Motion Planning for a Mobile Manipulator Based on Joint Motions for Error Recovery

Kimitoshi Yamazaki
Graduate School of Systems and Inf. Eng.
Univ. of Tsukuba
Tsukuba, Japan
yamazaki@roboken.esys.tsukuba.ac.jp

Masahiro Tomono
Dept. of System Robotics
Toyo Univ.
Saitama, Japan
tomono@eng.toyo.ac.jp

Takashi Tsubouchi and Shin'ichi Yuta
Inst. of Eng. Mech. and Systems
Univ. of Tsukuba
Tsukuba, Japan
{tsubo,yuta}@roboken.esys.tsukuba.ac.jp

***Abstract*— This paper describes motion planning for a mobile manipulator which works in real environment. Mobile manipulators that can manipulate an object was developed up to now. We assume that object grasping is not restricted to just one grasp way and robot can move freely as far as it is in its operational area of the object. This paper proposes the motion planning for object grasping under the previous explained conditions. There are two major issues to detect the robot pose. The first problem is pose error of the robot hand. The second problem is kinematical redundancy of the mobile manipulator. The pose is evaluated from the amount of joint motions for recovery of hand pose error. Experiments show the effectiveness of the proposed method.**

I. Introduction

Mobile Manipulators research is a widespread studied field. They consist of robotic arms mounted on mobile platform so they are used in a large variety of tasks such as carrying objects from one place to another. Several researches have addressed the problem of manipulating objects in real environments, where they use object information such as predefined object models[4][5], ID tags[1] or QR codes[3].

In this research we aim to develop a picking and carrying object tasks performed by a mobile manipulator in a real environment. Specifically, the robot has to find a small sized object placed in a real office desk environment, pick it up and take it to another location. Conventionally in other researches, object grasping is performed by previously teaching the manipulator how to grab certain objects or previously determining a specific posture of the mobile manipulator. So in these approaches, robot motion has been planned using previously object and environment knowledge. The objective of this research is to plan a robot pose for grasping under the condition that object grasping is not restricted to just one grasp way. In our assumption, innumerable robot poses can be selected in the workspace where the robot can move freely as far as it is in object range.

In order to select robot pose, we consider two important issues. Firstly, pose error in the mobile base implicitly introduces error on the end-effector's pose. We cope with this problem by selecting the robot pose which needs only small joint motions of a manipulator for recovering of this error. Secondly, the mobile manipulator has kinematical redundancy which increases its mobility but at the same time presents the problem of a large amount of possible grabbing postures. We cope with this problem by searching the best grasp pose from a global area while evaluating it locally in each particular area. Throughout this paper, 'mobile manipulator' means a robot which consists of one robotic arm mounted on mobile platform. We call such mobile manipulator 'robot' and discuss under the condition that 'manipulator' and 'mobile platform' are distinguished explicitly.

This paper describes as follows: In the next section, related works are described. Section III presents a scheme of this study and problem definition. Section IV and V present the outline of motion planning. Section VI provides experimental results. Section IV concludes this paper.

II. Related Works

Traditionally for motion planning of a mobile manipulator, end effector's pose or trajectory is given in advance. Nagatani et al.[6] and Shin et al.[7] proposed planning methods for deciding platform poses which can keep manipulability[11]. This kind of planning is applicable if only one target trajectory is given. However, in our research, as there are several grasping positions, motion planning also has to select an end effector's target pose.

Other approaches consider an uncertainly element of environment or robot was proposed. Yamashita[9] proposed a motion planning method for manipulation of an object by multiple mobile robots. The planning was performed considering motion errors of the mobile robots before they move. It can be expected to implement a carrying task stably, however a way to manipulate and a shape of the object were relatively simple. Our research is similar to these motion plannings at the point of considering errors in advance, however the purpose of our motion planning is to reduce the influence of end effector's pose error when it grasps a small object on the desk.

III. Problem Definition and Scheme

A. Assumed Task and Research Objective

We consider the task of grabbing a small object on a desk. It is assumed that the object can grasp from any direction. A map of desk environment is given in advance. The mobile platform is nonholonomic two-wheel drive

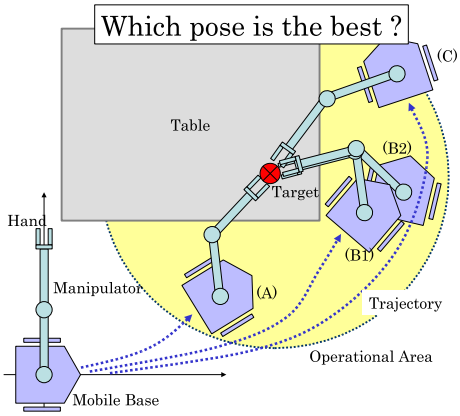

Fig. 1. Problem Definition

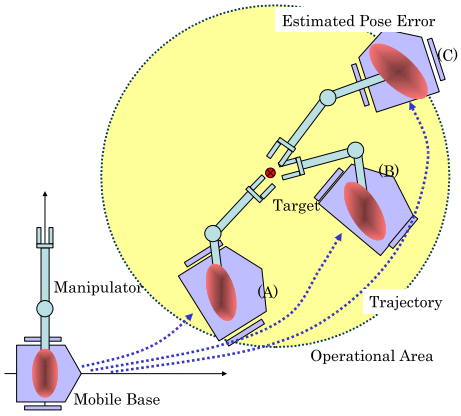

Fig. 2. Pose Error from Mobile Base

system which is considered to move on a flat surface. In this paper, we call pose to both, position and orientation.

The objective of this study is to detect the manipulator pose and the platform pose through motion planning. The task is performed according to the following procedure:

1) Using the object model which was acquired by a robot in advance, the object is found while the robot moves on the floor.
2) One robot pose is detected from other candidates(i.e. Fig.1 A,B and C) through motion planning.
3) After the robot moves to planned pose, the object is measured again. If there are pose error, new robot pose for grasping is re-calculated.
4) Grasp motion is performed.

While pose evaluation in 2), a good solution is found if less amount of manipulator motion can be estimated between planned pose to re-calculated pose.

B. Issues

The pose error of end-effector is a critical issue when the mobile manipulator picks up an object. This error is caused by a pose error of the mobile platform (Fig.2). Odometry is often used to estimate the pose in general, but this can include error which is derived from initial position or wheel motion. Although the error can be corrected by checking sensor data with the environment map, because of sensor inaccuracy, the error cannot be totally corrected. The challenge is to search a robot pose which satisfies both, a few pose error and to be able to correct the error easily.

Other problem is kinematical redundancy of the mobile manipulator. We assume that the degrees of freedom of the robot motion are more than needed to manipulate an object. An advantage is that it can increase a variety of the robot poses and improve its manipulability. However, poses can become infinite. Fig.1 is an example. The robot can select all poses from A to C. In addition, as B1 and B2 in Fig.1 shows, there are not only one determined pose in each position of the platform. The challenge is to detect the best robot pose from these pose candidates.

C. Approach

Our planning method consists of two steps. They are local pose evaluation and global pose searching.

1) Local Pose Evaluation: Local area means the fixed positions of mobile platform through global searching. In each of the local area, robot pose is evaluated whether the manipulator mounted on the mobile platform has high manipulability or not. In our definition, manipulability means the amount of joints motion when end-effector is moved from one pose to another. The manipulability becomes high when the end-effector pose is changed with less joints motion.

Conventionally, the measure of manipulability[11] is often considered, but it is decided from a robot kinematics. It is different comparing with our manipulability because our measure copes with such errors as pose error of robot.

2) Global Pose Searching: Achieving the grasping task, there are three contents to be detected as follows:

A. Pose of a manipulator
B. Position of a mobile platform
C. Path of a mobile platform

The pose of the robot is evaluated from item A. and B. Because many poses can be found even when the position of the mobile platform is detected, we prefer to take an approach to divide the workspace into small grids. The robot pose evaluation mentioned above is performed in each grid and a best pose is selected by the grid which has best evaluation.

Path planning for the mobile platform is performed by utilizing conventional method which can find feasible path.

IV. Evaluation of Robot Pose

In this section we describe pose evaluation method for a mobile manipulator when an end-effector pose and a platform position are given. Variables in this section are defined as follows:

- $\mathbf{x}_h$: End-effector pose in robot coordinates
- $\mathbf{x}_b$: Object pose in robot coordinates
- $\mathbf{x}_H$: End-effector pose in world coordinates
- $\mathbf{x}_B$: Object pose in world coordinates
- $\mathbf{x}_G$: The platform pose in world coordinates

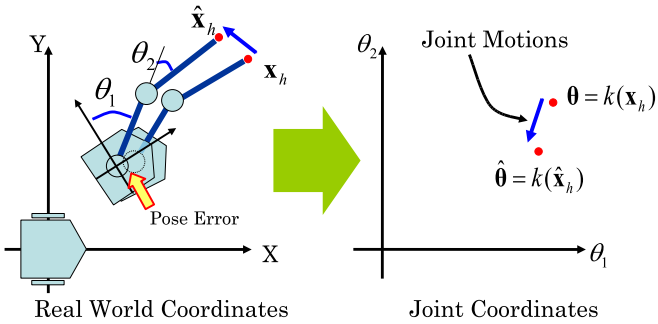

Fig. 3. Pose Error

At first, platform pose $\hat{\mathbf{x}}_G$ and object pose $\hat{\mathbf{x}}_B$ are given. End-effector pose $\hat{\mathbf{x}}_H$ is calculated from them as reference pose of end-effector.

A. Summary

Our pose evaluation is calculated from joint motions. For this reason, joint space is considered. Joint space consists of a set of the joint variables of the manipulator.

Evaluation function is represented by using the following equation:

$$C = \int |k(\mathbf{x}_h) - k(\hat{\mathbf{x}}_h)| P(\mathbf{x}_h) d\mathbf{x}_h, \tag{1}$$

where $\mathbf{x}_h$ is end-effector pose and $\hat{\mathbf{x}}_h$ is a target pose which is selected by motion planning. These are defined in mobile platform coordinates. $k(\mathbf{x})$ 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 end-effector pose. C becomes smaller, the pose is better.

The meaning of eq.(1) is illustrated with a planar mobile manipulator in Fig.3 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.3. In our index, it is important that less joint motions from $\mathbf{x}_h$ to $\hat{\mathbf{x}}_h$ for the adjustment are desirable. In other words, good evaluation is acquired if a distance between $\hat{\theta}$ and θ in Fig.3 becomes small in joints space. Eq.(1) calculates an expectation of joint motions for its adjustment utilizing a probabilistic distribution.

B. Pose Error of a Mobile Platform

A probabilistic distribution $P(\mathbf{x}_G)$ is calculated from the platform pose $\mathbf{x}_G = (x_G, y_G, \theta_G)^T$. Conventionally, odometry is often used for estimating the pose. In addition, normal distribution is used for representing an error of odometry.

$$P(\mathbf{x}_G) = N(\hat{\mathbf{x}}_G, \Sigma_G), \tag{2}$$

where $\hat{\mathbf{x}}_G$ is an average position of $\mathbf{x}_G$ with Σ_G. Σ_G is a covariance matrix of $\mathbf{x}_G$. If the mobile platform moves during a time t_0 to a time t_G, Σ_G is calculated such distribution as follows:

$$\Sigma_G = \Sigma_p(t_G), \tag{3}$$

where $\Sigma_p(t_G)$ is the calculated result of recurrence formula[8]. as follows:

$$\Sigma_p(t+\tau) = \mathbf{K}_1(t)\Sigma_p(t)\mathbf{K}_1(t)^T + \mathbf{K}_2(t)\Sigma_v(t)\mathbf{K}_2(t)^T + \Delta\mathbf{p}, \tag{4}$$

where τ is an interval of sampling time. $\Sigma_p(t)$ is a covariance matrix related to robot pose $\mathbf{x}(t)$ at a time t and $\Sigma_v(t)$ is a covariance matrix related to robot velocity $\mathbf{v}(t)$. $\mathbf{K}_1(t)$ and $\mathbf{K}_2(t)$ are Jacobian matrices. $\Delta\mathbf{p}$ is the error of linearization. T means transpose.

C. Pose error of end-effector

The probabilistic distribution $P(\mathbf{x}_h)$ is calculated by following equation:

$$P(\mathbf{x}_h) = \iint P(\mathbf{x}_h|\mathbf{x}_B, \mathbf{x}_G) P(\mathbf{x}_B) P(\mathbf{x}_G) d\mathbf{x}_B d\mathbf{x}_G, \tag{5}$$

where a probabilistic distribution of object pose $P(\mathbf{x}_B)$ is calculated from $\mathbf{x}_B$ which is defined in world coordinates. This is given by normal distribution which consists of average $\hat{\mathbf{x}}_B$ and covariance Σ_B as follows:

$$P(\mathbf{x}_B) = N(\hat{\mathbf{x}}_B, \Sigma_B). \tag{6}$$

$P(\mathbf{x}_h)$ represents a probabilistic distribution of the end-effector pose. To calculate $P(\mathbf{x}_h)$, Monte Carlo method is utilized. In particular, make a group of $\mathbf{x}_h$ which is calculated from $\mathbf{x}_B$ and $\mathbf{x}_G$ which are randomly sampled according to the normal distributions.

The calculation procedure is as follows, $\mathbf{x}_b$ in mobile base coordinates is calculated from coordinates translation as follows:

$$\mathbf{x}_b = \mathbf{R}^T_{(\mathbf{x}_G)}(\mathbf{x}_B - \mathbf{T}_{(\mathbf{x}_G)}), \tag{7}$$

where $\mathbf{R}_{(\mathbf{x}_G)}$ is a rotation matrix related to $\mathbf{x}_G$ and $\mathbf{T}_{(\mathbf{x}_G)}$ is translation vector. Meanwhile, $\hat{\mathbf{x}}_h$ is calculated from $\hat{\mathbf{x}}_G$ and $\hat{\mathbf{x}}_H$ according to following translation,

$$\hat{\mathbf{x}}_h = \mathbf{R}^T_{(\hat{\mathbf{x}}_G)}(\hat{\mathbf{x}}_H - \mathbf{T}_{(\hat{\mathbf{x}}_G)}), \tag{8}$$

and finally, $\mathbf{x}_h$ which belongs to $P(\mathbf{x}_h|\mathbf{x}_B, \mathbf{x}_G)$ is calculated by following equation:

$$\mathbf{x}_h - \hat{\mathbf{x}}_h = (\mathbf{x}_b - \hat{\mathbf{x}}_b) + |\hat{\mathbf{x}}_B - \hat{\mathbf{x}}_H| \begin{pmatrix} cos\phi_b - cos\hat{\phi}_b \\ sin\phi_b - sin\hat{\phi}_b \\ 0 \end{pmatrix}, \tag{9}$$

where ϕ_b is a pose of the object in mobile base coordinates.

D. Calculate Pose Evaluation

$P(\mathbf{x}_h)$ is calculated from $P(\mathbf{x}_G)$ and $P(\mathbf{x}_B)$. In our implementation, because $P(\mathbf{x}_G)$ and $P(\mathbf{x}_B)$ are normal distributions, the ellipsoidal areas where mahalanobis distance is less than predefined threshold D_1 and D_2 are considered.

$$\begin{aligned} (\mathbf{x}_G - \hat{\mathbf{x}}_G)^T {\Sigma_G}^{-1} (\mathbf{x}_G - \hat{\mathbf{x}}_G) = {D_1}^2 \\ (\mathbf{x}_B - \hat{\mathbf{x}}_B)^T {\Sigma_B}^{-1} (\mathbf{x}_B - \hat{\mathbf{x}}_B) = {D_2}^2. \end{aligned} \tag{10}$$

The evaluation is performed according to following procedure:

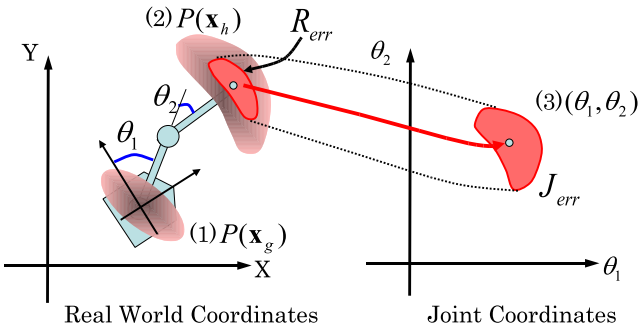

Fig. 4. Probabilistic representation

1) The end-effector pose in robot coordinates $\hat{\mathbf{x}}_h$ is calculated in eq.(8),
2) $\hat{\theta} = (\theta_1, \theta_2, \cdots, \theta_n)$ is calculated by solving inverse kinematics of $\hat{\mathbf{x}}_h$,
3) C is calculated iteratively by following procedure.
   a) $\mathbf{x}_G$ and $\mathbf{x}_B$ in world coordinates is detected from inside of ellipsoids in eq.(10). These are randomly sampled according to normal distribution $P(\mathbf{x}_G)$ and $P(\mathbf{x}_B)$.
   b) End-effector pose $\mathbf{x}_h$ is calculated in eq.(9) using $\mathbf{x}_b$ which is calculated in eq.(7).
   c) θ is calculated from this $\mathbf{x}_h$.
   d) An absolute difference between $\hat{\theta}$ and θ is added to C.

Good pose evaluation is acquired when the C becomes small. Fig.4 illustrates the probabilistic region of the probabilistic variables which appear in these calculations. If $\mathbf{x}_h$ exists inside of R_{err} according to calculation by the way to 3) b), the distribution θ forms a region J_{err} in joints space (Fig.4(3)). If J_{err} become smaller, a good evaluation is acquired in eq.(1).

E. Redundant manipulator

There are infinite solution to the manipulator inverse kinematics if the manipulator has redundant degrees of freedom. Taking account of this redundancy, evaluation of eq.(1) is calculated after the manipulator pose is optimized. The optimization function is as follows:

$$\theta_{new} = \theta + \lambda(\mathbf{I} - \mathbf{J}^{+}\mathbf{J})\frac{\partial q(\theta)}{\partial \theta}, \tag{11}$$

where $\mathbf{J}$ is Jacobian matrix of the manipulator, $\mathbf{J}^{+}$ is pseudo inverse matrix of $\mathbf{J}$. λ is positive constant. In our method, $q(\theta)$ is defined as following equation when the number of joints are n,

$$\frac{\partial q(\theta)}{\partial \theta} = \sum_{j=1}^{m}\sum_{i=1}^{n}\Delta\theta_{ij}^2 = \sum_{j=1}^{m}\mathbf{J}^{+}\mathbf{x}_{h,j} \tag{12}$$

Eq.(12) calculates minimum norm solution of joint motions to move from $\hat{\mathbf{x}}_h$ to $\mathbf{x}_{h,j}$ which is an arbitrary pose in R_{err}. This $\mathbf{x}_{h,j}$ will be selected by the same way which is described in 4.D. If the good manipulative pose is calculated in the optimization in eq.(11), final evaluation C becomes good.

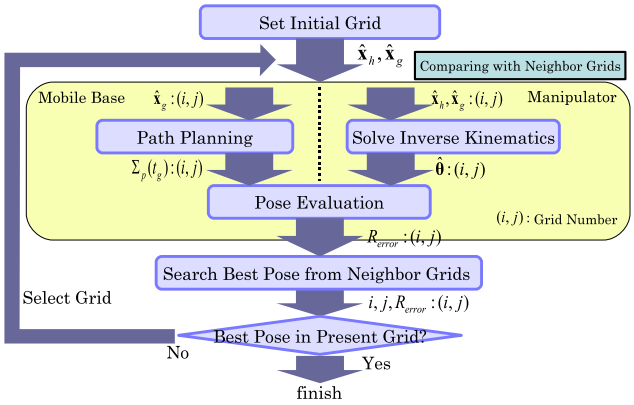

Fig. 5. Planning Algorithm

V. Global Pose Detection

In this section the global pose detection method is described.

A. Summary

In section IV, the evaluation method for the robot pose is presented under the condition that both grasp pose and the position of the mobile platform are given. The purpose of this section is to propose a method for which a good grasp pose and a platform position can find from the workspace.

The principles to find a good pose are as follows:

- The workspace is divided into small grids. As a position of the mobile platform is the center of each grid, the evaluation is performed.
- A planned path of the mobile platform is adopted if the path is sub-optimal.

In this condition, the grids which are used for pose evaluation can be selected from which the robot can reach its end-effector to the target object. Moreover, some grids can be removed if it exists inner obstacles (i.e. desks) for the mobile platform. Using environment map and operational area for the manipurator, these useless grids are found relative easily.

B. Algorithm

In the motion planning, an initial position of the mobile platform and the object is given. The best pose is searched according to the following procedure.

1) Firstly, with only operational area for object grasping, grid space is constructed in x-y coordinates. Moreover, some other grids which go into such object as desk are removed. As a result, a group of grids which are the position candidates of the platform are acquired.
2) A grid is randomly sampled until specified number, and
   a) the robot pose is evaluated by the method described in section IV,
   b) same evaluation is performed about 8 neighbor grids,

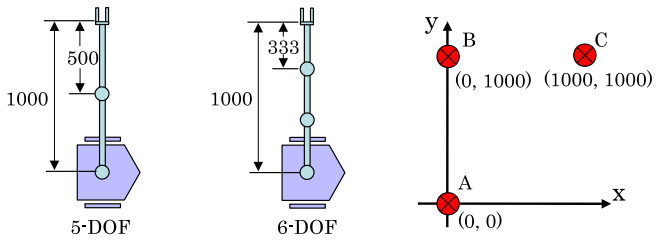

Fig. 6. Simulation

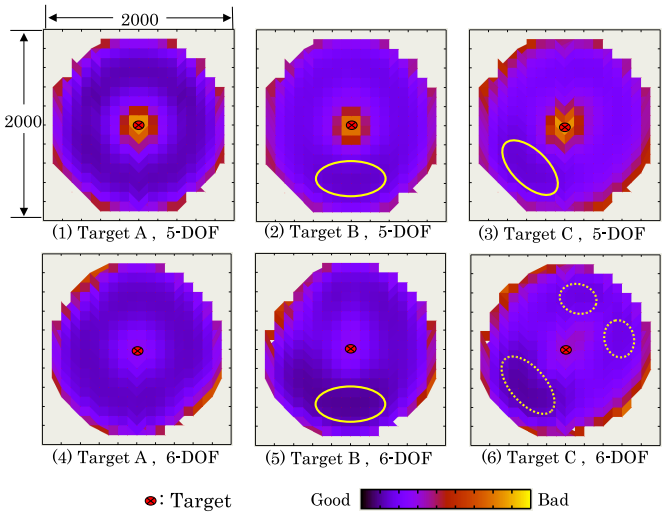

Fig. 7. Evalutation Example

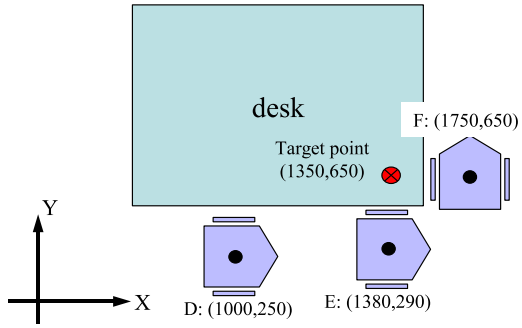

Fig. 8. Experiments

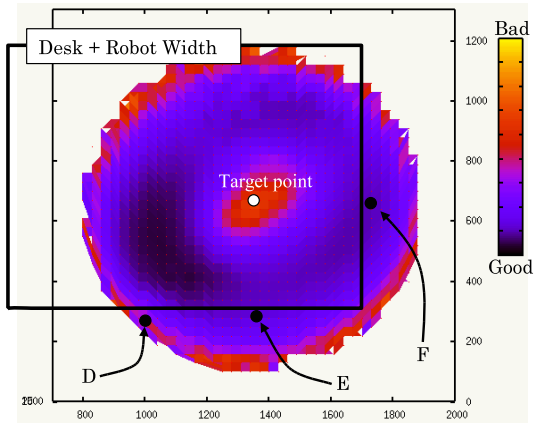

Fig. 9. Pose Evaluation

c) go to 3). if a best evaluation is acquired in present grid, otherwise selecting neighbor grid which has smaller evaluation than the present grid, and return a).

3) Finally, the smallest evaluated grid through processing in item 2) is selected as the best position of the mobile platform.

Fig.5 shows the algorithm.

As described in next section, the result of pose evaluation is composed as smoothly curved surface which has local minimum.

VI. Experiments

Experiments are performed with a mobile manipulator.

A. Simulation

The initial pose error of a mobile platform is 1σ=10mm and 1σ=10deg with respect to normal distribution. The position error of an object is 1σ=5mm and direction error is not considered. To plan a path of the mobile platform, a planning method using a Laplacian potential field [2] was utilized. Fig.6 shows a planar mobile manipulator which has a horizontal manipulator. The pose evaluation is performed under the condition that both of joint limits and collision between arms are not considered.

The robot is set on the origin in world coordinates and target end-effector positions are set such three patterns as A:$(x, y) = (0, 0)$, B:$(x, y) = (0, 1000)$ and C:$(x, y) = (1000, 1000)$. Fig.7 shows the pose evaluation about A to C. In this simulation, x-y coordinates are divided into grids something which size is 100mm width. The center point in each graph represents the object position.

If the mobile platform do not have to move so much in its operational area, good evaluated position is acquired from large area which has high manipulability (Fig.7(1),(4)). In this case, the robot should move slightly to the position where good manipulability is saved.

Solid line in Fig.7(2) to (6) shows that the robot should not move so much when the initial position is near to the goal position. However, good evaluated position can be found another distant positions because they have good manipulability against pose error of end-effector (i.e. Fig.7(6)). In our method, evaluated result has some local minimum and its form is changed smoothly.

B. Evaluation using real robot

Utilizing the mobile platform which has 3-DOF planar manipulator, global pose detection is experimented. Fig.8 shows experimental environment. We assume that the robot grasps a cylinder type object which can grasp from anywhere at x-y coordinates. The best position of mobile platform is detected as F in Fig.8

In this experiment, the positions of mobile platform are set three patterns as D:$(x, y) = (1000, 250)$, E:$(x, y) = (1380, 290)$ and F:$(x, y) = (1750, 650)$. Errors are added

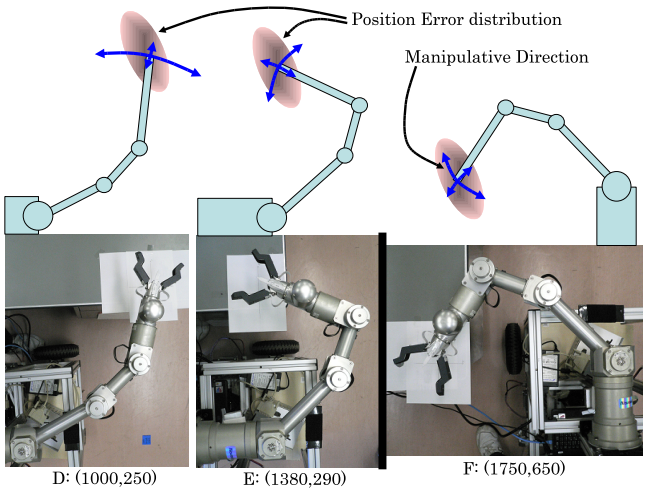

Fig. 10. Grasp Poses

to the initial robot pose randomly. The position error is at the maximum 20mm and the orientation error is at the maximum 5deg.

Fig.9 shows the result of pose evaluation. It can be seen that the position F is a neighbor of a local minimum. Fig.10 shows the pose of manipulators. Good pose evaluation is acquired if error distribution and manipulability spread similar direction. Fig.11 shows the pose error of end-effector. Fig.12 shows the amount of joint motions for recovering the pose error. In this graph, horizontal axis shows the trial number and vertical axis shows a sum of joint motions for pose recovery. The recovery motion is the smallest at the F, otherwise the pose errors of end-effector are not changed so much during three patterns which is shown in Fig.11. The motion planning is executed in 2.5sec(using Pentium IV, 2.8GHz).

VII. Conclusion

In this paper, we presented motion planning for object grasping under the condition that grasp pose is not restricted to just one way and robot can move freely as far as it is in its operational area of the object. In our method, a position of the mobile platform and the manipulator pose are detected by investigating the amount of joint motions for recovery of hand pose error. Experiments show the effectiveness of the proposed method.

As a future work, development of our method for pose selection is desired in the case that several end-effector pose candidates are given. In addition, more effective algorithm for pose evaluation is needed for implementing to real robot.

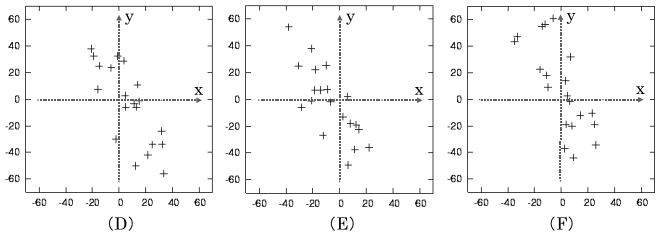

Fig. 11. Position Error of End-Effector

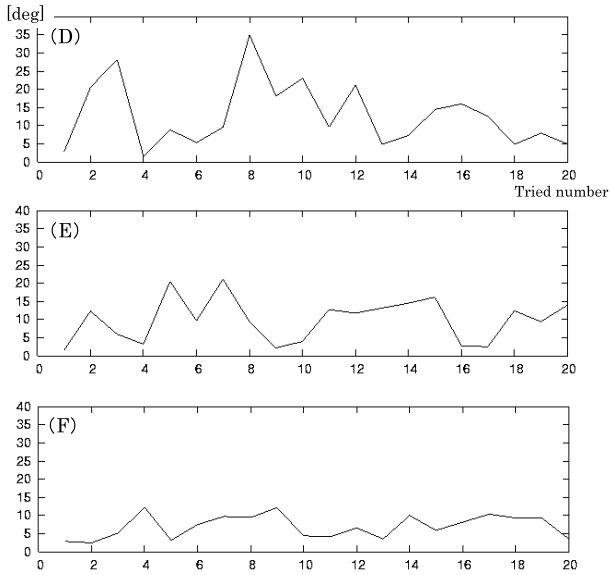

Fig. 12. Sum of Three Joint Motions

References

[1] N. Y. Chong and K. Tanie: "Object Directive Manipulation Through RFID", Proc. Int. Conf. on Control, Automation, and Systems, 2003.

[2] C. Connolly, J. Burns and R. Weiss: "Path Planning using Laplace's Equation", Proc. Int. Conf. on Control, Automation, and Systems, pp.2102 – 2106, 1990.

[3] 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. 2003 IEEE Int. Conf. Robotics and Automation, pp.995–1000, 2003.

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

[5] K. Nagatani and S. Yuta: "Autonomous Mobile Robot Navigation Including Door Opening Behabior-System Integration of Mobile Manipulator to Adapt Real Environment-", International Conference on Field and Service Robotics (FSR'97) , pp.208–215, 1997.

[6] K. Nagatani,T. Hirayama,A. Gofuku and Y. Tanaka: "Motion Planning for Mobile Manipulator with Keeping Manipulability", Proc. of IEEE/RSJ Int. Conference on Intelligent Robots and Systems, pp.1663-1668, 2002.

[7] D. Shin, B. Hamner, S Singh and M Hwangbo: "Motion Planning for a Mobile Manipulator with Imprecise Locomotion", Proc. Int. Conf. on Control, Automation, and Systems, 2003.

[8] Y. Watanabe and S. Yuta: "Position estimation of mobile robots with internal and external sensors using uncertainly evolution technique, IEEE Int. Conf on Robotics and Automation, Seiten 2011-2016, 1990.

[9] A. Yamashita, J. Sasaki, J. Ota and T. Arai: "Cooperative Manipulation of Objects by Multiple Mobile Robots with Tools", Proc. of the 4th Japan-France/2nd Asia-Europe Congress on Mechatronics,pp.310–315, 1998.

[10] K.Yamazaki, M.Tomono, T.Tsubouchi and S.Yuta: "A Grasp Planning for Picking up an Unknown Object for a Mobile Manipulator", Proc. 2006 IEEE Int. Conf. Robotics and Automation, (to be appeard).

[11] T. Yoshikawa "Analysis and Control of Robot Manipulators with Redundancy", Preprints of 1st Int. Symposiumu of Robotics Research, 1983.