A Survey on Different Methods Applied in Humanoid Deep Reinforcement Learning

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Abstract

This thesis surveys various Deep Reinforcement Learning (DRL) methods for humanoid environment in the Mujoco, focusing on Proximal Policy Optimization (PPO), Advantage Actor-Critic (A2C), Deep Deterministic Policy Gradient (DDPG) Twin Delayed Deep Deterministic Policy Gradient (TD3), and Soft Actor-Critic (SAC). By comparing these algorithms, the study identifies their strengths, weaknesses, and performance impacts on feature engineering. Results show that while PPO and SAC benefit from feature engineering, TD3 and A2C perform worse, highlighting the need for careful feature selection. Future work includes integrating Physic-Informed Neural Networks (PINNs)[6], hyperparameter fine-tuning, and exploring advanced methods like Maximum-Entropy Reinforcement Learning using Energy-Based Normalizing Flows (MEOW) to enhance the robustness and effectiveness of DRL in humanoid control.

1 Introduction

The field of Deep Reinforcement Learning (DRL) has witnessed significant advancements over recent years, driven by the intersection of deep learning and reinforcement learning techniques. DRL algorithms have been successfully applied to a wide range of tasks, including game playing, robotic control, and autonomous driving, demonstrating their potential to solve complex, high-dimensional problems.

One particularly challenging application of DRL is in the domain of humanoid robot control. Humanoid robots, which mimic human form and movement, present unique challenges due to their high degrees of freedom, complex dynamics, and the need for precise, continuous[5] and stable control. The Mujoco (Multi-Joint Dynamics with Contact) simulation environment has emerged as a popular platform for testing and developing DRL algorithms for humanoid robots due to its accurate physical modeling and flexibility.

This thesis aims to provide a comprehensive survey of different DRL methods, mainly focusing on Proximal Policy Optimization (PPO)[7], Advantage Actor-Critic (A2C), Deep Deterministic Policy Gradient (DDPG)[4], Twin Delayed Deep Deterministic Policy Gradient (TD3)[2], and Soft Actor-Critic (SAC)[3]. Apply those methods to humanoid robot control using the Mujoco humanoid

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environment. The focus is on comparing the performance and characteristics of various DRL algorithms, identifying their strengths and weaknesses, and understanding the underlying factors that contribute to their effectiveness.

In the subsequent sections, we will review related work in the field, describe the methods and algorithms used, present the results of our experiments, discuss future work, and conclude with a summary of our findings. By systematically evaluating multiple DRL methods in a standardized environment, this thesis seeks to contribute to the ongoing research efforts in humanoid robot control and provide insights for future advancements in the field.

2 Related Work

In the field of Deep Reinforcement Learning (DRL), several algorithms have emerged as leading methods for solving continuous control tasks, such as those involved in humanoid robot control. In this section, we briefly explain five prominent DRL algorithms: Proximal Policy Optimization (PPO)[7], Advantage Actor-Critic (A2C), Deep Deterministic Policy Gradient (DDPG), Twin Delayed Deep Deterministic Policy Gradient (TD3)[2], and Soft Actor-Critic (SAC)[3].

2.1 On-Policy Algorithms

A key feature of this kind of algorithm is that all of these algorithms are on-policy: that is, they don't use old data, which makes them weaker in sample efficiency. But this is for a good reason: these algorithms directly optimize the objective you care about—policy performance—and it works out mathematically that you need on-policy data to calculate the updates. So, this family of algorithms trades off sample efficiency in favor of stability.

2.1.1 Proximal Policy Optimization (PPO)

Proximal Policy Optimization (PPO)[7] is an on-policy algorithm that strikes a balance between the stability and reliability of Trust Region Policy Optimization (TRPO) and the simplicity of vanilla policy gradient methods. PPO utilizes a clipped surrogate objective function that limits the size of policy updates, ensuring that the new policy does not deviate excessively from the old one. This clipping mechanism stabilizes training and makes PPO robust to hyperparameter variations. PPO has demonstrated strong performance across a wide range of reinforcement learning tasks, including robotic control, due to its ability to maintain a stable learning process.

2.1.2 Advantage Actor-Critic (A2C)

Advantage Actor-Critic (A2C) is a synchronous version of the Asynchronous Advantage Actor-Critic (A3C) algorithm. A2C combines the strengths of value-based and policy-based methods by simultaneously learning a policy (actor) and a value function (critic). The critic estimates the value of states, while the actor updates the policy parameters in the direction suggested by the advantage function, which measures the relative value of an action compared to the average. By leveraging both value and policy gradients, A2C achieves efficient learning and robust performance in various environments.

2.2 Off-Policy Algorithms

Off-policy algorithms are able to reuse old data very efficiently. They gain this benefit by exploiting Bellman's equations for optimality, which a Q-function can be trained to satisfy using any environment interaction data.

2.2.1 Deep Deterministic Policy Gradient (DDPG)

Deep Deterministic Policy Gradient (DDPG) is an off-policy algorithm that combines the advantages of DQN (Deep Q-Network) and policy gradient methods. It operates by learning deterministic policies in high-dimensional, continuous action spaces. DDPG maintains a critic network, which estimates the Q-value of state-action pairs, and an actor-network, which updates the policy deterministically by following the policy gradient of the expected return. The algorithm also employs a target network and experience replay to stabilize training and improve learning efficiency. DDPG is known for its ability to handle complex environments with continuous action spaces effectively.

2.2.2 Twin Delayed Deep Deterministic Policy Gradient (TD3)

Twin Delayed Deep Deterministic Policy Gradient (TD3)[2] is an improvement over DDPG designed to address issues of overestimation bias and variance. TD3 introduces three key modifications: the use of a pair of critic networks to provide more reliable Q-value estimates, the delayed updating of the target networks to reduce error accumulation, and the addition of noise to the target action to smooth out Q-value estimation. These enhancements make TD3 more stable and efficient, especially in high-dimensional continuous action spaces, making it well-suited for complex tasks like humanoid control.

2.2.3 Soft Actor-Critic (SAC)

Soft Actor-Critic (SAC)[3] is an off-policy algorithm that aims to improve sample efficiency and stability by incorporating an entropy term into the reward function. This entropy term encourages exploration by maximizing the policy's entropy, leading to more diverse actions and avoiding premature convergence to suboptimal policies. SAC uses a stochastic actor, a value network, and two Q-networks to provide more accurate value estimates and improve training stability. Its entropy-augmented objective and off-policy nature make SAC highly effective in continuous action environments, showing superior performance and robustness compared to many other DRL algorithms.

In summary, these algorithms—DDPG, TD3, PPO, A2C, and SAC—represent a spectrum of approaches to solving continuous control problems in DRL. Each has its unique strengths and weaknesses, making them suitable for different types of environments and tasks. The following sections will explore the methods and results of applying these algorithms to the Mujoco humanoid environment, highlighting their performance and practical considerations.

3 Methods

In this thesis, feature engineering plays a crucial role in preparing the state and action spaces for effective learning by the DRL algorithms. The Mujoco humanoid environment provides a rich set of features representing the robot's state, including joint angles, velocities, and external forces. The primary goal of feature engineering is to ensure that these features are normalized and scaled appropriately to enhance the learning process.

3.1 Feature Engineering

1. **Positional Values:** As we only care about if the humanoid falls or not, we discard both x and y coordinates.
2. **Orientation and Angular Values:** Then, we takes the orientation of the torso into account. Also, angles from each part of the body are considered.
3. **Torso Velocity:** Torso velocity is important for us to get the information of how the humanoid is moving in space.
4. **Angular Velocity:** In addition to plain angular values, we incorporate angular velocities to help the agent understand the motion happening to the humanoid.
5. **Mass and Inertia:** For each body part, we extract its information about the mass, center of mass, and inertia relative to the center of mass of the whole body. This information helps the agent to adapt to each body part. We normalize the vector of the center of mass and the 6 components of inertia and append them at the end.
6. **Center of Mass Based Velocity:** For each body part, we also take its center of mass-based velocity into account. We normalize the velocity vector and append this information at the end.
7. **Constraint Force Generated as the Actuator Force:** For each joint, there is an actuator force generated by the torque we applied to the humanoid. This is also useful to the agent. We normalize the force vector and append this information at the end.

Table 1: Off-Policy Algorithms Hyperparameters

Algorithm	Learning Rate	Discount γ	Batch Size	Horizon T	GAE λ
PPO	$3 \cdot 10^{-4}$	0.99	64	2048	0.95
A2C	0.007	0.99	-	5	1

Table 2: On-Policy Algorithms Hyperparameters

Algorithm	Learning Rate	Discount γ	Batch Size	Replay Size	Smoothing τ
DDPG	0.001	0.99	256	10^6	0.001
TD3	0.001	0.99	256	10^6	0.005
SAC	$3 \cdot 10^{-4}$	0.99	256	10^6	0.0005

8. **Center of Mass Based External Force:** For each body part, there is an external force, e.g. gravity, normal force. This is also useful to the agent. We normalize the force vector and append this information at the end.

3.2 Reinforcement Algorithms

Here, we go over the settings we have for implementation of each algorithm in Table 1 and Table 2. Most of them are inspired by the original paper of which the algorithm was proposed.

4 Experiments

This section outlines the experiments conducted to evaluate the performance of various deep reinforcement learning algorithms on the Mujoco humanoid simulation. The goal of these experiments is to assess each algorithm's ability to learn efficient and stable control policies for humanoid robots.

4.1 Experimental Setup

The experiments were carried out using the Mujoco simulation environment, which is specifically designed for testing the dynamics of multi-joint humanoid robots with complex interactions with their environment. The humanoid model used in the experiments is equipped with 17 degrees of freedom and various sensors that provide comprehensive state information.

Each algorithm was evaluated under identical conditions to ensure comparability. The simulations ran for a total of 5 million timesteps, and the performance was evaluated every 10 epochs to monitor the learning progress. The primary metrics for evaluation were the total cumulative reward and the stability of the learning curve, indicating the effectiveness and consistency of the policy learned by each algorithm.

4.2 Implementation Details

The experiments involved five reinforcement learning algorithms: Soft Actor-Critic (SAC), Advantage Actor-Critic (A2C), Proximal Policy Optimization (PPO), Twin Delayed DDPG (TD3), and Deep Deterministic Policy Gradient (DDPG). Each algorithm was implemented with and without feature engineering (No F.E./F.E.). So we will have ten results finally, and we will compare them in Result Part.

4.2.1 Software Configuration

The following software was used across all setups:

- Python version 3.11.9
- OpenAI Gymnasium-Humanoid V4
- PyTorch 2.3.1 (cu121)

Table 3: Reward results

Algorithm	Reward w/o F.E.	Reward w/ F.E.	Improvement
PPO	473	487	2.9%
SAC	6557	6888	5%
DDPG	57.159	61.485	7.57%
TD3	367.80	74.119	-
A2C	131.18	78.781	-

4.2.2 Hardware Configuration

Since SAC and TD3 require lots of training resources and time, so I deploy the training environment into different hardware configurations to handle the computational demands of various training scenarios:

- Intel Core i7-13700 with 32GB DDR5 RAM and NVIDIA RTX 4080 was used for the initial experiments involving SAC and its variants without features engineering.
- AMD Ryzen 9 7950X with 128GB DDR5 RAM and NVIDIA RTX 4090 was used to train SAC for extended steps (20M, 10M, and 50M).
- AMD Ryzen 9 5900HS with 24GB DDR4 RAM and NVIDIA RTX 3070 Laptop GPU supported TD3, A2C, PPO, and their no features engineering configurations.
- Another setup involving Ryzen 9 5900HS but with 32GB DDR4 RAM and NVIDIA RTX 2070 Super was used for TD3 no features engineering and DDPG.
- MacBook Air M2 with 24GB of RAM was utilized for running DDPG without a features engineering, highlighting the versatility and adaptability of the implementation across various computing platforms.

5 Results

Table 3 shows the reward outcomes for various algorithms with and without feature engineering (F.E.). The results indicate that both the Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC) algorithms benefit from feature engineering, showing improvements of 2.9% and 5%, respectively. The Deep Deterministic Policy Gradient (DDPG) algorithm sees the most significant improvement at 7.57%. However, for the Twin Delayed DDPG (TD3) and Advantage Actor-Critic (A2C), the results with feature engineering are significantly worse, indicating a decrease in performance. We think the reason is that two algorithms are unsuitable for the task.

5.1 Analysis of Features Engineering Impact on SAC and PPO Performance

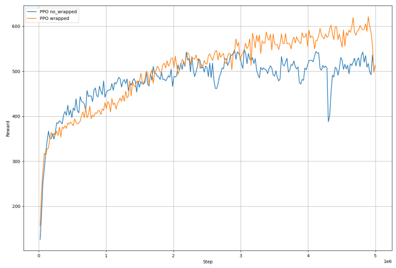
The experimental results demonstrate the impact of using custom observation space features engineering on the performance of SAC and PPO algorithms. The data, visualized through reward progression over time, provides insights into the initial performance, learning stability, and long-term effectiveness of the reinforcement learning strategies under different observation settings.

5.1.1 Initial Performance

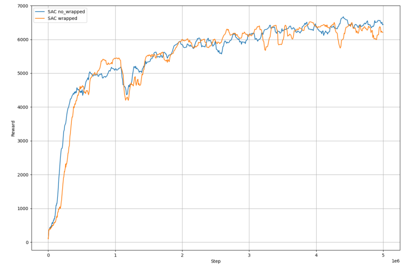
Both SAC and PPO algorithms exhibited higher initial rewards when utilizing the observation space features engineering, suggesting that the additional information provided might be advantageous for initializing more effective policies. This observation is consistent with the hypothesis that enriched observations can enhance the agent's understanding of the environment, potentially leading to better initial decision-making processes.

5.1.2 Learning Stability

The plots reveal distinct differences in learning stability between the two algorithms. The SAC algorithm, when equipped with the features engineering, showed increased variability in reward



(a) PPO with no F.E. and F.E.



(b) SAC with no F.E. and features F.E.

Figure 1: Comparisons of PPO and SAC with and without features engineering

progression, indicating potential challenges in learning stability. This might be due to the complexity or noise introduced by the enriched observation space, which could affect the algorithm's ability to consistently learn effective policies. In contrast, the PPO algorithm maintained a stable upward trend in rewards, similar to its performance without the features engineering, but with slightly higher peaks, suggesting that PPO might be better suited to leverage the enriched data without compromising learning stability.

5.1.3 Long-Term Performance

Over the course of the experiments, both algorithms achieved comparable levels of performance by the end, with or without the features engineering. However, the PPO algorithm with the features engineering showed a slight advantage in terms of reaching higher reward levels faster than its no-feature engineering counterpart. This could indicate that the features engineering not only aids in quicker learning but also helps in maintaining robust performance over time.

5.2 Analysis of Features Engineering Impact on DDPG, A2C and TD3 Performance

The experimental results illustrate the complex influence of feature engineering on the performance of the DDPG, A2C, and TD3 algorithms. While DDPG exhibits substantial improvement, TD3 and A2C performance deteriorates significantly with the integration of feature engineering. This disparity in results suggests that the benefits of feature engineering depend heavily on the specific attributes and operational mechanisms of each algorithm.

5.2.1 DDPG Performance

Although DDPG shows an enhancement of 7.57% in performance with feature engineering, its performance is poor compared with SAC and PPO. This is because humanoid has a high dimensional continuous action space, and DDPG often struggles in high-dimensional action spaces compared to other algorithms like SAC and PPO. So this is the reason that the reward of DDPG is smaller than SAC and PPO.

5.2.2 TD3 and A2C Performance

Conversely, TD3 and A2C register a decline in performance when augmented with feature engineering, attributed to several key factors:

1. **Overfitting and Complexity:** The complexity introduced by additional features might lead to overfitting, where TD3 and A2C fail to generalize from overly detailed or irrelevant signals, resulting in decreased performance in varied or long-term scenarios.
2. **Exploration Inefficiency:** Enhanced features may adversely affect the exploration strategies critical for TD3 and A2C, hindering their ability to explore beneficial action spaces effectively due to increased dimensionality or misleading gradients.

3. **Bias-Variance Tradeoff:** The integration of more observational data can potentially reduce bias but increase variance if the added features do not consistently align with successful outcomes, complicating policy updates and stability.
4. **Algorithmic Sensitivity:** The intrinsic mechanisms of TD3 and A2C might be less compatible with the types of modifications introduced by feature engineering. For example, TD3's efforts to mitigate overestimation bias might be compromised by noisy or variable features, whereas A2C might struggle with abrupt changes in policy space due to volatile features.

In conclusion, while feature engineering holds potential in enhancing reinforcement learning algorithms, its implementation in DDPG, A2C, and TD3 underscores the need for careful selection and customization of features to match the specific requirements and sensitivities of each algorithm. This analysis highlights the importance of further research and tailored experimentation to optimize the integration of feature engineering in complex environments, ensuring improvements in observation space translate into more effective decision-making and learning.

6 Future Work

6.1 PINN Integration

Physic-Informed Neural Network, or PINN, is what inspired this project. The PINN is basically a neural network that is aware of the laws of physics. It computes various partial derivatives such as gradients of a velocity flow or divergence of a fluid flow. Those derivatives can then be used to compute an additional loss term to further fine tune the model more efficiently. Our initial motive was to integrate such networks to reinforcement learning. However, due to time constraints, we had no choice but to cut it out in the end. In the future, we aim to integrate this concept into humanoid to make it more robust.

6.2 Hyperparameters Fine-Tuning

Fine-tuning hyperparameters is also something on which we had no time to test. This can be used to potentially alleviate the problem that our algorithm gets stuck in local minimums just like what happened in our experiments.

6.3 MEOW

Lastly, we are aware that our dear Professor Lee has published a paper "Maximum Entropy Reinforcement Learning via Energy-Based Normalizing Flow"[1]. In the paper, they utilize a method called Maximum-Entropy Reinforcement Learning using Energy-Based Normalizing Flows or MEOW as they call it. We believe integrating such algorithms with PINN can have substantial improvement in physic-related environments. And in the future, we will go in this direction.

7 Conclusion

This thesis explored various Deep Reinforcement Learning (DRL) algorithms—PPO, A2C, DDPG, TD3, and SAC—for controlling humanoid robots in the Mujoco simulation environment. The study compared these algorithms, highlighting the significant impact of feature engineering. Results showed that while PPO and SAC improved with feature engineering, TD3 and A2C performed worse, indicating the need for careful feature selection. Future work includes integrating Physic-Informed Neural Networks (PINNs), hyperparameter fine-tuning, and exploring Maximum-Entropy Reinforcement Learning using Energy-Based Normalizing Flows (MEOW). These efforts aim to enhance the robustness and effectiveness of DRL in humanoid robot control. This thesis provides valuable insights for advancing DRL research in complex control tasks.

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