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CAVSim: A Microscope Traffic Simulator for Connected and Automated Vehicles Environment

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***Abstract*—Connected and automated vehicles (CAVs) are expected to play a vital role in the next-generation intelligent transportation system. In recent years, researchers have proposed various cooperative driving methods for CAVs' decisions and planning, and there is an urgent need for a suitable and unified traffic simulator to evaluate and test these methods. However, existing traffic simulators have three critical deficiencies for CAV simulation needs: (1) most of them are from the perspective of traffic flow simulation and have strong simplification and assumptions for vehicle modeling; (2) CAVs are different from traditional human-driven vehicles (HVs) and have new properties, which require new driving models; (3) the existing traffic simulators are inconvenient to deploy the emerging cooperative driving methods because their modeling of the traffic system architecture is traditional. In this paper, we introduce CAVSim, a novel microscope traffic simulator for the CAV environment, to address these deficiencies. CAVSim is modularly developed according to the emerging architecture for the CAV environment, emphasizes more detailed driving behaviors of CAVs, and highlights the decision and planning components in the CAV environment. With CAVSim, researchers can quickly deploy decision and planning methods at different levels, evaluate and test their performance, and explore their impact on the traffic flow in the CAV environment.**

I. Introduction

V2X based connected and automated vehicles (CAVs) are one of the leading technologies to achieve autonomous driving and have received extensive research attention in recent years [1]-[4]. With the aid of V2X, vehicles can communicate with roadside units (RSUs) and surrounding vehicles, sharing their state information and driving intentions, which is expected to address the safety challenges faced by autonomous driving effectively. Meanwhile, using the shared information, the researchers have proposed cooperative driving for CAVs. Cooperative driving refers to the driving strategy that coordinates driving behaviors and motion control of multiple vehicles with the support of connected vehicle technology to improve traffic safety and efficiency and reduce energy consumption [5].

As various cooperative driving methods for CAVs mature, evaluating and testing these methods, and exploring their effects on traffic flow, is a growing focus of current researchers. Several projects have been supported to build real-world CAV test fields [6], [7]. However, building a real-world test field is expensive and time-consuming, and deploying cooperative driving methods in it is costly and may carry traffic safety risks. Therefore, researchers are in dire need of a virtual simulator for the CAV environment. The virtual simulator aims to reduce the cost of experiments and accelerate the research schedule. Meanwhile, by controlling the different components of the simulated environment, we can highlight the focused decision and planning links for the CAV environment.

According to the characteristics of the CAV environment and the critical links that are of primary concern to researchers, the traffic simulation for the CAV environment needs to focus on three crucial requirements. First, the simulator needs to emphasize the cooperative decision and planning for multiple vehicles within the CAV environment. Researchers have proposed various methods for multi-CAV cooperative decision and planning in the typical traffic scenarios, which include signal-free intersections [3], [8], [9], on-/off-ramps [10], lane-changing scenarios [11], etc., covering various driving scenarios within general traffic environments. The simulation of these methods is a major demand for CAV-oriented traffic simulation.

Second, the simulator needs to highlight the driving model for CAVs. Since CAVs can obtain a more accurate perception of the surrounding environment and have a shorter reaction time than human-driven vehicles (HVs), researchers have found that CAVs have more efficient driving behaviors, such as shorter and stable car-following gaps [2]. Meanwhile, the cooperative driving methods generally adopt a distributed strategy for planning the multi-CAV trajectories [8], [12], allowing individual vehicle driving behavior to be heterogeneous and optimize their respective objectives such as energy consumption, comfort, and emissions. This requires that the simulation should be a microscopic traffic simulation, and it is essential to choose appropriate driving models to distinguish the differences between CAVs and HVs.

Third, the simulator should consider the particularity of the CAV environment, such as the roads with RSUs, and the communication between CAVs. This may bring new simulation requirements, such as communication delay, data packet loss, and vehicle communication disconnection.

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Microscopic traffic simulation plays a vital role in research areas such as vehicular technology, traffic system control, and traffic flow. Microscopic traffic simulators are designed to simulate the behaviors of individual vehicles and their interactions, where each vehicle and its dynamic are modeled separately. The classic microscopic traffic simulators include SUMO [13], VISSIM [14], MATSIM [15], SEMSim [16], etc. These simulators are widely used in many traditional traffic simulation studies, such as traffic signals, public transportation priority schemes, and vehicle routing. However, the existing microscopic traffic simulators have many deficiencies in the simulation of CAVs. First, these simulators are not detailed enough for vehicle modeling. For example, most simulators assumed that the lane changes could be accomplished instantaneously, which loses the characteristics and effects of lane changes and is not suitable for the simulation of CAV cooperative lane change methods [2], [17]. Second, most of the vehicle driving models in these simulators are oriented to HVs, which is different from CAV driving models. To capture the impact of CAVs on traffic flow, a driving model more in line with CAVs should be applied. Finally, a common drawback of the existing microscopic traffic simulators is their incompatibility with the emerging CAVs and their cooperative driving technologies, which causes great inconvenience for the deployment and testing of CAV based methods.

In this paper, we propose a novel microscopic traffic simulator, CAVSim, for the CAV environment according to the above simulation requirements. CAVSim is developed along with the emerging architecture for multi-CAV cooperative driving in terms of framework design, module decomposition, road segmentation, which can be conveniently used to deploy, evaluate and test the cooperative driving methods at different levels about CAVs. Meanwhile, CAVSim emphasize the difference between CAVs and HVs by choosing a more detailed vehicle driving model that is more compatible with CAVs. CAVSim allows researchers to easily build typical traffic scenarios and deploy their decision and planning methods at different levels. Meanwhile, we can build the highway scenario and urban road networks with CAVSim to explore the impacts of CAVs and cooperative driving on the traffic flow.

Furthermore, all traffic simulators suffer from a common drawback in that simulated HVs mostly move based on rule-based driving behaviors. Researchers have tried to emulate human driving behaviors in recent years using learning-based methods, such as deep reinforcement learning, but the learned driving behaviors remain simple and clumsy. This leads to the gap between human driving behaviors within the simulation environment and the real-world behaviors. To address this drawback, the proposed CAVSim provides import and playback functions for real traffic data. By importing driving trajectory from real HVs into the simulation environment, CAVSim can simulate a more realistic traffic environment and provide a more realistic mixed traffic environment, including CAVs and HVs.

To better present our work, the rest of this paper is organized as follows. *Section II* describes the simulation framework of CAVSim and the functionality of each module. *Section III* gives our realization of CAVSim, especially the driving model setting for CAVs. *Section IV* presents some demonstrations. Finally, we conclude the whole paper in *Section V*.

II. Methodology

This section will introduce the framework and main modules of the CAVSim traffic simulator in detail. To facilitate the various traffic simulation on CAVSim, we decompose and develop CAVSim according to the idea of modular development to increase its scalability. The details are elaborated below.

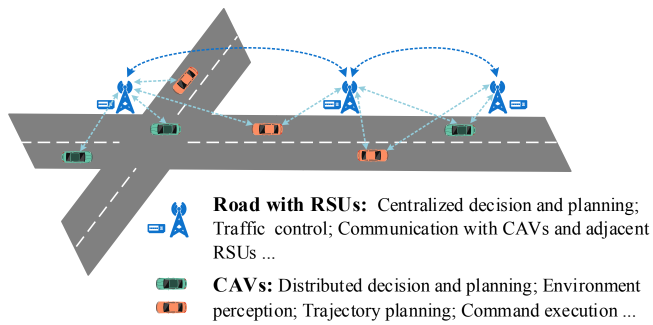


Fig. 1. A general traffic scenario in environment.

A. Framework

Within the CAV environment, vehicles generally follow the following steps to solve their respective perception-decision-action loop. First, each vehicle sends its own state information and driving intentions to the RSUs. After collecting the information of all vehicles in the local scenario, the RSUs make the centralized decision and planning, such as right-of-way scheduling and assignment for multiple vehicles. Then, the RSUs send the decision and planning results to each vehicle in the scenario. Meanwhile, each vehicle can also access the RSUs to obtain the states and intentions information of its surrounding vehicles, i.e., it achieves the perception and localization with the aid of RSUs. After receiving the surrounding information and centralized commands from RSUs, each vehicle solves its own vehicle level decision, planning, and motion control, and finally executes the motion actions. In a general CAV environment, the communication relationship between vehicles and RSUs, and the respective main computation task are illustrated in Fig. 1.

To simulate microscopic traffic in the CAV environment, it can be seen from Fig. 1 that the roads with RSUs and the CAVs are the two core objects. With these two objects and the relevant decision and planning algorithms, we can achieve the microscopic traffic simulation of CAVs. Here, to increase the scalability of CAVSim and facilitate the deployment of various decision and planning algorithms, we adopt a modular idea to develop the CAVSim simulator. As illustrated in Fig. 2, there are two main modules within the CAVSim simulator: the objects and algorithms. The interaction between RSUs and vehicles simulates the CAV environment, and the algorithms provide all the decision and planning concerning vehicle and traffic. The algorithms module is dedicated to providing various interfaces and methods so that researchers can easily

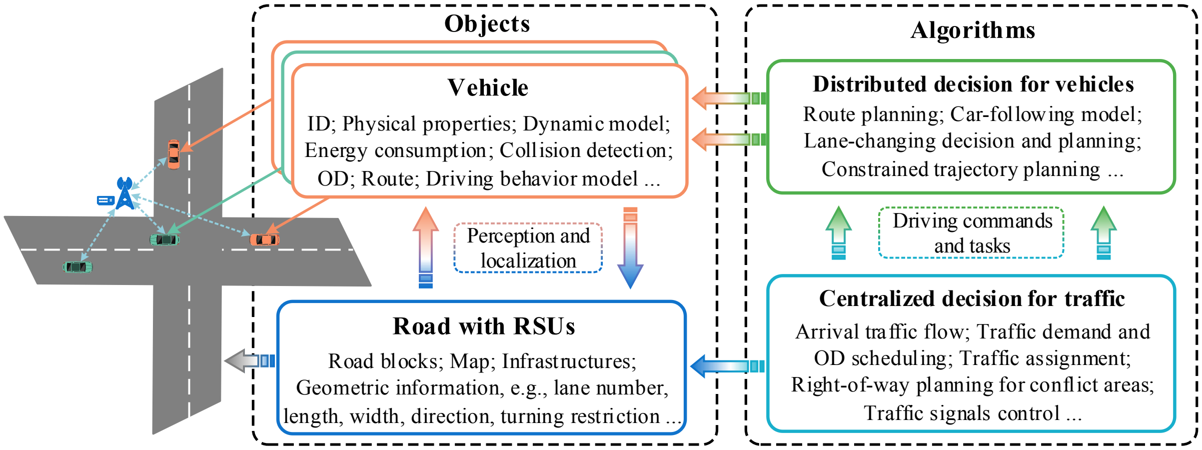


Fig. 2. The overall framework of the CAVSim simulator.

deploy different algorithms by changing a certain method, and then perform microscopic traffic simulation on CAVSim to evaluate and test their algorithms. Moreover, such module decomposition enables users to not only use CAVSim from the perspective of traffic simulation, but also simulate the single-vehicle decision and planning algorithms on CAVSim. In the following, the design of the above two core modules in CAVSim is presented in detail.

B. *Objects module*

1) Road with roadside units: The road is the environment component for the microscopic traffic simulation. In the CAV environment, RSUs give the road additional roles and functions. To increase the scalability of traffic scenarios in CAVSim and take into account the localization of RSUs, we segment the road based on typical traffic scenarios to obtain basic road blocks, as illustrated in Fig. 3. We can use these road blocks to construct arbitrary traffic scenarios. There are many advantages in building road scenarios with road blocks. First, we can take the road blocks as the unit and equip them RSUs separately, which is consistent with the practical CAV environment and can reduce the computational burden on each RSU. Second, it will increase the speed of the vehicles' perception of surrounding environment, thereby increasing the simulation speed. Third, using the basic road blocks, we can construct typical traffic scenarios (such as highways, on-/off ramps, intersections, etc.) and large-scale urban network scenarios through reasonable splicing.

We take the intersection block shown in Fig. 3 as examples to illustrate the basic properties of road blocks and their reasonable splicing. The intersection block consists of two-way lanes in four directions and a conflict area in the center. The main properties and settings of an intersection block are its geometric information, including its location, the number, length, and width of lanes in each direction, speed limit, the turning restriction of each lane, the topology of the conflict area, etc. Each intersection block is equipped with a separate RSU for communication with vehicles in the intersection and corresponding centralized calculations. We can build various road scenarios with these basic road blocks. For example, multiple straight blocks can be spliced to construct a highway scenario; the urban network traffic scenario with multiple intersections can be built by splicing straight blocks and intersection blocks. It should be illustrated that in CAVSim, the intersection can be either signalized or signal-free. Different intersections are independent, and multiple intersections in a road network can adopt different control methods. Moreover, the map provides the splicing relationship between different road blocks, while the infrastructures (such as traffic lights and virtual loops) are used to detect and record traffic status.

In a scenario composed of multiple road blocks, RSUs in adjacent road blocks can communicate and share the collected traffic information, which is similar to the practical CAV environment. Such a setting is beneficial because, for the vehicle, the segmentation of the road and the communication range of a single RSU will not affect its perception of the surrounding environment, even if the vehicle is driving at the junction of the two blocks. Moreover, if users need to simulate the limitation of CAVs' perception range, corresponding settings can be made on RSUs.

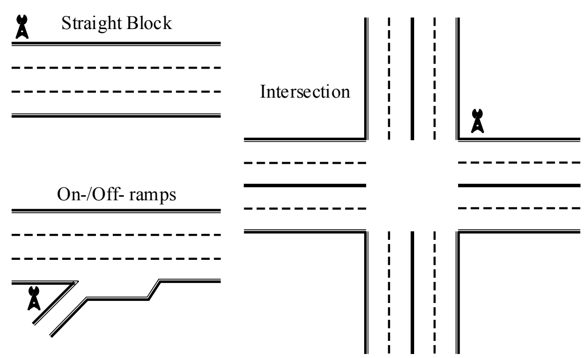


Fig. 3. Typical road blocks in CAVSim, which can be used to build various traffic environments.

2) Vehicles: In the CAV environment, as the problem of environment perception can be effectively solved by accessing RSUs, decision and planning become the main focus of researchers [18]. To achieve the microscopic simulation of vehicles, the vehicles in CAVSim have the following basic properties. First, each vehicle is independent. It has its own identity (ID), physical properties (length, width, acceleration, speed limitation, etc.), dynamic model, origin-destination (OD), collision detection, etc. Second, in terms of function, the vehicle can send its own location, lane, real-time state, driving intentions, and other information to RSU. Meanwhile, the vehicle can carry out distributed path planning, trajectory planning, and motion control. Finally, each vehicle can have an independent driving model, i.e., the vehicles in CAVSim can be heterogeneous. The particularity of CAVs driving behavior will be discussed in *Section III*.

C. Algorithms module

The algorithms module provides all decision and planning algorithms related to traffic and vehicles in the CAV environment. We emphasize the primary decision and planning links involved in the CAV environment from the perspective of vehicles. First, the vehicles continuously reach the boundary of the simulated traffic scenario. The arrival of vehicles can be obtained from the simulation model, such as the commonly used *Poisson* flow, or the real traffic flow extracted from real-world traffic data. When a vehicle arrives, the algorithms module assigns the destination and then solves the route according to its OD. Then, the vehicle begins to move in the road blocks along its route. We use time-driven discrete closed-loop control to solve the motion action, i.e., the speed, of each vehicle at each time step.

At each step of the simulation, the vehicle first accesses the RSUs to obtain the information of the surrounding vehicles and the driving commands from the centralized decision. Here, it should be noted that the driving commands generally vary according to different road scenarios. For example, at a signal-free intersection, the centralized decision will plan the time when the vehicle is allowed to enter the conflict area. After obtaining the surrounding information and centralized commands, the vehicle can use the distributed decision to solve the motion action. The motion action will be input to the vehicle dynamic model, and the vehicle updates its state and position accordingly. Finally, the vehicle sends the updated state information and driving intentions to the RSU for the simulation of the next time step. So far, the vehicle has completed the closed-loop control of one-time step. Similarly, other vehicles will solve their respective closed-loop control to update their positions and states with the same procedure.

Therefore, we can see that there are generally two levels of decision in the CAV environment, i.e., centralized traffic decision and distributed vehicle decision. The former carries out decision and planning in a centralized manner, such as arrival traffic flow, traffic demand and OD scheduling, right-of-way planning, traffic signals, etc. The latter makes the vehicle-level decision and planning in a distributed manner, such as route planning, car-following model, lane-change model, constrained trajectory planning, etc. Using these decision and planning methods provided by the algorithms module, CAVSim can achieve the microscopic simulation of vehicles in various traffic scenarios.

III. Realization

Based on the above framework and two core modules, this section will present our realization for CAVSim. First, we set up driving models in CAVSim that better match the characteristics of CAVs. One of the critical advantages of CAVs is the more efficient driving behaviors compared to HVs [2]. However, existing simulators often overlook this essential characteristic. We clarify and highlight it in CAVSim through the driving model settings. Generally, compared with HVs, CAVs have a shorter reaction time and more accurate perception so that CAVs can maintain a shorter distance or time headway from the leading vehicle. Meanwhile, CAVs often have independent driving objectives, such as efficiency, safety, and energy consumption, so CAVs may have personalized driving behavior, which should be considered in driving models.

Second, to have a satisfactory simulation speed, the core programs of CAVSim are developed with C++. Meanwhile, some of the decision and planning links in the algorithms module have interfaces with Python to facilitate the deployment and testing of methods developed with Python language. To capture the microscopic driving behaviors of the vehicles while balancing the simulation speed, the discrete time-driven mechanism of CAVSim has a time step T of 0.1s.

Moreover, the following are some driving models developed for CAVs in CAVSim, which emphasize the special driving behavior of CAVs.

A. Car-following model

The car-following model is the most widely used driving model in microscopic traffic simulation. Similarly, in CAVSim, the car-following model can be used to solve the longitudinal motion action of vehicles in most scenarios. Suppose that at time t, the speed and position of the preceding vehicle are respectively denoted as $p_p(t)$ and $v_p(t)$, and the speed and position of the following vehicle are $p_f(t)$ and $v_f(t)$. The car-following model aims to solve the speed of the following vehicle at time $t+T$, i.e. $v_f(t+T)$, according to the above four quantities and the vehicle properties.

In recent years, researchers have proposed many car-following models for HV or CAV, such as the desired measure models, safety distance models, and optimal velocity models. Interested readers can see [2] for more details. In CAVSim, we apply the widely used intelligent driver model (IDM) and its modified version to model HVs and CAVs respectively. First, the car-following behavior of human drivers are modeled as follows:

$$a(t) = a_{f,\max}\left[1-\left(\frac{v_f(t)}{v_{f,0}}\right)^{\delta}-\left(\frac{S^*(t)}{p_p(t)-p_f(t)}\right)^2\right] \tag{1}$$

where $a_{f,\max}$ is the maximum acceleration/deceleration of the following vehicle and is determined by its physical properties; $v_{f,0}$ is the desired speed of the following vehicle; δ is the free acceleration exponent. The desired headway $S^*(t)$ of the following vehicle is defined as

$$S^*(t) = S_0 + \max\left(0, v_f(t)T_0 + \frac{v_f(t)\left(v_f(t)-v_p(t)\right)}{2\sqrt{ab}}\right) \tag{2}$$

where S_0 is the minimum desired distance headway; T_0 is the desired time headway; a is the comfortable acceleration; b is the comfortable braking deceleration.

Second, the modified IDM model proposed in [19] aims to simulate the car-following behaviors of CAVs. It changes the equation. (1) as follows:

$$a(t) = a_{f,\max} \min\left(1-\left(\frac{v_f(t)}{v_{f,0}}\right)^{\delta}, 1-\left(\frac{S^*(t)}{p_p(t)-p_f(t)}\right)^2\right) \quad (3)$$

i.e., CAVs selects the minimum value of the free flow term and the interaction term. The modified IDM model has shorter and stable car-following gaps under the same traffic conditions, which is more in line with the driving behavior of CAVs. We can simulate the heterogeneity of CAVs driving behaviors by changing the above parameters. Moreover, interested readers can refer to our survey [2] for other car-following models to describe CAVs' driving behaviors.

B. Cooperative driving at signal-free intersection

In the CAV environment, the problem of multiple CAVs driving through the signal-free intersection is generally solved in two levels. In the upper level, the centralized algorithm schedules the right-of-way of the conflict area, and in the lower level, the distributed algorithm plans the trajectory and motion action based on the results of the upper level. For the upper level, we develop the widely used first-in-first-out (FIFO) based right-of-way scheduling method. Meanwhile, the centralized algorithm plans the desired time t_{desire} for each vehicle to enter the conflict area. The lower level algorithm solves the motion control of the vehicle according to the desired time t_{desire}. In CAVSim, the distributed trajectory planning for CAVs that take the energy consumption as the driving objective is:

$$\min_{a(t)} \frac{1}{2}\int_{t_0}^{t_{desire}} a^2(t)dt \quad (4)$$

$$s.t. \quad p(t_0) = 0, \quad p(t_{desire}) = D \quad (4a)$$

$$v(t_0) = v_0, \quad v(t_{desire}) = v_{desire} \quad (4b)$$

$$p(t) + \delta_p \le p_p(t) \quad (4c)$$

$$\dot{p}(t) = v(t), \quad \dot{v}(t) = a(t) \quad (4d)$$

$$v_{\min} \le v(t) \le v_{\max}, \quad a_{\min} \le a(t) \le a_{\max} \quad (4e)$$

$$\forall t \in [t_0, t_{desire}] \quad (4f)$$

where D is the distance to the conflict area; v_0, v_{desire} are the initial speed and desired speed, respectively; δ_p is the safe distance to the preceding vehicle. The remaining constraints come from the dynamic and physical properties of the vehicle. In particular, since solving the above problem directly is time-consuming, we deploy the approximate analytical solution of the problem [20], which can quickly solve the discrete motion action of multiple vehicles with time step T.

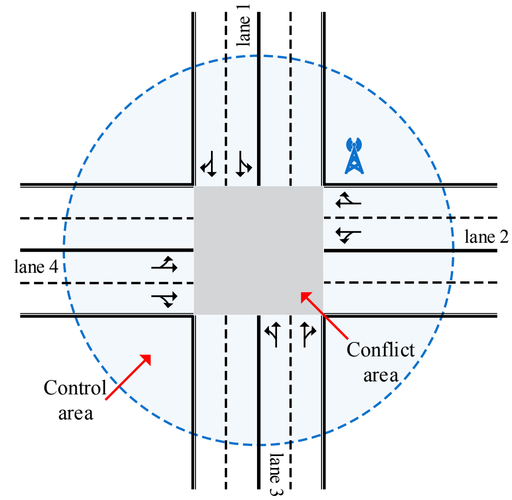
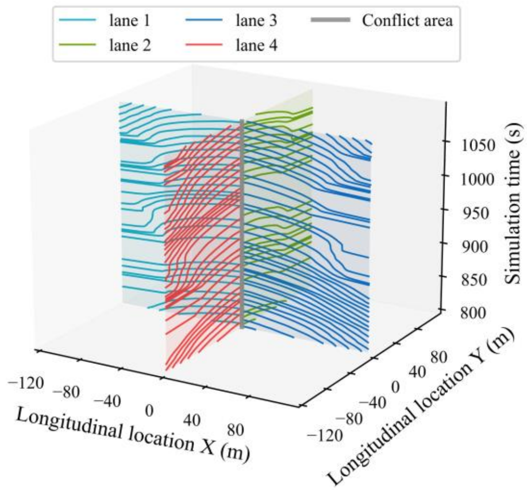


Fig. 4. The simulated signal-free intersection under cooperative driving environment. The radius of the control area is 100m long.

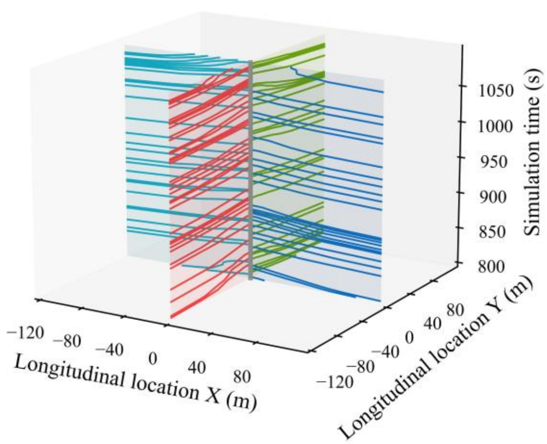
IV. Demonstrations

In order to demonstrate the microscopic traffic simulation capacity of CAVSim for the CAV environment, we discuss a typical CAV scenario case: multi-CAV cooperative driving at the signal-free intersection. We build a typical signal-free intersection in the CAVSim simulator, as illustrated in Fig. 4. Before entering the control area, vehicles move based on the car-following model; after entering the control area, each vehicle plans its motion control according to the decision results of the centralized cooperative driving method. In the signal-free intersection, we quickly deploy two typical cooperative driving methods: the FIFO based cooperative driving method and the MCTS based cooperative driving method [3]. Generally, the MCTS based method can find the right-of-way scheduling solution with shorter travel delay than the FIFO based method [21]. Here, to intuitively show the characteristics of vehicles driving under different cooperative driving methods, we draw the vehicle trajectories in Fig. 5.

As can be seen from Fig. 5, CAVSim effectively simulates the microscopic driving of vehicles at signal-free intersection. Under different cooperative driving methods, vehicles have significantly different trajectories. For the FIFO based method, when vehicles enter the control area, vehicles slow down obviously because the vehicles entering in other directions have been assigned the right-of-way of the conflict area. However, since the MCTS based method can find better right-of-way scheduling solutions, the corresponding vehicle trajectories are smoother, and the vehicles do not decelerate significantly. Moreover, it can be seen that under the MCTS based method, vehicles in the same lane pass through the conflict area in groups. However, the FIFO based method leads to vehicles in all directions passing in turn, which may be the critical factor leading to the performance difference between the two methods. It should be noted that the purpose of the above representative case study is not to compare these methods but to demonstrate the use of CAVSim and show what results can be extracted. Similarly, we can quickly deploy various cooperative driving methods on the CAVSim to test their performance.



(a) Vehicle trajectories under FIFO based cooperative driving.



(b) Vehicle trajectories under MCTS based cooperative driving.

Fig. 5. Vehicle trajectories at signal-free intersection under different cooperative driving methods. The lane indexes correspond to the labels illustrated in Fig. 4.

V. CONCLUSION

This paper proposes CAVSim, a microscopic traffic simulator for the CAV environment. The framework of CAVSim is consistent with the realistic CAV environment, including module decomposition, road segmentation, computing task allocation, which can be conveniently used to deploy and test the cooperative driving methods at different levels about CAVs. Meanwhile, CAVSim emphasizes the critical properties and driving behaviors of CAVs and is dedicated to capturing the characteristics of CAVs and their impact on traffic flow. Modular development makes CAVSim have good scalability, which can simulate typical local traffic scenarios, and can also simulate large-scale network-wide traffic through reasonable splicing of road blocks. With CAVSim, users can conduct various traffic and vehicle simulations related to CAVs. Finally, CAVSim is an evolving project, and we will further refine and enhance it next. In particular, we will develop more benchmarking algorithms in CAVSim to promote the development of CAV with a unified platform.

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