Research on grasping of string foods in the home meal replacement industry

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Abstract

In recent years, automation by industrial robots has been desired in Japanese food manufacturing plants. This paper describes the development of an autonomous robot for automating the preparation of home meal replacement. The serving of lunchtime meals includes not only solid foods such as rice balls, but also string foods such as spaghetti. Unlike solidified foods, string foods require quantitative grasping. However, in the grasping experiments of string foods, the spaghetti deteriorates with time, and thus, a problem arises where an accurate quantitative grasping experiment cannot be performed. Therefore, in this study, we perform a quantitative grasping experiment by deep reinforcement learning using a material like string foods to verify the grasping and serving system for string foods.

Keywords: Factory automation robots, Arm robots, Deep reinforcement learning, Fake noodle, ROS

1. Introduction

In recent years, automation by industrial robots has been desired in Japanese food manufacturing plants. In this paper, we develop an autonomous work robot for automating the serving operation of midday meal. In the preparation of home-style meals, there are not only solid foods such as fried bean curd and rice balls, but also string foods such as spaghetti. Unlike solidified foods, string foods require quantitative grasping. However, in the grasping experiment of string foods, the spaghetti deteriorates with time, and thus, a problem arises that prevents an accurate quantitative grasping experiment from being carried out. Therefore, in this study, for the purpose of verifying the grasping and serving system for string foods, quantitative grasping by deep reinforcement learning is performed using materials with similar properties to string foods.

2. System configuration

The configuration of the string object grasping system is shown in Figure 1. In this system, a robot detects and grasps an object based on information from an RGB-D camera. The system consists of a visualization processing unit and a robot control unit. First, the visualization processing unit receives information from the RGB-D camera mounted on the robot, and object detection and center of gravity detection of the object are performed. Next, the robot control unit receives the information from the visualization processing unit, and based on the grasping information learned by deep reinforcement learning, the robot grasps the food by sending motion planning signals to the control unit using ROS.

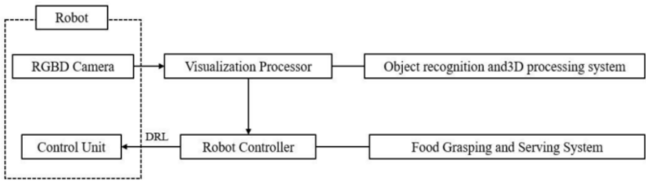

Fig1. System configuration diagram

3. Robot configuration

Figure 2 shows the appearance of the robot used in this study. Since this robot is designed to perform the same tasks as a human in a food manufacturing factory, it has a vertically articulated 7-axis arm with a high degree of freedom, and is equipped with an RGB-D camera, a force torque sensor, and a tong gripper. The gripper part is an actuator mechanism powered by a stepping motor.

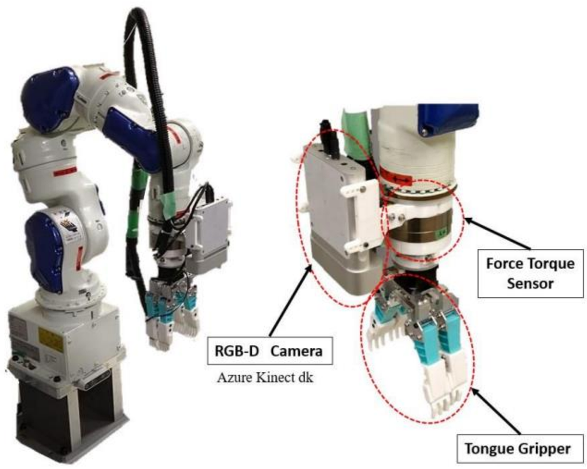

Fig2. Appearance of the robot

4. Deep Reinforcement Learning Models

Figure 3 shows an overview of the deep reinforcement learning used in this study.The deep reinforcement learning algorithm uses SAC [1]. The agent consists of SAC and CNN for large-scale image recognition [2]. Grasping is performed by the agent taking action against the environment based on the information from the RGB-D camera. During grasping, a weight measurement is taken, and the closer the value is to the target value, the higher the reward, and the weight and reward data are stored in a replay buffer. The data stored in the replay buffer is retrieved at random and used to train the agents. As the agents are trained, they optimize and update the network. The system learns by repeating this sequence of actions.

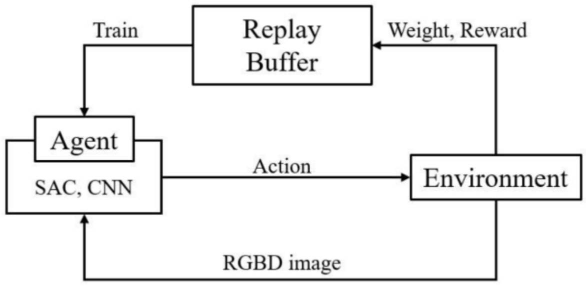

Fig3. Overview of deep reinforcement learning

5. Experiment

Fig4. (left) o-ring (right) rubber

The o-ring and rubber band shown in Figure 4 were used as materials with similar properties to the string foods, and were trained by a deep reinforcement learning model. In the previous study, the robot grasped spaghetti with a target weight of 50 g. Considering the robot's grasping ability, we set the number of training sessions to 2000, the target weight to 30 g, and the reward to be higher when the grasped weight was within ±10% of the target value. The mean absolute error MAE[g], mean squared error MSE[g^2], standard deviation, maximum error, and minimum error are used as evaluation indices and are shown in Table 2. As a characteristic, MAE evaluates the influence of outliers to a small extent, while MSE evaluates the influence of outliers to a large extent The calculation formulas for MAE and MSE are shown in Equations (1) and (2) as number of data N, correct answer value y_i and predicted value$\hat{y}_i$.

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i| \quad (1)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \quad (2)$$

5-1. Result

The amount of grasping is shown in Figure 5, and the rewards for learning are shown in Figure 6.
Table 1 shows the experimental results, and Table 2 summarizes the data for several evaluation index.

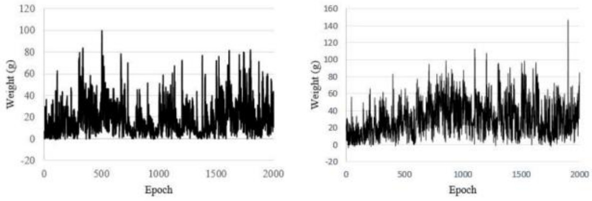

Fig5. Grasping amount （left） o-ring（right） rubber

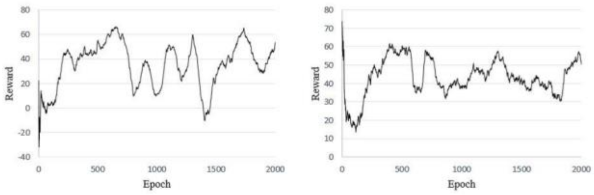

Fig6. Reward （left） o-ring（right） rubber

Table1. Experimental results

	O-ring	Rubber	Spaghetti
Before learning			
Average grasping amount [g]	9.19	12.35	15.47
Average reward	0.14	28.35	-15.23
After learning			
Average grasping amount [g]	25.80	24.89	43.70
Average reward	50.30	60.79	53.29

Table2. Evaluation index

	O-ring	Rubber	Spaghetti
Mean absolute error [g]	14.62	11.82	21.66
Mean squared error [g^2]	319.02	216.40	778.85
Standard deviation[g]	17.37	13.80	27.19
Maximum error [g]	58.47	51.65	76.47
Minimum error [g]	0.01	0.62	0.31

5-2. consideration

Table3. Error distribution

	0～10.0	10.1～20.0	20.1～30.0	31.1～40.0	41.1～
O-ring	37	38	20	3	2
Rubber	46	41	11	0	2

Although the rewards in Figure 6 should increase with each learning session and approach 100, they did not increase as expected after 2000 sessions in this experiment. However, Table 1 shows that the average rewards for the o-ring and rubber band are better after learning than before learning, indicating that learning has an effect. Therefore, it is conceivable that the rewards may approach 100 with further learning. Table 2 shows that both the o-ring and the rubber band show less variation than the spaghetti. However, since we were concerned about the size of the maximum error, the distribution is summarized in Table 3.
The maximum error was 5% above 30 g, suggesting that further study is needed.

6. Conclusion

In this study, we verified a system that enables grasping of food strings. As a result, it was confirmed that the grasping accuracy was increased by deep reinforcement learning, but it was found that this study alone was not sufficient to validate the system. In the future, we will search for more suitable products that can be used as food strings and improve the system. We will continue to search for more suitable products that can be used as food strings and to improve the system.

References

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