Exploiting the Environment for Object Manipulation

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***Abstract*— Inspired by biological systems, complex object manipulation can benefit from using the environment to stabilize the involved objects. We show that this holds as well for robotic manipulation by evaluating how the environment can be used to optimize a screwing task. We compared the same manipulation with and without using the environment. We were able to improve the success rate as well as to minimize the stress for the robots joints by stabilizing the object with pressing it against a table and by using the robots impedance mode to reduce the applied forces.**

I. INTRODUCTION

Animals use physical support provided by the static environments in complicated tasks that they cannot achieve using their sensorimotor skills with the tools that they actively control. For example, chimpanzees use stones as active tools in order to crack the nuts, but they need a stable and static surface to crash the stone against [6]. As another example, the chimpanzees can assemble long sticks by inserting one into another in order to extend their reachability but they again need a static support for stabilization [11]. While they are very skilled in bi-manual manipulation, insertion of one stick into the other one is still difficult as it requires very fine control of both objects. The stick needs to be inserted into a small hole while maintaining the collinear arrangement of the sticks. In order to achieve this task, the chimpanzees use ground surface to stabilize one of the objects while focusing on the control of the other one as shown in Fig. 1.

Fig. 1. These photographs taken during Wolfgang Kohler's seminal experiments[11] show that chimpanzees have the ability to benefit from support provided by the environment in order to stabilize one of the objects during bi-manual stick assembly task.

In this paper, we aim to utilize a similar support mechanism in order to increase the performance of a robotic bi-manual manipulation task, namely screwing. Screwing is a complicated task as it involves two objects that need to be grasped and aligned first, and manipulated with fine control in complex trajectories later. Manually coding such motor program is possible (actually this is done in factory settings in industrial robots), but is very time-consuming and do not scale well to changing objects and noisy environments. Learning such a complex action from scratch is not realistic as well because of the high dimensional search space.

We use learning by demonstration paradigm [4], where the robot observes a screwing performance, and imitates the observation to achieve the task autonomously. As the physical interaction dynamics between the robot and the objects is very crucial in screwing task, it is not straightforward to map observed human demonstration to robot's sensorimotor space. Thus, we formulate this problem in kinesthetic teaching framework, where the demonstration is performed with robot's own body, i.e. the robot is physically guided through screwing. The robot then is able to reproduce the task based on its one-shot experience. The exact replication of the demonstrated action trajectory does only perform well in the exactly same noise-free environment, which is not a realistic assumption. In this paper, we use Dynamic Movement Primitives (DMPs) to learn and reproduce complex screwing action where the action trajectory is encoded with a small number of parameters [13]. DMPs, inspired from human motor control, enable robots to learn complex tasks ranging from drum playing [8] to biped locomotion [12]. Recorded movements are represented as a set of differential equations that provide robustness against perturbations, reaching to the attractor point, adaptation to different initial and goal positions, and learning of non-linear movement trajectories.

The main focus of this paper is to realize the use of environment support in screwing task in order to increase the performance. This support is not explicitly encoded in robot control; but instead, the DMP-based screwing action that is learned through kinesthetic teaching is applied in various configurations with and without environment support. We also analyze the effect of joint stiffness in different settings, and conclude that the robot with flexible joints achieves this task best when one of the objects is pressed against a table.

The remainder of this paper is structured as follows. Section III provides an overview of our robotic system and its environment. Section IV then introduces our approach to robot object manipulation and how the robot actually exploits the environment. Next, in Section V we discuss the results of our experiments as well as positioning them w.r.t. related

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work. We conclude in Section VI with a summary of the major contributions and an outlook on future work.

II. Related Work

Aiyama [1] analysed the kinematics of environment-contacting tasks by a position-controlled manipulator with a free-joint structure. For this, both, a kinematic and geometric analysis of the manipulated object is done. Further, by the outcomes of these analyses, conditions to achieve desired manipulation against friction and loss of contact are determined. Aiyama applied his approach successfully for object sliding and insertion tasks. Verma et al. [16] investigated the robot box-pushing of stationary objects in interaction with a planar environment that is equipped with embedded sensors. The purpose of the sensors is to detect pushable objects. Verma et al. showed that pushes then are more accurate if the pose information of the objects, retrieved by the sensors, is used when pushing. Related work is done in the area of dynamic interaction, such as cooperative robot-human tasks. Amor et al. [2] employ interaction models between two humans in on-going interaction tasks with the aim to learn how to respond to human partners. Similar work has been done by Berger et al. [3], who infer guidance information from a cooperative human-robot task. They propose a machine learning approach, which learns statistical model during an interaction phase to predict the outcome of future interactions. If the actually measured forces deviate, this is considered as robot guidance. Traversaro et. al. [14] estimated friction, inertial and motor parameters by partial least-square method to be able to detect contacts with the environment.

III. System Description

Our work is implemented using two KUKA 7 DoFs Lightweight robot 4+ with Servo-electric 3-Finger SCHUNK SDH-2 hands mounted on them (Fig. 2). There are three different control strategies offered by the robot arms:

- Position control: Exact positioning in both joint angles and cartesian coordinates is enabled.
- Impedance control: In this mode the robot simulates a virtual spring-damper system, whenever external forces are applied to it. It is possible to define the impedance settings either in Cartesian or joint space. The robot allows to set the stiffness of the virtual spring, the spring damping as well as settings for maximum torque or deviation from the desired position. Important settings that have been used to implement the described experiments are listed with their respective minimum and maximum values in table I. Impedance control can be of great use in robot manipulation as it reduces the stress on the robot joints and enables the robot to react on unexpected behaviour (e.g. assembly of complex parts by Giordano et. al [9])
- Gravity compensation: This controller allows free guidance of the robot while it compensates for gravity.

Short Description	Min Value	Max Value	Unit
Cartesian spring stiffness	0.01	5000	N / m
Cartesian spring damping	0.01	1	N s / m
Maximum applied force (Cartesian space)	0	150	N
Maximum Cartesian deviation	0.01	100	mm
Maximum torque per joint	0	-	N m

TABLE I
ROBOT CONSTANTS

The KUKA LWR is able to safely pick up objects of an approximate weight of m = 15 kg (Maximum force F = 150 N). It provides force and torque sensors for each joint. Further, the controller computes the forces and torques in Cartesian space from the force/torque information in joint space. The arms can be programmed by a combination of the KRL (KUKA robot language) and the FRI (Fast Research Interface), which allows to control them via an Ethernet connection. The high level control has been done by a modified version of OROCOS [7] and the Kukadu framework [10], which provides support for dynamic movement primitives, regression techniques and reinforcement learning. For further information concerning the robot arm the interested reader might consult [5].

Two Schunk SDH-2 hands have been mounted on the arms. It is a dexterous robotic hand providing pressure sensor panels. It has a total length of 253 mm and consists of three modular fingers. Two fingers can rotate along their vertical axis, which can be used to implement different grasping types. Each finger itself has two degrees of freedom, which can be used to open and close the hand. Hence, in total it provides 7 degrees of freedom. The maximal momentum per joint is of special interest, as it defines the strength of the grasp. The joints 2, 4 and 6 can apply a momentum of $M = 2.1$ Nm, while the joints 3, 5 and 7 can provide a momentum of $M = 1.4$ Nm. However, the actually exerted momentum highly depends on the current hand temperature. High temperature leads to lower momentum and therefore weaker grasps. The hand expects a maximum current of $I = 5$A and a voltage of $U = 24$V. Each finger has two pressure sensor arrays, where all arrays are made of 6×14 sensor texels and each texel has a size of $s = 3.4$ mm. The communication for hand control and sensor data retrieval can be done by two separate serial ports.

In order to do the evaluation of the proposed approach, two environments have been used. In environment 1 the pendulum is pressed against the table during execution of the task (Fig. 2 left). Environment 2 does not use the table to support the screwing execution by stabilizing the pendulum. The table is used only for picking up the pendulum head (Fig. 2 right).

For the screwing task implementation we used the pendulum and the pendulum head shown in Fig. 3. To increase the tables friction coefficient, we used a rubber foam sheet on the table as it can be seen in the Fig. 2.

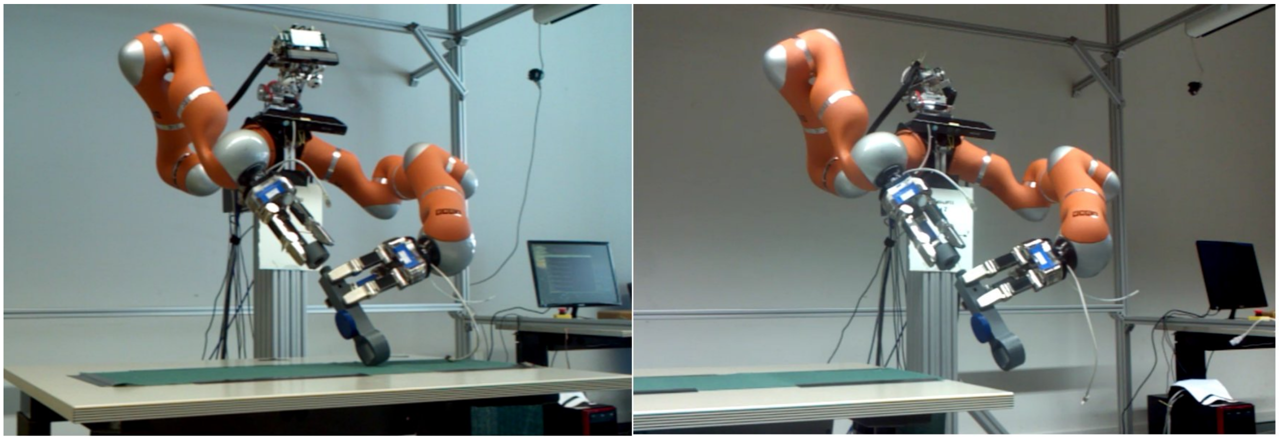

Fig. 2. The robot setup and different configurations used in experiments. Environment 1 uses table (left), whereas in Environment 2 the table has been removed (right)

Fig. 3. Objects used for screwing (pendulum head and pendulum); they are placed on the table and picked up by spherical (pendulum head) and cylindrical grasp (pendulum)

IV. Approach

This section describes the overall approach used in this paper. Firstly, the framework of *dynamic movement primitives* (DMP) is described. This section is followed by the description of the experimental approach that has been chosen to evaluate the influence of the usage of the environment for more complex manipulation tasks. We used a screwing task to evaluate the influence of the usage of the environment on the performance of the manipulation. The used robot setting as well as the used objects have been described in section III.

A. Evaluation environments

To evaluate the influence of the environment we used two different environments (see Fig. 2):

- Environment 1: The first environment applies the previously described screwing approach by pressing the pendulum onto the table to stabilize it (left arm). The two objects (pendulum and pendulum head) have been placed on a fixed position on the table, where the robot grasped it. The pendulum has been pressed on the table with force while the right arm applies the screwing operation. This force is due to the teaching process where the pendulum end is positioned slightly below the level of the table. This enforces the robot to press the pendulum against the table because it tries to reach the desired position.
- Environment 2: Here, the pickup procedure started the same as in environment 1. As soon as the objects have been grasped, the table has been removed, while the rest of the execution was the same. This has been done to ensure comparability of the two approaches as both scenarios use the same training data to do screwing.

As the table had to be moved to execute the experiment in env. 2 to avoid contact between table and pendulum, the environment had to be calibrated before every new execution to get reliable data. This had been required because it was not possible to move back the table to the exact desired position, which led to changed object locations. As the grasping positions had been fixed, calibration of the table position was necessary. This has been done by performing the screwing in env. 1 until it succeeded. Afterwards we performed the next evaluation in env. 2. The results of in total 20 trials (10 per environment) are presented in section V.

B. Learning of Screwing Operation

The screwing operation has been learned by a combination of programmed grasps and a screwing trajectory learned from kinesthetic teaching (a human provides a sample trajectory by guiding the robot). Therefore, the whole manipulation can be split up in two phases. The first part is responsible for grasping the two objects (pendulum head with right hand and pendulum with left hand). The objects are placed at predefined locations and orientations, where the grasping positions have been provided manually to the system. After moving the arms to the desired grasping point, the hands are closed with maximum force in order to be able to pick up the objects. Afterwards the objects are prepared for screwing (see Fig. 2). Depending on the used environment, the pendulum is pressed against the table (Env. 1) or moved to the same position without the presence of the table (Env. 2). In phase two the screwing itself is executed by a trajectory encoded with DMPs in joint space. The screwing operation is started by co-linearly aligning the arm, which is holding the pendulum head, to the pendulum. Afterwards, the last joint of the right arm is actuated, which yields a rotation of 360 degrees around the pendulum axis, while simultaneously pressing the pendulum head on the pendulum. To execute the supervised trajectory, we use dynamic movement primitives [13]. To determine the coefficients of a discrete DMP from the supervised trajectory, linear regression is used.

C. Dynamic Movement Primitives

A *Dynamic movement primitive* is a parametrized control policy formulation which comes up with some desirable properties out of the box. Here, a short overview on the mathematical formulation and the most important properties will be given. For further information the reader might be interested in [13].

The core of the mathematical formulation is given in equations 1 and 2. It consists of two dependent first order differential equations, which together form a system of differential equations. A dynamic movement primitive is a system of differential equations of the form

$$\tau \dot{z} = \alpha_z \left(\beta_z \left(g - y\right) - z\right) + f \tag{1}$$

$$\tau \dot{y} = z \tag{2}$$

where g is the goal state, α_z and β_z are time constants (spring stiffness, damping), τ is a temporal scaling factor and f is an arbitrary continuous function of the form

$$f(x) = \frac{\sum_{i=1}^{N} \psi_i(x) w_i}{\sum_{i=1}^{N} \psi_i(x)} x \tag{3}$$

where ψ_i are Gaussian basis functions. Here, the variables w_i have to be learned as they define the shape of the resulting trajectory. The constants α_z, β_z and τ should be selected such that the system converges to 90 percent of the goal state after $t = t_{\mathtt{max}}$. By design, DMPs guarantee that the trajectory will always reach the attractor point g. The execution can be stretched by changing the temporal scaling factor. The non-linear function f is responsible for the shape of the trajectory, thus containing the DMPs parameters that have to be learned. A detailed analysis on why DMPs can ensure these properties is given in [10]. The variable x itself is again defined by another differential equation (DE), which depends on the type of movement one wants to describe with DMPs.

DMPs provide two different types of movements, namely *discrete movement* and *rhythmic movement*.

1) Discrete Movement: A discrete movement is a movement of finite time. An example for this kind of movement is a reaching task. The DE defining $x(t)$ is given in equation 4.

$$\tau \dot{x} = -\alpha_x x, \quad x(0) = 1 \tag{4}$$

This differential equation can be adjusted to react on deviations during the trajectory execution. One possibility is the so-called phase stopping which slows down the trajectory execution in case of high deviations from the desired path. This can be formulated by the equation

$$\tau \dot{x} = -\alpha_x \frac{x}{1 + \alpha_c \left(y_{actual} - y\right)^2} \tag{5}$$

which takes into account the current state of the trajectory execution.

2) Rhythmic Movement: A rhythmic movement can be imagined as an infinite repetition of a cyclic movement (start and end point are the same). To be able to represent this, the Gaussian basis functions ψ_i are replaced by

$$\psi_i = e^{-h_i(cos(x - c_i) - 1)} \tag{6}$$

An example for this kind of movement is playing the drums with the same rhythm [15]. In this paper we only analyse the influence of the environment usage on discrete movements.

V. Results and Discussion

In this section the experimental results will be presented and discussed. The experimental setting has been described in section III. In total, 20 trials (10 per environment) have been performed. During the experiment, the success rate as well as the forces measured at end effector positions of both arms have been collected. Here, we define a trial to be successful if the pendulum head cannot be removed from the pendulum without further rotation. A comparison of the force data between trials in both environments, hand temperature dependent success rates in different environments and affects of impedance mode on the performance are given in the following section.

A. Measured Forces in both Environments

By analysis of our data, four representative samples have been identified:

- Sample 1 (*red*): Screwing in env. 1 with position mode. The execution succeeded.
- Sample 2 (*green*): Screwing in env. 2 with position mode. The execution failed because of the pendulum slipping through the hand holding it.
- Sample 3 (*cyan*): Screwing in env. 2 with position mode. The execution succeeded.
- Sample 4 (*magenta*): Screwing in env. 1 with impedance mode. The stiffness settings have been selected with values of 4000 and 250 for Cartesian stiffness and end-effector stiffness respectively. The damping was chosen with 0.7.

Figures 4-6 visualize the measured forces for all four samples. Fig. 4 presents the absolute value of the measured forces vectors, whereas Fig. 5 and Fig. 6 show the components of the Cartesian force vectors. We omitted the data measured until $t = 50$s as it contains data for grasping the objects, which is the same in all samples. They plot the evolution of the forces for all four samples over time. In 4, the most important phases are already identifiable.

B. Identification of Phases

In section IV-B the different phases of the manipulation have been listed. In Fig. 4, these phase can be identified. The first notable event has been observed at $t = 60$s, which shows a strong increase of the forces in samples 1 and 4 due to the robot pressing the pendulum on the table. Note that this does not occur in samples 2 and 3, as the robot holds

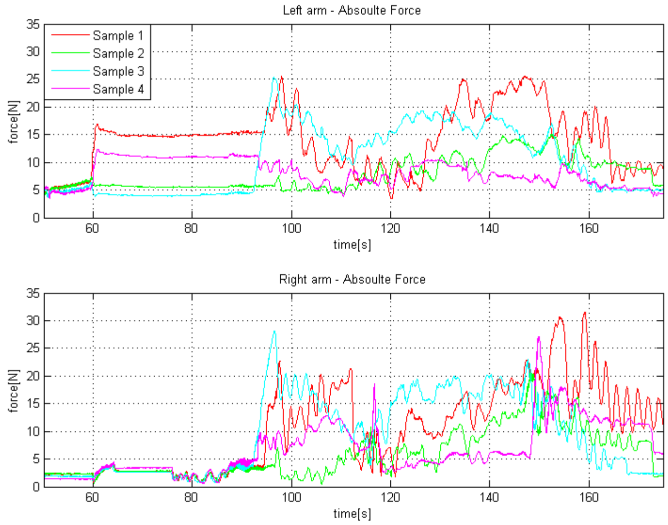

Fig. 4. Absolute value of the measure forces vectors for each arm (Right arm performs screwing, Left arm holds the pendulum). Colors: Red (Sample 1), Green (Sample 2), Cyan (Sample 3), Magenta (Sample 4)

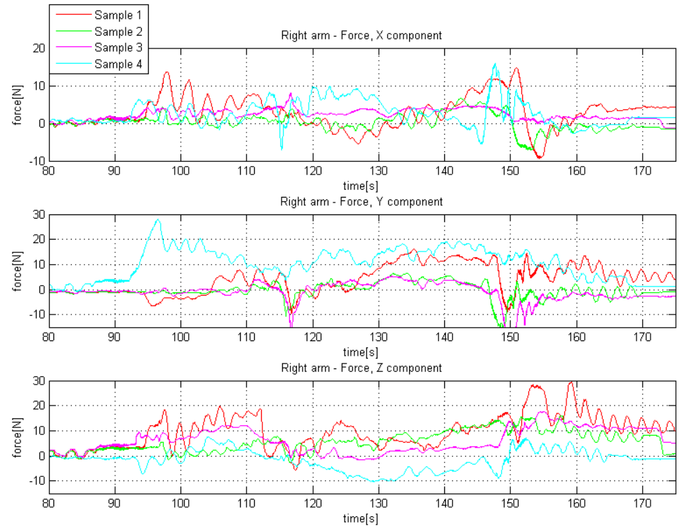

Fig. 5. Measured forces measured for each Cartesian dimension (Right arm - performing screwing operation), Colors: Red (Sample 1), Green (Sample 2), Cyan (Sample 3), Magenta (Sample 4)

the pendulum freely. The screwing operation starts at time $t = 90$s. This manipulation leads to increase of the exerted forces on both arms. The screwing phase is the longest one and continues until $t = 165$s, where the right arm stops to rotate the pendulum head. However, the right hand is still closed which is the reason, why some force is measured. Finally, in $t = 170$ the right hand releases the pendulum head.

C. Comparison of Absolute Forces

We will compare each sample to sample 1, as it had a very high success rate of 90 percent. In general, it can be seen, that by pressing the pendulum against the table, the robot is able to exert higher forces, which is a sign of high stability of the setting. However, this leads to higher stress of the robot joints (compare red and cyan line). Additionally, in the graph for an unsuccessful trial in env. 2 (Fig. 4) it can be seen that the reason for the failure is due to the inability of the robot to apply the forces required to do the screwing (green line). The higher forces in the end of the execution result from the right arm still pushing the pendulum head on the pendulum without being able to screw further.

Further, experiments in impedance mode have been performed (magenta line). It should be noted that this sample resulted in much lower forces while still being able to perform the screwing successfully. The forces are low compared with the unsuccessful sample 2. The difference can be found in the beginning of the screwing where a higher force during the phase of catching the pendulum and pendulum head is measured. Therefore it can be concluded that in the unsuccessful sample 2 the two objects lose contact in the beginning.

Indeed, evidence for this assumption can be found in the measured force at $t = 95$s, where the measured force jumps 8N to 5N (left arm) and 8N to 2N (green line). In the video that has been recorded during execution the reason can be found: the pendulum is slightly slipping through the left hand because the grasp of the left hand is not strong enough to stabilize the system. This motivates why the success rate for env. 1 is higher than the one for env. 2 (see section V-E). Still, this weakness is not always present, as sample 3 is showing (cyan line). In Fig. 4 the force measured at the right arm is even getting higher than the one for sample 1 at $t = 95$s. The success of the screwing in env. 2 is prone to slight variations in the initial grasp, which gives rise for the approach to use the environment. An inexact grasp in env. 1 can still be compensated by the stabilization that is achieved by pressing the pendulum on the table. This is not the case for env. 2, which leads to a lower success rate. This issue gets an even bigger problem as soon as the object locations are not fixed any more but estimated by some vision system, as these systems are not exact. However, the usage of the table (env. 1) does not come without any practical problems.

D. Disadvantages of Using Environment

One typical problem that has been observed over all trials is the slipping of the pendulum on the table while manipulating the two objects. Note that this should not be confused with the problem of pendulum slipping through the hands while holding it. This behaviour can be seen in Fig. 6 (Z component) for sample 1. At time $t = 95$s (begin of screwing) the force increases strongly until a certain maximum is reached, which then leads to a spontaneous reduction. This effect can be seen even stronger at $t = 150$s. Even though this had no influence on the success of the manipulation, it can potentially apply strong force changes on the robot, which can be harmful. These results for sample 1 may lead to future approaches to estimate the friction coefficient between objects. Similar work has been done by Aiyama [1], who used kinematic and geometric analysis to successfully estimate the friction coefficient for object sliding and insertion tasks. A possible solution to the slipping-pendulum problem has been found in the usage of

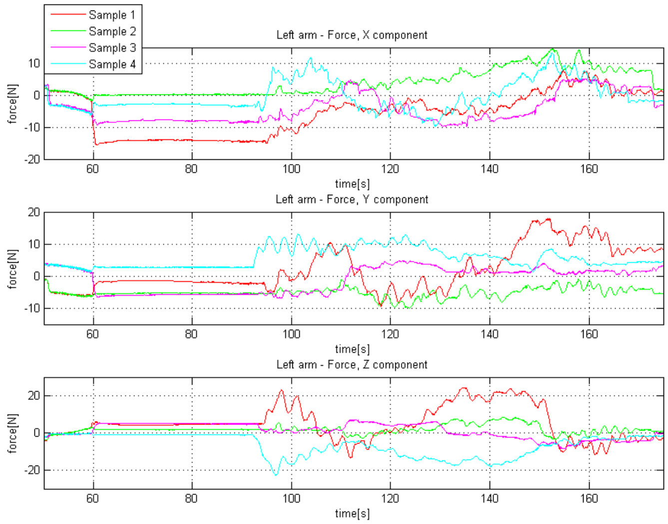

Fig. 6. Measured forces measured for each Cartesian dimension (Left arm - performing screwing operation), Colors: Red (Sample 1), Green (Sample 2), Cyan (Sample 3), Magenta (Sample 4)

the impedance mode where the measured forces have been smoothed and the slipping has not been observed at all. It can be seen that the usage of impedance mode led to smoothing of the measured forces (see Fig. 5) by preserving the success rates of sample 1 (see section V-E).

E. Success Rates

The success rates have been measured for the two different environments. The success rate for env. 1 has been determined with 90 percent, whereas the success rate for env. 2 has been much lower with 60 percent. By using impedance mode on top of reusing the environment, no significant change of the success rate has been observed. However, the applied forces were much lower and smoother as for the sample with position mode. Additionally, the influence of the robot hand temperature should be mentioned as overheating of the hand led to a strong reduction of the success rates for both environments. This is due to the fact that the hand was not able to apply sufficiently stable grasps if the temperature has been to high. Here, even the method with using of the environment was not able to improve the performance.

VI. Conclusion

In this paper we investigated the potential effect of environment exploitation to achieve a complex task. As main contribution we have shown that object manipulation in robotics can benefit from considering to use the environment tot stabilize the execution. We evaluated environment exploitation for a screwing task that requires bi-manual manipulation which potentially benefits from environment usage, as a table can be used to stabilize the objects. Experimental results show that the success rate can be improved significantly. Additionally, the stress on the robot joints can be reduced by setting the robots stiffness settings appropriately. Further, with this approach, problems such as slipping of the manipulated objects can be overcome. In future we plan to study how object manipulation can be optimized by the estimation of the friction coefficient.

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