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# An independent brain–computer interface using covert non-spatial visual selective attention

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**Abstract**
In this paper, a novel independent brain–computer interface (BCI) system based on covert non-spatial visual selective attention of two superimposed illusory surfaces is described. Perception of two superimposed surfaces was induced by two sets of dots with different colors rotating in opposite directions. The surfaces flickered at different frequencies and elicited distinguishable steady-state visual evoked potentials (SSVEPs) over parietal and occipital areas of the brain. By selectively attending to one of the two surfaces, the SSVEP amplitude at the corresponding frequency was enhanced. An online BCI system utilizing the attentional modulation of SSVEP was implemented and a 3-day online training program with healthy subjects was carried out. The study was conducted with Chinese subjects at Tsinghua University, and German subjects at University Medical Center Hamburg-Eppendorf (UKE) using identical stimulation software and equivalent technical setup. A general improvement of control accuracy with training was observed in 8 out of 18 subjects. An averaged online classification accuracy of $72.6 \pm 16.1\%$ was achieved on the last training day. The system renders SSVEP-based BCI paradigms possible for paralyzed patients with substantial head or ocular motor impairments by employing covert attention shifts instead of changing gaze direction.

## 1. Introduction

Brain–computer interfaces (BCIs) can provide a direct communication channel between the human brain and the external world without using the normal motor output pathways. A BCI offers an alternative method for people who suffer from severe motor disabilities but have intact cognitive capacities to interact with the environment. Great efforts have been made to develop methods for extracting control information from brain signals over the past decades [1–3].

One of the major BCI paradigms employs the modulation of steady-state visual evoked potentials (SSVEPs). In a typical SSVEP BCI system, multiple stimuli flickering at different frequencies are presented to the subject. The subject overtly directs attention to one of the stimuli by changing his/her gaze direction [4–6]. The attended stimulus elicits enhanced SSVEP responses at the corresponding frequency over occipital brain areas. The increase in SSVEP amplitude can be detected in the EEG signal of single trials, classified and translated into control commands. SSVEP BCIs show good performance with regard to speed and accuracy. They are considered, however, as 'dependent' BCIs since muscle activities such as gaze shifting may be needed [1, 7]. Therefore, SSVEP BCIs might not be applicable for patients with substantial head or ocular motor impairments.

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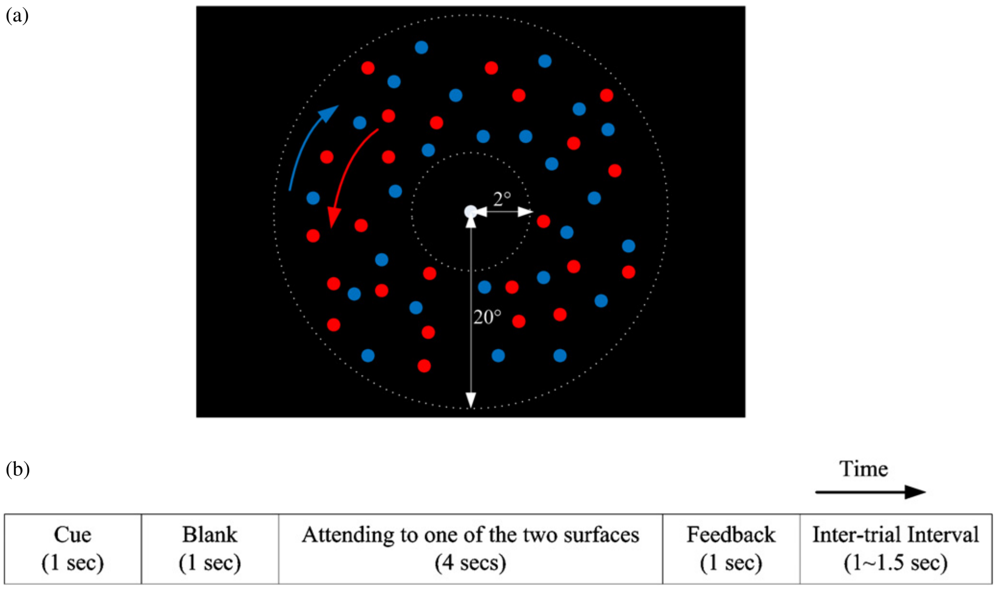


**Figure 1.** The experimental paradigm, (a) stimulus, (b) timing.

Nonetheless, 'independent' SSVEP BCIs are possible, too. A large number of psychophysical and neurophysiological studies have shown that people can covertly shift attention to different spatial locations without redirecting their gaze [8, 9]. In a binary decision task, for example, accuracies between 75% and 90% can be achieved with covert attention shifts [10, 11].

Visual selective attention could be shifted not only between spatial locations, but also between entities like surfaces or objects that are perceived at the same location. Shifting attention to one out of several superimposed objects improves behavioral performance (reaction time and accuracy) and increases neuronal responses compared to when the object is unattended [12–14]. Compared to the large number of studies in the field of non-spatial visual attention research, this effect is surprisingly little harnessed for independent BCIs. In the only available study, two superimposed images with vertical and with horizontal lines, oscillating at different frequencies, were used as visual stimuli. Offline analysis showed that 7 out of 14 subjects were able to exploit the system for binary selection, and the predicted accuracy was around 60–70% for most of them [15].

Adaptation is an important aspect of BCI research [16]. Here, 'adaptation' means co-adaptation between the human brain and the computer: not only the computer updates the algorithm for better classification, but also the human can learn how to optimize behavior for improved computer control. Although requiring little or no training is considered as one of the important advantages of SSVEP BCIs, improved performance by training has been reported [15, 17, 18]. The higher the cognitive demands of the BCI, the more likely performance will gain from training. Online feedback may be particularly effective in this training process.

In this paper, a novel, independent, online SSVEP BCI system is introduced. Two sets of dots with different colors and flicker frequencies, rotating in opposite directions, are used to induce the perception of two superimposed, transparent surfaces. Subjects control the BCI system by selectively attending to one of the two surfaces. A 3-day training program with online feedback was conducted to investigate the co-adaptation between BCI system parameters and human behavior.

## 2. Experimental methods

### 2.1. Subjects

The experiment was conducted first with Chinese subjects at Tsinghua University, and then continued with German subjects at University Medical Center Hamburg-Eppendorf (UKE) using identical stimulation software and equivalent technical setup to assess the cross-laboratory reproducibility of the new paradigm and the general reliability of the results.

22 subjects (11 graduate students from Tsinghua University, China (2 females and 9 males) and 11 graduate students from University Medical Center Hamburg-Eppendorf (UKE), Germany (5 females and 6 males)), between 20 and 35 years old, participated as paid volunteers. All of them showed normal or corrected to normal vision. Two subjects (one female and one male) from Tsinghua University were excluded in data analysis because they showed certain degrees of color blindness to the colors used in the experiment by self-report. Another two subjects (one female and one male) from Hamburg University were excluded due to a failure to evoke SSVEP at one of the stimulation frequencies. Therefore, a total of 18 subjects was included in this study.

### 2.2. Stimuli

The stimulus is illustrated in figure 1(a). It was displayed on an LCD monitor (DELL, USA) with 60 Hz refresh rate. The viewing distance was 60 cm. A white dot was presented in the center of the screen for fixation. Two dot sets of different colors (blue and red) and equal brightness were presented on a black background, and randomly distributed in an annular area between 2° and 20° visual angle from the central fixation dot. Equal brightness was achieved by adjusting the pixel intensities of the displayed color for each subject before the experiments. Each dot subtended 0.3° of visual angle. The blue dots flickered continuously at 10 Hz (2:4 duty cycle, 6 frames per cycle at 60 Hz refresh rate) and the red dots at 12 Hz (2:3 duty cycle, 5 frames per cycle) throughout each trial. In this study, the flickering frequencies of the dots were similar to those used in previous studies [2, 10, 11]. In addition, all blue dots were rotating clockwise around the central fixation dot with an angular velocity of 1° per frame, and all red dots rotated counter-clockwise with the same velocity. The coherence of color and motion within each set of dots induced the perception of two transparent, superimposed surfaces, to which the subjects were instructed to covertly direct their attention.

### 2.3. Experimental procedure

Before each trial, either a blue or a red dot was presented in the center of the screen for 1 s as a cue informing the subject about which surface to attend. After 1 s of blank screen, the stimulus was presented for 4 s. Subjects were asked to direct attention to the respective surface while maintaining fixation on the central white dot. A colored dot of either blue or red was shown after the stimulation period as feedback about the recognized brain state by the BCI system. The timing sequence of a single trial is shown in figure 1(b). The inter-trial interval varied from 1 to 1.5 s. Presentation of the stimuli was programmed in Matlab 7.7.0 (The Mathworks, USA) using the Psychophysics Toolbox 3.0 extensions [19, 20].

The experiment was run in a normal office environment with no electromagnetic shielding. We carefully monitored the daily online performance of the Chinese subjects and observed a significant improvement on three consecutive training days (see section 4.2). A 3 day training paradigm was therefore deemed sufficient, and later, all German subjects completed the same 3 day training program as well. On each day, the same procedure was used: preceded by a training session of 20 trials (10 trials per task, no feedback during the training sessions) to train the classifier, 4 online testing sessions with the same number of trials were carried out. The inter-session break was around 2–3 min. The total time for the experiment per day was less than 30 min including breaks. The preceding training session took only 3 min.

Since the characteristic of EEG may change over time of day, all subjects were required to conduct the experiment at the same time each day (2 subjects in the morning, 15 subjects in the afternoon and 5 subjects in the evening). See section 3.2 for details of the online algorithm. At the end of each testing session, the overall accuracy of the previous session was presented to the subjects. The feedback after each trial (a colored dot showing the classifier's result) and after each session (overall accuracy of the last session) helped the subjects to adjust their control strategy.

### 2.4. EEG and EOG recording

A 32-channel EEG amplifier (ActiveTwo system, Biosemi Instrumentation, The Netherlands) was used to record the EEG at a sampling rate of 128 Hz. The 32 electrodes were positioned according to the 10–20 system. Four additional electrodes were used to record horizontal and vertical EOG for eye movements for 9 out of the 18 subjects.

## 3. Analysis methods

### 3.1. SSVEP feature extraction: canonical correlation analysis

Effective management of inter-subject variability is an important issue in developing practical SSVEP BCI systems. The standard approach is to select the set of electrode channels carrying most information for each subject individually. Methods for automatic channel selection use independent component analysis for an optimal bipolar lead [21], or employ optimization techniques for multi-channel EEG [22]. Here we will use canonical correlation analysis (CCA) for automatic channel selection as introduced in Bin's study [23].

CCA is a way of measuring the linear relationship between two multidimensional variables. Specifically, CCA tries to find for each variable a basis vector that makes the correlation between the projections of each variable on its basis vector maximal [24, 25]. Recently, a parameter-free CCA-based algorithm was developed that showed improved performance over existing SSVEP BCI systems using gaze shifts [26].

We used the feature extraction procedure described in [26]. CCA was used to find for each condition the maximum linear correlation between the multi-channel EEG signals $E$ and a set of reference signals $R$ by solving the following problem:

$$\max \rho = \frac{\langle E \cdot R\rangle}{\sqrt{\langle E^2\rangle \cdot \langle R^2\rangle}} = \frac{w_E^T C_{ER} w_R}{\sqrt{w_E^T C_{EE} w_E w_R^T C_{RR} w_R}}. \quad (1)$$

The expressions $\langle\bullet\rangle$ denote expectation over trials, $w_E$ and $w_R$ are the basis vectors for $E$ and $R$, $C_{EE}$ and $C_{RR}$ correspond to the auto-covariance matrices and $C_{ER}$ to the cross-covariance matrix.

The set of reference signals corresponds to the stimulus signals. A square-wave periodic stimulus signal at frequency $f$, such as that used for the dot flicker, can be decomposed into the Fourier series of its harmonics. We considered the fundamental and second-harmonic frequencies, since only these can be observed in the SSVEP:

$$R(t) = \begin{pmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \sin(4\pi f t) \\ \cos(4\pi f t) \end{pmatrix}. \quad (2)$$

The number of non-zero solutions to equation (1) is limited to the smallest dimensionality of $E$ and $R$. In the online BCI system, 17 electrodes were selected to constitute $E$ and the rank of $R$ is 4. Thus, for each stimulation frequency, CCA will yield four pairs of $(w_E, w_R)$ and four corresponding correlation coefficients $\rho$. When one set of dots is attended,

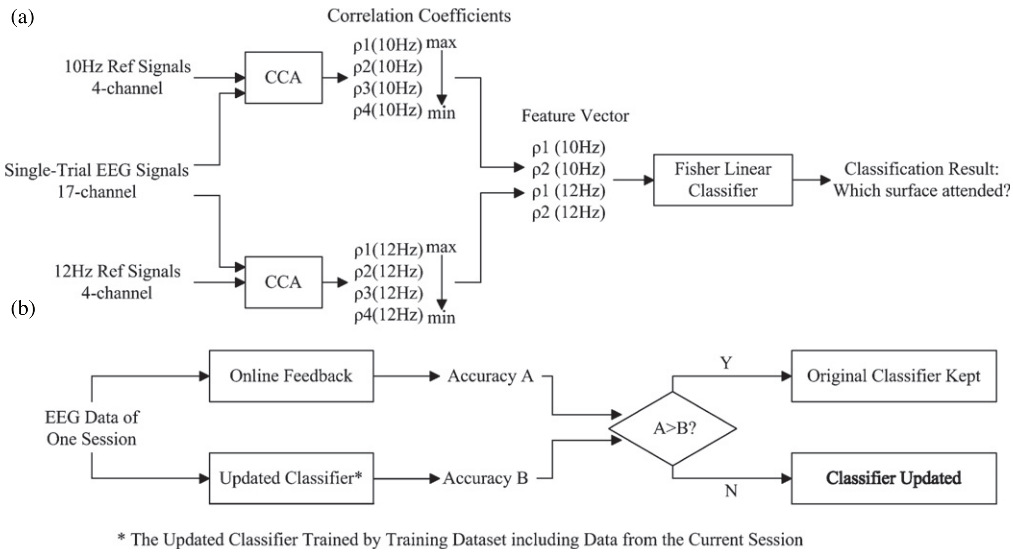


**Figure 2.** The classification procedure. (a) Illustration of the single-trial classification. (b) Strategy for online adaptation of the classifier.

an enhanced correlation is expected between the EEG signal $E$ and the reference signal $R$ at the corresponding frequency, leading to larger correlation coefficients $\rho$.

Correlation coefficients were computed for each trial. As the classifier was initialized using a small training set, only the largest two coefficients at each stimulation frequency were used to form the feature vector for classification to avoid over-training, resulting in a four-dimensional vector for each trial. The usage of the CCA method in our algorithm is depicted in figure 2(a).

### 3.2. Classification

Since EEG signals from electrodes far away from occipital cortex (e.g. frontal, temporal regions) do not contain much information about SSVEP, the data from 17 electrodes over central, parietal and occipital brain regions (Cz, CP1/2, CP5/6, Pz, P3/4, P7/8, PO3/4, Oz, O1, O2) were selected for the online classification. A pre-study showed that higher classification accuracies were obtained using these 17 electrodes than using all 32 electrodes.

CCA was used to calculate the linear correlation between the 17-channel EEG signals during the stimulation interval and the two sets of reference signals at 10 Hz and 12 Hz separately. The correlation coefficients extracted from the two types of trials were then used as features to train or update a Fisher linear classifier. The classification procedure is shown in figure 2(a).

The classifier was initialized with data from the training session. However, as the training session consisted of only ten trials per class, the sample size might be small, thus making the classifier unstable. Therefore, we developed the following strategy to update the parameters of the classifier (figure 2(b)): after each session, a new classifier was initialized with data of the current session and the training dataset was computed. If the accuracy of this classifier was equal to or higher than the online accuracy of the current session (based on the training dataset only), then the data of the current session were added to the training dataset and the new classifier was used for the next session. Otherwise, the training dataset and the previous classifier were kept. By using this strategy, the classifier could gradually increase the sample size for better and more stable performance while excluding sessions with poor subject performance.

While the parameters of the classifier were updated from session to session on each training day, we did not transfer them from day to day. On each training day, the subjects had to start with the training session. The purpose of this design is to investigate the adaptation of the human to the BCI system. With no parameter transferred between days, the only thing transferred is the human experience with the BCI system.

## 4. Results

### 4.1. Attentional modulation effects of SSVEP

SSVEPs at 10 Hz and 12 Hz, elicited by the two flickering surfaces under the attended condition, show similar spatial distributions over the parietal and occipital areas (figure 3(a)). When subjects directed their attention to one of the superimposed surfaces, the SSVEP amplitudes at the corresponding driving frequency were enhanced over approximately the same brain areas (figure 3(b)). A typical modulation of SSVEPs at electrode Oz in the time domain is shown in figure 3(c). In the spectral domain, the attentional modulation of SSVEP amplitudes could be observed not only at the fundamental, but also at the second-harmonic frequencies, with larger effects at the fundamental frequencies (figure 3(d)).

### 4.2. Online performances

For each testing session, the online classification accuracy value was computed, resulting in four accuracy values

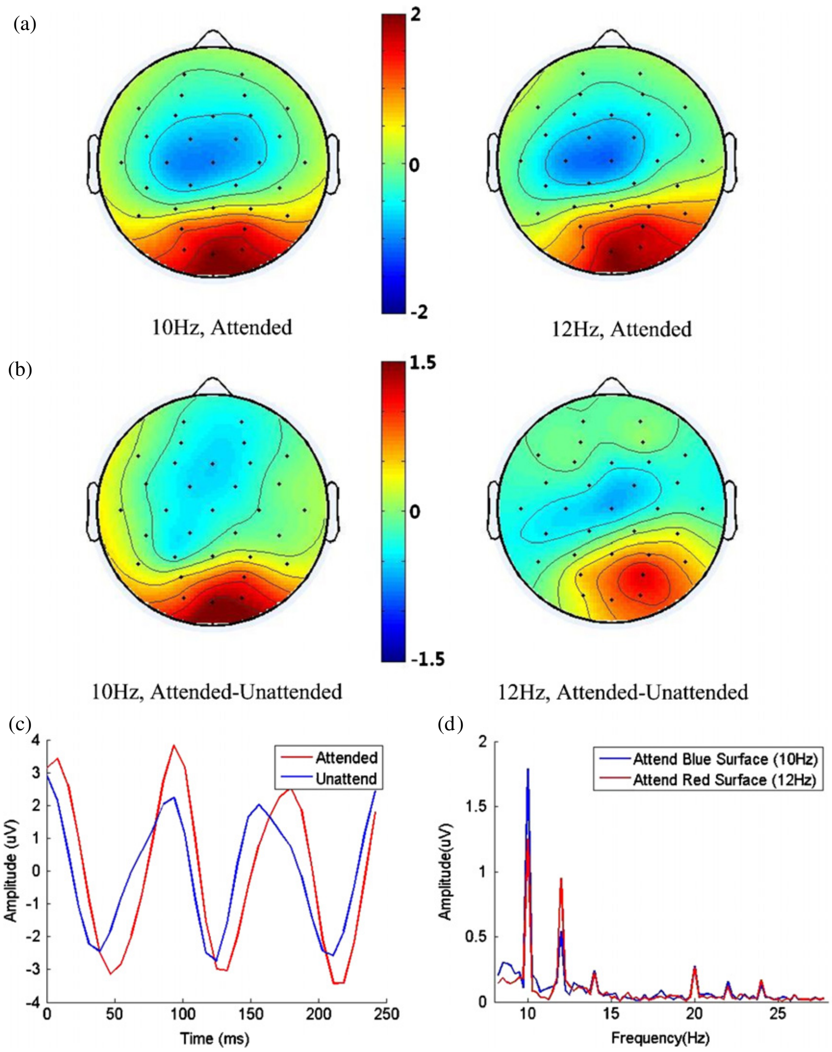


**Figure 3.** Attentional modulation effects of SSVEPs. (a) Topographies of grand-mean SSVEP amplitudes at the driving frequencies (10/12 Hz) under the attended condition. The SSVEP amplitudes were standardized to $z$ scores before computing grand averages in order to deal with inter-subject variability. Positive and negative values indicate responses above and below the mean level of all 32 electrodes, respectively. (b) Topographies of grand-mean attentional enhancement of SSVEP amplitudes. The differences of SSVEP amplitude between attended and unattended condition were also transformed to $z$ scores. (c) Time domain averages of 12 Hz SSVEP at electrode Oz in subject 9. (d) Spectrogram at electrode Oz for the two attentional conditions for subject 4.

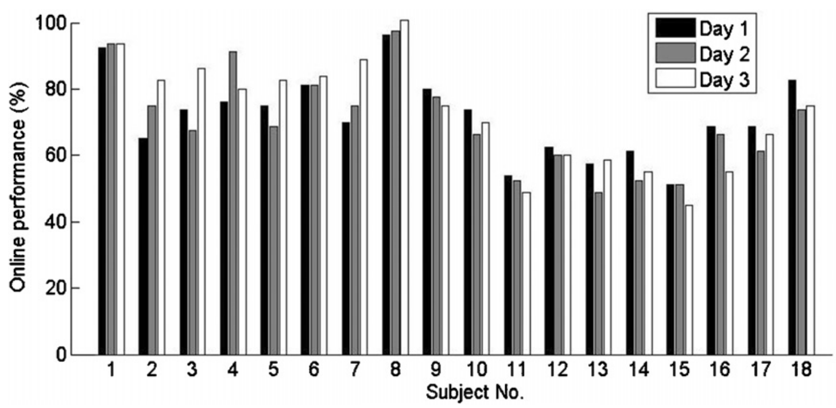


**Figure 4.** Averaged daily online classification accuracies for individual subjects.

per training day. The individual, daily averaged online classification accuracies are given in figure 4. Subjects 1–9 are Chinese; subjects 10–18 are German. The classification accuracies averaged overall subjects are $71.7 \pm 12.3\%$,

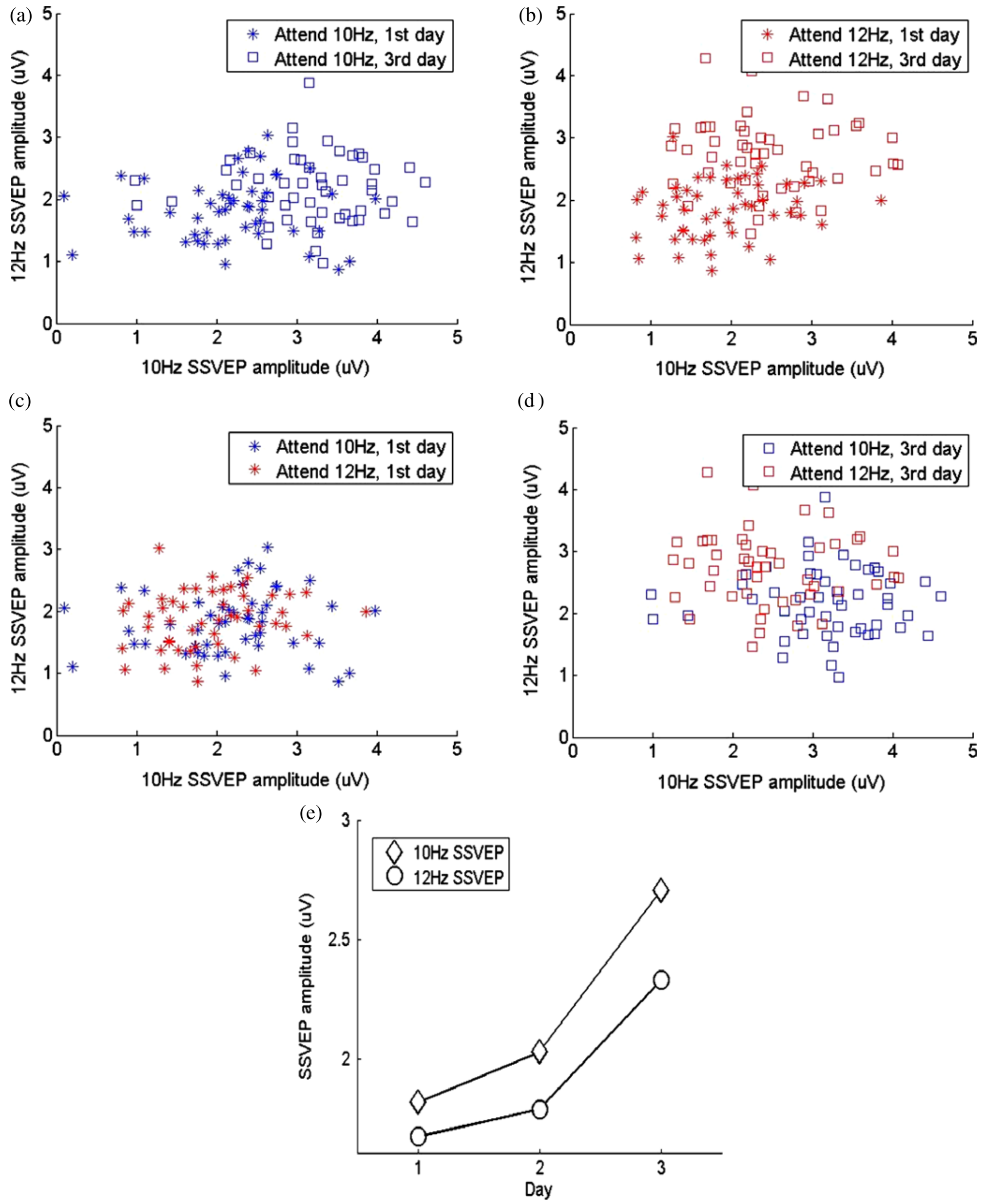


**Figure 5.** Effects of training on the SSVEP. (a–d) Scatter plots of the single-trial SSVEP amplitude response from subject 2 at electrode Oz. (a) and (b) show the amplitude response on the first and last training days under two attentional conditions. (c) and (b) show the discriminability of two types of trials before and after training. (e) Daily change of SSVEP amplitudes, subject 2, electrode Oz.

70.0 ± 14.7% and 72.6 ± 16.1% on the successive training days. There is a significant increase of performance within the Chinese group when comparing the performance of the third day to the first day ($p < 0.05$, paired $t$-test). However, no significant performance enhancement is found when the German subjects are included ($p > 0.5$, paired $t$-test). On the last training day, 2 subjects reached >90% accuracy; another 6 subjects achieved a performance well above 80%; 5 subjects showed a classification accuracy between 60% and 80%; the remaining 5 subjects had classification accuracies below 60%. In addition, the performance of the Chinese group is significantly higher than the German group on each day ($p < 0.01$, see figure 7(a)).

### 4.3. Training effects

Eight subject (subjects 1–8) showed an increase in daily averaged performance during the training program. All of them are Chinese subjects; none of the German subjects showed positive training effects.

For subject 2, who showed a performance increase of 17.5% (from 65.0% on the first day to 82.5% on the third day), the single-trial SSVEP amplitude on the first and last training days at the stimulation frequencies (10/12 Hz) is depicted in figures 5(a) and (b). SSVEP amplitudes at both frequencies were strongly enhanced on the last training day, no matter which surface was attended. Figures 5(c) and (d) show that the observed enhancement of SSVEP amplitude

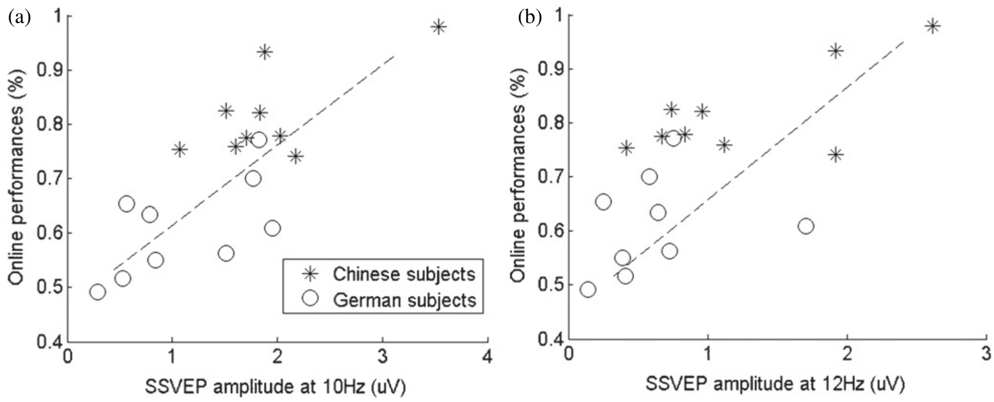


**Figure 6.** Correlation between SSVEP amplitude and online performance; Chinese subjects are represented by asterisks and German subjects by circles.

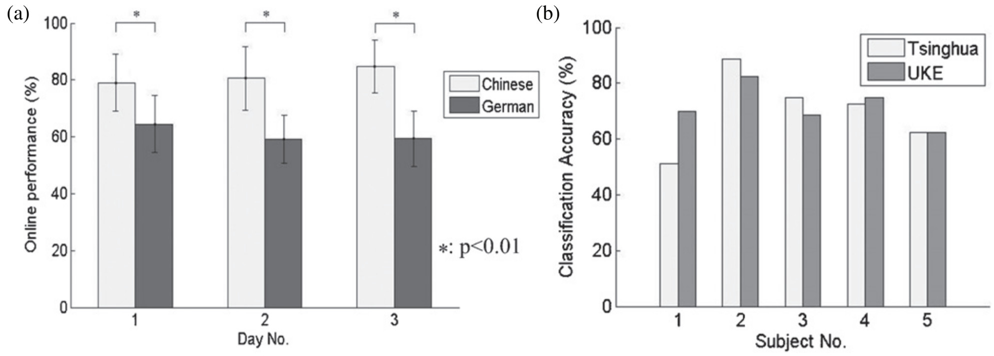


**Figure 7.** (a) Online performance of Chinese and German subjects, significant differences was observed on each day. (b) Individual performances of five German subjects tested in both Tsinghua and UKE.

responses improves the discriminability of the single-trial data under the two attentional tasks. Therefore, this enhancement could be responsible for the increased single-trial classification accuracy. Figure 5(e) shows the daily change of the SSVEP amplitude response averaged over both attentional conditions.

By plotting the individual SSVEP amplitude response against their online performance, a positive linear correlation can be observed (figure 6) which was quantified by a Pearson correlation analysis. The correlation coefficient between online performance and 10 Hz/12 Hz SSVEP amplitude is 0.765/0.647. $T$-test shows significant differences in the SSVEP amplitudes at 10/12 Hz between Chinese subjects and German subjects (both $p < 0.05$).

### 4.4. Different performances of the two cohorts

To check cross-laboratory reproducibility, we compared the results between the two laboratories, i.e. Tsinghua and UKE. Surprisingly, we observed a generally higher performance of subjects at Tsinghua (see figure 7(a)). To rule out technical differences that went unnoted, we repeated the same experiment in both labs using a new cohort of German subjects. 5 subjects (4 male, 2 of them had participated in the previous experiment, 1 female) were recorded at UKE and one week later at Tsinghua. Since we were not interested in training effects in this experiment, only the one-day performance was assessed. No significant difference is found in their performances ($p > 0.5$, paired $t$-test, see figure 7(b) for individual performances).

### 4.5. EOG differences

The EOG artifacts we considered here are low-frequency patterns caused by movements (such as rolling) of the eyes [27, 28]. EOG activity has a wide frequency range, peaking at frequencies below 4 Hz, and is most prominent over the anterior head regions [29]. Figure 8 shows the averaged EOG waveforms (4 Hz low-pass filtered) over all trials under the two attentional conditions for every subject. The low amplitude ($\ll 1\ \mu$V) indicates that there were no systematic eye movements accompanying one specific task. The point-wise $t$-test between 'attend red surface' and 'attend blue surface' trials was then carried out with all trials of each subject. No significant difference of EOG signals under the two attentional tasks could be found for all subjects for whom the EOG was recorded (9 out of 18, $t$-test, $p > 0.05$).

## 5. Discussion and conclusion

### 5.1. Attentional modulation of SSVEP

Color and motion are two commonly used features for studying non-spatial visual attention. Attention to either feature has been shown to increase the neuronal response to a stimulus.

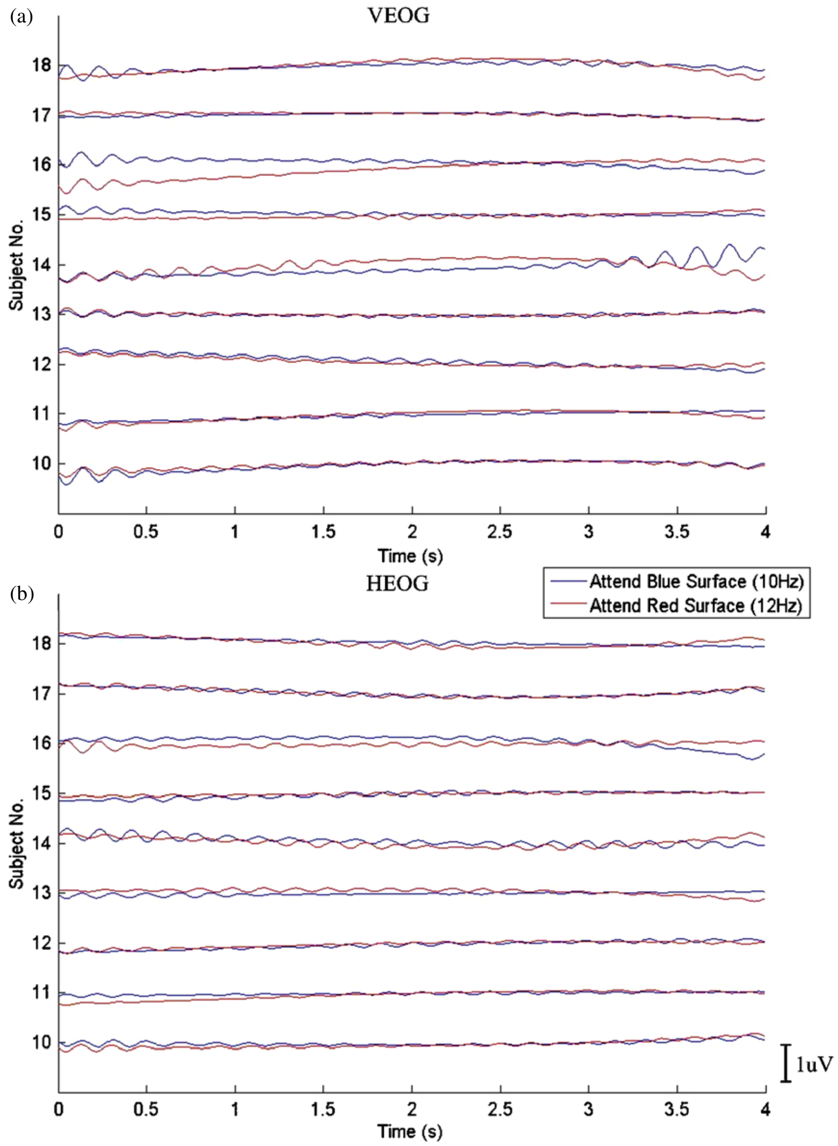


**Figure 8.** Averaged EOG waveforms.

This response enhancement is a global effect that occurs not only for attended location in the visual field, but also for unattended locations if they show the same feature [30], and involves several visual brain regions including V1, V2, V3, V3A, V4 and MT+ [30–32]. In an electrophysiological experiment with a similar paradigm to ours, selective attention to red or blue dot populations with random motion enhanced the amplitude of its frequency-tagged SSVEP, which was localized to early visual areas of the brain by a source modeling method [33].

In our study, two visual features, color and motion, are combined to form two superimposed, illusory surfaces. As we show here, attention to one of the illusory surfaces yields a strong and robust modulation of SSVEP. This modulation is strongest over occipital areas, which is in accordance with the previous reports [30, 33]. Since we recorded brain activities on the macroscopic scale using EEG, the attentional modulation is likely to reflect a global effect in several visual brain areas [30]. The online classification accuracy indicated that this attentional modulation effect is large enough for single-trial classification.

### *5.2. Comparison with other visual attention-based BCIs*

A previous study indicated that spatial attention shifts may have stronger modulatory effects on SSVEPs than non-spatial attention shifts [15]. This result may be due to a comparatively lower effectiveness of the stimuli employed in this study for the non-spatial condition. The authors used two spatially overlapping 'linebox' images, each of which consisted of a group of equally spaced parallel vertical or horizontal lines against a black background. The two images were displayed using an additive color model, i.e. the displayed color turned yellow if a red and a green line segment were shown at the same position. This may weaken the elicited SSVEP response because the two steady-state stimulations interacted with each other, especially when considering single-trial data. In our study, scattered dots were used to induce the perception of two superimposed, transparent surfaces. Although the perceived surfaces were spatially superimposed, all the dots displayed were physically non-overlapping. Because the dot size was relatively small compared to the visual space covered by the stimuli, the possibility for such overlaps was very low. If dots did nonetheless overlap, we always presented blue dots in front of red dots, thereby avoiding interferences between the two steady-state stimulations and retaining strong responses and optimal signal-to-noise ratio of SSVEP. None of the subjects noted the priority of blue dots.

The spatial separation of stimuli required for paradigms with spatial attention shifts may not fully exploit the SSVEP signals when the attention is shifted covertly. In such a paradigm, stimuli are perceived in the visual periphery [10, 11], which is known to reduce SSVEP amplitude and thus, signal-to-noise ratio [34]. In contrast, for non-spatial attention shifts all stimuli can be presented in the center of the visual field, thereby maximizing the SSVEP signal.

Our results show that with the non-spatial attention shifts in our paradigm a similar performance as in SSVEP BCIs using spatial attention can be achieved [10, 15]. The system could probably be extended to a multi-target paradigm by adding additional surfaces with different color, angular velocity and flicker frequency.

Since healthy subjects were investigated in this study, it is possible that they subconsciously followed the movement of the attended surface, thereby generating an easily recognizable signal which would be absent in patients. Analysis of the EOG confirmed that no significant differences in EOG signals between the two conditions were present. Even if the subjects rolled their eyes to follow the rotation of the attended surface, modulation of the SSVEP amplitude would likely not be affected because the two sets of dots were mixed on the screen. The most likely neural mechanism to modulate SSVEP amplitude in this paradigm and hence, control the BCI, is non-spatial visual covert attention. Therefore, our approach provides an independent BCI system that does not rely on muscle activity.

### *5.3. Co-adaptation and training effect*

Co-adaptation between the human and the BCI is an important issue investigated here. The BCI optimizes the algorithm parameterization for better recognition of the human brain activity, and the human adjusts his behavior for better control.

Adaptation of the BCI system comprised adaptation of a filter for EEG signals so as to maximize discriminability of the two mental states, and adaptation of the classifier. We employed the CCA method to effectively deal with inter-subject variability by finding the optimized spatial filter for each subject for extracting stimulation-related brain activities. Since we started from training sessions with only 3 min duration, the heuristic classifier updating strategy shown in figure 2(b) was used to deal with the small dataset problem by gradually adding reliable data into the training set. Offline simulation of the online classification process with the proposed updating strategy showed better performances than only using the initial data from the training session

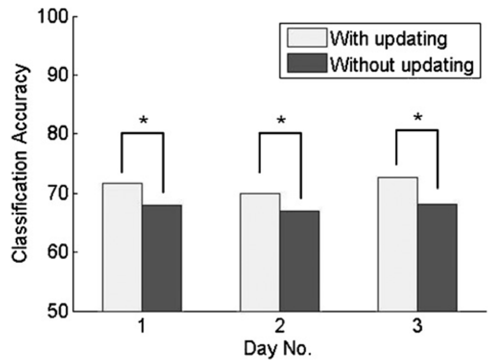


**Figure 9.** The daily averaged classification accuracies simulated offline with/without the proposed updating strategy described in 3.2. The asterisk (*) indicates significant difference at $p = 0.05$ level by paired *t*-test.

(figure 9). However, the strategy for updating the classifier should be further developed, since the current strategy is not a mathematically strict solution for the small training set problem.

To investigate the human adaptation to the BCI system, we trained the classifier from scratch on consecutive days. The general improvement in accuracy during the 3-day online training program is due to adaptation and learning of the subjects, suggesting that the subjects adjusted their brain activities to maximize individual performances. For Chinese subjects, our experiment showed a general improvement of control accuracy by feedback training on three consecutive days (30 min per day). After the adaptation on the first two days, only a 3 min session is needed to train the classifier and obtain an average performance of above 80% on the last day.

It is also interesting to note that there was no training effect within the German group. A closer look at German subjects' performances reveals that 5 out of 8 German subjects showed an improved performance from day 2 to day 3 (see figure 4). The relatively low performance might be discouraging to the subjects, hereby slowing down the training process. The investigation should have been extended to a larger number of sessions or training days in order to assess training effects in the German group. However, since the primary target of the current study is to present a new BCI paradigm and to give an initial assessment of the stability of the results across time and laboratories, investigation of the learning properties for a longer observation period will be at the focus of follow-up studies.

Previous studies on SSVEP BCI have shown that performance could be improved over continuous sessions [17, 18]. Here our results indicate that the improvement can be consolidated and transferred from day to day. The performance increase was reflected by an increase in SSVEP amplitude (figure 5(a)). A plausible explanation is that the trial-by-trial online feedback helped the subjects to adjust their strategies for better concentration and attention, which enabled enhanced perception of steady-state visual stimulation.

### 5.4. Cross-laboratory reproducibility

The comparison of the classification accuracies between the two labs revealed an unexpected difference with a statistical significance at the 1% level. Despite having taken great efforts to exclude technical differences as a possible cause (using same model and brand of hardware, verifying the timing, using identical software), average performance was significantly higher in the Chinese cohort on each of the 3 days. The results of a repetition of the experiment in both labs, using an identical cohort of subjects, confirm that technical differences in the setup can be excluded as a simple explanation.

It is not clear which factors may account for the significant group difference in performance between the Chinese subjects and German subjects. It is interesting to observe lower SSVEP amplitudes in the German group and the positive correlation between SSVEP amplitude and performance (see figure 6). It is likely that certain parameters in the current paradigm (e.g. stimulation frequencies, colors, motion) might not be optimal for German subjects. Finding the optimal parameters for individual subjects should be taken into consideration in further studies. However, exploration of possible causes is beyond the scope of this paper. The results presented here should be seen as a demonstration of the range and variability in the performance of the proposed BCI system.

### 5.5. Further directions with SSVEP BCIs based on visual attention

Paralyzed patients have been reported to be trained to use BCI on the basis of P300 evoked potential, self-regulation of slow cortical potential (SCP) or sensorimotor rhythm (SMR) (see [35] for a review). Although SSVEP BCIs based on gaze direction have been demonstrated to have good operability in challenging environments (electrical noise, uncontrolled distracters, etc) [4, 16, 18, 34, 36, 37], they are not frequently used for patients. The critical point is that patients with good control of their gaze direction may have other means of communication (eye tracker, etc) than BCI.

The BCI system proposed here requires no head or eye movements, which makes it potentially useful for those patients with substantial head or ocular motor impairments. The BCIs currently used in clinical application utilize either voluntary modulation of transient response to external stimuli (such as P300 evoked potential) or self-regulation of internal states (such as SCP and SMR) [35, 38–43]. In our study, the subjects operate the system by self-regulating the continuous responses of the external stimuli, which is different from the existing designs. Therefore, the proposed BCI system, as well as other visual attention based SSVEP BCIs [10, 15], could be considered as an additional approach for improving communication of paralyzed patients.

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