2018 IEEE International Conference on Robotics and Automation (ICRA)
May 21-25, 2018, Brisbane, Australia

Robotic Assistance-as-Needed for Enhanced Visuomotor Learning in Surgical Robotics Training: An Experimental Study

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Abstract— **Hands-on training is an indispensable part of surgical practice. As the tools used in the operating room become more intricate, the demand for efficient training methods increases. This work proposes a robotic assistance-as-needed method for training with surgical teleoperated robots. The method adapts the intensity of the assistance according to the trainee's current and past performance while gradually increasing the level of control of the trainee as the training progresses. The work includes an experiment comprising 160 acquisition sessions from 16 novice subjects performing a bimanual teleoperated exercise with a da Vinci Research Kit surgical console. Results capture the subtleties in the task's learning curve with and without robotic assistance and hint at the potential of robotic assistance for complex visuomotor training. Although robotic assistance for motor learning has received mixed results that range from beneficial to detrimental effects, this study shows such assistance may increase the rate of learning of certain skills in complex motor tasks.**

I. Introduction

Practical training has been an indispensable part of surgical education requirements since the early years of modern surgery [1]. In addition to reinforcing theoretical learnings, such training endows physicians with hands-on experience and psychomotor skills. The latter has increasingly become relevant as more innovative instruments and techniques are introduced into the operating room. For example, the advent of Minimally Invasive Surgery generated great demand for practical training [2]. The techniques were new to surgeons and they had little, if any, preparation to employ laparoscopic tools. Although robots such as the da Vinci Surgical System (Intuitive Surgical, CA, USA) greatly simplified operating with minimally invasive tools by adding intuitive master-to-slave kinematic mapping, 3D vision, and enhanced ergonomics, visuomotor training remains an essential and time-consuming part of preparation for today's residents and practicing physicians who wish to expand their surgical skills. The substantial demand for efficient training in surgery has driven researchers to continue the search for new approaches that can enhance the efficacy of the training process. Among the studied concepts, physical robotic assistance is one of the less visited. The cause of this lower popularity is twofold. First, providing such assistance for an elaborate task can be highly complicated. In addition, there are valid concerns that physical guidance may change the dynamics of the task to be learned, and consequently impair learning. As will be discussed in detail in the next section, the few experimental studies investigating robotic assistance methods for surgical tele-operation training, do not provide conclusive evidence on outcomes, which we believe can be due to lack of task complexity and short study duration. This work aims at addressing such shortcomings with a multiple-day experimental study of a skill-based haptic guidance method with an elaborate Virtual Reality (VR) task.

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II. Related Work

Early demands for practical training in laparoscopic procedures were met with live animal exercise [2]. Ethical issues and costs motivated the replacement of animal models with dry lab laparoscopic simulators, which were shown to be effective training tools [4]. Later, computer-based platforms were adopted making it possible to train psychomotor skills by consequence-free simulations from basic exercises to full operative procedures. It has been argued that a substantial progress in the learning curve can be achieved by using repetitive VR tasks before starting practice on patients [5]. Moreover, computer-based VR training offers objective performance assessment during and after training that can accelerate the learning process [6].

Robot-assisted minimally invasive surgery systems with actuated master manipulators provide a unique opportunity to act on motor inputs of the human user explicitly. The mediation is in form of Cartesian wrenches applied by the manipulator to the user's hand while the manipulator is controlled by the user to operate the slave (patient-side) robot arm [7]. These robotic assistive methods have been studied in the surgical robotics literature (under different terminologies such as active constraints, virtual fixtures, or haptic guidance) with the premises of increased safety and/or accuracy, and decreased cognitive load [8], [9]. Effects of robotic assistance in motor learning have been previously investigated in the fields of motor behavior, neuroscience and rehabilitation. When performance after training with and without robot assistance is contrasted, the findings range from beneficial effects [10], [11] through null [12] to detrimental effects [13], [14]. Few works have found significant benefits; a potential explanation is that haptic guidance can considerably alter the dynamics of the task and impede motor learning [15]. However, guidance may improve the learning curve of motor tasks during the cognitive phase, in which subjects acquire an understanding of what is required to successfully conduct the task [10]. In this initial stage of learning, especially for a complicated visuomotor task, haptic guidance may significantly improve learning, not by teaching the motor skill itself, but through the reduction of cognitive load and allowing for a more focused learning [11]. For instance, in training of surgical tasks with complex kinematics, where it has been shown that residents can face difficulties due to poor hand-eye

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coordination [16], robotic assistance may speed up the initial motor learning phase by letting the subjects focus on some aspects of the involved motor skills while other aspects are handled by the assistance. Therefore, the question this work attempts to answer is not whether trainees can acquire superior skills after training with robot-assistance, but whether they can acquire the skills faster.

To test such a hypothesis experimentally, the visuomotor task should be designed complex enough to have a considerable learning curve. This lets the subjects adapt to the assistance and to differentiate the skills required to execute the task successfully with and without the assistance. If the task is not demanding, the assistance is likely to result in null effect or even prolong the learning. Coad et al. [12] studied the effects of convergent and divergent guidance wrenches in a peg transfer task performed by 15 non-medical subjects divided in 3 groups, using a da Vinci research kit. Results show no statistically significant difference among the three training methods. As authors report, due to the simplicity of the task, most subjects reached a high level of proficiency in the initial non-assisted phase and by the time the robotic assistance was applied, the learning curve had almost reached its final phase. In [17], 7 non-medical subjects participated in a 7-session training experiment on tele-operated path tracking. Although the effects of robot-assistance on motor learning were not studied, the captured learning curve across 9 measured metrics can shed some light on what skills are learned in a simple tele-operation task. Concerns regarding creating dependency on the robotic assistance [18], can be addressed by gradually decreasing the guidance intensity as the user learns [19]. This approach, which has been formulated in the rehabilitation literature as assistance-as-needed [20], prevents the assistance from minimizing the voluntary control, which has been shown to reduce the effectiveness of learning. In this context, the Challenge Point Theory (CPT) [21] suggests that optimal learning correspondence to a specific Functional Task Difficulty (FTD), determined by the skill level of the trainee and the current conditions under which the task is executed. In a robot-assisted motor task, the latter is affected by the intensity of the assistance, such that higher assistance reduces the task difficulty level. Modulating the intensity of the robot assistance can thus provide a direct way of adapting the task difficulty in order to keep the user at the so-called Optimal Challenge Point (OCP). This can adapt the amount of information and the cognitive load to user´s performance and potentially speed up the visuomotor learning.

This paper presents an experimental study of a novel robot assistance-as-needed method in teleoperated surgical robotics training. The work aims to address some shortcomings of the previous experimental studies, namely, investigating a more demanding bi-manual motor task and increasing the number of training sessions.

III. Methods

A. Experimental Setup

A da Vinci Research Kit was used for the experimental study. This is a standard da Vinci surgical system that is integrated with control hardware and software that allow for reading the measurements and sending commands to the joints of each manipulator of the system directly [3]. The dVRK's surgeon console includes a stereo viewer (each viewer has a resolution of 640x480), a foot-pedal tray, two master manipulators each comprising 7 actuated joints and a passive gripper. The VR environment was designed using our recently developed open-sourced Assisted Teleoperation with Augmented Reality (ATAR) framework [22]. The developed software architecture for this study encompasses five Robot Operating System (ROS) nodes, namely: core simulation, teleoperation, assistance wrench generation, Graphical User Interface (GUI) and bridge to dVRK controllers. The core simulation node generates the graphics and physics of the virtual objects, along with the task logic and the desired poses for the guidance. The simulated environment runs at 25 Hz, while the desired pose of the ring is calculated in a separate thread at 500 Hz. The 3D graphics are produced using the Visualization Toolkit (VTK) and OpenGL libraries and are sent to the dVRK stereo displays through two output ports of a GeForce GTX 980 Ti GPU (Nvidia Corp.) with a refresh rate of 25 Hz. The Bullet physics library [23] was used to perform the dynamic simulation of 3D virtual objects. The robotic tools are simulated as kinematic objects resembling the da Vinci endoscopic tools and their pose is constrained to that of the master devices through the teleoperation node and with a translation downscaling factor of 2. To ensure real-time interactivity with realistic collision detection, mesh objects are approximated through convex hull decomposition [24]. Through the GUI node, the operator can control the task states and set various parameters. The node also collected, processed and recorded data at 30 Hz. Furthermore, the GUI node evaluated the performance of the user, and calculated and communicated the intensity of the haptic guidance as a normalized number to the guidance wrench generation node.

B. Task

The developed visuomotor task (Fig. 1) was a classic steady-hand game often included in surgical robotics training curricula [25]. A user moves a ring along a curved wire pathway, while attempting to avoid the ring and wire making contact and keeping the ring's plane perpendicular to the wire's tangent. The task is a test of both manual dexterity and hand-eye coordination in which the user must simultaneously control both the position and orientation of the ring. The curved wire was designed to span along the three Cartesian dimensions and to require three 90° wrist rotations from each hand for a successful completion. In each repetition, the subject had to grasp a ring from the right side of the wire with the right hand tool (Fig 1.b), carry it to the middle of the wire and transfer the ring to the left tool (Fig 1.c), and carry the ring to the left end of the wire (Fig 1.d).

An important factor in keeping subjects engaged and motivated is to provide them with intuitive performance feedback. This was provided in two ways. First, the ring's color shifted gradually from yellow to red as the ring approached the wire, encouraging the subject to keep the wire in the center of the ring. Second, upon the completion of each repetition, the subject's performance was reported to him/her by assigning a color from green to red (standing for good to bad performance), to one of the 4 gray spheres in the bottom of the screen that showed the performance history for the last

4 repetitions. Two small circular signs marked the start and end points respectively on the right and left ends of the wire. As soon as the ring passed the starting point and until it reached the end point, the performance was recorded and this was informed to the subject by changing the color of a cubic object in the scene to orange. The friction of the rings with the wire was intentionally reduced so that attention had to be paid while grasping the ring, since hitting the ring with gripper would result in the ring sliding away on the wire.

C. *Acquisition Procedure and Performance Metrics*

To study the effects of the performance-based haptic guidance, 16 non-medical participants (22 to 31 years old, 12 males and 4 females, all right-handed) were randomly divided in two groups of 8: a “null group” that performed the task without receiving assistance and an “assisted group”. A critical point in conducting a motor learning human subject study, where the performance of subjects is the principal metric, is to ensure that the subjects remain motivated during the entire experiment and that fatigue does not affect the outcomes. Therefore, the experiment proceeded in sessions of 8 repetitions lasting an average of 10 minutes (the longest session took 24 minutes), and with a brief break after the execution of repetition 4. Each subject attended two sessions per day: one session in the morning and the other in the afternoon. All subjects trained on the same path. To derive the natural learning curve of the task, as required to set some parameters of the assistance for the assisted group, the null group was studied first. Before the subjects began their first session, they were introduced to the dVRK, were shown a video of a successful task execution and received an explanation of the procedure, and were given 3 minutes to familiarize themselves with the dVRK and the task before the first acquisition started. The acquisition sessions were continued until the overall learning curve stopped showing a sign of progress. The assisted group underwent the same introductory procedure. However, their first session started with 3 null repetitions and continued with 5 assisted ones. The 3 null repetitions were acquired to validate that both groups belonged to the same statistical population of performance at the beginning of the experiment. In the next sessions of the assisted group, the intensity of the assistance was modulated as described in Section III.E. The experiments were carried out in accordance with the recommendations of our institution with written informed consent from the subjects in accordance with the declaration of Helsinki.

The performance was calculated in terms of completion time and the ring’s translation and rotation distance from its ideal pose. At any instant, the norm of the vector from the ring’s current position to its desired position was calculated as the translation error. The rotation error was computed as the angle of the rotation (axis and angle representation) taking the ring to its ideal orientation. The RMS of these quantities as well as the maximum translation error during an entire repetition was taken as accuracy performance metrics. These 4 metrics are standardized across all subjects to have a value from 0 to 1 representing respectively bad and good performance. Towards this goal, a metric $x^*_{repetition}$ is normalized, scaled (to utilize the entire normal range) and saturated as:

$$x^*_{repetition} = sat(0, \frac{x_{best} - x_{repetition}}{x_{best} - x_{worst}}, 1) \quad (1)$$

where the $sat(a, x, b)$ function saturates its input x between minimum a and maximum b. The constant values x_{worst} and x_{best} were selected for each metric after the learning curve of the null group was acquired.

D. *Robotic Assistance Method*

The ideal pose of the ring is defined as a pose that places the center of the ring on the center of the circular section of the wire and aligns the z-axis of the ring (the axis perpendicular to the plane passing through the ring’s large circular section) with the tangent of the wire. This is computed by finding the closest points on the wire mesh to a set of 3 points on the ring and using simple trigonometry. When the ring is grasped by a gripper, the relative transformation of the gripper with respect to the ring is used to find the gripper pose that would place the ring on its ideal pose. The calculated pose of each gripper is sent to the assistance wrench generation node so that a

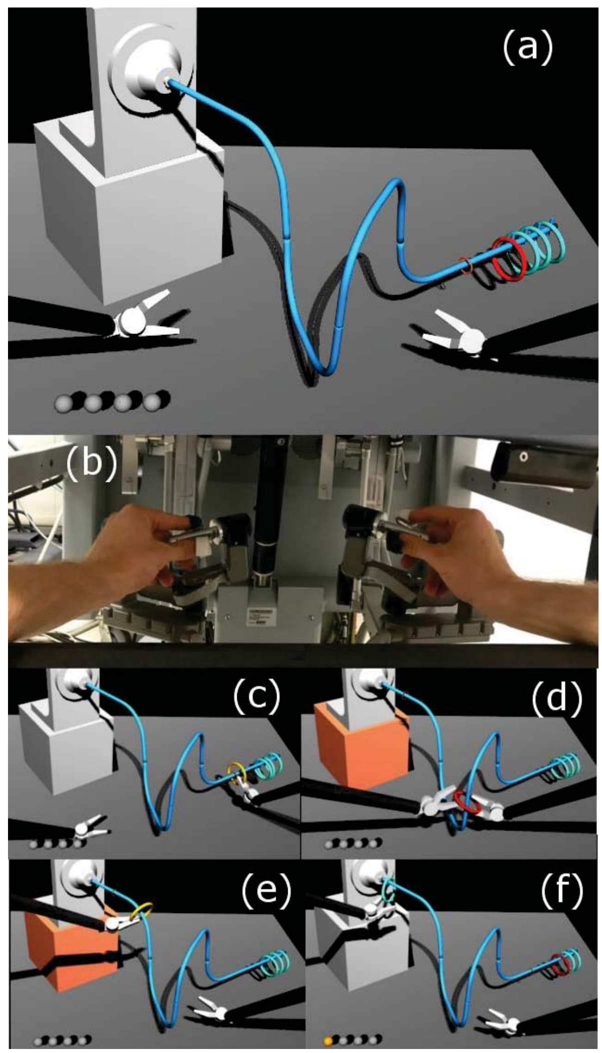

Figure 1. The virtual environment and the studied task. Figure (b) shows the master manipulators of the da Vinci Console. Figures (c) to (f) represent the steps involved in a repetition from grasping the ring (c), carrying it to the middle of the wire and transferring it to the left tool (d), carrying with the left tool to the left end of the wire (e) and releasing the ring after passing the end point (f).

corresponding wrench can be found for the master manipulator controlling the virtual gripper.

A simple viscoelastic Active Constraint (AC) is used as the guidance method. Given a desired pose T_d: $[\boldsymbol{p}_d, \boldsymbol{q}_d]$ and a current pose T_c: $[\boldsymbol{p}_c, \boldsymbol{q}_c]$, where $\boldsymbol{p}_x$ is the position vector in $\mathbb{R}^3$ and $\boldsymbol{q}_x$ is a unit quaternion in $\mathbb{R}^4$, a viscoelastic AC generates a force $\boldsymbol{f} \in \mathbb{R}^3$ and a torque $\boldsymbol{\tau} \in \mathbb{R}^3$as:

$$\boldsymbol{f} = K_T(\boldsymbol{p}_d - \boldsymbol{p}_c) - B_T\, \dot{\boldsymbol{p}}_c \tag{2}$$

$$\boldsymbol{\tau} = K_R[\boldsymbol{q}_c^* \boldsymbol{q}_d]_{rpy} - B_R\, \boldsymbol{\omega}_c \tag{3}$$

where $\boldsymbol{\omega}_c \in \mathbb{R}^3$ is the current angular rate, K_T and K_R are translational and rotational elastic coefficients, B_T and B_R are translational and rotational viscosity coefficients (Table 1) chosen to generate gradual guidance while not violating the passivity of the system. The $[\,]_{rpy}$ operator represents conversion from quaternion to roll-pitch-yaw orientation representation. The force and the torque were both saturated at values reported in Table 1. Some arrangements such as low-pass filtering the desired pose at the instance of grasping and enhancing velocity estimation through adaptive windowing helped render the assistance smooth. The relatively high frequency of the haptic loop and the damping element of the AC contributed to keeping the haptic interaction stable.

Following the challenge point theory [21], assistance intensity is calculated with to generate a level of functional complexity that can theoretically maximize the motor learning. The functional task difficulty $FTD_{r,s} \in [0,1]$ in repetition r of session s was calculated according to user skill level $\sigma_{r,s}$ and last repetition's assistance intensity $\alpha_{r-1,s}$ as:

$$FTD_{r,s} = 1 - \lambda\, \sigma_{r,s} - (1-\lambda)\, \alpha_{r-1,s} \tag{4}$$

where λ, a relative weight between the user's skill and assistance, is set to 0.8 to penalize more the performance of the user. The user skill level defined as a weighted average of user's last session average performance $\overline{p_{s-1}}$ and current session's average performance up to the current repetition $\overline{p_s}$:

$$\sigma_{r,s} = \frac{N\,\overline{p_{s-1}} + 2(r-1)\overline{p_s}}{N + 2(r-1)} \in [0,1] \tag{5}$$

We enforced the maximum assistance intensity during the first 2 sessions, since it was characterized by the maximum user cognitive load. An assistance feedforward term, $FFA \in [0,1]$, was introduced in order to impose a monotonic and session-based decrease of the assistance after the M^{th} session, where M was chosen to equal 2 for all subjects:

$$FFA_s = 1 - \frac{s - M}{S_{max} - \overline{p_{s-1}}(S_{max} - S_{min}) - M} \tag{6}$$

where S_{max} and S_{min} are respectively the maximum and minimum number of sessions after which the assistance is removed among all subjects. Finally, the level of assistance was computed under the *assistance-as-needed* principle (Fig. 2) using the following formula that combines the exploitation of the task functional difficulty (for a measure of intra-session variability) with the feed-forward term (for a measure of monotonic inter-session variability):

$$\alpha_{r,s} = \begin{cases} 1 & if\ s \le M \\ \max(0,\ FFA_s - \Delta_s(2FTD_{r,s} - 1)) & if\ s > M \end{cases} \tag{7}$$

with $\Delta_s = FFA_s - FFA_{s-1}$. Once the assistance intensity reaches a zero value, it is set to zero for all the following repetitions and sessions. The normalized $\alpha_{r,s}$ assistance intensity was finally sent to the wrench generation node.

E. Statistical Analysis

Since most of the performance measures were not normally distributed, non-parametric statistical significance tests were used to determine the effect of the robotic assistance. Kruskal-Wallis test was employed with the different metrics as dependent variables, and the training groups as independent factor. The statistical analysis was performed in MATLAB using the *kruskalwallis* and *multcompare* (to perform a pairwise comparison) commands.

TABLE I PARAMETERS OF THE IMPLEMENTED AC

K_T	B_T	K_R	B_R	f_{max}	τ_{max}
1000 N/m	30 $N.s/m$	0.03 $N.m/rad$	4 $N.m.s/rad$	4 N	0.03 $N.m$

IV. RESULTS AND DISCUSSION

The null group's acquisitions were continued for 10 sessions (i.e. 5 days) as some subjects still showed improvements during the 4th day's sessions. The data acquired from the non-assisted group was used to select the parameters of the assistive method and metrics standardization. The maximum number of assisted sessions was set as 10, assuming that the assisted subjects would not require more sessions than the null subjects. The minimum sessions was set equal to half of the maximum i.e. 5 sessions. The best and worst values for the normalization of the performance metrics were selected as reported in Table II. The learning curves acquired from both groups are depicted in the Fig. 3 for each repetition and in Fig. 4 for each session. Considering the null group, an evident progress in terms of average performance can be seen in the plot as the number of repetitions increases. In addition, both intra-subject variability and intra-session variability are considerably decreased during the first 6 sessions. Results suggest that the task comprised enough complexity to require multiple sessions of training to reach high performance. As expected, the assisted subjects experienced a different learning curve (Fig. 3, right). The first 3 non-assisted repetitions resulted in performances not statistically different from those of the null group ($p<0.05$), confirming that both groups belonged to the same population of expertise at the start of the experiment. When the assistance was fully active, the performance of the subjects rapidly increased as expected. It

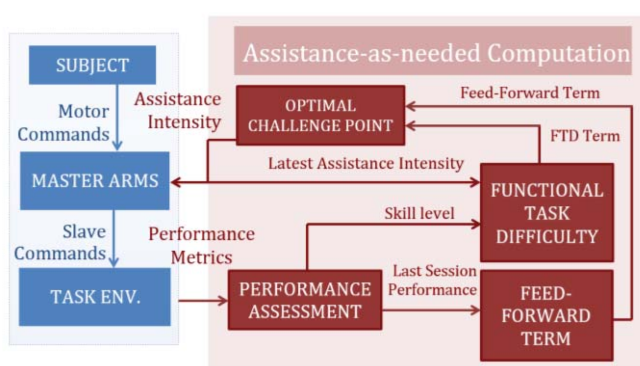

Figure 2. The assistance-as-needed framework.

can be seen that by the end of the second session, where the assistance was still fully deployed, the subjects had reached a level of performance equal to that of the final sessions of the null group. The high performance at this stage is of course due to the contribution of the haptic assistance. As the assistance is gradually diminished, the performance of the subjects first decreases and as the subjects gather more skills, the high performance is recovered.

Fig. 5 shows the assistance intensity that was generated for each subject of the assisted group at each repetition. At the end of the second session, each subject received a lower intensity assistance according to his/her 2nd session performance. The variability of the generated intensities increases as subjects gain skills with different rates and as the intensity is reduced. Subject 11 reaches null assistance in the 5th session, followed by Subject 10 in the 6th session, while the rest of the subjects lose the assistance in the 7th session. This emphasizes that the method responds to intra-subject skill variability and lets more skilled trainees end the training more rapidly. More details are revealed by the performance metrics shown in Fig. 4. These plots exhibit the average performances of all subjects during an entire session in terms of 4 individual metrics and an overall one computed as the average of translation RMSE, rotation RMSE and time. The shaded areas represent the best and worst performing subjects at each session to provide a measure of intra-subject performance variability. The null subjects demonstrate progress across most metrics until the 9th session and little progress in the 10th session. The reduced intra-subject variability confirms the convergence of the subjects to a skilled state. To interpret the results of the assisted users, it must be clarified that the assistance helped only with some aspects of the task execution that were limited to keeping the ring close to its ideal pose. The subjects had to learn how to grasp the

TABLE II BEST AND WORST VALUES USED TO NORMALIZE METRICS

	Trans. RMSE	Trans. Max	Rot RMSE	Time
Worst	2.4 mm	4.0 mm	20°	121 s
Best	1.0 mm	2.8 mm	57°	54 s

ring efficiently without causing it to slide on the wire, and how to perform ring transfer from one gripper to another. These actions required good depth perception and minute motor control and were not aided by the assistive method. The focused learning of these actions is captured by the time and maximum translation error curves shown in Fig. 4. Assisted subjects perform the task much faster, as the time-consuming task of keeping the ring at the ideal pose is simplified by the assistance and they have more cognitive vacancy to tackle the ring grasping and transfer actions. When the assistance is fully active, principal contributor to maximum translation error is failure in accurate ring transfer (ring can fall on the wire). As shown in the max-translation error plot in Fig. 4, assisted subjects demonstrate a considerable increase in performance in the second session with respect to the null group, which can hint at their focused learning of ring transfer. As the intensity of the assistance is diminished, assisted subjects require more time to complete the task while keeping the pose error low, explaining the performance reduction at the 7th session when assistance is null for all subjects. The significant reduction of the variability in time in the 3rd and 4th session can be explained by the better familiarity of the subjects in benefiting from the assistance. As the assistance is reduced to zero at the 7th session, the variability across time, translation errors and overall performance increases. However, these variabilities remain similar to the last session of the null group and show no significant difference. An interesting trend seen in the data,

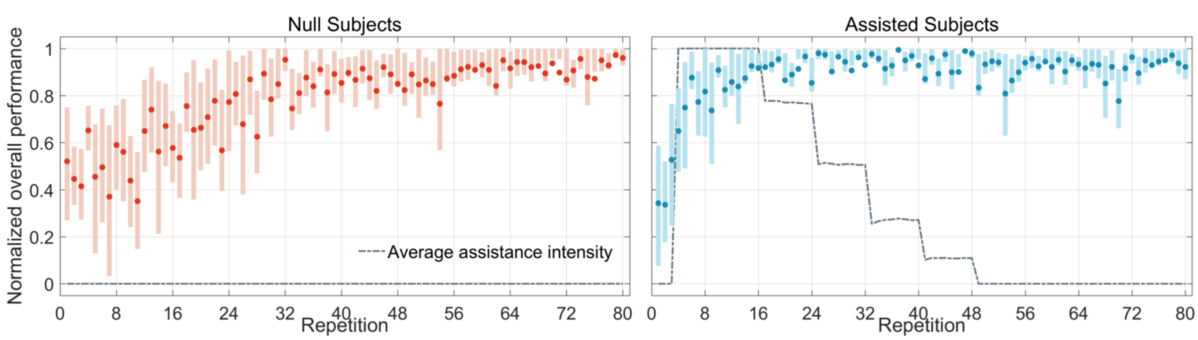

Figure 3. The overall performance of all subject per repetition calculated as the average of 3 normalized metrics: time, translation RMSE and rotation RMSE. Each dot represents the average performance of all subjects in a repetition. The overall performance is the average of time, translation and rotation RMS metrics. The bars show the 25th to 75th percentiles in each repetition. The dotted line shows the average of the assistance intensity in each repetition.

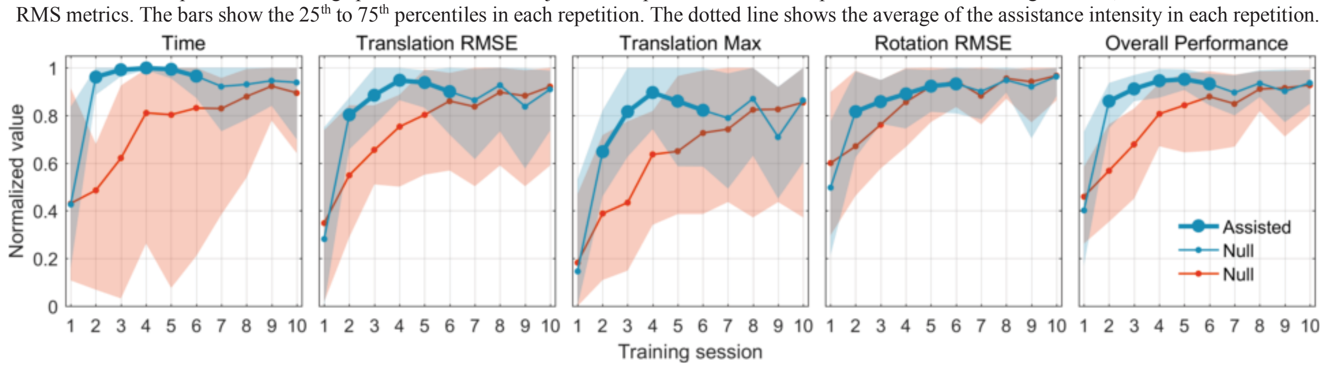

Figure 4. The performance metrics calculated per session as the average of all subjects performances. Blue represents the assisted group and red the null group. The sessions in which at least one subject of the assisted group received assistance are shown by thick line and marker. The shaded region represents maximum and minimum performance across all subjects. Note that for session 1, only the first 3 repetitions were considered here, because during those the assisted group did not receive assistance in order to compare their non-assisted performance to that of the null group.

especially in the last 4 sessions, is that both the assisted and the null groups demonstrated better performance improvement from a morning to the afternoon session of the same day, compared to the afternoon session to the next morning. In terms of completion time, it can be concluded that the assistance has helped 2 subjects reach final level of performance by the 6th session and the rest by the 7th session, while non-assisted subjects reach their final performance at the 8th and 9th sessions. In terms of accuracy, considering rotation and translation error, no statistically significant enhancement is observed in the non-assisted part of the learning curve of the assisted group with respect to that of the null group ($p<0.05$). However, considering the time-accuracy tradeoff present in a demanding motor tasks, it can be concluded that faster task completion of the assisted subjects at the 7th session ($p<0.05$), while having equal level of accuracy to that of the null's group 9th and 10th sessions can imply a slightly faster learning rate for the assisted-group.

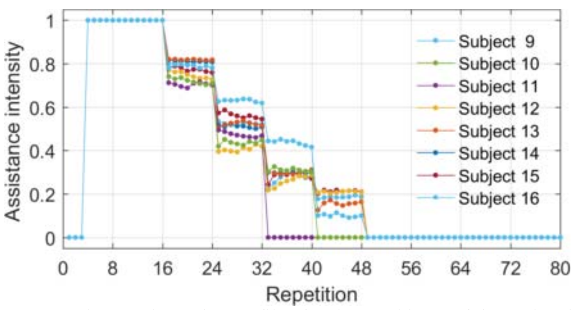

Figure 5. Assistance intensity profiles for the 8 subjects of the assisted group during the 10 acquisition sessions.

V. CONCLUSIONS

This work proposed a robotic assistance-as-needed method for visuomotor training in robotic surgery applications. The method was put to the test through a 10-session experiment in which 16 novice subjects performed a demanding bimanual visuomotor task. Results show that while both non-assisted and assisted groups achieved similar performances at the end of the training, subjects who received assistance achieved high performance in terms of completion time faster than the non-assisted subjects did. Although the achieved reduction in training time is not substantial, these results are promising and further investigations are needed. It must be noted that the beneficial effects of robot assistance could be limited to certain types of tasks. More experimental work is needed to validate the findings of this work with different tasks, including interaction with real objects. This study was performed on a relatively small sample size mainly due to the difficulty of recruiting subjects for a multiple-day study and the exponentially growing number of acquisition sessions with larger sample sizes. A larger sample size can lead to more statistical determinism.

VI. ACKNOWLEDGEMENTS

This study was supported by the Intuitive Surgical Technology Research Grant and the Smartsurg European project (to N. Enayati and E. De Momi). We received assistance on the dVRK software from Anton Deguet, with support from NSF NRI 1637789. We thank our subjects for kindly participating in the experiment.

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