Haptic Feedback Based on Movement Smoothness Improves Performance in a Perceptual-Motor Task

Jennifer L. Sullivan, Shivam Pandey, Michael D. Byrne, and Marcia K. O'Malley, *Fellow, IEEE*

***Abstract*—In many training scenarios, and in surgery in particular, feedback is provided to the trainee after the task has been performed, and the assessment is often qualitative in nature. In this paper, we demonstrate the effect of real-time objective performance feedback conveyed through a vibrotactile cue. Subjects performed a mirror-tracing task that requires coordination and dexterity similar in nature to that required in endovascular surgery. Movement smoothness, a characteristic associated with skilled and coordinated movement, was measured by spectral arc length, a frequency-domain measure of smoothness. The smoothness-based performance metric was encoded as a vibrotactile cue displayed on the user's arm. Performance on the mirror tracing task with smoothness-based feedback was compared to position-based feedback (where the subject was alerted when they moved outside the path boundary) and to a no vibrotactile feedback control condition. Subjects receiving smoothness-based feedback altered their task completion strategies, resulting in faster task completion times, but their accuracy was slightly worse overall than the other two groups. In procedures such as endovascular surgery, the reduction of procedure time that could be achieved with smoothness-based feedback training may be advantageous, despite the fact that accuracy was inferior to that observed with no feedback or position-based feedback.**

***Index Terms*—Cutaneous haptic feedback, vibrotactile stimuli, movement smoothness, haptic guidance.**

I. Introduction

PERFORMANCE feedback for training of complex motor tasks often relies on outcome-based performance measures delivered to the trainee after the task is completed, such as task completion time or some type of composite score of performance. Such outcome-based performance measures are limited in that they only indicate success versus failure, and do not necessarily instruct the trainee on *how* they should alter their strategy to achieve the desired result. Technological advancements in sensing and motion capture offer new opportunities for providing detailed performance feedback *during* task performance, and such feedback has the potential to accelerate the learning process and improve training outcomes. This motion-based approach to performance evaluation in manual control tasks is gaining traction in the research community, especially in the domain of surgical skill assessment. For example, some groups have measured hand and instrument movements to assess the skill level of novice and expert surgeons operating the da Vinci robotic surgical device [1]–[3]. Access to larger quantities of more detailed data about the human's control over the task and the task outcomes provides the possibility to identify performance metrics that offer multiple advantages over outcome-based metrics: insight into task performance, the ability to compare the performance of trainees in a detailed manner, and a mechanism to objectively track changes in performance as a result of training (e.g., learning curves).

We wish to further expand the utility of these motion-based performance metrics by displaying them as feedback *during* surgical skill training. Because traditional training exercises require an expert surgeon to be present to provide feedback, coaching time for trainees is expensive and extremely limited. Moreover, skill assessment is often provided informally through subjective feedback after the entire procedure is completed [4]. This delay decouples the feedback and performance in ways that can impede learning [5]. A well-designed, performance-based metric rendered as feedback to the trainee while the task is being conducted could overcome these limitations.

Our ultimate goal is to improve the efficiency of surgical skill training through the provision of performance-based feedback. Specifically, we aim to deliver haptic cues that convey information about the user's movement smoothness *during* training tasks. We choose a haptic modality for feedback because the application domain of endovascular surgery necessitates that feedback be practical in a surgical setting such as an operating room. These environments are inherently noisy, prohibiting auditory feedback to the surgeon. Further, endovascular surgery is extremely demanding of the visual channel, since the surgeon must observe two-dimensional live x-ray images and interpret the three-dimensional anatomy and trajectories of the endovascular tools in real-time. Movement smoothness is widely regarded as a hallmark of skilled, coordinated movement [6], [7], and metrics that capture movement smoothness have been used to assess motor performance in basic motor control tasks [8], rehabilitation applications [9]–[11], and robotic laparoscopic surgery [2]. In our more recent work [12], [13], we demonstrated the applicability of motion-based measures of performance to procedures in endovascular surgery.

Manuscript received November 2, 2020; revised May 24, 2021 and October 15, 2021; accepted November 2, 2021. Date of publication November 9, 2021; date of current version June 27, 2022. This work was supported by the National Science Foundation under Grant IIS-1638073. This article was recommended for publication by Associate Editor Prof. Ilana Nisky and Editor-in-Chief Dr. Seungmoon Choi upon evaluation of the reviewers' comments. *(Corresponding author: Marcia K. O'Malley.)*

The authors are with the Rice University, Houston, TX 77005 USA (e-mail: jsullivan415@gmail.com; shivam.pandey@alumni.rice.edu; byrne@rice.edu; omalleym@rice.edu).

Digital Object Identifier 10.1109/TOH.2021.3126017

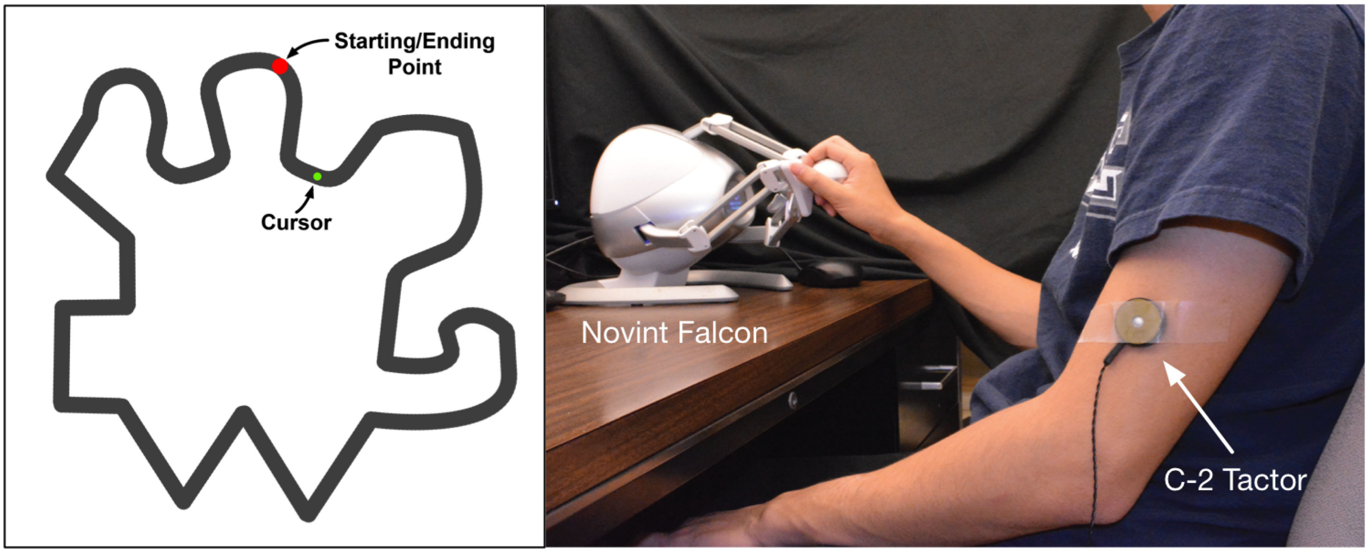

Fig. 1. The subject navigates the cursor around the abstract shape using a Novint Falcon as the input device. In the mirror-tracing task, the movements of the input device are inverted compared to the movements of the cursor on the screen. Tactile feedback of performance is provided by a C-2 tactor secured to the subject's non-dominant arm.

Our initial experiments focused on investigating how to convey motion-based metrics through haptic feedback: what form should that feedback take, and how should the information be encoded? As a first step, we identified and validated a proxy task, mirror tracing (see Fig. 1), that requires the same types of movement strategies identified as successful in endovascular surgery [14]. We previously demonstrated correlations between movement smoothness and performance in this mirror tracing task that we first observed for endovascular surgical tasks [15]. Thus, this proxy task offers a foundational experimental paradigm upon which we can design motion-based haptic feedback and evaluate the effect on manual task performance.

In conjunction with this proxy task, we have developed a system that renders cutaneous haptic feedback in the form of vibrotactile cues based on the smoothness of the user's tracing movement, which is calculated as spectral arc length [15], while trainees are performing the task. Spectral arc length (SPARC) is a metric that uses the frequency content of the velocity signal to evaluate movement smoothness [16]. As its name suggests, SPARC is computed from the arc length of the Fourier magnitude spectrum of the velocity signal. Consequently, SPARC values that are *smaller* in magnitude correspond to smoother movements. One of the main advantages of SPARC is its basis in the frequency domain. Other smoothness calculations, such as minimum-jerk correlation [6] and submovement decomposition [10], [17], utilize time-domain characteristics that require the velocity profile to have starting and ending values close to 0. Thus, these metrics are very sensitive to segmentation and are more reliable for post-hoc analysis of point-to-point motions. On the other hand, because SPARC is computed in the frequency domain, it is largely unaffected by segmentation and is therefore a better option for online calculation of smoothness and real-time performance feedback.

Our choice of cutaneous vibrotactile feedback as our method of haptic guidance, in contrast to haptic guidance provided via kinesthetic haptic feedback, is intentional. Kinesthetic feedback requires complex, custom haptic devices unique to a particular task (for example, multi degree-of-freedom devices to simulate rowing [18], [19] or tennis swings [20]). Further, some types of kinesthetic haptic guidance, while beneficial for enhancing performance, have been ineffective when it comes to demonstrating retention of skill or transfer to a similar task [21], [22]. Tactile feedback, on the other hand, has already been demonstrated as an effective technique for improving movement quality [23], [24]. In particular, tactile feedback has the potential to be widely applied for the training of complex movements in later stages of learning, when task execution strategies need to be refined. For example, studies on drawing different shapes [25] and on handwriting [26] have demonstrated an improvement in movement fluidity by the addition of haptic feedback during training. These findings strongly parallel our desire to train smooth manipulation of surgical tools during navigation tasks, wherein trainees are already familiar with the basics of navigating to anatomical locations, but lack the dexterity to do so efficiently and repeatedly.

To date, there has been little investigation into the effectiveness of vibrotactile feedback for conveying performance feedback other than positional or trajectory error. Motion-based feedback has the potential to enhance performance and training, but as the literature on training has shown repeatedly (e.g., [27]), the details of how this is done matter a great deal.

In this paper, we demonstrate the potential for real-time haptic feedback of movement smoothness, encoded as a simple vibrotactile cue displayed to the user during completion of a complex motor control task, represented in Fig. 1. We show that movement smoothness feedback has a significant effect on task performance, and changes task completion strategies compared to a no haptic feedback control condition and a position-based feedback condition. This work paves the way for developing real-time smoothness-based performance feedback in endovascular surgical simulation environments.

II. Method

A. Subjects

Subjects were recruited from Rice University undergraduates enrolled in psychology courses. There were 95 participants ranging in age from 18 to 22 (M = 19; 34 male, 61 female). Subjects received credit toward a course requirement for participation. In our previous research, we obtained an effect size of $f = 0.33$ (medium-large). According to standard power calculations, to reach 80% power for an effect of that size, 93 subjects were required, hence the large sample.

B. Design

Subjects were randomly assigned to one of three vibrotactile feedback conditions: smoothness-based feedback, position-based feedback, or no vibrotactile feedback (control group). They then performed 40 trials of an unfamiliar motor learning task, mirror tracing, while receiving haptic feedback. All subjects were instructed to execute the tracing task as quickly and as accurately as possible. The goal of the experiment was to evaluate the differences in completion strategy and tracing performance across feedback conditions. The dependent measure, tracing performance, was quantified by the following metrics:

- *Total time:* Total trial completion time, in seconds.
- *Time in:* Total time spent inside the figure, in seconds.
- *Time out:* Total time spent outside the figure, in seconds.
- *Path length out:* Total path length of trace falling outside the figure boundary, in cm.
- *SPARC:* The spectral arc length value (smoothness) of the full trial. For consistency across metrics, we chose to use the positive value of the arc length so that values decrease as tracing smoothness improves.

C. Mirror Tracing Task

The mirror tracing task used for this experiment was a modern version of Snoddy's (1926) original mirror tracing task [28]. Participants were asked to repeatedly trace an abstract shape displayed on a computer monitor as quickly and as accurately as possible, as shown in Fig. 1. Instead of using a mouse to control the cursor, subjects used a Novint Falcon device, a small, 3 °-of-freedom (DOF) haptic manipulator. Position data were acquired at a sampling rate of 500 Hz. The user's movement was constrained to the vertical plane (parallel to the computer screen) by rendering a stiff virtual spring along the Falcon's third DOF. Thus, horizontal and vertical movement of the Falcon corresponded to horizontal and vertical movement, respectively, of the on-screen cursor. However, unlike the original experiment, movement along *each* axis was mirrored so that moving the Falcon left would cause the cursor to move right (and vice-versa); similarly, moving the Falcon up would cause the cursor to move down (and vice-versa). The Falcon's 7 cm x 7 cm physical workspace was mapped to a virtual workspace of 1000 pixels x 1000 pixels.

D. Feedback Conditions

Haptic feedback was delivered in the form of vibrotactile cues using a single C-2 vibrotactor (Engineering Acoustics, Inc.), which was secured to participants' arms with medical tape. Pilot testing was conducted to design cues that were easily distinguishable.

Smoothness-based feedback: For subjects in the smoothness-based feedback condition (n = 32), a vibrotactile cue was rendered every five seconds to indicate their movement smoothness during the preceding time window. Movement smoothness was computed using SPARC with an amplitude threshold of 0.05, a cutoff frequency of 10 Hz, and 4 samples of zero padding. Smoothness was determined by SPARC and binned into three performance levels: good movement smoothness (SPARC < 3.57), average movement smoothness ($3.57 <$ SPARC < 3.94), and poor movement smoothness ($3.94 <$ SPARC). These ranges were determined from data collected from 28 subjects who participated in a continuation of the study reported by Pandey *et al.* [14], which identified that SPARC values greater than 8 corresponded to poor mirror tracing performance, and SPARC values below 6 corresponded to good mirror tracing performance. Those values of SPARC were post-processed, meaning they were computed based on data for an entire trial of mirror tracing. Computing SPARC for those participants based on moving windows of data rather than end-of-trial data resulted in the thresholds for feedback used in this work, implemented based on the methods described in Janstscher *et al.* [15]. Pilot testing showed that task completion times and SPARC values observed when tracing the abstract figure used in this study were comparable to those observed in both previous studies that required participants to trace a star-shaped figure.

Each smoothness performance level was mapped to a specific vibrotactile cue based on the pleasantness of the cue sensation. Good performance was mapped to the mildest stimulus, a single vibration pulse rendered at 50% of the maximum amplitude and a frequency of 200 Hz. Average performance was mapped to a slightly stronger stimulus, a double vibration pulse rendered at 60% of the maximum amplitude and a frequency of 230 Hz. Poor performance was mapped to the strongest stimulus, a triple vibration pulse rendered at 100% of the maximum amplitude and a frequency of 265 Hz. We felt that this mapping was the most intuitive way to encourage improvement when subjects' performance was poor. Additional details of the cue characteristics are summarized in Table I. Both the SPARC value ranges and cue stimuli have been implemented in a previous study [15]. Pilot testing was conducted to verify that the vibration cues were easily distinguishable.

Participants in this group were instructed that they would receive haptic feedback based on the smoothness of their tracing movements. For very smooth movements, participants were instructed that they would feel one low intensity pulse.

TABLE I
STIMULUS CHARACTERISTICS OF VIBRATION CUES FOR SMOOTHNESS-BASED FEEDBACK

	Smoothness		
	Good	**Average**	**Poor**
Number of pulses	1	2	3
Separation (ms)	N/A	50	50
Duration (ms)	200	100	50
Amplitude (% of max)	50%	60%	100%
Frequency (Hz)	200	230	265

For somewhat smooth movements, they were told they would feel two pulses of moderate intensity, and for non smooth movements, they were told they would feel three pulses of high intensity. In other words, the more pulses they feel, the less smooth their movements.

Position-based feedback: In the position-based feedback condition (n = 32), the tactor delivered a continuous stream of 50 ms pulses whenever the cursor position was outside of the trace boundary. Pulses were separated by 50 ms and were rendered at maximum amplitude and a frequency of 265 Hz. Participants in this group were instructed that they would receive haptic feedback based on their tracing accuracy (no vibration when inside the shape boundary, and continuous vibration when outside of the shape boundary).

Control: Subjects in the control group (n = 31) did not receive any haptic feedback while performing the tracing task.

E. Procedures

1) Setup: After providing informed consent, participants were seated in front of the experiment display and given a handout with instructions based on their assigned feedback condition. Chair height and Falcon positioning were adjusted so that they could comfortably maneuver the Falcon with their dominant hand. Although subjects were allowed to rest their elbow on the arm of the chair, they were instructed to keep their forearm and wrist off of the table, as shown in Fig. 1. For subjects in the smoothness-based and position-based feedback groups, the tactor was then secured to their non-dominant arm with medical tape.

A Dell OptiPlex 760 running Windows 7 was used to present the experiment on a Dell P2217 LCD monitor (55.87 cm or 22 in. diagonal) set to display at a resolution of 1680 by 1050 pixels. The user interface was programmed in Unity.

2) Protocol: Subjects in the smoothness feedback group were first given the opportunity to familiarize themselves with the sensations of the three smoothness-based vibrotactile cues and their meanings. Subjects in all groups were then allowed up to three practice trials on a simple square figure to familiarize themselves with the task, GUI, Falcon, and integration of haptic feedback. The experimenter supervised the practice trials and provided additional instruction and clarification as necessary.

Once subjects were comfortable with the experiment procedures, data collection began. To initiate each trial, subjects had to move the cursor to the starting point, a circle located at the twelve o'clock position on the shape, and hold it there until the circle changed from red, to yellow, to green. Once the circle turned green, they could begin tracing in the clockwise direction. A trial was completed once the cursor returned to the starting point. To discourage non-compliance by taking shortcuts or skipping sections of the figure, the length of the trace path was calculated in real time. If the total path length was less than 9.2, the subject was required to repeat the trial. This threshold was chosen through pilot testing such that it was extremely difficult to miss the cutoff value if an honest tracing attempt was made.

During the tracing task, participants wore headphones playing pink noise so that they would not be distracted by any extraneous sounds. They were permitted to take as many breaks as they needed between trials. The tracing task was complete once the subject had performed 40 acceptable trials.

III. Results

Task performance was evaluated by examining the overall time spent performing the mirror tracing task, the portions of time spent inside and outside of the path area, and the path length of the trace falling outside of the shape boundary. Movement smoothness was measured by spectral arc length. Results are plotted as a function of trial number, to allow for examination of learning curves, and the effect of feedback condition on performance is explored.

A. Data Analysis

During the experiments, we collected a total of 3800 data trials. Although the real-time path length criterion successfully mitigated compliance issues overall, it was clear in post-processing that some of the trials did not constitute a good-faith effort. Thus, subjects were removed from the analysis if 20% of their trials were flagged as non-compliant, which we defined as Time In less than 60% of the total Trial Time, or path length greater than 14.7 (60% more than the real-time cutoff). Based on this criterion, all data for one subject in the smoothness feedback group were discarded (26 non-compliant trials out of 40). Data from another subject in the smoothness feedback group were discarded as well due to hardware malfunction during data collection. The final data set included 93 subjects: 30 in the smoothness feedback group, 32 in the position feedback group, and 31 in the control group. Observations more than three IQRs from the subject-adjusted cell hinges were removed as outliers; this was less than 0.6% of the data (87 of 14,880 observations).

Data were analyzed using a linear mixed model (LMM) with three single degree-of-freedom terms in the model:

- Trial. This within-subjects variable treated trial as a continuous variable from 1 to 40, meaning tests on this variable are tests of the linear effect of trial.
- Condition, a between-subjects contrast between the smoothness-based feedback group and the other two groups. That is, this variable tests if mean performance differed between the smoothness-feedback group and the average of all other subjects.
- An interaction term; the cross-product of the previous two variables. This is a test of whether the slope of the

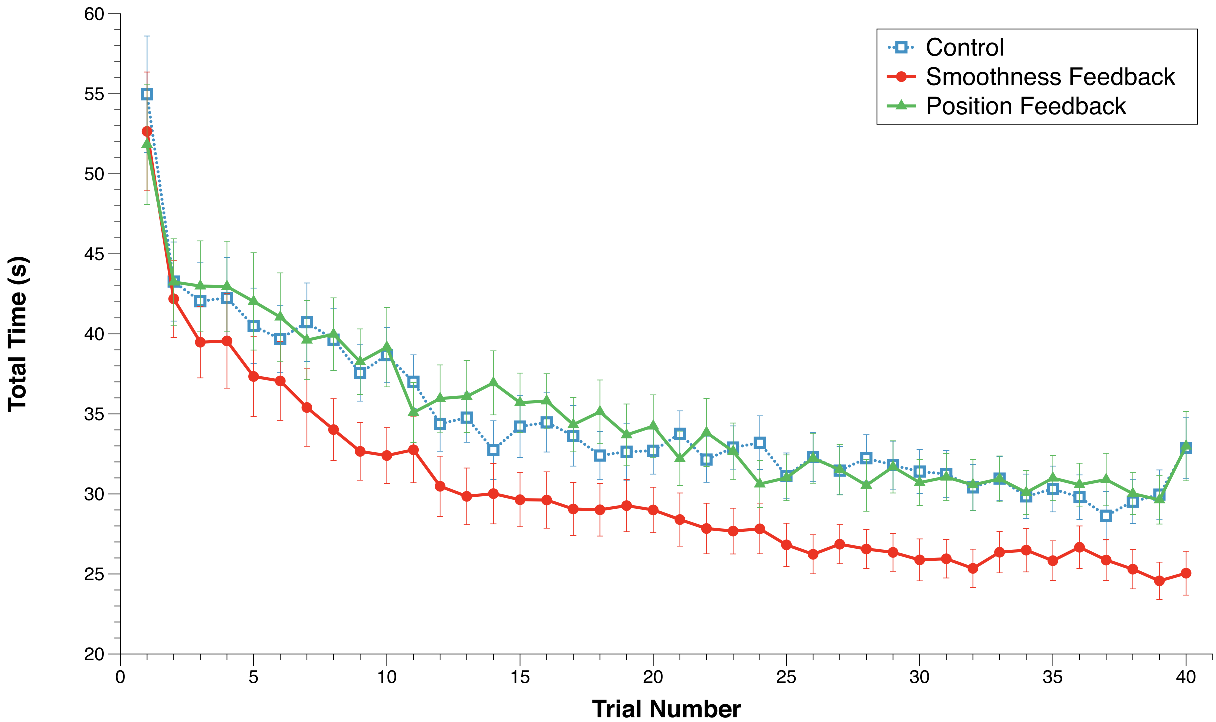

Fig. 2. Average total time to complete tracing the figure as a function of condition and trial. Error bars show standard error of the mean. The average standard error of the mean across all conditions was 1.8.

trial function is different for the smoothness-feedback group relative to the other two groups.

We chose this approach over a more general ANOVA-based approach because we had specific statistical questions that are not well-expressed by omnibus tests. For example, we are not interested in the general question of whether there are any differences at all between the three conditions, but specifically whether the more novel smoothness-based condition differs from more traditional treatments. Note that "subject" was included in the model as a random effect. Degrees of freedom were estimated using the Kenward-Roger procedure. One LMM was fit for each performance metric.

B. Total Time

Overall, subjects' tracing performance became smoother and faster over the course of the 40 trials, regardless of feedback group. However, the smoothness-based feedback group improved more than the others. Fig. 2 shows the learning curves for total time for each of the three feedback conditions. As can be seen on the graph, all three groups had similar average times for the first and second trials, and all showed considerable speedup from the first trial to the second. Past that, the smoothness-based condition separates from the other conditions. In fact, the overall slope of the learning curve for the smoothness-based feedback condition was steeper than for the average of the other two; interaction $b = 1.44$, $t(3600) = 2.21$, $p = .027$.

While the interaction is the primary result, the main effect of trial was also significant, $b = -.39$, $t(3600) = 42.96$, $p < .001$, indicating that all groups improved. While the overall mean performance for the smoothness-based group was somewhat faster than the other groups, this difference did not reach the conventional significance level, $b = 1.22$, $t(99) = 1.87$, $p = .065$.

C. Time Inside the Figure

While the total task time is important, it is also important to examine the constituents of that time: time spent inside the bounds of the figure and time spent outside. Because the total times for each group varied significantly, we report time inside the figure, which highlights changes in speed, and time outside the figure, which highlights changes in accuracy, as two additional performance metrics. These are reported in units of seconds, rather than percentages. If we were to report the percentage of time spent inside the figure, it would be unclear if changes would be attributable to the numerator or the denominator varying. Presenting the raw time inside and outside the figure allows for more insight into the behavior of each group, something that would be masked by measuring the percentage of time inside the figure.

Fig. 3 shows the learning curves for time spent inside the figure for each of the three feedback conditions. Clearly, the results here are quite similar to the results for total time, showing a large drop at the second trial, and then a separation between the group receiving smoothness-based feedback and the other two. Again, the learning slopes are different, interaction $b = -0.013$, $t(3610) = 1.99$, $p = .047$. Both main effects were also significant: for trial, $b = -0.39$, $t(3610) = 33.56$, $p < .001$; for the test of mean smoothness-based vs. the other groups, $b = -1.49$, $t(98) = 2.15$, $p = .034$.

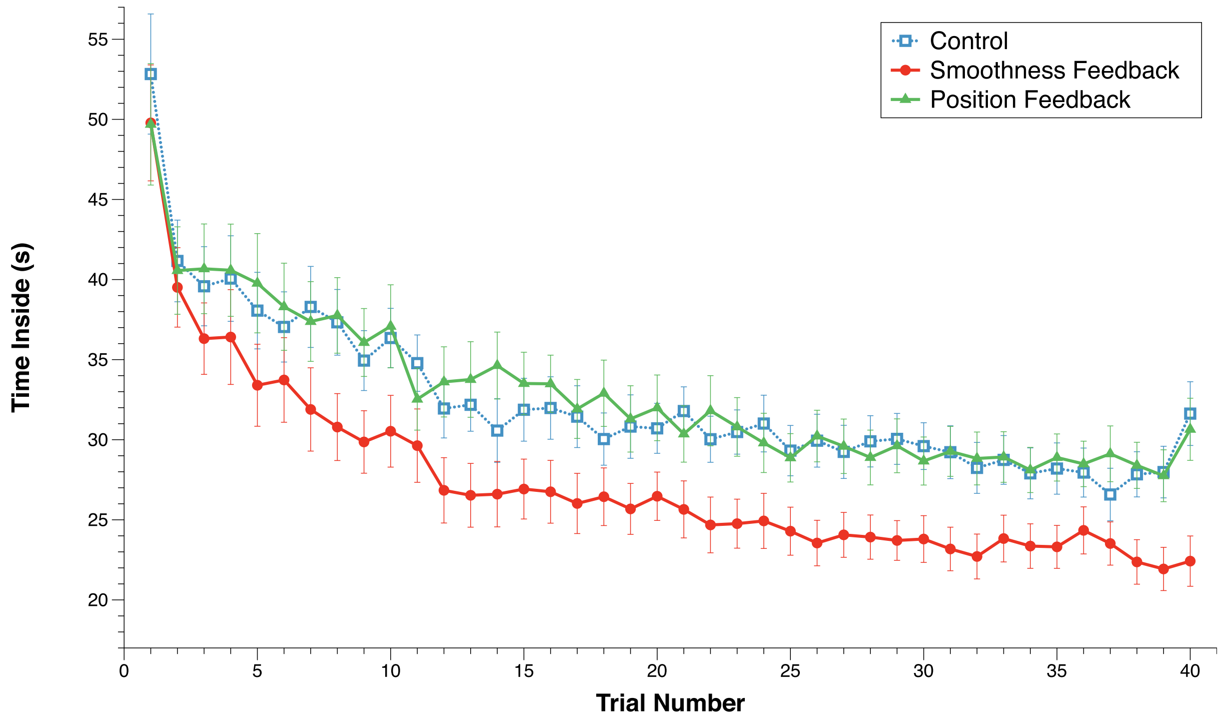

Fig. 3. Average time spent inside the figure as a function of condition and trial. Error bars show standard error of the mean. The average standard error of the mean across all conditions was 1.9.

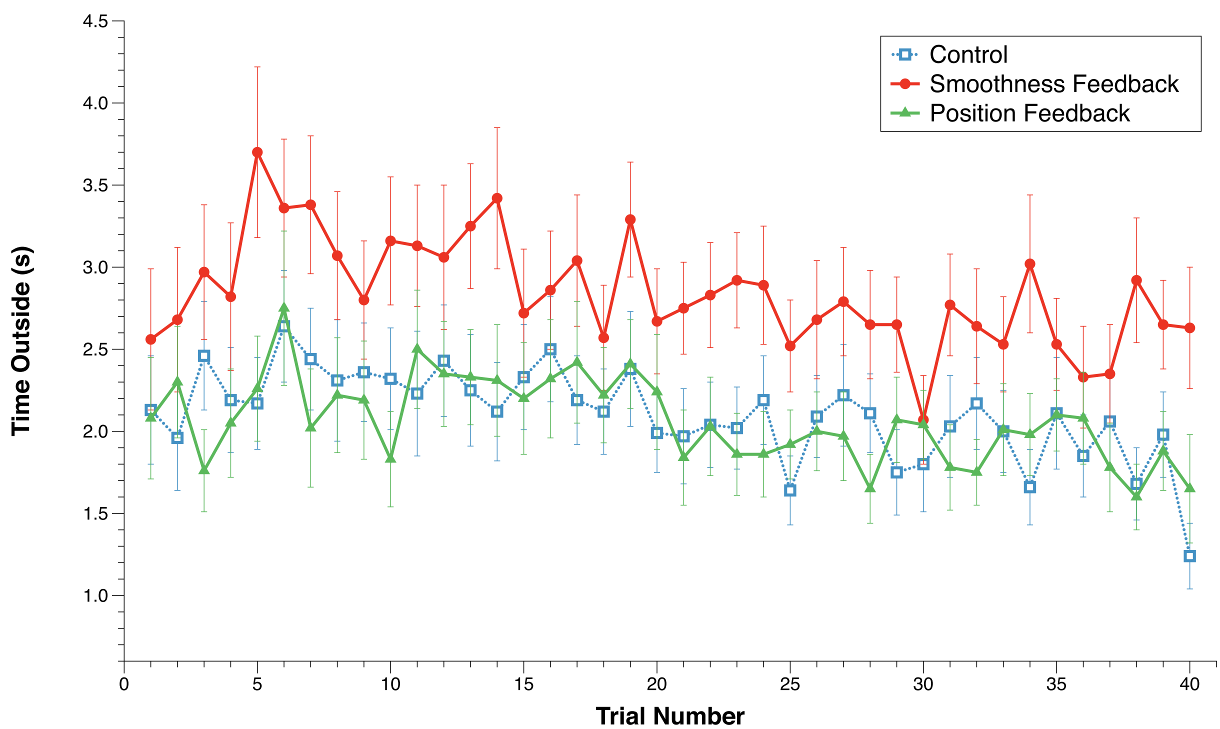

Fig. 4. Average time spent outside the figure as a function of condition and trial. Error bars show standard error of the mean. The average standard error of the mean across all conditions was 0.31.

D. Time Outside the Figure

Time spent outside the figure is akin to accuracy, the more time is spent outside the bounds, the less well the bounds are being tracked.

Fig. 4 shows the learning curves for time outside for each of the three feedback conditions. The first thing to note here is the overall time spent outside the figure was small; subjects in all groups did not spend much time out-of-bounds. The

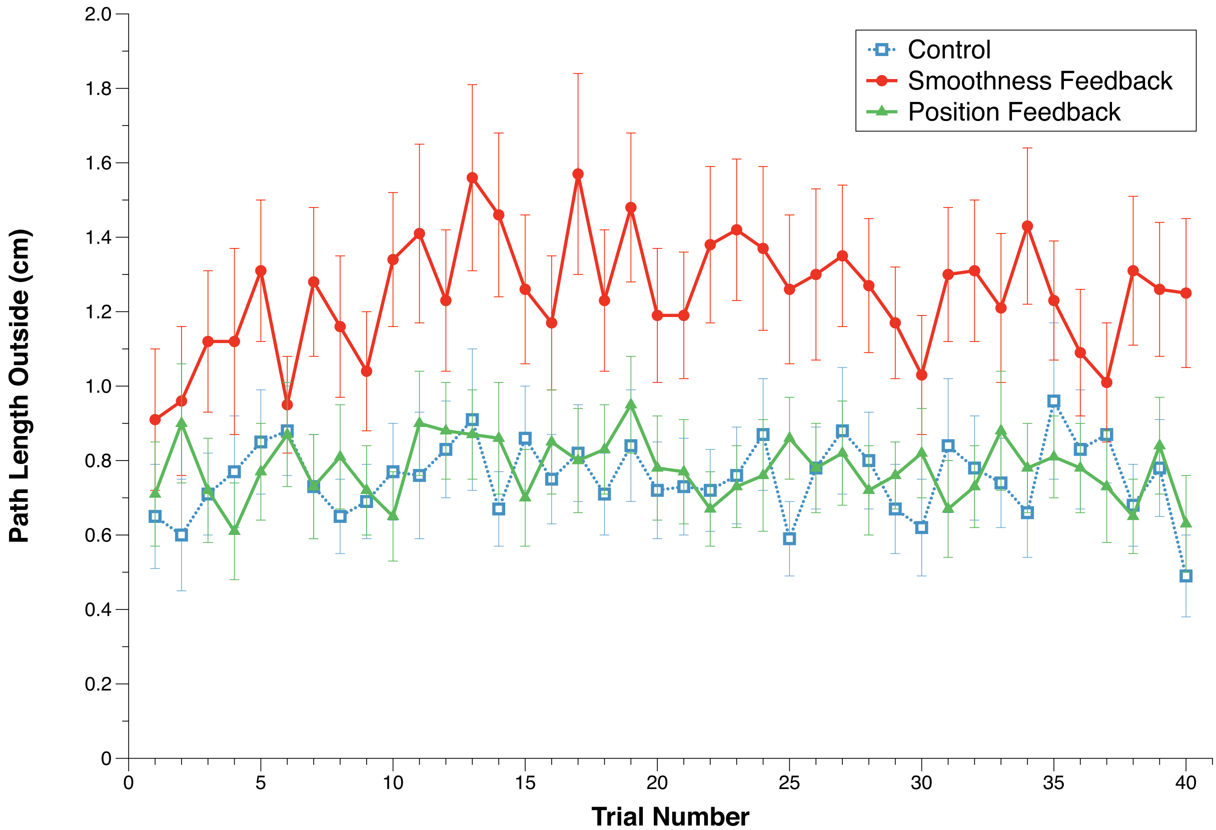

Fig. 5. Average path length outside the figure as a function of condition and trial. Error bars show standard error of the mean. The average standard error of the mean across all conditions was 0.15.

trajectory over time was also less smooth and consistent than for time inside the figure, with more peaks and valleys. On average, all groups did slightly improve on this measure as there was a significant main effect of trial, $b = -1.53$, $t(3590) = 7.53$, $p < .001$. However, there was no evidence for differential learning, as the interaction was not significant, $b = -0.0004$, $t(3590) = 0.42$, $p = .67$.

Overall, the group that received smoothness-based feedback did do somewhat worse on average than the other two groups, main effect $b = 0.26$, $t(101) = 2.51$, $p = .014$. However, as they did improve on this measure, it seems unlikely that they were strictly trading speed for accuracy, because both speed and accuracy improved for subjects who received smoothness-based feedback. In fact, speed and accuracy improved for all three groups; it is just that speed improved more for the smoothness-based group, which they managed without showing a decrease in accuracy over time. They simply showed somewhat worse overall accuracy than the other two groups.

E. Path Length Outside the Figure

Time outside the figure is not the only possible measure of accuracy; this can also be measured spatially. We also measured the total length (in cm) of all path segments when subjects were outside of the figure. If subjects were trading speed for accuracy, one would expect that as their speed increased, the distance traveled outside the figure would also increase. As shown in Fig. 5, this does not appear to be what happened. While overall the group that received smoothness-based feedback did have a higher overall average for outside-the-figure path length, $b = -0.15$, $t(9830) = 2.70$, $p = .008$, there was no evidence that this changed over the course of 40 trials for the subjects overall (main effect of trial $b = -0.0002$, $t(3530) = 0.30$, $p = .76$) or that there was differential change between the smoothness-based group and other groups (interaction $b = -0.0009$, $t(3530) = 1.65$, $p = .10$). That is, according to this measure, all groups maintained their level of accuracy throughout the experiment.

This is consistent with the results of time spent outside the figure in that overall the smoothness-based group was somewhat worse on average than the other two groups, but there is no evidence that they did worse on this measure of accuracy as a result of a trade-off with speed.

F. SPARC

Movement smoothness was measured using SPARC. Fig. 6 shows the learning curves for SPARC for each of the three feedback conditions. On average, movement smoothness improved for all conditions (effect of trial, $b = -0.039$, $t(3610) = 24.96$, $p < .001$) and the smoothness-based feedback condition had more smooth movement than the other groups (contrast $b = -0.15$, $t(106) = 2.17$, $p = .033$. There was no evidence for differential improvement (interaction $b = 0.0007$, $t(3610) = 0.75$, $p = .45$).

This last finding is particularly surprising. Because subjects are given explicit feedback regarding their movement

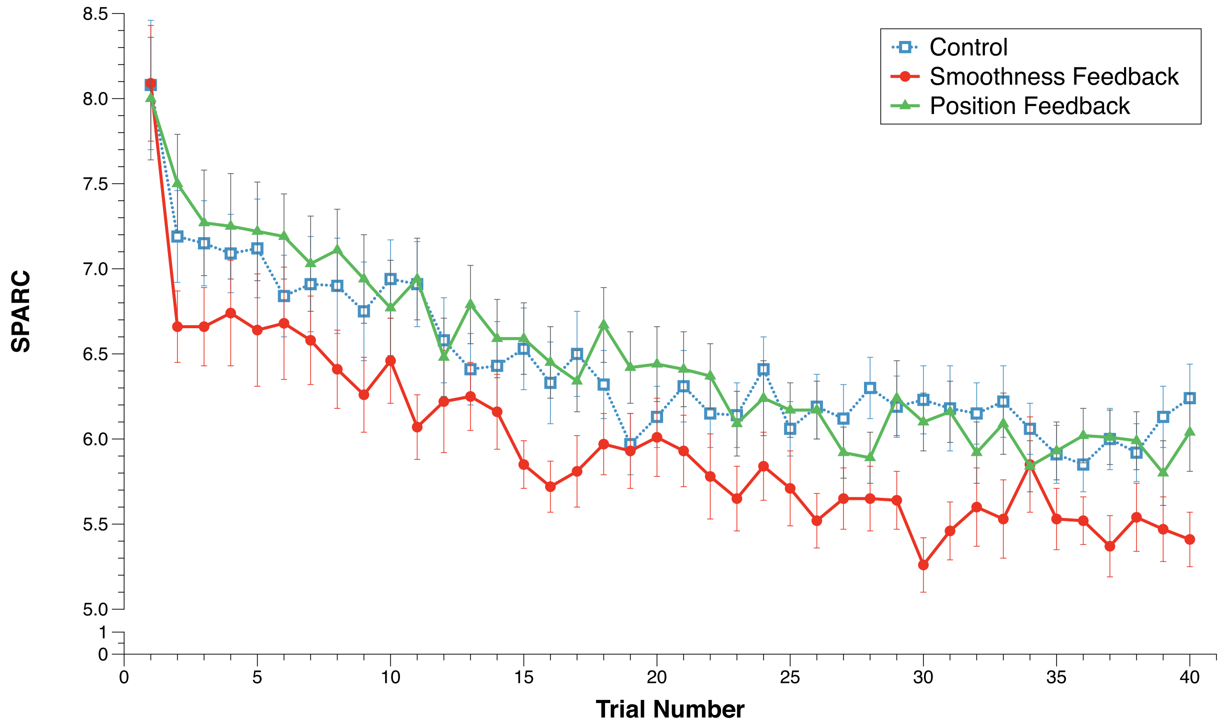

Fig. 6. Average SPARC (a measure of movement smoothness) as a function of condition and trial. Error bars show standard error of the mean. The average standard error of the mean across all conditions was 0.22.

smoothness, one would expect them to improve smoothness more than the other conditions. Instead, while there is evidence their overall smoothness is better, there's no evidence that their overall learning curve is any steeper.

This may be because of extremely rapid adaptation in the initial trial. While for the other measures, the improvement from trial 1 to trial 2 was similar across groups, here the improvement in the smoothness-based group was significantly larger than the average improvement in the other two groups, $t(91) = 2.31$, $p =. 023$. Obviously, this is a selective post-hoc analysis and this is at best suggestive. However, what it suggests is there may be differential improvement in smoothness, but only in the earliest part of the training. Future research should investigate whether there are particular differences early in training for movement smoothness.

IV. Discussion

In this work, we explored the effect of movement-smoothness based feedback, displayed to the trainee via a vibrotactile cue, on performance of a perceptual-motor task. We compared smoothness-based feedback to position-based feedback and to a no-vibrotactile-feedback control group.

Vibrotactile feedback has been effectively demonstrated to improve performance for simple tasks like movement guidance or pose matching [24], [23], [29]. Our mirror tracing task is more complex than simple trajectory following or pose matching. Prior work shows that "skill-oriented" haptic guidance, where feedback is based on component skills, might be more effective than "objective-oriented" haptic guidance, where feedback is based on task outcomes [30]. In our study, the task objective relayed to the participants was to follow the trace quickly and accurately. Position-based feedback was objective-oriented, with a focus on accurate path following, while smoothness-based feedback was skilloriented, focusing on a movement technique known to correlate with skill [14], but distinct from the primary outcome measure.

Haptic guidance has been demonstrated to improve performance in a wide range of perceptual motor tasks when the guidance is active, but retention of skill or transfer to a similar task has not been consistently demonstrated when kinesthetic haptic guidance has been used to convey task completion strategies [21], [22]. This is likely due to the fact that guidance forces conveyed kinesthetically can be confused with the forces arising from the task dynamics. When the guidance is removed, the participant is unfamiliar with the underlying behavior of the system they are controlling [31]. Haptic guidance conveyed through tactile feedback, on the other hand, has the potential to be widely applied for the training of complex movements in later stages of learning, when task execution strategies need to be refined [31], [26], [25]. Our study findings support further exploration of cutaneous rather than kinesthetic haptic guidance for conveying task completion strategies during training of perceptual motor tasks. Further exploration of mirror tracing performance after the real-time feedback is removed is needed to understand skill transfer and retention with cutaneous haptic guidance. In addition, it may be possible to maintain the use of real-time cutaneous haptic guidance during real task performance, since it is applied directly to the user's arm and not through the control interface [31].

Compared to our prior work, where we explored smoothness-based versus position-based feedback for a simpler mirror tracing task and failed to demonstrate statistically significant differences in group task performance [15], the mirror tracing task used in this study was more difficult. The path to be traced contained both curved areas, sharp turns, and multiple direction changes, and was also slightly longer compared to the previous star shape. The fact that we see statistically significant performance differences between groups performing the more difficult task supports earlier findings related to the efficacy of haptic guidance. It has been suggested that guidance paradigms should be applied to tasks where the difficulty is great enough to demonstrate significant improvement, and that if tasks are too easy, any effects of the haptic guidance may be overshadowed by normal practice effects [30]. Note that it is not simply haptic feedback that is responsible for the increased learning; subjects in the position-based feedback group also received haptic feedback but did not show the same learning rate as those receiving smoothness-based feedback.

Subjects in all conditions improved their performance on all of the time-based measures as well as SPARC; this is a standard effect of practice. By examining the amount of time subjects spent inside the trace area (Fig. 3) versus outside the trace area (Fig. 4), we get a sense of the strategy used by participants. The participants in the smoothness-based feedback condition showed both faster overall performance on time inside the figure as well as a faster learning rate. All groups, including the smoothness-based group, improved accuracy (according to the time outside measure) over the course of the experiment, but overall this improvement was small; a fraction of a second at best. According to the path length outside measure, there was no evidence for a change in accuracy over the course of the experiment for any group. Thus, all groups seemed to adopt a strategy wherein the focus of learning was improving speed more than accuracy. However, the smoothness-based group was much more able to accomplish this. We believe it is because the feedback provided information about how to execute this strategy: move more smoothly. While again, all groups improved in terms of smoothness, not surprisingly, the group that received smoothness-based feedback showed overall smoother movement.

Furthermore, while all groups at least maintained accuracy, the smoothness-based group was overall slightly less accurate. Accuracy did not get worse, so it does not appear that they were trading accuracy for speed. Instead, it appears that they were willing to tolerate overall slightly lower accuracy in order to achieve better gains on speed. However, this being a strategic decision on the part of the subjects is somewhat speculative. It is possible that this was not so much a strategic difference but an attentional one; participants may have been paying less attention to the visual accuracy feedback in order to concentrate more on the haptic smoothness feedback, which is what allowed them to improve their speed. This merits further research in the future.

Examining the differences in task completion strategies between feedback groups is relevant to many motor domains where an increase in task completion speed without loss of accuracy is ideal, particularly for specialized domains like endovascular surgery. Increased time on the surgical table exposes patients to increased radiation levels and doses of contrast agent, so a reduction in procedure time is beneficial. If we can demonstrate these same types of performance improvements in a surgical training scenario, we have the potential to positively impact training efficacy. Broad applications of this approach will depend on the sensitivity of the task to absolute accuracy.

Further research is necessary to determine if it is possible to realize the improvements in task completion time achieved with smoothness-based feedback while also achieving the accuracy performance observed in the nofeedback and position-based feedback groups. If we can solve the problem of the accuracy penalty that seems to exist with smoothness-based feedback, then this method of realtime performance feedback during training could be widely applicable.

V. Conclusion

While the link between expertise and movement smoothness is well-established in multiple motor domains, previous research using real-time vibrotactile feedback based on movement smoothness [15] suggested that such feedback might be useful for encouraging learners, but results were not conclusive. Using a larger sample and a more complex version of the mirror tracing task, we have now demonstrated that such feedback can lead to improved performance, in particular more rapid task completion (about 5 to 10 seconds faster). This is compared not only to a no vibrotactile feedback control but also to a condition where subjects received real-time vibrotactile feedback regarding position. There was a small difference in accuracy for those receiving smoothness-based feedback compared to the other two groups. Overall, the no feedback and position-feedback groups had consistently better accuracy in terms of both time outside and path length outside the figure, on the order of about 1 s less time spent outside the figure and just under 1 cm in path length outside the figure compared to the smoothness-based feedback group. While these differences were significant, they were a small percentage of the overall task completion time and overall path lengths recorded in all groups. We observed that the type of feedback provided resulted in different task completion strategies. To improve task completion times, the smoothness-based feedback was more successful, but the group receiving this type of feedback was less accurate than the other two groups. In applications such as surgery where reducing task completion times is advantageous in order to reduce exposure to contrast agent and radiation, movement smoothness appears to be appropriate for the purposes of improving training performance using vibrotactile haptic feedback. The next steps are to test this in an actual surgical context, and to explore methods of real-time performance feedback that might elicit improved accuracy while maintaining the reductions in completion times that were achieved with smoothness-based feedback.

Acknowledgment

The authors would like to thank Will Jantscher and Priyanshu Agarwal for their input on the experiment design and computational infrastructure for data collection and processing. We would also like to thank Hanna Wisdom and Patricia Garcia-Castineiras for their support in data collection and Charles Weeks for feedback on the manuscript.

REFERENCES

[1] T. J. Tausch, T. M. Kowalewski, L. W. White, P. S. McDonough, T. C. Brand, and T. S. Lendvay, "Content and construct validation of a robotic surgery curriculum using an electromagnetic instrument tracker," *J. Urol.*, vol. 188, no. 3, pp. 919–923, 2012.

[2] I. Nisky, A. M. Okamura, and M. H. Hsieh, "Effects of robotic manipulators on movements of novices and surgeons," *Surg. Endoscopy*, vol. 28, no. 7, pp. 2145–2158, 2014.

[3] J. Hernandez *et al.*, "Qualitative and quantitative analysis of the learning curve of a simulated surgical task on the da Vinci system," *Surg. Endoscopy Other Interventional Techn.*, vol. 18, no. 3, pp. 372–378, 2004.

[4] R. A. Chaer *et al.*, "Simulation improves resident performance in catheter-based intervention: Results of a randomized, controlled study," *Ann. Surg.*, vol. 244, no. 3, pp. 343–349, 2006.

[5] C. Wickens, J. Hollands, S. Banbury, and R. Parasuraman, *Engineering Psychology and Human Performance*, 4th Ed. Boston, MA, USA: Pearson, 2013.

[6] T. Flash and N. Hogan, "The coordination of arm movements: An experimentally confirmed mathematical model," *J. Neurosci.*, vol. 5, no. 7, pp. 1688–1703, 1985.

[7] M. K. O'Malley, S. N. Purkayastha, N. Howie, and M. D. Byrne, "Identifying successful motor task completion via motion-based performance metrics," *IEEE Trans. Human-Mach. Syst.*, vol. 44, no. 1, pp. 139–145, Feb. 2014.

[8] J. C. Huegel, O. Celik, A. Israr, and M. K. O'Malley, "Expertise-based performance measures in a virtual training environment," *Presence: Teleoperators Virtual Environ.*, vol. 18, no. 6, pp. 449–467, 2009.

[9] O. Celik, M. K. O'Malley, C. Boake, H. S. Levin, N. Yozbatiran, and T. A. Reistetter, "Normalized movement quality measures for therapeutic robots strongly correlate with clinical motor impairment measures," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 433–444, Aug. 2010.

[10] B. Rohrer *et al.*, "Movement smoothness changes during stroke recovery," *J. Neurosci.*, vol. 22, no. 18, pp. 8297–8304, 2002.

[11] A. U. Pehlivan, F. Sergi, A. Erwin, N. Yozbatiran, G. E. Francisco, and M. K. O'Malley, "Design and validation of the ricewrist-s exoskeleton for robotic rehabilitation after incomplete spinal cord injury," *Robotica*, vol. 32, no. 8, pp. 1415–1431, 2014.

[12] S. Estrada, C. Duran, D. Schulz, J. Bismuth, M. D. Byrne, and M. K. O'Malley, "Smoothness of surgical tool tip motion correlates to skill in endovascular tasks," *IEEE Trans. Human-Mach. Syst.*, vol. 46, no. 5, pp. 647–659, Oct. 2016.

[13] M. K. O'Malley, M. D. Byrne, S. Estrada, C. Duran, D. Schulz, and J. Bismuth, "Expert surgeons can smoothly control robotic tools with a discrete control interface," *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 4, pp. 388–394, Aug. 2019.

[14] S. Pandey, M. D. Byrne, W. H. Jantscher, M. K. O'Malley, and P. Agarwal, "Toward training surgeons with motion-based feedback: Initial validation of smoothness as a measure of motor learning," in *Proc. Hum. Factors Ergonom. Soc. Annu. Meeting*, vol. 61, no. 1. Los Angeles, CA, USA: SAGE Publications Sage CA, 2017, pp. 1531–1535.

[15] W. H. Jantscher *et al.*, "Toward improved surgical training: Delivering smoothness feedback using haptic cues," in *Proc. IEEE Haptics Symp.*, 2018, pp. 241–246.

[16] S. Balasubramanian, A. Melendez-Calderon, A. Roby-Brami, and E. Burdet, "On the analysis of movement smoothness," *J. Neuroengineering Rehabil.*, vol. 12, no. 1, pp. 1–11, 2015.

[17] B. Rohrer *et al.*, "Submovements grow larger, fewer, and more blended during stroke recovery," *Motor Control*, vol. 8, no. 4, pp. 472–483, 2004.

[18] G. Rauter, J. von Zitzewitz, A. Duschau-Wicke, H. Vallery, and R. Riener, "A tendon-based parallel robot applied to motor learning in sports," in *Proc. 3rd IEEE RAS EMBS Int. Conf. Biomed. Robot. Biomechatron.*, 2010, pp. 82–87.

[19] J. von Zitzewitz *et al.*, "Real-time rowing simulator with multimodal feedback," *Sports Technol.*, vol. 1, no. 6, pp. 257–266, 2008.

[20] L. Marchal-Crespo, G. Rauter, D. Wyss, J. von Zitzewitz, and R. Riener, "Synthesis and control of an assistive robotic tennis trainer," in *Proc. 4th IEEE RAS EMBS Int. Conf. Biomed. Robot. Biomechatron.*, 2012, pp. 355–360.

[21] Y. Li, V. Patoglu, and M. K. O'Malley, "Negative efficacy of fixed gain error reducing shared control for training in virtual environments," *ACM Trans. Appl. Percep.*, vol. 6, no. 1, pp. 1–21, 2009.

[22] L. M. Crespo and D. J. Reinkensmeyer, "Haptic guidance can enhance motor learning of a steering task," *J. Motor Behav.*, vol. 40, no. 6, pp. 545–557, 2008.

[23] A. A. Stanley and K. J. Kuchenbecker, "Evaluation of tactile feedback methods for wrist rotation guidance," *IEEE Trans. Haptics*, vol. 5, no. 3, pp. 240–251, Jul.–Sep. 2012.

[24] S. L. Norman, A. J. Doxon, B. T. Gleeson, and W. R. Provancher, "Planar hand motion guidance using fingertip skin-stretch feedback," *IEEE Trans. Haptics*, vol. 7, no. 2, pp. 121–130, Apr.–Jun. 2014.

[25] J. Bluteau, S. Coquillart, Y. Payan, and E. Gentaz, "Haptic guidance improves the visuo-manual tracking of trajectories," *PLoS One*, vol. 3, no. 3, 2008, Art. no. e 1775.

[26] R. Palluel-Germain, F. Bara, A. H. De Boisferon, B. Hennion, P. Gouagout, and E. Gentaz, "A visuo-haptic device-telemaque-increases kindergarten children's handwriting acquisition," in *Proc. 2nd Joint EuroHaptics Conf., Symp. Haptic Interfaces Virtual Environ. Teleoperator Syst. World Haptics*, 2007, pp. 72–77.

[27] D. E. Druckman and R. A. Bjork, *Learning, Remembering, Believing: Enhancing Human Performance*. Washington, DC, National Academy Press, 1994.

[28] G. S. Snoddy, "Learning and stability: A psychophysiological analysis of a case of motor learning with clinical applications," *J. Appl. Psychol.*, vol. 10, no. 1, pp. 1–36, 1926.

Jennifer L. Sullivan received the B.S. degree in mechanical engineering from Rice University, Houston, TX, USA, and the M.A.Sc. degree in mechanical engineering from the University of British Columbia, Vancouver, BC, Canada. She was a Research Engineer with Mechatronics and Haptic Interfaces Lab, Rice University. She is currently a Human Performance Engineer with NASA Johnson Space Center.

Shivam Pandey received the B.B.A. degree in management information systems and the M.B.A. degree in business administration from Angelo State University, San Angelo, TX, USA, the M.S. degree in applied health informatics from the University of Texas Health Science Center at Houston, Houston, TX, USA, and the Ph.D. degree in human-computer interaction and human factors from Rice University, Houston, TX, USA. He is currently a Human Performance Scientist with Canadian Nuclear Laboratories.

Michael D. Byrne received the B.S. degree in engineering and the B.A. degree in psychology from the University of Michigan, Ann Arbor, MI, USA, and the M.S. degree in computer science and also the M.S. and Ph.D. degrees in experimental psychology from the Georgia Institute of Technology, Atlanta, GA, USA. He is currently a Professor of psychological sciences and computer science from Rice University, Houston, TX, USA, and directs the Computer-Human Interaction Laboratory.

Marcia K. O'Malley (Fellow, IEEE) received the B.S. degree in mechanical engineering from Purdue University, West Lafayette, IN, USA, in 1996, and the M.S. and Ph.D. degrees in mechanical engineering from Vanderbilt University, Nashville, TN, USA, in 1999 and 2001, respectively. She is currently the Thomas Michael Panos Family Professor of mechanical engineering, computer science, and electrical and computer engineering with Rice University, Houston, TX, USA, and directs the Mechatronics and Haptic Interfaces Laboratory.