An Attempt to Predict Driver's Drowsiness Using Trend Analysis of Behavioral Measures

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Abstract. The behavioral measures such as neck vending angle and tracking error in steering maneuvering during the simulated driving task was recorded under the low arousal condition of all participants who stayed up all night without sleeping. We conducted trend analysis where time and the behavioral measure of drowsiness corresponded to an independent variable and a dependent variable, respectively. Applying the trend analysis technique to the experimental data of participants from whom the point in time when the participant would have encountered a crucial accident if he or she continued driving a vehicle (virtual accident), we proposed a method to predict in advance (before virtual accident occurs) the point in time with high risk of crash By applying the proposed trend analysis method to behavioral measures, we found that the proposed approach could identify the point in time with high risk of crash and eventually predict in advance the symptom of the occurrence of point in time of virtual accident.

Keywords: Drowsiness prediction · Behavioral measure · Virtual accident · Crash · Trend analysis

1 Introduction

McDonald, Schwartz, Lee, and Brown [1] showed that steering wheel angle could be used to predict drowsiness related lane-departures six seconds before they occurred. Hanowski, Bowman, Alden, Wierewille, and Carrol [2] made an attempt to assess driver drowsiness using 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 these studies succeeded in measuring lane deviation performance or the percentage eye closure and assessing or categorizing the drowsy level using these measures, these studies did not predict in advance the point in time or episode with a higher risk of crash (accident).

Attempts have been made to predict drivers' drowsiness using physiological and behavioral evaluation measures [3–10]. Here, the drowsiness is represented by the psychological evaluation of drowsiness using a 3-point scale (arousal, 2: a little drowsy, 3: very drowsy). In other words, an attempt was made to predict the drowsiness on the basis of the relationship between subjective drowsiness (sleepiness) and the physiological or behavioral evaluation measures. These studies made an attempt to

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predict the subjective rating on drowsiness using physiological and behavioral measures, and obtained prediction accuracy of more than 0.85. However, it is difficult to accurately predict the point in time with high risk of crash (accident) using the prediction outcome of subjective drowsiness.

Murata et al. [11] made an attempt to predict drivers' drowsiness using a trend analysis of behavioral (neck vending angle (horizontal and vertical), back pressure, foot pressure, COP on sitting surface, frequency of body movement, tracking error in driving simulator task, and standard deviation of quantity of pedal operation) evaluation measures. More concretely, each behavioral measure was used as the evaluation index of drowsiness (arousal level) as well as the self-reported evaluation of drowsiness, and thus we made an attempt to predict the participant's drowsiness for each base line.

Trend analysis of each evaluation measure was carried out by using a single regression model where time and the base line of drowsiness (one of eight evaluation measures) corresponded to an independent variable and a dependent variable, respectively. Using the result of trend analysis, Murata et al. [11] proposed a new approach (see Fig. 1 and Murata et al. [11]) to predict the point in time (we call this the point in time of virtual accident) when the participant would have encountered a crucial accident if he or she continued driving a vehicle. They found that the proposed approach could identify the point in time of virtual accident.

However, in Murata et al. [11], the interval of trend analysis, the intervals T and X in Fig. 1 are fixed to 4 min and 10 s, respectively. The behavioral data were averaged and obtained every 10 s. It is necessary to examine what values are proper for T, X, when applying the trend analysis in Fig. 1 to the prediction of drowsy state. The aim of this study was to explore the effects of these parameters T and X in the prediction on the prediction accuracy.

2 Method

2.1 Participants

Twelve healthy male students from 21 to 23 years old participated in the experiment. All signed the document on informed consent after receiving a brief explanation on the experiment. The visual acuity of the participants was matched and more than 20/20. They had no orthopedic or neurological diseases. They were required to stay up all night and visit the laboratory. In such a way, we induced a condition under which the participants readily felt asleep or carried out an experimental task under a drowsy or low arousal state.

We judged that the participant surely would have been encountered a serious accident with fairly high probability if continued driving, when the following two conditions simultaneously occurred. (i) Mean tracking error per one minute is more than 1.8 m. (ii) The participant could not report subjective drowsiness using a switch. The tracking error of 1.8 m corresponds to the half of lane width and indicates that the vehicle location is dispersive, and thus we cannot judge that the participant is driving normally. This judgment that the participant must surely encounter a crash if he or she was driving in a real-world driving environment was also visually checked by the experimenter while monitoring the behavior of the participants.

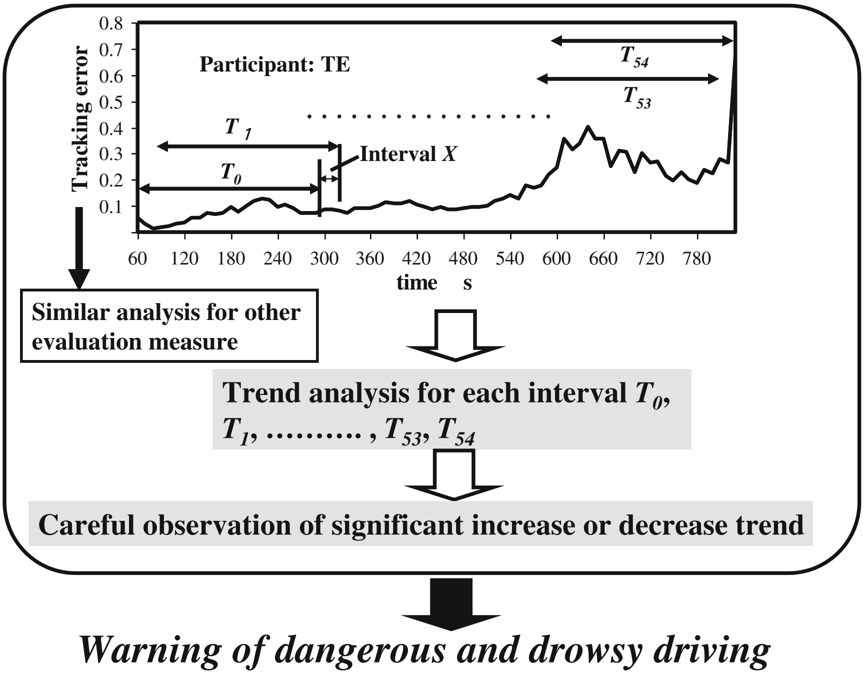

Fig. 1. Procedure for predicting drowsiness by trend analysis of behavioral measures (Murata et al. [11]).

As a result of checking the data of all participants according to the rule for judging the virtual accident below, the point in time of virtual accident was detected in ten out of twenty participants. As for other five participants, no definite virtual accident could be identified, although they tended to feel drowsy with the elapse of experimental time.

2.2 Apparatus

Pressure sensors (OctSense, Nitta) were attached to the shoes insole for measuring foot pressure. Pressure sensor (OctSense, Nitta) was attached to the backrest of the driving seat for measuring back pressure. Goniometers (DKH) for vertical and horizontal neck bending angle measurement were attached to the back of neck to measure the bend angle of neck. A measurement system of sitting pressure distribution (Nitta, Conform-Light) was placed on a driver's seat.

2.3 Design and Procedure

In the driving simulator task, the participants were required to keep the deviation from the moving line as small as possible and to keep the center of the road using a steering wheel. The participants were also ordered to keep the speed of a car within the predetermined range.

2.4 Method for Predicting Point in Time with High Risk of Crash

According to the proposed method and the experimental data in Murata et al. [11], an attempt was made to predict the point in time with high risk of accident. The following eight behavioral measures were used: neck vending angle (horizontal and vertical), back pressure, difference of back pressure, foot pressure, difference of foot pressure, COP movement on sitting surface, frequency of body movement, and tracking error in driving simulator task.

The approach for detecting significant trends (increase or decrease) and warning the state of drivers is explained in Fig. 1. First, the original time series are entered into a 5-point moving average algorithm. In this example, the interval T for the trend analysis was fixed to 4 min. The mean values of behavioral measures were calculated every X = 10 s. A total of 24 data were used for the trend analysis per one interval. The interval was moved forward by 10 s as in Fig. 1. In this figure, a total of 55 intervals (T_0, T_1,…., T_{53}, T_{54}) were used for the trend analysis, and the judgment of trend was conducted for each interval.

Using a single regression model, trend analyses for each interval were carried out for each evaluation measure. In the regression model, time and the measure of drowsiness (one of eight behavioral measures) corresponded to an independent variable and a dependent variable, respectively. Careful observation of the trend (significant increase or decrease) of each evaluation measure must be continued until the symptom of virtual accident is certainly extracted and identified.

In Murata et al. [11], T and X were set to 4 min and 10 s. We examined the effects of the parameters T and X for the original time series of behavioral measures on the effectiveness of the proposed method. It was examined what values of T and X are desirable for detecting most effectively the point in time with high risk of crash. From the practical viewpoint, T should be as short as possible so that the prediction accuracy is not damaged. In this study, T was set to 2, 3, 4, 5, and 6 min, and X was set to 3, 5, 10 s.

3 Results

Figure 2 shows the trend graph on the basis of tracking error for T = 120 s and X = 10 s (Participant: DF). In Fig. 3, the trend graph on the basis of tracking error for T = 360 s and X = 10 s (Participant: DF) is depicted. Figure 4 shows a similar trend graph on the basis of tracking error for T = 360 s and X = 5 s (Participant: DF). The procedure for plotting the trend graph was based on Murata et al. [11].

Table 1 summarizes the results of identification of time zone with high risk of crash for each behavioral measure when T was 120 s and X was 10 s. In Table 1, for example, the data (tracking error) "+40 (1820−2210 s)" of the participant C represents that the increasing trend was observed consecutively 40 times during the interval from 1820 to 2210 s. The data (foot pressure) "-54(600-1130 s)" of the participant I shows that the decreasing trend was observed 19 times in a row during the interval from 650 to 830 s. Table 2 shows the results of identification of time zone with high risk of crash for each behavioral measure (T = 360 s, X = 5 s). Table 3 also shows similar results of

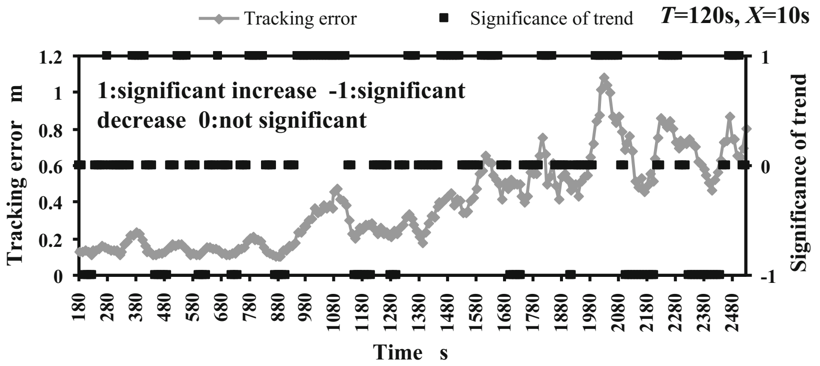

Fig. 2. Trend graph on the basis of tracking error for T = 120 s and X = 10 s (Participant: DF)

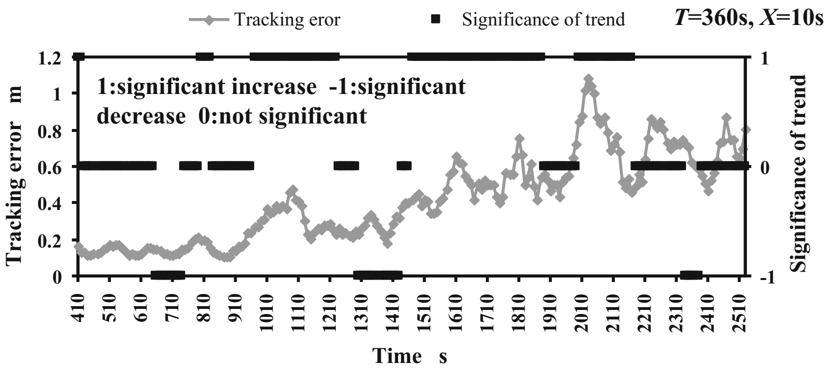

Fig. 3. Trend graph on the basis of tracking error for T = 360 s and X = 10 s (Participant: DF)

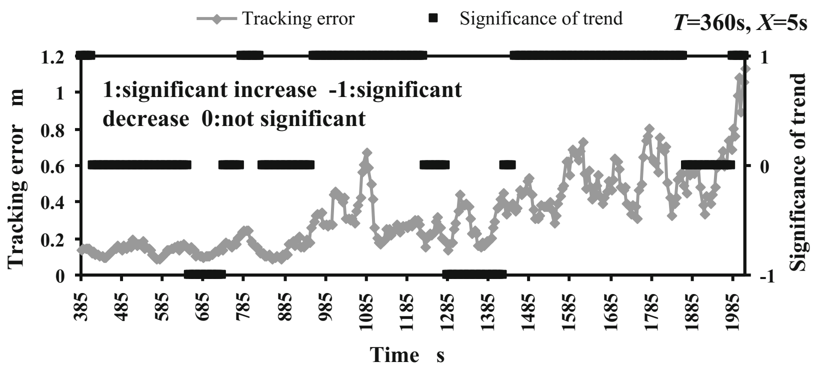

Fig. 4. Trend graph on the basis of tracking error for T = 360 s and X = 5 s (Participant: DF)

Table 1. Results of identification of time zone with high risk of crash for each behavioral measure (T = 120 s, X = 10 s).

Participants	Point in time of vertual accident	Tracking error	COP movement	Horizontal neck bending angle	Vertical neck bending angle	Back pressure	Foot pressure	Difference of back pressure	Difference of foot pressure
A	640s	+3(620-640s)	-10(540-630s)	-6(560-610s)	-6(570-620s)	-8(570-640s)	-5(490-530s)	-8(540-610s)	-7(420-480s)
B	2560s	+4(2450-2480s)	-12(2420-2530s)	+5(2270-2310s)	+3(2510-2530s)	+5(2520-2560s)	-6(2490-2540s)	+7(2500-2560s)	-5(2330-2370s)
C	2210s	+11(2010-2110s)	-4(2180-2210s)	-3(2190-2210s)	-3(2190-2210s)	+13(2040-2160s)	-10(1920-2010s)	-8(2080-2140s)	-4(2080-2110s)
D	750s	+14(550-680s)	+5(710-750s)	+5(660-700s)	+5(670-710s)	-4(680-710s)	-9(600-680s)	+10(620-710s)	-18(580-750s)
E	2530s	+5(2470-2510s)	-9(2340-2420s)	+9(2310-2390s)	+8(2430-2500s)	-6(2450-2500s)	-7(2370-2430s)	-6(2420-2470s)	-7(2210-2270s)
F	590s	+7(530-590s)	+4(560-590s)	-10(500-590s)	-7(530-590s)	+5(550-590s)	-5(550-590s)	-5(550-590s)	-5(550-590s)
G	2430s	+4(2400-2430s)	+5(2390-2430s)	+5(2260-2300s)	+5(2270-2310s)	-11(2280-2380s)	-7(2240-2300s)	+3(2290-2310s)	-9(2350-2430s)
H	850s	+17(680-840s)	+5(810-850s)	-7(790-850s)	-5(790-830s)	-21(650-850s)	-4(810-840s)	+9(650-730s)	-8(570-640s)
I	1180s	+9(1040-1120s)	-11(1030-1130s)	-5(1110-1150s)	-5(1110-1150s)	-9(1010-1090s)	-20(860-1050s)	+7(1120-1180s)	-11(1050-1150s)
J	760s	+8(690-760s)	+7(670-730s)	-5(720-760s)	-6(630-680s)	-8(590-660s)	-9(590-670s)	-5(720-760s)	-5(720-760s)

Table 2. Results of identification of time zone with high risk of crash for each behavioral measure (T = 360 s, X = 5 s).

Participants	Point in time of vertual accident	Tracking error	COP movement	Horizontal neck bending angle	Vertical neck bending angle	Back pressure	Foot pressure	Difference of back pressure	Difference of foot pressure
A	440s	+12(385-440s)	+8(405-440s)	+3(430-440s)	no	+4(425-440s)	no	no	+12(385-440s)
B	1325s	+169(485-1325s)	+13(1265-1325s)	+11(1275-1325s)	+50(1080-1325s)	-14(1260-1325s)	-59(1245-955s)	+76(950-1325s)	-68(570-905s)
C	2210s	+83(1800-2210s)	-42(2005-2210s)	-14(2145-2210s)	+36(1870-2045s)	+28(2075-2210s)	-42(1935-2140s)	-61(1910-2210s)	-7(2180-2210s)
D	750s	+34(585-750s)	+5(690-710s)	+28(615-750s)	+74(385-750s)	+74(385-750s)	-74(385-750s)	+21(650-750s)	-22(645-750s)
E	2015s	+7(1985-2015s)	+8(1970-2005s)	+7(1985-2015s)	+11(1965-2015s)	-91(1510-1960s)	-22(1590-1695s)	+8(1980-2015s)	-28(1595-1730s)
F	585s	+41(385-585s)	-41(385-585s)	-25(465-585s)	-9(545-585s)	+41(385-585s)	-5(565-585s)	+33(420-580s)	-16(510-585s)
G	1470s	+6(1420-1445s)	+61(1140-1440s)	+39(1280-1470s)	+66(1145-1470s)	+58(1185-1470s)	-3(1460-1470s)	+51(1185-1435s)	-4(1265-1280s)
H	505s	+25(385-505s)	+25(385-505s)	+25(385-505s)	+25(385-505s)	-25(385-505s)	-25(385-505s)	+25(385-505s)	+10(460-505s)
I	1175s	+39(985-1180s)	+36(970-1145s)	+24(970-1085s)	-10(1115-1160s)	-24(1060-1180s)	-106(595-1120s)	+14(965-1030s)	-7(1145-1180s)
J	755s	+16(680-755s)	+38(570-755s)	-20(635-730s)	+4(740-755s)	+45(505-725s)	-31(560-710s)	+69(415-755s)	-14(385-450s)

Table 3. Results of identification of time zone with high risk of crash for each behavioral measure (T = 360 s, X = 10 s).

Participants	Point in time of vertual accident	Tracking error	COP movement	Horizontal neck bending angle	Vertical neck bending angle	Back pressure	Foot pressure	Difference of back pressure	Difference of foot pressure
A	640s	+13(410-530s)	-3(620-640s)	+12(450-560s)	+7(460-520s)	+6(440-490s)	no	-9(470-550s)	no
B	2560s	+5(2340-2380s)	-13(2440-2560s)	+4(2500-2510s)	+3(2500-2520s)	-79(1570-2350s)	-22(1980-2190s)	+4(2530-2560s)	-26(2230-2480s)
C	2210s	+40(1820-2210s)	+5(2120-2160s)	-6(2160-2250s)	+19(1870-2050s)	+12(2100-2210s)	-19(2000-2140s)	-27(1950-2210s)	-4(2060-2090s)
D	750s	+18(580-750s)	+18(580-750s)	+13(630-750s)	+35(410-750s)	+35(410-750s)	-35(410-750s)	+9(670-750s)	-18(580-750s)
E	2530s	-5(2340-2390s)	+18(2270-2450s)	+17(2370-2530s)	+10(2440-2530s)	+11(2350-2450s)	-11(1610-1710s)	+6(2250-2400s)	-12(2380-2490s)
F	590s	+19(410-590s)	+5(550-590s)	-11(490-590s)	-5(550-590s)	+19(410-590s)	+12(410-520s)	+17(430-590s)	-6(540-590s)
G	2430s	+25(2090-2330s)	-6(2330-2380s)	+6(2100-2150s)	-3(2410-2430s)	+26(2170-2420s)	-11(2260-2360s)	+24(2170-2400s)	-7(2000-2060s)
H	850s	+8(780-850s)	-3(770-790s)	+39(410-790s)	+5(720-760s)	-14(720-850s)	-17(410-570s)	+15(680-820s)	-13(610-730s)
I	1180s	+20(990-1180s)	+11(960-1060s)	+12(990-1100s)	-6(1130-1180s)	-11(1080-1180s)	-54(600-1130s)	+6(990-1040s)	+19(930-1110s)
J	760s	+7(700-760s)	-21(560-760s)	+32(410-720s)	+22(410-620s)	+20(530-720s)	-16(590-730s)	+33(440-760s)	-5(410-450s)

identification of time zone with high risk of crash for each behavioral measure for $T = 360$ s and $X = 10$ s.

Figure 5 shows the graphic representation of the time zone with high risk of crash for each behavioral measure corresponding to Table 1 ($T = 120$ s, $X = 10$ s). Figure 6 shows the graphic representation of the time zone with high risk of crash for each behavioral measure corresponding to Table 2 ($T = 360$ s, $X = 5$ s). In Fig. 7, the graphic representation of the time zone with high risk of crash for each behavioral measure ($T = 360$ s, $X = 10$ s).

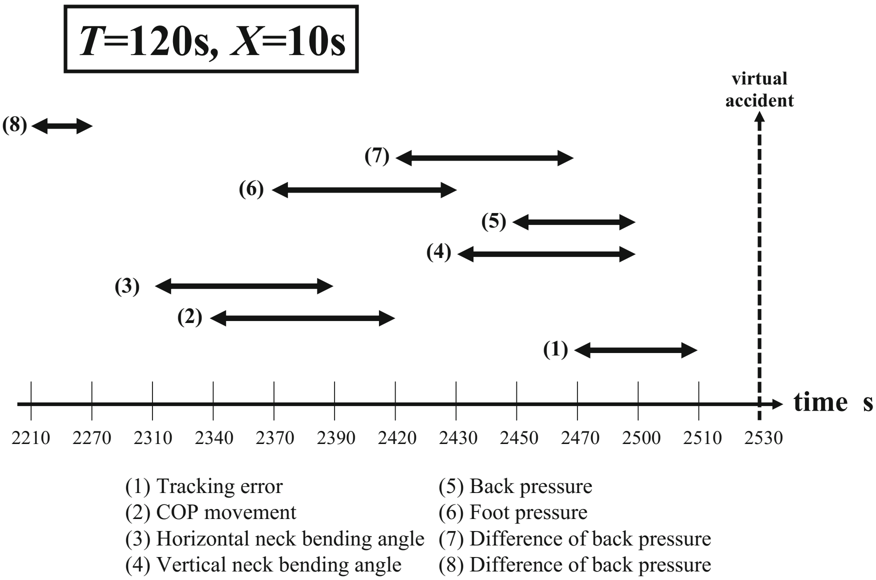

Fig. 5. Graphic representation of the time zone with high risk of crash for each behavioral measure ($T = 120$ s, $X = 10$ s).

4 Discussion

As a whole, the significant decrease or increase trend was observed in a row before the point in time of virtual accident. This suggests that such a trend analysis is effectively used for the identification of the point in time when it is definitely and firmly judged that the participant is about to reach inactive driving state and under a high risk of crucial traffic accident (This point in time will be called point in time with high probability of potential danger of accident reliably).

Table 1 suggests that the trend analysis can identify to some extent the point in time with high risk of crash (accident) before the virtual accident occurs. The consecutive increasing trends of tracking error were observed for ten participants analyzed. The consecutive decreasing trends of foot pressure and difference of foot pressure were observed for ten participants analyzed. For other five measures, either consecutive increasing or decreasing trends were observed.

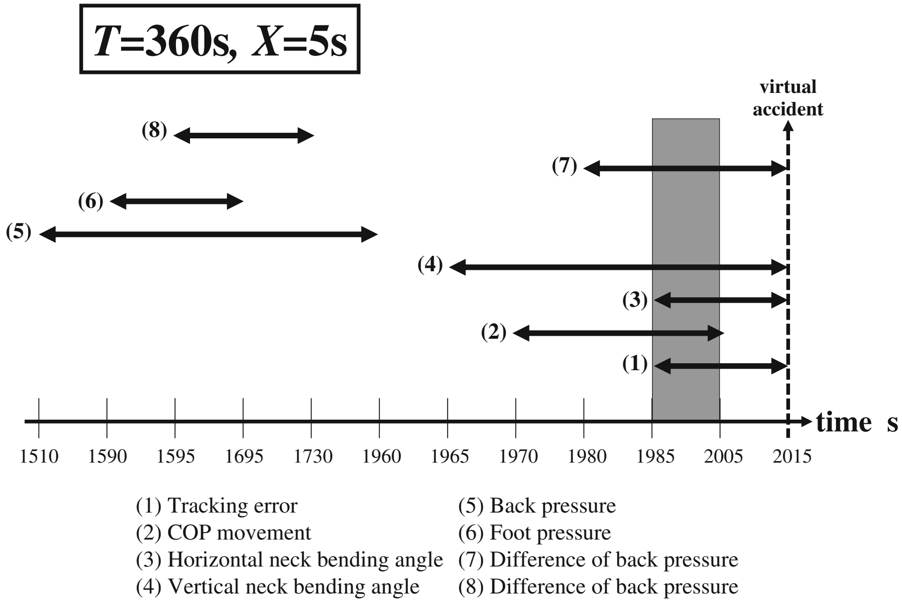

Fig. 6. Graphic representation of the time zone with high risk of crash for each behavioral measure (T = 360 s, X = 5 s).

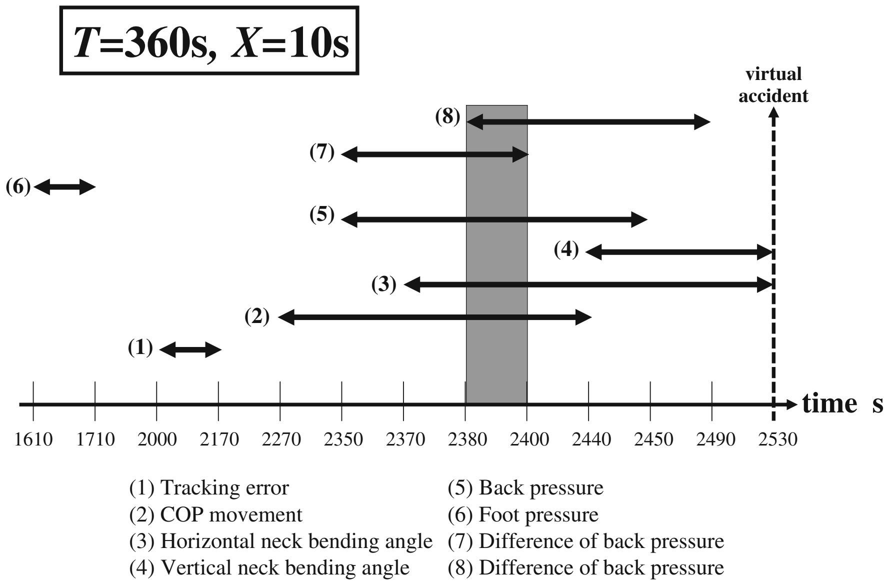

Fig. 7. Graphic representation of the time zone with high risk of crash for each behavioral measure (T = 360 s, X = 10 s).

On the basis of the data such as shown in Tables 1, 2, and 3, the point in time with high risk of crash can be identified as follows before the virtual accident. The identified time zones of significant trend for each behavioral measure were plotted as shown in Figs. 5, 6, and 7 (participant DF). In Fig. 5, we could detect no time zone of significant increase or decrease trend when not less than four behavioral measures overlapped. As shown in Fig. 6, when T = 360 s and X = 5 s, we could detect the time zone (from 1985 s to 2005 s) when four or more behavioral measures overlapped. This time zone was detected 10 s before the virtual accident occurred. In Fig. 7, a similar time zone was detected 130 s before the virtual accident. From 2380 s to 2400 s, the time with high risk of crash of five behavioral measures overlapped.

In such a way, the proposed method enables us to identify the point in time with high risk of crash before reaching the point in time of virtual accident. In order to make drivers cautious of the forthcoming risky state with high probability of crash and prevent traffic accidents from occurring, not only the assessment of the drowsiness but also the predicting in advance the occurrence of virtual accident (crash) is indispensable.

In the range of this study, longer T (240 s, 300 s, and 360 s) was found to be better than shorter T (180 s and 120 s) and can reliably detect the time zone with high probability of potential danger of accident. As for the parameter X, X = 10 s tended to lead to more accurate detection of point in time with high probability of potential danger of accident reliably than X = 3 s or 5 s. As there existed individual differences on the proper value of T and X, it might be necessary to adaptively change the value of T and X so that the point in time of virtual accident can be predicted in advance with higher accuracy. In such a way, the proper parameters for the prediction procedure of drowsiness in Fig. 1 were empirically identified.

Future research should also make an attempt to make use of the proposed method, predict the time in point with considerably high probability of potential danger of accident in real-world driving environment, and further verify the effectiveness of the proposed method. We should also make an attempt to apply the proposed method to the gradually decrease of arousal level without being informed of the existence of virtual accident, and predict the occurrence of virtual accident.

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