Minimally Invasive Surgery Task Decomposition - Etymology of Endoscopic Suturing

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Abstract. The analogy between Minimally Invasive Surgery (MIS) and the human language inspires the decomposition of a surgical task into its primary elements. The frequency of different elements or *words"* and their sequential associations or *"grammar"* both hold critical information about the process and outcome of the procedure. Modeling these sequential element expressions using a multi finite states model (Markov model) reveals the grammatical structure of the surgical task and is utilized as one of the key steps in objectively assessing surgical performance. The experimental protocol included 30 surgeons at different levels of training (5xR1,R2,R3,R4,R5, and experts) performing Laparoscopic suturing on an animal model (pig). The kinematics and dynamics of left and right endoscopic tools along with the visual view of the surgical scene were acquired by the Blue DRAGON system. The methodology of decomposing the surgical task is based on a fully connected, finite-states (30 states) Markov model (MM) where the left and right hands are represented by 15 states each. In addition to the MM objective analysis, a scoring protocol was used by an expert surgeon to subjectively assess the subjects' technical performance. An objective learning curve was defined based on measuring quantitative statistical distance (similarity) between MM of experts and MM of residents at different levels of training. The objective learning curve (e.g. statistical distance between MM) was similar to that of the subjective performance analysis. The MM proved to be a powerful and compact mathematical model for decomposing a complex task such as laparoscopic suturing. Systems like surgical robots or virtual reality simulators that inherently measure the kinematics and dynamics of the surgical tool may benefit from inclusion of the proposed methodology for analysis of efficacy and objective evaluation of surgical skills during training.

1. INTRODUCTION

Developing objective methodology for assessing technical skill is paramount to superior surgical training. Moreover, alternatives to the traditional apprenticeship model of surgical training are necessary in today's emphasis on cost containment and professional competency. There is a need to demonstrate continuing competency among practicing surgeons as well as for trainees early on, before trainee surgeons enter the operating room. The current measures of technical competency, beyond crude patient outcomes data such as survival, length of stay, or complication rates, have mainly been directed at measurement of one or two specific elements such as visual-spatial ability. No validated systems exist today for integrating or measuring surgical skill across all elements.

The practice of surgery and minimally invasive surgery (MIS), in particular, involves a multi-dimensional series of tasks requiring synthesis between visual information and the kinematics and dynamics of the surgical tools. The roots of a multi-dimensional objective methodology for assessing surgical skill lay in decomposing the tasks into its prime elements, and then selecting the appropriate model for representing the surgical task, ideally a model that is independent of the surgical platform (clinical surgery, simulator or surgical robotic interface). Surgical procedures are traditionally divided into steps or phases [1] in which suturing and tying a knot can be one of them. Additional hierarchical decomposition is based on identifying stages [1], tasks or subtasks [1,2], and actions or states [1,3]. In addition, other measurable parameters such as workspace [4] completion time, tool position [1] and forces and torque [3,5] were studied individually.

In the current study, the analogy between (MIS) and the human language inspires the decomposition of a surgical task into its primary elements. Modeling the sequential element expressions using a multi-finite states model (Markov model) reveals the grammatical structure of the surgical task and is utilized as one of the key steps in objectively assessing surgical performance. Based on this analogy, the MIS primary elements - 'words', or states in the model, are the tool/tissue or tool/object interactions. These interactions can be 'pronounced' differently or observed in the model by employing various forces/torques signatures applied on the tissues through the endoscopic tools by the surgeons. The aim of the current research was to study surgical suturing as one of the most common and yet complex task preformed in MIS. Calculating the statistical distance between Markov Model (MM) which are based upon the kinematics and dynamics of the endoscopic tools allows the objective assessment of surgical skills.

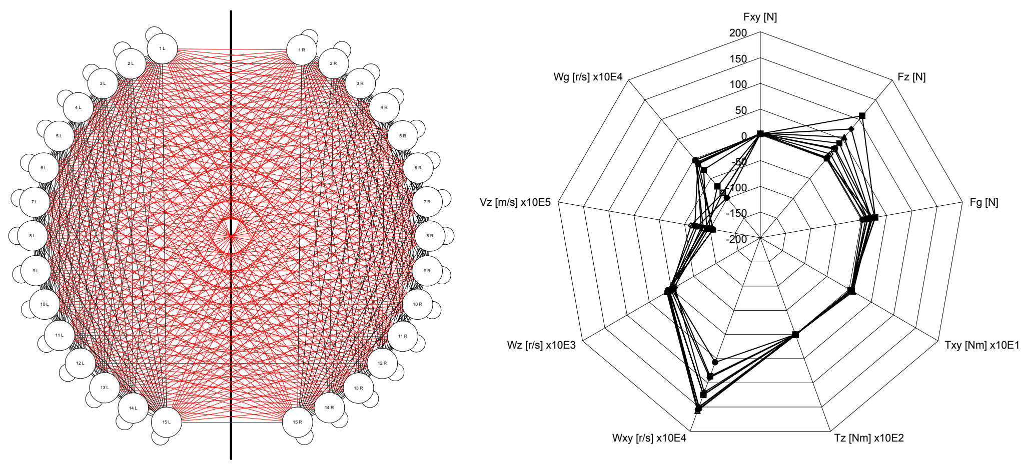
2. TOOLS AND METHODS

2.1 Experimental Protocol

The experimental protocol included 30 surgeons at different levels of expertise from residents in training to surgical attendings skilled in laparoscopic surgery. There were five residents from each of five years of residency, (5 x R1, R2, R3, R4, R5) and five surgeons trained in minimally invasive surgery (experts).Each subject was given instruction on how to perform an intracorporeal knot through a standard video. Subjects were then given a maximum of 15 minutes to complete this task in a swine model. This complex, integrative task includes many of the elements of advanced MIS techniques. In addition, each subject performed 15 predefined tool/tissue tool/needle-suture interactions (Table 1). The kinematics (the position/orientation – P/O of the tools in space with respect to the port) and the dynamics (forces and torque F/T applied by the surgeons) of the left and right endoscopic tools along with the visual view of the surgical scene were acquired by a passive mechanism that is part of the Blue DRAGON system previously described in [6]. All animal procedures were performed in an AALAC-accredited surgical research facility under an approved protocol from the institutional animal care committee of the University of Washington.

2.2 Objective Analysis - MIS Task Decomposition and Markov Model

The methodology of decomposing surgical task is based on a fully connected, symmetric finite-states (30 states) MM where the left and the right hands are represented by 15 states each (Fig. 2a). Each of the 15 states corresponds to a fundamental tool/tissue or tool/object interaction based on tool kinematics and is associated with unique F/T signatures defined as observations and measured at the hand/tool interface and then translated to the port coordinate system (Table 1). In view of this model, any MIS task can be described as a series of finite states. In each state, the surgeon is applying a specific F/T signature, out of several F/T signatures which are typical to that state, on the tissue by using the tool. The surgeon may stay within that state for specific time duration applying different F/T signatures associated with that state and then perform a transition to another state. The surgeon may utilize any of the 15 states by using the left and the right tools independently. However, the states representing the tool/tissue tool/object interactions of the left and the right tools are mathematically and functionally linked. A cluster analysis using the K-means algorithm was performed for defining typical kinematic and dynamic signatures (cluster centers) in the database. Ten signatures associated with each state were defined (e.g. Fig 2b) – allowing allocation of each observation to a cluster center and effectively encode the database into states and observations. This process that enabled surgical task decomposition into its elements which manifested as a substantial data reduction .



(a) (b)

Figure 1: *Finite State Diagrams (FSD) - (a) Fully connected FSD for decomposing MIS. The tool/tissue tool/object interactions of the left and the right endoscopic tools are represented by the 15 fully connected submodels. Circles represent states whereas lines represent transitions between states. Lines that cross the center-line represent different combination of states preformed by the left and the right tool. Force/torque signature associated with each state were omitted for simplifying the diagram;(b) Cluster centers definition - Typical 10 signatures of forces torques linear and angular velocities associated with Grasping-Pushing-Sweeping state. In this graph each of the 10 polar lines represent one cluster. Each of the 14 other states in Table 1 is associated with 10 different and unique signatures defined in terms of similar cluster analysis.*

The MM is defined by the compact notation (1). Each Markov sub-model representing the left and the right tool is defined by λ_L and λ_R (Eq. 1). The sub model is defined by: (*i*) The number of states - N whereas individual states are denoted as $S=\{s_1,s_1,\ldots s_N\}$, and the state at time t as q_t.; (*ii*) The number of distinct observation symbol - M whereas individual symbols are denoted as $V=\{v_1,v_1,\ldots v_M\}$; (*iii*) The state transition probability distribution matrix $-A=\{a_{ij}\}$, where $a_{ij}=P[q_{t+1}=s_j \mid q_t=s_i] \quad 1\le i,j\le N$; (*iv*) The observation symbol probability distribution matrix $-$ $B=\{b_j(k)\}$, where for state j $b_j(k)=P[v_k \text{ at } t \mid q_t=s_j] \quad 1\le j\le N, 1\le k\le M$; (*v*) The initial state distribution vector– π where $\pi_i=P[q_1=s_i] \quad 1\le i\le N$. The two sub models are linked to each other by the left-right interstate transition probability distribution matrix $-C=\{c_{lr}\}$, where $c_{lr}=P[q_{tL}=s_l \cup q_{tR}=s_r] \quad 1\le l,r\le N$

The probability of observing the state transition $Q=\{q_1,q_2,\ldots q_T\}$ and the associated observation sequence $O=\{o_1,o_2,\ldots o_T\}$, given the two Markov sub models (Eq. 1) and interstate transition probability distribution matrix, is defined by Eq. 2

$$\lambda_L = (A_L, B_L, \pi_L) \qquad \lambda_R = (A_R, B_R, \pi_R) \tag{1}$$

$$P(Q,O \mid \lambda_L, \lambda_R, C) = \pi_{q_L} \pi_{q_R} \prod_{t=0}^{T} a_{q_t q_{t+1} L} b_{q_t L}(o_t) a_{q_t q_{t+1} R} b_{q_t R}(o_t) c_{q_{tL} q_{tR}} \tag{2}$$

Due to the fact that probabilities by definition have numerical value in the range of 0 to 1. For relatively short time duration the probability calculated by Eq. 2 converge exponentially to zero and therefore exceed the precision range of essentially any machine. Hence by using logarithmic transformation the resulting values of Eq. 2 in the range of [0 1] are mapped by Eq. 3 into [-∞ 1].

$$Log(P(Q,O \mid \lambda_L, \lambda_R, C)) = Log(\pi_{q_L}) + Log(\pi_{q_R}) + \sum_{t=1}^{T} Log(a_{q_t q_{t+1} L}) + Log(b_{q_t L}(o_t)) + Log(a_{q_t q_{t+1} R}) + Log(b_{q_t R}(o_t)) + Log(c_{q_t L q_t R}) \tag{3}$$

Once the MMs were defined for specific subjects with specific skill levels, it is then possible to calculate the statistical distance factors between them. These statistical distance factors are considered to be an objective criterion for evaluating skills level if for example the statistical distance factor between a trainee and an expert is being calculated. Given two MMs λ_1 and λ_2 the nonsymmetrical statistical distances between them are defined as $D_{r1}(\lambda_1, \lambda_2)$ and $D_{r2}(\lambda_2, \lambda_1)$. The natural expression of the symmetrical statistical distance version is defined by Eq. 4.

$$D_r = \frac{D_{r1}(O_1,Q_1,O_2,Q_2,\lambda_1) + D_{r2}(O_1,Q_1,O_2,Q_2,\lambda_2)}{2} = \left(\frac{logP(O_2,Q_2 \mid \lambda_1)}{logP(O_1,Q_1 \mid \lambda_1)} + \frac{logP(O_2,Q_2 \mid \lambda_1)}{logP(O_1,Q_1 \mid \lambda_1)} \right) \Big/ \; 2 \tag{4}$$

Type	No.	State Name	State Acronym	Tissue Contact	Position / Orientation $\dot\theta_x$	$\dot\theta_y$	$\dot\theta_z$	$\dot L_z$	$\dot\theta_g$	Force / Torque F_x	F_y	F_z	T_x	T_y	T_z	F_g
I	1	Idle	ID	-	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\pm\varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$\pm\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$\pm\varepsilon_{F_g}$
	2	Closing Handle (Grasping / Cutting)	CL	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$\pm\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	3	Opening Handle (Spreading)	OP	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\dot\theta_g > \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$\pm\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g < -\varepsilon_{F_g}$
	4	Pushing	PS	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\pm\varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$F_z > \varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$\pm\varepsilon_{F_g}$
	5	Rotating (Sweeping)	RT	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\pm\varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$\pm\varepsilon_{F_z}$	$T_x > \lvert\varepsilon_{T_x}\rvert$	$T_y > \lvert\varepsilon_{T_y}\rvert$	$\pm\varepsilon_{T_z}$	$\pm\varepsilon_{F_g}$
II	6	Closing - Pulling	CL -PL	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z > \varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$F_z < -\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	7	Closing - Pushing	CL -PS	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$F_z > \varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	8	Closing - Rotating	CL-RT	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$\pm\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	9	Pushing - Opening	PS-OP	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\dot\theta_g > \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$F_z < -\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g < -\varepsilon_{F_g}$
	10	Pushing - Rotating	PS-RT	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\pm\varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$F_z > \varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$\pm\varepsilon_{F_g}$
	11	Rotating - Opening	RT-OP	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\dot\theta_g > \varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$\pm\varepsilon_{F_z}$	$T_x > \lvert\varepsilon_{T_x}\rvert$	$T_y > \lvert\varepsilon_{T_y}\rvert$	$\pm\varepsilon_{T_z}$	$F_g < -\varepsilon_{F_g}$
III	12	Closing - Pulling - Rotating	CL-PL-RT	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z > \varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$F_z < -\varepsilon_{F_z}$			$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	13	Closing -Pushing - Rotating	CL-PS-RT	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$F_z > \varepsilon_{F_z}$	$T_x > \lvert\varepsilon_{T_x}\rvert$	$T_y > \lvert\varepsilon_{T_y}\rvert$	$\pm\varepsilon_{T_z}$	$F_g > \varepsilon_{F_g}$
	14	Pushing - Rotating - Opening	PS-RT-OP	+	$\dot\theta_x > \lvert\varepsilon_{\dot\theta_x}\rvert$	$\dot\theta_y > \lvert\varepsilon_{\dot\theta_y}\rvert$	$\pm\varepsilon_{\dot\theta_z}$	$\dot L_z < -\varepsilon_{\dot L_z}$	$\dot\theta_g > \varepsilon_{\dot\theta_g}$	$F_x > \lvert\varepsilon_{F_x}\rvert$	$F_y > \lvert\varepsilon_{F_y}\rvert$	$F_z > \varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$\pm\varepsilon_{T_z}$	$F_g < -\varepsilon_{F_g}$
II	15	Closing Handle - Spinning	CL-SP	+	$\pm\varepsilon_{\dot\theta_x}$	$\pm\varepsilon_{\dot\theta_y}$	$\lvert\dot L_z\rvert > \varepsilon_{\dot\theta_z}$	$\pm\varepsilon_{\dot L_z}$	$\dot\theta_g < \varepsilon_{\dot\theta_g}$	$\pm\varepsilon_{F_x}$	$\pm\varepsilon_{F_y}$	$\pm\varepsilon_{F_z}$	$\pm\varepsilon_{T_x}$	$\pm\varepsilon_{T_y}$	$T_z > \lvert\varepsilon_{T_z}\rvert$	$F_g > \varepsilon_{F_g}$

Table 1: *Definitions of the 15 states based on spherical coordinate system with an origin at the port. Each state is characterized by a unique set of angular/linear velocities, forces and torques. A non zero threshold value is defined for each parameter by ε . The states' definitions are independent from the tool tip being used e.g. the state defined as Closing Handle might be associated with grasping or cutting if a grasper or scissors are being used respectively.*

2.3 Subjective Analysis – Scoring

The subjective performance analysis was based on an off-line unbiased expert review (blinded to the subject and training level of each individual) of digital videos recorded during the experiment. The review utilized a scoring system of 4 equally weighted criteria: (a) overall performance (b) economy of movement (c) tissue handling (d) number of errors including drop needle, drop suture, lose suture loop, breaking suture, needle injury to adjacent tissue, inability to puncture bowel with needle. Criteria (a) ,(b), and (c) included 5 levels. The final scores were normalized to the averaged experts scoring.

3. RESULTS

Typical raw data of F/T and tool tip position were plotted in a 3D space showing the kinematics and dynamics of the left and right endoscopic tools measured by the Blue DRAGON while performing MIS intracorporeal knot by junior trainee (R1 – Fig 2 a,c) and expert surgeon (E – Fig. 2 b,d). The F/T as vectors can be depicted as arrows with origins at the ports, changing their lengths and orientations as a function of time as a result of the F/T applied by the surgeon's hand on the tool while interaction with the tissues needle and suture. The traces of the tool tips with respect to the ports as are described in Fig. 2 c,d as their position were changing during the surgical procedure. These raw data demonstrated the complexity of the surgical task. Deeper understanding of the MIS task is gained by decomposition into its discrete elements.

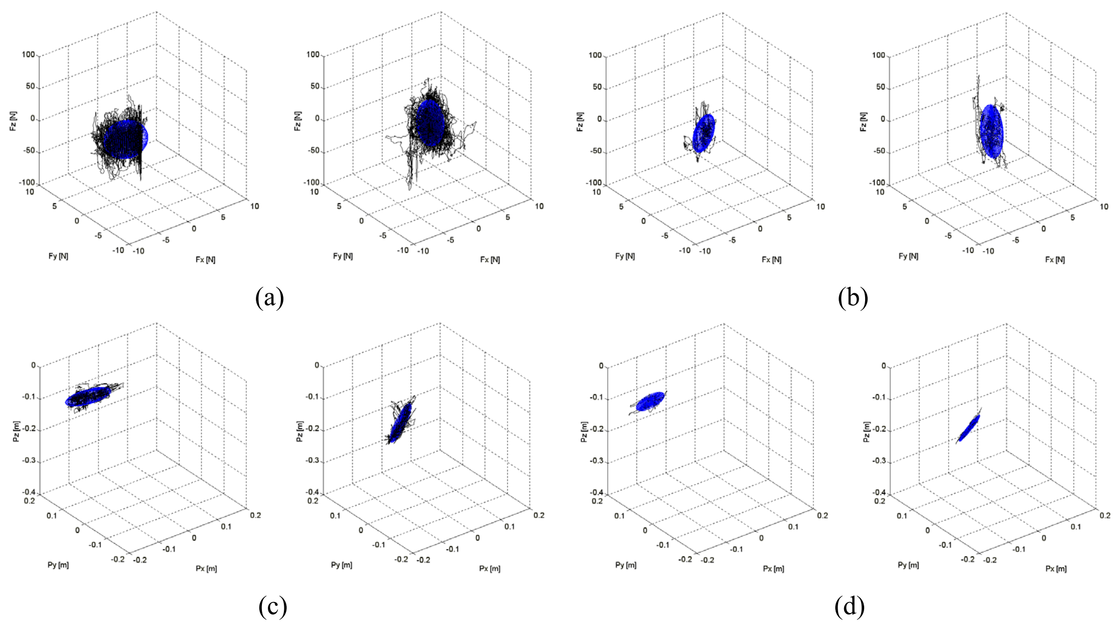


Figure 2: *The kinematic and dynamic data from left and the right endoscopic tools measured by the Blue DRAGON while performing MIS suturing and knot tying a trainee surgeon (R1 – a,c) and an expert surgeon (E – b,d) - (a,b) Forces; (b,c) Tool tip position. The ellipsoids contain 95% of the data points.*

As part of the encoding process the multi dimensional data were encoded into sequential tools' interactions (states) and the various signatures associated with them (observations). The encoded data is then used to calculate the MM defining the probabilities for performing certain tool transition ([A] matrix), the probability of combining two states ([C] matrix), and the probability of using the various signatures in each state ([B] matrix) (Fig. 3)

The normalized MM based statistical distance as a function of the training level as well as the normalized completion time and the normalized path length of the two tool tips are plotted in Fig. 4a-c. The complementary subjective normalized scoring is depicted in Fig. 4b. The data demonstrate that substantial suturing skills are acquired during the first year of the residency training. The learning curves do not indicate any significant improvement during the second and the third years of the training. The rapid improvement of the first year is followed by lower gradients learning cures as the residences' performance is progressing toward the expert level. However, the MM based statistical distance along with the completion time criteria show yet another gradient in the learning curve that occurs during the fourth year of the residency training followed by slow conversion to expert performance. Similar treads in the learning cure are also demonstrated by the subjective assessment.

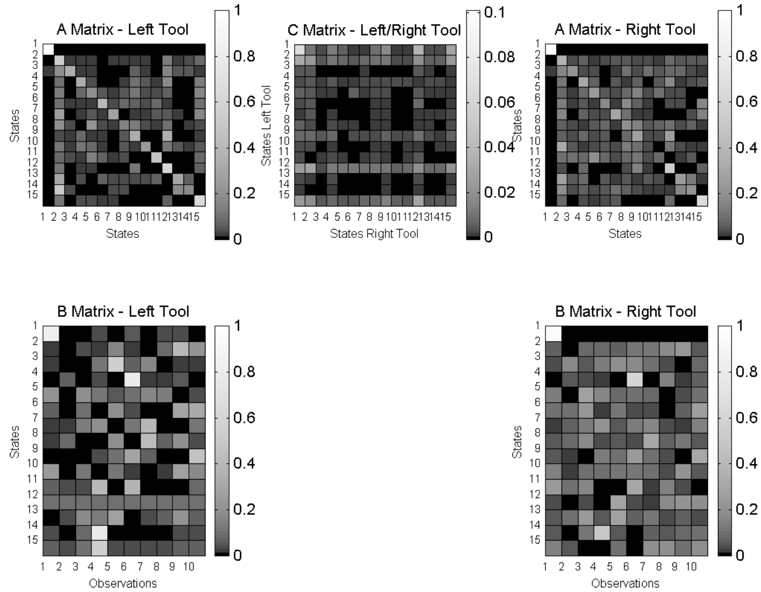


Fig. 3: A typical Markov Model where the matrices [A], [B], [C], are represented as color-coded probabilistic maps.

Detailed analysis of the MM shows that major differences between surgeons at different skill levels were: (*i*) the types of tool/tissue interactions being used, (*ii*) the transitions between tool/tissue interactions being applied by each hand, (*iii*) time spent while performing each tool/tissue interaction, (*iv*) the overall completion time, and (*v*) the variable F/T magnitudes being applied by the subjects through the endoscopic tools (*vi*) two hand collaborative.

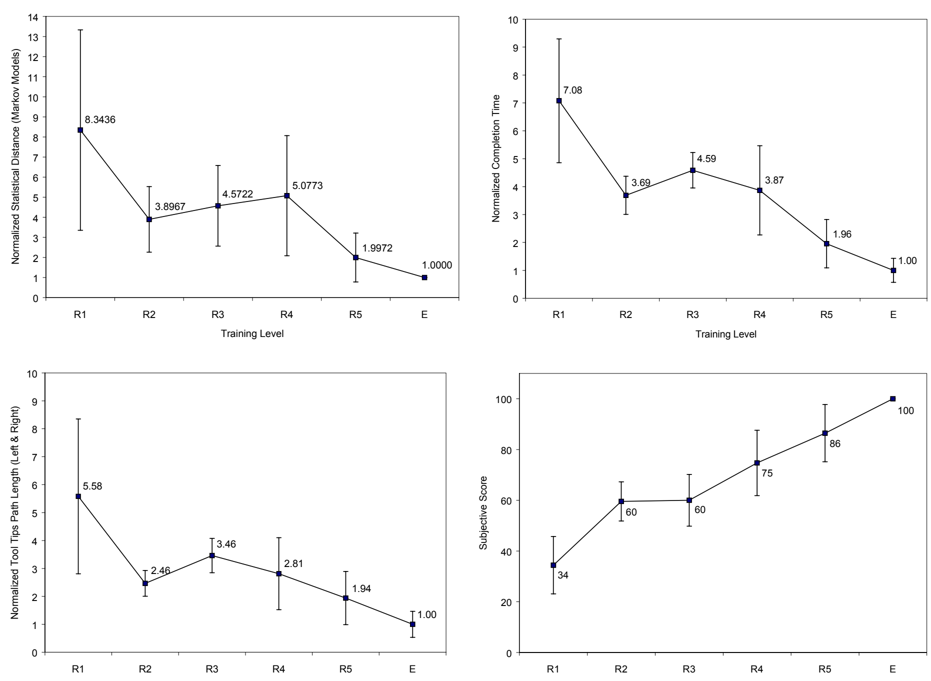


Fig. 4: Objective and subjective assessment of MIS suturing learning cure: Objective analysis based on Markov model normalized statistical distance (top left), normalized completion time (top right), and normalized path length of the two tool tips (bottom left), Subjective analysis – normalized scoring(bottom right). The average task completion time of the expert group is 98 sec and the total path length of the two tools is 3.832m

4. DISCUSSION

The Markov model proved to be a very powerful method encompassing multi modal sources of information (tools' kinematics and dynamics and completion time) into compact mathematical representation of the process associated with a complex task such as surgery. Moreover, once the model's architecture is determined and its parameters are calculated, it provides a quantitative and objective measure of surgical performance. Markov model capability to assess technical skill is supported by comparing the learning curve generated by other commonly accepted objective parameters like completion time, tool tip path length and by subjecting scoring analysis of an expert reviewer.

A feasible analogy to the proposed methodology for decomposing the surgical task is the human language. Based on this analogy, the basic states - tool/tissue interactions are equivalent to '*words*' of the MIS '*language*' and the 15 states forming the MIS '*dictionary*' or set of all available words. In the same way that a single word can pronounced differently by different people, the same tool/tissue or tool/object interaction can be performed differently by different surgeons. Differences in F/T magnitudes account for this different on *'pronunciation'*, yet different pronunciation of the *'word'* have the same meaning, or outcome, as in the realm of surgery. The cluster analysis was used to identify the typical F/T and velocities associated with each one of the tool/tissue tool/object interactions in the surgery '*dictionary*', or using the language analogy, to characterize different pronunciations of a word. Utilizing the '*dictionary*' of surgery, the MM was then used to define the process of each task or step of the surgical procedure, or in other words, '*dictating chapters*' of the surgical '*story*'. The proposed methodology retains its power by decomposing the surgical task to its fundamental elements - tool/tissue and tool/object interactions. These elements are inherent in MIS no matter which modality is being used.

Decomposing MIS and analyzing it using MM is one approach to developing objective criteria for surgical performance. The availability of validated objective measures of surgical performance and competency is considered critical for training surgeons and evaluating their performance. Systems like surgical robots or virtual reality simulators that inherently measure the kinematics and the dynamics of the surgical tools may benefit from inclusion of the proposed methodology. Using this information in real-time during the course of learning as feedback to the trainee surgeons may, increase performance efficiency in MIS, , and improve patient outcome.

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