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Review Article

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Lane Change Decision Making for Autonomous Vehicles by using Adversarial Learning Methods

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ABSTRACT

The primary purpose of this thesis is to analyze the effectiveness of generative adversarial imitation learning and adversarial inverse reinforcement learning in typical highway driving scenarios. The current consensus within the literature indicates that data-based techniques such as IL and IRL when combined with adversarial approaches can produce satisfactory results for autonomous driving on highways. Hence, the central hypothesis is: Can data driven reinforcement learning through adversarial inverse reinforcement learning or generative adversarial imitation learning produce reasonable behavior in a highway driving environment? This research adds to the knowledge base by combining inverse reinforcement learning and imitation learning using generative adversarial network for autonomous driving in highway driving.

Keywords: AIRL, Autonomous Driving, CARLA, GAIL, GAN

Material and Method

Initially, a highway driving simulation environment was created using CARLA and Highway-env to generate the datasets required to train the imitation learning and inverse reinforcement learning models, a human driver performed multiple driving maneuvers [1]. Highway-Env environment was initially trained and validated for simple tasks and to generate various driving scenarios [2]. This environment basically mimics highway conditions and helps in the analysis of vehicle dynamics and interactions. The capability of the developed models to generalize and their performance was evaluated by testing under different traffic conditions and driving scenarios. As a next step, CARLA's detailed scenario modeling, autonomous driving validation capabilities were combined with Highway-env's policy testing and driving maneuver generating capability to create a through validation of autonomous driving algorithms. The recorded data suitable for offline learning was stored in a dataset after filtering outliers [3]. Then, the imitation learning and inverse reinforcement learning models were trained of ne using these datasets. To further improve the vehicle's performance, a generative adversarial network (GAN) deep neural architecture was used [4]. Within the combination of the methods, Generative Adversarial Imitation Learning (GAIL) and Adversarial Inverse Reinforcement Learning (AIRL) models were achieved [5]. The trained models were then transferred to an ego vehicle in a highway driving environment using a policy-based approach [6]. Proximal policy optimization (PPO) was utilized to perform this task and to improve the learning performance [7]. At each step, the agent receives the distance to the nearest vehicle n each lane, along with the lane number of the ego vehicle, and decides whether to change lanes or stay in its current lane. Each state-action pair represents the expected future reward. After running the simulation for a finite number of steps, the rewards converge to constant values. In the test phase, the model selects the maneuver with the highest expected reward to achieve its goal, which is closely aligned with human controlled driving behavior. The complexity of highway driving tasks in the context of autonomous vehicles was analyzed and evidence was provided in the form of state-action rewards and collision measurements to validate the analysis. Moving to a realistic simulation environment that includes modules that provide a mathematical representation of the ego vehicle's environment validated the practical benefits of the research conducted in the study.

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Findings

One of the most significant parts of autonomous driving is autonomous lane change during highway driving with decision making. Almost all car makers and suppliers develop autonomous driving strategies to come up with reasonable decision making based on the context of the traffic. Over the last few years, Reinforcement Learning algorithms have been able to produce discrete actions in both discrete and continuous environments. The HighwayEnv environment was used initially to train and validate for simple tasks and to generate various driving scenarios. Later on, we trained our model in CARLA and performed our test in CARLA environment since it is capable of simulating critical safety scenarios that are necessary for assessing collision risks and for improving the performance of autonomous driving systems [8]. We applied the mentioned GAIL and AIRL algorithms together with PPO in this thesis for the decision-making planning of highway controls in autonomous vehicles. Finally, we compare the result of two different offline learning approaches and assessed appropriateness of the use.

Conclusion

The primary contribution of this thesis to the research literature is the approach to evaluate two different but similar reinforcement learning paradigms in an autonomous driving environment. Instead of applying the methods used in this study to tasks unrelated to autonomous driving, this research contributes to the existing knowledge by integrating inverse reinforcement learning and imitation learning through adversarial learning networks. The results of the performance measurements and the rewards (Figure 1) obtained during training, together with the crash assessments in the highway environment and the generalization assessments, support the hypothesis that data-driven learning methods (inverse reinforcement learning and imitation learning) can be used as effective learning approaches in advanced applications. With this approach, t was observed that the vehicle can learn a policy similar to a human driver's policy to avoid collision with other vehicles (Figure 2). However, challenges may arise due to driving maneuvers that were not sufficiently represented in the training dataset.

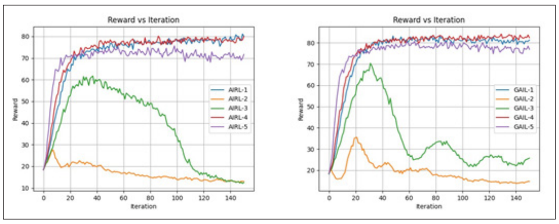

Figure 1: Reward Rate versus Iteration for AIRL and GAIL

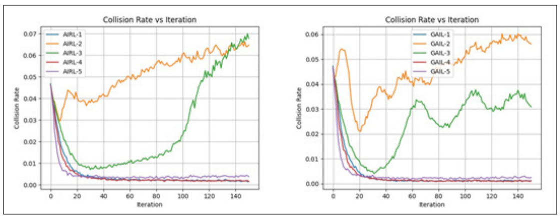

Figure 2: Collision Rate versus Iteration for AIRL and GAIL

The study focuses on a specific driving task, enabling a meaningful and domain-specific application of reinforcement learning. Additionally, we demonstrate the feasibility and benefits of comparing driving tasks n a minimalist environment.

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