

Deep RL Arm Manipulation

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Abstract—Deep RL Arm Manipulation project! For this project, My goal is to create a DQN agent and define reward functions to teach a robotic arm to carry out two primary objectives:

Have any part of the robot arm touch the object of interest, with at least a 90% probability
Have only the gripper base of the robot arm touch the object, with at least a 80%

Index Terms—Robot Software, Udacity, Gazebo, Jetson TX2.

1 INTRODUCTION

THE A key difference between RL and Deep RL is the use of a deep neural network. Think of the collection of value-action pairs that define what actions an agent should take in any situation as a function of the observations that the agent receives from its environment.

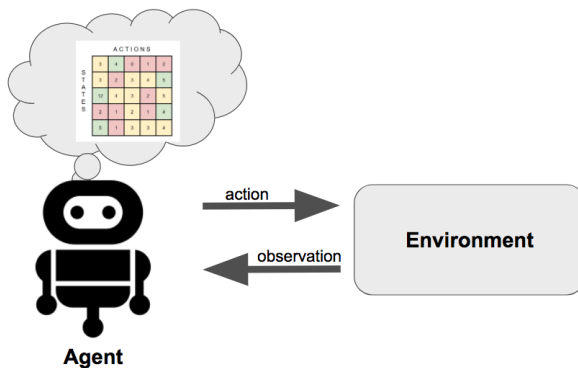


Fig. 1. RL.

2 BACKGROUND

A deep Q-network (DQN), which is able to combine reinforcement learning with a class of artificial neural network known as deep neural networks. In Fig. 3 the gazebo environment loads up, there are the robotic arm, a camera sensor, and an object in the environment.

3 REWARD FUNCTIONS

1. Robot arm touch the object.

Because only arm touching the object and base joint is fixed, So just reward function, $\text{reward} = -\text{abs}(\text{gripperBox.min.z} - \text{probBox.max.z})$.

2. Arm's gripper base touch the object. base on the distance between gripper and object, compute the reward " $\text{distGoal} = \text{BoxDistance}(\text{propBBox}, \text{gripBBox})$ ", and then compute the smoothed moving average of the delta of the distance to the goal, " $\text{avgGoalDelta} = (\text{distDelta} * \alpha) + (\text{distGoal} * (1.0f - \alpha))$ "; final, reward function is " $10 * \text{avgGoalDelta} - \text{distGoal}$ "

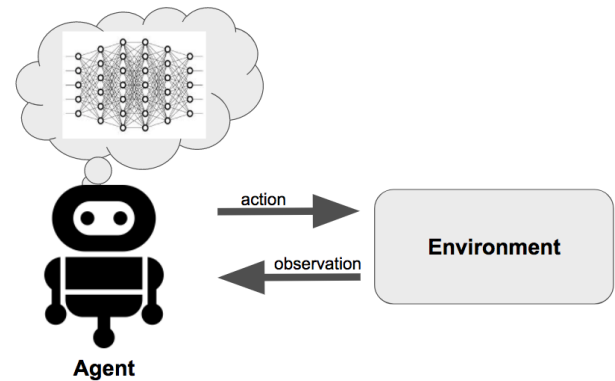


Fig. 2. DRL.

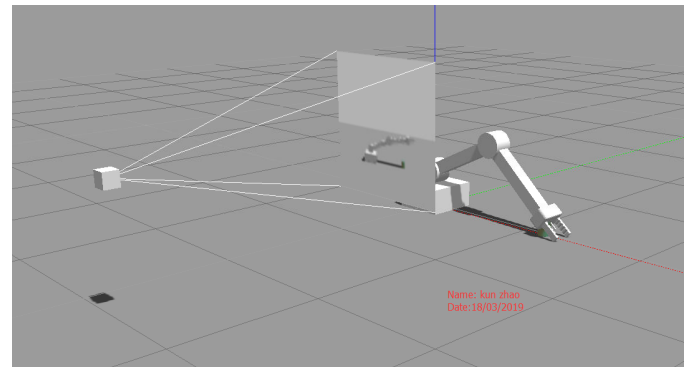


Fig. 3. Arm touching the object1

4 HYPERPARAMETERS

I choose same hyperparameters for both objectives, but using different reward function to reach different objectives. camera picture input resolution is $64 * 64$, optimizer is "Adam", learning rate is 0.0001, due to limit computation resource in cloud, I set replay buffer size to 2000 (default 10000), batch size is 4. use LSTM is true, LSTM's size is 32. Because arm have 3 joint, every joint have two actions, so the action number is 6. if arm reach the goal (arm touching or gripper touching the objective), give reward to 2.0, or -2.0

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camera 64 x 64 24 bpp 12288 bytes
camera 64 x 64 24 bpp 12288 bytes
camera 64 x 64 24 bpp 12288 bytes
camera 64 x 64 24 bpp 12288 bytes
episode frame = 1
ArmPlugin - agent selected action 3
distance('gripper_middle', 'tube') = 1.427306
camera 64 x 64 24 bpp 12288 bytes
episode frame = 2
ArmPlugin - agent selected action 0
distance('gripper_middle', 'tube') = 0.148519
ArmPlugin - issuing reward 0.000000, EOE=false      ZERO
camera 64 x 64 24 bpp 12288 bytes
episode frame = 3
ArmPlugin - agent selected action 2
distance('gripper_middle', 'tube') = 0.000000
ArmPlugin - issuing reward 0.000000, EOE=false      ZERO
Collision between[tube::tube_link::tube_collision] and [arm::gripper_middle::middle_collision]
ArmPlugin - issuing reward 2.000000, EOE=true POS+
Collision between[tube::tube_link::tube_collision] and [arm::link2::collision2]
Current Accuracy: 1.0000 (110 of 110) (reward=+2.00 WIN)
cf

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Fig. 4. Arm touching the object2

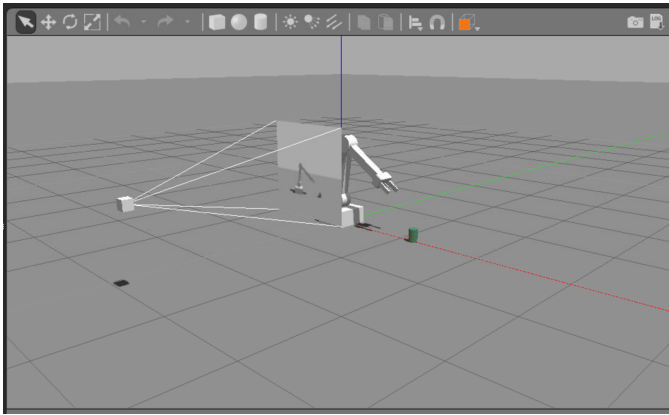


Fig. 5. gripper base touch the object1

5 RESULTS

The robot arm touching the object with 100% accuracy for more than 100 runs. Please see Fig.3 and Fig.4 The Arm's gripper base touch the object with 100% accuracy for more than 100 runs. Please see Fig.5 and Fig.6

6 FUTURE WORK

Above result is based on the LOCK base joint setting. If you unlock the base joint, it will be harder to train than LOCK-BASE, because this increases the free degrees of arm, more action space, more state space.

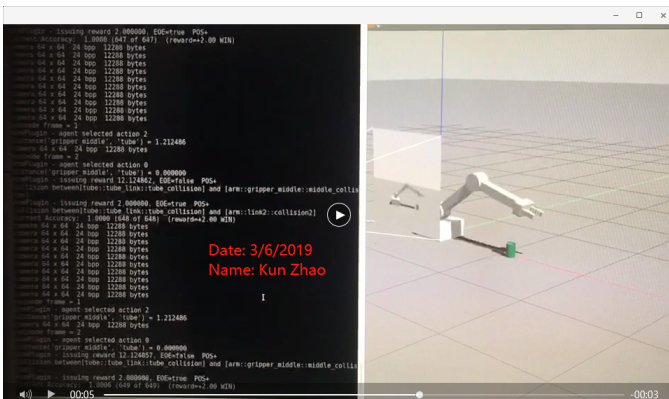


Fig. 6. gripper base touch the object2