Design and Evaluation of a Trilateral Shared-Control Architecture for Teleoperated Training Robots

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***Abstract*— Multilateral teleoperated robots can be used to train humans to perform complex tasks that require collaborative interaction and expert supervision, such as laparoscopic surgical procedures. In this paper, we explain the design and performance evaluation of a shared-control architecture that can be used in trilateral teleoperated training robots. The architecture includes dominance and observation factors inspired by the determinants of motor learning in humans, including observational practice, focus of attention, feedback and augmented feedback, and self-controlled practice. Toward the validation of such an architecture, we (1) verify the stability of a trilateral system by applying Llewellyn's criterion on a two-port equivalent architecture, and (2) demonstrate that system transparency remains generally invariant across relevant observation factors and movement frequencies. In a preliminary experimental study, a dyad of two human users (one novice, one expert) collaborated on the control of a robot to follow a trajectory. The experiment showed that the framework can be used to modulate the efforts of the users and adjust the source and level of haptic feedback to the novice user.**

***Keywords-* Trilateral Teleoperation; Stability and Transparency; Motor Learning; Haptic Feedback; Multilateral; Surgical Robotics; Surgical Training**

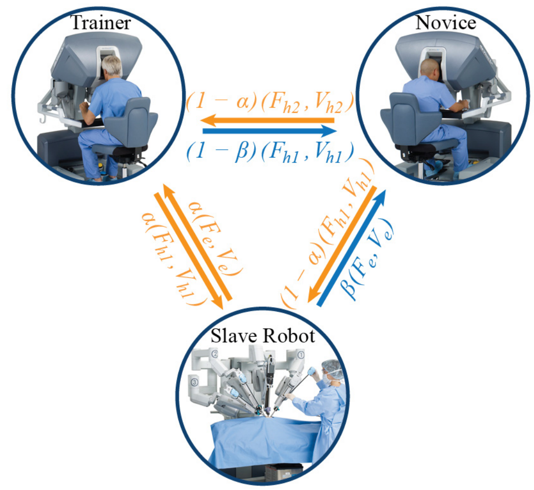

Fig. 1. Schematic shared-control architecture designed for trilateral teleoperated training robots. The inputs (*F*'s and *V*'s) to the robots are scaled using a dominance factor ($\alpha \in [0,1]$) and an observation factor ($\beta \in [0,1]$).

I. Introduction

TELEOPERATED robotic systems allow humans to perform remote tasks that require movement/force scaling and additional degrees of freedom [1]. This has led surgeons to use teleoperated robotic systems to perform thousands of minimally invasive general abdominal, gynecologic, urologic, and cardiac surgeries every year [1]. As the popularity of such systems grows, there will be an increasing need for platforms and methods to train novice surgeons to use them [2-5]. Improved training devices and methods that allow novice surgeons to learn while doing (rather than the traditional method of "see one, do one, teach one") on the job can pave the way for more prevalent and effective use of teleoperated robotic systems in surgical procedures [4, 6].

Training novice surgeons to perform robot-assisted surgery has been explored separately as a motor learning problem [7-12] and a control problem [13-17]. In the current study, we integrate knowledge in motor learning and control of teleoperated systems to create a framework (Fig. 1) for trilateral teleoperated systems that can be used to teach robot-assisted surgical procedures.

It is currently unknown how to implement transparent and stable multilateral control architectures that consider motor learning characteristics of the human neuromuscular system. Researchers have extensively studied motor learning in able-bodied humans, with the most relevant finding being that *observational practice*, *focus of attention*, *feedback*, and *self-controlled practice* determine motor learning progress in humans [18].

The *observational practice* determinant suggests that humans should physically and observationally interact in dyads to better learn new motor skills [18]. This factor has been shown to be effective in both expert-novice and novice-novice dyad forms and for both observational and physical practice [19], suggesting that a platform for training surgical procedures should allow for dyadic training with possibility of observation and physical interaction between the novice and expert, as well as novice and environment.

The *focus of attention* determinant suggests that in order to improve motor learning, the trainee's attention should be directed towards the effects of a movement synergy on the environment rather than an internal synergy [18, 20]. For example, to teach a complex suturing task in a surgical procedure, the trainee should be directed to focus on the knot tying rather than the associated movements of the hands and fingers. This factor has been shown to be effective even in the late phases of motor learning [19].

To improve motor learning, various studies suggest that *feedback and augmented feedback* should be provided to novice users in a more informed way, depending on the

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learning phase and task complexity [4, 10, 11, 21-23]. Humans undergo three learning phases when acquiring a motor skill including an early phase where a motor program of the task is generated, a mid-phase where the motor program is refined, and a late phase where the movements are automatized [21]. A task is considered "complex" if it requires more than one session to be mastered [21, 24]. This categorizes laparoscopic surgical tasks as complex. Previous research suggests that novice users need more concurrent feedback (and probably augmented feedback) during the early phases of learning complex tasks [18, 21, 24], implying that a surgical training platform should be able to provide more feedback at the early stages of acquiring the surgical tasks; this hypothesis is supported by previous studies [11, 25].

The *self-controlled practice* determinant states that the learner should be able to control the practice conditions by exploring the movement possibilities and adjusting the level of feedback [26, 27], which in addition to the third factor imply that any training platform should allow the learner to explore and obtain feedback on the movements of the trainer and slave robot as desired.

Multilateral teleoperated robots can be used to train new motor skills to healthy humans, as well as rehabilitate impaired limbs of patients with neuromuscular deficiency [28, 29]. This includes teaching robot-assisted teleoperated surgical procedures and aviation, manipulation of objects in remote environments, and physical therapy to patients in remote locations. Despite substantial research in the design of multilateral robots, these systems have seen limited use for training motor skills and performing cooperative surgical tasks at a clinical level. The current study is a first step toward implementing a multilateral training robot for training novice surgeons to use robotic laparoscopic devices.

Among various multilateral teleoperated platforms, trilateral dual-user single-slave architectures have been well studied in terms of stability and transparency [14-17, 30-32]. Despite differences in the control architectures, trilateral teleoperated robots generally have one common characteristic: They give authority over the performance of a task to one side inherently or using a dominance factor, which can range from zero to one [15, 30, 31]. For example, in a trainer-novice dyad interacting with the environment through a trilateral system, the trainer would have full control over the slave robot and the novice when the dominance factor is one; whereas, the novice would have full control when the dominance factor is zero. A two-master-console version of the da Vinci Si system (Intuitive Surgical Inc., Sunnyvale CA) is an example of a trilateral system that allows for dominance factors of only zero and one.

Implementation of the determinants of motor learning in trilateral robots for training surgical tasks is challenging. First, it is not clear how the authority of the trainer and trainee should be arbitrated to ensure safety during the learning process. Second, the ideal tradeoff between the ability of a learner to control the practice conditions and the ability of a trainer to supervise the execution of surgical tasks is unknown. Finally, it is difficult to provide force feedback using current surgical systems given that there is a tradeoff between the system stability and transparency.

In this paper, we present the design of a shared-control architecture for trilateral teleoperated robots tailored to training motor skills. The architecture allows for any level of authority over the slave robot as a well as adjustment of force feedback source to the learner. We analyze the stability and transparency of the controller and show how the architecture considers the motor learning determinants in that it allows:

a. for dyadic practice between two users
b. the trainee to set the level of the haptic feedback
c. direction of the learner’s focus of attention to external effects on the environment, and
d. the trainee to explore the possibilities and environment.

As a proof of concept, we present a preliminary experiment involving two participants collaborating in a trajectory-following task with three haptic devices (two masters and one slave) on which the trilateral architecture was implemented.

II. Design and Performance Analysis

A. Shared-Control Architecture

The proposed shared-control architecture includes two master ports for the trainer and novice and one slave port for the robot that performs tasks in the environment, as shown in Fig. 1. The input signals to the robots are modulated using a dominance factor $\alpha \in [0,1]$ set by the trainer, and an observation factor $\beta \in [0,1]$ set by the novice. For consistency, we use parameters similar to those used in previous studies [15, 30, 31], as shown in Table I. The control architecture of Fig. 1 is characterized as:

$$F_{h1d} = \alpha F_e + (1-\alpha)F_{h2} \quad \text{(1-a)}$$
$$V_{h1d} = \alpha V_e + (1-\alpha)V_{h2} \quad \text{(1-b)}$$
$$F_{h2d} = \beta F_e + (1-\beta)F_{h1} \quad \text{(1-c)}$$
$$V_{h2d} = \beta V_e + (1-\beta)V_{h1} \quad \text{(1-d)}$$
$$F_{ed} = \alpha F_{h1} + (1-\alpha)F_{h2} \quad \text{(1-e)}$$
$$V_{ed} = \alpha V_{h1} + (1-\alpha)V_{h2} \quad \text{(1-f)}$$

where F_{ed} and V_{ed} are the desired force and velocity of the slave robot, F_{h1d} and V_{h1d} the desired force and velocity of the trainer robot, and F_{h2d} and V_{h2d} are the desired force and velocity of the novice robot. F_e and V_e are the measured force and velocity of the slave robot, F_{h1} and V_{h1} the measured force and velocity of the trainer robot, and F_{h2} and V_{h2} are the measured force and velocity of the novice robot.

We chose to constrain the (α , β) values to the space of direct feedback defined as $\mathbf{\Omega} = \{(\alpha , \beta) \mid 0 \le \alpha \le 1 , 0 \le \beta \le 1$, and $\beta \ge 1 - \alpha \}$ to ensure that the novice obtains force and velocity feedback directly from the environment at least as much as the authority of the novice over the tasks being performed. For example, if the novice user has 80% authority over the slave robot (α = 0.2), the system ensures that at least 80% of the force and velocity feedback to the novice comes directly from the environment and not from the trainer. As another example, when the trainer is performing a task using α = 1, the novice user can observe the movements of the expert setting $\beta \rightarrow 0$, the environment setting $\beta \rightarrow 1$, or any case in between as shown in Fig. 2-left; whereas, when the trainer gives the full control to the novice using α = 0, the novice

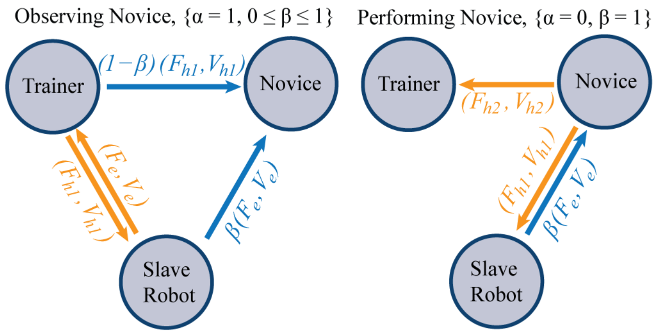

Fig. 2. Two special cases of the shared-control architecture. Left: Using α = 1, the trainer is the primary performer and the novice is primarily observing the movements of the trainer (β = 0) or slave (β = 1). Right: Using α = 0, the novice is the primary performer and β = 1 given that (α , β) values are chosen from Ω. In this case, the controller gives the full control over the trainer master robot and slave robot to the novice.

would primarily interact with the environment given that β can only be 1, as shown in Fig. 2-right.

For the block diagram of the closed-loop shared-control architecture of Fig. 4, we have:

$$\begin{bmatrix} F_{h1} \\ F_{h2} \\ F_e \end{bmatrix} = Z \begin{bmatrix} V_{h1} \\ V_{h2} \\ V_e \end{bmatrix} \quad (2)$$

Here the impedance matrix $Z = A^{-1}B$ assuming linear time-invariant impedances and terminations [31], where:

$$A = \begin{bmatrix} 1 + C_{6m1} & \frac{-(1-\alpha)C_{2m1}}{e^{sT}} & \frac{-\alpha\, C_{2m1}}{e^{sT}} \\ \frac{-(1-\beta)C_{2m2}}{e^{sT}} & 1 + C_{6m2} & \frac{-\beta C_{2m2}}{e^{sT}} \\ \frac{\alpha C_3}{e^{sT}} & \frac{(1-\alpha)C_3}{e^{sT}} & -1 - C_5 \end{bmatrix} \quad (3)$$

and

$$B = \begin{bmatrix} C_{m1} + Z_{m1} & \frac{(1-\alpha)C_{4m1}}{e^{sT}} & \frac{\alpha C_{4m1}}{e^{sT}} \\ \frac{(1-\beta)C_{4m2}}{e^{sT}} & C_{m2} + Z_{m2} & \frac{\beta C_{4m2}}{e^{sT}} \\ \frac{-\alpha C_1}{e^{sT}} & \frac{-(1-\alpha)C_1}{e^{sT}} & C_s + Z_s \end{bmatrix} \quad (4)$$

Here, C_{mi}, C_s, C_{6mi}, and C_5 are local position and force feedback gains, and C_{4mi}, C_1, C_{2mi} and C_3 are position and force feedforward gains. Using the abovementioned architecture, we can implement several designs including position-position-position (PPP), and position-position-force (PPF) spanning a range of stability and transparency characteristics [33]. In the case of the PPP architecture, we can use $C_{mi} = -C_{4mi} = K_{dmi} + K_{pmi}/s$ and $C_s = C_1 = K_{ds} + K_{ps}/s$, and $C_{2mi} = C_{6mi} = C_5 = C_3 = 0$; whereas, in a FFF architecture we would use $C_{2mi} = C_3 = 1$, $C_{mi} = C_{4mi} = C_{6mi} = C_s = C_1 = C_5 = 0$. In the implementation considered in this paper, we use the PPP architecture.

B. *Performance Analysis*

The stability and transparency of shared-control trilateral architectures have been analytically studied elsewhere [15, 30, 31, 33]. Researchers implemented a series of criteria for the assessment of unconditional stability of the shared-control architectures and showed that it is not possible to design PPP and FFP shared-control architectures that include derivative gain for the position controllers and are unconditionally stable for all α values [31]. Other researchers developed a framework for analysis of unconditional stability of shared-control architectures where the trilateral architecture is reduced to a two-port architecture and investigated using Llewellyn's criterion [29]. This framework allows us to investigate a shared-control architecture for given values of Z_e, ω, α, and β. Here, we use this framework to develop a numerical method to investigate the stability of the proposed class of architecture that includes dominance and observation factors.

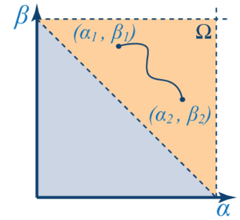

Fig. 3. The space of direct feedback defined as Ω = {(α , β) | 0 ≤ α ≤ 1 , 0 ≤ β ≤ 1, and β ≥ 1 – α } and shown by orange. The trainer and novice should be able to set values of (α , β) during a training session.

First, we obtain the equivalent two-port impedance matrix of the architecture as:

$$Z' = \begin{bmatrix} \frac{-Z_{13}Z_{31}+Z_{11}Z_{33}-Z_{11}Z_e}{Z_{33}-Z_e} & \frac{-Z_{13}Z_{32}+Z_{12}Z_{33}-Z_{12}Z_e}{Z_{33}-Z_e} \\ \frac{-Z_{23}Z_{31}+Z_{21}Z_{33}-Z_{21}Z_e}{Z_{33}-Z_e} & \frac{-Z_{23}Z_{32}+Z_{22}Z_{33}-Z_{22}Z_e}{Z_{33}-Z_e} \end{bmatrix} \quad (5)$$

where, Z_{jk} ($j, k \in \{1,2,3\}$) are the elements of the impedance matrix Z. Next, we evaluate the unconditional stability of the architecture using the Llewellyn's criterion [34], which confirms that the proposed architecture is unconditionally stable if and only if [29]:

1. Z'_{11} and Z'_{22} are positive real, where Z'_{jk} ($j, k \in \{1,2\}$) are the elements of the impedance matrix Z'.
2. $\eta(\omega) = \frac{2Re\{Z'_{11}\}Re\{Z'_{22}\} - Re\{Z'_{12}Z'_{21}\}}{|Z'_{12}Z'_{21}|} \geq 1,\ \forall \omega \geq 0$

where $Re\{X\}$ is the real component of X and $|X|$ is the absolute value of X. We evaluate these two conditions across all Z_e values on the right hand plane using the transformation of $Z_e = \frac{1+\Gamma_e}{1-\Gamma_e}$ and evaluating the stability criterion in $|\Gamma_e| < 1$ [29]. For certain values for the controller gains, the system might not have an impedance matrix. In that case, Z and Z' should be replaced by the hybrid or scattering matrix of the system [29].

Alternatively, we can numerically and experimentally study the stability of the proposed architecture via the input energy of the trainer E_{h1} and also novice E_{h2}, in that the system is stable if and only if:

$$E_{hi}(t) = \int_0^t F_{hi}(\tau)V_{hi}(\tau)d\tau \geq 0 \quad (6)$$

for all $t > 0$, when the other two ports are connected to passive components [31]. This method requires force measurement at the master ports.

We also study the transparency of the proposed architecture by evaluating the transparency transfer function of the trainer (G_{t1}) and novice (G_{t2}) defined as [30]:

$$G_{t1} = \frac{Z_{t1}}{\alpha Z_e + (1-\alpha)Z_{h2}} \quad (7\text{-a})$$

$$G_{t2} = \frac{Z_{t2}}{\beta Z_e + (1-\beta)Z_{h1}} \quad (8\text{-b})$$

where, Z_{ti} are impedances transferred to the users [33, 35]:

$$Z_{t1} = \left.\frac{F_{h1}}{V_{h1}}\right|_{\tilde{F}_e=0\,,\,\tilde{F}_{h2}=0} \quad (9\text{-a})$$

$$Z_{t2} = \left.\frac{F_{h2}}{V_{h2}}\right|_{\tilde{F}_e=0\,,\,\tilde{F}_{h1}=0} \quad (9\text{-b})$$

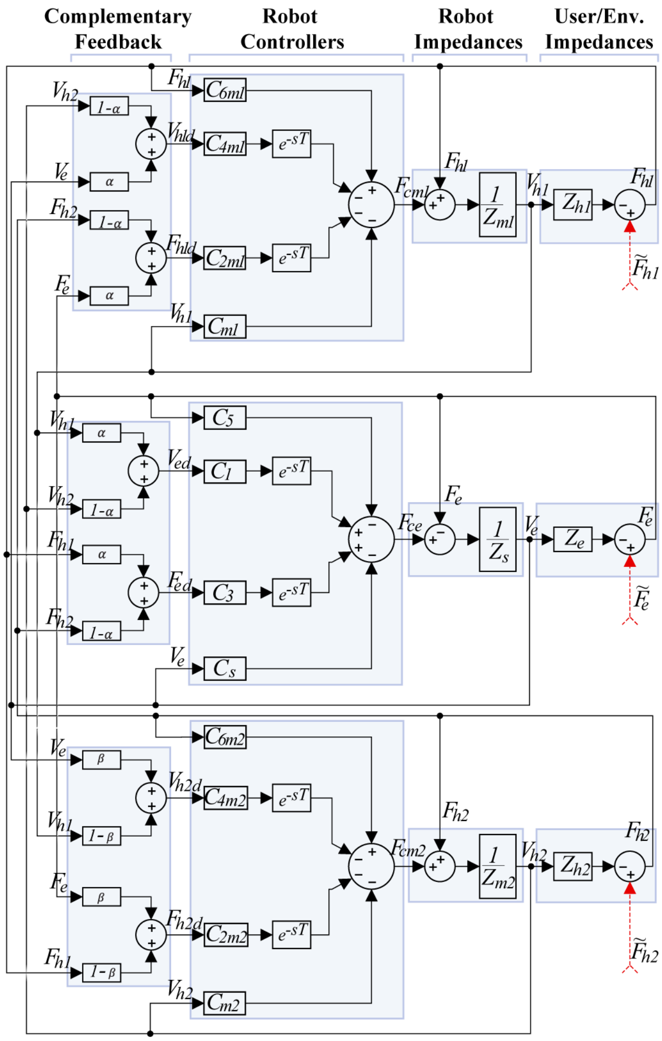

Fig. 4. Trilateral shared-control architecture. The input signal to the trainer and slave robot are gauged using the dominance factor α, and the input to the novice robot is gauged using the observation factor β.

The transparency transfer function approaches 1 when the system is transparent.

III. Performance Evaluation

We numerically studied the stability and transparency of a PPP version of the proposed architecture and experimentally studied the performance of two human participants using a trilateral system with the proposed architecture implemented.

A. *Analysis of Stability and Transparency*

A PPP architecture was investigated with $C_{mi} = -C_{4mi} = C_s = C_1 = 5 + 120 / s$, and $C_{2mi} = C_{6mi} = C_5 = C_3 = 0$ for the control parameters. Our analysis included $Z_{mi} = Z_s = M\,s = 0.3\,s$ for the robot impedances, and T = 0.001 s. for the system delay. Our analysis were across 6 values of {0, 0.2, 0.4, 0.6, 0.8, 1} for α and β as well as 4 frequencies of ω (rad/s) = {0.1, 1, 10, 100} for analysis of stability and ω (rad/s) = [0.1, 100] for analysis of transparency. We found that this system remains unconditionally stable for all values of (α , β). We found similar results for the sampling time T = 0.0001 s. and T = 0 s.

TABLE I. Definition of Mathematical Parameters

Prm.	Definition	Prm.	Definition
F_{hi}	Master robots force	F_{hid}	Master robots desired force
F_e	Slave robot force	F_{ed}	Slave robot desired force
V_{hi}	Master robots velocity	V_{hid}	Master robot desired velocity
V_e	Slave robot velocity	V_{ed}	Slave robot desired velocity
α	Dominance factor	β	Observation factor
Ω	Space of allowable (α , β) values	$i = 1$	Trainer identifier
$i = 2$	Novice identifier	$i = 3$	Slave identifier
C_{mi}	Position feedback gain of master robots	C_{2mi}	Force feedforward gains of master robots
C_{4mi}	Position feedforward gain of master robots	C_{6mi}	Force feedback gain of master robots
C_s	Position feedback gain of slave robot	C_3	Force feedforward gains of slave robot
C_1	Position feedforward gain of slave robot	C_5	Force feedback gain of slave robot
T	Time delay	M	Robot mass
Z_{mi}	Master robot impedance	Z_s	Slave robot impedance
Z_{hi}	Human operator impedance	Z_e	Environment impedance
F_{cmi}	Master robot controller force	F_{cs}	Slave robot controller force
$\tilde{F}_{hi}$	Human operator endogenous force	$\tilde{F}_e$	Environment endogenous force
Z	Impedance matrix with elements of Z_{jk} (j, k = {1,2,3})	Z'	Equivalent two-port impedance matrix with elements of Z'_{jk} (j, k = {1,2})
η	Stability parameter	ω	Frequency
Γ_e	Transformed impedance	E_{hi}	Operator energy
K_{pmi}	Master robot controller position gain	K_{dmi}	Master robot controller derivative gain
K_{ps}	Slave robot controller position gain	K_{ds}	Slave robot controller derivative gain
Z_{ti}	Impedance transferred to the operators	G_{ti}	Transparency transfer function
C_i	Motion jerk of the ith robot	(x,y)	Coordinates of the haptic devices
e_{ij}	Position error	P_i	Position of the haptic device stylus
T_c	Completion time	$\bar{F}_i$	Average force

Fig. 5-left and right respectively show the transparency transfer function for the trainer under soft and hard contacts with the environment. In Figs. 5 and 6, the first columns include the data for the no grasp condition and the second columns for the average grasp condition. The figures additionally show G_{t1} for the (α , β) values chosen from the bottom left half of Ω in red.

It can be seen that the original selection of Ω (upper right half shown in Fig. 3) renders the system transparency relatively independent of the β values, given that the red graphs in Fig. 5 are unacceptable. It can also be seen that the system transparency transfer function remains close to 0 dB up to ω = ~10 Hz across different values for α, implying that the system is transparent for a given α value. However, as α value changes the perceived impedance for the trainer also changes suggesting that the system transparency is dependent on the dominance factor. This finding suggests a tradeoff between the ability to arbitrate authority and the system transparency.

Comparing the transparency transfer functions of the loose and firm grasps in Fig. 5 shows that the transparency of the system from the trainer's point of view remains relatively independent of the novice impedance at frequencies of up to 10 Hz except for the case with $\alpha = 0$. Comparing the left and right columns of Fig. 5 shows that the transparency of the system decreases when the slave robot is in contact with hard surfaces. The transparency of the system presented here is from the trainer's prospective, because the impedance transferred to the novice (Z_{t2}) is a subcase of Z_{t1} and we found similar results for Z_{t2}, not presented here.

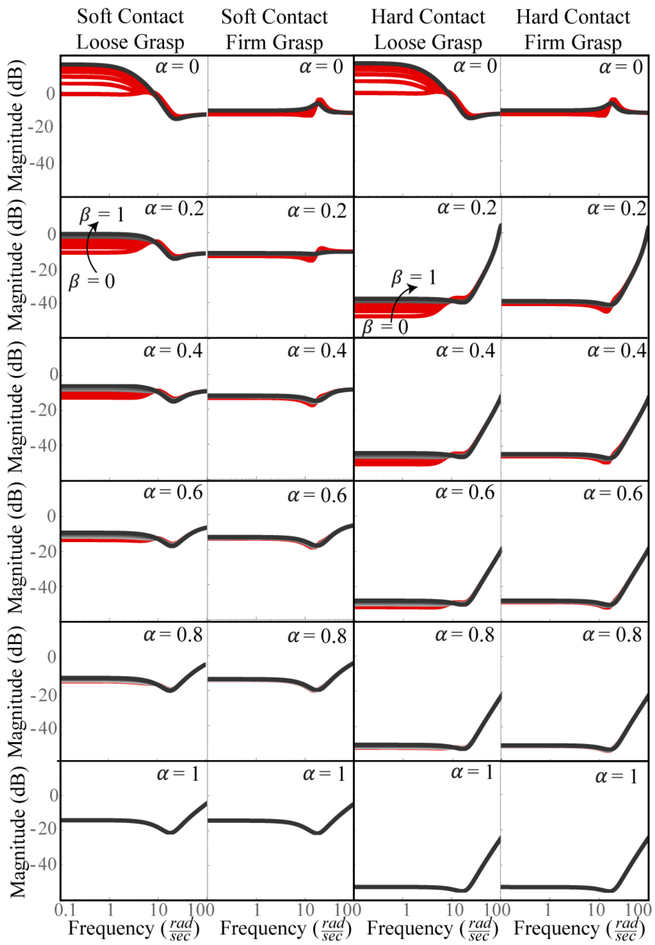

Fig. 5. Impedance transferred to the trainer (Z_{tl}) versus frequency for contact with a simulated soft surface (left) and hard surface (right). For each contact condition, the left column includes the data for the case without the user grasping the robot and the right column data for the case with an average grasp impedance. Six values of {0, 0.2, 0.4, 0.6, 0.8, 1} are included for α and similarly for β. The gray scale indicates the value of β, with the darker being closer to 1. The red curves indicate the condition where (α , β) are chosen from the bottom left half of space.

B. Experimental Implementation and Evaluation

We implemented a trilateral PPP architecture on three Phantom Omni haptic devices, as shown in Fig. 6. The proportional and derivative gains selected were K_p = 90 N.m^{-1} and K_d = 1 N.s.m^{-1}, and the sampling time was chosen to be T = 0.001 s. The velocity values were filtered using a Butterworth 3rd order filter with cutoff frequency of 150 Hz, but we were not able to increase the derivative gains more than 1 N.s.m^{-1}and still have a stable system. This unexpected instability could be related to the quantization noise, which were not captured in the analysis of the previous section. Having stated that, the system remained stable under different contact and grasp conditions.

The trilateral system was used in a simple experiment involving two normal participants as the trainer and novice (Fig. 6) with the details being:

Task: The users were asked to move the stylus is the grasped master manipulator in order to cause motion of the stylus of the slave robot along a star-shape path, with less than ±*4* mm

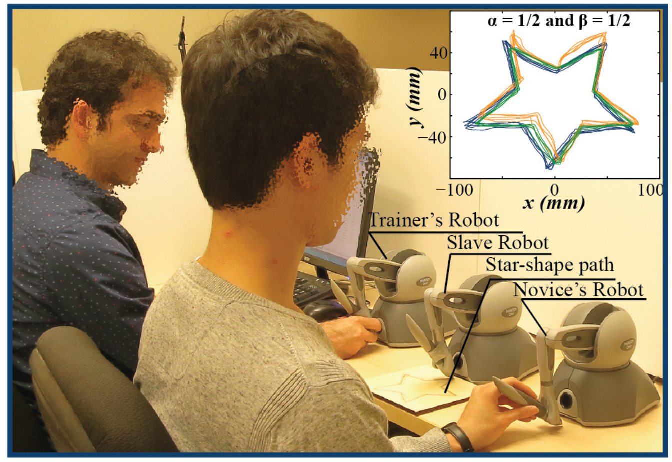

Fig. 6. A dyad of human users performed a trajectory following task. The first user was given more control and moved the stylus of his haptic device by the dominant hand (allowed to be supported on the table). The second user was the novice and moved the stylus of the haptic device using the non-dominant hand (not allowed to be supported on the table). The gimbals of the trainer and slave robots were similarly fixed using tape.

deviation from the desired path. The gimbals of the slave robot stylus were taped allowing rotation only in 3 degrees of freedom (DOFs).

Trainer: The trainer was given more control over the task performance in that the stylus gimbals of the trainer haptic device were taped similarly to those of the slave robot, and the trainer used the dominant hand supported on the table. The trainer was instructed to focus on the movement of the slave robot and make sure it remains within the trajectory boundaries.

Novice: The novice participant was instructed to focus on the movement of the stylus endpoint of the slave haptic device and try to move it along the trajectory with the non-dominant hand and remain inside the boundaries. The gimbals of the novice haptic device were free leaving more DOFs to the novice who was moving his stylus without his hand supported on the table.

The experiments used 5 values of {0, 1/4, 1/2, 3/4, 1} for α and β making a total number of 25 trials which were randomized using a randomized 5×5 Latin square design. The participants practiced using the setup for 4 min., then performed the experiment. For each set of α and β values, the participants practiced the trajectory following task 10 times, rested for 20 s, performed the task 5 times for data analysis, and then rested for 1 min. All sessions took place subsequently and within one day.

For each trial, we collected the position of the endpoints of the haptic devices' stylus and calculated the sum of position errors as the sum of distance between the robot position and the closest point on the trajectory. We also calculated the effort of the users as the average magnitude of the forces generated by the haptic devices (i.e. F_{cmi} and F_{cs}). The time of completion of the task was also recorded.

C. Experimental Results

Fig. 6 shows also the trajectories of the haptic device styluses for a sample trial with $\alpha = \beta = 1/2$. Figs. 9 shows the time of completion, sum of position errors, and average forces across

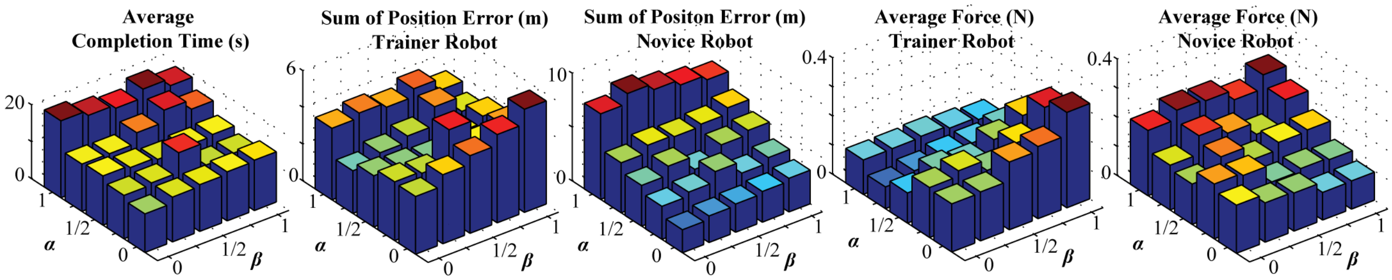

Fig. 9. Average time of completion, sum of position error (absolute value of the difference between the robots position and the trajectory) and average force magnitude for the trainer, and novice robots across different α and β values.

different α and β values, respectively. The following trends can be observed in these figures.

Completion Time: The completion time increased as α increased, implying that the trainer preferred slower performance of the task. An increase in β value resulted in an increase in the completion time, implying that when the novice received haptic feedback from the slave robot, the task was performed more slowly.

Position Error: The slave robot position error was maximum for the case where the trainer had full control ($\alpha = 1$), implying that collaboration resulted in better performance. It can be seen that for $\alpha = 0$ case, an increase in β value resulted in an increase in slave robot error; whereas, no noticeable trend was observed for other cases.

Robot Force: An increase in the β value and a decrease in α value resulted in an increase in the trainer effort and a decrease in the novice effort. Interestingly, the less authority the participant had over the task performance, the more efforts they contributed to the task performance suggesting that both and were involved in modulation of the trainee's effort. The slave robot force remained mostly constant, as expected.

IV. Discussion and Conclusions

This paper presents the design and performance evaluation of a control architecture for master-master-slave trilateral teleoperated robots that can be used for training robot-assisted surgical procedures. The proposed architecture allows for regulation users' authority over the slave robot using a dominance factor determined by the trainer, and coordination of the attentional focus and feedback for the novice using an observation factor that is determined by the novice.

The numerical analysis showed that the system remains stable and relatively transparent across different values for the dominance and observation factors, novice grasp impedance, and frequencies. It was found that the main contributors to the decrease in the system transparency were the contact impedance and dominance factor, which is in in agreement with the findings of others [30].

The experimental evaluation of the system showed that an increase in the authority of the users resulted in a decrease in the efforts they made. The dyadic performance was superior to the individual performance and also the control framework allows for the trainer supervision and modulation of the efforts of the users. The experiment only included one dyad to validate the framework and identify trends, thus no statistical inference should be made using the results. It is unclear how the trainer and novice contributed to the task. Future research could measure the leader/follower contributions and corrective roles that users take across different α and β values.

The design of the control architecture was inspired by the determinants of motor learning in humans, including observational practice, focus of attention, feedback, and self-controlled practice. Using a trilateral platform that implements this architecture, a trainer-novice dyad can perform collaborative training procedures giving supervision to the trainer using the dominance factor. The combination of the dominance and observation factors allows for modulation of the level of feedback and focus of attention for the novice. Moreover, the observation factor allows the novice user to control the source of feedback and explore the environment and motor variability, as suggested by others [26].

The proposed architecture is a continuation to the efforts of other researchers who studied shared-control architectures from a control point of view [15, 16, 29-32], with the difference being that we integrated the determinants of motor learning in humans into the design of the control architectures. Particularly, the proposed architecture allows for modulation of the determinants of motor learning, which allows us to study the human response to different levels and profiles of haptic feedback and focus of attention.

Researchers have previously obtained contradictory results regarding the effects of haptic feedback on performing and learning surgical procedures [4, 10, 36]. One potential explanation could attribute these contradictory results to uninformed administration of haptic feedback during task performance or skill acquisition. Previous research shows that humans need more feedback in the early stages of learning complex motor skills [21], implying that more feedback (and probably augmented feedback) should be provided at the beginning of learning surgical tasks; with the evidence shown in a previous study [11]. One aim of the current line of study is to understand how haptic feedback should be provided in training surgical tasks. The proposed architecture provides a combination of visual feedback and adjustable haptic feedback, which were shown to have the potential to significantly improve the performance and perception of surgeons and skill transfer [4, 36].

In this study, we explained the steps to investigate transparency and stability of the architecture for different controller gains, dominance and observation factors, and environment impedance. We used this methodology to study the stability and transparency of a case with local position control at the robots (i.e. position-position-position). Similar methodology can be used for cases with other control forms (e.g. force-force-force or position-position-force) and environment impedances. Alternatively, designers can use the generic analytical stability criteria proposed by others [31], to design unconditionally stable architectures.

The design of the proposed architecture assumes that the trainer and the novice can constantly adjust the dominance and observation factors using a pedal, grasp force sensors, or other means. Future research efforts could be devoted to the development of methods to convey information on the dominance and observation factors within the dyad.

It is unclear at this point how human users respond to training systems that realize this framework. As a future research direction, we intend to implement this framework on a trilateral teleoperated platform for training laparoscopic robotic surgeries and experimentally evaluate the response of the human users under different feedback and task complexity conditions aiming to implement a platform for training surgical skills "on the job", as suggested by others [4, 37].

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