Deep RL Arm Manipulation

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Abstract—Deep reinforcement learning has enabled robotic systems to learn control or predictive policies directly from camera inputs and raw pixels. In this project, a simulated 3 degree-of-freedom robotic arm is trained to reach and touch an object of interest using a deep *Q*-network. We have simulated two tasks, and show that the robot is successfully leaned the abilities to complete the scenarios.

Index Terms—Robot, IEEEtran, Udacity, LaTeX, Deep RL, LSTM.

1 Introduction

Deep reinforcement learning algorithms have been successfully applied to wide range of robotic control tasks, e.g., locomotion, robotic arm manipulation, and autonomous vehicle control [1]. With the development of the deep Q-networks and its variants [2] [3] [4], the reinforcement learning paradigm has been scale to problems that were previously deemed intractable, e.g., learning to play video games from direct raw pixels.

In this project, we have used an LSTM based deep Q-network, similar to presented in [5], on 3 degree-of-freedom (DoF) robotic manipulator arm to reach and touch an object of interest in two scenarios:

1) have any part of the robot arm touch the object of interest, with at least a 90% accuracy for a minimum of 100 runs, and
2) have only the gripper base of the robot arm touch the object, with at least a 80% accuracy for a minimum of 100 runs.

The robot and the two tasks have been simulated in Gazebo [6], and we show that the robot is successfully leaned the abilities to complete the tasks with the given project requirements.

2 Reward Functions

The first task requests to have any part of the robot arm touch the object of interest. The following reward structure has been used:

1) any part of the robot touches the object with reward +500.
2) any part of the robot, including gripper, collides with ground or itself, the reward has been set to -500.
3) an interim reward based on smoothed moving average. This function is composed of two parts:
    a) For the time step t and $t+1$, lets assume the robot gripper has incrementally moved $\delta_t = d_t - d_{t+1}$ distance, where, d_t is the distance to the object from gripper. If $\delta_t > 0$, it is an indication of the gripper moved closer to the object. Lets assume $\bar{\delta}_t$ is the moving average of δ_t distances. Then, we use the smoothing formula, $\bar{\delta}_{t+1} = \bar{\delta}_t \times \alpha + \delta_t \times (1-\alpha)$, where $\alpha \in [0,1]$.
    b) In order to encode the objective of completing the task as soon as possible, we have introduced a time step penalty, $time\_penalty$. This penalty has eliminate the gripper oscillating near the object of interest.

    Hence, using the prior decomposition, each step we have provided the reward $\bar{\delta}_t - time\_penalty$.

For the second task, we have used the following reward structure:

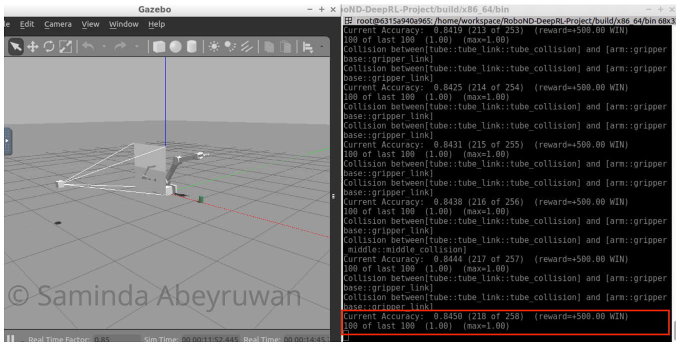
1) Only gripper touches the object with +500.
2) Any other collision resulted in a reward of -50.
3) Similar to the first task, an interim reward based on smoothed moving average use been used.

3 Hyperparameters

We have used images of size $64 \times 64 \times 3$. The *RMSprop* optimizer has been used in both tasks, while setting the learning rate to 0.1. Neither tasks required changing the learning rate. We set the replay memory 10000, and a batch size of 32 has been used. We have enabled the LSTM mode, and the LSTM size has been set to 512. The exploration rate, γ, has been set to 0.9 and annihilated to 0.05 over 200 steps. α and $time\_penalty$ have been set to 0.9 and 0.5 respectively. We have used position control method to control the arm. Please refer to the definitions, INPUT_WIDTH, INPUT_HEIGHT, OPTIMIZER, LEARNING_RATE, REPLAY_MEMORY, BATCH_SIZE, USE_LSTM, LSTM_SIZE, GAMMA, EPS_START, EPS_END, EPS_DECAY, and VELOCITY_CONTROL, in the associated code for the value binding.

4 Results

The two tasks have been trained with the hyperparameters described in Sec. 3. The robot has completed the first task within 113 episodes, and achieved 100% accuracy over a minimum of 100 runs around 191 episodes, and the performance has been held consistently. The performance of the robot is shown in Fig. 1. We have observed that without the time penalty, the robot has started oscillating near the goal, but, not reaching the goal as expected. We have also

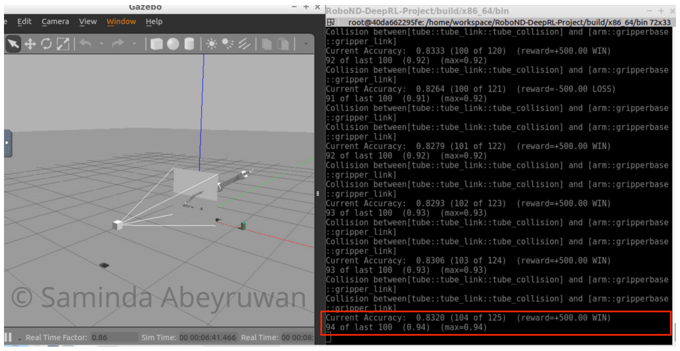

Gazebo
Edit Camera View Window Help
© Saminda Abeyruwan
Real Time Factor: 0.85
Sim Time: 00:00:11:52.445
Real Time: 00:00:14:45
oND-DeepRL-Project/build/x86_64/bin
root@6315a940a965: /home/workspace/RoboND-DeepRL-Project/build/x86_64/bin 68x3

```
Current Accuracy:  0.8419 (213 of 253)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Current Accuracy:  0.8425 (214 of 254)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Current Accuracy:  0.8431 (215 of 255)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Current Accuracy:  0.8438 (216 of 256)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripper
_middle::middle_collision]
Current Accuracy:  0.8444 (217 of 257)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripper
base::gripper_link]
Current Accuracy:  0.8450 (218 of 258)  (reward=+500.00 WIN)
100 of last 100  (1.00)  (max=1.00)
```

Fig. 1. Task 1: have any part of the robot arm touch the object of interest.

observed that the robot has taken a longer time to reach the target performance for LSTM output size less than 512.

The second task has achieved the target performance within 100 episodes. We have used the same set of parameter as described in Sec. 3 and in task one. Fig. 2 shows the development of the target performance. Both tasks have used position based control. We have also experimented with velocity based control, which has shown unstable training trajectories, that has required more parameter tuning, which is not reported in this document. Finally, we conclude that the robot has learned successful control policies for both tasks less than 200 episodes.


Gazebo
Edit Camera View Window Help
© Saminda Abeyruwan
Real Time Factor: 0.86
Sim Time: 00:00:06:41.466
Real Time: 00:00:08:
RoboND-DeepRL-Project/build/x86_64/bin
root@40da662295fe: /home/workspace/RoboND-DeepRL-Project/build/x86_64/bin 72x33

```
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8333 (100 of 120)  (reward=+500.00 WIN)
92 of last 100  (0.92)  (max=0.92)
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8264 (100 of 121)  (reward=-500.00 LOSS)
91 of last 100  (0.91)  (max=0.92)
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8279 (101 of 122)  (reward=+500.00 WIN)
92 of last 100  (0.92)  (max=0.92)
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8293 (102 of 123)  (reward=+500.00 WIN)
93 of last 100  (0.93)  (max=0.93)
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8306 (103 of 124)  (reward=+500.00 WIN)
93 of last 100  (0.93)  (max=0.93)
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Collision between[tube::tube_link::tube_collision] and [arm::gripperbase
::gripper_link]
Current Accuracy:  0.8320 (104 of 125)  (reward=+500.00 WIN)
94 of last 100  (0.94)  (max=0.94)
```

Fig. 2. Task 2: have only the gripper base of the robot arm touch the object.

5 Conclusion / Future work

In this project, we have trained 3 DoF robotic arm to successfully complete two tasks in simulation using LSTM based deep-Q-networks. A generalized set up based on the current project would help to train other robotic problems. Even though we have used position control, a more realistic robotic control is based on velocity control, which requires continuous control for best performance. The algorithms such as Deep Deterministic Policy Gradient (DDPG), and Normalized Advantage Function algorithm (NAF) [1] have shown state-of-the-art results, and will be benefited to the tasks presented in this project to obtain more realistic results.

References

[1] S. Gu*, E. Holly*, T. Lillicrap, and S. Levine, "Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates," in *Proceedings 2017 IEEE International Conference on Robotics and Automation (ICRA)*, (Piscataway, NJ, USA), IEEE, May 2017. *equal contribution.

[2] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg, and D. Hassabis, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, pp. 529–533, Feb. 2015.

[3] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Harley, T. P. Lillicrap, D. Silver, and K. Kavukcuoglu, "Asynchronous methods for deep reinforcement learning," in *Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48*, ICML'16, pp. 1928–1937, JMLR.org, 2016.

[4] K. Arulkumaran, M. P. Deisenroth, M. Brundage, and A. A. Bharath, "A brief survey of deep reinforcement learning," *CoRR*, vol. abs/1708.05866, 2017.

[5] M. J. Hausknecht and P. Stone, "Deep recurrent q-learning for partially observable mdps," in *AAAI Fall Symposia*, pp. 29–37, AAAI Press, 2015.

[6] M. Quigley, K. Conley, B. P. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Y. Ng, "Ros: an open-source robot operating system," in *ICRA Workshop on Open Source Software*, 2009.