Haptic Bimanual System for Teleoperation of Time-Delayed Tasks

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***Abstract*— This paper presents a novel teleoperation system, which has been designed to address challenges in the remote control of spaceborne bimanual robotic tasks. The primary interest for designing this system is to assess and increase the efficacy of users performing bimanual tasks, while ensuring the safety of the system and minimising the user's mental load. This system consists of two seven-axis robots that are remotely controlled through two haptic control interfaces. The mental load of the user is monitored using a head-mounted interface, which collects eye gaze data and provides components for the holographic user interface. The development of this system enables the safe execution of tasks remotely, which is a critical building block for developing and deploying future space missions as well as other high-risk tasks.**

I. Introduction

Future space missions aim to establish long-term habitats and support facilities on lunar and planetary surfaces. These missions will see robotic systems distributed on the remote surfaces in advance of human crews to perform the initial development of these facilities, and long-term maintenance.

Ideally, much of the preliminary work required to establish these surface facilities will be accomplished autonomously; however, given the complexity of construction, assembly, and maintenance tasks, it is inevitable that human intervention and teleoperation will be required. Rather than purely relying on terrestrial operators for the control of these robot systems, it has been proposed that robot systems could also be controlled by astro/cosmonauts on the planetary surface in a secure location, or in-orbit prior to landing. In the more near-term, such assembly capabilities would also be of great benefit to maintenance of in-orbit assets, potentially mitigating the need for high-risk extravehicular activities.

The use of non-terrestrial operators significantly reduces the travel distance of communication signals, mitigating latency and data loss as in terrestrial control. However, this shift in control location introduces new challenges for the operators, who must work in cramped conditions, with equipment limited by the mission payload, and subject to microgravity effects. These factors all lead to increased mental load, and impose a challenging environment for achieving safe task executions. This paper presents an experimental system that has been designed to investigate and better understand these challenges on the bimanual assembly tasks through haptic interfaces.

A. Contributions

Addressing real-world applications is challenging and requires the integration of several components, where each is an extensively investigated research theme. Safe and stable physical interactions with the environment require some forms of compliant and force-based control [1], where stability is critical for tasks involving heterogeneous mechanical properties. Robots are often redundant with many degrees of freedom, and high-level operator commands need to be mapped into the morphology of the robot through postural optimisation.

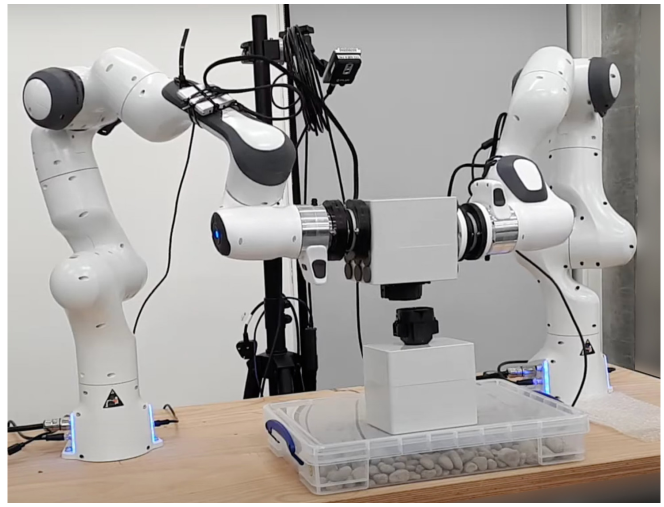

Fig. 1. Bimanual teleoperation system consisting of dual 7-axis manipulators, performing a task involving the connection of a power socket.

Teleoperated tasks strongly rely on the quality of feedback provided to the human operator, which should provide effective situational awareness. The quality of feedback also depends on the latency introduced by the communication link, which is well known to affect the whole loop severely. The complexity of the task itself, the quality of the feedback, the choice of human-robot interfaces, and possible external perturbations, all influence the mental load of the operator, and therefore the overall human-robot system performance. It is important to be able to monitor this mental load and reduce it through careful design choices, such as providing shared control or partial autonomy approaches to mitigate potential mistakes in high-risk situations.

This work developed a teleoperation system to remotely perform a bimanual manipulation and assembly task (see Section II). We have designed and integrated the following components to enable solving tasks in real-world scenarios:

- a dual arm robot system for bimanual grasping of large and heavy objects,
- visual and haptic feedback to the remote operator for system transparency,
- artificial communication latency to replicate space communication conditions,
- seamless integration of shared control between direct

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command and autonomous sub-task planning,
- an intuitive holographic interface for hands-free options control, and
- a mental load estimation and monitoring system.

We conducted hardware and long distance remote experiments, which are presented in the accompanying video.

B. Related Work

We detail in the following the challenges and key previous works associated with the different components of the presented system.

1) Haptic feedback and force control for space applications: Early bimanual teleoperation systems featured many common elements with modern systems, including haptic control, early forms of shared control, and even voice-based user interfaces [2]. The first teleoperation system deployed in space in 1993 had both shuttle- and groundcrew-based control interfaces, and used a 6 Degrees of Freedom (DoF) robot with a sensorised gripper for a connector coupling task under time-delayed conditions [3]. The space mission in 1999 demonstrated the value of haptic feedback, where contact rich tasks, e.g. peg-in-hole, were conducted using force-feedback in a bilateral control scheme without visual feedback [4]. More recent research on teleoperated systems, especially for space missions, have further developed in the core areas of intuitive interfaces [5], autonomy, force control [6] and stability of control systems [7], [8].

The main challenges for teleoperated systems for space missions are network quality and operational time. Network quality can be judged by (i) latency, (ii) packet loss, and (iii) bandwidth. It can be seen in the available communications channels between Earth and the International Space Station (ISS) that systems designers must make multiple trade-offs between network quality, and operational time. For example, the Haptics-2 system communicated from the ISS to earth via geosynchronous relay satellites, providing a long operational time for a 1 DoF haptic robot (90 minutes), but also increased latency, as the signal had a longer distance to propagate [9]. An alternative approach can be seen in the KONTUR-2 experiments, where a haptic 2 DoF system on the ISS was used to control a 2 DoF manipulator on Earth using a direct communications link for lower latency, but lower operational time (about 10 minutes), and lower bandwidth [7].

2) Imperfection of communication link: Latency, packet loss, and jitter can all have significant negative effects on the control of the manipulator system and the haptic feedback provided to the user. In order to ensure safe, transparent control, a large body of research has investigated the stability of systems subject to varying time delays. Several recent works have considered energy-based methods, such as the *Time-Domain Passivity Approach* (TDPA) [7], [8], fuzzy control modelling approaches for non-linear systems using *Practically Prescribed-Time Stability* (PPTS) [10] or novel fractal impedance control [11]. Ensuring fail-safe conditions, and system stability continues to be an important area of research for enabling space-based experimentation with human operators [9].

3) Bimanual Robots: A natural direction for enhancing the capabilities of complex manipulation involves the deployment of bimanual or anthropomorphic robots. The physical configuration of a bimanual robotic system offers the ability to manipulate larger and/or heavier objects over a larger workspace [12]. Such capabilities come at the cost of the operator needing to manage an increased number of degrees of freedom [8], [13], [14]. The challenge of managing the increased DoF leads to the use of shared control systems to help the user execute the target task while minimising cognitive load [13], [14], as discussed further in Section IV.

Beyond bimanual systems, *multi-operator multi-robot* (MOMR) systems offer potentially greater manipulation capabilities, but introduce further challenges around multi-operator coordination. This challenge can be seen during haptic interactions, where two operators can haptically communicate task goals when collaborating on a shared task [15], but haptic communication may be hindered by network quality issues or through task-specific dynamics, as found when manipulating flexible objects [8].

4) Human-Robot Interface: Recent works on haptic teleoperation systems for space missions have emphasised the need for intuitive, transparent, and safe control of remote systems [16], [17]. Aside from the control design aspects of a teleoperated system, these works consider enhanced feedback to operators through augmented display overlays. These displays can provide additional task and positioning information, specific to the task at hand. In addition to feedback systems, operator monitoring systems have been proposed as part of the Kontur-3 system [17], involving the use of head-mounted displays (HMD's) with gaze tracking features for evaluating operator cognitive load in ergonomics studies. A challenge with operator feedback systems is the limited space available in an in-orbit vessel, which can lead to unintuitive interfaces as designers attempt to fit interfaces to smaller displays [16]. A potential solution is to combine the mental load estimation capabilities of gaze-tracking HMDs with augmented reality interfaces to provide significantly greater flexibility in interface design for these systems, as explored in Section III-B.

II. Task Description

The chosen application scenario is to remotely pick and place assembly blocks that shall be connected via standard industrial power connectors. The manipulated building blocks have a rectangular shape ($12 \times 16 \times 14\,\mathrm{cm}$), weigh $0.8\,\mathrm{kg}$, and are fitted with interconnecting industrial fittings (Anderson Power Mid-Power Spec-Pak), see Fig. 1 and Fig. 3. The blocks must be re-orientated, grasped, transported, and then connected while both visual and haptic feedback are provided to the human operator.

The specific shape of the connector requires accurate positioning (sub-millimetre) to enable the insertion task. This task strongly relies on human-in-the-loop teleoperation, as the accuracy of our visual marker-based pose estimation, used for autonomous behaviour, is limited to centimetre accuracy, in addition to forward kinematic errors ($2-4$mm).

This bimanual assembly task intends to showcase the ability of the system to manipulate potentially large and heavy building blocks, while applying accurate contact forces to execute the assembly task with millimetre precision[1]. The operator provides a stream of desired Cartesian 6 DOF pose commands using two haptic devices. This helps to reduce the operator's mental load compared to providing commands in joint space. In Fig. 2, the block "*Posture and force-torque optimisation (IK)*" computes the individual desired joint positions from the Cartesian space target. At the same time, the operator also receives force feedback that improves awareness of the remote contact state, while a shared-autonomy system automatically enforces a set of safety limits to prevent dangerous actions.

III. System Design

While the system is suited to the task described in Section II, the hardware and architecture choices have been made such that the system can be readily extended to a diverse set of tasks, such as cleaning, tool use, or sample collection. A high-level system architecture is shown in Figure 2, and the following describes some of the salient features.

A. Robot Manipulation System

Assembly and construction tasks involving bulky items will often require either the use of larger manipulators, or multiple manipulators working collaboratively. A bimanual manipulation system is considered here as a good compromise between overall lifting capacity of the system, volume of objects that can be manipulated, capability in terms of the range of tasks that can be done bimanually, and the overall weight of the system. This bimanual system consists of two torque-controlled, 7 degrees of freedom Franka Emika robot arms. The arms each have a maximum reach of $80\,\mathrm{cm}$, a maximum payload of $3\,\mathrm{kg}$ and are fixed on a workbench at $1\,\mathrm{m}$ apart, see Figure 1. They are both equipped with an OptoForce 6 degrees of freedom force-torque sensor and a flat contact plate mounted on the end-effector.

Impedance control provides the compliant behaviour required by the system to mitigate damage caused by unexpected contact with the environment (see the block "*Bimanual impedance controller*" in Fig. 2). The general form of our impedance control is written as follows:

$$\begin{aligned}\boldsymbol{\tau} = &\boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}}) + \boldsymbol{G}(\boldsymbol{q}) + \\ &\boldsymbol{J}(\boldsymbol{q})^{\mathsf{T}}\left(PD(\boldsymbol{x}^d,\boldsymbol{x},\dot{\boldsymbol{x}})\right) + PD(\boldsymbol{q}^d,\boldsymbol{q},\dot{\boldsymbol{q}}),\end{aligned} \tag{1}$$

where $\boldsymbol{\tau}$ is the computed joint torque command, $\boldsymbol{q},\dot{\boldsymbol{q}}$ are the measured joint position and velocity vectors, $\boldsymbol{q}^d$ is the desired joint position computed by inverse kinematics, $\boldsymbol{C},\boldsymbol{G}$ are the nonlinear Coriolis and centrifugal, and gravity force vectors in joint space, $\boldsymbol{J}$ is the stacked kinematic Jacobian matrix of the two end-effectors, $\boldsymbol{x},\dot{\boldsymbol{x}}$ are the measured Cartesian pose and velocity of the two end-effectors, and $\boldsymbol{x}^d$ is the desired Cartesian pose for the two end-effectors. A proportional-derivative controller (PD) is used to track the end-effector poses as well as the joint positions. It is defined as follows for the joint space:

$$PD(\boldsymbol{q}^d,\boldsymbol{q},\dot{\boldsymbol{q}}) = \begin{cases} F_{\max} sign(\boldsymbol{q}^d-\boldsymbol{q}) - K_d\dot{\boldsymbol{q}} & \text{if } |\boldsymbol{q}^d-\boldsymbol{q}| > e_{\max} \\ \frac{F_{\max}}{e_{\max}}(\boldsymbol{q}^d-\boldsymbol{q}) - K_d\dot{\boldsymbol{q}} & \text{else,}\end{cases} \tag{2}$$

where $F_{\max}$ is the maximum torque effort, $e_{\max}$ is the angular error threshold before effort saturation, and K_d is the damping gain. The Cartesian PD controller follows a similar formulation. The control parameters for joint space, Cartesian position and orientation are different and are manually tuned for stability. Typically, the $F_{\max}$ parameter defining maximum Cartesian interaction forces is set to $20\,\mathrm{N}$.

A further challenge when teleoperating the system is that the range of motion possible with the end-effectors is greater than the haptic device interface used by the operator. In order for the operator to make full use of the robot workspace, while still allowing fine motion control for accurate positioning, two separate control modes are implemented:

$$\begin{cases} \boldsymbol{x}^d = \boldsymbol{x}^{\text{ref}},\ \dot{\boldsymbol{x}}^{\text{ref}} = \frac{\boldsymbol{x}^{\text{cmd}}}{\Delta t} & \text{velocity mode} \\ \boldsymbol{x}^d = \boldsymbol{x}^{\text{ref}} + \boldsymbol{x}^{\text{cmd}} & \text{offset mode}\end{cases} \tag{3}$$

The first is velocity control, where the haptic device displacements $\boldsymbol{x}^{\text{cmd}}$ are used to set end-effector velocities and move a reference position $\boldsymbol{x}^{\text{ref}}$. Velocity control is used to "jog" the end-effectors across larger pose changes. The second mode is offset control, where haptic device displacements $\boldsymbol{x}^{\text{cmd}}$ are directly mapped to a robot pose. Offset control allows for much finer motion control, and more accurate application of force interactions with the environment, as is required for securely connecting the two boxes in the main task.

Alternating between these two control modes is a decision currently left to the operator, either through a keyboard selection, or through a hands-free mixed-reality holographic interface, as described in Section III-B.1.

B. Operator Systems

In order for the operator to be effective at performing a remote teleoperation task, it is important to achieve transparent control of the remote system, while minimising the cognitive load of the operator. This section describes the control interfaces, feedback systems, and user monitoring systems that have been developed to ensure safe, effective operation of remote robot manipulators.

1) User Interfaces: Transparent control of the manipulation system can be achieved through the use of intuitive and informative feedback systems, combined with natural controls. Multiple camera views, interactive visualisations, and haptic control interfaces are all technologies deployed in this system to help achieve transparent teleoperation.

The operator provides input commands with two ForceDimension Sigma-7 haptic devices, with 6 force controlled degrees of freedom (position, orientation), for each arm.

The primary feedback system for the operator is a set of cameras around the manipulators, which provide visual feedback on the task. The camera frames are captured, encoded, transmitted through the UDP protocol for minimal latency, then decoded and displayed on the operator's screen as represented by the blue blocks pipeline in Fig. 2.

[1]A video of this system being tested has been attached with this submission, and a video is also available online: `https://youtu.be/KJJZQ0BhPDI`

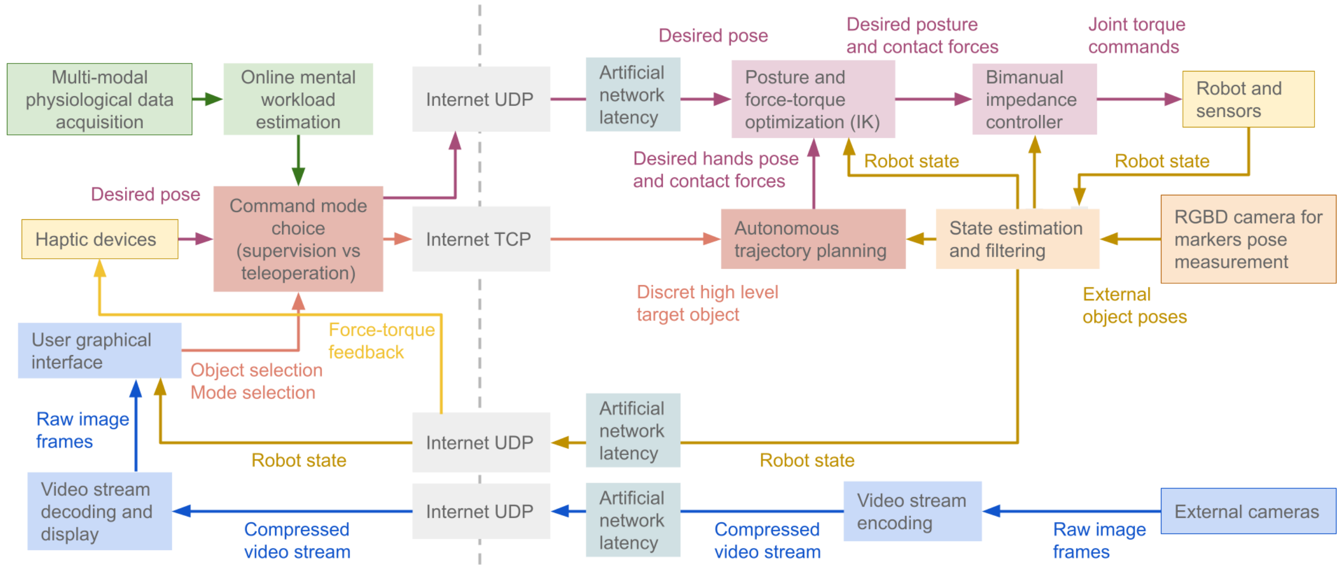

Fig. 2. Overall system architecture summary. Left of dashed line is represents the local operator side systems, right of the line is the remote robot manipulation system.

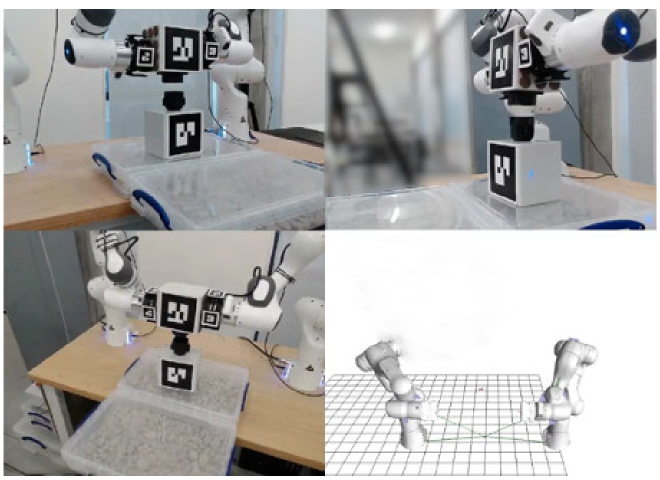

Fig. 3. Multiple camera views offered to the user, plus an interactive 3D scene generated from the transmitted robot system state. The images show the operator attempting to align the connectors.

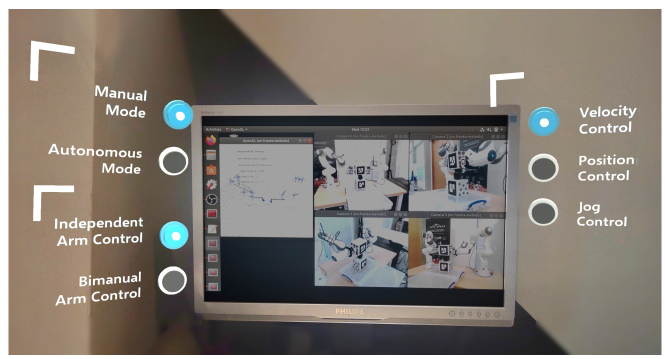

Fig. 4. Holographic user interface, providing the user with gaze-activated control interfaces for triggering various teleoperation system actions, such as switching between velocity and offset control, and for providing feedback text on the current system state.

These camera views are augmented using a virtual interactive interface, that shows a visualisation of the robot's proprioceptive state based on the joint angle and torque sensors. This interactive view can be further enhanced with a representation of the task state through the use of fiducial markers placed on the target objects, which offer pose estimates that can be visualised, see Figure 3. Future improvements will incorporate computer vision-based pose estimation [18].

As discussed in III-A, the operator can activate a variety of control modes. Switching between these modes is achieved either through a keyboard interface, or through a hands-free holographic interface using a Microsoft Hololens 2 system, see Fig. 4, and the block "User graphical interface" in Fig. 2. The holographic interface presents interactive mixed-reality elements which can be positioned where the user chooses in the real-world using hand gesture tracking. These holographic control interfaces can be activated using built-in gaze-tracking, avoiding the need for the operator to remove their hands from the haptic controllers. This helps reduce operator effort and mental load associated with switching attention from the main task to a keyboard interface.

2) Mental Load Estimation: Estimating the user's mental load can enable a system to adaptively interact with the user to ensure safety. In the event that an excessively high mental load is estimated, the system can take precautionary actions, e.g. activating a safety stop. A more advanced system might be able to mitigate mental load through a sliding-scale shared control scheme, i.e. the autonomous system assumes more control as the user's mental load increases. A mental load estimation (MLE) system is implemented in this early-stage system that primarily uses eye tracking data provided by the Microsoft Hololens 2 (see the green blocks in Fig. 2). Gaze focused features, such as saccade frequency, fixations duration, blink frequency, and blink duration, have all been shown to be correlated with mental load in prior works [19], [20], [21], and are being explored in this system.

The current system favours monitoring mental load using eye gaze from the HMD for the ease of acquiring the signals, in terms of donning the HMD; however, eye-related features are just one of many signals that can be used for mental load estimation. Brain-computer interfaces are commonly used for this task, such as functional near infrared spectroscopy (fNIRS) [22] and electroencephalography (EEG) [19] [23]. However, BCI systems are typically more difficult to analyse and deploy in the field, especially when the operator has only a limited time to apply the system and to perform a task in a high-risk environment. Other physiological signals relevant to mental load that could be considered include temperature, heart rate and electrodermal activity (EDA) [23].

C. Network Communications

In the proposed experiment, a human operator is located remotely at Imperial College London, while the manipulator system is in the University of Edinburgh, giving a $\sim 200\,\mathrm{km}$ straight-line separation. The latency resulting from this distance over a standard UDP connection is quite low, with typical values varying depending on the type of information being transmitted; of which there are two main one-way communication packets from the remote system to the operator as shown in Fig. 2, (i) communication of the robot system state recorded at $100\,\mathrm{Hz}$, with a latency of 10-$20\,\mathrm{ms}$, and (ii) transmission of camera streaming recorded at $30\,\mathrm{Hz}$, with a latency of between 120-$250\,\mathrm{ms}$. The operator system then also sends user commands to the robot in a one-way communication stream recorded at $100\,\mathrm{Hz}$, with a latency of 10-$20\,\mathrm{ms}$.

In real-world space applications, the latency and packet loss encountered are typically worse, and affected by other factors such as the operational time available. For example, in missions featuring control between the International Space Station and Earth, a direct S-Band connection provides the lowest latency (20-30 ms), but also the shortest operation window ($\sim$10 minutes), dictated by the time the station is over the communication site [7], [17]. Alternatively a Ku-Band connection can be used, which uses a relay satellite to increase the operational window ($\sim$90 minutes), but also increases the latency (600-1000 ms) [17]. Similar trade-offs could be expected for future Mars or Moon missions featuring surface robots controlled by operators in-orbit, so for the purpose of experimentation, configurable artificial latency and packet loss is added to the network stream, as marked in the system diagram in Figure 2.

D. Software Implementation

The dual arm impedance controller, inverse kinematics, autonomous trajectory planning, state estimation and external camera streaming run at the robot operation site in Edinburgh on a desktop computer with a real time Linux kernel. The haptic device controller, the mental load bio-monitoring, and the user interface run at the operator site in London on a regular laptop. We use the commercial *libFranka* and *ForceDimension* APIs to control the robot and the haptic devices, using C++. We rely on the rigid body dynamic library *Pinocchio* for all model computations and *EiQuadProg++* to solve the quadratic program of the inverse kinematics.

IV. System Autonomy

Three autonomous or semi-autonomous modes can be manually activated by the user to assist with positioning of the arms for the specified task.

First, a hybrid command mode is used to help the operator manage the many degrees of freedom of the system more effectively. This mode allows the operator to control a primary subset of the end-effectors' movement, while the autonomous system handles the secondary axes of motion. For example, the operator may command the position of the hand while the orientation is autonomously controlled to maintain an upright position. This mode lets the operator focus on task-relevant aspects of the task, helping to improve the overall performance of the system.

Second, during bimanual manipulation, the operator only provides the commanded pose for the centre of the manipulated object, and the coordination of the two arms is automatically computed to ensure the object is securely held. This mode helps to reduce the mental load associated with coordination of the two arms during bimanual manipulation.

Finally, a fully autonomous mode can be activated by the user to perform automatic bimanual *object capture*. The operator can select an object detected by the system that they wish to pick up, and the system will then plan and execute coordinated trajectories for both arms to pick up the target (see the block "*Autonomous trajectory planning*" in Fig. 2). This planning uses a minimum time trajectory, with bang-bang acceleration and velocity limits, and is continuously updated online to allow adaptation to a moving target. Control is returned to the operator when the capture sequence is completed and the object is grasped by the two hands, or when the user disengages the autonomy. In this case, the user assumes a supervisory role, allowing the system to handle the large-scale movements involved in the task, before resuming manual control to provide fine control. As well as assisting in terrestrial missions, this autonomous capture system can be extended to assist manipulation tasks in low-gravity environments, where the movement and inertia of objects may not be intuitive.

In addition to reducing mental load, the autonomous behaviours help mitigate issues of communication latency [2], and errors arising from the operator control inputs. A caveat to this autonomous control is that it requires some knowledge of how to perform the task, and relies on accurate state estimation, limiting it to relatively simple tasks compared to what can be achieved by the operator directly.

Encoding knowledge of the task can be achieved in a number of ways. Future iterations of this system will consider the use of Learning from Demonstration (LfD), where representations are learned directly from the examples of the task being performed [24]. Recent work has shown the value of this approach for teleoperated systems that experience varying time delays [25], [26], [27], and the flexibility of the underlying methods in adapting the learned skills to changes in the task from the original conditions [28], [29].

V. Future Work

This paper demonstrates the capabilities of a sequence of tests of long distance remote teleoperation between *London* and *Edinburgh* (see accompanying video): successful switching between different operation modes to complete the manipulation and assembly task qualitatively. Our preliminary findings indicate that the configuration of multi-view camera is essential to task performance, operators' perception and mental load, and requires further study.

Currently, the current system is being evaluated with human subjects to assess its usability and performance. The initial evaluation will be the ability of the operator to conduct bimanual assembly tasks, in terms of completion time and success scores. Also, users' mental load and performance of the system, while conducting the previously described task, will be considered in the following conditions: (1) Optimal conditions (low latency, no time constraints); (2) Network degradation (varying latency, packet loss); (3) Limited duration tasks (time pressure).

In future work, we will compare the system-estimated cognitive load with subjective reports from the users, using standard questionnaires, e.g. NASA TLX [30].

VI. Conclusions

The presented system is the first proof of concept in the development of an operator training and assessment system for remote construction activities. This is an important research direction, as teleoperated robotic systems will play a critical role in future space missions. Additionally, given the general design of the system, insights relating to control and interface design for remote teleoperation activities in the proposed experiments will be useful for a variety of related fields, from under water inspection systems to nuclear waste decommissioning. Through the use of intuitive control interfaces, informative user feedback, and intelligent control systems, this project aims to help humans perform challenging tasks in harsh, dangerous environments by improving the performance of bimanual dexterous teleoperated robots.

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