Maximizing the Use of Environmental Constraints: A Pushing-Based Hybrid Position/Force Assembly Skill for Contact-Rich Tasks

Yunlei Shi1,2, Zhaopeng Chen2,1, Lin Cong1, Yansong Wu3, Martin Craiu-Müller2, Chengjie Yuan3, Chunyang Chang2, Lei Zhang1,2, Jianwei Zhang1

Abstract—The need for contact-rich tasks is rapidly growing in modern manufacturing settings. However, few traditional robotic assembly skills consider environmental constraints during task execution, and most of them use these constraints as termination conditions. In this study, we present a pushing-based hybrid position/force assembly skill that can maximize environmental constraints during task execution. To the best of our knowledge, this is the first work that considers using pushing actions during the execution of the assembly tasks. We have proved that our skill can maximize the utilization of environmental constraints using mobile manipulator system assembly task experiments, and achieve a 100% success rate in the executions.

I. INTRODUCTION

In most advanced computer, communication, and consumer electronics (3C) product manufacturing factories, the vast majority of production processes requiring high-precision operations have been efficiently realized by fixed, dedicated automation systems or position-controlled robots [1]. The requirement for the quick setup and reprogram of new robotic assembly lines for new products in 3C factories is rapidly growing [2], [3], [4]. However, dedicated automation systems and position-controlled robots require tedious programming and tuning, thereby prolonging the time to install a new production line. Moreover, they cannot adapt to any unexpected variations in assembly processes [5].

Collaborative robots (cobots) assist in tackling the challenges posed by onerous setup, programming tasks [6], and unexpected variations in assembly processes through force-control techniques [7]. Mobile manipulator systems were designed to accelerate the long installation and setup times of cobots, as they integrated all the required devices on a “plug-and-play” mobile platform [8], [9]. However, the repeatability of these mobile robots is much worse than that of cobots [10], [3].

In this paper, we analyze the constraint case when the object and the environment have relative motion, and thus propose a pushing-based hybrid position/force assembly skill accordingly to address the aforementioned challenge. We demonstrated that the proposed skill can maximize the utilization of environmental constraints through a comparative experiment (Figure 1).

II. RELATED WORK

A. Robotic Assembly in 3C Manufacturing Industries

The 3C manufacturing industry is one of the most important industries around the world [11]. A typical manufacturing process can be divided into four main phases: module manufacturing, assembly, testing and packaging, where the latter three majorly depend
dependent on human labor \(^1\). Robots have been extensively used in structured production environments to ensure consistent yields and efficient manufacturing \([12]\). However, reinstalling, setting up, and reprogramming robots take several weeks because they cannot rapidly adapt and reorganize with changes in assembly lines.

### B. Mobile Manipulator Programming

Mobile manipulators were designed to accelerate the setup of robots by integrating the required task devices into a mobile platform. Additionally, several mobile manipulators have been developed and deployed in real manufacturing environments. Traditional robot programming is complex. For example, a typical “pick-and-place” teaching process comprises several steps (Figure 2) \([13]\).

Skill-based task programming methods were designed to enable an easy set up for mobile manipulators \([14]\), \([15]\), in which the predefined functional blocks are adapted to a specific task via several parameters \([16]\). Although numerous skills have been developed to simplify mobile manipulator programming \([14]\), the research and development of the contact-rich task skills have not been adequately reported.

### C. Operational Space Position/Force Control

Direct/indirect force control techniques have been previously used to overcome the limitation of performing contact-rich manipulation tasks \([17]\), \([18]\). Additionally, force/motion control is crucial in robotics \([19]\). A passive compliance element (i.e., remote center compliance) in industrial robots can automate assembly tasks \([20]\), \([21]\). However, they have to adjust according to the given applications and can only perform well on small deviations in the assembly tasks. To generalize the robotic assembly capabilities, assembly skills based on hybrid position/force trajectories, such as, linear, zigzag, spiral, sinus, and lissajous trajectories, have been developed for robots equipped with force and torque sensors \([22]\).

### III. PROBLEM STATEMENT

#### A. Positioning Accuracy of Mobile Manipulators

In the traditional magnetic tracking approach, the positioning accuracy of mobile manipulators exceed \(\pm 5\) mm, which does not meet the requirements of many industrial applications, such as precision assembly and tending \([10]\), \([23]\). Visual feedback is an effective method for overcoming position uncertainties during assembly tasks \([24]\), \([25]\). However, visual feedback includes errors introduced by imaging sensors, lenses, as well as intrinsic and extrinsic parameters \([3]\), steering some researchers to focus more on execution methods than on using accurate vision sensors \([3]\).

#### B. Positioning Uncertainty of Flexible End Effector

Vacuum grippers are employed to grasp horizontal or vertical flat objects using suction cups because they can avoid strong contact forces between the object and gripper \([26]\). Therefore, they are frequently used in 3C production factories \([27]\). Most studies consider assembly tasks as moving already-grasped objects to their goal positions by minimizing the distance between an object and its goal position \([28]\). However, this assumption has problems owing to contact-rich tasks, particularly when using flexible vacuum grippers \([26]\).

Teach-pendant is frequently employed in factories, particularly in heavily constrained spaces, as shown...
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holder. According to our analysis, there are several
(numbered 1–6) are used to adjust the tension of the
on the holder are used to fix the object. The fixtures
A. Constraints Analysis

According to the contact states analyzed in Figu-
fixtures may generate a strong contact force
between the object and robot, causing a stuck situ-
Moreover, owing to the elastic effect of the EE
(e.g., vacuum gripper), the concrete contact situation
is difficult to distinguish with the force/torque sensor
mounted at the wrist of the robot.

Through the simulations of robot assembly ma-
ipulations with human hands, we found that the
constraints provided by the fixtures can guide the
object alignments with the holder geometry. Figure 6
was used to analyze this phenomenon according to a
simplified contact situation, whereas Figure 6(a)–(d)
illustrate the pushing action along the X direction.

\[ e = \text{initial position error between object and holder}, \]
\[ \mathbf{P} = \text{translational movement command along the X direction}, \]
\[ O = \text{center of the object}, \]
\[ \theta = \text{angle between the object and holder surface}, \]
\[ \mathbf{A} \text{ and } \mathbf{B} = \text{the adjustable fixtures on the holder}, \]
\[ f_1 \text{ and } \mu_1 = \text{the maximum static friction and coefficient of static friction between the vacuum gripper and object (the vacuum gripper is released), respectively}, \]
\[ f_2 \text{ and } \mu_2 = \text{the static friction and coefficient of static friction between the object and holder/fixtures, respectively}. \]

\[ F_{N1}, \quad F_{N2}, \quad F_{N3}, \quad F_{N4}, \quad F_{N5} \text{ and } F_{N6} = \text{the normal forces exerted by the holder/fixtures on the object}. \]

Fig. 4. Assembly task illustration: aligning two parts (object and holder) with a certain geometric feature and maintaining the alignment using a certain operation process.

Fig. 5. 14 possible contact states. The pink fixtures indicate contact with the object. Due to the space limitations, some contact states were not listed.

in Figure 2. However, avoiding strong contact forces
is difficult owing to nontransparency issues (Fig-
re 3). Based on our experiments using a vacuum
gripper (Model: Bellows Suction Cups SPB1, 1.5 Folds), a contact force of 10 N can produce a transla-
tional deformation of up to 1 mm and the respective
rotational deformation is even more accentuated.

IV. CONSTRAINTS ANALYSIS AND SKILL DESIGN

A. Constraints Analysis

As shown in Figure 4, several adjustable fixtures
on the holder are used to fix the object. The fixtures
(numbered 1–6) are used to adjust the tension of the
holder. According to our analysis, there are several
contact states that can cause object and holder misa-
lignments (Figure 5).

According to the contact states analyzed in Figu-
re 5, fixtures may generate a strong contact force
between the object and robot, causing a stuck situ-
tion. Moreover, owing to the elastic effect of the EE
e.g., vacuum gripper), the concrete contact situation
is difficult to distinguish with the force/torque sensor
mounted at the wrist of the robot.

We performed general force analysis on the ob-
ject along the X and Y directions of frame O. In
Figure 6(a), the object was assumed to be stationary.
The force analysis performed along the Y direction
is represented by the following equation:

\[ F_{N1} \cos \theta + F_{N2} \cos \theta + F_{N3} + f_2 \sin \theta = 0 \quad (1) \]
\[ F_{v-o} \text{ represents the force between the vacuum} \]
gripper and object in X direction:
\[ F_{v-o} = f_1 + F_{N1} \sin \theta \]
(2)
\[ F_{o-h} = f_2 \cos \theta + f_3 = \mu_2 F_{N2} \cos \theta + \mu_2 F_{N3} \]
(3)
Based on Equation (1),
\[ F_{o-h} = -\mu_2 F_{N1} \cos \theta - \mu_2 f_2 \sin \theta \]
(4)
Considering angle \( \theta \approx 0 \), negligible terms were removed from Equation (2) and (4) (when \( \theta \approx 0 \), \( \sin \theta \approx 0 \)), Equation (5) was obtained as follows:
\[ F_{o-h} = -\mu_2 F_{N1} \cos \theta \]
(5)
\[ F_{v-o} = \mu_1 F_{N1} \cos \theta \]

From Equation (5) and Figure 6, we can infer that the coefficient of static friction determines the object’s direction of motion. The same conclusion can be obtained from Figure 6(b). The vacuum grippers are mainly made of rubber \(^2\) with a high coefficient of static friction, thus \( \mu_1 > \mu_2 \) is an easily obtainable condition.

The following results are obtained from Figure 6(c) and (d):
\[ \max(F_{N4}) = \max(F_{N5}) \gg f_1 = \mu_1 F_{N1} \]
(6)
Thus, the entire operation was performed based on the following condition (Figure 6):
\[ \max(F_{N4}) = \max(F_{N5}) \gg F_{v-o} > F_{o-h}. \]
(7)

The object can be pushed by the vacuum gripper until it is constrained by the fixtures thereby maximizing the use of environmental constraints. Based on the aforementioned analysis, we designed a pushing-based hybrid position/force assembly skill model to execute the tending task.

B. Skill Design

A pushing-based hybrid position/force assembly skill was designed, as shown in Figure 7. Once the state is confirmed, 6 linear hybrid position/force movements are executed according to the skill parameters (i.e., position and force). An inspection was performed after the execution.

We implemented a hybrid position/force controller under the EE frame for the skill execution (Figure 8), where \( p_d \) and \( R_d \) are command pose, \( p, R \) are current pose; \( h_d \) is a command force/torque, and \( h_d \) is a feedback force/torque. The diagonal matrices \( K \) and \( K' \) were used to indicate position or force control under the EE frame. In this study, force control along the Z direction was defined by Equation (8):
\[ K = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 
\end{bmatrix}, K' = I - K \]
V. EXPERIMENTS AND CONCLUSIONS

A. Experiments

The experiment setup can be found in Figure 9. A UR5e robot was used to implement the machine tending task. The UR5e features a 6-axis and 5-kg payload, a working radius of 850 mm. It is equipped with a 6-DOF force/torque sensor on its EE and uses admittance controller [18] to achieve operational space force control. A workflow was designed to perform the experiment as shown in Figure 10. The skill parameters for the 6 actions (The sequence is shown in Figure 7) are set as:

\[
\begin{align*}
1 : [ &+P_{\sigma x}^d, 0, +F_z] \\
2 : [-2 * P_{\sigma x}^d, 0, +F_z] \\
3 : [ &+P_{\sigma x}^d, 0, +F_z] \\
4 : [ &0, +P_{\sigma y}^d, +F_z] \\
5 : [ &0, -2 * P_{\sigma y}^d, +F_z] \\
6 : [ &0, +P_{\sigma y}^d, +F_z].
\end{align*}
\]  

(9)

\(P_{\sigma x}^d\) and \(P_{\sigma y}^d\) denote the amplitudes of the discrete actions. \(P_{\sigma x}^d\) and \(P_{\sigma y}^d\) is set to 8 mm which twice bigger than the error \(e\) to ensure that the environmental constraints are fully explored. \(F_z\) is set to 5 N.

In this experiment, contrary to the perfect group, an error of \(e \in [2, 4] \text{ mm}\) was added along a random direction to the desired final pose to simulate the pose uncertainties in the uncertainty group. We evaluated our proposed method compared with the following baselines:

**Baseline 1: spiral search [29]**. A spiral search path was used to survey the entire environment surface. Here, the maximum search radius was set to 10mm.

**Baseline 2: learning-based search**. In this study, a double deep Q-network (DQN) with proportional prioritization [30] was trained as the search policy \(\pi_\theta(s)\). This baseline comes from the previous research [13]. The 6-dimensional force-torque vector \(s = [F_x, F_y, F_z, M_x, M_y, M_z]\) under the robot EE’s frame \(x_e\) was sent to the double DQN, and the force actions along the \(X, Y,\) and \(Z\) directions were output to the robot controller.

B. Conclusions

Overall, the results of 600 group robot assembly tasks were recorded, as presented in Table I. Baseline 1 (spiral search) always ended when stopped by one or two fixtures and thus insertion failed, moreover, it always generates sufficiently strong contact force between the objects and the holder. Baseline 2 (learning-based search) offered a high success rate. However, because Baseline 2 uses a neural network to estimate the state, it may sometimes lead to unexpected actions and thus failed. Our method achieves the best success rate in this comparison experiment.

To verify the generalization of our method, we also tested it on two other type holders using our method and obtained a 100% success rate (100/100 trials). Due to space limitation, we do not describe the details in this paper. The test scenes can be seen in the video submitted with the paper.

In future work, the aforementioned results will be combined with other learning-based pushing methods [31] (our previous work) to improve the efficiency and safety of the tending task.

### Table I

**Comparison of the success rates for different baselines**

| Baselines      | Perfect | Uncertainty |
|----------------|---------|-------------|
| Baseline 1     | 69/100  | 47/100      |
| Baseline 2     | 95/100  | 91/100      |
| Our method     | 100/100 | 100/100     |

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