SSVEP-Based Brain-Computer Interface With a Limited Number of Frequencies Based on Dual-Frequency Biased Coding

Sheng Ge, *Member, IEEE*, Yichuan Jiang, Mingming Zhang, *Senior Member, IEEE*, Ruimin Wang, Keiji Iramina, Pan Lin, Yue Leng, Haixian Wang, *Senior Member, IEEE*, and Wenming Zheng, *Member, IEEE*

***Abstract*— How to encode as many targets as possible with a limited-frequency resource is a difficult problem in the practical use of a steady-state visual evoked potential (SSVEP) based brain-computer interface (BCI) speller. To solve this problem, this study developed a novel method called dual-frequency biased coding (DFBC) to tag targets in a SSVEP-based 48-character virtual speller, in which each target is encoded with a permutation sequence consisting of two permuted flickering periods that flash at different frequencies. The proposed paradigm was validated by 11 participants in an offline experiment and 7 participants in an online experiment. Three occipital channels (O1, Oz, and O2) were used to obtain the SSVEP signals for identifying the targets. Based on the coding characteristics of the DFBC method, the proposed approach has the ability of self-correction and thus achieves an accuracy of 76.6% and 79.3% for offline and online experiments, respectively, which outperforms the traditional multiple frequencies sequential coding (MFSC) method. This study demonstrates that DFBC is an efficient method for coding a high number of SSVEP targets with a small number of available frequencies.**

***Index Terms*— Brain-computer interface, steady-state visual evoked potential, EEG, speller.**

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Sheng Ge, Yue Leng, Haixian Wang, and Wenming Zheng are with the Key Laboratory of Child Development and Learning Science, School of Biological Science and Medical Engineering, Ministry of Education, Southeast University, Nanjing 210096, China (e-mail: wenming_zheng@seu.edu.cn).

Yichuan Jiang is with the Key Laboratory of Child Development and Learning Science, School of Biological Science and Medical Engineering, Ministry of Education, Southeast University, Nanjing 210096, China, and also with the Department of Biomedical Engineering, Southern University of Science and Technology, Shenzhen 518055, China.

Mingming Zhang is with the Department of Biomedical Engineering, Southern University of Science and Technology, Shenzhen 518055, China.

Ruimin Wang is with the Research Center for Brain Communication, Kochi University of Technology, Kami 782-8502, Japan.

Keiji Iramina is with the Graduate School of Systems Life Sciences, Kyushu University, Fukuoka 819-0395, Japan.

Pan Lin is with the Cognition and Human Behavior Key Laboratory of Hunan Province, Department of Psychology, Hunan Normal University, Changsha 410081, China (e-mail: linpan@hunnu.edu.cn).

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I. INTRODUCTION

BRAIN-computer interfaces (BCIs) provide a direct communication pathway between the brain and the external environment by translating the brain activity patterns of a user into commands for an interactive application [1]. BCIs are used in a wide range of areas such as wheelchair operation [2], [3], text spelling [4], [5], robotic device control [6], [7], unmanned aerial vehicle remote control [8], and game play [9]. Among them, the BCI aided spelling application allows the user to select the desired characters and feeds them back on a screen or other output device; this intuitive and easy-to-use approach allows end-users to be more independent and rebuild their social lives to a considerable extent [5], [10], [11].

The vast majority of BCI spelling systems use the electroencephalograph (EEG) approach, which includes P300, motor imagery, and steady-state visual evoked potential (SSVEP) [5], [12]. SSVEPs are brain electrical signals evoked by visual stimuli that flash at specific frequencies. This neural response consists of oscillatory activity of the base frequency and harmonics of the visual stimulus and is mainly concentrated in the visual cortex, which is located in the occipital region of the brain [13]. Tagging visual stimuli by different frequencies, phases, temporal or spatial patterns of visual flicker and classifying the respective features from SSVEPs enables a BCI system to identify the command selected by the user. SSVEP is widely used in BCI spelling because of its advantages of ease of use, little or no required training, multi-command output, and high signal-to-noise ratio (SNR) together with a high information transmission rate (ITR) [14], [15].

The coding method plays an important role in SSVEP-based BCI system design and implementation. An efficient target encoding method can improve the visual evoked potentials and the SNR, thereby increasing the discriminability of different targets. Traditional SSVEP-based BCI spelling system coding methods can be categorized as frequency-division multiple access (FDMA), time-division multiple access (TDMA), space-division multiple access (SDMA), code-division multiple access (CDMA), and hybrid multiple access (HMA) methods [16], [17].

FDMA is the most intuitive coding method for SSVEP studies, in which each target is flashed at a different frequency, generating periodic evoked responses with the same fundamental frequency and harmonics as the flickered stimulus. Chen *et al.* proposed a high-ITR 45-target BCI speller with a narrow frequency band range from 7.0 to 15.8 Hz using the FDMA method [12]. However, since only the 4-50 Hz bandwidth has an amplitude and SNR of SSVEP that are large enough to be distinguished [18], [19]. In addition, a sufficiently large frequency interval between SSVEP frequencies is required to ensure better classification accuracy [20]. Because of these constraints, the frequency resources available for FDMA method are limited.

In the TDMA coding method, the flash sequences of different targets are independent. In Lin *et al.*'s study [21], the temporal information was used to encode the SSVEP stimuli. Half of the stimuli flashed first and stopped first, whereas the remaining half of the stimuli flashed after a predefined delay period and stopped later. Such time-frequency joint coding method performs significantly better than the traditional FDMA method. However, because TDMA uses the same frequency coding strategy as FDMA (see [12] and [21]), TDMA has same frequency resource scarcity problem that FDMA has.

In SDMA, targets appear at different locations in the visual field. Yan *et al.* suggested that spatial information could be used as an alternative coding approach. In their study, each target was composed of two flickers flashed at different frequencies, which were placed on the right and left visual fields [22]. This arrangement ensured that the bilateral flicker stimuli could be projected onto the contralateral visual regions and generate visual evoked potentials. By combining spatial and frequency information, this coding method can increase the number of coding targets. Another study found that visual stimuli at different spatial locations induced distinct differences in SSVEP power topography [23]. Such kinds of SDMA-coded BCI systems have stringent restrictions on stimulus size, spacing, and number as well as the relative position between stimuli and is therefore not commonly used in BCI system design.

In CDMA, each target has its own codeword consisting of binary digits. Kimura *et al.* proposed a new approach, in which ten targets were translated into different codewords that correspond to flickering patterns with distinct frequencies [24]. Similarly, in Shyu *et al.*'s study, they encoded six targets using a permutation of four frequencies [25]. However, because it is limited by the number of codewords, this method is not suitable for a speller system with a large number of targets.

The HMA method is a hybrid of multiple accesses and has been recently used to improve system performance. For instance, to overcome the frequency resource constraints faced by the traditional FDMA approach, Chen *et al.* [4] added phase information into FDMA and proposed the joint frequency-phase modulation (JFPM) method to achieve 40-target classification within a flicker duration of 0.5 s, which considerably improved the ITR of the system (from 2.52 bps in the same group's early study [26] to 4.45 bps). However, the phase information needs to be obtained from the individual calibration collected for training canonical correlation analysis (CCA) based spatial filters, so the JFPM method has limitations in practical applications. Yin *et al.* subsequently introduced the row/column approach to encode rows and columns with traditional FDMA. Thus, the target could be detected by determining the row and column coordinates [27]. Essentially, this row/column coding method is a hybrid coding approach that combines SDMA and FDMA. A space-frequency hybrid coding method was introduced to generate binocular visual stimulation [28], i.e., each of the eyes was individually stimulated by stimuli with identical flickering frequencies but different phases. However, this method needs a specially designed binocular head mounted display, which may limit its range of application. A multi-phase cycle hybrid coding method was proposed by Tong and Zhu [29] in which each target was coded by multi-phase codewords and a specific flickering frequency. Similarly, a novel HMA method was proposed by Zhao *et al.* [30] in which multi-bit temporal codewords were linearly combined with three frequencies to generate trinary frequency shift keying modulated SSVEP stimuli. However, these two methods need a relatively long coding cycle for coding a large number of targets. Recently, Tang *et al.* combined a spatial pattern coding method and FDMA to form a novel hybrid coding method in which each target is composed of five fan-shaped flickers in a circle, while each flicker is modulated by different frequencies [31]. Simultaneously, a 5-bit binary code was implemented by turning each flicker on or off. However, an additional training process was needed for calibrating the classifier of each target. Liang *et al.*, [32] proposed a novel dual-frequency and phase modulation method, in which each SSVEP stimulus was presented in the form of a checkerboard that consists of small squares flicking at different frequencies and phases. In the study by Yan *et al.*, the authors proposed a light-flashing and motion hybrid coding method, where the stimulus consisted of a circular light-flashing pattern and a rotational motion pattern; both patterns were modulated with different frequencies [33]. Compared with the traditional FDMA method of using one frequency for a target, these two methods can reduce the number of frequencies to a certain extent; they still need to use a large number of frequencies. Moreover, the number of spatial filters is not reduced. Some studies have also proposed using the multiple frequencies sequential coding (MFSC) method, in which each target is coded by the permutation of several frequencies from an available frequency set. Each cycle of the target presentation is divided into several epochs, and during each epoch, the SSVEP stimuli flicker at a certain frequency; the different permutations of frequencies in the epochs will lead to different encodings for multiple targets [25], [34]. By adding the time factor and using the permutations of frequencies in the coding scheme, MFSC can code many more targets with limited frequency resources than can the traditional FDMA method. For this reason, fewer spatial filters are needed. Conversely, MFSC increases the duration of the SSVEP stimuli presentation cycle, which may decrease the ITR of a BCI system. In addition, the target recognition needs to recognize the flickering frequency in each epoch, so the final accuracy is a concatenation of the accuracies of all the individual epochs, which may increase the system error. In general, the above studies have shown that the HMA method performs better than a single mode for multiple access.

Despite the existence of various HMA studies, little research has been reported on hybrid coding methods combining frequency information and time information. Therefore, in this study, we propose a dual-frequency biased coding (DFBC) method to extend the traditional MFSC method, in which each cycle of the target presentation is divided into two biased flickering periods, and each period flashes at different frequencies. The different permutations of the temporal arrangement of periods and the frequencies in each period correspond to different codewords for multiple targets. This coding strategy will have better coding efficiency and fault tolerance than traditional MFSC methods.

II. Materials and Methods

A. Participants

In this study, 11 participants (mean age $= 22.0 \pm 1.5$ years) voluntarily participated in the offline experiment. Then the online experiments were carried out separately with a three month interval. Since four of the 11 participants who participated in the offline experiment were not available, the remaining 7 participants (mean age $= 21.5 \pm 1.3$ years) participated in the online experiments. All participants had normal or corrected-to-normal vision and were confirmed to be right handed using the Edinburgh Handedness Inventory. They were free of any neurological or ophthalmological disorders. All the participants had no previous experience of BCI experiments and did not receive any pretraining before the experiment in order to simulate an actual BCI application to the greatest extent. All the participants had been informed about and consented to the experimental contexts. All participants provided written informed consent in accordance with the Declaration of Helsinki [35] before the experiment, which was approved by the Ethics Committee of Affiliated Zhongda Hospital, Southeast University (2016ZDSYLL002.0 and 2016ZDSYLL002-Y01). Each participant received 200 RMB for participating after the experiment.

B. EEG Recording and Preprocessing

EEG data were collected with the EGI 400 Geodesic EEG System (GES 400, EGI Inc., USA), using a whole head 32-channel HydroCel Geodesic Sensor Net referenced to Cz (fixed by the EGI system) according to the international 10-20 system at a sampling frequency of 1,000 Hz. The Netstation^{TM} software package (EGI) were used for data recording and the impedances of all the channels were kept below 50 kΩ [36]. In this study, to simplify the BCI system as much as possible, only three electrodes over the occipital region (O1, Oz, and O2) were used as input signals. The EEG data were first band-passed filtered with a 6-36 Hz IIR filter using the $cheb1ord$ function in MATLAB R2017b (Mathworks, USA). Next, zero-phase digital filtering was performed using MATLAB's $filtfilt$ function.

To account for the latency delay in the visual evoked potentials [37], similar to the study by Chen *et al.* [4], we extracted the lagging data segments 130-2,130 ms (0-2,000 ms corresponds the SSVEP stimuli presentation stage) as the SSVEP response to process.

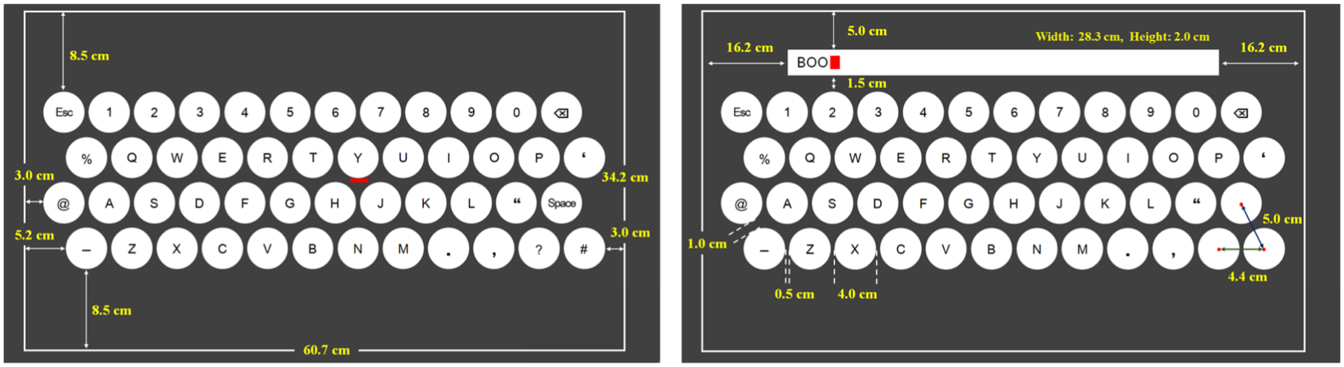
C. System Configuration

The experiment was carried out in a normal room without electromagnetic shielding. SSVEP stimuli were presented on a 27-inch LED screen (Dell S2719DGF) with a resolution of $2,560 \times 1,440$ pixels and a refresh rate of 144 Hz. Each participant was seated in a comfortable chair that was 60.0 cm away from the display (H: 60.7 cm, 53.7° in visual angle; V: 34.2 cm, 31.8° in visual angle). The horizontal line of sight of the participants fell in the center of the keyboard.

For this study, a 48-target BCI virtual speller graphical user interface (GUI, 48-character keyboard) using the proposed DFBC approach (Fig.1.a) was designed. As shown in Fig.1.a, the GUI is a 4×12 matrix containing 48 characters in a QWERTY layout, including 26 letters of the English alphabet, 10 digits, and 12 other symbols (i.e., space, comma, period, backspace, escape, at sign, pound sign, percent sign, hyphen, apostrophe, question mark, and quotation mark). In this study, a circular stimulus was used instead of the traditional square stimulus to maximize the spacing between stimuli, thus reducing the influence of adjacent stimuli. The diameter of the circular stimulus was 4.0 cm (3.8°) and the distance between horizontal adjacent stimuli was set as 0.5 cm (0.5°). To increase the distance between adjacent stimuli as much as possible in a limited space, in this study, we used a staggered layout instead of the traditional aligned layout. The staggered layout has distances of 4.4 cm (4.2°) and 5.0 cm (4.8°) between the horizontal and vertical adjacent stimuli, respectively. Fig. 1.a and Fig. 1.b show screenshots of the GUIs for the offline and online experiments, respectively. The virtual keyboard was set in the center of screen. All the settings of the offline and online experiments were the same except for the following: there was a text box (H: 2.0 cm, 1.9° in visual angle; V: 28.3 cm, 26.5° in visual angle) above the virtual keyboard in the online GUI to display the characters that the participant selected.

D. Offline Experiment Design

To verify the performance of the proposed DFBC method, we performed a contrastive study of the DFBC and MFSC [34] coding strategy. Each trial started with a 1 s cue stage, during which a small red square was presented below one SSVEP stimulus to indicate the next target stimulus. Participants were instructed to shift their gaze to the indicated target stimulus and prepare for the forthcoming presentation stage. The SSVEP stimuli presentation stage lasted 2 s, during which participants kept their gaze on the target stimulus. The presentation stage was followed by a 1 s resting stage, in which participants remained in a relaxed state. The whole



(a) (b)

Fig. 1. GUI of the proposed SSVEP-based speller system for the (a) offline experiment, and (b) online experiment, respectively.

experiment consisted of a total of 480 trials and was divided into five sessions, each of which consisted of 96 trials. During each session, each character of the 48-character keyboard was displayed as the target and coded once using MFSC and once using DFBC, where the encoding order was randomly balanced across these two conditions. There was a 90 s break between sessions. All the attributes of the SSVEP stimuli corresponding to these two conditions were equal, including the layout, number, position, and color of the characters; duration and procedure of stimulus presentation; and the number of the trials for each condition. The only difference in the two conditions is the coding strategy of the SSVEP stimuli.

E. Online Experiment Design

Each trial of the online experiment started with a 3 s cue, in which the target word that the participants needed to spell in the current trial was displayed on the center of a black screen. Next, a spelling stage followed, during which the GUI was displayed and the participant was instructed to spell the target word character by character. The participant selected each character during one 3 s stimulus phase. This phase began with a short beep, and the virtual keyboard did not flash. Then, after a 1 s interval, the keyboard flickered for 2 s. The participant was instructed to gaze at the target character during this 2 s. At the end of each stimulus phase, the correctly detected character or a red box indicating an error was displayed in the text box for 1 s. The participant was asked to re-enter the erroneously entered character until the whole word was correctly spelled. Twenty common four-letter words were used as the target words in the online experiment. Each word was detected using DFBC or MFSC once, presented in random order.

F. Stimulus Design

Figure 2 shows the coding principle of the proposed DFBC method. For one target to be coded, There are M ($M \geq 4$) coding epochs in one coding cycle, which are divided into short and long flickering periods. The short flickering period (SP) occupies one epoch and the long flickering period (LP) occupies the remaining $M - 1$ epochs. Because the SP can occur anywhere in the M epochs, the LP can be a continuous time segment or two time segments separated by the SP. In one coding cycle, there are two different frequencies selected from the available frequency set, which contains $N(N \geq 2)$ frequencies $\{f_1, f_2, \ldots, f_N\}$, and these two frequencies will be assigned to the SP and LP, respectively. Thus, as shown in Fig. 2, the number of words that can be coded is calculated as $C = C_N^2 \times 2 \times M$, where C_N^2 is the number of combinations of two different frequencies selected from N frequencies. Two frequencies could be assigned to the SP and LP with two combinations, while the number of permutations for the temporal placement of the SP and LP equals M.

In the current study, we adopted four epochs ($M = 4$) in one coding cycle while the available frequency set consisted of four frequencies ($N = 4$), and each target is coded by two frequencies from the available frequency set. As shown in Fig. 3, every two frequencies can generate eight permutations as codewords. Figure 3 indicates that target can be coded by both the temporal pattern composed of short and long flickering periods (e.g., Target 1 by f_i-f_j-f_j-f_j and Target 2 by f_j-f_i-f_j-f_j), and the frequency allocation scheme for short and long flickering periods (e.g., Target 1 by f_i-f_j-f_j-f_j and Target 5 by f_j-f_i-f_i-f_i). In the current study, we set $M = 4$ and $N = 4$, therefore, $C = C_N^2 \times 2 \times M = C_4^2 \times 2 \times 4 = 48$ targets can be coded, which meets the number of coding targets required by the virtual keyboard in this study. The coding scheme based on the DFBC method with four epochs and four frequencies for 48-character keyboard is shown in Fig.4.a.

Previous studies have shown that both the SSVEP amplitude and SNR have a global peak around 13-15 Hz [18], [38]. Therefore, we used four frequencies, i.e., 10, 12, 14 and 16 Hz in the low frequency band, as the available frequency set in the current study.

Because the DFBC method is an extension of the traditional MFSC method, to evaluate the performance of the DFBC, we compared its classification accuracy with that of the traditional MFSC in this study. The details of the recognition algorithm used by MFSC can be found in Zhang *et al.*'s study [34]. According to Zhang *et al.*, MFSC can code N^M targets, where, the definition of M and N are the same in our

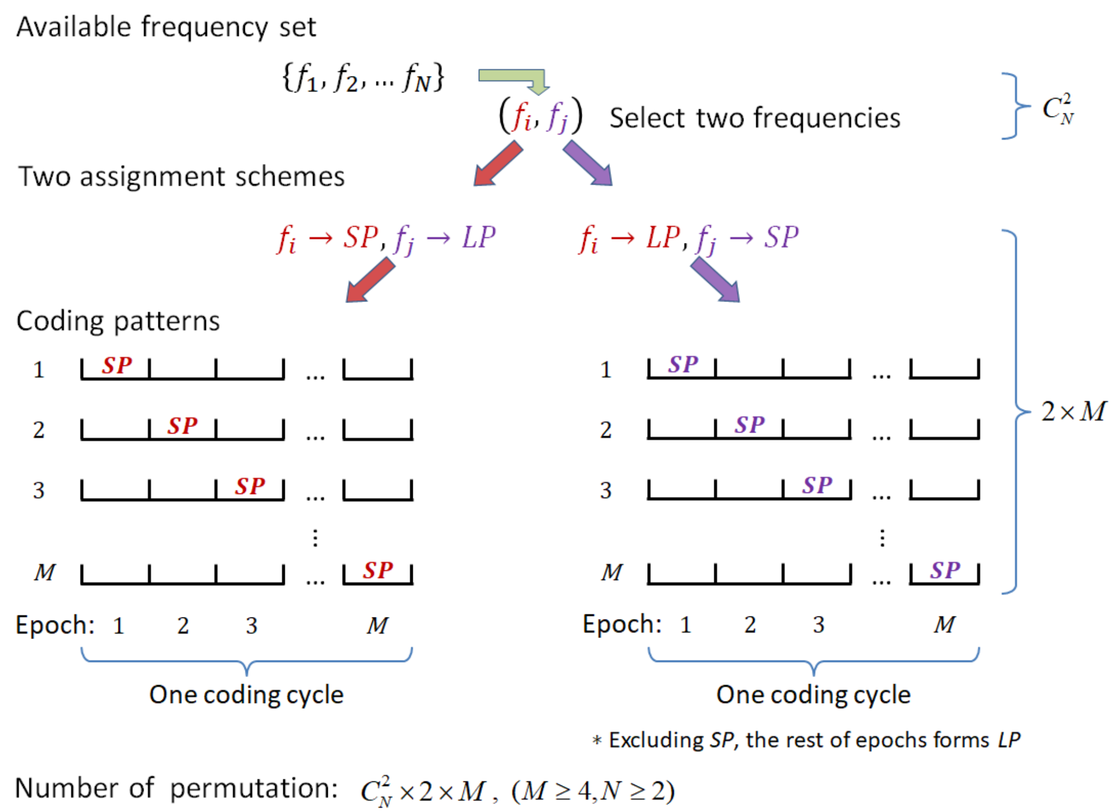


Fig. 2. Coding principle of the DFBC method. One coding cycle is divided into M epochs. Two different frequencies are selected from the available frequency set and assigned to *SP* and *LP*, respectively. The number of permutations for the temporal distribution of *SP* and *LP* equal M. Thus, the number that can be coded is $C_N^2 \times 2 \times M$.

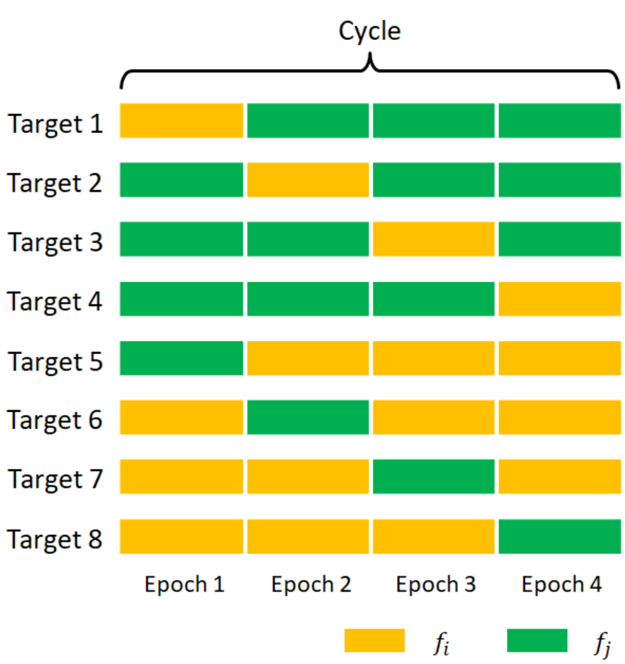


Fig. 3. Coding scheme of DFBC when there are four epochs in one coding cycle. In each coding cycle, the yellow bar indicates the flickering period with the first frequency (f_i), the blue bar indicates the flickering period (*LP*) with the second frequency (f_j). Two frequencies f_i and f_j can encode eight targets using different frequency-temporal patterns generated by the *SP* and *LP*.

study. In this study, MFSC uses the same available frequency set as DFBC, i.e., $N = 4$ to provide enough coding targets for a 48-target BCI speller. In addition, M is set as three for MFSC method. The coding approach based on the MFSC method is shown in Fig.4.b.

Chen *et al.*'s study showed that the classification performance of square-wave SSVEP stimuli was notably higher than that of sine-wave SSVEP stimuli [38]. Thus, in this study, we used square-wave SSVEP stimuli for both the DFBC and MFSC methods by adjusting the luminance of the target in each epoch according to the following equation:

$$S(f,k) = \frac{1}{2}\{1 + square\left[2\pi f(k/f_{ref})\right]\} \quad (1)$$

where, S is the luminance of the SSVEP target, f is the flickering frequency of the target in each epoch, which follows the coding principle described earlier in this section, k is the frame index, $square()$ indicates a square waveform, and f_{ref} is the refresh rate of the screen.

G. SSVEP Recognition

Because the SSVEP stimuli are encoded by the temporal arrangement of flickering periods and the frequencies in each period, the recognition algorithm accordingly consists of the following two steps.

Step 1: Flickering frequency sequence recognition

Determine the flickering frequency of each epoch (f_k) using frequency recognition algorithm and then combine the detected frequency of each epoch in chronological order to obtain the flickering frequency sequence f_1-$f_2 \dots f_M$ of the coding cycle. Obtain the temporal pattern of the coding

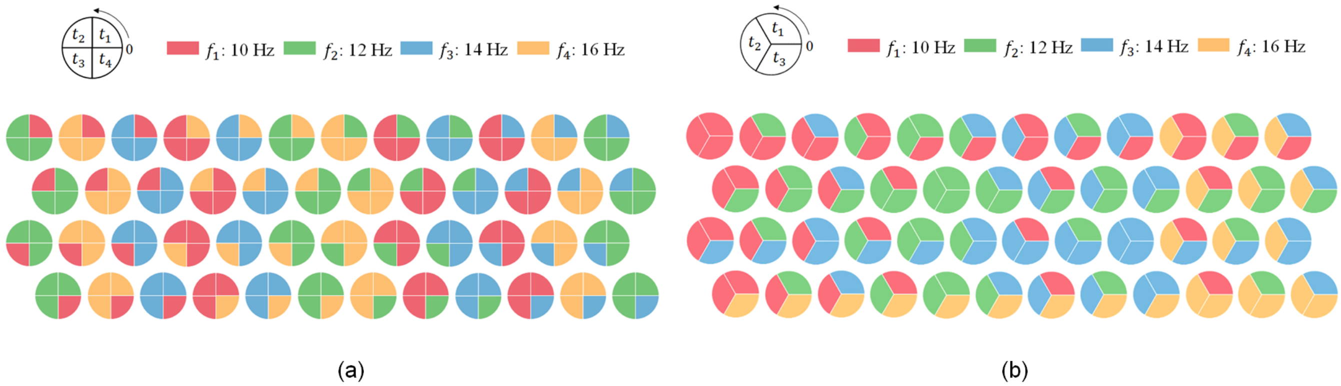


Fig. 4. Coding scheme for a 48-character keyboard based on the DFBC and MFSC methods. (a). DFBC, using four epochs and four frequencies to code the SSVEP stimuli. (b) MFSC, using three epochs and the same four frequencies to code the SSVEP stimuli.

cycle based on the flickering frequency sequence f_1-$f_2 \ldots f_M$ detected in this step.

Step 2: Target stimulus identification

Compare the flickering frequency sequence obtained by *Step 1* with the predetermined sequence of each target stimulus. The stimulus with the identical frequency sequence is considered to be the target stimulus.

The filter bank canonical correlation analysis (FBCCA) [26] is a powerful classification algorithm for the detection of SSVEP. FBCCA decomposes SSVEPs into multiple sub-band components and then performs separate standard CCAs on each of the sub-band components so that independent information embedded in the harmonic components can be extracted more efficiently. FBCCA has been shown to have better performance than the standard CCA, individual template-based CCA (ITCCA), multi-set CCA (MsetCCA), and L1-regularized multi-way CCA (L1-MCCA) [26], [39]. Some of the latest supervised methods, such as extended CCA (ECCA) [4] and task-related component analysis (TRCA) [40], were reported to have better performance than FBCCA. However, the additional calibration or training required by supervised methods may increase the complexity and inconvenience of BCI in practice. Therefore, in this study, FBCCA, which requires no training, was used for the SSVEP recognition for both the DFBC and MFSC methods. Based on the spectrum analysis of the preliminary experiment, it was found that only the fundamental frequency and first harmonic of the SSVEP frequencies have significant peaks. Therefore, two sub-band filters were used for FBCCA (8–18 Hz and 18–34 Hz for the fundamental frequency and first harmonic, respectively) in this study.

H. DFBC With Self-Correction

In the MFSC method, one coding cycle is divided into multiple epochs, and the recognition of one cycle is based on the frequency identification of each epoch, where the identification accuracy of one cycle is the product of the identification accuracy of the individual epoch. For this reason, the accuracy of one certain epoch can determine the final accuracy of the whole cycle. In the current study, our proposed DFBC has the same essential nature as MFSC in that it divides one cycle into multiple epochs. To reduce the aforementioned decrease in accuracy due to the multiplication of multiple epochs, according to the coding principle of the DFBC method, we propose the use of a majority vote (MV) to enable the DFBC method to self-correct misclassified epochs as follows:

In our study, the four epochs in one cycle are divided into SP and LP, which flickering at different frequencies (here, we defined the frequencies corresponding to SP and LP are f_{SP} and f_{LP}, respectively). According to the results of FBCCA classification, one of the five following situations must occur:

1) All epochs are classified as having the same frequency (say f_i). Because there can be one and only one epoch identified as the SP with f_{SP}, there must be one epoch that has been misclassified, i.e., it should have been identified as having a frequency different from f_i. Based on the classification principle of FBCCA, the smaller the FBCCA coefficient is, the higher the probability it has been misclassified. Thus, according to the value of the coefficient of each epoch obtained from the FBCCA, we find the epoch corresponding to the smallest coefficient. For this epoch, we use the frequency (say f_j) with the second largest coefficient as its identified frequency ($f_{SP} = f_j$). The initially identified frequencies of the remaining three epochs ($f_{LP} = f_i$) are not changed.

2) Three epochs are classified as having one frequency (say f_i) and one epoch is classified as having another frequency (say f_j). We use this identification as the output ($f_{LP} = f_i$, $f_{SP} = f_j$).

3) Two epochs are classified as one frequency (say f_i) and the other two epochs are classified as another frequency (say f_j). Because there can be one and only one epoch identified as the SP with f_{SP}, the epoch with the smallest coefficient has the highest probability of being misclassified. Therefore, this epoch (assume it has been classified as having f_j) should be re-identified as having another frequency ($f_j \rightarrow f_i$). After this correction, three epochs are identified as LP (in this case $f_{LP} = f_i$) and the remaining epoch is identified as SP (in this case $f_{SP} = f_j$).

4) Two epochs are classified as one frequency (say f_i). One of the remaining two epochs is classified as having a different frequency (say f_j), and the other is classified as having

TABLE I
CLASSIFICATION ACCURACY AND ITR OF THE MFSC AND DFBC METHODS FOR EACH PARTICIPANT IN THE OFFLINE EXPERIMENT

Subject	Accuracy (%)			ITR (bit/min)		
	MFSC	DFBC*	DFBC	MFSC	DFBC*	DFBC
S1	79.6	71.7	88.8	55.8	47.3	66.9
S2	64.2	55.0	69.2	39.8	31.4	44.7
S3	62.9	47.1	70.0	38.6	24.7	45.6
S4	58.3	35.0	61.7	34.3	15.6	37.5
S5	86.7	90.0	96.7	64.2	68.4	77.9
S6	74.2	51.7	75.4	49.9	28.5	51.2
S7	62.9	45.4	63.3	38.6	23.4	39.0
S8	73.8	55.8	76.3	49.5	32.1	52.2
S9	55.4	37.5	61.3	31.7	17.4	37.1
S10	96.7	89.2	97.5	77.9	67.4	79.2
S11	77.5	66.3	82.1	53.5	41.9	59.2
Mean	72.0	58.6	76.6	48.5	36.2	53.7
SD	12.7	18.8	13.2	13.9	18.3	15.3

DFBC*: DFBC without self-correction; Chance level = 2.1%;
Each trial lasted 4 s including 1 s cue, 2 s target character gazing and 1 s resting.

TABLE II
CLASSIFICATION ACCURACY AND ITR OF THE MFSC AND DFBC METHODS FOR EACH PARTICIPANT IN THE ONLINE EXPERIMENT

Subject	Accuracy (%)		ITR (bit/min)	
	MFSC	DFBC	MFSC	DFBC
S1	70.4	83.5	46.0	60.3
S2	46.4	61.8	24.2	37.6
S3	81.8	85.6	58.3	62.9
S4	77.9	79.7	53.9	55.9
S5	76.9	79.4	52.8	55.6
S6	77.5	80.5	53.5	56.9
S7	72.2	84.9	47.8	62.0
Mean	71.9	79.3	48.1	55.9
SD	11.9	8.1	11.3	8.6

Chance level = 2.1%;
Each trial lasted 4 s including 2 s target character gazing, 1 s detected character display and 1 s resting.

yet another frequency (say f_l). The epoch with the smaller coefficient has a higher probability of being misclassified, so for these remaining two epochs, the one with the smaller coefficient (assume it corresponds to f_l) is identified as having the same frequency as the first two epochs ($f_l \rightarrow f_i$). After this correction, three epochs are identified as LP (in this case $f_{LP} = f_i$) and the remaining epoch is identified as SP (in this case $f_{SP} = f_j$).

5) All epochs are classified as having different frequencies. Because this case is not in accordance with the coding strategy and cannot be corrected, there is no output for a cycle in this case.

After processing according to one of the above five possible situations, the frequencies for both SP and LP can be identified. Then, after comparison with the coding strategy (i.e., frequency setting for the LP and SP corresponding to each target), it is possible to identify the target at which the participant is gazing. The coding principle of the DFBC method provides a self-correction, described as the above-mentioned MV method, which gives DFBC a chance to self-correct some misclassified trials, thereby improving its classification performance.

III. RESULTS

The classification accuracy of each participant for MFSC, DFBC without self-correction and DFBC in the offline experiments are respectively shown in Table I. The mean classification accuracy of DFBC is 76.6%, which is 4.6% higher than that of the MFSC method. A statistical analysis found that the classification accuracy of DFBC is significantly higher than that of MFSC ($p < 0.001$, one-tailed t-test). Moreover, the classification accuracy of each participant for MFSC and DFBC in the online experiments are respectively shown in and Table II. The mean classification accuracy of DFBC is 79.3%, which is also significantly higher than 71.9% of MFSC ($p < 0.01$, one-tailed t-test).

According to the Table I, it is found that there were many trials that were misclassified in DFBC without self-correction. However, such misclassified trials can be corrected in DFBC with the MV method. The results in Table I show that even for the participants with the worst correction effect (35.0% for S4 and 37.5% for S9), the accuracies are increased to 61.7% and 61.3%, respectively. Whereas the classification accuracy is increased by 18.0% on average for all the participants after self-correction. These results testify that the proposed MV method for DFBC has excellent misclassification self-correction ability.

Based on the definition of ITR by Wolpaw *et al.* [41], the ITRs of the offline and online experiments were calculated by the formula proposed in [42], and the ITRs are shown in Table I and II, respectively. The ITR of DFBC is significantly higher than MFSC and DFBC without self-correction in the offline experiment, respectively ($p < 0.01$ and $p < 0.001$, one-tailed t-test). Whereas the ITR of DFBC is significantly higher than MFSC in the online experiment ($p < 0.01$, one-tailed t-test).

The averaged classification time per trial (1200 repeated calculation with Intel Core i7-3970X CPU @ 3.5 GHz and 64 GB RAM) for MFSC, DFBC without correction and DFBC are respectively 8.7±2.2 ms, 9.6±2.4 ms and 10.0±2.7 ms in the offline experiment; Moreover, these values are respectively 9.4 ± 2.3 ms, 10.5 ± 2.6 ms and 10.6 ± 2.9 ms in the online experiment (see Fig.5). The paired-sample t-test results show that these three methods are significantly different ($p < 0.001$, one-tailed t-test). Moreover, the online and offline experiment results for all three methods are significantly different ($p < 0.001$, one-tailed t-test).

IV. DISCUSSION

Regardless of the coding method, most of the current SSVEP-based BCIs use a one-to-one correspondence between stimulating frequency and stimuli. Hence, a BCI spelling system based on a virtual keyboard requires a large number of

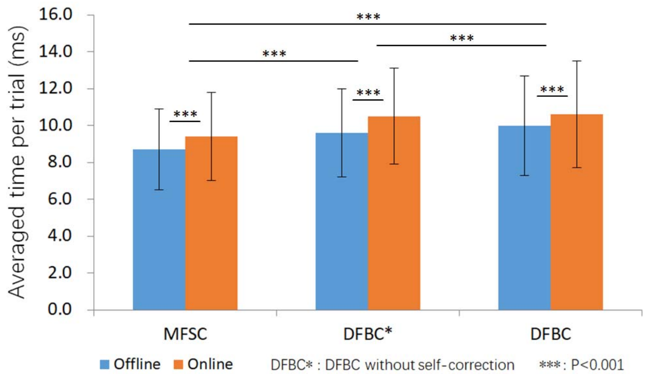


Fig. 5. Averaged time of 1200 repeated classifications per trial in the offline and online experiments for the MFSC, DFBC method with and without self-correction, respectively.

frequencies. However, due to limitations in the monitor refresh rate and visual neural response, the range of frequencies available for SSVEP is finite [11], [19], which may greatly limit the number of SSVEP stimuli and preclude the application of an SSVEP-based spelling system. For a traditional single frequency encoding method [14], [15], [43], each SSVEP stimuli occupies one frequency and the frequency interval is very narrow, which may affect the recognition algorithm. This bottleneck problem has become a common concern of SSVEP-based BCI and is the research object of this study.

To address this problem, some studies have tried to modulate a single SSVEP stimulus with two frequencies to increase the number of targets that can be coded [25], [34], [44]. However, because the number of permutations is small if only a simple combination of two frequencies is used, the number of targets that can be added by such dual-frequency coding protocols is extremely limited. Kimura *et al.* adopted frequency shift keying technology used in the field of digital communication, where the BCI commands were first translated into codewords consisting of binary digits (e.g., 001, 010). Then, based on the binary codewords, two different frequencies were allocated to the corresponding epoch (e.g., f_1-f_1-f_2 for 001, f_1-f_2-f_1 for 010) [24]. This frequency shift keying method encoded BCI commands using binary codewords, but the frequency information was not used in the coding strategy (e.g., f_1-f_1-f_2 and f_3-f_3-f_4 are both translated to 001), which reduces the number of encoding targets. Some studies have also attempted to use multiple frequencies to increase the number of targets that can be encoded. Zhang *et al.* proposed the MFSC protocol, which used time and frequency information to code the targets [34]. Under the MFSC protocol, each cycle is divided into several epochs, and each epoch flickers at a certain frequency. Such temporal and frequency information constitutes the permutation sequence by which the SSVEP target is coded. In the current study, we extended the traditional MFSC method by displaying two frequencies at unequal sequences. The unequal multiple frequency sequences in our proposed DFBC method mean that temporal factors become involved, which makes the proposed DFBC method a frequency-temporal coding scheme. In addition, with the pre-set spatial arrangements of the unequal multiple frequency sequences, the restriction relationship among the epochs also becomes a type of codeword, which allows the proposed DFBC method to vastly increase the number of permutations and thus enables it to code more targets with limited available frequencies.

According to the MFSC coding strategy, the final identification result of one cycle is based on the identification result of each individual epoch in the cycle. By distinguishing the frequency of each epoch, the permutations of the temporal and frequency patterns of the cycle are determined, which enables the cycle to be finally identified. For this reason, MFSC is faced with a problem similar to the "Cannikin Law" problem, i.e., if a certain epoch is misclassified, the whole cycle will be wrongly identified. Conversely, in the proposed DFBC method, most misclassified epochs can be self-corrected using the proposed MV method. This error correction function of DFBC better alleviates the "Cannikin Law" problem the MFSC method faces, which enables the DFBC method to improve the classification performance and have a good application prospect. Compared with MFSC takes 8.7 ms and 9.4 ms, and DFBC without self-correction takes 9.6 ms and 10.5 ms for the offline and online experiments, respectively, DFBC with self-correction takes 10.0 ms and 10.6 ms, respectively (see Fig.5). Although DFBC with self-correction yields an increase in computing time with respect to MFSC, this increase is negligible. Considering the reduction in misclassification obtained by DFBC, which is more important in BCI applications, this small increase in computational cost is acceptable.

In DFBC, the permutations of the short and long flicking periods as well as the flicking frequencies of each period consist of different codewords. Such a coding strategy means that all the epochs in the DFBC method are constrained and correlated with each other (see Sections II.F and II.G). Conversely, the epochs in the MFSC method are independent and have no constraint relationships among them. Thus, once an epoch has been misclassified in MFSC, it will not be able to self-correct using the restrictions and correlation relationships among the epochs. This is the reason why we believe that although the DFBC method proposed in this study can be regarded in many ways as an extension of MFSC, there are essential differences between the two methods.

Suppose there are M epochs in one coding cycle and N frequencies are available for flickering in these epochs, Then, MFSC can encode N^M targets whereas DFBC can encode $C_N^2 \times 2 \times M$ targets. Obviously, MFSC has more codewords than DFBC. However, for a BCI speller in common use, 40 to 50 characters are sufficient. For this kind of demand, the coding cycle should be as short as possible and the number of available frequencies is limited; hence, there are two alternative combinations of epochs and frequencies for MFSC, i.e., three epochs and four frequencies (yielding 64 targets) or four epochs and three frequencies (yielding 81 targets). DFBC also has two alternative combinations, i.e., four epochs and four frequencies (yielding 48 targets) or four epochs and five frequencies (yielding 80 targets). Therefore, for numbers of targets in both the forties and eighties, MFSC needs a smaller number of epochs than does DFBC. Moreover, suppose MFSC and DFBC have a coding cycle with the same duration. In this case, MFSC will have a longer epoch than DFBC. Alternatively, if the epochs have the same duration, then MFSC will have a shorter coding cycle than DFBC. These two points may help MFSC obtain a better classification performance than DFBC theoretically. However, the final recognition accuracy of one cycle with the MFSC method is the multiplication of the recognition accuracies of each epoch. As the number of epochs increases, the classification error of each epoch will multiply continuously, and then the classification accuracy and the ITR will be sharply reduced as a result. In contrast, DFBC can avoid the "Cannikin Law" problem facing MFSC by using its self-correcting ability, which MFSC does not have. For this reason, although MFSC can code more targets than DFBC, DFBC may obtain a higher accuracy (and a higher ITR as a result), which gives the proposed method good potential for application in multi-character BCI spellers.

V. Conclusion and Future Work

This study developed a 48-character virtual speller based on the proposed DFBC method, which combines the frequency-temporal pattern of flickering periods and the restriction relationship among epochs to code targets. The experimental classification results confirmed that this method can effectively use the limited number of available frequencies to code more targets. In addition, the self-correcting ability of this method can effectively improve the classification accuracy, which improves the SSVEP-based BCI speller performance.

The system could be further improved in the following directions. Firstly, this study used the training-free FBCCA method to extract SSVEP feature. In general, training-free systems are more practical but the performance might not be as good as the training method. Further investigation of how the DFBC combined with training method can improve the classification accuracy is required. Secondly, system parameters such as the epoch length, stimulation frequencies, and preprocessing on EEG signals also can be optimized to achieve a better system performance. Thirdly, more channels of SSVEP signals from the occipital region can boost the system performance. On the other hand, fewer electrode channels are user-friendly in the BCI application. The accuracy and convenience should be balanced according to the configuration of the system and application environment.

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