特集

Rain and Fog Recognition System Using Multiple in-Vehicle Sensors *

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This paper describes a system for rain and fog recognition using multiple in-vehicle sensors. Fog density was calculated from both the preceding-vehicle images captured by an in-vehicle camera and the inter-vehicle distance measured by a millimeter-wave (mm-wave) radar. Rainfall determination is achieved by detecting raindrops on the windshield using images captured by the in-vehicle camera. Experiments using in-vehicle camera images and radar data collected while driving vehicles in foggy or rainy and fair conditions demonstrated the accuracy and the applicability of our system.

1．INTRODUCTION

Recently great advances have been seen in the development of ITS technology. Driver assistance and navigation with the aid of computers and sensors are being actively developed. In particular, in-vehicle camera images are commonly utilized since they contain important visual information. Driving is more difficult in adverse weather conditions than in fair conditions, so accident rates dramatically increase. Weather changes temporally and spatially, so it is important to develop techniques that recognize weather in real-time by in-vehicle sensors for driver assistance.

In this paper, we propose a weather recognition system and focus on rain and fog using an in-vehicle camera and a mm-wave radar device. **Figure 1** shows an overview of our system. From in-vehicle camera images and mm-wave radar data, our system outputs two kinds of weather information around a vehicle: fog density and a determination of rain. Auto-wiping, automatic lighting of fog lamps, speed and break control, and rousing of attention are examples of potential assistance that can be realized with respect to our system.

2．FOG RECOGNITION

2.1 Related works

Koschmieder's model expresses the degradation of brightness by atmospheric scattering[1]. Based on this model, Narashimhan and Nayar proposed a method that restores the contrast of images captured in foggy conditions[2]. Techniques of visibility enhancement and contrast restoration for driving assistance which use this model have also been developed[3)4]. 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[5]. For real-time estimation of visibility in foggy conditions using in-vehicle stereo cameras, Kuwon proposed Motorists Relative Visibility (MRV)[6], and Hautiere et al. proposed a method to estimate visibility distance[7]. To realize fog lamp automation, Leleve and Rebut tried to estimate visibility using an in-vehicle camera[8].

2.2 Algorithm

Our system calculates fog density using both an in-vehicle camera and a mm-wave radar device[9)10] (**Fig. 1**). To evaluate fog density, we focus on the relationship between visibility degradation of a preceding vehicle and inter-vehicle distance (**Fig. 2**). mm-wave radar is utilized with an in-vehicle camera, since it can measure distance without being influenced by adverse weather.

2.2.1 Vehicle image clipping

Figure 3 shows the process of vehicle image clipping. A preceding vehicle region is detected by template matching in a candidate rectangle area with a vehicle template image. The candidate area's size and position are determined from information provided by mm-wave radar, including inter-vehicle distance and vehicle position in the image. The template image and each rectangle image in the candidate area are normalized to restore the contrast degraded by fog before calculating their similarity. Similarity is defined as their inner product. Our system clips a

＊ITS JAPANの了解を得て，「14th World Congress on Intelligent Transport Systems, 3168, Oct. 2007」より，一部加筆して転載

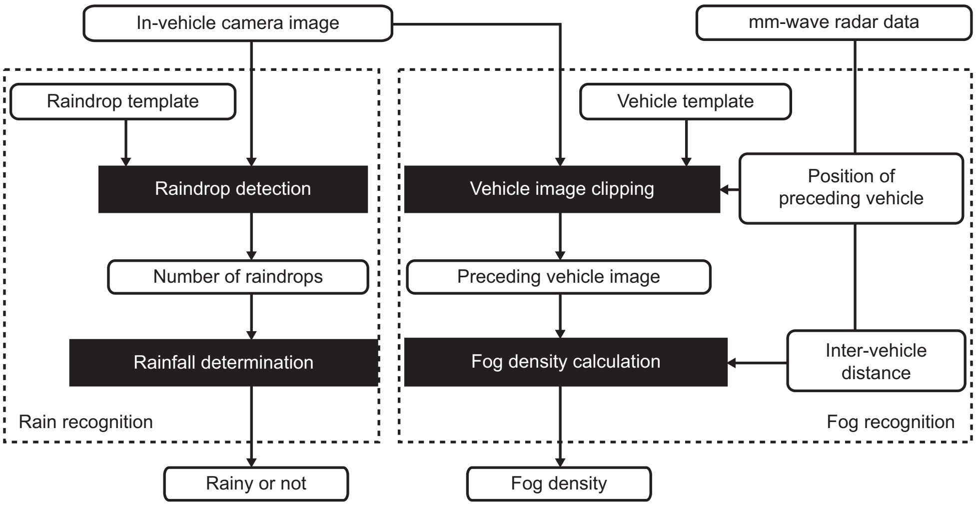


Fig. 1 System overview

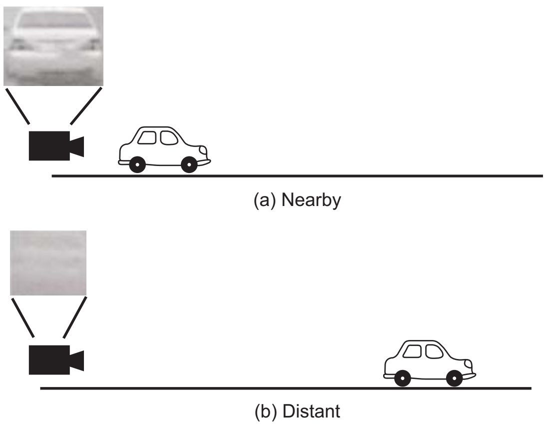


Fig. 2 Visibility difference according to the distance from the preceding vehicle

rectangle image that gives the largest similarity as the preceding vehicle image.

When this method was applied to 10,028 images, clipping accuracy was 92.86%. Here, all images included a preceding vehicle. In this experiment, a typical vehicle image captured under fair conditions was used as the template image.

2.2.2 Fog density calculation

An scattering coefficient of the atmosphere represents fog density, which is expressed using Koschmieder's model as

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

The scattering coefficient is calculated from both the visibility of the preceding vehicle and distance to it. In Equation (1), L is observed luminance, L_0 is the intrinsic luminance of an object, L_f is the luminance of the sky, k is the scattering coefficient of the atmosphere, and d is distance to the object. To evaluate vehicle visibility, we use the relationship between the variance of pixel values of the image and an original image and derive the following equation from the Equation (1).

$$k = -\frac{\log V/V_0}{2d} \quad \cdots\cdots(2)$$

where V and V_0 represent the variance of pixel values of the vehicle image and the original image, respectively. The original image is a vehicle image captured in fair conditions ($k = 0$). **Figure 4** shows fog images and their k calculated by our system. We can observe that k gets higher as fog gets denser.

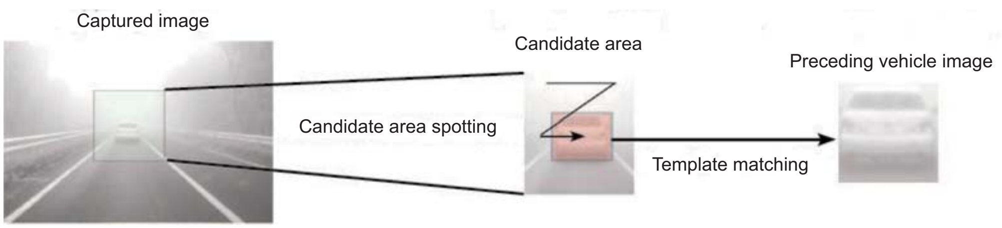
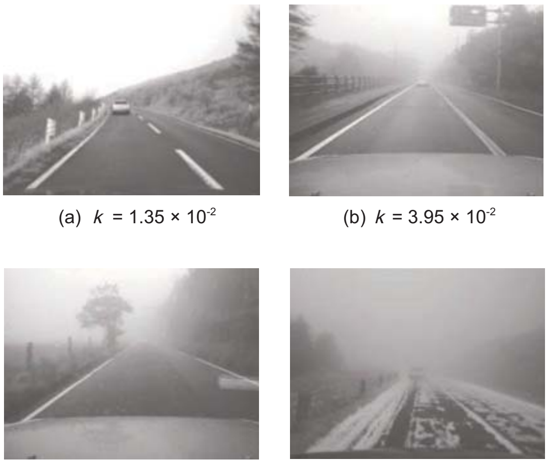


Fig. 3 Clipping of a preceding vehicle image



(a) $k = 1.35 \times 10^{-2}$　(b) $k = 3.95 \times 10^{-2}$

(c) $k = 8.28 \times 10^{-2}$　(d) $k = 1.38 \times 10^{-1}$

Fig. 4 Scattering coefficients for various foggy conditions

Table 1 Determinations by the proposed system and human subjects

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

2.3 Experiment

2.3.1 Setup

We equipped a vehicle with an in-vehicle camera and a mm-wave radar device, which provides two kinds of information: distance and relative speed to preceding objects. From such information, our system finds the candidate position and size of a preceding vehicle in a captured image. Two vehicles of different colors and shapes were prepared as preceding vehicles. We collected data for this experiment while driving the vehicle in fair and various foggy conditions. Data were classified into three classes of fog density: Light, Moderate and Dense, by human subjects. Some were used as training data to determine the thresholds about fog density between two classes, and others were used as test data for system evaluation.

2.3.2 Results and discussion

We compared the determinations obtained by our system with human subjects to evaluate the performance of our system. Table 1 shows the confusion matrix for determinations by the proposed system 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. For all classes, the overall precision rate was 84%. As for the precision of each fog density level, Light 88%, Moderate 73%, and Dense 92% were obtained. The results demonstrate that our system worked well, despite the variation of vehicles.

3. RAIN RECOGNITION

Actually, auto-wiping systems, which have already been implemented on some commercial cars, are controlled by a “rain sensor.” However, the target region for detection covered by the sensor is small, so it does not necessarily reflect changes in the visibility from a driver’s viewpoint. On the contrary, an in-vehicle camera covers most of the driver’s visual field because it targets the entire windshield.

3.1 Algorithm

Our system detects raindrops on a windshield and judges whether to identify them as rain from the number of detected raindrops[11)12)] (Fig. 1).

Raindrops have a uniform shape; any drop basically appears circular when seen through a windshield, and although a raindrop itself is clear and colorless, it is visible due to the reflection of its background (Fig. 5). Raindrop texture varies since the background reflecting them varies. However we believe that at least raindrops share the above features. We automatically extract such image features using PCA.

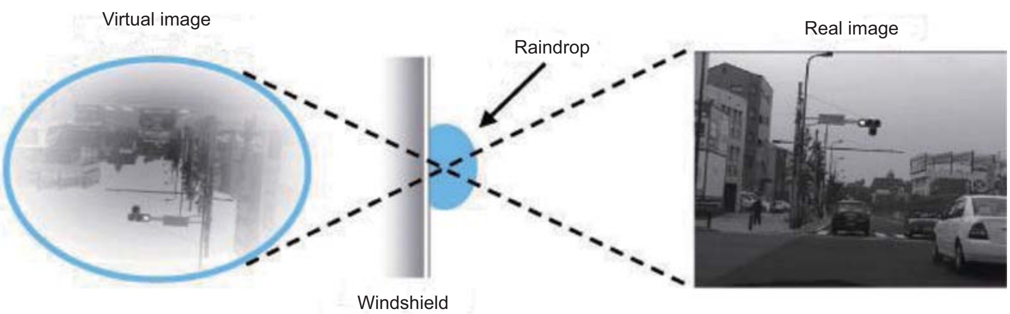
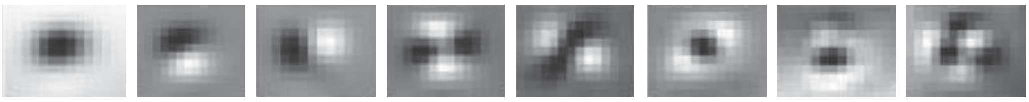


Fig. 5 Refraction of the background and surface of a raindrop on the windshield



1st: 45.6%　2nd: 13.8%　3rd: 8.6%　4th: 4.0%　5th: 3.6%　6th: 3.1%　7th: 2.4%　8th: 1.8%

Fig. 6 Eigendrops and their contribution rates

While raindrop positions on the windshield do not move in relation to the in-vehicle camera, the external view changes when the vehicle is running. Therefore, raindrops are highlighted by background changes. Exploiting this phenomenon, we improve detection accuracy by focusing on the temporal change of the image with raindrops difficult to detect from a single frame by the influence of complex backgrounds.

3.1.1 Raindrop detection

Beforehand, raindrop templates are created and used for raindrop detection as follows. A rectangular region circumscribing each raindrop on a windshield is manually clipped from in-vehicle camera images captured in rainy weather. By applying PCA to the set of clipped images, eigenvectors corresponding to the largest eigenvalues are selected. A subspace generated by these eigenvectors is called “eigendrops,” which we use as raindrop templates in the same manner as a subspace method[13].

Raindrops are detected from input images as follows. To highlight the image features of raindrops, an averaged image is made from multiple sequential frames obtained from input images. Our system computes similarity between an image of each small area in the average image and the eigendrops. The area is detected as a raindrop candidate if the similarity is larger than a threshold. Finally, precise raindrop areas are obtained by frame-wise matching the raindrop candidates.

3.1.2 Rainfall determination

Rainfall is determined by counting the number of raindrops detected in the detection stage. When the number of raindrops in the image exceeds a certain threshold, we determine that it is rainy.

3.2 Experiment

3.2.1 Setup

We mounted an in-vehicle camera and captured images while driving the vehicle in rainy and fair conditions. Our system was applied to the input video sequence. Then recall and precision ratios of raindrop detection were calculated to evaluate detection accuracy. The eigendrops were made from 500 raindrop images (**Fig. 6**). In this experiment, the subspace dimension was six.

3.2.2 Results and discussion

Figure 7 shows examples of raindrop detection, while **Fig. 8** depicts the recall and precision curves. When the number of frames used for averaging increased, although recall improved significantly, the precision fell somewhat. Furthermore, when the number of frames used for frame matching increased, although precision improved, recall dropped. The best results were precision = 97% and recall = 51% when similarity threshold = 0.70 with 5 frame-averaging and 10 frame-matching. Precision is more important than recall for practical use as a windshield wiper controller, since incorrectly recognizing raindrops and letting windshield wiper malfunction must be avoided.

An 89% successful rainfall determination rate was achieved using raindrop detection results when we varied the threshold of the number of raindrops.

(a) Input image　(b) Detection result

Fig. 7 Raindrop detection results

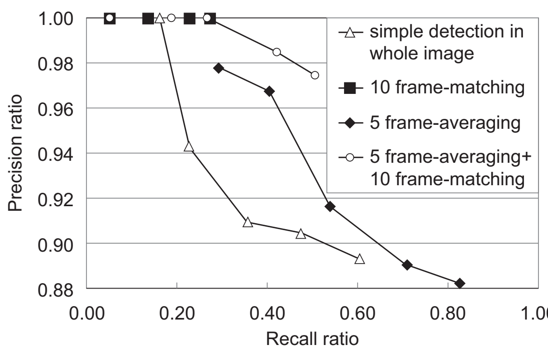


Fig. 8 Accuracy of raindrop detection

４．SUMMARY

In this paper, we proposed a weather recognition system that recognizes fog density level and determines whether it is raining using an in-vehicle camera and mm-wave radar. Experiments were conducted using actual data collected while driving vehicles. The fog level recognition rate achieved 84%, and the rainfall determination success rate was 89%. From these results, we confirmed the effectiveness of the proposed system for rain and fog recognition.

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http://mist.suenaga.m.is.nagoya-u.ac.jp/.

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