

# Visibility Estimation in Foggy Conditions by In-vehicle Camera and Radar

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## Abstract

*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 revealed that judgments made by the proposed method achieved an 85% precision rate compared to that made by human subjects.*

## 1. Introduction

Recently, many systems have been developed that use computers and various sensors to assist driving. 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 [1].

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. Therefore, a close relationship exists between driver assistance and weather recognition.

In this paper, we focus on fog detection. Fog negatively influences human perception of traffic conditions, making for potentially dangerous situations. Automatic lighting of fog lamps, speed control, and rousing of attention are examples of potential assistance to be realized with respect to fog recognition. 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 [2]. Furthermore, fog changes significantly both temporally and spatially, and as a result there is a need for real-time detection using in-vehicle sensors. One method that involves installing large numbers of sensors along roads might be one solution, though it may not accurately reflect a

driver's visual condition. It would also be a very expensive system to establish.

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. We therefore use a mm-W radar together with the in-vehicle camera, since it can measure distance without being influenced by adverse weather. 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, we introduce some works that deal with features of a fog image. The proposed method is described in Section 3. Experiments to show the potential of the proposed method are reported in Section 4. Then we discuss the results in Section 5 and summarize the paper in Section 6.

## 2. Related Works

In this section, we introduce some works on image processing related to features of fog images. Narashimhan and Nayar proposed a method that restores the contrast of images captured in adverse weather conditions, especially foggy conditions [3]. This restoration method is based on the

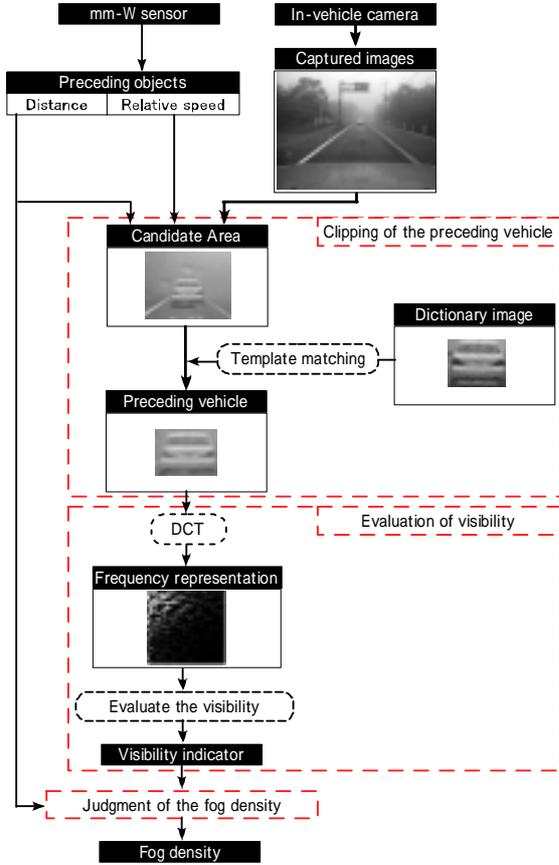


Fig. 1. Flowchart of the proposed method.

brightness deterioration model that was proposed by Koschmieder [6].

Hasegawa proposed a method that evaluates the road visibility and image features of an image captured from a digital still camera in foggy conditions [4]. This work focused on the administration of roads by security cameras installed along them, which is different from our purpose.

Furthermore, Hautiere et al. proposed a method that estimates visibility distance using two in-vehicle cameras, and evaluated the degradation of visibility distance in a foggy condition compared with in a fair one [5].

In this paper, we aim to classify fog density for a driving assist system in a way that accurately reflects the driver's visual conditions. To achieve this, we employ two effective sensors, an in-vehicle camera and a mm-W radar.

### 3. Visibility Estimation under Foggy Conditions

In this section, we explain our method in detail. Figure 1 shows the flow of the method. Fog density is judged using both the distance to the preceding vehicle and the indicator calculated from the region of the preceding vehicle.

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

Fig. 2. Sample images and corresponding indicator values.

#### 3.1. Evaluating visibility by referring to a preceding vehicle

The image region of a preceding vehicle is clipped from a captured image and an indicator that represents the visibility from the image is output.

**3.1.1. Clipping the region of a preceding vehicle.** First, preceding objects are detected by referring to the distance obtained from the mm-W radar. Moving objects are extracted according to their speed relative to the vehicle with an in-vehicle camera on board. Next, the position and size of the preceding vehicle region are accurately detected by template matching in the candidate area, referring to the dictionary image.

The accuracy was 90.17% when this method was applied to 4,149 images. All the images included a preceding vehicle. In this paper, the preceding vehicle is 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 as a template.

**3.1.2. Evaluating the visibility indicator.** Here we define an indicator that represents the visibility of the preceding vehicle. 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 of the 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  $32 \times 32$  pixels by linear interpolation. The resulting image is then converted into the frequency domain using the Discrete Cosine Transform (DCT). In the frequency domain, pixels with the same Manhattan distance  $n$  from the zero-frequency pixel belong to the  $n$ -th group. The zero-frequency pixel is located at  $(0, 0)$ , and the  $n$ -th group's total energy is defined as follows:

$$E(n) = \sum_i \sum_j I_n(i, j), \quad (1)$$

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

$$I_n(i, j) = \begin{cases} I(i, j) & i + j = n \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

Here,  $I(i, j)$  represents the power spectrum of a pixel located at  $(i, j)$ . The mean energy  $M(n)$  equals  $E(n)$  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 2 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 its 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 the lighting of tail lamps can negatively affect the indicator. This process was done automatically using the fact that tail lamps of a resized vehicle image are generally in fixed positions.

### 3.2. Judging fog density

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. To judge the fog density, we use the distance to the preceding vehicle to correct the indicator value.

Visibility-meters are often used to measure fog density. In our work, however, we focus on the driver's perception rather than on absolute physical visibility measures. Our method instead features three levels of fog density, dense, moderate, and light, where the judgment of fog density is considered to be the level into which the fog is classified.

The classification method is as follows. First, we calculate the regression curve that has the minimum squared error to the training data in each class. To classify an input data, the distance between the input data and each regression curve is measured. The input data are then classified to the class with the nearest regression curve.

A regression curve is an exponential function referring to Koshmieder's model on the deterioration of brightness [6]. Koshmieder's model is represented as follows:

$$L = L_0 e^{-kd} + L_f (1 - e^{-kd}), \quad (3)$$

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. Therefore,  $L$  deteriorates exponentially according to  $d$  when  $k$  is fixed. Assuming that the indicator deteriorates according to Koshmieder's model, we use Eq. (3) for the regression curve.

## 4. Experiments

In this section, we report the results of experiments to show the possibility of the proposed method. Images of a specific preceding vehicle were prepared. We first explain the preparation of training data and then describe the results obtained by applying our method. In this experiment, we did

Table 1. Specifications of the mm-W radar.

Parameter	Value
Range	5 - 150 m
Relative velocity	-200 - 100 km/h
Azimuth angle range	-10 - 10 deg
Processing cycle time	100 ms
Operating frequency	76 - 77 GHz
Modulation principle	FM-CW
Azimuth detection method	Electronic scanning
Range accuracy	3%
Range resolution	1.5 m
Azimuth accuracy	0.5 deg
Azimuth resolution	5 deg

not use clipped images without a correctly detected preceding vehicle. Table 1 shows the parameters of the mm-W radar that was used.

### 4.1. Preparation of training and test data

To design the classifier, we need training data with the most appropriate class for each image. This was done by the following procedure, in which we used images captured while driving a vehicle. Five sets of images were tested, where one set included ten images that had been selected randomly from the captured images. Four different 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," and "Light Fog."

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

### 4.2. Evaluating the judgments

We compared the judgments attained using the method described in Sect. 3.2 and that by human subjects. In the following experiments, the test data set was different from the training data set.

We assume that  $L_0$  and  $L_f$  in Eq. (3) are invariables because the preceding vehicle is always the same in the experiment, as mentioned in Sect. 3.1.1., as was the sky luminance when the images were captured. Consequently, Eq. (3) may be simplified as Eq. (4).

$$L = ae^{-kd} + b \quad (4)$$

First, the regression coefficients  $a$ ,  $b$ , and  $k$  in Eq. (4) were calculated for each class. The training data were compiled according to the method described in Sect. 4.1. Because four subjects evaluated the same set, some images could be

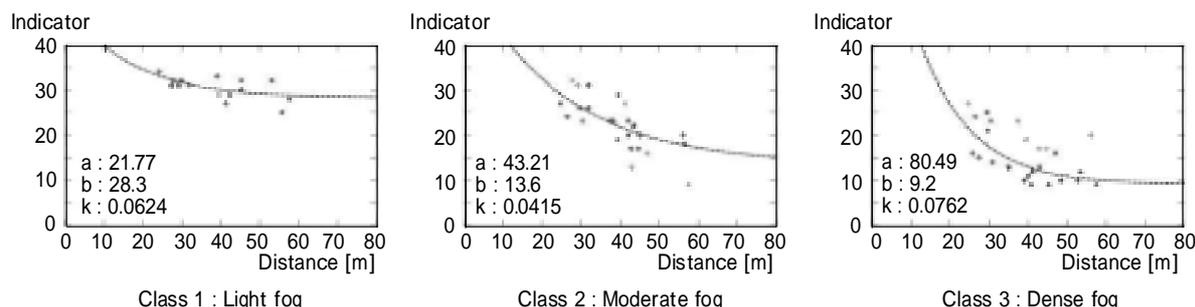


Fig. 3. The training data and the regression curve for each fog density class.

Table 2. Comparison of judgments by the proposed method and by humans. The numbers in parentheses are the ratio of the element to the total number of elements in each row, meaning that, the numbers in parentheses in diagonal elements represent the precision rate of each class.

By the methods \ By the examinees	Class 1	Class 2	Class 3
Class 1	51 (100%)	0 (0%)	0 (0%)
Class 2	9 (13%)	59 (82%)	4 (5%)
Class 3	0 (0%)	17 (22%)	60 (78%)

classified into different classes. We take this into account and allow 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 3 shows the distribution of the training data and the calculated regression curve in indicator-distance coordinates.

## 5. Results and Discussion

The results are presented in Table 2, which shows the confusion matrix for judgment by the proposed method and that by the human subjects. The total 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, improvement of the indicator is our next challenge.

## 6. 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 the vehicle. We obtained promising results through an experiment using 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 consider an improved visibility feature 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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