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Multiscale Noise Suppression and Feature Extraction in SSVEP Based on Underdamped Second-order Stochastic Resonance

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Abstract

Objective. As one of the commonly used control signals of brain-computer interface (BCI), steady-state visual evoked potential (SSVEP) exhibits advantages of stability, periodicity and minimal training requirements. However, SSVEP retains the non-linear, non-stationary and low signal-to-noise ratio (SNR) characteristics of EEG. The traditional SSVEP extraction methods regard noise as harmful information and highlight the useful signal by suppressing the noise. In the collected EEG, noise and SSVEP are usually coupled together, the useful signal is inevitably attenuated while the noise is suppressed. Besides, an additional band-pass filter is needed to eliminate the multi-scale noise, which causes the edge effect. *Approach.* To address this issue, a novel method based on underdamped second-order stochastic resonance (USSR) is proposed in this paper for SSVEP extraction. *Main results*. A synergistic effect produced by noise, useful signal and the nonlinear system can force the energy of noise to be transferred into SSVEP, and hence amplifying the useful signal while suppressing multi-scale noise.The recognition performances of detection are compared with the widely-used canonical coefficient analysis (CCA) and Multivariate synchronization index (MSI). *Significance.* The comparison results indicate that USSR exhibits increased accuracy and faster processing speed, which effectively improves the information transmission rate (ITR) of SSVEP-based BCI.

Keywords: brain-computer interface, steady-state visual evoked potential, canonical coefficient analysis, multivariate synchronization index, underdamped second-order stochastic resonance

1. Introduction

The brain-computer interface (BCI) can transform human thinking activities into relevant control commands and establish direct communication between the human brain and the external environment [1,2]. This technique provides a new method to communicate with the outside world for patients who have lost muscle control functions [3-5]. Recently, the BCI has become a research hotspot in the fields of rehabilitation and biomedical engineering.

Associated with physiological activities of the brain, EEG can be affected by cognitive activities, environmental stimuli and self-regulation of biological tissues, it exhibits non-linear, non-stationary characteristics [6]. The difference in the transmission path from EEG, EMG, EOG and ECG to their

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sensors causes the amplitude of EEG to remain in the range of μV, whereas the amplitudes of the other three bioelectric signals are in the range of mV [7-9]. The singal sources of EMG and ECG are far from the scalp, so EOG is the main bioelectric siganl artifact. Meanwhile, limb shaking and baseline drift can also result in high-intensity, low-frequency noise [10,11]. In addition, in the process of signal acquisition, EEG is inevitably accompanied by power frequency interference, electrostatic interference and electromagnetic interference. Thus, the recorded signal is always mixed with high-frequency interferences. The low-frequency such as EOG, limb shaking and baseline drift and high-frequency interferences constitute the multi-scale noise, which makes EEG have an extremely low signal-to-noise ratio (SNR).

Many EEG signals can be used as control signals for BCI systems, which include miniature event-related potentials (ERPs), event-related desynchronization (ERD), P300 and steady-state visual evoked potential (SSVEP) [2,12,13]. With frequency ranging from 5 Hz to 80 Hz, SSVEP is a group of specific EEG evoked in the occipital lobe of the brain after visual stimulation [14,15]. This signal has the advantages of stability, periodicity and minimal training requirements, and thus, SSVEP-based BCI is widely used as a communication paradigm [16-18].

Currently, most SSVEP extraction methods regard noise as a harmful signal and improve the detection ability of weak signal by suppressing noise [19]. The power spectrum (PS) method [20-22] employs Fast Fourier Transform (FFT) to calculate the energy of a particular frequency component. Then, the power of a certain frequency of spontaneous EEG is used as a threshold for the corresponding SSVEP detection in evoked EEG. This method has low complexity and high computational efficiency, but the frequency resolution is limited by the sampling time and the required data length usually lasts a few seconds. In 2007, Canonical Correlation Analysis (CCA) [23], which calculates a correlation coefficient between the EEG and a series of stimulus harmonics, was applied to SSVEP extraction. CCA overcomes the dependence of frequency resolution on sampling time and reduces the required data length. However, the sensitivity of the correlation coefficient to the initial phase of SSVEP makes it necessary to increase the acquisition channel to maintain the stability of this method. Unlike CCA, Multivariate Synchronization Index (MSI) [24] uses the synchronization between the actual mixed signals and the reference signals as a potential indicator for identifying the feature frequency of SSVEP. It establishes the s-estimator as an index based on the entropy of the normalized eigenvalues of the correlation matrix of multivariate signals. This method is a non-linear measurement method that avoids the loss of useful information caused by the linear combination of multi-channel signals. By maximizing the reproducibility of time-locked activities across trials, the Task-related component analysis (TRCA) method showed good performance in extracting task-related components. Nakanishi [25] first applied this method to the extraction of SSVEP feature frequencies. The SNR of the SSVEP is enhanced by removing the background EEG activities, thereby the recognition accuracy of the feature frequency is improved. Independent Component Analysis (ICA) [7,8,26] has also been used to isolate SSVEP from evoked EEG, but the low temporal resolution makes it unsuitable for real-time systems. To address the obstacles encountered by conventional approaches in single electrode EEG signal co-channel interference suppression, a method based on time-frequency image dimensionality reduction was proposed by Wang [5]. In addition, many other methods are also applied to SSVEP extraction, such as Autoregressive (AR) model parameter estimation [27], the Stability Coefficient (SC) method [28] and the Reconstruction Extraction (RE) method [29].

All of these methods can extract information contained in EEG and reflect a certain SSVEP detection capability, however, none of these models can avoid the following problems. (1) To eliminate the multi-scale noise contained in the EEG, it is necessary to select a suitable band-pass filter. In this way, the edge effect of the filter greatly reduces the effective data length and significantly increases the detection time. In addition, the adaptive matching of the filter's trial band with the signal's feature frequency also needs to be considered. (2) If extracting SSVEP with obvious nonlinear and non-stationary characteristics by suppressing the noise, the useful signal is also attenuated or lost while the noise is suppressed. When the stability of the evoked signal is insufficient, the suppression of useful signal can even far exceed the suppression of noise. Therefore, the information contained in the original EEG cannot be completely utilized, which seriously affects the detection sensitivity and recognition accuracy.

Since it was proposed by Benzi et al. in 1981, stochastic resonance (SR) has become a hot research topic in the field of nonlinear signal processing [30,31]. In contrast to traditional weak signal detection methods, SR can exploit the energy of noise to enhance the weak useful signal through a nonlinear system [32,33]. To resolve these two issues, this study seeks to use the nonlinear processing method to extract the feature frequency of SSVEP. To obtain the noise-enhanced SSVEP, the pre-processed signal with a certain intensity of noise is sent into the corresponding model to conduct stochastic resonance processing. Then, the power spectrum of the output signal is calculated to identify the feature frequency. Subsequently, the recognition frequency is matched to all stimulus frequencies to determine whether the feature frequency of the SSVEP is successfully extracted. CCA and MSI can make full use of multi-channel EEG information and has strong recognition stability, therefore, the experiment procedure is simplified and the subject-specific training is avoided. Thus, they have become the most commonly used SSVEP extraction methods. Therefore, to investigate the performances of the proposed method, CCA , MSI and two different stochastic resonance methods are used to extract SSVEP with different feature frequencies. The comparison results indicate that underdamped second-order stochastic resonance (USSR) exhibits increased recognition accuracy and faster processing speed, reflecting the superiority of nonlinear methods in EEG processing.

The remainder of this paper is organized as follows: Section 2 analyzes the output response of two stochastic resonance models and then illustrates the SSVEP extraction based on the nonlinear stochastic resonance in detail. In section 3, the proposed method is applied to extract the feature frequency of SSVEP to verify the effectiveness of the method. The recognition effect and processing performances of each method are discussed in section 4. Finally, Conclusions are provided in section 5.

2. Methods

2.1 Ethics statements

Six males and five females (20-27 years old) participated in this experiment. The subjects had normal or corrected normal visual acuity. This study was approved by the Human Research and Ethics Committee of the Xi'an Jiaotong University. Before the experiment, all the subjects were told the purpose and procedure of the experiment in detail and signed a consent form. These forms were approved by Xi'an Jiaotong University Ethics Committee Data Acquisition.

2.2 Stimulus design

The sampled sinusoidal stimulation method [18,34] was used in this study to present visual flickers on a computer monitor. In this method, the stimulus sequence $s(f,i)$ corresponding to frequency f can be generated by modulating the luminance of the screen, and the expression of $s(f,i)$ is as follows:

$$s(f,i)=\frac{1}{2}\left\{1+\sin\left[2\pi f\left(i/refreshrate\right)\right]\right\} \tag{1}$$

where sin() generates a sine wave, and i indicates the frame index in the stimulus sequence. The dynamic range of the stimulation signal is from 0 to 1, where 0 represents dark and 1 represents the highest luminance.

2.3 Data acquisition

This study performed a simulated BCI experiment to record data for offline analysis. Our BCI design utilized the motion checkerboard [35] patterns to construct visual stimulus and displayed them on 21" EIZO FlexScanT966 CRT monitor with a high refresh rate (setting 100 frames/s, measured ~98 frames/s) and a resolution of 1280×800 pixels. The outer diameter of motion checkerboard pattern in our experiment was set at 100 pixels and the inner diameter was set at 20 pixels. The amplitude of expansion-contraction motion process was set at 5 to 15 pixels and the width of one pixel was 0.31 mm. As shown in Figure 1, the stimuli were arranged in a 4×6 matrix containing 24 stimulus tagets (the stimuli were divided into 4 lines, each line includeed 6 targets). Besides, all the targets were tagged with different frequencies (the stimulus frequency range was 5.2-14.4Hz, and the frequency interval was 0.4Hz). The horizontal and vertical intervals between two neighbouring stimuli were 4 cm and 3 cm, respectively.

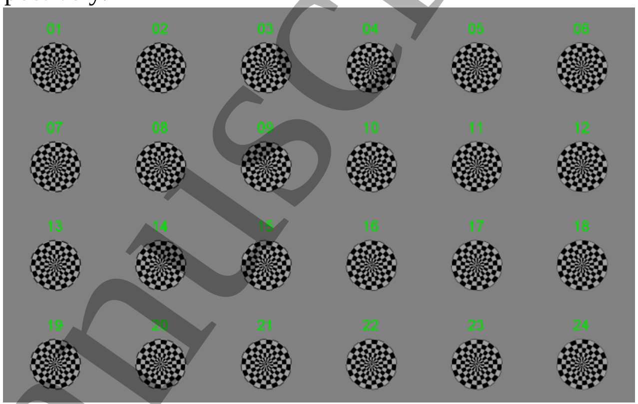

Figure 1 The user interface of the 24-target BCI system

EEG signals were referenced to a unilateral earlobe, grounded at frontal position (Fpz), and sampled at 1200 Hz using a g. USBamp (g.tec Inc., Austr ia) system. Six electrodes sites (OZ, O1, O2, POZ, PO3 and PO4) closer to the occipital lobe were selected to record SSVEP. To remove the common power-line noise, a notch filter at 50 Hz was applied in data recording.

Event triggers that indicate the onsets of visual stimuli were sent from the parallel port of the computer to the EEG system and recorded on an event channel synchronized to the EEG data. Experiments were performed in a quiet and ordinarily lighted room with no electromagnetic shielding. All subjects were seated in a comfortable chair 70 cm in front of the LCD monitor. They were asked to stare at the target stimulator and not to track the movement of the stimulator with their eyes. Each stimulus was applied within a 100-pixel-diameter ring. Twenty four trials corresponding to 24 frequencies were performed. During the experiment, subjects were asked to gaze at the motion checkerboard with different stimulation in turn. The stimuli on the monitor lasted for 5s and then disappeared, the next stimulation was perforned after 1s (the stimulation time of each trial is 5s and the time interval between two trials is 1s).

2.4 Methodology

Stochastic resonance is a typical nonlinear method that subverts people's perception of noise [36]. The basic idea of

SR is to make the weak signal, stochastic noise and a nonlinear system produce a synergistic effect by adjusting the intensity of noise and system parameters, forcing the energy of the noise to be transferred into the useful signal and hence suppressing the noise and amplifying the weak signal.

2.4.1 Bistable stochastic resonance

As the most widely studied model, bistable stochastic resonance (BSR) can be described by the long-range equation obtained by neglecting the inertia force of the motion differential equation of Brownian particles [37].

$$\frac{dx}{dt} = ax - bx^3 + s(t) + \varepsilon(t) \tag{2}$$

The corresponding potential function of the bistable system is noted as follows:

$$U(x) = -ax^2/2 + bx^4/4 - x\left(s(t) + \varepsilon(t)\right) \tag{3}$$

where a and b are the system parameters and satisfy $a, b \in R^+$, $s(t) = A\cos(2\pi ft)$ represents a deterministic periodic excitation signal, $x(t)$ is the output signal of the bistable system, $\varepsilon(t)$ represents Gaussian white noise and satisfies the statistical mean and autocorrelation function as follows:

$$\langle \varepsilon(t) \rangle = 0 \tag{4}$$

$$\langle \varepsilon(t+\tau)\varepsilon(t) \rangle = 2D\sigma(\tau) \tag{5}$$

where $\langle . \rangle$ denotes the expectation operator, τ is the delay time, D is the noise intensity, and $\sigma(t)$ represents the unit pulse function.

The traditional SR is based on the theory of adiabatic approximation [38-40], which requires that the input frequency of the system is far less than 1. To achieve high-frequency signal stochastic resonance, Leng [41] put forward the concept of "large parameter variable scale stochastic resonance". The purpose of variable substitution is achieved by adjusting the step of the numerical calculation. The driving frequency in the differential equation after transformation is reduced to satisfy the conditions with small frequency parameters. Increasing the step can obtain a larger instantaneous moving distance and make the output of the system more easily cross the potential barrier. However, blindly increasing the step will cause the output to diverge, resulting in detection distortion. To ensure that the output converges, the system parameters and calculation step must satisfy the following constraint [42]:

$$ah \le \frac{1}{2} \; and \; |x_0| < \sqrt{(ah+2)/bh} \tag{6}$$

where x_0 represents the initial value of the system, h is the calculation step for solving differential equation.

2.4.2 Underdamped second-order stochastic resonance

BSR ignores the inertia term and normalizes the damping factor. The corresponding Langevin equation belongs to overdamped first-order differential equation. However, the inertia and damping can also influence the output of nonlinear system. Considering the above two factors, the Langevin equation evolves into the second-order differential equation [43]. The nonlinear system composed of second-order differential equation is called the underdamped second-order stochastic resonance (USSR) model. The differential equation for the USSR model is as follows:

$$\frac{d^2x}{dt^2} = -\frac{dU(x)}{dx} - \beta\frac{dx}{dt} = ax - bx^3 - \beta\frac{dx}{dt} + s(t) + \varepsilon(t) \tag{7}$$

where a and b are the system parameters and satisfy $a, b \in R^+$, $0 < \beta < 1$ denotes the damping factor, $s(t) = A\cos(2\pi ft + \phi)$ represents a deterministic periodic excitation signal, and D is the noise intensity.

Substituting the expression of $s(t)$ into the above equation yields the following expression:

$$\frac{d^2x}{dt^2} = ax - bx^3 - \beta\frac{dx}{dt} + A\cos(2\pi ft + \phi) + \varepsilon(t) \tag{8}$$

2.4.3 Effects of damping factor on USSR output

To discuss the effect of damping factor on the output of USSR, here we consider a pure sinusoidal signal as the input signal and its parameters, including amplitude A ,frequency f , noise intensity D , system parameters a, b , sampling frequency fs , sampling time t . The output responses of the system under different damping factors are presented in Figure 2.

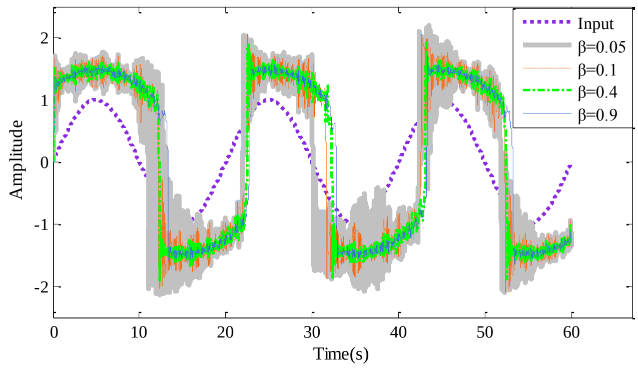

Figure 2 USSR output signal with different damping factors. Input amplitude $A = 1$, frequency $f = 0.05Hz$, noise intensity $D = 0.1$, system parameters $a = b = 1$, sampling frequency $fs = 100Hz$, sampling time $t = 60s$.

When the damping factor is small, a large random fluctuation appears in the output signal. The random noise plays a leading role in this process. As the damping factor increases, the ripple in the output signal is gradually suppressed, and the system response effect is improved. However, excessive damping factor will make the system output unable to keep up with the change of the input signal during the transferring process. The amplitudes of the noise and the driving signal will be largely attenuated, causing the distortion of output signal. Therefore, for different input signals, there is an optimal damping factor that allows the USSR system to achieve the best filtering performance.

2.5 Stochastic resonance output frequency response

2.5.1 Output frequency response comparison of BSR and USSR

To measure the effect of stochastic resonance, an effective fitness function needs to be defined. For periodic signals with a known driving frequency, SNR is the most commonly used method to measure the stochastic resonance effect. SNR is the ratio of the spectral amplitude of the driving frequency to that of the noise, and the definition is as follows:

$$SNR = 10\log_{10}\left(A_d \Big/ \left(\sum_{i=1}^{N/2} A_i - A_d \right) \right) \tag{9}$$

where A_d is the amplitude of the driving frequency in the output signal spectrum, N represents the sum of all the spectrum lines in the spectrum of the output signal, and A_i is the amplitude corresponding to each frequency component in the output signal spectrum.

The frequency response (FR) of BSR and USSR output signals under different system parameters using SNR as the fitness function are presented in Figure 3.

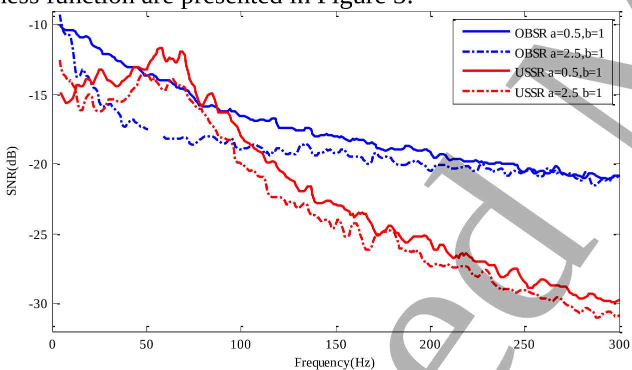

Figure 3 Output frequency responses of BSR and USSR. Input signal amplitude $A=1$, noise intensity $D=2$, sampling frequency $fs=1.2KHz$, sampling time $t=2s$, damping factor β=0.15, numerical calculation step $h=1/10$, driving frequency range: 3~300Hz.

As the driving frequency increases, the SNR of the BSR output signal decreases monotonously, revealing the characteristic of low-pass filtering. However, the output FR of the USSR is no longer a monotonic function of the driving frequency. As the driving frequency increases, the SNR of the USSR first increases and then decreases, which is similar to a group of band-pass filters. BSR can only remove high-frequency noise to retain low-frequency signals. On the contrary, the USSR is equivalent to a secondary filtering of the BSR output signal, which can eliminate the multi-scale noise. All of these features suggest that USSR is more suitable for the actual engineering signals.

2.5.2 Effects of step on the system output frequency response

The variable scale detection method can change the instantaneous moving distance by changing the instantaneous excitation length acting on the system output. Thus, the calculating step determine whether the output can pass the potential barrier and achieve the transition between the two potential wells. Therefore, with different calculation steps, the output FR of the same SR model will be different. Thus, it is necessary to clarify the relationship between the step size and the output FR of BSR and USSR. Using the same simulation parameters employed in the previous section, the output FR of the two SR models with steps of 1/5, 1/10, and 1/20 are presented in Figure 4. Table 1 shows the feature frequencies and bandwidth of the equivalent filter corresponding to different steps (where f_s represents the cut-off frequency, f_c denotes the center frequency, and bw indicates the passband bandwidth).

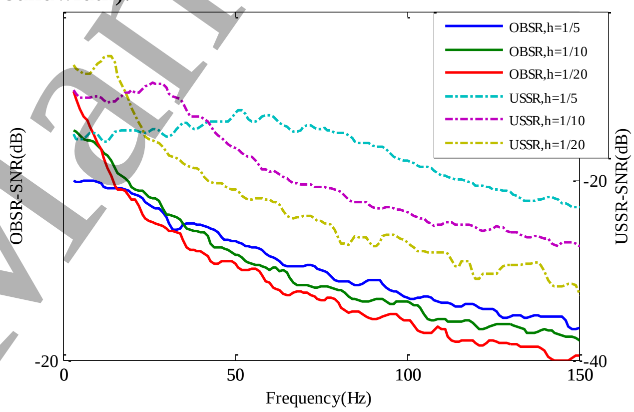

Figure 4 Output frequency responses of BSR and USSR with different calculation steps.

Table 1 Equivalent frequency response parameters of BSR and USSR with different steps.

Step	BSR(Low-pass filter)	USSR(Band-pass filter)
1/5	f_s =33Hz	f_c =41, bw =76Hz
1/10	f_s =21Hz	f_c =20Hz, bw =30Hz
1/15	f_s =16Hz	f_c =15.5Hz, bw =20Hz
1/20	f_s =11Hz	f_c =11Hz, bw =10Hz
1/25	f_s =7Hz	f_c =10.5Hz, bw =6Hz

As the step size increases, the cut-off frequency of BSR gradually increases, and the passband range is widened. For USSR, the equivalent center frequency and bandwidth of the output FR also have a positive correlation with the step of the numerical calculation. This phenomenon reveals that the step of the numerical calculation determines the filtering range of the SR model. Practically, we need to select the best matching step according to the frequency range of the signal to achieve a better stochastic resonance effect.

2.6 SSVEP extraction method based on nonlinear stochastic resonance

In general, the best stimulus frequency range for SSVEP-based BCI is 5-30 Hz [44,45]. To improve the recognition accuracy, a traditional band-pass filter needs to be used to eliminate the multi-scale noise beyond the frequency band. The output FR of USSR is equivalent to a nonlinear band-pass filter. Besides, the passband frequency range and cut-off frequency can be set in advance by adjusting the step of numerical calculation. Therefore, SSVEP extraction based on USSR not only directly suppresses multi-scale noise but also effectively avoids the edge effect and adaptive parameter selection of the traditional filter. Thus, this paper proposes a novel SSVEP extraction method.

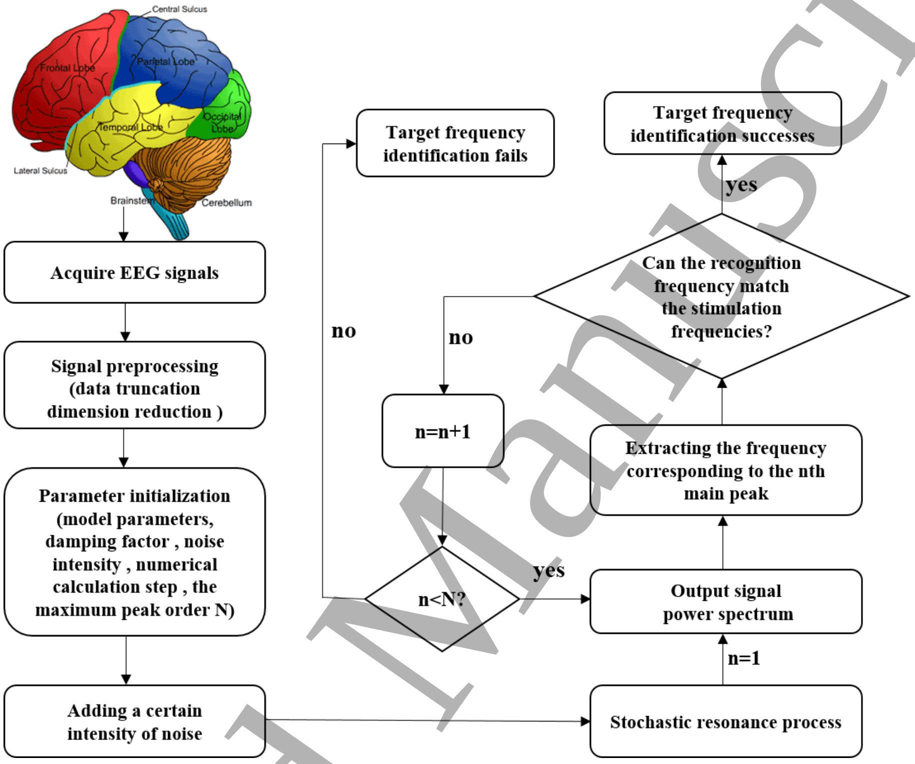

Figure 5 Flowchart of SSVEP extraction based on nonlinear stochastic resonance.

The new method only requires a single channel EEG. To make full use of the useful information contained in the six channels, principal component analysis (PCA) is used to reduce the dimensionality. When the number of channels is reduced, the stability of the signal is not guaranteed, and the useful information cannot be completely retained. The flowchart of the proposed method is illustrated in Figure 5. Detailed procedures are listed as follows:

(1) Invalid data truncation. Subjects' attentiveness often cannot be completely concentrated during the initial experiments. The data collected in the first 0.5 seconds typically do not have a stable SSVEP, which will affect the recognition of target frequencies and need to be removed.

(2) Multi-channel signal dimensionality reduction. To completely utilize the information contained in each channel, PCA is used to reduce the dimensionality of multi-channel signals.

(3) Parameter initialization. It is necessary to set the appropriate parameters (model parameters a and b, damping factor β, noise intensity D, numerical calculation step h, and the maximum peak order N that needs to be identified) according to the characteristics of collected signals and actual analysis needs.

(4) Stochastic resonance processing. The pre-processed signal and a certain intensity of noise are sent to the corresponding model to perform stochastic resonance processing. Then, the power spectrum of the noise-enhanced SSVEP is calculated to identify the target frequency.

(5) Peak frequency identification. The feature frequency corresponding to the n-th main peak from the power spectrum of the output signal obtained in step (4) is extracted.

(6) Frequency matching detection. The recognition frequency is matched to all stimulus frequencies. If the match is successful, the target frequency is effectively identified. If

the match fails, it is necessary to detect whether the current identified order is greater than the set maximum order. If the termination condition is satisfied, then the test is terminated, indicating that the target frequency identification fails. Otherwise, the calculation returns to step (5).

3. Results

The previous sections demonstrate that SR has a strong nonlinear detection ability and can use the energy of the noise to highlight useful weak signal. Therefore, nonlinear stochastic resonance is applied for SSVEP extraction. To verify the effectiveness of the proposed method, the same EEG signals were identified by CCA, MSI and two different SR methods.

3.1 Application of CCA and MSI in SSVEP extraction

Limited by the length of the paper, one subject's offline data was randomly selected for processing to demonstrate the recognition effect of the four methods. The stimulus frequency of the date set was 5.2-14.4Hz, and the frequency interval was 0.4Hz. Meanwhile, Each group of date consists of six channels of signals with the sampling frequency of 1200Hz. First, CCA is used to extract SSVEP, and a butterworth filter with the passband range of 4-31Hz is needed to eliminate the multi-scale noise. The correlation coefficient spectrums between the filtered EEG and the template signals (the template signal refers to a set of standard sinusoidal signals with known frequencies used to identify the SSVEP feature frequency by CCA and MSI) are presented in Figure 6.

For most (71%) EEG, the target frequency can be effectively identified by the CCA method (the coefficient value is greater than 0.4, and there are no large interference peaks). However, the coefficients corresponding to the four frequencies of 9.2 Hz, 11.6 Hz, 12.8 Hz and 14 Hz (the CCA spectrum denoted by green boxes) are no longer the maximum value in the CCA spectrum. Thus, the target frequency identification fails. The coefficients corresponding to the three frequencies of 12 Hz, 12.4 Hz and 13.6 Hz (the CCA spectrum denoted by orange boxes) are the maximum values in the entire spectrum. However, several interference peaks whose values are very close to the maximum value are presented in the correlation coefficient spectrums, making the recognition effect unsatisfactory.

The MSI method extracts the feature frequency of the SSVEP by estimating the synchronization of the actual mixed signals and the reference signals. It can achieve a nonlinear combination of multi-channel signals to extract more useful information. To verify the recognition effect, the MSI method is used to identify the feature frequencies of the same band-filtered EEG, and the synchronization index spectrums of 24 groups of signals are shown in Figure 7.

It can be found that for frequencies that can be correctly identified by CCA, MSI can increase the amplitude difference between the feature frequency and other frequencies, so that the feature frequency is further highlighted. For the two frequencies 9.2Hz and 11.6Hz (the index spectrum denoted in green boxes)that cannot be identified by the CCA, the MSI also failed to extract the feature frequencies. However, the synchronization indexs corresponding to 12.8Hz and 14Hz (the power spectrum denoted in red boxes) becomes the maximum values in the synchronization index spectrums, which means that the two feature frequencies are correctly identified. On the other hand, since the MSI does not have a good inhibitory effect on the interference peaks, the synchronization index of 12.4 Hz is submerged in the interference peaks, and the feature frequency extraction fails.

3.2 Application of BSR and USSR in SSVEP extraction

To verify the advantages of stochastic resonance in SSVEP feature extraction, the weak signal detection method based on BSR is applied to extract the target frequencies of SSVEP. To satisfy the small parameter requirement, it is necessary to adjust the step size of the numerical calculation. As shown in Table 1, when the sampling frequency is 1.2 kHz, the cut-off frequency of the equivalent low-pass filter of BSR has a negative correlation with the calculation step. The analysis frequency range is 5.2-14.4Hz in our experiment, which matches the passband range corresponding to the step of 1/10. Thus, the calculation step is set as 1/10.

The 24 sets of signals are first subjected to stochastic resonance processing. Then, the FFT is used to calculate the power spectrum of the noise-enhanced signals with the data length of 5 s. Figure 8 shows all the power spectrums of the BSR output signals.

Compared with Figure 5 , the three target frequencies of 9.2 Hz, 11.6 Hz and 14 Hz cannot be effectively identified by BSR. In addition, the corresponding power spectrum of 12.8 Hz still has several interference peaks, but the amplitude of the target frequency has been clearly highlighted. However, the interference peaks corresponding to 12 Hz and 12.4 Hz are effectively suppressed, and the recognition effect of the two frequencies are enhanced. At the same time, affected by the randomness of this algorithm, the target frequencies are completely submerged by the interference peaks when the stimulus frequencies are set as 13.2 Hz and 13.6 Hz.

Extracting SSVEP by BSR, the interference peaks around the stimulation frequency are significantly inhibited. BSR can improve the identification effect of the target frequency to a certain extent and reflect the validity of nonlinear stochastic resonance in extracting SSVEP. However, for the unrecognized signals of CCA, BSR also cannot effectively extract useful information and the number of identification errors increases. As discussed in section 2.5, USSR is employed to perform secondary filtering on the output of BSR, and the filtering effect is improved from low-pass filtering to band-pass filtering. Thus, using this method to process the

EEG should yield a better recognition effect. The original EEG is subjected to the same pretreatment and fed into a non-linear, second-order underdamped system. Similarly, considering the equivalent filtering range obtained in Table 1, the numerical calculation step is set as 1/10, and the damping factor is set as 0.85. The power spectrums of USSR output signals are presented in Figure 9.

Compared with BSR, the effect of USSR on EEG recognition has been greatly improved. For the signals with large interference peaks around the target frequency, the interference frequencies are more obviously suppressed. In addition, the dominance of the target frequency in the power spectrum is further highlighted (the power spectrum denoted in blue boxes). The more gratifying phenomenon is that for the unidentifiable signals using both CCA, MSI and BSR, USSR can also effectively identify the corresponding target frequencies (the power spectrum denoted in red boxes). In the power spectrum corresponding to 9.2 Hz, 12.8 Hz and 13.6 Hz, the amplitudes of the target frequency have exceeded the amplitude corresponding to the interference peaks. In the spectrum corresponding to 13.2 Hz and 14 Hz, although the amplitudes corresponding to the target frequencies are not the maximum values of the spectrum, they have also been strengthened to become the second peak or the third peak. At the same time, the frequencies corresponding to the first peak and the second peak (5.4 Hz and 5.8 Hz, respectively) are not matched with all the stimulation frequencies used in the experiment. Therefore, post-treatment can be used to eliminate the interference peaks with amplitudes greater than the target frequency and effectively identify the stimulus frequencies of SSVEP.

The above analysis demonstrates that the weak signal extraction based on USSR has a high degree of matching with non-linear EEG. This method uncovers the information that can't be extracted by CCA, MSI and BSR, thereby effectively improving the recognition accuracy.

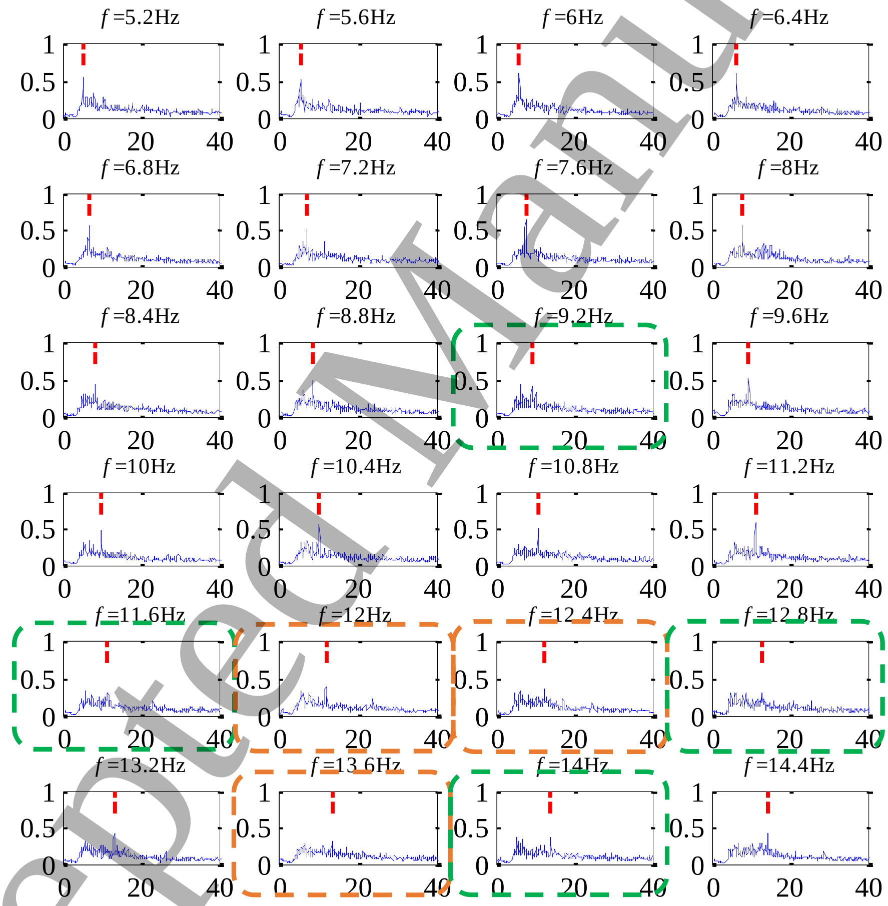

Figure 6 The CCA coefficient spectrums of EEG signal and template signal.

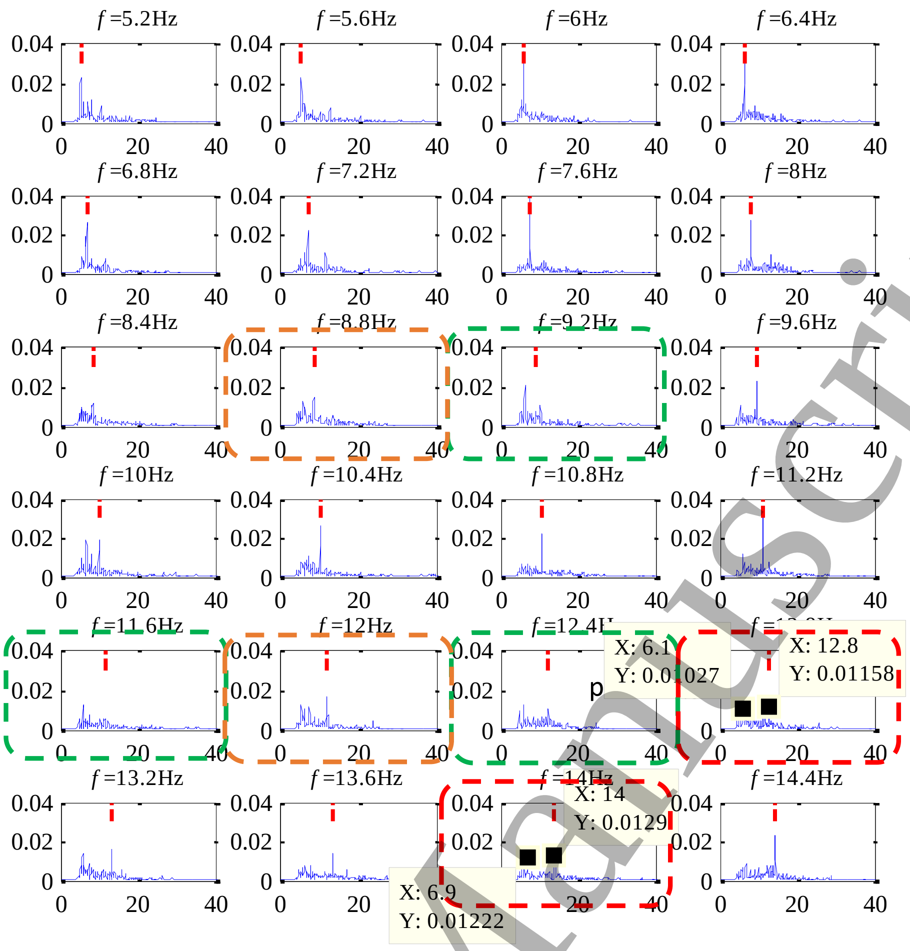

Figure 7 The synchronization index spectrums of EEG signal and template signal. .

3.3 Processing performances comparison

The information transmission rate (ITR) expresses the amount of information transmitted in a unit of time. It is a commonly used indicator to measure the performance of the BCI system. ITR can be calculated by:

$$ITR = \frac{60}{T}\left[\log_2 M + \sigma\log_2\sigma + (1-\sigma)\log_2\left(\frac{1-\sigma}{M-1}\right)\right] \quad (10)$$

where T is the sum of stimulation time of each trial and the time interval between two trials (according to Section 2.3, the value of T in this experiment is 6s), M is the number of targets, and σ is the average recognition accuracy.

Using the same stimulus paradigm, the factors affecting the TTR are not exclusively determined by recognition accuracy, the calculation speed also needs to be considered [46]. In addition to the hardware device (signal acquisition system and computer response speed), the complexity of the relevant extraction method is the most important factor that restricts the BCI online processing capabilities.

To further compare the processing performances, the offline data sets of the remaining ten subjects (each data set contains 24 experimental data) were also identified by the above four methods. The recognition accuracy, single stimulation processing time, and ITR of each subject were calculated respectively, and then the average of each performance was obtained. The correct rates for every subject using the CCA, MSI, BSR and USSR methods are presented in Figure 10 and Table 2 shows the average processing performances of the four methods.

Table 2 Comparison of the processing performance of the four algorithms.

Performance	Correct rate	Processing time	ITR
CCA	84.47%	0.82s	32.60 bit/min^{-1}
MSI	85.98%	0.44s	33.66 bit/min^{-1}
BSR	80.30%	0.14s	29.79 bit/min^{-1}
USSR	94.70%	0.15s	40.46 bit/min^{-1}

For the same EEG, four methods are used to extract the feature frequencies. Using CCA to identify the feature frequencies of 11 subjects, the average correct rate was 84.47%, the processing time was 0.82s, and the ITR was 32.60bit/min^{-1}. The correct rate of MSI was slightly improved to 85.98%, the corresponding processing time was 0.44s, and the ITR was 33.66bit/min^{-1}. The processing performances of BSR were 80.30%, 0.14s, and 29.78bit/min^{-1}, respectively. For USSR, these performances were increased to 94.70%, 0.15s, and 40.46bit/min^{-1}. Compared with CCA and MSI, the USSR method exhibits increased recognition accuracy and reflects the strong non-linear detection ability. On the other hand, the processing speed of the proposed method increases by four-fold, and the online processing capability is also significantly improved. Therefore, under the same stimulus paradigm, the USSR-based SSVEP extraction method can achieve increased ITR.

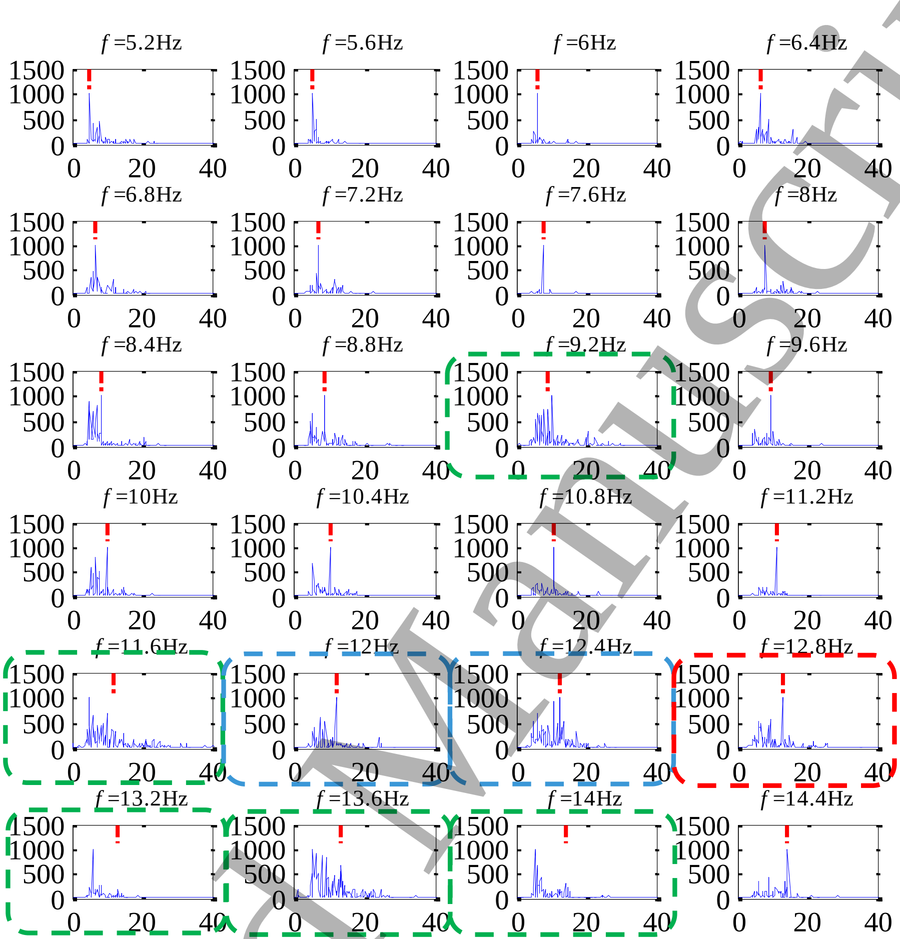

Figure 8 The power spectrums of bistable stochastic resonance output signal.

4. Discussion

When dealing with EEG, the current methods have the problem that signal characteristics do not match with the processing method, and the useful signal is subsequently suppressed as noise. To preserve more information contained in the original EEG, the non-linear processing method is applied to extract SSVEP. SR uses the synergy caused by noise, useful signals, and a nonlinear system to transfer the energy of noise into the useful signal. This method can preserve and highlight the useful information as much as possible.

To clarify the output responses of different models, the SNR is employed as the fitness function, and the output FR under different system parameters are obtained. The results indicate that the output response of BSR is equivalent to a set of nonlinear low-pass filters, which cannot suppress the multi-scale noise. Considering the influence of the damping term and inertial term on the output of the system, USSR is equivalent to the secondary filtering of the output signal of BSR. Hence, the output signal is smoother and the filtering effect is also improved from low-pass to band-pass. Therefore, USSR is more suitable to extract SSVEP from a nonlinear EEG.

By processing the same EEG with CCA, MSI, BSR, and USSR, we found that large interference peaks may exist around the feature frequency in the CCA coefficient spectrums. When the evoked signal quality is poor, and the amplitudes of interference peaks even exceed the amplitude of the feature frequency, resulting in identification errors. MSI retains more useful information contained in the original EEG by implementing a nonlinear combination of multi-channel signals. Compared with CCA, the recognition accuracy is slightly improved. However, this method still treats noise as unwanted information and suppresses noise through traditional filters. The SNR of SSVEP has not been improved, so there are still some interference peaks around the target frequency. BSR can significantly suppress the interference peaks around the target frequency. However, for the unrecognized signals of CCA and MSI, BSR also cannot effectively extract useful information, and the number of identification errors increases due to the randomness of the method. USSR not only has a more prominent interference peak suppression effect but also further enhances the energy of the target frequency. By matching the target frequency with the stimulus frequencies, the signals that cannot be extracted by CCA and BSR can be effectively identified. On the other hand, compared with CCA, the algorithm complexity has also been greatly reduced. Therefore, USSR can improve the processing speed by four-fold and demonstrates a strong online processing capability.

In our experiment, the stimulus frequency range is 5.2-14.4Hz, which matches the passband range corresponding to the step of 1/10. Therefore, the step is usually set to 1/10. However, it doesn’t mean that the proposed method presents a limitation on the SSVEP frequency. When the stimulus freqnencies change, the step size can also be adjusted to adapt to the new frequency range. Besides, all parameter selections in this paper are based on experience. Figure 2-4 are obtained by simulation signals. The purpose is to clarify the basic laws of damping factor, step size on the output of stochastic resonance system, and provide guidance for the actual EEG signal processing. For system parameters, the actual strategy is to fix a, b, and only adjust D to achieve better stochastic resonance effect. According to the experience of parameter adjustment, the recognition effect is ideal when the damping factor is set to 0.82-0.87. This selection strategy separates these parameters and ignores the interaction between different parameters, which limits the further improvement of the SSVEP recognition effect. Constructing a suitable fitness function to achieve adaptive selection of USSR multi-parameters will be the core issue that needs to be solved in the future.

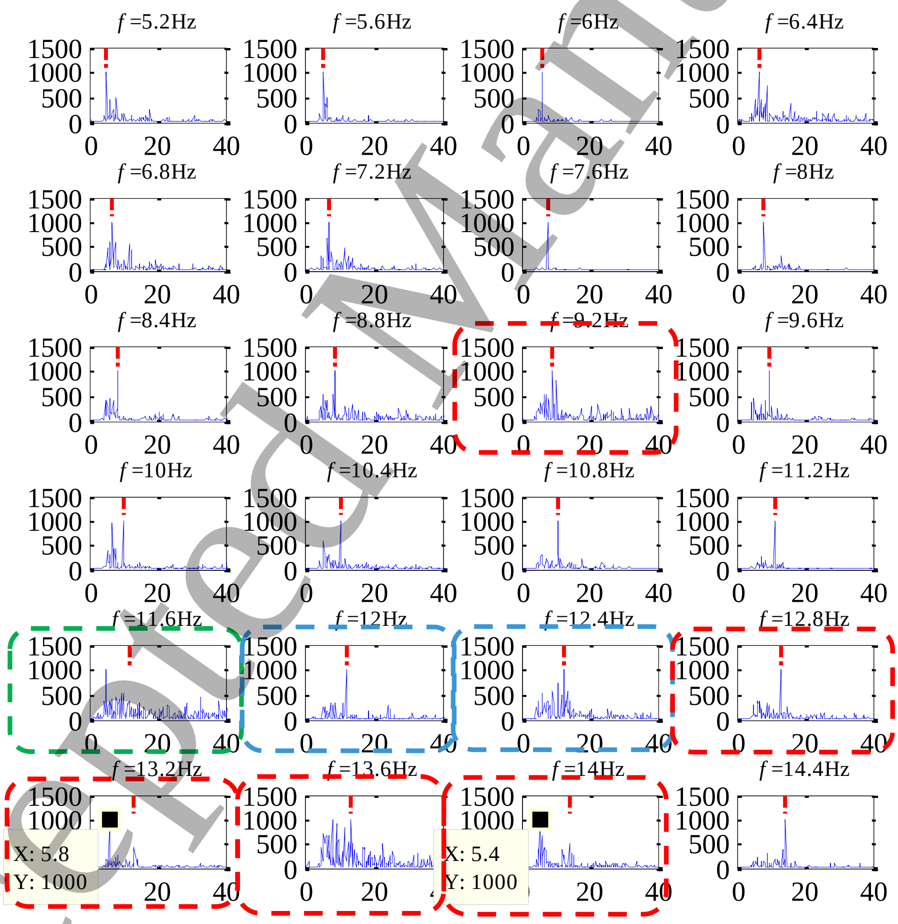

Figure 9 The spectrum of underdamped second-order stochastic resonance output signal.

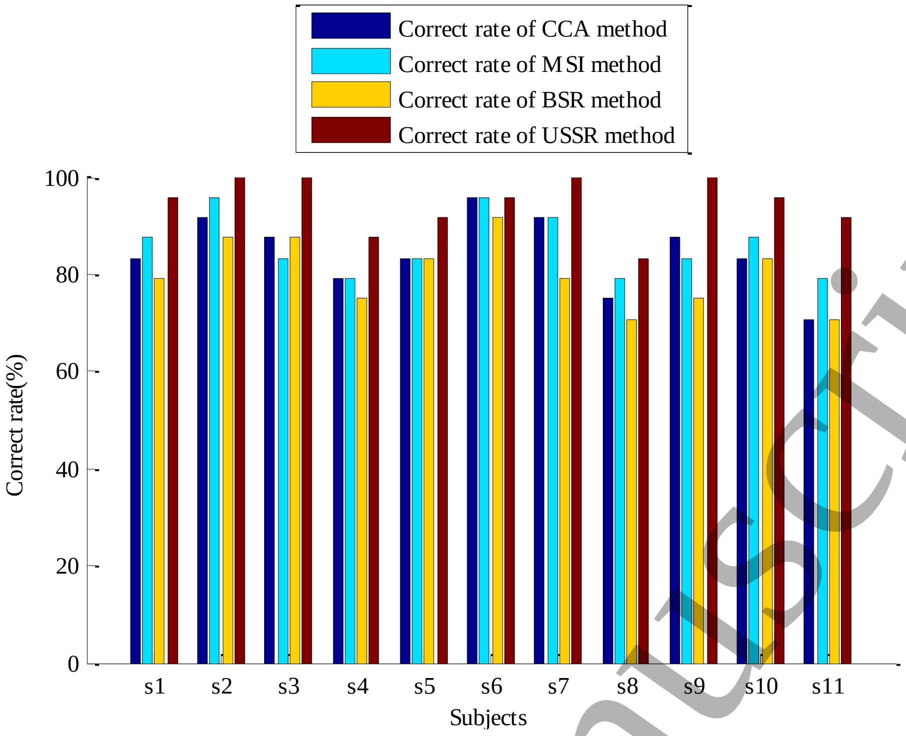

Figure 10 The correct rates resulting from the CCA, MSI, BSR and USSR for every subject.

5. Conclusion

To address the shortcomings that useful information is seriously damaged when signal features do not match with the processing method and that the use of traditional filters will cause the edge effect, a novel SSVEP extraction method based on nonlinear stochastic resonance is proposed. Through experimental verification, we found that BSR can effectively suppress the interference peaks around the target frequency. However, the output FR of the BSR is low-pass and cannot suppress multi-scale noise. On the other hand, the output FR of USSR is similar to a set of nonlinear band-pass filters. After secondary filtering, the output signal is smoother and the suppressing effect of interference peaks is enhanced. Moreover, the energy of the target frequency is further amplified, significantly improving the recognition effect of the target frequency. Thus, compared with CCA and MSI, USSR exhibits increased accuracy and faster processing speed, effectively improving the ITR. All of these features suggest that the USSR method is more suitable for the real-time BCI system.

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