

Comparative Data Analysis for Quality Assessment of On-Street Parking Information

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Extended Abstract

1. Introduction

Substantial congestion within a transport network originates from vehicles searching for an on-street parking spot (Friedrich et al., 2019). This causes noise, air pollution, time delays, and even poses threats to local businesses by repelling potential customers. As a parking management measure, cities have invested in parking guidance signs to direct cars to primarily off-street parking lots and multistorey car parks. Comparable systems have also been developed for finding parking spots on the streets, denoted as on-street parking information (OSPI). One of the benefits of such systems is reduction of traffic congestion caused by cruising for a parking space (Gkolia & Vlahogianni, 2018; Pel & Chaniotakis, 2017).

Developments towards more cooperative intelligent transport systems (C-ITS), such as OSPI, have the potential to efficiently and better distribute vehicles within a transport network and achieve a traffic state that is closer to the system optimum. Reliability and quality of information systems must be ensured to offer reliable services that contribute to this goal. One reliability metric to measure is the comparison of ground truth information against the prediction model estimates. Ground truth data include observations by on-site surveyors or cameras, detection by sensors, satellite imagery, global positioning system (GPS) coordinates, and others. This study looks into the comparative analysis of the different data sources available for assessing the quality of mobility-related information that is transmitted to connected vehicles by tackling the case of OSPI.

2. Problem Statement

Researchers have mainly looked into two approaches in tackling OSPI services, which are often interconnected: (1) developing on-street parking availability models which estimate the probability of a spot being available on a certain street, and (2) developing algorithms to improve parking search times and routes that increase the probability of finding a spot. Typically, the former is an input to the latter. However, the challenge is how to efficiently validate the quality of these models and whether they are reliable enough.

Quality assessment of information systems within the area of mobility have mainly focused on the broadcasting of information and not necessarily the accuracy of the content (Bogenberger & Weikl, 2012).

The content for state-of-the-art OSPI systems are mostly created through complex non-linear machine learning techniques. The main difference between the models available are the data gathered for training the models and considered attributes. The different input data play a major role in the reliability and quality. The aim of all of these models is to best estimate the dynamics of the parking pattern of drivers by inferring from ground truth and various factors (e.g. closest point of interest (POI), land use, functional road class, time and day, traffic flow, etc.) (Badii, Nesi, & Paoli, 2018).

There are service providers offering parking prediction apps¹ that aim to reduce the amount of time to find an appropriate on-street parking spot. Despite the deployment of such offers, the level-of-service and reliability remains a challenge. This is attributed to the lack of accurate data with adequate spatial and temporal coverage relative to the detail needed for scalability. The challenge is to assess the quality with a scalable data collection strategy (i.e. using smart systems and not sending surveyors everywhere), validate the correctness, and thereby enhance such services.

3. Research Objective

This study is part of a research project that aims to find a scalable method to efficiently measure OSPI quality on a large scale and test the potential of the transferability of the OSPI prediction models to different cities. The comparative analysis of the data sources is an initial step to find a quality assessment and enhancement solution that scales in terms of reliably rolling out the OSPI in more cities. The objective of the comparative analysis in this paper is to understand which data source or a combination of these can be utilised to efficiently evaluate OSPI. An analysis criteria is discussed in the following section.

4. Methodological Approach

The comparative data analysis on the different sources is done against the following aspects:

1. **Spatial and temporal coverage** – check for the area coverage and time distribution within a city. The density distribution within the city will also be checked. The output can be used for understanding the correlation of parking spots and POIs considering the density spread of available validation data.
2. **Relation to expected accuracy of the dynamic model evaluation** – check for the impacts of the data errors on accuracy of evaluation. Measure the extent to which the data can improve the quality.
3. **Technical complexity** – difficulty in processing data to become useful.
4. **Data costs** – check for the associated fixed and variable costs.
5. **The potential for scalability** – measure the scalability by weighing the importance of the above aspects and the interrelation among each other.
6. **Data input and representation in the parking simulator** – how the data can be added as a dynamic attribute in the simulation model. The parking simulator will be used to recreate parking scenarios and test for current and future scenarios. The simulator can abstract the real-world environment and the quality assessment can be conducted. An advantage the simulator provides is to also investigate areas within a city which are not covered by the empirical data.

5. Expected Results

Quality assessment of mobility-related information systems depends on the data that is being investigated and the method used for analysis. For each data, there exists a trade-off between cost, coverage, technical complexity, and quality. Higher cost does not necessarily guarantee superior quality. For instance, having direct ground truth data from sending people in a neighbourhood to count the number of parking spots and vacant spots could arguably be the most accurate source. However, the associated costs to expand spatial and temporal coverage is rather costly. Conversely, parking data

¹ ParkMe: <https://www.parkme.com/>; Parkopedia: <https://www.parkopedia.com/>, AIPARK: <https://www.aipark.io/>, Parknav: <https://parknav.com/>; Parkbob: <https://www.parkbob.com/>

indirectly gathered and inferred from floating car data (FCD) will require considerable effort for analysis and extraction of parking movements. Nonetheless, FCD is easier deployed for coverage as it only requires a mobile or GPS device on board any car. FCD has the advantage of coming in large volumes with a certain loss in the quality of detecting which movements are considered for parking. The challenge is to analyse how much loss in quality is allowed relative to the amount of data gathered. These different data sources still have the issue of coverage and strategy used to gather data, which lead to certain biases and latent errors.

The expected results will be the comparative analysis of the data sources below. These data are acquired from a mix of own testers, agencies, service providers, open data, and customer data.

- Ground truth observations and GPS recordings
- Floating car data (FCD) and real-time traffic information (RTTI)
- Park in and out information
- Crowd sourced images/videos (e.g. mapillary, fleet data, Google streetview)
- Ultra-Sonic Sensor (USS) data
- Aerial imagery
- *Upon availability: Open public information (e.g. webcams and parking guidance systems in smart cities)*
- *Upon availability: In-street sensor data from smart cities*

The results of the comparative analysis will be used as input to the following next steps of the overall research on quality assessment of OSPI systems:

- Input into machine learning model for parking probability. A sample model will be developed for this paper.
- Input into traffic simulation for the recreation of parking scenarios. For instance, camera for real-time information; certain penetration rate for USS-equipped vehicles that sends back information to the parking probability model. This is then checked whether it improves own parking probability model.
- Identifying the different street types or areas where parking probability model is transferrable (e.g. road types linked to land-use functions within a certain distance).

6. References

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