Learning Contact-Rich Manipulation Tasks with Rigid Position-Controlled Robots: Learning to Force Control

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Abstract—To fully realize industrial automation, it is indispensable to give the robot manipulators the ability to adapt by themselves to their surroundings and to learn to handle novel manipulation tasks. Reinforcement Learning (RL) methods have been proven successful in solving manipulation tasks autonomously. However, RL is still not widely adopted on real robotic systems because working with real hardware entails additional challenges, especially when using rigid position-controlled manipulators. These challenges include the need for a robust controller to avoid undesired behavior, that risk damaging the robot and its environment, and constant supervision from a human operator. The main contributions of this work are, first, we propose a framework for safely training an RL agent on manipulation tasks using a rigid robot. Second, to enable a position-controlled manipulator to perform contact-rich manipulation tasks, we implemented two different force control schemes based on standard force feedback controllers; one is a modified hybrid position-force control, and the other one is an impedance control. Third, we empirically study both control schemes when used as the action representation of an RL agent. We evaluate the trade-off between control complexity and performance by comparing several versions of the control schemes, each with a different number of force control parameters. The proposed methods are validated both on simulation and a real robot, a UR3 e-series robotic arm when executing contact-rich manipulation tasks.

I. INTRODUCTION

In the age of the 4th industrial revolution, there is much interest in applying artificial intelligence to automate industrial manufacturing processes. Robotics, in particular, holds the promise of helping to automate processes by performing complex manipulation tasks. Nevertheless, safely solving complex manipulation tasks in an unstructured environment using robot manipulators is still an open problem[1].

Reinforcement learning (RL) methods have been proven successful in solving manipulation tasks by learning complex behaviors autonomously in a variety of tasks such as grasping [2], [3], pick-and-place [4], and assembly [5] among others. While there are some instances of RL research validated on real robotic systems, most works are still confined to simulated environments due to the additional challenges presented by working on real hardware, especially when using rigid position-controlled robots. These challenges include the need for a robust controller to avoid undesired behavior that risk collision with the environment, and constant supervision from a human operator.

So far, when using real robotic systems with RL, there are two common approaches. The first approach consists of learning high-level control policies of the manipulator. Said approach assumes the existence of a low-level controller that can solve the RL agent’s high-level commands. Some examples include agents that learn to grasp [2], [3] or to throw objects [6]. In said cases, the agent learns high-level policies, e.g., learns the position of the target object and the grasping pose, while a low-level controller, such as a motion planner, directly controls the manipulator’s joints or end-effector position. Nevertheless, the low-level controller is not always available or easy to manually engineer for each task, especially for achieving contact-rich manipulation tasks with a position-controlled robot. The second approach is to learn low-level control policies using soft robots [7], [8], [9], manipulators with joint torque control or flexible joints, which are considerably safer to work with due to their compliant nature, particularly in the case of allowing an RL agent to explore its surroundings where collisions with the environment may be unavoidable. Our main concern with this approach is that most industrial robot manipulators are, by contrast, rigid robots (position-controlled manipulators). Rigid robots usually run on position control, which works well for contact-free tasks, such as robotic welding, or spray-painting [10]. However, they are inherently unsuitable for contact-rich manipulation tasks since any contact with the environment would be considered as a disturbance by the controller, which would generate a collision with a large contact force. Force control methods [11] can be used to enable the rigid manipulator to perform tasks that require contact with the environment, though the controller’s parameters need to be properly tuned, which is still a challenging task. Therefore, we propose a method to safely learn low-level force control policies with reinforcement learning on a position-controlled robot manipulator. The RL agent learns the nominal trajectory and the time-variant force control parameters of the manipulator’s controller through safe interaction with the environment.

This paper presents three main contributions. Firstly, we developed a control framework for safely train an RL agent on manipulation tasks using a real position-controlled robot manipulator. Secondly, we propose a learning force control scheme where the RL agent learns the controller’s parameters.
Within this control scheme, we implemented two different conventional approaches to achieve force control with position-controlled robots; one is a modified hybrid position-force control, and the other is an impedance control. Thirdly, we empirically study both control schemes when used as the action space of an RL agent. The proposed methods are validated both on simulation and real hardware using a UR3 e-series 6 degrees of freedom robotic arm.

II. RELATED WORK

1) Force control: Force control methods address the problem of interaction between a robot manipulator and its environment, even in the presence of some uncertainty (geometric and dynamic constraints) on contact-rich tasks [12], [13], [14]. These methods provide direct control of the interaction through contact force feedback and a set of parameters, which describe the dynamic interaction between the manipulator and the environment. However, prior knowledge of the environment is necessary to properly define the controller’s parameters at each phase of the task, such as stiffness. Existing methods address said problem by either scheduling variable gains [15], using adaptive methods for setting the gains [16] or learning the gains from demonstrations [17]. Instead, we propose to directly learn the time-variant force control gains from experience, by interacting and observing of the environment.

2) Reinforcement learning and force control: Previous research has also studied the use of RL methods to learn force control gains. Buchli et al. [18] uses policy improvements with path integrals (PI2) [19] to refine initial motion trajectories and learn variable scheduling for the joint impedance parameters. They showed that energy consumption could be optimized while achieving a task using variable impedance control. Similarly, Bogdanovic et al. [20], proposed a variable impedance control in joint-space, where the gains are learned with Deep Deterministic Policy Gradient (DDPG) [21]. Likewise, Martín-Martín et al [22], proposed a variable impedance control in end-effector space (VICES). They show that thanks to the classical dynamically consistent operational space formalism, VICES is more robust to transfer across robots with different dynamics. However, in all these cases, access to the robot manipulator’s low-level control of joint torques is assumed, which is not available for most industrial manipulators. Instead, we focus on position-controlled robot manipulators and provide a method to learn manipulation tasks using force feedback control where the controller’s gains are learned through RL methods.

Additionally, both Bogdanovic [20] and Martín-Martín [22] study the importance of different action representation in RL for contact-rich robot manipulation tasks. We similarly provide an empirical study comparing different choices of action space based on force feedback control methods for rigid robots on contact-rich manipulation tasks.

3) Learning with real-world manipulators: Some research projects have explored the capabilities of RL methods on real robots by testing them on a large scale, such as Levine et al. [3] and Pinto et al. [23], both in which a massive amount of data was collected for learning robotic grasping tasks. However, in both works, a high-level objective, grasp posture, is learned from the experience obtained. In contrast, contact-rich tasks require learning direct low-level control to, for example, to reduce contact force for safety reasons. On the other hand, Mahmood et al. [24] propose a benchmark for learning policies on real-world robots, so different RL algorithms can be evaluated on a variety of tasks. Nevertheless, the tasks available in [24] are either locomotion tasks with a mobile robot or contact-free tasks with a robot manipulator. In this work, we propose a framework for learning contact-rich manipulation tasks with real-world robot manipulators based on force control methods.

III. METHODOLOGY

Our proposed framework for safely training an RL agent directly on rigid manipulators is described in Section III-A. In addition, our proposed method for learning force control parameters of force-feedback controllers for manipulation tasks with a position-controlled robots are described in Section III-D.1 and Section III-D.2.

A. Safe Learning Framework

Most modern robot manipulators already include a layer of safety in the form of an emergency stop. Nonetheless, the emergency stop exists at the extreme ends of the robot limits and completely interrupts the entire training session if triggered. To reactivate the robot a human operator is required. On the contrary, we propose a framework that allows the robot to operate within less extreme limits. Thus, training of an RL agent can be done directly on the position-controlled manipulator with minimal human supervision.

We consider the episodic RL problem, where the tasks have a finite number of time steps per episode, after which the agent goes to its initial state. The RL agent controls the robot as if teleoperating it by providing a real-time stream of task-space motion commands for the robot to follow. Therefore, we added our safety layer between the streamed motion command and the actual actuation of the robot. The safety layer validates that the intended action is within a defined set of parameters. As shown in Algorithm 1 our framework checks whether an inverse kinematics (IK) solution exists for the desired position command \( X_c \), if so, whether the joint velocity required to achieve the IK solution, \( q_v \), is within a speed limit. Finally, we check if the contact force at the robot’s end-effector is within a defined range limit. If any of these validations are not satisfied, the intended action is ignored, and the robot remains in its current state. The first two validations are proactive and prevent unstable behaviors of the manipulator before they occur. In contrast, the third validation, contact force, is reactive, i.e., only after the limit has been violated, the robot is prevented from further actions.

During an episode, the robot state may violate one of the validations but recover to a valid state. For example, if the defined maximum force/torque is exceeded, but the end-effector bounces on a surface of the environment, then the manipulator may end up in a valid state and continues with the remaining steps of the episode. However, if the robot ends up in an unrecoverable state, the episode would quickly end.
There is no time-delay accounted for actions not taken. After the episode ends, the robot executes a reset sequence and goes to the following episode’s initial state.

**Algorithm 1 Safe Manipulation Learning**

1. Define joint velocity limit \( \dot{q}_{\max} \)
2. Define contact force limit \( F_{\max} \)
3. Define initial state \( X_0 \)
4. for \( n = 0, \ldots, N - 1 \) episodes do
5. for \( t = 0, \ldots, T - 1 \) steps do
6. Get current contact force \( F_t \)
7. Get policy action \( a_x = \pi_{\theta}(a|s) \)
8. \( X'_c = X_c + a_x \)
9. \( X_c = \text{control method}(X'_c) \)
10. \( \dot{q}_c = IK_{\text{solver}}(X_c) \)
11. if \( \dot{q}_c \) not exists then continue
12. if \( (\dot{q}_c - \dot{q}_e)/dt < \dot{q}_{\max} \) then continue
13. if \( F_t < F_{\max} \) then continue
14. Actuate \( \dot{q}_c \) on robot
15. Reset to \( X_0 \)

**B. Pose Control Representation**

The position of the robot manipulator’s end-effector is described by a vector \( x \in \mathbb{R}^3 \) in Cartesian coordinates with respect to the inertial frame at the base of the robot. The orientation of the end-effector, w.r.t the inertial frame, is described using Euler parameters (unit quaternions) denoted as \( Q = \{\eta, \varepsilon\} \), where \( \eta \in \mathbb{R} \) is the scalar part of the quaternion and \( \varepsilon \in \mathbb{R}^3 \) the vector part. Using unit quaternions allows the definition of a proper orientation error for control purposes with a fast computation compared to using rotation matrices [25].

The action commands from the agent are twists \( X_v = [\tilde{x}_t, \omega_t]^T \), where \( \tilde{x}_t \) and \( \omega_t \) are the robot’s end-effector linear velocity and angular velocity respectively. The position command for the robot is given in the manipulator’s task-space, \( X_c = [x_t, Q_t] \), where \( x_t \) is the desired translation, and \( Q_t \) is the desired rotation with respect to the base frame, for the time step \( t \). The position command, \( X_c \), is computed by integrating the twist, \( X_v \) as follows

\[
X_c = \begin{bmatrix}
    x_{t+1} = \dot{x}_t dt + x_t \\
    Q_{t+1} = 0.5 Q_t \omega_t dt
\end{bmatrix}
\]

where \( dt \) is the control frequency. Afterwards, the position command \( X_c \) is inputted to an IK solver to obtain the joint positions \( q_e \) to command the robot. The general control scheme is shown in **Fig. 1**.

**C. Learning Force Control**

To enable a rigid robot manipulator to perform contact-rich manipulation tasks, different types of force feedback control schemes have been proposed. These control schemes require a force/torque sensor to perceive the contact forces between the robot’s end-effector and its environment. The two most common force control schemes are considered in these work, hybrid position/force control [12] and impedance control [13]. The main drawback of said control schemes is the requirement of properly tuning its parameters for each specific task. Changes in the environment (e.g. surface stiffness) may require a new set of parameters. We propose a self-tuning process using an RL method. Our general control scheme is depicted in **Fig. 1**, where the RL agent learns both the nominal trajectory and the force control parameters of the controller. The inputs to the system is a goal pose or trajectory, of the manipulator’s end-effector. The RL agent actions are twists, \( a_x \), and controller’s parameters, \( a_p \). The actions \( a_x \) are combined with the input signal, and then this command is processed through the interaction control module that produces the actual position command to be sent to the robot. Both the RL agent and the interaction control module receive feedback from the environment, the position of the current robot’s end-effector \( X \), and the contact force \( F \).

**D. Force control implementation**

The following subsections present the implementation details of the proposed framework for the hybrid position/force control scheme and the impedance control scheme.

1) Hybrid Position/Force Control: In the traditional hybrid position/force controller [12], a selection matrix, \( S \), is defined to divide the task space into two subspaces, one of which is controlled using position control and the other using pure force control. During manipulation, the position control law and the force control law are employed in their corresponding subspaces. The selection matrix is \( S \in \mathbb{Z}_2^3 \), where for a direction 1 indicates position control and 0 indicates force control. In the traditional hybrid method, we should not specify forces and motions in the “same direction” as then they are independent. The most important step of this method is to determine a proper division of the subspaces, which relies on the prior knowledge of the structure and geometry of the environment. However, in the case of unstructured and dynamically changing environments, it is difficult to obtain the precise geometry information about the environment in advance. This drawback limits the hybrid controller application range.

To overcome said limitations, we propose a modified version of the hybrid controller, shown in **Figure 2**. We do not assume independence of motions and forces in a given direction, thus the selection matrix becomes \( S \in [0,1]^9 \), where the values correspond to the degree of control that each controller has over a given direction. Our modified control
scheme assumes the presence of an adaptive controller, i.e. the RL agent, that resolves the trade-off between accurately following the motion trajectory or the contact force objective. Thus, our hybrid controller’s aims to closely follow the motion trajectory while giving a degree of compliance that allows the robot to safely interact with the environment without excessive contact forces.

With our proposed hybrid control, the robot can operate in an unknown environment without prior knowledge of the environment. The hybrid controller typically receives both a reference position signal and a reference force signal. However, if the reference force signal is set to zero for all directions, the hybrid controller will only seek to minimize the contact force, similarly to an impedance controller.

The hybrid controller has a total of 30 parameters, 12 from the position controller’s proportional and derivative (PD) gains, 12 from the force controller’s proportional and integral (PI) gains, and 6 from the selection matrix $S$. We reduced the number of controllable parameter to prevent unstable behaviour and to reduce the system’s complexity. For the PD controller, only the proportional gain, $K_{x,p}$, is controllable while the derivative gain, $K_{x,d}$, is computed based on the $K_{x,p}$. $K_{x,d}$ is set to have a critically damped relationship as $K_{x,d} = 2\sqrt{K_{x,p}}$.

Similarly, for the PI controller, only the proportional gain, $K_{f,p}$, is controllable, the integral gain $K_{f,i}$ is computed with respect to $K_{f,p}$. In our experiments, $K_{f,i}$ was set empirically to be 1% of $K_{f,p}$. In total 18 parameters are controllable per time step.

To narrow the agents choices for the force control parameters, we follow a similar strategy as in [20]. Assuming we have access to some baseline gain values, $P_{\text{base}}$. We then define a range of potential values for each parameter as $[P_{\text{base}} - P_{\text{range}}, P_{\text{base}} + P_{\text{range}}]$ with the constant $P_{\text{range}}$ defining the size of the range. We map the agent’s actions $a_p$ from the range $[-1,1]$ to each parameter’s range. $P_{\text{base}}$ and $P_{\text{range}}$ are hyperparameters of both controllers.

2) Impedance Control: Impedance control is used to achieve a desired dynamic interaction between the manipulator and its environment. In comparison with traditional hybrid position/force control, impedance control provides simultaneous control over the manipulator’s motion and contact forces by designing a proper interaction between the manipulator and its environment.

The impedance relationship can be expressed in Laplace-domain as

$$ \frac{X}{F}(s) = \frac{1}{M_d s^2 + B_d s + K_d} $$

(2)

where $M_d$, $B_d$, and $K_d$ represent the desired inertia, damping, and stiffness matrices respectively. $F(t)$ is the actual contact force vector. $X(s)$ is the displacement of the manipulator’s end-effector.

Adopting conventional expression of a the second-order system, (2) can be rewritten as

$$ \frac{X}{F}(s) = \frac{1/M_d}{s^2 + (B_d/M_d)s + K_d/M_d} $$

(3)

$$ = \frac{1/M_d}{s^2 + 2\zeta \omega_n s + \omega_n^2} $$

where $\zeta$ is the damping ratio and $\omega_n$ is the natural frequency, and they can be expressed by the impedance parameters as

$$ \zeta = \frac{B_d}{2\sqrt{K_d M_d}} \quad \omega_n = \sqrt{\frac{K_d}{M_d}} $$

(4)

We are proposing a variable impedance controller, where the inertia, damping, and stiffness parameters are learned by the RL agent. Additionally, a PD controller is included in our impedance control scheme to regulate the input motion trajectory, as shown in Fig. 3. The PD gains are also controlled by the RL agent at each time step.

For our impedance control scheme, there are a total of 30 parameters; 12 from the proportional and derivative gains and 18 from the inertia, damping, and stiffness parameters. Similarly, as mentioned in Sect. III-D.1, we reduced the number of controllable parameters to prevent unstable behavior of the robot and reduce the system’s complexity. Following the same strategy described in Sect. III-D.1 of the PD controller only the proportional gain is controllable. Additionally, we considered the inertia gain for each direction as a constant, 1$kg m^2$ in all our experiments as a similar payload is used across tasks. Furthermore, we compute the damping with respect to the inertia gain and the stiffness gain by defining a constant damping ratio. From (4) we have that $B_d = 2\zeta \sqrt{K_d M_d}$.
Therefore, only the stiffness gains are controllable. In total, the controllable parameter of the impedance control are reduced to 12 parameters; 6 PD gains and 6 stiffness gains.

E. Reinforcement Learning

The RL problem, there is an agent described by a state $s$. The agent can perform actions $a \in A^m$, where $m$ is the number dimensions, and observe only part of the state, denoted as observations $o \in O$. We consider a finite interaction of the agent with its environment during $T$ time steps, a complete run of these time steps is denoted as an episode. The agent’s goal is to find a policy $\pi(a_t, o_t)$ that selects actions $a_t$ conditioned on the observations $o_t$ to control a dynamical system. Given an stochastic dynamics $p(s_{t+1}|s_t, u_t)$ and a reward function $r(s, a)$, the aim is to maximize the expected reward under the policy’s trajectory distribution, $\sum_{t=1}^{T} r(s_t, a_t)$ [26].

For training the control policies, we consider two state-of-the-art RL methods.

1) Guided Policy Search: First, we use a model-based RL method called Mirror Descend Guided Policy Search (MDGPS) [27], a variant of the Guided Policy Search method [28]. MDGPS addresses the RL optimization problem by dividing the problem into two components: a trajectory optimization part and a supervised learning one. In the trajectory optimization component, local policies, corresponding to each initial condition that is considered, are optimized with respect to the reward function $r(s, a)$ of the given task and with respect to a global policy via Kullback-Leibler divergence. The global policy is learned in a supervised fashion using sample trajectories drawn from executing the local policies on the robot. Through iterations of optimizing the local policies and learning a global policy, an optimal global policy can be learned. Our implementation is based on the open-source project GPS[1].

2) Soft-Actor-Critic: Secondly, we use a model-free RL method called Soft-Actor-Critic (SAC) [29]. SAC is an off-policy actor-critic deep RL algorithm based on the maximum entropy reinforcement learning framework. SAC aims to maximize the expected reward while optimizing a maximum entropy. The SAC agent optimizes a maximum entropy objective which encourages exploration according to a temperature parameter $\alpha$. The core idea of this method is to succeed at the task while acting as randomly as possible. Since SAC is an off-policy algorithm it can use a replay buffer to reuse information from recent rollouts for sample-efficient training. We use the SAC implementation of the TF2RL repository without further modification[2].

Task’s reward function: For all the manipulation tasks considered, the same cost function was used:

$$r(s_t, x_t) = w_1 ||\Delta X_t^e||_T^2 + w_2 |a_t|^T + w_3 |F_t|^T + w_4 \rho + \kappa$$

where $\Delta X_t^e$ is the distance between the manipulator’s end-effector and the target goal at time step $t$. $a_t$ is the action taken by the agent. $F_t$ is the contact force. $\rho$ is a penalty given at each time step to encourage completion of the task as fast as possible. $\kappa$ is a reward given if the task is successfully completed. $|| \cdot ||$ is the Frobenius norm of the vector, $||A|| = \sqrt{\sum_{i=1}^{n} a_i^2}$ $A \in \mathbb{R}^m$. Finally, each component is given a weight $w$, all $w$’s are hyperparameters.

IV. Experiments

We propose a framework for safely learning manipulation tasks with position-controlled manipulators using RL techniques. Two control schemes where implemented. With the following experiments we seek to answer the following questions: Can a RL agent learn to control a high dimensional force controller with the proposed method on a position-controlled manipulator? Which action space, based on the number of controllable parameters of the control schemes, provides the best learning performance?

This section is organized as follows, first, a description of the materials used for experimentation in Section IV-A. An insertion task was used for evaluating the learning performance of the RL agents with the proposed method on a simulated environment, described in Section IV-B. Finally, the proposed method is validated on a real robot manipulator.

A. Technical details

Experimental validation was performed both in a simulated environment using the Gazebo simulator [30] version 9 and on real hardware using the Universal Robot’s UR3 e-series robotic arm, with control frequency of up to 500 Hz. The robotic arm has a Force/Torque sensor mounted at its end-effector. For training in both simulation and real robot, a computer with the following specifications was used; CPU Intel i9-9900k, GPU Nvidia RTX-2800 Super.

B. Action spaces for learning force control

Each control scheme proposed in Section III has a number of controllable parameters. The curse of dimensionality is a well known problem in RL. Controlling few dimensions, number of parameters, makes the task easier to learn at the cost of losing dexterity. In the following experiment, several versions of the controllers are proposed that allow the RL agent to control some or all the available parameters. Each version corresponds to a different action space of RL agent. We evaluate the learning performance of the action spaces described in the Table I four versions per control scheme. All versions have 6 parameters to control the position and orientation of the manipulator, and a different number of parameters to tune the controller’s gains. From now on we refer to each version by the name given in Table I.

To make a fair comparison, the action spaces were evaluated on a simulated peg-insertion environment so that we could guarantee the exact same initial conditions for each training session. The task is to insert a cube-shaped peg into a task board, where the hole has a clearance of $1mm$, as shown in Figure 7. Both RL agents mentioned in Section III-B GPS and SAC, were used to train with each action space. For each pair of RL agent-Action Space, the training session was performed

1See more information at http://rl.berkeley.edu/gps/
2TF2RL: Deep reinforcement learning library using TensorFlow 2.0. https://github.com/keiohta/TF2RL
Fig. 4. Learning curves of peg-insertion task on simulation. a) Impedance control with GPS agent. b) Hybrid position/force control with GPS agent. c) Impedance control with SAC agent. d) Hybrid position/force control with SAC agent. For each condition considered, 3 training session were done. Bold line represents the average cumulative reward per episode across the training sessions and the shaded colored region represents the standard deviation error.

| Control Scheme | Name | Pose | Gains | Selection Matrix S |
|----------------|------|------|-------|-------------------|
| Hybrid         |      |      |       |                   |
|                | H-9  | 6    | 1     | 1                 |
|                | H-14 | 6    | 1     | 1                 |
|                | H-19 | 6    | 6     | 1                 |
|                | H-24 | 6    | 6     | 6                 |
| Impedance      |      |      |       |                   |
|                | I-8  | 6    | 1     | -                 |
|                | I-13 | 6    | 1     | 6                 |
|                | I-13pd | 6 | 6 | 1 |
|                | I-18 | 6    | 6     | -                 |

TABLE I
ACTION SPACES EVALUATED ACCORDING TO THE NUMBER OF CONTrollable PARAMETERS PER CONTROL SCHEME.

For 12000 (12k) steps with a maximum of 200 steps per episode, and the complete training session was repeated three times. The manipulator control frequency was set at 100 Hz, so each episode lasts a maximum of 20 seconds. The episode stops if a minimum distance error from the target position is achieved, or if the maximum of time steps is reached. In general, a complete training session takes about 30 minutes with GPS and 20 minutes with SAC, including reset times.

Results: The learning curve for each pair of action space - RL agent is shown in Figure 4. In the figure, the average cumulative reward per episode across training sessions (bold line) is displayed along with the standard deviation error (shaded colored area). The results have been smoothed out using the exponential moving averages, with a 0.6 weight, to more clearly see the tendency of the learning curves.

From Figure 4 the overall best performance is achieved by learning using the pair SAC agent - Impedance controller. The SAC agent quickly and consistently learns the task and the force control parameters of the impedance controller; as a result, the greater reward is obtained. The SAC agent finds an optimal policy with all impedance control’s action spaces, each at a similar learning rate. The more complex version SAC I-18 shows episodes with the highest number of drops of cumulative reward during the training session. However, by the end of the training, the final policy of SAC I-18 yields reward equally good as the other action spaces. In contrast, the simpler version of the controller SAC I-8 is the most stable action space during learning in terms of reward obtained. Finally, both SAC I-13 and SAC I-13pd performed similarly. On average, SAC I-13pd yields the highest reward of all action spaces.

The second-best overall performance is achieved by the pair of GPS agent - Impedance control. The versions GPS I-8, I-13, and I-13pd can be learned, achieving a high reward comparative to the results obtained using the SAC agent. Compared to SAC, the GPS agent more consistently achieve similar optimal policies. The version GPS I-18 slowly improves but does not achieve high reward within the limit of 12k steps per training session. In the GPS agent case, the I-13 version yields the highest reward of all action spaces.

In the case of the hybrid controller, the GPS agent shows the best performance. GPS H-9 yields high rewards similar to the impedance controller, but it is not a consistent result. Other action spaces learn overtime slowly with a similar learning rate as the impedance controller. In contrast, the SAC agent with hybrid control has a higher likelihood of starting from a good policy and slowly improve until the policy achieves high reward, again, similar to SAC with impedance control.

C. Real robot experiments

We evaluate the ability of the RL agent to learn the force control parameters on a real position-controlled robot with the proposed method. Additionally, we validate the feasibility of our proposed safe framework for learning contact-rich manipulation tasks directly on a real rigid robot with minimal human interaction.

Our proposed method was validated on real hardware using two contact-rich insertion tasks, shown in Figure 7. The first task involves an insertion task of a wooden block with four holes into a board with four pins. For the insertion to succeed, the block needs to be aligned with all four pins. For the second task, we 3D printed the same peg and task board used on the simulation task, so it is a peg-insertion task with a cube-shaped peg. For this peg-insertion task, the initial position starts at the corner of the task board; therefore, the manipulator needs to slide across the surface until reaching the hole. Both position and orientation have to be aligned properly for the insertion to be possible. For both tasks, the relative distance error, between the manipulator’s end-effector and the target
pose, and the contact force were measured. The SAC agent was trained using the I-13pd and H-14 action spaces since they provided the most consistent results in simulation. We compared the performance of the learned policy vs. a fixed policy. For the fixed policy, the parameter’s base values were used, as described in Section III-D.1. For both tasks, the training session had 5000-time steps.

1) Wooden toy results: From Figure 5, both the SAC I-13pd and SAC H-14 agents are able to learn a policy that solves the task twice faster than the fixed policy. In addition, both learned policies completed the task while also reducing the contact force with the environment. In terms of contact force, the SAC H-14 agent reduces the contact force more than three times compared to the fixed policy. In contrast, the impedance control fixed policy starts already with a good performance, for which the learned policy SAC I-13pd improved just slightly. On the other hand, the SAC H-14 learned policy shows great improvement, reducing more than 50% of the contact force.

2) Cube-shaped peg insertion: In this task, the improvement is not as pronounced as the Wooden Toy task. Still, both the SAC I-13pd and SAC H-14 found policies that completed the insertion task 50% faster than the fixed policy. Similarly to the previous task, the fixed policy for the impedance controller already has a good performance, for which the learned policy SAC I-13pd improved just slightly. On the other hand, the SAC H-14 learned policy shows great improvement, reducing more than 50% of the contact force.

V. DISCUSSION

In this work, we have presented a framework for safely learning contact-rich manipulation tasks using RL with a position-controlled robot manipulator. The RL learns a control policy that defines the motion trajectory, as well as, the force control parameters of the manipulator’s controller. To validate the effectiveness of our framework, we proposed two learning force control schemes based on two standard force control methods, hybrid position/force control, and impedance control.

Our framework is not dependent on a specific RL agent; we proved it with extensive experiments using two state-of-the-art RL methods, GPS a model-based, and SAC a model-free RL method. We empirically study the trade-off between control complexity and learning performance by using several versions of the proposed control schemes as the RL agent’s action space, each with a different number of controllable force control parameters. Results show that the SAC agent can learn optimal policies with all versions of the action space considered. Notably, both the SAC I-13pd and H-14 action spaces, for impedance and hybrid control, respectively, yielded the highest cumulative reward by the end of a training session. On the other hand, the model-based RL method, GPS, works better with action spaces with a fewer number of force control parameters. In particular, GPS I-13 and H-9 provide the best performance results. Additionally, experimental results on a real rigid robot manipulator show the effectiveness of our method to learn a contact-rich manipulation task.

One of the limitations of our proposed force control schemes is that the performance results are highly dependent on the
choice of controller’s hyperparameters, more specifically, the base and range values of the controller’s gains. In our experiments, we empirically defined said hyperparameters. However, to address said limitation, an interesting avenue for future research is to obtain these hyperparameters from demonstrations either by teleoperation or from human demonstrations and then refine the force control parameters using RL. Additionally, for simplicity, we assume knowledge of the goal pose of the end-effector for each task. However, vision could be used to get a rough estimation of the target pose and perform an end-to-end, from vision to low-level control, learning as proven in previous work [7]. Finally, to prove the capability of our proposed framework to safely learn control policy for contact-rich manipulation tasks with position-controlled robots, we performed each training from scratch, starting from a random policy. However, learning could be sped up by incorporating ideas from residual learning [31], combining a random policy. However, learning could be sped up by incorporating ideas from residual learning [31], combining a random policy. 

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Conclusions:

- We showed that an RL agent can safely learn contact-rich manipulation tasks on a position-controlled robot using our proposed method. Furthermore, our proposed framework is not dependent on specific RL methods.
- The RL agent can learn time-variant force control parameters for the two proposed learning control schemes.
- The effectiveness of our method is proven experimentally on a real position-controlled robot manipulator.

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