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# Video Processing to Locate the Tooltip Position in Surgical Eye–Hand Coordination Tasks

**Xianta Jiang, MSc[1,2], Bin Zheng, MD, PhD[3], and M. Stella Atkins, PhD[2]**

**Abstract**

*Introduction*. Trajectories of surgical instruments in laparoscopic surgery contain rich information about surgeons' performance. In a simulation environment, instrument trajectories can be taken by motion sensors attached to the instruments. This method is not accepted by surgeons working in the operating room due to safety concerns. In this study, a novel approach of acquiring instrument trajectories from surgical videos is reported. *Methods*. A total of 12 surgical videos were obtained for this study. The videos were captured during simulated laparoscopic procedures where subjects were required to pick up and transport an object over 3 different targets using a laparoscopic grasper. An algorithm was developed to allow the computer to identify the tip of the grasper on each frame of video, and then compute the trajectories of grasper movement. *Results*. The newly developed algorithm successfully identified tool trajectories from all 12 surgical videos. To validate the accuracy of this algorithm, the location of the tooltip in these videos were also manually labeled. The rate of accurate matching between these 2 methods was 98.4% of all video frames. *Discussion*. Identifying tool movement from surgical videos creates an effective way to track instrument trajectories. This builds up the foundation for assessing psychomotor performance of surgeons in the operating room without jeopardizing patient safety.

**Keywords**

tool tracking, motion detection, video processing, laparoscopy, surgery simulation

## Introduction

Laparoscopy (keyhole) surgery involves using long-handled tools to perform surgery inside the body while viewing the internal scene on a 2-dimensional (2D) display through an endoscopic camera. This requires difficult eye–hand coordination, often taught by performing simulated tasks, for example, peg transporting using a grasper in a training box where the scene is illuminated with an endoscopic camera called a laparoscope, as shown in Figure 1. For monitoring the effectiveness of surgery training, it is helpful to perform analysis of the tool trajectory.[1] For such eye–hand coordination studies, the location of relevant objects such as the tool and hand is essential[2] even for simple pointing tasks, and the trajectory of the pointer is often recorded using a motion tracker.[3] However, when performing a laparoscopic task, it is impossible to put a motion tracking system or markers inside the abdominal cavity to record the tool positions. Even in a simulated laparoscopic task being performed in a training box, it is inconvenient to record the tool positions using a motion tracker. Anderson[4] developed a collar with infrared markers that can be attached on the shaft of the tool at its part outside of the training box. The tooltip position can be calibrated from the array of the positions of these markers. However, the extra weight of the collar and the interference caused by the wires connecting to the markers must be considered.

Advances in image and video processing techniques offer the opportunity to noninvasively detect the tool from surgical videos recorded during laparoscopic surgery procedures or training on simulators,[5] without adding any extra equipment or altering the instruments. The characteristics of the instrument, for example, the rigid direction, distinct color, and straight line edges of the instrument, are usually considered as advantages taken in tool recognition algorithms.[6-9] These tool segmentation

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**Figure 1.** Experimental setting.

approaches are mostly color-based, sometimes aided by attaching color markers to the tip of the instrument,[7,9] and also reconstructing the 3D position of the tool utilizing the information of the instrument's insertion point and the camera's optical center.[6,7,9] For example, Allen et al[6] located the tooltip in the image by firstly extracting the instrument contours via color space analysis, then fitting lines to the contours to estimate the direction of the instrument shaft, and lastly identifying the most probable position of the tooltip of the instrument. However, color-based analysis methods do not always work, for example, in situations when it is difficult to distinguish between the instrument and the background in their colors. Instead, since the instrument usually is the most significant moving part in the consecutive images, video processing techniques, such as background subtraction techniques,[10] are suitable to be applied to effectively locate the tooltip.

Video-based eye-trackers are widely used in eye–hand coordination studies[11] and applied in surgery training both in laboratory and operating room environment, for example, evaluating the surgeon's vigilance in simulation settings, investigating the surgeon's eye–hand coordination in performing laparoscopic tasks, and recording the surgeon's gazes in the real operating room for teaching purposes.[12] Besides the eye motions, the scene of the work area is also recorded and saved as task videos. The eye gaze can be superimposed onto the task videos to observe the interaction between eye and hand (or tool).[13,14] This is the case in simulated laparoscopic tasks performed in a training box, where the background of the task videos is stable. For example, in a peg transport task commonly used for surgical training,[15,16] where a peg is moved from one location to another, only the tool and peg move during the whole procedure. Thus it is very suitable to employ background subtraction[10] and biggest connected object searching techniques[17] to track the moving tool in the foreground image, as the tool usually is the biggest moving object in the foreground image and the tool is consistently oriented (eg, a right-handed tool is always north-west oriented and connected to the right or bottom edge of the image), as is shown in Figure 2A and B. Hence several hard problems when using background subtraction such as the effects of background oscillating, shadows, and sleeping foreground[18] will be avoided.

In this article, we report a simple but effective algorithm to automatically extract the tooltip positions from the eye-tracker output task videos, by using video processing techniques, that is, background subtraction and connected object searching techniques. To evaluate the algorithm, we compared the manually annotated tooltip positions to the calculated tooltip positions from the task videos. This work shows an effective way of automatically extracting tooltip positions from task videos for the analysis of the eye–hand coordination under a simulated laparoscopy environment.

## Methods

### *Experimental Settings and Tasks*

The task videos were recorded from a surgical eye–hand coordination study, in which the participants were asked to transport a green peg between 3 cups using a long shaft grasper with their eye motions recorded by a Tobii 17/50 eye-tracker, as shown in Figure 1. The scene inside the training box was illuminated and recorded by the endoscopic camera attached to the training box, saved in the format of Audio Video Interleave (AVI) at 30 fps with a resolution of 352 × 288 pixels. The video stream was synchronized by Tobii eye-tracking software (Tobii Clearview) with the eye movements in time sequence and blown-up to fit the 17-in. screen (1280 × 1024 pixels). Details of the experimental setting are given in Jiang et al.[16]

### *Tool Tracking Algorithms*

The algorithm for tooltip detection was developed using C++ (Microsoft Visual Studio) and OpenCV Library.[19] The videos were read in and processed frame by frame. The video frame first underwent a background subtraction, and then the tool was located by searching the biggest connected object from the thresholded foreground binary

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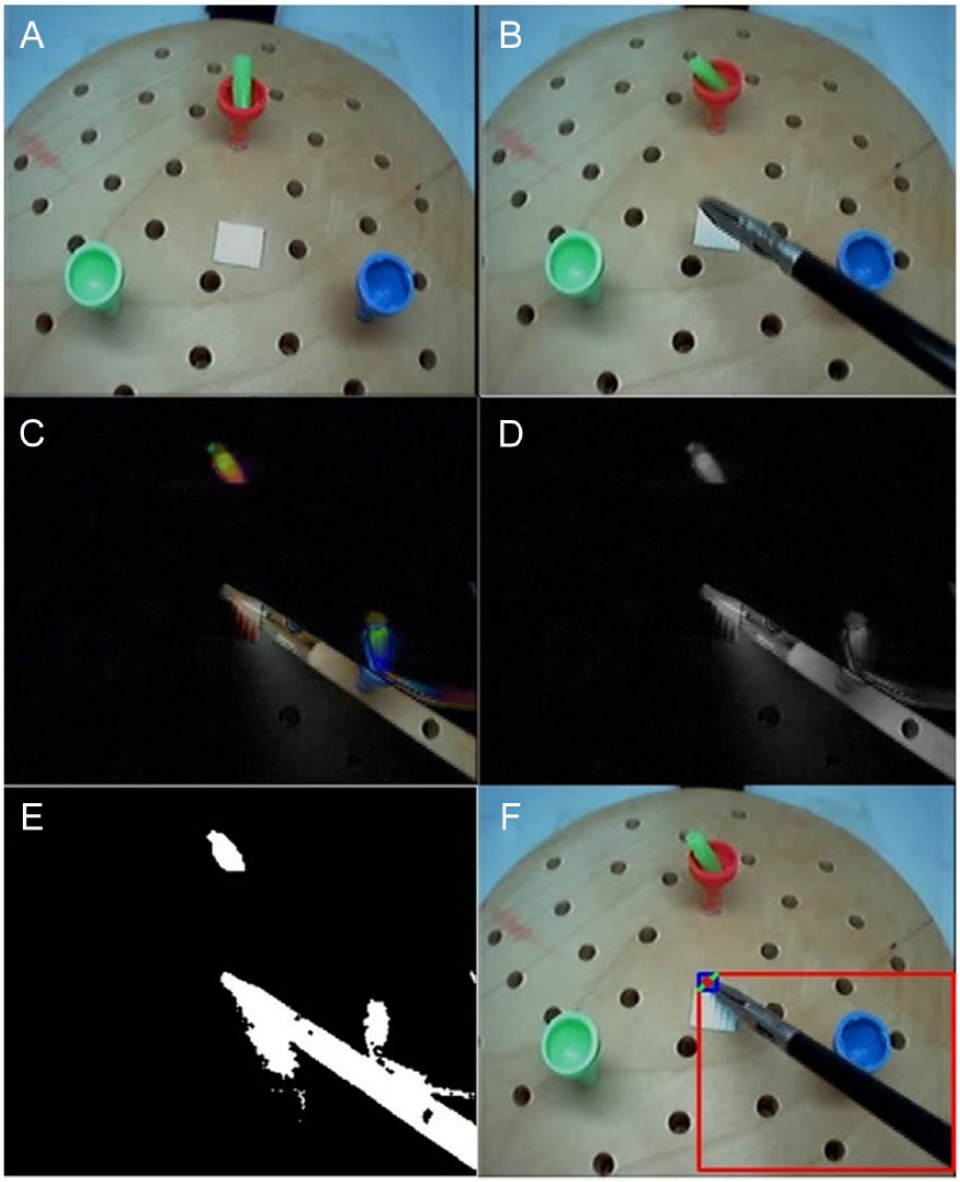


**Figure 2.** An example of the processing of tooltip location: (A) a background image, (B) a target image for tool tracking, (C) the foreground image in RGB color mode, (D) the foreground image in grayscale color mode, (E) the thresholded binary image from (D), and (F) the located tool position as is shown in the red rectangle, in which the red dot on the green line segment is the tooltip position.

image. Lastly, the tooltip position was determined according to the status of the grasper, that is open or closed.

*Background Subtraction.* The background subtraction algorithm has 2 steps, including selecting an initial background image and updating the background image (see Figure 2A and B for examples of typical task video frames with the tool absent and present). A frame without the tool in the image (which usually can be found at the first frame of the video) was used as the initial background image for the background subtraction, as shown in Figure 2A. In this study, only 1 frame was needed for all trial videos of a subject, since the camera setting (the distance and the direction to the scene) did not change over the trials for a particular subject. However, different background images had to be chosen for different subjects, since they performed the task on different days and the camera setting might have been changed. The initial

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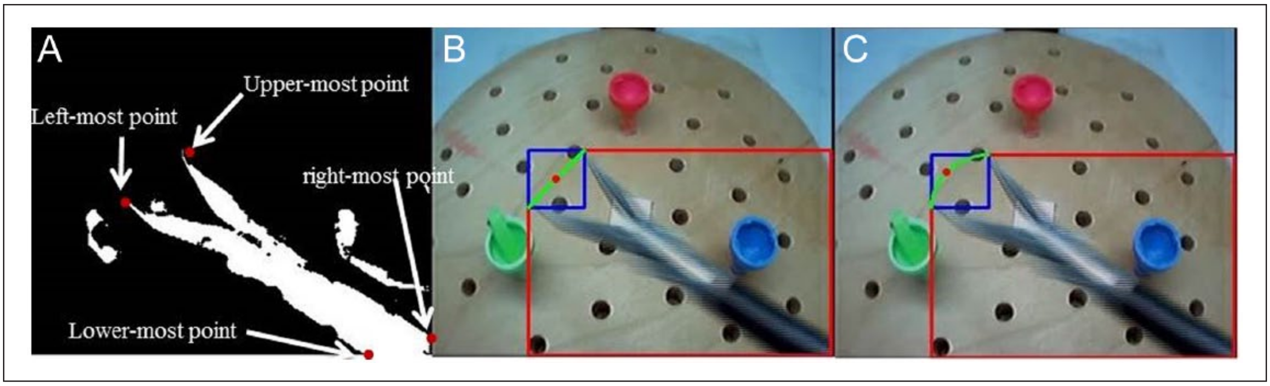


**Figure 3.** Illustration of tool rectangle and opened tooltip location: (A) shows the 4 points to determine the tool rectangle, (B) shows the approximated tooltip position using the middle point of the line segment between the two tooltips (the red point on the green line segment), and (C) shows the approximated tooltip position using the middle point of the arc between the 2 tooltips

background frames for the subjects were manually chosen from the videos, and the frame IDs were recorded in a list for the system to automatically read in.

A partial background updating strategy[20] was employed to update the background image. Only the part of the image outside the rectangle of the recognized tool (see the tooltip location section below) was updated to the background image, since there usually was some noise in the tool rectangle such as shadows. The criterion whether the background image needed to be updated was defined based on the detected object numbers and the number of consecutive noisy frames, where the number of separate objects detected in the frame was greater than a value. For example, when 3 consecutive noisy frames happened, the background was updated. This criterion was set up to avoid some recoverable image changes, for example, the effect of a sudden strong flash of light or an incidental touch to the cups or plate by the grasper, which usually caused 1 to 2 frames of noisy images and then recovery to clean images. When there was no valid tooltip detected in the image and the image was noisy, the current background was replaced by the initial background image.

*Tool Location.* Each frame was subtracted by the background image to get the foreground image, mostly with only the tool left in the foreground image, as shown in Figure 2C. Then the foreground images were transformed to grayscale images, and were thresholded to binary images, as shown in Figure 2D. A width-first pixel-wise search strategy was employed to search the connected objects in the binary images. Any adjacent pixels in the binary image were included in an object.

To locate the tool, a horizontal rectangle was derived to surround the found tool, shown as a red rectangle in Figure 2F. The rectangle was determined by the upper-left and lower-right corners of the tool, that is, the $x$-axis value of the left-most point and the $y$-axis value of the upper-most point in the tool object were used as the $x$- and $y$-axis values of the upper-left corner of the rectangle. Similarly, the $x$-axis value of the right-most point and the y-axis value of the lower-most point in the tool object were used as the $x$- and $y$-axis values of the lower-right corner of the rectangle, as shown in Figure 3A.

*Tooltip Location.* The calculations for the locations of the closed and opened tooltip are different. For most surgical tasks performed in a laparoscopic environment, the direction of the tool is consistently oriented, for example, right-handed tool is north-west oriented. When the grasper is closed, the position of the tooltip is derived from the position of the north-west corner of the red rectangle, as is shown in Figure 2F, and when the grasper is opened, the position of the tooltip is approximated from the middle point of the 2 opened tooltips, which is the middle point of the line segment between left-most and upper-most points, as shown in Figure 3B. As an alternative, the algorithm also provides the tooltip approximation from the middle point of the arc of the 2 opened tooltips, as shown in Figure 3C.

Several situations might arise which could provide erroneous location of the tool.

*Disconnection*. To avoid unnecessary disconnected parts belonging to the tool caused by the thresholding problem, as is shown in Figure 4, pixels with gap less than a certain value were grouped to the same object. Usually the biggest object was selected as the tool from the connected objects according to the total number of pixels in the object.

*Tool as largest object.* Criteria needed to be set up for judging a valid tool object, since the biggest object in the

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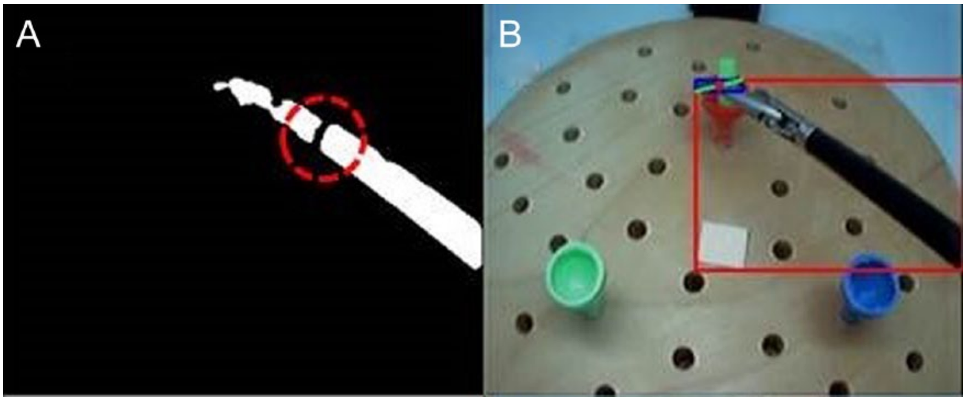


**Figure 4.** Example of the disconnection of tool parts: (A) the disconnected part (in the red circle) of the tool and (B) the recognition of the whole part of the object as a tool.

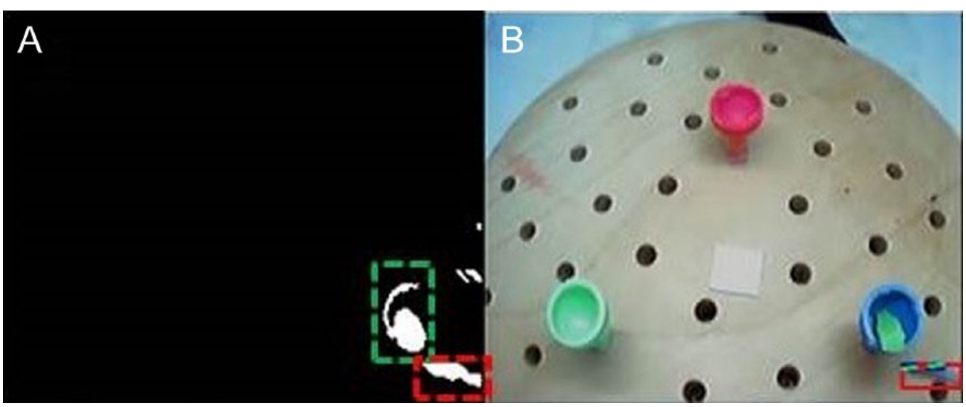


**Figure 5.** Example of taking the second largest object as the tool: (A) the largest object (in the green dashed-line rectangle) caused by the sleeping foreground object (the green peg) and (B) the recognized tool (in the red rectangle).

image was not necessarily always the tool. For example, when the grasper was moved nearly out of the image or inserted into the working field (especially in parallel to the optical axis of the camera) with only a very small part visible in the image, the tool was smaller than some other objects in the image, as shown in Figure 5. The valid tool judgment criteria were defined on the basis of the characteristics of the tool in the task videos. For example, the lower-right end of the tool should always be connected with the bottom or right edge of the image, as is shown in Figure 2B. Also the open amount of the tooltip should be less than a certain value, for example 80 pixels in the image (which is roughly twice the diameter of a cup in the image.).

*Peg in the grasper*. When the green peg is picked up by the grasper, it may be misrecognized as a part of the tool, as shown in Figure 6A. We take this as tool opened situation as shown in Figure 6B.

### *Algorithm Validation*

We manually annotated the tooltip positions from the task videos as the ground truth data for the evaluation of the algorithm. The task videos were examined frame by frame using an open source video analysis software,[21] in which the $x$ and $y$ coordinates of the tooltip were automatically recorded into a spreadsheet by mouse-clicking at the observed tooltip position in the image.

During the manual tooltip annotation, the tooltip was defined as the end point of the grasper when the grasper was closed and the middle point of the 2 opened tooltips when the grasper was open.

Two parameters were used to indicate the accuracy of the algorithm: the average distance between the pairs of true tooltip and computed tooltip positions, and the percentage of the pairs of true tooltip position and computed tooltip position with the distance within a certain value.

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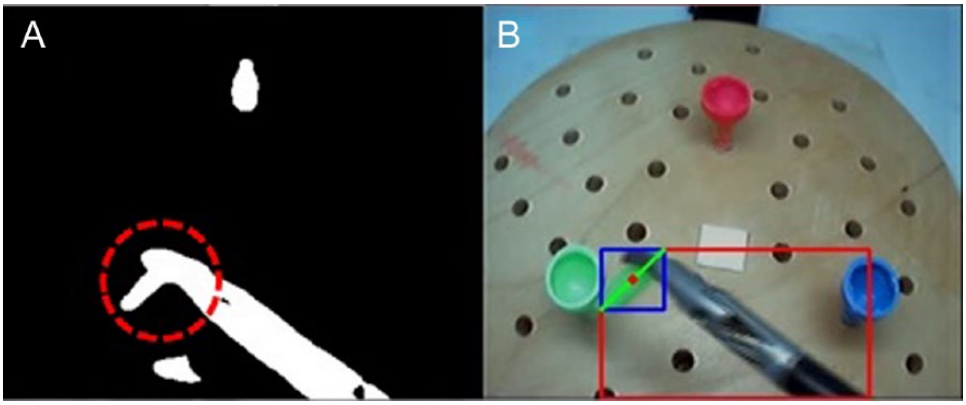


**Figure 6.** Example of peg in the grasper: (A) the binary image with the connected peg and grasper (in the red circle) and (B) the recognition result.

## Results

A total of 12 task videos (the first trial of each participant) were processed by the algorithm to output the tooltip positions, and these task videos were manually annotated to record the true tooltip position in each frame as the ground truth data.

The average root mean square error of the true tooltip positions to the calculated tooltip positions on the captured video was 9.2 ± 2.1 pixels (about 2.4 mm in physical distance on the 17-in. display). The average overlay rate between the true tooltip and the calculated tooltip from 12 task videos was 98.4% ± 1.7%. An overlay was determined when the distance between the true tooltip and the calculated tooltip was within a 0.75° viewing angle (the definition for the radius of a fixation, about 28 pixels in the video frames, corresponding to 7.4 mm in physical distance on the 17-in. display when the participants were 60 cm away from the eye-tracker.

Two examples of the computer output tooltip positions overlaid with the true tool positions over time are shown in Figure 7. In the example shown in Figure 7A, the computer-captured tooltip matched the true tooltip positions very well with the tooltips overlaid within 0.75° viewing angle on the display for 99.5% of the video frames. Figure 7B shows an example with slight displacement between true and recognized tooltip positions, where the green peg was recognized as a part of the grasper when the participant was holding the green peg in a special direction as shown in Figure 6. Even in the second example, most of the distances between the computer-recognized tooltip and the true tooltip were less than 0.75° viewing angle (the overlay rate for this trial was 98.9%).

Several hard problems when using background subtraction such as the effects of background oscillating, shadows, and sleeping foreground[18] were successfully avoided. Figure 8A shows an example of background oscillation, which arose when the tool inadvertently touched the cups; in this situation the tooltip was correctly located; Figure 8B shows the correctly recognized result. Figure 9A shows an example of sleeping foreground object from the green peg and the shadow of the tool in the binary image; Figure 9B shows the correctly recognized result.

## Discussion

The performance is good with root mean square error of about 2.4 mm, which is far less than the accuracy of the eye-tracker (0.5° viewing angle, corresponding to around 5.2 mm at 60 cm standing distance).

The present tool tracking method is simple but effective, and does not require attaching any extra sensors or color markers to the instruments, which makes it likely to succeed in terms of market dissemination. Some hard problems encountered in moving object detection using background subtraction, for example, the effects of background oscillation, sleeping foreground objects, and shadows,[18] were overcome in this case by employing object searching and the tooltip point determining strategy.

The background oscillation did not cause problems because the tool was still the biggest connected object in the binary foreground image most of the time (see Figure 8). In some cases, even when the tool was not the biggest object in the foreground image, the tool location algorithm can successfully distinguish the valid tool according to the criteria described in the method section; similarly, the false alarm object from the sleeping foreground objects (eg, caused when the green peg was transported to and stayed in another cup) was mostly smaller than the tool object in the foreground images too, as is

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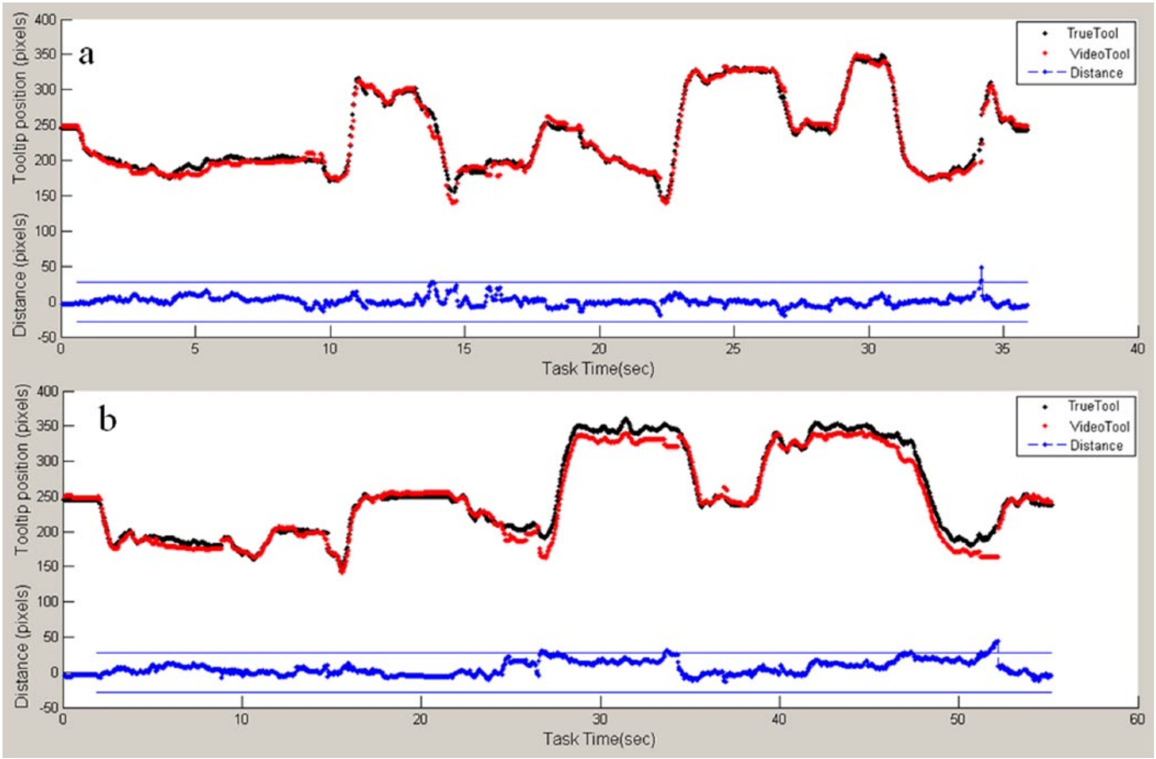


**Figure 7.** Examples of the overlay between the computer output tooltip positions and the true tool positions over time. The black curve and red curve in the figure are the manually annotated true tooltip and the computer output tooltip (video tooltip) positions (Euclidian distance to the origin (top-left corner of the image)), respectively. The blue dots are the distances between the true tooltip and video tooltip positions. The blue horizontal lines are overlay threshold (0.75° viewing angle, 28 pixels in the video frames, corresponding to 7.4 mm on the physical display). Panel A shows an example (subject 6) with well-matched computer output tooltip to the true tooltip positions. Panel B shows an example (subject 9) with slight displacement between the true tooltip position and recognized tooltip position during some segments, since the green peg was recognized as a part of the grasper as is shown in Figure 6.

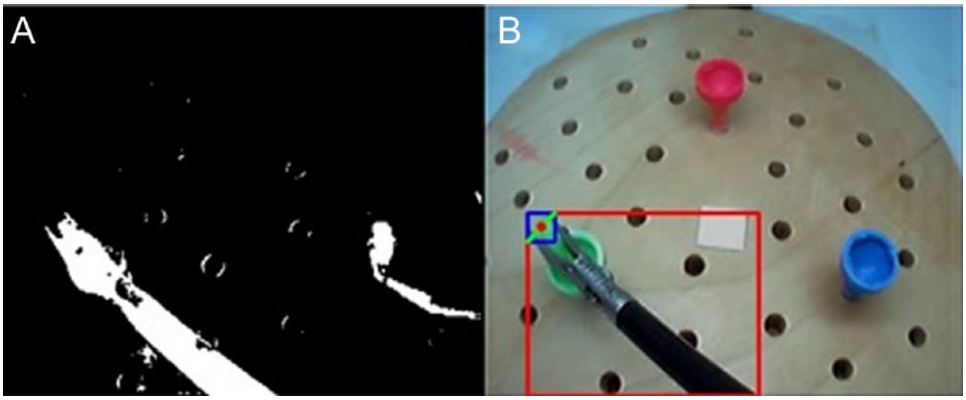


**Figure 8.** Example of the effect of oscillation: (A) the binary image having small objects caused by the oscillation and (B) the recognition result.

shown in Figure 9A, and also could be avoided when it was bigger than the tool object, by using the tool validation criteria, as is shown in Figure 9B. The sleeping object (see Figure 9) in the foreground also was updated

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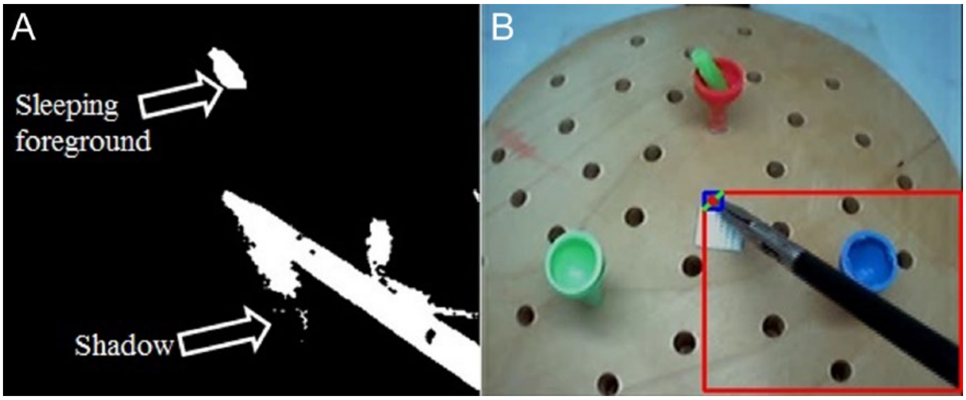


**Figure 9.** Example of the sleeping foreground and shadow: (A) the binary image having sleeping foreground and shadow of the tool and (B) the recognition result

to the background after several frames (according to the parameters in the background updating strategy). The shadow (see Figure 9) by the illumination from the upper-front side of the tool which mostly lay on the downside of the tool, also did not affect the accuracy of the tooltip position, as the tooltip always was in the upper-left corner of the rectangle of the tool object, as illustrated in Figure 2F, and only the part outside of the tool rectangle was updated to the background image.

The initial background image was manually selected from the task videos instead of being dynamically generated in this study.

The peg would be recognized as the part of the tooltip when the grasper carried the peg in such a position as shown in Figure 6. By using the middle point between the touching points on the edges (the left-most and upper-most points), the estimated tooltip was pretty close to the actual tooltip. A similar situation happened when the tool was open—the estimated tooltip position was more reasonable than taking the top-left corner of the rectangle as the tooltip position, as shown in Figure 3B and C.

Although only 2D tooltip locations were derived from task videos instead of the actual 3D tooltip movement information in the training box, the tooltip locations were still sufficiently accurate for the eye–hand coordination analysis in laparoscopic tasks, since the performers looked at the same 2D images from the eye-tracker display screen.

The results were very good. There was nearly no misrecognition of the tool. There was a slight displacement between the true tooltip and the recognized tooltip, as is shown in Figure 7B, which was mainly contributed from 2 factors, one was that the peg in the grasper caused a problem as discussed before, and the other was the poor image quality when the tool was moving quickly.

The algorithm could easily be extended to detect more than one moving tool in the training box from the task videos by enhancing the background subtraction and tool detection algorithms, for example, by enabling multiple objects detection during the tool object searching.

This method was designed for the analysis of eye–hand coordination under simulated laparoscopy environments. In the future, however, the algorithms could be enhanced for applications to laparoscopic surgery for tracking tool trajectories from real surgical videos recorded in the operating room. Challenges would arise because the videos recorded from real patients would present much more noise, and the algorithm would need to employ dynamic background calculations to work in a changing view. However, the scope view often remains unchanged when the tools are working on a site, so we still could take advantage of the stable background for tracking important actions. Surgeons believe tool trajectories are associated tightly with their surgical skills.[22] Therefore, we would expect results from such a study would allow us to further assess surgeons' skills in the operating room, as the characteristic orientations of the tools are similar.

## Conclusions

A method was presented for tracking the tooltip surgical videos using background subtraction and object searching techniques. This method is perfectly adequate for the analysis of eye–hand coordination in tasks employing stable backgrounds such as laparoscopic tasks using a training box, by taking advantage of the characteristics of the videos, that is, the stable background and the orientation of the tool in the video. This work achieves the first step toward tool tracking in a real laparoscopic operating room and training environment, where the surgical videos are more complex and more sophisticated video processing methods are needed.

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## Declaration of Conflicting Interests

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