Clinical Neuroscience

A new hybrid BCI paradigm based on P300 and SSVEP

Minjue Wang, Ian Daly, Brendan Z. Allison, Jing Jin, Yu Zhang, Lanlan Chen, Xingyu Wang

* Key Laboratory of Advanced Control and Optimization for Chemical Processes, Ministry of Education, East China University of Science and Technology, Shanghai, PR China
b Brain Embodiment Lab, School of Systems Engineering, University of Reading, Reading, UK
c Cognitive Neuroscience Laboratory, Department of Cognitive Science, University of California at San Diego, La Jolla, CA, USA

HIGHLIGHTS

- The new hybrid P300/SSVEP BCIs paradigm could obtain as high classification accuracy as the traditional SSVEP paradigm.
- This pattern also could obtain as high classification accuracy of P300 as the traditional P300 paradigm.
- P300 did not interfere with the SSVEP response using the new hybrid paradigm.

ARTICLE INFO

Article history:
Received 20 December 2013
Received in revised form 24 April 2014
Accepted 3 June 2014
Available online 2 July 2014

Keywords:
Brain–computer interface (BCI)
Hybrid paradigm
P300
SSVEP

ABSTRACT

Background: P300 and steady-state visual evoked potential (SSVEP) approaches have been widely used for brain–computer interface (BCI) systems. However, neither of these approaches can work for all subjects. Some groups have reported that a hybrid BCI that combines two or more approaches might provide BCI functionality to more users. Hybrid P300/SSVEP BCIs have only recently been developed and validated, and very few avenues to improve performance have been explored.

New method: The present study compares an established hybrid P300/SSVEP BCIs paradigm to a new paradigm in which shape changing, instead of color changing, is adopted for P300 evocation to decrease the degradation on SSVEP strength.

Result: The result shows that the new hybrid paradigm presented in this paper yields much better performance than the normal hybrid paradigm.

Comparison with existing method: A performance increase of nearly 20% in SSVEP classification is achieved using the new hybrid paradigm in comparison with the normal hybrid paradigm. All the paradigms except the normal hybrid paradigm used in this paper obtain 100% accuracy in P300 classification.

Conclusions: The new hybrid P300/SSVEP BCIs paradigm in which shape changing, instead of color changing, could obtain as high classification accuracy of SSVEP as the traditional SSVEP paradigm and could obtain as high classification accuracy of P300 as the traditional P300 paradigm. P300 did not interfere with the SSVEP response using the new hybrid paradigm presented in this paper, which was superior to the normal hybrid P300/SSVEP paradigm.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

A brain–computer interface (BCI) is a communication system that allows users to send messages or commands to a computer or other external device through direct measures of brain activity.

Hence, BCIs can provide communication and environmental control to people with motor disabilities, as well as healthy people when other means of communication are not practical (Wolpaw et al., 2002). Most BCIs rely on the electroencephalogram (EEG) to measure brain activity in real-time. The three most common approaches to EEG-based BCIs are named after the types of EEG phenomena used for control, namely the P300 visual evoked potential, steady-state visual evoked potential (SSVEP), and event-related (de) synchronization (ERD/ERS) (Vidal, 1973; Cheng et al., 2002; Pfurtscheller and Neuper, 2001; Sellers and Donchin, 2006; Jin et al., 2011a; Zhang et al., 2012; Wang et al., 2006).

http://dx.doi.org/10.1016/j.jneumeth.2014.06.003
0165-0270/© 2014 Elsevier B.V. All rights reserved.
The P300 is an event-related potential (ERP) with a positive deflection in the EEG that develops approximately 300 ms after an event the user considers relevant. Farwell and Donchin (1988) first described a BCI based on the P300. They designed a 6 × 6 matrix layout 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”, and count each time it flashed 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 P300 is 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) (Wolpaw et al., 2002; Pritch, 1981; Fazeli-Rezaei et al., 2012).

The SSVEP reflects attention to a rapidly oscillating stimulus (Pritch, 1981; Regan, 1989). It is a steady-state response that is elicited when people focus attention on a rapidly flickering external stimulus. The SSVEP is dominant over occipital sites and is apparent at the same frequency as the flickering stimulus, as well as higher or lower harmonic frequency components (Muller-Putz et al., 2005). The SSVEP BCI was the first BCI described in the literature (Vidal, 1973), and has also been extensively studied (Ortnet et al., 2011). In a typical SSVEP BCI, subjects are asked to view a variety of flickering items, such as LEDs or boxes on a monitor. 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 show stronger activity. Another typical paradigm is the checkerboard pattern which can produce a more pronounced SSVEP than a flicker stimulus modulated at the same frequency. It is widely used in eliciting SSVEPs (Lalor et al., 2005; Trejo et al., 2006; Martinez et al., 2007; Allison et al., 2008). 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.

Pfurtscheller and Neuper (2001) have used the synchronization and desynchronization (ERD/ERS) of sensorimotor rhythms for BCIs. In an ERD 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 by performing different tasks while imagining different movements. This approach has also been studied by many groups and can allow simultaneous control of up to three dimensions of movement in a few subjects (Guger et al., 2009; Hammer et al., 2012; Lu et al., 2013). However, the ERD approach typically requires more training than other BCI approaches and – like other BCI approaches – may not work in some subjects (Vidaurre and Blankertz, 2010). 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 (Fazeli-Rezaei et al., 2012; Allison et al., 2010a). For example, Allison et al. (2010b) 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, Allison et al. (2007) and Pfurtscheller et al. (2010) 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 (Muller-Putz et al., 2011). Panicker et al. (2011) proposed an asynchronous BCI spelling system based on P300 and SSVEP, in which SSVEP was used to detect whether subjects were paying attention to the P300 BCI. Xu et al. (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. 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) (Panicker et al., 2011). 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 (Allison et al., 2012). 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, Allison et al. (2010a) combined SSVEP with motor-imagery. Their results suggested that subjects who cannot use a certain BCI might consider switching to a different BCI approach (Pfurtscheller et al., 2010; Brunner et al., 2010).

It has been proved that there were subjects who could not use one of the P300 or SSVEP paradigms (Guger et al., 2009; Allison et al., 2010b), 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 (Yin et al., 2013; Allison et al., 2014). 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 et al. (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.

2. Materials and methods

2.1. Subjects

Ten healthy right-hand volunteers (9 males, aged 22–27, mean 24.1) without visual impairments or any known cognitive deficits participated in our experiments. Among them, s4, s6, s7, s9, and s10 had no experience with any BCI before this study. The subjects were seated in a comfortable chair 60 cm from a standard 17 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.
2.2. Experimental stimuli and paradigms

In our study, we designed a normal hybrid paradigm (Flash and Flickering-Hybrid) and the new hybrid paradigm (Shape Changing 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 interfaces 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. 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 10 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 red 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 Shape Changing-P300 condition was the same as the Flash-P300 condition except that the white boxes were replaced by red arrows during the flash (see Fig. 1c).

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 counting flashes. It has been reported that it would be better to use the frequency that was higher than 10 Hz (Bakardjian et al., 2010). However, the software “presentation” was used to program the stimulus and it would be hard to get higher frequency stimuli using this software. Furthermore, the frequency that under 10 Hz was still commonly used in other studies, e.g. (Müller-Putz and Pfurtscheller, 2008; Ortner et al., 2011). Because of these reasons, 6 Hz, 8 Hz, 9 Hz, and 10 Hz were selected in our study.

The ‘Flash and Flickering-Hybrid’ and ‘Shape Changing and Flickering-Hybrid’ conditions were the same as the ‘Flash-P300 and Shape Changing’ and ‘Flickering-P300’ conditions respectively, with two exceptions (see Fig. 1b 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.

2.3. EEG acquisition

EEG signals were sampled at 250 Hz through the NeuroScan 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.
2.4. Feature extraction procedure

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

SSVEP: The following channels were used for SSVEP signal recording and analysis (see Fig. 2): Pz, P3, P4, T5, T6, Oz, O1, and O2. We used the 32 electrodes cap of NeuroScan, 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 (Bin et al., 2009). 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 4 s. 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).

2.5. Classification scheme

We adopted different algorithms to classify SSVEP and P300 activity:

Canonical correlation analysis (CCA) is a common algorithm in BCI (Lin et al., 2006; Bin et al., 2009; Daly et al., 2013). CCA is a multivariate statistical algorithm which attempts to reveal correlations between two sets of data. Consider two sets of random demeaned variables \( X \in \mathbb{R}^{n \times l} \) and \( Y \in \mathbb{R}^{n \times l} \), CCA tries to find a pair of linear transforms \( w \in \mathbb{R}^l \) and \( \nu \in \mathbb{R}^k \) to maximize the correlation between \( x = w^T X \) and \( y = \nu^T Y \). The optimization problem is described as the following formula:

\[
\rho = \max_{w, \nu} \frac{E[x'y']}{\sqrt{E[x'^2]E[y'^2]}} = \frac{E[w^T X Y^T \nu]}{\sqrt{E[w^T X X^T w] E[\nu^T Y Y^T \nu]}}
\]

\[
= \frac{w^T \Sigma_{xy} \nu}{\sqrt{w^T \Sigma_{xx} w \nu^T \Sigma_{yy} \nu}}.
\]

(1)

where \( \rho \) denotes the correlation coefficient; \( \Sigma_{xx} \) and \( \Sigma_{yy} \) denote 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 (Hoffmann et al., 2008; Jin et al., 2011b, 2012a). BLDA uses regularization to prevent overfitting 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 (Hoffmann et al., 2008).

We assume the target \( t \) and feature vectors \( x \) are linearly related with additive white Gaussian noise \( n \):

\[
t = w^T x + n
\]

(2)

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

\[
p(D|\beta, w) = \left( \frac{\beta}{2\pi} \right)^{N/2} \exp \left( -\frac{1}{2} \| w^T X - t \|^2 \right)
\]

(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 \( \{X, t\} \), \( \beta \) 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:

\[
p(w|\alpha) = \left( \frac{\alpha}{2\pi} \right)^{D/2} \left( \frac{\varepsilon}{2\pi} \right)^{1/2} \exp \left( -\frac{1}{2} \| w \|^2 \right)
\]

(4)

Here, \( \Gamma(\alpha) \) is a \( D \times 1 \) dimensional diagonal matrix (\( D \) is the number of features).

\[
\Gamma(\alpha) = \begin{bmatrix} \alpha & 0 & \cdots & 0 \\ 0 & \alpha & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \varepsilon \end{bmatrix}
\]

(5)

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

\[
p(w|\beta, \alpha, D) = \frac{p(D|\beta, w)p(w|\alpha)}{\int p(D|\beta, w)p(w|\alpha)dw}
\]

(6)

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

\[
p(\hat{t}|\beta, \alpha, \hat{x}, D) = \int p(\hat{t}|\beta, w)p(w|\beta, \alpha, D)dw
\]

(7)

The predictive distribution can be characterized by its mean \( \mu \) and its variance \( \sigma^2 \):

\[
\mu = m^T \hat{x}
\]

(8)
Fig. 3. Results from three SSVEP paradigms derived from offline analysis of the average using channels Oz, O1, and O2. The three columns reflect the three paradigms, and the rows reflect different analyses across four stimulus frequencies. Each stimulus frequency denoted on the left includes two rows of figures. The top rows are the spectrograms. The vertical axis denotes the frequency (Hz), and the horizontal axis denotes time (s). The bottom rows contain the power spectral density of different frequencies. The vertical axis denotes the power spectral density (PSD), and the horizontal axis the frequency (Hz).

\[ \sigma^2 = \frac{1}{n} + \lambda^2 \text{CT} \]  

(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.

2.6. Information transfer rate evaluation

ITR is used to evaluate the communication performance of BCI systems (Wolpaw et al., 2002). For a trial with N possible choices in
Table 1
The accuracy and ITR (bits/min) of each of the SSVEP conditions.

<table>
<thead>
<tr>
<th></th>
<th>Flash and flickering-hybrid (SSVEP)</th>
<th>Shape changing and flickering-hybrid (SSVEP)</th>
<th>Traditional-SSVEP (SSVEP)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc (%)</td>
<td>ITR (bits/min)</td>
<td>Acc (%)</td>
</tr>
<tr>
<td>s1</td>
<td>73.75</td>
<td>11.30</td>
<td>97.50</td>
</tr>
<tr>
<td>s2</td>
<td>47.50</td>
<td>2.55</td>
<td>77.50</td>
</tr>
<tr>
<td>s3</td>
<td>67.50</td>
<td>8.63</td>
<td>68.75</td>
</tr>
<tr>
<td>s4</td>
<td>80.00</td>
<td>14.42</td>
<td>96.25</td>
</tr>
<tr>
<td>s5</td>
<td>88.75</td>
<td>19.71</td>
<td>98.75</td>
</tr>
<tr>
<td>s6</td>
<td>78.75</td>
<td>13.75</td>
<td>95.00</td>
</tr>
<tr>
<td>s7</td>
<td>72.50</td>
<td>10.73</td>
<td>96.25</td>
</tr>
<tr>
<td>s8</td>
<td>58.75</td>
<td>5.53</td>
<td>85.00</td>
</tr>
<tr>
<td>s9</td>
<td>67.50</td>
<td>8.63</td>
<td>95.00</td>
</tr>
<tr>
<td>s10</td>
<td>87.5</td>
<td>16.87</td>
<td>96.25</td>
</tr>
<tr>
<td>Avg</td>
<td>72.25 ± 12.69</td>
<td>11.41 ± 5.46</td>
<td>90.63 ± 10.16</td>
</tr>
</tbody>
</table>

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

\[
B = \log_2 N + Acc \log_2 Acc + (1 - Acc) \log_2 (1 - Acc) \left( \frac{1 - Acc}{N - 1} \right) \tag{10}
\]

\[
ITR = B \times \frac{60}{t} \tag{11}
\]

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.

2.7. Subjective report

After completing each session, each subject was asked three questions about the current paradigms. These questions could be answered on a 1–5 scale indicating strong disagreement, moderate disagreement, neutrality, moderate agreement, or strong agreement. The three questions were (Jin et al., 2012b)

1. Was this paradigm annoying?
2. Was this paradigm hard?
3. Did this paradigm make you tired?

2.8. Statistical analysis

Before statistically comparing classification accuracy and raw bit rate, data were statistically tested for normal distribution (One-Sample Kolmogorov Smirnov test) and sphericity (Mauchly’s test). Significant analysis is generally based on the hypothesis testing of normal distribution. The Mauchly test (or Mauchly’s test) assesses the validity of the sphericity assumption that underlies repeated measures analysis of variance (ANOVA). Post hoc comparison was performed with Tuckey-Kramer tests. Since three paradigms of our study contained SSVEP and four paradigms of our study contained P300, the alpha level was adjusted according to Bonferroni–Holm with \( \alpha = 0.025 \) for SSVEP comparison and \( \alpha = 0.016 \) for P300 comparison.

3. Results

3.1. SSVEP

We plot the time–frequency information calculated with the Morlet wavelet transform (MWT) and power spectral density (PSD) calculated with the fast Fourier transform (FFT) using the average data from Oz, O1, and O2 (see Fig. 3). All paradigms (Flash and Flickering-Hybrid (SSVEP), Shape Changing and Flickering-Hybrid (SSVEP), and Traditional-SSVEP (SSVEP)) evoked effective SSVEP signals when the frequency of stimulus was 6 Hz. The fundamental signal and the second harmonic were evoked in three paradigms. However, SSVEP responses were less distinct in the Flash and Flickering-Hybrid paradigm when the frequencies of stimulus were 8 Hz, 9 Hz, and 10 Hz. In the Shape Changing and Flickering-Hybrid (SSVEP) and Traditional-SSVEP paradigms, the stimuli evoked clear SSVEP signals across all the different frequencies. Thus, we speculate that color changes (like the white boxes in the Flash and Flickering-Hybrid paradigm) may disrupt the SSVEP signals. On the other hand, shape changes (like the red arrows in the Shape Changing and Flickering-Hybrid paradigm) may not affect the response of the SSVEP signals. The classification accuracies of the three paradigms shown in Table 1 further clarify the impact of SSVEP activity on performance.

Table 1 presents the accuracy and ITR of the SSVEP classification from three paradigms (Flash and Flickering-Hybrid (SSVEP), Shape Changing and Flickering-Hybrid (SSVEP), and Traditional-SSVEP). We mark the worst result across all paradigms in each subject in italics, the best paradigm in bold and the average in italics and bold. An ANOVA directly compared these three paradigms (Flash and Flickering-Hybrid (SSVEP), Shape Changing and Flickering-Hybrid (SSVEP), and Traditional-SSVEP) within subjects, revealing significant differences in terms of classification accuracy (\( F(2,27) = 7.56, p = 0.0025 \)) and ITR (\( F(2,27) = 8.11, p = 0.0017 \)). In a separate comparison, the three different paradigms were compared to each other. A significant difference was found between Flash and Flickering-Hybrid (SSVEP) and Shape Changing and Flickering-Hybrid (SSVEP) in terms of classification accuracy (\( F(1,18) = 12.78, p = 0.0022 \)) and ITR (\( F(1,18) = 15.7, p = 0.0009 \)). There were significant differences between the Flash and Flickering-Hybrid (SSVEP) and Traditional-SSVEP paradigms in classification (\( F(1,18) = 8.45, p = 0.0094 \)) and ITR (\( F(1,18) = 0.89, p = 0.0056 < 0.016 \)). This means that in the case of the SSVEP pattern, the traditional ‘Flash and Flickering-Hybrid’ paradigm shows worse performance than the ‘Shape Changing and Flickering-Hybrid’ and the ‘traditional SSVEP’ paradigms.

3.2. P300

Fig. 4 shows the grand averaged ERPs across subjects 1–10 over channels Cz and Pz. It shows that all four P300 paradigms can evoke identifiable P300 signals.

Fig. 5 shows the performance of four P300 paradigms only using the P300 features with the BLDA classifier accuracy (Flash and Flickering-Hybrid (P300), Shape Changing and Flickering-Hybrid (P300), Flash-P300, and Shape Changing-P300) of all subjects and the average. We measured the classification accuracy and bit rate using single trial for four paradigms. No significant difference was found between these four paradigms (classification
Fig. 4. Waveforms of ERPs recorded at Cz and Pz elicited by the flash and flickering-hybrid, Flash-P300, shape changing and flickering-hybrid, and shape changing-P300 conditions, averaged across all subjects.

Fig. 5. Accuracy (a) and bitrate (b) of four P300 paradigms derived from the offline analysis of all subjects and the average. The left vertical axis indicates the classification accuracy and the right vertical axis indicates the bitrate (bits/min) estimated from this offline data. The x-axis reflects results based on averages of different numbers of trials.
3.3. Subjective report

Table 2 presents the subjects’ responses to the three questions. No significant difference was found between the five paradigms in terms of difficulty ($F(4,45) = 1.12, p = 0.361$) and tiredness ($F(4,45) = 1.42, p = 0.2415$). However, post hoc comparison of annoyance showed significant differences ($p = 0.001$). In the separate comparison of annoyance between Shape Changing and Flickering-Hybrid and Shape Changing-P300, there was a significant difference ($F(1,18) = 20.95, p = 0.0002$).

4. Discussion

The primary goal of this study was to propose a new hybrid paradigm (Shape Changing and Flickering-Hybrid) based on the use of P300 and SSVEP as command outputs to expand the group of BCI users. The performance across different paradigms was evaluated through the dependent variables classification accuracy and estimated ITR.

Using SSVEP features, the classification accuracy of our new hybrid paradigm (Shape Changing and Flickering-Hybrid, classification accuracy: 90.63%) is significantly better than the conventional hybrid paradigm (Flash and Flickering-Hybrid, classification accuracy: 72.25%) by over 15% ($F(1,18) = 12.78, p = 0.0022$), and almost the same as the traditional SSVEP paradigm (Traditional-SSVEP, classification accuracy: 87.75%, $F(1,18) = 0.37, p = 0.5532$; see Table 1). The reason is that the frequency of random “Flashes” is unstable in the Flash and Flickering-Hybrid condition. Unlike the traditional checkerboard pattern, this “unstable checkerboard
phenomenon” will make the frequency of the evoked SSVEP unstable and decrease the classification accuracy. Fig. 3 shows that the Flash and Flickering-Hybrid condition evoked the SSVEP with a wider range of frequencies than the other two patterns, which supports the result of our study. Comparing the Shape Changing and Flickering-Hybrid SSVEP and Traditional-SSVEP conditions (in Fig. 3), the spectrums and PSD of these two paradigms are almost the same and elicited good performance. In the Shape Changing and Flickering-Hybrid condition, color changing is replaced by shape changing, which may not decrease the degradation on SSVEP strength. This indicates that the SSVEP from the Shape Changing and Flickering-Hybrid alone can be used as an effective output mechanism.

Using P300 features, our new hybrid paradigm (Shape Changing and Flickering-Hybrid) also performed well (classification accuracy using all eight trials: 100%). No significant difference was found between Flash and Flickering-Hybrid, Shape Changing and Flickering-Hybrid and the traditional P300 paradigms (waveforms seen in Fig. 4, classification accuracy: \(R^2 = 0.36\), \(p = 0.1132 > 0.05\) and ITR: \(R^2 = 1.14, p = 0.3444 > 0.05\)). This result indicates that the P300 can work well in hybrid paradigms. Many studies have reached the same conclusion (Allison et al., 2010a,b; Panicker et al., 2011; Xu et al., 2013; Li et al., 2010; Guo et al., 2008; Hong et al., 2009). In addition, the “Shape Change” pattern can evoke P300 potentials as reliable as the traditional “Flash” pattern. In terms of difficulty \((F(4,45) = 1.18, p = 0.361)\) and tiredness \((F(4,45) = 1.25, p = 0.2415)\), the difference between these five paradigms is not significant. However, a high luminance contrast in traditional paradigms is usually required to elicit a prominent visible evoked potential for the paradigm with visual stimuli of intensification or pattern reversal, and this may cause visual fatigue and annoyance for the subjects (Brunner et al., 2011; Allison et al., 2012). This may explain the subjects’ feedback. Subjects felt less annoyance in the Shape Changing and Flickering-Hybrid paradigm (average score: 2.1) than the traditional P300 paradigm (Shape Changing-P300, average score: 3.7, \(F(1,18) = 20.95, p = 0.0002\)).

One of the goals of hybrid BCI was to reduce illiteracy (Pfurtscheller et al., 2010; Brunner et al., 2010). Brunner et al. (2010) reported that an illiterate subject could not effectively control a BCI, meaning that the classification accuracy was below a certain threshold (70%). In our study, subject 3 was an illiterate subject whose classification accuracy of SSVEP was 68%. However, subject 3 could obtain high classification accuracy of P300 potentials (see Fig. 5). Since the sample of subjects was small, we did not get a subject who could not use P300 BCI. However, it has been proved that there were subjects who could not use P300 (Guger et al., 2009). It indicated that this hybrid BCI system could help these users who show “illiterate” on P300 or SSVEP.

The presented hybrid paradigm of P300 and SSVEP (Yin et al., 2013; Allison et al., 2014) may affect the evoking of SSVEP. In our study, we present a new hybrid paradigm which will not affect the performance of SSVEP. The result shows that SSVEP could be evoked using the new hybrid method. In Fig. 5, it showed that the classification of P300 of the new hybrid paradigm was also as good as other paradigms, which helps to show the predominant performance of the new hybrid paradigm, i.e. in our paradigm the P300 did not interfere with the SSVEP response. Since the quality of evoked SSVEP was improved and the quality of evoked P300 was as good as the P300 only BCI using this hybrid paradigm, it would not only help to improve the performance of the hybrid BCI which combined the outputs of the individual P300 and SSVEP detections (Li et al., 2013), but also help to improve the performance of hybrid BCI which combines the features of SSVEP and P300 (Yin et al., 2013).

Edlinger et al. (2011) have shown that the P300 pattern in a hybrid BCI is very suitable for applications with several controllable devices and where a discrete control command is desired, while a SSVEP based system is more suitable if a continuous control signal is needed and the number of commands is rather limited. Our proposed new hybrid paradigm could work well both in the applications with discrete control commands and continuous control signals.

This work is significant because it introduces methods that can improve BCI performance for some users, which in some cases may overcome BCI illiteracy. Using traditional paradigms, we need to know which EEG pattern suits the subject in advance. Our new proposed hybrid paradigm performs well using either P300 features or SSVEP features.

5. Conclusions

In this study, we introduced a new hybrid BCI paradigm using multiple EEG patterns (P300 and SSVEP) and compared them to established hybrid and “single” BCIs. Experimental results based on ten healthy subjects demonstrated that the performance of the new hybrid paradigm was significantly improved relative to the normal hybrid paradigm using SSVEP features. The Shape Changing and Flickering-Hybrid condition also yielded promising performance (100% accuracy and 30 bit/min obtained with eight trials for average) using BLDA. These results indicate that the new paradigms introduced could influence BCI applications by improving performance for some users. Future work will focus on the novel display
and task parameters, further evaluation of frequency and stimulation parameters, reducing perceived annoyance, and online testing.

Acknowledgements

This work was supported in part by the Grant National Natural Science Foundation of China, under Grant numbers 61203127, 61074113, 6110122, 6120124 and 61305028 and supported part by Shanghai Leading Academic Discipline Project, Project Number: B504. This work was also supported by the Fundamental Research Funds for the Central Universities (WG1414005, WH1314023).

References


