LIM automatic generation method proposed in this paper consists of the initial recognition of road intersections, intersection layout detection, and lane-based intersection map-generation. The initial recognition process identifies intersection and non-intersection areas using spatial clustering algorithms based on the similarity of angle and distance. The intersection layout is composed of exit and entry points, obtained by combining trajectory integration algorithms and turn rules at road intersections. The LIM generation step is finally derived from the intersection layout detection results and lane-based road information, based on geometric matching algorithms. The effectiveness of our proposed LIM generation method is demonstrated using crowdsourced vehicle traces. Additional comparisons and analysis are also conducted to confirm recognition results. Experiments show that the proposed method saves time and facilitates LIM refinement from crowdsourced traces more efficiently than methods based on other types of sensor data.

1. Introduction

A road intersection is an area shared by two or more roads where vehicles turn in different directions to reach their desired destination. Traffic intersections are complex locations on any road since vehicles moving in different directions might need to occupy same space at the same time. Moreover, pedestrians also seek to use the same space when crossing streets or roads. Drivers have to make split second decisions at road intersections, considering their routes, intersection geometry, speed, and the behaviors of other vehicles. Even a small error in judgment can cause a severe accident. To ensure the safety of drivers and pedestrians in the urban environment, the research on emerging technologies in the field of transportation is one of the hot issues at present (Zhang et al., 2011; Zhou et al., 2017; Hacohen et al., 2018). A wide variety of driving applications based on the digital detailed map have been developed to navigate mobile robot cars across complex urban roads in safety. Therefore, a detailed map with LIM is an essential

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foundation for robotic vehicles to understand the situation, comply with traffic rules and achieve high system reliability (Pinto, 2012).

Generating detailed and comprehensive maps is labor intensive and time-consuming. At present, detailed map with LIM generated by companies fielding fleets of specialized vehicles equipped with GPS, spinning laser sensors and cameras driving roads and recording data (Watzenig et al., 2016). Google built and updated a detailed map manually employing human analysts. Their mapping team categorized interesting features on roads, such as driveways, fire hydrants, and road intersections from the data collected by sensors on their self-driving car (Timothy, 2016). The HERE company mapping car nicknamed “George” collects data to build up an extremely detailed, high definition map (Kent, 2015). The mapping firm, TomTom, captures a depth map using an onboard vehicular LIDAR system. This system continuously records the distinctive shapes and distances of roadside scenery, without trying to identify individual objects. These mapping firms have obtained detailed maps of areas using professional mapping vehicles; however, these methods are expensive, time-consuming, and labor-intensive.

In contrast to these sensor data collected by professional mapping vehicles, crowdsourced vehicle trace data are acquired by soliciting contributions from a large group of volunteers, and are a low-cost and efficient way to extract useful information (Kasemsuppakorn et al., 2013; Patire et al., 2015; Tang et al., 2016; Hong et al., 2017; Dabiri and Heaslip, 2018). Volunteered Geographic Information plays an increasingly important role in urban geography studies such as the analysis of city dynamics (Ben-Akiva et al., 2012; Castro et al., 2013; Hiribarren et al., 2014; Liu and Qu, 2016), mobile individual behaviors (Phithakkitnukoon et al., 2010; Calabrese et al., 2013; Fard et al., 2017; Cerni et al., 2017), and urban hot-spot detection (Chang et al., 2009). At the same time, the rapid update of crowdsourced data keeps the information mining results as fresh as possible.

The objective of our research is to automatically generate LIM from crowdsourced big trace data using a multi-hierarchy strategy and detailed data mining techniques. A LIM provides lane and intersection data essential to detailed map generation. It describes the connectivity at the lane-level between the spatial layout of intersections and the lane-based road information about road segments and can be used as fundamental data in route guidance models for self-driving vehicles and other intelligent transportation system (ITS) applications. To generate LIMs from crowdsourced vehicle traces, a multi-hierarchy feature extraction strategy is applied. The multi-hierarchy feature extraction strategy for a LIM automatic generation system includes three processes: road intersection initial recognition, intersection layout detection, and lane-based intersection map-generation. The initial recognition process includes intersection and non-intersection identification using spatial clustering algorithms, based on angle and distance constraints. An intersection layout is composed of exit and entry points obtained using trajectory integration algorithms based on an initial recognition layer and the rules for turns at road intersections. Lane-based intersection map-generation is derived from the intersection layout construction layer and lane-based road information based on geometric matching algorithms and turn rules constraints.

In the next section, we briefly discuss the intersection recognition and enhanced intersection map generation approaches found in the existing literature. Section 3 demonstrates our proposed LIM automatic generation method. In Section 4, we evaluate the effectiveness of the proposed methods and make comparisons with other methods for the same problem and discuss the accuracy and performance of the existing and proposed methods. Section 5 concludes the article and discusses future work on problems in detailed map generation.

2. Literature review

Road intersections consist of several functional areas used for making turns, and when integrated through intelligent design, allow roadways to cross at different levels or directions with complex access rules to prevent traffic collisions. Information on these intersections is often difficult to extract but vital when creating accurate, routable road maps. Approaches that detect road intersections from sensor data including high-resolution remote sensing images, laser point cloud data, GPS traces, and high-definition video are being continuously developed. This section starts with a brief review of road intersection recognition methods using various sensor data such as high-resolution remote sensing images, laser point clouds data, and high-definition videos. Road intersection detection using GPS traces is introduced in detail and their associated limitations are analyzed.

The methods of road intersection detection from images such as high-resolution remote sensing, videos, or raster road maps include two categories. The first recognizes road intersection by matching image road boundary data with prior knowledge of intersections (Kushner et al., 1987; Chen et al., 2004; Chiang et al., 2008). Prior knowledge of road intersections is derived from a priori map databases or extracted from other sensor data, which includes road height profiles (Kushner et al., 1987), the approximate location of intersections (Chen et al., 2004), and road intersection configurations (Kushner et al., 1987). The second method directly detects road intersection from images using road intersection detectors (Hu et al., 2007; Negri et al., 2006) including a line junction detector (Deschênes et al., 2000) and a link hypothesis (Wiedemann et al., 2000). However, poor lighting conditions such as overcasts, overexposure, and interference from moving vehicles and pedestrians limit image-based methods, and subsequently, these methods now gradually being replaced by other approaches such as road intersection recognition based on Lidar point clouds. Research on road intersection detection based on Lidar point clouds can be divided into two types: (1) directly recognizing road intersections from 3D Lidar point clouds (Kodagoda et al., 2002; Chen et al., 2011; Zhu, et al., 2012); (2) identifying intersections from 2D laser scanner data combined with data from CCD cameras (Wijesoma et al., 2003) or other sensors (Aycard et al., 2011). The high cost of intersection detection using laser cloud point data restricts the road intersection recognition area to a small-scale. Therefore, research on mining road information and identifying road intersections from low-cost, quickly updated GPS traces is an active area (Rogers et al., 1999; Cao et al., 2009; Schroedl et al., 2004).

Crowdsourced GPS big trace data has become an important data resource providing fresh, low-cost, and large-scale regional traffic information. This information includes both static and dynamic traffic information (Zockaie et al., 2018); in both instances,