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PARKING LOT OCCUPANCY DETECTION USING IMAGE OVERLAY AND INTERSECTION TECHNIQUE WITH HARRIS CORNER DETECTOR

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Abstract— Parking lots are essential to cities with a large number of populations, especially for countries that do not have many public modes of transport, which lead to the increase in the number of vehicles on the road. Locating for an empty parking lot can be time-consuming and may even lead to severe problems such as traffic congestion. Although numerous hardware-based parking monitoring systems have been achieved success in the market, the maintenance cost is still expensive. Hence, many researchers have started to explore other alternatives, such as vision-based approach. A current methodology using Harris Corner Detector for parking lot detection generates the corner data from the vehicle as well as any other unwanted surrounding corner data such as partially shaded shadows, which are non-vehicle data that will contribute as noise and impact the classification accuracy. By implementing image overlay with Harris Corner Detector, the strongest corner data around the vehicle region will be generated since the image overlay shape is added using the grayscale intensity at range zero, which is black. Thus, other unwanted objects beyond the image overlay can be excluded easily by analyzing the strongest corner data only. The datasets used in this research are the video source, which consists of full-day outdoor parking lot images in time-lapsed produced by Cambridge Consultants in the year 2017. Image overlay method improved the existing Harris Corner Detector implementation accuracy by 19.79% and proven better accuracy compared to image thresholding method in partially shaded outdoor parking lot environment by 1.04%. Hence, both can be used as a hybrid system.

I. Introduction

With the increase of vehicles on the road, the parking lot management system has also been improved to help the increasing number of drivers in locating parking lot occupancy. Many traditional parking lot management systems have been substituted with a smart parking system to detect occupancy and equipped with security video surveillance [1]. The two main categories of the parking lot systems are sensor-based [2] and vision-based [3].

Locating for parking lot availability can be time-consuming, especially in the cities, and the number of available parking lots is usually limited. Searching for parking lot availability has to become a norm for most people daily. To resolve this problem, many parking lot managements has implemented a sensor-based approach to help drivers locate available parking lot, which could help to reduce traffic [4].

With the advancement of technology, many research on parking lot have been emerged for indoor parking [5] and outdoor parking lots [11] to help commuters in locating parking lot [16]. There are still rooms for improvement in the outdoor parking lot, especially in poor lighting conditions, according to [6][7]. Large training datasets are needed to build a strong classifier for most of the existing methods [8] – [10].

In this research, vision-based outdoor parking lot occupancy detection will be studied along with simulation and performance evaluation. The free parking lot was chosen since the video source can be easily obtained from most of the public security video surveillance and could provide an affordable solution for the smart parking lot monitoring system. An existing method such as image thresholding will be chosen for the parking lot occupancy detection as a baseline data for comparison due to its simple implementation and often used by researchers. At the same time, the Harris Corner Detector algorithm [11][12] will be further studied, and the usage will be explored with image overlay to improve the accuracy due to the rich corner data for analysis. A list of existing methodologies is summarized in Table 1.

Table 1. Existing Methodologies

Summary		
Author	Method	Limitation
Ling et al., 2017	Grayscale	Needs to train a classifier with both positive and negative samples at different lighting conditions.
Bibi et al., 2017	Image thresholding	Accuracy reduced by 2% during a cloudy day.

Shih et al., 2014	Background subtraction	Needs training datasets at different lighting conditions.
Raj et al., 2019	Canny Edge Detector	Needs re-train classifier for a new vehicle.
Peng et al., 2018	Harris Corner Detector	Unable to eliminate false corners.
Shi et al., 1994	Shi-Tomasi Corner Detector	Same as Harris Corner Detector but better accuracy.
Becker et al., 2016	SIFT	Requires useful reference of datasets from multiple vehicles.
Cho et al., 2018	HOG	Requires useful reference of datasets from multiple vehicles.

II. Methodology

There are three modules for the proposed parking lot occupancy classification. First, one-time calibration is needed for the parking lot coordinate when setup for a new venue, which is done manually. The second module is the image pre-processing for image segmentation, grayscale conversion using the weighted method, noise reduction, and image overlay for each parking lot. The third module for feature extraction using the Harris Corner Detector and classification based on the number of intersection points that are based on the strongest vehicle corner data.

Figure 1 shows an overview of the proposed parking lot occupancy detection system for each video sequence. In the image pre-processing, the parking lot segmentation uses the pre-calibrated coordinates obtained during the one-time calibration setup. Each parking lot image will be converted into a grayscale image using a weighted method and followed by a Gaussian blur to smoothen the image and eliminate the unwanted noises since Harris Corner Detector is sensitive to noise [13]. The image will be resized to 480 x 360 in resolution and overlay with standard image overlay shape. The image overlay shape chosen for this research will be rectangular since it produces the best standard deviation on the number of intersection points threshold compared to the circle and rectangle during the calibration.

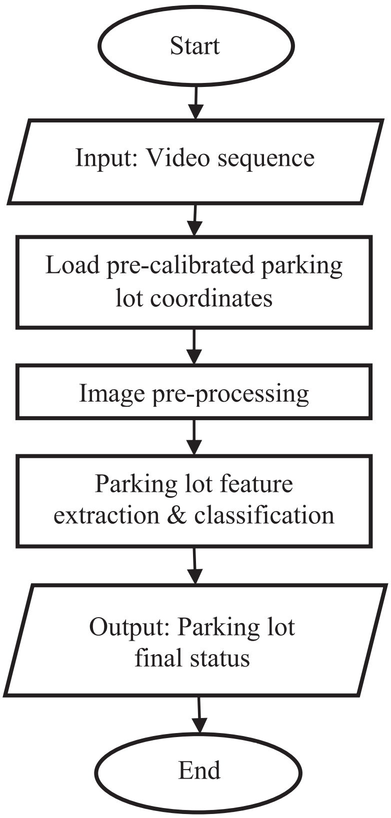


Figure 1: Flow diagram for parking lot occupancy detection

For the feature extraction, Harris Corner Detector will be used for the removal of vehicle corner data, and the intersection points will be calculated for classification based on the threshold. For parking lot that has the number of intersection points beyond the threshold value of eight for rectangle, image overlay will be considered as occupied otherwise will be considered as empty. Image overlay method was chosen because it can generate the most reliable vehicle corner data such as intersection corner data points with the image overlay shape, which is useful information for parking lot occupancy classification.

A. Image Overlay

Image overlay shape selection is critical for this research since it will be the main factor in resolving the problem on existing Harris Corner Detector, which detects the random non-vehicle corner data for classification, which can cause misclassification. Image overlay shape is used to define the potential vehicle region so that Harris Corner Detector can generate the most reliable vehicle corners data around the intersection of image overlay shape.

- Rectangle

For a rectangle, the image overlay has a standard deviation of 0.16 from the calibration result using 144 empty parking lots. The threshold value is obtained from the minimum, and a maximum number of Harris Corners detected. The intersection points produced by rectangle image overlay are consistent and precise for most samples which are ranging from seven and eight for minimum and maximum, respectively. Figure 2 shows the empty parking lots from the calibration result, where each parking lot has eight intersection points. Based on the calibration result from 144 vacant parking lots, only four samples (equivalent to 2.78%) have seven intersection points, while the other 140 samples have eight intersection points (equivalent to 97%), and therefore, the median threshold is used. In a rectangle, each vertex consists of two intersection points consistently compared to the circle and triangle. Hence, it is the most suitable shape for image overlay.

Figure 2: Rectangle image overlay for an empty parking lot

B. Pre-processing

The image pre-processing includes image segmentation, grayscale conversion, noise reduction, image resizing, perspective transformation, and image overlay. In this research, the shape chosen for image overlay is triangle since it has the best corner data threshold compared to the circle and triangle. The parking lots in the video sequence will be segmented on coordinates calibrated during the setup. Due to the viewing angle and position of the video source, each parking lot will result in an irregular four-sided polygon. Therefore, the perspective transformation will be applied to get the regular rectangle image. The perspective transformation used in the pre-processing work is the third party OpenCV library from https://pyimagesearch.com because the output of the corrected perspective parking lot does not overlap with the neighboring parking lots compared to the default library provided by OpenCV. The perspective transformation is performed using the API known as getPerspectiveTransform given by (1) referring to website (https://pyimagesearch.com) to compute the perspective transformation matrix and used by warpPerspective to generate the corrected regular rectangular image. Four points of input coordinates representing the region of a parking lot in the original video sequence are required for the perspective transformation.

$$M_{coordinates}[n] = [C_{pt1(x,y)}, C_{pt2(x,y)}, C_{pt3(x,y)}, C_{pt4(x,y)}] \quad (1)$$

where:

$M_{coordinates}[n] = Perspective\ Transformation\ Matrix$

$C_{pt1(x,y)} = (0, 0)$

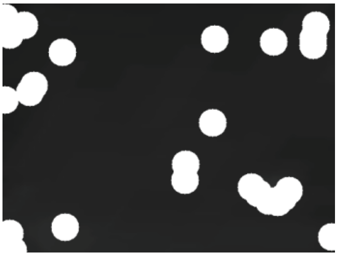
$C_{pt2(x,y)} = (Width_{max} - 1, 0)$

$C_{pt3(x,y)} = (Width_{max} - 1,\ Height_{max} - 1)$

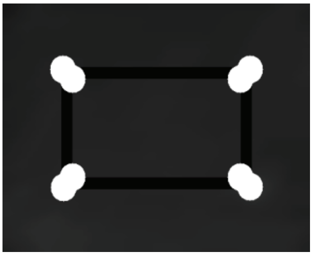
$C_{pt4(x,y)} = (0,\ Height_{max} - 1)$

C. Feature Extraction

The feature to be extracted in this research is the intersection points between the vehicle and the image overlay. The newly added rectangle image overlay shape is using the lowest grayscale intensity, which is at value 0. Therefore, the strongest corner data will be generated in each vertex and at the rectangle image overlay shape intersection with the vehicle corner data. These vertices corner data can be used as a threshold for classification at later stages in the parking lot occupancy detection. To extract these features, Harris Corner Detector will be used to remove these intersection corner data points. The vacant parking lot has a fixed number of intersection points, while the occupied parking lot has more intersection points. By analyzing the strongest Harris Corners data, the weak non-vehicle corner can be excluded to improve the classification accuracy in parking lot occupancy detection. In Figure 3 (a), an empty parking lot corner feature is extracted using existing Harris Corner Detector and Figure 3 (b) using the image overlay method. The corner feature of existing Harris Corner Detector for the empty parking lot is scattered and random in the number of corners compared to the image overlay method, which produces a consistent amount of corners.



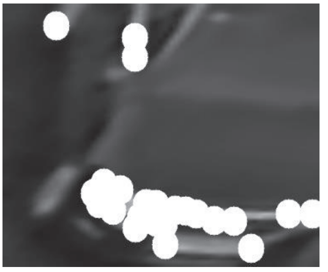
(a)



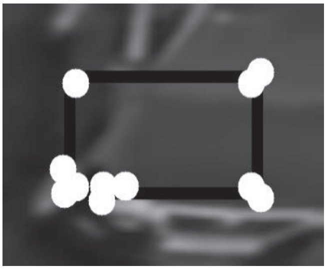
(b)

Figure 3: (a) Empty parking lot using existing Harris Corner and (b) Image overlay

While in Figure 4 (a), the occupied parking lot corner feature is extracted using existing Harris Corner and Figure 4 (b) using the image overlay method. It is observed that in the existing implementation of Harris Corner Detector, some of the corner data is far apart or also known as an outlier because there is no region of the vehicle defined for feature extraction compared to image overlay, which is clearly defined in the rectangle. Using the existing Harris Corner Detector, the number of extracted corner data points for the occupied and empty parking lot is ambiguous compared to the image overlay method, which can be easily classified.



(a)



(b)

Figure 4: (a) Occupied parking lot using existing Harris Corner and (b) Image overlay

- Rectangle Overlay

In this research, rectangle image overlay will be added as the boundary of the parking lot so that Harris Corner Detector only focus on the possible position where the vehicle would be located such as the centroid of a parking lot, and this led to the idea of adding image overlay to create the most robust corners data. Harris Corner Detector will be used in the extraction of vehicle corner data.

It identifies the edges and corners with reference to the direction. With I as the parking lot grayscale image, w (x, y) as image window, u, and v as the displacements in the direction of x and y respectively in the grayscale image. The changes in intensity represented as E(u, v) in (2) [14].

$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \quad (2)$$

where:

$w(x,y)$: window at position (x,y),
$I(x,y)$: the intensity at (x,y),
$I(x+u,y+v)$: intensity at the moving window $(x+u,y+v)$.

Using the maximized solution (3) to (7) [14] to find the windows substantial changes of intensity which representing the corners.

$$\sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \quad (3)$$

Using Taylor expansion:

$$E(u,v) \approx \sum_{x,y}\left[I(x,y) + uI_x + vI_y - I(x,y)\right]^2 \quad (4)$$

Expressed in the matrix form:

$$E(u,v) \approx [u \quad v]\left(\sum_{x,y} w(x,y)\begin{bmatrix} I_x{}^2 & I_xI_y \\ I_xI_y & I_y{}^2 \end{bmatrix}\right)\begin{bmatrix} u \\ v \end{bmatrix} \quad (5)$$

$$M = \sum_{x,y} w(x,y)\begin{bmatrix} I_x{}^2 & I_xI_y \\ I_xI_y & I_y{}^2 \end{bmatrix} \quad (6)$$

The Equation now is:

$$E(u,v) \approx [u \quad v]M\begin{bmatrix} u \\ v \end{bmatrix} \quad (7)$$

The score for each window is calculated to decide if it might contain a corner in the parking lot using (8) [14]:

$$R = \det(M) - k\big(trace(M)\big)^2 \quad (8)$$

where:

$\det(M) = \lambda_1\lambda_2$
$\mathrm{trace}(M) = \lambda_1 + \lambda_2$

If the window score, *R* is higher than the threshold value, then it is considered as corner data, as shown in Figure 5.

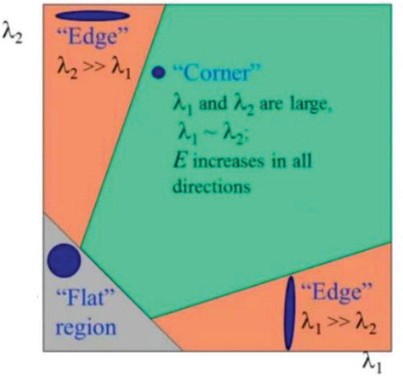


Figure 5: Harris Corner Detector score, *R*

The issue with the existing Harris Corner Detector implementation is because there is no method to specify which part of the parking lot is the real vehicle corner and non-vehicle corner data. The lack of information on where is the position of the vehicle could be parked in a parking lot or also can be described as no Region of Interest (ROI) in a parking lot is defined for vehicle feature extraction, which could cause misclassification. Therefore, by adding image overlay to create the most robust corners, when the corner value is meeting the criteria of Harris Corner score R, the algorithm will take it as a valid vehicle corner data.

D. Classification

In the classification, the threshold value of intersection points will be used. An empty parking lot using an image overlay of rectangle shape will yield eight intersection points from four vertices, where each of the vertex has two intersection points. In the occupied parking lot, when the numbers of intersection points are beyond the calibrated threshold value, it will be considered as occupied. Figure 6 and Figure 7 show the image overlay and existing Harris Corner data points, respectively.

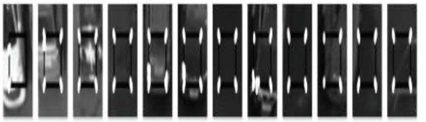


Figure 6: Image overlay with Harris Corner features on 12 parking lots

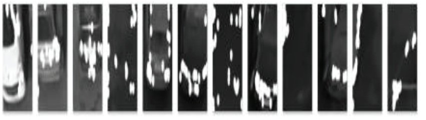


Figure 7: Existing Harris Corner feature on 12 parking lots

It is observed that empty parking lot in image overlay method has a consistent threshold value of eight intersection points compared to existing Harris Corner which is hard to classify the occupancy status due to an ambiguous number of Harris Corner data returned such as empty and occupied parking lot has the same number of corners detected. In the existing Harris Corner Detector, a vacant parking lot will yield the number of corners from a minimum of 4 to a maximum of 858 based on the calibration result. In this simulation, the maximum number of strongest corners is set at 25. The data indicated that 25 is the suitable cut off point for the strongest corner count since it is not densely populated, and it occupied 24% of circle and 32% triangle shapes. The maximum number of Harris Corner data values of 25 is the typical value used in the example provided by goodFeaturesToTrack in OpenCV API according to website address https://docs.opencv.org. Therefore, the existing Harris Corner Detector threshold value is set at less and equal to 25 will be considered as occupied and above as empty.

E. Performance Evaluation

To evaluate the performance of each method, the final status of the parking lot will be compared with the database result collected before the simulation. The database result was collected manually to serve as the baseline to assess the accuracy of each method. Accuracy is the fundamental method to evaluate the classification performance, which is defined as the correctly classified samples (TP & TN) to the total samples (TP, TN, FP, FN) using (9) [15]. To evaluate the system performance, False Positive Rate (FPR) and False Negative Rate (FNR) are calculated using (10) and (11) [15]. FPR represents the negative samples that were wrongly classified as positive samples, while FNR represents the positive samples that were improperly classified as negative samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \tag{9}$$

$$FPR = \frac{FalsePositive(FP)}{FalsePositive(FP) + TrueNegative(TN)} \times 100\% \tag{10}$$

$$FNR = \frac{FalseNegative(FN)}{TruePositive(TP) + FalseNegative(FN)} \times 100\% \tag{11}$$

III. Result And Discussion

The existing implementation of the Harris Corner Detector is used to extract the vehicle features such as head and rear lamps to classify the parking lot occupancy. These corner features might not be accurate when the road surface is uneven or due to partially shaded shadows and any other non-vehicle corner data. The corner data produced by the Harris Corner Detector for both occupied and empty parking lot potentially produces the same number of corners, which is ambiguous and difficult for classification due to overlapping threshold value. For image thresholding, the result is acceptable with filters applied such as Laplacian and Gaussian Blur, which highlight the areas of rapid change or edges in the vehicle and remove the noises from image to improve the image thresholding result so that it can be used as a benchmark against image overlay method. Shi-Tomasi Corner detector detected more corner features compared to Harris Corner Detector, and a slightly better result is expected since it is an enhanced algorithm. The implementation using image overlay has a better overall effect compared to image thresholding and existing Harris Corner Detector in shaded conditions. In Table 2, the data was collected on partially shaded parking lots using video source provided by Cambridge Consultants referring to website https://cambridgeconsultants.com/goldeneye.

A comparison line chart is plotted in Figure 8 to show the comparison of all methods used.

Table 2. Performance comparison for all methods

Parameter (%)	Performance Evaluation			
	Image Overlay	Existing Harris	Image Thresholding	Shi-Tomasi
Accuracy	82.03	62.24	80.99	84.37
FPR	20.49	37.76	8.07	14.12
FNR	8.70	0.00	34.16	18.60

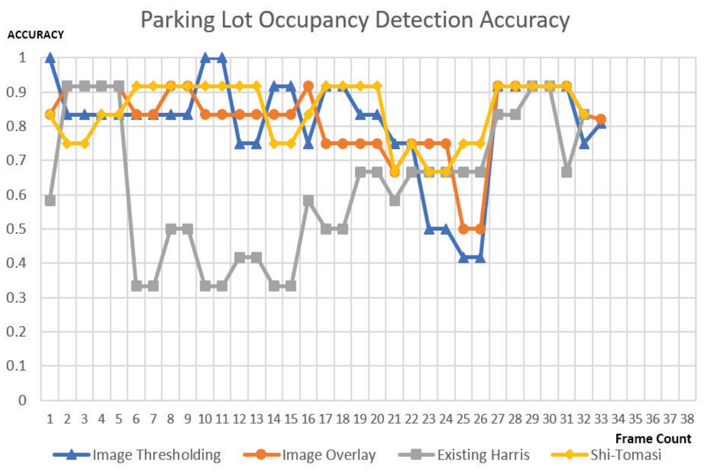


Figure 8: Summary for all simulated methods

Figure 9 and Figure 10 show the empty parking lots and occupied parking lots from the simulation works, respectively.

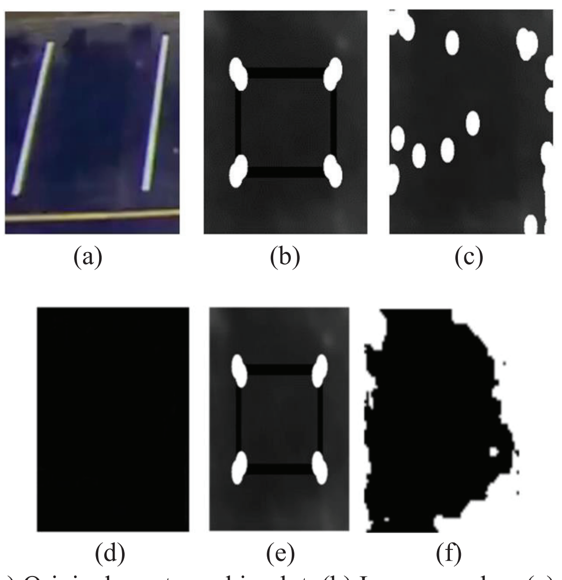


Figure 9: (a) Original empty parking lot, (b) Image overlay, (c) Existing Harris Corner Detector, (d) Image thresholding, (e) Shi-Tomasi, and (f) Image thresholding without a filter at video sequence 187

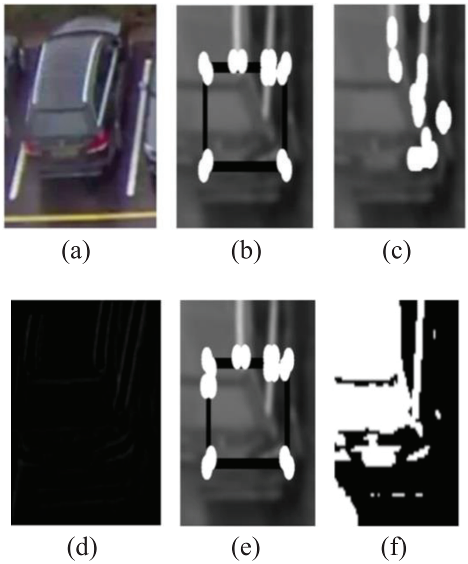


Figure 10: (a) Original occupied parking lot image, (b) Image overlay, (c) Existing Harris Corner Detector, (d) Image thresholding, (e) Shi-Tomasi, and (f) Image thresholding without a filter at video sequence 162

IV. Conclusion

This paper proposed an image overlay to improve the accuracy of the partially shaded parking lot in the outdoor environment by targeting the critical region of a parking lot to extract the vehicle corner data and eliminate other non-vehicle corner data with Harris Corner Detector. The image overlay method was chosen instead of existing implementation using the Harris Corner Detector due to its capability to generate the strongest corner data from vehicle intersection points, which is useful for classification. The objective of improving the existing Harris Corner Detector in parking lot occupancy detection is achieved with an improvement of 19.79% inaccuracy. The salient shape for image overlay method is identified from this research, where the rectangular image overlay shape produces the best threshold value with a standard deviation of 0.16 from the simulation result. The threshold value is obtained from the minimum, and a maximum number of Harris Corners detected. Therefore, the second objective to find a suitable shape for the image overlay method in an outdoor parking lot environment is achieved. The proposed image overlay method has better performance in terms of accuracy compared to the image thresholding method on a partially shaded parking lot in an outdoor environment. The simulation result on the partially shaded outdoor parking lot; image overlay produced 1.04% better in terms of accuracy compared to image thresholding. With this, the third objective of this research is achieved.

V. Acknowledgement

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