Modeling and Motion Planning for Handling Furniture by a Mobile Manipulator

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Abstract— This paper introduces a planning method for handling furniture which exists in real world. We propose a method which is easily expandable its handle able furniture such as closet, shelf and so on. If the robot can handle such furniture autonomously, it is expected that multiple daily tasks, for example, storing a small object in a drawer, can be achieved by the robot. Because perplexing processes is needed to give the knowledge of furniture handling to the robot manually, we propose direct teaching based approach which can easily give not only how to handle the furniture but also an appearance and 3D shape of it. Combining general knowledge given in advance and manipulation procedure instructed by human directly, the robot acquires how to manipulate the storing places. The performance of the proposed method is illustrated by experiments.

Fig. 1. Storing places

I. Introduction

In this paper we propose modeling and motion planning methods for a mobile manipulator which can handle furniture for storing an object in it. Utilizing direct teaching, we enables the robot to handle furniture such as drawer, cabinet and so on.

Recently, various robots such as humanoids are actively developed and these robots are expected to work in behalf of human in near future. Because these robots have both human-like many joints and high mobility in real environment, it is desired to make the robots doing our daily tasks. These days several researches achieved object handling tasks by humanoid robot which has both abilities of motion planning and environment recognition [5] [9].

The purpose of this research is to achieve such a dialy task as "a robot picks up a small object and stores it in furniture". In this paper we describe the method of modeling and motion planning to handle several types of furniture which often exist in dialy environment. Because we have continued to attack to this research issue, picking up a small object has already achieved by utilizing object modeling [11] and grasp planning [12]. In this paper, we propose the method related to handle furniture for storing the picked object in it.

Researches on mobile robots which handle objects can roughly classify into two groups. One is an approach that accurate knowledge for handling is given in advance. For example, alomost of the robot motion are implemented by manual and heuristically [7], motion procedure is given through tele-operation [10], ID tag or marks is given to an object assistance [3] [4] and so on. In our policy, because there are many objects which can be handled by robots in real environment, it is expected that manual efforts should be reduced when we want to add handleable object to the robot. From this viewpoint, traditinal approaches have a problem because these need pretty efforts or specefic tools.

The other approach is that the handling motion is learnt through observing human who handles his target. This approach has highly extensive because alomost no posterior knowledge about handling target is needed. However, all of results were completed under the condition of less constraints between handled object and arround environment such as sweeping [9] or dancing [8] in the present. In other words, it is pretty difficult to adopt this approach to drawer handling because of its high constraints.

Our approach belongs to former category with manually teaching. Thus, we notice that manually preparation should be reduced as much as possible. The approach is as follows:

- classify furniture into several groups along their handling method, and posterior knowledge about each group is defined by manually,
- instruct robot in handling way about individual furniture through manually teaching, and the robot makes a model of it.

In this paper, such furniture as drawer, cabinet and refrigerator are assumed (Fig.1). Notice that they are

needed to handle before we want to store an object in it. Although we must give handling knowledge to the robot, few manually efforts is needed in the definition. It means that the knowledge is utilized toward several series of furniture. On the other hand, to adjust the predefined knowledge to individual furniture, manually teaching is performed. The teaching is performed by means of direct teaching which needs not both of complicated procedure and specific tools. We call a finally created model "IM-model (Instructed motion model)" which includes the information of appearance, 3D shape and handling method.

This paper describes as follows: Section II presents a scheme of this study and problem definition. Section III presents modeling method through direct teaching, and Section IV presents motion planning method based on the created model. Section V provides experimental results and section VI concludes this paper.

II. Issues and Approach

A. Assumed Task

As an easily assumed daily task, we set "a robot conveys a small object and stores it in known furniture". Furniture is assumed that it is needed to handle for storing task, for example, drawers, cabinets or sliding doors. Environment map including furniture arrangement is given in advance or constructed by the robot autonomously.

We assume that the task is executed as following procedure. The main topics of this paper is 0: and 2:.

0. Handling motion is given to the robot through manual teaching. The robot constructs the handling model of the furniture,
1. sets a small object on the platform and conveys it to instructed position where furniture exists,
2. handles the funiture,
3. stores the object in.

We assume several types of furniture which needs any handling before storing objects in it. In a drawer case, the robot has to draw it for putting an object in.

B. Mobile Manipulator

Fig.2 shows a mobile manipulator in our use. A serial manipulator "Katana II" developed in Nueronics inc. is mounted on a mobile platform "Yamabico" developed in University of Tsukuba. End-effector is two fingered parallel gripper. A USB camera "Qcam 3000" and SOKUIKI sensor "URG 04–LX" developed by Hokuyo inc. are mounted as external sensors.

C. Issues

Because there is many types of furniture in real environment, we propose easily extendable framework when we want to add new handleable furniture to robot. In our framework, generalized prior knowledge for handling is only given to the robot. In the meantime, detail knowledge for handling is given through manual teaching. Both of these information, the robot models and plans its motion.

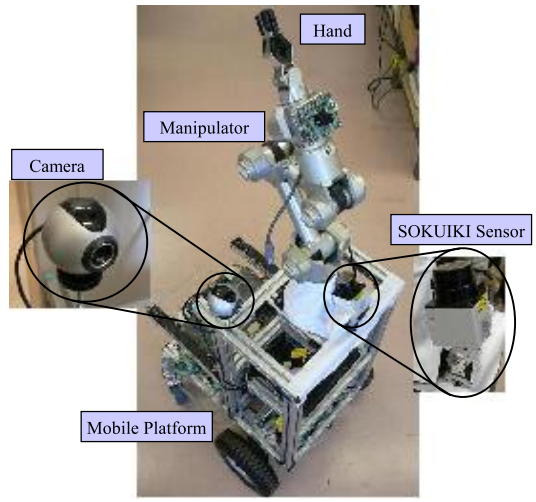


Fig. 2. A mobile manipulator

One of the issue is how to create handling model for furniture through manual teaching. The key technologies are prior knowledge and data processing. On the other hand, because the motion data from manual teaching is not always optimum for the robot, the motion for handling is needed to plan.

D. Approach

We aim to develop an easy extendable modeling method for the robot which can handle furniture. Our method is based on direct teaching [1] which needs no specific tools or detail instructions. We join this teaching with external sensing for acquiring appearance and 3D shape information of the furniture by using a camera and a SOKUIKI sensor.

The challenges of our approach are as follows: (1) how to extract modeled information from manual instructed data, (2) how to extract needed information from external sensor data. We solve these along following manners.

Various types of furniture in real world can classify along its handling way as shown in Table I. So we take an approach to give three types of generalized knowledge for handling to the robot. Although these

TABLE I
Variation of Furniture Manipulation

Type	Manipulation	Example
Drawer	pulling horizontal back or front trajectory	Cabinet
Sliding Door	pulling horizontal right or left side trajectory	Cupboard
Rotating Door	pulling rotational trajectory along fixed vertical axis	Refrigerator

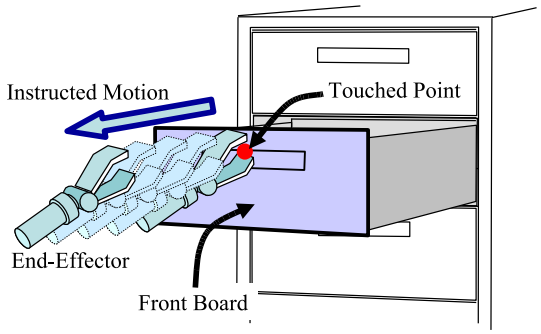


Fig. 3. IM model

knowledges are needed to define manually, this is effecient appraoch because one knowledge can adopt to several targets.

On the other hand, because furniture has various sizes or appearances, it is needed that detail handling motion should be defined individually. So we take an approach to teach the motion by manually. This means that the data acquired through manually teaching is applied to predefined generalized knowledge for modification. We call finally created model "IM-model (Instructed Motion Model)". IM-model includes not only the pose and trajectory of robot hand but also the size, shape and appearance of front board.

III. Manual Instruction for Furniture Handling

In this section, the modeling method of furniture handling is described. We call the handling model "IM-model" because it relies on direct instruction by human.

A. IM-model

IM-model is substantially constructed from following information with related to front board. Front board in Fig.3, Front Board is one of the element of furniture assumed in this paper, and it is a good part where reflects the instructed motion while teaching.

- Contact direction and position of hand
  Instructed contact direction and position of the tip of manipulator are needed for furniture handling. In our approach, instructed pose of a robot is not included in IM-model because such approach enables to easily cope with the changing of the state of the robot.
- Instructed trajectory of hand
  It means an instruced trajectory information of the front board. This is modeled with the contact direction and position of the robot hand.
- Size, shape and appearance of the front board
  Front board size and shape information enable the robot to estimate environment changing through furniture handling. These are the criteria of collision avoidance when the robot stores an object in the furniture. Appearance information is useful for finding the furniture from environment in future.

B. Teaching Procedure

The teaching procedure is as follows:

1) after installing a robot near to furniture, teaching is started. The robot measures the furniture by external sensors for creating initial model,
2) direct teaching is performed, that is, human handles a robot arm and mobile platform directly for instructing how to handle the furniture,
3) after teaching, one image is captured. Finally, IM-model is created using these sensor data and handled motion of the robot.

C. IM-model Creation

Front board is modeled by utilizing image edges. Conventionally, though image feature points are often utilized because of its robustness and stability, these are difficult to utilize in our case. Well-known feature point is extracted from high textured image region, such region is often found on bounds between front board and around environment. That is to say, the condition of such region is changed through teaching, feature points is not suitable for our purpose.

On the other hand, though image edge has difficulty in the way of segmentation, extraction itself can robustly do. Moreover, because shape and size of the front board is needed, edges are suitable to the purpose. From these reasons, we take an approach that contour of the front board is estimated by utilizing image edges.

1) Initial Model Creation: Initial model means 3D contour candidates of a front board. This is acquired before teaching through following procedure. First, using the SOKUIKI sensor, dense 3D points are measured with related to environment in front of the robot (in our assumption, the 2D scanner will be extended to 3D space scanner with tilting structure). Moreover, triangle patches are adopted to these 3D points. On the other hand, 2D line segments are extracted from image edges (Fig.4,(1)left) which are extracted from firstly captured image. 2D contour candidates are constructed from these line segments by combining these segments to quadrangle (Fig.4,(2)left). Finally, these 2D quadrangles are projected to 3D triangle patches, 3D quadrangles are acquired as contour candidates of the front board.

2) Trajectory Specialization: During the teaching, the robot records its directly handled motion by periodic interval. Because a part of this data indicates the information of the furniture handling, such part has to be extracted from all of the teaching data. Fig.5 shows an example of the trajectory for drawing motion. At first (1) Human leads the robot hand directly and starts the teaching from initial pose of the robot. Next, (2) the robot hand is inserted to the knob of the drawer, and (3) handling the drawer. After that, (4) releasing the hand, and (5) putting the manipulator back to initial pose. In this flow, (2) to (4) are needed for creating IM-model. So posterior knowledge is given to the robot

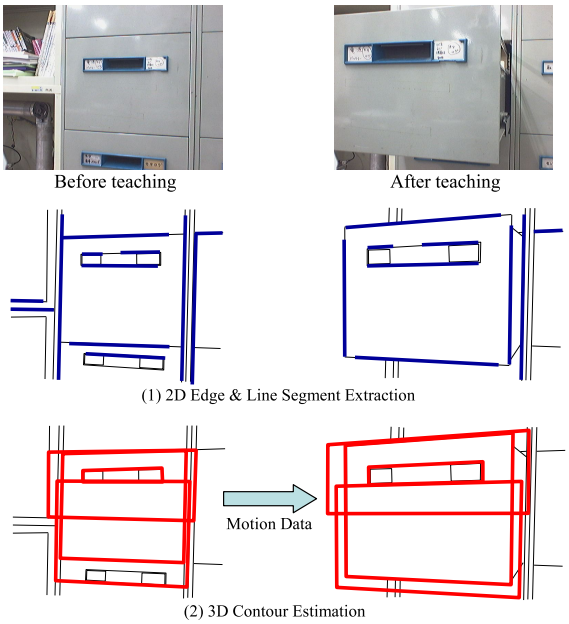


Fig. 4. Front board estimation

for extracting these information and modeling this handling procedure.

D. Front board selection from its candidates

The contour candidates of the front board can include several impertinent ones which are extracted from around environment. So it is needed to select proper contours by using image data which is captured after teaching.

The procedure is as follows: at first, after the robot hand is returned to initial pose, an image is captured. Because handled motion of the furniture is already known through teaching, the present state of the front board is estimated as shown in (Fig.4,(2)right). By superimposing these estimated result on the image edges which is captured after teaching (Fig.4,(1)right), well matched contours are selected.

According to these process, final IM-model is acquired as an approximated front board model which consists of several 3D contours, image data and handled information. By registering this model in database, it is expected to the robot automatic task implementation with finding the furniture autonomously.

IV. Motion Planning for Funiture Handling

A. Summary

Because instructed motion data through direct teaching relies on human, it is difficult to consider the condition of robot pose such as manipulability of its hand. So we propose motion planning method by inputting IM-model.

The planning is performed by utlizing following equation:

$$\mathbf{q}_{new} = \mathbf{q} + \lambda(\mathbf{I} - \mathbf{J}^{+}\mathbf{J})\{\mathbf{m}(\mathbf{x}_G, \mathbf{x}_h) + \mathbf{r}(\mathbf{x}_G, map)\}, \quad (1)$$

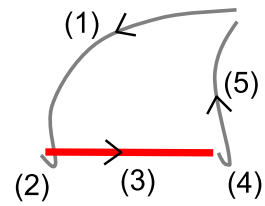


Fig. 5. Trajectory of end-effector

where $\mathbf{q} = (x_G, y_G, \phi, \theta_1, ...\theta_n)$ indicates pose parameters of a mobile manipulator, $\mathbf{J}$ indicates Jacobi matrix of the mobile manipulator. λ is positive constant, $\mathbf{I}$ is unit matrix. $\mathbf{x}_G = (x_G, y_G, \phi)$ indicates robot pose in world coordinates, $\mathbf{x}_h$ indicates hand pose in mobile base coordinates map is environment map (in this paper, given by manual). The function $\mathbf{m}(\mathbf{x}_G, \mathbf{x}_h)$ and $\mathbf{r}(\mathbf{x}_G, map)$ are described in rest of this paper.

$\mathbf{J}$ of eq.(1) indicate Jacobi matrix cosidering nonholonomic constraint of the platform proposed by Bayle et al [2]. This is calculated as follows:

$$\mathbf{J}(x_G, y_G, \phi, \theta_1, ...\theta_n) = \mathbf{J}_m(\theta_1, ...\theta_n)\mathbf{S}(\phi), \quad (2)$$

where $\mathbf{J}_m$ indicate Jacobi matrix of only manipulator, On the other hand,

$$\mathbf{S}(\phi) = \begin{bmatrix} \cos(\phi) & 0 & 0 \\ \sin(\phi) & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \mathbf{I}_n \\ \vdots & \vdots & \end{bmatrix}.$$

Eq.(1) can satisfy both of two following requirement:

- Manipulability of hand $(\mathbf{m}(\mathbf{x}_G, \mathbf{x}_h))$
- Collision avoidance $(\mathbf{r}(\mathbf{x}_G, map))$

Because hand pose error is crutial problem in the case of mobile robot, Manipulability should be included in criteria. So the evaluation method proposed in [13] is applied. On the other hand, collision avoidance should be considered in this planning because planned motion of the robot may be changed from instructed motion. In that case, new risks arise from the new planned motion.

However in the front board of the furniture becomes a movable obstacle for the robot, the pose streams planned by ed.(1) can overcome such case because it can plan the poses in order.

B. Manipulability against hand pose error

In the case of a mobile base has to move when the robot does handling tasks, some error can be included in its hand pose. Almost of the error is caused from wheel slip, odometory error and external sensing for positioning the handling target.

Our pose evaluation is calculated from joint motions for error recovery. Evaluation function is represented by using the following equation:

$$C = \int |k(\mathbf{x}_h) - k(\hat{\mathbf{x}}_h)| P(\mathbf{x}_h) d\mathbf{x}_h, \quad (3)$$

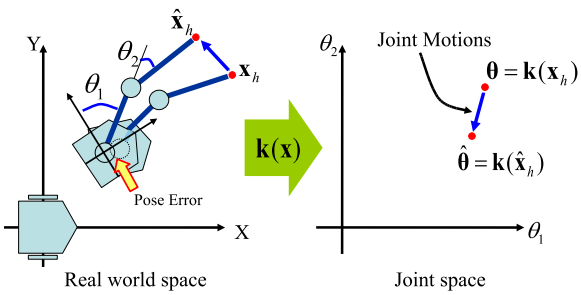


Fig. 6. Manipulability measure based on end-effector error

where $\mathbf{x}_h$ is hand pose and $\hat{\mathbf{x}}_h$ is a target pose. $k(\mathbf{x})$ is a function for solving inverse kinematics with respect to a given hand pose $\mathbf{x}$. The value of $k(\mathbf{x})$ are joint vector which is represented as $\theta = (\theta_1, \theta_2, \cdots, \theta_n)$. $P(\mathbf{x}_h)$ is a probabilistic distribution of hand pose. C becomes smaller, the pose is better.

The meaning of eq.(3) is illustrated with a planar mobile manipulator in Fig.6 as example as follows. The robot can grasp the target object at $\hat{\mathbf{x}}_h$ if it has no error in the pose. However, there may be some errors in real works so that the grasp pose will be shifted to such a pose as $\mathbf{x}_h$ in Fig.6. The good evaluation at eq.(3) is achieved if less joint motions from $\mathbf{x}_h$ to $\hat{\mathbf{x}}_h$ for the adjustment are needed. Eq.(3) calculates an expectation of joint motions for its adjustment utilizing a probabilistic distribution.

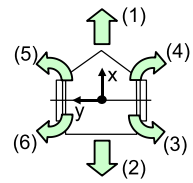
In eq.(1), this evaluation is performed at each pose of planned pose streams. In the optimization, as shown in Fig.7 left, several petterns of slightly motions are given to the robot and the evaluation C is calculated aboud each case. Then best evaluated motion is selected and the motion obeying Fig.7 is added to present position of the platform. That is,

$$\mathbf{m}(\mathbf{x}_G, \mathbf{x}_h) = \begin{bmatrix} w_{11}\ m_d \\ w_{12}\ m_\phi \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{4}$$

where w_{11} and w_{12} are weight factor which rely on the amount of platform motion in unit time. In spite of the vector in eq.(4) has only element of platform translation and rotation, the whole pose of the robot is changed because of redundant term $(\mathbf{I} - \mathbf{J}^+\mathbf{J})$.

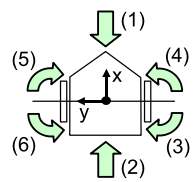
C. Collision aboidance of mobile platform

For avoiding around environment, the other function is defined. Basically, negative evaluation grows when the mobile platform comes up to obstacle. The function



	(1)	(2)	(3)	(4)	(5)	(6)
m_d	1	−1	−1	1	1	−1
m_ϕ	0	0	$\frac{\pi}{4}$	$-\frac{\pi}{4}$	$\frac{\pi}{4}$	$-\frac{\pi}{4}$

Fig. 7. Manipulability function



	(1)	(2)	(3)	(4)	(5)	(6)
r_d	−1	1	−1	1	1	−1
r_ϕ	0	0	$-\frac{\pi}{4}$	$\frac{\pi}{4}$	$-\frac{\pi}{4}$	$\frac{\pi}{4}$

Fig. 8. Collision avoidance function

is defined as follows:

$$\mathbf{r}(\mathbf{x}_G, map) = \begin{bmatrix} K\ w_{21}\ r_d \\ K\ w_{22}\ r_\phi \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{5}$$

where w_{21} and w_{22} are weight factors which are defined to grow when the mobile base come up to obstacle K is also weight factor which balanc between eq.(4) and eq(5).

In eq.(5), r_d and r_ϕ are output as shown in Fig.8, left if any obstacle exists around the robot. In this equation, the whole pose of the robot is also changed because of redundant term $(\mathbf{I} - \mathbf{J}^+\mathbf{J})$.

V. Experiments

A. Settings

We select cabinet as target furniture. Tha task is to store a small PET bottle in the cabinet. Roughly handling procedure for putting the object in was given by manual but detail procedure is automatically modified based on IM-model by the robot.

B. Teaching and Modeling of the Handling

Fig.9 shows experiment. In (B1) to (B4), human taught the way to handle the cabinet with handling the manipulator directly. In (A1) to (A4) shows images which are captured by the robot. While teaching, joint angles of the manipulator and odometry were recorded every 300 msec.

After teaching, IM-model creation and handling pose planning are performed. IM-model creation took 4.6[sec] and motion planning 2.5[sec] by utilizing laptop PC (Pentium M, 2 GHz) mounted on the robot.

Fig.10 is an example contour modeling. Firstly, 81 candidates of front board are found(II). However by corresponding estimated contours with image edges (III), the number of candidates was reduced to 5 (IV).

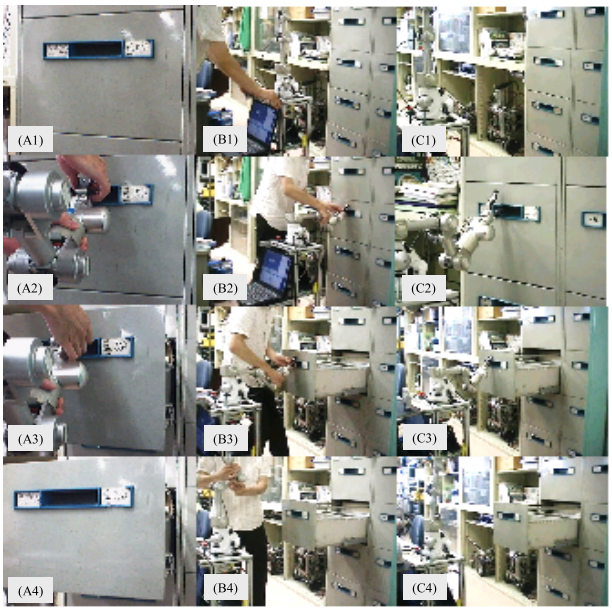


Fig. 9. Experiments

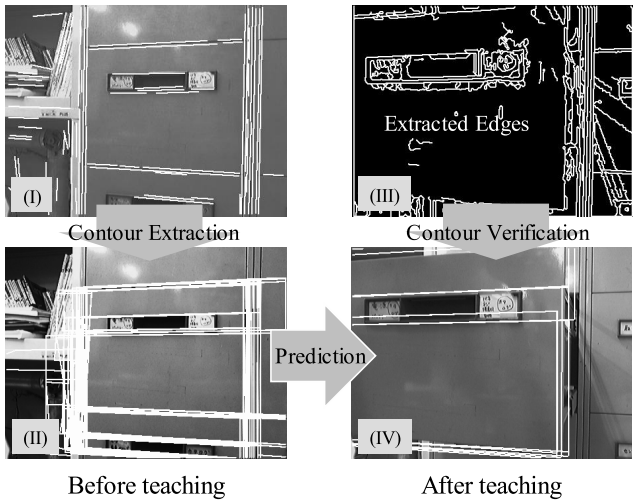


Fig. 10. Image processing result

In this experiment, all of these candidates are recorded as front board model.

C. Automatic Handling of the Cabinet

(C1) to (C4) in Fig.9 show the flow of task execution. We set the robot near to the cabinet and gave the position. The robot firstly moved to the initial position of handling and do the task. The initial position for handling was automatically selected by means of the evaluation method proposed in [13]. After drawing the cabinet, the robot achieved storing the object in. In this experiment, we decide the K in eq.(5) as experimentaly constant.

We tried to adopt our method to other types of furniture such as small drawer and sliding door. The handling tasks were completed as same as above example.

VI. Conclusion

In this paper modeling and motion planning methods for handling furniture were discribed. The charactristics of this research is that handleable objects can easily be added to the robot through direct teaching. We proposed "IM-model" for the solution of this request and motion planning by utilizing the model. Experiemtal results shows the feasibility of our method.

Future works, more types of furniture should be applied to our method.

References

[1] H. Asada and Y. Asari: "The Direct teaching of tool manipulation skills via the impedance identification of human motion", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.1269–1274, 1988

[2] B.Bayle, J.Fourquet and M.Renaud: "Manipulability Ayalysis for Mobile Manipulation", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.1251–1256, 2001

[3] N. Y. Chong and K. Tanie: "Object Directive Manipulation Through RFID", Proc. of Int. Conf. on Control, Automation, and Systems, Oct. 22-25, 2003.

[4] R. Katsuki, J. Ohta, T. Mizuta, T. Kito, T. Arai, T. Ueyama and T. Nishiyama: "Design of Artificial Marks to Determine 3D Pose By Monocular Vision", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.995–1000, 2003.

[5] K.Kitahama, K.Tsukada, F.Galpin, T.Matsubara and Y.Hirano: "Vision-based scene representation for 3D interaction of service robots", Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp.4756–4761, 2006.

[6] J. Miura, Y. Shirai and N. Shimada: "Development of a Personal Service Robot with User-Friendly Interfaces", Proc. of 4th Int. Conf. on Field and Service Robotics, pp.293– 298, 2003.

[7] K. Nagatani and S. Yuta: "Autonomous Mobile Robot Navigation Including Door Opening Behabior-System Integration of Mobile Manipulator to Adapt Real Environment", Proc of Int. Conf. on Field and Service Robotics, pp.208–215, 1997.

[8] S.Nakaoka, A.Nakazawa, K.Yokoi, H.Hirukawa and K.Ikeuchi: "Generating Whole Body Motions for a Biped Humanoid Robot from Captured Human Dances", Proc. of IEEE Int. Conf. on Robotics and Automation, pp.3905–3910, 2003.

[9] Y. Sagawa, K. Okada, T. Inamura and M. Inaba: "Recognition of Tool Manipulation and Emergence of Imitation on Humanoid Robots", Proc. of JSME Conf. on Robotics and Mechatronics, 2A1–D22, 2006(in Japanese).

[10] N.Sien, O.Stasse, Y.Kawai, T.Sakaguchi and K.Yokoi: "A Unified On-line Operation Interface for Humanoid Robots in a Partially-Unknown Environment", Proc. of IEEE Int. Conf. on Intelligent Robots and Systems, pp.4437–4439, 2006.

[11] K.Yamazaki, M.Tomono, T.Tsubouchi and S.Yuta: "3-D Object Modeling by a Camera Equipped on a Mobile Robot" Proc. of IEEE Int. Conf. on Robotics and Automation, pp.1399–1405, 2004.

[12] K.Yamazaki, M.Tomono, T.Tsubouchi and S.Yuta: "A Grasp Planning for Picking up an Unknown Object for a Mobile Manipulator" Proc. of IEEE Int. Conf. on Robotics and Automation, pp.2143–2149, 2006.

[13] K.Yamazaki, M.Tomono, T.Tsubouchi and S.Yuta: "Motion Plannning for a Mobile Manipulator Based on Joint Motions for Error Recovery" Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp.7–12, 2006.