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Drowsiness estimation from identified driver model

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This paper proposes an estimation method for a driver’s drowsiness that uses an identified driver model. In the previous report, it was shown that a driver’s involuntary response to a car’s motion can be extracted by pre-filtering and provided to the real-time identification method. The identified driver model contains meaningful parameters related to the driver’s characteristics. In the present research, the correlation between the identified driver model and drowsiness was investigated using the results of an actual driving test. Then, the drowsiness-estimation function was constructed which evaluated the delay, gain, uncertainties, and time variation of the steering behaviour of the identified driver model. The driving test showed that the proposed method had sufficient precision to provide a warning of inattentive driving.

Keywords: driver condition monitoring; drowsiness estimation; driver model

Nomenclature

| Symbol | Description |
|--------|-------------|
| \(d_{Ti}\) | estimated drowsiness of the \(i\)-th divided data set from the time constant, steady-state gain, residual error, and standard model error, respectively |
| \(H, H_{std}\) | driver model and standard driver model, respectively |
| \(J_{res,i}\) | cost function of the residual of the \(i\)-th divided data set |
| \(J_{std,i}\) | cost function of the standard model error of the \(i\)-th divided data set |
| \(K_i\) | steady-state gain of the \(i\)-th divided data set |
| \(L_i\) | time span of the \(i\)-th divided data set |
| \(\tilde{\gamma}\) | smoothed yaw rate |
| \(s\) | Laplace variable |
| \(t\) | time |
| \(t_{si}\) | beginning time of the \(i\)-th divided data set |
| \(T_i\) | time constant of the \(i\)-th divided data set |
| \(w\) | residual error |
| \(\delta_{es}, \delta_{std}\) | steering angle of driving test and standard driver model, respectively |
| \(\psi\) | yaw angle of car |
| \(\psi_d\) | desired yaw angle of car |
| \((\cdot)(s)\) | Laplace transform of time function \((\cdot)(t)\) |
| \((\cdot)\) | responses of \((\cdot)\) obtained using the pre-filter |

1. Introduction

A system to detect a driver’s condition will play an important role in the evolution of automotive intelligence. Especially, a driver’s condition in the autonomous car is a significant topic. A useful system can be constructed utilizing the detected condition of the driver. For example, car accidents caused by the inappropriate behaviour of the driver could be avoided by using an alert system based on the detection of deterioration in the driver’s performance. Several methods to detect the driver’s condition have been proposed. Drowsiness was detected from the driver’s eye movements (Nakagawa et al., 2007). In Nagai, Omi, and Komura (2008), the driver’s drowsiness was detected from the eyelid information. The driver’s heart rate was used to detect the drowsiness (Yanagidaira & Yasushi, 2006). These methods depend on the measurement of the driver’s vital signs and eye. However, it is difficult to implement the reliable vital sensors or eye tracking system to the production car. In Breuer, Bernzen, Hentschel, and Wagner (2008), the shortcomings of the camera-based drowsiness detection approaches were stated. A low-cost and reliable drowsiness detection system is necessary for practical use. In contrast, we proposed a real-time identification method for a driver model (Tokutake, Sugimoto, & Shirakata, 2015).
In this method, the driver’s involuntary steering response to the car’s motion is formulated as a differential equation using the measured rate-gyro and steering-angle data. Because cars are usually equipped with reliable sensors for measuring such data, implementation costs for the proposed method are low.

Identification and analysis of a driver model have been studied (Burnham, Seo, & Bekey, 1974; MacAdam, 2003; Plöechl & Edelmann, 2007). Recent research has focused on computer-aided analysis and design methods that use driver models (Boer, Ward, Manser, & Kuge, 2006; Fujinaga, Tokutake, & Miura, 2007; Miura, Tokutake, & Fukui, 2007; Tokutake, Fujinaga, & Miura, 2008; Tokutake, Miura, & Okubo, 2004; Tokutake & Sato, 2005). Chen and Ulsoy (2001) modelled the uncertainties of the identified driver model. Ishio, Ichikawa, Kano, and Abe (2008) evaluated the lead and delay of the identified driver model. Pilutti and Ulsoy (1999) investigated the variation in the identified parameters. On the other hand, Zhang, Lin, and Chin (2010) estimated the driving skill using the identified driver model. The model-based approach has an advantage because the formulated driver model directly contains useful driving characteristics such as the delay or gain. In our study, a driver model was identified and subjected to drowsiness detection tests. The real-time identification method was established by Tokutake et al. (2013). In the next step, an estimation method for the driver’s drowsiness using the identified driver model was constructed. Firstly, the present paper revealed the relations between the identified driver model and the driver’s condition. Since the identified model directly reflects the driver’s involuntary response, the driver characteristics related to careless driving can be predicted from the identified parameters. Secondly, the estimation method of the driver’s drowsiness using the identified parameters was established and it was validated by the actual driving testing. Because the vital sensor or eye tracking system is not required, implementation to the production car is not difficult. As a result, a low-cost and reliable system of drowsiness estimation can be realized.

It is possible to detect the driver’s drowsiness from only the car responses. In such a method, when the oscillation of the vehicle dynamics becomes large, the driver’s condition is judged to be inappropriate for safe driving. However, this system observes only the car dynamics and does not evaluate the cause of the oscillation directly. Therefore, it is difficult to distinguish the oscillation generated by the driver’s inappropriate driving from the oscillation caused by circumstances such as disturbance that cannot be compensated by the driver. On the contrary, the driver model-based method evaluates the driver’s response mechanism. In the proposed method, a driver is judged to be inappropriate for safe driving when the response of the driver to the vehicle dynamics is inappropriate. This is an essential difference for the driver’s condition detection.

Initially, actual driving tests were performed. Then the measured drowsiness and the identified driver model of the driving test were compared. Here, the identification process is based on the real-time method that was reported in Tokutake et al. (2013). Finally, the estimation function for drowsiness was constructed using the identified parameters and subsequently validated. A safety system to avoid accidents can be realized by combining the real-time identification method and proposed drowsiness-estimation method.

2. Real-time identification method

Firstly, the real-time identification method is briefly described (Tokutake et al., 2013). A driver’s actions are based on the sensing of many kinds of information, including information about the road surface condition, curvature of the road, and vehicle behaviour. A complicated driver model is required to precisely formulate the driver’s behaviour. However, a simple driver model can describe a driver’s involuntary responses to the car’s motion. The input to the driver model is the error between the desired motion of the car and its actual motion. The output of the driver model is the steering history. In the previous study (Tokutake et al., 2013), a driver’s involuntary responses to the yaw dynamics of the car were modelled as follows.

\[
\tilde{\delta}(s) = H(s)\Delta\tilde{\psi}(s) + w(s), \tag{1}
\]

\[
\Delta\tilde{\psi}(s) = \tilde{\psi}_d(s) - \tilde{\psi}(s). \tag{2}
\]

Here, \(H(s)\) is a driver model, \(\tilde{\delta}(s)\) is the filtered steering angle, \(\Delta\tilde{\psi}(s)\) is the filtered yaw angle error, \(\tilde{\psi}_d(s)\) is the filtered desired yaw angle, and \(\tilde{\psi}(s)\) is the filtered yaw angle. The involuntary responses to the yaw motion of the car are extracted by applying a band-pass filter. The desired yaw angle, \(\tilde{\psi}_d(s)\), determined by the driver, is necessary to identify the driver model. The method used to estimate the desired yaw angle from the measured yaw rate history of the car was constructed (Tokutake et al., 2013). Therefore, because the input to the driver, \(\Delta\tilde{\psi}(s)\), and the output from the driver, \(\tilde{\psi}(s)\), can be measured using the implemented sensors, real-time identification can be performed. It was reported that the proposed real-time identification method worked appropriately. It should be noted that a band-pass filter with a band-pass frequency of 10–100 rad/s is suitable for identifying the driver model. Additionally, the recorded data were divided into several data sets with similar driving conditions, and the driver model was identified for each data set. The identified driver model contains significant information about the driver’s characteristics. In the present paper, drowsiness is estimated from the identified driver model.
3. Parameters of obtained driver model

3.1. Structure

The identified driver model contains several parameters. These parameters express the driver’s behaviour. Although a high-order model can precisely express the driving history, it is difficult to analyse the characteristics of the obtained model. Therefore, a first-order model was used to model the driver’s involuntary responses to the filtered yaw dynamics of a car, as follows:

$$ H(s) = \frac{K}{Ts + 1}. \quad (3) $$

The obtained model contains several coefficients. The parameter $K$ is the steady-state gain, which reflects the size of the steering input. The parameter $T$ is a time constant that indicates the time delay of the response to the input.

3.2. Residual and time variant model

In the identification process, the driver model is determined so that the errors between the model responses and the measured driver’s responses, which are the residual $w$ values in Equation (1), are minimized. The sizes of the residuals are evaluated as follows:

$$ J_{resi} \Delta \frac{\int_{t_0}^{t_0+L_i} w(t)^2 dt}{L_i}, \quad (4) $$

$$ w(s) = \delta_s(s) - H(s)\Delta\bar{\varepsilon}_\psi(s). \quad (5) $$

Hereafter, the subscript $i$ indicates a divided $i$-th data set. The size of a residual, as expressed in Equation (4), reflects driver behaviour that cannot be expressed by the identified linear model, such as non-linear behaviour, impulsive steering input, or uncertainties in the driver model.

Furthermore, the time variation of the identified model can be estimated using the error between the standard model response and the measured response, as follows:

$$ J_{adi} \Delta \frac{\int_{t_0}^{t_0+L_i} (\delta_s(t) - \delta_{adi}(t))^2 dt}{L_i}, \quad (6) $$

$$ \delta_{adi}(s) = H_{adi}(s)\Delta\bar{\varepsilon}_\psi(s). \quad (7) $$

Here, $H_{adi}(s)$ is the standard driver model. The error from the responses of the standard driver model, as shown in Equation (6), reflects the variation in the driver’s behaviour from the standard driver model. In the present study, the identified driver model with the lowest residual error was selected as the standard driver model. Therefore, variation in the driver’s behaviour from the initial condition can be evaluated.

4. Driving experiment

4.1. Set-up

The identified driver models were analysed using the results of an actual driving test (Tokutake et al., 2013). The driven course was a banked oval track, and eight drivers, D1–D8, were tested. The drivers tried to maintain a given velocity along the course. The experimental conditions are listed in Table 1. All of the participants were recruited through an open call (a total of eight male participants; mean (SD) age = 32.8 (7.1) years). Before the test, we provided verbal and written instructions, and a written informed consent was obtained from each participant. When the participants indicated drowsiness or fatigue, the driving test was terminated.

4.2. Measurement of drowsiness

In the actual driving test, the driver’s drowsiness was evaluated objectively based on the facial expression (Kitajima, Numata, Yamamoto, & Goi, 1997). The estimated drowsiness was graded from 1 to 5, where the minimum drowsiness was 1 and the maximum drowsiness was 5. Hereafter, this grading is used to define the measured drowsiness for reference.

5. Results and discussions

5.1. Division of data

The driver’s behaviour depends on driving conditions such as the car velocity and road profiles. Then, the response data with the common conditions are prepared for identification. In real-time identification, the recorded continuous data are divided into data sets such that the yaw rate and the velocity in these data sets are approximately equal (Tokutake et al., 2013). In this analysis, yaw rate is used for the division of data.

The recorded data were divided into two kinds of data sets using the smoothed yaw rate, $\tilde{\dot{\psi}}$. One data set was for the straight course, with $|\tilde{\dot{\psi}}| < 1 \text{deg}/\text{s}$, and the other was for the curved course, with $|\tilde{\dot{\psi}}| > 3 \text{deg}/\text{s}$. Thereafter, the divided data sets were used in the identification process. Here, the bandwidth of the applied pre-filter was from 10 to 100 rad/s. Because the driven course was an oval track, the divided data sets consisted of alternating straight-course and curved-course data.

| Experiment | Course     | Intended velocity (km/h) | Number of drivers |
|------------|------------|--------------------------|-------------------|
| Actual driving | Closed circuit | 80                       | 8                 |
5.2. Time constant
Figure 1 shows the time history of the time constant for the divided straight course and curved course. Time constant values were obtained for each of the divided data sets and then smoothed using a moving average. The measured drowsiness was also plotted. In the results for some drivers, it is clear that their drowsiness increased with an increase in the driving time. For example, the time constant of driver

Figure 1. Time constant variations.

Figure 2. Steady-state gain variations.
D_1 on the curved course reached its maximum value at the end of the driving experiment. At the end of the experiment, the drowsiness had reached approximately grade 4. The high time constant meant a long delay in a steering manoeuver. Therefore, this tendency indicates that the

Figure 3. Residual variations.

Figure 4. Error from standard model.
delay of the driver’s involuntary responses lengthens when the drowsiness increases.

5.3. Steady-state gain

Figure 2 shows the time history of the absolute value of the steady-state gain of the divided straight course and curved course. Steady-state gain values were obtained for each divided data set and smoothed using a moving average. The measured drowsiness was also plotted. The gains of some drivers increased as their drowsiness increased. This means that the driver’s involuntary response to the car’s motion became aggressive when their drowsiness became pronounced.

5.4. Residual

Figure 3 shows the time histories of the sizes of the residual errors for the divided straight course and curved course, as evaluated by Equation (4). Residual values were obtained for each divided data set and smoothed using a moving average. The measured drowsiness was also plotted. It is obvious that the residual error of some drivers increased as the drowsiness increased. This indicates increases in the involuntary non-linear responses such as an uncertain steering input that did not correlate to the yaw rate of the car’s dynamics.

5.5. Standard model

The time variations of the driver model are discussed. Figure 4 shows the time histories of the error from the standard model of the divided straight course and curved course, which was evaluated using Equation (6). The error values were obtained for each divided data set and smoothed using a moving average. The measured drowsiness was also plotted. The standard operator model was the model identified at the beginning of the experiment with the lowest residual error. It is obvious that the standard model error of some drivers increased as their drowsiness increased. This means that the involuntary behaviour that can be formulated as a linear model varies as drowsiness increases.

Table 2. Initial parameters of identified driver model.

| Driver | Time constant (s) | Steady-state gain | Residual (rad²) | Measured drowsiness |
|--------|------------------|-------------------|-----------------|---------------------|
| D1     | 0.135/0.279      | 0.946/0.992       | 0.00097/0.000484| 1.0/1.0             |
| D2     | 0.134/0.256      | 0.852/1.042       | 0.00116/0.000469| 1.0/1.0             |
| D3     | 0.133/0.172      | 0.711/0.631       | 0.00061/0.000486| 1.0/1.0             |
| D4     | 0.140/0.179      | 0.920/0.790       | 0.00070/0.000577| 1.0/1.0             |
| D5     | 0.124/0.288      | 4.184/0.764       | 0.00195/0.000263| 1.0/1.0             |
| D6     | 0.136/0.179      | 0.549/0.881       | 0.00097/0.000527| 1.0/1.0             |
| D7     | 0.146/0.280      | 0.810/1.851       | 0.00098/0.000766| 1.0/1.0             |
| D8     | 0.128/0.169      | 1.045/1.038       | 0.00079/0.000448| 1.0/1.0             |

6. Drowsiness estimation from model parameters

6.1. Model parameters

As seen above, there are relationships between the identified parameters and the measured drowsiness. An attempt was therefore made to formulate an estimation method for drowsiness using the identified driver model. If this estimation method is combined with the real-time identification method (Tokutake et al., 2013), drowsiness can be estimated in real time and applied to a safety system.

Table 2 lists the initial smoothed parameters of the identified driver model of the divided straight course and curved course. Because the initial drowsiness levels of all the drivers are low, the basic characteristics of the drivers can be observed. Firstly, the identified drowsiness levels of all the drivers are low, the basic characteristics of the drivers can be observed. Secondly, the identified parameters of each driver are compared. It is clear that there are obvious differences between the drivers. In particular, the gain and residual error of driver D5 on the straight course are significant. The effect of the individual variations should be eliminated from the drowsiness-estimation function. Next, the identified parameters for the straight course and curved course are compared. The time constants for all the drivers on the straight course were smaller than those on the curved course. It should be noted that the driver models were identified using data filtered with a bandwidth from 10 to 100 rad/s. This tendency means that a driver on the curved course was not sensitive to the car’s motion in this frequency region. Additionally, the residual errors of all the drivers on the straight course were larger than those on the curved course. This means that the steering history for the straight course contains higher non-linearity or uncertainties than that for the curved course. These results motivated the formulation of separate estimation functions for the straight course and curved course.

Table 3 lists the correlation coefficients between the measured drowsiness and the parameters of the identified models for the straight course and curved course, and shows the linear relationships between the identified parameters and the measured drowsiness. The maximum positive correlation coefficient is that of the time constant for driver D6 on the straight course. However, the correlation coefficients of the residual and standard model errors of driver D6 are not good. In contrast, the correlation
coefficient of the time constant for driver D1 on the straight course is poor, whereas those of the residual error and standard model error of driver D1 on the curved course are good. The identified parameter with good correlation varies with the driver and course. However, all the drivers have at least one identified parameter that has good correlation with drowsiness. Therefore, separate estimation equations for drowsiness are constructed as functions of the individual identified parameters.

### 6.2. Estimation of drowsiness and alert time

The following estimation functions for drowsiness are assumed:

\[
d_{Ti} = k_{Ti} \times \frac{T_i}{T_0} + k_{T1}, \tag{8}
\]

\[
d_{Ki} = k_{Ki} \times \frac{K_i}{K_0} + k_{K1}, \tag{9}
\]

\[
d_{resi} = k_{resi} \times \frac{J_{resi}}{J_{res0}} + k_{res2}, \tag{10}
\]

\[
d_{stdi} = k_{stdi} \times \frac{J_{stdi}}{J_{std0}} + k_{std2}. \tag{11}
\]

Here, \(d_{Ti}, d_{Ki}, d_{resi},\) and \(d_{stdi}\) are the drowsiness values estimated from the identified time constant, steady-state gain, residual error, and standard model error, respectively. Because the basic characteristics of each driver model differ, the time variations of the parameter are normalized using the initial value, and are then evaluated.

The coefficients of the estimation functions were determined using the data with a high correlation with drowsiness. The data for driver D3 on the straight course and driver D1 on the curved course were used to determine the coefficients in Equations (8)–(11). These drivers showed good correlations between the identified parameters and the measured drowsiness. The coefficients were determined so that the least square errors between the measured drowsiness and the estimated drowsiness were minimized. The obtained coefficients are listed in Table 4.

Figure 5 shows the estimated drowsiness of driver D3 on the straight course that was obtained using the estimation function, Equations (8)–(11), with the obtained coefficient. Figure 6 shows the estimated drowsiness of driver D1 on the curved course that was obtained using the estimation function with the obtained coefficient. The measured drowsiness values are also plotted for comparison. Clearly, they agree very well.

The obtained estimation functions with the coefficients that were optimized for driver D3 on the straight course and driver D1 on the curved course were applied to the data from the other drivers, and drowsiness was estimated. Since the final goal of this research programme is to prevent car accidents caused by a driver’s carelessness, an alert time was introduced. The alert time was defined as the time when drowsiness reached grade 2. In the future, a driver will be given a warning by the safety system at the alert time. The drowsiness of each driver was estimated using Equations (8)–(11) and the optimized coefficient (Table 4). Then, the alert times were calculated from the measured drowsiness and estimated drowsiness. Table 5 lists the alert times and alert time errors. For some data, the alert time could not be defined because the estimated drowsiness was lower than grade 2. Here, the alert time error had the smallest value in the measured alert time minus the alert time calculated from all the identified parameters. A negative alert time error means that drivers will be given a warning before their actual drowsiness reaches grade 2.

Table 3. Correlation coefficients between measured drowsiness and identified parameters.

| Driver | Smoothed time constant and drowsiness | Smoothed steady-state gain and drowsiness | Smoothed residual and drowsiness | Smoothed standard model error and drowsiness |
|--------|---------------------------------------|------------------------------------------|--------------------------------|-----------------------------------------------|
| D1     | 0.295/0.861                           | 0.869/0.855                              | 0.753/0.831                    | 0.750/0.802                                    |
| D2     | 0.402/0.495                           | 0.667/0.679                              | 0.721/0.789                    | 0.721/0.772                                    |
| D3     | 0.866/0.669                           | 0.658/0.767                              | 0.911/0.268                    | 0.917/0.088                                    |
| D4     | 0.442/0.462                           | 0.361/0.535                              | 0.710/0.202                    | 0.714/0.109                                    |
| D5     | 0.899/0.669                           | −0.622/0.775                             | 0.831/0.941                    | 0.949/0.954                                    |
| D6     | 0.977/0.532                           | 0.817/−0.892                             | −0.810/−0.942                  | −0.797/−0.943                                  |
| D7     | 0.610/0.306                           | 0.292/0.800                              | 0.722/0.782                    | 0.732/0.704                                    |
| D8     | −0.369/0.130                          | 0.739/−0.044                             | 0.550/0.653                    | 0.529/0.726                                    |

Table 4. Coefficients of drowsiness-estimation functions.

|        | \(k_{T1}\) | \(k_{T2}\) | \(k_{K1}\) | \(k_{K2}\) | \(k_{res1}\) | \(k_{res2}\) | \(k_{std1}\) | \(k_{std2}\) |
|--------|------------|------------|------------|------------|-------------|-------------|-------------|-------------|
| Straight course | 50.81 | −49.47 | 5.14 | −3.62 | 7.82 | −6.71 | 8.01 | −6.9 |
| Curved course   | 3.14 | −2.01 | 4.89 | −3.53 | 11.7 | −10.21 | 3.06 | −1.86 |
In Table 5, it can be seen that there are some errors for the alert times. This is because the estimation functions that were used were optimized for the specific drivers. The tendencies of the identified parameters are different for other drivers. Additionally, the estimation functions were optimized so that the sum of the drowsiness errors for all the experiment times was minimized. The errors in the alert times were not minimized. However, the smallest value in the calculated alert times agrees with, or is smaller than, the measured alert time. It is therefore recommended that separate drowsiness values be calculated using the identified gain, time constant, residual error, and standard model error. The shortest time required for one of them to reach grade 2 can then be defined as the alert time.

It should be emphasized that the drowsiness measured in the present driving test contained measurement error, and there is a possibility that the measured drowsiness did not accurately reflect the driver’s characteristics. However, the identified parameters directly reflect the involuntary characteristics of the driver. When the estimated drowsiness levels calculated from the steady-state gain, time constant, residual error, and standard model error reach grade 2, it is obvious that the involuntary response gain to the car’s motion becomes high, the delay time in the involuntary response to the car’s motion becomes high, the non-linear behaviour increases, or the time variation...
### Table 5. Estimated alert times.

| Driver | Alert time in straight course [s] | Alert time in curved course [s] |
|--------|----------------------------------|---------------------------------|
|        | From time constant | From steady-state gain | From residual | From standard model error | Measured | From time constant | From steady-state gain | From residual | From standard model error | Alert time error [s] |
| D₁     | 552 | 457 | 457 | 457 | 506 | 784 | 784 | 784 | 784 | 784 | −95 |
| D₂     | 630 | 451 | 535 | 630 | 630 | 581 | 670 | 402 | 419 | 0 | −179 |
| D₃     | 555 | 646 | 555 | 555 | 581 | 663 | 663 | 663 | 663 | 0 | 0 |
| D₄     | 704 | 1680 | 1324 | 704 | 704 | 577 | 663 | 663 | 663 | 0 | 0 |
| D₅     | 653 | 829 | 1566 | 1458 | 690 | 1412 | 506 | 415 | −275 |
| D₆     | 420 | 508 | 601 | 284 | 284 | 1687 | 1057 | 598 | −284 |
| D₇     | 735 | 735 | 459 | 1281 | 1281 | 598 | 1687 | 1057 | 598 | −276 |
| D₈     | 368 | 552 | 552 | 552 | 552 | 415 | 507 | −690 | 415 | 0 | 0 |
of the driver model becomes high, respectively. Therefore, when the estimated drowsiness becomes high, it is appropriate to judge the driver’s behaviour as dangerous.

7. Conclusions
In this study, a method for estimating drowsiness from the identified driver model was proposed. Firstly, actual driving tests were carried out, and the measured drowsiness and identified parameters were compared. Then, drowsiness-estimation functions were constructed using several identified parameters, and the coefficients of these estimation functions were optimized. The usefulness of the proposed estimation functions for alert times was verified.

It was shown that the defined alert time based on the estimated drowsiness was effective at detecting the deterioration of the driving performance. A safety system to avoid accidents caused by deterioration in the driver’s performance can be constructed by combining the proposed method and the real-time identification method.

The proposed method evaluates the involuntary response of the driver to the stimulus from the vehicle motion. Because the involuntary response of the driver affects the car motion, the evaluated characteristics are essential for safe driving. The present paper validated the fundamental performance of the proposed method. In the future, it should be generalized for the various driving conditions and drivers.

Disclosure statement
No potential conflict of interest was reported by the authors.

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