Indonesian Journal of Electrical Engineering and Computer Science
Vol. 10, No. 3, June 2018, pp. 1221~1226
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v10.i3.pp1221-1226

Embedded Automated Vision for Double Parking Identification System

Norasyikin Fadilah, See Yoon Soon, Hadzfizah Radi
Faculty of Electrical and Electronics Engineering, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia

Article Info

Article history:

Received Dec 26, 2017
Revised Mar 2, 2018
Accepted Mar 20, 2018

Keywords:

Beaglebone
Computer vision
Embedded system application
Smart city

ABSTRACT

The aim of this work is to assist the city administration issue which involve the traffic flow disruption in an urban area. One of the causes of traffic flow disruption is double parking; thus, in this work, an automated double parking identification and alert system was developed using embedded vision system and internet of things. A camera was utilized to acquire the image of a parking area, and the image was processed using Beaglebone Black processor. A computer vision algorithm was developed to process the image using background subtraction, region of interest identification, and color analysis. When a double parked vehicle is detected, the data was sent into the cloud automatically to alert the city administrator for further action. The developed system achieved 91% accuracy in detecting the traffic violation of double parking

Corresponding Author:

Norasyikin Fadilah,
Faculty of Electrical and Electronics Engineering,
Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia

1. INTRODUCTION

In this modern era, the affordability of purchasing vehicles increases nowadays. It directly results in increasing number of vehicles and thus produces high volume of traffic in the urban area. An issue of illegal parking has become more apparent problem faced by the city administration as it is one of the reasons that lead to bottleneck on road and soon congestion. Before enforcing the law to solve this problem, detecting such violation has been a challenge by multiple parties, as the task of detection solely dependent on human operator for surveillance [1].

To aid with the detection of illegal parking, many techniques have been used which utilized various sensors. In sensor-based system, vehicles are detected using different kind of sensors such as inductive loop, magnetic sensor, ultrasonic sensor and infrared sensor. Inductive loop [2] and magnetic sensor [3] rely on the change of magnetic value due to parts of the vehicle to obtain the signal thus it is prevailing on tracking moving vehicles. Although these sensors provide high accuracy in detecting vehicles, the durability, installation and maintenance effort pose as major drawbacks as they require pavement cutting [4], [5]. Ultrasonic and infrared sensors are capable to determine whether a targeted spot is detected with vehicle, however due to the nature of using wavelets to sense objects, these sensors need direct line-of-sight on the targeted spot. Thus, they are very hard to protect against dust or accidental damage. Moreover, since individual sensor has to be placed on each targeted parking spot, implementation of such sensors on a large parking area and irregular surface will be costly and impractical due to many hardware installation and pavement cutting procedures.

Computer vision method is generally more robust and has less dependency on the characteristics of the road surface and specificity on individual vehicle detection. It provides image visualization of a wide area [6]-[7] even on irregular surface and pathway. Image processing techniques have to be considered to provide the efficiency and effectiveness of vehicle detection. Before the image is processed for the detection purpose, a pre-processing technique is needed to enhance and improve the acquired image for better image processing effectiveness. In [8], Soo proposed that in order to detect a vehicle in a particular placement, the detection region must be located at the region of interest (ROI). It means that the ROI should be placed on the prohibited area for detection of double-parked car. By defining ROI, the process of detecting vehicle availability can be simplified and use less processing power. Background subtraction algorithm will emphasize out the object on the foreground while removing the static background image which is the background model. This means that in practical, moving objects like vehicles and humans will be placed out and showed while the background model is replaced with a single color. As proposed in [9], this background subtraction algorithm is the simplest algorithm with optimal performance to be used in term of object detection. In [10], live videos were captured and analysed by comparing each frame with respect to any background scenes. As long as the capturing device is static, the object detection could be utilized in full performance.

Based on the advantages of using video acquisition and computer vision algorithm in detecting vehicles for enforcement applications as discussed in [11], we aim to develop a computer vision algorithm that will automatically detect the violation of double-parked vehicles.

2. RESEARCH METHOD

2.1. Hardware and Software Setup

The automated double parking identification and alert system hardware consisted of a USB Logitech C310 camera attached on Beaglebone Black (BBB) microcontroller. A model of a parking space area was constructed as illustrated in Figure 1 and the camera and BBB were placed at a height that generated elevated bird-eye view of the parking space area. A row behind the parking slots was defined as the prohibited parking area, which if a vehicle parks in the area, it would be considered as a double parked vehicle.

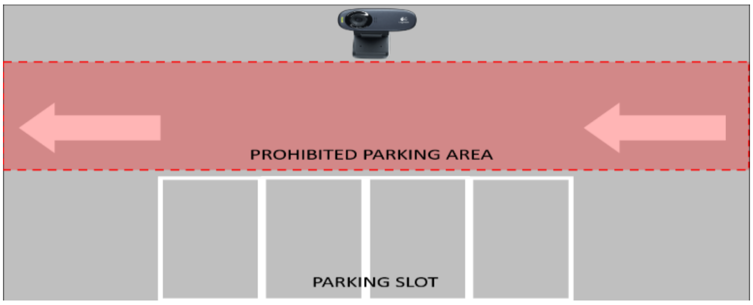


Figure 1. Model of a parking space area

The computer vision algorithm of the system was developed inside BBB by using OpenCV libraries. To execute and compile the coding within BBB, OpenCV was first installed inside the hardware. Figure 2 illustrates the proposed algorithm for double parking identification system.

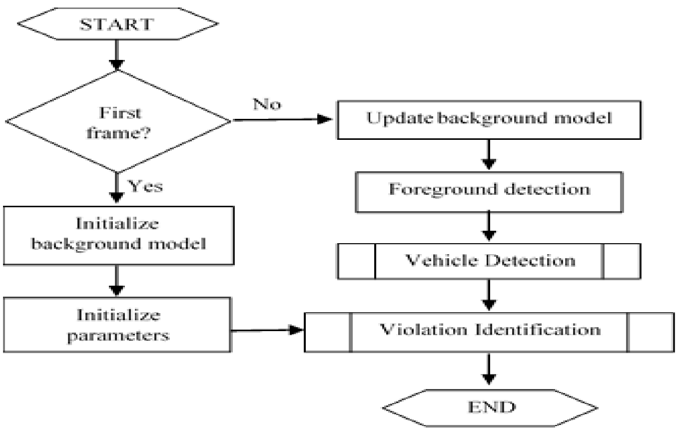
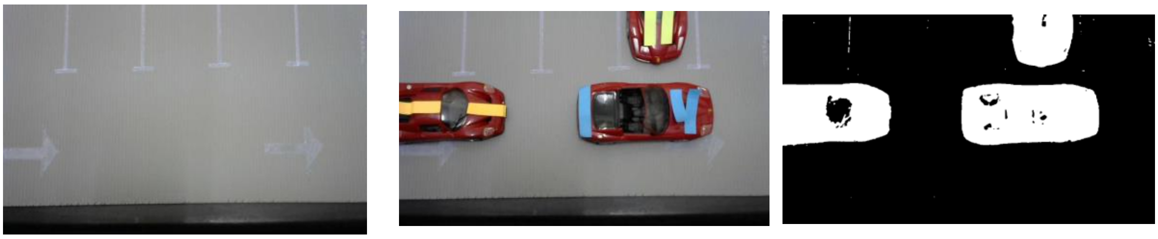


Figure 2. Proposed algorithm for double parking identification system

2.2. Background and Foreground Detection

In this stage, the camera started to acquire the current image into the BBB storage. Then, two functions were executed in parallel. The first function converted the captured image from RGB into HSV color space, while the second function executed the background subtraction algorithm using mixture of Gaussian (MOG) method [12]. Finally, the region of interest (ROI) of the image was defined.

Before generating the foreground model, the background model of the parking area was initialized. The background model consisted of the parking area without any vehicle, which was generated during the initialization (see Figure 3(a)). Then, the background subtraction using Gaussion Mixture Model [13], [14] was implemented on the RGB image (see Figure 3(b))to generate dynamic foreground model showing the vehicles as shown in Figure 3(c).



(a) (b) (c)

Figure 3. Sample image of (a)Background model, (b)Original image, (c)Foreground model

Multiple ROIs were segmented on the prohibited parking area as shown in Figure 4. Each ROI was separated and processed individually by the image processing algorithm discussed in the following sections. The separation of ROIs was implemented into the original RGB image, foreground model and HSV image to ease the extraction of parameters needed.

Figure 4. Multiple ROIs segmented on the prohibited parking area

2.3. Parameters Initialization

Four parameters were initialized before detecting any vehicles on the foreground model. They were set to 0 during the first frame of the image. The parameters are listed as below:

- *Count*: indicates the number of times the ROI detected there is a parking violation. If *Count*=2, it means that a vehicle is immobile for 2 program runs.
- *Mean(R,G,B)*: indicate the mean values for red, green and blue spaces respectively.
- *Mean(H,S,V)*: indicate the mean values for hue, saturation and value spaces respectively.
- *Area*: area of the foreground object (blob) by calculating the non-zero pixel in the foreground model image.

2.4. Vehicle Detection

The Area of the blob was calculated by counting the non-zero pixels in the ROI of the foreground model. To define the blob as a vehicle, the ratio of determination, *Ca* was introduced. This ratio was pre-determined by placing a vehicle to the specific ROI, with multiple attempts of calibration and defining on how sensitive the detection should be. For example, when *Ca*=0.5, the calculated area has to be more than half of the total area of the ROI to define that there is a vehicle on the ROI. If the area is less than half of the total area of ROI, it means that there is no vehicle detected, thus the *Count*=0. Equation (1) shows the condition when there is a vehicle detected on the ROI, where ROI.Area indicates the total area of the ROI.

$$Area >= Ca*ROI.Are \quad (1)$$

2.5. Violation Identification

To identify whether there is any parking violation, the parameters on the current frame and previous frame were compared by calculating the changes in *Mean(R,G,B)* and *Mean(H,S,V)* values. ∆*Parameter* was calculated and compared with an Identification Parameter Range (*IPR*) to show the fluctuation value from previous frame to define whether the detected vehicle was the same from current frame. We considered two cases:

Case 1: ∆*Parameter >IPR*: the fluctuation is high, therefore the vehicles from current and previous frames are different. Count will be set to 1, which means a vehicle is immobile for one time.

Case 2: ∆*Parameter <=IPR*: the fluctuation is low, thus vehicles detected from current and previous frames are the same. *Count* will be increased by one to signify the same vehicle is immobile for an additional *Count*. *IPR* was determined experimentally by tabulating the parameters collected from 222 set of data. When the *Count* number reached 6, the vehicle was identified as violating the double parking rules.

3. RESULTS AND ANALYSIS

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily [2], [5]. The discussion can be made in several sub-chapters.

3.1. Data Collection

For every program execution, previous image files were replaced with current files to conserve memory in BBB. Three types of images were stored for each ROI which consisted of the RGB image, HSV image and the foreground image. A data logger (see Figure 5) was produced to save the parameters needed which include *Count*, *Area*, *Mean (R,G,B)*, *Mean(H,S,V)* and ∆*Parameter*.

Executed= 21	22/4/2017, 21:20:53	
ROI1	count1= 13	
Vehicle double parked at region1		
Area1= 64989/119560		
R1= 118.0164	B1= 75.5158	G1= 89.7836
H1= 77.291	S1= 37.8996	V1= 48.0392
∆ R	∆ G	∆ B
0.513277	0.427681	0.551733
∆ H	∆ S	∆ V
2.79212	0.772981	0.208199
ROI2	count2= 7	
Vehicle double parked at region 2		
Area2= 46509/119560		
R2= 113.0219	B2= 111.4325	G2= 109.8199
H2= 60.627	S2= 13.6485	V2= 48.0355
∆ R	∆ G	∆ B
0.583763	0.535373	0.430728
∆ H	∆ S	∆ V
3.47965	0.561247	0.209845
ROI3	count3= 7	
Vehicle double parked at region 3		
Area3= 42002/119280		
R3=118.9857	B3= 117.9479	G3= 112.1459
H3= 87.828	S3= 18.4243	V3= 52.6676
∆ R	∆ G	∆ B
0.576931	0.547526	0.877612
∆ H	∆ S	∆ V
5.12249	0.0377711	0.324154

Figure 5. Data logger

3.2. Vehicle Detection

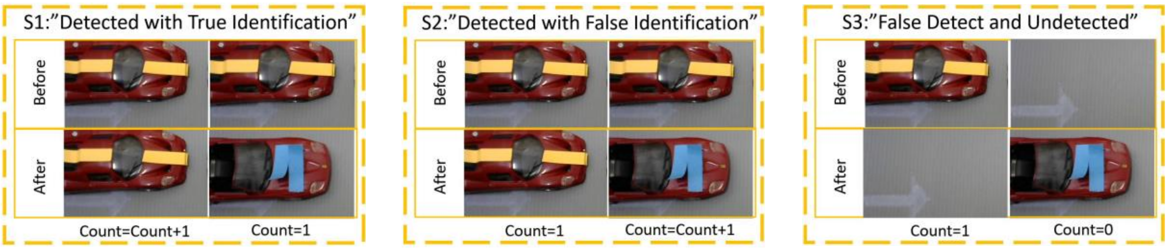
Since the system objective is to detect a vehicle that violate the double parking rules, it should be able to detect whether the vehicle on the specific ROI is the same or different vehicle. Thus, two deciding factors were obtained in determining the success rate. 222 consecutive frames were obtained to test for the same or different vehicle detection. Table 1 shows the detection accuracy for each different parameter. The changes of parameters were set as ΔR <=5, ΔG <=5, ΔB <=5, ΔH <=15, ΔS <=1.3, ΔV <=2.1. All parameters were able to detect the same vehicle correctly with 100% accuracy. However, using each parameter alone the failure rate of detecting different vehicle can be as high as 60.81%. Thus, the combinations of multiple parameters with AND logic were tested, which both detections produced 100% detection rate for ΔR & G & B <=5 & ΔH <=15 & ΔS <=1.3 as the best parameters combination.

Table 1. Detection Accuracy with Different Δ*Parameter* Combination

Detection Parameters	Same Vehicle		Different Vehicle	
	True Identify	False Identify	True Identify	False Identify
ΔR <=5	100.00%	0.00%	74.32%	25.68%
ΔG <=5	100.00%	0.00%	39.19%	60.81%
ΔB <=5	100.00%	0.00%	76.13%	23.87%
ΔH <=15	100.00%	0.00%	63.51%	36.49%
ΔS <=1.3	100.00%	0.00%	77.48%	22.52%
ΔV <=2.1	100.00%	0.00%	49.55%	51.80%
ΔH <=15 & ΔV <=2.1	100.00%	0.00%	70.27%	29.73%
ΔS <=1.3 & ΔV <=2.1	100.00%	0.00%	86.94%	13.06%
ΔH <=15 & ΔS <=1.3	100.00%	0.00%	91.89%	8.11%
ΔH <=15 & ΔS <=1.3 & ΔV <=2.1	100.00%	0.00%	91.89%	8.11%
ΔR & G & B <=5	100.00%	0.00%	96.85%	3.15%
ΔR & G & B <=5 & ΔH <=15	100.00%	0.00%	99.55%	0.45%
ΔR & G & B <=5 & ΔH <=15 & ΔS <=1.3	100.00%	0.00%	100.00%	0.00%

3.3. Violation Identification

In validating the parameters as mentioned in Section 3.2, an experiment to detect the vehicle violation was conducted. The results showed that out of 150 data collected, there were three cases identified. In the first case, S1 (see Figure 6(a)), the violation was correctly identified. The second case, S2 (see Figure 6(b) indicates that the system could not identify there was a vehicle violate the rule or miscounted the Count whenever different car passed by. In the final case, S3 there was an undetected vehicle or misdetected empty ROI with a vehicle. This could be due to inconsistent lighting conditions, which caused inaccuracy in background subtraction and foreground detection.



(a) (b) (c)

Figure 6.(a) Case S1, (b) Case S2 and (c) Case S3

A total of 143 data were correctly identified as case S1; whereas 6 and 1 data were identified as case S2 and S3 respectively. This resulted with 95.3% detection rate with true identification. In terms of violation identification, 75 violation occurances were tested and the system could identify 91% of the violations accurately.

4. CONCLUSION

In this paper, we present a development of algorithm for double park vehicle detection, which implements computer vision techniques. We first generated the background subtraction to generate the foreground model, which detects the vehicle on ROIs which are selected on the prohibited parking area. Then, the color spaces information of R, G, B, H, S and V are obtained. We use these parameters to determine whether the vehicle is immobile on the ROI. Finally, the vehicle which is immobile for more than 6 counts is identified as violating the double park rules. The result shows that out algorithm achieves 91% accuracy. However, it is observed that the performance is poor when the lighting is too bright or too dark. In the future, we will investigate image enhancement techniques, intelligent techniques and motion detection to address such issue to improve the performance.

ACKNOWLEDGEMENTS

This work was supported by Universiti Malaysia Pahang (RDU 1703227).

REFERENCES

[1] J. T. Lee, *et al*, “Realtime detection of illegally parked vehicles using 1D transformation,” *2007 IEEE Conference on Advanced Video and Signal Based Surveillance,* London, 2007, pp. 254-259.

[2] S. Sheik Mohammed Ali, B. George, L. Vanajakshi and J. Venkatraman, "A Multiple Inductive Loop Vehicle Detection System for Heterogeneous and Lane-Less Traffic," *in IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 5, pp. 1353-1360, May 2012.

[3] J. Wolff, T. Heuer, Haibin Gao, M. Weinmann, S. Voit and U. Hartmann, "Parking monitor system based on magnetic field senso," *2006 IEEE Intelligent Transportation Systems Conference,* Toronto, Ont., 2006, pp. 1275-1279.

[4] R. L. Anderson, "Electromagnetic loop vehicle detectors," in *IEEE Transactions on Vehicular Technology*, vol. 19, no. 1, pp. 23-30, Feb 1970.

[5] J. H. Kell and I. J. Fullerton, Traffic detector handbook, 2nd. ed., Washington, D.C.: U.S. Department of Transportation, Federal Highway Administration, 1990.

[6] R. O'Malley, E. Jones and M. Glavin, "Rear-Lamp Vehicle Detection and Tracking in Low-Exposure Color Video for Night Conditions," *in IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 2, pp. 453-462, June 2010.

[7] Y. K. Mac, H. Habe, et al, “Development of parking lot surveillance system with an outdoor camera using machine learning”, *The Institute of Electronics, Information and Communication Engineerst*, 111(441), pp.165-169, 2012.

[8] S. Soo, “Object detection using Haar-cascade Classifier,” University of Tartu, pp. 1–12, 2014.

[9] D. Hall *et al*., "Comparison of target detection algorithms using adaptive background models," *2005 IEEE International Workshop on Visual Surveillance and Performance Evaluation of Tracking and Surveillance,* 2005, pp. 113-120.

[10] V. Asari, Wide Area Surveillance, Volume 6. New York Dordrecht London: 53 Springer Heidelberg, 2013.

[11] M. Bommes, A. Fazekas, T. Volkenhoff, M. Oeser, “Video based Intelligent Transportation Systems – state of the art and future development”, *Transportation Research Procedia*, 2016, pp. 4495-4504 Vol. 14.

[12] Z. Zivkovic, "Improved adaptive Gaussian mixture model for background subtraction," *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004,* 2004, pp. 28-31 Vol.2.

[13] Thierry Bouwmans, Fida El Baf, Bertrand Vachon. Background Modeling using Mixture of Gaussians for Foreground Detection - A Survey. Recent Patents on Computer Science, *Bentham Science Publishers,* 2008, 1 (3), pp.219-237.

[14] Z. Zivkovic, "Improved adaptive Gaussian mixture model for background subtraction," *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004*., 2004, pp. 28-31 Vol.2.