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Recognition of foggy conditions by in-vehicle camera and millimeter wave radar

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Abstract— **Recently driving support techniques using in-vehicle sensors have attracted much attention 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 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 distance to it. Experiments showed that judgments made by the proposed method achieved a recognition rate of 84% when compared to the ground truth obtained by human judgments.**

I. INTRODUCTION

Recently, many driving support systems using computers and various sensors have been developed. 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 assistance system, we cannot ignore changes in weather conditions; in such adverse weather conditions as rain, snow, or fog, driving becomes more difficult than in fair conditions, leading to a significant increase in accidents. Actually, in Japan, accident rates in bad weather conditions are about 17 times higher than that in fair conditions. Therefore, a close relationship exists between driver assistance and weather recognition.

In this paper we focus on fog recognition. When driving, fog negatively influences human perception and creates potentially dangerous situations. According to Cavallo et al., under foggy conditions the distance to a preceding vehicle's tail light is perceived to be 60% further away than under fair conditions [2]. Furthermore, fog significantly changes both temporally and spatially, and as a result real-time detection is needed that uses in-vehicle sensors. A method that involves installing a large number of sensors along roads might be one solution, but it may not accurately reflect a driver's visual condition. In addition, it would also be very expensive.

Considering these problems, we propose a method that classifies fog density into three levels using in-vehicle cameras and millimeter-wave (mm-W) radar. To evaluate fog density, our method uses an extinction coefficient calculated from preceding vehicle images and distance information. An in-vehicle camera image reflects the driver's visual conditions, which are vital when driving. This is the prime advantage of using an in-vehicle camera. The visibility degradation of images captured in foggy conditions is evaluated, especially by focusing on the change in visibility of the preceding vehicle. And the distance to the preceding vehicle also needs to be taken into account to determine the fog density because under identical fog conditions, nearby objects are easy to see while distant objects are not (Fig. 1), therefore we use mm-W radar combined with an in-vehicle camera. Compared with laser or supersonic-wave radar that is influenced by bad weather conditions, especially fog when rays scatter, mm-W radar is robust to such conditions.

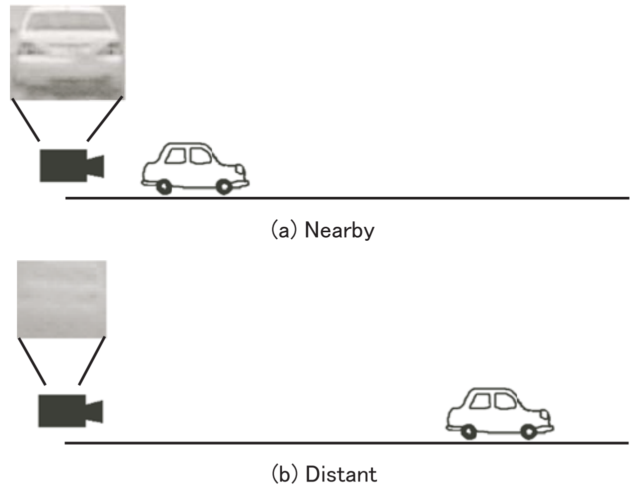

Fig. 1. The visibility of a preceding vehicle depends on distance.

The proposed method is composed of the following two steps:

- Calculation of extinction coefficient from both visibility and distance information of a preceding vehicle
- Classification of fog density using the extinction coefficient

To evaluate the performance of the classifier, we compared judgments by the proposed method with human judgments in experiments using actual data. Automatic lighting of fog lamps, speed control, and danger alerts are examples of potential assistance to be realized with respect to fog recognition.

This paper is organized as follows. In Sec. II-A, we introduce a model that expresses the degradation of brightness by atmospheric scattering. And in Sec. II-B, works are introduced that deal with features of fog images. The proposed method is described in Sec. III. Experiments to

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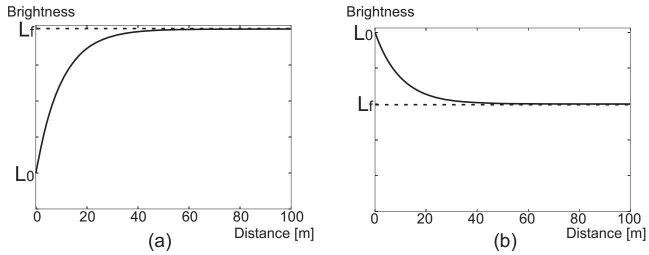


Fig. 2. The brightness degradation with distance ($k = 0.1$): (a) L_0 is smaller than L_f; (b) L_0 is bigger than L_f.

show the potential of the proposed method are reported in Sec. IV. Then we discuss our method in Sec. V and summarize the paper in Sec. VI.

II. Related Works

Koschmieder's model [3] that expresses the degradation of brightness by atmospheric scattering is explained using actual images in Sec. II-A, and works related to features of fog images are introduced in Sec. II-B.

A. Koschmieder's model

Koschmieder's model expresses the degradation of brightness [3], represented as follows:

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

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 means that it is difficult to recognize an object in conditions where the extinction coefficient is high, because in such conditions L approaches L_f. Fig. 2 shows the brightness degradation with distance when $k = 0.1$. The horizontal axis represents d and the vertical axis represents L. L approaches L_f with increasing distance.

This model explains two effects of fog in the images:

- Image contrast degradation
- Image whitens as a whole

Fig. 3(a) was captured in fair weather, while Fig. 3(b) was taken in fog. Both images include the same vehicle. When fog becomes dense, k becomes large, e^{-kd} approaches 0, and the value of $L_0 e^{-kd}$ becomes small. Therefore, the variation of pixel values becomes small, which causes contrast degradation. On the other hand, $L_f(1 - e^{-kd})$ increases and the mean of the pixel value shifts to the brightside, which whitens the images. We can see these phenomena in the actual data in Fig. 4 that shows the histogram of Figs. 3(a) and 3(b).

From these, the variance of brightness can be considered useful information to evaluate the visibility of a preceding vehicle. Since the mean of the brightness is affected by such camera settings as shutter speed, aperture, and so on, we only refer to the variance.

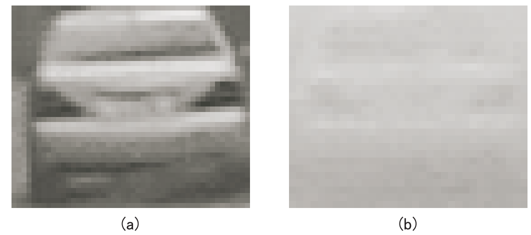


Fig. 3. (a) Image captured in fair condition, (b) Image captured in foggy condition

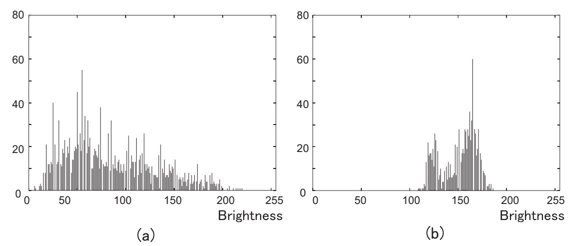


Fig. 4. (a) Brightness histogram of Fig. 3(a), (b) brightness histogram of Fig. 3(a)

B. Fog image processing

We introduce related works on the image processing of fog images.

Narashimhan and Nayar proposed a method that restores the contrast of images captured in adverse weather conditions, especially foggy conditions [4]. This restoration method also uses Koschmieder's model to model brightness deterioration.

Hagiwara proposed a method that evaluates road visibility and the features of images captured from a digital still camera in foggy conditions [5]. This work focuses on the administration of roads by security cameras installed along them, which is different from our purpose.

Some studies tried to estimate visibility while driving. Kuwon proposed the concept of Motorists Relative Visibility (MRV) [6], which is calculated by using the amount of recognizable objects in the surrounding area, the average luminance, and the acuity of objects measured by contrast in the image. This work supposes the use of a stereo camera. Hautiere et al. proposed a method that estimates visibility distance using in-vehicle stereo cameras and evaluated the degradation of visibility distance in foggy conditions compared with fair ones [7]. Leleve and Rebut tried to estimate visibility using an in-vehicle camera for fog lamp automation [8] and proposed a method to support night driving using the halation of ones own car's headlights.

III. Fog Density Recognition under Foggy Conditions

In this section, we explain our method in detail. Fig. 5 shows the flow of the method and its three steps: "clipping of preceding vehicle image," "calculation of extinction coefficient," and "classification of fog density."

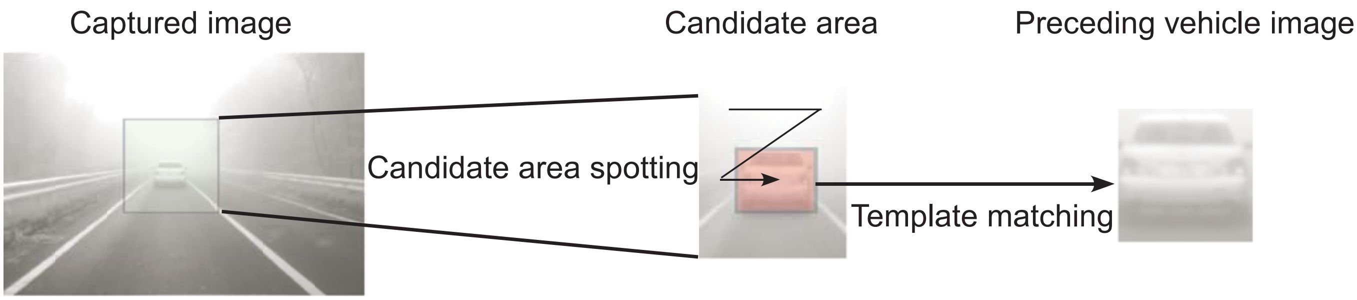


Fig. 6. Clipping of preceding vehicle image

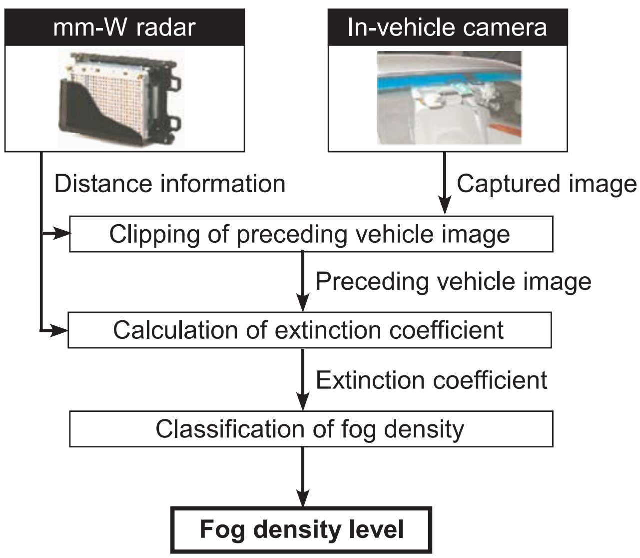


Fig. 5. Flowchart of proposed fog density classification method

Fig. 7. Target area for calculation of extinction coefficient

A. Clipping of preceding vehicle image

To evaluate the visibility of the preceding vehicle, first we clip a preceding vehicle image from the captured image.

First we spot a rectangle candidate area for the preceding vehicle using distance information to the vehicle. This information is provided by mm-W radar. The candidate area is larger than the size of the vehicle defined as a rectangle 1.5 m high and 1.7 m wide. The position and the size of the candidate area are obtained from mm-W radar.

Next, an accurate position of the vehicle is detected by template matching in the candidate area, referring to the template image of the vehicle. In experiments, the typical vehicle image captured under fair conditions was used as the template image. In template matching, the template image and each vehicle candidate image are normalized before calculating similarity. First, to restore the contrast degraded by scattering, we apply the following equation

$$L_{norm} = \frac{(L - L_{min}) \cdot MAX}{L_{max} - L_{min}} \qquad (2)$$

where L is the brightness of each pixel in the images. L_{min}, L_{max} are the minimum and maximum brightnesses in the image, and MAX is the upper limit of brightness, which is set to 255 in our environment. Next, we make vector $\tilde{\mathbf{x}}$ that contains brightness L_{norm} in the image and normalize this vector. From this, we obtain normalized vector $\mathbf{x} = \{x_1, x_2, \cdots x_N\}$. The i-th component of vector $\mathbf{x}$ is represented as

$$x_i = \frac{\tilde{x}_i}{\|\,\tilde{\mathbf{x}}\,\|}, \qquad (3)$$

where $\tilde{x}_i$ is the i-th component of vector $\tilde{\mathbf{x}}$. We define the similarity between a vehicle candidate and the template image, as their inner product. We detect the vehicle candidate region that gives the largest similarity as the preceding vehicle region.

Fig. 6 shows the process of clipping. The clipping accuracy was 92.86% when this method was applied to 10,028 images. Here, all the images included a preceding vehicle. The judgment to determine whether the images were correctly clipped was done manually.

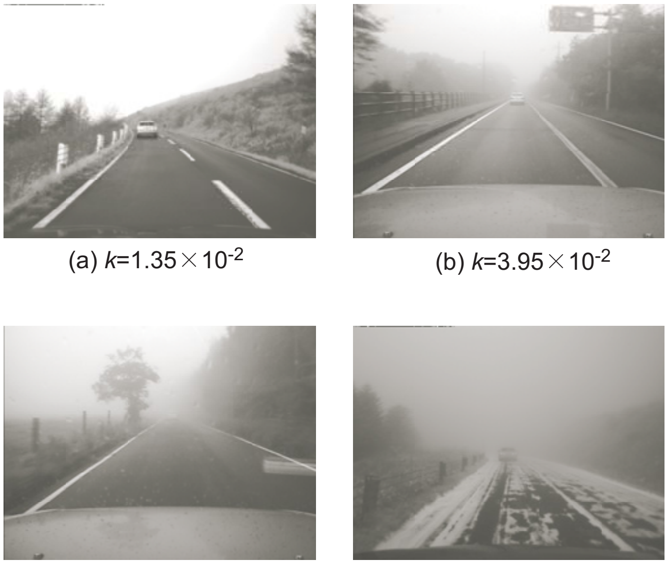
B. Calculation of extinction coefficient

Here, we describe the calculation of extinction coefficient k in Koschmieder's model shown in (1) using both the visibility of the preceding vehicle and distance to it.

To calculate extinction coefficient k, we use the relationship between the variance of pixel values of the preceding vehicle image and an original image of the vehicle. The original image is captured in fair condition ($k = 0$): that is, no degraded image.

The variance of pixel values of the vehicle image is expressed in

$$\begin{aligned}
\sigma^2 &= \frac{1}{N}\sum_{j=1}^{N}\left(L_j - \frac{1}{N}\sum_{i=1}^{N} L_i\right)^2 \\
&= e^{-2kd} \cdot \frac{1}{N}\sum_{j=0}^{N}\left(L_{0j} - \frac{1}{N}\sum_{i=0}^{N} L_{0i}\right)^2 \qquad (4)
\end{aligned}$$



(a) k=1.35×10^{-2} (b) k=3.95×10^{-2}

(c) k=8.28×10^{-2} (d) k=1.38×10^{-1}

Fig. 8. Extinction coefficients for various weather conditions

TABLE I

SPECIFICATIONS OF IN-VEHICLE CAMERA

Parameters	Values
Resolution	640Σ 480 pixels
Frame rate	10 frame/second
Scan mode	Interlace
Color	Grayscale
Number of tones	256

TABLE II

SPECIFICATIONS OF MM-W RADAR

Parameters	Values
Relative velocity	-200 to 100 km/h
Azimuth angle range	$-10°$ to $10°$
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°
Azimuth resolution	5°

by Koshimieder's model (1). Here, N represents the number of pixels in the image. On the other hand, the pixel values in original image $\acute{L}$ are

$$\acute{L} = L_0, \tag{5}$$

because the extinction coefficient of original image is 0. So, the variance of the original image $\acute{\sigma}^2$ is

$$\acute{\sigma}^2 = \frac{1}{N}\sum_{j=1}^{N}\left(L_{0j} - \frac{1}{N}\sum_{i=1}^{N} L_{0i}\right)^2. \tag{6}$$

From (4) and (6), σ^2 is expressed as

$$\sigma^2 = e^{-2kd}\acute{\sigma}^2. \tag{7}$$

From these, when the original image is given, extinction coefficient k of the vehicle image can be calculated by

$$k = -\frac{1}{2d}\log\frac{\sigma^2}{\acute{\sigma}^2}. \tag{8}$$

However, some factors will affect the calculation of the extinction coefficient. Actually the bottom part of the vehicle image includes tires and the road surface, and the upper part includes the sky or silhouettes of people onboard. They influence the variance of brightness more significantly than scattering. To avoid this, we only use the region shown in Fig. 7 as the target area when calculating the variance of brightness.

Fig. 8 shows the results of calculating the extinction coefficient. k becomes larger as the fog becomes denser.

C. Classification of fog density

Here, we introduce a system that classifies fog density into three classes by referring to extinction coefficient.

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.

For this, two thresholds of extinction coefficient need to be determined. We search two thresholds that give the minimum number of misclassifications. Each threshold θ_i is defined so that it meets

$$\begin{aligned} \theta_i &= \arg\min_{\theta} \sum_{k_j \in \mathbf{K}^-} (k_j - \theta)^2 \\ \mathbf{K}^- &= \{k_j \mid k_j \text{ is a misclassified sample}\}. \end{aligned} \tag{9}$$

IV. EXPERIMENTS

In this section, we report the results of experiments to show the performance of the proposed method. We explain data collection, the preparation of training data, and the evaluation of judgment by our method. In this experiment, we used images in which vehicle areas are correctly clipped. The image with the largest variance of brightness in the data set was defined as the original image.

A. Data collection

We equipped a car with an in-vehicle camera and mm-W radar. Two vehicles of different colors and shapes were prepared as preceding vehicles. The data for the experiments were collected while driving the vehicle in fair and foggy conditions. The mm-W radar gives two kinds of information: distance and relative speed to preceding objects. From the information, our system finds the candidate position and size of a preceding vehicle in a captured image. Tables I and II show the specifications of the in-vehicle camera and the mm-W radar used in this experiment. Detailed specifications of the mm-W radar are described in [9].

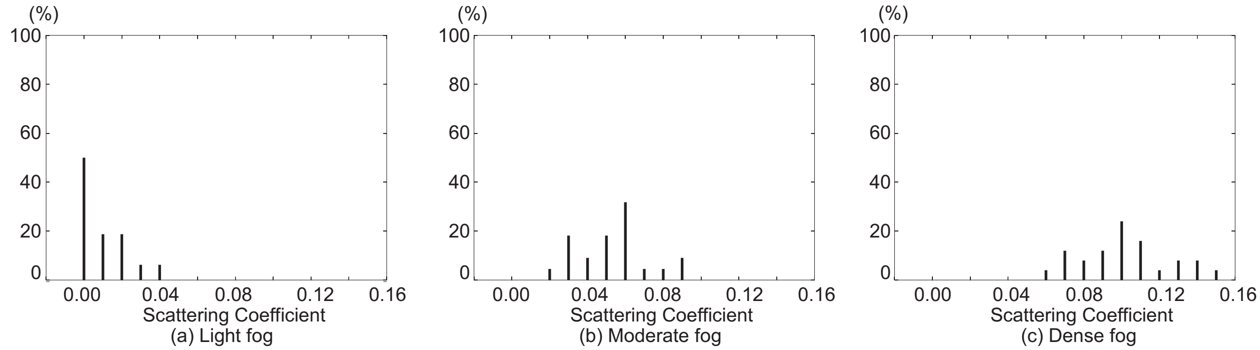


Fig. 9. Distribution of extinction coefficient calculated by our method from data set

TABLE III

JUDGMENTS BY PROPOSED METHOD AND HUMANS

		Proposed method		
		Light	**Moderate**	**Dense**
By humans	**Light**	**14 (88%)**	2 (12)	0 (0)
	Moderate	2 (9)	**16 (73)**	4 (18)
	Dense	0 (0)	2 (8)	**23 (92)**

B. Preparation of training data

To learn the thresholds of the extinction coefficient for fog density classification, the training data were classified into the most appropriate classes by the following procedure in which we used images captured while driving a vehicle.

First we prepared 10 data sets that met the following requirements.

- Each set includes 10 images.
- The images contain one of the two kinds of preceding vehicles described in Sec. IV-A.

Using these data sets, we conducted experiments in which 13 different subjects with valid driver's licenses, participated. Each subject was asked to conduct the following two steps for each set:

- Sort the 10 images in order of fog density
- Classify the 10 images into three classes: "dense," "moderate," or "light."

Images that less than 10 subjects classified into the same class were excluded for training, because they were considered difficult to classify uniquely by human perception. From this, 63 of 100 images were used in the following processes.

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

C. Evaluating the judgments

To show the performance of our method, we compared the judgments obtained by our method with human subjects. The validation methodology to determine the extinction coefficient thresholds was leave-one-out. Fig. 9 shows the distribution of extinction coefficients for each class.

Table III shows the confusion matrix for judgment by the proposed method and by human subjects. The numbers in parentheses are the percentages of the element to the total number of elements in each row; the percentages in diagonal elements represent the precision rate for each class. The overall precision rate for all classes was 84%. There were no misclassifications between "light" and "dense." The results show that our method worked well, despite the variation of vehicles.

V. DISCUSSIONS

A. Obtaining original images

Our method can recognize fog density when the original image is given. In the experiment, it is assumed that we already have the original image; however, in a practical system, this information seems difficult to obtain. To get the original image, we consider the following two approaches:

1) For the original image, we use the image that has the largest variance of brightness among the vehicle images captured while a car is running.
2) Obtain the original image by an inter vehicle communications system.

For 2), recently an inter-vehicle communications system has been developed whose popularity will probably increase. Now, it is possible to transmit an image sequence that indicates traffic conditions to following vehicles [10][11]. Thus we believe that it will be able to transmit the original image of own vehicle and that it can also be used as the template image for vehicle clipping. This problem is one of our future challenges.

B. Detection of brake lamps

The lighting of brake lamps is one noise that triggers the decline of the method's performance, because it significantly affects the variance of brightness. To improve the performance of fog density classification, images that include a vehicle with lit brake lamps should not be used when calculating extinction coefficient.

By focusing on the change of variance, the detection of lit brake lamps is possible. We checked the difference of variances between unlit and lit brake lamps. The results are shown in Fig. 10. When the brake lamps are turned on, the variance drastically changes in a short time. From this result, the change of variance is useful to detect lit brake lamps. In

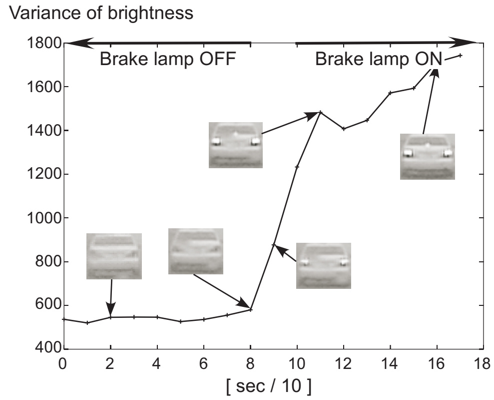


Fig. 10. Change of variance of brightness by lighting of brake lamps

addition, we consider that the relative speed between cars obtained from mm-W radar is also useful.

VI. Conclusion

In this paper, we proposed a method to classify fog density into three classes using an in-vehicle camera and mm-W radar. We obtained promising results through experiments using actual data collected while driving vehicles. The recognition rate achieved 84% compared to the ground truth obtained by human judgments. From the results, we confirmed that the proposed method could make judgments reflecting human perception.

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