Feature Extraction Method of EEG Signal Based on Synchroextracting Transform

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Abstract. Brain-Computer Interface (BCI) can convert the electrical activity signal of the cerebral cortex into a computer or other machine language to directly control external equipment. Aiming at the problem of low recognition accuracy of visual stimulation Electroencephalogram (EEG) signals. This paper adopts a method of EEG signal feature extraction based on Synchroextracting Transform (SET). The mean value filter method is used to remove the noise in EEG signal, and the time-frequency energy of EEG signal is taken as the characteristic parameter. Finally, the signal characteristics are input into the SVM model as characteristic parameters. The experimental results show that SET can extract the characteristic energy of EEG signal well and improve the resolution of signal.

Keywords: Synchroextracting Transform · Genetic algorithm · Support vector machine · Brain-Computer Interface

1 Introduction

BCI as an interactive system with the outside world, can realize the communication between human Brain and the outside environment by collecting human Brain electrical signals and transforming them into programs that can be read by instruments after recognition and classification [1]. There are several ways to collect neural movements in the brain, EEG has the advantages of convenient collection, simple equipment, low risk and non-invasiveness. It has become one of the most effective ways to collect data. Since the 21st century, BCI technology has gradually matured. A large number of research results have emerged which can help patients with damaged nerve pathways such as stroke to restore the

Supported by focus on research and development plan in Shandong province (2019JZZY021005).

W. Fu et al. (Eds.): ICMTEL 2021, LNICST 388, pp. 462–468, 2021.
https://doi.org/10.1007/978-3-030-82565-2_38

ability of their limbs to interact with the outside world and improve the quality of life. Its application fields also start from the initial medical diagnosis and medical treatment extends to recreational facilities and even military fields.

The research and development of BCI technology have also promoted the rapid development of many intersecting fields such as artificial intelligence, signal processing, and chip technology. Products related to BCI technology will emerge from the laboratory stage and be used in all areas of society.

Visual Evoked Potential (VEP) is a type of brain electrical evoked potential which refers to changes in the nerve potential in the cortex-occipital area when the brain is stimulated by simple flashes or images with alternating colors. As a characteristic signal reflecting brain activity, visually evoked EEG does not require any training. It has the advantages of high information transmission ability, strong anti-interference ability. In experiment, it is widely used in laboratory EEG signal measurement. When extracting features of EEG signals generated by VEP, it is necessary to find EEG features under different stimuli. The BCI technology includes signal acquisition, preprocessing, feature extraction and classification.

At present, traditional feature extraction methods include Short-time Fourier Transform (STFT), Wavelet Transform (WT) and Canonical Correlation Analysis (CCA). Guler et al. [2] designed five classifiers that used wavelet transform to classify different EEG signals. Lin et al. [3] obtained the EEG signals of VEP under moving conditions, and analyzed the signals using the CCA method, which proved the robustness of CCA to EEG signals. Zhou et al. [4] designed a dynamically optimized steady-state VEP BCI system and added post-processing on the basis of the CCA algorithm, thereby reducing frequency changes between different subjects and improving accuracy.

Although the traditional feature extraction method can reflect the EEG signals of different characteristics, the resolution is low and the accuracy is poor. Based on the above problems, this article uses SET [5] to extract different EEG signals various characteristics. The method of mean filtering is used to remove various interferences from EEG signals, and SVM was used to classify them.

2 Research Methods

2.1 Data Set Description

The data used in this paper are collected from the visual evoked Oddball BRAIN-machine interface experimental paradigm [6]. During the experiment, the subjects need to concentrate on looking at the display screen. The experimental paradigm is a 6×6 matrix composed of letters and numbers. Based on the EEG characteristics induced by visual stimuli, it recognizes the characters the subject is looking at and completes the task of spelling words. The character matrix used in the experiment is shown in Fig. 1.

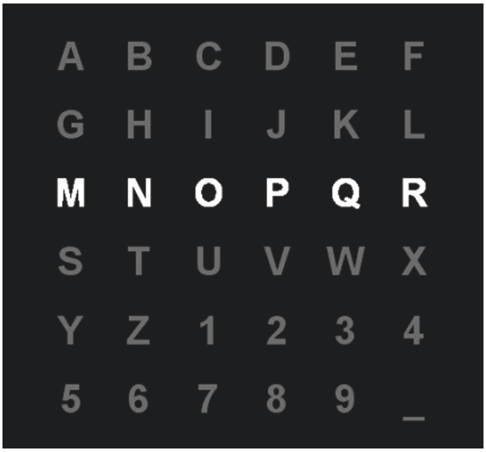

Fig. 1. The flicker interface used in the experiment.

2.2 Data Preprocessing

The EEG signal is a non-stationary and extremely weak physiological signal. All the collected EEG signals are easily interfered by external noise, which will cause the real EEG signal to be submerged. Therefore, before the identification of the EEG signal, the original signal needs to get rid of the noise. This article uses mean filtering to remove noise from EEG signals.

The results of the original EEG signals after mean filtering is shown in Fig. 2.

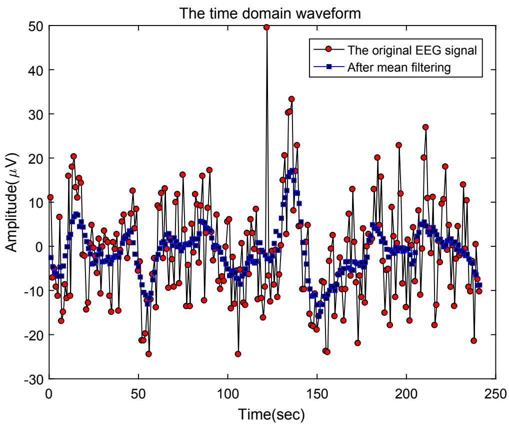

Fig. 2. EEG signal after mean filtering.

3 EEG Signal Feature Extraction and Classification

3.1 Short-Time Fourier Transform

After removing various noises, we need to perform feature extraction to extract the feature vectors of EEG signals under different stimuli. Fourier transform is to convert difficult-to-process time-domain signals into easy-to-analyze frequency-domain signals, and then use some tools to process the frequency-domain signals. But for some unstable signals, for example, the EEG signal, its frequency domain signal changes with time. For this changing signal, the Fourier transform cannot solve it. At this time, the STFT [7] is introduced, the complete signal was cut into time intervals consistent with the set window length through window function, so as to obtain the energy values of different time periods. The formula of the STFT is:

$$G(t, \omega) = \int \left[x(\tau)g(\tau - t)e^{-i\omega\tau}d\tau\right] \tag{1}$$

Among them, $x(\tau)$ is the signal function, $g(\tau)$ is the window function, and ω is the fundamental frequency in the signal function.

3.2 Synchroextracting Transform

When performing STFT, there will be constraints of Heisenberg's uncertainty principle, we cannot observe the signal in time and frequency direction at the same time with arbitrary accuracy, that is, time resolution High, will inevitably lead to poor frequency resolution. Therefore, we use the method of synchronous extraction and transformation for time-frequency analysis of the signal.

Under different stimuli, the energy of the collected EEG signals is different. By comparing the difference in energy value, the characteristics of the EEG signals under different stimuli can be obtained and the EEG signals are extracted after short-term fourier transform. The energy will be dispersed and the specific value of energy cannot be accurately obtained. SET can extract the energy at the center of gravity of the frequency, improve the resolution of the frequency and make the obtained characteristic value more optimized.

In the SET algorithm, the most important thing is to obtain the instantaneous frequency estimation operator through STFT, proceed as follows:

(1) Improve the frequency domain expression of the STFT, multiply it by a rotation factor $e^{i\omega t}$ to improve it, and convert it to its time domain expression. The formula is shown below:

$$G_e(t, \omega) = \int_{-\infty}^{+\infty} x(\tau)g(\tau - t)e^{-i(\tau - t)\omega}d\tau \tag{2}$$

Among them, $e^{i\omega t}$ is the rotation factor.

(2) For a harmonic signal:

$$x(t) = Ae^{i\omega_j t} \tag{3}$$

the partial derivative of its time domain expression can be obtained:

$$\omega_0(t,\omega) = -i\frac{\partial_t G_e(t,\omega)}{G_e(t,\omega)} \tag{4}$$

Among them, $\omega_0(t,\omega)$ is the estimated instantaneous frequency.

(3) As a non-stationary signal, the EEG signal is assumed to be expressed as:

$$x(\tau) = A(t)e^{i\left(\rho(t)+\phi'(t)(\tau-t)\right)} \tag{5}$$

By substituting its STFT into the formula (5). The equation is:

$$\omega_0(t,\omega) = -i\frac{\partial_t G_e(t,\omega)}{G_e(t,\omega)} = \varphi'(t) \tag{6}$$

Among them, $A(t)$ is the non-stationary signal.

(4) For a weak frequency modulation signal, the frequency estimation operator can accurately estimate the instantaneous frequency of the signal, and its expression is:

$$Te(t,\omega) = G_e(t,\omega)\delta\left(\omega - \omega_0(t,\omega)\right) \tag{7}$$

Among them, $\omega_0(t,\omega)$ is the estimated instantaneous frequency. SET is to construct an extraction operator to extract only the energy on the time-frequency ridgeline in the STFT, and ignore the rest of the energy to improve the resolution of the signal.

3.3 Support Vector Machine

SVM is a classifier, which is widely used in the human-machine interface recognition system of the two-class classification model, and it has good robustness and effectiveness [8]. The SVM algorithm obtains the maximum interval from the training samples by constructing the optimal hyperplane, thereby separating two or more training data sets and classifying the test data sets.

In the face of complex classification, when the data set is linearly inseparable in a finite-dimensional space, using kernel functions can put data into a high enough dimensional space. In this paper, radial basis function is chosen as kernel function. The formula is:

$$k\left(x_i, x_j\right) = \exp\left(-g\left\|x_i - x_j\right\|^2\right) \tag{8}$$

Among them, $k\left(x_i, x_j\right)$ is the mapping function, and g is the kernel function parameter.

4 Analysis and Results

According to the characteristics of event-related potentials, EEG signals generate a positive potential waveform after stimulation, namely, P300 potential.

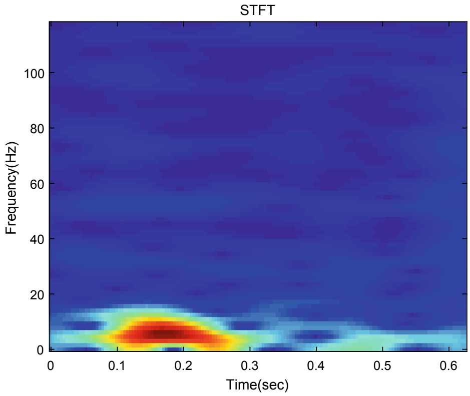

Fig. 3. Energy spectrum of EEG data after STFT.

The noise and artifact are removed by mean filtering and the P300 potential is extracted by SET. The energy spectrum of P300 potential after STFT is shown in Fig. 3. Due to serious energy divergence, the specific location of the stimulus potential cannot be seen.

When EEG signals use SET, the maximum energy near each potential can be extracted, and the P300 potential can be clearly seen from the figure, effectively extracting the required features is shown in Fig. 4.

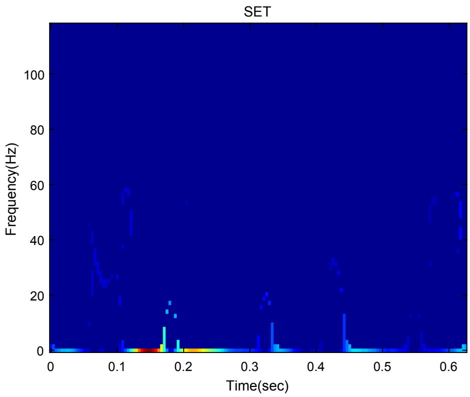

Fig. 4. Energy spectrum of EEG data after SET.

Compared with STFT, SET is more suitable for extracting the characteristics of EEG signal. After feature extraction, the classifier is used for classification. Each subject needs a total of 40 data sets, 20 data sets containing P300 signals, and 20 data sets without P300. Randomly use 24 groups as the training set and 16 groups as the test set. Table 1 shows the classifier accuracy.

Table 1. Classification results.

Experimenter	Contains P300 signal data set	Forecast data set	Accuracy (%)
A	10	9	90
B	9	8	88.9

5 Conclusion

In order to make up for the shortcoming of the traditional STFT algorithm, this article uses SET to extract the time-frequency coefficient on the time-frequency baseline as the characteristic parameter and ignore the energy around the ridge line. Data analysis results show that the proposed method has better resolution and noise robustness than the traditional time-frequency analysis method for EEG signals.

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