Optimal shared autonomy for contact-rich robotic manipulation

Optimal Shared Autonomy for Contact-rich Robotic Manipulation

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***Abstract*— This extended abstract proposes a conceptual framework for combining human user/operator input with autonomous reasoning for remote handling of contact-rich manipulation tasks, outlined in Fig. 1. We propose an optimal control (OC) paradigm that incorporates models from hybrid contact dynamics, compliant interaction, and operator intention as a means of expanding current robotic manipulation capabilities whilst ensuring safe and stable task execution. Through our formalism, we outline technical and scientific challenges of remote handling of contact-rich manipulation tasks and identify opportunities for novel research directions.**

I. Motivation and Background

Applications such as nuclear maintenance and decommissioning often require the remote handling of radioactive material using robotic manipulators, usually achieved by teleoperation [1]. Let's consider the **use case** of a bi-manual robot remotely operated to **place a large box on a cluttered shelf**, depicted in Fig. 2. In such scenario, a fully enclosed grasp, i.e. a grasp with complete restrain preventing any loss of contact, might be unachievable for parts or even the totality of the task execution. Therefore, the robot needs to explore and exploit other forms of contact interaction, such as pivoting and sliding the box on the shelf to achieve the desired goal. These type of tasks are on one hand difficult to fully automate, due to the high number of decision variables such as contact locations and timings, and on the other hand are also quite challenging to accomplish using simple teleoperation approaches, requiring high cognitive load from an experienced robotics teleoperator.

Shared Autonomy presents a paradigm for solving the problem of teleoperating complex robotic systems. Shared autonomy approaches typically consist in blending the user input with some level of autonomous reasoning, either by reducing the dimensionality of the user input or by modifying robot commands to achieve a given target [2], [3]. However, extending such paradigm to complex tasks that involve regulating multiple contacts with the object—increasing the number of decision variables—raises numerous questions on how to maintain an intuitive user interface [4] and retain the operator's sense of agency.

Contact-rich manipulation contains the set of tasks involving contact interactions between the robot, the manipulated objects, and the external environment. This requires reasoning beyond the robot kinematics and includes considerations on the dynamics and/or forces of the interaction.

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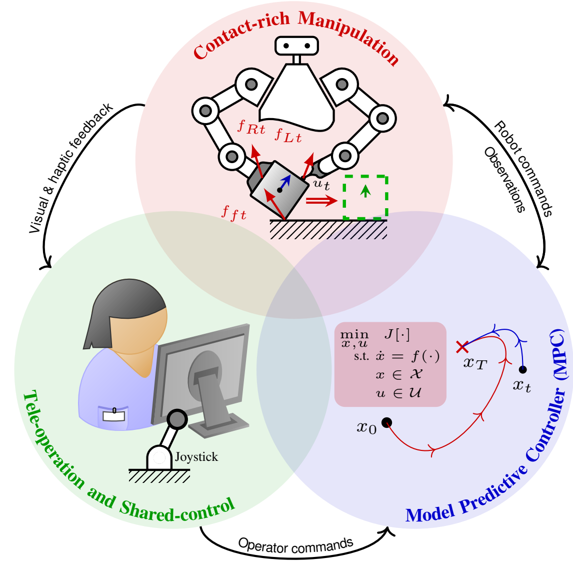

Fig. 1. Diagram illustrating an user remotely operating a robot to reposition and reorient an object through frictional contact interactions between the object, the robot, and the environment. The proposed optimal control (OC) framework modulates the user input such that the robot commands result in smooth and stable motions whilst ensuring critical physical constraints.

An important category of contact-rich manipulation is non-prehensile manipulation, in which the objects' motion can evolve independently from the robot as, for instance, when throwing, catching, and pushing objects [5], [6]. Such tasks, introduce additional contact modalities, for instance sliding and rolling contacts, and hybrid dynamics, e.g. the making and breaking of contact, significantly increasing the number of decision variables, such as surface, location within the surface, and timing of contact [7]. Additionally, frictional contacts—with possibility of impacts—introduce high uncertainty in the prediction of the motion of the objects, making it unfeasible to execute open loop plans and difficult to regulate the contact interaction.

Finally, efficient generation and reliable execution of whole-body robot motions, especially when including multiple contacts with the manipulated object, is still an extremely challenging area of research, with regards to the scalability of the approaches to high degree-of-freedom (DoF) robots, the number of contacts, and the task horizon.

II. Problem Statement

The goal of the proposed framework is to assist novice operators in remote handling activities towards reducing cognitive load and training requirements while enabling more complex remote manipulation capabilities. We assume users

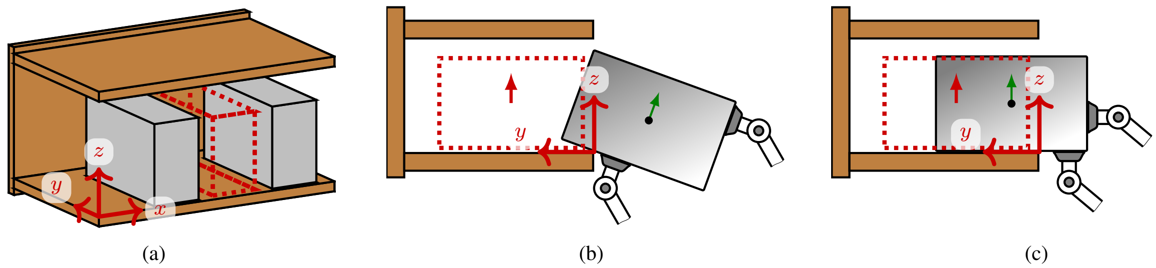

Fig. 2. Illustrations depicting a dual arm robot placing a large container onto a cluttered shelf where: (a) shows a three dimensional view of the shelf where the grey objects represent other containers stored on the shelf and the dotted red lines represent the target location; (b) portrays robot using the shelf to pivot the container while sliding its end-effectors to another contact position; and (c) portrays the robot pushing the container to the target position.

provide commands through a remote control interface, such as a simple joystick, and have access to visual and/or haptic feedback. In particular, we consider tasks requiring multiple contact interactions and different modes of manipulating objects, such as the pushing and pivoting scenarios illustrated in Fig. 2, which require force and compliance regulation. The problem is on how to utilise the input from a user, who has the domain knowledge to perform sequential tasks, such as decommissioning, with autonomous situation-aware reasoning of robotic agents in such contact-rich scenarios.

We postulate that for such tasks, the input of a novice robot operator is too coarse to achieve stable task completion, yet good enough to predict specific user task intentions, such as the object's target pose or where and when to establish contact. This can in turn inform an autonomous policy that can accurately compute an optimal robot motion to safely achieve the intended task. Recent work propose more sophisticated teleoperation setups with the goal of enabling fairly novice operators to collect data for learning from demonstration [8]. While these setups can greatly ease the teleoperation of robots, shared autonomy can aid in making such demonstrations both more stable and dynamic, further improving the data used for learning autonomous policies.

III. Problem Formulation

Inspired by [9], [10], we introduce the human input in an optimal control formulation as

$$\begin{aligned}
\text{min.}\quad & J[x(\cdot), u(\cdot), \bar{x}(\cdot)] && \text{(cost)} && \text{(1a)}\\
\text{s. t.}\quad & \dot{x}(t) = f(x(t), u(t), z(t)), && \text{(dynamics)} && \text{(1b)}\\
& \bar{u}(\cdot), \bar{x}(\cdot), \bar{z}(\cdot) = H[h_{t_0..t_t}], && \text{(user input)} && \text{(1c)}\\
& x(t_t) = x_t, && \text{(initial state)} && \text{(1d)}\\
& x(t) \in \mathcal{X}, u(t) \in \mathcal{U}, z(t) \in \mathbb{Z}, && \text{(domain)} && \text{(1e)}
\end{aligned}$$

where $J[\cdot]$ is a cost functional that contains running and endpoint costs, $f(\cdot)$ corresponds to the hybrid dynamics that depends on the system state x, actions u, contact mode z. We can abstract Eq. (1) as a function $\pi(x^t|h_{t_0..t_t})$, which outputs optimal action and state trajectories $u^*(\cdot), x^*(\cdot)$, as a function of the current state x^t and past operator inputs $h_{t_0..t_t}$. By computing $\pi(\cdot)$ at each control cycle and executing the first action $u(t^t)$, π becomes a model predictive controller (MPC), requiring solving Eq. (1) online.

IV. Challenges and Research Directions

One of the first challenges that this framework presents relates to how to introduce operator commands h into Eq. (1). One approach is to use the history of commands $h_{t_0..t_t}$ to estimate an intended goal and introduce it in the cost functional J, similar to [3]. Multiple recent works already propose several approaches on how to integrate human motion or intention prediction in motion planning [11]–[13]. However, as tasks become more complex, requiring the robot to execute dynamic motions with changes of contacts, as illustrated in Figs. 2b and 2c, we propose to use the human input to predict selection of contact faces and timings, encoded in $\bar{z}$, and contact locations, encoded in the state reference $\bar{x}$. We can then use the estimation of both $\bar{x}$ and $\bar{z}$ either as a warm start to the problem in Eq. (1) or as a reference motion in the cost functional J. This approach raises a few scientific and technical questions such as: how to effectively estimate such quantities from human input h and how to provide an intuitive interface for the operator to easily indicate changes of contacts, timings, and even types of manipulation primitives—e.g. does the operator intent to pick, push, or pivot the object?

Introducing continuous human input into a robotic system introduces an additional challenge on the speed of synthesising the robot motions. Having human-in-the-loop operating the robot, requires online motion planning due to changes of the operator's predicted intention and, hence, we need to consider how to efficiently plan constrained robot motions [14], which include considerations on optimal state and action representations [15] and trajectory parameterization [16]. In our previous work, we addressed the online generation of hybrid plans, i.e. optimise for z, given the partner intended goal [9]. However, the planning of hybrid modes without any human guide is still too slow for integrating it as an MPC. In other work, we achieved MPC that constantly updates the robot motions based on the estimated inteded pattern of motion [10]. However, this work applied the optimization to a simplified wiping task that requires no change of contacts. Both works only reason about task-space without considering online whole-body motion adaptation. Therefore, future research directions will include achieving online whole-body motion adaptation and accelerating the planning of contact switches via using human input.

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