Recent Advances of P300 Speller Paradigms and Algorithms

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***Abstract*—The P300 speller is the most common application that uses brain-computer interface (BCI) for object control. At present, many researches use the P300 for the application of text input. However, there is no unified standard in the design of P300 signal induced interface, signal acquisition process, and signal processing method. Therefore, we searched the articles about P300 speller design in recent years and summarized the key technical improvements. This review focuses on the design of signal induced interface, as well as the algorithms commonly used in signal processing. We particularly emphasized the design ideas of the induced interface, as well as the advantages and limitations of the algorithm. Only by improving or combining the existing induced interface morphology and processing algorithms, then creating new methods, can enhance the practical application capability of P300 speller.**

Keywords—Electroencephalogram (EEG), Brain Computer Interface (BCI), P300 speller

I. INTRODUCTION

The brain-computer interface (BCI) can establish a direct connection between the human brain and external devices[1]. We can extract brain activity as features and convert them into commands for controlling external devices. Therefore, brain-computer interfaces are widely used in scenarios such as nerve repair, neurofeedback training, emotion recognition, military, and entertainment. Brain-computer interfaces are divided into invasive and non-invasive brain-computer interfaces according to whether they penetrate the scalp. The non-invasive brain-computer interface has the most practical prospects because of its non-invasiveness and convenience. When the non-invasive brain-computer interface is located on the surface of the brain scalp, the collected signal is called EEG.

EEG signals can be divided into spontaneous and evoked EEG signals according to whether there is an external stimulus. Spontaneous EEG signals usually refer to the EEG signals spontaneously produced by the human brain without external stimulus. At present, the spontaneous EEG signals commonly used for BCI control include motor imaging (MI) related potentials, α spontaneous EEG, and slow cortical potentials (SCPs). Evoked EEG signals are also called evoked potentials (EP), which record the response of the nervous system to external stimuli. According to the type of stimulus, it can be divided into auditory evoked potentials, visual evoked potentials and somatosensory evoked potentials, as well as smell and taste evoked potentials. Different types of stimuli may evoke different evoked potential waveforms. P300 is an event-related potential generated by the subject in response to a specific stimulus, which is an evoked potential. Since its potential change often occurs about 300 ms after stimulation, and the peak value is positive, it is called the P300 potential. P300 was first discovered by Sutton et al[2]. In order to arouse P300, the subjects are required to observe a series of stimuli that appear randomly. Task-related stimuli rarely appear, and stimuli unrelated to the task appear frequently. When the subject observes a low-frequency stimulus 300ms later, a significant potential change will observe in the EEG signal. The smaller the probability that the target stimulus appears, the greater the amplitude of P300. Dochin believes that a target stimulus less than 30% can evoke a significant P300 signal[3]. The latency of P300 is less affected by the outside world, indicating that the latency of P300 signal is a relatively stable feature. By determining the time when the P300 response occurred, the participant's attention target can be obtained. The P300-based BCI system has been used in many areas, such as identifying traffic lights, dialing phone numbers, moving cursors, inputting text, and controlling robots.

Farwell and Donchin used the P300 in 1988 to realize the earliest and most famous P300 text input system[4](Figure 1a). In this system, the author arranges the letter and numbei symbols into a virtual keyboard with 6-by-6 matrix, and applies a specific frequency of flashing to each symbol button to achieve visual induction of the P300 signal, which can generate 12 bits of information per minute. The work provided guidance for later text input using P300 potential. At present, the use of P300 potential for text input can achieve 136 bits of information output per minute. Generally, the P300 text input system mainly includes four parts: P300 signal evoked interface, P300 signal acquisition part, signal processing part and text output part. The P300 signal evoked interface can evoke obvious P300 components through a specific design. Then the evoked EEG signals are sent to the signal processing part through the EEG acquisition system for processing, and the processed results are converted into text output instructions for word spelling.

II. PARADIGM IMPROVEMENT

A good experimental paradigm is a prerequisite for high-quality data acquisition. The following introduces some paradigm improvements from the P300 interface layout.

A. Evoked Interface Layout

Classic P300 speller allows subjects to select targets by flashing different rows and columns, but this paradigm does not take into account the effect of continuous flashing of two adjacent symbols on the results. Townsend et al. adjusted the sequence of symbol flashing to avoid continuous flashing of adjacent elements[5].

Based on the Farwell paradigm, Faraz Akram et al. imitated the nine-key text (T9) input interface of a mobile phone and designed a new speller layout (Figure 1b)[6]. In addition, they also integrated a customized input dictionary in the T9 layout, which can provide input suggestions when users perform typing tasks. Compared with the classic P300 speller, the improvement of the speller based on T9 greatly reduces the number of word typing and the time for word typing. At the same time, the T9 layout also improves the fault tolerance rate of the text input system to a certain extent. Da Silva-Sauer et al. compared the performance of classic speller, T9 speller, and speller with predictive functions. The results show that the combination of predictive functions and T9 interface is more efficient. In addition, due to the reduction in the number of commands for the T9 layout speller, subjects are more willing to actively participate in the experiment[7]. The speller design with word prompt function enables subjects to perform typing tasks for a long time. Reza Fazel-Rezai et al. proposed another layout improvement idea, designed two levels of interface. The first level interface contains seven areas (Figure 1c), and the location of the symbols is not distributed in rows and columns. Expanded to 49 symbols on the basis of 36 symbols. The flashing mode of the first level interface is similar to the classic P300 speller, the main difference is the addition of the second level interface. The user can determine the characters again in the second-level interface after fuzzy selection of area on the first-level interface[8]. Gabriel Pires and others also tried to change the matrix layout, removing the middle quadrant of the seven quadrants, and designing the symbol distribution into a ring. A pseudo-random strategy is also designed to control the flashing position so that the flashing position interval is maximized to eliminate the influence of adjacent symbol flashing[9].

Saman Noorzadeh et al. changed the previous two-dimensional structure design of speller interface and designed a pseudo-three-dimensional structure speller interface. The experimental results confirm that the 3D layout speller system has the following characteristics: the 3D layout speller has faster spelling speed than the 2D under the same number of characters, but the accuracy is lower[10]. Jun Qu and others have made further improvements to the above-mentioned three-dimensional structure. The interface will be displayed in a true three-dimensional form, and users need to wear 3D glasses when performing spelling tasks (Figure 1d). The author compared the performance of the two-dimensional layout speller and the three-dimensional layout speller with 40 symbols, and found that the addition of 3D elements significantly improved the accuracy and information transfer rate (ITR) of the P300 speller[11]. This not only improves the performance of P300 speller, but also expands the direction of P300 speller.

B. *Symbol Morphology*

Improvements to the overall layout can improve the performance of the P300 speller. Some researchers also found that changes to the shape of a single symbol also affect system performance. Related studies have shown that, compared with text characters, face symbol can induce a higher P300 potential. Therefore, many researchers try to replace numbers or letter symbols with the human face image, so that each

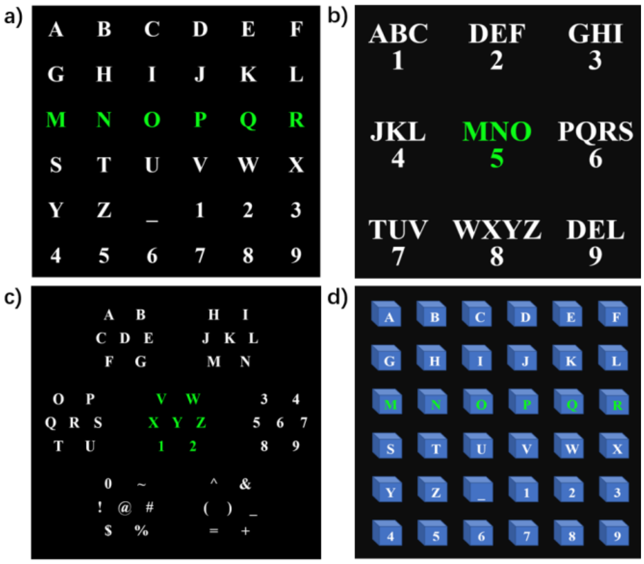

Fig. 1. P300 speller interface improvement (a) The layout of the classic P300 speller (b) T9 layout interface that imitates the mobile phone keyboard (c) Distributed 7-quadrant layout interface (d) Three-dimensional structure layout interface three-dimensional structure layout interface.

symbol will become a face image when flashing at a certain frequency, rather than a simple color or size change. Christoph Guger and others designed a five-row and ten-column layout and compared the two morphological changes. The first morphological change is that the symbol only changes in brightness and the second morphological change is that the human face image replaces the symbol and then changes the brightness. Experiments show that the face pattern P300 speller has higher accuracy rate. In addition, because the amount of information in the face image is greater than simple numbers or alphabetic symbols, subjects have a higher acceptance of the face P300 speller[12]. Qi Li et al. tried to replace numbers and letter symbols with adult facial images and applied them to the classic P300 speller paradigm. It is also proposed that replacing symbols with human face images can not only significantly improve the classification performance, but also get good classification results when the amount of data is small[13]. Subsequently, Qi Li et al. added a random selection strategy to the face image speller to further improve the accuracy of the classification results[14]. Andrew M et al. investigated the performance of the classic P300 speller, face pattern speller, and a speller with sequence stimulation, and conducted comparative experiments on 22 patients and 13 normal people. Experimental results show that patients with neurodegenerative diseases can get higher spelling accuracy using face pattern speller[15]. This also illustrates to a certain extent that the face image speller is more meaningful for patients to use the P300 speller and can produce better assistive effects. William Speier et al. not only compared the face image speller with the classic speller, but also imported the language model to classify the results on this basis, and finally achieved an accuracy of 94% and an information transmission rate of 140 bits per minute[16]. Recently, Zhaohua Lu and others have carried out a more detailed division of face images. The choice of face images is no longer random. It may be his own face or a sports star the subjects like. The author conducted a comparative experiment and found that the P300 signal induced by the subject's face image is more obvious than the star's face, but the accuracy and information transmission rate are limited, which can avoid the problem of portrait infringement to a certain extent[17].

In addition, some other attributes of the symbol will also affect the induction of the P300 signal, such as the color and shape of the symbol. Based on the classic speller paradigm, Mina R. Meshriky et al. compared the effects of color on spelling accuracy and information transmission speed. The research results show that, compared to pure gray-scale symbols, mixed-color symbols are more likely to evoke P300 EEG signals, which can increase the accuracy by 16%[18]. D.B. Ryan and others explored the effect of color matching on the performance of the P300 speller and reached the same conclusion[19]. In addition to color, Álvaro Fernández-Rodríguez et al. studied the effect of symbol shape on the performance of the P300 speller. The author designed four symbol patterns, namely white multilateral letters, colorful multilateral letters, white squares, and colorful squares. Combining the above four symbol patterns and conducting a control experiment on 15 subjects, it was found that the change of the symbol shape would affect the performance of the P300 speller[20]. In addition, related studies have also found that the stimulation time interval does not have a linear relationship with the P300 signal. When the stimulation time interval is greater than 6s, the stimulation time interval (ISI) has little effect on P300. When the interval between two adjacent stimuli was 6-8 seconds, the probabilistic effect of P300 disappears[21, 22].

C. *Stimulus Form*

Some recent studies have found that adding other forms of physical stimulation to the visually induced P300 speller system can improve the performance of the speller. Shenghong He et al. explored the influence of the lighting environment on the performance of the P300 speller during the experiment, and proposed that the use of a polarizer can enhance the spelling performance of the subjects[23]. Andrea Kübler and Loic Botrel set up two sets of control experiments to investigate the influence of auditory stimulation on the spelling ability of the participants. Experimental results show that the addition of different forms of auditory stimuli will indeed affect the spelling ability of subjects to varying degrees[24].

For those with severe neurological diseases and restricted eye movements, it may be difficult to use speller with only visual stimuli. Therefore, it is necessary to add another form of stimulation. Regarding the influence of sound stimulation, Patrick Schembri et al. set up four experimental paradigms and conducted control experiments on 8 subjects. The effects of quiet environment, environmental noise, passive speaking, and active speaking on the accuracy of the P300 speller have been studied. It is found that additional auditory interference will affect the accuracy, but the addition of specific auditory stimuli can improve the accuracy of the P300 speller[25]. Zhaohua Lu et al. did a quantitative analysis between the speller containing only facial images and the speller with auditory stimulation, and found that the speller based on the combination of vision and hearing based on positive emotions induced more pronounced P300 and P600 signal to improve the performance of the P300 speller[26].

Recently, Zhaohua Lu et al. did a more detailed research and analysis on the speller paradigm that combines visual and auditory stimuli, analyzed the characteristics of the P300 signal wave induced by the speller, and made a detailed analysis of the location of the P300 signal induced by speller [27]. Zeki Oralhan adds sound stimulation and video stimulation instead of static image stimulation, based on the circular layout speller. The final classification accuracy can reach 90.31%. The accuracy rate has increased by 66.99%[28], which is compared to the original classic P300 speller paradigm. Recently, Zhaohua Lu et al. carefully studied the physiological characteristics of the P300 signal evoked by the combination of audition and hearing through the analysis method of the brain network, and provided a theoretical basis for the P300 speller induced by the combination of vision and hearing[29]. At present, the P300 paradigm for tactile or olfactory stimulation is less improved.

III. ALGORITHM IMPROVEMENT

A well-designed experimental acquisition paradigm can obtain high-quality EEG signals, but how to extract useful information from the acquired signals is also a problem. The purpose of EEG signal processing is to obtain the user's intention from the EEG signal and convert it into control instructions to control external equipment. Table I summarizes the general steps and commonly used algorithms for P300 signal analysis.

TABLE 1. PROCEDURE AND ALGORITHMS OF P300 SIGNAL

Procedure	Algorithm
Preprocessing	Temporal Filter Spatial Filter Frequency Filter Time-Frequency Filter Time-Spatial Filter
Feature Extraction	Fast Fourier Transform（FFT） Wavelt Transform（WT） Auto Regression(AR) Independent Component Analysis(ICA) Principal Component Analysis(PCA)
Feature Classification	Bayes Decision Support Vector Machine(SVM) Linear Discriminant Analysis(LDA) Artificial Neural Network(ANN) Common Spatial Patterns(CSP)

A. *Signal preprocessing*

At present, the commonly used filters in the preprocessing part include time domain filter, frequency domain filter, time-frequency filter, spatial filter and time- spatial filter. A time filter generally restricts the geometric characteristics of the signal, the frequency domain filter limits the frequency of the signal. Common time-frequency filters include wavelet transform and short-time Fourier transform(STFT) and so on. Common spatial filters include Common Mean Reference (CAR) [12] and so on. If the analysis is combined with multi-channel spatial information, such as ICA and PCA, then such a filter is called a spatial filter [30]. After combining the above five kinds of filters and then filtering the signal, the signal-to-noise ratio of the filtered signal will increase, which is conducive to the next feature extraction and feature classification. If the frequency of the noise is very different from the frequency of the signal, the frequency filter can be used to remove the noise. For example, the frequency of general power frequency interference noise is relatively concentrated, so by performing frequency domain conversion on the original signal, the components concentrated around 50 or 60 Hz(may be different) are removed in the frequency domain, and finally the signal can be reconstructed to achieve the purpose of removing power frequency interference. At present, the preprocessing part does not have a fixed process for the removal of artifacts. ICA analysis can visually display

TABLE 2 EXAMPLES OF COMMON ALGORITHMS APPLICATIONS

Auther(s)	Data Set	Classification Algorithm	Accuracy
Chaurasiya, R. K et al[36]	10 subjects	SVM	92.20%
Rahul Kumar Chaurasiya et al[37]	9 subjects	WESVM	94.20%
Aya Kabbara et al[35]	10 subjects	SWLDA,SVM	95.00%
E. Chiou and S. Puthusserypady [30]	12 subjects	FLDA,SVM	94.20%
Qi Li et al[13]	17 subjects	BLDA,SVM	98.60%
Ji-Y oung Hwang et al[38]	4 subjects	CCA,LDA	83.90%
Kshirsagar, G. B and Londhe, N. D.[39]	4 subjects	DCNN	94.18%
Pina-Ramirez, O et al[34]	19 subjects	Linear-SVM,RBF-SVM,LASSO-LDA, Shrinkage–LDA, SWLDA	97.42%
Zhumadilova, A et al[40]	5 subjects	CNN	96.40%
Barsim, K. S.et al[41]	2 subjects	SVM,CNN	98.50%
Ramirez-Quintana, J. A.et al[42]	8 subjects	DCNN	96.00%
Kshirsagar, G. B.[43]	10 subjects	DCNN	92.64%

the artifact components, but this method has a low degree of automation and often requires manual selection of artifact components. Some people also tried to use neural network to remove artifacts, achieved good results.

B. *Feature extraction*

Commonly used algorithms for feature extraction include fast Fourier transform (FFT), wavelet transform (WT) [31], autoregressive model (AR), independent component analysis (ICA) and principal component analysis (PCA) [30]. Fourier transform is to display the frequency characteristics of the original signal through integral transformation of the signal, but this method has some disadvantages: for example, it is difficult to show how frequencies change over time, and different signals may look the same in the frequency domain. Wavelet transform overcomes the shortcomings of Fourier transform and can show the relationship between frequency and time transformation well. The core idea of wavelet transform is to convolve the original signal with a wavelet function, and decompose the signal into components of different frequencies and time periods. Finally, a certain coefficient suppression is performed on the decomposed components, and then the wavelet inverse transformation is performed to achieve the purpose of feature extraction. In addition, wavelet transform can effectively detect short-term pulses in EEG signals, which is a feature extraction algorithm that is widely used. The autoregressive model is to segment the P300 signal according to special standards to estimate the AR model parameters of each segment of the EEG signal. Each segment of the AR model parameter reflects the characteristic information of the signal. At present, the algorithms derived from the AR model include adaptive algorithm (AAR) and multivariable parameter AAR model algorithm (MVAAR), etc. This method relies on the construction of the model and has a low degree of automation. Independent component analysis and principal component analysis are completely different from time-domain and frequency-domain analysis methods. For some feature components with a large span in the time domain and frequency domain, independent component analysis and principal component analysis can effectively distinguish them, but traditional time domain and frequency domain feature extraction algorithms cannot do it. PCA is a principal component analysis method and a widely used data dimension reduction method. The core idea of PCA is to transform a set of linearly related variables into a set of new linearly unrelated variables through orthogonal transformation of features. These new variables are called principal components. PCA can not only achieve data dimensionality reduction, because the principal components can be selected, and the purpose of noise removal and feature extraction can be achieved during EEG signal processing. The core idea of ICA is to take advantage of the independence and non-Gaussianness of the source signal, and obtain some independent components in the signal through mapping transformation. But the ICA algorithm has a premise, that is, the EEG data is as clean as possible, so signal preprocessing should be done before ICA.

C. *Feature classification*

Commonly used algorithms for P300 signal feature classification include Bayesian decision [13, 32], linear discriminant analysis(LDA)[33-35], support vector machines(SVM)[18, 30], artificial neural networks(ANN) and Common spatial pattern(CSP). The Bayesian classifier is a classic classification algorithm. If the prior probability and conditional probability density of each feature in the EEG signal can be known in advance, then the Bayesian classifier can be designed to make the error rate reach The smallest. But the most important part and the most difficult part of this method is how to estimate the probability density of feature components. Linear discriminant analysis is one of the most commonly used algorithms in EEG signal processing because of its simple principle and easy modeling, but sometimes it performs poorly. The core idea of the support vector machine is to map data from low-dimensional space to high-dimensional space through nonlinear changes, and then find a classification interface in the high-dimensional space to maximize the distance between each type of sample. Support vector machines have strong generalization ability and are suitable for various signal classification problems. But it also has a difficult problem to solve, that is, how to find a suitable kernel function to map samples from low-dimensional space to high-dimensional space. Even if the kernel function is determined, due to individual differences between subjects or scenarios, good classification results may not be obtained. Artificial neural network is currently a popular EEG signal classification algorithm. It models the neural structure of the human brain and achieves the smallest loss function, that is, the smallest error by changing the weight between neurons.

This review selects some representative examples that use the above classification algorithm to classify EEG signals(Table 2). It can be seen that the CNN network has the most applications. The current neural network model is the second-generation artificial neural network (ANN). Compared with the third-generation Spike Neural Network(SNN), ANN lacks a certain physiological basis. However, SNN also has some difficult to solve problems, so there are few cases where SNN is applied to EEG signal processing. Common spatial pattern is also a common classification algorithm in EEG signal processing. The basic principle is to use the diagonalization of the matrix to find a set of optimal spatial filters for projection, so that the variance values between the two types of signals are maximal, so as to obtain a feature vector with a higher degree of discrimination. The advantage of CSP is that there is no need to select specific frequency bands in advance, but it is not suitable for situations where the number of electrodes is small. In actual situations, if there is no particularly excellent classifier, it is necessary to conduct comparative experiments on various classifiers, select a suitable classifier as the final choice, or design a combination of various classifiers, which is also reflected in Table 2.

IV. CONCLUSION

Here we reviews the improvements of the speller interface in the P300 speller experimental paradigm in recent years, including the overall layout, individual symbol shapes and stimulus forms. What's more, the combination of distributed layout and multi-modal stimuli can significantly improve the performance of the P300 speller.

Then, we introduced the general flow of signal processing in the current P300 speller, and we compare the advantages and disadvantages of some algorithms. It can be seen that artificial neural networks have been widely used in this field in recent years and have achieved good results. The classification performance of SNN is not clear for the time being, but it is an algorithm worth considering.

However, the current P300 speller still has some problems. For example, if you want to evoked a clear P300 signal, you need to train the subjects, which hinders the practicality of the P300. As the spelling time increases, the fatigue of the subjects will lead to a decline in the performance of the speller, which requires the algorithm to use the least data as much as possible to obtain the best classification results. In addition, the differences between individuals also affect the application of spellers, and how to find a highly applicable algorithm is the main problem. Finally, we found that many articles compare algorithms with different standards, we hold the option that they should follow the same protocol and use the same data set. This may require the establishment of a standard community.

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