Research Frontier

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VEP-Based Brain-Computer Interfaces: Time, Frequency, and Code Modulations

1. Introduction

A brain computer interface (BCI) translates human intentions into control signals to establish a direct communication channel between the human brain and external devices. Because a BCI does not depend on the brain's normal output pathways of peripheral nerves and muscles, it can provide a new communication channel to people with severe motor disabilities [1–3].

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Electroencephalograms (EEGs) recorded from the surface of the scalp are widely used in current BCIs for their non-invasive nature and easy applications. Among EEG based BCIs, systems based on visual evoked potentials (VEPs) have received widespread attention in recent decades [4–27].

VEPs are caused by sensory stimulation of a subject's visual field, and reflect visual information processing mechanisms in the brain. Stimulation of the central visual field evokes larger VEPs than peripheral stimulation. A VEP based BCI is a tool that can identify a target on which a user is visually fixated via analysis of concurrently recorded EEG. Fig. 1. shows the system diagram of a VEP based BCI. In a VEP based BCI, each target is coded by a unique stimulus sequence which in turn evokes a unique VEP pattern. A fixation target can thus be identified by analyzing the characteristics of the VEP. To ensure reliable identification, VEPs derived from different stimulus sequences should be orthogonal or near orthogonal to each other in some transform domain. Stimulus sequence design is an essential problem for a VEP based BCI. Depending on the specific stimulus sequence modulation approach used, current VEP based BCIs can be organized into three categories: time modulated VEP (t-VEP) BCIs [4-6], frequency modulated VEP (f-VEP) BCIs [11–27], and pseudorandom code modulated VEP (c-VEP) BCIs [7–10].

Due to the different modulation approaches and target identification methods employed, performance differs between systems. In this paper, a comparison study of the three systems is presented. We will first compare the designs of these systems, and then describe in detail our recent work on two online BCI systems using f-VEPs and c-VEPs.

2. System Design

2.1 t-VEP based BCI

In a t-VEP BCI, the flash sequences of different targets are mutually independent. This may be achieved by requiring that flash sequences for different targets are strictly non-overlapping [4], or by randomizing the duration of ON and OFF states of each target's flash sequence [5]. The briefly flashed stimuli elicit flash visual evoked potentials (FVEP) which have short latencies and durations. Fig. 2 shows a typical t-VEP stimulation sequence, and the waveform of a typical FVEP.

In a t-VEP BCI, a synchronous signal must be given to the EEG amplifier for marking the flash onset of each target. FVEPs are time-locked and phase-locked to visual stimulus onset. Thus, since the flash sequences for all targets are mutually independent, averaging over several short epochs segmented according to flash onset of a fixation target will enhance FVEPs corresponding to that target while suppressing contributions of FVEPs elicited by peripheral non-fixation targets. Since foveal FVEPs are larger than peripheral FVEPs, the target producing the largest averaged

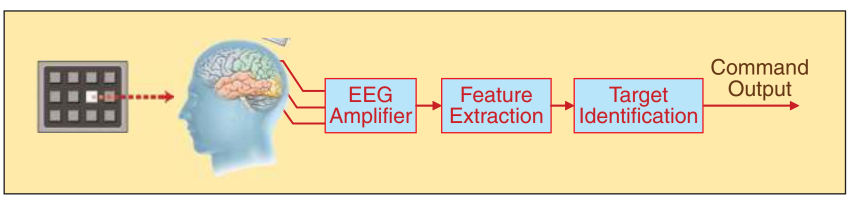

FIGURE 1 System diagram of a VEP based BCI.

Digital Object Identifier 10.1109/MCI.2009.934562

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peak-to-valley FVEP amplitude can be identified as the fixation target.

Accurate target identification in a t-VEP BCI requires averaging over many epochs. Furthermore, to prevent overlap of two consecutive FVEPs, t-VEP BCIs usually have low stimulus rates (<4 Hz). Thus t-VEP BCIs have a lower information transfer rate (ITR) (<30 bits/min). ITR is a performance measure for BCI systems [1].

2.2 f-VEP Based BCI

In an f-VEP based BCI, each target is flashed at a different frequency generating a periodic sequence of evoked responses with the same fundamental frequency as that of the flickered stimulus as well as its harmonics. Fig. 3 shows a stimulation sequence of an f-VEP BCI, and the power spectrum of the evoked response.

Power spectral analysis is most widely used for target identification of the f-VEP based BCI. For a segment of EEG data x obtained from a k-target f-VEP BCI with flicker frequencies $f_1, f_2 \ldots f_k$ respectively, target identification may be implemented through following steps:

1) Calculate the power spectrum $P(f)$ of the EEG signal x using a Fast Fourier Transform (FFT) or other spectral analysis technique.
2) Calculate the signal-to-noise ratio (SNR) S_k of each stimulus frequency f_k. Here, SNR is defined in terms of the ratio of $P(f_k)$to the mean value of the adjacent frequency points.
3) Identify the fixation target by selecting the target, K, corresponding to the maximum S_k.

Because the flicker frequency of f-VEP BCI usually are higher than 6Hz, the evoked responses from consecutive flashes of the target overlap with each other, generating a periodic sequence of VEPs—a steady-state visual evoked potential (SSVEP)—which is frequency-locked to the flickering target. As such, f-VEP BCIs are often referred to as SSVEP BCIs. In past decades, the robustness of f-VEP BCI systems has been demonstrated convincingly in many laboratory and clinical tests

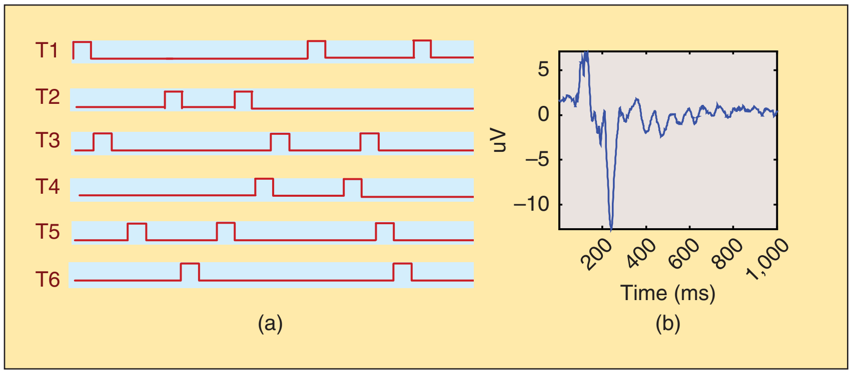

FIGURE 2 (a) The stimulus sequences of targets of a t-VEP based BCI. Target flashes are mutually independent. (b) The evoked response to a single stimulus.

[11–27]. Advantages of an f-VEP BCI include simple system configuration, little or no user training, and a high ITR (30–60 bits/min).

2.3 c-VEP Based BCI

In a c-VEP BCI, pseudorandom sequences are used. The m-sequence is the most widely used pseudorandom sequence [28]. A binary m-sequence is generated using maximal linear feedback shift registers which have many properties that make them valuable tools in linear and nonlinear systems analysis. An m-sequence has an autocorrelation function which is very close approximation to a unit impulse function, and it is nearly orthogonal to its time lag sequence. Thus an m-sequence and its time lag sequence can be used for a c-VEP BCI. Fig. 4 shows stimulation sequences of a c-VEP BCI as well as the time course, spectrum, and autocorrelation function of the evoked response.

As with t-VEP systems, a synchronous signal is necessary in the c-VEP based BCI system. At the beginning of each stimulation cycle, a synchronous signal providing a trigger for target identification should be given to the EEG amplifier.

A template matching method is generally used for target identification. To obtain the template, a training stage must be implemented. The steps of target identification are as follows:

1) In the training stage, the user is instructed to fixate on one of k targets, with the fixation target denoted by k_0. During N stimulation cycles, EEG data X_n, $n = 1, 2 \ldots N$ is collected.
2) A template $T(t)$ is obtained by averaging over N cycles.
3) The templates of all targets are obtained by shifting $T(t)$:

$$T_k(t) = T(t - (\tau_k - \tau_{k_0})),$$

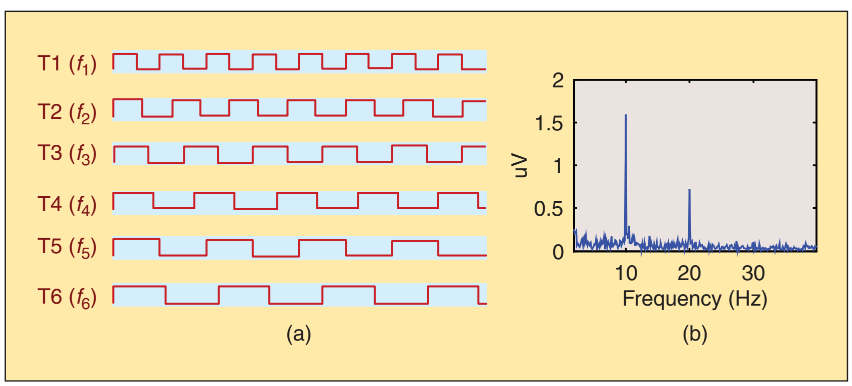

FIGURE 3 (a) The stimulus sequences for targets of an f-VEP based BCI. Targets flash at different frequencies. (b) The power spectrum of the evoked response derived from a target flickering at 10 Hz.

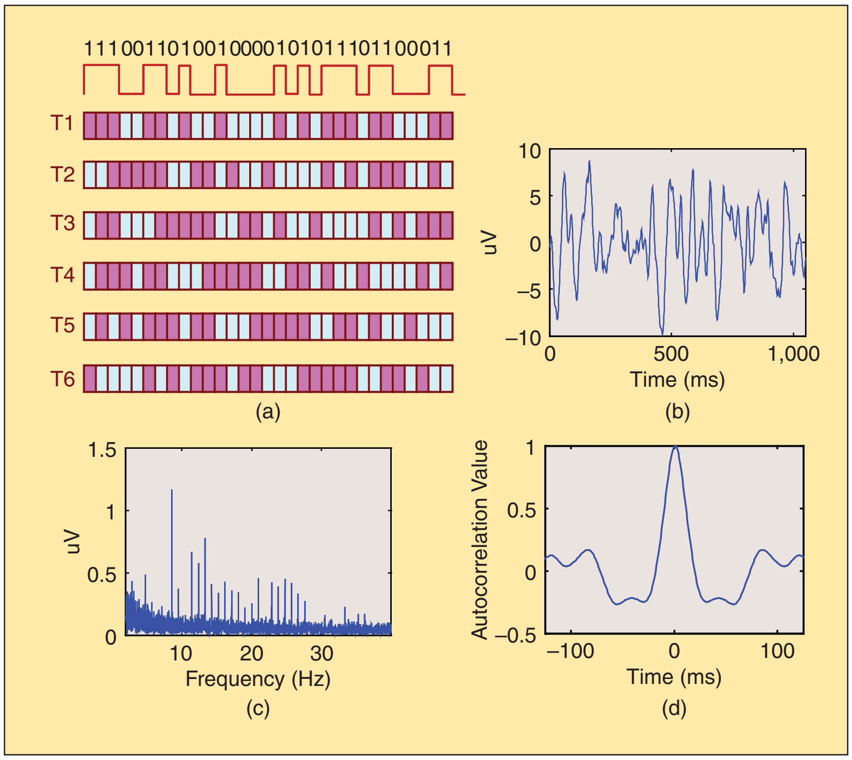

FIGURE 4 The stimulus sequences and evoked response of a c-VEP based BCI. (a) The sequences of targets in one stimulation cycle. Each sequence is from a binary m-sequence. There is a four-frame lag between two consecutive sequences. All targets were activated simultaneously, and the stimulation cycle was repeated constantly. (b) A waveform of the evoked response. (c) The power spectrum of the evoked response. (d) The auto-correlation of the evoked response.

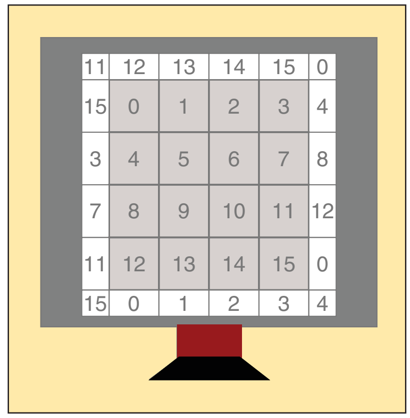

FIGURE 5 The target arrangement of the c-VEP based BCI. The sixteen targets distribute as a 4 × 4 array surrounded by a border to eliminate the effect of the array boundary. When the border fields are stimulated according to the wrap-around principle, all targets have equivalent neighbors. Thus the responses obtained when the subject fixates on different targets are practically identical.

where $\tau_k - \tau_{k_0}$ indicates the time lag between target k and target k_0.

4) For a segment of EEG data x, the correlation coefficient ρ_k between x and the template T_k is calculated as:

$$\rho_k = \frac{T_k x^T}{\sqrt{(T_k T_k^T)(x x^T)}}.$$

5) Identify the fixation target by selecting the target, K, which maximizes the correlation coefficient ρ_k.

The most representative c-VEP based BCI system was developed by Sutter [7, 8]. Sutter's system reached a very high communication rate of 10 to 12 words/minute (>100 bits/min). However, during the past decades, there have been few other studies on c-VEP and the performance of the proposed system was not satisfying. For example, Momose designed a c-VEP BCI system with four targets [9, 10]. It took five seconds for the system to identify a target (<20 bits/min).

3. Performance Comparison

3.1 Experiment Design and Analysis

Because of the lower performance of the t-VEP based BCI, relative to f-VEP and c-VEP systems, we will focus on a detailed comparison of the latter two systems. Two online systems based on f-VEP and c-VEP were implemented and tested on the same group of subjects under the same experimental environment.

In both BCI systems, a CRT display, with a screen refresh rate of 60 Hz and screen resolution of 1024 × 768 pixels, was used for stimulus presentation. A parallel port was used to synchronize EEG data acquisition with stimulus.

There were six targets in the f-VEP based BCI system, with flickering frequencies of 15 Hz, 12 Hz, 10 Hz, 8.6 Hz, 7.5 Hz and 6 Hz, respectively, corresponding to 4, 5, 6, 7, 8, 10 frames in single frequency cycle.

In the c-VEP based BCI system, stimulation targets were composed of 16 rectangular blocks displayed as a 4 × 4 matrix on the monitor as shown in Fig. 5. A binary m-sequence with 63 elements was used as the modulation signal. The lags $\tau(k)$ of different targets were decided by the following equation:

$$\tau(k) = 4 \times k \quad k = 0, 1 \ldots 15.$$

Twelve healthy right-handed adults (three females, nine males) with normal or corrected to normal vision served as paid volunteer subjects after giving informed consent. EEG was sampled at 1000 Hz from 47 scalp electrodes mounted in an elastic cap using SynAmps2 (NeuroScan).

The experiment was divided into a training stage and a testing stage. In the training stage, subjects were required to fixate on each of the targets sequentially for the f-VEP BCI, and fixate on the target "10" for the c-VEP BCI. Data from the training stage was used for offline analysis, including channel selection and to obtain the template for the c-VEP BCI.

Because of the large variation between subjects in the spatial distribution of VEP responses, channel selection is widely used in VEP based BCIs. In this study, an exhaustive method was adopted for channel selection. In practice, the channel with the highest VEP amplitude can be considered the signal channel. To reduce time complexity of the exhaustive search, in both the f-VEP and c-VEP systems, electrode Oz was chosen as the signal channel and the bipolar reference channel which maximized training accuracy was selected as the optimal reference channel.

In the testing stage, an online BCI application was implemented. The reference channel and template obtained from the training stage was used for online testing. Each subject was asked to input two strings of commands with 32 characters for both BCI systems. The online accuracy and corresponding ITR was used for evaluating the online system performance.

3.2 Results

The average training accuracy was $88 \pm 6\%$ and $95 \pm 6\%$ for the f-VEP and c-VEP system respectively. The online accuracy of the c-VEP system was higher than the f-VEP system (91% vs. 85%). The ITR was 39.7 ± 7.8 bits/min for the f-VEP BCI and 92.8 ± 14.1 bits/min for the c-VEP BCI.

4. Discussion

In this paper, a detailed introduction of the three VEP based BCI systems is presented. The similarities and differences between these systems are as follows.

First, the stimulus modulation approach is different for the three systems. In a t-VEP BCI, stimuli corresponding to different targets appear at different times. In an f-VEP BCI, each target is flashed at a unique frequency. In a c-VEP BCI, near-orthogonal pseudorandom codes are used for modulating targets. These three coding methods are similar to the three multiple access methods widely used in mobile communication: Time Division Multiple Access (TDMA), Frequency Division Multiple Access (FDMA), and Code Division Multiple Access (CDMA), respectively [28].

Second, while a training stage is necessary for c-VEP BCIs, it is not a fundamental requirement for f-VEP BCIs and t-VEP BCIs. While our f-VEP implementation utilized training data for channel selection, in multi-channel f-VEP BCI systems, channel selection and parameter optimization can be ignored [23, 24]. In contrast, in c-VEP BCIs, the temporal profile of the evoked response may differ substantially between users and is thus unknown for a new subject; a training stage is necessary to obtain the template of the evoked response.

Third, an f-VEP BCI has a simpler system configuration relative to t-VEP and c-VEP BCIs. Both c-VEP and t-VEP BCIs, require a stimulus onset trigger signal to be synchronized with the EEG data acquisition, increasing the complexity of hardware and software design.

Fourth, the identification accuracy of a c-VEP BCI is higher than an f-VEP BCI. A principal reason for the higher identification accuracy of the c-VEP BCI is that the stimulus sequences, and thus the neuronal responses evoked by each target, are equivalent except for the time shift. However in an f-VEP BCI, the amplitudes and topographies of evoked responses from targets flickered at different frequencies may differ substantially [14]. The disequilibrium of targets brings difficulty to target identification. Additionally, the wide-band evoked response of the c-VEP BCI may contribute to its superior accuracy. As shown in Fig. 4 (c), the neuronal response evoked by a c-VEP BCI has a broadband spectrum distributed over 5–25 Hz. In contrast, an f-VEP BCI generates a narrow-band response, with sharp peaks at the target flicker frequency and harmonics. Natural EEG activity includes many such narrow-band signals such as theta, alpha and beta rhythms, which may interfere with the f-VEP narrow-band response. However, this background "noise" is less likely to interfere with the wide-band c-VEP response.

The three BCI systems exhibit different characteristics, and they can be chosen for different applications. An f-VEP BCI is most suitable for applications requiring fewer options, such as wheelchair control, while a c-VEP BCI is more suitable for applications requiring more options, such as a speller application. All three systems, as described above, require the user to shift gaze to select targets. Thus they are unsuitable for users who cannot shift gaze, such as fully "locked-in" patients with late-stage ALS. However, for the majority of potential BCI users who still have eye movement control, VEP based BCI systems can provide a fast and accurate communication pathway. Recently, independent VEP based BCIs have been realized based on visual attention [25–27]. These systems provide evidence that a VEP based BCI may also be used without requiring gaze-shifting, rendering them suitable for use by fully locked-in patients.

5. Conclusion

We described the three stimulus modulation approaches used in current VEP based BCIs: time modulation (t-VEP), frequency modulation (f-VEP), and pseudorandom code modulation (c-VEP). We then carried out a detailed comparison of system performance between an f-VEP BCI and a c-VEP BCI. The results show that an f-VEP BCI has the advantage of little or no training and simple system configuration, while the c-VEP based BCI has a higher communication speed.

The stimulus modulation design is the crux of VEP based BCI systems. In future work, other stimulus modulation techniques, such as various multiple access methods used in communication systems, may be used to improve BCI performance.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under Grant (No. 30630022, No.90820304) and the National High Technology Research and Development Program of China (No. 2006AA01Z134). The authors would like to thank Tim Mullen for his helpful comments and careful proofreading of the manuscript.

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