Journal of Neural Engineering

An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method

J. Neural Eng. 6 (2009) 046002 (6pp) doi:10.1088/1741-2560/6/4/046002

An online multi-channel SSVEP-based brain–computer interface using a canonical correlation analysis method

Guangyu Bin, Xiaorong Gao[1], Zheng Yan, Bo Hong and Shangkai Gao

Biomedical Engineering Department, Tsinghua University, 100084 Beijing, People's Republic of China

E-mail: bgy06@mails.tsinghua.edu.cn, gxr-dea@tsinghua.edu.cn, yan-z07@mails.tsinghua.edu.cn, hongbo@tsinghua.edu.cn and gsk-dea@tsinghua.edu.cn

Received 9 December 2008
Accepted for publication 6 May 2009
Published 3 June 2009
Online at stacks.iop.org/JNE/6/046002

Abstract

In recent years, there has been increasing interest in using steady-state visual evoked potential (SSVEP) in brain–computer interface (BCI) systems. However, several aspects of current SSVEP-based BCI systems need improvement, specifically in relation to speed, user variation and ease of use. With these improvements in mind, this paper presents an online multi-channel SSVEP-based BCI system using a canonical correlation analysis (CCA) method for extraction of frequency information associated with the SSVEP. The key parameters, channel location, window length and the number of harmonics, are investigated using offline data, and the result used to guide the design of the online system. An SSVEP-based BCI system with six targets, which use nine channel locations in the occipital and parietal lobes, a window length of 2 s and the first harmonic, is used for online testing on 12 subjects. The results show that the proposed BCI system has a high performance, achieving an average accuracy of 95.3% and an information transfer rate of 58 ± 9.6 bit min^{-1}. The positive characteristics of the proposed system are that channel selection and parameter optimization are not required, the possible use of harmonic frequencies, low user variation and easy setup.

(Some figures in this article are in colour only in the electronic version)

Introduction

A brain–computer interface (BCI) is a direct communication pathway between a human or animal brain and an external device. Nowadays, non-invasive scalp electroencephalogram (EEG) measurements have become a popular solution in BCI research. The most commonly used signals in EEG-based BCI systems are event-related synchronization of mu and beta bands, event-related potentials and steady-state visual evoked potential (SSVEP) [1–3].

The SSVEP is a periodic response to a visual stimulus modulated at a frequency higher than 6 Hz [4]. It has the same fundamental frequency as that of the visual stimulus as well as its harmonics. The SSVEP can be recorded from the surface of the scalp over the visual cortex.

In recent years, there has been increasing interest in using SSVEP in BCI systems [5–10, 18–21]. In SSVEP-based BCI systems, several stimuli coded by different frequencies are presented in the field of vision. Different SSVEPs can be produced by shifting our interest or attention to one of a number of frequency-coded stimuli. The SSVEP-based BCI has many advantages over other BCI systems, including a higher signal-to-noise ratio (SNR) and information transfer rate (ITR). Also, since the SSVEP is an inherent response of the brain, very little training is required to enable a person to operate the BCI. These advantages of the SSVEP-based BCI make it a promising option in BCI applications. However, the speed, user variation and ease of use of the previous SSVEP-based BCI systems should be improved.

Many characteristics of SSVEP, such as the amplitude, distribution and available frequency range, show great user variation [4]. So in many of the previous research, parameter

[1] Author to whom any correspondence should be addressed.

optimization and channel selection for each subject to improve the performance of BCI have been widely adopted [4, 8, 11]. These optimizations limit the practical applicability of the SSVEP-based BCI. Moreover, the SSVEP has the same fundamental frequency as the visual stimulus as well as its harmonics. The traditional SSVEP detection techniques cannot identify the targets flickering at harmonic frequencies. Thus, stimuli with harmonic frequencies cannot be used in the previous system [5–9]. This limits the number of targets. This disadvantage looms large in a system with a monitor as the stimulus. In a monitor, the number of stimulus frequencies is limited due to the small variability of the screen refresh rate, and many of the obtainable stimulus frequencies are a whole-number multiple of some others (i.e. harmonics). Thus, the previous BCI system that used PC monitors as a visual stimulator usually had two to four targets and had low information transfer rates (3–20 bit min^{-1}) [5–7]. A method which can recognize the frequency with a harmonic relationship can greatly improve the performance of the BCI.

A multiple-channel SSVEP-based BCI may be able to improve these disadvantages. Recently, many methods were proposed for frequency recognition from multiple-channel EEG signals. Friman *et al* [9] proposed a minimum energy method (MEC) which shows many advantages such as high detection accuracy and no calibration data. Previously in our lab, Lin *et al* [11] proposed the use of a canonical correlation analysis (CCA) method for multi-channel SSVEP detection and also showed highly increased detection accuracy. Lin *et al*'s method was only tested in offline data and channel selection was required. The targets flickering at harmonic frequencies also cannot be recognized in Lin *et al*'s method. However, Lin *et al*'s paper indicates that CCA is a very promising method for the multi-channel SSVEP-based BCI.

In this paper, an online SSVEP-based BCI with six targets is presented. The CCA method without channel location selection and parameter optimization is used for the extraction of frequency information from multiple-channel EEG signals, and a LCD monitor is used as the stimulus. The online testing shows that the proposed BCI system achieves greater practicability and higher performance.

Methods

CCA method in the SSVEP-based BCI

CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation. It finds a pair of linear combinations, for two sets, such that the correlation between the two canonical variables is maximized. CCA extends ordinary correlation to two sets of variables and is widely used in statistical and information mining [12, 13]. Consider two multidimensional random variables X, Y and their linear combinations $x = X^T W_x$ and $y = Y^T W_y$, respectively. CCA finds the weight vectors, W_x and W_y, which maximize the correlation between x and y, by solving the following problem:

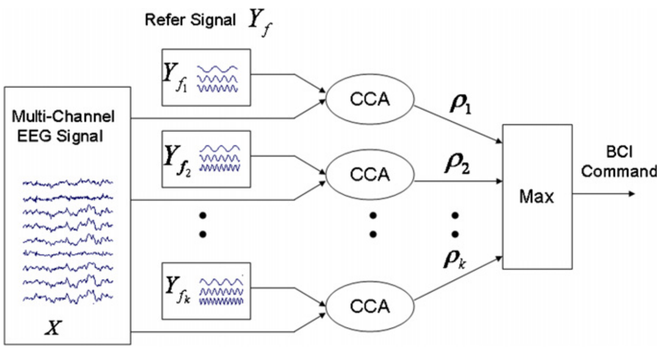


Figure 1. An illustration for usage of CCA in EEG signals analysis. X is the multi-channel EEG signals. Y_f is the reference signals with f Hz stimulus frequency.

$$\max_{W_x,W_y} \rho(x,y) = \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}} = \frac{E\left[W_x^T X Y^T W_y\right]}{\sqrt{E\left[W_x^T X X^T W_x\right]E\left[W_y^T Y Y^T W_y\right]}}. \quad (1)$$

The maximum of ρ with respect to W_x and W_y is the maximum canonical correlation. Projections onto W_x and W_y, i.e. x and y, are called canonical variants.

Lin *et al* [11] first proposed the use of the CCA method for multi-channel SSVEP detection. A similar method was adopted in our system. Figure 1 illustrates the use of CCA in frequency recognition of the SSVEP-based BCI where there are K targets, with the stimulus frequencies being $f_1, f_2, \ldots, f_K$, respectively. X refers to the set of N_t s long multi-channel EEG signals and Y_f refers to the set of reference signals which have the same length as X. The reference signals Y_f is set as

$$Y_f = \begin{pmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \bullet \\ \bullet \\ \sin(2\pi N_h f t) \\ \cos(2\pi N_h f t) \end{pmatrix}, \quad (2)$$

where N_h is the number of harmonics. The multi-channel EEG signals and each of the reference signals were used as an input of the CCA method. The output canonical correlation ρ can be used for frequency recognition.

The user's command C is recognized as

$$C = \max_i \rho_i, \qquad i = 1, 2, \ldots, K, \quad (3)$$

where ρ_i are the CCA coefficients obtained with the frequency of reference signals being $f_1, f_2, \ldots, f_K$.

Offline experiment

In an SSVEP-based BCI system, there are three important parameters: channel location, window length T and number of harmonics N_h. The offline analysis is aimed at investigating the influence of these three parameters on the performance of the proposed BCI system.

The offline data are from an EEG database of the Tsinghua University. This database has been built up for algorithm research. The data are from six healthy right-handed adults with normal or corrected-to-normal vision. The subjects were seated in a comfortable chair in a shielded recording chamber. Six square light-emitting diodes (LEDs), flickering at the frequencies of 13 Hz, 14 Hz, 15 Hz, 16 Hz, 17 Hz and 18 Hz respectively (i.e. $K = 6$), functioned as the visual stimulator. The brightness of the LED was modulated by a square wave. Each subject carried out six runs, with 3 s rest in between. In each run, the subjects were required to gaze at each of the six LEDs for 8 s. Thus, for each subject, six segments of 8 s data were acquired at each stimulus frequency.

Brain electrical activity (EEG) was recorded from 64 scalp electrodes mounted in an elastic cap. Electrode impedances were kept below 5 kΩ. Electrodes were placed at 10–20 electrode sites. Vertical eye movements and blinks were monitored with an electrode placed beneath the left eye. SynAmps2 (NeuroScan) was used for recording EEGs at the electrode sites. All of the above channels were recorded with reference to the linked mastoid. Lateral eye movements were monitored with a bipolar left-to-right outer canthus montage horizontal EOG. All channels were recorded with a bandpass of 0.3–300 Hz except for the horizontal EOG where the bandpass was 0.01–100 Hz. Signals in all channels were recorded at a 1000 Hz sampling rate for offline analysis.

A linear combination of the CCA mapping was used to guide the channel selection and offline performance was then evaluated. Bin *et al* [17] showed that the output linear combination of the CCA method can be employed for mapping and guiding the channel selection of a bipolar SSVEP-based BCI system. A similar method was used to guide the channel location of our system. For each stimulus frequency *f*, CCA was performed with an 8 s EEG data stream as the signal input, and sinusoids with the stimulus frequency and its harmonics were used as the reference inputs. The weight vectors W_x obtained were normalized and used for brain topographic mapping using the function 'topoplot.m' in EEGLAB [14].

After channel selection, nine channels were reserved. To compare the CCA method with the traditional power spectral density analysis (PSDA) method, two methods were run on the nine-channel EEG data. In the PSDA method, an exhaustive method was used to select the optimized bipolar lead to maximize the stimulus frequency SNR. The frequency with a maximal SNR was then recognized as the BCI output. Classification accuracy was used for evaluating the performance of the method. The influence of the time window length on the classification accuracy was also investigated.

Online SSVEP-based BCI system

Wu [16] studied the stimulator selection in the SSVEP-based BCI, and the result was guided for our stimulator design. In our online BCI system, an LCD display (VEIWSONIC, 17″, 60 Hz refresh rate, 1024 × 768 screen resolution) was used as the stimulus source. There were six targets in the BCI system, with flickering frequencies of 15 Hz, 12 Hz, 10 Hz, 8.6 Hz 7.5 Hz and 6.7 Hz respectively, which correspond to four, five, six, seven, eight and nine frames in one flicking period. Figure 2 shows the distribution of the six targets on screen. In each flickering period, one of the frames is white and the others are black. A computer with a 1.86 GHz CPU was used for controlling the stimulator and running the online program.

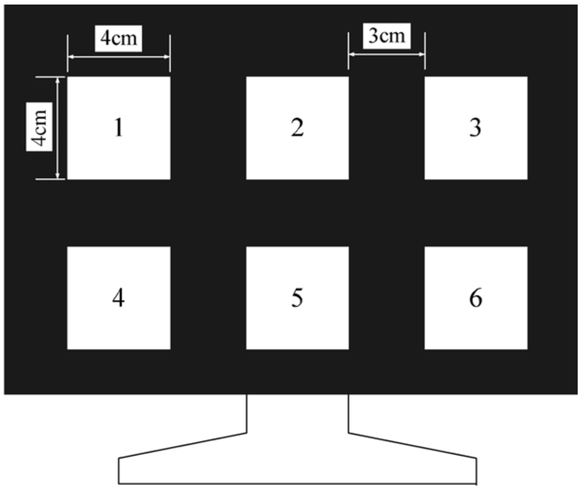


Figure 2. The distribution of six targets in the monitor.

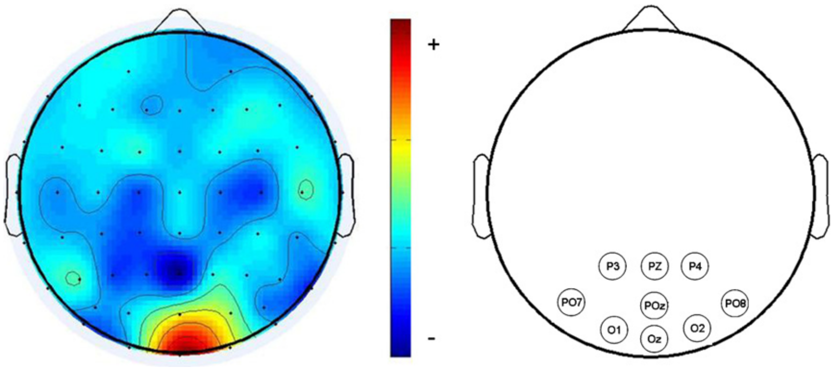
The EEG signals were recorded using a BioSemi ActiveTwo system (BioSemi, Amsterdam, The Netherlands). The sampling rate was 256 Hz. The subjects were seated in a comfortable chair in a room with normal lightness and they were instructed to focus their eyes on one of the six stimulus targets. EEG data were used for 2 s for target identification, and the following 0.3 s interval was given to the subject to shift his gaze. After a 2 min session of familiarization with the system, there was a test that asked the subject to input a string with 30 characters. The correct count out of 30 was used as the criterion for assessing the BCI performance.

Twelve healthy right-handed adults (two female, ten males) with normal or corrected-to-normal vision served as paid volunteer subjects after giving informed consent. Three of them had no experience in participating in EEG experiments.

Results

Channel location analysis

The power scalp maps based on CCA weights of each subject show strong activation of visual cortical areas in the occipital lobe with a large positive and negative value near the occipital lobe. The scalp distribution based on CCA weights sheds light on channel selection for SSVEP-based BCIs. These weights with large absolute values make a large contribution to correlation. Thus, the channels which lie in the strongly activated areas, i.e. the areas near the occipital and parietal lobes, should be selected for EEG recording in a SSVEP-based BCI system. Figure 3(a) shows the group average of the power scalp distribution of all the EEG segments. According to the power scalp distribution as shown in figure 3(a), nine channels, O1, O2, Oz, PO7, PO8, POz, P3, P4 and Pz, as shown in



(a) (b)

Figure 3. (a) Group average of scalp distribution. (b) Channel location selection in an online BCI system.

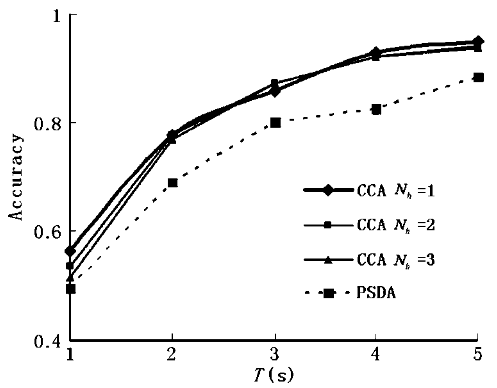


Figure 4. The relationship between recognition accuracy with T and N_{h}.

Table 1. Result of the online test.

Subject	Correct count	ITR (bit min^{-1})
S1	29	60
S2	30	67
S3	30	67
S4	25	40
S5	30	67
S6	30	67
S7	30	67
S8	28	54
S9	30	67
S10	26	45
S11	27	49
S12	28	54

figure 3(b) were selected in the proposed online BCI system.

Time window length and number of harmonics

Figure 4 shows the recognition accuracy obtained using the CCA method when different N_{h} (from 1 to 3) and T (from 1 s to 5 s) were selected. Moreover, for comparing the CCA with the PSDA method, the recognition accuracy obtained by the PSDA [15] method is also presented in figure 4.

ANOVA analysis was performed to evaluate the effects of different detection methods, CCA and PSDA, as well as different Ts and N_{h}s on the recognition rate. Results show that the multiple-channel detection method based on CCA achieved significantly higher accuracy than the PSDA method using bipolar lead ($p < 0.005$). The CCA method achieves about 10% recognition accuracy which is increased when compared with the bipolar lead method. The number of harmonics N_{h} had no significant influence on the performance of the multi-channel BCI system ($p > 0.1$). In the present online BCI system, the first harmonic was used. The time window length T significantly affects the performance of the BCI system ($p < 0.05$). In the study, a window length of 2 s was used to obtain acceptable recognition accuracy.

Online result

A BCI system adopting nine electrodes, as shown in figure 3(b), with a 2 s window length and the first harmonic was used for online testing on 12 subjects. The ITR was used to evaluate the performance of BCI systems. The ITR was measured in bits per minute [1]. In our system, the number of targets is six, and a BCI command was posted once every 2.3 s. The recognition accuracy is equal to the count of correct target selections divided by the total count.

The results are shown in table 1. The average of the correct count from 30 BCI commands was 28.6. The BCI system attained an average ITR of 58 ± 9.6 bits min^{-1}.

Discussion

This paper presents a multi-channel SSVEP-based BCI system using the CCA method. The following aspects of the proposed BCI are shown to be advantageous.

First, the weights vector W_x given by CCA, which maximizes ρ, can provide a spatial pattern which improves the SNR of the combined EEG signal. To demonstrate the improvement in the SNR, a 30 s, 13 Hz SSVEP data set was analyzed using the optimized bipolar lead method and CCA method respectively. In the optimized bipolar lead method, an exhaustive method was used to select the optimized bipolar lead which maximizes the stimulus frequency SNR. Figure 5

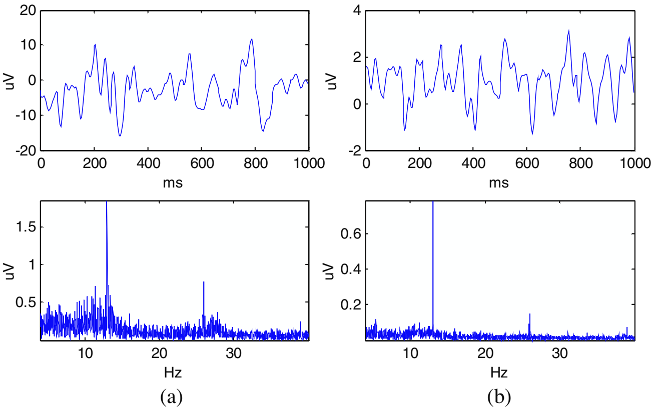


Figure 5. (a) The waveform and power spectrum of optimized bipolar lead. (b) The waveform and power spectrum of canonical variant x using the CCA method.

shows that the power spectral from canonical variant x has a larger peak value in the stimulus frequency than the optimized bipolar lead method. Furthermore, the power spectrum of the optimized bipolar lead method shows larger second harmonic components. When there were no harmonic frequency stimuli, higher harmonic information could be used for improved detection [7]. However, in our system, second harmonic components introduced interference. Moreover, the CCA method combines the functions of spatial filtering and feature selection. The previous multiple-channel method usually performed these two steps separately [9]. The integration of spatial filtering and feature selection simplifies the system and decreases the calculation. It took 1.77 ms to compute 2000 samples of 2 s of nine-channel EEG data on a PC with a 1.86 GHz CPU. The CCA method's amount of computation is about thrice that of traditional methods and can be easily applied to the online BCI system.

Second, the proposed system has low inter-subject variability. A fixed electrode cap and parameter can be used for all subjects. In our system, the selected nine channels were distributed across the visual cortex in a symmetrical way with a bias toward parietal positions. In most of the previous works on the SSVEP, a denser electrode array with preferences over the visual cortex were used [6–8]. The selection of parietal leads may contribute to the system performance. The signal from parietal positions, such as P3, P4, PO7 and PO8, has a lower SSVEP potential, but has similar noise with the signal from the visual cortex, such as O1, Oz and O2. Figure 3 shows that the CCA weight from two parts has the opposite sign. So by using the CCA weight, the noise will be eliminated and the SNR can be improved. Channels from occipital and parietal regions may be good selections for SSVEP-BCI systems. In our method, the subset of electrodes used for the online experiment was obtained from the offline analysis of six subjects, and the experimental settings between the online experiment and offline analysis are different. However, the online test shows high performance and lower inter-user variation. Of course, an optimization for each subject will improve the performance of the BCI. But a fixed channel location can bring great convenience for BCI application as the same electrode cap can be used for all users.

Not requiring parameter optimization also brings great convenience for the application. In our system, parameters such as the time window length and number of harmonics were fixed. A user can operate the BCI system with less training. These advantages make the BCI system significantly more practical for real-world use.

Though a fixed channel location and parameter are used, the online result shows that the system has low inter-subject variability. The ITR on all 12 subjects was higher than 40 bit min^{-1}, and the average ITR achieved 58 $\pm$ 9.6 bit min^{-1}.

Third, possible use of harmonic frequencies as stimuli is another advantage of the system. Our study shows that the number of harmonics N_h is not a crucial parameter for the practice system. These frequencies with a whole-multiple relationship, such as 7.5 Hz and 15 Hz, can be used in one system. This characteristic is of great advantage especially for an SSVEP-based BCI system using the monitor as the stimulator. Using a PC monitor, the number of stimulus frequencies is quite limited, and many of the obtainable stimulus frequencies are a whole-number multiple of some others. The present method can break these constraints. When the refresh rate increases to 120 Hz, 16 targets can be achieved. The use of a monitor as a stimulator brings many other conveniences. A PC and an EEG amplifier are all the components needed for a whole SSVEP-based BCI system, thus eliminating the need for additional specialized stimulus equipment. Furthermore, the position, size, color and luminance of targets can be easily adjusted. And feedback is also easily realized. However, the method presented in this paper can be widely used in the SSVEP-based BCI system. It can be easily used in the system with other numbers of targets, types of stimulators and stimulus frequencies.

Conclusions

A multi-channel SSVEP-based BCI system with high performance was presented in this paper. The CCA method is used for extracting frequency information from the multiple-channel EEG signals. The offline analysis showed that only the first harmonic component makes a significant contribution to the system performance. The online system with fixed nine electrode locations achieve an average ITR of 58 $\pm$ 9.6 bit min^{-1}. Comparing with the current SSVEP-based BCI system, the proposed system shows low inter-subject variability. Parameter optimization and channel selection are not needed for each subject. So the system is easy to set up and more practical for real-world use. The possible use of harmonic frequencies as stimuli which can increase the available stimulus frequency is another positive characteristic.

Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under grant no 30630022 and no 90820304, and the National High Technology Research and Development Program of China (no 2006AA01Z134). The authors would like to thank ShiYun Shao and Abe Caplan for improving the language of this paper.

References

[1] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain-computer interfaces for communication and control *Clin. Neurophysiol.* **113** 767–91

[2] Vaughan T M, Heetderks W J and Trejo L J 2003 Brain–computer interface technology: a review of the second international meeting *IEEE Trans. Neural Syst. Eng.* **11** 94–109

[3] Nijholt A, Tan D, Pfurtscheller G, Brunner C, del R Millan J, Allison B, Graimann B, Popescu F, Blankertz B and Muller K R 2008 Brain–computer interfacing for intelligent systems *IEEE Intell. Syst.* **23** 72–9

[4] Wang Y, Wang R, Gao X and Gao S 2006 A practical VEP-based brain–computer interface *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 234–40

[5] Middendorf M, McMillan G, Calhoun G and Jones K 2000 Brain–computer interfaces based on the steady-state visual-evoked response *IEEE Trans. Rehabil. Eng.* **8** 211–4

[6] Kelly S, Lalor E, Finucane C, McDarby G and Reilly R 2005 Visual spatial attention control in an independent brain–computer interface *IEEE Trans. Biomed. Eng.* **52** 1588–96

[7] Müller-Putz G, Scherer R, Brauneis C and Pfurtscheller G 2005 Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components *Neural Eng.* **2** 123–30

[8] Cheng M, Gao X and Gao S 2002 Design and implementation of a brain–computer interface with high transfer rates *IEEE Trans. Biomed. Eng.* **49** 1181–6

[9] Friman O, Volosyak I and Graser A 2007 Multiple channel detection of steady-state visual evoked potentials for brain–computer interfaces *IEEE Trans. Biomed. Eng.* **54** 742–50

[10] Sutter E E 1992 The brain response interface: communication through visually-induced electrical brain response *Microcomput. Appl.* **15** 31–45

[11] Lin Z, Zhang C, Wu W and Gao X 2006 Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs *IEEE Trans. Biomed. Eng.* **53** 2610–4

[12] Storch H and Zwiers F 1999 *Statistical Analysis in Climate Research* (Cambridge: Cambridge University Press)

[13] Friman O, Cedefamn J, Lundberg P, Borga M and Knutsson H 2001 Detection of neural activity in functional MRI using canonical correlation analysis *Magn. Reson. Med.* **45** 323–30

[14] Delorme A and Makeig S 2004 EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics *Neurosci. Methods* **134** 9–21

[15] Wang Y, Wang R, Gao X, Hong B and Gao S 2006 A practical VEP-based brain–computer interface *IEEE Trans. Neural Syst. Rehabil. Eng.* **14** 234–40

[16] Wu Z, Lai Y, Wu D and Yao D 2008 Stimulator selection in SSVEP-based BCI *Med. Eng. Phys.* **30** 1079–88

[17] Bin G, Lin Z, Gao X, Hong B and Gao S 2008 The SSVEP topographic scalp maps by canonical correlation analysis *30th Annual Int. Conf. IEEE* pp 3759–62

[18] Trejo L, Rosipal R and Matthews B 2006 Brain–computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or steady-state visual evoked potentials *IEEE Trans. Neural Syst. Rehabil. Eng* **14** 225–9

[19] Kluge T and Hartmann M 2007 Phase coherent detection of steady-state evoked potentials: experimental results and application to brain–computer interfaces *Proc. 3rd Int. IEEE EMBS Neural Engineering Conf.* pp 425–9

[20] Muller-Putz G R and Pfurtscheller G 2008 Control of an electrical prosthesis with an SSVEP-based BCI *IEEE Trans. Biomed. Eng.* **55** 361–4

[21] Wu Z and Yao D 2008 Frequency detection with stability coefficient for steady-state visual evoked potential (SSVEP)-based BCIs *IEEE J. Neural Eng* **5** 36–43