MVA2002 IAPR Workshop on Machine Vision Applications, Dec. 11 - 13, 2002, Nara - ken New Public Hall, Nara, Japan

15—4

Robust Vehicle Detection Under Poor Environmental Conditions for Rear and Side Surveillance

Osafumi Nakayama[1], Morito Shiohara[1], Shigeru Sasaki[1], Norio Hashiguchi[2] and Tomonobu Takashima[2]

1) Personal Systems & Services Laboratories, Fujitsu Laboratories Ltd.
2) ITS Business Group, Fujitsu Limited

Abstract

A rear and side surveillance system for vehicles has been developed that uses image processing. It uses two stereo cameras to monitor the areas to the rear and sides of the vehicle, i.e., the driver's blind spots, and to detect the positions of other vehicles and their relative speeds. During the period from dusk to dark, when it is difficult for a driver to see other vehicles, or when visibility is poor due to rain, snow, etc., the contrast between nearby vehicles and the background is lower. Under such conditions, conventional surveillance systems have difficulty detecting the outline of nearby vehicles and may thus fail to recognize them. The proposed system can estimate the shape of a vehicle from a partial outline of it, thus enabling the vehicle to be identified by filling in the missing parts. Testing of the system under various environmental conditions showed that the recognition failure rate was reduced to less than 10%, even at dusk and during rain or snow, conditions that are problematic for conventional processing.

1 Introduction

A major factor in the continuing increase in traffic accidents is inadequate checking by drivers for the presence of other vehicles. With the driver's attention focused in the forward direction, not only is it difficult for the driver to monitor the rear and sides of the vehicle, but there are also blind spots to the rear and both sides. These factors lead to accidents, particularly when the driver changes lanes or merges into traffic.

We have developed a *rear and side surveillance system* that warns the driver of vehicles approaching from the rear or side. This system monitors the rear and side, i.e. the driver's blind spot, with stereovision sensors, as illustrated in Fig. 1, and the position of each approaching vehicles is estimated using stereo-based distance measurement. It warns the driver of a possible collision when changing lanes or merging into traffic.

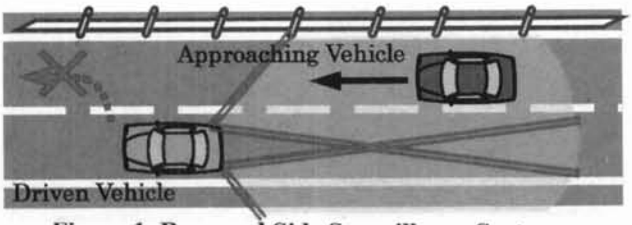


Figure 1. Rear and Side Surveillance System

The target accuracy is an error of 10% or less in the measured position. Assuming a mean relative speed between vehicles of 30 km/h and that it takes the driver 0.4 s to avoid a collision, the minimum distance for avoiding a collision with an approaching vehicle is 9 m. Adding a safety margin of 50% increases the distance to 14 m. The system must therefore have a measurement error no greater than 10% at a distance of 14 m to the rear and to the side.

This surveillance system is particularly helpful under poor conditions, such as the time between dusk and dark and during rain, snow, etc., because during these times it is difficult for the driver to monitor the vehicle's surroundings. The environmental changes that occur at dusk, for example, can reduce the contrast between nearby vehicles and the background in a video image, resulting in frequent failures by surveillance methods to detect vehicles. The stereo methods that have been proposed for detecting vehicle position ([1] - [4]) require precise vehicle outlines to detect vehicles, so they fail to detect vehicles when part of the outline is missing due to poor environmental conditions, which change a vehicle's shape in the image.

To cope with this problem, we developed an evidence-based vehicle detection method in which edge chunks are searched for at the missing parts of a vehicle outline, and if edge chunks are found, then the edges are regarded as evidence of the presence of the outline. They are then used to fill in the missing parts. The position of the vehicle is estimated by using the edge chunks as well as the remaining outline edges, which have 3D depth information. This makes it possible to estimate vehicle position within an error of 10% even at dusk.

2 Evidence-based vehicle detection

2.1 Vehicle position estimation using conventional stereo-based measurement

As illustrated in Fig. 2, two cameras (left and right) continuously monitor the areas to the sides and rear of the vehicle (Step1). Whenever an object is detected, the measurement system extracts the edge points (outline, inside patterns, etc.) (Step2). The correspondence between the edge points of the images captured by the two cameras is determined to obtain the distance to each point (we call edges having stereo correspondence *3D edge chunks*) (Step3). Finally, the 3D edges are compared to stored vehicle shapes, and if there is a match, the object is determined to be a vehicle (Step4).

---

[1] Address: 4-1-1 Kami-Kodanaka, Nakahara-ku, Kawasaki, Kanagawa 211-8588 Japan. E-mail: osafumi@jp.fujitsu.com

[2] Address: 4-1-1 Kami-Kodanaka, Nakahara-ku, Kawasaki, Kanagawa 211-8588 Japan

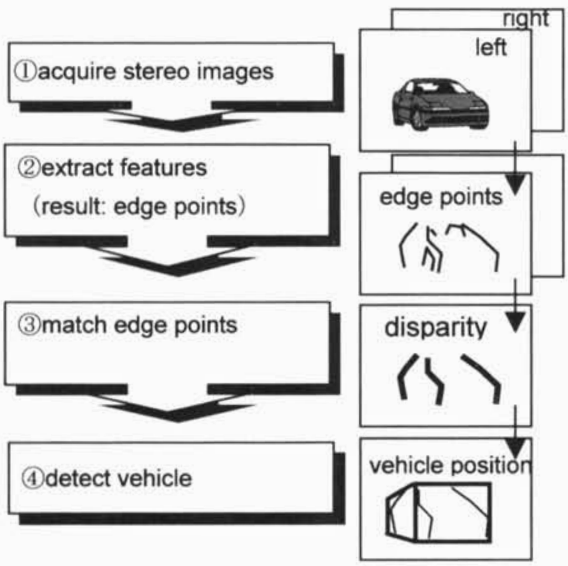


Figure 2. Vehicle position estimation using stereoscopic distance measurement

2.2 Effects of environmental conditions on stereo based measurement

Systems used for outdoor surveillance, such as our rear and side surveillance system, must be able to cope with changes in the environment, such as changes in the lighting conditions and the weather. These two changes in particular are situations that drivers must deal with daily, so it is essential that the system be able to cope with them. Here we consider their effects on stereo-based measurement.

Changes in the lighting conditions and the weather create two problems: 1) brightness saturation of the entire image caused by sunlight or bright lights, which makes it difficult to distinguish objects; 2) insufficient illumination, which makes it difficult to see objects. The first problem can be avoided by controlling the amount of light by shuttering the lens or other such means. For the second problem, however, there are limits to what can be done by the optical system because the light lost due to insufficient illumination cannot be restored.

An example of insufficient illumination during conditions of dusk is shown in Fig. 3(a). The contrast between the vehicles and the background is low, while the sky area is relatively bright. Under these conditions, if the camera has automatic gain control, the contrast between the vehicles and the background can be as low as 20 gradations (full range is 255).

Low contrast affects the edges near the surrounding vehicles; an edge position can easily shift or some parts of the vehicle outline can be missing The result is local differences in the edge shapes of the left and right images, which prevent correct determination of the correspondence between the edges. This lack of correspondence makes it impossible to obtain the distance from some parts of the vehicle outline. Such a missing part is shown as A in Fig. 3(b). If that missing part is large, such as either the left or right outline of the vehicle, the vehicle shape is greatly changed, causing the vehicle detection process to fail. Since conventional stereo methods for vehicle position estimation use precise vehicle outlines, they fail when part of the outline is missing.

2.3 Evidence-based vehicle detection rubst to changing in environment

Using tests in the field, we determined that under conditions of low contrast 1) the distance to some parts of a vehicle's outline can be estimated (we call them *3D chunks*) and 2) while the point-to-point correspondences cannot be established for missing parts, edges lie on the position of the missing parts (we call them *edge chunks*), such as B in Fig. 3(c). The latter finding is very important in that the edge chunks are evidence of the presence of a vehicle, which means that if these chunks are identified, the missing parts can be filled in, enabling the position of the vehicle to be determined.

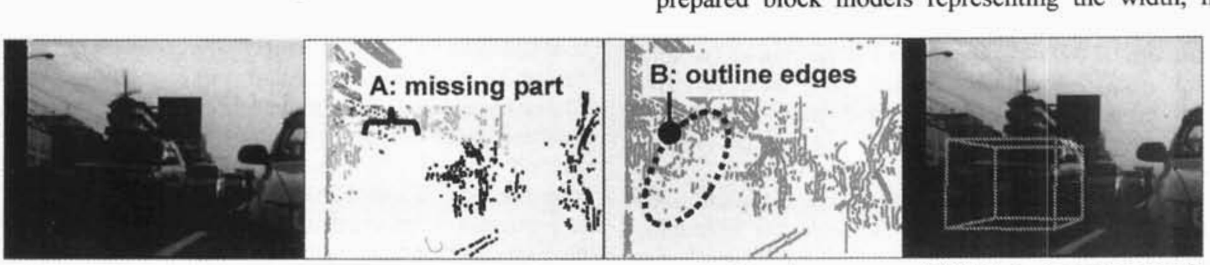
We thus developed an evidence-based vehicle detection method that searches in the images for the edge chunks of the missing parts. If these chunks can be detected, the 3D position of the vehicle is estimated using the measured distance to the detected chunks. Since this detection is qualitative, the important thing is whether or not the edge chunks exist, not the local shapes of edges, which are important for conventional stereo-based vehicle detection method.

2.3.1 Detection of edge chunks of missing parts

In an edge image, there are many edges of other objects, so the edge chunk corresponding to the missing part must be distinguished from among many other edge chunks. This is done using two processes: (1) the rough shapes of vehicles are represented by box models, which are fit to the image to predict the position of the missing parts, as shown in Fig. 4; (2) the image searching is done in both images so that only consistent edge chunks are obtained. Consistent means that the edge chunks in both images roughly correspond in the sense of stereo matching.

(1) Prediction of missing part positions using box models

The box models are made such that previously prepared block models representing the width, height,



(a) Original image (left image) (b) Distance image (darker is closer) (c) Edge image (d)Vehicle detection result (proposed method)

Figure 3. Result of vehicle position measurement for low light conditions in the evening

and depth of vehicles are placed on the position of the 3D

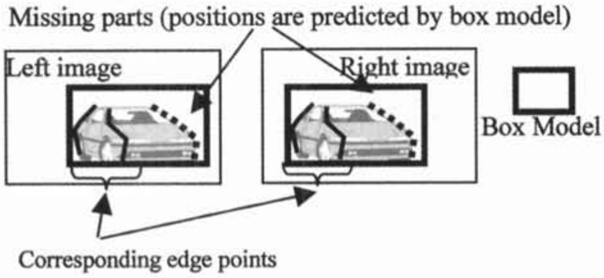


Figure 4. Example in which distance information is missing for part of outline

chunks, resulting in a box model represented by a rectangular area that determines the size of the vehicle as it is observed in the image.

To predict the position of the side outline of a vehicle and to check if the missing parts exist, the region covered with the box model is divided into three sub-regions; as shown in Fig. 5 they are the left-side outline detection sub-region (R1), the vehicle internal detection sub-region (R2), and the right-side outline detection sub-region (R3).

First, sufficiently long vertical 3D chunks are searched for in the disparity image in the left and right sub-regions. The chunks found are categorized as being (1) from both sides, (2) from one of the sides, or (3) from none of the sides. In the first case, the vertical outlines on both sides are obtained, so the 3D position of the vehicle can be determined by the distance to the 3D edges in the whole box model, in the same manner as conventional methods. In the second case, the outline of one of the sides is missing (we call this case *one-side correspondence*). Evidence of the presence of the missing part is instead sought in the *edge images*, as described in detail later. In the third case, the vehicle position cannot be determined because both sides of the vehicle outline are missing parts, making it impossible to distinguish between the vehicle and the background.

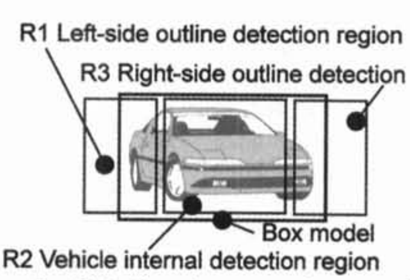


Figure 5. Relation between box model and outline detection sub-regions

In the one-side correspondence case, in the sub-region with no vertical 3D chunks, vertical edge chunks (which different from 3D chunks in that they have no 3D information) are sought not from the disparity image but from the edge image, because the edge chunk for a missing part can often be detected.

To obtain the edge chunk corresponding to the missing part, the length of the edge chunk is checked if its length should be similar to the height of its box model, because the edge chunk should cover the outline of one side of a vehicle.

(2) Dual evidence check for detecting correct edge chunks

In general, it is very difficult to detect the correct edge chunk because there are many other edges in the edge image; thus, edge chunk detection is performed not only in one image but also in the other image of the stereo pair (called *dual evidence check*).

When detecting edge chunks in the other image, the position of the sub-region where the corresponding edge chunk is sought is determined such that the sub-region is placed on the 3D position of the center and the other side of the sub-regions. It is projected on the other image, resulting in a rectangle that determines the size of the vehicle as observed in the other image.

If there is an edge chunk at the predicted position in each image, the two detected chunks match in the sense of stereo matching. They can thus be regarded as consistent edge chunks.

An example of vehicle position estimation at dusk is shown in Fig. 3(d). With a conventional method, the position of the vehicle cannot be estimated. With the proposed method, on the other hand, the parts for which distance information is missing can be filled in by using the edge chunks, as with edge B in Fig. 3(c), and the vehicle position can be estimated even if some edges are partially missing (Fig. 3(d)).

3 Experiment and Discussion

To evaluate the robustness of the proposed method to changes in the environment, we examined the relation between contrast near the vehicle and vehicle estimation accuracy with a conventional method and with the proposed method. We used 26 actual scenes: 10 samples had changes in illumination (from daylight [10,000 Lx] to night [100 Lx]) and 16 had changes in weather (rain and snow); there were about 100 frames in each sample (see Table 1). Example scenes for a change in illumination are shown in Fig. 6. The conventional method used is one in which the position of a vehicle is estimated by fitting vehicle shape models to the distance information for the complete vehicle outline.

The results are shown in Fig. 7. As a measure of vehicle detection accuracy, we used the proportion of the number of vehicle forms (position and size) detected by image processing to the number obtained manually for each video frame, as shown on the Y-axis of Fig. 7. The X-axis shows the contrast around the vehicle. This proportion is considered to be the rate of correct measurement. If the vehicle position was correctly detected, the rate is 100%.

The results show that, on the whole, the proposed method is very effective, producing a higher correct measurement rate than that of the conventional method. However, when the contrast (difference in brightness) was less than 30 (point A in Fig. 7), vehicles could not be detected for the most part with either method. When the contrast was above 30, on the other hand, the mean correct measurement rate was at or above 91% with the proposed method for all changes in illumination and weather (compared to about 63% for the conventional method), demonstrating that the proposed method achieves the target measurement error rate of 10% or less for vehicle position at a distance of 14 m.

(a) evening(bright)/white (b) evening(bright)/black (c) night/white (d) night/black

Figure 6. Example scenes for each experiment

Table 1. Experimental data

	Conditions	Brightness [Lux]	Vehicle color	Degree
Illumination change	Daylight	500-10,000	White/Black	
	Evening (bright background)	200 - 500	White/Black	
	Evening (dark background)	200 - 500	White/Black	
	Evening, reversed light	200 - 500	White/Black	
	Night	100 - 200	White/Black	
Weather change	Rain (snow) with drops adhering	5,000 – 20,000	White/Black	Moderate/heavy; day/night
	Fogging	5,000 – 20,000	White/Black	Moderate/heavy; day/night
	Fog + drops adhering	5,000 – 20,000	White/Black	Moderate/heavy; day/night
	Diffuse adhesion	5,000 – 20,000	White/Black	Moderate/heavy; day/night

In the case of evening/reverse lighting, point B, it was sometimes not possible to determine the distance on both sides of the vehicle, so the correct measurement rate was lower. For points A and B, edge detection processing and stereo correspondence processing must be improved.

4 Conclusion

We have developed a vehicle position estimation method that is robust against environmental changes (changes in light conditions and weather) that pose problems for rear and side surveillance systems in practical use. The proposed method predicts the shape of a vehicle from the obtained outline, even if part of the distance information of the outline is not available due to low light conditions or rain or snow. It can thus fill in the missing parts, enabling vehicle detection and position estimation. Testing using video image samples that included conditions of daylight, night, rainy weather, and snowy weather showed that vehicle position can be estimated with an accuracy of over 90% when the image contrast is at least 30, even at dusk or under conditions of rain or snow, which are problematic for conventional methods.

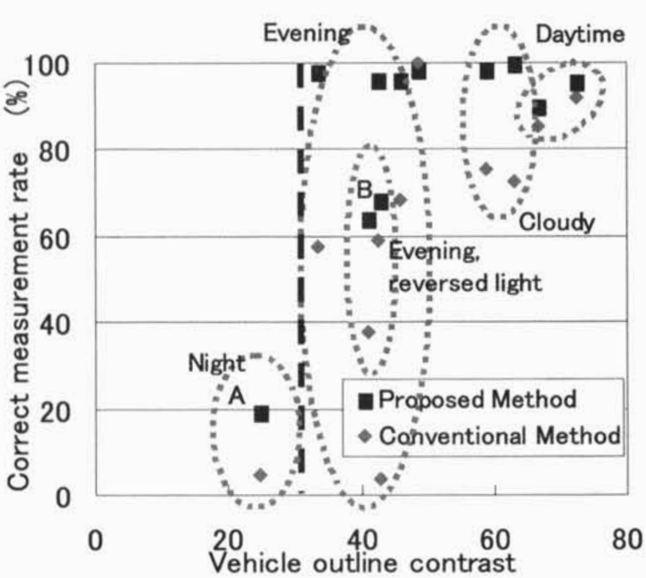


Figure 7. Relation between outline contrast and correct measurement rate

References

[1] Saneyoshi et al, "Forward Situation Recognition System using Stereoscopic Images for Driving Support", PRMU97□25,1997.

[2] Shimomura, "Forward Vehicle Tracking on Curved Roads with Stereoscopic Image Processing", PRMU97-25, 1997.

[3] Miyaoka, et al., "Rear and Side Surveillance by means of Video Image Processing", 4th Symposium on Sensing via Image Information, pp. 351-354, 1998.

[4] Suzuki, et al., "Peripheral Awareness Technology for Accident Prevention", TOYOTA TECHNICAL REVIEW, 1993.