Visualizing Instructor's Gaze Information for Online Video-based Learning: Preliminary Study

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ABSTRACT

Video-based online educational content has been more popular nowadays. However, due to the limited communication and interaction between the learners and instructors, various problems regarding learning performance have occurred. Gaze sharing techniques received much attention as a means to address this problem, however, there still exists a lot of room for improvement. In this work-in-progress paper, we introduce some possible improvement points regarding gaze visualization strategies and report the preliminary results of our first step towards our final goal. Through a user study with 30 university students, we found the feasibility of the prototype system and the future directions of our research.

CCS CONCEPTS

• **Human-centered computing → Interaction design**; **Empirical studies in visualization**; • **Applied computing → Interactive learning environments**.

KEYWORDS

Online learning, gaze sharing, gaze visualization, user study

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1 INTRODUCTION

Recently, a lot of educational institutions had to adopt various changes in environments and methods of teaching and learning, due to the prolonged COVID-19 situation [Oliveira et al. 2021; Revilla-Cuesta et al. 2021]. Accordingly, the demand for online educations like video-based remote learning has increased rapidly, since Face-to-Face (F2F) teaching was limited for recent two years [Bao 2020]. However, digital transformation on education was made without thorough preparation and analysis, therefore, various kinds of problems have been pointed by both instructors and learners. A huge number of instructors appealed that one of the main difficulties in online lectures is the lack of communication and interaction with students. This made it difficult for instructors to evaluate the students' learning performances, the level of satisfaction, and the quality of the lecture being provided, resulting in various problems of online lectures [Bojović et al. 2020; Revilla-Cuesta et al. 2021]. Similarly, a number of learners pointed out that they are likely to lose their attention to the online lecture in case the progress of a class is too fast to follow or the subject being addressed is too difficult to understand. This happens more often in case an instructor does not use a webcam to show his/her face or cannot use a mouse/pen to highlight the progress of the lecture.

In F2F class, the instructor could use several non-verbal real-time communication tools, such as eye contact, pointing with hands, body and arm gestures, knocking sounds, walking around students, etc. These facilitated the interaction between the learners and the instructor, making them more easily understand each other, thereby improving the quality of the class [Othman et al. 2020; Sutiyatno 2018; Wahyuni 2018]. Current online video-based distance learning services, however, has little support for these interaction tools despite their rapid growth and expansion in recent years. In particular, instructors and learners would experience more difficulties from asynchronous video-based learning.

Generally, eye contact was deemed one of the most efficient non-verbal communication tools [Rosch and Vogel-Walcutt 2013]. Moreover, one's gaze direction can provide various important aspects, such as one's attention and intention, therefore, play an important role in human interactions [Sibert 2000]. For this reason, the instructor's gaze already attracted many researchers in the HCI+education field as a suitable lightweight medium that can provide the instructors' intentions to the learners even in mobile or online environments, and has been employed in many recent studies. Several researchers attempted to support instructors by providing a set of features, such as student drowsiness detection [Lahoti 2020] and cheating detection [Jadi 2021]. The systems proposed in these studies give some feedback to the instructor by monitoring the learners' eye movements, however, they mainly focus on supervising the students [Cao et al. 2020; Sher 2009].

Conversely, studies presented in [Ahuja et al. 2021; Akkil et al. 2018; Sharma et al. 2015; Sung et al. 2021; Wang et al. 2019; Yao et al. 2018; Špakov et al. 2019, 2016] attempted to exploit the gaze information to understand and improve the instructors' and the learners' behaviors during online distance learning. The studies from [Sharma et al. 2015; Špakov et al. 2016] are early attempts that utilized the instructor gaze visualization/sharing in online education. In [Špakov et al. 2016], the instructor's gaze scanpath was employed as a pointer for presentation and the authors compared its usefulness with that of PowerPoint built-in pointer, manual laser pointer, and without pointing devices. The authors found that a gaze-based pointer and the PowerPoint pointer performed best, their implementation and experimental setting have some limitations though. For example, the length of a lecture video used in the experiment was relatively short (average 75s) and the slide consisted of graphic visualization contents (e.g., Boxplots, plot matrix, etc.) only. The work from [Sharma et al. 2015] analyzed how instructor gaze visualizations affect students' learning behaviors in the MOOC platform. They measured various students' navigation behaviors, such as the number of pauses, the ratio of pause time and video length, and the number of seek backs. As a result, they concluded that showing a teacher's gaze makes the content easier to follow even when complex visual stimuli present in the video lecture. The authors of [Akkil et al. 2018] proposed to support video-based mobile collaboration by providing shared gaze information and analyzed how gaze data can be used in mobile environments. On the contrary, some studies visualized students' gaze data to improve the quality of remote/in-person class [Ahuja et al. 2021; Yao et al. 2018]. By visualizing/sharing the learners' gaze, instructors can more easily check the progress of the study and find out the lecture segment which is difficult to follow from the learner's view. On the other hand, [Sung et al. 2021; Špakov et al. 2019] studied how sharing both the instructor's and the learner's gaze data in real-time can help professional instructors and novice learners communicate and understand each other during remote hands-on engineering work and teaching tasks.

Although several works have presented promising results of gaze visualization and sharing in various online video-based learning settings, we point out that there are still several limitations to overcome. First, most studies lack the consideration of the difference in the importance of gaze during the lecture. For example, [Akkil et al. 2018; Sharma et al. 2015; Špakov et al. 2019] provide gaze visualization all the time during the online lecture or remote collaboration (i.e., always-on without any weights). Conversely, [Špakov et al. 2016] triggered gaze visualization in a very simple way: showing the instructor's gaze whenever a long fixation (dwell time) is detected, which might cause a number of false alarms. We argue that different gaze visualization strategies (e.g., always-on, weighted gaze visualization, instant visualization based on the dwell time, etc.) would result in different effects for both instructors and learners. Second, the position of gaze visualization was generally determined based on the raw gaze coordinates. This could sound like a natural visualization strategy, however, we also argue that contents-aware gaze visualization (i.e., revising the position and size of gaze visualization based on the content/structure of a lecture slide) would produce different results. Finally, as mentioned above, eye contact is also an effective non-verbal communication way. However, most of the previous works do not discuss the possibility of realizing an eye contact feature even though they exploit the users' gaze data.

This work-in-progress paper, therefore, reports preliminary results of the initial research stage to realize our gaze visualization framework that can handle the aforementioned limitations. In particular, we focus on exploring how different visualization strategies (i.e., always-on vs filtered based on content importance) affect the learner's experience of watching online pre-recorded video lectures.

2 SYSTEM DESIGN

Our study is divided into the instructor phase and the learner phase. In the instructor phase, first, we record video lectures and collect the instructor's gaze movement data. Afterwards, we extract useful gaze events such as fixation and saccades from the raw gaze data. Finally, we generate a set of video lectures integrated with visualizations of the instructor's gaze events. In the learner phase, we record the learner's behaviors (e.g., gaze movements, postures, etc.) while they are watching the video lectures generated in the instructor phase. After watching the video, the learners are asked to complete a questionnaire and conduct an interview process with experimenters. Various recorded data during the learner phase are examined for further analysis and development. In this paper, we only report partial results based on the recorded data to answer some of our research questions.

2.1 Data Gathering

To implement a prototype of our system, the instructor's gaze movement data were recorded first. To do this, a single GazePoint GP3 research-grade eye tracker with a sampling rate of 60Hz was used. Using an eye-tracking UX analysis software provided by GazePoint, we recorded various eye movement-related data, such as frame IDs, timestamps, X/Y coordinates of gaze points, and so on. During the experiments, the eye tracker was installed between a desktop monitor and a participant. According to the recommended setting for the GP3 eye tracker, we set up the eye tracker around 65 cm (25 inches) away from the participant's face and each participant (both instructors and students) was asked to minimize head movements to reduce data loss. Before capturing gaze data, a 5-point calibration processes was applied. In addition to eye tracking, two Logitech C922 webcams were used for capturing learner behaviors.

2.2 Pre-processing and Contents Generation

Among various types of gaze events, we employed a fixation event and saccades event because they can effectively capture the instructors' teaching flow and attentions. First, raw gaze data are extracted from the GP3 eye tracker and then stored for further

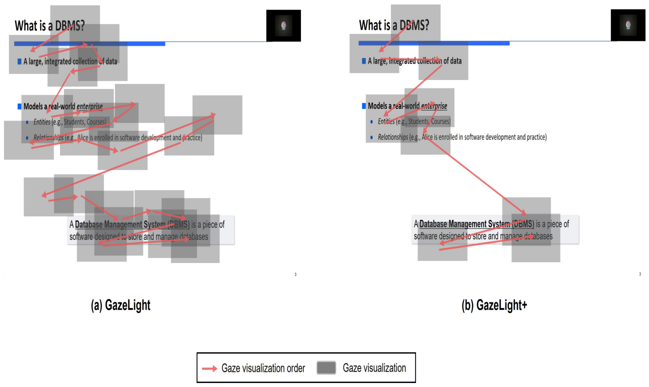

Figure 1: Difference between GazeLight and GazeLight+

pre-processing steps. Visualization of all the raw gaze events could produce a massive number of dots and lines which drastically degrade the quality of pre-recorded video contents. Therefore, Similar to the previous work [Špakov et al. 2016], we create video lecture contents by integrating the refined gaze visualization into the original video contents to provide the learners with an instructor gaze while preserving the visibility and readability of the video lecture. For this, we introduce two types of visualization techniques called GazeLight and GazeLight+.

2.3 GazeLight

This approach converts a series of fixation and saccades events into a series of translucent grey-colored rectangle visualizations. A rectangle's size was fixed as 300 (width) x 150 (height) and transparency was adjusted with an alpha value of 0.1. The translucent grey-colored rectangles sequentially appear on the screen and disappear according to the order and positions of fixation events. In addition, a set of temporally adjacent fixation events are grouped into a single fixation event to avoid unnecessary duplicate rectangles, thereby improving the visibility of the video contents. The rectangle overlays added to each video content were implemented using python OpenCV library. Figure 1(a) shows how GazeLight works. As shown in the figure, GazeLight works like always-on mode. From the beginning of the lecture, the students always can see instructor gaze visualizations.

2.4 GazeLight+

This approach also works similarly to GazeLight, except that the gaze visualizations only related to the important segment of a lecture are presented. Therefore, GazeLight+ can be considered a modified version of GazeLight where filtering gaze visualizations based on the importance of lecture segments is applied. Based on these two visualization techniques, we conduct a user study to figure out how different visualization strategies affect the learner experience. However, in the current phase of our study, we used the Wizard of Oz approach to implement GazeLight+ feature. That is, an experimenter fully reviewed the video lectures created by instructors and marked the timestamps of important segments in advance. Afterward, a set of gaze fixations corresponding to those timestamps were collected and presented. Figure 1(b) depicts how GazeLight+ works. Compared to GazeLight, GazeLight+ provides fewer, but more meaningful visual cues. Figure 1 illustrates how GazeLight and GazeLight+ work differently for the same segments of the same video. Working examples of GazeLight and GazeLight+ can be best viewed with our supplementary video.

3 USER STUDY

3.1 Research questions

We conducted a controlled user study, using a within-subject experimental design, with the following three experimental conditions: Baseline (No highlight presented), GazeLight, and GazeLight+. In this study, we focus on addressing the following research questions:

- **RQ1: Does GazeLight (GazeLight+) help the students concentrate on the lecture?** & **RQ2: Does GazeLight (GazeLight+) help the students understand the lecture contents?** The objective of GazeLight and GazeLight+ is to improve the learner's satisfaction in video-based distance learning by providing a visual guide on the area in the slide addressed by the instructor. Therefore, we expect that the visualization of the instructor's gaze would provide the learners with explicit visual highlights, so they more easily concentrate on the contents of a slide as well as the instructor's speech. In addition, we also examine if the instructor gaze-based highlight can affect the learner's understanding of the lecture contents.
- **RQ3: Does GazeLight (GazeLight+) help the students recognize the part (position) of a slide that the instructor is currently explaining?** Students participating in online video-based learning are more likely to be disturbed than ones in face-to-face lectures, which may result in decreased learner satisfaction. We attempt to verify if the proposed method can facilitate the recognition of the part (position) of a slide that the instructor is currently explaining, even when the students got disturbed due to external unavoidable events (e.g., phone calling, etc.).
- **RQ4: Does GazeLight (GazeLight+) give the feeling of participating in class with the instructor?** One of the main drawbacks of online learning can be the lack of interaction/relationship between the instructor and the learner. We investigate if the gaze visualization helps 1) make the learners feel like they and the instructor are looking at the same area of the slide, 2) therefore make them feel like they participate in the class with an instructor together.
- **RQ5: GazeLight (GazeLight+) does NOT interfere with the student's learning process?** As illustrated in Figure 1, visualization of the instructor's gaze path could fully or partly obscure the contents in the slide, which could rather interrupt the student's learning process. In this study, we investigate if students find it visually confusing/inconvenient when using GazeLight (GazeLight+) during the video-based online learning task.

3.2 Participants

For learner experiments, we recruited a total of 30 university students (17 males and 13 females, 10 freshmen and 15 sophomore, and 5 junior), with ages between 19-22 years (M=20.7, SD= 1.69). Due to the COVID-19 outbreak, half of the students took online undergraduate courses only, and the others had at least one year of experience in a face-to-face class. All the students were not familiar with eye tracking and gaze estimation technologies. To prepare high-quality video lecture contents, two professors from the department of industrial engineering were recruited. Both instructors had at least five years of experience in offering university-level computer science-related major lectures as well as at least two years of experience in creating online video lecture content. In this study, we decided to start designing our preliminary experimental protocol using a set of beginner-intermediate level CS-related lectures. Finally, "Database management" and "Computer language" courses were selected as our target classes for the experiment. All the recruited subjects were from CS-related departments (e.g., industrial engineering, IT management, etc.) and interested in studying this courses. Most of the sophomore and junior students had some prior knowledge of these classes.

3.3 Method

Our experiment consists of two phases. In the instructor phase, each instructor was asked to create an approximately 10-minutes video lecture. The recording was made in a controlled laboratory to capture the instructor's gaze data and voice more precisely. During the eye-tracking setup, the instructors were informed that their gaze data would be recorded. Also, they were asked to naturally look at the lecture slide based on their own teaching styles. We used Zoom and GazeAnalys software from Gazepoint to record and store all the lecture-related data. Through the process described in Section 2.2, a set of video contents with and without gaze visualizations were generated. Finally, GazeLight produced 28.9 boxes/min while GazeLight+ produced 10.9 boxes/min. In the learner phase, each student was first asked to complete an informed consent upon entering the laboratory. Then, we explained the overall experimental procedures to subjects. Afterwards, a brief calibration process was made and then each student was asked to watch our video lectures. Each video consisted of two sessions: the original video segments without any gaze visualization (baseline) and the modified video segments with gaze visualization (GazeLight or GazeLight+). Each session was 4–5 mins long and the order of sessions was counterbalanced. The experiment protocol was set up to watch all kinds of video lecture segments (i.e., baseline contents without gaze visualization, GazeLight contents, and GazeLight+ contents). During the experiment, we randomly interrupted the subject's learning process and tried to make them lose their attention. This random step was made to examine if they can easily/quickly return back to the video lecture. When all experimental procedures were over, subjects were asked to complete questionnaires and have an interview with an experimenter. The questionnaires consist of various questions (Likert 7 scale) to address our research questions.

4 RESULT AND ANALYSIS

4.1 RQ1: Does GazeLight (GazeLight+) help the students concentrate on the lecture?

The students responded that the use of GazeLight (M: 4.9, SD: 1.5) and GazeLight+ (M: 5.77, SD: 1.14) were both very helpful to concentrate on the video lectures. Specifically, 20 out of 30 and 27 out of 30 subjects responded positively for GazeLight and GazeLight+,

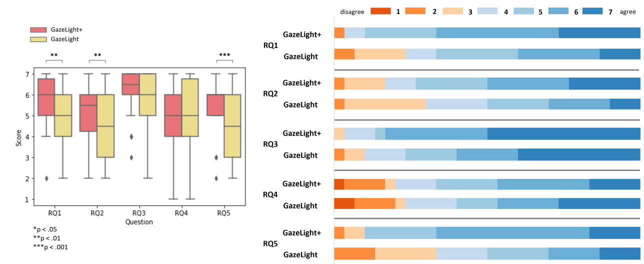

Figure 2: Summary of the Student Responses

respectively, mentioning that both gaze-based approaches were better than the baseline. As shown in the boxplot of Figure 2, paired t-test revealed that GazeLight+ was more useful ($p<0.01$) than GazeLight. In contrast to the baseline and GazeLight, the visualization strategy of GazeLight+ could resemble the instructor's "clapping" in F2F class, which would have more advantages for drawing students' attention. Qualitatively, some subjects commented about GazeLight+ that "*It was helpful to catch the lecture contents. It allowed me to focus on the difficult stuff*". For GazeLight, we could find a negative comment like "*It was rather confusing when I was focusing on a certain part where I find it important*", "*My eyes were enforced to follow the empty area in the slide!*".

4.2 RQ2: Does GazeLight (GazeLight+) help the students understand the lecture contents?

A paired t-test revealed that GazeLight+ (M: 5.27, SD: 1.14) is more useful than GazeLight (M: 4.57, SD: 1.43) in terms of understanding lecture contents ($p<0.01$). However, both GazeLight and GazeLight+ got lower scores compared to RQ1, which shows their lower effectiveness in terms of understanding contents. Both GazeLight and GazeLight+ had the following common negative comments: "*Apparently, gaze visualization was helpful for concentrating on the lecture, but hardly affected my understanding of the lecture contents*". We also found that the average score from the sophomore/junior group (5.05) was higher than that from the freshmen group (4.65). As is well known, this implies that a degree of understanding of the lecture is also affected by the student's prior knowledge of the content. In particular, the sophomore/junior group (5.50) rated GazeLight+ higher than the freshmen group (4.80), which implies that the students with prior knowledge preferred the filtered/summarized view of gaze visualizations. However, the ease of understanding lecture contents also depends on various aspects including, for example, the difficulty/type of a subject, the instructor's pedagogic strategies, teaching styles, etc. Our next research step will take account into these dimensions as well as add a set of tests to assess actual learning outcomes.

4.3 RQ3: Does GazeLight (GazeLight+) help the students recognize the part of the slide that the instructor is currently explaining?

Responses to RQ3 are related to the random interrupt taken during the experiment. The experimenter's interruption distracted the student from the lecture, and after a few seconds of conversation, the student was supposed to continue to watch the video. In this way, we attempted to validate whether gaze-based visualization helps the students recognize the part of a slide the instructor is currently explaining. As a result, both GazeLight (M: 5.63, SD: 1.47) and GazeLight+ (M: 6.17, SD: 1.12) were valued high scores without a statistical difference as shown in Figure 2, indicating that gaze-based approaches are very effective in terms of RQ3. Subjects added comments like "*I used to find and look at supplementary resources to better follow the online lecture, often missing the flow of the lecture though. This system helped me quickly return back to the concentration mode*", "*It would be very helpful when taking the lecture which provides the instructor's voice only*". It is also interesting to note that some mentioned that GazeLight produces a number of gaze visualizations irrelevant to the instructor's explanations or moving so quickly, thereby rather disturbing the flow of the lecture.

4.4 RQ4: Does GazeLight (GazeLight+) give the feeling of participating in class with the instructor?

We were also interested in how gaze-based visualizations affect the learners' affective perspectives. Therefore, we examined if subjects can have the feeling of participating in class with an instructor together when they use GazeLight and GazeLight+. The students' feedback, however, was not as positive as our expectations. There was no significant difference ($p=0.83$) between GazeLight (M:4.83, SD:1.98) and GazeLight+ (M:4.9, SD:1.75). From the interview, we could find some positive feedback like "*It feels like the explanation is being made at the same time! It feels like the instructor is actually presenting it, so it was easy to follow the classes*". These responses were quite encouraging because it is quite difficult to have a feeling of being with an instructor together in the pre-recorded video lectures. However, we could also note that several participants mentioned *"the absence of direct interaction with an instructor"* for both GazeLight and GazeLight+. In addition, they added "*Since there was no direct interaction with the instructor, it seems unreasonable to call it 'participating together'*". We also agree with these negative comments on the intrinsic limitation of an asynchronous video-based learning environment. This motivated us to extend our work to a real-time framework that can handle various challenging issues regarding gaze visualization and sharing.

4.5 RQ5: GazeLight (GazeLight+) does NOT interfere with the student's learning process.

Since the presented methods produce a series of grey-colored rectangles, one would have some concerns on the visibility and the readability of the slide. Therefore, we also examined whether GazeLight (GazeLight+) may have interfered with students while watching lectures. As shown in Figure 2, GazeLight+ acquired more positive responses (M:5.6, SD:1.19) compared to GazeLight (M:4.47, SD:1.63). The paired t-test revealed that GazeLight was worse ($p<0.001$) than GazeLight+ in terms of learning interference. From the interview, we could also confirm that the students complained more about the visualization from GazeLight. For example, some emphasized "*Visualization from GazeLight was so confusing!*", "*The GazeLight visualization moves so often that it gets in the way sometimes*". Because of this, they suggested that the system needs additional functions such as toggle to turn on/off the visualization.

5 LIMITATIONS AND EXTENSIONS

Finally, we asked if a subject is willing to use the proposed system in the future or not. As a result, 80 percent of the subjects revealed a willingness to use our system, which is a quite encouraging result. In particular, some of the subjects said that "*It would be great and really helpful if applied to the video lectures produced by instructors who NEVER use a mouse or a pen throughout the class ;(*", and "*In the case of classes made in an unfamiliar language (i.e., not mother language), it is really difficult to recognize which part is being explained if the instructor's voice is presented only. Therefore, I would love to use this system if it is fully integrated into our LMS*". As mentioned in Section 2.2, however, we used the Wizard of Oz approach to provide GazeLight+ feature. Therefore, our future work will include a development of an algorithm to automatically extract important part of the lecture content. Based on the experimental results, we plan to extend our framework to support both 1) pre-recorded video lectures and 2) real-time video-based lectures. For the pre-recorded video lectures, we will exploit and enhance the NLP/NLU-based techniques for document summarization and highlight extraction [Altmami and Menai 2020; Cohan and Goharian 2017; Yasunaga et al. 2019]. We expect that detection of important segments from the instructor's script would facilitate the implementation of GazeLight+. In the case of real-time remote learning, we will develop a multi-modal approach for detection and recognition of attention switching, change of atmosphere, etc. We believe that both techniques would compensate each other, improving the quality of GazeLight+.

Furthermore, we will improve our GazeLight+ to support contents and context-aware visualization, as stated in Introduction. Instead of drawing fixed-sized rectangles, we will take into account the layout and structure of a slide for determining the design of visualizations dynamically. Our future system will provide different types of visualization to support various kinds of lecture content. For example, we can expect a rectangle-shaped visualization for table columns, double-dashed underline visualization for equations, arrow-shaped visualization for big figures, etc. This would resemble the students' note-taking or marking behaviors on the slides, making our system more friendly. Also, gaze sharing between the instructor and students can be extended to support eye-contact feature which could bring more tension to the class. We plan to extend our system to support gaze visualization on the lecture slides (for lecture highlight) as well as a user grid (for eye contact) of a teleconferencing software (e.g., Zoom). By this, students can be aware of when and whom the instructor stares at, thereby motivating themselves to focus on the lecture. We expect that the instructor of a real-time one-to-many class would benefit from this feature in particular. Based on these extensions, we also plan to extend our study to analyze how our extended framework affects the instructor's behaviors and satisfaction on creating/delivering online lectures.

Finally, in our future study, the experimental setting will be extended to figure out online teaching and learning behavior in the wild. Instead of a controlled lab setting, we will conduct remote experiments in more natural places like dormitories and coffee shops. We will also try to figure out how gaze visualization and a mouse/pen interaction can be combined to improve the quality of online lectures.

6 CONCLUSION

In this paper, we discussed various limitations and future directions of the gaze visualization/sharing technique for online video-based learning environment. Through the experiments, we explored how different gaze visualization strategy affect the learners taking online video lectures. Except RQ3 and RQ4, GazeLight+ valued higher from the students. We could observe that the learners tend to prefer GazeLight+ because it provides a weighted view of the instructor's gaze, thereby being more useful to make the learners concentrate on the lecture. Our future work will include various themes described above.

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