Abstract—Teleoperated robot-assisted minimally-invasive surgery (RAMIS) offers many advantages over open surgery. However, there are still no guidelines for training skills in RAMIS. Motor learning theories have the potential to improve the design of RAMIS training but they are based on simple movements that do not resemble the complex movements required in surgery. To fill this gap, we designed an experiment to investigate the effect of time-dependent force perturbations on the learning of a pattern-cutting surgical task. Thirty participants took part in the experiment: (1) a control group that trained without perturbations, and (2) a 1Hz group that trained with 1Hz periodic force perturbations that pushed each participant’s hand inwards and outwards in the radial direction. We monitored their learning using four objective metrics and found that participants in the 1Hz group learned how to overcome the perturbations and improved their performances during training without impairing their performances after the perturbations were removed. Our results present an important step toward understanding the effect of adding perturbations to RAMIS training protocols and improving RAMIS training for the benefit of surgeons and patients.

I. INTRODUCTION

In robot-assisted minimally-invasive surgery (RAMIS), surgeons use robotic manipulators to control the movements of instruments, which are inserted into patients’ bodies via small incisions [1]. RAMIS offers many advantages over open surgery [2]. However, to reap the benefits of RAMIS, surgeons must be well trained to use the robotic systems [3]. Currently, there are training guidelines for open and laparoscopic surgery, but not for RAMIS [4].

An important step to mitigate this gap is to study how surgeons acquire RAMIS skills, and to discover what affects their learning. Previous studies attempted to influence the acquisition of RAMIS skills, e.g. by choosing which exercises the trainees perform. For example, in [5] learning was sped up by focusing the training on high difficulty exercises. In [6], an adaptive training protocol was proposed in which the exercises are chosen based on the trainee’s performance, leading to improved performance of participants compared to participants who chose their exercises on their own.

Another way to affect RAMIS skill acquisition is to combine task execution examples of an experienced user during training. For example, in [7] participants who watched their own performances along with a video of an expert performing the same exercise learned better than participants who did not have access to such feedback. In addition, many research groups developed training platforms that combine haptic guidance that enables the trainee to follow the movement of an experienced user who performs the exercise [8]–[10].

Important sources of knowledge about how to train RAMIS surgeons are motor learning theories [11]. Motor learning studies investigate the different processes that enable learning. These studies define skill acquisition as an improvement in performance beyond previous levels or the acquisition of completely novel abilities [12]. Adaptation is defined as when participants improve their performances in response to altered conditions such as a perturbing force field [13] or visuomotor transformations [14]. It is important to note that in contrast to skill acquisition, in adaptation, the participants can restore their baseline performance but will not improve beyond it [12].

Recent findings in motor learning propose ways to affect learning. For example, in reach movements, manipulating the consistency of the perturbations [15]–[17], the error that is presented to the trainee [18]–[20], and the balance between punishment and reward [21], can affect the rate of adaptation. In error-based learning, the sensorimotor system is hypothesized to estimate the error between the desired or predicted outcome of a movement and the actual outcome, and update the motor commands in the following movement [22]. These ideas may be used to optimize surgical skill learning [11], but there is a gap between the current knowledge that is based on simple movements and the needed knowledge to train RAMIS surgeons, who perform complex motor tasks. There are a few studies that begin to fill the gap [23], [24], but more work is needed to develop efficient training protocols.

In this study, for the first time, we examine the effect of time-dependent perturbations on the learning of a surgical task. In our experiment, the participants cut circles drawn on gauze while they were exposed to perturbations that alternately pushed their hands inwards and outwards in the radial direction. We chose a time-dependent perturbation because while acting on the human body, surgeons encounter various time-dependent perturbations; for example, as a result of the periodic movement of the heart and blood vessels. To
develop RAMIS training protocols, we need to understand how surgeons learn to deal with such perturbations, and their effects on performance.

More specifically, it is important to understand whether surgeons can improve their performance under time-dependent perturbations. Our task has a clear desired path, and the perturbations increase the error between the desired movement and the actual movement. Hence, we hypothesized that the motor system would adjust motor commands and reduce error with training. If surgeons do manage to improve performances during exposure to the perturbations, it is important to test whether this learning impairs their ability to cope with other conditions (such as an environment without perturbations), and whether it gives them resistance to other perturbations as well. We designed our experiment to answer four specific research questions:

- **Q1** – Whether participants that are exposed to force perturbations can learn and improve their performance under these perturbations?
- **Q2** – Whether training with force perturbations impairs the performance when the perturbations are removed?
- **Q3** – Whether training with force perturbations can give an advantage when later encountering these perturbations, compared to those who trained without perturbations?
- **Q4** – Whether training with force perturbations can give an advantage when encountering different types of perturbations, compared to those who trained without perturbations?

A preliminary version of this study which included an initial analysis of the pilot experiment was presented in an extended abstract form [25].

II. METHODS

A. Experimental Setup

1) the da Vinci Research Kit (dVRK): The dVRK is a development platform for researchers in the field of RAMIS [26], provided by Intuitive Surgical. Its hardware consists of components from the first-generation da Vinci Surgical System [27]. Our dVRK (Fig. 1) consists of a pair of Master Tool Manipulators (MTMs), a pair of Patient Side Manipulators (PSMs), a foot-pedal tray, a high resolution stereo viewer, and four manipulator interface boards. In this study, the participants sat at the master-side (Fig. 1b), and used the MTMs to remotely teleoperate curved scissors and a large needle driver at the patient side, where the task board was placed (Fig. 1c). The MTMs and PSMs electronics were connected via firewire to a single Ubuntu (UNIX) OS computer with an Intel Xeon E5-2630 v3 processor. The vision system consisted of a pair of Blackfly S cameras (FLIR Integrated Imaging Solutions Inc.) that acquired the visual scene in the patient side. The cameras were fixed such that the task board was in the center of the field of view. The participants could not control the cameras or the zoom. The video was broadcasted to the stereo viewer, which presented a 3D view at 35 Hz refresh rate and with 1080 X 810 resolution per eye. The visual information was transmitted using a custom-developed software on a dedicated computer. The movement scaling was set to 0.4, such that each movement of the PSM was 0.4 times of the movement of the MTM, and the participants could reach the entire workspace without using the clutch.

2) The Pattern-Cutting Task: The task in this experiment was based on the FLS pattern-cutting task [28], and modified to our needs. In this task, participants used their right hands to control curved scissors and cut a 5cm diameter circle drawn on a two-layered 10X10cm non-woven gauze. The width of the black circle line was 2mm. To complete the task participants could cut one layer or both layers. The task sequence consisted of (Fig. 2a): (1) cutting the gauze toward point A; (2) cutting along the left half of the circle, until point B; (3) moving the scissors back to point A; (4) cutting the right side of the circle. The participants used their left hands to control a large needle driver and maintain the tension of the gauze. Participants were instructed to cut as quickly and as accurately as possible, which meant within the black line.

3) Force Perturbations: In some of the trials during the experiment, planar radial force perturbations were applied on each participant’s hand using the right MTM – away from the center of the circle and toward the center, alternatingly (Fig. 2c)-(d)):

\[
\vec{f}_M = A \left[ \frac{x_P}{\sqrt{x_P^2 + y_P^2}}, \frac{y_P}{\sqrt{x_P^2 + y_P^2}}, 0 \right]^T,
\]

where \(x_P\) and \(y_P\) are the x and y position coordinates of the scissors’ tip, relative to the center of the circle (see Fig. 2d), and A defines the type of the trial. There were three types of trials during the experiment (see Video 1):

- No perturbations: \(A = 0\).
sequence (without cutting), catching the gauze with the left tool, and cutting a straight line with the right tool.

The participants were randomly assigned into two groups (15 participants per group): a 1Hz group, and a control group. During the experiment each participant performed 24 consecutive trials (Fig. 3):

- **Baseline (B)** – five trials without perturbations. These trials were the same for both groups, and their purpose was to assess baseline performances of each participant.
- **Training (T)** – 10 trials that were used to answer Q1: the control group trained without perturbations, and the 1Hz group trained with 1Hz perturbations.
- **Post training (P)** – nine trials for testing the effect of the training on performance post training, i.e. answering Q2-Q4; these trials were the same for both groups. The first three trials (P1) were without perturbations, and were included to assess the performances of both groups after the different training protocols (Q2). The next three trials (P2) were with 1Hz perturbations, and were included to asses the resistance to 1Hz perturbations (Q3). The last three trials (P3) were with unpredictable perturbations, and were included to assess the resistance to new perturbations, which participants had not practiced before (Q4). The five frequencies of the unpredictable trials were different between the three trials, but the same for all the participants.

### C. Data Acquisition and Segmentation

All the kinematic data of the MTMs and PSMs were recorded at 100Hz. The video data of the left camera were recorded at 35Hz. In addition, all the cut circles were scanned. In 20 trials out of the 720 trials there were technical issues that resulted in the trial stopping before the task completion. In all those trials, participants completed the trial after fixing the issue, and these trials were not included in the analysis. We used the recorded videos and the scissors’ opening angle to manually segment each trial into its stages.

---

**Fig. 2:** The pattern-cutting task and the force perturbations.
- (a) The task sequence.
- (b) The task board and the two PSM tools (right – curved scissors, left – large needle driver).
- (c) The MTMs.
- (d) The circle; the position of the right PSM’s tip \( \vec{x}_P \) (blue); the force applied on the participant’s hand \( \vec{f}_M \) (red), and the reference base frame (yellow).

**Fig. 3:** The experimental protocol.
- Baseline (B)
- Control group
- 1Hz group
- Training (T)
- No perturbations (five trials)
- 1Hz group
- Post training (P)
- No perturbations (three trials)
- 1Hz perturbations (three trials)
- Unpredictable perturbations (three trials)

---

### B. Experimental Protocol

Thirty right-handed volunteers without surgical background (aged 21-30; 15 females) participated in the experiment after signing an informed consent approved by the Human Participants Research Committee of Ben-Gurion University of the Negev. The participants were instructed on how to use the dVRK and how to perform the pattern-cutting task. Since the perturbations are based on the position of the circle, the experimenter emphasised the importance of keeping the gauze in its place, i.e., not pulling it in a way that distorts the marked circle. The instructions were accompanied by videos of the pattern cutting task – a task that performed according to the instructions, and a task in which the participant stretches the gauze in a prohibited way, and also cuts with many errors (not within the black line). Before the experiment, each participant practiced the following actions with the robot: pressing the right pedal to start teleoperation, moving the right tool through the task...
D. Metrics

We used four metrics to assess the progress of the participants: combined error-time, path length, number of cuts, and perturbation MSE. The first two metrics quantified the task performance, and the other two metrics allowed us to follow different approaches of the participants.

1) Combined error-time: participants were instructed to cut as quickly and as accurately as possible. According to the speed-accuracy trade-off [30], we expected that shorter task times might be accompanied by larger errors and vice versa. Hence, we combined these two measures of performance. The task time was calculated as:

\[ TT = t_{\text{end}} - t_{\text{start}}, \]  

where \( t_{\text{start}} \) is the time when the participant first closes one of the tools on the gauze, and \( t_{\text{end}} \) is the time of the last cut, when the circle was completely removed from the gauze.

To quantify the amount of errors, we used a custom-written image processing algorithm (MATLAB) that detected error areas in the scanned circles. The error areas were defined as areas in which the cutting was not on the line – outside or inside the circle (Fig. 3). The total error was calculated as:

\[ TE = E_{\text{outside}} + E_{\text{inside}}, \]  

where \( E_{\text{outside}} \) and \( E_{\text{inside}} \) are the numbers of pixels in the error areas outside and inside the circle, respectively.

The combined error-time of trial \( j \) was calculated as [31]:

\[ CET_j = \frac{TT_j - TT}{S_{TT}} + \frac{TE_j - TE}{S_{TE}}, \]  

where \( TT \) and \( TE \) are the average values of the task times and the total errors across all the trials of all the participants in the experiment, \( S_{TT} \) and \( S_{TE} \) are the standard deviations. Note that the value of this metric can be positive or negative and that lower value means better performance.

2) Path Length: this metric is a common measure of surgical skill performance which quantifies the economy of motion, and it was calculated as:

\[ PL = \sum_{i=1}^{N-1} ||\vec{x}_P[i+1] - \vec{x}_P[i]||_2, \]  

where \( \vec{x}_P[i] \) is the position of the scissors’ tip at the \( i \)th sample, and \( N \) is the number of samples.

3) Number of cuts: one approach to dealing with the perturbations may be to time the cuts according to the perturbations. Such an approach would lead to a change in the number of cuts during training. Hence, we counted the number of times the scissors were closed during the task. To find these closing events, we used the MATLAB function \texttt{findpeaks()} to find the local minima of the recorded scissors’ opening angle. We included in the analysis only cuts that were made for cutting the circle itself (i.e., steps 2 and 4, Fig. 2a).

4) Perturbation MSE: this metric quantifies the effect of the perturbations on the participant’s movement. The higher the value of this metric, the greater the 1Hz radial fluctuations in the hand movement are. The size of the fluctuations is a measure of coping with the perturbations by either adaptation—i.e., actively cancelling the perturbation by opposing forces—or by increasing of arm stiffness. To calculate this metric, we first extracted the planar radial component of the scissors’ path (Fig. 5 upper panel):

\[ R_{xy_P}[i] = \sqrt{x_P[i]^2 + y_P[i]^2}. \]  

Where \( x_P \) and \( y_P \) are the x and y position coordinates of the scissors’ tip. We then filtered \( R_{xy_P} \) using a moving average of 100 samples:

\[ \bar{R}_{xy_P(100)}[i] = \frac{1}{100} \sum_{k=-49}^{49} R_{xy_P}[i+k]. \]  

At the edges of the signal, the average of the available samples was calculated. The 1Hz perturbation was periodic with a period duration of 1sec, and there were 100 samples per second. Therefore, \( \bar{R}_{xy_P(100)} \) is the radial component without the contribution of the perturbation (Fig. 5 magenta line). To isolate the contribution of the perturbation (Fig. 5 lower panel) we used:

\[ Per[i] = R_{xy_P}[i] - \bar{R}_{xy_P(100)}[i] \]  

The perturbation MSE was calculated as:

\[ Per.MSE = \frac{1}{N} \sum_{i=1}^{N} (Per[i])^2 \]  

We calculated \( Per.MSE \) for steps 2 and 4 – cutting the circle (Fig. 2a), and summed them to get one metric value per trial. Since the unpredictable perturbations in P3 (Fig. 3) was a combination of five sine waves with different frequencies, we did not calculate this metric on trials in P3.

E. Statistical analysis

Our metrics were not normally distributed, and therefore we tested our hypotheses using permutation tests [32]. For each participant we calculated the average metric values of: the last three trials of the baseline (B); the first three trials of the training (T\(_{\text{start}}\)); the last three trials of the training (T\(_{\text{end}}\)); the post training trials without perturbations (P1); the post training trials with 1Hz perturbations (P2); the post training trials with unpredictable perturbations (P3).
We first tested Q1 – whether participants that are exposed to force perturbations can learn and improve their performance under the perturbations. For each metric, we calculated the difference between $T_{start}$ and $T_{end}$ of each participant. We then used a matched-pair permutation test for each group to test whether the mean of these differences was significantly different than zero. Additionally, we used a permutation test to test whether the means of the individual differences between $T_{start}$ and $T_{end}$ were significantly different between the two groups (control and 1Hz).

We then tested Q2 – whether training with force perturbations can give an advantage when encountering these perturbations, compared to those who trained without perturbations. We performed two permutation test between the groups: (1) $P2$ values, (2) $P2 - P1$ values.

Lastly, we tested Q4 – whether training with force perturbations can give an advantage when encountering different perturbations, compared to those who trained without perturbations. We performed two permutation test between the groups: (1) $P3$ values, (2) $P3 - P1$ values.

To control for multiple comparisons, we used the Bonferroni correction. For each of the research questions separately, we multiplied the p-values by the number of tests (two or three). Statistical significance was determined at the 0.05 threshold.

III. RESULTS

Fig. 5 shows the scissors’ path when the participant cut the circle. The deviations from the circle in Fig. 5(b) are more prominent than those in Fig. 5(a), showing that the perturbations affect the scissors’ path. Fig. 7 depicts the approach metrics showed that the participants in the 1Hz group improve significantly more than those in the control group. Because the perturbations directly increase the path length, the improvement of the 1Hz group probably consists of an improvement as a result of learning the task (similar to the control group) and an additional improvement caused by coping with the perturbations.

The approach metrics showed that the participants in the 1Hz group significantly reduced the number of cuts during training, whereas in the control group, no such change was observed (Fig. 8a-f). A possible explanation is that participants in the 1Hz group had to time their cuts according to the perturbations, forcing participants who cut quickly to lower the pace. In addition, the participants in the 1Hz group significantly reduced their perturbation MSE scores during training. This means that at the end of the training, the 1Hz fluctuations in their movement were smaller than at the beginning of the training.

B. Q2 – The effect of the training protocols on post-training trials without perturbations (P1)

After the training (P1), the groups reached a similar level of performance in combined error-time and path length (Fig. 8a-c). There was a small and not significant difference between the average improvement in combined error-time of the two groups (Fig. 8d). This small difference may stem from the fact that the control group had a slightly higher score in the baseline trials, thereby having more room for improvement during training. The number of cuts of the 1Hz groups: (1) $P1$ values, (2) $P1 - P2$ values.

For all the four metrics, there was no significant difference between the two groups at the baseline stage ($p_{combined\ error-time} = 0.2165, p_{path\ length} = 0.9985, p_{number\ of\ cuts} = 0.1810, p_{perturbation\ MSE} = 0.7355$). In the following subsections we will describe the results of the tests we conducted to examine our research questions. Table I summarizes the statistical analysis.

A. Q1 – The effect of the training protocols on the learning curves and approaches

Participants from both groups improved their combined error-time and path length scores during training (Fig. 7a-b, and Fig. 8a-d). These improvements were statistically significant. In addition, the average path length improvement of the 1Hz group was significantly higher than the improvement of the control group. Because the perturbations directly increase the path length, the improvement of the 1Hz group probably consists of an improvement as a result of learning the task (similar to the control group) and an additional improvement caused by coping with the perturbations.

The approach metrics showed that the participants in the 1Hz group significantly reduced the number of cuts during training, whereas in the control group, no such change was observed (Fig. 8e-f). A possible explanation is that participants in the 1Hz group had to time their cuts according to the perturbations, forcing participants who cut quickly to lower the pace. In addition, the participants in the 1Hz group significantly reduced their perturbation MSE scores during training. This means that at the end of the training, the 1Hz fluctuations in their movement were smaller than at the beginning of the training.

B. Q2 – The effect of the training protocols on post-training trials without perturbations (P1)

After the training (P1), the groups reached a similar level of performance in combined error-time and path length (Fig. 8a-c). There was a small and not significant difference between the average improvement in combined error-time of the two groups (Fig. 8d). This small difference may stem from the fact that the control group had a slightly higher score in the baseline trials, thereby having more room for improvement during training. The number of cuts of the 1Hz
Fig. 7: The values of the four metrics as a function of trial number. Pale color lines are individual scores, dark color lines are means, and shaded areas are 95% bootstrap confidence intervals.

A group was significantly smaller than of the control group, suggesting that after getting used to a lower number of cuts caused by the perturbations, they did not raise it even after the perturbations were removed.

C. Q3 – The effect of the training protocols on post-training trials with 1Hz perturbations (P2)

In all four metrics, the average value of the 1Hz group was slightly lower than the control group, but these differences were not statistically significant. For the number of cuts, the value of the difference ($P_2 - P_1$) of the control group was significantly smaller than the 1Hz group (Fig. 8). In Fig. 8e, we can see that while participants in the 1Hz group kept the same number of cuts for P1 and P2, participants in the control group reduced this number. Apparently, participants who chose an approach of high number of cuts were forced to change it due to the perturbations.

D. Q4 – The effect of the training protocols on post-training trials with unpredictable perturbations (P3)

The small differences in combined error-time and path length values between the groups in the P2 stage were further
reduced in P3. Looking at Fig. 3a,c, it seems that the control group improved their performances in P3 relative to P2, while the 1Hz group had no improvement in combined error-time and a smaller improvement in path length. There was a significant difference between the P3 – P1 values of the two groups because the control group continued to cut with less cuts than in P1, while the 1Hz group did not change the number of cuts.

IV. DISCUSSION

In this letter we presented a new experimental protocol for testing the effect of time-dependent force perturbations on the learning of a RAMIS task. Our aim was to harness motor learning theories to improve the training of RAMIS surgeons. Our analysis revealed several approaches that participants used to overcome the perturbations without impairing their performance when the perturbations were removed. Our results form a basis for further research that could improve the way surgeons acquire RAMIS skills.

So far the effect of assistive and resistive forces on RAMIS training has been investigated [23], [24], [33]; however, to the best of our knowledge, the effect of time-dependent perturbations had not been explored. We found that participants improved their performance during training with 1Hz periodic perturbations. Compared to at the beginning of the training, at the end of the training the perturbations had less impact on their movement. Such a result can be caused by an adaptation in which the motor system learns the force perturbations and applies force in the opposite direction, which reduces the impact of perturbations on the movement. When adaptation occurs, an after-effect can be seen after the perturbations are removed. In our experiment, such after-effect would have been expressed as 1Hz fluctuations in the P1 trials. Because the perturbation MSE of the 1Hz group returned to the baseline level as soon as the perturbations were removed, we conclude that adaptation did not occur. This result is consistent with previous studies that showed that participants do not adapt to time varying perturbations [34].

Although adaptation did not occur, the participants did develop approaches to improve. Previous studies showed that participants stabilize unstable conditions by co-contraction of the muscles and an increase in the impedance of the arm [35]. Such an increase can be the cause of the decrease in perturbation MSE during training in our experiment. Another approach revealed by our analysis is a change in the number of cuts during the training. This result is consistent with [36], where a surgeon who performed a pattern-cutting task with a moving platform timed the cuts according to the movement of the platform.

Importantly, we showed that when the perturbations were removed both groups reached a similar performance level. This means that learning how to deal with the perturbations was not at the expense of learning how to perform the task better. This result suggests that trainees can be exposed to challenging conditions during training without impairing their learning. When the participants encountered the 1Hz perturbations after training the advantage of the 1Hz group was not significant. This small advantage was further reduced when participants encountered the unpredictable perturbations. It is possible that after a long training on the task under simple conditions the control group was able to learn quickly how to deal with the perturbations, and that therefore the gap between the groups was small. Additional research is required to examine protocols that will incorporate perturbations in a way that may increase the advantages over learning without perturbations.

This is the first study of time-dependent perturbations in RAMIS training, and hence we chose simple and not fully realistic perturbations. Now that we have found that training will incorporate perturbations in a way that may increase the advantages over learning without perturbations.

V. CONCLUSIONS

We developed a novel experimental protocol and new analysis tools to examine how time-dependent perturbations affect the learning of a surgical task. The data collected for this study are available (on request to the corresponding author), and can be used to advance surgical robotics and motor learning research. We found that participants learned how to overcome these perturbations and that this learning was not at the expense of learning the task. Our results lead the way toward developing training protocols that will incorporate time-dependent perturbations, which could improve the way surgeons acquire RAMIS skills. From the perspective of the
motor learning field, this study is an important step toward understanding learning in real life tasks.

ACKNOWLEDGMENT

The authors would like to thank Anton Deguet, Simon DiMaio, Eli Peretz, and Gilat Malka for their help with the dVRK integration in our lab, and Alon Lempert and Noa Yamin for running the experiments.

REFERENCES

[1] 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,” Ann. Surg., vol. 252, no. 2, pp. 254–262, Aug. 2010.

[2] K. Moorby, Y. Munz, A. Dosis, J. Hernandez, S. Martin, F. Bello, T. Rockall, and A. Darzi, “Dexterity enhancement with robotic surgery,” Surg. Endosc., vol. 18, no. 5, pp. 790–795, May 2004.

[3] D. L. Crawford and A. M. Dwyer, “Evolution and literature review of robotic general surgery resident training 2002–2018,” Updates Surg., vol. 50, no. 3, pp. 363–368, Sep. 2018.

[4] K. Ahmed, R. Khan, A. Mottrie, C. Lovegrove, R. Abaza, R. Ahlawat, T. Ahlering, G. Ahlgren, W. Artibani, E. Barret, X. Cathelineau, B. Challacombe, P. Coloby, M. S. Khan, J. Hubert, M. S. Michel, F. Montorsi, D. Murphy, J. Palou, V. Patel, P-T. Piechaud, H. Van Poppel, R. Rischmann, R. Sanchez-Salas, S. Siemen, M. Stoeckle, J-U. Stolzenburg, J-E. Terrier, J. W. Thuroff, C. Vaessen, H. G. Van Der Poel, B. Van Cleynheneguel, A. Volpe, C. Wagner, P. Wiklund, T. Wilson, M. Wirth, J. Witt, and P. Dasgupta, “Development of a standardised training curriculum for robotic surgery: A consensus statement from an international multidisciplinary group of experts,” BJU Int., vol. 116, no. 1, pp. 93–101, 2015.

[5] P. M. S. Gurung, T. Campbell, B. Wang, J. V. Joseph, and A. E. Ghazi, “Accelerated Skills Acquisition Protocol (ASAP) in optimizing robotic surgical simulation training: A prospective randomized study,” World J. Urol., vol. 38, no. 7, pp. 1623–1630, Jul. 2020.

[6] A. Mariani, E. Pellegrini, and E. D. Momi, “Skill-Oriented and Performance-Driven Adaptive Curricula for Training in Robot-Assisted Surgery Using Simulators: A Feasibility Study,” IEEE Transactions on Biomedical Engineering, vol. 68, no. 2, pp. 685–694, Feb. 2021.

[7] K. Yang, M. Perez, N. Hubert, G. Hossu, C. Perrenot, and J. Hubert, “Effectiveness of an Integrated Video Recording and Replaying System in Robotic Surgical Training,” Ann. Surg., vol. 265, no. 3, pp. 521–526, Mar. 2017.

[8] S. Jacobs, D. Holzhey, G. Strauss, O. Burght, and V. Falk, “The Impact of Haptic Learning in Telemanipulator-assisted Surgery,” Surgical Laparoscopy Endoscopy & Percutaneous Techniques, vol. 17, no. 5, pp. 402, Oct. 2007.

[9] M. Shahbazi, S. F. Atashzar, C. Ward, H. A. Talebi, and R. V. Patel, “Multimodal Sensorimotor Integration for Expert-in-the-Loop Telerobotic Surgical Training,” IEEE Transactions on Robotics, vol. 34, no. 6, pp. 1549–1564, Dec. 2018.

[10] A. E. Abdelaal, M. Sakr, A. Avisnash, S. K. Mohammed, A. K. Bajwa, M. Sahni, S. Hor, S. Fels, and S. E. Salcudean, “Play Me Back: A Unified Training Platform for Robotic and Laparoscopic Surgery,” IEEE Robotics and Automation Letters, vol. 4, no. 2, pp. 554–561, Apr. 2019.

[11] A. M. Jarc and I. Nisky, “Robot-assisted surgery: An emerging approach to surgical training,” Proc. IEEE Int. Conf. Robot. Autom., vol. 10, no. 2, pp. e0117901, 2015.

[12] H. G. Wu, Y. R. Miyamoto, L. N. G. Castro, B. P. Olveczky, and M. A. Smith, “Temporal structure of motor variability is dynamically regulated and predicts motor learning ability,” Nat. Neurosci., vol. 17, no. 2, pp. 312–321, 2014.

[13] J. E. Duarte and D. J. Reinkensmeyer, “Effects of robotically modulating kinematic variability on motor skill learning and motivation,” J. Neurophysiol., vol. 113, no. 7, pp. 2682–2691, Apr. 2015.

[14] D. J. Herzfeld, P. A. Vaswani, M. K. Marko, and R. Shadmehr, “A memory of errors in sensorimotor learning,” Science, vol. 345, no. 6202, pp. 1349–1353, Sep. 2014.

[15] K. van der Kooi, E. Bremner, R. J. van Beers, and J. B. Smeets, “Visuomotor adaptation: How forgetting keeps us conservative,” PloS one, vol. 10, no. 2, pp. e0117901, 2015.

[16] M. M. Coad, A. M. Okamura, S. Wren, Y. Mintz, T. S. Lendvay, A. M. Jarc, and I. Nisky, “Training in divergent and convergent force fields during 6-DOF teleoperation with a robot-assisted surgical system,” in IEEE World Haptic. Conf., 2017, pp. 195–200.

[17] J. I. Diederich and W. Schulz, “Scaling prediction errors to reward variability benefits error-driven learning in humans,” J. Neurophysiol., vol. 114, no. 3, pp. 1628–1640, Sep. 2015.

[18] J. M. Galea, E. Mallia, J. Rothwell, and J. Diedrichsen, “The dissociable effects of punishment and reward on motor learning,” Nat. Neurosci., vol. 18, no. 4, pp. 597–602, 2015.

[19] D. M. Wolpert, J. Diedrichsen, and J. R. Flanagan, “Principles of sensorimotor learning,” Nature Reviews Neuroscience, vol. 12, no. 12, pp. 739–751, Dec. 2011.

[20] M. M. Coad, A. M. Okamura, S. Wren, Y. Mintz, T. S. Lendvay, A. M. Jarc, and I. Nisky, “Training in divergent and convergent force fields during 6-DOF teleoperation with a robot-assisted surgical system,” in IEEE World Haptic. Conf., 2017, pp. 195–200.

[21] J. E. Duarte and D. J. Reinkensmeyer, “Effects of robotically modulating kinematic variability on motor skill learning and motivation,” J. Neurophysiol., vol. 113, no. 7, pp. 2682–2691, Apr. 2015.

[22] D. J. Herzfeld, P. A. Vaswani, M. K. Marko, and R. Shadmehr, “A memory of errors in sensorimotor learning,” Science, vol. 345, no. 6202, pp. 1349–1353, Sep. 2014.

[23] K. van der Kooi, E. Bremner, R. J. van Beers, and J. B. Smeets, “Visuomotor adaptation: How forgetting keeps us conservative,” PloS one, vol. 10, no. 2, pp. e0117901, 2015.