Modeling Interactive Car-Following Behaviors of Automated and Human-Driven Vehicles in Safety-Critical Events: A Multi-Agent State-Space Attention-Enhanced Framework

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Introduction

Automated vehicles (AVs) are becoming increasingly prevalent, leading to mixed traffic environments where AVs and human-driven vehicles (HDVs) must interact. Despite the growing prevalence of AVs, research on AV-HDV interactions—especially in safety-critical events—remains limited. Understanding and modeling the interactive car-following behavior of AVs and HDVs in high-risk scenarios is crucial for traffic safety, particularly as rear-end crashes remain a major crash type on highways. Traditional car-following models, such as the Intelligent Driver Model (IDM) and Gipps' model, primarily describe normal driving behaviors but fail to capture evasive maneuvers in high-risk situations. Moreover, while recent studies (e.g., (Kontar and Ahn 2024)) examine AVs' ability to avoid collisions with lead vehicles, they often overlook how following HDVs adapt their responses to AVs. This is a critical gap, as AV maneuvers can influence human drivers' risk perception, reaction times, and decision-making, ultimately affecting traffic stability and crash risks. Addressing this gap is essential for improving safety-aware traffic simulations and informing AV control strategies to enhance crash prevention.

Third Generation Simulation Dataset (TGSIM) (Talebpour *et al.* 2024) developed by the U.S. Department of Transportation provide opportunities to enhance our understanding of AV-HDV interactions in safety-critical events, the. While the Next Generation Simulation (NGSIM) dataset (Alexiadis *et al.* 2004) primarily focuses on HDVs , TGSIM offers detailed trajectory data for both HDVs and SAE Level 1–3 AVs, capturing the complexities of mixed-traffic environments. The dataset contains high-resolution vehicle trajectories recorded through fixed-position aerial videography, moving aerial videography, and infrastructure-based videography. It covers urban and highway environments, including Chicago, IL, and Washington, D.C., with major highways such as I-90/I-94, I-294, and I-395. Key data fields include time-stamped vehicle positions, lane assignments, speed, acceleration, and vehicle type, making TGSIM a valuable resource for analyzing AV-HDV interactions, safety-critical events, and adaptive vehicle control strategies in mixed traffic.

This study aims to model interactive car-following behaviors in safety-critical scenarios involving a leading HDV, an AV, and a following HDV. Specifically, we examine how the AV responds to the leading HDV and how the following HDV adapts its behavior to the AV's maneuvers to mitigate collision risks. A multi-agent state-space attention-enhanced deep deterministic policy gradient (MA-ASS-DDPG) framework is proposed, leveraging a multi-agent structure to capture dynamic interactions while integrating state-space modeling for temporal dependencies and attention mechanisms for prioritizing critical motion features. By integrating TGSIM, which offers high-resolution trajectory data on real-world AV-HDV interactions, the proposed framework enables a more data-driven analysis of AV behavior and its impact on traffic dynamics, enhancing mixed-traffic modeling and AV deployment strategies.

Data Collection

The TGSIM dataset examines the impact of automated driving and advanced driver assistance systems on human behavior in real-world conditions. It is publicly available via the U.S. Department of Transportation (https://catalog.data.gov/organization/dot-gov). This study focuses on AV's car-following behavior on highways and HDV's corresponding behaviors following AV. To ensure precise analysis of these interactions, the I-294 and I-395 datasets were utilized compassing extensive data on SAE Level 1 and Level 2 automated systems.

AVs and HDVs were classified systematically, as shown in Figure 1. To quantify the potential collision risk between an AV and a leading human-driven vehicle (LHDV), the TTC is calculated. TTC represents the time required for an

AV to reach the rear end of LHDV, assuming both vehicles maintain their current speeds and directions. It is expressed as:

$$TTC = \frac{location_{LHDV} - location_{AV} - \frac{L_{AV}}{2} - \frac{L_{LHDV}}{2}}{speed\ \_kf_{AV} - speed\ \_kf_{LHDV}} \qquad if\ speed\ \_kf_{LHDV} < speed\ \_kf_{AV} \tag{1}$$

where $\mathrm{xloc\_kf}_{\mathrm{AV}}$ and $\mathrm{xloc\_kf}_{\mathrm{L}}$ are the xloc_kf coordinates of the AV and LHDV, respectively, L_{AV} and L_{LHDV} are their respective vehicle's lengths, and $speed\ \_kf_{AV}$ and $speed\ \_kf_{L}$ are their respective speeds. If the two vehicles have the same speed, TTC is set to infinity, indicating no risk of collision under these conditions.

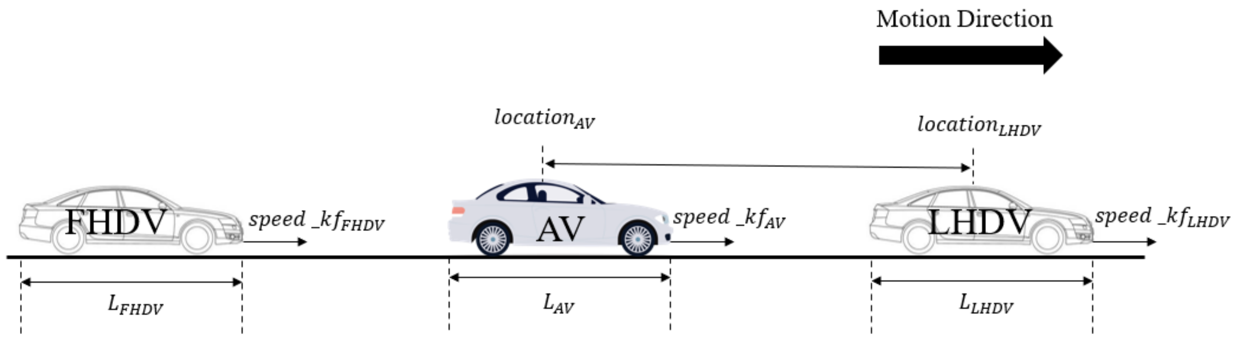


Figure 1: Car-Following Scenario in a Mixed-Vehicle Platoon of HDVs and AVs

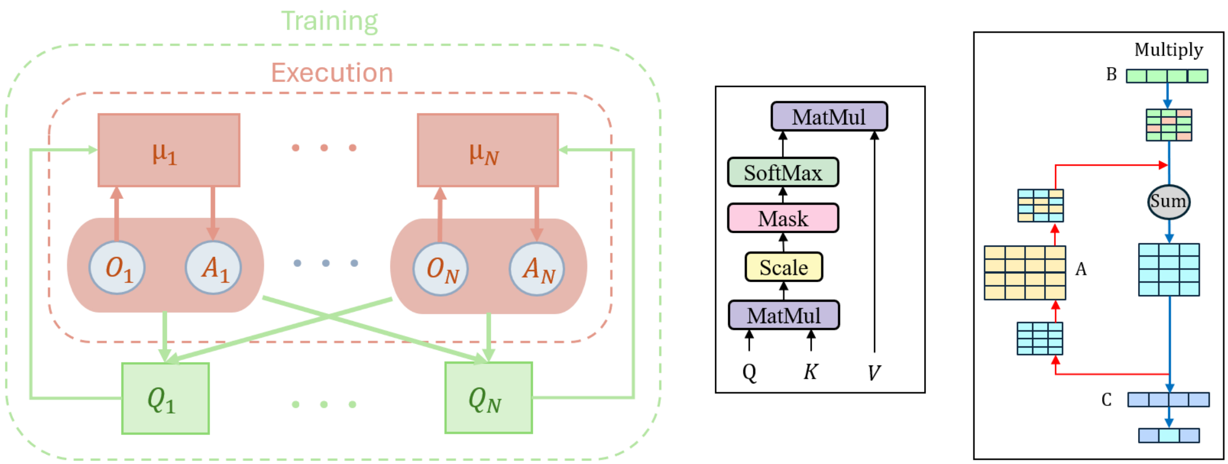
After processing, records meeting specific AV conditions and their corresponding LHDV and following human-driven vehicles (FHDV) were identified. TTC values between 0 and 10 seconds quantified interaction dynamics. A valid interaction dataset was generated from the combined data (id, L_id, F_id) after removing records with missing values. Vehicle pairs with more than 10 recognition instances were selected, resulting in 150 valid AV-surrounding vehicle pairs across 4504 time steps. This dataset is the foundation for developing the MA-ASS-DDPG framework, facilitating a deeper understanding of vehicle interactions in mixed-traffic environments.

Methodology

This research models the car-following dynamics of two agents (AV and HDV) as a two-player interaction framework. The AV adjusts its actions based on the leading HDV's acceleration or deceleration to prevent collisions, while the following LHDV observes the AV's behavior and changes its actions accordingly. This creates a dynamic interaction where one agent's decisions impact the other's behavior, reflecting a cooperative-competitive relationship in mixed-vehicle platoons.

The MA-DDPG is adopted in this study to model the car-following behaviors of HDVs and AVs in mixed-traffic environments. This approach extends the DDPG, an off-policy reinforcement learning algorithm that leverages deep function approximators to learn policies in continuous action spaces (Pu *et al.*). By employing centralized training with decentralized execution, MA-DDPG effectively handles the complexities in multi-agent systems, as shown in Figure 2 (a). In the setup, each actor μ_i operated using only its local observations O_i to make decisions. While the critic O_i gains access to extra information, such as the actions A_i of other agents, during training. This centralized training with a decentralized execution framework allows the model to learn efficiently by leveraging the global context during training while maintaining independent operation during execution. By incorporating this approach, the model stabilizes the learning environments, even as agents adapt and update their policies, ensuring consistent and effective performance in dynamic, multi-agent scenarios. Thus, MA-DDPG may be suited for modeling mixed cooperative-competitive behaviors between vehicles and pedestrians in safety-critical scenarios.

Simultaneously, traditional reinforcement learning algorithms often prioritize common safe driving behaviors while neglecting rare but crucial near-miss scenarios. The interactions between HDVs and autonomous vehicles (AVs) in car-following situations are highly dynamic, with strong temporal dependencies and varying traffic states. Conventional methods struggle to capture these complexities and reconstruct safety-critical behaviors. To address this, the Attention Mechanism and State-Space Model dynamically extract key temporal features from HDV-AV interactions, as shown in Figure 2 (b). The State-Space Model further complements the Attention Mechanism by capturing complex temporal dependencies. As illustrated in Figure 2 (c), the model processes input features through structure state transitions using matrix multiplications and summations. The red arrows in the figure represent updates during training, ensuring that the model learns effectively over time, while the blue arrows represent the state representation, capturing the evolving traffic states.



(a) (b) (c)

Figure 2: (a) Overview of MA-DDPG structure (Lowe *et al.* 2017); (b) The Transformer Attention Mechanism (Vaswani 2017) ; (c) Mamba: State-Space Model (Gu and Dao 2023)

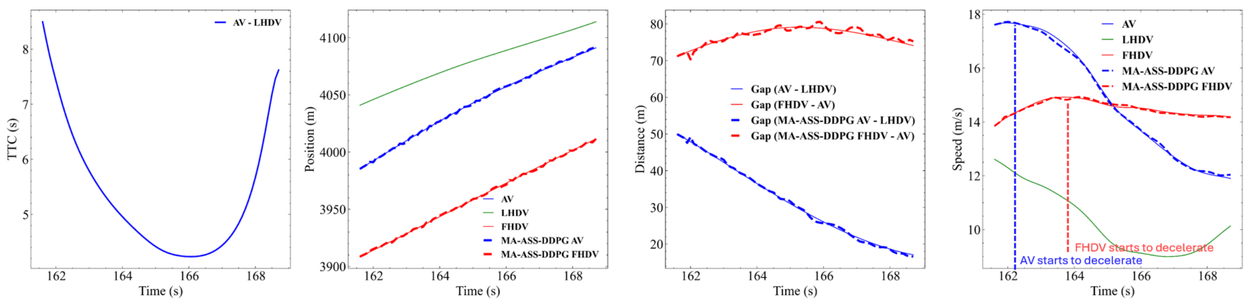
Results and discussion

To assess the performance of the MA-ASS-DDPG model, a comparative study was conducted against several baseline models, including DDPG, MA-DDPG, MA-LSTM-DDPG, MA-Transformer-DDPG, MA-Mamba-DDPG, and supervised learning models such as Transformer, LSTM, IDM, and Neural Network (NN). The model's reward function (Reward_v) serves as the basis for evaluation. The MA-ASS-DDPG model consistently achieves the lowest RMSE across critical variables, including velocities (v_{AV} and v_{FHDV}), accelerations ($\hat{a}_{AV}$ and $\hat{a}_{FHDV}$), and distances (ΔD_{AV} and ΔD_{FHDV}). The detailed analysis reveals that:

- For AVs, the MA-ASS-DDPG model delivers outstanding performance with the lowest RMSE values for velocity ($v_{AV} = 0.193$) and acceleration ($\hat{a}_{AV} = 0.236$), effectively capturing evasive maneuvers. Furthermore, its distance predictions ($\Delta D_{AV} = 0.292$) emphasize its reliability in handling near-miss scenarios.
- For FHDVs, the model achieves similar results, with minimal RMSE values for velocity ($v_{FHDV} = 0.181$), acceleration ($\hat{a}_{FHDV} = 0.251$), and distance ($\Delta D_{FHDV} = 0.265$), validating its ability to replicate human driving behavior in response to AV actions.

In conclusion, the MA-ASS-DDPG model is the most effective framework for reconstructing AV and FHDV behaviors in safety-critical scenarios. Its integration of the velocity-based reward (Reward d_v) enables it to balance the proactive strategies of AVs with the reactive responses of FHDVs, achieving unparalleled accuracy. This capability is essential for advancing traffic safety research and improving the realism of vehicle interaction modeling in near-miss scenarios.

Figure 3 illustrates the dynamic car-following interactions between LHDV, AV, and FHDV. The first subpicture shows the TTC between the AV and LHDV, where the TTC drops at 162 seconds, prompting the AV to decelerate and restore a safe following distance, while the FHDV adjusts its speed accordingly. The position and distance curves indicate that the AV maintains a stable trajectory between the LHDV and FHDV, adapting its speed to prevent unsafe proximity. The speed curve shows that as the LHDV slows at 162 seconds, the AV follows suit, and the FHDV modulates its speed to maintain stability. The MA-ASS-DDPG framework accurately replicates real-world car-following dynamics, effectively replicating real-world interactions and ensuring safe car-following behaviors under mixed-traffic conditions.



ID=5, LHDV=88, FHDV=474

Figure 3: Example of trajectory reconstruction

Conclusion

This study introduces the MA-ASS-DDPG framework, a novel approach for modeling AV-HDV interactions using TGSIM, marking the first exploration of this dataset for reconstructing real-world car-following scenarios and validating the proposed framework. By integrating an Attention Mechanism and State-Space Model within a multi-agent framework, the model prioritizes critical motion features and captures temporal dependencies, enhancing the accuracy of car-following and collision avoidance dynamics. The findings reveal that AVs execute collision avoidance in near-miss scenarios and influence the adaptive behavior of following vehicles, improving traffic safety and stability. This research provides valuable insights for autonomous vehicle deployment and mixed-traffic modeling, with future work focused on expanding dataset diversity and refining reward structures to further optimize performance.

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