Cooperative Decision-Making in Mixed Urban Traffic Scenarios

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***Abstract*—As the number of highly automated and autonomous vehicles on public roads continues to rise, gaining trust becomes a crucial aspect for their acceptance in society. Particularly challenging situations arise when these vehicles drive at low speeds, as they frequently encounter interactions with vulnerable road users. Consequently, addressing these interactions becomes essential for the vehicle's automation. This abstract has two key contributions: the introduction of an approximate vulnerable road user model and the comparison of the model-based and model-free decision-making algorithms. The simulation results showed the effectiveness and practicality of the proposed model-based algorithm even for real-world applications due to the traceability of this decision-making algorithm.**

***Index Terms*—Shared Control, Human-Machine Interaction, Human-Machine Cooperation, Human Motion Prediction, Urban Traffic**

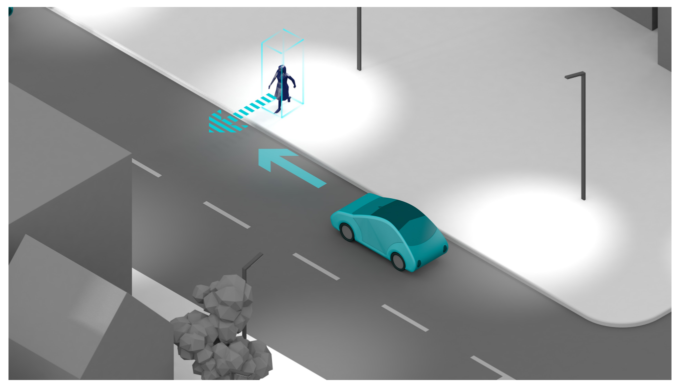

Fig. 1. An example scenario, in which an interaction between the VRU and the AV happens. With courtesy of version1 GmbH.

I. Introduction

Highly automated and autonomous vehicles (AVs) have become a crucial part of our daily lives. Their acceptance in our society relies heavily on the trust of vulnerable road users (VRUs), such as cyclists and pedestrians. Ensuring their safety is of utmost importance [1]. Instances of accidents involving automated driving functions have received significant public attention and have contributed to skepticism of such systems [2]. Consequently, extensive research efforts have been dedicated to equipping AVs with effective communication channels and decision algorithms capable of handling challenging situations, particularly in urban scenarios where vehicles operate at low speeds and VRUs may unpredictably cross the street [3]. Figure 1 illustrates a representative scenario exemplifying these challenges. Interactions between VRUs and AVs, referred to as human-machine interactions, occur at low speeds and necessitate careful handling to increase trust in AVs [3].

Therefore, this abstract provides an application of a novel prediction model of the VRU, which enables explicit handling of the prediction of the VRU future system states and the interactions with an AV. Using the proposed model, a model predictive controller is established. Furthermore, a reinforcement learning (RL) decision-making using proximal policy optimization (PPO) is implemented to provide a comparison with the proposed model-based decision-making.

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II. State of the Art

In the state of the art, there are various approaches to handle the interaction between VRUs and AVs.

A. Model-Based Approaches

Using model-based decision-making approaches means that the handling of the VRUs and the interactions between the VRU and the AV are characterized through explicit mathematical models. Such models are e.g. the *social force model* [4] or the *Markov decision process* (MDP) [5], [6]. Their limitation is that a simultaneous characterization of the prediction of the VRU's motion and the handling of the interaction between an AV and the VRU is not possible with the models from the literature.

B. Data-Driven Methods

Model-free or data-driven methods do not use an explicit mathematical model to characterize the motion or the interaction of VRUs. As an alternative, general neuronal networks are utilized in order to reconstruct the interaction from measurement data, see e.g. [7], [8]. A common approach is the utilization of RL approaches for modeling more complex scenarios without the need of mathematical models [9].

The limitation of these methods that safety performance assessment of unforeseeable situations can not be done easily. These algorithm are not traceable and verifiable, thus their admission to public traffic can be challenging.

III. Concept and Simulation Results

A. Proposed Explicit Model of a VRU

The proposed approximate model assumes that the VRU's future velocity has the followings dynamics

$$\dot{y}_{\mathrm{ped}}(i+1) = \frac{1}{1+e^{(-TTC(i)+c)}} \cdot \dot{y}_{\mathrm{ped}}^{\mathrm{ref}}, \tag{1}$$

where c is a personalizing factor, which depends on the character of the VRU. The time-to-collision (TCC) in (1) is computed such as

$$\mathrm{TTC}(i) = \frac{x_{\mathrm{ped}}(i) - x_{\mathrm{veh}}(i)}{\dot{x}_{\mathrm{veh}}(i)} - \frac{y_{\mathrm{veh}}(i) - y_{\mathrm{ped}}(i)}{\dot{y}_{\mathrm{ped}}^{\mathrm{ref}}}, \tag{2}$$

where $\dot{y}_{\mathrm{ped}}^{\mathrm{ref}}$ is the reference velocity of the VRU. In this framework, $\dot{y}_{\mathrm{ped}}^{\mathrm{ref}}$ can vary over the time enabling a more realistic behavior of the VRU. The model is explained by the following: The output of (1) is a sigmoid-like function and ranges between 0 and 1. Therefore, it could be interpreted as the probability of the crossing of the VRU. The larger the TTC value is, the more possible is that the VRU would choose to walk with the reference velocity.

Using this proposed approximate model, a model predictive controller (MPC) is formulated, which suits for the simultaneous prediction of VRUs and the handling of interactions. With the use of the framework proposed in [10], it is possible that the complex intention estimation of the VRU and the traceable decision-making are separated enabling a real world usage and the approval of automated street vehicles.

B. Simulation Results and Discussion

In our simulation setup, we compared the proposed a crossing scenario, in which both the VRU and the AV approach the intersection and intend to cross. For the comparison, a PPO-based model-free decision-making is implemented. Figure 2 shows the results of the decision-making algorithms. The results show that both algorithm can avoid collision in this crossing scenario. Since the MPC provides traceable and verifiable results, it may suit better AV functions in real-world scenarios.

IV. Summary and Outlook

In this abstract, an approximate model of a VRU is proposed, which enables the modeling of the interaction between VRUs and AVs in mixed traffic scenarios. Using this model, an MPC is formulated and tested in simulations. Furthermore, the proposed MPC is compared with model-free a PPO decision-making algorithm. The results showed that both decision-making algorithm can handle the interaction with a VRU, who intends to cross the street.

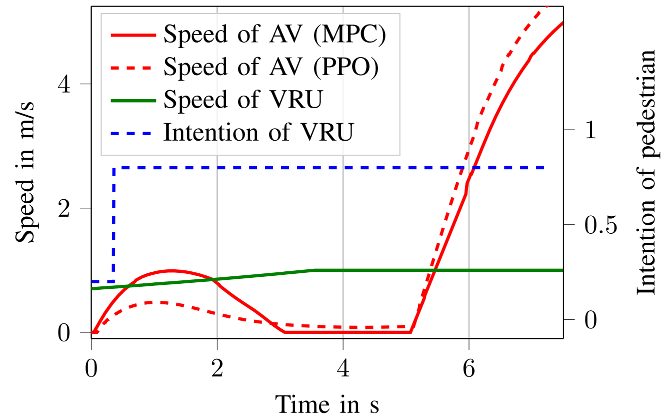

Fig. 2. Simulation results of the scenario. The red lines are the speeds of the AV using MPC (solid) and PPO (dashed). Moreover, the speed (green solid line) and the intention (blue dashed line) of the VRU are shown.

In our further work, we plan to run the algorithms on a real vehicle to address the challenges of the human behavior in such mixed traffic scenarios.

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