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Improving Parking Availability Maps using Information from Nearby Roads

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Abstract

Parking search traffic causes increased travel times and air pollution in many cities. Real-time parking availability maps are expected to help drivers to find a parking space faster and thus to reduce parking search traffic. A possibility to create such maps is the aggregation of parking availability information from crowdsourcing solutions like probe vehicles and mobile phone applications. Since these sources cannot sense the whole city at the same time, estimation methods are necessary to fill uncovered areas. This paper investigates the estimation of parking availability based on spatial methods using sensor data from San Francisco. First, spatial similarities in parking availability are evaluated for different aspects like time of day and number of parking spaces depending on the distance to reveal the parking characteristics. Then, interpolation methods are examined to estimate parking availability in unobserved road segments. Results show that relevant similarities mainly exist for short distances of less than hundred meters. Their similarity values are lower than the temporal similarity even for multiple hours of time gap. Nevertheless, spatial information is useful to interpolate parking availability. Investigated interpolation methods show significantly better results than random guess. Inverse distance weighting method outperforms a simple averaging by up to 5%.

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Keywords: parking availability estimation; parking statistics; crowd-sensing; spatial data analysis; similarity measures; spatial interpolation

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1. Introduction

Parking search is a challenging problem in many cities. If drivers cannot find a parking space at their destinations, they start to circle around the blocks, causing parking search traffic which contributes up to 30% of the total traffic in dense urban scenarios (Shoup 2007). In a nation-wide survey in the Netherlands, 30% of car trips end with a parking search if employer-provided and residential parking are excluded (Van Ommeren et al. 2012). On the one hand, searching drivers suffer from this phenomenon by wasted time, wasted gas, and therefore additional costs. On the other hand, other traffic participants are affected by increased traffic, and the environment is impaired by additional air pollution.

The provision of information about available parking spaces is a promising solution to tackle the parking problem. However, while data can easily be collected for off-street parking facilities by controlling entrance and exit, the data acquisition for on-street parking is still an open issue. There only exist first approaches both for static and mobile sensors that gather information about the availability in real-time. Static sensors are permanently installed in the roads and provide periodic parking information (e.g. SFMTA 2014). However, these systems are too expensive to cover a larger area. Thus, crowd-sensing solutions like mobile sensors installed in modern vehicles or mobile phone applications are more promising to sense complete city districts. Probe vehicles detect available parking spaces while driving through the streets and communicate this parking information to other users or to a central parking management instance (Mathur et al. 2010; Bock et al. 2015). Mobile phone applications are proposed to either detect parking events automatically (Ma et al. 2014) or based on user input (Chen et al. 2012). Such crowd-sensed parking information can also be used for the automated generation of on-street parking maps (Coric and Gruteser 2013; Bock et al. 2016). Nevertheless, the coverage of mobile sensors always is incomplete as long as the penetration rate of these systems remains low. Therefore it is not possible to have real-time parking availability data for the complete area based on crowdsourcing solutions. This effect is amplified by the highly irregular usage of different roads. Main roads have a regular coverage, while smaller streets are only sensed from time to time. Since parking availability does not change in a random manner, parking information from the past and nearby roads can be helpful. While some studies focused on the temporal aspects, spatial similarities of parking availability are barely researched (Rajabioun and Ioannou 2015).

The focus of this work is the investigation of spatial similarities in parking availability of on-street parking spaces and the use of these spatial relations for parking availability estimation. We examine the similarity of the time series from pairs of road segments depending on their distance. Also the impact of further factors like the number of parking spaces in a road segment and the time of day is investigated. For a better assessment of the strength of spatial similarities, the results are compared to temporal similarity. Finally, we compare multiple interpolation methods for the parking availability estimation in adjacent roads. In this evaluation, we vary the rate of observed road segments and evaluate the interpolation result on the remaining road segments.

2. Methodology

2.1. Evaluation data

The evaluations of this work are based on data from the SFPark project (SFMTA 2014). The municipality of San Francisco ran this large project between 2011 and 2014 where they installed sensors in more than 8,000 parking spaces. Information about the number of available parking spaces per road segment was provided to the public via an application programming interface (API) at 5-minute intervals. A road segment corresponds to one side of a road between two subsequent intersections. A recording of this data from August 1st until October 31st 2013 is used for our evaluations. During that time period, there was only one major system breakdown on September 19th where about 18 hours are missing in the data set. The evaluation area is limited to the Financial District and South of Market (see Fig. 1) where 250 road segments with 2,668 on-street parking spaces are monitored.

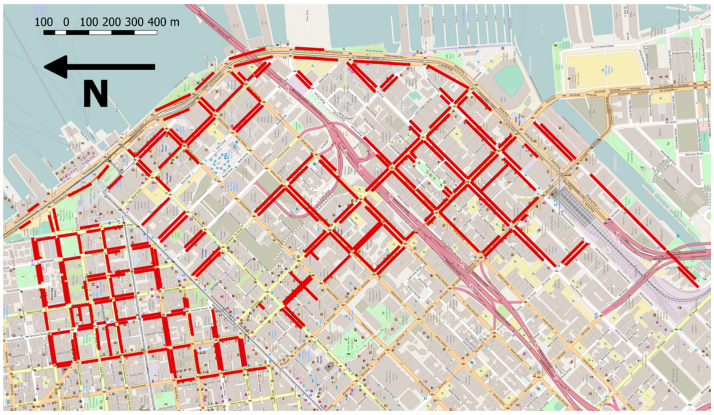

Fig. 1 Map of investigated area in San Francisco (Financial District and South of Market) with monitored road segments in red (underlying map from *OpenStreetMap*).

2.2. Similarity measures

For the examination of spatial similarities in parking availability, we create pairs of road segments. To examine the relation between similarity and distance, such pairs of road segments with similar bee-line distances are grouped together. The similarity is then calculated for the availability values of these sets of road segment pairs. The parking availability rate $A_r(t)$ is defined as the number of available parking spaces divided by the total number of parking spaces on a road segment r at a time instance t. An example for the temporal variation of the availability rate for three road segments is shown in Fig. 2.

For the similarity computations, we use two measures: the Pearson correlation coefficient

$$pCorr(\mathbf{A}(t), d_c) = \frac{\sum_{|d(i,j)-d_c|<\Delta, i\neq j} (A_i(t) - \overline{A}(t)) \cdot (A_j(t) - \overline{A}(t))}{\sqrt{\sum_{|d(i,j)-d_c|<\Delta, i\neq j} (A_i(t) - \overline{A}(t))^2 \cdot \sum_{|d(i,j)-d_c|<\Delta, i\neq j} (A_j(t) - \overline{A}(t))^2}} \quad (1)$$

and the inverse of the average of absolute differences (called *iAAD* in the following)

$$iAAD(\mathbf{A}(t), d_c) = 1 - \frac{\sum_{|d(i,j)-d_c|<\Delta, i\neq j} |A_i(t) - A_j(t)|}{\sum_{|d(i,j)-d_c|<\Delta, i\neq j} 1} \quad (2)$$

where $\mathbf{A}(t)$ is the vector of parking availability rates for all road segments at time instance t, d_c is the desired distance for similarity calculation, $d(i,j)$ is the distance between the road segments i and j, Δ is the distance buffer (15 meters in our evaluations), and $\overline{A}(t)$ is the mean of availability rate over all road segments at time t. The Pearson correlation has a value range between -1 and 1 where $pCorr$=1 is perfect correlation and $pCorr$=0 means both inputs are uncorrelated. For *iAAD*, the possible range is between 0 and 1 where *iAAD*=1 corresponds to a perfect match. Both measures are calculated for each time instance separately. Measurements are taken from the data set for every hour. These similarity values are averaged then over all time instances of the time period. The inverse temporal average of absolute differences is calculated with the following formula for the set of road segments R:

$$iAADtemp(\mathbf{A}(t), \mathbf{A}(t-\Delta t)) = 1 - \frac{\sum_{i\in R} |A_i(t) - A_i(t-\Delta t)|}{\sum_{i\in R} 1}$$

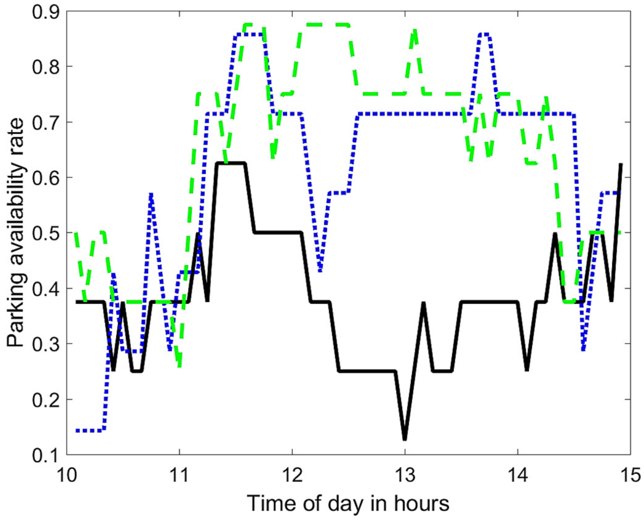

Fig. 2 Example for the parking availability rate of three road segments on August 1st 2013: the dashed green line and the dotted blue line show two road segments with a very similar parking pattern, while the solid black line reveals a very different parking behavior.

2.3. Interpolation methods

For the interpolation of parking availability rates, two methods are compared: inverse distance weighting (IDW) (Shepard 1968) which calculates a weighted average based on the distances,

$$A_{IDW}(\boldsymbol{x},t) = \begin{cases} A_i(t), & d(\boldsymbol{x},\boldsymbol{x}_i) = 0 \text{ for any i} \\ \frac{\sum_{i\in R} w_i(\boldsymbol{x})\cdot A_i(t)}{\sum_{i\in R} w_i(\boldsymbol{x})}, & d(\boldsymbol{x},\boldsymbol{x}_i) \neq 0 \text{ for all i} \end{cases} \quad \text{with weights } w_i(\boldsymbol{x}) = \frac{1}{d(\boldsymbol{x},\boldsymbol{x}_i)^e} \tag{3}$$

and simple averaging of availability rates from all observed road segments in the investigated area

$$A_{AVG}(\boldsymbol{x},t) = \frac{\sum_{i\in R} A_i(t)}{\sum_{i\in R} 1} \tag{4}$$

where $\boldsymbol{x}$ is the position vector, R is the set of all road segments, and e is the weighting exponent. The simple averaging corresponds to the special case e=0 in the IDW method. Additionally, the results are compared against a random guess of parking availability with random values between 0 and 1 as a baseline. For the evaluation, the set of road segments is divided into two sets: observed road segments and predicted road segments. As a measure of the estimation quality, the mean of the absolute error in availability rate is computed.

3. Results

3.1. Similarities in parking availability rates

The results for both similarity measures depending on the distance are shown in Fig. 3. The similarity measures are evaluated for different thresholds of the minimal number of parking spaces on a road segment (1, 3, 6, and 9 parking spaces) since a parking event of only one car leads to a drastic change in the availability rate for road segments with very few parking spaces. For example, in a road segment with two parking spaces, a parking event changes the availability rate by 50%. Fig. 3 (a) shows this relation between distance and similarity for the Pearson correlation. For all thresholds of parking spaces minimum, the highest values are observed for short distances less

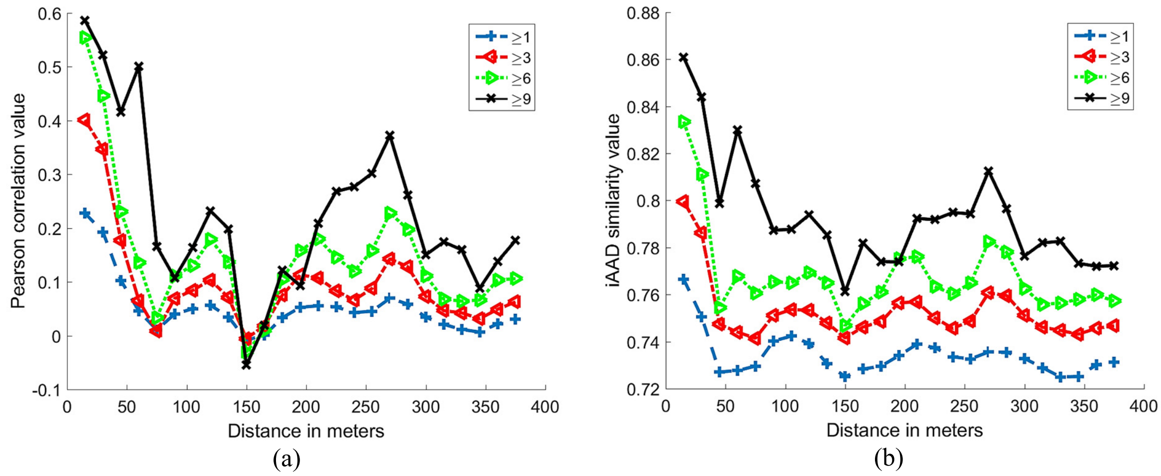

Fig. 3 (a) Pearson correlation and (b) inverse average of absolute differences (iAAD) for different distances of the road segment pairs and different minima of parking spaces per road segment (colors).

than 100 meters. The similarity strongly decreases with increasing distance to values close to zero. Similarly, the inverse of the average of absolute differences *iAAD* in Fig. 3 (b) is high for short distances and then decreases to a nearly constant value. Both figures also show a clear impact of the minimal number of parking spaces: the higher this threshold, the higher the similarity of the road segment pairs. Choosing this threshold to be at least 9 parking spaces reduces the number of investigated road segments from 250 to 138 which still provides more than 75% of the parking spaces. This result suggests that clustering of adjacent road segments could improve estimation results in future work. In the following evaluations, a minimal number of three parking spaces is used.

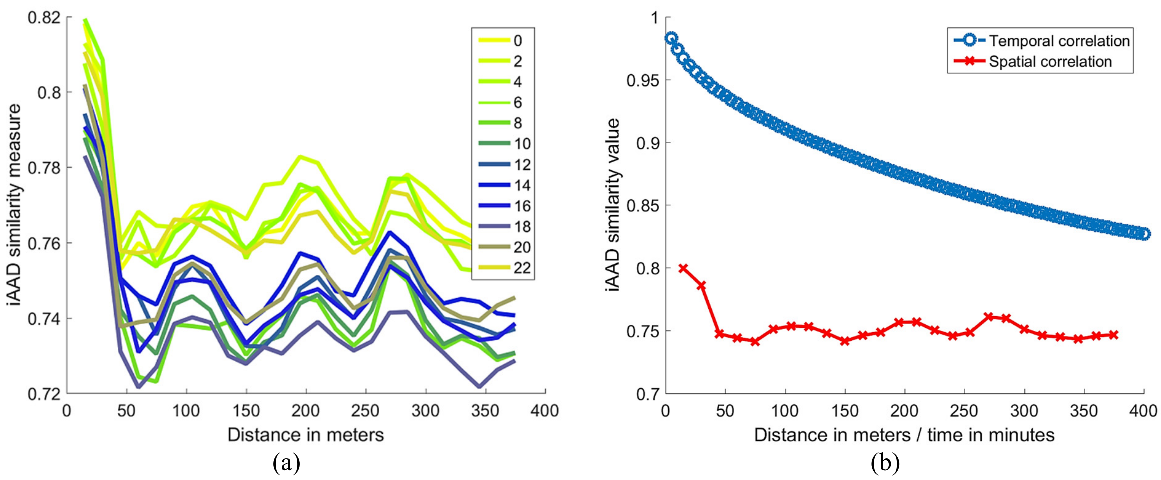

Fig. 4 Inverse verage of absolute differences for different hours of the day (a), comparison for average of absolute differences between spatial and temporal similarity (b).

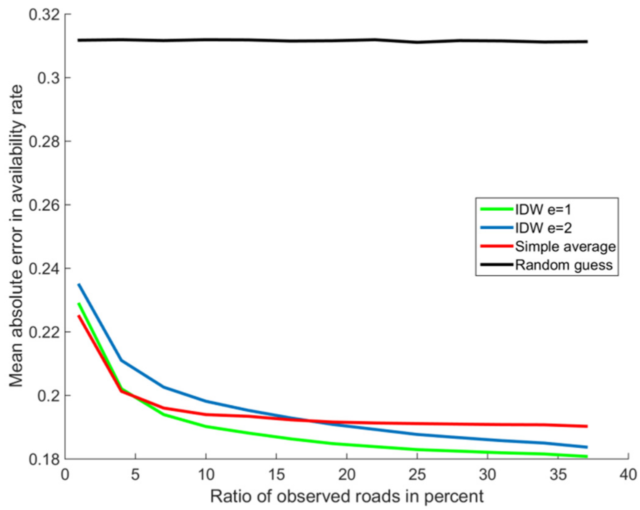

Fig. 5 Comparison of spatial interpolation methods for different ratios of observed road segments.

The dependence of the *iAAD* on time of day is illustrated in Fig. 4 (a). During the night and morning hours, the similarity measure is clearly higher than during the day. However, the critical distance where the value strongly decreases, is always between 50m and 75m. Also, the difference of this measure at short and longer distances is similar for all times of the day.

Finally, the spatial similarity is compared to the temporal similarity for parking availability rates in our data set (Fig. 4 (b)). In this illustration, the *iAAD* is always higher for the temporal than for the spatial case. This means that, on average, the similarity of availability rates is higher even after multiple hours at the same street segment than at adjacent streets at the same time.

3.2. Parking availability estimation using interpolation methods

The comparison of different interpolation methods is shown in Fig. 5. The results show a clear improvement of both interpolation methods compared to the baseline (random guess). Both interpolation methods lead to lower error values for larger ratio of observed road segments. For the inverse distance weighting method, the weighting exponent is also varied. While IDW with e=1 is better than the simple average for nearly all amounts of observed roads by up to 5%, the case e=2 is only better when more than 18% of the roads are observed and contribute to the estimation.

4. Discussion

4.1. Spatial and temporal similarities in parking behavior

The strong decrease in both similarity measures for higher distances implies that parking availability information is especially valuable for short distances less than 100 meters. Such a short distance corresponds to opposite parking lanes or directly connected road segments. For higher distances, the similarities are on a nearly constant level and therefore, a benefit of adjacency is not given anymore. A comparison of the results for both similarity measures (Fig. 3) shows that both measures reveal the same similarity patterns and therefore the presentation of only the *iAAD* measure is sufficient in the remaining evaluations.

Higher similarity during night hours (10pm until 6am) implies a more homogeneous parking behavior than at daytime. This result is intuitive since hotspots like shops and restaurants are more relevant during the day while parking can be assumed to be mostly residential parking at night which is not concentrated on hotspots. The comparison to the temporal similarity reveals that parking availability information from few hours ago is much more relevant than current information from other road segments in the vicinity in contrast to results in (Rajabioun and Ioannou 2015). Our result suggests that recent information should be integrated in parking availability estimation if available. A combination of both temporal and spatial information from nearby roads is assumed to be promising.

4.2. Interpolation of parking availability data

The results of spatial interpolation show that there is a clear information gain using parking availability information from further roads compared to the random guess. The error reduction with increasing ratio of observed roads for all interpolation methods emphasizes this point. The IDW algorithm, which gives stronger weights to nearby roads, shows especially better results compared to the simple average for large ratios of observed roads. This result is reasonable since more nearby roads, which are higher weighted, are observed at a higher observation ratio. The simple average over the full investigation area shows solid results. However, it is assumed that the results become worse for larger investigation areas because parking behavior varies for different districts.

4.3. *Limitations and future work*

Since this evaluation is only based on two districts in San Francisco, it is not certain whether the results describe a general pattern and therefore need be verified with data from other cities. In addition, the dynamic price adjustments and provision of real-time parking information by the SFPark project might have affected parking behavior. Also, we assume that all measurements of the parking sensors are correct although some issues are reported that affect the accuracy (SFMTA 2014).

In the future, we plan to investigate spatio-temporal estimation models in comparison with spatial and temporal models. Also the impact of clustering adjacent roads will be investigated. Furthermore, the estimation of day trends shall be included in the estimation to distinguish between typical and atypical parking availability patterns. Finally, the estimation of parking availability rates will be compared to a binary classification with the classes 'fully parked' and 'parking spaces available'.

5. Conclusions

This work presents an evaluation of spatial similarities in parking availability based on a large data set from static parking sensors in San Francisco. The investigation reveals that relevant spatial similarities in parking availability exist only for short distances of less than hundred meters. The magnitude depends on the minimum number of parking space per road segment, but rarely on the time of day. Compared to temporal similarity, the spatial similarities of parking availability rates are lower, but still contribute valuable information for nearby roads. This result is substantiated by the investigation of spatial interpolation methods for these availability rates. All interpolation methods show clearly better results than a random guess. The inverse distance weighting method also outperforms a simple average of all availability rates by up to 5%.

Based on these results, we conclude that spatial similarities should be considered in parking availability estimation approaches. However, since relevant similarities only exist for short distances, the potential for improvement is limited.

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