A Platform for Tracking Surgeon and Observer Gaze as a Surrogate for Attention in Ophthalmic Surgery

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Purpose: To develop and validate a platform that can extract eye gaze metrics from surgeons observing cataract and vitreoretinal procedures and to enable post hoc data analysis to assess potential discrepancies in eye movement behavior according to surgeon experience.

Design: Experimental, prospective, single-center study.

Participants: Eleven ophthalmic surgeons observing deidentified vitreoretinal and cataract surgical procedures performed at a single university-based medical center.

Methods: An open-source platform was developed to extract gaze coordinates and metrics from ophthalmic surgeons via a computer vision algorithm in conjunction with a neural network to track and segment instruments and tissues, identifying areas of attention in the visual field of study subjects. Eleven surgeons provided validation data by watching videos of 6 heterogeneous vitreoretinal and cataract surgical phases.

Main Outcome Measures: Accuracy and distance traveled by the eye gaze of participants and overlap of the participants' eye gaze with instruments and tissues while observing surgical procedures.

Results: The platform demonstrated repeatability of > 94% when acquiring the eye gaze behavior of subjects. Attending ophthalmic surgeons and clinical fellows exhibited a lower overall cartesian distance traveled in comparison to resident physicians in ophthalmology ($P < 0.02$). Ophthalmology residents and clinical fellows exhibited more fixations to the display area where surgical device parameters were superimposed than attending surgeons ($P < 0.05$). There was a trend toward gaze overlap with the instrument tooltip location among resident physicians in comparison to attending surgeons and fellows (41.42% vs. 34.8%, $P > 0.2$). The number and duration of fixations did not vary substantially among groups ($P > 0.3$).

Conclusions: The platform proved effective in extracting gaze metrics of ophthalmic surgeons. These preliminary data suggest that surgeon gaze behavior differs according to experience. *Ophthalmology Science 2023;3:100246 © 2022 by the American Academy of Ophthalmology. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).*

Supplemental material available at www.ophthalmologyscience.org.

Surgical procedures are dynamic events comprising complex visual scenes requiring that the surgeon observe evolving anatomy, tissue-instrument interactions, and the effects of surgical instrumentation and anticipate subsequent events. When performing or observing a surgical procedure, surgeons may have divergent visual spatial attention and awareness corresponding to each subject's experience, specialization, training, or environment.[1-4] Gaze tracking has been employed in diverse disciplines, including autonomous driving, learning and knowledge transfer, surgery, and other activities that rely on visual processing, with the goal of gaining a better understanding of how humans perform numerous tasks by systematically assessing gaze as a surrogate for attention.[5-13]

Eye movement studies have been responsible for significant findings in human behavior in health care: previous studies identified the difference in eye movement patterns among radiologists, surgeons, and nurses by extracting data that led to improved training for diagnostics, patient interaction, and intraoperative situational awareness by informing novice health care providers as to the areas of interest (AOIs) of experienced professionals.[1,14,15] Few studies in ophthalmology have focused on gaze tracking in clinical care, and most studies have assessed the interpretation of static images used for diagnostic purposes. Shahimin et al[16] analyzed patterns in eye movements between ophthalmologists and optometrists when assigning diagnoses to digital fundus photographs assessing fixed AOIs such as the optic disc, macula, and blood vessels. Shirley et al[17] identified that trainees could improve their search strategy after analyzing gaze data from expert clinicians when viewing retinal images. The extraction of metrics and features in eye-tracking research during surgery is currently limited: contemporary platforms fail to

provide integration with relevant tools and heterogeneous methods for gaze acquisition. Commercially available solutions require costly equipment and licensed software. An open-source platform for intraoperative gaze analysis has the potential to facilitate research into the complex and dynamic environment of ophthalmic microsurgery.

In this work, we developed a novel open-source platform for processing eye-tracking data from a diverse set of eye-tracker devices, extracting standard gaze metrics together with the dynamic generation of AOIs during vitreoretinal procedures via deep learning neural networks. To validate our platform, ophthalmic surgeons observed critical or complex elements of cataract and vitreoretinal procedures. By linking gaze coordinates with the detection of AOIs, including surgical instrumentation and intraocular anatomic landmarks, we hope to establish a platform for the investigation of visual attention during ophthalmic surgery via generating semantically rich feature vectors for real-time or post hoc data processing throughout complex intraoperative visual scenes.

Methods

Acquisition of Gaze Coordinates

The data flow of the proposed platform for the acquisition and feature extraction of eye gaze data is displayed in Figure 1. The platform is designed to be compatible with eye trackers that provide gaze coordinates in real time, such as eye-tracker bars, glasses, and gaze tracking via webcams (Figure 1A). Constraints related to display size, resolution, and distance of the subject to the screen are dependent solely on the technical restrictions of the hardware employed.

An eye tracker (Tobii 4C Eye Tracker, Tobii AB) was attached to a portable computer (system configuration details in the Supplemental Material Section 1, available at www.ophthalmology science.org) displaying video from intraocular surgical procedures, and gaze tracking was performed to measure and analyze visual attention. Screen recorder software (OBS Studio, OBS Project) acquired the gaze location frame-by-frame based on a trackable bubble overlay (Tobii Experience and Tobii Ghost, Tobii AB) at a frequency of 60 Hz (Fig S1, available at www.ophth almologyscience.org). The user did not have access to the spatialotemporal data, and the trackable bubble overlay was recorded in a separate file. A computer vision−based algorithm was developed to extract the cartesian coordinates from the recorded video with trackable bubble overlay, employing OpenCV Computer Vision Library color threshold and blob detection methods. Supplemental Material Section 1 provides the method for extraction and calibration of the eye-gaze acquisition method, and the developed code can be accessed in Supplemental Material Section 2, available at www.ophthalmologyscience.org.

Identification of Dynamic AOI with Instance Segmentation via Deep Learning

As a proof of concept to generate dynamic spatial data of surgical elements, a deep learning instance segmentation model based on YOLACT[18] was trained to identify 3 different surgical instruments and 1 retina landmark: vitrector, intraocular microvitrectomy forceps, and endolaser tooltips, together with the optic disc (Fig S2, code and implementation details available in Supplemental Material Sections 2 and 3, available at www.ophthalmologyscience.org). The

data used to train the model consisted of frames extracted from 100 pars plana vitrectomy surgeries for which the instrument tooltips and optic disc were annotated. Supplemental Material Section 3 and Figure S3 describe the model training and evaluation (available at www.ophthalmologyscience.org).

Advanced Features Extraction

An open-source algorithm to evaluate gaze metrics based on the velocity of eye movements was employed to detect saccades and fixations (Saccade/fixation detection in R, code implementation in the Supplemental Material Section 2, available at www.ophthalmologyscience.org). The algorithm was built on the saccade detection method proposed by Engbert et al,[19] and it was configured to process gaze data acquired at a sampling rate of 60 Hz. The algorithm defines a fixation as the period between 2 detected saccades. If the spatial distance between saccades is near 0, the algorithm classifies the movement as a blink or artifact. The beginning of each saccade is determined when the eye movement exceeds a threshold of 20°/s. Involuntary microsaccadic movements are identified and discarded by detecting amplitudes of up to 120 arcminutes.

To identify smooth pursuits that attend surgical instruments, we based our algorithm on a set of parameters for eye movements established by previous research.[20] Smooth pursuits can be distinguished from saccadic movements via the nature of the movement of the gaze and target: smooth pursuits occur in response to the velocity of the target, whereas saccadic movements are generated in reaction to the spatial translation of the target itself.[21] In this study, the surgeon's gaze must be located within the AOI (instrument tooltip) defined by a distance of 3° or less of visual angle from the gaze point to the cartesian coordinates of the tooltip. Next, the algorithm compares the velocities of the instrument tooltip and surgeon's gaze. Smooth pursuit of the instrument is detected if both eye and object move at an average speed between 0.35°/s (15 px/s) and the threshold of 100°/s (433 px/s). We based these parameters on the work of Linnéa et al,[20] who identified an upper limit of 100°/s for smooth pursuit in humans. Because there is no established lower boundary for smooth pursuit velocity in the literature, we chose 0.35°/s as a means to minimize potential noise during data analysis.

The platform outputs a feature vector that includes the distance traveled by the observer's gaze and the magnitude of the velocity and acceleration vectors via the moving average of these variables in subsets of 100 ms. It also produces the distance to the centroid of the instrument tooltip, distance to the area of anatomic elements, such as the optic disc, and detection of fixation and smooth pursuit eye movements (Figure 1C).

Validating the Platform by Extracting Features from Subjects

The acquisition of gaze data from ophthalmic surgeons observing intraocular surgery was approved by the Institutional Review Board of the University of Illinois at Chicago. To extract the cartesian coordinates of participants' gaze, the eye tracker—with an operating distance between 50 cm and 95 cm—was interfaced with a 15.6" video display at a resolution of 1920 × 1080 pixels (additional technical details of the display hardware may be found in the Supplemental Material Section 1, available at www.ophthalmologyscience.org). The observer's viewing distance was fixed at 65 cm from the display, and surgeons were asked to use optical correction appropriate to their needs for the computer monitor at this operating distance. The surgical videos employed for gaze data acquisition consisted of 6 video segments of comparable duration, one for each of the following
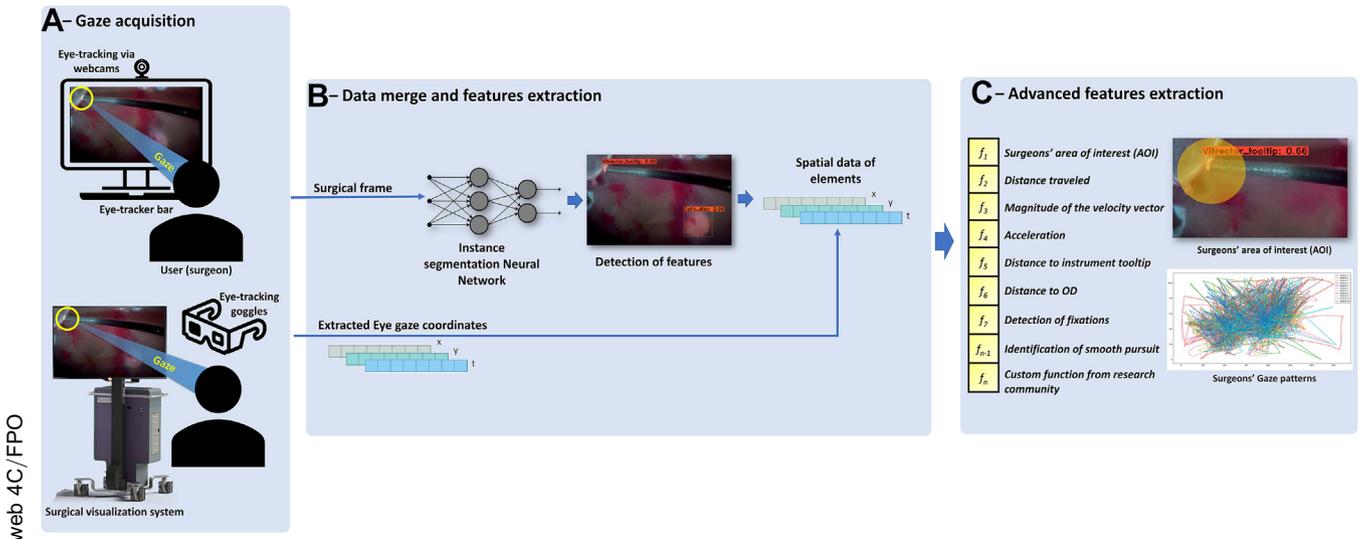
Figure 1. Method for attention tracking during ophthalmic microsurgery using gaze tracking: (**A**) gaze tracking is performed using any of a variety of commercially available solutions; (**B**) detection and segmentation of instrument tooltip and optic disc via an instance segmentation neural network, integrating spatial data with gaze coordinates; (**C**) automated extraction of advanced features from gaze data allows for analysis of attention during ophthalmic surgery.

surgical procedure types: cataract surgery, including uncomplicated capsulorrhexis, nuclear disassembly and phacoemulsification, and cortex removal (from 3 different cataract procedures); pars plana vitrectomy, including core vitrectomy, membrane peeling, and endolaser application (from a set of 3 vitreoretinal procedures). The durations and sample frames from each video clip are available in Supplemental Material Section 4, Table S2, and Figure S4 (available at www.ophthalmologyscience.org). Validation was performed by 11 ophthalmic surgeons grouped by 3 distinct levels of experience (Table 1).

Statistical Analysis

Statistical analysis of the generated data was performed using Pandas and scikit-learn, open-source libraries for data manipulation and analysis. Descriptive statistics (mean ± standard deviation) were calculated for the extracted features of this study. The level of statistical significance was set at $P < 0.05$ using a 2-tail Student *t* test for each pair of surgeon groups (Table S3 in the Supplemental Material, available at www.ophthalmologyscience.org).

Results

Extraction of Fixation Values

Table 2 gives the extracted number and length of fixations for all 3 groups of surgeons during each surgical phase measured by the algorithm. Although there was a trend toward expert surgeons performing fewer fixations than residents during most surgical phases, statistical significance was not attained, and the average length of fixations was similar among experts. No statistical significance was identified for this discrepancy in the number of fixations between groups ($P > 0.3$, Table S2).

Table 3 shows the average gaze distance traveled per observer during each surgical phase (cartesian distance in

pixels). Attending and fellow surgeons had an overall lower gaze travel distance than residents during all surgical phases, regardless of subspecialty ($P < 0.02$, Table S2).

Surgeons' Dwell Time within AOI

To investigate how visual attention among the 3 groups of surgeons differed for superimposed machine parameter information displayed on screen, the platform quantified the number of fixations in the area where parameters such as vacuum level and laser energy are displayed (Table 4). Experienced surgeons had fewer fixations in the area where overlayed instrument parameters were displayed on the screen than fellows and residents (Table S2, $P < 0.05$). Figure S5 shows the extent of superimposed information considered for analysis (available at www.ophthalmologyscience.org).

Identifying Surgeons' Attention to Surgical Instruments and Anatomic Elements

The platform combined the cartesian coordinates detected by the neural network from surgical instruments and the optic disc area with the gaze coordinates. With this combination, the platform estimated the time spent by each individual's gaze at the selected AOIs, also known as dwell time. Table 5 shows the percentage of dwell time and the average distance to the instrument tooltip and optic disc for each surgical phase. Residents' gaze consistently visited the instrument tooltip and its surroundings up to 6% more often than attendings and fellows. However, no statistical significance was detected when comparing the dwell time percentage values among the 3 groups ($P > 0.2$, Table S2).

Table 1. Distribution of Participants

Position	Average Years of Experience (SD)	No. of Participants	Subspecialties
Attending physician	24.83 (23.82)	3	2 retina; 1 cornea
Clinical fellow	4.8 (1.82)	5	4 retina; 1 comprehensive
Resident physician	1 (0)	3	1 comprehensive; 1 not applicable

SD = standard deviation.

Data Visualization

To facilitate data visualization and analysis, we created a graphical representation of gaze behavior among subjects: Figure S6 shows the gaze trajectory for the 3 groups, Figure S7 demonstrates the change in cartesian coordinates during the experiment, and Figure S8 shows the gaze velocity per participant during all surgical phases. Figure S9 and Supplemental Video 1 demonstrate the capability to track and observe the gaze path for multiple participants simultaneously. Figure S10 exemplifies the ability of our platform to visualize participants' eye movement patterns relative to the position of the instrument tooltip or any feature tracked by the instance segmentation neural network. The horizontal line indicates the threshold where gaze overlapped with the AOI (vitrector tooltip), defined as a distance of $\leq 3°$ in visual angle (130 px) consistent with established norms for gaze overlap[22,23] and following the hardware limitation specified by the eye-tracker manufacturer (maximum resolution of $1.5°$ in visual angle, or 75 px with our setup). Moreover, Figure S11 provides a graphical representation of the identification of potential smooth pursuit movements, following the requirements for smooth pursuit recognition previously detailed in the methods section. Supplemental Video 2 shows the smooth pursuits indicated by the red rectangle in Figure S11 (available at www.ophthalmologyscience.org). All parameters can be altered in the source code according to the eye-tracking device, screen size, and resolution used during the gaze acquisition: screen pixels can be converted to visual degrees via equation (1):

$$size_{pixels} = \frac{\tan^{-1}\left(\frac{\left(\frac{h}{2}\right)}{d}\right)}{\left(\frac{r}{2}\right)}, \quad (1)$$

in which h is the screen display height in centimeters, d the distance from the subject to the screen in centimeters, and r the vertical resolution of the display in pixels.

Discussion

There has been increasing attention on gaze behavior during surgical procedures such as laparoscopy and analysis of interpretation of still images in radiology and pathology.[1,16] To our knowledge, there have been no reports of assessment of gaze behavior during ophthalmic microsurgery. Several potential barriers include the significant cost of research-grade eye-tracking equipment combined with the proprietary software used for eye-tracking analysis, which may serve to inhibit investigations. We have developed an open-source and hardware-agnostic platform for acquiring and processing eye-tracking data during ophthalmic microsurgery. Our platform extracts a series of features by linking the surgeon's gaze as a proxy for visual attention with a deep learning neural network that can incorporate multiple AOIs, enabling the investigation of surgeons' gaze behavior during cataract and vitreoretinal procedures.

The eye-tracking data acquired during the calibration phase of this study show that the method employed to validate our platform is consistent, within the constraints of the limitations in hardware used for the study. Moreover, Feit et al[24] demonstrated significant variability in precision and accuracy for both commercial and scientific-grade eye-tracker models, reporting discrepancies in accuracy reported by manufacturers. In our study, we achieved an overlap of $> 94\%$ when directing a subject to follow an object on the screen, demonstrating the reliability of extracting gaze position using a commercially available eye-tracker device and computer vision algorithms

Table 2. Characteristics of Fixation between Attending, Fellow, and Resident Surgeons

	Attending		Fellow		Resident	
	No. of Fixations	Avg. Duration (ms)	No. of Fixations	Avg. Duration (ms)	No. of Fixations	Avg. Duration (ms)
Capsulorrhexis	25 ± 1	378 ± 37	24 ± 4	362 ± 68	26 ± 5	378 ± 18
Phacoemulsification	30 ± 1	360 ± 34	35 ± 9	340 ± 22	44 ± 6	325 ± 53
Cortex removal	34 ± 17	305 ± 28	31 ± 7	401 ± 24	42 ± 3	360 ± 73
Core vitrectomy	41 ± 2	341 ± 17	41 ± 7	366 ± 57	50 ± 3	360 ± 39
Membrane peeling	36 ± 7	287 ± 30	31 ± 4	280 ± 60	37 ± 1	354 ± 86
Endolaser photocoagulation	43 ± 7	356 ± 17	34 ± 9	343 ± 28	51 ± 7	360 ± 1

Avg. = average.

Table 3. Average Distance Traveled in Cartesian Coordinates for Each Group of Surgeons (Pixels, Mean ± SD)

	Attendings	Fellows	Residents
Capsulorrhexis	9758 ± 1279	14 037 ± 2209	18 581 ± 3116
Phacoemulsification	9528 ± 1339	17 089 ± 3483	24 219 ± 4250
Cortex removal	16 002 ± 3513	21 400 ± 3533	27 148 ± 4623
Core vitrectomy	18 591 ± 3169	22 559 ± 3308	33 148 ± 4793
Membrane peeling	13 683 ± 3701	20 316 ± 3949	28 294 ± 4770
Endolaser photocoagulation	15 709 ± 3512	20 564 ± 3233	35 457 ± 4772

SD = standard deviation.

(Supplemental Material Section 1, Table S1). In addition, fixation values extracted by our platform are compatible with previous studies: considering a wide set of activities, mean fixation durations in adult subjects range from 150 to 400 ms,[25,26] comparable to the results of our platform's output as shown in Table 3. Finally, it is important to note that our platform is hardware agnostic: it is likely that increased reliability of acquired gaze data can be achieved by employing state-of-the-art eye-tracking hardware, that is, research-grade equipment such as eye-tracking glasses that can identify subjects' attention in a 3-dimensional environment as well,[27] whereas lower data fidelity is expected to be observed when using low-cost/lower-resolution equipment such as webcams. Surgeons' gaze extraction via diversified equipment is the subject of ongoing studies by our group.

The dynamic generation of an AOI in real time via deep learning neural networks enabled our platform to store eye-gaze data and spatial position of elements concurrently during surgery for subsequent analysis. Deep learning neural networks have been widely applied for image segmentation in clinical applications, including the diagnosis and classification of pathologies[28-30] and real-time surgical guidance.[31-34] Our instance segmentation neural network tracked 3 different instruments and 1 anatomic element during 3 surgical phases, reaching area under the precision-recall curve values of up to 98%, demonstrating the capability of identifying AOIs in real time. This instance segmentation neural network is also capable of being trained to track and segment additional surgical landmarks according to the needs and goals of researchers, with several elements selected in this work to serve as a proof of concept. The identification of salient elements in surgical frames is

Table 4. Number of Fixations for Each Group within the AOI for Overlayed Surgical Device Parameters (IOP, Vacuum, Vitrector Cut-Rate, and Laser Shot Count/Energy)

Group	No. of Fixations in the Superimposed Information Area (Mean ± SD)
Attendings	3.333 ± 4.714
Residents	91.333 ± 21.892
Fellows	81.8 ± 33.358

AOI = area of interest; IOP = intraocular pressure; SD = standard deviation.

directly related to the data with which we trained the neural network; the occurrence of high signal-to-noise ratio in surgical videos, such as suboptimal lighting conditions or vitreous hemorrhage, may affect detection and segmentation performance. Likewise, heterogeneous instrument arrangements, such as different forceps shapes for internal limiting membrane peeling, may lead to a drop in performance. Network validation for implementation in a clinical setting may require a larger and more heterogeneous set of cases for training. In this preliminary work, we leveraged our algorithm to demonstrate the potential of dynamically generating multiple AOIs together with the acquisition of eye gaze data to create 2 tools of potential utility: automated detection of overlap between gaze and location of surgical instrumentation and the identification of likely episodes of smooth pursuit during intraocular surgery.

The preliminary data generated in our study indicate a potential relationship between the surgeon's procedural experience and gaze behavior. Table 2 suggests that experience may affect the number and length of fixations, with fewer fixations performed by experienced surgeons. These data may be inconsistent with some studies of the eye movement patterns among surgeons: previous research has suggested that experts, compared with nonexperts, have more focused attention and elaborate visual representation during the performance of a task; this can be represented by increased fixation rates and a higher proportion of fixation within an area of interest.[11,17,35] However, Sodergren et al[36] suggested that, even though experts can demonstrate a greater perceptual span and more rapid information acquisition with more fixations of shorter length, in some situations, this group may concentrate their gaze only on pertinent areas of view, with the AOI having a prominent place in the analysis. When analyzing the average gaze distance traveled by each group in Table 3, our data reveal that expert surgeons may focus on more relevant loci without loss of attention, represented by decreased cartesian distances traveled by their gaze. In contradistinction, trainee resident physicians may shift their gaze more frequently to regions not considered relevant or as critical by experienced surgeons. In addition, we observed that experienced surgeons had fewer fixations in the area where overlayed surgical device parameters were displayed on screen, indicating that this superimposed information may draw the attention of novice surgeons from instrument maneuvers and tissue handling. Alternately, less experienced physicians may rely more heavily on feedback from surgical device parameters in real time in comparison with more experienced surgeons for the phases and types of procedures analyzed herein.

The concurrent assessment of gaze coordinates with spatial data generated by the instance segmentation neural network allowed our platform to estimate the percentage of time the surgeon's gaze attended the surgical instruments and the optic disc. One possible interpretation of the values in Table 5 could suggest that more experienced surgeons frequently scan peripheral areas and may anticipate subsequent movements of intraocular instruments or the effects of instrument maneuvers on the tissue environment. In contrast, novice surgeons may tend to

Table 5. Dwell Time Percentage of Participants within the AOI (Surgical Instrument Tooltip), with Their Corresponding Average Distance to the Object Being Tracked

	Attendings		Fellows		Residents	
	Dwell Time	*Avg. Distance*	*Dwell Time*	*Avg. Distance*	*Dwell Time*	*Avg. Distance*
Vitrector tooltip	21.86% ± 7.94%	334 ± 230	21.97% ± 2.29%	356 ± 216	27.74% ± 1.05%	378 ± 230
Membrane peeling forceps	45.88% ± 1.05%	310 ± 196	44.95% ± 17.20%	338 ± 203	51.11% ± 2.38%	369 ± 218
Endolaser tooltip	39.76% ± 2.00%	279 ± 140	30.05% ± 8.50%	284 ± 142	45.41% ± 0.77%	270 ± 161
Optic disc	4.58% ± 0.84%	371 ± 202	5.14% ± 6.81%	418 ± 210	4.39% ± 6.08%	406 ± 206

AOI = area of interest; Avg. = average.

focus their visual attention more uniformly on surgical instruments, specifically the tooltip, where instrument-tissue interactions are most likely to occur. No significant divergence in visual attention was identified among groups with respect to the optic disc area.

Identifying potential smooth pursuit movement is another advantage of tracking features using a neural network while synchronously acquiring gaze data. When following previous requirements for a gaze movement to be considered a smooth pursuit,[20] our platform offers a tool that detects and indicates, in a timeline manner, the presence of these movements. This approach may, in the future, relieve the need for manual annotation in smooth pursuit studies while also helping to investigate how smooth pursuit movements may differ between different groups of subjects. However, a deeper evaluation of the accuracy of these detections compared with manually annotated data is made necessary.

The multiple potential applications of this platform may be broadly classified into several related areas: (i) facilitating research relating to attention and awareness during intraocular surgery; (ii) monitoring surgeon gaze and acquiring data in furtherance of surgical training; and (iii) monitoring attention and awareness during surgery in real time to potentially improve safety and efficacy. We propose that promoting an open-source and hardware-agnostic platform for the acquisition of gaze data from relatively inexpensive consumer-grade eye trackers will likewise facilitate the study of attention and awareness during microsurgery. Current eye-tracking platforms suitable for research are often costly, are dependent on software solutions for data analysis that are not open-source, and, with few exceptions, require data generated by the manufacturer.[37] Training in ophthalmic microsurgery could potentially be facilitated through gaze metrics that may distinguish patterns among expert and novice surgeons. These data could potentially be used to inform a learner as to how experienced ophthalmic surgeons attend to the visual surgical landscape or even perhaps how the experienced surgeon reacts to intraoperative complications (i.e., before a posterior capsular rupture or iatrogenic retinal break). Fichtel et al[35] have reported that assessment of gaze patterns from expert surgeons identified the occurrence of adverse events in observed laparoscopic surgical procedures. Ultimately, with the advent of 3-dimensional visualization systems—in which the surgeon performs

procedures using heads-up technology[38]—and the existence of head-mounted wearable eye-tracker devices,[39] future studies can assess surgeon attention and gaze in real time during the surgical procedure.

The gaze behavior of surgeons observing a procedure retrospectively may differ from patterns observed in the surgeon actively performing the procedure and managing the equipment parameters, which may also differ from the surgeon supervising a trainee in real time. Atkins et al[40] demonstrated similarity in eye movement when comparing "doing" versus "watching" simulated laparoscopy surgery, with overlap values of up to 82% observed and a consistent delay in reaction time of over 600 ms. Nonetheless, future studies will be required to assess these differences. Another potential limitation of our study is the hardware employed for gaze acquisition: although the primary goal of our platform is to offer an accessible solution for image processing of gaze data and extraction of features, the relatively low sample rate and lack of technical specifications in selected consumer-grade eye trackers—such as head tracking to compensate for potential pitch and yaw of the surgeon's head during gaze acquisition—may impact the fidelity of our results. A method that relies on computer vision may introduce errors because of the inaccessibility of raw data generated by the eye tracker and gaze data processed by the manufacturer's software may be subject to high levels of data transformation and processing, resulting in delay or lower accuracy in tracking than research-grade equipment. Finally, previous studies indicated that other factors such as age and eye color might affect the accuracy of the collected data, although we calibrated the platform with the manufacturer's software and performed a reproducibility test asking all subjects to follow objects on screen to assess for confounding variables.[41,42]

In summary, we have developed a platform for eye tracking that integrates open-source software for data analysis with deep learning neural networks to generate dynamic AOIs. To validate our approach in this proof-of-principle study, we extracted gaze patterns comparing experienced ophthalmic surgeons with trainees of varying degrees of experience using cataract and vitreoretinal procedures. Preliminary data indicated quantifiable differences in eye movement behavior among groups. Additional studies are ongoing to begin to elucidate the role of visual attention during ophthalmic microsurgery.

Footnotes and Disclosures

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