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Robust Trash Can Lid Opening System

Kosei Isomoto*, Yuga Yano*, Yuichiro Tanaka†, and Hakaru Tamukoh*
*Graduate of Life Science and Systems Engineering, Kyushu Institute of Technology Japan
†Research Center for Neuromorphic AI Hardware, Kyushu Institute of Technology, Japan

***Abstract*—In recent years, home service robots have gained attention due to the growing aging society around the world. Furniture recognition and handling are essential for home service robots. Home service robots need a specific approach for each piece of furniture. One such task is to collect a trash bag from a trash can. During collecting the trash bag, a robot has to recognize and open the trash can lid. The existing method for opening a trash can lid uses You Only Look Once for lid recognition. However, this method does not recognize the lid handle orientation and height, and the size of the trash can has to be predetermined. Therefore we propose a robust recognition and opening system regardless of trash can types (color and height) and lid orientations. We conduct experiments with the system robustness against three lids, two trash can heights, and six handle orientations. The experimental result shows that our system successfully recognizes and opens the lids with a success rate of over 70%. The existing method can not adapt to a trash can height changes without manually adjusting. Therefore, we conclude our system is more robust than the existing method.**

I. Introduction

In recent years, the demand for automation of work has grown against the shortage of manpower caused by the aging society with a declining birthrate. As a result, the market for service robots is expanding [1] and various research on service robots is conducted [2-8].

Furniture recognition and handling are essential for home service robots. To handle furniture, it is necessary to estimate a grasping point. Some methods that estimate the grasping point of an object and approach it use deep learning (DL), such as Dense Fusion [9] and Volumetric Grasping Network [10] to estimate the point. However, it is difficult to use these approaches for furniture in general, because the position to be grasped varies greatly depending on the type of furniture, such as height and shape. In addition, to apply the DL-based methods to many types of furniture, a large number of data need to be prepared and trained, which is not practical due to the enormous amount of time involved.

One of the handling furniture tasks is to collect a trash bag from a trash can. Before collecting the trash bag, a robot has to recognize and open the trash can lid. Shah et al. [11] proposed a system that uses DL-based object recognition to open trash can lids. In this method, a robot hand is moved above a trash can lid, and a camera attached to the hand is pointed to capture an image of the lid. The image is processed with You Only Look Once [12] to detect the position of the lid. The system determines the position for the hand to approach based on the center position of the lid and the previously measured height of the trash can. Then, the robot hand is moved to that position. The hand then grasps the lid and opens it. In this method, the height of the trash can must be known in advance, and if the height changes, the parameters in the system must also be changed manually. Moreover, the system does not recognize the posture of the handle, hence the robot cannot adapt to all postures of the handle.

In this study, we propose a trash can lid opening system that is robust to changes in the type of trash can and the posture of the lid handle by focusing on the geometric shape of the handle without requiring training. We verify the effectiveness of our proposed system using real-world equipment.

II. Proposed methods

This section describes our trash can lid opening system using depth images. Fig. 1 shows an overview of the proposed system. In this system, images are acquired from the RGB-D camera mounted on the robot (Fig. 1(a) and (b)). The depth images, which are not affected by the color of objects, are used for processing to recognize lid handle position and posture (Fig. 1(c)-(e)). Finally, the robot moves the robot hand to the estimated position and opens the lid (Fig. 1(f)).

Fig. 2 shows the process in our method where a region of the image is extracted and transformed into an edge detected image. Both ends of the contour of the handle in the image are detected as the vertices (x_1, y_1) and (x_2, y_2). As shown in Fig. 3, we denote the horizontal distance between the vertices as Δx and the vertical distance as Δy and calculate the angle θ of the handles using (1).

$$\theta = \arctan(\Delta y/\Delta x) \tag{1}$$

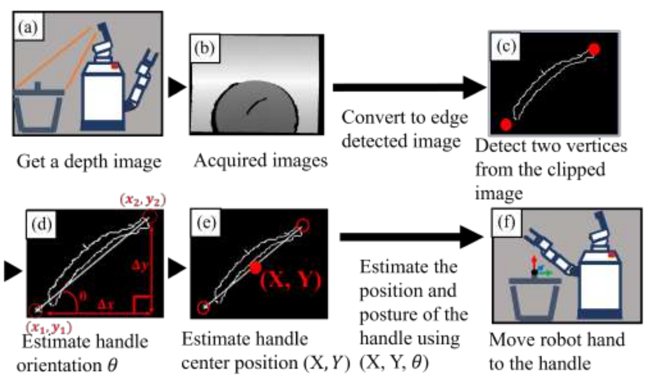

Fig. 1. Overview of the proposed trash can lid opening system

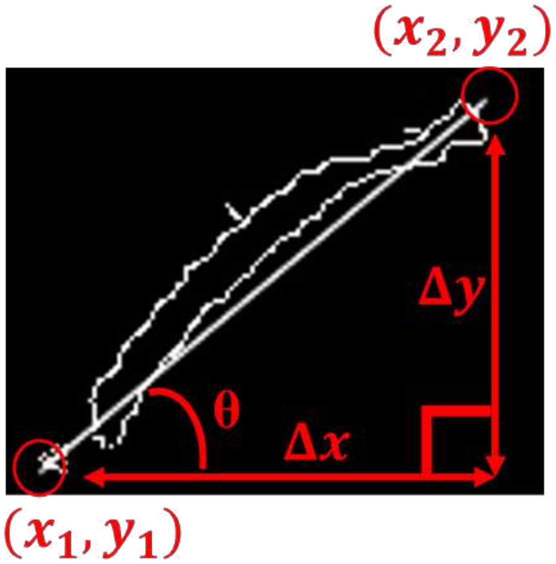

Fig. 2. Calculation of the angle of the handle from the two outermost vertices

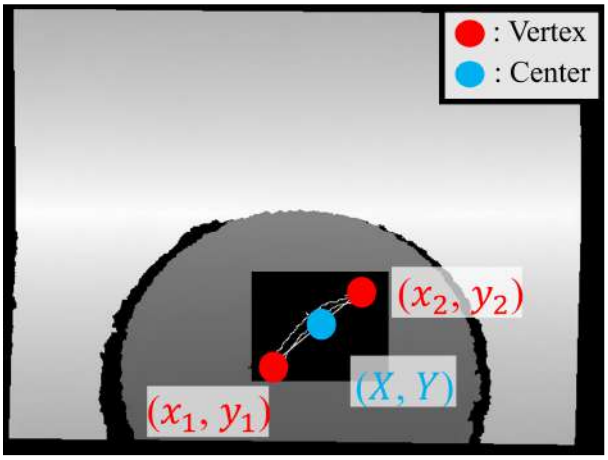

Fig. 3. Calculation of the center coordinates of the handle from the two vertices

Fig. 3 shows how to compute the center coordinates (X, Y) for the robot hand to handle. The coordinates (X, Y) are calculated using (2) and (3), as the centers of the vertices.

$$X = (x_1 + x_2)/2 \tag{2}$$

$$Y = (y_1 + y_2)/2 \tag{3}$$

The center position of the handle in 3D space is estimated from the principle of a pinhole camera using the center coordinates (X, Y), depth information, and parameters inside the camera. The axis that is perpendicular to the floor is the yaw axis (shown in the red axis in Fig. 4), and the rotation of that axis is the yaw angle. Assuming that the trash can is placed perpendicular to the floor, the yaw angle of the handle can be approximated by the angle θ. Note that in Fig. 5, the coordinate axes are shifted 10 cm parallel to the top of the trash can for visualization. The positional relationship between the robot and the trash can is shown in Fig. 5. MoveIt [13] is used to generate a route to approach the estimated position and posture of the handle in 3D space.

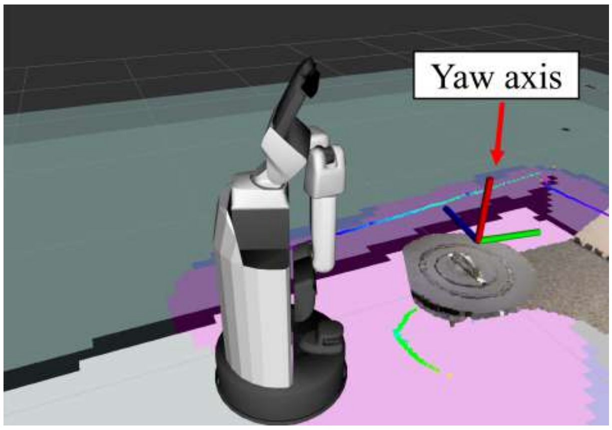

Fig. 4. Estimated 3D spatial position and posture of a trash can handle in the 3D environment

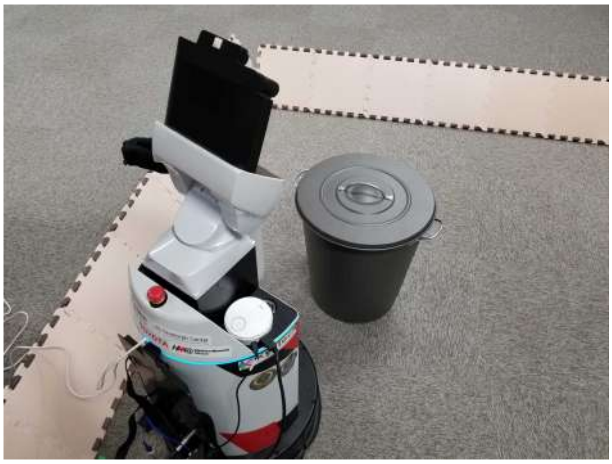

Fig. 5. Location of robot and trash can

III. Experimental Result

We conducted an experiment to evaluate the performance of the proposed system in terms of robustness against variations in lid type and handle posture.

A. Experiment Environment

We set angle reference lines on a platform whose height could be changed as shown in Fig. 6, and placed a trash can lid on top of it.

B. Human Support Robot

We conduct this experiment using Human Support Robot (HSR) [14]. HSR is a robot developed by Toyota Motor Corporation to support daily lives. Fig. 7 shows an overview of the HSR hardware. An RGB-D camera is mounted on the top

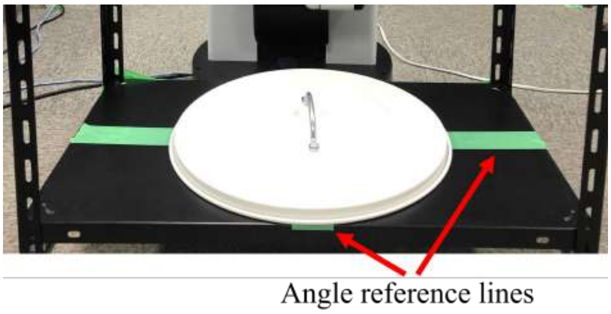

Fig. 6. Experiment environment

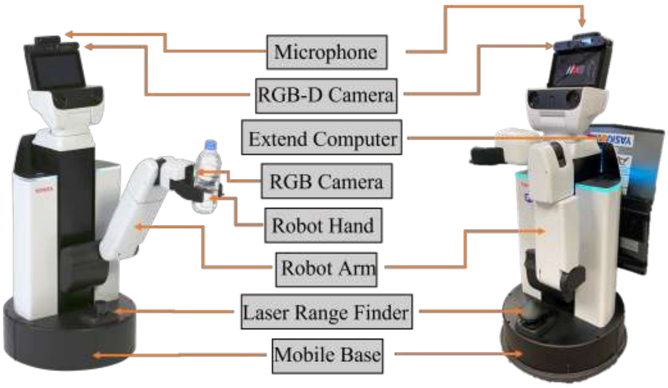

Fig. 7. Overview of HSR

of HSR, and a camera is mounted on the hand to recognize the grasping position. HSR can be equipped with a laptop computer with a graphics processing unit for image processing and others.

C. Experiment Method

The experiment involved performing handle recognition and manipulation three times for each combination of conditions as indicated in Table I. The success criterion in the experiment was defined as lifting the bottom surface of the lid to a position where it is not in contact with the platform. We used three types of lids as shown in Fig. 8. For the trash can lids, Lids A and B had the same handle shape but different lid colors, and Lid C was prepared as a lid with a different handle shape from Lids A and B.

D. Experiment Result

The respective success rates for different lid heights and types are shown in Table II. Experimental results show that our proposed system has a success rate of more than 70 % for all heights and lid types.

TABLE I
EXPERIMENT SETTINGS

Height [mm]	210, 383
Orientation [deg]	0, 30, 60, 90, 120, 150
Number of lid type	3(see Fig. 8)

Fig. 8. Lids used in the experiment (**Left**: Lid A, **Center**: Lid B, **Right**: Lid C)

TABLE II
SUCCESS RATE OF THE EXPERIMENT

Height [mm]	Lid A [%]	Lid B [%]	Lid C [%]
210	77.8 (14/18)	72.2 (13/18)	88.9 (16/18)
383	72.2 (13/18)	88.9 (16/18)	100.0 (18/18)

IV. DISCUSSION

If the same experiment is conducted to evaluate Shah's method needs manual adjusting due to the inability to cope with changes in the height of the trash cans. On the other hand, our method can adapt to changes in the height of the trash cans automatically and shows that the success rate is over 70 % for all combinations of lid types and heights. Therefore, the proposed method is more robust against the types of trash cans and the postures of their handles compared with Shah's method.

One of the reasons for the failure in lifting the lid was an error in the estimated distance from the camera to the handle. This sometimes caused the hand to approach the lid too close. For Lids A and B, the position obtained from (2) and (3) sometimes indicated the lid below the handle, rather than the handle. This was because the handle width was narrow and the point (X, Y) for the depth estimation was not on the handle but on the lid. This error resulted in a lower success rate for Lids A and B than for Lid C. In addition, since the tilt angle of the camera was not set to a fixed value, the amount of displacement of the depth information varied from experiment to experiment, which may have affected the difference between the results for Lids A and B.

In the experiment, the success rate differed depending on the height of the lid. For Lids B and C, the depth image was noisy when the camera was far away, and the recognition of the handle and the estimation of the depth became unstable.

V. CONCLUSIONS AND FUTURE WORKS

We proposed a method that performs robust trash cans recognition. Our method displays robustness against the type of trash can and the posture of the lid. In addition, because the proposed method does not require training of furniture, we conclude that the proposed system is more effective in terms of implementation time compared to DL-based methods, which require the preparation of appropriate data for furniture in the home environment. Since our method is based on geometric information, we believe that our proposed method can generalize to any objects with similar handles. In the future, we will verify this hypothesis with other types of furniture such as doorknobs and drawer handles.

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