International Journal of Internet, Broadcasting and Communication Vol.16 No.4 141-147 (2024)
http://dx.doi.org/10.7236/IJIBC.2024.16.4.141

IJIBC 24-4-16

Online Education Platform with Real-time Personal Visual Attention Monitoring

Seung-Keun Song† and Suk-Ho Lee††

† *Professor, Dept. Practical Content Creation, Dongseo University, Korea*
††*Professor, Dept. Computer Engineering, Dongseo University, Korea*
E-mail: songsk7@gmail.com

Abstract

One of the biggest drawbacks of online education using virtual environments is that teachers cannot see students' facial expressions. In offline classes, teachers usually observe students' expressions to determine if they are focused or enjoying the lesson, and they can adjust their teaching accordingly. For example, if a teacher notices that students are losing focus, they can slow down the pace of the lesson or tell an interesting story to regain their attention. However, in a virtual environment, it is impossible to see students' expressions, making it difficult to gather any information about them. As a result, instructors may feel like they are teaching in isolation and are unable to appropriately respond to students' reactions. This can easily lead to a lack of interaction between the teacher and students. This issue has already been raised in other studies, and research has been conducted to measure student engagement and attention. However, existing systems typically measure overall engagement for the entire class or represent the data in numbers or graphs, which doesn't provide impactful real-time feedback to the instructor. This study proposes an online education system that visually displays each student's level of engagement and attention in real time to address this issue. The key advantage of this system is that it allows teachers to quickly and intuitively grasp students' reactions and adjust their teaching in real time accordingly.

Keywords: *Online Education, Virtual environment, Student engagement, Attention monitoring, Teacher-student interaction*

1. Introduction

Nowadays, educational platforms using virtual environments or the metaverse are on the rise globally. The widespread experience of online education during the COVID-19 pandemic has contributed to this trend, as people have become more familiar with online learning[1]. Additionally, the increasing globalization of education is playing a significant role. For example, according to the British daily The Guardian, the global language learning app Duolingo, which has over 500 million users worldwide, reported a significant increase in Korean language learners in English-speaking countries due to the success of Squid Game. Today, more than 100,000 people in 120 countries are learning Korean through government-established Korean language education institutions.There are two main methods for conducting online education: using video

Manuscript Received: September. 17, 2024 / Revised: September. 23, 2024 / Accepted: September. 28, 2024
Corresponding Author: Seung-Keun Song
Tel: *** - **** - **** Fax: +82-51-302-1703
Author's affiliation : Dept. Practical Content Creation, Dongseo University

conferencing platforms like Zoom, and utilizing virtual classrooms in the metaverse. Each platform has its own advantages and disadvantages.Video conferencing platforms allow real-time visibility of both the instructor and students, which is a key benefit. However, people often feel fatigued from having their faces constantly on display, a phenomenon known as "Zoom fatigue." As a result, some students turn off their cameras during online classes. Another method involves using virtual reality classrooms for online education. The advantage of this approach is that it creates an immersive experience, giving students the feeling of being in an actual classroom, rather than just interacting on a flat screen like in video conferencing. However, a major drawback is that it’s difficult to see facial expressions, making it challenging to determine whether students are fully engaged in the lecture.

The issue of not being able to see students' facial expressions in virtual classrooms, which makes it difficult to assess their level of concentration in real-time, has already been highlighted in several studies[2][3][4]. To address this, many researchers have emphasized the need for an attention monitoring system that provides hints on how focused students currently are[5][6][7]. However, most existing systems generally assess engagement on a class-wide level or present the information through numerical data or graphs, which fails to offer meaningful real-time feedback to the instructor. For instance, if student engagement is provided to the instructor as numerical data, it can be difficult for an instructor who is focused on teaching to interpret these numbers effectively and respond in real time. Therefore, the students' engagement levels should be presented to the instructor in a more intuitive way.

In this paper, we introduce an online education system which is designed to visually present each student's engagement and attention levels in real time. The main benefit of this system is that it enables educators to swiftly and intuitively understand student responses, allowing them to adjust their teaching strategies in real time as needed.

2. Current Online Monitoring Systems

In this section, we will explore the functioning of current online monitoring systems and identify their limitations. These systems assess attention levels using various factors, with facial analysis being the most crucial. Typically, online monitoring systems start by detecting the face and then proceed to extract facial landmarks or expressions. When evaluating attentiveness through facial analysis, there are two primary approaches. The first approach involves extracting facial landmarks and analyzing their positions. For instance, if the landmarks corresponding to the eyes are aligned in a straight line, this indicates that the eyes are closed, suggesting the student might be sleeping. The second approach involves extracting specific facial features and applying machine learning techniques to directly predict the attention level. Today, deep learning-based models excel at both feature extraction and prediction, making them highly effective for attentiveness prediction. Figure 1 provides a simplified process diagram illustrating these two methods.

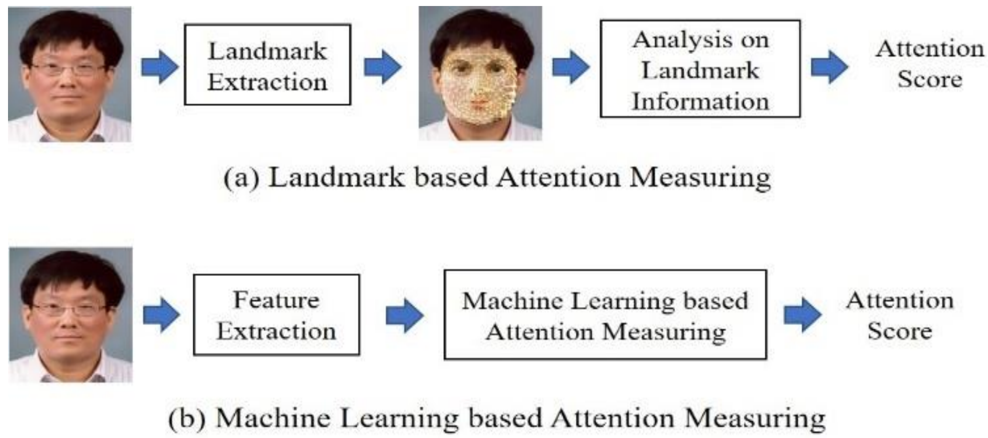

Figure 1. Diagram illustrating the two methods of measuring attention: (a) Landmark-based attention measurement, (b) Machine learning-based attention measurement. attention measuring

The facial expression is subsequently converted into information that reflects the user's attention level. For example, in [9], they introduce an algorithm designed to develop a system for monitoring student attention during online classes, referred to as the Students Attention Monitoring and Alert Model (S-AMAM). The system employs face detection and facial landmark detection techniques to identify key facial regions, specifically the eyes and mouth. Metrics such as Eye Aspect Ratio (EAR), Mouth Ratio (MR), and threshold values (ThEAR and ThMR) are calculated using the coordinates of the detected facial landmarks to assess whether the student is in one of three states: 'Normal,' 'Dozing,' or 'Yawning.' The identified state is then displayed in real-time as a message on the screen for both students and instructors. However, the message format is not easily noticed by the instructor, and when there are many students, it becomes difficult to identify which student is in a non-attentive state and needs assistance.

In the work of [9], machine learning techniques are used to assess student attentiveness. Specifically, they employed the XGBoost classifier to detect attention levels, which was trained and tested on a dataset containing 4,000 records of students either paying attention or not during online lectures. The way this attentiveness is presented to the instructor is illustrated in Figure 1. The attentiveness is displayed as a percentage, along with additional information, such as whether the student is looking left or right. However, even though this information is provided in real-time, the instructor may struggle to accurately assess a student's state unless he focus intently on the specific student's data. Since the percentage is constantly changing in real-time, it is difficult to recognize the number clearly. Additionally, the instructor must match the attentiveness percentages to the corresponding student numbers in real-time, which becomes challenging when dealing with a large number of students. As a result, it is difficult for the instructor to quickly identify and assist a student with low attentiveness during the lecture.

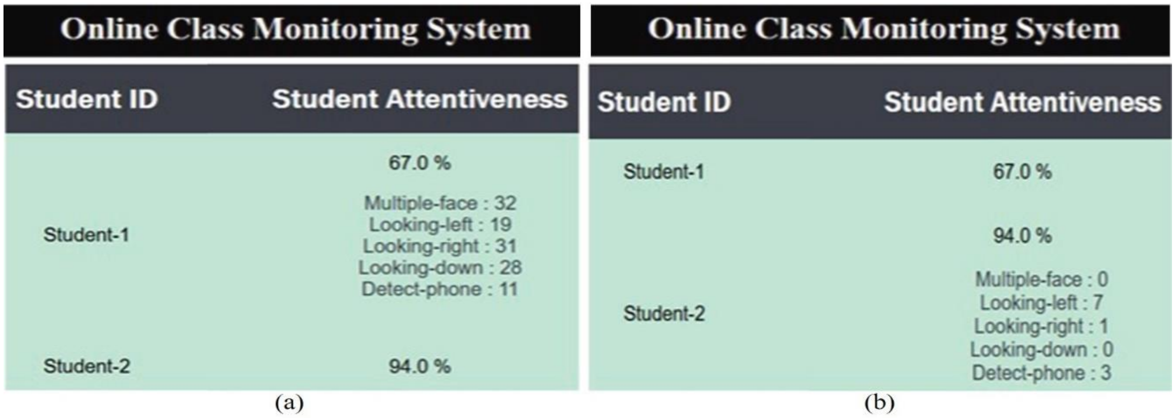

Figure 2. Display format of student attentiveness in the system proposed in [9]. The attentiveness is shown as numbers that update in real-time, making it challenging for the instructor to identify them accurately during the session (Figure adapted from [9]).

3. Proposed Real-time Personal Visual Attention Monitoring System

In this section, we propose a real-time personal visual attention monitoring system which can perceive the student's attentiveness and display it in a format so that the instructor can perceive it immediately in an intuitive way. The proposed system displays the attentiveness in a visually simple form, i.e., with an emoticon over the virtual avatar of the student that shows whether the student is in an attention mode or not. A similar display method has been incorporated into the education system developed by Marvus Inc. [].

However, the proposed system saves also However, the proposed system also records recent attentiveness history and displays this information above the student's avatar. For instance, if the attentiveness of a student is updated every minute, each segment of the history represents a 1-minute period. By displaying the history of the last three consecutive segments, the system shows the student's attentiveness over the past three minutes in addition to their current status.

The reason for displaying the results of the last three consecutive segments alongside the current attention status is to provide a more comprehensive understanding of the student's engagement during the lecture and the trend in their attentiveness. While the current attention status reflects the student's immediate level of focus, the recent attention history can reveal patterns in their overall performance. For example, a student may currently appear attentive, but if the previous three segments indicate a lack of attention, it could suggest an overall decline in focus, with the student making an effort to recover. Conversely, if students have histories of high attentiveness but show drops in their current status, it might indicate a temporary lapse in focus, suggesting that a break or an activity to re-engage their attention might be necessary. This information helps lecturers better understand the momentum and current state of the students, and it provides analysts with valuable data for making predictions or conducting in-depth analysis..

There are also other education platforms that collect data to analyze student achievement, but these systems typically use the data for post-analysis. The difference with the proposed platform is that it not only uses this history for post-analysis but also allows the instructor to monitor these changes in real-time during the lecture. This enables the instructor to cognitively and spontaneously recognize the current lecture dynamics and individual students' attention trends, allowing for interactive adjustments to the lecture accordingly.

Figure 3 illustrates the facial recognition and analysis capabilities integrated into our education system. We employ both landmark extraction and feature extraction, along with machine learning-based recognition. Landmarks are used to detect actions such as eye blinking or mouth yawning, while the extracted features are processed through a machine learning algorithm to predict the student's emotions and level of attentiveness.

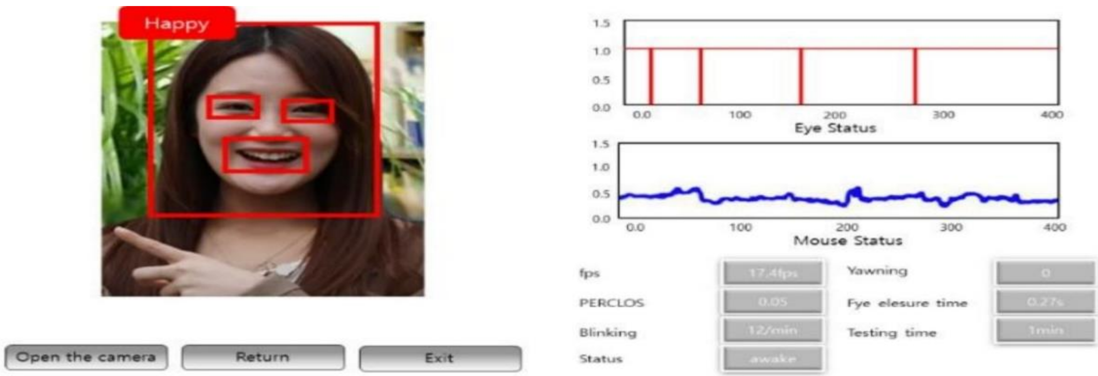

Figure 3. Information Extraction from Facial Expression inside the detected face region

Figure 4 illustrates the overall flowchart of the algorithm. Upon entering the education system, the student's camera is connected to the platform, and the video feed begins streaming into the system. The face region is detected by our built-in face region detector, and this region is then extracted for further processing. Basic image preprocessing algorithms are applied to the extracted region to address issues such as low illumination, blurriness, or noise. Next, facial features and landmarks are extracted from the face region. The landmarks are analyzed in the landmark analysis module, which examines the eye and mouth regions, while the features are fed into a machine learning module that predicts the student's attention score.

The combined information is processed by the attention evaluation system, which provides a final overall assessment of the student's attentiveness. The current attention score is simultaneously stored in the database and sent to the display module. The display module shows the current attention status as an emoticon above the student's avatar, as shown in Figure 5. Meanwhile, the attention history is updated in the database. The three most recent attention states are retrieved from the database and displayed as small history emoticons above the current attention emoticon, as illustrated in Figure 5. By analyzing the saved history of student attentiveness, the platform can assess both individual student performance and overall class success, and generate a comprehensive report.

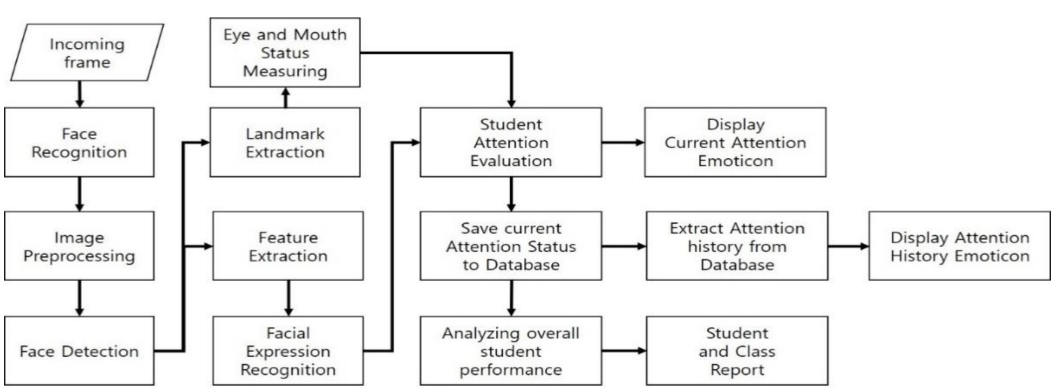

Figure 4. Overall flowchart of the proposed attention monitoring method

Figure 5 demonstrates the application of the proposed platform with four students in the virtual classroom. The large emoticon directly above each avatar's head represents the current attentiveness of the respective students. The three smaller emoticons above the large ones indicate the three most recent attentiveness states.

Figure 5. Displaying the current and most recent attentiveness in the form of emoticons above the heads of the avatars. The small-sized emoticons visualize the history of attentiveness of each student

This setup shows that even if a student's current attentiveness is high, his previous states may have been less focused, indicating that the student had difficulty paying attention earlier but is now starting to engage with the lecture. This type of information can be quickly and intuitively perceived by the instructor, allowing him to recognize that the current lecture content is becoming more interesting for the student.

Finally, we conducted an assessment involving 20 lecturers to evaluate the impact of using the proposed real-time personal visual attention monitoring system. The evaluation criteria are listed in Table 1. After using the system, the lecturers were asked whether they found the items in the assessment criteria helpful during their lectures or not. As shown in the results in Table 1, the majority of lecturers found that the real-time visual attention monitoring system, particularly the format in which attentiveness was displayed, was quite helpful across several evaluation criteria.

Table 1. Result of assessment on the effect of the proposed system

Assessment Criteria	Helpful	Not helpful
Perceiving real-time information of overall attentivess of the class	20	0
Real-time adjustment of lecture content	16	4
Real-time Interaction with students	14	6
Perceiving individual student's history of attentiveness	16	4

4. Conclusion

In this paper, we introduced a real-time personal visual attention monitoring system designed to assess and display students' attentiveness in an intuitive manner for instructors. The proposed system offers an intuitive way for instructors to assess and respond to students' attentiveness during lectures. By displaying both current and recent attention levels through simple visual cues, the system allows for immediate instructional adjustments, providing a more dynamic and responsive teaching environment compared to traditional post-analysis methods.

References

[1] A. Bashir, S. Bashir, K. Rana, P. Lambert, and A. Vernallis, "Post-COVID-19 adaptations; the shifts towards online learning, hybrid course delivery and the implications for biosciences courses in the higher education setting," Frontiers in Education, Vol. 6, Aug. 2021. DOI:https://doi.org/10.3389/feduc.2021.711619

[2] Y.H. Hu, "Effects of the COVID-19 pandemic on the online learning behaviors of university students in Taiwan," Educ Inf Technol., Vol. 27, pp. 469–491, Jan. 2022. DOI:https://doi.org/10.1007/s10639-021-10677-y

[3] S.G.T. Ong, G.C.L. Quek, "Enhancing teacher–student interactions and student online engagement in an online learning environment," Learning Environ Research, Vol. 26, pp. 681–707, Oct. 2023. DOI:https://doi.org/10.1007/s10984-022-09447-5

[4] S. Dhawan, "Online learning: A panacea in the time of COVID-19 crisis," Journal of Educational Technology Systems, Vol. 49, No. 1, pp. 5-22, June 2020. DOI:https://doi.org/10.1177/0047239520934018

[5] A. Bedi, "Keep learning: Student engagement in an online environment," Online Learning, Vol. 27, No. 2, pp. 119-136, June, 2023. DOI: https://doi.org/10.24059/olj.v27i2.3287

[6] N.R. Moşteanu, "Teaching and learning techniques for the online environment. How to maintain students' attention and achieve learning outcomes in a virtual environment using new technology", International Journal of Innovative Research and Scientific Studies, Vol. 4, No. 4, pp. 278-290, 2021. DOI:https://doi.org/10.53894/ijirss.v4i4.298

[7] G.S. Parvathy, R. Smitha, "A review on students attention monitoring systems," International Research Journal of Engineering and Technology, Vol. 9, No. 11, pp. 688-691, Nov. 2022.

[8] M.L. Roy, D. Malathi and J.D.D. Jayaseeli, "Students Attention Monitoring and Alert System for Online Classes using Face Landmarks," in Proc. 2021 IEEE International Conference on Computing, Power and Communication Technologies, pp. 1-6, Sep. 24-26, 2021. DOI:https://doi.org/10.1109/GUCON50781.2021.9573793.

[9] M. K. Hossen and M. S. Uddin, "Attention monitoring of students during online classes using XGBoost classifier," Computers and Education: Artificial Intelligence, Vol. 5, 2023, DOI:https://doi.org/10.1016/j.caeai.2023.100191.

[10] Marvrus education system. http://www.marvrus.com