Game-Theoretic Integration in Imitation Learning for Safe Lane-Changing

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***Abstract*— Safe driving remains a major challenge for autonomous vehicles, particularly in complex and safety-critical scenarios. While imitation learning (IL) has shown promising driving performance, IL-based models often struggle with robustness when faced with rare or high-risk events. In this paper, we propose a game-theoretic integration within the IL pipeline to enhance decision-making in safety-critical situations. Specifically, we incorporate a game-theoretic solution into the IL framework to improve lane-changing safety. We evaluated the proposed approach in the CARLA simulator. Our experimental results demonstrated that our method improved the safety of a baseline IL model during lane-changing. These findings highlight the potential of combining game theory with deep imitation learning to address safety challenges in autonomous driving.**

I. INTRODUCTION

Autonomous vehicles have the potential to make transportation safer and more efficient, and accessible. Deep learning, particularly Imitation Learning (IL), offers a promising approach, but safety remains a critical challenge, especially in vehicle-to-vehicle interactions. IL models, trained on fixed datasets, often struggles with out-of-distribution scenarios, leading to model failures in less frequent but safety critical scenarios. Game theory can be a valuable approach to address the limitations of learning-based model by modeling vehicle-to-vehicle interaction as a game. This paper proposes a game-theoretic framework to improve safety in lane-changing scenarios and compares its performance against a state-of-the-art IL model.

II. LITERATURE REVIEW

Chen et al. [1] highlighted the lack of safety guarantees as a key challenge for end-to-end autonomous driving in their survey. Various existing approaches have proposed safety modules incorporated into different layers in the autonomous driving architecture, such as perception, control, or planning. For instance, the Simplex-Drive framework [2] introduced an adaptive runtime safety mechanism that monitors the system and switches from a learning-based controller to a verified safety controller when unsafe behavior is detected. Similarly, InterFuser [3] integrated a safety module into their learning-based pipeline, which filters unsafe trajectories based on defined constraints, ensuring safe operation in critical scenarios.

Beyond rule-based or learning-based safety controllers, game theory can be a potential solution. It models strategic interactions between agents such as vehicles, pedestrians, and cyclists, whose actions influence one another. The Stackelberg game [4] is commonly used to model vehicle-pedestrian negotiations at interactions, while the Sequential Chicken model [5] analyzes decision-making between an autonomous vehicle and a pedestrian approaching a crossing. For vehicle-to-vehicle interactions, Tian et al. [6] used a level-k game-theoretic model to simulate multi-vehicle behaviors at unsignalized intersection.

While game theory has demonstrated strong potential for enhancing autonomous vehicle decision-making by modeling interactions among road users, most implementations address specific safety challenges in isolation rather than being integrated into the autonomous driving pipeline.

III. METHODOLOGY

We propose to apply game theory to model vehicle-to-vehicle interactions and incorporate it into the deep learning model. TransFuser [7] is selected as the representative model, as it predicts waypoint sequences that can be modified when the predicted trajectory is deemed unsafe. The proposed game-theoretic solution shown in Fig. 1 comprises: (1) The deep learning system (TransFuser) that predicts ego-vehicle waypoints based on perception input. (2) An integrated game-theoretic safety module that filters unsafe trajectories. (3) A Proportional-Integral-Derivative (PID) controller that generates the control signals (steering angle, throttle, and brake) to drive the ego-vehicle based on the filtered trajectories.

The safety module adopts a simplified game-theoretic-inspired approach, leveraging principles from game theory to model interactions between vehicles. Unlike classical game theory, it employs heuristic rules to decide the optimal ego-vehicle strategies without computing equilibria. The ”game” involves two players: the ego-vehicle and a surrounding vehicle. Both players act independently and simultaneously, without knowledge of the other’s intentions. We only have control of the ego-vehicle. Thus, its available strategies are: (1) **Compete**: If a surrounding vehicle **moves slower**, the ego-vehicle will compete by accelerating and proceeding with changing lane. (2) **Yield**: If the surrounding vehicle **moves faster**, the ego-vehicle will yield by maintaining its speed and staying in the lane, allowing the surrounding vehicle to pass. The decisions will be based on the evaluation

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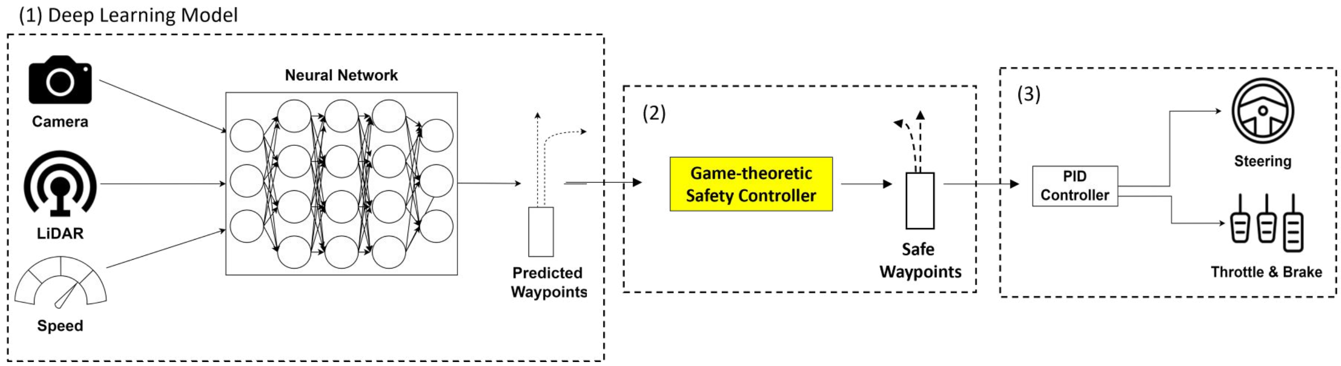

Fig. 1. Overview of proposed integration of the game-theoretic safety controller in deep learning pipeline.

of collision risks based on the relative speeds of both players, ensuring the ego-vehicle always prioritizes safety while making optimal decisions. Another condition added for decision-making is the gap between the vehicles, whose purpose is to give a safe buffer between the vehicles.

IV. EXPERIMENTS

We used CARLA to evaluate the performance of the integration of the game-theoretic solution in the TransFuser system. We used the pre-trained TransFuser model to control the ego-vehicle. The kinematic bicycle model [8] was adopted to forecast future states and trajectories of the vehicles in the scene, which we replicated based on the work of Jaeger's privileged agent for TransFuser [9]. For the ego-vehicle, its future trajectories were generated from TransFuser's predicted waypoints. Fig. 2 visualizes these future states, where green and blue bounding boxes represent the ego and surrounding vehicles, respectively.

Collision risk is triggered when the ego-vehicle's and surrounding vehicle's predicted bounding boxes overlap, as shown in Fig. 2. When collision risks are predicted, the game-theoretic framework decides whether the ego-vehicle should yield or compete. We deployed the solution in CARLA Town05 and evaluated using the CARLA offline leaderboard with three evaluation metrics: driving score, route completion, and infraction score. The proposed game-theoretic framework was evaluated alongside TransFuser, which served as the baseline. Two setups were considered: (1) an incoming rear vehicle moves slower than the ego-vehicle in the target lane, and (2) an incoming rear vehicle moves faster in the target lane.

We compared the performance of the baseline TransFuser model without the game-theoretical safety module, with the performance when the game-theoretic safety module was added.

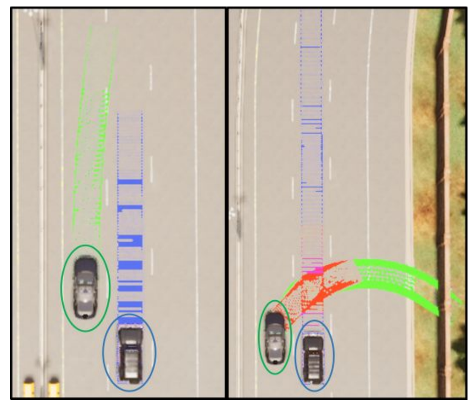

Fig. 2. (Left) Future states generated using the kinematic bicycle model for the ego-vehicle (green) and a surrounding vehicle (blue). (Right) Collision risk (red) is predicted when oriented bounding boxes overlap.

Fig. 3. Examples of unsafe lane changing behavior of the baseline TransFuser without safety controller. The ego-vehicle is circled in green.

V. RESULTS & DISCUSSIONS

A. Performance of baseline TransFuser in lane-changing scenario

Although TransFuser demonstrates consistent driving performance, the baseline model without safety module had high infraction score primarily due to vehicle collisions, particularly in unseen scenarios. A common failure occurred when the ego-vehicle was performing lane change but collided with surrounding vehicles in adjacent lanes, as shown in Fig. 3.

B. Performance of the proposed integrated game-theoretic framework in lane-changing scenario

When the surrounding vehicle was faster, the ego-vehicle made the optimal decision to yield, as shown in Fig. 4. In another setup, when facing a slower surrounding vehicle, the ego-vehicle competed and performed lane changing in Fig. 5,

C. Discussion

The results are summarized in the Table I and Table II for fast- and slow-appraoching surrounding vehicles, respec-

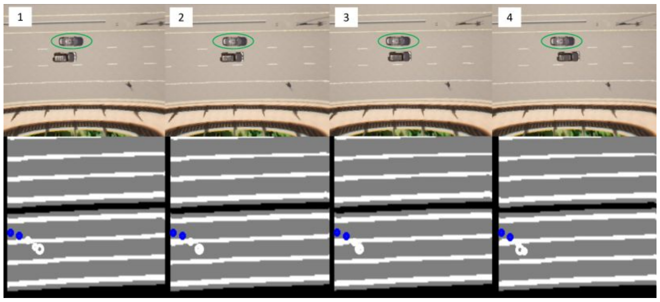

Fig. 4. Game-theoretic inspired: Four time steps showing the yielding ego-vehicle.

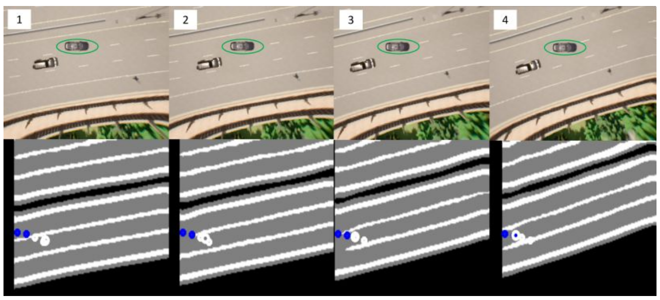

Fig. 5. Game-theoretic inspired: Four time steps showing the competing ego-vehicle.

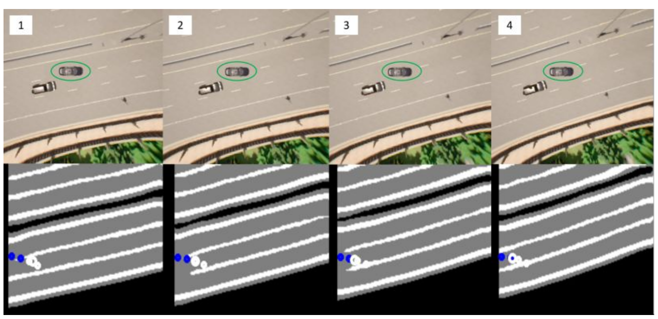

Fig. 6. Baseline IL model (without game theory): Ego-vehicle (circled) successfully changes lane against a slower vehicle without considering a safe distance.

tively. Since the test route only involved a single lane-change task, perfect route completion (100%) was expected when the ego-vehicle made correct decisions. As seen in Table I, TransFuser alone performed poorly when facing a fast-approaching vehicle, it followed its predicted waypoints to change lane but failed to perceive incoming rear vehicle, resulting in collisions. In contrast, the game-theoretic-inspired solution avoided these collisions by yielding properly, achieving perfect score.

TABLE I

RESULTS WITH A FAST-APPROACHING SURROUNDING VEHICLE.

Method	RC ↑	IS ↑	DS ↑	Veh. ↓
TransFuser (baseline)	100.0	0.60	60.0	0.49
GT-inspired	100.0	1.0	100.0	0.0

RC: Route Completion, IS: Infraction Score, DS: Driving Score, Veh.: Collisions with vehicles

When the surrounding vehicle was slower, both the baseline TransFuser and the game-theoretic inspired solution achieved perfect driving scores without collisions. However, as shown in Fig. 6, TransFuser's lane change left minimal distance between vehicles, relying heavily on the rear incoming vehicle to yield. This behavior is unsafe. By incorporating a distance gap condition into the decision-making, the game-theoretic-inspired solution enabled safe lane changing.

TABLE II

RESULTS WITH A SLOW-APPROACHING SURROUNDING VEHICLE.

Method	RC ↑	IS ↑	DS ↑	Veh. ↓
TransFuser (baseline)	100.0	1.0	100.0	0.0
GT-inspired	100.0	1.0	100.0	0.0

RC: Route Completion, IS: Infraction Score, DS: Driving Score, Veh.: Collisions with vehicles

VI. CONCLUSIONS

This paper introduced a game-theoretic safety controller integrated into the TransFuser model for safe lane-changing. The method's performance motivates further exploration in other safety-critical scenarios, such as lane merging in dense traffic. The experiments serve as a proof-of-concept, highlighting the effectiveness and potential of combining deep learning with game-theoretic models to reduce collision risks during lane-changing. However, the current implementation has limitations: it has used simple heuristics and was only tested in lane-changing scenarios. Further improvements are needed before real-world deployment.

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