Parking slot detection system based on structural similarity index

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Abstract. A quest of vacant parking space in the public area can indirectly lead to traffic congestion which can be troublesome for drivers in terms of time efficiency. This study is expected to assist drivers to get the available parking slots information in a real-time manner and support the parking control systems by constantly updating the information of vacant parking slots positions in public areas. A vision-based parking slots recognition method is proposed to identify occupied areas by vehicle which is divided into two main parts: setup configuration and object detection. Canny Edge and Hough Line Transform are used to achieve line detection for parallel parking slot marking; contour extraction and bounding rectangular are then applied for an initial parameter to form a reference area as a region of interest (ROI). Moreover, Structural Similarity Index Measurement (SSIM) exploits the reference image and target image to identify whether the area is empty or occupied by vehicle depending on structure comparison. Experimental result shows, from 50 sample images of parking slots attained by surveillance camera, the detection accuracy of 92% and precision of 89% are obtained using selected features with tuning SSIM threshold level of 0.4.

1. Introduction
Indonesia, which is ranked as the 4th place most populous countries in the world with about 264 million population, makes it the most populated country in the Association of Southeast Asian Nations (ASEAN) [1]. This high population density certainly associates with the increasing number of vehicle ownership. Statistics Indonesia stated the number of motor vehicles is around 138 million in 2017 and will still arise with trend of growth of ±1 million cars per year [2]. In urban areas where the number of vehicles is much greater as than the availability of parking spaces, the ineffectiveness use of the parking area may lead to traffic congestion near the parking lots. In most cases, drivers have to circle around the parking area and can spend up to 1 hour for time spans only to locate a vacant parking slot [3].

Recent studies have proposed several methods to tackle the problem of parking management system in the urban areas. Methods based on Wireless Sensor Network (WSN) are well known for simple implementation, low costs, and great flexibility in supporting different sensors that can accurately keep track of parked vehicles. Various sensors such as ultrasonic sensor, magnetic sensors, infrared sensors and inductive loop sensors are commonly used for WSN application research in smart parking systems [4-7]. However, these approaches can be troublesome to be implemented in the real
case applications where the total number of parking slots and observation area is too large and can lead into high maintenance management cost.

The other detection methods are employing vision based methods. To overcome the scalability problems in WSN, vacant parking slots can be examined through surveillance cameras. The image or livestream video from camera is processed and the methods will determine the particular number and location of empty parking slots. The advantages of this method are low cost, simple installation, and the optical sensor placement can be easily adjusted according to requirements. However, even though the data obtained from images is various, the drawback of vision techniques occurs where its accuracy is highly related to the position of the camera [8]. Feature extraction techniques held important role in image processing to translate raw image into meaningful features to further being processed into a region of interest (ROI). The ROI is applied on every partition of the parking slot which increases the reliability of detecting vehicles. Several feature extraction methods in vacant parking detection system have been addressed [9-13].

In this paper, we have designed and implemented vision-based parking slot detection system using structural similarity index measurement (SSIM) to identify vacant slot in outdoor parking area. The simulation and experimental result have shown the satisfactory mark. In Section 2, the proposed method of the image processing is discussed in detail. Moreover, experimental results and conclusion are given in Section 3 and Section 4, respectively.

2. Methodology
The block diagram of proposed image processing for setup configuration and occupancy detection is described in Figure 1.

**Figure 1.** The proposed image processing flowchart of parking slot detection.
2.1. Setup configuration

Primarily, livestream video was being processed for initialization of reference space in setup configuration. The video was segmented into frames then converted into grayscale to simplify computation. Gaussian filter with 5 by 5 kernel size was performed to remove noise in the image. Moreover, edge detection was obtained by using Canny edge algorithm with tuning threshold parameter of the minimum and the maximum value of 50 and 200, respectively. Since the output from Canny edge detection could be in the form of fragments, Hough line transform was applied to interpolate these points to shape straight lines. In addition, we utilized contour detection and bounding rectangular to define ROI of each parking slot. The ROIs’ were then labeled with unique number and stored in our memory as reference space.

2.2. Occupancy detection and SSIM

Once the reference of ROI was achieved, we employed occupation detection by grabbing frame image from livestream video and transformed it into grayscale. Furthermore, we conducted a structural similarity index measurement from the perspective of ROI reference. The method is divided into three comparisons: luminance, contrast and structure [14]. A brief description of SSIM algorithm will be explained as follows:

Supposed we have 2 image signals with common size $N \times N$, where $x$ represents reference discrete image signal and $y$ is assigned discrete image signal. The initial calculation of SSIM algorithm is luminance comparison of those two signals, which can be defined as

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$ (1)

where $\mu_x$ and $\mu_y$ are the mean intensity of $x$ and $y$; constant variable $C_1$ is used to avoid instability whilst denominator $\mu_x^2 + \mu_y^2$ is approaching to zero.

Next, contrast comparison is presented by function $c(x, y)$. The principal feature of contrast comparison function is that with the equal number of contrast change $\Delta = \sigma_x - \sigma_y$, this measure is less sensitive to the case of high base contrast $\sigma_x$ than low base contrast. The function of contrast comparison is given by

$$c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$ (2)

where $\sigma_x$ and $\sigma_y$ are corresponding to the standard deviation of $x$ and $y$; constant variable $C_2$ has similar function as $C_1$.

Additionally, the signal is normalized with the intention of each signal that being compared has the unit of standard deviation. These normalized signals $(x - \mu_x)/\sigma_x$ and $(y - \mu_y)/\sigma_y$ are then processed with the function of $s(x, y)$. The structure comparison is operated once luminance subtraction and variance normalization are done. Hence, the structure comparison function is given as

$$s(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$ (3)

where $\sigma_{xy}$ is the covariance of $x$ and $y$; constant variable $C_3$ is set as $C_2/2$ for simplification purpose in the future.

Lastly, the three formula components from (1), (2) and (3) are combined to yield an overall similarity measurement which is defined as follows

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\mu_x^2 + \mu_y^2 + C_1(\sigma_x^2 + \sigma_y^2 + C_2)}$$ (4)

The output calculation of SSIM function is decimal value scaling from -1 to 1. It will give us a score of 1 when only in the case of two images are perfectly having identical structural similarity. On the
other hand, a score of 0 indicates no structural similarity at all. Note that the image domain SSIM implementation can also take negative values when the local image structure is inverted [15].

\[
\text{slot state} = \begin{cases} 
\text{occupied} & \text{SSIM} \leq \text{threshold} \\
\text{vacant} & \text{otherwise}
\end{cases}
\] (5)

In this study, we compared the ROI reference with the ROI target using SSIM algorithm to identify whether the parking slot is empty or not. We add a conditional function and threshold parameter to define the slot state as if the SSIM score is less than or equal to threshold value, it means the parking slot is occupied by a vehicle. Otherwise, while the SSIM score is greater than threshold value, then the parking slot is supposed to be in the vacant state.

Besides, false detection might be occurred due to the placement of the surveillance camera which is for outdoor observation. The environment condition could be unpredictable depends on the weather, shadows or blocked by another object. Thus, to minimize this problem, in this research we also proposed adaptive condition by updating the particular ROI reference space whenever there is a structural difference between the ROI reference and the ROI target which is in the range of 10%. Or else, the occupancy detection will decide the slot state; this result will be parallelly presented in the information display and stored in the database. The function of the database here is for the data aggregated occupancy by time slots analytic in the future. After performing the SSIM algorithm and deciding the slot state, the method will be running back to the main loop condition.

3. Result and discussion

3.1. Simulation performance

To test our hypothesis of ROI formation, we simulated our proposed algorithm into ideal sample image without any noise which is illustrated in Figure 2. The raw image of parking slot is shown in Figure 2(a), where Figure 2(b) pictures the result of automatic line detection for initialization phase. From 24 parking slots available in raw image, our proposed algorithm succeeded to define 24 virtual spaces with the accuracy of 100%.

The occupancy detection was also tested on the simulation before we implemented into our prototype system. Figure 2(c) illustrates the original image of parking spaces which are occupied by 10 cars. The result of SSIM algorithm depicts in the Figure 2(d) provides us the information of vacant and occupied parking spaces. Where the green virtual blocks portray empty space and the red virtual blocks indicate reserved space. The simulation results have been shown to behave consistently and gave us 0% of error calculation.

![Figure 2](image)

**Figure 2.** Simulation results (a) original image of parking lots; (b) ROI detection; (c) original image of parking lots that is occupied by vehicles; and (d) Occupation detection using SSIM.

3.2. Experimental results

This study conducted experiments using the dataset that was obtained by the proposed system. The occupancy detection from the experimental result is shown in Figure 3. Data acquisition of livestream video is obtained from the surveillance camera which is placed and adjusted on a rooftop of the building next to observation area with the altitude of 4 meters above the ground. The experimental data retrieval were taken during daytime and clear weather in parking lots area of Politeknik Negeri
Bandung. There are 10 outdoor parking slots which can be detected from our camera which represent 10 individual ROI. Since the placement of camera node is likely to be positioned statically in the parking lot, for each parking slots we defined a unique numeric label to each parking slot from 1-10.

![Figure 3. The implementation of occupancy detection using the proposed method.](image)

To assess our proposed algorithm, we evaluated 5 different images which consist of 50 ROIs. Two metric parameters: accuracy and precision were utilized to verify the reliability of the proposed method which are given by

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{7}
\]

where TP is the number of true positives, TN the number of true negatives, FP the number of false positives and FN the number of false negatives.

For the evaluation performance, we altered the SSIM threshold parameter as an independent variable ranging from 0.1 to 0.9 with the step of 0.1. This approach was intended to find the best accuracy and precision based on various SSIM thresholds. Table 1 presents the evaluation comparison of different SSIM thresholds based on experimental results. Even though the highest consistency result was produced by level threshold of 0.8 and 0.9, yet these parameter setups portrayed poor performance in term of the accuracy measurement. This low prediction accuracy occurs because the SSIM threshold is too large, which makes our algorithm is too sensitive. That means, even if there is a small object in the region of target image that is not necessarily a vehicle, this area is automatically detected as a filled condition that may increase error prediction. Regarding the evidence from the experimental result, we decided the best performance based on the preeminent accuracy and precision. The most optimum performance for occupancy detection was obtained by tuning SSIM parameter threshold of 0.4. The accuracy of 92% and the precision of 89% were yielded from this parameter setup.

| SSIM Score | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| TP         | 0   | 3   | 5   | 8   | 8   | 8   | 8   | 9   | 9   |
| TN         | 40  | 40  | 39  | 38  | 35  | 30  | 28  | 24  | 11  |
| FP         | 10  | 7   | 4   | 1   | 1   | 1   | 1   | 0   | 0   |
| FN         | 0   | 0   | 2   | 3   | 6   | 11  | 13  | 17  | 30  |
| Accuracy   | 0.8 | 0.86| 0.88| 0.92| 0.86| 0.76| 0.72| 0.66| 0.4 |
| Precision  | 0   | 0.3 | 0.56| 0.89| 0.89| 0.89| 0.89| 1   | 1   |
4. Conclusion

In this paper, we have presented vision based parking slot detection using the comparison of structural similarity. The main purpose of this research is to assist drivers to get a real-time information of the available parking slots. The proposed algorithm yielded satisfactory marks either in the simulation or the experimental results, where the best SSIM parameter threshold was set on the level of 0.4. Additionally, the proposed system also can be implemented for the alternative approach of multiple sensors integration to improve the scalability of parking slots detection.

Acknowledgments

The authors would like to thank Hertog Nugroho, Ph.D. for the valuable feedback to this research.

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