Detecting Travel Time Variations in Urban Road Networks by Taxi Trajectory Intersections

Andreas Keler[*1], Jukka M. Krisp[†1] and Linfang Ding[‡1]

[1]Institute of Geography, Applied Geoinformatics, University of Augsburg, Augsburg, Germany

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Summary

Floating Car Data (FCD) of taxis provides useful traffic information. Its handling needs effective analysis steps, including Map Matching (MM) onto road segments. Another challenge is to compute realistic FCD-based travel times in complex urban road networks with different elevation levels. We propose a method for inferring travel time variations in intersections of these networks. Based on intersecting recorded taxi trajectories in Euclidean space, we assign average travel time differences. Additionally, the same technique allows distinguishing between elevated and non-elevated road intersections in complex urban environment. In the end we test and evaluate the method with taxi FCD from Shanghai.

KEYWORDS: Taxi Trajectories, Floating Car Data (FCD), Urban Transportation Infrastructure, Crossroad Detection, Spatial Analysis.

1. Introduction

Floating Car Data (FCD) is one possibility of the big variety of sensor data for deriving traffic information. It is often provided by taxi fleets or commercial navigation system providers as TomTom and can describe the recent traffic situations (Cohn, 2014). Processing FCD for an effective traffic information service is nevertheless dependable on the number of observed vehicles and its percentage of the overall traffic participants. These can be estimated by the use of other sensors as for example Automatic Plate Number Recognition (ANPR) or inductive loops (Wang and Tsapakis, 2010; Klein et al., 2006). The main traffic information is in this case the travel time, which can be associated with a certain road element. With the use of FCD devices each vehicle acts as a sensor itself (Cohn and Bischoff, 2012). FCD of numerous vehicles may be used for modelling the traffic flow and delivers information on the current transportation conditions.

Movement of concrete objects is often collected as trajectories (Demšar and Virrantaus, 2010), which consist of spatial positions connected to sequences by ascending time components. The later are often time stamps associated to the object (Cohn and Bischoff, 2012). The connection of subsequent positions is consequently a multiline element and can be referred to as trajectory, because it describes the path of a moving object (Spaccapietra et al., 2008). In the field of traffic engineering and transportation, the term trajectory data describes positions of vehicles over time within a given road section (Treiber and Kesting, 2013). Vehicle trajectory data can base on positioning information (FCD), but as well from photographs and video footages. With the term trajectory it is possible to label a specific vehicle route or any other movement event.

[*] andreas.keler@geo.uni-augsburg.de
[†] jukka.krisp@geo.uni-augsburg.de
[‡] linfang.ding@geo.uni-augsburg.de

2. Using vehicle trajectories for detecting road intersections and travel time differences

The inspection of vehicle trajectories as overlapping polyline elements and the consecutive detection of certain patterns in movement may give indications on the underlying transportation infrastructure. One possibility is to use vehicle trajectories for map inference (Ahmed et al., 2015), which is useful when knowledge on the road network is missing. Map inference can include data mining techniques for automatically constructing road maps (Liu et al., 2012).

The detection of road intersections by using automated methods for FCD was already described by Fathi and Krumm (2010). Important results of this approach are detected exact positions of road intersections and their accurate modelling within a routable road network.

We want to follow up on a different approach on detecting crossings: detecting the crossings by inspecting the vehicle trajectory intersection patterns and subsequently give indication on the type of intersection by classification.

Our approach includes mainly 4 parts:

1. Connecting consecutive taxi FCD records to polyline elements
2. Computing the attributes average time and average velocity for each segment of the trajectory polyline
3. Intersecting all available taxi trajectory polyline with each other
4. Extracting all trajectory intersection points and computing time and velocity differences for each extracted point

3. Initial test data set properties

The investigated test data set in this work is a cutout of observed taxis in Shanghai ('SUVnet-Trace Data', http://wirelesslab.sjtu.edu.cn/taxi_trace_data.html). Each taxi trajectory is connected by specific taxi ID and by ascending time component t depending on an explicit time stamp. In a preprocessing step we connect each taxi ID to polyline elements, which show the entire movement of one object within a certain time window (in our case 10 minutes). For the partition between 8:20 and 8:30 AM on the 13th of February (Tuesday) in the year 2007 there are for example 7078 generated trajectories corresponding to the same number of individual taxis, which are pictured in Figure 1.

Figure 1 Generated 7078 taxi trajectory polylines between 8:20 and 8:30 AM on the 13th of February (Tuesday) in the year 2007 in the city centre of Shanghai.

Each trajectory record has additional attributes, which are created supplementary to the process of connecting points to polylines, with the form < length, start_time, end_time, time_diff, x_start, y_start, x_end, y_end >. Important for the following steps are the trajectory attribute values length (of the trajectory) and time_diff, which is the time difference between starting and end point (in our case always 10 minutes).

4. Results and Conclusion

For exemplary representation of our test results, we focus on a certain location in Shanghai. There are 68 taxi trajectories within the area of the Nanpu on-ramp. We extract the intersection points of these 68 taxi trajectories. From 2750 intersection points there are 282 self-intersections in certain parts of this complex transportation infrastructure. Figure 2a shows the taxi trajectories in black and their self-intersections by red dots.

For finding correlations of calculated velocity values we are performing cluster analysis on all 2750 intersection points. Our aim is to detect velocity-dependent hotspots by using the Getis-Ord GI* method (Getis and Ord, 1992; Ord and Getis, 1995). Figure 2b pictures hotspots by warmer colours, which show high correlation between our estimated average velocity values.

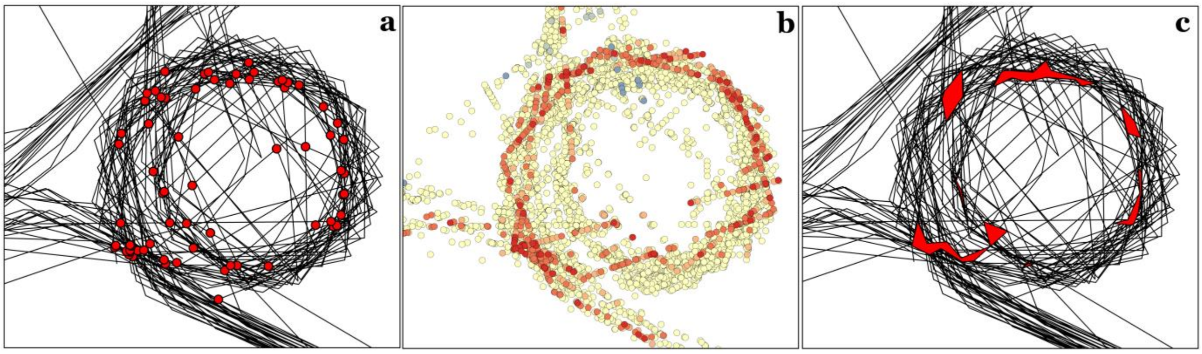

Figure 2 Analysis of the taxi trajectories within the Nanpu on-ramp with (a) self-intersection points, (b) velocity hotspots from the Getis-Ord GI* method and (c) distance-clustered self-intersections as convex hulls.

Since the self-intersections in Figure 2a include several illegitimate positions due to smaller jumps in space, we perform distance-based clustering with a search radius of 30 meters. After defining clusters, we exclude the outliers and use the convex hull generation method based on Jarvis (1973). The resulting convex hulls for the trajectory self-intersections are pictured in Figure 2c.

Based on the distribution of trajectory intersection points, we can distinguish between general types of crossings: higher trajectory intersection point densities indicate elevated crossings or two-dimensionally overlapping road segments, since many intersection points result from two road levels. The intersection points in elevated crossings imply smaller time differences in trajectory intersections. This means that vehicle trajectories may intersect each other within the same time and same 2-D space, but hold different z-coordinates.

Another helpful information in this detection is the inspection of speed differences in each intersection point: higher speed differences of the interpolated individual speed values indicate vehicle movement on two road levels. The presence of regularly ordered and density-connected intersection points with comparably less point density is an indicator for a non-elevated crossing. Nevertheless, results are heavily dependent on the way instantaneous speed values are interpolated (vector-wise or trajectory-dependent) and how we select our time windows of inspection.

5. Outlook

Future Work may include the selection of appropriate clustering techniques for taxi trajectory intersection points. Furthermore it might be useful to define each transportation infrastructure type by its efficiency, which might be helpful for understanding the relationships between traffic flow, complex crossings and other transportation infrastructure elements. This definition might be helpful for simplifying the urban planning process in the way of providing more overview on the connections of different transportation infrastructure elements.

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7. Biography

Dipl.-Ing. (TUM) Andreas Keler is a scientific staff member, Applied Geoinformatics (Institute of Geography) at the University of Augsburg. His research interests include the analysis and visualization of traffic congestion, air quality and massive movement data, routing applications for vehicle drivers and Location Based Services (LBSs).

Prof. Dr. Jukka M. Krisp, Professor of Applied Geoinformatics at the University of Augsburg. His Research interests include Geovisualization and Location Based Services (LBSs).

Dr. Linfang Ding is a researcher, Applied Geoinformatics at University of Augsburg. Her research interests include Geovisualization and Spatial data mining.

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