AUTOMATIC ACTIVITY IDENTIFICATION FROM RAW GPS VEHICLE TRACKING DATA

Lian Huang\textsuperscript{a,b,*}, Qingquan Li\textsuperscript{a,b}, Biju Li\textsuperscript{a,b}

\textsuperscript{a} State Key Laboratory of Information Engineering in Survey, Mapping and Remote Sensing, Wuhan University, No. 129, Luoyu Road, Wuhan, 430079, PR China, \{huangliansinc@hotmail.com, qqli@whu.edu.cn\}, \textsuperscript{b} Engineering Research Center for Spatio-Temporal Data Smart Acquisition and Application, Ministry of Education of China, No.129, Luoyu Road, Wuhan, 430079 PR China

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ABSTRACT:

Recently, activity-based analysis using GPS equipment as data collector has become a hot issue. Most researches focus on data from wearable GPS recorder for person because of easy detailed activity logging and interactive validation with users. Nevertheless, available floating car data and geographic context databases provide the possibility for activity-based analysis based on GPS vehicle tracking trajectories, this paper presents a novel and efficient approach to automatically identify activity-locations as well as activity-types from raw GPS vehicle tracking data. A number of contextual variants related to the activity locations including temporal information, spatial information and probability information are considered with the help of digital map containing Points of Interest (POIS). Taking the three aspects of inputs mentioned above into a Multi-Variants Analysis framework, detailed information of each activity will be identified. Finally, experiments using real world floating car data are conducted for evaluation and to show how this approach will help in varieties of applications in both traffic and activity-based analysis.

1. INTRODUCTION

1.1 Background

As a widely-used traffic data acquisition technique, floating car system can not only provide historic and real-time traffic information but also network constraint trajectories travelled through. Generally floating car data (FCD) is used for traffic parameters calculation such as road segment average speed and link travel time estimation, but actually with rich background knowledge, digital urban district region map for example, more in-depth FCD based analysis becomes possible.

In recent decades, activity-based analysis using GPS equipment as data collector has been a hot issue. Most this kind of researches focus on data from wearable GPS recorder for person because of easy detailed activity logging and interactive validation with users (B. Kochan, T. Bellemans, D. Janssens and G. Wets, 2006). Nevertheless, existing huge FCD and geographic context databases provide the possibility for conductible activity-based analysis based on GPS vehicle tracking trajectories such as finding out hottest locations at certain time of a day (Stefan SCHÖNFELDER and Kay W. AXHAUSEN, 2002). However, different from conventional activities analysis applications, activity- types (at home, at work, or shopping) and activity-locations are not labelled in raw tracking data, and this information is difficult and not reliable to be manually added. With the motivation to solve this problem, this paper presents a novel and efficient approach to automatically identify activity-locations as well as activity-types from raw GPS vehicle tracking data.


2. PROBLEM STATEMENT

For a trajectory composed of discrete GPS tracking points, conceptual data model can be used to reduce data redundancy and enrich semantic information (Lian, 2009). Then locations where activities probably occurred in a trip as well as routes between these locations will be recorded to represent original points based trajectories. In this way, the problem discussed in this paper is that: given a network constraint trajectory \(Tr(CarID,T)\) with a series of potential activity-locations \(Al(x, y, st, et)\), a POI (point of interest) database \(AP(x, y, \varepsilon(t))\), where \(T\) is the time span of \(Tr\) including starting time and ending time; \(CarID\) is a tag indicating the corresponding vehicle; \(x\) and \(y\) are horizontal coordinates; \(st\) is the time when the driver stopped; \(et\) is time when the driver left, \(\varepsilon(t)\) is the time-attractiveness function of each POI, figure out possible activities \(AT(Ap, st, et, Ac)\), where \(Ap\) is the POI where an activity was going on and \(Ac\) is the confidence for \(Ap\) to be assigned to \(AT\).

* Corresponding author. This is useful to know for communication with the appropriate person in cases with more than one author.
We use floating car data collected by taxies in Wuhan city, China, and thus the method proposed is based upon this type of data source.

### 3. METHODOLOGY

Generally candidate locations for activities identification from raw GPS tracking data are not directly available. In this case, tracking points clustering methods (Daniel Ashbrook, 2003) will be developed to find the centre of clustered points as the location where an activity was conducted since GPS points during activities will be recorded as series of "floating" points around the place where the vehicle stopped, which results from a systematic error of GPS sensors. Then, activity duration, starting time, ending time are obtained using the time stamps of the first and last points in the cluster. Whereas, if taxies are used for floating car to collect GPS tracking points, passengers on/off information is recorded additionally and usually used for trips division. In this paper, the on/off changing points along trajectories from taxies are considered as confident places for passengers’ activities identification.

#### 3.1 Defined Temporal and spatial rules

A detailed activity normally includes activity type like “dining”, “working”, activity spot which refers to a specific construction like “Starbucks at 5th avenue”, and duration indicates how long people stayed. However, GPS tracking data from taxies are not validate to obtained durations because in most cases taxi drivers won’t wait for the passengers they just dropped. Therefore, time of day and day of week are the only temporal factors will be used for activities identification.

Network distances from POIs those within a predefined circular buffer zone to on/off changing points are taken as spatial-aware factor. The closest POI has the greatest possibility in space to be identified as Ap. The radius of the buffer zone will be adaptively changed according to the density of nearby POIs, generally the more POIs around the smaller the radius is.

The available database includes three types of POIs: restaurants (coffee/tea house included), shops, and public servings. Accordingly, we define three types of activities: dining, shopping, and others. Table 1 and Table 2 show basic rules of temporal factors on these three types. Possibilities of “high”, “medium”, “low” will return scores of 3, 2, and 1 respectively.

#### 3.2 Activity chains

Temporal and spatial factors are used for single activity identification. In a complete trip, the origin sometimes has a significant impact on destination and vice versa. For example, people rarely go to another restaurant immediately after a meal, so “shopping” or “other” is more likely to be assigned to the corresponding activity of destination when “dining” is assigned to previous activity. Based upon investigated information from internet, how the activity chains will affect activities identification is described in Table 3.

#### 3.3 Multi-inputs analysis method

As discussed above, temporal information, spatial information and probability information are considered for activities interference. Furthermore, POIs have different kinds of attractiveness to people which will provide a fourth aspect for identification.

Taking the four factors mentioned above into a multi-variants analysis framework, the inputs of proposed method are temporal factor Wt, spatial factor Wg, activity chain factor Wa, and attractiveness factor We (Equations (1)).

\[ W_t = W_g(W_f) \]

\[ W_g = F_k(A_i(x, y), A(x, y), G) \]

\[ W_a = \begin{cases} \frac{1}{F_a(AT_{o/d})} & \text{if } AT_{o/d} \text{ exist} \\ 0 & \text{otherwise} \end{cases} \]

\[ W_e = AP(\epsilon(t)) \]

Where,

- \( F_g() \) is the function to calculate Wt according to temporal rules in section 3.1;
- \( F_g() \) returns network distance between Ai and Ap, G is road network;
- \( F_d() \) is the function to calculate Wa according to Table 3 in section 3.2;

In the case of taxi GPS tracking data, \( st \) and \( et \) of \( Ai \) are the same. To collect the attractiveness function of each POI, we use information from restaurant/shopping/facilities ranking website as showed in Figure 1. The higher the POI ranks the greater value the \( \epsilon(t) \) will returns.
To figure out the confidence of each candidate POI $i$, $A_c$ is defined as Equation (2).

$$A_c = \alpha W_t + \beta W_g + \gamma W_a + \zeta W_e$$  (2)

Where, $\alpha, \beta, \gamma, \zeta$ are coefficients corresponding to the inputting factors.

Neuron-network are used for the configuration of $\alpha, \beta, \gamma, \zeta$, with a number of simple trajectories as training sample where activities identifications are obvious, for example, only two or one POI around a $A_l$.

To reduce possible misjudge on activities, we select top 3 POIs with highest confidence when candidates are more than 3, and record relative confidence $A_{c_j}$ as Equation (3) instead of $A_{c_i}$.

$$A_{c_j} = \frac{A_{c_i}}{\sum_{j=1}^{k} A_{c_j}}$$  (3)

Where, $k$ is total number of candidate POIs.

4. EXPERIMENTS AND EVALUATIONS

4.1 Data description and experiment setup

Trajectories data from a taxi’s one-day collection along with road map of Wuhan city, China and restaurant/shopping/public serving POIs are taken for experiment setup to evaluate proposed method (Figure 2).

The whole trajectory is divided into sub trajectories according to on/off changing information from raw tracking data. The origin and destination of each sub trajectory are used as $A_l$s for activities identification.

4.2 Results and evaluations

As shown in Figure 4, only one restaurant (Mantingxuan Restaurant) POI falls into the trajectory’s origin’s buffer zone (upper left), thus the activity will be identified as “dining”, and related $A_p$ and time stamp are recorded. Whereas, four restaurant POIs fall into destination’s buffer zone, then their confidences are calculated as mentioned in section 3.3. “Hulinyuan Restaurant”, “Dongyingge Restaurant” and “Double Lakes Restaurant” are selected as potential $A_p$ with relative confidence 51%, 34%, 15% respectively. In this case, the type of POIs are all “restaurants”, thus attractiveness and $W_g$ shows greater impact on the activity interference. Trip purpose based on the result can be described as “heading for a more preferable restaurant”.

Figure 2. Tracking points and context map
Figure 5 shows a more difficult case for activities identification where plenty of POIs fall into buffer zone at both origin and destination. Four POIs are found as candidate $A_p$ when the trip started (Figure 6 (a)), and “Xiangshulin Coffee” is the one with the highest confidence. Five POIs, two shopping mall and three restaurant, show probability to be selected as $A_p$ to destination (Figure (b)), and finally a public serving POI obtains the highest confidence with regards to the time stamp 16:00, and previous activity identified as “dining” even though the poi “Hongdingdoulao Restaurant” is closer to the end of the trajectory.

5. CONCLUSIONS

Booming available GPS tracking data and rich context maps provide possibility to infer activities along trajectories. This paper proposes a multi-variants inputting method considering temporal, spatial as well as probability factors, which can automatically identify activities in both simple and complex environments. Experiment with field data validates this approach. Our future work will focus on in-depth activities identification where more types POIs are available, and developing online validation system to further evaluate the effectiveness of this method.

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