A Study on Behavior of Autonomous Vehicles Cooperating with Manually-Driven Vehicles

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***Abstract*—Autonomous vehicles will bring tremendous benefits to society. However, it is expected to take a considerable period of time for their spread, and during the transition period, autonomous and manually-driven vehicles will share the same roads. Under such situations, the driving behavior of autonomous vehicles will influence manual drivers, for example, manually-driven vehicles may be stuck behind the autonomous vehicles and overtake them frequently if autonomous vehicles drive slowly for safety. In this paper, we investigate how the traffic flow and driving stress vary with autonomous vehicles by microscopic traffic simulation. We develop a microscopic traffic simulator that can reproduce traffic flow with autonomous vehicles and manually-driven vehicles. The behavior of these vehicles can be modeled by the combination of Intelligent-Driver Model (IDM) and Lane change Model with Relaxation and Synchronization (LMRS). These models can express various driver characteristics through simulation parameters such as driving speed and distance between vehicles (net distance), and we are able to create realistic scenarios like overtaking autonomous vehicles by manually-driven vehicles with faster speed than the legal speed. From the simulation results, we found that there is a desirable combination of speed and time headway that achieves both smooth traffic and less stress of drivers with a given percentage of autonomous vehicles.**

***Index Terms*—autonomous vehicle, driving behavior, microscopic traffic simulation, driving stress**

I. Introduction

Autonomous vehicles are expected to bring huge benefits such as avoiding traffic accidents and providing drivers more free time. According to the roadmap of public and private ITS framework [1], autonomous vehicles with level 3 capability are expected to show up in the market between 2020 and 2025, and full self-driven vehicles will be popular in the coming decade or earlier. However, all manually-driven vehicles will not be replaced by autonomous vehicles in the same period because the number of manually-driven vehicles is more than 81 million in Japan [2]. Therefore, we cannot avoid the prolonged transition time where autonomous vehicles share roads with manually-driven vehicles. In this transition period, autonomous and manually-driven vehicles are on the same roads, and driving behaviors of autonomous vehicles may influence manual drivers under such situations. For example, since autonomous vehicles are strict regarding the legal speeds, manually-driven vehicles may frequently overtake the autonomous vehicles. This new phenomenon with autonomous vehicles could cause traffic disturbances, and autonomous vehicles could become factors in new stresses on drivers and passengers [3]. In fact, in 2015, a traffic officer in the state of California USA pulled over a Google's driver-less car which was traveling only 16 km/h [4]. London School of Economics and Goodyear Tire and Rubber Company conducted a questionnaire to survey consciousness for autonomous vehicles on about 12,000 drivers in 11 different countries. Approximately 41 % of respondents said that they felt uncomfortable about traveling with autonomous vehicles. Since the driving behavior of autonomous vehicles has a big influence on traffic flow like traffic capacity and safety, the traffic flow would be chaotic with co-existence of autonomous vehicles and manually-driven vehicles.

In this paper, we investigate how traffic flow and driving stress vary with autonomous vehicles by microscopic traffic simulations. We develop a microscopic traffic simulator that can reproduce traffic flow with autonomous vehicles and manually-driven vehicles. The behavior of these vehicles can be represented by integrating two models, namely, Intelligent-Driver Model (IDM) [5] and Lane change Model with Relaxation and Synchronization (LMRS) [6]. As a longitudinal driving behavior model, IDM decides the acceleration or deceleration based on the desired speed, the desired time headway, the speed difference from a preceding vehicle, and the distance between own vehicle and the preceding vehicle (net distance). Meanwhile, as a lateral driving behavior model, the lane change model decides to what extent drivers want to change lanes and when and where they change their lanes. Moreover, certain delays are inserted after the above decisions to take into the consideration that autonomous vehicles can react to surrounding situations faster than manually-driven vehicles. These models can express various driver characteristics through simulation parameters such as driving speed and distance between vehicles (net distance). For example, we can create such situations where autonomous vehicles never exceed legal speed although manually-driven vehicles drive faster than them to overtake them.

We have varied the simulation parameters through simulation experiments on a multi-lane straight road and measured the driving speed and the number of unsafe lane changes for each vehicle to evaluate the driving stress. From the simulation results, we found that there exist such situations that can achieve both the smooth traffic flow and less driver stress simultaneously. For example, with the 20% or less of the autonomous vehicle ratio, the ideal driving speed and the desired time headway can be $70-80$km/h and $1.0 \sim 2.0$s respectively for the best traffic smoothness and least driver stress.

II. Related Work

A. Traffic Simulator

Fundamental technologies and systems for Intelligent Transport Systems (ITS) often target a large number of vehicles traveling over a wide range of road networks, commercial and open source traffic simulators that precisely simulate the actual driving behaviors are normally used. Traffic simulators used widely nowadays are classified into microscopic and macroscopic ones according to the granularity of their driving models. The microscopic traffic simulators design the driving behavior of an individual vehicle on the road network in more details. They usually determine the driving behavior based on the relative speed to a preceding vehicle and the distance between own vehicle and the preceding vehicle (net distance). Typical simulators of the microscopic model include VISSIM [7], SUMO [8], and S-Paramics [9]. On the other hand, the macroscopic traffic simulators determine the driving behavior of entire vehicles on the road network by vehicle density, vehicle flow density and so on, and most of them incorporate the fluid dynamics. Typical simulators of the macroscopic model include SOUND [10] and NETSTREAM [11]. Integrating multiple simulators for the use of different models with different granularity has been considered in [12].

B. Cooperative Driving among Autonomous Vehicles

When autonomous vehicles become sufficiently popular, cooperative driving among autonomous vehicles will bring various good impacts on traffic situations. For example, if autonomous vehicles make the net distance short enough by forming high-density platoon and fleet, it will reduce CO_2 emissions by mitigating air resistance and also reduce traffic jams by the increase of vehicle density. In [13], the authors propose a driving model that acquires the vehicle status in a group of autonomous vehicles running through platoons via inter-vehicle communication and takes cooperative actions based on the vehicle status. They evaluated the correlation of the ratio of autonomous vehicles with the speed and fuel consumption by simulation experiments, and said that when the ratio of autonomous vehicles is low (*e.g.* 10%), the influence of manually-driven vehicles become the main cause of congestion. In [14], the authors propose an algorithm for lane change when a new autonomous vehicle joins a two-vehicles platoon that consists of a leading manually-driven vehicle followed by an autonomous vehicle. To verify that the minimum necessary net distance is kept and unnatural speed change does not occur at lane change, they implemented the lane change algorithm on actual vehicles and conducted experiments on test courses. As a result, the difference between the actual net distance and the minimum net distance was suppressed to 2m or shorter, and the change of speed was also kept minimal. In [15], the authors assume a situation that vehicles are equipped with Cooperative Adaptive Cruise Control (CACC), which can realize more efficient and precise car-following, and evaluate the effectiveness of introducing lanes dedicated to CACC vehicles near intersections by simulation with VISSIM. Then it clarified the change of the average stop time, average speed and the number of vehicles passing through, depending on the ratio of vehicles equipped with CACC and presence or absence of the dedicated lane. In [16], the authors propose a method to estimate the net distance using LiDARs and exchange information using Visible Light Communication (VLC) among vehicles in the platoon.

C. Our Contributions

In the previous studies, it is assumed that autonomous vehicles share information such as positions and speeds of surrounding autonomous vehicles by inter-vehicle or infrastructure-based communications. Therefore, their goals are generating ideal traffic flows by cooperation among autonomous vehicles. However, autonomous vehicles that appear in the early stage of penetration will not have such functions, and most of them are expected to work standalone. When such autonomous and manually-driven vehicles exist on the same roads, the traffic flow is likely to be chaotic where the leading vehicle of each fleet is not clearly defined in the traffic system. Therefore, the decision of autonomous vehicles has a big influence on traffic flow, such as traffic capacity and safety. In our approach, considering such situations, we try to give the guidelines on the parameters to model the decision making of autonomous vehicles. This has not been done yet in previous studies such as [13] [14], which evaluated the influence of platoon. In addition, we evaluate the traffic in term of the driving stress in a transition period, which has not also been considered in the previous work introduced in this section.

III. Driving Model

Driving behavior consists of lateral driving behavior and longitudinal driving behavior. The lateral driving behavior is basically lane-change operations, and the longitudinal behavior is composed of acceleration or deceleration operations. In our approach, we implement a driving model that has been validated assuming manually-driven vehicles into the multi-agent simulator called Scenargie [17]. Then we reproduce the physical positioning relationship between autonomous and manually-driven vehicles by reflecting the driving characteristics of each driver through parameters of the driving model such as the speed, net distance, and lane change intention.

A. Lane Change Model

A driver determines whether or not to change the lane based on the speed of surrounding vehicles and net distance. The lane change model consists of "necessity and safety judgment", and the driver carries out lane change when these conditions are satisfied.

1) Necessity of Lane Change: Based on the existing lane change model [6] which quantifies the intention of desire for the lane change, it judges the necessity of lane change. In [6], the following three items are listed as representative motives for lane change behavior where i and j denote the current and target lanes, respectively.

1) desire to follow lane j to reach the destination (denoted as d_r^{ij}),
2) desire to gain more speed in the new lane j (denoted as d_s^{ij}), and
3) desire to keep the left lane j (denoted as d_b^{ij}) (keep right in the right-hand traffic countries)

This model formulates the lane change desire of each of the above motives based on the speed of the surrounding vehicles, the net distance and the distance to the destination. Then the model combines those quantified desires to quantify a driver's lane change desire. The desire to change from lane i to lane j (denoted as d^{ij}) is given as the following equation (1).

$$d^{ij} = d_r^{ij} + \theta_v^{ij}(d_s^{ij} + d_b^{ij}) \tag{1}$$

θ defines the level of desire for the voluntary lane change. The driver needs to change from lane i to lane j when d^{ij} is equal to or greater than a given threshold d_{free} (*i.e.* $d^{ij} \geq d_{free}$).

2) Safety Condition: The safety condition is defined using the following four sub-conditions.

1) Let $d_{b'}$ denote the distance between a target vehicle and the following vehicle (say b') on the target lane. $d_{b'}$ must be equal to or longer than the minimum net distance (denoted as GD_{MIN}).
2) Let $d_{f'}$ denote the distance between a target vehicle and the preceding vehicle (say f') on the target lane. $d_{f'}$ must be equal to or longer than the minimum net distance.
3) Let $\tilde{b}_{b'}$ denote the deceleration of the following vehicle on the target lane after changing the lane. $\tilde{b}_{b'}$ must not exceed the maximum allowable deceleration of a target vehicle (denoted as b_{safe}).
4) Let $\tilde{b}_b$ denote the deceleration of a target vehicle after changing the lane. $\tilde{b}_b$ must not exceed the maximum allowable deceleration of a target vehicle (*i.e.* b_{safe}).

The driver can safely change the lane when all these conditions are satisfied, that is, (2) must be satisfied.

$$\begin{aligned} d_{b'} \geq GD_{MIN} \wedge d_{f'} \geq GD_{MIN} \wedge \\ \tilde{b}_{b'} \leq b_{safe} \wedge \tilde{b}_b \leq b_{safe} \end{aligned} \tag{2}$$

GD_{MIN} is the minimum net distance when driving at speed $v(t)$. This is given as (3).

$$GD_{MIN} = gd_0 + T * v(t) + \frac{v(t)(v_f(t) - v(t))}{2\sqrt{a_{safe}b_{safe}}} \tag{3}$$

gd_0 is the minimum net distance when the vehicle stops, T is the desired time headway and $v_f(t)$ is the speed of the preceding vehicle at the current time. a_{safe} is the maximum allowable acceleration of a target vehicle.

B. Acceleration Model

In our acceleration model, the driver determines the acceleration in the next timeslot based on the speeds of the target and preceding vehicles as well as the net distance in the current timeslot. The acceleration model considers two states, *free-flow state* and *car-following state*. In the free-flow state, there is no vehicle ahead in the current lane and the driver can accelerate his/her vehicle freely. Meanwhile, in the car-following state, the driver is following a preceding vehicle. We build different sub-models for these states.

1) Acceleration in Free-Flow State: When there is no vehicle ahead in the current lane, the driver decides to accelerate based on the speed of vehicle ($v(t)$), the maximum allowable acceleration of vehicle (a_{safe}), the desired speed of vehicle (v_d), and the simulation time (δt). This is given in (4).

$$\frac{dv(t+1)}{dt} = \begin{cases} 0 & (v(t) = v_d) \\ v_d - v(t) & (v_d - a_{safe} * \delta t \leq v(t) \leq v_d) \\ a_{safe} & (v(t) \leq v_d - a_{safe} * \delta t) \end{cases} \tag{4}$$

The driver does not accelerate when $v(t)$ has already reached v_d. On the other hand, the driver accelerates with a_{safe} when $v(t)$ has not yet reached v_d. Moreover, the driver adjusts acceleration so that the speed of vehicle at the next time

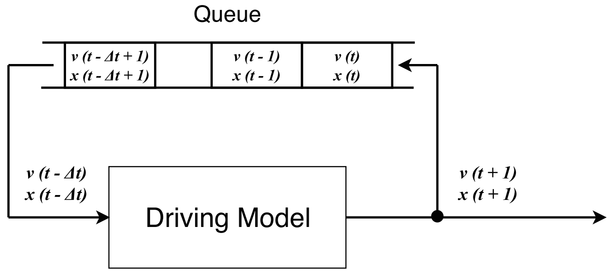


Fig. 1. Feedback System in Speed/Position Updates

($v(t+\delta t)$) cannot exceed v_d when $v(t+\delta t)$ exceeds the desired speed due to acceleration a_{safe}.

2) Acceleration in Car-Following State: When there is a preceding vehicle on the current lane, the driver adjusts the speed of vehicle so as to follow the preceding vehicle based on Intelligent Driver Model (IDM) [5] that can express smooth acceleration and deceleration to avoid collision with the preceding vehicle. This is given as (5).

$$\frac{dv(t)}{dt} = a[1 - (\frac{v(t)}{v_d})^4 - (\frac{GD_{MIN}}{gd})^2] \qquad (5)$$

C. Speed Adjustment for Lane Change

The driver adjusts the speed in order to generate a safe net distance according to the lane change desire when the driver cannot keep the safety net distance at lane change by the vehicle itself or other vehicles. More specifically, if the value of lane change desire is equal to or greater than the threshold (say d_{sync}) and it does not satisfy the safety condition, the driver regards a preceding vehicle (f') on the target lane as a virtual preceding vehicle (vf) on the current lane and decides acceleration or deceleration which is given by (5). In addition, if the driver of the preceding vehicle (f") on the adjacent lane has the lane change desire equal to or greater than the threshold (d_{coop}) and it does not satisfy the safety condition, the driver regards f" as vf and decides acceleration or deceleration given by (5).

D. Delay in Reflecting Driving Behavior

Driving activity is generally modeled as a cycle of recognition, judgment, and operation. More precisely, a normal driver recognizes the surroundings, judges the necessity of depressing or stepping the pedals and operating the steering wheel and then carries out the operations. Since there is a certain delay in the judgment process which is affected by human perception and reaction, we model the delay t_d (in other words, "reaction time") of judgment to represent the fundamental difference between autonomous vehicles and manually-driven vehicles.

Here, general traffic simulators calculate speeds and positions of vehicles at next time ($t + \delta t$) based on those at the current time t. On the contrary, we calculate speeds and positions of vehicles at next time ($t + \delta t$) based on those at $t - t_d$ as shown in Fig. 1 to reproduce such recognition and reaction delay.

E. Determining Parameter Values in Driving Model

Finally, we reflect the characteristics of the driving behavior of autonomous and manually-driven vehicles through parameters included in the driving model.

When the traffic flow is modeled using microscopic modeling techniques, the flow can be expressed by the probability distributions of state quantities such as speed, time headway, and net distance [18]. In fact, in our driving model, the decisions on a lane change, acceleration and deceleration are made based on the speeds of the own vehicle and the surrounding vehicles and the distance between the own vehicle and the surrounding vehicles. Table I shows the parameters of the driving model. Among these parameters, the desired speed and desired time headway have a great influence on the determination of the speed and net distance. Therefore, we use probability distributions to assign values to these two parameters to reproduce natural variations of driving behavior.

The desired speed of manually-driven vehicles is determined following the normal distribution (average 79.8km/h, standard deviation 8.28km/h) with reference to the distribution of actual speed on the road with limit speed 60km/h [19]. The desired time headway of manually-driven vehicles is determined following the probability distribution (average 1.69s, standard deviation 0.35s) estimated by the kernel density estimation method from the data measured from the Osaka Prefecture Route 2 Osaka Central Ring Road.

The characteristics of the driving behavior of autonomous vehicles are also reflected through the parameter values of the desired speed and the desired time headway. We assign the values described in [6] to other parameters.

IV. Driving Behavior Analysis

We conduct microscopic traffic simulations to reproduce traffic flow with autonomous and manually-driven vehicles by implementing the driving models described in Section III on the multi-agent simulator Scenargie. In the simulations, we analyze how different the traffic flow and driving stress are, under the different characteristics of the driving behavior of autonomous vehicles and ratios of autonomous vehicles.

A. Metrics

We measure *traffic capacities* to evaluate the traffic efficiency in the simulations. A traffic capacity represents the maximum number of vehicles that can pass through across line of a road within a unit time [20]. We also measure *travel time*, which is the time required for a vehicle to travel a certain section [21]. *Driving stress* is evaluated based on the behavior of a target vehicle and the surrounding vehicles. In [22], the authors summarized the stresses experienced during driving as follows, (i) frustration when drivers have to slow down, (ii) anxiety caused by unsafe lane changes by surrounding vehicles, and (iii) anxiety caused by undesired lane driving (this happens when drivers feel difficulty to come into the desired lanes, for example). In order to investigate how much stress is caused, we analyzed (i) the difference between the desired and traveling speeds, (ii) the number of unsafe lane

TABLE I
PARAMETERS OF DRIVING MODEL

Parameter Symbol	Manually-Driven Vehicles	Autonomous Vehicles
Desired Speed (v_d[km/h])	$N(\mu = 79.8, \sigma = 8.28)$	Depends on the Scenario
Desired Time Headway (T[s])	$N(\mu = 1.69, \sigma = 0.35)$	Depends on the Scenario
Reaction Time (t_d[s])	0.7	0.1
Maximum Acceleration (a_{safe}[m/s^2])	1.25	
Maximum Deceleration (b_{safe}[m/s^2])	2.09	
Stopping Net Distance (gd_0[m])	3	
Vehicle Length (l[m])	4	
A Threshold for Judgment of Lane Change (d_{free})	0.365	
A Threshold for Judgment on Speed Adjustment for Lane Change of A Target Vehicle (d_{sync})	0.577	
A Threshold for Judgment on Speed Adjustment for Lane Change of Another Vehicle (d_{coop})	0.788	

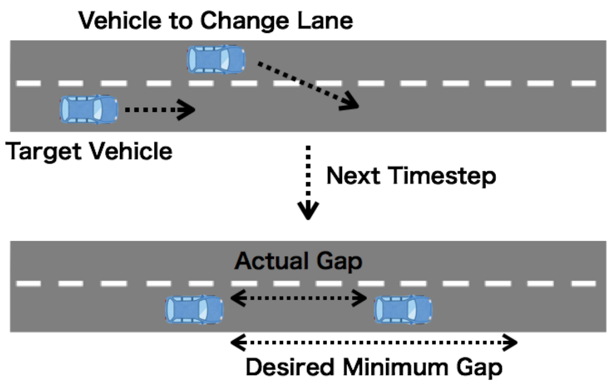


Fig. 2. Unsafe Lane Change

TABLE II
SIMULATION PARAMETERS

Simulation Time	$3,600$[s]
Time Step	0.1[s]
Speed Limit	60[km/h]
Vehicles' Initial Lanes	Random
Target Lane	Initial Lane
Vehicle Generation Interval	Reciprocal of Traffic Volume

TABLE III
PARAMETER VALUES OF AUTONOMOUS VEHICLES IN SCENARIO I

Parameter	Value
v_d[km/h]	$50, 60, 70, 80, 90, 100, 110, 120$
T[s]	1.69 (Average Value of Manually-Driven Vehicles)

TABLE IV
PARAMETER VALUES OF AUTONOMOUS VEHICLES IN SCENARIO II

Parameter	Value
v_d[km/h]	79.8 (Average Value of Manually-Driven Vehicles)
T[s]	$0.1, 0.3, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0$

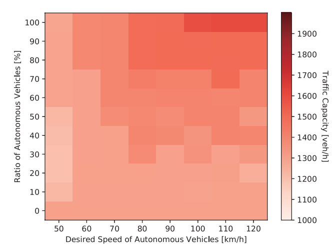


Fig. 3. Traffic Volume (Scenario I)

changes, and (iii) the ratio of incomplete travels (*i.e.*, the ratio of travels in which drivers were unable to reach the destinations). Unsafe lane changes are defined as lane changes such that the distance between a target vehicle and a vehicle performing the lane change is less than the minimum net distance GD_{MIN}. Fig. 2 shows the illustration of the positions of the target vehicle and the surrounding vehicle when such an unsafe lane change occurs.

B. Environment

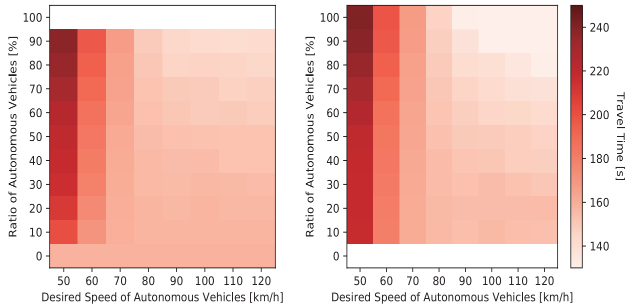
We used a straight road with three lanes with 3km long and 6m lane width. The traffic volumes are varied from $1,000$veh/h to $2,000$veh/h in order to calculate the maximum traffic volumes. When we evaluate other metrics, we set traffic volume as $1,000$veh/h in order to reproduce free flow with a large number of traveling vehicles. The other simulation parameters are shown in Table II.

C. Simulation Scenarios

As described in Section III-E, the characteristics of the driving behavior of autonomous vehicles are configured via two parameters, desired speed (v_d) and desired time headway (T). In order to investigate how each parameter affects traffic flow and driving stress, we fix one parameter to the average value of manually-driven vehicles and vary the other parameter sequentially. We conducted a simulation experiment (referred to as Scenario I) to vary the desired speed of autonomous vehicles and another simulation experiment (referred to as Scenario II) to vary the desired time headway. The parameter values in Scenarios I and II are shown in Tables III and IV, respectively.

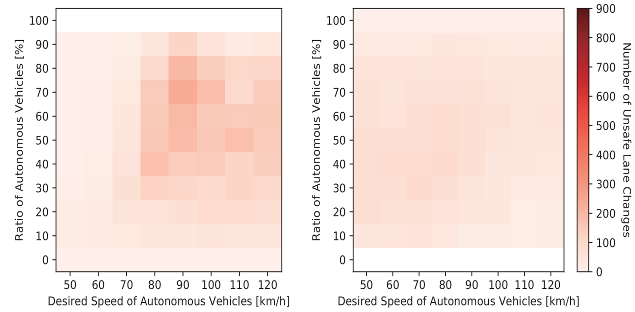
D. Evaluation Results

1) Scenario I: The traffic flow in Scenario I is shown in Fig.3. As seen, when the desired speed of autonomous vehicles is over the speed limit (60km/h) and the ratio of autonomous vehicles is less than 20%, the traffic capacity has almost the same value. However, when the desired speed of autonomous vehicles is over the average value of manually-driven vehicles and the ratio of autonomous vehicles is more than 30%, the traffic capacity increases correspondingly as the desired speed of autonomous vehicles and the ratio of



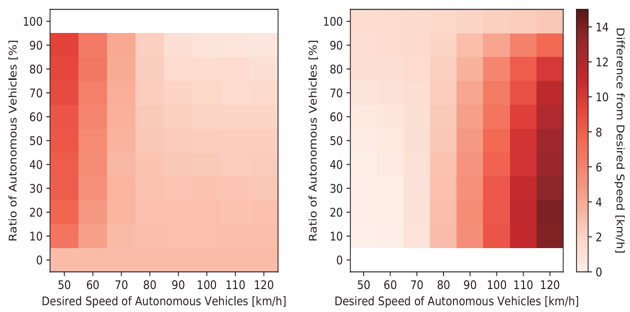
(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 4. Travel Time (Scenario I)



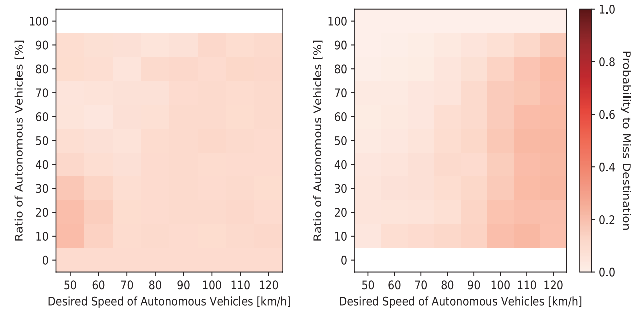
(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 6. Number of Unsafe Lane Changes (Scenario I)



(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 5. Difference between Desired Speed and Driving Speed (Scenario I)



(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 7. Ratio of Incomplete Travels (Scenario I)

autonomous vehicles increase. The travel time is shown in Fig. 4. The travel time of manually-driven vehicles decreases as the ratio of autonomous vehicles increases when the desired speed of autonomous vehicles is higher than 80km/h. On the other hand, the travel time of autonomous vehicles decreases as the desired speed of autonomous vehicles increases. The reason why the traffic flow does not vary when the ratio of autonomous vehicles is less than 20% is that autonomous vehicles are likely to follow (slow) manually-driven vehicles even though their desired speeds are high. On the contrary, when the ratio of autonomous vehicles is higher than 30%, the traffic efficiency improves. This is because the autonomous vehicles with higher speeds are likely to be the leading vehicles of fleets.

The metrics to evaluate the driving stress in Scenario I are shown in Figs. 5, 6, and 7. The difference between the desired speed and the travel speed of manually-driven vehicles increases as the ratio of autonomous vehicles increases when the desired speed of autonomous vehicles is lower than 70km/h. On the other hand, when the desired speed of autonomous vehicles is higher than 80km/h, the difference between the desired speed and the travel speed of autonomous vehicles increases as the desired speed of autonomous vehicles increases. When the desired speed of autonomous vehicles is lower than 70km/h, manually-driven vehicles often follow autonomous vehicles traveling with slow speeds. Similarly, when the desired speed of autonomous vehicles is higher than 80km/h, autonomous vehicles often follow manually-driven vehicles traveling with slow speeds. In addition, when the desired speed of autonomous vehicles is higher than 80[km/h] and the ratio of autonomous vehicles is $40 \sim 80$[%], autonomous vehicles more frequently cut into manually-driven vehicles (unsafe lane change) compared to the other situations because autonomous vehicles often overtake manually-driven vehicles. Oppositely, the number of manually-driven vehicles' cut-in operations to autonomous vehicles does not vary with the change of the desired speed of autonomous vehicles. When the desired speed of autonomous vehicles is slower than 60km/h and the ratio of autonomous vehicles is $10 \sim 30$%, the ratio of incomplete travels of manually-driven vehicles increases compared to the other situations. This is because manually-driven vehicles traveling with high speeds cannot keep the safe net distance to return to the original lane after overtaking autonomous vehicles. Similarly, when the desired speed of autonomous vehicles is over 100km/h, the ratio of incomplete travels of autonomous vehicles increases because, this time, autonomous vehicles traveling with high speeds cannot keep the safe net distance to return to the original lane after overtaking manually-driven vehicles.

From these simulation results, there are certainly some situations with better traffic flow and less driver stress. In such cases that the percentage of the autonomous vehicles is under 20%, we can say that the desired driving speed and the desired time headway can be $70 \sim 80$km/h and $1.0 \sim 2.0$s, respectively, while driver stress is mitigated. Besides, the desired speed is 90km/h when the ratio of autonomous vehicles

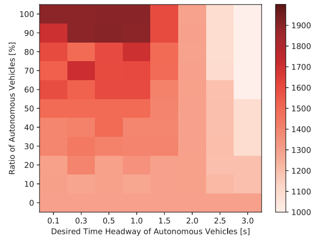
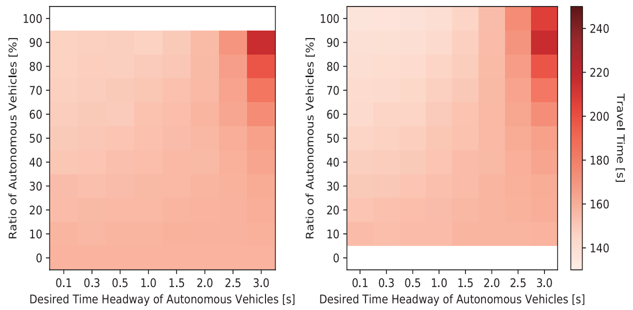
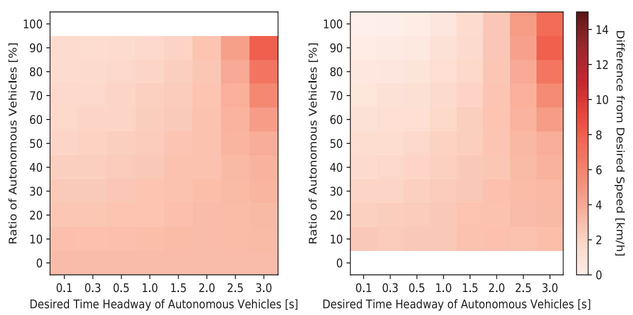


Fig. 8. Traffic Volume (Scenario II)



(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 9. Travel Time (Scenario II)



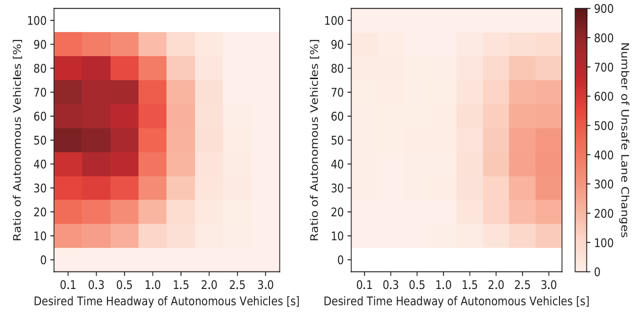
(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 10. Difference between Desired Speed and Driving Speed (Scenario II)

is 30% or 90%, and the desired speed is 70km/h when the ratio of autonomous vehicles is $40 \sim 80\%$.

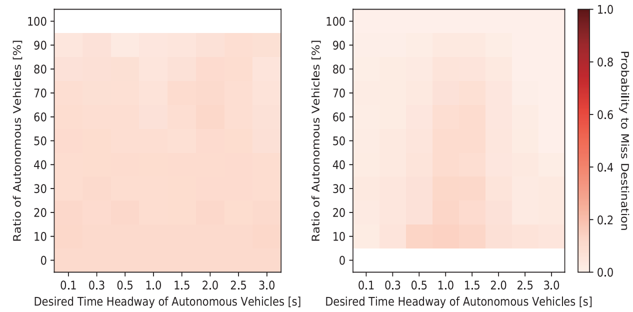
2) Scenario II: The traffic flow in Scenario II is shown in Fig.8. When the desired time headway of autonomous vehicles is less than 1.5s and the ratio of autonomous vehicles over 30%, the traffic capacity increases compared to the traffic flow with manually-driven vehicles only. The travel time is shown in Fig. 9. The travel time of both manually-driven vehicles and autonomous vehicles somehow decreases as the ratio of autonomous vehicles increases when the desired time headway of autonomous vehicles is less than 1.5s. The reason why the efficiency of traffic flow improves when the desired time headway is less than 1.5s is that the net distance of each vehicle decreases and the occupation ratio of the road increases. The metrics to evaluate the driving stress in Scenario II are shown in Figs.10, 11, and 12.

The difference between the desired speed and the travel speed of both autonomous and manually-driven vehicles rather



(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 11. Number of Unsafe Lane Changes (Scenario II)



(a)Manually-Driven Vehicles (b)Autonomous Vehicles

Fig. 12. Ratio of Incomplete Travels (Scenario II)

decreases as the ratio of autonomous vehicles increases. This is because the net distance of each vehicle decreases when the desired time headway of autonomous vehicles is less than 1.5s. On the other hand, when the desired time headway of autonomous vehicles is over 2.5s, it increases as the ratio of autonomous vehicles increases because the net distance of each vehicle increases. The number of unsafe lane changes by autonomous vehicles to manually-driven vehicles increases when the desired time headway of autonomous vehicles is less than 1.5s. Especially, it increases greatly when the desired time headway of autonomous vehicles is less than 0.5s and the ratio of autonomous vehicles is $30 \sim 80\%$. The number of unsafe lane changes of manually-driven vehicles to autonomous vehicles increases when the desired time headway of autonomous vehicles is over 2.5s. Especially, it increases greatly when the ratio of autonomous vehicles is $20 \sim 70\%$. This is because autonomous vehicles judge whether the lane change is safe or not based on the minimum net distance determined in proportion to the desired time headway. The ratio of incomplete travels does not vary with the change of the desired time headway of autonomous vehicles.

From the simulation results, we can say that the desired time headway of autonomous vehicles is $1.0 \sim 2.0$s when the ratio of autonomous vehicles is less than 20%, while driver stress is mitigated. Besides, the desired time headway can be $1.0 \sim 1.5$s when the ratio of autonomous vehicles is over 30%.

V. Conclusion

In this study, we have modeled the behavior of autonomous and manually-driven vehicles by focusing on their fundamental difference. In addition, we naturally reproduced the variations of driving behavior of manually-driven vehicles and modeled the driving behavior of autonomous vehicles via known parameters such as desired speed and desired time headway investigating the state-of-the-art study on driving models. We implemented these models on Scenargie in order to carry out microscopic traffic simulations in which autonomous and manually-driven vehicles coexisted. Then, we showed the influence of the driving behavior of the autonomous vehicle and the ratio of autonomous vehicles on traffic flow and driving stress. We also evaluated the quality of traffic flow from the viewpoints of efficiency and smoothness of traffic, and the driving stress caused by frustration when drivers have to slow down and feel anxiety about unsafe lane changes and passing destinations.

Through the simulation experiments, in such cases that the percentage of the autonomous vehicles is under 20%, we conclude that the desired driving speed and the desired time headway are $70 \sim 80$km/h and $1.0 \sim 2.0$s, respectively, keeping driver stress sufficiently low. Similarly, we have shown that the desired speed is 90km/h and the desired time headway is $1.0 \sim 1.5$s when the ratio of autonomous vehicles is 30% or over 90%, and the desired speed is 70km/h and the desired time headway is $1.0 \sim 1.5$s in other cases.

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