Deceleration Timing Relating a Driver’s State Based on Naturalistic Driving Behavior Database during Approach to Intersection

Motoki Shino 1) Kengo Minami 1) Minoru Kamata 1)
Machiko Hiramatsu 2) Takashi Sunda 2)

1) The University of Tokyo, Graduate School of Frontier Sciences
5-1-5 Kashiwanoha, Kashiwa, Chiba, 277-8563, Japan (E-mail: motoki@k.u-tokyo.ac.jp)
2) Nissan Motor Co., Ltd.
1-1 Aoyama, Morinosato, Atsugi, Kanagawa, 243-0123, Japan

Received on June 13, 2018

ABSTRACT: The objective of this study was to develop indices for detecting a driver’s state that consider the driver’s judgment process in various circumstances using a naturalistic driving behavior database. The deceleration timing when a driver approaches a non-signalized intersection was considered, and a deceleration strategy for the approach to an intersection was formulated based on a naturalistic driving behavior database compiled from the real world. A deviated state detection method that incorporates the formulated strategy is proposed, and the validity of the method was examined.

KEY WORDS: human engineering, driver behavior/ Driver state detection, Naturalistic driving behavior[C2]

1. Introduction

In Japan, the number of traffic accidents each year remains high. To decrease this number, studies on active safety technologies, including driver assistance systems, are ongoing. Typically, unsafe driving behavior is ascribed to the following:

1. The driver is accident-prone person in general.
2. The driver is not accident-prone, but the driving behavior in a given situation differs from normal driving behavior.

In this study, we focused on the second type of drivers, and we defined driving behavior that differs from the usual pattern as “deviated” driving behavior. Individuals have unique driving behaviors, and the driver state is assumed to affect the driving behavior. Thus, in the deviated state, the driver’s behavior and state are not normal. We assumed that unsafe driving is part of deviated driving behavior. Many researches related to driver state detection and driving behavior evaluation are carried out (1). There are previous work showing that driving behavior indices can detect hurry driving trips (2)(3), inattentive driving (4), drowsy driving (5) and driver risk (6). Also, there are researches reporting that driving behavior models using Bayesian network models (7) and Hidden Markov models (8) have the possibility to detect deviated driving of drivers. Although measurement of driving behavior has the possibility to detect deviated driving behavior and driver state, the trend along the time-axis needs to be observable for driver assistance systems to assist the driver timely. If a driver’s deviated state can be detected and a driver assistance system that recovers a deviated driver state to normal is realized, we can prevent accidents that result from unsafe driving behavior. Fig. 1 shows the concept of such a system.

We focused on detecting the deviated state based on driving behavior. When driving in various circumstances, a driver varies the steering wheel and pedal operation based on the road environment. Thus, the road environment as well as the driving behavior must be considered when detecting the driver state. The driver’s judgment process, through which the driver behaves based on the road environment, must also be considered as it is influenced by the driver state. In this paper, we propose indices relating deviated states, such as hurried driving and inattentive driving, with an advanced driver assistance system. We examined the validity of the indices through the use of a naturalistic driving behavior database.

Fig. 1 Concept diagram of deviated state detection and driver assistant

2. The scope of this paper to detect deviated state

2.1 Outline of this paper to detect deviated state

Fig. 2 shows a schematic diagram of the deviated state detection system based on the naturalistic driving behavior. The driving behavior database records not only the driving behavior data but also the road environment data. We used this database to design an action-select model that takes road environment data as input and predicts suitable driving behavior data as output. Thus, the driving behavior is predicted, and the deviated driver state is detected by comparing the predicted and measured driving behaviors. To realize this detection method, we first need to materialize an action-select model that relates to the driver state when driving in various circumstances.

2.2 Deviated states based on transition of driving behavior in previous studies

Copyright © 2019 Society of Automotive Engineers of Japan, Inc. All rights reserved
We analyzed the driver’s judgment for deceleration timing by using the database collected by the Research Institute of Human Engineering of Quality Life (HQL), Japan. The HQL database contains the individual driving behavior data of approximately 100 ordinary drivers. Each driver repeatedly drove a car along the same course on public roads (13). Each set of driving behavior data contains information on the vehicle state and road environment; this was adequate for analysis.

In this study, we used driving data for a course with a distance of approximately 14 km that was driven 37 times by an individual driver. The data for one drive along the course was called one trip. The driving data of five drivers were extracted from the database for analysis. For the sake of anonymity, the five drivers were labeled as IA, IB, and ID (on the I course) and LA and LD (on the L course).

Fig. 3 shows the frequency distribution of the maximum deceleration value during deceleration behavior of each driver. $\bar{X}_{BG}$ denotes the average value and $\sigma_{BG}$ denotes the standard deviation when a driver conducted a braking maneuver. Although there was a difference in distribution shape depending on each course, there was almost no difference in the characteristics of decelerating behavior among drivers.

![Fig. 3 Frequency distribution of maximum deceleration in each driver](image-url)

Fig. 4 shows the deceleration behavior during approach to a same intersection with stop sign repeatedly. The blue line shows the velocity along the distance from the stop line when the near miss incident happened. From the incident analysis, the velocity with the deviated state becomes higher than the normal state. And then, the deceleration timing with deviated state becomes slower than the normal state. We assumed that the change of driver state appears prominently in the change of driving behavior set according to the distance to the intersection.

3. Deviated driver state indices for approach to intersections

3.1 Driving situation

To set the driver state indices that are related to the driver’s judgment process, we chose driving situations when the driver needs to be proactive in judgment. We defined the driver state during the approach to an intersection as the driving situation in this study. In this situation, drivers are required to decelerate so that the vehicle can enter the intersection safely. The driver sets the start and end points of deceleration by considering the velocity of the vehicle and distance left to the intersection when the intersection is recognized. The driver’s judgment is important in this situation because insufficient deceleration to safely enter the intersection leads to unsafe driving behavior, such as sudden and hard braking or passing through the intersection at high velocity.

However, we only considered the start point in this research because the ending point is often influenced by traffic conditions and thus is inadequate for formulation. The formulation of the deceleration timing makes it possible to detect delayed deceleration behavior as a deviation compared to normal behavior. In this study, we aimed to detect a deviated driver state from recorded naturalistic driving behaviors by focusing on formulating the judgment process relative to the road environment.

Driving scenes when the driver performs a usual braking maneuver can be classified as a deceleration against a preceding vehicle, a deceleration against an intersection with red signal, and a deceleration against an intersection with stop signs. In addition, Kurahashi et al. clarify that the deceleration an intersection with red signal does not reflect the usual drivers’ decelerating behavior (15). Behavior of preceding vehicle also affect the usual drivers’ decelerating behavior. Therefore, we assumed that the driving behavior depends on the intersection environment. We adopted the following conditions for accurate evaluation of the driving behavior at an intersection. The end point of deceleration can be determined under these conditions:

- at an intersection without signals and with stop signs
- when there is no leading vehicle.

3.2 Analysis of naturalistic driving behavior database

- According to previous studies (9–11), when the driver state changes from the normal state to a deviated hurried state, the target velocity and relative distance between the preceding vehicle and host vehicle set by the driver change in cruising, following, and curving situations. Therefore, we extracted the average velocity $V_{avg}$ in a cruising situation, average time headway $TH_{avg}$ in a following situation, and average velocity $VC_{avg}$ around a curve as indices to detect the hurried state along the time axis. The thresholds of the deviated state indices are calculated based on normal driving trips extracted from the driving behavior database. The calculated thresholds are used to detect the deviated hurried state driving in each operation mode among the road environment types.

Fig. 2 Schematic diagram of deviated state detection method

![Fig. 2 Schematic diagram of deviated state detection method](image-url)
Based on the hypothesis, the analysis process is as follows. First, four intersections were selected as the object intersections under the conditions described in section 3.1. The conditions were confirmed by deceleration behavior data at the object intersections and visual images. Second, the two following indices were selected to evaluate the deceleration timing as shown in Fig. 5: the velocity at deceleration timing $V$ and the distance for deceleration $L$.

The velocity tended to be higher when the required distance to decelerate safely was longer; the rate of increase in the required distance was not clear. We assumed that an ordinary driver judged the deceleration timing to be proportional to the deceleration distance and velocity as shown in Fig. 6. Thus, we adopted the two indices $V$ and $L$ to evaluate the deceleration timing of a driver during the approach to an intersection. We calculated the correlation coefficients between $V$ and $L$ to examine their relationship; the results are given in Table 1.

![Fig. 4 Deceleration behavior dataset during approach to a same intersection with stop sign (Subject IA) (a) Subject IA (b) Subject IB]

Table 1 Results of correlation coefficient t-test ($V$ and $L$) based on brake group data

| Driver ID | Correlation coefficient | Brake data frequency | P value  |
|-----------|-------------------------|----------------------|----------|
| IA        | 0.689                   | 158                  | 9.35E-23 |
| IB        | 0.742                   | 126                  | 3.25E-22 |
| ID        | 0.601                   | 67                   | 4.17E-16 |
| IA        | 0.737                   | 159                  | 4.27E-23 |
| LD        | 0.646                   | 144                  | 1.08E-40 |

### 3.3 Hypothesis of index using deceleration behavior

We analyzed the driver’s judgment on the deceleration timing for the approach to an intersection. If there is an adequate correlation between $L$ and $V$, as given in Table 1, a driver approaching an intersection should set the deceleration timing by considering the time left to the intersection. The shape of the cluster of $L$ and $V$ dots on a Cartesian plot is assumed to represent the judgment of the deceleration point of time in proportion to the deceleration distance and velocity. In order to examine this hypothesis, we considered two patterns for the relationship between $L$ and $V$, as shown in Figs. 7(a) and 7(b).

Fig. 7(a) shows a good linear correlation between $L$ and $V$. This means that the time to intersection ($TTI$) with the deceleration timing given in Eq. 1 is constant, and a driver who approaches an intersection decides the deceleration timing by considering the time left to the intersection.

$$TTI = \frac{L}{V}$$

(1)

This equation means that the driver sets the deceleration timing based on a constant $TTI$ regardless of the velocity.

We found that the relationship between $L$ and $V$ is a quadratic curve rather than a linear correlation, as shown in Fig. 7(b). This means that the average deceleration ratio during deceleration $D_{avg}$, as shown in Eq. 2 is constant, and a driver approaching an intersection calculates the necessary distance to satisfy a particular deceleration ratio by considering the current velocity and distance left to the intersection.

$$D_{avg} = \frac{V^2}{2L}$$

(2)

where $VE$ denotes the velocity at the point of the ending deceleration. This equation means that the driver decides the deceleration timing based on a constant value of $D_{avg}$ regardless of the velocity.

After examining the HQL database, we made two assumptions on the deceleration behavior as a driver approaches an intersection. First, the driver adapts the deceleration strategy according to $TTI$; second, the driver adapts the deceleration behavior according to $D_{avg}$.

### 3.4 Influence of deceleration behavior according to road environment around intersection

We investigated how an intersection affects the driver’s judgment about the deceleration timing because the driving behavior is influenced by the road environment. The dataset for the second hypothesis in section 3.3 showed that $L$ tended to become longer with respect to $V$ when the velocity was high. From detailed data analysis, there were several situations where a vehicle was parked before the intersection, and this potential hazard tended to cause the driver to decelerate gradually by 0.1G or less as shown in Fig. 8. In this study, to distinguish the driver state, we needed to acquire data on the deceleration behavior of a driver at an intersection that is intended.

Fig. 9 shows the relationship between the deceleration of the vehicle and the brake pedal operation of each driver for one trip. Based on these results, we considered a deceleration of 0.1G or more to be intended deceleration, and the threshold of the deceleration timing was set to 0.1G to distinguish deceleration behavior during an approach to an intersection.

Copyright © 2019 Society of Automotive Engineers of Japan, Inc. All rights reserved
4. Deviated Driver State Detection Method for Drivers Approaching Intersection

4.1 Formulation of deceleration strategy for approach to intersection

We formulated the deceleration behavior based on $TTI$. Concretely, the velocity at deceleration timing according to the distance for deceleration is formulated using Eq. 1 since $TTI$ is constant regardless of the velocity at deceleration timing. First, we calculated the correlation coefficient between $L$ and $V$ to examine their relationship, as shown in Fig. 10. The results showed a good correlation between $L$ and $V$. Then, we performed a simple linear regression analysis to examine the hypothesis that the value of $TTI$ is constant. Based on the results, the distance for deceleration that depends on the velocity is expressed as follows:

$$L = \alpha V + \beta.$$  \hspace{1cm} \text{(3)}

The deceleration distance can be predicted by using Eq. 3, where $\beta$ is an intercept. However, $TTI$ is not always constant. Therefore, we established the time to intersection based on speed ($TTIS$), which we propose as an alternative to $TTI$. When there is an adequate linear correlation between $L$ and $V$, a driver approaching an intersection sets the deceleration timing by considering the time left to the intersection $TTIS$ as follows:

$$TTIS = L_i(V - V_o). \hspace{1cm} \text{(4)}$$

Fig. 11 shows the relation between the deceleration timing and the index $TTIS$ when the driver state changes. $V_o$ was determined from the calculation results of a single regression analysis based on the characteristics of the relationship between $V$ and $L$ for each individual.

$$V_o = -\beta \alpha. \hspace{1cm} \text{(5)}$$

where $\beta$ and $\alpha$ were determined from the calculation results of a single regression analysis.

4.2 Deviation Detection Method for Drivers

Fig. 12 shows the re-analysis results considering the deceleration threshold. The distance for deceleration $L$ was almost linearly related to the velocity at the deceleration timing $V$ when the deceleration threshold was considered. Based on these results, the deceleration timing of a driver to an intersection is based on $TTIS$. The assumptions on deceleration behavior are formulated in the next section.

![Fig. 9 Relation between deceleration and brake pedal operation](image)

![Fig. 10 Relation between $L$ and $V$ considering brake threshold](image)
5. Calculate the current value

1. Extract the driving dataset for a driver approaching an intersection by using the vehicle velocity, deceleration, and distance for deceleration.
2. Calculate \( V_0 \) as the speed intercept of the TTIS diagram based on the dataset for \( V \) and \( L \) (Fig. 12).
3. Identify TTIS based on the distribution of \( TTIS \) by using the speed intercept and deceleration behavior dataset.
4. Set the deviated deceleration behavior threshold \( TTIS_p \) as -1 standard deviation of the mean value.
5. Calculate the current value \( TTIS_m \) by using measured values such as \( V \) and \( L \).
6. Distinguish the deviated state by using \( S \).

4.2 Distinction between normal and deviated states

The predictive value \( TTIS \) is calculated from the deceleration behavior dataset as the driver approaches the intersection using \( V \) and \( L \) based on \( TTIS \) and is formulated here. The deviated deceleration behavior threshold \( TTIS_p \) is set as -1 standard deviation of the mean value of \( TTIS \) in one-sided probability distributions. The driver state is distinguished by using \( TTIS_p \) and \( TTIS_m \), which are calculated from the measured values of \( V \) and \( L \). The discriminant equation in the driver state is as follows:

\[
S = TTIS_m - TTIS_p.
\]  

(6)

When \( S \) is negative, the driver is in a deviated state. To detect the deviated state by using \( S \), thresholds to determine whether the current driving behavior is deviated or not need to be calculated based on the driving behavior dataset of an individual driver as he or she approaches an intersection.

4.3 Proposed deviated state detection method for approach to intersection

To determine whether the current driving behavior is deviated or not, the threshold of an individual driver needs to be determined. The procedure to set the threshold is as follows:

1. Extract the driving dataset for a driver approaching an intersection by using the vehicle velocity, deceleration, and distance for deceleration.
2. Calculate \( V_0 \) as the speed intercept of the TTIS diagram based on the dataset for \( V \) and \( L \) (Fig. 12).
3. Identify \( TTIS \) based on the distribution of \( TTIS \) by using the speed intercept and deceleration behavior dataset.
4. Set the deviated deceleration behavior threshold \( TTIS_p \) as -1 standard deviation of the mean value.
5. Calculate the current value \( TTIS_m \) by using measured values such as \( V \) and \( L \).
6. Distinguish the deviated state by using \( S \).

5. Validation of Deviated State Index

To verify the effectiveness of the deviated state detection method, we applied the proposed method to the HQL database, which contained the naturalistic driving behavior data of five individual drivers.

5.1 Examination of normal driving trips based on near-miss incidents

In this study, we assumed that the deviated driving behavior is related with unsafe driving behavior, and observed near-miss incident data are relevant to unsafe driving behavior. Near-miss incidents are defined as sudden braking or steering maneuvers that result in vehicle decelerations of larger than 0.5G against other vehicles, pedestrians, etc. \(^{14}\)(\(^{15}\)). As a criterion to classify normal and deviated driving trips, we analyzed the frequency distribution of the maximum deceleration when a driver conducted a braking maneuver \(^{10}\). This criterion was assumed to be independent of the traffic environment. In this analysis, the HQL database was used for the naturalistic driving behavior. The threshold value of the maximum deceleration was set to (average value + 1σ)G. With this threshold value, we classified normal and deviated trips including near-miss incident data based on previous research \(^{10}\). Table 2 lists the number of deceleration behavior data which classified normal and deviated trips for each driver.

| Driver ID | Total deceleration behavior frequency [-] | Normal trip deceleration behavior frequency [-] | Deviated trip deceleration behavior frequency [-] |
|-----------|------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| IA        | 258                                      | 114                                          | 144                                          |
| IB        | 225                                      | 134                                          | 141                                          |
| ID        | 283                                      | 136                                          | 146                                          |
| LA        | 132                                      | 78                                           | 54                                           |
| LD        | 139                                      | 68                                           | 71                                           |

5.2 Validation of Deviated State Detection Method

Fig. 13 compares \( TTIS_m \) for the normal and deviated trip data of each driver. The results show that \( TTIS_m \) of the deviated trip data was significantly lower than that of the normal trip data for drivers excluding LA, which indicates that the index is related to the driver state. This result means that LA has the possibility which not appear the difference of the driver state as the deceleration timing.

Fig. 14 shows the deceleration behavior of a subject in the normal trip and the deviated trip with the TTIS diagram. The red mark indicates the driving data in the deviated trip and the blue mark indicates the driving data in the normal trip. The green area shows the deviated state region calculated based on the dataset of a subject. We calculated the deviated trip rate and misdetection ratio to verify the effectiveness of the proposed method using the discrimination results.

To verify the effectiveness of the deviated state detection method, we applied the proposed method to the HQL database, which contained the naturalistic driving behavior data of five individual drivers.

Table 2: Classified deceleration behavior freq. of HQL database

Fig. 13 Results of two-sample t-test between normal trip and deviated trip data

Fig. 14 Deceleration behavior in the normal trip and the deviated trip with the TTIS diagram (Subject IA)

The ratio of the deviated trip data in the range of the deviated state is defined as the deviated trip rate. The ratio of the normal trip data in the range of the deviated state is defined as the misdetection rate. Table 3 lists these values. Based on the results, the proposed method could detect the deviated state at a rate of more than 50% among the five drivers. However, the deviated state was sometimes

Copyright © 2019 Society of Automotive Engineers of Japan, Inc. All rights reserved
not detected in the deviating trip data. This is because the definitions of the deviated trip and deviated state used in the proposed method are different. Concretely, the proposed method is an index that distinguishes the deviated state based on the driving behavior of each intersection, but the deviated trip is an index that is distinguished based on the driving behavior of one trip.

The deviated state detection method based on the proposed index confirmed the possibility of detecting deviated trips that include a near-miss incident.

Table 3 Discrimination results of HQL database

| Driver ID | Deviated trip rate | False detection rate |
|-----------|--------------------|---------------------|
| IA        | 0.678              | 0.152               |
| IB        | 0.515              | 0.129               |
| ID        | 0.561              | 0.141               |
| LA        | 0.63               | 0.155               |
| LD        | 0.714              | 0.088               |

5.3 Relativity of proposed index and other deviated state index for driving

In addition to the proposed index, there is a deviated driver state index for cruising situations in hurry driving \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \). We extracted the average velocity \( V_{\text{avg}} \) in the cruising situation as an index to detect the deviated driver state along the time axis. We set the threshold value to be the average value + one sigma in the cruising situation in the database of an individual driver. In this section, we compare the results of the deviated state in the cruising situation within 50 m of the object intersection and the results of the deviated state with the proposed index in a deceleration situation as shown in Fig. 15.

Fig. 15 Relativity of proposed index and other deviated state index during approach to an intersection

Table 4 lists the combinations of deviated driver state indices. Table 5 lists the number of data points on the deceleration behavior for each combination. As given in Table 6, four of the five drivers showed relativity as a result of an independence test on the relativity of the discrimination results with the proposed index and with the deviated driver state index in a cruising situation (\( p < 0.05 \)). Fig. 16 shows the percentage of each index combination with respect to the maximum deceleration as the driver approaches an intersection. With regard to summations \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \), the percentage of the deviated driver state increased with the maximum deceleration. When the maximum deceleration was large, the percentage of \( \text{BG}_2 \), where the only proposed index is discriminated as the deviated driver state, increased. This means that the proposed index can detect unsafe driving behavior with large deceleration that is undetected by the index in hurry state during driving.

Table 4 Definition of evaluation data group

| Brake data group | \( \text{BG}_1 \) | \( \text{BG}_2 \) | \( \text{BG}_3 \) | \( \text{BG}_4 \) |
|------------------|----------------|----------------|----------------|----------------|
| Result based on  | \( \text{TTIS} \) (Deceleration index) | Deviated | Deviated | Normal | Normal |
| Result based on  | \( V_{\text{avg}} \) (Cruising index) | Deviated | Normal | Deviated | Normal |

Table 5 Brake data classification

| Driver ID | Brake data frequency |
|-----------|----------------------|
| IA        | \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \) |
| IB        | \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \) |
| ID        | \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \) |
| LA        | \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \) |
| LD        | \( \text{BG}_1 \text{BG}_2 \text{BG}_3 \text{BG}_4 \) |

Fig. 16 Relationship between the maximum deceleration region and evaluation data group of each driver
6. Conclusion

For detecting the deviated state based on driving behavior on public roads, we focus on the deceleration timing when a driver approaches a non-signalized intersection and we formulated based on a naturalistic driving behavior for five drivers collected by HQL. The major conclusions are as follows:

- We propose the index TTIS based on the formulation of deceleration behavior when a driver approaches an intersection that consists of the distance for deceleration and the velocity at deceleration timing.
- The proposed index of the deviated trip data was significantly lower than that of the normal trip data for drivers.
- The deviated state detection method confirmed the possibility of detecting deviated trips at a rate of more than 50% among the five drivers.
- The proposed index can detect deviated driver states that are undetected by the index in hurry state during driving.

In the future, we plan to examine the validity of the index TTIS by increasing the target course and the number of subjects. Especially, we plan to examine the influence of traffic-environment elements (e.g. Road geometry, existence of other traffic participants) on the driving behavior features to enlarge the application range of this study’s results.

This paper is written based on a proceeding presented at the AVEC’ 14.

References

(1) W. W. Wierwille et al.: Research on Vehicle-Based Driver Status/Performance Monitoring; Development, Validation, and Refinement of Algorithms for Detection of Driver Drowsiness, Final Report DOT HS 808 247, National Highway Traffic Safety Administration (1994).
(2) P. Raksincharoensak et al.: Hurry Driving State Detection Algorithm Based on Urban Driving Database, Trans. of JSAE, Vol. 41, No. 3, p. 751-758 (2010) (in Japanese).
(3) Y. Hotta et al.: A Study of Driving Behavior when Driver is Feeling Hurried and a Potential Method for Their Detection, Journal of JSAE, Vol. 58, No. 12, p. 60-65 (2004) (in Japanese).
(4) S. Saigo et al.: Investigation of Inattentive Driving Estimation Method by Using Longitudinal and Lateral Driver Operational Models, SAE International Journal of Passenger Cars- Electronic and Electrical Systems, Vol. 6, No. 1, p. 27-33 (2013).
(5) S. Hachisuka et al.: Facial expression measurement for detecting driver drowsiness, Proc. of HCI International 2011, p. 135-144 (2011).
(6) C. Miyajima et al.: Driver Risk Evaluation Based on Acceleration, Deceleration, and Steering Behavior, Proc. of ICASSP 2011, p. 1829-1832 (2011).
(7) Y. Sakaguchi et al.: Measuring and Modeling of Driver for Detecting Unusual Behavior for Driving Assistance, Proc. of ESV 2003, No. 456 (2003).
(8) T. Hayashi et al.: Prediction of the Possibility a Right-Turn Driving Behavior at Intersection Leads to an Accident by Detecting Deviation of the Situation from Usual when the Behavior is Observed, Trans. of IEEJ C, Vol. 131, No. 7, p. 1361-1367 (2011) (in Japanese).
(9) M. Shino et al.: Driving State Deviation Detection Based on Naturalistic Driving Behavior Database for Driver Assistance Systems, Proc. of AVEC 10, p.737-742 (2010).
(10) H. Yoshitake et al.: Driver State Detection Method of Hurry State Based on Naturalistic Driving Behavior Database, Proceedings of FAST-zero’11 (CD-ROM), TS2-6-2-3, 2011
(11) M. Shino et al.: Formulation of Driver Judgment Process Around Curves For Deviated State Detection, Proceedings of 7th International Driving Symposium on Human Factor in Driver Assessment (CD-ROM) (2013).
(12) T. Kurahashi et al.: Analysis of Normal Driver’s Braking Timing on Public Roads, Trans. of JSAE, Vol.39, No.2, p.363-367 (2008) (in Japanese).
(13) M. Akamatsu: Establishing Driving Behavior Database and its Application to Active Safety Technologies, Journal of JSAE, Vol. 57, No. 12, p. 34-39 (2003) (in Japanese).
(14) M. Nagai et al.: Research on Near-miss Incident Analysis using Drive Recorder (First Report): Drive Recorder Specifications and Incident Capturing Trigger Algorithm, Journal of JSAE, Vol. 38, No. 2, p. 219-224 (2007) (in Japanese).
(15) M. Shino et al.: Research on Incident Analysis Using Drive Recorder Part 3: Analysis on Relationship Driving Behavior and Traffic Circumstance Based on Forward Collision Near-miss Incident Data in Car Following Situation, Proc. of FISITA convention, F2008-08-123 (2008).

Table 6 Test results on independence between TTIS in the deceleration situation and $F_{avg}$ in the cruising situation

| Driver ID | N  | $\chi^2$ | $P$ value |
|-----------|----|----------|-----------|
| IA        | 193| 4.35     | 0.0371    |
| IB        | 190| 7.12     | 0.0076    |
| ID        | 210| 10.78    | 0.0010    |
| LA        | 124| 0.57     | 0.4511    |
| LD        | 134| 4.20     | 0.0405    |

Copyright © 2019 Society of Automotive Engineers of Japan, Inc. All rights reserved