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Connected autonomous vehicles for improving mixed traffic efficiency in unsignalized intersections with deep reinforcement learning

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ABSTRACT

Human driven vehicles (HDVs) with selfish objectives cause low traffic efficiency in an un-signalized intersection. On the other hand, autonomous vehicles can overcome this inefficiency through perfect coordination. In this paper, we propose an intermediate solution, where we use vehicular communication and a small number of autonomous vehicles to improve the transportation system efficiency in such intersections. In our solution, two connected autonomous vehicles (CAVs) lead multiple HDVs in a double-lane intersection in order to avoid congestion in front of the intersection. The CAVs are able to communicate and coordinate their behavior, which is controlled by a deep reinforcement learning (DRL) agent. We design an altruistic reward function which enables CAVs to adjust their velocities flexibly in order to avoid queuing in front of the intersection. The proximal policy optimization (PPO) algorithm is applied to train the policy and the generalized advantage estimation (GAE) is used to estimate state values. Training results show that two CAVs are able to achieve significantly better traffic efficiency compared to similar scenarios without and with one altruistic autonomous vehicle.

1. Introduction

The connected autonomous vehicle (CAV) with the ability of communication, coordination and autonomous driving has shown significant potentials of improving transportation systems (Rios-Torres and Malikopoulos, 2016; Li et al., 2017). In recent years, it has been applied to longitudinal velocity and lane changing maneuvers (Bahram, 2017), car-following (Wei et al., 2019), traffic smoothing (Kamal et al., 2016; Keskin et al., 2020), bottleneck decongestion (Vinitsky et al., 2018b), roundabout (Zhao et al., 2018), unsignalized intersection with only CAVs (Ahn and Del Vecchio, 2016; Azimi et al., 2014; Guney and Raptis, 2020; Campos et al., 2014; Hafner et al., 2013; Zhang et al., 2017) and un-signalized intersection with mixed traffics (both CAVs and human driven vehicles (HDVs)) (Vinitsky et al., 2018a). The objective of traffic efficiency optimization is realized by combinatorial optimization (Bahram, 2017), analytical control (Zhao et al., 2018; Malikopoulos et al., 2018; Hafner et al., 2013; Zhang et al., 2017), mixed integer linear programming (Ahn and Del Vecchio, 2016), protocol-based control (Azimi et al., 2014), scheduling-based optimization (Guney and Raptis, 2020), model predictive control (MPC) (Kamal et al., 2016; Keskin et al., 2020; Wei et al., 2019) and deep reinforcement learning (DRL) (Vinitsky et al., 2018a,b). DRL makes a series of decisions based on the observation of environment states, in order to maximize the expected long-term reward, and has been applied to games (Silver et al., 2018), robotics (Kober et al., 2013) and resource allocation for wireless networks (Ye et al., 2019; Lee et al., 2019). Relevant to our context, DRL has also been applied to CAV control in a signalized intersection (Yang et al., 2017), an unsignalized single-lane intersection with desired speed as objective (Kheterpal et al., 2018) lane changing behavior (Wang et al., 2018), roundabout (Jang et al., 2019).

In this paper, we consider the application of CAVs in mixed traffics, i.e., the traffic flow comprises both CAVs and HDVs, which is more plausible in the foreseeable future than pure CAV traffic flow. Unlike autonomous vehicles that maximize its own benefit (e.g., safety, efficiency and comfort), CAVs with altruistic objectives influence adjacent HDVs with their behavior in order to optimize the overall traffic flow. In particular, we consider a two-lane unsignalized intersection with mixed traffic. Two fleets are placed on the two lanes and each fleet is led by a CAV. The objective is to avoid queuing in front of the intersection by cooperation of the two CAVs. Since there are two CAVs leading the two fleets, cooperation between the two CAVs is required to achieve the objective and the approaches in the existing literature (e.g., desired speed) do not apply to this scenario. In this study, we expand the figure-eight scenario presented in (Vinitsky et al., 2018a) to two lanes and the

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coordinated behaviors of the two CAVs are evaluated with respect to the overall traffic efficiency. To the authors' best knowledge, multi-lane traffic optimization with cooperation between the CAVs in an unsignalized intersection with mixed traffic has not been studied before. We expect that this work would be another step towards efficient mixed-autonomy urban traffic optimized by CAVs with altruistic control strategy. DRL is applied to determine the CAVs' behavior. We show that DRL works for our scenario as well with properly defined state, action and reward that eliminate local optima during the training.

2. Scenario description

We consider a two-lane unsignalized intersection (one lane in each direction) as shown in Fig. 1, which appears frequently in reality. In order to make the scenario close such that vehicles stay in the scenario and pass through the intersection again and again, entries and exits are connected with ring-shaped roads, such that vehicles can cross the intersection multiple times.

Without traffic light, the human driving behavior would result in a low efficiency, as will be shown later. In this paper, we aim to improve the traffic efficiency with CAVs powered by the DRL algorithm. Unlike the "selfish" autonomous vehicles, the objective of the CAVs is to optimize the whole traffic flow instead of their own benefit. Two CAVs are available in the considered scenario. They are assumed to be able to communicate with each other and coordinate their behaviors, which are shown as the red vehicles in Fig. 1. The HDVs are depicted as white vehicles, which imitate the human driving behavior with the intelligent driver model (IDM) Treiber et al. (2000).

The scenario, vehicle dynamics, and the reinforcement learning (RL) algorithms are implemented based on the Flow project Wu et al. (2017). In our configuration, the Flow project uses simulation of urban mobility (SUMO) Behrisch et al. (2011) as traffic simulator and RLlib Liang et al. (2017) as DRL algorithm implementation.

3. Algorithm

3.1. Review of RL

DRL addresses the problem of optimal actions in a dynamic environment with the objective of maximizing the cumulative reward of all time steps. Formally, the RL problem can therefore be formulated as

$$\begin{aligned} \max_{\theta} \quad & \mathbb{E}\left(\sum_{t=0}^{H} \gamma^t r_t\right) \\ \text{subject to} \quad & r_t = r(s_t, a_t), \\ & s_{t+1} = f(s_t, a_t), \\ & a_t = \pi_\theta(s_t), \end{aligned} \tag{1}$$

where $\gamma \in [0, 1]$ is a discounting factor, r_t is the reward at time step t and is decided by state s_t and action a_t at the same time step (the first constraint), action a_t updates state s_t to state s_{t+1} at the next time step (the second constraint), a_t is decided by policy π parameterized by θ given state s_t and H is the horizon, i.e., the number of time steps in an episode.

If reward function and system dynamics are unknown to the agent, the problem is model-free RL. We choose the state-of-the-art stochastic policy optimization algorithms proximal policy optimization (PPO) and value estimation algorithm generalized advantage estimation (GAE) for actor and critic, respectively. The reason to choose PPO is that it realizes a stable training process with the trust region and requires reasonable computation effort. GAE is applied because of its flexible bias-variance tradeoff.

PPO Schulman et al. (2017) optimizes the policy in an iterative manner. In each iteration, data samples are collected with the old policy and the new policy is improved in the proximal region of the old policy (called trust region). It is proved that the expected reward is guaranteed to improve if the Kullback-Leibler (KL) divergence between the old and new policies is smaller than a certain threshold Schulman et al. (2015a). Based on this, trust region policy optimization (TRPO) Schulman et al. (2015a) uses Lagrange multiplier to optimize the policy subject to the KL divergence constraint to realize a stable training. On the other hand, PPO introduces a loss function, which has a nonzero gradient only in the proximal region and hence confines the optimization region. It achieves similar performance with lower computational complexity and is therefore chosen in this paper.

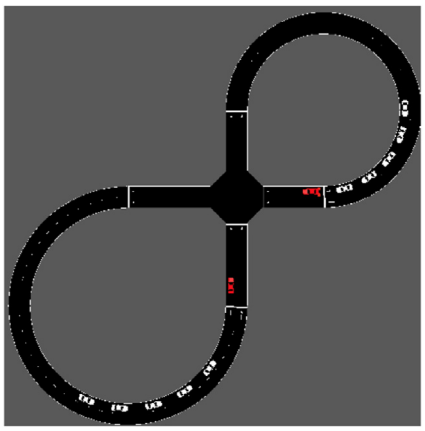

Fig. 1. Considered scenario and the initial vehicle positions. Red vehicles are CAVs whereas white ones are HDVs. We denote the bottom red car CAV 0 and the right red car CAV 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

The GAE Schulman et al. (2015b) is applied as critic to estimate state value. The state value $V^\pi(s)$ is the expected (discounted) sum of rewards given current state s and assuming the agent behaves according to policy π. Furthermore, the Q-value $Q^\pi(s, a)$ is the expected (discounted) sum of rewards given current state s and corresponding action a and assuming the agent behaves according to policy π thereafter. The difference between $Q^\pi(s, a)$ and $v^\pi(s)$ is defined as advantage $A^\pi(s, a)$, which is used to compare action a and policy π. In this paper, we apply GAE Schulman et al. (2015b) to estimate the advantage.

3.2. Definitions of state and action

The state definition should contain all information needed to make the optimal decision. Besides, it should be directly correlated with the reward, making the learning process easier. Intuitively, the CAVs need their own positions and velocities as well as positions and velocities of vehicles in front of the intersection in both entries (from bottom and from right in Fig. 1). Other vehicles are far away from the intersection and have little impact on the CAVs' decision. Based on these considerations, we define the state as

$$\begin{aligned} s \quad = \{ & x_0^{\mathrm{A}}, x_1^{\mathrm{A}}, v_0^{\mathrm{A}}, v_1^{\mathrm{A}}, x_{\mathrm{first}}^{\mathrm{B}}, x_{\mathrm{last}}^{\mathrm{B}}, v_{\mathrm{first}}^{\mathrm{B}}, v_{\mathrm{last}}^{\mathrm{B}}, \\ & x_{\mathrm{first}}^{\mathrm{R}}, x_{\mathrm{last}}^{\mathrm{R}}, v_{\mathrm{first}}^{\mathrm{R}}, v_{\mathrm{last}}^{\mathrm{R}} \} \end{aligned} \tag{2}$$

where x_a^{A} and v_a^{A} are longitudinal coordinate and velocity of CAV a, respectively, with $a \in \{0, 1\}$; x_m^{B} and v_m^{B} are longitudinal coordinate and velocity of vehicle $m \in \{\text{first, last}\}$ within 30 m on the bottom entry of the intersection, respectively, with $m =$ first, the first vehicle (closest to the intersection) and $m =$ last, the last vehicle (farthest to the intersection within 30 m); x_n^{R} and v_n^{R} are state description of the right entry with similar meaning to x_n^{B} and v_n^{B}, respectively. If there is no vehicle within 30 m in front of the intersection, the coordinate is set to 30 m in front of the intersection and the velocity is set to 0. In this way, the state includes information on the CAVs (with superscript "A") and on vehicles approaching the two entries of the intersection (with superscripts "B" for

bottom and "R" for right). Hence the scenario state is represented in a compact manner.

The action is the accelerations of the two CAVs. Therefore, the action space is a two dimensional continuous space $[-3\ \mathrm{m/s^2}, 3\ \mathrm{m/s^2}]^2$ considering the realistic acceleration and deceleration.

3.3. Reward shaping

The objective is to reduce the queues in front of the intersection, similar to the one-lane, one CAV scenario from Vinitsky et al. (2018a). We cannot apply the same reward as Vinitsky et al. (2018a), to encourage vehicles to approach a desired velocity v_{des} because the initial distances from the two CAVs to the intersection are similar (see Fig. 1). A CAV needs to adapt its velocity such that there is enough time difference between the other CAV and itself to pass the intersection in order to avoid congestion. Once the proper time difference is created, the CAVs should maintain the time difference such that there is no congestion every time thereafter they pass through the intersection. Therefore, constant velocities can not realize the goal to avoid congestion. Based on the above consideration, the reward is defined as sum of the three terms with the following objectives: (i) maintaining desired velocity; (ii) minimizing queues; (iii) avoiding local optima. Based on this, we proposed the following rewards:

1) CAV 0 should keep its desired velocity. Therefore, the first term is defined as

$$r_1 = -\|v_0^{\mathrm{A}} - v_{\mathrm{des}}\| \tag{3}$$

where $\|\cdot\|$ is the Euclidean distance operator. CAV 1 does not have a desired velocity.

2) The number of queuing vehicles should be minimized. A slow threshold velocity v_{th} is defined and vehicles moving slower than the threshold velocity are considered as queuing vehicles. The second term of the reward is thus defined as

$$r_2 = -|\{i|v_i < v_{\mathrm{th}}\}| \tag{4}$$

where v_i is the velocity of vehicle i (the vehicle is either a CAV or an HDV, the set $\{i|v_i < v_{\mathrm{th}}\}$ is therefore the set of vehicles that has a speed less than v_{th}) and $|\cdot|$ is the cardinality operator.

3) Training according r_1 and r_2 tends to suffer from a local optimum,[1] where CAV 1 tries to accelerate to its maximum velocity in order to reduce the queuing time of the fleet led by CAV 0 rather than slowing down to let the fleet led by CAV 0 pass the intersection first. To avoid this local optimum, we add a small correction term to discourage high velocities:

$$r_3 = -\|\mathbf{v}\| \tag{5}$$

where $\mathbf{v}$ is the vector of all vehicles' velocities.

The total reward is defined as

$$r = \alpha r_1 + \beta r_2 + \kappa r_3, \tag{6}$$

where α, β, and κ are non-negative tuning parameters.

4. Selected results

The training process and testing results are presented in this section. We choose ADAM as the optimizer with the learning rate of 5×10^{-4}, the clip of PPO ε is set to 0.2. The discounting factor γ is set to 0.999 where as the tradeoff coefficient of GAE δ is 0.99. In each iteration, 60 rollouts are run and the policy is optimized based on the sampled data. In our setup, desired velocity v_{des} is defined as 3 m/s, threshold velocity v_{th} is chosen as 1.1 m/s. Factors α, β, and κ are set to 10, 1, and 0.1, respectively.

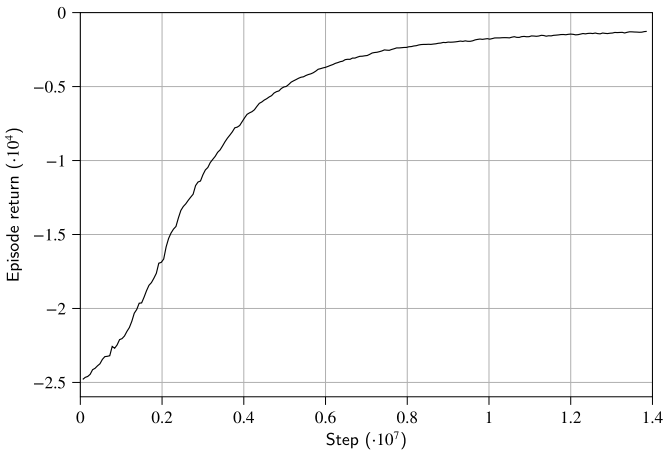

Fig. 2. Episode return in training showing monotonic improvement due to the selected reward shaping.

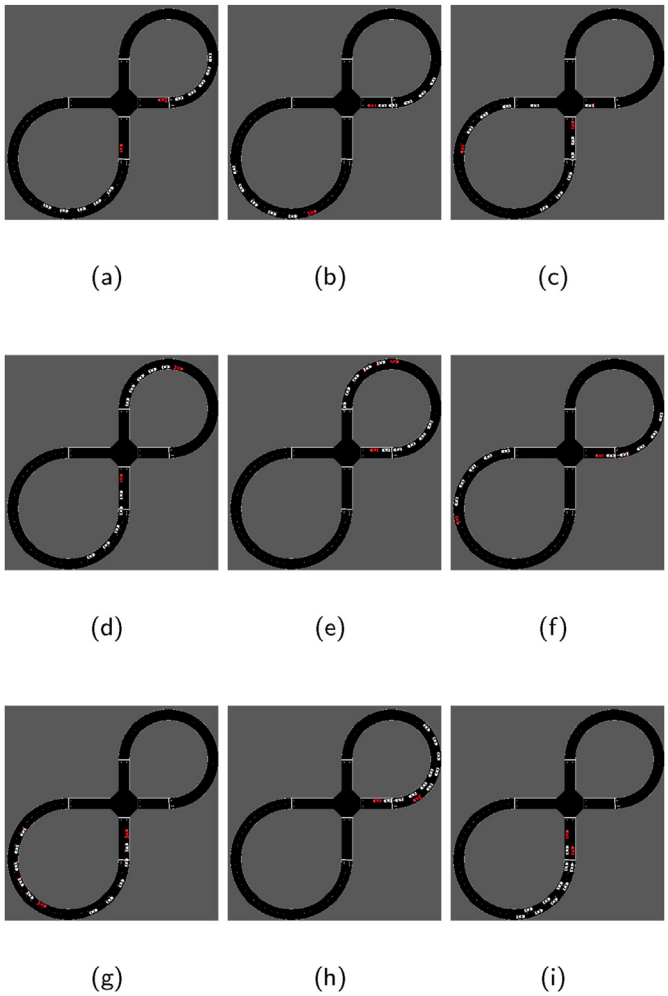

Fig. 3. Nine screenshots of the testing results when one CAV is approaching the intersection. It can be observed that the two CAVs gradually synchronize their longitudinal positions to avoid congestion.

[1] Due to the expectation operation of PPO, convergence to poor local optima is possible.

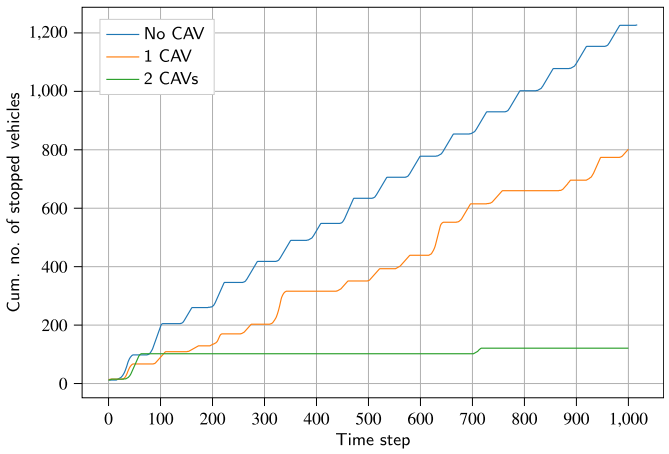

Fig. 4. Cumulative numbers of stopped vehicles in front of the intersection.

Fig. 2 shows the episode reward (sum of rewards in an episode) during training. It can be observed that the performance has been improved constantly during training. It was observed that without the r_3 term, the return was much lower (results not shown).

Fig. 3 shows nine screenshots of the testing result when one CAV is approaching the intersection. While CAV 0 remains a constant velocity, CAV 1 adjusts its velocity to reach similar longitudinal position of CAV 0 and thus avoid congestion of the intersection.

Fig. 4 shows the cumulative numbers of stopped vehicles (numbers stopped vehicles up to that time) during the testing without CAV, where we define vehicles slower than 0.01 m/s as stopped, with 1 CAV and with 2 CAVs. The unique differences between the three setups are the numbers of CAVs. It is clear that 2 CAVs significantly reduce the stopped vehicles in front of the intersection and improve the traffic efficiency.

5. Conclusions

In this paper, DRL is applied to CAVs, which have an altruistic objective to optimize the traffic flow and the ability to communicate and coordinate their behaviors. The proposed algorithm uses the actor-critic framework with PPO as policy optimizer and GAE as value estimator. After the training, two CAVs are able to lead multiple HDVs in a closed scenario with an intersection. One CAV keeps a constant velocity whereas the other CAV adjusts its velocity to avoid congestion. A designed reward function is able to avoid local optima such that the policy converges in the desired behavior. Testing results show that the number of waiting vehicles in front of the intersection is considerably less with 2 CAVs than without and with 1 CAV. This work proves the potential of the altruistic CAVs in improving traffic efficiency. In future works, more general traffic behaviors (e.g., lane changing and turning) and situations (e.g., different numbers of HDVs) should be considered in order to make the approach closer to reality.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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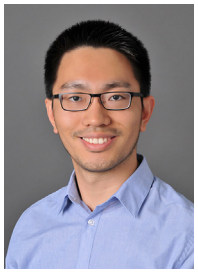

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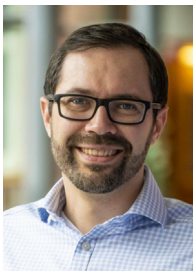

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