Investigation of Merge Strategies at Ramp Area in Connected Vehicle Environment based on Multi-Driver Simulator System

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A Report on Research OR Education Sponsored by

SAFER-SIM University Transportation Center

Federal Grant No: 69A3551747131

January 2022

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
UCF-2-Y4		

4. Title and Subtitle
Investigation of merge strategies at ramp area in connected vehicle environment based on multi-driver simulator system

5. Report Date
January 15, 2022

6. Performing Organization Code
Enter any/all unique numbers assigned to the performing organization, if applicable.

7. Author(s)
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8. Performing Organization Report No.
Enter any/all unique alphanumeric report numbers assigned by the performing organization, if applicable.

9. Performing Organization Name and Address
University of Central Florida
Research & Commercialization
12201 Research Pkwy Ste 501
Orlando, FL
32826 USA

10. Work Unit No.

11. Contract or Grant No.
Safety Research Using Simulation (SAFER-SIM) University Transportation Center
(Federal Grant #: 69A3551747131)

12. Sponsoring Agency Name and Address
Safety Research Using Simulation University Transportation Center
Office of the Secretary of Transportation (OST)
U.S. Department of Transportation (US DOT)

13. Type of Report and Period Covered
Final Research Report (August 2020 – January 2022)

14. Sponsoring Agency Code

15. Supplementary Notes
This project was funded by Safety Research Using Simulation (SAFER-SIM) University Transportation Center, a grant from the U.S. Department of Transportation – Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program.

16. Abstract
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17. Key Words		18. Distribution Statement	
Driving simulator, Connected and autonomous vehicle, Merge strategy, Merge behavior, Safety and comfort.		No restrictions. This document is available through the SAFER-SIM website, as well as the National Transportation Library	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 43	**22. Price**

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Abstract

This study aims to investigate the impacts of merge strategies of a ramp CAV on mainline human drivers. Previous studies evaluated CAV merge strategies mostly based on either the simulation or the restricted field testing, which lacks consideration of realistic driving behaviors in the merging scenario. To deal with this research gap, this study developed a multi-driver simulator system and embedded realistic driving behaviors in the validation of merge strategies.

Four CAV merge strategies were evaluated regarding their impacts on driving safety and comfort of the mainline human drivers. A set of driving safety and comfort metrics was adopted to verify the merge strategies. The results show that these algorithms might not have consistent performance when evaluated by different safety and comfort metrics. In addition, results revealed significant variations of the algorithm influences between the merging and the following periods. Moreover, the AHS and GFM may have some superiority when evaluated at specific dimensions in terms of driving safety and comfort; nevertheless, the AHS may outperform other merge strategies in more scenarios. Findings suggest that the CAV merge strategy should not only ensure the ramp vehicle's merging task but also consider mainline vehicles' driving performance.

1 Introduction

Connected and autonomous vehicle (CAV) technology has been gaining more and more attention in recent years; it releases drivers from heavy driving tasks and avoids driver errors. One challenge of CAV technology is its adaptability in critical traffic scenarios. A typical critical scenario is the merging scenario at the freeway ramp area; it is a hotspot of traffic crashes. 18% of all interstate freeway crashes, 17% of the injury crashes, and 11% of the fatal crashes occurred at interchanges, and most proportion of these crashes took place at the entrance or exit ramps [1, 2]. Given that there is usually significant vehicle interaction at the merging areas, the design of the CAV merge strategy is critically important; the algorithm is supposed to ensure a safe merging behavior; meanwhile, it is expected to disturb the mainline driving as little as possible.

Generally, the merge strategies can be categorized into two types: reference-trajectory-based merge strategy and social-psychology-based merge strategy. The objective of the first type is to find a reference trajectory to guide the autonomous vehicle by considering physical and kinematic restrictions to fulfill a successful merging. Lu and Hedrick [3, 4] designed a set of kinematical restriction functions in terms of the acceleration and position, to ensure that the vehicles can reach the merging points at an appropriate time. Wang et al. [5] proposed a cooperative driving algorithm based on vehicular operation characteristics for the ramp merging. They considered the position and speed requirements for both one and two vehicles on the ramp. The second type considers driving preferences and manipulates the merging model based on factors such as desired gap distance, desired mainstream speed, etc. Basically, this type of algorithm defines the model in a form of preferred and actual accelerations and distance gap [6-10]. An advanced form of the second type is to consider multiple optimization targets and generate the reference merging path by solving the optimal solution. Ding et al. [11] proposed a rule-based merge strategy with minimizing travel time and delay as the target; they formed a closed-form analytical solution to achieve a near-optimal merging sequence. Letter and Elefteriadou et al. [12] presented a longitudinal freeway merging control algorithm which used the average travel speed as the optimization target, and they used LINGO to resolve the optimal solution.

The verification of the above algorithms is usually based on simulation platforms, either through a single platform or a co-simulation based integrated simulation platform. Some single platforms are basically microscopic traffic flow simulation software (TFSS) such as Vissim and SUMO; they have driving behavior models which can mimic car following and lane change behaviors. For example, Vissim uses a rule-based algorithm to initiate lateral lane change behavior and uses a psychophysical model for the longitudinal car following movement [13]. Different from Vissim, SUMO uses a Krauss model as its default car-following model [14]. However, vehicle dynamics modeling is not a strength for these platforms. On the contrary, some other single platforms, such as CarMaker, have a better ability of modeling vehicle dynamics such as the powertrain and sensor system. The driver behavior model used in the CarMaker is based on a proportional-integral-derivative (PID) controller, with considerations of psychological studies and measurements from real test drivers[15]. Whatever driver behavior models they are, the models result from speed, speed difference, distance gap, vehicle dynamic restrictions or individual driver characteristics.

Integrated simulation platforms provide more explicit simulation regarding individual vehicle dynamics or a better power to optimize CAV control algorithms during the running time; the integrated platform can consist of a TFSS and several other simulators such as IPG Carmaker and Matlab/SIMULINK. Basically, the TFSS is more efficient at simulating microscopic traffic flow while it ignores the vehicle dynamics; to the contrary, the IPG Carmaker can better simulate the vehicle dynamics; while the Matlab/SIMULINK is mainly for algorithm optimization; its mathematical toolboxes can be used to resolve optimization problems and generate optimized parameters/outputs of control algorithms. When complicated traffic flow simulation is not necessary, IPG Carmaker is often used to verify CAV control algorithms, such as longitudinal cruise control[16], lateral lane change [17], overtaking path planning [18] and tactical behavior planning [19]; while when the CAV algorithm is required to be tested in certain traffic flow conditions, a co-simulation between CarMaker, TFSS and Matlab/SIMULINK is often used [20-22].

However, the lack of realistic driver behavior in the algorithm validation deteriorates the credibility of the algorithm. As pointed by Andrei Aksjonv et al[23], pure computation simulation does not guarantee realistic environments for a testing vehicle, and this is the reason that in recent years the concept of "hardware-in-the-loop" or "human-in-the-loop" becomes more prevalent[23-26]. Basically, using real hardware or a driver to test the algorithm is more reliable than using a driver behavior model particularly when it is necessary to observe vehicle interactions and possible improper driving adaptation behaviors. Theoretically speaking, a driver behavior model is controlled by many kinematical restrictions, and it is hard to mimic improper driving adaptations[21].

Regarding the CAV merging algorithms, most of the aforementioned studies were based on simulation, which is hard to represent realistic driver behaviors in the merging scenario. Very few of them conducted field testing; however, due to the safety consideration, only conservative algorithms and restricted testing conditions (such as low driving speed) were tested. Many studies proved that driver behavior can significantly affect the crash and safety level at the merging area. Weng et al. [27] found that the drivers' merging behavior is highly correlated with the rear-end crash risk; there will be high rear-end crash risks when the merging vehicle travels at either a very high or low speed. Weng and Meng [28] found that if the merging action initiates earlier, there will be a lower rear-end crash potential. Reinolsmann et al. [29] also suggested earlier lane change since it can contribute to smooth maneuvers and gradual speed reductions particularly at the rural expressway ramp area. Moreover, Potzy et al. [30] concluded that drivers on the mainline prefer an efficient lane change of the autonomous vehicle on the ramp, and results show that drivers would tolerate less compliance with safety distance to have less interacting traffic. It is quite necessary to consider the realistic driver behavior for CAV merging algorithms so that the CAV merging behavior can be more acceptable and predictable for mainline drivers.

Therefore, the objective of this study, is to evaluate the influence of CAV merge strategies on driver behaviors of mainline human-driven vehicles, by using the human-in-the-loop concept. Several classical merge strategies were tested in this study, representing the reference-trajectory-based merge strategy and social-psychology-based merge strategy; then their influence on the mainline driver behaviors was analyzed given their algorithm framework features. The study is expected to conclude principles of designing merge strategies that have less influence on the mainline traffic. The driving safety and driving comfort of mainline human drivers would be analyzed to distinguish the performance of different merge strategies. To account for crash risks in a realistic field testing, a driving simulator experiment would be used instead.

The study is organized as follows, CAV Merge Strategy section introduces classical CAV merge strategies that tested in this study; Experimental Design section presents the UCF-SST's multi-driver simulator system developed for this study, experimental scenarios and data analysis method; Resutls section presents the results and Discussion and Limitation section investigates the results; finally, the Conclusion section summarizes the study.

2 CAV Merge Strategy

Almost all CAV merge strategies adopt a concept of “virtual platoon”, with a connotation of projecting the CAV’s position from the merging ramp to the mainline, and generating a “virtual platoon” that consists of both human-driven vehicles (yellow) and projected CAV (grey) (Figure 2-1). The projection is exactly based on geometric parameters of the CAV, and it determines the relative position of the projection vehicle to other mainline vehicles. The core idea of the CAV merge strategy is to manipulate the speed and acceleration of the projected CAV, so that it can maintain a safe headway distance to the front vehicle under a desired traveling speed. Basically, in a fully connected and automated environment, a central controller will be set up to cover the upstream and downstream of merging area, and collect speed and location information of all vehicles (both on mainline and ramp) entering the control area; the vehicles in the control area will be manipulated so that the speed and headway distance of each vehicle in the virtual platoon can be well accommodated. Specifically, the controller will accommodate the autonomous vehicle (projected) based on its relative speed and position to the leading vehicle (1st vehicle in the platoon), and consecutively accommodate the 2nd and 3rd vehicle based on similar safety considerations toward the vehicles in front of them.

In this study, the driving environment is partially connected, and only the CAV can manage its movement by sensing the leading vehicle; for the 2nd and 3rd vehicles, drivers need to determine the driving by themselves rather than follow the central controller. Therefore, the controller, which is embedded with the merge strategy, will take the information of the frist vehicle as input to manage the movement of the CAV.

Two types of classical CAV merge strategies, reference-trajectory-based merge strategy and the social-psychology-based merge strategy, were reproduced in this study based on previous studies. The study verified their effects on the mainline human-driven vehicles. These tested merge strategies and their examples are listed as below,

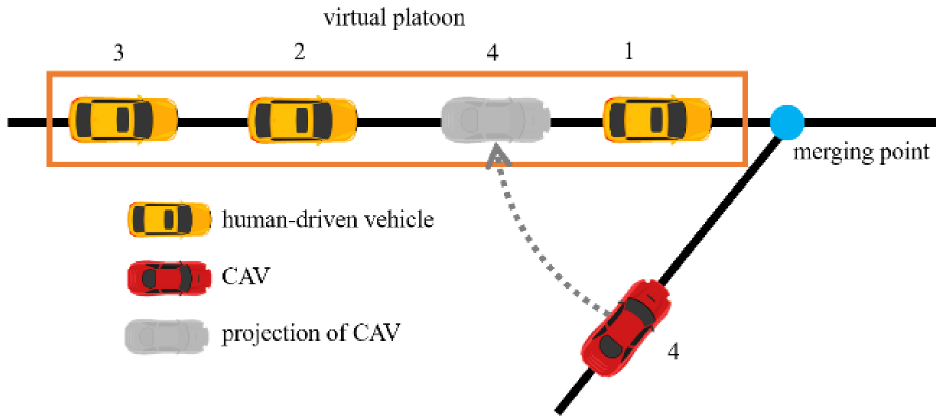


Figure 2-1 Virtual platoon and projected CAV

(1) Reference-trajectory-based merge strategy. The algorithm (denoted as AHS) tested in this study was proposed by Lu et al.[3, 4], which defined the reference trajectory $v_{md}(t)$ as,

$$v_{md}(t_i) = \begin{cases} v_{md}(t_{merg}) = v(t_{merg}); \\ (1-\alpha(t_i))v(t_{merg}) + \alpha(t_i)v_p(t_i - 1) \\ when\ t_{merg} \le (t_{merg} + i\Delta t) \le T_{virt}; \\ v_p(t_i - 1) \\ when\ T_{virt} < (t_{merg} + i\Delta t) \le T_{merg}; \end{cases} \tag{2.1}$$

$$\alpha(t_i) = \alpha_0^{\beta}(t_i), \beta > 0 \tag{2.2}$$

$$\alpha_0(t_i) = \frac{\sum_{j=1}^{i} v_p(t_j - 1)\Delta t}{\sum_{j=1}^{i} v_p(t_j - 1)\Delta t + dist\_para} \tag{2.3}$$

Where $v(t)$ is the merging vehicle speed; $v_p(t)$ is the speed of the first vehicle in the platoon on mainline; t_{merg} is the time when the merge strategy starts; T_{virt} is the time when the virtual platoon is established but merging is not complete yet; T_{merg} is the time when the merging is finished; β is a coefficient; $dist\_para$ is the initial distance relationship between vehicles considering desired distance before and after the merging. Detailed variable definitions can be found in the study[3, 4].

(2) Social-psychology-based merge strategy. This study tested three examples, which were borrowed from car-following models, by considering the driver's desire to main a certain speed and distance to the leading vehicle. The intelligent driver model (IDM) [31], the generalized force model (GFM) [32] and the k-leader fuel-efficient (KLFE) model [8, 9] were used as examples in this study. The model parameters were identical to the ones in corresponding studies.

The IDM is given by,

$$a = A\left[1 - \left(\frac{v}{V}\right)^{\delta} - \left(\frac{S_{desire}(v, \Delta v)}{S}\right)^2\right] \tag{2.6}$$

$$S_{desire}(v, \Delta v) = g_0 + g_1\sqrt{\frac{v}{V}} + vT + \frac{v\Delta v}{2\sqrt{Ab}} \tag{2.7}$$

Where a is the suggested acceleration; v and V are the current speed and desired speed respectively; Δv is the speed difference to the preceding vehicle; S and S_{desire} are the current following distance and desired following distance respectively. The A and b are maximum desired acceleration and deceleration respectively. g_0 and g_1 are different jam distance parameters and δ is a constant coefficient. Detailed variable definitions can be found in the study[31].

The GFM is given by,

$$a_n = \frac{V\left(1 - e^{-\frac{s_n - s_{desire}(v)}{R_a}}\right) - v}{\tau_a} - b \quad (2.8)$$

$$b = \frac{\theta(\Delta v)\Delta v e^{-\frac{s_n - s_{desire}(v)}{R_d}}}{\tau_d} \quad (2.9)$$

$$S_{desire}(v) = s_0 + vT \quad (2.10)$$

Where a_n is the nth vehicle's acceleration, v and V are the current speed and desired speed respectively; Δv is the speed difference to the preceding vehicle; s_n, s_{desire} and s_0 are the current following distance, desired safe following distance and minimum following distance respectively; θ is the Heaviside function; T is the safe time headway; τ_a and τ_d are the acceleration time and braking time respectively; R_a and R_d are the range of the acceleration and range of the braking interaction respectively. Detailed variable definitions can be found in the study[32].

The KLFE is given by,

$$v_n(t + \Delta t) = min\left[v_{n,m}(t + \Delta t)\right] \quad (2.11)$$

$$v_{n,m}(t + \Delta t) = \max\left(0, \min\left(v_{n,m}^{a}(t), v_{n,m}^{safe}(t)\right)\right) \quad (2.12)$$

$$v_{n,m}^{a}(t) = v_n(t) + k \quad (2.13)$$

$$k = A\Delta t\left[1 - \left(\frac{v_n(t)}{V}\right)^4 - \left(\frac{v_n(t)s_{n,m}^{desire}(t)}{V_{S_{n,m}}}\right)^2\right] \quad (2.14)$$

$$p = 2[x_m(t) - x_n(t) - l'] - v_n(t)\Delta t - \frac{v_m(t)^2}{b^*} \quad (2.15)$$

$$v_{n,m}^{safe}(t) = \begin{cases} b\Delta t + q \ \ if\ q \geq 0 \\ b\Delta t + \ v_n(t)\ \ if\ q < 0 \end{cases} \quad (2.16)$$

$$q = \sqrt{b^2(\Delta t)^2 - bp} \quad (2.17)$$

$$s_{n,m}^{desire}(t) = [S_0 + \mathrm{b}] * (n - m) \quad (2.18)$$

$$\mathrm{b} = \max\left(0, v_n(t)T + \frac{v_n(t)\{v_n(t) - v_m(t)\}}{2\sqrt{A|b|}}\right)] \tag{2.19}$$

Where n and m stand for the nth and mth vehicles in the platoon; $s_{n,m}^{desire}$ is the desired following distance between the nth and mth vehicles; $v_{n,m}^{a}$ is the following vehicle speed when the distance between the following and preceding vehicle is large, while the $v_{n,m}^{safe}$ is the following vehicle safe speed when the gap distance is small; v_n, v_m and V are the current following speed, current preceding speed, and desired speed respectively; x_n and x_m are the following and preceding vehicle positions; l' is the effective size plus a margin; A is the maximum desired acceleration; b is the maximum braking rate; b^* is the estimated braking rate of the preceding vehicle; T is the safe time headway; S_0 is the jam distance. Detailed variable definitions can be found in the study[8, 9].

3 Experimental Design

3.1 Apparatus

A multi-driver driving simulator system (Figures 3-1 and 3-2) was developed by the UCF SST lab to test a vehicle platoon in a virtual driving scenario. Compared with a realistic field test, the advantage of using the driving simulator is that it can test dangerous driving scenarios without real collision risks. The simulator system had a data collection module, a vehicle physics module, a scenario management module and a communication module. The data collection module collects driver behavior data in the scenario, such as brake, throttle, steering wheel, speed and position; the vehicle physics module simulates vehicle dynamics and physical features, such as engine dynamics and collision effects; the scenario management module configures scenario control scripts, and it manages all types of scenario objects and their actions; as for the communication module, it connects multiple driver clients and distributes the simulation data between clients simultaneously.

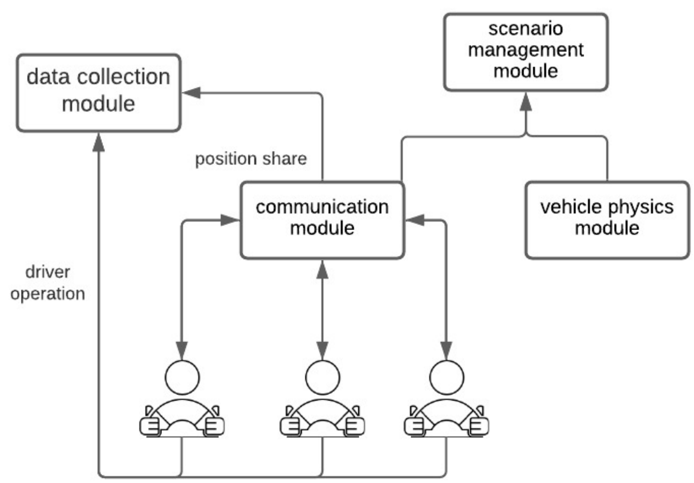


Figure 3-1 Multi-driver driving simulator system framework

(a) three drivers were simultaneously connected

(b) scenario screenshot of one driver

Figure 3-2 Multi-driver driving simulator experiment

3.2 Merging Scenario Design

The study designed a merging scenario as illustrated in Figure 3-3. Three human-driven vehicles (the 1st ~ 3rd yellow vehicle) are traveling on the mainline, and they form a stable vehicle platoon. A CAV (4th red vehicle) is merging into the mainline from a ramp, and it is supposed to cut in between the 1st and 2nd vehicles in the platoon; the CAV is controlled by the automatic merge strategy. The 2nd human-driven vehicle determines whether to yield to the CAV, based on the safety consideration. Normally, the CAV would appear ahead in the 2nd human-driven vehicle's view; therefore, the 2nd human-driven vehicle would slow down. However, in rare cases, the 2nd human-driven vehicle decides to accelerate and overtake the CAV; in these cases, the merge strategy will recognize that the 2nd human-driven vehicle would arrive at the merging point before the CAV, thus the algorithm will change its goal to following the 2nd human-driven vehicle. The study arranged a 5th environmental vehicle (blue) in front of the vehicle platoon in the mainline; the vehicle follows a predefined path and speed, and it is used as a reference vehicle to control the speed of the vehicle platoon.

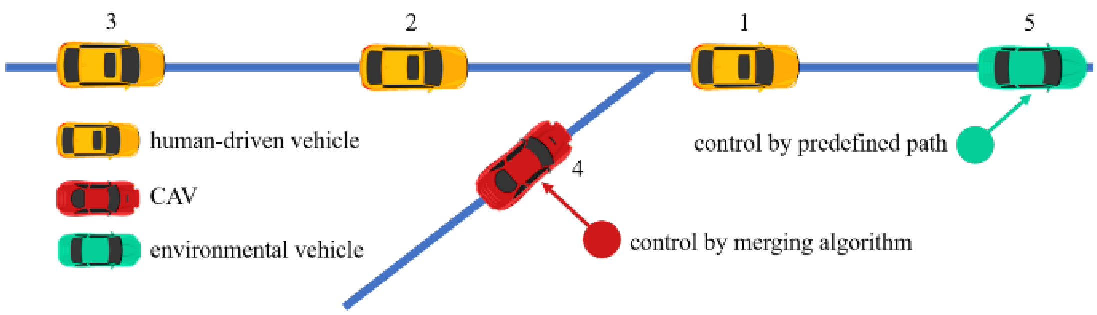


Figure 3-3 Merge scenario in experiment

In each experiment, a set of three connected drivers drove a track which contains five merging scenarios. These five scenarios have the same merge strategies and the driver's average driving performance was analyzed. The experiment was a within-subjects experiment, and three drivers experienced all four merge strategies; therefore, in total four experiments were conducted. The merge strategies were presented in a randomized way to account for the order effect [33]. In the experiment, the distance to the front vehicle and its speed information was displayed on the following vehicle's screen; referring to this information display, each driver was asked to follow the front vehicle keeping a distance of 60 to 80m; the speed limit was 55 mph.

3.3 Experimental Procedure

In total 16 groups of drivers (i.e. 48 drivers) conducted the experiment. They were driving on the mainline and an autonomous car controlled by the merge strategy was merging from the ramp. Before the formal experiment, each group of drivers was given a practice driving so that they can be familiar with the driving environment. During the formal experiment, each group drove four tracks and each track had one type of merge strategy repeated five times. In other words, the drivers experienced five merging scenarios in one track.

3.4 Influence Period During Merging

Due to the sight of the 2nd driver's view, only when the CAV is close enough, the 2nd driver would be affected and accommodate driving behaviors to the merging vehicle. This period is defined as the influence period.

Given that the driving behaviors are assumed to be different between the normal and influenced driving periods, the finite Gaussian Mixture Model (GMM) was used to distinguish two periods in the merging scenario. The GMM assumes that data of different features is coming from a mixture of two or more Gaussian distributions (i.e. clusters), and the GMM allocates data points to most probable distributions by Expectation-Maximization (EM) algorithm [34]. Similar trajectory clustering practice was conducted by Mohammed et al [35], the researchers used finite GMM to cluster cyclists overtaking and following trajectories into different states.

In the merging scenario, the 2nd driver manages the throttle and brake pedals to maintain the safety buffer between both the first vehicle and CAV. Therefore, this study used 2nd vehicle's speed, throttle and brake positions, and distances to the 1st vehicle and CAV as trajectory features to be clustered. Figure 3-4 shows an example of the throttle clusters generated by GMM. It shows that at the time of around 100, the 2nd driver noticed the merging CAV and began to monitor the collision risk; then at the time of around 160, the 2nd driver began to release the pedal position to slow down; During the time of 100~160, the throttle position didn't change, this might due to the driver's reaction time delay. It is worth mentioning that the driving periods of the 2nd driver were applied to the 3rd driver in this study.

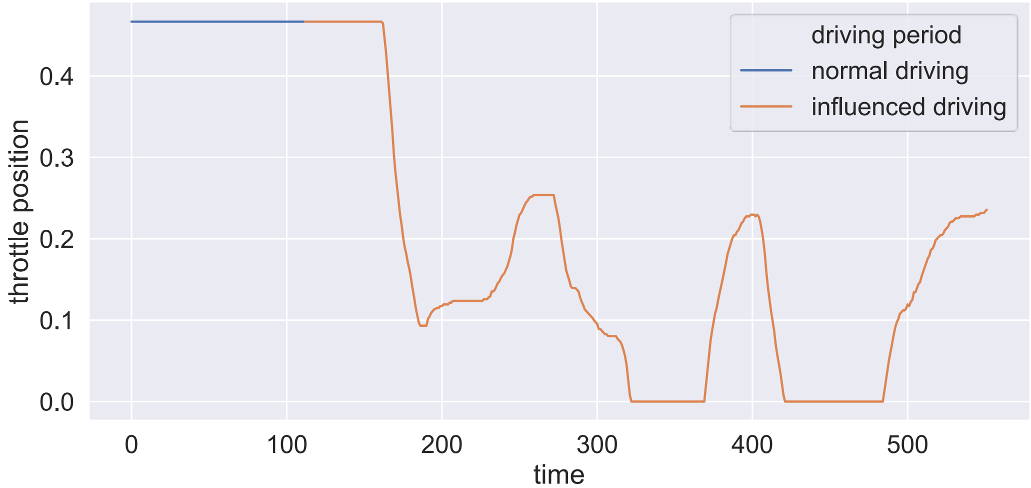


Figure 3-4 Throttle position during merge scenario

3.5 <u>Driving Performance Metrics</u>

The study mainly investigated the influence of CAV merge strategies on the 2nd and 3rd human-driven vehicles. Two driving periods were analyzed: the merging and following periods. The merging period is defined as the period from the time the CAV begins to move on the ramp to the time it arrives at the merging point. The following period (Figure 3-5) is from the time that the CAV finishes merging and begins to drive with the vehicle platoon, to the time that the CAV leaves the lane of vehicle platoon (the leaving point is given); the following actions specifically refer to the actions of 2nd human-driven vehicle (following the CAV) and 3rd human-driven vehicle (following the 2nd human-driven vehicle). For each driving period, two aspects of metrics were collected in terms of both driving safety and driving comfort; these metrics were evaluated with a significance level of 95%.

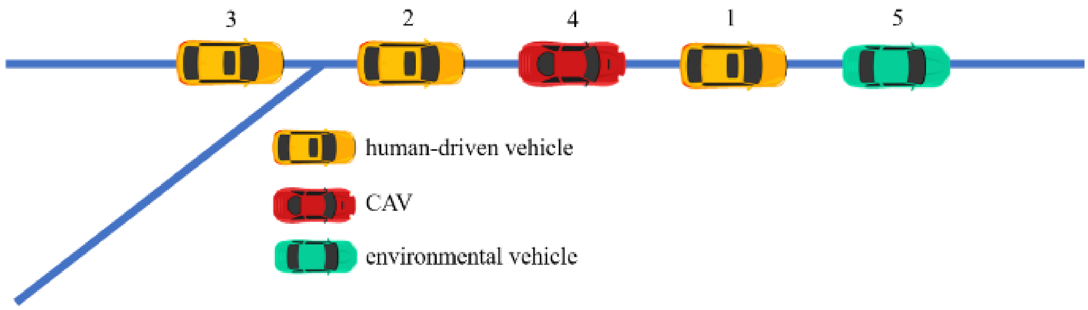


Figure 3-5 Following period when a CAV cuts in between the 1st and 2nd vehicles

3.5.1 Safety Metrics

The time-to-collision related metrics were used to measure the safety impacts. The time-to-collision (TTC) was introduced by Hayward [36] and is the most widely used surrogate safety measure (SSM); it indicates the time that is left for the following vehicle to hit a leading vehicle. The TTC is given by,

$$TTC = \begin{cases} \dfrac{S-L}{v_2 - v_1}, v_2 > v_1 \\ \infty, \quad otherwise \end{cases} \tag{4.1}$$

Where S is the distance gap between the leading and following vehicles; L is the vehicle length; v_2 and v_1 are speeds of following and leading vehicles respectively. TTC can be calculable only when v_2 is greater than v_1. In this study, TTC was assigned a large value of 100 when $v_2 < v_1$. Obviously, a large value of minimum TTC indicates a high safety level.

In this study, the minimum TTC was adopted. Given that minimum TTC only accounts for the most critical time point that a vehicle may encounter, the Time Exposed Time-to-collision (TET) and Time Integrated Time-to-collision (TIT) proposed by Minderhoud and Bovy [37] were used to quantify the safety performance over a period of time.

The TET is given by,

$$TET = \sum_{t=0}^{T} \delta_i(t) * \tau_{sc} \tag{4.1}$$

$$\delta_i(t) = \begin{cases} 0, else \\ 1, \forall 0 \leq TTC_i(t) \leq TTC^* \end{cases} \tag{4.2}$$

The TIT is given by

$$TIT = \sum_{t=0}^{T} [TTC^* - TTC_i(t)] * \tau_{sc} \tag{4.3}$$

$$\forall 0 \leq TTC_i(t) \leq TTC^* \tag{4.4}$$

Where TTC^* is a pre-defined threshold (2.0s) and τ_{sc} is the time step.

The TET quantifies the total amount of time that the TTC is below the threshold over a period of time; the smaller the TET, the better the safety. However, the TET does not distinguish different TTCs that are all below the threshold, i.e. it is unable to distinguish a small TTC from a large TTC when both of them are below the threshold. The TIT deals with this limitation; the longer a small TTC lasts, the larger the TIT would be. Both the TET and TIT were weighted by the length of corresponding data series.

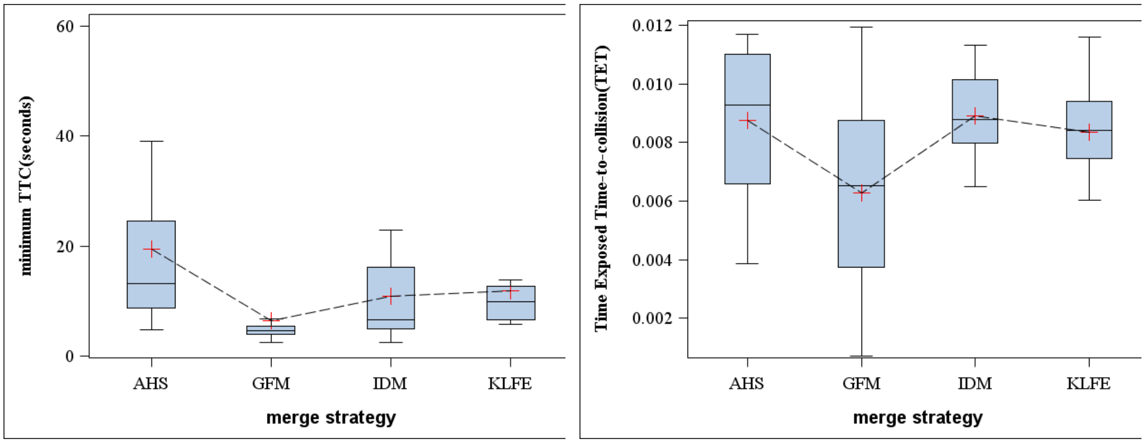
3.5.2 Comfort metrics

The average jerk, average acceleration, and minimum headway distance were used to measure the driving comfort. The jerk and acceleration were demonstrated to have a negative relationship with the driving comfort [38-41], while the headway is the opposite[39]. Basic statistics regarding the three variables were analyzed, including the average, minimum and maximum values. In addition, the time to minimum distance at the moment when the acceleration pedal was released (TTMD) and the longitudinal quickness proposed by Bellem [39] were also used. Intuitively, the larger the TTMD, the better the driving comfort. In terms of the longitudinal quickness, a larger value indicates a worse driving comfort. The longitudinal quickness is the ratio of the average longitudinal acceleration and the change in longitudinal speed. Intuitively, the longitudinal quickness considers the length of the period of a particular average acceleration level. A large acceleration may indicate less driving comfort; however, if this acceleration lasts for a sufficiently long time (in which case the change of the speed would be sufficiently large), the quickness variable states that the driving comfort can be improved.

4 RESULTS

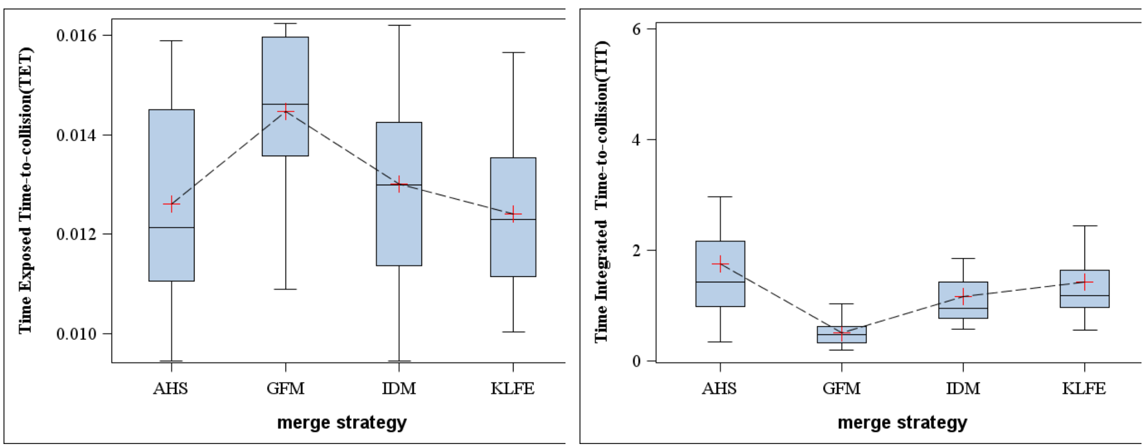
4.1 Influence on Driving Safety

For the 2nd driver, during the merging period, both the minimum TTC and TET between the four merge strategies were significantly different ($F = 5.62$, p-value<0.01 and $F=7.04$, p-value<0.01 respectively). Figure 4-1 shows the statistics of minimum TTCs for the merge strategies. The AHS had the largest minimum TTC (19.45s) and TET (0.0091); while the GFM had the smallest minimum TTC (6.49s) and TET (0.0063). During the following period, both the TET and TIT were found significantly different between merge strategies ($F=10.22$, p-value<0.01 and $F=6.58$, p-value<0.01 respectively). Figure 4-2 shows the statistics of TET and TIT for the merge strategies. For TET, the KLFE had the smallest one (0.013) while the GFM had the largest one (0.015); for TIT, the GFM had the smallest one (0.48) while the AHS had the largest one (1.71). It is worth mentioning that the KLFE and AHS had a similar TET and TIT in the following period.



(a)minimum TTC **(b)TET**

Figure 4-1 Safety metrics among four merge strategies during 2nd car's merging period



(a)TET **(TIT)**

Figure 4-2 Safety metrics among four merge strategies during 2nd car's following period

For the 3rd driver, the merge strategies were not found to have a significantly different safety performance during the merging period. In the following period, the 3rd driver had significantly different minimum TTCs between merge strategies ($F = 3.81$, p-value< 0.01). In Figure 4-3, specifically, the AHS had the largest minimum TTC (11.61s), whereas the GFM and IDM had the smallest minimum TTC of around 8.35 s. The minimum TTC of KLFE was 9.58 s.

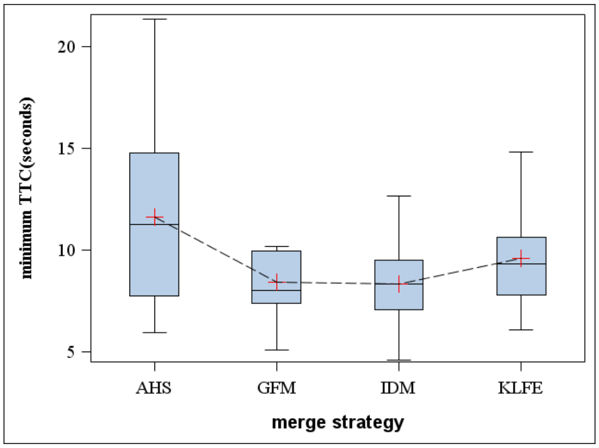
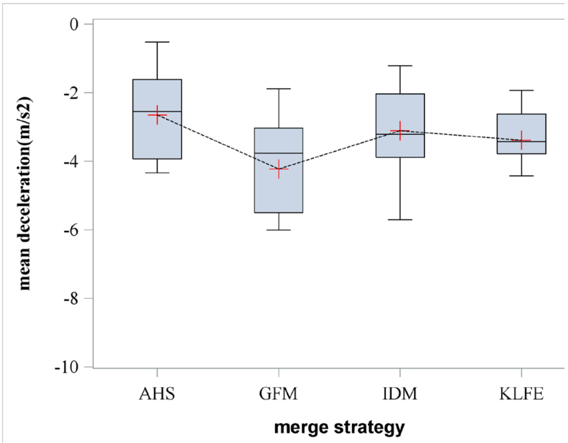
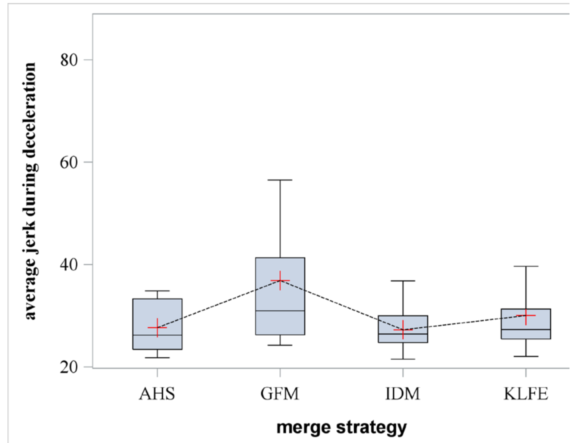


Figure 4-3 Safety metrics among four merge strategies during 3rd car's following period

4.2 Influence on Driving Comfort

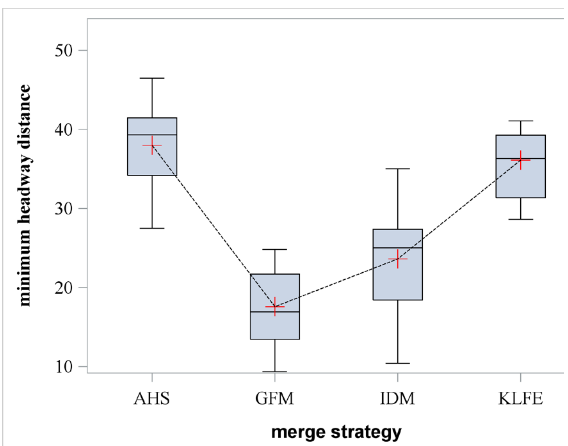
For the 2nd driver, during the merging period, the mean deceleration was significantly different between the four merge strategies (F=4.74, p-value=0.002). In Figure 4-4 (a), the AHS had the smallest deceleration of 2.64m/s2, while the GFM had the largest deceleration of 4.23 m/s2. The average jerks during the deceleration process were also found significantly different between the merge strategies (F=2.84, p-value=0.032). In Figure 4-4(b), the GFM had the largest average jerk during the deceleration process, which was 36.86; the IDM and AHS had relatively smaller average jerks, which are similar to each other of around 27.50. In terms of the minimum headway distance, a significant difference was found due to the merge strategies (F=62.26, p-value<0.01). In Figure 4-4(c), the AHS had the largest minimum headway distance (37.99m) while the GFM had the smallest minimum headway distance (17.57m).





(a)mean deceleration

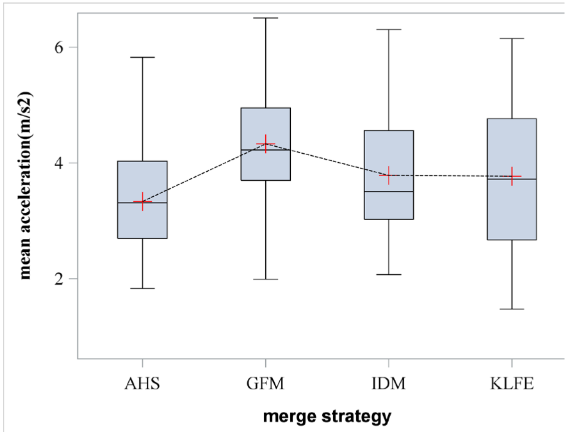
(b)jerk



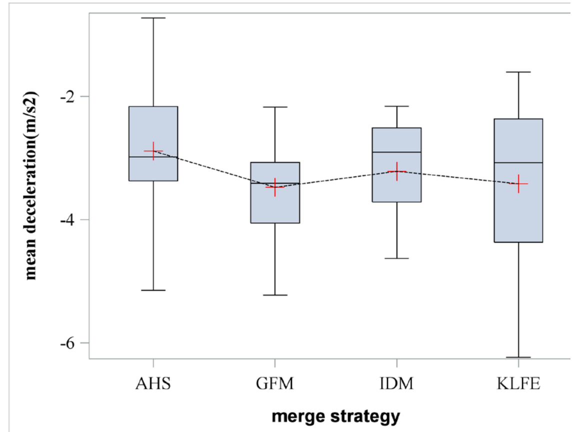
(c)minimum headway distance

Figure 4-4 Comfort metrics among four merge strategies during 2nd car's merging period

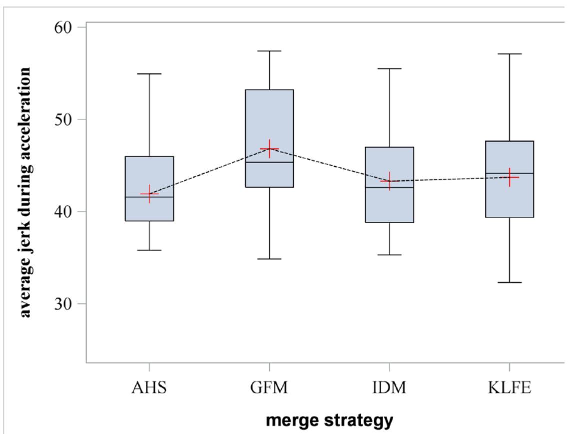
For the 2nd driver, during the following period, both the mean acceleration and deceleration were found to be significantly affected by the merge strategies. In Figure 4-5(a), for mean acceleration, the GFM had the largest one of 4.33m/s^2, while the AHS had the smallest one of 3.34m/s^2. Additionally, in Figure 4-5(b), the GFM had the largest mean deceleration of 3.47m/s^2, while AHS had the smallest mean deceleration of 2.89 m/s^2. In terms of the average jerk, it was found to be significantly affected by the merge strategies during the acceleration process ($F=4.92$, $p\text{-value}<0.01$). In Figure 4-5(c), the GFM had the largest one of 46.81, while the AHS had the smallest one of 41.93. For the minimum headway distance, a significant difference was also found ($F=47.21$, $p\text{-value}<0.01$). In Figure 4-5(d), the GFM had the smallest one of 21.60m, while the AHS had the largest one of 41.01m. The 2nd driver's TTMD during the following period was also significantly different due to the merge strategies ($F=3.11$, $p\text{-value}=0.036$). In Figure 4-5(e), the GFM had the largest TTMD (86.07s) while the AHS had the smallest one (66.59s). In addition, the longitudinal quickness during the acceleration period was found to be affected by the merge strategies ($F=3.21$, $p\text{-value}=0.033$). In Figure 4-5(f), the GFM had the smallest value (5.18) while the AHS had the largest value (8.15).



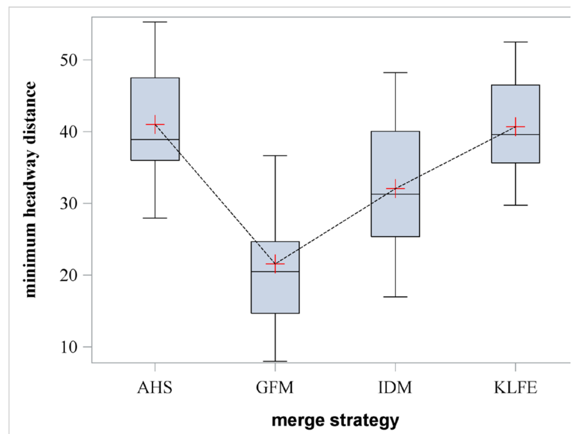
(a)



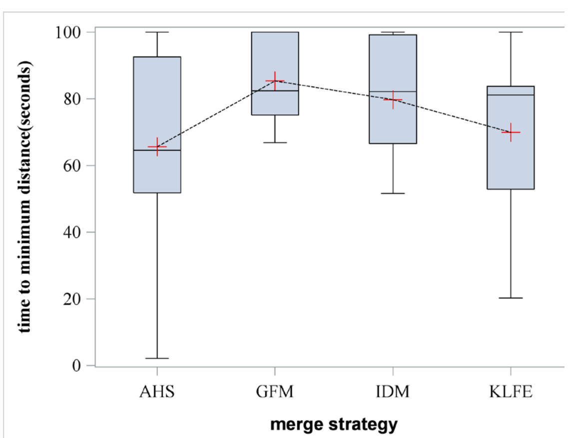
(b)



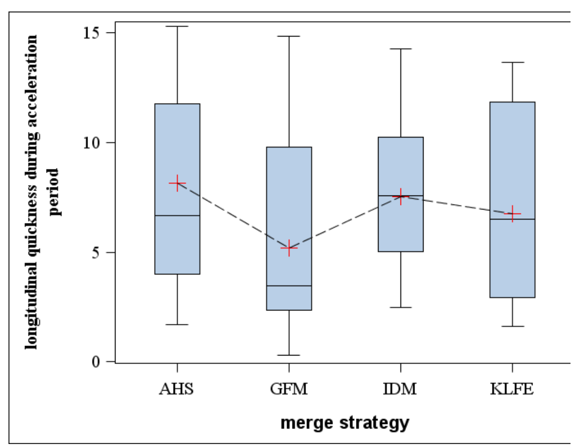
(c)



(d)



(e)



(f)

Figure 4-5 Comfort metrics among four merge strategies during 2nd car's following period

For the 3rd driver, during the merging period, the comfort metrics were not found to be significantly affected by merge strategies. In the following period, the minimum headway distance was found to be significantly affected by the merge strategies ($F=4.11$, $p\text{-value}<0.01$). In Figure 4-6, the AHS had the largest one (53.59m), while the GFM had the smallest minimum headway (47.24m).

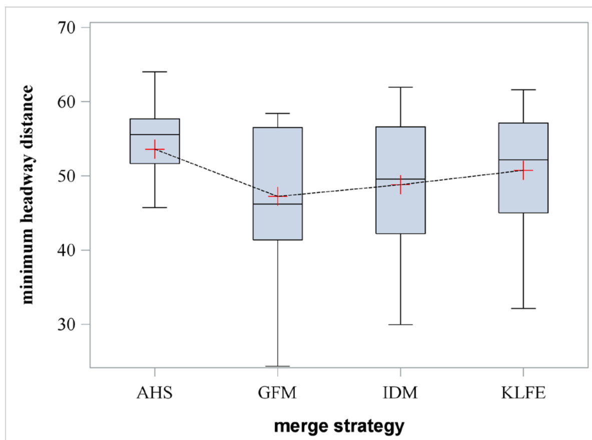


Figure 4-6 Comfort metrics among four merge strategies during 3rd car's following period

5 Discussions and Limitations

Table 5-1 summarizes the findings of this study. Given that multiple driving performance metrics were used, a comprehensive understanding can be made about the influence of CAV merge strategies on the mainline vehicles.

The 2nd car was the most affected vehicle in terms of both the merging and following periods. Regarding the driving safety, during the merging period, the GFM had the smallest TET which means it had a larger TTC over the whole merging period; however, it also had the smallest minimum TTC, which means at some time points it faced a much severer conflict compared with other merge strategies. On the contrary, the AHS had the largest TET which means it had more frequent small TTCs; however, it didn’t meet with the critical conflict as the GFM since its minimum TTC was larger than the GFM. Regarding the driving comfort, the AHS outperformed other merge strategies; it is worth mentioning that although the IDM had the best comfort performance in terms of the average jerk during the acceleration period, the AHS had a similar performance as the IDM.

For the 2nd car, during the following period, the KLFE and the AHS had a similar safety performance regarding the TET, and they can be regarded as the best merge strategy since they had less frequent of small TTCs; while in terms of the metric TIT, the GFM had the smallest TIT which means it had a TTC distribution close to the threshold, in other words, it had “mild” TTCs larger than other merge strategies.

It is interesting that the safety effects of merge strategies varied between merging and following periods. To be specific, in the merging period, the GFM had a higher safety most of the time but it had very severe conflicting situation at some time points; while the AHS had an opposite effect; moreover, this phenomenon turned over between two strategies in the following period.

Regarding the driving comfort in the following period, the GFM gave the 2nd car a comfortable start (i.e. the largest TTMD), and it made the 2nd car constantly accelerate for a longer time (i.e. the smallest longitudinal quickness during acceleration); however, if evaluated by metrics of the mean acceleration/deceleration, jerk and minimum headway distance, the AHS was superior to other merge strategies. Obviously, the evaluation of the AHS does not consider the time dimension of the metric, i.e. how long this level of metric lasted in the experiment.

For the 3rd car, it was less affected by the merge algorithm compared with the 2nd car; the AHS was the best merge strategy regarding both driving safety and comfort.

The selected algorithms are not the most recent; nevertheless, they are very classical and representative that many more advanced algorithms developed their framework based on the extension of these classical algorithms. Given that it is hard to evaluate all merge strategies, the evaluation on classical algorithms would be a more practical way. While that the four algorithms selected in the research may not be enough to represent the two categories of the merge strategies, more merge strategies should be evaluated in the future.

Table 5-1 Driving performance summary for merge strategies

Vehicle	Period	Metrics		Metric Relationship	Best Strategy
2nd car	merging	safety metrics	TET	GFM < KLFE < IDM < AHS	GFM
			minimum TTC	GFM < IDM < KLFE <AHS	AHS
		comfort	mean deceleration	AHS < IDM < KLFE < GFM	AHS
			average jerk during acceleration period	IDM < AHS < KLFE < GFM	IDM*
			minimum headway distance	GFM < IDM < KLFE < AHS	AHS
	following	safety metrics	TET	KLFE < AHS < IDM < GFM	KLFE*
			TIT	GFM < IDM < KLFE < AHS	GFM
		comfort	TTMD	AHS < KLFE < IDM < GFM	GFM
			longitudinal quickness during acceleration	GFM < KLFE < IDM < AHS	GFM
			mean acceleration	AHS < KLFE < IDM < GFM	AHS
			mean deceleration	AHS < IDM < KLFE < GFM	AHS
			average jerk during acceleration period	AHS < IDM < KLFE < GFM	AHS
			minimum headway distance	GFM < IDM < KLFE < AHS	AHS
3rd car	following	safety metrics	minimum TTC	IDM < GFM < KLFE < AHS	AHS
		comfort	minimum headway distance	GFM < IDM < KLFE < AHS	AHS

Note: IDM* and KLFE* had similar performance as AHS. All values were evaluated at 95% significance level.

6 Conclusions

This study analyzed the effects of CAV merge strategies on mainline human driven vehicles, considering both driving safety and comfort. Four merge strategies were evaluated using a UCF self-developed multi-driver simulator system, including the reference-trajectory-based merge strategy and the social-psychology-based merge strategies. The results show that these algorithms might not have consistent performance when evaluated by different safety and comfort metrics. In addition, merge strategies may have a variation of effects between the merging and following periods. Moreover, the AHS and GFM may have some superiority when evaluated at specific dimensions in terms of driving safety and comfort; nevertheless, the AHS may outperform other merge strategies in more scenarios. More merge strategies need to be verified and compared in the future to form a comprehensive conclusion. Finally, findings suggest that the CAV merge strategy should not only ensure the ramp vehicle’s merging task but also consider mainline vehicles’ driving performance.

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