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INTELLIGENT EYE GAZE LOCALIZATION METHOD BASED ON EEG ANALYSIS USING WEARABLE HEADBAND

Romaniuk V., Kashevnik A. **Intelligent Eye Gaze Localization Method Based on EEG Analysis Using Wearable Headband.**

Abstract. In the rapidly evolving digital age, human-machine interface technologies are continuously being improved. Traditional methods of computer interaction, such as a mouse and a keyboard, are being supplemented and even replaced by more intuitive methods, including eye-tracking technologies. Conventional eye-tracking methods utilize cameras to monitor the direction of gaze but have their limitations. An alternative and promising approach for eye-tracking involves the use of electroencephalography, a technique for measuring brain activity. Historically, EEG was primarily limited to laboratory conditions. However, mobile and accessible EEG devices are entering the market, offering a more versatile and effective means of recording bioelectric potentials. This paper introduces a gaze localization method using EEG obtained from a mobile EEG recorder in the form of a wearable headband (provided by BrainBit). The study aims to decode neural patterns associated with different gaze directions using advanced machine learning methods, particularly neural networks. Pattern recognition is performed using both ground truth data collected from wearable camera-based eye-tracking glasses and unlabeled data. The results obtained in this research demonstrate a relationship between eye movement and EEG, which can be described and recognized through a predictive model. This integration of mobile EEG technology with eye-tracking methods offers a portable and convenient solution that can be applied in various fields, including medical research and the development of more intuitive computer interfaces.

Keywords: eye-tracking, EEG, neural networks, wearable EEG, supervised learning, unsupervised learning.

1. Introduction. In an ever-evolving world humans predominantly rely on vision as the primary conduit for gathering information and making decisions. This centrality of vision is mirrored in modern computing interfaces, which are predominantly graphical and designed for interaction through screens. As technology advances, new methods of control – ranging from body movements to eye movements, speech, and even brain activity – are being developed to foster more natural and intuitive human-computer interactions.

Eye-tracking technologies have witnessed significant advancements in terms of accessibility and ease of use. These technologies record eye movements to pinpoint an individual's focal point and are increasingly being employed in both academic research and commercial applications. Traditional eye-tracking methods often utilize video cameras to capture the shape of the pupil or other markers. While effective, these methods come with limitations, such as sensitivity to light levels and the necessity for open eyes [1].

An alternative and promising approach to eye tracking is the use of electroencephalography, a technique for measuring brain activity. Eye movements affect EEG recordings by adding muscle and eye dipole potentials to signals recorded by EEG electrodes [2]. This effect can be used to extract eye movements from recording. Like traditional eye-tracking methods, EEG does come with its own set of challenges. It is highly constrained by environmental factors, such as electromagnetic interference, but it doesn't require specific lighting conditions or opened eyes, making it versatile in different scenarios. Historically, EEG was predominantly limited to laboratory settings and required specialized equipment and trained personnel. However, mobile and affordable EEG devices are revolutionizing this domain, offering a more versatile yet effective means of capturing biopotentials [3].

This study aims to investigate the correlation between EEG collected by BrainBit – wearable headband [4], and eye movements recorded by eye tracker. We hypothesize that there exists a correlation between eye gaze direction based on a change of coordinates for 0.1 second and electrical activity from O1, O2, T3, and T4 leads recorded by wearable EEG. We aim to decode the neural signatures associated with different gaze directions using advanced machine learning techniques, particularly neural networks. Our approach combines the strengths of both EEG and eye-tracking technologies, offering a comprehensive perspective on gaze localization. The use of a wearable EEG headband facilitates data collection in more naturalistic settings, enhancing the ecological validity of our findings.

Objectives of the study:

1. Collect and find recordings of eye activity recorded by camera-based devices and EEG recorded by wearable devices;

2. Preprocess and normalize the data;

3. Develop predictive models using supervised and unsupervised machine learning methods.

The scientific novelty of the paper includes employing a wearable EEG headband for collecting a unique dataset with an uncommonly low number of EEG channels and a correlational research of this data with eye movements to localize gaze.

The rest of the paper is structured as follows: Section II provides a comprehensive review of existing literature on eye movements, EEG data, and the challenges posed by artifacts in EEG data. It also discusses the integration of EEG and eye-tracking, the challenges and solutions associated with mobile EEG systems, and the combination of EEG and eye-tracking in mobile scenarios. Section III explains the methodology of the study. It begins with a general description of the study's objectives and approach. The dataset subsection provides details about the participants, experimental setup, and methodology for the two used in the study datasets. The first dataset is collected during this study using the BrainBit EEG headband and PupilLabs eye tracker. The second one is the open NeuMa dataset [5]. The preprocessing subsection discusses the challenges and solutions for handling eye movements in EEG data. The neural network architecture subsection describes the supervised and unsupervised machine learning models used in the study. Supervised learning is presented by feedforward and recurrent neural networks. They use previously discussed datasets to build predictive models based on known ground truth. Unsupervised learning is presented by clustering datasets with time-specific distance calculation. Section IV presents the results of the study. It provides a detailed analysis of the performance of different machine-learning models. The results from both supervised and unsupervised learning approaches are discussed. Section V summarizes the main findings of the study, discusses its implications, and suggests directions for future research.

2. Related work. The integration of EEG and eye-tracking technologies has garnered significant attention in the realm of cognitive and neuroscientific research over the past years. Numerous studies have sought to harness the complementary strengths of these two methodologies.

In study [6] the authors provide a comprehensive discussion on the challenges posed by eye movements in EEG data. They emphasize the importance of identifying and effectively correcting them to ensure the accurate interpretation of underlying neural signals.

The use of Independent Component Analysis (ICA) combined with a high temporal resolution eye tracking has been highlighted as a promising approach for identifying and correcting ocular artifacts in laboratory EEG data [7]. In study [8] the authors introduced the VME-DWT algorithm, which efficiently detects and eliminates eye blinks from short segments of single EEG channels using Variational Mode Extraction (VME) and the automatic Discrete Wavelet Transform (DWT) algorithm. In [9] the authors developed the "Optimized Fingerprint Method" that utilizes spatial, temporal, spectral, and statistical features to automatically classify artifactual independent components in EEG, achieving over 90% accuracy in identifying artifacts of physiological origin. In study [10] the authors proposed a framework combining unsupervised machine learning with singular spectrum analysis (SSA) to remove eye blink artifacts without altering the uncontaminated EEG regions.

The integration of EEG and eye tracking provides a comprehensive understanding of cognitive processes during visual tasks. In paper [7] the authors developed a system that captures EEG signals during eye movement and employs a random forests classification algorithm to categorize them into 6 classes – eyes open, close, left, right, up, down.

In [11] the authors introduced the BeMoBIL Pipeline, a MATLAB-based solution that supports the synchronized handling of multimodal data, including EEG and eye tracking. It presents a new robust method for region-of-interest-based group-level clustering of independent EEG components.

In paper [12] the authors explored a multimodal approach for identifying Autism Spectrum Disorders of children by fusing EEG and eye-tracking data, demonstrating the potential of such integrative methods in clinical applications. The approach consists of extracting EEG and eye-tracking features from data and using two separate deep learning models for feature processing accordingly at the first step and one deep learning model for processing the outputs of the first step.

In study [13] the authors used an eye tracker to improve the detection of evoked responses to complex visual stimuli during EEG by excluding moments when the gaze was disoriented. This approach increased the accuracy of detection by 15%.

In paper [14] the authors employed a wearable EEG headset with stationary eye tracker for prediction of decisions made during the product design selection. They concluded that the fusion of eye movements and EEG characteristics can significantly improve the efficiency of decision-making in projects compared to using a single data processing method. In their experiment, the accuracy improvement was more than 10%.

Mobile EEG systems, while offering the advantage of capturing brain activity in naturalistic settings, come with inherent challenges.

One of the challenges associated with mobile EEG is the reduced number of channels compared to traditional stationary EEG systems. This limitation can potentially impact the quality and interpretability of the recorded data.

In [15] the authors conducted a study where participants performed an auditory oddball task while concurrently completing various motor tasks outdoors. The study utilized a 30-channel mobile EEG montage and observed that increased movement complexity imposed a higher workload on the cognitive system, effectively reducing the availability of cognitive resources for the cognitive task.

In paper [16] the authors explored a human EEG-based emergency stop interface designed to activate when the human operator detects or foresees a potential emergency. The study employed a mobile EEG recorder with 14 channels and utilized a decision tree for classifying the operator's state. While the use of mobile EEG introduced complexities to the classification task, the findings indicated consistent EEG signal patterns across various potential emergencies.

In study [17] the authors specifically addressed the challenges of Independent Component Analysis (ICA) decomposition in both mobile and stationary EEG experiments. They found that while commonly used settings (like stationary experiments with 64 channels and a 0.5 Hz filter) yield acceptable ICA results, mobile experiments with fewer channels require higher high-pass filter cutoff frequencies for optimal decomposition.

In study [18] the authors researched the existence of cardiogenic artifacts in EEG recorded by single-channel mobile EEG and proposed an algorithm for automated artifact detection and removal.

These studies underscore the importance of considering the limitations and specific requirements of mobile EEG systems, especially when working with a reduced number of channels. While mobile EEG offers unique opportunities for research in real-world settings, careful preprocessing and data analysis are crucial to account for the challenges posed by the limited channel count.

The combination of EEG and eye tracking in mobile scenarios offers valuable insights into cognitive processes during visual tasks.

In [19] the authors explored this domain by investigating the automatic detection of visual attention using pre-trained computer vision models in conjunction with human gaze in mobile eye-tracking scenarios.

In [20] the authors investigated the impact of swiping direction on the interaction performance using mobile EEG and eye-tracking technology.

Table 1 provides a summary of these works. Many researchers are affected by eye activity in their data and remove it as well as use of additional devices to collect such activity. There is no one-size-fits-all solution. The choice of method often depends on the specific application, the nature of the artifacts, and the constraints of the mobile device. Continuous research and development in the area of mobile EEG and eye tracking are essential to further enhance the reliability and utility in real-world scenarios for improving and extending existing ways of working with human activity.

3. Method. The primary objective of this study is to investigate the intricate relationship between eye movements and neural activity as captured by EEG recordings. The method of this study includes dataset collection and selection, preprocessing of this data and applying two different deep learning techniques – supervised and unsupervised learning of predictive models.

Table 1. Summary of the related work

Paper	Eye-tracking	Wearable EEG	Identifying eye activity in EEG	Removing eye activity from EEG	Description of found activity	Combining eye tracking and EEG features	Find relation between eye activity and EEG	Research differences of mobile EEG
Plöchl et al. [6]	-	-	ICA, regression	+	+	-	+	-
Antoniou et al. [7]	+	-	+	+	+	-	+	-
Shahbakhti et al. [8]	-	-	VME	Blinks only	+	-	+	-
Stone et al. [9]	-	-	+	+	-	-	+	-
Maddirala and Veluvolu [10]	-	+	SSA	Blinks only	+	-	+	-
Klug et al. [11]	-	-	ICA	Blinks only	-	-	+	-
Han et al. [12]	-	-	-	-	-	+	-	-
Ahtola et al. [13]	+	-	-	Bandpass filter	-	+	-	-
Wang et al. [14]	+	+	-	Bandpass filter	-	+	-	-
Reiser et al. [15]	-	+	ICA	+	-	-	+	-
Buerkle et al. [16]	-	+	-	Bandpass filter	-	-	-	-
Klug and Gramann [17]	-	+	ICA	+	-	-	-	+
Chiu at el. [18]	-	+	-	-	-	-	-	+
Barz and Sonntag [19]	+	-	-	-	-	-	-	-
Zhou et al. [20]	+	+	-	-	-	-	+	-

3.1. General Description. The study involves the collection and analysis of EEG and eye-tracking data from participants engaged in predefined tasks. The data is then subjected to a series of preprocessing steps to extract meaningful patterns and eliminate potential noise or artifacts. Subsequent to preprocessing, the data is fed into neural network models, both supervised and unsupervised, to discern patterns and relationships.

Figure 1 provides a visual overview of the entire process, showing the flow from data collection to analysis. The subsequent sections explain the specifics of the dataset, the experimental setup, and the models employed. The first section describes data collection in terms of devices, tasks and information that we collected. The second section gives an overview of datasets with the recordings of information. The third section lists the models and classes that were used to do predictions.

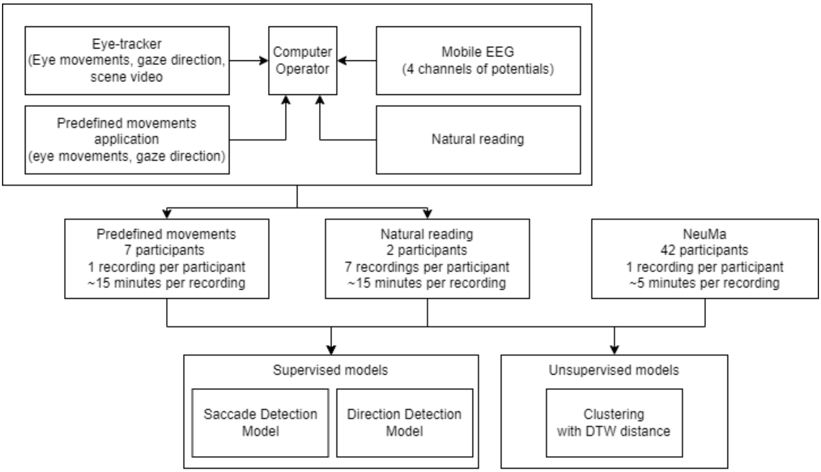

Fig. 1. A general description of the proposed method (from data collection with the signal collecting sources to deep learning models that use it)

3.2. Dataset. The dataset used in a study plays a pivotal role in shaping the outcomes and conclusions drawn from the research. In this section, we provide a comprehensive overview of two datasets employed in this study and preprocessing of these data. The first dataset is collected for this study using wearable devices. The second an one is open NeuMa dataset that can be used in the same way as the first o ne. The preprocessing part includes specifics of work and extracting valuable information from EEG and eye-tracking data.

3.2.1. Our Dataset. A new dataset was recorded for the purpose of this study. Data were collected during two tasks: predefined movements and natural reading. The recording involved the use of a wearable EEG recorder in the form of a headband and a wearable eye tracker in the form of glasses.

Seven (6 males; 1 female; age 21 $\pm$ 3 years) healthy volunteers with no neurological or vision deficits participated in this study. All seven participants were recorded in an experiment with predefined movements for $\approx$ 15 minutes, in total 90 minutes of recording. Two participants were recorded in 6 sessions of natural reading experiments 15 minutes each, in total of 180 minutes of recording.

EEG was recorded using a 4-channel mobile band (BrainBit, 100Hz sampling rate). Dry electrodes were placed at O1, O2, T3, and T4 points according to the 10/20 system. Eye gaze data was collected using glasses with video cameras that point to the pupils (Pupil Invisible [21], 60Hz sampling rate). The computer showing tasks with a Full HD resolution 23-inch display was positioned at a distance of 1 meter in front of the person with a refresh rate of 60Hz.

The structure of the experiments remained consistent regardless of the specific task assigned to the participants. The typical procedure for each experiment is as follows:

1. The participant sits in a comfortable position in front of a computer screen, at a distance of 1 meter. Relaxation and minimization of body movements are emphasized.
2. Connection and calibration of the glasses are performed.
3. Connection and verification of electrode contact with the mobile recorder are conducted.
4. Instructions specific to the current experiment are provided.
5. The participant performs the assigned task.
6. Devices are disconnected and the experiment concludes.

For the predefined movement experiment, a graphical application was developed. This application displayed fixation points alternately to the participant. These fixation points were located centrally and at 16 surrounding points as shown in Figure 2. The participants would fixate on each point in a randomized sequence, and then return to the central point. The points alternate each other in the interval from 2.5 to 3.5 seconds.

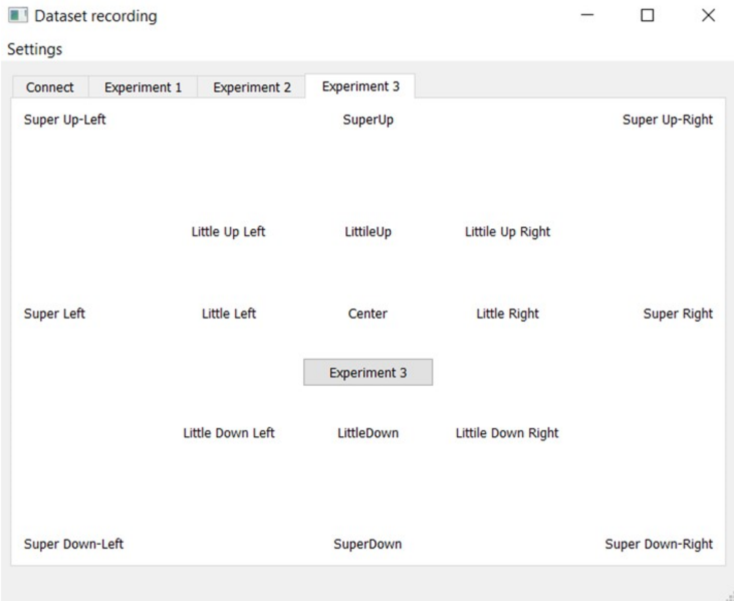

Fig. 2. The interface of an application for predefined movement experiments showing the position of points before the start

3.2.2. NeuMa Dataset. In addition to our dataset, an open dataset with the recorded EEG and eye tracker data named NeuMa was also utilized [5].

The NeuMa dataset stores raw experimental data for 42 subjects (23 males and 19 females, aged 31.5 ± 8.84).

Structure of dataset:

1. EEG Data: Continuous mode brain activity recording. This includes a time series of the 128 channels of EEG activity and corresponding timestamps recorded at 600 Hz.

2. Eye Tracker Data: Gaze data metrics for both left and right eyes recorded in 200Hz.

3. Mouse Clicks: Sequence of mouse clicks.

4. Mouse Positions: 2D screen coordinates corresponding to each mouse click.

5. Markers: Information regarding alterations among brochure pages, initiation, and completion of the experiment.

During the NeuMa dataset experimental procedure the participants were seated comfortably in an armchair positioned 50 cm away from a 28-inch LCD monitor. Although the participants had the freedom to move their heads during the procedure, they were advised to restrict their movements, including those of the head, to reduce potential artifacts in the EEG signals. However, they were also encouraged to ensure their comfort to prevent any negative impact on their overall experience. Before the presentation of the products, a resting state EEG was recorded for a duration of two minutes. Following the resting state recording, the participants were presented with brochures. They were allowed to navigate freely through these brochures using the left and right arrow keys on the keyboard to move forward and backward.

3.2.3. Dataset comparison. A wearable EEG recorder and a camera-based eye tracker were used to record both of these datasets according to our objectives. Despite this, it had different additional channels of information and different amounts of the recorded EEG channels. A comparison is presented in Table 2.

For the purpose of this article, only 4 channels (O1, O2, T3, T4) from the NeuMa dataset were selected and used. This decision was based on the fact that our dataset only contained these channels, ensuring consistency and comparability.

Table 2. The comparison of our and NeuMa datasets

Name	Eye tracking	Wearable EEG	EEG channels	EEG rate	Mouse data	Electrodes placement system
Our	+	+	4	100 Hz	-	10/20
NeuMa	+	+	128	600 Hz	+	10/20

3.2.4. Preprocessing. In the recordings obtained with eye-tracking glasses, two key moments are distinguished: fixations and saccades.

Fixations refer to the concentration of a person's attention on a specific point in the visual field, indicated by reduced eye movement amplitudes. During fixations, the brain processes the visual information from the point of focus, making it a crucial moment for understanding cognitive processes and attention. Saccades, on the other hand, are rapid eye movements that shift the gaze from one fixation point to another. These movements are essential for redirecting the line of sight to new areas of interest. The amplitudes of movements during saccades and fixations differ by an order of magnitude. In data processing, the period between saccades is considered as fixations because the brain is actively processing visual information during these periods, while saccades themselves are represented by significant changes in gaze coordinates, indicating shifts in attention. The detected saccades along with EEG data are presented in Figure 3 as vertical lines denoting the start of the saccade on the eye gaze coordinates graph.

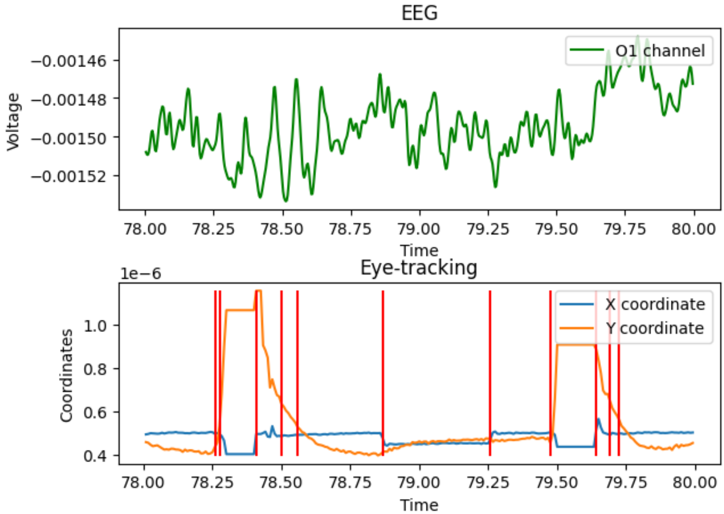

Fig. 3. Saccades on the graph of eye gaze coordinates along with EEG data

Eye movements, particularly saccades, induce large electrical potentials due to the movement of the eye's retinal dipole. The retina has a natural electrical polarity, with the front of the eye being positively charged and the back being negatively charged. When the eyes move, this retinal dipole also shifts its orientation. This movement generates electrical fields that can propagate through the tissues of the head and influence the electrical recordings on the scalp, including those of EEG. Because the eyes are anatomically close to the frontal EEG electrodes, these electrical fields generated by the retinal dipole can have a significant impact on EEG recordings. The influence of the retinal dipole's movement is so substantial that it can sometimes be mistaken for brain activity if not properly accounted for.

The EEG data is divided into series with a duration of 300 ms – the average duration of a saccade. EEG is highly dependent on the physiological state of the participant. The values of the potentials are not constant even within a single individual throughout the day due to factors like fatigue, caffeine intake, or even time of day. Therefore, each series is normalized to the average change in the potential to account for these variations and ensure that the data are comparable across different time points and participants. Normalization helps in emphasizing the relative changes in EEG signals, which are more informative than the absolute values. It can be shown as $X_{\text{normalized}} = \frac{X - median(X)}{mean(X - median(X))}$, where X is a series of one EEG channel signal in the form of voltage value.

Additionally, EEG is influenced by physical parameters of the surrounding environment, such as electromagnetic oscillations, high-frequency signals, and other phenomena. Such noise can be eliminated using frequency filters. The relevant brain activity signals are typically found within the range of 1 to 40 Hz; it is common to remove other frequencies. However, it is necessary to retain low frequencies from 0 to 2 Hz. These are EEG oscillations of sufficient duration that are associated with eye movement and provide valuable insights into the correlation between eye movements and brain activity.

3.3. Model Architecture. Collected and preprocessed datasets are used to build predictive models of eye movements. This can be done in two ways: with the use of ground truth (known eye movements) or without it. These approaches are called supervised and unsupervised learning, respectively. Supervised learning includes the use of two types of neural networks to classify data into different classes based on direction and amplitude. Unsupervised learning consists of clustering data using the k-means algorithm with time-specific distance calculations.

3.3.1. Supervised learning. Supervised learning models require a structured data for training and testing. The dataset was split into the train, validation and test parts as 64%, 16% and 20% accordingly. Classes in every part have a balanced amount of entries. So, the saccade classification task has a dataset with 50% of saccades and 50% of fixations, direction classification has 12.5% of each direction.

Feedforward neural networks and recurrent neural networks are commonly used to determine eye activity due to their architecture and effectiveness in pattern recognition. The most effective configuration of a feedforward neural network consisted of a network with an input of 120 our dataset or 800 NeuMa dataset EEG points – they represent 300 ms of 4-channel EEG recording from the dataset, 1 hidden layer with 8 neurons, and output with 8 neurons for direction classification and 2 for saccade classification. ReLu is used as an activiation function. Optimization is done by the Adam algorithm.

Unlike the previous approach, a recurrent neural network can feed its output back as input in addition to the new signal. This allows for processing sequences of variable lengths, rather than strictly fixed networks. There are several types of neural networks that implement this principle, such as RNN, LSTM, and GRU. The key difference among them is their ability to remember and forget data from previous iterations. The best results were obtained using a GRU network with 2 hidden layers of 16 neurons each, where 4 potential values from different electrodes were sequentially provided as an input.

Support Vector Machine offers a distinct approach to the classification of EEG data, complementing the feedforward and recurrent neural networks discussed earlier. Its core principle involves finding the optimal hyperplane that distinctly classifies the data points into different categories. The model would treat each EEG series as a feature vector in a high-dimensional space. The SVM would then find the hyperplane that best separates saccades from fixations or classifies the direction of eye movement.

The obtained results are presented in Table 3.

Table 3. Comparison of the results of supervised learning models

Model	Dataset	Classes	Accuracy	Recall	Precision	F1
FF	Our	2	73%	72%	**66%**	69%
		8	**66%**	**67%**	**56%**	**62%**
	NeuMa	2	73%	74%	73%	71%
		8	62%	62%	62%	62%
RNN	Our	2	**76%**	**75%**	65%	**70%**
		8	61%	69%	55%	62%
	NeuMa	2	73%	64%	**81%**	66%
		8	**68%**	**68%**	**68%**	**67%**
SVM	Our	2	54%	66%	51%	58%
		8	62%	59%	56%	57%
	NeuMa	2	**81%**	**81%**	**81%**	**81%**
		8	55%	40%	39%	35%

3.4. Unsupervised Learning

3.4.1. Unsupervised learning. Data clustering is a pivotal technique in the realm of data analytics and machine learning. It involves grouping data points into distinct clusters or sets based on intrinsic patterns or similarities. Unlike supervised learning paradigms where data is labeled, and models are trained to recognize these labels, clustering operates in the unsupervised domain. In unsupervised data clustering, the algorithm sifts through datasets without the guidance of ground truth labels. Instead, it relies solely on the intrinsic differences and similarities between the data points or series.

Among the many clustering techniques available, the k-means clustering algorithm has garnered widespread acceptance and utilization. The crux of the k-means algorithm lies in partitioning the dataset into k distinct clusters. These clusters are formed by minimizing the distance between data points within the cluster and maximizing the distance to data points in other clusters.

While the k-means algorithm predominantly utilizes the Euclidean distance to ascertain the difference between series, our dataset mandated a slightly nuanced approach. Given the temporal nature of our data, traditional distance measures might fail to capture the underlying intricacies. For instance, physiological factors such as reaction time, event duration, and amplitude can variably affect the series, leading to potential discrepancies in clustering outcomes.

To mitigate these potential inconsistencies, we employed the Dynamic Time Warping (DTW) algorithm. At its core, DTW is a time-scale transformation technique. Unlike traditional distance computation methods that compare data points in a point-to-point fashion, DTW aligns the two series in a way that the alignment minimizes the overall distance. Essentially, DTW can stretch or compress the series along the temporal axis to achieve an optimal alignment. This transformation accounts for time-dependent variances like elongated reactions or variations in amplitude, ensuring a more robust clustering outcome.

4. Results

4.1. Supervised Learning. The performance of different machine learning models on both the Our and NeuMa datasets is summarized in Table 3. The metrics used for evaluation include Accuracy, Recall, Precision, and F1 Score. These metrics provide a comprehensive view of the model performance, taking into account both the true positive rate and the false positive rate.

Among the three models, RNN showed the most balanced performance across different metrics, making it a strong candidate for further optimization and real-world testing. However, the SVM's strong performance on the NeuMa dataset suggests that with sufficient data, simpler models can also achieve high accuracy.

In the segmentation of the dataset, we discerned nine distinct clusters.

The unsupervised learning approach, specifically clustering using the k-means algorithm combined with Dynamic Time Warping (DTW) for distance computation, resulted in distinct clusters representing different gaze trajectories.

The number of clusters was determined using a widely accepted method for finding the optimal number, known as the 'elbow method.' In the context of k-means, the elbow method involves plotting the total within-cluster variation against the number of clusters. As the number of clusters increases, this variation decreases. However, there is a point, resembling the bend in an elbow, where the rate of decline sharply changes, indicating the optimal number of clusters for the dataset. The critical points for the dataset are illustrated in Figure 5. There are multiple points on the graph and interpretations of each clusterization result remain ambiguous. Upon scrutinizing video segments associated with each cluster, following the segmentation to every k amount of clusters shown in Figure 5, we observed congruent behaviors among the participants. Notably a consistent shift in gaze in a uniform direction when k equals 9. This observation is substantiated by an evaluation of the mean displacement along both the vertical and horizontal axes.

As depicted in Figure 4, the x and y axes represent these respective displacements. Each cluster has a distinction from all others at a minimum of 0.1 distance along one or two axes. This distance represents 10% human visual field. The visualization distinctly demarcates eight saccade trajectories and a central fixation, which collectively characterize the identified clusters.

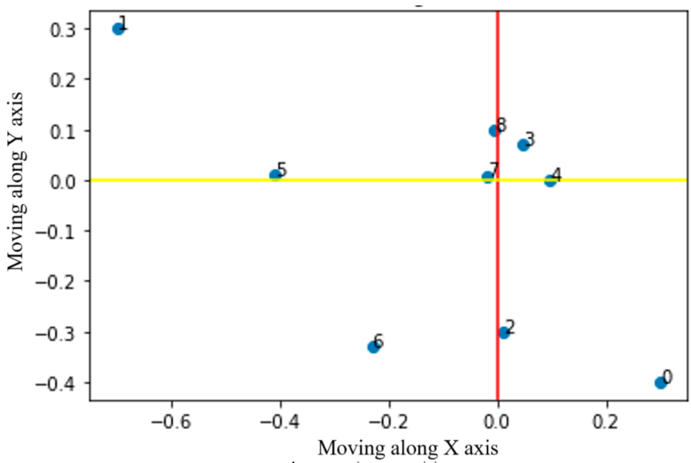

Fig. 4. Mean movement distance for every cluster along vertical and horizontal axis

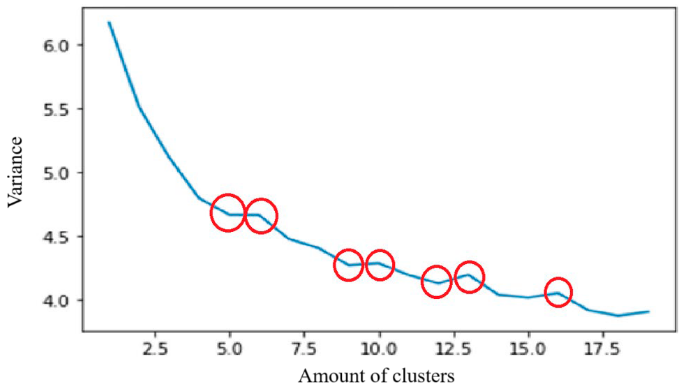

Fig. 5. Graph delineating the relationship between the number of clusters and the corresponding total within-cluster variation

The unsupervised learning approach, specifically the clustering using the k-means algorithm combined with Dynamic Time Warping (DTW) for distance computation, yielded distinct clusters that represent different gaze trajectories.

5. Conclusion. This study represents an endeavor in the realm of eye-tracking technologies, specifically focusing on the integration of wearable EEG headbands and machine-learning techniques. The results affirm that there is a discernible correlation between eye movements and EEG signals. This opens new directions for non-intrusive eye-tracking methods that can operate in various environmental conditions. The use of BrainBit as a mobile EEG recorder has proven to be effective for tracking eye activity. This is a significant step towards making eye-tracking technology more accessible and versatile. The study also introduces a methodology for the automatic labeling of EEG datasets, which can significantly expedite the data analysis process. Both supervised and unsupervised machine-learning techniques were employed to analyze the EEG data, demonstrating promising results in terms of accuracy, precision, and F1 scores.

This research has multiple implications. In the medical field, such technology could be used for diagnosing and monitoring neurological conditions. In human-computer interaction, it could lead to the development of more intuitive and responsive interfaces. Moreover, the technology has the potential to be used in safety-critical applications, such as fatigue detection in drivers.

While this study lays the groundwork for mobile EEG-based eye tracking, there are several avenues for future research:

– Optimizing Machine Learning Models: Further tuning of the neural network architectures could lead to even more accurate results.

– Real-world Applications: Testing the technology in real-world scenarios, such as driving or operating machinery, would provide valuable data on its effectiveness and limitations.

– Multi-modal Approaches: Combining EEG with other biometric data could offer a more comprehensive understanding of human behavior and cognitive states.

In conclusion, this study marks a significant step forward in the integration of EEG technology and eye-tracking, offering a potentially transformative approach to understanding human cognition and behavior.

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МЕТОД ИНТЕЛЛЕКТУАЛЬНОЙ ЛОКАЛИЗАЦИИ ВЗГЛЯДА НА ОСНОВЕ АНАЛИЗА ЭЭГ С ИСПОЛЬЗОВАНИЕМ НОСИМОЙ ГОЛОВНОЙ ПОВЯЗКИ

Романюк В.Р., Кашевник А.М. **Метод интеллектуальной локализации взгляда на основе анализа ЭЭГ с использованием носимой головной повязки.**

Аннотация. В стремительно развивающейся цифровой эпохе интерфейсы человеко-машинного взаимодействия непрерывно совершенствуется. Традиционные методы взаимодействия с компьютером, такие как мышь и клавиатура, дополняются и даже заменяются более интуитивными способами, которые включают технологии отслеживания глаз. Обычные методы отслеживания глаз используют камеры, которые отслеживают направление взгляда, но имеют свои ограничения. Альтернативным и многообещающим подходом к отслеживанию глаз является использование электроэнцефалографии, техники измерения активности мозга. Исторически ЭЭГ была ограничена в основном лабораторными условиями. Однако мобильные и доступные устройства для ЭЭГ появляются на рынке, предлагая более универсальное и эффективное средство для регистрации биопотенциалов. В данной статье представлен метод локализации взгляда с использованием электроэнцефалографии, полученной с помощью мобильного регистратора ЭЭГ в виде носимой головной повязки (компании BrainBit). Это исследование направлено на декодирование нейрональных паттернов, связанных с разными направлениями взгляда, с использованием продвинутых методов машинного обучения, в частности, нейронных сетей. Поиск паттернов выполняется как с использованием данных, полученных с помощью носимых очков с камерой для отслеживания глаз, так и с использованием неразмеченных данных. Полученные в исследовании результаты демонстрируют наличие зависимости между движением глаз и ЭЭГ, которая может быть описана и распознана с помощью предсказательной модели. Данная интеграция мобильной технологии ЭЭГ с методами отслеживания глаз предлагает портативное и удобное решение, которое может быть применено в различных областях, включающих медицинские исследования и разработку более интуитивных компьютерных интерфейсов.

Ключевые слова: отслеживание глаз, ЭЭГ, нейронные сети, носимый ЭЭГ, обучение с учителем, обучение без учителя.

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