EEG-Based Eye Tracking for Consumer-Grade BCIs:

Evaluation of Different Approaches with a Focus on Functional Data Analysis

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Introduction

EEG-based eye tracking (ET) is an emerging application of brain-computer interfaces (BCIs). EEG, typically used for recording brain activity, also captures eye movement artifacts that can be leveraged for tracking eye movement. This approach offers advantages over traditional camera-based ET, especially in poor lighting or with closed eyes. It also reduces hardware requirements and simplifies experiments that require both eye movement and EEG data. Despite its potential, EEG-based ET research has been limited to laboratory settings and expensive equipment. This thesis investigates its feasibility using consumer-grade hardware under more realistic conditions, filling a gap in current research. For this, methods based on Functional Data Analysis (FDA) are explored, a framework well-suited to the continuous nature of eye movement data, but one that has yet to be applied in this context.

Dataset Acquisition and Specifications

A novel EEG-ET dataset, the "Consumer EEG-ET Dataset" using consumer-grade hardware was created. The dataset consists of simultaneous recordings of EEG and eye-tracking data from 113 participants across 116 sessions. The recordings were conducted using a consumer-grade Muse S 2 headband (with five electrodes, sampling at 256 Hz) to capture EEG signals and a Logitech StreamCam to record eye movements at 60 frames per second. Participants were seated 60 cm away from a 24-inch monitor (2560x1440 resolution, 60 Hz refresh rate), with a webcam placed just below the screen. Stimuli presentation and data synchronization were managed through a custom Python program, with all data streams synchronized via the Lab Streaming Layer Protocol.

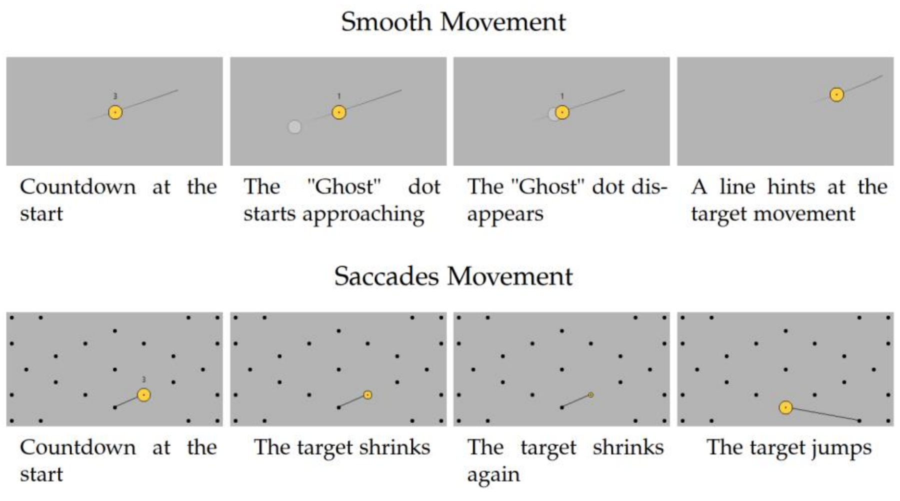

Figure 1: Stimuli presentation in the Consumer EEG-ET dataset.

Each session lasted around 10 minutes and consisted of four experimental paradigms, divided into smooth and saccades tasks. In smooth tasks, participants followed a moving dot in a continuous, predictable motion, while in saccades tasks, the dot jumped between predefined points on the screen. These paradigms progressively increased in difficulty as the dot's movement became less restricted. The dataset contains approximately 11 hours and 45 minutes of data, which totals 1.54 GB. The duration of each task varied, with level-1 tasks lasting 1 minute and level-2 tasks lasting 2 minutes. The structured presentation allowed participants to closely follow the dot, ensuring accurate eye-tracking data for each task.

Methods

The SpatialFilterCNN utilizes a novel neural network architecture that incorporates a learnable spatial filter inspired by Canonical Correlation Analysis, enhancing the signal-to-noise ratio by maximizing the correlation between EEG data and eye movement data. Similarly, the Battery Model of the Eye (BMOTE), which models the eye as a battery, leverages Electrooculography (EOG) to estimate gaze angle, providing a physically-driven approach relevant for understanding eye movements.

Using functional dense and convolutional layers, which address the challenges of registering functions in Functional Data Analysis, we constructed three distinct Functional Neural Network (FNN) architectures:

- **Fully Functional:** All layers are functional.
- **Partially Functional:** The "body" of the architecture (which is responsible for "feature extraction") employs functional layers.
- **Minimally Functional:** Only one layer is functional.

To isolate and evaluate the impact of the functional layers, we also developed control architectures that mirror the structure of each FNN but utilize traditional layers instead.

Results

Both the SpatialFilterCNN (SFCNN) and functional neural networks (FNNs) demonstrated strong performance, particularly in capturing the timing of directional in movements effectively. They both surpassed all baseline results, except for the level-1 smooth task.

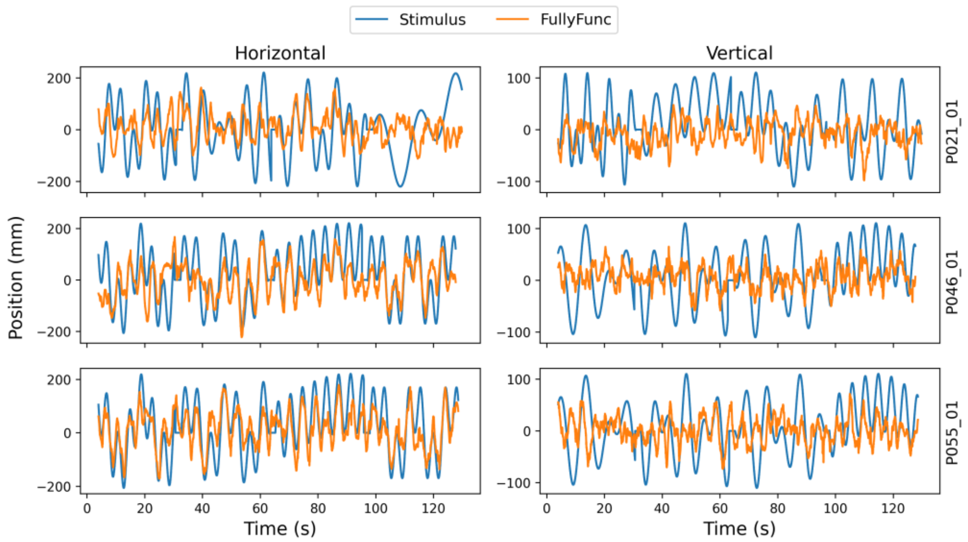

Figure 2: Fully Functional Model on level-2 smooth task

Conversely, the BMOTE experiment showed nearly random performance, with over 97% of predictions discarded due to issues related to electrode positioning and differences between our EEG data and the original EOG data used in prior studies.

Notably, the FNNs achieved state-of-the-art (SOTA) results on the EEGEyeNet benchmark, although the control models also performed competitively.

Model	MED	MAE
FullyFunc	$\mathbf{68.5} \pm 1.0$	$\mathbf{42.7} \pm 0.6$
FullyFunc (control)	69.9 ± 1.3	43.6 ± 0.8
FuncBody	$\mathbf{68.0} \pm 0.8$	42.4 ± 0.6
FuncBody (control)	68.1 ± 0.5	$\mathbf{42.3} \pm 0.3$
MinFunc	66.8 ± 0.5	41.5 ± 0.4
MinFunc (control)	$\underline{\mathbf{66.2}} \pm 0.8$	$\underline{\mathbf{41.1}} \pm 0.5$
SpatialFilterCNN	68.8 ± 1.4	42.9 ± 0.8

Figure 3: SOTA results on the EEGEyeNet Dataset in millimeter

Overall, while progress was made, consumer-grade EEG-based eye tracking methods did not outperform webcam-based systems.

Contributions, Limitations and Outlook

The first contribution is exploring whether eye tracking is possible using EEG recorded with consumer-grade hardware. In pursuit of this goal, the largest EEG-eye tracking dataset using consumer equipment was collected. The results from both existing and newly developed methods demonstrate that EEG-based eye tracking is indeed feasible with consumer hardware. Specifically, on simpler tasks, the performance of consumer EEG-based eye tracking was competitive with that of consumer camera-based systems.

The second contribution focuses on assessing the effectiveness of functional neural networks (FNNs) for EEG-based eye tracking. Across two datasets—our custom dataset and EEGEyeNet—the FNNs proved to be competitive with or even superior to the current state-of-the-art methods. On our dataset, the functional models generally outperformed their control counterparts, delivering better precision. However, on the EEGEyeNet dataset, the results were more varied.

More experiments are needed to conclusively evaluate the benefits of functional layers. These could include tuning hyperparameters, applying more filtering, and increasing the number of cross-validated repetitions. Additionally, new architectures that are more "functionally aware" could help further explore the potential of functional outputs.

For ground-truth comparisons, no high-end camera was used. Instead, a consumer webcam was employed to adjust for reaction times and to filter out non-compliance in the recordings.

This research has shown that EEG-based eye tracking using consumer hardware is viable, with functional models offering promising results. However, the current state of EEG-based eye tracking is only scratching the surface of what may be possible. With more focused efforts, the technology could see significant advancements, revealing its full potential.