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Vision-based Vehicle Detection and Inter-Vehicle Distance Estimation

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Abstract: In this paper, we propose a vision-based robust vehicle detection and inter-vehicle distance estimation algorithm for driving assistance system. It uses the directional edge features, as well as the Haar-like features of car rear-shadows for detection of front vehicles. The use of additional vehicle edge features greatly reduces the false-positive errors. And, after analyzing two inter-vehicle distance estimation methods: the vehicle position-based and the vehicle width-based algorithm, a novel improved inter-vehicle distance estimation algorithm that uses the advantage of both methods is proposed. Various experimental results show the effectiveness of the proposed method.

Keywords: vehicle detection, inter-vehicle distance estimation

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 second, 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 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, distance estimation algorithm can be added for vehicles that already have optical sensor for black-box.

A stereo-vision algorithm was proposed to estimate the inter-vehicle distance [2]. But it can only measure vehicle distance within 20 m. Most of target vehicles are located in 20 m or more. Therefore, it is not suitable for measuring distance of driver assistance systems.

The vision-based vehicle distance estimation consists of two main steps: 1) detection and tracking the vehicles, and 2) distance estimation for each vehicle. One way to detect vehicles is to use learning algorithm [3][4][5], and the others are to find distinctive features, such as edge or intensity distribution of vehicles [5][6]. In the learning-based approaches, they need to gather many sample images for learning. Little is shown of the studies of distance estimation based on vision system [3][6], because it is very difficult to estimate the distance. Theoretically, to get 3-Dimension information from 2-Dimension is impossible.

Our study assumes that the camera is located at fixed position and road vehicles are moving on the flat road, so that we can get the 3D distance information from 2D single image. In this paper, both of the position-based method [6] and the width-based method [3] are combined to make up for their drawbacks.

The remainder of the paper proceeds as follow. The approach of vehicle detection is described in section 2. In section 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 section 4.

2. THE VEHICLE DETECTION SYSTEM

The whole system of our approach is visualized in Fig. 1. Firstly, the adaptive sliding window in [4] is also used to pick out reasonable candidate windows in the view of geometry. For each reasonable window, we detect the distinctive vehicle features, distribution of intensity and directional edge. The information of

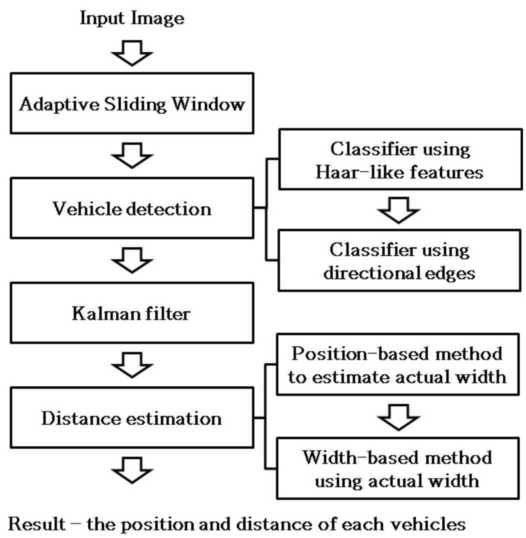


Fig. 1 Block diagram of the proposed algorithm

detected vehicles passes through the Kalman filter[7] and finally is verified. Then, each vehicle's distance will be estimated by the information of the detected vehicles, the position-based and the width-based of the vehicles in the image sequences.

A. Proposed vehicle detection method

Overall block diagram of the proposed vehicle detection is described in Fig. 1. First, the algorithm finds the important features (Haar-like features) in the input images using the adaptive sliding windows; second, the vehicle detection algorithm verifies the detected areas using the directional edge features. The most important intensity features of front vehicles are the shadows under the vehicle and the rear-wheels as shown in Fig. 2.

Our detection algorithm uses the additional edge features of vehicle in order to reduce the false detection errors. Fig. 3 shows the vertical edge features in the car left and right sides, while the horizontal edges are located in the middle part. Car rear center has more horizontal edges than vertical edges. We also use the integral image method [8] for efficient processing time. Fig. 4 shows some comparative simulation results. The Haar-like feature detector (Fig. 4.(a)) finds the location of cars in some case (true positive). However, there are still many false positive errors. The false positive errors can be rejected by the additional directional edge features as shown in Fig. 4 (b).

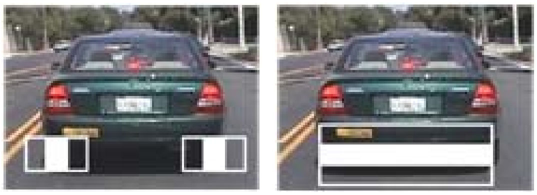
B. Tracking of detected vehicles by the Kalman filter

Kalman filter [5] is used for refinement of the detection and to get rid of some false positives. The state variables for 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 assume that the ratio of width and height of vehicles is constant and we also use the constant velocity state model[4]. The velocities of these components are also added, so the state is defined as $[x\ y\ w\ vx\ vy\ vw]$. If the detected vehicles in the next frame are in the range of filter prediction, the detected vehicles by the proposed vehicle detection algorithm are real ones. We use the same process and measurement model as given in [4].

3. INTER-VEHICLE DISTANCE ESTIMATION

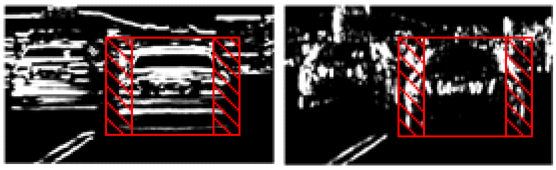
Inter-vehicle distance estimation using a single camera with no other sensors has been developed in the two ways. The first method [6] is to use the width of vehicles in the image sequences as shown in Fig. 5(a) with red arrows. The distance and the vehicle-width are inversely proportional. This estimation method is good at comparing with the vehicles in the sequential images and predicting the next distance, but it is impossible to estimate the absolute distance if we don't know the real car's width. In order to measure the exact actual distance, we should know the actual width of the vehicle and the focal length of the camera. And all kinds of vehicles have different width, for example, sedan, truck and buses, etc. The previous works [6] approximate that all vehicles have the same width.

The second method [3] is to use the vertical position of vehicles in the image as shown in Fig. 5(b). The distance and the vertical position of detected vehicles are proportional. However, this method needs to assume that the road is flat, even though the slope has nothing to do with it.



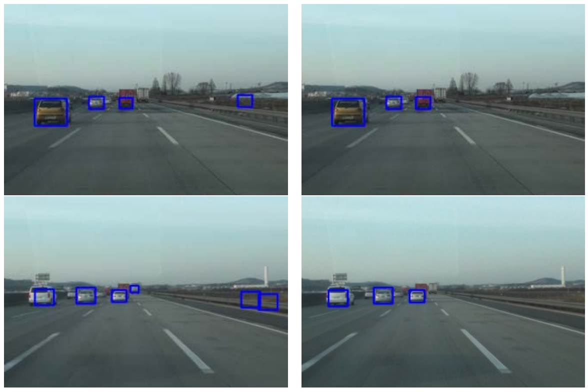
(a) rear-wheels (b) shadow under vehicles

Fig. 2 Strongest Haar-like features of front vehicles



(a) horizontal edges (b) vertical edges

Fig. 3 Directional edge features of vehicles



(a) (b)

Fig. 4 Comparing with (a) vehicle detection using only Haar-like features and (b) adding directional edge features

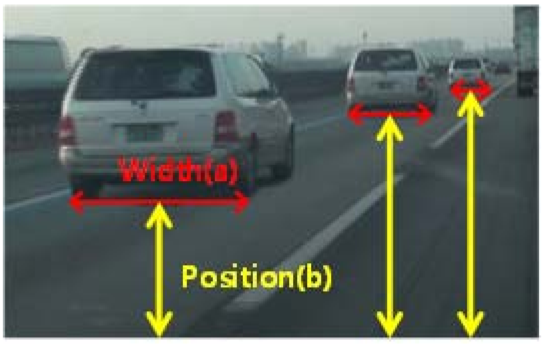


Fig. 5 Two inter-vehicle distance estimation methods, (a) the width-based, (b) the position based.

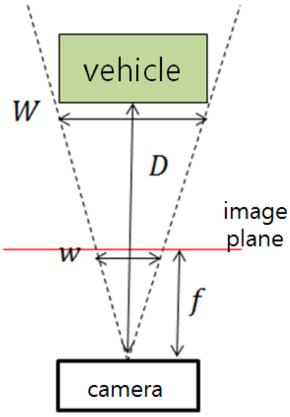


Fig. 6 Top view of the system for the width-based method.

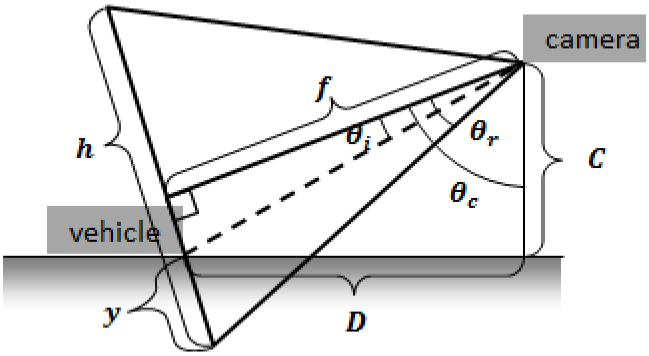


Fig. 7 Side view of the system for the position-based method.

If the assumption is guaranteed, the position-based method can be used to estimate the absolute real distance for all kinds of objects on the floor. Despite of this advantage, the distance estimation by the position-based method is very sensitive. Even a small pixel measurement noise results in a big distance error. To get rid of these disadvantages of both methods, we combine the advantages of two methods.

A. The width-based distance estimation

The width-based distance estimation is illustrated in Fig. 6. W is the actual width of vehicle and D is the real distance from the camera to the vehicle. The parameter w is the width of vehicle in the image plane, and f is the focal length in pixel space. These parameters are related and approximated by

$$W:D \cong w:f \tag{1}$$

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

$$D \cong \frac{f \cdot W}{w} \tag{2}$$

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

Table 1 Comparison of two distance estimation methods.

	Width-based	Position-based
Advantages	Robust to noise not related on the state of the floor	Can measure absolute distance for all kinds of object
Disadvantages	It needs to know the actual width of the detected vehicle	It is very sensitive to noise. It assumes that the floor is flat.

$$D \cong \frac{R}{w}, \quad \text{where } R = f \cdot W \tag{3}$$

The R is always constant for the fixed camera and the same detected vehicle. We tested it with real camera and several vehicles.

B. The position-based distance estimation

Fig. 7 shows the configuration of the position-based distance estimation. A CCD camera is mounted at height with its optical axis parallel with the ground. The parameter D is the distance(m) that we want to estimate, C is the height(m) camera fixed from floor, and θ_c is angle of camera direction. C and θ_c are constant values that can be measured before operation. θ_i is the angle of the vehicle and camera direction. The wanted distance parameter D can be derived by the following :

$$D = C \cdot \tan(\theta_c - \theta_i). \tag{4}$$

When the position of the vehicle is identified, the number of pixels between the position of the vehicle's bottom and the last row of images is y. f is the focal length of the CCD camera as same as Fig. 6. θ_r is a half of the camera angle of view, h is the height of image. The parameter can be determined by (5) and (6).

$$\theta_i = \tan^{-1}\frac{\left(\frac{h}{2} - y\right)}{f}, \tag{5}$$

$$\text{where,} \quad f = \frac{h}{2tan\theta_r}. \tag{6}$$

C. The proposed distance estimation method

We analyze two methods for estimating the distance. Table 1 summarized the advantages and disadvantages of both methods. 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 determine the R values of the width-based method for each tracked vehicle by the position-based method. For each frame, R^{-} is calculated by the estimated distance and the image width of the vehicle using Eq. (3). In the past n

Table 2 Pseudocode of proposed distance estimation.

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 $\sigma_v(t) < \sigma_{th}$, then $R_v := \mu_v(t)$
    else
      estimate the distance using the width-based method
      $D_v(t) = \frac{R_v}{w_v(t)}$
  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

frames, if $R^-(t-n, \ldots, t)$ shows stable result, the width-based method is adopted to estimate the distance using the determined R value. For every frame, the determined R is examined by the y. The farther vehicles must have higher y value than those of other closer vehicles. If not, we need to re-determine the R since the values of both vehicles are not accurate.

For each frame, R is tested by y (pixel distance from image center to bottom of the vehicle). A farther vehicle must have higher y than other closer vehicles. If the supposition is wrong in the image, we can consider that R of both vehicles are not accurate and step backward to get R again.

4. EXPERIMENTAL RESULTS AND CONCLUSIONS

The proposed distance estimation algorithm is implemented on Intel T6400(Dual Core 2.0 GHz) using C++. We experiment various illustrative images and sequences. First, in order to verify the proposed distance estimation algorithm, we compared the result of our algorithm with the real measured distance by a distance measuring device with several stopped vehicle images. Fig. 8 shows two comparison results between real measurement and the proposed estimation results. The graph shows two illustrative distance estimation results with two different camera configurations (1.15 m and 1.4 m camera height from floor).

The overall performance test is evaluated for 1,000 sequential images with 640x480 resolutions. The representative results are shown in Table 3. In Table 3, we achieved the 94.9 % of accuracy in total. The number, 3138/3335 means ‘detected vehicles/total vehicles in the all sequential images’. And Fig. 9 shows the results of the proposed vehicle detection and distance estimation. The detection accuracy of heavy vehicles (truck and buses) is lower than that of sedans. The proposed algorithm is fast enough to process 32.2 frames per second.

Table 3 The result of vehicle detection(The number means ‘detected vehicles/total vehicles’).

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

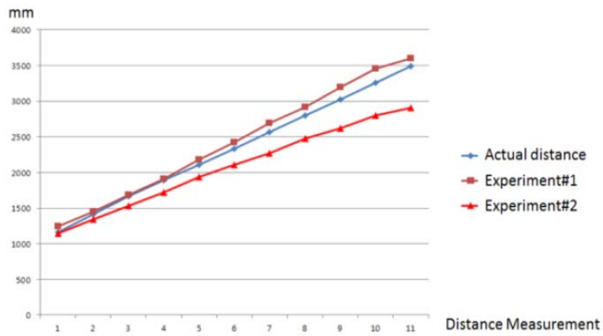


Fig. 8 The graph shows two illustrative distance estimation results with two different camera configurations. (1.15m and 1.4m camera height from floor in Experiment#1 and #2, respectively)

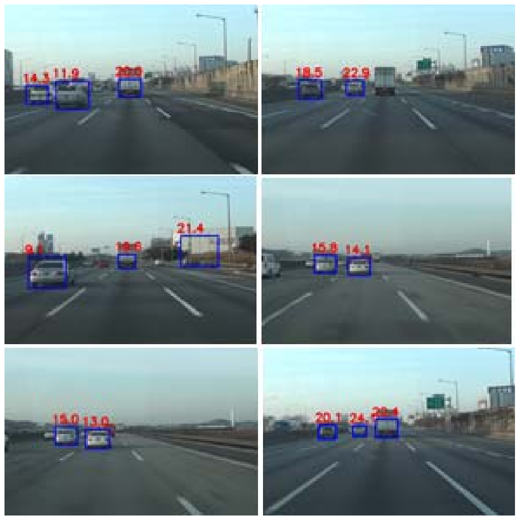


Fig. 9 Vehicle detection and distance estimation results by the proposed method.

Even though some distance error exits in the far ranges, the proposed vehicle detection and distance estimation algorithm is enough for applications of Driver Assistance Systems. For the future of work, we need to research a nighttime vehicle distance estimation algorithm.

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