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Vision-Based Vehicle Detection and Inter-Vehicle Distance Estimation for Driver Alarm System

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In this paper, we propose a robust real-time vehicle detection and inter-vehicle distance estimation algorithm for vision-based driving assistance system. The proposed vehicle detection method uses the combination of multiple vehicle features, which are the usual Harr-like intensity features of car–rear shadows and additional Haar-like edge features. The combination of two distinctive Haar-like intensity and edge features greatly reduces the false-positive vehicle detection errors in real-time. And, after analyzing two inter-vehicle distance estimation methods: the vehicle position-based and the vehicle width-based, we present a novel improved inter-vehicle distance estimation algorithm that uses the advantage of both methods. Various experimental results show the effectiveness of the proposed method.

Keywords: vision-based vehicle detection, Haar-like features, inter-vehicle distance estimation, driving assistance system

1. Introduction

Driver assistance system can help drivers to keep themselves safe from rear-end collision. Rear-end collision is a great part of the total accident (29.5% in USA and 29% in Germany). Lack of attention (sleeping, using communication devices, etc.) is 91% proportion of the driver related accident. If drivers can aware of collision earlier on 0.5 s, 60% of rear-end collision can be prevented, and 90% of collision can be prevented by noticing earlier on a second.[1)]

Distance measurement by lasers or other sensors is more accurate than the method using optical sensors and image processing. On the other side, we cannot get any other information except for the vehicle distance. If we use the optical sensor, we can classify the front objects and analyze the state of road, and other environments. Using these information from optical sensor, driver assistance system can be expanded on the various way. For example, lane detection system can be added and be utilized for preventing drivers from leaving the correct line. Most of all, optical sensor is more economical than other sensors, therefore, the vehicle detection and distance estimation algorithm can be simply implemented to the various driver assistance systems, for example, car navigation and car black-box, etc.

The vision-based vehicle distance estimation consists of two main steps: 1) detection and tracking the vehicles, and 2) distance estimation for each vehicle. The fundamental problem is to identify vehicles in changing environment and illumination. Modern vision-based object detection systems often rely on filter-based feature extraction by means of Gabor, Haar-like, or Gaussian derivative filters. Different combinations of feature extraction methods and learning algorithms are proposed.[2–6)] In recent years, the Viola and Jones rapid object detection approach became very popular.[5,6)] The system is computationally efficient due to fast computation of the Haar-like features by means of the integral image and the cascaded structure of the classifier. But, although there have been numerous publications on general vehicle detection and tracking, or a combination of them, not many of these techniques could successfully be applied in real driver assistance system.

Hasan *et al.* proposed a method for vehicle distance estimation using stereo vision.[7)] But it can only measure vehicle distance within 20 m. Most of target vehicles are usually located in 20 m or more. Therefore, the stereo-vision method is not suitable for measuring vehicle distance in the driver assistance systems. Except for the stereo-vision algorithm, there are a few vehicle distance measuring methods based on single charge-coupled device (CCD) image,[8,9)] because it is very difficult to estimate the distance. Theoretically, to get three-dimension information from two-dimensional (2D) image is impossible.

Our study assumes that the camera is located at fixed position and all objective vehicles are on the flat road, so that we can get the 3D distance information from 2D image sequences. The remainder of the paper proceeds as follow. The approach of vehicle detection is described in §2. In §3, previous works for vision-based distance estimation are introduced, and our new approach is presented. Finally, the illustrative simulation results and conclusions are presented in §4.

2. Vehicle Detection and Tracking

The whole system of our approach is shown in Fig. 1. At first, the adaptive sliding window[4)] is also used to pick out reasonable candidate windows in the view of geometry. For each reasonable window, we examine the distinctive Haar-like intensity and edge features, distribution of intensity and directional edge features. The detected vehicle candidate regions should be verified by the additional Haar-like edge

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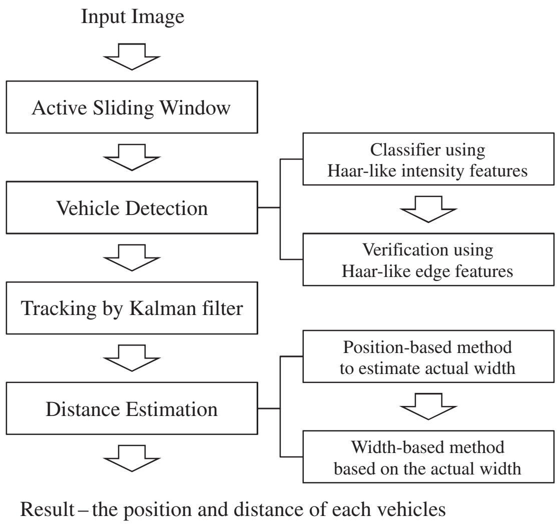


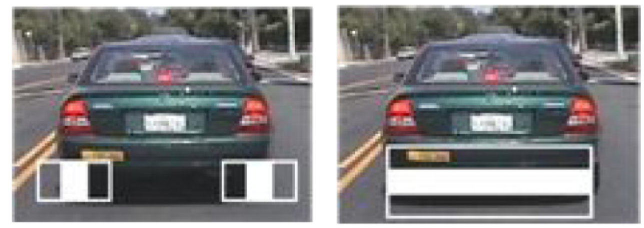
Fig. 1. Block diagram of the overall proposed algorithm.

features. The false detection for the non-vehicles can be reduced by the additional Haar-like edge features. The information of detected vehicles passes through the Kalman filter for tracking of the detected vehicles. Then, each vehicle's distance can be estimated by the information of the detected vehicles using the proposed distance estimation method.

2.1 *Proposed vehicle detection method*

Due to the real time processing constraint and robust vehicle detection, the proposed vehicle detection method follows two main phases: (i) generation of hypotheses, in charge to select those image regions likely to hold vehicles; and (ii) verification of hypotheses, whose objective is to verify the presence of vehicles, among the selected areas. The hypothesis generation has been solved in many other literatures by using different approaches, such as knowledge-based, stereo-based, and motion-based strategies. On the other hand, the verification of these hypotheses is still a widely open field of research.

Our proposed vehicle detection method is as followings. (i) Generation of hypotheses; (i) first, the algorithm finds the important vehicle features (Haar-like intensity features) in the input images using the adaptive sliding windows; and (ii) verification of hypotheses; second, the vehicle detection algorithm verifies the detected sub-regions using the Haar-like edge features. The most important intensity features (Haar-like intensity features) of front vehicles are the shadows under the vehicle and the rear-wheels as shown in Fig. 2. The Haar-like intensity features mean conventional Haar-like features.[5] The proposed Haar-like edge features are the directional edge strength in the rear-vehicles as shown in Fig. 3. Figure 3 shows the rear center of vehicles has more horizontal edges than the vertical edges. The directional edge images for the Haar-like edge features have the same role as the gray images for the conventional Haar-like intensity features. The sum of edge strength which lies within the center rectangles are subtracted from the sum of



(a) (b)

Fig. 2. (Color online) Haar-like features of front vehicles: (a) rear-wheels, and (b) shadow under vehicles.

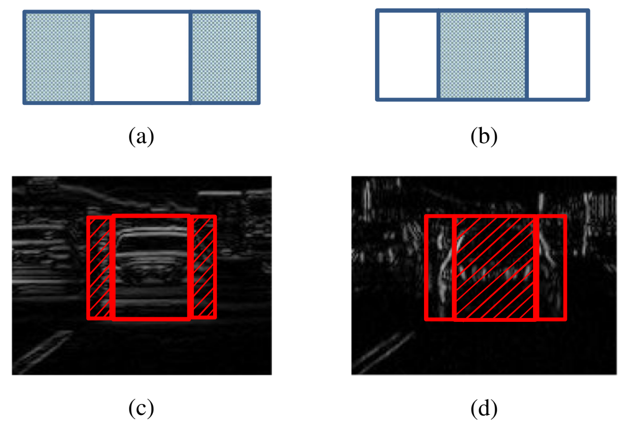


Fig. 3. (Color online) Haar-like edge features of front vehicles: (a, b) two types of Haar-like features, (c) Haar-like edge feature for the horizontal edge image, and (d) another type of Haar-like edge feature for the vertical edge image.

edge strength in the outside two gray rectangles. The two Haar-like edge features in combination with the Haar-like intensity features are used as the basis for the verification of hypotheses. If we use only the Haar-like intensity features as shown in Fig. 2, there happen to be many false detection errors in the whole input image sequences. But, the additional Haar-like edge features as presented in Fig. 3 are able to reduce the false detection errors for non-vehicle regions. This additional edge features makes use of second order differential intensity of the image, while the conventional Haar-like features can find out first order differential. Also it makes ease to construct manual Haar-like features for first order differential.

We also use the integral image method[5] for efficient processing time. Figure 4 shows some comparative simulation results. The conventional Haar-like intensity feature detector [Fig. 4(a)] finds the candidate locations of vehicles (true positive). However, there are still many false positive errors. The false positive errors can be rejected by the additional Haar-like edge features as shown in Fig. 4(b). Figures 4(c) and 4(d) show the vertical and horizontal edges of false detection regions, which reveal that these areas do not have the proposed Haar-like edge features. Figure 5 also shows another directional Haar-like edge features of the detected vehicles, while Fig. 6 shows the directional edges

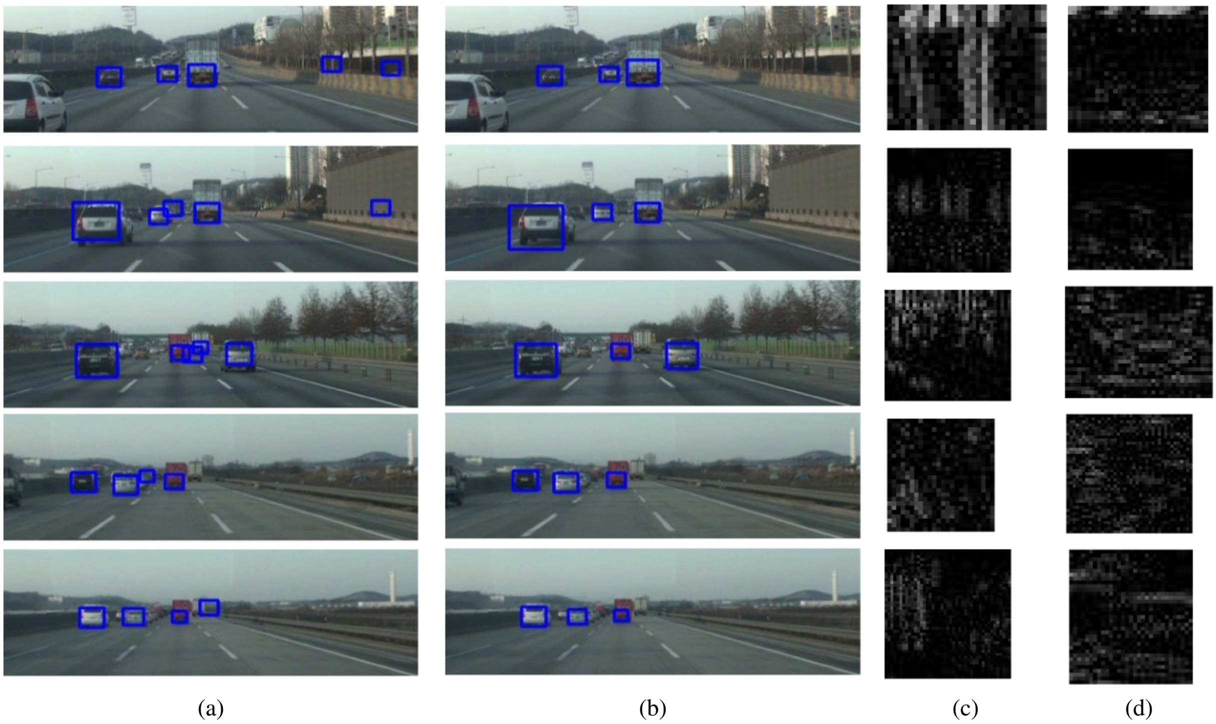


Fig. 4. (Color online) Comparing with (a) conventional Vehicle Detection using only Haar-like intensity features, (b) proposed vehicle detection verifying the detected regions by Haar-like edge features, (c, d) vertical and horizontal edges of false detection regions, respectively.

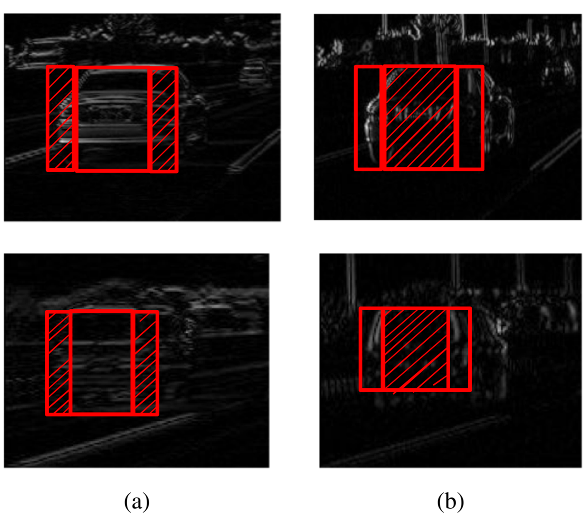


Fig. 5. (Color online) Various directional Haar-like edge features of vehicles: (a) horizontal Haar-like edge features, and (b) vertical Haar-like edge features.

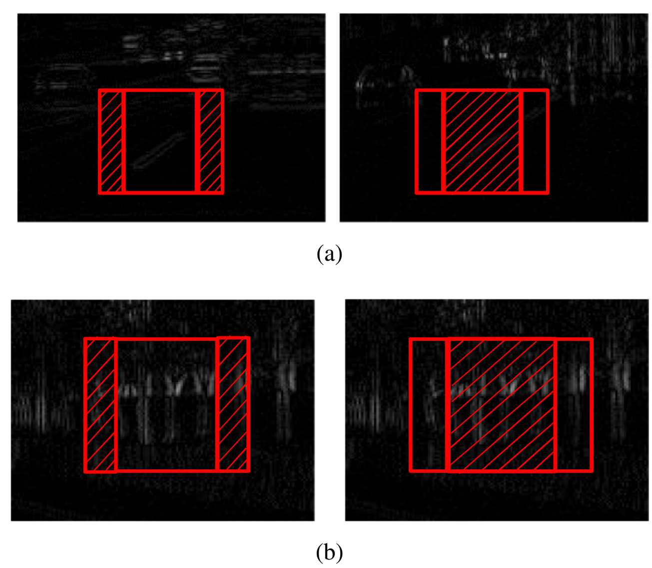


Fig. 6. (Color online) The detected non-vehicles do not have Haar-like edge features even though they have Haar-like intensity features (left: horizontal edge, right: vertical edge), (a) a lane area and (b) a tree area.

of non-vehicles [(a) a lane and (b) a tree regions]. Many false positive rectangles (or detections) were filtered out, when we applied the additional edge features after detecting the Haar-like intensity features.

2.2 Tracking of the detected vehicles by Kalman filter

Kalman filter is also used for refinement of the detection and to get rid of some false positives. The variables that are integrated in the tracking are the vehicle position (x, y) and the width of detected vehicles (w). Since the height of vehicles is not important to estimate the distance, we assumes that the ratio of width and height of vehicles is constant. For the detected vehicles it is assumed that they

(a) (b)

Fig. 7. (Color online) Two distance estimation methods: (a) the width-based method and (b) the position based-method.

move with almost constant velocity. With this assumption the state vector is defined as $\dot{\boldsymbol{X}}_t = [x_t\ y_t\ w_t\ vx_t\ vy_t\ vw_t]^{\mathrm{T}}$, with vx_t, vy_t, and vw_t being the according velocities. The used state and measurement z_t model[4] is defined by

$$\dot{X}_t = AX_{t-1} + \omega_t, \tag{1}$$

$$z_t = HX_t + v_t, \tag{2}$$

where ω_t and v_t are the process noise and the measurement noise, respectively. They are random variables in practice, which are assumed the Gaussian distributions.
The system matrix A for the constant velocity assumption is

$$\boldsymbol{A} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \tag{3}$$

where Δt is the time difference of the current and last frame.

3. Inter-Vehicle Distance Estimation

Inter-vehicle distance estimation using a single camera with no other sensors has been researched in two ways. The first method[9] is to use the width of vehicles in the image sequences as shown in Fig. 7(a), which has been used for nighttime. The vehicle distance and the vehicle-width are inversely proportional. This estimation method is good enough to compare with the vehicles in the sequential images and predict to the next distance. But it is impossible to estimate the absolute distance if we do not know the actual width of vehicles. In order to measure the actual distance, we should know the actual width of the vehicles and the focal length of the camera. But, there are many kinds of vehicles which have different width, for example, sedans, trucks and buses, etc. The previous work[9] approximates that all vehicles have the same width.

The second method[8] is the position-based distance estimation as shown in Fig. 7(b). The detected vehicle is mapped onto the 3D space. But, even though the position-based method is possible to measure absolute distance for all kinds of vehicles, it is very sensitive to noise and assumes that the floor is flat.

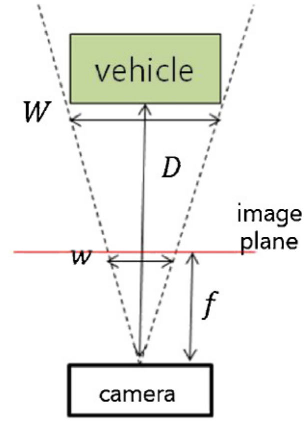


Fig. 8. (Color online) Top view of the system for the width-based method.

3.1 *Width-based distance estimation*

The width-based distance estimation is illustrated in Fig. 8. W is the actual width of vehicle, D the real distance from the camera to the vehicle, w the width of vehicle in the image plane, and f is the focal length in pixel space. These values are related and approximated by

$$W : D \cong w : f. \tag{4}$$

Finally, the inter-vehicle distance, D can be calculated as

$$D \cong \frac{f \cdot W}{w}. \tag{5}$$

Since the camera is not changed, the focal length, f is constant. If we know the pixel width of detected vehicle W, the distance D can be expressed as

$$D \cong \frac{R}{w}, \quad \text{where } R = f \cdot W. \tag{6}$$

R is always constant for the fixed camera and the detected vehicle. And, W is the actual width of the detected vehicle. If we know the actual width, we can estimate the vehicle distance D. But, the problem is that we can not know the real width of the detected vehicles.

3.2 *Position-based distance estimation*

Figure 9 shows the camera configuration of the position-based distance estimation method. The parameter D is the distance (m) that we want to estimate. A CCD camera is mounted at height C with its optical axis parallel with the ground. The parameter θ_c is the angle of camera direction. These parameters (C and θ_c) are constant values that can be measured before operation. θ_i is the angle of the vehicle and camera direction. D can be derived by

$$D = C \cdot \tan(\theta_c - \theta_i). \tag{7}$$

When the position of the vehicle is identified, the parameter y is the number of pixels between the position of the vehicle's bottom and the bottom row of image. f is also the focal length of the CCD camera as same as Fig. 8 and θ_r is half of the camera view angle and h is the height

Table 1. Analysis of the distance estimation methods.

	Width-based method	Position-based method
Advantages	— Robust to noise — No assumption of the flat floor condition	— Possible to measure absolute distance for all kinds of vehicles
Disadvantages	— Needs to know the actual width of the detected vehicles	— Very sensitive to noise. — Assumes that the floor is flat.

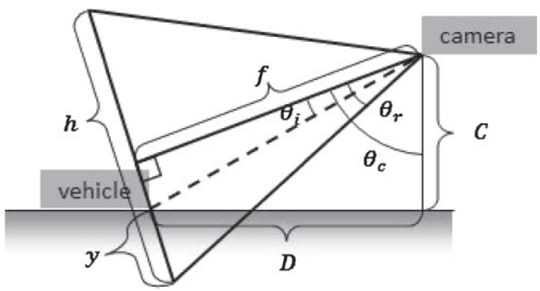


Fig. 9. Side view of the system for the position-based method.

of image, which is constant determined by the camera resolution. The parameter y is the pixel distance from the bottom of the image to the detected vehicles. And, the parameter θ_i can be determined by

$$\theta_\mathrm{i} = \tan^{-1} \frac{\left(\dfrac{h}{2} - y\right)}{f}, \tag{8}$$

where

$$f = \frac{h}{2\tan\theta_\mathrm{r}}. \tag{9}$$

3.3 Proposed distance estimation method

We analyzed the previous two distance estimation methods with various vehicle image sequences. Advantages and disadvantages of both methods for estimating the distance are shown in Table 1. Even though the width-based method is robust to noise, it needs to know the actual width of the detected vehicles. Conversely, the position-based method is possible to measure absolute distance for all kinds of detected vehicles, but it is very sensitive to noise and it assumes that the floor is always flat.

Our proposed distance estimation method is to combine the advantages of both methods. The pseudocode of the proposed distance estimation method is presented in Table 2. Initially, we find the parameter R of the width-based method for each tracked vehicle by the position-based method. For each frame, the inter-vehicle distance D is calculated by the position-based method, and the priori R, R^- is driven by eq. (6). In that case, w is the pixel width of the tracked vehicle. In the past n frames from the current t frame, if the standard deviation σ is smaller than a constant threshold σ_th, it is regarded that the distance estimation is in the stable state and we adopt the expected R in the past n frames, R^μ as the determined R. This determined R includes information of the actual width of the vehicle. After the determination of the R, the width-based method is used to estimate the inter-vehicle distance. The reason why we should determine the R value from the position-based method is that there are many kinds of vehicles with different widths. Practically, after determination of a stable R by the position-based method, we can estimate the inter-vehicle distance by the width-based method.

Table 2. Pseudocode of proposed distance estimation method.

for each t frame image...
■ for each being tracked vehicle v
  if R_v = null
    • estimate distance using the position-based method
    $D_v(t) := C \cdot \tan(\theta_x(t))$
    $R_v^-(t) := D_v(t) \cdot w_v(t)$
    • calculate the mean ($\mu_v(t)$) and the standard deviation ($\sigma_v(t)$) of R using $R_v^-(t-n, \ldots, t)$
    • if $\sigma_v(t) < \sigma_\mathrm{th}$, then $R_v := \mu_v(t)$
  else
    • estimate the distance using the width-based method
    $D_v(t) := \dfrac{R_v}{w_v(t)}$
■ for each pairs (a, b) of all being tracked vehicles
  if $y_a(t) > y_b(t)$ and $D_a(t) < D_b(t)$ then $R_a, R_b :=$ null

For each frame, the determined R is examined by the comparison of y (pixel distance from the detected vehicle position to the bottom of the image) and the estimated distance. A farther vehicle must have higher y value than those of other closer vehicles. If not, we need to re-determine the determined R using the position-based method since the determined R of both vehicles are not accurate.

4. Experimental Results

The proposed distance estimation algorithm is implemented on Intel T6400 (Dual Core 2.0 GHz) using C++. First, in order to verify the proposed distance estimation, we tested the performance of the position-based method with several stopped vehicle images and measured the real distance by a distance measuring device. Figure 10 shows two illustrative results with two different camera configurations (1.15 and 1.4 m camera height from floor). Even though there are some distance errors in the far distance ranges, the errors in the long distance do not affect to the application of vehicle alarm system.

The representative vehicle detection results are shown in Table 3. The overall detection performance test is evaluated for 1,000 sequential images with 640×480 resolution.

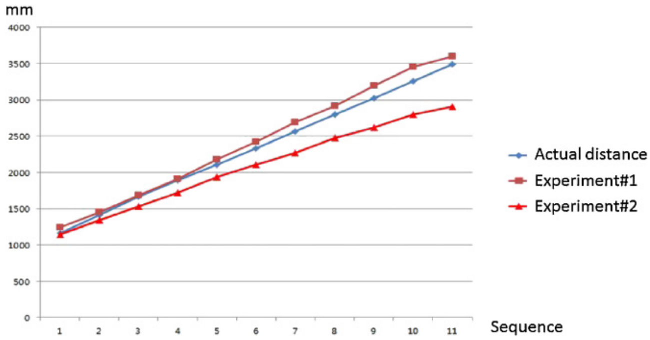


Fig. 10. (Color online) The graph shows two illustrative distance estimation results with two different camera configurations (Experiment #1: 1.15 m camera height, Experiment #2: 1.4 m camera height).

Table 3. The result of vehicle detection.

Heavy vehicles	Sedans	Total
711/876 (81.6%)	2427/2459 (98.7%)	3138/3335 (94.9%)

In Table 3, we achieved 94.9% of accuracy in total. The number, 3138/3335 means 'detected vehicles/total vehicles' in the all sequential images. And, Fig. 11 shows some result of the proposed vehicle detection and distance estimation. The detection accuracy of heavy vehicles (trucks and buses) is lower than that of sedans. The proposed algorithm is fast enough to process 32.2 frames per second. Therefore, it can be practically implementable for various driver assistance systems.

5. Conclusions

In this paper, we proposed a vision-based vehicle detection and inter-vehicle distance estimation algorithm for the driver assistance system. The proposed vehicle detection method uses the directional Haar-like edge features, as well as the Haar-like intensity features of car rear-shadows, which resulted in reducing the false detection errors. And, a novel improved inter-vehicle distance estimation method is also proposed. Various experimental results show that the proposed method is practically applicable to the driver alarm system for driver safety. But, the proposed method is only applicable to the day time. For the future of work, we need to research a nighttime vehicle distance estimation algorithm.

Fig. 11. (Color online) Some result image by the proposed method.

References

1) National Transportation Safety Board: Special Investigation Report (2001).
2) Z. Sun, G. Bebis, and R. Miller: IEEE Trans. Pattern Anal. Mach. Intell. **28** (2006) 694.
3) D. Ponsa, A. Lopez, F. Lumbreras, J. Serrat, and T. Graf: Proc. Int. Intelligent Transportation Systems, 2005, p. 1096.
4) A. Haselhoff and A. Kummert: Proc. IEEE Int. Vehicles Symp., 2009, p. 261.
5) P. Viola and M. Jones: Int. J. Comput. Vision **57** (2004) 137.
6) G. Monteiro, P. Peixoto, and U. Nunes: Proc. 6th Natl. Festival Robotics Science (ROBOTICA), 2006, p. 258.
7) A. Hasan, R. Hamzah, and M. Joha: IEEE Int. Vehicle Symp., 2002, p. 465.
8) J. Choi presented at final report of a course CS543 (computer vision), 2006.
9) M. Lu, W. Wang, C. Chen, and C. Tsai: Proc. Int. Conf. Systems Man and Cybernatics, 2008, p. 226.