Robotic surgery training and performance

Kenji Narazaki
University of Nebraska at Omaha

D. Oleynikov
University of Nebraska Medical Center

Nikolaos Stergiou
University of Nebraska at Omaha, nstergiou@unomaha.edu

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Identifying objective variables for quantifying the extent of proficiency

K. Narazaki,[1] D. Oleynikov,[2] N. Stergiou[1]

[1]University of Nebraska at Omaha, 6001 Dodge Street, Omaha, NE 68182, USA
[2]University of Nebraska Medical Center, 983280 Nebraska Medical Center, Omaha, NE 68198-3280, USA

Abstract

Background: To understand the process of skill acquisition in robotic surgery and to allow useful real-time feedback to surgeons and trainees in future generations of robotic surgical systems, robotic surgical skills should be determined with objective variables. The aim of this study was to assess skill acquisition through a training protocol, and to identify variables for the quantification of proficiency.

Methods: Seven novice users of the da Vinci Surgical System engaged in 4 weeks of training that involved practicing three bimanual tasks with the system. Seven variables were determined for assessing speed of performance, bimanual coordination, and muscular activation. These values were compared before and after training.

Results: Significant improvements were observed through training in five variables. Bimanual coordination showed differences between the surgical tasks used, whereas muscular activation patterns showed better muscle use through training. The subjects also performed the surgical tasks considerably faster within the first two to three training sessions.

Conclusions: The study objectively demonstrated that the novice users could learn to perform surgical tasks faster and with more consistency, better bimanual dexterity, and better muscular activity utilization. The variables examined showed great promise as objective indicators of proficiency and skill acquisition in robotic surgery.

Key words: Bimanual coordination — Electromyography — Roboticsurgery — Skill assessment

Minimally invasive surgery is a revolutionary technique that has altered the course of technological advancements in nearly all surgical fields. Laparoscopic procedure, an effective form of minimally invasive surgery, has numerous benefits for patients including shorter recovery time, less pain, fewer adhesions, and better postoperative quality of life than traditional open procedures [6, 15, 22, 32]. However, the limitations of conventional manual laparoscopy seem to have held back the progress of minimally invasive surgery. These limitations include lack of depth perception, poor camera control, limited degrees of freedom for the instrument tips, and inverted hand–instrument movements [1, 12, 14, 29]. These limitations, which lead to unnatural posture and range of motion, have been linked to undesirable fatigue experienced by surgeons [5, 28].

The introduction of the da Vinci Surgical System (dVSS) (Intuitive Surgical, Inc., Sunnyvale, CA) in the latter half of the past decade has been met with enthusiasm by clinicians and researchers interested in minimally invasive surgery. In fact, more than 300 dVSS are in place in hospitals and other institutions worldwide [20]. The excitement about the dVSS stems from the systems ability to overcome the common limitations of manual laparoscopy by providing three-dimensional (3D) images, seven degrees of freedom at the instrument tip, restoration of hand–eye coordination, and a seated position for comfortable posture [2, 7, 9, 17, 19, 20].

The primary goals of research since the introduction of robotic laparoscopy have been to ensure the benefits of the system in terms of dexterity and performance, and to develop objective criteria and scoring systems for determining proficiency in robotic surgery. Many of the early studies involved comparing the performance of laparoscopic tasks between manual and robotic techniques. In one of the earliest studies, Garcia-Ruiz et al. [13] focused on the time required for task completion and the number of errors made between performing manual laparoscopy and using an early robotic proto type. Several subsequent studies have evaluated improvement of performance during robotic laparoscopy [8, 10, 13, 27]. In most of these studies, the parameters measured again have been only the time required for task completion and the number of errors made. Furthermore, in other studies designed to measure acquisition of skill in performing robotic laparoscopic tasks using the dVSS, the subjects performance again was evaluated using only the time required for task completion, the number of errors, or both [10, 27, 30].

However, several investigators have asserted that the time required for task completion is not a sufficient quantitative parameter for measuring skill acquisition [3, 18, 26, 30, 31]. In fact, Smith et al. [31] conducted a study in which accuracy was measured by comparing kinematic data collected by a surgical assessment device with a calculated ideal trajectory. These authors found that the learning curve for task time is much more rapid than the learning curve for accuracy [31]. Furthermore, error reduction, one of the most important goals in training, has been addressed only subjectively using error counts from videotapes [10, 27, 30]. Although this type of subjective visual analysis can be useful in certain circumstances, such analysis tends to be very laborious and impractical when objective scoring systems are needed.

Recently, researchers have used a novel method for proper identification of skill proficiency during robotic surgery. They extracted real-time kinematics from the dVSS Application Programming Interface (API; Intuitive Surgical Inc.) [11, 18, 26, 34]. This allowed assessment of surgeons actual movements during a task, and permitted objective conclusions to be drawn about the quality of performance. Moorthy et al. [26] recently compared API data from the dVSS with data collected during manual laparoscopy using the Imperial College Surgical Assessment Device. Their specific variables of interest were the time and length of instrument movement during a task. Hernandez et al. [18] also used API to measure time, length of path, and number of movements, with each movement defined as a change in velocity [18].

Our research group has previously used the kinematics from the API to examine proficiency [11, 34]. However, despite these improvements, our findings still have been limited for two major reasons. First, assessment of bimanual coordination has been ignored, although surgical tasks usually require movements of both arms in a specific time-phasing relationship. Second, previous studies actually measured the movements of the surgeons indirectly by examining their reflections on the instrument tips. There are practically no data directly from the surgeons arm movements during robotic surgical procedures. Such data could provide a realistic profile of the surgeons arm movements while learning to use the dVSS. An example of such data would be the electromyography profiles of the involved muscles during performance.

Therefore, the aim of this study was to assess skill acquisition through a designed training protocol using not only commonly researched variables, but also bimanual coordination and electromyography. Our goal was to identify feasible variables for better quantifying the extent of proficiency and skill acquisition.

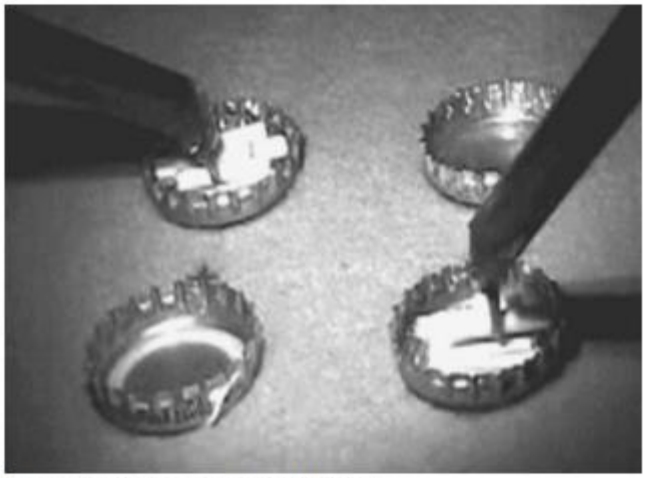

Fig. 1. The bimanual carrying (BC) task.

Materials and methods

Subjects

Seven first- and second-year medical students (6 men and 1 woman) at the University of Nebraska Medical Center (UNMC), novice users of the dVSS, were recruited to participate in this study. The age of the participants was 26.4 ± 3.1 years. All were right-handed. Informed consent, approved by the Institutional Review Board of the UNMC, was obtained from each subject before participation.

Tasks

The following three inanimate robotic surgical tasks were performed or practiced in this study:

1. *Bimanual carrying* (BC), a ‘‘pick and place’’ task: picking up six 15 x 2-mm rubber pieces from a 30-mm metal cap with the right and left instruments, respectively, and carrying them to the opposite caps simultaneously (Fig. 1)

2. *Needle passing* (NP), a ‘‘translational’’ task: passing a 26-mm surgical needle through six pairs of holes made on the surface of a latex tube (Figs. 2 and 3)

3. *Suture tying* (ST), a ‘‘precision navigation’’ task: passing a 150 x 0.5-mm surgical suture through a pair of holes made on the surface of a latex tube and making three knots using intracorporeal knotting (Fig. 3).

All three tasks were designed to mimic real robotic surgical tasks, and to require consistent repetition of the same movements with bimanual coordination for quality performance. The participants were required to complete five BC, five NP, and three ST movements for each trial.

Experimental protocol

All the participants were asked to engage in the experimental protocol during a 4-week period. This protocol included one pretraining test, six training sessions, and one posttraining test.

Pretraining test

At the beginning of the test, the participants received a verbal explanation about the use of the dVSS and testing procedures from the investigators and familiarized themselves with the system, but not with the tasks, for 5 min. During this familiarization or ‘‘warming-up’’ period, the participant was allowed to ask questions and receive further verbal explanation and suggestions from the investigators. After the familiarization, the subject performed one trial for each of the three tasks while data were acquired.

Fig. 2. The needle-passing (NP) task.

Fig. 3. The suture-tying (ST) task.

Training sessions

Within 3 days after the pretraining test, the participant started the training sessions. In each session, the subject practiced the three tasks, three or four times each, within a period of 45 min. During practice, the participant was allowed to ask questions and receive verbal explanation and suggestions from the investigators. At the end of the session, the participant performed a trial for each task while data were acquired.

Posttraining test

After completion of the training period, and within 3 days after the sixth training session, the posttraining session was conducted in the same manner as the pretraining session.

Measurements

For all trials of the pre- and posttraining tests and training sessions, we measured elapsed time and kinematic variables with respect to the position and angular movement of the surgical instruments. The variables were measured from the force transducers built into the system. They were extracted at a frequency of 11 Hz by the dVSS API. These data sets then were processed using MATLAB (version 6.5, The MathWorks Inc., MA, USA) to obtain linear kinematics with respect to the movement of the surgical instrument tips. Additionally, for all trials of the pre- and posttraining tests, the muscular activation of four muscles was monitored from the participants right arm and forearm. These muscles were the flexor carpi radialis (FCR), the extensor digitorum (ED), the biceps brachii (BB), and the triceps brachii (TB). We chose the FCR as a primary wrist flexor muscle, the ED as a primary wrist extensor muscle, the BB as a primary elbow flexor muscle, and the TB as a primary elbow extensor muscle, all of which are superficial and can be monitored by a surface electromyography (EMG) system. Although many other types of movements (e.g., flexion and extension of thumb and index and middle fingers, forearm pronation and supination) and thus many other muscles are involved, we assumed that the contribution of these four muscles in the three tasks was considerably high, and that consequently, measurement of the EMG activities performed by these muscles was important for the purpose of this study. Surface electrodes were placed over the bellies of these muscles, as described by Basmajian and Deluca [4]. The EMG data were collected using a DelSys surface EMG (DelSys, Inc, MA) and extracted at 1,000 Hz through the PEAK Motus (Version 7.0; Peak Performance Technologies, Englewood, CO, USA) data acquisition system. These data sets then were processed using MATLAB to obtain normalized EMG outputs.

Dependent variables

To quantify the nature of the participants performance, dependent variables were calculated on the basis of temporal, kinematic and EMG analyses.

Temporal analysis

For each trial, task completion time (T) was calculated. Moreover, respective time intervals for all the movements in each trial were identified from the dVSS API using the open/close parameters for the instruments forceps. The coefficient of variation between the intervals (CVI) also was calculated.

Kinematic analysis

Total traveling distance (D) with respect to the robot surgical instrument tips was calculated for each trial from the linear kinematics. Moreover, to quantify the extent of bimanual dexterity, a coordination analysis was conducted. This type of analysis is commonly used in psychobiologic studies to evaluate bimanual coordination [16, 21, 23, 33]. Central to this approach is the advantageous evaluation of the direct relationship between velocity and position using phase portraits. The phase portrait is practically a plot of angular position versus velocity (Fig. 4) of the moving segment in question (i.e., the robots surgical tip). From the phase portrait, the phase angle can be identified (Fig. 4). The phase angle is calculated as $\phi = \tan^{-1}$ (velocity/displacement). After the phase angle from the right segment is calculated (i.e., right robot surgical tip), the same procedure can be used to calculate the phase angle of the left segment. After this calculation, subtraction of the two phase angles leads to very interesting results. If the subtracted value is zero, it can be said that the two segments move in the same manner, or that they are in-phase (Fig. 5). If the value is 180, then it can be said that the two segments move in an opposite way, or that they are out-of-phase. Using these procedures in the current study, we were able to evaluate how the robots instrument tips were moving: in-phase or out-of-phase.

We applied these procedures in the current study as follows. First, a dominant direction of each task was identified, after which a phase portrait (Fig. 4) was generated for each trial and for both the right and left instrument tips using the data set of the normalized linear displacement and velocity. Second, phase angles for both tips (ϕ_{right} and ϕ_{left}) were identified from the phase portraits, and relative phases ($\phi_{RP} = \phi_{right} - \phi_{left}$) were subsequently calculated [24, 25]. Finally, the mean absolute relative phase (MARP) was calculated from the relative phase curves using the following equation:

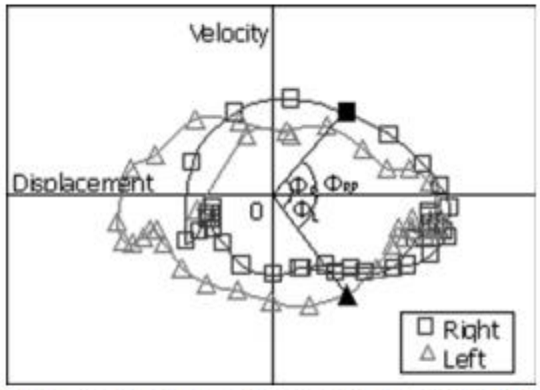

Fig. 4. A representative phase portrait (velocity vs displacement) from both right and left instrument tips where the phase angles (Φ) are identified.

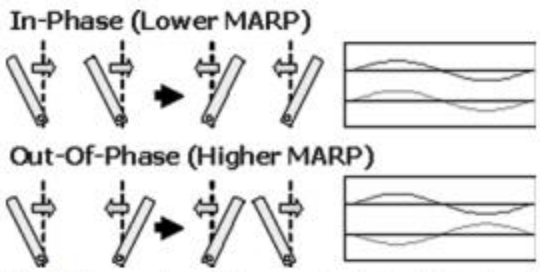

Fig. 5. The meaning of the mean absolute relative phase (MARP).

$$MARP = \sum_{i=1}^{N} \frac{|\Phi_{RPi}|}{N},$$

where *N* is the total number of data points in the relative phase curve.

Practically, MARP is a tool that can quantify whether two robot surgical instrument tips move in a similar fashion. If the two tips move simultaneously in the same direction, the MARP value is toward 0°, or in-phase. If they move in opposite directions, the MARP value is toward 180°, or out-of-phase (Fig. 5).

Moreover, maximum velocities of the robot surgical instrument tips in the respective movements were identified for each trial, and the coefficient of variation between the velocities (CVV) was calculated.

EMG analysis

To quantify the extent of muscular activation, the relative EMG outputs (i.e., percentage of raw EMG outputs relative to maximal EMG output) for each muscle in each trial were integrated for the entire task completion time, and the total volume of muscular activation (EMGV) was obtained. Moreover, the activation rate (EMGR) was calculated by dividing EMGV by T (Fig. 6).

Statistical analysis

The mean values for the dependent variables of T, CVI, D, MARP, CVV, EMGV, and EMGR were compared between the pretraining (PRE) and posttraining (POST) testing sessions with dependent *t*-tests ($\alpha = 0.05$) using SPSS (version 12.0, SPSS Inc, IL, USA).

Results

The means and standard deviations of all the dependent variables for both testing sessions are summarized in Tables 1 (temporal analysis), 2 (kinematicanalysis), and 3 (EMG analysis).

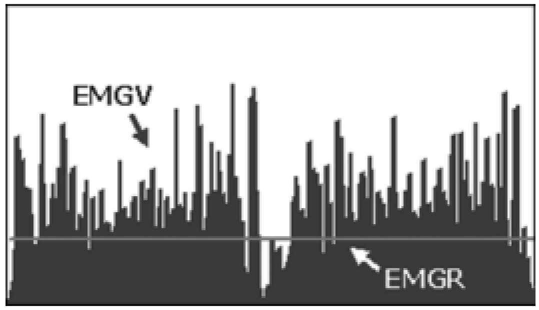

Fig. 6. The muscular activation volume (EMGV) and muscular activation rate (EMGR). The EMGV is practically the entire area under the curve, whereas the EMGR is the average value of this area.

Temporal analysis

The results showed a significantly shorter T for all the tasks in the POST condition ($p \leq 0.05$) (Table 1). The relative differences in T between the PRE and POST testing sessions were 53.9% for the BC task, 63.8% for the NP task, and 67.4% for the ST task. The learning curves with respect to T for all these tasks showed that they achieved, respectively, 78.8%, 76.8%, and 74.6% of the time reductions by the end of the second training session (Figs. 7–9). There were no significant differences in CVI between the PRE and POST testing sessions ($p > 0.05$) (Table 1). However, considerably larger reductions in CVI were observed in the NP and ST tasks: 26.6% and 47%, respectively.

Kinematic analysis

Significantly shorter D was observed for the NP and ST tasks in the POST testing session ($p \leq 0.05$) (Table 2). The relative differences in D were 33.4% for both the NP and ST tasks. The learning curves with respect to D for the NP and ST tasks showed that the participants recorded 89.1% of the distance reductions by the end of the third training session (NP) and 94.8% by the end of the second session (ST), respectively (Figs. 10 and 11).

The participants demonstrated significantly larger MARP for the BC task in the POST testing session ($p \leq 0.05$) (Table 2). The learning curve with respect to MARP for the BC task showed that the subjects recorded a 30.0% change after the six training sessions (Fig. 12). Although no significant differences between conditions were found regarding MARP for the other two tasks ($p > 0.05$), a considerably larger increase was also observed for the NP task (31.8%). In contrast, MARP for the ST task decreased only 6.8% after the training sessions.

No significant differences were found for CVV between the PRE and POST testing sessions ($p > 0.05$) (Table 2). However, considerably larger CVI reductions were observed for all three tasks.

Table 1. Mean (M) and standard deviation (SD) values for the temporal analysis of both pre- and posttesting sessions

	Pretraining (n = 7)		Posttraining (n = 7)		
	M	SD	M	SD	p Value
Task completion time (T), s					
BC	49.9	4.6	23.0	4.4	0.000
NP	88.4	15.4	32.0	6.1	0.000
ST	81.6	17.7	26.6	4.2	0.000
CV between intervals (CVI), %					
BC	23.8	13.7	24.4	13.7	0.478
NP	23.0	15.6	16.8	12.8	0.211
ST	47.8	24.4	25.3	25.0	0.077

BC, bimanual carrying; NP, needle passing; ST, suture tying

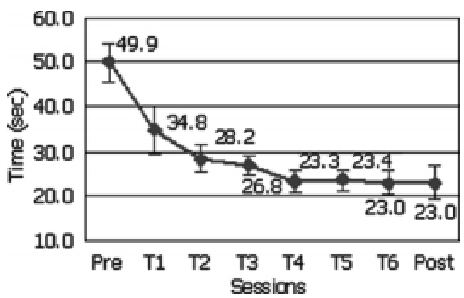

Fig. 7. The learning curve of the task completion time (T) for bimanual carrying.

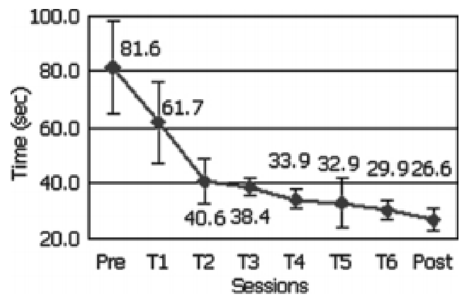

Fig. 9. The learning curve of the task completion time (T) for suture tying.

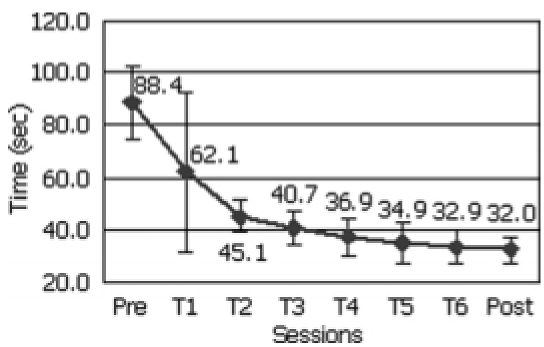

Fig. 8. The learning curve of the task completion time (T) for needle passing.

EMG analysis

As expected, significant reductions in EMGV were demonstrated for all the muscles observed in all three tasks except for the FCR muscle in the BC and ST tasks ($p \leq 0.05$) (Table 3). The relative differences in EMGV between testing sessions ranged from 33.2% to 68.6%, indicating a significant decrease in muscular activity.

Significant increases in EMGR were observed for the FCR and TB muscles in all three tasks, and for the ED muscle in the ST task ($p \leq 0.05$) (Table 3). The relative differences in EMGR for these muscles between conditions ranged from 30.3% to 84.5%. Although no significant difference was observed, the EMGR for the ED muscle in the BC task also showed an increase of 31.6% after training.

Discussion

This study objectively demonstrated the change in robotic surgical performance for the novice users of the dVSS before and after their engagement in a designed training protocol. As in previous studies [11, 34], the novice users in this study demonstrated a significant reduction in task completion time (T) after the training sessions ($p \leq 0.05$). Remarkably, their learning curves for the time score showed that they achieved drastic time reduction with only a few training sessions (Figs. 7–9). Similar results were obtained for the total traveling distance of the surgical instruments (D). Specifically, the subjects showed significantly shorter distance for two of the three experimental tasks through training ($p \leq 0.05$). In addition, rapid improvement was observed in the first two or three training sessions (Figs. 10 and 11).

These results clearly suggest that the novice users could rapidly learn to perform the simulated surgical tasks with less time and distance traveled (i.e., economy of motion). One possible reason for these results may involve the user-friendly interface of the robotic surgical system. The system was designed to overcome visual, mechanical, and postural difficulties experienced during conventional manual laparoscopy [20]. The instrumentation of the system with the designed training protocol may induce such training effects. This speculation is consistent with the results of the study conducted by Yohannes et al. [35]. Our results confirm that task completion time (T) and traveling distance (D) can be used to represent improvements in the extent of proficiency and/or skill acquisition. Another explanation for these results is that the robot system is designed specifically to mimic the same hand motions as those used during open surgery.

Table 2. Mean (M) and standard deviation (SD) values for the kinematic analysis of both pre and posttesting sessions

	Pretraining (n = 7)		Posttraining (n = 7)		
	M	SD	M	SD	p Value
Traveling distance (D), m					
BC	1.9	0.2	1.9	0.3	0.468
NP	1.6	0.2	1.1	0.2	0.001
ST	1.8	0.4	1.2	0.2	0.003
Mean absolute relative phase (MARP), °					
BC (y-axis)	38.4	8.3	50.0	6.1	0.009
NP (x-axis)	40.6	11.0	53.5	15.1	0.068
ST (x-axis)	56.7	19.9	52.8	9.6	0.265
CV between velocities (CVV), %					
BC	12.0	4.6	9.3	2.9	0.167
NP	20.9	8.0	15.8	5.5	0.087
ST	34.6	9.9	18.7	12.5	0.051

BC, bimanual carrying; NP, needle passing; ST, suture tying

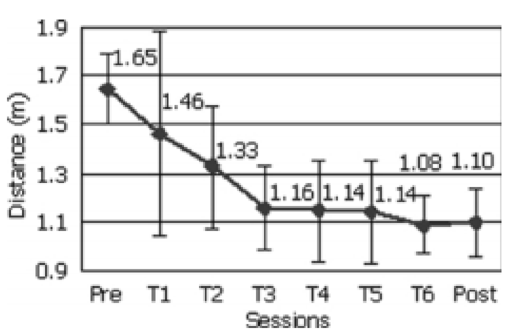

Fig. 10. The learning curve of the total traveling distance (D) for needle passing.

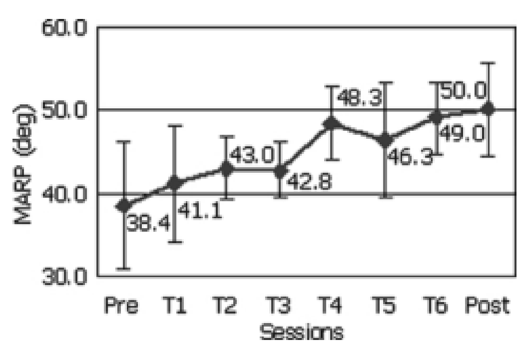

Fig. 12. The learning curve of the mean absolute relative phase (MARP) for bimanual carrying.

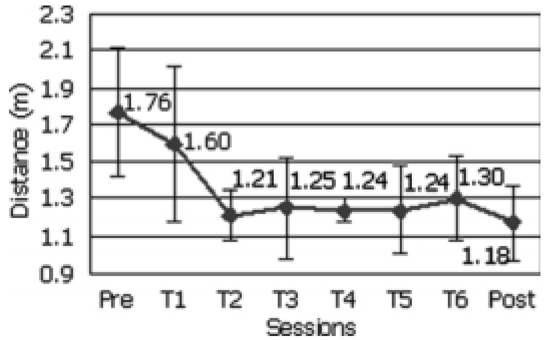

Fig. 11. The learning curve of the total traveling distance (D) for suture tying.

However, as previous studies have emphasized, these conventional variables are regarded as insufficient to explain fully the aspects of surgical performance [3, 18, 26, 30, 31]. That is, skilled performance with the robotic system may include other qualitative aspects, and these should be addressed in the performance of objective assessment. If someone is faster at completing a task, this does not mean that the person has improved dexterity. Surgeons using the dVSS not only should be faster in performing an operation, but also should be better able to coordinate the actions of both arms, more consistent and accurate, and consequently able to complete the operation with less muscular exertion. We explored these important aspects using further dependent variables including bimanual coordination, variability/consistency, and muscular activation patterns.

A possible limitation of the current study is that error reduction, one of the most important goals of training, was not measured. This measurement can be performed subjectively using error counts from videotapes [10, 27, 30]. Although this type of subjective visual analysis can be useful in certain circumstances, such analysis tends to be very laborious and impractical when objective scoring systems are needed.

Mean absolute relative phase (MARP) generally is used to quantify whether interacting segments (e.g., right and left surgical instrument tips) display an in-phase or out-of-phase relationship during movement [24, 25; Fig. 5]. As mentioned earlier, out-of-phase patterns are associated with higher MARP values, whereas in-phase patterns are associated with smaller MARP values (Fig. 5).

Table 3. Mean (M) and standard deviation (SD) values for the electromyographic (EMG) analysis of both pre- and posttesting sessions

	Pretraining (n = 7)		Posttraining (n = 7)		
	M	SD	M	SD	p Value
EMG activation total volume (EMGV), (EMG/EMGmax) × Sec					
BC					
FCR	0.83	0.44	0.69	0.47	0.150
ED	1.66	0.64	0.99	0.38	0.013
BB	1.89	1.28	0.65	0.37	0.019
TB	0.12	0.08	0.08	0.07	0.004
NP					
FCR	1.15	0.97	0.59	0.39	0.033
ED	3.81	0.91	1.41	0.73	0.000
BB	1.56	1.11	0.69	0.53	0.034
TB	0.29	0.24	0.14	0.12	0.011
ST					
FCR	1.42	1.14	0.87	0.43	0.093
ED	2.79	1.19	1.26	0.44	0.009
BB	2.27	1.35	0.71	0.33	0.007
TB	0.22	0.13	0.10	0.08	0.004
EMG activation rate (EMGR), %EMGmax					
BC					
FCR	1.69	0.93	3.11	2.47	0.035
ED	3.33	1.23	4.38	1.70	0.055
BB	3.77	2.53	3.06	2.03	0.281
TB	0.24	0.20	0.32	0.21	0.041
NP					
FCR	1.28	0.92	1.85	1.29	0.024
ED	4.41	1.16	4.25	1.76	0.410
BB	1.76	1.20	2.13	1.63	0.314
TB	0.31	0.23	0.41	0.31	0.039
ST					
FCR	1.90	1.81	3.27	1.61	0.014
ED	3.35	0.98	4.80	1.73	0.045
BB	2.76	1.45	2.81	1.49	0.462
TB	0.26	0.15	0.36	0.20	0.017

BC, bimanual carrying; FCR, flexor carpi radialis; ED, extensor digitorum; BB, biceps brachii; TB, triceps brachii; NP, needle passing; ST, suture tying

The novice users in this study demonstrated significantly larger MARP in the BC task after training ($p \leq 0.05$). Additionally, although it was not significant ($p = 0.068$), a considerably large increase was observed in the NP task. Because the participants scored higher MARP values for these two tasks, it can be suggested that learning to perform these surgical tasks requires an out-of-phase coordinative relationship of bimanual dexterity. The reduced MARP in the ST task indicates that this task requires a completely different type of bimanual coordination. This demonstrates the sensitivity of our coordination analysis for distinguishing between different tasks. Thus, coordination analysis is important for distinguishing better between surgical tasks for quality training.

The coefficients of variation between intervals (CVI) and velocities (CVV) were considered to represent whether the task was performed with a variable or a consistent manner. Skilled performance should show a more consistent nature. Although no significant differences were observed in these variables ($p > 0.05$), considerably larger reductions in CVI and CVV were observed for all conditions except for CVI in the BC task. These results may suggest that through the training protocol, the participants learned to perform these surgical tasks in a more consistent manner. However, the lack of significant differences detected for these variables questions the previous findings regarding task completion time, and it is possible that the expected results found for T and D should be interpreted with caution and within the context of the study design.

Electromyographic analysis was performed to examine the extent to which the amount of muscular activation was increased or decreased during performance as a result of the designed training. Such analysis can allow more direct insights into the effects of training on the surgeons arm movements. Decreases or increases in muscular activity can allow us to quantify muscular involvement. The EMGV and EMGR indicate the amount and rate of muscular activation in each muscle, respectively. Our results collectively indicate significant reductions in EMGV attributable to training. However, because the equation for calculating EMGV includes T as a factor, these results may be considerably affected by the significant reductions in time scores mentioned previously.

Significant increases in EMGR were observed for the FCR and TB in all three tasks, and for the ED in the ST task. These results suggest that training affected the subjects muscular activation profiles as they learned to involve more the forearm muscles (i.e., flexor carpi radialis and extensor digitorum) and the arm extensor muscle (i.e., triceps brachii) in performing the surgical tasks. Although further assessment is required, we can speculate that this change may be closely related to dexterity enhancement of surgical performance attributable to training. Thus, EMG analysis that focuses on the muscles examined in the current study may be very useful in assessing the extent of proficiency and/or skill acquisition. However, further studies and additional frequency analysis of the EMG data acquired may be able to shed more light in this topic. Factoring out the effect of T in a way that can unmask the true improvement in muscular activation is important.

In conclusion, identification of appropriate variables that can quantitatively demonstrate the extent of proficiency and/or skill acquisition is important for the development of objective scoring criteria that lead to the establishment of rational educational formats. In the current study, several variables (i.e. coordination) were automatically collected through the real-time kinematics from the dVSS Application Programming Interface (API), which emphasizes the importance of incorporating robotic surgical systems into surgeon training programs. Moreover, such variables are needed to build algorithms for the new generation of improved surgical systems and/or training devices that may allow more effective training experience with real-time feedback of surgical performance. These variables should be composite and obtainable from direct data acquisition, without any subjective judgment.

In this study, we quantified change in robotic surgical performance using a training protocol designed with a variety of variables. These variables included bimanual coordination, variability/consistency, and muscular activation analyses directly from the arms of the participants. Although further validation is required, these variables showed great potential for representing the extent of proficiency and/or skill acquisition, and for use in achieving the aforementioned purposes. Future studies should evaluate expert surgeons with more realistic involved tasks (e.g., laparoscopic cholecystectomy) to gain further insight into the nature of proficiency in real robotic laparoscopy, and to identify more applicable variables for practical use. Comparisons between novice and expert surgeons using the variables demonstrated in this study also would provide further insight. Objective quantification of error profiles also needs to be addressed in the future investigations.

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