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Eye tracking in surgical education: gaze-based dynamic area of interest can discriminate adverse events and expertise

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Abstract

Background Eye-gaze metrics derived from areas of interest (AOIs) have been suggested to be effective for surgical skill assessment. However, prior research is mostly based on static images and simulated tasks that may not translate to complex and dynamic surgical scenes. Therefore, eye-gaze metrics must advance to account for changes in the location of important information during a surgical procedure.

Methods We developed a dynamic AOI generation technique based on eye gaze collected from an expert viewing surgery videos. This AOI updated as the gaze of the expert moved with changes in the surgical scene. This technique was evaluated through an experiment recruiting a total of 20 attendings and residents to view 10 videos associated with and another 10 without adverse events.

Results Dwell time percentage (i.e., gaze duration) inside the AOI differentiated video type ($U = 13508.5$, $p < 0.001$) between videos with the presence (Mdn = 16.75) versus absence (Mdn = 19.95) of adverse events. This metric also differentiated participant group ($U = 14029.5$, $p < 0.001$) between attendings (Mdn = 15.45) and residents (Mdn = 19.80). This indicates that our dynamic AOIs reflecting the expert eye gaze was able to differentiate expertise, and the presence of unexpected adverse events.

Conclusion This dynamic AOI generation technique produced dynamic AOIs for deriving eye-gaze metrics that were sensitive to expertise level and event characteristics.

Keywords Eye tracking · Laparoscopic surgery · Area of interest · Expertise · Surgical events

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With increasing cost of surgical training, and the decrease in working hours for residents [1], it is necessary to develop solutions that will augment and expedite the learning curve for trainees in surgery. Eye tracking thus offers a technological solution to enhance surgical training and assessment that can help mitigate the estimated $37 billion training costs of surgical workforce to maintain current access levels by 2030 [2–4]. Eye tracking is increasingly used in surgical education for assessment and training due to improved technological capabilities, cost-effectiveness, and portability. The intuitive appeal of eye tracking is in revealing differences in eye-gaze location for novice and expert surgeons in the surgical scene. Surgical skills of novices have been assessed by comparing their eye-gaze locations and durations to those of expert surgeons [5–8]. Expert eye gaze, when shown to novices, can be used to train novices on where to look during a procedure [9–11].

Previous work has focused on developing objective metrics to assess whether novices are looking at relevant anatomical structures, or similar regions receiving expert visual attention [7, 12]. These critical regions of the visual scene are referred to as areas of interest (AOIs) [13] for deriving common assessment metrics such as time to first fixation, fixation count, and fixation duration inside of the AOI [8, 14].

Previous research in healthcare has indicated that AOI-based metrics can differentiate expertise. Expert radiologists consistently have shown faster time to first fixation on AOIs compared to novices [12]. In addition, expert radiologists have exhibited lower fixation duration on AOIs for detection only tasks [12]. Similar results have been found in determining orientation of static images from endoscopic surgeries, where participants demonstrating the strongest performance exhibited lower number of fixations and dwell time per AOIs [11, 15]. However, different medical tasks can have a reverse effect on these gaze metrics. For tasks involving interpretation, expert radiologists have exhibited higher fixation duration on AOIs than novices [12]. For assessing progress and next steps based on images taken from micro-neurosurgery, experts have also demonstrated longer fixation durations on AOIs [16]. In simulated laparoscopy tasks demanding sustained attention on critical areas, expert surgeons have demonstrated greater fixation duration inside non-instrument AOIs [6, 10, 17].

Eye tracking research involving realistic and dynamic surgical scenes, however, remains in paucity. The visual scenes in the aforementioned studies using trainer boxes and simulators are deliberately simplistic for practice and are not representative of the complex and dynamic scenes observed in surgery. The literature only contains a limited number of eye tracking studies involving representative visual scenery. Two studies showed that machine learning of eye-gaze data from a physiological perspective (e.g., pupil dilation, vergence) can differentiate expertise [18, 19], but such an approach cannot indicate whether novices and experts are gathering the same visual information diagnostic for training and assessment. For example, machine learning algorithms could be differentiating expertise based on workload as indicated by pupil diameter, as opposed to whether the experts and novices sample the same visual information (i.e., gaze locations). Another study found that eye gaze collected during surgeries performed by the experts overlapped more with eye gaze of those same experts than the novices watching the videos of the recorded surgeries [5]. Although this study investigated whether experts and novices gathered the same information in complex and dynamic visual scenes, it was limited by only recruiting two experts who had the benefit of watching their past work. It is therefore worth investigating differentiation of gaze without prior, repeated viewing *of experts' own gaze*.

Existing methods to generate AOIs for assessment with complex, dynamic scenery are arduous and sometimes infeasible [14, 20] which may be one reason for the limited eye tracking research on live or recorded surgery. Realistic surgical scenes are very visually complex (e.g., organs and blood vessels as opposed to discs in a trainer box), so medical expertise is necessary to *draw* the AOIs, as the defining features are virtually ineffable. However, hand-drawing AOIs over videos would require impractical amounts of time. Further, the expert gaze is sensitive to specific timing in the context of the surgical procedure; thus, relevance of an AOI changes as the surgery progresses. Gaze metrics based on AOIs that are insensitive to timing can be invalid given the complex and temporal aspects of realistic surgical scenery. For example, understanding the surgical field and progression of the procedure with fixation of gaze at the critical and dangerous features is an indication of expertise to avoid accidental injury; whereas, once the injury has occurred, fixation at the injured location does not suggest expertise. To translate eye-gaze research on static images and abstract simulation tasks for generating valid and diagnostic metrics in representative surgical settings, AOIs must be dynamically defined with respect to the changing visual scenes.

To address the limitation of eye-gaze analysis based on AOIs, we developed a technique for generating AOIs by synthesizing prior gaze analysis methods [5, 21]. We further conducted an empirical study for evaluating the technique. The first part of this paper describes the technique for generating AOIs whose locations update according to how the expert changes his or her gaze location over time in realistic and dynamic laparoscopic surgical scenes. The latter part describes an empirical study recruiting attendings and residents to test whether the dynamic AOI generation technique can produce gaze metrics that are sufficiently sensitive to differences in surgical video types (presence and absence of adverse events) and participant groups (attendings and residents).

We hypothesize that if surgery videos have adverse events, dwell time inside the expert dynamic AOIs will be reduced more than surgery videos without adverse events. Adverse events are unanticipated and thus disrupt default gaze strategies acquired from experience and training. Further, we hypothesize that attendings have greater dwell time inside the expert dynamic AOIs than residents because surgical experience correlates with fixation time on task-relevant areas [8, 22]. If significant changes in dwell time gaze metric are revealed between video types and participant groups, the proposed expert dynamic AOI generation technique should be able to support eye-gaze analysis that accounts for the complex and temporal aspects of visual scenery in surgery, thereby improving assessment in surgical education.

Materials and methods

Dynamic AOI generation technique

The technique to generate dynamic AOIs for changing visual scenes in surgery requires three steps:

(1) *Collecting expert eye-gaze data*. This technique relies on collecting eye tracking data from an expert viewing the dynamic scenes. The eye tracker must gather or export the locations (usually in Cartesian coordinates) and corresponding time of each eye gaze to indicate when and where the expert looked.
(2) *Cleaning expert eye-gaze data*: The eye tracker typically collects a small sample of "invalid" eye gazes. For example, the remote eye tracker cannot determine the gaze location when the individual is looking at something outside the computer monitor. These invalid location and time data are deleted from the expert gaze data set.
(3) *Specifying AOI refresh rate, center, and size*: Three substeps are performed on the final expert gaze data set to produce the dynamic AOI for computing eye-gaze metrics. *The first step is setting the time interval or refresh rate for updating the AOI* (e.g., changing its location and size) to limit over-sensitivity to time as well as computational requirements. That is, eye gazes at the same location between individuals should be considered the same if they occur at approximately, not exactly, the same time because the visual information at the specific location has not changed within the time interval. Otherwise, individuals would be falsely identified as collecting different visual information (i.e., many false positives due to over-sensitivity to timing). Further, this downsampling reduces computational requirements. In this study, the time interval for refreshing the AOI is set to 367 ms or every 11 sample points given the 30 Hz sampling rate of the eye trackers. Then the mid (i.e., the sixth) sample point is selected as the expert gaze representing the entire time interval.

The second step is setting the center point of the AOI for each time interval. The center point of the AOI is set to the gaze location (i.e., single-pixel coordinate) of the expert gaze.

The third step is setting the shape and size of the AOI to balance the false positives and negatives in identifying whether the eye gazes of different individuals are gathering the information from the same location. That is, when the AOI is too small, eye gazes of different individuals gathering the same visual information are considered different (i.e., false positives), whereas, when the AOI is too large, eye gazes of different individuals gathering different visual information are considered the same (i.e., false negatives). Holmqvist et al. [13] suggested an AOI margin of 1.5° visual angle. Orquin et al. [23] found little difference between AOI margins ranging from 0° to 1.5° and recommended larger margins for well-dispersed and simple AOIs, and smaller margins for complex and highly proximal AOIs. In this study, the AOI is set to a circle center at the expert eye-gaze location with a size of 3° visual angle center. Thus, the center of the AOI should be in the foveal vision of the individual gazing at the perimeter of the AOI. Note that the size based on the 3° visual angle must be translated into the number of pixels based on the visual angle equation for computation data analysis. In our study, the AOI diameter is 100 pixels to approximate 3° visual angle for a 15″ HD (i.e., 1920 × 1080 pixels) monitor at a viewing distance of 65 cm.

In summary, the proposed technique generates an AOI that updates its location according to how the expert changes his or her gaze location over time in complex and dynamic visual scenes. This dynamic AOI generation technique can be automated with common scripting languages (e.g., R, Python) and imported into commercial eye tracking data analysis software (e.g., SMI BeGaze, Tobii Pro Lab) for computing gaze metrics (e.g., dwell time and number of fixations on AOI). This study employed R and SMI Begaze for AOI generation.

Participants

Following approval of Carilion Clinic/Virginia Tech IRB, ten attending surgeons (ten males; mean years as an attending, 21.7) and ten resident surgeons (seven males, three females; mean PGY, 2.6) from the Carilion Roanoke Memorial Hospital participated in this study. Table 1 shows experience of the attendings and residents. The attendings, on average, performed 62.4 (SD = 57.4) procedures and observed/assisted 65 (SD = 66.7) laparoscopic cholecystectomy procedures. Residents, on average, performed 36.2 (SD = 26.2) and observed/assisted 39.1 (SD = 27.3) procedures.

Table 1 Years of participant experience

Attendings		Resident	
Years attending	Number of participants	PGY	Number of participants
1–10	0	1	3
11–20	4	2	1
21–30	4	3	4
31–40	2	4	1
41–50	0	5	1

Measures

Percentage dwell time was used to determine how often the participants visually sampled the same information as the expert. Percentage dwell time is defined as the sum of all fixation durations and saccades (i.e., eye movements between fixations) falling inside versus outside the AOI. Fixations were defined by SMI BeGaze software using a dispersion-based algorithm with a 100 ms threshold.

Three additional measures are mentioned to clarify the study procedure but they are beyond the scope of this paper. The three measures are (1) *general confidence* questionnaire containing seven questions on confidence of the participants in their own laparoscopic surgical skills; (2) *post-video confidence* questionnaire containing two questions on their confidence in the performance of the surgeon in that video; and (3) *anxiety ratings* collected through keyboard presses reflecting anxiety levels as the participants viewed the videos.

Apparatus

All data collection occurred in a quiet office setting in the surgical suite at Carilion Roanoke Memorial Hospital, Roanoke, Virginia. All participants were seated approximately 65 cm in front of a computer monitor. The SMI REDn Professional (SMI, Teltow, Germany) remote eye tracker was attached to the bottom of the monitor to collect eye-gaze data at a 30 Hz sampling rate (Fig. 1).

Our data collection system was set up to record participant eye gaze while being presented with 20 surgical video clips. The video clips were selected by the expert surgeon from publicly available sources (e.g., Sages TV). Individual video clips contained one of the following key procedural elements: port placement, dissection of the gall bladder and liver bed, and clipping of the cystic duct and artery. Half of the video set contained elements of a successful surgical procedure. The other videos contained the same procedural elements associated with a surgical error that resulted in bleeding. The video lengths ranged from approximately 50 s to 3 min.

Fig. 1 The remote eye tracker (enclosed by the cyan boarder) attached to the laptop monitor

Procedure

Participants were first given an overview of the experimental procedure, followed by informed consent. The experimenter verbally provided detailed instructions about the tasks and then calibrated the eye tracker to each participant. Next, participants completed a 5-min training session to practice the experimental protocol. The experimental protocol then required participants to watch short video clips of a laparoscopic cholecystectomy. While viewing each video, participants were asked to input their *anxiety ratings* using the keyboard. An auditory cue sounded every 15 s to prompt a minimum response rate. Participants were encouraged to input their anxiety rating as frequently as they felt necessary. After each video, participants completed a *post-video confidence* questionnaire. The training session included two videos, after which the experimenter responded to any questions from the participants.

After the training session, the formal data collection began with the participants completing the *general confidence* questionnaire. Following the experimental protocol above, the participants watched 20 video clips divided into two blocks. The participants were given a short break between the blocks. Ten videos contained adverse surgical events (~ 20 min total), and the other ten videos did not (~ 20 min total). The presentation order of the videos was randomized across participants and blocks, whereby each block contained an equal amount of adverse and non-adverse videos. At the end of the final block, the participants completed the *general confidence* questionnaire again.

Analysis

The expert surgeon in our research team viewed the same surgical videos prior to collecting data from the participants, thereby provided the expert eye-gaze data for applying the dynamic AOI generation technique. That is, we used the expert eye gaze to generate the AOIs, which were then used to generate eye-gaze metrics of the attendings and residents for hypothesis testing. Due to an experimental error, eye-gaze data of the expert were only collected for 19 of the 20 videos. Figure 2 presents the AOI of the expert and the recorded eye gaze of all 20 participants for one video frame. The eye gaze inside the AOIs indicates that the participants were sampling the same information in spatial and temporal accordance with the expert

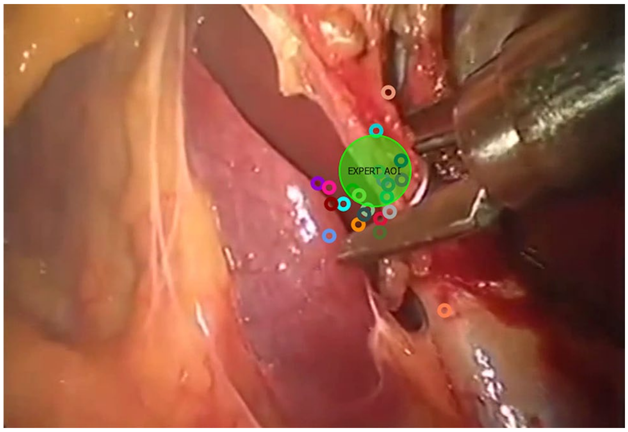

Fig. 2 Expert-defined AOI (green) and eye gaze of 20 participants. (Color figure online)

surgeon. This study computed the percentage of dwell time on the expert AOI of 19 videos for each participant.

To test our hypothesis, the non-parametric Mann–Whitney U test was performed to examine the main effect of video type (presence vs. absence of adverse events) and participant group (attendings vs. residents) on percentage dwell time inside the expert AOIs. We omitted the participant eye gaze collected on the one video for which we did not successfully capture expert eye gaze.

Results

The dwell time percentage inside the expert AOI is significantly lower ($U = 13508.5$, $p < 0.001$; Fig. 3) for videos with adverse events (Mdn = 16.75, $n = 180$) than those without adverse events (Mdn = 19.95, $n = 200$). The dwell time percentage inside the expert AOI is significantly lower ($U = 14029.5$, $p < 0.001$; Fig. 4) for the attendings (Mdn = 15.45, $n = 190$) than residents (Mdn = 19.8, $n = 190$).

Discussion

This novel AOI generation technique efficiently and effectively produced AOIs capable of dynamically following the gaze of the expert as the surgery progressed throughout videos of laparoscopic surgery. Further, the significant effects of video type (adverse events vs. no events) and participant group (attendings vs. residents) on dwell time percentage inside the expert AOIs indicated that the proposed technique could yield sensitive gaze metrics.

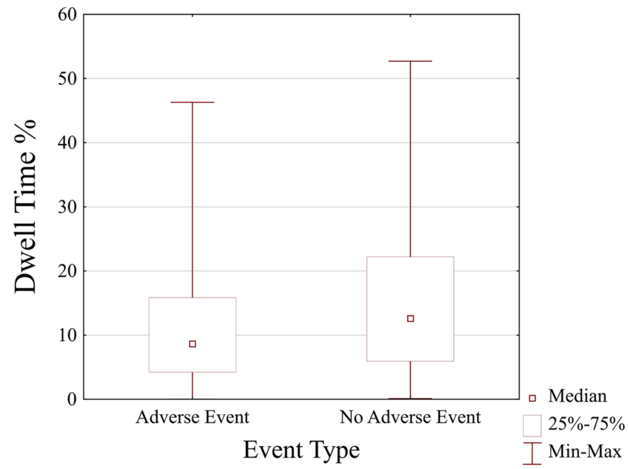

Fig. 3 Significant difference between dwell time percentage on expert AOIs ($U = 13508.5$, $p < 0.001$) between surgical videos with and without adverse events

Video type: adverse versus non-adverse event

Both attending and resident groups exhibited significantly less dwell time on the expert AOIs for videos with than without adverse events. This finding confirmed our first hypothesis that the inclusion of an adverse event likely compromises or disrupts the default gaze patterns or behaviors of the attendings and residents developed through experience and training. This confirmation is also an indication that the proposed AOI generation technique can yield gaze metrics that can differentiate (i.e., be sensitive to) novelty or unexpectedness of surgical events.

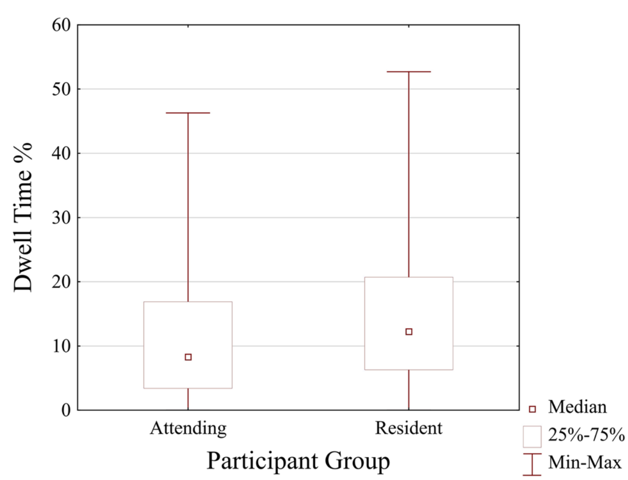

Fig. 4 Significant difference between dwell time percentage on expert AOIs ($U = 14029.5$, $p < 0.001$) between residents and attendings viewing the same surgical videos

Besides indicating sensitivity of the AOI technique, this finding also sheds light on how adverse surgical events influence gaze patterns across surgeons, contributing to the empirical research on the relationship between eye gaze and task complexity. Khan et al. [5] found that "complex" tasks (e.g., cystic artery dissection) led to higher gaze agreement between two surgeons than "simple" tasks (e.g., gall bladder removal) in laparoscopic cholecystectomy because they are explicitly trained to concentrate on specific anatomical structures and equipment positions for complex surgical procedures. However, task complexity associated with adverse events is qualitatively different in that rehearsed gaze patterns for gathering visual information might not be applicable, resulting in lower gaze agreement with experts as indicated by the results of this study. The results in this study relate to the work by Di Stasi et al. [24] revealing that higher gaze entropy (i.e., "…a measure of the uncertainty over the gaze position at any point in time" p. 5035) and velocity (i.e., "…how fast the gaze is continuously moving through the exercises" p. 5038) among surgical residents is associated with more complex tasks in laparoscopic simulation training. However, gaze entropy and velocity metrics are not directly comparable to dwell time inside the AOIs. Our finding suggests that surgical research and training should further investigate response to adverse events that may unexpectedly arise during a procedure and demand immediate response for patient safety.

Expertise level: attending versus resident surgeons

The attendings demonstrated significantly lower dwell time inside the expert AOIs than residents, contrary to our hypothesis and prior research. While the literature suggests that eye-gaze behaviors can discriminate expertise in surgical skills [7, 8, 12], the findings highlight that greater expertise generally yields higher gaze agreement [5] or fixation time on a target object or AOIs [6, 9, 17, 25]. Thus, our results suggesting that the proposed AOI technique can yield gaze metrics sensitive to surgical expertise needs to be interpreted with caution.

One plausible explanation for the unexpected difference in dwell time on AOI is that the attendings might have sampled or explored a larger visual space than residents did, thereby reducing the likelihood of gazing inside the expert AOIs. Our gaze data provide preliminary support for this explanation. The variance in Cartesian coordinates is greater for the attendings ($M = 2.19 \times 10^6$ pixels, SD = 1479.72) than the residents ($M = 1.72 \times 10^6$ pixels, SD = 1312.56), albeit not statistically significantly different. Thus, there is some preliminary support in the data set suggesting that the attendings visually sampled a larger area. The literature also contains some suggestive evidence supporting this finding and explanation that experts sometimes perform more visual sampling than novices. Experts have been shown to employ more fixations than novices for three-dimensional visualizations in a meta-analysis [22] and for landing an aircraft in a simulator experiment [26]. Further, experts have shown to be better at parafoveal processing than novices [22, 27]. That is, experts can gather information for a greater region with each fixation than novices. More frequent sampling or fixation could reduce the likelihood of gazing inside the expert AOIs.

Potential implications for surgical education

The main implication of this study is that the AOI technique can generate sensitive metrics for assessing surgical skills of novices given the two significant effects on the hypotheses. More specifically, a metric indicating whether eye-gaze behavior reflects the presence of an adverse event can be a good indicator of *situation awareness*. If eye-gaze behavior is not influenced by the presence of an adverse event, the novice may be unaware of the severity of the surgical situation and unprepared to respond appropriately. Thus, the training should direct the novice to identify characteristics of adverse events. Second, the lower dwell time on AOI for attendings than residents leads to the recommendation that training may need to instill both the confidence and ability of novices to sample beyond the routinely sampled areas. While our results support this recommendation, further research is necessary to ensure that attendings are productively sampling greater AOIs than residents.

The study contains two limitations. First, eye-gaze behavior can differ between performing and observing a surgery, as some research shows differences [5, 21, 28] while others do not [19]. Thus, the generalization of our results requires caution. Nevertheless, medical students and residents observe surgery for a period of time before performing procedures. The findings in this study should still be applicable for assessment and training purposes, even if differences between observing and performing exist [12]. Another potential limitation is the lack of information on the participant familiarity with the specific surgical events in all videos as familiarity likely affect eye-gaze behavior. Future studies would need to first establish valid measurements on familiarity to surgical events on videos and then investigate the relationship between familiarity and gaze patterns. We hypothesize that familiarity with a video would result in anticipatory gaze patterns.

Future work should refine this dynamic AOI generation technique in terms of size and shape. The adopted AOI size was the minimum size recommended by the literature [13, 14, 23]. Research should investigate the optimal AOI size for capturing eye gazes sampling the same information in dynamic scenery [23]. Neither anatomical structures nor medical equipment can typically be encapsulated by simple shapes, such as a circle or regular polygon, thereby erroneously registering gaze in the AOI [13]. Future work therefore should refine this technique to allow for an AOI to change shape and size in response to attributes of the visual scene.

This dynamic expert-defined AOI generation technique addresses the limitation of other AOI generation techniques that are not suitable for complex and dynamic scenery. Specifically, the proposed technique can efficiently generate AOIs to account for the temporal nature of surgical procedures in accordance to how experts gaze as the surgery progresses. Further, the empirical study demonstrated that the gaze metric of dwell time percentage inside AOI is sensitive to discriminating adverse events and expertise levels. By efficiently and effectively generating AOIs based on expert gaze to derive metrics, this technique can help evaluate surgeon gaze in visually complex environments for both skill assessment and training.

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Compliance with ethical standards

Disclosures Eric Fichtel, Nathan Lau, Sarah Hendrickson Parker, Siddarth Ponnala, Juyeon Park, Shimae Fitzgibbons, and Shawn D. Safford have no conflicts of interest or financial ties to disclose.

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