Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 21 (2017) 169–179

Transportation Research Procedia

www.elsevier.com/locate/procedia

2016 International Symposium of Transport Simulation (ISTS'16 Conference), June 23~25, 2016

An analysis of the impact of driving time on the driver's behavior using probe car data

Satoshi Hyodo[a] Tohio Yoshii[b] Matstushita Satoshi[b] Shirayanagi Hirotoshi[b]

[a] *Department of Transportation Systems Engineering, College of Science and Technology, Nihon University, 7-24-1 Narashinodai Funabashi-City, 274-8501 Chiba, Japan*

[b] *Department of Civil and Environmental Engineering, Ehime University, Bunkyo-cho Matsuyama city, 790-8577 Ehime, JAPAN*

Abstract

Driver's fatigue is an important factor of traffic accidents. Therefore, a fatigue detection system which achieves a small burden on a driver is expected to be developed, which stimulates drivers after long hour driving to take a rest at an appropriate timing when the driver's fatigue is detected. In order to give warning at an appropriate timing, knowledge about the impact of continuous driving hours on driver's behavior should be obtained. Recently, a rapid spread of ITS technologies enables us to analyze driving behavior in detail by using a large quantity of probe car data. This study analyses the impact of continuous driving hours on driving behavior when a vehicle is traveling on an expressway based on the probe car data. It is shown that the continuous driving hour affects driving behavior significantly. From the results, it can be concluded that driver had better take a rest every 5,000 [s] approximately.

Keywords: "the driver's behavior, continuous driving hour"

1. Introduction

Detection of driver condition is a major concern in road safety. In particular, professional drivers have been characterized as experiencing heavy fatigue resulting from long distance or long hour driving in their work. Therefore, an alert system is expected to be developed, which stimulates drivers after long hours driving to take a rest at an appropriate timing. In order to give a warning at an appropriate timing, the knowledge about the impact of driving time on driver's behavior should be obtained.

10.1016/j.trpro.2017.03.086

This study aimed at developing a methodology to evaluate the relationship driver condition (such as driver fatigue, loss of alertness etc.) indices and driver behavior indices when a car is traveling on an expressway.

There are many factors that may cause the driver to be fatigued. It results from the effect of monotony on alertness, vigilance and so on. For example, if you drive a car for a long time, it might cause physical and psychological changes such as the reaction time delay and delay in responding to traffic situation.

Several methods of driver performance have been used to perform real time driver's condition detection using field experiment or driving simulators. These methods are divided into the vehicle based methods and the driver based methods.

The vehicle based methods based on monitor vehicle operational indices. The vehicle based methods observe the vehicle operating parameters such as change in the steering, acceleration, speed of the vehicle, braking and lane tracking and so on. For example, Apostoloff and Zelinsky (2003) represented the development and application of a novel multiple-cue visual lane tracking system. Moreover, Jagannath and Balasubramanian (2014) used seat pressure distribution and other measures of physical index like blood pressure such as heart rate, oxygen saturation level to quantify driver fatigue during monotonous simulated driving.

On the other hand, the driver based methods based on devices that directly monitor driver condition. the driver based methods are physical movement parameters such as eye closure and blink rates, tracking of facial expression by using video imaging techniques (Zhu and Ji, 2004). For example, Nillson et al,(1997) demonstrated average fatigue scores of experiment subjects increased rapidly during the first 80 minutes of driving. In addition to, Iwakura et al. (2001) investigated the possibility of a quantitative assessment of stress to measure the stress with long- distance driving which wearing heart rate interval RRI. This survey asks in seven ranks from "not tired at all" to "exhaustion", as an overall investigation. As the result, although it is not clear trend because it changes periodically during the day, as the driving time increase, RRI to be long, and this survey result agree with rate of the RRI change. So, it is supported that stress occurs by long distance or hour driving. Furthermore, Warita et al. (2012) conducted the driving survey to investigate the correlation between the driver's psychological condition and road structures, traffic conditions using a biosensor and an eye mark recorder and drive a car equipped with a drive recorder for these car experiments. And, Wu et al. (2013) conducted to examine the changes in driver's eye movements, driver performance and heart rate. Those analyses have been performed to analyze sings of driver's condition through the driving car experiments or driving simulators.

However, these have never been tested in practice or realistic traffic environment. In addition to, the limitation data obtained by these vehicles may not represent the whole population. Furthermore, it need to reduce the experiment burden on a driver.

On the other hand, a rapid spread of ITS technologies enables us to analyze driving behavior in detail by using a large quantity of probe car data. These data are the identification of the location of car using the global positioning system (GPS). The advantage of probe data analysis is that we direct observe the travel time. Therefore, the driving history is included in these data. It seems to easily trace driver behavior or performance and obtain realistic environment driving data. Therefore, it is expected that detailed driver's behavior analysis could be carried out using these data.

In this study, the methods are proposed to investigate the relationship the continuous driving hours and driver's behavior using probe car data. Specifically, we will propose an index that can be used to evaluate driver's behavior based on the probe car data using piece wise liner regression model.

2. Concept of this study

2.1. Methods

The study purpose was to understand the relationship the continuous driving hours and driver's behavior indices. In general, the driving behavior is regulated by drivers' functions of recognition, judgment, and operation. Therefore, the changes of psychological and physiological responses occurring as driving fatigue would be reflected in the changes of the driving functions. If a driver feels tired while driving, we were difficult to keep a proper driving operation such as adjusting velocity. Such changes of driving conditions are affected by the changes of conditions of driving performance. In this section, we demonstrated the concept of a method of quantifying drive condition or fatigue by using prove data.

As shown in fig.1., a sag section is freeway road section which gradient gradually changes from downwards to upwards. In this section, driver often don't notice this slight change. Accordingly, these sections are often decreasing speed for a long time. Therefore, it is well known that sag sections become capacity bottlenecks (Oguchi , 1995). Especially, if a driver became tired while driving, he is difficult to keep a proper speed at sag section with upgrade gradient. This study aims to investigate the impact of the continuous driving hours on driver's behavior for the sag section. If we can find the degrees of correlations of driving behavior indices on driving condition indices and define a model expression representing driving conditions in the form of synthesis of driving-behavior indices, we will be able to find quantitatively the relation between the and the internal responses driver's fatigue. The indices of driving velocity, distance from the car ahead, etc. showing driving conditions are called "driving-condition indices."

In this study, two indices for representing the driver's behavior are proposed. The first one is "*V*" represents that the relative velocity in comparison to the velocity on beginning sag point. Second one represents that driver deceleration distance. These indices are explained below.

2.2. Definition of indices representing driver behavior at sag section

Fig.1. shows a vehicle's trajectory by his velocity.
time series of velocity at a sag section by a driver. As shown in this figure, first index V is defined which represents the velocity drop at a sag section. If it appears that the relative velocity tends to increase, we suppose that low driving performance level. In order to calculate this index, we identify the time of two points and the velocity at those points were used. The first point means the time when velocity drop started and the velocity at that moment. The second point means the time when the probe car accelerates for the first time at sag section.

$$V = v(t_0) - v(t_1) \tag{1}$$

Where,
V: the amount of velocity drops [km/h]
$v\ (t)$: the velocity of vehicle at time interval t [km/h]
t_0: the time when the probe car arrives the bottom of sag [s]
t_1: the time when the probe car starts to recover his speed [s]

Second index L is defined it represents the distance on which the vehicle moves with deceleration. It appears that this distance tends to increase, the corresponding performance level could be classified as low performance level. Similarly, in order to calculate this index, we identify the time of two points and the velocity at those points were used. The first point means the time when velocity drop started and the velocity at that moment. The second point means the time when the probe car accelerates for the first time at sag section.

$$L = \int_{t_0}^{t_1} v\ (t)dt \tag{2}$$

Where,

L: the deceleration distance [m]

v (t): the velocity of vehicle at time interval t [km/h]

t_0: the time when the probe car arrives the bottom of sag [s]

t_1: the time when the probe car starts to recover his speed [s]

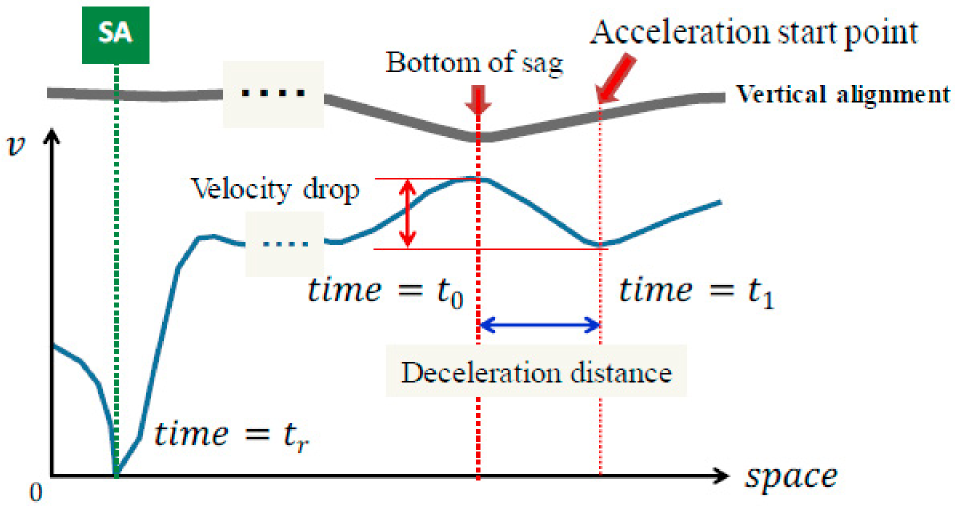

Fig. 1. Sag section and the driving condition or behavior indices

2.3. Definition of indices representing driver condition

The continuous driving hours T is defined as the time is calculated from the probe car data. The dummy variable D is a variable which represent whether or not the vehicle takes a rest at the SA/PA area. The continuous driving hours T defined by equation. (3) and (4). Firstly, we used the probe car data to identify the car whether or not stopping at service areas or rest areas. If the driver has stopped at rest area, we calculate the continuous driving hours from a rest area to current position. Therefore, the time t_r is the time which represent the vehicle arriving at a rest area. On the other hand, the driver has never stopped at rest area, we calculate the driving time from origin point to current position. In this case, the time t_r is the time which represent the vehicle arriving at origin point.

Fig. 1. shows the method used to calculate the driving time measured by the car probe data.

$$\mathrm{D} = \begin{cases} 1, (taking\ a\ rest) \\ 0, (without\ a\ break) \end{cases} \tag{3}$$

$$T = t_0 - t_r \tag{4}$$

Where,

D : the dummy variable is a variable which represent whether or not the vehicle takes a rest at the SA/PA area.

T : the continuous driving hours of the probe vehicle j [s]

t_r: the time when the probe vehicle leave the service area or parking area [s]

t_o: the time when the probe car arrives the bottom of sag [s]

2.4. Piece wise liner regression model

In this study, it is assumed that the driver condition state be roughly divided into three stages by the continuous driving time. First stage (Stage I) is a healthy or normal state. Second stage (Stage II) is a transitional state between healthy condition and fatigue condition. Third stage (Stage III) is a fatigue condition state.

It appears first fatigue stage under Break-point k_1 (Stage I), and then the reduction of the driver performance due to driver fatigue condition (Stage II) and the more reduction of the driver performance due to driver fatigue (Stage III). Obviously, driver condition becomes worse from Stage I to Stage III. For identifying these stages efficiently, the selection of the proper taking rest timing is important. The fig.2 summarized the relationship between the continuous driving hours and the driving performance index considering the three stages.

In this study, it was assumed that there was the piece wise linear relationship between the driving-condition indices corresponding to the continuous driving hours and the driving-behavior indices corresponding to the amount of velocity drop and deceleration distance, and the model represented by the following expression was developed by using the piece wise liner regression model. The piece wise linear regression also known as segment regression or broken-stick regression is a method in regression analysis which the independent variable divided into some intervals and fit separated line segment to each interval. This method can also be performed on multivariate data by separate the various independent variables.

In particular, it is effectiveness when the independent variable distributes different groups in the scatter diagram and shows different relationship in the separated section. As shown in fig.2., the boundary is called break-point. In addition to, Using the least squares method to estimate, three regression lines applied and made to fit as much as possible in each divided section while the square sum of the difference between calculated and observed values of the dependent variable residual to minimize. In order to find certain ranges of x that yields the best fitting model, we conducted to use least-squares estimation every ranges of 500 [s].

$$y_j = \alpha + \beta_1(xd_1 + k_1d_2 + k_1d_3) + \beta_2\{(x-k_1)d_3 + (k_2-k_1)d_3\} + \beta_3(x-k_2)d_3 \tag{5}$$

$$= \begin{cases} \alpha + \beta_1 x \ \ (x \le k_1) \\ \alpha + \beta_1 k_1 + \beta_2(x-k_1) \ \ (k_1 < x \le k_2) \\ \alpha + \beta_1 k_1 + \beta_2(x-k_1) + \beta_3(x-k_2) \ \ (k_2 < x) \end{cases}$$

Where,

y : Dependent variable of the driving performance index (the continuous driving hours)

x : the measured value of the driving-behavior indices (the amount of velocity drop, the deceleration distance)

k : Break-point (threshold)

d_1 : Dummy variable (1, when $x \le k_1$)

d_2 : Dummy variable (1, when $k_1 < x \le k_2$)

d_3 : Dummy variable (1, when $x > k_2$)

α : Intercept

β : Slope each section

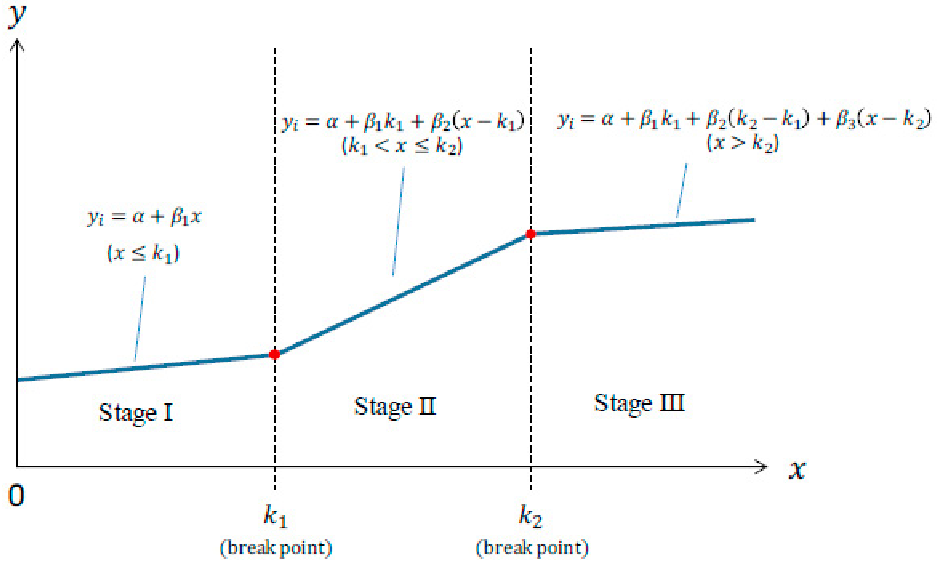

Fig. 2. Example of a piecewise linear model

3. Description of data and study network

This section briefly reviews the data used in this analysis.

3.1. Outline of the Probe Data

In this study, the commercial vehicle probe data manufactured by Fujitsu Ltd. using for this analysis. This probe data have been collected from the cargo vehicle (probe car) installed a network type digital tachograph. The data of the car ID, the position coordinates, the velocity, the acceleration and engine velocity can obtain from the probe car every 1 second, and using the car ID, position coordinates and velocity data. The data used in this study was acquired from the records collected over 2 months from October 1, 2014 to November 31, 2014.

These probe data is composed three data: the dot data, the OD data, the SA and PA usage history. Outline of these three data show below section.

3.2. The Dot Data

The dot data is a data written about the running position and the driving behavior which recorded in every one second of each vehicle trip. Specifically, it is written about car ID, trip ID, date and time (year/month/day hour: minute: second), latitude, longitude, velocity and so on. The data from commercial vehicle 465 cars passing through a section between Iyo-Saijo IC and Kawauchi IC along Matsuyama Expressway in westbound for two months period of October 1, 2014 to November 31, 2014 is total of 2,738 trips. In addition to, the target vehicle type is composed 4 light and standard size cars, 162 medium size cars, 162 large size cars, 51 extra-large size cars and 86 unknown cars which investigated from the actual usage of ETC vehicle mount device. This study focuses on the target vehicles for large size vehicle and extra-large size vehicle, which are provided by 145 cars and the number of 490 trips data.

3.3. The OD Data

The OD data is an origin and destination data written about car ID, trip ID, area name and code of origin-destination, the departure/ arrival date and time of trip (year/month/day hour: minute: second). When same vehicles have multiple trip, the OD data shown some lines. The total number of vehicles that are listed in the OD data is 465 units, and the total number of trips is 2,738 trips. In addition, the number of origin zone is 302 places and destination zone is 105 places.

3.4. The SA and PA Data

The Service Areas/Parking Areas (SA or PA) usage history is a data written about time and date of the vehicle inflow and outflow to the service area or parking area (year/month/day hour: minute: second), and the area name and the code of rest facilities. On the expressway, there is no change to the trip ID before and after taking a rest at the SA or PA, it is treated as the same trip. If the vehicle uses some rest facilities during one trip, the SA and PA usage history shows some lines. In addition to, the usage history has been written all of the rest facilities from the trip of origin to destination, regardless of the analysis section inside and outside.

3.5. Sag section

This Study section is from Iyo-Saijo to Kawauchi interchange (93.5KP ～ 129.5KP) of the Matsuyama Expressway (in westbound direction) located Ehime prefecture, in japan as shown in Fig .3.(a). This section has a light traffic of about 10,000 vehicles per day. And then, this section recorded the worst accident rate in the Matsuyama Expressway. Road extension is approximately 36 km. There were 16 sag sections. Table 1 shows the geometric factors of each sag section. And the fig.4 shows the terminologies in Table 1. Where, the percentage of the deceleration is the ratio of the number of deceleration to the number of entered vehicles at the bottom of sag. As shown in Table1, the percentage of the deceleration vehicle at these sag sections. In this study, we chose subject sag section (103.7 kp) that is high percentage of the decelerating vehicle and the basic road section (the section at the tunnel doesn't located) as shown in Fig .3. (b) .

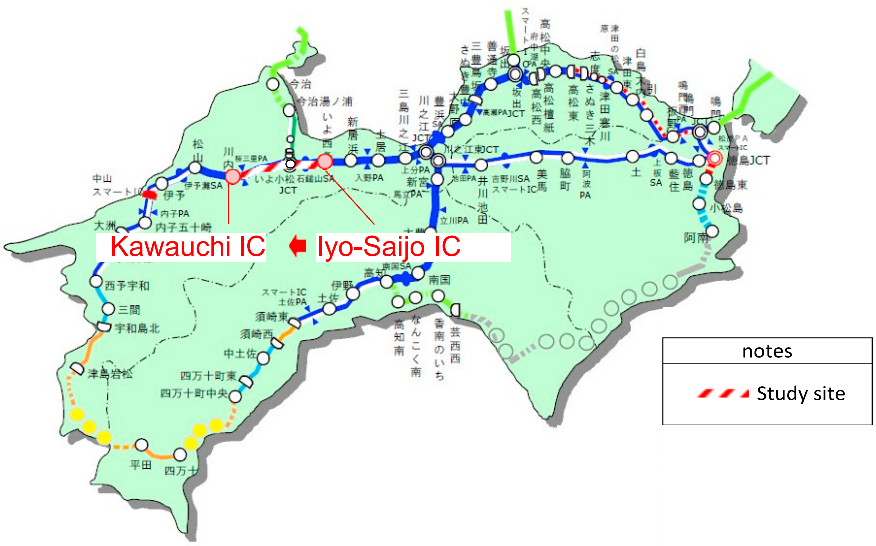

Fig. 3. (a) Study network

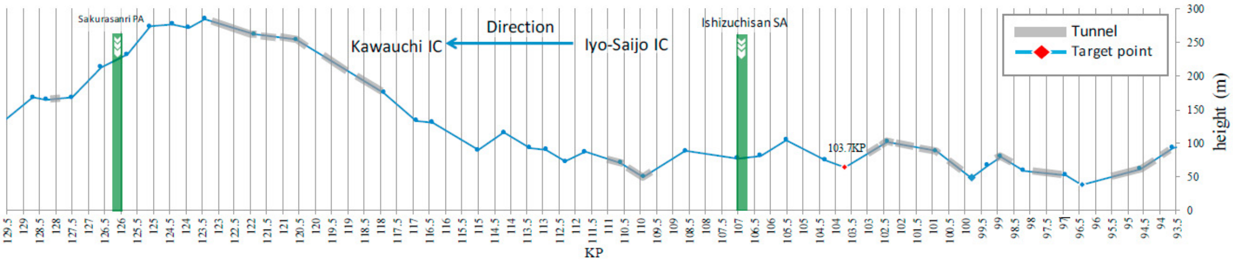

Fig. 3. (b) Study section

Table 1. Percentage of the deceleration vehicle at each sag sections

Point (KP)	upstream gradient (%)	downstream gradient (%)	Deference of gradient (%)	Length of upstream section (m)	Length of downstram section (m)	Percentage of the deceleration vehicle (%)	Remarks
94.6	-3.0%	-1.4%	1.6%	1040	1750	57.6%	Inside of tunnel
96.4	-1.4%	3.0%	1.6%	1750	500	54.0%	-
98.2	0.5%	3.0%	2.5%	1310	701	62.8%	Upstream of tunnel
99.8	-3.7%	3.6%	7.3%	488.7	1100	88.1%	Downstream of tunnel
103.7	-3.0%	1.7%	4.7%	1280	600	67.0%	-
104.3	1.7%	2.5%	0.8%	600	1220	52.6%	-
106.3	-3.0%	-0.5%	2.5%	800	650	64.2%	-
109.9	-3.0%	3.0%	6.0%	1290	710	61.1%	Inside of tunnel
112.3	-2.3%	3.0%	5.3%	620	590	50.1%	-
113.4	0.4%	3.2%	3.4%	550	710	28.9%	-
115	-3.0%	3.0%	6.0%	870	1380	54.2%	-
116.9	0.5%	4.0%	3.5%	490	1050	43.4%	-
121.9	0.6%	1.5%	0.9%	1349	1470	27.0%	Inside of tunnel
123.9	-2.5%	1.2%	3.7%	520	450	42.3%	-
127.5	-5.0%	-0.5%	4.5%	900	790	70.0%	Upstream of tunnel
128.3	-0.5%	0.7%	1.1%	790	440	41.1%	Downstream of tunnel

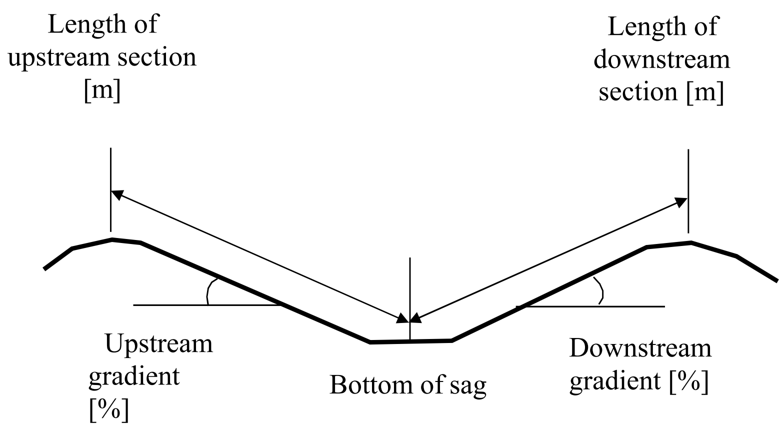

Fig. 4. Overview of sag section

4. Result

4.1. The relationship between continuous driving hours and velocity drop

Fig. 5. shows the relationship of continuous driving hours and the velocity drop. As shown in this figure, the relationship continuous driving hours and the velocity drop has positive relationship and the excessive continuous driving hours significantly increased the velocity drop. ($p < 0.01$) And then, Table 2 shows the piece wise linier models which the amount of velocity drop was chosen as independent variable. As this result, there is no significant difference in continuous driving hours as the velocity drop increases up to a certain point in 5,000 [s]. And after that point, there is an upward trend in continuous driving hours as the velocity drop increases up to 6,000 [s]. And over 6,000 [s], there is a downward trend in continuous driving hours as the velocity drop increases. This shows that other factor, such as the characteristics of driver might have an impact on driving performance. As one of these factors, we supposed that perception of risks is reduced in familiar situations due to habituation effects.

Table 2. The estimated result (the relationship between continuous driving hours and the amount of velocity drop, k_1=5,000, k_2=6,000)

Variable	Coefficient	Standard error	t-value	P-value
Intercept-α	3.025	0.646	4.68	0.000
β1	0.000	0.000	-0.46	0.648
β2	0.004	0.001	4.92	0.000
β3	-0.001	0.000	-3.41	0.001

Total cases	490
R-squared value	0.067

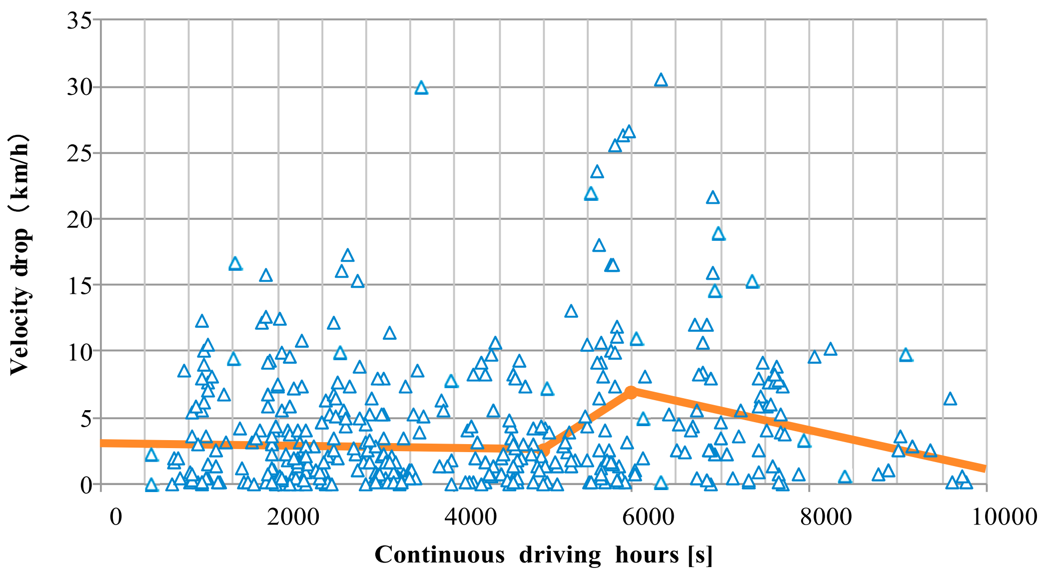

Fig. 5. The relationship between continuous driving hours and velocity drop

4.2. The relationship between continuous driving hours and deceleration distance

Fig .6. shows the relationship of continuous driving hours and deceleration distance of large size and extra-large size vehicle. As shown in this figure, the relationship continuous driving hours and deceleration distance has positive relation and the excessive continuous driving hours significantly increased the deceleration distance. ($p <$ 0.001) And then, Table 4 shows drive-fatigue models which the deceleration distance was chosen as independent variable. As this result, there is not a significant trend in continuous driving hours as the deceleration distance increases up to a certain point in 5,000 [s]. And after that point, there is an upward trend in continuous driving hours as the deceleration distance increases up to 5,500 [s]. Finally, over 5,500 [s], there is a downward trend in continuous driving hours as the deceleration distance increases.

Table 3. The estimated result (the relationship between continuous driving hours and deceleration distance, k_1=5,000, k_2=5,500)

Variable	Coefficient	Standard error	t-value	P-value
Intercept-α	368.87	53.39	6.91	0.000
β1	-0.021	0.017	-1.21	0.227
β2	0.739	0.134	5.50	0.000
β3	-0.075	0.029	-2.63	0.009
Total cases		490		
R-squared value		0.080		

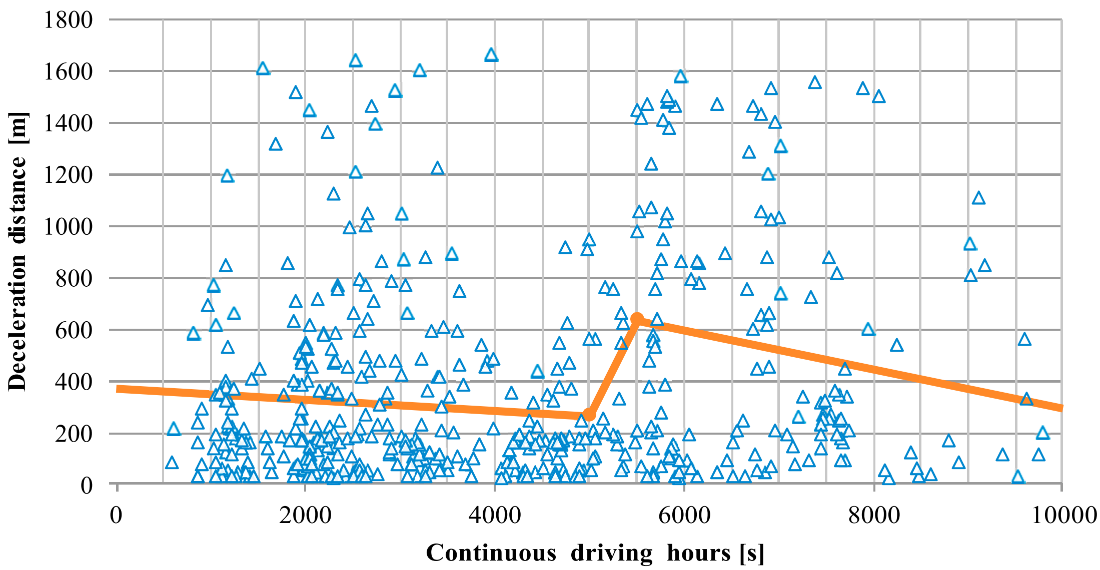

Fig. 6. The relationship between continuous driving hours and deceleration distance

5. Conclusion

This study analyzed the relationship the continuous driving hours and the driver's behavior when driving at sag section. By using probe car data, drive-condition models were constructed in the form of expressing driving conditions by synthesizing driving behavior indices based on the levels of correlations between driving behavior indices and driving-condition indices. Quantitative analysis of drive fatigue was performed by using the piece wise liner models to quantitatively grasp to the changes of responses of drivers. The analytical results clearly indicate that the driver behavior indices change significantly over time. As a result, the following findings were obtained in this study;

1) According to the relationship between the continuous driving hour and the indices representing driver behavior (the amount of velocity drop and the deceleration distance), it shown that three stage of driver performance in extending driving.
2) As the continuous driving hour increased, the state of driver is changed in approximately 5,000 [s] of driving.
3) In case of the Stage III, the driving behavior indices are improved.

On the other hand, this study did not take into account the several things. In the future study, we should take into consideration time of day effect such as daylight and night. Also, weather and traffic condition one of the factors which affecting driver behavior, we should take into account these factors.

Acknowledgements

Fujitsu Co. Ltd. provided the probe data. The authors would like to thank the relevant parties for their support.

References

Apostoloff, N., Zelinsky, A., 2003. Robust vision based lane tracking using multiple cues and particle filtering. In proceedings of the IEEE Intelligent Vehicles Symposium, Columbus, OH, 558-563.

Iwakura,S., 2001. Measurement of drive stress during a long-distance trip: Keeping measurement of advantages of AHS in mind, Journal of Infrastructure Planning 2001, Japan Society of Civil Engineers, No. 18, 439-444. (*in japanese*)

Jagannath, M., Balasubramanian, V., 2014. Assessment of early onset of driver fatigue using multimodal fatigue measures in a static simulator. Applied Ergonomics. No. 45(4), 1140–7.

Nilsson T, Nelson TM, Carlson D., 1997. Development of fatigue symptoms during simulated driving. Accident Analysis & Prevention No. 29(4), 479–88.

Oguchi, T.: Relationship between Geometric Design and Generation of Traffic Congestion at Motorway Sag Sections. Journal of Japan Society of Civil Engineers, No.524/IV-29, 1995, pp.69-78. (in Japanese)

Warita, H , Tanaka, A, Goto, H , Umeda, S , Daimon, T.,2012. Analysis of Interrelationship between Traffic Conditions and Driver's Stress for Introduction of Effective ITS Measures, 19th Intelligent Transport System World Congress, ITS2012

Wu, Y., Zhao, X., Rong, J., Ma, J., 2013. Effects of chevron alignment signs on driver eye movements, driving performance, and stress, Transportation Research Record: Journal of the Transportation Research Board, No. 2365 (1), 10–16

Zhu, Z., Ji, Q., 2004. Real time and non-intrusive driver fatigue monitoring. In proceedings. of the 7th International IEEE Conference on Intelligent Transportation Systems, Washington, D.C2 Harvard.