Bringing Diversity to Autonomous Vehicles: An Interpretable Multi-vehicle Decision-making and Planning Framework

Extended Abstract

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ABSTRACT

With the development of autonomous driving, it is becoming increasingly common for autonomous vehicles (AVs) and human-driven vehicles (HVs) to share the same roads. We propose a hierarchical multi-vehicle decision-making and planning framework with several advantages. The framework makes decisions jointly for all vehicles within the traffic flow and reacts promptly to the dynamic environment through a high-frequency planning module. The decision module produces interpretable action sequences that can explicitly communicate self-intentions to the surrounding HVs. We also present the cooperation factor and the trajectory weight set, which bring diversity to autonomous vehicles in traffic at both the social and individual levels.

KEYWORDS

Autonomous Driving; Trajectory Generation; Vehicle Flow; Monte-Carlo Tree Search

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1 INTRODUCTION

With the combined efforts of academia and industry, research on autonomous driving has flourished over the past decade. A growing number of companies are testing their autonomous vehicles (AVs) on the road, becoming new participants besides human-driven vehicles (HVs). The real-world vehicle flow encompasses a diversity of behaviors at both the social and individual levels, known as *social behavior* and *driving habit*. Social behavior [15, 18] implies how a vehicle interacts with others. When another vehicle is changing lanes, overtaking or merging, the driver chooses whether to continue the current movement or yield based on experience. Drivers also have their own driving characteristics. Driving habits [12, 17, 19] are therefore introduced to describe the individual difference, especially on cruising comfort and driving safety.

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The behavioral diversity of AVs is mainly expressed through the decision-making and planning modules, which are core components of the automated driving system. The prevailing single-vehicle planning approaches [3, 5, 7] struggle to game with other traffic participants in the real world, and therefore exhibit an insufficient understanding of social interactions. Multi-vehicle centralised trajectory planners effectively address the complex interactions in traffic flow, including optimization-based [6, 14], MCTS-based [8, 9] and learning-based approaches [1, 2, 11]. However, these methods fail to express driving intentions explicitly and are thus poorly understood by passengers onboard or by surrounding HVs. Popular open-source autonomous driving simulators [4, 10] also provide solutions for background traffic generation, but they apply rigid driving behavioral models, resulting in overly conservative and non-diverse trajectories.

We propose a hierarchical framework for decision-making and planning in a multi-vehicle environment. By adding a vehicle cooperation factor in the decision module and introducing the trajectory weight set in the planning module, our framework produces solutions with social and individual level diversity. We also consider all AVs and HVs in the traffic flow when making decisions and can therefore explore complex interactions between them.

2 HIERARCHICAL FRAMEWORK

Consider a set $\mathcal{V} = \{V_1, V_2, \cdots, V_N\}$ containing N vehicles including AVs and HVs, where K AVs available for the centralized planning, denoted as $\mathcal{V}_C = \{V_1, \cdots, V_k\} \subseteq \mathcal{V}$. The remaining AVs and all HVs are treated as uncontrolled vehicles that make decisions and motion planning independently. Our task is to generate feasible trajectories with behavioral diversity for each controllable vehicle $V_i \in \mathcal{V}_C$ and collaborating with other uncontrolled vehicles in the environment. We propose a two-stage multi-vehicle framework containing both decision making and trajectory planning modules. The schematic diagram of our proposed framework is illustrated in Figure 1, where vehicles with IDs 2 and 3 (in red) are AVs while vehicle 1 (in blue) is an uncontrolled vehicle.

The input to the framework is a perceivable environment which contains road conditions, route information, vehicle status and predictions of uncontrolled vehicles. In the first stage, we propose a decision-making module to address the social interactions among vehicles. This module proposes a modified Monte-Carlo tree search algorithm to generate long-term, coarse decisions for all vehicles

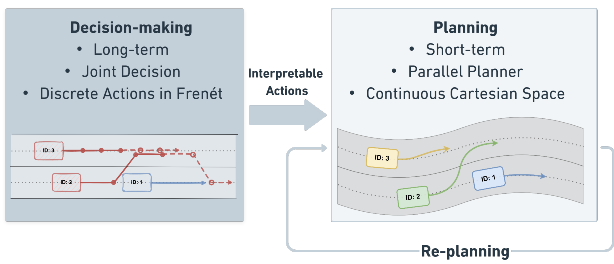

Figure 1: The proposed decision and planning framework

jointly and simultaneously. The environment is constructed on the Frenét frame [13] for decision-making, which allows the decision module to focus on inter-vehicle interactions without considering road constraints. Since actions like continuous lane-changing and overtaking take a relatively long time to complete, the decision module is required to be forward-looking and consistent. The decision module solves the interactions between vehicles by making centralized joint decisions on the vehicle flow. It can generate diverse social behaviors via setting different cooperation factors in the reward function. The decision module generates a temporal sequence of discrete actions for each controlled vehicle V_i. Since each action in the sequence has a physical meaning, such as changing lane, accelerating, maintaining speed, etc., the output of our decision module is interpretable.

In the second stage, the planning module receives discrete action sequences and generates short-term kinematic-feasible trajectories for each controlled vehicle. Our planning module adopts a distributed parallel architecture, i.e. running a planner independently for each vehicle, which more closely resembles human driving in the real world. For each parallel planner, the leading part of its received action sequence is selected as the guidance to generate a continuous trajectory that satisfies to the vehicle kinematic constraints in Cartesian space. This module reflects the driving habits of different drivers through planner's selection strategy for different trajectories. The planner maintains a high replanning frequency and continuously predicts surrounding vehicles to avoid collisions.

3 MCTS FOR MULTIPLE VEHICLES

3.1 Metanode

Several multi-vehicle decision methods based on the Monte-Carlo tree search, also known as MCTS, have been developed [8, 9]. Our approach takes the HVs in the traffic flow into account and there is no priority between vehicles in the decision-making process. We replace the node in the general MCTS method with a *metanode* that can generate multi-vehicle actions simultaneously.

For a metanode extended to time step t, it receives all controlled vehicle's state at the current moment. The state for vehicle V_i at time step t can be described as $\mathbf{x}_i^t = [s, d, v]^T$, s and d are the Frenét coordinates of the vehicle and v is the longitudinal velocity. We define a set of possible actions for each controlled vehicle to take in one time step. There are five actions - maintain speed (KS), accelerate (AC), decelerate (DC), change lanes to the left (LCL) and to the right (LCR). By selecting different actions, the vehicle can then calculate its corresponding state at the next time step. As for uncontrolled vehicles in the flow, we assume they performing a lane-keeping (KL) action. This action dynamically adjusts their velocity and always maintains an appropriate distance from the leading vehicle during the decision-making process.

3.2 Pruning

Although each vehicle has five optional actions, not every one of them is feasible and some may lead to a potential collision. According to [16], vehicles in traffic should maintain a shortest safe distance D_s from its leading vehicle, which is defined as:

$$D_s \quad = \quad v \cdot \tau + MTH \cdot \Delta v \tag{1}$$

where $\tau > 0$ and $MTH > 0$ are both time constants, representing reaction time and minimum time headway respectively. v denotes vehicle longitude velocity and $\Delta v = v - v_l$ denotes the velocity difference between the self and lead vehicles. Further, the velocity limit that each controlled vehicle in the flow should satisfy is:

$$v \quad \in \quad \left[v_f - \frac{\Delta s_f - \tau \cdot v_f}{MTH}, \min\left(\frac{MTH \cdot v_l + \Delta s_l}{\tau + MTH}, \frac{\Delta s_l}{\tau}\right) \right] \tag{2}$$

where Δs_l and Δs_f indicate the gap between the current vehicle and its leading/following vehicle, respectively. v_l and v_f denote the velocity of the leading and following vehicle.

In the metanode at time t, when vehicle V_i takes an action a and the resulting state $\mathbf{x}_i^{t+1}$ does not satisfy Equation (2), action a becomes invalid and the corresponding state $\mathbf{x}_i^{t+1}$ will be abandoned.

3.3 Reward Function with Social Behavior

We first calculate the reward R_i separately for each vehicle V_i in the traffic flow. The reward $R_i \in [0, 1]$ has three parts, namely driving in the target lane, driving in the lane's center line and maintaining the consistency of the actions. For the vehicle flow to exhibit a diversity of social behaviors, the cooperative tendency of the vehicle should be characterized by the reward. Similar to [15], we introduce a social behavior reward for vegicle V_i considering both reward to self and reward to others:

$$R_i \quad = \quad R_{\text{self}} \; + \; \gamma_i \, R_{\text{other}} \tag{3}$$

where $\gamma_i \in [0, 1]$ being the cooperation factor. $\gamma_i = 0$ implies the vehicle is egoistic and takes no account of the behavior of other vehicles, whereas $\gamma_i = 1$ denotes the vehicle treats other vehicles equally important to itself when making decisions. Each vehicle V_i in the flow possesses its own factor γ_i.

Since each metanode in the search tree handles the actions of the whole vehicle flow, the reward of the simulation is obtained by combining all vehicles' behavior rewards:

$$X_{\text{flow}} \quad = \quad \frac{1}{K} \sum_{1 \le i \le K} \frac{R_i + \gamma_i \sum_{j \ne i} R_j}{1 + (K-1)\gamma_i} \tag{4}$$

The distribution of X_{flow} is guaranteed to stay in $[0, 1]$. Finally, reward X_{flow} is used to update the average rewards of all selected metanodes in the back-propagation phase of MCTS.

The superiority of our proposed framework is validated through experiments in multiple scenarios, and the diverse behaviors in the generated vehicle trajectories are demonstrated through closed-loop simulations. For detailed discussion and experiment results, we refer the reader to the full version [20].

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REFERENCES

[1] Sergio Casas, Wenjie Luo, and Raquel Urtasun. 2021. IntentNet: Learning to Predict Intention from Raw Sensor Data. CoRL (jan 2021). arXiv:2101.07907 http://arxiv.org/abs/2101.07907

[2] Dian Chen and Philipp Krähenbühl. 2022. Learning From All Vehicles. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 17222–17231.

[3] Laurene Claussmann, Marc Revilloud, Dominique Gruyer, and Sébastien Glaser. 2019. A review of motion planning for highway autonomous driving. *IEEE Transactions on Intelligent Transportation Systems* 21, 5 (2019), 1826–1848.

[4] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. 2017. CARLA: An Open Urban Driving Simulator. In *Proceedings of the 1st Annual Conference on Robot Learning*. 1–16.

[5] Haoyang Fan, Fan Zhu, Changchun Liu, Liangliang Zhang, Li Zhuang, Dong Li, Weicheng Zhu, Jiangtao Hu, Hongye Li, and Qi Kong. 2018. Baidu Apollo EM Motion Planner. (2018). arXiv:1807.08048

[6] Jaime F Fisac, Eli Bronstein, Elis Stefansson, Dorsa Sadigh, S Shankar Sastry, and Anca D Dragan. 2019. Hierarchical game-theoretic planning for autonomous vehicles. In *2019 International conference on robotics and automation (ICRA)*. IEEE, 9590–9596.

[7] Christos Katrakazas, Mohammed Quddus, Wen-Hua Chen, and Lipika Deka. 2015. Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. *Transportation Research Part C: Emerging Technologies* 60 (2015), 416–442. https://doi.org/10.1016/j.trc.2015.09.011

[8] David Lenz, Tobias Kessler, and Alois Knoll. 2016. Tactical cooperative planning for autonomous highway driving using Monte-Carlo Tree Search. *IEEE Intelligent Vehicles Symposium, Proceedings* 2016-Augus, Iv (2016), 447–453. https://doi.org/10.1109/IVS.2016.7535424

[9] Chenran Li, Tu Trinh, Letian Wang, Changliu Liu, Masayoshi Tomizuka, and Wei Zhan. 2022. Efficient Game-Theoretic Planning With Prediction Heuristic for Socially-Compliant Autonomous Driving. *IEEE Robotics and Automation Letters* 7, 4 (2022), 10248–10255. https://doi.org/10.1109/LRA.2022.3191241

[10] Pablo Alvarez Lopez, Michael Behrisch, Laura Bieker-Walz, Jakob Erdmann, Yun-Pang Flötteröd, Robert Hilbrich, Leonhard Lücken, Johannes Rummel, Peter Wagner, and Evamarie Wießner. 2018. Microscopic Traffic Simulation using SUMO, In The 21st IEEE International Conference on Intelligent Transportation Systems. *IEEE Intelligent Transportation Systems Conference (ITSC)*.

[11] Zhenghao Peng, Quanyi Li, Ka Ming Hui, Chunxiao Liu, and Bolei Zhou. 2021. Learning to Simulate Self-Driven Particles System with Coordinated Policy Optimization. *Advances in Neural Information Processing Systems* 34 (2021), 10784–10797.

[12] Thomas A Ranney. 1994. Models of driving behavior: a review of their evolution. *Accident analysis & prevention* 26, 6 (1994), 733–750.

[13] Vladimir Y. Rovenski. 2006. *Differential geometry of curves and surfaces: A concise guide*. Birkhäuser, Boston, MA. https://doi.org/10.1007/b137116

[14] Dorsa Sadigh, Shankar Sastry, Sanjit A Seshia, and Anca D Dragan. 2016. Planning for autonomous cars that leverage effects on human actions. In *Robotics: Science and systems*, Vol. 2. Ann Arbor, MI, USA, 1–9.

[15] Wilko Schwarting, Alyssa Pierson, Javier Alonso-Mora, Sertac Karaman, and Daniela Rus. 2019. Social behavior for autonomous vehicles. *Proceedings of the National Academy of Sciences of the United States of America* 116, 50 (2019), 2492–24978. https://doi.org/10.1073/pnas.1820676116

[16] D. Swaroop and K. R. Rajagopal. 2001. A review of constant time headway policy for automatic vehicle following. In *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*. IEEE, Oakland, CA, 65–69. https://doi.org/10.1109/itsc.2001.948631

[17] Junhua Wang, Wenxiang Xu, Ting Fu, Hongren Gong, Qiangqiang Shangguan, and Anae Sobhani. 2022. Modeling aggressive driving behavior based on graph construction. *Transportation Research Part C: Emerging Technologies* 138 (2022), 103654.

[18] Wenshuo Wang, Letian Wang, Chengyuan Zhang, Changliu Liu, and Lijun Sun. 2022. Social Interactions for Autonomous Driving: A Review and Perspectives. *Foundations and Trends in Robotics* 10, 3-4 (2022), 198–376. https://doi.org/10.1561/2300000078

[19] Yunpeng Wang, Junjie Zhang, and Guangquan Lu. 2018. Influence of driving behaviors on the stability in car following. *IEEE Transactions on Intelligent Transportation Systems* 20, 3 (2018), 1081–1098.

[20] Licheng Wen, Pinlong Cai, Daocheng Fu, Song Mao, and Yikang Li. 2023. Bringing Diversity to Autonomous Vehicles: An Interpretable Multi-vehicle Decision-making and Planning Framework. arXiv:2302.06803 http://arxiv.org/abs/2302.06803