特集 Drowsiness Detection Using Facial Expression Features *

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This paper presents the method of detecting driver's drowsiness level from the facial expression. The motivation for this research is to realize the novel safety system which can detect the driver's slight drowsiness and keep the driver awake while driving.

The brain wave is commonly used as the drowsiness index. However, it is not suitable for the in-vehicle system since it is measured with sensors worn over the head. We precisely investigated the relationship between the change of brain wave and other drowsiness indices that can be measured without any contact; PERCLOS, heart rate, lane deviation, and facial expression. We found that the facial expression index had the highest linear correlation with the brain wave. Therefore, we selected the facial expression as the drowsiness-detection index and automated the drowsiness detection from the facial expression.

Three problems need to be solved for automation; (1) how to define the features of drowsy expression, (2) how to capture the features from the driver's video-recorded facial image, and (3) how to estimate the driver's drowsiness index from the features. First, we found that frontalis muscle, zygomaticus major muscle, and masseter muscle activated with increase of drowsiness in more than 75 percents of participants. According to the result, we determined the coordinates data of points on eyebrows, eyelids, and mouth as the features of drowsiness expression. Second, we calculated the 3D coordinates data of the features by image processing with Active Appearance Model (AAM). Third, we applied k-Nearest-Neighbor method to classify the driver's drowsiness level. Eleven participants' data of the features and the drowsiness level estimated by trained observers were used as the training data. We achieved the classification of the drivers' drowsiness in a driving simulator into 6 levels. The average Root Mean Square Errors (RMSE) among 12 participants was less than 1.0 level.

Key words: Drowsiness detection, Facial expression, Active Appearance Model

1. INTRODUCTION

Although active safety systems in vehicles have contributed to the decrease in the number of deaths occurring in traffic accidents, the number of traffic accidents is still increasing. Driver drowsiness is one reason for such accidents and is becoming an issue. The National Highway Traffic Safety Administration (NHTSA) estimates that approximately 100,000 crashes each year are caused primarily by driver drowsiness or fatigue in the United States [1]. In Japan, attention lapse, including that due to driving while drowsy, was the primary reason for traffic accidents in 2008. The Ministry of Economy, Trade and Industry in Japan reports that the number of such accidents has increased 1.5 times in the 12-year period from 1997 to 2008 [2].

One solution to this serious problem is the development of an intelligent vehicle that can predict driver drowsiness and prevent drowsy driving. The percentage of eyelid closure over the pupil over time (PERCLOS) is one of the major methods for the detection of the driver's drowsiness [3]. We developed a method for the detection of driver drowsiness using the whole facial expression, including information related to the eyes. This method is based on the results of observational analyses. The results of such analyses revealed that features of drowsiness appear on the eyebrows, cheeks, and mouth, in addition to the eyes [4]. The aim of using the facial expression is to detect drowsiness in the early stages, on the basis of the many minute changes in the facial parts. Our goal is to develop an intelligent safety vehicle that can relieve drivers from struggling against drowsiness by detecting their drowsiness and keeping them awake naturally. Two systems are necessary for the establishment of such an intelligent vehicle; one is a system for detecting the information predictive of driver drowsiness in the early stages, and the other is a system for providing feedback to keep the driver awake. In this paper, we discuss a method for detecting driver drowsiness in the early stages. Our method detects drowsiness with accuracy equivalent to that of brain waves, which is the general index of drowsiness. The method does not require any attachment of sensors. We developed the drowsiness detection method with a system comprising a camera set on the dashboard, an image processing algorithm, and a drowsiness detection algorithm.

This method categorizes drowsiness into 6 levels using features of facial expression based on the mechanism of facial muscle activities. This paper presents a novel drowsiness detection method and assesses its effectiveness.

2. EARLY-STAGE DROWSINESS DETECTION

The changes in brain waves, especially alpha waves, are one of the indices used to detect changes in the level of drowsiness [5]. Although change in brain waves is an effective index for detecting drowsiness, it is not feasible to apply this index in a vehicle because of the electrodes that are used as contact-type sensors. However, it is recognized in the field of cerebral neuroscience that the facial nerve nucleus is contained in the brain stem, which is defined as an organ of drowsiness [6]. Therefore, we adopted facial expression as the index of drowsiness as an alternative to brain waves. In addition, it is apparent from our experience that we can recognize drowsiness in others from their facial expressions.

In Japan, Kitajima's trained observer rating is a commonly used method for the detection of driver drowsiness on the basis of appearance [7]. The method divides drowsiness into 5 levels with criteria such as "slow blink", "touching the face with the hand", "frequent yawning", and so on. Since these criteria are qualitative, the method is not appropriate for automatic detection of drowsiness. In general, percentage of eye closure time, heart rate, and lane deviation are considered to be suitable drowsiness measurement indices that do not require the attachment of sensors [3), 8)-14)]. To determine the best index as an alternative to brain waves, we examined the correlation between brain waves and other indices such as PERCLOS, heart rate, lane deviation, and facial expression [15]. **Figure 1** indicates that facial expression has the highest correlation with brain waves (correlation coefficient = 0.90) and it detects drowsiness at an earlier stage than other indices. This indicates that facial expression is the most appropriate index to use for the detection of driver drowsiness in the early stages. Therefore, to be able to predict and prevent drowsy driving, the development of a method that detects driver drowsiness from facial expression is necessary.

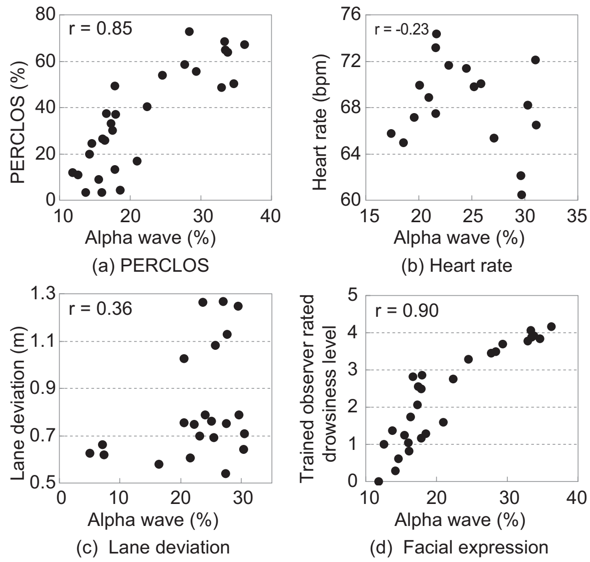

Fig. 1 Correlations between brain waves and other indices. Facial expression has the highest correlation with brain waves.

3. AUTOMATIC DROWSINESS-DETECTION SYSTEM USING FACIAL EXPRESSION

It was necessary to solve 3 problems for the development of an automatic drowsiness-detection system:

(1) How to define the features of drowsy expression.
(2) How to capture the features from the driver's video-recorded facial image.
(3) How to estimate the driver's drowsiness index from the features.

Our approaches to solving these problems are explained in this chapter.

3.1 FEATURES OF DROWSY EXPRESSION

We clarified the particular features of drowsy expression by comparing the facial muscle activities of the waking expression with those of the drowsy expression [16]. We measured 9 facial muscles of each of 17 volunteer participants during the task of monotonous driving in the driving simulator for 1 hour. **Figure 2** shows the 9 facial muscles; inner frontalis, upper orbicularis oculi, lower orbicularis oculi, zygomaticus major, masseter, risorius, upper orbicularis oris, lower orbicularis oris, and mentalis. We divided the reference states of drowsiness into 6 levels, i.e., "not sleepy", "slightly sleepy", "sleepy", "rather sleepy", "very sleepy", and "sleeping" (Table 1) by adding the "sleeping" level to Kitajima's trained observer rating scale.

Figure 3 shows the comparison results of the drowsiness levels and the facial muscle activities. The contractions of the frontalis and the relaxation of the zygomaticus major were detected in more than 75 percent of participants, and the relaxation or contraction of the masseter muscle was detected in 82 percent of participants. In addition, contraction of the frontalis, which was detected in 94 percent of participants, was the characteristic expression of resisting drowsiness. This characteristic expression does not appear during the natural drowsy state without any struggle against drowsiness. According to the result, we chose the eyebrows, edges of the mouth, and the lower lip as the facial features related to the frontalis, zygomaticus major, and masseter, respectively, in addition to the eyelids, which are the general features of the drowsiness expression (Fig. 4).

3.2 IMAGE PROCESSING FOR MEASURING FEATURES OF DROWSY EXPRESSION

We developed a method of image processing for measuring the features of drowsy expression, without any sensor contact, from a driver's video-captured facial image [17]. The method, which is based on the Active Appearance Model (AAM) [18], detects three-dimensional coordinates of 68 points on the driver's face per frame (Fig. 5). Our AAM consists of the specific 2-dimensional model (Fig. 6 (a)) and the generic 3-dimensional model (Fig. 6 (b)). The specific 2-dimensional model has information relating to the shape and texture of the individual driver's facial image. The generic 3-dimensional model has the 3-dimensional vectors of each of the 68 points. We developed a method that extracts change in facial expression without individual differences in the shape of each driver's face by using the generic 3-dimensional model.

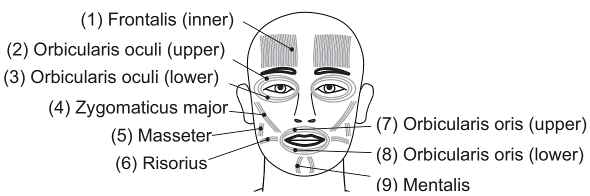

Fig. 2 Nine facial muscles. Facial muscles were measured by facial electromyograph.

Table 1 Drowsiness levels by trained observer rating

Category (Drowsiness level)	
0	Not sleepy
1	Slightly sleepy
2	Sleepy
3	Rather sleepy
4	Very Sleepy
5	Sleeping

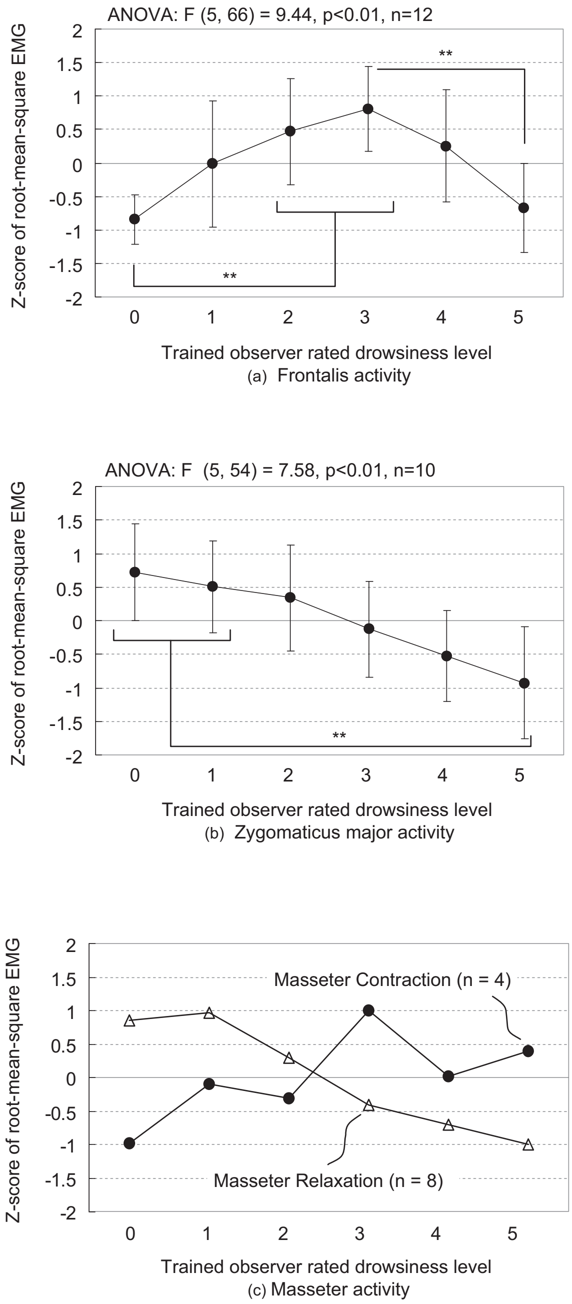

Fig. 3 Typical comparison results of the drowsiness levels and the facial muscle activities. The contractions of frontalis and the relaxation of zygomaticus major were detected in more than 75 percent of participants, and the relaxation or contraction of the masseter muscle was detected in 82 percent of participants.

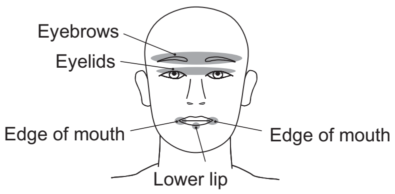

Fig. 4 Features for detecting drowsiness

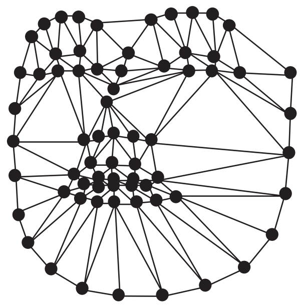

Fig. 5 Sixty-eight points on face

(a) 2-dimensional model　(b) 3-dimensional model

Fig. 6 Specific 2-dimensional model and generic 3-dimensional model for AAM

This method is an effective way of detecting the coordinates of the points on the face in the vehicle, which is expected to be driven by an unspecified number of drivers. The process of this method is shown in **Fig. 7**. First, the specific 2-dimensional model is generated by a captured static facial image of the driver. This process is performed once for each driver. Next, the specific 2-dimensional model is fitted on each frame of the driver's facial image and the 2-dimensional coordinates of the 68 points are output. Finally, the generic 3-dimensional model is deformed based on the 2-dimensional coordinates and the 3-dimensional coordinates of each of the 68 points are output per frame. We employed the method of steepest descent to the fitting of the specific 2-dimensional model and the deforming of the generic 3-dimensional model.

3.3 METHOD OF DETECTING DROWSINESS LEVEL

We adopted 17 points as the measurement objects to detect the drowsy expression. **Figure 8** shows the 17 points: 10 points on the right and left eyebrows (5 points on each side), 4 points on the right and left eyelids (2 points on each side), 2 points on the right and left edges of the mouth (1 point on each side), and 1 point on the lower lip. As the features of drowsy expression we used scalar quantities of the change in the 17-point positions, which were measured from the positions on the waking-state expression. The individual differences of the waking-state expressions are reduced by defining the positions on the waking-state expressions as reference positions. According to this normalization, it is possible to detect the changes in the driver's facial expression based on drowsiness. We employed the k-Nearest-Neighbor method, which is one of the pattern classification methods, for detecting the drowsiness level. This decision was based on the result of a preliminary experiment in which we compared the results of the drowsiness levels detected by the trained observer with other estimation methods: multiple regression analysis method, subspace method, and k-Nearest-Neighbor method. The drowsiness level estimated by the k-Nearest-Neighbor method had the highest correlation with the drowsiness level as estimated by the trained observer. In accordance with this result, we regarded the facial change of drowsy expression as multidimensional data that were nonlinear, nonparametric, and unpredictably distributed. Our method uses the prebuilt database that consists of the 6-level drowsy expression features of several individuals. The driver's features are compared with the whole database, and the similarities of each comparison are applied to detect the drowsiness level. The similarity-based method is able to detect drowsiness with higher time resolution than the method using trends in the change in the facial expression at a specific time interval, such as 30 seconds [19].

The every 5-second (150-frame) average features are used as the feature data in this method. The 5-second block time is applied as the bare minimum sampling time for the trained observer rating for facial expressions [7]. According to the averaging, it is possible to detect the difference between "eye closure based on blinking" and "eye closure based on drowsiness", which is difficult to distinguish from a still frame. Therefore, it is possible to reduce erroneous detection of the drowsiness level.

We investigated the accuracy of our drowsiness detection off-line. We used the driving simulator in a sound-proof room (**Fig. 9**). Motion system was excluded from the driving simulator to induce drowsiness in the participants efficiently and to measure basic data of participants' drowsy

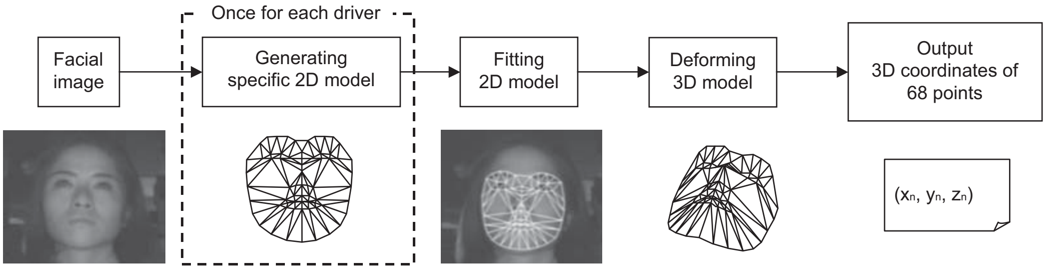

Fig. 7 Flow of the image processing with AAM

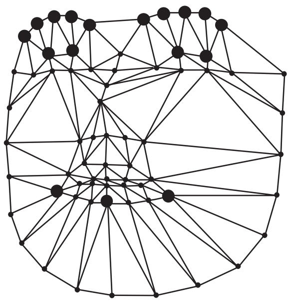

Fig. 8 Seventeen measurement points for detecting drowsy expressions

Fig. 9 Image of the driving simulator

expressions accurately. The driving task was also designed monotonously for the purpose of inducing drowsiness in the participants efficiently. The longitudinal flows of two sine curves, from the top to the bottom of the screen, were projected on the screen. The circle indicating the position of the vehicle from an overhead view was also projected on the screen between the sine curves (Fig. 10). We instructed the participants to operate the driving simulator with the steering wheel to maintain their position between the sine curves. The participants' facial images were recorded by the digital video camera (480 x 640 pixels, 30 fps, progressive scan) on the dashboard. The participants were instructed to remain awake during the driving and maintain the same position they would adopt while driving a real vehicle, even if they became drowsy. As a reference for the 6 drowsiness levels, we used the results of ratings for the drivers' recorded facial images from 2 trained observers. The 12 volunteer participants had drivers' licenses and were aged in their 20s to 40s. They were informed of simulator sickness before the experiments and required to sign an informed consent document. During the experiments, at least one examiner observed the participant's appearance from outside the sound-proof room. After the experiment, the participant rested with the examiners for approximately 10-15 minutes. Drowsiness detection was performed off-line using the leave-one-out cross validation procedure with the features, which were calculated by referring to the 12 participants' recorded facial images. All of the 12 participants fell asleep during the experiment. In the leave-one-out cross validation, data for 11 arbitrarily chosen participants were used as training data and used to detect the drowsiness of the remaining participant, who was excluded from the training data; this was performed repeatedly. Figure 11 shows the training data image. The training data consist of the 5-second average features and the reference of the drowsiness levels, which are labeled on the features. The flow of drowsiness detection is shown in Fig. 12. The entered driver's features are compared with all of the

Fig. 10 Projected sine curves and circle on the screen

training data. The top 80 training data points, which have a strong similarity to the driver's features, are picked up. The driver's drowsiness level is estimated based on a majority decision of what the referential sleeping levels are, which are labeled on the 80 training data points. We employed the Euclidean distance as the index of similarity between the driver's features and the features of the training data. A small distance indicates strong similarity.

We investigated the effectiveness of the method by comparing the detected drowsiness level with the referential drowsiness level. To detect the facial change based on the drowsiness accurately, we clipped the parts of the video of the participants' facial images before the comparison, and detected the drowsiness levels from those partial videos. The 3 criteria for clipping the partial videos were as follows.

(1) The facial image of the driver in a front-facing position.

(2) The facial image without any occlusion such as a steering wheel and/or a hand.

(3) The facial image without any actions that cause facial change, such as yawning, smiling, or laughing.

Figure 13 shows the one participant's result of the detected drowsiness levels which were detected by our method, and the referential drowsiness levels which were estimated by trained observers. The Root Mean Square Errors (RMSE) of 12 participants are shown in **Table 2**. These results demonstrate that our method detects the drowsiness with a RMSE of less than 1.0 for 8 participants. The average RMSE among 12 participants is 0.91. On the other hand,

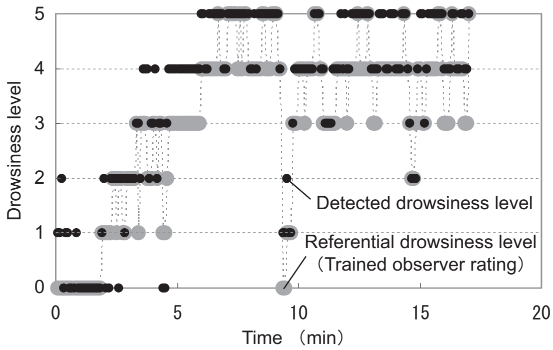

Fig. 13 Comparison result of the detected drowsiness levels and the referential drowsiness levels of participant No. 12.

RMSE was increased when we used fewer or more feature points than 17 such as 10 points on eyebrows, 4 points on eyelids, or 68 points on whole face to detect the drowsiness. Therefore, 17 points, which described in chapter "METHOD OF DETECTING DROWSINESS LEVEL", were the best features for our drowsiness-detection method. In addition, it is shown that our method detects the drowsiness level of the participant who does not fall asleep during the examination with the same level of accuracy (**Fig. 14**). The detected drowsiness levels were indicated as being below level 3 ("rather sleepy") for the participant who does not fall asleep during the examination and the referential drowsiness levels of the participant were below level 2 ("Sleepy"). These results indicate that our drowsiness detection method is able to detect the drowsiness level as accurately as that of the trained observer in 5-second time resolution.

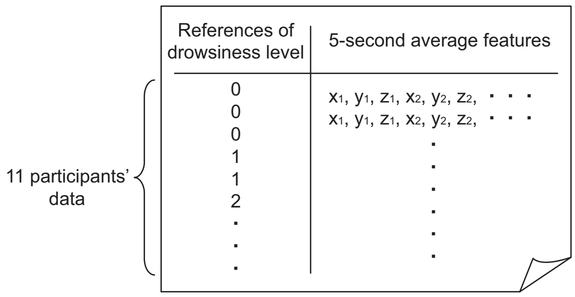

Fig. 11 Image of training data. The training data consist of the 5-second average features and the reference of the drowsiness levels labeled on the features.

4. EARLY-STAGE DROWSINESS DETECTION

As described in chapter "AUTOMATIC DROWSINESS-DETECTION SYSTEM USING FACIAL EXPRESSION", we developed an off-line detection method that determines the driver's drowsiness level from the driver's facial expression. To apply this method in practice, it is imperative to perform image processing and drowsiness detection in real time. Therefore, we developed a real-time drowsiness detection method and tested the accuracy of this method for detecting drowsiness.

The experimental set-up is shown in **Fig. 15**. The

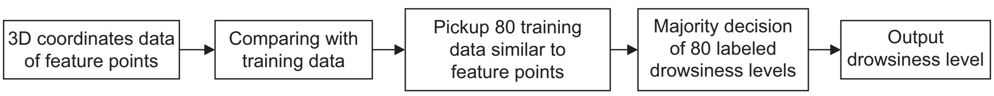

Fig. 12 Flow of the drowsiness detection with k-NN

Table 2 Root Mean Square Errors of drowsiness detection

Participant #	Root Mean Square Error (RMSE)
1	1.11
2	0.90
3	1.16
4	0.90
5	0.78
6	1.08
7	0.69
8	1.02
9	0.82
10	0.81
11	0.94
12	0.77
Average	0.91
SD	0.15

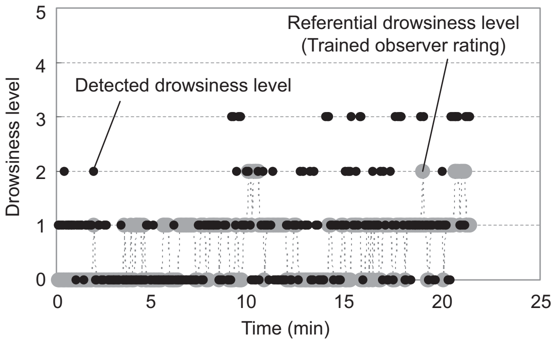

Fig. 14 Comparison result of the participant who does not fall asleep during the examination.

Complementary Metal-Oxide Semiconductor (CMOS) camera (IEEE-1394a, 640 x 480 pixels, 60 fps, progressive scan) was placed on the dashboard of the driving simulator in the sound-proof room. Motion system was excluded from the driving simulator to induce drowsiness in the driver efficiently and to measure basic data of participants' drowsy expressions accurately. The band pass filter with a center wave-length of 845 nm (half width: 52 nm) was placed in front of the lens on the CMOS camera. The CMOS camera takes the driver's facial image through the filter. Two infrared Light-Emitting Diodes (LEDs) with a secondary lens (peak wavelength: 850 nm, half-value angle: 15 deg.) were placed at the right and left side of the camera, respectively. The camera was able to record the driver's facial image without any interference from ambient light by using the filter and the infrared LEDs. The artificial daylight (standard illuminant D65) was set up in the sound-proof room to simulate the outdoor lighting environment. The programs of the image processing and the drowsiness detection were executed on the Linux-based computer (Pentium D, 2.8 GHz CPU, 3GB

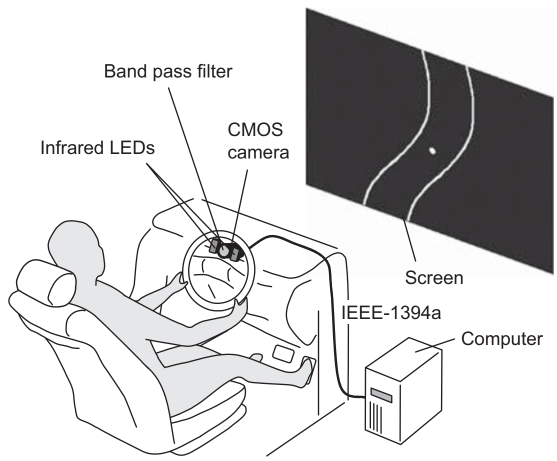

Fig. 15 Image of the set-up for real-time drowsiness detection

memory). As the training data for the k-NN method, the 12 participants' data (3004 data sets) that had been recorded off-line (mentioned in chapter "AUTOMATIC DROWSINESS-DETECTION SYSTEM USING FACIAL EXPRESSION") were used. The 2 volunteer participants had drivers' licenses and were in their 30s to 40s. As the reference of the 6 drowsiness levels, we adopted the results of the ratings from 2 trained observers. We instructed the participants to operate the driving simulator with the steering wheel held in such a manner as to maintain the position of the projected circle between the sine curves and, to remain awake during the experiment while adopting the same stance employed when driving a real vehicle, even if they became drowsy. The participants were informed of the possibility of simulator sickness before the experiments and were required to sign an informed consent document. During the experiments, at least one examiner observed the participant's appearance from outside the sound-proof room. After the experiment, the participant rested with the examiners for approximately 10-15 minutes.

To detect facial change based on the drowsiness accurately, we clipped the video and compared the detected drowsiness levels from those partial videos with the referential drowsiness levels. The 4 criteria for clipping the partial videos were as follows:

(1) The facial image of the driver in a front-facing position.
(2) The facial image without any occlusion such as a steering wheel and/or a hand.
(3) The facial image without any actions that cause facial change, such as yawning, smiling, or laughing.

(4) The facial image with appropriate fitting position of 2-demensional model.

The Root Mean Square Errors (RMSE) of 2 participants are shown in Table 3. The results of our study demonstrate that our method detects the drowsiness level with an average RMSE approximately 1.0 in real time.

5. CONCLUSION

In this paper, we presented the driver's drowsiness detection method using facial expression, and we established the effectiveness of this method experimentally. Our method is executed according to the following flow: taking the driver's facial image, tracing the facial features by image processing, and rating the driver's drowsiness according to a 6-level scale from the features by pattern classification, in real time. The results of the drowsiness detection correspond to the drowsiness reference as estimated by a trained observer with an average RMSE of less than 1.0 level. The distinguishing feature of our method is that it uses 17 facial features based on the activities of facial muscles.

The limitations of this paper were the reality of driving environment and the number of the participants. In future work, we will verify practical effectiveness of our drowsiness detection method using motion-based driving simulator and/or real car. Additionally, we will increase the number of participants in our experiments and develop the effective training data for detecting drowsiness of a large number of drivers.

On the other hand, we tested the partial videos to detect the drowsiness expression accurately. The criteria from the clipped partial videos were to use the driver's facial image in a front-facing position, without any occlusion such as a steering wheel or a hand, and without any actions such as yawning, smiling, or laughing. However, in the real vehicle, these events will occur frequently. Therefore, we have started to develop an artifact detection and cancellation method. It will also be possible to develop methods for the detection of other expressions in addition to drowsiness, and apply these to a novel Human-Machine Interface (HMI) such as emotion estimation and agent communication in the vehicle. In addition, the integration of personal verification into our method will lead to the development of a highly precise drowsiness-detection method.

It is also necessary to develop a feedback system to achieve an intelligent safety vehicle that can relieve drivers struggling against drowsiness. We have now started to develop a feedback system that keeps the driver awake effectively and naturally.

Table 3 Root Mean Square Errors of drowsiness detection

Participant #	Root Mean Square Error (RMSE)
1	1.24
2	0.83
Average	1.04

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