Demo Abstract: A User-Centric Mobility Sensing System for Transportation Activity Surveys

Fang-Jing Wu[1], Hock Beng Lim[1], Francisco Pereira[2], Chris Zegras[3], Moshe Ben-Akiva[3]
[1]Intelligent Systems Center, Nanyang Technological University, Singapore
[2]Singapore-MIT Alliance for Research and Technology, Singapore
[3]Massachusetts Institute of Technology, Cambridge, MA, USA

ABSTRACT

The UrbanMobSense is a mobility sensing system designed to collect the travel patterns of people for transportation planning purposes. This system makes use of smartphones with various built-in sensors to capture human mobility automatically in a non-intrusive manner. To improve the user experience of smartphone users, the system is designed to be user-centric to address energy conservation and privacy preservation issues. The UrbanMobSense has been deployed in Singapore to support the Land Transport Authority (LTA)'s household travel survey.

Categories and Subject Descriptors

C.3 [**SPECIAL-PURPOSE AND APPLICATION-BASED SYSTEMS**]: [Real-time and embedded systems]

General Terms

Algorithms

Keywords

cyber-physical systems, participatory sensing, pervasive computing, transportation activity survey

1. INTRODUCTION

Transportation activity surveys collect data on the travel patterns of people in urban areas for transportation planning purposes. In Singapore, the Land Transport Authority (LTA) carries out a transportation survey amongst households every four years. The surveys are conducted through conventional questionnaires and travel diaries. However, the conventional surveys are problematic and error-prone. In this work, we developed the UrbanMobSense system to conduct real-world transportation activity surveys, where users carry smartphones to seamlessly capture their daily mobility data. Through learning algorithms, the collected sensing data will be analyzed to derive useful information such as the transportation modes (e.g., Mass Rapid Transit (MRT), bus, walking) and travel stops.

To improve user experience, the UrbanMobSense system must be energy-efficient and privacy-preserving. The first goal is to optimize the smartphone battery usage while collecting mobility data. The second goal is to avoid exposing the users' personal locations to third parties. The main idea is to avoid using the GPS sensor

SenSys'13, November 11–15, 2013, Rome, Italy.
ACM 978-1-4503-2027-6/13/11.

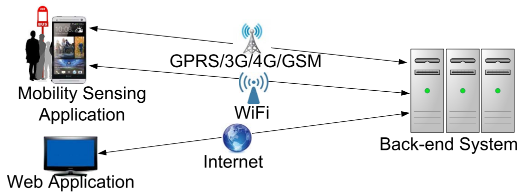


Figure 1: System architecture of UrbanMobSense.

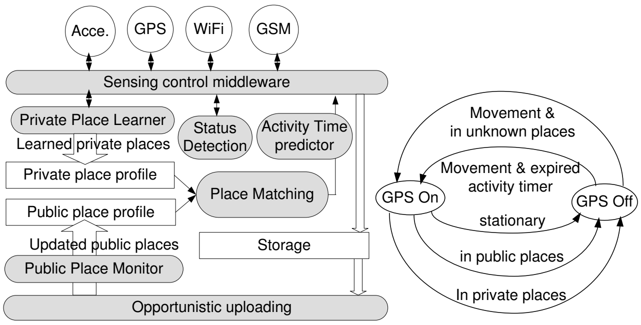
at the users' *long-stay places*. However, keeping personal long-stay place information may compromise the users' privacy. We then separate each user's long-stay places into two place profiles, *private places* and *public places*. The private place profile maintains the privacy-protected places (e.g., home and offices) which are only kept by each user's smartphone, while the public place profile maintains the public places (e.g., the zoo) which are allowed to be shared among users. Note that the privacy protection is by policies because public places usually provide location-based services which force users to expose their location information.

As our work is motivated by a real-world problem, the UrbanMobSense has several important features. First, unlike duty-cycle-based GPS control schemes [1] [2] which may not capture accurate traces all the time for such real deployment due to different sensitivity of GPS sensors on smartphones, the UrbanMobSense can support large-scale and highly dynamic mobility data collection in the real world. Second, instead of high-accuracy GPS localization [1][3], our system works with uncertain localization technologies (i.e., the availability and high accuracy of location information is not always provided). Finally, compared to [4], our system will not expose the ambient fingerprints of users' private places to remote servers for performing place matching. The urbanMobSense has been deployed in Singapore to support the LTA's household travel surveys.

2. SYSTEM DESIGN

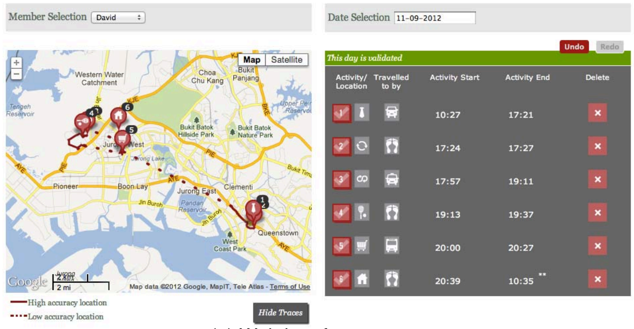
Fig. 1 shows the UrbanMobSense system architecture. The mobile sensing application is a background program running on the smartphone which collects GPS, WiFi, cellular network and accelerometer data to the back-end system for data analysis. Intelligent learning algorithms running on the back-end system will analyze the intermittent and uncertain sensing data to derive the transportation activity patterns of the users. A web application enables the users to validate the information on their travel trips.

Fig. 2(a) shows the smartphone sensing system design, which consists of six main components. (1) The *sensing control middleware* determines the sensing timing of sensors. The accelerometer, WiFi, and GSM data is collected periodically so that WiFi and GSM data can compensate for missing GPS data. In addition to periodical

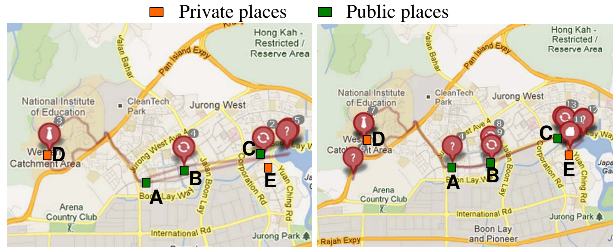


(a) Software design on a smartphone. (b) State transition of a GPS sensor.

Figure 2: System design and GPS state transition.



(a) Web interface.



(b) Traces with our scheme. (c) Traces with always-on GPS

Figure 3: The web application and sample trip traces.

GSM data collection, we also collect the changes of GSM pattern if the signal strength or GSM cell ID has changed.

(2) The *private place learner* maintains the WiFi signatures of the user's private place profile $\mathcal{F}$. Initially, $\mathcal{F} = \emptyset$. When the user's smartphone enters an unknown place at time t, it starts learning the place's signatures $P_i = P(t)$, where $P(t) = \{W_1, W_2, \ldots, W_k\}$ which contains all visible WiFi BSSIDs $W_1, W_2, \ldots, W_k$ at t. The P_i will be updated by $P_i = P_i \cap P(t+1)$ at time $t+1$ if $P_i \cap P(t+1) \neq \emptyset$. Otherwise, it gives up learning the place P_i because the user leaves from the current place P_i. The learning process will be repeated for Δ_L duration. Then, $\mathcal{F}$ is updated by $\mathcal{F} = \mathcal{F} \cup P_i$. In this way, $\mathcal{F}$ will be updated from time to time.

(3)The *public place monitor* checks whether the samrtphone has cached the newest public place profile. If not, the smartphone downloads the newest one from the back-end system if an Internet connection is available. Based on the density of GPS data in the back-end system, the public place profile $\mathcal{H} = \{Q_1, Q_2, \ldots, Q_n\}$ maintains the hotspots of users' mobility that includes common public places (e.g., MRT stations, parks, zoo, etc). Here, $Q_i = (x_i, y_i)$ is the pair of latitude and longitude coordinates of public place Q_i. The Density-based Spatial Clustering of Applications with Noise (DBSCAN) is adopted to figure out the public place profile $\mathcal{H}$.

(4) The *place matching* detects whether the user is at private or public places. Let Φ denote the real-time set of visible WiFi BSSIDs. If these exists $P_i \in \mathcal{F}$ and $\Phi \cap P_i \neq \emptyset$, then the user is at private place P_i. Let Ω denotes the real-time GPS fixes. If there exists $Q_i \in \mathcal{H}$ such that $d(\Omega, Q_i) < R_a$ and $d(\Omega, Q_i) < d(\Omega, Q_j)$ for $Q_i, Q_j \in \mathcal{H}$, then the user in public place Q_i, where $d(\Omega, Q_i)$ is the distance between Ω and Q_i, and R_a is the predefined activity range.

(5) The *status detection* determines whether the user is in movement/stationary status. Let $a(x)$, $a(y)$, and $a(z)$ denote the accelerometer's reading in x-, y-, and z-axis, respectively. If either $a(x)$, $a(y)$, or $a(z)$ is greater than the predefined threshold τ_a, the smartphone detects a shaking event. When the smartphone detects consecutive shaking events for a time period T_m, then the user is in movement status. Similarly, if there is no shaking event for a time period T_m, the user is in stationary status.

(6) The *activity time predictor* estimates how long the user will move out of the activity range of a public place. Once the user is detected in a public place, the smartphone turns off the GPS for R_a/v duration, where v is the real-time speed.

With the interaction between these six components, the GPS follows the state transition shown in Fig. 2(b). On the back-end system, we implemented two learning algorithms to detect travel stops and transportation modes. We use DBSCAN to detect stops. We consider factors such as the maximal speed, between stop average speed, accelerometer force variance, and distance to the closest bus and MRT stops to construct a decision tree for detecting transportation modes.

3. DEMONSTRATION

The UrbanMobSense has been implemented as Android-based and iOS-based smartphone apps. On the back-end system, we have implemented MapReduce-based distributed processing for the transportation activity data analysis and learning algorithms. Fig. 3(a) shows the web application for user trip validation. In Fig. 3(b) and (c), the sample mobility traces processed with the system is shown. The system is accurate enough to be deployed for the LTA's transportation activity survey involving 1000 smartphone users in Singapore. We will demonstrate the key components of the smartphone app and the backend system.

4. ACKNOWLEDGMENT

This research is supported by the Singapore National Research Foundation (NRF) through the Singapore-MIT Alliance for Research and Technology (SMART) Future Urban Mobility program.

5. REFERENCES

[1] Y. Chon, E. Talipov, H. Shin, and H. Cha, "Mobility prediction-based smartphone energy optimization for everyday location monitoring," in *ACM Int'l Conf. Embedded Networked Sensor Systems*, 2011, pp. 82–95.

[2] J. Paek, J. Kim, and R. Govindan, "Energy-efficient rate-adaptive gps-based positioning for smartphones," in *ACM Int'l Conf. on Mobile Systems, Applications, and Services*, 2010, pp. 299–314.

[3] C.-H. Lo, W.-C. Peng, C.-W. Chen, T.-Y. Lin, and C.-S. Lin, "CarWeb: A traffic data collection platform," in *Int'l Conf. Mobile Data Management*, 2008, pp. 221–222.

[4] M. Azizyan, I. Constandache, and R. R. Choudhury, "SurroundSense: mobile phone localization via ambience fingerprinting," in *ACM Int'l Conf. Mobile Computing and Networking*, 2009, pp. 261–272.