Enhancing User Performance by Adaptively Changing Haptic Feedback Cues in a Fitts's Law Task

Drake Rowland, *Student Member, IEEE*, Benjamin Davis, Taylor Higgins *Member, IEEE*, and Ann Majewicz Fey, *Member, IEEE*

***Abstract*— Enhancing human user performance in some complex task is an important research question in many domains from skilled manufacturing to rehabilitation and surgical training. Many examples in the literature explore the effects of both haptic assistance or guidance to complete a task, as well as haptic hindrance to temporarily increase task difficulty for the ultimate goal of faster learning. Studies also suggest adaptively changing guidance based on expertise may be most effective. However, to our knowledge, there has not yet been a conclusive study evaluating these enhancement modes in a systematic experiment. In this study, we evaluate learning outcomes for 24 human subjects in a randomized control trial performing a Fitt's law reaching task under various haptic feedback conditions including: no haptics, assistive haptics, resistive haptics, and adaptively changing haptics tied to current performance measures. Subjects each performed 400 trials total and this paper reports results for 40 pre-test and 40 post-test trials. While most conditions did show improvements in performance, we found statistically significant results indicating that our adaptive haptic feedback condition leads to faster and more effective learning as evidenced by metrics of movement time, overshoot, performance index, and speed when compared to the other groups.**

I. INTRODUCTION

As interest in human-robot interaction continues to grow, a number of researchers have become interested in how robots can physically assist human movement. Movement assistance, which results in the user gaining a skill that can ultimately be accomplished independently, is a particularly challenging and desirable goal for applications in motor rehabilitation settings, as well as in surgical training, and general human-robot interaction [1]. Conventionally, motor learning in areas such as physical therapy, rehabilitation, surgical training, vocational training, and sports is initiated through instruction and is solidified through repetition [2]. However, the need for movement repetition can cause inefficiencies in the motor learning process, demanding time and effort from the instructor and allowing for human error along desired movement paths. In addition, if subjects are not engaged in deliberate practice, there could be a risk of learning repeated mistakes rather than the intended skill [3], [4]. The use of robotic intervention or haptic guidance can provide consistency during repetition, and has even yielded promising results to accelerate motor or skill learning, when compared to conventional methods [5], [6].

This work was supported in part by NIH #R01EB030125 and NSF #2109635

D. R. and A. M. F. are with the Department of Mechanical Engineering, The University of Texas at Austin, Austin, TX 78712, USA. e-mail: rowland.drake@austin.utexas.edu

B.D. is currently with the Department of Mechanical Engineering at UC Berkeley and T.H. is currently with the Department of Mechanical Engineering at Florida State Univeristy

While robot-aided motor learning has shown potential as a whole, how to implement these learning strategies in a controlled and effective way is still unknown. Prior literature has predominantly focused on two major forms of feedback: (1) haptic guidance to improve performance, and (2) haptic hindrance to degrade performance [7]. Haptic guidance helps users along a path or toward an endpoint through demonstration [8], [9], physical assistance [10]–[15], or cueing/signaling [16]–[18], limiting the extent of user error. Haptic hindrance encourages error through noise [19], resistance [20], or amplification of mistakes [21]–[23].

Haptic guidance has shown limited success in aiding motor learning but fails to provide consistent improvement across all levels of expertise. A study on teaching Chinese handwriting found that haptic guidance improved line smoothness, but only for beginners [10]. In a steering task, it was observed that less-skilled subjects saw a particular increase in long-term retention with haptic guidance that was not noticeable for more highly skilled subjects [11]. These studies demonstrate the feasibility of using haptic guidance to improve motor learning in novices, but suggest that an alternative control method may be better for more experienced users. To account for differences in expertise, some studies have proposed adaptive guidance controllers with promising results. In a follow-up to the steering study, the same author compared training with no feedback, static assistance, and guidance that fades with user experti. The study found that users saw the most significant benefit from an adaptive guidance condition [12]. This study, along with similar work on adaptive feedback for surgical skill training [17], suggest that haptic learning is more effective when the feedback is adaptive to user expertise, rather than static. However, the specific benefit of adaptive guidance is still unclear. Another study on surgical training showed that in a complex motor task, adaptive guidance increased the rate of learning but did not significantly effect performance [15].

Haptic hindrance has also shown promise as an effective motor learning tool but encounters a similar issue related to expertise or ability. In a path-tracing study involving subjects with arm impairments, error amplification enhanced motor learning for a group of subjects with less severe impairment but showed no benefit for the remaining subjects [21]. Rather, these subjects saw improvement through active assistance therapy, suggesting that some threshold of ability exists above which hindrance becomes more effective than guidance. Similarly, in a virtual pinball task, error amplification

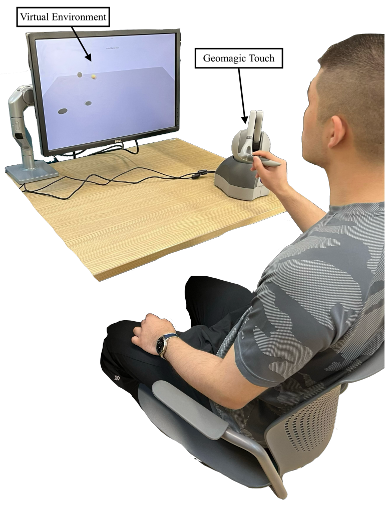


Fig. 1: Experimental setup with a subject interacting with a Geomagic touch to perform Fitts's Law-inspired point-to-point tasks.

generated significantly greater learning for subjects with high initial performance, while guidance showed more benefit for subjects with low initial performance [22]. These results indicate that optimal motor learning may occur when a user experiences a mix of haptic guidance or haptic hindrance according to their current level of expertise.

Based on these findings, we propose an adaptive haptic feedback condition for motor learning that gradually transitions from maximal guidance to zero guidance and then from zero hindrance up to maximal hindrance as the user's measured expertise grows. This solution provides haptic guidance for beginners, involves gradual change with expertise, and employs haptic hindrance once users reach a certain threshold of skill, all strategies which have shown particular benefit for accelerated motor learning [11], [12], [15], [21], [22]. In addition, the proposed haptic feedback condition is closely aligned with the challenge point framework, a prominent motor learning theory which states that optimal learning occurs when the level of task difficulty correlates to the subject's expertise [24].

The aim of this study is to compare motor learning outcomes when training with no haptic feedback, static haptic guidance, static haptic hindrance, and our novel adaptive feedback approach. Our experiment uses a simple point-to-point movement test in a 3D virtual environment (Fig. 1) inspired by Fitts's Law, which states that the time necessary to move a pointer to a target area is a function of the distance to the target divided by the width of the target [25]. Fitts's Law has been well-established in the literature as a metric of task difficulty [1], [26] and has been utilized in a similar study on the effect of discrete haptic feedback modalities on task success in a 3D virtual environment [18]. We hypothesize that adaptive feedback will lead to greater improvements in task learning when compared to the other feedback modes.

II. Haptic Feedback Design

The haptic feedback in this study uses virtual springs to provide guidance or hindrance depending on the distance between the user's current cursor location and another point in the reachable workspace. Virtual springs are a natural choice to either push the user towards (guidance) or away (hindrance) from a goal position and are often used for haptic force feedback. In this study, we evaluate four feedback conditions: Null, Resistive, Assistive, and Adaptive. Figure 2 demonstrates the implementation of the haptic feedback conditions along with their respective equations. $\vec{F}$ is the force to apply to the user, k is the spring constant ($10\left[\frac{N}{m}\right]$ for each condition), g_{learn} is the learning rate (a measure of user performance), $\vec{p_u}$ is the coordinates of the user's cursor, $\vec{p_{t_i}}$ is the coordinates of the current target, and $\vec{p_{t_{i-1}}}$ is the coordinates of the previous target. The following sections describe each haptic feedback option and its motivation.

A. Null Condition

Null is the feedback mode that does not apply any guidance or hindrance to the user. The user will only experience free space with no virtual fixture implemented. This is visually shown in Figure 2a with no spring between the user and another point in space. The Null control group represents how the user would improve naturally at the task by simply repeating the proposed task without robotic/haptic intervention.

B. Assistive Feedback Condition

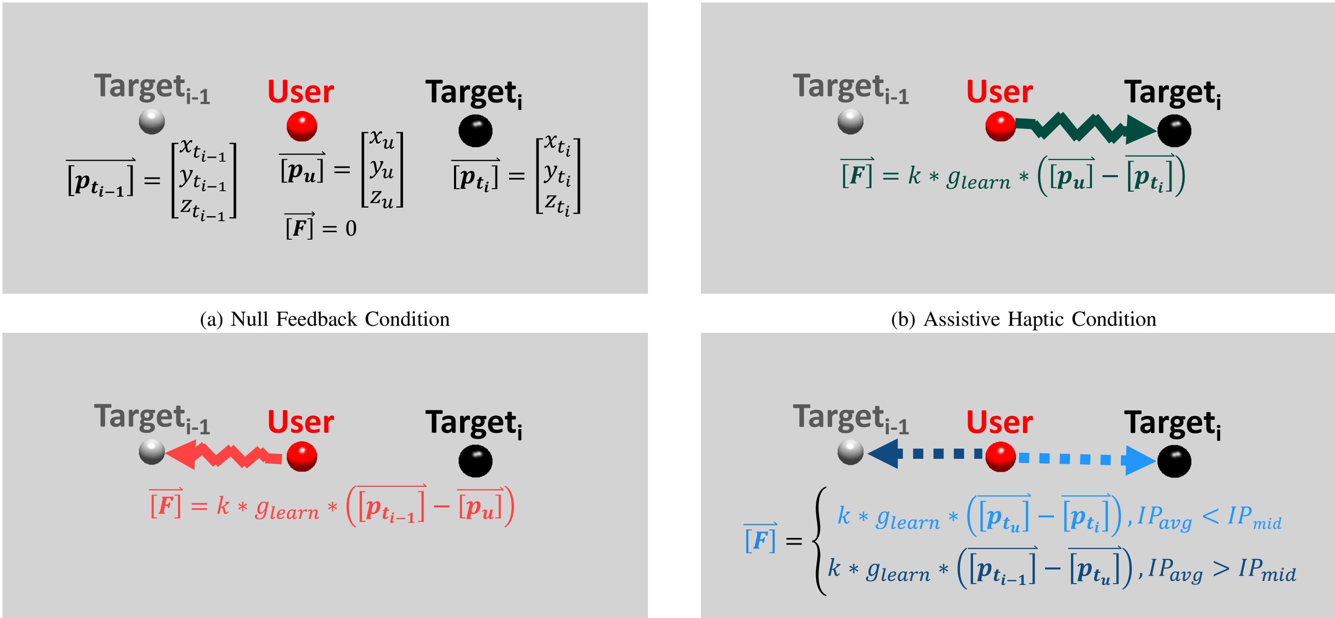
The Assistive haptic feedback condition implements a virtual spring between the user and the current target, such that the user experiences a guidance force pulling them toward the goal. This feedback scheme is shown in Figure 2b. The g_{learn} variable is set to a constant $+0.5$ since this condition will not adapt to the user's performance, similar to prior work evaluating constant guidance.

C. Resistive Feedback Condition

The Resistive haptic feedback condition always hinders the user's movement. It simulates a virtual spring between the user and the previous target (which is always a different point than the new target). As the user moves away from the previous target, they must resist the spring while moving to the new target point. Figure 2c visually shows the spring's location. Similar to the Assistive condition case, g_{learn} is held constant at -0.5 and does not adjust based on the user's performance. The Resistive group represents previously studied control designs that provide constant hindrance regardless of the human's changing performance.

D. Adaptive Feedback Condition

Adaptive, the final haptic feedback condition, is the experimental condition that we hypothesize will accelerate the user's motor learning. This condition continuously adjusts the strength of the virtual spring and toggles from guidance mode to hindrance mode only when the user is performing above a set performance threshold. This option uses metrics from Fitts's Law to adapt the haptic feedback based on the



(a) Null Feedback Condition

(b) Assistive Haptic Condition

(c) Resistive Haptic Condition

(d) Adaptive Haptic Condition

Fig. 2: Haptic algorithm implementation guide. The $User$ sphere represents the user's location in the virtual environment. $Target_i$ is the goal position for the Fitts's Law-inspired point-to-point task. Then $Target_{i-1}$ is the previous point-to-point goal target. Variables required to calculate the force back to the user, $\vec{F}$, are the coordinates of the user ($\vec{p_u}$), current target ($\vec{p_{t_i}}$), and previous target sphere ($\vec{P_{t_{i-1}}}$), the spring constant (k), and the learning rate (g_{learn}). a displays the implementation of the Null condition which applies no feedback to the user. b is the pure guidance case that attaches the virtual spring between the user and the current target. c is the pure hindrance that attaches the spring between the user and the previous target point. d displays the proposed haptic feedback condition that changes between guidance and hindrance modes based on, IP_{avg}.

user's performance history. These metrics are the Index of Difficulty, ID, which measures the task's difficulty, and the Index of Performance, IP, which quantifies how well the user performed the task. These metrics can be calculated after each point-to-point movement trial is executed. Equation 1 shows how ID is calculated as a function of the distance from the starting position to the center of the target, D, and the target's tolerance, W. D and W are illustrated in Figure 3, with W being the radius, r, of a sphere. Once the user's cursor is within the allowable radius, they can end the trial and proceed to the next trial. Once a single point-to-point movement is completed, the Index of Performance can be calculated for that movement, following Equation 2, which is a function of the trials's total movement time, MT.

$$ID = log_2\left(\frac{2D}{W}\right) \tag{1}$$

$$IP = \frac{ID}{MT} \tag{2}$$

A moving average of the IP metric was utilized to determine the virtual spring's appropriate feedback mode and strength. The moving average of the previous twenty-five calculated IP values was defined as IP_{avg}. The feedback condition adjusts the spring by comparing IP_{avg} against a set threshold, IP_{mid}, which is the midpoint between the initial IP, IP_{init}, and a target IP, IP_{targ}. IP_{targ} can be interpreted as the level of performance the user might wish to achieve but cannot currently achieve before task training. IP_{mid} is defined as the level of performance at which the feedback condition switches from guidance to hindrance. The exact methodology for determining IP_{init}, IP_{targ}, and IP_{mid} is explained in the following section. If IP_{avg} is below IP_{mid}, then guidance is given to the user, setting the virtual spring between the user and the target point. If IP_{avg} is above IP_{mid}, the user is given hinderance, setting the spring between the user and the prior target point. Figure 2d portrays the Adaptive feedback condition implementation with the spring location switching depending on the IP_{avg} value. Finally, the effective spring stiffness is the baseline stiffness, k, multiplied by the variable g_{learn} which adjusts the strength of the spring depending on the user's performance. The g_{learn} variable is calculated with Equation 3. The spring constant increases as the IP_{avg} diverges from the IP_{mid} constant.

Figure 4 shows a set of hypothetical results for the progression of the moving average IP throughout a series of point-to-point movements. The user receives guidance in the lower zone, while in the upper zone, they receive hindrance. We hypothesize that users will follow the trend shown in Figure 4 in which they spend the first portion of the experiment within the guidance zone and the second portion within the hindrance zone. This figure shows how the condition will adjust to the user's high performance by making it more challenging or to the user's lowered performance by easing up on the task difficulty. We hypothesize that by adapting to the user's proficiency, this condition will accelerate the user's motor learning as compared to the other three condition. The following section describes how these conditions were assessed through a human user study.

$$g_{learn} = \frac{IP_{avg} - IP_{mid}}{IP_{mid}}, [-1, +1] \tag{3}$$

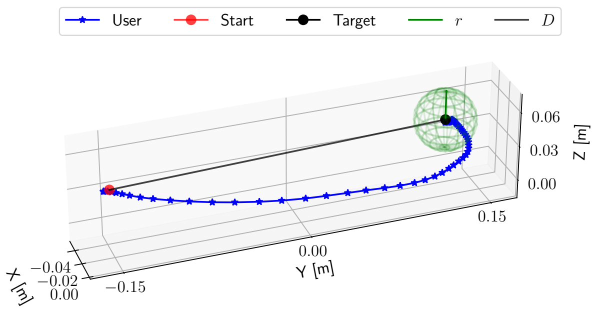


Fig. 3: Example of user motion for a single trial. The starting point is shown in red and the target is in black. The blue path represents subject motion and the black line is the linear path from the starting point to the target point, also known as D from the Fitts's Law equation. The green sphere with radius r is the allowable threshold for the subject to be within range of finishing the trial, W of Fitts's Law.

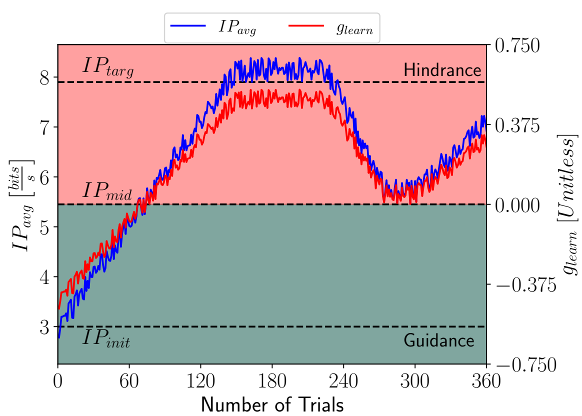
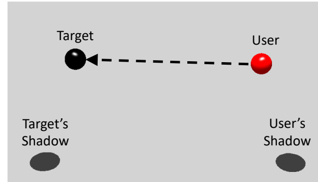


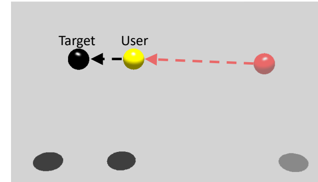
Fig. 4: Example of IP_{avg} and g_{learn} changing over repetitive point-to-points for the Adaptive haptic feedback condition. The figure has two different zones that visually show that if IP_{avg} is within that zone, then that type of feedback is applied to the user. Then, as the IP_{avg} moves away from IP_{mid}, then the effective spring stiffness increases.

III. Experimental Methods

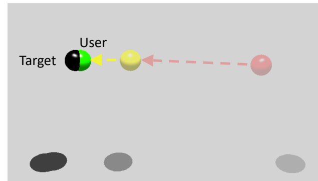
We conducted a human user study with twenty-four participants (age 25.4 ± 4.8, five female). All participants, except one, were right-handed, and none suffered from any physical or cognitive impairment that could affect their ability to perform the study. The methods and procedures described in this paper were carried out per the recommendations of the Institutional Review Board of the University of Texas at Austin (UT Study #00000278), with written informed consent obtained from all subjects. The participants interacted with a virtual environment using a haptic device (Geomagic



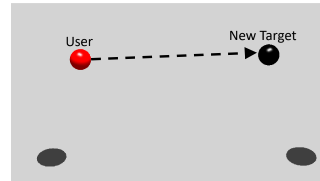
(a) Start of a Trial



(b) Traveling to the Target



(c) Reached the Target



(d) Start of the Next Trial

Fig. 5: Visual diagram of a point-to-point trial. The user moves their cursor, the red sphere, toward the target (the back sphere), a. To convey depth, each sphere is given a shadow that is cast onto the floor of the workspace. As they move and approach the target their color changes from red to yellow, b, then yellow to green. The green color signifies that they are within the target's allowable tolerance and can complete the trial, c. After completing the point-to-point motion, the target moves to the opposite side of the reachable workspace, d. The arrows represent the direction the user is traveling while the transparent objects show the user's previous motion.

Touch, 3D Systems) with their dominant hand. The virtual environment was created in C++ utilizing the open-source library Chai3D [27] to manage the haptic rendering and record user data (sampled at $60\,[hz]$). The subjects completed a pre-experiment survey to check if they had any current impairments that could hinder their ability to perform the experiment and to gauge their familiarity with human-machine interactive devices and virtual-reality environments. To measure their background, the survey asked questions by providing a scale from one to four, one being this is their first interaction and four being they feel comfortable enough to program one. After the subject finished the survey, the experimenter explained the task and experiment.

A. Experimental Task

Figure 5 visually describes the task. The user interacted with the haptic device, and the position of the device's end-effector was represented by the red sphere in Figure 5a. The user's goal was to move the red sphere toward the target point, the black sphere. As the user's sphere approached the target, the color of the user's sphere gradually changed from red to yellow to portray to the user that they were approaching the goal point, Figure 5b. As the user continued moving towards the target sphere, the color again gradually changed from yellow to green, Figure 5c. This green color indicated to the user that they were within the allowable threshold, W which was set to $0.025\,[m]$, of the target point. Finally, the subject pressed the dark grey button on the Geomagic Touch's stylus to complete the trial. After each trial, a new target point was randomly placed on the opposite side of the workspace while the previous target was removed from the screen (illustrated in Figure 5d). The coordinates of the new target were generated from a uniformly distributed random number generator that was limited to the reachable area of the haptic device and forced the new target to be on the opposite side of the screen. The subjects were also allowed to make mistakes while they performed the task. These mistakes included passing the target and pressing the dark grey button on the Geomagic Touch while outside the allowable threshold. If the subject made a mistake it did not result in a failed attempt, as they were allowed to continue the current task until they successfully completed it. There was also no imposed time limit on the task. Lastly, subjects were instructed to complete the trials as quickly and accurately as possible and were prompted to adjust the seat, monitor, and Geomagic Touch for comfort before beginning the experiment.

B. Experiment

The experiment was divided into three sections. The first section was the pre-test, which contained forty trials. In the pre-test, every subject used the Null condition so there was not any robot interaction. This section allowed the user to get accustomed to the haptic device and the virtual reality environment. At the end of this section, the user's average IP value throughout the pre-test was calculated. This was the baseline for the subject's proficiency at the start of the experiment. For the Adaptive condition only, this average IP value is the initial IP, IP_{init}, and is then used in Equation 4 to calculate the target IP, IP_{target}. The target IP was determined following Equation 4, which was a relationship that was determined through pilot testing. The pilot testing determined that this relationship sets that IP_{target} at a high enough value to challenge the user while being low enough to ensure that the user can reach the resistive zone within the time limits of the experiment.

$$IP_{Target} = 10 - 0.3 * (10 - IP_{init}) \tag{4}$$

Following the pre-test the first of several break phases. During each break phase, the virtual environment displays the break screen, which removes the target sphere, shows the user's position as a black sphere, and indicates the amount of time spent in the current break phase. The users must pause for at least ten seconds at every break phase to prevent arm fatigue. The experimenter then reminds the subjects to take a longer break if needed. After this break, they can move on to the next section of the experiment.

After the pre-test and first break phase, the subjects moved on to the training phase. Each subject is randomly assigned to one of the four haptic feedback conditions: Null, Assistive, Resistive, or Adaptive. The haptic feedback condition does not change throughout the training phase. The subjects are unaware of which haptic condition they are receiving and only know that the device may assist or resist them from reaching the current target. The training phase contains sixteen sets of twenty trials, with a break phase between each set for a total of three hundred and twenty trials.

Once the training phase is completed, the subjects moved into the final section, the post-test. This section reapplied the Null condition to all subjects, and they performed forty consecutive trials. After the final trial, the subjects completed a post-experiment survey. It had two questions: if they had noticeable arm fatigue and whether they believed their performance improved from the pre- to post-tests. The experiment took approximately twenty minutes to complete a total of four hundred point-to-point trials.

C. Statistical Analysis

The collected data for each metric was first checked for normality. This check confirmed that none of the collected data was normally distributed. That result meant we had to use non-parametric tests for the statistical analysis of the results. Then the Mann-Whitney U Test was used to determine if there was a difference between the pre and post-test for each haptic condition. If the resulting p-value was less than 0.05, the two samples were considered to be statistically different. Next, we inspected if any of the groups statistically differed from each other in the post-test. The Kruskal-Wallis test was used instead of a more traditional ANOVA to test for a difference between the groups. The results from this test are in Table II. When the Kruskal-Wallis test resulted in a statistically significant result, Dunn's post hoc test was utilized to display which haptic conditions differed statistically.

IV. Results and Discussion

The responses from the two surveys were collected and compiled. The pre-experiment survey that gauged the background experience of each subject had an average response of 2.8 ± 1.1 for human-machine interactive devices and 2.5 ± 1.0 for virtual-reality environments backgrounds. This indicates that the majority of the subjects had some prior experience using a human-machine device to interact with a virtual environment. Then for the post-experiment survey, every subject believed they improved during the experiment when comparing the pre-test to the post-test. Only three subjects reported light arm fatigue (two in the Resistive condition and one in the Adaptive condition).

To verify the effectiveness of each condition, we used five specific metrics. These metrics are MT, Error, IP, Overshoot, and Speed. MT is the Movement Time, which is the total time to complete a single trial and is used to calculate IP. The MT was selected as a performance metric because as the subjects train and improve at the task their MT should decrease. Error is the absolute linear distance from the final user position to the target point. IP is the Index of Performance described in section II with Equation 2. Overshoot is the difference between the total distance traveled by the user and the linear distance, D, from the starting point to the center of the target. Figure 3 displays D and the user's path, the blue line, of a single trial. Finally, Speed is the average speed for the trial and was calculated as the total distance traveled by the user divided by the MT. Speed was calculated along with MT to act as an isolated version of MT. Since MT is influenced by target distance, D, to confirm that subjects were improving, we also selected to calculate average speed since that would

TABLE I: Post-Test Metric Means with Standard Deviation

Metric Mean ± Std Dev.	Error $[m]$	MT $[s]$	Overshoot $[m]$	IP $\left[\frac{bits}{s}\right]$	Speed $\left[\frac{m}{s}\right]$
Null	0.012 ± 0.006	0.977 ± 0.265	0.0345 ± 0.040	4.594 ± 1.034	0.287 ± 0.065
Resistive	0.013 ± 0.006	0.931 ± 0.300	0.0373 ± 0.048	5.127 ± 2.006	0.325 ± 0.120
Assistive	0.012 ± 0.007	0.968 ± 0.427	0.0387 ± 0.073	5.173 ± 2.034	0.316 ± 0.114
Adaptive	0.014 ± 0.006	0.784 ± 0.197	0.0226 ± 0.040	5.713 ± 1.190	0.348 ± 0.080

not depend on the travel distance. In total, 9,600 trials were recorded (2,400 for each condition). Our main goal was to measure how performance changed from pre-test to post-test, rather than instantaneous improvements during the training phase. The instantaneous improvement during training would include the effects of the haptic condition and would not reflect the motor learning of only the subject. This means only eighty trials from each subject were analyzed (forty trials for the pre-test and forty for the post-test). For the analysis none of the filtered trials were removed if a mistake was made. This was because subjects were allowed to make a mistake during the experiment and had to complete each trial in order to continue with the experiment. The data analysis was completed in Python. Results are displayed in Figure 7 with boxplots showing each condition's mean (the white dot), median, and quartiles. Each boxplot was divided by pre and post-test and separated between each haptic condition. This allowed us to determine if (1) there was an improvement from pre-test to post-test and then (2) see which feedback condition had the best results in the post-test. Also, Table I displays the mean value from the post-test for each metric with its standard deviation. Finally, to confirm that the values were affected purely by the training, the ID for each section of the experiment and each haptic group were inspected to verify that each group received a similar difficulty distribution.

Figure 6 shows the distribution, rather than the quartiles, for the ID distribution for each section of the experiment and haptic feedback condition. This figure confirms that each haptic condition received a similar ID throughout the experiments. The ID variable was only a function of target distance, D. Since the ID variable was similarly distributed for each group, this confirms that each group was provided an equivalent difficulty of target positions.

Statistical analysis was used to determine significance in the data. Due to the large number of significant results, the results are described generally and the corresponding p-values are reported in the various tables.

TABLE II: Krustal Wallis Results for All Metrics

Metrics:	Error	MT	Overshoot	IP	Speed
p-value:	1.07e-01	1.97e-15	2.99e-07	6.44e-18	7.90e-13
H_0	Accept	Reject	Reject	Reject	Reject

a) Error: As seen in Figure 7a, the error metric did not significantly change from pre-test to post-test for the Null and Resistance conditions. For the Adaptive and Assistive conditions, however, error increased from pre-test to post-test, meaning that users finished each trial further away from

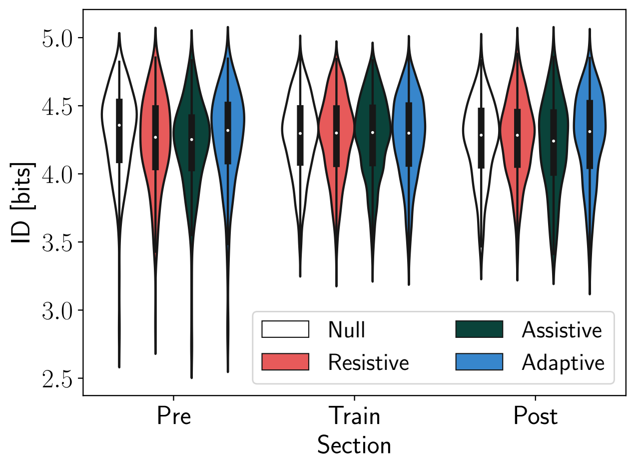


Fig. 6: ID Distribution

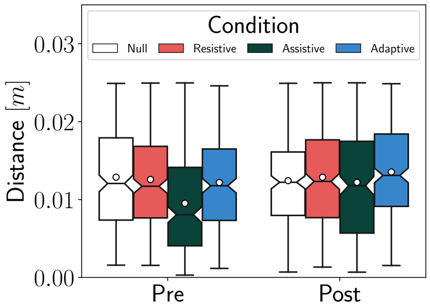
the target's center during the post-test. None of the haptic conditions were statistically significantly different from one another for the post-test error results, Table II. This result is expected as the mean values and standard deviations in Table I are almost identical. This result is likely due to experimental design in that a threshold was used to allow subjects to advance the trial. Subjects in the adaptive and assistive conditions may have exploited the allowable threshold to optimize some other performance metric over the course of the experiment.

b) Movement Time: All haptic conditions resulted in statistically significant changes to MT from pre-test to post-test (illustrated in Figure 7b). In other words, every condition effectively decreased the duration required for subjects to finish each trial. As shown in Table II, the Kruskal-Wallis test confirmed that at least one of the haptic conditions differed from the others. The post hoc test (Table III) revealed that the Adaptive condition differed from all of the other conditions and had the lowest mean value MT. Hence, the Adaptive condition was the best haptic condition in training the user to decrease MT.

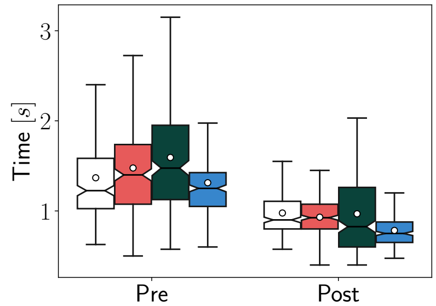
TABLE III: Dunn's Post-Hoc Test Results for MT

Group	Adaptive	Assistive	Null	Resistive
Adaptive		1.08e-06	3.32e-15	3.88e-11
Assistive	1.08e-06		2.69e-03	8.33e-02
Null	3.32e-15	2.69e-03		2.04e-01
Resistive	3.88e-11	8.33e-02	2.04e-01	

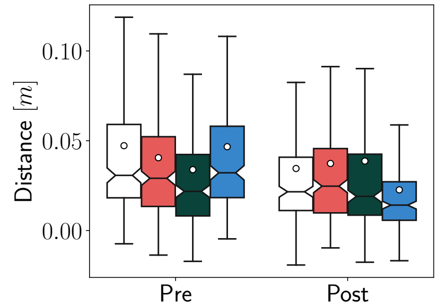
c) Overshoot: For Overshoot, the Mann-Whitney U Test returned that the Assistive and Resistive conditions did



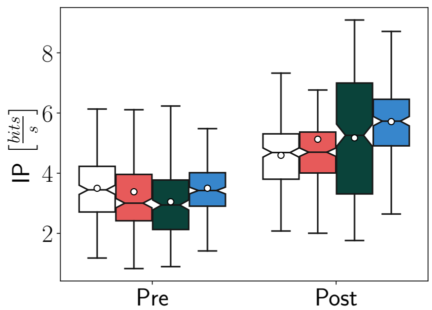
(a) Error



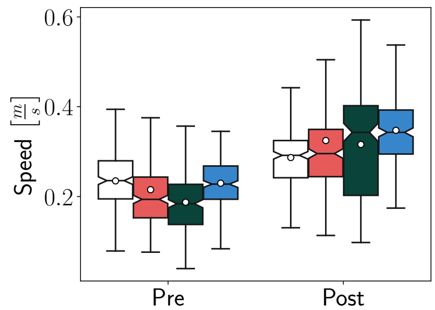
(b) MT



(c) Overshoot



(d) IP



(e) Speed

Fig. 7: Boxplots for each calculated metric. Each subfigure contains the resulting boxplot for one metric. The boxplots are split between pre and post-tests along with each haptic feedback condition. Inside each boxplot is a white dot representing that conditions' mean value.

not produce statistically different results from the pre-test to the post-test while Adaptive and Null did. This result is visually confirmed in Figure 7c. The Kruskal-Wallis test resulted in rejecting the null hypothesis so at least one of the haptic conditions differed from the other in the post-test results. Table IV shows that only the Adaptive condition differed from the other conditions while the other conditions were statistically comparable. Table I shows that the Adaptive condition resulted in the lowest mean Overshoot in the post-test, meaning that subjects trained with this condition had the best performance for this metric.

TABLE IV: Dunn's Post-Hoc Test Results for Overshoot

Group	Adaptive	Assistive	Null	Resistive
Adaptive		7.32e-04	6.49e-07	2.14e-07
Assistive	7.32e-04		1.10e-01	7.04e-02
Null	6.49e-07	1.10e-01		8.33e-01
Resistive	2.14e-07	7.04e-02	8.33e-01	

d) Index of Performance (IP): All haptic conditions resulted in statistically significant increases to the IP metric from pre-test to post-test. In other words, each haptic condition resulted in improved task performance (IP), which stayed elevated after the haptic feedback was removed from the subjects. The Kruskal-Wallis test also found that at least one of the haptic conditions differed from the others in the post-test. Table V shows that the Adaptive condition differed from the others while Table I shows that the Adaptive condition had the highest mean IP value. This means that the Adaptive condition resulted in the greatest improvement in task performance when compared to all other condition conditions.

TABLE V: Dunn's Post-Hoc Test Results for IP

Group	Adaptive	Assistive	Null	Resistive
Adaptive		1.95e-07	9.17e-18	3.45e-12
Assistive	1.95e-07		7.26e-04	7.95e-02
Null	9.17e-18	7.26e-04		1.04e-01
Resistive	3.45e-12	7.95e-02	1.04e-01	

e) Speed: Finally, all conditions resulted in statistically significantly increased speed from pre-test to post-test, visually confirmed in Figure 7e. The Kruskal-Wallis and Dunn's post hoc analysis showed that each condition was statistically significantly different from one another except for Assistive and Resistive. Table VI confirms that, again, the Adaptive condition outperformed all other conditions in increasing the subject's speed after training.

TABLE VI: Dunn's Post-Hoc Test Results for Speed

Group	Adaptive	Assistive	Null	Resistive
Adaptive		3.76e-04	4.17e-14	8.33e-07
Assistive	3.76e-04		6.35e-05	1.70e-01
Null	4.17e-14	6.35e-05		8.58e-03
Resistive	8.33e-07	1.70e-01	8.58e-03	

V. Conclusion

With these results, we can confidently state our proposed Adaptive haptic control algorithm was more effective at accelerating motor learning for the point-to-point task than the other feedback conditions of no guidance, resistive guidance, or assistive guidance. The Adaptive algorithm eliminates the concerns with pure haptic guidance of the user becoming dependent on the device to perform the task and reduces the likelihood that the user loses interest in the task because it has become too easy. The Adaptive condition also addresses the problem inherent to applying only haptic hindrance in that it allows the user to become familiar with the task and keeps the difficulty low enough to keep frustration at bay. Then, allowing the amount of guidance, or hindrance, to actively adjust based on the performance history ensures that the users were receiving the correct amount of feedback to complement their current performance. Our study's results can conclude that allowing feedback to actively adapt to user performance leads to a higher level of motor learning than pure repetition, pure guidance, or pure hindrance.

In future work, we will explore methods to predict future user motion and infer the user's intent for future motion targets as this will enable adaptive haptic guidance to any type of task, not just point-to-point reaching tasks [28], [29].

REFERENCES

[1] Z. Wang and A. Majewicz Fey, "Human-centric predictive model of task difficulty for human-in-the-loop control tasks," *PloS one*, vol. 13, no. 4, p. e0195053, 2018.

[2] J. Classen, J. Liepert, S. P. Wise, M. Hallett, and L. G. Cohen, "Rapid Plasticity of Human Cortical Movement Representation Induced by Practice," *Journal of Neurophysiology*, vol. 79, no. 2, pp. 1117–1123, Feb. 1998.

[3] V. N. Palter and T. P. Grantcharov, "Individualized deliberate practice on a virtual reality simulator improves technical performance of surgical novices in the operating room: a randomized controlled trial," *Annals of Surgery*, vol. 259, no. 3, pp. 443–448, 2014.

[4] E. Battaglia, B. Mueller, D. Hogg, R. Rege, D. Scott, and A. M. Fey, "Evaluation of pre-training with the da vinci skills simulator on motor skill acquisition in a surgical robotics curriculum," *Journal of Medical Robotics Research*, vol. 6, no. 03n04, p. 2150006, 2021.

[5] P. S. Lum, C. G. Burgar, P. C. Shor, M. Majmundar, and M. Van Der Loos, "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke," *Archives of Physical Medicine and Rehabilitation*, vol. 83, no. 7, pp. 952–959, July 2002.

[6] J. R. Boehm, N. P. Fey, and A. M. Fey, "Shaping human movement via bimanually-dependent haptic force feedback," in *2023 IEEE World Haptics Conference (WHC)*. IEEE, 2023, pp. 266–272.

[7] C. K. Williams and H. Carnahan, "Motor Learning Perspectives on Haptic Training for the Upper Extremities," *IEEE Transactions on Haptics*, vol. 7, no. 2, pp. 240–250, Apr. 2014.

[8] J. Liu, S. C. Cramer, and D. Reinkensmeyer, "Learning to perform a new movement with robotic assistance: comparison of haptic guidance and visual demonstration," *Journal of NeuroEngineering and Rehabilitation*, vol. 3, no. 1, p. 20, Dec. 2006.

[9] J. Lüttgen and H. Heuer, "Robotic guidance benefits the learning of dynamic, but not of spatial movement characteristics," *Experimental Brain Research*, vol. 222, no. 1-2, pp. 1–9, Oct. 2012.

[10] C. Teo, E. Burdet, and H. Lim, "A robotic teacher of Chinese handwriting," in *Proceedings 10th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. HAPTICS 2002*, Mar. 2002, pp. 335–341.

[11] L. Marchal-Crespo, S. McHughen, S. C. Cramer, and D. J. Reinkensmeyer, "The effect of haptic guidance, aging, and initial skill level on motor learning of a steering task," *Experimental Brain Research*, vol. 201, no. 2, pp. 209–220, Mar. 2010.

[12] L. Marchal-Crespo, M. Van Raai, G. Rauter, P. Wolf, and R. Riener, "The effect of haptic guidance and visual feedback on learning a complex tennis task," *Experimental Brain Research*, vol. 231, no. 3, pp. 277–291, Nov. 2013.

[13] C. E. Lewiston, "MaGKeyS: A haptic guidance keyboard system for facilitating sensorimotor training and rehabilitation," Ph.D. dissertation, Massachusetts Institute of Technology, Boston, 2009.

[14] G. Grindlay, "Haptic Guidance Benefits Musical Motor Learning," in *2008 Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*. Reno, NV, USA: IEEE, Mar. 2008, pp. 397–404.

[15] N. Enayati, A. M. Okamura, A. Mariani, E. Pellegrini, M. M. Coad, G. Ferrigno, and E. De Momi, "Robotic Assistance-as-Needed for Enhanced Visuomotor Learning in Surgical Robotics Training: An Experimental Study," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, May 2018, pp. 6631–6636.

[16] D. Morris, H. Tan, F. Barbagli, T. Chang, and K. Salisbury, "Haptic feedback enhances force skill learning," in *Second Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (WHC'07)*. IEEE, 2007, pp. 21–26.

[17] Y. Zheng, M. Ershad, and A. M. Fey, "Toward correcting anxious movements using haptic cues on the da vinci surgical robot," in *2022 9th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)*. IEEE, 2022, pp. 1–8.

[18] P. Kourtesis, S. Vizcay, M. Marchal, C. Pacchierotti, and F. Argelaguet, "Action-Specific Perception & Performance on a Fitts's Law Task in Virtual Reality: The Role of Haptic Feedback," *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 11, pp. 3715–3726, Nov. 2022.

[19] J. Lee and S. Choi, "Effects of haptic guidance and disturbance on motor learning: Potential advantage of haptic disturbance," in *2010 IEEE Haptics Symposium*. IEEE, 2010, pp. 335–342.

[20] J. Stein, H. I. Krebs, W. R. Frontera, S. E. Fasoli, R. Hughes, and N. Hogan, "Comparison of Two Techniques of Robot-Aided Upper Limb Exercise Training After Stroke:," *American Journal of Physical Medicine & Rehabilitation*, vol. 83, no. 9, pp. 720–728, Sept. 2004.

[21] B. Cesqui, S. Aliboni, S. Mazzoleni, M. Carrozza, F. Posteraro, and S. Micera, "On the Use of Divergent Force Fields in Robot-Mediated Neurorehabilitation," in *2008 2nd IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics*. Scottsdale, AZ: IEEE, Oct. 2008, pp. 854–861.

[22] M.-H. Milot, L. Marchal-Crespo, C. S. Green, S. C. Cramer, and D. J. Reinkensmeyer, "Comparison of error-amplification and haptic-guidance training techniques for learning of a timing-based motor task by healthy individuals," *Experimental Brain Research*, vol. 201, no. 2, pp. 119–131, Mar. 2010.

[23] J. L. Patton, M. E. Stoykov, M. Kovic, and F. A. Mussa-Ivaldi, "Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors," *Experimental Brain Research*, vol. 168, no. 3, pp. 368–383, Jan. 2006.

[24] M. A. Guadagnoli and T. D. Lee, "Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning," *Journal of Motor Behavior*, vol. 36, no. 2, pp. 212–224, July 2004.

[25] P. M. Fitts, "The information capacity of the human motor system in controlling the amplitude of movement." *Journal of Experimental Psychology*, vol. 47, no. 6, pp. 381–391, 1954, place: US Publisher: American Psychological Association.

[26] I. S. MacKenzie, "Fitts' law as a research and design tool in human-computer interaction," *Human-Computer Interaction*, vol. 7, no. 1, pp. 91–139, 1992.

[27] F. Conti, F. Barbagli, R. Balaniuk, M. Halg, C. Lu, D. Morris, L. Sentis, J. Warren, O. Khatib, and K. Salisbury, "The chai libraries," in *Proceedings of Eurohaptics 2003*, Dublin, Ireland, 2003, pp. 496–500.

[28] C. Shi, Y. Zheng, and A. M. Fey, "Recognition and prediction of surgical gestures and trajectories using transformer models in robot-assisted surgery," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2022, pp. 8017–8024.

[29] C. Shi, J. Madera, H. Boyea, and A. M. Fey, "Haptic guidance using a transformer-based surgeon-side trajectory prediction algorithm for robot-assisted surgical training," in *IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2023, pp. 1942–1949.