Bulletin of Networking, Computing, Systems, and Software – www.bncss.org, ISSN 2186-5140
Volume 10, Number 1, pages 17–19, January 2021

Reinforcement learning of electric prosthetic hand with depth camera in simulation environment

Takuya Ayukawa, Nobuhiko Yamaguchi, Osamu Fukuda, Hiroshi Okumura
Graduate School of Science and Engineering, Saga University
1 Honjo-machi, Saga-city, Saga, 840-8502, Japan
Email:19704001@edu.cc.saga-u.ac.jp
Email:{yamag, fukudao, okumurah}@cc.saga-u.ac.jp

***Abstract*—In this paper, we propose a control scheme for electric prosthetic hand system based on depth camera images. We develop a simulation environment of an electric prosthetic hand based on depth camera images by Unity and acquire control scheme by reinforcement learning in the simulation environment. The performance of the proposed method is assessed in experiments with stick picking task. The experiment highlights the electric prosthetic hand based on depth camera produces higher cumulative reward and outperforms the conventional electric prosthetic hand based on 2D camera images.**

***Keywords*— Electric prosthetic hand, Reinforcement learning, Depth camera, Unity**

I. Introduction

Prosthetic hands have been developed to improve the quality of life of users. As a prosthetic hands myoelectric prosthetic hand that controls the grasping motion by electromyographic (EMG) signals was proposed. However, the problem of myoelectric prosthetic hands is that myoelectric prosthetic hand can only perform simple grasping motions such as grasping and holding, because it judges grasping based on weak EMG signals. To solve this problem, there is an attempt to support the grasping motion by installing a camera in the myoelectric prosthetic hand [1]. The camera is used for object recognition and the predetermined grasping motion is executed according to the camera images. However, there is a concern that this method does not work well for the cases where the object is misrecognized, or the unknown object is not learned.

Therefore, we propose to use that the reinforcement learning method to perform appropriate grasping motions even when the object is not recognized. Since the prosthetic hand has cameras on the back of the hand and the arm, the prosthetic hand hides the object during the grasping motion and the reinforcement learning cannot be performed properly. We propose that a camera is mounted on the palm of the hand to keep the camera capturing the object during the grasping motion. To develop a five-finger electric hand prosthesis for flexible grasping motion, we construct a simulation environment and perform reinforcement learning of the prosthetic hand from the camera images.

This work was supported by JSPS KAKENHI Grant Number 18K11439.

II. System Overview

A. Building a simulation environmen

The simulation environment was built using Unity [2], developed by Unity technologies. Unity is an integrated development environment with a built-in physics engine, PhysX. The five-fingered prosthetic hand model was imported into Blender[3], which is a 3DCG editing software, based on CAD data[4], and the parts were isolated and output as a 3D model in fbx format and imported into Unity.

The Rigidbody was added to give each part physical properties. The joints are connected by a HingeJoint and the fingers flex along it. When each finger bends and extends, the first, second and third joints rotate in conjunction. Fig. 1 shows the state of the fingers when they are opened and closed to the maximum. The base of the thumb can be rotated and the total Degree of Freedom (DOF) of the prosthetic hand is 6. The HingeJoint's parameter, Spring, is strengthened to some extent, and its rotation angle is controlled by a script, which works like a servo motor. The rotation angle of each finger is limited to [0,90] degrees for the index finger, [-60,0] degrees for the middle to little finger, [-90,30] degrees for the thumb, and [-30,90] degrees for the base of the thumb. The difference in the angle of rotation between the index and middle to little finger is due to the difference in the initial values. The camera is placed in the palm of the hand to catch the object in the camera during the grasping motion. The camera is placed perpendicular to the palm of the hand and acquires information in the range shown in Fig. 2. In this experiment, two training sessions are conducted with a visible camera and a depth camera. For the depth camera, we created a shader to draw the closest area in blue and the farthest area in red. An example of a screen with this shader is shown in Fig. 3.

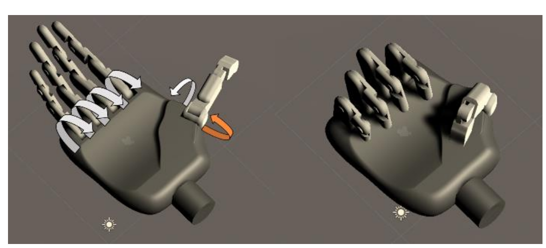

Fig. 1. Five finger prosthetic model

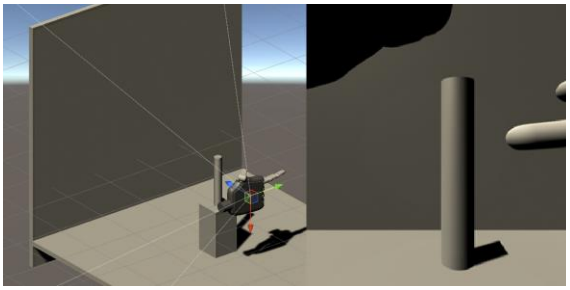

Fig. 2. Camera ranges

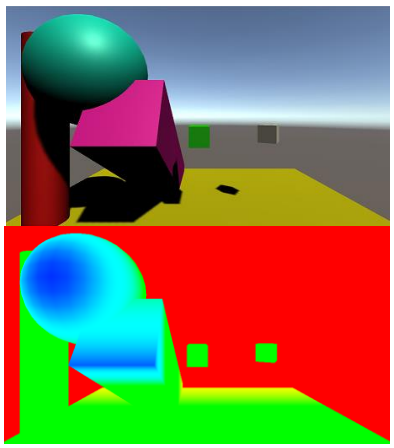

Fig. 3. Depth camera conversion

B. *Reinforcement Learning*

Reinforcement learning was done using ML-Agents [5], a plugin that enables machine learning in the Unity environment. ML-Agents adds two components, Agents and Behaviors, to Unity. Agent takes care of getting state, executing actions, and allocating rewards from actions. Behavior exists above Agents and specifies the number of actions to be performed and the number of states to be observed by Agents. It also receives status and rewards from Agents and returns their actions. There are three types of Behavior, Learning, Heuristic, and Inference, which enable the Agent to switch its actions. Each type of behavior is as follows: in Learning, Agents are trained, in Heuristic, they carry out the scripted actions, and in Inference, the trained neural network is used to make inferences. Although reinforcement learning by PPO and SAC and imitation learning by GAIL and BC are provided in ML-Agents, we used PPO in the present experiments.

III. EXPERIMENTS

In this study, we verified whether a target can be grasped by visual camera images and depth camera images with the developed five-fingered prosthetic hand, respectively. The task is to lift a cylinder as a target. Reward, Observations and Actions are shown in Table 1. Note that Step is the unit in which Agent performs one action.

Table 1 Experimental Parameters

Reward	The target's y-coordinate is more than 6 ⇒The y-coordinate of the target object * 0.01 The y-coordinate of the target object is 3 or less ⇒ -1 other than that ⇒ 0
Observations	Camera image [84 * 84] pixel * 3 channels Rotation angle of the index finger [0,90] degrees Rotation angle of Middle finger [-60,0] degrees Rotation angle of ring finger [-60,0] degrees Rotation angle of the little finger [-60,0] degrees Rotation angle of the thumb [-90,30] degrees Rotation angle of the base of the thumb [-30,90] degrees.
Actions	Flexion of the thumb to the little finger (5 actions) [-3,3] degrees per step Rotation of the base of the thumb [-3,3] degrees per step

The training environment is shown in Fig. 4. The five-fingered prosthetic hand model automatically approaches the target and remains stationary for 50 steps. Thereafter, each step increases by 0.02 in the y-axis direction. When the target y-coordinate becomes more than 6 or less than 3, Agent is reset. The higher the target is raised from 6, the higher the Reward is. On the other hand, if the target is dropped and the y-coordinate falls below 3, the reward is -1. Observations for Behavior are the camera images of the five-fingered prosthetic hand model, which are [84*84] pixel color images (3 channels) and the current rotation angle of the fingers, i.e., how much the fingers are bent. The Actions of the Agent consist of six actions, i.e., flexion of each finger and rotation of the base of the thumb of the five-fingered prosthetic hand model. Actions are given values up to [-1,1] and for each Step, the finger is flexed up to the value * 3 degrees. As a result, we can acquire the grasping action by using the depth camera as shown in Fig. 5. The evolution of the evaluation values for each experiment is shown in Fig. 6.

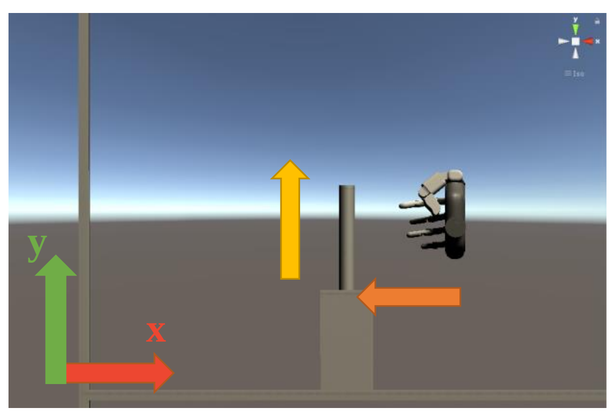

Fig. 4. The learning environment

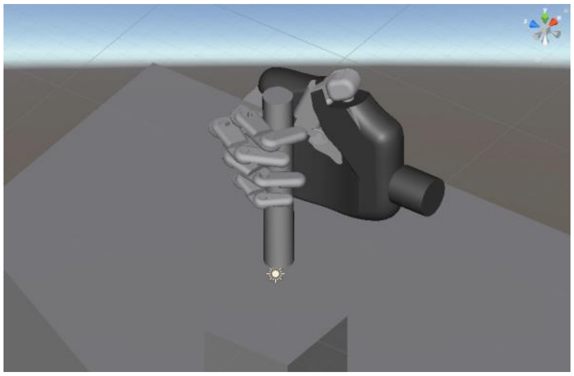

Fig. 5. Learning results

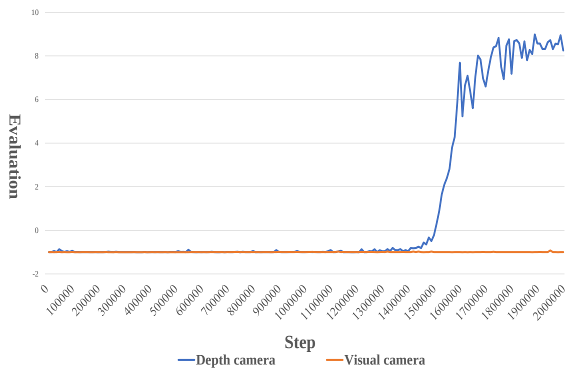

Fig. 6. Changes in evaluation

IV. CONCLUSION

In this study, a simulation environment was constructed, and a five-finger prosthetic hand model was used to learn reinforcement of grasping movements. As a result, we confirmed that the acquisition of grasping movements can be performed using the depth camera.

Currently, we cannot call it a flexible prosthetic hand because we have only learned to perform a grasp when the camera image turns blue. Therefore, we would like to develop a more flexible prosthetic hand by increasing the DOF of the five-fingered prosthetic model and experimenting with grasping a target from various angles.

REFERENCES

[1] He,Y.,Shima,R.,Fukuda,O.,Bu,N.,Yamaguchi,N.,Okumura,H.(2019).:Development of distributed control system for vision-based myoelectric prothetic hand, IEEE ACCESS

[2] Unity, https://unity3d.com/jp

[3] Robotichand,https://grabcad.com/library/robotic-hand-8

[4] Blender,https://blender.jp/

[5] Juliani, A., Berges, V., Vckay, E., Gao, Y., Henry, H., Mattar, M., Lange, D. (2018). Unity: A General Platform for Intelligent Agents. arXiv preprint arXiv:1809.02627. https://github.com/Unity-Technologies/ml-agents.