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FOG DENSITY RECOGNITION BY IN-VEHICLE CAMERA AND MILLIMETER WAVE RADAR

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ABSTRACT. *Driving support techniques using in-vehicle sensors have attracted much attentions and have been applied to practical systems. We focus on supporting drivers in poor visibility conditions. Fog is one of the causes that lead to lack of visibility. In this paper, we propose a method of judging fog density by using in-vehicle camera images and millimeter-wave (mm-W) radar data. This method determines fog density by evaluating both the visibility of a preceding vehicle and the distance to it. Experiments showed that judgments made by the proposed method achieve a precision rate of 85% when compared to the ground-truth obtained by human judgments.*
Keywords: Weather recognition, Fog, Visibility, ITS.

1. **Introduction.** Recently, many systems have been developed that use computers and various sensors to assist driving [1]. Some notable examples include self-steering by white-line detection, a rear-end collision-prevention system that operates by measuring the distance to the vehicle ahead, a danger notification system that recognizes pedestrians, and a system that automatically operates the windshield wipers upon recognizing rain drops[2][3].

When considering a driving assist system, we cannot ignore changes in weather conditions, since in such adverse weather conditions as rain, snow, or fog, driving is more difficult than in fair conditions, leading to a significant increase in the accident rate. Actually, in Japan, it is said that accident rates in bad weather conditions are about 17 times higher than that in fair conditions.

In this paper, we focus on fog detection. Though fog negatively influences human perception of traffic conditions gradually, drivers are not aware of this. This is the cause of making dangerous situations. According to Cavallo et al., under foggy conditions the distance between a preceding vehicle's tail lamp is perceived to be 60% further away than under fair conditions [4]. This leads to the need of driving assist systems, such as danger alerts or automatic lighting of fog lamps.

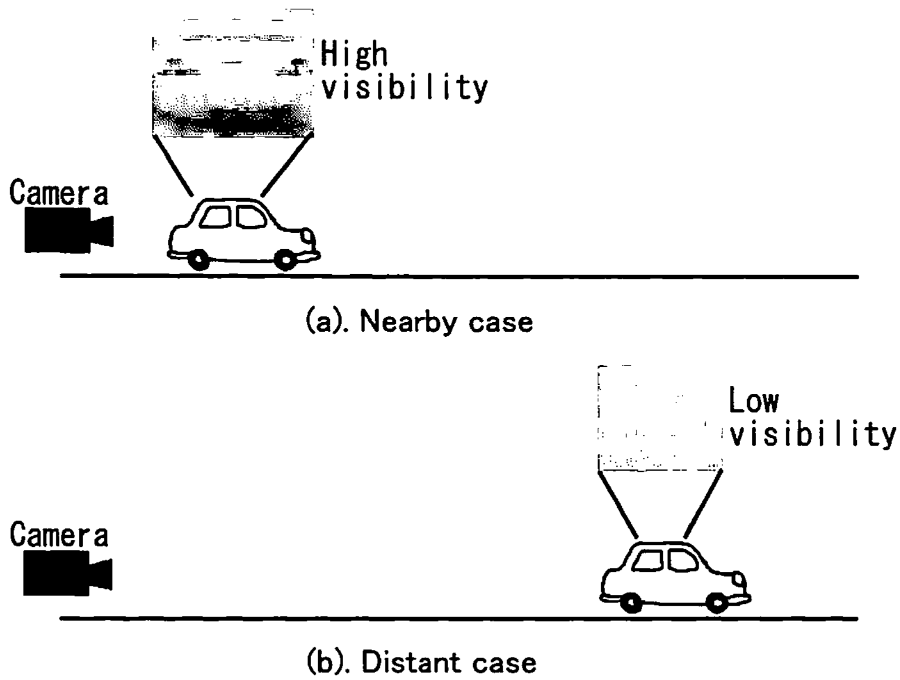


FIGURE 1. The visibility of a preceding vehicle varies depending on the distance to it.

Considering these problems, we propose a method that classifies fog density into three levels using in-vehicle camera images and millimeter-wave (mm-W) radar data. The image from the in-vehicle camera reflects the driver's visual conditions, vital when driving. This is the prime advantage of using an in-vehicle camera. We also evaluate the degradation in visibility of images that are captured in foggy conditions, especially by focusing on the change in visibility of a preceding vehicle. We must also take into account the distance to the targets to determine the fog density, because under the same fog condition, nearby objects are easy to see while distant objects are not (Figure 1). We therefore use a mm-W radar together with an in-vehicle camera to obtain reliable distance information. The proposed method is composed of the following two steps:

- Extract a visibility feature from an image of a preceding vehicle captured by an in-vehicle camera
- Classify the fog density into three levels considering the visibility feature and the mm-W radar data

This paper is organized as follows. In Section 2, some works are introduced that deal with features of fog images captured while driving. Koschmieder's model [5] that expresses the degradation of brightness by atmospheric scattering is also explained using actual images in this section. The proposed method is described in Section 3. Experiments to show the potential of the proposed method are reported in Section 4 and the paper is summarized in Section 5.

2. Related Works.

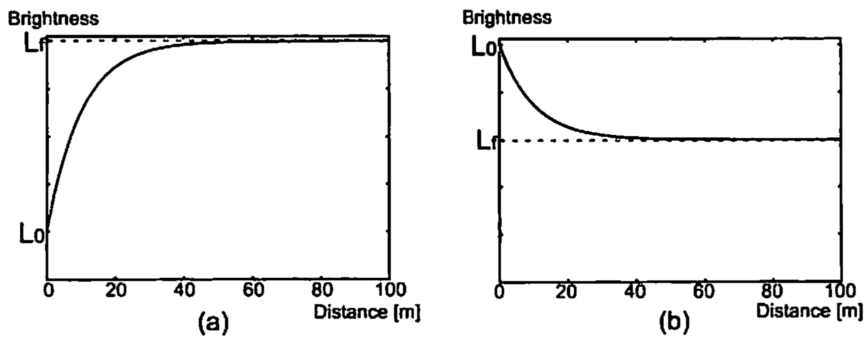


FIGURE 2. The brightness degradation with distance ($k = 0.1$): (a) L_0 is smaller than L_f; (b) L_0 is larger than L_f.

2.1. **Fog image processing for driving support.** Hagiwara proposed a method that evaluates the road visibility and the features of images captured from a digital still camera in foggy conditions [6]. Kuwon proposed the concept of Mortorists Relative Visibility (MRV) in [7]. MRV is calculated using the amount of recognizable objects in the surrounding area, average luminance and acuity of objects measured by contrast in the image. These works suppose the use of large numbers of still cameras installed along the roads. It may not accurately reflect a driver's visual condition and is a very expensive system to establish. And so, we use in-vehicle camera images that could be expected to reflect the driver's visual condition.

Some works try to estimate the visibility while driving a vehicle. Hautiere et al. proposed a method that estimates visibility distance using a stereo camera, and evaluated the degradation of visibility distance in foggy conditions compared with a fair one [8]. Leleve and Rebut tried to estimate visibility using an in-vehicle camera for fog lamp automation [9] and proposed a method to support night driving using the halation of the car's own headlights. But the distance estimated from only visual information in these works is not reliable, because it includes some error from the differences of the attitude of the vehicle or the surrounding environment. To overcome these problems, we use a mm-W radar that can measures distances to preceeding objects.

2.2. **Koschmieder's model.** Koschmieder's model expresses the degradation of brightness, as represented as follows:

$$L = L_0 e^{-kd} + L_f(1 - e^{-kd}) \tag{1}$$

where L is the observed luminance, L_0 is the intrinsic luminance of an object, L_f is the luminance of the sky, k is the extinction coefficient of the atmosphere, and d is the distance to the object. This model represents that it is difficult to recognize an object in conditions where the extinction coefficient is high, because in such conditions, L approaches L_f. Figure 2 shows the brightness degradation with distance when $k = 0.1$. The horizontal axis represents d and the vertical axis represents L.

This model represents two effects of fog in images;

a: Contrast becomes low.
b: Images are whitened.

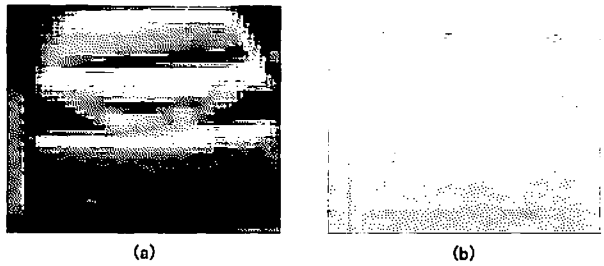


FIGURE 3. (a) Image captured in fair condition, (b) Image captured in foggy condition.

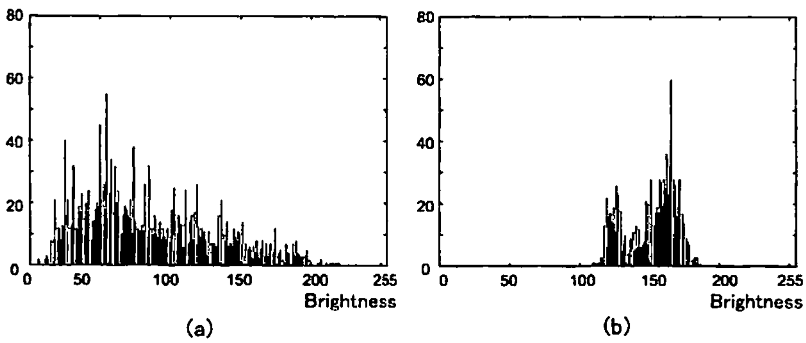


FIGURE 4. (a) Brightness histogram corresponding to Figure 3(a), (b) brightness histogram corresponding to Figure 3(b).

Figure 3(a) was captured in fair weather, while Figure 3(b) was taken in a foggy condition. Both images include the same vehicle. If fog becomes dense, k becomes large, which makes e^{-kd} approach to 0, and the value of L_0e^{-kd} becomes small, therefore, the variation of the histogram becomes small and the contrast of the image degrades. On the other hand, $L_f(1-e^{-kd})$ becomes large and the distribution of the histogram shifts to the bright side. This leads to the whitening of the images. We can see these phenomena in actual data shown in Figure 4 that shows the histogram of image shown in Figure 3.

Using this model to model the brightness deterioration, Narashimhan and Nayar proposed a method that restores the contrast of images captured in adverse weather conditions, especially foggy conditions [10].

3. **Fog Density Recognition by in-vehicle Camera and mm-W Radar.** In this section, we explain the proposed method in detail. Figure 5 shows the flow of the method and its three steps, "Clipping of the preceding vehicle," "Evaluation of visibility," and "Judgment of fog density". Based on Koschmieder's model, fog density is judged using both the distance to a preceding vehicle and the visibility calculated from the region of the preceding vehicle.

3.1. **Clipping of the preceding vehicle.** To evaluate the visibility of the preceding vehicle, first we clip the preceding vehicle image from the captured image. Recently, obstacle detection techniques are widely researched [11][12]. In foggy conditions, however, it is difficult to achieve accurate detection using these techniques.

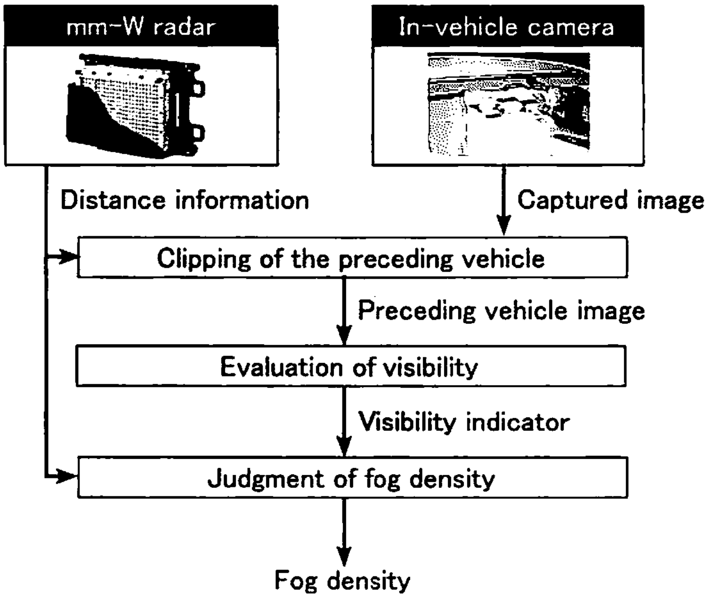


FIGURE 5. Flowchart of the proposed method.

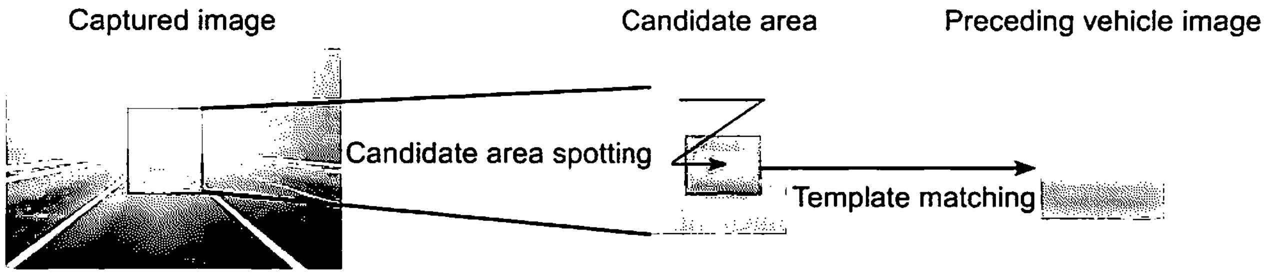


FIGURE 6. Clipping of the preceding vehicle image.

First we spot a candidate area by using distance information to the preceding vehicle. This information is provided by the mm-W radar. Next, the accurate position of the preceding vehicle region are detected by template matching in the candidate area, referring to the dictionary image. Figure 6 shows the process of the clipping.

The clipping accuracy was 90.17% when the method was applied to 4,149 images. All the images included a preceding vehicle. The judgment whether the images were correctly clipped was done manually. In this paper, the preceding vehicle is the same vehicle in all images. At present, we only consider a specific vehicle as the preceding vehicle, so a dictionary image manually cropped from a captured image was used for the template matching.

3.2. **Evaluation of visibility.** When fog appears, the outline of a preceding vehicle becomes more difficult to distinguish than in a fair condition because the captured images become whitish and blurred. This is the point on which we focused. Since contrast in images captured in foggy conditions becomes low, we considered that the amount of high-frequency energy should also decrease in the frequency representation. Figure 7 shows two

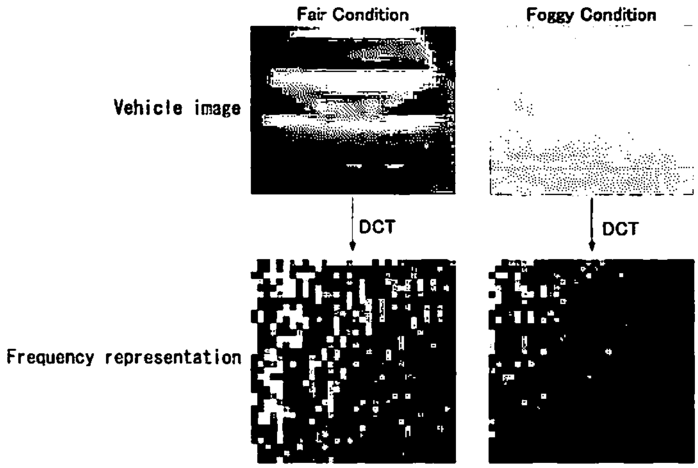


FIGURE 7. Vehicle images captured in fair and foggy conditions and their frequency representations.

images and the corresponding DCT (Discrete Cosine Transform) images. The left hand side image was captured in a fair weather condition, while the right one was captured in a foggy condition. DCT transforms discrete signals into frequency domain. The value of the most upper left pixel represents the energy of the DC component that represents the lowest frequency component. On the other hand, the most right bottom one represents the highest frequency component. From Figure 7, we confirmed that high frequency energy of a foggy image is obviously less than that of a fair image.

Considering this loss of contrast, we define an indicator that represents the visibility of a preceding vehicle. First, the image of the preceding vehicle is resized to 32×32 pixels by linear interpolation. The resulting image is then converted into the frequency domain by DCT. In the frequency domain, pixels with the same Manhattan distance n from the zero-frequency pixel $(0,0)$ belong to the n-th group. The n-th group's total energy is defined as follows:

$$E(n) = \sum_i \sum_j I_n(i,j) \tag{2}$$

where $I_n(i,j)$ satisfies the following equation.

$$I_n(i,j) = \begin{cases} I(i,j) & i+j=n \\ 0 & otherwise \end{cases} \tag{3}$$

Here, $I(i,j)$ represents the power spectrum of a pixel located at (i,j). The mean energy $M(n)$ equals to $E(n)$ divided by the number of pixels in the n-th group. The indicator is defined as the smallest n such that $M(n)$ is less than a pre-defined threshold.

Figure 8 shows sample images and corresponding indicator values. An exploratory experiment with human subjects was done to investigate the relation between human perceptions of visibility and the indicator. From the result, we confirmed that the preceding vehicle becomes indistinguishable in proportion to the decrease in the indicator value. Note that we replaced the pixels in the tail-lamp regions with the mean brightness of the entire vehicle region, since lighting tail lamps on and off can negatively affect the

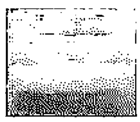
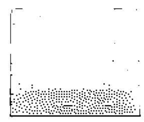
Image					
Indicator	33	30	29	26	25
Image					
Indicator	22	20	16	15	9

FIGURE 8. Sample images and corresponding indicator values.

indicator. This process was done automatically using the fact that tail lamps of a vehicle image are generally in fixed positions.

3.3. **Judgment of fog density.** Here, we introduce a system that classifies fog density into three classes by referring to both the visibility indicator and the distance information.

Using the visibility indicator alone is insufficient to determine the fog density, since in the same fog condition, nearby objects are easier to distinguish than distant ones.

Visibility-meters are often used to measure fog density. In our work, however, we focus on driver's perception rather than on such physical visibility measures to determine classes of fog density instead. The classes, which reflect human perceptions, are "dense", "moderate", and "light".

To judge the fog density, the relationship between the indicator and the distance had to be learned for each class. This relationship is represented as:

$$I = ae^{-bd} + c, \tag{4}$$

where I is the indicator value and d is the distance. This exponential function is obtained from Eq.(1), when L_0 and L_f are assumed to be invariables. For each classes, the unknown parameters a, b and c are calculated so that the exponential curve gives the minimum squared error to the training data.

To classify input data, the distance between the input data and each regression curve is measured. The input data is then classified to the class of the nearest regression curve.

4. **Experiments.** In this section, we report the results of experiments to show the performance of the proposed method. We first explain the data acquisition and the preparation of training data and then report the results obtained by applying the proposed method. Note that in this experiment, we manually excluded clipped images without a correctly detected preceding vehicle.

4.1. **Data collection.** We equipped a car with an in-vehicle camera and a mm-W radar. We used a mm-W radar to obtain the distance information instead of a laser or a supersonic-wave radar. This is because, compared with laser or supersonic-wave radar that is easily influenced by bad weather conditions, especially fog when rays scatter, mm-W radar is robust to such conditions. The mm-W radar gave two kinds of information,

TABLE 1. Specifications of in-vehicle camera.

Parameter	Value
Resolution	640 × 480 pixels
Frame rate	10 frames / second
Scan mode	Interlace
Representation	Gray scale
Number of tone	256

TABLE 2. Specifications of the mm-W radar.

Parameter	Value
Relative velocity	-200 to 100 km/h
Azimuth angle range	-10 to 10 degree
Processing cycle time	100 ms
Operating frequency	76 to 77 GHz
Modulation principle	FM-CW
Azimuth detection method	Electronic scanning
Range accuracy	3 %
Range resolution	1.5 m
Azimuth accuracy	0.5 degree
Azimuth resolution	5 degree

distance to preceding objects and relative speed to them. From the information, our system finds the position of a preceding vehicle in the captured images. Table 1 and Table 2 show the specifications of the in-vehicle camera and the mm-W radar that was used. Detailed specifications of the mm-W radar are described in [13].

The data for the experiments were collected by driving a vehicle in both fair and foggy conditions, at a speed of 40 km/h to 60 km/h.

4.2. **Preparation of training and test data.** To design the classifier, we need training data for each class. The training data were prepared by the following procedure, in which we used images captured while driving a vehicle. For the experiment, we use the data captured when the distances to the preceding vehicle were from 20m to 60m. Five sets of images were tested, where one set included ten images chosen randomly from the captured images. Four different human subjects, each with a valid driver's license, participated in the experiment. The subjects were asked to conduct the following two steps for each set.

- Sort the ten images in order of fog density.
- Classify the ten images into three classes: "Dense Fog," "Moderate Fog," or "Light Fog."

From the results of this experiment, we obtained an appropriate class for each training image, complying with human perception.

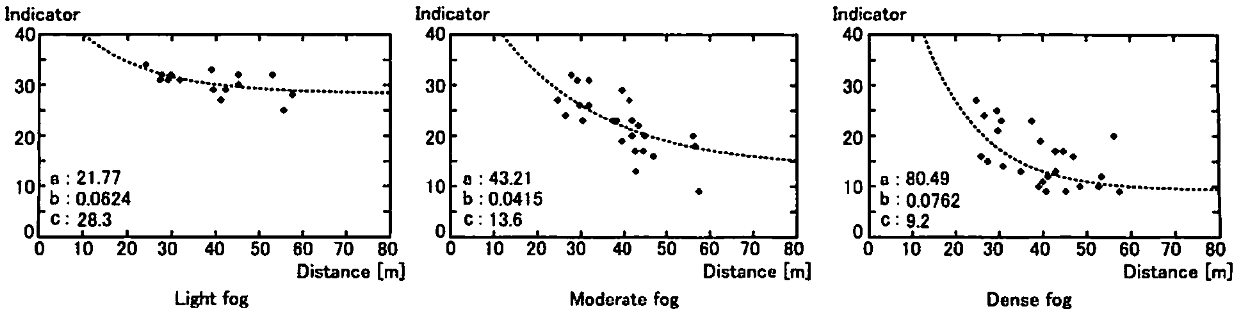


FIGURE 9. The distribution of training data.

TABLE 3. Comparison of judgments by the proposed method and by human subjects. Numbers in parentheses in diagonal elements represent the precision rate of each class.

		By the proposed method		
		Light Fog	Moderate Fog	Dense Fog
By the human subjects	Light Fog	**51 (100%)**	0 (0%)	0 (0%)
	Moderate Fog	9 (13%)	**59 (82%)**	4 (6%)
	Dense Fog	0 (0%)	17 (22%)	**60 (78%)**

4.3. **Evaluating the judgments.** We compared the judgments attained using the proposed method and that by human subjects. In the following experiments, the test data set was different from the training data set. Because four subjects evaluated the same set of images, some images were classified into different classes.

We took this into account and allowed an image to belong to multiple classes, using the number of subjects who classified a certain image into a class as the weight of training data in that class. Figure 9 shows the distribution of the training data and the calculated regression curve in indicator-distance coordinates.

The results are presented in Table 3, which shows the confusion matrix for judgment by the proposed method and that by the human subjects. The overall precision rate for all classes was 85%. In the experiment, however, we dealt with only one vehicle. In reality, the indicator is affected by the variety of colors and shapes of vehicles, though the indicator should not be affected by these variances for reliable judgment of fog density. Thus, the development of other visibility indicators is one of our next challenges.

5. **Conclusion.** In this paper, we proposed a method that classifies fog density according to a visibility feature of a preceding vehicle and the distance to it. We obtained promising results through an experiment using actual data collected from an in-vehicle camera while driving the vehicle. From the results, we confirmed that the proposed method could make judgments that comply with human perception.

In future, we will develop a new visibility indicator that does not vary depending on the type or color of the preceding vehicle. In addition, we will consider a situation when there is no preceding vehicle at all.

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