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Gazing as actual parameter for drowsiness assessment in driving simulators

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ABSTRACT

Many traffic accidents are due to drowsy driving. However, to date, only a few studies have been conducted on the gazing properties related to drowsiness. This study was conducted with the objective of estimating the relationship between gazing properties and drowsiness in three facial expression evaluation (FEE) categories: alert (FEE = 0), lightly drowsy (FEE = 1−2), heavily drowsy (FEE = 3−4). Drowsiness was investigated based on these eye-gazing properties by analyzing the gazing signal utilizing an eye gaze tracker and FEE in a driving simulator environment. The results obtained indicate that gazing properties have significant differences among the three drowsiness conditions, with $p < 0.001$ in a Kruskal–Wallis test. Furthermore, the overall classification accuracy of the three drowsiness conditions based on gazing properties using a support vector machine was 76.3%. This indicates that our proposed gazing properties can be used to quantitatively assess drowsiness.

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1. INTRODUCTION

Drowsiness during driving is a severe problem and is believed to be a direct contributing cause of traffic accidents [1, 2]. It places the lives of drivers and passengers at risk and can cause serious accidents on major roads. According to a U.S. National Highway Traffic Safety Administration (NHTSA) report in 2017 [3], drowsiness and falling asleep while driving was responsible for at least 100,000 automobile crashes and 846 deaths within a year. The National Police Agency of Japan also released data showing that approximately 434,000 traffic accidents occurred in 2017 [4]. Previous studies theorized that the causes of accidents might be related to factors such as lack of concentration during driving and poor driving skills. However, those shortcomings can be rectified by improving driver awareness and driving skills.

Various methods for detecting drowsiness have been proposed. Among the most popular is implementing a trajectory sensor inside the target vehicle [5, 6]. This sensor measures the magnitude of the steering wheel angle and its velocity, as well as the frequency with which the drowsy driver correctly positions the steering wheel angle. Placing the sensor inside the vehicle is more convenient for the driver instead of attaching it to the driver directly. However, the road surface and condition may reduce the detection accuracy of the sensor.

We theorize that drowsiness itself is strongly related to the physical condition of a person, and therefore, drowsiness detection can be improved by directly investigating this condition. Fundamentally, the actual state of the human body is usually determined by placing electrodes or bio-sensors on the body itself. However, several previous studies have reported another approach for detecting drowsiness that involves using human biological signals, such as eye movements and eye blinking obtained using an electrooculogram (EOG) [7, 8], heartbeats using an electrocardiogram (ECG) [9-11], brain activity using an electroencephalogram (EEG) [12-14], monitoring muscle activity using an electromyogram (EMG) [15, 16], and also pulse rate activity [17]. However, skin contact by electrodes or a bio-sensor could cause driver discomfort during driving. Another appropriate method for detecting and estimating the drowsiness state of a driver with minimal or no skin contact is therefore needed.

An alternative method of estimating drowsiness is by using a camera to record eye behavior. Previous studies reported that it is possible to detect drowsiness using numerous less-intrusive techniques and minimizing skin contact by placing a camera in front of the driver to capture the face and eye. For instance, eyelid movement [18], gaze and head [19, 20], eye tracking and pupil position [21], face expression detection [22], face expression monitoring [23], blink detection [24], eye state analysis [25, 26], portion of eye closure [27], and eyelid closure [28] have been investigated. These methods had the same goal of providing information related to the subject/driver condition while performing various tasks or under various conditions (e.g., rest, fatigue, and drowsiness). However, although previous approaches could estimate the drowsy condition, there were drawbacks such as the necessity to provide a clear view and stable positioning of the camera during the recording process.

Our proposed system employs an eye tracker sensor mounted on the head to obtain eye properties during driving. We confirmed that this kind of arrangement has rarely been used to date, even though a head-mounted eye tracker can overcome view and position limitations while evaluating the driver's eye properties. As previously described, most studies used the subject's eye and facial movement images to evaluate their condition, especially drowsiness. However, we could not find any clear information on how to utilize the gazing of the driver to determine his/her condition. In this study, we focused on eye-gazing because of the limited extent to which it has been utilized. To evaluate the drowsiness condition, we evaluated the subject's condition using facial expression evaluation (FEE) [29] in accordance with the experiment's location and environment. We utilized this evaluation method with the objective of observing the actual condition of the subject by considering several points of view with the same source information.

Thus, we estimated the relationship between drowsiness and gazing parameters in three categories of drowsiness. We hypothesized that these three categories have a strong relationship with the eye-gazing properties, especially for estimating the condition before actual drowsiness to prevent accidents. We investigated whether each feature of the gazing properties has a significant difference and examined the performance of related features using a support vector machine (SVM). Finally, we confirmed whether the gazing signal could be used as an actual parameter to assess drowsiness while driving.

2. METHODS

2.1. Subjects

Eleven healthy males of ages in the range of 21−35 years participated in this study. Before the experiment, written informed consent for this study was obtained from each participant. The participants were asked to get sufficient sleep during the night and have their lunch before participating in the experiment. They were also asked not to consume alcohol or caffeine before the experiment.

2.2. Tasks

We used a driving simulator (DA-1110, Honda Motor, Japan), eye gaze tracker (TalkEye Lite, Takei Scientific Instruments, Japan), web camera (HD Pro Webcam C920, Logicool, China), computer to record the driver's facial expression, and driving simulator system control, as shown in Figure 1. Each subject was asked to drive on the oval track without obstacles during the daytime in an automatic transmission car while maintaining a speed of 100 km/h for 50 minutes. The experiment was scheduled twice per day from 8:00 am to 10:00 am and from 1:00 pm to 3:00 pm, respectively. Thus, each subject participated in eight trials during the experiment on different days. All procedures used in this study were approved by the Ethical Committee of the Faculty of Advanced Science and Technology, Kumamoto University.

2.3. Recordings

2.3.1 Physiological Measurement

We mounted the eye gaze tracker, as shown in Figure 2, on the head to obtain and record the eye gaze signal at a sampling rate of 30 Hz. In addition, the subject's face was recorded using the web camera for psychological measurement.

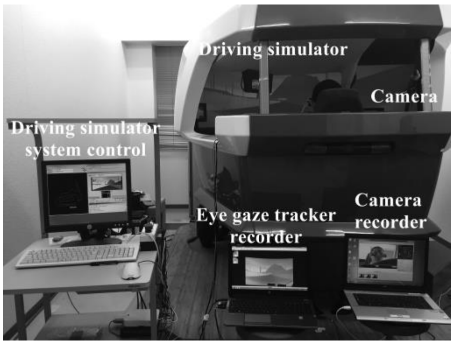

Figure 1. Research environment

Figure 2. Eye gaze tracker

2.3.2 Psychological Measurement

FEE is performed with evaluation from different perspectives by evaluators. The evaluators must evaluate the subjects' state with the same facial expression recording source during driving. Evaluators also need to match their judgment while providing the evaluation and strive for the perception of different evaluators to be relatively similar. The matching of perceptions is carried out jointly at the end of the evaluation. Therefore, we expected FEE to provide a reliable measure of the condition of the subject.

FEE was used to evaluate each subject's drowsiness condition. It consists of a five-level (0−4) drowsiness questionnaire, in which every number represents a drowsiness degree, from very alert to very sleepy. On completion of the experiment, four examiners evaluated each subject's drowsiness condition every epoch (1 epoch = 30 s), according to the FEE questionnaire shown in Table 1, by watching the video of the subject's facial expression recorded by the web camera while the subject was driving. The final FEE evaluation score was decided by the majority vote of the four examiners.

Before and after each trial, each subject was instructed to maintain a resting state in the driving simulator's seat for 5 min. Then, the subjects were asked to drive for 50 min in the driving simulator, and a video of each subject's face recorded.

Table 1. Facial Expression Evaluation and its Criteria

Grade	Drowsiness stage	Action criteria
0	Not drowsy	Quick and frequent eye shift, active body movement
1	Somewhat drowsy	Open lip, slow eye movement
2	Drowsy	Slow and frequent eyeblink, mouth movement
3	Quite drowsy	Conscious eyeblink, head shake, frequent yawn
4	Very drowsy	Close eyelid, head tilt forward or fall behind

2.4. Analyses

2.4.1 Feature Extraction

Before extracting gazing properties, the threshold to judge the gazing had to be determined. Gazing was considered as a feature when the moving speed was maintained below the considered threshold. To confirm the optimum threshold, we calculated the number of frames in which gazing occurred (1 frame = 1/30 s) per epoch by using the minimum and maximum threshold. By considering the maximum sum of the differences (SOD) value as the optimum threshold candidate, we calculated the SOD of the frames in which gazing occurred, as shown in Figure 3. In this experiment, a threshold of 2−3 deg/s was found to be the maximum SOD value. According to that condition, we therefore chose 2 or 3 deg/s as our final SOD threshold candidate. During this experiment, based on this data, the left side of the threshold candidate was the threshold 1−2 deg/s and the right side was the threshold 3=4 deg/s. If the neighboring gap from the maximum SOD value was closer to the left, then 2 deg/s became the optimum threshold; otherwise, if the gap from the maximum SOD of the candidate of the final threshold value was closer to the right, then a threshold of 3 deg/s became the optimum threshold. In this case, from the optimum SOD candidate, a threshold of 2 deg/s was considered as the optimum threshold. Therefore, we used a threshold value of 2 deg/s as our gazing occurrence threshold. Every subject had a different optimum threshold in each trial. In a total of 88 trials, there were 31 trials with an optimum threshold of 2 deg/s, 30 trials with an optimum threshold of 3 deg/s, and 27 trials with an optimum threshold of 4 deg/s.

The gazing signal was generated by moving speed. On obtaining the optimum threshold, we constructed and extracted the gazing signal, as shown in Figure 4. When the moving speed was less than the threshold and more than zero, gazing occurred. In contrast, when the moving speed was greater than the threshold, there was no gazing. When the moving speed was zero, blinking occurred. In this example, a threshold of 2 deg/s was used. The number of gazing occurrences, blinking occurrences, or non-gazing occurrences could be calculated on a frame by frame basis. The continuous occurrences during a certain period were counted as a cluster. Nine features of the gazing signal, listed in Table 2, could be extracted and computed every epoch. The process was repeated for all the features in each trial.

Table 2. Features Extracted from Gazing Signal

Parameter	Abbrev	Feature
Gazing frame	GF	Number of frames in which gazing occurred per epoch
Gazing cluster	GC	Number of clusters in which gazing occurred per epoch
Non-gazing frame	NF	Number of frames in which non-gazing occurred per epoch
Non-gazing cluster	NC	Number of clusters in which non-gazing occurred per epoch
Blink frame	BF	Number of frames in which blinks occurred per epoch
Blink cluster	BC	Number of frames in which blinks occurred per epoch
Ratio of gazing frames vs. clusters	RG	GF/GC
Ratio of non-gazing frames vs. clusters	RN	NF/NC
Ratio of blink frames vs. clusters	RB	BF/BC

2.4.2. Statistics

Before conducting statistical analysis, we investigated whether each feature correlated with the condition of the subject by using FEE. Then, a Kolmogorov–Smirnov test was used to examine whether the gazing signal showed a normal distribution. One-way ANOVA analysis was used if the distribution data had a normal distribution; otherwise, Wilcoxon-rank sum analysis was used. The results of the feature extraction process were divided into three categories: alert (FEE = 0), lightly drowsy (FEE = 1−2), and heavily drowsy (FEE = 3−4). After dividing the gazing signal into these three categories, statistical analysis was performed to investigate the significant differences within the three categories. A value of $p < 0.05$ was considered to be statistically significant.

2.4.3. Classification

In our study, an SVM was used as a classifier to conduct performance evaluation of the features in the three categories—alert (FEE = 0), lightly drowsy (FEE = 1−2), and heavily drowsy (FEE = 3−4)—by using the LIBSVM library [30], which has also been utilized by Akbar et al. [31]. The features were first combined into one dataset; then, one half was used to make the training data and the other half the testing data (training set: 50%, test set: 50%). The average percentage of total true detection from 4-fold cross-validation was used as a measure of classification accuracy. A radial basis function (RBF) was used as the SVM kernel function. The best value of cost and gamma parameter of the RBF kernel was set automatically by using LIBSVM.

To optimize the classification process, we used the SVM recursive feature elimination (RFE) method for each subject, which is a wrapper-based method. The SVM RFE was developed by Guyon et al. [32] and has been used in gene selection for cancer classification, and by Ebrahimi et al. [33] for automatic sleep staging. The steps in the SVM RFE feature selection algorithm used in this study were as follows: first, one feature was removed, and the accuracy computed. Subsequently, the feature that contributed to the highest accuracy was eliminated. The feature eliminated in the previous step could be used in the next step. This operation was repeated for every feature removed. The feature eliminated first was considered as the worst contributing feature and the feature eliminated last was considered as the best-contributing feature. The final step was to sort the features from best to worst, then compute the accuracy from the best features combination of each subject.

3. RESULTS

Figure 5 shows the relationship between features according to the condition represented by FEE. Gazing frame (GF), gazing cluster (GC), non-gazing cluster (NC), and the ratio of GF/GC (RG) show a decreasing tendency with increasing FEE. In contrast, blink frame (BF), blink cluster (BC), the ratio of BF/BC (RB), and the ratio of non-gazing frame (NF)/NC (RN) show an increasing tendency with increasing FEE. NF does not show any tendency and is inconsistent with FEE.

Table 3 summarizes the typical statistical results of all the features in the three categories: alert, lightly drowsy, heavily drowsy. It can be seen that the GF, GC, and NC exhibit a statistically significant difference ($p < 0.001$; Kruskal–Wallis test) according to the differences in each category followed by the decreasing trend as well. BF, the ratio of BF/BC (RB), and the ratio of NF/NC (RN) also exhibit a statistically significant difference ($p < 0.001$; Kruskal–Wallis test) according to the differences in each category followed by the increasing trend as well. In another case, even though BC and the ratio of GF/GC (RG) tended to FEE during the drowsiness state, these parameters were not considered to have a significant difference in any of the drowsiness categories. Moreover, the NF also has no significant difference owing to its inconsistent tendency to FEE during the drowsiness state. Regarding the statistical results in these three classes, we obtained the results for both increased and decreased properties to represent the drowsiness condition, especially for category 2, which describes the state before becoming drowsy.

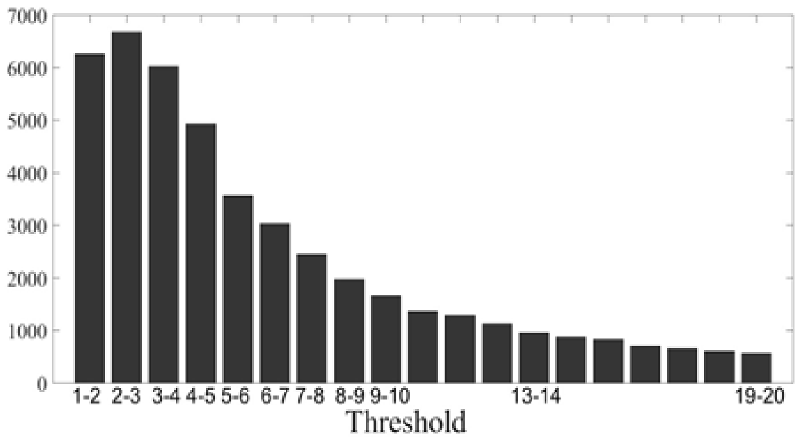

Figure 3. SOD of frames in which gazing occurred

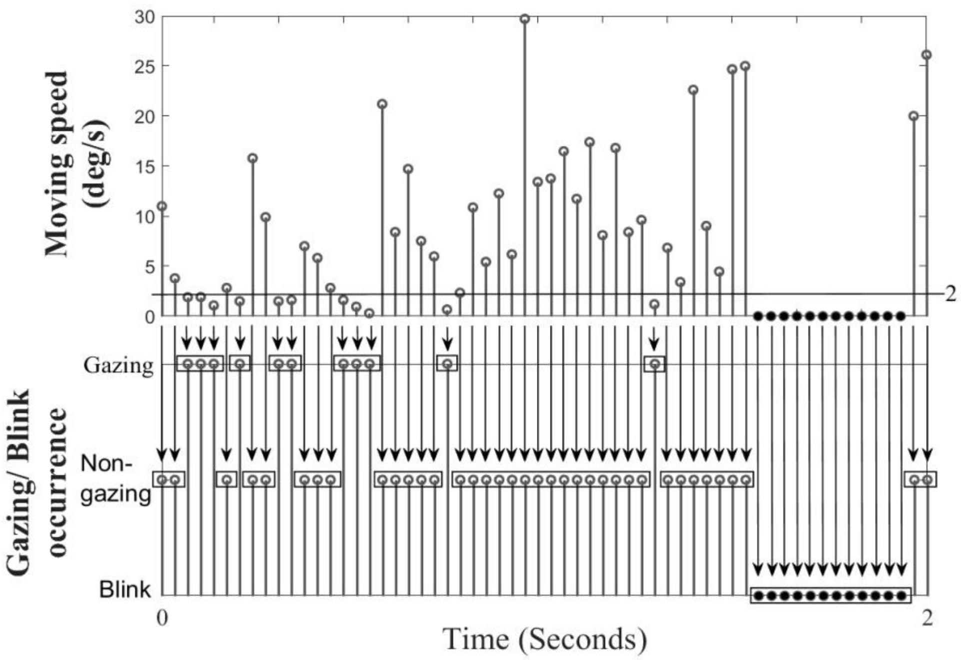

Figure 4. Production of gazing from moving speed for feature extraction

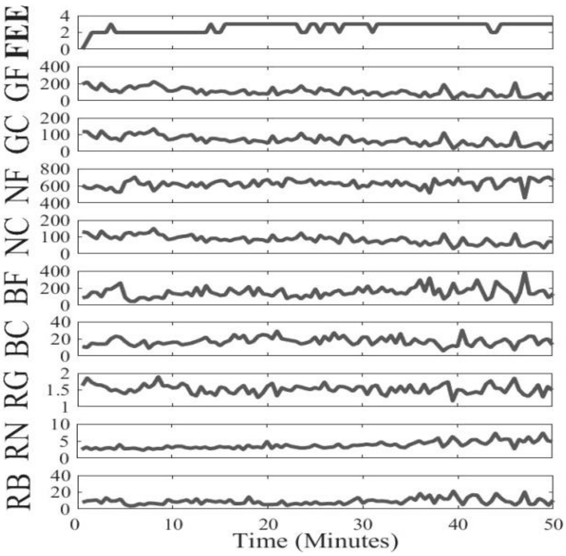

Figure 5. Features tendency according to FEE

Table 3. Statistical Results of all Features, Three Categories: Alert, Lightly Drowsy, Heavily Drowsy

Parameter	Alert	Lightly drowsy	Heavily drowsy
GF	211.39 ± 50.86	165.88 ± 59.91 ***	112.34 ± 58.34 ***, ###
GC	128.33 ± 21.78	98.63 ± 30.28 ***	69.08 ± 30.61 ***, ###
NF	658.36 ± 50.10	667.54 ± 76.45 ***	627.28 ± 109.76 ###
NC	133.67 ± 20.68	106.06 ± 28.84 ***	78.45 ± 28.13 ***, ###
BF	22.06 ± 26.74	36.15 ± 32.86 ***	128.31 ± 114.43 ***, ###
BC	5.16 ± 3.39	7.54 ± 4.78	10.07 ± 5.93 ***, ###
RG	1.63 ± 0.18	1.58 ± 0.16	1.48 ± 0.19 ***, ###
RN	5.10 ± 1.20	6.86 ± 2.39 ***	9.01 ± 3.69 ***, ###
RB	4.82 ± 1.41	9.95 ± 4.66 ***	21.18 ± 17.02 ***, ###

*** p < 0.001 vs. alert, ### p < 0.001 vs. lightly drowsy; all values are expressed as mean ± SD

The results of the three categories show that the gazing parameters could be used to estimate drowsiness. However, several subjects did not show any significant differences corresponding to the psychological measurements using FEE in all categories. We assumed that it was caused by the differences in perception during the examiners' evaluation while examining the subjects' physical state during driving and when watching the video recording of the subjects driving as well.

We used all nine parameter features during the classification analysis. Table 4 shows that the SVM was able to detect the drowsiness with an overall accuracy of 76.3% in the three categories of state: alert, lightly drowsy, and heavily drowsy.

Table 4. Classification Results of all Features for the Three Categories: Alert, Lightly Drowsy, Heavily Drowsy

Subject	Accuracy [%]	Best combination
1	85.4	NC, BF, BC, RG
2	66.2	GF, GC, NF, BC, RG, RN
3	69.2	GF, GC, NF, NC, BC
4	68.0	NC, BF, RG, RN
5	63.8	NF, BF, BC, RG, RN
6	73.8	GC, NF, NC, BF, BC, RG, RN
7	78.3	GF, GC, NF, BF, BC, RG, RN
8	85.8	GC, NF, BF, BC, RG, RN
9	77.6	GF, GC, NF, NC, BC, RG, RN, RB
10	87.6	RB
11	83.4	GF, GC, NF, BF, BC, RG, RB
Overall	76.3	

4. DISCUSSION

We investigated the relationship between gazing properties and drowsiness using features of the gazing parameter and the drowsiness condition using FEE scores during driving. Drowsiness is considered to be related to the human condition. The simplest way to determine the state of the human body is by directly asking the subject their present condition or having them and the examiner complete a drowsiness assessment. Several researchers have used facial expression evaluation (FEE) in questionnaires to obtain the physical condition, especially the drowsiness condition, of a subject. Moreover, previous studies have also evaluated the performance of the FEE (as a drowsiness evaluation tool). Consequently, it has been concluded that the fluctuation of FEE values represents the condition of the subject becoming drowsy. In this study, we observed the drowsiness condition of subjects during driving using an actual driving simulator. We obtained the gazing signal by using a head-mounted eye-tracking device, then extracted and analyzed the features of the gazing parameter using the FEE properties as our evaluation drowsiness method to evaluate drowsiness.

Several studies have investigated drowsiness based on eye properties. For instance, Jackson et al. [34] investigated slow eyelid closure as a measure of driver drowsiness by measuring slow eye closure (PERCLOS) while drivers performed a simulated driving task. However, their study is still limited in its discussion of the parameters associated with the physical condition, especially the drowsiness condition. Moreover, they placed the camera in front of the driver, which does not provide a clear view for the driver and is unstable in terms of position.

Ma'touq et al. [35] used eye blinking to detect driver drowsiness. They proposed a device for monitoring a driver's drowsiness by detecting and classifying the eye blinking into normal blinking (NB) or prolonged blinking (PB). However, they did not discuss the relationship of the parameters associated with the physical condition, especially the drowsiness condition.

Wang and Xu [36] investigated drowsiness based on eye properties. They detected the drowsiness by using eye features: percentage of eye closure (PERCLOS), average pupil diameter, and blink duration combined with driving behavior parameters. They further used multilevel ordered logit (MOL), order logit (OL), and artificial network (ANN) to determine drowsiness in three drowsiness categories. The results of their study showed that the overall accuracy using MOL was 64.15 %, OL was 52.70 %, and ANN was 56.04 % (MOL had the highest detection accuracy). Their study also confirmed that eye features performed better than driving behavior in drowsiness detection. It was confirmed by removing the eye features that the accuracy was reduced. However, their study has a lower accuracy in the detection of drowsiness than our study.

Drowsiness has also been investigated based on eye properties using machine learning or classification methods. Hu and Zheng [37] used an SVM to classify the drowsiness condition in three categories with an overall accuracy of 80.74% in a driving simulator environment. They detected drowsiness via eyelid related parameters using EOG. Although they obtained a higher accuracy than that obtained in our study, their study has a drawback in that electrodes were attached to the driver, which could cause discomfort during driving.

In this study, we used a head-mounted eye tracker to overcome view and position limitations, and to eliminate intrusion while extracting eye properties. This kind of investigation has rarely been conducted. To assess the drowsiness condition, we conducted a subjective evaluation of each subject's physical condition using FEE. We focused on three categories for estimating the condition before actual drowsiness to prevent accidents. Only a few studies have been conducted on gazing properties related to drowsiness. A novel parameter was presented in this study. We found that the features of the gazing had significant statistical differences in three drowsiness categories: alert (FEE=0), lightly drowsy (FEE=1−2), and heavily drowsy (FEE=3−4). Several features of the gazing—gazing occurrence frames per epoch (GF), gazing occurrence clusters per epoch (GC), blink occurrence frames per epoch (BF), non-gazing occurrence clusters per epoch (NC), ratio of blinking frames versus clusters (RB = BF/BC), and the ratio of non-gazing frames versus clusters (RN = NF/NC)—had significant statistical differences with $p < 0.001$; Kruskal-Wallis test. Overall, seven features were sufficient to detect the drowsiness condition in three categories.

Based on those results, an SVM was used to examine the performance of the features to classify the drowsiness condition. In the three categories, alert (FEE=0), lightly drowsy (FEE=1−2), and heavily drowsy (FEE=3−4), the SVM was able to detect the drowsiness with an overall accuracy of 76.3%. In addition, in two categories, alert (FEE=0) and drowsy (FEE=1−4), the SVM was able to detect the drowsiness with an overall accuracy of 89.0%. Note that the result of the classification is subject-dependent as it was calculated using each subject's data. The classification results show that the features of gazing can be used to detect three drowsiness categories from the best features combination of each subject; these results were confirmed via the FEE questionnaire.

The features of the gazing parameter could be used as a new parameter or variable in drowsiness to obtain the characteristics and state of the eyes. We believe that these combinations effectively represent the aspects of the eye properties and could be used to determine the drowsy condition effectively. The eyes are commonly known to be a part of the human body that can clearly represent the human condition of being asleep or awake. Using the gazing properties, we can generally say that a human's eyes easily become unfocused while starting to fall asleep or becoming drowsy when he/she starts getting sleepy or become drowsy. In contrast, a human's gaze is focused when concentrating on a specific object. By considering those specific phenomena and using the gazing properties, we obtained useful parameters and showed that using the ratio of different parameters provided significant differences and could induce classification results between subjects as well as the gazing features themselves. Gazing parameters are composed of several features that could improve the estimation of drowsiness by combining specific parameters.

However, our current study has the following limitation. In order to induce drowsiness, we asked each subject to drive in unrealistic conditions, such as on an oval track with no obstacles and no speed changes. In reality, people drive on various roads while controlling their vehicle's speed and discerning signposts and other vehicles. In such a scenario with obstacles, the subject would have to look at the obstacles in order to drive safely. Consequently, we hypothesize that non-gazing would occur more frequently. We will examine whether our proposed features show the same results regardless of the scenario in future work.

5. CONCLUSION

In this study, a novel parameter and its features were proposed to detect drowsiness and statistical and classification techniques were used to quantify the performance of gazing properties representing several drowsiness condition levels. Our results indicate that the proposed gazing parameter can effectively assess the drowsiness level of a driver.

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