Development of Computer Vision Algorithm for Surgical Skill Assessment

Gazi Islam[1], Kanav Kahol[1], John Ferrara[2], and Richard Gray[3]

[1] Dept. of Biomedical Informatics, Arizona State University, Phoenix, AZ 85004
[2] Phoenix Integrated Surgical Residency, Phoenix, AZ 85006
[3] Department of Surgery, Mayo Clinic, Scottsdale, AZ 85054
{gislam,kanav}@asu.edu, johnj@ferrara.cc, gray.richard@mayo.edu

Abstract. Advances in medical field have introduced new and progressive ways to intensify surgical resident training and surgical skills learning by developing systematic simulator training programs alongside traditional training. Both training methods need constant presence of a competent surgeon to subjectively assess the surgical dexterity of the trainee. Several studies have been done to measure user's skill objectively and quantitatively, but all use sensors which could interfere with skill execution. Also the sterilization process in an actual surgery makes the use of sensors impossible. This paper proposes a novel video-based approach for observing surgeon's hand and surgical tool movements in both surgical operation and training. Data is captured by video camera and then explored using computer vision algorithm. Finally by analyzing basic statistical parameters, observer-independent model has been developed through objective and quantitative measurement of surgical skills.

Keywords: Skill Assessment, Surgical Training, Computer Vision, Motion Tracking.

1 Introduction

In last few decades, as the health care delivery is faced with demands for greater accountability and patient safety, the effective surgical performance measurement has gained an increasingly high profile. Development and advances in medical field have made the surgical skill acquisition more challenging than ever. To ensure the best surgical performance, systematic simulator training programs are being developed alongside traditional training in hospitals. It has been a new and progressive way to intensify surgical resident training and surgical skills learning. The traditional training method needs constant presence of a competent surgeon for measure the progress of the trainee. The assessment is done to evaluate the surgical dexterity, is highly subjective and lacking the quantitative data [1]. Simulator-based training has become very popular as it does not involve risk and patient discomfort. Several researches have been done to address the issue of evaluating the user's performance in the simulator-based training system. For accurately measure user's skill objectively and quantitatively, the system must satisfy the following requirements [2]: (1) the system

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must possess adequate sensing techniques to monitor the user's operation; (2) the system must extract relevant features from the sensing data; and (3) the system needs a good computational model to represent the skill demonstrated in the operation. Such a model is essential for accurately measuring the technical competence of the performance.

Tracking hand and surgical tool movement is one of the most important features in assessing surgical performance. Many sensor-based systems have been developed for accurate tracking of surgeon's hand or surgical tool movement. However, the integration of sensors often causes interference with the surgical execution. Moreover in actual surgery it is very difficult to use sensors as they need to be sterile. Also the extensive use of sensors makes the entire surgery and the training procedure more expensive.

This paper proposes a novel video-based approach for observing continuous, long sequence of surgeon's hand and surgical tool movements in both surgical operation or surgical training, and then modeling and evaluating the skill demonstrated in the observation. Hand movement of entire surgical procedure is captured using inexpensive video camera. Video data of the tool movement can also be obtained for minimal invasive surgery (MIS). Both of the video data are analyzed using computer vision algorithm and then integrated to correlate with user's skill level. For modeling the surgical skill, a stochastic approach is proposed that uses simple arithmetic mean and standard deviation of the processed data. Using this technique, observer-independent models can be developed through objective and quantitative measurement of surgical skills. Because of the non-contact nature of the tracking technique, the system is free from sterile issue and there is minimal interference with the skill execution, unlike other methods that employ instrumented gloves or sensor-based surgical tools.

2 Related Work

Specialized instrumented systems with the ability to measure surgical proficiency have been proposed. Examples of such systems are the BLUE-DRAGON system, MISTVR system, LapSim, ProMIS system, ROVIMAS system, WKS system, WB system, BSN technology, Immersion Simulators, etc. Many of these systems use time as a metric for measurement of surgical proficiency. Other measures of proficiency include kinematics of the laparoscopic tools (BLUE-DRAGON [3-5], ROVIMAS systems [1]). Some systems use generic measures such as smoothness of the movements as a measure of proficiency (ProMIS system [6]). WKS system [7-9] measures force and movement of the dummy skin in suture/ligature training system to evaluate performance. By using wireless sensor glove and body sensor network (BSN) technology [10], hand gesture data can be captured and analyzed with Hidden Markov Model (HMM) for surgical skill assessment. Several systems have been developed to measure performance in actual surgery. Wasada Bioinstrumentation (WB) system [11] uses a series of sensors to track head, arm and hand movement and as well as several physiological parameters to analyze surgeon's performance during laparoscopic surgery. Sadahiro, T et al. used force platform to measure fluctuations of operator's center of pressure (COP) [12] to estimate the skill level in the operating room. Most of these systems need multiple wearable sensors, which could interfere in operator's skill execution. Also the sensors need to sterile to be used in actual surgery and can make the entire surgery very expensive.

Chen, J. et al proposed a video-based system to track special markers on the glove [2]. However it requires consistent lighting and direct line-of-sight to the markers which might not be possible during actual surgery.

3 The Proposed Approach

3.1 Data Capture Setup

20 residents from different PGYN-levels have done the peg transfer exercise on Fundamental of Laparoscopic Surgery (FLS) [13] wearing purple colored gloves. Two video cameras were steadily used to capture video data of the hand movement. The internal videos from the FLS have also been recorded for capturing the tool movement.

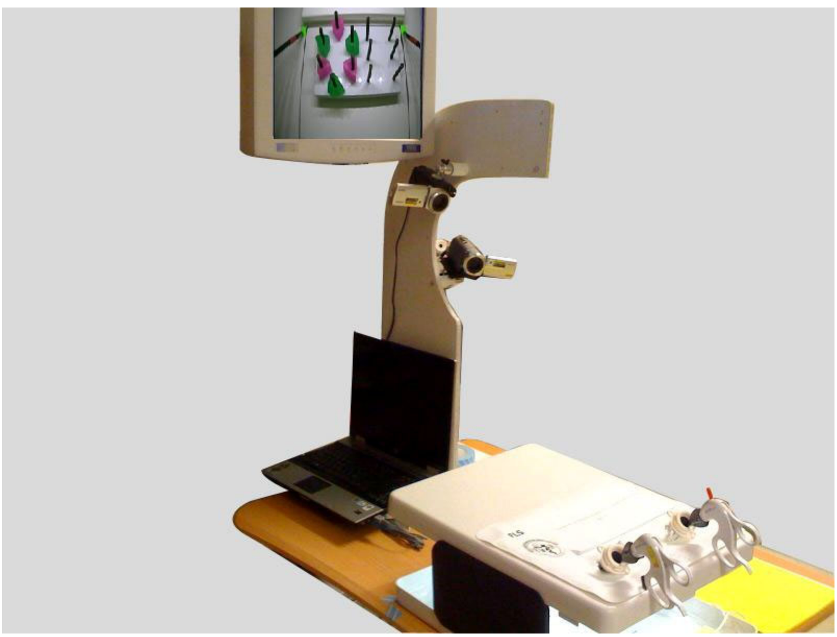

Fig. 1. Experimental setup

3.2 Methodology

Every participant has been asked to wear purple-colored surgical gloves. This color has been particularly chosen for easier detection of glove from the background objects. Then the participants chose two laparoscopic graspers and performed the pegboard transfer exercise on the FLS. The protocol for the exercise is – "Grasp a colored object with the non-dominant hand, transfer to the dominant hand and place it on the opposite side of the board. Repeat until all six have been transferred. Reverse process until initial state achieved."[13] During the exercise, hand movement has been captured using both the video cameras. Also the internal FLS video that captures tool movement has been written to the disk.

Fig. 2. Purple surgical gloves

All these video data have been analyzed by 'compute vision' algorithms [14]. In the late 1950s/early 1960s a new approach to the study of vision emerged in the form of 'compute vision'. Since then it's a rapidly developing technology that extracts and use information present in visual images. The potential practical benefits of computer vision systems are immense. The advancement of computer vision makes it very popular in the field of medical image analysis, human computer interaction (HCI), industrial inspection, security scanning, military intelligence, etc. in this paper computer vision has been applied in two steps –

1) Glove/object detection: Hand and tool movement videos have been analyzed using Open Source Computer Vision (OpenCV) [14] programs. The program uses histogram matching algorithm and quite accurately detects the purple gloves from the hand movement video and blue/pink colored objects from the tool movement video (Figure 5). Glove and tool detection are important as it reduces the noise that comes from other background movement captured in the video.
2) Motion capture: Once the glove/object detection is done, another OpenCV [14] program is used to capture movement data. The algorithm uses motion segmentation to show how an image changes over time. The trail of hand and object movement observation is done and pixel data for every frame are captured to analyze smoothness of movement (Figure 6).

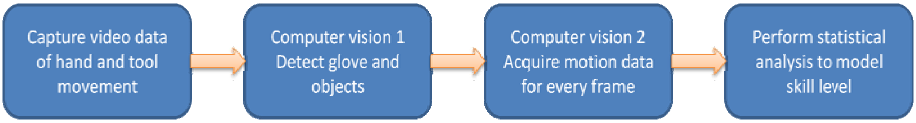

Fig. 3. Methodology

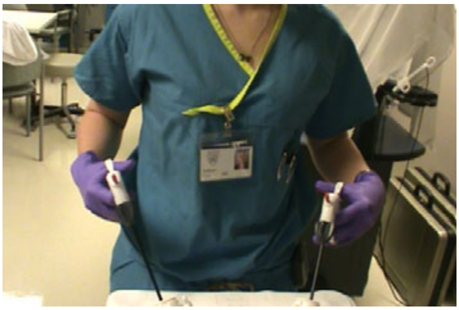

Fig. 4a. Hand movement capture

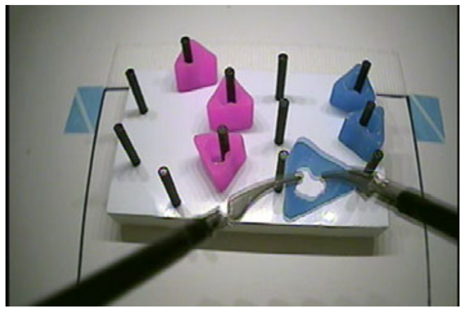

Fig. 4b. Tool movement capture

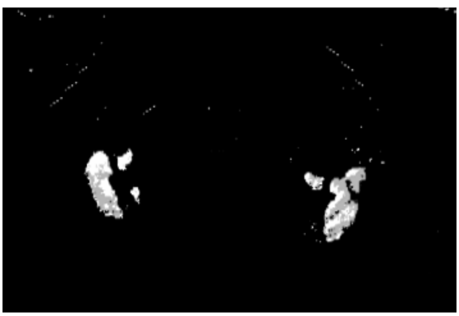

Fig. 5a. Glove detection

Fig. 5b. Colored object detection

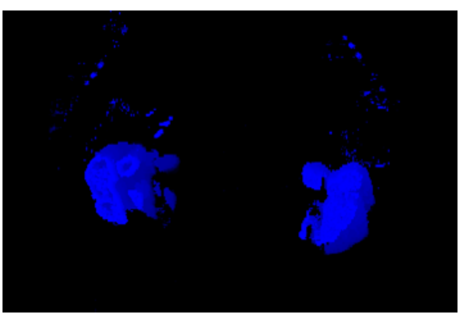

Fig. 6a. Hand movement detection

Fig. 6b. Tool movement detection

3.3 Data Analysis

The number of pixel value per frame for each participant has been studied with Matlab program for the hands and tools movement analysis. The lowest number of pixel value per frame is considered as the idle frame i.e. minimum or no motion. For every data-set, pixel values on each frame have been normalized using the corresponding idle frame. Arithmetic mean and standard deviation have been calculated for all the data sets. Finally, the ANOVE procedure [15] has been performed in SAS-a statistical analysis tool to observe the variance analysis.

4 Experimental Analysis/Results

The hand movements of 20 residents (5 experts, 5 intermediate and 10 novices) have been observed. Number of blue pixel per frame is inversely proportional to the smoothness of the hand movement. As we plot the normalized number of pixel over time, a clear distinction is observed between an expert, intermediate and novice (Figure 7). For expertise recognition, mean and standard deviation of each class of data have been calculated (Table 1).

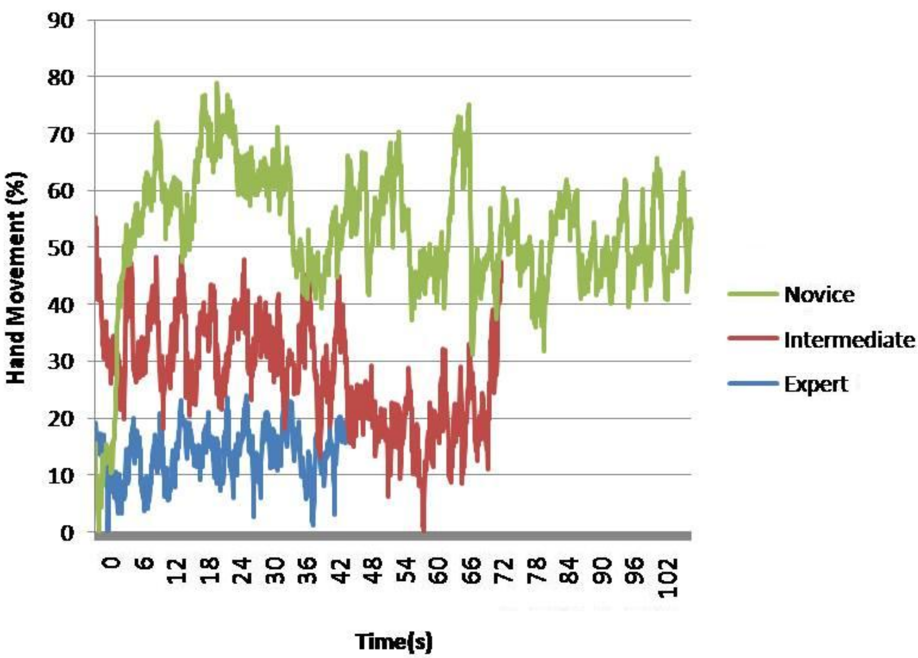

Fig. 7. Movement smoothness

Finally one-way ANOVA analysis [15] in SAS shows that the difference in mean is significant (significance probability = 0.0014). Arithmetic means with standard errors have been plotted in figure 8.

Table 1. Mean and standard deviation of data

	Expert	Intermediate	Novice
Mean	24.51	31.31	36.3
Std. Deviation	3.83	5.45	19.97

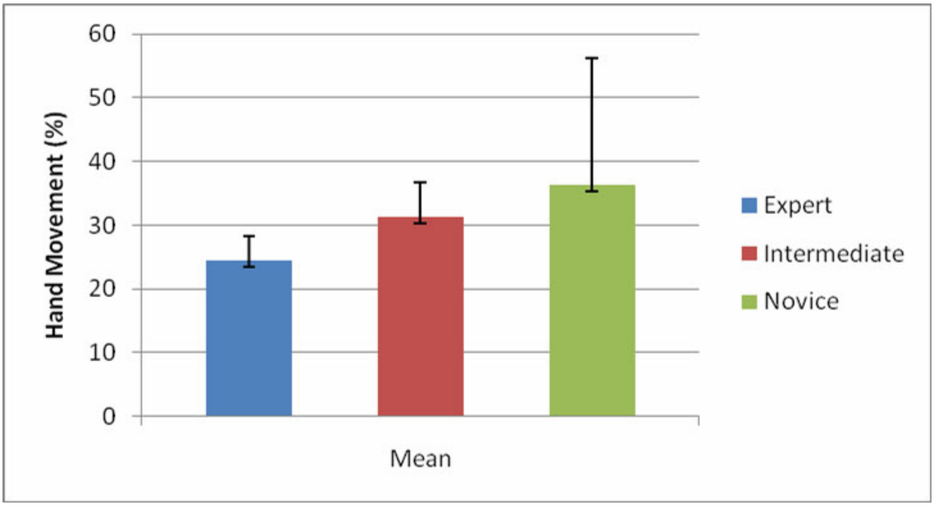

Fig. 8. ANOVA analysis

5 Conclusion and Future Work

The proposed approach indicates that computer vision based analysis of surgical movements may provide a suitable basis for expertise level analysis. Such a system will be a natural tool for evaluating surgical residents. As the system is based on the video data analysis of hand and tool movement rather than sensor-based data, it can easily be extended to provide real-time feedback to surgical interns while doing surgical exercise or to surgeons while performing an actual surgery. In, future we intend to extensively test the proposed methodology through controlled studies. Longitudinal studies will be conducted to evaluate surgical proficiency at various stages of training to fully evaluate the methodology and plot the learning curves.

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