ENHANCING ONLINE LEARNING FOCUSING ON THE RELATIONSHIP BETWEEN GAZE AND BROWSING MATERIALS

Hironori Takeuchi, Kenji Matsuura and He Lei
Tokushima University, Japan

ABSTRACT

Online synchronous classes and seminars are increasing in universities along with the outbreak of COVID-19. Since the online classes are not in-person condition, it is difficult for a teacher to monitor the learners. In the field of distance education, the need to support learner's concentration has been identified. More effective methods adapted to online classes in universities should be discussed. In this paper, we focus on the teacher's and learners' attention to the material in online real-time classes. We then propose a system that provides feedback on the differences in learners' gaze in order to improve the followability of learners. The proposed system assumes an online environment using Microsoft Teams PowerPointLive and acquires the "gazing point" at every slide-material and "page change history" of the teacher and learners. The results of using the proposed system suggest that it can improve the learner's followability to the teacher.

KEYWORDS

Microsoft Teams, Online Classes, Gazing point, Online Learning, Online Seminars

1. INTRODUCTION

Since COVID-19 widely spread all over the world, universities have been shifting to online classes with synchronous/asynchronous communication tools. According to a report by the Ministry of Education, Culture, Sports, Science and Technology (MEXT), 90% of the 86 national universities offer online classes in Japan. One of the advantages of online classes is needless to carry out in shared place and time. The style is expected to continue. In terms of environmental improvement, MEXT has proposed the "GIGA School" educational reform plan to realize "one device for one student" throughout Japan (MEXT, 2020). Combined with the spread of online classes, the online learning environment in the educational field is gradually being developed.

On the other hand, it is problematic that the motivation of online learners is to be lower. Conventional university classes are carried out in face-to-face situation and include factors such as the teacher's articulate gestures and the classroom environment. These factors have been found to influence learners' attention (Zhang et al, 2018). The field of distance learning has shown the need to support learners' attention and discuss more effective ways to provide those supports (Wang & Antonenko, 2017; Sharma et al, 2016). No clear solution to them has been found so far, and continued discussion is needed.

With the above background, this paper describes the design, development and trial use of a learning support system to enhance the learner's ability to concentrate. Assuming a widely used online class environment, the system is intended to be converted to an educational setting.

2. RELATED WORKS

One of possibilities to objectively estimate a learner's condition in online learning is to measure the electroencephalogram (EEG). Some previous studies have evaluated the α and β wave values of EEG (Yoshida et al, 2016). It is possible to evaluate the subjective level of difficulty to some extent when learners are given learning materials (Umezawa et al, 2016). Therefore, EEG is an effective tool, but it is difficult to use in general online classes because it requires a dedicated tool for measurement at each location of a learner.

By contrast, eye-tracking can be used to assist learners in general online classes. There are various studies that use eye tracking techniques and refer to learners' ability to concentrate. For example, studies have been conducted to understand how the presence of the teacher in the video affects the distribution of the learner's visual attention. It has been shown that the teacher's behavior has a positive impact on the learner (Wang & Antonenko, 2017). In addition, research has been conducted to improve learners' attention. For example, there is an evaluation of whether the learner can follow the instructor (with-me-ness) by analyzing the learner's eye movements. If the learner cannot follow the instructor's gaze beyond a certain point, presenting visual objects to the learner has been to improve the learner's attention (Sharma et al, 2016). Thus, analyzing the learner's gaze may provide a measure of the learner's ability to concentrate, and there is room for further research in situations other than video viewing.

On the other hand, there are also possible ways to utilize the learning history stored in the system. For example, there is a study to grasp the learning status from the page transitions of teaching materials (Nakano et al 2018). In those studies, page transitions have been confirmed to have a relationship with class time, explanation time, and so forth. Although these studies aim to provide feedback to learners, few studies have been found to contribute to a learner’s concentration.

Based on the above considerations, the purpose of this paper is to support individual learners' cognition in online classes by focusing on eye movements and reading materials in online classes. We design a system that visualizes the differences between the teacher and the learner and provides feedback to the learner and describe its trial use.

3. METHODOLOGY

The proposed system is designed for synchronous online classes using "Microsoft Teams PowerPointLive", a conferencing tool frequently used in online classes. The greatest feature of this tool is that students can independently change the pages of the teaching material shared by the teacher and students. As with distributed textbooks, students are free to choose which pages of the teaching material they wish to view. We collect eye gaze information from the teacher's and students' web-camera when they use online conferencing tool for remote learning and also analyze Microsoft Teams' Window to collect the history of page changes. The differences between the teacher and students are then visualized using GIF animations and graphs to provide feedback to the learners (Figure 1).

The proposed system was designed with general-purpose specifications for use in widely used online classes. That is, the system runs on a typical teacher's or student's laptop. It requires Python, Microsoft software, and a web-camera or in-camera.

Figure 1. Microsoft Teams PowerPointLive screen. The data collection targets the gaze-transition and page-transition in the teaching materials

3.1 Acquisition of Gaze-Transition Data

Although dedicated devices such as Tobii are commonly used to collect eye tracking data, for versatility, this study designs an eye tracking system that utilizes a web-camera. In this study, we apply "GazeMap" (Park et al 2018), one of the frameworks for this purpose. GazeMap is used and applied for collecting eye tracking information. GazeMap has neural nets for estimating gaze direction and representing the centers of the eyeball, iris, and pupil as abstract figures. One of its functions is applied to obtain gaze coordinates. In order to accommodate general online classes, original modifications are introduced that consider the indefinite distance between the teacher, the learner, and the screen. The distance to the screen is estimated from the face width ratio projected on the screen, and the gazing point coordinates are calculated.

The method of eye detection is shown below, where it calculates the distance to the screen based on the width ratio of the faces on the screen. First, $\boldsymbol{W_i}$ as the width of the face on the screen is defined. Next, the minimum value as $\boldsymbol{W_1}$ = 45 and the maximum value as $\boldsymbol{W_2}$ = 70 are set. The distance between the learner and the screen is defined as $\boldsymbol{d_i}$, $\boldsymbol{W_1}$ as $\boldsymbol{d_1}$, and $\boldsymbol{W_2}$ as $_2$. In that case, $\boldsymbol{W_i}$ can be calculated by the following equation.

$$W_i = \left(\frac{W_1 - W_2}{d_1 - d_2}\right)(d_i - d_1) + W_1 \tag{1}$$

If the resolution of the screen used is ($\boldsymbol{a} \times \boldsymbol{b}$), the coordinates of the gazing point ($\boldsymbol{X}, \boldsymbol{Y}$) can be calculated as follows.

$$X = d_i \times \tan(yaw) + \frac{a}{2} \tag{2}$$

$$Y = d_i \times \tan(pitch) + \frac{b}{2} \tag{3}$$

The purpose of the proposed system is not to collect data, but to visualize the differences between the teacher and the learners, and to make the learners aware that they are not keeping up with the teacher. Using the teacher's data in class as a reference, the system visualizes and outputs the differences in learners' eye movement and page transitions.

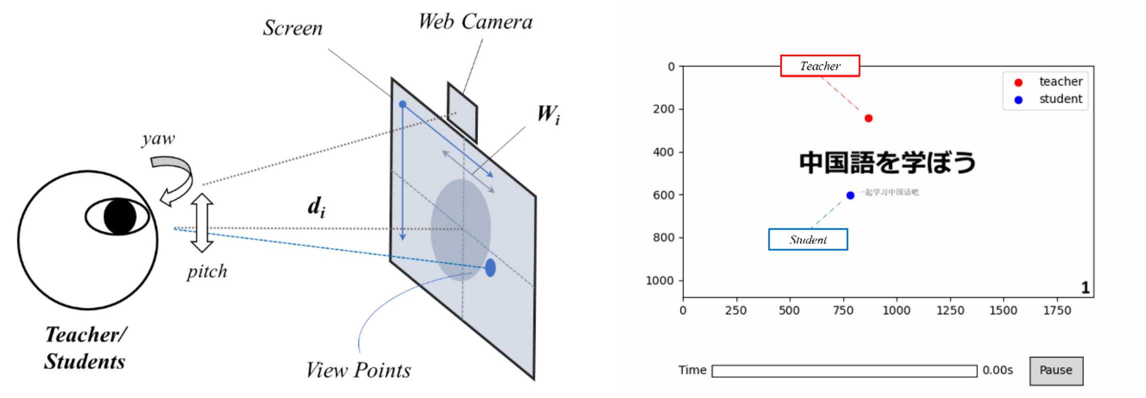


Figure 2. Gaze-transition data acquisition & Feedback content to learner

Feedback content uses GIF animations to represent differences in gazing points. The teacher's and student's gaze information are simultaneously depicted in the teaching material, allowing students to see their eye movement during the lecture through the animation. This output information is based on page-by-page (Figure 2).

3.2 Acquisition of Page-Transition Data

Detection of page switching during online lectures is performed using image recognition technology. The page number region of the slide displayed on the screen is clipped and converted into a numerical value using EasyOCR, an image recognition library in Python.

The screen resolution of the screen and the window differences between the presenter (instructor) and the participants (students) of "Microsoft Teams PowerPointLive" must be taken into account when defining the areas to be detected. These settings need to be made individually according to the environment of the teacher and the learner. In this study, the screen resolution was defined as 1920×1080 and the presenter's area as (1156-1230, 733-786). We also defined the participant's region as (1480-1556, 850-910) for region extraction. Feedback on page changes is depicted graphically with page numbers. This feedback is distributed as a single image after the lecture, so that students are aware of their page change history during the lecture (Figure 3).

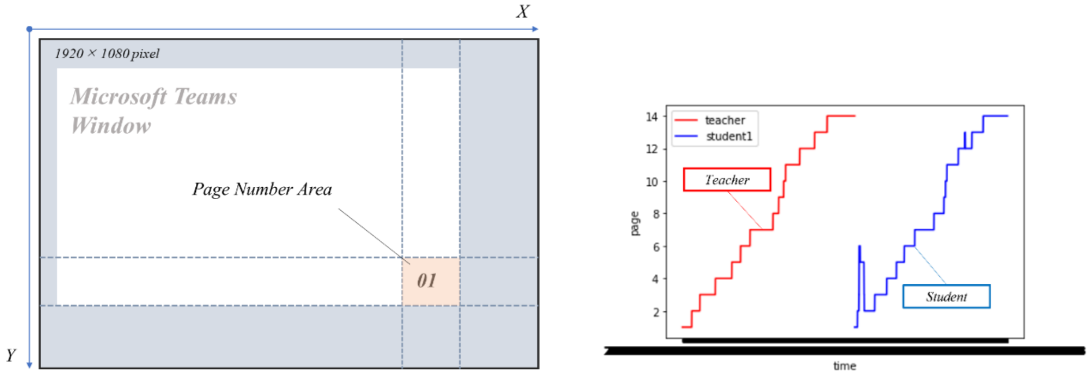


Figure 3. Page-transition data acquisition & Feedback content to learner

There are considerations for feedback on page transitions. Feedback on gazing point differences can be evaluated as correct for the instructor 's gazing point. However, this is not always the case with page transitions. For example, there is a pattern in which the learner checks the page before the teacher for the purpose of independent learning. The purpose of the proposed system is to enhance concentration. In other words, patterns in which the learner is focused on learning, such as self-study, should not compensate for differences with the teacher. To distinguish these situations, we categorized the changes in the student's page transitions as learner models in Table 1. Support is provided only if the learner needs assistance.

Table 1. Learner model of page transitions. Models that do not require support do not need to follow the instructor

Model	Supported	Summary
Sync	No	instructors and students synchronize
Self-study	No	Students ahead of instructors
Delay(small)	Yes	Students are 2-4 pages behind instructors
Delay(large)	Yes	Students are more than 4 pages behind instructors
Repeat(short)	Yes	Students repeatedly reviews (1-2 times)
Repeat(long)	Yes	Students repeatedly reviews (more than 3 times)

4. EXPERIMENTAL USE AND THE RESULTS

Using this system, we conducted an experiment with a mock class. There are 20 subjects in total: 10 Japanese and 10 Chinese beginning students. Within each group, the subjects are divided into an experimental group which uses proposed functions (Group A) and a control group which does not use the proposed system but the ordinary environment (Group B). These two groups are compared and evaluated to measure the effectiveness of the system. The class content was conducted in Japanese and Chinese for the purpose of second language acquisition. The class duration was 10 minutes and 8 seconds, with 14 pages of content. In addition, a simple confirmation test was administered after each class to ensure a certain level of concentration on the class.

The experimental flow consists of two classes. After the first classes, the difference between the teacher's and learner's gaze during the classes is output and fed back to the learners. After the feedback is completed, they take the same class again. Based on the data from these first and second classes, we compare and verify the degree to which students follow the teacher's gazing point.

4.1 Gaze Similarity per Page

The difference of gazing points between the teacher and students is verified for each page. The gazing point data sets in the slides were clustered using the Ward method, and the distance between groups was calculated. Figure 4 shows the mean change of Group A, and Figure 5 shows the mean change of Group B. Note that there are times when the page numbers of the teacher and students do not match because students can freely change pages in this experiment. In this case, the value is uniformly set to "0".

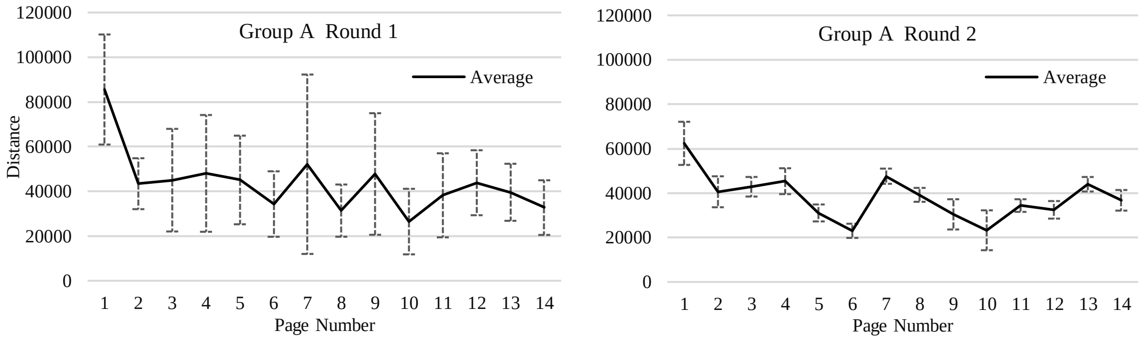


Figure 4. Distance between instructor and student per page in Group A (with feedback)

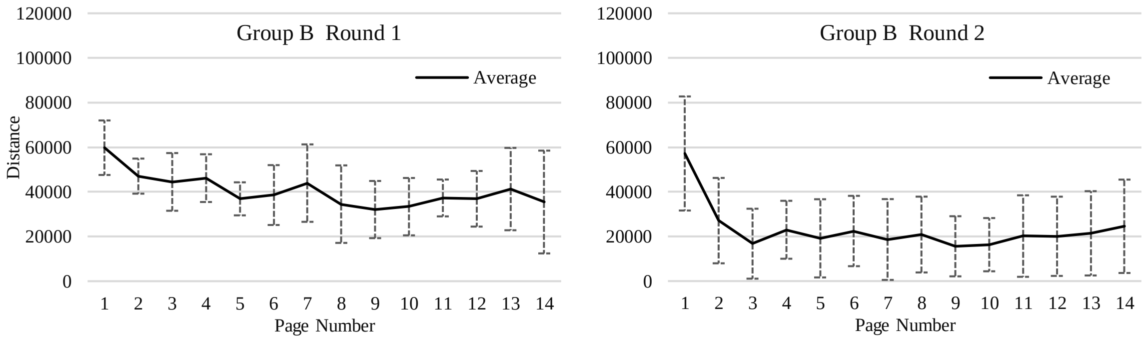
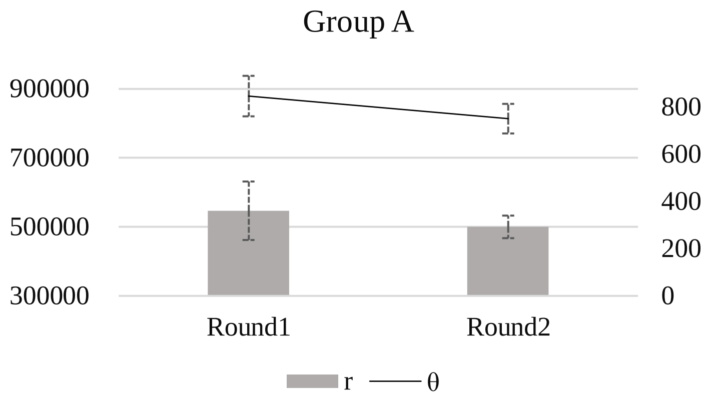


Figure 5. Distance between instructor and student per page in Group B (No feedback)

4.2 Gaze Similarity in Class

Next, we compared the degree of proximity of the gazing points throughout the class using DTW (Dynamic Time Warping). In order to compare the movement of the gazing points more accurately, we transformed the Cartesian coordinate system data into polar coordinate system data to check the similarity of the radius r and declination angle θ. The results for Group A and Group B are shown in Figure 6 and Figure 7, respectively.



.

Figure 6. Average DTW score in Group A (with feedback)

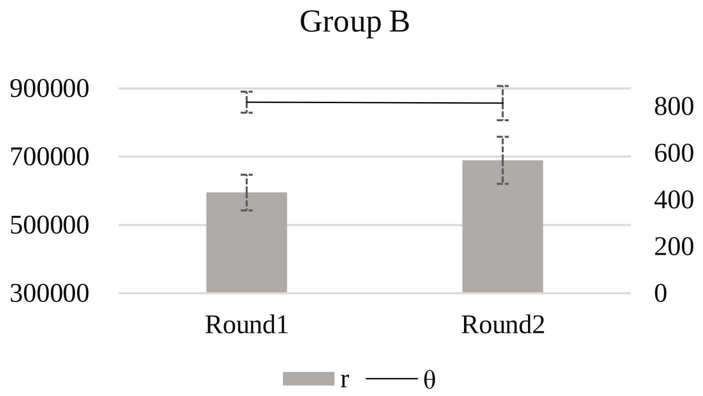


Figure 7. Average DTW score in Group B (No feedback)

5. DISCUSSION

Looking at the results per page, Group A had significantly less variance and tended to converge at a certain distance (Figure 4). This is caused by the feedback of the viewpoint difference, which is corrected to a viewpoint closer to the class teacher's viewpoint. On the other hand, in Group B, the distance is generally closer and the dispersion tended to be larger (Figure 5). This is due to the fact that they had memorized the material to some extent. Furthermore, it can be seen that the students' attention became distracted, and they lost the regularity of their gaze. These results suggest that a variety of feedback from the system would be effective in tracking the teacher's gazing point.

Next, when we look at the class-wide case, Group A shows an improvement in tracking for both radius r and declination angle θ (Figure 6). Convergence was also observed in the variance, indicating that the tracking improved as a result of the feedback as well as the page-by-page feedback. On the other hand, for Group B, the distance between the two images was greater the second time for radius r (Figure 7). The dispersion also tended to increase. This may be due to the fact that the same lesson was repeated twice, which distracted the students' concentration and worsened their tracking performance.

While these results support the effectiveness of feedback using this system, it is also suggested that simply repeating similar content in a synchronous online class result in poor tracking performance.

6. CONCLUSION

We designed a system to visualize the differences in gazing points and content transitions between teachers and students in synchronous online classes, and measured the effect of the system on improving students' following of the teacher.

The results suggest that the feedback of gazing points and page differences is effective and has a certain effect on improving the students' ability to follow the teacher.

In this initial experiment, we evaluated tracking performance by visualizing the gazing point and its feedback but did not take into account differences due to class content or the influence of teacher instruction. In the future, it is necessary to conduct multiple evaluations, taking into account these details. Another limitation of this study is that although it provides clues as to the state of attention to class content, it is difficult to obtain direct corroboration of class comprehension. A new approach is needed for this purpose.

In addition, this differential feedback is presented to the learners after the class, but feedback presented in real time is also possible. Continued evaluation is needed in the future while considering these factors.

ACKNOWLEDGEMENT

This work was supported by JSPS KAKENHI Grant Numbers JP18K11572.

REFERENCES

Mavlankar, A., Agrawal, P., Pang, D., Halawa, S., Cheung, N.M., Girod, B., 2010. An interactive region-of-interest video streaming system for online lecture viewing. *18th International Packet Video Workshop*, 13-14

Conference of Research Collaborators on Improvement of Facilities such as National University Corporation (5th) https://www.mext.go.jp/en/content/20200716-mxt_kokusai-000005414_04.pdf (Accessed 2022/9/18).

Zhang, J., Bourguet, M.L., Venture, G., the effects of video instructor's body language on students' distribution of visual attention: an eye-tracking study. 2018. *Proceedings of the 32nd International BCS Human Computer Interaction Conference (HCI)*,4 – 6.

Umezawa, K., Ishida, T., Saito, T., Nakazawa, M., Hirasawa, S., A judgment method of difficulty of task for a learner using simple electroencephalograph. 2016. *IPSJ Technical Report*, Vol.2016-CE-137, No.4,1-6 (Translated from Japanese)

Yoshida, K., Sakamoto, Y., Miyaji, I., Yamada, K., Analysis comparison of brain waves at the learning status by simple electroencephalographhttps. 2012 *IEICE Tech. Rep*., vol. 112, no. 224, ET2012-35, pp. 37-42, Sept. 2012

Nakano, Y., Furukawa, M., Owatari, T., Kubota S., Sugiya, K., Shimada K., Attempt to analyze the page transition of the learner in class by Levenshtein distance. 2018. *IPSJ Technical Report*, Vol.2018-CLE-26, No.4,1-6 (Translated from Japanese)

Park, S., Spurr, A., Hilliges, O., Deep Pictorial Gaze Estimation. 2018. *Proc. ECCV in LNCS*, Vol. 11217, pp. 741-757

Sharma, K., Alavi, H. S., Jermann, P., \& Dillenbourg, P. A gaze-based learning analytics model: in-video visual feedback to improve learner's attention in MOOCs. 2016. *In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 417–421). Edinburgh, Scotland: ACM

Wang, J., Antonenko, P. D., Instructor presence in instructional video: effects on visual attention, recall, and perceived learning. 2017. *Computers in Human Behavior*, 71, 79-89.

Tokiwa, Y., Sumitomo, H., The current state of e-learning in universities and proposals for the next generation. 2002. *IBM Professional Treatise PROVISION L4063A, 35: 64-73 (*Translated from Japanese).