IEEE Open Journal of
Intelligent Transportation Systems

Received 7 December 2021; revised 22 February 2022; accepted 3 April 2022. Date of publication 8 April 2022; date of current version 20 April 2022.

Digital Object Identifier 10.1109/OJITS.2022.3165769

A Nationwide Impact Assessment of Automated Driving Systems on Traffic Safety Using Multiagent Traffic Simulations

SOU KITAJIMA[1], HANNA CHOUCHANE[1], JACOBO ANTONA-MAKOSHI[1], NOBUYUKI UCHIDA[1], AND JUN TAJIMA[2]

[1]Autonomous Driving Research Division, Japan Automobile Research Institute, Tsukuba 305-0822, Japan

[2]R&D Department, Misaki Design, Tokyo 103-0025, Japan

CORRESPONDING AUTHOR: H. CHOUCHANE (e-mail: channa@jari.or.jp)

ABSTRACT The objective of this paper is to propose a methodology to estimate nationwide traffic safety impacts of automated vehicle technologies using multi-agent traffic simulations. The influence of three levels of driver trust in the automation system (appropriate, over trust, distrust) is considered in the simulation and takes different transition modes of control between the driver and the system into account. The nationwide estimation of crashes is obtained by projecting results of the simulations using traffic data for three different and representative municipalities. Results indicated that Automated Driving Systems and Advanced Driver Assistance Systems significantly reduced the number of casualties and fatalities compared to manual driving. Simulation results in consideration of the influence of driver trust also found that this reduction may be negatively affected by over- and under-trust parameters. However, even with the introduction of these parameters, the reduction rate was still significant compared to manual driving. The proposed methodology using multi-agent traffic simulations may thus address concerns surrounding the deployment of automated driving systems which is a feature not found in conventional simulations, provide useful insight for interested parties to develop research and policy making strategies that accelerate traffic safety improvements, and to support social acceptance efforts.

INDEX TERMS Simulation, autonomous driving system, driver model, multi-agent simulation, impact assessments.

I. INTRODUCTION

HUMAN failures (i.e., human error and violations) are a main trigger in the sequence of events that result in a collision. According to [1] and [2], the percentage of traffic crashes that involve some form of human failure as the last event in the causal chain leading to light vehicle crashes is as high as 94 [%] in the U.S. In Japan, this percentage is even higher, at 97% of traffic accidents [3]. This has driven the development of key driving assistance technologies (e.g., Automated Emergency Braking (AEB) and Lane Departure Warning (LDW) systems) which have contributed to lower crash occurrences [4]–[7], thus creating opportunities for increased traffic safety.

In spite of automated vehicles' (AVs) potential to mitigate one of the biggest public health burden [8], efforts to advance these technologies face concerns surrounding their safety, debilitating their introduction into society. As such, while it is important to further raise the potential of automation, it is also important to develop innovative methods that are capable of providing a realistic projection of their expected impacts on safety.

Multi-agent traffic simulation-based estimations are an effective way of determining a priori-forecasts of automated vehicle safety impacts. If we consider that a comparison between the overall human performance (manual driving)

The review of this article was arranged by Associate Editor J. Ma.

and automated vehicle performance is needed to estimate the potential safety benefits of AD systems, simulation methodologies capable of modeling human error [9] within their analyses are invaluable to ensuring the reliability of results. As AVs are expected to not cause dangerous situations, these should also include errors that could arise as a result of the introduction of automation itself (until the driver is removed entirely from the driving task). As such, in addition to sensor configuration, detection ranges, and operating characteristics for automated driving, it is necessary to consider the delegation of authority between the system and driver as shown by SAE J3016 [10]. To this end, this paper builds on a multi-agent traffic simulation methodology developed by [9] to estimate nationwide safety impacts of Automated Driving Systems (ADS) and Advanced Driver Assistance Systems (ADAS) while accounting for human error. This study aims to overcome limitations in [9] by enhancing the methodology's capabilities to account for different levels of driver trust in the system. Due to limits in the area for which detailed road networks, signal control information, traffic volume, and other data can be reproduced (all required for simulation execution), an estimation process for expanding the developed simulation results to the nationwide scale was also devised in this paper.

The aim of this research is to estimate nationwide traffic safety impacts of automated vehicle technologies using a multi-agent traffic simulation methodology that accounts for the influence of three levels of driver trust in the automation system (appropriate, over trust, distrust).

II. METHODOLOGY

The task of the safety impact assessment is to evaluate the probability P(A) such that P(A) = E[A/N], where A is number of accidents, N is the total amount of the traffic, and E[A/N] denotes Expectation of the ratio of A over N. It is important to explain the process and show the rationale behind the calculation of the probability to make the calculation results comprehensible.

Placing the emphasis on the interaction among the driver, vehicle and environment, the following accident model is assumed in this paper,

$$\mathrm{P(A) = P(f|S)P(S)} \tag{1}$$

where S expresses the hazardous situation. An accident would occur in the situation where a driver performs an unsafe driving act(driver failure) denoted as 'f' in the equation. For example, a single vehicle accident such as lane departure can be happen anytime and anywhere, so that $\mathrm{P(S_{LD})} = 1$ and probability of the accident $\mathrm{P(A_{LD})}$ coincident with the driver error probability $\mathrm{P(f_{LD}|S_{LD})}$. For rear-end collisions, the situation $\mathrm{S_{REC}}$ is interpreted such that the preceding vehicle exists and the headway distance becomes shorter. The accident will occur if the driver does not recognize the preceding vehicle and/or do not respond correctly.

The concept of hazardous situations and driver error should be given concrete shape to evaluate the accident probability. For driver errors, we should specify where and how frequently they happen, their duration, and how they affect the drivers in the dynamic process of driving. Concerning the hazardous situation, it is unfortunately hard to clearly define all situations in general traffic due to a large variation in road shape, other road users involved and their states. It is worth noting that for the assessment of ADAS, which is mainly aimed at crash reduction, it is sufficient to evaluate the change of P(f) by ADAS since ADAS would be considered not to affect the occurrence of the hazardous situation P(S). Meanwhile, normal operation of ADS will strongly affect the emergence of traffic situations, thus for the safety assessment of ADS, it is necessary to take into account the evaluation of the changes in the probability P(S) by ADS.

The multi-agent traffic simulation (hereinafter referred to as the simulation) provides a straightforward solution to these difficulties. Namely, the simulation enables us to reproduce the various hazardous situations that occur in real traffic, without explicitly defining them, but by generating traffic flow resulting from the movement of each vehicle controlled by the driver-agent model (which mimics realistic driver behavior). The occurrence probabilities of hazardous situations P(S) depends on the input to the simulation, that is, road shape, measurable traffic volume and verifiable driver behavior. In other words, P(S) is implicitly considered in the simulation. In addition, a traffic accident is observed as a dynamic process in the simulation, caused by implemented the driver-agent's unsafe behavior model, and initiated with a probability associated to it.

From the discussion above, the important aspect of this simulation is how well the characteristics of real traffic flow is reflected in the simulated traffic flow, which accounts for P(S) in Eq.(1). The essential part of the simulation for this is the driver-agent model, which determines the position, orientation and velocity of the vehicles in the traffic flow. Aside from this, the model allows the driver-agent to act the same as a human driver in the simulation. It is a difficult software development problem to implement the driver-agent to act the same as a human driver in the simulation. Hence, the level of detail exhibited by the driver-agent model should be selected according to the purpose of the simulation, e.g., first-order analysis of effect of introduction of ADS into society, investigation of the driver attribute or characteristics on traffic accident occurrence, evaluation of Positive Risk Balance for ADS development and social acceptability discussion. For our purpose, as we recognize that the simulation numerically evaluates the probability given by Eq. (1), and thus a driver-agent model capable of simulating real traffic volume and high accident locations is required as the baseline. It also implies that vehicle behavior in the simulation would correspond well to real vehicle behavior, since these macroscopic statistics are obtained through a bottom-up approach by the microscopic simulation.

It should be pointed out that the driver error probability is treated as a parameter of the simulation in the following sense. Suppose that the simulated traffic flow is found to closely resemble real traffic and given P(A) of the real traffic, it is achieved to obtain same level of accident rate in the simulation by adjusting value of driver error probability. The ideal way of providing the value of the driver error probability is to estimate it from available official data. However, it would be difficult to obtain the same accident rate in spite of such effort because the driver-agent model is just a rough approximation of a complex and flexible human driver.

Interestingly, an acceleration of the calculation is possible by introducing the factor α which is multiplied by the driver error probability [21]. Traffic accidents in the real traffic are considered to be statistically independent, which is also true in the simulation. Therefore the frequency of appearance of hazardous situations would not be affected by the value of the driver error probability. With this assumption, the expected interval of traffic accidents would be shortened by setting a larger value of driver error probability, and the following relation holds:

$$\alpha\ \mathrm{P(f|S)P(S)} = \alpha\ \mathrm{P(A)} \tag{2}$$

This is quite useful for obtaining safety impact assessment results in practical calculation time.

Based on the concept described above, we have developed the simulation to estimate the impact of ADS and ADAS on traffic safety [9]. The simulation is further enhanced by including the driver characteristic of trust in the system and by introducing transitions of control between the system and the driver in the simulation. This paper also proposes a method to project the results of the simulations using traffic data for three different and representative municipalities to those for the nationwide level.

This section will be split into two main sub-sections. The first will briefly describe the baseline simulation (necessary to understand the current study) (A) developed in [9], and the second will elaborate on the enhancements of the simulation methodology (B).

A. BASELINE SIMULATION

Target accident type selection from real world traffic accidents: In the development of the simulation, the selection of crash patterns was based on the number of fatal crashes, crash type, and fatality rates. Five types of crashes were selected from the accident statistics in 2013: vehicle-to-vehicle (rear-end collision, crossing, head-on collision), human-to-vehicle (crossing pedestrian), and single vehicle (lane departure). By developing a software that can reproduce these crashes, we provided a potential coverage of 64% of fatal crashes and 66% of injurious crashes.

Realistic traffic environment: framework to reproduce traffic accidents: An important feature of this simulation is that each traffic participant (driver, pedestrian, etc.) can autonomously reproduce individual behavior within flowing traffic. Traffic participants are capable of not only acting independently by recognizing the surrounding environment, but can also adopt crash inducing/dangerous behaviors. In

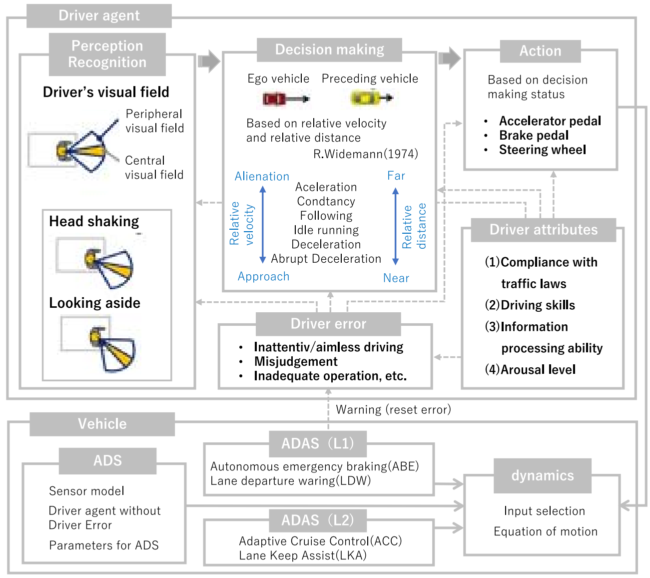

FIGURE 1. Outline of driver agent and ADAS/ADS models and their interactions.

addition, evaluation indices, such as the number of crashes and the number of casualties, can be calculated after the execution of a simulation.

Driver behavior model: Figure 1 shows an outline of the driver behavior model. Modeling was performed in consideration of the driver's basic behavioral processes of perception, recognition, judgment, and operation. The driver agent perceives an object such as a vehicle that exists in the line-of-sight and field-of-view range. The agent then calculates the relative states (distance and speed) and size of the objects, and adds recognition labels to them, such as preceding, oncoming, crossing, and so fourth. Among the recognized objects, the hazardous objects are identified in the current traffic situation, and the risk of collision with those are evaluated based on expected time to collision using the relative distance and relative speed of the objects. For example, as shown in Fig. 1, reaction to the preceding vehicle is determined based on the Weidemann following model. Another example, not shown in Fig. 1, is the evaluation of the gap time between oncoming vehicle to make turn at intersection. Depending on such judgment results, the agent decides on operations, content amounts, and actions (accelerator, brake, steering).

One of the authors developed an open-source multi-agent traffic simulation software, named Re:sim which is a limited edition of our simulation system. The source code of Re:sim is provided in GitHub [25]. Interested readers may refer to it for further information on the implementation of driver agent model.

Implementation of driver failures that cause crashes: Driver errors and violations should be related to information processing inside the driver agent. For instance, inattentive or distracted driving involves the acquisition of information from the surrounding environment, and are hence treated the same in the simulation and implemented as skipping the perception function of the agent with an associated driver error probability. In summary, driver errors and violations would be implemented in such a way that:

- necessary function call/processing is skipped
- flag variables in the logic are altered
- offset values are added to variables, e.g., position and/or speed of other road users, control input to the vehicle

With this scheme of error implementation, the rear-end collision, for example, will occur due to inattentive/aimless driving, which means that the driver-agent skips the perception process, leading to inappropriate information being passed to the Wiedemann following model. Hence, no braking action would be taken during the driver error. If the driver agent recovers from the error before it crashes, correct information on preceding vehicle would be passed to the Wiedemann following model, thus initiating braking if necessary. However, whether the vehicle is able to avoid collision or not depends on the timing of recovery. In this sense, the process can be considered a probabilistic evaluation of occurrence of accidents rather than detailed physical simulation of vehicle behavior.

As mentioned above, it is assumed that driver errors are a stochastic process where parameters affect the probability of occurrence, distributions of the interval of error occurrence, time duration and strength of the error effect. These parameters can reflect driver diversity characteristics. In this study, the following four characteristics were chosen based on the results of two previous studies [11], [12]: information processing ability, driving skill, arousal level, and compliance with traffic law. Information processing ability was determined based on a survey that measured the information processing ability of 64 participants using a standardized Trail Making Test (TMT). The result linked reaction times, visual acuity, and effective visual field to the simulation by assigning different parameter values (e.g., view angles and distance) to three age-groups (young 20-44yo, middle-age 45-64yo, elderly 65yo+). Driving skill was determined based on pedal activation time, degree of acceleration/deceleration, and surrounding traffic participants behavior prediction to avoid a hazard [13]. Arousal level was incorporated as drowsiness and excitement parameters. Finally, compliance with traffic law was determined based on differences in the sex-dependent tendencies to drive over the speed limit and violate traffic signs and lights [12].

Based on these driver diversity characteristics, inattention, aimless driving, and insufficient safety confirmation were then implemented to represent driver errors. Inattention was modeled as a function of the aversion of a driver's gaze away from an object of interest, as well as the duration of the gaze aversion. *Aimless driving* and *insufficient safety confirmation* were modeled by removing safety gaze confirmation upon entering an intersection from a non-priority lane.

Errors modeled in the simulation were prioritized based on real crash data by setting occurrence probabilities of driver errors as described above. The percentage of fatal crashes by crash type and the respective human factors that cause them are as follows: Aimless driving (leading to 49%) of rear-end crashes, 34% of head-on crashes, and 28% of pedestrian crossing collisions), inattentive driving (leading to 35% of rear-end collisions 33% of pedestrian crossing crashes), insufficient confirmation (leading to 54% of crossing collisions and 29% of pedestrian crossings crashes), and inadequate operation (leading to 52% of lane departures and 19% of head-on collisions). For a more detailed account of the driver error implementation method, please refer to [14].

Pedestrian behavior model: The basic framework of the pedestrian behavior model is similar to that of the driver model. It reflects differences in behavioral characteristics (walking speed, crossing angle, etc.) according to age and gender obtained by fixed point observation and walking experiments [14]. In addition, dangerous crossings were simulated by omitting safety checks for crossing roads (as was in the driver model).

Modeling driver assistance systems (level 1): In this paper, we refer to SAE's classification [10] of driving automation when predicting the effect of driver assistance and automated driving systems shown in the following four sections.

As shown in Fig. 1, the AEB and LDW systems are implemented in the vehicle object, which is independent from the driver agent. If a warning is issued from the systems, the error states of driver agent are reset after the elapse of driver response time. The distribution of driver response time to the AEB warning were set by referring to the reaction time distribution (average 0.9 [s] $\pm$ 0.4 [s]). These were obtained under conditions with low risk expectations from driver volunteer experiments and using a real vehicle equipped with augmented reality instrumentation [13]. The LDW judges the distance between the ego vehicle and the center of the lane, activating a warning when a deviation of more than 1 [m] occurs. At this point, the driver takes over control to return to the original lane. The driver reaction time distribution was assumed to be equal to that of the AEB. For a schematic of AEB and LDW features incorporated in the current simulation work, please refer to the Appendix (Figure A1).

Modeling partial automation (level 2): In partial driving automation, Adaptive Cruise Control (ACC) and lane keeping assistance (LKA) are modeled in addition to level 1 functions. The ACC controls the speed so that the Time-Head Way (= Relative Position [m] / Ego-vehicle Velocity [m / s]) with the preceding vehicle is 1.8 [s]. The LKA detects the driving lane and road curvature. Lateral positions are controlled so that the vehicle drives near the center of the lane [16]. For a schematic of ACC and LKA, please refer to the Appendix (figure A2).

Modeling Automated Driving System (level 4): Sensor configuration for automated driving consists of sensors for the front (long distance (a) / periphery (b)), rear (c1), rear side (c2). For a schematic of the sensor arrangements please refer to figure A3 in the Appendix. Specific values, such as angle and distance, were set with reference to [17]. Judgement and

TABLE 1. Definition of function and operational design domain.

System	Function					ODD		
	AEB LDW	ACC LKA	Lane change	Right/left turn	Request to Intervene	Main road		Municipal road
						National road	Prefectural road	
ADAS (SAE Lv.1)	✓	–	–	–	–	–	–	–
ADAS (SAE Lv.2)	✓	✓	–	–	–	✓	✓	–
ADS (SAE Lv.3)	✓	✓	✓	✓	✓	✓	✓	–
ADS (SAE Lv.4)	✓	✓	✓	✓	–	✓	✓	✓

action were implemented in this paper based on that of an exemplary driver who does not cause errors and operates without reaction delay. However, when it is difficult to continue system operation, the system itself achieves a minimum risk state without generating a Request To Intervene (RTI). It should be noted that, as shown in Fig. 1, the vehicle object has the flag variable for input selection and function implementation. The take over behavior of driver agent can thus be realized by switching this flag variable in the simulation.

Parameters that express the personal characteristics of the driver: In order to express various driver behaviors, (a) legal compliance tendency, (b) information processing ability, (c) driving skill, and (d) arousal level were included as parameters in the simulation based on survey data verified with driving simulators [14].

B. MULTI-AGENT SIMULATION ENHANCEMENTS

In [9], level 3 automation was not modeled, nor were projected safety estimations of ADAS and ADS expanded to the nationwide level. This section details how both are incorporated as enhancements to the simulation in this study.

Modeling driver trust in the system (for conditional automation-level 3): When considering SAE level 3 systems, it is necessary to examine the transfer of control between the driver and the system. Lubbe and Kiuchi [18] emphasizes the importance of two forms of trust in the relationship between highly automated systems and humans; over-trust (a false subjective judgment that the system can be trusted in situations where it should not be) and distrust (a false subjective judgment that the system cannot be trusted in situations where it can be). Based on these definitions, the authors introduce a new parameter (e) "trust in the system" into the simulation. This parameter expresses three states (appropriate, distrust, and over trust) to simulate - at the time of delegation of control in a level 3 system- when take over by the driver can be executed correctly, and when it cannot.

Control delegation between the driver and the system: Sensor configuration, specification and judgment, and the operation model are the same as in the level 4 ADS model of control delegation between the driver and the system

TABLE 2. Technology penetration scenarios.

Scenario	0	1	2	3	4	5
Penetration ratio	*Base*	25%	50%	75%	100%	Upper bound
Manual driving (MD)	100%	75%	50%	25%	-	-
ADAS (SAE Lv. 1)	-	20%	20%	15%	10%	-
ADAS (SAE Lv. 2)	-	5%	20%	25%	15%	-
ADS (SAE Lv. 3)	-	-	10%	25%	50%	-
ADS (SAE Lv. 4)	-	-	-	10%	25%	100%

In conditional automation, if continued operation proves difficult due to a departure from the Operational Design Domain (ODD) or due to system failure, the system will communicate a RTI to the driver who will then be required to resume control within a set time frame. According to [13], for an RTI response time of 10 [s], the average response time of a driver in an appropriate state was 2 [s] (± 1 [s]), while the average response time of a driver in a state of over trust was 5 [s] (± 4 [s]). For states of over trust, manipulating this delay within the simulation allows for the introduction of situations in which neither the driver nor the system is in control of the vehicle. In the case of distrust on the other hand, driver behavior is modeled to continue driving manually even when operating within the ODD range of the system.

Simulation settings: System-specific functions and ODD specifications: Table 1 shows a list of four types of system-specific functions and ODD specifications that are the focus of the safety impact estimations. Driver assistance systems are equipped with AEB and LDW functions and only operate when the ODD conditions are met. ACC and LKA features are added to partial automation systems but their ODD is limited to national and prefectural roads. Conditional automation systems include lane change, right/left turn functions at intersections and RTI from the system, and their ODD is limited to national and prefectural roads. Automated Driving Systems have the same conditions and functions, but their ODD is expanded to national, prefectural and municipal roads, and RTI from the system does not occur.

Penetration scenarios for ADAS and ADS: In this paper, we set up manual driving (MD) and five types of technology penetration scenarios in which four system features coexist (Table 2).

While the proportions of market penetration rates for automated driving systems cannot be reliably predicted, in this study scenarios are artificially generated to test accident reduction rates associated with increasing penetration levels of ADAS and ADS. These scenarios are not expected to become a reality in the forecastable years, but are tested to demonstrate the potential effects of a fully automated future.

Evaluation index for quantifying crash reduction effects: The following metrics were used to estimate the accident reduction effect of ADS and ADAS:

(1) *Number of crashes (case):* A case in which the relative distance between two or more traffic participants is zero is defined as a crash, and aggregated.

(2) *Crash rate (cases / km):* The number of crashes per kilometre is calculated by dividing the number of accidents by the total distance. The relative crash rates are then compared to manual driving conditions.

(3) *Fatal injury probability (%):* Fatal injury probability can be calculated based on an algorithm of Advanced Automatic Collision Notification. This algorithm uses logistic regression of large accident data, such as collision velocity and age of passenger. The probability of fatal injury [19] is calculated based on collision type, collision speed, occupant age, etc., to determine the degree of injury at the time of the crash [20].

(4) *Number of casualties (people):* The probability of death or serious injury is defined as less than 1% as uninjured, 1-5% as minor injury, 5-30% as severe injury, and 30% or more as death.

Method of estimating crash reduction effects on a nationwide scale: In order to expand the crash reduction effects of ADS and ADS for a single city to the whole country, three main steps are undertaken: (i) calculation of accident reduction ratio per representative city and for each accident type, (ii) projection of that accident reduction ratio to other municipalities and the accumulation of the reduction effect, (iii) integration of three reduction effects for nationwide estimation. Figure 2 shows this estimation process.

First, the maps of three cities in Japan were selected to be representative municipalities based on the characteristics of population and population density data from the 2015 census (i).

Second, the road network of each model city was replicated, and realistic traffic volume and traffic flow were reproduced for each by combining traffic census data and field surveys. The occurrence of crashes following major driver errors were also reproduced as a baseline. In a next step, the simulation of the six technology penetration scenarios (Table 2) was executed to calculate the accident reduction rate (difference in the number of accidents per kilometre between two specific scenarios) for each model city (ii).

Finally, based on the assumption that the accident reduction rate of each model municipality can be extended to other cities with similar population and population densities, the crash reduction estimations were predicted for the entire area using the previously obtained accident reduction rate. This

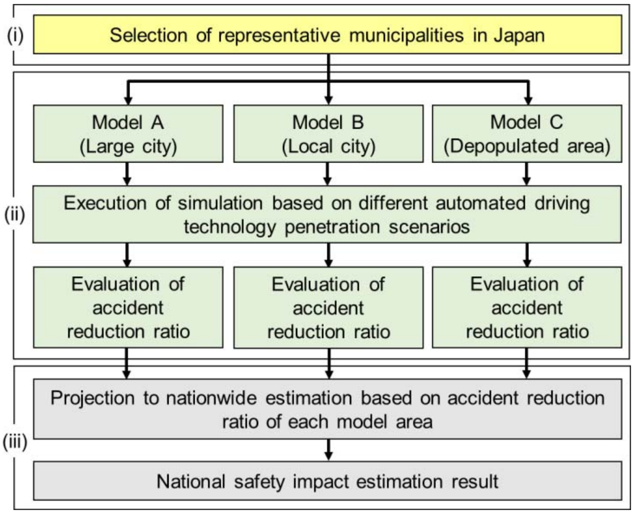

FIGURE 2. Estimation processes for nationwide safety impact assessment.

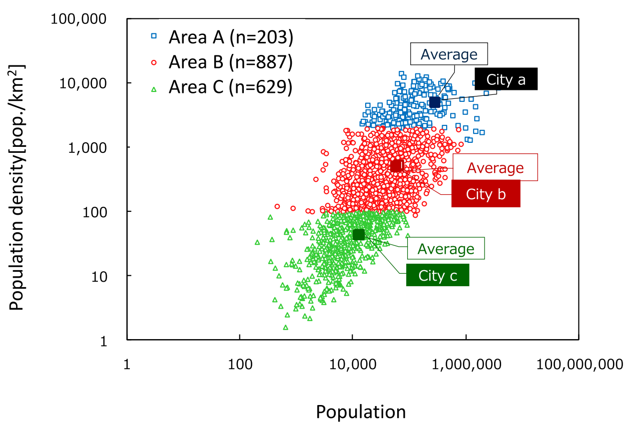

FIGURE 3. Relation between population and population density (n=1,719).

rate was then converted to the number of casualties and the number of deaths according to the probability of fatal injury for each party. In this way, a nationwide reduction effect was estimated for each penetration scenario (iii).

One simulation for each penetration scenario was run per model city to estimate the effectiveness of each scenario based on the accumulated travel distance of all driver agents (bringing the total number of simulations run to 15). When the accumulation of the total travel distance per simulation amounted to 500,000 [km], the execution of each simulation was terminated.

III. RESULTS & DISCUSSION

A. CONSTRUCTION OF THE SIMULATION EXECUTION ENVIRONMENT FOR EFFECT PREDICTION

Representative cities in Japan were selected to estimate nationwide traffic safety benefits of ADAS and ADS. Figure 3 shows the relationship between the population and population density of 1,719 municipalities in Japan (2015). In this paper, referring to the definition of [22], a population density of 3,000 [persons / km2] or more is

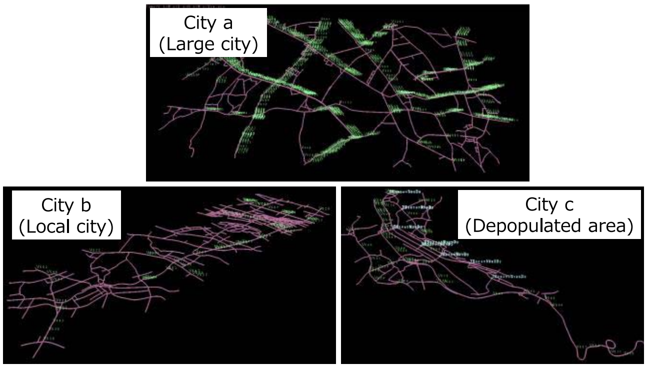

FIGURE 4. Road networks of three representative municipalities.

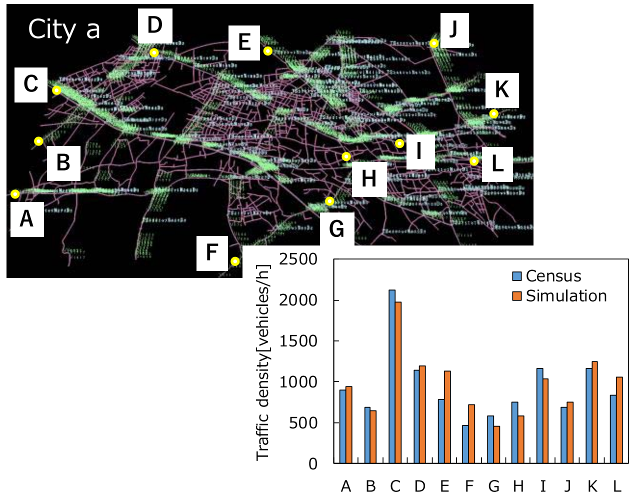

FIGURE 5. Comparison between road traffic census and simulation results.

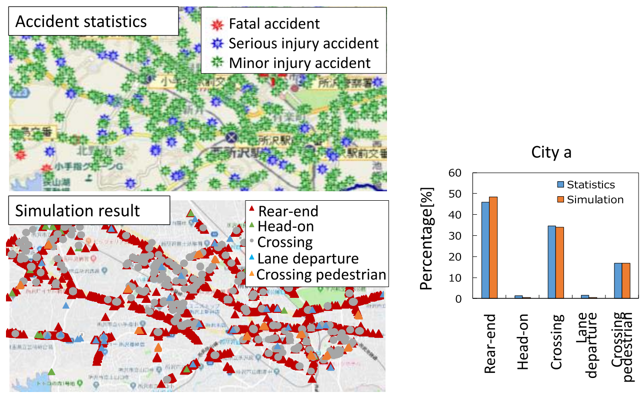

FIGURE 6. Comparison between locations of real-world crashes and locations of crashes occurring in the simulations.

defined as a "large city (area A)", 100 to 3,000 [persons / km2] as a "local city (area B)", and 100 [persons / km2] or as a "depopulated area (area C)".

The municipalities that represent each area are selected based on the following criteria: population, population density, number of casualties / deaths per 100,000 people, and the availability of accident location information. As a result, the following cities were selected as model municipalities:

- *Model city in Area A (large city):* Tokorozawa City, Saitama Prefecture (city a) with a population of 34.2 [10,000] and a population density of 4,750 [person/km2].
- *Model city in Area B (local city):* Joso City, Ibaraki Prefecture (city b) with a population of 6.5 [10,000] and a population density of 529 [persons/km2].
- *Model city in Area C (depopulated area):* Yamanouchi Town, Nagano Prefecture (city c) with a population of 1.4 [10,000] and a population density of 51 [person/km2].

Construction of the simulation execution environment for model municipalities: Figure 4 shows the road network of the three model cities (a, b, c) constructed for the simulation. The road network is formed of national roads, prefectural roads, municipal roads, and of non-arterial municipal roads. The road network coverage constructed in this paper ranges from 24 to 28 [km2].

In order to reproduce realistic traffic flow in the simulation, the traffic volume was set based on road traffic census data for arterial roads and on traffic survey results for major non-arterial roads. Figure 5 shows a comparison between traffic census data and simulation results for the traffic volume at different points in the road network of city a. This comparison showed that realistic traffic flow could be reproduced at point C, with a traffic volume of 2,000 [veh / h] or more, at points A, D, I, K, L with a traffic volume of approximately 1,000 [veh / h], and at points B, E, F, G, H, J with a traffic volume of approximately 500 [veh / h]. Similar reproducibility of traffic density was achieved for cities b and c using the same procedure.

Reproduction of crash occurrence for manual driving scenario: Driver agent behavior critical to crash occurrence was introduced by modeling inattention, aimless driving, insufficient safety confirmation, misjudgment, and inadequate operation, so that such errors appear stochastically in the simulation. In order to obtain the baseline for impact prediction for each model city, reproducibility of real traffic was assessed by comparing crash occurrence and crash statistics with scenario 0 (100% manual driving).

Figure 6 illustrates the results of a comparison between crash statistics and simulation results for crash location and crash type of "city a". Comparing the crash occurrence points showed the reproducibility of crash concentration along the main road and near intersections. In addition, comparing the composition rates by accident type showed that the major accident types (rear impact, encounter, pedestrian) were reproducible at a level close to the actual composition rate. The same procedure was used to confirm the reproducibility of crash occurrence for cities b and c.

As described in the previous section, this simulation is required to reproduce the real encounter frequency of hazardous vehicles and other traffic participants from the view point of probability evaluation. The traffic flow volume and the crash occurrence points are the most basic measures for

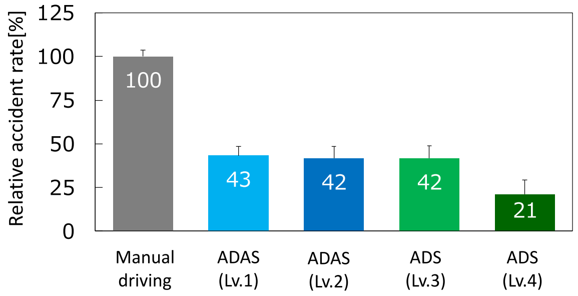

FIGURE 7. Relative crash rates of each system (Manual Driving: 100).

confirmation of this requirement, and these results indicate that the simulation is competent to its purpose.

It is worth noting that the calculation time of this simulation is practical owing to the acceleration technique mentioned above. For instance, using a AMD Ryzen 9 3900X 12-Core (24 threads) processor, with a 3.79GHz CPU, and simulation's calculation (integral) time step of 0.1[s], it took approximately 5∼6 hours to obtain a steady value of accident probabilities for "city a", where almost 2,000 vehicles appear simultaneously.

B. EVALUATION OF DRIVER ASSISTANCE/ AUTOMATED DRIVING SYSTEM CRASH REDUCTION IMPACTS

In estimating nationwide traffic safety benefits of automated vehicle technologies, an evaluation of ADS and ADAS safety impacts compared to manual driving was conducted.

Figure 7 shows a comparison between the relative crash rate of manual driving and each system, calculated from the simulation results (scenarios 0 to 5). For a crash rate of 100 for manual driving, the relative crash rate for driver assistance systems was 43, 42 for partial driving automation, 42 for conditional driving, and 21 for advanced driving automation. The low crash rate for advanced driving automation is due to the assumption used in this simulation that level 4 has no failures or performance limitations inside its ODD. Because this is not yet achieved in the real world, the level 4 crash reduction results are considered 'ideal' or the 'expectation' of ADS. For level 2 and level 1 ADAS, while the former differs from the latter in that it has the additional function of Assisted Cruise Control (ACC) and Lane Keep Assistance (LKA), these do not directly affect collision avoidance and thus do not result in a significant difference in their respective accident reduction rates. For the marginal difference between ADAS levels 1 and 2, and ADS level 3 the effectiveness of ADS level 3's collision avoidance when turning left/right only becomes apparent on municipal roads. Therefore, our simulation can flexibly estimate the effectiveness of the assumed system from the perspective of expansion of both functionality and operational design domain.

Considering the relative crash rates of each system, ADS and ADAS can be expected to greatly reduce the accident rate of manual driving, with the spread of these systems and their ODDs bringing about further crash reduction effects.

TABLE 3. Results of crash reduction rates of ADAS.

	Simulation result	Ex-post evaluation result		
		Ref. 1[21]	Ref. 2[22]	Ref. 3[23]
Total	-57%	-61%	-69%	-
Car to car	-62%	-62%	-	-
Rear-end collision	-79%	-84%	-77%	-90%
Car to pedestrian	-33%	-49%	-59%	-

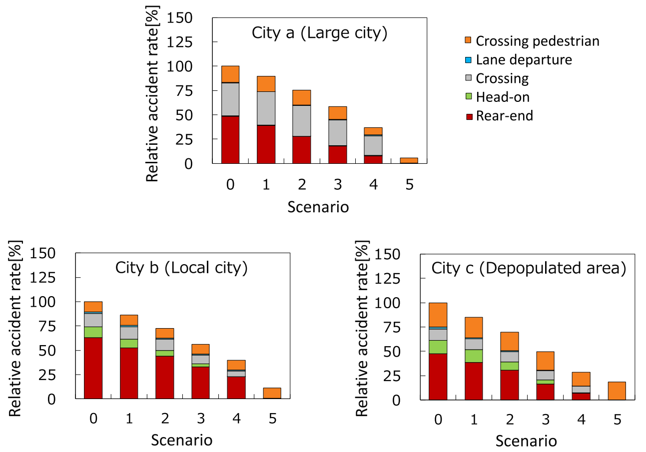

FIGURE 8. Accident reduction rates of three model municipalities.

A comparison was made with ex-post crash evaluation data (an evaluation of crash reduction from year to year based on real accident data, in consideration of the introduction of ADAS into real traffic) used by automobile manufacturers [23]–[25] to determine crash reduction impacts of vehicles equipped with driver assistance technologies (level 1) (Table 3). The overall accident reduction rate was 57% for simulation results, and 61-69% for ex-post evaluation results. In the case of car to car collisions, the accident reduction rate was 62% in the simulation, compared to 62% for post-evaluation results, and 79% compared to 77-90% for rear-end collisions. This comparison showed that the simulation can evaluate results in a manner consistent with the ex-post evaluation data for the driver assistance systems.

The reduction rate of car to pedestrian collisions on the other hand was 33% for simulation results, while ex-post evaluation results were 49-49%. This may be due to a difference in the crash type being reproduced, as crashes in the simulation were limited to "other crossing", while those targeted by the post evaluation results were different (include turning left and right at an intersection).

C. CALCULATION OF CRASH REDUCTION IMPACTS FOR EACH MODEL CITY

The crash reduction effect for each municipality model was calculated from the simulation results of scenarios in which manual driving and various automated systems coexisted. Figure 8 shows a breakdown of the relative crash reduction rates for model cities a, b, and c by accident type (in respect to scenario 0 with a crash rate of 100).

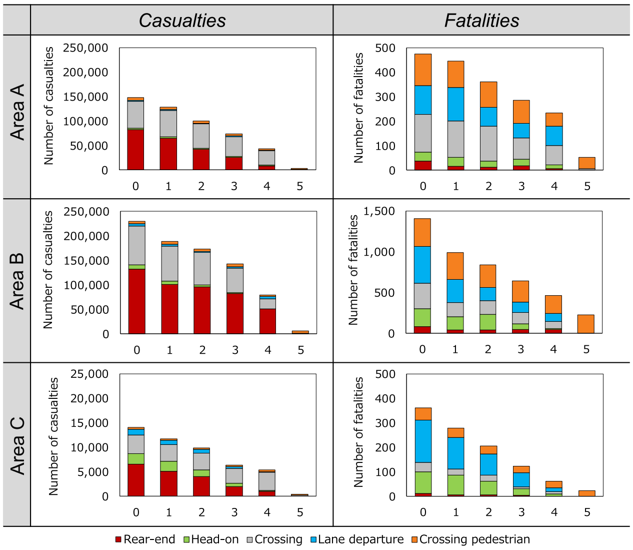

FIGURE 9. Safety impact estimation results for each area.

As described in Section III-B, the relative crash rate decreased as systems with higher safety impacts than manual driving were employed. Compared to scenarios 1, 2 and 3 where the usage of systems was mixed, the relative crash rate was lower in scenarios 4 and 5 where certain systems were installed in all vehicles. In terms of crash type, rear-end collisions were clearly reduced with the widespread use of driver assistance technologies. At a first glance, the crash rate in scenario 5 was also significantly reduced by advanced driver automation system. However, even in this scenario, pedestrian crossing crashes still occurred. These results suggest that, in order to drastically prevent crashes in which pedestrians jump out into the road, ADS and ADAS systems alone may be insufficient and complementary approaches such as, for example, the use of vehicle-to-vehicle or vehicle-to-infrastructure communication may be required for early detection of pedestrians and possible elimination of such crashes.

D. ESTIMATING NATIONWIDE ACCIDENT REDUCTION EFFECTS

Figure 9 shows safety impact estimation in terms of the number of casualties and fatalities by area. These were obtained by multiplying the accident reduction rate for each scenario and accident type described in 3.3 by the number of injuries and deaths in the entire area.

It was estimated that the number of casualties by 10,000 people in Area A decreased from 14.8 in scenario 0 to 0.3, and the number of deaths from 474 to 51. In Area B, the number of casualties decreased from 23.0 to 0.5, and the number of deaths from 1,407 to 226. In Area C, a decrease in the number of casualties was estimated from 1.4 to 0.04, while the number of deaths decreased from 361 to 21.

Figure 10 shows the national safety impact estimation results in term of casualties, integrating the results for each scenario in the three areas. For a total of 39.1 [10,000] casualties, a reduction of 16% was estimated in scenario 1, 28% in scenario 2, 43% in scenario 3, 67% in scenario 4, and 98% in scenario 5.

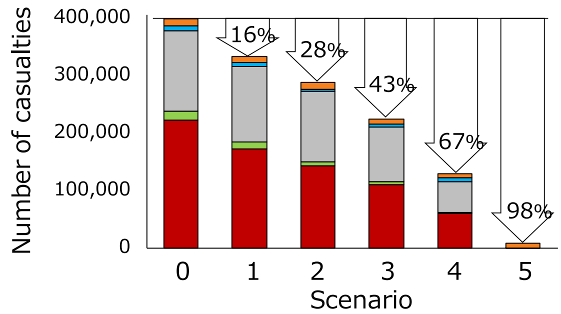

FIGURE 10. National safety impact estimation result in terms of casualties.

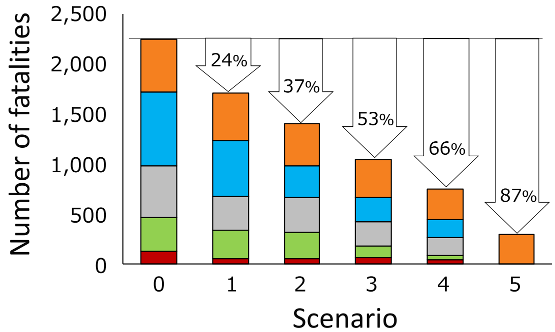

FIGURE 11. National safety impact estimation result in terms of fatalities.

Figure 11 shows the national safety impact estimation results in term of fatalities, integrating the results for each scenario in the three areas. For 2,242 fatalities, a reduction of 24% was estimated for scenario 1, 37% for scenario 2, 53% for scenario 3, 66% for scenario 4, and 87% for scenario 5.

E. DRIVER STATUS ON AUTHORITY TRANSFER EFFECT ESTIMATE

The national safety impact estimation results shown in Fig. 10 and Fig. 11 are calculated on the assumption that the driver uses the system properly. In regards to the transfer of control between the system and the driver, Ito [26] points out that it is important to have an HMI that can provide appropriate information on prior knowledge and system status through education and training. Therefore, in scenarios 2, 3, and 4 that contain conditional automation penetration, it is necessary to confirm whether control can be taken over properly. As such, the relative accident rate was calculated under conditions that employed trust parameters with education, training and HMI countermeasures (appropriate 96%, overconfidence 4%, distrust 0%) and under conditions that didn't (appropriate 10 %, overconfidence 57%, distrust 33%).

Figure 12 shows simulation results in consideration of driver trust and its influence on the relative crash rate for each scenario compared to scenario 0 (the baseline). In scenario 2, the difference in the relative crash rate (compared to

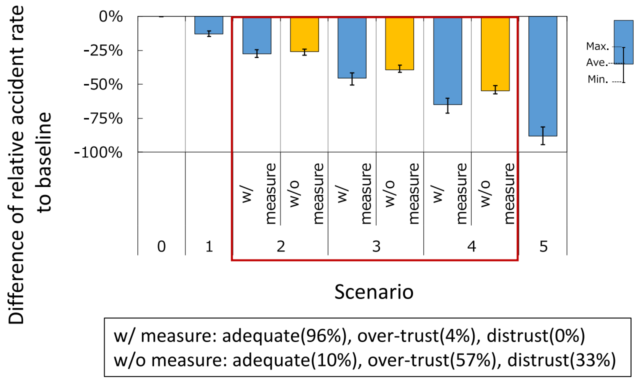

FIGURE 12. Simulation results in consideration of driver trust and its influence on safety.

the baseline) was −27% with countermeasures and −26% without. In scenario 3, it was −45% and −39% an in scenario 4, it was −65% −55%. Results show that overconfidence and distrust may have a negative impact on accident reduction effects, and this impact is greater as the penetration rate increases. Even when these negative effects were taken into account however, the results showed that the accident rate was still lower than in scenarios 0 and 1. This means that a higher penetration rate of level 3 ADS could bring about a positive impact that would exceed the negative impact, suggesting that while the proper use of the system cannot be guaranteed, spreading the usage of the system is a basic strategy for reducing crashes. Moreover, if misuse can be prevented through education and training, etc., the full potential of ADS and ADAS for safety can be achieved. The fact that effects of concerns surrounding the deployment of automated driving systems can be estimated and compared is considered to be a feature not found in conventional simulations.

IV. CONCLUSION

Simulation-based estimations of safety impacts support the idea that Automated Driving Systems and Advanced Driver Assistant Systems will contribute to a reduction in the number and the severity of crashes. Since the simulation can also take into account future traffic demand changes and traffic congestion along with traffic safety, the proposed methodology is relevant for developing policies that emphasize the penetration of the technologies. The results of study are summarized as follows.

(1) A method to expand crash reduction estimations of automated driving systems to the nationwide level was proposed. This was conducted by selecting three model municipalities based on city size and crash occurrence, after which the accident reduction rate was expanded by scenario and accident type in each of them. It was estimated that there was a reduction effect of 16 to 98% in the number of casualties and 24 to 87% in the number of deaths compared to a 100% manual driving scenario.

(2) In conditional driving automation, we devised parameters related to the driver behavior model in which the driver takes over control from the system, and introduced a framework to estimate the influence of driver state at that time. In this way, it was possible to estimate the impact of measures to prevent negative effects on the transfer of control while considering both positive and negative aspects of the automated driving system.

(3) Future tasks are to further verify the validity of simulation results (current replicability, accident reduction effects, etc.) and to develop and integrate bicycle agents. For the discussion of positive risk balance or social acceptability of ADS, it is necessary to implement realistic agent behavior to generate more diverse traffic situations. In addition, the performance limitations of ADS (i.e., missed detection rate of sensors and hardware failure rate) should be reflected in the simulation.

(4) Another future task will be to consider ODD restrictions for different levels of automation in the simulation. In order to further refine estimations, adding road geometry related ODD conditions, among others, for Advanced Driver Assistant Systems usage on real roads will further affect safety impact projections. Results on the study addressing this will be presented in future publications.

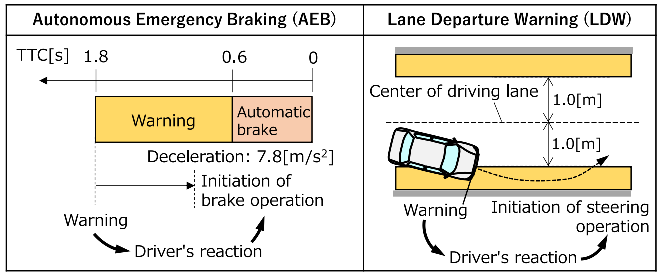

FIGURE A1. Schematics of AEB and LDW.

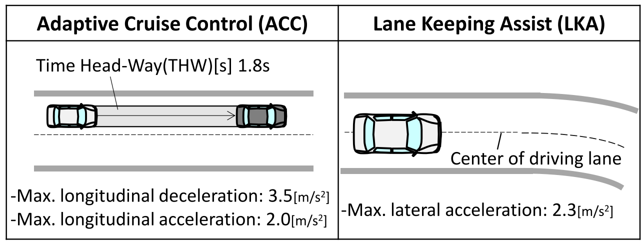

FIGURE A2. Schematics of ACC and LKA.

DATA AVAILABILITY STATEMENT

The Multi-Agent Traffic Simulation software (limited edition of the simulation used in this study) is developed under an Open Source license. We encourage other researchers to download and use it. Download it from GitHub: https://github.com/Reisim.”

APPENDIX

See Figs. A1, A2, and A3.

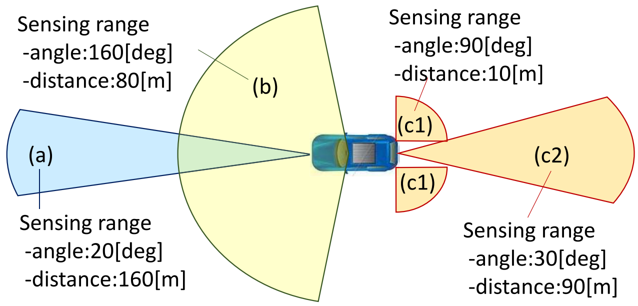

FIGURE A3. Specification of sensors for Automated Driving System.

ACKNOWLEDGMENT

The fundamental framework of our traffic simulation was supported by Cross-ministerial Strategic Innovation Promotion Program (SIP). (https://en.sip-adus.go.jp/sip/sip_01.php). This paper contains some of the research results of a research project conducted under the Cabinet Office SIP (Cross Ministerial Strategic Innovation Promotion Program) in 2018.

REFERENCES

[1] T. A. Dingus *et al.*, "Driver crash risk factors and prevalence evaluation using naturalistic driving data," *Proc. Nat. Acad. Sci.*, vol. 113, no. 10, pp. 2636–2641, 2016.
[2] S. Singh, "Critical reasons for crashes investigated in the national motor vehicle crash causation survey," Traffic safety facts crash stats," U.S. Dept. Transp., NHTSA, Washington, DC, USA, 2015.
[3] Japan Police. "Annual Report on Road Traffic Fatal Accidents and Traffic Law Enforcement Violations [In Japanese]." 2015. [Online]. Available: http://www.npa.go.jp/toukei/index.htm#koutsuu (Accessed: Apr. 24, 2018).
[4] J. B. Cicchino, "Effectiveness of forward collision warning systems with and without autonomous emergency braking in reducing police-reported crash rates," Insurance Inst. Highway Safety, Arlington, VA, USA, 2016.
[5] B. Fildes *et al.*, "Effectiveness of low speed autonomous emergency braking in real-world rear-end crashes," *Accid. Anal. Prevent.*, vol. 81, pp. 24–29, Aug. 2015.
[6] I. Isaksson-Hellman and M. Lindman, "Evaluation of the crash mitigation effect of low-speed automated emergency braking systems based on insurance claims data," *Traffic Injury Prevent.*, vol. 17, pp. 42–47, Sep. 2016.
[7] J. B. Cicchino, "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates," *Accid. Anal. Prevent.*, vol. 99, pp. 142–152, Feb. 2017.
[8] *Findings From the Global Burden of Disease Study 2017*, Inst. Health Metrics Evaluat., Seattle, WA, USA, 2018.
[9] S. Kitajima, K. Shimono, J. Tajima, J. Antona-Makoshi, and N. Uchida, "Multi-agent traffic simulations to estimate the impact of automated technologies on safety," *Traffic Injury Prevent.*, vol. 20, pp. S58–S64, Aug. 2019.
[10] *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*, SAE Int., Warrendale, PA, USA, 2018.
[11] S. Kitajima *et al.*, "Development of simulation for estimation of multiple effects to prevent traffic accident by diffusion of advanced driver assistance system and automated vehicle—Analysis of relationship between driver's characteristics and driver behavior for adequate modeling," in *Proc. 26th JSME Conf. Transport. Logist. (TRANSLOG)*, 2016.
[12] M. Ishibashi, "Development of a check sheet to classify driver characteristics and driving styles," in *Proc. JSAE Conf.*, 2002, pp. 9–12.
[13] R. Homma *et al.*, "Evaluation of forward vehicle collision mitigation systems how drivers respond to warnings under the low expectation of the hazardous situation?" *Trans. Soc. Automo. Eng. Japan*, vol. 43, no. 3, pp. 769–775, 2012.
[14] S. Kitajima *et al.*, "Development of simulation technology for estimating detailed effects of traffic accident reduction," in *Proc. Conf. JSAE*, 2018, pp. S58–S64.
[15] Ministry of Economy and Trade and Industry, "Demonstration of automatic valet parking and advanced automatic driving required to realize the system outcome report," in *Proc. METI*, 2017, pp. IV-28–IV-49.
[16] T. Inagaki, *Designing a Coexistence of Man and Machine-Exploring "Human-Centered Automation"*. Tokyo, Japan: Morikita Publ., 2012, pp. 75–87.
[17] T. Kiuchi, S. Katsumata, T. Nishimoto, S. Ito, and S. Nobuo, "Study on performance evaluation of d-call net algorithm using HELPNET data," in *Proc. JSME Autumn Meeting*, 2016.
[18] N. Lubbe and T. Kiuchi, "Injury estimation for advanced automatic collision notification," in *Proc. AACN Germany*, 2015.
[19] J. Tajima, S. Kitajima, and N. Uchida, "Reduction of calculation time of multi-agent traffic simulation for safety impact assessment by introducing an acceleration factor," in *Proc. JSAE Congress (Autumn)*, 2018.
[20] H. Suzuki and H. Tachikawa. "Who Will Change, Autonomous Driving and Mobility System." 2017. [Online]. Available: https://tech.nikkeibp.co.jp/dm/atcl/column/15/012700094/
[21] H. Kumagai, "Analysis of traffic accident reduction effect of driver assistance system," in *Proc. Acad. Lecture Meeting JSME Spring Conf.*, 2016.
[22] *The Effectiveness of Volvo's Automatic Braking System HAS Proved the Number of Accidents on Vehicles is 69.0% Lower Than on Non-Equipped Vehicles*," Volvo Cars Japan, Tokyo, Japan, 2016.
[23] *What Toyota Can Do for a Society With Zero Traffic Casualties, Toyota Cars*, Toyota Safety Technol., Plano, TX, USA, 2018.
[24] M. Ito, "2017 Summary of results regarding the understanding of functions, states, and operations of automated driving systems," in *Proc. SIP Autom. Driving Syst. Human Fact. Res. Develop. Results Present. Symp.*, 2018.
[25] "Re:sim (Multi-Agent Traffic Simulation Software)." [Online]. Available: https://github.com/Reisim (Accessed: Dec. 2, 2021).
[26] *Intelligent Transport Systems-Adaptive Cruise Control (ACC) Systems-Performance Requirements and Test Procedures*, Int. Org. Standard., Geneva, Switzerland, 2012, pp. 5–11.

SOU KITAJIMA received the M.Sc. degree in engineering from the Musashi Institute of Technology, Japan, and the Ph.D. degree in engineering from the University of Tsukuba, Japan. He is currently a Senior Researcher with the Japan Automobile Research Institute. His research interests include human error analysis based on drive video recorder data, automated driving safety assessment methodology, and multiagent traffic simulation development.

HANNA CHOUCHANE received the M.Sc. degree in policy and planning sciences from the University of Tsukuba, Japan, where she is currently pursuing the Ph.D. degree. She is currently a Researcher with the Japan Automobile Research Institute. Her research interests are automated vehicle safety research and standardization, human factors research related to situation awareness, driver trust, and driver education.

JACOBO ANTONA-MAKOSHI received the bachelor's degree in mechanical engineering from the Polytechnique University of Madrid, Spain, and the M.Sc. degree in automotive engineering and the Ph.D. degree in brain injury biomechanics from Chalmers University of Technology, Sweden. He has extensive automotive safety related research experience with the Japan Automobile Research Institute, including real-world accident data collection and analysis, injury biomechanics experimental and computational research, human behavior and traffic flow simulation modeling, automated driving safety assurance methodology development, and large scale international strategic research development.

NOBUYUKI UCHIDA received the M.S. degree in experimental psychology from Hiroshima University in 1994 and the Ph.D. degree in risk engineering from the University of Tsukuba, Japan, in 2014. He is a Senior Chief Researcher with the Japan Automobile Research Institute, and has been a Deputy General Manager of Autonomous Driving Research Division since April 2019. His research interests include the understanding of human factor related accident causation mechanisms and simulation of the common accident scenarios, for developing better preventive measures.

JUN TAJIMA received the Ph.D. degree in aerospace engineering from Nihon University, Japan, in 2001. He founded Misaki Design LLC in 2013, and has been developing multiagent traffic simulation, traffic simulator systems, and automatic driving system for small electrical mobilities. His works focus specially on interdisciplinary practices on the basis of the human behavior modeling, control theory, and system safety.