2017 11th Asian Control Conference (ASCC)
Gold Coast Convention Centre, Australia
December 17-20, 2017

A Lane-change Maneuver of Automated Vehicles for Improving Traffic Flow on Highways with Multiple Lanes

Yuko Shiomi, Yasuaki Wasa and Kenko Uchida

***Abstract*— This paper investigates a smart lane-change mechanism of automated vehicles with intelligent driver model on highways with multiple lanes. In particular, we propose an autonomous lane-change maneuver to improve traffic flow. The key technique of the proposed maneuver is to consider not only selfish conditions to track individual velocity tracking performance but also altruistic conditions to improve the driving performance of the succeeding vehicles by using vehicle-to-vehicle communications. To realize the conditions, this paper presents cost functions and criteria mathematically. We also demonstrate through simulation that the proposed algorithm enhances heterogeneous traffic flow efficiency while avoiding collisions and wasteful traffic congestion in dense traffic. As a result, each vehicle with the proposed maneuver can travel about 1 minute per 10 km faster than only the conventionally selfish condition on average.**

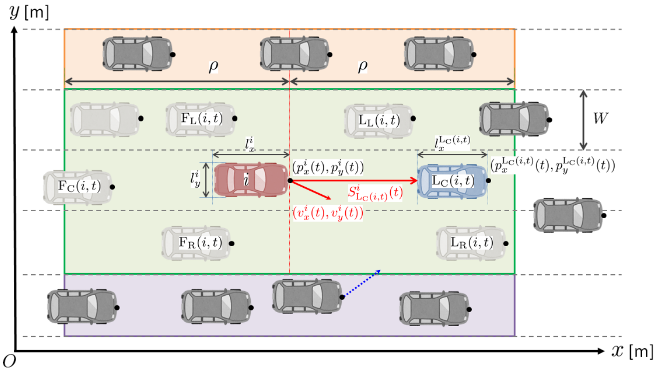


Fig. 1. An illustration of vehicles traveling on multiple lanes. The vehicle i (red car) normally chases the nearest preceding vehicle $L_C(i,t)$ (blue car) of the lanes involved with i at time t. When the vehicle i tries to execute lane-changes under collision avoidance, i needs to predict his motion trajectory based on traffic information on the adjacent lanes (green zone) and communicate with neighbors (purple and orange zones).

I. Introduction

Developing smart traffic management systems with self-driving vehicles is one of the most pivotal technologies to embody system and control design for future urban infrastructure. In particular, a vehicle platooning control with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication is expected to enhance safety and reduce traffic jams, environmental impacts and economic losses.

This paper investigates efficient lane-change maneuvers for autonomous vehicles on highways with multiple lanes in order to reduce the traffic congestion on the road networks, shorten the traveling time and avoid collision with vehicles. Regarding the longitudinal dynamics, which is an acceleration model along a single-lane road on the highway, many advanced driver-assistance systems for improving traffic safety have been proposed [1]. Typical microscopic models of such longitudinal dynamics are adaptive cruise control (ACC) systems including car-following models such as so-called intelligent driver model (IDM) [1], [2], and (cooperative) vehicle platooning control using a model predictive control (MPC) [3], [4], [5] and V2V/V2I communications [6]. Assuming that each vehicle has a different desired velocity, it is necessary to consider a multi-lane traffic model in order to introduce a passing lane, where a faster vehicle can pass slower vehicles, and admit heterogeneous traffic flow [7].

Many lane-change maneuvers have been also presented. Lots of them optimize an anticipated lane-change trajectory by using MPC [8], [9] and utility-based approach [10] while reducing the risk associated with lane change. [11] presents a rule-/scenario-based approach. However, the above papers more or less assume that the vehicles travel on two-lane roads or on light-traffic multiple lanes and that all surrounding vehicles keep the current lane during the lane-change of the host vehicle. To predict collision avoidance conditions completely, the host vehicle requesting a lane-change must observe the vehicles' behavior traveling on a lane next to the adjacent lane. Hence, it is not straightforward to extend the two-lane model to arbitrary-lane models. For more than three-lane roads, [12] presents a centralized algorithm maximizing the number of safe lane changes with satisfying collision avoidance conditions in dense traffic flow. On the other hand, all the above articles [8], [9], [10], [11], [12] do not mention a rigorous selection method of the lane-change vehicles and their lane-change directions.

Therefore, this paper presents a novel lane-change maneuver of automated vehicles with a car-following model-based longitudinal dynamics and a heterogeneous desired velocity on arbitrary-lane roads as shown in Fig. 1. To achieve the above realistic objectives, we extend a lane-change criterion called Minimizing Overall Braking Induced by Lane changes (MOBIL) presented in [7], [1]. The MOBIL uses IDM as longitudinal dynamics and evaluates an anticipated acceleration led by IDM. However, MOBIL also assumes that the host vehicles executing lane-change and their appropriate lane-change directions are determined in advance. Hence, the main challenge of this paper is to formulate a cost function and a criterion of the selection. As the key technique for selecting lane-change vehicles, we present that it is necessary to consider not only selfish conditions to track individual ve-

Y. Shiomi, Y. Wasa and K. Uchida are with the Department of Electrical Engineering and Bioscience, Waseda University, 179-8555 Tokyo, Japan wasa@aoni.waseda.jp, kuchida@waseda.jp

TABLE I

VARIABLES AND CONSTANT PARAMETERS ON VEHICLE i AT TIME t.

Symbol	Description	Unit
$(p_x^i(t), p_y^i(t))$	Center position of the front bumper	[m]
$(v_x^i(t), v_y^i(t))$	Velocity of the vehicle	[m/s]
$(u_x^i(t), u_y^i(t))$	Control input (acceleration) of the vehicle	[m/s^2]
$v_d^i(t)$	Desired velocity on the x-axis	[m/s]
$p_d^i(t)$	Desired position on the y-axis	[m]
l_x^i, l_y^i	Vehicle length and width (l_x^i=3.0, l_y^i=2.0)	[m]
ρ	Maximum range of V2V communication	[m]
$\mathrm{L}(i,t)$	Pursued vehicle used in (3)	
$\mathrm{L_L}(i,t)$	Nearest leading vehicle on the left lane	
$\mathrm{L_C}(i,t)$	Nearest leading vehicle on the current lane	
$\mathrm{L_R}(i,t)$	Nearest leading vehicle on the right lane	
$\mathrm{F_L}(i,t)$	Nearest following vehicle on the left lane	
$\mathrm{F_C}(i,t)$	Nearest following vehicle on the current lane	
$\mathrm{F_R}(i,t)$	Nearest following vehicle on the right lane	
$V_{\mathrm{L}}^i(t)$	Velocity relative to the leading vehicle L	[m/s]
$S_{\mathrm{L}}^i(t)$	Bumper-to-bumper distance between L and i	[m]
$g_{\mathrm{L}}^i, g_{\mathrm{R}}^i$	Incentive scores to change to left/right lane	

TABLE II

PARAMETERS AND VALUES USED IN INTELLIGENT DRIVER MODEL (3).

Symbol	Description	Unit	Value
a_0	Maximum acceleration	[m/s^2]	1.0
b_0	Comfortable deceleration	[m/s^2]	1.5
s_0	Minimum inter-vehicle distance	[m]	2.0
T_{hd}	Headway time for safely following L	[s]	2.0
δ	Acceleration exponent		4

locity tracking performance, but also altruistic conditions to improve the driving performance of the succeeding vehicles. Through simulations, we demonstrate that the proposed algorithm enhances heterogeneous traffic flow efficiency while avoiding collisions and wasteful traffic congestion in dense traffic. We also illustrate that the case without the altruistic conditions cannot improve velocity tracking performance due to wasteful traffic jams. The proposed model is newly added as follows: (i) Each vehicle can apply his own lane-change maneuver even if nearby vehicles are moving. (ii) Similarly to [12], we can apply the proposed model to the case of more than three-lane roads. This paper determines lane-change directions based on the incentive score led by MOBIL whereas [12] fixes them as a prerequisite.

The rest of this paper is organized as follows: Section II gives a traffic model on highways and a longitudinal acceleration model based on IDM. Section III presents a novel lane change rules and Section IV illustrates the effectiveness of the proposed algorithm through simulations. Section V finally shows the summary and future prospects.

II. AUTOMATED VEHICLE MODEL ON HIGHWAYS

This paper considers a microscopic traffic model on highways with m-lanes ($m \geq 1$) as shown in Fig. 1.

Let us first introduce the parameters and vehicle dynamics of vehicle i on the highway. We define x-axis along the downstream direction on the highways and y-axis as the lateral direction of x-axis. Table I lists all of the state variables on the vehicle i at time $t \in \mathbb{R}$. Note that $(p_x^i(t), p_y^i(t)) \in \mathbb{R} \times [0, mW]$, $v_x^i(t) \geq 0$ and W [m] is the lane width. Following to [13], [1], the vehicle dynamics of the vehicle i are divided into the longitudinal traffic model along the road (x-direction) and the lateral (lane-change) model. Therefore, the vehicle i's dynamics are expressed by

$$\dot{v}_x^i(t) = u_x^i(t),\ \dot{p}_x^i(t) = v_x^i(t), \tag{1a}$$
$$\dot{v}_y^i(t) = u_y^i(t),\ \dot{p}_y^i(t) = v_y^i(t). \tag{1b}$$

The main challenge of this paper is to systematically control the acceleration input $u_x^i(t)$ and $u_y^i(t)$ achieving the best trajectory of each vehicle i under collision avoidance sequentially. $u_x^i(t)$ and $u_y^i(t)$ normally depend on the states of the host vehicle i and the surrounding vehicles within the considerable distance ρ (green zone in Fig. 1). In this paper, we suppose that each vehicle can communicate with the vehicles within ρ (colored zone in Fig. 1) via V2V communication. The symbols of i's surrounding vehicles are defined in Appendix. Human-drivers practically change lanes with using a turn signal to inform the surroundings of their lane-change behavior in advance. Then, a following car starts to track the new preceding car instead of the current leading car even though the new preceding car travels on the lane before lane-change. The symbols of i's surrounding vehicles take into account such situations clearly. For i's preceding vehicle j at time t, the bumper-to-bumper distance between j and i and its relative velocity are respectively described by

$$S_j^i(t) \ := \ \left(p_x^j(t) - l_x^j(t)\right) - p_x^i(t), \tag{2a}$$
$$V_j^i(t) \ := \ v_x^i(t) - v_x^j(t), \tag{2b}$$
$$D_j^i(t) \ := \ v_d^i(t) - v_d^j(t). \tag{2c}$$

We next introduce a longitudinal acceleration model to determine $u_x^i(t)$. This paper uses a typical longitudinal acceleration model called *Intelligent Driver Model (IDM)* [2], which is a car-following model during normal driving on single-lane. IDM is known as an accident-free model producing realistic acceleration profiles and depends on i's local information and the relative position $S_{\mathrm{L}}^i(t)$ and velocity $V_{\mathrm{L}}^i(t)$ to the preceding vehicle $\mathrm{L} = \mathrm{L}(i,t)$. To be concrete, i's IDM-based dynamic acceleration/deceleration at time t is represented by

$$u_x^i(t) = a_0 \left[1 - \left(\frac{v_x^i(t)}{v_d^i(t)}\right)^{\delta} - \left(\frac{s^*\left(v_x^i(t), V_{\mathrm{L}}^i(t)\right)}{S_{\mathrm{L}}^i(t)}\right)^2\right], \tag{3a}$$

$$s^*(v_x^i, V_{\mathrm{L}}^i) = s_0 + \max\left\{0, v_x^i T_{hd} + \frac{v_x^i V_{\mathrm{L}}^i}{2\sqrt{a_0 b_0}}\right\}, \tag{3b}$$

where s^* represents an ideal inter-vehicle distance and the other parameters are described in Table II. If L does not exist, we conveniently set $S_{\mathrm{L}}^i(t) = \infty$ and $V_{\mathrm{L}}^i(t) = 0$. The velocity v_x^i of the vehicle i with (3) eventually approaches L's steady-state velocity (i's desired velocity v_d^i if L does not exist) [1].

We finally introduce a lateral acceleration model. The optimal lateral trajectory during lane change is generally

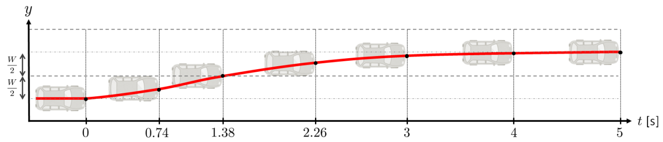


Fig. 2. Time evolution of lateral positions $p_y^i(t)$ along (1b) and (4) with $p_y^i(0) = W/2$ and $p_d^i(t) = 3W/2$ for $t \geq 0$ during lane change. The vehicle completes lane-change within $\Delta T = 5$s.

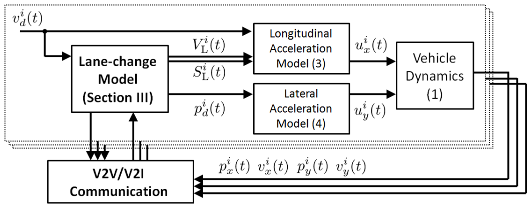


Fig. 3. Block diagram of multi-vehicle traffic system on highways.

described by a quartic polynomial curve or a spline curve, which is a solution of an optimization problem on lane-change maneuvers [10], [11], [13]. In this paper, to generate a lateral acceleration control input (1b), let us consider a pre-defined lateral trajectory (see Fig. 2) given by

$$u_y^i(t) = 1.3(p_d^i(t) - p_y^i(t)) - 2v_y^i(t), \tag{4}$$

by referring to the optimal trajectory shown in Fig. 3 of [13]. The desired position p_d^i on the y-axis takes the center line of the desired lane, i.e., $p_d^i(t) \in \{(2k+1)W/2, k = 1, \ldots, m\}$. We see from Fig. 2 that the vehicle completes lane-change within $\Delta T := 5$s.

The main objective of this approach is that, in order to compute acceleration levels based on (3) and (4), each vehicle i autonomously determines his desired longitudinal velocity $v_d^i(t)$, desired lateral position $p_d^i(t)$ at every decision time while communicating with neighboring vehicles and an infrastructure. The block diagram of the overall traffic system is shown in Fig. 3. In the next section, given $v_d^i(t)$, we will present a lane-change maneuver to determine $p_d^i(t)$.

III. Lane Change Maneuvers

A. Objective and Procedure Outline

In this section, we propose a novel lane-change rule taking into account the traffic model shown in Section II in order to improve the traffic flow and reduce the traffic jam. To be concrete, as the traffic dynamics and the corresponding trajectory planning of the vehicles have already provided, the main objective of this section is how each vehicle i appropriately selects (i) a lane-change to the left-side lane ($j = \mathrm{L}$), (ii) a lane-change to the right-side lane ($j = \mathrm{R}$), or (o) a current mode (lane-keep or during lane-change) at each decision time while guaranteeing the safety space between the neighbor vehicles. All vehicles with IDM guarantee the safety condition unless someone changes lanes. Therefore, the key issue is to predict and make a safety motion trajectory of the vehicles by using V2V information and the above common dynamical model.

To achieve the objectives, we propose a novel lane-change rule, which is divided into the following four steps:

Step 1. (Necessity) Each vehicle independently determines whether he concretely considers the lane-change motion while taking into account his current states.

Step 2. (Priority) Each vehicle independently prioritizes the options (i), (ii) and (o) in the order of the safest motion trajectory based on his cost function.

Step 3. (Feasibility) Each vehicle selects the most suitable option of $p_d^i(t)$ from (i), (ii) or (o) while communicating his lane-change information to the neighbors.

Step 4. (Implementation) Each vehicle travels along (1) with (3) and (4) until the next lane-change decision. Return to Step 1.

In this procedure, each vehicle makes decisions autonomously by using his desired states, his own measured data and V2V information in real time. However, many of the previous papers, at least [7], [1], assume that a specific vehicle tries to travel on a specific lane. Hence, it is necessary to reveal the prerequisites mathematically to achieve the objective presented in this paper. Then, we formulate the cost functions and the conditions achieving the objective at Steps 1–3 in the next subsection.

B. Cost Function and Criteria at Each Step

Step 1. Let us first consider candidates of host vehicles requesting a lane-change. This paper introduces two options for each target lane $j = \mathrm{L}, \mathrm{R}$, respectively.

Option (I): The objective of each vehicle is that his actual velocity $v_x^i(t)$ approaches to a suitable specified velocity $v_d^i(t)$. However, a slower preceding vehicle prohibits the personal objective. Therefore, the vehicle i needs to change lane if the following conditions hold:

$$
\begin{aligned}
|p_y^i(t) - p_d^i(t)| &< \epsilon_p && \text{(5a)}\\
v_x^i(t) &< v_d^i(t) - \epsilon_v^1 && \text{(5b)}\\
v_x^{\mathrm{L_C}(i,t)}(t) &< v_d^i(t) + \epsilon_v^2 && \text{(5c)}
\end{aligned}
$$

where $\epsilon_p > 0$, $\epsilon_v^1 > 0$ and $\epsilon_v^2 > 0$ are appropriately small values. (5a), (5b) and (5c) mean a lane-keep mode, a underspeed condition and a slack condition of the current preceding vehicle $\mathrm{L_C}(i,t)$, respectively.

Option (II): From the knowledge acquired through simulations (see Section IV for more details), we see that, under the only selfish condition, several vehicles traveling at the same velocity make a chain-like form on multiple lanes and cause traffic congestions in dense traffic. To solve the issue, we need to identify and move the head vehicle of the platoon. Hence, we give the following altruistic condition.

$$
\begin{aligned}
|p_y^i(t) - p_d^i(t)| &< \epsilon_p && \text{(6a)}\\
v_x^i(t) &\geq v_d^i(t) - \epsilon_v && \text{(6b)}\\
D_i^{\mathrm{F_C}(i,t)}(t) &> 0 && \text{(6c)}\\
V_i^{\mathrm{F}_j(i,t)}(t) &\leq 0 && \text{(6d)}
\end{aligned}
$$

Even if the host vehicle i travels at the desired velocity, the desired velocity of the current following car $\mathrm{F_C}(i,t)$ is faster than that of i and the velocity of the post following car $\mathrm{F}_j(i,t)$ after lane-change is slower than or equal to that of i. Then, if i changes lane, a passing lane for faster vehicles (at least $\mathrm{F}_{\mathrm{C}}(i,t)$) occurs.

Step 2. We next introduce safety and incentive criteria based on MOBIL [7], [1] in order to change lane safely and enhance traffic flow efficiency. Similarly to [7], [1], we assume that i's neighbor vehicles keep the current driving mode and i's preceding vehicles keep their current velocity until the host vehicle i completes lane-change to the lane $j \in \{\mathrm{L}, \mathrm{R}\}$. Then, the basic perspective of MOBIL is to evaluate the accelerations for not only the host vehicle i traveling from the current lane to the target lane but also the current $\mathrm{F}_{\mathrm{C}}(i,t)$ and new followers $\mathrm{F}_j(i,t)$ during lane-change, which can be described by

$$g_j^i = \Delta a_j^i + \alpha \left(\Delta a_j^{\mathrm{F}_{\mathrm{C}}(i,t)} + \Delta a_j^{\mathrm{F}_j(i,t)} \right), \tag{7}$$

where $\alpha \geq 0$ indicates a politeness factor. $\Delta a_j^h := a_j^h - a_c^h$ indicates the difference of the acceleration of the vehicle h when the vehicle i selects a lane-change to the lane j ($k = j$) or keeps on traveling on the current lane ($k = c$), respectively. For each scenario $k(= j, c)$, the h's predicted average acceleration a_k^h for the next ΔT is given by

$$a_k^h := \frac{1}{\Delta T} \int_t^{t+\Delta T} u_x^h(\tau) d\tau \tag{8}$$

along the dynamics shown in Section II. Note that the vehicle i can compute g_j^i by using V2V communication with the neighbors.

MOBIL imposes a safety criterion to avoid urgent deceleration of the succeeding vehicles during i's lane-change, which is described by

$$a_j^i(\tau) > -b_s,\ a_j^{\mathrm{F}_{\mathrm{C}}(i,t)}(\tau) > -b_s,\ a_j^{\mathrm{F}_j(i,t)}(\tau) > -b_s, \tag{9}$$

for all $\tau \in [t, t+\Delta T]$, where $b_s > 0$ [m/s] is maximum deceleration. Under the above condition, the vehicle i basically executes the lane-change motion to j if the following incentive criterion holds:

$$g_j^i > g_{th} \tag{10}$$

where g_{th} is the lane-change threshold. In case of (I) selfish condition, we basically use $g_{th} := g_{th}^{\mathrm{I}} > 0$ following to [7], [1]. On the other hand, in case of (II) altruistic condition, as i and $\mathrm{F}_j(i,t)$ need to decelerate their own longitudinal velocity, we set an appropriate negative value as g_{th}, i.e., $g_{th} := g_{th}^{\mathrm{II}} < 0$. It is consequently expected that i's surrounding vehicles decelerate temporarily but that the future traffic flow is greatly improved. Finally, following to [1], the vehicle i preferentially selects an action maximizing an incentive score g_j^i from all admissible options. Of course, if there is no the left-side lane $j = \mathrm{L}$ (the right-side lane $j = \mathrm{R}$), i.e, $p_d^i(t) + W$ ($p_d^i(t) - W$) $\in [0, mW]$, the lane-change motion is removed from admissible candidates.

One of additional options is to consider the preference for each lane. To solve the problem, we can use g_{th} depending on the relationship between the current lane and the destination following to [2], [1]. However, the application will be discussed in a separate paper due to page constraints.

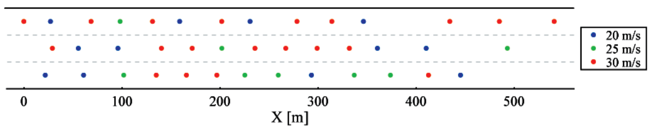


Fig. 4. Initial configuration of 40 vehicles on highways. The vehicles with $v_d^i = 20, 25, 30$ m/s are drawn as blue, green and red dots, respectively.

Step 3. As each vehicle can compute the conditions and g_j^i independently in Steps 1 and 2, we need to guarantee two action constraints on the surrounding vehicles. One is the assumption that the neighbors keep the current driving mode as mentioned in Step 2. The other is to prevent the vehicle with the blue arrow on the purple lane from invading the target lane as shown in Fig. 1. To satisfy the two constraints, we propose a novel algorithm based on g_j^i as follows.

If the longitudinal distance between arbitrary two vehicles is more than ρ, the whole platoon can be divided into two groups because there is no causal relationship between the groups about collision avoidance. We thus focus on a divided group, in which the set of the vehicles is denoted by $\mathcal{N}$ and the set of g_j^i for feasible options in $\mathcal{N}$ is denoted by $\mathcal{G}$. The supervisor (infrastructure) firstly finds the vehicle i and the corresponding lane-change direction j maximizing g_j^i from $\mathcal{G}$. As a pair of i and j maximizing g_j^i is accepted, $\mathrm{L}_{\mathrm{C}}(i,x)$, $\mathrm{F}_{\mathrm{C}}(i,x)$ $\mathrm{L}_j(i,x)$ and $\mathrm{F}_j(i,x)$ are compelled to keep the current mode. In addition, to prevent $\mathrm{L}_{-j}(i,x)$, $\mathrm{F}_{-j}(i,x)$ ($-j = \mathrm{R}$ if $j = \mathrm{L}$ and vice versa) and the vehicles between $p_x^{\mathrm{L}_j(i,x)}$ and $p_x^{\mathrm{F}_j(i,x)}$ on a lane next to the j-side lane from invading the lanes related to i's lane-change, their feasible actions are also restricted. The set of the remaining feasible g_j^i is redefined as $\mathcal{G}$. The above decision procedure is repeated until all the vehicles in $\mathcal{N}$ determine the next strategy. The other groups also execute the above methodology, respectively.

IV. Simulation

We finally demonstrate the effectiveness of the proposed algorithm through simulations on highways with $m = 3$ lanes. Each constant is basically based on a realistic situation [1], [7], [14] and defined in Tables I and II. In addition, we set $W = 3.5$ m, $b_s = 2.0$ m/s^2 and $\rho = 150$ m. Then, we run the lane-change algorithms proposed in Section III for 480s from the initial configuration of 40 vehicles shown in Fig. 4, where the vehicles with $v_d^i = 20, 25, 30$ m/s are drawn as blue, green and red dots, respectively. Each vehicle executes the lane-change decision at every 0.5 s.

Let us first consider the only (I) selfish condition with $\epsilon_p = 0.01$, $\epsilon_v^1 = 0.5$, $\epsilon_v^2 = 1.0$, $\alpha = 0.5$ and $g_{th}^{\mathrm{I}} = 0.1$ [1], [7]. Fig. 5 shows the configuration of the platoon at $t = 5$, 20, 40 s and the terminal time 480 s. Now, we focus on the slowest (blue) vehicles 1, 2, 3 and the fastest (red) vehicle 4 around $p_x^i(5) = 500$ m shown in Fig. 5 (a). We

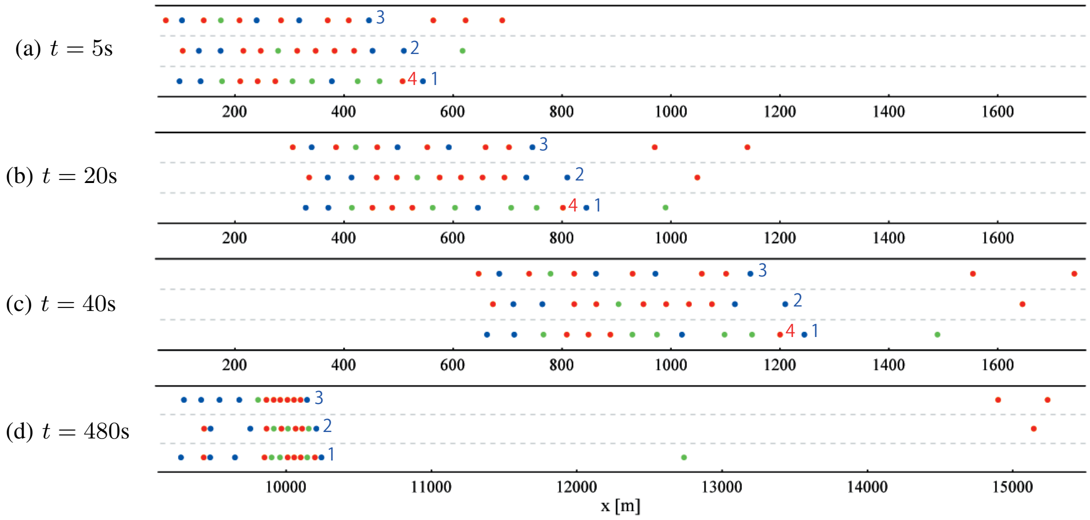


Fig. 5. Configuration of the target platoon in case of (I) the selfish condition at $t = 5, 20, 40$ and 480 s.

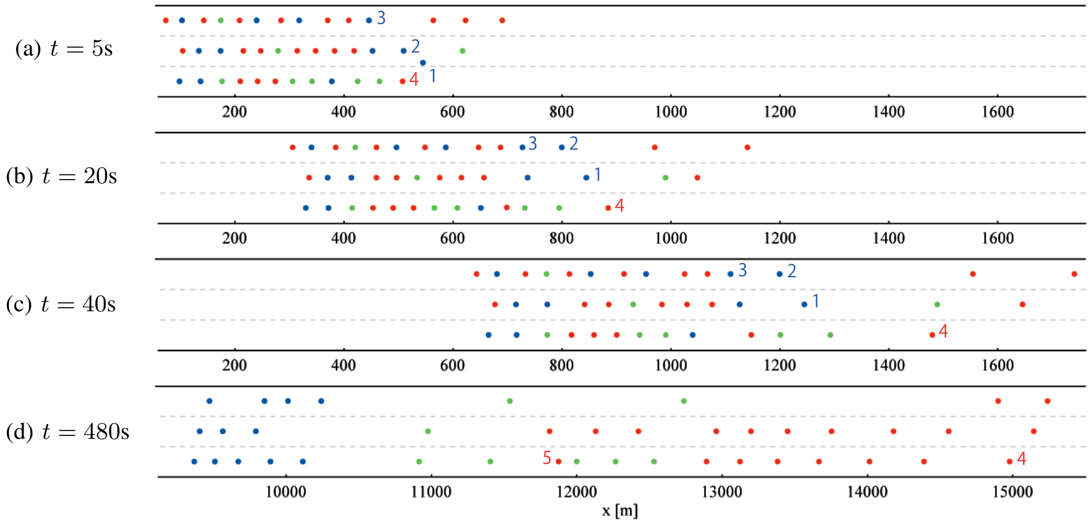


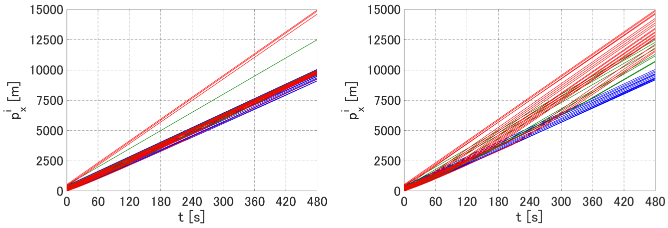
Fig. 6. Configuration of the target platoon in case of not only (I) the selfish condition but also (II) the altruistic condition at $t = 5, 20, 40$ and 480 s.

see from (a)–(c) that the vehicles 1 and 2 do not change lanes in order to avoid urgent deceleration of the succeeding vehicles and that the vehicle 4 cannot overtake the vehicles 1 and 2. As a result, we see from Fig. 5 (d) that the vehicles 1, 2 and 3 cause traffic jams of the succeeding cars. On the other hand, we next consider the case of not only (I) the selfish condition but also (II) the altruistic condition with $g_{th}^{\mathrm{II}} = -1.0$ and the configurations of the platoon at the same time as Fig. 5 are shown in Fig. 6. We see from Fig. 6 (a) that the vehicle 1 encourages lane-changes thanks to the condition (II). Consequently, we see from Fig. 6 (b) and (c) that the vehicle 2 moved to adjacent lane in order to avoid collision and that the vehicle 4 passed the vehicle 1. Fig. 6 (d) indicates that the faster vehicles pass the slower vehicles as a whole. Figures 7 and 8 illustrate the time evaluation of longitudinal positions and velocity of each vehicle, respectively. From Fig. 7, we can confirm the observations for Figs. 5 and 6. Furthermore, from Fig. 8, it can be seen that the proposed method with (I) and (II) eventually leads most of the vehicles to their desired velocity whereas the case without (II) cannot improve the velocity tracking performance of the vehicles with $v_d^i = 25, 30$ m/s. Note that the red vehicle with $v_x^i(480) = 27$ m/s in Fig. 8 (b) indicates the vehicle 5 in Fig. 6 (d) and decelerates because of the preceding vehicle with a desired velocity 25 m/s.

We next compare the two conditions by using a performance index introduced in [14]. The index is wasteful travel time (delay) per unit distance, compared with the desired travel time. Here, this paper uses the average of the wasteful travel time of each vehicle, i.e.,

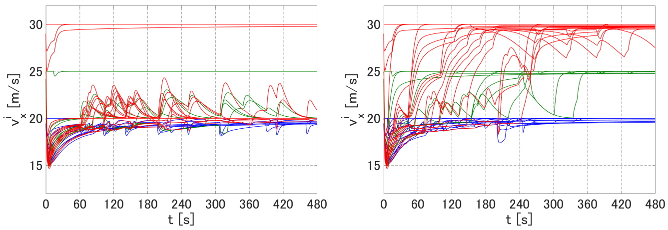
$$I := \frac{1}{40}\sum_{i=1}^{40}\frac{1}{480}\int_0^{480}\left(\frac{1}{v_x^i(t)} - \frac{1}{v_d^i(t)}\right)dt. \tag{11}$$

Under the above setting, the score in the case of (I) is $I =$



(a) In case of (I). (b) In case of (I) and (II).

Fig. 7. Time evolutions of the vehicles' longitudinal positions $p_x^i(t)$. The line colors indicate the same as Fig. 4.



(a) In case of (I). (b) In case of (I) and (II).

Fig. 8. Time evolutions of the vehicles' longitudinal velocity $v_x^i(t)$.

9.66×10^{-3} s/m and the score in the case of both (I) and (II) is $I = 3.35 \times 10^{-3}$ s/m. Therefore, by taking into account (II) altruistic condition, each vehicle can travel 63 s per 10 km faster than the simple condition with (I) on average. The result indicates that the presented lane-change maneuver with both (I) and (II) can greatly reduce economic losses caused by wasteful traffic jams.

V. Conclusions

We have investigated a smart lane change mechanism of autonomous vehicles with IDM on highways with multiple lanes. In particular, we have proposed an autonomous lane-change maneuver in continuous space. The key technique of the proposed maneuver is to consider not only selfish conditions to track personal velocity tracking performance but also altruistic conditions to improve the driving performance of the succeeding vehicles. We have also demonstrated through simulation that the proposed algorithm enhances heterogeneous traffic flow efficiency while avoiding collisions and wasteful traffic jams in dense traffic. As a result, each vehicle with the proposed maneuver can travel about 1 minute per 10 km faster than the conventional condition on average. One of the future directions is to determine a desired longitudinal velocity $v_d^i(t)$ and the most preferred lane of each vehicle by using V2I communication and real-time traffic information.

Appendix

The symbols on the vehicle i's neighbor vehicles at time t shown in Table I are defined as

$$\mathrm{L_L}(i,t) := \arg\min_{j \in L_t^i \cap \mathcal{L}_t^i} p_x^j(t),\ \ \mathrm{F_L}(i,t) := \arg\max_{j \in L_t^i \cap \mathcal{F}_t^i} p_x^j(t),$$
$$\mathrm{L_C}(i,t) := \arg\min_{j \in C_t^i \cap \mathcal{L}_t^i} p_x^j(t),\ \ \mathrm{F_C}(i,t) := \arg\max_{j \in C_t^i \cap \mathcal{F}_t^i} p_x^j(t),$$
$$\mathrm{L_R}(i,t) := \arg\min_{j \in R_t^i \cap \mathcal{L}_t^i} p_x^j(t),\ \ \mathrm{F_R}(i,t) := \arg\max_{j \in R_t^i \cap \mathcal{F}_t^i} p_x^j(t),$$

where $\mathcal{L}_t^i := \{j \mid p_x^i(t) < p_x^j(t) \le p_x^i(t) + \rho\}$, $\mathcal{F}_t^i := \{j \mid p_x^i(t) + \rho \le p_x^j(t) \le p_x^i(t)\}$, $L_t^i := \{j \mid c_t^i W < p_l^j \le (c_t^i + 1)W$ or $c_t^i W < p_r^j \le (c_t^i + 1)W\}$, $C_t^i := \{j \mid (c_t^i - 1)W < p_l^j \le c_t^i W$ or $(c_t^i - 1)W < p_r^j \le c_t^i W\}$, $R_t^i := \{j \mid (c_t^i - 2)W < p_l^j \le (c_t^i - 1)W$ or $(c_t^i - 2)W < p_r^j \le (c_t^i - 1)W\}$, $p_l^j := \max\{p_y^j(t), p_d^j(t)\} + l_y^j/2$, $p_r^j := \min\{p_y^j(t), p_d^j(t)\} - l_y^j/2$, $c_t^i := \lceil p_y^i(t)/W \rceil$, and $\lceil x \rceil := \min\{m \in \mathbb{Z} \mid m \ge x\}$ is the ceiling function. From $\mathrm{L_L}(i,t)$, $\mathrm{L_C}(i,t)$ and $\mathrm{L_R}(i,t)\}$, we detect candidates $\mathcal{L}$ on lanes included in $[p_r^i, p_l^i]$ and set $\mathrm{L}(i,t) := \mathrm{argmin}_{j \in \mathcal{L}}\, p_x^j(t)$.

Acknowledgment

The authors would like to thank Mr. S. Wataya and Mr. S. Kobayashi for their contributions in the simulations.

References

[1] M. Treiber and A. Kesting, *Traffic Flow Dynamics: Data, Models and Simulation*, Springer-Verlag, 2013.

[2] M. Treiber, A. Hennecke and D. Helbing, "Congested traffic states in empirical observations and microscopic simulations," *Physical Review E*, vol. 62, no. 2, pp. 1805–1824, 2000.

[3] X. Liu, K. Ma and P.R. Kumar, "Towards provably safe mixed transportation systems with human-driven and automated vehicles," *Proc. IEEE 54th Conf. Decision and Control*, pp. 4688–4694, 2015.

[4] M.A.S. Kamal, J. Imura, T. Hayakawa, A. Ohata and K. Aihara, "Smart driving of a vehicle using model predictive control for improving traffic flow," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 2, pp. 878–888, 2014.

[5] W. Cao, M. Mukai, T. Kawabe, H. Nishira and N. Fujiki, "Cooperative vehicle path generation during merging using model predictive control with real-time optimization," *Control Engineering Practice*, vol. 34, pp. 98–105, 2015.

[6] T. Takagi, T. Hatanaka and M. Fujita, "Collision avoidability analysis of vehicle platoon under V2V2I communication," *Trans. the Institute of Systems, Control and Information Engineers*, vol. 25, no. 7, pp. 181–188, 2012 (in Japanese).

[7] A. Kesting, M. Treiber and D. Helbing, "General lane-changing model MOBIL for car-following models." *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1999, pp. 86–94, 2007.

[8] M.A.S. Kamal, S. Taguchi and T. Yoshimura, "Efficient vehicle driving on multi-lane roads using model predictive control under a connected vehicle environment," *2015 IEEE Intelligent Vehicles Symposium*, pp. 736–741, 2015.

[9] M. Mukai and T. Kawabe, "Model predictive control for lane change decision assist system using hybrid system representation," *SICE-ICASE International Joint Conference*, pp. 5120–5125, 2006.

[10] J. Nilsson, J. Silvlin, M. Brannstrom, E. Coelingh and J. Fredriksson, "If, when, and how to perform lane change maneuvers on highways," *IEEE Intelligent Transportation Systems Magazine*, vol. 8, no. 4, pp. 68–78, 2016.

[11] Q.H. Do, H. Tehrani, S. Mita, M. Egawa, K. Muto and K. Yoneda, "Human drivers based active-passive model for automated lane change," *IEEE Intelligent Transportation Systems Magazine*, vol. 9, no. 1, pp. 42–56, 2017.

[12] D. Desiraju, T. Chantem and K. Heaslip, "Minimizing the disruption of traffic flow of automated vehicles during lane change," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 3, pp. 1249–1258, 2015.

[13] M. Werling, J. Zeigler, S. Kammel and S. Thrun, "Optimal trajectory generation for dynamic street scenarios in a Frenet frame," *Proc. 2010 IEEE International Conference on Robotics and Automation*, pp. 987–993, 2010.

[14] U. Lhan, P. Basaras, L. Schmidt-Thieme, A. Nanopoulos and D. Katsaros, "Analyzing cooperative lane change models for connected vehicles," *Proc. 2014 Inter. Conf. Connected Vehicles and Expo*, pp. 565–570, 2014.