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RESEARCH ON A P300-BASED BRAIN-COMPUTER INTERFACE SYSTEM FOR ROBOT MOVEMENT CONTROL

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Abstract- **BCI have ignited extensive research interest in fields such as neuroscience, artificial intelligence, and biomedical engineering, as they offer an opportunity to interact directly with the external environment using brain signals. Despite the immense potential for applications, practical use of BCI still faces several challenges, including equipment cost and operational complexity. This study aims to develop a Brain-Computer Interface system based on P300 visual stimuli, utilizing a low-cost, user-friendly portable Muse EEG equipment for data acquisition. We designed and implemented a P300 visual stimulator in a 3x3 grid pattern, acquire the user's EEG signals using the Muse EEG equipment, and classify the data using a SVM classifier, ultimately realizing control over robot movement. Offline experimental results demonstrated an accuracy of 84.1% for the classifier under offline stage, while online stage achieved a successful execution rate of 81.2%. These findings substantiate the feasibility and potential of using low-cost, portable devices like the Muse EEG equipment for BCI research, opening new avenues in the field.**

Keywords – EEG, BCI, P300, Robot Control

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) as a frontier technology, have sparked wide-ranging interest in scientific research [1]. The crux of its novelty lies in allowing users to interact and control the external environment directly using brain signals [2], providing vast new horizons for the advancement of fields such as neuroscience, artificial intelligence, and biomedical engineering. Particularly in aiding disabled individuals to regain perceptual and behavioral abilities [3], as well as applications in gaming and virtual reality (VR) [4], BCIs have shown limitless potential.

However, despite the countless possibilities that BCIs present, their realization also faces significant challenges, such as high equipment costs, complex data processing requirements, and noise interference issues [5]. One of the major challenges in the BCI field at present is enhancing its practicality in mobile devices and home environments [6]. This includes speeding up signal processing, reducing equipment costs, and designing more intuitive and convenient human-computer interfaces. In this study, we used a low-cost portable electroencephalogram device, Muse, to explore its potential applications in P300 visual stimulus experiments and established a robot movement control BCI system based on P300 visual stimuli.

P300, Steady-State Visually Evoked Potentials (SSVEP), and Motor Imagery (MI) represent the three most used neurophysiological signal types in BCI research, each carrying its unique advantages and challenges. P300 is a widely recognized event-related potential (ERP), typically elicited during tasks demanding decision-making or attention. The "P" stands for positive, and the "300" stands for 300 milliseconds, which is roughly the peak latency of this signal following a stimulus. Its strengths lie in the relative simplicity of its identification process and its stable existence in

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the majority of individuals [7]. Nevertheless, P300 has limitations, in that its amplitude and latency may be influenced by factors like task difficulty, attention, and fatigue, which could compromise the performance and reliability of BCI systems. SSVEP represents a SSVEP induced by visual stimuli of specific frequencies. Its advantages include high frequency resolution, rapid information transfer rate, and the ability to be utilized without prior training [8]. However, SSVEP requires users to fix their gaze on flickering stimuli for extended periods, potentially leading to visual fatigue or discomfort. MI, or Motor Imagery, involves users imagining performing specific motor tasks, such as the movement of the left or right hand, thereby generating particular brain activity patterns. The strength of MI lies in its provision of a freely controlled signal source by users, rendering MI widely applicable in areas like neurofeedback and motor rehabilitation [9]. Yet, MI typically requires extensive training, which could pose a burden to users. In comparison to SSVEP and MI, the main advantage of P300 is its ease of use and broad adaptability. Unlike the complex visual attention demanded by SSVEP or the extensive training required for MI, P300 does not necessitate these laborious preparatory procedures. Moreover, P300 can be applied to various types of stimuli and application scenarios, thereby enhancing the flexibility and applicability of BCI systems.

In exploring the practical applications of BCI technology, device cost and operational complexity represent significant challenges [10]. While precise electroencephalogram (EEG) and Magnetoencephalogram (MEG) devices can provide high-resolution brain electrical signals, their high costs and maintenance complexities limit their usage in everyday environments [11]. In this study, we utilize the Muse EEG equipment, which is low-cost, user-friendly, and portable. The Muse EEG equipment can acquire and feedback frontal lobe EEG signals in real-time, allowing users to conduct EEG acquisition and analysis conveniently in any setting [12]. Although the accuracy and signal-to-noise ratio of the Muse EEG equipment cannot compete with high-precision EEG equipment, its low cost and user-friendliness make it an ideal choice for BCI experiments. Figure 1. and Figure 2. shows the Muse EEG equipment and the position of the 4 electrodes.

Figure 1. The Muse EEG equipment

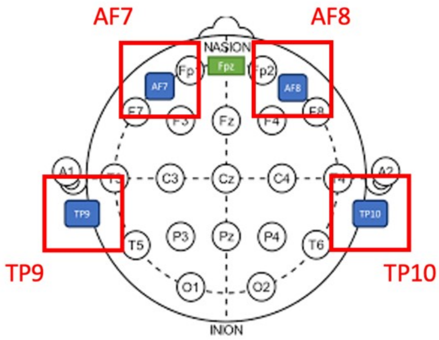

Figure 2. The position of the 4 electrodes

In this study, we focus on developing a 3x3 grid pattern stimulator reliant on P300 visual stimuli. This stimulator elicits the user's P300 responses by probabilistically flashing a white circular target stimulus. To verify the efficacy of our design, we initially conducted a series of offline experiments, acquiring subjects' EEG data using the Muse EEG equipment. The results indicated that the Muse EEG equipment could effectively capture P300 EEG components. Subsequently, we extracted feature data from the experimental data collected from 3 subjects, which was then used to train a Support Vector Machine (SVM) classifier. The trained classifier achieved an accuracy rate of 84.1% in an offline environment. Upon successful completion of the offline experiments, we proceeded with real-time experiments. In the real-time experiments, we used by the pre-trained SVM classifier to process in real time the EEG signals containing P300 components acquired from the Muse EEG equipment and successfully transformed the classification results into control commands for robots. The success rate of this process reached 81.2%, further affirming the reliability of our system in practical operational environments. Our research offers a beneficial practical example for the design of P300 visual stimulus based BCIs and opens a new path for conducting BCI experiments using the Muse EEG equipment. Our results also suggest that the utilization of SVM for EEG signal classification can effectively enhance the accuracy and reliability of BCI systems.

In this paper, we will elaborate on our research findings in detail. In the upcoming Chapter II, we will delve into the research methodologies we employed, including the detailed design of the P300 visual stimulator, the construction of the SVM classifier, and the architecture of our comprehensive robot movement control BCI system based on P300. Our Chapter III will present our offline and online experiments and the resulting findings. In Chapter IV, we will interpret and discuss our experimental results, along with the strengths and limitations of our study. Lastly, in Chapter

V, we will summarize the entire study and discuss potential future research directions and challenges that may be encountered.

II. METHOD

A. P300 Visual Stimulator

The primary focus within our designed BCI system lies in the design and realization of the P300 visual stimulator. Various forms of P300 stimulators exist, encompassing visual, auditory, and tactile stimulators [13]. Due to their intuitive and easy-to-manipulate nature, visual stimulators have found widespread application in practice [14]. In this study, we developed a P300 visual stimulator based on a 3x3 grid pattern.

Unlike the traditional row-column P300 visual stimulator, our 3x3 grid pattern stimulator utilizes nine graphical units, each bearing a white circular image serving as the stimulus signal. For five control commands, the white circular image appears and disappears in five units in one epoch. Any instance of the white circular image appearing in a specific unit, in contrast to the image in other units at other time points, is considered a rare stimulus. The interval between two successive stimuli can be freely set, generally required to be at least 400ms but adjustable according to the individual differences of subjects. The graphical interface of the P300 visual stimulator we designed is shown in Figure 3.

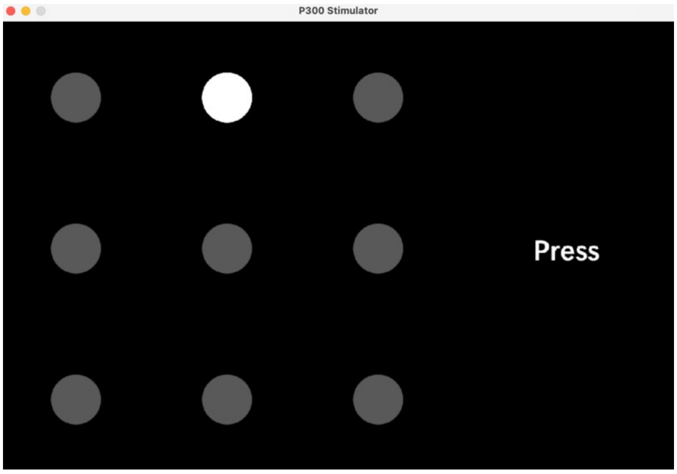

Figure 3. The graphical interface of the P300 visual stimulator

The P300 visual stimulator we designed sends EEG data through the Lab Streaming Layer (LSL) encompassing three columns. The first column is time stamps in units of 1/256 seconds, the second column represents the stimulus labels corresponding to the time stamps, and the third column indicates the moment at which the subject presses the space bar when their chosen stimulus signal appears, defaulting to 0 if no key is pressed. By default, our P300 visual stimulator sends data once per second, with data shape as (3, 256). This setting ensures the provision of stimulus signals to the subject in a steady and continuous manner within the unit time. The sending frequency of this stimulator can be flexibly adjusted to suit different experimental needs and the reaction speeds of subjects. This structured data design facilitates subsequent data processing and analysis, aiding in the precise capture and understanding of subjects' responses to various stimulus signals. An advantage of our designed stimulator is the capability of customizing the flashing frequency of the stimuli according to the needs of the subjects. More importantly, while ensuring the effective stimulation, subjects are less likely to feel fatigued, significantly enhancing the user experience in the experiment.

B. Support Vector Machine

Support Vector Machines (SVM) is a supervised learning algorithm that has been widely applied to various problems, particularly in classification issues within BCI systems. Proposed by Cortes and Vapnik in 1995, the main goal of SVM is to find an optimal hyperplane that maximizes the margin between different classes, thereby effectively partitioning the binary classification problem. In a typical dataset (x_i y_i), x_i denotes input features, and y_i represents class labels. The primary task of SVM is to find a hyperplane that maximizes the distance from the hyperplane to the nearest points of the two classes.

In BCI systems, SVM is often employed as a classifier to categorize features extracted from EEG signals, thereby enabling the decoding of EEG signals. Notably, in P300-based BCI systems, SVM can be used to recognize the presence of P300 potentials and their corresponding stimulus sources. Compared to other classification methods, such as Linear Discriminant Analysis (LDA) or K-Nearest Neighbors (KNN), SVM exhibits superior performance in handling high-dimensional feature spaces, especially in non-linear separable problems. Furthermore, SVM can effectively solve non-linear problems by choosing an appropriate kernel function, providing a significant advantage in handling complex EEG signals.

In our constructed P300-based robot movement control BCI system, we initially verified the effective capture of P300 signals using EEG signals collected with the Muse EEG equipment headset in offline experiments. Subsequently, we employed SVM as the classifier to train and test our obtained EEG dataset. The experimental results showed that the trained SVM classifier exhibited good performance in real-time testing during online experiments. These experimental results provided empirical support for the superiority of SVM in BCI research and application and offered useful references for further development and optimization of supervised learning algorithms in BCI systems.

C. P300-based Brain-Computer Interface System

In this study, we developed a P300-based BCI system for real-time robot control. The core parts of this system include a self-designed 3x3 grid pattern visual stimulator, a Muse EEG equipment, a Nao robot as the controlled object, and an offline trained SVM classifier.

Our visual stimulator was developed using the Pygame package in the Python programming language, adopting a 3x3 layout design and independently adjustable stimulus flashing frequency to meet different experimental needs. To synchronize event markers and timestamps, we adopted the LSL protocol. This protocol not only recorded labels and timestamps of the stimulator but also precisely captured the time points of the subject’s pressing keys, and these data were transmitted in real-time to the signal processing script. The Nao robot we used in the experiment, developed by Aldebaran Robotics in France, is an autonomous walking, highly interactive robot capable of facial and object recognition. It is widely used in education, research, and medical rehabilitation fields. In our experiment, the Nao robot performed corresponding movements upon receiving control commands corresponding to positional information.

The Muse EEG equipment we selected, with a sampling frequency of 256Hz, served as the EEG signal acquisition device, transmitting real-time collected EEG signals to the signal processing script via Bluetooth wireless. In the signal processing part, we synchronized the timestamps when subjects pressed keys with corresponding labels through the LSL protocol. When the number of key presses reached a predetermined threshold, the script automatically extracted all 1-second-long EEG signals corresponding to the timestamps, followed by filtering and arithmetic mean operations. Subsequently, we used by the pre-trained SVM classifier to classify the pre-processed signals, differentiating them into 0 (no P300 component) and 1 (P300 component present). When the classification result was 1, the script located on the flashing label of the stimulator signal corresponding to the subject’s keypress event, determined the position of the target signal, and then translated this positional information into a control command for the Nao robot. Figure 4. shows the block diagram of the designed P300-Based BCI system.

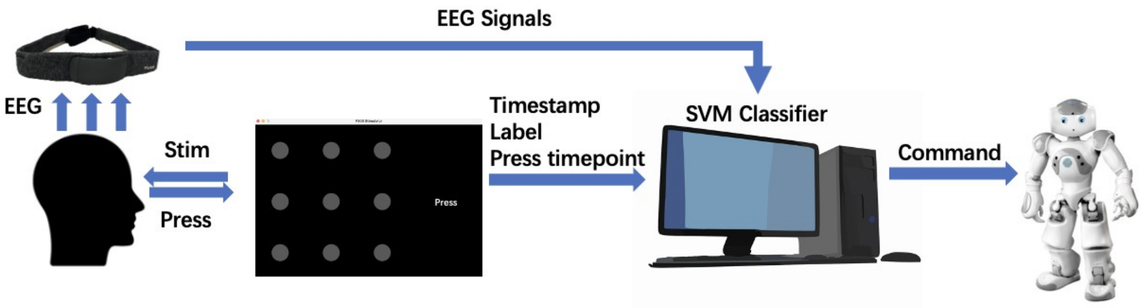

Figure 4. The block diagram of the designed P300-Based BCI system.

III. EXPERIMENT AND RESULT

In P300-Based BCI systems, there are generally some basic assumptions and constraints. Firstly, the subject is required to maintain sustained concentration, as the generation of P300 signals necessitates that the subjects remain attentively focused on visual stimuli [7]. If the subject becomes distracted or fatigued, the resulting P300 may be diminished, thereby affecting the performance of the system. Secondly, the variety of P300 signals presents a challenge. The amplitude and latency of P300 signals may vary among individuals, and even within the same individual at different times. This variability may impact the training and performance of the classifier [15]. Finally, the acquisition of training data is important. Due to the high variability of P300, the classifier may require a large amount of training data to achieve optimal performance [15].

In consideration of these assumptions and constraints, we took a series of measures to optimize our experimental design. During the experiments, we asked the subjects to rest after a certain number of trials to ensure that they maintain sufficient attention throughout the experiment. To ensure the consistency of the experimental environment, we chose to conduct the experiment in a relatively dark, noise-free environment. We also asked the subjects to clean the electrodes of the Muse EEG equipment and the area of skin in contact with the electrodes using alcohol wipes before each experiment to minimize noise and interference.

Our experimental design is mainly divided into offline and online stages. In the offline stage, our primary task is to verify whether the Muse EEG equipment can effectively collect EEG signals containing P300 components. We had the subjects focus on target stimuli on the visual stimulator, then carried out preprocessing and feature extraction, and trained the SVM classifier, performing parameter selection and optimization at this stage. The results of the offline stage provide an important premise and the basis for the subsequent online stage. Once in the online stage, we utilized the SVM classifier trained in the offline stage to classify the real-time EEG signals acquired from the Muse EEG equipment. In this stage, we simulated actual application scenarios, requiring the subjects to generate EEG signals containing P300 components by focusing on the target stimuli on the visual stimulator, then implemented real-time control of the Nao robot based on the output of the classifier. The results of the online stage directly demonstrate the system's performance in practical applications. Figure 5. shows the flow chart of the experiment.

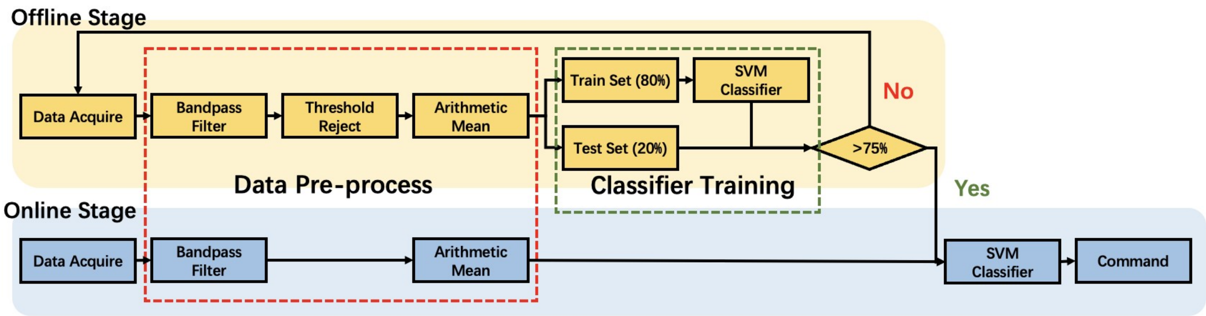

Figure 5. The flow chart of the offline and online experiment.

A. *Offline Stage*

Step 1 The subjects cleaned their foreheads, the edge part of their ears, and the electrodes of the Muse EEG equipment using alcohol wipes. The subjects then wore the Muse EEG equipment, and the current EEG readings from the electrodes were confirmed through an oscilloscope program to ensure that the collected EEGs contained minimal or no noise components.

Step 2 The stimulator was run, and the space key was randomly pressed to test whether the stimulator could receive real-time hit times.

Step 3 The EEG recording code was executed. Taking a recording duration of 60s as an example, after running the EEG recording code, the subject immediately looked at the stimulator. The flashing interval of the stimulator was set to 400ms, and the duration of the stimulus block was 100ms. After selecting a specific stimulus unit, the subject pressed the space key each time the stimulus appeared and was asked to count, acquiring EEGs containing P300 components. After the EEG recording time was reached, the recording was completed.

Step 4 Step 3 was run to collect n pieces EEG signals of length 256.

Step 5 The EEG signal processing code was executed. The collected EEGs were averaged out using the arithmetic mean by using the TP9 and TP10 channel EEG data, converted to one-dimensional data. The resulting data was passed through a 0.5-35Hz band-pass filter and reshaped into n sets of data of length 256. Data with a maximum amplitude exceeding 80 were removed, resulting in m sets of data.

Step 6 The obtained m sets of EEG signals containing P300 components were averaged out using the arithmetic mean. Figure 6. shows the P300 component of the EEG signals after using the arithmetic mean.

Step 7 The m sets of data were randomly shuffled and averaged in sets of 4, resulting in k sets of EEG data containing P300 components.

Step 8 Steps 2-4 were run, g sets of EEG data of length 256 were randomly collected, the subject did not look at the stimulator, and pressed the space key randomly, obtaining EEGs without P300 components. Step 5 was run to obtain h sets of arithmetic mean EEG data without P300 components.

The obtained k sets of averaged EEG data with P300 components and h sets of averaged EEG data without P300 components were combined and randomly shuffled, and the shuffled data was split into an 80:20 ratio. 80% was used as training data input into the SVM, yielding the SVM classifier. 20% was used as test data to test the accuracy of the obtained SVM classifier. When the classifier's accuracy reached above 75%, the obtained SVM classifier was used in the online experiment for real-time classification of EEG signals.

B. *Offline Stage Results*

In the offline stage of the P300-based robot control BCI system experiment, we validated the conclusion that the Muse EEG equipment can capture P300 components in the subject's EEGs. We collected 2173 pieces of EEG signals, each of length 256, containing P300 components from 3 subjects. After filtering and reject high-amplitude noise, the data were randomly shuffled, and 1600 pieces of signals were selected. The data were then subjected to arithmetic mean every 4 signals, converting them into a single one-dimensional data sequence of length 256, yielding a total of 400 pieces of signals. Non-target signals were processed in the same way, producing 400 pieces of non-target signals. Both categories of data were merged and shuffled, with 80% selected for training the SVM classifier, and the remaining 20% used as a test set to assess the performance of the SVM classifier. The test set consisted of 160 signals, of which 133 were successfully classified, resulting in a classifier accuracy rate of 84.1%. As shown in Figure 6, after 1600 pieces of target EEG signals and 1600 pieces of non-target EEG signals averaged out using the arithmetic mean, we can see that the noise components in the signal are suppressed, and a clear positive wave appears at 300ms, proving the existence of P300 components.

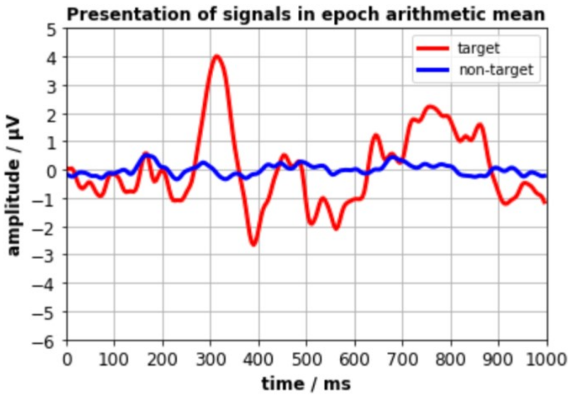

Figure 6. The P300 component of the EEG signals after using the arithmetic mean.

C. *Online Stage*

Step 1 The subjects cleaned their foreheads, the edge part of their ears, and the electrodes of the Muse EEG equipment using alcohol wipes. The subjects then wore the Muse EEG equipment, and the current EEG readings from the electrodes were confirmed through an oscilloscope program to ensure that the collected EEGs contained minimal or no noise components.

Step 2 The stimulator was run, and the space key was randomly pressed to test whether the stimulator could receive real-time hit times.

Step 3 The online P300-based BCI robot control program was run. By default, the experiment considered 4 or more space key presses as a command. That is, when the subjects visually targeted the stimulator, they selected one stimulus unit, and each time this stimulus unit displayed a white circular image, they pressed the space key. After pressing, a command was generated.

Step 4 After 4 or more keypress, the program filtered and averaged the EEGs corresponding to the keypress times, and the resulting EEG signal was transmitted to the SVM classifier.

Step 5 The SVM classifier performed classification calculations on the received EEG signals. If the classification result was 1, indicating that the transmitted EEGs contained P300 components, the experiment was deemed successful. Using timestamps, the stimulator label corresponding to the keypress was identified, obtaining the position of the stimulus unit that the subject was visually targeting at the time of the keypress, i.e., the subject's command. This command was then transmitted to the Nao robot, realizing EEG-controlled robot operation.

D. *Online Stage Results*

We invited 3 subjects to participate in a total of 500 trials. 406 trials were classified successfully. The control commands for the robot given by the subjects were random, but they were asked to ensure that the quantity of each command was as balanced as possible. The online experiment accuracy rate of the 3 subjects reached 81.2%.

IV. Discussion

In our study, we designed and implemented a P300-based BCI system for real-time control of robot movements. The results of the offline experiment demonstrate that our system can effectively identify and classify P300 signals, while the online experiment further validates the feasibility and effectiveness of our system in practical applications.

In our system, we employed a SVM classifier, a tool proven to be powerful in many studies aiming at classifying EEG signals. The SVM classifier also displayed exceptional performance with an accuracy rate of 84.1%, consistent with the results obtained in previous research. In regard to portable Muse EEG equipment, the positioning of its electrodes does not coincide with the central cranial region traditionally utilized in P300 experiments, resulting in a relatively lower volume of P300 components within the collected brainwave data. Consequently, for BCI systems established using Muse EEG equipment, acquiring quality signals takes precedence over merely accumulating a large quantity. The introduction of an excessive number of ineffective signals contributes substantially to noise interference, thereby significantly impacting the classification performance.

However, it should be noted that while our experimental results are promising, there are still some limitations. Firstly, our sample size was limited, involving only 3 subjects, which may restrict the universality of our results. To verify the effectiveness of our system in a broader population, larger scale sample testing is needed. Secondly, our online experiment was conducted only in the specific task of controlling robot movements, and further exploration of its application in other tasks is necessary, such as controlling a robot in complex operations. Thirdly, although we have demonstrated that P300 component-containing EEG signals can be collected from subjects using the Muse EEG equipment, the success rate of our experiment is still not high. Additionally, the results are prone to be affected by external environmental factors and individual differences among participants, leading to instability in the experimental outcomes. In future experiments, we will consider more effective and stable stimulation techniques and classification methods.

Despite these limitations, our research still provides valuable evidence for the development of EEG-based control systems. Our results offer a promising direction for the realization of everyday application of portable EEG equipment like the Muse, that is, real-time and efficient EEG control by identifying and classifying P300 signals. Particularly in assisting people with disabilities or those unable to perform regular operations in their daily activities, our research has enormous potential and practical application value.

V. Conclusion

The practical application of BCI confronts multiple challenges, including device costs and complexity of operation. We designed and implemented a 3x3 grid pattern P300 visual stimulator, wore the Muse EEG equipment to acquire user's EEG signals, and classified the EEG data using a SVM classifier to ultimately achieve control over robot movement. Our experiment comprised both offline and online stages. The offline stage was primarily for training the SVM classifier and verifying its efficacy in identifying EEG signals containing P300 stimulus components. The online stage sought to validate the system in actual operation. After analyzing the offline experiment, we found that the SVM classifier exhibited well accuracy in identifying EEG signals containing P300 components. The online experiment demonstrated that the real-time success rate of the system in controlling robot actions could exceed 81.2%, which showcases the feasibility and efficacy of our system in practical application.

Overall, our study showcases the potential of portable EEG equipment in experiments involving real-time robot control systems based on P300 visual stimulus. Although there are current limitations, our research provides fresh insights for future study in this field and presents possible directions for further optimizing and refining brain control systems. Particularly in assisting individuals with disabilities or those unable to perform regular operations in their daily activities, our research holds substantial application potential.

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