Developing an AI-Based Framework for Modeling Autonomous Vehicles in Microsimulation

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Abstract

Automated vehicles (AVs) are one of the hottest technological trends these days. Giant automotive companies and leading research institutes are extensively investing on these technologies claiming that the future of transportation will dramatically change as a result of these efficient and safe vehicles. Findings from the literature, however, do not necessarily comply with these claims. The results are two-faceted indeed. While initial research had argued that automated vehicles will significantly improve traffic efficiency and safety, recent findings have put doubt upon such optimistic expectations. Predicting the impacts of automated vehicles on traffic flow, however, is challenging due to several reasons. Firstly, there will be a transition period towards full autonomy where there will be a mix of fully automated, partially automated, and human-driven vehicles. This will result in more complexity and uncertainty in traffic flow. Secondly, different manufacturers will probably use their own driving automation algorithms and control logic, which will further complicate the problem. Finally, the performance and driving behavior of AVs are continuously changing based on newly collected data and their improved backend algorithms. On the other hand, current attempts for evaluating the impacts of AVs on traffic efficiency and safety usually are limited to modifying traditional traffic flow models, which consider a limited number of surrounding objects and thus are not suitable for complex urban environments, where there are multi-agents of different types. Accordingly, the purpose of this research is to develop a diverse and realistic microsimulation environment suitable for the impact assessment of automated vehicles in complex environments, where there are also human-driven vehicles and vulnerable road users (VRUs). To this end, we will develop a generic framework for training a set of diverse motion planning models by combining theory and AI, and utilizing both available datasets and simulation environments. The output of the proposed framework would be models for automated vehicles that are applicable in microsimulation tools and can replicate different driving policies and strategies and undertake complex maneuvers in urban areas. This set of models is used as a base for building a diversified simulation environment that aims at traffic and safety impact assessment of automated vehicles and unraveling the complex interactions between AVs and their surrounding environment in urban areas. Moreover, this simulation environment could be used for evaluating the performance of state-of-the-art motion planning and prediction (MPP) algorithms as current simulation environments developed for such purposes lack diversity, meaning that the behaviors of other agents in the simulation environment are simplified and assumed relatively homogeneous. Therefore, the actual performance of MPP algorithms in complex and diverse environments is questionable. Using a diverse simulation environment is an opportunity to evaluate the more realistic performance of such algorithms.

Introduction

Automated vehicles have been a matter of debate for a long time in both public and academic circles. While many believe that these technologies will positively revolutionize the future of smart cities and roads condition, others cast doubt upon the benefits of automated vehicles for traffic flow efficiency and safety and believe expectations won't be met at least in the short and mid-term [1]–[3]. Predicting the true impacts of these technologies on traffic flow is challenging and faces a lot of uncertainties. Firstly, recent findings in vehicle automation have revealed that achieving full automation, where the vehicle is able to run autonomously in all conditions, will take a longer time compared to initial expectations, and there will probably be intermediate levels (i.e., partial automation) before achieving full autonomy [4]. Therefore, in the transition period toward full automation, a mixed traffic flow comprising human-driven vehicles and different levels of automated vehicles (AVs) will exist, which will increase the complexity and uncertainty of traffic flow. Moreover, even if we achieve full autonomy, it will probably take a long time for fully automated vehicles to dominate the traffic flow [5]. Thus, at each stage, we will face different penetration rates of multi-level automated vehicles.

However, these are not the only challenges of modeling and predicting the dynamics of traffic flow with the presence of automated vehicles. In the transition period (and even after achieving full autonomy), different manufacturers will probably use their own driving automation algorithms and control logic. In other words, two (fully) automated vehicles from different companies will probably behave differently in the same situation. However, most of the current studies assume a harmonized and homogeneous behavior for automated vehicles [6]–[8]. Accordingly, in order to evaluate the impacts of automated vehicles on traffic flow, it is important to take into account the heterogeneities in their control logic and driving strategies.

Moreover, most of the current microscopic traffic flow models have been developed based on deterministic physics rules and human perception and decision-making logic [6], while the control logic behind current driving automation systems covers a wide range from deterministic and theory-based approaches to probabilistic and data-driven methods (or a combination of them) [9]–[14]. As it happens, recent advancements in artificial intelligence have pushed the automation efforts even more toward data-driven and learning-based methods [12], [15]–[17]. This implies that the automated vehicles' behavior will probably change and improve over time based on evolving technologies and algorithms, as well as newly collected data. Therefore, traditional microscopic models might not be sufficient for replicating these learning-based, evolving control logics, especially if we are interested to study the dynamics of traffic flow in the transition period toward a harmonized, relatively stable society of automated vehicles. In addition, traditional microscopic traffic flow models usually take a limited number of surrounding objects into account to make decisions about their future states. This simplification might not be realistic in complex urban environments where multiple agents of different types, such as cyclists and pedestrians, exist and therefore, intricate maneuvers are required [18].

Wrapping the above discussions, the main objective of this research is to develop an AI-based framework for modeling the motion planning of automated vehicles in complex environments, which can reproduce diverse driving styles and strategies suitable for evaluating the impacts of such technologies on traffic flow efficiency and safety. AI-based here means the developed framework is built upon artificial intelligence (learns from data and over time), but at the same time may benefit from theory (it is not purely data-driven). This framework is used as a base for building a diversified simulation environment that aims at traffic and safety impact assessment of automated vehicles and unravelling the complex interaction between AVs and their surrounding environment in urban areas including human-driven vehicles and vulnerable road users (VRUs). Moreover, this diverse and rich simulation environment could be also used for evaluating the true performance of state-of-the-art AVs' motion planning and prediction (MPP) algorithms. Current simulation environments for testing and evaluating the newly developed MPP algorithms lack diversity, which means the behavior of other agents in the simulation environment are simplified and assumed relatively homogeneous [19], [20]. Therefore, the actual performance of such algorithms in complex and diverse environments is questionable.

Methodology

Figure 1. shows an overview of the methodology for conducting the proposed research. It consists of three main steps: Design, Development, and Application. These three phases are further elaborated on in the following sections.

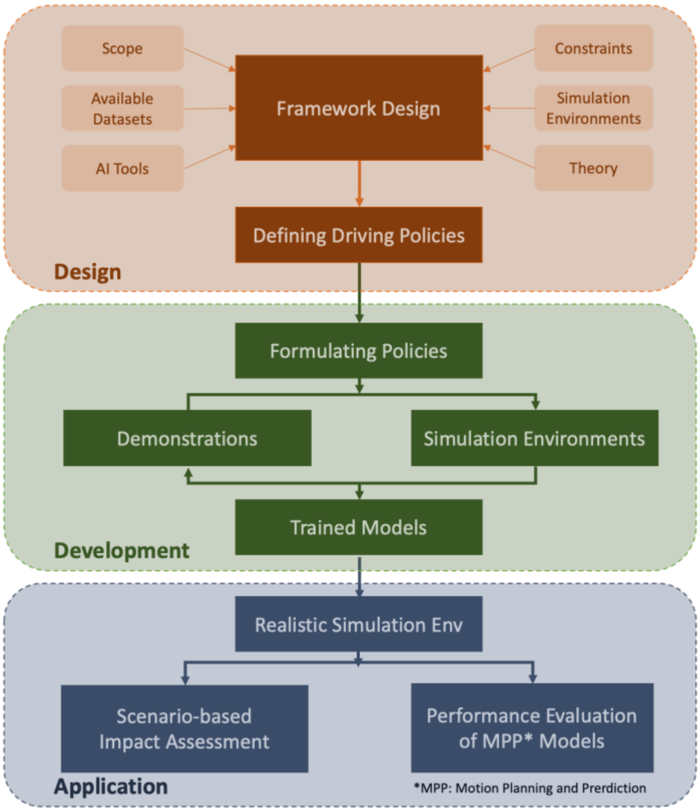

Figure 1 The overall structure of the proposed research

Design

The main objective of this phase is to come up with a generic framework for developing motion planning algorithms for automated vehicles that have the following characteristics:

1. They are learning-based, which means they can learn and improve over time (based on new inputs). This is important because the current trend toward developing motion planning and control algorithms for automated vehicles is using learning-based methods that improve over time and based on new input data. This is in contrary to traditional efforts for modeling AVs in simulation tools, which mainly try to modify the parameters of mathematical car-following or lace-changing models.
2. They benefit from theory and are not a purely data-driven, black-box framework. This is also important because the resulting trajectories from the developed framework should be interpretable, consistent with physics laws, and transferable to unseen conditions.
3. They learn from both demonstrations and simulation environments. This gives us the opportunity to train and enrich the developed motion planning models for the purpose of our research. Due to the scarcity of autonomous vehicles' datasets, relying only on available datasets will probably lead to a model trained for specific conditions for which there has been enough training data. Relying only on simulations environments also has the risk that those environments are not the perfect representation of the real world.

4. Finally, the designed framework should enable the resulting motion planning models to learn and reproduce different driving styles and strategies based on the enforced policies. It is the final aim of this research to build a diverse and realistic simulation environment, which is representative of different driving policies that is the result of distinct motion planning algorithms developed and used by different companies and research institutes (instead of assuming a harmonized, homogeneous logic for all Avs in the simulation).

In this framework, the role of AI and theory are clearly defined, and the procedure through which the model is going to learn different driving policies and strategies is described. Also, this framework considers the constraints applicable to the scope of the research, which is urban areas with multiple objects of different types including human-driven vehicles, pedestrians, and cyclists.

Another important prerequisite for developing such a diverse simulation environment is to identify the relevant and meaningful driving policies that replicate the real-world situation. Therefore, the aim of the second sub-section of this phase is to define the appropriate driving policies that are going to reproduce different driving styles and strategies for automated vehicles. The driving styles and strategies include (but are not limited to) different levels of aggressiveness, selfishness, and safety assurance.

Development

In the next step, which is referred to as the development phase, the defined policies are formulated into mathematical terms and equations to make them implementable by artificial intelligence methods, such as reinforcement learning. Then, the available datasets and simulation environments are used to train a set of diverse AI-based motion planning models suitable for microsimulation studies. Offline learning (learning from demonstrations) and online learning (learning via actions and rewards in simulation environments) are combined with the aim to compensate for the shortcomings of each of these learning methods. For instance, there are few demonstrations (true trajectories) of automated vehicles available, and relying on these limited datasets will result in models with unknown behavior in unseen conditions. Moreover, utilizing only available, limited datasets will prohibit us from developing a diverse set of models that replicate different driving strategies because those datasets, in the best case-case scenario, will represent the driving policies behind the vehicles used for data collection. On the other hand, relying only on simulation tools is not the best solution because they might not be the best representatives of the real world, either because the models behind other surrounding objects (like human-driven vehicles and VRUs) might not be realistic enough or the environment itself is a simplified version of the real world. Therefore, we intend to benefit from both approaches.

In a nutshell, we make use of the already-existing datasets to pre-train a base model and then utilize the simulation environments to enrich it. Enriching here means to improve a pre-trained model for edge case scenarios or situations for which there were not enough data in the training dataset, or to enforce the defined driving policies into it. The output of this step will be a set of motion planning models that can replicate a variety of driving styles and strategies, which are the bases for building the intended simulation environment that is suitable for the impact assessment of AVs and performance evaluation of MPP algorithms.

Application

In the third and last phase, we utilize the developed framework to build a diverse and rich simulation environment. This simulation environment is then utilized for two main purposes:

1. **conducting scenario-based impact assessments:** After developing a set of diverse motion planning models for Avs, we try to answer an important question: “how will automated vehicles affect traffic flow in the transition period towards a harmonized, fully automated society?” To this end, we apply the developed motion planning models for automated vehicles, in conjunction with suitable models for human-driven vehicles (HVs) with acceptable perception mechanisms, in a simulation environment to reproduce diverse driving behaviors for both AVs and HVs. This

behavior-aware simulation environment will be used to evaluate the impacts of automated vehicles on traffic flow under different assumptions about the penetration rate of AVs at different levels of automation and driving styles and strategies.

2. **evaluating the applicability of (other) newly developed AI-based motion planning models in a diverse and complex simulation environment:** Finally, we are going to address a relatively neglected issue in testing and evaluating the motion planning and prerdiction algorithms for AVs. Most of the current simulation environments for evaluating such algorithms lack diversity, which means the behaviors of other agents in the simulation environment are assumed relatively homogeneous [19], [20]. Therefore, the actual performance of such algorithms in complex and diverse environments (such as mixed traffic flow with a variety of AVs and HVs) is questionable. Using a diverse simulation environment is an opportunity to evaluate the more realistic performance of these algorithms.

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