A Learning Method for a Daily Assistive Robot for Opening and Closing Doors Based on Simple Instructions

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Abstract— **Remote-controlled daily assistive robots that can help handicapped individuals are expected to be a key technology in supporting aging communities. We present a method to simplify user instruction via a human-machine interface for robotic manipulation of various types of doors. Using our system, the user can teach the robot to open an unknown door by just a few clicks on an image generated from the robot's perspective. After the teaching stage, the robot is able to manipulate the door based on just a single user click on the position of the door handle, and an instruction determining if the door is to be opened or closed. The contributions of this paper to the research area are to (i) present a method to detect door candidates effectively from the point cloud of the surrounding environment using hypotheses on the plane and the shape of doors, to (ii) introduce a door feature to learn and remember the manipulation model, and to (iii) implement the system on a daily assistive robot and evaluate it. We tested our system on doors with various shapes and manipulation models, obtaining results supporting the effectiveness of our approach.**

I. INTRODUCTION

Based on current technology development trends, it is likely that handicapped people who want to live independently will be assisted by robots on a daily basis. One key technology that needs to be considered in the development of these robots is the remote control method. It needs to be as simple as possible. The ability to let robots manipulate objects in a home environment can provide valuable support in daily tasks, especially for users in wheelchairs, users confined to bed, and users living away from their families. Therefore, the authors are developing approaches to simplify daily assistive robot remote control methods using Human Machine Interfaces (HMIs) [1][2].

One important task in this area is the manipulation of doors, as this skill is indispensable for allowing the robot itself to move between rooms and support the user's movement. Door manipulation is also crucial for operation of furniture, drawers and consumer electronics. In this research, we propose a method to simplify user instruction via the HMI when the user wants to make a remotely controlled robot open and close a door.

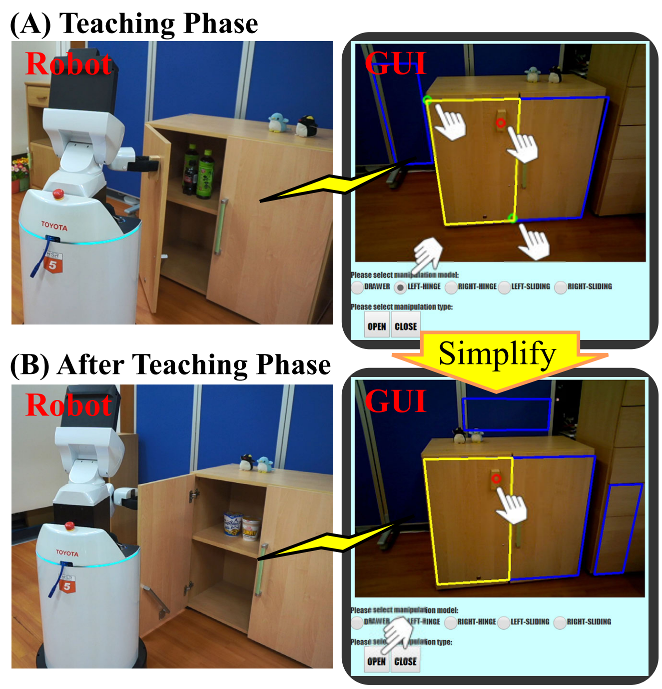

Fig. 1. Experimental environment and GUI

The robot, home environment and the operating terminal adopted in this research are shown in Fig. 1. The robot and the terminal (PC or tablet) are connected via a network. An view from the robot's perspective is presented on the Graphical User Interface (GUI). In the proposed system, the robot autonomously detects door candidates in the environment using an RGB-D camera and displays it on the GUI so that the user can easily instruct it. The user can then complete the request to manipulate an unknown door by teaching it the shape of the door with two clicks or touches (hereinafter referred to as clicks) on the GUI, the position of the handle with one click, and the operation model of the door (drawer, right-hinged door, etc.) with one click. During this process, the shape and the manipulation model of the door are memorized by the robot. Therefore, the user can request the manipulation of a known door by just clicking on the position of the handle and pushing the open or close

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button. Clicking of the handle position is considered to be natural for users because users normally find and reach for the handle when they operate doors themselves.

One of the problems in designing this system is how to detect the position and shape of the door efficiently from the environment. These pieces of information are required for the robot to propose door candidates to the user and provide the parameters for operation of the door by the robot itself. Another problem is how to remember the steps involved when manipulating doors so that the user does not have to tell the robot how to manipulate them many times.

To solve these problems, we propose a method to efficiently detect door candidates based on hypotheses about the door planes and door shapes. In addition, we propose a door shape feature, which is related to the structure of the door, and use it for learning and recalling the manipulation model.

The contributions of this research to the study area are as follows:

- A novel method to detect door candidates effectively from the point cloud of the environment is proposed.
- A novel method to learn and recall manipulation models using door features is proposed.
- A simple remote control system for daily assistive robots is constructed, and evaluated using experiments on various types of doors.

II. RELATED WORK

In a typical room, doors and some of the furniture are fixed parts of the environment. Therefore, if the robot does not calculate the hand trajectory corresponding to the door's structure, it cannot open and close the door. Forcing an incorrect trajectory could lead to the destruction of the door and the robot itself. In order to calculate the correct hand trajectory, the door's position, direction, shape and a manipulation model is required. Here, the manipulation model specifies how the door must be operated, distinguishing drawers, right or left hinges, etc.

Since it is cumbersome for the user to specify all this information for the robot, recent studies have been trying to give the robot part of the information as prior knowledge or make the robot autonomously estimate the parameters.

In related work [3][4][5][6], researchers have successfully enabled robots to open doors in disaster environments using few inputs. However, in these studies, the shape and the manipulation model of the door was given, or it was assumed that the door could be opened just by hooking the hand on the knob, and door closing was omitted. These solutions do not easily generalize to arbitrary doors and drawers.

Meanwhile, as a method to remotely instruct a robot how to operate an unknown door, Azuma et al. [7] developed a HMI for teaching a robot's hand trajectory directly from a multi-touch terminal. However, it required teaching for each operation since the structure of the furniture was not modeled.

Some research has also been done on making the robot itself estimate the structural parameters of furniture. Kojima et al. [8] proposed a furniture manipulation model, where geometric shape and the three dimensional features of the furniture are obtained by visual recognition of orbits of the furniture parts when a person manipulate them. Pillai et al. [9] also obtained the trajectory knowledge for a door by means of feature tracking during human demonstration. Sturm et al. summarized their approach for estimating a moving structure in [10]. They proposed a method to estimate the structure of a general multi-link system by observing and operating it. According to [11], the trajectory of a rectangular door can be estimated even if its size is unknown. In another study [12], markers were used to deal with complex shaped doors. Yamazaki et al. [13] proposed a method for generating a 3-D shape with an articulated link from the observation of human operation of a hinged door and a drawer, using a 3-D range camera. In contrast, the purpose of this study is to let a robot manipulate unknown furniture on basis of remote instructions from a user. Methods relying on human demonstration are not straightforwardly applicable in this problem setting. Using an observational approach as above during remote controlled operation by the robot itself is conceivable. However, limitations in the observation range of the robot's sensors and occlusion of the door by the robot's own arm as it approaches the target door would complicate such an approach.

Sturm et al. proposed a method to estimate a door's structure while a robot is operating the door itself [14]. As a robot with a flexible arm manipulates a door, this method acquires the kinematics model of the door from the hand trajectory. The above problems arising from vision are avoided by not relying on vision. This method requires hardware compliance like the robot proposed in [15] or impedance control with a sufficiently fast frequency. These features are not available in current daily assistive robots.

A study has also been made to estimate the operation model based on only visual information of the stationary door. Klingbeil et al. [16] proposed a method to learn the appearance features of handles. However, the method to estimate the movable axis, which is required to determine the hand trajectory, was not described in detail.

In light of the above, for remote-controlled robots, a method that can estimate door information based on few manual clues from a user is considered as an effective way of reducing the human burden associated with reliable acquisition of the required information. Albeit on the assumption that there is only one door on the same plane, the method described in [17] succeeded in operating an unknown hinged door from click instructions indicating the door's handle and hinge. Another study [18] also succeeded in operating an unknown hinged door from instructions given as six user clicks. These approaches are similar to this study, but the proposed method simplifies the instructions, and expands the manipulation repertoire to include door closing and drawer operation.

The proposed method efficiently detects door candidates from a point cloud representation of the environment and presents them to the user, who controls the robot remotely.

This method enables a robot to open doors and drawers based on just three clicks and the selection of a manipulation model. Furthermore, by storing the door information, subsequent operation instructions after the teaching phase are further simplified to require just a single click on the door handle followed by clicking the open or close button. This further reduces the burden on the user.

III. MANIPULATING DOORS BASED ON SIMPLE INSTRUCTIONS

This section describes the behavior of the proposed system and gives an overview of the system structure.

A. User Instructions for Manipulating Doors

The proposed GUI for simple teaching and reproduction of the door operation is shown in Fig. 1. Since the GUI is installed on a web browser, the user can instruct the robot from any mobile device or computer connected to the robot via a network. The GUI is operated by clicks in the case of a normal display setup and by touch if there is a touch screen interface.

The instructions from the user and the operation of the robot when teaching it to operate an unknown door are as follows.

1) The user moves the robot in front of the door so that the camera view of the robot captures the entire target door.
2) The image from the robot is displayed and the automatically detected door candidates are superimposed with blue lines in the GUI (as shown in the right column of Fig. 1)
3) The user first selects the door that the robot should operate. When the user clicks two vertices of the diagonal of the door (the green circles in Fig. 1 in the upper right), the door is selected and the color of the border changes (the yellow rectangle in the upper right of Fig. 1).
4) Next the user instructs the robot on the position of the door handle. When the handle is clicked, the point is displayed as a red circle (Fig. 1 upper right).
5) Finally, the user selects the manipulation model (LEFT-HINGE button in Fig. 1 upper right).
6) Based on the above instructions, the robot operates the door (Fig. 1 upper left).

Note that the manipulation model expresses how the door should be operated, e.g. as a drawer or as a left-hinged door.

After being taught the shape and operation method of the door, the robot stores the taught information. Subsequent operation of the same door can then be performed with fewer instructions. The instructions and the actions of the robot after the teaching phase are as follows.

1) The user moves the robot so that the camera captures the target door.
2) The instructions that the user has to provide now are simply to click the door handle and push the OPEN button (Fig. 1 bottom right). The robot recalls the shape of the door and how to open it by retrieving the manipulation model from memory. The remembered shape of the door is displayed as yellow lines (Fig. 1 bottom right).
3) The user can also close the door by clicking the handle of an open or half-opened door and clicking on the CLOSE button.

B. System overview

Figure 2 shows an overview of the proposed system for simple instruction and automatic reproduction of the door opening and closing mechanism. Fig. 2-(A) and Fig. 2-(B) show the system structure for the teaching phase and the post-teaching phase, respectively. The red rectangle shows the input from a user through the GUI. The modules in the green and blue rectangles are automatically processed by the robot.

For the teaching phase (A), first the Door Candidates Detector receives the RGB-D camera point cloud, and outputs the door candidates, which are then displayed to the user through the GUI. Here, a door candidate uniquely represents the shape of the door in the environment. 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 details of the method are described in Section IV. The robot observes the door handle position as instructed by the user and the Handle Grasp Planner automatically calculates how to grasp the handle stably. While grasping, the encoder and the force sensor value of the gripper are monitored for purpose of recovery in case of failure. After the robot grasps the handle, it calculates the trajectory of the end effector from the selected door shape, handle position, and manipulation model. While operating the door, the robot uses the force sensor value to determine when to terminate the manipulation.

When automatically reproducing the door operation after teaching (B), the instruction by the user is simplified: only the door handle position and the OPEN or CLOSE command are needed. Therefore a mechanism to compensate for the missing information is required. We designed the system to store the door shape, handle position, and the manipulation model and to recall them at the time of reproduction. To reproduce them, first the door candidates are detected by the same visual function as the one used at the teaching time, and the stored door shape and manipulation model are recalled using the detected candidates and the handle position. The details of this method are described in Section V. The robot finally operates the door based on the recalled door shape and manipulation model, using the same manipulation plan as was used in in the teaching phase. When the robot receives the CLOSE instruction, the robot calculates a trajectory in the opposite direction from the teaching time.

IV. VISUAL DETECTION OF DOOR CANDIDATES

In this research, the visual detection of door candidates is used to ensure that the teaching by the user is simple and automatic repetition after teaching is possible. This section describes our approach in detail.

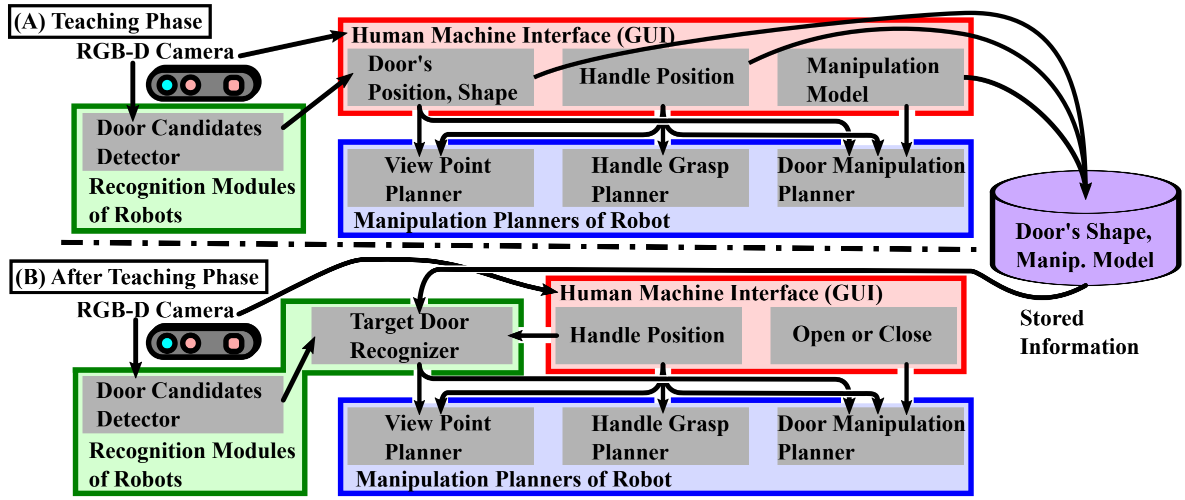

Fig. 2. Proposed system flow to teach how to manipulate doors. (A) System flow for teaching phase, (B) the flow after teaching

The Door Candidates Detector receives a 3-D point cloud of the environment obtained from the robot's RGB-D camera and outputs the door candidates. To ensure that the calculation is efficient, we employed the following hypotheses.

1) The planes containing door and wall surfaces are orthogonal to the floor surface in the room (this is the expanded Manhattan World Hypothesis).
2) A door is a horizontally or vertically oriented rectangle.

Using the above hypotheses, it is possible to detect doors as rectangular parallelepipeds vertically intersecting or running parallel to a wall surface. The details of the door detection method using these hypotheses are as follows.

1) A bilateral filter is applied to the point cloud obtained from the RGB-D camera to reduce noise, and the normal of each pixel is calculated.
2) The pixel normals are clustered, and each plane whose normal runs perpendicular to the floor surface is extracted as a plane candidate (as well as a door candidate).
3) For each plane candidate, a corresponding 2-D plane is generated using the obtained 3-D point cloud and the normal direction.
4) The edges on the 2-D plane are detected using the Canny operator.
5) The Probabilistic Hough transform is employed to detect straight edge elements that are parallel or perpendicular to the floor surface.
6) Quadrangular closed loops comprising the detected straight edge elements are calculated and outputted as door candidates.

Figure 3 shows an example of the processing steps and output of the Door Candidates Detector. Fig. 3-(A) shows the environmental setup, with the robot in front. An Xtion PRO LIVE RGB-D camera mounted on the robot was used for the experiment. Fig. 3-(B) shows the outputs of the detector, with the blue rectangles indicating the result of the door candidate detection. Fig. 3-(C) shows the robot model and the 3-D shapes of the door candidates simultaneously in the 3-D viewer.

Two types of drawers and one left-hinged door were captured in the input sensor data. One drawer was closed, the other was open, and the left-hinged door was open at 45 degrees. It can be seen in (B) and (C) that these doors' size, shape, position and angle were detected correctly. The proposed method was able to detect doors even if there were various door candidates in various positions and various angles simultaneously. The successful detection of doors opened halfway indicates that this visual function is suitable for the door closing task as well. Note that some quadrangles that are not actually doors were also detected as door candidates. In this study, the user selects the door from the candidates when teaching, and the robot searches for stored doors from candidates when repeating the task. Therefore, it is no problem that candidates not corresponding to actual doors are included in the output.

Figures 3-(D) and 3-(E) show the midstream state of the visual process. Figure 3-(D) shows the result of step of the door detection method: the plane candidates containing the door candidates were detected and the edges on the 2-D planes were extracted. Three plane candidates were detected in this experiment, and they are illustrated as white regions in (D-1), (D-2) and (D-3). The green lines in Fig. 3 show the edges detected on each plane. In (E-1) to (E-3), closed loops consisting of straight edges vertical to the floor (red lines) and straight edges horizontal to the floor (blue lines) are indicated in brown. Since the edge of the plane calculated from the normal direction image of the Xtion is very noisy, it is difficult to correctly estimate the outline of the door. However, since the proposed method extracts the edges from color images, it can estimate the correct contours. Compared to the method which uses dense 3-D point clouds obtained from a tilting laser scanner [19], the proposed method has a lower computational cost.

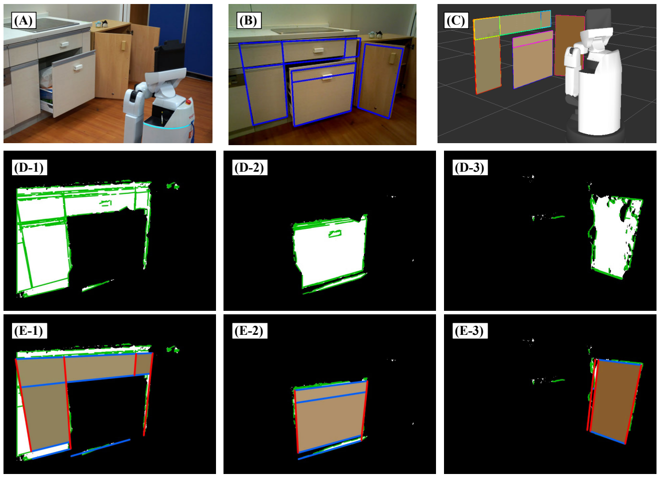

Fig. 3. The processing steps and output of the Door Candidates Detector

(A) Experiment 1

	Open Small	Open Large
Drawer	○	○
Left-hinged	○	○
Right-hinged	○	○

(B) Experiment 2

Pos.1 \ Pos.2	Open Small	Open Large	Close Small	Close Large
Drawer	M \ ○	○ \ ○	V \ ○	○ \ ○
Left-hinged	○ \ ○	M \ ○	○ \ ○	○ \ ○
Right-hinged	G \ ○	○ \ ○	V \ ○	V \ M

Fig. 4. The detailed results of (A) Experiment 1, (B) Experiment 2

V. STORING AND RECALLING DOOR INFORMATION

As described in Section III, detection of door candidates and instruction on handle positions are performed both in the teaching and automatic reproduction phase. During the teaching phase, it is the user that selects the shape of the door, and provides the handle position, door position and door type information. This information is used for manipulation planning. In addition, the door information is stored for the automatic repetition phase. During automatic repetition, the system autonomously recalls the stored door information from the detected door candidates and the handle position as instructed by the user (Target Door Recognizer in Fig. 2-(B)).

In this study, door information used for memorization and recall is described using features that take into account the characteristics of the door. A door may change its location and it may rotate around a rotation axis perpendicular to the floor, depending on the movement of the furniture. However, rotation around an axis not perpendicular to the floor is rare, as are changes in door height and handle position. Therefore, the features used for memorization and recall can be determined as follows.

1) The height D_H and width D_W of the door
2) The height of the center of the door D_Z,
3) The position of door handle relative to the center of the door (H_Y, H_Z)

All of these features were found to yield similar values over multiple observations of the same door in preliminary experiments.

The method used to compare the detected door candidate i with the stored door j was as follows. If we let D_H^i indicate the height of a door candidate and $\hat{D_H}^j$ the height of a door in memory, their similarity is given by:

$$\left\{\begin{array}{l} (i,j) = \underset{(i,j)}{\arg\max}[\max\{C_1,(C_2 \\ \quad -||[D_H^i, D_W^i, D_Z^i]^T - [\hat{D_H}^j, \hat{D_W}^j, \hat{D_Z}^j]^T||)\} \\ \cdot \max\{C_1,(C_2 - ||[H_Y^i, H_Z^i]^T - [\hat{H}_Y^j, \hat{H}_Z^j]^T||)\}], \end{array}\right. \quad (1)$$

where $||\boldsymbol{v}_x - \boldsymbol{v}_y||$ denotes Euclidean distance between vector $\boldsymbol{v}_x$ and $\boldsymbol{v}_y$. C_1 and C_2 are constants to keep the similarity positive. They are set as $C_1 = 0.1$ and $C_2 = 0.5$ in the experiments in Section VI. We use this formula to find the combination (i,j) of doors that maximizes similarity. When the similarity for a door combination (i,j) falls below a given threshold, it is classified as a detection failure.

VI. EXPERIMENTS AND DISCUSSION

We implemented and evaluated the proposed method using Toyota's Human Support Robot (HSR, visible on the left robot in Fig. 1), which the authors are developing [1][2]. The HSR has an arm with four degrees of freedom, one lifting joint, an end effector, and a moving base that can move in all directions and rotate. The trajectories of the joints are calculated using rapidly exploring random trees (RRT). The Xtion PRO LIVE, an RGB-D camera, was mounted on the HSR's head. The experimental environments are shown in Fig. 5.

A. Experiment 1: teaching

First, we conducted experiments to evaluate the HSR's manipulation capabilities based on a single user's instruction. The doors used for the evaluation experiments are the six types shown in Fig. 5. The doors included two types of drawers of different sizes and heights, two left-hinged doors of different sizes, heights and handle shapes, and two right-hinged doors of different sizes and heights.

In the experiment, the user instructed the robot about the door, handle and manipulation model using the simple GUI. The initial position of the HSR before door detection was at in front of the door at a distance of 90 cm. We conducted a total of 6 trial evaluation experiments. The HSR succeeded in opening all the drawers and furniture doors. The success rate was 100%. The details of the result are shown in Fig. 4-(A). A circle in the figure signals a success. Information stored in Experiment 1 was used for automatic repetition in the next Experiment 2.

B. Experiment 2: repetition

Next we carried out an evaluation experiment using simplified instructions to open and close the door based on the door shapes and manipulation models taught in Experiment 1. The six types of doors taught in Experiment 1 were used and both types of instructions, i.e., opening and closing were tested. Two positions (one in front of the door at 90 cm

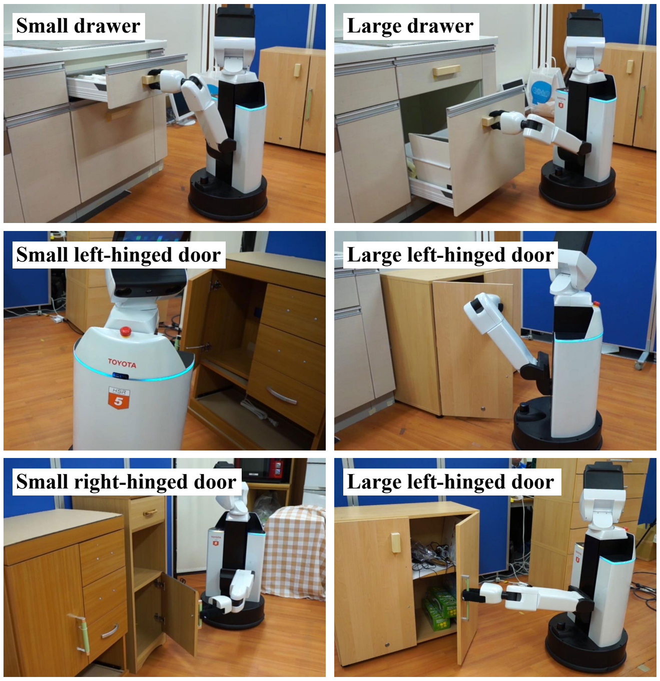

Fig. 5. Results of Experiment 2

distance, and the other at an additional 30 cm offset to the right) were chosen to evaluate whether the door shape and manipulation model can be estimated if the target door is observed from a different angle than in the teaching phase. Thus we conducted a total of $6 \times 2 \times 2 = 24$ evaluation trials. The position of door handle is clicked in each trial.

Note that the position of the furniture is not necessarily the same in Experiment 1 and Experiment 2. Open door states refer to 60 cm of extraction for drawers, and maximum rotation (i.e. 80 degrees to 100 degrees) for hinged doors. The success state for a drawer is defined as when it is 60 cm of extraction during opening, and within 5 cm from the completely closed position when closing; that of the hinged door is defined as 90 degrees plus/minus 10 degrees open when opening and within 10 degrees from the completely closed angle when closing.

Seventeen out of the 24 trials succeeded, yielding a success rate of 71%. Detailed results are given in Fig. 4-(B). A circle in the figure indicates a success; V, G and M indicate failure because of problems with the visual estimation of door candidates, grasp planning, and manipulation, respectively. Broken down by subskill, the success rates are as follows: visual estimation: 88%, grasp planning: 95%, manipulation: 85%. Note that the success rate of recalling the correct door model was 100%.

C. Discussion

The proposed visual function succeeded in recognizing all the closed doors even if the viewing angle and distance to the door changed. The proposed method uses not only distance information but also color images. Therefore, even if the gap between one door and another is small and not visible in the distance information, the methods can easily detect it by means of the edge information extracted from the color image. The experimental results showed the effectiveness of the proposed approach. Furthermore, the door candidates displayed to the user's GUI helped the user select the target door easily when teaching.

In addition, the results confirmed that the simple teaching and automatic repetition of door operation by the proposed method succeeded with a high success rate. Although the positions of the hinged doors were moved after the teaching phase, this posed no problem for the system, because of the proposed similarity calculation method. The robot realized not only opening but also closing of doors despite being taught only opening operations by the user. This showed the effectiveness of the proposed method. The remaining failures could be avoided by implementing the following improvements.

Three of the visual function failures ("V" in Fig. 4) occurred in situations where the door was open. In these cases, no door of the stored shape was detected by the Door Candidates Detector. This detection failure occurred because the colors of the door and the background were similar, so the edges were not adequately extracted from the color image. This failure could be reduced by adding a mechanism to adjust the intensity of the image. Relying on edges calculated from the distance images is conceivable as well. However, detecting accurate edges from an inexpensive infrared pattern projection type distance camera is difficult. It would be worthwhile to explore improvements to edge detection from color images first. Further, memorization of locational information along with the door features could help improve recall of the correct door shape.

Of the remaining failures, "G" in Fig. 4 indicates failure of the door handle grasp planning process. The grasp planner used in this study first detects the plane on which the handle is located, and then estimates the back face of the volume of the handle and searches for a stable grasping posture. It became apparent that the estimation of the back face was difficult when observing a handle attached to the edge of a door. This type of failure could be reduced by improving the grasp planner or changing the standing position of the robot adequately when observing the handle.

In one of the failures indicated as "M" in Fig. 4, the HSR's hand hit the door handle and re-opened the door after it has successfully closed it; in the other failures, the HSR's hand slipped off the door handle while manipulating it. Both of these failures occurred due to minute recognition errors, offsetting the door hinge positions, or errors in motion. For these failures, it is apparent that there is a need for failure recovery based on the observation of the actual movement of the door. However, during operation the door is so close to the robot that it falls outside the observable distance range of typical infrared pattern projection distance cameras. Therefore, the authors are developing a method to estimate door motion from 2-D images. For future work, it may be possible to reduce the failure rate by utilizing such motion estimation methods.

VII. CONCLUSION

In this paper, we proposed a method to simplify the instruction process for making a remote controlled daily assistive robot operate various types of doors via a HMI. Using this method, the user can request the robot to open an unknown door with just four clicks on an image generated from the robot's perspective. Furthermore, the user can request the robot to open or close a door for which the user has provided instructions once, by simply clicking on the door handle and on the open or close button. 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 parameters for the robot's motion.

This research realized the system described above by means of (i) a method for efficiently detecting door candidates from a point cloud of the environment using hypotheses about the door plane and the door shape, and (ii) a system to learn and recall the manipulation models of doors using door features.

In our experiments with a daily assistive robot in which this system was installed and used to operate furniture of various sizes and manipulation styles, we obtained a success rate of 100% for unknown doors, and 71% with simplified instructions and known doors. These results demonstrate the effectiveness of the proposed approach.

In future work, the success rate could be improved by visual confirmation and failure recovery processes during door operation. Furthermore, we are considering an extension to the system for autonomous estimation of the manipulation model for unknown doors, by use of machine learning applied on a database of furniture features recorded using the present method.

REFERENCES

[1] H. Yaguchi, K. Sato, M. Kojima, et al., Development of 3D viewer based teleoperation interface for Human Support Robot HSR, ROBOMECH Journal, 2014 1:10, pp.1–12, 2014.

[2] K. Nagahama, H. Yaguchi, H. Hattori, et al., Learning-Based Object Abstraction Method from Simple Instructions for Human Support Robot HSR, Proceedings of the 2016 IEEE International Conference on Advanced Intelligent Mechatronics, pp.468–475, 2016.

[3] J. Lim, I. Lee, I. Shim, et al., Robot System of DRC-HUBO+ and Control Strategy of Team KAIST in DARPA Robotics Challenge Finals, Journal of Field Robotics, vol. 34, issue 4, pp. 802–829. doi:10.1002/rob.21673, 2017.

[4] M. Schwarz, M. Beul, D. Droeschel, et al., DRC Team NimbRo Rescue: Perception and Control for Centaur-like Mobile Manipulation Robot Momaro, Springer Tracts in Advanced Robotics (STAR), vol. 121, pp. 145–190, 2018.

[5] M. DeDonato, V. Dimitrov, R. Du, et al., Human-in-the-loop Control of a Humanoid Robot for Disaster Response: A Report from the DARPA Robotics Challenge Trials, Journal of Field Robotics, vol. 32, issue 2, pp. 275–292, 2015.

[6] P. Marion, M. Fallon, R. Deits, et al., Director: A User Interface Designed for Robot Operation With Shared Autonomy, Journal of Field Robotics, vol. 34, issue 2, pp. 262-280, 2017.

[7] H. Azuma, Y. Kakiuchi, M. Saito, et al., View-base Multi-touch Gesture Interface for Furniture Manipulation Robots, Proceedings of the IEEE Workshop on Advanced Robotics and Its Social Impacts, 2011.

[8] M. Kojima, K. Okada and M. Inaba, Manipulation and Recognition of Objects Incorporating Joints by a Humanoid Robot for Daily AssistiveTasks, Proceedings of the 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, pp.1564–1569, 2008.

[9] S. Pillai, M. R. Walter and S. Teller, Learning Articulated Motions From Visual Demonstration, Proceedings of the 2014 Robotics: Science and Systems workshop on Robot Manipulation, 2014.

[10] J. Sturm, C. Stachniss and W. Burgard, A Probabilistic Framework for Learning Kinematic Models of Articulated Objects, Journal on Artificial Intelligence Research, vol. 41, pp.477–526, 2011

[11] J. Sturm, K. Konolige, C. Stachniss, et al., Vision-based Detection for Learning Articulation Models of Cabinet Doors and Drawers in Household Environments, Proceedings of the 2010 IEEE International Conference on Robotics and Automation, pp. 362–368, 2010.

[12] J. Sturm, V. Pradeep, C. Stachniss, et al., Learning Kinematic Models for Articulated Objects, Proceedings of the International Joint Conference on Artificial Intelligence, 2009.

[13] K. Yamazaki, K. Sogen, T. Yamamoto et al., 3D Shape Modeling of Movable Parts of Furniture Based on Time-Series Surface Correspondence, Proceedings of the 2014 IEEE International Conference on Automation Science and Engineering, pp. 249–254, 2014.

[14] J. Sturm, A. Jain, C. Stachniss et al., Operating Articulated Objects Based on Experience, Proceedings of the 2010 IEEE International Conference on Intelligent Robot and Systems, pp. 2739–2744, 2010.

[15] A. Jain and C. C. Kemp, Pulling Open Doors and Drawers: Coordinating an Omni-directional Base and a Compliant Arm with Equilibrium Point Control, Proceedings of the 2010 IEEE International Conference on Robotics and Automation, pp. 1807–1814, 2010.

[16] E. Klingbeil, A. Saxena and A. Y. Ng, Learning to Open New Doors, Proceedings of the 2008 Robotics: Science and Systems workshop on Robot Manipulation, 2008.

[17] G. C. Haynes, D. Stager, A. Stentz, et al., Developing a Robust Disaster Response Robot: CHIMP and the Robotics Challenge, Journal of Field Robotics, vol. 34, issue 2, pp. 281–304, 2017.

[18] S. Karumanchi, K. Edelberg, I. Baldwin, et al., Team RoboSimian: Semi-autonomous Mobile Manipulation at the 2015 DARPA Robotics Challenge Finals, Journal of Field Robotics, vol. 34, issue 2, pp. 305–332, 2017.

[19] W. Meeussen, M. Wise, S. Glaser, et al., Autonomous Door Opening and Plugging In with a Personal Robot, Proceedings of the 2010 IEEE International Conference on Robotics and Automation, pp. 729–736, 2010.