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# On-Road Vehicle Detection and Verification by using a Mobile Camera

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**ABSTRACT---** ***Recently, extensive research on driver assistance systems has focused on applications such as lane departure warnings, traffic sign recognition, and pedestrian and vehicle detection systems. This paper presents a real-time vehicle detection and tracking system for detecting on-road vehicles in front of a vehicle with mobile camera. The system consists of two main steps: generating candidates with respect to a vehicle by using the AdaBoost learning algorithm, and verifying the candidates according to symmetry measurement and horizontal and vertical edge analysis. The proposed system was experimentally proven to be effective in various traffic scenarios.***

**Keyword---** Vehicle detection, AdaBoost, Vehicle verification, Symmetry measurement.

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## 1. INTRODUCTION

Vehicle detection is a particular challenge in applications involving self-guided vehicles, driver assistance systems, or intelligent parking systems. One of most common approaches to vehicle detection is using vision-based techniques based on images or videos. However, because of the various vehicle colors, sizes, orientations, shapes, and poses, developing a robust and effective system for vision-based vehicle detection is extremely challenging. To solve the problems related to these variations, many approaches involve using various features and learning algorithms for detecting vehicles effectively. Previous developments have involved using available sensing methods for vehicle detection, such as radar, stereo vision, and a combination of stereo vision and laser. Hilario *et al*. (2006) proposed employing a geometrical model for characterizing vehicles by using evolutionary algorithms. Broggi *et al*. (2004) presented a multi-resolution vehicle detection method for localizing vehicles of differing sizes and computed the symmetry property of the vehicles. Song *et al*. (2008) developed a system capable of extracting vehicles in front of or behind the ego-vehicle by a single camera mounted on the vehicle. Kowsari *et al*. (2011) proposed a three-stage vehicle detection method that includes hypothesis generation based on ground plane estimation, hypothesis verification according to Haar-like features, an AdaBoost classifier, and disparity histogram. Lim *et al*. (2009) presented a monocular lane-vehicle detection and tracking system comprising lane boundary detection, lane region tracking, and vehicle detection applying a proposed vertical asymmetry measurement. Kate *et al*. (2004) combined knowledge-based methods for midrange and distant vehicle detection. Tsai et al. (2007) presented a novel vehicle detection approach for detecting vehicles based on a new color transform model and edges in static images. Chan *et al*. (2007) proposed an automatic system for detecting preceding vehicles under various lighting and weather conditions based on fusion of four cues: underneath, vertical edge, symmetry, and taillight feature through a particle filter.

This paper presents a real-time vehicle detection system in which the AdaBoost algorithm, symmetry measurement, horizontal and vertical edge analysis, and a machine-learning classifier are used. The remainder of this paper is organized as follows: Section 2 presents the main approach, and the AdaBoost algorithm, symmetry measurement, and vertical edge analysis are also described. Section 3 presents the experimental results, and Section 4 offers a conclusion.

## 2. DESCRIPTION OF APPROACH

This paper presents a set of real-time vehicle detection and tracking systems in which the AdaBoost algorithm, symmetry measurement, and horizontal edge analysis technology are combined, enabling synchronous identification and tracking of the location of the vehicle in front. This technology is integrated in the mobile DVR to achieve real-time motion vehicle detection and tracking. The proposed system was experimentally proven to be effective in various traffic scenarios. Fig. 1 shows a flowchart of the system.

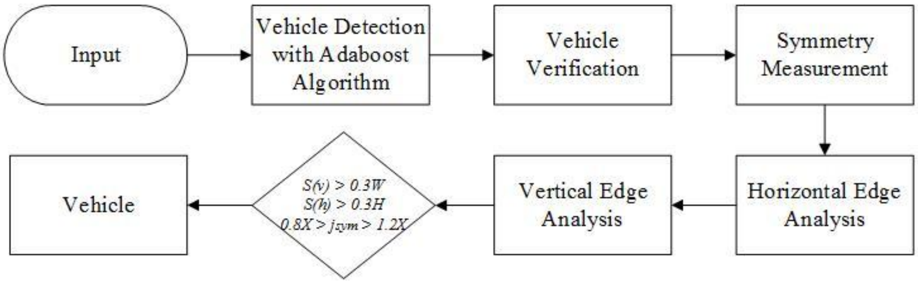
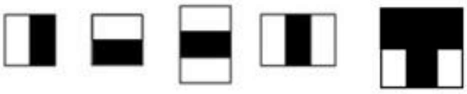



Figure 1: The vehicle detection system flowchart.



(a) (b)

Figure 2: The proposed AdaBoost classification features: (a) Haar-like feature and (b) the proposed car-like feature.

### *2.1 Vehicle Detection with Adaboost Algorithm and Proposed Car-like Feature*

The AdaBoost algorithm, introduced in 1995 by Freund and Schapire (1995), solved the numerous practical difficulties of earlier boosting algorithms. In this paper, the verification module used to classify the extracted candidates as vehicles or non-vehicles is based on simple features known as Haar-like filters (Viola Jones, 2004). To cope with the vehicle detection purpose, we also designed a car-like feature mask as depicted in Fig. 2(b). By changing the size of the rectangles within a detection window, a high number of features can be defined. In this study, the detection window was set at 64 × 64 pixels. A training set containing 500 vehicle samples and 14903 non-vehicle samples was manually built from the candidates extracted using the vehicle candidate generation module. The size of the selected candidates, which can be vehicles or non-vehicles, as shown in Fig. 3, was normalized to 64 × 64 pixels. A sub-window with size of 40 × 40 pixels is used as detection window.

### *2.2 Symmetry Measurement*

Vehicle verification is a crucial process in testing whether the detected region is a vehicle or non-vehicle. For solving the aforementioned problems, we propose a novel system for verifying vehicle candidates, as the flow diagram depicted in Fig. 4.

(a) (b)

Figure 3: Training data set: (a) vehicle samples, (b) non-vehicle samples.

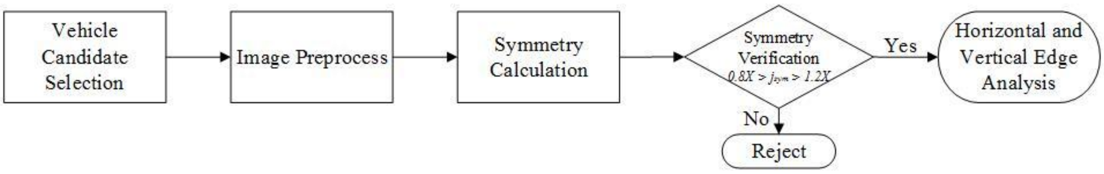
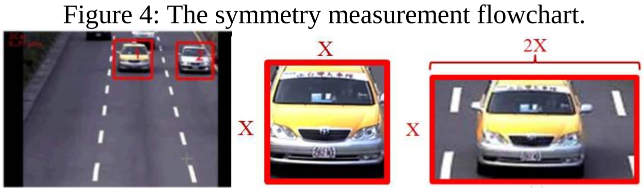



Figure 4: The symmetry measurement flowchart.




(a) (b) (c)

Figure 5: Vehicle Candidate Area Selection: (a) Vehicle Detection Results, (b) Original Vehicle Candidate, (c) Vehicle Candidate Symmetry Measurement Area.

As illustrated in Fig. 5, for each vehicle candidate's width X, a rectangle bounding box with width 2X and height X is selected. The entire bounding box contains the vehicle candidates. To reduce image noise and interference, the median filter is applied to the image for smooth processing. For verifying vehicle candidates further, symmetry detection is performed horizontally. The horizontal grayscale symmetry axis could be determined in Lim et al. (2009) by using the following formula:

$$HS(j) = \sum_{j=x_l}^{X_l+W} \sum_{i=Y_h}^{Y_h+H} \sum_{\Delta x=1}^{W/2} |G(i, j + \Delta X) - G(i, j - \Delta X)| \quad (1)$$

$$j_{sym} = arg\ min\ HS(j) \quad (2)$$

where $\mathrm{HS(j)}$ is the horizontal symmetry measurement with the symmetry axis located at $\mathbf{x}$=j. As illustrated in Fig. 6, the horizontal symmetry axis of the possible vehicle region occurs at the local minimum where the point x = 90. For each vehicle candidate's width 2X, a rectangle bounding box with width 2X and height X is selected. The entire bounding box contains the vehicle candidates and the allowable range of the axis of symmetry must be within the allowable range: 0.8X~1.2X.


(a) (b) (c)

Figure 6: (a) Original image, (b) symmetry measurement, (c) symmetry measurement result with local minimum at x= 90.

***2.3 Horizontal and Vertical Edge Analysis***

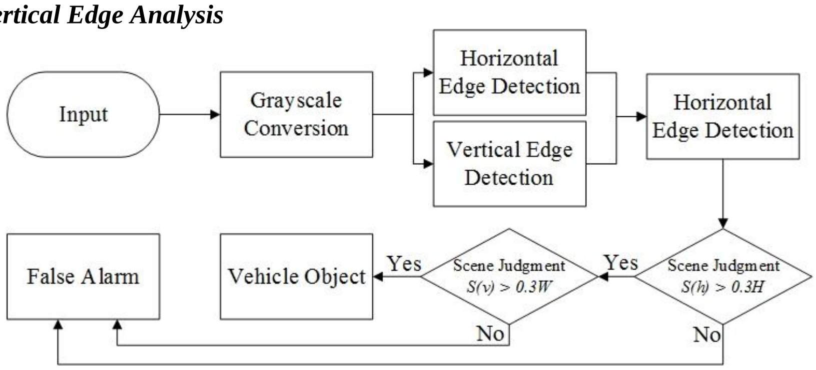



Figure 7: The horizontal and vertical edge analysis flowchart.

The vehicle candidates from the AdaBoost algorithm, which may include vehicle objects and false alarms, are used in horizontal and vertical edge analysis. Fig. 7 shows a flowchart of the system. After applying Sobel operator, vertical and horizontal edge scanning is completed, the number of edges is calculated to determine whether the images contain false alarms. First, for an image calculated after horizontal edge detection, the following formula is used:

$$\omega_i = \begin{cases} 1, & \frac{\sum_{i=1}^{W} Gray(i,j)}{255} > 0.5W \\ 0, & otherwise \end{cases} \quad S(h) = \sum_{i=1}^{H} \omega_i\ , S(h) > 0.3H \quad (3)$$

where $Gray(i, j)$ is the gray value on image coordinate $(\mathrm{i}, \mathrm{j})$, H is the image height, and $\mathrm{W}$ is the image width. If $S(\mathrm{h})$ is greater than 0.3$H$, the images exhibit the horizontal edge features of the vehicle. The same process is applied to vertical edge detection. The vertical edge detection formula is defined as follows:

$$\omega_i = \begin{cases} 1, & \frac{\sum_{i=1}^{H} Gray(i,j)}{255} > 0.5H \\ 0, & otherwise \end{cases} \quad S(v) = \sum_{i=1}^{\mathrm{W}} \omega_i\ , S(v) > 0.3W \quad (4)$$

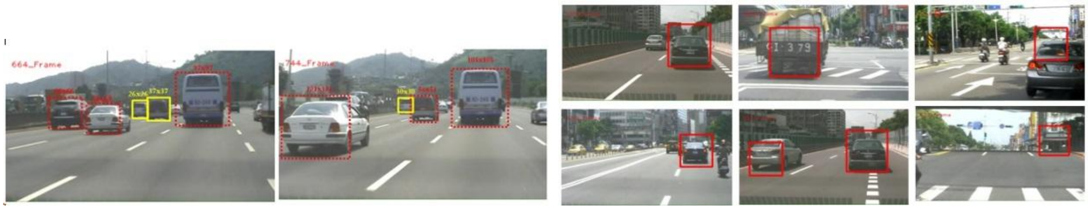
When $\mathrm{S(v)}$ is greater than $0.3\mathrm{W}$, the images exhibit vertical edge features for the vehicle. Finally, whether the test image satisfies the two aforementioned conditions must be determined. If the result is true, then they are classified as vehicle objects. In this method, the number of edges in the horizontal and vertical portions of the entire image is calculated. Because the vehicle image and background image have substantially different numbers of edges, this feature can be used for object classification.

## 3. EXPERIMENTAL RESULTS

(a) (b) (c)

Figure 8: The sample scenes: (a) highway normal-traffic, (b) city street normal-traffic, (c) city street high-traffic.

The vehicle detection system was tested under several conditions involving illumination changes, scene complexity, highways, city streets, traffic conditions, front/back vehicle views, and background motion. Four video sequences recorded by a mobile camera were tested. Video 1 depicts a high-traffic highway scene; Video 2 shows a normal-traffic highway scene. A high-traffic city street scene is depicted in Video 3, and Video 4 shows a normal-traffic city street scene. The video resolution is 480 × 270 at a frame rate of 25 FPS; the videos are 42 s long, and the frames include the front and back views of the vehicle. Figure 8 shows the sample scenes. In the experiments, we discarded objects whose height and width are lower than 40 pixels each because of the difficulty of recognizing a small license plate. For example, Figure 9(a) shows five vehicle objects; however, only three vehicles were detected, as plotted in red squares. Two objects (plotted in yellow squares) are too small, 26 × 26 and 37 × 37, which are smaller than 40 × 40. The three vehicles in Figure 9(b) were detected similarly.
Table 1 presents the results of vehicle candidate detection based on using the Adaboost algorithm and the proposed Car-like features. The correct detection ratios are 95.5%, 88.3%, 82.8%, and 88.1% for the four videos. Figure 9(c) shows examples of the detection results. However, the number of false alarms was still high. Reducing the number of false alarms is necessary when using the proposed verification method.



(a) (b) (c)

Figure 9: (a) (b) The vehicle identification process,.(c) Examples of detection results.

Table 1: Vehicle detection results.

| | Video 1 | Video 2 | Video 3 | Video 4 |
|---|---|---|---|---|
| Total Objects | 2419 | 1026 | 379 | 413 |
| Detected Candidates | 2566 | 1034 | 777 | 493 |
| Correct Hit | 2311 | 906 | 314 | 364 |
| Miss | 108 | 120 | 65 | 49 |
| False Alarm | 255 | 128 | 463 | 129 |
| Hit Ratio | 95.5% | 88.3% | 82.8% | 88.1% |

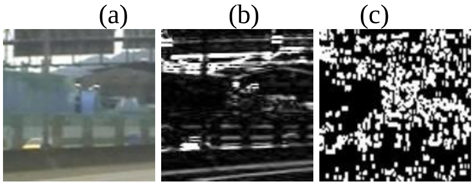
Figure 10 illustrates the process of vehicle verification in a hit case. Figure 10(a) shows the media filtering result of detecting a vehicle candidate by using the Adaboost algorithm. The solid black line shown in Figure 10(b) indicates the central line based on the calculation result of symmetry measurement, denoted by a red arrow in Figure 10(c), where the horizontal symmetry axis of the possible vehicle region occurs at the local minimum with x = 106. Next, the candidate region of a vehicle is obtained, as shown in Figure 10(d). Finally, horizontal and vertical edge detection is performed, as illustrated in Figure 10(e) and Figure 10(f), respectively, and the edge numbers are analyzed. In this case, the numbers of horizontal and vertical edges are both higher than the threshold value; therefore, this case is verified as true vehicle detection. Conversely, Figure 11 illustrates the process of vehicle verification for a false case. As expected, the central line (plotted in the red line shown in Figure 11(b)) is not located in the symmetry margin (plotted in yellow lines). Thus, we conclude that this image is not a vehicle object.
Tables 2 and 3 list the statistics of the integrated system detection performance. After applying the proposed verification scheme, the number of false alarms for the Video 1 experiment was reduced by as many as 242 of 255. The false alarm reduction rate is as high as 94.9%. As shown in Table 2, substantial improvements were achieved for the other test video sequences. The false alarm reduction rates are 96.0%, 97.4%, 93.0% for the sequences in Videos 2, 3, and 4, respectively. On the other hand, the rejection rates for hit cases are as low as 2.7%, 2.4%, 4.4% and 4.6% in Videos 1, 2, 3, and 4, respectively. The experimental results show that the proposed system successfully detects the vehicles under various conditions and reduces the false alarms.


(a) (b) (c)

(d) (e) (f)

Figure 10: The vehicle verification for a hit case: (a) median filtering result of vehicle candidate image, (b) (c) symmetry measurement result, (d) vehicle candidate region, (e) horizontal edge detection result, (f) vertical edge detection result.


(a) (b) (c)



(d) (e) (f)

Figure 11: The vehicle verification for a false case: (a) median filtering result of vehicle candidate image, (b) (c) symmetry measurement result, (d) vehicle candidate region, (e) horizontal edge detection result, (f) vertical edge detection result.

Table2: Vehicle verification for hit cases.

| | Video 1 | Video 2 | Video 3 | Video 4 |
|---|---|---|---|---|
| False Alarm | 255 | 128 | 463 | 129 |
| False Alarm Reduction | 242 | 123 | 451 | 120 |
| False Alarm Reduction Rate | 94.9% | 96.0% | 97.4% | 93.0% |

Table 3: Vehicle verification for false alarm cases.

| | Video 1 | Video 2 | Video 3 | Video 4 |
|---|---|---|---|---|
| Hit | 2311 | 906 | 314 | 364 |
| Verification Rejection | 64 | 22 | 14 | 17 |
| Rejection Rate | 2.7% | 2.4% | 4.4% | 4.6% |

## 4. CONCLUSION

We developed an intelligent vehicle technology based on symmetry measurement, horizontal and vertical edge analysis, and an AdaBoost classifier. This system relies on the AdaBoost classifier to determine vehicle candidates, and uses edge information and symmetry measurement to verify them. The experimental results show that the proposed system effectively detects vehicles on roads under various environmental conditions. Based on vehicle detection and verification, the system may provide important information to the driver. In the future, vehicle detection and tracking systems will be investigated further under various road conditions. For example, horizontal symmetry analysis accompanied by vertical asymmetry analysis could facilitate obtaining the center point of a vehicle for vehicle tracking in the future. Research is currently underway to determine whether vehicular odometers can provide additional constraints to improve the quality of our results.

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