Robust Adversarial Reinforcement Learning with Dissipation Inequation Constraint

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Abstract

Robust adversarial reinforcement learning is an effective method to train agents to manage uncertain disturbance and modeling errors in real environments. However, for systems that are sensitive to disturbances or those that are difficult to stabilize, it is easier to learn a powerful adversary than establish a stable control policy. An improper strong adversary can destabilize the system, introduce biases in the sampling process, make the learning process unstable, and even reduce the robustness of the policy. In this study, we consider the problem of ensuring system stability during training in the adversarial reinforcement learning architecture. The dissipative principle of robust $H_{\infty}$ control is extended to the Markov Decision Process, and robust stability constraints are obtained based on $L_2$ gain performance in the reinforcement learning system. Thus, we propose a dissipation-inequation-constraint-based adversarial reinforcement learning architecture. This architecture ensures the stability of the system during training by imposing constraints on the normal and adversarial agents. Theoretically, this architecture can be applied to a large family of deep reinforcement learning algorithms. Results of experiments in MuJoCo and GymFc environments show that our architecture effectively improves the robustness of the controller against environmental changes and adapts to more powerful adversaries. Results of the flight experiments on a real quadcopter indicate that our method can directly deploy the policy trained in the simulation environment to the real environment, and our controller outperforms the PID controller based on hardware-in-the-loop. Both our theoretical and empirical results provide new and critical outlooks on the adversarial reinforcement learning architecture from a rigorous robust control perspective.

1 Introduction

Deep reinforcement learning (DRL) has become a popular method for training continuous controllers. It is widely used in the fields of robotic control and navigation (Duan et al. 2016; Lee et al. 2020; Hodge, Hawkins, and Alexander 2021). Although the performance of DRL is better than that of the traditional methods in simulation, realistic application examples are rare (Zhao, Queraltà, and Westerlund 2020). There are available methods for direct operation in actual physical tasks to collect data (Haarnoja et al. 2018; Hwangbo et al. 2019), the policy is unstable in the initial training period, and repeated training may result in aging and failure of the actuator (Li et al. 2020). Another cheaper method is to deploy the policies trained in simulation directly in the real environment. However, the differences (such as modeling error and disturbance) between the simulation and the real environment reduce the performance of the policies (Christiano et al. 2016). To this end, learning policies that are robust to environmental change, mismatched configurations, and mismatched control actions are becoming increasingly more preferable for sim-to-real tasks (Kamalaruban et al. 2020).

One effective method to learn robustness is domain randomization (Peng et al. 2018; Tobin et al. 2017) whereby a professionally knowledgeable designer determines the uncertain model components in the task. Thereafter, a set of training environments is constructed, and the uncertain components are randomly assigned to ensure the average robustness of the agent assigned to the set. Nevertheless, it requires significantly designers’ experience in the test domain (Vinitsky et al. 2020); the uncertainty in the training environment will also lead to the instability of policy learning. Another method to learn robustness that is easier to automate is to model environmental differences as adversarial disturbances (Ilahi et al. 2020). Through the alternate update of the normal and adversarial agents, a two-player-zero-sum game is constructed. This makes the normal agent robust to the disturbance of the adversary. The method does not require much knowledge of domain. Nonetheless, it increases the difficulty of the training domain. This may make the training unstable, causing the policy to fall into a local suboptimal solution, or resulting in a non-convergence (Tessler, Efroni, and Mannor 2019). The instability during training is because adversarial-policy acquisition is significantly faster than stable-control-policy acquisition for an underactuated or unstable system. For example, in an inverted double pendulum system, a disturbance acting on the pendulum arm can easily make the system unstable (Mackenroth 2008). If the adversary can always destroy the stability of the system during learning, it will lead to task failure. In addition, the
Related Work. The adversarial architecture is originated from the $H_\infty$ control theory, which makes the controller robust against model uncertainty by introducing adversarial disturbances into the controlled system (Modares, Lewis, and Sistani 2014; Wu and Luo 2012) or real robot system (Pinto, Davidson, and Gupta 2017). (Morimoto and Doya 2005) converted the $H_\infty$ problem into a differential game and solved the minimax value function of the normal and adversary agents to update the policies. It was the first study wherein the adversarial architecture was introduced into RL theory. This idea of minimax was then extended in the robust adversarial reinforcement learning (RARL) architecture (Pinto et al. 2017), with considerable empirical success, subsequently adopted and improved in (Kamalaruban et al. 2015; Gleave et al. 2019). However, as discussed earlier, the adversarial architecture sometimes fails to improve the robustness of the normal agent because a strong adversary affects the stability of the training process (Zhang, Hu, and Basar 2020). To reduce the influence of the adversary on the training stability, the main methods include manual adjustment of frequency (Pan et al. 2019) or magnitude (Tessler, Efroni, and Mannor 2019) of the interaction between the adversary and the environment or reducing the update frequency of the adversarial policy (Gu, Jia, and Choset 2019). These methods ensure the stability of training to a certain extent, but it is difficult to achieve an effective trade-off between robustness and training stability.

More closely related work from a theoretical perspective is that of (Han et al. 2019) who introduces and extends the idea of Lyapunov stability and $H_\infty$ control to design policies with robustness guarantee. This work introduces a Lyapunov function as a critic to provide the policy gradient, simultaneously find the Lyapunov function and policy that can guarantee the robust stability of the closed-loop system. Our work differs from this work in a number of respects: (1) Their critic is represented by a Lyapunov function which tends to bring the system state to a balance point, it is difficult to apply this method to robot locomotion tasks, or it is necessary to design a specific reward function. Our method adopts the auxiliary optimization strategy and retains the reward-driven mechanism to be applied in more general environments. (2) The Lagrangian term from (Han et al. 2019) is only used for the constraints of the normal agent, whereas the Lagrangian term in our formulation constrains both the normal and the adversarial agents simultaneously to ensure the stability of the system during the training process.

2 Preliminaries

2.1 Adversarial Reinforcement Learning

An adversarial environment may be expressed as a two-player $\gamma$ discounted zero-sum Markov game (Perolat et al. 2015). The Markov Decision Process (MDP) of this game can be expressed as a tuple $(S, A_1, A_2, P, r, \gamma, s_0)$, where $A_1$ and $A_2$ are the continuous action sets for the normal and adversarial agents, respectively. Moreover, $P : S \times A_1 \times A_2 \times S \rightarrow \mathbb{R}$ is the transition probability function, and $r : S \times A_1 \times A_2 \rightarrow \mathbb{R}$ is the reward signal of the two agents. If the policy of the normal agent is $\pi_\mu$, and the policy of the adversarial agent is $\pi_\omega$, the reward function can be expressed as $r_{\pi_\mu, \pi_\omega} = E_{s_0, \omega, \omega}[\sum_{t=0}^{T-1} \gamma^t r(s, a, \omega)]$, where $s \in S$, $a \sim \pi_\mu (|s) \in A_1$, $\omega \sim \pi_\omega (|s) \in A_2$. The two-player zero-sum game can be considered as an environment, where the goal of the normal agent is to maximize the return of $\gamma$ discount (accumulative reward) $G = E_{s_0, \omega, \omega}[\sum_{t=0}^{T-1} \gamma^t r(s, a, \omega)]$, where $T$ is the horizon length of each episode; whereas, that of the adversarial agent is to minimize the return of $\gamma$ discount. (Perolat et al. 2015) demonstrated that for a game with optimal equilibrium return $G^*$, minimax and Nash equilibriums are equivalent.

$$G^* = \min_{\pi_\omega} \max_{\pi_\mu} G(\pi_\mu, \pi_\omega) = \max_{\pi_\mu} \min_{\pi_\omega} G(\pi_\mu, \pi_\omega), \quad (1)$$

(Pinto et al. 2017) indicated that optimal return might be approached by directly learning the optimal policy $\pi_\mu^*, \pi_\omega^*$. 

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2.2 Characteristics of $L_2$ Gain in a Reinforcement Learning System

The basic idea of robust $H_\infty$ control is to suppress the maximum gain of the system to impair the influence of the disturbances signal on the evaluation signal, which describes the system quality (i.e., the reward signal in RL system) (YingMin 2007). The $L_2$ norm is introduced into the signal space to measure the evaluation signal. The maximum gain of the system can be expressed as the induced norm of the operator from the system input signal space (disturbance space) to the output signal space (reward space). Therefore, if the maximum gain of the system is designed to be small enough, the influence of any input disturbance signal in $L_2$ space on the evaluation signal will be suppressed within the allowable range, which means that the system is Bounded Input Bounded Output (BIBO) stable. To solve the problem of achieving the robustness stability of an agent under the RL system, (Han et al. 2019) extended the $L_2$ gain in robustness control theory as:

**Definition 1.** If an RL system is mean square stable (MSS) when $\omega = 0$, and $\sum_{i=0}^{\infty} E[||r_\pi(s_t)||/\sum_{i=0}^{\infty} E[||\omega(s_t)||]] \leq \lambda^2$ holds for all $\omega \in L_2 = \{ \omega | \sum_{t=0}^{\infty} \omega^2(s_t) < \infty \}$, the system is referred to as the MSS with an $L_2$ gain less than or equal to $\lambda$.

Where $||.||$ is the 2-norm of the signal and $\omega(s_t)$ is the uncertainty of system, which may contain modeling errors and external disturbances of the system. $\lambda$ is a positive constant and $r_\pi$ is the reward signal of policy $\pi$. Definition 1 guarantees that the influence of uncertainty on reward function is always bounded.

2.3 Dissipation Inequation in $H_\infty$ Controlled Theory

$H_\infty$ control is an important method for solving robust control problems. It reduces the influence of disturbance on the reward/quality signals by restraining the $H_\infty$ norm of the system (Hongye 2010; Luo, Wu, and Huang 2014; Modares, Lewis, and Sistani 2014). Consider the following nonlinear uncertain systems:

$$\begin{cases}
\dot{s} = f(s) + g(s)\omega, \\
r = h(s).
\end{cases}$$

(2)

Where $s^T = [s^1, s^2, \ldots, s^n] \in M$ is a state vector, and the superscript representing each component of the vector is distinguished from the subscript representing the time step. In a small abuse of notation, $\omega$ is an uncertain disturbance signal and denote the adversarial action in Section 3, $M$ is the invariant set of the system (2), $r$ is a reward signal, $f(s)$, $h(s)$ and $g(s)$ are differentiable functions. Note that because the control variable can be expressed as a function of the state variable, we incorporate the control variable into the functions $f(s)$ and $h(s)$ for clarity. The following theorem exist (TieLong 1996):

**Theorem 1.** For a given $\lambda > 0$, the sufficient condition for $L_2$ gain being less than or equal to $\lambda$ in the nonlinear uncertain system (2) is that a continuous differentiable Lyapunov function $F(s) \geq 0$ exists, and $\forall s \in M$ satisfies the following dissipation inequation:

$$\frac{\partial F}{\partial s}(s)f(s) + \frac{\partial F}{\partial s}(s)g(s)\omega \leq \frac{1}{2}\{\lambda^2\|\omega\| - \|r\|\}$$

(3)

Where the left side of the inequation can be viewed as the total derivative of the Lyapunov function. Therefore, (3) can be further simplified as:

$$\frac{dF(s)}{dt} \leq \frac{1}{2}\{\lambda^2\|\omega\| - \|r\|\}$$

(4)

Thus, it is clear that there is a close correlation between the characteristics of the $L_2$ gain and the dissipativeness of an uncertain system. Please refer to (Willems 1972; Byrness, Isidori, and Willems 1991) for a specific proof.

3 Methodology

In this section, we introduce the $L_2$ gain constraint into the RL architecture to ensure the stability of the system during training and enhance the robustness of normal agent. The constraint conditions of a robust RL based on dissipative inequality are presented in Section 3.1. In Section 3.2, we show the method of introducing this constraint into the adversarial architecture. Finally, in Section 3.3, we introduce the overall architecture and optimization process of the proposed algorithm.

3.1 Dissipation Inequation-Based Robust Reinforcement Learning Constraint

In this section, we will extend the relationship between $L_2$ gain and dissipativeness of $H_\infty$ control theory (Theorem 1) to the RL system described in Section 2.1. First, the basic assumption is presented.

**Assumption 1.** The limit of k-step transition probability from state $s_0$ to state $s$ under policy $\pi$ exists: $\lim_{k\to\infty} P_{r}(s | s_0, k, \pi)$.

**Assumption 2.** For any policy $\pi$ which belongs to policy space $\Pi$, the rewards as received in each step during an interaction with the environment are always bounded, i.e., $\forall s \in \{ s | r_\pi(s) < \infty \}, \pi \in \Pi$.

Assumption 1 is the basic assumption in reinforcement learning theory. Because real systems are always bounded, Assumption 2 is easy to satisfy. On this assumption, we propose sufficient conditions for the MSS of the RL system.

**Theorem 2.** Given that $\lambda > 0$, the sufficient condition for $L_2$ gain being less than or equal to $\lambda$ under Definition 1 with regard to the RL system as defined in Section 2.1 is that there exist positive constants $a, b, \text{ and continuous differentiable Lyapunov function } F(s)$ such that $0 \leq ar_\pi(s) \leq F(s) \leq br_\pi(s)$ and satisfies:

$$E_{\mu(s)}[E_\pi[F(s')] - F(s)] \leq E_{\mu(s)}\frac{1}{2}\{\lambda^2\|\omega(s)\| - \|r_\pi(s)\|\}$$

(5)

Where $s'$ is the successor state, and $\mu(s)$ is the state distribution of policy $\pi$. Intuitively, the left-hand side of Eq.(5) can be regarded as the difference of the Lyapunov function,
that is, the concept of derivative in the discrete-time system. Therefore, the Eq.(5) has the same structure as the dissipation inequation (4) and is a generalization in the RL discrete-time systems, and Theorem 2 can be regarded as an alternative statement of Theorem 1 in the MSS. It should be noted that Theorem 2 in our paper has a similar structure and assumptions to Theorem 1 of (Han et al. 2019). However, Theorem 1 of (Han et al. 2019) gives constraints from the perspective of Lyapunov stability theory, while Theorem 2 in our paper is a generalization of the dissipative inequality in the robust $H_{\infty}$ control theory. The dissipative theory is an idea of disturbance suppression, which suppresses the influence of disturbance on the reward of the RL system to the desired minimum. The complete proof is given in Appendix A.1. In the next subsection, we will show how to introduce Theorem 2 into the policies update functions of the adversarial architecture and approximate the Lyapunov function $F(s)$.

### 3.2 Policy Updating Functions with Lagrange Multiplier Method

In our adversarial game, at each moment $t$, the normal and adversarial agents observe the state $s_t$ at the same time and select actions $a_t \sim \pi_{\mu}(s_t)$ and $\omega_t \sim \pi_{\omega}(s_t)$, where $\pi_{\mu}$ and $\pi_{\omega}$ are the policies of the normal and adversarial agents, respectively. The normal agent maximizes the long-term return whereas the adversarial agent minimizes the long-term return. The two agents are constrained by inequality (5). Let $\theta^\mu$ and $\theta^\omega$ denote the parameters of the policies $\pi_{\mu}$ and $\pi_{\omega}$ respectively. The theoretical update will be:

$$
\begin{align*}
\theta^\mu_{k+1} &= \arg\max_{\theta^\mu} \frac{1}{s_t, a_t, \omega_t} \mathbb{E} \left[ G_{\mu}(s, a, \omega, \theta^\mu_k, \theta^\omega_k) \right], \\
\theta^\omega_{k+1} &= \arg\max_{\theta^\omega} \frac{1}{s_t, \omega_t} \mathbb{E} \left[ -G_{\omega}(s, \omega, \theta^\mu_k, \theta^\omega_k) \right], \\
\text{s.t. } &E_{s_t} \left[ F(s') - F(s) \leq \frac{1}{2} \left( \lambda^2 \|\omega(s)\| - \|\rho(s)\| \right) \right]
\end{align*}
$$

(6)

Where $G_{\mu}(s, a, \theta^\mu_k, \theta^\omega_k)$, $G_{\omega}(s, \omega, \theta^\mu_k, \theta^\omega_k)$ are the “surrogate” objectives for updating the policies of the normal and adversarial agents, respectively. We will let $G_{\mu}$, $G_{\omega}$ denote above “surrogate” objectives for concise. They represent different optimization objectives in different RL algorithms such as the clipped advantage function in the proximal policy optimization (PPO) algorithm (Schulman et al. 2017). The Lagrange multiplier method is then used to bring the constraint term into the update equation as,

$$
\begin{align*}
\theta^\mu_{k+1} &= \arg\max_{\theta^\mu} \frac{1}{s_t, a_t, \omega_t} \mathbb{E} \left[ G_{\mu}(s, a, \omega, r, s') - \alpha \Delta L(s, a, \omega, r, s') \right], \\
\theta^\omega_{k+1} &= \arg\max_{\theta^\omega} \frac{1}{s_t, \omega_t} \mathbb{E} \left[ -G_{\omega}(s, \omega, \theta^\mu_k, \theta^\omega_k) - \alpha \Delta L(s, a, \omega, r, s') \right], \\
\text{where } &\alpha \text{ is the Lagrangian multiplier of the corresponding items, } \Delta L(s, a, \omega, r, s') \text{ is the Lagrangian of dissipation inequation (5) and we will let } \Delta L \text{ denote this for concise,}
\end{align*}
$$

(7)

$$
\Delta L = F(s', \tau_{\pi_{\omega}}(s')) - F(s, a) + \frac{1}{2} \left( \|\omega\| - \lambda^2 \|\omega\| \right)
$$

(8)

Where $\tau_{\pi_{\omega}}(s')$ is the parameterized policy of the normal agent. When the adversarial agent is updated, the parameterized policy $\tau_{\pi_{\omega}}(s)$ of the adversarial agent is adopted to substitute $\omega$ in (8).

Note that (8) is derived from the right-half shift term of the constraint inequality in (6). This Lagrangian has different meanings in the update equations of the normal and adversarial agents. For the normal agent, the Lagrangian multiplier can give the agent an additional gradient with respect to the stability of the system, whereas for the adversarial agent, the Lagrangian multiplier restrains the update of the policy that leads to system instability. We will discuss this mechanism in more detail in Appendix A.2. The Lyapunov function is calculated using a neural network for fitting through the data-driven method. The objective function of the Lyapunov network $F_{\theta}$ is defined as:

$$
J_{Lya}(F_{\theta}) = E_{(s, a)} \sim D_{\mu} \left[ \frac{1}{2} (F_{\theta}(s, a) - F_{\text{target}}(s, a))^2 \right]
$$

(9)

The target function of the Lyapunov function can be defined differently (Mayne et al. 2000). In this study, we use a generalized advantage function (Schulman et al. 2015): $F_{\text{target}}(s, a) = \hat{A}(s_t, a_t)$. (Luo, Wu, and Huang 2014) proved that the approximation of the Lyapunov function obtained from a model-free data-driven calculation would not influence the performance of the $H_{\infty}$ controlled policies.

### 3.3 Dissipation Inequation Constraint-Based Adversarial Reinforcement Learning Method

Our algorithm optimizes both the normal and adversarial agents using the following alternating procedure. In each rollout, the trajectories of the normal and adversarial agents interacting with the environment are collected. Following that, the advantage function is estimated by the trajectories, and the normal agent and Lyapunov network are updated. The Lyapunov network and the trajectories are then used to update the adversarial agent. This sequence is repeated until convergence.

Algorithm 1 describes our method in detail, where $\theta^F$ is the parameter of the Lyapunov network; the subscripts of all the network parameters represent the iteration step; $N_{\text{iter}}$ is the total number of the rollout; $N_{\text{Sample}}$ is the length of each rollout trajectory; $\text{Optimizer}(\cdot)$ is a policy optimizer that can use different algorithms according to different tasks and "surrogate" objectives such as PPO, trust region policy optimization (TRPO), and soft actor-critic (SAC). The Lyapunov network is only optimized with the normal agent, and the network parameters are fixed in the optimization process of the adversary. Furthermore, before update the adversary, the successor action $a'$ is resampled using the updated normal agent network and stored in $D_{\omega}$ buffer in order to calculate the first term in Eq. (8).

### 4 Experiment

In this section, we describe the three sets of experiments performed. The first and second sets of experiments were carried out in MuJoCo. The purpose of the first group of ex-
Table 1: Success rates and standard deviations of different algorithms with 100 mass combinations are compared. Where the Pendulum and Double denote the InvertedPendulum and InvertedDoublePendulum tasks, respectively. The trained policies are initialized by 7 random seeds, and 700 episodes are tested for each mass group. Significantly better results from a t-test with \( p < 0.1 \) are highlighted in bold.

| Algorithm          | Pendulum | Double | HalfCheetah | Hopper |
|--------------------|----------|--------|-------------|--------|
| Vanilla PPO        | 59.2 ± 0.4 | 36.3 ± 1.19 | 66.7 ± 2.24 | 14.6 ± 0.49 |
| RARL               | 72.8 ± 0.75 | 40.6 ± 1.62 | 82.5 ± 1.96 | 20.4 ± 0.66 |
| NR-MDP             | 71.2 ± 0.4 | 26.9 ± 1.37 | 46.8 ± 2.18 | 12.9 ± 1.14 |
| Oracle             | 78.0 ± 0.2 | 33.3 ± 1.49 | 84.3 ± 1.27 | 22.0 ± 0.45 |
| DICARL (ours)      | 77.1 ± 0.7 | 44.1 ± 1.87 | 87.3 ± 0.9 | 38.4 ± 1.28 |

**Algorithm 1: DICARL (proposed algorithm)**

Initialize Environment \( \mathcal{E} \), rollout buffer \( D_\mu, D_\omega \), Lagrangian multiplier \( \alpha \)

Initialize Lyapunov network \( F(s, a) \), constant \( \lambda \), normal agent policy \( \pi_\mu(a|s) \), adversarial agent policy \( \pi_\omega(\omega|s) \) and corresponding parameters \( \theta_\mu^k, \theta_\omega^k \).

1. for \( k \) in \( N_{iter} \) do
   2. \( \theta_\mu^k \leftarrow \theta_\mu^{k-1}, \theta_\omega^k \leftarrow \theta_\omega^{k-1}, \theta_F^k \leftarrow \theta_F^{k-1} \)
   3. for \( i \) in \( N_{Sample} \) do
      4. Run policies \( a_t \sim \pi_\mu(a|s_t, \theta_\mu^k), \omega_t \sim \pi_\omega(\omega|s_t, \theta_\omega^k) \) in environment \( \mathcal{E} \)
      5. Get successor states \( s_{t+1}, r_t \), store \( (s_t, a_t, w_t, r_t, s_{t+1}) \) in \( D_\mu, D_\omega \)
   6. end for
   7. Compute advantage estimates \( \hat{A}_1, \ldots, \hat{A}_{Sample} \) and store in \( D_\mu, D_\omega \)
   8. \( \theta_\mu^k, \theta_\omega^k \leftarrow \text{Optimizer}(D_\mu, \theta_\mu^k, \theta_\omega^k, \mathcal{G}_\mu, J_{Lyap}(F_\theta^k)) \)
   9. \( \theta_F^k \leftarrow \text{Optimizer}(D_\omega, \theta_\omega^k, \mathcal{G}_\omega, J_{Lyap}(F_\theta^k)) \)
10. end for

8700k CPU.

**4.1 Robustness Under the Modeling Error**

We chose four MuJoCo tasks: InvertedPendulumAdv-v1, InvertedDoublePendulumAdv-v1, HopperAdv-v1, and HalfCheetahAdv-v1 from an improved adversarial Gym (Pinto et al. 2017) to test our algorithm. In each task, the agent was a robot composed of several joints. Considering our method and the RARL, the adversary acted on different body parts of the robot. For the NR-MDP, the adversary acted on the actuator of the robot. For the Oracle method, the environmental variables (body parts of robots with different masses) in the test domain were initialized randomly before each rollout. The Vanilla PPO trained directly in the original environment without any adversaries. The detailed description of the environment can be found in Appendix C.1. In addition, all the shared hyper-parameters were the same, and we run all algorithms with the same amount of simulation steps. The detailed settings of the hyper-parameter of each algorithm are reported in Appendix C.2.

The modeling error between the simulation and the real world can cause controllers to fail, requiring a robust control policy. In the training domain, the body mass of the robot remained unchanged. In the test domain, we changed the masses of the two body parts of the robot. The range of change in the mass was the original mass multiplied by [0.1-2.1] with an interval of 0.2, and a total of 100 groups of different mass combinations. The threshold of time steps was set for each task. If the time steps of the agent is larger than the threshold, it will be regarded as a successful task. If otherwise, it will be a failure. Each mass group was trained on seven random seeds and is evaluated across 700 episodes in the training domain.

In safety-critical tasks or real robot tasks, any failure may be fatal and can cause damage to the robot. Therefore, we counted the number of combinations with a failure rate of less than 2\% in different mass groups in the test domain as a measure of the adaptability of the controller. The results in Table 1 demonstrate that the proposed algorithm outperforms all the baselines in most environments. In the InvertedPendulum environment, our algorithm also has competitive performance. The heat-maps of accumulative reward and failure rates can be found in Appendix C.3. The training curves can be found in Appendix C.4. Moreover, we observed that the Oracle method is the most competitive base-
We used the same environmental settings and shared hyper-parameters as in Section 4.1 to compare the robustness of the two algorithms. The upper limit of the magnitude of the adversary is set to [1.3 – 5.8].

We calculated the adaptability of the two algorithms to the test domain under training with different magnitudes of the adversary. The evaluation method is the same as mentioned in Section 4.1: the result is shown in Figure 1. In the environment of InvertedPendulum and InvertedDoublePendulum, it can be seen that in the RARL algorithm, when the magnitude of the adversary increases to a certain extent, the performance of the controller degrades rapidly, and a stable control policy cannot be acquired. This result is consistent with the observation of (Tessler, Efroni, and Mannor 2019; Pan et al. 2019; Pinto et al. 2017) because these two environments are more sensitive to disturbance, and the powerful adversary in RARL can always prevent the normal agent from successfully performing tasks. However, DICARL can adapt to a more powerful adversary. This supports our viewpoint that DICARL can effectively use adversary attacks to improve robustness and maintain environmental stability during training. For the HalfCheetah environment, the increase in the magnitude of the adversary has no significant effect on the normal agent because the half-cehetah robot has a greater stability margin and is insensitive to disturbances. Moreover, we also observed that the performance of the two algorithms in the Hopper environment fluctuated greatly with the change in the magnitude of the adversary. For a forward hopping robot, the forward disturbance force is more likely to cause task failure than that of the backward disturbance. This indicates that the increase in the force of the magnitude does not necessarily obtain a sufficiently strong adversary, resulting in the difference in the robustness of the normal agent. In general, our algorithm has more advantages when used with a powerful adversary during training and has a controller with optimal adaptability to the environment. This provides a potential method for improving robustness through more complex and diversified adversarial training in the future.

### 4.3 Sim-to-Real Task

In the last set of experiments, we used the GymFc to train the quadrotor angular velocity controller based on a neural network. We compared the two baselines, including Vanilla PPO and NR-MDP. We set the same shared hyperparameters for the three algorithms. Thereafter, the neural network controller was used to replace the PID angular velocity controller based on the HIL method and deployed to the actual quadrotor flight control system. Finally, we tested our method in a real environment. The environmental setting and real quadrotor parameters can be found in Appendix F.1 and Appendix F.2 detail the setting for the hyper-parameter of the algorithm.

**Simulation Environment.** In the simulation environment, the signal supplied to the motor is added to 10% random noise. (Fei et al. 2020) reported that this kind of attack on the motor signal could cause the aircraft to deviate from the normal operating point, resulting in serious performance degradation, requiring a robust control policy. We visually
compare the step responses of PPO, NR-MDP, and DICARL angular velocity controllers under a disturbance of 10% random noise in Figure 2. DICARL has the smallest overshoot on the pitch and roll axes. Although NR-MDP has a better performance on the pitch and roll axes than that of the PPO algorithm, both of them have larger control signals (i.e., $u$ in Figure 2), which will increase the motor load, reducing the service life. By contrast, our algorithm ensures lower overshoot and control signal, rendering it more suitable for an actual system. We notice that the three algorithms have large oscillations on the yaw axis. This may be because of the disturbance acting on the motors, causing each motor to have a random moment of inertia noise. This increases the difficulty of controlling the yaw axis.

**Real Environment.** Without further optimization, we evaluated the policy learned in the simulation on the real quadrotor. We used a quadcopter assembled with a QAV250 frame and pixhawk 2.4.6 flight controller. Details of the deployment method can be found in Appendix F.3. To test the robustness of the DICARL algorithm, we made the quadcopter perform the task of flying over the racing gates. We conducted three tests, where the quadcopter carried a different mass of payload in each test. For a small UAV, approximately 10-100 mW is required for 1 g additional take-off weight for hovering (Leutenegger et al. 2016). Even a small extra load will affect the performance. In this test, we tested the performance of the quadcopter under three payloads: no-load, load mass of 63.3 g and 98.68 g. We visualized the flight trajectories of these three tasks as shown in Figure 3. It can be seen that the quadcopter can smoothly and quickly cross the two racing gates under different payloads.

Finally, we compared the angular velocity error of the DICARL controller and the HIL-based PID controller (Dai et al. 2019) on the real quadcopter. The normalized mean error is shown in Table 2. Our method has a smaller tracking error on the pitch and the roll axes and delivers competitive performance with the PID controller on the yaw axis. See Appendix F.4 for the visualized tracking curve. In the actual test, the expected angular velocity tracked by our method is most greater than that of the PID controller. This proves that our controller has a faster response speed; however, to some extent, it also reduces the performance of the yaw axis.

| Controller | Pitch error | Roll error | Yaw error |
|------------|-------------|------------|-----------|
| PID        | 0.3595      | 0.3168     | 0.0514    |
| DICARL     | **0.2206**  | **0.1158** | **0.0721**|

Table 2: Normalized average error of pitch, roll, and yaw axes of DICARL and PID attitude controllers in the real world. Significantly better results from a t-test with $p < 1\%$ are highlighted in bold.

**5 Conclusion**

In this study, we show that the effective method for improving the robustness of the policy and stabilizing the training
is to introduce robust stability constraints in the adversarial RL architecture. From the perspective of robust control, we propose a sufficient condition for the RL strategy to satisfy $L_2$ gain and develop a new robust adversarial reinforcement learning architecture based on this constraint. Theoretically, our architecture is suitable for the current mainstream RL algorithms, such as PPO, TRPO, and SAC. The PPO and SAC algorithms were used in the policy optimizer to instantiate our architecture and conduct extensive experiments to validate the effectiveness of our algorithm. The experiment on a real quadcopter proves the potential of our algorithm in a sim-to-real task. Both our theoretical and empirical results provide new and critical outlooks about adversarial RL architecture from a rigorous robust control perspective. We do not believe that our research will cause any social problem or put anyone at any disadvantage.

Experiments on Hopper show that the use of a single adversary to approximate the solution to a minimax problem does not consistently lead to improved robustness. Interesting future research directions include increasing the diversity of adversaries, such as using multiple adversaries to train together with a normal agent or attacking different functional components of the RL process. In this process, the stability of the system is also important to the performance of the normal agent. The increase in the number of adversaries may further deteriorate the stability of the system. It is necessary to introduce our method into the aforementioned multi-agent adversarial architecture.

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