This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

A dynamically optimized SSVEP brain-computer interface (BCI) speller

Erwei Yin, Zongtan Zhou*, Jun Jiang, Yang Yu and Dewen Hu, *Senior Member, IEEE*

***Abstract*—The aim of this study was to design a dynamically optimized steady-state visually evoked potential (SSVEP) brain-computer interface (BCI) system with enhanced performance relative to previous SSVEP BCIs in terms of the number of items selectable on the interface, accuracy and speed. In this approach, the row/column (RC) paradigm was employed in a SSVEP speller to increase the number of items. The target is detected by subsequently determining the row and column coordinates. To improve spelling accuracy, we added a posterior processing after the canonical correlation analysis (CCA) approach to reduce the inter-frequency variation between different subjects and named the new signal processing method CCA-RV, and designed a real-time biofeedback mechanism to increase attention on the visual stimuli. To achieve reasonable online spelling speed, both fixed and dynamic approaches for setting the optimal stimulus duration were implemented and compared. Experimental results for eleven subjects suggest that the CCA-RV method and the real-time biofeedback effectively increased accuracy compared with CCA and the absence of real-time feedback, respectively. In addition, both optimization approaches for setting stimulus duration achieved reasonable online spelling performance. However, the dynamic optimization approach yielded a higher practical information transfer rate (PITR) than the fixed optimization approach. The average online PITR achieved by the proposed adaptive SSVEP speller, including the time required for breaks between selections and error correction, was 41.08 bit/min. These results indicate that our BCI speller is promising for use in SSVEP-based BCI applications.**

***Index Terms*—Brain-computer interface (BCI), BCI speller, electroencephalogram (EEG), steady-state visually evoked potential (SSVEP), canonical correlation analysis (CCA).**

I. INTRODUCTION

AN electroencephalogram (EEG)-based brain-computer interface (BCI) can provide a direct and non-invasive pathway for re-establishing communication to severely disabled persons [1], [2]. In recent years, researchers have increasingly focused on BCI systems for alphabetic writing known as BCI spellers [3]. EEG signals used for spelling mainly include sensorimotor rhythm (SMR) [4], P300 event-related potential (ERP) [5] and steady-state visually evoked potential (SSVEP) [6]. The SSVEP is a periodic neural response located in the subject's central visual field that is induced by a repetitive visual stimulus [7]. Due to the high information transfer rate (ITR), simple system configuration and minimal required user training time [8], [9], the SSVEP speller has become one of the most promising paradigms for practical BCI applications.

ITR is widely used for evaluating the performance of BCI systems because ITR simultaneously considers the number of selectable items, accuracy and speed [2]. Consequently, BCI researchers have generally focused on enhancing the ITR of SSVEP spellers in terms of these three factors.

- To increase the number of items, several methods have been introduced to realize more distracters than stimulus frequencies. Zhang *et al.* proposed a multiple frequencies sequential coding (MFSC) protocol to implement more targets with limited frequencies. The BCI system with four targets was carried out in an offline experiment [10]. Hwang *et al.* proposed a new dual-frequency stimulation method to generalize twelve visual stimuli by combining four different frequencies [11]. Chen *et al.* presented an innovative coding method using intermodulation frequencies induced by luminance flicker (three frequencies) and color alternating (two frequencies) to build a SSVEP speller with eight targets [12]. Jia *et al.* realized a BCI system comprising 15 targets with three stimulus frequencies using the frequency and phase information [13]. However, the number of items in these studies was insufficient to allow every character of the BCI speller to be presented on the monitor.
- To enhance spelling accuracy, several signal processing methods have been proposed, such as canonical correlation analysis (CCA) [14] and minimum energy combination (MEC) [15], which have yielded better recognition results than power spectral density analysis (PSDA) [16], a traditional method for SSVEP recognition. Among these methods, CCA has demonstrated the best performance and has been widely used in previous SSVEP BCI studies [17]. Because the features of SSVEP responses are highly dependent on the participant, recent studies have achieved further progress in terms of classification accuracy by optimizing the reference signals [18] and selecting suitable stimulus frequencies [8], [19], [20] using additional calibration runs. Unfortunately, misspellings induced by inter-frequency variations in the SSVEP re-

This work was supported in part by the National High-Tech R&D Program of China (863 Program) under Grant 2012AA011601, the National Natural Science Foundation of China under Grant 61375117.

This paper has supplementary downloadable material available at http://ieeexplore.ieee.org. This includes a multimedia AVI format movie clip, which shows a natural scene. The size of the video is 7.35 MB.

E. Yin, J. Jiang, Y. Yu and D. Hu are with the Collage of Mechatronic Engineering and Automation, National University of Defense Technology, Changsha, Hunan, 410073, P.R. China.

*Z. Zhou is with the Collage of Mechatronic Engineering and Automation, National University of Defense Technology, Changsha, Hunan, 410073, P.R. China. e-mail: (narcz@163.com).

sponses at different frequencies still occur.

- To improve spelling speed under reliable control, Volosyak proposed an adaptive mechanism of time segment length adaptation for SSVEP-based BCI spellers [21]. In this system, the fixed thresholds of the SSVEP response were determined based on the offline analysis of EEG data collected from many subjects, with no individual information employed for threshold selection. The recognition performance may deteriorate when directly using the classification thresholds as a result of overfitting during the SSVEP-based spelling, particularly with a short time window. Therefore, studies focusing on adaptive SSVEP spellers have been limited to [21].

In this study, we proposed a dynamically optimized SSVEP speller with enhanced performance in terms of the number of items classified, classification accuracy and spelling speed relative to previous SSVEP spellers. First, we introduced a row/column (RC) paradigm into the SSVEP BCI to establish a SSVEP speller with 36 items that uses only six frequencies. Second, to enhance classification accuracy, we reduced the inter-frequency variation in SSVEP responses by adding posterior processing after the CCA approach and named the new signal processing method CCA-RV (RV means reducing variation). In addition, we implemented a real-time biofeedback mechanism to increase attention on the visual stimuli. Third, two optimization approaches for setting the stimulus time, fixed and dynamic, were compared using practical ITR (PITR), and the dynamic optimization approach was implemented in our SSVEP speller design.

The remainder of this paper is organized as follows: the stimulation paradigm design, signal processing, real-time biofeedback, optimization approaches and experimental setup are described in Section II; the experimental results are presented and discussed in Sections III and IV, respectively; Section V concludes the paper.

II. METHODOLOGY

A. Stimulation paradigm design

The RC paradigm is widely used in P300-based BCI research. In this paradigm, all items in the same row or column are flashed simultaneously, and the targets are detected by their row and column coordinates [22]. Here, the proposed SSVEP speller is established by using the RC paradigm. The most common size used for a BCI speller is 36 characters arranged in a 6×6 matrix because this arrangement includes all basic items necessary for spelling [23], [24].

Fig. 1 represents the graphical user interface (GUI) of the proposed SSVEP speller, which has same number of items as the classic BCI speller. Each cell in the proposed SSVEP speller flickers between white and black at a unique, constant frequency. The flickering was created using a white rectangular object whose appearance and disappearance alternated on a black background. Because the available frequencies in a SSVEP speller are often restricted and to decrease the difficulty of the stimulus mechanism design and maintain a high classification accuracy of the SSVEP, we employed only six frequencies, namely, 8.18, 8.97, 9.98, 11.23, 12.85, and 14.99 Hz, in the design of a periodic stimulus mechanism. The selection of these frequencies has been discussed thoroughly in previous studies [25], [26]. Fig. 2 demonstrates the sequence in which each item on the BCI interface flickers, with each number on a rectangular cell denoting a stimulus frequency. As the RC paradigm, the target is detected by determining the row and column coordinates. To identify the row coordinate of the target, all items in same row flicker at the same frequency (see Fig. 2(a)). Subsequently, all items in the same column flicker at the same frequency to detect the target's column coordinate (see Fig. 2(b)). This two-step stimulus mechanism occurs without stopping in between steps.

B. CCA-RV method and real-time biofeedback mechanism

1) CCA-RV method: Traditional SSVEP processing methods choose the target frequency by using the SSVEP response with the largest score. Because the SSVEP response is likely to be contaminated by background noise present in the subject's brain [18], the amplitude of the SSVEP response exhibits a complex inter-frequency variation among different subjects. As a result, some items on the BCI interface (corresponding to a less noisy SSVEP response) may be executed more easily than others [27], [28]. CCA achieves better classification performance than other frequency detection approaches [14], but some misspellings still occur due to the inter-frequency variation of the SSVEP response at different frequencies. For instance, a non-target SSVEP response may be stronger than that of the target because the frequency associated with the non-target is measured from an area of the subject's brain that is less contaminated by background noise.

To address this issue, we propose a CCA-RV method to reduce the variation of the SSVEP response. In our approach, CCA was used to calculate the correlation between the stimulus frequency ($X_f(t)$) and the multi-channel EEG data ($Y^{ssvep}(t)$). The stimulus frequency is represented as a square-wave periodic signal that can be decomposed into a Fourier series of its harmonics:

$$X_f(t) = \begin{bmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \sin(2 \cdot 2\pi f t) \\ \cos(2 \cdot 2\pi f t) \\ \vdots \\ \sin(M \cdot 2\pi f t) \\ \cos(M \cdot 2\pi f t) \end{bmatrix}, t = \frac{1}{S}, \frac{2}{S}, \cdots, \frac{N}{S} \quad (1)$$

where M is the number of harmonics, N is the number of sampling points per selection, t is the current time point and S is the sampling rate. The correlation coefficient of each stimulus frequency is then calculated as follows:

$$\mathrm{score}_i(t) = r_i(X_{f_i}(t), Y^{ssvep}(t)) \quad (2)$$

where r is the correlation coefficient, f is the stimulus frequency and i is the sequence number of the stimulus frequency. The correlation coefficient r was calculated using the function 'canoncorr.m' in the MATLAB toolbox [29]. Subsequently,

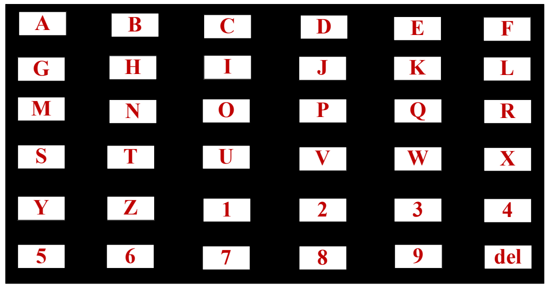
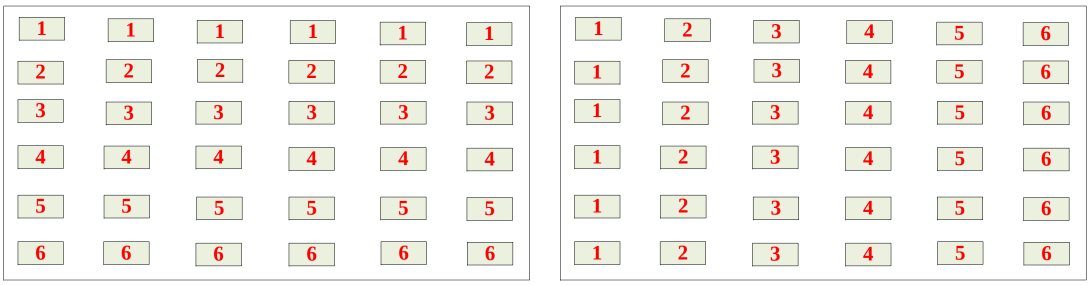


Fig. 1. The GUI of the proposed SSVEP speller. The white rectangular objects represent the periodic flickers used as SSVEP stimuli.



(a) (b)

Fig. 2. Illustrations of the stimulus configuration of the SSVEP speller. The numbers in the cells represent the frequency numbers. Each cell in a row (a) or column (b) flickered at the same frequency to enable detection of the target row and column coordinates, respectively.

to reduce the inter-frequency variation of SSVEP responses, we obtained the average non-target scores ($score_i^{NT}(t)$) of each frequency associated with different time points following the initial stimulus presentation using data from calibration runs collected prior to online spelling. During online spelling, the SSVEP response scores were evaluated in the following manner:

$$Score_i(t) = \frac{score_i(t) - score_i^{NT}(t)}{score_i(t) + score_i^{NT}(t)} \tag{3}$$

Finally, the target coordinates of each time point were determined based on the maximum score of row and column SSVEP responses, respectively. The target coordinates can be represented as follows:

$$\mathrm{C}(t_1, t_2) = \underset{i,j \in [1,\cdots,6]}{\arg} [\max(Score_i^r(t_1)), \max(Score_j^c(t_2))] \tag{4}$$

where x and y denote the row and column coordinates of the target, respectively. $Score_i^r(t_1)$ and $Score_j^c(t_2)$ are the real-time SSVEP scores associated with row and column coordinates.

2) Real-time biofeedback mechanism: Because variation in the subject's visual selective attention significantly influences the amplitude of the SSVEP response, the performance of a SSVEP speller strongly depends on the subject's level of concentration [30], [31]. In traditional SSVEP spellers, feedback is only given at the end of each selection as a spelling result. During the spelling process, a subject might reduce the level of attention on the center of the SSVEP flicker, leading to a decrease in spelling accuracy. In the proposed protocol, we designed a real-time biofeedback mechanism to improve the efficiency of the SSVEP speller. Feedback is given in real-time to the subject by changing the color of the current target characters (see the supplementary data file available at stacks.iop.org). Specifically, the system first changes the color of the characters within the selected row and then changes the color of the character associated with selected row and column coordinates. The real-time biofeedback is updated every 0.04 s. If subjects find that the character they are looking at has not changed color during the spelling process, they must increase their focus on the target stimuli. This mechanism helps the subject enhance their level of visual selective attention on the target stimulus, which should consequently increase spelling accuracy.

C. Optimization approaches for stimulus time

Typically, a longer stimulus time results in a higher classification accuracy but lower spelling speed in the SSVEP spelling process, whereas a shorter stimulus time results in lower accuracy but higher speed. Due to the variation in spelling performance among subjects, there is a subject-specific tradeoff between accuracy and speed, which leads to an optimization problem [32].

ITR is widely used in the BCI community as an important metric [2]. However, as discussed in [32], [33], to complete the spelling task without error, a BCI speller needs to have an error-correcting function in practical applications. Error correction requires the BCI user to erase a wrongly selected option by selecting a "del" item and then select the correct option. We employ the PITR proposed by Townsend *et al.*, which provides a more realistic estimation of ITR [34]. The

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

PITR can be expressed as follows:

$$PITR = \begin{cases} (2P-1)\log_2 N/T, & P > 0.5 \\ 0, & P \leq 0.5 \end{cases} \quad (5)$$

where N is the number of items and P is the spelling accuracy. Here, T is the time interval per selection, which is computed from the following expression:

$$T = [(t^{row} + t^{column}) + I]/60 \quad (6)$$

where t^{row} and t^{column} are the row and column stimulus times, respectively, and I is the time between successive selections (2s). Note that I is necessary for practical BCI application and cannot be ignored.

In our approach, the PITR was evaluated by a fivefold cross-validation procedure with the offline data, which updated every 0.04 s. To ensure practical online spelling, we set both minimum and maximum stimulus times, which were determined from the offline training results. The minimum stimulus time was set to the time point where the offline spelling accuracy reached 70% because an accuracy of greater than 70% is commonly required to achieve effective communication with a BCI [35]. To avoid extensive waiting periods and visual fatigue, we set the maximum stimulus time to 10 s. The peak PITR was taken as a measure of the possible performance of the SSVEP speller. In particular, we proposed fixed and dynamic optimization approaches for selecting the stimulus time duration by calculating the maximum PITR for each subject:

- Fixed optimization approach. The optimal stimulus time is estimated using calibration data and is fixed prior to online BCI use. During online spelling, the SSVEP speller provides the spelling results once the optimal stimulus time is met.
- Dynamic optimization approach. The optimal threshold of the SSVEP response is estimated from the calibration data and used for online spelling. In this optimization approach, the SSVEP stimuli stop at any time and give the spelling result once the current SSVEP response reaches the threshold.

Fig. 3 presents the estimated optimal stimulus time for each subject using the fixed optimization approach and the SSVEP threshold for the dynamic optimization approach. Here, the optimal stimulus time includes the time for both row and column detections.

D. Experimental Setup

1) Subjects: Eleven healthy subjects (five females and six males, age 24-29 years, mean age 27.4 years) participated in the study. All subjects had normal or corrected-to-normal vision. Four of the subjects had previous experience with the SSVEP-based BCI, while the other subjects did not. All subjects signed an informed consent form in accordance with the Declaration of Helsinki. The purpose of this study and the task required were explained to each subject in detail before preparation for the EEG recording.

2) Data collection: EEG signals were recorded using a BrainAmp DC Amplifier (Brain Products GmbH, Germany). Using the 64-channel extended international 10/20 system, nine-channel active electrodes were selected for the SSVEP detection and were placed at Pz, P3, P4, Oz, O1, O2, POz, PO7 and PO8, referenced to P8 (right mastoid) and grounded to Fpz (forehead) [36]. Each of the impedances was kept below 10 kΩ prior to recording. The EEG signals were sampled at 250 Hz and filtered using a 50-Hz notch filter. To improve the signal-to-noise ratio (SNR), the data collected from the SSVEP channels were filtered using a 4-35-Hz bandpass filter. The data collection and experimental procedure associated with the BCI speller were controlled using the BCI2000 platform [37], which provides a Python interface for stimuli presentation and a MatLab interface for signal processing.

3) Experimental procedures: The experiments were performed in a normal office room. After preparation for the EEG recording, the subjects were seated in a comfortable chair located approximately 70 cm from a 27$''$ LED monitor with a refresh rate of 60 Hz and resolution of 1680×1080 pixels. A short familiarization session was performed prior to the initiation of the experiments. To verify the feasibility of the proposed approaches, the experiments consisted of offline and online sessions. To avoid confusing the subjects and fatigue bias, a 2-s break was provided between successive selections to allow the subjects to locate the next symbol, and a 5-min break was provided after every run. Additional details of the experimental design are illustrated in the supplementary video (see the supplementary data file available at stacks.iop.org) and are described as follows:

(1) To verify the effectiveness of the CCA-RV approach and the real-time biofeedback, the offline session consisted of two different stimuli conditions - one with real-time feedback and one without. Six runs of each condition were collected. In each run, the subjects were required to input 12 symbols in a random order to avoid adaptation. During the offline session, the spelling target was marked by a green square before the stimuli appeared, and the subjects focused their visual attention on the marked symbol during the entire stimulus period. For each letter selection, the SSVEP stimuli appeared on the screen and remained for 10 s, with the first 5 s used for row coordinate detection and the subsequent 5 s used for column coordinate detection..

(2) To compare the performance of the proposed optimization approaches for setting stimulus time, the online session was performed using both the fixed and dynamic optimization approaches. During online spelling, subjects were not given a word to spell. Rather, to provide a standardized spelling task, the subjects were required to spell their own names in Latin letters three times (three runs). When an incorrect symbol was detected, the subject had to correct the misspelling by selecting the 'del' option located at the bottom right of the matrix, followed by the correct letter. In addition, the minimum and maximum stimulus times were set beforehand (see section II-C). For the fixed optimization approach, the stimulus time for each subject was determined using

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

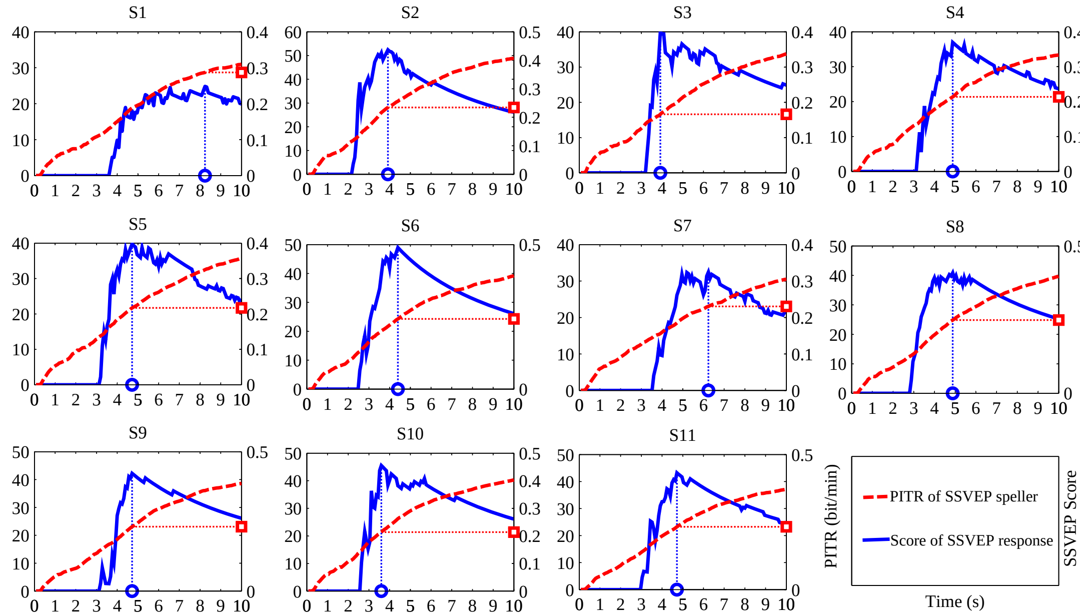


Fig. 3. The optimization process for stimulus time for each subject using the fixed and dynamic optimization approaches. The curves were estimated using the calibration data. In each subfigure, the circular maker represents the optimal stimulus time for the fixed optimization approach and the quadrate marker represents the SSVEP threshold for the dynamic optimization approach.

calibration data from the offline session. Note that the stimulus times were identical for row and column detection. For the dynamic optimization approach, when the current SSVEP score exceeded the optimal threshold, the system stopped flashing and gave the spelling result.

III. EXPERIMENTAL RESULTS

A. Online performance

During the online session, each participant spelled his or her own name three times. The number of task characters M_c and practical selections M_p were recorded directly. To facilitate PITR calculation, we employed the formula presented in [26]:

$$\text{PITR} = \frac{M_c \cdot \log_2 N}{T \cdot M_p}. \tag{7}$$

In addition, we performed a difference analysis of the performance using paired *t*-tests.

The online performance of the proposed SSVEP speller using the two optimization approaches is summarized in Table I. Specifically, the average PITR obtained across all subjects with the dynamic optimization approach (41.08 ± 7.43 bit/min) was significantly greater than the average PITR obtained using the fixed optimization approach (37.71 ± 7.50 bit/min) ($p < 0.0392$). In addition, the spelling speed achieved using dynamic optimization was significantly faster than that obtained using fixed optimization (3.73 s versus 4.89 s, $p < 0.0015$). In terms of the number of practical selections made, the approach used to set the stimulus duration did not significantly affect the results ($p > 0.9955$). Collectively, the results demonstrated that although both optimization approaches for determining the stimulus duration achieved reasonable spelling, the dynamic optimization approach was significantly better than the fixed optimization approach. Therefore, the dynamic optimization approach was selected for our SSVEP speller design.

B. Offline analysis

Fig. 4 presents a comparison of the average classification results achieved using the proposed approaches (CCA-RV and real-time biofeedback) and traditional SSVEP approaches (CCA and without real-time biofeedback). The results indicate that the proposed approaches consistently achieved higher average classification accuracy than the traditional SSVEP approaches. Because offline analysis is typically used to s-elect the optimization approach for online spelling, only the accuracy between the minimum and maximum stimulus times is considered here (see section II-C). Note that the illustrated accuracy is not spelling accuracy but the classification accuracy associated with row and column detections. To make the spelling accuracy higher than 70% and stimulus time shorter than 10 s, an accuracy higher than 83.67% ($\sqrt{0.7}$) and a corresponding time shorter than 5 s were considered for offline analysis. In particular, the accuracies achieved using the CCA-RV and CCA approaches were compared using data collected with and without real-time biofeedback (Fig. 4 (a) and (b)). The shaded areas indicate the significant differences ($p < 0.05$) of classification accuracies between the CCA and CCA-RV approaches. Moreover, the accuracies obtained under the two stimulus conditions (with and without real-time biofeedback) were compared for each of the signal processing approaches (CCA-RV and CCA) (Fig. 4 (c) and (d)). The results demonstrate that the provision of real-time biofeedback yielded higher accuracies. However, there were no significant differences in the accuracies achieved with and without feedback for either classification approach, even

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

TABLE I

ONLINE PERFORMANCE COMPARISON OF THE FIXED AND DYNAMIC OPTIMIZATION APPROACHES. THE RESULTS WERE OBTAINED FROM THE ONLINE SPELLING TESTS USING THE SELECTED OPTIMAL STIMULUS TIME AND THE SSVEP THRESHOLD, RESPECTIVELY. THE PITR (BIT/MIN) INCLUDED THE TIME BREAKS BETWEEN SELECTIONS AND ERROR CORRECTING.

Subject	Task Characters	Fixed Optimization			Dynamic Optimization		
		Stimulus Time (s)	Practical Selections	PITR (bit/min)	Stimulus Time (s)	Practical Selections	PITR (bit/min)
S1	30	8.24	30	30.29	4.41	30	48.36
S2	24	3.92	28	44.91	3.07	32	45.90
S3	24	3.92	32	39.30	3.57	32	41.79
S4	15	4.48	19	35.59	3.86	19	41.79
S5	36	4.72	50	33.24	3.86	56	34.02
S6	27	4.40	31	42.21	3.26	39	40.83
S7	36	6.24	58	23.37	4.56	66	25.81
S8	30	4.88	42	32.20	3.32	46	38.04
S9	39	4.72	45	40.01	3.95	57	35.68
S10	24	3.60	28	47.48	3.32	28	50.02
S11	33	4.72	33	46.16	3.89	35	49.68
AVG	28.91	4.89	36	37.71	3.73	40	41.08
STD	7.01	1.31	11.40	7.50	0.48	14.48	7.43

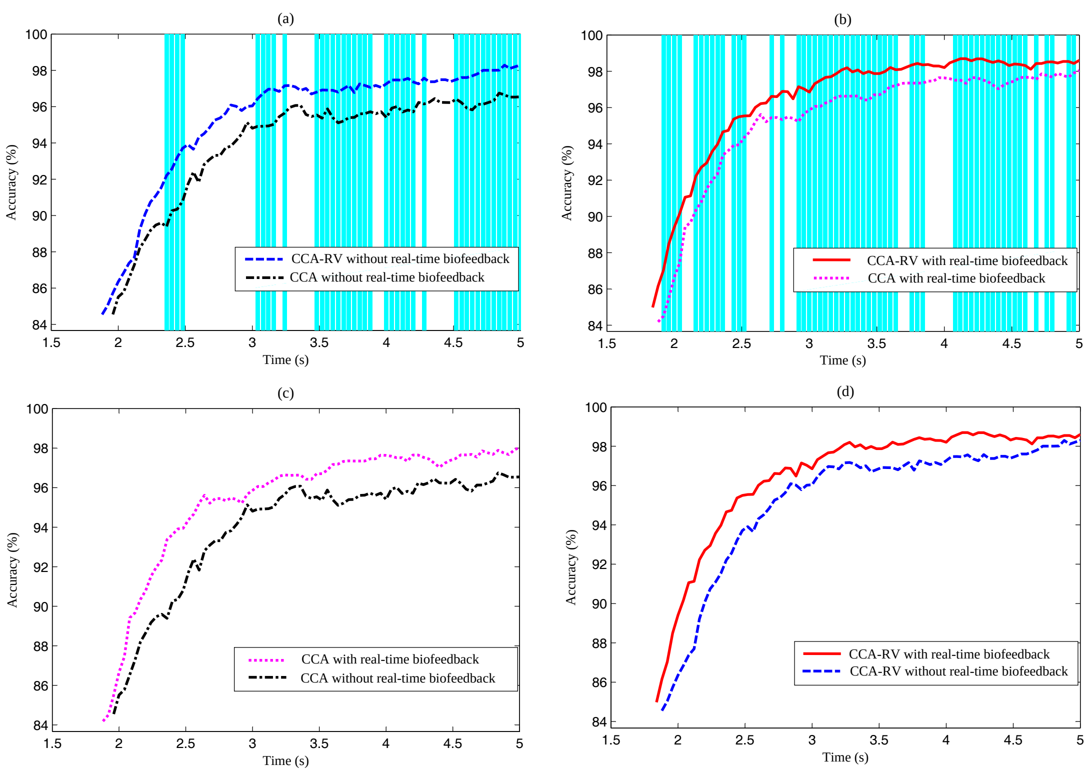


Fig. 4. Average classification accuracy (%) comparisons between CCA and CCA-RV ((a) and (b)) and between with and without real-time biofeedback ((c) and (d)). The shaded areas indicate significant improvement ($p < 0.05$) achieved by the proposed approach.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

though the differences in several parts of the curves appeared more noticeable than the shaded areas in Fig. 4 (a) and (b).

IV. Discussion

A. Explanation for the performance improvement

To understand and explain why the approaches used in the adaptive SSVEP speller design outperformed other approaches, we analyzed the performance improvement in terms of three aspects:

1) Dynamic optimization versus fixed optimization: Because each individual will have different spelling capabilities when using the SSVEP speller, the fixed optimization approach for setting stimulus duration achieves reasonable online spelling performance by setting a simple fixed time for each subject. However, the performance of any one individual varies from one selection to the next during online spelling. Fixing the optimal stimulus time beforehand can hinder the achievable accuracy by either specifying a stimulus time that is too short or impeding communication rates by using a stimulus time that is too long. The dynamic optimization approach allows the SSVEP speller to adjust to the subject's current state by increasing or decreasing the spelling speed, thus reducing the average time required for a selection without significantly increasing the number of misspellings. Therefore, the PITR of the system increases (see Table I).

2) CCA-RV versus CCA: As discussed in section II-B1, SSVEP amplitudes have an inter-frequency variation due to the background noise in the subject's brain; this variation can induce misspellings. To demonstrate the existence of this variation and the superiority of CCA-RV compared with CCA, we performed an offline analyses of the data collected during the calibration runs with real-time biofeedback. Fig. 5 (a) and (b) depict the average and standard deviation (SD) scores of the SSVEP responses associated with targets and non-targets obtained from CCA and CCA-RV, respectively. The obvious decrease in the SD score induced by CCA-RV demonstrates that the inter-frequency variation was significantly decreased, which may explain the accuracy improvement obtained through the use of CCA-RV. Note that both the target and non-target scores obtained by the CCA approach are higher at the beginning of the stimulus interval than those that follow due to the overfitting that occurs within a short time window [38] (see Fig. 5 (a)). However, the target scores obtained by the CCA-RV approach increase smoothly (see Fig. 5 (b)), which may facilitate the threshold setting for the dynamic optimization design. Moreover, due to the reduction of the inter-frequency variation in SSVEP responses, this simple and effective signal processing approach may help expand the available frequencies of SSVEP speller design.

3) With versus without real-time biofeedback: Because the subjects' visual selective attention may move around a visual scene independent of gaze direction [30], [31], the amplitude of a SSVEP response generally decreases when subjects reduce their level of concentration on the center of the SSVEP stimulus. This phenomenon often occurs with traditional SSVEP spellers due to the absence of real-time biofeedback. However, in the proposed paradigm with real-time biofeedback, subjects are more likely to concentrate on the target stimulus when they realize an error has been made, potentially enhancing accuracy. Interestingly, no significant improvement in accuracy as a result of biofeedback was observed, even though a noticeable difference in accuracy obtained by the two conditions was observed (see Fig. 4 (c) and (d)). This surprising result could be explained by the variation in the subject's attention. The real-time biofeedback mechanism may have only been helpful when the reduction in a subject's attention had a significant effect on the SSVEP detection instead of the specific stimulus time, resulting in an inconsistent enhancement due to feedback.

B. Accuracy comparison between row and column detections

Because the target detection of the proposed SSVEP speller consisted of successive row and column detections with no rest period in between the two-step recognition, the column detection (the second step) could have been influenced by the row stimuli (the first step), which would reduce accuracy. To graphically investigate this problem, we performed comparisons of classification accuracy between the row and column detections under different signal processing approaches and visual stimuli situations. As shown by the cyan dashes in Fig. 6, the results only indicate significant differences in accuracy between row and column detections before 1.5 s post-stimulus in all situations. However, only the gray areas are considered for practical spelling (see the minimum and maximum stimulus time selections in section II-C), and significant differences in accuracy were not apparent during these time periods. Overall, the column detection should not be influenced by the row stimulus during practical spelling.

C. Future directions

Recent work has introduced a new framework for BCI research called the hybrid BCI, in which multiple BCI approaches are combined [39]–[42]. Such systems provide new directions for enhancing BCI performance. Our principal objective was to design a dynamically optimized SSVEP speller for BCI spelling. The system performance remains unexplored, which could be facilitated by a hybrid BCI approach. Future directions for further enhancing the performance of the proposed SSVEP speller are discussed below:

First, because the target detection of our approach directly depends on both the row and column detections, a mistake in one of these two detections will lead to misspelling. To achieve more robust performance, future work could incorporate error-related potentials (ErrPs) into the proposed SSVEP speller to enhance the spelling accuracy. Here, ErrPs are a certain type of ERP that are present in the EEG signals when the user is aware of erroneous behavior [43], [44]. We could record the ErrPs response from the moment the speller finishes the row or column detections and superimpose them onto the SSVEP responses to reduce the misspelling, thus building a SSVEP-ErrPs-based hybrid BCI system to increase the spelling accuracy.

Second, the spelling accuracy is somewhat improved by real-time biofeedback, whereas target detection is only dependent on the SSVEP response. The proposed SSVEP speller is a

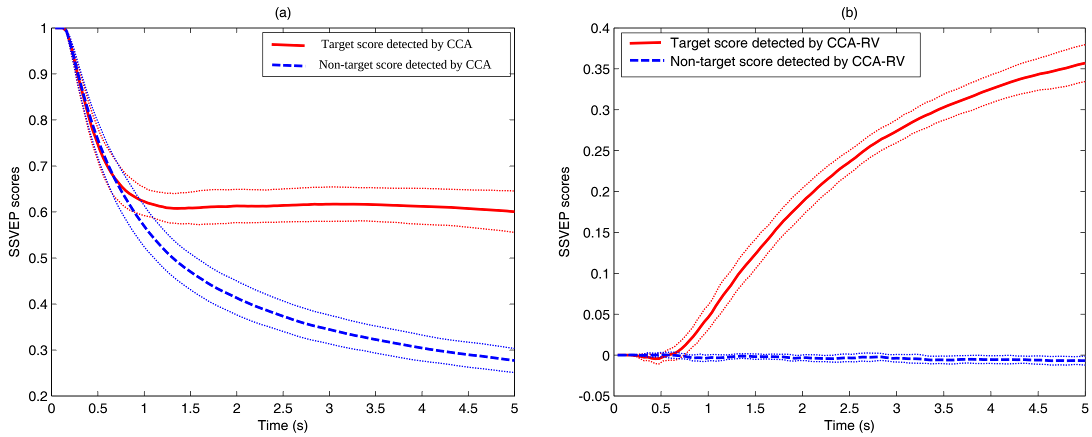


Fig. 5. The target and non-target scores of SSVEP responses calculated by CCA (a) and CCA-RV (b). The dashed lines represent the standard deviation (SD) of the scores among different frequencies.

closed-loop BCI system, and the subjects also could use their active brain information. For instance, we could incorporate the SMR induced by a motor imagery (MI) task into the SSVEP speller to enhance the spelling speed. In particular, we could employ the left and right MI tasks as 'speed up' and 'slow down' commands, respectively. The subjects could implement the 'speed up' command for a certain MI task if they find that the target character changes color and vice versa. Therefore, we could build a SSVEP-SMR-based hybrid BCI system for variable-speed spelling.

V. Conclusion

In this paper, we propose a dynamically optimized SSVEP speller with real-time biofeedback. In this approach, the RC paradigm was first introduced into an SSVEP speller to increase the number of items. An SSVEP speller with 36 items was established using only six frequencies. To our knowledge, the proposed SSVEP speller is the only monitor-based SSVEP speller whose number of items reaches 36. In addition, we proposed a CCA-RV signal processing method and a real-time biofeedback mechanism to enhance the spelling accuracy. To achieve reasonable online performance, we designed two optimization approaches for selecting stimulus duration, and the dynamic optimization approach was employed for the adaptive SSVEP speller design. Experimental results with eleven subjects suggest that the proposed SSVEP speller can provide improved performance compared to traditional BCI approaches. More specifically, the CCA-RV method outperformed the CCA method by decreasing the inter-frequency variation of the SSVEP response, and the real-time feedback also increased spelling accuracy by reducing visual selective attention out of the center of target stimuli. Both the fixed and dynamic optimization approaches for setting stimulus duration achieved reasonable spelling rates, and the dynamic optimization approach yielded a higher PITR than the fixed optimization approach. The online average PITR achieved by the proposed SSVEP speller, including the time for breaks between selections and for error correcting, was 41.08 bit/min.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, 2002.

[2] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: a review of the first international meeting," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 2, pp. 164–173, 2000.

[3] H. Cecotti, "Spelling with non-invasive brain-computer interfaces-current and future trends," *J. Physiol. - Paris*, vol. 105, pp. 106–114, 2011.

[4] K. R. Müller, M. Tangermann, G. Dornhege, M. Krauledat, G. Curio, and B. Blankertz, "Machine learning for real-time single-trial EEG-analysis: from brain-computer interfacing to mental state monitoring," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 82–90, 2008.

[5] J. N. Mak, Y. Arbel, J. W. Minett, L. M. McCane, B. Yuksel, D. Ryan, D. Thompson, L. Bianchi, and D. Erdogmus, "Optimizing the p300-based brain-computer interface: current status, limitations and future directions," *J. Neural Eng.*, vol. 8, p. 025003, 2011.

[6] X. Gao, D. Xu, M. Cheng, and S. Gao, "A BCI-based environmental controller for the motion-disabled," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 11, no. 2, pp. 137–140, 2003.

[7] F. B. Vialatte, M. Maurice, J. Dauwels, and A. Cichocki, "Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives," *Prog. Neurobiol.*, vol. 90, pp. 418–438, 2010.

[8] K. Shyu, Y. Chiu, P. Lee, J. Liang, and S. Peng, "Adaptive SSVEP-based BCI system with frequency and pulse duty-cycle stimuli tuning design," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 5, pp. 697–703, 2013.

[9] Y. Kimura, T. Tanaka, H. Higashi, and N. Morikawa, "SSVEP-based brain-computer interfaces using FSK-modulated visual stimuli," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 10, pp. 2831–2838, 2013.

[10] Y. Zhang, P. Xu, T. Liu, J. Hu, R. Zhang, and D. Yao, "Multiple frequencies sequential coding for SSVEP-based brain-computer interface," *PLoS One*, vol. 7, no. 3, p. e29519, 2012.

[11] H. Hwang, D. Han, and C. Im, "A new dual-requency stimulation method to increase the number of visual stimuli for multi-class SSVEP-based brain-computer interface (BCI)," *Brain Research*, vol. 1515, pp. 66–77, 2013.

[12] X. Chen, Z. Chen, S. Gao, and X. Gao, "Brain-computer interface based on intermodulation frequency," *J. Neural Eng.*, vol. 10, p. 066009, 2013.

[13] C. Jia, X. Gao, B. Hong, S. Gao, "Frequency and phase mixed coding in SSVEP-based brain-computer interface," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 1, pp. 200–206, 2011.

[14] Z. Lin, C. Zhang, W. Wu, and X. Gao, "Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 6, pp. 1172–1176, 2007.

[15] O. Friman, I. Volosyak, and A. Graser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 4, pp. 742–750, 2007.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

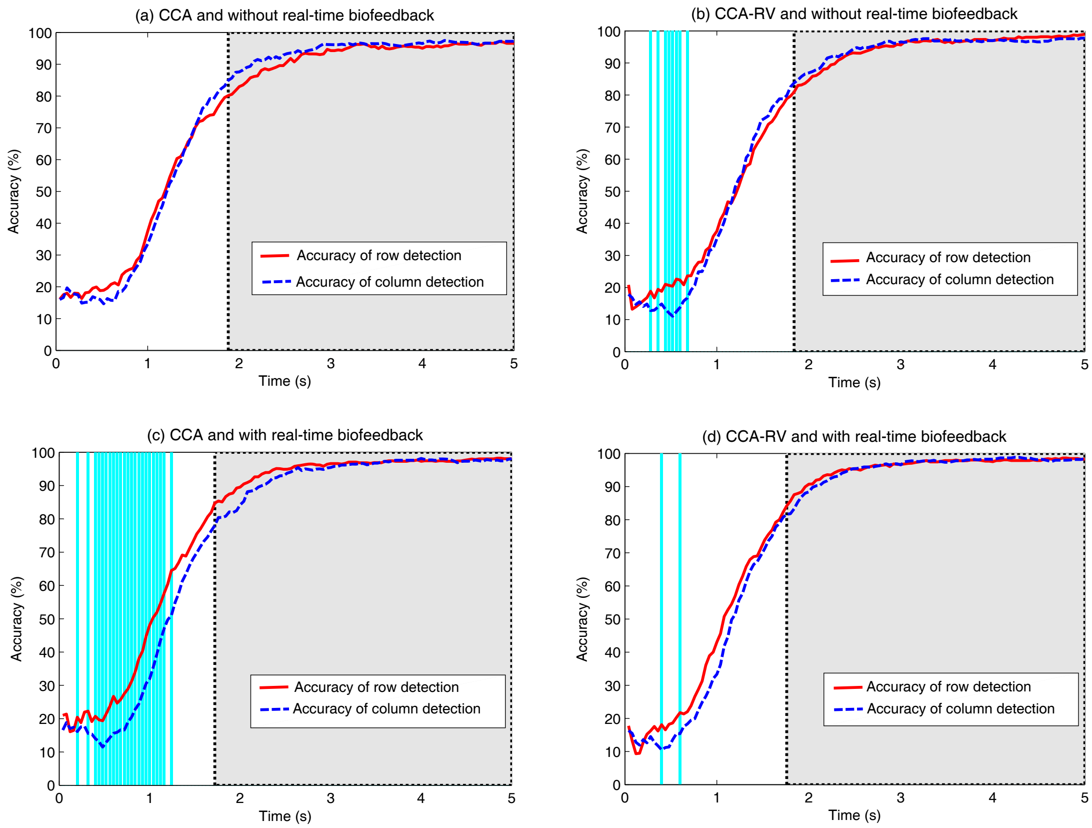


Fig. 6. Average classification accuracy (%) comparisons between row and column detections under different signal processing approaches and visual stimuli situations. The cyan shaded areas indicate significant differences ($p < 0.05$) between the accuracy of the row and column detections, and the gray areas (surrounded by the single-dashed line) represent the periods considered for practical spelling.

[16] M. Cheng, X. Gao, S. Gao, and D. Xu, "Design and implementation of a brain-computer interface with high transfer rates," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 10, pp. 1181–1186, 2002.

[17] G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," *J. Neural Eng.*, vol. 6, p. 046002, 2009.

[18] Y. Zhang, G. Zhou, J. Jing, M. Wang, X. Wang, and A. Cichocki, "L1-regularized multiway canonical correlation analysis for SSVEP-based BCI," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 6, pp. 887–896, 2013.

[19] R. Kus, A. Duszyk, P. Milanowski, M. Labecki, M. Bierzynska, Z. Radzikowska, M. Michalska, J. Zygierewicz, P. Suffczynski, and P. J. Durka, "On the quantification of SSVEP frequency responses in human EEG in realistic BCI conditions," *PLoS ONE*, vol. 8, p. e77536, 2013.

[20] J. Fernandez-Vargas, H. U. Pfaff, F. B. Rodriguesz, and P Varona, "Assisted closed-loop optimization of SSVEP-BCI efficiency," *Front. Neural Circuits*, vol. 7, p. 27, 2013.

[21] I. Volosyak, "SSVEP-based bremen-BCI interface-boosting information transfer rates," *J. Neural Eng.*, vol. 8, p. 036020, 2011.

[22] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials electroencephalogr," *Clin. Neurophysiol.*, vol. 70, no. 6, pp. 510–523, 1988.

[23] E. Donchin, K. M. Spencer, and R. Wijesinghe, "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," *IEEE Trans Rehabil. Eng.*, vol. 8, no. 2, pp. 174–179, 2000.

[24] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "Toward enhanced P300 speller performance," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 15–21, 2008.

[25] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, and D. Hu, "A novel hybrid BCI speller based on the incorporation of SSVEP into the P300 paradigm," *J. Neural Eng.*, vol. 10, p. 026012, 2013.

[26] E. Yin, Z. Zhou, J. Jiang, F. Chen, Y. Liu, and D. Hu, "A speedy hybrid BCI spelling approach combing P300 and SSVEP," *IEEE Trans. Biomed. Eng.*, vol. 61, no. 2, pp. 473–483, 2014.

[27] M. A. Pastor, J. Artieda, J. Arbizu, M. Valencia, and J. C. Masdeu, "Human cerebral activation during steady-state visual-evoked responses," *J. Neurosci.*, vol. 23, no. 37, pp. 11621–11637, 2003.

[28] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao, "Apractical VEP-based brain-computer interface," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 234–239, 2003.

[29] W. J. Krzanowski, "*Principles of Multivariate Analysis: A User's Perspective.*" *New York: Oxford University Press*, 1988.

[30] S. Kelly, E. Lalor, C. Finucane, G. McDarby, and R. Reilly, "Visual spatial attention control in an independent brain-computer interface," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 9, pp. 1588–1596, 2005.

[31] S. Kelly, E. Lalor, C. Finucane, R. Reilly, and J. Foxe, "Visual spatial attention tracking using high-density SSVEP data for independent brain-computer communication," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 2, pp. 172–178, 2005.

[32] B. D. Seno, M. Matteucci, and L. T. Mainardi, "The utility metric: a novel method to assess the overall performance of discrete brain-computer interfaces," *IEEE Trans. Rehabil. Eng.*, vol. 18, no. 1, pp. 20–28, 2010.

[33] P. Yuan, X. Gao, B. Allison, Y. Wang, G. Bin, and S. Gao, "A study of the existing problems of estimating the information transfer rate in online brain-computer interfaces," *J. Neural Eng.*, vol. 10, p. 026014, 2013.

[34] G. Townsend, B. K. LaPallo, C. B. Boulay, D. J. Krusienski, G. E. Frye, C. K. Hauser, N. E. Schwartz, T. M. Vaughan, J. R. Wolpaw, and E. W. Sellers, "A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns," *Clin. Neurophysiol.*, vol. 121, no. 7, pp. 1109–1120, 2010.

[35] G. Pires, U. Nunes, and M. Castelo-Branco, "Comparison of a row-column speller vs. a novel lateral single-character speller: Assessment of BCI for severe motor disabled patients," *Clin. Neurophysiol.*, vol. 123, no. 6, pp. 1168–1181, 2012.

[36] Y. Liu, Z. Zhou, and D. Hu, "Gaze independent brain-computer speller with covert visual search tasks," *Clin. Neurophysiol.*, vol. 122, no. 7, pp. 1127–1136, 2011.

[37] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1034–1043, 2004.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2014.2320948, IEEE Transactions on Biomedical Engineering

[38] J. Pan, X. Gao, F. Duan, Z. Yan, and S. Gao, "Enhancing the classification accuracy of steady-state visual evoked potential-based brain-computer interfaces using phase constrained canonical correlation analysis," *J. Neural Eng.*, vol. 8, p. 036027, 2011.

[39] G. Pfurtscheller, B. Z. Allison, C. Brunner, G. Bauernfeind, T. Solis-Escalante, R. Scherer, T. O. Zander, G. Müller-Putz, C. Neuper, and N. Birbaumer, "The hybrid BCI," *Front. Neurosci*, vol. 4, no. 30, p. 00003, 2010.

[40] B. Z. Allison, C. Brunner, V. Kaiser, G. R. Müller-Putz, C. Neuper, and G. Pfurtscheller, "Toward a hybrid brain-computer interface based on imagined movement and visual attention," *J. Neural Eng.*, vol. 7, p. 026007, 2010.

[41] J. Long, Y. Li, T. Yu, and Z. Gu, "Target selection with hybrid feature for BCI-based 2-D cursor control," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 1, pp. 132–140, 2012.

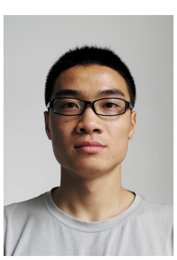
[42] Y. Li, J. Pan, F. Wang, and Z. Yu, "A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 11, pp. 3156–3166, 2013.

[43] T. Zeyl, and T. Chau, "A case study of linear classifiers adapted using imperfect labels derived from human event-related potentials," *Pattern. Recogn. Lett.*, vol. 37, pp. 54–62, 2014.

[44] N. M. Schmidt, B. Blankertz, and M. Treder, "Online detection of error-related potentials boosts the performance of mental typewriters," *BMC Nerosci.*, vol. 13, p. 19, 2012.

Erwei Yin was born in Heilongjiang, China, in 1985. He received the B.Sc. from Jilin University and M.Sc. degrees from the National University of Defense Technology, China, in 2008 and 2010, respectively. He is currently working toward the doctoral degree in the National University of Defense Technology. His research interests include brain computer interfaces and machine learning.

Zongtan Zhou was born in Henan, China,in 1969. He received the B.Sc., M.Sc. and Ph.D. degrees from National University of Defense Technology, China, in 1990, 1994 and 1998, respectively. He was promoted Professor in 2007. His research interests include brain-computer interface, cognitive neuroscience, image/signal processing, computer/biologicalvision and neural networks.



Jun Jiang was born in Zhejiang , China, in 1987. he reveived the B.Sc and M.Sc degrees from National University of Defense Technology, China, in 2009 and 2011, respectively. He is currently working toward the doctoral degree in the National University of Defense Technology. His research interests include brain computer interfaces and machine learning.

Yang Yu was born in Liaoning, China, in 1987. He received the B.Sc degree from Tianjin University, Tianjin, China, in 2010, and the M.Sc degree from the National University of Defense Technology, Changsha, China, in 2012, where he is currently working towards the PH.D degree. His research interests include brain-computer interface, machine learning, and neuroimage.

Dewen Hu was born in Hunan, China, in 1963. He received the B.Sc. and M.Sc. degrees from Xi'an Jiaotong University, China, in 1983 and 1986, respectively. From 1986, he was with the National University of Defense Technology. From October 1995 to October 1996, he was a Visiting Scholar with the University of Sheffield, UK. He got his Ph.D degree from the National University of Defense Technology in 1999. He was promoted Professor in 1996. His research interests include cognitive science, brain-computer interface, image processing and neural networks. He is an action editor of Neural Networks.