2024 IEEE International Conference on Robotics and Automation (ICRA 2024)
May 13-17, 2024. Yokohama, Japan

Human Robot Shared Control in Surgery: A Performance Assessment

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***Abstract*— While surgical robots, such as the da Vinci Surgical System, have become prevalent in minimally invasive surgery, they are predominantly used by the human operator to directly teleoperate the tools. This paper aims to analyse the different methods of human robot shared control in the surgical domain. We propose a reinforcement learning algorithm, transverse generative adversarial imitation learning (tGAIL), which is employed to train the robot from the expert's demonstration and show competitive generalization ability compared to inverse reinforcement learning and conventional GAIL. We then propose a priority-changing shared control method to effectively combine the surgeon and robot's strengths by dynamically adjusting control priority based on the deviation distance. We show that using this method in a supervision framework boosts the performance of the human operator when completing the peg transfer task. By learning from the expert and collaborating with the human during the task, the intelligent agent can help to reduce operation time by 31.7% and the human input by 60.5% compared to direct teleoperation.**

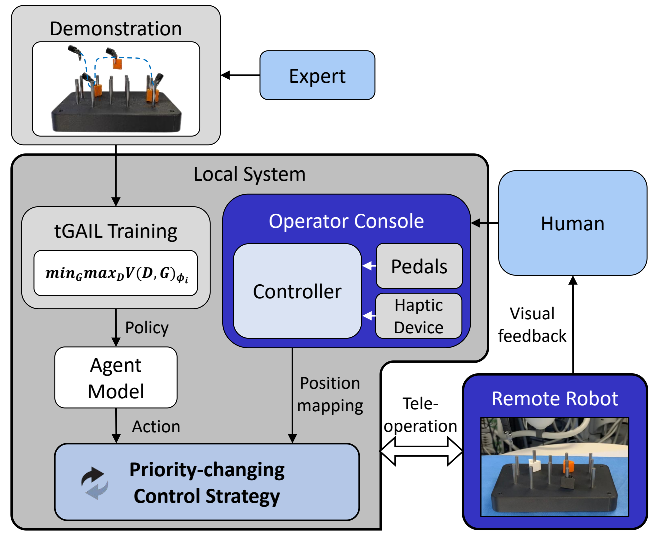

Fig. 1. Control system and experimental setup. The agent is trained from the demonstration of an expert (i.e. a user with more than 300 hours of experience with the control interface). The priority-changing strategy incorporates the input from both operator and agent to control the robot.

I. INTRODUCTION

Robotic-assisted surgery employs robotic systems to assist a human operator during the surgical procedure [1]–[4]. These systems are designed to provide surgeons with increased dexterity and precision, allowing them to perform complex procedures with greater accuracy and less effort than traditional surgical methods [5]. Despite these advantages, fully autonomous robotic surgeries remain unrealistic due to the inherent complexity of surgical decision-making, potential unpredictability, as well as ethical and legal implications. These issues have led to the concept of shared control, which is gaining prevalence in the field [6]–[8].

Shared control attempts to combine the advantages of humans and robots to effectively complete the surgical task. This approach allows the surgeon to retain control over the procedure while also taking advantage of the robotic system's advanced precision and efficiency. Furthermore, the robotic system can also be programmed to perform certain tasks automatically, such as maintaining a specific surgical position [9] or performing repetitive motions [10]. Therefore, shared control systems can help to reduce the surgeon's cognitive load and fatigue, which could lead to improved surgical outcomes. Several benchmarks [11] are available to evaluate the performance of these controllers, however, the operator can struggle with the task due to inexperience or limited environmental information. Therefore, a study involving novices who operate in an adequately challenging environment is necessary. Performance assessments have been used before to analyse different shared control methods in [6], however the analysis was not performed on standardised tasks of laparoscopic surgery [11], such as peg transfer.

Common techniques used for shared control include collaborative [12] and supervisory [13] methods. Collaborative methods, such as segmentation, have a level of predetermined and fixed autonomy, meaning that the operator cannot obtain control authority unless the agent permits it or a specific switch event occurs. [12] and [14] implement a switch of the control authority between a human operator and a fully autonomous agent according to the task demands. However, to ensure the constant presence of the human surgeon, the fully autonomous component of the segmented control could be replaced by a supervisory type of control. Supervisory methods in shared control allow a dynamic adjustment of the level of autonomy in a surgical robot based on the current task demands and the capabilities of the human operator. An example is the Smart Tissue Autonomous Robot (STAR) [15], which is a robot that uses supervisory shared

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control to perform surgical procedures autonomously, under the supervision of a surgeon. The controller can achieve seamless switching by adopting real-time context awareness of the surgery. Another supervisory method called guidance priority adaptation, or priority-changing [13], [16], allows the human operator to provide both forces and high-level priority commands to the robot if errors or issues occur during completion of the task. Guidance priority adaptation allows for the reduction of the human operator's cognitive load, by providing the robot with the appropriate level of autonomy while performing the surgical task, which can also be divided into different stages. In [17], the control during the peg transfer task is divided into a supervised autonomous phase during coarse operation and a manual control phase during precise operation. Compared to peg transfer, in suturing [14] the task can be broken down into more stages and the robot can perform needle pulling, translating, and reorienting. Simple or repetitive stages are usually allocated to the robot, while the human is responsible for the most important tasks.

The prevalent shared control methods involve authority switching between surgeon and trained agent, with the latter primarily handling course control. Therefore, a more focused study on the role of supervision-based shared control can help understand how performance and acceptance affect novices and inexperienced users of a surgical robotic system.

In this paper, we propose a control strategy based on guidance priority adaptation to increase the automation in surgical robots. The priority is determined by the distance between the agent's trajectory and the robot hand, and represents the surgeon's trust in the agent. We choose to implement this supervision control strategy on both a virtual and physical da Vinci Research Kit (dVRK) [12], [18], [19] and conduct experiments with two detailed user studies. The main contributions of the paper are as follows:

- We introduce tGAIL, a novel reinforcement learning algorithm designed to learn from expert demonstrations. The algorithm offers improved robustness and consistency in learning.
- We implement a novel priority-changing shared control approach on the dVRK.
- We perform an evaluation study on supervision, segmented, and manual control in a real surgical robotic system in the peg transfer task.

The paper is structured as follows: Section II introduces tGAIL, the priority-changing shared control, and the simulation user study findings. Section III details the real-world experiment. Section IV elaborates on the results. Section V discusses the findings of the user study, ending with conclusions in Section VI.

II. METHODOLOGY

A. Transverse Generative Adversarial Imitation Learning

In the first experiment, we implement an epsilon-greedy maximum entropy inverse reinforcemnt learning (EG MaxEnt IRL) algorithm to validate the feasibility of utilizing our expert trajectories dataset for LfD in a peg transfer task, as in [12]. As an EG MaxEnt IRL trained agent has already been established to be working effectively in [12], we aim to use the same agent and perform a first study in a simulated environment to determine the most effective role of supervision in shared control. Subsequently, for the real dVRK study, we present a refined supervisory algorithm which we call *transverse generative adversarial imitation learning* (tGAIL), shown in Fig. 1 and Algorithm 1. Built upon GAIL, tGAIL traverses the expert's trajectory τ_E, encompassing the expert's policy π_E. Starting from the worst point ϕ_i responsible for most failures, tGAIL seeks to minimize the generator's score while maximizing the expert's score. Unlike sequential learning, tGAIL covers all scenarios simultaneously, resulting in accelerated learning, as demonstrated in Fig. 2.

The EG MaxEnt IRL agent's discretised observation space, governed by the q-table, encounters challenges in high-resolution observation spaces. In contrast, GAIL leverages generative adversarial network techniques, accommodating a continuous workspace. By training both the generator and discriminator, the GAIL agent can potentially exhibit higher generalization compared to the EG MaxEnt IRL agent. Both training methods utilize the same expert demonstrations and environment.

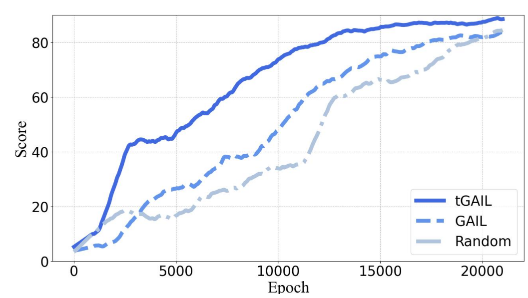

Fig. 2. Training comparison between GAIL, Random GAIL and tGAIL, with same initial settings. Random GAIL starts training at random points and tGAIL starts at points with the most failure rates.

Algorithm 1 Transverse Generative Adversarial Imitation Learning

Input: Expert trajectories $\tau_E \sim \pi_E$, initial policy and discriminator setting parameters

for $i = 1, 2, 3...$ **do**
  Sample trajectories τ_i and find the worst starting point ϕ_i
  Update the discriminator D and the generator (policy) G with cost function $\min_G \max_D V(D, G)_{\phi_i}$
end for

B. Priority-changing Shared Control

Control priority governs the operator's influence relative to the agent's input. Dynamic control priority enables the surgeon to exert control as needed, saving effort when the robot operates effectively. The shared control strategy that switches control priority is defined as:

$$\Delta x(t) = (1 + k_\alpha)\Delta x_h(t) + (1 - k_\alpha)\Delta x_a(t) \qquad (1)$$

where $\Delta x(t)$ is the overall command passed to the robot, $\Delta x_h(t)$ is the human input and $\Delta x_a(t)$ is the agent's input. The parameter k_α is the relative coefficient that achieves guidance priority adaptation, defined as:

$$k_\alpha = \begin{cases} 0, & D \leq D_{min} \\ \frac{1}{2}\left[1 - cos\frac{\pi(D - D_{min})}{D_{max} - D_{min}}\right], & D_{min} < D \leq D_{max} \\ 1, & D_{max} < D \end{cases} \qquad (2)$$

where D is the distance between the autonomous agent pattern and end-effector position in one time step, while D_{min} and D_{max} are the minimal and maximal interference distances, respectively.

The guidance priority is determined by the deviation of the robot's end-effector from the path generated by the agent. While the distance between these is less than the minimum interference distance D_{min}, slight trembling will not affect the agent's task. As the distance increases, the control priority is gradually transferred to the human. If the deviation becomes larger than the threshold of maximum interference D_{max}, the human receives full control priority.

The work in [13] uses force and deviation distance to achieve guidance priority adaptation, but the human needs to apply a relatively large force to get involved in decision-making when the end-effector follows the robot's desired trajectory. By allocating the same control priority at the start of the task, the human and the robot can work as partners. This allows the robot to perform its assigned task without scaling, which will later occur during the negotiation of the control authority after the switching point. Using our proposed method, the agent can conduct the task without external aid; if any correction is needed, the human can get involved in the task with partial priority.

C. Shared Control Methods

Initially, we validate the supervised control method in simulation, integrating it with EG MaxEnt IRL, as it is well established for discrete observation space applications. Eight participants (4 females and 4 males, 22-27 years old, with little to no experience with teleoperation devices) used a local console in a shared control framework to operate a virtual environment with a simulation of the dVRK robot. We employed a real-time simulator, integrating the modified SurRoL environment [12] with a hand interface (Omega7, Force Dimension) to control a virtual dVRK. The participants were instructed on how to use the interfaces and how to complete the peg transfer task by using three types of control: supervision, segmented, and manual control. In this initial study, we aimed to use the established EG MaxEnt IRL to determine the overall user experience with the three different methods and investigate the effectiveness of the proposed supervisory control formulation. We also decided to integrate the guidance priority adaptation with a collaborative framework [20] in order to allow more freedom and control to the human when using segmented control.

1) Supervision Control (SUP): The agent generates the trajectories required for completing the peg transfer while the human operator can provide high-level commands to the agent at any time in a shared control fashion.

2) Segmented Control (SEG): The control priority is exchanged between human and agent. The task stages where the human operator has full control were determined according to [12]. During movements towards targets, the agent performs the task under supervision (SEG-S) or autonomously (SEG-A). This corresponds to the approach and repositioning of the block. When in close range to the target, the authority is switched to the human that performs the necessary physical interactions. This corresponds to picking up and placing down the block.

3) Fully Manual Control (FC): The controller simply filters tremors from the human operator's hand but no agent is involved in controlling the surgical tool.

The controllers used to teleoperate in the surgical simulator are summarised in Table I, where the operator is the human and the agent refers to the trained model.

During the experiment, successful peg transfers are defined as the relocation of the block from the starting peg to the goal peg without failures, which are events such as peg dropping or collisions with the environment. The participants were required to complete three successful peg transfers with each controller and the success rate was calculated as $success\ rate = \frac{3}{failures+3} * 100$. The entire experiment consisted of a total of 4 phases: a first training phase in which the participants would get familiar with the interface and simulator, followed by two phases for SUP and SEG-S, and a fourth phase for FC. The order of SUP and SEG-S was randomised to prevent bias due to learning. While conducting the experiments with each participant, the success rate, operator input, and temporal performance of the user were measured. The evaluation of the participants' subjective workload was performed using a custom NASA TLX [21] to score the perceived Control, Mental, Temporal (i.e. perceived time spent on the task), and Physical effort experienced.

TABLE I
CONTROLLERS SUMMARY

	Approach target	Interact with target
Supervision	Operator+Agent	Opertaor+Agent
Segmented	Opertaor+Agent	Operator
Manual	Operator	Operator

D. Simulation Experiment Results

The data was normally distributed through the Shapiro-Wilk's test. We use one-way ANOVA to analyse the effect of the control modes and post-hoc comparison with Bonferroni correction between single pairs. The results from the study conducted with eight participants are shown in Fig. 3(a-b). We compared the data of the single controllers with each

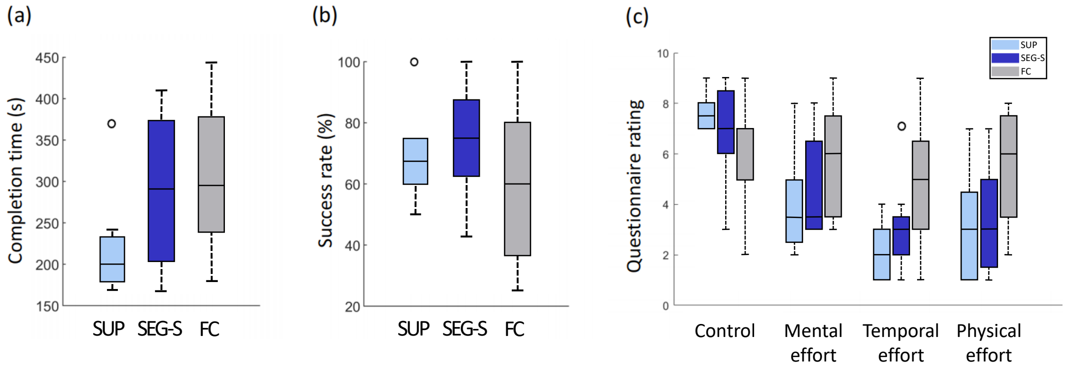

Fig. 3. Performance and questionnaire results from an experiment with participants. (a-b) Completion time and success rate of each participant using the three controllers: supervision (SUP), segmented with supervision (SEG-S) and manual control (FC). (c) Subjective rating of NASA TLX questionnaire.

other using the least significance difference test. We found that SUP is faster than FC ($p = 0.055$) and similar to SEG-S ($p = 0.118$), while SEG-S and FC resulted in a similar average and standard deviation, i.e. $(\sigma, \mu) = (289.2, 93.6)$ and $(305.9, 92.7)$, respectively. All three controllers exhibited similar success rates with the SEG-S $(74.1, 20.3)$ showing moderately better performance than SUP $(69.4, 15.5)$ and FC $(59.7, 28.3)$. Overall, both newly proposed methods revealed a tendency to outperform the manual teleoperation.

The responses obtained from the questionnaire are illustrated in Fig. 3(c). The participants felt similar control confidence when using the three controllers ($p = 0.398$), with SUP being the highest rated $(7.6, 0.74)$, followed by SEG-S $(6.9, 1.9)$, and FC $(6.1, 2.1)$, with the latter presenting the largest standard deviation of the three. The user's rating of mental effort shows the same pattern with a similar standard deviation for all three methods. The subjects' temporal effort was felt different among the three modes ($p = 0.028$). SUP demonstrates less effort than traditional FC ($p = 0.028$). This is followed by SEG-S which required less temporal effort compared to FC, but with no statistical significance ($p = 0.196$). The same result is reflected in the scoring of the participants' physical effort, with SUP $(3.1, 2.2)$ and SEG-S $(3.3, 2.1)$ having analogous ratings. From users' feedback, a common issue with SEG-S is the switching between manual and supervised control. The users found that a sudden and not voluntary switch between the two controllers initially caused confusion and it could only be fully learned towards the end of the block.

Overall, the integration of the supervision in the segmented framework does not seem to outperform SUP. Therefore, we decided to proceed to implement the same controllers in the user study on the dVRK, with the supervision component of the segmented control converted back to fully autonomous, i.e. SEG-A.

III. Experiment

A user study was conducted on the real dVRK with 20 participants (10 females and 10 males, 22-44 years old, all without previous experience with the surgical robot system). The experiments were approved by the College Research Ethics Committee of Imperial College London (21IC7042). Participants were informed about the experiments' purpose and protocol and signed a consent form before starting.

A. User study on dVRK

While the majority of the experimental settings remain consistent with the simulated study, the real-world experiment introduces an added layer of complexity by including a physical obstacle. This increases the difficulty of the task and tests how the control strategies affect the user's experience and performance when interacting. To ensure safety throughout the study, we allow the operator to switch back to manual by pressing a pedal. Another pedal is used as a clutch to uncouple the controller from the robotic arms and allow repositioning for better ergonomics [22].

The task commences from a random position and encompasses twelve distinct trials, representing different combinations of mode, target, and obstacle. The experiment includes three modes (SUP, SEG-A, and FC) and two target objectives: placing the block into either a close peg or a far peg, as depicted in Fig. 5. As inexperienced participants are more prone to causing collisions between the pegs and the robot's arm, pegs on the right are excluded from the experiment to mitigate this risk. The trials are evenly divided, with six incorporating an obstacle and the other six without. The obstacle's function varies depending on the stage of the experiment. During the transfer of the peg to the closer pillar, the obstacle serves as a visual barrier, challenging the perception of the user and reliance on the agent. Conversely, when the peg is transferred to the more distant pillar, the obstacle takes on a physical role. The situation reflects challenges in surgery that the agent may struggle to overcome, such as unpredictable events not encountered in the training data.

Each participant, initially, is allocated a five-minute training to familiarize with the system and task. Following this phase, the experiment commences with a randomised sequence of inclusion and exclusion of the obstacle. At each round, the experiment is then conducted across three different control modes, in a randomized sequence to ensure unbiased evaluations. Upon completion of all trials, participants are requested to complete a questionnaire.

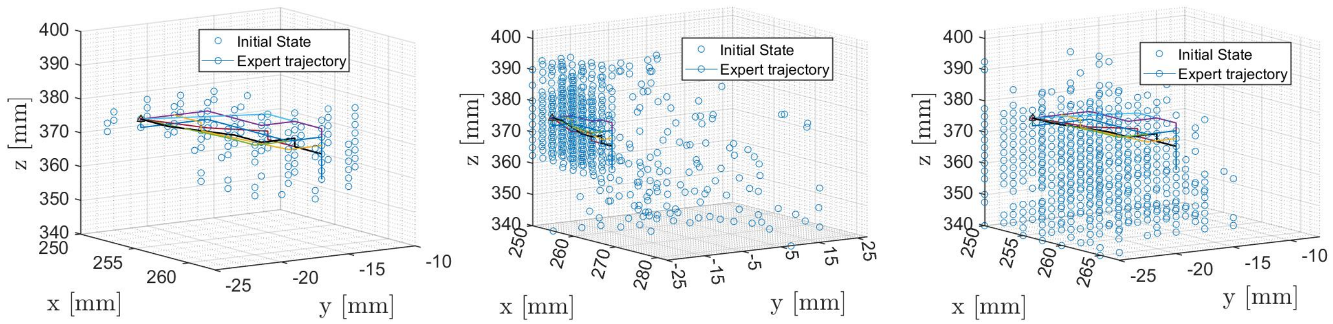

Fig. 4. Generalization ability test of EG MaxEnt IRL (left), GAIL (middle) and tGAIL (right). The three algorithms are trained with the same ten expert trajectories (marked with colored lines), and the successful trials' starting points are marked as initial states.

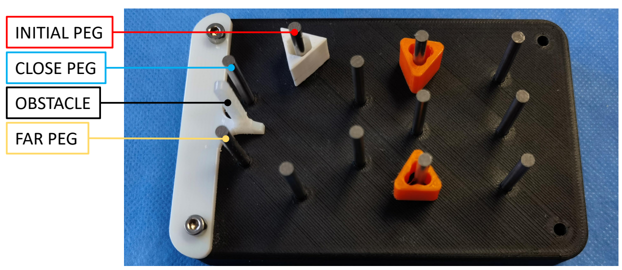

Fig. 5. Obstacle in the peg transfer task. The obstacle features a soft top and hard base. When transferring to a close peg, it serves as a visual barrier; when transferring to a far peg, it becomes a physical impediment.

IV. RESULTS

A. Generalisation Assessment

A test was conducted to assess the generalization ability and performance between EG MaxEnt IRL and tGAIL. In this generalization ability test (Fig. 4), both methods were trained on the same dataset, which consists of ten expert trajectories, all starting and ending at the same locations. By providing a limited number of expert trajectories, the evaluation focuses on the algorithms' adaptability and robustness.

Following training, the agent's performance is assessed by starting it from random points. Each initial state is denoted by a blue circle in Fig. 4, representing the agent's starting positions. In the generalization ability test, EG MaxEnt IRL succeeded in 117 states, GAIL achieved success in 452 states, and tGAIL succeeded in 508 states. Despite the added complexity of training GAIL and tGAIL with discriminator and generator components, it demonstrated superior learning and adaptability compared to EG MaxEnt IRL. GAIL excels near expert trajectories and in reaching distant positions, however it lacked consistency and robustness. In contrast, tGAIL consistently maintained steady performance.

B. Real-world Experiment

In the user study, despite the presence of a far obstacle, SEG-A exhibited an 85% success rate, a notable decrease compared to other tasks, which all achieved near 100%. The increased success rate compared to the simulation can be attributed to gaining 3D perception. The likelihood of obstacle interaction varied across modes: it was highest in FC, reduced in SEG-A, and minimum in SUP.

The performance analysis from the real-world experiment is depicted in Fig. 6 (a-b). The three control modes showed difference in efficiency ($p < 0.001$). SUP demonstrates to be faster compared to SEG-A ($p < 0.001$) and FC ($p = 0.001$), aligning with the simulation results. SEG-A and FC showed similar time performance ($p = 0.075$). The average and standard deviation (σ, μ) for FC, SEG-A, and SUP are $(92.1, 26.0)$, $(78.9, 19.3)$, and $(62.9, 13.8)$, respectively. The human input results showed to be not normally distributed, therefore we used Friedman test which reveled a difference in the group ($p < 0.001$). SUP not only completes the task in the least time but also requires the least operator's input $(0.047, 0.029)$ compared to FC ($p < 0.001$) and SEG-A ($p = 0.005$). FC exhibits the largest average and standard deviation $(0.105, 0.033)$, and SEG-A falls in the middle with $(0.084, 0.037)$. The experiment also examined clutch usage, as illustrated in Fig. 6 (c). The clutch is used to adjust the hand pose when it reaches workspace limits, and its use costs time and diverts the surgeon's attention [23]. Fig. 6 (c) represents the average time spent with the clutch enabled for each trial. Compared to FC, both SUP and SEG-A allow the operator to concentrate on the task rather than the workspace limits. This focus enhances efficiency and safety by potentially reducing surgery time.

As shown in Fig. 6 (d), SUP scored the lowest across all metrics, albeit with greater variability than SEG-A. Some participants exhibited conflicting decisions with the agent in SUP, a phenomenon absent in SEG-A. Both SUP and SEG-A were found to conserve participants' mental and physical effort, with SUP showing higher performance on average.

V. DISCUSSION

tGAIL's strategy of training from the worst starting point improved the policy generalisability, when compared to EG MaxEnt IRL and GAIL. This approach improves on the algorithm's ability to overcame learning challenges and exhibits enhanced robustness compared the other methods.

In the simulation study, increased autonomy in the task reduced the completion time, enhanced and stabilized the success rate, and predominantly saved participants' effort. This suggests that inexperienced users have a preference for shifting the control authority to the agent in order to improve performance, possibly due to unfamiliarity with the task.

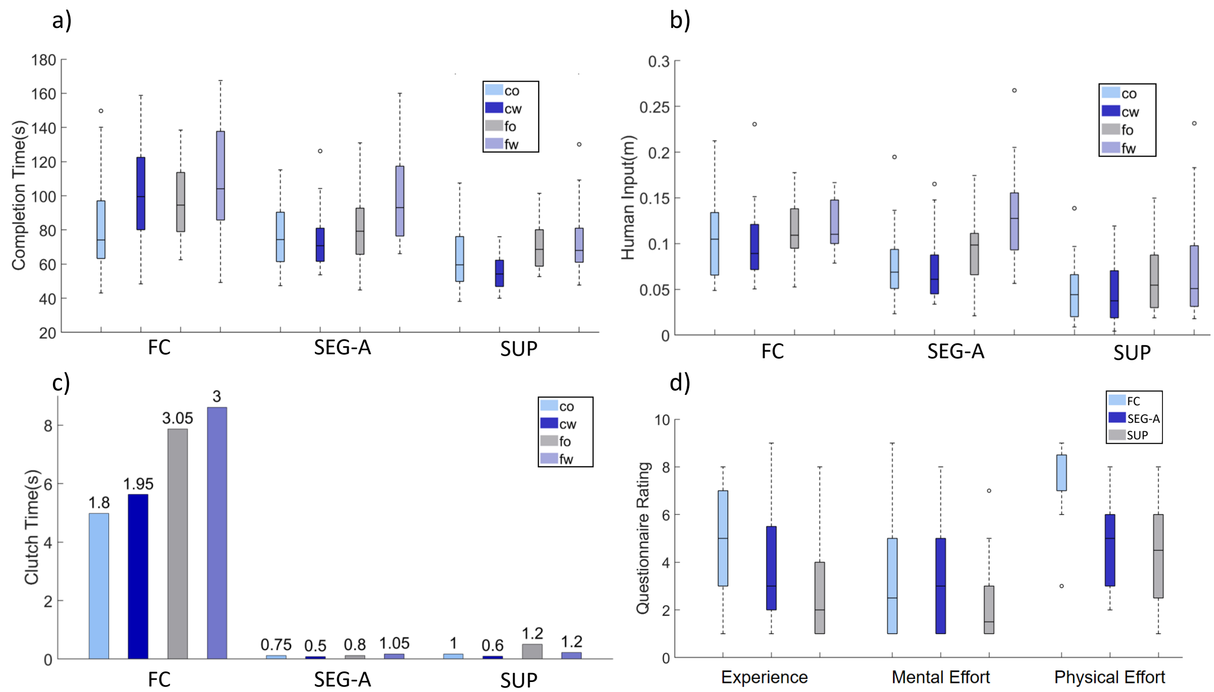

Fig. 6. Performance and questionnaire results from real-world experiment. (a-c) Completion time, human input and clutch usage of each participant using the three controllers. (d) Subject rating to questionnaire using NASA TLX. The terminology co, cw, fo, and fw stand for close obstacle, close without obstacle, far with obstacle, and far without obstacle, respectively.

In the real dVRK user study, SUP surpassed SEG-A in completion time, human input, and questionnaire ratings. In contrast, FC consistently demonstrated higher standard deviations. As autonomy increases, efficiency rises, simplifying the task for new users by reducing the required effort and minimizing variability. Although the increased complexity introduced visual and physical barriers to the operators, users' feedback after failing indicated that failures often arose from participant overconfidence as they became familiar with the task. Furthermore, the use of clutch significantly decreased in SEG-A and SUP compared to FC. This can be attributed to the fact that in FC the participants required more time and attention to adjust the controller. Conversely, in SUP and SEG-A, the clutch served as a pause to observe the environment or make quick adjustments.

Approximately 10% of users found SUP challenging due to conflicts with the agent's path selection, leading to varied user experiences. Users who effectively collaborate with the agent reported smoother experiences with minimal manual intervention. In contrast, 90% of users perceived FC as the most demanding mode, requiring full concentration and significant physical and mental effort. Among users, 45% preferred SEG-A for its reduced attention demands, while 55% favored SUP. When considering the user's perspective as potential patients, 45% expressed a preference for SUP, 30% for FC, and 25% for SEG-A. These preferences indicate the feasibility of implementing shared control methods in surgery. It is important to note that all participants were new to the surgical system. Due to their inexperience, they are likely to have found SUP akin to autonomous control, which offered a sense of safety, while still having the ability to make adjustments to the robot.

The user study in the peg transfer task highlights SUP's advantages in reducing completion time, human input, and enhancing the overall user experience. Although obstacles were used to emulate the challenge of a physical or visual barriers during the task, it is essential to acknowledge that, due to the simplified nature of this standardised task, the results cannot be directly translated to real surgical scenarios and that further work is needed to study more complex tasks that can actively engage the user, such as suturing.

VI. CONCLUSIONS

In this paper, we introduced and validated a novel priority-changing shared control method used with tGAIL, which demonstrated improved learning ability and robustness. The experiment conducted on the dVRK system demonstrated the feasibility of this shared control strategy.

The user study with the dVRK has further revealed the advantages of the various shared control approaches, with SUP showing notable performance improvements over SEG-A and FC. These findings, together with the higher acceptance of SUP than FC, highlight the feasibility of shared control methods for surgical applications. In future work, additional tasks will be investigated, such as needle manipulation and suturing, in order to prove the wide applicability of the controllers proposed.

ACKNOWLEDGMENT

This work was carried out with the resources provided by the Hamlyn Centre at Imperial College London.

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