Performance-driven tasks with adaptive difficulty for enhanced surgical robotics training

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***Abstract*— Surgical robotics training most often occurs through standardized curricula and exercises that lack customization and do not adapt to the different levels of proficiency that trainees often present. This work proposes a Virtual Reality (VR) simulator for surgical robotics that autonomously adjusts difficulty levels based on trainee performance, aiming to enhance skill retention and transfer. The study employs a performance-based adaptive difficulty approach, dynamically adjusting parameters of each task's morphology to match individual proficiency levels. The proposed adaptive simulator is evaluated against a non-adaptive counterpart through a week-long training program. The results demonstrate the effectiveness of the adaptive simulator in enhancing performance at higher difficulty levels, supporting its potential to benefit surgical education by providing a tailored and scalable training approach.**

Surgical Training, Adaptive, Difficulty, Performance

I. Introduction

Over the past few decades, the field of surgery has undergone a profound transformation with the introduction of Robot-Assisted Minimally Invasive Surgery (RAMIS). The widespread adoption of robotic surgical platforms has introduced a new era in surgical practice. However, realizing the full potential of these systems requires a highly skilled surgical workforce. Proficiency in using robotic surgical systems is essential for ensuring patient safety and optimizing surgical outcomes. Attaining this level of skill and expertise necessitates comprehensive and rigorous training programs that guarantee a proper skill transfer towards the real surgical scenario. More specifically, surgeons must become adept at manipulating robotic instruments, interpreting visual feedback, and adapting to a novel surgical environment [1].

Surgical simulators have emerged as indispensable tools for training, and in most cases companies sell a simulator alongside the robot to ease the integration into the surgical workflow. However, such simulators often lack the capability to provide an adaptive and customized learning experience, offering a range of different exercises that only have a couple of pre-defined difficulty levels which often have to be manually chosen by the trainee or its supervisor. A limited range of available difficulty levels does not allow the trainees to properly explore their capabilities and might cause their learning curve to saturate earlier.

This work proposes to overcome such limitation through the development of a Virtual Reality (VR) simulator for surgical robotics that autonomously tailors its difficulty to the trainee's performance, allowing him to be constantly challenged during the execution of the training tasks.

II. State of the Art

The role of VR simulators as alternatives to the traditional dry-lab setups has already been studied and accepted [2]; moreover, their capability of translating the acquired skills to the real operating room has been demonstrated and reported [3]. Simulated robotics platforms offer a wide range of exercise to train on, real-time video feedback, performance analysis and personalized curricula: these features have been shown to enhance robotic surgical education and improve surgical skills [4]. In a virtual environment, all geometrical and kinematic information is readily available and the calculation of quantitative and objective performance metrics is precise, unbiased and facilitated, allowing for a comprehensive and accurate assessment of performance and progress [5].

Although self-assessment is a key factor in surgical learning [6], the role of an expert supervisor that monitors the learning process and adjusts it according to the proficiency remains crucial. Still, surgical simulators are not yet fully capable of carrying out a comprehensive, effective and completely personalized training program for novel surgeons [7], which still necessitate a considerable amount of supervision from more expert residents. Proficiency-based personalized training has been linked to skill retention [8], and as a matter of facts in recent years several research works have demonstrated that trainees benefit from the introduction of a higher level of personalization into the training programs. Mariani *et al.* introduced an adaptive training curriculum for robotic surgery that dynamically adjusts the training schedule according to an objective evaluation of the subject's performance [9]. In contrast to a task-dependent performance assessment strategy, Ershad *et al.* presented a framework enabling adaptive training through near real-time performance evaluation based on intuitive styles of surgical motions, and designed a task-independent haptic feedback system intended to aid in the correction of movement styles [10]. Fan *et al.* developed a surgical simulator that embeds "assistance-as-needed" force feedback [11]. Similarly, Oquendo *et al.* found beneficial effect of both haptic guidance and haptic error amplification in the context of surgical simulation [12]. Caccianiga *et al.* [13] investigated the effect of a personalized balance between guidance and feedback in augmented training. The extent to which these approaches offer adaptiveness varies considerably: many of these simulators provide performance metrics and feedback to subjects during [14] or after each task completion, allowing them to understand aspects

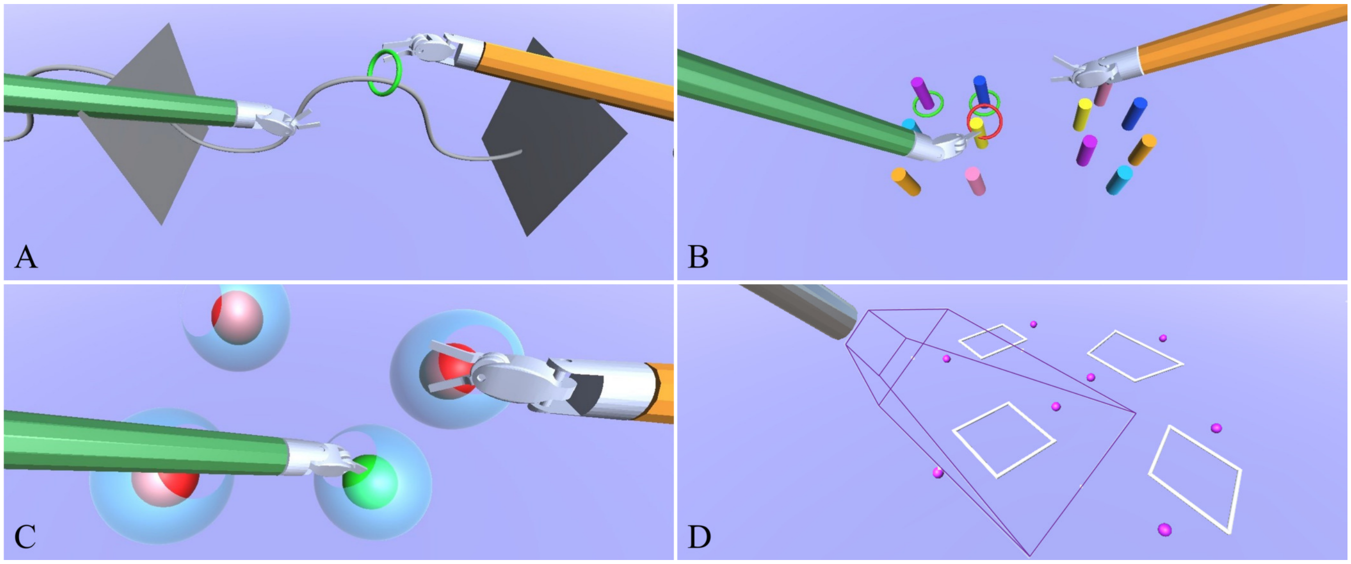

Fig. 1. The four training tasks featured in the simulator. A: Path Chaser, B: Peg Transfer, C: Target Touch, D: Camera Navigation

that need improvement. Some simulators offer progressively more challenging tasks as subjects master basic skills [15]. With the potential of adaptive training in enhancing skill acquisition and retention [16], in recent years there has been a growing interest in adaptive training methods in medical education [17].

Although other research works have been conducted on performance-based adaptive curricola [18] where the order in which tasks are shown to the trainee varies in relation to its proficiency according to skill levels, the possible benefits of changing the difficulty level of the tasks has not been explored yet. Under the hypothesis that effective knowledge acquisition hinges on the accessibility and comprehensibility of information during a performance instance, if a training task is insufficiently challenging for a trainee's current abilities, it may not provide enough information for skill improvement.

The Optimal Challenge Point (OCP) [19] represents the ideal difficulty level for an individual of a specific proficiency to maximize learning. Surpassing the OCP, however, can lead to an overload of information, exceeding the individual's processing capabilities and thus diminishing learning benefits.

Aim of this work is the development and evaluation of performance-driven tasks within an adaptive simulator in a Virtual Reality environment, tailored for surgical training using a teleoperated robotic system. This adaptive simulator dynamically adjusts the level of task difficulty based on the subject's performance aiming to improve skill retention and transfer, as well as enhance generalization capability towards the intraoperative phase.

III. Materials and Methods

A. The Simulated Training Environment

The surgical training simulator features four training exercises, shown in Fig. 1. Each exercise targets a different surgical skill and is characterized by one morphological feature parametrized with respect to the difficulty level:

- **Path Chaser**: The trainee grabs a ring and carres it along a curvilinear path firstly using the right hand, then, upon reaching the midpoint, exchanging to the left hand. This task is designed to train wrist articulation. The path to be chased is shaped as a sinusoid with a frequency proportional to its difficulty. With higher difficulty, the path has higher curvatures and requires more complex wrist articulation
- **Peg Transfer**: The user slides a ring off a peg with the left hand, passes it to the right hand, and re-thread it onto a correspondingly colored peg. This task is designed to train hand-eye coordination. The pegs have a diameter linearly related to its diffucuty. At higher difficulty, the gap between the ring and the peg gets narrower, requiring more accurate hand-eye coordination.
- **Target Touch**: The trainee touches red spheres with the instrument's tip passing through the circular opening of a transparent shell without touching the latter. This task targets depth perception skills. The target spheres have a radius inversely related to its difficulty. At higher difficulty, the targets become smaller and they are harder to reach, requiring enhanced depth perception.
- **Camera Navigation**: The user controls the endoscope camera to frame specific shapes. This task is designed to develop camera navigation skills. The obstacles are positioned at a distance inversely proportional to the task difficulty. At higher difficulty, the obstacles are closer to the targets, requiring higher camera positioning skills to correctly frame them.

Fig. 2 shows the tasks at the minimum (D = 0) and maximum (D = 1) difficulty levels, and the task can be assigned a difficulty level form a continuous range between the two extrema. This continuum provides a comprehensive spectrum

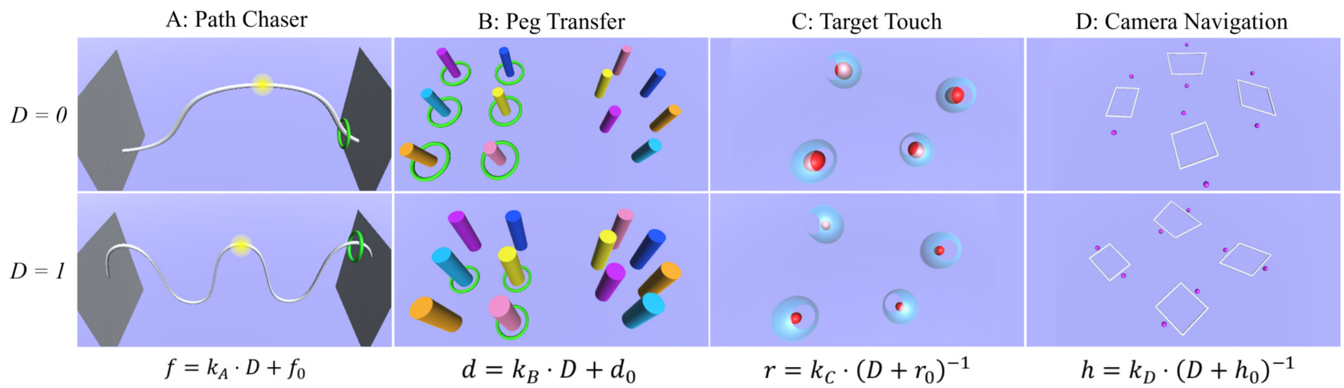

Fig. 2. Description of the task adaptivity, with the minimum (top row) and maximum (bottom row) difficulty level of each task featured in the simulator. The easier version of the tasks correspond to $D = 0$ and the most challenging to $D = 1$: the difficulty level is linear ranging from 0 to 1. In Task A, f is the frequency of the sine wave path; in Task B, d is the diameter of the pegs; in Task C r is the radius of the red spheres; in Task D h is the distance between the purple balls and the white frames. f_0, d_0, r_0 and h_0 determine the task morphology at $D = 0$

for adaptive challenges. The morphology of the task at the minimum and maximum level is set *a priori*.

B. Performance-based Adaptive Difficulty

The novelty of this research consists in dynamically adjusting the geometry and morphology of the featured tasks so that they adapt to the user's performance. Each of the above tasks has one key morphological parameter which determines its difficulty level D. The value of D ranges from 0 to 1, where at $D = 0$ the task is at its least difficulty and at $D = 1$ at its most challenging.

The difficulty level D for each task is set to be a function of a Performance index P calculated upon completion. P is a numerical indicator of the quality of the task execution in relation to the task's target skills, and it is derived as the weighted sum of a set of task-specific performance metrics m_i: these metrics are described in Table I, along with the respective weight. The value of the weights is chosen in such a way that errors like collisions more significantly penalize the final score, whereas metrics like completion time have a lesser impact, as precision and accuracy are prioritized over speed in the context of RAMIS. More specifically, we took inspiration from [18] to sensibly determine their value.

Metrics are each normalized as:

$$m'_i = sat\left(0, \frac{m_i^{best} - m_i}{m_i^{best} - m_i^{worst}}, 1\right) \tag{1}$$

with $sat(\cdot)$ being the saturation function that clips the co-domain to the $[0; 1]$ range and where m_i^{best} and m_i^{worst} are the best and worst values for the i-th metric respectively, measured in a pre-experimental phase. Precisely, m_i^{best} and m_i^{worst} are set as the subject-wise maximum an minimum values of each metric recorded during the task execution prior to the experimental phase. For all metrics, lower is better. The performance index P of the k-th task repetition is then calculated as a linear combination of the normalized metrics m'_i:

$$P_k = 1 - \frac{\sum_i m'_i w_i}{\sum_i w_i} \tag{2}$$

TABLE I

DESCRIPTION OF PERFORMANCE METRICS FOR EACH TASK WITH THE RESPECTIVE WEIGHT

Task	m_i	Description	Weight
A	m_1	Cumulative distance updated for each frame between the current position of the ring's centre and the ideal path [m]	3
	m_2	Number of collisions between the ring and the wire [adim.]	2
	m_3	Completion time of the task [s]	1
B	m_1	Number of collisions between the ring and the peg [adim.]	3
	m_2	Completion time of the task [s]	1
C	m_1	Number of collisions between the tip of the instrument and the external shell [adim.]	3
	m_2	Completion time of the task [s]	2
D	m_1	Number of framings with the shape partially inside the camera frustrums [adim.]	3
	m_2	Number of framings with the error points inside the camera frustrums [adim.].	2
	m_3	Completion time of the task [s]	1

The performance ranges therefore from 0 to 1, with 0 corresponding to poor and 1 to optimal. The adaptive simulator dynamically adjusts the task's difficulty in response to the trainee's performance with the following rationale: 1) the trainee executes the task at a generic repetition k; 2) upon the completion of the task, P_k is computed from the set of metrics; 3) the difficulty level for the next repetition of the task D_{k+1} is directly mapped one-to-one to the P_k value as:

$$D_k = P_{k-1} \tag{3}$$

4) the trainee executes the task at the next repetition $k + 1$ and the cycle repeats. At $k = 0$ the task is initialized by setting $D = 0$.

C. Surgical Robotic Framework

This research was conducted on a daVinci® surgical robot integrated with the dVRK framework [20]. The virtual scenes of the surgical simulator are developed in the Unity physics engine: the virtual environment consists of a 3D replica of the dVRK and virtual objects of the training task. A ROS network allows the communication between the Master-Tool Manipulators (MTMs), moved by the trainee at the teleoperation console, and the Patient-Side Manipulators (PSMs) in the virtual environment. The virtual PSMs move in the exact same way as the real ones would. Two virtual cameras, positioned at the tip of the virtual Endoscope-Camera Manipulator transmit the rendered 3D scene to the two oculars of the High-Resolution Stereo Viewer at the teleoperation console in real-time. The whole system runs at 30 frames per seconds.

D. Pre-Experimental Phase

Prior to the experimental phase, a data acquisition phase was conducted to perform variance analysis crucial for determining the required sample size for the experimental group. Nine volunteers—six males and three females, aged between 21 and 25 years and all right-handed—participated in this phase. Of these, seven were novices with no prior experience using a VR surgical robotics simulator. Each volunteer was asked to perform each task once at an intermediate difficulty level $D = 0.5$. This level was chosen based on the assumption that it would neither be too simple nor too challenging, aiming to standardize the experience across participants. Tasks were assigned in a random order. At the conclusion of this phase, participants were asked to rank the tasks by perceived difficulty. To achieve a confidence level of 0.80, calculations initially indicated that a sample size of 12 was required. The sample size calculation was based on an anticipated medium effect size, standard deviation estimates from preliminary data, and a power of 0.80, using formulas from Cohen's statistical power analysis.

E. Experimental Protocol

To evaluate the effectiveness and advantages of the developed adaptive simulator, an experimental study is carried out with a group of 12 subjects, consisting of seven males and five females, aged between 19 and 30 years, all of whom are right-handed. Subjects did not have a medical background and all of them had under 10 hours of experience in teleoperating the surgical robot. Subjects are randomly divided into two groups of six selected samples:

- **Adaptive Group:** Undertakes the training using the adaptive simulator.
- **Control Group:** Undertakes the training using a standard non-adaptive simulator.

The non-adaptive simulator is implemented using the same environment and tasks as the adaptive one, but D is consistently set to 0.5 and it is not dependent on the performance. We designed a training curriculum of a duration of one week, wherein the subjects are required to repeat every task four times each training day, as short practice sessions across a long period are more beneficial than one long massed practice session [21]. Indeed, the skills being learned have more time to be cognitively consolidated between practices.

The training phase, the schedule of which is outlined in Table II, is conducted as follows:

- **Day 1:** Both groups receive an explanation of the dVRK and its teleoperation principles, undergo practical demonstrations, and perform each task at intermediate difficulty $D = 0.5$ for baseline consistency. To aid acclimation to console commands and the virtual environment, the tasks are presented in ascending order of difficulty (Camera Navigation, Target Touch, Peg Transfer, Path Chaser), based on the feedback from participants in the preliminary phase. This strategy intends to gradually increase the information load, enhancing the learning process's smoothness. The best and worst values recorded for each task metric are used for metric normalization.
- **Day 2 - Day 5:** The adaptive group completes each task four times with a dynamically adjusted difficulty level D based on the adaptive algorithm. The control group performs tasks four times with a fixed $D = 0.5$. The randomization of task order is implemented to mitigate potential biases in performance due to the sequence of task execution. The performance index is immediately communicated to the trainees of both groups at task completion.
- **Day 6:** A final test is conducted, with subjects from both groups performing each task three times with sequentially increasing difficulty $D \in [0, 0.5, 1]$. The tasks are presented in a random order.

IV. Results

A. Training phase

Line plots in Fig. 3 report the performance trends in relation to the repetition number: trends increase for both the groups. The adaptive group shows qualitatively higher performance oscillations due to the D adjustments made by the adaptive algorithm, while the control group's performance increases more uniformly.

TABLE II

Training Schedule: On Day 1 the tasks are presented in the following order: Camera Navigation, Target Touch, Peg Transfer, Path Chaser. From Day 2 to Day 6 the tasks are presented in a random sequence

	Day 1 Set Up	**Day 2** Training	**Day 3** Training	**Day 4** Training	**Day 5** Training	**Day 6** Test
ADAPTIVE Group	$D = 0.5$ 1 repetition	$D_k = P_{k-1}$ 4 repetitions	$D_k = P_{k-1}$ 4 repetitions	$D_k = P_{k-1}$ 4 repetitions	$D_k = P_{k-1}$ 4 repetitions	$D = [0, 0.5, 1]$ 3 repetitions
CONTROL group	$D = 0.5$ 1 repetition	$D = 0.5$ 4 repetitions	$D = 0.5$ 4 repetitions	$D = 0.5$ 4 repetitions	$D = 0.5$ 4 repetitions	$D = [0, 0.5, 1]$ 3 repetitions

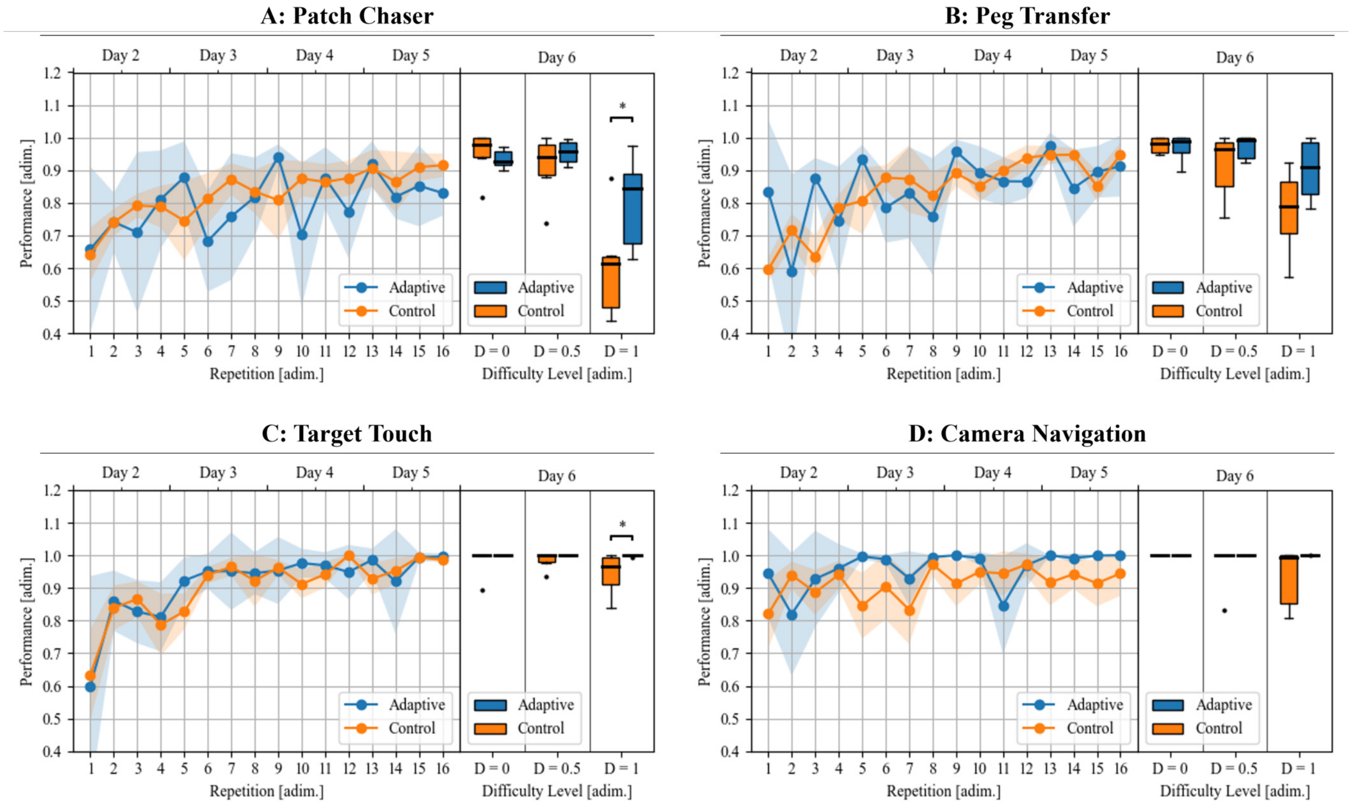

Fig. 3. Performance trend during the training phase from Day 2 to Day 5, and performance distibutions on the final testing phase on Day 6. In the trends, the dots represent the average performance of trainees belonging to each group, while the shaded area cover the standard deviation. Boxplots are referred to the median and IQR of the groups, at each difficulty level. For task C: Target Touch and D: Camera Navigation, most trainees saturate the learning curve and the performance is optimal, hence a boxplot squished on the median value.

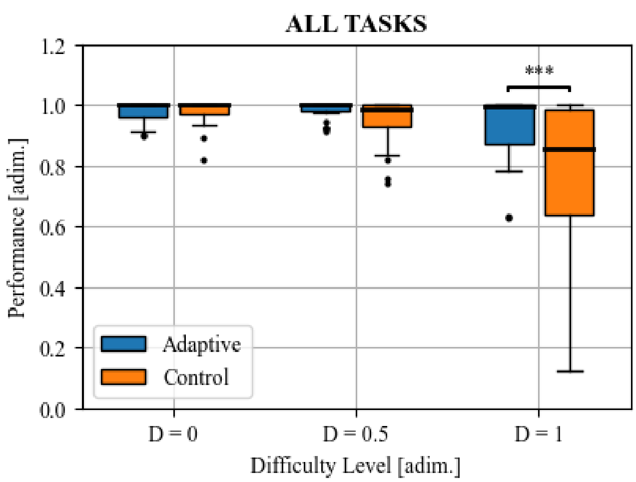

Fig. 4. Performance on the test phase performed on Day 6. Boxplots consider all tasks together.

B. Test phase

Fig. 3 also shows performance distribution on the final test day, where the performance of the two groups is compared across 3 difficulty levels. Additionally, Fig. 4 shows performance distributions across difficulty levels without task differentiation. The performance gap between the group that underwent adaptive training and the control group is more evident at higher difficulty levels. To compare the two groups, we employ an un-paired Mann-Whitney U-Test. A *p-value* less than 0.05 is considered significant.

TABLE III

p-values FROM THE STATISTICAL TESTS

Task	$D = 0$	$D = 0.5$	$D = 1$
Path Chaser	0.2290	0.4848	0.0411
Peg Transfer	1.0000	0.2257	0.1320
Target Touch	0.4047	0.0740	0.0263
Camera Navigation	1.0000	0.4047	0.0608
ALL TASKS	0.8495	0.0707	0.0059

At low and medium difficulty ($D = 0$ and $D = 0.5$) there is no difference between the performance of the the two groups: crucially though, in each tasks the adaptive group outperforms the control group when tested on the tasks at highest difficulty ($D = 1$). This difference in performance is significant for two out of the four tasks, and it is strongly significant for a U-Test that compares a distribution of performance across tasks (Fig. 4). All *p-values* are repoted in Table III

V. Discussion

Performance trends in Fig. 3 show that both groups achieve skill learning as their performance increase with the number of repetition. In the Path Chaser and Peg Transfer tasks, decreasing oscillations suggest performance stabilization at high P scores, despite the absence of a visible plateau. As expected, trainees in the adaptive group are subject to higher performance variability: this seems to be beneficial, as in this adaptive framework it allows to explore more difficulty levels and improve their abilities as a consequence.

The boxplots in Fig. 3 display P values on the final test day: at this stage, we compare the performance of the two groups at three distinct difficulty levels. All tasks show similar performance between the two groups at the low and medium difficulty (as confirmed by the *p-values* in Table III) confirming that both groups reached the same proficiency. Crucially, when performing the tasks at their most challenging versions, the adaptive group outperformed the control group in all cases, two of which are statistically significant. The adaptive framework allowed the trainees to become proficient at all skill levels: while the control group trained on a fixed difficulty, their skills developed in relation to that difficulty specifically. The adaptive group, instead, was constantly challenged in relation to the proficiency reached at every repetition: we argue that this factor allowed them to obtain a more comprehensive and robust skillset. Limitations of this study include the enrollment of non-medical partecipants in the experimental study, which might be subject to different learning curves, and in the limited population size. Moreover, the long term effectiveness of the adaptive protocol have not been explored.

VI. Conclusions

This research work investigated the benefits of performance-driven tasks with adaptive difficulty in the context of surgical robotics training: through the development and experimental evaluation of an adaptive framework, the study has shown that dynamically adjusting task difficulty levels to individual performance can significantly improve skill acquisition in surgical training. Key findings are that an adaptive simulator leads to quicker proficiency in tasks when compared to a non-adaptive one. Overall, the results of this study support the integration of adaptive training methods in surgical education. The application of the adaptive simulator in a VR setting not only enhances learning outcomes but also offers a scalable, safe, and efficient approach to training future surgeons.

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