

# Objective evaluation of expert and novice performance during robotic surgical training tasks

Timothy N. Judkins · Dmitry Oleynikov ·  
Nick Stergiou

Received: 31 July 2007 / Accepted: 5 April 2008 / Published online: 29 April 2008  
© Springer Science+Business Media, LLC 2008

## Abstract

**Background** Robotic laparoscopic surgery has revolutionized minimally invasive surgery for the treatment of abdominal pathologies. However, current training techniques rely on subjective evaluation. The authors sought to identify objective measures of robotic surgical performance by comparing novices and experts during three training tasks.

**Methods** Five novices (medical students) were trained in three tasks with the da Vinci Surgical System. Five experts trained in advanced laparoscopy also performed the three tasks. Time to task completion (TTC), total distance traveled (D), speed (S), curvature ( $\kappa$ ), and relative phase ( $\Phi$ ) were measured.

**Results** Before training, TTC, D, and  $\kappa$  were significantly smaller for experts than for novices ( $p < 0.05$ ), whereas S was significantly larger for experts than for novices before training ( $p < 0.05$ ). Novices performed significantly better after training, as shown by smaller TTC, D, and  $\kappa$ , and

larger S. Novice performance after training approached expert performance.

**Conclusion** This study clearly demonstrated the ability of objective kinematic measures to distinguish between novice and expert performance and training effects in the performance of robotic surgical training tasks.

**Keywords** Performance · Robotic surgery · Skill assessment · Training

Laparoscopy, a form of minimally invasive surgery, has revolutionized the treatment of abdominal pathologies. The benefits for patients include shorter recovery time with less pain [1], fewer adhesions [2], and better postoperative quality of life [3] than experienced with traditional open procedures. However, manual laparoscopy also has shown several limitations during surgery. These limitations include lack of depth perception, poor camera control, limited degrees of freedom of the instrument tips, and inverted hand–instrument movements [4–6]. Furthermore, these limitations lead to unnatural and painful surgical postures that result in fatigue for the surgeon [4–6].

The advent of robotic surgical systems, such as the da Vinci Surgical System (dVSS; Intuitive Surgical, Inc., Sunnyvale, CA, USA), has overcome some limitations of manual laparoscopy. The addition of three-dimensional visualization has provided depth perception [7] and increased dexterity [8, 9]. The wrist-like articulations of the instruments also have been shown to improve surgeons' dexterity [9]. The coordinated hand–instrument movements have reduced the training time for the use of robotic systems versus manual laparoscopy [10]. In addition, tremor abolition and motion scaling have been shown to enhance dexterity with the use of robotic systems compared with manual techniques [9].

---

T. N. Judkins (✉)  
Intelligent Automation, Inc., Rockville, MD, USA  
e-mail: tjudkins@gmail.com

D. Oleynikov  
Department of Surgery, University of Nebraska Medical Center,  
Omaha, NE, USA

N. Stergiou  
HPER Biomechanics Laboratory, University of Nebraska  
at Omaha, Omaha, NE, USA

N. Stergiou  
Department of Environmental, Agricultural and Occupational  
Health Sciences, College of Public Health, University  
of Nebraska Medical Center, Omaha, NE, USA

As of 2000, more than 100 dVSS systems were in use worldwide [11]. Currently, more than 400 systems are used worldwide (personal communication with Intuitive Surgical). As of January 2001, it was estimated that the dVSS had been used to perform more than 2,000 surgeries, and that number is rising rapidly [12]. At our clinical facility alone, 204 laparoscopic procedures have been performed using the dVSS as of February 2005.

According to hospitals that responded to a survey, 45% of dVSS procedures are cardiac, 33% are urologic, 11% are general surgery, 7% are gynecologic, and 4% are pediatric [13]. The growing prevalence of dVSS procedures poses a clear need to establish standardized training and evaluation for robotic laparoscopic surgery. In addition, no clearly established measures exist for judging performance during surgery.

The current means for evaluating surgical performance and skill acquisition during training are limited to measurement of task completion time and number of errors [9, 14–17] or a subjective evaluation by an expert. In all the cited studies, task completion time and number of errors were reduced with training. Errors are important to evaluate, but review by an expert is required to identify the errors. Furthermore, the aforementioned measures do not characterize the movements (e.g., speed or distance covered). Moreover, it is not known whether faster is better. The speed–accuracy trade-off is a well-known phenomenon in motor control, in which speed increases cause decreases in accuracy and vice versa [18]. More accurate movements may take more time to complete. Therefore, additional objective measures are needed to quantify surgical performance improvements and differentiate between expert and novice surgeons.

This study aimed by the use of objective measures to compare robotic surgical performance between novices and experts, specifically after a short training period. We previously identified task completion time, distance traveled, and relative phase (coordination) as potential measures of surgical proficiency, as shown by changes over a 4-week training period [19]. We also showed previously that task completion time and relative phase can distinguish novice from expert performance during three inanimate tasks [20]. In addition, we determined that path curvature and grip force improve with training, as shown by changes over only one session comprising 10 trials of training [21].

In this study, we performed a comprehensive evaluation of all previously identified objective measures by comparing experts and novices (before and after training) during three inanimate tasks of increasing difficulty. We focused in using only a short training period due to restrictions that exist with long training periods (i.e., availability of the robot, availability of experts). We hypothesized that expert and novice performances in speed,

curvature, and grip force are significantly different, and that novice performance will improve with training. Specifically, we hypothesized that experts and trained novices will make faster, straighter movements and use less grip force. These objective measures provided the foundation for quantifying movement characteristics and improved robotic surgical evaluation.

## Materials and methods

### Subjects

Five novice users (first- and second-year medical students, ages 22–24 years) and five expert users (advanced laparoscopic surgeons, ages 35–45 years) of the dVSS were recruited to participate in this study. Novice users had no prior experience using the dVSS. Expert users were trained as advanced laparoscopic surgeons and had performed at least five human procedures using the dVSS. All participants were right-handed. Informed consent was obtained from each subject before his or her participation in accordance with the Institution Review Board of the University of Nebraska Medical Center.

### Experimental protocol

Subjects performed and/or practiced three tasks using the dVSS throughout this study: bimanual carrying (BC), needle passing (NP), and suture tying (ST). The bimanual carrying task required that two  $15 \times 2$ -mm rubber pieces (one each with left and right graspers) be picked up from 30-mm (diameter) metal caps and placed in two other metal caps 50 mm away (Fig. 1A). The caps were arranged in a square configuration such that the left graspers removed pieces from the top left cap and placed them in the bottom left cap. The right grasper removed pieces from the bottom right cap and placed them in the top right cap. The subject repeated the movement six times in succession.

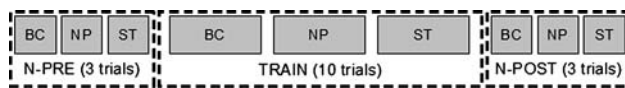
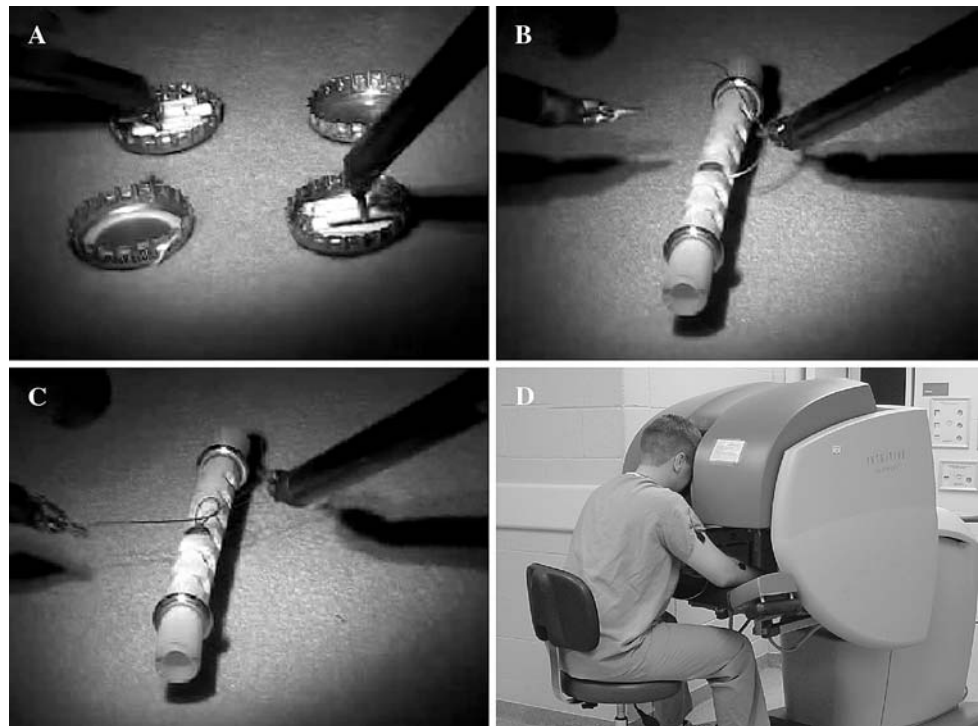
The needle-passing task required that a 26-mm surgical needle be passed through six holes in a latex tube (Fig. 1B). Subjects started from the proximal holes and proceeded to the distal holes.

The suture-tying task required that two knots be tied with a  $100 \times 0.5$ -mm surgical suture using the intracorporeal knot (Fig. 1C). The subjects performed the tasks by manipulating the dVSS from the surgeon's console (Fig. 1D).

All three tasks were cyclic tasks designed to mimic actual laparoscopic tasks that required significant bimanual coordination.

Novices performed 16 trials of each task divided into 3 training blocks (Fig. 2): 3 pretraining trials (N-PRE), 10

**Fig. 1** The tasks performed in the current study using the da Vinci Surgical System (dVSS). (A) Bimanual carrying. (B) Needle passing. (C) Suture tying. (D) Subject seated at the surgeon's dVSS console



**Fig. 2** Training paradigm for the novice subjects. Each novice performed each task in three training blocks: 3 pretraining trials (N-PRE), 10 training trials (TRAIN), and 3 posttraining trials (N-POST). Task order was randomized between subjects, but remained the same between training blocks

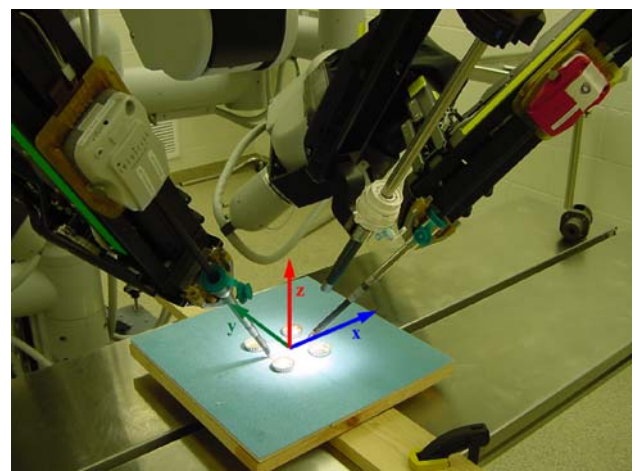
training trials, and 3 posttraining trials (N-POST). All trials were performed during one session. The task order was randomized between subjects, but remained the same between training blocks. Experts performed five trials of each task. The last three trials of each task by the experts were used for data analysis. Subjects were not allowed to practice with the dVSS before the experiment.

### Data analysis

All objective measures of performance were based on kinematic measures of the dVSS instrument tips. Kinematics of the dVSS were collected using the Application Programmer's Interface (API) provided by Intuitive Surgical. A custom LabView program (National Instruments, Inc., Concord, MA, USA) was written to interface with the dVSS via an Ethernet connection. Data were streamed at 75 Hz (determined by API). All postprocessing of data was performed in MATLAB (version 6.5; Mathworks, Inc., Natick, MA, USA). All kinematic data were down-sampled to 5 Hz using a cubic spline to enforce a constant sampling

rate between data points. Variables of interest streamed from the API were position ( $x$ ,  $y$ , and  $z$  location) of the right and left instrument tips and the grip force applied by the left and right grasper.

Before data collections for training tasks, a local coordinate system was defined for all kinematics:  $x$  (left/right),  $y$  (forward/backward), and  $z$  (up/down) (Fig. 3). A local coordinate system is necessary for accurate measurements of relative phase (described later). The local coordinate system was defined by measuring the location of the instrument tip at the local origin ( ${}^G P_{Lorig}$ ), at a point on the local  $x$ -axis ( ${}^G P_{Lx}$ ), and at a point on the local  $y$ -axis ( ${}^G P_{Ly}$ ). A transformation matrix was computed from these three



**Fig. 3** Local coordinate system of measurement for training tasks

points to transform points in the global coordinate system to the local coordinate system [22].

All measurements acquired from the robot kinematics were computed from position, velocity, and acceleration of the instrument tips. All measurements were calculated for the left and right instruments (or graspers) unless noted. Velocity and acceleration of the instrument tips were calculated directly by computing the first and second derivatives, respectively, of the positions of the instrument tips.

### Objective measures

The objective performance measures were time to task completion (TTC), total distance traveled (D), speed (S), curvature ( $\kappa$ ), and relative phase ( $\Phi$ ). Time to task completion was the time required to complete a given training task. Start and end times were identified as the time when the instrument tips were within 1 cm of the starting positions. Total distance traveled was the sum of Euclidean distances between each time sample. Speed was calculated as the magnitude of the velocity. The mean ( $S_{mean}$ ) and standard deviation ( $S_{std}$ ) of speed were computed for each trial.

Curvature measured the straightness of the path and was calculated at each point on the path by the following equation [23, 24]:

$$\kappa = \frac{|\dot{r} \times \ddot{r}|}{\dot{r}^3} \quad (1)$$

where  $\dot{r}$  is the velocity of a point  $r$  on the three-dimensional path, and  $\ddot{r}$  is the acceleration of point  $r$ . The median ( $\kappa_{med}$ ) and 95% confidence interval ( $\kappa_{CI}$ ) were computed for each trial. The 95% confidence interval was computed as defined by Campbell and Gardner [25]. Values of  $\kappa_{med}$  close to zero indicate relatively smooth and straight movements, whereas larger values indicate curved and jerky movements.

Relative phase was computed to determine the coordination of the instrument tips in the dominant direction of movement ( $x$  for needle passing and suture tying,  $y$  for bimanual carrying). It is measured as the difference in phase angle between the left and right instruments, as given in the following equation [26]:

$$\Phi = \varphi_A - \varphi_B$$

$$\Phi = \tan^{-1} \left( \frac{\dot{x}_A}{x_A} \right) - \tan^{-1} \left( \frac{\dot{x}_B}{x_B} \right) \quad (2)$$

where  $\varphi_A$  is the phase angle of point A,  $\varphi_B$  is the phase angle of point B,  $x_A$  is the position of point A in the  $x$  direction,  $x_B$  is the position of point B in the  $x$  direction,  $\dot{x}_A$  is the speed of point A in the  $x$  direction, and  $\dot{x}_B$  is the speed of point B in the  $x$  direction. Note that the  $\text{atan2}$

function was used to calculate the inverse tangent in order for  $\varphi$  to range from  $-\pi$  to  $\pi$ . Circular statistics were used to calculate the mean ( $\Phi_{mean}$ ) and standard deviation ( $\Phi_{std}$ ) of the relative phase as defined by Stergiou [26]. Values of  $\Phi_{mean}$  close to zero show an in-phase relationship, whereas values close to 180 show an antiphase relationship.

Grip force (F), provided by the dVSS API, represented a percentage of the maximum torque of the servos that drive the graspers. To verify the linearity of the grip force and its correlation with applied pressure, a force sensing resistor (FSR) was squeezed while measurements from the dVSS and FSR were collected simultaneously ( $R^2 > 0.91$ ). The resistance of the FSR is proportional to the force applied. Therefore, grip force could be measured directly. The dVSS and FSR grip force measurements were compared using a linear regression fit. Right and left grip force measured by the dVSS was very well correlated ( $R^2 = 0.97$  and  $0.91$ , respectively) with FSR measurements. Mean grip force ( $F_{mean}$ ) was computed for each trial. Small values of  $F_{mean}$  are desirable because they indicate that little pressure would be applied to tissue.

### Statistical analysis

Group means were calculated for all the dependent variables: time to task completion (TTC), total distance traveled (D), speed (S), curvature ( $\kappa$ ), and relative phase ( $\Phi$ ). Subsequently, independent  $t$ -tests were used to compare the group means between the untrained novices (N-PRE) and the experts (EX) and between the trained novices (N-POST) and the experts (EX) for each objective measure and each task at  $\alpha = 0.05$ . Dependent  $t$ -tests were used to compare the group means of novices before and after their training (N-PRE vs N-POST) for each objective measure and each task at  $\alpha = 0.05$ . Bonferroni corrections due to the number of comparisons were not used. However, the actual  $p$  values are presented in our results, as considered in the Discussion section later. All statistical analyses were performed using SPSS 12.0 (SPSS, Chicago, IL, USA).

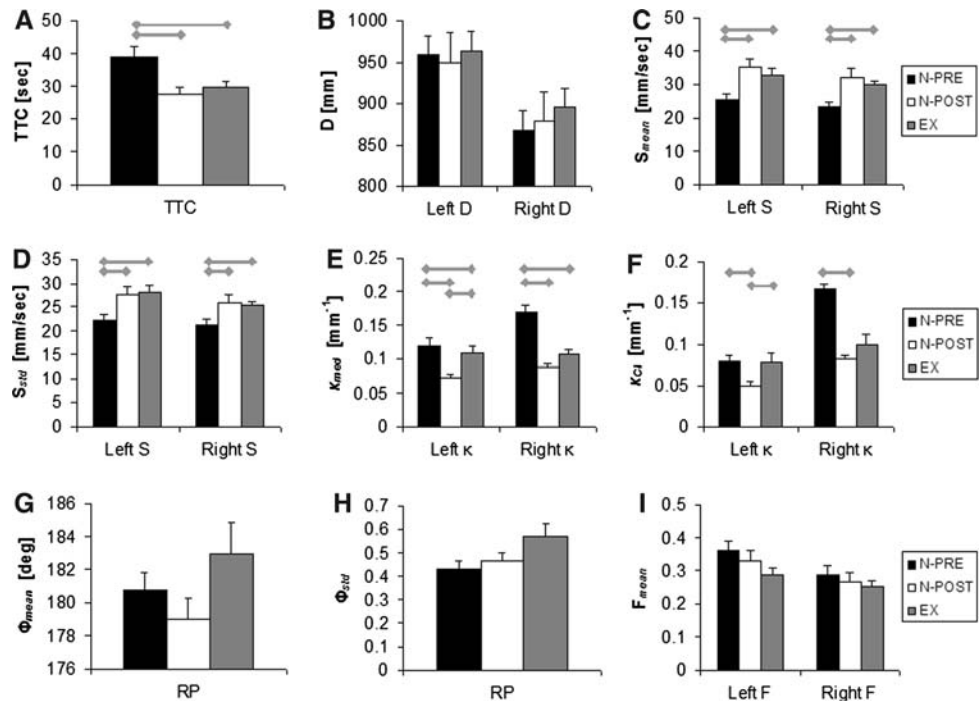
## Results

### Bimanual carrying

**Task completion time, speed, and curvature** successfully distinguished between novice (before training) and expert performance as well as before and after novice training (Fig. 4). Expert TTC was significantly less than that of novices before training ( $p = 0.014$ ), whereas expert right  $S_{mean}$  was significantly larger ( $p = 0.003$ ). Expert left  $S_{mean}$  was significantly larger than that of novices before training ( $p = 0.011$ ), as was right  $S_{std}$  ( $p = 0.004$ ). Left



**Fig. 4** Group means for pretraining trials (N-PRE), posttraining trials (N-POST), and experts (EX) during the bimanual-carrying (BC) task for time to task completion (TTC) (A), D (B),  $S_{mean}$  (C),  $S_{std}$  (D),  $\kappa_{med}$  (E),  $\kappa_{CI}$  (F),  $\Phi_{mean}$  (G),  $\Phi_{std}$  (H), and  $F_{mean}$  (I). Horizontal bars indicate a significant difference between groups ( $p < 0.05$ )



$S_{std}$  was significantly larger for experts than for novices ( $p = 0.005$ ), and experts made significantly straighter movements for right  $\kappa_{med}$  than novices ( $p = 0.022$ ).

Novices also improved performance after training, as shown by smaller task completion time, faster movements, and straighter movements. After training, TTC was significantly smaller ( $p < 0.0005$ ). Both and left  $S_{mean}$  were significantly larger after training (right  $p < 0.0005$  vs. left  $p = 0.001$ ), as were both right and left  $S_{std}$  (right  $p = 0.002$  vs. left  $p < 0.0005$ ). Both right and left  $\kappa_{med}$  were significantly smaller after training (right  $p = 0.009$  vs. left  $p < 0.0005$ ), as were both right and left  $\kappa_{CI}$  (right  $p = 0.023$  vs. left  $p = 0.002$ ). Novice performance after training was very similar to expert performance. Only left  $\kappa_{med}$  and  $\kappa_{CI}$  were significantly different between experts and novices after training ( $p = 0.005$  and  $p = 0.023$ , respectively).

#### Needle passing

**Task completion time, distance traveled, speed, curvature, relative phase standard deviation, and grip force successfully distinguished between novice (before training) and expert performance, and the same measures, except for distance traveled, distinguished before and after training (Fig. 5).** Expert TTC was significantly smaller than that of novices before training ( $p = 0.004$ ). Right D was significantly smaller for experts than for novices before training ( $p = 0.002$ ). Expert left  $S_{mean}$  was significantly larger than

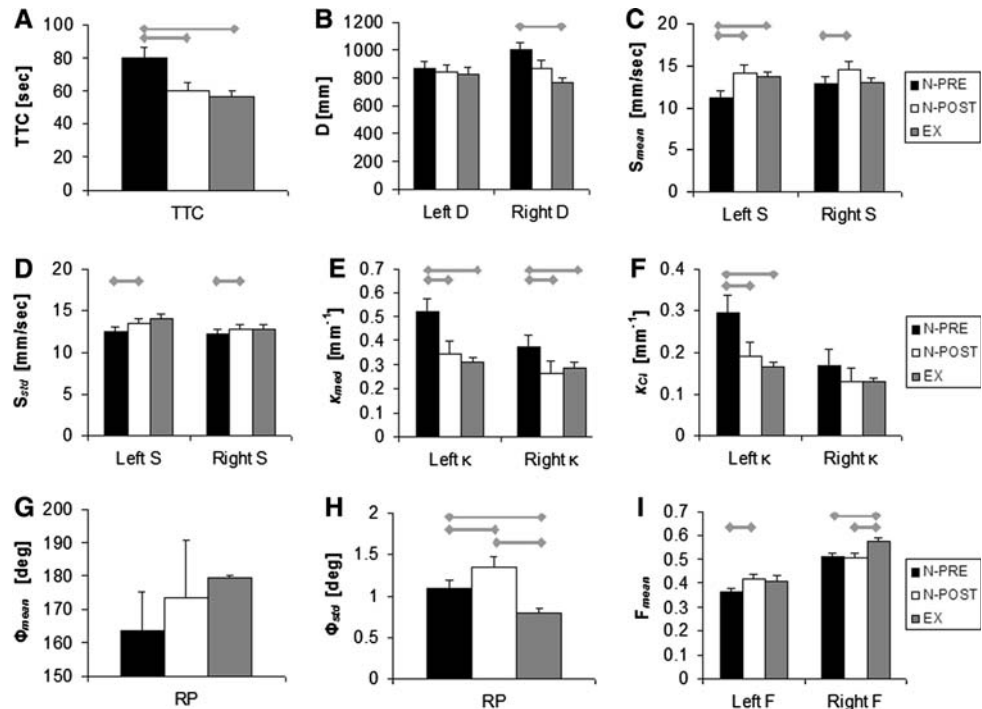
that of novices before training ( $p = 0.016$ ). Experts made significantly straighter movements for right  $\kappa_{med}$  ( $p = 0.027$ ) and left  $\kappa_{med}$  ( $p < 0.0005$ ) than novices before training. Left  $\kappa_{CI}$  was significantly smaller for experts than for novices ( $p = 0.01$ ). Experts had significantly less variation in relative phase than novices before training ( $p = 0.006$ ). Right F was slightly, but significantly, larger for experts than for novices ( $p = 0.019$ ).

Novices also improved performance after training, as shown by shorter task completion time, faster movements, straighter movements, and increased deviations of relative phase. After training, TTC was significantly smaller ( $p = 0.001$ ). Both right and left  $S_{mean}$  were significantly larger after training (right  $p = 0.012$  vs. left  $p = 0.001$ ), whereas both right and left  $\kappa_{med}$  were significantly smaller (right  $p = 0.001$  vs. left  $p = 0.006$ ). Left  $\kappa_{CI}$  was significantly smaller after training ( $p = 0.022$ ), whereas left  $\Phi_{std}$  was significantly larger ( $p = 0.043$ ). Left F was significantly larger after training ( $p = 0.042$ ). Novice performance after training was very similar to expert performance. Only  $\Phi_{std}$  and right  $F_{mean}$  were significantly different between experts ( $p = 0.001$ ) and novices ( $p = 0.003$ ) after training.

#### Suture tying

**Task completion time, distance traveled, speed, curvature, and grip force successfully distinguished between novice (before training) and expert performance, and the same**

**Fig. 5** Group means for pretraining trials (N-PRE), posttraining trials (N-POST), and experts (EX) during the needle-passing (NP) task for time to task completion (TTC) (A), D (B),  $S_{mean}$  (C),  $S_{std}$  (D),  $\kappa_{med}$  (E),  $\kappa_{CI}$  (F),  $\Phi_{mean}$  (G),  $\Phi_{std}$  (H), and  $F_{mean}$  (I). Horizontal bars indicate a significant difference between groups ( $p < 0.05$ )



measures, except for grip force, distinguished performance before and after training (Fig. 6). Expert TTC was significantly smaller than that for novices before training ( $p < 0.0005$ ). Both right and left D were significantly smaller for experts than for novices before training (right  $p = 0.001$  vs. left  $p = 0.001$ ). Both right and left  $S_{mean}$  were significantly larger for experts than for novices before training (right  $p = 0.001$  vs. left  $p < 0.0005$ ), as were both right and left  $S_{std}$  (right  $p = 0.004$  vs. left  $p = 0.005$ ). Experts made significantly straighter movements for right  $\kappa_{med}$  ( $p = 0.001$ ) and left  $\kappa_{med}$  ( $p < 0.0005$ ) than novices before training. Left F was slightly, but significantly, smaller for experts than for novices before training ( $p = 0.007$ ).

Novices also improved performance after training, as shown by shorter task completion time, shorter distance traveled, faster movements, and straighter movements. After training, TTC was significantly shorter ( $p < 0.0005$ ). Both right and left D were significantly smaller after training (right  $p = 0.006$  vs. left  $p = 0.001$ ), whereas right and left  $S_{mean}$  were significantly larger (right  $p < 0.0005$  vs. left  $p < 0.0005$ ). Both right and left  $S_{std}$  were significantly larger after training (right  $p < 0.0005$  vs. left  $p < 0.0005$ ), whereas right and left  $\kappa_{med}$  were significantly smaller (right  $p = 0.002$  vs. left  $p = 0.042$ ). Novice performance after training was very similar to expert performance. Only left  $\kappa_{med}$  was significantly different between experts and novices after training ( $p = 0.036$ ).

## Discussion

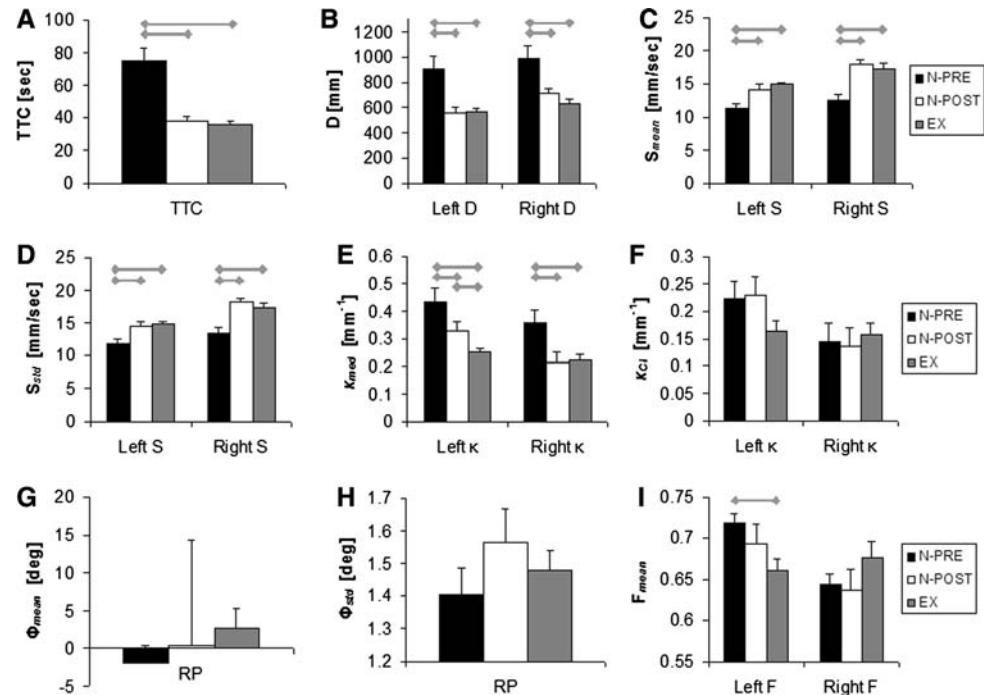
This study clearly demonstrated the ability of objective kinematic measures to distinguish between novice and expert performance and training effects in the performance of robotic surgical training tasks. All objective measures except  $\Phi_{mean}$  were significantly different between novices and experts, and after training for at least one task. Therefore, these variables have the potential to measure and evaluate robotic surgical performance.

These results agree with those of previous studies that found decreases in task completion time and distance traveled [16, 17, 27, 28]. These results also agree with our previous findings of reduced task completion time and decreased distance traveled after training [19, 21] as well as our more recent findings comparing novices and experts [20].

Remarkably, we found that novices required relatively few trials ( $n = 10$ ) to reduce task completion time significantly. In general, the total distance traveled (D) was shorter, the average speed ( $S_{mean}$ ) was faster, the standard deviation for speed ( $S_{std}$ ) was larger, the movements were straighter ( $\kappa_{med}$ ), the confidence intervals of curvature ( $\kappa_{CI}$ ) were smaller, and the standard deviation of relative phase ( $\Phi_{std}$ ) was smaller for experts and novices after training than for novices before training.

Although these results are expected with improved performance, mean grip force ( $F_{mean}$ ) was larger for experts

**Fig. 6** Group means for pretraining trials (N-PRE), posttraining trials (N-POST), and experts (EX) during the suture-tying (ST) task for time to task completion (TTC) (A), D (B),  $S_{mean}$  (C),  $S_{std}$  (D),  $\kappa_{med}$  (E),  $\kappa_{CI}$  (F),  $\Phi_{mean}$  (G),  $\Phi_{std}$  (H), and  $F_{mean}$  (I). Horizontal bars indicate a significant difference between groups ( $p < 0.05$ )



than for novices. This is likely due to the lack of tactile feedback from the dVSS (i.e., the inability to “feel” the amount of force applied by the graspers). Using too much force could potentially damage delicate tissue during surgery. Future studies should investigate other training means for providing alternative feedback to reduce grip force.

Furthermore, the performance of the novices after training was similar to expert performance (i.e., the difference between novice performance before and after training was similar to the difference between the performance of experts and novices before training). Few objective measures ( $\kappa_{med}$  and  $\kappa_{CI}$  for BC,  $\Phi_{std}$  and right F for NP, and  $\kappa_{med}$  for ST) were significantly different between novice performance after training and expert performance. For the BC tasks, novices actually made straighter movements than experts. For the NP and ST tasks, novice performance approached expert performance, but may require slightly more training.

Although nearly all objective measures improved overall, there were task differences. The number of objective measures with significant differences increased with task complexity. For the bimanual carrying task (the easiest task), six objective measures were significantly different between novices and experts, and nine measures were significantly different between pre- and posttraining. For the needle-passing task (a moderately difficult task), eight measures were significantly different between novices and experts, and eight measures were significantly different

between pre- and posttraining. For the suture-tying task (the most difficult task), nine measures were significantly different between novices and experts, and nine measures were significantly different between pre- and posttraining.

It is likely that novices performed better on less complex tasks, reducing the likelihood of training effects and differences between novice and expert performance. However, further investigation is needed to explore task complexity and robotic surgical performance.

One measure, the mean relative phase, did not show any differences between novice and expert performance nor between pre- and posttraining. Our previous study did find relative phase differences for long-term training [19]. It is possible that coordination requires additional training before differences are apparent.

Alternatively, normalization techniques for calculating relative phase differed between this study and our previous work. In our previous work, position and velocity were normalized during postprocessing. In the current study, a local coordinate system was calculated before data collection. Kurz and Stergiou [29] showed that normalization can affect relative phase calculations. Other researchers have used the local minimum and maximum of the relative phase curve because they are reversal points in the segment relationships. It has been noted previously that these points provide insight on the specific changes in coordination [30]. However, this analysis may not be appropriate for our study. Our tasks did not have clearly defined cycles (e.g.,

gait) because of mistakes such as missed grabs, dropped needles, and the like. Also, suture tying does not have multiple cycles because it is just one knot. Further investigation is needed to determine the extent to which normalization affects relative phase for robotic surgery or whether differences between our previous and current studies are due to the amount of training given.

Previous studies emphasized that task completion time and distance traveled are insufficient to explain fully all aspects of robotic surgical performance (i.e., there may be qualitative aspects of robotic surgical performance that one should consider when identifying objective measures of performance) [9, 17, 26, 31, 32]. The results from this study clearly suggest that these additional objective measures of robotic surgical performance, particularly speed and curvature, can distinguish between expert and novice performance and training effects and have the potential to identify additional aspects of robotic surgical performance not quantified by task completion time and distance traveled alone. Finally, relatively little training (10 trials per task) is needed for novices to perform well during the training tasks.

**Acknowledgments** This study was supported by NIH (K25HD047194), NIDRR (H133G040118), and the Nebraska Research Initiative.

## References

1. Talamini MA, Stanfield CL, Chang DC, Wu AW (2004) The surgical recovery index. *Surg Endosc* 18:596–600
2. Gutt CN, Oniu T, Schemmer P, Mehrabi A, Buchler MW (2004) Fewer adhesions induced by laparoscopic surgery? *Surg Endosc* 18:898–906
3. Korolija D, Sauerland S, Wood-Dauphinee S, Abbou CC, Eypasch E, Garcia Caballero M, Lumsden MA, Millat B, Monson JRT, Nilsson G, Pointner R, Schwenk W, Shamiyeh A, Szold A, Targarona E, Ure B, Neugebauer E (2004) Evaluation of quality of life after laparoscopic surgery. *Surg Endosc* 18:879–897
4. McClure N, Gallagher AG, McGuigan J, Ritchie K, Sheehy NP (1997) An ergonomic analysis of the fulcrum effect in endoscopic skill acquisition. *Gynaecol Endosc* 6:90
5. Berguer R, Smith WD, Chung YH (2001) Performing laparoscopic surgery is significantly more stressful for the surgeon than open surgery. *Surg Endosc* 15:1204–1207
6. Berguer R, Rab GT, Abu-Ghaida H, Alarcon A, Chung J (1997) A comparison of surgeons' posture during laparoscopic and open surgical procedures. *Surg Endosc* 11:139–142
7. D'Annibale AMD, Fiscon VMD, Trevisan PMD, Pozzobon MMD, Gianfreda VMD, Sovernigo GMD, Morpurgo EMD, Orsini CMD, Del Monte DMD (2004) The da Vinci robot in right adrenalectomy: considerations on technique. *Surg Laparosc Endosc Percutan Tech* 14:38–41
8. Munz Y, Moorthy K, Dosis A, Hernandez JD, Bann SD, Bello F, Martin S, Darzi A, Rockall T (2004) The benefits of stereoscopic vision in robotic-assisted performance on bench models. *Surg Endosc* 18:611–616
9. Hernandez JD, Bann SD, Munz Y, Moorthy K, Datta V, Martin S, Dosis A, Bello F, Darzi A, Rockall T (2004) Qualitative and quantitative analysis of the learning curve of a simulated surgical task on the da Vinci system. *Surg Endosc* 18:372–378
10. Chang L, Satava RM, Pellegrini CA, Sinanan MN (2003) Robotic surgery: identifying the learning curve through objective measurement of skill. *Surg Endosc* 17:1744–1748
11. Jacobsen G, Elli F, Horgan S (2004) Robotic surgery update. *Surg Endosc* 18:1186–1191
12. Bann SD, Khan MS, Hernandez J, Munz Y, Moorthy K, Datta V, Rockall T, Darzi A (2003) Robotics in surgery. *J Am Coll Surg* 196:784–795
13. Smillie MF (2003) Intuitive surgical. The Seidler Companies, Inc., Los Angeles, CA
14. Hashizume M, Shimada M, Tomikawa M, Ikeda Y, Takahashi I, Abe R, Koga F, Gotoh N, Konish K, Maehara S, Sugimachi K (2002) Early experiences of endoscopic procedures in general surgery assisted by a computer-enhanced surgical system. *Surg Endosc* 16:1187–1191
15. Hubens G, Coveliers H, Balliu L, Ruppert M, Vaneerdeweg W (2003) A performance study comparing manual and robotic assisted laparoscopic surgery using the da Vinci system. *Surg Endosc* 17:1595–1599
16. Prasad SM, Maniar HS, Soper NJ, Damiano RJ, Klingensmith ME (2002) The effect of robotic assistance on learning curves for basic laparoscopic skills. *Am J Surg* 183:702–707
17. Sarle R, Tewari A, Shrivastava A, Peabody J, Menon M (2004) Surgical robotics and laparoscopic training drills. *J Endourol* 18:63–67
18. Rose DJ (1997) A multilevel approach to the study of motor control and learning. Allyn & Bacon, Needham Heights, MA
19. Narazaki K, Oleynikov D, Stergiou N (2006) Robotic surgery training and performance: identifying objective variables for quantifying the extent of proficiency. *Surg Endosc* 20:96–103
20. Narazaki K, Oleynikov D, Stergiou N (2007) Objective assessment of proficiency with bimanual inanimate tasks in robotic laparoscopy. *J Laparoendosc Adv Surg Tech* 17:47–52
21. Judkins TN, Oleynikov D, Stergiou N (2005) Real-time augmented feedback benefits robotic laparoscopic training. *Stud Health Technol Inform* 119:243–248
22. Craig JJ (1989) Introduction to robotics: mechanics and control. Addison-Wesley Longman Publishing Co., Inc., Reading, MA
23. Gray A (1997) Modern differential geometry of curves and surfaces with mathematica. CRC Press LLC, Boca Raton, FL
24. Weisstein EW (2006) Curvature. Retrieved August 2006 at <http://mathworld.wolfram.com/Curvature.html>. Mathworld—a Web resource
25. Campbell MJ, Gardner MJ (1988) Calculating confidence intervals for some nonparametric analyses. *BMJ* 296:1454–1456
26. Stergiou N (2004) Innovative analyses of human movement. Human Kinetics, Champaign, IL
27. Yohannes P, Rotariu P, Pinto P, Smith AD, Lee BR (2002) Comparison of robotic versus laparoscopic skill: is there a difference in the learning curve? *Urology* 60:39–45
28. DeUgarte DA, Etzioni DA, Gracia C, Atkinson JB (2003) Robotic surgery and resident training. *Surg Endosc* 17:960–963
29. Kurz MJ, Stergiou N (2002) Effect of normalization and phase angle calculations on continuous relative phase. *J Biomech* 35:369–374
30. Barela JA, Whittall J, Black P, Clark JE (2000) An examination of constraints affecting the intralimb coordination of hemiparetic gait. *Hum Movement Sci* 19:251–273
31. Smith CD, Farrell TM, McNatt SS, Metreveli RE (2001) Assessing laparoscopic manipulative skills. *Am J Surg* 181:547–550
32. Moorthy K, Munz Y, Dosis A, Hernandez J, Martin S, Bello F, Rockall T, Darzi A (2004) Dexterity enhancement with robotic surgery. *Surg Endosc* 18:790–795