Context-Sensitive Hazard Anticipation Based on Driver Behavior Analysis and Cause-and-Effect Chain Study

Y. Saito & P. Raksincharoensak
Tokyo University of Agriculture and Technology, Tokyo, Japan

H. Inoue
Kanagawa Institute of Technology, Kanagawa, Japan

M. El-Haji & T. Freudenmann
EDI GmbH - Engineering Data Intelligence, Karlsruhe, Germany

E-mail: y-saito@cc.tuat.ac.jp

Topics/Advanced Driver Assistant Systems, Driver Behaviors and Assistance

The near-miss events involved road users can lead to serious accidents. This study proposes a context-sensitive hazard anticipation for predicting the criticality of situations depending on driving context and driving behavior state. The data of 901 near-miss events were extracted to analyze human error as well as cause-and-effect chain studies of accidents, and the annotations that describe the driving context were investigated to find their influence on the criticality of the recorded incidents. The results can be used to develop next generation ADAS or to improve algorithms for autonomous driving technology, increasing their safety performance as well as the driver acceptance.

1 INTRODUCTION

Pedestrians are exposed to accident risk when initiating a road crossing in urban areas, due to share the road space [13]. 47.9% of all fatal traffic accidents in Japan involve pedestrians and cyclists [10], and one of the most common types of traffic fatalities [10] is being hit in a traffic accident while walking along the road (34.9%).

Near-miss incidents or accidents involved road users are the result of conflict and/or interaction between driver behavior and pedestrian behavior [9, 11]. While the environment surrounding humans leads drivers to (i) cognitive errors, such as internal/external distractions, and inattention, (ii) decision errors, such as false assumption, and aggressive behaviors, and (iii) performance errors, such as panic/freezing [14, 8], pedestrians also cause them; for example, distractor [11] and/or risk taker may forget to look for an approaching car while crossing a road, due to talking to friend and walking with the dog which can cause distraction, using cell phone and camera, and reading a magazine which can cause inattentive blindness. As stated by [16], essential key point to reduce traffic-accidents involved pedestrians is to quantify the potential conflict between the driver behavior and the pedestrian behavior.

When expert drivers, who have accumulated a wealth of driving experience, are confronted with uncertainty, they will naturally seek to reduce the uncertainty by obtaining more information and attempting to fit their current driving context into a pre-existing category they have already developed [7]. Based on context information, e.g. parked vehicles in an urban area, they estimate the probability for possible road surprises, e.g. a playing child dashing out between the parked vehicles. If necessary, they take preventive measures, so-called "a hazard-anticipatory driving", that depend on the current driving context, such as increasing the lateral distance to other road users or decreasing the vehicle velocity or acceleration. They ensure that sufficient braking distance is available in case of the occurrence of one of the possible road surprise [4]. The additional braking distance that becomes available due to this preventive driver action is refereed to as *"Safety Cushion"*, as shown in Figure 1. Our study goal is to develop next generation ADAS to attain "a hazard-anticipatory driving" based on the prediction of the criticality of situations depending on driving context and driving behavior state.

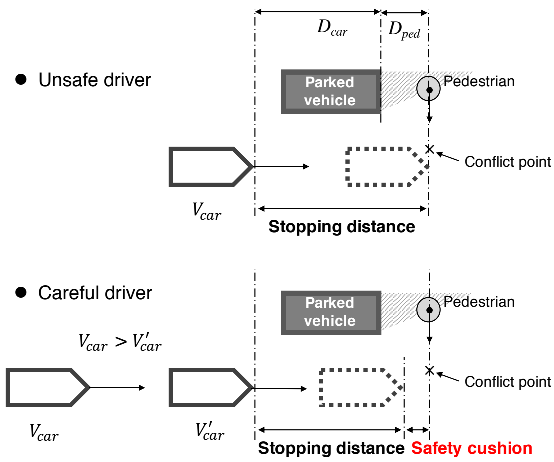

Figure 1: Safety cushion.

The aim of this paper is to propose a context-sensitive hazard anticipation method to predict the criticality of situations depending on driving context and driving behavior state. The related works that investigated the factors that influence the vehicle-pedestrian crashes can be categorized into two levels: (1) the microscopic spatial analysis [9, 11] is carried out at specific locations in order to identifying the factors and solving safety issues, and (2) the macroscopic spatial analysis [12, 18, 15, 1] focuses on zonal-level traffic accidents at various level of the entire specified area and captures the spatial trends and safety issues. However, most of the studies that investigated the macroscopic spatial analysis cannot be accurately tracked on the driver behavior when an accident occurs. As stated by [3], accuracy improvements in reporting are expected to improve the preciseness of quantified built environment factors and the counted number of crashes. Against this background, this paper describes a method for quantifying the potential conflict between the driver behavior and the pedestrian behavior, and is based on investigations with the near-miss incident database which includes time-series data with driver behavior and built environmental factors just before the crash or near-miss; thus, this study couples the macroscopic- and microscopic-spatial analyses.

2 METHODOLOGY

The investigation of this paper was based on the near-miss incident database, which has been constructed and managed by the Smart Mobility Research Center (SMRC) of Tokyo University of Agriculture and Technology in JAPAN since 2004. The vehicle dynamics and location as well as the driver operations were recorded by the driver-recorders mounted on more than 200 taxis. When the longitudinal acceleration exceeds -0.45G, the driving data were recorded automatically in 10 seconds before the trigger and 5 seconds after the trigger. By using the driver-recorders, information such as the velocity, the acceleration, the braking operation of drivers were acquired. In addition to automatically measured data, annotations composed of category data were manually added by ratings expert of SMRC.

In this paper, our targeted scenario was the intersection entry scenario with blind areas, as shown in Figure 1. The data of 901 events included the our targeted scenario (parked vehicle overtaking scenario) were extracted from the near-miss incident database. Among 901 events, 709 events data without multiple events mixed were used to conduct the driver behavior analysis as well as the cause-and-effect chain studies of accidents.

The study was divided into four phases. The purpose of Phase I (Safety cushion time) was to define the safety measure for representing the conflict between the driver behavior and the pedestrian behavior: it means the level of the criticality of situations. The purpose of Phase II (Driver behavior analysis) was to quantify the risk value related to the driver behavior under the approaching scenario to blind areas, and Phase III (Cause-and-effect chain study) was to quantify the risk value related to the annotations through the statistical processing. Finally, the purpose of Phase IV (Machine learning) was to construct the prediction model with the machine learning techniques, which predicts the level of the criticality of situations under the approaching scenario to blind areas. The feature quantities for constructing the prediction model were based on the driver behavior analysis (Phase II) and the cause-and-effect chain study (Phase III), and the teacher data of machine learning was the safety measure defined in Phase I.

3 SAFETY CUSHION TIME

Safety measures have been used widely to predict the safety margin. Literature review on the safety measures has done by Y. Ni et al. [9]. These different conflict indicators [9, 5, 6, 2, 17] can be useful for representing different severity levels, and can be used depending on interaction pattern and the point of view of the analysis. This study introduces the *safety cushion time* SCT which shows time margin allowed for drivers to perform evasive actions to avoid a crash. When a pedestrian crosses the road from blind spot, the following condition must be satisfied at least to avoid a crash:

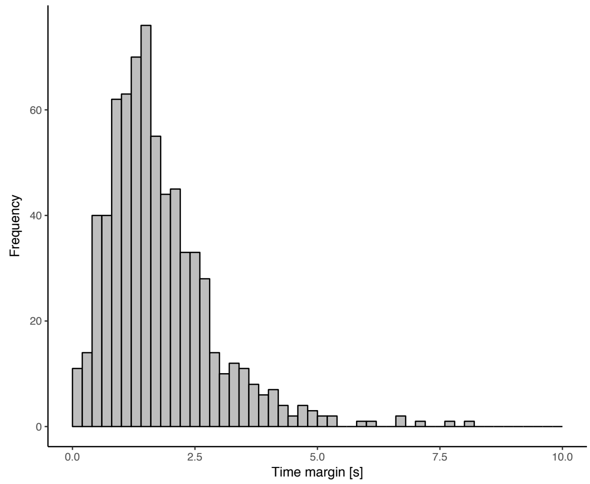

Figure 2: Frequency distribution of safety cushion time.

$$D_{car}(t^*) + D_{ped}(t^*) - \left((SCT + \tau) \cdot V_{car}(t^*) - \frac{V_{car}^2(t^*)}{2a_{max}} \right) = 0, \quad (1)$$

where D_{car} is the distance to the parked vehicle at time t^* when the pedestrian initiated the road crossing, as shown in Figure 1, D_{ped} is the distance between the pedestrian and the parked vehicle, and V_{car} is the vehicle speed. The assumed machine's reaction time τ (=0.25 seconds) means the required time from the initiation of brake action by the driver to the execution of braking by the vehicle, and a_{max} (= -6 m/s^2) is the assumed achievable maximum acceleration at the evasive action phase. Thus, the SCT, which shows time margin allowed for drivers, is expressed as the following equation:

$$SCT = \frac{\left\{ (D_{car}(t^*) + D_{ped}(t^*)) + \frac{V_{car}^2(t^*)}{2a_{max}} \right\}}{V_{car}(t^*)} - \tau. \quad (2)$$

As can be seen in $Eq.$ 2, the factors, that reduce the safety cushion time SCT, can be mainly distinguished into the followings:

- Factor related to the pedestrian behavior, which denotes the distance to the pedestrian ($D_{car}(t^*) + D_{ped}(t^*)$),
- Factor related to the driver behavior, which denotes the vehicle velocity ($V_{car}(t^*)$), and
- Factor related to the vehicle dynamics, which means limitation or constraint on the stopping distance to avoid a crash (τ, and $a_{max} = -\mu g$).

Thus, the safety cushion time SCT represents the result of conflict of these factors. In this study, the level of criticality was classified into three levels:

- *High level* is defined as the condition that SCT is less than 1 second,
- *Middle level* is defined as the condition that SCT is in the range of 1 second and 2 seconds,
- *Low level* is defined as the condition that SCT is more than 2 seconds.

The distributions of the SCT is shown in Figure 2. The mean values of the SCT was 1.8 seconds. The distributions of SCT appear as gamma or lognormal distribution, due to the driver behavior in the occurrence of the possible road surprise: (1) If there was enough time margin when the pedestrian initiated a road crossing, the driver would not immediately perform an evasive action; thus, the number of records of the road surprise

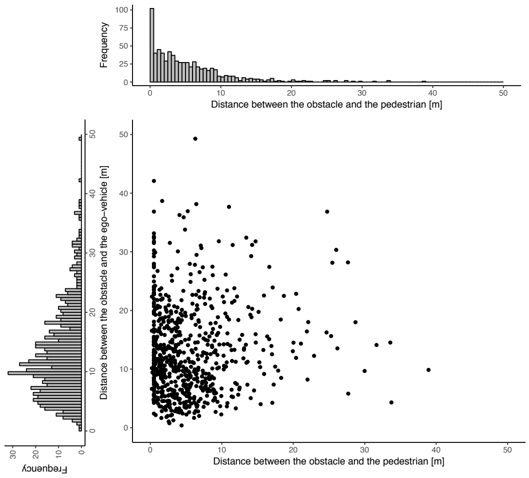

Figure 3: Relationship between $D_{ped}(t^*)$ and $D_{car}(t^*)$.

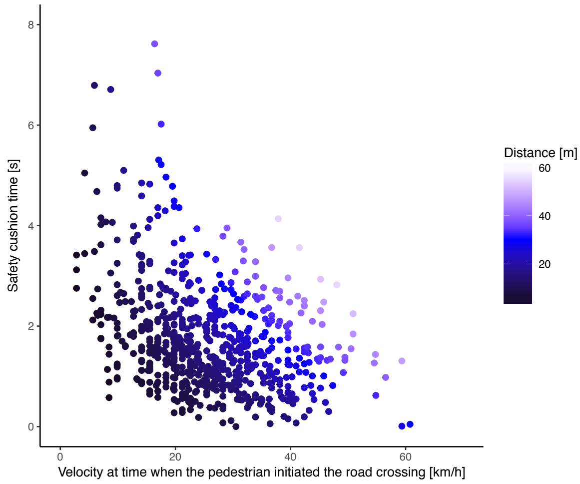

Figure 4: Relationship between SCT and $V_{car}(t^*)$.

decreases, as the time margin increases, (2) if the time margin was only a few seconds and the evasive action was required, the driver would immediately perform an evasive action by braking to avoid a crash, and (3) if the time margin can not be secured ($SCT \leq 0$) and the sufficient braking distance was unavailable, the driver would take a steering action to avoid crash; thus, the number of records of the road surprise decreases. Figure 3 shows the scatter plot and the frequency distributions of both $D_{car}(t^*)$ and $D_{ped}(t^*)$, which means factor related to the pedestrian behavior. Interestingly, the most frequent value of $D_{ped}(t^*)$ was in the range of 0 and 0.5 m. Figure 4 shows relationship between SCT, $V_{car}(t^*)$, and the distance (=$D_{car}(t^*) + D_{ped}(t^*)$). The conflict pattern between the factor related to the pedestrian behavior and the factor related to the driver behavior with respect to the safety cushion time can be seen in Figure 4. Figure 5 shows relationship between $V_{car}(t^*)$ and the distance (=$D_{car}(t^*) + D_{ped}(t^*)$). As the vehicle speed at time t^* when the pedestrian initiated the road crossing decreases, the remaining distance tends to be shorter. As can be seen in the color of scatter plot according to the incident level, it was clear that taxi drivers were required to lower speed in order to ensure the larger safety cushion time. Approximately 90% of the extracted 709 events occurred at speeds less than 40 km/h.

4 DRIVER BEHAVIOR ANALYSIS

This section describes the quantification of the risk value related to the driver behavior. The purpose of the driver behavior analysis is to identify context parameters, which lead drivers to increase the safety cushion, i.e., lowering the vehicle speed to gain additional braking distance in case an obstacle suddenly appears

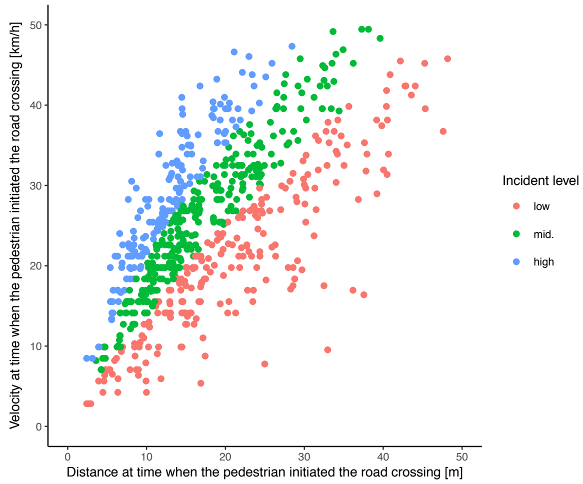

Figure 5: Relationship between $V_{car}(t^*)$ and $D_{car}(t^*) + D_{ped}(t^*)$.

from driver's blind areas. In general, the hazard-anticipatory driving, which interacts with an on-road hazard, requires a separated tasks of (a) spotting, (b) comprehending, (c) appraising and/or anticipating, and (d) responding. This paper assumes that the hazard anticipation process of expert drivers takes place in a long-term time span a couple of seconds before the time instant of the potential conflicts or crashes. This means that the different driver's execution of the long-term tasks navigation and guidance depending on the specific driving context properties (area of driving, potential traffic opponent, intersection type, and so on) -not the short-term vehicle stabilization and control- are focused. Thus, the analysis concentrates on the start of the recording (-10 s before the incident) until -4 s before the incident. The reactive behavior would be influenced by a decision-making at tactical level due to such as their caution and/or awareness of potential situations, the limitations of a driver's own abilities and sensation seeking: It is assumed that the speed profile of safe (careful) and unsafe (aggressive) drivers is an acceptable trade-off between driving comfort (i.e. desired vehicle velocity) and driving safety.

Not all recorded incidents include information regarding a meaningful adjustment of the safety cushion, i.e. context-sensitive vehicle navigation and guidance. A large number of incidents represent driving situations in which the taxi driver did not adjust the safety cushion to driving context properties. In this study, a parameter that describes the driver behavior regarding the driver's hazard anticipation of the incident in the time span of -10 s to -4 s was developed: Long-term Hazard Potential (LHP) can be defined as follows.

$$LHP = w_1 \cdot v_{max} + w_2 \cdot \tilde{v} + w_3 \cdot \dot{v}, \tag{3}$$

where, each parameter are defined in Table 1, and w_i is the weighting factor. High speeds generally lead to a high probability of critical situations, the LHP of drivers driving constantly at high speeds should be higher than the LHP of drivers that reach high speeds only for a short period of time, and deceleration before the incident correlates with a "good anticipation". In contrast, drivers that accelerate shortly before the incident are assumed to "not anticipate" possible road surprise.

The distribution of the LHP is shown in Figure 6, and the mean value of LHP was at 1.85. As mentioned in the section 3, one of the factor that reduce the safety cushion time SCT is the speed at time t^* when the pedestrian initiated the road crossing. The relationship between $V_{car}(t^*)$ and the weighted linear sum of each normalized parameter were found to have a strong correlation, as shown in Figure 7; the Pearson's correlation r was 0.81 (Table. 2). In particular, the acceleration or deceleration before the incident correlates with a "good anticipation" or "poor anticipation" of possible road surprise. Therefore, it is clear that the

Table 1: Parameters of the LHP related to the driver behavior

Parameter	Description
v_{max}	Maximum of velocity in interval $t \in$ [-10, -4] normalized to $v_{max} \in$ [0, 1]
$\tilde{v}$	Median of velocity in interval $t \in$ [-10, -4] normalized to $\tilde{v} \in$ [0, 1]
$\dot{v}$	Mean of acceleration in interval $t \in$ [-7, -4] normalized to $\dot{v} \in$ [0, 1]

Table 2: Evaluation of correlation coefficient

Parameters	r
LHP (w_1=1, w_2=1, and w_3=2) vs. $V_{car}(t^*)$	0.81
v_{max} in the interval $t \in$ [-10, -4] vs. $V_{car}(t^*)$	0.71
$\tilde{v}$ in the interval $t \in$ [-10, -4] vs. $V_{car}(t^*)$	0.63
$\dot{v}$ in the interval $t \in$ [-7, -4] vs. $V_{car}(t^*)$	0.25

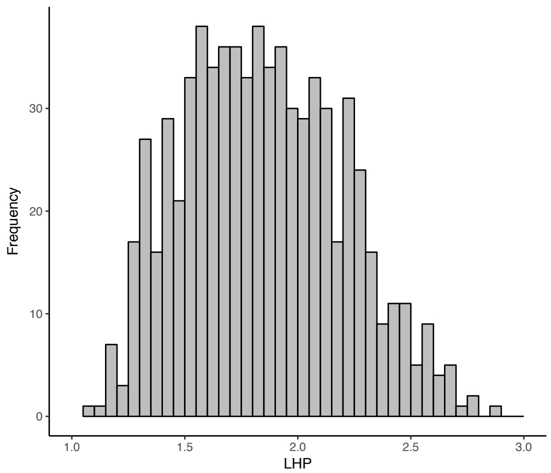

Figure 6: Distribution of the LHP. The weighting factors w_1 and w_2 were set at 1, and w_3 was set at 2.

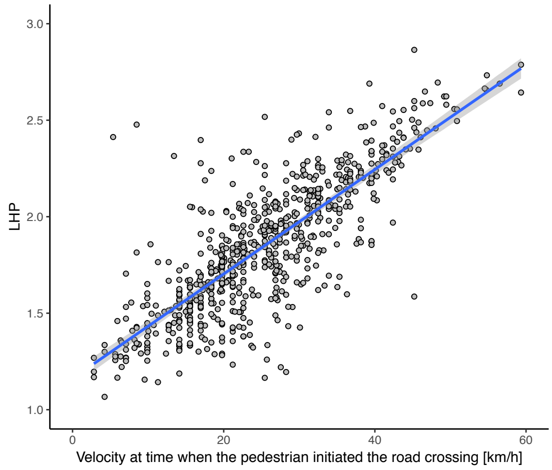

Figure 7: Relationship between the LHP and $V_{car}(t^*)$. The blue line is an ordinary least squares regression with a confidential interval. The Pearson's correlation r was 0.81.

vehicle speed $V_{car}(t^*)$ when the anticipated obstacle appears in front of the vehicle can be estimated by using the LHP indicator regarding the driver's hazard anticipation of the incident in the time span of -10 s to -4 s.

5 CAUSE-AND-EFFECT CHAIN STUDY

This section describes the quantification of the risk value related to the annotations added by the ratings expert. The qualitative context properties (e.g. intersection type: Y, T, and so on) must be transformed into quantitative parameters. Additionally, all influencing parameters should feature a comparable value range and the effects of the parameters should be determined independent of their frequency. The last requirement is particularly important in order to avoid that the prediction model for determining a context-sensitive safety cushion is biased by the frequency of occurrence of specific parameter values. For example, there are not many incidents that the pedestrian initiates a road-crossing on the road where road and sidewalks are not completely separated (Cond. 1), as shown in Figure 8, and many incidents involve the conditions of 3 and 4. However, we assume that incidents under the Cond. 1 would be lead to a relative high percentage of critical events with the high level, which was defined as that the safety cushion time SCT was less than 1 second.

For achieving above mentioned quantification, a total number of 13 quantified influencing parameters were evaluated regarding their effect on the incidents level. Table 3 displays the number of occurrences of near-miss event on each incident level (high, mid., and low), the percentage of each incident level between the individual qualitative properties (annotations), the normalized scale on the percentage between each incident level, and a risk value of the individual qualitative context properties. The percentage of each incident level was ordered according to its frequency (%) of occurrence for each incident level on a normalized scale $\in$ [1, 10], in order to ensure the comparability between different parameter values. In this paper, the risk values on the qualitative properties were calculated as the weighted linear sum for each normalized scale:

$$risk\ value = w_{high} \cdot f_{high} + w_{mid.} \cdot f_{mid.} + w_{low} \cdot f_{low}, \quad (4)$$

where, w_i is the weighting factor, and f_i is the normalized scale in the qualitative property (annotation). The weighting factor w_{high} was set at 10, $w_{mid.}$ was set at 3, and w_{low} was set at 1. As can be seen in Table 3, the quantitative values for all qualitative context properties were calculated.

6 PREDICTION MODEL

The purpose of machine learning phase was to construct the prediction model, which predicts the level of the criticality of situations under the approaching scenario to blind areas. Linear regression model was developed using Open-source R to find out the risk factor relative to the safety cushion time SCT and predict the level of the criticality of situations. The feature quantities for constructing the prediction model were based on the LHP index relative to the driver behavior and the quantified context parameters relative to the driving context (annotations), and the teacher data of machine learning was the SCT. This paper shows an example of applying a linear regression model as an initial study result. Among the near-miss event data of 709, event data of 600 were selected as training data in the process of regression analysis, event data of 109 were selected as test data.

Table 4 shows the used explanatory variable, estimation of the regression coefficients, standard error, t-value, and p-value. A stepwise search for performing variable selection, so that the AIC value is improved, was executed; the explanatory variable extracted in the stepwise search were LHP, Area type, Sidewalk type, Intersection type, Traffic, Leading vehicle, Weather, Time, and Age factors. It clearly shows that the LHP index relative to the driver behavior is a factor that most influence the vehicle-pedestrian near-miss incident. Figure 9 shows the comparison between predicted and measured SCT. As indicated in Table 4, there is a significant relationship between the independent variables and dependent variable with an R-square of 0.137; however, further studies will be required to improve prediction accuracy.

Table 3: Statics and risk value on qualitative context properties.

Property	Condition	N			Percentage			Normalized scale			Risk value
		High	Mid.	Low	High	Mid.	Low	High	Mid.	Low	
Area type	Residential area	16	14	10	40.0	35.0	25.0	9.7	1.0	4.3	104.5
	Business area	134	267	206	22.1	44.0	33.9	4.3	4.9	6.7	64.7
	Rural area	16	22	14	30.8	42.3	26.9	6.9	4.2	4.8	86.8
	Other area	1	5	3	11.1	55.6	33.3	1.0	10.0	6.6	46.6
Road type	Other	4	11	8	17.4	47.8	34.8	2.9	6.6	7.0	55.8
	One way	26	53	34	23.0	46.9	30.1	4.6	6.2	5.7	70.3
	Both way	137	244	191	23.9	42.7	33.4	4.9	4.4	6.6	68.4
Sidewalk type	Cond. 1	9	11	3	39.1	47.8	13.1	9.5	6.6	1.0	115.5
	Cond. 2	16	26	12	29.6	48.2	22.2	6.6	6.8	3.5	89.7
	Cond. 3	78	165	138	20.5	43.3	36.2	3.8	4.6	7.4	59.6
	Cond. 4	64	106	81	25.5	42.2	32.3	5.3	4.2	6.3	72.2
Intersection type	T or Y types	55	113	71	23.0	47.3	29.7	4.6	6.4	5.6	70.7
	4 or 5 types	66	117	114	22.2	39.4	38.4	4.4	2.9	8.0	60.3
	Straight	46	78	49	26.6	45.1	28.3	5.7	5.4	5.2	78.2
Road width	Other	3	9	5	17.7	52.9	29.4	3.0	8.9	5.5	61.8
	1 lane	43	89	47	24.0	49.7	26.3	4.9	7.4	4.6	76.0
	2 lanes	72	140	129	21.1	41.1	37.8	4.0	3.7	7.8	59.0
	3 lanes	10	21	19	20.0	42.0	38.0	3.7	4.1	7.9	56.9
	4 lanes over	33	35	24	35.9	38.0	26.1	8.5	2.3	4.6	96.4
Cross walk	Without	119	222	160	23.8	44.3	31.9	4.8	5.1	6.2	69.6
	With	48	86	74	23.1	41.3	35.6	4.6	3.8	7.2	64.7
Parked vehicle	0∼2 (Low density)	40	63	48	26.5	41.7	31.8	5.6	3.9	6.1	74.4
	3∼5 (Mid. density)	43	86	68	21.8	43.7	34.5	4.2	4.8	6.9	63.6
	More (High density)	84	159	118	23.3	44.0	32.7	4.7	5.0	6.4	68.0
Pedestrian	0∼2 (Low density)	76	122	80	27.3	43.9	28.8	5.9	4.9	5.3	79.0
	3∼9 (Mid. density)	66	139	101	21.6	45.4	33.0	4.2	5.6	6.5	64.8
	More (High density)	25	47	53	20.0	37.6	42.4	3.7	2.1	9.1	52.3
Traffic	0∼2 (Low density)	65	106	77	26.2	42.7	31.1	5.6	4.4	5.9	74.7
	3∼9 (Mid. density)	91	172	138	22.7	42.9	34.4	4.5	4.5	6.9	65.2
	More (High density)	11	30	19	18.3	50.0	31.7	3.2	7.6	6.1	60.6
Leading vehicle	Without	140	247	164	25.4	44.8	29.8	5.3	5.3	5.6	74.7
	With	27	61	70	17.1	38.6	44.3	2.8	2.6	9.6	45.4
Time	6:00∼10:00 (rush hour)	29	37	22	32.9	42.1	25.0	7.6	4.1	4.3	92.5
	10:00∼16:00	63	126	85	23.0	46.0	31.0	4.6	5.8	5.9	69.3
	16:00∼20:00 (rush hour)	43	80	45	25.6	47.6	26.8	5.4	6.5	4.8	78.1
	20:00∼6:00	32	65	82	17.9	36.3	45.8	3.0	1.6	10.0	45.2
Weather	Sunny or cloudy	158	290	212	24.0	43.9	32.1	4.9	4.9	6.2	69.7
	Rain or snow	9	18	22	18.4	36.7	44.9	3.2	1.8	9.7	46.9
Age of pedestrian	Unknown	5	13	13	16.2	41.9	41.9	2.5	4.0	8.9	46.2
	Elderly	21	25	22	30.9	36.8	32.3	7.0	1.8	6.3	81.3
	Mature	51	114	101	19.2	42.9	37.9	3.4	4.4	7.8	55.5
	Young	81	146	94	25.2	45.5	29.3	5.3	5.6	5.5	74.9
	Child	9	10	3	40.9	45.5	13.6	10.0	5.6	1.2	117.9

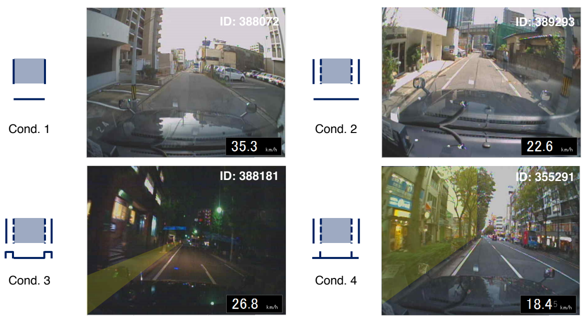

Figure 8: Definition of the sidewalk type. The condition can be distinguished according to the degree of a border between the car driving corridor and the footpath.

7 CONCLUSIONS

The paper introduced initial study results of a method for anticipating hazardous situations based on the current driving behavior as well as the driving context, and investigated the factors that influence the vehicle-pedestrian near-miss incident. Our study goal is to develop next generation ADAS to attain a hazard-anticipatory driving to lead an adequate safety cushion based on the prediction of the criticality of situations. The design philosophy is as follows: Using the generated prediction model, if an immediate adjustment of the LHP is required due to a very critical prediction of incident level, a speed profile that features deceleration should be chosen; In case the predicted incident level is not very critical it might be sufficient to determine a speed profile that prevents further acceleration. Future works include 1) to update the driver behavior model (LHP), 2) to update quantification method of risk index related to driving context (annotations), and 3) to improve prediction accuracy as well as exploring risk factors using various machine learning methods.

APPENDICES

This study has been conducted as a part of the research project “Autonomous Driving Intelligence System to Enhance Safe and Secured Traffic Society for Elderly Drivers” granted by Japan Science and Technology Agency. The authors would like to

Table 4: Model results: statistically significant variables in the linear regression model.
** Statically significant at 1 % level, * Statically significant at 5 % level, and · Statically significant at 10 % level.

	Variable	Coefficient β_i	Std. Error	t-value	p-value
	Intercept (β_0)	4.027	1.083	3.717	2.21e-4**
Driver behavior	LHP	-0.204	0.032	-6.241	8.26e-10**
Driving context	Area type	0.089	0.045	1.974	0.049*
	Road type	0.023	0.184	0.123	0.902
	Sidewalk type	-0.045	0.037	-1.213	0.225
	Intersection type	-0.081	0.058	-1.416	0.157
	Road width	-0.035	0.029	-1.227	0.220
	Cross walk	-0.004	0.181	-0.019	0.984
	Parked vehicle	-0.025	0.108	-0.237	0.813
	Pedestrian	-0.028	0.045	-0.617	0.537
	Traffic	0.141	0.085	1.657	0.098·
	Leading vehicle	-0.075	0.034	-2.196	0.028*
	Weather	-0.136	0.069	-1.973	0.049*
	Time	-0.069	0.026	-2.620	0.009**
	Age of pedestrian	-0.086	0.029	-2.934	0.003**
				R-square	0.137**
				N	600

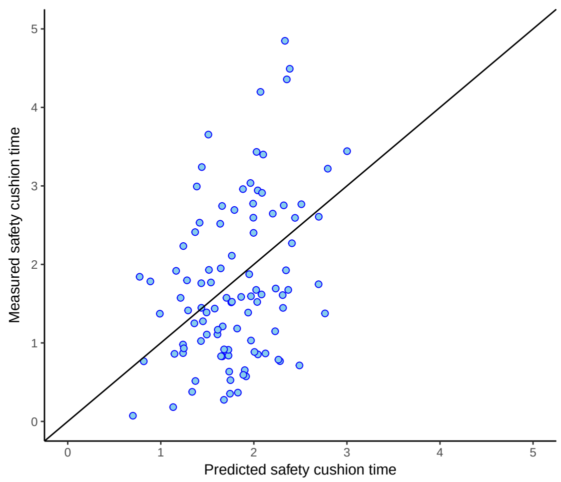

Figure 9: Comparison between predicted and measured safety cushion time.

thank the agency for providing financial support.

REFERENCES

[1] Mohamed Abdel-Aty et al. "Geographical unit based analysis in the context of transportation safety planning". In: *Transportation Research Part A: Policy and Practice* 49.Supplement C (2013), pp. 62–75.

[2] B.L. Allen, B.T. Shin, and P.J. Cooper. *Analysis of traffic conflicts and collisions*. Tech. rep. Report No. TRR 667. Transportation Research Board, Washington, D.C., 1978.

[3] Peng Chen and Jiangping Zhou. "Effects of the built environment on automobile-involved pedestrian crash frequency and risk". In: *Journal of Transport & Health* 3.4 (2016), pp. 448–456.

[4] DEKRA Automobil GmbH. *Strategies for preventing accidents on European roads*. Tech. rep. ROAD SAFETY REPORT 2015 A future based on experience, 2015.

[5] J.C Hayward. "Near Misses as a Measure of Safety at Urban Intersections". PhD thesis. Pennsylvania State University, 1971.

[6] C. Hupfer. "Deceleration to safety time (DST) -a useful figure to evaluate traffic safety". In: *1997 ICTCT Conference Proceedings of Seminar 3*. Department of Traffic Planning and Engineering, Lund University, Lund. 1997.

[7] Rose McDermott. "Decision Making Under Uncertainty". In: *Proceedings of a Workshop on Deterring Cyberattacks: Informing Strategies and Developing Options for U.S. Policy*. The National Academies Press. 2010.

[8] NHTSA. *National Motor Vehicle Crash Causation Survey: Report to Congress*. Tech. rep. National Highway Traffic Safety Administration Technical Report DOT HSHS, 2008.

[9] Ying Ni et al. "Evaluation of pedestrian safety at intersections: A theoretical framework based on pedestrian-vehicle interaction patterns". In: *Accident Analysis & Prevention* 96 (2016), pp. 118–129.

[10] NPA. *Traffic accidents situation in 2016*. Tech. rep. National Police Agency of JAPAN, 2017.

[11] Noelle C. Ortiz, Monika Ramnarayan, and Krista Mizenko. "Distraction and road user behavior: An observational pilot study across intersections in Washington, D.C." In: *Journal of Transport & Health* 7.Part A (2017), pp. 13–22.

[12] Ahmed Osama and Tarek Sayed. "Evaluating the impact of connectivity, continuity, and topography of sidewalk network on pedestrian safety". In: *Accident Analysis & Prevention* 107.Supplement C (2017), pp. 117–125.

[13] Shalini Rankavat and Geetam Tiwari. "Pedestrians perceptions for utilization of pedestrian facilities – Delhi, India". In: *Transportation Research Part F: Traffic Psychology and Behaviour* 42.Part 3 (2016), pp. 495–499.

[14] James Reason. *Human Error*. Cambridge University Press, 1990.

[15] Chowdhury Siddiqui, Mohamed Abdel-Aty, and Keechoo Choi. "Macroscopic spatial analysis of pedestrian and bicycle crashes". In: *Accident Analysis & Prevention* 45.Supplement C (2012), pp. 382–391.

[16] Salem Pedestrian Safety Study. *Exective Summary*. Tech. rep. DKS & Associations, 2017.

[17] Katja Vogel. "What characterizes a "free vehicle" in an urban area?" In: *Transportation Research Part F: Traffic Psychology and Behaviour* 5.1 (2002), pp. 15–29.

[18] Xuesong Wang et al. "Macro-level safety analysis of pedestrian crashes in Shanghai, China". In: *Accident Analysis & Prevention* 96.Supplement C (2016), pp. 12–21.