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Training in Divergent and Convergent Force Fields During 6-DOF Teleoperation with a Robot-Assisted Surgical System

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Abstract— **The technical skills of surgeons directly affect patient outcomes, yet how to train surgeons in a way that maximizes their learning speed and optimizes their performance is an open question. Recent studies in human motor learning have shown benefits of using force fields during training in point-to-point reaching tasks. Teleoperation systems enable the application of these force fields during the learning of more complex and real-world activities. We performed a study in which participants used the da Vinci Research Kit, a teleoperated robot-assisted surgical system, to perform a peg transfer task – a standard manipulation task used in minimally invasive surgery training. We investigated the effect on learning of training in three different groups: (1) without applying any force, (2) with a divergent force field, which pushes the user away from the desired path if they deviate from it, and (3) with a convergent force field, which pushes the user back to the desired path. We found no statistically significant differences in performance among the different training groups at the end of the experiment, but some differences were evident throughout the training. Thus, training in the divergent and convergent fields may involve different learning mechanisms, but does not worsen performance.**

I. Introduction

Surgery is a complex sensorimotor skill: surgeons must master hand-eye coordination, sensory integration, and fine motor control to create the best possible outcome for their patients. A successful surgical procedure requires clinical and technical skills, identification of anatomical structures, and precise interaction with tissue through dissection, retraction, suturing, and other maneuvers. Sub-optimal technical skills decrease patient safety and may result in adverse surgical outcomes [1].

In teleoperated robot-assisted minimally invasive surgery (RMIS), the surgeon grasps a pair of robotic master manipulators that control the movements of the instruments and the endoscopic camera inside the abdomen of the patient. Compared to open surgery, the patient benefits from reduced pain, injury, and recovery time. Compared to manual laparoscopy, intuitive and dexterous motion, motion scaling, and enhanced visualization make teleoperated RMIS surgery easier for surgeons and safer for patients [2], leading to wide adoption across surgical disciplines [3, 4]. However, teleoperation also has drawbacks: surgeons need to learn new dynamics of the master manipulators and instruments [5, 6, 7], and to compensate for missing haptic feedback [8]. Until teleoperation systems become completely transparent and surgeons feel as if the instruments are their hands [9], training in RMIS is needed to teach surgeons how to exploit the system's advantages while overcoming its challenges.

Conventional surgeon training curricula are largely defined by expert opinion and consensus, and are based on the apprenticeship model [10]. They seek to teach fine motor skills through repetition of simulation, inanimate, animal, or cadaveric training exercises until an acceptable proficiency is achieved. Continued prevalence of operative inefficiencies and errors, as well as pressure on trainee work hours [11, 12], suggests that these curricula need to be improved. To that end, there is substantial effort to design and validate new training curricula [13, 14], to develop surgeon warm-up strategies [15], and to use virtual and augmented reality simulators [16]. Nevertheless, there are many open questions about what comprises surgical skill and what is the most efficient strategy to improve it [17].

Due to its teleoperated nature, RMIS allows for recording of surgeon behavior to model surgeon performance. Movement and force data in RMIS have been used to classify surgical skill [15, 18, 19, 20], and recently, metrics grounded in behavioral neuroscience and human sensorimotor control have shown promise [5, 6, 21, 22]. Moreover, RMIS creates an opportunity to provide assistance and improve the speed and quality of surgical training: the master manipulators of RMIS systems are capable of applying forces to the hands of the surgeon, and the video stream may be altered to provide augmented visual information [23]. In this way, novel methods to improve surgeon training may provide guidance towards a desired path or temporal trajectory [24], make the task easier and potentially expedite learning [25], exaggerate errors or add resistance to make the task more difficult [26, 27], or even provide random perturbations. To efficiently navigate this design space, it may be useful to harness computational models of sensorimotor learning theories [28].

Recent findings in motor learning have identified various factors, such as the error displayed to the learner or the variability of movement, that affect the rate and extent of learning of a motor skill and adaptation to altered conditions [29, 30, 31]. Related research in motor rehabilitation and skill acquisition [27, 32, 33] has shown that people can learn to

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perform tasks faster and more accurately when their environment is augmented to exaggerate negative effects of errors [34]. Error augmentation techniques have yet to be applied to RMIS; the closest application has been a translational micromanipulation task [26].

In the current paper, we present an investigation of error augmentation in a teleoperated RMIS system. We examined the effect of null, divergent, and convergent force/torque fields on the learning of novice non-medical participants during a 6-DOF peg transfer task using the da Vinci Research Kit. The peg transfer task is important for surgical training because transfer of objects is frequently done in an operative setting during manipulation and passing a suture needle or tissue, and it is part of the Fundamentals in Laparoscopic Surgery (FLS) tasks [35]. We hypothesized that training in a divergent force/torque field may lead to enhanced performance.

II. METHODS

A. Surgical Robotic Platform

The experiment used the da Vinci Research Kit (dVRK), a teleoperated robot-assisted surgical system [7, 36]. Participants sat at the master console with their finger and thumb in the straps of the right master gripper, as shown in Figure 1. They looked into the stereoscopic viewer to see a 3-D real-time video of the patient-side instrument. The position and orientation of the instrument gripper were controlled using proportional-derivative (PD) control based on the position and orientation of the master gripper. All experiments were carried out with the teleoperation scale factor set so that the change in position of the patient-side instrument was 0.6 times the change in position of the master, which is within the range of scale factors used on the clinical da Vinci Surgical System. Participants were not allowed to use the clutch to change the position mapping between master and slave, move the camera, or change the zoom level. All experiments were carried out using a mega needle driver as the patient-side instrument.

B. Procedure

Participants were asked to transfer a foam cylinder between two metal pegs, similar to a standard MIS training task. They were instructed to do their best to follow the desired path shown in Figure 2. This desired path was defined as a series of 6-DOF poses (3-DOF in position and 3-DOF in orientation). The white line in Figure 2 indicates the desired position of the tip of the gripper. The orientation of the gripper should be horizontal at the upper left end of the path and vertical at the lower right end of the path.

Before the participants began the experiment, they were introduced to the dVRK and shown a picture of the desired path as well as a video of several good cylinder transfers. For each trial, they were instructed to transfer the cylinder from one peg to the other and then release their grasp of the cylinder and move away from it before getting closer and grasping it for the next trial. Participants were not allowed to close the gripper on the cylinder until they were close enough to the desired starting position and orientation for that trial. The background of the stereoscopic viewer's video screen changed color to help participants through the segments of the task and ensure that they did not grasp the cylinder from a wrong starting position or orientation. The screen was yellow

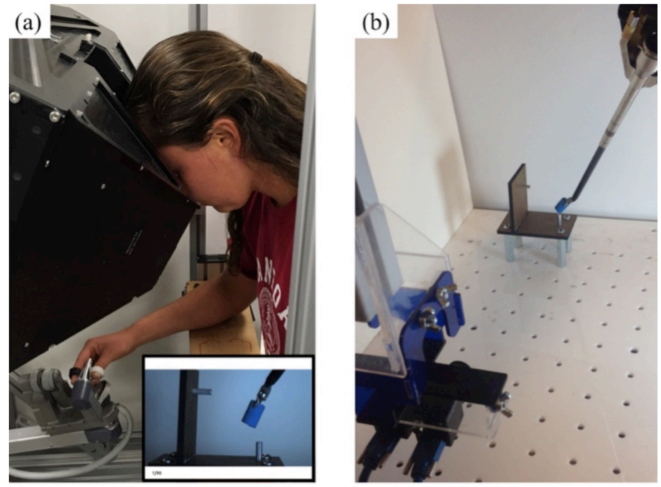

Figure 1. The da Vinci Research Kit. (a) A participant sits at the master console and moves the gripper while looking through the stereoscopic viewer to see a real time video of the patient-side robot, as shown in the inset. (b) The patient-side robot is in the view of the stereoscopic cameras as the participant controls it to move a cylinder between two pegs.

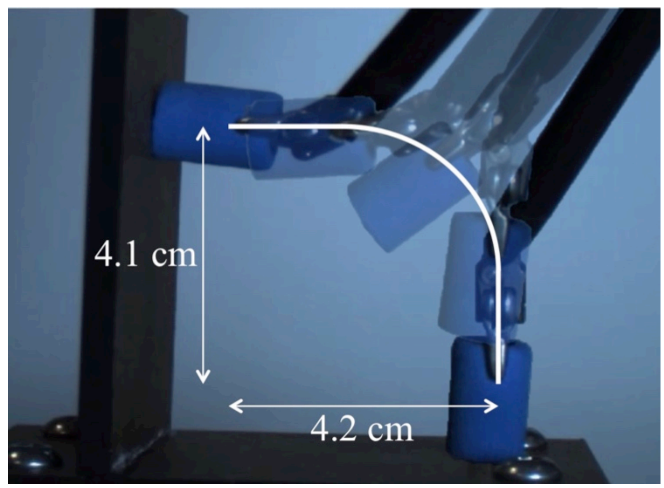

Figure 2. The 6-DOF path that participants were asked to follow. The position of the tip of the gripper followed a straight line, a quarter of an ellipse, and then another straight line. The orientation of the gripper was horizontal along the upper left straight line, and then followed a uniform rate of rotation until it reached vertical at the lower right straight line.

when they needed to get closer to the starting position and/or orientation (as measured at the master). It turned green when they were within 1.25 cm of the desired starting position and within 0.5 radians of the desired starting orientation for that trial, and then white when they closed the gripper on the cylinder. Once they placed the cylinder on the other peg and opened the gripper within 2.5 cm of the desired ending position, the screen turned red. When the participants moved 2.5 cm away from the ending position, the screen turned back to yellow, indicating that they should get closer to the starting position and/or orientation for the next trial. Participants were instructed to complete the portion of the task while the screen was white as accurately and quickly as possible.

Each participant completed a total of 90 trials of cylinder transfer between the two pegs. They alternated between moving the cylinder from lower right to upper left and moving the cylinder from upper left to lower right, such that 45 trials were performed in each direction. Participants were given a short break after each session of 30 trials. The control group completed all 90 trials with no force field. The two test groups received force feedback applied to the master gripper during the second session (trials 31-60). Force feedback was only applied when the gripper was closed on the cylinder. For one test group, a *divergent* force/torque field was applied, which pushed the participant's hand away from the path in the direction that they were off the path, with magnitude proportional to their distance away from the path (Figure 3). This force/torque field was applied in both position and orientation, with a 3-DOF force vector applied based on how far their position was from the position of the closest point on the desired path, and with a 3-DOF torque vector applied based on how far their orientation was from the orientation of the closest point on the desired path. For the other test group, a *convergent* force/torque field was applied, which was the same as the divergent force/torque field, except that it pushed the participant's hand towards the path, rather than away from it (Figure 3). Participants in the two test groups were told before the second session that they would feel a force field pushing them away from or towards the desired path, and that they should still do their best to move as accurately and quickly as possible.

C. *Force Field Algorithm*

The desired path for the 6-DOF configuration of the right master gripper was encoded as 200 data points, each of which contained a position and a rotation matrix. The desired positions between data points were generated by joining two line segments with a quarter of an ellipse. The desired orientations between data points were generated by linearly interpolating (using the angle-axis representation) between a starting and an ending rotation matrix on the curved section of the path and holding the rotation matrices constant on the straight sections of the path.

Each time through the software control loop, which ran at 1000 Hz, the current master gripper position was compared with all 200 positions stored in the desired path to find the closest point. That data point's position vector $\vec{x}_{desired}$ and rotation matrix $R_{desired}$ were used to calculate the appropriate force and torque vectors to apply to the master gripper.

The force vector was calculated as

$$\vec{F} = -k_{translational} * (\vec{x}_{current} - \vec{x}_{desired}) - d_{translational} * \vec{v}_{current}, \quad (1)$$

where $k_{translational}$ is the translational spring constant, $\vec{x}_{current}$ is the 3-DOF current position vector, $d_{translational}$ is the translational damping constant, and $\vec{v}_{current}$ is the current 3-DOF velocity vector. A small damping constant was necessary to prevent the master manipulator from going unstable when the spring constant was nonzero. For all three force fields, the translational damping constant was 5 N-s/m. The translational spring constant was 0 N/m for the null field, -60 N/m for the divergent field, and 60 N/m for the convergent field.

The torque vector was calculated analogously using

$$\vec{T} = -k_{rotational} * R_{current} * rdiff_{angle} * rd\vec{iff}_{axis} - d_{rotational} * \vec{\omega}_{current}, \quad (2)$$

where $k_{rotational}$ is the rotational spring constant, $R_{current}$ is the current rotation matrix, $rdiff_{angle}$ and $rd\vec{iff}_{axis}$ are the angle-axis representation of the matrix $R_{current}^{T} * R_{desired}$, $d_{rotational}$ is the rotational damping constant, and $\vec{\omega}_{current}$ is the current angular velocity vector. For all three force fields, the rotational damping constant was 0.001 N-m-s/rad. The rotational spring constant was 0 N-m/rad for the null field, -0.03 N-m/rad for the divergent field, and 0.03 N-m/rad for the convergent field.

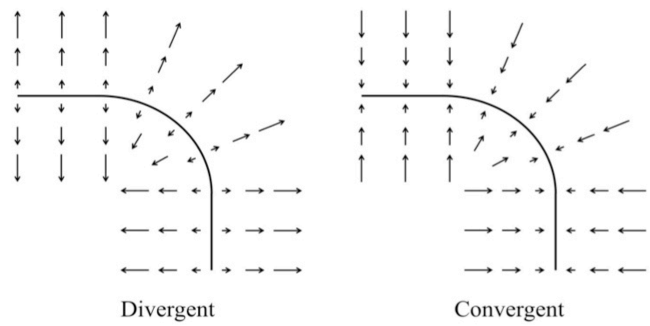

Figure 3. 2-D representation of the divergent and convergent force fields that were applied in 3-D to the master gripper. In the divergent force field, forces were applied pointing away from the desired path, with magnitude proportional to the distance of the gripper away from the closest point on the desired path. In the convergent force field, the forces had the same magnitude as those in the divergent force field, but they pointed towards the path. A torque field was also applied in both the divergent and convergent cases, with magnitude proportional to the angle difference between the gripper orientation and the orientation of the closest point on the path.

D. *Performance Metrics*

To evaluate user performance, we calculated trial time, translational path error, rotational path error, and combined path error multiplied by trial time (which we refer to as error-time) for each trial.

Trial time was calculated as the time from when the master gripper was closed within 1.25 cm of the desired starting position and within 0.5 radians of the desired starting orientation to when the gripper was opened within 2.5 cm of the desired ending position. This metric quantifies speed and is a classical measure of surgical skill [16].

Translational path error was calculated as the area of a surface between the actual path and the desired path, as shown in Figure 4a. For each position data point on the actual path ($\vec{x}_{n,actual}$), we calculated the distance to the closest point on the desired path ($\vec{x}_{n,desired}$). We also calculated the distance between the data point's closest point on the desired path and the previous data point's closest point on the desired path ($\vec{x}_{n-1,desired}$). We multiplied these two distances to get an area for each data point on the actual path, and then we summed the areas for all of the data points on the actual path to get the final metric. This metric quantifies accuracy, and is related to the classical measure of economy of motion [16].

Rotational path error was calculated analogously to translational path error, as shown in Figure 4b, except that we used an angle difference rather than a distance between the actual and desired data points. For each orientation data point in the actual path ($R_{n,actual}$), we calculated the angle difference to the closest point on the desired path's orientation ($R_{n,desired}$). We multiplied this by the previously calculated distance between the data point's closest point on the desired path and the previous data point's closest point on the desired path to get a "rotational area" in units of rad-m. We then summed these rotational areas for all of the data points on the

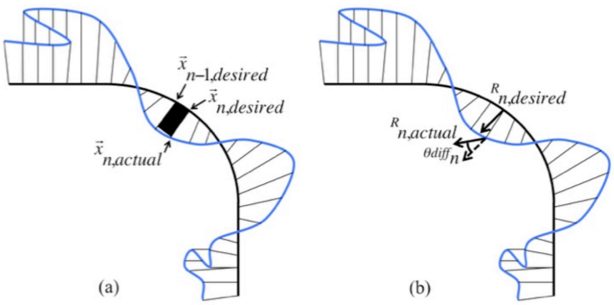

Figure 4. (a) Calculation of translational path error. This metric can be visualized as the area of a surface that stretches between the desired and actual paths. It was calculated for each data point as the distance between $\vec{x}_{n,actual}$ and $\vec{x}_{n,desired}$ multiplied by the distance between $\vec{x}_{n,desired}$ and $\vec{x}_{n-1,desired}$. (b) Calculation of rotation path error. Instead of multiplying by distance between desired and actual points, we multiplied by the angle difference between the orientations of desired and actual points.

actual path to get the final metric. This metric quantifies rotational accuracy, an important aspect of surgical skill [20].

Combined path error times trial time (called error-time) was calculated as a combination of the other three metrics. For each trial, we added rotational path error and a constant factor of 39 rad/m multiplied by translational path error to get combined path error. The constant factor was chosen to be equal to the ratio of the average rotational path error and the average translational path error across all subjects and all trials. We multiplied combined path error by trial time to get the final metric of error-time. This metric takes into account the speed-accuracy tradeoff [37] to provide an overall measure of performance. It also reflects the importance of balancing accuracy with time for the successful and fast completion of surgical procedures.

E. Participants

The experiment was conducted with a total of fifteen right-handed participants, nine male and six female, aged between 24 and 43 years old. Seven of the participants had never operated a da Vinci Surgical System or dVRK before, four had used it once or twice for a laboratory demonstration, and four had participated in a prior experiment with a dVRK. Participants were divided into three groups of five, with an approximately even distribution of experience levels in each group. The protocol for this study was approved by Stanford University's Institutional Review Board, and participants gave informed consent.

F. Statistical Analysis

To determine the effects of training under different conditions on the metrics described above, we performed Kruskal-Wallis (KW) tests with the different metrics as dependent variables, and the training group as independent factor. Post hoc tests using Dunn's test were used to determine significant differences between pairs of groups. To determine the improvement within each group, we used the Wilcoxon rank sum test. We chose these non-parametric tests because several of the metrics were not normally distributed and the variances of the groups were not always equal. To make sure that the statistical power was consistent across tests, we always used the nonparametric tests. Statistical analysis was conducted using Matlab `kruskalwallis()`, `multcompare()`, and `ranksum()` functions. Statistically significant effects were evaluated at $p < 0.05$.

III. Results and Discussion

Figure 5 presents adaptation curves for each of the four metrics, averaged trial-by-trial across all five participants in each of the three groups, with the respective standard errors depicted as the shaded area around each curve. In order to correct for small differences in starting ability between participants, each participant's baseline ability, measured as their average performance on each metric during the end of the first session (trials 25-30), was subtracted from their data. Table 1 shows the averages and standard errors of the values that were subtracted off for each group and each metric.

Movement variability decreased from the first session to the third session for all groups and all metrics. Variability among participants was lower in the third session than in the first session. For translational path error, the average standard error among all participants was 0.12 m^2 during trials 1-30 and decreased to 0.05 m^2 during trials 61-90 (Wilcoxon rank sum test, $p < 0.001$), indicating that participant movements became more uniform as they practiced the task. Trial-to-trial variability for individual participants also decreased, with participants averaging 0.13 m^2 of standard error among trials 1-30 for translational path error and 0.03 m^2 among trials 61-90 (Wilcoxon rank sum test, $p < 0.001$). Note that the zigzag pattern of the adaptation curve is due to the fact that every other trial was a different movement: from bottom right to upper left vs. upper left to bottom right.

All groups improved dramatically on all metrics within the first session and less dramatically throughout the rest of the experiment. Table 2 shows average improvements across all participants from trials 1-6 to 25-30 and from trials 25-30 to 85-90 for each metric. For translational path error, participants improved by 1.13 m^2 from trials 1-6 to trials 25-30 and then improved by only 0.19 m^2 from trials 25-30 to trials 85-90. Thus, the majority of the learning had occurred before the training in the convergent or divergent fields had begun, but learning still continued at a slower pace throughout the experiment.

During the second session, the divergent field group performed the worst and the convergent field group performed the best on all metrics. During trials 31-60, there was a statistically significant effect of training group for trial time (KW test $\chi^2_{14} = 10.3$, $p = 0.006$), translational path error (KW test $\chi^2_{14} = 12.5$, $p = 0.002$), and error-time (KW test $\chi^2_{14} = 7.5$, $p = 0.02$), but not for rotational path error (KW test $\chi^2_{14} = 4.2$, $p = 0.12$). Post hoc analysis revealed that the divergent field group was statistically significantly worse than the convergent field group for trial time ($p = 0.004$), translational path error ($p = 0.001$), and error-time ($p = 0.02$). For translational path error, the null field group averaged a baseline-adjusted -0.05 m^2, the divergent field group averaged 0.18 m^2, and the convergent field group averaged -0.20 m^2. This pattern is to be expected, as the divergent field should make task completion more difficult by augmenting any errors present, and the convergent field should make task completion easier by minimizing any errors present.

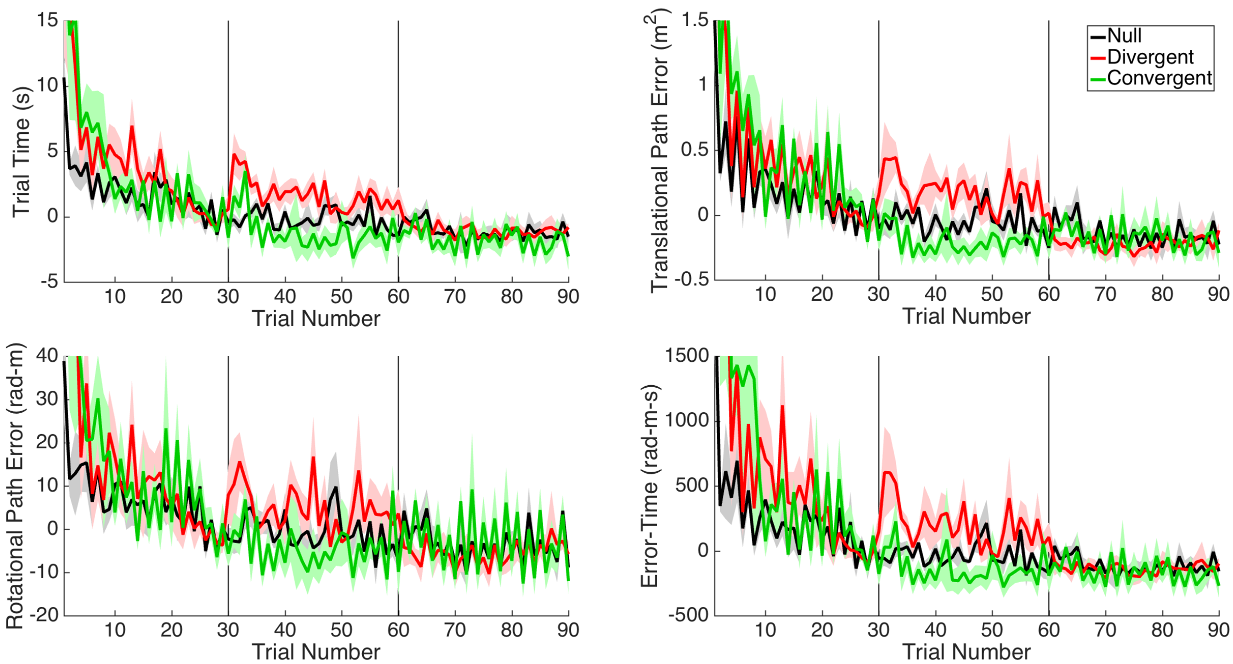

Figure 5. Adaptation curves for all four metrics. Metrics were calculated for each trial for each participant and then averaged across all five participants in each group. Shaded background is the standard error for each group. Each participant's baseline ability (average performance on trials 25-30) was subtracted from their data.

There was no statistically significant difference between the performance of the groups on any metrics at the end of the experiment. For trials 85-90, none of the groups performed statistically significantly differently from the other groups on any metric (KW test $\chi^2_{14} < 2.1$, $p > 0.36$ for all the metrics and all the comparisons). This implies that all of the training methods worked equally well, and training with a convergent or divergent field did not improve or worsen performance compared to training with the null field.

Interestingly, the divergent field group performed better than the other two groups on translational path error at the start of the third session. During trials 61-66, there was a statistically significant effect of training group ($\chi^2_{14} = 7.5$, $p = 0.02$) for translational path error. Post hoc analysis revealed that the divergent field group performed statistically significantly better than the null field group ($p = 0.02$), with the null field group averaging a baseline-adjusted -0.03 m^2, the divergent field group averaging -0.21 m^2, and the convergent field group averaging -0.11 m^2. This indicates that training in the divergent field caused a desirable aftereffect for translational path error. While the null and convergent field groups took several trials to remember how to do the task at the start of the third session, the divergent field group performed well from the beginning of the session.

TABLE I. BASELINE ABILITIES IN TRIALS 25-30 (MEANS AND STANDARD ERRORS) THAT WERE SUBTRACTED FROM DATA.

	Null	Divergent	Convergent
Trial Time (s)	6.3 (±1.2)	6.6 (±0.9)	7.7 (±1.0)
Trans. Path Error (m^2)	0.52 (±0.08)	0.60 (±0.10)	0.60 (±0.04)
Rot. Path Error (rad-m)	20 (±3)	21 (±3)	22 (±3)
Error-Time (rad-m-s)	300 (±100)	330 (±80)	390 (±80)

TABLE II. IMPROVEMENTS FROM TRIALS 1-6 TO 25-30 AND 25-30 TO 85-90 (P-VALUES ARE FROM THE WILCOXON RANK SUM TEST).

	Trials 1-6 to 25-30	Trials 25-30 to 85-90
Trial Time (s)	9.01 ($p < 0.001$)	1.46 ($p < 0.001$)
Trans. Path Error (m^2)	1.13 ($p < 0.001$)	0.19 ($p < 0.001$)
Rot. Path Error (rad-m)	37.7 ($p < 0.001$)	3.8 ($p = 0.005$)
Error-Time (rad-m-s)	2600 ($p < 0.001$)	140 ($p < 0.001$)

IV. CONCLUSIONS AND FUTURE WORK

This study compared training in null, divergent, and convergent force/torque fields during a peg transfer task using a teleoperated RMIS system. Our results showed that there was no statistically significant difference between the three training methods, as the performance of all three groups of participants was almost identical at the end of the experiment.

The sample size in our study is relatively small, and our study may be underpowered. Therefore, we may be missing some statistically significant differences. Another reason why we did not see the hypothesized improvement in performance of the participants who trained in the divergent field might be that the task chosen for this experiment was relatively simple, and participants were able to reach a high level of proficiency during the first session, before the training began. Future work will test the effects of error augmentation and minimization on learning of more complicated surgical tasks. Additionally, there may be benefits to training in the divergent and convergent fields that were not uncovered by this study. For example, because the divergent field group participants practiced getting out of large-error situations during training, they may be able to recover better from unexpected perturbations. This hypothesis will be tested in our future studies. Future work can also examine the effect of teleoperation scaling factor on performance and learning. Finally, both training methods will need to be tested in a long-term retention protocol where performance benefits will be measured several days or weeks after the training.

REFERENCES

[1] J. D. Birkmeyer, J. F. Finks, A. O'Reilly, M. Oerline, A. M. Carlin, A. R. Nunn, J. Dimick, M. Banerjee, and N. J. O. Birkmeyer, “Surgical skill and complication rates after bariatric surgery,” *New England Journal of Medicine*, vol. 369, no. 15, pp. 1434-1442, 2013.

[2] K. Moorthy, Y. Munz, A. Dosis, J. Hernandez, S. Martin, F. Bello, and A. Darzi, “Dexterity enhancement with robotic surgery,” *Surgical Endoscopy and Other Interventional Techniques*, vol. 18, no. 5, pp. 790-795, 2004.

[3] S. Maeso, M. Reza, J. A. Mayol, J. A. Blasco, M. Guerra, E. Andradas, and M. N. Plana, “Efficacy of the da Vinci surgical system in abdominal surgery compared with that of laparoscopy: a systematic review and meta-analysis,” *Annals of Surgery*, vol. 252, no. 2, pp. 254–262, 2010.

[4] C. A. Peters, “Robotic Surgery in Pediatric Urology: State of the Art and Future Horizons,” *Pediatric Urology*, Springer, pp. 75-86, 2015.

[5] I. Nisky, M. H. Hsieh, and A. M. Okamura, “Uncontrolled manifold analysis of arm joint angle variability during robotic teleoperation and freehand movement of surgeons and novices,” *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 12, pp. 2869-2881, 2014.

[6] I. Nisky, A. M. Okamura, and M. H. Hsieh, “Effect of robotic manipulators on movements of novices and surgeons,” *Surgical Endoscopy*, vol. 28, no. 7, pp. 2145-2158, 2014.

[7] I. Nisky, Y. Che, Z. Quek, M. Weber, M. Hsieh, and A. M. Okamura, “Teleoperated versus open needle driving: Kinematic analysis of experienced surgeons and novice users,” *Proc. IEEE International Conference on Robotics and Automation*, pp. 5371–5377, 2015.

[8] A. M. Okamura, “Haptic feedback in robot-assisted minimally invasive surgery,” *Current Opinion in Urology*, vol. 19, no. 1, pp. 102-107, 2009.

[9] I. Nisky, F. A. Mussa-Ivaldi and A. Karniel, “Analytical Study of Perceptual and Motor Transparency in Bilateral Teleoperation,” *IEEE Transactions on Human-Machine Systems*, vol. 43, no. 6, pp. 570-582, 2013.

[10] K. Moorthy, Y. Munz, S. K. Sarker, and A. Darzi, “Objective assessment of technical skills in surgery,” *British Medical Journal*, vol. 327, no. 7422, pp. 1032-1037, 2003.

[11] I. R. Holzman and S. H. Barnett, “The Bell Commission: ethical implications for the training of physicians,” *Mount Sinai Journal of Medicine*, vol. 67, no. 2, pp. 136–139, 2000.

[12] S. R. Moonesinghe, J. Lowery, N. Shahi, A. Millen, and J. D. Beard, “Impact of reduction in working hours for doctors in training on postgraduate medical education and patients’ outcomes: systematic review,” *British Medical Journal*, vol. 342, 2011.

[13] R. Smith, V. Patel, and R. Satava, “Fundamentals of robotic surgery: a course of basic robotic surgery skills based upon a 14-society consensus template of outcomes measures and curriculum development,” *International Journal of Medical Robotics and Computer Assisted Surgery*, vol. 10, no. 3, pp. 379-384, 2014.

[14] M. H. Vetter, I. Green, M. Martino, J. Fowler, and R. Salani, “Incorporating resident/fellow training into a robotic surgery program,” *Journal of Surgical Oncology*, vol. 112, no. 7, pp. 684-689, 2015.

[15] T. S. Lendvay, T. C. Brand, L. White, T. Kowalewski, S. Jonnadula, L. D. Mercer, D. Khorsand, J. Andros, B. Hannaford, and R. M. Satava, “Virtual Reality Robotic Surgery Warm-Up Improves Task Performance in a Dry Laboratory Environment: A Prospective Randomized Controlled Study,” *Journal of the American College of Surgeons*, vol. 216, no. 6, pp. 1181-1192, 2013.

[16] H. Abboudi, M. S. Khan, O. Aboumarzouk, K. A. Guru, B. Challacombe, P. Dasgupta, and K. Ahmed, “Current status of validation for robotic surgery simulators—a systematic review,” *British Journal of Urology International*, vol. 111, no. 2, pp. 194-205, 2013.

[17] A. K. Ericson, “Deliberate practice and the acquisition and maintenance of expert performance in medicine and related domains,” *Academic Medicine*, vol. 79, no. 10, pp. S70–S81, 2004.

[18] 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.

[19] 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.

[20] Y. Sharon, T. Lendvay, and I. Nisky, “Instrument tip angular kinematics in teleoperated needle-driving,” *Proc. Hamlyn Symposium on Medical Robotics*, pp. 96-97, 2016.

[21] 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 Transactions on Human-Machine Systems*, vol. 46, no. 5, pp. 647-659, 2016.

[22] A. M. Jarc and M. J. Curet “Viewpoint matters: objective performance metrics for surgeon endoscope control during robot-assisted surgery,” *Surgical Endoscopy*, vol. 31, no. 3, pp. 1192-1202, 2017.

[23] A. M. Jarc, S. H. Shah, T. Adebar, E. Hwang, M. Aron, I. S. Gill, and A. J. Hung, “Beyond 2D telestration: an evaluation of novel proctoring tools for robot-assisted minimally invasive surgery,” *Journal of Robotic Surgery*, vol. 10, no. 2, pp. 103-109, 2016.

[24] S. A. Bowyer, B. L. Davies, and F. Rodriguez y Baena, “Active Constraints/Virtual Fixtures: A Survey,” *IEEE Transactions on Robotics*, vol. 30, no. 1, pp. 138-157, 2014.

[25] E. H. van Asseldonk, M. Wessels, A. H. Stienen, F. C. van der Helm, and H. van der Kooij, “Influence of haptic guidance in learning a novel visuomotor task,” *Journal of Physiology-Paris*, vol. 103, no. 3, pp. 276-285, 2009.

[26] E. L. M. Su, G. Ganesh, C. F. Yeong, C. L. Teo, W. T. Ang and E. Burdet, “Effect of Grip Force and Training in Unstable Dynamics on Micromanipulation Accuracy,” *IEEE Transactions on Haptics*, vol. 4, no. 3, pp. 167-174, 2011.

[27] F. C. Huang and J. L. Patton, “Augmented dynamics and motor exploration as training for stroke,” *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 3, pp. 838-844, 2013.

[28] D. M. Wolpert, J. Diedrichsen, and J. R. Flanagan, “Principles of sensorimotor learning,” *Nature Review Neuroscience*, vol. 12, no. 12, pp. 739-751, 2011.

[29] H. G. Wu, Y. R. Miyamoto, L. N. G. Castro, B. P. Ölveczky, and M. A. Smith, “Temporal structure of motor variability is dynamically regulated and predicts motor learning ability,” *Nature Neuroscience*, vol. 17, no. 2, pp. 312-321, 2014.

[30] D. J. Herzfeld, P. A. Vaswani, M. K. Marko, and R. Shadmehr, “A memory of errors in sensorimotor learning,” *Science*, vol. 345, pp. 1349-1353, 2014.

[31] K. M. J. Diederen and W. Schultz, “Scaling prediction errors to reward variability benefits error-driven learning in humans,” *Journal of Neurophysiology*, vol. 114, no. 3, pp. 1628-1640, 2015.

[32] D. J. Reinkensmeyer, J. L. Emken, and S. C. Cramer, “Robotics, motor learning, and neurologic recovery,” *Annual Review of Biomedical Engineering*, vol. 6, pp. 497-525, 2004.

[33] 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, 2006.

[34] J. L. Patton and F. C. Huang, “Sensory-Motor Interactions and Error Augmentation,” *Neurorehabilitation Technology*, Springer, pp. 79-95, 2016.

[35] A. L. McCluney, M. C. Vassiliou, P. A. Kaneva, J. Cao, D. D. Stanbridge, L. S. Feldman, and G. M. Fried, "FLS simulator performance predicts intraoperative laparoscopic skill," *Surgical Endoscopy*, vol. 21, no. 11, pp. 1991-1995, 2008.

[36] P. Kazanzides, Z. Chen, A. Deguet, G. S. Fischer, R. H. Taylor, and S. P. DiMaio, "An open-source research kit for the da Vinci Surgical System," *Proc. IEEE International Conference on Robotics and Automation*, pp. 6434-6439, 2014.

[37] 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.