Adversarial Imitation Learning via Random Search in Lane Change Decision-Making

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Abstract

As the advanced driver assistance system (ADAS) functions become more sophisticated, the strategies that properly coordinate interaction and communication among the ADAS functions are required for autonomous driving. This paper proposes a derivative-free optimization based imitation learning method for the decision maker that coordinates the proper ADAS functions. The proposed method is able to make decisions in multi-lane highways timely with the LIDAR data. The simulation-based evaluation verifies that the proposed method presents desired performance. Note that this framework is accepted to be published in proceedings of IJCNN 2019 and IJCAI 2019.

1. Introduction

Ever since the introduction of autonomous vehicles, autonomy of vehicles has been a subject of great interest among researchers. Deep reinforcement learning (DRL) has been considered as one of feasible solutions to replace human involvement with autonomous control systems. As the advanced driver assistance system (ADAS) functions become more complex, the strategies that properly coordinate interaction and communication among the ADAS functions are required for autonomous driving (Cioran, 2015). The architecture of ADAS enabled autonomous vehicle control is in Fig. 1. The low-level ADAS controllers are connected to the sensors (i.e., LIDAR sensor) directly. The controllers determine the data from sensors to grasp the situation and transmit the determined operations to mechanical components through actuators. The systems of the autonomous vehicles are managed by a supervisor that coordinates the low-level controllers. The objective of the supervisor is to be a decision maker for the overall system that consists of ADAS functions during driving. Especially, lane change decision-making is one of the challenging problems in this research. It is essential to form efficient long term driving assistance strategies in limited situations such as multi-lane highway environments. Recent work focuses on DRL to make the driving policies of supervisor to be lane change decision-maker in highway scenarios (Hoel et al., 2018). However, when the driving policies are trained through DRL, the problem of safety as well as the robustness of the trained policy is caused by the presence of undesirable policy to maximize the expected rewards at the expense of violating the implicit rules of the environments (Pan et al., 2018). These problems motivate the researchers to adopt imitation learning (IL) to optimize the driving policy. Among IL frameworks, generative adversarial imitation learning (GAIL) has shown remarkable performance in the areas of robotics, autonomous vehicles, and etc (Pomerleau, 1991). However, since GAIL framework uses trust region policy optimization (TRPO), a large amount of data is required to achieve remarkable performance (Schulman et al., 2015). To address this issue, the DRL algorithms that optimize policy in GAIL framework become complicated; and thus the models ultimately lead to reproducibility crisis. Recently, augmented random search (ARS) that consists of the natural gradient policy algorithm is proposed (Mania et al., 2018). In this work, we present an IL-based method adversarial imitation learning via random search (AILRS) that combines the concepts of ARS and GAIL. Since AILRS is based on derivative-free policy optimization, it is relatively easy to reconfigure the robust trained policy (Shin & Kim, 2019a:b).
Algorithm 1 Adversarial imitation learning via random search (AILRS)

Input: step size $\alpha$, number of sampled directions $N$, $K$ number of directions to update
Initialize: $\theta_0 = 0 \in \mathbb{R}^{n \times n}$, $\mu_0 = 0 \in \mathbb{R}^n$, $\sum_0 = \mathbf{I}_n \in \mathbb{R}^{n \times n}$
repeat
Sample $\delta_t = \{\delta_1, \delta_2, \ldots, \delta_N; \delta_i \in \mathbb{R}^{n \times n}\}$ with i.i.d.
Collect $2N$ rollouts and their corresponding rewards using the $2N$ policies.
\[
\pi_t + \delta_i(s) = (\theta_t + \nu \delta_i) \text{diag}(\sum_i)^{-1/2} (s - \mu) \\
\pi_t - \delta_i(s) = (\theta_t - \nu \delta_i) \text{diag}(\sum_i)^{-1/2} (s - \mu_t)
\]
for $i \in \{1, 2, \ldots, N\}$
Update discriminator parameter $\phi_t$:
\[
\nabla_{\phi_t} L_{LS} = \frac{1}{2} E_{s,a} \left[ \left( \nabla_{\phi_t} \mathcal{D}_\phi(s,a) - b \right)^2 \right] \\
+ \frac{1}{2} E_{s,a} \left[ \left( \nabla_{\phi_t} \mathcal{D}_\theta(s,a) - a \right)^2 \right]
\]
Update the policy parameter $\theta_t$:
\[
\theta_{t+1} = \theta_t + \frac{\alpha}{N \sqrt{K}} \sum_{i=1}^{K} \left[ r(\pi_t + \delta_i(s)) - r(\pi_t - \delta_i(s)) \right] \delta_i(s)
\]
where trajectories $T$ sampled from $\pi_t + \delta_i$
and $r(\pi_t(s, a)) = E_{s,a}^{\pi_t(s,a)} \left[ - \log(1 - \mathcal{D}_\phi(T)) \right]$
Set $\mu_{t+1}$, $\sum_{t+1}$ to be the mean and covariance of the states encountered from the start of training
$t = t + 1$
until $t \leq$ Max Iteration

2. AILRS

In this section, the proposed method, called Adversarial imitation learning via random search (AILRS), is briefly introduced (Shin & Kim, 2019a; b). As shown in Algorithm 1, the finite differences are used to adjust a parameterized linear policy. To train the weights of policy $\pi_0$, a random matrix with a small value is added to $\theta$. The matrix with the same value is subtracted to $\theta$. As a result, two temporal weights $\pi_{t+\delta_i(s)}$ and $\pi_{t-\delta_i(s)}$ are generated; the trajectories of state-action pairs are collected through these weights. The discriminator returns the probability of classifying the trajectories from expert; and it is used as rewards.

3. Experiments

The host vehicle continuously obtains lane change rewards during driving. The number of lane change in Fig. 2 has a different tendency from the lane change reward in Fig. 3. The lane change cannot be done in a single determined action. Until the lane change is completed, the host vehicle can change the decision according to the observation. If more than half of the host vehicles do not cross the lane, the lane change reward increases whereas the number of lane changes does not. Therefore, the trained policy through AILRS shows more number of lane changes whereas it presents the smaller lane change reward, comparing to expert. This is because the trained policy changes more lanes than expert’s behaviors. However, BC has a small number of lane changes as well as a small lane change reward due to frequent decision changes.

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