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The Effect of a Robot-Assisted Surgical System on the Kinematics of User Movements*

Ilana Nisky[1], Michael H. Hsieh[2], and Allison M. Okamura[1]

Abstract— **Teleoperated robot-assisted surgery (RAS) offers many advantages over traditional minimally invasive surgery. However, RAS has not yet realized its full potential, and it is not clear how to optimally train surgeons to use these systems. We hypothesize that the dynamics of the master manipulator impact the ability of users to make desired movements with the robot. We compared freehand and teleoperated movements of novices and experienced surgeons. To isolate the effects of dynamics from procedural knowledge, we chose simple movements rather than surgical tasks. We found statistically significant effects of teleoperation and user expertise in several aspects of motion, including target acquisition error, movement speed, and movement smoothness. Such quantitative assessment of human motor performance in RAS can impact the design of surgical robots, their control, and surgeon training methods, and eventually, improve patient outcomes.**

I. Introduction

Robot-assisted surgery (RAS), depicted in Fig. 1A, is gaining popularity over traditional minimally invasive surgery due to its improved visualization, dexterity, and intuitive control of the surgical instruments. However, RAS has not yet realized its full potential in terms of patient outcomes, and it is not clear how to optimally train surgeons to use these systems [1], [2]. We suggest that a quantitative understanding of how the movements of users change when they manipulate the master of a teleoperated robot and how they adapt to its dynamics can help to remedy these shortcomings. Combining this understanding with computational motor control and learning theories [3], [4] could facilitate the development of more efficient robot design and control, and improve training and skill assessment methods for RAS.

Surgical skill includes cognitive as well as motor aspects, but most current training curricula invoke only task completion time and number of errors for skill assessment [5]. These metrics do not allow differentiating between the different components, and it has been suggested that they are not sufficient for skill assessment [6]. RAS facilitates collection of data about the trajectories of the surgeon's hands and instruments [7], [8], and therefore, there is an unexploited potential for using computational techniques to understand and improve skill acquisition in RAS. One prior approach broke down trajectories into gestures to create a ”language of surgery” [9]. Other studies have used Hidden Markov Models for modeling surgery and skill evaluation [10], [11]. Our approach is unique in that we use the framework of human motor control to quantify the effects of teleoperation and user expertise on motor performance in RAS.

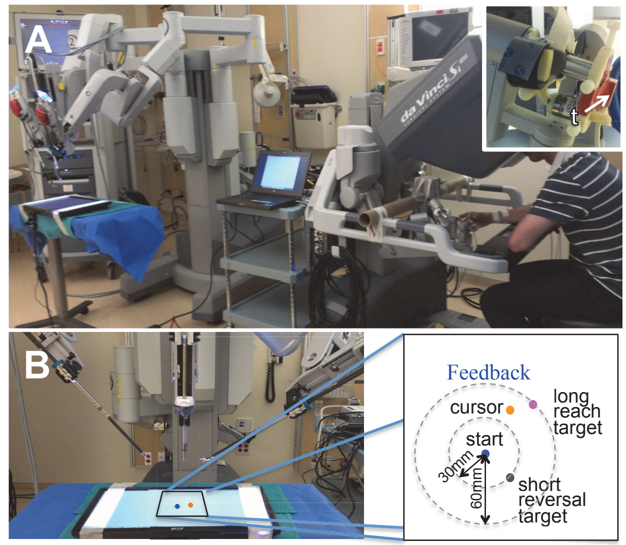

Fig. 1. (A) Experimental setup with participant holding an externally mounted fixture (inset) with a magnetic tracker (labeled 't'). (B) A monitor, placed on the surgical table, presents the experimental scene.

In the current study, we focus on the effects of master manipulator dynamics on user movements. To isolate these effects from procedural knowledge, we studied two simple movements – reach and reversal. Reach is a movement between two points that is characterized by a straight path and bell-shaped velocity trajectory [12]. Reversal is an out-and-back movement, and can be modeled as a concatenation of two reaches in opposite directions with overlap [13]. While these movements are of limited clinical relevance in isolation, they allow us to utilize the theoretical framework of human motor control, and represent building blocks for more complicated surgical motions to be studied in future work. We presented the experimental paradigm of this study and preliminary results in [14].

II. Methods

A. Experimental Procedures

Thirteen volunteers participated in the experiment, approved by the Stanford University Institutional Review Board, after giving informed consent. Ten participants were

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[1]I. Nisky and A. M. Okamura are with the Department of Mechanical Engineering, Stanford University, Stanford, CA, 94305, USA. E-mail: nisky@stanford.edu and aokamura@stanford.edu

[2]M. H. Hsieh is with the Department of Urology, Stanford University, and the Pediatric Urology Service, Lucile Salter Packard Children's Hospital at Stanford, Stanford, CA, 94305, USA. E-mail: mhhsieh@stanford.edu

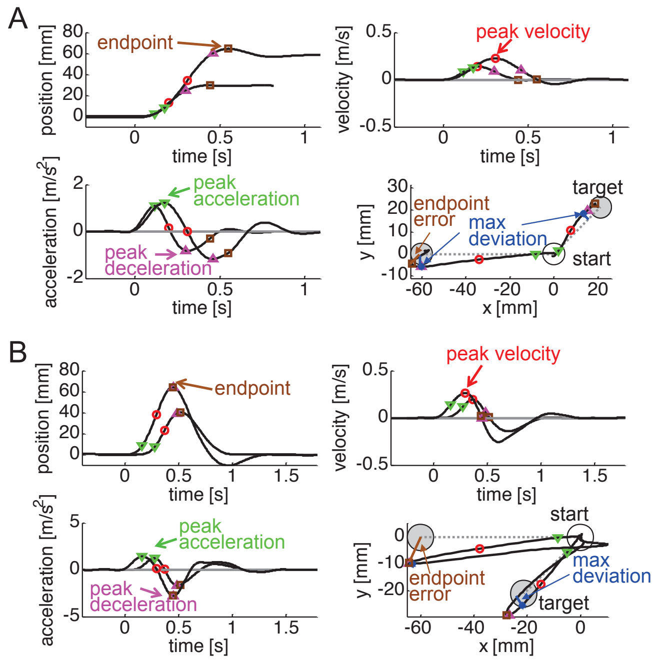

Fig. 2. Examples of position, velocity, and acceleration trajectories and x-y paths of one short and one long reach (A) and reversal (B) movements. Points of interest for quantitative movement analysis metrics are marked.

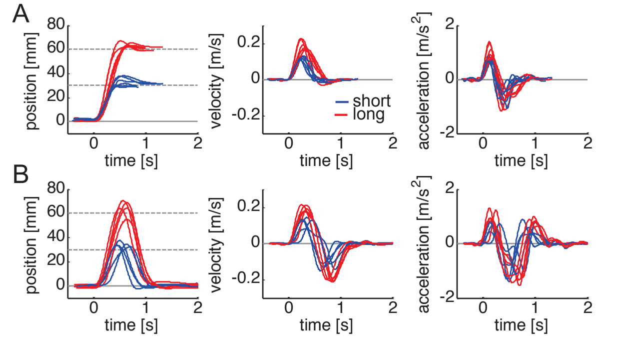

Fig. 3. Teleoperated reaches (A) and reversals (B) of a novice participant.

engineering graduate students who had no experience manipulating a da Vinci, and three were experienced urology surgeons with a high volume of RAS cases (>100).

Participants sat in front of the master console of a da Vinci Si system at Lucile Packard Children's Hospital (Fig. 1A). They were asked to make consecutive center-out planar movements as fast and as accurately as possible. They held a custom grip fixture (inset of Fig. 1A) with magnetic pose tracker (TrakStar, Ascension Technologies). Seven of the participants (five novices and two experts) first performed the experiment freehand, by holding the fixture detached from the master manipulator, and then via teleoperation. Six of the participants (five novices and one expert) performed the freehand and teleoperated conditions in the reverse order. A monitor placed on the surgical table presented to the user (via the endoscopic camera) targets and a cursor that represented the position of the position tracker attached to the fixture, as depicted in Fig. 1. This ensured consistent visual feedback in both conditions. In the teleoperated condition, the master manipulator did control the movement of the (non-visible) patient-side manipulator, ensuring dynamics identical to standard clinical teleoperation. In both conditions, participants could rest their elbow on the armrest, but were not specifically instructed to do so.

The targets were centered on one of two circles with radii 30 mm (short) or 60 mm (long) in one of eight directions: -135, -90, -45, 0, 45, 90, and 135 degrees (Fig. 1B). Target color indicated the desired type of movement (reach or reversal). Each combination of movement type, distance, and direction was repeated 10 times, and the sequence of presentation of all 320 trials was pseudorandom and identical for all participants and for both conditions of each participant. The participants were instructed to complete a reach within 1 s, and a reversal within 1.5 s, and after completion of each movement, they were provided with feedback about the movement time. A movement was considered complete when the cursor stayed within 5 mm from the target center for 0.5 s for a reach movement, and the cursor returned to within 5 mm from start point for a reversal movement.

B. Data Analysis

We sampled the x-y position information ($\vec{x}$) at 120 Hz, and filtered the data offline with a 4th-order low-pass Butterworth filter with a cutoff at 6 Hz. We calculated velocity and acceleration by successive backward differentiation and filtering. We discarded reaches that were longer than 2.5 s, and reversals that were longer than 3 s. To facilitate comparison across movement directions, we calculated the position (p), velocity (v), and acceleration (a) projections on target directions, as depicted in the examples in Fig. 2 and 3. We used the method described in [10] to identify movement onset time (t_0) and estimate the initial jerk of each movement (j_0). Then, we identified points of peak speed, peak acceleration, and peak deceleration, as depicted in Fig. 2. For analysis of endpoint error, we defined reach endpoint $\vec{x}_{\text{end}}$ (and its time t_{end}) based on the main reach motion in each trial, without subsequent corrections (Fig. 2A), and reversal endpoint as the maximal point of position trajectory (Fig. 2B). For analysis of curvature of movement path, we calculated projection of position on direction orthogonal to target (p_{o}), and identified the point of maximal deviation from straight line connecting start and target positions.

Next, for each movement, we calculated the following metrics:

- *Endpoint error*: $e_{\text{end}} = ||\vec{x}_{\text{end}} - \vec{x}_{\text{target}}||$
- *Movement time*: $t_{\text{m}} = t_{\text{end}} - t_0$
- *EE*MT*: $e_{\text{end}} \cdot t_{\text{m}}$
- *Peak speed*: $\max(|v|)$
- *Peak acceleration*: $|\max(a)|$
- *Peak deceleration*: $|\min(a)|$
- *Initial jerk*: j_0
- *Max deviation*: $\max(|p_{\text{o}}|)$
- *Sum of absolute deviation*: $\sum |p_{\text{o}}|$
- *Peak A / Peak D*: $|\max(a)|/|\min(a)|$

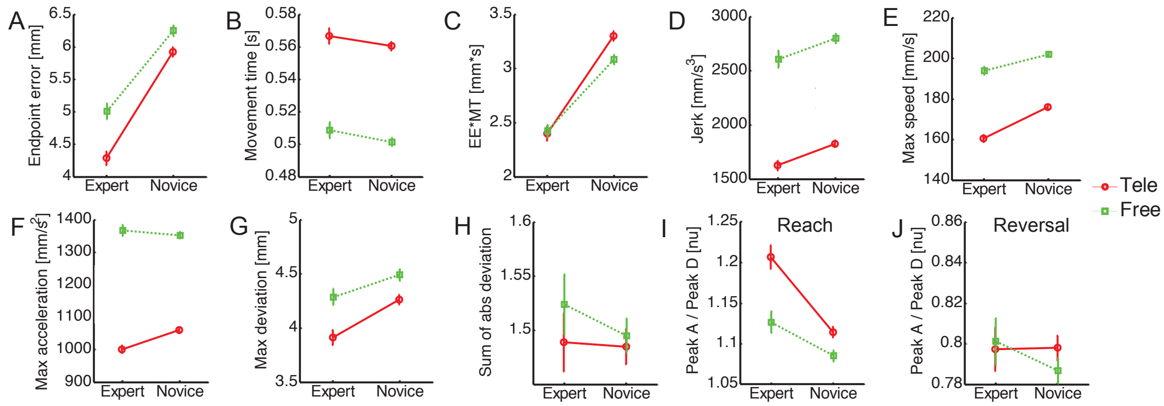

Fig. 4. The effect of teleoperation and expertise on the kinematics of user movements. Markers are estimated means, and error bars are ±standard error

The last metric quantifies different aspects for reach and reversal movement types. In reaches, this metric quantifies the symmetry of the velocity trajectory, and value greater than one indicates the existence of a fused corrective movement. In reversals, it distinguishes between a real reversal (∼0.5) and two reaches with a pause between them (∼1).

C. Statistical Analysis

In the current paper, our main focus is on the effects of teleoperation and expertise factors across movement types, distances, and directions. Therefore, for all metrics except *Peak A / Peak D*, we performed a 2-way ANOVA on all non-discarded movements from both experiments of all subjects. The degrees of freedom of all F tests were (1,7563) unless specified otherwise. Because of the different meaning of the *Peak A / Peak D* metric for reach and reversal movements, we performed separate 2-way ANOVA for each movement type. Statistical significance was defined as $\alpha < 0.05$. When interaction effects were statistically significant, we performed post-hoc comparisons using the appropriate Bonferroni correction for the number of multiple comparisons.

III. Results

Examples of teleoperated movement trajectories of a novice participant are depicted in Fig. 3. Visual examination of these trajectories reveals that the reach movements possess bell-shaped velocity profiles, with corrective movements when necessary [12], and reversal movements resemble two back-and-forth overlapping reaches [13]. The majority of the movements were completed within the required time window. In accordance with the isochrony principle [15], participants moved faster at long movements to maintain similar movement time regardless to distance.

Consistent with our hypothesis, the analysis revealed statistically significant effects of teleoperation, expertise, or their interaction in most of the metrics that we tested, as depicted in Figure 4. The *endpoint error* (Fig. 4A) was 23% smaller in expert movements than in novices (F=167, p<0.0001) and 9% smaller in teleoperated than freehand movements (F=22.17, p<0.0001). The difference between experts and novices was more pronounced in the teleoperated movements, but the interaction effect was not statistically significant (F=3.11, p=0.08). Interestingly, only the mean teleoperated endpoint errors of experts were smaller than the task tolerance for acceptable error of 5 mm. The *movement time* (Fig. 4B) of teleoperated movements was 12% smaller than of freehand (F=229, p<0.0001), and there was no significant effect of expertise or interaction (F=3, p=0.08 and F=0.03, p=0.86, respectively). Users likely moved slower in the teleoperated condition due to the inertial and damping effects of the dynamics of the master manipulator, and it might partially account for the improved endpoint error in teleoperated movements, in accordance with Fitt's law [16]. Indeed, the *EE*MT* metric that reflects overall performance (Fig. 4C) revealed that experts were 25% better than novices (F=157, p<0.0001) without a statistically significant effect of teleoperation (F=2.38, p=0.12). The difference between experts and novices was even slightly larger (27%) if only teleoperated movements are taken into account, but the interaction effect did not reach statistical significance for the current sample size (F=3.78, p=0.05). Notably, the performance of experts in teleoperated and freehand conditions is nearly identical according to this metric.

The inertial and damping effects of the teleoperator are also likely responsible for the statistically significantly smaller *maximum speed* (15%), *initial jerk* (36%), and *peak acceleration* (25%) and *deceleration* (27%) in the teleoperated movements versus freehand, as depicted in Fig. 4D-F (F=325, p<0.0001; F=315, p<0.0001; F=628, p<0.001; and F=520, p<0.001, respectively). Interestingly, there was also a decrease of 6%, 9%, 2%, and 4% for these metrics in experts compared to novices. This was statistically significant in all metrics but *peak acceleration* (F=51, p=p<0.001; F=12.97, p=0.0003; F=2.84, p=0.09; and F=8.37, p=0.004, respectively), and the decrease in these metrics due to teleoperation was always more pronounced in experts, yielding a significant interaction in all metrics except for *initial jerk* (F=4.91, p=0.03; F=0.01, p=0.94; F=7.81, p=0.005; and F=7.09 , p<0.008, respectively). Since all these metrics are related to the smoothness of movements, these findings suggest that experienced surgeons generally move more smoothly than novices, and that this difference is more pronounced in teleoperated than freehand movements. The smoothness of surgeon movements could be the result of a strategy that they adopt to overcome the effects of teleoperator dynamics on their performance, but future studies are needed to test this hypothesis.

We expected to find increased curvature of teleoperated movements; however, *sum of absolute deviation* from straight line, Fig. 4H, was similar across different conditions (F=0.95, p=0.32; F=0.61, p=0.47; and F=0.28, p=0.59 for the teleoperation, expertise, and interaction factors, respectively). Moreover, *max deviation* from straight line of teleoperated movements was 7% smaller than freehand (F=17, $p<0.0001$), likely due to smaller speed and acceleration. The deviation of experts' movements was 6% smaller than of novices (F=16, p=0.0001), but the interaction of teleoperation condition and expertise was not statistically significant (F=1, p=0.3).

The *Peak A / Peak D* metric quantifies the shape of the velocity profile. The results of separate analysis of reach and reversal movements are depicted in Fig. 4I-J. In reaches, a value larger than unity indicates that the user smoothly fused corrective movements rather than correcting after initial stop. Our results indicate that teleoperated velocity profiles were 5% less symmetric than freehand ($F_{1,3706}$=30, $p<0.0001$), that experts' profiles were 6% less symmetric than novices' profiles ($F_{1,3706}$=44, $p<0.0001$), and that the interaction was statistically significant ($F_{1,3706}$=6.38, p=0.01). Notably, the teleoperated velocity profiles of experienced surgeons were least symmetrical, indicating that when their hand comes to stop, it is within target tolerance without additional corrections, especially during teleoperation. Such a strategy is particularly beneficial in a surgical context, where the cost of making initial error is high in terms of patient outcomes. The analysis of reversal movements reveals no effects of teleoperation, expertise, or their interactions on the tendency of users to momentarily stop at the target.

IV. Discussion and Conclusions

We explored the effect of teleoperation and expertise on kinematic aspects of simple movements. We used metrics based on the human motor control literature, and found differences between teleoperated and freehand movements. Interestingly, even though the tested movements were very simple, there were pronounced differences between expert surgeons and novices. Often, these effects were stronger in teleoperated rather than freehand movements. Thus, RAS expertise is apparent not only in cognitive (procedural) aspects or automation of complex motor sequences, but also in the basic kinematics of movement.

We hypothesize that the dynamics of the master, the patient side robot, and the control law that couples them could be responsible for such effects. In the current study, because the clinical da Vinci system has effectively no haptic feedback, only the passive dynamics of the manipulator played an important role.

Due to space limitations, we leave computational modeling the inertial effects outside of the scope of this paper. Such modeling will allow us to predict the effects of teleoperation on performance of more complicated and clinically relevant movements like needle driving or suturing. Testing these movements in more realistic scenarios may validate whether our results generalize. This could have direct implications for assessment and training of the motor aspects of surgical skill, independent of the cognitive aspects. In addition, such modeling can be used in improving the design and control of surgical teleoperators. For example, current results suggest that reducing the inertia of the master manipulator would improve performance. Furthermore, analysis of the effect of teleoperator tracking errors could lead to the design of different controllers.

References

[1] J. Martell, T. Elmer, N. Gopalsami, and Y. S. Park, "Visual measurement of suture strain for robotic surgery," *Computational and Mathematical Methods in Medicine*, vol. 2011, pp. 1–9, 2011.

[2] S. Jacobs, D. Holzhey, G. Strauss, O. Burgert, and V. Falk, "The impact of haptic learning in telemanipulator-assisted surgery," *Surgical Laparoscopy Endoscopy & Percutaneous Techniques*, vol. 17, no. 5, pp. 402–406, 2007.

[3] R. Shadmehr and S. P. Wise, *The Computational Neurobiology of Reaching and Pointing: A Foundation for Motor Learning*. MIT Press, 2005.

[4] R. Shadmehr and S. Mussa-Ivaldi, *Biological Learning and Control: How the Brain Builds Representations, Predicts Events, and Makes Decisions*. MIT Press, 2012.

[5] D. A. Ugarte, D. A. Etzioni, C. Gracia, and J. B. Atkinson, "Robotic surgery and resident training," *Surgical Endoscopy*, vol. 17, no. 6, pp. 960–963, 2003.

[6] K. Narazaki, D. Oleynikov, and N. Stergiou, "Robotic surgery training and performance," *Surgical Endoscopy*, vol. 20, no. 1, pp. 96–103, 2006.

[7] 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," *The Journal of Urology*, vol. 188, no. 3, pp. 919–923, 2012.

[8] J. Hernandez, S. Bann, Y. Munz, K. Moorthy, V. Datta, S. Martin, A. Dosis, F. Bello, A. Darzi, and T. Rockall, "Qualitative and quantitative analysis of the learning curve of a simulated surgical task on the da vinci system," *Surgical Endoscopy And Other Interventional Techniques*, vol. 18, no. 3, pp. 372–378, 2004.

[9] H. Lin, I. Shafran, D. Yuh, and G. Hager, "Towards automatic skill evaluation: Detection and segmentation of robot-assisted surgical motions," *Computer Aided Surgery*, vol. 11, no. 5, pp. 220–230, 2006.

[10] J. Rosen, J. D. Brown, L. Chang, M. N. Sinanan, and B. Hannaford, "Generalized approach for modeling minimally invasive surgery as a stochastic process using a discrete markov model," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 3, pp. 399–413, 2006.

[11] G. Megali, S. Sinigaglia, O. Tonet, and P. Dario, "Modelling and evaluation of surgical performance using hidden markov models," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 10, pp. 1911–1919, 2006.

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

[13] R. A. Scheidt and C. Ghez, "Separate adaptive mechanisms for controlling trajectory and final position in reaching," *Journal of Neurophysiology*, vol. 98, no. 6, pp. 3600–3613, 2007.

[14] I. Nisky, S. Patil, M. Hsieh, and A. Okamura, "Kinematic analysis of motor performance in robot-assisted surgery: A preliminary study," in *Studies in Health Technology and Information*, vol. 184, 2013, pp. 302–308.

[15] P. Viviani and T. Flash, "Minimum-jerk, two-thirds power law, and isochrony: converging approaches to movement planning." *Journal of Experimental Psychology: Human Perception and Performance*, vol. 21, no. 1, pp. 32–53, 1995.

[16] P. 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.