A Demonstrative Research for Daily Assistive Robots on Tasks of Cleaning and Tidying up Rooms

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***Abstract*— This paper describes a demonstrative research of daily assistive robots. Several tasks related to cleaning and tidying up rooms are focused on, a real robot performs these tasks. A software system combining environment recognition with motion generation provides functions of finding failures and planning retry behaviors, the robot can do the given tasks with recovering the failures in some cases. This enables the robot to perform several daily tasks with handling tools and furniture.**

I. Introduction

Various types of furniture and tools exist for humans in daily environments. Daily assistive robots are expected to work with handling such daily things. This paper describes a daily assistive robot which can perform a "cleaning and tidying up rooms" task in the environments. One of the characteristics of this robot is to have failure detection and recovery abilities which are based on our integrated system combining recognition functions with motion generation functions.

Daily assistive robots have been developed over several decades. Petersson[11] et. al. developed a mobile manipulator system which could pick an instructed object up, convey, and give it to a person. In recent years, daily assistance by humanoid robots becomes an active area[1][9]. Researchers have evaluated their control system, intelligent system or teaching system with applying their method to a single daily task in real environment[6]. This means that sequentially execution of daily routines in real environment have not been focused in the past.

Our purpose is to develop and to proof an integrated robot system which can achieve various tasks imposed in daily life. One of important things is that the robot must continue to work over different types of tasks. We have already developed daily assistive robots provided perception, learning and motion planning skills [10], and this research extends these works. Our system provides a robot with failure detection and recovery skills for achieving all given tasks.

II. Approach

A. The task of cleaning and tidying rooms

We focus on following 3 series of tasks which are very popular in daily life: (1) pick up a tray from a table, convey it, and put it onto a kitchen. (2) Gather clothes and put it in a washer. This task also includes pushing the washer button, and opening and closing the washer door. (3) Sweep a floor by using a bloom. This task also includes pulling out or pushing back the chair for cleaning under the table.

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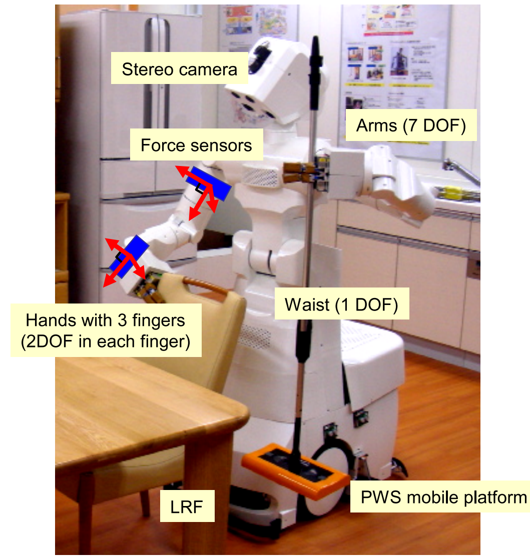

Fig. 1. A prototype robot

The tasks described above are good examples of daily assistance because these require a plenty of behavior such as dualarm manipulation, soft-objects and lengthy goods handling. In the case of furniture and tools handling, we give a robot to 3D geometrical object shape and its positions in advance. What the robot have to do while working is to recognize the pose of target objects by using external sensors, and to plan how to handle the object on the spot. On the other hand, we apply an appearance based recognition method for clothes which are difficult to define its 3D shape.

B. Architecture of the daily assistive robot

Fig.1 shows a daily assistive robot in our use. Upper body consists of arms (7 DOFs), a head (3 DOFs), and a waist (1 DOF). End-effector equips 3 fingers and each finger are composed of 2 joints. On the other hand, lower body is 2 wheeled mobile platform. This robot mounts a stereo camera on the head, and a LRF (Laser RangeFinder) on the base. Force sensors are equipped on the wrist and the shoulder of the both arms.

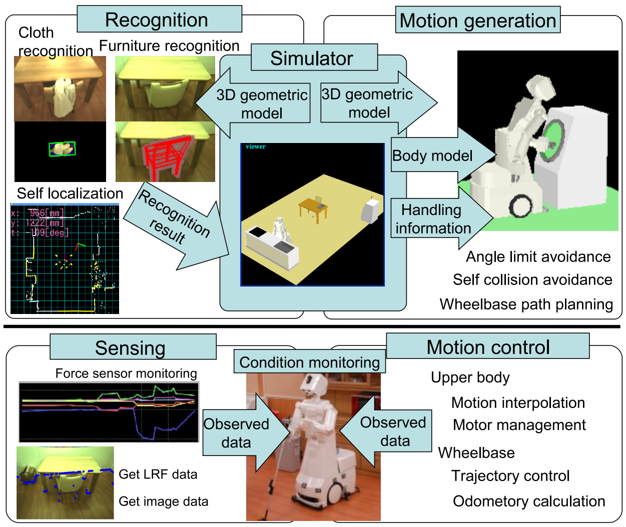

Fig. 2. Software Architecture

III. INTEGRATED BEHAVIOR GENERATION SYSTEM

A. summary

Fig.2 shows the overview of our system architecture. Recognition and motion generation functions are placed on high layer combined with 3D geometrical simulator. On the other hand, sensing and motion control functions are placed on low layer, and they work for robot state managements in realtime.

By applying 3D models, the geometrical simulator provides the model-based recognition functions with a series of visual information such as 3D edges and colors. In addition, the simulator also provides the motion generation functions with an initial relative pose between a robot and a target object. When a task will be executed, the pose of the target object is firstly estimated by using external sensors, the estimation result will be reflected to the simulator in online. Robot motions will be generated with referring the pose.

B. Recognition functions

To achieve the tasks of cleaning and tidying rooms, we assume several daily objects, for instance, a tray, a chair, a washer machine, a broom and clothes. The robot has two types of recognition functions which are applied to solid objects (other than clothes) or soft objects (clothes).

1) Object pose recognition based on geometrical model: For solid objects as a chair, pose recognition method by using 3D geometrical model is applied. This approach is based on the method described in [10] which uses several types of image features, but we also use LRF to cope with furniture.

The recognition procedure is as follows: initial pose candidates of a target object are estimated by using LRF data, and the candidates are inserted as a group of geometrical models in the simulator. Next, edge segments of the candidate models are projected to an image which is captured from the stereo camera. A particle filter is applied to the estimation process, these results are evaluated by matching between the projected model and several types of image features which includes edges, geometrical shape, color and so on. Scan data of the LRF are also utilized to this evaluation.

Because sensory features used in this method can be extracted from low textured object, this approach is suitable for applying to furniture recognition.

2) Cloth recognition based on wrinkle feature: Because soft objects are difficult to recognize by using geometrical model, shape independent features are useful in this case. We take an approach to find wrinkles on a cloth which is assumed to readily be placed on rooms.

Through image learning based on SVM, a feature vector was generated about wrinkles on clothes[4]. Cloth regions can be extracted through discriminant functions. Combining the result with stereo data, the robot can detect the 3D position of the cloth to be grasped.

C. Motion generation functions

In our approach, upper body is controlled independently of a wheelbase. This is because the wheelbase has non-holonomic constraint in its mobility, and it is easy to have pose error caused of wheel slip and so on. From these reasons, we take an approach to reduce the pose error derived from wheelbase motion by replanning upper body motion.

1) Motion generation of upper body: In order to generate the pose of manipulation, jacobian based inverse kinematics is applied. Especially we utilize SR-inverse[8] which has a good track record in stability around singular points.

The equation to calculate the velocity of an end-effector is as follows:

$$\dot{\theta} = \mathbf{J}_w^{\#}\dot{\mathbf{x}} + (\mathbf{I} - \mathbf{J}_w{}^{\#}\mathbf{J})\mathbf{y}, \quad (1)$$

where $\mathbf{J}^{\#}$ is a SR-inverse of a jacobi matrix $\mathbf{J}$, and $\mathbf{J}_w^{\#}$ is a multiplication result of $\mathbf{J}^{\#}$ and a matrix $\mathbf{W}$. $\mathbf{W}$ denotes a diagonal weight matrix[3], and $\mathbf{y}$ denotes an optimization function for avoiding self collision by using redundant degrees of freedom.

2) Wheelbase motion generation: Basically the trajectory of the platform is defined as a set of coordinates which are discretely allocated on the floor. Line tracking method[12] is implemented to follow the line which connects former coordinates with next coordinates. Motion controller outputs velocity v and angular velocity ω with considering relative pose of the coordinates.

D. Localization

Environment map was generated by means of SLAM (Simultaneous Localization And Mapping) in advance, and a present robot pose is calculated by means of scan matching. In the map generation phase, we apply SLAM approach which combines ICP algorithm [2] and GraphSLAM[7]. Because the map is represented as dozens of a set of reference scans and robot positions, ICP algorithm can be used to match between input scan and reference scans in the localization phase. Moreover, in order to eliminate mismatching while rotating, the odometory information is also added.

IV. Structure of failure detection and recovery

One of the main purposes of this research is to establish a system which can provide the robot with abilities to execute tasks consequently. We incorporate motion verification and retrying routine based on recognition and motion generation functions.

A. Classification of failures and its countermeasures

We divide a simple task constructed one manipulative behavior into 2 phases: (1) detect and approach to a target object, and (2) handle it. The word "Failure" used in this section indicates the condition that the robot cannot plan its motion or cannot verify the success of executed motion in the middle of or after the task.

Firstly we classify the failures to 3 groups from the viewpoint of the levels of recovery intractableness.

1) Failures observed before manipulation: One of the examples is that the robot cannot plan its handling pose because of wheelbase motion error, when it approaches and grasps the back of a chair.

2) Failures observed after manipulation without almost no changes of the manipulation target: One of the examples is that the robot cannot push the button to open the door of a washer.

3) Failures observed after manipulation with changing a target condition significantly: Examples in our case are that a cloth hangs out of a washing tab, or a broom lies down on a floor because the robot failed to grasp it.

Because almost of the failures classified to 1) cause of the errors of environment recognition and wheelbase motion, these failures should be recovered by retrying the recognition and the motion again. In the case of failure 2), verification functions are implemented to check the state of manipulated objects and the pose of the robot itself. For instance, appearance changes of the target object can be checked by using images which are captured before and after the manipulation. In the case of failure 3), other type of recognition functions might be needed to detect the failure occurrence and to know current state. Moreover, a motion generation function is needed to make recovery motion based on the recognition result.

V. Continuously cleaning and tidying execution

A. Experimental setup

Fig.3 shows our experimental environments. Popular furniture and tools were settled in the room, we imposed following tasks: (1)carry a tray to a kitchen (move from A to B in Fig.3), (2)pick up a cloth at the position C, (3)put the cloth in a washer which placed on the position D, (4)pick up a broom, (5)pull a chair back, (6)sweep under the table, (7)put the chair back in place, and (8)sweep the floor with moving around the room. Through hundreds of trials, failures were listed and its countermeasures were taken by modifying and adding functions.

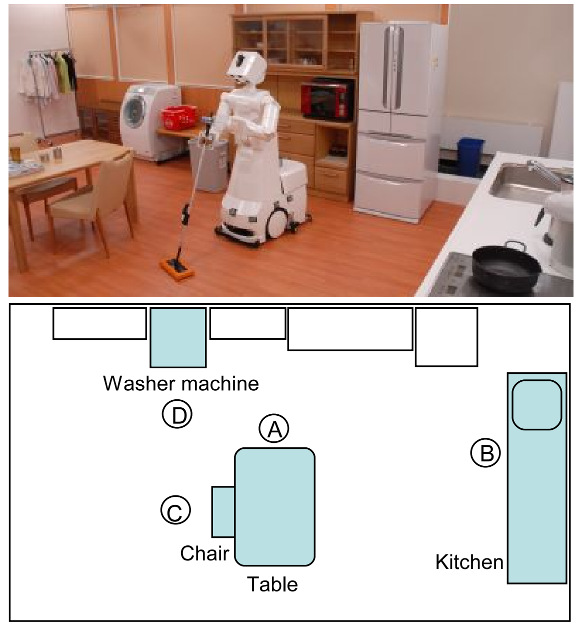

Fig. 3. Experimental Environment

B. Experimental results

One cleaning and tidying task took about 8 and a half minute without any failure classified to 2) or 3) described in section IV. When the robot caught a failure which needed recovery motion, more time was consumed by just that much.

Fig.4 shows an example of failure detection and recovery in the case of pushing a washer button. This can be classified to the 2) described in section IV, because the door was not opened despite pushing execution. The failure detection could be achieved by observing an "effect" which arises from an "action", that is, whether or not the pose of the door was changed by pushing the button. The recovery was achieved by performing pushing motion again.

Fig.5 shows another example of failure detection and recovery in the case of picking up a cloth from the back of a chair. The figure indicates the situation that the robot dropped down the cloth on a floor. Failure detection can be achieved by checking the joint angles of the fingers. This was classified into 3) described in section IV because failure recovery cannot be achieved by repeating the picking up motion from the chair. So we added a new behavior that the robot searched the cloth on the floor and picked it up.

Fig.6 shows the cleaning and tidying execution.

VI. Conclusion

This paper presented a demonstrative research of a daily assistive robot. Several tasks related to cleaning and tidying rooms were focused on, recognition and motion generation functions were integrated. Failure detection and recovery framework was also implemented. Through experiments, effectiveness of our approach was illustrated demonstratively.

Future works, we try to develop more applicable functions to find failures and to plan recovery motion automatically.

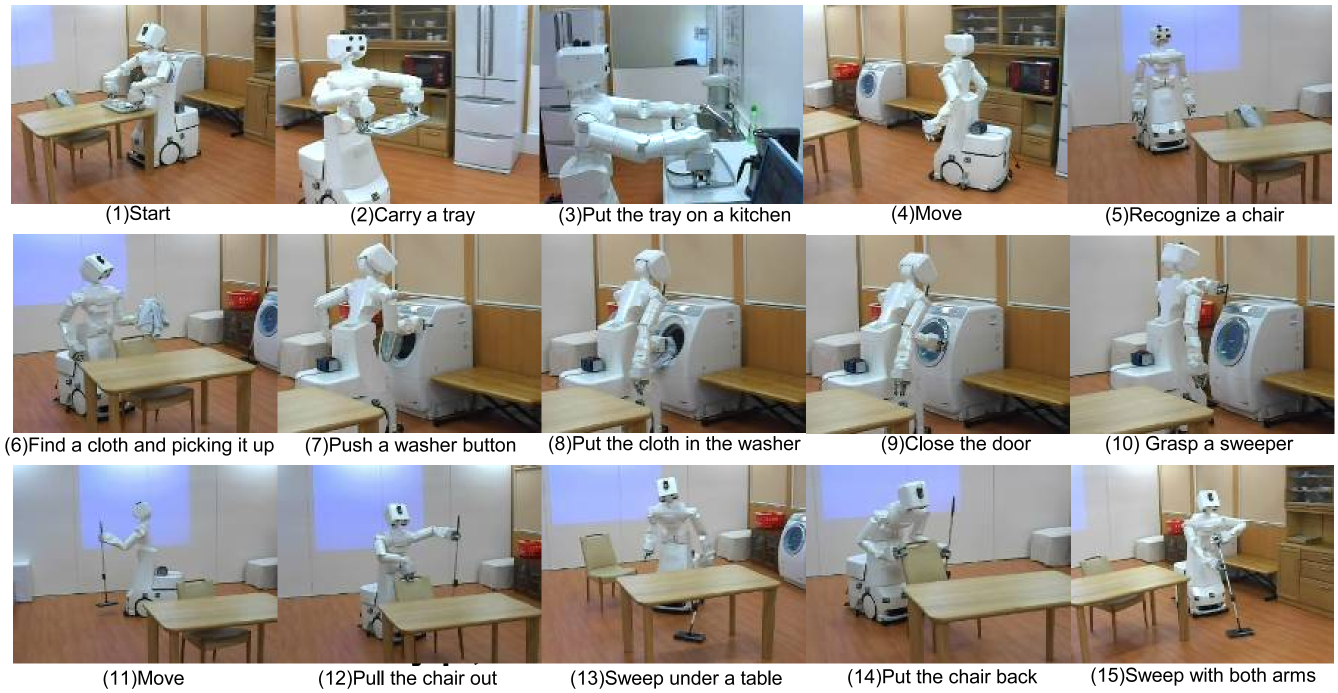

Fig. 6. An experiment

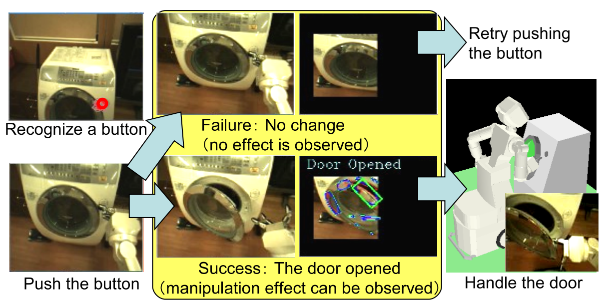

Fig. 4. Failure Detection in washer door opening

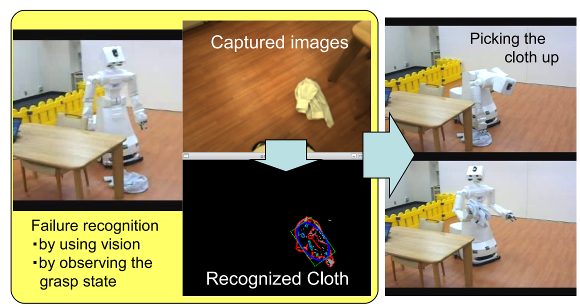

Fig. 5. Failure Recovery by picking up a cloth

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