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Analysis of Energy-based Metrics for Laparoscopic Skills Assessment

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***Abstract*— *Objective:* The complexity of Minimally Invasive Surgery (MIS) requires that trainees practice MIS skills in numerous training sessions. The goal of these training sessions is to learn how to move the instruments smoothly without damaging the surrounding tissue and achieving operative tasks with accuracy. In order to enhance the efficiency of these training sessions, the proficiency of the trainees should be assessed using an objective assessment method. Several performance metrics have been proposed and analyzed for MIS tasks. The differentiation of various levels of expertise is limited without the presence of an external evaluator. *Methods:* In this study, novel objective performance metrics are proposed based on mechanical energy expenditure and work. The three components of these metrics are potential energy, kinetic energy, and work. These components are optimally combined through both one-step and two-step methods. Evaluation of these metrics is accomplished for suturing and knot-tying tasks based on the performance of 30 subjects across four levels of experience. *Results:* The results of this study show that the one-step combined metric provides 47% and 60% accuracy in determining the level of expertise of subjects for the suturing and knot-tying tasks, respectively. The two-step combined metric provided 67% accuracy for both of the tasks studied. *Conclusion:* The results indicate that energy expenditure is a useful metric for developing objective and efficient assessment methods. *Significance:* These metrics can be used to evaluate and determine the proficiency levels of trainees, provide feedback and, consequently, enhance surgical simulators.**

I. Introduction

Minimally invasive surgery (MIS) promises certain advantages for patients such as lower pain levels, reduced blood loss and better cosmesis. However, it demands the manipulation of long instruments in difficult positions with limited degrees of freedom. In addition, dealing with the fulcrum effect and a different sense of force compared to conventional open surgery are among the complications of MIS. Consequently, MIS tasks must be practiced repeatedly to achieve mastery prior to performing them in the operating room. Surgical simulators are helpful in providing the opportunity to practice in a safe environment with fewer time constraints. These simulators will be more efficient when equipped with objective assessment methods [1]. Appropriate assessment methods are essential to quantify the level of expertise of trainees, to provide them with feedback about their performance, to allow independent training, and to certify the proficiency level of a resident or a surgeon before operating on a patient [2]. Section I-A provides a review of the commonly used performance metrics.

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A. Review of Performance Metrics

The metrics proposed for surgical skills assessment can be classified in different ways. McCrory, *et al.* [2] considered three main groups of metrics: 1. the group related to patient safety—e.g., force magnitude, 2. the group related to the success of the procedure—e.g., task outcome metrics, and 3. the group that deals with efficiency—e.g., path length [3], [4]. However, the ability of the provided examples to represent safety, success, or efficiency depends on the task and should be further investigated. A more detailed classification was performed in [5] by dividing metrics into temporal, task outcome, motion-based, force-based, and combined metrics, as described bellow:

Temporal metrics are among the most commonly used metrics for assessing the performance of trainees. *Task completion time* has been shown to best discriminate between novice and expert subjects and has been used in [6]–[9] for skills assessment. Inclusion of this metric in skills assessment enhances discrimination between various levels of expertise [10]. Although experts are faster than novices in performing surgical tasks, a short task completion time does not necessarily mean a superior performance. Consequently, in most studies, *time* has been combined with other performance metrics to provide a more complete assessment. Other examples of temporal metrics include the number of repetitions required to complete a task successfully [3] and hesitation. Hesitation can be determined by the time intervals between subtasks [5] or by short intervals in which the instrument does not move [11].

Task outcome metrics are developed based on the outcome of task completion regardless of how it is performed. These metrics are defined based on the proposed tasks and are usually evaluated by an external observer. Examples of outcome metrics include the number of instrument collisions, the number of successful identifications of landmarks or structures, and the score assigned to a performance assessment [12]. The number of instrument collisions can also be an indication of safety and can be determined by identifying the number of times a certain force threshold has been exceeded.

Motion-based metrics are defined using instrument and hand position to extract biomechanical parameters [5]. Several metrics are extracted from motion information such as *path length*—the distance that the instrument travels, *speed*—the first derivative of position, *acceleration*—the second derivative of position, and *jerk*—the third derivative of position, which represents smoothness of motion. Different parameters can be considered to further characterize *speed* and *acceleration* metrics. These include the mean, the peak, the magnitude, and the normalized speed/acceleration [5]–[7], [13].

Force-based metrics are developed based on force profile of performance [8], [9]. It is essential for trainees to learn to apply sufficient force when needed and to be gentle enough with the tissues. Applying too much force may result in tissue damage; however, applying less force than required may lead to ineffective performance. Force-based metrics include average force, maximum force, the integral of the force, force range, force direction, derivatives of the force, and smoothness of the applied force [3], [5]. These metrics can also be an indication of performance safety and efficiency.

Combined metrics are established by combining different metrics together. These metrics consider multiple characteristics of the performance in one unified metric. Different combined metrics are defined and studied in [5], [8], [14] [15], [16].

The following section describes the development of a new metric for laparoscopic skills assessment.

B. Using Energy Expenditure for Metric Development

Guthrie's definition of *skill* [17] recognizes *maximum certainty*, *minimum time* and *minimum energy* as features of a skilled performance. *Certainty* has been investigated in qualitative studies [18], [19] and will not be explored here. *Time* has been extensively used for skills assessment but this metric cannot completely represent the level of proficiency of a trainee. *Energy expenditure* has been also considered as a feature of skilled performance in other literature [20], [21]. Elliot, *et al.* [22], [23] indicate that through practice, energy expenditure optimization can be achieved, as well as optimization in accuracy and speed of performance. To reach the minimum energy expenditure, removal of unnecessary and undesirable movements is required [24].

Energy expenditure can be quantified by measuring the heart beat, body temperature, and the rate of oxygen–carbon dioxide exchange [25], [26]. However, for MIS tasks, it is possible to measure force and position information related to energy expenditure at the tip of the instrument. According to Sparrow, *et al.* [27] the human body tends to minimize metabolic energy expenditure in relation to the task to be performed, the environment in which the task is conducted, and the constraints imposed on the performer's action. An important part of energy expenditure minimization relates to receiving appropriate sensory information and adapting motions based on the received information. Unfortunately, the sensory information received by the MIS performer is reduced due to the lack of direct visual and force feedback. Limited degrees of freedom in motion is another constraint that makes energy expenditure optimization challenging.

C. Objectives

Although various metrics have been proposed and used for MIS skills assessment, as reviewed in Section I-A, a metric that can objectively determine the detailed level of expertise of subjects is still lacking. The goal of this study is to enhance MIS skills assessment by developing objective metrics based on energy expenditure and to validate these metrics.

II. Metric Development

Previous studies [5], [7], [9], [28] reported a difference in the velocity and the applied force profiles of novices and experts. Thus, experts use different techniques or movements, coordinating both hands, to perform MIS tasks. The differences observed in velocity and force when experts perform surgical tasks might be due to a different amount of energy expenditure. This information can be incorporated into an energy formula. In this study, the types of energy that can be quantified using force and position information are considered. Energy expenditure, in the form of mechanical energy and work, has been used in human movement studies [29], [30]. However, these forms of energy expenditure are not currently used in surgical skills assessment.

The proposed metrics in this study consist of three components, which are defined based on potential energy, kinetic energy, and work. These components are combined to optimize the ability of the proposed metrics to discriminate various skills levels. Four levels of experience are considered in this study with two levels in each of the novice and expert groups. In this study, it is assumed that the level of experience of the subjects correlates with their level of expertise. However, in some cases, this assumption may not hold for all the subjects. The basic components and the combined method are described in Sections II-A and II-B, respectively.

A. Basic Components

Gravitational potential energy is the form of energy that is generated or consumed due to changes in the position of an object in the gravitational field, as follows:

$$E_{\mathrm{P}} = mgh \ \ [\mathrm{J}], \tag{1}$$

where m is the mass of the surgical instrument [kg], g is the gravitational acceleration [9.8 m/s^2], and h is the height of the tip of the instrument [m]. In laparoscopic skills assessment, the sum of the absolute changes in potential energy is considered:

$$\text{Potential-based component} = \sum_{i=\text{start}}^{\text{end}} |\Delta E_{\mathrm{P}_i}| \quad [\mathrm{J}], \tag{2}$$

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where i represents the index of the sampling time, which ranges from the start to the end of the task.

Kinetic energy is another form of mechanical energy. Here, kinetic energy due to translational velocity is considered, as follows:

$$E_{\mathrm{k}} = \frac{1}{2} m v^2 \ \ [\mathrm{J}], \tag{3}$$

where v is the translational velocity of the tip of the instrument [m/s]. Similar to potential energy, the sum of the absolute changes in kinetic energy is considered for laparoscopic skills assessment, as follows:

$$\text{Kinetic-based component} = \sum_{i=\text{start}}^{\text{end}} |\Delta E_{\mathrm{K}_i}| \quad [\mathrm{J}]. \tag{4}$$

The kinetic-based and potential-based components were calculated assuming a constant mass for the instruments. However, due to interaction of the instruments with their environment, there may be additional mass carried by the instruments, which increases the total value of these components. Consequently, the potential-based and kinetic-based components represent the minimum amount of change in the potential and kinetic energies.

The amount of *work* done on the surgical simulator through the surgical instruments is another component of the energy-based metric proposed in this study. The total amount of the absolute work during task completion forms this component:

$$\text{Work-based component} = \sum_{i=\text{start}}^{\text{end}} |W_i| \quad [\mathrm{J}], \tag{5}$$

where W_i represents the amount of work in each sampling time and can be calculated according to work formula:

$$W = F \cdot d \ \ [\mathrm{J}], \tag{6}$$

where F and d are vectors of the applied force [N] and displacement [m] at the tip of the instrument.

B. Combined Energy-based Metrics

Each of the above components represents a part of the change in energy expenditure. In order to study the relationship between the level of experience (LOE) and energy expenditure, *combined metrics* were defined to estimate the minimum energy expenditure. These combined energy-based metrics are the weighted sum of all of the components for the left and right hands.

$$\begin{aligned} \text{Combined metric} \ = \ & \alpha_{\mathrm{W_L}} \times W_{\mathrm{L}}^{\beta_{\mathrm{W_L}}} + \alpha_{\mathrm{W_R}} \times W_{\mathrm{R}}^{\beta_{\mathrm{W_R}}} + \\ & \alpha_{\mathrm{P_L}} \times P_{\mathrm{L}}^{\beta_{\mathrm{P_L}}} + \alpha_{\mathrm{P_R}} \times P_{\mathrm{R}}^{\beta_{\mathrm{P_R}}} + \\ & \alpha_{\mathrm{K_L}} \times K_{\mathrm{L}}^{\beta_{\mathrm{K_L}}} + \alpha_{\mathrm{K_R}} \times K_{\mathrm{R}}^{\beta_{\mathrm{K_R}}}, \end{aligned} \tag{7}$$

where W_{L} and W_{R} represent the work-based components for the left and right hands, P_{L} and P_{R} represent the potential-based components for the left and right hands, and K_{L} and K_{R} represent the kinetic-based components for the left and right hands.

In this formula, the α values are the corresponding coefficients for each component. Higher values of α mean a higher contribution of the related component. β values are the exponents of each component, where β equal to 1 means a linear relationship between the *combined metric* and the corresponding component. Incorporating exponents into this formula allows non-linear relationships between LOE and energy-based components to be identified. A positive value of β corresponds to a direct relationship and a negative value reflects an inverse relationship. For instance, $\alpha_{\mathrm{W_L}}$ is the coefficient of the work-based metric for the left hand in the combined metric and $\beta_{\mathrm{W_L}}$ is the exponent of this basic component. Due to differences in task requirements, particular combinations of the basic components should be established for each task, such that the difference between the energy expenditure of various levels of experience is maximized.

Optimization methods were investigated to find the coefficients (α) and exponents (β) that maximize the Spearman's rho correlation of the combined metric (Eq. 7) with LOE.

Two approaches were explored for developing combined metrics as follows:

1) One-step combined metric: In the one-step combined metric, a set of coefficients and exponents is obtained through optimization of the correlation of the combined metric with the four LOE considered in this study.

2) Two-step combined metric: The four levels of experience considered in this study can be classified in two main groups of novices (Levels 1 and 2) and experts (Levels 3 and 4). In this approach, the discrimination between different levels of experience is accomplished in two steps. The first step consists of recognizing the main LOE (novice or expert). The optimization is performed for this step to find the set of coefficients and exponents that maximize the correlation with the two main levels of experience. In the second step, different coefficients and exponents are determined to distinguish between LOE 1 and 2 (novice) or between LOE 3 and 4 (expert). Fig. 1 outlines this method.

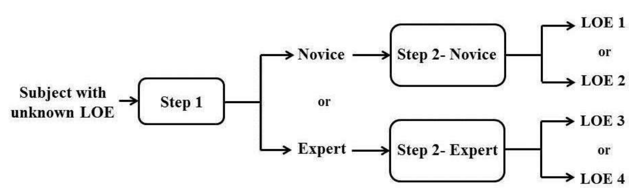

Fig. 1: Diagram of the two-step combined metric.

Two methods of optimization were investigated to determine the appropriate set of coefficients and exponents: the Genetic Algorithm (GA) function of the global optimization toolbox and the *fmincon* function of MATLAB (The Mathworks, Inc., Natick, MA). Since each basic component might have a different range, as can be seen in Section IV-A.1, a normalization process was implemented before combining these components. This was accomplished by dividing each component by the range of variation of that component. The upper and lower limits for the coefficients were set to +1 and -1 and for the exponents were set to +3 and -3.

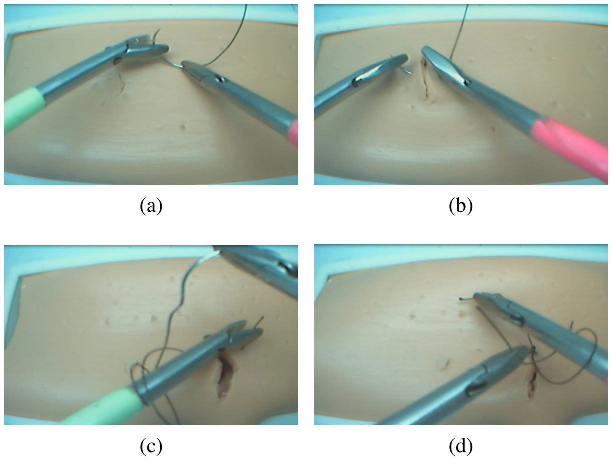

Fig. 2: The laparoscopic tasks. (a), (b) Passing the needle through the tissue for the suturing task. A double knot (c) and two single knots (d) constitute the knot-tying task.

III. Materials and Methods

The proposed metrics were investigated for two laparoscopic tasks. In this section, the design of the experiment for the data collection and the data processing are described.

A. Experimental design

The setup for this experiment is composed of a standard laparoscopic training box. Inside the training box, an ABS plastic frame was placed to hold a soft tissue model made of silicone and foam. A layer of soft rubber was placed on top of the soft tissue model to mimic the skin layers.

For this experiment, 30 subjects with different levels of experience in laparoscopy were recruited. The participants in the study were divided into four levels of experience as follows: LOE 1— with no medical background (n = 6), LOE 2— medical students with no surgical training, surgeons with no MIS experience, and postgraduate year (PGY) 2–3 who had no exposure to MIS (n = 11), LOE 3— PGY 4–5 and trained fellows (n = 7), and LOE 4— expert surgeons (n = 6). This division constitutes the reference for evaluating the proposed metrics. All subjects were right-hand dominant.

Each subject was asked to perform a suturing and a knot-tying task in each trial. All participants were asked to repeat these tasks in four trials. In the suturing task, participants were asked to pass a needle through both sides of an incision in the simulated skin. The exact starting point for the suturing task was left to the participant's discretion. The knot-tying task consisted of one double knot and two single knots (Fig. 2). The skills required to perform these tasks included proper handling and placement of the needle, and controlling the instrument tip and the suture.

The Sensorized Instrument-based Minimally Invasive Surgery (SIMIS) [31] System was used to perform the tasks [32]. Two SIMIS instruments were used to record forces applied perpendicular to the shaft of the instrument, in two Cartesian directions, and position information of the tip of the instrument in 6 degrees of freedom. The mass of each instrument is 170 g.

B. Data processing

Before calculating the proposed metrics, the recorded data for each subject was segmented to isolate the data of the suturing and knot-tying tasks. Time frames for the start and end of the task were identified by video recordings during the experiment. In addition, the intervals where there was an interruption in task completion were determined and removed to focus on the movements related to the task. The recorded data was then low-pass filtered with a second-order Butterworth filter at the cut-off frequency of 40 Hz. This cut-off frequency was selected by investigating the power spectrum of the force and position signals to ensure that no significant information was lost by filtering and that the data was not affected by high-frequency noise. To identify outliers, the boxplot function of MATLAB was used. The data points outside $[q_1 - w(q_2 - q_1), q_2 + w(q_2 - q_1)]$ were recognized as outliers, where q_1 and q_2 represent 25th and 75th percentiles and w represents the whisker length which was set to 1.72 (equivalent to 3 standard deviations). Each of these outliers was then investigated by watching the corresponding video to find the cause of the outlier. For the outlier points that dealt with a reasonable cause, the data point was replaced with the maximum nonoutlier value for the corresponding LOE. The accepted causes were sliding the skin layer out of the tissue model frame or breaking the suture. Among 120 trials executed, 8 trials were recognized for including outlier data for the suturing task and 11 trials were recognized for including outlier data for the knot-tying task.

IV. Results and Validation

Among the four trials executed in this study for each subject, the data from the first, second, and fourth trials were considered as the training data set. These data were used to determine the coefficients and exponents of the combined metrics. The basic components and the resulting combined metrics obtained from the training data set, as presented in Section IV-A, were used to determine the margins of the four levels of experience. Based on these margins, the LOE of a subject with an unknown LOE can be determined. The third trial was considered as the test data set and was utilized in order to validate the proposed metrics. Since the test data consisted of the data that was collected from all of the participants in their third trial, the distribution of LOE over the test data set was the same as the distribution of LOE over the training data. The validation results are presented in Section IV-B.

A. Results of Metric Development

1) Basic components: The basic components were shown to be successful in discriminating novice and expert subjects for both tasks. This was demonstrated in a previous study considering subjects in two main levels of novice and expert [32]. However, more detailed classification of subjects would be beneficial in guiding trainees and improving the learning quality. This detailed classification is investigated in the current study. The three basic components of the proposed

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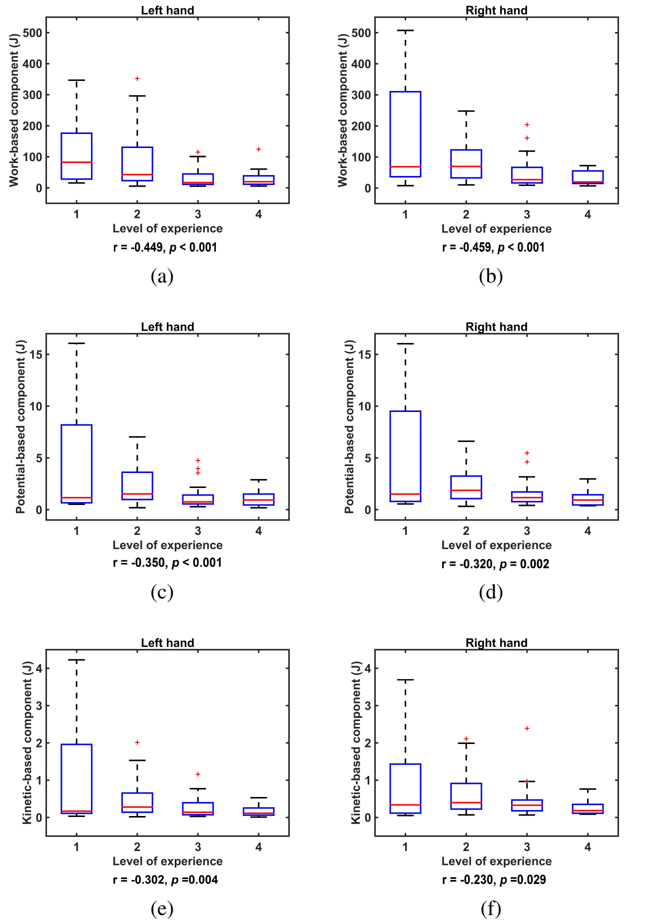

Fig. 3: Basic components for the suturing task based on the training data set. The Spearman's rho correlation of each basic component with LOE (r) and the corresponding p value are shown below each sub-figure. All correlations are statistically significant.

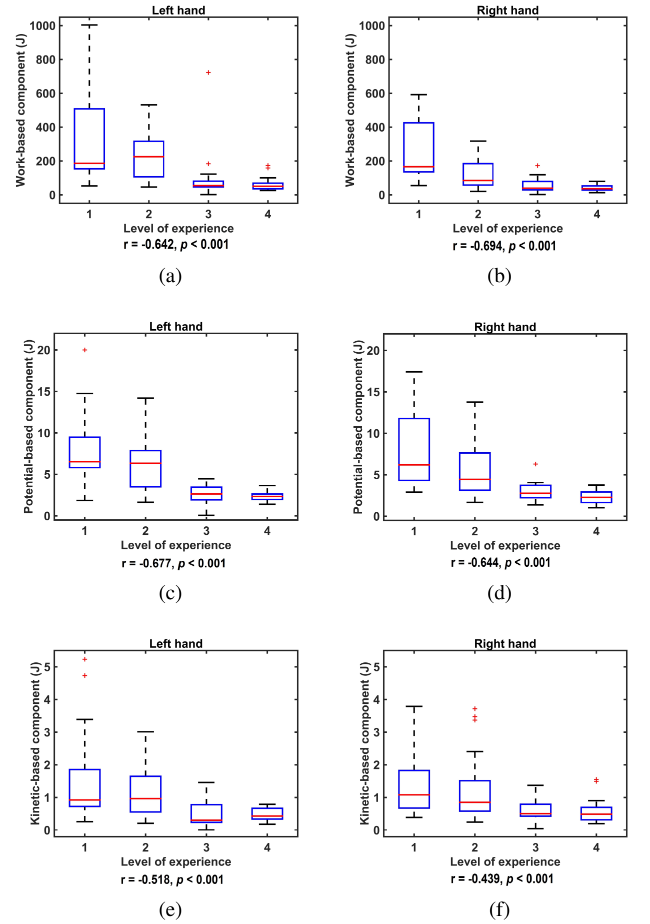

Fig. 4: Basic components for the knot-tying task based on the training data set. The Spearman's rho correlation of each basic component with LOE (r) and the corresponding p value are shown below each sub-figure. All correlations are statistically significant.

metrics versus the four LOE for the left and right hands are shown in Fig. 3 (suturing task) and Fig. 4 (knot-tying task). Since the axial force was not measured in these experiments, the work-based component presented in this study represents the work performed perpendicular to the shaft of the instrument. The maximum correlation was obtained for the work-based component for both tasks. In order to assess the effect of additional mass on the potential-based and kinetic-based metrics caused by the interaction of the instruments with tissue, a sensitivity analysis was performed (Appendix I). The results showed that the possible additional mass does not affect the relationship between these components and the various LOEs. This is likely due to the additional mass having a similar effect on the performance of all the subjects.

The amount of each basic component decreased as the LOE increased for both tasks. The difference between the first two LOE and the last two LOE was significant, while the difference between LOE 1 and LOE 2 and also between LOE 3 and LOE 4 was limited. Consequently, discriminating between subjects with various levels of experience could not be accomplished completely by defining margins for those levels.

2) One-step Combined Metric: Comparing the results obtained from the two optimization methods (fmincon function and GA algorithm) showed that the resulting coefficients and exponents from the GA algorithm demonstrated higher correlations of the combined metrics with LOE. Therefore, the values obtained from the GA algorithm were used for both combined metrics in this study.

Fig. 5 shows the results of the one-step combined metric for the suturing and knot-tying tasks. By combining the basic components using the one-step combined metric, the correlation with LOE for the suturing task was improved from -0.459 (the maximum correlation that was obtained for the work-based component for the right hand) to -0.506. For the knot-tying task, the one-step combined metric resulted in an improvement of the correlation with LOE from -0.694 to -0.795. It may be observed in Fig. 5 that the overlap between various levels of experience for the one-step combined metric was relatively smaller than the overlap of the basic components (as seen in Figs. 3 and 4).

The margins of variation for each LOE were also derived from the results of the training data set for all of the metrics presented in this study. For instance, the lower margin of

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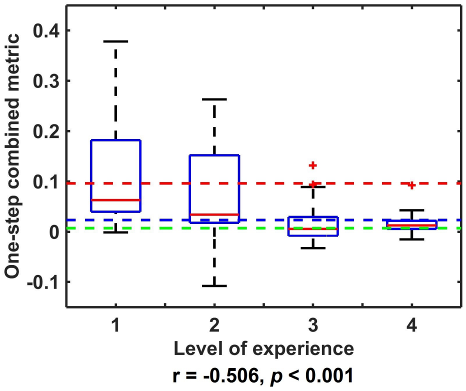
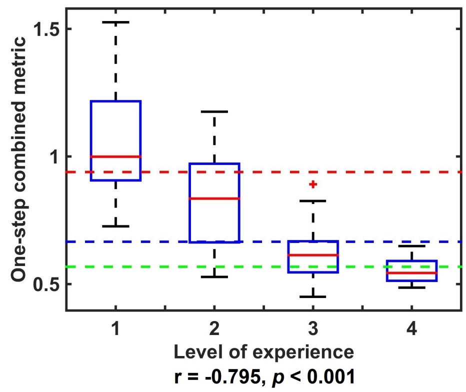
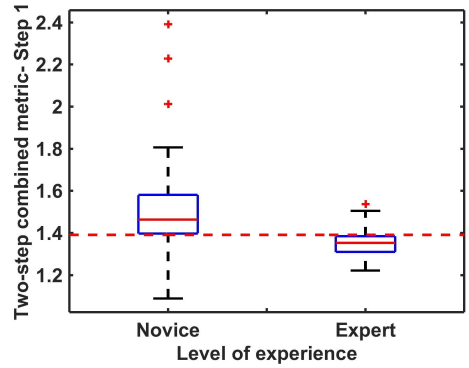


(a)

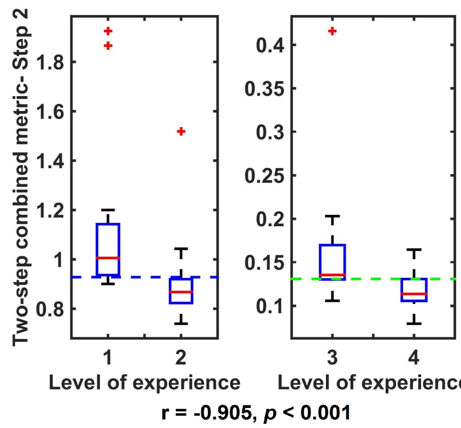


(b)

Fig. 5: The one-step combined metric for (a) the suturing task and (b) the knot-tying task for the training data.



(a)



(b)

Fig. 6: The two-step combined metric for the suturing task for the training data: (a) Step 1 for two main LOE and (b) Step 2 for detailed LOE for the novice and expert groups.

LOE 1, which was also the upper margin of LOE 2, was the average of the 25th percentile of LOE 1 subjects and the 75th percentile of the subjects in LOE 2 for each metric. These margins for the one-step combined metric are shown by dashed lines in Fig. 5. The area above the red dashed line indicates the area of variation for LOE 1, the area between the red and blue dashed lines relates to LOE 2, the area between the blue and green dashed lines defines LOE 3, and the area below the green dashed line indicates LOE 4.

3) Two-step combined metric: Figs. 6 and 7 show the results of the two-step combined metric for the suturing and knot-tying tasks. The correlation with LOE was calculated for this metric based on the results of the second step. For the suturing and knot-tying tasks, the correlations with LOE were -0.905, which are considerably higher than the corresponding values obtained from the individual components and the one-step combined metric.

The margins of variation for this metric were also calculated using the same method explained in Section IV-A.2. The red dashed lines in Figs. 6(a) and 7(a) show the margin for discriminating between experts and novices. The blue and green lines in Figs. 6(b) and 7(b) indicate the margins for differentiating between LOE 1–2 and between LOE 3–4.

B. Validation

In this part of the study, it was assumed that the LOE of the subjects were unknown. The margins extracted in Section IV-A were used in MATLAB to determine the LOE of subjects based on the test data set. Afterwards, the determined levels of experience were compared to the true levels of experience to investigate the accuracy of each metric. Thus, the validation was performed blindly.

The results of the one-step combined metric for the test data set are shown in Fig. 8 along with the margins for each LOE. The two-step combined metric for the test data set related to the suturing and knot-tying tasks are presented in Figs. 9 and 10, respectively. Due to variations in the performance of the subjects in each trial, the margins obtained based on the training data set do not necessarily match the values that could be obtained from the test data set.

The accuracy, defined as the total number of correct identifications over the total number of subjects expressed as a percentage, is represented in Fig. 11 for all of the energy-based metrics. The basic components provided a maximum accuracy of 30% and 37%, for the suturing and knot-tying tasks, respectively. Using the combined metrics, the discrimination is significantly improved compared to the basic components. The one-step combined metric can

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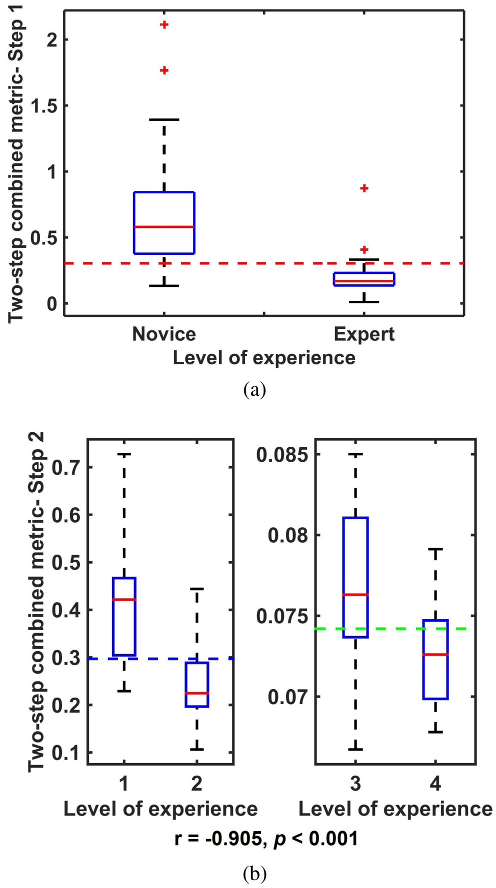

Fig. 7: The two-step combined metric for the knot-tying task for the training data: (a) Step 1 for two main LOE and (b) Step 2 for detailed LOE for the novice and expert groups.

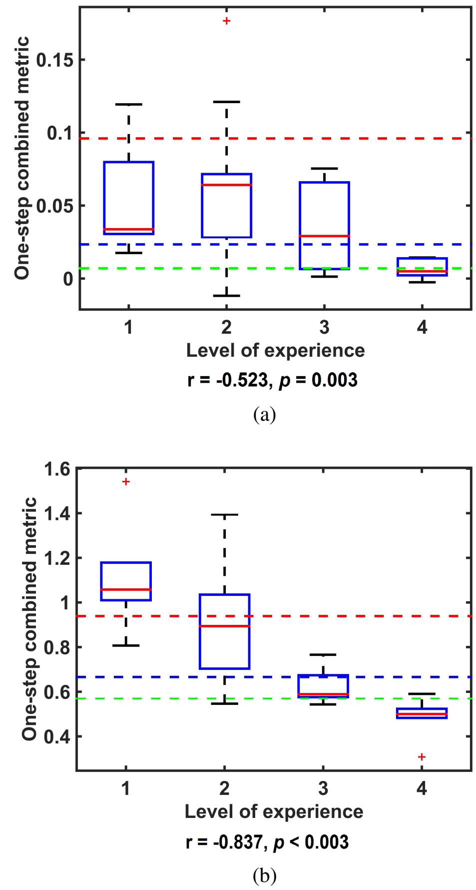

Fig. 8: The one-step combined metric for the test data set for (a) the suturing task and (b) the knot-tying task. The margins specified in this figure are obtained from the training data set.

accurately identify the LOE of 14 and 18 subjects (47% and 60%) for the suturing and knot-tying tasks. Using the two-step combined metrics, the LOE of 20 subjects (67%) was properly recognized for both tasks. In addition, 29 subjects (97%) were identified within ± 1 level of the correct LOE for the knot-tying task. For the suturing task, the number of participants identified within ± 1 level of the correct LOE was 28 (93%) for both combined metrics.

TABLE I: The correlation with LOE and the corresponding p values for the basic components applied to the test data set. The statistically significant correlations ($p < 0.05$) are displayed in bold.

Task	Basic component	Left hand	Right hand
Suturing	Potential-based component	-0.292, p = 0.118	-0.260, p = 0.165
	Kinetic-based component	**-0.367, p = 0.046**	-0.280, p = 0.133
	Work-based component	-0.326, p = 0.079	**-0.582, p <0.001**
Knot-tying	Potential-based component	**-0.741, p <0.001**	**-0.713, p <0.001**
	Kinetic-based component	**-0.651, p <0.001**	**-0.388, p = 0.003**
	Work-based component	**-0.791, p <0.001**	**-0.684, p <0.001**

These combined metrics were compared with two metrics commonly used in MIS skills assessment: path length and task completion time (Fig. 11). The margins of variation for these metrics were determined based on the training data and using the same method explained in Section IV-A.2. These margins were utilized for LOE determination of the subjects based on the test data. For the suturing task, path length of the right hand demonstrates better accuracy in identifying LOE than the basic and the one-step combined metrics. However, the two-step combined metric provided superior accuracy compared to the path length and time. For the knot-tying task, both one-step and two-step combined metrics provided more accurate identifications than path length and time.

The correlation with the LOE for the basic components, and for path length and time, calculated for the test data set, are shown in Tables I and II, respectively. The maximum amount of correlation among the path length and task completion time for the suturing task was obtained for time: -0.369 (Table II). Among the basic components for the suturing task, the highest correlation was obtained for

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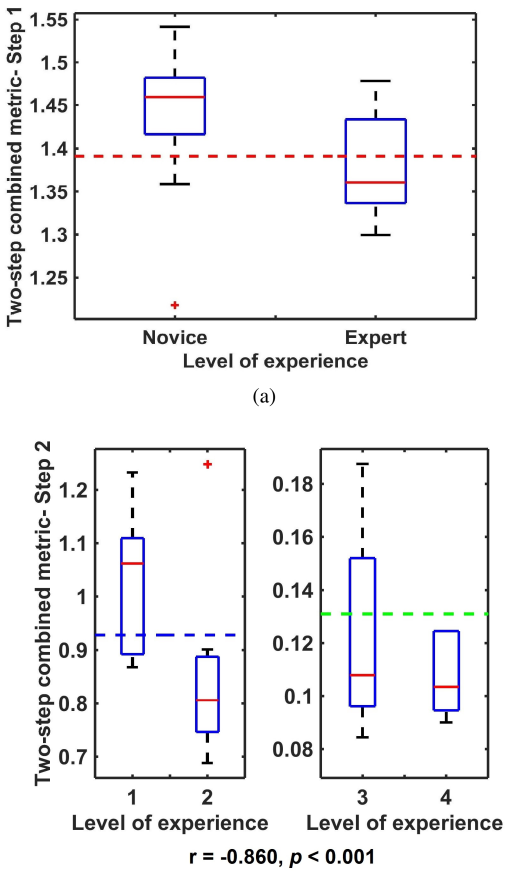

Fig. 9: The two-step combined metric for the test data set for the suturing task: (a) Step 1 and (b) Step 2. The margins specified in this figure are obtained from the training data set.

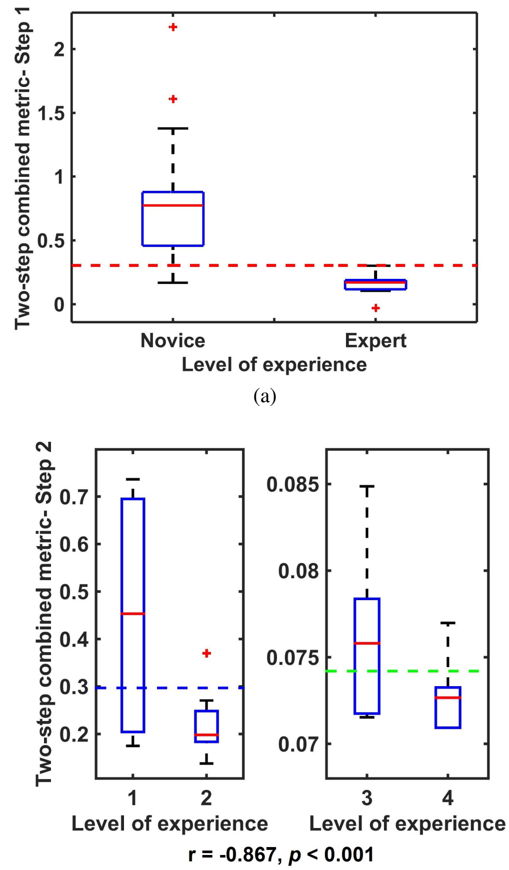

Fig. 10: The two-step combined metric for the test data set for the knot-tying task: (a) Step 1 and (b) Step 2. The margins specified in this figure are obtained from the training data set.

TABLE II: The correlation with LOE and the corresponding p values, for path length for the left and right hands (PL_{L}, PL_{R}), and time for the test data set. The statistically significant correlations ($p < 0.05$) are displayed in bold.

Task	PL_{L}	PL_{R}	Time
Suturing	-0.318, 0.087	-0.345, 0.062	**-0.369**, **0.045**
Knot-tying	**-0.747**, **<0.001**	**-0.745**, **<0.001**	**-0.754**, **<0.001**

the work-based component for the right hand: -0.582 (Table. I). The correlation for the one-step combined metric was -0.523 (Fig. 8 (a)). The highest correlation was obtained for the two-step combined metric, which was -0.860 (Fig. 9).

For the knot-tying task, the maximum correlation of the path length and the task completion time was obtained for time: -0.754 (Table II). This correlation was smaller than the one for the work-based component (the maximum among the basic components), which was -0.791 (Table I). This was also smaller than the correlations of the one-step and two-step combined metrics with LOE, which were -0.837 (Fig. 8 (b)) and -0.867 (Fig. 10), respectively.

V. Discussion

In this study, the accuracy in determining LOE and the Spearman's rho correlation were used to assess several proposed energy-based metrics and compare them with commonly used metrics for minimally invasive skills assessment.

The basic components (potential-based component, kinetic-based component, and work-based component) showed a decreasing trend as the LOE increased for both the suturing and knot-tying tasks. This indicates that as the LOE increases, subjects become more efficient in performing the task and expend less energy. In this study, the work-based component represented the amount of work that was produced perpendicular to the shaft of the instrument. Incorporating the axial force into the work-based metric can enhance the discriminatory capability of this component.

The combination of these components was analyzed in the one-step combined metric. Using this metric, accuracies of 47% and 60% in recognizing LOE were obtained for suturing and knot-tying tasks. However, due to overlaps between the one-step combined metric for the different levels of experience, it was not possible to locate margins between different LOE to allow for complete differentiation between all subjects. In terms of correlation with LOE, the one-step combined metric demonstrated smaller correlation with LOE

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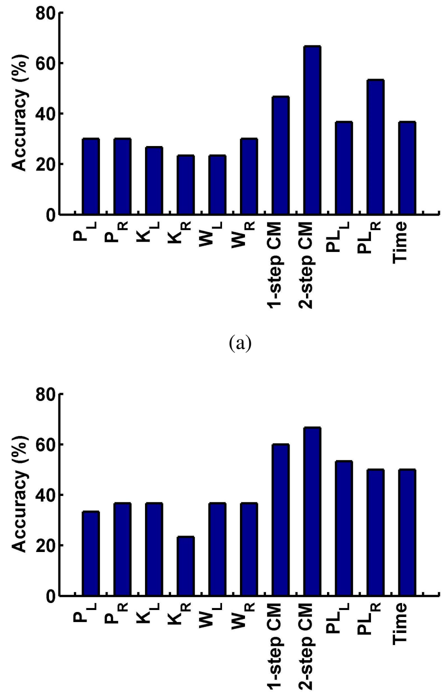

(a)

(b)

Fig. 11: Accuracy of the energy-based metrics and path length for the left hand (PL_L), path length for the right hand (PL_R), and task completion time for the test data set. (a) The suturing task and (b) the knot-tying task.

than the basic component of work for the right hand for the test data of the suturing task. This reduced correlation is most likely due to the optimization weights of the combined metric based on the training data. These weights do not necessarily provide higher correlations for every set of data. This issue might be mitigated by using larger data sets for the optimization process and determining a metric that can compensate for the variations in task executions. However, the one-step combined metric for the knot-tying task and the two-step combined metrics for both tasks also provided higher correlations with LOE than the basic components for the test data.

Decomposing the discrimination into two steps facilitated the determination of appropriate coefficients and exponents for each main LOE. This metric resulted in 67% accuracy for both the suturing and knot-tying tasks. In addition, higher amounts of correlation with LOE were obtained using the two-step combined metric for the training and test data sets compared to other energy-based metrics and the time and path length. The superior performance of the two-step combined metric is due to using different combinations of the basic components for each main LOE (novice and expert). The pattern of expending different forms of energy (potential energy, kinetic energy, and work) among novice subjects can be different from that of expert subjects. Another set of weights for combining these components is required to demonstrate the major differences between the two main levels of experience.

Among the four trials that were performed by each participant, the third trial was used to evaluate the performance of the proposed metrics. This trial was chosen because it represented a trial in which the subjects were already familiar with the setup and the tasks, but had not yet performed at their best. In other words, this trial represents the average state of their performance during the four trials. To further investigate the effect of using this third trial, an evaluation of the proposed metrics was performed by selecting the test trial randomly between the second and fourth trials, and also between the third and fourth trials. The first trial was excluded from the randomization to avoid the effect of the learning curve. The results showed the same trend and similar values when using a random trial for testing.

Comparing the energy-based metrics proposed in this study with two commonly used metrics in MIS skills assessment (path length and task completion time), demonstrated superior performance for the one-step and two-step combined metrics for the knot-tying task, and superior performance of the two-step combined metric for the suturing task.

The superior results obtained for the knot-tying task—better accuracy and correlation with LOE—is likely due to the difficulty of the task. The knot-tying task consists of three knots, which requires a larger number of movements compared to the suturing task. The higher complexity of this task more clearly demonstrates the difference in subject proficiency. Another point that might affect the results of this study was that the level of expertise of the subjects in our experiment was determined based on their experience in MIS. However, having more experience does not necessarily result in demonstrating higher level of expertise. The motor skills of subjects might influence their performance more than their direct experience in MIS. It should be noted that the developed metrics in this study can be used for providing feedback to trainees about their level of expertise at the end of the task. Developing instructions for trainees based on these metrics requires additional research.

The results obtained in this study are not at a level that they can be relied upon blindly for automatic discrimination of skill level. However, the energy-based metrics demonstrated a better performance than the commonly used metrics and can be used for enhancing these metrics. In order to improve the proposed energy-based metrics, additional investigation should be performed. Using a larger number of subjects would provide the opportunity to develop a more comprehensive metric in terms of the weights of the combined metrics. A larger number of subjects would also help to define more accurate margins for each LOE and provide increased robustness to the different possible ways of executing the same task. The weight factors that were used in this study were determined based on performance of right-handed subjects. Investigation of the performance of left-handed subjects is also required to establish an appropriate set of weight factors for them. Overall, there is a trade-off between speed, energy expenditure, and accuracy of performance. This trade-off should be further investigated to obtain more knowledge about how different subjects deal with task requirements.

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Consequently, there cannot be a single set of weights to discriminate subjects ranging from those with no expertise to expert subjects. At each main LOE, such as novice or expert, there should be a different set of weights to establish the appropriate combination of components.

VI. Conclusion

In this study, novel metrics were proposed based on analyzing energy expenditure. The three components of these metrics were potential energy, kinetic energy, and work. Two methods of using these components for determining combined metrics were proposed in this study and were tested on a data set recorded for two laparoscopic tasks performed by subjects of various levels of experience. In conclusion, the accuracy of the one-step combined metric in identifying LOE was 47% and 60% for the suturing and knot-tying tasks, respectively. The two-step combined metric demonstrated an accuracy of 67% for both tasks. The metrics proposed here, reflect the efficiency of the performance. In these metrics, different aspects of the subjects' performance, such as motion of the instrument and the amount of force applied to the tissue, are considered for both hands. These metrics provide an objective method for assessing the LOE of subjects, can be computed automatically, and can be used for other tasks and other MIS applications. However, for each task, a particular combination of these components should be established due to different task requirements.

VII. Future Work

One of the future directions for this study is to run experiments using force sensing instruments that are capable of measuring force in the axial direction. This additional information may improve the energy expenditure calculations. Furthermore, extending the number of trials for each subject and recruiting a larger group of subjects will allow for study of learning curves, the development of a more comprehensive metric, and increasing the reliability of the validation.

Including other performance metrics, such as hesitation and jerk, into the combined metric may enhance the ability of the metric to differentiate between the subjects' LOE in more detail. In addition, investigating the proposed metrics for other MIS tasks is among our planned future work.

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Appendix I: Sensitivity Analysis of Energy-based Metrics to Additional Mass

The mass in the formulas used to compute the kinetic/potential energy was considered to be a constant equal to 170 g, which is the mass of each instrument. The mass of the needle, which is less than 5 g, was negligible compared to that of the instrument. However, the interaction of the instruments with the setup, directly or through the needle contact, might increase the effective mass of the instruments and as a consequence increase kinetic/potential energy. In this appendix, the kinetic/potential energy, which was calculated based on the constant mass of the instruments, is called the minimum kinetic/potential energy. The following investigation was performed to estimate the effect of the possible additional mass on these metrics. To start, it was assumed that if the instrument's velocity or vertical displacement were small, the effect of additional mass on kinetic or potential energy, respectively, would be negligible. Moreover, if the additional mass was not significant, its effect would be negligible as well. The existence of the additional mass can be shown by the force at the tip of the instrument. Hence, the intervals in which the force was beyond a certain threshold were considered as those in which an additional mass was being carried. During those intervals, if the velocity/vertical displacement was higher than their corresponding thresholds, then the corresponding data could have a significant impact on the kinetic/potential energy (Fig. 12).

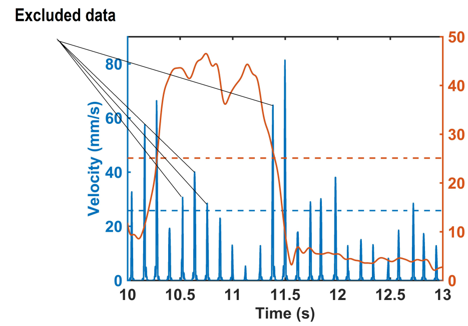

Fig. 12: Sample exclusion criteria. The data points that occur when the force is higher than the red dashed line and velocity is higher than the blue dashed line can have a considerable effect on kinetic energy and were excluded from the data for partial energy-based metrics.

Based on the characteristics of the sensorized instruments, specifically their maximum error and the coupling effect of grasping on bending forces [33], a value of 0.5 N was considered for the force threshold. To avoid the effect of drift on force analysis, the minimum amount of force for each trial was added to the threshold of force for that trial. The vertical displacement or velocity that can produce 1% of the maximum potential energy or maximum kinetic energy were considered as the threshold for vertical displacement or velocity. Consequently, the threshold of vertical displacement was considered to be $0.01 \times \Delta Z_{\max}$. Since kinetic energy is proportional to squared velocity, the threshold for velocity

TABLE III: Sensitivity of kinetic-based and potential-based metrics to additional mass. The force threshold was considered to be 0.5 N + the minimum force of the trial.

Metric	Task	Hand	Maximum percentage of affected data among 120 trials	Correlation of the partial energy-based metrics with LOE (r, p value)	Correlation of the minimum energy-based metrics with LOE (r, p value)
Kinetic energy	Suturing	Left	6.49%	-0.310, 0.003	-0.302, 0.004
		Right	4.65%	-0.179, 0.090	-0.230, 0.029
	Knot-tying	Left	4.47%	-0.478, <0.001	-0.518, <0.001
		Right	4.01%	-0.484, <0.001	-0.439, <0.001
Potential energy	Suturing	Left	14.04%	-0.351, <0.001	-0.350, <0.001
		Right	12.29%	-0.324, 0.002	-0.320, 0.002
	Knot-tying	Left	12.15%	-0.703, <0.001	-0.677, <0.001
		Right	10.43%	-0.651, <0.001	-0.644, <0.001

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was considered to be $0.1 \times V_{\max}$.

Using the above-mentioned criteria, the percentage of the data that might be affected by a varying amount of mass was calculated for each trial. The maximum values among the 120 trials for each task and both the left and right hands are shown in Table III. The different percentages of the affected data for kinetic and potential energy are due to having different criteria for each of these energy-based metrics. Altogether, the number of affected data samples is small enough to ignore. To confirm this statement, the affected parts of data were removed and the kinetic and potential-based metrics were recalculated. Herein, these metrics are named partial kinetic/potential-based metrics. The correlation of these metrics with the 4 LOEs are shown in Table III. To compare the partial metrics with the minimum kinetic/potential-based metrics, correlations of these metrics with the 4 LOEs are also shown in Table III. As can be seen in the table, removing the part of the data associated with the additional mass does not change the relationship between these metrics and the level of experience. A sensitivity analysis was performed by varying the force threshold level by up to 1 N. Using higher thresholds than 0.5 N results in more similar correlations with LOE for the partial and minimum kinetic/potential-based metrics. Based on the above analysis, extracting the parts of data that correspond to possible additional mass does not affect the relationship between these metrics and the LOEs.

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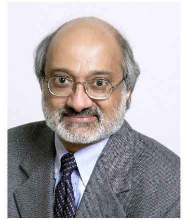

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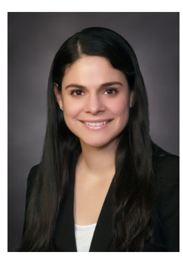

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