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The Effects of Artificial Intelligence Assistants on the Acquisition of Laparoscopic Surgical Spatial Navigation Skills

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***Abstract*—Laparoscopic surgery requires the surgeon to map their motor (motion) space to a misaligned visual space. For this reason, laparoscopic surgery requires spatial navigation skills for proficiency. There are several training and simulation methods to decrease the difficulty of learning these skills. As artificial intelligence (AI) systems increase in sophistication and prevalence, researchers are developing AI systems to assist in laparoscopic surgery. The concern is that consistent use of AI systems during training will limit the skills acquired and cause a potentially unsafe reliance on AI systems. This study examined naive participants learning and trying to improve at a simulated laparoscopic surgical navigation task with no assistance, passive assistance, or active assistance. The results of a small pilot study suggested that all groups improved throughout the training sessions. However, the data did not demonstrate a significant reliance on AI assistance from the active assistance group, indicating minimal impact on dependency.**

I. Introduction

As artificial intelligence (AI) becomes more sophisticated it is used for an increasing number of tasks that would otherwise be performed by humans. This shift raises concerns that greater reliance on AI could lead to the loss of important cognitive and motor skills, as people practice these tasks less often. Evidence of skill decline has been noted with automated systems in fields such as aviation, where pilot dependence on automation has correlated with decreased manual proficiency during situations requiring direct intervention [1], [2]. While there are operational distinctions between automated systems, which follow pre-set rules, and AI, which adapts and makes complex decisions, AI assistants are designed to mimic cognitive skills to a much higher degree [3]. Thus, compared to traditional automated systems, AI assistants are more likely to result in skill degradation since they offer fewer opportunities for users to actively practice and retain their abilities [3]. To the best of our knowledge, no prior research have been conducted on AI assistants' effects on users' surgical skill retention and acquisition. This paper focuses on the use of AI systems in laparoscopic surgery and training simulations and how it may affect the acquisition of spatial reasoning and navigation skills that are essential to performing minimally invasive surgeries.

A. Spatial Navigation in Laparoscopic Surgery

In order to manipulate a laparoscope in manual laparoscopic surgery, the user needs to be able to map the visual field to the motor workspace [5], [6]. As the laparoscope is maneuvered there are various misalignments between the visual and motor fields that arise, making moving in the correct direction less intuitive. These misalignments must be reconciled in the surgeon's mental model of the workspace to correctly understand the relative position and orientation of the camera with respect to the motor workspace.

Rotational misalignments from rotating the probe along its axis are challenging to mentally track. Rotating the scope rotates the coordinate frame of the visual space, but not the motor space, meaning that a movement along the axis in the motor space will look like a movement along an angle in the visual space. It is well documented that a rotational misalignment decreases task performance across a variety of spatial navigation tasks; performance deteriorates the most when rotation approaches 90 degrees [7]. Bernatot found that in 2D point to point tracking simulations errors occur the most when there is a 90 or 270 degree mismatch between the reference system and a moving object's reference frame [8]. Blackmon et al. also found that in 3D reaching tasks a 90 degree rotational mismatch led to a significant decrease in performance [9]. Fu et al. saw a decrease in performance of a 3D Fitts task (point to point motion) for 90, 135, and 225 degree azimuth rotations [10].

B. Training Tools

There are several training tools used to develop spatial navigation skills. These tools include simple box models used to practice motor skills [11] and virtual reality simulators that can replicate surgical scenarios with high levels of detail and accuracy [12]. There are also robot-assisted surgery (RAS) simulators designed for specific systems such as the da Vinci surgical system [13].

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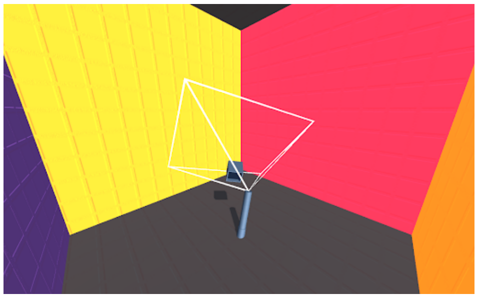
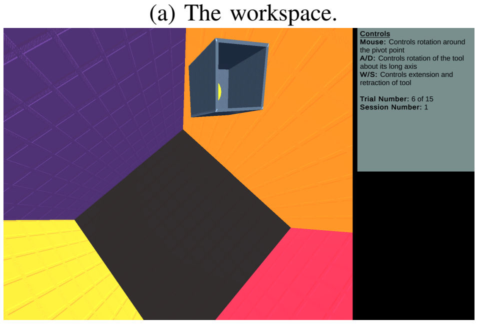


(a) The workspace.



(b) The main screen of the experiment.

Fig. 1: (a) The workspace of the experiment. (b) The screen that the participants see.

There are also artificial intelligence assistants (AIAs) that are in development. One form of assistance is guidance virtual fixtures that provide haptic feedback to guide the user in the correct direction [14] and [15]. Researchers are also developing AIAs that can complete simple surgical tasks such as suturing [16].

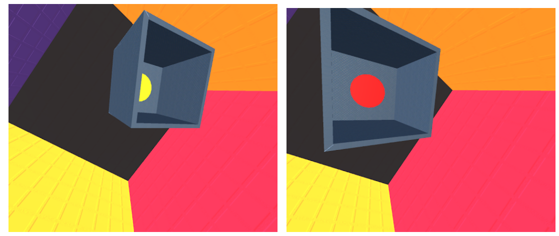
As more tools to decrease the cognitive load on users for RAS and laparoscopic surgery are developed, there is a need to examine the effects that using these tools in a training environment may have on the acquisition of users' skills. While these forms of autonomy are still in development, it is important to start considering regulatory and ethical frameworks to manage risk [17]. AI is never completely reliable, thus as these AIA systems become more and more common, work needs to be done to determine how surgeons' skills are acquired when using and training with these systems. There needs to be clarity on whether or not the user is gaining the necessary skills or if they are relying on the AIA to bear the cognitive load.

II. Methods

In order to test whether or not skills are learned when using AIAs during training, a basic surgical task was simulated for naive participants. Participants had to complete a 3D spatial navigation task similar to maneuvering a laparoscope. The following human experiment protocol has been approved by the Institutional Review Board of Case Western Reserve University, where these experiments were performed.

A. Spatial Navigation Task

The navigation task was designed as a simulated surgical task meant to mimic the spatial reasoning skills a surgeon needs to properly maneuver a laparoscopic camera. However, the task was designed to be an abstraction of the laparoscopic camera navigation task rather than a realistic simulation of a surgical environment. As such, the task was not designed to teach users skills to be used in real life laparoscopic surgery, rather the experiment was designed to be similar so that it tests the same skill, but without the real life context.



(a) Incomplete trial (b) Completed trial

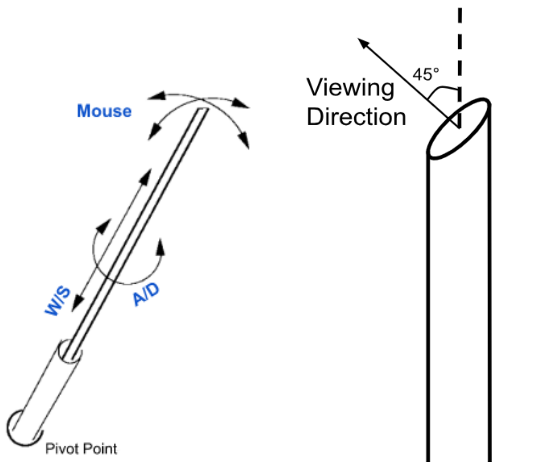
Fig. 2: Completion criteria

Specifically, in the proposed surgical navigation task, the participants were asked to use their mouse and keyboard to control a tool with a virtual camera at the end to view a circle inside a box that was placed randomly in the workspace, rather than maneuvering a camera in a patient to view a specific anatomic structure. The tool was represented by a long cylinder, and was placed in a "room" with 4 different colored walls. The walls were different colors so the user could keep track of where they were in space, even when rotating the probe. The camera was placed at the end of the tool with a 45 degree viewing angle and a 90 degree field of view along the horizontal axis. Figure 1a shows the probe and workspace. The white lines show the field of view of the camera. Figure 1b shows the screen that the participants saw during each trial. The large picture is the view that the camera at the end of the probe sees.

To complete each trial the participants needed to position the tool so that the entire target was visible in the camera view as shown in Figure 2. Once the trial was completed, the circle at the bottom blinked and the participant moved to the next trial.

1) The Tool: The tool mimicked a 4 degrees-of-freedom (DOF) laparoscope. The participants could control the pitch (rotation about the side to side axis) and yaw (rotation about the front to back axis) of the tool, as well as the rotation about the tool's long axis. The tool could also be lengthened, mimicking inserting a laparoscope into a body cavity (Figure 3a).

The challenge with controlling a tool like this is that there are often misalignments between the motion and what is seen. These are similar to the challenges presented by an actual laparoscope. The first misalignment is that the camera is placed at a 45 degree angle so that the viewing direction is offset from the direction of movement (Figure 3b). For example, if the tool is extended one might expect to simply zoom in close to an object, but instead, the field of view shifts. Another challenge comes when rotating the tool about its own axis. At the start of each trial, controlling the tool's pitch and



(a) Controls (b) Viewing direction

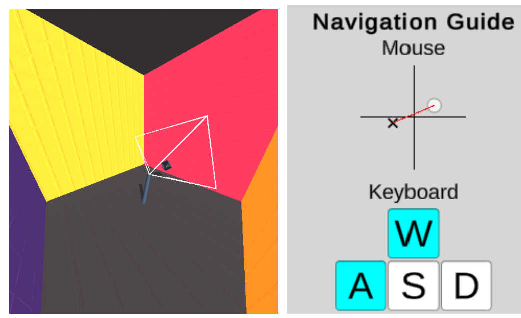
Fig. 3: (a) The mouse and keyboard controls manipulated the 4DOF tool. Adapted from [20]. (b) Camera points at an angle of 45° off the tool's axis.

yaw aligned with the participants' perceived x and y axes, however after rotating the tool this would no longer be the case. A change in pitch, which would normally be perceived as vertical motion, now seemed to be at an angle, or even backwards due to the fact that the camera has rotated, but the axes of motion have not. To overcome these difficulties, the participants must develop a keen understanding of how the tool is positioned and oriented, relative to the surrounding environment.

2) Tool Movement Controls: In this study, a virtual representation of the task was created where a mouse and keyboard controlled the tool. This interface differs from how surgeons typically manipulate a laparoscope, either manually (e.g., as it was done in [18]) or with a robotic device. This mapping was designed as an abstraction to focus on the spatial navigation skills rather than replicating the exact surgical manipulation. Use of such an abstract interface will also allow the full study to be conducted remotely with a large number of participants.

The mouse controlled the rotation of the scope about its pivot point. Moving the mouse forward and backward tipped the tool forward and backward respectively. Moving the mouse left and right similarly tipped the tool left and right. The W and S keys extended and retracted the tool, respectively and the A (counterclockwise) and D (clockwise) keys rotated the tool about its own axis. The WASD keys were used instead of the arrow keys to avoid identifying a key with a particular direction.

3) Target Placement: Each target needed to be placed so that there was at least one solution - a position from which the entire circle could be viewed. To ensure this, a random probe position was generated and the target placed at a distance away from this position so it could be clearly viewed. This position will be referred to as the ideal or optimal position.



(a) Passive AIA (b) Active AIA

Fig. 4: (a) Passive AIA: 3rd person point of view. (b) Active AIA: Navigation guide.

B. Artificial Intelligence Assistants

Participants were split randomly into three groups. The first group was a control group and received no assistance with the task. The second group received guidance from a passive AI assistant which gave extra information, but did not explicitly tell the participant how to complete the task. The last group used an active AI assistant which directed participants on the necessary movements to complete each trial. The AI assistants in this experiment were simulated representations, designed to mimic potential future clinical AI tools rather than AI systems used in real surgical environments. Graphics showing the AIAs were placed in the bottom right corner of the main screen, whereas the control group simply had blank space, as shown in [21].

1) Passive AIA: The passive AIA was a static 3rd-person point of view (POV) of the workspace. This represents an AI reconstruction of what a surgical workspace might look like based on the combination of imaging data and positional and visual data from the laparoscopic camera. This is an abstraction of an assistance paradigm similar to the one proposed in [19].

For this experiment, this AI was implemented by placing a virtual camera in the corner of the workspace. In the layout shown in Figure 1b, the live camera feed, depicted in Figure 4a, was displayed in the bottom right corner for participants in the passive AIA group. This reconstruction also showed the field of view of the main camera with a white wire-frame. Using this AI, the participant could view the 3D spatial configuration, where the tool was positioned, and how it moved relative to what mouse movements were done and what keys were pressed.

2) Active AIA: The active AIA was a navigation guide where once the target was in view, the AI assistant could determine the position and orientation of the target and thus determine a point where the target could be viewed and plan a path to that position and orientation. The navigation guide was only activated after the participant had seen the box. This is something that could be achieved clinically using imaging data and positional data, thus serve as a feasible assistant.

The navigation guide operated similar to the virtual fixtures mentioned in [14] and [15], but since there was no haptic feedback it was a visual guidance system as opposed to a physical force guided system.

All of the variables were known and there were no obstacles, so the ideal path was a linear path in the configuration space of the robot. The path went from the current position of the tool to the ideal position.

To implement this guide, the graphic shown in Figure 4b was created, showing the current position of the mouse, represented as a circle, and the ideal position of the mouse, represented as an x. These were both shown on a 2D plane with an x and y axis. There was also a graphic showing the WASD keys. If one of these keys had been pressed to move the tool to its ideal position, it would light up blue. In theory, if this AIA functioned perfectly, a participant could look only at the navigation guide and complete the task without looking at the main screen and thus not learn the task at all. Similarly, for the active AIA group, the layout in Figure 1b displayed the navigation guide, depicted in Figure 4b, in the bottom right corner.

3) AIA Imperfections: To account for the imperfections inherent in real AI systems, errors were introduced. Both the active and passive AI rely on correctly localizing the position and orientation of the target, but it is unlikely that an AI system could pinpoint the position and orientation without any error. To simulate this, noise was introduced in the perceived orientation of the target, such that the AI's perception of the target's orientation was slightly rotated relative to its actual position.

The amount of rotation was given by a normal distribution with a mean of 0 degrees and a standard deviation of 15 degrees which was empirically chosen. For the passive AI the field of view one might expect to see from the third person point of view did not match up exactly with what the participant saw in the main view. For the active AI, the AI would guide the user to a position where they may not see directly into the box, because the orientation was not correctly perceived and thus the box was angled too sharply to see the entire circle from the AI's calculated 'ideal position'.

Since there is a range of positions to orient the probe to successfully complete the task, the AI errors should only hinder participants when there are large angles of error.

C. Study Design

For this experiment each participant was required to complete 5 sessions during the day approximately 1 week apart and each session lasts 1 hour long. These sessions included 4 training sessions and 1 test session. Each trial had a one minute time limit, so that if the trial was not completed within one minute the participant was automatically moved to the next trial. This was done to avoid someone getting stuck on one trial indefinitely.

For the first session, participants completed a demographics questionnaire, video game experience questionnaire, and a spatial reasoning test. During this session participants also read through the instructions (specific to the experimental condition they were assigned), and completed 15 trials.

After the initial questionnaires, the participants were directed to the online experimental platform. The participants then read the instructions and completed a brief tutorial to become familiar with the controls. They then completed 15 trials. For the second, third, and fourth sessions the participants completed 60 trials per session. The first four sessions constituted the learning phase, where participants learned to perform the task either by themselves or with the assistance of the given AIA.

The fifth session was an evaluation session where participants completed 45 trials. No group received assistance for this session. They were told that they should try to complete each trial quickly and in a controlled fashion. Afterwards, the subjects completed a short debrief questionnaire.

All participants completed the same trials in the same order.

D. Implementation and Data Collection

The platform was created using Unity, a development platform to create and run video games. Unity WebGL was used to build the web application and Microsoft Azure was used to host the web app.

All data from the trials were stored on Microsoft Azure. All of the key presses and mouse movements were recorded, as well as time, screen size, dpi, probe position, and probe rotation. Whether or not the box was in view was recorded, as well as whether or not the target was in view. The point at which the target comes into view separates the search phase (where the subject is simply looking for the box) and the navigation phase (where the subject has located the box and is moving towards it). There were many trials where the target was immediately visible, thus having no search phase at all. This distinction was made to separate when the subject may be making random movements while looking for the target, and when they are able to make intentional movements towards the target.

III. Results

These results are from a pilot study. A larger version of the study will be completed later with a larger subject pool to improve statistical power. Due to the small number of subjects, statistical power is low. Thus, there are many trends that are observed from the data, but few that can be supported by statistical significance.

Twenty-four subjects (ages 18-25) completed the study. The participants were split into 3 groups of 8. The first group did not receive any assistance, the second group received assistance from the passive AIA and the third group from the active AIA.

Four measures of performance were used: path length in configuration space, path length in the workspace, completion time, and the number of corrective movements. All of these metrics were tracked for each of the participants across all 5 sessions. The mean for each metric was computed for each session for each participant. All of the metrics were only calculated for the navigation phase of each trial.

In the box plots of the experimental results presented in the subsequent subsections, the medians are marked by red

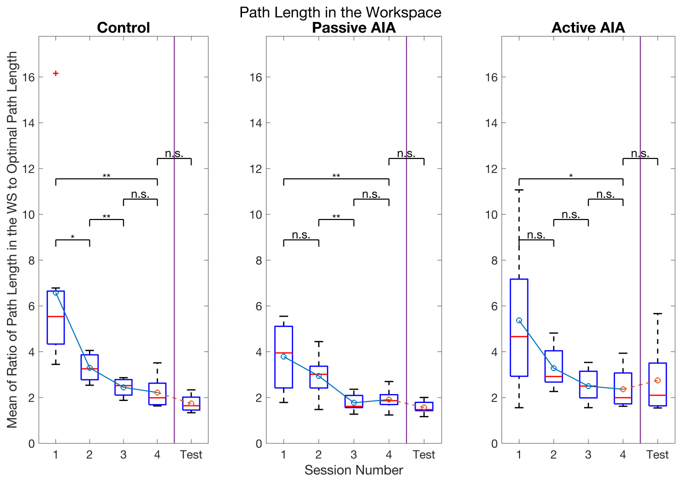


Fig. 5: Path length in the workspace for each group.

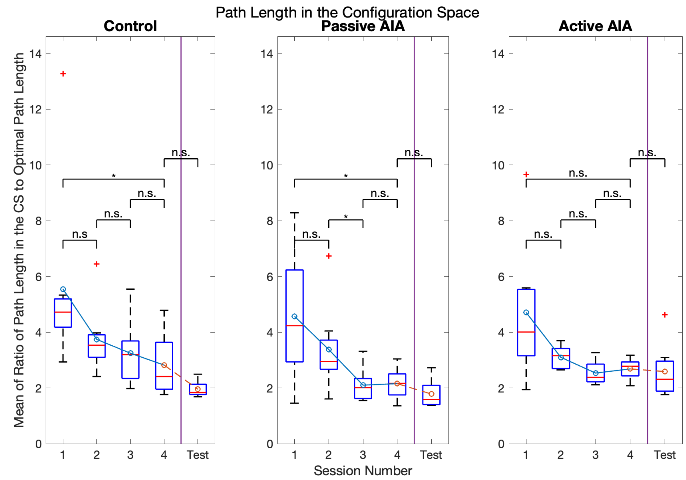


Fig. 6: Path length in configuration space for each group.

lines, session means by blue dots, and outliers by red crosses. Statistical significance is denoted as follows: ns ($p > 0.05$), * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$), and **** ($p \leq 0.0001$).

A. *Path Length in the Workspace*

The workspace path length incorporates the probe's incremental 3D displacement (x, y, z) and its rotation about the probe's axis θ, in degrees scaled by $\frac{1}{18}$, summed across all individual navigation steps.

$$\text{wsPathLength} = \sum_i \sqrt{\Delta x_i^2 + \Delta y_i^2 + \Delta z_i^2 + \left(\frac{\Delta\theta_i}{18}\right)^2}. \quad (1)$$

The scaling coefficient of $\frac{1}{18}$ was picked to match the ranges of the displacement and angle variables in the workspace.

Each path length was normalized by the optimal path length. This was determined to be the distance from the point where the navigation phase started to the ideal viewing position that was predetermined for each target, also using coordinates in the workspace. This normalization was done so that the difficulty of each trial did not affect the distribution of path lengths.

Figure 5 shows the distributions of means across sessions for each group. All three groups demonstrated significant improvements across the first four sessions. During the test session the passive AIA group had the lowest mean path length (1.57 ± 0.28), outperforming the active AIA group (2.75 ± 1.51, $p < 0.05$). No significant difference was observed for the control group. Although the active AIA group showed a slight decline in the test session, the difference was not statistically significant ($p > 0.05$).

B. *Path Length in Configuration Space*

The configuration path length sums the changes in the probe's extension length, l, and rotational angles α (pitch), β (yaw), and γ (roll), in degrees, with all angles scaled by $\frac{1}{18}$:

$$\text{csPathLength} = \sum_i \sqrt{\left(\frac{\Delta\alpha_i^2 + \Delta\beta_i^2 + \Delta\gamma_i^2}{18^2}\right) + \Delta l_i^2}. \quad (2)$$

The scaling coefficient of $\frac{1}{18}$ was picked to match the ranges of the displacement and angle variables in the configuration space.

All three groups improved throughout the training sessions as seen in Figure 6. Path lengths in the workspace significantly decreased for the control and passive AIA groups ($p < 0.05$), while the active AIA group showed no statistically significant change ($p > 0.05$) between sessions 1 and 4.

The passive AIA group continued to improve into the test session. The active AIA group showed similar performance between the final training session and the test session. The passive AIA group had the shortest mean path length in the test session (1.78 ± 0.49), compared to the control (1.95 ± 0.29) and active AIA (2.59 ± 1.01) groups, though these differences were not statistically significant ($p > 0.05$).

C. *Completion Time*

The completion time was measured as the time between when the box first came into view until the trial was completed, normalized by the optimal path length of the trial in configuration space. Thus, the completion time only includes the navigation phase and is not dependent on the difficulty of the trial.

As shown in Figure 7, all three groups had significant decreases in mean completion times. The passive AIA group performed the best throughout all the session, including the test session. While significant differences were observed in Sessions 1, 3, and 5 ($p < 0.05$), most sessions showed no statistically significant differences among groups ($p > 0.05$). The active AIA group had a slight decrease in performance between the last training session and the test session, but there was not enough statistical power to confirm this ($p > 0.05$).

D. *Corrective Movements*

Corrective movements are defined as the number of local maxima of the acceleration and are a way to measure the smoothness of the path. The workspace trajectory during the navigation phase was used to calculate the acceleration,

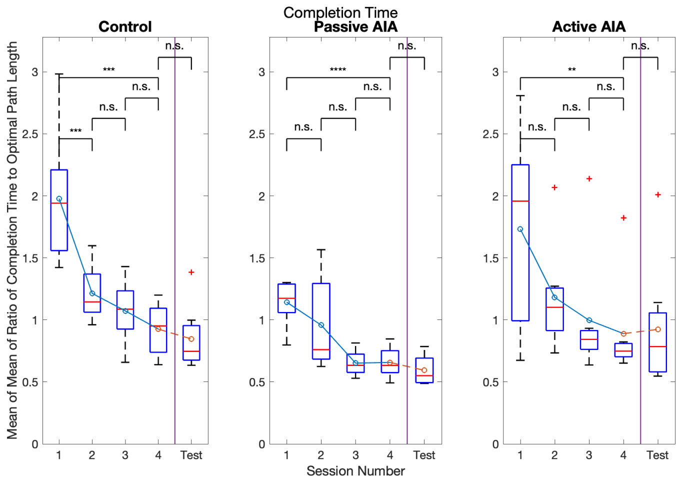


Fig. 7: Completion time for each group.

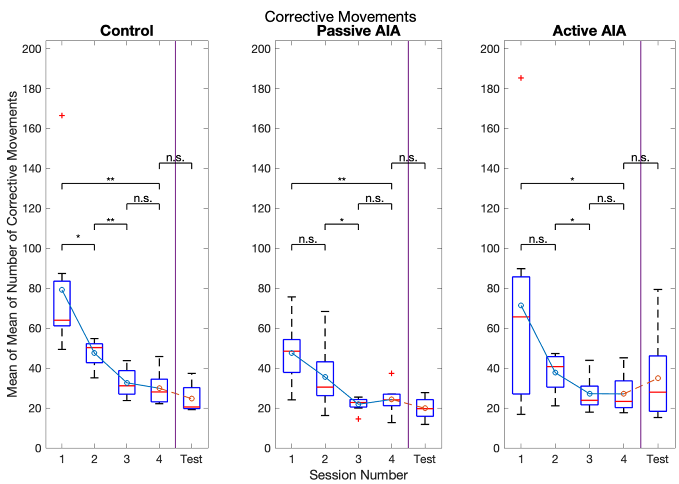


Fig. 8: Corrective movements for each group.

using the same scaling method with the angle of rotation of the probe. Due to the fact that the key presses were one way to change the trajectory, there were a lot of discrete and jerky motions. In order to overcome this, a low pass filter was applied to smooth the edges caused by these discrete movements while retaining the overall shape of the trajectory. The magnitude of the acceleration vector was calculated and the peaks of this signal that were greater than 5 units/s^2 were counted as corrective movements. As with the above performance metrics, the mean number of corrective movements was calculated per participant for each session. The results are shown in Figure 8.

All three groups had noticeable and significant improvement throughout the training sessions($p < 0.05$). The passive AIA group had the lowest corrective movements (19.84 ± 5.56), outperforming both active AIA (34.85 ± 22.98) and control (19.84 ± 5.56) groups in the test session. However, these differences were not statistically significant ($p > 0.05$).

IV. Discussion

Despite the limited number of subjects, there are still many interesting trends.

A. Learning

It is clear that each group improved at the task over time. Each of the four metrics consistently showed the same trends and improvements. Generally, path lengths decreased, completion times decreased, and the number of corrective movements decreased. This shows that the participants were becoming both faster and more efficient with their movements.

One interesting result is that the AI groups plateaued more quickly than the control group meaning that participants became proficient at the task more quickly when using the AIAs. This means that the AIAs were indeed helping the participants to complete the task in a quicker and more efficient way.

Another result to note is that both the passive AIA group and the control group performed better than the active AIA group in the test session across all metrics. This could mean that the active AIA group did not learn the task as well. Another possible explanation is that the imperfections in the active AIA had a greater negative effect on learning performance than the imperfections in the passive AIA did.

It is important to note that the noise introduced to AIAs were based on empirical choices rather than error probability distributions of existing validated surgical AIA models. The relative magnitudes of the noise terms may have influenced the results, and this remains a limitation of the study.

B. Reliance on the AIA

Contrary to what was expected, there was no significant reliance on the AIAs. In the passive AIA group, the participants seemed to perform the same, or even better in the test session across all metrics. If this result is replicated with a larger sample size in order to have sufficient statistical power, this would indicate that the AIA helped them to learn to do the task on their own, as there was no difference in their performance with or without the AIA. The other possible explanation is that they simply did not use the AIA at all, but given that they consistently outperformed the control group, this explanation seems unlikely.

In the active AIA group, there were trends in the workspace path length, completion time, and corrective movements that suggest there may have been some reliance on the AIA, but this was not a very strong effect. It is possible that the task was simply too easy and thus the active AIA was not relied upon as much as expected.

V. Conclusion

This pilot study shows promise as a tool to track the surgical skills acquisition of naive participants. Despite the limited number of subjects, there were many clear trends that were observed. There were also clear differences in the performance between different groups. Executing this study with a larger pool of participants and a slightly more challenging task would provide an evaluation with sufficient statistical power to better determine whether these differences are real.

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