Robustness Exploration of the Twin-Delayed Deep Deterministic Policy Gradient Algorithm Under Noise Attack

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Abstract. This research focuses on exploring the robustness of the reinforcement learning algorithm Twin Delayed Deep Deterministic Policy Gradients (TD3), especially in terms of its performance in the face of uncertainty, noise, and attacks. Reinforcement learning is a machine learning paradigm in which an agent learns how to perform tasks and optimize long-term rewards through interaction with its environment. This learning approach has a wide range of applications in areas such as autonomous driving, gaming, robot control, and many others. TD3 is an advanced reinforcement learning algorithm that performs remarkably well in various complex tasks and environments. Additionally, TD3 possesses some unique performance advantages, such as the dual Q-Critic structure and target policy smoothing, which potentially make it robust when facing uncertainty and noise. While there has been extensive research on the robustness of reinforcement learning, there is a relative lack of research specifically targeting TD3. This study aims to fill this gap and investigate how TD3's performance changes when different types of noise are added or when it is subjected to attacks. This research aims not only to gain a deeper understanding of the TD3 algorithm itself but also to provide strong support for the theory and practice of reinforcement learning robustness. This research has broad applications and academic value and has the potential to drive further advancements in the field of reinforcement learning.

Keywords: Reinforcement Learning, TD3, Robustness Exploration.

1 Introduction

Reinforcement Learning (RL) has found extensive applications in various fields, including but not limited to autonomous driving, robot control, financial trading, healthcare, energy management, and gaming. For instance, in autonomous driving, RL can be used to optimize path planning and decision-making; in financial trading, RL algorithms can automate trading strategies; in healthcare, RL can be employed for generating personalized treatment plans.

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Twin Delayed Deep Deterministic Policy Gradients (TD3) is an advanced RL algorithm and an improvement upon Deep Deterministic Policy Gradients (DDPG). Compared to other RL algorithms, TD3 has several significant advantages and unique features:

1. Dual Q-Critic Structure: TD3 employs two independently trained Q-Critic networks to estimate action-value functions, reducing the problem of overestimation and enhancing algorithm stability and performance.

2. Target Policy Smoothing: TD3 introduces noise in the selection of the target policy, which helps maintain robustness in the face of environmental noise and uncertainty.

3. Delayed Policy Updates: Compared to DDPG, TD3 updates the policy network less frequently, reducing instability between the policy and value functions, further enhancing algorithm stability.

4. Efficiency and Scalability: TD3 excels not only in low-dimensional problems but also effectively scales to high-dimensional and complex tasks and environments.

Due to these advantages, TD3 has performed exceptionally well in various tasks and environments, making it an ideal candidate for research into the robustness of reinforcement learning.

In the realm of reinforcement learning robustness, there have been notable studies. For example, the paper titled "Deep reinforcement learning with robust deep deterministic policy gradient" explores improving RL performance by introducing robust deep deterministic policy gradients [1]. The paper titled "Robust reinforcement learning via adversarial training with Langevin dynamics" enhances RL algorithm robustness through adversarial training and Langevin dynamics [2]. The paper titled "Efficient and robust reinforcement learning with uncertainty-based value expansion" enhances RL algorithm efficiency and robustness through uncertainty-based value expansion [3]. However, research on the robustness of TD3 algorithm under different types of noise and attacks remains relatively limited, which is the issue this study aims to address [4,5].

This research aims to fill this research gap and investigate the performance of the TD3 algorithm under less-than-ideal conditions, including uncertainty, noise, or attacks. This not only contributes to improving the algorithm's reliability and robustness but also holds broad practical value in fields such as autonomous driving, robot control, and financial trading. Furthermore, this study may drive advancements in the theory and practice of reinforcement learning robustness and introduce new methods or metrics for quantifying and assessing algorithm robustness.

This research will delve into the TD3 algorithm using FGSM and IGM attacks, as well as adding Uniform, Gaussian, and Ornstein-Uhlenbeck noise.

The primary objective of the research is to quantify the performance changes of the TD3 algorithm when subjected to different types of noise and various attacks.

2 Method

2.1 Dataset

The experiment utilized the BipedalWalker Hardcore v3 as the test environment, which includes various slopes, obstacles, and pits, posing challenges to reinforcement learning algorithms [6]. Data collection was primarily achieved through interaction with the environment, with the TD3 algorithm's agent performing actions within the environment and collecting information such as states, actions, rewards, and more.

2.2 Models

TD3 Algorithm. In this TD3 implementation, it mainly consists of several components [7,8]. 1) Environment Setup and Parameter Initialization: The environment named "BipedalWalkerHardcore-v3" was created using the 'gym' library, and parameters such as state dimension, action dimension, and maximum action value were initialized. 2) Network Architecture: One network is named actor network. It is responsible for generating policies, i.e., given state s, it outputs action a. Another one is the Q-Critic network, for comprising two independent Q networks ($Q1$ and $Q2$), responsible for estimating the Q-value for state-action pairs. 3) Replay Buffer: Used to store interaction history for experience replay. 4) Training Loop: In each episode, the agent interacts with the environment, collects data, and then uses this data to train the Actor and Q-Critic networks. 5) Model Saving and Loading: Functionality for saving and loading models is provided.

The learning process of TD3 is as follows:

Firstly, action selection: The Actor network is used to select an action, possibly with some exploration noise added. Secondly, environment interaction: The selected action is executed, and the resulting next state and reward are observed. Thirdly, data storage: The state, action, reward, and next state are stored in the Replay Buffer. Fourthly, model training. The training process has three steps: 1) A batch of data is randomly sampled from the Replay Buffer. 2) Target Q-values are computed, and the Q-Critic networks are updated using mean squared error (MSE) loss. 3) The Actor network is updated using the output of the Q-Critic networks.

In TD3, the Q-Critic Loss is:

$$\text{Q-Critic Loss} = E\left[\left(Q(s,a) - \left(r + \gamma \min_{i=1,2} Q_i^{'}\left(s^{'},a^{'}\right)\right)\right)^2\right] \tag{1}$$

where $Q(s,a)$ is the current Q-value, r is the reward, γ is the discount factor, and $Q_i^{'}\left(s^{'},a^{'}\right)$ is the target Q-value.

The actor loss is:

$$\text{Actor Loss} =- E\left[Q\left(s,\pi(s)\right)\right] \tag{2}$$

where $\pi(s)$ is the policy output by the Actor network.

This design and mathematical formulation enable TD3 to perform exceptionally well in complex and uncertain environments.

Attack Algorithms. To evaluate the robustness of TD3, an attack algorithm called Fast Gradient Sign Method (FGSM) is leveraged. FGSM is a method for attacking deep learning models by adding a small, directional perturbation to input images to cause incorrect predictions by the model [9,10].

The attack procedure is as follows. Given a model f, a loss function $\mathcal{L}(x, y)$, an input sample x, and its true label y, the FGSM attack generates a perturbed sample x' as follows:

$$x' = x + \varepsilon \cdot sign(\nabla x\mathcal{L}(x, y)) \tag{3}$$

where ε is a small constant controlling the magnitude of the perturbation, and $\nabla x\mathcal{L}(x, y)$ is the gradient of the loss function with respect to the input x.

Noise Models and Adaptivity.
Three different types of noise is also leveraged: Uniform noise, Gaussian noise, and Ornstein-Uhlenbeck noise. The mathematical models are as follows:

Uniform noise: $U(a, b)$

Gaussian noise: $N(\mu, \sigma^2)$

Ornstein-Uhlenbeck noise: $dx_t = \theta(\mu - x_t)dt + \sigma dW_t$

The TD3 algorithm itself includes target policy smoothing, which helps mitigate the impact of noise.

3 Result

Through the aforementioned designs, this work can evaluate not only the performance of the TD3 algorithm under normal conditions but also gain a comprehensive understanding of its robustness when facing various attacks and noise. Specifically, TD3's dual Q-Critic structure and target policy smoothing mechanism adapt well to the attack algorithms and these noise models, making this research practically valuable.

3.1 Robustness of TD3 under Different Seeds

The model's average score under various random seeds consistently exceeded 286 points, demonstrating its efficiency. The consistent performance across different random seeds indicates a model that does not overfit to specific initial conditions and possesses good generalization capabilities. Results are demonstrated in Fig. 1.

Multi-Seed Evaluation: The model maintains high performance across a range of seeds, which is a crucial indicator of robustness. This multi-seed evaluation effectively mitigates the risk of overfitting to specific initial conditions, enhancing the model's generalization capabilities.

Oscillation Behavior and Convergence: Despite experiencing oscillations during training, the model still converges to a stable and high-performing solution. This resistance to variations within episodes further emphasizes the model's robustness.

Uniformity in Performance: The closeness of average scores under different random seeds further confirms the model's robustness. This uniformity in performance indicates the model's ability to withstand changes in initial conditions and random elements within the environment.

The studied TD3 model not only exhibits excellent performance metrics but also demonstrates significant robustness under various initial conditions. This is evidenced by its consistently high scores across different random seeds. Here are detailed descriptions of these key attributes.

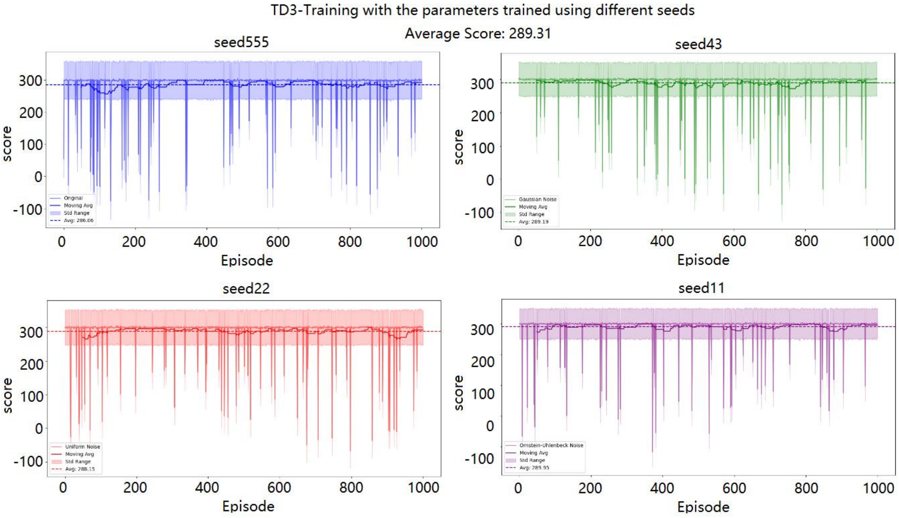

Fig. 1. Result of TD3 under different seeds (Figure Credits: Original).

3.2 Robustness of TD3 under Different Noise Interference

The performances under different noise levels are shown in Fig. 2. The original state, as a baseline, the model achieved an average score of 288.35 in the absence of noise interference. After introducing Gaussian noise with a variance of 0.25, the model's average score slightly decreased to 273.69. However, this decrease remains within an acceptable range compared to the original state, indicating the model's robustness to Gaussian noise. Under the influence of uniform noise with a variance of 0.25, the model's average score was 285.43, nearly on par with the original state's score, further demonstrating the model's robustness. With Ornstein-Uhlenbeck noise at a perturbation coefficient of 0.25, the model's average score was 275.47. Although it experienced a slight decrease, it still indicates the model's resilience.

In the evaluation under various noise conditions, it could be observed that the model exhibited varying degrees of oscillation in each assessment. Despite the fluctuations, the overall score trend remained stable above the average score. This phenomenon further confirms the model's ability to maintain stable performance in the presence of uncertainty and noise interference, showcasing its excellent robustness.

The results of this experiment indicate that the TD3 model can maintain relatively stable performance under various noise conditions. This performance is not only highly effective in specific tasks but also demonstrates significant robustness in different environmental conditions. This robustness is a critical factor in the application of reinforcement learning models in complex and uncertain environments.

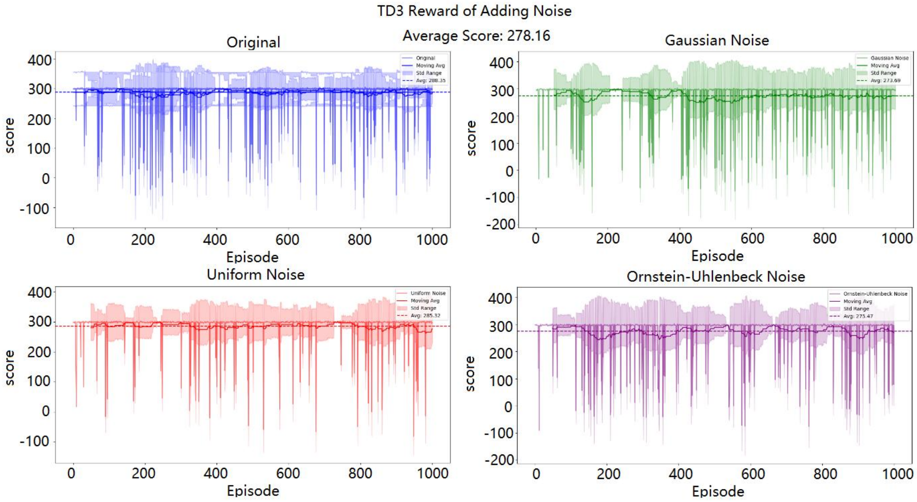

Fig. 2. Result of TD3 under different noise levels (Figure Credits: Original).

3.3 Robustness of TD3 under FGSM Attacks

The results are shown in Fig 3. In the absence of any attacks, the model achieved an average score of 288.35, serving as a baseline for comparison. At a lower perturbation coefficient of 0.1, the model's average score decreased to 274.15. Although it experienced a decrease, it remained within an acceptable range compared to the original state. When the perturbation coefficient increased to 0.25, the model's average score significantly dropped to 117.25, indicating a noticeable performance decline under this level of perturbation. With the perturbation coefficient further increased to 0.5, the model's average score became negative (-84.85), and the oscillation amplitude increased. This suggests that the model has nearly lost its original performance under this level of perturbation. At a low perturbation coefficient (e.g., 0.1), the model can maintain relatively high performance, indicating a degree of robustness. As the perturbation coefficient increases (e.g., 0.25 and 0.5), the model's performance sharply declines, even becoming negative under the highest perturbation level. This indicates that the model is highly sensitive to high-level perturbations.

Oscillation and Instability: Under high perturbation conditions, the model exhibits increased oscillation, further confirming its lack of robustness under these conditions.

These experimental results clearly demonstrate the differences in TD3 model robustness under different perturbation coefficients. Particularly, under high perturbation coefficients, the model's performance sharply declines, highlighting its vulnerability. These findings provide valuable insights into the design of robustness in reinforcement learning models when facing adversarial attacks.

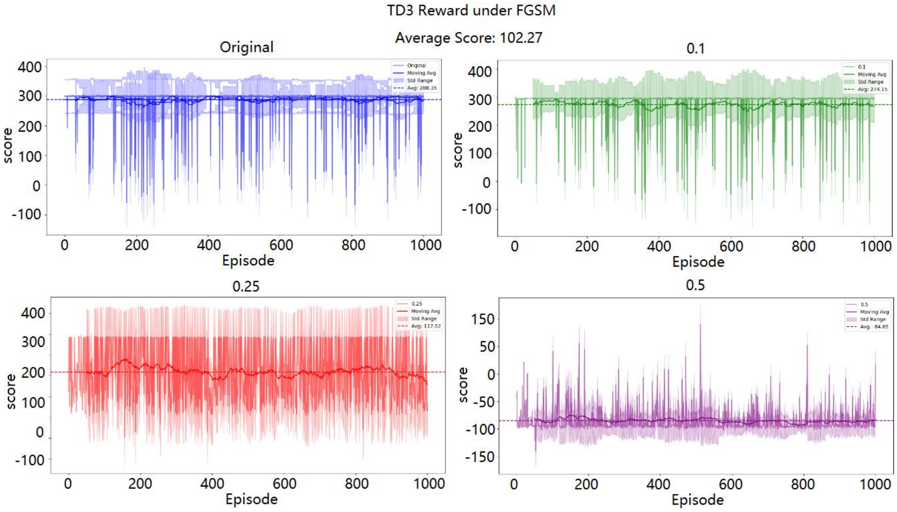

Fig. 3. Result of TD3 under different levels of FGSM attacks (Figure Credits: Original).

4 Conclusion

This study comprehensively evaluated the robustness of the TD3 algorithm under different environmental conditions and attack scenarios. Experimental results showed that TD3 exhibited excellent performance consistency and generalization ability under multiple random seeds and different initial conditions. The average score of the model under various random seeds exceeded 286 points, demonstrating its efficiency and robustness. After adding different types of environmental noise (such as Gaussian noise, uniform noise, and Ornstein-Uhlenbeck noise), the performance of TD3 get lower, but the decrease was relatively small and within an acceptable range. However, when facing FGSM attacks, the robustness of TD3 showed obvious hierarchical characteristics. At lower perturbation coefficients (such as 0.1), the model was able to maintain relatively high performance. But when the perturbation coefficient increased to 0.25 and 0.5, the performance of the model plummeted, even achieving negative average scores. This result revealed that TD3 was vulnerable to high-level adversarial attacks. Overall, the TD3 algorithm demonstrated good robustness against environmental noise and uncertainty, but was sensitive and fragile under high-amplitude adversarial attacks. These findings provide valuable insights for further improving the robustness of TD3 and other reinforcement learning algorithms.

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