1. Introduction

* 1. Context  
       
     In the context of robotics, there has been a significant advancement in the application of robots in various areas. Reinforcement Learning (RL) has emerged as a powerful approach to enable robots to learn movement and perform tasks autonomously. However, controlling all the detailed torque of actuators manually by humans is often impractical and inefficient. To address this challenge, Variational Autoencoders (VAE) come into play as a valuable tool to assist in learning actions and compressing motion data.
  2. Aim and Objectives  
       
     The aim of this study is to apply reinforcement learning in a physics environment using mujoco to enable a virtual swimmer to perform various tasks. The objectives of the study are as follows:

1. Train the virtual swimmer to perform forward and backward swimming, turning right, and dancing using reinforcement learning techniques with Mujoco.
2. Collect motion data of the virtual swimmer and utilize Variational Autoencoders (VAE) to learn the underlying representations of the motion data.
3. Utilize the learned VAE model to compress the motion data into a latent space, which represents a lower-dimensional and meaningful representation of the swimmer's actions.
4. Investigate the characteristics of the latent space, where different motions are associated with specific mean and log\_var values, allowing for the creation of new motions by manipulating these parameters.

By achieving these objectives, the study aims to enhance the capabilities of the virtual swimmer and demonstrate how VAEs can assist in learning complex motions and generating novel actions, contributing to the broader field of robotics and reinforcement learning.

1. **Survey**
   1. **background of methods**
      1. **Reinforcement Learning**
         1. **MDP - Markov Decision Process (Markov Decision Processes-Martin L. Puterman)**

텍스트, 스크린샷, 폰트, 번호이(가) 표시된 사진

자동 생성된 설명

Markov Decision Process (MDP) represents the fundamental learning mechanism in Reinforcement Learning. In this MDP environment, there are states (S), actions (a), and rewards(R). This process is referred to as a greedy process. The current state reflects the accumulation of all previous experiences or history. In the figure, arrows point to the state (S), illustrating that the state contains all the information from its history. When performing an action, there is no need to consider previous episodes.  
  
Policy = P\left(s=s\_{i+1} \mid s=s\_{i}, a=a\_{i}\right)

폰트, 화이트, 텍스트, 서예이(가) 표시된 사진

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Return = G\_{t} \doteq R\_{t}+\gamma R\_{t+1}+\gamma^{2} R\_{t+2}+\cdots

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In this environment, there are two key components: Policy and Return. Policy refers to the probability of taking action (a) in state (s). When the agent takes an action, it receives the sum of the rewards, which is referred to as the Return.

* + - 1. State value function and Action value function (Reinforcement Learning: An Introduction – p.58)

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G\_{t} \doteq \sum\_{k=t+1}^{T} \gamma^{k-t-1} R\_{k}

G\_t is the Return, representing the total reward that the agent will receive at each timestep. Gamma is the discount factor, aiding in the calculation of the return value as a present value. Gamma determines that the future value is less important than the present value. If I increase gamma, the future value becomes more significant.

State value function

v\_{\pi}(s) \doteq \mathbb{E}\_{\pi}\left[G\_{t} \mid S\_{t}=s\right]=\mathbb{E}\_{\pi}\left[\sum\_{k=0}^{\infty} \gamma^{k} R\_{t+k+1} \mid S\_{t}=s\right] \text {, for all } s \in \mathcal{S}

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The State value function represents the expected return or the expected value of all states from the current state. This method calculates the current value of the agent's state, encompassing all past, present, and future state values.

Action value function

q\_{\pi}(s, a) \doteq \mathbb{E}\_{\pi}\left[G\_{t} \mid S\_{t}=s, A\_{t}=a\right]=\mathbb{E}\_{\pi}\left[\sum\_{k=0}^{\infty} \gamma^{k} R\_{t+k+1} \mid S\_{t}=s, A\_{t}=a\right]

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On the other hand, actions can have their own current values. These must contain both state value and action value. The difference between the state value function and the action value function lies in the inclusion of the action value. The state value function does not consider previous episodes' actions since the state contains all the historical information. Therefore, the state value function considers only the state, while the action value function requires the state in the same episode.

* + - 1. Optimal Policy(Reinforcement Learning: An Introduction – p.73(pdf-p.95))

Finding policy to maximize state value function is the definite goal of the reinforcement learning. This policy is optimal policy. Policy is action value function. So, If we find the optimal policy, we need to find out the optimal action value function.

q\_{\*}(s, a) \doteq \max \_{\pi} q\_{\pi}

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q\_{\*}(s, a)=\mathbb{E}\left[R\_{t+1}+\gamma v\_{\*}\left(S\_{t+1}\right) \mid S\_{t}=s,\right.

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Equation below is Bellman optimality equation. Bellman Optimality equation can transform V\_t to V\_t+1 or Q\_t to Q\_t+1.

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* + - 1. Soft Actor-Critic

Chapter. 1

1. Introduction
   1. Context
      1. Robot spread out in many areas.
      2. Robot learn the movement with RL.
      3. Human can’t control all the detail torque of actuator.
      4. VAE can help to learn the actions.
   2. Aim and Objectives
      1. Reinforcement learning with mujoco for physics environment.
      2. Swimmer swim forward and backward. And turn right and dance.
      3. Collecting swimmer’s motion data and learning VAE.
      4. VAE can compress all the data to latent space.
      5. Many motion has special mu and log\_var
      6. Increasing or changing mu and log\_var allows us to create new motions.

Chapter 2

1. Survey
   1. background of methods
      1. Reinforcement Learning
         1. Q-learning
         2. MDP
         3. State Value function & action value function
         4. Optimal policy
         5. Soft Actor-Critic
         6. Ppo
         7. A2c
         8. Mujoco experiment summary
      2. Variational Autoencoders
         1. AutoEncoder
         2. Decoder
         3. Mu and log\_var

Chapter 3

1. Experiments
   1. Software and env(library and api)
      1. Pytorch, Mujoco, stable-baseline3, rl-baseline3-zoo
      2. Pytorch
   2. Reinforcement Learning(RL-Baseline3-zoo)
      1. Mujoco Swimmer-v3. Action space and observation space
      2. Comparing algorithms by each pose
      3. Output of RL
   3. Variational Autoencoder
      1. Preprocessing Dataset from RL
      2. Model Architecture
      3. Rendering
2. Evaluation
   1. Loss plot
   2. Rendering compare
   3. Action and observation plot between original data and reconstructed data.

Chapter 5

5.1 Conclusion

5.2 Future work.  
  
Bibliography