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Measurement of Visibility Conditions toward Smart Driver Assistance for Traffic Signals

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Abstract— **We propose a method to recognize the visibility of traffic signals from a driver's perspective. The more that driver assistance systems are equipped for practical use, the more information that is being provided for drivers. So each information provision system should select appropriate information based on the situation. Our goal is to realize a system that recognizes the visibility of traffic signals from images taken by in-vehicle cameras and appropriately provides information to drivers. In this paper, we propose a method to measure visibility by two criterions, detectability and discriminability. Each index is computed using image processing techniques. Experiments using actual images showed that the proposed indices correspond well to human perception.**

I. INTRODUCTION

Recently, various driver assistance systems have been actively developed that use both state-of-the-art information communication technology and on-board sensors. These systems provide drivers with such assistance as information provisions, hazard warnings, and driving aid by understanding the environment around the car. However, with the realization of such systems, the amount of information provided to drivers is increasing both in terms of visual and auditory senses. Since watching the screen of a car navigation system while driving disturbs driving, many systems now use sound to provide important information. Information provision by sound is superior to vision, but even by sound, information provision creates a certain level of load on drivers [1][2]. Moreover, providing too much information can be annoying. Hence, the amount of information provided to drivers must be decreased, especially when already recognized or known: we must judiciously select the information to provide to drivers.

For example, let us consider a system using an eye camera that provides the movement of a driver's head and eyes [3]. Such information may reveal what the driver cannot see and provide assistance. Even though the driver's eyes are focusing on an object, that does not necessarily mean that he/she recognizes it (mind distraction). The recognition of head and eye movements does not warrant the selection of information that should be provided to drivers.

Some reminder systems have already been enabled that provide information on previously registered places such as intersections with high accident ratio or a railroad crossing when approaching. Since the driver's visibility condition, however, can be influenced by weather and time, it is not enough to provide information only at places registered beforehand.

In light of the above background, we consider it important to take into account the driver's visibility condition when selecting information that should be provided. In this paper, we focus on traffic signals and propose a method to recognize their visibility from the driver's perspective. Traffic signals were originally developed to be seen clearly by humans, but sometimes situations exist where they are difficult to see. Under such situations, drivers need assistance, although not if it were a normal situation. Our proposed method recognizes the visibility of traffic signals by capturing the frontal view with an in-vehicle camera used in many assistance systems. Visibility is evaluated in terms of two indices, detectability and discriminability. In this paper, we discuss and report the following terms.

- Factors that affect the visibility of traffic signals
- Proposal of a method to recognize the visibility of traffic signals
- Evaluation of the proposed method by experiments with subjects and real images

The rest of this paper is organized as follows. In Section II, we introduce systems that consider driver's visibility conditions and related works to detect and recognize traffic signals. We discuss the visibility decision factors of traffic signals in Section III and describe our method in Section IV. In Section V, we report the experimental results and discuss them. The paper is summarized in Section VI.

II. RELATED WORKS

2.1. Driver assistance systems considering visibility

Danger warning and driver assistance systems that consider the driver's visibility conditions have been developed by recognizing such bad weather as fog and snowstorms. Mori et al. proposed a method to estimate fog density from the image of a preceding vehicle taken by an in-vehicle camera and the distance to it measured by mm-wave radar [4]. The automatic lighting of fog lamps and speed control are expected with this method. Kumon et al. proposed an adaptive cruise control system that considers the driver's visibility condition [5]. The larger a preceding vehicle is, the greater distance drivers would like to maintain. The height and width of the preceding vehicle are measured

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TABLE I

VISIBILITY DECISION FACTORS OF TRAFFIC SIGNALS

○: Factor that affects visibility and discussed in this paper| △: Factor that affects visibility but not mentioned in this paper|
c: Factor regarded as constant in this paper| v: Factor that needs temporal information| -: Factor that does not affect visibility.

Visibility decision factors of traffic signals		Daytime		Nighttime	
		Detectability	Discriminability	Detectability	Discriminability
Property of human eye	Eyesight	c	c	c	c
	Sensitivity state of retina	c	c	c	c
Property of object	Luminance and chromaticity of object	c	c	c	c
	Luminance ratio of tricolor signal lamps	-	○	-	-
	Size of object	c	c	c	c
	Displaying time of object	v	v	v	v
	Expectation of object's existence and its place	v	v	v	v
Property of background	Background texture	○	-	-	-
	Background (neighborhood) luminance	△	-	△	-
	Glare source in peripheral vision	△	△	○	-

using mm-wave radar and camera sensors. They proposed keeping appropriate inter vehicular distance based on the size of the preceding vehicle.

2.2. Traffic signal detection and recognition

Methods that detect and recognize traffic signals have also been proposed [6][7]. Lindner et al. proposed a method to recognize traffic signals from in-vehicle camera images [6]. Their method correctly recognized more than 90% of them using color images. Wada et al. proposed a method to detect and recognize traffic signals with high accuracy by capturing LED traffic signals with a high speed camera [7]. However, even if the status of traffic signals is recognized perfectly, no one wants such information at every intersection.

In this paper, we develop a system that recognizes traffic signal visibility from the driver's perspective. It enables us to develop a driver assistance system that only provides traffic signal information when visibility is poor.

III. Visibility of Traffic Signals

In this section, we discuss the visibility of traffic signals from the driver's perspective. There are two situations when it is difficult for drivers to see traffic signals:

- when a driver cannot find a traffic signal
- when a driver cannot recognize the color

Hence, the visibility of traffic signals is defined by the following two criterions.

- Detectability of traffic signals
- Discriminability of signal lamps

Both detectability and discriminability are differently influenced by numerous factors. Luminance Difference Threshold is a factor that decides the visibility of a general object [8]. For humans to perceive an object and recognize it, its object luminance needs to be different from its background luminance, and the difference of luminance has to be larger than the minimum luminance difference (Luminance Difference Threshold) that the human eye can perceive. This Luminance Difference Threshold is influenced by such factors as observer's visual ability and mental condition, property of an object, luminance condition in eyesight, and so on.

We list such visibility decision factors of traffic signals in Table I. In this paper, the visibility of traffic signals

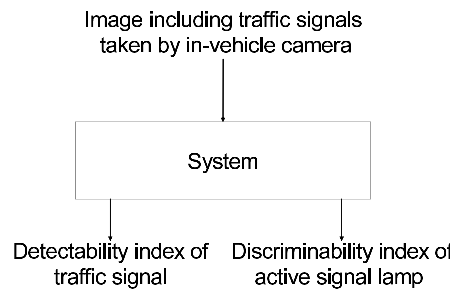

Fig. 1. System overview

is recognized by three factors: glare source in peripheral vision, background texture, and luminance ratio of tricolor signal lamps. In the following sections, we consider the visibility of traffic signals by two criterions, detectability and discriminability.

IV. Method to Measure Visibility based on Visibility Decision Factor

Here, we propose a method to recognize the visibility of traffic signals using the factors discussed in Section III. Fig. 1 shows an overview of the method. Input data are images taken by an in-vehicle camera and output data are two indices: detectability and discriminability.

4.1. Detectability of traffic signals

The following two factors in Table I are used to recognize detectability.

- Glare source in peripheral vision
- Background texture

These two different factors are used to recognize detectability for daytime and nighttime. We chose these two factors because we consider them important for measuring detectability. Fig. 2 shows the process flow. In the following, we explain the details of these factors and describe methods to calculate the indices by image processing.

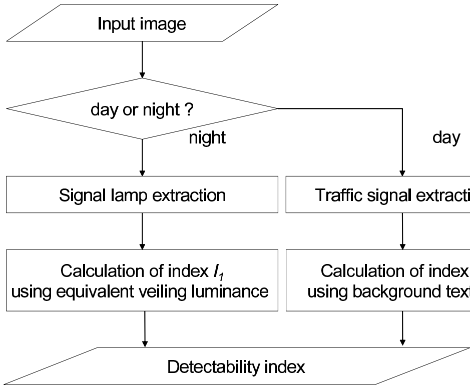

Fig. 2. Flowchart for calculating detectability index

(a) Less glare sources (b) More glare sources

Fig. 3. Examples of situations where (a) traffic signal is found easily due to less influence of glare sources and (b) hardly due to strong influence.

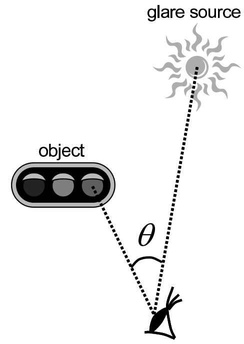

Fig. 4. Positional relationship between object and glare source

(a) Simple background (b) Complicated background

Fig. 5. Examples of situations where (a) detectability of a traffic signal is high due to simple background and (b) detectability is low due to a complicated background

A. Process for nighttime

1) Glare source in peripheral vision

When there is an object with extremely high luminance or strong luminance contrast in the eyesight, it sometimes causes discomfort or a decline of visual function. Therefore, the visibility of an object that should have high perception priority is sometimes degraded. For example,

- when we see the headlights of an oncoming car while driving at night
- when we look directly at the sun

These strong light sources are called glare sources. We often feel it is more difficult to find traffic signals while driving in a neon-lighted downtown than in a street with few street lamps. This is also the effect of glare source (Fig. 3). The brighter the luminance of a glare source and the closer the position to an object that should be perceived, the more object visibility is degraded. The influence degree of a glare source, which is called Equivalent Veiling Luminance, is defined as:

$$L_{eq} = \frac{kE_v}{\theta^2}, \tag{1}$$

where E_v represents glare source luminance [lx] and θ the angle between the object and the glare source direction (Fig. 4). Coefficient k is a constant that depends on photometric units, angle units, observer's age, etc. In this paper, we set $k = 10$, which is generally used for metric units. The bigger the Equivalent Veiling Luminance is, the poorer object visibility is [8]. If there are multiple glare sources in the eyesight, Equivalent Veiling Luminance is simply defined as their total.

2) Process flow

The location of an active signal lamp is detected. Considering the center of the signal lamp region as the position of the target object, Equivalent Veiling Luminance L_{eq} of each glare source is calculated. In this paper, we assume the entire image region to be eyesight. Angle θ is approximately defined by the Euclidean distance between the signal and each glare source on image θ'. Luminance E_v is also defined by the average pixel intensity of glare source E'_v. Consequently, the Equivalent Veiling Luminance of target traffic signal I_1 is calculated by the following equation:

$$I_1 = \frac{1}{R_1} \sum_{j}^{J} \frac{kE'_{vj}}{\theta'^2_j}, \tag{2}$$

where J is the number of glare sources in the image and R_1 is a constant to normalize the index.

B. Process for daytime

1) Background texture

While driving in daytime, it is more difficult to find a traffic signal when it exists in a complicated background than in a simple background such as a clear sky (Fig. 5). So we focus on the background texture feature around traffic signals. The more the texture feature of a traffic signal is similar to its background, the more difficult to find it. We use spatial frequency analysis to quantify texture dissimilarity between a traffic signal region and its background; dissimilarity of power spectrum is calculated.

2) Process flow

A traffic signal image $f_0(x, y)$ is extracted from an input image as a circumscribed rectangular region of the traffic signal. Then power spectrum $F_0(u, v)$ is calculated by applying FFT to the signal image. Eight regions of interest (ROI) are also set as background images $f_i(i = 1, \dots, 8)$. The size of each ROI is identical to $f_0(x, y)$. The position of each ROI is illustrated in Fig. 6. Then texture dissimilarity I_2 is

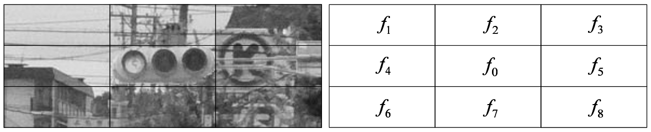

Fig. 6. Traffic signal image $f_0(x, y)$ and eight background images $f_i(i = 1, \ldots, 8)$

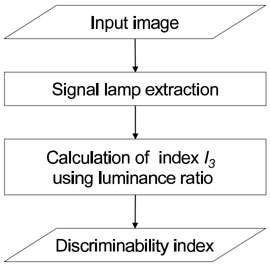

Fig. 7. Flowchart for calculating discriminability index

defined by the total sum of absolute differences between F_0 and $F_i(i = 1, \ldots, 8)$, where the size of $F_0(u, v)$ is $U \times V$. Index I_2 is defined as

$$I_2 = \frac{\sum_{i=1}^{8} \sum_{u=0}^{U} \sum_{v=0}^{V} |F_0(u, v) - F_i(u, v)|}{R_2}, \quad (3)$$

where R_2 is a normalization coefficient.

4.2. Discriminability of signal lamps

To evaluate discriminability, we use the luminance ratio of tricolor signal lamps, as shown in Table I. Fig. 7 shows the process flow. A significant decline of luminance ratio only occurs in a situation where a strong light source (e.g, sunlight) is incident on the signal lamp directly in daytime. So in the proposed method, we only apply this process to images taken in daytime.

1) Luminance ratio

In daytime, when sunlight is directly incident on a traffic signal, especially from an electric bulb signal, pseudo lighting occurs, and it becomes difficult to judge which color is most prominent (Fig. 8). In such situations, the visibility of a LED traffic signal, where pseudo lighting rarely occurs, also declines, because its color fades. If the luminance ratio of two adjacent light sources is small, human vision cannot perceive each light source respectively. The luminance ratio that human can perceive is defined as the Brightness Discrimination Threshold [10], which changes depending on the luminance of an object. This threshold is the value where human eyes can barely discriminate the difference between two light sources. A bigger value is needed so that driver can discriminate the difference easily.

2) Process flow

All signal lamps of a traffic signal are detected and average luminance is calculated. If two light sources have luminance b_1 and b_2 ($b_1 > b_2$), the luminance ratio is defined as $|b_1 - b_2|/b_1$. The smaller the luminance ratio is, the more difficult it is to discriminate them. Discriminability index I_3

(a) High luminance ratio (b) Low luminance ratio

Fig. 8. Examples of situations where (a) signal status is easily seen and (b) active color is not easily discriminable because luminance ratio is not enough

for the active signal lamp is defined as

$$I_3 = \min_i \frac{b - b_i}{b}, \quad (4)$$

where b is the luminance of the active signal lamp and $b_i (i = 1, 2)$ are those of the inactive signal lamps.

V. Experiments

To confirm that the proposed method could recognize the visibility of traffic signals, we applied it to actual images taken by an in-vehicle camera. The experiment contained the following two steps.

- Calculation of two indices, detectability and discriminability
- Evaluation of the validity of these indices by subject experiments

All images were captured at a $1,600 \times 1,200$ pixels resolution and as RGB (8 bits per channel). In this paper, the diaphragm was fixed to 7.1 to avoid severe color saturation. The shutter speed was fixed to $1/800$ for daytime and $1/400$ for nighttime. Grayscale images were used for the calculation of indices, and color images were used for experiments with subjects. In this experiment, images that contained traffic signals with active green lamps were used to avoid visibility changes caused by color differences. Drivers also get more annoyed when provided with green signal information that they have already recognized than yellow or red that leads to warning. Therefore, we investigated the visibility of green signals. Traffic signal regions and traffic lamp regions were extracted manually, as shown in Figs. 2 and 7. This process can be automated by methods proposed in [6] or [7] etc.

Table II shows examples of calculated indices corresponding to images in Fig. 3, 5 and 8. Each index was calculated as follows.

5.1. Calculation of detectability index

1) Glare source in peripheral vision

Since the diaphragm value used in this experiment was very high, the entire image was very dark especially when taken at night. Objects with equivalent or more luminance compared to traffic signals had brighter pixel value. Thus the image is binarized by Otsu's method [9], and the brighter regions are regarded as glare sources. Normalization factor

TABLE II

SAMPLE IMAGES AND CORRESPONDING VALUES OF INDEX

(I_1) The larger the value, the more difficult it is to detect.
(I_2 and I_3) The smaller the value, the more difficult it is to detect or discriminate.

Index		Figure	value of index
Detectability	I_1	Fig.3(a)	0.036
		Fig.3(b)	0.960
	I_2	Fig.5(a)	0.72
		Fig.5(b)	0.51
Discriminability	I_3	Fig.8(a)	0.53
		Fig.8(b)	0.01

(a) For calculating index (b) For displaying to subjects

Fig. 9. Sample images (a) to calculate index and (b) to display to subjects

R_1 was determined experimentally.

2) Background texture

Index I_2 is calculated by the dissimilarity of the power spectrum between the traffic signal region and its adjacent background regions. Normalization factor R_2 was also determined experimentally. Visibility is influenced by various factors. If images with different traffic signals are used, it is hard to accurately evaluate the effect of background texture variation. So, composite images are used in this experiment. A traffic signal is extracted manually, and composite images are synthesized by putting the signal image on various background images.

5.2. Calculation of discriminability index

Index I_3 is calculated from the average luminance of each traffic lamp region.

5.3. Subject experiment

An experiment with subjects was conducted to investigate whether the index calculated in Sections 5.1 and 5.2 reflects human perception. To avoid the influence of other factors, these experiments were implemented independently for each index.

1) Subjects 15 subjects (include 13 males) with driving licenses

2) Test images For each index, 20 images printed by a color ink jet printer were prepared. The size of the prepared images depended on the index to avoid visibility changes caused by other factors in the images. Concretely, the images prepared for each index were as follows.

[Dataset for I_1] Whole image shown in Fig. 3
[Dataset for I_2] Region of traffic signal and adjacent background shown in Fig. 5
[Dataset for I_3] Region that includes traffic signal shown in Fig. 8

Since the diaphragm was set high, the images taken by the in-vehicle camera to calculate the index especially at night were quite different from human perception. For experiments with subjects, images with auto mode were also taken at night by the same kind of camera simultaneously while collecting the images (Fig. 9). These images corresponded more accurately to human perception, so they were presented to subjects.

3) Evaluation method We investigated the consistency between human perception and the index values of all 190 combinatory pairs of images for each dataset. These combinations were randomly divided into five subsets with 38 pair combinations each. For each subset, three subjects were asked to answer the following questions.

- Image pair for detectability evaluation (I_1, I_2)
  Question: In which image is it easier to find a traffic signal?
- Image pair for discriminability evaluation (I_3)
  Question: In which image is it easier to recognize the active signal lamp?
- All image pairs
  Question: How certain are your answers from one to five? Five means absolutely certainty and one means unsure.

Each subject took part in only one subset of each dataset.

5.4. Experimental results

If the image decided by the proposed method equals the image decided by a majority vote of answers given by three subjects, then the answer of our system was correct. Table III shows accuracy rates using all answers and only using answers with a certainty level higher than or equal to four. In the latter case, for one image combination, if two subjects answered a certainty level higher than or equal to four and their answers were different, this image pair was regarded as invalid because a majority vote cannot be decided. As shown in Table III, we confirmed that our method can recognize the visibility of traffic signals with more than 70% accuracy using all answers and with more than 75% using only answers with higher than or equal to certainty level four. Indices I_1 and I_3 showed especially good results.

5.5. Discussions

1) Relationship between indices and human perception

We investigate why index I_2 did not show a good result. Fig. 10 shows a sample image combination for I_2 where all three subjects gave opposite answers to the proposed method, and in addition, their certainty was high. Fig. 10(a) shows the image that our method recognized as more detectable, and (b) is the image that all three subjects answered as more detectable. Perhaps this result is influenced by the difference of luminance and color contrasts between an active green lamp and its background, since the visibility of an object changes

(a) $I_2 = 0.62$ (b) $I_2 = 0.58$

Fig. 10. Sample images and corresponding index values whose answers of subjects are completely different from output of proposed method: (a) image where index I_2 output as more detectable and (b) image where all three subjects answered more detectable.

TABLE III

ACCURACY RATE OF EACH INDEX

Accuracy rate decided by a majority vote of three subject's answers and accuracy rate decided by a majority vote of only answers with certainty higher than or equal to four.

Index		Using all answers	Using only answers with certainty ≥ 4
Detectability	I_1	84.9%	86.8%
	I_2	70.0%	76.8%
Discriminability	I_3	76.8%	86.9%

based on its background luminance and color. It is common knowledge that an object put in a dark background looks brighter than it in light background [10]. In Fig. 10, a bright signal lamp exists in the background of an umber brown signboard. Subjects might believe it is easier to find the traffic signal in image (b) than in image (a). Luminance and color ratios between an object and its background have the same relationship between the luminance and chromaticity of an object and background luminance, as shown in Table I. Hence, in the future, considering other visibility decision factors that are not mentioned in this paper, investigating the relationship between them will enable us to recognize visibility more accurately. Considering color information is one main future work.

2) Digital cameras and human eyes

In this paper, we assumed that an image taken by a digital camera is identical to an image perceived by human eyes. But actually these images are quite different in some situations due to the difference of dynamic range between human eyes and a digital camera. The dynamic range of human eyes is between four and six times as wide as a general digital camera. Therefore, these two are different, especially in situations where strong luminance contrast exists.

On the other hand, when humans recognize traffic signals, they are greatly affected by color information [8]. Digital color cameras can capture color information more similar to humans than by other devices. From this point of view, they are suitable for visibility recognition. Because the dynamic range of existing general cameras is narrower than human eyes, the correct color information of an object cannot be captured where the object has high brightness such as an active signal lamp. But in recent years, new cameras have been developed with higher dynamic range [11], which will enable more accurate recognition of driver's visibility conditions.

VI. CONCLUSION

We proposed a method to recognize the visibility of traffic signals. Visibility is divided into two criterions: detectability and discriminability. The proposed method calculates each index by image processing. Experiments using actual images showed that detectability indices I_1 and I_2 reflect human perception correctly by 86.8% and 76.8%, respectively, and discriminability index I_3 by 86.9%.

In the future, we will consider the effect of other visibility decision factors, especially those related to color information, and recognize visibility more accurately. Moreover, toward a practical system, we also intend to implement a process combined with traffic signal detection and develop a method that provides appropriate information to drivers only when required.

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