A Cost-Effective Approach for Evaluating On-Street Parking Utilization using Simple Cameras*

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Abstract—This study proposes an algorithm to integrate bay-based parking occupancy, captured using an image processing system, with information from a common conventional parking payment management system. The algorithm enables the use of simple and inexpensive cameras to collect parking utilization to complement conventional payment transaction data. Details about the design, implementation, testing, and validation of the algorithm are provided. Validation was performed using data collected through an accurate observational survey, including plate numbers of all vehicles parked in the areas of analysis. Results from a case study using the proposed algorithm provided an accuracy of 76% in terms of correct data integration. Logistic regression analysis was used to improve parameters used by the proposed algorithm. To illustrate the value of the algorithm, the integrated data were used to evaluate parking payment behavior. Various performance measures can be proposed and estimated using the integrated data. The integrated data can be used to address questions of high importance for more efficient and effective management of parking facilities.

I. INTRODUCTION

Previous research has developed and validated highly accurate (85%+ accuracy) and reliable algorithms to infer parking bay occupancy using conventional cameras [1]–[4]. These algorithms, often using advanced machine learning techniques, can even filter visual obstructions [2] and work reliably under different weather and lighting conditions [3], [5]. The resulting approach for monitoring parking bay occupancy is very efficient, especially for open space parking lots [2]. This approach does not require expensive technologies, such as magnetic or infra-red sensors. The approach is not labor-intensive in terms of installation and maintenance, which is often the case for inground sensors [3]. A single camera can cover many parking bays simultaneously. Finally, this approach is often more reliable and its results more accurate compared to other methods and technologies [4].

Reliable occupancy data can effectively be used for parking monitoring and management. This includes real-time monitoring/off-line evaluation of general parking utilization (e.g., parking accumulation), and parking rule violations (e.g., illegal parking location) in terms of individual bays or as an aggregate. Reliable data can also be used to more effectively enforce parking rules/policies, dynamically manage parking pricing, and more efficiently use the parking space [6].

A significant challenge for the deployment of cameras and advanced algorithms for the collection of parking occupancy data is the integration with information from other sources. The data often lacks unique identification features, such as vehicle plate numbers, because of the low resolution of images captured by simple, inexpensive cameras and environmental distortions including natural obstructions, poor lighting or severe weather conditions. This type of data integration challenge is not exclusive for videos. Data from other parking management systems (payment systems) often lack details such as accurate position, including bay numbers, because they are hard to capture (needs extra effort from parking users) while they do not add much value for the purpose of the corresponding system. Most often, vehicle plate number is of central importance for payment management and enforcement.

This research proposes a heuristic algorithm to integrate occupancy data collected using a camera-based detection approach with information from a conventional parking payment management system. The accuracy of the proposed algorithm is validated using a third dataset, collected through an accurate observational survey, which includes plate numbers of all vehicles parked in the study area. The results of the proposed algorithm are used to show the usefulness and efficiency of the integrated datasets for evaluating parking payment behavior, which in turn is of central importance for assessing the efficiency of enforcement procedures and the effectiveness of parking policies. This study focuses on the development, tuning and validation of the algorithm using the data captured/generated by parking monitoring and payment systems; generating occupancy data from videos or other sources has widely been addressed in the literature and is not in the scope of this research.

This study makes a unique contribution by proposing and validating the data integration algorithm. Simple, inexpensive cameras can be used to collect actual parking utilization data to complement conventional payment transactions data relying on this algorithm. The integrated data can address questions of high importance for more efficient and effective management of parking space, including but not limited to: What are the parking performance indicators for each parking bay and how do these indicators correspond with the bay payments? Are there any patterns in parking payment behavior? What is the likelihood of underpaid/overpaid/unpaid parking utilization in different locations? What types of unpaid parking utilization occur in different locations? How effective are different parking management policies in improving parking

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performance? To what extent do parking enforcement prevent illegal use of parking space?

The remainder of this paper is structured as follows. Section II describes the study’s methods, including the data, proposed data matching algorithm and the analysis techniques. Section III presents the study results including the exploratory analysis findings, the algorithm validation outcomes and the results of the analysis of an integrated dataset. This section also discusses the study findings and the proposed approach’s contribution to both theory and practice of open space parking management. Section IV concludes the study.

II. METHODS

A. Data Collection and Existing Data

This study investigates on-street parking in three separate streets in the Brisbane central business district (CBD) which are assumed to be representative of different spatio-temporal characteristics of parking behavior in the CBD. These streets include Turbot Street, Elizabeth Street, and Alice Street which are referred to as the CBD West, CBD Center, and CBD East throughout this paper, given their geographical positions, depicted in Fig. 1. The sections of these streets considered in this study include 32, 14 and 20 parking bays, respectively. Furthermore, each of the sections have three, two and two parking meters, respectively. On-street parking bays in the study area, including its surroundings in the CBD, are paid parking spaces regulated by Brisbane City Council from 7 am to 10 pm weekdays and 7 am to 7 pm on the weekends. A mixture of other parking types exists around these locations, including loading zones and bus zones, which are not the focus of this study. During paid parking hours, parking fees can be paid through a nearby parking meter or a smartphone application. The maximum allowed length of stay in this area is three hours for Alice Street and Turbot Street, while it is one hour for Elizabeth Street. Weekday clearway restrictions are also in place between 7 am and 9 am in Turbot Street, and between 4 pm and 7 pm in all the three streets (except for 7 bays in Elizabeth Street).

Three main sources of data were collected in the study area to develop, validate and examine the usefulness of the proposed approach. These data sources include: a) all parking payment transactions corresponding different methods of payment, b) parking bay occupancy data captured using low-resolution cameras, and c) parked vehicle plate numbers captured using high-resolution cameras [7]. These datasets are referred to as a) “payments”, b) “low-resolution videos”, and c) “high-resolution videos”, respectively, throughout the remainder of this paper. The data collection was performed during paid parking hours throughout a week in June 2019 using both parking payment management system and low-resolution cameras, and was repeated for three days in December 2019 using the parking payment management system and high-resolution cameras. Fig. 1 illustrates the places of parking meters and low/high resolution cameras used for data collection (the high-resolution cameras used for the second data collection were installed in the same locations where the low-resolution cameras were installed for the first data collection).

Payments were obtained from the parking payment management system for the duration of this study. Parking payment transactions may include a wide range of details about parked vehicles and the corresponding parking behavior, depending on the technologies used for parking payment management. On-street parking fees in Brisbane need to be paid using the corresponding vehicle’s plate number, commonly referred to as pay-by-plate, similar to many other cities in Australia and around the world. The payment transactions incorporate the payment method (cash/credit card/mobile application) and the respective details (meter ID and transaction ID for payments made by parking meters and the mobile application, respectively). Overall, each parking payment transaction includes the corresponding vehicle’s plate number, purchase time, start time (can be different to purchase time), expiry time and payment type details. Purchase time can be up to nine hours before the parking start time; mobile application users can pay in advance for a parking spot in a given parking zone, although the payment does not guarantee the availability of space. Therefore, the payment-based start time does not exactly match with the actual parking start time, and thus the payment-based start time is indicative only. This time might be before or after the actual parking start time. The expiry time is only defined by the payment amount and does not reflect the actual finish time of parking. The data do not include bay numbers used by parked vehicles.

As mentioned in Section I, this study is not interested in the methods of inferring bay-level parking occupancy using videos
and merely uses the generated data to integrate with parking payment transactions. The low-resolution videos were carefully processed by a third party to determine the exact time period (arrival–departure time) for which each single vehicle used a parking bay in the parking study area. The resulting dataset includes actual parking transactions that occurred in the study area, although vehicle plate numbers are not available. Each transaction in this dataset consists of parking zone number, bay number, start time, end time and vehicle type.

The high-resolution videos were also processed by a third party manually to extract similar data to those obtained from the low-resolution videos, while each vehicle plate number could also be identified. Given the availability of plate numbers in the payments, the data obtained from the high-resolution videos could easily be integrated with the payment transactions for validation of the proposed algorithm.

B. Data Integration Algorithm

This study proposes and evaluates a heuristic algorithm to integrate the parking payment transactions (payments) with the parking occupancy data captured using low-resolution cameras (low-resolution videos), as mentioned in Section I. Due to a lack of identical identifiers in the two datasets, this algorithm relies on parking start/expiry time and stay period from the payments as well as parking start/end time and stay period from the low-resolution videos to find the highest probable matches from the two datasets. Fig. 2 provides a pseudocode for the proposed algorithm.

1) Variables and functions

The variables and functions used in the algorithm are defined as follows.

- $Z$: Set of all parking zones in the study area, a parking zone $z \in Z$ usually consists of multiple parking bays stretches across a section of or a whole street
- $D$: Set of days during which the parking transactions were studied
- $TP$: Set of all parking transactions for the period and area of the study, extracted from the payment management system
- $t$: A parking transaction extracted from payments; $t \in TP, i = 1, \ldots, |TP|
- $TL$: Set of all parking transactions for the period and area of the study, extracted from low-resolution videos
- $t$: A parking transaction extracted from low-resolution videos; $t \in TL, j = 1, \ldots, |TL|
- $TH$: Set of all parking transactions for the period and area of the study, extracted from high-resolution videos
- $TI$: Set of integrated parking transactions
- $zone(t)$: This function returns the zone of a parking transaction $t$
- $day(t)$: This function returns the day of a parking transaction $t$
- $plate(t)$: This function returns the vehicle plate number from a parking transaction $t$

2) Main algorithmic assumptions

The main assumptions based on which the algorithm is developed are listed next.

- When a customer pays for on-street parking (and thus there is $t \in TP$), they occupy a parking bay even for a very short period of time.
- For each $t \in TP$, there is a $t \in TL$ in low-resolution videos for the same day and at the same location.
- There might exist $t \in TL$ which cannot be matched with any $t \in TP$, because of unpaid parking utilization.
- When paying by parking meters, people use a machine which is in the same parking zone $z \in Z$ as their occupied parking bay.
- The timing of each $t \in TP$ – especially its start time – is relatively close to the timing of the corresponding $t \in TL$. However, the start/expiry time and the duration of $t$ do not necessarily perfectly match with the arrival/departure time and the period of the corresponding $t$ – people may under- or over-pay for their parking utilization.
- On-street parking users may extend their initial length of stay by paying through a parking meter/mobile application after their initial parking period expires. Therefore, there can be payment transactions $t, t' \in TP$ which correspond to one single transaction $t \in TL$, as both $t$ and $t'$ are associated with single, continuous act of parking occupancy.
proximity of departure where they belong to the same vehicle and they have extended their length of stay by
while they actually park their vehicle on-street. However, expiry time is merely based on the amount paid for
parking, especially for meter transactions, and its proximity to the actual departure time depends on how accurate the respective customer could estimate their length of stay. Hence, the largest and smallest weights are given to $\sigma_1$ and $\sigma_2$, respectively. This assumption is shown to be true in Section III. Accordingly, the following values were used in the algorithm:

$$\sigma_1 = 0.5, \quad \sigma_2 = 0.5, \quad \text{and} \quad \sigma_3 = 1.5.$$ However, more accurate weights $\omega$'s can be estimated using some ground-truth data. As discussed in the next section, we fit a logistic regression model to a small subset of $TH$ to obtain more accurate $\omega$'s as well.

### III. Results and Discussion

This section initially elaborates on a street parking performance indicator, namely relative parking occupancy, estimated at an aggregate level using payments and low-resolution videos, separately. It presents the results of validating the proposed algorithm using high-resolution videos. Finally, it examines the usefulness of integrating parking payment transactions with low-resolution video data in revealing parking and payment behavior.

#### A. Parking Utilization Indicators

An important indicator of parking performance, namely relative parking occupancy, is used to contrast the overall parking performance of the CBD West, CBD Center and CBD East, estimated using payments and low-resolution videos. This indicator is estimated at an aggregate level for each of these three locations. They do not correspond to single bays; rather they represent an aggregate measure for each of the three street sections.

Fig. 3 illustrates the relative parking occupancy indicator over one week. The relative parking occupancy is calculated at 15-minute intervals by dividing the accumulation by the capacity. Each of the subfigures in Fig. 3 (a) and (b) represents a day of data collection from the 18th (Tuesday) through the 24th (Monday) of June, 2019. The black horizontal line in these figures represent the 80% occupancy level; it is considered as the threshold above which the cruising for parking and its impact on traffic become evident [10].

As shown in Fig. 3, the payment-based occupancy resembles the (low-resolution) video-based occupancy in the CBD West (similar results were obtained for the CBD East). The video-based occupancy is slightly lower than the payment-based occupancy in the CBD West (except for Sunday, the 23rd of June), while it is slightly higher than the payment-based

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**Figure 2.** Pseudocode for proposed data integration algorithm

| for each parking zone $z$ in $Z$ do |
| --- |
| for each day of observation $d$ in $D$ do |
| $TP^z = list\{t \in TP | zone(t) = z \land day(t) = d\}$ |
| while $(\exists t_i \in TP^z and t_j \in TP^z)$ where $(i \neq j$ and $zone(t_i) = zone(t_j)$ and $day(t_i) = day(t_j)$ and $plate(t_i) = plate(t_j)$ and $abs(\Delta(departure(t_i), departure(t_j))) \leq 60min)$ do |
| merge($t_i, t_j$) in $TP'$ |
| $TL^z = list\{t \in TL | zone(t) = z \land day(t) = d\}$ |
| if $TL^z \neq \emptyset$ then |
| for each $t_i$ in $TP'$ do |
| $A_i = list\{order(\alpha, \text{asc}) | \alpha = abs(\Delta(arrival(t_i), \text{arrival}(t_j \in TL')))\} |
| $SA_i = list\{\sigma_1, \sigma_2 = index(\alpha) | TL'\}$ |
| $B_i = list\{order(\beta, \text{asc}) | \beta = abs(\Delta(departure(t_i), departure(t_j \in TL')))\} |
| $SB_i = list\{\sigma_3, \sigma_4 = index(\beta) | TL'\}$ |
| $\Theta = list\{order(\gamma, \text{asc}) | \gamma = \Theta(t_i, t_j) / \text{duration}(t_j)\} |
| $\Theta(t_i, t_j) / \text{duration}(t_j)$ |
| $ST_i = list\{\sigma_5, \sigma_6 = index(\gamma) | TL'\}$ |
| $S_j = list\{s \in S | s = (\omega_1, \sigma_1, \omega_2, \sigma_2, \omega_3, \sigma_3, \omega_4, \sigma_4) \sum \omega\} |
| else |
| alert(“no data to be matched with $t_i$”) |
| end |
| $S' = \text{matrix}(S_j)$ |
| $TI' = H(TP', TL', S')$ |
| end |
| end |

The algorithm creates a matrix $S'$ where for each $s'_j \in S'$, $s'_j = (\omega_1, \sigma_1, \omega_2, \sigma_2, \omega_3, \sigma_3, \omega_4, \sigma_4) \sum \omega$. $s'_j$ reflects the overall similarity between each pair of transactions ($t_i, t_j$). Then, it uses the Hungarian optimization method [7] to match each $t_i$ with one and only one $t_j$, where $2s_j$ is maximum for matrix $S'$. This method finds an optimal solution in polynomial time $O(n^3)$ [8].

Among the three known and matchable characteristics of each transaction, the start–arrival time has the highest likelihood of similarity for each pair of corresponding transactions ($t_i, t_j$), while the expiry–departure time has the lowest likelihood of similarity. Parking customer usually start their parking transaction by paying the fee approximately at the same time when they actually park their vehicle on-street. However, expiry time is merely based on the amount paid for parking, especially for meter transactions, and its proximity to the actual departure time depends on how accurate the respective customer could estimate their length of stay. Hence, the largest and smallest weights are given to $\sigma_1$ and $\sigma_2$, respectively. This assumption is shown to be true in Section III. Accordingly, the following values were used in the algorithm:

$$\sigma_1 = 0.5, \quad \sigma_2 = 0.5, \quad \text{and} \quad \sigma_3 = 1.5.$$ However, more accurate weights $\omega$’s can be estimated using some ground-truth data. As discussed in the next section, we fit a logistic regression model to a small subset of $TH$ to obtain more accurate $\omega$’s as well.

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3) Algorithm

As shown in Fig. 2, the algorithm initially merges potential $t$’s where they belong to the same vehicle and they have happened on the same day and in the same zone with a maximum of 60 minutes gap between them. As discussed before, these transactions most probably correspond to a single $t_j \in TL$, the customer has extended their length of stay by repaying at the end of their initial parking transaction.

The algorithm then estimates a similarity index $\alpha_i$ for each pair ($t_i, t_j$), where $t_i \in TP$ and $t_j \in TL$. This index is estimated based on the proximity of arrival($t_i$) and arrival($t_j$) – $\sigma_1$, the proximity of departure($t_i$) and departure($t_j$) – $\sigma_2$, the overlap of $t_i$ and $t_j$ – $\sigma_3$, using proximity/similarity weights $\omega$’s.
occupancy for the CBD East (the latter is not shown due to space limitations). This can be attributed to the spatial characteristics of these two locations and the differences between their potential parking users. The CBD West is relatively closer to businesses, and it is more likely that its parking space is used by people travelling for work/business. The CBD East is relatively closer to attractions and the Queensland University of Technology; the parking users are potentially more leisure or education-oriented. The former group of users tends to overestimate their length of stay and overpay, while the latter tends to underestimate their length of stay and underpay. However, the high similarity between the video-based and payment-based occupancy in these two locations, even when the video-based occupancy is above 80%, provides the opportunity to rely on payment transactions to evaluate/forecast on-street parking occupancy relatively accurately, without a need for video-based occupancy data.

However, the video-based and payment-based occupancy from the CBD center do not resemble each other well; the video-based occupancy is often higher than the payment-based occupancy. This is especially important, given that the former group of users are highly inaccurate.

As outlined in Fig. 4, the median difference is close to zero for both the start–arrival and expiry–departure times, and the median for stay period overlap is approximately one; this confirms the usefulness of these characteristics for integrating the two datasets. Furthermore, it is evident that the start–arrival time has the highest level of similarity for matched transactions, as the difference is less than 10 minutes for almost all transactions. The variation is larger for the other two characteristics, indicating the necessity of assigning lower weights to them in the proposed algorithm.

To estimate more accurately the weights $\omega_i$’s, we used a random sample of the ground-truth data ($n=163, 20\%$ of the transactions in $TH$) to develop a logistic regression model with the three variables used in the algorithm, namely the absolute difference between start–arrival times, the absolute difference between expiry–departure times, and the stay overlap for each pair of transactions selected from $TP$ and $TH$, as the model parameters. The model results are summarized in TABLE I. The parameter estimates and z-values obtained by the model also confirm the order of importance of the algorithm variables.

![Figure 3. Relative occupancy in the (a) CBD West, and (b) CBD Center](image)

**TABLE I. RESULTS FROM LOGISTIC REGRESSION**

| Coefficient                  | Estimate | Std.Err. | z Value |
|------------------------------|----------|----------|---------|
| Intercept                    | -0.739   | 0.455    | -1.623  |
| Absolute Arrival Difference  | -0.231***| 0.025    | -9.088  |
| Absolute Departure Difference| -0.032** | 0.006    | -5.699  |
| Stay Period Overlap          | 1.051    | 0.447    | 2.351   |
| Significance levels: *** < 0.001; ** < 0.01; * < 0.05 |
| AIC: 603.78 McFadden Pseudo $R^2$: 62.16 |

We evaluated the accuracy of the algorithm having used both intuitive and model-based weights determined by the logistic regression model. The former resulted in correct matching of 440 out of 625 (70.4%) transactions in the ground-truth dataset. The latter increased the accuracy of the model to 76.2% (476 correct matching). Overall, the proposed approach could correctly match at least 62.4% of the transactions, regardless of the value of the weights.
C. Parking Payment Behavior

The integration of the two datasets provide opportunities to monitor and evaluate complex parking behavior. As an example, we demonstrate how the integrated data can be used to investigate parking payment behavior. While parking payment data include all paid transactions, the data cannot be used to study underpayments and overpayments, occurred intentionally or unintentionally due to mis-estimation of the length of stay. Moreover, the data completely lack any detail on unpaid/illegal parking. These missing details can be obtained by integrating payment-based and video-based occupancy data.

TABLE II illustrates a summary of the parking payment behavior in June 2019, aggregated over the three locations of study. Overall, 53.7% (2,356 out of 4,388) of all parking transactions are unpaid; they are missing in the payment transactions data. This is especially important, given that the average length of stay is more than 16 minutes (more than 31 minutes on the weekends) for these transactions; this is 39.1% of the average length of stay for all transactions (60.2% on the weekends). The length of unpaid stays could reach as high as eight hours in our study. However, such illegal parking utilization directly corresponds to parking bay occupation, and therefore significant analytic inaccuracies when relying merely on payment-based occupancy data.

One interesting finding is that the average length of stay obtained from parking payment transactions (82.1 minutes) is almost twice the size of the video-based average length of stay (42.7 minutes), which is due to overpayments. As presented in TABLE II, the average length of underpay/overpay (31.9 minutes) is approximately twice the size of the average length of overstay/underpay (14.3 minutes), while the number of transactions is relatively similar in both categories (1036 versus 995, respectively). This means that people are equally likely to underpay or overpay, while they tend to misestimate their length of stay significantly longer when they overpay (potentially to prevent parking fines). Overall, the combined overpaid and underpaid transactions at the aggregate occupancy level are mutually compensated.

IV. Conclusion

Detailed information about occupancy at bay-level is required for an effective parking management. This is specifically relevant for parking zones with longer usability limits and small turnovers. Obtaining this type of information can be expensive and difficult. This study developed and tested an algorithm to capture this information using parking payment transactions and inferred video-based occupancies. The algorithm was validated and various analyses demonstrated its value. This study elaborated on how the integrated data can be used to evaluate under-/over-payment and unpaid parking, while the required details for estimation are not included in isolated data sources such as payment information. For the case study in this paper, the monetary value of underpaid and overpaid parking is approximately the same. However, half of the parking transactions were unpaid, although their lengths are not usually long. Other interesting finding is that the actual parking occupancy is usually underestimated, when only payment transactions are considered.

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| Variable          | Sample | Mean   | Median | Std.Dev. | Max  |
|-------------------|--------|--------|--------|----------|------|
| Video-based stay  | All n = 4388 | 42.7   | 18.4   | 53.0      | 494.5|
|                   | Weekdays n = 3315 | 39.5   | 15.0   | 50.7      | 291.1|
|                   | Weekends n = 1073 | 52.7   | 34.1   | 58.6      | 494.5|
| Pay stay          | All n = 2032 | 82.1   | 61.0   | 50.3      | 265  |
|                   | Weekdays n = 1499 | 78.6   | 61.0   | 49.8      | 265  |
|                   | Weekends n = 533 | 91.8   | 82.0   | 50.5      | 233  |
| Overstay          | All n = 995 | 14.3   | 6.9    | 21.3      | 225.8|
|                   | Weekdays n = 759 | 14.4   | 6.9    | 21.9      | 225.8|
|                   | Weekends n = 236 | 14.2   | 6.9    | 19.3      | 160.7|
| Understay         | All n = 1036 | 31.9   | 17.0   | 39.5      | 243.7|
|                   | Weekdays n = 739 | 27.3   | 15.3   | 33.9      | 243.7|
|                   | Weekends n = 297 | 43.5   | 23.5   | 48.9      | 200.6|
| Unpaid stay       | All n = 2356 | 16.7   | 2.7    | 37.4      | 494.5|
|                   | Weekdays n = 1816 | 12.3   | 2.4    | 29.0      | 284.1|
|                   | Weekends n = 540 | 31.7   | 4.7    | 54.7      | 494.5|
* Minimum length of stay is approximately zero for all rows.