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DETECTION OF RAINDROPS ON A WINDSHIELD FROM AN IN-VEHICLE VIDEO CAMERA

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Abstract. *In this paper, we propose a method to detect raindrops from in-vehicle camera images and recognize rainfall using time-series information. We aim to improve the accuracy of raindrop detection by averaging the test images and frame-matching the result of raindrop detection in multiple adjoining frames. According to an evaluation experiment, raindrops were detected precisely enough for automatic wiper control by the proposed method.*
Keywords: Raidrop detection, In-vehicle camera, Time-series information, Subspace method

1. **Introduction.** Recently, driver assistance with computers and various sensors [2-5], especially in-vehicle camera systems are being actively developed, since images taken from such systems contain important visual information [6]. Human beings visually recognize rapidly changing traffic conditions when driving. In-vehicle cameras may also capture similar visual conditions. The following are examples of driver-assistance systems that use video images to impart traffic-related information; self-steering from white line recognition [7]; distance adjustment between cars from leading vehicle recognition [8]; automatic braking systems from pedestrian recognition [9], and so on.

A close relation exists between driver assistance and weather recognition [10][11]. Since in rain, driving is more difficult than in fair conditions, accident rates dramatically increase. Weather changes temporally and spatially, so we believe that it is important to develop techniques that recognize weather in real-time by in-vehicle sensors for driver assistance. Actually, auto-wiping systems are already implemented on some commercial cars by rain recognition, controlled by a so-called “rain sensor.” But employing a specific sensor for each purpose increases the number of sensors which is undesirable from the viewpoint of appearance, space, cost, and maintenance. Since raindrops scatter light, a rain sensor detects rainfall by observing changes in the amount of light received from infrared rays emitted from a LED. However, the target region for detection covered by the sensor is small, so it does not necessarily reflect the changes in the visibility from

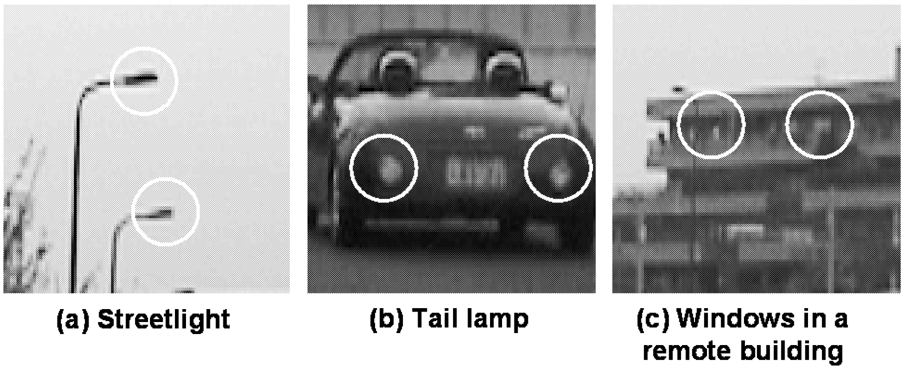


FIGURE 1. Objects whose characteristics resemble the image features of a raindrop.

a driver's view point. On the contrary, an in-vehicle camera covers most of the driver's visual field since it targets the entire windshield.

We have previously proposed a method of detecting raindrops from in-vehicle camera images by template matching using the subspace method and judging rainfall from the detected results [1]. This method suppresses false detection of raindrops by limiting the detection to the sky region which does not have complex patterns in the background as exemplified in Figure 1. However, it was ineffective in that the ratio of sky region to the entire image is small, such as in an urban district crowded with high buildings or in a tunnel.

Hence, in this paper, we propose a method that does not require region restriction for stable raindrop detection, by using time-series information. While positions of raindrops on the windshield do not move in relation to the in-vehicle camera, the external view changes when a car is moving. Because of this, raindrops are emphasized by the change of the background. Taking advantage of this phenomenon, we try to improve the detection accuracy by focusing on the temporal change of the image with raindrops which is difficult to detect from a single frame by the influence of complex backgrounds. By using time-series information, we expect to obtain the following advantages:

- Emphasis of the feature of raindrop on complex background patterns by averaging adjoining frames
- Reduction of false detections by matching candidates of raindrop positions between sequential frames

The proposed method is described in Section 2 and the evaluation in Section 3. Then the paper is summarized in Section 4.

2. Raindrop Detection Method.

2.1. Overview of the process.

As shown in Figure 2, our method is composed of three stages; Learning, Detection, and Judgment. In this section, we describe the flow and the improvement of the method by using time-series information. The previous method detected raindrops only from the sky region in an input image [1]. However, this approach restricted the application of the method to in-vehicle camera images with a relatively

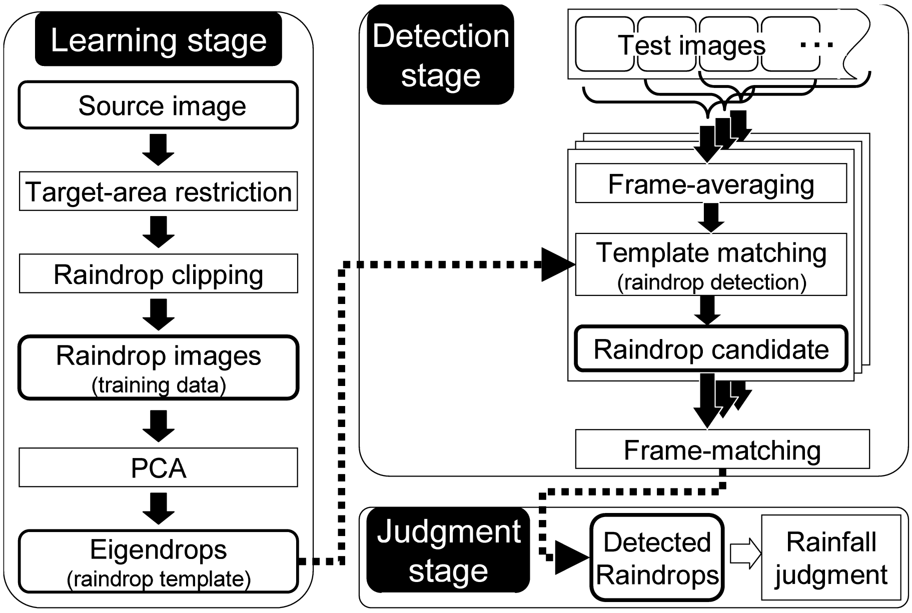


FIGURE 2. The flow diagram for rainfall recognition.

large sky region. The method which we propose in this paper revises this problem by emphasizing the raindrops using time-sequence information in the detection stage.

Learning Stage. In this stage, we extract image features of raindrops on a windshield using PCA that represent the essential characters of raindrops. Raindrop image features are defined as having the following characteristics: edges that feature a raindrop outline, blurry edges behind raindrops, and refraction of light by raindrops. 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 as in Figure 3. Raindrop texture varies since the background reflecting them varies. However we believe that raindrops share at least the above features.

First, as a training set, a rectangular region circumscribing each raindrop is cut manually from images of a windshield taken in rainy weather. Only raindrops are cut out to obtain stable image features in the sky region. A total of K images are prepared for learning. Next, they are normalized in size to width W and height H, represented as one-dimentional vectors, which are then normalized so that they become unit vectors with means of 0, represented as:

$$\mathbf{x}_i = (x_1, x_2, \cdots, x_N)^T, \tag{1}$$

where $N = W \times H$. Let a matrix arranged by K randomly selected vectors from the test images be

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_K] \tag{2}$$

and its covariance matrix be $\mathbf{Q} = \mathbf{X}\mathbf{X}^T$. The eigenvectors $\{\mathbf{e}_1, \mathbf{e}_2, \cdots, \mathbf{e}_R\}$ corresponding to the largest R eigenvalues of $\mathbf{Q}$ are selected as the feature vectors. A subspace generated by these eigenvectors are named as "eigendrops".

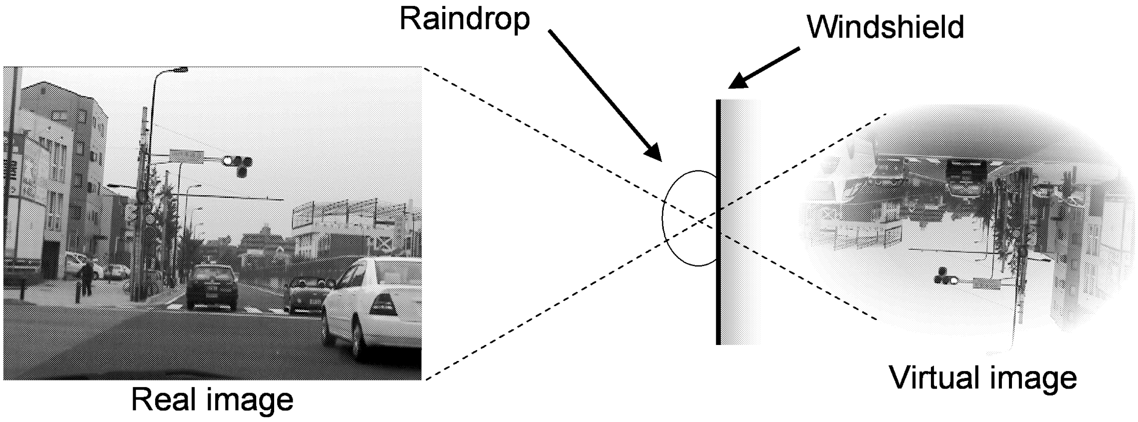


FIGURE 3. Image feature of raindrop.

Detection Stage. Raindrops are detected from the test images as follows. First, an averaged image is made from multiple sequential frames obtained from the input video. In the averaged image, we focus on rectangular areas with the size of $W \times H$. Let the area be represented by a one-dimensional normalized vector $\mathbf{a}$. Next, we compute the degree of similarity $S(\mathbf{a})$ of $\mathbf{a}$ with the eigendrops. $S(\mathbf{a})$ is defined as:

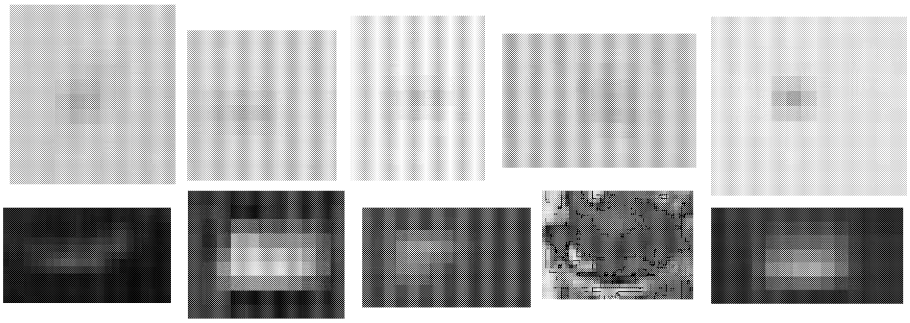
$$S(\mathbf{a}) = \sum_{r=1}^{R} (\mathbf{a}, \mathbf{e}_r) \qquad ((\mathbf{x}, \mathbf{y}) : innerproduct). \tag{3}$$

The area is detected as a raindrop candidate if $S(\mathbf{a})$ is larger than a threshold. They are detected by computing $S(\mathbf{a})$ throughout the frame by shifting the focused rectangular area. Finally, raindrop regions are obtained by frame-wise matching the raindrop candidates.

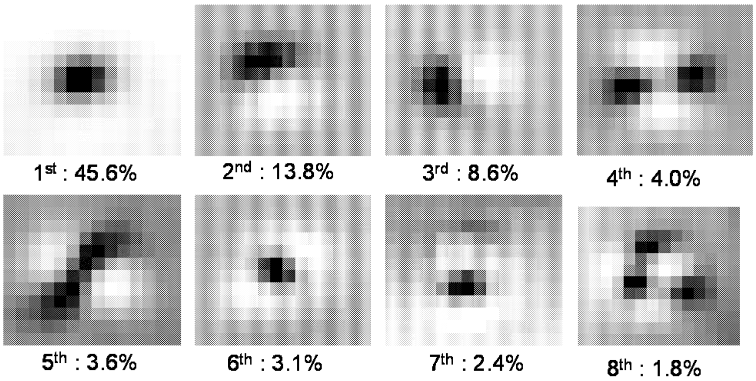
Judgment Stage. Rainfall is judged by counting the number of raindrops detected in the detection stage. If the number of raindrops in the image exceeds a certain threshold, we judge that it is rainy and not rainy if it does not.

2.2. **Raindrop detection from an entire image by averaging adjoining frames.** The original method of raindrop detection described in 2.1, had a risk to false-detect non-raindrop regions as raindrops by the influence of complex background patterns. Hence, in this paper, we propose to emphasize the raindrops by averaging multiple adjoining frames in the detection stage. By detecting raindrops from the averaged image, robust raindrop detection from the entire frame is expected.

2.3. **Reduction of false detection by frame-matching raindrop candidates.** If positions of raindrops are stable on the windshield, a raindrop should be detected at the same position in the next frame. On the other hand, a position of a falsely detected raindrop by complex background patterns should be instable. Hence, we considered that false detection could be reduced by matching the results of raindrop detection across adjoining frames. An AND operation is applied to raindrop candidates across multiple adjoining frames.



(a) Various raindrop images



(b) Eigendrops and their contribution rates

FIGURE 4. Example of raindrop images and eigendrops.

3. Experiments.

3.1. Conditions. We mounted a digital video camera on a car and took images (30 fps, 640×480 pixels, grayscale).

The proposed raindrop detection method was applied to each frame of the input video sequence. Then recall and precision ratios of the raindrop detection were calculated to evaluate the detection accuracy. In the learning stage, the eigendrops were made from 500 raindrop images. Template matching in the detection stage was achieved by shifting the templates (eigendrops) 1 pixel at a time.

We also experimented the rainfall judgment using the results from the raindrop detection. First, we chose at random 100 images for each of fair and rainy weather. Next, we determined the threshold (the number of detected raindrops). Then the number of images judged as correct weather was counted. We observed changes of rainfall judgment by changing the threshold.

Figure 4 shows the clipped raindrops and the eigendrops created from them. The dimension of the subspace was six when they were made.

3.2. Results.

3.2.1. *Raindrop detection.* Figure 5 shows examples of raindrop detection in various experimental conditions, while Figure 6 shows the recall and precision curves. The four

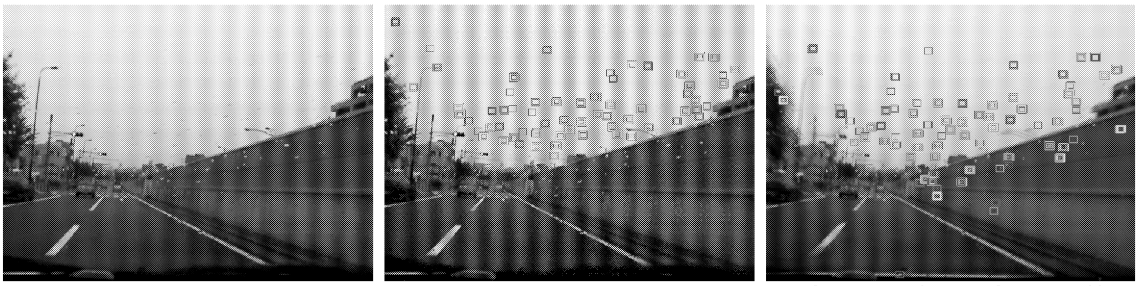


FIGURE 5. Result of raindrop detection result.

curves represent precision and recall ratios of raindrop detection with various thresholds. Compared to a simple method that detects raindrops without frame-matching and frame-averaging, we can see that the precision ratios when 10 frame-matching were applied are high, and the recall ratios when 5 frame-averaging were applied are high. Moreover, the proposed method that employ frame-matching and frame-averaging improved both precision and recall ratios. The recall and precision ratios represent the degree of detection failure and false detection, respectively; if the detector performs well, each ratio will be close to 1.0. When the number of ground truth raindrop areas is A, and the number of detected raindrop areas is B: Precision $= (A \cap B/B)$, Recall $= (A \cap B/A)$. When the number of frames used for averaging increases, although recall improves significantly, precision drops somewhat. When the number of frames used for frame-matching increases, although precision improves, recall drops.

We checked the condition that recall improved the most when precision was over 0.95 by changing the number of frames used for the averaging and the frame-matching. The best result was precision = 0.97 and recall = 0.51 when similarity threshold = 0.70, 5 frame-averaging, and 10 frame-matching.

3.2.2. *Rainfall judgement.* Figure 7 shows the results of fair or rainy weather judgments while changing the threshold for detection, from the results of the raindrop detection by the proposed method in case of 5 frame-averaging, 10 frame-matching, and similarity threshold = 0.70. We judged the weather correctly by 88 percent when the threshold for detection was set to 8, for example.

3.3. **Discussion.** The precision is more important then the recall for practical use as a windshield wiper controller, since to incorrectly recognize raindrops and let a windshield wiper malfunction must be evaded most. However it is also a problem when recall is too low.

Table 1 makes a comparison of the raindrop detection accuracy between the proposed method and other methods. [1], Method 1 is our previous method proposed in [1]. This method restricts the target region of raindrop detection to the sky region to reduce false detections which occured from complex patterns in the background as shown in Fig. 1. Method 2 is the method that applied Method 1 to the entire image including complex backgrounds, therefore the precision ratio decreased because of many false detections compared to Method 1. By using time-series information, the proposed method however reduced the false detections drastically. Moreover, while the proposed method detected

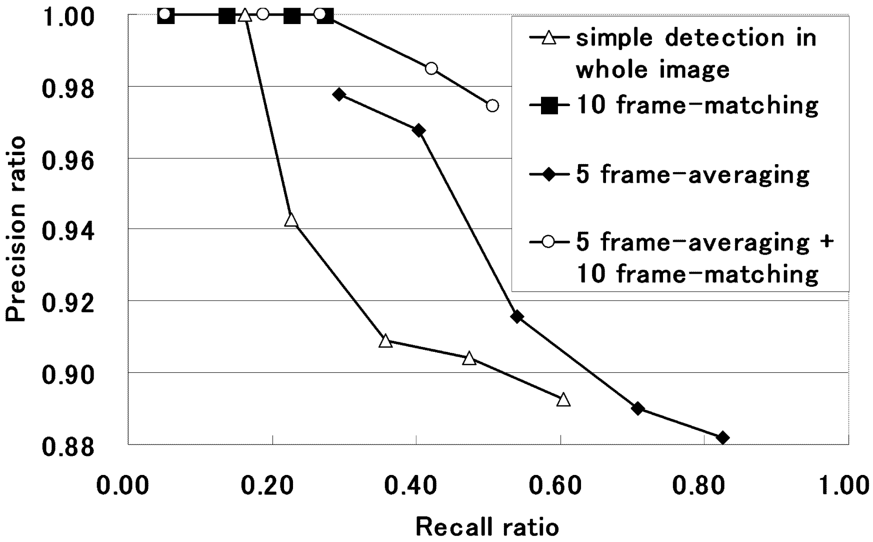


Figure 6. Accuracy of raindrop detection by the proposed method.

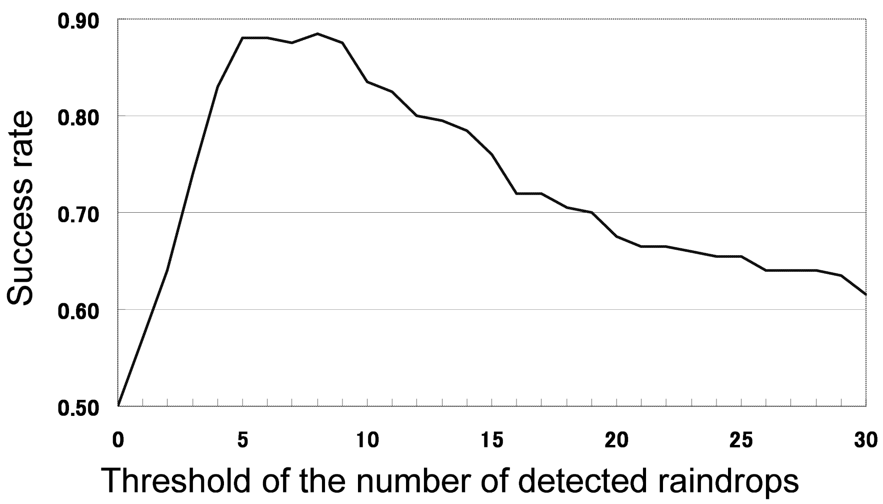


Figure 7. Success rate of rainfall judgment by changing the threshold.

raindrops from the entire image, the accuracy was not inferior to that of Method 1 by restricting the target region of raindrop detection to the sky region. This enables accurate raindrop detection from images captured while driving in urban districts crowded with high buildings or in a tunnel, where a large sky region does not exist.

When the proposed method is applied to rainy weather conditions that are extremely different from the experimental condition, we consider that the size and the shape of eigendrops needs to be changed to obtain high detection accuracy. Evaluation of the proposed method under various rainy weather conditions is one for future work.

The success rate of rainfall judgment using the result of the proposed method showed 0.88. From this, we confirmed that the accuracy of raindrop detection was high enough to judge rainfall. As for rain fall judgment in night time driving, a method that uses the refraction of light as an image feature, the method proposed in [1] seems to be appropriate rather than the proposed method.

4. **Conclusion.** In this paper, we proposed an improved method which detects raindrops from in-vehicle camera images without detection region restriction. The experimental results using actual images revealed the effectiveness of the proposed method:

- The proposed method detected raindrops precisely (precision = 0.97, recall = 0.59) from entire images using time-series information.
  - Emphasizing raindrop features by averaging frames made it possible to detect raindrops on complex background patterns.
  - Frame-matching of the results of raindrop detection reduced dramatically the false detections.
- The raindrop detection accuracy was high (success rate = 0.88) enough to judge rainfall.

Future work will include evaluation of the method under various rainy weather situations according to time and place.

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The works are developed based on the MIST library, available at *http://mist.suenaga.m.is.nagoya-u.ac.jp/*.

REFERENCES

[1] Kurihata, H., T. Takahashi, Y. Mekada, I. Ide, H. Murase, Y. Tamatsu and T. Miyahara, Rainy weather recognition from in-vehicle camera images for driver assistance, *Proc. of the IEEE Intelligent Vehicles Symposium 2005*, pp.204-209, 2005.

[2] Wada, M., T. Yendo, T. Fujii and M. Tanimoto, Road-to-vehicle communication using LED traffic light, *Proc. of the IEEE Intelligent Vehicles Symposium 2005*, pp.600-605, 2005.

[3] Watta, P., Y. Hou, S. Lakshmanan and N. Natarajan, Improving driver pose estimation, *Proc. of the IEEE Intelligent Vehicles Symposium 2002*, pp.310-315, 2002.

[4] Reyher, A., A. Joos and H. Winner, A lidar-based approach for near range lane detection, *Proc. of the IEEE Intelligent Vehicles Symposium 2005*, pp.146-151, 2005.

Table 1. Comparison of the detection accuracy with the previous method

	Target region	Time-series information	Precision	Recall
Method 1	Only sky region	Not used	0.97	0.59
Method 2	Entire image	Not used	0.54	0.59
Proposed method	**Entire image**	**Used**	**0.97**	**0.51**

[5] Shang, T. and S. Wang, Knowledge acquisition and evolution methods for human driving intelligence, *International Journal of Innovative Computing, Information and Control*, vol.2, no.1, pp.221-236, 2006.

[6] Koyamaishi, M., H. Sakai, T. Fujii and M. Tanimoto, Acquisition of position and direction of in-vehicle camera for HIR system, *Proc. of the IEEE Intelligent Vehicles Symposium 2004*, pp.848-853, 2004.

[7] Collado, J. M., C. Hilario, Arturo de la Escalera and J. Armingol, Detection and classification of road Lanes with a frequency analysis, *Proc. of the IEEE Intelligent Vehicles Symposium 2005*, pp.77-82, 2005.

[8] Liu, T., N. Zheng, L. Zhao and H. Cheng, Learning based symmetric features selection for vehicle detection, *Proc. of the IEEE Intelligent Vehicles Symposium 2005*, pp.123-128, 2005.

[9] Mochizuki, D., Y. Yano, T. Hashiyama and S. Okuma, Pedestrian detection with a vehicle camera using fast template matching based on background elimination and active search, *IEICE Trans. Inf. & Syst.*, vol.J87-D-II, no.5, pp.1094-1103, 2004 (in Japanese).

[10] Narasimhan, S. G. and S. K. Nayar, Contrast restoration of weather degraded images, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.25, no.6, pp.713-723, 2003.

[11] Hasegawa, T., Visibility assessment methods on road – Development of visibility assessment methods using digital images under daytime fog condition, *Tech. Rep. of IEICE Pattern Recognition and Media Understanding*, 2004-31, 2004 (in Japanese).