MVPTrack: Energy-Efficient Places and Motion States Tracking

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Abstract. Contextual information such as a person's meaningful places (Different from a person's location (raw coordinates), place is an indoor or outdoor area where a person usually conducts some activity, in other words where it is meaningful to the person, such as home, office rooms, restaurants etc.) could provide intelligence to many smartphone apps. However, acquiring this context attribute is not straightforward and could easily drain the battery. In this paper, we propose M(Move)V(Vehicle)P(Place)Track, a continuous place and motion state tracking framework with a focus on improving the energy efficiency of place entrance detection through two techniques: (1) utilizing the mobility change not only for finding the sleeping opportunities for the high energy sensors, but also for providing hint for place entrance detection, (2) leveraging the place history for fast place entrance detection. We evaluated MVPTrack based on traces collected by five persons over two weeks. The evaluation results showed that MVPTrack used 58 % less energy than previous work and provided a much faster place entrance detection approach.

Keywords: Place sensing · Energy efficiency · Place awareness

1 Introduction

Continuous sensing of a person's daily visited places has been motivated by many use cases. For instance, *Nihao* [1], a place-aware smartphone app launcher that could dynamically arrange the app icons according to the user's current place since users tend to use different apps in different places. Another example is a *Smart Profile Switcher*. It could automatically change the smartphone profile according to the current places since phones are required to be muted for some place such as an office meeting room.

To support the place and motion-aware apps, we propose MVPTrack, a continuous place (detected based on WiFi fingerprint to offer room/floor level

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indoor place discriminability) and motion (based on accelerometer) state tracking framework with a focus on the energy efficiency. We evaluated our system based on traces collected by five persons over two weeks. The results showed that our framework used 58 % less energy than previous work [2] and provided a faster place entrance detection algorithm.

Previous WiFi fingerprint based place tracking solution [2] utilizes the accelerometer to find sleeping opportunities for the high energy sensors such as WiFi and GPS. But after a place exit was detected, the place sensors are kept on for entrance detection of next place which could potentially waste lots of energy if the transit between places took long time. Our contributions in this work is to (1) provide an energy efficient place entrance detection algorithm leveraging both mobility change and place history, (2) implement and evaluate the proposed work with detailed analysis about the characteristics of such a system.

The rest of this paper is organized as follows. In Sect. 2 we first discusses design of the system. Then, we show the system evaluation results in Sect. 3. Finally, Sect. 4 concludes with planned future work.

2 System Design

In this section we present the architecture of the MVPTrack framework, as shown in Fig. 1. The goal of this framework is to support *Place-aware* (focus of this paper) and *Motion-aware* applications robustly and in an energy efficient manner.

Motion Intensity Monitor (MIM) is a binary(Move or still) classifier continuously classifies the user's motion intensity (Eq. 2) with duty-cycling.

$$Acceleration = \sqrt{x^2 + y^2 + z^2} \tag{1}$$

$$Motion\ Intensity\,(MI) = Standard\ Deviation(Acceleration\ of\ samples) \tag{2}$$

we choose 1.2 as the threshold since it achieves the best place detection accuracy due to our experiment. When *MIM* captures the transition from mobile state to

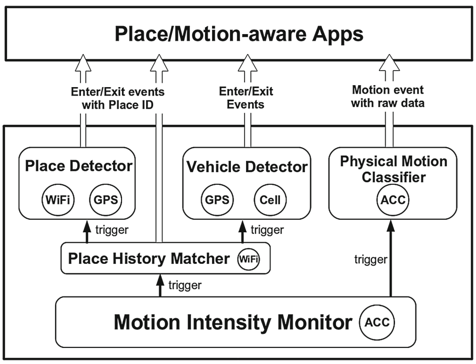
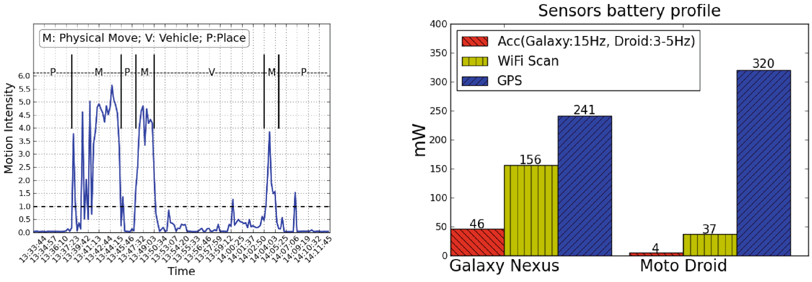


Fig. 1. Framework architecture



(a) (b)

Fig. 2. (a) User motion intensity variation through a day (Smartphone is placed in the front pant pocket), (b) Sensors' battery profile for Galaxy Nexus and Motorola Droid

still and being still for a while (defined by a sliding window with window capacity C_m, the rationale is that people are tend to being still in a indoor place or in a vehicle), *Place history matcher (PHM)* is triggered. *PHM* tries to match the current WiFi fingerprint with the records stored in a place history table. This step is very powerful since it not only help avoid the unnecessary GPS readings used for vehicle detection comparing to the case without *PHM* but also shorten the place entrance detection time comparing to the time necessary to sense a stable radio environment in SensLoc. We choose Tanimoto Coefficient,

$$Similarity(v_1, v_2) = \frac{v_1 \cdot v_2}{||v_1||^2 + ||v_2||^2 - v_1 \cdot v_2} \tag{3}$$

as the metric of WiFi fingerprints similarity. If the similarity value is larger than a threshold δ_{fp}, an place enter event is fired immediately. Otherwise *Place Entrance Detector (PED)* is finally triggered. (We omit the discussion of *PED* since it shares the similar algorithm with SensLoc)

3 Evaluation

We evaluated the system against a dataset collected locally and compare the performance with SensLoc from three different perspectives, i.e. system accuracy, battery efficiency and detection delay.

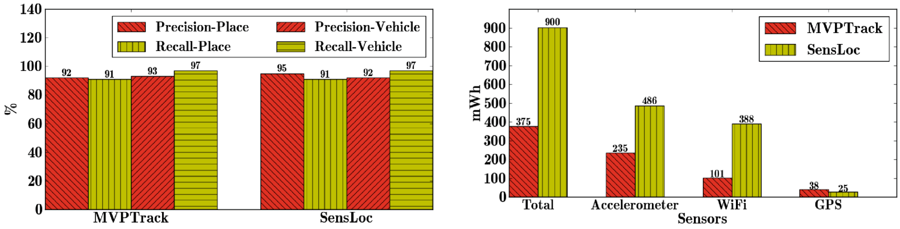
3.1 Dataset

The dataset we collected contains the place/vehicle ground truth(enter/exit time and place name), a WiFi scanning trace and a GPS trace. We asked 5 testers to follow their daily routine for 2 weeks. This dataset is used to run both our algorithm and the algorithms we are comparing with. The recorded places includes home, office rooms, meeting rooms, school labs, library rooms, restaurants, shopping malls, supper markets, beaches, parks etc. The recorded vehicle includes cars, buses and subways.

3.2 System Accuracy

Evaluation Metrics. We evaluated the system accuracy based on the metrics defined in[2]:

$$Precision = \frac{\#\ of\ Correctly\ Detected}{\#\ of\ Total\ Detected}; Recall = \frac{\#\ of\ Correctly\ Detected}{\#\ of\ Ground\ Truth} \tag{4}$$



(a) Overall precision and recall for place/vehicle entrance/exit detection

(b) Daily average energy consumption for all testers

Fig. 3. Evaluation result

As the Fig. 3a suggests, for the places, our framework achieves 92 precision and 91 recall which maintains a comparable accuracy level with SensLoc.

3.3 Energy Efficiency

Sensor energy consumption estimation. We developed three battery profiling apps which only open one particular sensor and read it at the highest frequency. We ran the apps after the phone is fully charged until the battery is almost drained. Android system reports the percentage of the battery used by each app. Combining with the percentage value of how many battery consumed and the total battery capacity, we are able to estimate the power profile of an individual sensor. Figure 2b is generated through this method.

Figure 3b shows both the comparison of the overall energy consumption as well as the energy consumption of individual sensors. The accelerometer component of our system uses about half of the energy comparing to SensLoc since we use 25 % duty cycle while SensLoc uses 50 % which is not necessary. Our WiFi component uses one forth of the energy comparing to SensLoc due to our place entrance detection algorithm. Overall, our system use 58 % less energy than SensLoc which is a significant improvement.

3.4 Detection Delay

Besides the system accuracy and energy efficiency, the detection delay is also an importance metric for such a system since it reflects the real-timeness of the

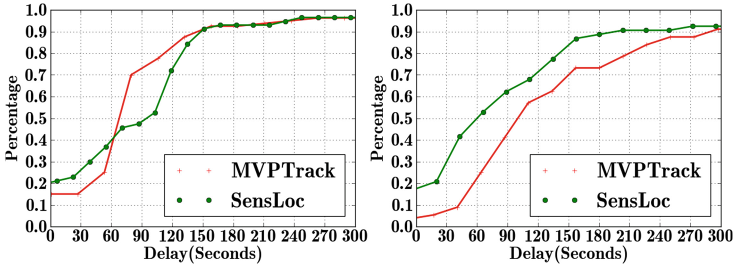


Fig. 4. Place and vehicle entrance detection delay. The left side is for the place and the right side is for the vehicle.

system. Figure 4 shows the CDF of both place and vehicle entrance detection delay. As we can see, about 65–70 % of the time, place entrance is detected between 60 seconds and 90 seconds which indicates that about 65–70 % of the total place visits were re-visits and they took the advantage of the *Place History Matcher* to effectively shorten the detection delay. Actually, after a longer period of time, a person's regularly visited places converge thus place history could constantly offer great real-timeness for the system.

4 Conclusion

In this paper, we propose a novel place entrance detection algorithm leveraging the user's mobility change and place history. The evaluation result shows it used 58 % less energy than previous work and provided a faster place entrance detection algorithm.

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