**1、 Background**

In the 19th century, scientists occasionally recorded EEG activity in the monkey brain. Since then, the scientific community began to study the EEG phenomenon.It was not until the middle of last century that German scientist Berger recorded the brain waves in the true sense, and thus produced EEG.Human brain wave is a kind of spontaneous and rhythmic potential change on neurons. According to different frequency of change, it can be roughly divided into four types

1) Delta brain wave, the frequency range of 0.5 ~ 4 Hz, at this time, the human brain is in a deep sleep state, the human brain at this frequency movement, resulting in brain waves, slow down the human heart rhythm, blood pressure.

2) Theta brain wave, the frequency range of 4 ~ 8Hz, this stage is the early stage of human sleep, at this time, the human brain just produces drowsiness, which is a state of half sleep and half awake.

3) Alpha brain wave,the frequency range of 8 ~ 14Hz, when the human brain is in a completely relaxed or focused on something generated by the brain wave, at this time the human brain can better learn and absorb information from the outside world.

4) Beta brain wave, the frequency range of 14 ~ 30Hz, this kind of brain wave is the brain wave when the human body is awake under normal conditions. At this time, the human body can think, analyze and deal with problems well.In this frequency of brain waves, the human body can concentrate on dealing with the problems encountered in life, but too much beta wave will produce certain pressure and anxiety.

As a matter of fact, scientists have not reached a consensus on the division of brain waves. The classification criteria listed above are just a kind of commonly accepted classification methods in academic circles.Among them, some scholars believe that there are brain waves higher than 35Hz in human brain, which will pose a threat to life safety if the human body is exposed to this frequency for a long time.

**Evoked EEG signal** EEG signals can be divided into evoked EEG signals and spontaneous EEG signals.Evoked electroencephalogram (EEG) is a kind of electroencephalogram activity, which is formed by the change of brain potential through some external stimulation; spontaneous EEG signal refers to the EEG activity generated spontaneously by the brain without special external stimulation.

In daily life, the human brain controls the functions of perception, thinking, movement and language, and sends instructions to all parts of the body through peripheral nerves.Therefore, when the peripheral nerves or muscles are damaged, the transmission path of brain instructions will be blocked, and the human body will not be able to normally complete the output of brain instructions, and thus lose the ability to communicate and control with the outside world.It has been found that in the case of peripheral nerve loss, the human brain can still function normally, and part of the information it sends out can be represented by some paths.Brain computer interface (BCI) technology aims to realize the communication between brain and external auxiliary equipment without relying on the normal communication system composed of peripheral nerve or muscle tissue.

P300 event-related potential (ERP) is a kind of evoked electroencepha -logram signal. It has a positive peak about 300 ms after the occurrence of small probability stimulation (the wave with upward trend relative to the baseline).Due to the differences among individuals, the occurrence time of P300 is also different. Fig. 1 shows the P300 waveform about 450 ms after stimulation.As an endogenous component, P300 potential is not affected by the physical characteristics of stimulation, and is related to perceptual or cognitive psychological activities, and closely related to attention, memory, intelligence and other processing processes.The advantage of brain computer interface based on P300 is that the user can obtain high recognition accuracy without complicated training, and has stable time locking and high time precision characteristics.



Fig. 1 P300 related potential waveform

**2、 Related research**

The research on EEG has been carried out for about 30 years. Most of the researches focus on P300 signal, which is mainly due to some advantages and characteristics of P300 signal. This part has been described in the previous section.At present, a basic framework of P300 signal research can be roughly divided into the following steps: test to obtain P300 signal data, data preprocessing, feature extraction, classification and recognition, so as to realize the training of brain computer interface.

As for the way to obtain P300 signal, most of the existing work is based on the oddball normal form [1] [2] [3] [5] [7]. We can refer to [1] for the specific operation steps of this kind of normal form. In this paper, the influence of different matrix sizes on P300 signal is analyzed in detail (the oddball paradigm adopts a 36 character matrix of 6 × 6).In addition, Tomasz et al. [4] proposed a new tbcabci paradigm and conducted experiments to obtain P300 signals.Most of the traditional experiments are based on visual stimuli to generate P300 time-related potentials. These experiments are based on different paradigms. However, in recent years, quite a lot of work has tried to solve the problem of visual impairment from other aspects that can generate stimuli, such as hearing [7] [15], touch [4] [16], etc., so as to further expand the application scope of BCI.

Data preprocessing is also an important step in P300 signal test. In addition to the signals generated by stimulation, the human brain's brain waves also include the spontaneous EEG fluctuations and noise fluctuations caused by other factors. Therefore, a complete P300 signal can not achieve the ideal situation in Figure 1.The purpose of this paper is to fuse the data from the p30.00 to the frequency of the p30.00, which can be used to extract the data from the p30.00 to the p30.00.

Feature extraction of processed data is also a crucial step. The existing feature extraction methods can be roughly divided into independent component analysis [8], adaptive autoregressive model [6], principal component analysis [9] and other methods.Different from the previous feature extraction methods, Guillermo et al. [10] proposed a new method normalized compression distance to extract the main structural features of P300 signal.With the development of neural network, part of the current research also introduces neural network into the feature extraction of data, souravOthers [11] proposed a deep feature learning technology based on sparse automatic encoder (SAE) and stacked sparse automatic encoder (ssae) for feature extraction, and further utilized the potential features of P300 signal. Other effective feature extraction studies [5] [12] [13] focused on the classical convolutional neural network structure and improved it to adapt to the feature extraction of P300 signal.

The last step of P300 signal wave analysis is to classify and identify the processed data, and then control the machine equipment by analyzing the recognition results. One common device is external speller.Previous work is based on support vector machine [3] [14] [11], neural network [14] [6] and linear discriminant [14] to classify the input data. Although these methods are effective, they have not reached the ideal situation.In recent work, the classification function of convolutional neural network [5] [9] [12] was introduced into the process of P300 signal recognition. Mingfei Liu et al. [5] modified the convolutional neural network and proposed a new neural network named bn3, which has a faster training speed.In addition, Feng Li et al. [12] also carried out similar research and proposed a parallel convolution method. The experimental results show that this method can improve the recognition rate of P300 signal.Sajedeh morabbi et al. [17] studied the training process and proposed a new method to improve the training process based on the original deep belief network by using nesterov momentum. This method indeed improves the detection result of P300 signal.

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