Driver Drowsiness Estimation from Facial Expression Features
Computer Vision Feature Investigation using a CG Model

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Abstract: We propose a method for estimating the degree of a driver's drowsiness on the basis of changes in facial expressions captured by an IR camera. Typically, drowsiness is accompanied by drooping eyelids. Therefore, most related studies have focused on tracking eyelid movement by monitoring facial feature points. However, the drowsiness feature emerges not only in eyelid movements but also in other facial expressions. To more precisely estimate drowsiness, we must select other effective features. In this study, we detected a new drowsiness feature by comparing a video image and CG model that are applied to the existing feature point information. In addition, we propose a more precise degree of drowsiness estimation method using wrinkle changes and calculating local edge intensity on faces, which expresses drowsiness more directly in the initial stage.

1 INTRODUCTION

In recent years, the rate of fatal motor vehicle accidents caused by distracted driving has been increasing. This problem results from factors such as sleeping at the wheel. Therefore, there is an urgent need for an alert system that detects driver drowsiness and prevents accidents by warning drivers before they fall asleep.

To detect drivers' drowsiness, Hiroki et al. (1997) and Nakaho et al. (1997) measured physiological indexes, such as brain waves, by attaching a sensor to a driver's body in a driving simulator. Hong et al. (2005), Chin et al. (2005), Pai, et al. (2009), Rami et al. (2011), and Huang et al. (2012) also used physiological indexes, such as electroencephalogram (brain activity), electrooculography (eye movement), and electrocardiogram (heart rate). Minoru et al. (2008) used the pupillary response to estimate drowsiness. However, because sensors must be attached to the driver's body in the above-mentioned techniques, they are not suitable for in-vehicle systems.

To increase driver comfort, non-contact measuring systems using computer vision techniques have been studied. In particular, many studies have focused on changes related to the eyes. Hiroshi et al. (1994), Chu et al. (2004), D'Orazio et al. (2007), Ayumi et al. (2009), Marco et al. (2010), Artem and Jong (2012), and Garc´ıa et al. (2012) estimated drowsiness on the basis of changes in the appearance of the eyes. However, drowsiness-induced changes in facial features do not involve just the eyes. Moreover, the appearance of the eyes change only when a person is extremely drowsy, which is the exact case just before an accident.

Vidyagouri and Umakant (2013), Mohammad and Mohammad (2011), and Ping and Lin (2012) have reported several studies considering other facial features. They detected drowsiness using blinking and yawning features with vision techniques. They determined that a driver is drowsy when he/she is yawning or his/her blink becomes slow, which is very simple and remains questionable.

Esra et al. (2007, 2010) considered various facial expressions by detecting facial action units. However, their goal was to detect facial expressions just one minute before an accident, which are clearly detectable only by using eye features. Therefore, whether the expression features were effective is unclear. In addition, it is too late to warn a driver just one minute before an accident. A system that warns in the initial stage of drowsiness is needed.

After analyzing a video of captured facial expressions, Satori et al. (2010) and Kenji et al. (2010) focused on the movement of facial feature

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points on the eyes, eyebrows, and mouth. In these studies, the drowsiness degree was evaluated on the basis of changes in these points with reference to an awakened state. However, because these studies considered only facial feature points, capturing drowsiness-induced changes in facial skin, such as wrinkles, is impossible.

In this study, we detect a new drowsiness feature by comparing video images and a CG model that adapted existing feature point information. In addition, we propose a drowsiness-degree estimation method that considers both scalar distance between feature points and textural changes in specific areas of the face. As a result, drowsiness can be estimated more precisely without increasing driver discomfort. The rest of this paper is organized as follows. In section 2, we explain the experimental environment and define degrees of drowsiness. Section 3 introduces a way of selecting facial features and explains drowsiness features. In section 4, we describe our learning and estimation method. In sections 5 and 6, we evaluate our method. Finally, we conclude our study in section 7.

2 DEFINITION OF DROWSINESS LEVELS

Using an IR camera (60 fps frame rate and 320 × 240 pixels resolution) installed on the steering wheel base (Figure 1), we first recorded a video of drivers' faces while they were operating a driving simulator (freeway circuit track). We instructed the subjects to maintain a constant speed of 80 km/h and follow a lead vehicle. The driving operation was recorded over a maximum capture time of 1 h, and if accidents occurred as a result of the driver falling asleep, we aborted the recording process. This process was performed for 30 subjects. Figure 2 illustrates the expressions recorded during the experiment.

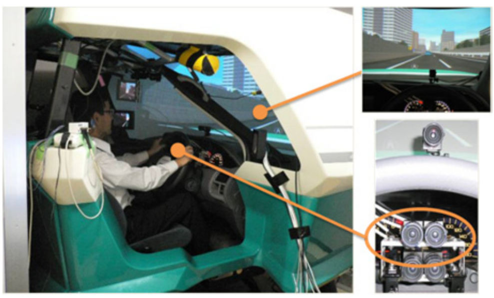


Figure 1: Experimental environment.

To estimate the degree of drowsiness, an objective index of drowsiness is needed and Hiroki's facial expression estimation method (1997) is often used (Ayumi, 2009; Satori, 2010; Kenji, 2010). In this method, the drowsiness degree was divided into the following five levels on the basis of the captured video: "level 1: not sleepy," "level 2: slightly sleepy," "level 3: sleepy," "level 4: rather sleepy," "level 5: very sleepy." Most existing studies have attempted to capture the exact drowsiness feature just before an accident, which corresponds to level 4 or 5. However, according to Hiroki et al. (1997), traffic accidents occur when the drowsiness degree is greater than or equal to level 3. Therefore, our objective is to accurately estimate the transition from level 2 to level 3, and then detect the initial stage of drowsiness.

The relationship between the drowsiness levels and their distinctive behaviors are shown in Table 1. Two assessors who studied the psychological measurement technique estimated drowsiness on the basis of the following procedures. First, the assessors observed the facial expressions of the participant and defined his evaluation criteria (measure of evaluation) independently. Next, they evaluated the drowsiness level every 5 s on the basis of his individual criterion. Finally, the drowsiness degree was set by taking the average of these two drowsiness levels.

Table 1: Drowsiness Level and Behavior.

Drowsiness Level	Behavior Example
1	"eyes move quickly" "motion is active"
2	"eyes move slightly slow" "lip opens a little"
3	"mouth moves" "touches the face" "reseating"
4	"shakes head" "frequent yawning" "blinks are slow"
5	"closes eyes" "head inclines forward" "head falls backward"

(a) Awake (b) Drowsy

Figure 2: Example of expressions in the video.

3 DROWSINESS ESTIMATION FEATURES

In this section, we introduce our drowsiness estimation feature. In subsection 3.1, we explain the drowsiness feature related to facial feature points. In subsection 3.2, we introduce a new drowsiness feature related to facial texture. Then, we propose a way of investigating the computer vision feature using a CG model.

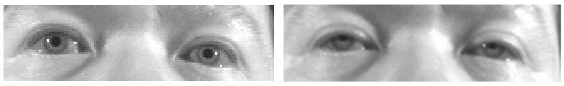
3.1 Variation of Distance between Feature Points

Drowsiness changes the facial expression. For example, it affects the opening and closing of the eyes. Eyes in both awake and drowsy states are shown in Figure 3 (a) and (b), respectively. In the drowsy state, the eyes of the subject are partially closed. To capture changes in such facial expressions, the variation of the distance between two feature point positions from one awakened state to another is considered as a feature parameter. By calculating the variation, we can normalize the individual distance of facial parts. When this feature parameter increases, it acquires a positive value, and vice versa.

In each video frame, Atsushi's technique (2011) detected forty feature points at 30 fps. Because we used images from an IR camera, we could obtain feature points even if the driver was wearing glasses or sunglasses. We calculated 38 sets of distances between two feature points related to eyes, eyebrows, mouth, etc. We normalized the distance between the eyes, to prevent any changes in the size of the face with the driver's movement. The distances presumably reflect the expression changes caused by drowsiness, and the feature parameters are the lengths of the arrows in Figure 4 (a).

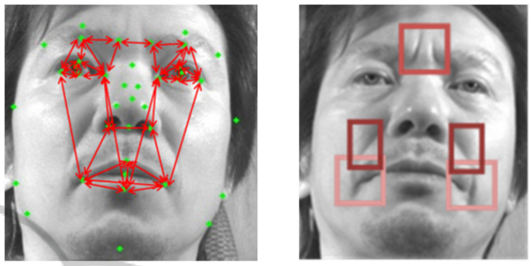
3.2 Variation of Edge Intensity

Although selection of features is very important in any computer vision technique, demonstrating whether the selected features are useful is often difficult. In many cases, output from a vision task is a numerical value. Therefore, we cannot always understand essential phenomenon captured by each feature. In this subsection, we introduce a way to visualize vision features, allowing us to confirm which feature should be captured.



(a) Awake (b) Drowsy

Figure 3: Feature of eyes.



(a) Distance parameters (b) Filtering area

Figure 4: Distance parameters and filtering area.

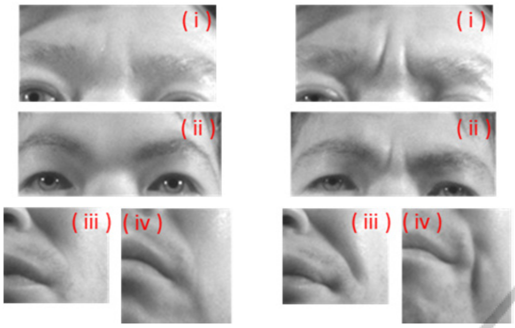
(a) Awake (b) Drowsy (c) CG face model

Figure 5: Detecting a new feature.

3.2.1 Investigation of a New Drowsiness Feature

To estimate drowsiness more precisely, we need to select an effective feature. To detect a new feature, we used a drowsy CG face model applied to feature point information. We deformed the shape of 661 points 3D mesh according to 40 feature points of a drowsy face using radial basis functions (Jun, 2000). Then, we mapped an awakened texture (Figure 5 (a)) to this deformed model frame by frame. We compared the original images and CG models and identified features that should be captured.

We can see that the drowsiness feature of closing eyes is captured by the feature points (Figure 5(b) and 4(c)). However, compared with the real video, the CG model does not look sufficiently sleepy. We postulate that a drowsiness model based on feature points cannot emulate all features of drowsiness. For instance, we noticed that wrinkles affect the impression of drowsiness, appearing on brows, mouth, and nasolabial folds when a subject resists drowsiness (Figure 6). Although many existing studies have focused on cases of extreme drowsiness just before an accident, the facial expressions that indicate resistance to drowsiness, such as wrinkled expressions, emerge in the initial stages of drowsiness. It is impossible to acquire such textural changes solely from feature points.



(a)Awake (b)Drowsy

Figure 6: Wrinkle feature at brows, mouth, and nasolabial fold.

3.2.2 Capturing Wrinkled Expressions

To capture wrinkled expressions, the variation of edge-intensity from the awakened to drowsy states is considered as a feature. Some subjects had deep wrinkles even in the awakened state, as shown Figure 2. Therefore, by calculating the variation, we normalized individual differences. These edge-intensity features were calculated by applying Laplacian filtering at five areas on the face, as shown in Figure 4 (b): between the eyebrows, nasolabial folds, and corners of the mouth. We defined edge intensity as the average luminosity value obtained after filtering with a 3 × 3 Laplacian filter. We adopted the Laplacian filter because the correlation between the wrinkles and edge intensity calculated by applying it has been proven to be higher compared to that obtained by adopting the Sobel filter and Gabor filter used in our pre-examination.

4 DROWSINESS ESTIMATION ALGORITHM

4.1 K-NN based Learning and Estimation

Drowsiness was estimated using the k-NN method with the feature vector connecting the variations of the distance between two feature points and edge intensity. We used the k-NN method because Satori et al. (2010) estimated drowsiness levels on the basis of future point and reported that the k-NN method yields the best accuracy compared to other methods such as the multiple regression and subspace methods. Feature vectors corresponding to each frame of the videos were calculated and averaged every 300 frames (5 s) in both learning and testing stages. Naturally, the absolute scale and range of "distance" and "edge intensity" in the feature vector differed. Therefore, we introduced the generalized Mahalanobis distance. The dispersion matrix corresponding to the Mahalanobis distance was calculated by the learning data as the distance measured in the search of k-NN.

4.2 Drowsiness Transition Constraint

Usually, the drowsiness level does not rapidly increase or decrease. Observation of the recorded videos confirmed that the drowsiness level gradually increases for almost all subjects. In addition, drowsiness increases almost monotonically and decreases in some limited situations, for example, when the driver notices that his/her car is deviating from the traffic lane, he/she startled. Therefore, we constrained that the current estimated level increases by only one level or remains constant with respect to the present level over 30 s and decreases by only one level or remains constant with respect to the current level over 10 min. Using these constraints, rapid increases or decreases in the estimated drowsiness level and gradual changes in the drowsiness level could be prevented.

5 EVALUATION (I)

We conducted an evaluation experiment to confirm the validity of the proposed method. We considered the following three cases.

Case 1: Only the "variation of the distance between two points" was used as a feature.

Case 2: Only the "variation of edge intensity" was used as a feature.

Case 3: Both "variation of the distance between two points" and "variation of edge intensity" were used as features.

We used the following two criteria in each case for the evaluation index.

- Correct answer rate:

The correct answer rate is defined as the percentage of the number of correctly estimated data compared to the ground truth level, which is the integer level from 1 to 5.

- Root mean square error (RMSE)

RMSE is the root mean square error between the estimated and ground truth levels and is expressed as follows.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(X_i - x_i)^2}{N}} \tag{1}$$

where N is the number of test data, X_i is a correct level of test data i, and x_i is the estimated level.

In estimation of useful features, the correct answer rate will be high and RMSE will be low. If the estimation performance improves by using both features, the following two things can be proved. First, combining the variations of the distance between two feature points and edge intensity feature is possible. Second, each feature is able to capture different drowsiness features.

5.1 Learning and Testing for the Same Subject

Because of the difficulty in collecting data from subjects, a small dataset was used in this study. Eight experimental subjects fulfilled the following conditions:

- subjects with a high correlation between self-assessed and adjudged drowsiness levels.
- subjects with a stable state of drowsiness between levels 1 and 5.

The videos were divided into levels on the basis of the assessed ground truth level, and each video was further divided into alternate halves. One half was used for learning data, while the other half was used for testing data. The correct answer rate and its average value for the eight subjects are shown in Figure 7. RMSE and its average value for the eight subjects are shown in Figure 8. Our proposed method recorded the highest correct answer rate with an average of 71% and the lowest RMSE with an average of 0.58.

5.2 Discussion

By using both features, the highest correct answer rate and lowest RMSE were evaluated. We confirmed that combining two types of features is possible and each feature is able to capture different drowsiness features.

In the case of subjects #5 and #8, the contribution of the edge feature is not significant because few wrinkles were generated on their faces when they resisted drowsiness. On the other hand, subject #2 was appropriate for our method with the best correct answer rate of 82.4% because he resisted drowsiness with deep wrinkles.

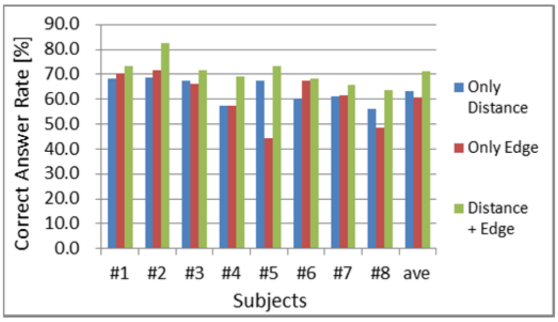


Figure 7: Correct answer rate.

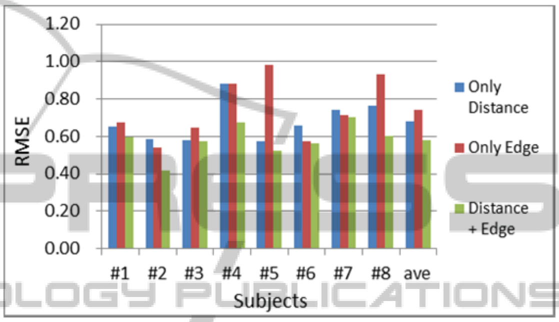


Figure 8: RMSE.

6 EVALUATION (II)

6.1 Learning and Testing by Leave-one-out

In an actual driving situation, generating learning data beforehand from subjects other than the driver is necessary. Therefore, we attempted to use the leave-one-out approach. Because our purpose is to provide a warning when the drowsiness level reaches 3, verifying whether level 3 or higher levels have been correctly distinguished from level 2 or lower levels is necessary. Furthermore, the boundary between levels 2 and 3 must be detected precisely to alert the driver at the right time. Therefore, the time difference between a detected boundary and ground truth boundary was selected as a criterion to evaluate the detector performance. Then, using the distance and edge features, the following experiment was conducted.

This test targeted 10 subjects with a high correlation between the self-assessed and adjudged drowsiness levels. The test targets #9 and #10 did not exhibit the level 1 state. We selected one person for this test and the other nine for learning data. First, levels 1–5 were separated into five classes, using the k-NN method. Next, the result was categorized as the awakened class represented by levels 1 and 2 and the drowsy class, represented by levels 3, 4, and 5. Finally, the correct answer rate of two class separations was calculated. The correct answer rate was defined as the percentage of correctly estimated data compared to the ground truth class (awake or drowsy class).

We confirmed that the average correct answer rate of 10 subjects was 82.2% (Table 2). The time difference between detected boundaries from levels 2 to 3 and ground truth is shown in Table.3. All values in Table 3 are positive because boundary moment is detected before real boundary in all subjects' cases. Drivers will be able to park their car and prevent an accident in 319 s.

Table 2: Correct Answer Rate.

Subject	Correct Answer Rate [%]
#1	64.5
#2	93.8
#3	71.8
#4	83.1
#5	80.5
#6	94.0
#7	78.1
#8	85.5
#9	88.2
#10	82.9
Average	82.2

Table 3: Time Difference.

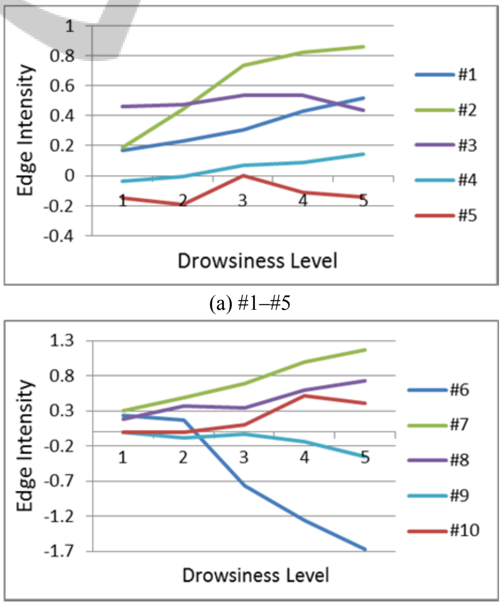
Subject	Time Difference [s]
#1	1005
#2	120
#3	45
#4	70
#5	655
#6	125
#7	560
#8	380
#9	215
#10	15
Average	319

6.2 Discussion

The correct answer rate of subject #1 was low because wrinkles appeared on his nasolabial folds, even though the drowsiness level was level 1. Therefore, for this subject, the drowsiness level was incorrectly estimated to be level 3. For people with the peculiarity involving frequent movements of the mouth, appropriate management is necessary, such as lowering the weighting of the wrinkles feature. Subjects resisting drowsiness with facial expressions, such as #2 and #9, showed high correct answer rates.

6.3 Subject Variation

Because expressions accompanying drowsiness differ from person to person, the problem of individual adaptation must be considered for common use. Another problem is the normalization of the degree of expression. The average value of edge intensity on the brow domain in each drowsiness level is shown in Figure 9. In the case of subjects #1, #2, #4, #6, and #7, the edge intensity increases with the drowsiness level having a different absolute value and gradient. However, in the case of subject #3, the edge intensity is nearly constant for all levels. In the case of subject #6, his hair was considerably long and extended into the brow domain, resulting in an erroneous estimation. Furthermore, there were subjects whose brow wrinkles hardly changed, such as #9, but the wrinkles around the mouth changed clearly and could be correctly estimated. The adaptation method for individual variations will be subsequently considered.



(a) #1–#5

(b) #6–#10

Figure 9: Edge intensity feature.

7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

In this study, we proposed a drowsiness-estimation method by combining facial feature point and textural feature information.

First, we proposed a way of investigating vision features, which is a comparison of an original video and a 3D model that adapted existing features. Then, we introduced the wrinkle feature, which has not been studied till today, and we used it to improve the estimation accuracy. Thereafter, we tested the subject who was excluded from the learning data, and we evaluated the corresponding RMSE and correct answer rate.

The evaluation results with open tests for the same subject are summarized in Table 4. We evaluated the highest correct answer rate and lowest RMSE value and compared these values with those obtained using other single feature methods. We used data from the same subject for both learning and testing. When both the “variation of the distance between two points” and “variation of the edge intensity” were applied as features, the average correct answer rate and average RMSE were found to be 71.0%, and 0.58, respectively. Therefore, we conclude that our method significantly improved estimation accuracy. Concretely, the value of estimation accuracy obtained from our method was significantly higher than that obtained from methods applying only a distance feature or an edge feature.

Evaluation results with open tests for different subjects are summarized in Table 5. We realized two classes of recognition (awake or drowsy class) with an accuracy of 82.2% and average error of 319 s.

Table 4: Evaluation (I).

	Only Distance	Only Edge	Distance + Edge
Correct answer rate[%]	63.4	60.9	71.0
RMSE	0.68	0.74	0.58

Table 5: Evaluation (II).

	Correct Answer Rate [%]	Time Difference[s]
Average	82.2	319

7.2 Future Work

Following are the three future tasks.

First, to realize more precise drowsiness estimation, we need to develop an optimization and normalization technique individually for every user. For example, we will select effective drowsiness feature individually based on first 10 minutes driving.

Second, we need to consider the option of adapting the lighting environment. Although we can capture the driver’s face even at night using IR camera, there are some situations with which we would have to cope in real driving conditions. For example, when a vehicle exits a tunnel, the expression of a driver may change as he/she is dazzled by the light. However, environmental transformations are estimated from the surrounding luminance, and sequences of a vehicle exiting the tunnel are presumably removed. We would have to consider the influence of environment and lighting on facial expressions to normalize and distinguish the drowsiness information in an actual driving scenario.

Third, for the test described in section 6, we took 2 h to extract drowsiness features and 10 min to estimate drowsiness levels using k-NN for 1 h test data (Intel Core i7-2600, 3.80 GHz). We estimated drowsiness levels every 5 s. Therefore, the current drowsiness level could be known after approximately 6 s. Although, as shown in Table 3, it is possible to detect drowsiness before 319 s, we must examine the maximum allowable time delay. If we need to estimate the drowsiness level in a real time application, reducing the video frame rate from 60 fps to 30 fps can be considered as a solution.

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