Demonstrating Eye Movement Biometrics in Virtual Reality

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ABSTRACT
Thanks to the eye-tracking sensors that are embedded in emerging consumer devices like the Vive Pro Eye, we demonstrate that it is feasible to deliver user authentication via eye movement biometrics.

CCS CONCEPTS
• Security and privacy → Biometrics; • Human-centered computing → Empirical studies in HCI.

KEYWORDS
eye tracking, user authentication, virtual reality, deep learning

1 INTRODUCTION
There is an emerging use of eye-tracking sensors in virtual reality devices like the Vive Pro Eye and in augmented reality devices like the HoloLens 2. The inclusion of these eye-tracking sensors is motivated in part to enable foveated rendering [Guenter et al. 2012], which can make higher-resolution displays viable in tethered devices and can offer significant power savings in untethered devices. As such, these devices already include the hardware necessary for performing user authentication via eye movement biometrics. We believe that eye movement biometrics could become the leading biometric authentication technique in these devices, similar to how fingerprint and facial recognition have become ubiquitous in smartphones.

Eye movement biometrics is a behavioral biometric modality that has been thoroughly studied since its introduction in 2004 [Kasprowski and Ober 2004]. Most studies focus on high quality eye-tracking signals [Friedman et al. 2017; George and Routray 2016; Lohr and Komogortsev 2022; Makowski et al. 2021]. The current state-of-the-art model [Lohr and Komogortsev 2022] is able to approach a level of authentication accuracy suitable for real-world use using these high quality signals. However, modern virtual- and augmented-reality headsets exhibit a much lower level of signal quality than the datasets used for such studies.

Prior live eye movement biometrics frameworks [Holland and Komogortsev 2014; Lohr et al. 2018] also use lower levels of signal quality but often do not report results. The present study can be differentiated by its use of a more modern model and by the fact that we report performance measures. Additionally, the model we employ is pre-trained using artificially degraded eye-tracking signals from a different eye tracker. The model did not see data from the eye-tracking device we use in this study—the Vive Pro Eye—prior to our final evaluation.

2 TRAINING THE MODEL
We employ the state-of-the-art Eye Know You Too architecture [Lohr and Komogortsev 2022] which is a DenseNet-based convolutional neural network. The network is visualized in Figure 1. The model is trained using the GazeBase dataset [Griffith et al. 2021] which comprises recordings from 322 college-aged participants. Each participant was present for up to 18 recording sessions, and each session consisted of 7 different eye-tracking tasks: horizontal saccades (HSS), random saccades (RAN), reading (TEX), an interactive ball-popping game (BLG), two video-viewing tasks (VD1 and VD2), and a fixation task (FXS).

We follow the training methodology described in the Eye Know You Too manuscript [Lohr and Komogortsev 2022] with a couple differences to better fit our purposes. The first difference is that we artificially degrade the eye-tracking signals by downsampling from 1000 Hz to 125 Hz and by adding white (Gaussian) noise with mean 0 and standard deviation 0.1 to the training data after performing z-score normalization. We chose a sampling rate of 125 Hz to closely match the 120 Hz sampling rate of the Vive Pro Eye, and the addition of spatial noise was intended to improve performance on the lower signal quality of the Vive Pro Eye. The second difference is that we do not train an ensemble of models, but rather we train only the one model that uses the first data fold as the validation set. The use of only one model instead of the ensemble of 4 models was mostly intended to minimize the computational burden of the model at inference time, but using the ensemble would likely have led to superior performance.
To evaluate our model’s performance, we collected data from 5 participants (3 male, 2 female) with normal or corrected-to-normal vision. Each participant (labeled A–E) was recorded twice using the Vive Pro Eye. The first recording (e.g., A1) is used for enrollment, and the second recording (e.g., A2) is used for verification against each participant’s enrolled template (A1–E1).

Our measured similarity scores are reported in Table 1. We achieve an equal error rate (EER) of 20% (1-in-5 false rejection rate and 4-in-20 false acceptance rate) with a similarity score threshold of 0.8. It is important to keep in mind that our model was not trained on data from the Vive Pro Eye, yet it still performed better than chance.

| Enroll | Verify | A1    | B2    | C2    | D2    | E2    |
|--------|--------|-------|-------|-------|-------|-------|
| A1     | 0.8119 | 0.7014| 0.7155| 0.6596| 0.7473|
| B1     | 0.7814 | 0.8551| 0.6858| 0.7664| 0.7377|
| C1     | 0.8034 | 0.7441| 0.7987| 0.6468| 0.8169|
| D1     | 0.8440 | 0.8546| 0.7580| 0.8169| 0.7613|
| E1     | 0.7718 | 0.7974| 0.7160| 0.6904| 0.8494|

5 CONCLUSION

We demonstrated eye movement biometrics in virtual reality using the Vive Pro Eye. We achieved 20% EER on a dataset of 5 participants using a deep learning model pre-trained on a different dataset with no fine-tuning. As larger datasets in virtual reality become available (e.g., [Lohr et al. 2020]), better performance could likely be achieved.

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