Who do you look like? – Gaze-based authentication for workers in VR

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ABSTRACT

Behavior-based authentication methods are actively being developed for XR. In particular, gaze-based methods promise continuous authentication of remote users. However, gaze behavior depends on the task being performed. Identification rate is typically highest when comparing data from the same task. In this study, we compared authentication performance using VR gaze data during random dot viewing, 360-degree image viewing, and a nuclear training simulation. We found that within-task authentication performed best for image viewing (72%). The implication for practitioners is to integrate image viewing into a VR workflow to collect gaze data that is viable for authentication.

Keywords: Eye Tracking, Virtual Reality, Authentication, Future of Work

Index Terms: Human-centered computing—Systems and tools for interaction design; Computing methodologies—Virtual reality

1 INTRODUCTION

Behavior-based authentication methods are actively being developed in the XR community. In particular, user authentication based on gaze cues offers the promise of seamless and continuous authentication. Current literature on gaze-based authentication in VR has focused on reading [4, 6] or image viewing [1] tasks. Maximum identification rates reported in these works range from 85% [1] to 97% [6]. Authentication algorithms performed best when the classifier was trained and tested on data from the same task [5].

In this study, we compared three scenarios for gaze-based authentication: random dot viewing, image viewing, and completing a VR simulation of a nuclear reactor startup procedure. The first two scenarios were drawn from published literature [1, 3]. The third scenario was designed by our motivating context: remote VR-based training for nuclear reactor operators.

We hypothesized that we would observe identification rates comparable to published literature for the first two tasks. We hypothesized that identification rate would be lower for the simulation task, but above chance level. We found that identification rates are highest (72% within-task) for image viewing, which is consistent with prior literature. Identification for random dot viewing and the VR simulation task was marginally above chance level (15% and 12%). The implication for practitioners is to integrate image viewing into VR training, for example, by instructing users to familiarize themselves with sample environments before proceeding to the main task.

2 METHODOLOGY

An IRB-approved experiment was used to collect eye-tracking data from various tasks in VR to explore the feasibility of gaze-based authentication within the context of nuclear engineering.

2.1 Equipment

The wireless Pico Neo 2 Eye head-mounted display (HMD) was used due to its compatibility with Unity3D and native eye-tracking capabilities. The Pico HMD uses two handheld controllers for menu navigation and interaction within the training environment.

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2.2 Participant Recruitment

Participants were recruited from the undergraduate student population enrolled in departments related to nuclear engineering and materials science at the University of Florida via email and flyers. Seventeen appointments were scheduled, and ten were fulfilled.

2.3 Study Flow

Upon arrival, participants heard an explanation of the protocol and gave informed consent. The HMD eye tracker was calibrated using the default Tobii User Calibration. Participants viewed a plane with five circular targets that spanned three degrees of visual angle with a dynamic sphere visualizing gaze position. Participants were asked to view each target and indicate whether the sphere accurately followed their gaze. If the gaze sphere did not fall within the five targets the calibration was repeated until gaze accuracy was validated.

The participant was provided instructions before each of the three authentication tasks (Sec. 2.4). Random dot viewing was the first task, followed by image viewing. A break of up to five minutes was provided at the midpoint of the image viewing set. The HMD eye tracker was then re-calibrated and validated. After image viewing, the participant took another break before moving on to the nuclear training simulation. Once all tasks were completed, an end of study survey gathered demographics and level of VR experience.

2.4 Authentication Tasks

Figure 1 illustrates three VR authentication tasks. These tasks were motivated by past studies and the remote training workflow in VR.

2.4.1 Random Dot Viewing

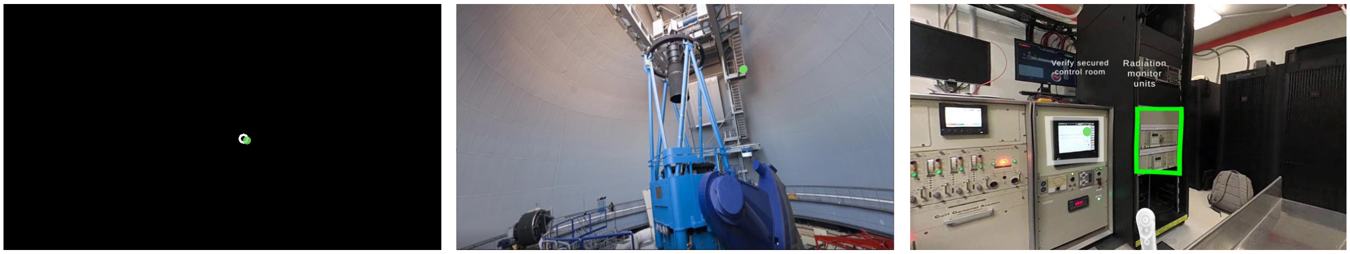
A random dot viewing task was adapted to VR based on past work [3]. Participants followed the jumping dot with their eyes for 100 seconds. In the previous study, participants viewed a stationary screen using a chin restIn this study, we simulated the setup by presenting the random dot video on a virtual plane at a fixed distance in front of them without considering head movements or rotations.

2.4.2 Image Viewing

Participants viewed 50 randomly ordered 360-degree images. The number of stimuli was justified by previous work indicating that gaze-based authentication can be viable using 50 two-dimensional images [5]. Participants were instructed to view each omnidirectional image for 25 seconds with five second transitions after each image, for a total duration of 25 minutes. The image set included 30 images of natural scenes previously used for authentication in VR [1] and 20 free-use images of laboratory and plant scenes.

2.4.3 Nuclear Training Simulation

This task was justified as a prototype of a VR-based nuclear training scenario for powering up a reactor. Participants viewed a 360-degree image of a nuclear training reactor. Areas of Interest (AOIs) were outlined to indicate equipment. Duration ranged from four to eight minutes depending on the participants' progress. To advance, participants performed point and click button presses on the AOIs corresponding to the current step in powering up the reactor.



Random Dots   Image Viewing   Simulation

Figure 1: VR environments for each task. Gaze position is visualized as a green sphere in this figure, but was not visible to participants. The center image was made available by ESO with a Creative Commons license at https://www.eso.org/public/images/3m60-pan-2007/.

Table 1: Identification rate for authentication across tasks.

	Test: Dots	Test: Images	Test: Sim.
Train: Dots	15%	8%	9%
Train: Images	10%	72%	25%
Train: Simulation	11%	15%	12%

2.5 Authentication Model

Authentication was performed using a Radial Basis Function Network and a set of features from fixation and saccade events previously applied to VR data [1]. Features were generated for each participant and task and then segmented into blocks. Random dot viewing, image viewing, and simulation were segmented by time, image, and simulation step, respectively. These blocks were then randomly selected to compose the training dataset which was used to fit the model, and the testing dataset which was used to evaluate the accuracy of identity predictions. For within-task and between-task evaluation, 50% of the data was used for training and 50% for testing. Identification rate was determined by classifying features from each individual in the testing set to make one identity prediction. Classification succeeded when the model matched the individual's features to the correct identity. This was done for each individual. The percentage of correct classifications was computed as identification rate. The evaluation was repeated ten times for each task combination with a random selection of training and testing blocks.

3 Results

Table 1 presents the identification rates. Most attempts achieved an identification rate better than the chance rate (10%). Within-task authentication generally performed better than between-task. The highest within-task identification rate was for image viewing at 72%. The best between-task identification rate was 25%.

4 Discussion

We evaluated within-task and between-task authentication using eye movements in a VR environment. Within-task authentication was generally more accurate than between-task authentication. Between-task authentication was highest for similar tasks. Within-task authentication for image viewing had the highest identification rate at 72%. This task was longer than the others, generating 21 minutes of data excluding breaks. We hypothesize that the volume of data and elicitation of repetitive exploratory behavior impacted image viewing performance as seen in past studies [1,5]. A 50/50 training/testing split was used due to our motivating context of collecting equal volumes of data during initial data collection and authentication, although more typically an 80/20 split is used for model evaluation.

Higher rates for random dot viewing were expected based on past work achieving 96% accuracy. However, our experiment varied in that our eye tracker sampling rate of 90Hz compared to 1000Hz. We only showed the random dot sequence once, resulting in a data volume of 100 seconds compared to 200 seconds, generating training and testing datasets that did not contain repeated dot movements [3].

The simulation and image-viewing tasks both involved 360-degree images, but simulation had lower within-task accuracy. This could be due to the volume of data, which varied and was at most eight minutes. Varying experience levels among nuclear engineering students may impact whether eye movements were exploratory or direct, influencing gaze behavior. The results indicate that comparing tasks which elicit exploratory behavior to tasks eliciting prescribed behavior may lower identification rate. The best between-task performance (25%) was achieved from training on image viewing and testing on simulation, suggesting that the tasks' similarity has a positive impact and potential for identification with more data.

Future Work Our observations suggest that both the type and duration of task impact authentication performance. To explore duration's effect, we could analyze subsets of the image-viewing dataset. Additionally, the random dot viewing task may be executed twice to elicit repetitive eye movements, following previous work [3]. Exploring the eye movement behaviors and subsequent feature distributions elicited by each task would be a valuable step in understanding individual differences in between-task authentication. The use of expanded feature sets including pupil biometrics, different classification models, and methods that map feature distributions between tasks would support this [2]. In this exploration, image viewing was found to be the most viable task for authentication. In a potential job training authentication pipeline, integrating image-viewing scenes early in the training program could permit within-task authentication. For example, an exploration period at the task's start could produce data for authentication naturally.

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