Master Thesis

EFFICIENT REINFORCEMENT LEARNING IN ROBOTICS MANIPULATION CONTROL BY MIMICKING REAL WORLD ENVIRONMENT WITH SIMULATOR

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HCI - Robotics

UNIVERSITY OF SCIENCE AND TECHNOLOGY

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Supervisor Dr. Lee Woosub

Declaration of Student

I, HUONG VAN DO, declare that the title of the thesis, 'EFFICIENT REINFORCEMENT LEARNING IN ROBOTICS MANIPULATION CONTROL BY MIMICKING REAL-WORLD ENVIRONMENT WITH SIMULATOR' with the tasks presented in it are my own. I confirm that:

- This work was done mainly while in the candidate for a master degree at this University.
- When I consulted the published work of others always clearly attributed.
- When I quoted from the work of others, the source was given. This thesis entirely is my own works.
- I have made clear what was done by myself and what was done by others.

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“From too much study, and from extreme passion, cometh madness.”

— Isaac Newton —

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Abstract

Major: *HCI - Robotics* in Department of *Media and Robotics Institute*

Korea Institute of Science and Technology

Master of Engineering

by Huong Van Do

Nowadays, with the development of software and reinforcement learning research reached a huge step in robotics research. In addition, recent achievement in Deep Neural Network allows us to apply machine learning algorithms to various fields including vision, recognition, and robotics[6] achieved the significant result in implementation artificial intelligent in robotics. Adapting the deep neural network to train the policy of Reinforcement Learning successfully solved manipulators or navigation tasks. However, the training process requires numerous experiments to repeat the task until finding a satisfying policy. To avoid this expensive experimental training, we implemented an idea for hardware and software test-bed to share the control and training process. Based on that this thesis will build and develop the software and hardware for implementation Reinforcement Learning in Manipulator control using ROS programming. Thanks to the training agent in the virtual environment do we save a bunch of time tine training with the hardware. Follows that are some test-beds were taken to demonstrate the consistency between the simulation and the real world. The result of performance was tested under the Monte-Carlo algorithm. The software platform was built in ROS Programming (Robot Operating System) for implementation learning algorithms. . . .

Keywords: *Reinforcement Learning; Markov Decision Processes; Monte-Carlo; Deep Deterministic Policy Gradient; Hindsight Experience Replay; ROS; Gazebo; OpenAI; Q-Learning; UR5.*

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I would like to thank Dr.An Byungchul for his insightful knowledge in some research problems we discussed. It helps me a lot when I struggle to evaluate the effectiveness of some ideas. In addition, I would like to thank other colleagues in the Center for Medical Robotics for their bits of help and it helps me have an unforgettable time in the lab and in KIST.
I acknowledge the Korea Institute of Science and Technology for financial support during my studies.
Last but not least, I wish to thank my parents and my girlfriend. Their unconditional supports absolutely bolster my motivation. By dint of complete this master thesis will be a great meaningful gift of me would like to spend to my whole family and my girlfriend . . .

Contents

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Abbreviations

MDP	**M**arkov **D**ecision **P**rocesses
DRL	**D**eep **R**einforcement **L**earning
RL	**R**einforcement **L**earning
HSV	**H**ue **S**aturation **V**alue
PCL	**P**oint **C**loud **L**ibrary
RGB	**R**ed **G**reen **B**lue
ROS	**R**obot **O**perating **S**ystem
TCP	**T**ransmission **C**ontrol **P**rotocol
XML	E**X**tensible **M**arkup **L**anguage
DP	**D**ynamic **P**rogramming
URDF	**U**niversal **R**obotic **D**escription **F**ormat
PID	**P**roportional **I**ntegral **D**erivative
GPI	**G**eneralized **P**olicy **I**teration
ES	**E**xploring **S**tarts

Chapter 1

Introduction

1.1 Motivation

Nowadays, with the development of technology and the significant achievement in reinforcement learning researching, especially in high-dimensional problems such as Atari games [6] and Go [7]. Regarding the robotics field was saw a huge benefit from this technique to get a better result on robotics tasks. In addition, the transfer learning control policies from simulation to reality still in challenge due to the uncertainties of dynamic and environment[10] and real observation[11].

Reinforcement learning(RL) has been achieved outstanding results in virtual environments such as GO, Atari games, etc. Although many kinds of research applying RL to real hardware systems are conducted based on these results not to come up to those achieved in simulation environments. Since the simulation environments cannot model the real-world perfectly, it is natural that real-world experiments do not reach those results. To overcome the limitation of simulation, there are many attempts to train a policy using real hardware.

With the development of technology and software aid in design and programming nowadays, there are simulators software for robotics have been developed in the main focus on complexity, accuracy, and flexibility in the manipulation task. By dint of using Robot Operating System (ROS) and Gazebo[1] can support simulate robotics structures. However, some simulators have limited by two-dimensional or the interaction between robots and the environment just in approximately dynamics.ROS contained libraries and tools for creating the application of robots. Playing a part of the Player Project[5], Gazebo provides 3D simulation tools. Thanks to a well-designed in the simulator for making rapidly test algorithms, robot designs or perform regression testing even in training Artificial Intelligent (AI) by using realistic scenarios. Moreover, Gazebo provides the ability in efficiently simulate and accurate robots in both indoor and outdoor environments. This thesis is aimed to apply a framework to share the control and training process for the Robotics system. In order to do that, we mimicked the real-world physics in the simulation environment to avoid take experiment with the real robot. By dint of comparing the result of training a simple ball putting problem both simulation and in the real world, we can see how consistency between simulation to the real. In detail, we completed building a virtual environment for UR5 (Universal Robot) with the golf putting task. This is the task of pushing an object on the table to a determined target from a randomly selected start position is trained using the Monte-Carlo algorithm[32]. The trained policies are testing on simulation.

1.2 Reinforcement Learning

1.2.1 Fundamental

The interaction between the agent with the environment was described by figure 1.1. In basically, the reinforcement learning system contains four main elements: *a policy, a value function, a reward signal and the model of the environment.*

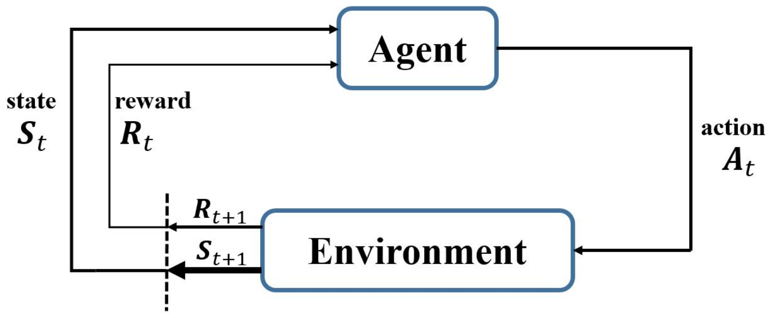


FIGURE 1.1: The graph shows the reinforcement learning system.

A policy describe the behavior of agents with the environment at a time. Beyond the given states of the environment, a policy will take a map from the set of states to the set of actions accordingly. The policy is the core of the agent to determine behavior with the environment. It is can be deterministic or stochastic of policy in reinforcement learning.
A reward signal reflect how good or bad of agent while interacting with the environment. It is a goal for the agent to maximize the value of the reward signal, it is a scalar data. The *value function* describes how status in each state of the agent for the long run. In each state will have its own value function which means the value of the expected reward value will be received from these states until the terminate state.
model of the environment is the last element in the reinforcement learning problem which

allows how the environment will behave with the agent. Nowadays, the main methods for solving reinforcement learning rely on use models or planning.

1.2.2 Markov decision processes definition

This section will introduce the most essentials we will use in reinforcement learning formulation, which is the theory of Markov Decision Process (MDPs)[36]. All of the equations explanation and mathematical formulation is reference from book *"Algorithms for Reinforcement Learning"*[36].

1.2.2.1 Formulation of Markov Decision Processes

MDP defined with $\mathcal{M} = (\mathcal{X}, \mathcal{A}, \mathcal{P}_0)$, at here $\mathcal{X}$ stand for non-empty set of states. $\mathcal{A}$ stands for non-empty set of the actions. The transition probability of the state-action pair $(x, a) \in \mathcal{X} \times \mathcal{A}$ is $\mathcal{P}_0$. The transition probability of the next state with reward will belong to the set of Z from the current state x and action a was taken - $\mathcal{P}_0(Z|x, a)$, discount factor $0 \leq \gamma \leq 1$.
$\mathcal{P}$, the *state transition probability kernel* for the set of $(x, a, z) \in \mathcal{X} \times \mathcal{A} \times \mathcal{X}$ show the probability from state x to state z by action a:

$$\mathcal{P}(x, a, z) = \mathcal{P}_0(z \times \mathbb{R}|x, a).$$

The immediate reward function r: $\mathcal{X} \times \mathcal{A} \rightarrow \mathbb{R}$ at the action a was taken from state x, then:

$$r(x, a) = \mathbb{E}[\, R_{(x,a)}]$$

For any for any $(x, a) \in \mathcal{X} \times \mathcal{A}, |R_{(x,a)} \leq \mathcal{R}$. From that we have the *return* behavior is defined by the total discounted sum of the rewards:

$$\mathcal{R} = \sum_{t=0}^{\infty} \gamma^t R_{t+1} \tag{1.1}$$

The goal for reinforcement learning with Markov Decision Process is to choose the behavior to maximize the expected return. Only when we reach the maximum expected return, we can get the optimal behavior of the agent.

1.2.2.2 The value functions

In MDP formulation, we need to find the optimal behavior of the agent relies on the highest value of each state. The great idea is to calculate the value function. $V^*(x)$ is called as an optimal value function of state $x \in \mathcal{X}$. Regarding *deterministic stationary policies,* show a special class of behavior in then agent. In fact, that is mapping π of states and actions from:

$$A_t = \pi(X_t) \tag{1.2}$$

We fix policy $\pi \in \prod_{stat}$, π is defined:

$$V^{\pi}(x) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t.R_{t+1}|X_0 = x\right], \quad x \in \mathcal{X} \tag{1.3}$$

From the equation 1.3 we need to maximize the expected reward in each states for the fix policy.

1.2.3 Monte-Carlo method

From this environment, I used the value iteration methods to discover optimal policies in golf-putting. Because of the simple of Monte-Carlo algorithms, it just requires experience from states, actions, and rewards by interacting with the environment[32].

1.2.3.1 Monte Carlo Prediction

From the deterministic policy, the Monte-Carlo methods will be learning the state-value function. It is simply to average the return expected value from experience after visits from those states. That means the more return of observed, the more average should converge in this algorithm. We looking for estimate $v_\pi(s)$ from policy π. By dint of recurrent of state s that agent visited in the episode, we called that is a visit s. In the Figure1.2 below show how Monte-Carlo algorithm works for optimal $v_\pi(s)$.

First-visit MC prediction, for estimating $V \approx v_\pi$

```
Initialize:
        $\pi \leftarrow$ policy to be evaluated
        $V \leftarrow$ an arbitrary state-value function
        Returns(s) $\leftarrow$ an empty list, for all $s \in S$

Repeat forever:
        Generate an episode using $\pi$
        For each state $s$ appearing in the episode:
            $G \leftarrow$ the return that follows the first occurrence of $s$
            Append G to Returns(s)
            V(s) $\leftarrow$ average(Returns(s))
```

FIGURE 1.2: First-visit MC prediction, for estimating value function[32]

1.2.4 The Monte Carlo Control

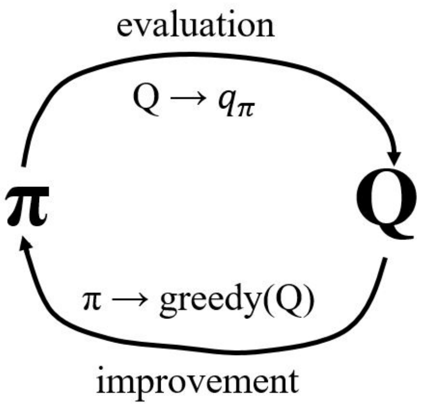


FIGURE 1.3: The greedy policy[32]

In this case, we analysis how Monte-Carlo use in control to approximate the policy optimal. The idea behind this is used to the same pattern of DP, which means generalized policy iteration (GPI). By dint of keeping the approximate value function and the approximate policy. The value will be repeated to close to the optimal value. Besides, it is the same with the policy repeated to improved with current value function to reach the optimal value function.
From the policy greedy with respect to the current state value function, the policy will be improved to the optimal value. Therefore, for any action-value function q we can determine for chose action based on maximize the value of the action-value function.

$$\pi(s) = \underset{a}{argmax} q(s, a). \tag{1.4}$$

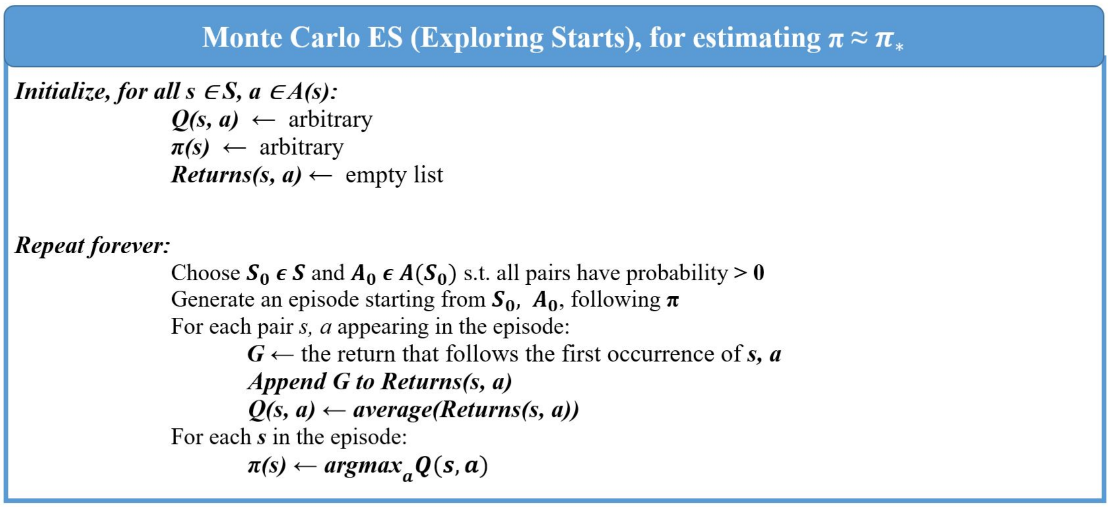
The greedy policy from q_{π_k} was improved to the π_{k+1}. This improvement will be apply to π_k and π_{k+1}, for all $s \in \mathcal{S}$:

$$q_{\pi_k}(s, \pi_{k+1}(s)) = q_{\pi_k}(s, \underset{a}{argmax} q_{\pi_k}(s, a)) \tag{1.5}$$

$$= \underset{a}{max} q_{\pi_k}(s, a) \tag{1.6}$$

$$\geq v_{\pi_k}(s). \tag{1.7}$$

For Monte-Carlo policy evaluation that is a natural for valuation an episode-by-episode basis. From observed value return for policy, the policy will be improved in all states in the episode. In figure 1.4 shows the detail of the algorithm.



Monte Carlo ES (Exploring Starts), for estimating $\pi \approx \pi_*$

```
Initialize, for all $s \in S$, $a \in A(s)$:
        $Q(s, a) \leftarrow$ arbitrary
        $\pi(s) \leftarrow$ arbitrary
        $Returns(s, a) \leftarrow$ empty list

Repeat forever:
        Choose $S_0 \in S$ and $A_0 \in A(S_0)$ s.t. all pairs have probability $> 0$
        Generate an episode starting from $S_0, A_0$, following $\pi$
        For each pair $s, a$ appearing in the episode:
            $G \leftarrow$ the return that follows the first occurrence of $s, a$
            Append $G$ to $Returns(s, a)$
            $Q(s, a) \leftarrow average(Returns(s, a))$
        For each $s$ in the episode:
            $\pi(s) \leftarrow argmax_a Q(s, a)$
```

Figure 1.4: Monte Carlo ES (Exploring Starts)[32]

1.3 Contributions

The thesis is divided into two distinct parts, but their common background mainly relates to reinforcement learning theory and control. In the first part consisting of chapter 2 is mainly related to the problem definition and how to implement the reinforcement learning algorithms of the robot and the environment. The following parts belong to how to transfer the result from the simulation into the real hardware, the result will be shown in chapter 6.

1.3.1 Test-bed for Reinforcement Learning algorithms

In chapter 3, we describe our hardware system for mimicking in the virtual environment. After that, we show how to transfer the result of the training from software into the real environment. By the dint of policy output from the virtual environment, we can execute that directly in the manipulator and check the output accordingly.

1.3.2 Building virtual environment for Reinforcement Learning algorithms

In chapter 4, we describe our software structure with the combination of ROS and Gazebo simulation and how to communicate between hardware and the virtual environment for all systems. After that, we rely on how to build a virtual environment with the aid of software and mimic the real environment by the 3D model.

In addition, we implemented the reinforcement learning algorithms - the Monte-Carlo algorithm - in a virtual environment to get optimal policy and control.

1.4 Outline of master thesis

The thesis contains seven chapters that were included in the current chapter. We would like to briefly summarize the thesis as follows. This thesis contains six parts. In part I contains the introduction chapter, which sets the motivation and outlines the contribution for part III and IV. In part I will show out the fundamental of the reinforcement learning algorithm after that the description of the Monte-Carlo policy gradient algorithm will be implemented in this thesis belong to chapter II, after that is the formulation of the golf-putting problem under reinforcement learning mathematically. Part III presents the real hardware environment and set up the real test with golf putting stuff. Then, part IV presents for building the virtual environment based on mimicking the physic hardware and real environment by dint of ROS programming language and Gazebo libraries. Each chapter in part II and part III contain the problem formulation, motivation, mathematically analysis, numerical simulations. In addition, part V describes the virtual environment after mimicking from real hardware. Following by part VI makes a summary and discusses some further promising directions with the current problem. Finally, in chapter VII will be the summarize of this thesis and some conclusion from this thesis and promising research in the future.

Chapter 2

Problem definition

2.1 Problem formulation

The sections above show the general definition of the reinforcement learning algorithm and how to solve problems related to reinforcement learning from implementing a simple algorithm - Monte Carlo. In this thesis, I worked to build a virtual environment of the golf putting task. In this environment has a manipulator plays as an agent and the set of actions will be count the distance from the end-effector of manipulator UR5 (Universal Robot) to the ball object. The golf platform and the golf ball will play as an environment to interact with the agent. When the end effector of the manipulator will push the golf ball, if the golf ball moves to the goal position, the agent will be received a reward, otherwise, the agent will be punished. The detail of the action set has 4 parameters inside: $(l_1, l_2, \theta_1, \theta_2)$. Figure 2.1 shown how to define the action set with 4 parameters and the set of state will be inside the blue circle to represent the initial state of the golf-object.

As below is the mathematical definition of the problem in golf putting under reinforcement learning formulation.

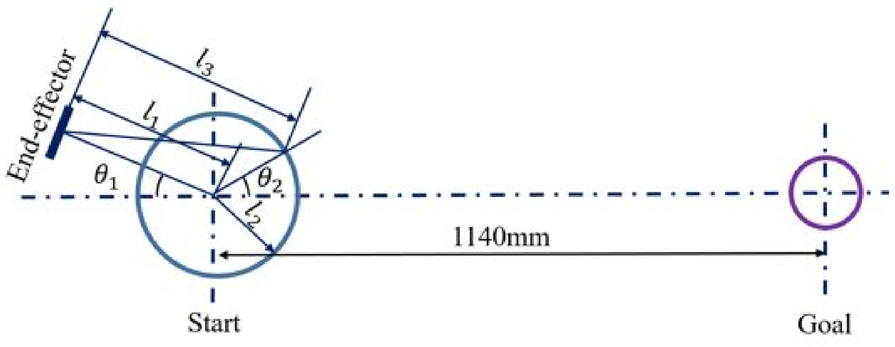


Figure 2.1: Illustration the set of action and state.

Action set

$$(l_1 = [0.3; 0.35]; \;\; l_2 = [0.15; 0.25]; \;\; \theta_1 = [-8^o; 8^o]; \;\; \theta_2 = [-8^o; 8^o])$$

The dimension of action set equal to 4 stands for 4 parameters.

Set of state

From figure 2.1, the coordinate of the initial start state object will be inside the blue circle with a radius equal to l_2 with respect to (x, y). The goal state will be inner the goal circle from figure 2.1. In this case, the dimension of the state equal to 2.

The distance threshold

Defined by the final position of golf-ball after a push by the end-effector of the manipulator with the goal position. It can be called a success when the distance is ≤ 0.1(m). Thanks to this value, do we can evaluate the success of the manipulator task or not.

The reward function

In order to work with reinforcement learning, we need to define the reward function to evaluate how good of action in agent with the environment or not. In this case, I used the sparse reward value. It will be calculated by $-d$ (d is the distance between the golf ball and the target position.

2.2 Strategy and algorithm implementation

From the theoretical analysis of reinforcement learning and problem formulation of the golf putting task. I would like to propose a strategy to solve the current problem under the Monte-Carlo policy gradient algorithm as below.

From the actor-critic methods, we will have the definition as below:

- **Critic** will updates the value function of parameters w. It can be a action-value $Q_w(a|s)$ or a state-value $V_w(s)$.
- **Actor** will updates the policy parameters θ for $\pi_\theta(a|s)$, the actor function will depend on the critic to get update value.

We use two neural networks: a *target policy*, action-value function is *critic*$\mathcal{Q} : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$. At here, the critic will play a role for make approximate actor's value function Q^π. From the figure 2.2, we can the model mapped the states to the actions.

Network structure

In figure 2.3 we can see the dimension of input state dimension and the output of the

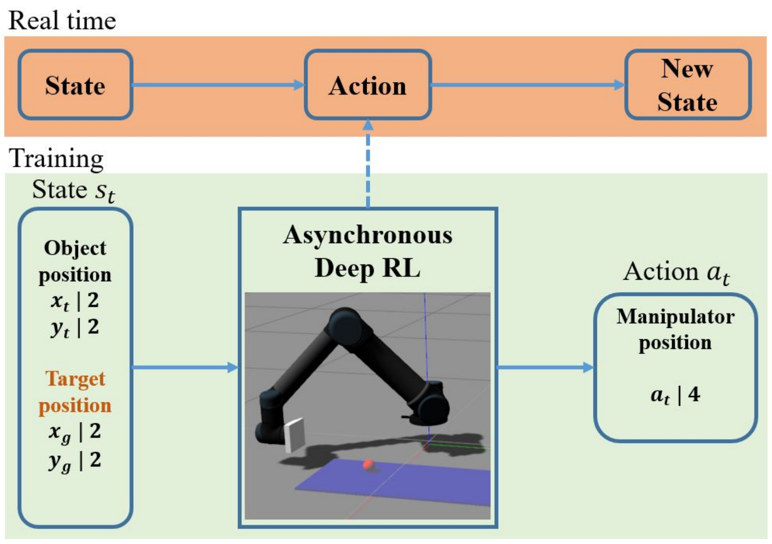


FIGURE 2.2: A map-less action was trained through asynchronous deep-RL.

action dimension. Here, the dimension of state input is 2 and the dimension of action is 4. In both network also used 2 hidden layers with 512 nodes and activation function is ReLU function, it was a fully connected network. After that it was blobs into the merged layer for action value are the position and angle of the end effector in the manipulator. At here, we used a sigmoid function to calculate the output of position in the manipulator. For the angle, we used tanh function to calculate the angle of the end effector of the manipulator. The critic network is similar to the actor network for the output is used the linear function to the value of Q function.

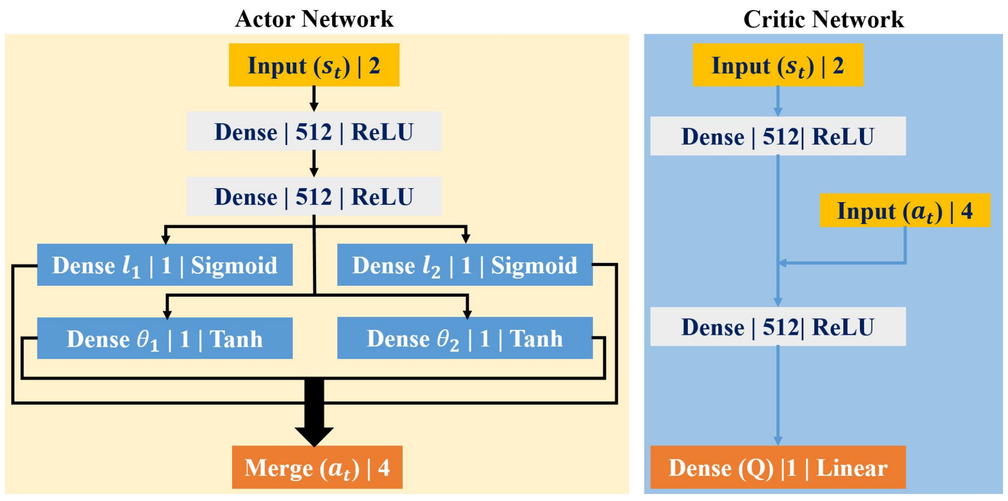


FIGURE 2.3: The network model for the DDPG model.

2.3 Summary

From the analysis of implementing the Monte-carlo algorithm for optimizing the value function and policies by experience. We will show out some advantages from these algorithms:

- Firstly, learn optimal behavior from experience and interact with the environment. The environment's dynamics are not needed.
- Secondly, they can be used with simulation or *sample models*.
- In the last, with the small set of states and actions, the Monte-carlo methods are more efficient.

In this thesis I implemented the Monte Carlo algorithm to find out the best policies for golf putting in both on the virtual environment and real hardware with the result will be shown in the following chapters.

Chapter 3

Hardware for Test-bed with Reinforcement Learning

From the problem definition with the golf putting stuff, we come up with the determine the hardware structure first after that we will be mimicking that environment. In this chapter, we will show out the hardware setup of the physical environment. How to mimic the real world will be shown in the next chapter with software structure and libraries accordingly.

3.1 Golf-platform and the ball object

Base platform for putting golf-ball with dimension weight$\times$ height $\times$ length: $300 \times 1300 \times 85 (mm)$. The hardware setup environment was shown as in Figure 3.1. The ball of object with a diameter is 42.67mm under the solid type object.

3.2 Manipulator and work-space platform

3.2.1 Universal Robot UR5

In this thesis, the industrial manipulator Universal Robot UR5[31] was used for learning the task in both virtual and real environment in Figure 3.2. UR5 is controlled by TCP/IP, 100BASE-TX Ethernet socket. It is programmed with the poly-scope graphical user interface. UR5 has worked in a temperature range of $0 - 50°$. In the following part is the specification of UR5:

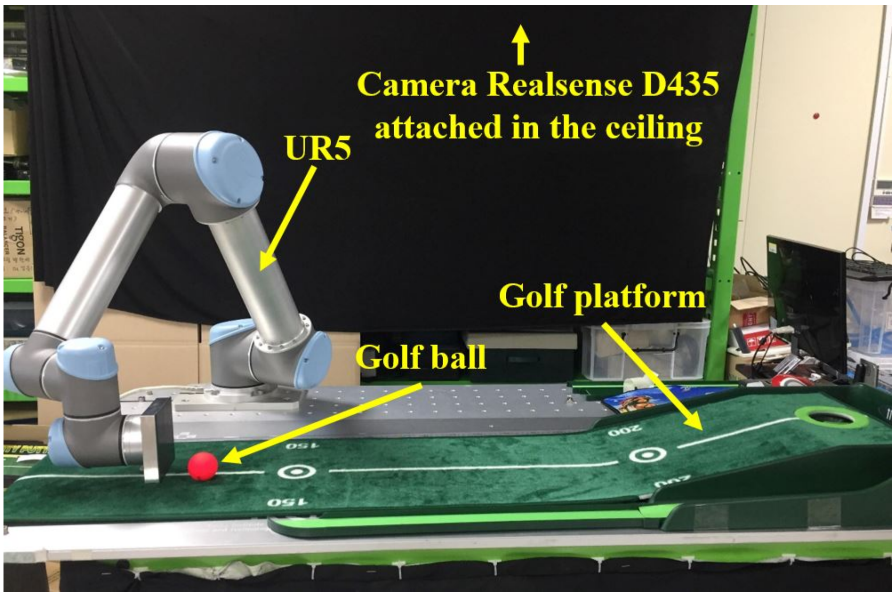


FIGURE 3.1: Hardware setup environment: *UR5 robot, golf-platform and vision based system.*

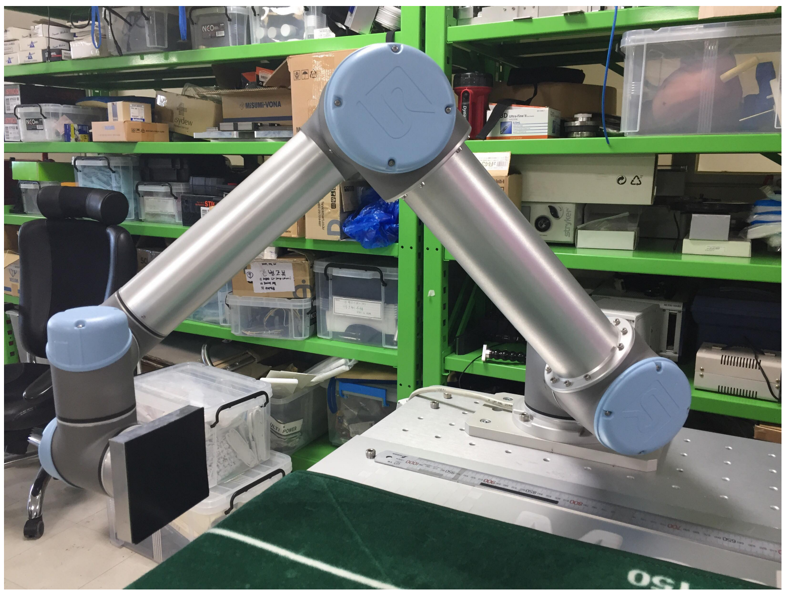


FIGURE 3.2: Universal Robot UR5.

- **Weight:** 18.4kg/ 40.6lbs
- **Payload:** 5kg/ 11lbs
- **Repeatability:** $\pm 0.1mm/ \pm 0.0039in$ (4mils)
- **Footprint:** ϕ149mm /5.9in
- **Degrees of freedom:** rotating joints is 6
- **Control box size (W×H×D:)** 475×423×268(mm) /18.7×16.7×10.6(in)

- **I/O power supply:** 24V 2A in the control box and 12V/24V 600mA in the tool

In order to programmed UR5, we can communicate over a TCP/IP connection called URControl in the low level robot controller. That is controlled by the script-level with programming language URScript.

3.3 Vision Based System

In order to work with determine the position and detect the goal-ball object, the vision system was used by a camera Intel Realsense D435[34]. A specific object recognition systems were taken. The first system operates on color images and mainly use facilities of the OpenCV library[25]. The last system operates on point clouds and mainly uses facilities of the PCL library[26]. This chapter describes the underlying algorithm of each of the two systems for each solution.

3.3.1 Depth camera Intel Realsense D435

Regarding the vision system, a depth camera Intel Realsense D435 was used to tracking the object and send information about the position of the object to the controller. This camera was used as a stereo vision to calculate depth. It was powered by the USB-power depth camera and consist of pair depth sensors, RGB sensor. In the following is some specification of realsense camera:

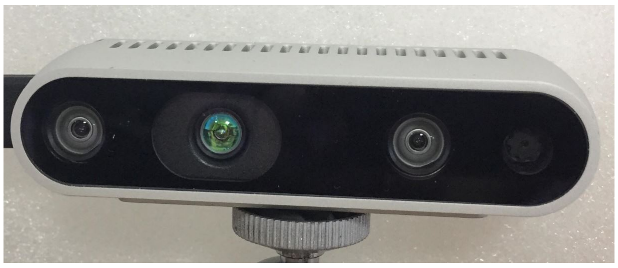


FIGURE 3.3: Camera Intel Realsense D435.

- The vision processor uses 28 nanometer (nm) and support up to 5MIPI[30]
- Advance stereo depth for accurate depth perception.
- Capturing the disparity between images up to 1280 x 720 resolution.
- Support for the cross-platform.
- The signal processor for image adjustments and scaling color.

3.3.2 HSV detection algorithm

The main idea of the algorithm as in Figure 3.4. The HSV detection system detects objects with noticeable colors. The naive approach, filtering images on RGB values since RGB values are strongly affected by the overall brightness[27]. Therefore, the images are first transformed into HSV color space are transformed into a corresponding set of Hue, Saturation, and Value values. This is done by the ***cv:cvtColor*** function[28].

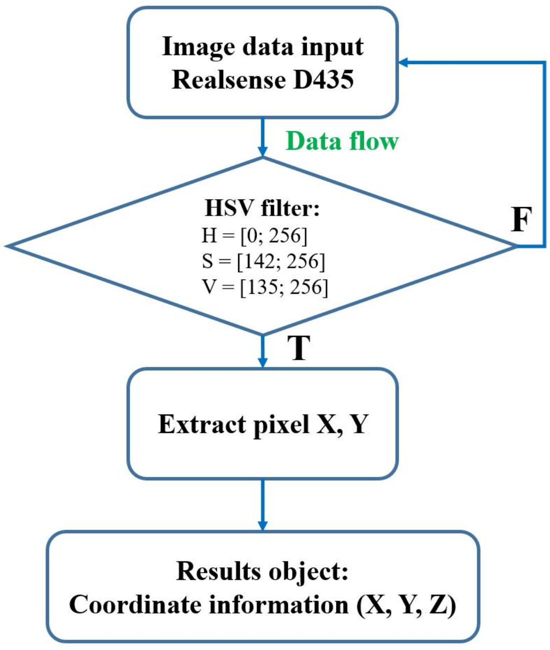


FIGURE 3.4: Object detection main algorithm.

The actual filtering is done with the ***cv::inRange*** function[28], which takes a lower and an upper limit for each channel of the image as its arguments. Only pixels have hue(H), saturation(S), and value(V) values satisfy the following conditions pass through the filter:

$$h\_min \leq H \leq h\_max$$

$$s\_min \leq S \leq s\_max$$

$$v\_min \leq V \leq v\_max$$

The result is a one-channel image that contains the value 255 where these conditions are fulfilled and zero where they are not. An example, from Figure 3.5 describes an image origin on the right and the result of applying the filter to it on the left.
Carefully inspecting the figure reveals that the result of the filter is not perfect, and adjusting the parameters reveals that it is hard to make the result much better under varying lighting conditions. To remove the white speckle noise in the image, a morphological transformation is applied to it; the ***erosion*** and ***opening*** is capable of applying

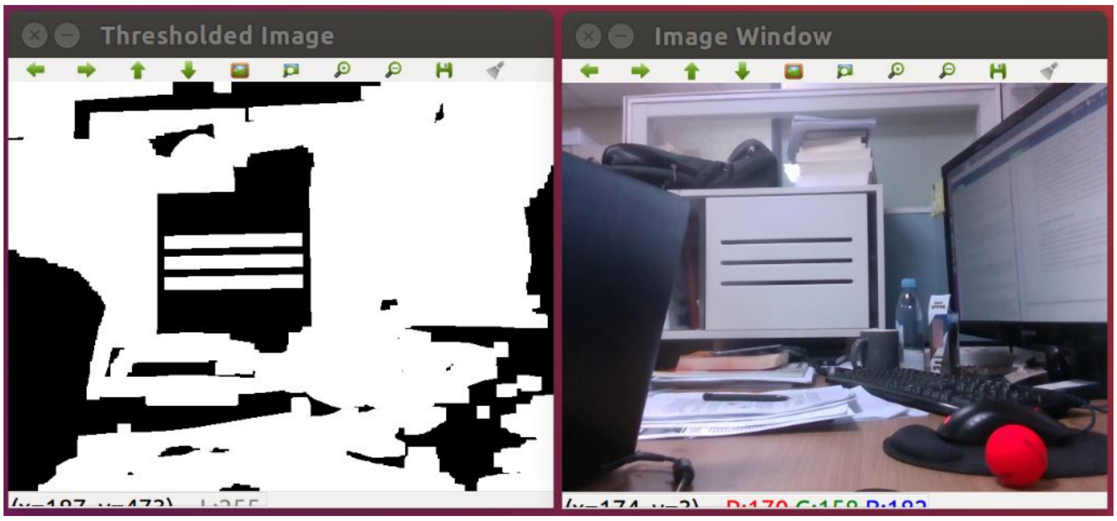
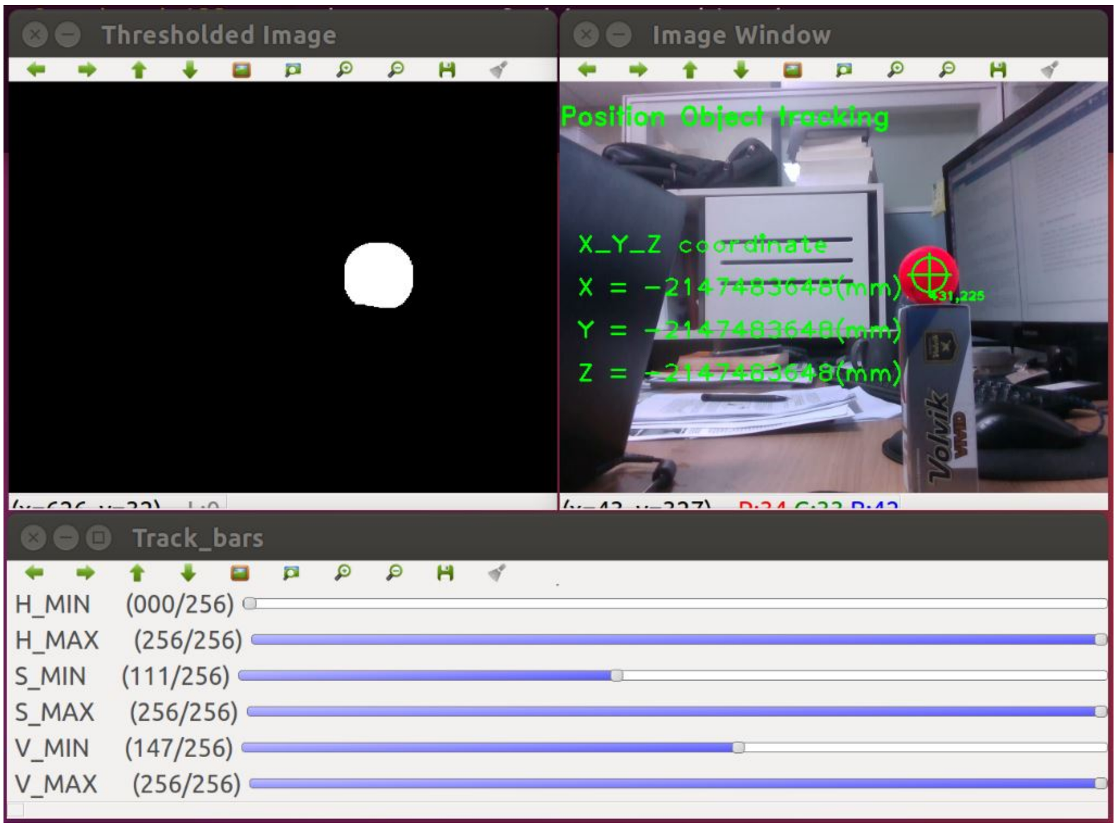


FIGURE 3.5: Image before(right) and after(left) applying the *cv::inRange* function.

these transformations are suited for this task. The *cv::morphologyEX* function[28] is capable of applying these transformations to the image. Parameters of this function, which should also be parameters of the object recognition system, are the kind of operation (erode, dilate, open, etc.).

3.3.3 Position of object extraction

For extracting the position of the object in (X,Y,Z) coordinate, we used PCL library[29] after the object was detected from HSV algorithm. Thanks to information of the object in 2D, we found the pixel point of the object in 2D image and converted that into the 3D point by the algorithm in Figure 3.4.
After the position of the object was found, the detail information of object with X, Y, Z coordinate will be published in a topic name ***position_object***.

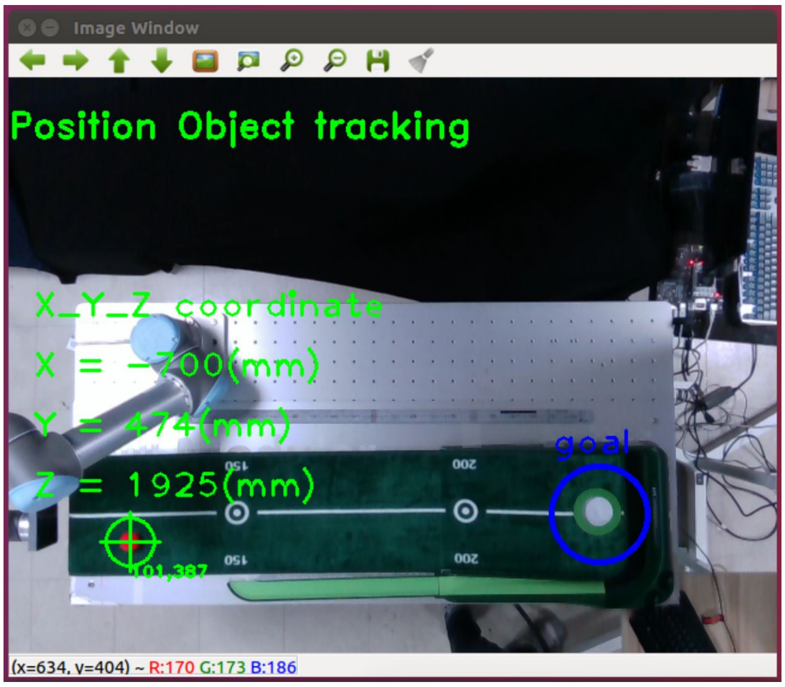


```
Position Object tracking

X_Y_Z coordinate
X = -2147483648(mm)
Y = -2147483648(mm)
Z = -2147483648(mm)
```

```
H_MIN   (000/256)
H_MAX   (256/256)
S_MIN   (111/256)
S_MAX   (256/256)
V_MIN   (147/256)
V_MAX   (256/256)
```

FIGURE 3.6: Track bars from HSV filter for the object detection and information of the object detected



```
Position Object tracking

X_Y_Z coordinate
X = -700(mm)
Y = 474(mm)
Z = 1925(mm)
```

```
(x=634, y=404) ~ R:170 G:173 B:186
```

FIGURE 3.7: Output information of object tracking with Realsense D435.

Chapter 4

Software structure

In order to use simulation to mimic the real-life of golf-putting, our system includes Gazebo simulation environment, a robot arm UR5 (Universal Robot)[31], a golf platform put in a table play as a work-space of the manipulator. The target object is a golf-ball with diameter 42.67mm. All software and libraries were used in Linux LTS 16.04 version 64bit and ROS Kinetic platform system.

4.1 Software structure

With the combination of ROS and Gazebo simulation, we create the software structure that connects the virtual environment and the real hardware where we can share policies between the virtual environment and the hardware. From figure 4.1 is the general system to show how we can share the policies for both of the hardware and the virtual environment. From this structure, we can use good policies for both the virtual environment and the real hardware.
In fact, from the initial, we generate the policies from the virtual environment after implement reinforcement learning algorithms. After that, we transfer those policies into the real hardware and test the performance of the robot. When we have the policies output we can use that for both of the virtual and the real hardware. Both hardware and the virtual environment working under the ROS platform via topics shared and messages package.

In figure 4.2 show the detail of communication between hardware and simulation under ROS platform.
Robot hardware: communicate under topic of *ros_controller* package. Topic *ur_gazebo_ros_control_plug*
to control general actuators in joints of robot under Gazebo environment. Inside gazebo

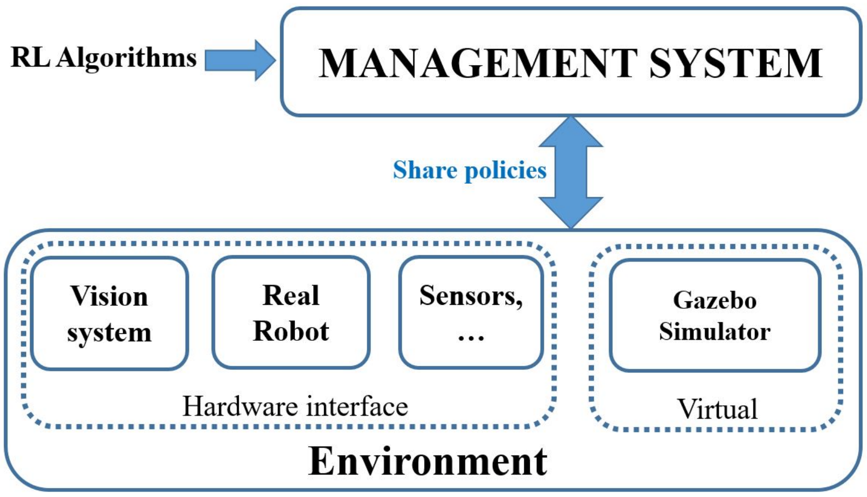


FIGURE 4.1: Software structure of system

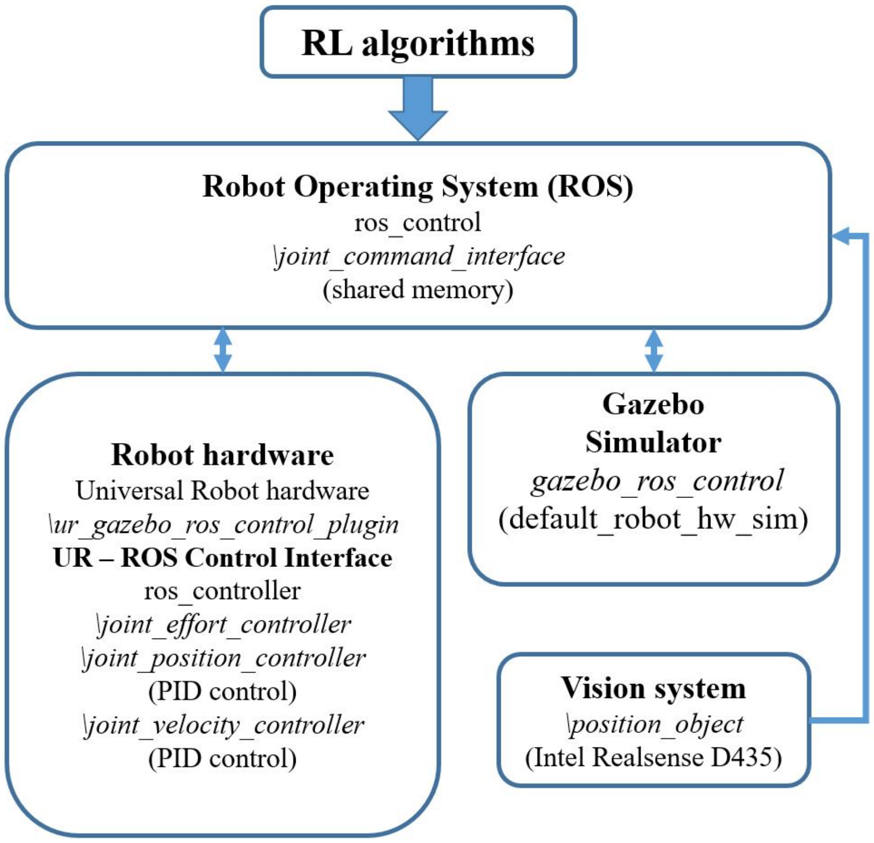


FIGURE 4.2: Detail of software structure under ROS platform

ros control plugin we have 3 types of controls: effort control, position control, and velocity control. In this system we used *position control* in each joint of UR5 under topic *joint_position_controller* to control actuators in each joint. Based on the position controller we use the PID control type to control the actuators.

Vision system based: generate a topic under name *position_object* in order to send information of object coordinate into ROS master and the UR5 will subscribe this topic to evaluate how the success of actions or generate action accordingly.

Gazebo simulator: will contain the virtual environment of UR5 and golf-platform and golf ball coordinate inside of the 3D environment. The UR5 also uses the gazebo control plugin to control actuators in each joint. All of the communication from Gazebo to robot hardware under to ROS master.

Reinforcement learning algorithms: where we can implement any reinforcement learning algorithms from this into the Gazebo simulator. The Gazebo simulator plays to execute algorithms and generate the output of the best policies file. After that input into the real hardware to test performance. Thanks to this way all of the training time will be taken inside the virtual environment. In order to get a better result, we should have good algorithms to increase performance.

Chapter 5

Virtual environment for Reinforcement Learning

From the definition of hardware, problem and software libraries, this chapter will describe how to build a virtual environment for mimicking the real environment. The detail of manipulator modeling and golf platform will be shown in this part. In addition, the method to demonstrate the consistency between the real-world and the virtual environment will be shown too.

5.1 Manipulator modeling and golf platform

In order to describe our robot, we need to have the Unified Robot Description Format (URDF)[20]. This file was created with the support from Computer Aided Design (CAD), design software as Blender, Solidworks, Pro-engineer, ...
In the figure 5.1 shows the basic structure of a robot. In the robot description model, regard to describe the link of robot will be used tag $< link >$ and tag $< /link >$. In addition, describe the joint of robot will be used tag $< joint >$ and tag $< /joint >$.
We can import model as meshes by STereoLithography (STL)[21] and Collada[22] files into URDF.
The robot UR5 environment contains all the functions to the specific UR5 robot we want to train. In this case, we implement to use a joint trajectory controller to let our UR5 robot work[39].

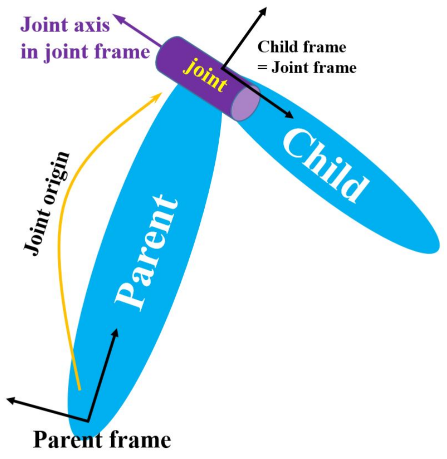


FIGURE 5.1: Connection of two links by one re-volute joint.

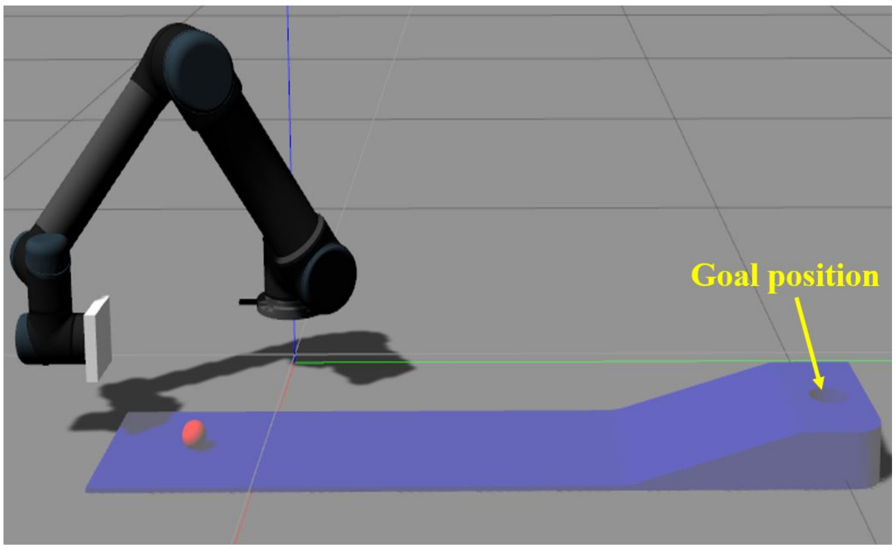


FIGURE 5.2: The virtual environment of golf-putting and UR5.

5.2 Calculation friction value between surface and the ball

In this environment, we should consider the friction value between the surface and the golf-ball. There is some research to evaluate the friction of golf-ball and surface[16]. In this thesis, I proposed a solution on how to calculate the friction value. In this case, we count the golf ball rotating in the surface an angle is α(radian), the radius of the ball is R(m) with massive m(kg) of the golf ball. We measured the distance of the object traveled until that stop with d_1, d_2 sequence. According to figure 5.3 we can see the angle of the golf platform is θ(radian), the force analysis was shown in the same graph.

From that, we will have equations following the rule of energy:

$$mgh = F_{friction_1} d_1 + F_{friction_2} d_2$$

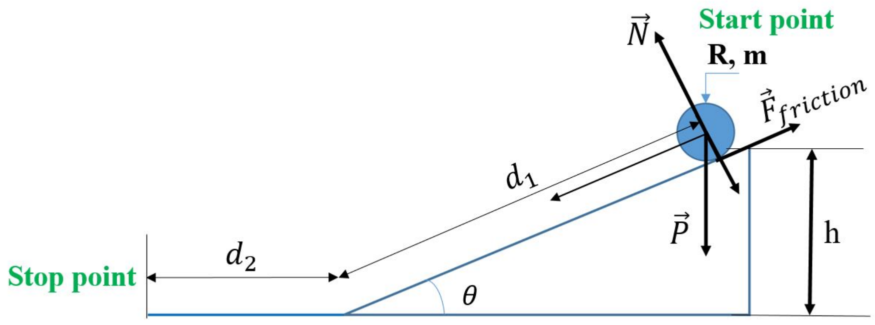


FIGURE 5.3: Friction between the golf ball and surface analysis.

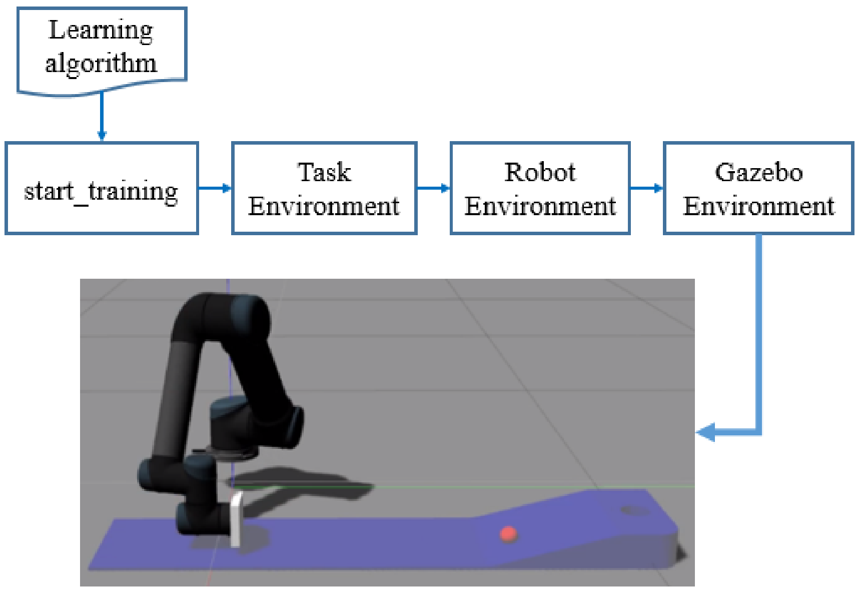


FIGURE 5.4: Reinforcement Learning algorithm training in the virtual environment

We assume that the value of friction will be same in all surface of platform. From the force analysis in figure 5.3 we will have the energy in distance d_1, d_2 will be:

$$F_{friction_1} d_1 = mg\mu cos\theta d_1$$

$$F_{friction_2} d_2 = mg\mu d_2$$

After the calculation we will have friction value:

$$\mu = \frac{h}{d_1 cos\theta + d_2}$$

From the figure 5.6 shows how we measure the distance of the ball after the free drop from the top of the platform until that ball stopped. After take the experiment with 109 times to measure the distance d_1 and d_2 sequence, we have the mean of friction value $\mu = 0.10378$. From figure 5.5 shows the value of friction value and mean friction value after the experiment.

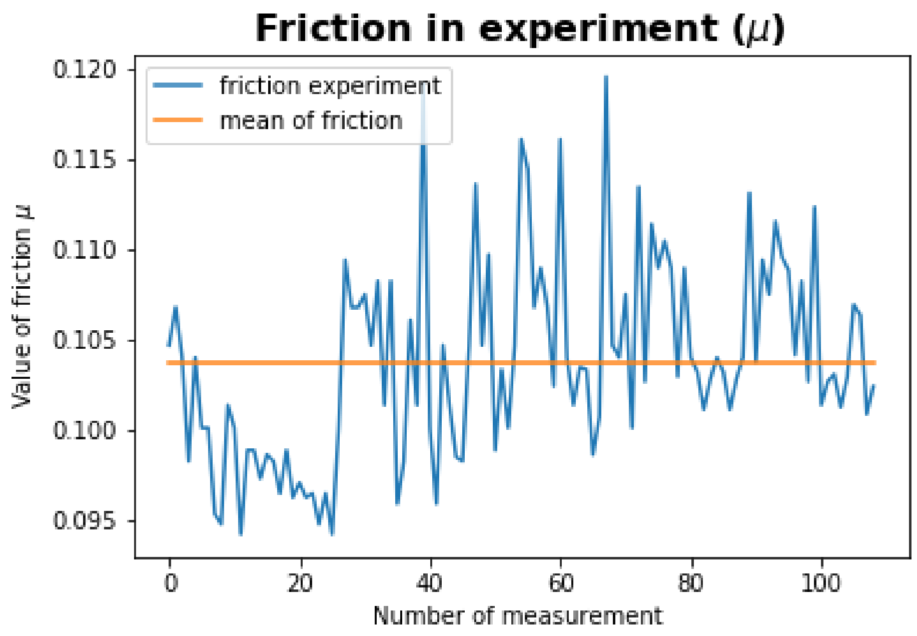


FIGURE 5.5: Friction value in experiment with 109 times measured.

In order to validate the value of friction from the experiment. We input that value into the simulation environment and test the same method with the experiment. After that we measure the value of distance d_1 and d_2 after release the ball from the top of the platform until it stops. We will make a comparison between the mean of d_2 in the real world with a value of d_2 in the virtual environment. In the figure 5.8 shows the position of the ball will be a free drop-in the virtual environment. After that, the figure 5.9 describes the position stopped of the ball after the free drop from the top of the platform with the detail of coordinate in the virtual environment.
First, from the real environment, we measured the mean of distance $d_2 = 484.11(mm)$. From the figure 5.7 shows the value of distance d_2 and the mean value after 109 times. Second, from the virtual environment we take the value of distance $d_2 = 471.98(mm)$.

Therefore, the different between simulation and physic will be: $\Delta d_2 = 0.01214$. From that we will have the error between simulation and physic will be described as below:

$$d_2 = 0.4841 \pm 0.01214(mm)$$

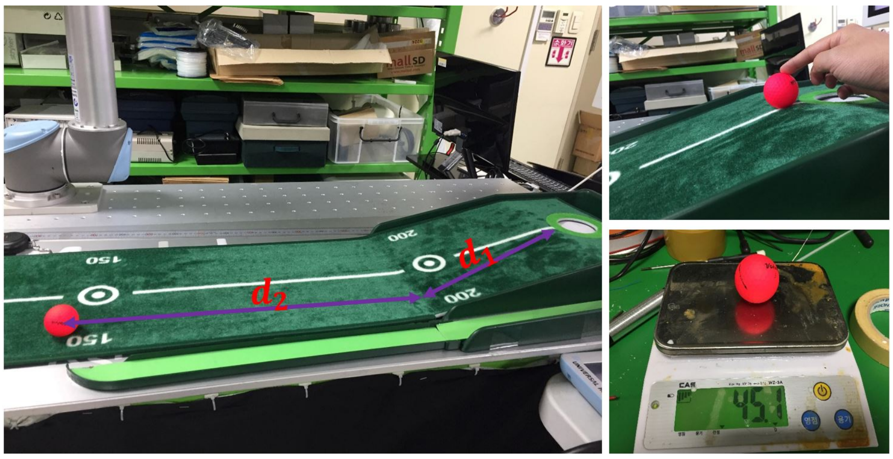


FIGURE 5.6: The real measurement from experiment with d_1, d_2 and the weight of ball

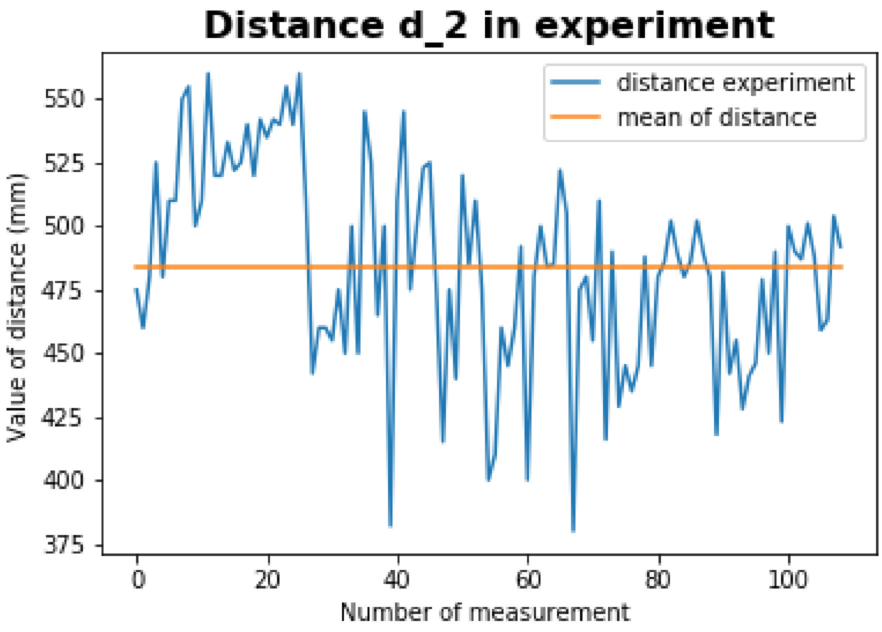
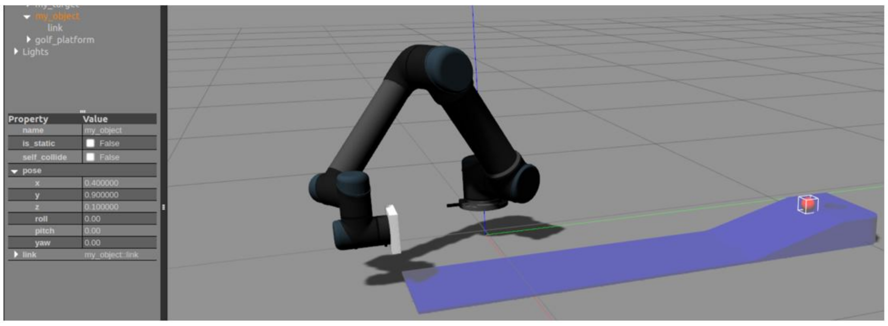
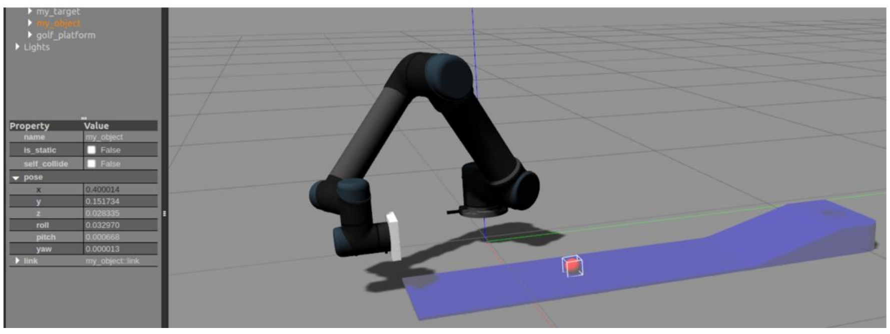


FIGURE 5.7: The distance d_2 measured in experiment



Property	Value
name	my_object
is_static	☐ False
self_collide	☐ False
pose	
x	0.400000
y	0.900000
z	0.100000
roll	0.00
pitch	0.00
yaw	0.00
link	my_object::link

FIGURE 5.8: Ball drop from start position in virtual environment. The coordinate of ball: (x,y,z) = (0.4, 0.9, 0.1)



Property	Value
name	my_object
is_static	False
self_collide	False
pose	
x	0.400014
y	0.151734
z	0.028335
roll	0.032970
pitch	0.000668
yaw	0.000013
link	my_object::link

FIGURE 5.9: Ball stopped position in virtual environment. The coordinate of ball: (x,y,z) = (0.4, 0.1517, 0.02)

Chapter 6

Training result

6.1 The results in simulation and the real hardware

6.1.1 Result from simulation in the virtual environment

From the Gazebo environment, we completed to mimicking the virtual environment from physical data. The tasks of manipulator were completed execute in the Gazebo environment. Figure 6.1 was shown the process of the UR5 task with golf putting in the virtual environment.

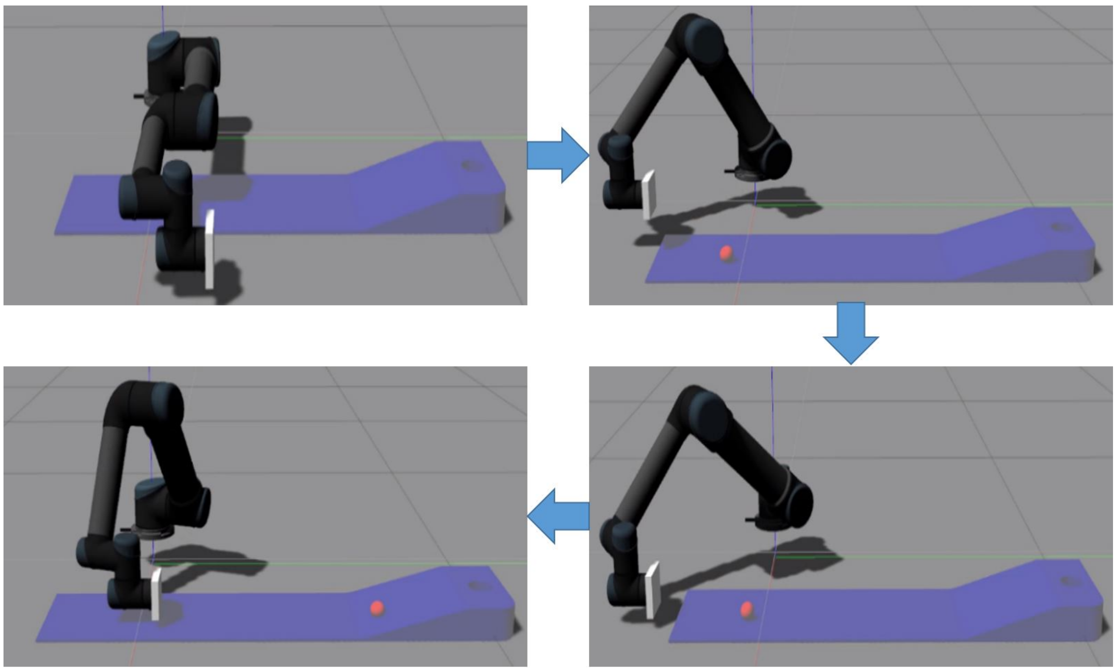


FIGURE 6.1: Task simulation in the virtual environment.

After implemented with the Monte-Carlo algorithm the result of the training was improved with the success rate for golf putting increased as in the graphs as in below.

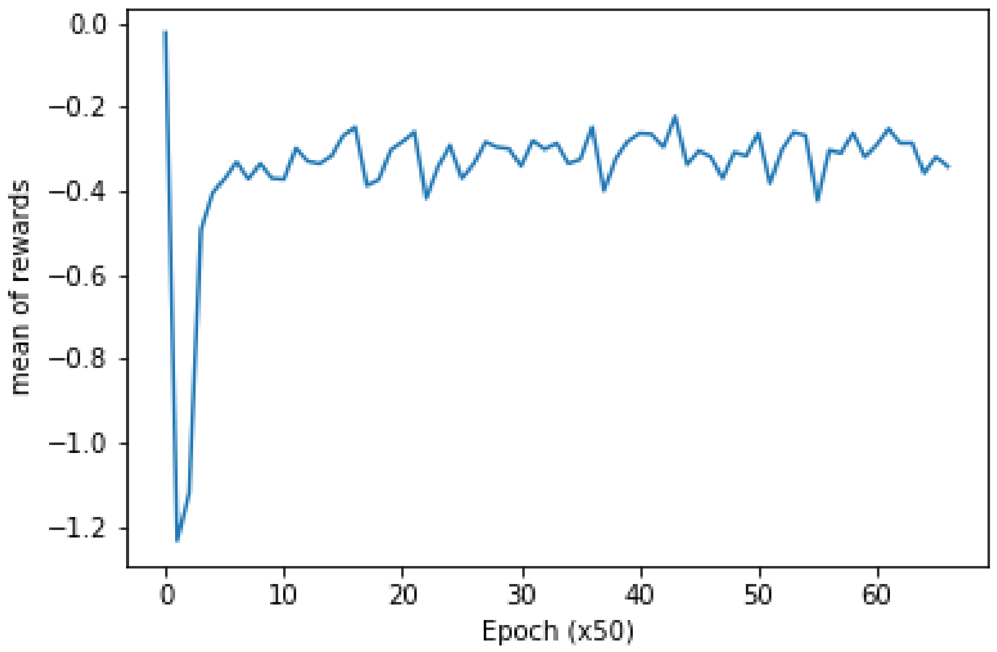


Figure 6.2: Normal of rewards over epoch.

After training with 3000 episodes, we had the result of rewards as in figure 6.2 with the accumulate of reward increased over time. In addition, the mean success rate in figure 6.3 also increase however the average is lower than 68(%).
Furthermore, in the link as below is the result from simulation: https://youtu.be/HVbtnGaIi-s

6.1.2 Result in test-bed with hardware setup.

From the result of the simulation and training for UR5 how to putting golf. We transfer that policy result in the real hardware and make a comparison between the simulation and the real. Figure 3.1 was shown the detail of the real hardware setup with a vision system, a golf platform environment, and a ball. All of the hardware was set up in a table as a work-space of robot UR5.
We are working on the task of training by Monte-Carlo algorithm for UR5 and after that, we will transform the result into the real hardware setup. From figure 3.1 and figure 6.1 were shown how consistency between the simulation and real hardware. https://youtu.be/HdxvACGRTwI

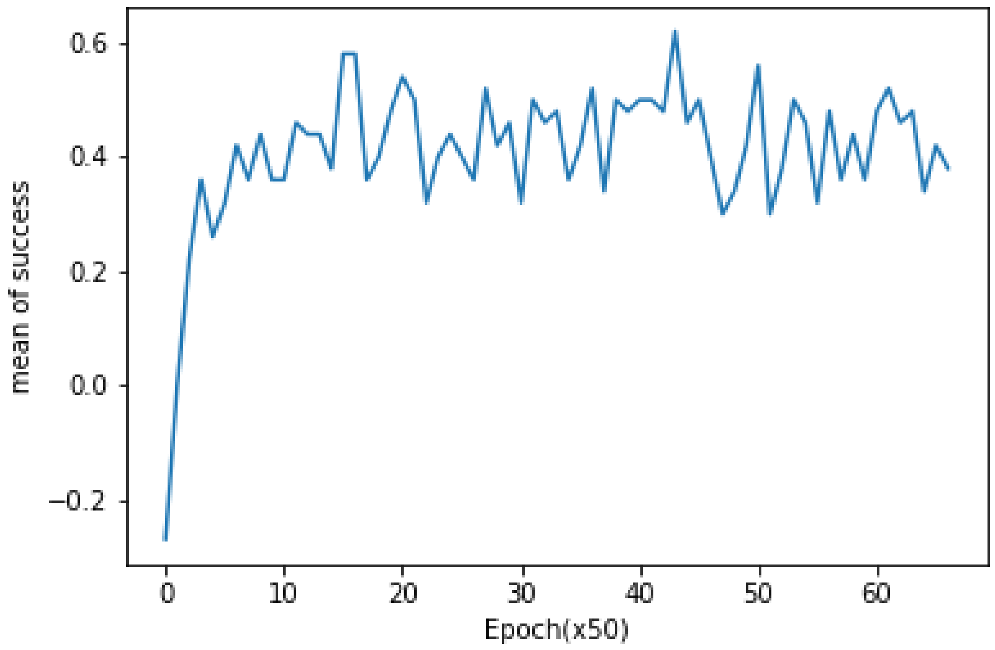


FIGURE 6.3: Mean of success rate.

6.2 Sum up from simulation result

Thanks to the Gazebo simulator. It is simple to simulate our robot by tasks in daily life. Thanks to that, the time spent in robotics research will be reduced significantly. In this thesis proposed an approach helps to reduce time to train in hardware with the reinforcement learning algorithm by the virtual environment and transfer policy into real hardware.

However, the consistency between reality and virtual environment still exists some gap such as the impact of wind in the environment and the friction value. These factors can impact a lot on the result of the agent. In order to solve current issues, simulation tools should increase accuracy and high consistency with impact factors from reality. The current result from simulation still low, it should be improved for future works and increase the performance of the algorithm to have a better result.

Chapter 7

Conclusions

This thesis presents the method to mimic the real environment with the aiding of software and libraries. After that, we implemented the state of the art of the reinforcement learning algorithm in the virtual environment to training agents on how to reach good results.

In chapters 1 and 2, we provided the introduction of the reinforcement learning algorithm. After that, we determine our problem formulation under the reinforcement learning problem and mathematics accordingly. The Monte-Carlo algorithm was used in this problem to the training agent in the virtual environment.

Hardware and test-bed

In chapter 3, we determined our target hardware structure will be implemented with the combination of manipulator UR5, golf platform, and the vision system. In each hardware part plays unique roles to determines in the whole system: UR5 will generate actions from the policies input from the virtual environment, golf platform provide environment task for UR5 and the vision system will determine how success of UR5 by sending the feedback signal of object position as a reward function from reinforcement learning algorithm.

The detail of algorithms and control implementation with the hardware system was shown in chapter 3.

Software structure

In chapter 4, we have shown the software structure and libraries were used in this thesis to mimicking the hardware system. With the support of the ROS programming framework and Gazebo libraries, we completed to mimicking the real-hardware in the virtual environment.

From chapter 5, we generated the UR5 and golf-platform model in the virtual environment. In addition, to demonstrate the consistency between the virtual environment and the real-hardware, we calculated the friction value between golf-ball and the surface of

the platform as in detail from this chapter.
Following that is the reinforcement learning algorithm was used in the virtual environment to generate the best policies. The detail of the result under the Monte-carlo algorithm was shown in chapter 6. After that in the real-hardware will receive the best policies from the virtual environment and the result of the test-bed was shown in this chapter too.
Overall, this thesis was the success of mimicking the hard-ware environment by the support of software and libraries to build the virtual environment. Moreover, the implementation of the reinforcement learning algorithm was used in the virtual environment for agents to generate the best policies before transfer to the real hardware. Some results were shown in this thesis.
However, with the current simulation about 66% of success rate over 3000 episodes of training still in the low performance. In opposite, by dint of applying the virtual environment, we can utilize time in training from the hardware. Thanks to simulating reinforcement learning algorithms in the virtual environment do we save a bunch of time in real hardware of training.
The future work of this thesis will be the focus on how to implement better algorithms for reaching the higher success rate of training.

Appendix A

Source code for execute algorithm and connection

A.1 Source code of thesis project

https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019

A.2 Virtual environment for Reinforcement Learning tasks

Virtual Golf platform description
https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/tree/master/golf_platform
Virtual golf ball object
https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/ur_gazebo_test2/urdf/golf_ball_object.sdf

A.3 Virtual environment with python

UR5 virtual environment with python definition
https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/ur_gazebo_test2/scripts/ur5_env.py
Golf putting task in virtual environment
https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/ur_gazebo_test2/scripts/slide_puck.py

A.4 Reinforcement learning algorithm implementation

DDPG algorithm

https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/ur_gazebo_test2/scripts/ddpg_ur5_20190416.py

The Monte-Carlo policy gradient algorithm

https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/ur_gazebo_test2/scripts/q_learning_20190503.py

A.5 Vision system code with Realsense D435

https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/opencv_object_tracking/src/object_filter.cpp

A.6 Hardware connection from virtual to real environment

https://github.com/dovanhuong/master_thesis_hci_robotics_june_2019/blob/master/modman_comm/src/ur_comm.cpp

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