2012 15th International IEEE Conference on Intelligent Transportation Systems
Anchorage, Alaska, USA, September 16-19, 2012

Visibility Estimation of Traffic Signals under Rainy Weather Conditions for Smart Driving Support

Ryuhei Sato*, Keisuke Doman†,*, Daisuke Deguchi**, Yoshito Mekada***,
Ichiro Ide*, Hiroshi Murase*, and Yukimasa Tamatsu****

* Graduate School of Information Science, Nagoya University, Japan
** Information and Communications Headquarters, Nagoya University, Japan
*** School of Information Science & Technology, Chukyo University, Japan
**** DENSO CORPORATION, Japan
† Japan Society for the Promotion of Science, Japan

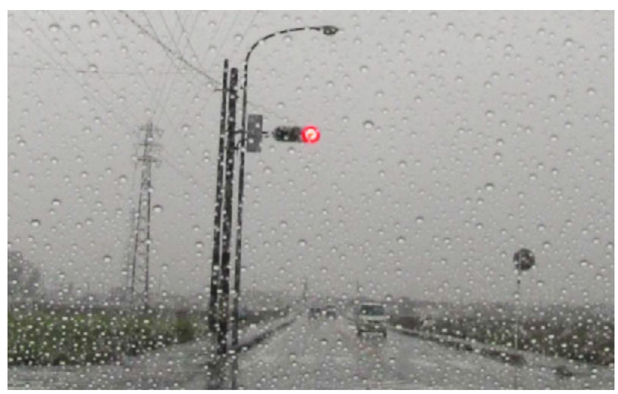
Email: sator@murase.m.is.nagoya-u.ac.jp, murase@is.nagoya-u.ac.jp

Abstract— **The aim of this work is to support a driver by notifying the information of traffic signals in accordance with their visibility. To avoid traffic accidents, the driver should detect and recognize surrounding objects, especially traffic signals. However, when driving a vehicle under rainy weather conditions, it is difficult for drivers to detect or to recognize objects existing in the road environment in comparison with fine weather conditions. Therefore, this paper proposes a method for estimating the visibility of traffic signals for drivers under rainy weather conditions by image processing. The proposed method is based on the concept of visual noise known in the field of cognitive science, and extracts two types of visual noise features which ware considered that they affect the visibility of traffic signals. We expect to improve the accuracy of visibility estimation by combining the visual noise features with the texture feature introduced in a previous work. Experimental results showed that the proposed method could estimate the visibility of traffic signals more accurately under rainy weather conditions.**

I. INTRODUCTION

Recently, the demand for driver assistance systems is increasing. In particular, the development of an assistance system for rainy weather conditions is an important task because of the difficulty of driving under rainy weather conditions. The main factor which causes such a difficulty is the existence of raindrops on the windshield, which may disturb a driver's vision. Even if the driver turns on wipers, many raindrops may still exist on the windshield just before wiping. As a result, they decrease the visibility of objects (e.g. traffic signals, traffic signs, and pedestrians) which are important for driving safety, and consequently, the driver may miss such important objects. Especially, missing a traffic signal leads directly to driving accidents. Therefore, providing the information of a traffic signal in accordance with its visibility is considered useful to assist a driver for preventing traffic accidents. For example, it may be useful for driver assistance to control the warning volume in accordance with the visibility of the traffic signal. Thus, we focus on a method to estimate the visibility of traffic signals for drivers under rainy weather conditions.

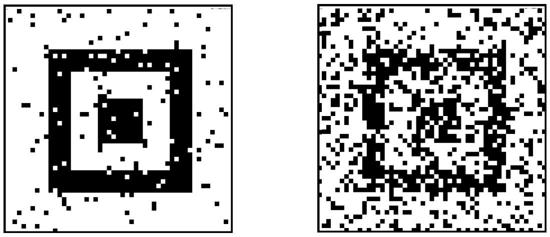
(a) A small number of raindrops (fine visibility).



(b) A large number of raindrops (poor visibility).

Fig. 1. Examples of the same traffic signal captured in different rainy weather conditions.

Kimura et al. proposed a method for estimating the visibility of traffic signals by evaluating the contrast of image features between a traffic signal and its surroundings [1]. They evaluated their method with in-vehicle camera images captured at daytime and nighttime under fine weather conditions. Also, they reported that a texture feature is important



(a) Low visual noise. (b) High visual noise.

Fig. 2. Example of visual noise.

to estimate the visibility of traffic signals in daytime under fine weather conditions. This is calculated as the difference between a traffic signal and its surroundings in the frequency domain. However, in the case of rainy weather conditions, the visibility of traffic signals will be affected by factors different from those under fine weather conditions. Therefore, their method cannot be applied directly for the purpose of visibility estimation under rainy weather conditions.

Under rainy weather conditions, the visibility of drivers is strongly affected by raindrops on the windshield. Figure 1 shows examples of the same traffic signal captured under different rainy weather conditions. The visibility of the traffic signal in Fig. 1 (b) is lower than that in Fig. 1 (a) because of the numbers of raindrops. From this point of view, it can be considered that a raindrop is an important factor affecting the visibility of traffic signals for drivers under rainy weather conditions. In addition, raindrops on the windshield can be considered as visual noise that decreases the visibility of traffic signs, since raindrops are quite small and also obscure the field of the driver's vision. As reported in an experiment in [2], visual noise may cause the delay of action. Figure 2 shows examples of visual noise. Figure 2 (a) is an example of low visual noise, and Fig. 2 (b) is an example of high visual noise. As we can see in these images, the visibility of the square pattern in Fig. 2 (b) is much lower than that in Fig. 2 (a). Therefore, this paper introduces visual noise features that significantly affect the visibility of traffic signals. The proposed method estimates the visibility of traffic signals for drivers by image processing with visual noise features in combination with the texture feature introduced in the previous work for fine weather conditions [1]. In this way, we expect to improve the accuracy of visibility estimation of traffic signals under rainy weather conditions.

Contributions of this paper are as follows

1) Introduction of visual noise feature for visibility estimation
2) Experiments of visibility estimation for traffic signal under rainy weather condition.

This paper is organized as follows, section II describes the works related to the proposed method, and section III explains the details of the proposed method. Section IV shows the experimental setup and results using in-vehicle camera images that were captured under rainy weather conditions. Then, we discuss the results in section V. Finally, conclusions and future works are described in section VI.

II. Related works

Several research groups have proposed methods to estimate the visibility of unspecified objects. Itti et al. proposed a method for generating a saliency map to detect salient objects in an image [3]. Based on visual characteristics of human eyes, they computed a saliency map by constructing image pyramids of several image contrast features. This method took a bottom-up approach, and did not focus on the estimation of the visibility of specific objects. In contrast, some research groups proposed methods for estimating the visibility of specific objects, such as traffic signals, traffic signs, and pedestrians. As described above, Kimura et al. proposed a method for estimating the visibility of traffic signals at daytime and nighttime under fine weather conditions [1]. They employed texture features calculated from the contrast between a traffic signal and its surroundings, and reported the effectiveness for the visibility estimation under fine weather conditions. Doman et al. extended this idea to estimate the visibility of traffic signs [4]. They computed several image features, such as texture features, appearances of a traffic sign, and then the visibility is computed by integrating these image features. Engel et al. tried estimating the detectability of pedestrians by using SVR (Support Vector Regression), and various image features including HOG (Histograms of Oriented Gradient) for the regression [5]. Basically, these methods estimated the visibility by evaluating the contrast of image features between a target object and its surroundings.

On the other hand, some research groups tackled problems of visibility estimation or visibility enhancement under adverse weather (esp. foggy) conditions. Narasimhan et al. proposed a method to improve the contrast of an image captured under foggy conditions by using Koschmieder's model [6]. Hautiére et al. extended this idea to estimate the visibility of the entire road environment, and they proposed several methods to estimate the visibility distance of the entire road environment under foggy conditions [7], [8]. Also, they evaluated their method by applying them to both in-vehicle camera [7] and roadside camera [8]. Mori et al. proposed a method for estimating the visibility of a forward vehicle under foggy conditions by using an in-vehicle camera and a millimeter wave radar [9]. However, foggy conditions have different characteristics in comparison with rainy weather conditions. Therefore, these methods cannot directly be applied to estimate the visibility of traffic signals under rainy weather conditions.

III. Visibility estimation of traffic signals under rainy weather conditions

Figure 3 illustrates the process flow of the proposed method. The proposed method is composed of three parts: (A) computation of visual noise feature, (B) computation of texture feature, and (C) feature integration of visual noise and texture for estimating the visibility of traffic signals. Here, we assume that the position and the size of the target traffic signal in the input image can be obtained with an existing technique [10], [11]. The following sections describe the details of each part of the process flow.

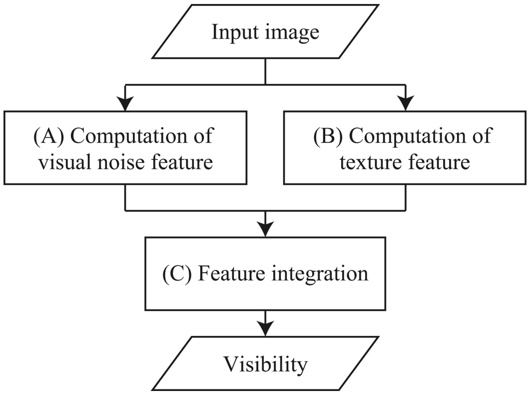


Fig. 3. Process flow of the proposed method.

A. Computation of visual noise feature

As mentioned earlier, raindrops on the windshield affect the visibility of traffic signals for drivers as visual noise. If higher visual noise was observed in the field of a driver's vision, the visibility of traffic signals for the driver will decrease in proportion to the amount of visual noise. Therefore, the proposed method evaluates the amount of visual noise by computing two types of features from an in-vehicle camera image. The first is the amount of raindrops observed on the windshield denoted as I_r, and the second is the average size of raindrops denoted as I_s. Concretely, each feature value is calculated by

$$I_r = N_{\text{rain}}, \tag{1}$$

$$I_s = \frac{1}{N_{\text{rain}}} \sum_{i=0}^{N_{\text{rain}}} S_i, \tag{2}$$

where N_{rain} is the number of raindrops, and S_i is the area of the i-th raindrop.

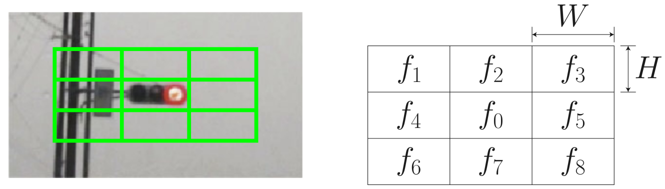
For example, Kurihata et al. proposed a method to extract raindrops by evaluating their appearances on eigenspace [12]. Gormer et al. simply extracted raindrops by applying an edge detection filter [13]. The proposed method detects raindrops on the windshield by a simple and fast method based on the edge of raindrops considering the shape and area of raindrops. First, the raindrop candidates are extracted using the Canny edge detection. Erosion and dilation are applied to the results of the edge detection and each region is labeled by connected-component labeling. After this, the raindrops are detected by the following two criteria.

1) The difference between the area of each region and the average is below a threshold.
2) The aspect ratio of a minimum circumscribing rectangle of each region is above a threshold.

If both criteria are met, the proposed method detects the region as a raindrop. Then, N_{rain} and the size of each raindrop are calculated by the detection result.

B. Computation of texture feature

As reported in [1], it is easy to detect a traffic signal for drivers if it has a different texture from its surroundings.



(a) Example of a traffic signal and its surrounding areas.

(b) Schematic diagram of reagions.

Fig. 4. Regions for computing the texture feature. W and H are the width and the height of the target traffic signal respectively.

That is, the visibility of a traffic signal tends to increase in proportion to the degree of the texture difference from its surrounding. Therefore, by working in the frequency domain, the proposed method evaluates the texture difference between a traffic signal and its surroundings, and uses it for computing the visibility.

First, as shown in Fig. 4 (a), the proposed method puts 3×3 blocks surrounding a traffic signal. Here, the width and the height of the traffic signal are W and H, respectively, and the i-th block is represented as f_i $(i = 0, 1, \cdots, 8)$. Then, the proposed method transforms pixel values in each block into the frequency domain by applying FFT (Fast Fourier Transform), which yields the power spectrum $F_i(j, k)$ of each block. Finally, the texture difference between the traffic signal and its surroundings is computed as

$$I_t = \sum_{i=1}^{8} \sum_{j=0}^{W} \sum_{k=0}^{H} |F_0(j, k) - F_i(j, k)|, \tag{3}$$

C. Feature integration

This section explains the computation of the visibility of a traffic signal for drivers by integrating features of visual noise and textures. As proposed in [4], this paper employs linear regression for integrating these features. The visibility of a traffic signal is calculated as

$$\hat{V} = \sum_{n=1}^{N} \lambda_n I_n, \tag{4}$$

where N is the number of features for estimating the visibility, I_n is the n-th feature calculated by applying the method described earlier, and λ_n is a weight of the n-th feature. Here, we determine these coefficients by a linear regression with training data, since it is difficult to choose these coefficients appropriately in a top-down fashion.

Finally, we regard the higher $\hat{V}$ as the finer visibility of the target traffic signal.

IV. Experiment

We conducted an experiment to evaluate the effectiveness of the proposed method. In this experiment, we evaluated the accuracy of the visibility estimated by the proposed method by using in-vehicle camera images captured under rainy weather conditions. To evaluate the accuracy of the proposed method, visibility values calculated by the proposed method were compared with their target visibility values. Here, the

(a)

(b)

Fig. 5. Examples of images used in the experiment.

target visibility values were obtained through experiments following Thurstone's paired comparison method [14]. The following sections describe details of the dataset and the evaluation method used in the experiment.

A. Dataset

We prepared 29 images (600×375 pixels) captured by an in-vehicle camera. These images contained traffic signals with three kinds of traffic signal lamp conditions (red, yellow, and green). Figure 5 shows examples of images used in the experiment. These images were captured in daytime under rainy weather conditions. Each image was manually cropped so that the traffic signal exists in the horizontal center of the image in an equal size. Here, the sizes of the all images were normalized under assumption that a driver assistance system alerts the driver when the vehicle reaches a certain distance from a traffic signal.

For quantitative evaluation, a target visibility value for each traffic signal was determined through experiments with nine human subjects (males whose ages were between 20 and 40). Here, Thurstone's paired comparison method [14] was used for computing the target visibility values. This method can compute quantitative values corresponding to human perception through comparisons of two objects, such as in-vehicle camera images, in this experiment. By using this method, the target visibility values for 29 images were calculated. Note that the number of image pairs was ${}_{29}\mathrm{C}_2 = 406$, and each pair was compared by four human subjects.

TABLE I

EXPERIMENT RESULT

Method	Features	MAE	SD
Previous method [1]	Texture feature I_t	0.192	0.135
Comparative method 1	Texture feature I_t Number of rain drops I_r	0.147	0.085
Comparative method 2	Texture feature I_t Size of rain drops I_s	0.168	0.115
Proposed method	Texture feature I_t Number of rain drops I_r Size of rain drops I_s	0.137	0.085

The lower mean absolute error (MAE) and standard deviation (SD) are, the higher the estimation accuracy is.

That is, $1,624$ paired comparisons ware performed through this experiment in total. In this experiment, the output values of Thurstone's method were normalized within [0,1]. The value 0 and 1 correspond to the worst and the finest visibility of traffic signals in the experimental dataset, respectively. Figure 6 shows examples of the images and their target visibility values V in the experiment.

B. Conditions

To confirm the effectiveness of the proposed method, we compared the following four methods that employ different image features.

1) Previous method [1]: I_t
2) Comparative method 1: I_t and I_r
3) Comparative method 2: I_t and I_s
4) Proposed method: I_t, I_r, and I_s

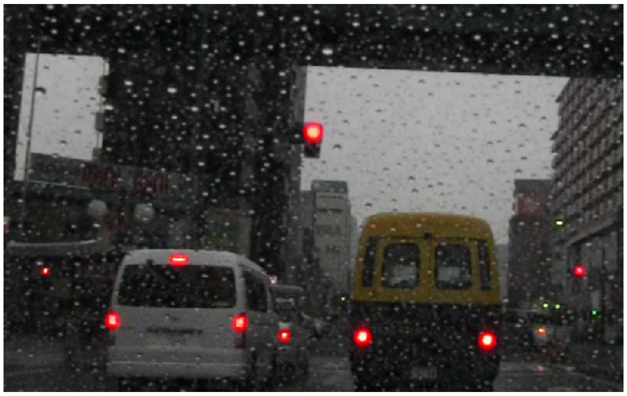
Here, I_r and I_s represent the visual noise features described in section III (A), and I_t the texture feature described in section III (B).

The accuracy of each method was evaluated by 3-fold cross validation. First, we randomly divided the experimental dataset (29 images) into three subsets: Set A (10 images), Set B (10 images), and Set C (9 images). Then, one subset was used for evaluating the estimation error while the remaining two subsets were used for training the coefficients λ_n $(n = 1, 2, 3)$ in Eq. (4), and a total of three results for all subsets were averaged. Here, linear regression was used for computing λ_n. The mean absolute error (MAE) and the standard deviation (SD) were used to observe as the estimation errors; the lower the MAE and SD are, the higher the estimation accuracy is.

V. RESULTS AND DISCUSSIONS

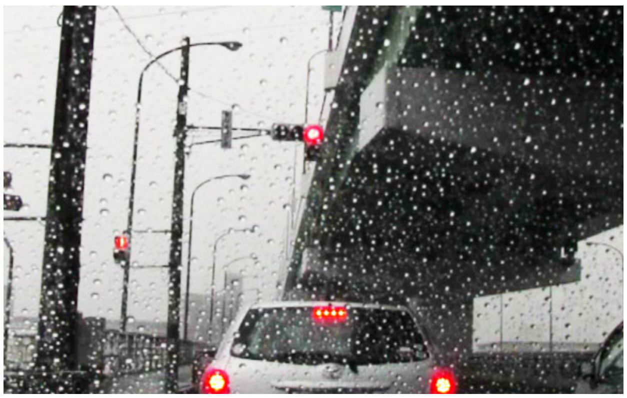
Table I shows the results of the experiment. The lowest MAE and SD were obtained by the proposed method. To confirm the significance of the proposed method, we evaluated MAEs of the proposed method and the previous method by t-test with 5% significance level. From these results, it was confirmed that the proposed method considering visual noise estimated the visibility of traffic signals for drivers more accurately under rainy weather conditions in comparison with the previous method.

As seen in Fig. 7, the visibility of traffic signals decreased greatly under heavy rain conditions. However, the proposed

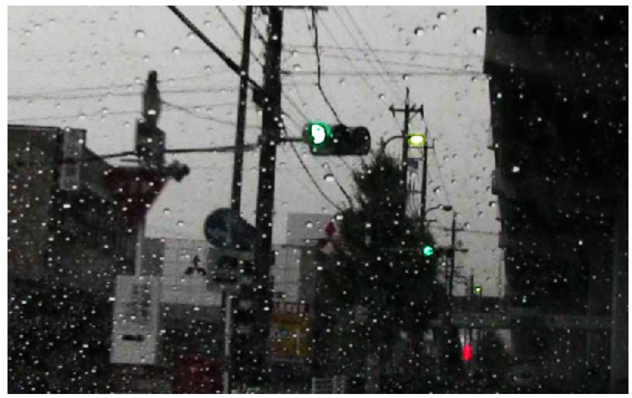


(a) V= 0.000

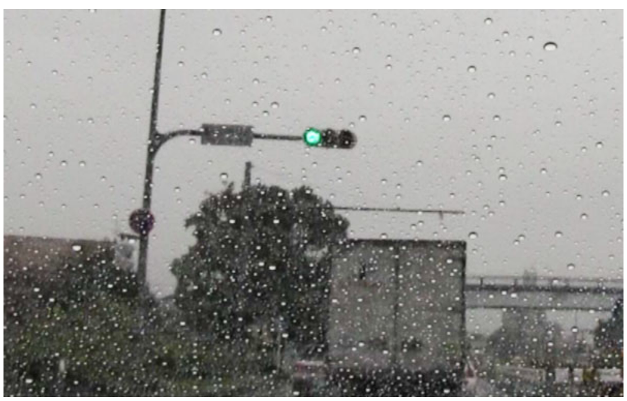
(b) V= 0.066



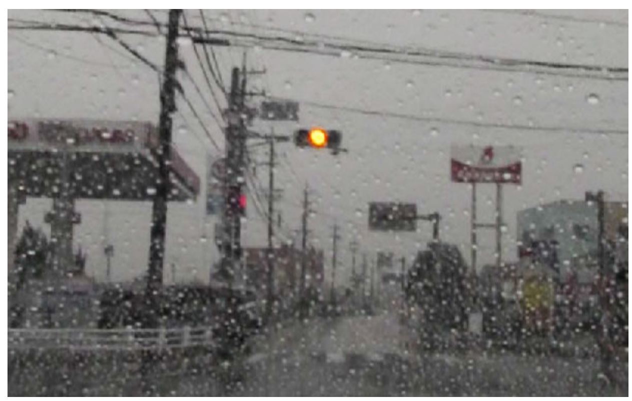
(c) V= 0.165



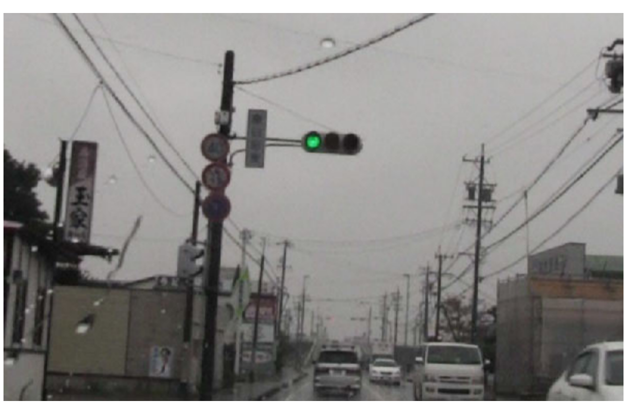
(d) V= 0.351



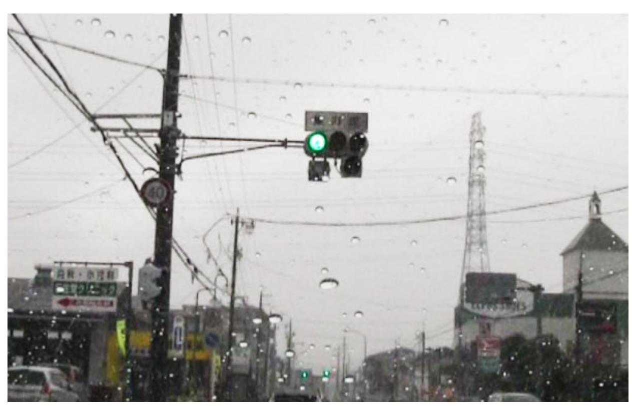
(e) V= 0.527



(f) V= 0.615



(g) V= 0.811



(h) V= 1.000

Fig. 6. Examples of images and their target visibility values V in the range of [0, 1] obtained by Thurstone's paired comparison method with human subjects. The higher the value of V is, the finer the visibility is.

Fig. 7. An example of an in-vehicle camera image captured under a heavy rain condition.

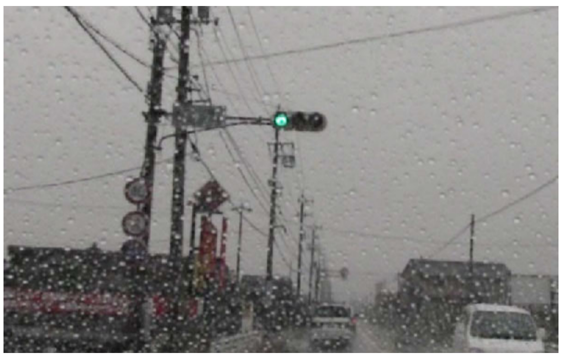


Fig. 8. An example of an in-vehicle camera image whose visibility value was 0.489.

method output 0.456 for the visibility of Fig. 7, because raindrops could not be observed anymore in the image. Here, an image with a visibility value of 0.456 should be similar to Fig. 8. As we can confirm from these images, the proposed method did not estimate the visibility of Fig. 7 correctly. Since the proposed method computes the effect of visual noise by the number of raindrops and their sizes, the method could not compute the visibility correctly in the case that raindrops could not be observed. Therefore, additional image features should be considered to estimate the visibility of traffic signals under heavy rain conditions. In addition, traffic signals have three kinds of traffic signal lamp conditions (red, yellow, and green), which may also affect their visibility. However, The experimental dataset contained traffic signals with all kinds of traffic signal lamp conditions, and the proposed method did not consider their difference. Thus, the estimation accuracy may be improved by considering the color of a traffic signal lamp.

VI. Conclusions and Future Works

This paper proposed a method for estimating the visibility of traffic signals for drivers by image processing under rainy weather conditions. The proposed method introduced visual noise corresponding to visual characteristics of human eyes, and used it for estimating the visibility of traffic signals for drivers. Visual noise was evaluated by computing the number of raindrops and their sizes on the windshield. Then, visual noise features and texture features were combined to estimate the visibility of traffic signals for drivers. We conducted an experiment using in-vehicle camera images. Experimental results showed that the proposed method could estimate the visibility of traffic signals for drivers accurately under rainy weather conditions in comparison with the previous method.

Future works will include: (1) the introduction of additional image features, (2) the evaluation of the proposed method at night time under rainy weather conditions, and (3) the experiments on large datasets.

Acknowledgements

Parts of this research were supported by the Grant-in-Aid for Young Scientists from MEXT, the Grant-In-Aid for Scientific Research from MEXT, the Core Research for Evolutional Science and Technology (CREST) project of JST, the Research Grant (K23-XVI-373) from Kayamori Foundation of Informational Science Advancement and Grant-in-Aid for JSPS Fellows. MIST library (http://mist.murase.m.is.nagoya-u.ac.jp/) was used for developing the proposed method.

References

[1] F. Kimura, T. Takahashi, Y. Mekada, I. Ide, H. Murase, T. Miyahara and Y. Tamatsu, “Measurement of Visibility Conditions toward Smart Driver Assistance for Traffic Signals,” Proc. 2007 IEEE Intelligent Vehicles Symposium, pp. 636–641, June 2007.

[2] M. Shidara and B.J. Richmond, “Effect of Visual Noise on Pattern Recognition,” J. of Experimental Brain Research, vol.163, no. 2, pp. 239–241, March 2005.

[3] L. Itti, C. Koch and E. Niebur, “A Model of Saliency-Based Visual Attention for Rapid Scene Analysis,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol.20, no. 11, pp. 1254–1259, Nov. 1998.

[4] K. Doman, D. Deguchi, T. Takahashi, Y. Mekada, I. Ide, H. Murase and Y. Tamatsu, “Estimation of Traffic Sign Visibility Considering Temporal Environmental Changes for Smart Driver Assistance,” Proc. 2011 IEEE Intelligent Vehicles Symposium, pp. 667–672, June 2011.

[5] D. Engel and C. Curio, “Pedestrian Detectability: Predicting Human Perception Performance with Machine Vision,” Proc. 2011 IEEE Intelligent Vehicles Symposium, pp. 429–435, June 2011.

[6] S.G. Narasimhan and S.K. Nayar, “Contrast Restoration of Weather Degraded Images,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol.25, no. 6, pp. 713–724, June 2003.

[7] N. Hautiére, J.-P. Tarel, J. Lavenant and D. Aubert, “Automatic Fog Detection and Estimation of Visibility Distance through use of an Onboard Camera,” Machine Vision and Applications, vol.17, no. 1, pp. 8–20, April 2006.

[8] N. Hautiére, E. Bigorgne and D. Aubert, “Daytime Visibility Range Monitoring through use of a Roadside Camera,” Proc. 2008 IEEE Intelligent Vehicles Symposium, pp. 470–475, June 2008.

[9] K. Mori, T. Takahashi, I. Ide, H. Murase, T. Miyahara and Y. Tamatsu, “Recognition of Foggy Conditions by In-Vehicle Camera and Millimeter Wave Rader,” Proc. 2007 IEEE Intelligent Vehicles Symposium, pp. 87–92, June 2007.

[10] J. Gong, Y. Jiang, G. Xiong, C. Guan, G. Tao and H. Chen, “The Recognition and Tracking of Traffic Lights Based on Color Segmentation and CAMSHIFT for Intelligent Vehicles,” Proc. 2010 IEEE Intelligent Vehicles Symposium, pp. 431–435, June 2009.

[11] R. de Charett and F. Nashashibi, “Real Time Visual Traffic Lights Recognition Based on Spot Light Detection and Adaptive Traffic Lights Templates,” Proc. 2009 IEEE Intelligent Vehicles Symposium, pp. 358–363, June 2009.

[12] H. Kurihata, T. Takahashi, I. Ide, Y. Mekada, H. Murase, T. Miyahara and Y. Tamatsu, “Rainy Weather Recognition from In-Vehicle Camera Images for Driver Assistance,” Proc. 2005 IEEE Intelligent Vehicles Symposium, pp. 205–210, June 2005.

[13] S. Görmer, A. Kummert, S.-B. Park and P. Egbert, “Vision-based Rain Sensing with an In-Vehicle Camera,” Proc. 2009 IEEE Intelligent Vehicles Symposium, pp. 279–284, June 2009.

[14] L.L. Thurstone, “Psychophysical Analysis,” The American J. of Psychology, vol.38, no. 3, pp. 368–389, July 1927.