Uncontrolled Manifold Analysis of Arm Joint Angle Variability During Robotic Teleoperation and Freehand Movement of Surgeons and Novices

Ilana Nisky, *Member, IEEE,* Michael H. Hsieh, and Allison M. Okamura, *Fellow, IEEE*

***Abstract*—Teleoperated robot-assisted surgery (RAS) is used to perform a wide variety of minimally invasive procedures. However, current understanding of the effect of robotic manipulation on the motor coordination of surgeons is limited. Recent studies in human motor control suggest that we optimize hand movement stability and task performance while minimizing control effort and improving robustness to unpredicted disturbances. To achieve this, the variability of joint angles and muscle activations is structured to reduce task-relevant variability and increase task-irrelevant variability. In this study, we determine whether teleoperation of a da Vinci Si Surgical System in a non-clinical task of simple planar movements changes this structure of variability in experienced surgeons and novices. To answer this question, we employ the UnControlled Manifold (UCM) analysis that partitions users' joint angle variability into task-irrelevant and task-relevant manifolds. We show that experienced surgeons coordinate their joint angles to stabilize hand movements more than novices, and that the effect of teleoperation depends on experience – experts increase teleoperated stabilization relative to freehand whereas novices decrease it. We suggest that examining users' exploitation of the task-irrelevant manifold for stabilization of hand movements may be applied to: (1) evaluation and optimization of teleoperator design and control parameters, and (2) skill assessment and optimization of training in RAS.**

***Index Terms*—Teleoperation, robot-assisted surgery, redundancy exploitation, uncontrolled manifold, surgical skill.**

I. Introduction

ROBOT-assisted minimally-invasive surgery (RAS) is gaining popularity in many procedures [1]–[3] because of its potential to improve patient outcomes in comparison to standard minimally invasive surgery (MIS). RAS offers surgeons many advantages over standard MIS, including improved dexterity, an intuitive mapping from hand to instrument motion, improved precision via motion scaling, tremor reduction, 3D visualization, and an ergonomically comfortable setup [4], [5]. RAS also maintains the benefits of standard MIS to the patient, including reduced recovery time and loss of blood when compared to open surgery [6].

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

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

Manuscript received January 7, 2014; revised May 1, 2014. The study was supported by an Intuitive Surgical Technology Research Grant (to AMO and MHH). IN is supported by the Marie Curie International Outgoing Fellowship (FP7-PEOPLE-2011-IOF project 300393) and the Weizmann Institute National Postdoctoral Award Program for Advancement of Women in Science.

However, many robotic procedures do not show a significant improvement in patient outcomes over standard MIS [2], and there are procedures for which robotics seem promising but have not been broadly adopted. Understanding how surgeons control the movement of a teleoperated robot can improve robot design, skill evaluation, and training. Robot design may be improved as a result of a quantitative analysis of the effect of different teleoperators on user movement, and skill evaluation and training may be improved by studying skilled surgeons in comparison to novices.

Inherent to its teleoperated nature, RAS facilitates recording information about the movements of surgeons' hands and patient-side instruments. Prior approaches to quantitative movement analysis in RAS focused on the surgical tools [7]. In an effort to understand the "language of surgery", Lin et al. broke down the trajectories into gestures – surgemes – that were suggested by senior surgeons [8]. Other approaches used statistical methods, and applied Hidden Markov Models to position and force information for modeling surgery and skill evaluation [9]–[11].

In this study, we focus on the movement of surgeons' hands and arms, and employ theories and methods from the study of human motor control in our analysis. In a recent study [12], [13], we analyzed the trajectories of the gripper tip of the master manipulator during performance of canonical motor tasks with an RAS system during virtual cursor control. The dynamics of the master manipulator affected all users' movements, but the experienced surgeons previously adapted to these dynamics, and performed better than novices. For example, experts movements were more accurate, faster, and smoother, especially in teleoperation. Here, we focus on the trial-to-trial variability of the movement of the entire arm of the surgeon during virtual cursor control.

Motor variability is prominent in human motion [14], [15], and is a sign of a healthy motor system [15]–[17]. One of the origins of this variability is that many levels of the execution hierarchy of standard motor tasks are highly redundant. There is a redundancy in neural control, muscle actuation, and mechanical degrees of freedom of the arm [18]. This redundancy is beneficial because it allows for flexibility in movement in the face of perturbations, obstacles, or fatigue. It is also a burden because it creates an ill-posed control problem for the motor system [19], [20]. Many recent studies suggest that the motor system exploits redundancy to structure motor variability in order to maximize performance while minimizing control effort [21]–[26].

Several frameworks quantify redundancy exploitation by examining the structure of variability in the control/execution variables (e.g. arm joint angles) with respect to task/result variables (e.g. hand Cartesian coordinates). In redundant tasks, such as goal-directed unconstrained arm movement, the dimension of the control space is larger than that of the task space. Therefore, a task-irrelevant manifold (TIM) exists in the control/execution space. Variability in the TIM does not change task performance.

The UnControlled Manifold framework (UCM) examines the control variables are coordinated with respect to task variables. If a particular task variable is stabilized, the variability of the configurations of the control variables that are within its TIM is larger than that of configurations that change task performance. In the UCM framework, the TIM is calculated with respect to the average experimentally recorded trajectory [21], [22], [27], [28]. The TIM is related to the self-motion manifold [29], and for linear systems, it is the null space of the matrix that relates control variables to task variables. The related Minimum Intervention Principle (MIP) suggests a stochastic optimal control theory model for such coordination [23], [30]. According to this principle, task performance and control effort are included in the optimization cost function, and as a result, task-irrelevant variability is not restricted.

Other related frameworks are the Tolerance Noise Covariation (TNC) [24], [31], [32] and the Goal-Equivalent Manifold (GEM) [25], [26] that also define a TIM, but with respect to the task goal. This relaxes the assumption that the average trajectory represents the intended trajectory [26], but requires knowledge of the dynamics of the task for the analysis. The TNC is evaluated entirely in task space, and therefore, it is less sensitive to the choice of control space coordinates [32]. Recently, a coordinate independent extension of the UCM method was developed for static pointing [33]. Here, we use the UCM analysis because it was successfully used for the analysis of a variety of tasks, including isometric finger force exertion [34], [35], reaching movements [27], bimanual pointing [36], pistol aiming [37], stone knapping [38], and standing up and sitting down [39]. In addition, this analysis has the potential to be extended in the future to surgical maneuvers where the goal is not defined a priori, and to be combined with the MIP for computational modeling.

In previous studies, significant differences in the movements of the surgical tools [7] and the hands [12], [13] of experienced RAS surgeons and novices were reported. At least part of these differences are likely related to the familiarity of the surgeons with teleoperating the RAS master manipulators [12], [13]. The ability of a user to exploit redundancy and structure movement variability was suggested to be related to skill [24], [31], [38]. Therefore, we hypothesized that there are differences in how experienced surgeons and novice users exploit their arm redundancy to stabilize hand movements, with potential implications for surgical skill assessment and training.

In addition to expertise, redundancy exploitation depends also on task structure [26] and dynamics [27]. Therefore, we also hypothesized that teleoperating a RAS system may reduce redundancy exploitation compared to moving freehand. We analyzed separately the exploitation of redundancy for stabilization of the horizontal (x-y task) and the vertical (z task) hand trajectories while participants did not receive visual feedback of their vertical movements. We expected to find that their motor system stabilizes x-y hand trajectories but not z hand trajectories.

To test these hypotheses, we used the UCM method to analyze simple movements that were performed by novices and experienced surgeons while teleoperating a da Vinci manipulator and while moving freehand. We chose to focus on non-clinical simple and well-studied movements: reach (movement between two targets) [40] and reversal (out and back movement towards a target without resting at the target itself) [41]. We chose these simple movements because we are interested in the motor capabilities of the participants rather than in their clinical competence. Specifically, we aim to determine the effect of users' experience in physical interaction with the master manipulator on redundancy exploitation for hand movement stabilization. In addition, studying these movements is important because they are the building blocks for many surgical maneuvers.

A preliminary demonstration of this analysis was presented in a recent conference [42]. In the current study, we present a comprehensive statistical analysis with more participants, an analysis of within-trial variability, an analysis of the effects of movement direction and experimental sessions order on trial-to-trial variability, and an extensive discussion.

II. Methods

A. Experimental procedures

Fourteen volunteers participated in the experiment, approved by the Stanford University Institutional Review Board, after giving informed consent. Ten were novices (engineering graduate students) with no prior experience with surgery on a da Vinci manipulator, and four were experienced surgeons (three urologists, $n_{\text{robotic cases}} > 120$, and one gynecologist, $n_{\text{robotic cases}} > 80$, self reported).

Participants sat at the master console of a da Vinci Si Surgical System (Intuitive Surgical, Sunnyvale, CA, Fig. 1) at Lucile Salter Packard Children's Hospital at Stanford. They held a lightweight (50 g) custom-built grip fixture (Fig. 2A) equipped with a force sensor (Nano-17, ATI Industrial Automation, Apex, NC) and magnetic pose tracker (TrakStar, Ascension Technologies, Milton, VT) in their right hand. In addition, we attached magnetic pose trackers to the shoulder, elbow, and wrist of their right arm. The wrist and shoulder sensors were aligned (as well as anatomical constraints allowed) with the medial line of the forearm and the upper arm, respectively, as depicted in Fig. 1B-C. To maximize the signal quality of the magnetic pose trackers and to minimize magnetic interference from the metal parts of the da Vinci console, the magnetic transmitter was placed on a bar in front of the user Fig. 1A-C). We ensured prior to the experiment that there were no metal components between the trackers and the transmitter, and tested the integrity of the recorded signal using the Ascension Technologies proprietary software. All the signals except the elbow sensor signal had a quality number below 10, which

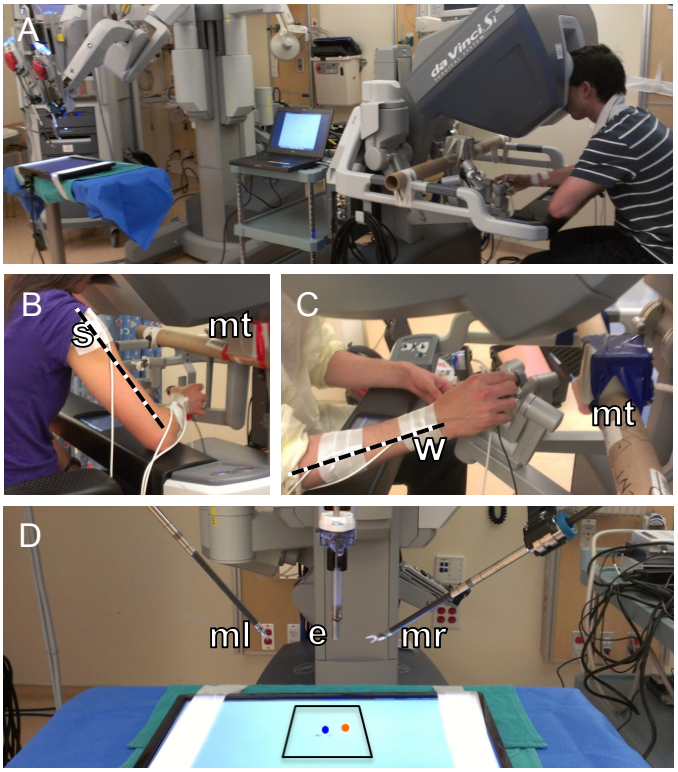

Fig. 1. Experimental setup. A. A participant sits in front of a master console of a da Vinci Si Surgical System, and a monitor is placed on the surgical table. B-C. The dashed lines depict the directions of the shoulder and wrist trackers, labeled 's' and 'w', and aligned as well as anatomical constraints allowed with the medial line of the upper arm and the forearm, respectively. The magnetic transmitter, labeled 'mt', was positioned in front of the user. D. A monitor presented the virtual reality scene to the user via the endoscopic camera, labeled 'e'. The left and right patient-side manipulators, labeled 'ml' and 'mr', respectively, were outside of the camera field of view at all time.

was deemed to be acceptable by Ascension Technologies. (A similar analysis of a different electromagnetic tracker is given in [43].) Because the signal of the elbow tracker was significantly distorted due to magnetic interference from the da Vinci armrest, we estimated the position of the elbow based on the wrist and shoulder sensors, as described in detail in the Appendix.

Participants performed the experiment under two conditions, in two consecutive sessions: (1) *teleoperation*, with the grip fixture attached to the master manipulator (Fig. 2B), and (2) *freehand*, holding the grip fixture alone (Fig. 2C). The order of the sessions was balanced within the *experts* and *novices* groups. In both conditions, they were asked to make planar movements from a central starting point to a target as accurately and as quickly as possible while looking at a virtual cursor displayed on a monitor. The movement of the cursor was mapped one-to-one to the x-y movement of the grip fixture, regardless of whether the fixture was attached to the master manipulator or moved freehand. The movements were not restricted to a plane, but the vertical position of the fixture did not affect the movement of the cursor. The monitor was placed on the surgical table such that users could see the cursor and targets via the endoscopic camera (Fig. 1D). The camera was placed at a distance such that the apparent

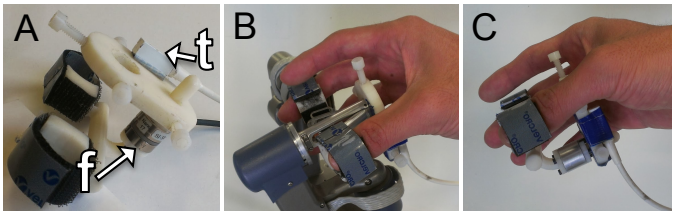

Fig. 2. A. A custom designed grip fixture with embedded force sensor, labeled 'f', and magnetic pose tracker, labeled 't'. B. In the *teleoperation* condition, the fixture was attached to the master manipulator. D. In the *freehand* condition, participants held the fixture alone.

movement of the cursor was mapped approximately one-to-one to the movement of the grip fixture. In the *teleoperation* condition, the master manipulator controlled the movement of the patient-side manipulator, but the instrument was moved outside of the camera view, such that the visual feedback was consistent between the conditions, and the only difference was the effect of the dynamics of the master manipulator. To ensure that the dynamics of the master manipulator are identical to the clinical setting (except for the addition of the grip fixture), we did not disable the movement of the patient-side manipulator.

Each session consisted of 320 movements organized in 10 blocks consisting of 32 possible targets of two *types* (reach and reversal), eight *directions* (-135, -90, -45, 0, 45, 90, or 180 degrees, where 0 degrees indicates a movement to the right), and two *distances* from center (30 and 60 mm). The movements within each block were pseudo-randomly interleaved, in an order identical for all participants and for both sessions. Each trial started when the participant placed his or her hand (represented by the cursor) at start position; then a target was presented, with its color communicating the desired movement *type* (gray for a reach, and magenta for a reversal). The movement was completed when the participant's hand stopped within 5 mm of the target center in reaches, and when the hand returned to within 5 mm from the start center in reversals. Error tolerance of 5 mm was chosen such that the task was difficult enough to maintain participants' enthusiasm, but not too difficult to avoid frustration. Such tolerance is too large for delicate surgical maneuvers, but it may be acceptable in coarse surgical maneuvers such as grasping and pulling or pushing on large tissues for retraction or exposure.

To encourage participants to perform fast and consistent movements, after completion of the movement they received a text feedback on the screen about their movement time. "Too slow" was displayed if a reach took longer than 1 sec, or if a reversal took longer than 1.5 sec; otherwise, "Good" was displayed. Fast movements are necessary to mitigate the effect of online corrections due to visual feedback, and movements with consistent velocity are important for the assumption underlying the UCM analysis that at similar time points along the movement trajectories, a similar reference postural state is defined by the nervous system [21]. In addition, such rapid movements are occasionally needed in clinical scenarios. For example, fast teleoperated movements are typical to prompt instrument responses to acute bleeding.

B. Data processing

We sampled marker positions and orientations at 120 Hz. To remove measurement noise, we filtered the data off-line using Matlab `filtfilt()` function with a 2nd-order low-pass Butterworth filter with a cutoff at 6 Hz. This function filters the original signal twice: in its original and reversed order. This results in an off-line 4th-order filtering with a cutoff (-3 dB frequency) at 4.82 Hz and without phase-shifting the signal. Then, we calculated joint angles as explained in Appendix A. We calculated velocity by backward differentiation and filtered the data again after differentiation.

Movement segmentation was performed based on the trajectories of the sensor that was attached to the grip fixture, representing the endpoint of the master manipulator. To obtain a consistent set of standard movements, we discarded all reaches longer than 2 sec, and reversals longer than 3 sec (8% of the movements, and without substantial change in the results with all data included). We time-normalized all trajectories between movement *onset* (identified as in [44]) and *end*, and interpolated them at equal normalized time intervals of 0.01. Movement *end* was calculated differently for the two movement kinds. For reaches, it was the end of the main movement, without subsequent corrections, and was identified as either the time of first local minimum of speed trajectory after the time of peak speed, or the time when the speed reduced to less then 5% of its peak value for the particular trial. For reversals, it was the time of path reversal – when the distance from start that was traveled in the direction of the target was maximal. This ensured that we analyzed a single movement from start to target. In general, the trajectories of reach and reversal movements are different, but we found no differences in the trial-to-trial variability of both movement types, and therefore, we pooled them together in our analysis.

Detailed analysis of movement kinematics is outside of the scope of the paper, and was described elsewhere [12]. However, to determine whether the coordination of trial-to-trial variability is related to performance, we used a metric that quantifies both operating time and operating accuracy: endpoint error multiplied by movement time ($Er \cdot Mt$[mm·sec]). This metric takes into account the speed-accuracy tradeoff [45], which is typical of point-to-point movements, and corresponds with instructions to the participants to make movements to the target as accurately and as quickly as possible. Endpoint error (Er[mm]) was calculated as the distance between the position of the cursor at movement end and the target, in the x-y plane. Movement time (Mt[sec]) is the temporal difference between movement end and onset.

C. UCM analysis of variability structure

We analyzed variability in the 3-DOF task space that is defined by the Cartesian coordinates of the grasp fixture sensor $\mathbf{x_t} = (\ x_t \quad y_t \quad z_t\ )^T$, and in the 6-DOF control space that is defined by the user's arm joint angles $\boldsymbol{\theta} = (\ \alpha_s \quad \alpha_e \quad \alpha_w \quad \beta_s \quad \beta_e \quad \beta_w\ )^T$, where the 's', 'e', and 'w' subscripts stand for 'shoulder, 'elbow', and 'wrist', respectively, α_s, α_e, α_w are the horizontal absolute angles of the joints, and β_s, β_e, β_w are the vertical absolute angles of the joints (Fig. 3). This definition is equivalent to representing the orientation of each joint using the first two ZYX Euler angles. We tested the structure of variability in joint-space with respect to two separate task components: the 2-DOF horizontal movement (the x-y task) and the 1-DOF vertical movement (the z task).

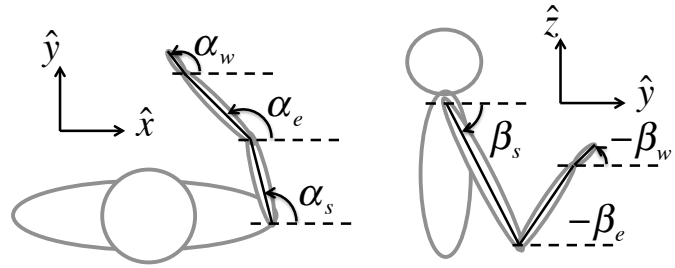

Fig. 3. Definition of the horizontal, α_i, and vertical, β_i, joint angles in top and side views (x-y and y-z plane projections, respectively).

In the analysis of movement, there are two kinds of variability: within-trial variability, calculated with respect to time, and trial-to-trial variability, calculated at similar normalized time trajectory points. The within-trial variability is the extent of change in the variable during movement. In the case of simple ballistic movements, such as reaches and reversals, it can be estimated by calculating the range of the variable during the trial. In contrast, the trial-to-trial variability measures the stability of a variable around a time-varying reference point. The structure of this variability is the main focus of our paper, and we refer to this variability as *variance*.

We assume that, at each moment during the time-normalized trajectory, the same reference postural state is defined by the nervous system [21]. Within the UCM framework, this reference trajectory is estimated as the average trajectory across trials [22] for each movement kind (a unique combination of movement type i, distance j, and direction k) at each normalized time sample t: $\bar{\mathbf{x}}_{ijk}[t]$ (in task-space) and $\bar{\boldsymbol{\theta}}_{ijk}[t]$ (in joint-space).

The range of movement in each of the joint-space average trajectories is an estimation of the *within-trial variability*:

$$\mathbf{M}_{ijk} = \max(\bar{\boldsymbol{\theta}}_{ijk}[t]|t \in [0,1]) - \min(\bar{\boldsymbol{\theta}}_{ijk}[t]|t \in [0,1]), \quad (1)$$

where $\max()$ and $\min()$ operate separately on each of the elements of the joint space trajectory vector.

The *task-space variance* is calculated separately for each of the task components as:

$$V_{\mathbf{x}_{ijk}}[t] = \sum_{l=1}^{N_{ijk}} \|\mathbf{x}_{ijkl}[t] - \bar{\mathbf{x}}_{ijk}[t]\|^2 d_{\text{task}}^{-1} N_{ijk}^{-1}, \quad (2)$$

where $\mathbf{x}$ is a task-space vector, $\|\mathbf{x}\|$ is the Euclidean norm of the vector $\mathbf{x}$, d_{task} is the DOF of the task space (2 for the x-y task, and 1 for the z task), corresponding to the number of elements in $\mathbf{x}$, and N_{ijk} is the number of movements. Similarly, the total *joint-space variance* is:

$$V_{\boldsymbol{\theta}_{ijk}}[t] = \sum_{l=1}^{N_{ijk}} \|\boldsymbol{\theta}_{ijkl}[t] - \bar{\boldsymbol{\theta}}_{ijk}[t]\|^2 d_{\text{joints}}^{-1} N_{ijk}^{-1}, \quad (3)$$

where d_{joints} is the joint-space DOF, 6 in this study.

For the analysis of *joint-space variance* structure, we write the analytical relationship between the task and joint variables (arm forward kinematics). For the x-y task it is:

$$\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \begin{pmatrix} L_{\text{se}}\text{c}\alpha_s\text{c}\beta_s + L_{\text{ew}}\text{c}\alpha_e\text{c}\beta_e + L_{\text{wt}}\text{c}\alpha_w\text{c}\beta_w \\ L_{\text{se}}\text{s}\alpha_s\text{c}\beta_s + L_{\text{ew}}\text{s}\alpha_e\text{c}\beta_e + L_{\text{wt}}\text{s}\alpha_w\text{c}\beta_w \end{pmatrix}, \tag{4}$$

and for the z task it is:

$$z_t = -L_{\text{se}}\text{s}\beta_s - L_{\text{ew}}\text{s}\beta_e - L_{\text{wt}}\text{s}\beta_w, \tag{5}$$

where c• and s• are short for cosine and sine of •, respectively, and L_{se}, L_{ew}, and L_{wt} are the lengths of the upper arm, forearm, and hand, respectively, as described in Appendix A and Fig. 12. The joint-space of the z task has 3 DOF, and hence, we use a reduced joint angle vector $\boldsymbol{\theta} = (\ \beta_s \quad \beta_e \quad \beta_w\ )^T$ in the analysis of the z task. This is an important step, because including in the analysis variables that cannot influence the task variables artificially inflates task-irrelevant variability [22].

The TIM of these forward kinematics equations is nonlinear, but for small deviations around the average trajectories, we can linearize the kinematics using the Jacobian matrix:

$$\mathbf{x}[t] - \bar{\mathbf{x}}_{ijk}[t] = \mathbf{J}(\bar{\boldsymbol{\theta}}_{ijk}[t])(\boldsymbol{\theta}[t] - \bar{\boldsymbol{\theta}}_{ijk}[t]), \tag{6}$$

where the Jacobian matrices for the x-y and z tasks are

$$\mathbf{J}_{xy}(\boldsymbol{\theta}[t]) = \begin{pmatrix} -L_{se}\text{s}\alpha_s\text{c}\beta_s & -L_{ew}\text{s}\alpha_e\text{c}\beta_e & -L_{wt}\text{s}\alpha_w\text{c}\beta_w \\ L_{se}\text{c}\alpha_s\text{c}\beta_s & L_{ew}\text{c}\alpha_e\text{c}\beta_e & L_{wt}\text{c}\alpha_w\text{c}\beta_w \end{pmatrix}$$

$$\cdots \begin{pmatrix} -L_{se}\text{c}\alpha_s\text{s}\beta_s & -L_{ew}\text{c}\alpha_e\text{s}\beta_e & -L_{wt}\text{c}\alpha_w\text{s}\beta_w \\ -L_{se}\text{s}\alpha_s\text{s}\beta_s & -L_{ew}\text{s}\alpha_e\text{s}\beta_e & -L_{wt}\text{s}\alpha_w\text{s}\beta_w \end{pmatrix}[t] \tag{7}$$

and

$$\mathbf{J}_z(\boldsymbol{\theta}[t]) = (\ -L_{se}\text{c}\beta_s \quad -L_{ew}\text{c}\beta_e \quad -L_{wt}\text{c}\beta_w\ )[t], \tag{8}$$

respectively. Note that the Jacobian depends on the average configuration, and is different for each movement type, distance, direction, and normalized time sample.

The null space of the Jacobian is a linear approximation of the TIM, and its dimension is $d_{\text{TIM}} = d_{\text{joints}} - d_{\text{task}}$. The matrix of the d_{TIM} basis vectors, $\boldsymbol{\epsilon}$, was calculated for each mean configuration using Matlab `null()` function such that:

$$\mathbf{J}(\bar{\boldsymbol{\theta}}_{ijk}[t]) \cdot \boldsymbol{\epsilon} = 0. \tag{9}$$

Next, the deviations from the mean trajectories in joint-space are projected onto the null space:

$$\boldsymbol{\theta}_{\text{TIM}}[t] = \boldsymbol{\epsilon}\boldsymbol{\epsilon}^T(\boldsymbol{\theta}[t] - \bar{\boldsymbol{\theta}}_{ijk}[t]) \tag{10}$$

and onto the range space (orthogonal to the null space), which is a linear approximation of the task-relevant manifold, TRM:

$$\boldsymbol{\theta}_{\text{TRM}}[t] = (\boldsymbol{\theta}[t] - \bar{\boldsymbol{\theta}}_{ijk}[t]) - \boldsymbol{\theta}_{\text{TIM}}[t]. \tag{11}$$

The variance per DOF of the projected deviations is:

$$V_{\text{TIM}_{ijk}}[t] = \sum_{l=1}^{N_{ijk}} \|\boldsymbol{\theta}_{\text{TIM}_{ijkl}}[t]\|^2 d_{\text{TIM}}^{-1} N_{ijk}^{-1}, \tag{12}$$

and

$$V_{\text{TRM}_{ijk}}[t] = \sum_{l=1}^{N_{ijk}} \|\boldsymbol{\theta}_{\text{TRM}_{ijkl}}[t]\|^2 d_{\text{task}}^{-1} N_{ijk}^{-1}, \tag{13}$$

The ratio between these two variances quantifies to what extent the joint variables are coordinated to stabilize the average trajectory in task space. Because ratios of variance suffer from mean-variance dependency leading to non-normal distribution, we use a variance-stabilizing transformation and calculate the logarithm of this ratio [46]:

$$R_V[t] = \ln\left(\frac{V_{\text{TIM}}[t]}{V_{\text{TRM}}[t]}\right). \tag{14}$$

Importantly, this ratio is not necessarily related to the overall joint-space variance, which can be large or small; instead, it quantifies its structure with respect to the task space.

Finally, R_V is used to test a hypothesis about the extent of stabilization of the particular task variable in question. If R_V is larger than zero, joint space variables are coordinated such that the task variable is stabilized. If R_V is equal to or smaller then zero, the coordination in joint space is indifferent to the particular task variable, or even destabilizes it, probably because the motor system of the user is aiming at stabilizing a different task variable. With skill acquisition, this ratio can be increased by either reducing $V_{\text{TRM}}[t]$, or by increasing $V_{\text{TIM}}[t]$. While reducing $V_{\text{TRM}}[t]$ will have direct impact on task performance, increasing $V_{\text{TIM}}[t]$ may lead to robustness to unexpected perturbations or improved performance of more complicated tasks involving the same task space variables.

D. Statistical analysis

To test the effects of teleoperation and expertise factors on arm joint-angle variability, we used multi-factor ANOVA. For factors that included more than 2 levels, or in cases of statistically significant interactions, we performed planned comparisons using the Tukey's honest significance criteria for multiple comparisons. The ANOVA models described below were fit with all factors relevant for each analysis together. However, for clarity of presentation in the graphical representation and in our report of the results, we first pooled the analysis across different directions, distances, and movement types, and focused on the effects of teleoperation and expertise. Then, we described the effect of movement direction and session order. Overall, for each participant, in each teleoperation condition, there were 32 data points in the analysis (except for 2 participants who had 31 data points, because they only made 1 successful movement in one of the directions).

For the analysis of within-trial variability, we performed two separate 6-way ANOVAs, with the horizontal and vertical joint angle movement ranges as dependent variables. The independent variables were: teleoperation condition (teleoperation, freehand), expertise (expert, novice), joint (wrist, elbow, shoulder), movement type (reach, reversal), movement distance (short, long), and direction (8 directions), first-order interactions between all factors, and a second-order interaction between teleoperation, expertise, and joint.

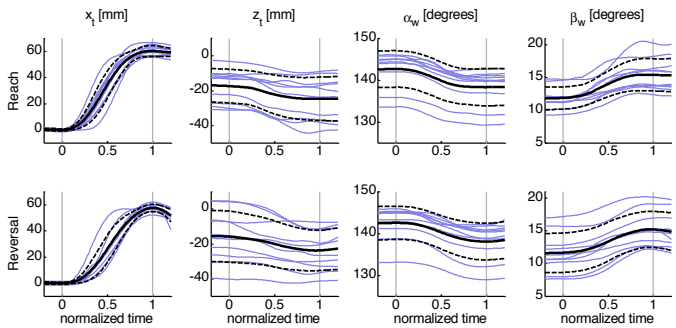

Fig. 4. Examples of experimental trajectories (recorded horizontal x_t and vertical z_t tool position, and calculated horizontal α_w and vertical β_w wrist angles) of one novice participant in reach (upper row) and reversal (lower row) movements toward the 0 degree target. Thin blue traces are individual trial trajectories, and the thick black solid and dashed traces are mean and ± 1 standard error, respectively.

For the analysis of the trial-to-trial variability, we calculated the V_{XY}, V_{Θ}, V_{TIM}, V_{TRM}, and R_V at the time of peak speed and the end of movement. We log-transformed all the variances prior to statistical analysis to correct for their non-normal, skewed distribution [46].

We performed four separate 7-way ANOVAs, with $\ln(V_{\mathrm{XY}})$, $\ln(V_{\Theta})$, $R_{V_{\mathrm{XY}}}$, and $R_{V_{\mathrm{Z}}}$ as dependent variables. The independent variables were teleoperation condition, expertise, movement type, distance, direction, time (peak speed, movement end), and sessions order (freehand first, teleoperated first), first-order interactions between all factors, and second-order interactions between teleoperation, expertise, and time, and between teleoperation, expertise, and order. In addition, we performed an 8-way ANOVA with the projected variance ($\ln(V_{\mathrm{TIM}})$ and $\ln(V_{\mathrm{TRM}})$) as a dependent variable. The design of the model was the same as the other models in this paragraph, with an additional factor of the manifold (TIM, TRM), and its first-order interactions with the other independent variables as well as a second-order interaction between teleoperation, expertise, and manifold.

To assess the correlation between variability coordination and performance, we log-transformed the $Er \cdot Mt$ metric because its distribution was non-normal and skewed. Then, we fitted a linear regression model with $\ln(Er \cdot Mt)$ as the dependent variable and R_V as the independent variable.

III. Results

A. Within-trial variability

In Fig. 4, examples of the trajectories of movements of one participant to a single target are depicted together with their mean. All the trajectories are smooth, and exhibit sufficient degree of similarity to justify an analysis of variability around an average trajectory. In the x coordinate, which was relevant for the task, the within-trial variability (the extent of variation of the mean trajectory with respect to time) was large (approximately 60 mm). Compared to this within-trial variability, the trial-to-trial variability around the mean was small (<20 mm). The z coordinate, which was irrelevant for task performance, stayed nearly constant within a trial, but varied substantially from trial-to-trial. The α_w and β_w trajectories showed intermediate behavior, and they are the main focus of the current study.

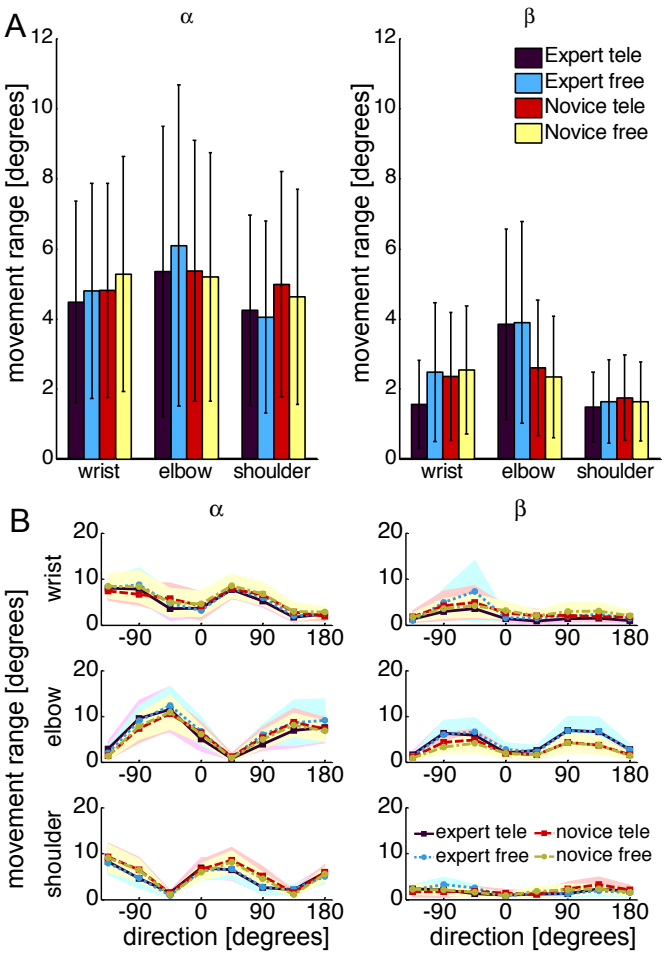

Fig. 5. Movement ranges of horizontal (α, left panels) and vertical (β, right panel) joint angles. (A) Group analysis with respect to joint, teleoperation condition and expertise. Bars are the means averaged across movement kind, distance, direction, and subjects. Error bars are ± 1 mean absolute deviation. (B) Group analysis as a function of movement direction. Symbols are means and shaded areas are ± 1 mean absolute deviation.

The within-trial variability was evaluated using the movement range metric, Eq. (1), and the results of the analysis are depicted in Fig. 5. In both horizontal, α, and vertical, β, angles, the elbow movement range was largest, followed by wrist, and then by shoulder (joint factor in horizontal angles $F_{2,2616} = 42, p < 0.001$, and in vertical angles $F_{2,2616} = 128, p < 0.001$). The horizontal joint movement range was smaller in experts than in novices ($F_{1,2616} = 5, p = 0.02$), but the opposite trend was observed in the vertical angles ($F_{1,2616} = 12, p < 0.001$). Moreover, the trends depended on the particular joint (experience-joint interaction $F_{2,2616} = 13, p < 0.001$ and $F_{2,2616} = 51, p < 0.001$ for α and β, respectively). There were no consistent effects of teleoperation – some movement ranges were larger and some were smaller in teleoperated movements when compared to freehand (teleoperation-joint first-order interactions $F_{2,2616} = 5, p = 0.006$ and $F_{2,2616} = 6, p = 0.002$ for the horizontal and vertical joints, respectively).

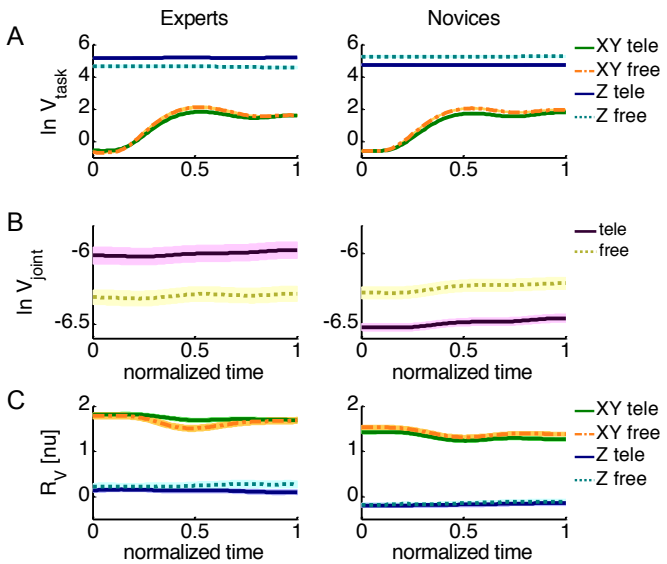

Fig. 6. Trial-to-trial variability as a function of normalized movement time, averaged across movement kinds, distances, directions, and participants. A. Task space variance (in the horizontal x-y and vertical z planes). B. Total joint space variance. C. Ratio between variance per DOF projected on the task-irrelevant and on the task-relevant manifolds for the x-y and z tasks. Lines are means and shaded regions are ± 1 standard error.

Consistent with biomechanics, the main effect of direction on joint angle movement range was statistically significant in both horizontal and vertical angles (Fig. 5B, $F_{7,2616} = 40, p < 0.001$, and $F_{7,2616} = 66, p < 0.001$, respectively), and had small, but statistically significant interaction with expertise ($F_{7,2616} = 3, p = 0.007$, and $F_{7,2616} = 4, p < 0.001$) as seen most clearly in the case of α_s and β_e.

Overall, we found variations of joint angle movement range as a function of direction and statistically significant differences between the joints, but the effects of teleoperation and expertise were small even when they did reach statistical significance. Therefore, we conclude that teleoperation and expertise have minimal effect on the within-trial variability of joint angles.

B. Trial-to-trial variability

1) Size of task-space and joint-space variance: In Fig. 6A, the logarithms of task-space variances are depicted as a function of time. Consistent with our prediction, V_{Z} was larger by at least 2 orders of magnitude than V_{XY}. In addition, the x-y variability changed with normalized movement time, peaking at mid-movement and slightly decreasing towards the end of movement. Therefore, we focused on the times of peak speed and end of movement for the statistical analysis, as summarized in Fig. 7A.

The x-y space variance was larger at the time of peak speed than at movement end ($F_{1,1715} = 64, p < 0.001$). This is consistent with the minimum-intervention principle [23] – the error at the end of movement was more relevant for successful task performance. The variance in teleoperated movements was smaller than in freehand ($F_{1,1715} = 49, p < 0.001$), and

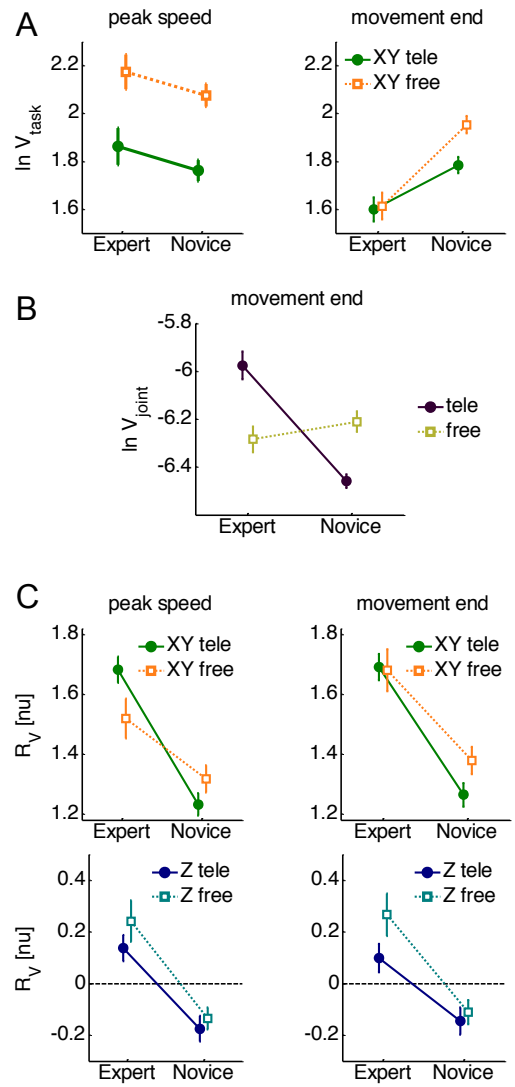

Fig. 7. Trial-to-trial variability analysis at the the time of peak speed and movement end. A. Task space – x-y variance. B. Joint space – total variance. C. Joint space – the ratio between variance per DOF projected on the TIM and on the TRM for the x-y and z hypotheses. Symbols are means and error bars are ± 1 standard error.

this difference was more pronounced at the time peak speed (time-teleoperation interaction, $F_{1,1715} = 15, p < 0.001$). Finally, the variance of experienced surgeons was statistically significantly smaller when compared to novices at the end of movement but not at the time of peak speed (time-expertise interaction, $F_{1,1715} = 39, p < 0.001$).

Interestingly, a very different picture is revealed when examining joint-space variability. The total variability in joints-space is depicted in Fig. 6B as a function of time. There was no statistically significant effect of time ($F_{1,1715} = 0.27, p = 0.6$), and therefore, statistical analysis is summarized in Fig. 7B only at the end of movement. The joint-space variance of experienced surgeons was larger than of novices ($F_{1,1715} = 64, p < 0.001$), and there was no statistically significant effect of teleoperation condition ($F_{1,1715} = 0.66, p = 0.4$). In the freehand condition, the variances of experienced surgeons and novices were similar, but when teleoperating,

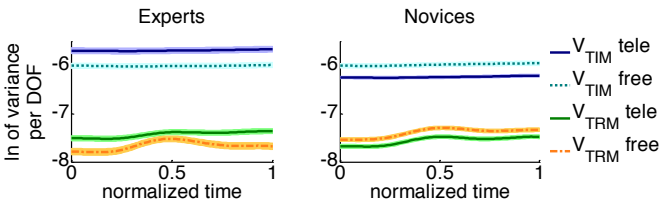

Fig. 8. Joint-space variance projected on the TIM and TRM of the x-y task. Lines are means and shaded regions are ± 1 standard error.

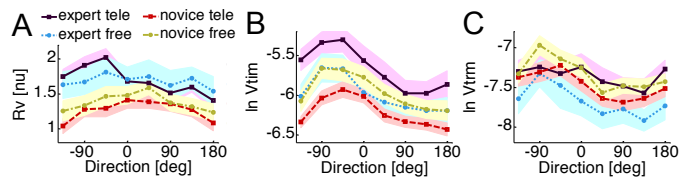

Fig. 9. The effect of movement direction on trial-to-trial variability: (A) R_V, (B) TIM variance, and (C) TRM variance. Lines and symbols are means, and shaded areas are ± 1 standard error.

their variances were shifted upward and downward, respectively (teleoperation-expertise interaction, $F_{1,1715} = 112, p < 0.001$).

2) Coordination of joint-space variance to stabilize hand movement: The logarithm of ratio of TIM and TRM variances, R_V, is depicted for both x-y and z tasks in Fig. 6C as a function of time, and summarized in Fig. 7C for the times of peak speed and end of movement. $R_{V_{\mathrm{XY}}}$ was statistically significantly larger than zero regardless of the experience of the participants, teleoperation condition, or time (upper raw of Fig. 7C). This indicates that joint-space variance was coordinated such that the horizontal (x-y plane) movement was stabilized. This stabilization was achieved by limiting the TRM variance, but allowing large TIM variance, as depicted in Fig. 8 and supported by the statistically significant effect of the manifold on $\ln(V_\Theta)$ ($F_{1,3488} = 4437, p < 0.001$).

Consistent with our prediction, $R_{V_{\mathrm{XY}}}$ was much larger than $R_{V_{\mathrm{Z}}}$. Novices did not coordinate joint-space variability to stabilize the vertical movements of their hand, as indicated by negative values of $R_{V_{\mathrm{Z}}}$. Interestingly, $R_{V_{\mathrm{Z}}}$ of experienced surgeons was very small, but statistically significantly larger than zero, indicating some (minimal) stabilization of vertical movement even in the absence of visual feedback in this dimension. However, because it was very small, we did not further analyze the stabilization of the z task.

$R_{V_{\mathrm{XY}}}$ of experienced surgeons was 26% larger than of novices ($F_{1,1717} = 89, p < 0.001$). There was no statistically significant effect of teleoperation, because novices decreased their R_V in teleoperation, but experienced surgeons increased it at the time of peak speed, and did not change it at the end of movement (teleoperation-expertise interaction, $F_{1,1717} = 6, p = 0.001$). The variability in the TIM in freehand movements was similar between novices and experienced surgeons, and did not change with movement progress (Fig. 8). In teleoperated movements, experienced surgeons increased variability in both manifolds, whereas novices decreased it (teleoperation-expertise interaction $F_{1,3488} = 123, p < 0.001$). However, the extent of these changes was larger in the TIM than TRM (teleoperation-expertise-manifold interaction $F_{1,3488} = 120, p < 0.001$), and resulted in the differences in R_V depicted in Fig. 6C.

3) The effect of movement direction: The dependence on movement direction was statistically significant for all variances, including: V_{XY} ($F_{7,1715} = 4, p < 0.001$), V_Θ ($F_{7,1715} = 20, p < 0.001$), V_{TIM} and V_{TRM} (main effect of direction $F_{7,3488} = 20, p < 0.001$, and direction-manifold interaction $F_{7,1715} = 3, p = 0.009$), and R_V ($F_{7,1717} = 3, p = 0.001$). In Fig. 9, R_V, V_{TIM}, and V_{TRM}, are depicted as a function of direction. The depth of modulation of TIM and TRM variances was large, but it was smaller for R_V. In fact, the only statistically significant contrasts between R_V in different directions were between the $180°$ and the $0°$ and $-45°$ targets. The stabilization was smallest for the $180°$ target.

4) Changes in trial-to-trial variability between experimental sessions: Half of the participants performed the experiment first freehand and then teleoperated, and the other half performed first teleoperated followed by a freehand session. In Fig. 10, V_{XY}, V_Θ, and R_V at time of peak speed are presented as a function of session number. There was a statistically significant interaction between teleoperation, expertise, and order in task-space ($F_{1,1715} = 7, p = 0.01$) and joint-space ($F_{1,1715} = 72, p < 0.001$) variances, and in R_V ($F_{1,1717} = 4, p = 0.03$). However, the patterns of differences were specific to each variance.

Horizontal task-space variance (x-y plane) was smaller in teleoperated movements than in freehand regardless of the experience of the user and the order of sessions. However, the size of the difference depended on order of sessions (teleoperation-order interaction $F_{1,1715} = 22, p < 0.001$): the difference was smaller when the first session was teleoperated than when it was freehand. There was no statistically significant main effect of order of sessions on task-space variance ($F_{1,1715} = 0.82, p = 0.36$).

In contrast, joint-space variance was smaller when participants performed freehand movements first than when they started with teleoperation ($F_{1,1715} = 185, p < 0.001$). The differences between experienced surgeons and novices were substantial. Pooled across sessions, the variance of experienced surgeons who started freehand was smaller than those who teleoperated first; this difference was in the opposite direction and much smaller in novices (experience-order interaction $F_{1,1715} = 562, p < 0.001$). Novices decreased their joint-space variance in the second session regardless of which teleoperation condition they performed first. For experienced surgeons, the direction of change depended on the order: they decreased the variance after teleoperation, and increased it (but not statistically significantly) after the freehand session.

We observed similar trends in R_V – it was smaller in the second session in all expertise-order combinations except for the experienced surgeons who started freehand. Experienced surgeons and novices who performed the freehand session first had the same level of stabilization, but in the transition to teleoperation, experts had no reduction of R_V, and novices had large reduction. In the teleoperated-first group, the R_V of

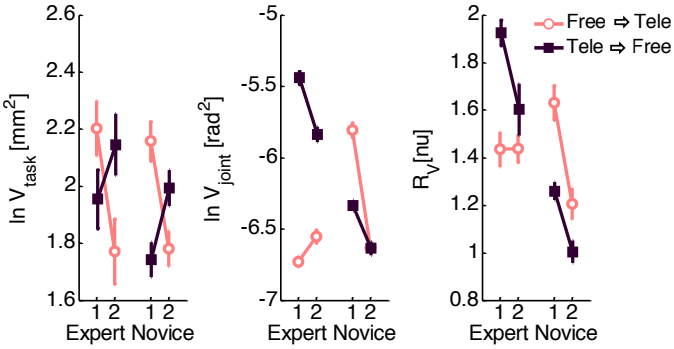

Fig. 10. Trial-to-trial variability as a function of experimental session: task-space variance (left), joint-space variance (middle), and R_v (right) at the time of peak speed. Symbols are means, and error bars are ± 1 standard error. The pink empty circles represent participants who performed the experiment first freehand and then teleoperating (Free⇒Tele), and the purple solid squares represent participants who performed the experiment first teleoperating and then freehand (Tele⇒Free).

experts was statistically significantly larger than of novices, but the extent of reduction in the transition between sessions was similar between experience groups. For experts, the stabilization of the teleoperated movements was higher, and reduced to a level comparable to the freehand movements of the freehand-first group. In contrast, the stabilization of the teleoperated movements of novices was comparable to the teleoperated movements of the freehand-first group, and decreased in the transition to freehand.

5) Correlation between R_v and performance: In Fig. 11, $\ln(Er \cdot Mt)$ is presented as a function of R_V. There was a small but statistically significant negative correlation between this performance metric and R_V (Pearson's $\rho = -0.14$, transformed t-test $t_{893} = -4.5, p < 0.001$), suggesting that large redundancy exploitation for hand trajectory stabilization is related to improved performance. However, the linear regression trend was very weak, and the $R^2 = 0.02$ is extremely small, suggesting that other factors influence performance to a much greater extent.

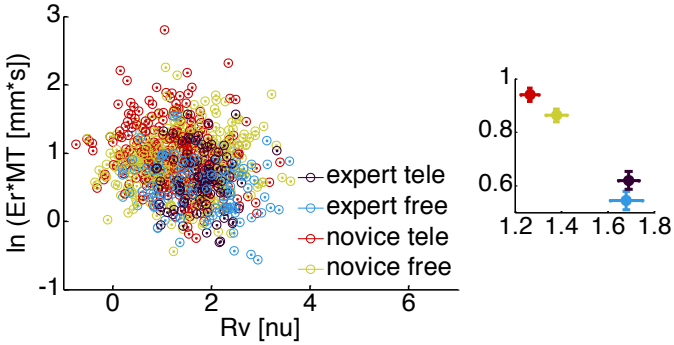

Fig. 11. Correlation between task performance and R_v. In the large panel each symbol represents one of 32 different types of movement for each participant and teleoperation condition. Inset depicts the mean values ± 1 standard error.

IV. Discussion

A. Factors affecting joint angles variability

Experienced surgeons exploitated arm redundancy and coordinated their arm joints for hand movement stabilization of experienced surgeons more than novices, and teleoperation with the da Vinci Si Surgical System master manipulator changed the stabilization relative to freehand performance of the same task. Interestingly, the effect of teleoperation depended on the expertise of the user: for experienced surgeons, the coordination of arm joint angles when teleoperating was larger than when moving freehand, but it was smaller for novices.

The participants coordinated the trial-to-trial variance of their joint angles such that the horizontal but not vertical trajectories of their hand were stabilized. Similar stabilization of movement by coordination of arm joints was previously reported in various tasks [27], [36]–[38]. The lack of stabilization of the vertical trajectory was not surprising because participants were only provided with visual feedback about the horizontal movement of their hand-held grasper tip. Therefore, we expected the horizontal trajectories to be more stabilized compared to the vertical. In the remainder of the discussion, we address only x-y task stabilization.

Experienced surgeons stabilized task trajectory more than novices. Their task variance was smaller at the end of movement than of novices, but their joint-space variance was larger, especially in the teleoperated condition. The UCM analysis suggests that this is due to their superior exploitation of redundancy, as evident by larger variance in TIM than TRM. This is consistent with many previous reports that task variability is reduced by coordination rather than reduction of redundant effector variability [47]. The ability to exploit redundancy and structure the variance of control variables to increase TIM without deteriorating performance was recently studied in expert stone knappers [38], cello players [48], and golfers [49]. It may be related to the external focus of attention (on the effects of actions rather than body mechanics) of experts [50]. Our study is the first one to examine the structure of arm movement variability in the context of surgical expertise.

The superior exploitation of redundancy by the experienced surgeons in our study may have resulted from factors that are not necessarily related to their RAS expertise. They may have better motor skills than the general population, especially in manual tool operation. This is particularly relevant in the current study, because we used simple non-medical movements that do not reflect surgical competence. In future studies, it would be interesting to study participants without RAS experience who have varying levels of surgical expertise, and determine whether early trainees, such as residents or fellows, would exhibit redundancy exploitation that is similar to experienced surgeons in our task. Another interesting control population for such a study would be participants without medical background who are skilled in other forms of fine manual manipulation, like silversmiths, watchmakers, opticians, or microassemblers [51], [52].

An additional factor that may have contributed to the increased exploitation of redundancy by experienced surgeons

is their familiarity with the surgeon console, regardless of teleoperation condition. It is possible that the experienced robotic surgeons, unlike the novices who interacted with the system for the first time, were able to increase their TIM variability because of familiarity with the ergonomic settings of the da Vinci. Furthermore, novices may have attempted to limit the redundancy in their movement if they experienced anxiety when using an expensive robotic surgical system for the first time.

The task space variance in teleoperated movements was smaller than in freehand. This might be related to the teleoperated movements being slower, as reported in details elsewhere [12]. It was previously established that the noise in the motor system is signal-dependent [53], and therefore, faster movements that require stronger muscle activations are very likely to be more variable.

The effect of teleoperation on the coordination of arm joints angles for hand movement stabilization was different between experts and novices. Novices, who were unfamiliar with the dynamics of the master manipulator, decreased the overall variability of their arm angles, but experienced surgeons increased the joint-space variability without increasing its task-space counterpart. The R_V of novices when teleoperating was smaller than when moving freehand. This is consistent with previously reported effect of reducing the coordination of variance during initial exposure to a force field [27]: novices were not familiar with the dynamics of the da Vinci master manipulator, and therefore, had to adapt to these dynamics, resulting in reduction of R_V. However, [27] also reported that at late exposure to the force field, variance coordination was restored. This is consistent with our observation that experts showed similar R_V in freehand and teleoperated movements at movement end, and larger teleoperated R_V compared to freehand at the time of peak speed. While the effect of the dynamics of a hand-held tool on redundancy exploitation in experienced and novice users was not studied extensively, a recent study showed that adding a back-carrying load leads to increase of stabilization of body center of mass during walking [54]. Healthy adults are experienced in carrying loads during locomotion – this is another example of experienced users increasing the ratio between TIM and TRM in the presence of familiar but challenging dynamics.

The joint-space variance and R_V depended on movement direction, and the pattern of dependence was similar across teleoperation conditions and expertise groups. This suggests that it might be related to the control of arm movement rather than being a specific effect of teleoperation that a user can learn with sufficient practice, and that the ability to exploit redundancy may depend on dextrous workspace limitations.

In the analysis of within-trial variability, consistently with biomechanics, we found large variations of joint angle movement range as a function of direction, but the effects of teleoperation and expertise were minimal. In particular, the wrist angle range of experienced surgeons was not larger than that of novices, even though wrist articulation is part of the training goals in robotic surgery, and one of the advantages of RAS over standard MIS is improved dexterity due to the addition of wrist articulation. One potential reason is that we analyzed absolute angles of the arm, which do not describe the degree of the participation of a particular joint in the movement, but the degree of the absolute change in the appropriate arm-link orientation. For example, a movement in which the elbow is rotated while keeping the wrist locked would result in identical movement ranges of the absolute wrist and elbow angles. Another viable explanation is related to the task, which did not require articulation of the surgical tool for successful performance.

B. Limitations and potential remedies

The UCM framework is used extensively in the study of human motor control, but it has several limitations. The projection of variance on linearized manifolds in joint space is dependent on the choice of coordinates [32], [33]. In our study, we tried to mitigate these potential limitations by means of the experimental design. We compared the x-y task stabilization to z task, teleoperated movements to freehand, and experienced surgeons to novices, rather than making absolute statements.

Evaluation of trial-to-trial variability requires many repetitions of similar movements. This limits the ability to study the learning curves of novice surgeons, and generally hampers the analysis when the dynamics of trial-to-trial adaptation are substantial. For static tasks, a single-trial method was developed [35], but it is not appropriate for the case of surgical maneuvers that are rarely static.

In our study, we identified joint angles as control variables, and used the Jacobian to calculate a linear approximation of the TIM. When a candidate set of control variable is not defined, principal component analysis may be used to identify them [22], and linear regression may be used to identify the mapping between control and task variables [28], [35].

Finally, more complicated surgical scenarios may involve sequences of surgical maneuvers that have functional outcomes. In these cases, there may be a hierarchy of redundancy coordination: joint angles may be coordinated to control hand or surgical tool movement, but additional, higher level, task goals may affect movement coordination, such as minimizing tissue damage or blood loss, and successful performance of the intended procedure. Future studies are needed to explore extensions of our framework to explore such hierarchy.

C. Directions for future studies and applications

We found statistically significant but weak correlation between R_V and performance, suggesting that other factors influence performance to a greater extent. This is likely related to the "floor effect" of our simple task, which did not require a full exploitation of the TIM for improved performance. In previous studies, it was suggested that exploitation of redundancy, as indicated by a large value of R_V, induces robustness in face of fatigue, unpredicted perturbations, obstacles, and provides the user with a reacher repertoire of motor strategies [19], [55]. This may allow performance of secondary tasks [19], [56]. For example, in surgical suturing such secondary tasks can be adjusting the orientation of a needle in preparation for tissue penetration, or applying forces and torques that are necessary for the needle to puncture the tissue. Hence, we expect the

advantage of redundancy exploitation to be revealed in more complicated tasks.

In the current experimental design, we could not explore the progress of evolution of R_V as a function of repeated training with a robotic manipulator due to experiment length limitation. However, to gain a preliminary insight into how the coordination of arm joint angles changes, we examined task and joint space variances as well as R_V as a function of session number. Interestingly, R_V was reduced in the second session of all groups except for the experienced surgeons who transitioned from freehand to teleoperated movements. This may be a result of fatigue that caused reduction of TIM variance, consistent with a similar tendency that was reported in a recent study of locomotion [54]. The participants might have attempted to mitigate these effects by choosing trajectories that involved less used muscles, similarly to the model that was suggested in [57], and reduced the TIM variance.

The effect of fatigue may be studied specifically by performing multiple repetitions of a few movements over prolonged experimental sessions. This may contribute to the understanding of the effects of the length of a surgical case on the performance of the surgeon and the ability of his motor system to respond to unpredicted situations, and may have important implications on fatigue management in clinical settings. Previous studies suggested that decreased mobility of the head and trunk [58] alongside with awkward arm movements [59] are responsible for increased fatigue in laparoscopic surgery when compared to open surgery. Ergonomic considerations are gaining attention also in RAS [60]. Future studies may reveal the importance of redundancy exploitation for mitigating fatigue effects. In addition, we did not record the position of the head, neck, and trunk of the participants, and therefore, we could not evaluate the movement of the shoulder relative to the trunk, or the movement of the trunk in space during the performance of the task. In future studies, the role of these movements in the coordination of arm joint angles variance may be explored. Studying how they are affected by teleoperation and expertise may further advance the understanding of movement coordination in RAS.

Large R_V is not by itself a goal for optimization. In face of perturbations, R_V is expected to decrease in the attempt to minimize the deteriorating effect on task performance. However, we suggest that telemanipulators and training strategies could be designed to maximize the ability of the motor system of the surgeon to exploit redundancy, and hence maximize R_V for any given situation. Further studies are needed to suggest general principles or specific guidelines for manipulator physical structure, dynamics, or control that can maximize redundancy exploitation. Preliminary insights can be inferred from this study. For example, in the design of the master manipulators we suggest that spatial degrees of freedom should not be restricted even if only a subspace is relevant to the performance of a particular task. That is, dextrous workspace should be maximized such that it allows the surgeons to exploit the natural redundancy of their arms. This opens interesting questions for future studies, such as what is the optimal degree of redundancy and whether it might be beneficial to increase it by introducing additional redundancy in the master manipulator, or how various forms of force feedback and virtual fixtures may affect redundancy exploitation. Answering these questions may advance RAS as well as the understanding of human motor control.

Our finding of larger redundancy exploitation by experienced surgeons when compared to novices in a non-clinical task opens a promising avenue for exploring redundancy exploitation in surgically relevant procedures for surgical skill assessment. If our current findings generalize to the performance of surgical procedures, this will mean that redundancy exploitation for movement stabilization is an important motor skill that is characteristic of experienced surgeons. This may allow for a development of a novel metric for skill assessment. In addition, drills that induce redundancy exploitation could be developed. If these drills are found to improve surgical outcomes, they could be incorporated in RAS training curricula.

V. Conclusions

In a study of simple non-clinical point-to-point movements, we showed for the first time that there are differences between experienced surgeons and novice users of a da Vinci Surgical System in their exploitation of arm joint angle redundancy. Experienced surgeons coordinate their arm joint angles to stabilize hand movements more than novices, and the effect of da Vinci teleoperation depends on experience – experienced surgeons increase teleoperated stabilization relative to freehand, whereas novices decrease it.

These results open a promising and exciting avenue for exploring how redundancy exploitation benefits clinical task performance, and its potential for skill assessment and surgical training optimization. Enabling redundancy exploitation may also serve as an optimization goal for the design and control of surgical manipulators. Eventually, such improvement in system design, skill assessment, and training may promote RAS by taking advantage of the flexibility of the motor control system of surgeons.

Appendix: Joint Angle Measurement

We placed magnetic pose trackers as close as possible to the centers of the joints ($\boldsymbol{x}_i$ and $\boldsymbol{R}_i$, $i = t, w, e, s$ in Fig. 12A). Because the elbow sensor readouts were distorted due to magnetic interference from the da Vinci armrest, we estimated the position of the elbow joint, $\hat{\mathbf{x}}_e[t]$, as the spatial average of two estimations:

$$\hat{\mathbf{x}}_e^s[t] = \mathbf{x}_s[t] + \hat{L}_{\text{se}}\mathbf{r}_{xs}[t], \tag{15}$$

$$\hat{\mathbf{x}}_e^w[t] = \mathbf{x}_w[t] + \hat{L}_{\text{ew}}\mathbf{r}_{xw}[t], \tag{16}$$

where $\mathbf{x}_{(s/w)}$ and $\mathbf{r}_{x(s/w)}$ are the position and the direction of the longitudinal axes of the shoulder/wrist sensors that were aligned with upper arm and forearm, respectively, and $\hat{L}_{\text{se}}$, and $\hat{L}_{\text{ew}}$ are the measured lengths of the upper arm, forearm, and hand, respectively (Fig. 12).

To assess the accuracy of our estimation algorithm, we recorded one experimental session in a metal-free environment, and calculated the average error between $\hat{\mathbf{x}}_e[t]$ and the

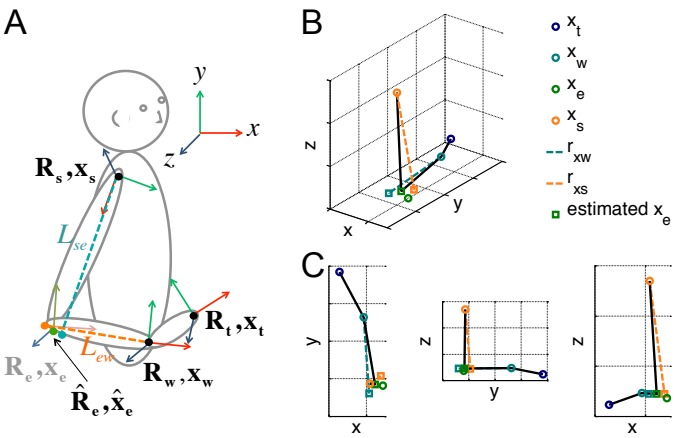

Fig. 12. Extraction of joints positions and orientations: (A) Schematic representation: $\boldsymbol{x}_i$ and $\boldsymbol{R}_i$ are the origins and rotations of the reference frames that are attached to the joints, where $i = s, e, w, t$ for the shoulder, elbow, wrist, and gripper tip, respectively. (B-C) Example of an extraction that was performed in a metal-free environment. Circles are recorded positions, and the green square is an estimation of the elbow joint center. Black solid lines depict the estimated links. Grid spacing is 100 mm.

reading of the sensor located as close as anatomical constraints allowed to the center of the elbow joint, $\mathbf{x}_e[t]$, which was (mean $\pm$ std) 20 ± 5 mm. The bias is likely related to inaccuracy of sensor placement, and the variance to their movement due to movement of the skin, which affects the orientation of the wrist and shoulder sensors as well as the position of the elbow sensor.

Estimation of the orientation of a pose tracker is more sensitive to accurate marker placement and skin movement than estimation of its position. Therefore, we estimated the orientations of the hand, forearm, and upper from the estimated positions of adjacent joint centers in 3D. We also estimated the limb segment lengths (L_{wt}, L_{ew}, and L_{se}, respectively) by calculating the median value of the distances between the appropriate joint centers across all the trials of each participant, rather than using the measured values.

To assess the effects of the different sources of estimation errors on our analysis, we calculated the mean distance between the measured master tool-tip path and its reconstruction based on the forward kinematics from the extracted joint angles. The gripper-tip path is estimated more accurately than the rest of the magnetic pose trackers, because its pose tracker was rigidly attached to the grasp fixture, and because it was very close to the magnetic transmitter leading to an improved signal quality compared to the other sensors. The forward kinematics reconstruction error was 8.5 ± 0.13 mm (mean $\pm$ std). This error was statistically significantly smaller in the freehand condition compared to teleoperated ($16\%, F_{1,1788} = 18, p < 0.001$), and in the expert group compared to novice group ($9\%, F_{1,1788} = 8, p = 0.005$).

In addition, we used a Jacobian-based linearization of the forward kinematics. The mean reconstruction error of the linearized approximation was 11.5 ± 0.16 mm. It was also statistically significantly smaller in the freehand condition compared to teleoperated ($24\%, F_{1,1788} = 49, p < 0.001$), and in the expert group compared to novice group ($23\%, F_{1,1788} = 76, p < 0.001$).

Acknowledgment

The authors would like to thank Taru Roy and Sangram Patil for assistance with the experiment, and the participants of our experiments for their time.

References

[1] W. R. J. Chitwood, L. W. Nifong, W. H. H. Chapman, J. E. Felger, B. M. Bailey, T. Ballint, K. G. Mendleson, V. B. Kim, J. A. Young, and R. A. Albrecht, "Robotic surgical training in an academic institution," *Annals of Surgery*, vol. 234, no. 4, pp. 475–486, 2001.

[2] 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.

[3] F. Rodriguez y Baena and B. Davies, "Robotic surgery: from autonomous systems to intelligent tools," *Robotica*, vol. 28, pp. 163–170, 3 2010.

[4] K. Moorthy, Y. Munz, S. K. Sarker, and A. Darzi, "Objective assessment of technical skills in surgery," *BMJ*, vol. 327, no. 7422, pp. 1032–1037, 2003.

[5] A. R. Lanfranco, A. E. Castellanos, J. P. Desai, and W. C. Meyers, "Robotic surgery: A current perspective," *Annals of Surgery*, vol. 239, no. 1, pp. 14–21, 2004.

[6] J. Rassweiler, M. Hruza, D. Teber, and L.-M. Su, "Laparoscopic and robotic assisted radical prostatectomy – critical analysis of the results," *European Urology*, vol. 49, no. 4, pp. 612–624, 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," *Journal of Urology*, vol. 188, no. 3, pp. 919–923, 2012.

[8] 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.

[9] 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.

[10] 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.

[11] F. Cavallo, S. Sinigaglia, G. Megali, A. Pietrabissa, P. Dario, F. Mosca, and A. Cuschieri, "Biomechanics–machine learning system for surgical gesture analysis and development of technologies for minimal access surgery," *Surgical Innovation*, in press.

[12] I. Nisky, M. H. Hsieh, and A. M. Okamura, "The effect of a robot-assisted surgical system on the kinematics of user movements," in *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2013, pp. 6257–6260.

[13] I. Nisky, A. M. Okamura, and M. H. Hsieh, "Effects of robotic manipulators on movements of novices and surgeons," *Surgical Endoscopy*, in press.

[14] A. A. Faisal, L. P. J. Selen, and D. M. Wolpert, "Noise in the nervous system," *Nature Reviews Neuroscience*, vol. 9, pp. 292–303, 2008.

[15] N. Stergiou and L. M. Decker, "Human movement variability, nonlinear dynamics, and pathology: Is there a connection?" *Human Movement Science*, vol. 30, no. 5, pp. 869 – 888, 2011.

[16] B. C. Touwen, "How normal is variable, or how variable is normal?" *Early Human Development*, vol. 34, no. 1–2, pp. 1–12, 1993.

[17] J. P. Kaipust, J. M. Huisinga, M. Filipi, N. Stergiou *et al.*, "Gait variability measures reveal differences between multiple sclerosis patients and healthy controls," *Motor Control*, vol. 16, no. 2, pp. 229–244, 2012.

[18] N. A. Bernstein, *The Co-ordination and regulation of movements*, first english edition ed. Pergamon Press Ltd., 1967.

[19] M. L. Latash, "Stages in learning motor synergies: A view based on the equilibrium-point hypothesis," *Human Movement Science*, vol. 29, no. 5, pp. 642 – 654, 2010.

[20] A. Karniel, R. Meir, and G. Inbar, "Exploiting the virtue of redundancy," in *International Joint Conference on Neural Networks*, vol. 3, 1999, pp. 2204–2209.

[21] J. P. Scholz and G. Schoner, "The uncontrolled manifold concept: identifying control variables for a functional task," *Experimental Brain Research*, vol. 126, no. 3, pp. 289–306, 1999.

[22] M. L. Latash, J. P. Scholz, and G. Schöner, "Toward a new theory of motor synergies," *Motor Control*, vol. 11, no. 3, pp. 276–308, 2007.

[23] E. Todorov and M. I. Jordan, "Optimal feedback control as a theory of motor coordination," *Nature Neuroscience*, vol. 5, no. 11, pp. 1226–35, 2002.

[24] H. Muller and D. Sternad, "Decomposition of variability in the execution of goal-oriented tasks: Three components of skill improvement," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 30, no. 1, pp. 212–233, 2004.

[25] J. Cusumano and P. Cesari, "Body-goal variability mapping in an aiming task," *Biological Cybernetics*, vol. 94, no. 5, pp. 367–379, 2006.

[26] J. B. Dingwell, R. F. Smallwood, and J. P. Cusumano, "Trial-to-trial dynamics and learning in a generalized, redundant reaching task," *Journal of Neurophysiology*, vol. 109, no. 1, pp. 225–237, 2013.

[27] J.-F. Yang, J. Scholz, and M. Latash, "The role of kinematic redundancy in adaptation of reaching," *Experimental Brain Research*, vol. 176, no. 1, pp. 54–69, 2007.

[28] S. M. S. F. Freitas, J. P. Scholz, and M. L. Latash, "Analyses of joint variance related to voluntary whole-body movements performed in standing," *Journal of Neuroscience Methods*, vol. 188, no. 1, pp. 89–96, 2010.

[29] D. N. Nenchev, "Tracking manipulator trajectories with ordinary singularities: A null space-based approach," *The International Journal of Robotics Research*, vol. 14, no. 4, pp. 399–404, 1995.

[30] S. Scott, "Optimal feedback control and the neural basis of volitional motor control," *Nature Reviews Neuroscience*, vol. 5, no. 7, pp. 532–546, 2004.

[31] R. Cohen and D. Sternad, "Variability in motor learning: relocating, channeling and reducing noise," *Experimental Brain Research*, vol. 193, no. 1, pp. 69–83, 2009.

[32] D. Sternad, S.-W. Park, H. Muller, and N. Hogan, "Coordinate dependence of variability analysis," *PLoS Comput Biol*, vol. 6, no. 4, p. e1000751, 04 2010.

[33] D. Campolo, F. Widjaja, H. Xu, W. T. Ang, and E. Burdet, "Analysis of accuracy in pointing with redundant hand-held tools: A geometric approach to the uncontrolled manifold method," *PLoS Comput Biol*, vol. 9, no. 4, p. e1002978, 04 2013.

[34] N. Kang, M. Shinohara, V. Zatsiorsky, and M. Latash, "Learning multi-finger synergies: an uncontrolled manifold analysis," *Experimental Brain Research*, vol. 157, no. 3, pp. 336–350, 2004.

[35] F. J. Valero-Cuevas, M. Venkadesan, and E. Todorov, "Structured variability of muscle activations supports the minimal intervention principle of motor control," *Journal of Neurophysiology*, vol. 102, no. 1, pp. 59–68, 2009.

[36] D. Domkin, J. Laczko, S. Jaric, H. Johansson, and M. Latash, "Structure of joint variability in bimanual pointing tasks," *Experimental Brain Research*, vol. 143, no. 1, pp. 11–23, 2002.

[37] J. P. Scholz, G. Schöner, and M. L. Latash, "Identifying the control structure of multijoint coordination during pistol shooting," *Experimental Brain Research*, vol. 135, no. 3, pp. 382–404, 2000.

[38] R. Rein, B. Bril, and T. Nonaka, "Coordination strategies used in stone knapping," *American Journal of Physical Anthropology*, vol. 150, no. 4, pp. 539–550, 2013.

[39] D. S. Reisman, J. P. Scholz, and G. Schöner, "Differential joint coordination in the tasks of standing up and sitting down," *Journal of Electromyography and Kinesiology*, vol. 12, no. 6, pp. 493 – 505, 2002.

[40] 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.

[41] 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.

[42] I. Nisky, M. H. Hsieh, and A. M. Okamura, "A framework for analysis of surgeon arm posture variability in robot-assisted surgery," in *IEEE International Conference on Robotics and Automation*, 2013, pp. 245–251.

[43] C. Nafis, V. Jensen, L. Beauregard, and P. Anderson, "Method for estimating dynamic em tracking accuracy of surgical navigation tools," p. 61410K, 2006.

[44] L. Botzer and A. Karniel, "A simple and accurate onset detection method for a measured bell-shaped speed profile," *Frontiers in Neuroscience*, vol. 3, 2009.

[45] 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.

[46] J. Verrel, "Distributional properties and variance-stabilizing transformations for measures of uncontrolled manifold effects," *Journal of Neuroscience Methods*, vol. 191, no. 2, pp. 166 – 170, 2010.

[47] K. M. Newell and E. G. James, "The amount and structure of human movement variability," *Routledge Handbook of Biomechanics and Human Movement Science*, pp. 93–104, 2008.

[48] J. Verrel, S. Pologe, W. Manselle, U. Lindenberger, and M. Woollacott, "Coordination of degrees of freedom and stabilization of task variables in a complex motor skill: expertise-related differences in cello bowing," *Experimental Brain Research*, vol. 224, no. 3, pp. 323–334, 2013.

[49] P. Glazier, "Movement variability in the golf swing," *Research Quarterly for Exercise and Sport*, vol. 82, no. 2, pp. 157–161, 2011.

[50] K. R. Lohse, M. Jones, A. F. Healy, and D. E. Sherwood, "The role of attention in motor control," *Journal of Experimental Psychology: General*, 2013.

[51] R. E. Riggio and Y. Sotoodeh, "Screening tests for use in hiring microassemblers," *Perceptual and Motor Skills*, vol. 65, no. 1, pp. 167–172, 1987.

[52] S. Vieluf, J. Mahmoodi, B. Godde, E.-M. Reuter, and C. Voelcker-Rehage, "The influence of age and work-related expertise on fine motor control," *The Journal of Gerontopsychology and Geriatric Psychiatry*, vol. 25, no. 4, pp. 199–206, 2012.

[53] C. M. Harris and D. M. Wolpert, "Signal-dependent noise determines motor planning," *Nature*, vol. 394, no. 6695, pp. 780–784, 1998.

[54] X. Qu, "Uncontrolled manifold analysis of gait variability: Effects of load carriage and fatigue," *Gait & Posture*, vol. 36, no. 2, pp. 325 – 329, 2012.

[55] M. V. Butz, O. Herbort, and J. Hoffmann, "Exploiting redundancy for flexible behavior: Unsupervised learning in a modular sensorimotor control architecture." *Psychological Review*, vol. 114, no. 4, pp. 1015–1046, 2007.

[56] O. Khatib, E. Demircan, V. D. Sapio, L. Sentis, T. Besier, and S. Delp, "Robotics-based synthesis of human motion," *Journal of Physiology-Paris*, vol. 103, no. 3–5, pp. 211 – 219, 2009.

[57] V. Potkonjak, V. M. Petrovic, K. Jovanovic, and D. Kostic, "Human-robot analogy - how physiology shapes human and robot motion," in *Advances in Artificial Life*, vol. 12, 2013, pp. 136–143.

[58] R. Berguer, G. Rab, H. Abu-Ghaida, A. Alarcon, and J. Chung, "A comparison of surgeons' posture during laparoscopic and open surgical procedures," *Surgical endoscopy*, vol. 11, no. 2, pp. 139–142, 1997.

[59] N. T. Nguyen, H. S. Ho, W. D. Smith, C. Philipps, C. Lewis, R. M. D. Vera, and R. Berguer, "An ergonomic evaluation of surgeons' axial skeletal and upper extremity movements during laparoscopic and open surgery," *The American Journal of Surgery*, vol. 182, no. 6, pp. 720 – 724, 2001.

[60] P. Rosenblatt, J. McKinney, and S. Adams, "Ergonomics in the operating room: Protecting the surgeon," *Journal of Minimally Invasive Gynecology*, vol. 20, no. 6, pp. 744–744, 2013.