IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 12 May 2022, accepted 29 June 2022, date of publication 4 July 2022, date of current version 11 July 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3187995

RESEARCH ARTICLE

Sensitivity of PERCLOS70 to Drowsiness Level: Effectiveness of PERCLOS70 to Prevent Crashes Caused by Drowsiness

ATSUO MURATA[1], TOSHIHISA DOI[1],
AND WALDEMAR KARWOWSKI[2], (Senior Member, IEEE)
[1]Department of Intelligent Mechanical Systems, Graduate School of Natural Science and Technology, Okayama University, Okayama 700-8530, Japan
[2]Department of Engineering and Management Systems, University of Central Florida, Orlando, FL 32816, USA

Corresponding author: Atsuo Murata (a.murata.koma@gmail.com)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Ethical Committee at the Department of Intelligent Mechanical Systems, Okayama University, Japan, under Application No.2019-sys-04.

ABSTRACT It has been reported that many crashes are caused by drowsiness. Thus, it is critical to predict the occurrence of severe drowsiness that may result in a crash by means of an effective measure. The aim of this study was to investigate whether percentage closure (PERCLOS) of 70% was useful for evaluating drowsiness level of individual drivers and preventing crashes caused by drowsy driving using a driving simulator system. The first experiment measured PERCLOS70 during both aroused and drowsy states in a driving simulator task and investigated how PERCLOS70 changes when a participant fell asleep. In the second experiment, we measured PERCLOS70 and investigated the relation between PERCLOS70 and Karolinska Sleepiness Scale (KSS) ratings during a simulated driving task. The aggregated mean PERCLOS70 was significantly higher when participants fell asleep than when they were aroused. This tendency was also observed for individual participants. The aggregated mean PERCLOS70 was found to be sensitive to changes in KSS scores and increased with increasing KSS score. Linear trend analysis revealed a significant increasing trend for PERCLOS70 as a function of the KSS rating. This tendency was also observed for individual participants. PERCLOS70 was found to be sensitive to the drowsiness level both for data aggregated across all participants and data for individual participants. The main findings of the two experiments reported herein suggest that PERCLOS70 can be used effectively to evaluate drowsiness of individual drivers and prevent crashes caused by drowsy driving.

INDEX TERMS Arousal level, drowsiness, PERCLOS70, Karolinska sleepiness scale, trend analysis.

I. INTRODUCTION

It has been reported that approximately 21% of crashes are caused by drowsiness [1], [2] in US. In Japan, drowsy driving caused 15.2% of fatal crashes in 2021 [3]. Gender, age, job stress, psychological distress, health state, hours of duty, and working environment have shown to cause drowsiness and contribute to crashes [4], [5]. As autonomous driving has become widespread, reduced vigilance among drivers has become a major issue to be addressed to ensure that the transition from autonomous driving to manual driving is executed appropriately without a reduction in vigilance caused by drowsiness during the monotonous monitoring of road risks and hazards [6]–[8]. Therefore, effective methods are needed to warn drivers of the risk of a crash caused by drowsiness and to predict the occurrence of severe drowsiness that may result in a crash. The percentage closure (PERCLOS) of an eye has received increasing attention as an indicator for assessing drowsiness and preventing drivers from driving in a drowsy state and causing a crash.

The associate editor coordinating the review of this manuscript and approving it for publication was Lorenzo Ciani.

PERCLOS represents the percentage of time that an individual's eyes are closed by a certain amount, for example, 70%, during a time window shorter than 1 min. This indicator is widely accepted as an effective tool for detecting drowsiness [9], [10]. There appears to be a relationship between the drowsiness level judged by the Karolinska Sleepiness Scale (KSS) [11] and the duration of eye closures [12]. Ji *et al.* [13] and Ji *et al.* [14] showed that the relationship between performance measures, such as the response time to a stimulus, and PERCLOS changes in accordance with these performance measures.

Kusuma and Sunitha [15] suggested the possibility of monitoring eye closure to detect drowsiness. Based on eye closure measurements and facial image processing, Singh and Banga [16] showed that eye closure measures are related to the level of a driver's drowsiness to some extent. However, these studies did not report the sensitivity of eye closure measurements in assessing drowsiness; that is, the studies did not describe the effectiveness of these measurements for accurately and reliably assessing drowsiness.

It is necessary to assess states with a high risk of crash caused by drowsiness to prevent crashes. PERCLOS has been reported to be a promising parameter for assessing driver fatigue or drowsiness and should be used to detect states that may lead to a crash caused by drowsy driving [17]–[25]. However, these studies have compared PERCLOS between aroused and drowsy condition using aggregated data across participants and have not sufficiently examined the sensitivity of PERCLOS70 to changes in drowsiness for individual drivers. In other words, these studies used only data aggregated across participants to assess drowsiness and did not show that their results apply to individual participants. Thus, there is a need to verify that PERCLOS70 reliably responds to changes in drowsiness even for individual participants to ensure that PERCLOS70 can be used to effectively detect states with a high risk of a crash caused by drowsiness.

Although Salvati *et al.* [23] investigated the relationship between PERCLOS and subjective (self-reported) drowsiness measures represented by KSS and showed that PERCLOS changed in accordance with changes in KSS to some extent, this study showed the data of only three participants and did not statistically test the sensitivity of PERCLOS to drowsiness level of KSS both for each participant and for aggregated data.

If PERCLOS is not sensitive to changes in self-reported drowsiness for each driver, it would be impossible to use PERCLOS to detect a drowsy state of each driver that may lead to a crash. Moreover, to detect a state with a high risk of crash for an individual driver, it is not sufficient to show that only the aggregated PERCLOS is sensitive to changes in self-reported drowsiness. Rather, it is necessary to verify that the PERCLOS of individual drivers changes sensitively in accordance with changes in self-reported drowsiness measures, such as the KSS score. In other words, the sensitivity of PERCLOS to self-reported drowsiness measures such as the KSS score must be confirmed not only for data aggregated across all participants but also for the data of individual participants because the detection of a state with a high crash risk must be conducted for each driver.

The differences between past studies on PERCLOS [10], [17]–[25] and this study are summarized in Table 1. Studies [10], [17], [20], [21] attempted to estimate PERCLOS by applying machine learning techniques to an image of face-tracking camera and suggesed the effectiveness of PERCLOS to assess drowsiness using small samples of eye-opened and eye-closed states. These studies neither compared PERCLOS between aroused and drowsy states nor investigated how PERCLOS changed as subjective sleepiness scale such as KSS changed. Although studies [18], [19], [22]–[25] compared PERCLOS or task performances between aroused and drowsy (or less alerted) states, or attempted to verify the relationship between PERCLOS and KSS, these studies did not appriopriately address these issues (difference of PERCLOS between aroused and drowsy states and sensitivity of PERCLOS to KSS) for both individual participants and data aggregated across all participants using appropriate statistical techniques such as an ANOVA or a trend analysis. As show in Table 1, ERCLOS under drowsy states has not been appriopriately investigated for individual data and data aggregated across all participants using statistical analysis techniques. Moreover, the sensitivity of PERCLOS to drowsiness level has not been explored statistically for individual data and data aggregated across all participants.

In order to address the two issues that were not conducted in past studies (statistical verification of the effectiveness of PERCLOS for individual participants and for data aggregated across participants) summarized in Table 1, this study conducted two experiments and investigated the sensitivity of PERCLOS70 to the drowsiness level for data aggregated across all participants and data of individual participants, and attempted to explore the effectiveness of applying PERCLOS70 to assess drowsiness of individual drivers. Some implications of this study for the development of a system for predicting drowsy states of individual drivers with a high crash risk are discussed.

II. METHOD

A. PARTICIPANTS

Thirteen healthy 21- to 25-year-old males (graduate or undergraduate students) were recruited from the Department of Intelligent Systems, Okayama University to participate in Experiment 1. Seven of the thirteen participants from Experiment 1 agreed to take part in Experiment 2. All participants were licensed drivers with 1–5 years of experience in driving. All participants provided written informed consent after receiving a brief explanation of the aim and content of the experiment. Both experiments were approved by the Ethical Committee at the Department of Intelligent Mechanical Systems, Okayama University, Japan. As Useche et al [5] found that the percentage of crashes was negatively related with age

TABLE 1. Summary of references on PERCLOS and difference between this study and past studies.

Reference	Method (or Approach)					
	Estimation of PERCLOS using machine learning techniques applied to an image of face-tracking camera and suggestion of potential applicability of PERCLOS to assess drowsiness	Experimental comparisons of PERCLOS or task performance between aropused and drpowsy or less alerted states	PECLOS under less alerted or drowsy states : aggregated data	PECLOS under less alerted or drowsy states : individual data	PECLOS vs. drowsiness scale such as KSS : aggregated data	PECLOS vs. drowsiness scal such as KSS : individual dat
[10]	○	×	×	×	×	×
[17]	○	×	×	×	×	×
[18]	×	○	○ (no statistical analysis)	×	×	×
[19]	×	○	×	×	×	○ (no statistical analysis)
[20]	○	×	×	×	×	×
[21]	○	×	×	×	×	×
[22]	×	○	○ (no statistical analysis)	×	×	×
[23]	×	○	×	×	×	○ (no statistical analysis)
[24]	×	○	○ (no statistical analysis)	×	×	×
[25]	×	○	×	×	×	○ (no statistical analysis)
this study	×	○	○	○	○	○

○: applicable × : not applicable

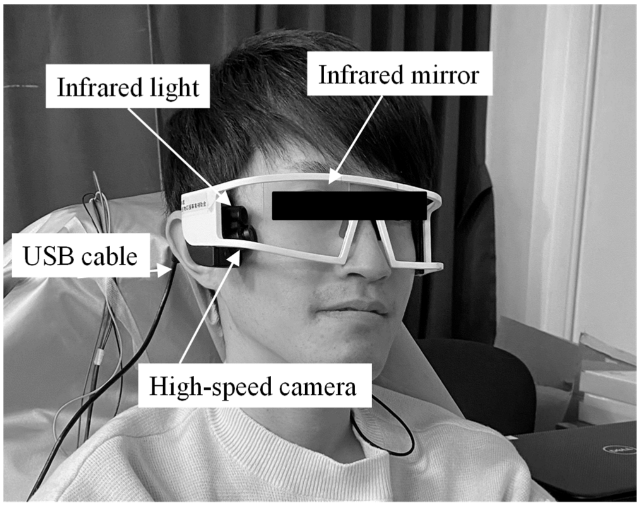


FIGURE 1. Setup of the drowsimeter (Phasya).

of drivers and was higher for young drivers than for other drivers, young male participants were adopted as partcipants.

B. APPARATUS

Drowsimeter R100 (Phasya) (see Figure 1) was used to measure PERCLOS70. This apparatus applies infrared light to the right eye of the participant to project an image to an infrared mirror. The image is recorded at 120 fps using a high-speed camera. The recorded image is processed via image processing software (Drowsilogic V4.2.5). Based on the image of the recorded eye, the software (Drowsilogic V4.2.5) obtains the eyelid position, pupil position, and pupil diameter at a sampling frequency of 120 Hz. The software can derive the PERCLOS70, mean blink duration, and blink frequency every 1 s by using the eyelid position, pupil position, and pupil diameter. PERCLOS70 corresponds to the percentage (ratio) of time during which an eye is closed by more than 70% of the standard (calibrated) eyelid position during the measurement duration of 60 s. The standard (calibrated) eyelid position is obtained through a calibration procedure. One minute prior to the measurements, the calibration is executed as follows. The standard (calibrated) eyelid position, which is representative of the aroused state, is calculated as the mean of the eyelid position sampled at a frequency of 120 Hz for 1 min.

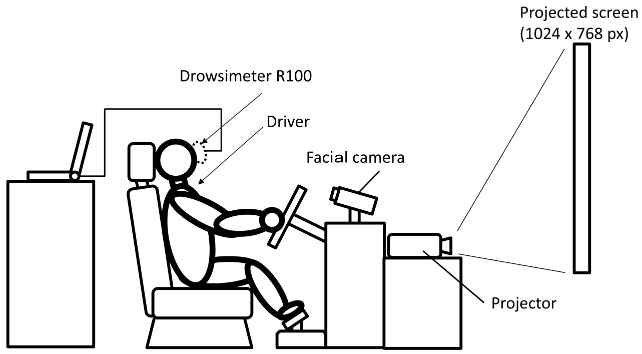


FIGURE 2. Schematic of the driving simulator.

This study used the driving simulator system shown in Figure 2. Participants were asked to perform a simulated driving task using a steering controller (Logicool, LPRC-14000). The driving simulator was programed using Hot Soup Processor 3.4. We used a personal computer (PC) (OS: Windows 10 Pro 64bit, CPU: Intel Core i7-10700 2.9 GHz, GPU: NVIDIA GeForce GT710 DDR3 2 GB, Memory: 32 GB DDR4 2666), a graphic box for multiple-monitor outputs (Matrox, TripleHead2Go digital edition), and a projector

(EPSON, EB-S12H) to display a simulated driving task in front of the participant. The steering controller was connected to the PC. The resolution of the projector was 1024 x 768 pixels, and the brightness around the steering controller was approximately 4.9 lx. The mean luminance of five locations (four corners and the center) on the simulator display in front of the participant was approximately 36.0 cd/m^2. A video camera (Sony, Handycam HDR) was used to observe the facial expression of the participant.

This study consisted of two stages (Experiment 1 and Experiment 2). First, Experiment 1 (stage 1) was conducted to compare PERCLOS70 between an aroused condition and a drowsy condition for individual participants. For both aggregated data and individual data, such comparisons were conducted using a statistical analysis (t-test). Next, we carried out Experiment 2 (stage 2) to investigate the relationship between self-reported drowsiness measures (KSS score) and PERCLOS70 and to explore the sensitivity of PERCLOS70 to a subjective drowsiness level for individual participants. Both aggregated data and individual data were analyzed statistically using a one-way (KSS level) ANOVA and a trend analysis between KSS and PERCLOS70.

C. EXPERIMENT 1-STAGE 1: COMPARISON OF PERCLOS BETWEEN AROUSED AND DROWSY STATES-

1) TASK

The participants were required to perform a simulated driving task, driving along the central lane of a straight road with three lanes. The participants were also required to follow a leading car, suppress the deviation of their own car from the center of the second (center) lane as much as possible, and maintain a distance of 16.5–38.0 m between their car and the leading car. The speed of the leading car was randomly altered. A green rectangular frame was displayed around the image of the leading car to inform each participant that he was maintaining an appropriate distance. If the distance between the cars fell below 16.5 m or exceeded 38.0 m, the participant was informed of this change in status by a change in the color of the rectangular frame.

2) DESIGN AND PROCEDURE

The experiments were conducted in (i) aroused and (ii) drowsy conditions. For the aroused condition (i), each participant was asked to get a sufficient sleep and visit the laboratory in the early morning. The duration for condition (i) was 660 s for each participant. For the drowsy condition (ii), each participant was asked to stay up all night and visit the laboratory in the early morning. The experiment continued until the participant fell asleep and it was difficult to continue the experiment further. We applied the following criteria to judge whether the experiment was complete. Three experimenters judged the images of the participant's facial expression; when at least two of the three experimenters judged that the participant had fallen asleep, it was determined that it was difficult to continue the experiment further. All thirteen participants were judged to have fallen asleep according to the criteria. The duration from the beginning of the experiment to the time point at which the participant was judged to have fallen asleep according to the above criteria ranged from 490 s to 1330 s. The reason of different range of experimental duration is stated as follows. As the degree of induced drowsiness differed among participants and it was impossible to control the degree of induced drowsiness of each participant during the experiment, the duration consequently differed among participants.

The software (Drowsilogic V4.2.5) utilized in this experiment derives the state of eye closure from completely closed (100% closure) to completely open (0% closure) corresponding to the standard (calibrated) eyelid position. PERCLOS70 corresponds to the percentage (ratio) of time during which an eye is closed by more than 70% of the standard (calibrated) eyelid position during the measurement duration of 60 s. PERCLOS70 outliers were removed based on the interquartile range. Data points above 75 percentile + interquartile range*1.5 or below 25 percentile – interquartile range*1.5 were removed from the data as outliers. Each outlier was replaced with the PECLOS70 mean before and after the outlier was detected.

3) STATISTICAL ANALYSIS

The mean data of all participants for conditions (i) and (ii) were statistically tested using a paired t-test. The mean data for each participant in conditions (i) and (ii) were also statistically tested using an unpaired t-test.

D. EXPERIMENT 2-STAGE 2: RELATIONSHIP BETWEEN KSS AND POERCLOS-

1) TASK AND DESIGN

An experiment similar to Experiment 1 was conducted between 2 p.m. and 6 p.m. for all participants. Unlike the drowsy condition (ii) in Experiment 1, the participants were not required to stay up all night and visit the laboratory. This experiment required participants to rate their drowsiness every 30 s using the KSS [11]. The meaning of ratings 1–9 in the KSS was explained to each participant. A message instructing the participant to enter their KSS rating was shown on the simulator display every 30 s. The duration of the experiment was 2400 s for all participants. When there was no response to the message four times in a row, we judged that the participant had fallen asleep, and the experiment was terminated.

2) STATISTICAL ANALYSIS

The mean PERCLOS was calculated for each rating category (3–9). A one-way (category in KSS rating) analysis of variance (ANOVA) was conducted on PERCLOS70. A linear trend analysis was also conducted on PERCLOS70 to confirm whether PERCLOS70 increased with increasing KSS rating. The KSS ratings ranged from 3 to 9 for all participants, and ratings of 1 and 2 were not reported in this experiment.

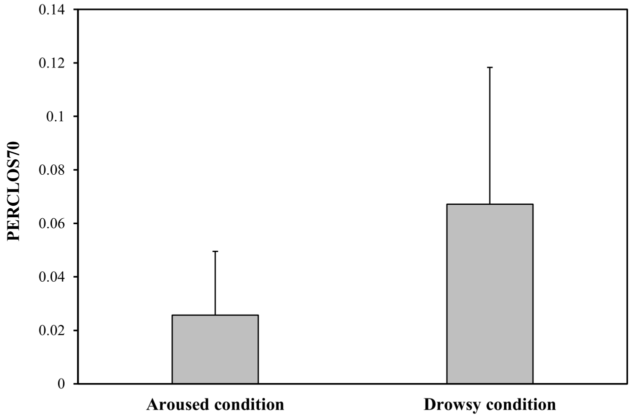


FIGURE 3. Aggregated mean PERCLOS (bar: standard deviation (SD)) for the aroused and drowsy state (Experiment 1).

TABLE 2. Results of a paired*t*-test conducted on PERCLOS70 (Experiment 1).

Participants	Mean difference	t
A	0.042	$t(1858)=66.431^{**}$
B	0.038	$t(1518)=19.064^{**}$
C	0.020	$t(2298)=21.220^{**}$
D	0.020	$t(1198)=33.538^{**}$
E	0.091	$t(1178)=49.179^{**}$
F	0.008	$t(1508)=22.362^{**}$
G	0.013	$t(1868)=12.290^{**}$
H	0.029	$t(1868)=15.944^{**}$
I	0.074	$t(1078)=24.420^{**}$
J	0.023	$t(1148)=33.921^{**}$
K	0.047	$t(2288)=48.048^{**}$
L	0.020	$t(1698)=30.65^{**}$
M	0.114	$t(1568)=50.026^{**}$

**: $p < 0.01$

A similar one-way ANOVA was carried out for each participant to confirm whether the trends observed for data aggregated over all participants were observed for individual PERCLOS70 data. Linear trend analysis was also carried out on the relationship between KSS rating and PERCLOS70 for each participant.

III. RESULTS

A. EXPERIMENT 1

In Figure 3, the aggregated mean PERCLOS over all participants is compared between the aroused and drowsy state. A paired t-test revealed a significant difference between the aroused and drowsy states ($t(12) = 4.597, p < 0.01$). PERCLOS tended to be significantly higher in the drowsy state than in the aroused state. Figure 4 shows the PERCLOS70 of each participant for the aroused and drowsy states. The results of a paired t-test for each participant are summarized in Table 2. For all participants, PERCLOS was higher in the drowsy state than in the aroused state. Examples of changes in PERCLOS over time are shown in Figure 5. Similar results were obtained for other eleven participants. The results indicate that PERCLOS is promising for assessing drowsiness.

TABLE 3. Results of a multiple comparison conducted on PERCLOS70 (Experiment 2).

	KSS=3	KSS=4	KSS=5	KSS=6	KSS=7	KSS=8	KSS=9
KSS=3							
KSS=4	n.s.						
KSS=5	n.s.	n.s.					
KSS=6	n.s.	n.s.	n.s.				
KSS=7	*	*	n.s.	n.s.			
KSS=8	*	*	n.s.	n.s.	n.s.		
KSS=9	**	**	**	**	*	*	

**: $p < 0.01$, *: $p < 0.05$, n.s.: not significant

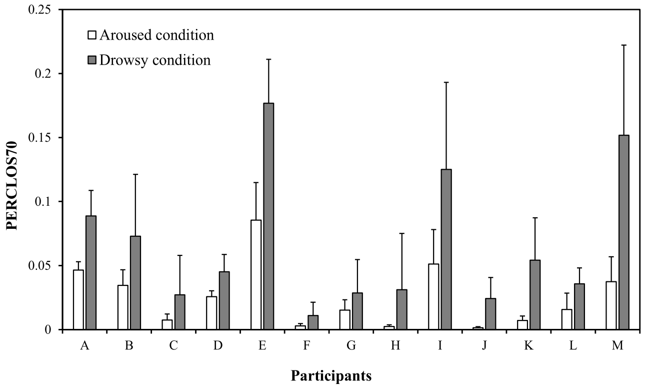


FIGURE 4. PERCLOS (bar: SD) in the aroused and drowsy state for each of the thirteen participants (Experiment 1).

The reason of different values of PERCLOS among participants is stated as follows. Although it is known that eye closure might be an effective measure of decremented alertness or drowsiness [21], [22], the physiological manifestation of eye closure accompanied by drowsiness or decremented alert level is different among participants. While 50% eye closure might be regarded as drowsy for one participant, this state might not be regarded as drowsy for another participant. For this participant, the eye closure of more than 70% might be regarded as drowsy or less alerted states. In other words, the degree of eye closure accompanied by drowsiness or decremented alertness differs among participants. Therefore, the values of PERCLOS were different among participants.

B. EXPERIMENT 2

The aggregated mean PERCLOS70 over all participants is plotted as a function of KSS rating in Figure 6. A one-way ANOVA (KSS value: seven levels) conducted on PERCLOS70 revealed a significant main effect of KSS value ($F(6, 36) = 12.485, p < 0.01$). The results of a Tukey–Kramer multiple comparison are summarized in Table 3. Linear trend analysis conducted on PERCLOS70 revealed a significant linear increasing trend, as shown in Figure 6 ($F(1, 36) = 117.383, p < 0.01$). The relation

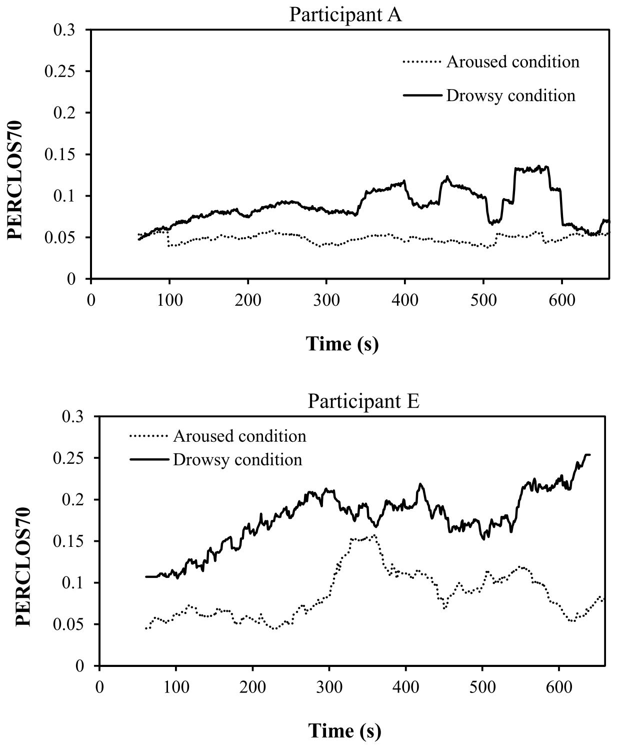


FIGURE 5. Examples of changes in PERCLOS70 in the aroused and drowsy state (Experiment 1).

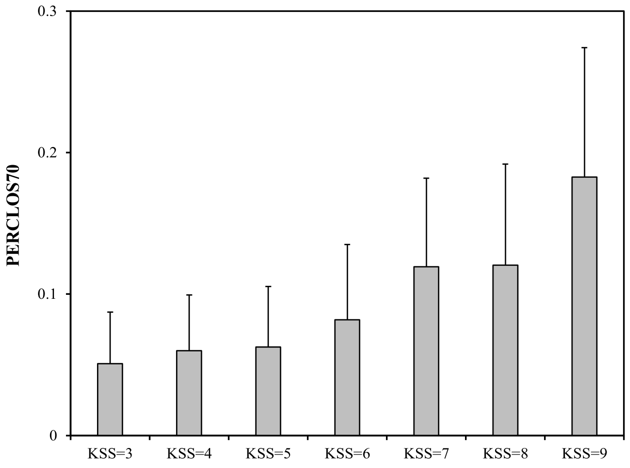


FIGURE 6. Aggregated mean PERCLOS (SD: bar) as a function of KSS rating (3–9) (Experiment 2).

between the KSS and PERCLOS values for each participant is shown in Table 4. The results of linear trend analysis between the KSS rating and PERCLOS70 for each participant are also included in Table 4. The results of a similar one-way ANOVA conducted on PERCLOS70 for each participant are shown in Table 5. Examples of changes in KSS rating and PERCLOS70 are shown in Figure 7. It appears that PERCLOS tends to increase with increasing KSS rating for data aggregated across all participants (Figure 6) and for data of each participant (Table 3 and Figures 6 and 7).

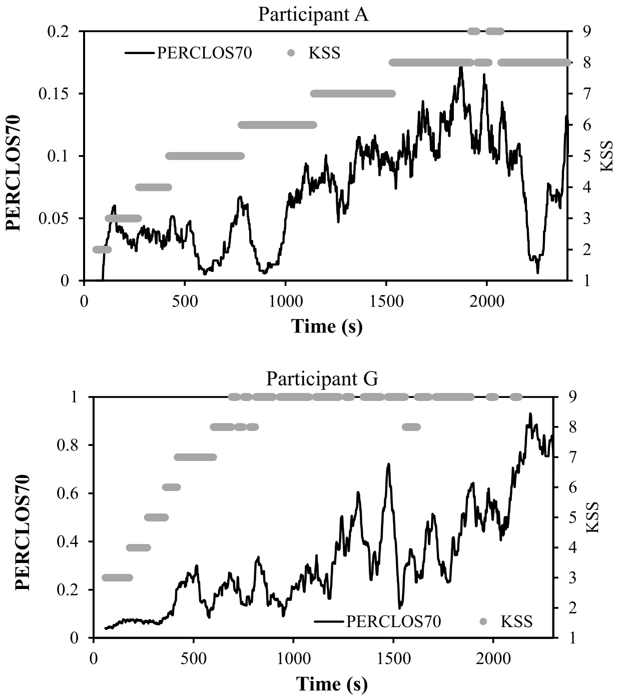


FIGURE 7. Examples of changes in PERCLOS70 and KSS rating over time (Experiment 2).

IV. DISCUSSION

The Federal Highway Administration (FHWA) and National Highway Transport Safety Administration (NHTSA) recommend that the PERCLOS value be used by in-vehicle drowsiness detection systems to assess drowsiness. In accordance with this recommendation, many studies have demonstrated that PERCLOS is sensitive to inattentive, fatigued, or drowsy states [10], [17]–[25].

Dinges and Grace [18] showed that PERCLOS was significantly correlated with performance in a psychomotor vigilance task and concluded that PERCLOS may be effective for assessing and predicting a reduction in vigilance. Although it is plausible to assume that the decrease in vigilance is induced by a reduced arousal level (increased drowsiness), this study did not investigate the relationship between PERCLOS and drowsiness for each participant.

Hanowski *et al.* [10], for example, sought to assess driver drowsiness based on an eye-closure measure and lane deviation performance and showed that a multi-metric assessment system was more robust and effective than a single-metric assessment system (using only an eye-closure measurement). Although this study succeeded in measuring the lane deviation performance or PERCLOS and assessing a drowsy state, the authors did not attempt to predict in advance the time point of an episode with a higher crash risk.

Jackson *et al.* [19] also revealed that PERCLOS is related to variability in both vigilance performance and variation in driving lane position to some extent. However, these results were based on mean data aggregated across all participants. The sensitivity of PERCLOS to changes in KSS was not

TABLE 4. Rating for each participant (Experiment 2).

		KSS=3	KSS=4	KSS=5	KSS=6	KSS=7	KSS=8	KSS=9	F_{model}		Regression coefficient (Slope)	
Participant A	Mean (SD)	0.039 (0.009)	0.036 (0.004)	0.029 (0.016)	0.043 (0.027)	0.088 (0.016)	0.100 (0.038)	0.109 (0.008)	$F(1,2361)$= 2279.461	**	29.944	**
	Number of samples	150	150	360	360	390	802	90				
Participant B	Mean (SD)	0.033 (0.021)	0.062 (0.022)	0.055 (0.012)	0.069 (0.040)	0.143 (0.022)	0.135 (0.050)	0.248 (0.076)	$F(1,2365)$= 3324.725	**	15.275	**
	Number of samples	181	150	180	180	240	450	956				
Participant C	Mean (SD)	0.136 (0.012)	0.1467 (0.013)	0.163 (0.008)	0.195 (0.021)	0.213 (0.033)	0.229 (0.033)	0.231 (0.026)	$F(1,2359)$= 3605.546	**	36.302	**
	Number of samples	211	210	90	240	380	450	780				
Participant D	Mean (SD)	0.020 (0.003)	0.023 (0.003)	0.030 (0.006)	0.035 (0.007)	0.039 (0.015)	0.033 (0.021)	0.042 (0.031)	$F(1,2364)$= 313.325	**	27.075	**
	Number of samples	121	180	180	210	390	475	690				
Participant E	Mean (SD)	0.042 (0.004)	0.056 (0.019)	0.043 (0.010)	0.068 (0.007)	0.087 (0.017)	0.060 (0.025)	0.227 (0.115)	$F(1,1769)$= 889.780	**	14.652	**
	Number of samples	120	240	120	150	240	270	450				
Participant F	Mean (SD)	0.029 (0.005)	0.025 (0.003)	0.050 (0.015)	0.042 (0.013)	0.063 (0.015)	0.068 (0.033)	0.104 (0.049)	$F(1,2059)$= 1183.651	**	29.805	**
	Number of samples	120	90	90	270	270	420	680				
Participant G	Mean (SD)	0.058 (0.013)	0.071 (0.004)	0.067 (0.007)	0.119 (0.036)	0.201 (0.060)	0.217 (0.079)	0.318 (0.145)	$F(1,2357)$= 1884.509	**	5.981	**
	Number of samples	121	90	90	60	180	228	990				

**: $p < 0.01$

explored for each participant (see Table 1) using a statistical analysis technique. Trutschel *et al.* [25] showed that the combination of Electroencephalography (EEG)/ Electrooculography (EOG) data and PERCLOS is more effective for predicting KSS ratings and performance decrements. Their results indicated that PERCLOS is the most reliable and valid parameter for determining driver alertness levels. However, as summarized in Table 1, this study did not investigate statistically the effectiveness of applying PERCLOS to assess the drowsiness represented by the KSS for both individual data and data aggregated across all participants.

By using data aggregated across all participants or individual data, the past studies [18], [19], [22]–[25] suggested that PERCLOS tended to increase under drowsy states in comparison to aroused states or tended to increase with the increase in KSS score; however, these studies did not verify statistically the effectiveness of PERCLOS for individual participants or for data aggregated across all participants as summarized in Table 1. Although Jackson *et al.* [19], Salvati *et al.* [23], and Trutschel *et al.* [25] showed that PERCLOS changed in accordance with changes in KSS for a few individuals, they did not verify statistically the relationship between PERCLOS and KSS score for individual data. Moreover, they did not verify the assumed relationship between PERCLOS and KSS score for data aggregated across all participants. Dinges *et al.* [18], Nie *et al.* [22], and Thropp *et al.* [24], using the aggregated data across all participants, showed the difference of PERCLOS between drowsy or less alerted states and aroused states and suggested that PERCLOS might be effective for assessing drowsiness. However, these studies did not statistically verify the validity of their results. Therefore, we conducted Experiments 1 and 2 to investigate the issues that past studies did not address appropriately as summarized in Table 1, verified statistically the higher PERCLOS values under drowsy states (aggregated data: Figure 3, individual data: Figure 4 and Table 2), and verified statistically the relationship between PERCLOS and KSS score (aggregated data: Figure 6, individual data: Tables 4 and 5).

TABLE 5. Results of one-way (KSS rating) ANOVA conducted on PERCLOS data for each participant (Experiment 2).

Participant	F
A	$F(7,2355)$=485.295**
B	$F(6,2330)$=834.502**
C	$F(6,2354)$=676.281**
D	$F(6,2239)$=35.757**
E	$F(7,1763)$=379.322**
F	$F(7,2053)$=221.263**
G	$F(6,1752)$=212.424**

**: $p < 0.01$

Based on the results of Experiment 1 (Figures 3–5), this study showed that PECLOS70 differs between the aroused and drowsy states. Using both data aggregated across all participants (Figure 3) and data for each participant (Figures 4–5), we demonstrated that PERCLOS70 is effective for differentiating the aroused state and the drowsy states at an individual level. Experiment 2 aimed to further explore the sensitivity of PERCLOS70 to self-reported drowsiness (KSS) by assessing not only data aggregated across all participants but also data for individual participants. The results (Figures 6–7 and Tables 4–5) demonstrated that PERCLOS was sensitive to changes in KSS ratings in both aggregated data and data for individuals. Addressing the issues to validate the effectiveness of PERCLOS for individual participants (Table 1), this study showed that PERCLOS70 was sensitive to drowsy states even for individual participants, which demonstrates that PERCLOS can be used to assess individual drivers' drowsiness and to prevent crashes caused by drowsiness.

The use of goggles, as shown in Figure 1, enables us to measure PERCLOS more accurately than images of the eye from a video camera, because using the image of an eye from a video camera as studies [10], [17], [20], [21] (see Table 1) may not be recorded accurately and it is sometimes difficult to record this image when the driver is outside the recording area. In contrast, the goggle-type apparatus can acquire images of the eye as long as the driver is wearing it. The results in this study suggest that PERCLOS measured by a goggle-type instrument is promising for detecting the drowsy state (based on KSS ratings) of an individual driver. It must be noted, as a limitation of this study, that goggle-type equipment is currently expensive.

The issue of reduced vigilance during autonomous driving must be addressed so that drivers can appropriately take over the driving of an autonomous car without a reduction in vigilance while monitoring driving risks and hazards [6]–[8]. Reduced vigilance should be avoided in autonomous driving because an appropriate takeover may be unexpectedly required for a driver under autonomous driving levels 1–3 to secure safety in driving. Using data for individuals, this study showed that PERCLOS may be effective for detecting in advance drowsy states that may lead to a crash, allowing for a warning to the driver of a crash risk caused by drowsiness. To address the issue of reduced vigilance during autonomous driving, effective methods are needed to warn drivers of reduced vigilance or a low arousal state that may result in a failure of takeover and a crash. The sensitivity of PERCLOS70 to drowsiness, even within individuals, can be applied to effectively address the issue of reduced vigilance during autonomous driving.

Based on this study, future research should be directed to apply PERCLOS70 for developing a detection system of drowsiness with a high risk of a crash. A state of drowsiness with a high crash risk might be detected by using, for example, the methods proposed by Murata [26], Murata and Fukuda [27], or Murata *et al.* [28]. For the findings in this study and other studies to be used to effectively prevent crashes or unsafe driving caused by drowsiness, PERCLOS70 must be successfully combined with driving performance measures, such as lane deviation performance [19], to detect states with high risk of a crash or unsafe driving.

Although the combination of physiological measures, such as EEG or heart rate variability, might increase accuracy in detecting a drowsy state leading to a crash, detection methods based on many measures are not practical. As mentioned above, the goggle-type PERCLOS measurement apparatus might be more acceptable to a driver if it would lead to an accurate detection of drowsiness and be helpful for preventing crashes.

As a limitation of this study, we have not yet proposed and established a method for detecting a drowsy driving state with a high crash risk using mainly PERCLOS70 that was found to be sensitive to the change of drowsiness level and secondary performance measures such as lane deviation. In light of requirements for appropriate takeovers in autonomous driving, the use of PERCLOS70 is promising for assessing drowsiness to ensure that the driver is always alert and prepared for a sudden request to take over from an autonomous driving car.

As another limitation of this study, the percentage of eye closure exceeding 70% was selected empirically, and there is no definitive rationale for using a percentage of 70% as a measure of drowsiness. Future research should further verify the validity of PERCLOS70 as an indicator of drowsiness.

Future research should also verify the validity of the results of young male participants for other populations such as female participants or older adults to generalize the results. Moreover, as suggested by Zhang *et al.* [4] and Useche *et al.* [5], we should investigate how daily shift intensity (hours of duty), health states, psychological distress, or job stress affect the results of this study so that the results can be further generalized.

V. CONCLUSION

By conducting Experiments 1 and 2, we examined how PERCLOS70 and self-reported KSS ratings (drowsiness levels) were related. The conclusions are summarized as follows.

(1) The PERCLOS70 was significantly higher when participants fell asleep in comparison to the aroused state for data aggregated across all participants and data of individual participants.

(2) PERCLOS70 tended to increase significantly as a function of KSS, indicating the high sensitivity of PECLOS70 to self-reported drowsiness for both aggregated and individual data.

Hight sensitivity of each participant's PERCLOS70 to the change of drowsiness level is effective for detecting a state with a high risk of a crash and for preventing crashes caused by drowsy driving.

ACKNOWLEDGMENT

The authors would like to thank S. Ono at the Department of Intelligent Mechanical Systems, Okayama University, for his support in this work.

REFERENCES

[1] AAA Foundation for Traffic Safety. (2014). *Prevalence of Motor Vehicle Crashes Involving Drowsy Drivers, United States, 2009–2013*. Accessed: Nov. 29, 2021. [Online]. Available: https://aaafoundation.org/wp-content/uploads/2017/12/PrevalenceofMVCDrowsyDriversReport.pdf

[2] D. S. Bowman, W. A. Schaudt, and R. J. Hanowski, "Advances in drowsy driver assistance systems through data fusion," in *Handbook of Intelligent Vehicles*, vol. 2, A. Eskandarian, Ed. London, U.K.: Springer, 2012, pp. 895–909.

[3] National Police Agency. (2021). *Statistics About Road Traffic*. Accessed: Nov. 29, 2021. [Online]. Available: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00130002&tstat=000001027458&cycle=7&year=20200&month=0&tclass1val=0

[4] G. Zhang, K. K. W. Yau, X. Zhang, and Y. Li, "Traffic accidents involving fatigue driving and their extent of casualties," *Accident Anal. Prevention*, vol. 87, pp. 34–42, Feb. 2016.

[5] S. A. Useche, F. Alonso, B. Cendales, and J. Llamazares, "More than just 'stressful'? Testing the mediating role of fatigue on the relationship between job stress and occupational crashes of long-haul truck drivers," *Psychol. Res. Behav. Manage.*, vol. 14, pp. 1211–1221, Jul. 2021.

[6] M. Kyriakidis, J. C. F. de Winter, N. Stanton, T. Bellet, B. van Arem, K. Brookhuis, M. H. Martens, K. Bengler, J. Andersson, N. Merat, N. Reed, M. Flament, M. Hagenzieker, and R. Happee, "A human factors perspective on automated driving," *Theor. Issues Ergonom. Sci.*, vol. 20, no. 3, pp. 223–249, 2019.

[7] J. S. Warm, R. Parasuraman, and G. Matthews, "Vigilance requires hard mental work and is stressful," *Hum. Factors, J. Hum. Factors Ergonom. Soc.*, vol. 50, no. 3, pp. 433–441, 2008.

[8] A. Whitmore and N. Reed, "The role of physiological monitoring in the implementation of vehicle automation," *Eng. Technol. Reference*, pp. 1–9, Jan. 2015.

[9] D. F. Dinges, M. M. Mallis, G. Maislin, and J. W. Powell, "Final report: Evaluation of techniques for ocular measurement as an index of fatigue and as the basis for alertness management," Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. HS-808-762, 1998.

[10] R. J. Hanowski, D. Bowman, A. Alden, W. W. Wierwille, and R. Carroll, "PERCLOS+: Moving beyond single-metric drowsiness monitors," SAE Tech. Paper 2008-01-2692, 2008.

[11] T. Åkerstedt and M. Gillberg, "Subjective and objective sleepiness in the active individual," *Int. J. Neurosci*, vol. 52, nos. 1–2, pp. 29–37, Jul. 1990.

[12] S. Samiee, S. Azadi, A. Nahvi, A. Eichberger, and R. Kazemi, "Data fusion to develop a driver drowsiness detection system with robustness to signal loss," *Sensors*, vol. 14, no. 9, pp. 17832–17847, Sep. 2014.

[13] Q. Ji, Z. Zhu, and P. Lan, "Real-time nonintrusive monitoring and prediction of driver fatigue," *IEEE Trans. Veh. Technol.*, vol. 53, no. 4, pp. 1052–1068, Jul. 2004.

[14] Q. Ji, P. Lan, and C. Looney, "A probabilistic framework for modeling and real-time monitoring human fatigue," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 36, no. 5, pp. 862–875, Sep. 2006.

[15] K. B. M. Kusuma and K. M. Sunitha, "Non intrusive drowsy driver detection," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 3, pp. 32–35, Jan. 2014.

[16] I. Singh and V. K. Banga, "Development of a drowsiness warning system using neural network," *Int. J. Adv. Res. Electr., Electron. Instrum. Eng.*, vol. 2, pp. 3614–3623, Aug. 2013.

[17] S. Darshana, D. Fernando, S. Jayawardena, S. Wickramanayake, and C. DeSilva, "Efficient PERCLOS and gaze measurement methodologies to estimate driver attention in real time," in *Proc. 5th Int. Conf. Intell. Syst., Modelling Simulation*, Jan. 2014, pp. 289–294.

[18] D. F. Dinges and R. Grace, "PERCLOS: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance," Federal Highway Admin., Washington, DC, USA, Tech. Rep. FHWA-MCRT-98-006, 1998.

[19] M. L. Jackson, S. Raj, R. J. Croft, A. C. Hayley, L. A. Downey, G. A. Kennedy, and M. E. Howard, "Slow eyelid closure as a measure of driver drowsiness and its relationship to performance," *Traffic Injury Prevention*, vol. 17, no. 3, pp. 251–257, Apr. 2016.

[20] S. Junaedi and H. Akbar, "Driver drowsiness detection based on face feature and PERCLOS," *J. Phys., Conf. Ser.*, vol. 1090, Sep. 2018, Art. no. 012037.

[21] S. Kim, I. Wisanggeni, R. Ros, and R. Hussein, "Detecting fatigue driving through PERCLOS: A review," *Int. J. Image Process.*, vol. 14, nos. 1–7, p. 1, 2020.

[22] B. Nie, X. Huang, Y. Chen, A. Li, R. Zhang, and J. Huang, "Experimental study on visual detection for fatigue of fixed-position staff," *Appl. Ergonom.*, vol. 65, pp. 1–11, Nov. 2017.

[23] L. Salvati, M. d'Amore, A. Fiorentino, A. Pellegrino, P. Sena, and F. Villecco, "On-road detection of driver fatigue and drowsiness during medium-distance journeys," *Entropy*, vol. 23, no. 2, p. 135, Jan. 2021.

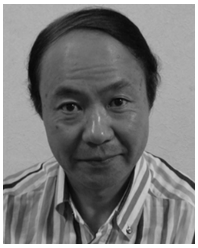
[24] J. E. Thropp, J. F. V. Scallon, and P. Buza, "PERCLOS as an indicator of slow-onset hypoxia in aviation," *Aerosp. Med. Hum. Perform.*, vol. 89, no. 8, pp. 700–707, Aug. 2018.

[25] U. Trutschel, B. Sirois, D. Sommer, M. Golz, and D. Edwards, "PERCLOS: An alertness measure of the past," in *Proc. 6th Int. Driving Symp. Hum. Factors Driver Assessment, Training, Vehicle Design*, 2011, pp. 172–179.

[26] A. Murata, "Proposal of a method to predict subjective rating on drowsiness using physiological and behavioral measures," *IIE Trans. Occupat. Ergonom. Hum. Factors*, vol. 4, nos. 2–3, pp. 128–140, Jul. 2016.

[27] A. Murata and K. Fukuda, "Development of a method to predict crash risk using trend analysis of driver behavior changes over time," *Traffic Injury Prevention*, vol. 17, no. 2, pp. 114–121, Feb. 2016.

[28] A. Murata, K. Naitoh, and W. Karwowski, "A method for predicting the risk of virtual crashes in a simulated driving task using behavioural and subjective drowsiness measures," *Ergonomics*, vol. 60, no. 5, pp. 714–730, May 2017.



ATSUO MURATA received the M.E. and Ph.D. degrees in industrial engineering from the University of Osaka Prefecture, in 1985 and 1987, respectively. He was a Professor at Hiroshima City University, from 1997 to 2006. Since 2006, he has been a Professor with the Department of Intelligent Mechanical Systems, Okayama University. His current research interests include accident analysis and safety management and automotive ergonomics.

TOSHIHISA DOI received the M.E. and Ph.D. degrees from Wakayama University, in 2012 and 2015, respectively. He was a Research and Development Engineer at Lenovo Japan Ltd. Since 2016, he has been a Junior Assistant Professor with the Department of Intelligent Mechanical Systems, Okayama University. His research interests include human-interface design and automotive ergonomics.

WALDEMAR KARWOWSKI (Senior Member, IEEE) received the M.S. degree in production engineering and management from the Technical University of Wroclaw, Poland, in 1978, the Ph.D. degree in industrial engineering from Texas Tech University, in 1982, and the D.Sc. and P.E. degrees. He is currently a Pegasus Professor and the Chairman of the Department of Industrial Engineering and Management Systems and the Executive Director of the Institute for Advanced Systems Engineering, University of Central Florida, Orlando, USA. He has over 500 publications focused on mathematical modeling and computer simulation with applications to human systems engineering, human-centered-design, safety, neuro-fuzzy systems, nonlinear dynamics and chaos, and neuroergonomics. He serves as the Co-Editor-in-Chief of the *Theoretical Issues in Ergonomics Science* journal (Taylor & Francis Ltd.), the Editor-in-Chief of the *Human-Intelligent Systems Integration* journal (Springer), and the Field Chief Editor of the *Frontiers in Neuroergonomics* journal.

• • •