Xishun Liao, Ziran Wang, Kyungtae Han, Xuanpeng Zhao,
Matthew Barth, and Guoyuan Wu

15 Driver Behavior-Aware Cooperative Ramp Merging for Intelligent Vehicles

Abstract: Ramp merging is one of the major causes of traffic accidents and congestion along freeways due to its inherent chaotic nature. To handle this, researchers have proposed globally optimal ramp merging coordination strategies using intelligent vehicles, such as connected vehicles (CVs), autonomous vehicles (AVs), and connected and automated vehicles (CAVs). However, few of them have been able to systematically weave personalized driver behavior consideration into ramp merging strategies. In a foreseeable future, intelligent vehicles still need to understand the intentions and behaviors of surrounding vehicles during interactions. Toward this end, challenges to be addressed include: (1) predicting the behavioral interactions with other human-driven vehicles; (2) providing personalized driving guidance (e.g., Advanced Driver-Assistance Systems (ADAS) for better performance; and (3) boosting the user's acceptance and trust in intelligent vehicles. In this chapter, we design a ramp merging coordination system considering both longitudinal and lateral personalized driver behaviors. This system provides a holistic solution to the traffic environment with different levels of driving automation and wireless connectivity. Cooperative ramp merging algorithms that aim to address human-vehicle harmonization and intervehicular coordination are developed. A simulation platform and a real-world testbed are built for data collection and algorithm validation.

Keywords: Cooperative ramp merging, driver behavior, prediction, cosimulation, field implementation

15.1 Introduction

Traffic-related notions such as safety, efficiency, and environmental sustainability have drawn significant attention as transportation is more involved in people's daily lives. Among the factors leading to traffic congestion and accidents, ramp merging has a significant amount of impact [1]. Vehicles merging near the ramp area have been a major concern that generates numerous potential conflicts, due to the chaotic nature of driving behaviors and the lack of coordination in the merging area. The difficulty arises for drivers of ramp vehicles (RVs) along the on-ramp, where drivers must discern to accelerate/decelerate to enter the mainline safely without a clear line

Xishun Liao, Xuanpeng Zhao, Matthew Barth, Guoyuan Wu, University of California, Riverside, USA
Ziran Wang, Kyungtae Han, Toyota InfoTechnology Center, USA, INC

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of sight regarding the mainline traffic. Meanwhile, drivers of mainline vehicles may have to modify their vehicle speeds to permit the entrance of RVs, thus affecting upstream traffic flows and consuming excessive energy.

The emergence of connected and automated vehicle (CAV) technology brings about solutions to ramp merging issues. By taking the advantage of vehicle-to-everything (V2X) communications, vehicles can communicate with other road participants. As a typical example of CAV technology implementation, the cooperative merging of vehicles at ramp has been studied and applied by various researchers around the globe, where connected vehicles (CVs) communicate with vehicles coming from the other lane directly or through roadside infrastructure, and hence conduct cooperative merging maneuvers in a safe and smoothed manner [2–4].

Since CAVs are supposed to share the road with legacy vehicles in a foreseeable future, considering the mixed traffic environment is more pragmatic, though more challenging in terms of regulating the entire traffic stream. The well-planned operation for CAVs may be interrupted by legacy vehicles (human-driven vehicles); hence the interaction between CAVs and legacy vehicles should not be ignored. Specifically, CAVs need to understand human-driven vehicles' behaviors, make decisions dynamically regarding the actions to be taken, and execute such actions through the planner and controller. Therefore, many researchers incorporate driving behavior modeling into their planning and control design [5–7], recognized as the driver behavior-aware system.

The remainder of this chapter is organized as follows: in Section 15.2, the state of the art of ramp merging coordination and driver behavior modeling are reviewed. Section 15.3 explains the methodology of the behavior-aware ramp merging coordination system. Section 15.4 elaborates on how the proposed algorithms are validated in both simulation and real-world testbeds. Finally, the chapter is concluded with future directions in Section 15.5.

15.2 Literature Review

15.2.1 Ramp Merging Algorithms for CAVs

Numerous cooperative ramp merging methodologies have been proposed for some time now. The concept of utilizing virtual vehicles in the highway on-ramps cooperative merging case originated from Uno et al. [8] and got adopted by some consecutive studies [9–11]. This approach maps virtual copies of the real vehicles onto the other merging lane before the actual merging happens, so CVs can adjust their formation in advance and avoid last-minute speed changes.

Other than the virtual vehicle concept, the merging cooperation is formulated as two optimal trajectory planning problems for a pair of the ramp and mainline vehicles by Zhou et al. [12], without presuming a merging location. Rios-Torres and Malikopoulos

[13] presented an optimization framework and an analytical closed-form solution that allowed online coordination of CAVs at ramp merging zones and further studied the impact of partial penetrations of CAVs on fuel consumption and traffic flow for the ramp merging scenario [14]. Besides the numerical simulation and/or microscopic traffic simulation, game engine simulation (e.g., Unity and CARLA) was also used to evaluate the cooperative ramp merging system, where human-in-the-loop (HuiL) simulation can be conducted and compared with the proposed methodology as a baseline [15].

Apart from these methods, game theory has also been widely adopted in ramp merging strategies for CAVs decision-making, as it can model how human drivers decide to compete or cooperate with others, hence enabling the analysis of the interaction between them [16]. To get a global perspective and obtain the optimal solution, centralized optimization algorithms have been developed to coordinate the ramp merging maneuvers. Jing et al. [17] designed a cooperative game-based merging sequence coordination system to arrange CAVs into platoons and used optimal control to guarantee the best sequence in terms of mobility and fuel consumption. To mitigate shockwaves caused by merging maneuvers, Akti et al. [18] proposed a game theory-based algorithm to organize the longitudinal and lateral movements for merging vehicles, in a fully connected environment. By estimating surrounding vehicles' aggressiveness as their utilities, Zhang et al. [19] presented a game theory-based model predictive controller to find out the optimal gap and perform mandatory lane-changing, by searching up to three gaps on the adjacent lane.

However, most of these studies rely on a strong assumption of a 100% CAV penetration rate, allowing for a centralized complete game approach that can utilize full information [20]. In contrast, especially in mixed traffic with a low penetration rate, CAVs can only form an incomplete game with limited information from the legacy vehicles within the detection range of CAVs.

15.2.2 Driver Behavior Modeling

Since driver behavior study plays a significant role in the system that involves human beings, to design an interactive and cooperative system, CAVs are required to consider both human–machine coordination inside a vehicle and intervehicular coordination inside a vehicle. Therefore, a number of researchers investigated human–machine interaction from different angles, such as driver type (e.g., driving style [21] and demands [22]) clustering and driver preference recognition [23]) and driver condition (e.g., driving performance [24] and mood states [25]) classification.

However, most of these driver behavior modeling algorithms only consider the ego vehicle (instrumented vehicle) state and ignore the interaction with the surroundings. It is noted that intervehicular coordination is significant in a ramp merging system design. The behavior modeling for intervehicular coordination requires not only the ego vehicle states but also the surroundings and vehicular interaction. Sun et al. [26] introduced a hierarchical inverse reinforcement learning (IRL)-based algorithm to predict both discrete decisions and continuous trajectories of a target vehicle involved in a two-vehicle ramp merging interaction. The driver's preference for vehicle state and interactions can be expressed by the cost function recovered by IRL [27], which assumed that the driver was driven by optimizing the unknown reward function. In [28], the interaction behavior under different conditions was formulated as a cost function with different combinations of features and learned by continuous IRL.

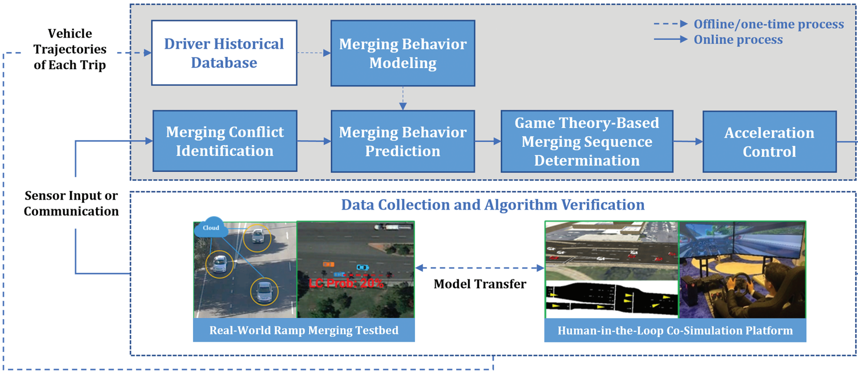

Fig. 15.1: Schema of the proposed behavior-aware ramp merging coordination system.

15.3 Methodology

15.3.1 Schema of Ramp Merging Coordination System

This section elaborates about the design of a cooperative ramp merging system for both fully connected traffic and mixed traffic. The proposed system is designed from a decentralized agent-based model perspective for CAV, allowing vehicles to act independently. For algorithm development and verification, we establish a database, a local server for real-world algorithms implementation, and a HuiL cosimulation platform. The strategy workflow is shown in Fig. 15.1, where every vehicle goes through these modules connected by the solid line at each time step.

1. *Merging conflict identification module*: Based on the information from the perception system or other CAVs, this module judges whether conflicts anticipates in the future and identifies the vehicle type of competitor (e.g., CAV, CV, AV, or legacy vehicle).
2. *Merging behavior modeling* and *merging behavior prediction modules*: These two modules comprise the behavioral layer to understand and predict the involved drivers' behavior. By modeling the driver behavior during merging, the prediction module can estimate whether, when, and where the merging will happen.

3. *Merging sequence determination module*: This module captures the interaction between the ego vehicle and its surroundings based on game theory. Ego vehicle forms an individual (two-player) game with each of its competitors (i.e., each potential conflicting vehicle). In each game, each player chooses to be a follower or a leader to determine the merging sequence.
4. *Acceleration control module*: This module is responsible for ensuring the ego vehicle run at the desired speed and tracks the lane (e.g., by providing speed guidance).

15.3.2 Merging Behavior Modeling and Prediction

Unlike the case of two conflicting CAVs with direct communication, CAVs need to estimate the merging intention (i.e., yes or no), location, and timing of their human-driven competitors. The proposed algorithm [29] can be used to model and predict the behavior of human-driven vehicles, every time encounter a human-driven vehicle. If the human-driven vehicle is connected to the cloud (e.g., by cellphone), the CAV can identify and obtain the model of the driver to facilitate the prediction.

The system consists of an offline learning process and an online validation process as depicted in Fig. 15.2. In the offline modeling process, based on the historical trajectory dataset, a long short-term memory (LSTM) model [30] is trained to predict the lane change decision, whose input is a trajectory sequence $\xi = \left(s_{t-T}^{\mathrm{lstm}}, \ldots, s_{t}^{\mathrm{lstm}}\right)$ of the last T steps vehicle states. The output of the sequence-to-sequence LSTM model is the predicted lane change action sequence $(A_{t+1}, \ldots, A_{t+T+1})$ for the next T steps. The cost function inferring the driver preference is learned by IRL. In the online prediction process, at each time step, the vehicle states will be analyzed by the LSTM network to recognize the merging maneuver and select a proper cost function. Next, the cost function is used to evaluate the confidence of all possible trajectories provided by the trajectory generator. Finally, the system outputs are the most probable trajectory and lane change probability at the current step.

15.3.3 Driver Preference Inference and Trajectory Prediction

The driver behavior and preference are usually represented by a cost function, and rational drivers behave by optimizing their cost function. Considering the continuity of the trajectory space, this study adopts continuous IRL with locally optimal examples [31] to recover this unknown cost function from expert demonstrations.

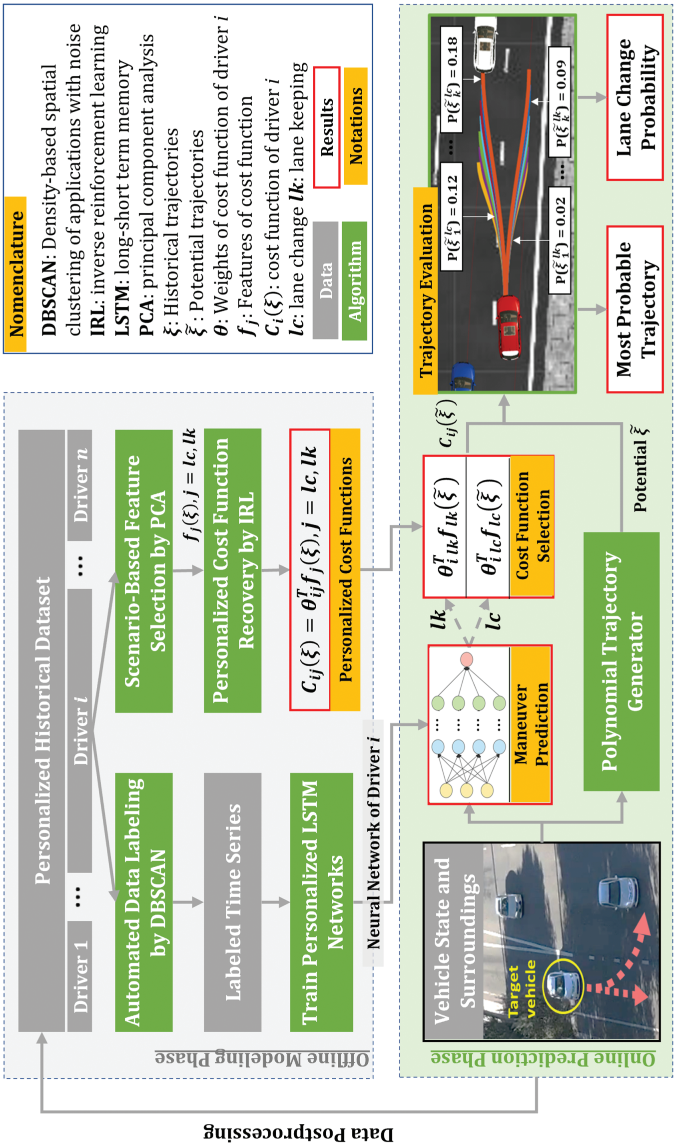

Fig. 15.2: Merging behavior modeling and prediction: A hierarchical learning-based approach for lane change prediction with an offline modeling phase (in gray) and online prediction phase (in green).

15.3.3.1 Continuous IRL

The cost function is a linear combination of a set of features, that is, $C_i(\theta_i, \xi) = \theta_i^T f_i(\xi), i = \{a_{\text{change}}, a_{\text{keep}}\}$, where θ_i^T is the weights vector emphasizing the features and $f_i(\xi) = \|f_i(s_1, s_2, \ldots, s_t)\|_2$. The goal of the IRL is to figure out the optimal weights θ_i^* to describe each driver's preference, which maximizes the likelihood of the driver's historical trajectories $\Xi = \{\xi_k\}$, shown as follows:

$$\theta_i^* = \arg\max_{\theta_i} P(\Xi \mid \theta_i). \tag{15.1}$$

According to the principle of maximum entropy [32], a trajectory with a low cost has a higher probability, which is proportional to the exponential of its cost. To handle the computational complexity, the continuous IRL approximates eq. (15.1) and reformulates the problem as a minimization of $-\log P(\Xi \mid \theta_i)$:

$$\theta_i^* = \arg\min_{\theta_i} \sum_{k=1}^{K} \frac{1}{2} \mathbf{g}_{\theta_i}^T(\xi_k) \mathbf{H}_{\theta_i}^{-1}(\xi_k) \mathbf{g}_{\theta i}(\xi_k) - \frac{1}{2} \log |\mathbf{H}_{\theta i}(\xi_k)|, \tag{15.2}$$

where $\mathbf{g}^T$ and $\mathbf{H}$ are the gradient and Hessian, respectively.

The selected features $f(\xi)$ present the vehicle state in an interpretable way and can capture the preference of the driver. To calculate the cost function, we select the features based on their contribution to the dataset variance, considering the available IMU and GNSS information, including (a) car-following risk $f_{\text{risk\_f}}$, (b) lane change risk $f_{\text{risk\_lc}}$, (c) lane change urgency f_{urge}, (d) mobility f_m, (e) longitudinal comfort f_a and lateral comfort f_{yaw}, and (f) lane deviation f_{dev}.

15.3.3.2 Trajectory Generation and Probability Estimation

To execute the decision of lane change or lane keeping, planning of the trajectory is essential. Considering the real-time performance, instead of exploring arbitrary trajectory, we adopt a polynomial trajectory generator [33] to plan the candidate trajectories $\tilde{\xi}_k$. As the trajectory evaluation module is shown in Fig. 15.2, at each time step, this trajectory generator plans multiple trajectories within a prediction window, taking the vehicle state as the input. Based on eq. (15.3), the cost function $C_i(\theta_i, \tilde{\xi}_k)$ is used to evaluate the probability of each possible trajectory $\tilde{\xi}_k$ and select the most probable trajectory. The probability of the lane change maneuver prediction is evaluated by eq. (15.4), that is, the probability of lane change equals the sum of the probability of all sampled lane change trajectories. Based on eqs. (15.3) and (15.4), we can obtain the most probable trajectory and lane change probability. Therefore, this module can predict whether, when, and where the human driver will perform the merging:

$$P(\xi_k|\theta_i^*) = \frac{e^{-c_i\left(\theta_i^* \xi_k\right)}}{\sum_{k=1}^{K} e^{-c_i\left(\theta_i^*, \xi_k\right)}}, \tag{15.3}$$

$$P(\hat{a}_i) = \sum_{k=1}^{K} P\left(\tilde{\xi}_k|\theta_i^*\right) \tag{15.4}$$

15.3.4 Ramp Merging Coordination

15.3.4.1 Merging Sequence Determination

After predicting the merging behavior of surrounding vehicles and knowing the conflict cannot be avoided, a game between a mainline vehicle and a RV is played in each time step whenever a conflict exists [34]. The game starts when the conflict emerges and ends until this conflict is solved. During the merging process, complex conflict can be summarized with three types of scenarios including the interactions between (1) two legacy vehicles, (2) two CAVs, and (3) a CAV and a legacy vehicle. This chapter will only discuss the CAV(s) involved conflicts since the conflicts between two legacy vehicles cannot be coordinated directly by CAVs. Hereafter, this section will analyze the merging strategy from the perspective of the ego vehicle (CAV).

15.3.4.2 Game Formulation and Cost Function Design

When a potential conflict exists in the merging area, at least one of the mainline vehicles and RVs needs to adjust its speed for a certain merging sequence. For the decision-making purpose, Game Theory [35] is adopted for CAVs to evaluate their situation and then figure out the optimal merging strategy. A two-player non-zero-sum game is used for handling each conflict. In such a game, the ego vehicle is named *Player 1* (P1), while its competitor is *Player 2* (P2). Both P1 and P2 can choose either to be a leader or a follower, with the action set defined as $A(P1) = \{1\text{: leading},\ 2\text{: following}\}$, and $A(P2) = \{1\text{: leading}, 2\text{: following}\}$.

Safety is always the highest priority to be considered in a valuable cost function. The cost of rear-end collision risk (J_{risk}^{c}) for each action is calculated by combining predicted TTC ($\hat{t}_{\text{TTC}}$) and predicted time headway of ego vehicle ($\hat{h}_{\text{ev}}$). To consider the merging urgency of a RV, the distance to the end of the merging area should be added to the risk value of the RV as the risk of merging (J_{risk}^{m}). To summarize, the risk for mainline vehicles and RVs used in this study can be expressed as follows:

$$J_{\text{risk}} = \begin{cases} J^{c}_{\text{risk}}, & \text{mainline vehicles} \\ \left(J^{c}_{\text{risk}} + J^{m}_{\text{risk}}\right)/2, & \text{ramp vehicles} \end{cases}. \tag{15.5}$$

Saving travel time may be another target for players in the game. Adding a mobility term helps CAVs find the balance between safety and speed and improve traffic efficiency at the same time. The cost of travel mobility (J_{mobility}) can be evaluated by comparing the ego vehicle speed difference of either being a follower or a leader in the game.

To improve the driving comfort, hard braking and drastic acceleration are penalized as the cost term of comfort (J_{comfort}), by evaluating the acceleration.

In conclusion, the overall cost ($\bar{J}$) is

$$\bar{J} = \alpha_1 J_{\text{risk}} + \alpha_2 J_{\text{mobility}} + \alpha_3 J_{\text{comfort}}, \tag{15.6}$$

where each cost term is normalized; $\alpha_i \geq 0,\ \ i = 1, 2, 3$, is the weight for each term in the cost function, and $\sum_i \alpha_i = 1$.

15.3.4.3 Noncooperative Game and Cooperative Game

After estimating the cost of each player's action, the optimal merging sequence can be obtained from a decision table, which depends on the game type, either noncooperative or cooperative game, and a game can be only initiated by CAV. If the CAV receives no response from the other party, a noncooperative two-player game will be formed, where the CAV will adopt a selfish strategy, as the *noncooperative game* in Tab. 15.1. To avoid a collision, the ego vehicle will not choose to play the same role as its competitor at the same time. Therefore, the costs for both players being the leaders or followers simultaneously are set to be infinity (or very large). The game between two CAVs would be a cooperative one, where players can make decisions together. The

Tab. 15.1: Decision table for two-player game.

Noncooperative game		**Competitor**	
Ego vehicle	Role	Leader	Follower
	Leader	∞	$\bar{J}_{\text{lead}}$
	Follower	$\bar{J}_{\text{follow}}$	∞
Cooperative game		**Partner**	
Ego vehicle	Role	Leader	Follower
	Leader	∞	$\bar{J}^{\text{ego}}_{\text{lead}} + \bar{J}^{p}_{\text{follow}}$
	Follower	$\bar{J}^{\text{ego}}_{\text{follow}} + \bar{J}^{p}_{\text{lead}}$	∞

decision table of the cooperative game between two CAVs is shown as *cooperative game* in Tab. 15.1. A cooperative game can optimize the total cost (based on the information shared via vehicle-to-vehicle communication) for both CAVs. Once the merging sequence of various merging vehicles is decided by the proposed model, the merging maneuver between any two vehicles is simplified into a car-following problem [36], with their leaders assigned by the *merging sequence determination module*.

15.4 Experiment Platforms and Case Study

To develop and validate the proposed behavior modeling, prediction, planning, and control algorithms, a simulation platform, and a real-world test bed are built. Besides the introduction of these two experiment platforms, case studies for merging prediction and cooperative ramp merging coordination will be elaborated in this section.

15.4.1 Algorithm Validation on Human-in-the-Loop Co-simulation Platform

As shown in Fig. 15.3, based on a real road network, an integrated co-simulation platform is set up to connect Unity, SUMO, and AWS, where vehicle models, traffic networks, and cloud computing are seamlessly combined [37]. The HuiL simulation is supported by the Logitech driving set, providing high-fidelity interactions between a human-controlled vehicle and other background traffic. Moreover, it is a scalable cloud-based platform connecting to AWS, which is extended for synchronous or asynchronous multiplayer games and driving data collection, storage, and mining for driver behavior modeling.

Before envisioning the real-world implementation, the proposed ramp merging coordination system is developed and validated in simulation. In this study, 37 trips with lane changes and 22 trips without any lane change within the on-ramp/off-ramp area are collected on the HuiL co-simulation platform. A neural network is trained to predict the lane change maneuver, and the cost function of both merging and lane keeping is recovered by IRL. The online merging behavior prediction is visualized as in Fig. 15.4, including lane change maneuver and the most likely trajectory. The proposed algorithm recognizes the lane change maneuver in 3 s before the vehicle crosses the borderline, and the mean Euclidean distance is used to quantify the accuracy of trajectory prediction, and it achieves 0.39 m within a 4 s prediction window in an average of 10 test trips [29].

Furthermore, a traffic flow level simulation is carried out to evaluate how the system benefits from different traffic conditions, where three congested levels and four levels of CAV penetration rate are discussed. A typical merging interaction during the simulation is shown in Fig. 15.5, where two CAVs solve a similar conflict with a cooperative game. The actions of two CAVs are exclusive, with one being the follower and

Fig. 15.3: Cloud-based human-in-the-loop co-simulation platform.

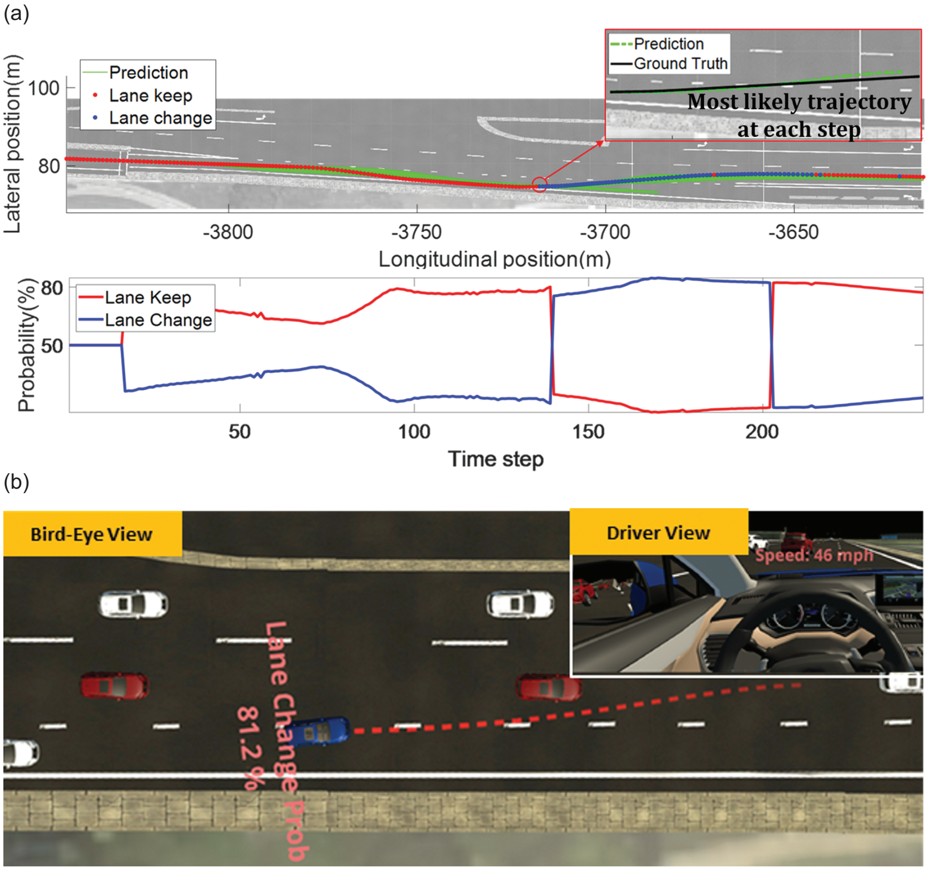

Fig. 15.4: Ramp merging behavior prediction. (left) The whole process of lane change prediction. (right) The most likely trajectory visualization in the simulation platform.

the other one being the leader. Before the conflict starts, the on-ramp CAV accelerates to reach the mainline speed. At the instant two CAVs encounter each other, the merging sequence is decided. The cooperative merging between two CAVs takes only 2.86 s to solve the conflict, which is much faster than 5.26 s in a noncooperative game. Compared with the baseline model provided by SUMO [38,39], the average speed of traffic flow can be increased up to 210%, while the fuel consumption can be reduced up to 53.9%. In addition, the driving volatility can be stabilized to a level with 0% extreme values.

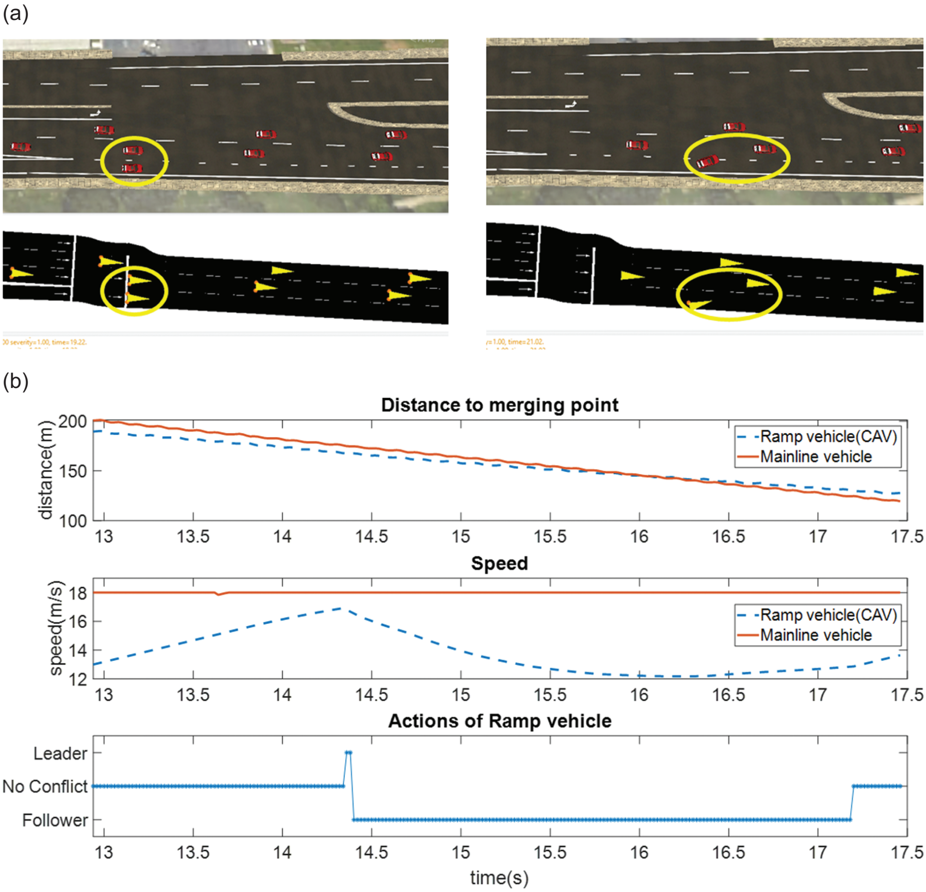

Fig. 15.5: Process of a cooperative game: (left) Two CAVs compete for merging; (middle) Merging order is determined; (right) the whole process of the game.

15.4.2 Real-World Experiments Using Cloud-Based CAV Ramp Merging Testbed

As a realization of the "digital twin" concept, a flexible cloud-based CAV system framework has been developed and demonstrated [40]. Real-world field implementation of the proposed ramp merging system has been conducted with three passenger vehicles. As the prototype of the simulation road network, the test track consists of a ramp and a mainline, where the mainline spans from the intersection of Columbia Avenue and Chicago Avenue to the intersection of Iowa Avenue in Riverside, California. In the digital twin framework presented in Fig. 15.6, onboard devices upload the data to the cloud server through the 4 G/LTE cellular network. The server creates digital twins of vehicles and drivers whose parameters are synchronized in real time with their counterparts in

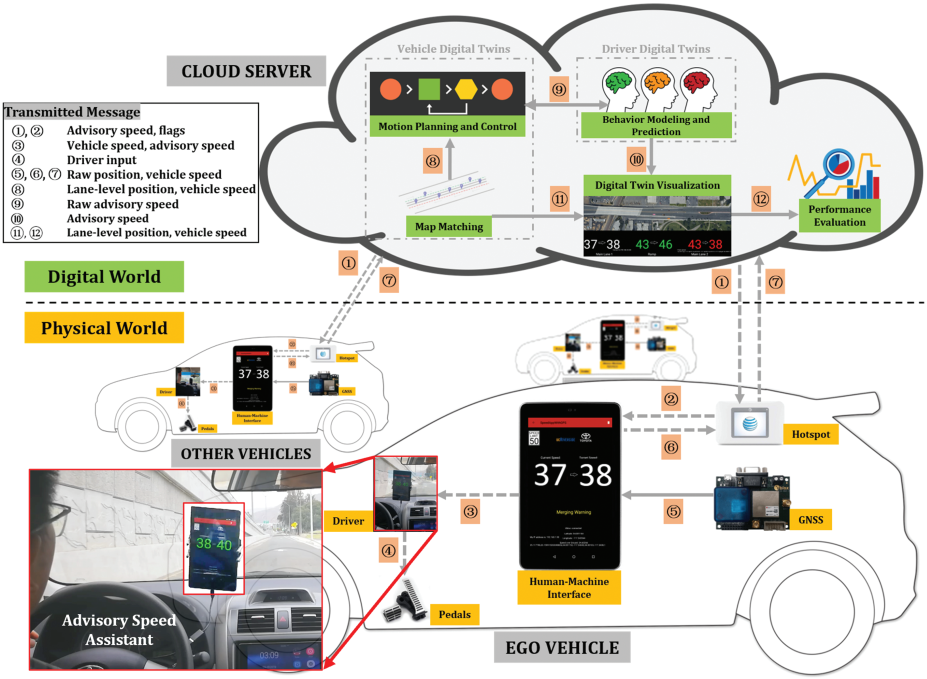

Fig. 15.6: General architecture of the vehicle-to-cloud-based cooperative ramp merging system.

the physical world, processes the data with the proposed models in the digital world, and sends advisory information back to the vehicles and drivers in the physical world. Fig. 15.6 shows how the speed guidance is shown in a uniquely built user interface.

Once the merging sequence is determined by the upstream planning module, the cooperative merging control is responsible for guiding the vehicle to the defined sequence with a safe merging gap. Four merging stages are introduced in Fig. 15.7. In stage 1 (i.e., Fig. 15.7(a)), the mainline following vehicle (MV2) is assigned to follow the mainline leading vehicle (MV1) and enters the interacting zone at a constant speed. At the same time, the RV receives the countdown information from the approaching MV1. In stage 2 (i.e., Fig. 15.7(b)), RV is assigned to follow MV1 and starts to accelerate based on the speed suggestion. In stage 3 (i.e., Fig. 15.7(c)), MV2 is assigned to follow RV when RV satisfies the requirement. RV is ready to merge, while MV2 is notified to slow down and generates a gap for the merge. In stage 4 (i.e., Fig. 15.7(d)), given enough intervehicle gap, RV merges into the vehicle string.

Specifically, compared with the baseline scenario with no advisory information during the merging process, the proposed system reduces the average speed variance by 67.41%, reduces pollutant emissions by up to 31.21%, and reduces fuel consumption by 7.45%, respectively.

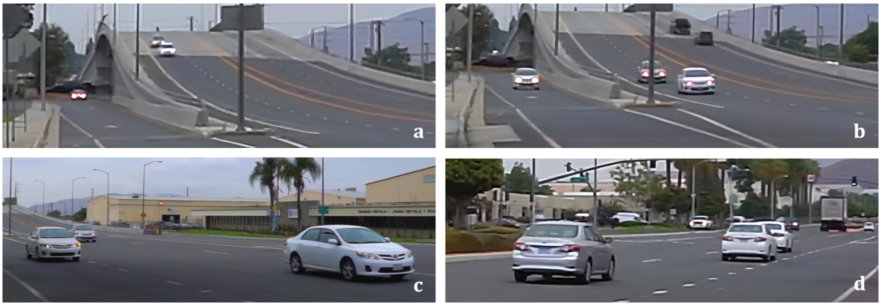

Fig. 15.7: Cloud-based cooperative merging stages.

15.5 Conclusions

This chapter presents a behavior-aware cooperative ramp merging system for CAVs in the mixed traffic environment. The proposed system has been evaluated in a HuiL simulation platform, and the field implementation has been conducted in the real world using a V2C digital twin approach. The result shows that the proposed system improves the current ramp merging scenario in terms of safety and environmental sustainability. As one of the few ramp merging algorithms developed for mixed traffic, some challenges need to be addressed along its future development pathway: (1) In addition to general driving behavior, algorithms need to consider personalized preference by modeling the personalized driving behavior; (2) the lateral planning and control algorithms for ramp merging at both traffic and vehicle must be explored; (3) to allow CAV to drive like a human, the algorithm should consider user acceptance and trust issues; (4) more discussions on how the simulation can be combined with real-world experiments are in demand.

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