An Eye Opener on the Use of Machine Learning in Eye Movement Based Authentication

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Abstract

The viability and need for eye movement-based authentication has been well established in light of the recent adoption of Virtual Reality headsets and Augmented Reality glasses. Previous research has demonstrated the practicality of eye movement-based authentication, but there still remains space for improvement in achieving higher identification accuracy. In this study, we focus on incorporating linguistic features in eye movement-based authentication, and we compare our approach to authentication based purely on common first-order metrics across 9 machine learning models. Using GazeBase, a large eye movement dataset with 322 participants, and the CELEX lexical database, we show that AdaBoost classifier is the best performing model with an average F1 score of 74.6%. More importantly, we show that the use of linguistic features increased the accuracy of most classification models. Our results provide insights on the use of machine learning models, and motivate more work on incorporating text analysis in eye movement-based authentication.

Keywords

Eye Tracking, Machine Learning, Biometrics, Authentication

Introduction

Traditional Authentication

- Examples: passwords, dual-factor authentication, and etc
- Require memory and timely access to second device
- Unsuitable for modern interactive systems

Biometric Authentication

- Examples: eye movement, iris scan, fingerprints, and etc
- Identify users based on their physical and behavioral characteristics

Eye Movement-Based Authentication

- Identify users based on their eye movement
- Viable for contactless biometric authentication because the way we move our eyes across text or images is influenced by physical and cognitive factors [Rayner 1998]
- Especially useful since the pervasive introduction of eye trackers and cameras in smartphones and VR/AR devices, and during the COVID-19 pandemic in public, such as train stations, ATMs, and shopping malls

Background

Previous Research

- The use of eye movement in biometrics was first introduced in 2004 [Kasprowski and Ober 2004].
- Various research has been carried out to improve its performance [Lohr et al. 2022].
- Demonstrated the practicality of eye movement-based authentication.
- Focused primarily on first-order metrics such as fixations and saccades in eye movement-based authentication.

Types of Eye Movement Tasks Used (See Figure 1)

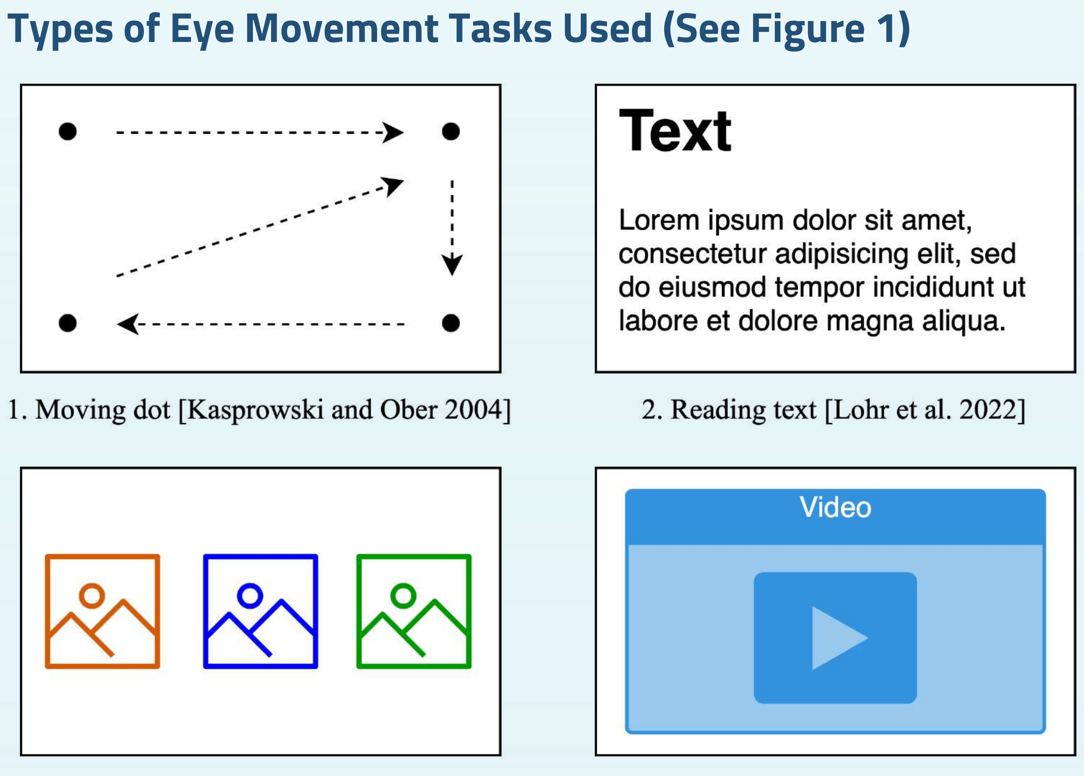

Figure 1. Typical Types of Eye Movement Tasks

Methodologies to Improve Authentication Accuracy

- Radial basis function network [George and Routray 2016]
- Deep learning [Jia et al. 2018]

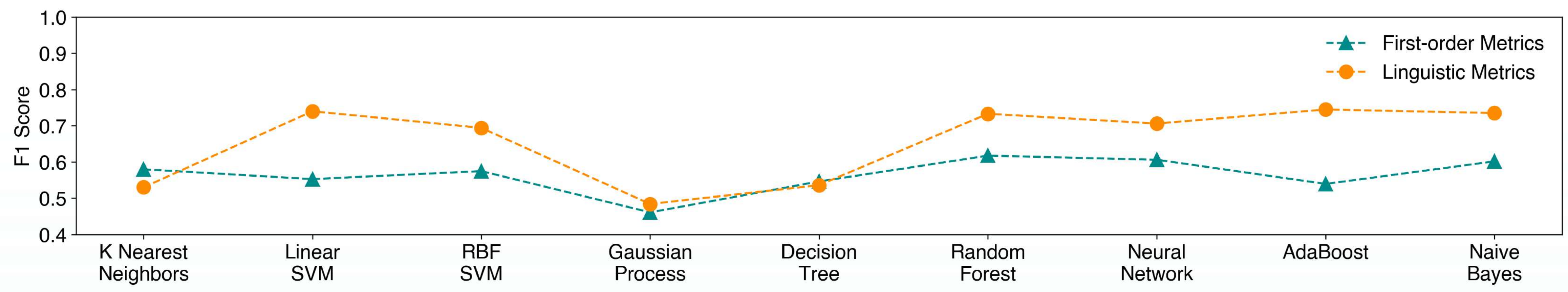

Figure 3. Comparing First-order Metrics to Linguistic Metrics Based on F1 Score

Objective

With machine learning, we aim to accomplish a more accurate performance in eye movement-based authentication using linguistically enriched eye movement data in reading tasks.

Method

Guiding Principle

- Cognitive research has established that linguistic metrics influence eye movement behavior during reading [Rayner 1998].

What Influence Reading Behavior?

- Reading experience [Ashby et al. 2005].
- Age [Rayneret al. 2006].
- Consistent individual traits for each reader.

How to See the Differences on Eye Movement?

- These individual differences are most clearly seen in the influence of frequency, length, and predictability on eye movement.
- Previous research shows that an experienced reader is more influenced by the frequency of common words as a factor of repeated reading.
- Example: in the following sentence, the word "liver" is a highly predictable word in the given context. In fact, experienced readers are likely to skip this word without making a fixation. We aimed to leverage these linguistic phenomena to aid in eye movement-based authentication.

"The doctor told Fred that excessive drinking would damage his ____."

Dataset

- GazeBase, an existing large eye movement dataset collected from 322 participants over a 37 months period [Griffith et al. 2021].
- Multiple types of tasks: reading, image viewing, interactive game, etc.

Data Preprocessing

1. Extract eye movement data of all participants in reading tasks.
2. Convert the original data to first-order metrics (fixations)
3. Filter fixations that were too short (<100ms) or whose recorded position did not overlap with any nearby text
4. Map each fixation to its underlying token (See Figure 2).
5. Add word frequency and length data for each token from the CELEX database [Baayen et al. 1996].

Metrics

For each token, we calculated eight eye movement metrics [Rayner 1998], shown below.

Duration Metrics	Probability Metrics
- Single fixation duration	- Fixation probability
- First fixation duration	- Probability of making exactly one fixation
- Total time	- Probability of making two or more fixations
- Gaze duration	- Probability of skipping

Classification

1. Combine the eight metrics, reading rate, word length, and word frequency.
2. Normalize data and remove redundant features.
3. Split the data into training and testing sets in ratio of 80% to 20%.
4. Use cross validation of 10 folds and 9 machine learning classifiers.
5. Obtain accuracy, precision, recall, and F1 scores.

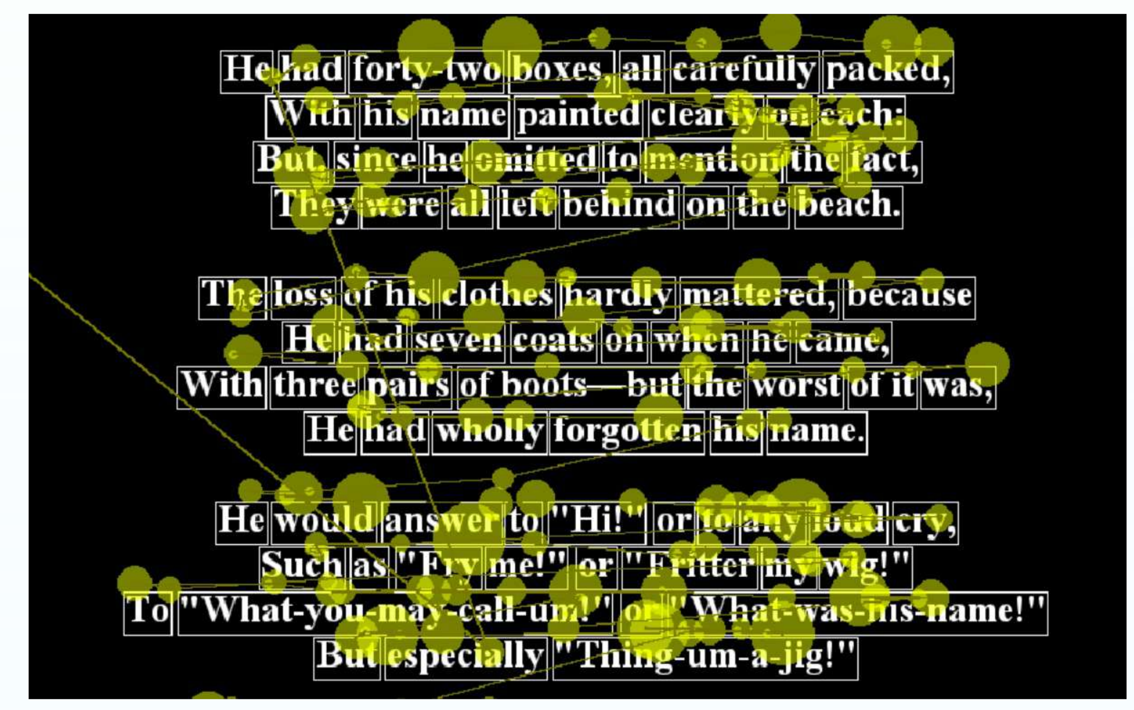

Figure 2. A sample paragraph, where yellow circles represent fixations and the size of the circle represent fixation duration, generated using Eye Movement Toolkit

Results

- We compared F1 scores across the 9 models using first-order metrics in contrast to using linguistic metrics (Figure 3).
- Using first-order metrics, the best F1 score of 61% was produced from the random forest classifier
- Using linguistic metrics, the best F1 score of 74.6% was produced from the AdaBoost classifier.
- Our initial results suggested that machine learning classifiers had better performance in identifying subjects based on their eye movement using linguistic metrics rather than first-order metrics.
- Moreover, the AdaBoost classifier showed the best performance among all 9 models with linguistic metrics.

Contribution and Future Work

- Our results provide insights on the use of machine learning models and linguistic metrics in eye movement-based authentication.
- Our future work includes plans to use more robust classifiers and new datasets to improve the accuracy in authentication.
- Our hypothesis is that using a combination of physical and cognitive features, including linguistic metrics, would increase the accuracy of identifying participants based on their eye movement.

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