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Motion Regulation Solutions to Holding & Moving an Object for Single-Leader-Dual-Follower Teleoperation

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Abstract—This paper provides solutions for a single-leader-dual-follower (SLDF) teleoperation system to collaboratively transport an object. First, to regulate the direct-teleoperated follower robot (DFR), we employ a relative pose transformation algorithm, based on “re-fixing” the leader and DFR together, to enable that the operator can ergonomically guide DFR without requiring any specific initial position, ensuring a higher teleoperation precision at the same time. Second, to regulate the assistive follower robot (AFR), we provide an efficient technique to acquire the right orientation to achieve holding. In addition, we devise an adjustable artificial potential field method (APFM) to autonomously regulate AFR’s position to a ready-to-hold pose, where the operator’s motion is involved. At last, based on the combination of the auto-regressive model and the impedance model, we generate a reference trajectory for AFR to follow, which enables the followers to hold a rigid or deformable object with a desired contact force. Simulations and experimental results verify the feasibility and effectiveness of the proposed method.

Index Terms—artificial potential field, dual-arm robot, object hold-and-move task, single-leader-dual-follower teleoperation.

I. INTRODUCTION

Robot teleoperation has been widely investigated in various applications [1], including healthcare [2] and aerospace [3] etc. Most of the existing teleoperation methods are based on a leader-follower mode, where the operator manipulates a leader to tele-manipulate or send commands to the remote follower robot(s) [1]. Within this mode, the single-leader-dual-follower (SLDF) teleoperation system, as shown in Fig. 1, has drawn numerous researchers’ attention recently because it has a unique advantage of alleviating the operator’s workload while conducting almost the same amount of work [4], compared to the basic single-leader-single-follower system [5], the multiple-leader-single-follower system [6]–[8] and the multiple-leader-single-follower system [9], [10]. In an SLDF teleoperation system, the two follower robots are usually divided into one direct-teleoperated follower robot (DFR) and an assistive follower robot (AFR). Researches in this area mostly focus on enabling AFR to assist in completing a task autonomously, without any instruction from the operator. For example, a semi-autonomous SLDF framework was proposed in [11] to conduct suturing tasks in the minimally invasive surgery (MIS); an automated relay SLDF technique was devised in MIS [12]; a multi-layer controller was developed in [4] to generate target poses and forces for the followers to perform manipulation of a hard-contact object. Despite the great achievement in the literature, there is still room to improve the current methods, for example, in [4], the desired movement is obtained according to tasks instead of the operator’s motion, which is lack of versatility in response to the operator’s motion intent.

Besides teleoperation, the SLDF is also found in the field of multiple robots system (MRS) since there are two followers in the system. Note that in this paper we discuss manipulators’ MRS [13], other than mobile robots’ MRS. In this field, there are many papers on using MRS to transport a rigid object, but few works about holding and moving a non-rigid volumetric object [14]. There is a challenge for SLDF system to hold and move a volumetric-type deformable object [15]: to generate a reference trajectory for AFR according to the operator’s random movement, while the desired holding force is required to be maintained.

To improve the ability of motion regulation of a robot, the artificial potential field method (APFM) has been verified to be a practical means. Its use is found to cover a large number of application scenarios, which are mostly about mobile robots’ or unmanned aerial vehicles’ (UAVs’) [16] path planning. There are few works about APFM for manipulators’ motion regulation [17], [18]. Researchers have made great efforts to enhance the performance of an APFM, e.g., the reinforcement learning technique is integrated in [19] to deal with moving obstacles. However, it can be more challenging if the regulation of the manipulator’s target poses take human factors (discussed later) into consideration, which is critical in
SLDF teleoperation.

The problem of the internal force regulation in an object-holding task for MRS is different from a pick-and-place grasping task for only single robot [20], because it requires to plan coordination trajectories and to control to execute the collaborating holding movements for at least two manipulators. Researchers has put forward methods targeting to certain aspects. For example, in [21], the proposed task-space regulators maintain a desired internal force of the rigid object held by two collaborative manipulators. These methods share features in common: i) the manipulated objects are rigid and ii) the holding pose is horizontal, i.e. the gravity does not affect the contact force. To extend the MRS’s ability to hold and move especially volumetric deformable objects [15], different physical models of deformable objects are introduced in [22]. Besides other kinds deformable object, e.g., in [23], S. Zimmermann et. al. generated optimal trajectories for one or both robot arms for dynamic manipulation, such as swinging a soft rod as a whip, a pendulum as a wrecking ball to knock off other objects, laying soft sheets onto a table, which are model-based and the whole trajectories are calculated ahead of execution, there have been some works concentrating on the manipulation of these volumetric deformable objects. A generalized learning algorithm for dual robots and a force predictor under time-delay and F/T sensor-less condition for the dual-arm tele-robot to hold and move a yoga ball in one axis [25]. These works are likewise limited to a condition that the object is held in a pre-defined and fixed manipulation pose. However, in a hold-and-move SLDF teleoperation scenario, the contact force varies because of influences of the object’s mass, varying internal force and the operator’s random pick-up poses, holding poses and movements (human factors) etc., where those predefined-trajectory methods are doomed to fail as the manipulating pose is not fixed and unpredictable.

To propose a complete set of solutions for an SLDF system to hold and move an object, the contributions of this paper include:

- We derive a series of techniques to regulate two followers based on single operator’s motion. First, the re-“fixing” pose transformation enables the precise/flexible and ergonomical teleoperation, which also reduces the tedious whole-task-space matching work. Second, we provide a proved efficient technique to obtain the holding orientation for AFR via DFR’s quaternions. And third, we design an adjustable APFM, which takes operator’s random motions into consideration to update weights. These adjustable weights endow AFR with intelligence to judge whether to assist holding or prepare to assist holding, despite random holding poses specified by the operator.

- We extend our previous publication [26] to the SLDF teleoperation system for the first time, where an autoregressive model and the impedance model are combined to generate AFR’s reference trajectory such that AFR can actively move to the right position to track the desired contact force, regardless of the decoupled DFR’s random movement and the object’s unknown parameters and time-varying internal forces. The reference trajectory can be directly applied without the need to wait for parameters estimation to converge.

The rest of the paper is organized as follows. Section II introduces an SLDF teleoperation system and the challenges that we are going to address. Section III presents the methods to manage the poses for DFR and AFR before holding the object. Section IV devises the motion regulation method when the deformable object is held with a desired force requirement. Section V analyses the conducted simulations and experiments. Section VI draws conclusions of the paper.

II. PROBLEM FORMULATION

A. System Description

An SLDF teleoperation system generally consists of three robots, as depicted in Fig. 1. One serves as the leader and the other two as followers. The leader is manipulated by the operator and two followers are teleoperated according to the single leader. Two followers usually play different roles when carrying out a task, where one (DFR) is directly teleoperated by the leader and the other (AFR) provide assistance to DFR.

A robot teleoperation system usually applies a mapping between the task spaces (Eq. (1)) or the joint spaces (Eq. (2)) of the leader and the follower:

\[ X_{follower} = f(X_{leader}), \]

\[ \theta_{follower} = g(\theta_{leader}), \]

where \( X_* \) stands for the end-effector (EE) pose of the follower or the leader, \( \theta_* \) are their joint positions and \( f(\cdot) \) and \( g(\cdot) \) are the mappings. Compared to joint space transformation Eq. (2) which may encounter problems such as mismatching degrees of freedom (DOF), task space transformation in Eq. (1) is more preferable and it is used in this paper. When task space movement commands are received, target joint positions can be computed via inverse-kinematics methods, e.g., the closed-loop inverse kinematics [27]:

\[ \hat{\theta}_d = J^\dagger(X_d + k_E(X_e - X_d)), \]

where \( \theta_d \) are the desired joint positions that lead to the desired EE position \( X_d \). \( X_e \) is EE’s current position, \( k_E \) is a user-defined gain and \( J^\dagger \) is the inverse/pseudo-inverse of the robot’s Jacobian matrix \( J \).

Note that all poses/positions etc. mentioned in the following are about EE, but “EE” is left out for brevity.

B. Problem Statement

In the SLDF teleoperation for objects hold-and-move tasks, i) DFR is expected to be teleoperated ergonomically, i.e., with easeful gesture/posture in operator’s hands/arms and without causing any pain or discomfort to any arthrosis or muscle; ii) AFR should be able to autonomously regulate its motion both before and during holding the object; and iii) their collaboration needs to maintain a certain holding force. These expectations can be achieved if the following three problems are addressed.
Firstly, awkward postures, e.g., upper arm abduction, contribute to musculoskeletal disorders [28], [29] and many results reveal that it is important to re-design the tasks involving static or repetitive forearm twisting, based on ergonomic analysis [30]. In a typical screw driving scenario (with repetitive pronation/supination motions) [29], the method of mapping leader’s entire task space to follower’s can lead to problems, e.g., as shown in Fig. 3, where the awkward gesture (the right palm twists toward outsides the body) causes discomfort to the operator or even pain to his/her wrist/forearm if keeping using the same gesture for long. Also seen in Fig. 4, it is hard for the operator to teleoperate DFR to precisely move along a short trajectory since industrial manipulators (followers) usually have a much larger workspace than a desktop joystick (the leader). In this situation, the enlarged movement also enlarges the operator’s tremors and manual motion error. Therefore, a new design to facilitate an ergonomic teleoperation to achieve precise/flexible manipulation is in demand.

Finally, when the contact force on the deformable object is required to be maintained within a small range, it can be challenging to generate a collaborative movement for AFR when the object’s shape changes, its mass and stiffness are unknown and DFR’s (the operator’s) movement is not pre-defined and subjected to uncertainties.

To address these problems, we devise a series of methods, which is developed in Sections III and IV. The flowchart to summarize the whole structure of these algorithms is depicted in Fig. 2.

**Assumption 1:** Before the following discussion, we assume that all followers perfectly track the commanded poses that they receive, with no time delay. And the teleoperation precision discussed in this paper are the precision under the circumstance that the problems caused by time delays are assumed to be already tackled.

**III. Motion Regulation before Holding**

This section corresponds to the first contribution of the paper, which contains the motion regulation methods for both the orientation and the position of DFR and AFR.

**A. DFR’s Orientation**

For the sake of universality, we use rotation matrices and quaternions to discuss orientations in this paper.

![Fig. 5. Orientation transformation from the leader to DFR.](image)

In Fig. 5, the rotation $^L_0 R_{t_0}$ between bases of the leader and DFR is known via calibration. The leader’s rotation $^L_0 R_{L,t}$ can be read in real time. $^L_0 R_{D,t_0}$ is an initial pose set at any time $t_0$ ($t > t_0$), corresponding to DFR’s orientation $^F R_{D,t_0}$ at the same time. To derive DFR’s orientation when the leader rotates from $t_0$ to $t$, we let DFR’s rotation be consistent with the leader’s after $t_0$ by “fixing” them together at $t_0$. In other words, their relative pose $^D_0 R$ should stay constant from $t_0$ on. Note that it is easy to repeatedly “fix” a pose by a press on a keyboard or a click on a mouse.

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For the inner closed transforming chain (ABCD and AD in Fig. 5), we have
\[ F R^L R_{L,t_0} R_{\text{fixed}, t_0} = F R_{D,t_0}. \] (4)

Then, the fixed relative rotation is obtained
\[ R_{\text{fixed}, t_0} = \left( F R^L R_{L,t_0} \right)^{-1} F R_{D,t_0}. \] (5)

For the outer closed transforming chain (ABEF and AF in Fig. 5), letting \( R_{\text{fixed}, t} = R_{\text{fixed}, t_0} \), then, the target DFR’s orientation at any time \( t \) is
\[ F R_{D,t} = F L R^L R_{L,t} R_{\text{fixed}, t_0}. \] (6)

By repeatedly re-setting the initial orientation at \( t_0, t_1, \ldots \), the operator can reach any desired position in DFR’s task space. In quaternions is of the leader, such that we can enlarge/shrink the relative user-defined initial position via \( s \).

Premultiplying both sides of Eq. (8) by \( F \) and the leader and \( D \), respectively.

Then, the fixed relative rotation is obtained
\[ F X_D = F X_{D,t} - F X_{D,t_0}, \] (9)

where \( F X_{D,t} \) and \( F X_{D,t_0} \) are DFR’s target position at \( t \) and the initial position set by the operator at \( t_0 \), respectively.

Premultiplying both sides of Eq. (8) by \( s F L R \), we have
\[ s F L R \Delta X_L = s F L R (L X_{L,t} - L X_{L,t_0}) = F X_{D,t} - F X_{D,t_0} = F \Delta X_D. \] (10)

Then, we derive the target position of DFR referring to the user-defined initial position via
\[ F X_{D,t} = F X_{D,t_0} + F \Delta X_D = F X_{D,t_0} + s F L R \Delta X_D. \] (11)

By repeatedly setting new but different initial positions, we can reach any desired position in DFR’s task space. In practice, the setting of the scaling factor \( s \) can be achieved easily, e.g., via pressing the “+” or “-” button on a keyboard or by adaptively self-adjusting based on the moving speed of the leader, such that we can enlarge/shrink the relative displacement and thus achieve a flexible/precise teleoperation.

C. AFR’s Orientation

The basic transformation from rotation matrices to unit quaternions is
\[ q_0 = \frac{1}{2} \sqrt{1 + r_{11} + r_{22} + r_{33}}, \]
\[ q_1 = \frac{r_{32} - r_{23}}{4q_0}, \]
\[ q_2 = \frac{r_{13} - r_{31}}{4q_0}, \]
\[ q_3 = \frac{r_{21} - r_{12}}{4q_0}, \] (12)

where \( q_0, q_1, q_2, q_3 \) are elements of a quaternion \( Q \) and \( r_{ij} \) \((i, j = 1, 2, 3)\) is the \( ij^{\text{th}} \) row and \( ij^{\text{th}} \) column element of a rotation matrix. Detailed discussions on situations where \( 1 + r_{11} + r_{22} + r_{33} < 0 \) can be found in literature, e.g., [31].

When DFR’s orientation (in quaternion) \( Q_D \) is obtained from \( F R_{D,t} \) through Eq. (12), we acquire the desired AFR’s quaternion \( Q_A \) by employing the computationally efficient algorithm in Lemma 1, which is proved in Appendix A.
Then, three distances \( \rho_m = \|X_2 - P_m\|_2, m = 1, 2, 3 \) from \( P_m \) to \( X_2 \) are used to determine three sub-fields:

\[
U_1 = \begin{cases} 
\frac{1}{2} \eta_1 (\rho_1 - 1) \frac{1}{\rho_1} \eta^2_1, & \text{if } \rho_1 \leq \rho_{1,0} \\
0, & \text{otherwise}
\end{cases}, \quad U_2 = \frac{1}{2} \eta_2 \rho_2^2, \quad U_3 = \frac{1}{2} \eta_3 \rho_3^2,
\]

where \( \eta_m \) are constant gains and \( \rho_{1,0} \) is set by the operator and determines the distance boundary in which \( U_1 \) takes effect. The resultant force acting on AFR is

\[
F = -\nabla[U] = w_1 F_1 + w_2 F_2 + w_3 F_3
\]

\[
= w_1 \eta_1 (1 - \frac{1}{\rho_1} \frac{1}{\rho_1^2}) \frac{1}{\rho_1} \partial \rho_1 - w_2 \eta_2 \rho_2 \frac{1}{\partial \rho_2} - w_3 \eta_3 \rho_3 \frac{1}{\partial \rho_3}.
\]

For the adjustable weights, they are affected by \( d_{D,o} \):

\[
w_{u_1} = \max \left\{ 0, \min \left\{ 1, \frac{P_{\rho D,o} - \rho_{D,o}}{P_{\rho D,o} - \rho_{D,o}} \right\} \right\}, \quad w_{u2} = w_{u1}, \quad w_{u3} = 1 - w_{u1},
\]

where \( \rho_{D,o} \) is the lower bound for computing weights and \( P_{\rho D,o} \) is the projection of \( d_{D,o} \) in the holding line. These time-varying weights contribute to a smooth adjustment of the field \( U(X_2) \): when DFR is far from the object, only \( U_1 \) and \( U_2 \) play the role in regulating AFR’s motion; when DFR gets close to the object, \( U_3 \) gradually takes over and the effect of \( U_1 \) and \( U_2 \) fades away.

Finally, we have the updated AFR position

\[
X_{A,t} = X_{A,t-\Delta t} + \Delta X_A
\]

with \( \Delta X_A = \text{sgn}(F) \times \min\{|k_p F|, \Delta X_{A,max}\} \), where \( \Delta t \) is the sampling time and \( \Delta X_A \) is the increment displacement for AFR due to the field force \( F \), with \( k_p \) standing for a proportional coefficient that transfers a force into a displacement, and \( \Delta X_{A,max} > 0 \) limits the AFR’s moving speed.

**IV. Motion Regulation during Holding**

This section corresponds to the second contribution of the paper, which mainly contains the motion regulation for AFR to assist to hold a deformable object with desired force. Based on Eqs. (16) and (17), \( P_3 \) will finally go “inside” the object and AFR will get in contact with the object. The contact force is a signal to invalidate the artificial field and to initialize the regulation when holding the object. The objective is to generate a reference trajectory for AFR in order to maintain a desired contact force, which is an extension of our previous work [26]. As the previous sections have aligned the two followers’ z axes in one line \( (X_{D,F3}) \), most of the variables and calculations discussed in this section are one-dimensional along the this line. Thus, we leave out the left-side superscripts/subscripts for brevity.

We depict a general case in Fig. 7, where two followers hold an object and AFR’s current contact force \( f_d \) is not equal to the desired contact force \( f_d \) which corresponds to an unknown position \( z_d \). We model the object as a spring. And thus, we have

\[
(-f_z) - (-f_d) = k_o (z_A - z_d) = -e_f,
\]

where \( e_f = f_z - f_d \) is the force tracking error and \( k_o \) is the unknown elastic coefficient. For AFR, we consider the contact with the object satisfies an impedance model. As our purpose is to derive a trajectory \( z_r \) for AFR to track such that \( e_f \to 0 \), it satisfies

\[
M \ddot{z}_e + D \dot{z}_e + K z_e = e_f,
\]

where \( e_z = z_A - z_r \), \( M, D \) and \( K \) represent positive impedance model parameters.

As \( z_d \) is a desired continuous trajectory, based on autoregressive model, we can model it by

\[
\dot{z}_d(t) = w_0 + w_1 z_A(t) + w_2 z_A(t - \Delta t) + \cdots + w_m z_A(t - (m - 1) \Delta t),
\]

which can be rewritten as

\[
\dot{z}_d = W_z^T Z,
\]

where \( W_z = [w_0, w_1, w_2, \cdots, w_m]^T \) is the weight and \( Z = [1, z_A(t), z_A(t - \Delta t), \cdots, z_A(t - (m - 1) \Delta t)] \). In this paper, we approximate \( \dot{z}_d \) via

\[
\dot{z}_d = \dot{W}_z Z - L \ddot{z}_d(t - \Delta t),
\]

where \( \dot{z}_d \) and \( \dot{W}_z \) are the approximations of the desired velocity and \( W_z \), and \( L \) is a positive constant. The updating law for \( \dot{W}_z \) is designed as

\[
\dot{W}_z = - (\ddot{z}_d(t - \Delta t) + \beta e_f) Z(t),
\]

where \( \beta \) is a positive constant and

\[
\ddot{z}_d(t - \Delta t) = \dot{z}_d(t - \Delta t) - z_d(t - \Delta t) = \ddot{z}_d(t) - z_A(t).
\]

As AFR’s position \( z_A \) always tracks \( z_d \), we have \( z_d(t - \Delta t) = z_A(t) \). Then, the reference trajectory \( z_r \) for AFR is

\[
\dot{z}_r = \dot{z}_d - \alpha e_f + L \ddot{z}_d(t - \Delta t),
\]

where \( \alpha \) is a positive constant. To generate the reference trajectory \( z_r \), the updating law Eq. (29) is based on three parts: \( \dot{z}_d \) is the estimation of the desired contact position; \( -\alpha e_f \) is a correction based on contact force feedback; and \( L \ddot{z}_d(t - \Delta t) \) is a compensation for the coupling effect.

As the above calculations are along the \( z_r \) axis of DFR’s tool frame, the reference trajectory should be transformed into the follower’s frame via

\[
X_{A,t} = X_{D,t} + F R_{D,t}[0, 0, z_r]^T.
\]

With Eq. (30), we can simplify the problem to find AFR’s 3D position into a problem to determine its 1D holding distance. Convergence analysis can be found in Appendix B.
V. SIMULATION AND EXPERIMENT STUDY

In this section, we perform simulations to verify the contact force regulation and experiments to demonstrate the whole proposed solution.

A. Simulation

As depicted in Fig. 8, the simulation is performed on a platform with two 3-DOF manipulators. Two followers are commanded to manipulate a deformable object, where DFR tracks predefined teleoperating trajectories, AFR regulates its motion and the object’s physical parameter is time-varying.

As seen in the first row of Fig. 9, the proposed method performs the best among three controllers with less force tracking error during most time period. In the second row, we see that reference trajectories for AFR are generated, leading to the desired contact force, despite the unknown movement of DFR and different unknown parameters of objects. Thus, we can conclude that the proposed force controller performs robustly and depends little on unknown factors including the random DFR’s movements and a large range of object’s stiffness (40-60 N/m).

B. Experiments

The experimental configuration is depicted in Fig. 10, where two arms of the Baxter robot are used as two follower robots and the Touch X is the leader robot. The Touch X has a built-in button on the joystick, which is used to trigger re-“fixing” technique for pose transformation. To position the object, we resort to a RGB-D camera Kinect V1 and the coordination between the camera and the followers is calibrated before conducting experiments. The whole system runs in a frequency of 100Hz and the images are processed 15 frames per second.

The object’s position is obtained via calculating the average position \( \frac{1}{4} \sum_{n=1}^{4} O_{En} \) of four edge points illustrated in Fig. 11.

1) Demonstration on Motion Regulation before Holding:
There are two key points that worth demonstrating before holding. One is the effectiveness of the relative pose transformation technique. The other is the regulation of AFR, including the adjustable APFM to regulate AFR’s position and the practical technique to obtain AFR’s orientation.

The relative pose transformation technique largely improves the ergonomics and the precision of the teleoperation, which is intuitively demonstrated by Fig. 12 and 13.
Fig. 9. The simulation results. The first row: force tracking errors by three methods. The second row: updating system states $x_d, x_r$ and $k_0$. Each column shares one set of system parameters illustrated in the second row.

Fig. 13. Task 1: An ergonomic and precise teleoperation based on the proposed relative pose transformation method. A-initial pose; B-working pose; C-working pose but the operator can re-set an ergonomic initial operating pose to tighten/unscrew a nut; D-easier to accurately move to another nut’s position; E-comfortably tighten/unscrew another nut.

When the operator teleoperates DFR to tighten/unscrew two nuts, in Fig. 12, the operator can hardly control DFR to precisely move from one nut to the other, and the operator has to do an uncomfortable (unergonomic) gesture to tighten/unscrew a nut; while in Fig. 13, the operator use a smaller scaling factor and the re-“fixing” technique, he/she can perform a precise teleoperation and use any comfortable (ergonomic) gesture as he/she desired to tighten/unscrew a nut. To be specifically, comparing Fig. 12C to Fig. 13C, we can see that when tightening/unscrewing the same nut, the proposed method provides a more ergonomical operating pose. As the manipulator’s (Baxter’s) workspace is much larger than a desktop device’s (Touch X’s), when the follower needs to move to another position, the operator finds it hard to precisely control the leader (Fig. 12D). By setting a smaller scaling coefficient in the relative pose transformation method, we can achieve accurate teleoperation (Fig. 13D). Obviously, if the scaling factor is set to a larger value, we can also achieve a flexible teleoperation.

We do not really drive a nut because the pure position control can not achieve that, whereas the general compliant control can not clearly demonstrate the advantage of the proposed method which performs better in the aspect of telemanipulation precision. Thus, we conduct another experiment (Fig.14(a)): to teleoperate the DFR to perpendicularly hit six dartboard centers.

(a) A task to teleoperate DFR to use marker pens to perpendicularly hit 6 dartboard centers.

(b) When DFR gets close to a dartboard center, the operator slows down and thus $s$ becomes smaller in order to conduct precise teleoperation.

(c) When precision is not important, the operator can move faster and thus $s$ increases to boost DFR’s moving speed.

(d) The proposed re-fixing method enables the operator to use any posture to conduct teleoperation.

Fig. 14. Task 2: The experiment of teleoperating DFR to hit dartboard centers with marker pens.
dartboards centers one by one on a wall, using marker pens (blue pen for the general match-the-whole-space method, red pen for the proposed re-fixing method). Compared to the general method, the adaptive scaling factor $s$ facilitates a precise/flexible teleoperation. It updates in real time based on the moving speed of the operator’s hand via Eq. (31)

$$s = \begin{cases} 
    s_b, & \text{if } v < v_{\text{min}} \\
    s_b + \frac{\min(v, v_{\text{max}}) - v_{\text{min}}}{v_{\text{max}} - v_{\text{min}}} \ast s_p, & \text{otherwise} 
\end{cases}$$

(31)

where $s_b = 1$ is a basic scaling factor, $v$ is the moving speed of the leader, $v_{\text{max}} = 0.3$ and $v_{\text{min}} = 0.05$ are predefined upper and lower bounds of moving speeds and $s_p = 7$ is a linear transform to in-/decrease $s$. For instance, the faster the hand moves ($v \leq v_{\text{max}}$), the larger the $s$ becomes.

The experimental results are shown in Fig.14. To complete this task, when the DFR get close to a dartboard center, it slows down and tries to precisely hit the center (e.g. Fig.14(b)). This can be achieved only if the operator slow down his/her hand’s movement and gently teleoperate the DFR. When the DFR moves from one dartboard center to another (e.g. Fig. 14(c)), the operator can move faster as this movement requires less precision. The faster hand movement contributes to that the DFR moves fast and longer than the operator’s hand’s displacement. Therefore, the adjustable $s$ facilitates the precise/flexible teleoperation.

We ask 13 persons (3 females, 10 males; age from 22 to 30) to conduct this experiment via the general match-the-whole-space method and the proposed re-fixing and adaptive-scaling method. We record the hit points by a blue pen and a red pen to respectively show the results by the general method and the proposed method. The statistical results show that: (i) 12 subjects get higher scores via the proposed method, only 1 subject gets the same scores via the two methods; (ii) all subjects mention that they easily get fatigue or feel even pain in the forearm when using the general method (as it required him/her to keep a pronation posture for long time), but feel relaxed when using the proposed re-fixing method.

Consequently, we can conclude that our method facilitates a flexible/precise and ergonomic teleoperation.

Fig. 15. Task 3: A demo on regulating AFR’s (Baxter’s left arm’s) pose. A-AFR tracks the object that moves left-/rightwards; B-AFR tracks the object that moves for-/backwards; C-AFR tracks the object that moves up-/downwards; D-DFR starts to track the moving target holding point (the black circle); E-DFR hits the target holding point and AFR assists in holding at the right time; F and G-AFR keeps assisting holding the object in a facing pose regardless of DFR’s rotations.

The demonstration on regulating AFR’s pose is illustrated in Fig. 15, where AFR (Baxter’s left arm) tracks the object and also avoids collision when the object moves left-/rightwards (A), for-/backwards (B) and up-/downwards (C); and AFR regulates its motion to a ready-to-hold pose (D and E) when DFR moves close to the object and the target holding point. The efficient quaternion-based technique to obtain AFR’s holding orientation is also verified as shown in D, E, F and G, where we can see that AFR always keeps pointing to DFR.

2) Demonstration on Motion Regulation during Holding:

In this section, we conduct two groups of experiments.

The first is as shown in Fig.16, we use the SLDF system to transport general rigid objects with different sizes: a hardboard box with different side lengths - holding different sides every time to pretend to hold different objects. With the help of the proposed motion regulation solutions for AFR, the AFR successfully and autonomously assist the DFR to complete a task of holding and moving the object from one position into a box. Combined with the demo in Fig.18 (discussed later), intuitively, as the force controller is devised based on an impedance model, we can tell that the proposed method is capable to compliantly transport different volumetric objects, no matter rigid or deformable, small or large in size.

Fig. 16. Task 4: The experiment of holding and moving rigid objects with different sizes. A hardboard box with different side lengths - holding different sides every time to pretend to hold different objects. With the help of the proposed motion regulation solutions for AFR, the AFR autonomously assists in holding the object, moving it and dropping it into a box.

The second is as shown in Fig. 18, where we consider a scenario of holding and moving a deformable object, which aims to verify if the generated reference trajectory helps to maintain the contact force within a small range despite DFR’s random movement and the object’s time-varying internal force. As seen in the caption of Fig. 18, this task contains linear and angular acceleration of the held object, which can cover most
real-world hold-and-move tasks. Note that during this task, AFR will suffer from irregular time-varying contact force.

The operator executes this task three times and three teleoperation trajectories are recorded, which are used for comparing three holding methods: fixed-distance holding; holding with passive impedance controller to adjust AFR’s position; and holding with the proposed controller to adjust AFR’s position. For the fixed-distance holding, the holding distance is set as 0.38. For the passive impedance controller, the passive impedance model is set as $10\ddot{z}_D + 2\dot{z}_D = e_f$. For the proposed method, the initial parameters are set to be $W_z = [0, 0, 0]^T$, $L = 50$, and $\alpha = 0.25$, $\beta = 0.0001$. The comparisons are shown in Fig. 17. Results of the comparisons are shown in Fig. 17.

Obviously, the proposed method perform the best in force tracking, being the most stable and the closest to the desired force regardless of different teleoperation trajectories and the object’s varying internal force conditions. The force tracking errors are the smallest when using the proposed method, with the root mean square errors (RMSE) (blue, green, red; after the 8th second): 0.87, 1.22, 2.48 in Fig.17(a); 0.82, 1.21, 2.61 in Fig.17(b); 0.77, 1.31, 1.93 in Fig.17(c). Besides, the proposed method is the fastest way to reach the desired force with neglectable overshoot, which in other aspect demonstrate that the adaption law (26) converges fast. These results validate that with the design of the force controller targeted on this kind of hold-and-move task, our method can best adjust AFR’s motion to maintain the desired force, outperforming the general passive-impedance model based force controller and the position based controller.

It is also worth mentioning that, the quaternion-based technique to obtain AFR’s orientation is also employed in this experiment, and from the frames shown in Fig. 18 (also seen in the attached video), we can see that with this technique, AFR can assist in holding and rotating the held object without causing any twist/torque to the object.

VI. CONCLUSIONS

This paper provides a set of solutions for an SLDF teleoperation system to hold and move a deformable object. It includes the kinematic solutions to deriving the relative DFR’s pose and AFR’s ready-to-hold pose, where we present a technique of relative pose transformation, the practical quaternion-based solution to obtain AFR’s orientation that assists in holding and the adjustable APFM to regulate AFR’s position. Besides, based on autoregressive model and impedance model, the force controller is designed to ensure AFR to adjust itself to the right position to maintain a desired force when AFR collaborates with DFR to hold and move a deformable object. Simulations and experiments are conducted, verifying the feasibility and effectiveness of the proposed methods.

In the future, we will continue improving the solutions in at least three aspects: i) to automatically switch the teleoperation modes by balancing flexibility and precision according to different task requirements; and ii) to introduce multi-agent theory to integrate AFR’s and DFR’s local knowledge about the task to achieve global task objectives.

APPENDIX A

For two robots to perform holding pose in a unified coordinate system, taking Fig. 19 as an example, they firstly need to align their EEs into a face-to-face pose, which results in rotating DFR and AFR about $x$ axis $-90^\circ$ and $+90^\circ$ respectively. Then, to keep the object held properly at all time, AFR’s and DFR’s rotations should always stay in a relation described as

$$\theta_{x,A} = \theta_{x,D} + 180^\circ, \theta_{y,A} = \theta_{y,D}, \theta_{z,A} = \theta_{z,D},$$

(32)
With \( \hat{z}_d = \hat{z}_d - \hat{z}_d \), employing the reference trajectory updating law Eq. (29), we have
\[
\hat{z}_d = \hat{z}_d - \hat{z}_d = \hat{z}_d + \alpha e_f - L\hat{z}_d(t - \Delta t) - \hat{z}_d.
\]
Substituting Eq. (43) into \( \dot{V}_f \) and resorting to Eq. (40), we obtain
\[
\dot{V}_f = e_f(\hat{z}_d - (\hat{z}_d + \alpha e_f - L\hat{z}_d(t - \Delta t) - \hat{z}_d))
\]
(44)
Finally, substituting Eqs. (42) and (44) into Eq. (37), we have
\[
\dot{V} = -\frac{1}{\beta}\hat{z}_d^2 - D\hat{e}_z^2 - \alpha e_f^2 \leq 0,
\]
which means \( \dot{z}_d, \hat{e}_z \) and \( e_f \) converge when \( t \to \infty \). As a result, it is worth pointing out that we have \( f_z \to f_\alpha \) with \( e_f \) converging, namely the desired contact force is maintained.

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REFERENCES

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