Applications of BCI in ADHD Assistive Diagnosis
腦訊號源獨立成份分析於穿戴式腦機介面應用

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Introduction

Attention Deficit Hyperactivity Disorder (ADHD) is a common neurodevelopmental disorder in children, characterized by inattention, hyperactivity, and impulsivity, which impair daily functioning. Diagnosing ADHD is challenging due to the reliance on subjective methods, highlighting the need for objective tools. Recent advancements in Brain-Computer Interface (BCI) technology, using electroencephalography (EEG) to capture and analyze brainwave patterns, offer a promising solution. This project reviews brain functioning and BCI methodologies in the focus of ADHD Assistive Diagnosis, and has completed EEG data preprocessing for 50 subjects up to the Independent Component Test.

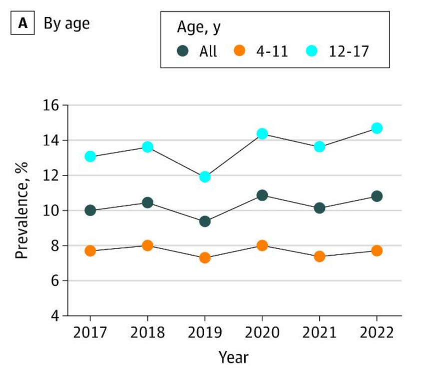

Figure. 1. Trend in Prevalence of Children Ever-Diagnosed with ADHD in the US (Li et al., 2023)

Background Knowledge Learning

Nervous System Pathways

System	Functions
Central Nervous System (CNS)	Coordinates and integrates sensory information, processes thoughts, emotions, and memories, and controls voluntary movements.
Peripheral Nervous System (PNS)	Connects the CNS to the body, facilitating voluntary muscle actions and regulating involuntary functions such as heart rate, digestion, and reflex responses.

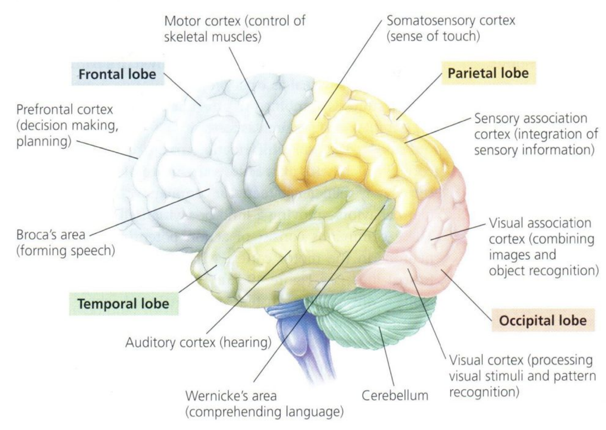

Figure 2. The human cerebral cortex (Campbell, 2011)

BCI Equipment and Experiment Process

BCI Equipment can be invasive or non-invasive.

- **EEG Equipment Considerations:**
  - Number and positions of electrodes.
  - Monitoring electrode resistance with conducting liquids.
  - Placement of event markers for data analysis facilitation.

Experiment Process

- **Data Acquisition:**
  - EEG data collection upon stimuli or user intent.
  - Signal transmission through an amplifier.
  - Conversion into analog-to-digital signals (A/D).
- **Data Preprocessing:**
  - Signal processing to eliminate noise and artifacts.
  - Enhancement of relevant EEG components.
- **Translation Algorithm:**
  - Use deep-learning techniques to learn long-term dependencies of processed EEG data (with algorithm such as LSTN model).

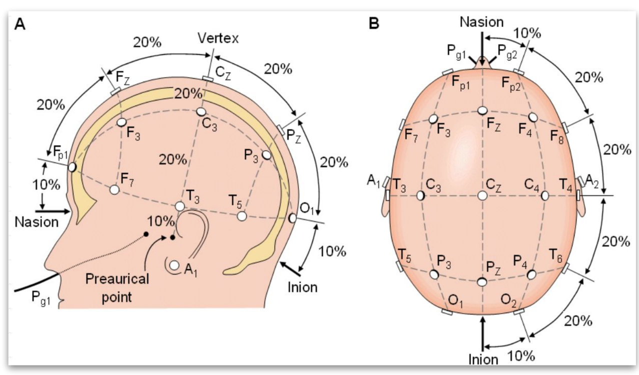

Figure. 3. Illustration of the 10-20 system (Wolpaw, 2012)

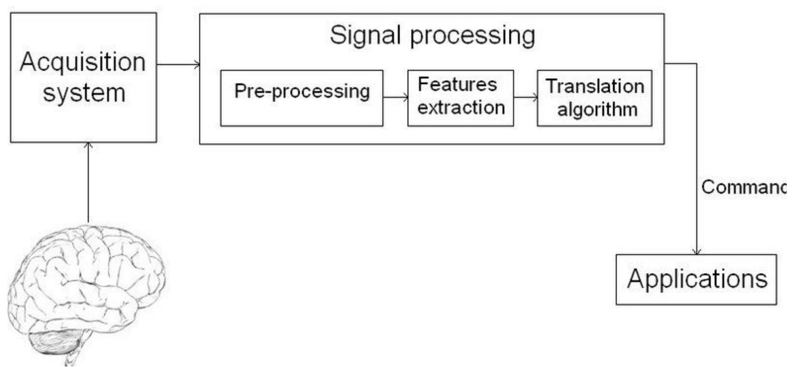

Figure 4. Illustration of the utilization process of a BCI system (Talab, 2010)

ADHD and its Related Neural Pattern

- Affects 8%-12% of children worldwide, with persistent symptoms into adulthood.
- Causes include genetic, environmental, and neurobiological factors.
- Includes deficits in attention and executive functions.
- Significantly impacts academic, occupational, and social functioning, often co-occurring with other psychiatric disorders.

Recent EEG Studies:

- Show that ADHD patients produce distinct EEG patterns during concentration tasks.
- Exhibit impaired suppression of faster alpha and beta wave activity.

Material & Methods

Dataset

The dataset is comprised of EEG recordings from demographics shown in Figure 5, with three types of equipments including the St. EEG VEGA with 32 channels, the CGX Quick-20m system with 19 channels, and the Mindo BR8 wearable wireless 8-channel system.

Participants completed two concentration-related tasks:

- **Continuous Performance Test (CPT):** participants pressed the space key when seeing any character except 'X'.
- **Conners Continuous Auditory Test of Attention (CATA):** participants pressed the space key to respond to specific auditory stimuli.

Both tests assess sustained attention and cognitive control through reaction time, accuracy, omissions, commissions, and response time variability.

Demographics of Participants

	St. EEG VEGA	CGX Quick-20m	Mindo BR8	Total
ADHD-diagnosed Participants Count	53	31	65	149
Normal Development Participants Count	19	17	4	40
Number of Male Participants	56	38	59	153
Number of Female Participants	16	10	10	36

Figure 5. Dataset Participants Demographics

Method

After collecting the data, the following preprocessing techniques were applied to enhance quality:

1. **High-Pass Filter (1 to 50 Hz):** Retains frequencies between 1 and 50 Hz, eliminating low-frequency noise and high-frequency artifacts.
2. **Identifying and Rejecting Bad Channels:** Excludes channels with poor signal quality or excess noise.
3. **Removing Noise and Artifacts:** Eliminates artifacts caused by muscle movements, eye blinks, or electrical interference using Artifact Subspace Reconstruction (ASR).
4. **Independent Component Analysis (ICA):** Applied the Infomax algorithm to separate EEG signals into statistically independent components.
5. **ICLabel for Further Noise Removal:** Uses machine learning to classify and remove remaining noise components after ICA.

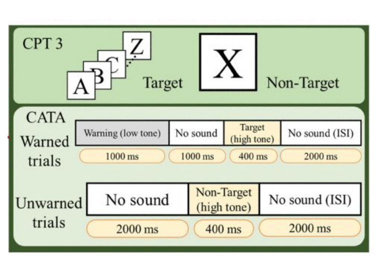

Figure. 6. Illustration of CPT and CATA test (Lin et al., 2024)

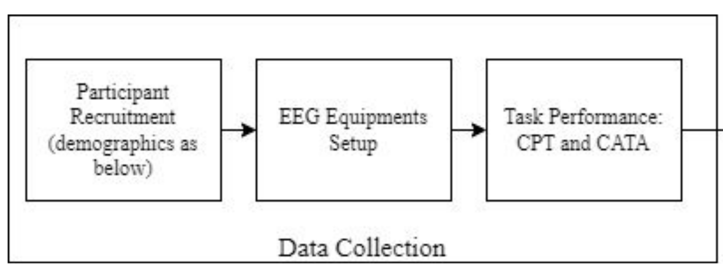

Figure. 7. Illustration of the experiment process

Results

In this study, all data collected with the CGX Quick-20m system has been preprocessed with EEGLAB and is ready for further analysis with a translational algorithm. The specialty in the CGX Quick-20m system lies with its dry sensor and wireless technology, built upon the 10-20 system. Currently, a total of 76 EEG data collected from subjects 74 to 120 have been processed through high-pass filters, ASR, ICA, and IClabel.

In the process of IClabling, we discovered some notable patterns that distinguished between cognitive-related components and artifact components, as shown in the table below.

Component Type	Characteristics
Cognitive-related components	• consistent, rhythmic patterns • spatially distributed across regions associated with cognitive functions, such as the frontal or parietal lobes
Eye artifact components	• smoothly decreasing EEG spectrum, the projection could be strongly tilted toward the far-frontal • individual eye movement could be spotted from the component activity graph, characterized by sharp, high amplitude
Muscle artifact components	• spatially localized and show high power at high frequency • scattered and non-focal topographical distribution, sometimes localized near the periphery of the scalp • activity graph often appears as short bursts of high-frequency activity, indicating muscle contractions
Artifact components from other factors	• irregular, non-rhythmic patterns across a wide frequency range • due to sources such as electrical noise, loose electrodes, or subject movement • show non-specific topographical distributions, inconsistent activity patterns

Of the EEG data processed, an average of about 4 components is removed for each IClabeling of subjects' data. Examples of cognitive-related components, eye artifact components, muscle artifact components, and artifacts from other factors are shown below.

Cognitive-related Components

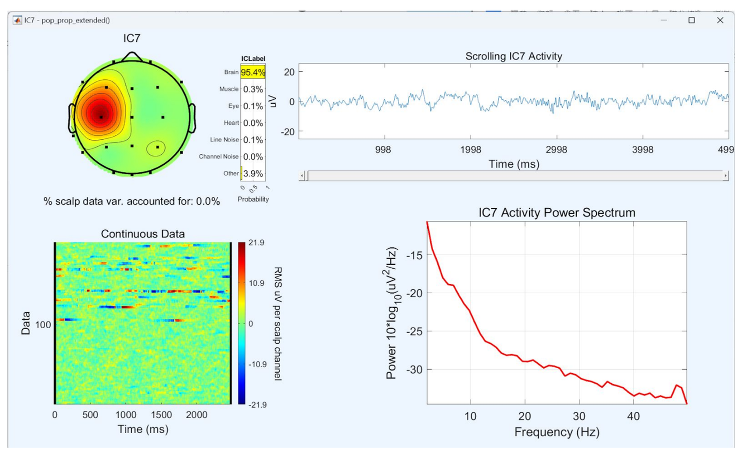

Figure 8. ICA Component Analysis from Subject 91

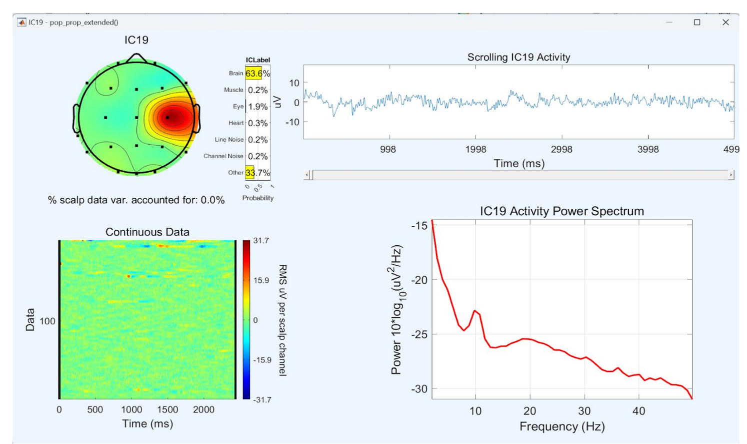

Figure 9. ICA Component Analysis from Subject 102

Eye Artifact Components

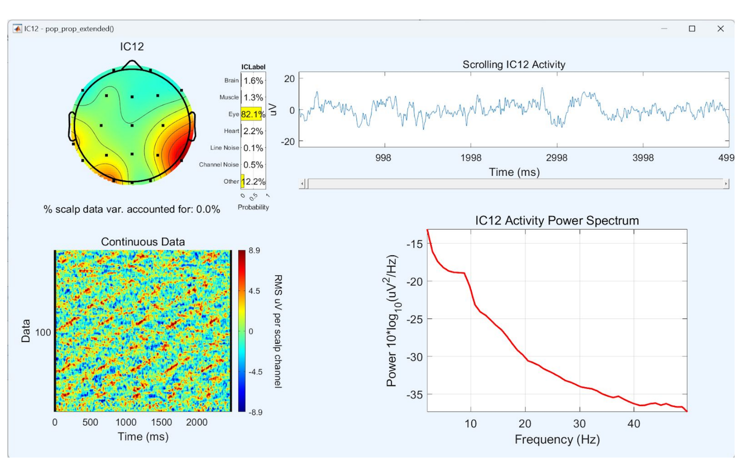

Figure 10. ICA Component Analysis from Subject 102

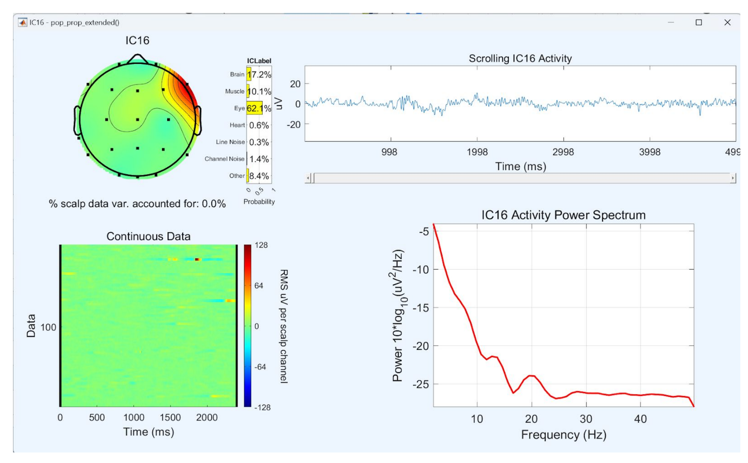

Figure 11. ICA Component Analysis from Subject 113

Muscle Artifact Components

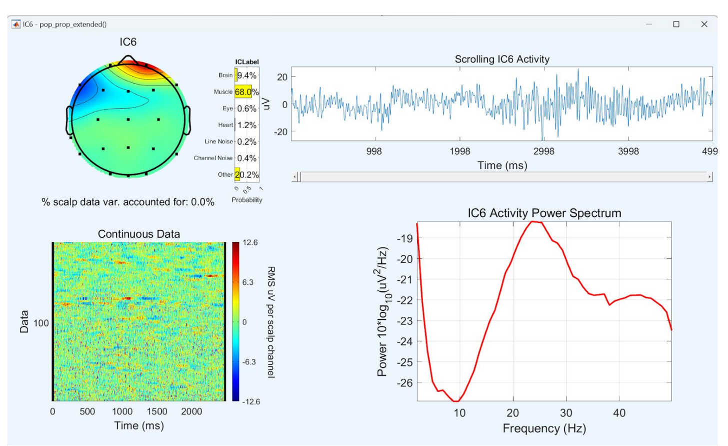

Figure 12. ICA Component Analysis from Subject 102

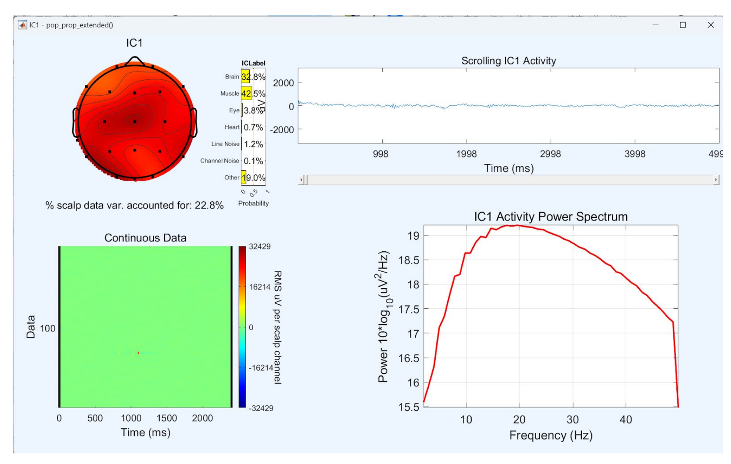

Figure 13. ICA Component Analysis from Subject 113

Artifact Components From Other Factors

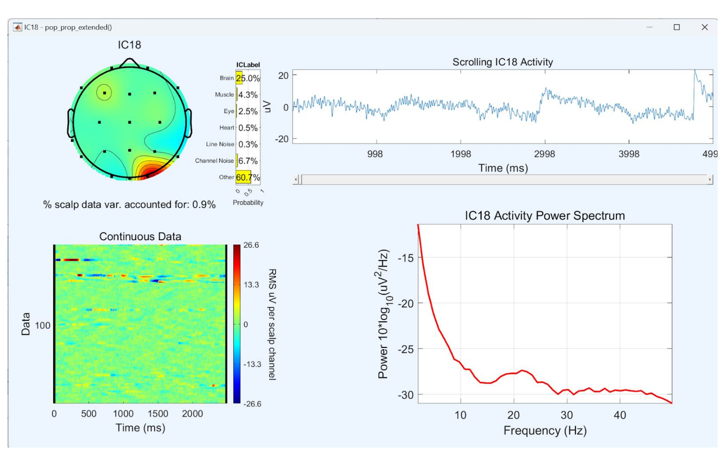

Figure 14. ICA Component Analysis from Subject 108

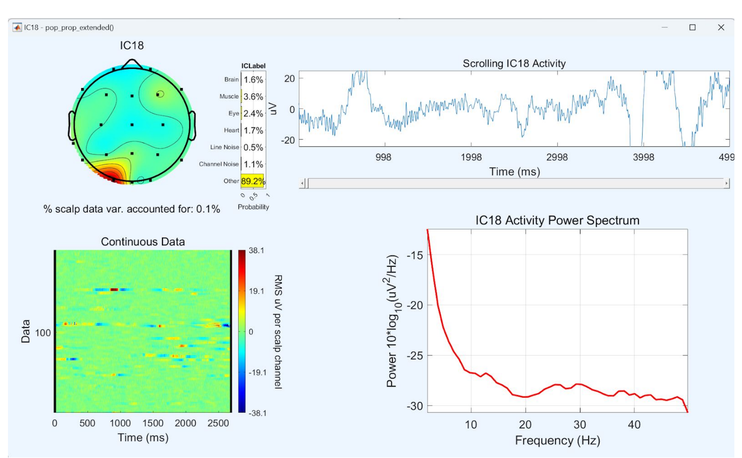

Figure 15. ICA Component Analysis from Subject 116

Conclusion

In this project, we explored Brain-Computer Interface (BCI) technology to aid in diagnosing Attention Deficit Hyperactivity Disorder (ADHD) in school-aged children. We investigated the functions of the human brain and the collection and processing methods of EEG data. Using a pre-collected EEG dataset of children with and without ADHD during a continuous performance test, we experimented with preprocessing techniques, including a high-pass filter (1 to 50 Hz), Artifact Subspace Reconstruction (ASR), ICA, and ICLabel.

In future work, we will apply the preprocessed data with machine learning models to create comprehensive tools for diagnosing ADHD. Similar data collection and processing methods can be applied to analyze different types of EEG data and neurological behaviors.