Eye Movement Assessment Methodology Based on Wearable EEG Headband Data Analysis

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Abstract—**This study investigates the classification of eye movements using EEG data recorded from a wearable device, with eye tracking data employed as ground truth for model training. We aim to classify various eye movements, including fixations, saccades, and directional movements, utilizing long short-term memory (LSTM) neural networks. Data were collected from 22 participants using the BrainBit headband, which recorded EEG signals at 250 Hz with four dry electrodes, and the Pupil Labs Invisible eye tracker, which recorded 2D gaze coordinates at 100 Hz during computer-based tasks. The EEG data underwent preprocessing and feature extraction to capture essential characteristics relevant to eye movement classification. Our LSTM model, trained and validated on this dataset, achieved a classification accuracy of 90% for the saccade detection task and 65% and 62% for up versus down and left versus right movement classification accordingly. These results demonstrate the potential of using EEG data alone for promising eye movement classification, laying the groundwork for future research in neural signal processing and its applications in human-computer interaction and neurotechnological systems.**

I. Introduction

Eye movements are a fundamental aspect of human interaction with the world, reflecting a wide range of cognitive processes, including attention, perception, and decision-making. The ability to accurately track and classify eye movements holds significant promise for applications in areas such as human-computer interaction, neurological research, and assistive technologies. Traditional eye tracking methods, which rely solely on optical devices to monitor gaze direction and fixation points, provide valuable insights but are often limited by their reliance on external cameras and their inability to capture the underlying neural mechanisms driving these movements.

Electroencephalography, a non-invasive method for recording electrical activity in the brain, offers a powerful approach to understanding the neural processes underlying eye movements. EEG data can reveal a wider spectrum of human physiological and cognitive states, which makes it applicable in various fields such as emotion recognition, cognitive load assessment, and even sleep studies. Unlike eye trackers, which capture only the observable gaze behaviors, EEG provides direct insight into brain activity, making it a versatile tool for understanding the neural basis of eye movements and other related phenomena.

Electroencephalography (EEG) and Electrooculography (EOG) are two methods that can be used for eye-tracking. EOG measures the corneo-retinal standing potential that exists between the front and the back of the human eye. When the eyes move, this potential generates a signal that can be captured by electrodes placed around the eyes. Typically, these electrodes are placed near the outer corners of the eyes to measure horizontal eye movements and above and below the eyes to measure vertical movements. This makes EOG a direct method for tracking eye movement. EEG, on the other hand, is used to record electrical activity generated by the brain. However, it can also pick up potentials from eye movements due to surface conductivity. When the eyes move, they generate electric potentials that can be captured by EEG electrodes placed on the scalp. Although EEG is not primarily designed for eye-tracking, it can provide useful information about eye movements due to these recorded potentials.

In this study, we focus on classifying different types of eye movements using EEG data. Specifically, our goal is to classify eye movements such as fixations, saccades, and directional movements (left, right, up, and down) by leveraging long short-term memory (LSTM) neural networks, which are well suited for processing sequential data. The EEG data was collected using the BrainBit headband, a wearable device equipped with four dry electrodes, while the eye movements were recorded using the Pupil Labs Invisible eye tracking system.

The findings have important implications for the development of advanced human-computer interfaces and neurotechnological applications, where understanding and interpreting eye movements based on EEG data alone could enable more flexible and wearable systems.

The rest of the paper is divided as follows: Section II explores related works on the classification of eye movements using EEG and optical tracking systems. Section III describes the proposed methodology, including data collection and preprocessing, model architecture, training procedures, evaluation metrics, and encountered challenges. Section IV concludes the study and discusses future directions for research.

II. Related work

The classification of eye movements has traditionally relied on optical eye tracking systems, which capture gaze positions to analyze eye movements such as fixations and saccades. Fixations and saccades are two primary components of gaze behavior. Fixations occur when the eyes remain relatively still and focus on a particular object or area, typically reflecting cognitive processes such as attention, information encoding, and scene analysis. On the other hand, saccades are rapid, ballistic eye movements that shift the point of gaze from one fixation to another, allowing the eyes to quickly scan the visual environment. The identification and classification of these movements provide key insights into underlying cognitive functions and behaviors [1]. For instance, Martinez-Marquez et al. [2] provide a comprehensive overview of eye tracking technologies and their applications in real-life interactions, showing the importance of accurate eye movement classification in both research and practical applications.

EEG-based systems have opened new opportunities for analyzing eye movements without relying on external cameras. Jia and Tyler [3] showed that the electrooculography methodology allowed an accurate analysis of the amplitude and direction of fixation locations and saccadic dynamics. Sun et al. [4] employed 64 channel EEG to track gaze position with an average accuracy of 1.008 degrees of the person's visual angle. Müller et al. [5] validated that optical and EEG eye tracking methods are suitable for estimating the processing duration of individual participants.

Several approaches have combined EEG and eye tracking data to enhance classification accuracy. Kang et al. [6] proposed a method that integrates EEG signals with optical eye tracking data to classify mental workload during task execution. Their study showed that combining these two data streams improved the overall classification accuracy compared to using either data source alone, showing potential for hybrid systems in neurocognitive studies.

Ma et al. [7] present a novel human–machine interface based on both EOG and EEG and verify the effectiveness of the proposed system by different online experiments. One is to control a multifunctional humanoid robot, and the other is to control four mobile robots.

Traditional EEG systems that use wet electrodes and lab setups show success in capturing eye movements and brain activity, but they are often restricted to controlled environments due to their size, setup complexity, and sensitivity to external interference. These systems, although accurate, are not practical for use in everyday settings or for long-term monitoring, limiting their applicability in real-world scenarios. The emergence of wearable EEG technology has addressed these limitations by providing a more portable and user-friendly solution.

One of the biggest challenges in using EEG from wearable devices is the quality of the signal. Unlike traditional, wearable devices such as the BrainBit headband rely on dry electrodes that often suffer from poor contact quality, leading to noisy signals. Additionally, the reduced number of electrodes in wearable systems limits the amount of brain activity data captured, making it more difficult to extract the fine-grained neural information necessary for accurate classification of complex behaviors such as eye movements. Park et al. [8] discussed optimal electrode placement of wearable EEG devices for different tasks. Wearable EEG devices are also more susceptible to motion artifacts, where body movements or changes in electrode position introduce significant noise, further complicating data analysis [9].

Klug and Gramann [10] specifically addressed the challenges of Independent Component Analysis (ICA) decomposition in both mobile and stationary EEG experiments. They concluded that fewer brain Independent Components were found in mobile experiments, but cleaning the data with ICA has been proved to be important and functional even with low-density channel setups. Seok et al. [11] reviewed and introduced motion artifact reduction methods for data collected using wearable EEG.

Despite these challenges, wearable EEG systems offer a flexible and portable approach to studying brain activity in everyday environments. Several studies have demonstrated the potential of wearable EEG devices for a variety of applications, including mental state monitoring and cognitive load assessment. For example, Pierrick et al. [12] demonstrate the capacity of the wearable EEG to both monitor sleep-related physiological signals and process them accurately into sleep stages. Yu and Guo [13] combined Virtual Reality technology and EEG measurements from wearable EEG with flexible electrode placement. Krigolson et al. [14] showed that portable, low-cost EEG systems can be used for event-related potential research without event markers, effectively identifying key components in experiments.

More recently, deep learning techniques have been applied to EEG data for eye movement classification tasks. Gong et al. [15] discussed the application of deep learning in EEG processing for past ten years. Long Short-Term Memory (LSTM) networks, in particular, have shown promise in capturing the temporal dependencies in sequential EEG data. For example, Zhang et al. [16] utilized LSTM networks to classify mental states based on EEG signals, achieving improved accuracy over traditional machine learning models.

In this work, we extend the current body of research by focusing on the classification of eye movements using EEG data captured by a wearable device.

III. Methodology

A. General Description

This study investigates the classification of eye movements using a combination of wearable EEG devices and eye tracking technology. The primary aim is to classify different types of eye movements, including fixations, saccades, and directional movements such as left, right, up, and down. Data was collected from participants who participated in various tasks designed to stimulate different patterns of eye movement. The collected data was then processed and used in deep learning techniques, which aimed to achieve an accurate classification of these eye movements.

Figure 1 provides a visual overview of the methodology, from data exploration, preprocessing, and feature extraction, followed by the generation of sequences of varying lengths corresponding to different types of eye movements, to training of a neural network model for classification tasks. We presented each step in details further.

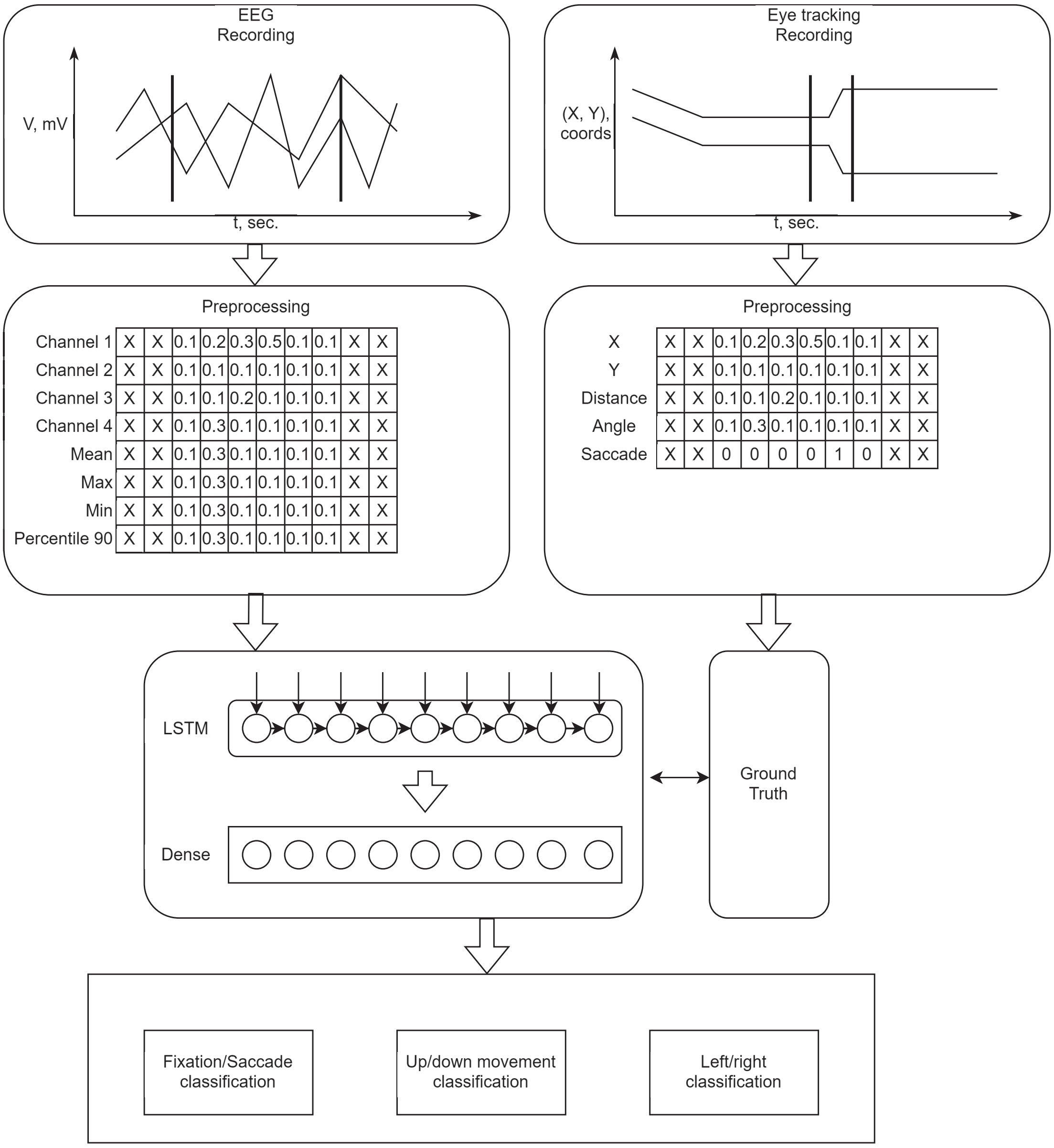

Fig. 1. Proposed Eye Movement Classification Methodology

B. Data Collection

For this study, two primary devices were employed. The first device was the BrainBit headband, a wearable EEG device equipped with 4 dry electrodes that recorded raw EEG signals at a sampling rate of 250 Hz, providing data in volts. BrainBit is shown on the Fig. 2. The second device was the Pupil Labs Invisible, an eye tracking system that recorded 2D gaze coordinates at a sampling rate of 100 Hz.

The study involved 22 participants who were selected without specific criteria regarding age, gender, or vision status.

Data collection was performed during computer-based sessions in which participants were seated in front of a laptop, as shown at Fig. 3. Each session lasted approximately 3 hours and involved a variety of tasks designed to elicit a range of eye movements. These tasks included reading passages displayed on the screen, completing standardized Landolt C tests, and playing simple computer games.

C. Data Preprocessing

Each data source, including both eye tracking and EEG, contained individual timestamps for the recorded events. However, since these signals were collected using different devices, synchronization between the datasets was required. The use of different recording systems resulted in a temporal drift, with a shift exceeding 300 milliseconds between the timelines. Manual synchronization was performed to address this discrepancy by identifying and aligning distinct events common to both recordings. Specifically, high-amplitude eye movements observed in the eye tracking data were detected by calculating the

Fig. 2. The BrainBit Headband, Wearable EEG Device with 4 Dry Electrodes

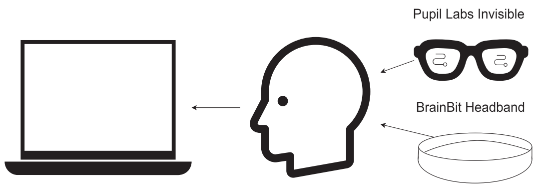

Fig. 3. Data Collection Setup

distance traveled by the eye from the previous recording point. These movements were then aligned with the corresponding segments in the EEG recordings that exhibited large-amplitude oscillations, ensuring precise temporal alignment between the two data streams. An example of this synchronization process is illustrated in Fig. 4, which highlights the matching of eye movements with high-amplitude EEG fluctuations.

To ensure the quality of the EEG data, preprocessing steps were implemented to remove noise. A bandpass filter was applied, allowing frequencies below 40 Hz to pass through, effectively filtering out higher-frequency noise. This filtering ensured that the EEG data retained the most relevant signal components for subsequent analysis.

It is common practice to apply a bandpass filter that includes only frequencies above 0.5 Hz or 1 Hz, as low-frequency components are often associated with slow, non-specific brain activity or noise. However, in the context of this study, low-frequency EEG signals were preserved because these frequencies contain vital information related to eye movements.

By not filtering out the low-frequency signals, we ensured that essential data specific to eye movements remained intact.

D. Feature Extraction

Several features were extracted from the eye tracking data, including the distance between consecutive gaze points, the speed of eye movements, and the angular direction of these movements. These features were used to classify periods of eye movement into different categories, such as fixation or saccade, as well as directional movements (left, right, up, down). Each identified sequence was labeled accordingly. Due to the natural variability in gaze behavior, the sequences varied

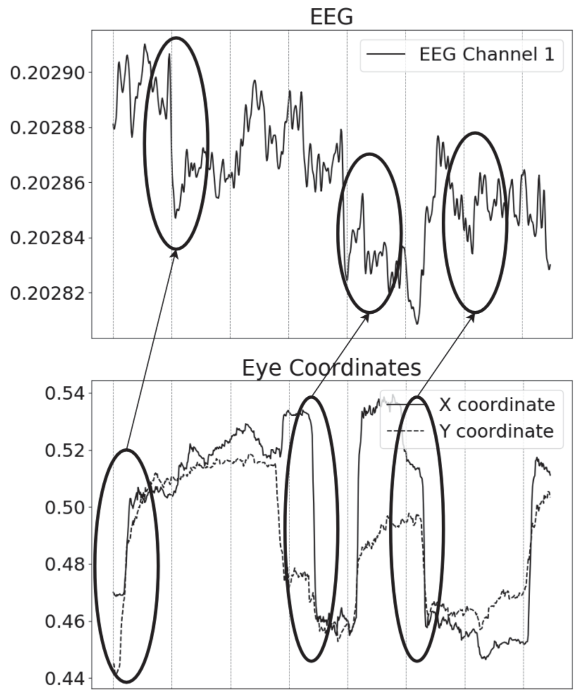

Fig. 4. Synchronization Example Showing Gaze Coordinates and EEG with Found Synchronization Point

in length. To standardize the data for model training, the sequences were padded to match the length of the longest sequence.

For each eye movement sequence, a corresponding EEG sequence was selected and included in the dataset. To ensure the quality of the EEG data, it was normalized to reduce variability between different examples and participants. This normalization process involved adjusting the sequences to account for baseline shifts and applying additional statistical feature extraction techniques, including the calculation of mean, minimum, maximum, and 90th percentile values. These statistical features enhanced the distinctive properties of the EEG data, aiding in the accurate classification of eye movements.

In addition to these preprocessing steps, we utilized the Event-Related Potential (ERP) technique to further improve the accuracy of feature extraction. This technique allowed us to align specific EEG segments with corresponding eye movement events detected by the eye tracking system. For every eye movement event (e.g., fixation or saccade), we located the corresponding EEG sequence, enabling us to capture the brain's electrical activity associated with each event.

Eye movement events are influenced by both muscle and brain activities, meaning the neural processes surrounding an eye movement event often extend beyond the exact time of the event itself. To capture this additional neural activity, we expanded the boundaries of the EEG segments to include extra information both before and after each event. Through experimentation, we found that including an additional 0.1 seconds of EEG data before and after each eye movement event significantly improved classification accuracy. This expanded window allowed us to capture not only the neural activity directly related to the eye movement but also the preparatory and post-event signals, which are crucial for accurately classifying movements.

Process is shown at the Fig. 5. When saccade or fixation is detected in the data, corresponding EEG is found, boundaries are extended, features like distance, angle are calculated.

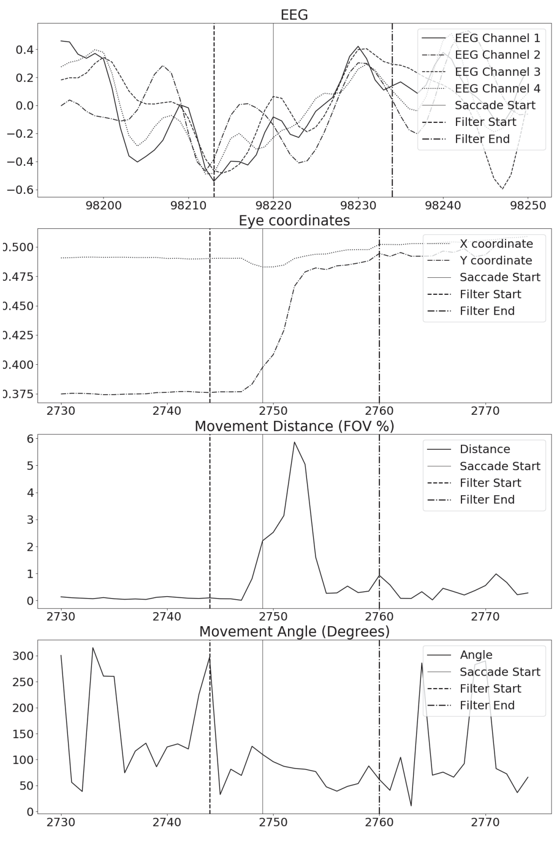

Fig. 5. Saccade Extraction with Corresponding EEG Sequence and Filter Boundaries

E. Model Architecture and Training

The classification tasks were performed using a Long Short-Term Memory (LSTM) neural network. The model architecture was designed with an input size that corresponds to the number of selected EEG channels plus additional features. The hidden layers consisted of 128 units distributed in four layers. After the LSTM layers, a fully connected (dense) layer was applied, with the number of neurons in the output layer equal to the number of target classes in the classification tasks, two for each.

The dataset was divided into training, validation, and test sets using an 80/10/10 split.

For training, the model used a cross-entropy loss function, commonly used for multiclass classification tasks, which evaluates the difference between the predicted class probabilities and the true class labels. The optimization process was driven by the Adam algorithm, a widely used method that adapts the learning rate during training to handle sparse gradients effectively.

To further stabilize training, a learning rate scheduler was used to decrease the learning rate by a factor of 0.9 every three epochs. This helps in achieving a more stable learning process.

F. Evaluation Metrics

To evaluate the performance of the model, the accuracy and the F1 score were used as primary metrics. This precision was calculated for each classification task: fixation versus saccades, left versus right movements, and up versus down movements. In addition, a confusion matrix was generated to assess the distribution of the predictions in the different classes.

TABLE I. PERFORMANCE METRICS FOR DIFFERENT TASKS

Task	Accuracy	Precision	Recall	F1
Fixation/Saccade	90%	90%	90%	90%
Left/Right	62%	58%	63%	60%
Up/Down	68%	65%	68%	68%

The results of the model evaluation demonstrate varying degrees of classification performance across different tasks. The model showed high accuracy in distinguishing between fixation and saccade movements. However, the classification task involving left versus right movements showed a significantly lower accuracy of 62%, indicating that the model struggled to differentiate between these directional movements. Similarly, the task of classifying up versus down movements achieved moderate results, with an accuracy of 68%. Although this performance is better than that of the left/right classification, it still reflects some challenges in correctly identifying these movements.

G. Challenges and Solutions

This study encountered several key challenges, particularly in the preprocessing and synchronization of EEG and eye tracking data. The use of dry electrodes in wearable devices, while more convenient for users, resulted in noisier signals compared to traditional wet electrodes. Noise introduced by poor contact quality and motion artifacts had to be mitigated through filtering techniques, but some loss of data quality is inevitable.

Moreover, the inter-participant variability in EEG signals posed a significant obstacle. Individual differences in neural patterns cause impossibility to use a single model for all participants.

The task of accurately classifying directional movements, particularly left versus right and up versus down, also proved challenging. These movements often result in almost similar changes in EEG signals, making it difficult for the model to differentiate between them.

These limitations suggest the need for more advanced approaches in future work, such as personalization strategies, the use of transfer learning to adapt models to individual users or deeper feature engineering.

IV. Conclusion

In this study, we explored the potential of classifying various types of eye movements using EEG data collected by a wearable EEG headband, leveraging the capabilities of Long Short-Term Memory (LSTM) neural networks. The results demonstrated that it is possible to distinguish between fixations, saccades, and directional movements (left, right, up, and down) using only EEG signals, achieving high precision in certain tasks, such as fixation versus saccade classification. However, the results also revealed challenges in accurately classifying directional movements, particularly left versus right and up versus down, highlighting the complexities involved in decoding such movements purely from EEG data.

A key strength of our approach is the ability to handle sequences of varying lengths, making the model adaptable to different types of eye movements that may occur over different time frames. This flexibility also positions the model for potential near real-time applications, where sequences of eye movements could be classified as they occur, enabling the model to be integrated into dynamic, real-world systems such as human-computer interaction interfaces or assistive technologies.

One of the primary limitations was the high variability in EEG patterns across individuals. Techniques such as transfer learning, personalization strategies, or domain adaptation may offer potential solutions to this issue in future research.

Additionally, future work could explore extending the model beyond eye movement classification to the detection of continuous gaze coordinates, providing a more comprehensive solution for real-time gaze tracking.

In summary, this study establishes the foundation for real-time, EEG-based eye movement classification and sets the stage for advancements that could enhance precise gaze tracking and expand neurotechnological applications.

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