Estimating Door Shape and Manipulation Model for Daily Assistive Robots based on the Integration of Visual and Touch Information

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***Abstract*— We propose a method for a robot to manipulate an unknown door based on a single user instruction. The primary contributions of this paper are (i) to reduce the user instruction to a single click and (ii) to develop an efficient method to estimate an appropriate shape and manipulation model for a target door by integrating visual and touch information obtained by a robot. The proposed method first detects door candidates using a 3-D camera and then estimates the manipulation model of each candidate based on prior learning results. During door manipulation, the system integrates visual and touch information to estimate the shape and manipulation model to generate an appropriate motion. We evaluated the proposed method experimentally, and the results prove that the proposed method is effective.**

I. INTRODUCTION

Daily assistive robots are expected to play an important role in aging societies. Techniques to simplify remote-control of such robots to manipulate environments and objects will be key to helping the elderly and handicapped live independently. If a user with restricted mobility can instruct a robot via a human-machine interface (HMI), it will be possible for the robot to perform tasks this user is unable to perform themselves. Therefore, we are developing HMI techniques to simplify the remote control of daily assistive robots [1][2][3].

The ability to open a door expands the scope of such support robots because it would support not only wheelchair users to open out of reach doors, but also robots to move to different rooms, open shelves and operate appliances. Therefore, we propose a method that enables a remote-controlled robot to operate a door from a single user instruction.

The experimental environment, the robot, and the operating terminal (e.g., a personal computer or a tablet) are shown in Fig. 1. The robot and terminal are connected via a wireless network. An image captured by the robot is displayed to the user via the terminal's graphical user interface (GUI). The proposed method enables the robot to open an unknown door when the user selects (hereafter "clicks") the door handle in the image.

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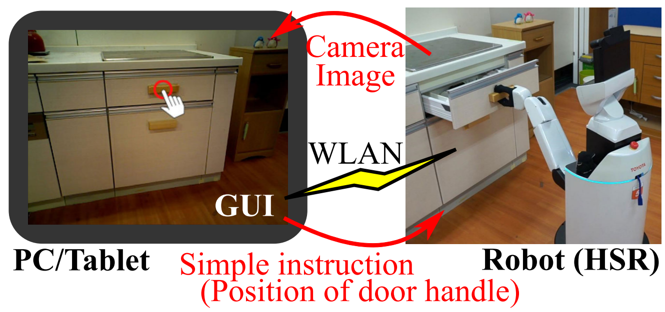

Fig. 1. Experimental environment

In this task, the robot must autonomously estimate unknown information required to determine how to open the door. The unknown information includes the position and shape of the door and door handle, as well as a manipulation model, i.e., a model that represents how the door must be operated. When objects have multiple doors, determining the shape of a single door without prior information is difficult. Even with doors that appear similar, it is often difficult for humans to operate drawers or right-hinged doors.

Therefore, we have developed a method to estimate the shape of doors efficiently using an RGB-D camera. Note that we make several assumptions about doors. We also use the sense of robot's hand when manipulating a door to determine more effective parameters.

The primary contributions of this study are as follows.

- We enable a remote-controlled robot to open an unknown door based on a single click, which reduces user burden.
- We proposed a method that estimates the manipulation method for an unknown door quickly. The proposed method integrates a visual estimation and the robot's hand sensory data during manipulation. The proposed method was evaluated using various types of doors.

II. RELATED WORK

Most doors are structured to be partially fixed in the environment. Therefore, if a robot does not plan a hand trajectory that corresponds to the door's structure, it cannot open and close the door. In addition, inaccurate trajectories can damage both the door and the robot. To calculate an accurate hand trajectory, various data, such as the position, direction, shape, and manipulation model of the door, are required. Here, the manipulation model involves how the door must be operated, e.g., drawers and right or left hinges.

It can be difficult for a user to provide all necessary information remotely; therefore, some studies have investigated providing prior information or enabling the robot to estimate such information autonomously.

Previous studies [4][5][6][7] reported methods that enable remote controlled disaster response robots to open doors with few inputs. However, this was possible because the door's shape and manipulation model, i.e., a hinged door, were known or it was assumed that there was no door closer and the door could be opened by simply hooking the robot's hand to the knob. Thus, generalizing such methods to a broader range of doors and drawers is difficult.

Azuma et al. [8] developed a method to instruct a robot to operate an unknown door remotely using an HMI with a multi-touch terminal. With this method, the user can teach the robot appropriate hand trajectories directly. However, this method did not model the structure of furniture; thus, complicated instruction was required for each operation.

Other studies have proposed methods that enable a robot to estimate the structural parameters of furniture autonomously. For example, Kojima et al. [9] obtained the manipulation model of furniture whose geometric shape and 3-D features are known by visually recognizing the trajectories of furniture parts when people are operating them. Pillai et al. [10] obtained the orbit knowledge of a door from a manual demonstration based on feature tracking. Sturm et al. summarized their approaches to estimate moving structures [11], and they proposed a method to estimate the structure of a general multi-link system by observing the system while operated by a person. Another study [12] indicated that the trajectory of the rectangular doors can be estimated even if the precise shape is unknown. In addition, markers have been employed to address doors with complex shapes [13]. However, the purpose of our study is to enable a robot to manipulate unknown furniture based on remote instruction from a user. Therefore, it is impossible to use methods that require prior human demonstrations. Using the same visual function when the robot is operating a door is conceivable; however, a shielding problem due to the hand could occur or the sensor observation range could be problematic if the robot is too close to the door.

Other studies have investigated methods that allow a robot to partially estimate parameters autonomously when a person communicates information cues remotely. Haynes et al. [14] proposed a method that enabled a robot to operate an unknown hinged door with click instructions for the door handle and hinge under the condition that only one door exists on the same plane. Another system [15] also succeeded in operating an unknown hinged door; however, that system required six clicks. The proposed method only requires the user to provide door handle position information via a single interaction because the robot estimates the other required information autonomously.

Klingbeil et al. [16] proposed a method to learn the appearance features of door handles to estimate manipulation models. However, the method employed to estimate the movable axis, which is required to determine an appropriate hand trajectory, was not described in detail.

Sturm et al. proposed a method to estimate a door's structure during a robot's door operation [17]. This method acquires a kinematics model of the door from the robot's hand coordinates when manipulating the door using a flexible arm. This method does not depend on vision data; thus, it avoided the shielding problem. However, parameter estimation based on only touch information requires sufficiently fast impedance control or flexible hardware [18], which are not common in current daily assistive robots.

The proposed system uses touch information from the robot during manipulation. In addition, prior to the manipulation, the proposed system estimates the shape of the door and manipulation model using visual information captured by the robot's RGB-D camera. By using these multiple information sources, it is possible to estimate effective parameters and enable a general robot to operate a door based on a single click instruction.

III. Door Manipulation Based on Single Click Instruction

Here, the main problem is that a robot does not possess the shape and manipulation model (drawer or right-hinged door, etc.) of an unknown door. Therefore, the proposed system assumes that all trajectories calculated from all shape and manipulation model candidates can potentially be correct and expresses the possibility as a score. This score addresses problems related to uncertainty and estimation efficiency because it is calculated using the robot's vision system and touch information obtained during manipulation.

A. System Overview

Figure 2 shows an overview of the proposed method. The robot is at a position where the target door can be seen in the initial state. Using the GUI, the user clicks on the handle of the door in the image captured by the robot. Clicking the door handle is considered a natural style of instruction because users normally find and reach for the door handle when they operate a door themselves. The information provided by this click is also useful for calculating a Door feature and parameters for the robot's motion. The clicked position and point cloud obtained from the robot's RGB-D camera are the initial inputs to the system. When the "Grasp planner[1]" receives the inputs, it estimates the direction of the door handle, calculates how to grasp the handle, and communicates the result to the "Shape, manipulation model estimator (based on vision)" (SME-V). Simultaneously, the "Door candidates estimator" detects door candidates $\{D_m\}$ and sends the results to the SME-V. This visual function is explained in Section IV-A.

Then, the SME-V calculates hand trajectory candidates $\{\boldsymbol{p}_j^{(D_m,\Theta_k)}\}$ for door candidate D_m and a manipulation model Θ_k. The SME-V also uses the direction of the door

[1] Japanese patent JP5983506

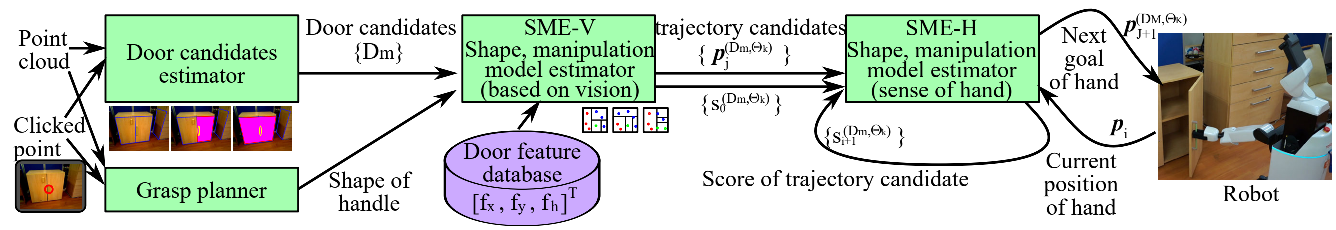

Fig. 2. Overview of the proposed method

handle and outputs the score of each trajectory candidate based on vision $s_0^{(D_m,\Theta_k)}$. This score expresses the possibility that door candidate D_m is of manipulation model Θ_k and is calculated using the learned "Door feature database." This calculation is described in Section IV-B.

Then, the robot grasps the handle and begins operating the door. The "Shape, manipulation model estimator (sense of hand)" (SME-H) uses touch information obtained during the operation and corrects the hand coordinates to a more correct trajectory, which is achieved by updating the score of each trajectory candidate $s_{i+1}^{(D_m,\Theta_k)}$ during operation. The details of this method are described in Section V.

The proposed method uses both the visual and touch information to calculate the "Score of trajectory candidate" $\{s_{i+1}^{(D_m,\Theta_k)}\}$ and update the score during operation for future trajectory calculations.

B. Terms and Symbols

Here, the terms and symbols used in this paper are defined. We denote a set or series by enclosing variables in brackets $\{\}$.

- Door shape: uniquely represents the shape of the door in the environment. As described in Section IV-A, we assume that the door is a rectangle. Therefore, the door shape is represented by the position and orientation of the door's center and its width and height. The m-th door shape candidate and the candidate set are denoted D_m and $\{D_m\}$, respectively.
- Manipulation model: indicates how to operate the door. The k-th manipulation model is denoted Θ_k. For example, a drawer and right-hinged door are denoted Θ_D and Θ_R, respectively.
- Trajectory: the series of hand target coordinates $\{\boldsymbol{p}_j^{(D_m,\Theta_k)}\}$ calculated using the door shape and manipulation model, or the series of the hand's actual coordinates $\{\boldsymbol{p}_j\}$.

IV. TRAJECTORY ESTIMATOR BASED ON VISION

In this section, we describe the details of the door candidates estimator and the SME-V.

A. Door candidates estimator

The door candidates estimator inputs a 3-D point cloud of the environment obtained from the robot's RGB-D camera and outputs door candidates. To realize efficient calculation, we employed the following hypothesis.

1) The groups of planes, including a door and a wall surface, are orthogonal to the floor surface in the room (expanded Manhattan World Hypothesis).
2) A door is a rectangle that is horizontal or vertical to the floor surface.

Using the above hypothesis, it is possible to detect a door on a wall that intersects vertically and a rectangular parallelepiped door placed parallel to such a wall surface. The details of the door detection method using this hypothesis are as follows.

1) When the point cloud obtained from the RGB-D camera is input, noise is reduced using a bilateral filter and the normal direction of each pixel is calculated.
2) The normal direction is clustered and each plane whose normal direction is perpendicular to the floor surface is extracted as a plane candidate (including a door).
3) For each plane candidate, a corresponding 2-D plane is generated using the obtained 3-D point cloud and normal direction.
4) Edges on the 2-D plane are detected using the Canny operator.
5) Stochastic Hough transform is employed to detect straight edge elements that are vertical or horizontal to the floor surface.
6) The closed loops of the quadrangle comprising the detected straight edge elements are calculated and output as door candidates.

The left two columns in Fig. 3 show processing result examples obtained by the proposed method, where the shapes superimposed with blue lines represent the detected door candidates. As can be seen, eight and four door candidates are detected in the left and middle columns, respectively. When the door handle is clicked by the user, the door candidate that includes the handle is searched and sent to the SME-V as the output of the door candidates estimator. Here, when the handle in the right side of Fig. 3(B) Furniture 2 was clicked, the outputs were D_1 and D_2, as shown in the right column of Fig. 3. Compared to an existing method using dense 3-D point clouds obtained from a tilting laser scanner [19], the proposed method has a lower computational cost.

B. SME-V

As mentioned in the previous section, the SME-V inputs door candidates $\{D_m\}$ and the shape of the door handle as obtained by the Grasp planner and outputs the score

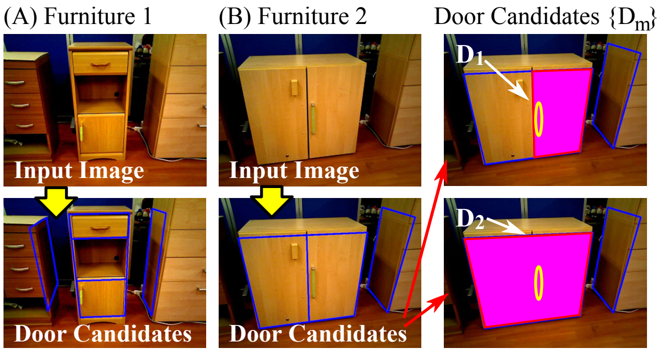

Fig. 3. Detected door candidates and candidates that include the pointed door handle $\{D_m\}$

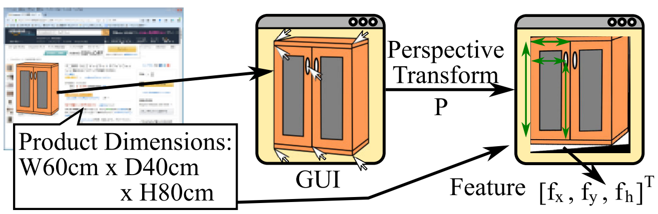

Fig. 4. Obtaining doors' features from online market webpages

$s_0^{(D_m,\Theta_k)}$, which expresses the possibility of door candidate D_m being of manipulation model Θ_k.

To obtain the above input and output, we first designed a door feature $\boldsymbol{f}(D_m)$ that represents the property of door candidate D_m. It is assumed that the door handle is attached to a position such that a person can easily operate the door, e.g., where it is possible to operate with a small force. Since the position of the handle is likely to be related to the manipulation model in many cases, the position is used as a feature in the proposed method. The orientation of the handle is also considered to be attached in a direction that allows a person to easily grip the handle for operation, and this orientation is also used as a feature in the proposed method. Door feature $\boldsymbol{f}(D_m)$ is expressed as follows.

$$\boldsymbol{f}(D_m) = [f_x(D_m), f_y(D_m), f_h(D_m)]^T \tag{1}$$

Here, $f_x(D_m)$ and $f_y(D_m)$ are calculated as follows.

$$\begin{cases} f_x(D_m) = H_X/L_W, \\ f_y(D_m) = H_Z/L_H, \end{cases} \tag{2}$$

where L_W and L_H represent the width and height of the door, and H_X and H_Z represent the horizontal and vertical position of the handle, respectively. f_h represents the direction of the door handle. This feature utilizes the property of a door that its shape and height are not changed when the furniture is moved.

The relationship between this feature and the manipulation model is learned preliminarily using random forests [20] to construct an estimator. When creating a door feature database for learning, manually measuring actual furniture is the simplest way to obtain appropriate data. Although collecting accurate data is possible with this method, this approach is time-consuming and requires actual furniture to measure. Therefore, it is unsuitable for collecting a large amount of data.

Therefore, we employed method that utilizes product photographs and size information from online furniture market webpages. Since the information from online market webpages can be referenced without purchasing furniture, it is suitable for collecting large amounts of data. However, such webpages typically contain only external size information, which differs from the data required for our database. Therefore, we constructed a system that utilizes photographs of furniture to calculate the required dimensional information (Fig. 4).

1) The system displays a photo of the furniture in the GUI.
2) The user clicks the four vertexes on the front of the furniture, the two diagonal vertexes on the door, and the position of the handle.
3) The user inputs the width and height from the external size information obtained from the webpage. The user also inputs the direction of the handle for f_h.
4) The system calculates perspective transformation P that makes the four points of the furniture's front face fit the input external size information.
5) The system obtains L_H, L_W, H_X, and H_Z using P to convert the two diagonal vertexes and the handle position of the input door. Finally f_x and f_y are calculated.

Note that this interface assumes furniture with a rectangular parallelepiped shape.

When unknown door D_m and the direction information of the handle are input, the estimator generates an estimated manipulation model using random forests and outputs the ratio of the decision trees that generate manipulation model Θ_k for each door candidate D_m as the score $s_0^{(D_m,\Theta_k)}$ for each trajectory. Furthermore, the system calculates trajectory $\{\boldsymbol{p}_j^{(D_m,\Theta_k)}\}$ using the shape of door candidate D_m and manipulation model Θ_k.

V. TRAJECTORY UPDATER BASED ON SENSE OF HAND

This section describes the details of the SME-H module. Note that it is effective to use visual and touch information obtained by the robot to deal with a door whose exact trajectory is unknown because different doors have different manipulation models even though they may have similar appearance.

Therefore, the proposed system uses the trajectory with high score calculated from the SME-V as the initial target trajectory, and then manipulates the door via impedance control with low frequency. During this manipulation, the score of each trajectory is updated sequentially using the touch information, and the target trajectory is changed to the one with a high score.

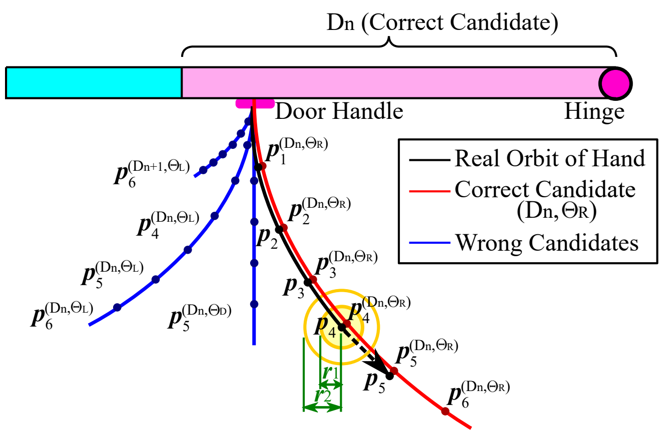

Fig. 5. Estimation of the appropriate trajectory to manipulate a door based on hand position

When the target trajectory is represented as a series of hand target coordinates $\boldsymbol{p}_j^{(D_m,\Theta_k)}$ (hereafter referred as a target), and the operation to close the hand around one of the targets is defined as a single step, the proposed method can be described as follows.

At the $i+1$ step ($i = 0, 1, ...$),

1) A door candidate and manipulation model pair (D_m, Θ_k) with high score $s_i^{(D_m,\Theta_k)}$ is selected. When the pair is represented as (D_M, Θ_K), the target coordinate $\boldsymbol{p}_J^{(D_M,\Theta_K)}$ in $\{\boldsymbol{p}_j^{(D_M,\Theta_K)}\}$ that is closest to the current hand position $\boldsymbol{p}_i$ is searched.
2) The robot moves its hand to the target coordinate $\boldsymbol{p}_{J+1}^{(D_M,\Theta_K)}$, which is the next target to the found target $\boldsymbol{p}_J^{(D_M,\Theta_K)}$. The robot uses impedance control with an elastic element of zero only in the direction orthogonal to the direction the door is pulled. This control is designed such that the hand's movement follows the correct door trajectory. Note that we confirmed in the experiments in Section VI that the frequency of this impedance control does not have to be very high.
3) The score is updated according to the distance between hand position $\boldsymbol{p}_{i+1}$ and the position of the target coordinate $\boldsymbol{p}_{\tilde{J}}^{(D_m,\Theta_k)}$ closest to $\boldsymbol{p}_{i+1}$. The rule to update the score is as follows.

$$\begin{cases} s_{i+1}^{(D_m,M_k)} = s_i^{(D_m,M_k)} \cdot C, & (\text{when } r_{i+1,\tilde{J}}^{(D_m,M_k)} < r_1), \\ s_{i+1}^{(D_m,M_k)} = s_i^{(D_m,M_k)} / C, & (\text{when } r_{i+1,\tilde{J}}^{(D_m,M_k)} > r_2) \end{cases} \quad (3)$$

Here, $r_{i+1,\tilde{J}}^{(D_m,M_k)}$ is the distance between $\boldsymbol{p}_{\tilde{J}}^{(D_m,\Theta_k)}$ and $\boldsymbol{p}_{i+1}$, C is a constant greater than 1 used to update the score, r_1 and r_2 are positive constants used to evaluate orbital distance, and $r_1 < r_2$.
4) $i+1$ step is finished. If the manipulation is not completed, the system returns to 1) and continues $i+2$ step's manipulation.

Figure 5 shows a situation in which the current hand coordinate is $\boldsymbol{p}_i = \boldsymbol{p}_4$, and the correct pair of shape and manipulation model is (D_n, Θ_R). Note that point $\boldsymbol{p}_4^{(D_n,\Theta_R)}$ of right-hinged door is close to the current hand position $\boldsymbol{p}_4$. Therefore, the score for trajectory (D_n, Θ_R) is increased. On the other hand, the scores for the drawer (D_n, Θ_D) and the left-hinged door with incorrect shape (D_{n+1}, Θ_L) are reduced. Since the trajectory candidate with the highest score is (D_n, Θ_R), the next target is set to $\boldsymbol{p}_5^{(D_n,\Theta_R)}$ of the right-hinged door.

VI. EXPERIMENTS AND DISCUSSION

We implemented and evaluated the proposed method using a daily assistive robot. The experimental results and a discussion are provided in this section.

A. Basic SME-V Experiment

First, SME-V was trained to create a manipulation model estimator (Section IV) and evaluated.

For the SME-V learning data, 36 items were collected: (a) six items were manually measured and (b) 30 items were collected from shopping webpages. Note that there were 12 items for drawer (Θ_D), left hinge (Θ_L), and right hinge (Θ_R).

In this basic experiment, cross validation was performed using two-thirds of the data as training data and one-third as test data. In this experiment, the estimation success rate was calculated as the correct answer when the manipulation model with the maximum score matched the actual manipulation model. The estimated success rate, which was calculated as the average of three verifications, was 91.7%. This is sufficient estimation accuracy because the manipulation model is estimated by both the SME-V and SME-H in the proposed system.

Note that the SME-V constructed in this experiment was used in the experiments discussed in the next subsection.

B. Integrated Experiment

We implemented and evaluated the proposed method using Toyota's Human Support Robot (HSR, Fig. 1), which the authors are developing [1][2][3]. The HSR has an arm with four degrees of freedom, an end effector, and a moving base that can move in all directions and rotate. Xtion PRO LIVE, an RGB-D camera, is mounted on its head. The six doors manipulated by the HSR in this experiment are shown in Fig. 7. Note that all of these doors were unknown to the HSR, i.e., the robot had not been trained with the parameters required for their operation. In addition, the experiment included two types of drawers of different heights and sizes (Fig. 7, upper row), two left-hinged doors of different heights, sizes, and handle shapes (Fig. 7, middle row), and two right-hinged doors of different heights and sizes (Fig. 7, bottom row).

In this experiment, we evaluated whether the robot could open a door appropriately based on the door handle position information provided by an operator using the GUI. Here, the HSR stood in front of the door in the initial state. The standing positions in the initial state for each door are shown in Fig. 6(A). These positions (Pos. 1 and Pos. 2) were chosen to evaluate whether the door shape and manipulation model can be estimated if the target door looks different relative to the standing position. In total, the evaluation comprised 12 different trials (six door types $\times$ two standing positions).

The constants $C = 2.0$, $r_1 = 30$ mm, $r_2 = 50$ mm were used, and the target coordinate was calculated every 5 cm for drawers, every 10 degrees for hinged doors. Note that the result was judged as success if the HSR opened 20 cm for drawer and 70 degrees for hinged doors.

C. Results and Discussion

The experimental results are shown in Fig. 6(B). Here, the circles indicate success. As shown, the HSR successfully opened the doors in all 12 trials. Figure 7 shows the experimental results of opening each of the six doors using Pos. 2 as the robot's initial position.

The right side of Fig. 3 shows the door candidate detection result obtained using the visual information when the large right-hinged door was manipulated from Pos. 2, and Fig. 8 shows the transition of score $s_i^{(D_m,\Theta_k)}$ of each trajectory under this condition. Here, two door candidates $\{D_m\}$ (including the door handle) were detected and six trajectories (three manipulation models) were identified as candidates. Here, the score of the trajectory with which the door can be manipulate correctly using an appropriate manipulation model (red line in Fig. 8) was greater than the scores of other trajectories at the visual score s_0. The difference between the score for the appropriate trajectory and that for an inappropriate trajectory increased at the first step and the second step. However, the score for the appropriate trajectory did not increase before the end of the operation. This is considered to be due to an error in the visual estimation of the door's shape by the vision, which may have been due to the influence of the offset of the position of the hinge relative to the door plane. When an error occurs between the true trajectory and the trajectory calculated from the correct shape and correct manipulation model, the trajectories may not be evaluated as sufficiently close. However, it was found that the manipulation could be completed even if some error was present in the visually estimated manipulation trajectory because the score of the correct trajectory will not be too far away from the hand and the scores of the other errant trajectories will fall sufficiently.

The HSR has only four degrees of freedom in its arm, therefore it needed to move the moving base cooperatively to move the hand coordinate. The frequency of the impedance control of the robot was sufficiently low for that reason; the target force and position of the impedance control were updated at every step of SME-H, i.e, every 5 cm for drawers and every 10 degrees for hinged-doors. However, the HSR could open the doors appropriately with the proposed method. The experimental results prove the effectiveness of the proposed method.

Although many pieces of furniture and room doors in households can generally be classified into the three types of door manipulation models evaluated in this experiment, other types of doors can be operated using the proposed method, such as ovens with bottom-hinged doors.

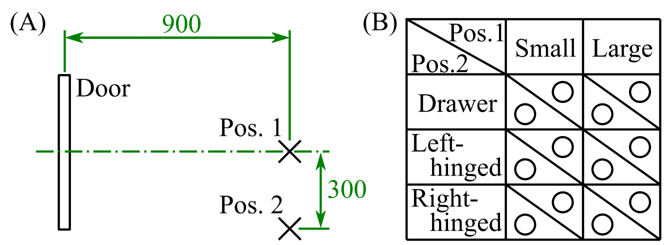

Fig. 6. (A) Start position for each experiment and (B) experimental results

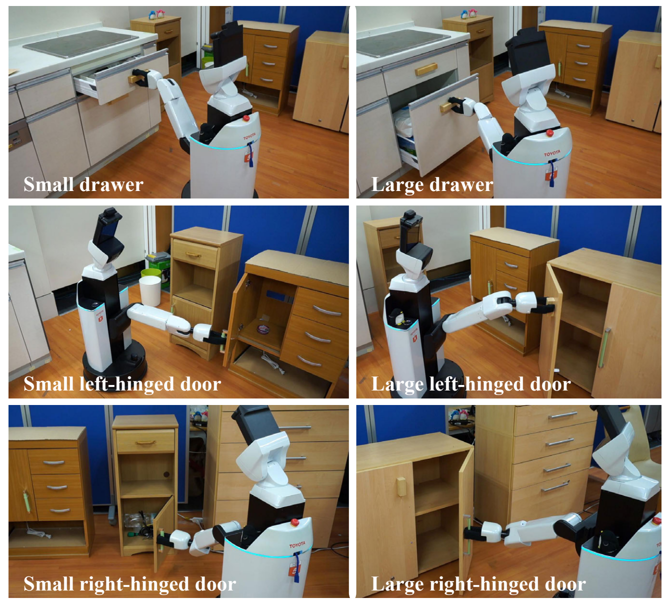

Fig. 7. Experimental results of manipulating various known doors

The limitation of the proposed method depends on the limitation of the Door candidates estimator's abilities. For example, when a door is transparent, most RGB-D cameras cannot observe an appropriate door plane and therefore door candidates cannot be detected. In this case, it is necessary to switch to a method in which a user teaches the position of a hinge and manipulation model manually.

VII. CONCLUSION

In this paper, we have proposed a system that enables a daily assistive remote control robot to manipulate unknown doors based on only a single click from the user. However, to realize this, the shape of the target door and an appropriate manipulation model must be known.

Therefore, we have proposed a method to express the possibility as a score for the operation trajectory calculated from all door candidates and manipulation models. This score is calculated using the robot's visual system and is updated using touch information obtained during manipulation of the door.

Evaluation experiments using the HSR confirmed the effectiveness of the proposed method with various unknown

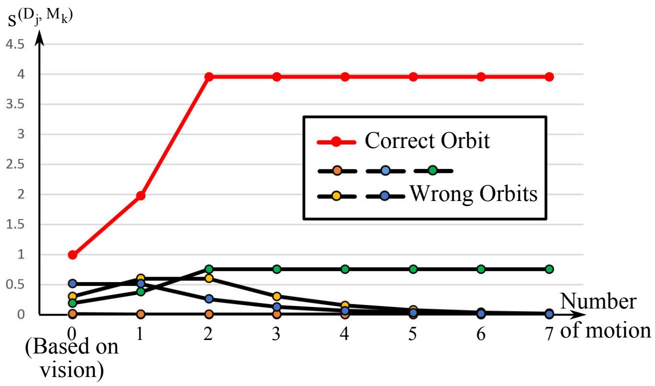

Fig. 8. Transition of $s^{(D_j,\Theta_k)}$ during manipulation of the large right-hinged door (initial position: Pos. 2)

door operations. Uncertainty and estimation efficiency issues were addressed by integrating the visual and touch information obtained by the robot.

For future work, we will integrate the proposed method with the previous method [3] to teach a robot the shape and manipulation model of a door manually using GUI. When the measurement of the door using the RGB-D camera is impossible, e.g., the target door is transparent, the robot cannot operate the door with the proposed method. However, if a robot can autonomously decide that it can operate a door by itself or it should ask a user more detailed operations, the robot will expand the capability of manipulation while the user instruction will be simpler. In addition, it will be effective for some doors to use the proposed method repeatedly. A hinged door that can be opened by twisting the handle is considered to be a combination of objects with a hinge. Since there are various types of handles, it is considered that the proposed method to use visual and touch information is effective. For this situation, the door candidates estimator should be replaced with a handle candidates estimator.

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