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Quadrotor-Enabled Autonomous Parking Occupancy Detection

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***Abstract*—Large special-events parking involves various parking scenarios, e.g., temporary parking and on-street parking. Their occupancy detection is challenging as it is unrealistic to construct gates/stations for temporary parking areas or build a sensor-based detection system to cover every single street. To address this issue, this study develops a quadrotor-enabled autonomous parking occupancy detection system. A camera-equipped quadrotor is flying over the parking lot first; then the images are captured by the on-board camera of the quadrotor and transferred to the ground station; finally, the ground station will process and release the occupancy information to the driver's mobile devices. The decision tree learning algorithm is adopted to determine the optimal flying speed for the quadrotor to balance the trade-off between the detection efficiency and accuracy. In order to tackle the complex environment in real-life parking, a convolutional neural network (CNN)-based vehicle detection model has been trained and implemented, where the realistic factors, e.g., passing pedestrians and tree blocking, are considered. Experiments are conducted to illustrate the effectiveness of the proposed system.**

***Index Terms*—Parking occupancy detection, quadrotor, optimized flying speed, decision tree algorithm, convolutional neural network (CNN).**

I. Introduction

PARKING occupancy detection makes a meaningful contribution to reducing traffic congestion [1], especially during large special events, e.g., sports occasions, or music festivals. However, the large special-events parking usually involves various parking scenarios, e.g., temporary parking and on-street parking. Therefore, the occupancy detection becomes challenging: for the temporary parking area, constructing parking gates/stations are time-consuming and labor-intensive; for on-street parking, sensor-based vehicle detection systems [2]–[4] are infeasible to cover every single street.

Fortunately, the object detection techniques are investigated extensively in the computer vision fields [5]–[7], which provides promising solutions to the parking occupancy detection problem. In [8], a multi-camera system for parking management is proposed, where vehicle detection and counting are achieved with image occlusions and different weather conditions considered. In [9], a parking space detection and tracking approach is developed, where the parking slots are detected by estimating parallel line pairs and free spaces are calculated by recognizing the vehicles. A similar system is built in [10], where an adaptive parking lot background model for vehicle detection is established. In [11], a convolutional neural network (CNN)-based object detection algorithm, YOLO [12], is adopted to achieve the detection of vehicles and license plates. Compared to the feature detection-based techniques, YOLO has the outstanding capability to detect images under poor contrast, adverse lighting, and partial occlusion conditions. Besides, in comparison with other CNN-based methods, YOLO offers a much faster real-time processing speed [13]. Nevertheless, the aforementioned methods are based on pre-installed surveillance cameras so that each detection system is binding with only one specific parking lot. Besides, the fixed surveillance cameras cannot guarantee full coverage of all the potential parking area.

Recently, the quadrotors are being used in various applications [14]–[18], and bring new opportunities to evolve the large special events parking occupancy detection system. In [19], a vehicle counting approach is presented based on images taken from a quadrotor. Such a quadrotor-based system is portable and applicable to various parking scenarios with low maintenance costs. To this end, based on quadrotor images, many results regarding vehicle detection have been reported [20]–[24]. However, there still exist some challenges.

Firstly, few existing studies provide real-time service for drivers who are looking for parking spaces along the road. Secondly, considering the complex environment in realistic outdoor parking, e.g., pedestrians and tree blocking, few of the existing vehicle recognition methods can ensure accuracy. Therefore, a detection system designed for outdoor parking is required to deal with the real-life uncertainties. Thirdly, the trade-off of the quadrotor flying speed and the image quality remains an open problem. Ideally, a quadrotor should maneuver as fast as possible to ensure efficiency. However, image processing is sensitive to image quality, while a fast-moving camera can potentially cause low-quality images that might lead to a detection failure [25]. Although many studies have been conducted to improve the robustness of image processing [26]–[29], the superior maneuverability of a quadrotor might still lead to the high occurrence of the low-quality images and image detection failures. Therefore, an optimized speed that can balance the trade-off between the detection efficiency and accuracy would be expected.

To overcome the challenges mentioned above, this study aims to develop an autonomous parking occupancy detection system for large special-events parking, in which the occupancy information is accessible to the driver's mobile devices and the real-life uncertainties would be considered. The main

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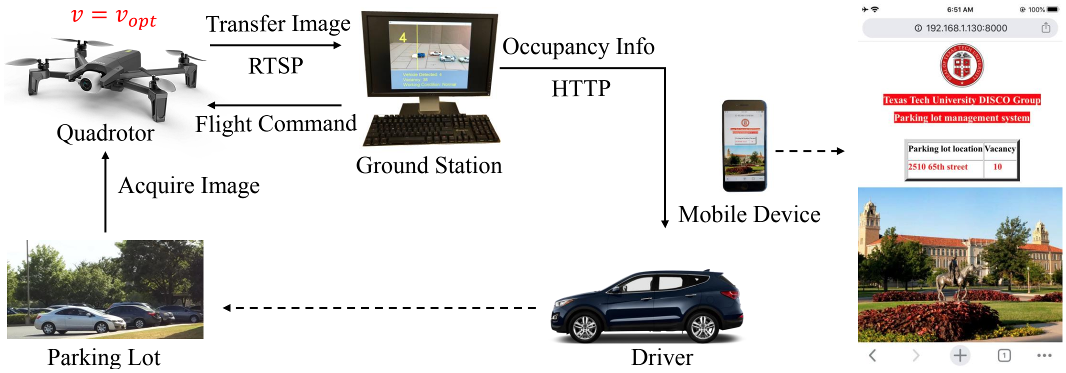


Figure 1. Proposed autonomous parking occupancy detection system. v is the quadrotor speed, v_{opt} is the optimized speed. The communication protocol: Real time streaming protocol (RTSP), hypertext transfer protocol (HTTP). The mobile device interface indicates that the parking area located on 2510 65th street has a vacancy of 10.

contributions of this paper are listed as follows:

- A portable parking occupancy detection system for large special events is developed. The proposed system is applicable to various parking scenarios, e.g., temporary parking and on-street parking. On top of that, the proposed system can release real-time occupancy information to mobile devices so that drivers along the road can plan their routes efficiently.
- A CNN-based vehicle detection model has been trained and implemented, with realistic factors, e.g., parking lots with pedestrians present, covered parking, parking lots with tree blocking, and vehicles with opened trunks, being considered.
- Experiments are conducted to generate a data set that contains different quadrotor flying speeds and corresponding image detection conditions, e.g., detection success or detection failure. Based on that, the classification tree learning algorithm is adopted to determine the optimal flying speed, which balances the trade-off between the detection efficiency and accuracy.

II. Proposed Parking Occupancy Detection System

As shown in Fig. 1, the proposed parking occupancy detection system consists of a camera-equipped quadrotor and a ground station. The images of the parking lot will be acquired by the on-board camera of the quadrotor, then processed by the ground station. After that, the occupancy information will be generated and released to the driver's mobile devices.

Theoretically, the parking detection can be achieved by analyzing a single picture of the entire parking lot, which, however, suffers from some limitations. Particularly, it naturally requires experienced pilots or advanced technologies to align the camera view with the parking lot boundary. In addition, the larger the parking lot is, the higher the quadrotor needs to be maneuvered, as shown in Fig. 2(a), which increases the detection difficulty. Furthermore, it cannot be applied to the covered parking lots, e.g., Fig. 2(b).

(a) (b)

Figure 2. (a) Large parking lot. (b) Covered parking lot.

Therefore, in the proposed system, the quadrotor is flying over the parking lot from one side to the other side. Meanwhile, instead of transferring a single picture of the entire parking lot, the complete video stream is transferred to the ground station. This allows the quadrotor to finish the image acquisition at a lower altitude, which not only reduces the requirements for the camera hardware, but also facilitates the quadrotor to detect vehicles at covered parking lots.

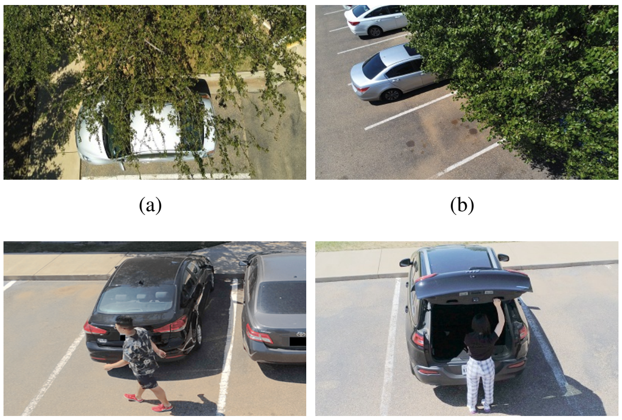
A. Ground Station

The ground station is a desktop computer with Intel Core i5-8400 CPU, 16GB DDR4 RAM, NVIDIA GeForce GTX 1050 Ti graphics, and Qualcomm Atheros AR8171/8175 PCI-E Gigabit ethernet controller. In the proposed system, the ground station is in charge of three tasks: (1) processing the video stream from the quadrotor; (2) releasing the occupancy information to the driver's mobile devices; (3) sending the control command to the quadrotor.

1) Vehicle Detection and Counting: On the ground station, the CNN-based object detection algorithm, YOLO [12], is used to train and implement a prediction model that can recognize vehicles. The adopted YOLO network has 53 convolutional layers with the successive 3×3 and 1×1. In order to improve the robustness for realistic applications, a training data set is constructed specifically for the parking lot vehicle detection. Particularly, images of vehicles under trees, e.g., Figs. 3(a) and (b); images of vehicles blocked by the passing pedestrians, e.g., Fig. 3(c); images of vehicles with a driver checking the trunk, e.g., Fig. 3(d), are included.

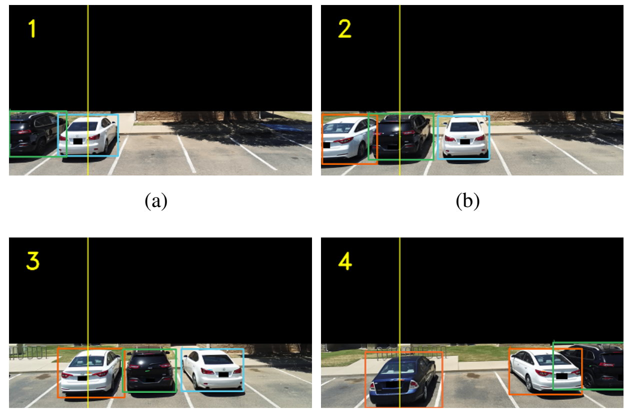
Table I
DATA SET FOR OPTIMAL SPEED SELECTION

i	speed v_i (m/s)	Test #1	Test #2	Test #3	Test #4	Test #5	Detection result y_i
1	1.0	1	1	1	1	1	1(Success)
2	1.2	1	1	1	1	1	1(Success)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
50	10.8	1	1	1	0	1	0 (Failure)
51	11.0	1	0	0	1	1	0 (Failure)



(a) (b) (c) (d)

Figure 3. Example images used in the data set for vehicle detection. (a) (b) Vehicles under trees. (c) Vehicles blocked by passing pedestrians. (d) Vehicles with a driver checking the trunk.



(a) (b) (c) (d)

Figure 4. Demonstration of the vehicle counting.

The total data set contains 2250 images. The training takes 50,000 iterations and results in an average loss of 0.21.

Moreover, a counter is developed to count the detected vehicles. As shown in Figs. 4(a)-(d), the quadrotor is moving from the right to the left, and the detected vehicles are marked with rectangle frames. During the detection, once the rectangle frame intersects with the defined yellow line, a summation calculation will add one to the total. The yellow number on the top-left indicates the total number of counted vehicles.

2) Occupancy Information Release: A Hypertext Transfer Protocol (HTTP)-based local server is set up on the ground station to release the occupancy information. A mobile device-friendly GUI is constructed to display the parking lot location and vacancy information. As the example shown in Fig. 1, the parking lot located on 2510 65th street has a vacancy of 10. Based on this, drivers on the road can conveniently access the occupancy information on their mobile devices and plan their routes efficiently.

B. Quadrotor

The quadrotor used in this study is *Parrot Anafi* [30], which weights 0.32 kg and spans a dimension of $0.17 \times 0.23 \times 0.06$ (m). The maximum flight speed is 14.7 m/s and the maximum flight time is around 25 minutes. A 3-axis Gimbal is attached at the bottom to stabilize the camera and the video stream can be transferred to the ground station via real time streaming protocol (RTSP). During the experiment, a set of waypoints that cover the parking area will be sent to the *Parrot Anafi* for autonomous flight, where the desired velocity between waypoints can be specified.

III. CLASSIFICATION TREE LEARNING FOR THE OPTIMAL SPEED SELECTION

In this section, the trade-off between the quadrotor flying speed and the image quality is investigated to obtain the optimal flying speed. First, experiments are conducted to generate the data set that contains the quadrotor speed and the corresponding image processing working condition, i.e., detection success and detection failure. Then, the classification tree learning algorithm is applied to determine the optimal speed of the quadrotor, i.e., the highest speed that allows a successful vehicle detection. Finally, the obtained optimal speed will be applied to the quadrotor throughout the experiment.

1) Preliminaries: Define $V = \{v_1, v_2, v_3, ...v_i\}$ as the set of attributes with domains $\mathcal{D}_{v1}, \mathcal{D}_{v2}, \mathcal{D}_{v3}, ...\mathcal{D}_{vi}$, respectively. Define $Y = \{y_1, y_2, y_3, ..y_i\}$ as the output with domain $\mathcal{D}_y$. Consider the data set $D^* = \{(v_i, y_i)\,|v_i \in \mathcal{D}_{v1} \times \mathcal{D}_{v2} \times \mathcal{D}_{v3} \times ...\mathcal{D}_{vi}, y_i \in \mathcal{D}_y\}$, where each of v_i is associated with an output y_i. Define

$$\mathcal{L} = \sum\nolimits_{(x_i,y_i)\in D^*}^{i} (y_i - \hat{y}_i)^2 \quad (1)$$

be a loss function, where $\hat{y}_i$ are the predicted results. Given the data set D^*, the goal of the classification tree learning

Algorithm 1 BuildTreeModel

Input: node v_i, data D^*

($v_i \rightarrow$ split, D_L, D_R) = GetBestSplit(D^*)
if StoppingCriteria(D_L)
    $v_i \rightarrow$ LEFT = GetPrediction(D_L)
else
    BuildTreeModel($v_i \rightarrow$ left, D_L)
if StoppingCriteria(D_R)
    $v_i \rightarrow$ RIGHT = GetPrediction(D_R)
else
    BuildTreeModel($v_i \rightarrow$ right, D_R)

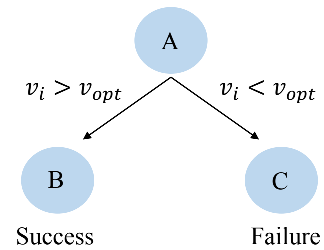


Figure 5. The classification tree for the quadrotor speed range selection. v_{opt} is the split condition for the tree, which in this paper, is also considered as the optimal speed.

is to obtain a model M that best approximates the true distribution of D^*, and minimizes the loss $\mathcal{L}$.

2) Generation of Data Set: To generate the data set, the quadrotor is commanded to maneuver above the parking lot with specific speeds: from 1 m/s to 11 m/s, where 11 m/s is the maximum speed of the Parrot Anafi in autonomous mode. For each specific speed, 5 tests are conducted and the images are processed by the ground station. Once a detection failure happens in any of those 5 tests, the detection results of the corresponding speed will be marked as 0 (Failure). On the other hand, if all 5 tests succeed, that is, no detection failure happens, the corresponding speed will be marked as 1 (Success). The results are gathered in Table I, where the tested flying speeds are recorded as v_i and the detection results are marked as y_i. A total of 51 speeds have been tested, and the entire data set can be found in [31].

3) Classification Tree Model: The classification tree model of this study is straightforward, as shown in Fig. 5, where the root node A is the quadrotor speed, and it has 1 split leading to 2 leaves, i.e., node B (detection success) and node C (detection failure).

As described in *Algorithm 1* [32], the entire data set D^* is explored to find the best split for the root. Then the whole data set is divided according to the split and the process is repeated recursively. D_R and D_L define the left and right partitions of the node, respectively. *StoppingCriteria* function defines how much the tree learns and pruning can be used to improve generalization on a learned tree. In this case, the stopping criteria is set to $count = 1$. *GetPrediction* function defines the tree partitioning. The function *GetBestSplit* is to find the best split for the node, i.e., the maximum speed that allows a successful vehicle detection.

4) Prediction: Define the testing set

$$\Omega_v = \{v_j | v_{j+1} = v_j + 0.1,\ v_1 = 1,\ v_j < 11.0\} \quad (2)$$

where $j = 1...101$. The process of prediction is given as follows. First, feed the set Ω_v to the trained model, then observe the output $\hat{y}_i$. Second, define the maximized speed that ensures $\hat{y}_i = 1$ as v_{opt}. Finally, there is

$$v_{opt} = 9.8 \quad (3)$$

The optimal speed $v_{opt} = 9.8$ will be used throughout the experiments.

IV. Experimental Results

In this section, the effectiveness of the proposed system will be tested in different scenarios, e.g., covered parking, on-street parking with human factors and trees. It should be noted that the occupancy detection for covered parking and on-street parking are normally challenging, as mentioned in Section I. However, the following results demonstrate that the proposed system can successfully handle those challenging scenarios. The videos can be found in [31].

A. *Case I: Normal Condition*

This case will demonstrate the parking occupancy detection with the optimized speed under normal condition, i.e., without any obstacles. The experiment is carried out at an on-street parking lot with a total of 18 parking spots, with 7 parked vehicles and 11 vacancies. As shown in Figs. 6(a)-(f), the quadrotor takes off at the right side of the parking lot, then flies over the parking lot from the right to the left. The results have shown that, with the optimized speed, no detection failure happens and the system can successfully release the occupancy information to the driver's mobile device, as shown in Fig. 10(a).

B. *Case II: Covered Parking*

In this case, the parking occupancy detection for covered parking is demonstrated. In this experiment, the number of the total parking spots is 13, with 6 occupied and 7 vacant. Since the proposed system adopts the detection strategy described in Section II, the quadrotor can carry out a low-altitude flight, which makes the vehicle detection for covered parking possible. Similar to Case I, the quadrotor flies over the parking lot form the right to the left. The detection results are shown in Figs. 7 (a)-(f). It is clear that the system works efficiently for the covered parking lot and the results displayed at the mobile device end are shown in Fig. 10(b).

C. *Case III: With Pedestrians*

In this case, two pedestrians are present in the parking lot, where one pedestrian is passing by and the other is checking the vehicle trunk. The parking lot remains the same as Case I with a total of 18 parking spots. During the experiment, 13 parking spots are occupied. From Figs. 8 (a)-(f), the

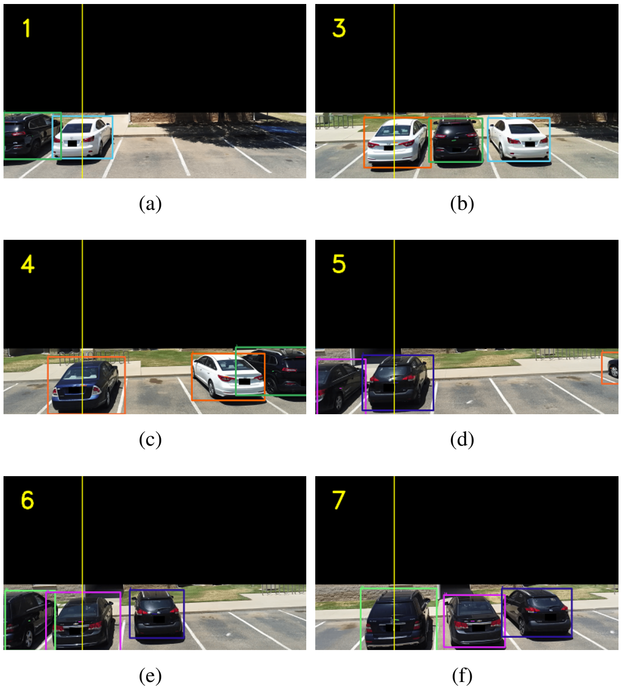


Figure 6. Case I: Parking occupancy detection without obstacles.

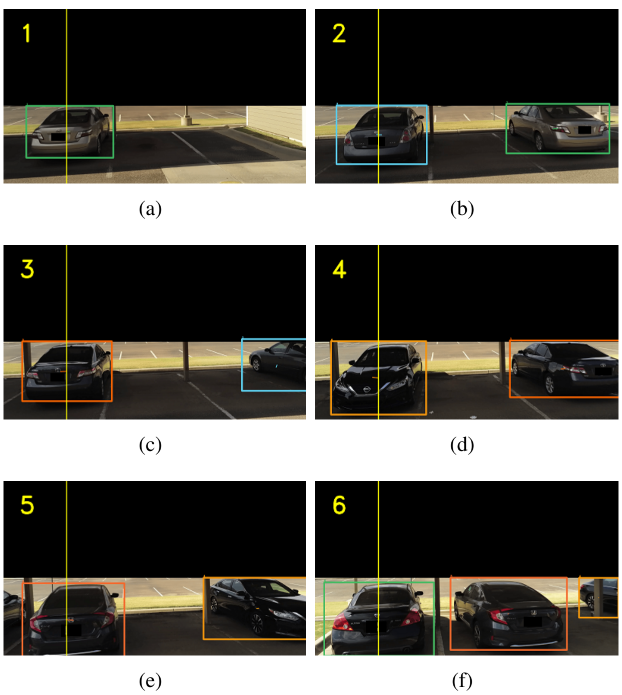


Figure 7. Case II: Parking occupancy detection for covered parking.

quadrotor takes off at the left side of the parking lot, then flies over it from the left to the right. It can be seen that the counting is accurate and no detection failure happens. In Figs. 8 (c) and (d), a pedestrian is passing by and partially blocking the vehicle; in Fig. 8 (e), the silver vehicle has an open trunk and the driver blocks part of the vehicle. However, the system works efficiently with accurate counting. The results from the driver's end are shown in Fig. 10(c).

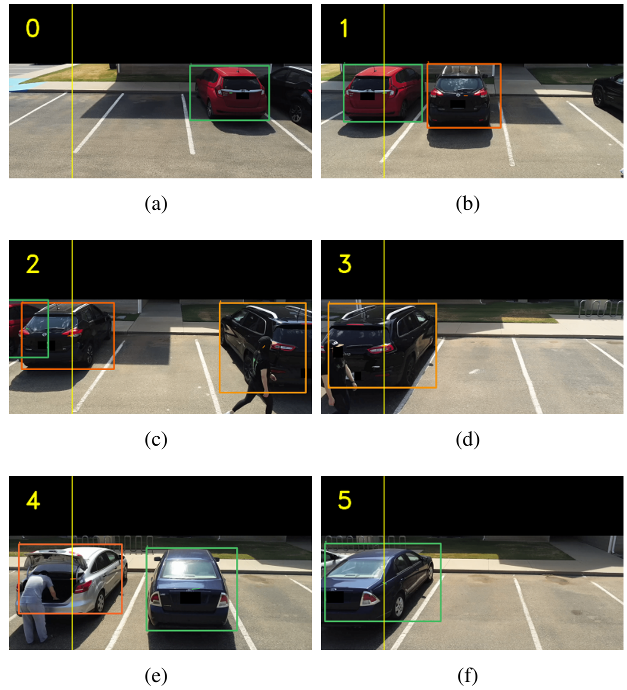


Figure 8. Case III: Parking occupancy detection with pedestrians present.

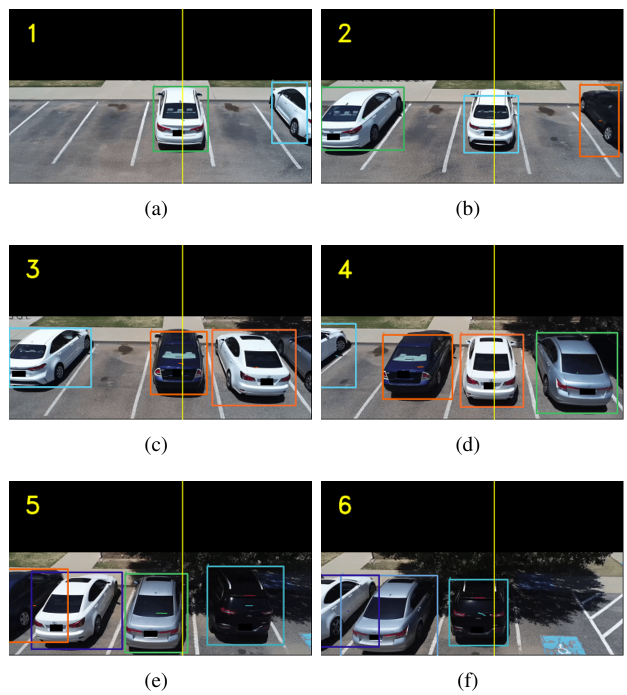
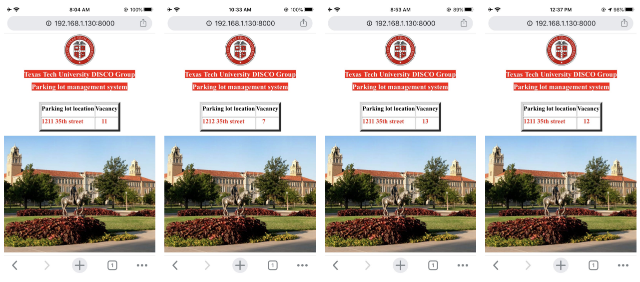


Figure 9. Case IV: Parking occupancy detection with trees.

D. Case IV: With Trees

In this case, the parking occupancy detection is examined in scenarios with trees. The parking lot has 18 parking spots, with 7 occupied and 11 vacant. From Figs. 9 (a)-(f), the quadrotor takes off at the left side of the parking lot and maneuvers to the right. From the results, it can be concluded that no detection failure happens and the counting is successful. In Figs. 9 (e) and (f), the silver vehicle and the



(a) (b) (c) (d)

Figure 10. Mobile device interfaces. (a) Case I. (b) Case II. (c) Case III. (d) Case IV.

black vehicle are partially blocked by trees and the shadow. However, the system can work successfully with accurate detection. The results sent to the driver's end are shown in Fig. 10(d).

V. Conclusion

In this paper, a portable autonomous parking occupancy detection system has been developed for large special-events parking. The parking lot images are obtained by a camera-equipped quadrotor and the drivers can access the real-time occupancy information from their mobile devices. A CNN-based vehicle detection model has been trained and implemented by considering real-life uncertainties. Besides, the trade-off between the detection efficiency and accuracy was investigated to obtain the optimal flying speed for the quadrotor via the decision tree algorithm. Accordingly, a successful parking occupancy detection can be achieved. Experimental results have illustrated the effectiveness of the proposed parking occupancy detection system.

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