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Automated Robotic-Assisted Surgical Skill Evaluation: Predictive Analytics Approach

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Category: Original article

Number of figures: 7

Number of tables: 3

Author Justifications/Contributions:

Mahtab J. Fard: Worked on developing model, analysis of results and writing the manuscript

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R. Darin Ellis: Worked on analysis of results, and writing the manuscript

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The manuscript has been read and approved by all the authors.

The paper contains original, unpublished work and is not being submitted for publication to any other journal.

Abstract

Background: Surgical skill assessment has predominantly been a subjective task. Recently, technological advances such as robotic-assisted surgery, open great opportunities for objective surgical evaluation. In this paper, we introduce predictive framework for objective skill assessment based on the trajectory movement data. Our aim is to build a classification framework to automatically evaluate performance of the surgeons with different levels of expertise.

Methods: Eight global movement features are extracted from movement trajectory data captured by da Vinci robot for surgeons with two levels of expertise; novice and expert. Three classification methods, k-nearest neighbors, logistic regression and support vector machines are applied.

Results: Result shows that the proposed framework can classify surgeons' expertise to novice and expert with accuracy of 82.3% and 89.9% for knot tying and suturing task.

Conclusion: This study demonstrates and evaluates the ability of machine learning methods to automatically classify expert and novice surgeons using global movement features.

Keywords: Automated skill evaluation, Skill assessment, Surgeon dexterity, Robotic-assisted surgery, Global movement features, Machine learning

1 Introduction

Despite advances in computer systems and simulation methods, surgical training is still based on direct observation involving expert surgeons (1). These methods are limited by lack of consistency, reliability and efficiency due to the subjective nature of human observation (2). As the medical profession is faced with demands for greater accountability and patient safety, there is a critical need for developing consistent and reliable methods in order to evaluate clinical performance objectively. Surgical training is undergoing a paradigm shift and clinical competence of practicing surgeons is a matter of growing public concern. More emphasis is being placed on competency-based training and earlier development of technical skills for new surgeons. Hence, training is not only based on the total time spent or subjective evaluation, but also on dexterity in various skills. Therefore, Objective Structured Assessment of Technical Skills (OSATS) (3) is being surrendered for more structured techniques, which are still subjective and require the presence of an expert surgeon.

The new technology innovations such as robotic surgery, open great opportunities for automated objective skill assessment and prompt feedback system, which was not available before. Robotic surgical devices such as da Vinci (Intuitive Surgical, Sunnyvale, CA) (4) record motion and video data, enabling development of computational models to analyze surgical skills through data-driven approaches (5). Techniques such as data mining and machine learning are likely to have a huge impact on ongoing clinical decision support studies (6). The ability of machine learning methods to uncover concealed patterns in a large dataset, such as kinematic and video data, offer the possibility to better understand and model surgical data in order to evaluate surgeons' skill and individualized training (7). The key step is to extract meaningful features from quantitative motion data that explains the underlying pattern of surgeons' dexterity.

In this paper, we extend our previous work (8) by introducing new features to quantify smoothness, variability and complexity of the surgical flow. The key differentiation between the proposed method and existing work is its accuracy, robustness and time efficiency. The proposed method also has the ability to automatically evaluate surgeons' skill and provide prompt feedback to trainee by comparing their surgical skills' with other surgeons using the comprehensive dataset. To our knowledge, this is the first time that such a study is conducted in the area of robotic surgery skill evaluation using more advanced techniques such as machine learning methods. The proposed framework has the important characteristics of objective skill evaluation such as repeatability, stability and clinical relevance.

The rest of the paper is organized as follows. In Section 2, we provide background on surgical skill evaluation methods. In Section 3, we present details of experimental methods and the proposed skill assessment framework. We demonstrate and discuss the performance of our method on real world robotic surgery data in Sections 4 and 5. Finally, in Section 6, we conclude our paper with a summary of the main results and directions for possible future research.

2 Background

Surgical skill evaluating has been traditionally conducted by an expert observer via direct observation. This procedure is very time-consuming and can be unreliable (9). Therefore, a range of structure-based techniques such as OSATS (3) and the Global Assessment of Laparoscopy Skills (GOALS) (10) have been introduced and validated. Using these evaluation methods, the trainees perform standardized surgical tasks while an expert surgeon evaluates their performance. The expert surgeon gives scores to surgical trainees based on predefined criteria such as flow of surgery, time to motion, efficiency, tissue handling and overall performance by observing the surgical procedure in person or watching the recorded video of the operation (11). However, these methods are threatened with a lack of consistency, reliability and efficiency due to the subjective nature of experts' intervention. With the advent of minimally invasive surgery (MIS) and robotic-assisted minimally invasive surgery (RMIS), the need for automated objective surgical assessment methods is even more pressing because they require surgeons to perform a much longer and difficult training and pose new challenges for surgical training (12).

Evaluation of surgical skills can be performed by utilizing two different modalities: decomposing surgical tasks into pre-defined surgical gestures and comparing the experts' and novices' gesture to assess surgical skill or evaluate surgeon's overall performance by defining competency metrics (13–15). The former approach has been studied thoroughly for MIS skill evaluation using techniques such as hierarchical decomposition of surgical tasks (16), Hidden Markov Model (HMM) (17–19) and multivariate autoregressive (20). For robotic minimally invasive surgery, HMM (21,22) and descriptive structure method (23) have been developed to assess surgeons' skill. Although these methods have the ability to find the underling structure of MIS or RMIS tasks, they are context-based and suffer from requiring large number of training samples and complex parameter tuning, causing lack of robustness in the results (24).

While the first approach focuses on skill evaluation in more granular level, in contrast, second approach evaluate overall surgical skill using global motion features (GMF), which is easier to implement and interpret (25). Metrics such as operation time, speed, number of hand movements (26), force and torque signatures (27,28), path length and motion smoothness (25,29) have been used to identify the relation between the global features and basic psychomotor skills of expert and novices during minimally invasive surgery. However, development of quantitative method to automatically recognize surgeons' skill level in robotic surgery has always lagged behind. Previous work built the foundation of objective surgical skill assessment (30), but the current state-of-the-art has few shortcomings. First, they mostly focus on descriptive statistics, which is not an adequate proficiency measurement to classify surgeons by their skill level. Second, robotic-assisted surgery is a completely different technique than laparoscopic surgery, requiring new methods of training and evaluation. Finally, the ability to capture all movements during robotic surgery, open up new opportunities for automated surgical skill assessment, real-time feedback and individualized training by developing more advanced techniques such as machine learning algorithms (31).

Machine learning techniques have risen to prominence in many fields because of their advantages over traditional statistical methods such as robustness, better prediction ability and higher tolerance violence of assumptions (e. c. normality or undependability of data) (32,33), but it is only recently that these methods have been considered to analyze RMIS tasks (7,34). Thus, developing quantitative classification techniques that can automatically and accurately evaluate surgical skills needs to be investigated. In this paper, we address the limitation of previous methods by introducing skill assessment framework using global movement features and machine learning algorithms to automatically classify surgeons based on their expertise.

3   Materials and Methods

We implemented our model on real robotic-assisted minimally invasive surgery data presented in (35). This comprises of eight surgeons with varying robotic surgery experience who performed five trials of different surgical tasks including suturing and knot tying (Figure 1). We analyze kinematic data captured using the da Vinci robot for both right and left hand, which result in total of 160 data points. Data includes global rating score (GRS) for each trial. Score is from 1 to 5 for each six criteria: respect for tissue, suture or needle handling, time and motion, flow of operation, overall performance and quality of final product. Therefore, the range of score is between 6 and 30 for each surgical trial. Using the GRS for knot tying and suturing task the threshold of 15 and 19 is used respectively to divide surgeons into two skill levels: experts and novices. Hence, we try to solve a binary classification problem, which is very common in data mining community.

The aim of this paper is to develop a predictive method for objective skill assessment based on the trajectory movement of the surgical robot arms. For this purpose, we quantify surgical task by extracting global movement features (GMFs) from the raw motion data for each task. Based on the extracted features, different classifiers, including k-nearest neighbor, logistic regression and support vector machines have been applied. The classifier with the highest accuracy can be used to automatically predict the skill level of surgeon.

3.1   Global Movement Features (GMFs)

Surgical tasks have different characteristics, such as smoothness, straightness or response orientation, which account for competence while relying only on instrument motion (24). For instance, studies have shown that the tool motion of an experienced surgeon has more clearly defined features than that of a less experienced surgeon while performing the same task (36). Figure 2 illustrates the Cartesian position plots of an expert and a novice surgeon doing suturing on the da Vinci surgical robot.

In order to transform surgical task characteristics into quantitative metrics, we applied kinematic analysis theory that has been successfully used in previous works to study psychomotor skills (25). Metrics such as task completion time, length of path, depth perception and velocity can show several aspect of surgeon's dexterity. However, other aspects such as smoothness, curvature, torsion and

complexity of the motion need to be quantified. In the following, we explain the six important global movement features from the clinical point of view and introduce our two new features that measure the average turning angle and tortuosity of the task.

- **Task Completion Time:** is defined as total time required to complete the task, measured in seconds from the moment surgeon starts to move the instrument till (s)he finishes the task and drop the robot arm devices.
- **Path Length:** is the length of the curve described by the tip of the instrument while performing the task (in cm). We calculate it using sum of all consecutive pairs' Euclidean distance based on the (x, y, z) trajectory data that captured during the surgery.
- **Depth Perception:** is the total distance traveled by the instrument along its axis (in cm).
- **Speed:** can be defined as the magnitude of velocity and calculated as the rate of position change from previous time step as $\dfrac{dis(p_i, p_{i-1})}{\Delta t_i}$, where $dis(p_i, p_{i-1})$ can be calculated as a Euclidean distance between i^{th} point and of $(i-1)^{th}$ point (in cm/s). Given that the time difference between two consecutive frames is constant, Δt_i is equal to 1.

- **Motion Smoothness:** is a measure of the rhythmic pattern of acceleration and deceleration. Smoothness has most often been based on minimizing jerk, the third time derivative of position, which represents a change in acceleration (in cm/s^3).
- **Curvature:** measures the straightness of the path and is calculated at each point by the following equation (25)

$$\kappa_i = \left(\frac{v_i \times a_i}{v_i^3} \right) \qquad (1)$$

  where v_i and a_i are instantaneous velocity and acceleration of the instrument tips respectively, which can be calculated directly by computing the first and second derivatives of the positions of the instrument tips. For straight and smooth movement, the mean of curvature is close to zero, while larger values indicate curved and jerky movements.
- **Turning Angle (TA):** is calculated as the direction of the movement with regard to the previous and next time steps. It can be defined as

$$TA_i = \theta_i = Arccos \left(\frac{u_{i-1} \cdot u_{i+1}}{\|u_{i-1}\| \|u_{i+1}\|} \right) \qquad (2)$$

  where u_{i-1} is the vector from p_{i-1} to p_i and u_{i+1} is vector from p_i to p_{i+1} as shown in Figure 3.
- **Tortuosity:** is a property of a curve being twisted or having many turns. It has been used successfully in variety of research such as analyzing animal path (37), evaluating the performance of human robot interaction (38) or distinguishing cognitive impairment through walking behavior (39). In this paper, tortuosity is introduced as a new metric, to measure the path complexity or in other words, movement path variability of surgical instrument during

robotic surgery. Tortuosity can be quantified using the Fractal Dimension (F) (40) where a ratio of a pattern changes with respect to the measurement scale, providing a statistical index for variability. More specifically, the length of the path is measured by walking a pair of dividers of a certain size along the path (see Figure 4).

Tortuosity can be derived from the linear relationship between the logarithm of total distance (D) and the logarithm of the currently employed measuring scale (S) based on the knowledge that the total length is highly dependent on the scale adopted (37), as follows:

$$\log(D_i) = b + a \log(S_i) \quad i \in [1,2,\dots,n] \qquad (3)$$

where n is the number of different measurement scales employed to calculate the total distance of a trajectory path, b is the regression intercept and a is the slope of the regression line . A regression model can be constructed from the (D_i,S_i) pairs, and F is then calculated as $F = 1 + a$. The Fractal Dimension for movement paths lays between 1 and 2 where F is 1 when the path is straight and 2 when the path is so tortuous that it occupies whole plane (Brownian motion). As an example in Figure 2, the path of an expert's right hand has a tortuosity of 1.14 while the path tortuosity of a novice's right hand is 1.67. In order to make this metric more robust to different measuring scales, the average of F value for different measuring scales is computed (41).

We extract GMFs for both hands using Cartesian positions of right and left patient-side manipulator end-effectors of da Vinci arms. More precisely, we only need (x, y, z) trajectory data for both hands to derive the proposed metrics. Speed, motion smoothness, turning angle and curvature are temporal features, which are calculated for each data point. The mean and standard deviation of these features are derived for each trial. On the other hand, remaining features such as task completion time, path length, depth perception and tortuosity have only one value for each trial. For instance, we measure time needs to complete a surgical trial from start to the end and report it as task completion time. Finally, a total of 23 global movement features are derived from each trajectory: 12 spatial characteristics of tool tip movement (including path length, depth perception, mean and standard deviation of speed and motion smoothness for each hands) and 10 features that captures the curvature and torsion of movement (including tortuosity, mean and standard deviation of turning angle and curvature for each hands) and time to complete the task.

3.2 Surgical Skill Classification

Extracted features in the previous section are used to quantify the movement pattern of surgeons. Our aim is to build a classification model to differentiate between surgeons with different levels of expertise while doing RMIS tasks. Surgeons are categorized into two skill levels, expert and novice, result in a binary classification problem that can be solved by applying machine learning algorithms. Although, there is no particular rule to choose the best classification method but there are various aspects to take

into consideration (42). Criteria such as number of training examples, dimensionality of the feature space, independency of the features from each other, linear or non-linear dependency between features and target and overfitting play an important role when different classification methods are applied. Aiming for interpretability of the method to make inference easy, practical use and characteristic of the robotic surgery dataset, we applied and compared three frequently used and well-suited machine learning techniques, k-nearest neighbor (kNN) (43), Logistic regression (44) and Support Vector Machine (45).

3.2.1 k-nearest neighbor (kNN)

The first classifier that we used is k-nearest neighbor. The principle of this technique is to predict the label for the new point based on the closest distance to predefined number (k) of training samples. kNN classifier is an instance-based learning where instead of constructing a general model, it simply stores instances of training data. Therefore, it is a non-parametric classifier, which does not rely on any assumptions on the underlying data distribution. This is very important characteristic since most of the practical data does not obey the typical theoretical assumptions. During the classification phase, the majority of the k nearest neighbors for each point are computed. Thus, the label for the query point is assigned based on the most representatives within the nearest neighbors of the points. We examined different k where the best results obtained with k=3.

3.2.2 Logistic regression (LR)

One of the well-established statistical models is the Logistic regression where the dependent variable is categorical. Logistic regression is quite robust to noise in the dataset and avoid overfitting. In this model, logit transformation of a linear combination of features is used to resolve a binary classification problem. Formally, the logistic regression model can be formalized as

$$p(x) = \frac{1}{1 + e^{-(\beta_0 + \beta.x)}} \tag{4}$$

Where β_0 is the intercept (often labeled the constant), β is the coefficient for corresponding x feature and $p(x)$ is the probability of belonging to one of the classes.

3.2.3 Support vector machine (SVM)

Support vector machine (SVM) constructs a hyperplane and tries to maximize the margin that separate two class of data shows as $2/\|\vec{\omega}\|$ (Figure 5). The ability to learn the non-linear separable function by mapping the data to a higher dimensional space makes this classifier unbeatable for some problems. Linear SVM can be formalized as

$$maximize \ \frac{2}{\|\vec{\omega}\|} \tag{5}$$
$$s.t. \ \ y_i(\vec{w}.\vec{x_i} + b) \geq 1, \ \ \forall \ i = 1, \dots, n$$

where y_i is the class label for i^{th} data. In order to solve the non-linear classification problem, SVM uses a kernel transformation. The radial basis function (RBF) is one of the most popular kernel functions used in SVM (46), defined as

$$K(x_i, x_j) = e^{(-\gamma \|x_i - x_j\|^2)} \tag{6}$$

where γ controls the width of RBF function. The γ parameters can be seen as the inverse of the radius of influence of samples selected by the model as support vectors. If γ is too large, the radius of the area of influence of the support vectors only includes the support vector itself. While for a very small value of γ, the model is too constrained and cannot capture the complexity or "shape" of the data. The region of influence of any selected support vector would include the whole training set. It is suggested to choose γ as inverse of number of features, which in this study we set $\gamma = 0.1$.

Another important parameter in SVM algorithm is C, the penalty associated to the instances which are either misclassified or violates the maximal margin. Therefore, Eq. (5) can be rewrite as

$$maximize \quad \frac{2}{\|\vec{\omega}\|} + C \sum_{i=1}^{n} \xi_i \tag{7}$$

$$s.t. \quad y_i\left(\vec{w}.\overrightarrow{\phi}(x_i) + b\right) \geq 1 - \xi_i, \quad \forall\, i = 1, \dots, n$$

$$\xi_i \geq 1, \quad\quad\quad\quad\quad \forall\, i = 1, \dots, n$$

$$where \quad \phi(x_i)^t.\phi(x_j) = K(x_i, x_j)$$

where ξ_i is the smallest non-negative number satisfying $y_i(\vec{w}.\vec{x_i} + b) \geq 1$ and C is a regularization term, which provides a way to control over-fitting. If C becomes large, it is unattractive to respect the data at the cost of reducing the geometric margin and on the other hand, when it is small, it is easy to account for some data points with the use of slack variables and to have a fat margin placed so it models the bulk of the data. In this study we set $C = 1$.

3.3   Performance Evaluation

Classifier validation was conducted using two model validation schemas as suggested in (35): Leave-one-super-trial-out (LOSO), where one trial for each one of the surgeons is left out for testing and leave-one-user-out (LOUO), where all the trials from one surgeon are left out for testing. While the first validation method evaluates the robustness of a method for repeating a task, the second schema evaluates the robustness of a method when a subject is not previously seen in the training data. The performance of the different classification methods was determined by classification accuracy, which is expressed as a percentage of surgeons that their skill level is correctly classified. We implement the three classification algorithms using the Weka software (47), one of the best known open source data mining and machine learning toolkits.

4 Results

We start our skill assessment analysis by providing some exploratory statistics. Table 1 summarized the mean and standard deviation for the eight GMFs extracted from RMIS motion trajectory data. From the table we observe that the basic descriptive statistic might not be an adequate proficiency measurement for surgical skills recognition. The box plots for each task are shown in Figures 6 and 7. Plots show that for some features such as turning angle and curvature in knot tying or tortuosity and smoothness in suturing, novices and experts are able to be distinct. Table 2 shows 10 most relevant features to skill level of surgeons doing RMIS tasks. Features are selected based on statistically significant ($p < 0.05$) and sorted according to Spearman's correlation coefficient ρ.

The results of performing three classification methods, kNN, logistic regression and SVM using spatial-base features (S), curvature-based features (C) and combination of both based on two validation schemas, LOSO and LOUO for knot tying and suturing, are shown in Table 3. The best accuracy is obtained for the combination of all global movement features. Table 3 shows that for knot tying, the highest overall accuracy for LOSO is 82.3% and for LOUO is 77.9%. For suturing, the best overall accuracy is 89.9% in LOSO and 79.8% in LOUO.

Results also show that for knot tying, 86.4% of experts and 79.2% of novices are classified correctly in LOSO while for LOUO, the classification accuracy reduces respectively to 80.5% and 75.3% for experts and novices. For suturing, using LOSO as a validation schema, 95.2% of experts and 88.9% of novices are correctly classified. For LOUO, we achieved the accuracy of 81.2% for experts and 74.7% for novices.

5 Discussion

The results of descriptive analysis (Figures 6 and 7) illustrate several important aspects of surgical skill assessment. First, contrary to prior belief (29), not lower value of all global features describes a better performance. For instance, we observed that in average experts have a higher curvature compared to novices for both suturing and knot tying. This can be explained by looking at Figure 2 where an expert surgeon makes a decisive sharp turn with his left hand. This can be translated as surgeon's skill to make a necessary curve in order to successfully finish the task. Also, for suturing, the path length of left hand is longer for experts compared to novices. This pattern may give the surgeon enough room for planning and performing further movement. In addition, although all the surgeons in this study are right-handed, Table 2 shows that features extracted from the non-dominant hand can be equally, if not more, important compare to the dominant hand's features. This is in complete agreement with literature in skill acquisition where dexterity can be assessed based on non-dominant hand performance (25).

From results shown in Table 3, the classification accuracy improves when combination of spatial and curvature features are used. This is consistent with previous studies (30), which emphasized task completion time and distance traveled are insufficient to explain all aspects of surgical assessment. The results from this study clearly suggest that the proposed objective metrics for robotic surgery, such as

curvature, turning angle and particularly tortuosity can help further to distinguish expert and novice surgeons. These features can be applied globally on RMIS tasks as they have the potential to identify additional aspects of surgeon dexterity that could not be quantified by task completion time and distance traveled alone.

Table 3 shows that the overall skill classification accuracy decreases 6% for knot tying and 11% for suturing when we switch from LOSO to LOUO schema. This suggests that surgeons with same level of expertise perform knot tying in a more similar way compared to suturing. Furthermore, the best overall accuracy for LOSO obtained either from logistic regression or kNN while SVM gives the best result for LOUO. Hence, more sophisticated method such as SVM with nonlinear kernel (e.g. RBF) is needed to assess the skill level of surgeons who are not previously seen in the training data. In another words, SVM is more generalizable in the context of surgical skill evaluation compared to other classification methods. This result confirmed the conclusion drawn from previous work in minimally invasive surgery (48) and brought out the value of machine learning approaches such as SVM for more accurate surgical skill evaluation.

Our analyses also show that experts can be classified with higher accuracy compared to novices due to the stability (less variation) in the values of global movement features. It is also important to mention that the overall classification accuracy for suturing is higher than knot tying. This suggests that surgical skill levels are better distinguished in more complex tasks such as suturing. The reason could be special characteristics of these tasks and also the need follow specific procedure in order to finish them successfully. However, larger dataset consisting of different surgical tasks and surgeons is needed to generalize this conclusion.

The time required to classify surgeons based on their skill using proposed framework is only few seconds. This stands in bold contrast with current state-of-the-art methods for surgical skill assessment, which have very time consuming process for parameter tuning and feature extraction. It suggests the potential of incorporating the proposed method for prompt feedback and evaluation of surgeons during training and individualized skill assessment while performing different robotic surgery tasks.

6 Conclusion

In this paper, we described the development of an automated objective skill assessment method based on global movement features extracted from trajectory motion data of the surgical robot arms. Previous attempts in objective surgical skill assessment are mostly based on conventional statistical methods such as HMMs. However, robotic-assisted surgical tasks have specific complexity which cannot be modeled effectively unless more advanced methods are employed. Therefore, in this study we demonstrated the ability of machine learning methods to automatically distinguish between expert and novice performance during robotic surgery, where all movements are already digitalized and available for analysis. It is generally accepted that the skill levels of surgeons vary and each surgical task has different levels of complexity. This complexity is not only captured through more sophisticated global

features such as tortuosity, but also through more advanced machine learning methods to model the underlying pattern of surgical skill level. The results presented in this study could form a foundation for decision support tools that effectively, objectively and automatically evaluate surgeon's dexterity and provide more personalized skill assessment and online feedback to trainees based on their performance. Furthermore, the proposed method can be applied on a more granular level of tasks in robotic–assisted surgery, such as surgical gestures, to provide more insight into the surgeons' skill level. Future research could focus on performing more validation studies with a larger number of participants. This would yield a larger training set that has the potential to improve the classification results.

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Figure Captions

Figure 1: Snapshot of the two fundamental RMIS tasks.

Figure 2: Illustration of the 3D Cartesian trajectory path in blue line where red arrows show movement direction for an expert and a novice surgeon doing knot tying and suturing on the da Vinci surgical robot.

Figure 3: Illustrative example for computing movement trajectory features.

Figure 4: Example for measuring tortuosity by walking a pair of dividers of a certain size along the path.

Figure 5: Illustration of support vector machine (SVM) method for a binary classification with two features.

Figure 6: Box plots for Exp (experts) and Nov (novices) for eight GMFs during knot tying for L (left hand) and R (right hand) of surgeons.

Figure 7: Box plots for Exp (experts) and Nov (novices) for eight GMFs during suturing for L (left hand) and R (right hand) of surgeons.

Table 1: Mean and standard deviation of the eight extracted global movement features (GMFs) for both right and left hand of expert and novice surgeons during knot tying and suturing tasks.

Task		Path Length (cm)	Depth Perception (cm)	Speed (cm/s)	Smoothness (cm/s^3 x10-7)	Turning Angle (degree)	Curvature (1/cm x10-4)	Tortuosity	Time (second)
Knot Tying	Expert	48.43 (8.65)	0.71 (0.13)	0.04 (0.013)	10.70 (8.66)	5.74 (1.49)	18.68 (6.33)	1.24 (0.05)	45.11 (11.44)
Knot Tying	Novices	50.37 (14.18)	0.73 (0.20)	0.02 (0.009)	8.50 (8.19)	3.86 (1.40)	11.01 (3.52)	1.25 (0.11)	69.86 (19.87)
Suturing	Expert	78.28 (23.49)	1.16 (0.41)	0.03 (0.011)	1.27 (1.23)	2.54 (0.50)	7.64 (2.34)	1.26 (0.04)	99.81 (20.82)
Suturing	Novices	75.99 (26.81)	1.14 (0.39)	0.02 (0.015)	3.30 (2.38)	2.59 (1.32)	6.70 (3.62)	1.33 (0.08)	126.84 (55.86)

Table 2: Spearman's correlation coefficient $|\rho|$ for the GMFs with the highest the relevance to class label for different hands for knot tying and suturing.

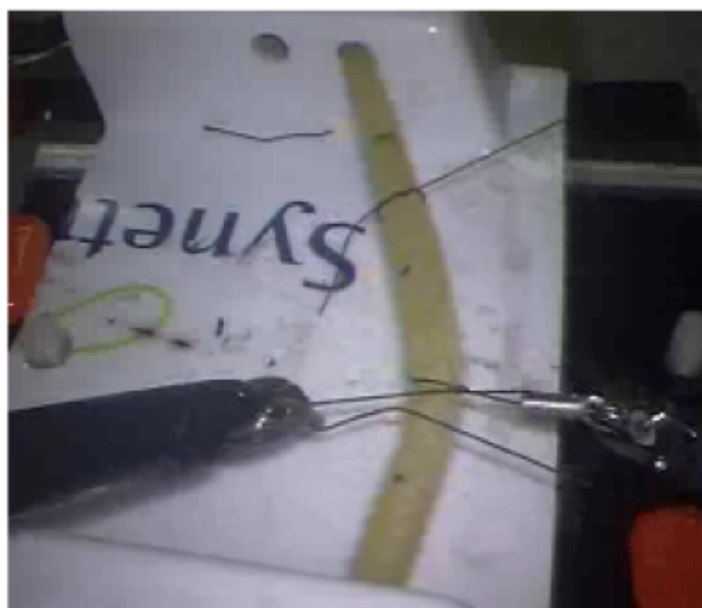| Knot tying		Suturing	
Feature, hand, stat	**$\|\rho\|$**	**Feature, hand, stat**	**$\|\rho\|$**
turning angle, right, mean	0.45	tortuosity, left, mean	0.47
curvature, right, mean	0.43	tortuosity, right, mean	0.44
turning angle, left, mean	0.39	time to complete task	0.43
time to complete task	0.37	curvature, right, mean	0.38
speed, right, mean	0.29	smoothness, left, mean	0.34
tortuosity, right, mean	0.22	smoothness, right, std	0.33
speed, left, mean	0.19	speed, left, std	0.28
smoothness, right, std	0.17	path length, left	0.27
tortuosity, right, mean	0.14	curvature, left, mean	0.21
smoothness, left, std	0.12	speed, right, std	0.15

Table 3: Classification accuracy for skill level evaluation in knot tying and suturing using kNN, Logistic regression (LR) and SVM for two validation schema (LOSO and LOUO) based on spatial motion features, curvature features and combination of both (best accuracy is highlighted in bold and numbers are in %).

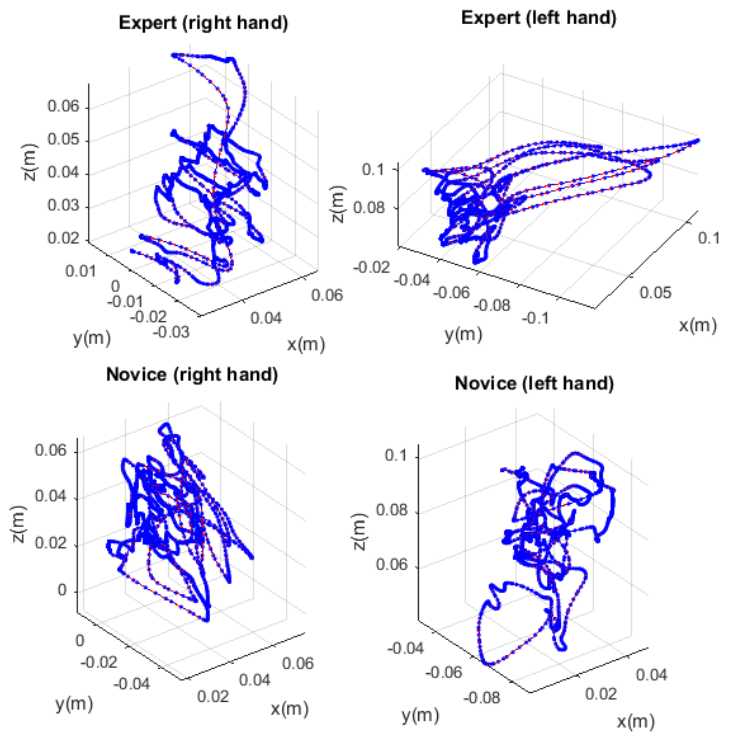| Task	Validation schema	Features	NOVICES			EXPERTS			OVERALL		
			kNN	LR	SVM	kNN	LR	SVM	kNN	LR	SVM
Knot Tying	LOSO	S	72.2	72.2	63.3	77.8	72.2	70.9	75.1	72.2	62.6
		C	76.1	76.9	69.1	79.3	77.6	71.3	77.7	79.3	67.3
		S+C	75.3	**79.2**	71.1	**86.4**	85.4	77.7	82.1	**82.3**	75.4
	LOUO	S	65.7	66.0	65.1	66.2	68.2	74.2	66	67.1	69.6
		C	63	69.1	75.1	71.2	68.5	79.9	67.1	68.7	74.7
		S+C	69.5	68.7	**75.3**	76.3	71.6	**80.5**	72.9	70.2	**77.9**
Suturing	LOSO	S	66.7	72.2	65.0	85.7	85.7	67.9	76.9	79.5	65.3
		C	72.2	88.9	67.1	95.2	85.7	71.9	84.6	87.2	69.5
		S+C	83.3	**88.9**	69.3	**95.2**	90.5	78.7	89.7	**89.9**	75.4
	LOUO	S	63.9	66.9	64.2	68.3	73	70.5	66	69.7	67.1
		C	70.6	67.9	69.9	72.1	77.1	79.5	71.3	72.5	77.5
		S+C	68.7	69.7	**74.7**	75.0	78.9	**81.2**	71.9	74.4	**79.8**

Suturing

Knot Tying

RCS_1850_F1.tif

Knot Tying

Expert (right hand)

Expert (left hand)

Novice (right hand)

Novice (left hand)

Suturing

Expert (right hand)

Expert (left hand)
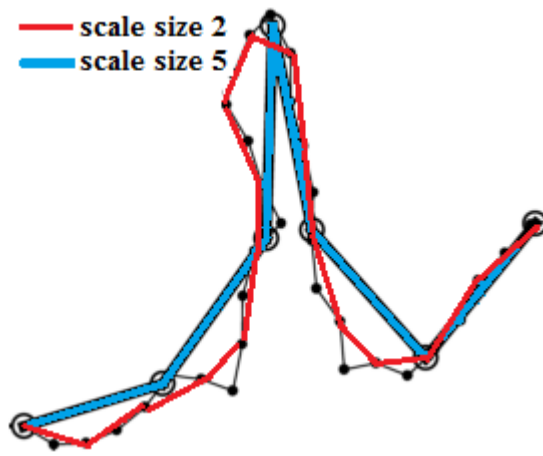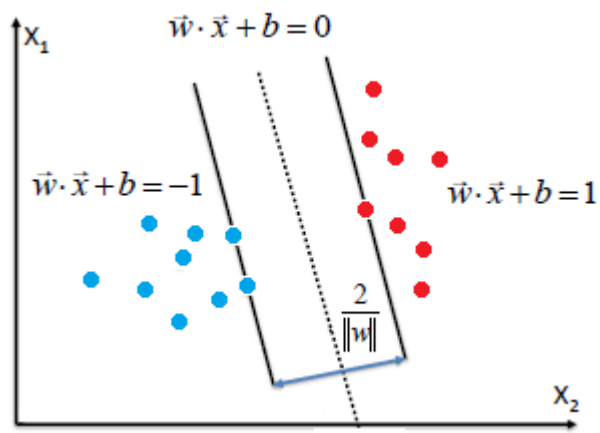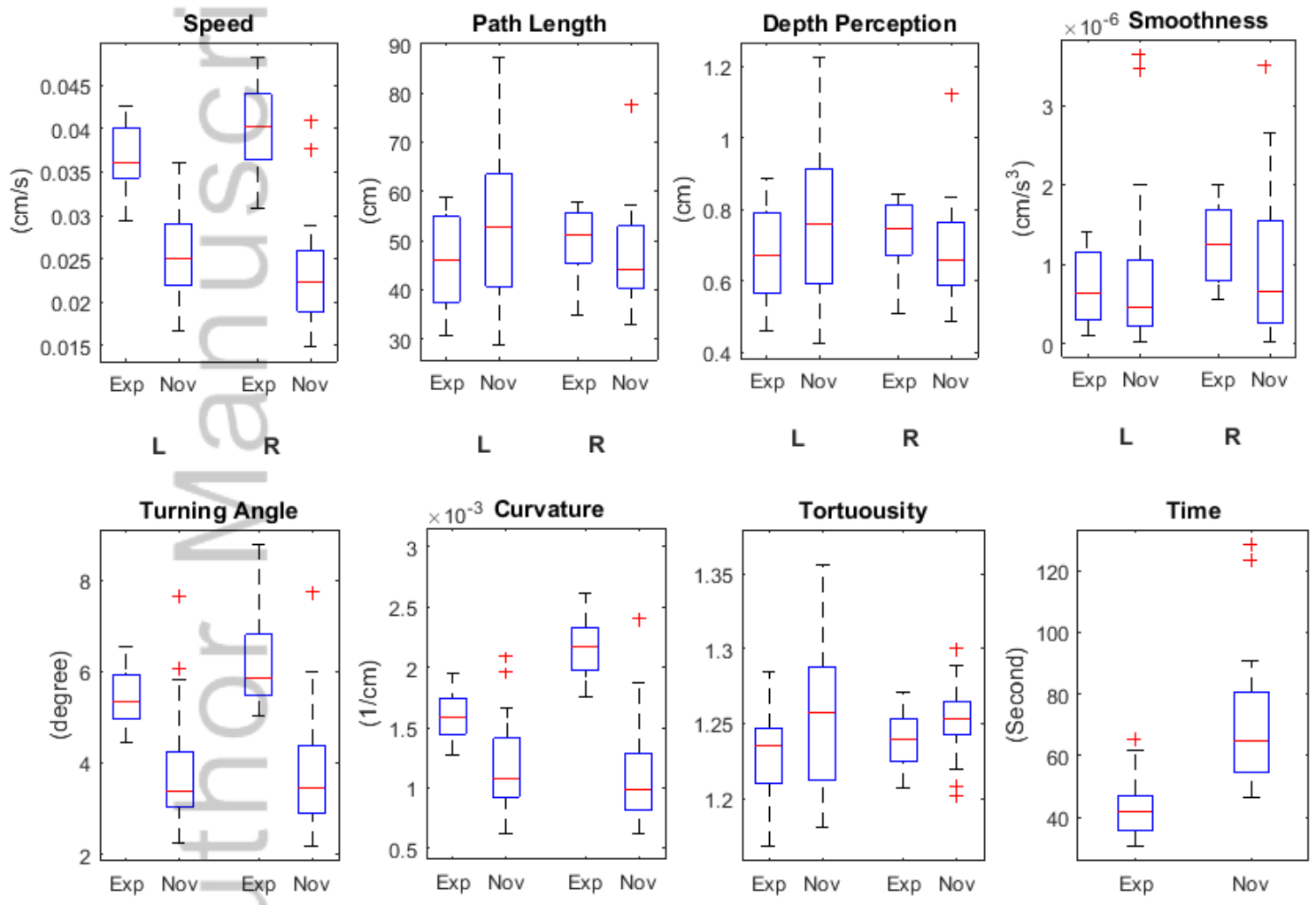
Novice (right hand)
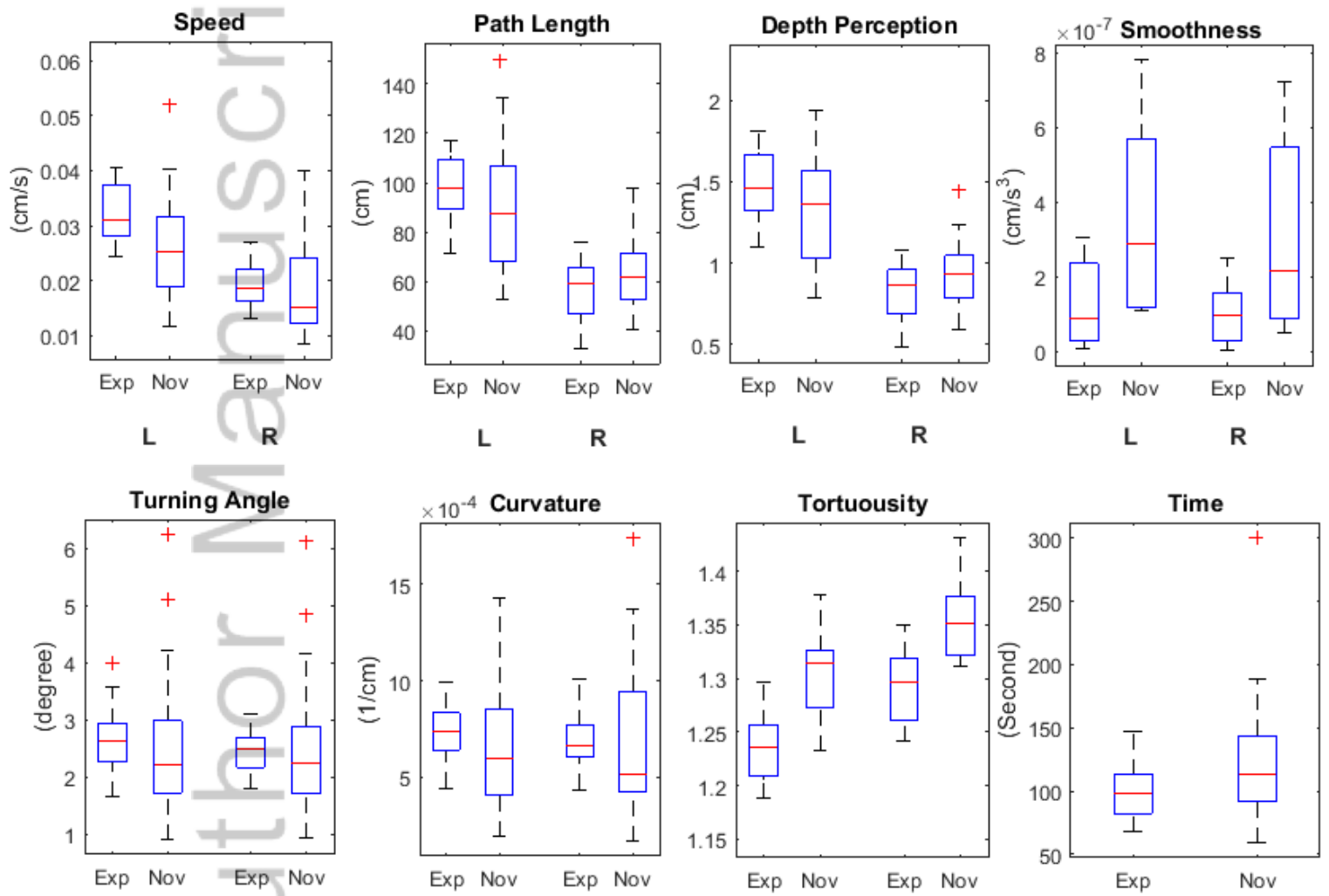
Novice (left hand)
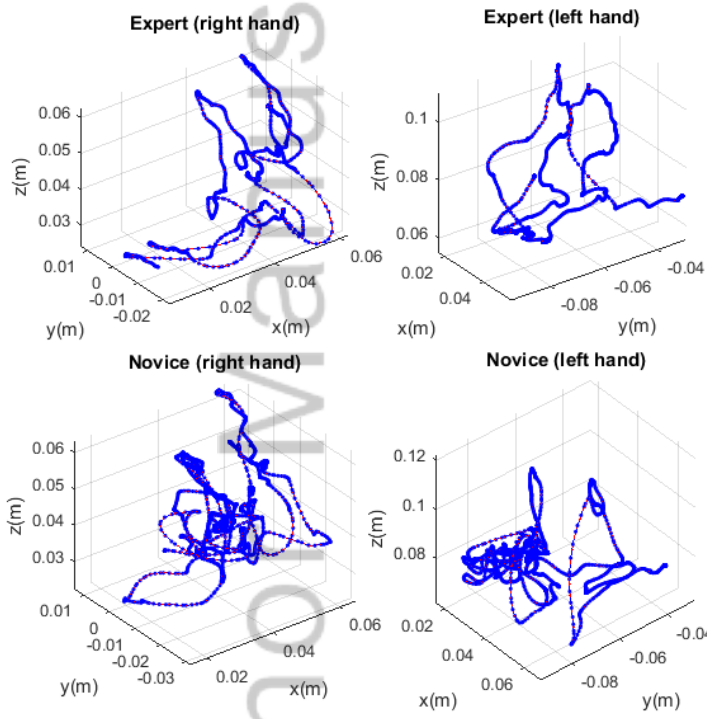
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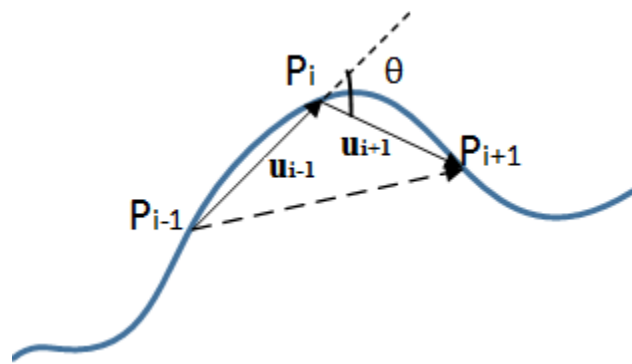
RCS_1850_F3.tif

RCS_1850_F4.tif

RCS_1850_F5.tif

RCS_1850_F6.tif

RCS_1850_F7.tif