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An adaptive motion-onset VEP-based brain-computer interface

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***Abstract*—Motion-onset visual evoked potential (mVEP) has been recently proposed for EEG-based brain-computer interface (BCI) system. It is a scalp potential of visual motion response, and typically composed of three components: P1, N2 and P2. Usually several repetitions are needed to increase the signal-to-noise ratio of mVEP, but more repetitions will cost more time thus lower the efficiency. Considering the fluctuation of subject's state across time, the adaptive repetitions based on the subject's real-time signal quality is important for increasing the communication efficiency of mVEP-based BCI. In this paper, the amplitudes of the three components of mVEP are proposed to build a dynamic stopping criteria according to the practical information transfer rate (PITR) from the training data. During online test, the repeated stimulus stopped once the predefined threshold was exceeded by the real-time signals and then another circle of stimulus newly began. Evaluation tests showed that the proposed dynamic stopping strategy could significantly improve the communication efficiency of mVEP-based BCI that the average PITR increases from 14.5 bit/min of the traditional fixed repetition method to 20.8 bit/min. The improvement has great value in real-life BCI applications because the communication efficiency is very important.**

***Index Terms*—motion-onset visual evoked potential (mVEP), brain-computer interface (BCI), dynamic stopping, practical information transfer rate (PITR)**

I. Introduction

BRAIN-COMPUTER interface (BCI) establishes an alternative direct communication channel between brain and computer or other external devices. Patients with peripheral nervous system impaired can use it to improve quality of life [1, 2], meanwhile healthy people can extend their communication and control function through BCI technique, too [3, 4]. A lot of brain signals, including electroencephalography (EEG) [5], magnetoencephalography (MEG) [6], functional magnetic resonance imaging (fMRI) [7], functional near-infrared spectroscopy (fNIRS) [8], electrocorticography (ECoG) [9], local field potentials (LFP), and single-unit activity, have been applied in BCI systems. Among them, EEG-based BCI system has great values in practical applications due to its low cost and portability, and visual evoked potentials (VEP)-based BCI is one of the important branches in EEG-based BCI system. In most of the VEP-based BCI, brain signals evoked by light flash or pattern reversal were utilized [10, 11], where a high contrast and a bright luminance of a visual object are usually required. In real-life situation, this may cause visual fatigue of the BCI user, especially after a long time use.

Recently, motion-onset VEP (mVEP) has been proposed to apply in EEG-based BCI system [12, 13]. The mVEP represents visual motion response from middle temporal area (MT) and the medial superior temporal area (MST). Among all visual motion-related VEPs, mVEP displays the largest amplitudes and the lowest inter- and intra-subject variability [14]. The mVEP is typically composed of three main peaks: P1, N2 and P2. The positive peak P1 with a latency of about 130 ms was regarded as the main motion-onset related potential in the earlier studies [15, 16], representing pattern-related activity of the parvo-cellular subsystem. The late negative peak N2 with a latency of 160-200 ms, which generated from the extrastriate temporo-occipital and associate parietal cortical areas, delineates motion-processing system activity [14]. The peak P2 with a latency of about 240 ms increases with more complex visual moving stimulus, and has a parietal (up to central) topography [17]. Kuba *et al* concluded that the N2 (N200) peak of mVEP is the main motion specific component [14], and the N200 potential has been already utilized in a novel BCI speller which allow subjects to spell out messages by scalp EEG [18].

Compared with the traditional VEP-based BCI using pattern-onset or pattern-reversal stimulus, the mVEP-based BCI requires no sudden change of luminance or a high contrast of visual objects, thus subjects have less visual fatigue and feel more comfortable. However, the amplitude of mVEP is small compared with the spontaneous EEG signal, that is, the signal-to-noise ratio (SNR) is low. Generally, several repetitions are needed in order to improve the SNR of mVEP. Theoretically, more repetitions will increase the classification accuracy of one trial, but decrease the output speed of the BCI system. Therefore, like other ERP-based BCIs, optimizing the number of stimulus repetitions for individual subject is a challenge for mVEP-based BCI in practical application [19].

The simplest way of optimizing the number of repetitions is to estimate an optimal fixed number of repetitions based on the calibration data and then applying the obtained number for the online application. Because the SNR of mVEP also varies

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across time even for one subject, and the fixed method cannot adapt to the changes for online situation, thus more dynamic methods need to be developed. Liu *et al* have proposed an approach which sums the outputs of a linear classifier for each class over repetitions, and the repetitions stop until the outputs exceed the predefined threshold during online application [20]. Jin *et al* set stop criterion as the same class prediction of a minimum number of consecutive trials for P300-based BCI system [21]. Lenhardt *et al* estimated the scores of each choice in the P300 speller array, being the target from training data, and set an empirical threshold [22]. Zhang *et al* proposed a probabilistic approach to continuously tracking the BCI user's state, and subsequently derived the likelihood of each state [23]. The stopping strategies mentioned in these previous studies are mainly based on the output of the classifier, and only Liu *et al*'s study specifically focuses on the mVEP-based BCI.

Practical information transfer rate (PITR) is a measure for evaluating the realistic communication efficiency of the BCI systems [24]. It not only takes into account accuracy, speed, and the number of possible selections of common communication systems, but also the error-correcting function of BCI systems [24], therefore, it is quite suitable to serve as a measure to find the balance between accuracy and repetitions of the mVEP-based BCI. For mVEP, the three main peaks, P1, N2, and P2, responding with the moving visual stimulus are the main discriminative features, and these information may be directly used to build the stopping strategy during online BCI application. In the current study, we will build the dynamic stopping strategy by using the three main peaks of mVEP as threshold baseline, and optimizing the threshold coefficients according to PITR, finally evaluate the performance of the proposed feature level-based adaptive repetition method.

II. MATERIALS AND METHODS

A. Experiment setup

11 subjects (3 females, aged 23.6 ± 1.2 years) participated in the experiment. They were with normal or corrected to normal vision. The experimental protocol was approved by the Institution Research Ethics Board of the University of Electronic Science and Technology of China. All participants were asked to read and sign an informed consent form before participating in the study. After the experiment, all participants received monetary compensation for their time and effort.

Ten Ag/AgCl electrodes (CP1, CP2, CP3, CP4, P3, P4, Pz, O3, O4, Oz) from extended 10-20 system were placed for EEG recordings by using a Symtop amplifier (Symtop Instrument, Beijing, China). All electrode impedances were kept below 5 kΩ, and AFz electrode was adopted as reference. The EEG signals were sampled at 1000 Hz and band-pass filtered between 0.5 and 45 Hz.

The visual stimulus were presented on a 14-inch LCD monitor with a 60 Hz refresh rate and 1280 × 1024 resolution, and viewed from a distance of 50 cm. Fig. 1 illustrated the graphical user interface (GUI) to the subjects in the experiment, with a visual field 30° × 19° on the screen. Six virtual buttons, representing 1, 2, 3, 4, 5, and 6 respectively, were embedded in the rectangle interface, each with a visual field 4° × 2°. In each virtual button, a red vertical line appeared in the right side of the button, and moved leftward until it reached the left side of the button, forming a brief motion-onset stimulus. The entire move took 140 ms, with a 60 ms interval between the consecutive two moves. The motion-onset stimulus in each of the six buttons appeared in a random order, and a trial was defined as a complete series of motion-onset stimulus of all six virtual buttons successively. The interval between two trials was 300 ms, thus each trial lasted 1.5 s (Fig. 2). Five trials comprised a block, which cost 7.5 s.

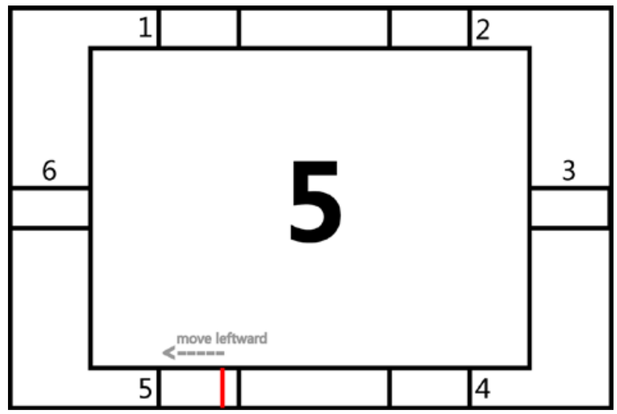

Fig. 1. Graphical user interface for the offline data recording in mVEP-based BCI. The number "5" in the center instruct the target button that subjects should pay attention to. The red vertical line moves leftward with a random order in each of the six buttons to form the motion-onset stimulus.

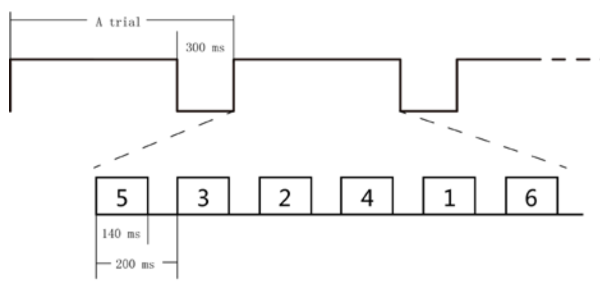

Fig. 2. The timing scheme. Each block contains 5 trials. In each trial, the motion-onset stimulus appears in the virtual button for 140 ms. There is a 60 ms interval between consecutive two stimulus and 300 ms interval between consecutive two trials.

During experiment, the subject needed to focus on the button which is indicated in the center of the graphical user interface, and the instructed number was randomly appeared. To increase their attention, the subject was further asked to count in silence the times of moving stimulus appearing in the target button. A total of 72 blocks, including 360 trials, were collected for each subject in two equal separate sessions, with a 2 minutes rest between the sessions. The first session was used as training set

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and the second session was used as test set for the following analysis.

B. Preprocessing

The scalp recorded EEG signals are usually contaminated with noise, and those trials with absolute amplitude above 50 μv threshold were considered to be contaminated with strong artifacts and removed from the following analysis. The remaining EEG data were band-pass filtered between 0.5 Hz and 10 Hz, because the mVEP is usually distributed in the low frequency band.

C. Analysis of mVEP

For the filtered EEG data, epochs were firstly derived according to the motion-onset stimulus, beginning with the stimulus onset time and lasting for 800 ms. The instructed stimulus on the GUI center was defined as target, and the others were defined as nontarget. Then all data epochs were group averaged (according to target and nontarget condition) over all trials for each subjects to obtain the grand average responses for each condition. Finally, two sample t test was applied to the target and nontarget EEG epochs, and the time periods with statistically significant difference ($p < 0.05$) were found.

D. Offline analysis with fixed repetition method

As shown in the normal procedures of Fig. 3, the EEG epochs of 5 trials in each block were averaged by stimulus. According to both the mVEP distribution of all subjects in current work and the proposed mVEP-related channels [25], channel CP1, P3, and Pz were utilized, and the averaged EEG epochs from 150 ms to 300 ms were selected as features in this section. In order to avoid the overfitting problem, the selected EEG epochs were further downsampled to 20 Hz, thus a 12-point feature vector was generated for each stimulus in the block. Then the features were classified as target and nontarget based on the instructed number, where the target features were labeled with 1 and -1 was set as label for the nontarget features. Finally, the equal number of target and nontarget features were selected for training the classifier. The recognition of mVEP can be considered as a binary classification problem. Due to its high efficiency and easy implementation, linear discriminant analysis (LDA) was chosen as the classifier. The linear discriminant function is expressed as

$$y(X) = w^T X + w_0 \tag{1}$$

Where X is the feature vector, $y(X)$ is the corresponding label, w is the weight vector, and w_0 is the bias term. Since X and $y(X)$ are already known, w and w_0 could be estimated by least square method [26, 27]. The parameters of the LDA were used to classify the target and nontarget stimulus during online test process.

E. Dynamic stopping strategy

To comprise between classification accuracy and communication efficiency, the repetitions of the motion-onset stimulus were determined real-time based on the preset stopping criterion during online test following the detailed procedures depicted in the dynamic stopping module of Fig. 3.

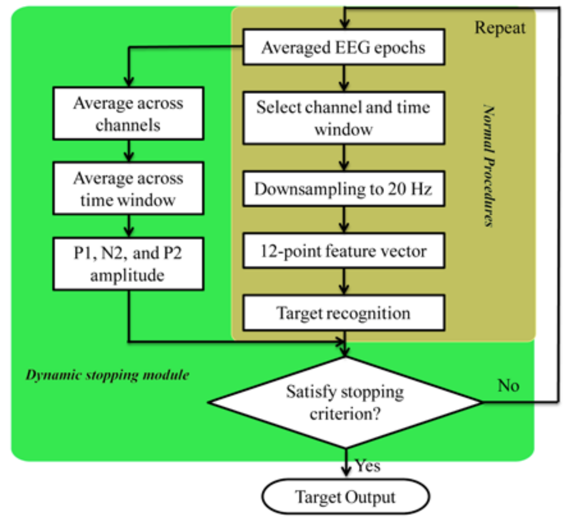

Fig. 3. The online motion-onset VEP recognition procedures which include dynamic stopping strategy. The right side is the normal online recognition procedures with fixed repetition, the left side is the dynamic stopping module.

The parameters of the stopping criterion were established from the training session of each subject. The three components, P1, N2, and P2, of mVEP were utilized to build the stopping criterion. Firstly, the EEG epochs of channel CP1, P3, and Pz were averaged across channels. Then according to the literature [14] and our analysis results, the average signals between time periods of [140 170] ms, [190 230] ms, and [290 330] ms were considered as the threshold baselines of P1, N2, and P2, respectively, and they were further denoted as A_1, A_2, and A_3, respectively. The stopping thresholds were defined as the product of threshold baselines (A_1, A_2, and A_3) and three corresponding coefficients (σ_1, σ_2, and σ_3), thus the component thresholds were $\sigma_1 A_1$, $\sigma_2 A_2$, and $\sigma_3 A_3$ with σ_1, σ_2, and σ_3 being positive number within 0-3.0, respectively. Therefore, the aim turned to find the optimal σ_1, σ_2, and σ_3 that can provide the stopping criteria to improve the BCI efficiency.

PITR is proposed as a metric for evaluating the realistic performance of BCI systems recently, and it simultaneously considers the number of selectable items, accuracy, and speed [24]. The PITR is defined as

$$PITR = \begin{cases} 60 \times (2P-1)\log_2 N / T, & P > 0.5 \\ 0, & P \le 0.5 \end{cases} \tag{2}$$

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where N is the number of selectable items, P is the selection accuracy, and T is the average time in second for finishing one selection. The weight of the selection accuracy is strengthened in PITR, because in practical BCI application subjects need two additional correct selections, one for erasing the wrong option and one for selecting the desired option again, for compensation when a wrong option is selected [28, 29]. Townsend *et al* proved that the expected time needed for one correct selection becomes to $T' = T/(2p-1)$ after correcting all the errors [24].

In current work, we used PITR to quantitatively delineate the BCI performance. All three coefficients were exhaustively optimized within 0-3.0, with a step 0.2, separately, and the optimization was made by a 10×6-fold cross-validation analysis based on the offline training session. Since there are 16 possible values for each coefficient, we obtained a 16×16×16 PITR matrix after the cross-validation analysis. Finally, the coefficients corresponding to the highest average PITR were determined as the threshold coefficients for the online test.

During online test, as illustrated in Fig. 3, along with target recognition procedures, the real-time average amplitude of P1, N2, and P2 of the recognized target was calculated, and we denoted them as D_1, D_2, and D_3, respectively. Then the stopping strategy is defined as below:

$$x_i = \begin{cases} 1, & D_i < (-1)^i \sigma_i A_i \\ 0, & D_i \geq (-1)^i \sigma_i A_i \end{cases} \tag{3}$$

$$Output = \begin{cases} Yes, & \sum_{i=1}^{3} x_i \geq 2 \\ No, & otherwise \end{cases} \tag{4}$$

where i ranges from 1 to 3. If the output is *Yes*, the recognized target was output and a new stimulus circle began, otherwise the motion-onset stimulus repeated another time. The maximal number of repetition was set as 5, that is, the repetition would stop when it repeated 5 times regardless of the output of the dynamic stopping module.

III. Results

A. The characteristics of mVEP

The grand average of all the EEG epochs for each subject were calculated, and Fig. 4 illustrated the averaged scalp potential on channel P3 for one example subject (S2). The time periods showing significant difference between target-related signal (red) and nontarget-related signal (blue) were also shown in Fig. 4 ($p < 0.05$, two-sample t test), where the light green areas indicated the amplitude of target-related signal is significantly higher than that of nontarget-related signal for P145 and P275 components, whereas the light pink area denotes the significant difference existed in N195 component. The three time periods could be categorized to the three main components of mVEP. For the example waveform in Fig.4, P145, N195, and P275 with latencies of 145 ms, 195 ms, and 275 ms after the motion-onset stimulus could be classified into P1, N2 and P2 components of mVEP, respectively. Generally, the stronger N2 and P2 components were observed to be distributed on channel CP1, P3, and Pz, which is consistent with the previous findings [12, 14].

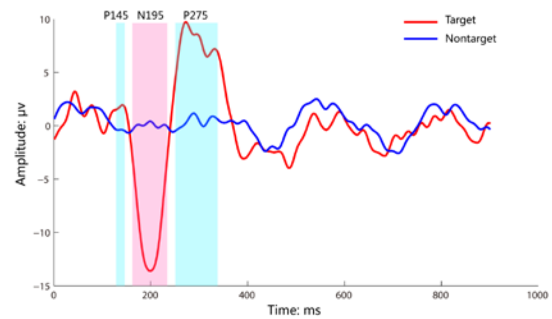

Fig. 4. The characteristics of motion-onset VEP (Subject S2, recorded on channel P3). P145, N195, and P275 are the three main components, the amplitude of the target-related signal is significantly higher than that of nontarget-related signal in the light green periods ($p < 0.05$), whereas in the light pink period the amplitude of the target-related signal is significantly lower than that of nontarget-related signal.

B. BCI performance

The parameters of the LDA classifier, the optimal thresholds, including the threshold baselines (A_1, A_2, and A_3) and the corresponding coefficients (σ_1, σ_2, and σ_3), of the dynamic stopping module were all obtained by cross-validation procedures which conducted in the first session. The second session was used to evaluate the performance of the proposed dynamic stopping strategy based on the parameters estimated from the first session. The evaluation results on all the 11 subjects were listed in Table I. As a companion, the performance of the fixed repetition strategy which utilized the averaged signals of all the five trials in a block was also presented. After applying the dynamic stopping strategy, the average repetition number for one recognition was reduced to 3.0 ± 0.6, on the other hand, the average classification accuracy decreased from $85.1 \pm 8.1\%$ of the fixed repetition method to $78.8 \pm 9.1\%$ ($p = 0.002$). Though approximately 6% accuracy is lowered when dynamic stopping strategy is applied, the PITR achieved by dynamic stopping method (20.8 ± 10.4 bit/min) is significantly higher than that obtained by fixed repetition method (14.5 ± 3.3 bit/min, $p = 0.013$).

The PITRs achieved by all the five possible fixed repetition strategies were illustrated in Fig. 5. Among them the highest average PITR (20.4 bit/min) was achieved by the fixed strategy with 1 repetition. It was close to the average PITR which obtained from the proposed dynamic stopping method, but varied a lot across subjects, with a standard error of 26.9 bit/min. Regarding to the PITRs obtained from the remaining four fixed repetition strategies, we found that they were significantly lower than that obtained from the proposed dynamic stopping method.

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TABLE I
THE BCI PERFORMANCES FOR DYNAMIC STOPPING METHOD AND FIXED REPETITION METHOD

Subject	Dynamic stopping			Fixed 5 repetitions	
	Accuracy (%)	PITR (bit/min)	R. N.	Accuracy (%)	PITR (bit/min)
S1	75.0	15.8	3.3	72.2	9.2
S2	97.2	48.2	2.0	100	20.7
S3	69.4	14.8	2.7	80.6	12.6
S4	77.8	19.9	2.9	80.6	12.6
S5	69.4	12.9	3.1	75.0	10.3
S6	66.7	13.9	2.5	83.3	13.8
S7	86.1	18.9	3.9	88.9	16.1
S8	75.0	16.3	3.2	86.1	14.9
S9	86.1	32.0	2.3	94.4	18.4
S10	83.3	17.9	3.9	86.1	14.9
S11	80.6	18.3	3.4	88.9	16.1
Mean± Std	**78.8± 9.1**	**20.8± 10.4***	**3.0± 0.6**	**85.1± 8.1****	**14.5± 3.3**

R.N. denotes the average repetition number from the dynamic stopping method.
* denotes the PITRs obtained from dynamic stopping method are significantly higher than that obtained from fixed 5 repetitions approach ($p < 0.05$, paired t test).
** denotes the accuracies obtained from fixed 5 repetitions approach are significantly higher than that obtained from dynamic stopping method ($p < 0.05$, paired t test).

C. *The effect of the three mVEP components on BCI performance*

The features of three components (P1, N2, and P2) together made up the proposed dynamic stopping strategy. In this section, we evaluated the BCI performance when only the single component is served as the stopping criteria. During online test, the repetition stopped when the real-time average amplitude exceeded the corresponding defined threshold, where the threshold is also the product of threshold baseline and the corresponding coefficient as defined in previous section. The PITRs and accuracies corresponding to the variations of each coefficient were shown in Fig. 6. For all of the three components, the accuracies rose up with the increase of the coefficient. On the contrary, the PITRs showed a declined trend along with the increase of the coefficient. Among all the three components, the PITRs achieved by using P1 alone as stopping criteria were significantly lower than that by N2 and P2, while for the accuracies, using P1 or N2 component as stopping criteria performed better.

IV. DISCUSSIONS

The mVEP-based BCI is suitable for practical application because it does not require flashing or sudden change of stimulus, subjects feel no uncomfortable and less visual fatigue even with a long-time use [20]. The mVEP could be considered as a response signal superimposed in the strong background spontaneous EEG, thus resulting in the low SNR. However, since the background EEG is random and mVEP is locked for both time and phase, repetitions could enhance the SNR of mVEP for facilitating the task recognition. Though more repetitions can achieve higher accuracy, the time efficiency is decreased. As a communication system, the fast response is very important for the practical mVEP-based BCI, therefore, we need to find a balance between accuracy and repetitions. In mVEP-based BCI system, the subject's mental state may be varied across time, that is, the SNR will be fluctuated. Therefore, if we can establish a scheme for capturing the subject's mental state to denote the real-time signal quality, the adaptive repetitions can improve the BCI efficiency.

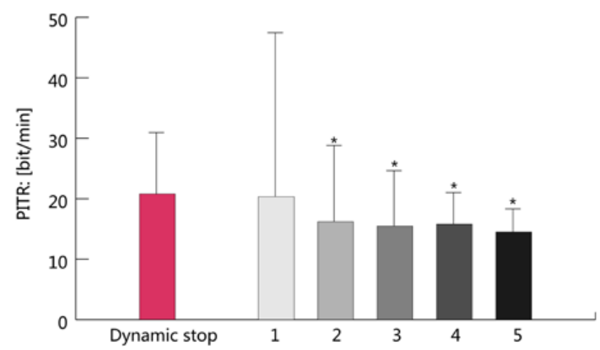

Fig. 5. The PITR for the dynamic stopping method and the five fixed repetition methods with repetitions of 1, 2, 3, 4, and 5. * denotes the PITR obtained from fixed repetition method are significantly lower than that obtained from dynamic stopping method ($p < 0.05$, paired t test).

A. *Performance improvement by dynamic stopping method*

According to the characteristics of mVEP, we proposed to use the average amplitude of the three components, P1, N2, and P2, to adaptively determine the numbers of repetition. Three corresponding coefficients were utilized to adjust the values of the threshold, and the coefficients were optimized by PITR based on the training set. As shown in Table I and Fig. 5, the average PITR is significantly improved by the dynamic stopping method compared with the traditional fixed repetition method, and more importantly the improvements are hold for each subject participated in the experiment. The improvements of PITR are mainly due to the effective reduction of the numbers of repetition. For those subjects with higher accuracy (S2, S9), usually less than 3 repetitions could support a reliable recognition (with accuracies above 85%). The highest possible PITR which achieved by the fixed method with 5 repetitions is 20.7 bit/min (S2 with accuracy 100%), however, after applying dynamic stopping strategy in the recognition procedures, the mean PITR can be increased to 20.8 bit/min compared to 14.5 bit/min achieved by 5-repetition averaging.

The proposed dynamic stopping method improves the communication efficiency of mVEP-based BCI consistently even compared with all the five possible fixed repetition methods (Fig. 5). Specifically, the average PITR obtained from the fixed method with 1 repetition is close to that obtained from the dynamic stopping method, but the variations among subjects are very large. The main reason is that for most of the subjects, 1 repetition could not support reliable recognition due

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to the low SNR of mVEP, and four subjects achieved PITRs of 0 bit/min. The fixed 1 repetition method does not consider the characteristics of individual subject's mVEP, for those subjects with a significant mVEP, 1 repetition could support a reliable classification, but for those subjects with a non-significant mVEP, the classification result based on 1 repetition is usually wrong, which accounts for the larger standard error achieved by 1 repetition method in Fig. 5. The advantage of the proposed dynamic stopping method is that it could reduce the repetitions based on the real-time signal quality of individual subject and maintain the recognition accuracy simultaneously.

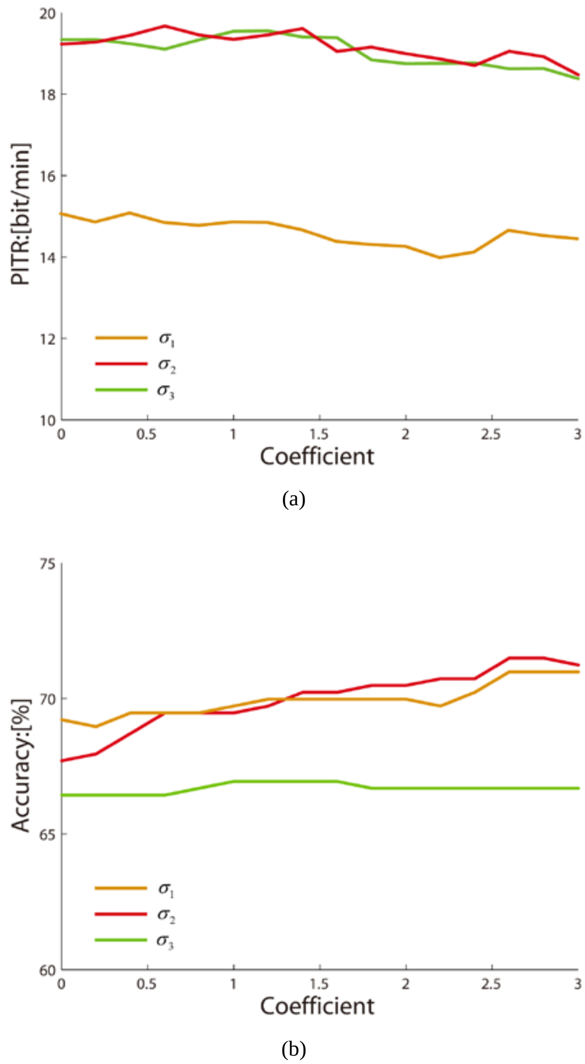

Fig. 6. The curves of the three individual coefficients vs PITR (A) and the three individual coefficients vs accuracy (B).

Among the three components, N2 is the best one to serve as the individual threshold in the dynamic stopping strategy, because the higher PITR and accuracy were achieved when using only N2 component as stopping criteria (Fig. 6). However, the highest PITR obtained by using N2 as threshold is still lower than that obtained by the proposed method which combines all the three components together (Table I). In contrast, the lowest PITR and accuracy were obtained when using P1 alone as the stopping criteria. The main reason is that the amplitude of P1 is very small when compared with that of N2 and P2 components, as shown in Fig. 4. And for some subjects, the P1 component even could not be observed. In this case, it is difficult to determine the optimal repetition number based on P1 component alone, thus the achieved PITR is obviously small.. However, the average accuracy obtained by the proposed combing strategy is higher than that obtained by using any of the three individual components as stopping criteria. The above comparisons consistently indicate that the combination of the three components together will provide more comprehensive information to build the adaptive stopping strategy for an efficient and robust mVEP-based BCI system.

B. Inter- subject variations

The PITRs, accuracies, and number of repetitions vary a lot across the 11 subjects. After applying the dynamic stopping strategy, the highest PITR of 48.2 bit/min could be achieved by S2, whereas the lowest 12.9 bit/min PITR is for S5. Similarly in the previous mVEP-based BCI studies, the achieved accuracies and information transfer rates also show the large variations across subjects [12, 18, 20]. At the same time, the similar variations in performance have also been observed in sensorimotor rhythm (SMR)-based BCI and P300-based BCI [30-32]. It has been revealed that the amplitude of SMR [30], alpha band power [33], and gamma rhythm [34] during rest are positively correlated with SMR-based BCI performance, whereas theta band power during rest is negatively correlated with SMR-based BCI performance [33]. For P300-based BCI, the N2 amplitude and the amplitude of a late ERP component between 400 and 600 ms which derived from auditory oddball paradigm were found strongly related with accuracy [35]. Finding measures to predict BCI performance has great value in practical application because the predictors could help to select a suitable paradigm for a potential subject. To our knowledge, there are no such studies in mVEP-based BCI until now. Since it is a fundamental problem in mVEP-based BCI system, we suggest the following two ways for the future predictor studies: on one hand, investigate the resting-state brain because the spontaneous activity during resting-state may reflect the brain's potential processing abilities [36]; on the other hand, explore the relationships between the temporal characteristics of mVEP and BCI performance since the recognition accuracy directly relies on the temporal features of mVEP signal.

C. Towards asynchronous BCI control

Asynchronous or self-pace control is another important issue should be considered in real-life BCI application [37, 38]. For an asynchronous BCI, the system should not only discriminate the desired command from the brain signals, but also detect when the user wants to operate it [23]. The evaluations in the current study are based on synchronous BCI paradigm, which assumes the subject is attending the stimulus all the time and a target is recognized at the end of each block. However, we could extend the proposed dynamic stopping method in an

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asynchronous BCI system by classifying the subject's state as idling when it does not satisfy the stopping condition even if a maximal number of repetitions have been made, and there is no target output from the BCI system in this case.

D. Effect of reference

In this work, AFz is adopted as the reference electrode, this is just because it is far away from the main regions of mVEP usually generated. In general, AFz is not a zero reference, especially it may be affected by eye moments, however, for this work, with just 10 electrodes, the widely adopted average reference is also not a good choice. If adopted linked-ear, it may affect the assumed CP1 electrode. In the future, we propose to realize the work on a multi-channel system, for example >32 channels, then the zero-reference technique (REST: http://www.neuro.uestc.edu.cn/rest/) may be adopted to get reference-free data [39], or a Laplacian filter can be adopted to reduce the effect of reference. However. what we mainly concerned in this work is the performance of our newly proposed stopping strategy, the comparison is based on the same data, thus reference issue may not affect the evaluation of our method, though a reference-free data may induce a little difference.

E. Relations with P300

P300-based BCI is one of the important branches of BCI, and the typical application is P300 speller [40]. P300 is related with the decision making process, and it usually could be obtained by oddball paradigm. In the traditional oddball paradigm, two types of stimulus labeled as target and standard stimulus are presented to subjects in a random order, and the probability of the target stimulus is typically lower than 20%, when subjects attend the lower probability target stimulus, a positive waveform with a latency about 300 ms could be observed. On the other hand, mVEP is related with the motion perception of the visual motion processing pathway. Generally in the EEG waveform, the latency of P300 is longer than mVEP. P300 could be evoked by visual, auditory, and tactile stimulus, whereas mVEP could be only elicited by moving visual stimulus.

Since the characteristics of mVEP and P300 are both in time domain, the proposed dynamic stopping strategy may also be suitable for P300-BCI. However, in practical application, the channels and time windows for calculating the threshold baseline should be carefully selected.

V. Conclusions

In this study, a dynamic stopping strategy based on the temporal characteristics of mVEP was proposed for mVEP-based BCI system. The strategy finds a trade-off between accuracy and required time for target recognition and can adaptively determine the suitable number of repetitions during online use for the individual subject. The evaluation results which obtained from a dataset including 11 subjects show that the PITR is significantly improved using the proposed stopping strategy when compared with the traditional fixed repetition method. The improvement has great value in real-life applications because the communication efficiency is very important. It is also possible to extend the proposed strategy in asynchronous BCI system and future studies are needed to explain the inter-subject performance variations phenomenon.

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