Deep RL Arm Manipulation

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Abstract—Deep Reinforcement Learning combines Reinforcement Learning with Deep Neural Networks to achieve human-level control in several applications. This report explains the parameters used by a DQN agent to teach a robotic arm with three degrees of freedom how to reach a target object. During evaluation success rates above 80% are achieved.

Index Terms—Robot, IEEEtran, Udacity, LaTeX, Deep Learning, DQN, Reinforcement Learning.

1 Introduction

Deep Reinforcement Learning is a paradigm shift for Robotics. In summary, the idea is to define a goal for the robot, provide raw sensor input and let it find out the best way to achieve the goal by trial and error. The main difference in this paradigm is that is not necessary to explicitly define the perception, internal state, planning, control, and even sensor measurement uncertainty. All those traditional steps necessary to take proper action are learned by a neural network.

2 Background / Formulation

This project is part of the Robotics Software Engineer Nanodegree Program - Term 2 from Udacity. The goal is to create a DQN agent and define reward functions to teach a robotic arm to carry out two primary objectives:

1) Have any part of the robot arm touch the target object with at least 90% accuracy.
2) Have only the gripper base of the robot arm touch the target object with at least 80% accuracy.

In this report, the first objective is referred to as ”Arm Collision”, where the second is ”Gripper Collision” Both goals are accomplished in a simulated environment through the development of a C++ plugin for Gazebo.

3 Reward Functions

The reward function definition is very important to guarantee the convergence of the reinforcement learning algorithm. In this project, the following types were defined.

- REWARD_WIN: Final reward when the target is reached.
- REWARD_LOSS: Negative reward when the robot touches the ground.
- REWARD_TIMEOUT: Negative reward when the maximum iteration is reached.
- REWARD_CLOSER: Positive reward when the gripper moves closer to the target
- REWARD_FARTHER: Negative reward when the gripper moves away from the target

The value for each reward was selected based on experimentation. The description can be found in the following subsections.

3.1 Arm Collision

The REWARD_WIN was issued when any part of the robot touched the target.

```
if (collisionCheckArm)
{
        rewardHistory = REWARD_WIN;
        newReward   = true;
        endEpisode = true;

        return;
}
```

The rewards based on the distance of the gripper and target used a smoothed average of the distance variation. It can be seen on the following code snippet.

```
// compute the smoothed moving average
avgGoalDelta  = (avgGoalDelta * 0.05) +
                (distDelta * 0.95);
if (avgGoalDelta > 0)
        rewardHistory = REWARD_CLOSER;
else
        rewardHistory = REWARD_FARTHER;
```

The values for the reward functions were defined as follows.

```
#define REWARD_WIN   100.0f
#define REWARD_LOSS  -50.0f
#define REWARD_TIMEOUT  -10.0f
#define REWARD_CLOSER 1.0f
#define REWARD_FARTHER  -2.0f
```

High values were selected for the final rewards as an incentive for the agent to learn how to reach the goal. It prevents the learning process to prioritize intermediate rewards.

The intermediary rewards guide the robot by providing incentives when it is moving towards the correct direction. The penalty when moving farther is stronger than the reward to move closer. The intention is to prevent the robot to oscillate in the same place. A penalty based on elapsed time could provide similar results.

For the first goal, the type of joint control was based on the position of the arm.

```
#define VELOCITY_CONTROL  false
```

Additionally, the delta was decreased by one third to guarantee a smooth arm movement.

```
actionJointDelta = 0.05f;
```

3.2 Gripper Collision

A similar approach was used to select the reward values when the accepted collision point was restricted to the gripper. The value selected for the parameters were:

```
#define REWARD_WIN     100.0f
#define REWARD_LOSS   −100.0f
#define REWARD_TIMEOUT −50.0f
#define REWARD_CLOSER  10.0f
#define REWARD_FARTHER −20.0f
```

The first difference was that a penalty was issued when the robotic arm touched the target with a link other than the gripper. It was necessary to avoid situations when the middle of the arm was touching the target and the episode did not finish.

```
if (collisionCheckGripper)
{
        rewardHistory = REWARD_WIN;

        newReward  = true;
        endEpisode = true;

        return;
}
if (collisionCheckArm)
{
        rewardHistory = REWARD_LOSS;

        newReward  = true;
        endEpisode = true;

        return;
}
```

The second difference was that the intermediate rewards were based directly on the distance variation, instead of the smoothed average. This was based on the assumption that the arm can always move towards the final goal.

```
if (distDelta > 0.0)
        rewardHistory = REWARD_CLOSER;

else
        rewardHistory = REWARD_FARTHER;
```

Finally, the type of joint control was based on the velocity of the joints. To guarantee a smooth arm movement, the velocity delta and maximum speed were decreased.

```
#define VELOCITY_CONTROL true
#define VELOCITY_MIN −0.05f
#define VELOCITY_MAX  0.05f
```

Similarly to the previous goal, the velocity increment was also reduced as follows.

```
actionVelDelta    = 0.05f;
```

4 Hyperparameters

To achieve higher accuracy the hyper-parameters for the Neural Network were defined as follows:

```
#define INPUT_WIDTH    64
#define INPUT_HEIGHT   64
#define OPTIMIZER "RMSprop"
#define LEARNING_RATE 0.1f // 0.001 for second goal
#define REPLAY_MEMORY 20000
#define BATCH_SIZE 32
#define USE_LSTM true
#define LSTM_SIZE 256
```

The only difference between each goal was the LEARNING_RATE. The reason for decreasing the learning rate from 0.1 to 0.001 was to prevent overfitting during the learning process.

The INPUT_WIDTH and the INPUT_HEIGHT parameters were defined according to the image resolution used in the simulation.

”RMSprop” was selected as the OPTIMIZER since it provided better results than ”Adam”.

The use of Long Short Term Memory was enabled to take into consideration multiple past frames from the camera sensor instead of a single frame.

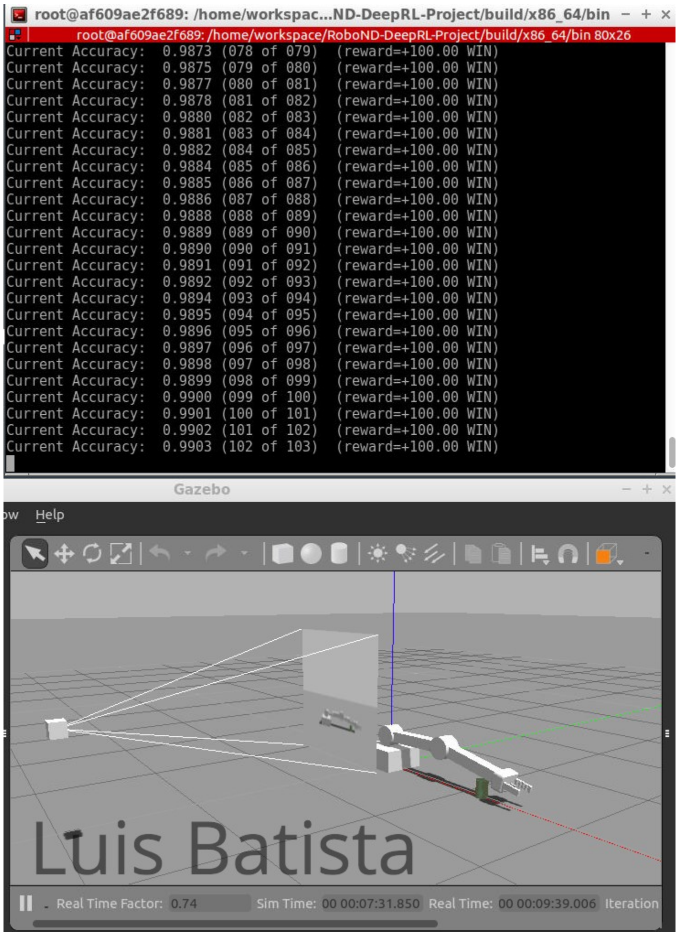
The remaining parameters were defined empirically to increase accuracy.

5 Results

5.1 Arm Collision

Due to the simplicity of the task, the robot learned fairly quickly that it was sufficient to only rotate the joint between the base and the first link to achieve the goal.

As a result, the minimum of 90% accuracy could be achieved after 10 episodes. The Figure 1 shows final accuracy above 99% after 100 episodes.



```
root@af609ae2f689: /home/workspace/RoboND-DeepRL-Project/build/x86_64/bin 80x26
Current Accuracy:  0.9873 (078 of 079)  (reward=+100.00 WIN)
Current Accuracy:  0.9875 (079 of 080)  (reward=+100.00 WIN)
Current Accuracy:  0.9877 (080 of 081)  (reward=+100.00 WIN)
Current Accuracy:  0.9878 (081 of 082)  (reward=+100.00 WIN)
Current Accuracy:  0.9880 (082 of 083)  (reward=+100.00 WIN)
Current Accuracy:  0.9881 (083 of 084)  (reward=+100.00 WIN)
Current Accuracy:  0.9882 (084 of 085)  (reward=+100.00 WIN)
Current Accuracy:  0.9884 (085 of 086)  (reward=+100.00 WIN)
Current Accuracy:  0.9885 (086 of 087)  (reward=+100.00 WIN)
Current Accuracy:  0.9886 (087 of 088)  (reward=+100.00 WIN)
Current Accuracy:  0.9888 (088 of 089)  (reward=+100.00 WIN)
Current Accuracy:  0.9889 (089 of 090)  (reward=+100.00 WIN)
Current Accuracy:  0.9890 (090 of 091)  (reward=+100.00 WIN)
Current Accuracy:  0.9891 (091 of 092)  (reward=+100.00 WIN)
Current Accuracy:  0.9892 (092 of 093)  (reward=+100.00 WIN)
Current Accuracy:  0.9894 (093 of 094)  (reward=+100.00 WIN)
Current Accuracy:  0.9895 (094 of 095)  (reward=+100.00 WIN)
Current Accuracy:  0.9896 (095 of 096)  (reward=+100.00 WIN)
Current Accuracy:  0.9897 (096 of 097)  (reward=+100.00 WIN)
Current Accuracy:  0.9898 (097 of 098)  (reward=+100.00 WIN)
Current Accuracy:  0.9899 (098 of 099)  (reward=+100.00 WIN)
Current Accuracy:  0.9900 (099 of 100)  (reward=+100.00 WIN)
Current Accuracy:  0.9901 (100 of 101)  (reward=+100.00 WIN)
Current Accuracy:  0.9902 (101 of 102)  (reward=+100.00 WIN)
Current Accuracy:  0.9903 (102 of 103)  (reward=+100.00 WIN)
```

root@af609ae2f689: /home/workspac...ND-DeepRL-Project/build/x86_64/bin
Gazebo
ow
Help
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Real Time Factor: 0.74
Sim Time: 00 00:07:31.850
Real Time: 00 00:09:39.006
Iteration

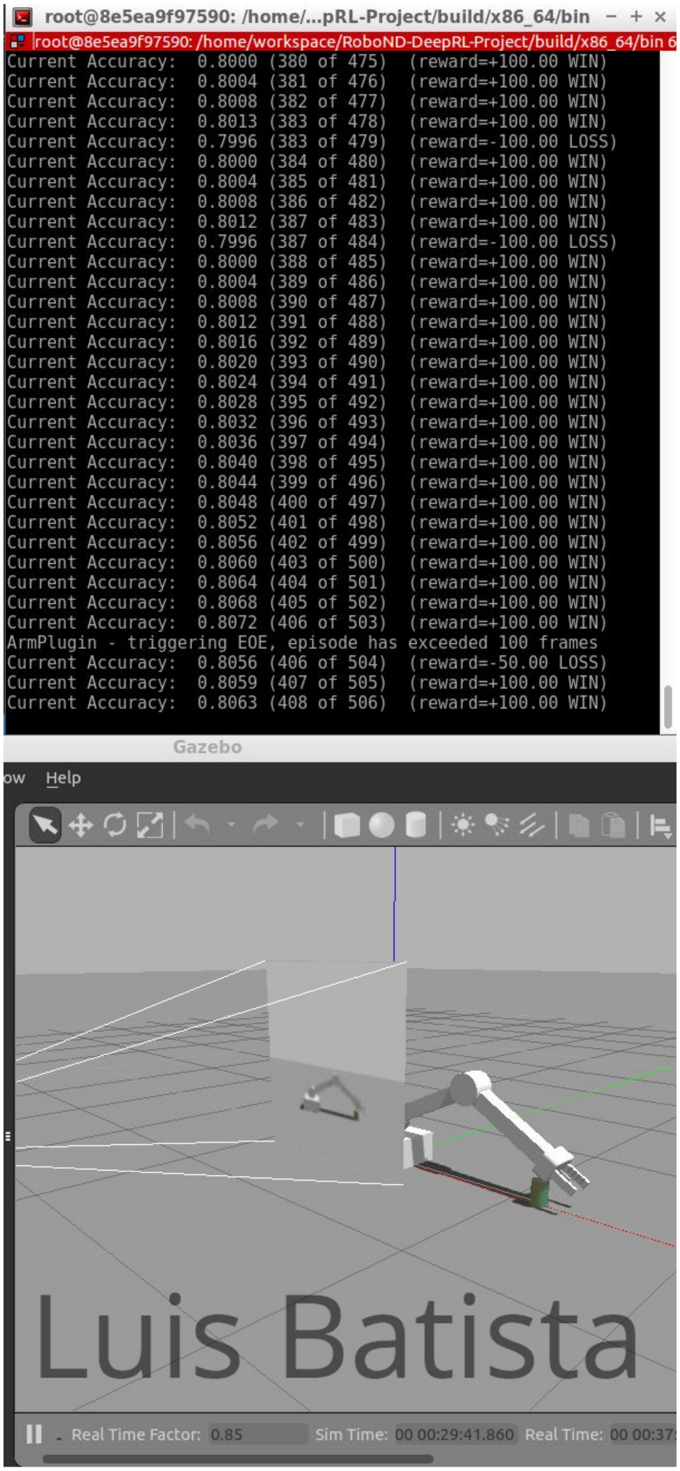
Fig. 1: Arm Collision Accuracy

5.2 Gripper Collision

It was more complex to train the robot to reach the target touching only the gripper.

The lower learning rate resulted in longer training time to achieve the minimum requirements.

The Figure 2 shows the accuracy surpassing the 80% requirement after 380 episodes.


root@8e5ea9f97590: /home/...pRL-Project/build/x86_64/bin
root@8e5ea9f97590: /home/workspace/RoboND-DeepRL-Project/build/x86_64/bin 6
Gazebo
ow
Help
Luis Batista
Real Time Factor: 0.85
Sim Time: 00 00:29:41.860
Real Time: 00 00:37

```
Current Accuracy:  0.8000 (380 of 475)  (reward=+100.00 WIN)
Current Accuracy:  0.8004 (381 of 476)  (reward=+100.00 WIN)
Current Accuracy:  0.8008 (382 of 477)  (reward=+100.00 WIN)
Current Accuracy:  0.8013 (383 of 478)  (reward=+100.00 WIN)
Current Accuracy:  0.7996 (383 of 479)  (reward=-100.00 LOSS)
Current Accuracy:  0.8000 (384 of 480)  (reward=+100.00 WIN)
Current Accuracy:  0.8004 (385 of 481)  (reward=+100.00 WIN)
Current Accuracy:  0.8008 (386 of 482)  (reward=+100.00 WIN)
Current Accuracy:  0.8012 (387 of 483)  (reward=+100.00 WIN)
Current Accuracy:  0.7996 (387 of 484)  (reward=-100.00 LOSS)
Current Accuracy:  0.8000 (388 of 485)  (reward=+100.00 WIN)
Current Accuracy:  0.8004 (389 of 486)  (reward=+100.00 WIN)
Current Accuracy:  0.8008 (390 of 487)  (reward=+100.00 WIN)
Current Accuracy:  0.8012 (391 of 488)  (reward=+100.00 WIN)
Current Accuracy:  0.8016 (392 of 489)  (reward=+100.00 WIN)
Current Accuracy:  0.8020 (393 of 490)  (reward=+100.00 WIN)
Current Accuracy:  0.8024 (394 of 491)  (reward=+100.00 WIN)
Current Accuracy:  0.8028 (395 of 492)  (reward=+100.00 WIN)
Current Accuracy:  0.8032 (396 of 493)  (reward=+100.00 WIN)
Current Accuracy:  0.8036 (397 of 494)  (reward=+100.00 WIN)
Current Accuracy:  0.8040 (398 of 495)  (reward=+100.00 WIN)
Current Accuracy:  0.8044 (399 of 496)  (reward=+100.00 WIN)
Current Accuracy:  0.8048 (400 of 497)  (reward=+100.00 WIN)
Current Accuracy:  0.8052 (401 of 498)  (reward=+100.00 WIN)
Current Accuracy:  0.8056 (402 of 499)  (reward=+100.00 WIN)
Current Accuracy:  0.8060 (403 of 500)  (reward=+100.00 WIN)
Current Accuracy:  0.8064 (404 of 501)  (reward=+100.00 WIN)
Current Accuracy:  0.8068 (405 of 502)  (reward=+100.00 WIN)
Current Accuracy:  0.8072 (406 of 503)  (reward=+100.00 WIN)
ArmPlugin - triggering EOE, episode has exceeded 100 frames
Current Accuracy:  0.8056 (406 of 504)  (reward=-50.00 LOSS)
Current Accuracy:  0.8059 (407 of 505)  (reward=+100.00 WIN)
Current Accuracy:  0.8063 (408 of 506)  (reward=+100.00 WIN)
```

Fig. 2: Gripper Collision Accuracy

6 FUTURE WORK

The required accuracy was achieved, but it is still possible to optimize the results especially for the Gripper Collision goal. Such optimization could be done by further adjusting the parameters including learning rate and LSTM values or also implementing more robust reward functions.

To make the problem more realistic scenarios, it is possible to train the agent when the target is in random locations and allow the robot to with additional degrees of freedom.