Poster: ParkGauge: Gauging the Congestion Level of Parking Garages with Crowdsensed Parking Characteristics

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ABSTRACT

Finding available parking spaces in dense urban areas is a globally recognized issue in urban mobility. Whereas prior studies have focused on outdoor/street parking, we target at (indoor) parking garages where the infrastructure supports (e.g., GPS and Wi-Fi) assumed by existing proposals are unavailable and counting vehicles by crowdsensing is difficult. To this end, we present ParkGauge as a system gauging the congestion level of parking garages; it infers (coarse-grained) parking occupancy from crowdsensed parking characteristics instead of counting the parked vehicles. ParkGauge adopts mostly low-power sensors in the driver's smartphone to determine driving states, contexts and temporal parking characteristics of a garage, including time-to-park and time-in-cruising/queuing. Mining such data collected from a crowd of drivers at various garages yields a good measure of their congestion levels and provide recommendations (in real-time) to drivers coming to these venues.

1. INTRODUCTION

Dense urban areas worldwide face high demand on parking infrastructure especially in mega-cities. While on-street parking has led to serious traffic congestion, multi-storeyed *car parks* (aka, *parking garages*), which are the major urban parking facilities for mega-cities, can also produce serious on-road congestion because of long queues of vehicles waiting to enter them. This is because their occupancy is not made available to drivers who could be otherwise guided towards less congested venues. Existing infrastructure-based systems require sensors and/or beacons at parking lots or on vehicles, making them expensive and not very scalable. Recent infrastructure-free works such as ParkSense [4] and PocketParker [3] have demonstrated crowdsensing for parking occupancy detection, however they focus on outdoor parking and are not able to get assistance from Wi-Fi and/or GPS mostly unavailable to indoor parking garages. Inertial sensing has been widely used for transportation mode detection (e.g., [2, 5, 1]), but it is very hard to infer occupancy information from direct inertial sensor readings: they may suggest driving states such as braking or turning, but such events seem unrelated to parking occupancy unless we use certain inference mechanisms and establish their connections.

We propose ParkGauge as a system to gauge the congestion level (or coarse-grained occupancy) of parking garages in urban areas. In order to apply infrastructure-free inertial sensing for this purpose, ParkGauge innovates in using (temporal sequences of) driving states (e.g., braking and turning) to infer temporal parking characteristics (e.g., time-to-park) that are in turn exploited to deduce garage occupancies. To the best of our knowledge, ParkGauge is the first crowdsensing system exploiting temporal information to indicate parking occupancy for indoor parking garages.

Unlike existing crowdsensing-based parking systems, ParkGauge does not require a "crowd" for sensing individual parking garages. A small amount of sensing data acquired from each parking garage is sufficient, whereas the "crowd" is needed only to enhance coverage across a large urban area.

2. SYSTEM OVERVIEW AND DESIGN

ParkGauge runs as an application in a driver's smartphone that can be docked in a standing position during driving and to be taken along with the driver upon completing a parking. The architecture of ParkGauge has a 4-layer presentation shown in Figure 1, so that connections between the seemingly unrelated sensing data and our gauging objectives can be made through a multi-stage inference. It uses the accelerometer and gyroscope to detect driving-relevant phone status, and a *Hidden Markov model* (HMM) to infer hidden *driving state* from observable phone status. Barometer is used to detect floor changes, and geo-fencing to trigger parking arrival detection. The (temporal) sequence of *driving state*s are classified to *driving context*s, which help to derive temporal parking characteristics such as time-to-park. This can be used to generate useful information presentable to drivers, such as coarse-grained occupancy (inferred by regression) and accurate Expected Time of Arrival (ETA).

3. EXPERIMENTS AND EVALUATION

We have implemented ParkGauge as an Android application, along with a back-end server. While the model learning procedure is done offline in the server using the collected datasets, all the online detections are performed on ParkGauge application, which periodically reports data to the server. Experiments were performed in parking garages at-

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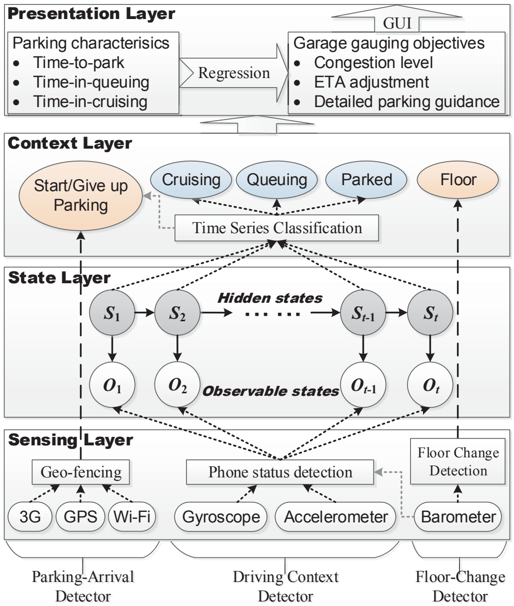

Figure 1: System architecture of ParkGauge.

tached to shopping malls, during which more than 100 traces were collected, including 46 self-parking sessions.

3.1 Inferring Driving States and Contexts

To demonstrate the inferred driving states and contexts, we use the raw sensor readings plotted in Figure 2 from a 4.5 minute long parking trial during a peak hour at a shopping mall. The vehicle arrived at an almost fully occupied garage, so it faced a queue at the entrance, and spent time in cruising to find a parking lot even after getting three levels down.

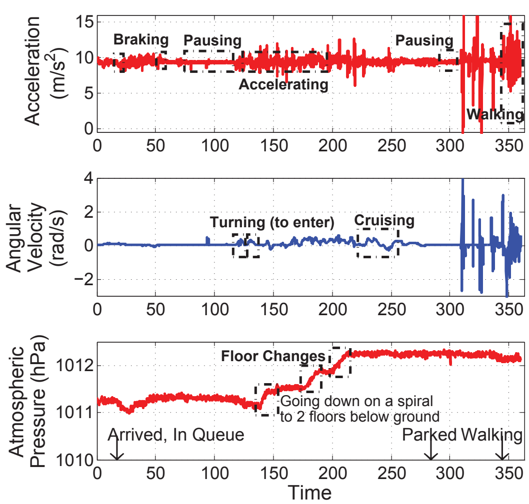

Figure 2: Raw data trace from a parking trial

3.2 Accuracy of time-to-park Estimation

As shown in Figure 3(a), the errors in estimating time-to-park may range from 5s to around 30s. Most errors are around the mean of 18s. Given that the normal values of time-to-park are in the order of minutes (or tens of minutes in the worst case), we deem this performance very accurate.

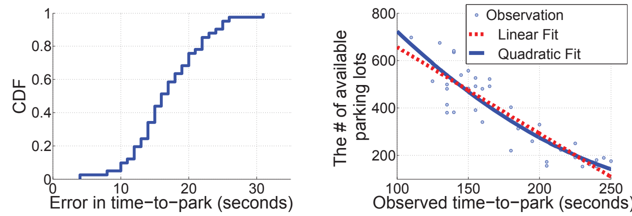

Figure 3: (a) CDF for the estimation errors of time-to-park. (b) Fitting the relation between parking occupancy and time-to-park through regression.

3.3 Gauging Parking Occupancy

We use regression to recover the relation between occupancy and time-to-park based on the collected data. We only show one set of results from a popular shopping mall in Figure 3(b); the experiments were done from 10:00am to 16:00pm. We perform both linear and quadratic regression on the data, and the results are very close to each other. For simplicity, we use the linear regression results to map an estimated time-to-park to occupancy, and store such a mapping in the server for individual parking garages. When a user queries a location, ParkGauge retrieves the estimated *time-to-parks* from nearby parking garages along with their corresponding mapping. It then computes the occupancies locally and displays it both numerically and graphically. The user may also choose to view the *time-to-parks* directly and feel the level of difficulty in finding a parking lot.

4. CONCLUSION AND DISCUSSIONS

ParkGauge innovates in using inertial sensing data (from low-power sensors) to gauge temporal characteristics and infer a coarse-grained occupancy of parking garages and this is demonstrated through extensive experiments. Our current implementation requires the smartphone to be docked in a standing position, but this can be addressed by existing phone attitude estimation algorithms. Finally, we strongly believe that the idea behind ParkGauge can be extended also to outdoor parking and other occupancy detection scenarios.

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