HYBRID BRAIN COMPUTER INTERFACE PARADIGM-A STUDY

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Abstract- P300 and steady-state visual evoked potential (SSVEP) approaches have been the most common paradigms used for BCI's world over. But these do not yield satisfactory results in some subjects. That gave birth to a new approach combining two or more existing approaches to improve accuracy and ITR for majority subjects. The present study compares an established hybrid P300/SSVEP BCIs paradigm to a new paradigm in which pictorial stimulus, instead of colour changing, is adopted for P300 evocation to decrease the degradation on SSVEP strength.

Index Terms- Brain–computer interface (BCI) Hybrid paradigm P300 SSVEP

I. INTRODUCTION

Brain Computer Interfaces (BCIs) are Assistive Devices (ADs) that are used for the communication of humans with the world or to command a computer/external device to accomplish a task or enhance the performance of the user using brain activity signals. The basal aim of the BCIs today is to provide communication and environmental control capabilities to people with motor disabilities [1]. BCIs generally rely the brain activity recorded in the form of electroencephalogram (EEG) as the communication basis between the subject and the machine. Commonly used EEG derivatives are P300, steady-state visually evoked potential (SSVEP), event related de-synchronization (ERD) & event related synchronization (ERS) [2-6].

The P300 is an event-related potential (ERP) shows a positive deflection in the EEG that develops approximately 300 ms after the occurrence of the stimulus the user considers relevant. Farwell and Donchin were the first to describe a BCI based on the P300 [7]. They designed a 6 × 6 matrix containing 10 numbers and 26 letters that was presented to subjects on a computer monitor. The subjects were asked to focus attention on one of the 36 items in the matrix, called the "target", while ignoring the rest of the matrix. Next, the display flashed rows or columns of the matrix. Whenever the row or column containing the target item flashed, the subject produced a P300, which could be used to identify the target item. P300 BCIs require very little training, and have been extensively validated with healthy users and patients. However, the P300is relatively weak amidst the background noise in the EEG. Thus, P300-based BCIs require averaging of the EEG responses resulting from several flashes to obtain acceptable performance, which may reduce the system speed and thus the overall information transfer rate (ITR)) [8].

The SSVEP is a result of concentrating attention to a rapidly oscillating stimulus [9,10]. It is a steady-state response that is elicited when Subject focuses attention on a flashing external stimulus with higher frequency. The SSVEP is dominant over occipital Region and is apparent at the same frequency as the flickering stimulus, as well as higher or lower harmonic frequency components [11]. The SSVEP BCI was the first BCI described by Vidal, 1973 [12], and has also been extensively studied and modified by Ortneret in 2011 [13]. SSVEP BCI requires subjects to view a variety of flickering items, such as LEDs or boxes on a monitor with different flickering frequencies. If subjects focus attention on one such item, called the target, then the SSVEP activity at corresponding frequencies will be stronger in the subject's EEG. Hence, an SSVEP BCI can determine which target item the subject was watching by detecting which SSVEP frequencies shows largest power in power spectrum analysis. Another typical paradigm is the checker-board pattern which can produce a more significant SSVEP than a flicker stimulus modulated at the same frequency. It is widely used in eliciting SSVEPs [14-16]. SSVEP BCIs and related approaches are among the fastest BCIs in the literature, and require very little training, but may be annoying or fatiguing to some users and entail a small risk of seizure.

In 2001 Pfurtscheller and Neuper used the synchronization and desynchronization (ERD/ERS) of sensorimotor rhythms for BCIs [17]. In a SMR BCI, users imagine different movements (such as clenching the right or left fist), which generates ERD/S activity that is dominant over sensorimotor areas. Thus, users can move a cursor to the left or right or perform other tasks by imagining different movements. This approach has also been studied extensively and can allow simultaneous control of up to three dimensions of movement in a few subjects [18,19]. However, the ERD approach typically requires more training than other BCI approaches and – like other BCI approaches – may not work in some subjects [20]. While there is little debate that this phenomenon is a concern, there

is tremendous disagreement over how to label it, with terms including “BCI illiteracy”, “BCI inefficiency”, or “poor BCI proficiency”. Many studies have shown a significant inter-subject variability when exploring different displays and task paradigms within P300 and SSVEP BCIs, which may sometimes leave a minority of users unable to communicate [21,22]. For example, [23] studied many SSVEP BCI users and found that SSVEP BCI performance varied substantially across subjects, and were ineffective for some users. Since BCIs based on a single approach may not work in some subjects, [24] and [17] proposed the idea of a hybrid BCI. In a hybrid BCI, one BCI approach may be combined with another BCI approach, which could help improve usability, speed, accuracy, or other features [25]. Panicker in 2011 proposed an asynchronous BCI spelling system based on P300 and SSVEP [26], in which SSVEP was used to detect whether subjects were paying attention to the P300 BCI. Xu in 2013 developed a hybrid BCI speller to evoke the P300 and SSVEP blocking (SSVEP-B) distinctly and simultaneously with the same target stimulus. The results indicated that the combination of P300 and SSVEP-B improved the target discrimination greatly [27]. This hybrid paradigm was superior to the control paradigm in spelling performance. For some hybrid BCI systems based on visual evoked potentials, only one EEG pattern (such as P300) is taken as the main command output, supplemented by others (such as SSVEP) [26]. Some hybrid BCI combinations might require effective control of two BCI approaches, such as SSVEP to control one dimension of movement while ERD controls another dimension [28]. Although this hybrid BCI combination may have many advantages, it would not reduce illiteracy; instead, users must be able to generate effective EEG signals. For subjects who are illiterate with one BCI approach, a hybrid BCI could provide an alternate BCI approach. Hybrid BCIs have recently gained considerable attention in the literature. For example, [22] combined SSVEP with motor-imagery. Their results suggested that subjects who cannot use a certain BCI might consider switching to a different BCI approach [29,30]. It has been proved that there were subjects who could not use one of the P300 or SSVEP paradigms [23,31] , which indicated that hybrid BCI system could help these users who show “illiterate” on P300 or SSVEP. Normal hybrid paradigms commonly use the “Flash and Flickering” paradigm to elicit P300 and SSVEP respectively. It has been proved that hybrid BCI combining SSVEP and P300 could improve the performance of a BCI system [32, 33]. In their study, a hybrid speller paradigm was designed, in which all cells flickered at six different frequencies to elicit SSVEPs and the row or column of the matrix flashed in a pseudorandom sequence to elicit P300.However, this paradigm will lead to a checkerboard phenomenon. A checkerboard pattern is a graphic consisting of squares in two alternating colors (often black and white) at the same frequency to obtain a double stable frequency which elicited SSVEP effectively. In the “Flash and Flickering” condition, the flash paradigm (color changing) occurs randomly inducing unstable flash frequencies which could disturb the frequency of flickering. In our study, we presented a new hybrid method of SSVEP and P300 to improve the hybrid performance further. In our paradigm, shape changing substitutes the color changing to elicit a P300, which avoids the unstable checkerboard pattern occurring. Li in 2013 presented a new strategy for hybrid BCI of P300 and SSVEP, which combined the outputs of the individual P300 and SSVEP detections to make decision. In our paradigm, the SSVEP was improved significantly which could help to improve this kind of hybrid BCI system [34].

II. MATERIALS AND METHODS

A. Subjects

Ten healthy right-hand volunteers (7 males, aged 22–30, mean 25.4) with no visual impairments or any known cognitive deficits participated in the experiments. Among them, s2, s5, s7, and s10 had no experience with any BCI before this study. The subjects were seated in a comfortable chair 90 cm from a standard 19 in.CRT monitor (75 Hz refresh rate, 1024 × 768 screen resolution) in a shielded room. Subjects were asked to relax and avoid unnecessary movement during the experiments.

In our study, we designed a normal hybrid paradigm (Flash and Flickering-Hybrid) and the new hybrid paradigm (Pictorial and Flickering-Hybrid) based on P300 and SSVEP, and compared them to the traditional P300 (Flash-P300 and Shape Changing-P300) and the traditional SSVEP (Traditional-SSVEP) paradigms. The five interfaces used in this study are shown in Fig. 1. All inter-faces contained four items against a black background. Each subject completed five offline experimental sessions (each session for each paradigm) on two separate days. Subjects did three of the paradigms on the first day and did the rest on the next day. The order of the paradigms was random. Each session contained 20 runs.

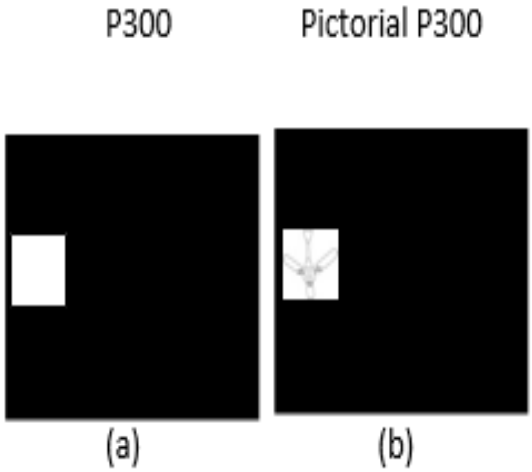
B. Experimental stimuli and paradigms

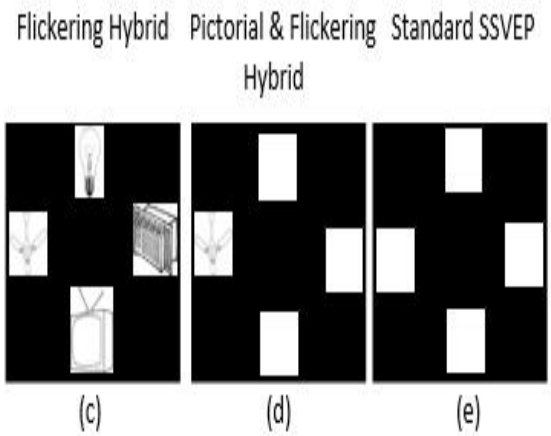
There were four targets in each run for each subject. The subject was asked to focus one target for 4 s each time. Each flashing target consisted of a guide message (2 s) and a flash process (4 s). Hence, the time of data recording of each run would cost (2 + 4) s × 4 = 24 s. Considering the preparation and rest time, the time of one session would cost about 30 min. Between every two sessions subjects would be given 15 min to rest. During the Flash-P300 conditions (see Fig. 1a),

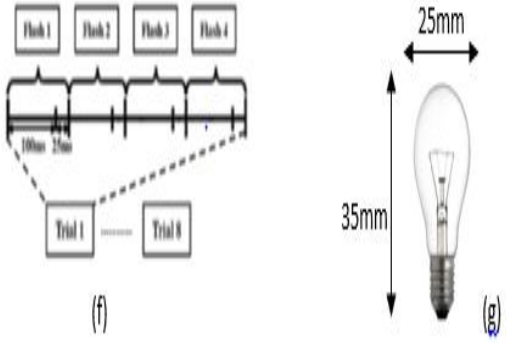
the subjects were instructed to silently count each time the target items flashed or changed. Each trial consisted of 4 flashes. Before each target task, the target item was cued by a white box lasting 2 s. Then, each of the four items flashed once in each trial. There were eight trials for each target task. During each flash, the red boxes changed from red to white for 100 ms, then a 25 ms delay followed until the next flash began (see Fig. 1g). The Pictorial -P300 condition was the same as the Flash-P300 condition except that the white boxes were replaced by pictures of devices during the flash (see Fig. 1b).

In the Traditional-SSVEP condition (see Fig. 1e), the display and procedure were identical to the P300 condition, with two exceptions. First, the boxes did not flash. Instead, each box flickered at a specific frequency (left: 10 Hz, top: 9 Hz, right: 8 Hz, bottom: 6 Hz). Second, subjects were asked to focus their attention on the target box, rather than count flashes. It has been reported that it would be better to use the frequency that was higher than 10 Hz [35]. However, the software "presentation" was used to program the stimulus and it would be hard to get higher frequency stimulus using this software.

Furthermore, the frequency that under 10 Hz was still commonly used in other studies, e.g [36,37]. Because of these reasons, 6 Hz, 8 Hz, 9 Hz, and 10 Hz were selected in our study.



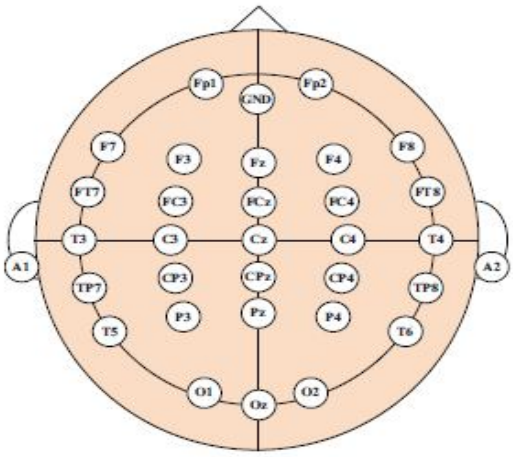




The 'Flash and Flickering-Hybrid' and 'Pictorial and Flickering-Hybrid' conditions were the same as the 'Flash-P300and Pictorial' and 'Flickering-P300' conditions respectively, with two exceptions (see Fig. 1c and d). First, during the flash, the red boxes changed to white boxes (Flash and Flickering-Hybrid) or red arrows (Shape Changing and Flickering-Hybrid) for 100 ms but kept flickering at the original frequencies. Second, subjects were asked to both count flashes and focus attention on the target box.

C. EEG acquisition

EEG signals were sampled at 250 Hz through the RMS Acquisition amplifier (high-pass and low-pass filters 0.1 Hz and 70 Hz) and 32-channel cap following the 10–20 international system (Fig. 2). All channels were used for signal recording and analysis, which were referenced to the average of the electrode A1 and A2 located over the left and right mastoid with a forehead ground (GND). All impedances were below 5 kΩ.



D. Feature Extraction Procedure

Our study involves two signals: SSVEP and P300. We applied different pre-processing operations to each signal type before further analysis.

SSVEP: The following channels were used for SSVEP signal recording and analysis (see Fig.): Pz, P3, P4, T5, T6, Oz, O1, and O2. We used the 32 electrodes cap of RMS Acquisition amplifier, which did not have POx electrodes. Therefore, we selected T5 and T6 which were near electrodes PO7 and PO8. Other electrodes were selected based on reference [38]. A sixth order Butterworth band pass filter was used to filter the EEG between 5 Hz and 30 Hz. Features were extracted from the flash start to the flash end and lasted for 4s. Therefore, the size of each feature matrix was 8 × 1000 (8 channels by 1000 time points). P300: All channels were used for P300 signal recording and analysis. A sixth order Butterworth band pass filter was used to filter the EEG between 0.5 Hz and 12 Hz. The EEG was down-sampled from 250 Hz to 50 Hz by selecting every fifth sample from the filtered EEG. Single flashes lasting 800 ms were extracted from the data. The size of each feature matrix was 30 × 40 (30 channels by 40 time points).

E. Classification Scheme

We adopted different algorithms to classify SSVEP and P300 activity: Canonical correlation analysis (CCA) is a common algorithm in BCI [39-41]. CCA is a multivariate statistical algorithm which attempts to reveal correlations between two sets of data. Consider two sets of random demeaned variables $X \in \mathbf{R}^{I_1 \times J}$ & $\in \mathbf{R}^{I_2 \times J}$, CCA tries to find a pair of linear transforms $w = \in \mathbf{R}^{I_1}$ and $v = \in \mathbf{R}^{I_2}$, to maximize the correlation between $x = w^T X$ and $y = v^T Y$. The optimization problem is described as the following formula:

$$\rho = \max_{w,v} \frac{E[xy]}{\sqrt{E[x^2]E[x^2]}} = \frac{E[w^T X Y^T v]}{\sqrt{E[w^T X X^T w] E[w v^T Y Y^T v]}} = \frac{w^T \sum_{xy} v}{\sqrt{w^T \sum_{xx} w v^T \sum_{yy} v}} \quad (1)$$

Where ρ denotes the correlation coefficient; $\sum_{xx}$ and $\sum_{yy}$ denotes the within-class covariance matrix. This algorithm detects the target frequency by identifying the dominant frequency component of the current EEG by maximizing the correlation between the EEG and the SSVEP stimulation frequencies (sin/cosine signals).We analyzed the data of eight channels (Pz, P3, P4, T5, T6, Oz, O1, and O2) by CCA. We also made a time–frequency and power spectral density analysis via the Morlet wavelet transform (MWT) and fast Fourier transform (FFT) respectively using the data from Oz, O1, and O2.

Bayesian linear discriminant analysis (BLDA) has been widely used in BCIs for P300 classification [42-44]. BLDA uses regularization to prevent over fitting to high dimensional and possibly noisy datasets. Through a Bayesian analysis the degree of regularization can be estimated automatically and quickly from training data without the need for time consuming cross-validation [42]. We assume the target t and feature vectors x are linearly related with additive white Gaussian noise n:

$$t = w^T x + n \quad (2)$$

The likelihood function for the weight w used in regression can be described as:

$$p(D|\beta, w) = \left(\frac{\beta}{2\pi}\right)^{N/2} \exp\left(-\frac{\beta}{2}\|X^T w - t\|^2\right) \quad (3)$$

Here, t denotes a vector containing the regression targets,

X denotes the matrix that is obtained from the horizontal stacking of the training feature vectors, D denotes the pair {X, t}, β denotes the inverse variance of the noise, and N denotes the number of examples in the training set. In the Bayesian setting, we specify a prior distribution for the latent variables w. The regression is described as:

$$p(w|\alpha) = \left(\frac{\alpha}{2\pi}\right)^{D/2} \left(\frac{\varepsilon}{2\pi}\right)^{1/2} \exp\left(-\frac{1}{2}\left|w^T I'(\alpha) w\right.\right) \quad (4)$$

Here, I'(α) is a D + 1 dimensional diagonal matrix (D is the number of features).

$$I'(\alpha) = \begin{bmatrix} \alpha & 0 & \dots & 0 \\ 0 & \alpha & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \varepsilon \end{bmatrix} \quad (5)$$

Using Bayes rule, the posterior distribution can be computed as:

$$p(\hat{t}|\beta, \alpha, D) = \frac{p(D|\beta, w) p(w|\alpha)}{\int p(D|\beta, w) p(w|\alpha) dw} \quad (6)$$

We obtain the predictive distribution by multiplying Eq. (3) for a new input vector $\hat{x}$ and Eq. (6). The function is:

$$p(\hat{t}|\beta,\alpha,\hat{x},D) = \int p(\hat{t}|\beta,w)p(w|\beta,\alpha,D)dw \qquad (7)$$

The predictive distribution can be characterized by its mean and its variance σ^2:

$$\mu = m^T \hat{x} \qquad (8)$$

$$\sigma^2 = \frac{1}{\beta} + \hat{x}^T C \hat{x} \qquad (9)$$

Mean values were summed over trials and the image corresponding to the maximum of the summed mean values was then selected. In our work, we recorded 20 data sets for P300. We arranged them into ten groups according to the recording order of the data sets. For an example, the first and second data sets were in group one. 10 × 10 cross-fold validation was performed based on the ten groups.

F. Information transfer rate evaluation

ITR is used to evaluate the communication performance of

BCI systems [45]. For a trial with N possible choices in which each choice is equally probable, the accuracy (Acc) that the desired choice will indeed be selected remains invariant, and each error choice has the same probability of selection.

Subjects	Pictorial and flickering-hybrid (SSVEP)		Flash and flickering-hybrid (SSVEP)		Traditional-SSVEP (SSVEP)	
	Acc (%)	ITR (bits/min)	Acc (%)	ITR (bits/min)	Acc (%)	ITR (bits/min)
s1	77.50	13.11	47.50	2.65	86.25	18.07
s2	97.50	26.76	73.75	11.30	96.50	26.88
s3	96.25	25.65	80.00	14.42	90.00	20.59
s4	98.75	28.25	88.75	19.71	98.75	28.25
s5	95.00	24.52	78.75	13.75	96.25	25.65
s6	96.25	25.65	72.50	10.73	82.50	15.80
s7	85.00	17.29	58.75	5.53	93.75	23.45
s8	95.01	24.52	67.50	8.63	73.75	11.30
s9	96.25	25.65	87.50	18.87	97.75	23.45
s10	68.75	9.13	67.50	8.63	65.00	7.67
Avg	91.63±10.06	20.07±6.22	71.25±12.69	11.41±46	87.75±11.10	20.11±6.84

The ITR (bit/min) can be calculated as:

$$B = log_2 N + Acc log_2 Acc + (1 - Acc) log_2 Acc \frac{1-Acc}{N-1} \qquad (10)$$

$$ITR = B \times \frac{60}{t} \qquad (11)$$

where, N denotes the number of items; Acc denotes the accuracy of classification; B denotes the bit rate of determining one target; t denotes the time that determining one target will cost.

RESULTS AND CONCLUSION

The improved accuracy and higher ITR shown in the case of Pictorial and flickering from flash and flickering and traditional SSVEP BCIs indicate that this paradigm is an upgrade from the previously used approaches. Most of the subjects responded well to the stimuli and showed lower levels of stress and irritation from the stimulus.

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