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Preceding Vehicle Detection Using Stereo Images and Non-Scanning Millimeter-Wave Radar

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Abstract

We developed a system that detects the vehicle driving immediately ahead of one's own car in the same lane and measures the distance to and relative speed of that vehicle to prevent accidents such as rear-end collisions. The system is the first in the industry to use non-scanning millimeter-wave radar combined with a sturdy stereo image sensor, which keeps cost low. It can operate stably in adverse weather conditions such as rain and snow, which could not easily be done with previous sensors. The system's vehicle detection performance was tested, and the system can correctly detect vehicles driving 3 to 50 m ahead in the same lane with higher than 99% accuracy in clear weather. Detection performance in rainy weather, where water drops and splashes notably degraded visibility, was higher than 90%.

1 Introduction

The technology to reduce traffic accidents is being actively developed. One approach is to use various sensors to reduce the major cause of traffic accidents: drivers overlooking vital information. Technologies using this approach have been extensively researched to locate vehicles driving around a given car to avoid collisions. The objective of our research was to introduce an on-board system that recognizes the vehicle immediately ahead in the same lane and determines its location and relative distance, thus providing information that can help avoid collisions, as shown in Figure 1.

Sensors are currently available that are primarily used to detect vehicles: image sensors, laser radar, and millimeter-wave radar. Among them, millimeter-wave radar seems most promising as a collision avoidance sensor because it is less affected by environmental changes than the others and has high distance accuracy. Thus, in recent years, millimeter-wave radar has been mounted on some commercial vehicles. However, the available millimeter-wave radar systems are costly and are not yet popular. One reason is that they have difficulty identifying what has been detected. Moreover, millimeter-wave radar is unable to recognize lanes and thus requires the assistance of some additional device to identify vehicles driving in the same lane in urban areas and on curved roads. To solve this problem, we have developed a preceding vehicle detection system using a stereo image sensor and a non-scanning millimeter-wave radar system that performs well without having a high price. The system combines millimeter-wave radar with a stereo image sensor to make up for each sensor's weaknesses, thereby consistently detecting vehicles with accuracy at long distances under varied conditions. The use of non-scanning, rather than scanning, millimeter-wave radar drastically lowers the price of the system.

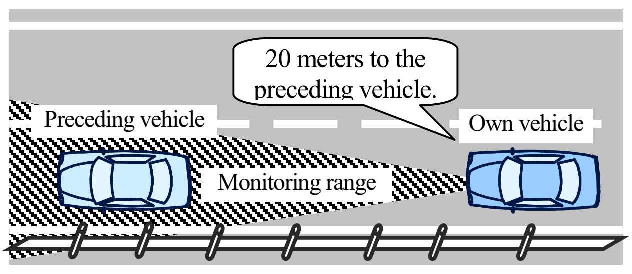

Figure 1. Preceding vehicle detection system.

2 Non-Scanning Millimeter-Wave Radar

Millimeter-wave radar is an active sensor that measures the distance to a remote object and the relative speed of that object using the time difference between a millimeter wave transmitted at the object and the resultant reflected wave. A scanning radar system transmits a transmission wave with a narrow spread (about 4°) in varying directions to observe a whole monitoring range, as shown in Figure 2(a). A scanning mechanism that alters the beam direction mechanically or electronically is needed, resulting in a larger and more costly sensor. Further, because the width of radiated beam is in

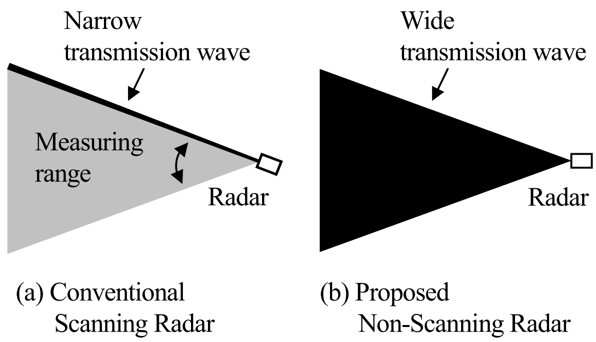

Figure 2. Millimeter-wave radar.

reverse proportion to the antenna size, the antenna has to be oversized to narrow the width of beams, and this detracts from reduced sensor geometry. A mechanical scanning mechanism requires approximately 100 ms to scan its entire monitoring range. This time is very difficult to reduce.

In the non-scanning millimeter-wave radar we developed, we stretched the width of the transmitted wave to about 30° degrees—the monitoring range required to detect the immediately preceding vehicle—as shown in Figure 2(b). Our radar eliminates the need for a scanning mechanism, cutting its price to about one fifth of the price of its other detection systems and offering drastically enhanced durability. Furthermore, because the time needed to measure the whole monitoring range is reduced, the measuring intervals can be reduced to about 1/30. The wider spread of the transmitted wave reduces the transmission/reception antenna to one fourth of the size of the previously available antennas. However, because non-scanning millimeter-wave radar receives reflected waves from all objects located in the monitoring range at once, it is unable to identify from which direction a particular reflected wave originated. Hence, the radar can measure the distance to and the relative speed of each object, but cannot determine which direction that object is in. An example of a millimeter-wave received on a congested urban road is shown in the lower part of Figure 3. An object is shown to exist at the distance (on the horizontal axis) associated with each peak in a curve representing the distribution of the strength of the received millimeter-wave in Figure 3. The presence of many peaks involving reflected waves from sources other than the preceding vehicle makes it very difficult to identify which peak represents the immediately preceding vehicle in the circumstances.

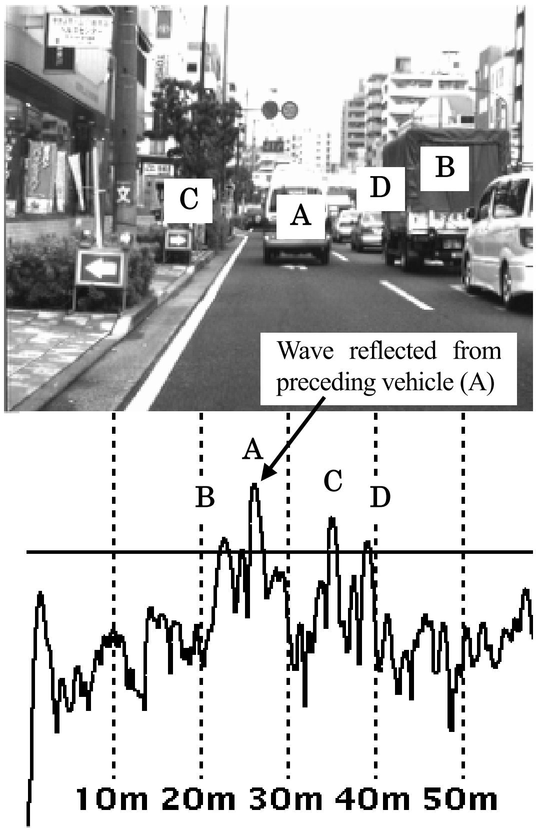

Figure 3. Congested urban road and distributions of millimeter-wave strength.

Moreover, if an equivalent of the previous radar output is maintained, the strength of the transmitted wave per unit area would be degraded, with a proportionate decline in the strength of the wave reflected from each object scanned. Thus the non-scanning millimeter-wave radar has a lower SNR than scanning radar.

3 Preceding Vehicle Detection

We developed a preceding vehicle detection system that combines a non-scanning millimeter-wave radar with a stereo image sensor to make up for the weaknesses of each sensing device while taking advantage of their strengths. The system accomplishes the goals of accurately measuring distance and relative speed and being robust to environmental changes, which are difficult to attain using image processing, and it identifies and locates the object using an image processing operation beyond the recognition capabilities of non-scanning millimeter-wave radar. More specifically, the system first determines the distance to an object detected using the millimeter-wave radar. It then verifies the features extracted from its images using a predefined vehicle model to determine whether the object is a vehicle or not. At the same time, it locates the upper, lower, left, and right corners of the object, which is beyond the abilities of conventional millimeter- wave radar. Because a non-scanning millimeter-wave radar has a low SNR, it needs to have a low threshold setting to distinguish between objects and noise. A verification process during image processing eliminates false detections resulting from noise interference.

3.1 Vehicle models

Numerous vehicle models have been suggested as methods of identifying vehicles from images. There are two representative models: those based on 3D geometries and those based on 2D geometries. One model based on a 3D geometry is a box model [1-2]. A box model takes advantage of the fact that the general geometry of a vehicle can be approximated in the form of a rectangle and is highly versatile because it does not rely on the vehicle type, color, or other characteristics for vehicle detection. However, because the 3D position of a vehicle calculated from its image typically degrades in accuracy in reverse proportion to the distance of the vehicle, box models are not suitable for consistently distinguishing a vehicle about 30 m or more ahead from its background and ambient objects. Models based on 2D geometries include those based on edge histograms created by projecting edge strengths either vertically or horizontally [3] and models that use patterns of varying shades pre-learned in a discriminator [4]. Models that use edge histograms can verify models with fewer calculations than other models but have little ability to distinguish vehicles from other objects because they reduce the features of a 2D geometry to those of a 1D geometry. Models that use patterns of varying shades pre-learned in an appropriate discriminator promise better identification, but have difficulty verifying a preceding vehicle if the entire vehicle is not captured within the field of view, such as when the vehicle is within several meters of the sensor. As explained above, 2D and 3D models each have advantages and disadvantages. Recognizing vehicles would be difficult using a single model to check the range from 3 to 50 m from

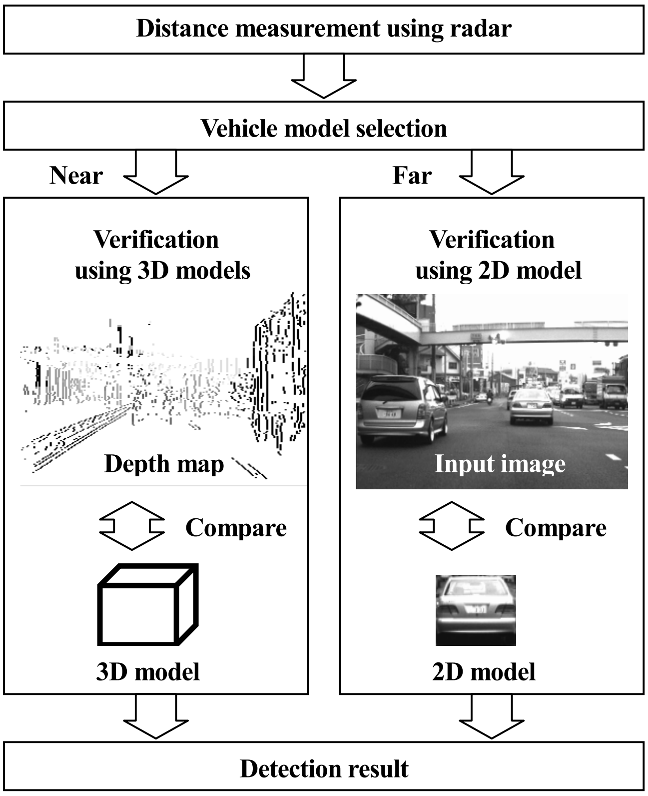

Figure 4. Flow of vehicle detection.

a sensor in varied environments.

The system we developed overcomes this difficulty by using both 2D and 3D models. The 3D models are box-shaped to recognize close vehicles, taking advantage of the accurate 3D information on close vehicles that can be calculated from stereo images. The 2D model is a pattern of varying shades pre-learned in a discriminator for recognizing remote vehicles whose overall geometry can be observed. Generally, as the number of models increases, so does the workload involved in the verification process. The system may not easily fit applications where real-time processing is of critical importance, such as vehicle-mounted sensors, but it can estimate the size and location of the model to verify a detected vehicle from the distance and relative speed information collected by its millimeter-wave radar, thereby allowing real-time verification. The flow of vehicle detection is shown in Figure 4.

3.2 Verification using 3D models

The degree of fitness of a vehicle to 3D models is evaluated using the depth map calculated from its stereo images. The depth map is calculated from the 3D positions of the edges detected in the image using the correspondence between the left and right cameras. Four types of 3D models are used, representing small vehicles, medium vehicles, medium trucks, and large trucks. First, each model is projected in a depth map, while its size in the depth map is set to the value calculated using the distance measured by the millimeter-wave radar. Then, the mode of the distance to each point in each plane on the rear and side of the projected model or in each in-plane depth map is used as a fitness evaluation value. A vehicle is assumed to be at the projected position of the model with the least evaluated value below a threshold.

3.3 Verification using a 2D model

A pattern of varying shades in the area that includes the rear of a vehicle of interest is used as a 2D model, which is then organized into a pre-learned three-layer neural net to distinguish between vehicles and non-vehicles. Input to the neural net is provided in 360 units associated with a pattern of varying shades measuring 20 pixels wide by 18 pixels high, in 10 units in the intermediate layer, and in one unit in the output layer. Our systems learned using back propagation method using 1,355 samples of vehicles and 5,739 samples of non-vehicles. The vehicle sample images were cut out manually, and the non-vehicle sample images were a mix of randomly cut-out images and images cut out when they were falsely recognized as being vehicle images during preliminary testing. When the box model is used, the area in the image that corresponded to the rear of a vehicle was normalized to 20 pixels wide by 18 pixels high during matching to distinguish between a vehicle and a non-vehicle in the neural net.

4 Experiment and Evaluation

We experimentally evaluated the ability of our system to detect vehicles under various environmental conditions. The system should be able to detect the immediately preceding vehicle in its lane and measure the vehicle’s location and relative speed. Because the system can use its millimeter wave radar to measure the distance to and the relative speed of the preceding vehicle with high accuracy, the remaining tasks are to correctly locate the upper, lower, left, and right corners of the vehicle and its size in the image. Therefore, as a performance evaluation measure, we used the rate at which vehicles within a distance of 3 to 50 m in the system’s lane were detected in the correct position in the image (detection rate). A vehicle was assumed to have been detected correctly when the detected location corresponded to at least 25% of an area manually specified as the vehicle in the image.

4.1 Evaluation under different weather conditions

Because visibility is degraded under certain weather conditions, such as rain and fog, and our system detects vehicles through image processing, the performance of the system could be affected by weather conditions. To determine differences in the system's detection performance caused by weather, data was collected on a clear day to represent favorable weather and during rain to represent adverse weather. The data from the rainy weather were collected on an expressway, and visibility was noticeably degraded by water drops and splashes. The data from both days were collected on expressways during 30 min. The detection rates are listed in Table 1. An example of a preceding vehicle detected in rainy weather is shown in Figure 5.

As Table 1 indicates, the system had a detection rate of above 99% in clear weather and above 90% even in rainy weather. The lower detection rate in the rainy weather was caused by a shortage of the image features needed to recognize vehicles.

Table 1. Detection rates under different weather conditions.

Weather	Clear	Rainy
Detection rate	99.6%	90.3%

4.2 Evaluation under different illuminance levels

Ambient illuminance can significantly affect images, which in turn influence system performance. To determine the effect of illuminance on the system's detection performance, data were collected in the daytime on a clear day with full illuminance and in the nighttime with an illuminance of approximately 5 lux. Both data sets were collected on city roads other than expressways during 30 minutes. The detection rates are listed in Table 2. Examples of vehicle detection in the daytime and nighttime are shown in Figures 6 and 7.

The detection rates were higher than 96% regardless of the illuminance, as shown in Table 2. The lower detection rate in the nighttime was caused by a shortage of image features due to the preceding vehicle being obscured in the headlights of an oncoming car on curved roads. The lower deterioration rate in the daytime than in the clear weather in Table 1 was caused by false recognition of the system’s own lane. Because the system detects only the vehicles found in the same lane, it fails to detect vehicles correctly once it falsely recognizes its own lane. A false recognition of its own lane occurs when the lane conditions change significantly and when the system is unable to observe the lane markings during left or right turns. This condition is likely to occur more often on roads other than expressways.

Table 2. Detection rates under different illuminance levels.

Illuminance	50,000 lux	5 lux
Detection rate	97.1%	96.1%

4.3 Discussion

Insufficient image features are a primary cause of lowered detection rates in adverse weather or low illuminance conditions. Due to the extreme difficulty of applying image-processing solutions to this problem, a scheme should be developed to automatically detect and post the status of the system’s ability to detect vehicles, such as degraded visibility, and thus boost system reliability. On city roads, the detection rate is lower than on expressways mostly due to false recognition of the system’s lane. This problem could be solved by using the output of a rudder sensor or an angular velocity sensor mounted on the vehicle to estimate the direction the vehicle is moving. Future efforts will be directed at enhancing system stability by taking advantage of the power of these sensors.

5 Conclusions

We developed a preceding vehicle monitoring system that combines non-scanning millimeter-wave radar with a stereo image sensor to keep cost low and maintain stability in different environments, which is hard to do using previous sensor solutions. More specifically, the system-equipped vehicle attempts to detect the vehicle driving immediately ahead in the same lane by checking the 3D geometry of the vehicle’s shape and the pattern of varying shades extracted from its stereo image against a vehicle model that it reduces based on the distance information generated by the non-scanning millimeter-wave radar. This radar is inexpensive, but does not provide orientation information for target objects. We tested the system’s vehicle detection performance, and the system consistently detected vehicles driving 3 to 50 m ahead in the same lane on expressways with higher than 99% accuracy in clear weather and higher than 90% accuracy in rainy weather where visibility was noticeably degraded by water drops and splashes.

Reference

[1] Saneyoshi, K., "3-D Image Recognition System by Means of Stereoscopy Combined With Ordinary Image Processing," In Proc. of Intelligent Vehicles '94 Symposium, pp. 13–18, 1994

[2] Nakayama, O., et al., “Robust Vehicle Detection under Poor Environmental Conditions for Rear and Side Surveillance,” IEICE Trans. Vol. E87-D, No.1, pp. 105–112, 2004

[3] Miyazaki, N., et al., “Offset Vertical Stereo System for Real-Time Range-Finding to Preceding Vehicles,” MVA’98, pp.459-462, 1998

[4] Kato, T., et al., “An Approach to Vehicle Recognition Using Supervised Learning,” In Proc. Fourth Symposium on Sensing via Image Information, pp. 279–284, 1998

Figure 5. Example of vehicle detection in rainy weather.

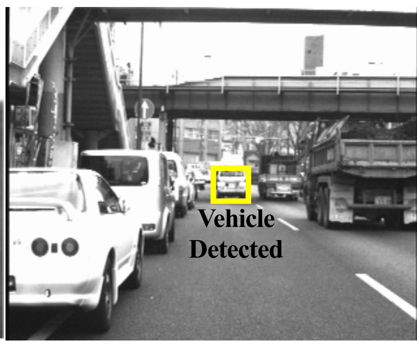

Figure 6. Example of vehicle detection in daytime.

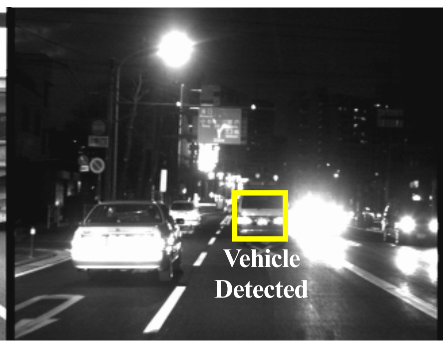

Figure 7. Example of vehicle detection at night.