



UNIVERSITÀ
DEGLI STUDI
FIRENZE

FLORE

Repository istituzionale dell'Università degli Studi di Firenze

Biomechanics-Machine Learning System for Surgical Gesture Analysis and Development of Technologies for Minimal Access Surgery

Questa è la Versione finale referata (Post print/Accepted manuscript) della seguente pubblicazione:

Original Citation:

Biomechanics-Machine Learning System for Surgical Gesture Analysis and Development of Technologies for Minimal Access Surgery / F. Cavallo; S. Sinigaglia; G. Megali; A. Pietrabissa; P. Dario; F. Mosca; A. Cuschieri. - In: SURGICAL INNOVATION. - ISSN 1553-3506. - ELETTRONICO. - 20:(2014), pp. 1-17. [10.1177/1553350613510612]

Availability:

The webpage <https://hdl.handle.net/2158/1210795> of the repository was last updated on 2022-01-31T14:09:22Z

Published version:

DOI: 10.1177/1553350613510612

Terms of use:

Open Access

La pubblicazione è resa disponibile sotto le norme e i termini della licenza di deposito, secondo quanto stabilito dalla Policy per l'accesso aperto dell'Università degli Studi di Firenze (<https://www.sba.unifi.it/upload/policy-oa-2016-1.pdf>)

Publisher copyright claim:

La data sopra indicata si riferisce all'ultimo aggiornamento della scheda del Repository FloRe - The above-mentioned date refers to the last update of the record in the Institutional Repository FloRe

(Article begins on next page)

Surgical Innovation

<http://sri.sagepub.com/>

Biomechanics–Machine Learning System for Surgical Gesture Analysis and Development of Technologies for Minimal Access Surgery

Filippo Cavallo, Stefano Sinigaglia, Giuseppe Megali, Andrea Pietrabissa, Paolo Dario, Franco Mosca and Alfred Cuschieri

SURG INNOV 2014 21: 504 originally published online 2 December 2013

DOI: 10.1177/1553350613510612

The online version of this article can be found at:

<http://sri.sagepub.com/content/21/5/504>

Published by:



<http://www.sagepublications.com>

On behalf of:



Institute for Research into Cancer of the Digestive System

Additional services and information for *Surgical Innovation* can be found at:

Email Alerts: <http://sri.sagepub.com/cgi/alerts>

Subscriptions: <http://sri.sagepub.com/subscriptions>

Reprints: <http://www.sagepub.com/journalsReprints.nav>

Permissions: <http://www.sagepub.com/journalsPermissions.nav>

>> [Version of Record](#) - Sep 11, 2014

[OnlineFirst Version of Record](#) - Dec 2, 2013

[What is This?](#)

Biomechanics–Machine Learning System for Surgical Gesture Analysis and Development of Technologies for Minimal Access Surgery

Surgical Innovation
2014, Vol. 21(5) 504–512
© The Author(s) 2013
Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/1553350613510612
sri.sagepub.com


Filippo Cavallo, PhD¹, Stefano Sinigaglia, PhD¹, Giuseppe Megali, PhD², Andrea Pietrabissa, MD³, Paolo Dario, PhD¹, Franco Mosca, MD², and Alfred Cuschieri, MD⁴

Abstract

Background. The uptake of minimal access surgery (MAS) has by virtue of its clinical benefits become widespread across the surgical specialties. However, despite its advantages in reducing traumatic insult to the patient, it imposes significant ergonomic restriction on the operating surgeons who require training for the safe execution. Recent progress in manipulator technologies (robotic or mechanical) have certainly reduced the level of difficulty, however it requires information for a complete gesture analysis of surgical performance. This article reports on the development and evaluation of such a system capable of full biomechanical and machine learning. **Methods.** The system for gesture analysis comprises 5 principal modules, which permit synchronous acquisition of multimodal surgical gesture signals from different sources and settings. The acquired signals are used to perform a biomechanical analysis for investigation of kinematics, dynamics, and muscle parameters of surgical gestures and a machine learning model for segmentation and recognition of principal phases of surgical gesture. **Results.** The biomechanical system is able to estimate the level of expertise of subjects and the ergonomics in using different instruments. The machine learning approach is able to ascertain the level of expertise of subjects and has the potential for automatic recognition of surgical gesture for surgeon–robot interactions. **Conclusions.** Preliminary tests have confirmed the efficacy of the system for surgical gesture analysis, providing an objective evaluation of progress during training of surgeons in their acquisition of proficiency in MAS approach and highlighting useful information for the design and evaluation of master–slave manipulator systems.

Keywords

surgical gesture analysis, biomechanical analysis of movement, machine learning approach, metrics and benchmarks, ergonomics, surgical robotics

Introduction

Minimal access surgery (MAS) introduced a paradigm shift in surgery by drastic reduction of the access trauma to the patient inherent to traditional open surgery. Instead of major laparotomies, operations are performed externally using images of the operative field with instruments inserted through small ports (5–10 mm). The downside to MAS is increased difficulty in surgical manipulation using long slender instruments with limited degrees-of-freedom (DoF; $n = 4$) compounded by marked degradation of the tactile feedback, eye–hand coordination, and loss of stereoscopic vision. All these adverse ergonomic factors contribute to a significant increase in the level of difficulty in the execution of the operations. Thus, the benefits of MAS (shorter recovery time, lower risk of infection, less pain/trauma, reduction in hospital stay) are

marred by increased risk of iatrogenic injuries, unless proficiency is acquired by training in the MAS approach.

In the quest for improved clinical outcome of patients treated by the MAS approach, 3 requirements are recognized: (a) efficient training programs and objective methodologies to evaluate surgical performance, (b) design of new

¹The BioRobotics Institute, Scuola Superiore Sant'Anna, Pisa, Italy

²Transplantation and New Technologies at Cisanello Hospital, Pisa, Italy

³University of Pavia, Fondazione IRCCS Policlinico San Matteo, Pavia, Italy

⁴University of Dundee, Dundee, United Kingdom

Corresponding Author:

Filippo Cavallo, The BioRobotics Institute, Scuola Superiore Sant'Anna, Viale Rinaldo Piaggio 34, Pontedera (PI) 56025, Italy.
Email: f.cavallo@sssup.it

ergonomic surgical instruments/handheld manipulators with increased DoF, and (c) the development of the next generation of robotic systems with tactile feedback for MAS surgery. In this context, the current literature indicates the importance of analysis of surgical gesture as a quantitative index analysis of surgical performance for the development and progress of advanced technologies for MAS.

The efficient training programs for novice surgeons use clearly defined metrics for the objective assessment of the proficiency–gain curve of surgeons by the Observational Clinical Human Reliability Analysis (OC-HRA)^{1–3} until they reach the proficiency zone when they can perform MAS operations consistently well and to an acceptable standard of surgical care, that is, become expert surgeons. Objectively this has to be based on studies on the perceptual and mechanical properties of surgical gesture during the training period. A similar approach can also be used for the design of surgical instruments/manipulators providing accurate evaluation of their ergonomics and functionalities, which confirm their advantages including the effect on the posture and fatigue of surgeons.⁴ The analysis of surgical gesture is of crucial importance for the development of smart surgical robotic systems,⁵ able to automate and enhance safety of surgical MAS operations through autonomous or shared control, by providing more accurate kinematics and dynamic constraints. Baseline data and evaluation methods for demonstrating relative improvement in performance will be a feature of the next generation of smart surgical robots, which will be based on systems able to learn from existing data, or at least learn to recognize, optimal surgical gestures.

In the reported literature, studies on the analysis of surgical gesture have been performed in several ways: observing operations and unsupervised (expert) and supervised (trainees) operating on models, human cadavers, and animals using embedded sensor systems in trainer boxes or virtual simulators. For all of these approaches, different metrics have been proposed, for example, execution time, trajectories, velocity, acceleration, smoothness, error rates segmentation procedures, and so on.⁶ Various methodologies have been used to evaluate parameters of movement including video-recording, virtual reality simulators, robotic systems such as da Vinci, and so on.^{7–10} Most of these approaches have mainly focused on the assessment of surgeons' or novices' abilities based on the measurement of the difference in the skill level between experts and novices performing exercises with clearly defined objective metrics.

To our knowledge, there has not been any description of a complete system for surgical analysis that evaluates not only surgical performance but also provides an ergonomic assessment that can be used for the design of the next generation of wristed manipulators/robots. This article reports on the efficacy of a modular system for surgical

gesture analysis that exploits a holistic biomechanical and machine learning model of surgical gesture. The biomechanical model is based on the development of a muscle–skeleton model of surgeon during MAS by means of the LifeMOD-Adams software platform (for kinematics, dynamics, and muscle parameters of surgical gesture) and the machine learning approach by means of the Hidden Markov Models (HMM) to segment and recognize principal phases of surgical gesture.

Methods

The proposed analysis of surgical gesture was based on a biomechanical approach and a machine learning approach. The first approach assumed that the surgeon and the laparoscopic instruments were components of one holistic mechanical system, for which a modeling process was implemented and kinematic and kinetic inverse and forward dynamic analysis were performed. In the second approach, the surgical performance was modeled with a learning process in which the machine learning algorithm automatically tuned its internal parameters to reproduce the physical process output values.

Modeling Process and Gesture Analysis on Adams-LifeMOD Platform

The Automatic Dynamic Analysis of Mechanical Systems software (ADAMS; MSC Software Corporation, Newport Beach, CA) in combination with the BRG.LifeMOD software module for emulation of human motion and activities was used to model and simulate the surgical setting, for example, subject performing surgical procedures with surgical instruments. The human structure (limbs, joints, muscles, and neuromuscular system [GeBOD anthropometric database]) and the surgical environment (surgical instruments and arrangement) were modeled initially. This was followed by simulation of the surgical procedures to compute the motion behavior and measure kinematic and kinetic parameters: (a) position, velocity, and acceleration of head, right and left hand, lower arm, scapular, upper arm, lower torso, neck, and upper torso; (b) torque values in sagittal, transverse, and frontal planes of the lower neck, right and left scapular, shoulder, arm, and wrist; and (c) force, translational displacement, and translational velocity of the trapezius, deltoids, pronator, biceps, latissimus dorsi, brachioradialis, E-carpi, and F-carpi.

Specifically, the simulation consisted of inverse and forward dynamic simulations. In the first inverse dynamic simulation, the motion was determined through position data from the ODL, using the Optotrack Certus system. Based on the trajectories of the 3D markers, joint angulations and muscle shortening/lengthening patterns were calculated for use in the subsequent dynamic simulation. After

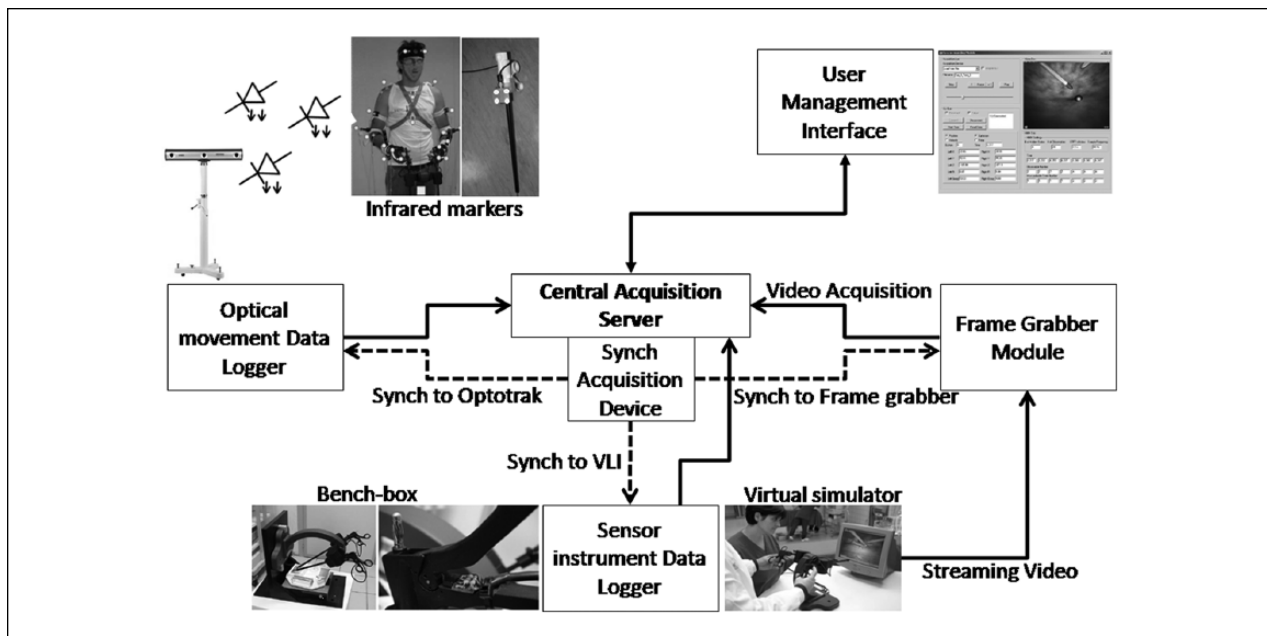


Figure 1. Overview of the entire modular gesture analysis system.

the inverse dynamics simulation was performed, the measured joint angulations and shortening/lengthening patterns were used in the forward dynamic simulation to calculate joint torques and muscle forces, taking into consideration the influence of the external forces (gravity, contact, etc).

Machine Learning

The Machine Learning¹¹ approach and in particular the HMM were used to create a statistical model describing the physical aspects of surgical procedures starting from observations of the whole data related to the process itself. The Machine Learning approach for surgical gesture analysis and recognition is necessary for a detailed strictly biomechanics analysis providing a high-level description of complex movements requiring high-level abstraction and multimodal data fusion.

The basic idea is to create an “expert model” able to describe, recognize, and better understand the expert gestures. Based on this, we modeled performances executed by expert surgeons through HMM as input kinematics of the laparoscopic instruments. The first relevant application of this expert model was its use as reference standard for surgical performance evaluation with objective metrics.^{9,10}

Instruments

The modular system for gesture analysis comprises 5 principal modules, allowing synchronous acquisition of multimodal surgical gesture signals from different sources and

scenarios. The 5 modules are the following: (a) a Central Acquisition Server (CAS), which acts as coordinator of the entire system and permits recording and online processing of incoming data from other modules; (b) User Management Interface (UMI) for managing the entire system, adding or removing data sources and setting the nature of experimental sessions; (c) Optical movement Data Logger (ODL) for the acquisition of 3D positions of surgeons’ limbs, body, and surgical instruments; (d) Sensor instrument Data Logger (SDL) for capturing movement signals and status of the surgical instruments being used; and (e) Frame Grabber Module (FGM) for video streaming from any video source included in the scenarios (Figure 1).

The system was designed to operate in 3 settings: virtual simulators (including daVinci simulator), trainer boxes, and actual operating room. In all these settings, different surgical gesture signals could be acquired depending on the sensors used.

Central Acquisition Server

The CAS module coordinates the other modules and records surgical gesture signals. It provides a synchronization of signals coming from the other modules to guarantee the same time scale of contemporaneous data from different sources. The synchronization of the systems is obtained by means of a Synch Acquisition Device, which generates 3 different kinds of trigger signals, each detected by different acquisition device.

User Management Interface

The UMI integrates all the data provided by other modules, allowing the user to set all parameters and to monitor data flow. Moreover, it allows mixing of real time and recorded data flow, enabling the software to act as a platform to reload and play raw acquired data for comparison with offline processed data.

Optical movement Data Logger

The ODL records body position and motion data of surgeon's limbs, that is, head and upper torso, and of surgical instruments through the Optotrak Certus system (Northern Digital Inc, Waterloo, Ontario, Canada). To date, the ODL has been used for the acquisition of movements of surgeon's limbs in settings related to virtual laparoscopic simulators and trainer bench-box, but it can also be used for the acquisition of movements of surgical instruments during live surgical operations. The Optotrak Certus System is an optical localization instrument that tracks up to 512 infrared LEDs at a maximum frame rate of $4600/(n + 2)$ Hz (n being number of LEDs used).

Supports have been designed to bind the markers on the subjects' upper body and on the surgical instruments. The upper body markers were placed according to a modified Adams "plug-in-gait" protocol¹² to import and process the positions of the 3D markers by means of LifeMOD-Adams software: 2 markers are placed over the temples, 2 on the torso (on the jugular notch and on the xiphoid process of the sternum), and 6 in each arm (on the acromio-clavicular joint, on the upper arm between the elbow and the shoulder marker, on the lateral epicondyle, on the lower arm between the wrist and the elbow marker, on the wrist, thumb, and little finger).

The markers for surgical instruments are mounted on a rigid frame, designed for connection to the surgical instrument and with a sterilizable self-lock/unlock system in order to use the same sensory system on different instruments with similar handles.

Sensor Instrument Data Logger

The SDL module records the position and orientation of surgical instruments (tips) and the status of the end effectors (grasp value) in the scenarios related to virtual laparoscopic simulators and trainer bench-box. Depending on different experimental setup, the SDL module can be implemented in 2 different ways. In the virtual laparoscopic setting, the position and orientation of the instruments and the status of the end effectors are recorded using the Virtual Laparoscopic Interface (VLI, produced by Immersion Corporation, San Jose, CA). The VLI tracks the motion of a pair of virtual laparoscopic surgical

instruments, each moving in with 5 degrees of freedom (position and orientation of tips and grasping value of end effectors), with acquisition frequency up to 1 KHz. In the trainer bench-box setting, the arrangement described above is modified by replacement with real surgical instruments. Infrared proximity sensors integrated on the handles are used to trace grasping values of the real instruments (Figure 1).

Frame Grabber Module

The FGM module consists of a digital frame grabber able to capture videos provided by the laparoscopic simulator (for exercises performed in virtual environment), by a standard camera (in bench-box) and by the endoscopic camera signal (for real interventions). For each exercise a *.avi file is created.

Experimental Protocols

The modularity of the system allowed to test different experimental protocols, according to the setting in which subjects operated. Potentially the system could be used in virtual reality, bench box, and operating room settings. Table 1 depicts how the sensorized modules of the system were installed and used for each setting.

For the virtual reality setting, we used a well-validated commercial laparoscopic simulator, LapSim Basic Skills 3.0 (Surgical Science AB, Goteborg, Sweden), as previously reported.¹³ The set of 5 exercises, described in Table 2, was chosen.

In the trainer bench box setting, the SDL, used for the virtual laparoscopic simulator, was fixed in vertical position to a home-made base and used in reverse orientation over the surgical trainer with real surgical instruments. The same virtual exercises were performed by the participating subjects with the addition of the knot tying exercise. In the operating room, the surgeon's instruments were tracked by using the optical localization system during the entire duration of the intervention.

To demonstrate the efficacy of this modular system for surgical gesture analysis both with a biomechanical and machine learning approach, this article preliminarily concentrates on the Virtual Laparoscopic setting, whose achieved results could be generalized also to the other settings.

Results

The 2 proposed methodological approaches allowed us to calculate kinematic and kinetic parameters and likelihood-based metrics.

The measurement of kinematic parameters was used to estimate quality metrics, such as duration, path length,

Table 1. Description of How the Sensorized Modules (ie, the Optotrak Certus, the Laparoscopic Virtual Interface, and the Frame Grabber) Could Be Used in the Different Experimental Settings.

	ODL	SDL	FGM
Virtual Reality	Infrared markers placed on the subject's body for measuring kinetic and kinematic parameters	Laparoscopic Interface placed on a table for measuring kinematic parameter of surgical instruments' tips	Frame Grabber plugged to the video board of the computer to acquire the virtual laparoscopic scenes and perform video analysis
Bench Box	Infrared markers placed on the subject's body for measuring kinetic and kinematic parameters	Laparoscopic Interface placed with the base in vertical position and used with surgical instruments in reverse orientation for measuring kinematic parameter of surgical instruments' tips	Frame Grabber plugged to a camera, pointed to the bench box, to acquire the laparoscopic scenes and perform video analysis
Operating Room	Infrared markers placed on the surgical instruments for measuring kinematic parameters	Not used	Frame Grabber plugged to the video output of the endoscope and perform video analysis

Table 2. Description of the 5 Exercises of the Virtual LAPAROSCOPIC simulator, Presented Also as Combination of Submovements/Tasks That Highlights Their Complexity.

Exercise Type	Description	Submovements/Tasks
Navigation Instrument (NVI)	Subject has to touch, alternatively with right and left instrument tip, balls that appear in the virtual operative field	Reaching
Coordination (COO)	Subject controls the camera with one hand to locate balls appearing sequentially in the virtual operative field and moves each ball toward the target site with the other hand	Reaching, moving/holding
Grasping (GRA)	Subject reaches and grasps blood vessels that appear sequentially in the virtual operative field, alternatively with right and left grasping instruments	Reaching, grasping, pulling
Lifting and Grasping (L&G)	Subject reaches and grasps blood vessels that appear sequentially in the virtual operative field, alternatively with right and left grasping instruments	Reaching, lifting, grasping, moving/holding
Cutting (CUT)	Subject grasps the extremity of a vessel with one instrument to cut it with an energized instrument (ultrasonic shears) activated by a foot pedal	Reaching, grasping (fine), holding, cutting, holding/moving

mean speed, maximum speed, mean acceleration, maximum acceleration, normalized jerk (measure of the motion smoothness and rate of change in acceleration, normalized with respect to duration of the exercise and path length), and energy expenditure (measured as the integral of the magnitude of the total Acceleration Vector, which is correlated to the energy expenditure).¹⁴ The measurement of kinetic parameters, such as the muscle forces, was used to estimate the load on muscles and, hence, quantitative fatigue resulting from performing the exercises. Particularly the fatigue was considered as the work (N m) done by each single muscle, which was computed integrating the force multiplied by the translational velocity among the time.

These metrics presented different values according to the nature of the exercise and the expertise of the subjects.

A group of 9 medical students from the last year of the Faculty of Medicine, University of Pisa, Italy, and 2 expert surgeons from the Department of Surgery, Transplantation and New Technologies at Cisanello Hospital, Pisa, Italy, were recruited to perform 5 cycles of the 5 exercises. The 2 surgeons had long experience in laparoscopy, respectively, with more than 200 and 600 laparoscopic interventions. Normalized Jerk and Energy Expenditure were higher in more complex exercises, such as combined L&G and CUT. Additionally, they were lower for expert surgeons compared to trainees (Figures 2 and 3).

Table 3 presents the energy expenditure on the right hand for one novice (Subj01) and surgeon (Surg02) for the first and last trial in the NVI and CUT exercise. It is evident that the subject performed the exercise with a

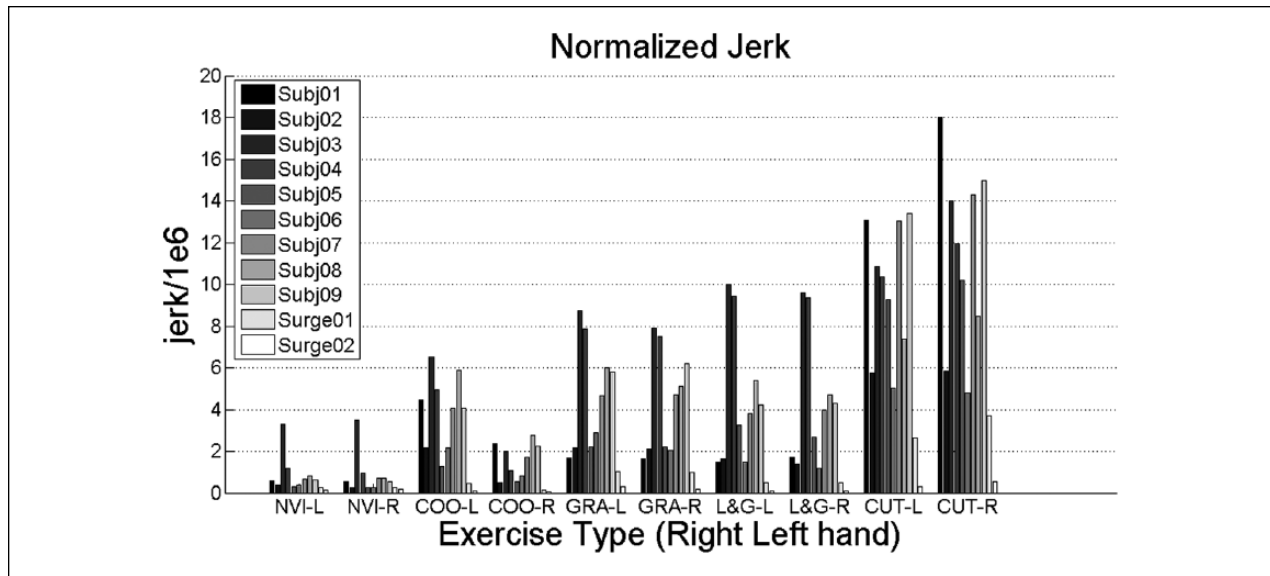


Figure 2. Normalized jerk of trainees and expert surgeons for each type of exercise, averaged on a session of 5 trials.

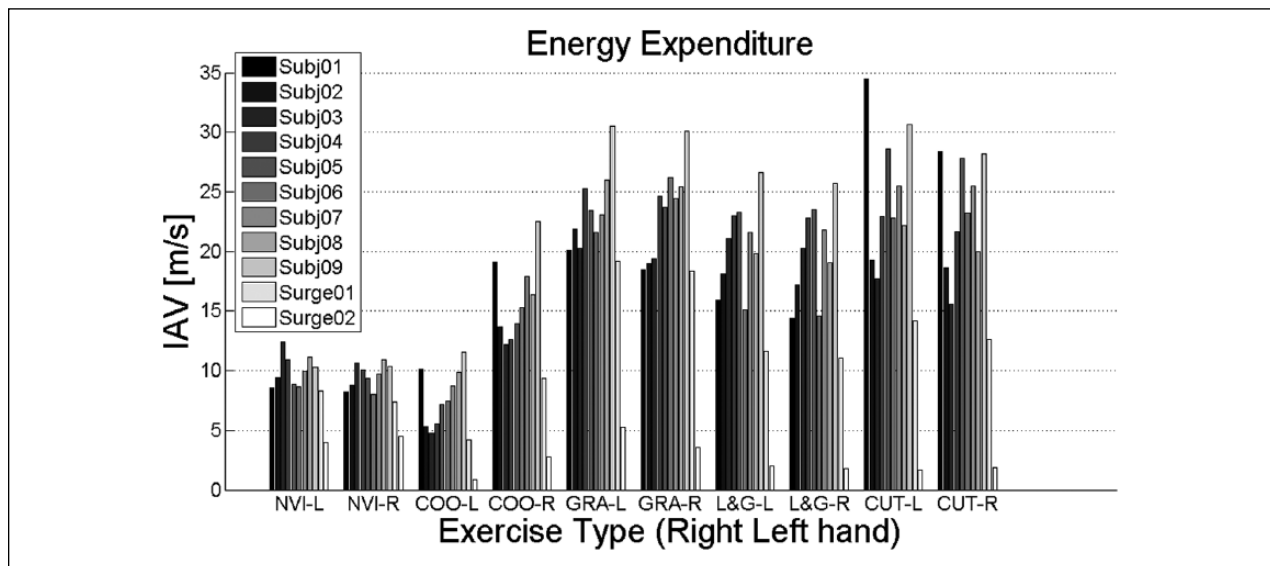


Figure 3. Energy expenditure of trainees and expert surgeons for each type of exercise, averaged on a session of 5 trials.

lower energy consumption in the fifth trial with respect to the first one, demonstrating to be more skilled at the end of the session. On the contrary, the surgeon, being already trained, had very low improvements during the session. Table 3 presents also the averaged energy expenditure and relative standard deviation, which are definitely lower in the expert surgeon.

As shown in Figures 2 and 3, there were similar loads between the left and right arms in exercises where both hands are used during manipulations with the same instrument (Navigation, Grasping, and Lift and Grasping), whereas in exercises where the hands manipulate different

Table 3. Energy Expenditure on the Right Hand for One Novice and Surgeon for the First and Last Trials in the NVI and CUT Exercises and Relative Averaged and Standard Deviation Values Calculated Over the 5 Trials.

	Trial 1	Trial 5	Mean	SD
NVI				
Subj01	9.84	6.23	8.21	1.29
Surg02	4.25	4.11	4.50	0.38
CUT				
Subj01	34.96	18.48	28.41	11.17
Surg02	1.85	1.71	1.90	0.14

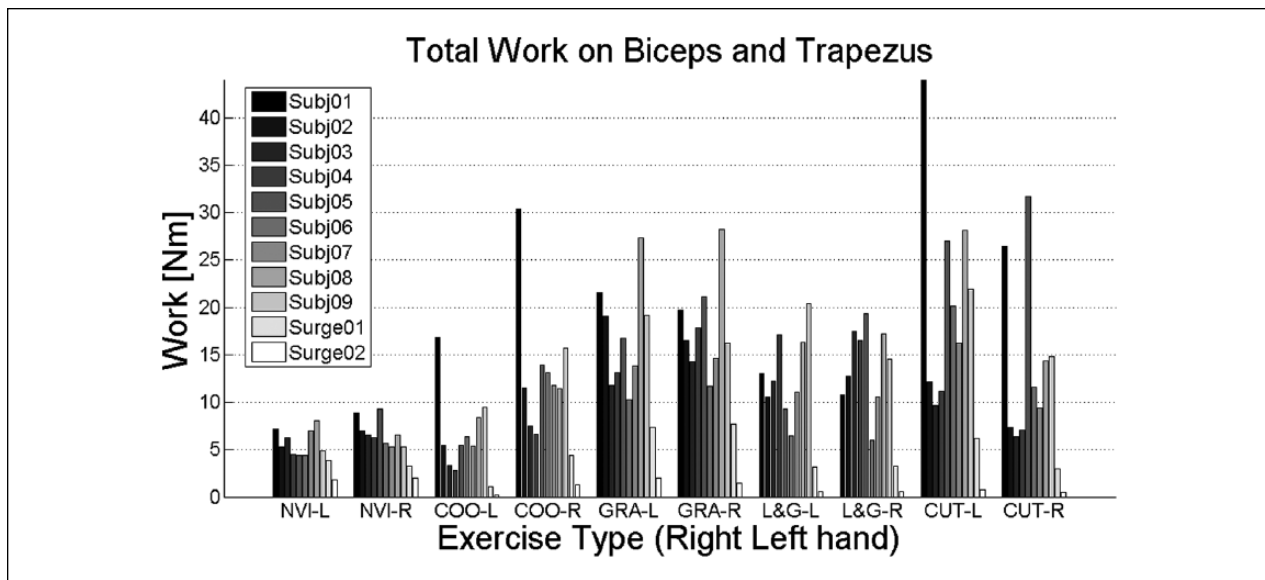


Figure 4. Total Work on Biceps and Trapezius in Right and Left Arms of 9 Novices and 2 Expert Surgeons for Each Type of Exercise, Averaged Data From Session of 5 Trials.

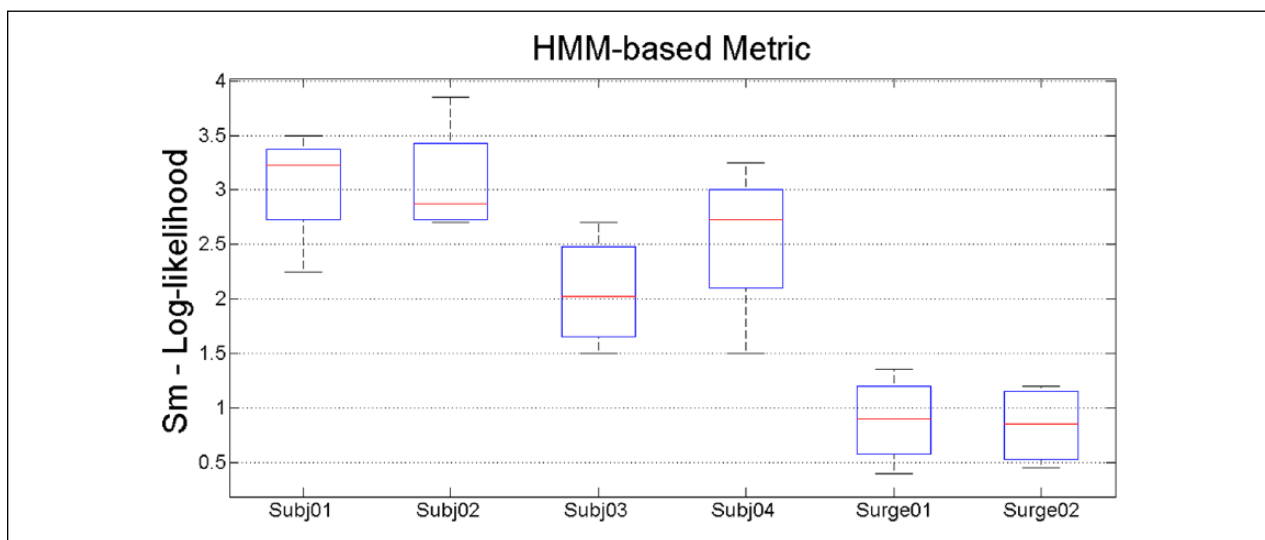


Figure 5. Evaluation of surgical performance in terms of log-likelihood.

instruments, such as COO where the left hand is used to hold the endoscope and the right for the grip, the loads were different. Again low loads on muscles were observed among expert surgeons (see Figure 4). More details about this approach can be found in Cavallo et al.¹³

The evaluation metric S_m is defined as the value of the log-likelihood of a generic performance compared to the expert model. The log-likelihood value gives a measure of the probability that a generic performance is generated by the expert model. The expert model created was able to recognize expert surgeon performances. In this case, 4 medical students and the same expert surgeons from the Department

of Surgery, Transplantation and New Technologies at Cisanello Hospital, Pisa, Italy, were recruited to perform 5 cycles of the NVI exercise. Observation sequences relative to performances executed by expert surgeons produced values of S_m smaller than the values produced by inexperienced surgeons using data on performance on the same exercises as shown in the Figure 5.

Discussion

The system proposed is characterized by high modularity and flexibility, which enable its use in different surgical

procedures and settings: surgical training centers and in operating rooms during live surgical operations. It represents a new paradigm for analysis of surgical performance and related surgical instrumentation including robotic systems and their development for MAS. In essence, the system provides a global evaluation of ergonomics and gesture analysis during execution of MAS operations, allowing us to identify expert models of trained surgeons and evaluate objective metric.

Indeed this metric had the advantage of being task independent because its input is based only kinematic data related to surgeon's movements. Moreover, it compares the character of the data acquired from trainees with data based on manipulations by expert surgeons. It is independent of both setting and nature of the exercises and objectively measures the level of skill of the operator. Thus, the expert model allows an improved understanding of surgical gesture as it includes information not otherwise obtainable (hidden states), which can discriminate highly between levels of expertise.^{9,10} The automatic recognition of these "hidden meaningful states" has formed the basis for the development of surgical robots with shared control between the human operator and the machine, in order to avoid dangerous movements, prevent incorrect or unproductive movements, and automate repetitive procedures. More details about this approach can be found in earlier studies.^{9,15} In surgical training, the system to date has been evaluated during training of residents on bench trainers and virtual simulators for direct manual laparoscopic surgery (Lapsim), but there is no reason why it cannot be profitably used during training on the da Vinci Surgical System (Intuitive Surgical, Sunnyvale, CA).¹⁵⁻²⁰ The recent acquisition of the da Vinci simulator in our unit will enable evaluation of the system in the transfer of skills for robotic-assisted surgery, and these studies are planned in the EndoCAS training centre of the Department of Surgery in Pisa.

We also envisage the system as being very useful in the design, development, and evaluation of new instrumentation including the next generation of surgical robots for MAS. In this respect, the key issues in the development of the next generation of surgical robots include interaction with the surgeon through effective human-machine interfaces and a full understanding of the surgical gesture, which has to be reproduced by the robot, and optimal integration of tactile feedback sensing, all of which can be addressed by the system.

Ongoing work in our laboratory is devoted to the analysis of surgical action in order to refine objective metrics of performance by the system during the training of surgeons. Further developments will focus on improved function and coordination of the component subsystems, increased automation, and machine learning potential of the system together with an interface with the OC-HRA.

Conclusions

We have developed and evaluated a machine learning platform for the construction of a holistic biomechanical model of the surgeon and of the instruments used for MAS that uses a Markov chain for gesture analysis. Preliminary studies indicate its potential for training of surgeons and for the research and development of manipulative technologies for MAS including robotic surgery.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

1. Tang B, Hanna GB, Joice P, Cuschieri A. Identification and categorization of technical errors by Observational Clinical Human Reliability Assessment (OCHRA) during laparoscopic cholecystectomy. *Arch Surg*. 2004;139:1215-1220. doi:10.1001/archsurg.139.11.1215.
2. Tang B, Hanna GB, Carter F, Cuschieri A. Competence assessment of laparoscopic operative and cognitive skills: Objective Structured Clinical Examination (OSCE) or Observational Clinical Human Reliability Assessment (OCHRA). *World J Surg*. 2006;30:527-534.
3. Talebpoor M, Alijani A, Hanna GB, Moosa Z, Tang B, Cuschieri A. Proficiency-gain curve for an advanced laparoscopic procedure defined by Observation Clinical Human Reliability Assessment (OCHRA). *Surg Endosc*. 2009;23:869-875. doi:10.1007/s00464-008-0088-5.
4. Tonet O, Focacci F, Piccigallo M, et al. Comparison of control modes of a hand-held robot for laparoscopic surgery. Paper presented at: Proceeding of the 2006 MICCAI Conference; 2006; Copenhagen, Denmark.
5. Lum MJH, Trimble D, Rosen J, et al. Multidisciplinary approach for developing a new minimally invasive surgical robotic system. Paper presented at: BioRob 2006; February 20-22, 2006; Pisa, Italy.
6. Cao CGL, Mackenzie CL, Payandeh S. Task and motion analyses in endoscopic surgery. Paper presented at: 1996 ASME IMECE Conference Proceedings: 5th Annual Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems; Atlanta, Georgia; pp. 583-590.
7. Cotin S, Stylopoulos N, Ottensmeyer M, Neumann P, Rattner D, Dawson S. Metrics for laparoscopic skills trainers: the weakest link! In: Dohi T, Kikinis R, eds. *MICCAI 2002* (Lecture Notes in Computer Science, No. 2488). Berlin, Germany: Springer Verlag; 2002:35-43.
8. Dario P, Guglielmelli E, Allotta B, Carrozza MC. Robotics for medical applications. *IEEE Robot Automat Mag*. 1996;3:4456.
9. Megali G, Sinigaglia S, Tonet O, Cavallo F, Dario P. Understanding expertise in surgical gesture by means of hidden Markov models. Paper presented at: BioRob 2006; February 20-22, 2006; Pisa, Italy.

10. Megali G, Sinigaglia S, Tonet O, Dario P. Modelling and evaluation of surgical performance using hidden Markov model. *IEEE Trans Biomed Eng.* 2006;53:1911-1919.
11. Rabiner LR. A tutorial on hidden Markov models and selected applications in speech recognition. *Proc IEEE.* 1989;77:257-286.
12. MSC Software. *ADAMS Manual*. Newport Beach, CA: MSC Software; 2003.
13. Cavallo F, Pietrabissa A, Megali G, et al. Proficiency assessment of gesture analysis by means of the surgeon's musculoskeletal model. *Ann Surg.* 2012;255:394-398.
14. Cavallo F, Megali G, Sinigaglia S, Tonet O, Dario P. A biomechanical analysis of surgeon's gesture in a laparoscopic virtual scenario. *Stud Health Technol Inform.* 2006;119:79-84.
15. Sinigaglia S, Megali G, Tonet O, Dario P. A machine learning approach to understand surgical performance. Paper presented at: CARS2006; June 2006; Osaka, Japan.
16. Payandeh S, Lomax AJ, Dill J, Mackenzie CL, Cao CG. On defining metrics for assessing laparoscopic surgical skills in a virtual training environment. *Stud Health Technol Inform.* 2002;85:334-340.
17. Risucci D, Cohen JA, Garbus JE, Goldstein M, Cohen MG. The effects of practice and instruction on speed and accuracy during resident acquisition of simulated laparoscopic skills. *Curr Surg.* 2001;58:230-235.
18. Verner L, Oleynikov D, Holtmann S, Haider H, Zhukov L. Measurements of the level of surgical expertise using flight path analysis from da Vinci robotic surgical system. *Stud Health Technol Inform.* 2003;94:373-378.
19. Kelly DC, Margules AC, Kundavaram CR, et al. Face, content, and construct validation of the da Vinci Skills Simulator. *Urology.* 2012;79:1068-1072.
20. Hung AJ, Patil MB, Zehnder P, et al. Concurrent and predictive validation of a novel robotic surgery simulator: a prospective, randomized study. *J Urol.* 2012;187:630-637.