Data Visualization for Asynchronous VR Classroom

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As a teaching tool for instructors, immersive Virtual Reality (VR) has the potential to deliver practice-oriented lessons to a large group of students. The instructor can record a demonstration inside VR and distribute the record to the students for viewing and practicing. Furthermore, the students' activities and other biometric data can be recorded while they are learning. The instructor can potentially use these data to improve the lesson or detect early signs of problems in the virtual classroom. However, evaluating entire classroom datasets of students in 3DVR can drastically increase the instructor's workload. To reduce this workload and improve the virtual classroom's scalability, a visualization tool is required to summarise and communicate crucial information to the instructor. In this paper, we examine existing visualization solutions and propose a 3D visualization design that is suitable for classroom contexts. We then discuss, how this tool could be evaluated.

Virtual Reality, Education, Learning, Asynchronous, Data Visualization.

1. INTRODUCTION

With VR technologies, both instructors and students can prepare and practice hands-on activities such as laboratory experiments without restrictions regarding location, time, equipment, or material using available authoring tools such as Mozilla Hub[1]. The virtual classroom has also been reported to enhance memory retention in preparation for the physical hands-on classes (Corter et al., 2007). Recording the instructor's lecture and demonstration inside the virtual environment and distributing the recordings for the students to learn asynchronously could be a potential direction to reduce the instructor's workload (record once, instruct unlimited times) and improve the scalability of the virtual classroom.

However, the instructor cannot effectively monitor students' learning activities in the asynchronous virtual classroom. This limitation prevents the instructor from performing class evaluations or detect problems in class, which would occur naturally in a non-virtual classroom setting. One possible way to try to re-create the feedback channel for the teacher is to record the students' activities in the VR. However, to analyse the student activities, the instructor has to view each student's recording individually, which is too time-consuming for an entire classroom to be viable in the school context. Therefore, VR data analysis and visualization tools that synthesise the students' activities and effectively communicate important information to the instructor are needed.

Although numerous existing VR research has analysed, tracked, and visualized user data in multiple contexts (Dey et al., 2017; Piumsomboon et al., 2017; Zeng et al., 2020) the data is often aggregated for comparison between two groups of users to perform statistical analysis. This type of data analysis might be useful for the instructor to compare two or more groups of students. Nevertheless, the instructor's capability of overviewing the data of the entire class and selecting specific data of individual students for further examination is still limited.

In this paper, we propose a 3D visualization, namely *Trace Plot*, that compares the instructor's and students' locations over time. This 3D visualization allows the instructor to observe the students' movement and spot when they pause, play, and rewind the recording. We aim to improve this visualization further, and therefore are motivated to address the research question: "*How to design a data visualization approach that encapsulates the students' activities in the asynchronous virtual classroom and effectively communicates important information to the instructor?"* In this paper, we investigate this research question by examining the existing approaches and the design of their visualizations. Then, we discussed a potential

[1] https://hubs.mozilla.com

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approach to incorporate different types of data into our proposed Trace Plot. To check if we have reached our goal, we then need to identify appropriate requirements for the tool and find ways how to appropriately measure them.

2. BACKGROUND

In this section, we categorize the student data that is attainable during the virtual classroom session into five categories. Each data category's importance, implication, and common visualization techniques are briefly discussed.

2.1 Location and Movement

The movement of the students and time spent in different locations can be calculated in the virtual environment to indicate the physical load of the lesson (Piumsomboon et al., 2019). In the existing work, a heat map is often used to visualize the physical movement in the virtual environment.

The distance between the instructor and students can be used to investigate engagement and proxemics interaction (Chow et al., 2019; Piumsomboon et al., 2019, 2017). For instance, students that move closer to observe the instructor's demonstration may be more engaged than the students that observe from afar. Prior research studies measured time spent in different interpersonal spaces (i.e., intimate, personal, social, public space) and visualized the average amount of time in each space as a bar graph.

2.2 Head Orientation, Eye Gazes, and Field of View

During the lesson, the students' head movement, eye gazes, and field of view can be used to quantify a student's focus and attention (Rahman et al., 2020). For example, eye tracking is used to investigate gaze behaviour in children with developmental coordination disorder (Parr et al., 2020). Sharing gaze location or field-of-view with the instructor is also another indicator of student's engagement to the lesson, since looking at the same area or objects is a common ground establishing process (Olson and Olson, 2000). The mutual gaze is often manually counted and calculated as follows:

$$\textit{Mutual gaze count per minute} = \frac{\textit{number of mutual gaze}}{\textit{task completion time}}$$

A radar graph (Figure 1) has been used to visualize the normalized difference in head orientation and eye gaze between two collaborators (zero degrees indicates no difference in gazing direction).

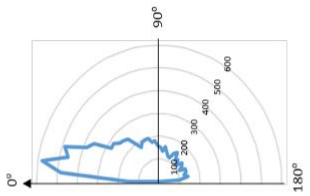

Figure 1*: A radar graph used to show a normalized difference in gaze direction, 0 degrees indicates no difference in gazing direction. Source: Dey et al., 2007*

2.3 Controllers and Hands

Modern VR hardware is often accompanied by controllers, which allow the users to interact with virtual objects in 3D spaces. The controllers' movement is a valuable measurement for users' physical load and ergonomic metrics. Thus, the controller's movement can be tracked to analyse students' activities in the virtual environments (Nguyen et al., 2017; Pontonnier et al., 2015; Yan et al., 2018).

Students' hand gesture detection is also possible by using additional hardware such as Leap Motion Sensor. Hand gestures, such as pointing gestures, are essential non-verbal cues when the students interact with the instructor. Hand gestures are another indicator of communicative behaviour or common ground establishing process (Piumsomboon et al., 2019; Yoon et al., 2020). The hand gestures and controllers are often represented by gesture count per minute.

$$\textit{Gestures per minute} = \frac{\textit{number of gesture}}{\textit{task completion time}}$$

2.4 Interaction and Events

In addition to the controller and hands gestures, the learning system may keep track of higher-level students-initiated events such as pausing the playback of the recording, asking for help, or moving objects from one location to another location. Using a desktop analogy, these events are equivalent to open a program or copy text, while controller and hands gestures are equivalent to keystrokes and mouse clicks.

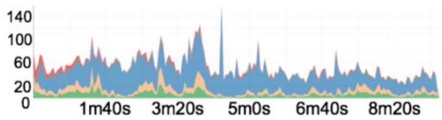

Figure 2*: Event Graph shows students accumulated input events during viewing an online tutorial video. Source: Shi et al., (2015)*

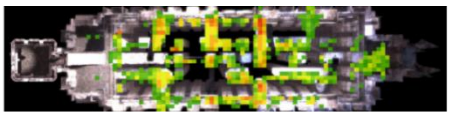

Figure 3: *A Grid-based Heat Map shows a range of events in the game level. Source: Drachen and Canossa, 2011*

Shi et al., (2015) proposed an Event Graph that visualized these events data as a distribution across recorded timestamps for Massive Open Online Courses. A stacked graph is used to show students' input events (play, pause, seek, and change speed) in different colors (Figure 2). While Event Graph allows the instructor to gain a temporal overview of the class, the instructor may want to find a location that students initiate these events. A Grid-based Heat Map (Figure 3), derived from game research and design (Drachen and Canossa, 2011), is a possible visualization that allows the instructor to perform spatial analysis.

2.5 Emotions and Expressions

Detecting students' facial expressions and emotions are becoming faster and reliable due to the advancement of artificial intelligence and deep learning research. Recently, students' facial expressions and emotions have been detected during an online classroom to provide feedback for the instructor. Emotional Graph is proposed by Zeng et al. (2020) to show emotions and facial expressions using a smooth line graph that shows positive emotion at the top, neutral emotion in the middle, and negative emotion at the bottom. An Emotional Graph can show how the student's emotions change throughout the lesson.

2.6 Physiological data

Wearable devices can be used to capture students' physiological data such as heart rate or oxygen level. These physiological data allow the instructor to investigate the student's level of excitement and increase the empathic connection between the instructor and students (Dey et al., 2019, 2017). Dey et al. visualized heart rate in real-time as an animated heart icon (with pulse and dynamic size) and simulated heartbeat sound for sharing between users. The heart rate is often analysed by calculating the average heart rate during the task and comparing it with the resting heart rate.

We summarized each data category, its representation, and visualization in Table 1.

***Table 1**: Potential data collected during the virtual classroom, representation, and visualization.*

Data type	*Representation*	*Visualization*
Location	*Average time spent in an area*	*Heat Map*
Proxemics	*Average time spent in each interpersonal distance*	*Bar Graph*
Head, Gaze, & FOV	*Mutual gaze count per minute*	*Radar Graph*
Controllers & Hands	*Gestures per minute*	*Bar Graph*
Events	*Average number of events*	*Event Graph, Grid-based Heat Map*
Emotion & Expression	*Positive, neutral, and negative emotion*	*Emotional Graph*
Heart rate	*Average heart rate*	*Bar Graph*

3. TRACE PLOT

After examining the existing VR research, we suspect that the existing data representation and visualization may not be suitable for the instructor to inspect an individual student, since the data is often represented as an aggregate value. In addition, the existing data visualization often omits changes of data over time. These changes are necessary for the instructor to spot parts of the lesson when students are engaged or disengaged.

To tackle the above issues, we designed Trace Plot to show student's location data over time and the instructor can select an individual student for further examination. The instructor's recorded location is also plotted for comparison. The X-Z plane of the Trace Plot denotes the virtual space. From the top view (Figure 4a), the Trace plot shows the instructor's and students' movement in the virtual environment. The instructor can use the top view to determine the physical load of the hands-on lesson. The Y-axis of the Trace Plot denotes the timestamp

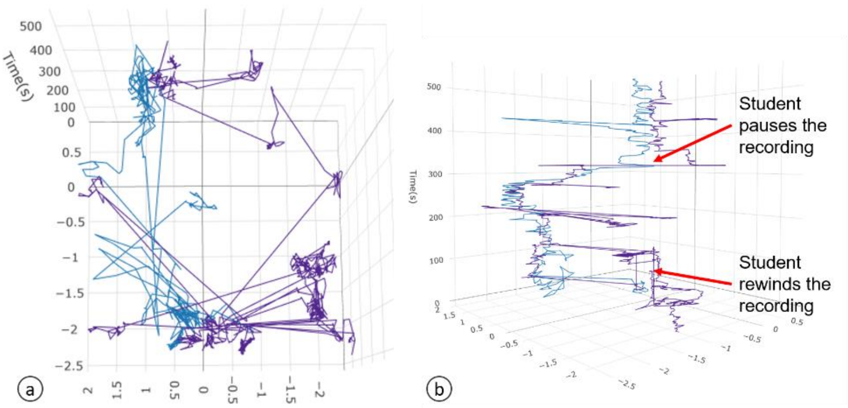

***Figure 4:** (a) Top view of Trace Plot shows the instructor's movement in blue and student's movement in purple. (b) Side view of the Trace Plot can show student's playback controls. Vertical lines show rewinding of the record. Horizontal lines show when the students pause the record.*

in the demonstration; thus, the plot cannot exceed the record duration in an asynchronous VR classroom. When the student rewinds the recording, the Trace Plot shows a straight vertical line downward (Figure 4b). A straight horizontal line from the side view shows when the student pauses the recording to change location or perform a task. In the Figure 4 example, the instructor and students are working in the laboratory with multiple workspaces. The instructor demonstrates in the instructor's workspace, and the student tries to replicate the laboratory in their own workspace. An interactive version of this Trace Plot is available at https://sites.google.com/view/exploratoryvr-3d-trace-plot/home.

In addition to the positional data, head orientational, gestural, event, emotional, and physiological data can be visualised in Trace Plot to help the instructor track changes in students engagement. Specifically, mutual gaze count and heart rate can be calculated and visualized on the Trace Plot student's line as two colors gradient value (cold color represents low value and warm color represents higher values). Gestures, events, and emotions can be categorized and assigned different colors, the Trace Plot can use each color to highlight when a gesture, event, or emotion is recognized during the recording. The instructor can switch between different data types to spot any points of interest.

4. REQUIREMENTS

To evaluate and improve Trace Plot further, first, we have to understand the instructor's requirements for the visualization. While the instructor's requirements for visualizing the classroom have not been standardized, Zeng et al. (2021) developed design requirements for Emotional Graph evaluation based on the data visualization mantra (Shneiderman, 1996) "overview first, zoom and filter, then details-on-demand" and feedback from the instructors and parents. Therefore, we adopt their design requirements as our preliminary requirements as follows:

(i) *The instructor can observe all students in the VR.* The instructor should be able to gain an overview of the VR classroom. For example, the instructor can understand whether the class's movement and attention follow the recorded instructor.

(ii) *The instructor can individually examine the students.* After gaining an overview of the classroom, the instructor can focus and understand an individual student's activities. The change of a student's location, engagement, and emotion should be clear to the instructor.

(iii) *The instructor can compare students.* The instructor may compare a selected student with the class average to identify an abnormality.

(iv) *The instructor can understand the lesson context.* During the class, the instructor may want to understand part of the lesson that caused the students to become disinterested.

(v) *The instructor can detect the inaccuracy of the data.* Since the VR hardware can be faulty and record inaccurate data that does not reflect students' activities, the visualization should notify the instructor of potential errors in recording.

Aside from the requirements we derived from Zeng et al. (2021), we consider two additional requirements based on cognitive load theory (Kirschner et al., 2009).

(vi) *The visualization should be easy to understand and operate by the instructor.* The visualization should have a low learning curve by utilizing user interfaces that the instructor has prior experience with.

(vii) *The amount of data should not overwhelm the instructor. O*nly the relevant data should be selected to help the instructor find the important information.

Using Trace Plot to visualize data from a practical asynchronous VR classroom would be a preferable approach to evaluate Trace Plot based on these requirements, then a semi-structured interview can be conducted to receive feedback from the instructor. However, few VR classroom systems are equipped to capture and record emotional and physiological data. To circumvent this limitation, synthetic data may be used to simulate a classroom situation to preliminary evaluate Trace Plot.

5. CONCLUSION

In this paper, we proposed Trace Plot for the instructor to observe an individual student's movement and playback usage. While additional data can be visualized in the Trace Plot via color-coded line segments, we expect a machine learning approach is needed to process these data and classify student's attention to further improve the Trace Plot's readability. In the future, we will also conduct studies to evaluate Trace Plot in different learning scenarios based on the requirements to improve the visualization design and better understand its limitations.

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