A Paced Shared-Control Teleoperated Architecture for Supervised Automation of Multilateral Surgical Tasks

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***Abstract*—Automation of repetitive tasks can improve laparoscopic surgical procedures by unloading surgeons and reducing duration, trauma, and expense. However, surgical procedures involve delicate manipulation of deformable tissues in a very dynamic environment, suggesting that automated execution of surgical tasks should be carried out under the supervision of the surgeon. We propose a teleoperated architecture that allows a surgeon to employ and supervise agents that can autonomously perform or assist with surgical tasks. The architecture is independent of the automation method. It includes a dominance factor that allows the surgeon to take control over the slave robot at any time, and an aggressiveness factor that sets the performance pace of the autonomous agent. We tested the architecture during execution of a multilateral tension-and-cut task, where a human operator and an autonomous agent are responsible for tensioning or cutting of a tissue. The architecture allowed for supervised and paced automation of the task. We found that collaboration of the human operator and autonomous agent can lead to shorter completion time compared to performance of only a human.**

***Index Terms*—Teleoperation, robot-assisted minimally invasive surgery, autonomy, supervision, shared control, cutting**

I. Introduction

TELEOPERATED laparoscopic surgical robots allow surgeons to perform procedures that require delicate movements, additional degrees of freedom, and dexterity [1], leading surgeons to use these systems to perform more than half a million minimally invasive general abdominal, gynecologic, urologic, and cardiac surgeries every year [2]. These surgical procedures are comprised of a series of kinematically complex and repetitive tasks including palpating, suturing, cutting, and debriding. Full or partial automation of these tasks has the potential to reduce surgeon errors, duration of procedures, trauma, and expense.

Researchers have explored the problem of surgical automation at different levels [3]. Learning by observation and demonstration were used to train autonomous agents to perform surgical tasks or subtasks [4-7]. Hidden and Discrete Markov Models have been used to detect task termination to transfer the control between human operators and autonomous agents [8, 9]. Servoing based on optical and ultrasound imaging has been used for autonomous control [10, 11]. Other researchers performed surgical tasks including suturing [5, 6, 10], cutting and debriding [7, 12], and palpating [13].

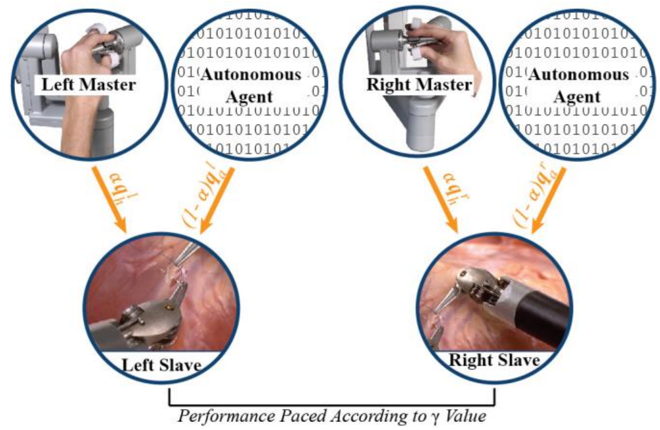

Fig. 1. Schematic of the shared-control architecture. Authority over the slave robots is arbitrated between the left and right master tool manipulators and an autonomous agent. The authority of the human operator and autonomous agent is defined according to the dominance factor (α) and the performance pace is defined according to the aggressiveness factor (γ). Images ©2015 Intuitive Surgical, Inc.

Given that surgeries involve critical and delicate tasks, automated surgical procedures should be carried out under the supervision and correction of the surgeon [14]. Yet, it is difficult to program a surgical robot because human tissues are variable, delicate, dynamic, and deformable, which introduce registration errors [4]. Also, tissue and vein localization using current sensing methods such as vision are still in the early stages and require substantial improvement. Despite the significant undertakings in supervised automation of surgical tasks, there are still many challenges to overcome.

Ideally, the design of any robotic surgical system should ensure that the surgeon can take the control of the slave robot at any time during the surgery, guide/correct the slave robot, and set the pace of performance. It is currently unclear how to best design robotic surgical systems that allow for supervised autonomous execution of surgical tasks. This paper is a first step towards the design of an architecture based on shared-control architectures that allows the human operator to supervise the automated tasks through seamless transfer of authority over the slave robot between a human operator and an autonomous agent.

Researchers have investigated supervised automation of surgical tasks. In one approach, researchers suggested the

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concept of "synergy" to allow the surgeon to supervise the automated performance of the slave robot [15]. Shared-control architectures have proved functional to allow the human operator to supervise automated task execution [16]. Researchers have explored shared-control architectures for multilateral teleoperated robots and the stability and transparency of trilateral dual-user single-slave systems [17-19]. In robot-assisted teleoperated surgeries, shared-control architectures have been used to apply virtual fixtures that are force fields that guide the movement of the human operators [20] and also for collaboration between human operators and autonomous agents [21, 22]. In the most common form, trilateral shared-control architectures give authority over the slave robot to one side using a dominance factor that ranges from zero to one [17-19]. When a dyad of two human operators interact with the environment through a trilateral system, the first operator has full control over the slave robot when the dominance factor is one, whereas the second operator has full control when the dominance factor is zero.

In this paper, we develop a shared-control architecture for collaboration between a human operator and an autonomous agent, as schematically shown in Fig. 1. The architecture is versatile and independent of the design of the autonomous agent. Using a dominance factor, the architecture allows the human operator to take the control over the slave robot at any time during the surgery to avoid unintended movements and to apply adjustments. Using an aggressiveness factor inspired by other work [23], the architecture sets the pace of the autonomous agent to perform multilateral tasks that involve high level of collaboration and coordination including suturing, cutting, and debriding. We implemented the architecture on a da Vinci® Research Kit (dVRK) [24], shown in Fig. 2, and experimentally tested it for performing multilateral coordinated cutting task. We found that using this architecture, a surgeon can partially (or potentially fully) automate surgical tasks that involve manipulating deformable tissues during surgical procedures.

II. Architecture Design

A. Notation

We use lower-case letters for scalars, lower-case bold letters for vectors, and upper-case bold letters for matrices. $\boldsymbol{q}$ is the joint angle vector, $\boldsymbol{x}$ is the Cartesian space position-orientation vector (with x, y, z position coordinates and θ, φ, and ψ orientation coordinates – roll, pitch, and yaw angles). $\boldsymbol{f}$ is the Cartesian space force-torque vector, and $\boldsymbol{\tau}$ is the joint-space torque vector. The "M" subscript stands for master side, "P" for patient side, "H" for human, "A" for the autonomous agent, and "s" for the scaled parameter. The dominance and aggressiveness factors are respectively noted by α and γ. The "r" and "l" superscripts respectively stand for right and left.

B. Collaboration Architecture

The architecture includes a paced shared-control architecture to allow for collaboration between a human operator and an autonomous agent and control the performance pace of the autonomous agent. The human operator interacts with a left master tool manipulator (LMTM) and a right master tool manipulator (RMTM), and the autonomous agent

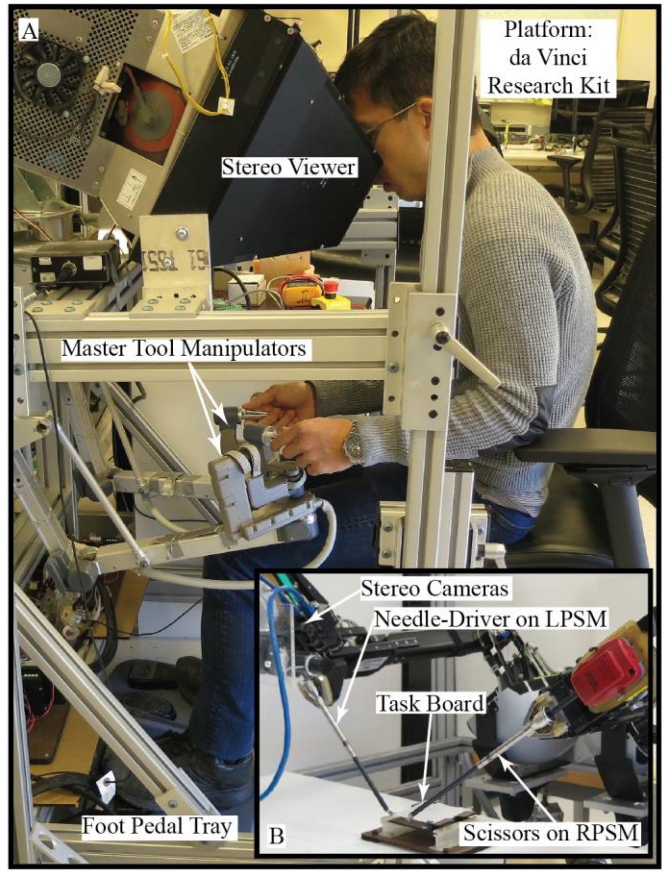

Fig. 2. The da Vinci Research Kit was used as the experimental platform. A: The participants were seated at the master side and used master tool manipulators, foot pedals, and stereo viewer, B: A needle driver and curved scissors were used on the left and right patient-side manipulators, respectively.

communicates with the controller, as schematically shown in Fig. 1. The architecture includes two main features:

Dominance Factor: A dominance factor ($\alpha \in [0 , 1]$) assigned by the human operator sets the authority of the human operator versus the autonomous agent over the patient side manipulators (PSMs), allowing the human operator to supervise the performance of the autonomous agent under a form of shared-control architecture as [17-19]:

$$\boldsymbol{x}_M^r = \alpha \boldsymbol{x}_H^r + (1-\alpha)\boldsymbol{x}_A^r \quad (1)$$
$$\boldsymbol{x}_M^l = \alpha \boldsymbol{x}_H^l + (1-\alpha)\boldsymbol{x}_A^l \quad (2)$$

For example, the human operator sets the α value to 1 to take full control over either PSM to properly position its end effector, to perform corrective tasks, or demonstrate a task to the autonomous agent. Then the human agent sets α to 0 to allow the autonomous agent to perform the assigned tasks.

Aggressiveness Factor: The aggressiveness factor ($\gamma \in [-1 , 1]$) assigned by the human operator allows pacing the performance of the slave robots. It assigns a leader role (i.e. aggressive performance) or follower role (i.e. submissive performance) to each side. Specifically, the autonomous agent performs the assigned task in coordination with the PSM of the other side according to the γ value, in that if γ holds a positive, zero, or negative value, the autonomous agent respectively performs the tasks ahead of (aggressively), at the same pace as (synchronously), or behind (submissively) the master tool

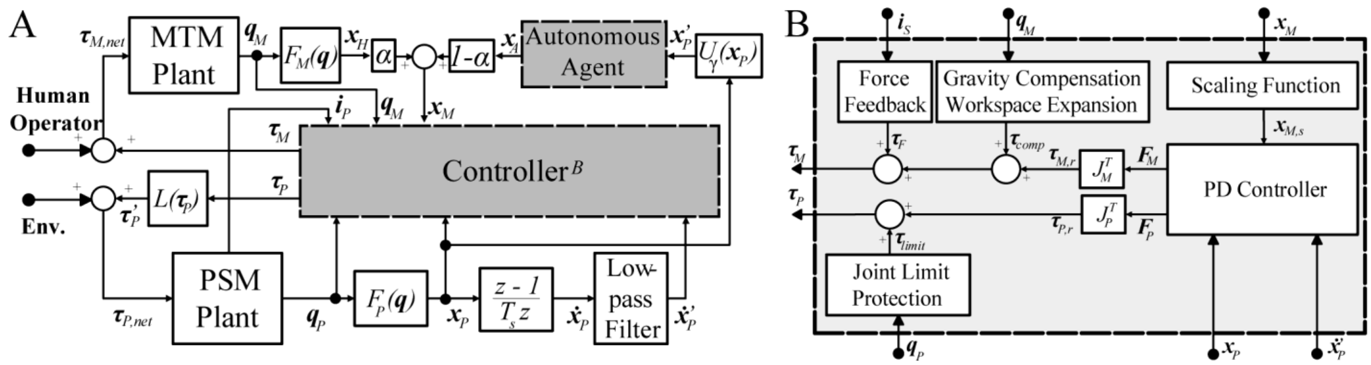

Fig. 3. Block diagram of the implementation of the architecture on the da Vinci Research Kit. A: General control structure, B: Controller design.

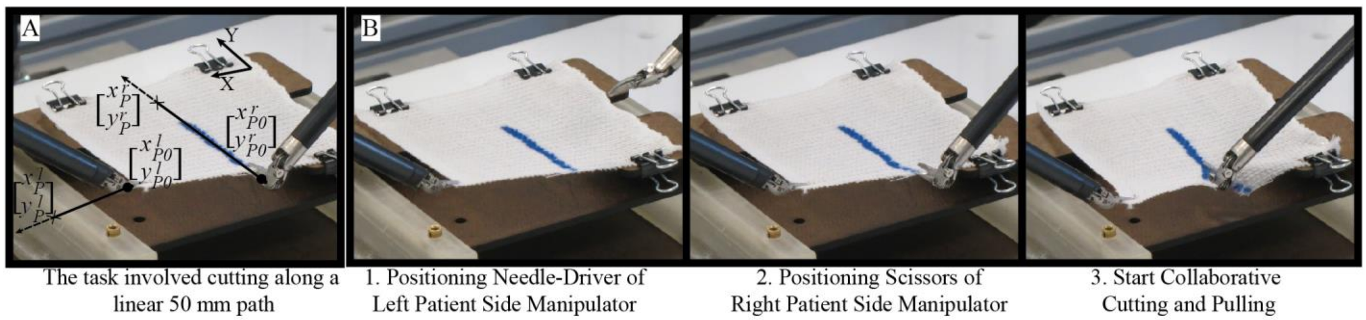

Fig. 4. Multilateral cutting task. A: Medical gauze was anchored at the three corners and held and pulled at the forth corner, using a needle driver on the left robot. A pair of scissors were mounted on the right robot to cut along a marked linear path that was 50 mm long. B: The scissors were positioned at beginning of the path and cut along it. The experiments included two cases with the human operator and autonomous agent performing the pulling or cutting tasks.

manipulator (MTM) of the other side, respectively. To this end, we define:

$$\boldsymbol{x'}_P = U_\gamma(\boldsymbol{x}_P) \tag{3}$$

where $\boldsymbol{x'}_P = [x'_p, y'_p, z'_p, \theta'_p, \varphi'_p, \psi'_p]^T$ is the paced Cartesian pose of the PSM end effector, which is used by the autonomous agent as the input arguments. The method of coordination depends on the task being performed. For collaborative tasks, the poses of the PSMs are interrelated according to the pace function (U_γ), which we define as:

$$U_\gamma(\boldsymbol{x}_P) = \boldsymbol{x}_P + \boldsymbol{\gamma} \cdot \Delta \boldsymbol{x}_P \tag{4}$$

where $\boldsymbol{\gamma} = [\gamma_x, \gamma_y, \gamma_z, \gamma_\theta, \gamma_\varphi, \gamma_\psi]$ is a vector of aggressiveness factors for the position and orientation. Alternatively, the task could be coordinated according to the task phase, surgeme [25], or progress time. $\Delta\boldsymbol{x}_P$ is a pace parameter that can be a positive constant or a function of the robot velocity depending on the task being performed.

III. Case Study: Multilateral Tissue Cutting

This section provides a case study of the collaborative architecture implemented for multilateral cutting of tissues where a left slave robot holds and pulls on tissue while the right slave robot cuts through the tissue. For this case study, we only implemented the autonomous agent on one side while the other side was teleoperated by the human operator. We considered two values for the dominance factor, $\alpha \in \{0, 1\}$. Researchers have studied stability and transparency of shared-control architectures across all values for α [17, 18], suggesting that one should make sure that the controller gains satisfy a series of stability criteria for any α value used.

A. Implementation Platform

We used the da Vinci Research Kit (dVRK) [24] as our experiment platform (Fig. 2). DeBakey forceps and curved scissors are used as LPSM and RPSM tools in this study, to manipulate and cut the medical gauze. All components are mounted on a custom-designed aluminum frame that allows for adjustment of relative positions of MTMs, stereo viewer, armrest and foot-pedal tray. We used a pair of Flea3 cameras (Point Grey, Richmond, BC) with 12 mm f1.8 compact lenses (Edmund Optics, Barrigngton, NJ) to obtain the visual scene. The 3D view was presented to users at 60 Hz refresh rate and 640×480 resolution via the stereo viewer.

Our control software is based on open-source *cisst* architecture [26], with customized operational space controller. The control architecture is presented in Fig. 3-A. Position-exchange law was implemented for teleoperation control. We used joint angles ($\boldsymbol{q}_M$ and $\boldsymbol{q}_P$) to calculate the Cartesian positions and orientations of the MTM ($\boldsymbol{x}_H$) and PSM ($\boldsymbol{x}_P$) tooltips, as shown in Fig. 3-B via forward kinematics ($\boldsymbol{F}_M(\boldsymbol{q})$ and $\boldsymbol{F}_P(\boldsymbol{q})$). Velocities ($\dot{\boldsymbol{x}}_P$) were calculated using numerical differentiation. A scaling factor of $a_i = 0.3$ from MTM side to PSM side was applied as:

$$x_{M,s,i} = a_i x_{M,i} \tag{5}$$

where $i = x, y, z$ and subscript "s" stands for the scaled parameter. Note that the orientation is not scaled.

Desired force and torque on PSMs in Cartesian space are determined by a PD control law:

$$f_{P,i} = k_{p,i}(x_{M,s,i} - x_{P,i}) + k_{d,i}\dot{x}'_{P,i} \tag{6}$$

We then compute the desired torques in joint space by multiplying the Cartesian forces and torques with the transposed Jacobian.

We implemented a workspace expansion algorithm that exploits the redundancy in MTMs to maximize the end effector's workspace. Gravity compensation was also implemented. Finally, environmental forces on PSMs are estimated by measuring motor currents, and displayed on MTMs during teleoperation. The forces displayed are down-scaled by the same scaling factor of 0.3. More details on the implementation can be found in [27].

B. Experimental Evaluation

Collaborative Task: We selected a common coordinated surgical task: tissue tensioning and cutting. In this task, tissue is held and pulled by a laparoscopic needle driver installed on the LPSM and cut by laparoscopic scissors installed on the RPSM. In this study, we used ~95 mm × ~85 mm square-shaped pieces of medical gauze anchored at three corners with the forth corner untethered to be held by the LPSM, as shown in Fig. 4-A. The RPSM cuts along a ~50 mm linear path that was marked in the middle of the gauze while the LPSM pulls and holds tension in the gauze.

Protocols: We conducted a series of experiments with 3 participants with prior dVRK experience. The experiments were across 6 conditions, including 2 tasks and 3 performance paces. In the first task, we automated *Pulling* in that the autonomous agent controlled the LPSM to pull the gauze, whereas in the second task we automated *Cutting* in that the autonomous agent controlled the RPSM to cut through the gauze. The three levels of performance pace varied according to the γ value: negative value for *Submissive* performance, zero for *Synchronous* performance, and positive value for *Aggressive* performance.

In the practice session, each participant was instructed to use the system in purely teleoperation to cut 5 pieces of medical gauze that were similar to those used during the data collection sessions. In the data collection session, the participants first performed the cutting task in the teleoperated mode to obtain the average completion time and then performed the cutting task for 3 times for each of the 6 conditions that were fully randomized. The collected data included time and Cartesian coordinates of the tools of the PSMs. Using a pedal on the pedal tray of the dVRK, the participants were allowed to transfer from the Teleoperated mode to the Autonomous mode (α: 1 to 0) only at the beginning of the Cutting and Pulling tasks after they positioned the needle driver and the scissors to start cutting.

Autonomous Agent: A linear mapping was used in this study as the autonomous agent to coordinate the movements of the LPSM and RPSM. For the first task, where the autonomous agent controls the LPSM to pull the gauze, the autonomous agent moves the needle driver of the LPSM along a trajectory ($\boldsymbol{x}_A = [x_P^l, y_P^l, 0]^T$) defined as a function of the y-position of the RPSM scissors as:

$$x_P^l = x_{P0}^l + K_x(y'^r_P - y_{P0}^r) \quad (7)$$

$$y_P^l = y_{P0}^l + K_y(y'^r_P - y_{P0}^r) \quad (8)$$

where K_x = -0.32 and K_y = -0.34 were empirically found according to the movements of human users, and:

$$y'^r_P = y_P^r + \gamma \Delta y_P \quad (9)$$

For the second task, where the autonomous agent controls the RPSM to cut through the gauze, the autonomous agent moves the scissors of the RPSM along the linear trajectory defined as:

$$x_P^r = x_{P0}^r \quad (9)$$

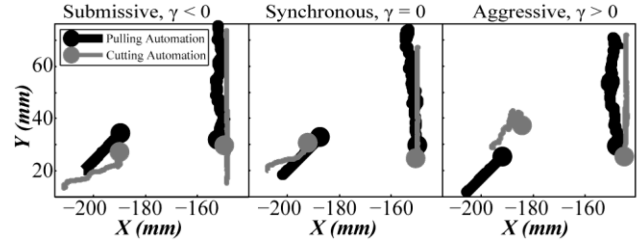

Fig. 5. Sample trajectories for a participant across the six conditions. The first to the third columns respectively include the sample trajectories for the Submissive, Synchronous, and Aggressive conditions The black traces show the trajectories of the conditions where the autonomous agent controlled the LPSM to pull the gauzes, and the gray traces show the trajectories where the autonomous agent controlled the RPSM to cut through the gauzes.

$$y_P^r = K_x\left(x'^l_P - x_{P0}^l\right) + K_y(y'^l_P - x_{P0}^l) \quad (10)$$

where, K_x = -1.82 and K_y = -1.19 where empirically found according to the movements of human users, and:

$$x'^l_P = x_P^l + \gamma \Delta x_P \quad (11)$$

$$y'^l_P = y_P^l + \gamma \Delta y_P \quad (12)$$

The value of γ included -1, 0, and 1 for the Pulling automation condition and -0.5, 0, and 0.5 for the Cutting automation condition. For the Submissive and Aggressive paces, the values of Δx_p and Δy_p were constant and chosen such that the automated side was 1 cm behind (for the Submissive mode) or ahead (for the Aggressive mode) of the teleoperated side, respectively.

C. Experimental Results

This study aimed to evaluate the feasibility and performance of the architecture in an experiment with only three participants; therefore, we did not perform any statistical analysis. The system remained stable for the tested values of α and γ and the transfer from teleoperated mode to the autonomous mode was seamless when visually inspected. Fig. 4-B shows a sample trial at different stages of the cutting task. Fig. 5 includes sample trajectories for the first participant across the six conditions with the circle indicating the starting point.

Overall, the cut path remained within ±5 mm boundaries of the indicated trajectory, except two trials of Cutting Automation with a maximum deviation of ~10 mm on the medical gauze (note that the gauze was slightly deformed when pulled by the LPSM). The participants were able to complete all trials with different completion time as shown in Fig. 6. In terms of the completion time, the participants overall performed better in conditions with Pulling Automation, followed by Teleoperated and Cutting Automation. The participants performed single-handed tasks in Pulling and Cutting Automation conditions, whereas they performed a double-handed task in the Teleoperated condition. For Pulling Automation case, the participants performed better in Submissive and Aggressive performance paces when compared with the Synchronous pace and Teleoperated mode in terms of the completion time.

Fig. 7 shows the displacement of the end effectors of the LPSM and RPSM, as an indication of the level of collaboration between the two sides and the amount of corrective movements occurred during the task performance. It was observed that the participants overall performed more corrective movements for the conditions with Cutting Automation because we merely used a simple trajectory-following autonomous agent for cutting, which was unable to compensate for deformation of the tissue. Also, there was large inter-subject variability implying

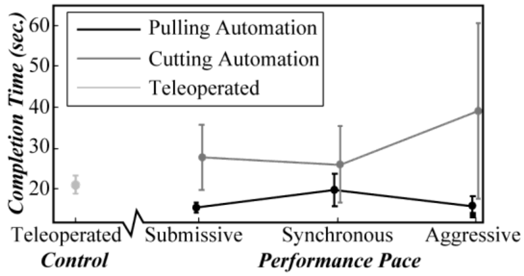

Fig. 6. Intersubject mean completion time across the six conditions and for the case where the participants performed the task under purely teleoperated mode for the left and right robots.

that training may influence performance of the participants.

IV. Conclusions and Discussion

We implemented an architecture for teleoperated surgical systems that enables collaboration between a human operator and an autonomous agent under the supervision of the human operator. The architecture relies on a paced shared-control architecture that includes a dominance factor to set the authority of the human operator and autonomous agent over the slave robot, as well as an aggressiveness factor to set the performance pace of the autonomous agent according to the state of the contralateral slave robot.

The architecture was tested on a da Vinci Research Kit (dVRK). Results showed that the architecture can be employed in the design of teleoperated surgical robots to allow for automation of surgical tasks under the supervision of the human operators. Participants performed better in the case with automated pulling and teleoperated cutting when compared with purely teleoperated pulling and cutting in terms of completion time. The autonomous agents showed a 100% completion rate, likely because the architecture allowed the participants to initially position the slave robots properly and also apply corrective movements on the contralateral slave robot. Researchers have shown that fully autonomous tasks can have a lower success rate [3]. These findings suggest that partial automation of surgical tasks may result in a higher success rate when compared with purely teleoperated or (by comparison with prior work) fully autonomous systems.

It was observed that the participants performed overall more slowly when the cutting task was automated. Moreover, it was found that the participants apply more corrective movements on the contralateral slave robot to guide the autonomous agent to perform the cutting task. These two observations can be associated with rudimentary automation method we used, which was a simple mapping between the left and right slave robots. A more careful design for the automation of cutting may lead to better performance and shorter completion time. This could include incorporation of visual feedback and tissue models in the design of the autonomous agent.

The experimental results showed that submissive and aggressive paces in the automated pulling task, and synchronous pace in the automated cutting task led to shorter completion time. This suggests that it is important to be able to adjust the performance pace of the autonomous agent according to the surgical tasks to achieve the shortest performance duration.

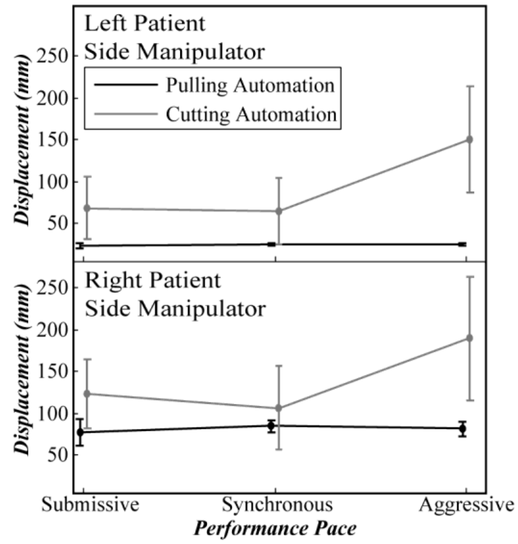

Fig. 7. Displacement for the left and right patient side manipulators across the six conditions as an indicator of the amount of corrective movements that the participants performed.

In this study, we did not focus of the quality of task execution given that it is a measure of the autonomous agent performance rather than the collaborative architecture. However, we found that the cut paths remained within ±5 mm boundaries of the marked path, except two case where the cut reached ~10 mm off the indicated path. We found two reasons for that: Firstly, the participants were not allowed to change to the mode of operation (i.e. teleoperated to autonomous) during the experiments to apply adjustments on the x-axis. Secondly, the automation method we used was a very simple mapping without any correction and learning.

This study has several limitations. First, the participants had different levels of experience working with dVRK, making it difficult to characterize the effects of skill on their performance. Second, the participants were only given 5 trials to practice the teleoperated task on the dVRK. Third, we only allowed the participants to transfer from the teleoperated mode to the automated mode once and after they positioned the instruments at the beginning of each trial. A more structured test should include more subjects with identical levels of training, with practice sessions that include tasks in the automated mode, and with the ability to change the operation mode at any time during the trials. Moreover, the study should consider analysis of architecture stability across different values for the dominance and aggressiveness factors [28].

In this study, we only implemented the architecture on one side of the dVRK as a case study. Future work can extend this architecture on both sides of the dVRK to perform fully autonomous collaborative tasks including cutting, debriding, and suturing. The architecture design is independent of the automation method, task to be performed, and user expertise. Future research can implement more sophisticated design for the automation of the surgical tasks and other values for the dominance and aggressiveness factors. Our future research will also include more realistic methods for selection of aggressiveness factor in presence of stochasticity and noise, and pertinent adjustment of performance for the employed surgical systems. We will also more rigorously study the effects of aggressiveness factor in the overall quality of execution of surgical tasks. Currently, the experiments included merely trajectory-following tasks; future research would include implementation of the architecture for automated tasks that might change on the fly, such as suturing and debridement.

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