

Real-Time Vehicle Detection using a Single Rear Camera for a Blind Spot Warning System

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ABSTRACT

This paper describes a vision-based vehicle detection system for a blind spot warning function. This detection system has been designed to provide ample performance as a driving safety support system, while streamlining the image processing algorithm so that it can be processed using the computational power of an existing ECU. The procedure used by the system to detect a vehicle in a blind spot is as follows. The system consists of four functional components: obstacle detection, velocity estimation, vertical edge detection, and final classification. In obstacle detection, a predicted image is generated under the assumption that the road surface is a perfectly flat plane, and then an object is detected based on a histogram that is created by comparing the predicted image and an actually observed image. The velocity of the object is estimated by tracking the histogram over time, assuming that both the object and the host vehicle are traveling in the same direction. Vertical edge detection is employed so as to avoid misdetection due to a vehicle shadow projected onto the road surface. In final classification, a vehicle is detected on the basis of these results. The effectiveness of the system was verified by conducting road tests on highways and narrow streets with two-way traffic.

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INTRODUCTION

Sensing technology for driving safety support systems (DSSSs) has been an active research area for the past twenty years, and various practical applications have been developed by many automobile manufacturers and suppliers. Detecting vehicles in the blind spot area of an adjacent lane has attracted considerable attention in particular.

Almost all of the available systems use dedicated devices, for example, millimeter wave radar or an added camera, making them expensive and limiting their scope of use. Development of a common sensor-based vehicle detection system is necessary for use on a variety of platforms, including low-cost vehicles.

In recent years, vehicles equipped with a rear-view camera have become more common in Japan. In the U.S., the National Highway Traffic Safety Administration (NHTSA) has proposed a new rule requiring a rear-view camera on all

vehicles, which can be expected to rapidly expand the use of these devices. Therefore, we have adopted a rear camera as a common sensor for a blind spot warning (BSW) system.

Obstacle detection using a single camera typically can be divided into two types of approaches: an appearance-based approach and a geometry-based approach. In the appearance-based approach, symmetry-based recognition [7], a template-matching method [3], AdaBoost using Haar-like features [6], a neural network using HOG features [5] and other many methods have been reported. These methods work well for vehicles at a far distance since the vehicle appearance does not change much. In a BSW system, however, the appearance of a vehicle can be distorted drastically due to a change in the positional relationship between the host vehicle and the target one, making it difficult to apply an appearance-based approach. On the other hand, almost all geometry-based approaches utilize optical flow information [4]. Optical flow

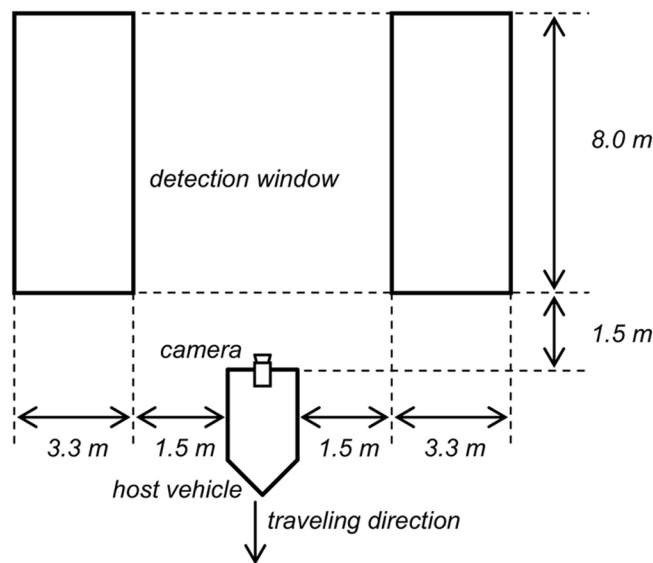


Figure 1. Position of detection windows.

is one of the most common geometric features and provides an important basis for vehicle detection. Optical flow calculations, however, are typically time-consuming and also impractical for a real-time onboard system. Batavia *et al.* [2] generated a predictive image based both on inverse perspective mapping (IPM) and the travel distance between two consecutive frames, and detected vehicles by comparing an actually observed image and the predicted one. This method allows fast processing, since it does not require explicit optical flow calculations.

The purpose of this research is to develop a blind spot vehicle detection system that can be deployed on a variety of vehicles, ranging from low-cost models to luxury cars. Our system mainly employs the geometry-based approach using IPM and also incorporates the appearance-based approach in consideration of cost and performance.

The rest of the paper is organized as follows: Section 2 presents the problem description. Our proposed system is described in Section 3. The effectiveness of the system is demonstrated in Section 4 based on road tests. Finally, our conclusions are given in Section 5.

PROBLEM DESCRIPTION

A BSW system requires capabilities for nearby detecting vehicles and judging collision possibilities. However, it is difficult to determine and track the exact positions of moving vehicles. On the other hand, it is easier to determine whether a pre-defined detection window contains a vehicle or not.

Based on this way of thinking, we simplified the problem as follows. Two detection windows are defined behind the host vehicle as shown in Figure 1. The width of the host vehicle is about 1.8 m, and the detection windows are located in the adjacent lanes at a distance of 1.5 m from each side of the host vehicle. The target relative velocity ranges from -40 km/h to 40 km/h and the target absolute velocity is larger than

10 km/h. This means that oncoming vehicles in two-way traffic are excluded. BSW functionality is maintained even in this simplified configuration.

OUR APPROACH

Our approach is strongly inspired by Batavia's research [2]. Obstacle detection using implicit optical flow based on IPM is the most promising approach in terms of computational cost.

Figure 2 shows a diagram of our proposed system. The system consists of four functional components: obstacle detection, velocity estimation, edge detection, and final classification. Obstacle detection, velocity estimation and edge detection set flags that serve as cues for vehicle detection based on the respective criterion of each component. The final classification unit decides whether a detection window contains a vehicle or not on basis of these flags and the previous output. The details of each component are described in following sub-sections.

OBSTACLE DETECTION

Assuming that the road surface is a perfectly flat plane and that the orientation of the camera does not change, a plan view image can be generated easily by IPM. In a plan view image, changes due to the movement of a vehicle traveling on the road surface are extremely simplified, which means that only translational motion is possible. Additionally, assuming that the egomotion of the host vehicle is limited to straight-ahead movement, only one-dimensional translation in the host vehicle's direction of travel is possible, and its magnitude corresponds to the travel distance between two consecutive frames.

Accordingly, we can easily predict the image to be observed based on the host vehicle's speed and the previous image. In a difference image between the predicted image

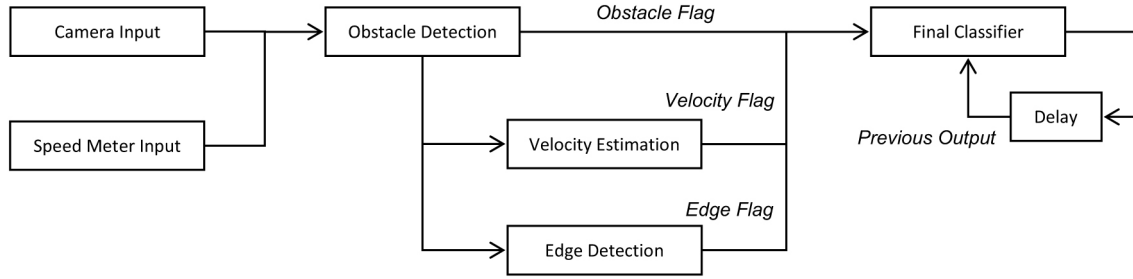


Figure 2. Diagram of the system.

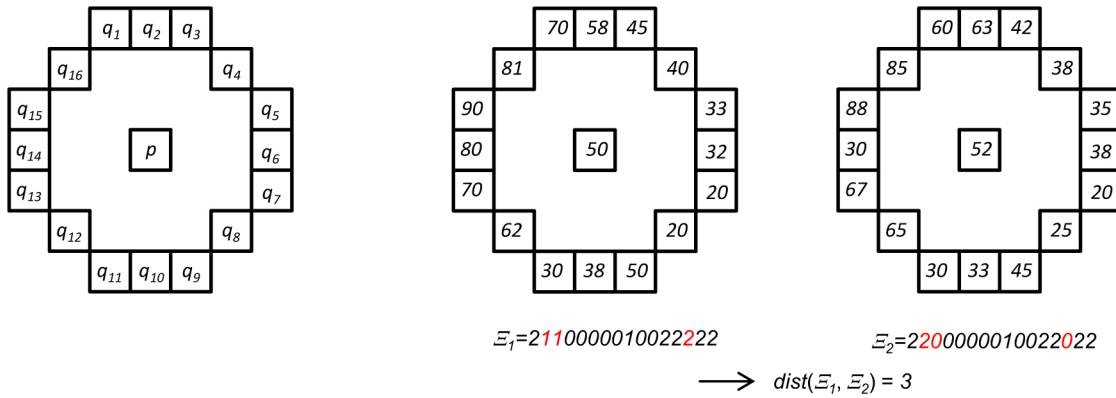


Figure 3. (Left) Reference point layout in our CT and (right) an example of a difference calculation based on CT.

and the actually observed image, the area corresponding to an obstacle generates much more difference than the area corresponding to the road surface. Therefore, vehicles and other objects can be identified by detecting the differences between the two images.

Though the most naive differencing operation is to calculate the difference in intensities between corresponding pixels, this operation is sensitive to illumination changes. Zabih *et al.* [9] proposed a non-parametric feature called the Census Transform (CT), which is robust to illumination changes. The census digits are given as

$$\xi(p, q) = \begin{cases} 2 & I(p) - I(q) \geq \varepsilon \\ 1 & |I(p) - I(q)| < \varepsilon \\ 0 & I(q) - I(p) \geq \varepsilon \end{cases} \quad (1)$$

where $I(p)$ represents the intensity at pixel p . The parameter ε is introduced to represent similar intensity and is tuned according to the variation of the noise level. In our system, we locate 16 reference points $q_i (i = 1, \dots, 16)$ around p in a circular pattern as shown on the left side of Figure 3. The feature vector of CT is defined as

$$\Xi(p) = \bigotimes_{i=1, \dots, 16} \xi(p, q_i), \quad (2)$$

where $\bigotimes$ represents concatenation. The difference between corresponding points p_t, p_{t-1} is given as the number of different elements between two feature vectors:

$$\begin{aligned} \text{difference}(p_t, p_{t-1}) \\ = |\{i \mid \xi_i \neq \xi'_i, \xi_i \in \Xi(p_t), \xi'_i \in \Xi(p_{t-1})\}| \end{aligned} \quad (3)$$

where ξ_i represents the i -th pair feature in the CT feature vector. Since the CT feature vector is invariant against illumination changes and noise to some extent, objects can be detected robustly even in a traffic environment with clutter and illumination disturbances. An example of a difference image based on CT is shown in Figure 4. The pixel value of the difference image is the difference calculated with Eq. 3, which ranges from 0 to 16.

A difference image is intractable since it is 2-dimensional information. Bertozzi *et al.* [1] converted a difference image into a polar histogram on the assumption that vertical edges are projected radially from the camera center. This makes the detection process much easier and more robust. Our system uses a similar histogram technique.

In our problem here, we can assume that the host vehicle and the target vehicle are traveling in the same direction. Thus, a histogram in the direction of travel can be made as shown in Figure 5. Each bin of the histogram corresponds to