On the Impact of Cooperative Autonomous Vehicles in Improving Freeway Merging: A Modified Intelligent Driver Model-Based Approach

Mofan Zhou, Xiaobo Qu, and Sheng Jin

***Abstract*—Transport researchers and practitioners have long been seeking capable solutions to deal with the traffic oscillations caused by freeway merging. Although existing approaches based on ramp metering have improved the overall efficiency of on-ramps, their performance is still far below the theoretical capacity. The recently proposed detecting technology of autonomous vehicles (AVs) provides an alternative for maximizing the merging efficiency by developing and using appropriate controllers for AVs. In this paper, we develop a cooperative intelligent driver model in order to examine the system performance under different proportions of AVs. The results show that, with a proper vehicle-to-vehicle controlling mechanism, an increasing percentage of AVs will reduce the total travel time and smooth traffic oscillations.**

***Index Terms*—Autonomous vehicles (AVs), vehicle-to-vehicle communication, adaptive cruise control (ACC), cooperative intelligent driver model (CIDM), detecting technologies.**

I. Introduction

In order to improve the urban mobility, researchers and practitioners have made numerous efforts to improve freeway efficiency and counter traffic congestion. It has been well recognized that most freeway congestion results from traffic oscillations (or stop-and-go) near freeway ramps, caused by merging activities. Mauch and Cassidy [1] use loop detector data to show that freeway oscillations frequently form and grow near ramps, suggesting that merging plays an essential role. Zheng *et al.* [2] describe how merging near freeway ramps affects the growth of traffic oscillation. Indeed, freeway sections near ramps are considered as the bottlenecks of the freeway system. In this regard, solutions have to be sought that are capable of addressing the oscillations caused by freeway merging.

Manuscript received November 23, 2015; revised April 24, 2016 and July 25, 2016; accepted September 1, 2016. Date of publication September 29, 2016; date of current version May 29, 2017. This work was jointly supported by the Sustainable Built Environment National Research Centre of Griffith University, Gold Coast, QLD, Australia, under Grant 1.45; by Zhejiang Provincial Natural Science Foundation of China under Grant LY16E080003; and by the Key Science and Technology Innovation Team of Zhejiang Province under Grant 2013TD09. The Associate Editor for this paper was L. M. Bergasa.
(Corresponding author: Sheng Jin.)

M. Zhou is with the School of Engineering, Griffith University, Gold Coast, QLD 4222, Australia (e-mail: m.zhou@griffith.edu.au).

X. Qu is with the School of Civil and Environmental Engineering, University of Technology Sydney, Broadway, NSW 2007, Australia (e-mail: drxiaoboqu@gmail.com).

S. Jin is with the College of Civil Engineering and Architecture, Zhejiang University, Hangzhou 310058, China (e-mail: jinsheng@zju.edu.cn).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2016.2606492

Ramp metering has been widely deployed in urban areas since the 1960s [3]. By managing on-ramp traffic inflows, the application of meters not only reduces the average freeway delay [4], but also has positive impacts on travel time, emissions and highway safety [5]. However, based on the Twin Cities freeways data, Zhang and Levinson [4] point out that ramp metering increases the queue discharge flow rate by only 3%. Even with this increase, oscillation still occurs from time to time. In light of this, additional efforts need to be made to improve the efficiency of freeway merging. The recent proposed merging technology of Inter-Vehicle Communication (IVC) and the connected vehicles [6]–[8] provides the potential for managing the freeway ramps efficiently. This technology is proposed to be the basis for the next generation of vehicles on roads [9]. In this research, we focus on IVC through detecting technology and Adaptive Cruise Control (ACC) as they have already been readily introduced to market. The longitudinal control in ACC has been studied extensively. However, due to the complexity of the lateral control, it has not yet been well developed. Further, self-driving cars (or autonomous vehicles (AVs)) have recently been designed and introduced [10]. Many believe that a combination of AVs and manually-driven vehicles (MVs) will soon share freeways and the AVs are most likely to be designed on the basis of detecting technology and ACC. In this regard, we assume the AVs, in this research, are not able to communicate but are capable of detecting the longitudinal and lateral driving conditions. This research is based on this critical assumption.

A Collaborative Driving System (CDS) with Cooperative Adaptive Cruise Control (CACC) has been proposed by Hallé and Chaib-draa [11]. CACC is based on ACC and designed for AVs to handle both longitudinal and lateral cooperation. In addition, van Arem *et al.* [12] conduct a simulation study for CACC vehicles. Their results indicate that AVs could improve the traffic stability only when a high-CACC-penetration rate ($>60\%$) occurs on freeways. Different from the above-mentioned two studies, this research is to improve the performance of CACC vehicles by modifying another widely accepted car-following model named Intelligent Driver Model (IDM). We incorporate a cooperative component within the well-established IDM developed by Treiber *et al.* [13] and rename the new model as Cooperative Intelligent Driver Model (CIDM) for AVs. In this research, the Full Velocity Difference Model (FVDM) is used to mimic MVs.

The contribution of this paper is threefold. First, a new CIDM model is developed to incorporate the cooperation of

AVs in the traditional IDM model. Second, we demonstrate that a proper vehicle to vehicle controlling mechanism with cooperation component could practically improve the freeway performance and smooth the traffic flow dynamics. Third, we conduct a sensitivity analysis to present the impact of AVs to freeway merging.

II. Microscopic Traffic Models

A. Modeling Human Driving Behavior

In recent decades, researchers have developed various microscopic car-following models. Some of the more prevalent are the Gazis-Herman-Rothery (GHR) [14]–[17] and Optimal Velocity (OV) styles of models [18]–[29]. OV-type models are microscopic models that clearly show the dynamic formation of congestion [21], [24], [26]. The FVDM, one of the improved OV-type models, is investigated by Jiang *et al.* [22]. This car-following model improves the performance when simulating a transition in traffic flow and estimating the evolution of the congestion.

The governing equation of the FVDM is:

$$a_n(t) = a\left[V(\Delta x) - v_n(t)\right] + \lambda\Theta(s_c - \Delta x) \times \Delta v \qquad (1)$$

where a_n denotes the acceleration rate of the nth vehicle at time t; a is the sensitivity constant; $v_n(t)$ is the vehicle velocity at time t; $V(\Delta x)$ is an empirical optimal velocity function; λ is a sensitivity factor; $s_c = 100$ m; $\Theta(x)$ denotes the Heaviside Function; Δx denotes the distance difference from the preceding vehicle; and Δv is the difference of the leader's velocity relative to the follower.

Developing a car-following model needs to take into account both relative speed and headway to a leading vehicle in order to describe all traffic situations [30], including the free non-interacting traffic which can be reflected by the an extra λ term: $\lambda\Theta(s_c - \Delta x) \times \Delta v$. By comparing speed trajectories generated by the OV model and the FVDM, the undesired high accelerations were avoided if the latter is chosen. Further, the vehicle motion delay time can be predicted more accurately using the FVDM [22]. In this regard, we choose the FVDM to simulate MVs.

B. Modeling Autonomous Vehicular Traffic

A well-defined AV model would allow subsequent vehicles to follow preceding vehicles with an optimal velocity and safe headway. Furthermore, from the perspective of a passenger, traveling in AVs is supposed to be an enjoyable experience. In other words, the discomfort induced by higher rates of acceleration or deceleration needs to be minimized by smoothing the travel trajectory. For the sake of creating a smooth trajectory, multi-detecting devices, such as equipping radars, could be incorporated into AVs. The AVs can then cooperate with and pre-act in relation to surrounding vehicles, depending upon the understanding of the detected traffic conditions.

In order to simulate the driving behaviors of AVs, in this paper, we use the CIDM with a cooperative driving strategy. The original IDM is first proposed by Treiber *et al.* [13] to simulate bottleneck congestions. Different from other traditional microscopic models, IDM provides collision-free behavior as well as a self-organized characteristic. IDM is also utilized in Adaptive Cruise Control (ACC) [31] for the following reasons: (a) it provides collision-free and smooth manner traffic flow; (b) environmental variable changes, such as deceleration of the preceding vehicle, will not result in turbulent traffic or, in particular, oscillation.

The IDM acceleration rate is presented as follows:

$$a_n = a\left[1 - \left(\frac{v_n}{v_0}\right)^4 - \left(\frac{s^*(v_n, \Delta v_n)}{\Delta x}\right)^2\right] \qquad (2)$$

This equation combines both an accelerating term $a_{\text{free}}(v) = a \times [1 - (v_n/v_0)^4]$ towards a desired speed v_0 on a free road, and a braking term $a_{\text{brake}}(\Delta x, v_n, \Delta v_n) = -a(s^*/\Delta x)^2$, where the s^* [32] is given by:

$$s^*(v_n, \Delta v_n) = s_0 + \max\left[0, v_n T + \frac{v_n \Delta v_n}{2\sqrt{ab}}\right] \qquad (3)$$

The minimum distance s_0 is designed for vehicles in low-velocity circumstances; a denotes the same parameter as in (2) that represents maximum acceleration; T is a safe time gap; b is the desired deceleration rate.

In order for cooperative AVs to obtain traffic information from one or more preceding vehicles, the capability for spatial anticipation is required in the CIDM. Based on the concept of spatial anticipation in the Human Driver Model (HDM), which has been proposed as an extension of the IDM [33], [34], this anticipation can now also be applied to the proposed CIDM, which splits the IDM's a_n into the following:

$$a_n(\Delta x, v_n, \Delta v_n) = a_n^{\text{free}} + \sum_{m}^{n-1} a_{\text{nm}}^{\text{int}}(\Delta x_{\text{nm}}, v_n, \Delta v_{\text{nm}}) \quad (4)$$

where $a_{\text{nm}}^{\text{int}}$ is a_{brake} with the consideration of vehicle-vehicle interaction, and a_n^{free} has the same definition as a_{free} above.

Given the multi-anticipation that strengthens their performance, AVs can theoretically detect more than one preceding vehicles in a longitudinal direction, but this still does not represent cooperative driving behavior well. Some critical scenarios, including forced merging from the on-ramp that triggers a large reduction in the preceding headway, would result in an unexpectedly high deceleration for following IDM-based vehicles. Therefore, more practical cooperative driving behavior needs to have greater predictive capabilities in both the longitudinal and latitudinal directions. Accordingly, cooperative rules are introduced here.

The first portion of these cooperative rules is from [31], [35], who conducted a traffic-state detection model using an Exponential Moving Average (EMA) concept (see (5)), by comparing v_{EMA} as the derivative term of x_{EMA} with the average velocity under a certain traffic condition. The best driving strategy then can be selected. Based upon this concept, the dynamic traffic changes that occur in front of AVs will be detected and responded (details can be found in [31].)

$$x_{\text{EMA}}(t) = \frac{1}{\tau}\int_{-\infty}^{t} e^{-(t-t')/\tau} x(t')dt' \qquad (5)$$

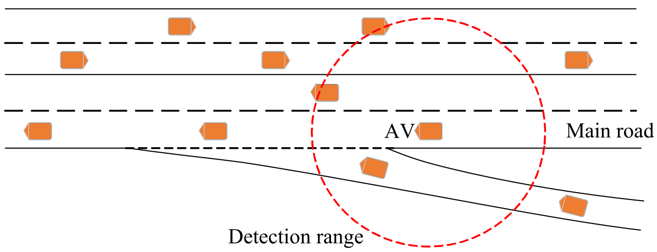

Fig. 1. Illustration of AVs' detection range.

TABLE I
λ_a, λ_b, λ_T, AND $\lambda_{\Delta x}$ VALUES FOR CIDM DURING MERGING

Merging condition	λ_a	λ_b	λ_T	$\lambda_{\Delta x}$
Before merge	1	1	2	Equation (7)
After merge	2	1	0.5	1

a, b, and T are replaced by the parameters shown in (6), and then substituted into (2) and (3) according to a certain driving strategy [31].

$$a = \lambda_a a, \quad b = \lambda_b b, \quad T = \lambda_T T \tag{6}$$

The second portion of the cooperative rules is a simplified Lane-Changing Impact (LCI) rule. Although LCI models have gradually been paid more attention over the last three decades, they normally focus on modeling macroscopic behavior [36]. Merging, as a mandatory type of lane-change, could significantly influence traffic dynamics on the main lane. With installing the detection equipment, ramp vehicles' can be detected instantly once they have entered the detection range as shown in Fig. 1. Within the detection ranges, AVs on the main road could thereby gently adjust their acceleration rates and prepare a larger gap in advance if they needed to cooperate with ramp vehicles.

Herein, we assume that AVs, to a certain extent, would give a larger gap for on-ramp vehicles in order to handle the uncertainty of human drivers and reduce the collision risk. Therefore, we introduce another multiplication factor, $\lambda_{\Delta x}$, to imitate the merging impact on the following traffic flow. In this paper, the aforementioned method is only being applied to AVs on the main road.

$$\lambda_{\Delta x} = \max\left[0.4, \left(\frac{\Delta x_0(t)}{R_d}\right)^2\right] \qquad \Delta x_0(t) \le R_d \tag{7}$$

$$\Delta x = \lambda_{\Delta x} \Delta x \tag{8}$$

where $\Delta x_0(t)$ is the remaining distance at time t from the merging point (or on-ramp entry), R_d is the detection range of the main-road AV, seen in Fig. 1. During the time when the main-road vehicles are preparing to accept the merged vehicles, other multiplication factors are adjusted according to Table I. The values for the multiplication factors are modified from [31]. The $\lambda_{\Delta x}$ is an extended factor to their original study in order to describe the merging cooperation.

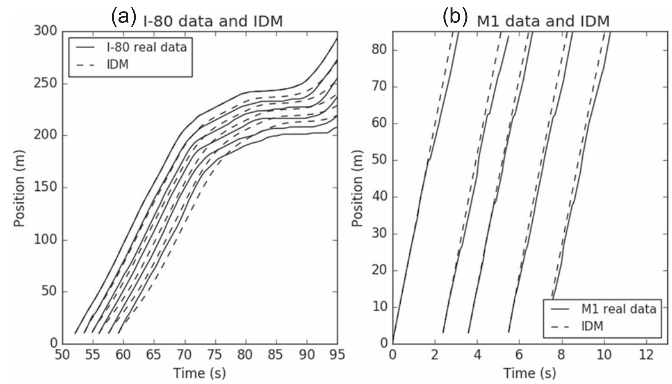

Fig. 2. Comparison of trajectories between real data and IDM.

III. AN ILLUSTRATIVE CASE STUDY OF PACIFIC MOTORWAY

A. Comparison of Trajectories

The CIDM is the model to simulate AVs' driving behaviors. Unfortunately, there is no any existing data to compare with. In order to evaluate the validity of the CIDM, we have to evaluate the similarity of the IDM with real data. Therefore, the trajectories data extracted from video images of northbound traffic on I-80 in Emeryville, California [37] and northbound traffic on M1 in Queensland are compared to the IDM trajectories. A section of trajectory data without lane-changing and merging are selected and shown in Fig. 2. A disturbance that is triggered by a lane-change maneuver, transmits forward to the selected platoon. In the IDM trajectories, by fixing the trajectory of the leading vehicle from the real data, the remaining trajectories are generated by the IDM model with default settings of: $v_0 =$ 110 km/h; $T = 1.1$ s; $a = 1.4$ m/s^2; $b = 2$ m/s^2; and $s_0 = 2$ m.

From Fig. 2(a), the IDM trajectory successfully reflects the propagation of disturbance and the oscillation phase. However, with these parameter settings, the gap distance tends to be shorter in the congested phase and longer in the free-flow phase. Furthermore, the deceleration and acceleration stages are more evenly compared to the real data. In addition, from Fig. 2(b), the IDM with default settings has the trajectories which are close to the traffic flow on the M1 if there is no disturbance. As a result, this property of IDM and IDM-based models could be utilized in the design of the AV car-following model.

B. Simulation Setup

We investigate a section of the freeway located in Brisbane, which is illustrated in Fig. 3. The freeway consists of three lanes in each direction. The figure only shows the northbound direction from the Gold Coast to Brisbane. At the on-ramp section, during traffic peak hours, vehicles from the Gold Coast and the southern suburbs of Brisbane contribute to a dense traffic flow.

In order to simulate the critical scenario, we assume the left blue lane (shown in Fig. 3) of the freeway to be the only lane affected by the merging maneuver, and we assume there is no lane changing from either the left or the right onto this blue lane. Apart from that, the main-road vehicles on the freeway are initialized with an incipient velocity (here taken to be

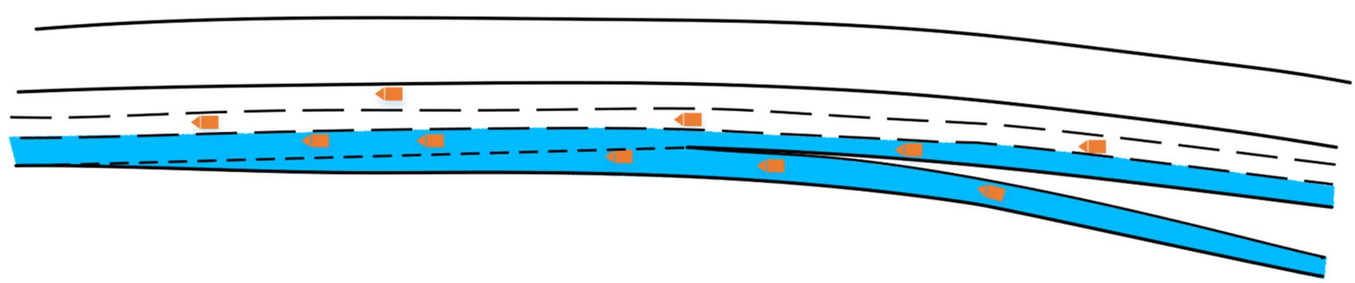

Fig. 3. Scenario of merging simulation.

TABLE II
MODEL PARAMETERS OF FVDM

Model parameter	CAR
a	0.41
s_c	100
λ	0.5

110 km/h as the speed limit) and time headway based on the flow circumstances. In this paper, the traffic flow on the freeway in the lane adjacent to the on-ramp and the ramp are set at 1800 veh/h. For this simulation, we generate 300 main road vehicles with the same initial state.

Lane-change types can be classified to two classes: discretionary lane change (DLC) and mandatory lane changes (MLC) [36], [38]. For vehicles on the ramp, their merging motion is MLC and can be represented by a lane-changing model introduced by Hidas [39]. Hidas [39] specified that the subject vehicle is the merging vehicle. The subject vehicle can merge into the target lane only if the gaps between the subject vehicle and leader on the target lane (g_l), and the subject vehicle and follower on the target lane (g_f) satisfy the following criteria:

$$g_l \geq g_{l,\min} \quad \text{and} \quad g_f \geq g_{f,\min} \tag{9}$$

$$g_{l,\min} = g_{\min} + \begin{cases} c_l(v_s - v_l), & \text{if } v_s > v_l \\ 0, & \text{otherwise} \end{cases}$$

$$g_{f,\min} = g_{\min} + \begin{cases} c_f(v_f - v_s), & \text{if } v_f > v_s \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $c_l = c_f = 0.9$; $g_{\min} = 2.0$ m which is the average minimum safe constant gap. All the parameter values are selected from [39] which are used in a simulation of on-ramp merging. Note that we assume the lane changing actions to be completed instantaneously while a lane change in reality is a continuous motion. Therefore, the estimated capacity could be overestimated as the duration of lane change is not taken into account.

MVs, which are simulated by the FVDM, are assumed to follow the parameters listed in Table II. The optimal velocity function in equation (1) is determined by the following: $V(\Delta x) = 16.8[\tanh 0.086(\Delta x - 25) + 0.913]$, which is calibrated from observed data on a Japanese motorway [24].

AVs, which are governed by the CIDM, are assumed to follow the parameters listed in Table III. Milanes *et al.* [40] and Milanés and Shladover [41] have conducted a test regarding the CACC vehicles. Considering the advantages of quick response and action by AVs, they found the shortest time gap to be 0.6 s.

TABLE III
MODEL PARAMETERS OF CIDM

Model parameter	CAR
Desired speed, v_0	110 km/h
Safe time gap, T	0.6 s
Maximum acceleration, a	1.4 m/s^2
Desired deceleration, b	2.0 m/s^2
Jam distance, s_0	2 m
Length of vehicle	4 m

As a result, we selected 0.6 s as the safe time gap for the CIDM. The other parameters remain the same as the IDM default. However, it should be noted that none of these parameters have been validated and tested. This needs to be accomplished in a future study. In addition, referring to Fig. 1, the detection range (R_d) is assumed as 30 m.

C. Trajectory

The trajectory of vehicles on the road represents the entire string stability and traffic dynamics. The trajectory graphs produced from the simulation results are depicted in Fig. 4. In this study, we compare four scenarios, with different proportions of AVs (0%, 5%, 15%, and 25%) to present the transitional phase as AVs are gradually introduced.

From (a) in Fig. 4, if there is 0% of AV penetration in the traffic stream, continuous and irregular merging behaviors would have a negative effect on string stability and result in an oscillation (stop-and-go scenario) in the upstream traffic flow. However, only a 5% AVs in the system can proportionately relieve the oscillation, as shown in Fig. 4(b). Further increases in the AV's proportion to 15% and 25% will lead to further improvements in the traffic flow stability.

AVs can smooth the trajectory and relieve the oscillation. However, the congestion occurs earlier and the oscillation may transmit further to the upstream when an AV-penetration-rate is less than 25%, which is illustrated in Fig. 4. In particular, the white gap between AV and MV trajectories, in Fig. 4(b)–(d), are evidence of how the oscillation is relieved and transmitted.

D. Driving Sensitivity

The previous IDM has the disadvantage of the high sensitivity due to the over-responding to lane-changing and merging. Kesting *et al.* [42] attempted to reduce the sensitivity issue for IDM-based vehicles. Their approach is a post-act method by making an assumption: *the leading vehicle will not change its*

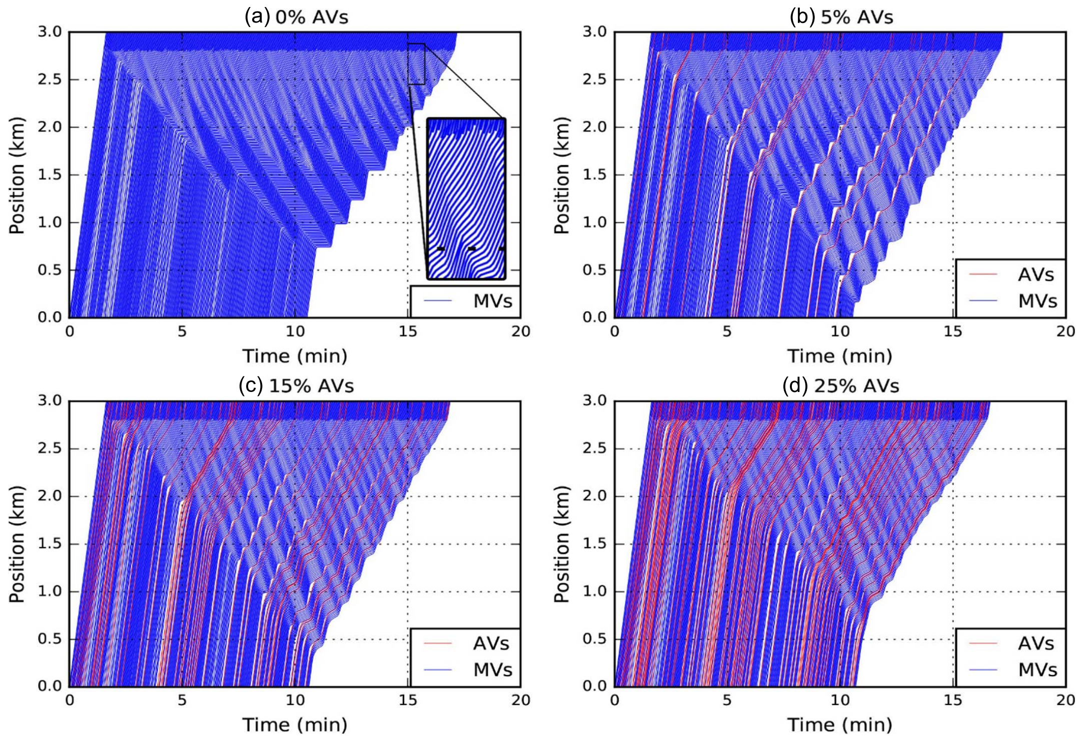

Fig. 4. Trajectories of 0%, 5%, 15%, and 25% of AVs.

acceleration for the next few seconds. Therefore, the acceleration adjustment will be delayed to after the cut-in maneuver. However, either a human or an AV should be able to take preaction to decelerate in advance, in order to avoid the potential collision. Therefore, our approach to reducing sensitivity is a proactive method. Therefore, the CIDM leads to a positive driving strategy that is more reliable and logical in an autonomous driving system.

E. Safety Analysis

The speed dispersion is well recognized as a measure for estimating the risk of traffic accidents or the safety of traveling [43]. Previous researchers have often used standard deviation (SD) to describe speed dispersion. Disturbed traffic flow has a greater value of SD, and a higher SD value indicates a higher risk of a traffic accident. By contrast, a lower level of SD represents a lower risk due to the fact that most of vehicles travel with similar speeds.

The SD results are shown in Fig. 5. These results indicate that without AVs on the road, the massive oscillation that is caused by merged-in vehicles results in a high SD (usually between 6 and 8). However, with an increasing number of AV penetrating into freeways, the SD could be reduced progressively. This also implies that the increase of AVs has a positive impact on traffic dynamics.

F. Travel Time

The travel time is used as a measure of driving efficiency. The average travel time is a performance measure for the overall transport system, evaluating the efficiency by looking at the economic cost of traffic jams.

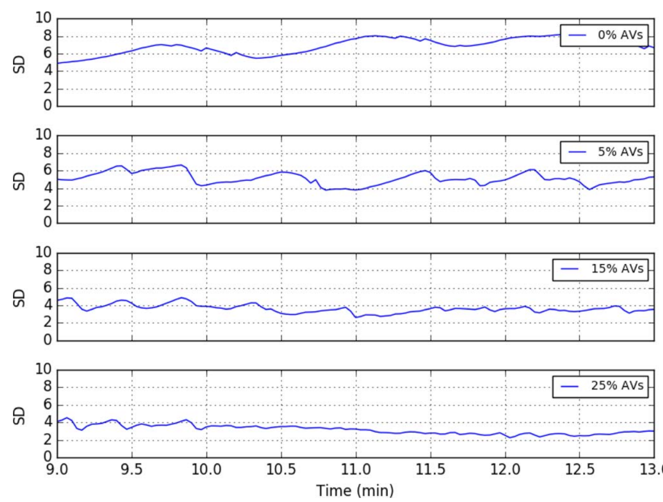

Fig. 5. Speed dispersion on a congested freeway segment (1.5–2.8 km), from 9th to 13th minute, under different proportions of CIDM-based AVs.

Based on the simulation result, the average travel times for the freeway traffic flow through the congested section, from 1 to 2.8 km, under different AV penetrations are shown in Fig. 6. In particular, it shows that the AVs can promote the efficiency of traveling on a congested road.

G. Space Mean Speed

The space mean speed takes a whole road segment into account and describes the speed more accurately than the time mean speed.

The result of space mean speed is shown in Fig. 7. Due to the severe oscillations when no AV is on the freeway, the space mean speed of this scenario tends to be lower than other cases. In addition, the penetration rate of AVs has a positive impact on space mean speed.

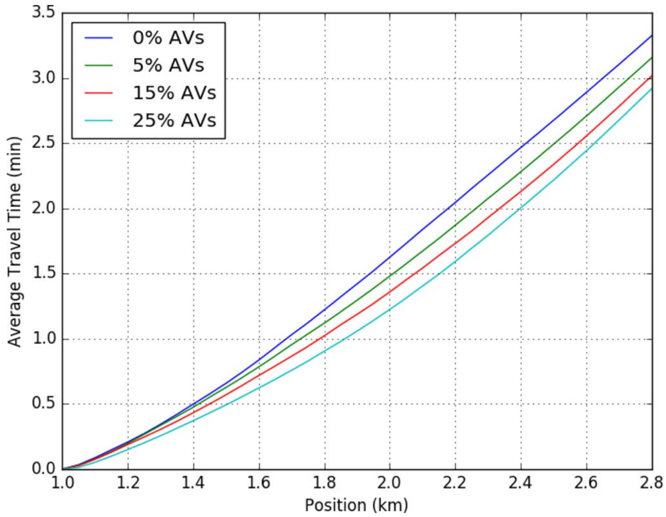

Fig. 6. Average travel time on the congested freeway segment (1–2.8 km).

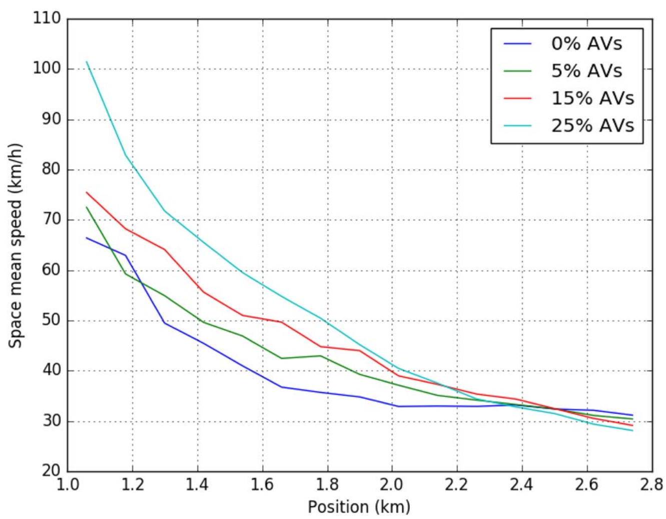

Fig. 7. Space mean speed on the congested road segment (1–2.8 km).

H. Sensitivity Analysis of Safe Time Gap

The safe time gap in the IDM has essential impacts on travel efficiency and safety when AVs are designed. Thus, the sensitivity analysis of the safe time gaps (0.4 s, 0.6 s, 0.8 s, 1 s and 1.2 s) has been carried out. For each safe time gaps, we simulate all cases (0%, 5%, 15% and 25% AVs) under the same initial condition. The average speed dispersion and average travel time for all cases are concluded in Tables IV and V.

The result in Table IV shows that with the increase of AVs' percentage in the mixed traffic flow, the overall speed dispersion for all cases reduces to a lower level, which indicates that the safety level is improved in all cases. However, the degrees of improvement are different, as a longer safe time gap can result in a greater improvement in speed dispersion. It can further relieve the oscillation. This is explainable as a longer safe time gap increases the average headway. As such, the overall travel speed can be harmonized and the safety level can be continuously improved.

TABLE IV
AVERAGE VALUE OF SPEED DISPERSION

Percentage of AVs	0.4 s	0.6 s	0.8 s	1.0 s	1.2 s
0%	6.86	6.86	6.86	6.86	6.86
5%	5.35	5.10	5.08	4.69	5.17
15%	3.59	3.61	3.51	2.86	3.07
25%	3.70	3.16	3.10	2.08	1.90

Note: These are average values of speed dispersion simulated by considering different safe time gap in the IDM for all cases.

TABLE V
AVERAGE TRAVEL TIME (IN MINUTES)

Percentage of AVs	0.4 s	0.6 s	0.8 s	1.0 s	1.2 s
0%	3.32	3.32	3.32	3.32	3.32
5%	3.12	3.15	3.23	3.18	3.24
15%	3.09	3.01	3.12	3.32	3.36
25%	2.81	2.91	2.92	3.45	3.49

Note: These are average travel time simulated by considering different safe time gap in the IDM for all cases. The unit for travel time is minute.

On the contrary, the trend of average travel time, shows in Table V, differs from the trend of average speed dispersion. Specifically, the safe time gap is negatively related to the average travel time. On the other hand, in this study, when the safe time gap is less than 1.0 s, the increase of the percentage of AVs can result in improving travel efficiency. Nevertheless, when the safe time gap is further increased to greater than 1 s, a higher AVs percentage does not improve the travel efficiency.

IV. CONCLUSION

It is anticipated that detecting technology is able to detect and foresee traffic conditions not only longitudinally (detecting several preceding vehicles) but also laterally (detecting vehicles in other lanes). A proposed CIDM-based controller determines the AV's acceleration/deceleration rate as a response to the actions of surrounding vehicles, with an aim to improve road capacity and string stability. CIDM-based AVs are, therefore, more capable of maximizing the impact of on-ramp merging vehicles. In doing so, CIDM-based AVs are able to eliminate or relieve freeway oscillations. According to the results of speed dispersion, a higher AV penetration rate indicates safer freeways if the proposed CIDM based controller is adopted. Further, a sensitivity analysis is carried out to illustrate that the safe time gap plays an essential role in improving travel efficiency and safety. In sum, the results show that the CIDM is a positive and proactive method that can be applied to freeway traffic.

REFERENCES

[1] M. Mauch and M. J. Cassidy, *Freeway Traffic Oscillations: Observations and Predictions*. Oakland, CA, USA: Univ. California, 2004.
[2] Z. Zheng, S. Ahn, and C. M. Monsere, "Impact of traffic oscillations on freeway crash occurrences," *Accident Anal. Prevention*, vol. 42, pp. 626–636, Mar. 2010.
[3] A. May, Jr., "Experimentation with manual and automatic ramp control," in *Traffic Control*, T. Horton, Ed. New York, NY, USA: Springer-Verlag, 1965, pp. 157–208.
[4] L. Zhang and D. Levinson, "Ramp metering and freeway bottleneck capacity," *Transp. Res. A, Policy Pract.*, vol. 44, pp. 218–235, May 2010.

[5] D. Levinson and L. Zhang, “Ramp meters on trial: Evidence from the twin cities metering holiday,” *Transp. Res. A, Policy Pract.*, vol. 40, pp. 810–828, Dec. 2006.

[6] M. Guériau, R. Billot, N.-E. El Faouzi, J. Monteil, F. Armetta, and S. Hassas, “How to assess the benefits of connected vehicles? A simulation framework for the design of cooperative traffic management strategies,” *Transp. Res. C, Emerg. Technol.*, vol. 67, pp. 266–279, 2016.

[7] J. Ma, X. Li, F. Zhou, J. Hu, and B. B. Park “Parsimonious shooting heuristic for trajectory design of connected automated traffic. Part II: Computational issues and optimization,” *Transp. Res. B, Methodol.* [Online]. Available: http://dx.doi.org/10.1016/j.trb.2016.06.010

[8] F. Zhou, X. Li, and J. Ma, “Parsimonious shooting heuristic for trajectory design of connected automated traffic. Part I: Theoretical analysis with generalized time geography,” *Transp. Res. B, Methodol.* [Online]. Available: http://dx.doi.org/10.1016/j.trb.2016.05.007

[9] P. Varaiya, “Smart cars on smart roads: Problems of control,” *IEEE Trans. Autom. Control*, vol. 38, no. 2, pp. 195–207, Feb. 1993.

[10] C. Urmson *et al.*, “Autonomous driving in urban environments: Boss and the urban challenge,” *J. Field Robot.*, vol. 25, pp. 425–466, 2008.

[11] S. Hallé and B. Chaib-draa, “A collaborative driving system based on multiagent modelling and simulations,” *Transp. Res. C, Emerg. Technol.*, vol. 13, pp. 320–345, 2005.

[12] B. van Arem, C. J. G. van Driel, and R. Visser, “The impact of cooperative adaptive cruise control on traffic-flow characteristics,” *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 4, pp. 429–436, Apr. 2006.

[13] M. Treiber, A. Hennecke, and D. Helbing, “Congested traffic states in empirical observations and microscopic simulations,” *Phys. Rev. E, Stat. Phys., Plasmas Fluids Relat. Interdiscip. Top.*, vol. 62, pp. 1805–1824, 2000.

[14] R. E. Chandler, R. Herman, and E. W. Montroll, “Traffic dynamics: Studies in car following,” *Oper. Res.*, vol. 6, pp. 165–184, 1958.

[15] G. F. Newell, “A simplified car-following theory: A lower order model,” *Transp. Res. B, Methodol.*, vol. 36, pp. 195–205, Mar. 2002.

[16] D. Hoefs, “Entwicklung einer messmethode uber den Bewegungsablauf des Kolonnenverrkehrs,” Universitat (TH) Karlsruhe, Karlsruhe, Germany, 1972.

[17] R. Herman, D. C. Gazis, and R. B. Potts, “Car-following theory of steady-state traffic flow,” *Oper. Res.*, vol. 7, pp. 499–505, 1959.

[18] H. X. Ge, S. Q. Dai, L. Y. Dong, and Y. Xue, “Stabilization effect of traffic flow in an extended car-following model based on an intelligent transportation system application,” *Phys. Rev. E, Stat. Nonlinear, Soft Matter Phys.*, vol. 70, pp. 1–6, 2004.

[19] K. Hasebe, A. Nakayama, and Y. Sugiyama, “Dynamical model of a cooperative driving system for freeway traffic,” *Phys. Rev. E, Stat. Nonlinear, Soft Matter Phys.*, vol. 68, pp. 1–6, 2003.

[20] L. C. Davis, “Modifications of the optimal velocity traffic model to include delay due to driver reaction time,” *Phys. A, Statist. Mech. Appl.*, vol. 319, pp. 557–567, Mar. 1, 2003.

[21] A. Nakayama, Y. Sugiyama, and K. Hasebe, “Effect of looking at the car that follows in an optimal velocity model of traffic flow,” *Phys. Rev. E*, vol. 65, Dec. 17, 2001, Art. no. 016112.

[22] R. Jiang, Q. Wu, and Z. Zhu, “Full velocity difference model for a car-following theory,” *Phys. Rev. E*, vol. 64, Jun. 22, 2001, Art. no. 017101.

[23] H. Lenz, C. K. Wagner, and R. Sollacher, “Multi-anticipative car-following model,” *Eur. Phys. J. B*, vol. 7, pp. 331–335, 1999.

[24] M. Bando, K. Hasebe, K. Nakanishi, and A. Nakayama, “Analysis of optimal velocity model with explicit delay,” *Phys. Rev. E*, vol. 58, pp. 5429–5435, Nov. 1, 1998.

[25] A. D. Mason and A. W. Woods, “Car-following model of multispecies systems of road traffic,” *Phys. Rev. E*, vol. 55, pp. 2203–2214, Mar. 1, 1997.

[26] M. Bando, K. Hasebe, A. Nakayama, A. Shibata, and Y. Sugiyama, “Dynamical model of traffic congestion and numerical simulation,” *Phys. Rev. E*, vol. 51, pp. 1035–1042, 1995.

[27] H. X. Ge, R. J. Cheng, and Z. P. Li, “Two velocity difference model for a car following theory,” *Phys. A, Statist. Mech. Appl.*, vol. 387, pp. 5239–5245, Sep. 1, 2008.

[28] Z. P. Li and Y. C. Liu, “Analysis of stability and density waves of traffic flow model in an ITS environment,” *Eur. Phys. J. B*, vol. 53, pp. 367–374, 2006.

[29] K. Hasebe, A. Nakayama, and Y. Sugiyama, “Equivalence of linear response among extended optimal velocity models,” *Phys. Rev. E*, vol. 69, Jan. 26, 2004, Art. no. 017103.

[30] M. Treiber and A. Kesting, *Traffic Flow Dynamics: Data, Models and Simulation*. New York, NY, USA: Springer-Verlag, 2013.

[31] A. Kesting, M. Treiber, M. Schönhof, and D. Helbing, “Adaptive cruise control design for active congestion avoidance,” *Transp. Res. C, Emerg. Technol.*, vol. 16, pp. 668–683, 2008.

[32] M. Treiber, Longitudinal Traffic model: The IDM2011. [Online]. Available: http://www.vwi.tu-dresden.de/~treiber/MicroApplet/IDM.html-IDMparameters

[33] M. Treiber, A. Kesting, and D. Helbing, “Influence of reaction times and anticipation on stability of vehicular traffic flow,” *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1999, pp. 23–29, 2007.

[34] M. Treiber, A. Kesting, and D. Helbing, “Delays, inaccuracies and anticipation in microscopic traffic models,” *Phys. A, Statist. Mech. Appl.*, vol. 360, pp. 71–88, 2006.

[35] A. Kesting, M. Treiber, M. Schönhof, and D. Helbing, “Extending adaptive cruise control to adaptive driving strategies,” *Transp. Res. Rec., J. Transp. Res. Board*, no. 2000, pp. 16–24, 2007.

[36] Z. Zheng, “Recent developments and research needs in modeling lane changing,” *Transp. Res. B, Methodol.*, vol. 60, pp. 16–32, Feb. 2014.

[37] “The Next Generation Simulation (NGSIM),” Fed. Highway Admin. (FHWA), Washington, DC, USA, 2008. [Online]. Available: http://www.ngsim.fhwa.dot.gov/

[38] Q. Wang, Z. Li, and L. Li, “Investigation of discretionary lane-change characteristics using next-generation simulation data sets,” *J. Intell. Transp. Syst.*, vol. 18, pp. 246–253, 2014.

[39] P. Hidas, “Modelling vehicle interactions in microscopic simulation of merging and weaving,” *Transp. Res. C, Emerg. Technol.*, vol. 13, pp. 37–62, Feb. 2005.

[40] V. Milanes, S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura, “Cooperative adaptive cruise control in real traffic situations,” *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 296–305, Feb. 2014.

[41] V. Milanés and S. E. Shladover, “Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data,” *Transp. Res. C, Emerg. Technol.*, vol. 48, pp. 285–300, 2014.

[42] A. Kesting, M. Treiber, and D. Helbing, “Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity,” *Philos. Trans. Roy. Soc. London A, Math. Phys. Eng. Sci.*, vol. 368, pp. 4585–4605, 2010.

[43] X. Qu, Y. Kuang, E. Oh, and S. Jin, “Safety evaluation for expressways: A comparative study for macroscopic and microscopic indicators,” *Traffic Injury Prevention*, vol. 15, pp. 89–93, 2014.

Mofan Zhou received the B.Eng. (Honours I) degree in civil engineering in 2015 from Griffith University, Gold Coast, Australia, where he is currently working toward the Ph.D. under the supervision of Dr. Xiaobo Qu.

Xiaobo Qu received the B.Eng. degree from Jilin University, Changchun, China; the M.Eng. degree from Tsinghua University, Beijing, China; and the Ph.D. degree from National University of Singapore, Singapore.

He is a Senior Lecturer with the School of Civil and Environmental Engineering, University of Technology Sydney, Broadway, Australia. He also holds an adjunct appointment with Griffith University, Gold Coast, Australia. His research is focused on traffic flow theory, intelligent transportation systems, traffic safety, maritime transportation, and public transport.

Sheng Jin received the B.Eng., M.Eng., and Ph.D. degrees from Jilin University, Changchun, China.

He is an Associate Professor with the College of Civil Engineering and Architecture, Zhejiang University, Hangzhou, China. His research areas include traffic flow theory, traffic safety, traffic control, and intelligent transportation systems.