Neuro-Endo-Activity-Tracker: An automatic activity detection application for Neuro-Endo-Trainer

Neuro-Endo-Activity-Tracker

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Abstract-Neuro-endoscopy is a highly demanding surgical specialty and requires dedicated training systems for imparting the skills. The assessment of surgical skills to identify the level of expertise of technical and cognitive skills, has primarily been performed subjectively by an expert. The development of objective motion analyses and automated skills evaluation can be a significant and suitable alternative. The video-based automatic segmentation can divide the primary activity into sub-tasks and then evaluate them by statistical analysis of motion. In this work, we developed an automated video-based surgical evaluation application. It identifies the basic eye-hand coordination and dexterity of a trainee, while performing a grasping and pick-place task on Neuro-Endo-Trainer. The activity was divided into subtasks using Mixture of Gaussian based background subtraction and Tracking Learning Detection algorithms. The kinematic analysis of the tool-tip trajectory was used to provide the synopsis of activity as feedback to the trainee for self-improvement.

Keywords— Neuro-endoscopy; video-analysis; Neuro endo trainer; skills evaluation; automated system

I. INTRODUCTION

Neurosurgery is a complex surgical procedure that demands various technical and cognitive skills. Minimally invasive techniques are gaining popularity in the field of neurosurgery due to the obvious advantages of the minimal incision, less blood loss, and fast post-operative recovery [1]. Neuroendoscopy is a minimally invasive surgery (MIS) or technique used to access the deep internal structures of the brain by making burr holes on the skull or through the nasal opening. The neuro-endoscope having a long rod-lens, a monocular camera view with its display projected on a 2-dimensional screen

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demands a different learning curve for the operating surgeon. It requires practice for eye-hand coordination, depth perception, bi-manual dexterity, and working with fulcrum effect in a limited space. So, the technical skills required for the surgery while using the microscope and endoscope varies and it demands different ways of evaluation techniques [2], [3]. The traditional surgical training in the operating room with the expert neurosurgeon is time-consuming, costly and involves patient risk factors [4].

Various technical skills necessary for neurosurgery can be imparted with the help of surgical simulation outside the operating room. Neuro-endoscopy training systems are available in the form of physical simulators, box trainers, virtual reality simulators, high fidelity cadavers and animal models [5] - [11].

Training systems should provide training for technical skills and should assess the particular skill imparted. The specific feedback provided to the trainee help them improve the learning curve. Such training systems should focus on a particular task rather than a procedure as a whole [12]. Simulation systems should contain various assessment methods and provide feedback to ensure efficient training, along with accreditation or certification [13] – [15]. Such training would ultimately lead to improved patient care. The assessment of surgical skills was always a subjective task performed by an expert [16] [17]. The component based objective evaluation is a good assessment method. This requires scoring to be performed using an objective scoring scale. The widely accepted objective scoring scale in laparoscopy is Objective structured assessment of technical skill (OSATS) [18]. The modified version of it applicable to neurosurgery is Neurosurgery Education and Training School- Skills Assessment Scale (NETS-SAS) [19]. The objective scoring to analyze the improvement of the trainee by an expert assessor would be a tedious task. The obstructing factors involved in repeated supervision either directly or while scoring from activity videos include human errors, bias, and boredom. This scoring task can be made easier with the help of sensors, physiological error detectors and use the video-based automatic surveillance [13], [20]- [23].

The video-based methods are the best opted technique for deployment in the real surgical setting [24]. The visualization of surgical site by microscopes or endoscopes can be directly recorded and does not require any external sensors or attachments that would hinder the surgical performance. Also, video based evaluation can be easily incorporated to the standard basic training systems for automated surgical skills assessment and feedback [25].

The aim of our current study is to discuss our progress in developing a video-based skills evaluation system for neurosurgeons while performing a grasping and pick-place task. The Neuro-Endo-Trainer was developed to impart the basic eyehand co-ordination and dexterity to the novices with variable angled neuro-endoscopes [7], [19]. We modified the design to incorporate an auxiliary static camera inside the training box to record and analyze the activity. An acquisition software was developed to obtain the synchronized video-feeds from the endoscope and auxiliary camera. We identified the parameters from the video stream closely related to the NETS-SAS objective scale [19]. The video analysis was performed by automatically segmenting the video stream into sub-tasks using Mixture of Gaussian based background subtraction and Tracking Learning Detection algorithms. For each sub-task, a synopsis was created from the kinematic analysis of the tool-tip trajectory. The objective feedback was provided to the trainees after the offline analysis.

II. BACKGROUND

Due to advancements in technology; data acquisition, data processing, and data analysis have provided an opportunity for the development of objective and automated assessment tools. The image analysis for the tool tracking started initially for the robotic intervention in surgery. Lee et.al used a color based Bayesian classifier to detect the instruments, grouped the pixels based on spatial adjacency and tracked the bounding box of the tool [26]. Wei et.al used artificial color marker on the tool and proposed a tracking method for stereo laparoscopes [27]. Doignon et.al proposed a method without using markers, but based on a recursive thresholding of the histogram of a new purity color attribute and region growing [28]. Tonet et.al used the color segmentation to obtain the perspective image of cylindrical representation of the instrument and identify the instrument position and orientation with five degree of freedom (DOF) [29].

The skills training using the virtual reality simulators helped the tracking and motion analyses to be integral part of skills evaluation. The virtual reality simulators like Minimally Invasive Surgery Trainer (MIST-VR), LapSim, Simulator for Endoscopy (SIMENDO) provided internal metric to evaluate the surgical skills. They used the tool tracking and analyses of the position, forces or time taken [30] – [32]. Rosen et.al used a pair of 3 DoF force sensors (modified ATI-Mini model) attached to the endoscope grasper outer tube and handle to identify the forces and torques applied. They developed Markov models to characterize surgical skills [33]. Dosis et.al developed The Imperial College Surgical Assessment Device (ICSAD), using electromagnetic trackers for identifying the dexterity [20]. Trejos et.al developed SIMIS system to obtain force and position data from the laparoscopic instruments for skills evaluation in MIS [34]. Yamauchi et.al used the force sensors attached to the left and right nostril of the endoscopic physical training system to identify the skills for endonasal sinus surgery [35]. Chhmarra et.al developed TrEndo consisting of two-axis gimbal mechanism with three optical sensors for tracking the activity for training systems and analyzed the skills using time, path length and depth perception [36]. Lin et.al developed ultraminiaturized inertial measurement unit (IMU) and incorporated into the forceps. The accelerometer and gyroscope data was analyzed to differentiate the skills of group of non-medical subjects and a neurosurgeon during a microscopic task of pick and place [37]. Watson in his study using a custom IMU (6 DoF) reported that experts have complex patterns of motion compared to novices while performing knot-tying task [38]. Nistor et.al used two 6 DoF DC magnetic trackers; one at the proximal and other at the distal end of the laparoscopic grasper to differentiate the skills of expert and novice surgeons performing pick-place task. The performance metrics included motion smoothness, total path length, and task completion time [39]. Kodama et.al developed a cyber-physical system using biometric sensors that include optical encoding of catheter motion, magnetic tracker for operator's hand, and photo elastic stress analysis for catheter and vessel membrane interaction measurement. They studied task completion time, tissue integrity, reaction time, and wasted motion to differentiate populations of expert and beginner [40]. Verner et.al used the da Vinci Surgical System data to identify the skills of the surgeons [41]. Lin et.al used the da Vinci Surgical system to automatically detect and segment surgical gestures (surgemes) for a suturing task. They used Bayes classifier for surgical skills evaluation of expert and intermediate surgeons [42].

Seung-Kook Jun et.al proposed an automated surgical skill evaluation method for minimally invasive surgeries. They used the well-established motion study methodology of segmenting a task into sub-tasks (Therbligs) and evaluating by statistical analyses of the motion. The da Vinci skills simulator was used as the standard and a simplified task of pick and place was analyzed based on manual annotation by expert and automated kinematic analysis of videos. They used the deformable part based model for various surgical tools and learned the annotated surgical tools by extracting the Histogram of Oriented Gradients (HOG) features using Latent Support Vector Machine (LSVM) [23], [43]. Zhang et .al used vision-based approach by capturing the activity of the subject's performance during simulationbased training using synchronized multiple camera feeds. Even though, the camera captures different scenes, they are obtained from the same physical process; the activity. A canonical correlation analysis (CCA) was performed to analyze the activity using Bag of words model. They used SVM to learn the classifier and found better performance in differentiating the novice and experts as compared to Principal Component Analysis combined with SVM method [25]. Allan et.al used region based level set segmentation for 3D pose estimation of instruments and linear motion based tracking from laparoscopic images [44]. The focus of our study was to evaluate the psychomotor skills using video based analysis involving segmentation of sub-tasks and evaluation of motion from the tracking output.

III. METHODOLOGY

A. Neuro-Endo-Trainer video acquisition setup

The top of the Neuro-endo-trainer was redesigned to incorporate the auxiliary camera and fabricated using fused deposition modeling (Dimension Elite Stratasys, Rehovot, Israel). An auxiliary camera (Basler ACE acA1300-60gc) was used to record the activity of trainee neurosurgeon. The lens (Fujinon Cmount 1:1.4/9mm) was attached to obtain a fixed field of view of the activity area. A demo video was provided to describe the activity to be performed. Figure 1 shows the setup, the internal activity plate and the pattern.



Fig. 1 Neuro-Endo-Trainer with auxiliary camera, internal plate and activity pattern

Acquisition system was developed to record the endoscopic and auxiliary camera video streams simultaneously using multithreaded OT 4.0 based application on Linux platform (Ubuntu 14.04, 64 bit). Endoscopic video stream was captured from the S-video output using capturing card (Pinnacle PCTV USB 2.0) at 25 fps, whereas auxiliary camera video stream was captured from the GiGE port at 60 fps. System spawned two pairs of producer and consumer threads for endoscopic and auxiliary stream. Producer-consumer pair shared the circular buffer. Producer would go to sleep or discard the frame if the buffer was full. If buffer was not full, producer owned the mutex lock and transferred the frame to the buffer and released the lock. Once consumer owned the lock it removed the frame from the buffer, decoded into the mp4 format and wrote it on to the hard disk. Consumer would go to sleep if the buffer was empty. Producer-consumer pair communicated using mutex locking mechanism.

B. Development of objective scoring

The parameters that could be identified from the video stream of the auxiliary camera was related to the developed NETS-SAS scale with the help of an experienced neurosurgeon. (Table1) TABLE I. OBJECTIVE MEASURE FROM VIDEO STREAM

Measure from	Related Objective measure from video stream From Auxiliary Camera	
NETS-SAS		
Grasper tissue manipulation	Grasping ability	Time taken to grasp
		Smoothness of the path
		Arc length of the path
	Tugging	Number of times tugging of ring
		happened
Eye hand coordination	Hitting the board	Number of times hitting happened
	Hitting the board by overshooting	Intensity with which hitting
	by overshooting	happened
	Hitting of the	Number of times hitting happened
	ring on the way	
Dexterity	Wavy motion	Time taken for moving ring from 1
		peg to other
		Smoothness of the path
		Arc length of the path
	Wrong Moves	Number of times wrong moves
		happens
	Wasted Moves	Time taken inter activity
Instrument manipulation	Sudden Jerk	Number of times jerk happened
Effectualness	Ring drop	Number of rings dropped

C. Video analysis for identifying sub-tasks-Neuro-Activity Tracker

The Neuro-Activity-Tracker was written in C++ using OpenCV implementation of the TLD tracking algorithm [45]. The video recorded from the training activity of grasping and pick-place was segmented into sub-tasks of grasping, moving and placing of the rings. Detailed logic for the activity detection or segmentation algorithm is given in the Figure 2.

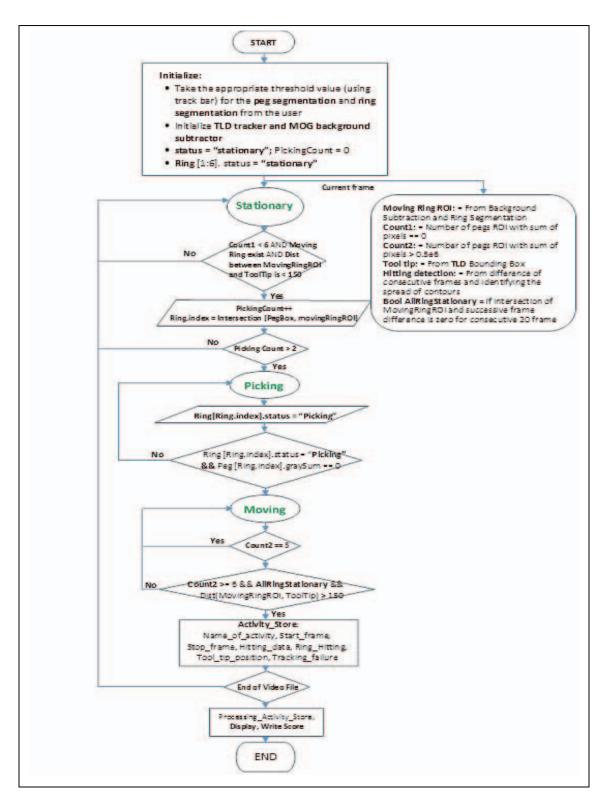


Fig. 2. Flow chat of neuro-endo-tracker-algorithm

The steps involved in the application are as follows:

1. HSV based peg and ring segmentation

A track bar was shown to the application operator on the first frame for ring and peg segmentation. Application doesn't proceed further until correct segmentation of pegs and rings.

2. Tracking Algorithm

Tracking of the tool tip was done using Tracking-Learning-Detection algorithm after initializing the bounding box of the tool. TLD is a robust tracking algorithm which is capable of tracking an unknown object from the initial bounding box [46]. It decomposes the long-term-tracking problem into tracking, learning and detection. The median flow based tracker follows the object from frame to frame and detect tracking failure. The cascaded classifier based detector consists of variance filter, random forest detector and nearest neighbor classifier to localize all the appearance of the object and corrects the tracker if necessary. A novel P-N learning method estimates the errors by a pair of "experts": 1) P-expert estimates missed detections, and 2) N-expert estimates false alarms used to update the object model.

3. Movement detection using Mixture of Gaussian based background subtraction method

Mixture of Gaussians is a widely used approach for background modeling to detect moving objects from static camera. The moving ring was detected by performing ring segmentation on the output of background subtraction.

As the background model of the endo-trainer was static, we used background subtraction output to detect the tool tip tracking failure. A tracking failure can occur due to significant variation in the appearance of the tool tip. In that case, TLD was not be able to learn the new appearance and eventually fails. However, background subtraction showed significant motion and was used to reinitialize the TLD algorithm.

4. Hitting detection based on successive frame difference:

Successive frame difference was used to determine whether trainee has hit the board. If the trainee hits the board, spread of contours in the difference image increases and the number of contours were used to detect the hitting on peg or board.

5. Automatic Activity Segmentation

Trainee neurosurgeon can be in either picking, moving or stationary phase at a time, according to the state of the tool and the ring.

- *No-activity* was defined as the state where the tool was present but all the rings were stationary. The number of frames, Hitting detection and tracking output was stored during this state.
- *Activity-Picking* was the state when the tool was near any Ring and moving-ring-detection was true for consecutive 3 frames. The number of frames during this state, hitting detection for each frame and tracking output was stored.

• Activity-Moving was the state when the tool and the ring moves from one Peg to another. The number of frames, Hitting detection for each frame and Tracking output was stored.

From the stored data, each activity was analyzed for the number of frames, hitting detection, smoothness of the tracking output and arc length of the path. The wrong moves were considered when the trainee fails to follow the pattern of activity and wasted moves were measured for the time in between the major activities.

IV. RESULTS

A. Neuro-Endo-Trainer video acquisition setup

The video acquisition setup receives the user input of the video file and capture path. The camera settings can be modified in 'settings.yml' file. The video stream corresponding to endoscope and auxiliary camera can be selected using the checkbox. The start capture button is used to start the capturing of the activity. (Figure 3)

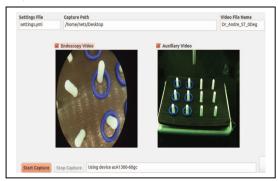


Fig. 3. Screenshot of acquistion software for endoscope and auxiliary camera *B.* Neuro-Endo-Tracker Software

The application provides the option for automatic or manual segmentation in the configuration file. When the path of the video to be analyzed is provided, the application starts. The TLD initializes from the learned model of tool and starts tracking it. The output of the current state of machine is shown (Figure 4)

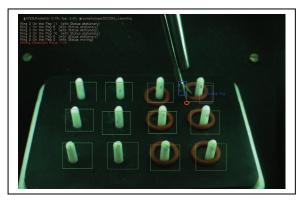


Fig. 4. Output of state machine at every frame

The activity summary of the video analyzed is provided at the end of the video file. The summary includes the number of times hitting happened and at which frame, time taken to grasp, move the ring from one peg to another, whether wrong moves happened, sudden jerks in the path and wasted movements. The sample synopsis created using the developed neuro-endo-activity tracker is shown in the Figure 5.

Scoring sheet for the
1. Hitting No hitting during the whole activity
2. Grasping Peg No(5) no of frames-> 81 Peg No(2) no of frames-> 82 Peg No(4) no of frames-> 65 Peg No(1) no of frames-> 65 Peg No(0) no of frames-> 42 Peg No(0) no of frames-> 63 Peg No(6) no of frames-> 61 Peg No(7) no of frames-> 61 Peg No(10) no of frames-> 34 Peg No(10) no of frames-> 34 Peg No(11) no of frames-> 34 Peg No(11) no of frames-> 59
3. Wavy motion Peg(5,3) Number of frames > 128 Peg(2,11) Number of frames > 308 Peg(4,7) Number of frames > 121 Peg(1,10) Number of frames > 241 Peg(0,3) Number of frames > 242 Peg(0,3) Number of frames > 228 Peg(0,2) Number of frames > 256 Peg(6,5) Number of frames > 289 Peg(7,4) Number of frames > 272 Peg(7,4) Number of frames > 272 Peg(8,3) Number of frames > 170 Per(11,0) Number of frames > 285
4. Ring hitting or wrong way of placement of the ring
5. Sudden movement Activity("Picking-Activity") Frame No-> 475 Activity("Moving-Activity") Frame No-> 2077 Activity("Moving-Activity") Frame No-> 2683 Activity("Moving-Activity") Frame No-> 3455 Activity("Moving-Activity") Frame No-> 3455 Activity("Moving-Activity") Frame No-> 3519 Activity("Moving-Activity") Frame No-> 3748 Activity("Moving-Activity") Frame No-> 4915 Activity("Picking-Activity") Frame No-> 5431 Activity("Moving-Activity") Frame No-> 5631 Activity("No-Activity") Frame No-> 5640
6. Wrong Moves
7. Wasted movements Total no of frames in the No-Activity -> 2580
8. Negative penality for excess/restraint activities No negative penality

Fig. 5. Sample Synopis of the activity

V. DISCUSSION

The video based evaluation algorithm developed helped the trainee neurosurgeon to identify their mistakes and improve the performance. The tugging of the ring to the peg was an objective measure for grasper tissue manipulation, but was not identified in this study from the videos. The trainee rarely dropped the rings while performing the task. Therefore, the effectualness parameter was not considered in the synopsis. The endoscope camera feed was not considered in this study for creating the objective evaluation. It can be used to identify the center of focus and the trainee exiting the field of activity.

The study can be extended to create scoring for the sub-tasks and the whole activity with the help of large sample size of the expert and trainee videos.

VI. CONCLUSION

The study presents the progress on development of Neuro-Endo-Activity-Tracker developed to identify the psychomotor skills of the trainee neurosurgeon. The tracker was able to objectively analyze the parameters involved in the surgical simulation task. The measures include the hitting, grasping, wavy motion, wrong moves, time taken, smoothness of the path and arc-length of the path.

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