Using spatial-temporal signatures to infer human activities from personal trajectories on location-enabled mobile devices

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1. Introduction

Location-enabled mobile devices, such as smartphones, allow people to interact with several services, which results in creating a log for their everyday life. Spatial and temporal information from the trajectories of these interactions can be employed as indices to organize the information related to people's activities, thereby facilitating personal information retrieval and management. Studies (Lamming & Newman, 1991; Partridge & Price, 2009; Tulving, 1973) show that activities are used by people as memory hooks to recall information. Therefore, in addition to space and time, activities can be used as indexes to organize personal data and enhance personal information retrieval. However, such activity information is not directly available from GPS trajectories and has to be extracted and learned from the user's behavior.

In order to associate personal trajectories with activity information, researchers have developed methods to overlay trajectories on land use data, business codes (e.g. the North American Industry Classification System – NAICS codes), as well as remotely sensed images (Wolf, Guensler, & Bachman, 2001). Methods have also been developed to manually annotate the purpose of trajectory segments (Guc, May, Saygin, & Körner, 2008). Unfortunately, this augmentation creates burden to the users because they must interpret the land use types, recall the activities, and annotate each part of their trajectories. In order to automatically detect the user's activities, sensors outside of GPS (such as accelerometers) have been employed (Aizawa, 2005; Kawamura, Kono, & Kidode, 2002; Nakamura, Ohde, & Ohta, 2000).

To develop a more efficient way to infer activities from personal trajectories, the spatial and temporal features of activities must be examined. Ye et al. (2011) demonstrated that spatial-temporal patterns, called signatures, of geographic features can be mined from location-based social network data, and such signatures can be employed to identify the types of unknown geographic target. In this research, we argue that not only geographic feature types (e.g. bars and schools) but also human activity types have their own spatial-temporal signatures, and such signatures can be mined and learned as well. Given this, methods can be used to infer the activities in which a person participates. Similar to *MyLifeBits* (Gemmell, Bell, & Lueder, 2006), *Stuff I've Seen* (Dumais, et al., 2003), *Haystack* (Karger, Bakshi, Huynh, Quan, & Sinha, 2005), *Beagle++* (Chirita, Costache, Nejdl, & Paiu, 2006), and other personal information management (PIM) systems, which organize personal information by linking related items, the inferred activities can be employed as central nodes to associate related personal data, thereby facilitating information retrieval.

We propose a method to infer human activities from personal trajectories on location-enabled mobile devices through the analysis of spatial-temporal signatures. The spatial-temporal signatures are extracted from a survey of 30 users' activities. We present our method to infer activities using such signatures, and developed two versions of prototypes (a web version and a mobile version) as proof-of-concept. Finally, the result and future work are discussed.

2. Spatial-temporal signatures of activities

The spatial-temporal signatures of different activity types are extracted from an activity survey, in which 30 students from University of California Santa Barbara were asked to report their daily activities for 14 days (11/21/2011 – 12/04/2011). Each record in the reported dataset contains the activity's start and end time, its address (e.g., the name of a specific restaurant), as well as a brief activity description.

Two activity types (lunch and shopping) were chosen for an exploratory analysis. All records related to the two activities were extracted, and histograms of start time, duration, and location are provided in Figure 1.

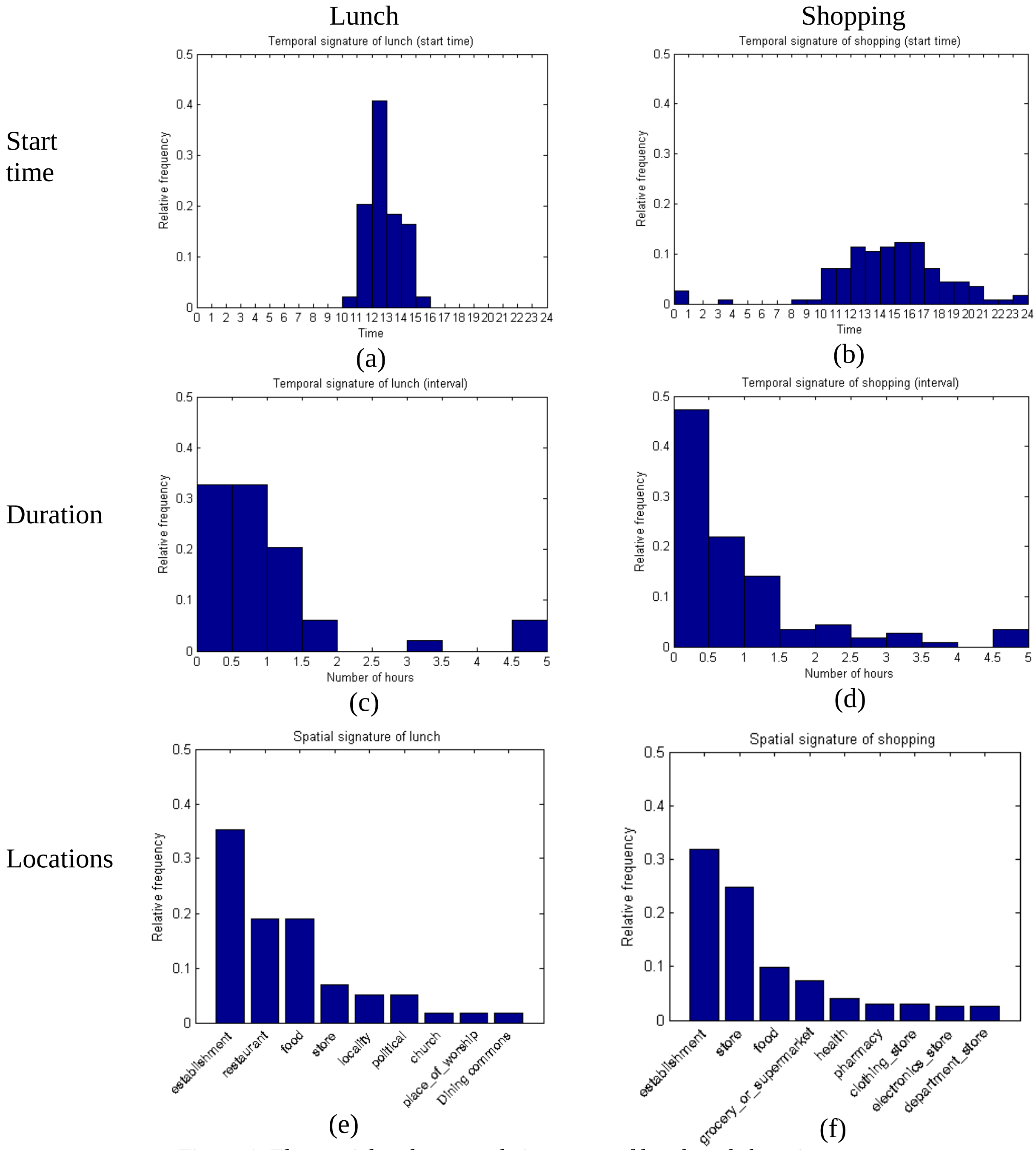


Figure 1. The spatial and temporal signatures of lunch and shopping.

These histograms show the spatial (location type) and temporal (start time and duration) signatures of the activities. The location types of the spatial signatures are obtained by geocoding the reported activity addresses to latitudes and longitudes (using a combination of TransCAD addresses matching and manual geocoding based on Google Maps), and then using Google Places API to identify the corresponding location types (such as restaurant and store[1]) of the coordinates.

Lunch activities typically take place between 11 am and 3 pm, and over 80% last less than 1.5 hours. The spatial signature for lunch shows that about 35% take place in an *establishment* and 20% take place in a restaurant. *Establishment* is a place type, defined by the Google Places API, that refers to a building or a place of residence when a more specific typing information is not available. The activity of shopping shows different signatures. It occurs in a wider time spectrum – from 10am to 9pm -- and approximately 50% of the activities last for 30 minutes or less. The majority of these rather short shopping activities were reported as grocery shopping. In total, more than 60% of shopping activities occurred in grocery stores, food, and other establishment, and only 5% of them occurred in stores selling clothes.

3. Software framework in acquiring trajectories for activity inference

A software framework for the acquisition of personal trajectories and activity inference has been developed. It contains three components: location tracker, geolocator, and activity reasoner. The location tracker (a background service) records spatial and temporal footprints in real-time. Once the location is obtained, the activity is detected by a moving window method and the averaged geographic coordinates at which activities take place are sent to the geolocator component. The geolocator communicates with Google Places API to retrieve detailed information of that place, including the street address, city, state, zip code, place name, and, most importantly, place type. With the place type as well as the temporal characteristic, the activity reasoner tries to infer the type of the activity and creates an index in the personal lifelog. The structure of the background database is provided in Figure 2. Each record corresponds to an activity. Attributes encapsulated by red boxes correspond to each respective component.

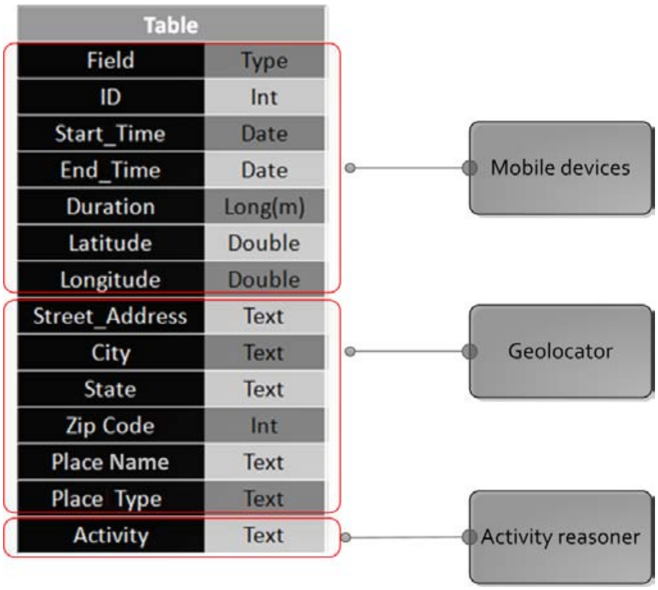
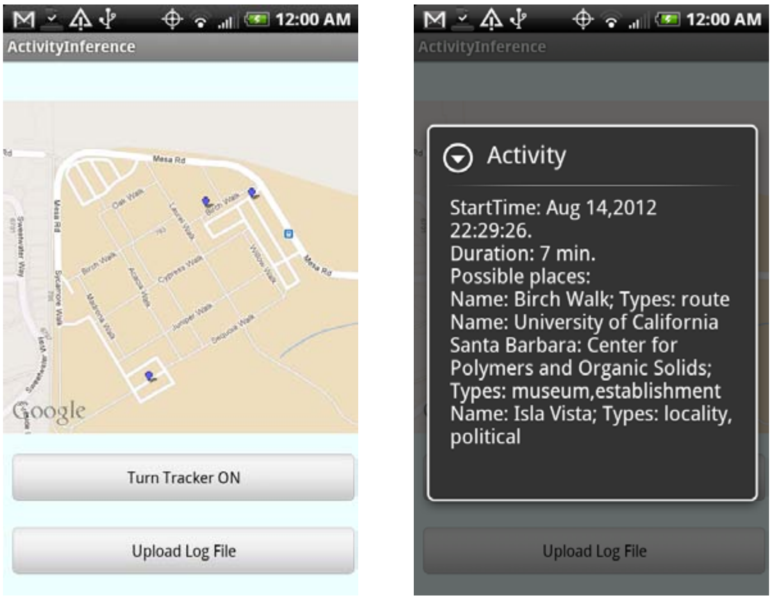


Figure 2. Database structure of the software framework

[1] A full list of place types of Google Places API can be accessed here: https://developers.google.com/places/documentation/supported_types

4. Two Prototypes

Two prototypes have been developed using the software framework (a mobile and a web version). The mobile application (Figure 3) monitors a user's real-time location, and automatically detects and records the user's activities using a 3-minute moving window. When the distance between two sequent GPS points is within 30 meters (which accommodates the GPS uncertainties), a reference location for potential activity is calculated by averaging the coordinates of the two. And if the distances between this reference location and later GPS points are also within this distance, then the reference location will be further calculated by averaging all those points. An activity will be initiated when the time difference between the first and current GPS points is longer than 3 minutes. And when the user moves more than 30 meters away from the reference location, a label (the blue dot) will be created (Figure 3a), and the duration of the activity will be automatically calculated. The user can click the dot to check the detailed log (Figure 3b). All activity data are saved in a file on the user's mobile device.



(a) (b)

Figure 3. Mobile application for real-time activity detecting and recording

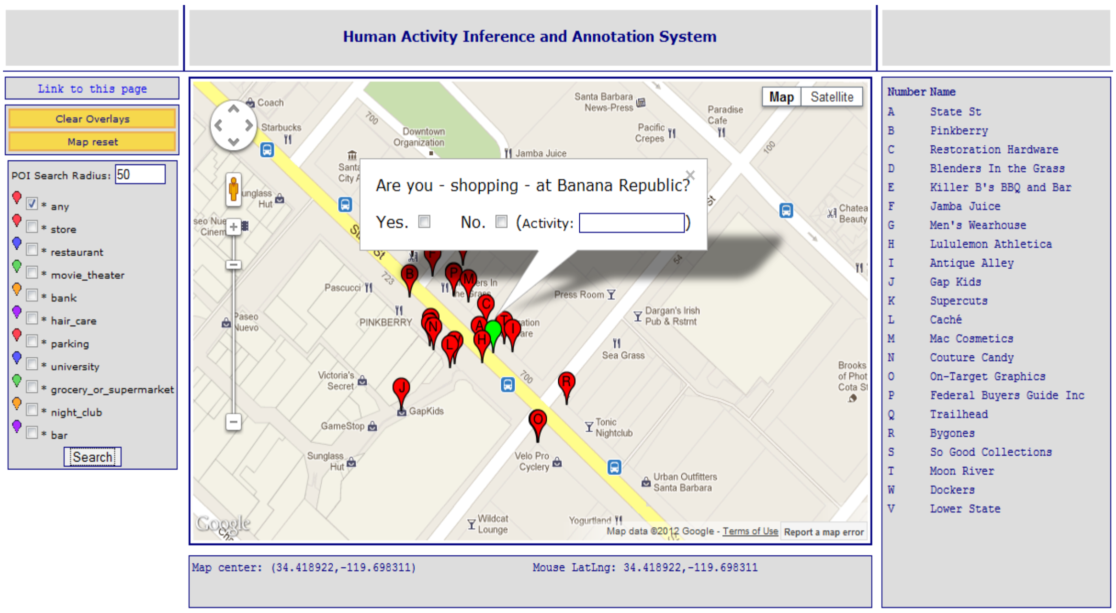


Figure 4. Web application for activity inference

The web application (Figure 4) allows the user to upload the activity data collected by the mobile application, and can infer the types of the activities that the user was participating. Green pinpoint shows the most likely location of an activity, and all red pinpoints show the other possible places of this activity. The user can choose among these places to specify the location of the activity. Based on the spatial and temporal information of the activity, the system will infer the activity type (see Figure 4) using the activity signatures. While we aim at developing a life logging software that has minimal user annotation by proposing activities based on the signatures, the system can also be used for other applications such as interactive surveys or advertizing.

5. Discussion and Future Work

In this extended abstract, we presented our initial work on an activity-based life logging system. This system uses spatial-temporal signatures to infer daily activities to improve personal information management and retrieval. As a starting point, we extracted spatial-temporal signatures for two frequently reported activities, shopping and going out for lunch. We discussed the software framework and database structure of this system, and also implemented two versions of prototypes as proof-of-concept.

A challenging issue to address in future is the positioning uncertainty associated with GPS data, which makes it difficult to accurately locate the place of the activity. To solve this problem, WiFi access points, historical trajectories, existing activities, and nearby places to are being explored to provide more accurate locations.

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