An optimized ERP Brain-computer interface based on facial expression changes

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Abstract

Objective: Interferences from spatially adjacent non-target stimuli are known to evoke event-related potentials (ERPs) during non-target flashes and, therefore, lead to false positives. This phenomenon was commonly seen in visual attention based Brain-computer interfaces (BCIs) using conspicuous stimuli and is known to adversely affect the performance of BCI systems. Although, users try to focus on the target stimulus, they cannot help but be affected by conspicuous changes of the stimuli (such as flashes or presenting images) which were adjacent to the target stimulus. Furthermore, subjects have reported that conspicuous stimuli made them tired and annoyed. In view of this, the aim of this study was to reduce adjacent interference, annoyance, and fatigue using a new stimulus presentation pattern based upon facial expression changes. Our goal was not to design a new pattern which could evoke larger ERPs than the face pattern, but to design a new pattern which could reduce adjacent interference, annoyance, and fatigue and evoke ERPs as good as those observed during the face pattern.

Approach: Positive facial expressions could be changed to negative facial expressions by minor changes to the original facial image. Although the changes are minor, the contrast is big enough to evoke strong ERPs. In this paper, a facial expression change pattern between positive and negative facial expressions was used to attempt to minimize interference effects. This was compared against two different conditions, a shuffled pattern containing the same shapes and colors as the facial
expression change pattern, but without the semantic content associated with a change in expression, and a face vs. no face pattern. Comparisons were made in terms of classification accuracy and information transfer rate as well as user supplied subjective measures.

Main results: The results showed that interferences from adjacent stimuli, annoyance, and the fatigue experienced by the subjects could be reduced significantly (p<0.05) by using the facial expression change patterns in comparison with the face pattern. The offline results show that the classification accuracy of the facial expression change pattern was significantly better than that of the shuffled pattern (p<0.05) and the face pattern (p<0.05).

Significance: The facial expression change pattern presented in this paper reduced interference from adjacent stimuli and decreased the fatigue and annoyance experienced by BCI users significantly (p<0.05) compared to the face pattern.

Introduction

A Brain-computer interface (BCI) is an emerging communication technology based on brain activities, which may have the potential to allow disabled patients to communicate with the external world without any physical actions. Brain-computer interfacing is commonly based on EEG recorded noninvasively via electrodes placed on the surface of the head [1]. Motor imagery and visual evoked potentials are commonly used in BCIs [2, 3, 4, 5, 6, 7, 8, 9].

The P300 BCI is one example of a BCI system that can make use of visual stimuli [10, 11, 12, 13]. P300 ERPs are evoked by asking users to focus their attention on a target and count its appearances [14, 15]. The P300 BCI was first used in speller applications and yielded good performance [10]. Currently, P300 BCIs have been tested not only on healthy users but also on patients [2, 6, 10, 11, 13-15]. Additionally, P300-speller BCIs have already been applied in a “BrainPainting” system, internet browser, and environmental control [16, 17, 18].

Although many P300 BCI systems have been developed, most of them are still in the lab stage due to their low speed and unstable accuracy. A large amount of research has been done to improve the P300 BCI system by using optimized signal processing and pattern recognition methods to improve the classification accuracy [19, 20, 21, 22, 23, 14], designing new ERP evoking paradigms (e.g. gaze independent BCIs) to expand the applicability for ALS patients [25, 26], and optimizing the stimuli configuration to increase speed and reliability [27, 28]. Enhancing the difference between attended and ignored events is one of the hot topics in the research of P300 BCIs.

Some groups adopted new stimulus presentation paradigms to increase other components of the ERP that occur before or after the P300. Guo et al., 2008 introduced a novel way to elicit visual evoked potentials in a BCI: the stimuli briefly moved, instead of flashed, to evoke a motion visual evoked potential (M-VEP). They reported that this BCI system might offer superior performance to a conventional P300 BCI [29, 30, 31]. Jin et al, 2012 combined the P300 and M-VEP by moving flash stimuli to improve the P300 BCI system [32]. Kaufmann et al. (2011) introduced stimuli that were transparently overlaid with famous faces to improve the classification accuracy by evoking a large
N400 [33, 34] Zhang et al. (2012) reported that N170 and vertex positive potentials (VPP) also improve classification accuracy in a P300 BCI with stimuli that change to faces [35].

However, while this research succeeded in increasing the reliability of identifying target flashes [28, 36], there is another way that could further improve the ERP-based BCI. If the false evoked ERP in non-target flashes caused by the interference of spatially adjacent stimuli and the fatigue experienced by users could both be decreased, it would provide benefits to BCI users in terms of accuracy and usability. Some studies have tried to reduce the interference by decreasing the number of adjacent flashes [27, 28, 37]. However, this increased the number of flashes in each trial, which reduced the speed of the BCI system. In this paper, a facial expression change pattern paradigm was designed to decrease the interference, the annoyance, and the fatigue experienced by users without decreasing the speed of the BCI system.

The primary goal of this study was to verify the performance of the facial expression change pattern in reducing the interference, annoyance, and the fatigue experienced by users. The key idea behind this work is that minor changes to some types of image cause a big enough contrast to evoke strong ERPs, while not producing large interference effects. It has been proven that the use of a face pattern is superior to a “flash only” pattern [33, 34, 35, 38] and, furthermore, that different facial expressions could evoke strong ERPs [39, 40, 41]. Human facial expression changes are simulated by changing the orientation of a curve in a dummy face. In this way, the subjects would not be aware of the changes of adjacent images when they are focusing on the target image. Because of the all previous reasons, a face expression change pattern was designed. This stimuli type was tested against two comparable conditions, a shuffled pattern and a face pattern.

The face pattern serves to test whether the accuracies and bit rates observed with the facial expression change pattern are due to the use of the expression change (as opposed to the use of a human face). The shuffled face pattern serves to test whether the particular semantic information attached to the facial expression change pattern (positive or negative facial expressions) leads to the observed accuracies and bit rates (as opposed to changes in the properties of the image, such as color, shape etc.).

These patterns were compared with each other in terms of accuracy and information transfer rate to verify the performance of the facial expression change pattern. We hypothesized firstly, that introducing small changes to the face would improve classification rates as compared to the shuffled patterns; secondly small changes to the face would decrease the interference and annoyance, and the fatigue as compared to the face pattern. In this study, the system is a gaze-dependent BCI system using a small visual angle interface, which could be used by patients who did not completely lose their ability to maintain eye gaze.

Materials and methods
2.1 Subjects
Ten healthy subjects (9 male and 1 female, aged 22-27 years, mean 24±1.6, all right handed) participated in this study. All subjects signed a written consent form prior to the experiment and were paid for their participation. The local ethics committee approved the consent form and experimental procedure before any subjects participated. All subjects’ native language was Mandarin Chinese. Eight
subjects had used a BCI before this study.

2.2 Stimuli and procedure
After being prepared for EEG recording, subjects were seated about 60 cm in front of a monitor that was 21.5 cm high (visual angle 19.7 degrees) and 38.5 cm wide (visual angle 32.7 degrees). The stimuli were presented in the middle of the screen. During data acquisition, subjects were asked to relax and avoid unnecessary movement. Figure 1 shows the display presented to all subjects. It was a hexagon with six small circles at each of the six corners. The distance between two adjacent circles’ centre points was 4cm (visual angle 3.8 degrees), the distance between the centre point of the hexagon and the centre point of the circle was 4cm (visual angle 3.8 degrees), and the radius of the small circle was 1cm (visual angle: 0.95 degrees). There were three conditions in the study, which differed only in the stimuli images.

The “facial expression change” pattern proposed in this study consists of a simple line drawing of a “happy face”. The drawing contains two eyes with eyebrows and a mouth, each of which are represented by simple arcs and circles drawn in monochrome. The target stimuli is generated by rotating the arc representing the mouth by 180° to produce a “sad face”. The “shuffled face” condition contains all the same elements as the “facial expression change” condition (the same arcs and circles) but randomly re-shuffled with orientations of all the elements randomly changed. Thus, the shuffled face condition provides a stimuli with identical image properties to the “facial expression change” pattern but without the attached semantic information that one face is “happy” and the other is “sad”. Finally, the “face pattern” consists of either a blank circle or a neutral face (with a straight line representing the mouth area).

![Figure 1. The display during the online runs. The five-letter target sequence is presented at the top of the screen, and the feedback is presented below it. Please see the text for a description of the different panels in this figure.](image-url)
The three conditions changed the stimuli in the purple box of figure 1. The purple box was not shown in the real interface. The stimulus off state (background state) can be seen in the left column of figure 1 and the stimulus on state can be seen in the right column of figure 1. The stimulus on time is 200ms.

We used the term “flash” throughout this paper to refer to each individual event, such as a change in the shuffled face pattern. In each trial of each condition, each circle was changed once. Hence, a single character flash pattern was used here [42], in which the single circle or facial image changed individually. For simplicity, we use the term “flash” throughout this paper to refer to these changes. In all three conditions, after the 200 ms flash, all circles or facial images reverted to their usual background state for 100 ms before the next flash began.

2.3 Experiment set up, offline and online protocols

EEG signals were recorded with a g.USBamp and a g.EEGcap (Guger Technologies, Graz, Austria) with a sensitivity of 100µV, band pass filtered between 0.1Hz and 30Hz, and sampled at 256Hz. We recorded from 62 EEG electrode positions based on the extended international 10-20 system (see Figure 2). The electrodes with black boxes were selected for the online experiment based upon work in [33, 35, 43]. The right mastoid electrode was used as the reference, and the front electrode (FPz) was used as the ground. Active electrodes were used and impedances of all the electrodes were less than 30KΩ, which is the smallest impedance that is shown on the g.tec active electrode device. Data were recorded and analyzed using the ECUST BCI platform software package developed through East China University of Science and Technology.

As noted, each flash reflected each time a stimulus changed from a background stimulus, such as each change in the shuffled pattern. One trial (equal to one sequence) contained all flashes with each of the six flash patterns. Since all conditions had 200 ms flashes followed by a 100 ms delay, each trial lasted 1.8 seconds. A trial block referred to a group of trials with the same target. During offline testing, there were 16 trials per trial block and each run consisted of five trial blocks, each of which involved a different target. Subjects had a five minute break after each offline run. During online testing, the number of trials per trial block was two. Subjects attempted to identify 40 targets continuously during online testing (see figure 3).
There were three conditions, which were presented to each subject in pseudorandom order. Double flashes were avoided in this stimuli presentation pattern [44]. For each condition, each subject first participated in three offline runs. Subjects had five minutes rest between each offline run. After all offline runs of the three conditions, subjects were tasked with attempting to identify 40 targets (i.e. 40 trial blocks) continuously for each condition in the online experiment. Feedback and target selection time was 4 seconds before the beginning of each trial block (counting the “flashes” in one of the six circles, see figure 1). Subjects had five minutes rest before starting the online task for each condition. Before each trial, a white arrow cue was used to show the target (face or circle) which the subjects should focus on and count the flash numbers of in both online and offline experiments. The feedback from an online experiment was shown on the top of the screen. The feedback was shown by using a white block around the target when the BCI system identified the target the subject was focused on. The feedback on the top of the screen was used to record the result of one online experiment and the white block feedback was shown to subjects.

![Figure 3 One run of the experiment for online and offline experiment](image)

2.4 Feature extraction procedure
A third order Butterworth band pass filter was used to filter the EEG between 0.1Hz and 30Hz. The EEG was then down-sampled from 256Hz to 64Hz by selecting every fourth sample from the filtered EEG. Single flashes lasting 800ms were extracted from the data. For the offline data, windsorizing was used to remove the electrooculogram (EOG). The 10th percentile and the 90th percentile were computed for the samples from each electrode. Amplitude values lying below the 10th percentile or above the 90th percentile were then replaced by the 10th percentile or the 90th percentile, respectively [21].

2.5 Classification scheme
Bayesian linear discriminant analysis (BLDA) is an extension of Fisher’s linear discriminant analysis (FLDA) that avoids over fitting. The details of the algorithm can be found in [21]. BLDA was selected
because of its demonstrated classification performance in P300 BCI applications [21]. Data acquired offline were used to train the classifier using BLDA and obtain the classifier model. This model was then used in the online system.

2.6 Practical bit rate
In this paper, we used two bit rate calculation methods called practical bit rate (PBR) and raw bit rate (RBR). The PBR is used to estimate the speed of the system in a real-world setting. The PBR incorporates the fact that every error requires two additional selections to correct the error (a backspace followed by selection of the correct character). The practical bit rate is calculated as \( RBR \times (1 - 2 \times P) \), where RBR is the raw bit rate and P is the online error rate of the system [27]. The PBR also incorporates the time between selections (4 seconds). Raw bit rate was calculated without selection time and is defined in [45].

2.7 Subjective report
After completing the last run, each subject was asked three questions about each of the three conditions. 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:
1) Was this paradigm annoying?
2) Did this paradigm make you tired?
3) Was this paradigm hard? We asked subjects if they are not able to catch the speed of the changes and count the number of the flashes. The question was asked in Chinese.

2.8 Statistical analysis
Before statistically comparing classification accuracy and practical bit rate, data were statistically tested for normal distribution (One-Sample Kolmogorov Smirnov test) and sphericity (Mauchly’s test). Subsequently, repeated measures ANOVAs with stimulus type as factor were conducted. The \( p \) value
was adjusted according to Bonferroni. Three levels of the factor were entered into the ANOVA. Condition (shuffled face pattern, facial expression change pattern and face pattern) was used as independent variable.

**Result**

### 3.1 Offline analysis

**Figure 5.** Grand averaged ERPs of non-target trials across subjects 1-10 over 16 electrode sites (see figure 2, the electrodes with black boxes)

<table>
<thead>
<tr>
<th>ERP</th>
<th>Electrodes</th>
<th>S-P</th>
<th>FEC-P</th>
<th>F-P</th>
<th>S-P</th>
<th>FEC-P</th>
<th>F-P</th>
</tr>
</thead>
<tbody>
<tr>
<td>N200</td>
<td>P7</td>
<td>-1.7764</td>
<td>-1.9248</td>
<td>-2.7680</td>
<td>267.19</td>
<td>264.45</td>
<td>267.97</td>
</tr>
<tr>
<td>P300</td>
<td>Pz</td>
<td>2.4068</td>
<td>1.8933</td>
<td>1.6849</td>
<td>355.86</td>
<td>358.20</td>
<td>360.55</td>
</tr>
<tr>
<td>N400</td>
<td>Fz</td>
<td>-1.8226</td>
<td>-2.3866</td>
<td>-1.7589</td>
<td>431.64</td>
<td>431.64</td>
<td>439.06</td>
</tr>
</tbody>
</table>

“S-P” denotes the shuffled pattern, “FEC-P” denotes the facial expression change pattern, and “F-P” denotes the face pattern.

Figure 4 shows the grand averaged amplitude of target and non-target flashes across subjects 1-10 over 16 sites used in the online experiment. We measured the peak points of N200 on electrode P7 (commonly chosen for measuring the N200 [31]), the peak points of P300 on Pz (commonly chosen for measuring the P300), and peak points of N400 on Fz (commonly chosen for measuring the N400 [46]) for each subject. A one way ANOVA was used to show the difference of ERPs among the patterns. It
was shown that there are no significant difference on N200 (F(2, 27)=0.51, p=0.6, Eta²=0.364), on P300 (F(2, 27)=0.66, p=0.5, Eta²=0.439) and on N400 (F(2, 27)=0.46 P=0.6, Eta²=0.404) between the patterns. The mean value of ERPs and latency averaged from 10 subjects is shown in table 1. This shows that the facial expression change pattern could evoke as large ERPs as the face pattern.

Figure 6. Energy of false evoked ERPs from Oz (panel A), topographic maps of absolute amplitude values between 0-800 ms of non-target flashes from 62 electrodes (panel B).

Figure 5 shows the grand averaged ERPs of non-target trials across subjects 1-10. The adjacent non-target “flashes” (interference) may evoke ERPs at any time, which will enlarge the non-target absolute amplitude values. We calculated the absolute amplitude value of non-targets averaged from 0-800ms on channel Oz (which was less affected by eye movement than other electrodes in central and frontal areas) for each subject (See Figure 6.A).

A one way repeated measures ANOVA was used to show the absolute amplitude value difference of non-target flashes among the three patterns (F(2, 18)=8.37 p<0.05, Eta²=0.482 ). It was found that the non-target absolute amplitude values on Oz during the face pattern were significantly larger than that of the face expression change pattern (p<0.05). Here, absolute amplitude value of non-targets was used as dependent value. Three level factors were used. We used repeated measures to define the factor function in SPSS to calculate the result. Figure 6.B shows the topographic maps of absolute amplitude values of non-target flashes from 62 electrodes. Note that the face pattern contains higher false evoked ERPs in non-target flashes than the patterns. We also calculate the peak value of N200, P300, and N400
on Oz during target flashes. This shows that there are no significant differences between the facial expression change pattern and the face pattern on Oz for N200 (F(2,27)=0.34, p=0.7, Eta²=0.276), P300 (F(2,27)=1.26, p=0.3, Eta²=0.482) and N400 (F(2,27)=0, p=0.9, Eta²=0.079). The face pattern contained larger interference (false evoked potentials) in non-target flashes and evoked ERPs which are not higher than the facial expression change pattern, which would make the classification accuracy of the face pattern lower than the facial expression pattern.

Table 2 Offline single trial classification accuracy using 15-fold cross-validation

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
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<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
<th>S10</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-P</td>
<td>93.3</td>
<td>83.8</td>
<td>77.1</td>
<td>88.3</td>
<td>58.3</td>
<td>90.0</td>
<td>90.8</td>
<td>83.3</td>
<td>65.4</td>
<td>64.6</td>
<td>79.5±12.5</td>
</tr>
<tr>
<td>FEC-P</td>
<td>96.4</td>
<td>92.1</td>
<td>85.8</td>
<td>90.8</td>
<td>89.6</td>
<td>86.3</td>
<td>97.1</td>
<td>98.3</td>
<td>90.4</td>
<td>77.1</td>
<td>90.5±6.3</td>
</tr>
<tr>
<td>F-P</td>
<td>92.1</td>
<td>89.2</td>
<td>72.9</td>
<td>82.9</td>
<td>72.1</td>
<td>87.1</td>
<td>94.6</td>
<td>91.7</td>
<td>91.3</td>
<td>72.9</td>
<td>84.7±8.9</td>
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</tbody>
</table>

“S-P” denotes the shuffled pattern, “FEC-P” denotes the facial expression change pattern, and “F-P” denotes the face pattern.

Figure 7. The classification accuracy, raw bit rate (RBR), and practical bit rate (PBR) are based on offline data using 1-16 trials to construct the average.

Table 3 Performance from online feedback runs using two trials to construct the average

<table>
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<tr>
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<th>S1</th>
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<th>S3</th>
<th>S4</th>
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</thead>
<tbody>
<tr>
<td>Acc (%)</td>
<td>S-P</td>
<td>95.0</td>
<td>82.5</td>
<td>87.5</td>
<td>87.5</td>
<td>90.0</td>
<td>95.0</td>
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<td>82.5</td>
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<tr>
<td></td>
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<td>92.5</td>
<td>97.5</td>
<td>90.0</td>
<td>95.0</td>
<td>100</td>
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<td>85.0</td>
<td>94.5±5.1</td>
</tr>
<tr>
<td></td>
<td>F-P</td>
<td>85.0</td>
<td>90.0</td>
<td>85.0</td>
<td>90.0</td>
<td>92.5</td>
<td>85.0</td>
<td>100</td>
<td>85.0</td>
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<td>89.8±6.1</td>
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<tr>
<td>RBR</td>
<td>S-P</td>
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<td>25.2</td>
<td>29.2</td>
<td>29.2</td>
<td>31.4</td>
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<td>25.2</td>
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<tr>
<td></td>
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<td>43.1</td>
<td>43.1</td>
<td>27.1</td>
<td>27.1</td>
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<tr>
<td>PBR</td>
<td>S-P</td>
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<td>7.7</td>
<td>10.4</td>
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<td>13.6</td>
<td>9.0</td>
<td>20.4</td>
<td>20.4</td>
<td>9.0</td>
<td>9.0</td>
</tr>
</tbody>
</table>

In this table, “Acc” refers to classification accuracy, “RBR” to raw bit rate and “PBR” to practical bit rate, measured in bits/min. “S-P” denotes the shuffled pattern, “FEC-P” denotes the facial expression change pattern, and “F-P” denotes the face pattern.

Table 2 shows the single trial classification accuracy using 15-fold cross-validation. There are 240 trials for each subject. A one way repeated measures ANOVA was used to show the classification difference among the three patterns (F(2, 18)=7.46, p<0.05, Eta²=0.453). The result shows that classification accuracy using single trials of the facial expression change pattern (mean accuracy 90.5±6.3) is significantly higher than that of the shuffled face pattern (mean accuracy 79.5±12.5)
(p<0.05) and the face pattern (mean accuracy 84.7±8.9) (p<0.05). In Figure 7, it also shows that the facial expression change pattern is better than the face pattern. Figure 7 shows the classification accuracy, raw bit rate, and practical bit rate based on offline data averaged from subjects 1-10 using 15-fold cross-validation. It also shows that the facial expression change pattern is better than the other two patterns in classification accuracy, raw bit rate, and practical bit rate, when one or two trials were used for constructing an average.

3.2 Online analysis

Table 3 shows the online classification accuracy, bit rate and practical bit rate using two trials to construct the average time series. Some subjects failed to control the online BCI using single trials in the pilot experiment. However, the performance improves when two trials were used for constructing the average. Therefore, two trials were used for constructing the average in the online experiment. A one way repeated measures ANOVA was used to show the classification accuracy (F(2, 18)=5.24, p<0.05, Eta²=0.376) and practical bit rate (F(2, 18)=5.61, p<0.05, Eta²=0.384) difference among the three patterns. This shows that the facial expression change pattern is significantly better than the shuffled pattern in terms of accuracy (p<0.05) and practical bit rate (p<0.05). The mean classification accuracy of the facial expression change pattern is 4.7% higher than that of the shuffled pattern and the face pattern, while the mean practical bit rate of the facial expression change pattern is 3.3 bits/min higher than that of the shuffled pattern and the face pattern.

3.3 Subjective report

Table 4 presents the subjects’ responses to the three questions. In order to show the difference between the face expression pattern and the face pattern, a paired-samples t-test was used. This shows that the facial expression change pattern is significantly less annoying (t=-6.708, p<0.05) and less tiring (t=-3.674, p<0.05) than the face pattern. No significant difference was found for difficulty (t=0, p=1).

In this table, “S-P” denotes the shuffled pattern, “FEC-P” the facial expression change pattern, and “F-P” the face pattern.

Table 4 Subjects’ responses to three questions for each of the three patterns.

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
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<th>S7</th>
<th>S8</th>
<th>S9</th>
<th>S10</th>
</tr>
</thead>
<tbody>
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<td>Annoying</td>
<td>S-P (%)</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>FEC-P</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
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<td>F-P</td>
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<tr>
<td>Tired</td>
<td>S-P (%)</td>
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<td>1</td>
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<tr>
<td>Hard</td>
<td>S-P (%)</td>
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<td>2</td>
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Table 4 presents the subjects’ responses to the three questions. In order to show the difference between the face expression pattern and the face pattern, a paired-samples t-test was used. This shows that the facial expression change pattern is significantly less annoying (t=-6.708, p<0.05) and less tiring (t=-3.674, p<0.05) than the face pattern. No significant difference was found for difficulty (t=0, p=1).

Discussion

The goal of this study was to verify the facial expression change pattern’s validity in reducing the
interference from adjacent stimuli, and decreasing user annoyance and fatigue. Although both the shuffled pattern and the facial expression change pattern could decrease the interference and the fatigue, the offline and online results both indicated that the facial expression change pattern could obtain significantly higher classification accuracies and practical bit rates than the shuffled pattern (p<0.05). The offline results show that the facial expression change pattern could obtain significantly higher classification accuracies than the face pattern (p<0.05). The online results also show a trend (p=0.06) towards indicating that the facial expression change pattern is better than the face pattern.

In the face pattern, the face picture was shown just like a flash (conspicuous changes of the stimuli) in the flash pattern, which could make the subject tired or feel annoyed. Additionally, such a pattern also causes the subject to be affected by adjacent non-target flashes when trying to focus on the target. In our paradigm, human facial expression changes are simulated by changing a curve in a dummy face. In this way, subjects are not aware of the changes of adjacent images when they are focusing on the target image. Since the stimulus of the expression change pattern is not as strong as the face and the flash pattern, it was hypothesized that subjects would be less fatigued using the expression change pattern than when using face pattern or the flash pattern and that this pattern would result in less interference effects from neighboring stimuli.

1. Reducing interference
In our study, our goal was not to evoke larger ERPs than that evoked by the face pattern. The goal of this paper was to evoke as large ERPs as the face pattern by using the facial expression change pattern and, in so doing, decrease the interference caused by adjacent non-target flashes and produce less fatigue and annoyance for the subjects. Figure 4 and table 1 show that there are no significant differences on N200, P300, and N400 between the face pattern and the facial expression change pattern in target flashes. Our results show that the interference of the facial expression change pattern realized by changing a curve in a dummy face (see Figure 1) is reduced in comparison with the face pattern (see figure 5) and the offline classification accuracy was increased significantly (p<0.05) in comparison with the shuffled pattern and the face pattern. The facial expression change pattern could evoke as large ERPs as the face pattern (see figure 4 and table 1). We also calculate the absolute amplitude value of non-target flashes (see figure 6) on channel Oz for each subject. This demonstrates that the absolute amplitude value of non-target flashes produced during use of the face pattern is significantly higher than the facial expression change pattern (p<0.05), which indicated that the interference induced by the face pattern is higher than the facial expression change pattern.

2. Reducing fatigue
Conspicuous stimuli make subjects tired and annoyed. Table 4 shows that the new stimuli presentation pattern we propose significantly decreases the fatigue and annoyance experienced by the subjects compared to the face pattern. Thus, subjects are more comfortable when using the proposed presentation pattern compared to the face pattern. This would be valuable for long time use of the BCI. Additionally, the shuffled pattern also decreased user fatigue and annoyance (see table 4) and the facial expression change pattern obtained a significantly higher classification accuracy (p<0.05) in offline and online experiments and a higher practical bit rates (p<0.05) in online experiments.

3. Single trial classification
Subjects may lose their focus or be otherwise adversely affected by adjacent flashes (adjacent interference), when using the BCI. This kind of mistake happens in one or two trails of one run and, hence, could not be found in the averaged amplitude of the ERPs. Therefore, the classification accuracy of single trials was used to test for this kind of mistake for each of the different patterns (shuffled face pattern, facial expression change pattern, and face pattern). When the interference of adjacent flashes was larger, the subject would be more likely to be affected by adjacent non-target flashes. If the subject was easily fatigued or annoyed when using one of the patterns, they would be more prone to loss of attention. This would result in a reduced single trial classification accuracy. In this paper, our results show that the offline single trial classification accuracy of the facial expression change pattern is significantly higher than that of the face pattern (p<0.05) and the shuffled face pattern (p<0.05). This also illustrates that the facial expression change pattern has an advantage in decreasing interference and attracting the attention of subjects, which reduces the amplitude of ERPs evoked by non-target flashes.

4. Potential advantage for patients and healthy users
The system is a gaze-dependent BCI system using a small visual angle interface, which could be used by patients who did not completely lose their ability to maintain eye gaze. Furthermore, the proposed facial expression change pattern was found to be less tiring and annoying than the other patterns, which would be welcomed by patients and other BCI users.

5. Subjective reports
We asked subjects three questions relating to annoyance, tiredness and hardness of each of the three conditions. However, these questions only reflect subjective feelings regarding the three patterns. BCI systems are developed for application to a wide range of user groups. Small samples of subjective reports do not comprehensively demonstrate desirability of the systems. In future studies a wide interview of BCI users may be a necessary step before designing a new BCI system.

This sounds pretty negative. However, subjective reports are essential and valuable if we wish to know about the subjects' perception and satisfaction of a BCI controlled application. It is almost inherent in BCI studies that we have to deal with low sample sizes. But with time also reports from small groups accumulate and we may, in the future, draw some conclusion if we merge results.

Conclusions
A facial expression change pattern for visual attention based BCIs was presented in this paper. It significantly reduces the interference from neighboring stimuli, improving classification accuracy and information transfer rate, while reducing subject annoyance and fatigue. The key idea behind this work is that minor changes to the image cause a large enough contrast to evoke strong ERPs. The result obtained in our work shows a new direction for designing BCI paradigms. Increasing user interest and decreasing annoyance could be an effective way to improve the performance of BCI system, which would also be welcomed by BCI users.

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Reference


interface presentation paradigm based on performance guided constraints Neurosci. Lett. 531 63-68


[40] Bediou B, Eimer M, D’Amato T, Hauk O and Calder A J 2009 In the eye of the beholder: individual differences in reward-drive modulate early frontocentral ERPs to angry faces Neuropsychologia. 47 825-834

[41] Calvo M G, Marrero H and Beltran D 2013 When does the brain distinguish between genuine and ambiguous smiles? An ERP study Brain Cogn. 81 237-246


