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Research and Development of Thought Input Systems for Patients with Amyotrophic Lateral Sclerosis (ALS)

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Abstract. With the launch of the "Ice Bucket Challenge", ALS, commonly known as amyotrophic lateral sclerosis (ALS), has gradually attracted wider attention in recent years. It is a progressive neurodegenerative disease characterized by the decline of motor neuron function. As the disease progresses, patients often experience symptoms such as muscle atrophy, weakness, and communication difficulties, leading to social isolation and reduced interaction. Based on brain-computer interface (BCI) technology, this project designs an intention recognition automatic output device. By collecting neural activity and converting it into recognizable intention signals, when the user looks at visual stimuli of a specific frequency, the visual cortex will produce steady-state visual evoked potentials (SSVEPs), which will be detected by the electroencephalogram (EEG) system and decoded through artificial intelligence deep learning algorithms. These recognized signals are converted into instructions for automated equipment to accurately control computer operations, allowing patients to use computers for text input and editing, significantly improving the convenience of communication and interaction in patients' daily lives.

Keywords: B Brain-Computer Interface (BCI), Steady-State Visual Evoked Potential (SSVEP), Electroencephalography (EEG), Deep Learning

1. Introduction

Amyotrophic lateral sclerosis (ALS) progressively impairs voluntary motor control and speech, leaving patients unable to communicate through traditional means [1]. As shown in Figure 1 (a), the scientist Stephen Hawking was a patient affected by this condition, rendering him unable to speak and necessitating the use of specialized assistive technology for communication. To address this critical need, we propose an intent recognition auto-output device that enables hands-free text input via steady-state visual evoked potentials (SSVEP), as illustrated in Figure 1(b). Our system presents multiple flickering visual targets at distinct frequencies; focusing attention on a desired target elicits a corresponding SSVEP in the occipital cortex, captured by electroencephalography (EEG). A convolutional neural network (CNN) processes raw electroencephalogram (EEG) data, extracting frequency-specific features and continuously adjusting detection thresholds based on the user's specific signal dynamics. The decoded intent is mapped to an automated typing program, enabling patients to compose and edit text in real time.

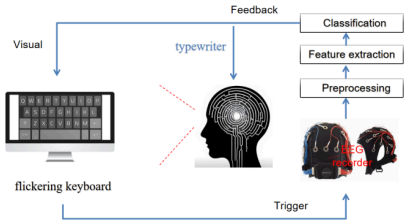
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The primary goals are: 1) to achieve rapid calibration and high classification accuracy (>90%), 2) to integrate deep learning algorithm for adaptive performance under nonstationary conditions, and 3) to demonstrate a functional text-entry interface that restores autonomous communication for individuals with severe motor impairments.



(a) Scientist Hawking communicated with others through the use of high-tech assistive devices



(b) Schematic diagram of a mind-input system based on SSVEP brain-computer interface

Figure 1: ASL patient example and BCI schematic diagram

2. Literature review

2.1. Research status

Brain–computer interface (BCI) research has progressed through several distinct phases, each characterized by breakthroughs in signal acquisition, processing, and application contexts. Initially, Vidal's pioneering work in 1973 laid the conceptual groundwork for noninvasive EEG-based communication by demonstrating that distinct patterns of scalp-recorded potentials could be mapped to device commands [1]. This era relied on analog amplifiers and rudimentary filters; researchers often manually identified characteristic waveforms rather than relying on automated classifiers.

In the late 1970s, Regan discovered steady-state visual evoked potentials (SSVEPs), showing that cortical responses to periodic light flicker were both robust and frequency-specific [2].

The 1980s saw practical demonstrations of real-time control. Wolpaw and McFarland (1980) used alpha and mu rhythm modulation to steer a computer cursor, validating continuous EEG control in an interactive setting [3].

Farwell and Donchin's introduction of the P300 speller in 1988 marked the first BCI focused on communication rather than simple control. By detecting event-related P300 components elicited in response to rare visual events, users could select alphanumeric characters on a screen [4]. This design remains foundational in modern assistive BCIs, with numerous variations incorporating matrix layouts or gaze-independent paradigms.

The turn of the millennium brought formalization of BCI architectures. Wolpaw et al. (2002) defined a three-stage pipeline—signal acquisition, feature extraction, classification—adopted universally in subsequent studies [5]. Advances in machine learning during the 2010s, especially convolutional neural networks (CNNs), enabled automated feature learning directly from raw EEG, improving robustness under noisy conditions.

Simultaneously, invasive BCIs achieved unprecedented spatial resolution. Hochberg et al. (2006) demonstrated intracortical electrode arrays steering a robotic arm in tetraplegic patients, paving the way for high-bandwidth neuroprosthetics [6]. Meanwhile, hybrid BCIs combining EEG with eye tracking or EMG (Allison et al., 2010) further enhanced reliability, especially in dynamic real-world tasks [7,8].

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Despite these milestones, challenges persist. SSVEP systems require conspicuous visual stimuli that can induce fatigue and have limited aesthetic integration. Signal variability across sessions and users demands frequent recalibration, and deep-brain implants face long-term biocompatibility issues. Finally, comprehensive ethical frameworks addressing data privacy, autonomy, and equitable access are still evolving, highlighting the need for interdisciplinary collaboration in future BCI research..

2.2. Project goal

This project combines artificial intelligence deep learning algorithms, project Goals as following：

•Design and develop an automated device that assists input, where each selectable key (letter, command) flashes at a unique frequency, allowing SSVEP-based selection without physical interaction.

•Develop a real-time EEG data pipeline (acquisition, preprocessing, classification) that can reliably identify the user's attention across multiple flashing frequencies.

•Enable people with disabilities to use computers normally by combining EEG and deep learning algorithms.

3. Methodology

3.1. System design

First, conduct an overall design of the operation process of the entire system as depicted in Figure 2. The entire system includes a flickering visual keyboard, an OpenBCI Cyton 8-channel acquisition board, an electroencephalogram (EEG) recorder, a typewriter, a computer, and a standard liquid crystal display (LCD).

The virtual flickering keyboard displayed on the screen emits stimulation signals. When the user focuses on the flickering stimuli, the brain generates signals that match the flickering frequency. The EEG recorder uses six electrodes (O1, O2, Oz, POz, PO3, PO4) placed around the occipital lobe to detect and record steady-state visually evoked potential (SSVEP) signals in real time. The OpenBCI Cyton board processes the real-time SSVEP brain signals, records the muscle activity status through surface electroencephalogram (EEG) signals. Based on the lightweight convolutional neural network (CNN) framework of deep learning, it classifies and identifies the multi-channel EEG signals. Finally, the typewriter can automatically input, and the output results are displayed on the LCD.

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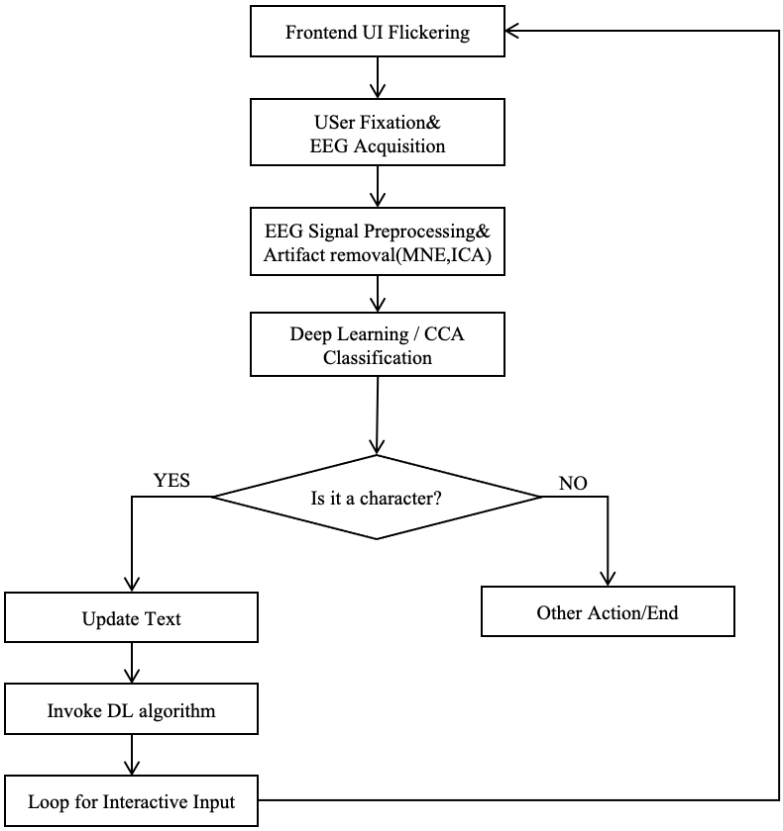
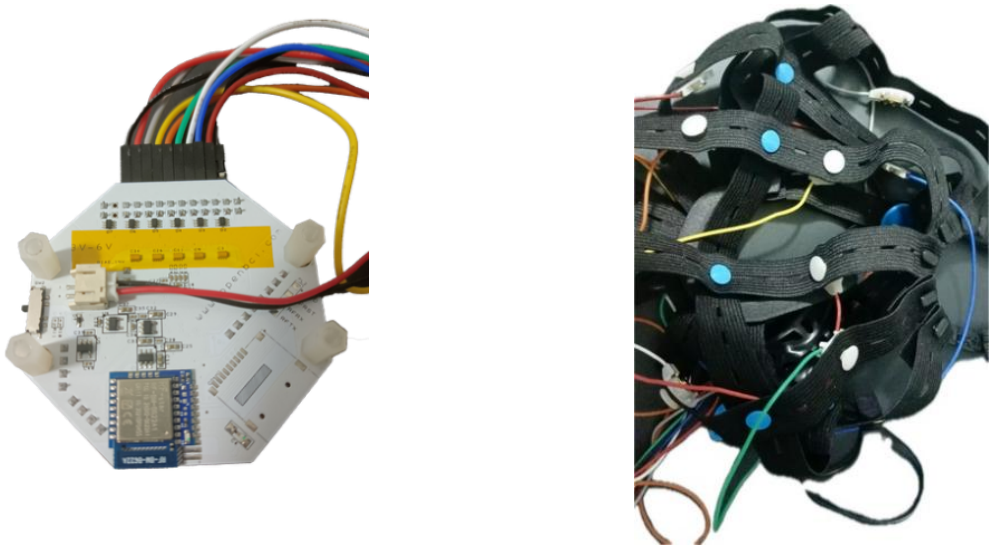


Figure 2: Overall flowchart of process

3.2. EEG signal acquisition

To record electroencephalogram (EEG) signals, electrodes should be evenly distributed across the scalp. We use the OpenBCI Cyton development board presented in Figure 3 (a), which is equipped with six electrodes (O1, O2, Oz, POz, PO3, PO4) around the occipital lobe to capture SSVEP brain signals in real time. First, the EEG cap presented in Figure 3 (b) is worn on the scalp to collect signal data, focusing on the occipital lobe area (O1, O2, Oz, etc.), because these parts usually produce the strongest steady-state visual evoked potentials (SSVEP).

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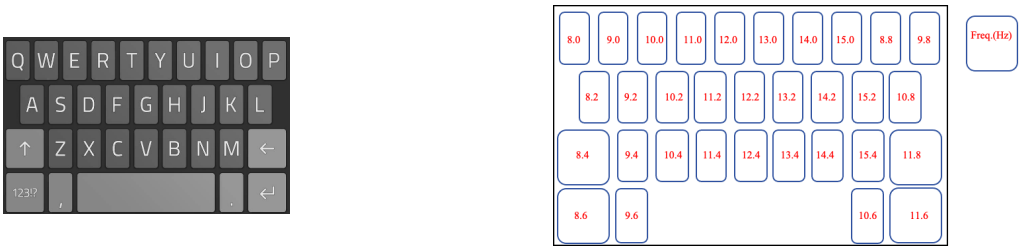


(a) OpenBCI cyton acquisition board (b) EEG acquisition cap

Figure 3: Signal acquisition device

3.3. Virtual keyboard and flicker frequency design

The virtual keyboard is shown on a standard LCD display with a 60 Hz refresh rate, and the overall input system is illustrated in Figure 5. The keyboard adopts a grid layout, as presented in Figure 4(a). Each character in the stimulation matrix is assigned a unique frequency-phase pair using a joint frequency-phase modulation method, as shown in Figure 4(b). The flickering frequencies range from approximately 8 to 15 Hz—safe and comfortable for human vision—with increments of 0.2 Hz. Additionally, a phase difference of 0.35π is maintained between adjacent frequencies.



(a) BCI keyboard layout (b) Target frequency and phase encoding conditions of the BCI keyboard

Figure 4: Virtual keyboard and flicker frequency design



(a) Typewrite 3D model (b) Overall of the device

Figure 5: Typewrite 3D model and overall input system

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3.4. Data preprocessing, model construction and training

First, a python script is used to load and preprocess surface electroencephalogram(EEG) data from multiple acquired data files. Each acquired data file contains EEG data and corresponding labels. The data is loaded in dictionary format, with EEG data and label data. After loading the data, the script extracts the EEG data and labels from each dictionary. The script filters out data points with a label of 0 by creating an index list for each dataset whose label is not 0, and then uses these indexes to extract the corresponding EEG data and labels. To ensure that the labels are continuous and unique across all datasets, the labels of subsequent datasets are adjusted by adding the last label of the previous dataset. The filtered and adjusted EEG data and labels from all datasets are stacked vertically using np.vstack. Finally, the number of labels is reduced by subtracting 1 from each label. Finally, the data processing results are saved as .h5 files. Figure 6 shows the collected electroencephalogram (EEG) signal diagram.

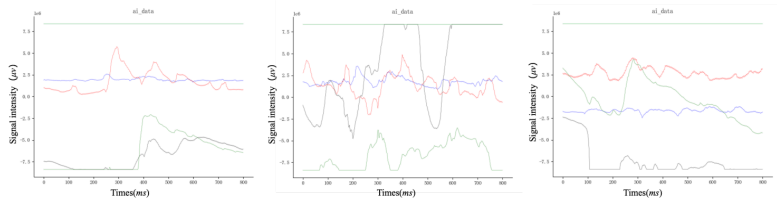


Figure 6: EEG signal acquisition graph

Subsequently, preprocesses the EEG data, followed by the construction of a CNN model. The data is processed using a deep learning algorithm, as illustrated in the neural network diagram in Figure 7. The specific steps are as follows: the preprocessed “imageData” (images) and “imageLabel” (labels) are read from the .h5 file. The image data is augmented 2000-fold to enhance feature representation, then randomly shuffled and reshaped by adding a channel dimension. The labels are one-hot encoded, and the dataset is split into training and test sets. A LossHistory class is defined to record the loss and accuracy for each batch and epoch, and to provide a method for plotting the corresponding curves. Next, the CNN function is defined to build a convolutional neural network model comprising multiple convolutional layers, pooling layers, fully connected layers, and Dropout layers, with model summary information output at the end. The model is then compiled and trained using the training data with the Adam optimizer and categorical cross-entropy as the loss function. After 100 training epochs with a batch size of 64, the model is evaluated. The loss curves during training are calculated and shown in Figure 8..

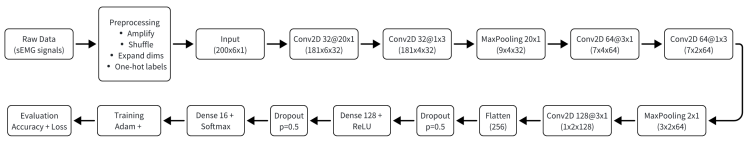


Figure 7: Structure diagram of the neural network for intent recognition

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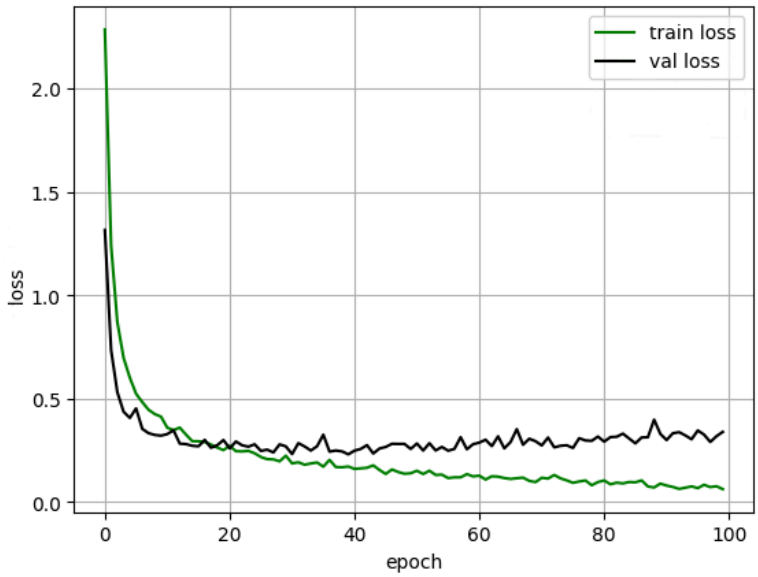


Figure 8: The curve of losses rates

3.5. Real-time classification and typing

After a period of calibration, the trained EEGNet model is loaded into the real-time data pipeline for actual use. At this time, the user only needs to observe the flashing of the target key. The system will process a sliding window of EEG data (usually about 1 second + 50%), and then apply bandpass filtering and artifact removal (for example, through MNE or ICA as needed) to classify which frequency is dominant in the current EEG segment.

When the classification output indicates a frequency with a high confidence level, it means that the corresponding character has been "entered" or selected. The text entered by the user is displayed in the text box or output area. To prevent accidental selection, we added a short dwell time and repeated confirmation mechanism to each key press to ensure accuracy.

4. Testing and results

The experiment required sit in front of a computer wearing an electrode cap, with the target character speller shown above on the screen.

The evaluation metrics for electroencephalogram (EEG) data recognition predominantly encompass two key aspects: target recognition accuracy and information transfer rate (ITR). The target recognition accuracy is defined as the proportion of correctly classified instances relative to the total number of classifications, serving as a fundamental measure of the system's classification reliability. Beyond accuracy, the brain-computer interface (BCI) system necessitates the computation of the ITR, which quantifies the amount of information conveyed per unit time. This metric is crucial for assessing the efficiency of the steady-state visually evoked potential-based BCI (SSVEP-BCI) system in completing a classification task.

The accuracy and efficiency of the BCI typewriter were evaluated using two control data sets, online testing (training) and offline testing (testing) shown in Table 1. The table shows the accuracy and throughput for all trials in the cued spelling task, where the system spelled at a rate of one character per second. Each trial lasted 1 second, with 0.5 seconds for stimulation and 0.5 seconds for gaze aversion.

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Table 1: Spelling test result (training and testing)

Number of trials	Training accuracy %	Testing accuracy%	Training throughput bps	Testing throughput bps
1	95.42	96.01	5.06	4.22
2	91.51	87.12	4.71	4.63
3	90.63	88.51	4.02	4.25
4	79.02	89.53	3.85	4.68
5	86.54	98.49	4.06	3.91
6	98.37	85.50	4.21	4.19
7	83.34	91.48	3.79	4.60
8	78.97	87.01	4.26	4.86
9	86.04	86.52	3.39	5.09
10	88.33	92.03	4.35	4.76
Mean±SD	88.71±7.007	89.30±5.55	4.261±0.49	4.511±0.31

5. Conclusion

The main innovation of this study is the development of an automated auxiliary input device specifically for special people with communication and movement disorders caused by diseases. This system integrates steady-state visual evoked potential (SSVEP) technology and brain-computer interface (BCI) technology, uses artificial intelligence neural network and deep learning algorithm to achieve high-precision intention recognition, and completes keyboard input operations through mechanical automation devices, effectively solving the human-computer interaction problem for people with disabilities.

Experimental data after actual testing showed that in the character spelling task (input speed of 1 character/second), the average accuracy of this system can reach 89.30%±5.55%, and the information transmission rate is also significantly improved.

These results not only verify the practicality and reliability of the system, but also confirm the application potential of brain-computer interface technology in the field of auxiliary communication, providing a new communication solution for patients with motor dysfunction such as amyotrophic lateral sclerosis (ALS), and also showing the broad application prospects of brain-computer interface technology in the field of medical assistance.

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