# Emotional faces boost up steady-state visual responses for brain-computer interface

Hovagim Bakardjian<sup>a,b</sup>, Toshihisa Tanaka<sup>a,b</sup> and Andrzej Cichocki<sup>a</sup>

Steady-state visual evoked potentials (SSVEPs) can be used successfully for brain-computer interfaces (BCI) with multiple commands and high information transfer rates. In this study, we investigated a novel affective SSVEP paradigm using flickering video clips of emotional human faces, and evaluated their performance in an 8-command BCI controlling a robotic arm in near real-time. Single-trial affective SSVEP responses, estimated using a new phase-locking value variability and a wavelet energy variability measures, were significantly enhanced compared with blurred-face flicker and standard checkerboards. For multicommand SSVEP-based BCI. affective face-flicker boosted up the information transfer rates from 50 to 64 bits/min, while reducing user fatigue and enhancing visual attention and reliability. In the 5-12 Hz flicker frequency range, the strongest affective SSVEP responses were obtained at 10 Hz. These findings

suggest new directions for SSVEP-based neural applications, including affective BCI and enhanced steady-state clinical probes. *NeuroReport* 22:121-125 © 2011 Wolters Kluwer Health | Lippincott Williams & Wilkins.

NeuroReport 2011. 22:121-125

Keywords: affective steady-state visual evoked potential, brain-computer interface, emotions, phase-locking value, steady-state visual evoked potentials, visual attention

<sup>a</sup>Laboratory for Advanced Brain Signal Processing, Brain Science Institute, RIKEN, Wako-shi, Saitama and <sup>b</sup>Department of Electronic and Information Engineering, Tokyo University of Agriculture and Technology, Koganei-shi, Tokyo, Janan

Correspondence to Hovagim Bakardjian, MSc, RIKEN, Brain Science Institute, Laboratory for Advanced Brain Signal Processing, 2-1 Hirosawa, Wako-shi, Saitama 351-0198 Japan

Tel: +81 48 4679665; fax: +81 48 4679686; e-mail: hova@brain.riken.jp

Received 7 September 2010 accepted 24 November 2010

# Introduction

A brain-computer interface (BCI) is a system able to identify a limited set of user intentions in near real-time from brain signal measurements [1]. Such a capability enables direct brain-based control of executive devices without the use of muscles. Although a few noninvasive electroencephalogram (EEG)-based BCI paradigms are able to offer several independent commands, the steadystate visual evoked potential (SSVEP)-based approach [2,3] is especially advantageous with its potential for high information transfer rates (ITRs), reliability, and design flexibility, while the necessity for user training is minimized. Selective attention to quickly flickering lights or patterns, each with its own unique frequency, evokes precisely synchronized SSVEP responses in the brain [4] and makes the user intent identifiable. However, singletrial SSVEP oscillations are very weak and difficult to detect within a short time span as they are usually buried in substantial nonstationary 'brain noise', some of which competes in the same frequency band as the stimulus trains. Another potential problem is that SSVEP responses are strongly dependent on a sustained attention effort by the user [5], which leads to fatigue and BCI performance degradation for standard light emitting diode or checkerboard stimuli.

The main objective of this study is to alleviate these existing problems by introducing novel visual stimuli to

Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Website (www.neuroreport.com).

0959-4965 © 2011 Wolters Kluwer Health | Lippincott Williams & Wilkins

enhance substantially the brain's flicker responses and to improve the performance of SSVEP-based BCI systems. In an earlier study [6] we investigated the properties of single-trial SSVEP elicited by very small reversing checkerboards, and showed that the optimization of their properties (stimulation frequency, dimensions, pattern type) was essential for improving the performance of our multicommand SSVEP–BCI platform used to control reliably the two-dimensional movement of an object on a computer monitor. Here, we propose the usage of emotionally charged face video clips as flicker stimuli to enhance attention and to improve the signal-to-noise ratio of the visual brain activity. Affective facilitation has been reported for multiple stages of the visual evoked potential, ranging from 120 to 600 ms [7,8], when viewing emotionally charged static images (e.g. from the International Affective Picture System [9]). Furthermore, the effect of emotional arousal (and possibly increased attention) was also shown when the static affective images were set to flicker at 10 Hz while viewed [10]. The resulting parieto-occipital SSVEP amplitudes were enhanced compared with viewing neutral flickering pictures.

In this study our results indicate that positive and negative face emotions could boost up the measurable single-trial cortical SSVEP activity. To our best knowledge, we show for the first time the feasibility of using flickering affective face video stimuli to achieve enhanced brain responses, and improved multicommand SSVEP BCI, with higher ITRs and better human user experience. The SSVEP strength evaluations in the first set of experiments were performed

DOI: 10.1097/WNR.0b013e32834308b0

offline by using a new single-trial phase-locking value variability (PLVV) measure, and verified using a more conventional wavelet energy variability (WTV) measure, whereas the online BCI platform in the second set of experiments operated by fast SSVEP narrowband energy estimation.

#### **Methods**

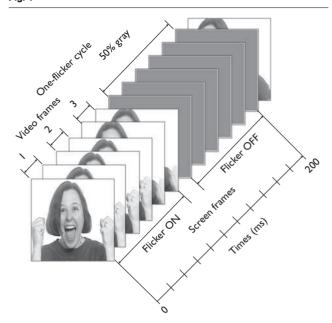
Eight healthy participants (four male and four female, age  $26 \pm 9$  years) with no known neurological disorders, and normal or corrected-to-normal vision, participated in this study. The participants were fully informed of all procedures and signed an informed consent, in accordance with the Declaration of Helsinki, and approved by the Riken Ethics Committee. All participants were first tested for photosensitive epilepsy, and during the experimental sessions their EEG patterns were continuously monitored for epileptic spikes. Participants were seated 1 m from a 40" liquid crystal display with a vertical refresh rate of  $60 \,\mathrm{Hz}$  (59.7  $\pm$  0.35 Hz). They were asked to empathize as much as possible with the observed emotional states. After each experiment, we recorded behavioral measures regarding emotional experiences and fatigue. We used a short questionnaire for a subjective self-estimate on a scale from 1 to 10 of the degree to which each emotion was experienced as depicted on the screen, and the baseline personal trait emotionality.

The brain signal acquisition was performed using a Biosemi active-electrode EEG system (Biosemi Inc., Amsterdam, The Netherlands) with a sampling rate of 512 Hz. Two independent sets of experiments were performed to evaluate the basic affective SSVEP brain response, and also the BCI performance using emotional SSVEP stimuli.

In the first set of experiments, the affective SSVEP response was studied using a 128-electrode whole-head coverage. Five different SSVEP stimuli were shown to each participant: two short flickering video clips (duration approximately 4s, dimensions  $7^{\circ} \times 7^{\circ}$  arc, no audio) with faces of UK actors [11] dynamically depicting positive and negative emotions of joy and anger on a white background, and their blurred versions in which faces and emotions were not recognizable [12], and a standard reversing  $6 \times 6$  checkerboard (video of the stimuli, Supplemental digital content 1, http://links.lww.com/WNR/ A101 available also on the following web page: http:// www.bsp.brain.riken.jp/~hova/). Each video stimulus was shown at five flickering frequencies (5.0, 6.67, 8.57, 10.0, and 12.0 Hz, at 60 Hz refresh rate) in separate sessions. These frequencies were measured using the individual vertical refresh rate of the computer screen during each recording session. Figure 1 shows an example for a 5 Hz SSVEP video stimulus.

Each recorded EEG trial was 10 s long and was preceded by a 2-s blank-screen baseline. The first step of the offline analysis was the removal of ocular artifacts using the Unbiased Quasi-Newton Algorithm for Independent

Fig. 1



A block diagram illustrating the design of a 5 Hz video flicker stimulus, assuming 60 Hz screen refresh rate and 25 frames per second video frame rate. Each flicker cycle should span over an integer number of screen refresh frames to display the stimulus properly. For the flicker frequency in this example, 12 screen refresh frames/cycle were required, in which the stimulus was displayed during half of the cycle (ON), and a blank 50% gray square image of the same size was shown during the other half (OFF). During each ON-period, a video frame was displayed for two screen refresh frames, which is the integer ratio of the screen refresh rate and the video frame rate. Individual video clips were replayed continuously.

Component Analysis (ICA) [13]. Unbiased Quasi-Newton Algorithm for ICA was selected after testing the performance of more than 20 ICA algorithms [14] because of its ability to perform unbiased ICA in the presence of strongly correlated Gaussian noise in the mixture. Although in our earlier work we performed single-trial SSVEP estimation using modified quadrature amplitude demodulation [6], in this study we calculated and compared the performance of two other measures - a singletrial PLVV<sup>f</sup> and a single-trial WTV<sup>f</sup>. Both measures were designed to quantify individual rapid changes in brain activity immediately after SSVEP onset. A PLV<sup>f</sup> [15], ranging from 0 to 1, is a measure used to represent the degree of phase stability for a specific frequency f. The single-trial PLVs used in this study were computed for each fixed flickering frequency f over time t as follows:

$$SPLV^{f}(t) = \frac{1}{N} \left| \sum_{i=1}^{N} \exp(j\{\Phi_{EEG}^{i}(f,t) - \Phi_{ref}^{i}(f,t)\}) \right|, \quad (1)$$

where N = 12 was the number of EEG channels (over the occipital cortex, in this case),  $j^2 = -1$ , and  $\Phi_{\text{EFG}}^{i}(f)$  and  $\Phi_{\text{ref}}^{i}(f)$  were the phases of the normalized EEG signal  $s^i$  (i = 1...N) and the flicker reference signal

 $s_{\text{ref}}^{i}$ , respectively. The reference  $s_{\text{ref}}^{i}$ , was a sine wave corresponding exactly to the flicker frequency f of the visual stimulus. The phase  $\Phi$  for frequency f was calculated using the imaginary and real components of the convolution of an input signal  $s^i$  with a complex Morlet wavelet W(t):

$$\Phi^{i}(f,t) = \arctan \frac{\operatorname{imag}\left[W(f) * s^{i}\right]}{\operatorname{real}\left[W(f) * s^{i}\right]}.$$
 (2)

Using these definitions, the normalized single-trial phase-locking value variability measure PLLV<sup>f</sup> was defined as the ratio:

$$PLLV^{f}(t) = \frac{\Delta SPLV^{f}(t)}{SPLV^{f}(t_{0})},$$
(3)

and  $\Delta SPLV^f(t)$  in (3) was calculated for each SSVEP frequency f as:

$$\Delta \text{SPLV}^f(t) = \text{SPLV}^f(t_{\text{max}}^{1s}) - \text{SPLV}^f(t_0), \tag{4}$$

where  $SPLV^f(t_{max}^{1s})$  was the maximum phase-locking value reached within one second after the onset of the visual stimulation, while  $SPLV^f(t_0)$  was the baseline PLV at SSVEP onset  $t_0$ , driven by the flicker phase reset of the occipital brain activity. In multitrial studies the PLV measure is usually computed over several trials, but here only single trials were evaluated because of real-time applications such as BCI. The single-trial phase-locking changes at the onset of SSVEP in this study were estimated for each sample by measuring the degree of wavelet phase stability over a block of N occipital channels, in reference to the phase of a sine wave corresponding to the frequency of the SSVEP flicker stimulus.

The second measure we applied to estimate SSVEP was the single-trial Morlet WTV<sup>f</sup> that we used to quantify the normalized energy increase of the brain response at the flicker frequency during the first second after the SSVEP onset, in a similar way to  $PLVV^f$ .

$$WTV^{f}(t) = \frac{\Delta SWT^{f}(t)}{SWT^{f}(t_{0})},$$
(5)

where:

$$\Delta SWT^{f}(t) = SWT^{f}(t_{\text{max}}^{1s}) - SWT^{f}(t_{0}), \tag{6}$$

 $SWT^f(t_{max}^{1s})$  was the maximum wavelet band energy value reached within one second after the onset of the SSVEP stimulation, and SWT $^f(t_0)$  was the baseline energy value at SSVEP onset  $t_0$ .

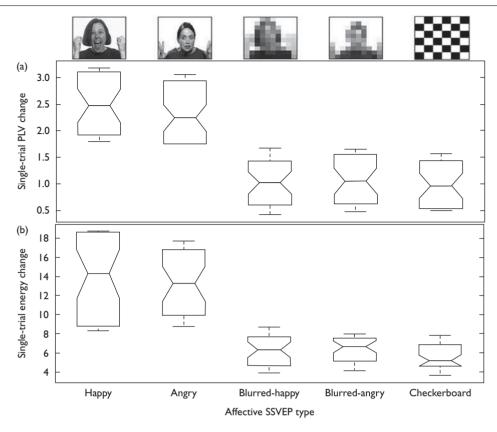
The goal of the second set of experiments was to study the effect of affective video stimuli on BCI performance. We used the energy-based feature extraction approach introduced in our earlier BCI work, which allowed a direct online evaluation of the proposed affective approach. The computer display used for BCI was from a compact 17" notebook personal computer and eight different emotion-loaded video clips flickered simultaneously at different frequencies (5.0, 5.4, 6.0, 6.67, 7.5, 8.55, 10.0, 12.0 Hz, at 60 Hz refresh rate). Each affective video clip was assigned as an independent command. The participants directed their attention during a limited period of time (up to 4s) to a selected video stimulus to evoke a response and initiate a corresponding movement of the robotic arm. The affective SSVEP-based BCI platform consisted of the following main modules: 6-channel occipital EEG data acquisition (Biosemi), an analysis (signal processing and evaluation) unit, a stimulus-control user interface, and a multijoint robotic arm executive device (iARM, Exact Dynamics Inc., The Netherlands). The BCI analysis module was based on signal energy measures, as described earlier in detail [6]. For evaluation purposes, each BCI command was performed at least three times in random order, and the participant attempted to execute each specific command as quickly as possible.

## Results

Data analysis showed that occipital SSVEP brain responses after stimulus onset were stronger when the stimuli included happy or angry faces (Fig. 2). Statistical analysis using two-way analysis of variance tests showed that the SSVEP activity (averaged over flicker frequency) was significantly dependent on stimulus type (P = 0.0007 for the phase-locking measure PLVV and P = 0.002 for the wavelet energy measure WTV). Testing specifically for the effect of emotion, the affective video flicker stimuli provided significantly stronger SSVEP responses than the emotionally neutral blurred versions of human faces  $(P = 0.0005 \text{ for PLVV}^f \text{ and } P = 0.0004 \text{ for WTV}^f)$ . However, we did not detect significant differences in the occipital SSVEP responses because of emotional valence only (joy vs. anger, P = 0.61 for PLVV<sup>f</sup> and P = 0.82 for  $W\Gamma V^f$ ). Furthermore, there were also no statistically significant differences between the brain responses of individual participants (P = 0.85 for PLVV<sup>f</sup> and P = 0.78for WTV<sup>f</sup>). The SSVEP frequency response was strongest for 10 Hz flicker (averaged over all stimulus types), in agreement with earlier findings [10]. Summarizing the behavioral measures for all participants, the degree to which they identified with the depicted emotions was  $7 \pm 1.9$  for joy and  $5.7 \pm 2.2$  for anger, whereas the degree of admitted personal emotionality was  $6.3 \pm 2.1$ . Each participant also stated that he/she did not experience any emotions while viewing the blurred video stimuli and the checkerboard.

In the second set of experiments, the affective SSVEP-BCI performance was measured while the participants operated a robotic arm in near real-time using eight emotional flickering video clips displayed on the screen simultaneously (see video of an example of our BCI system controlling a robotic arm, Supplemental digital content 2, http://links.lww.com/WNR/A102 available also on the following web page:  $http://www.bsp.brain.riken.jp/\sim hova/$ ). The BCI time-delays in the execution of the commands

Fig. 2



Affective steady-state visual evoked potential (SSVEP) video stimuli depicting face emotions of joy and anger evoked significantly stronger brain responses than their neutral blurred versions with concealed facial features, or a standard reversing checkerboard. The figure shows the strength of the occipital SSVEP activity immediately after onset. Statistical comparisons were made among all stimulus types using both the normalized singletrial phase-locking value variability measure (a) and the wavelet narrowband energy variability measure (b). PLV, phase-locking value.

were measured for all five types of stimuli used in the first set of SSVEP experiments. Performance measurements showed that BCI detection was faster for affective SSVEP than for emotion-free blurred video or reversing checkerboard stimuli (mean delay 2.7 vs. 3.4 s, and mean success rate 99 vs. 98%). In addition, emotional face video stimulation resulted in more stable SSVEP measures over time, and users reported increased motivation and reduced fatigue. Using the new affective SSVEP-BCI paradigm, we achieved mean BCI ITRs of 64 bits/min for affective face flicker compared with 50 bits/min for neutral stimuli.

### **Discussion**

The goal of this study was to evaluate the hypothesis that an emotional-face stimulus component is able to boost up SSVEP brain activity and contribute to improvements in BCI performance and reliability measures. We found that flickering affective videos of joy and anger enhanced significantly the visual SSVEP activity in the occipital cortex compared with their emotionally neutral blurred versions and standard checkerboards. Emotional face stimulation also decreased the time delay in the execution of BCI commands, and increased the mean ITR to 64 bits/min for our SSVEP-based BCI system. This 8-command BCI platform was designed and used to control a multijoint robotic arm with complex movements and tasks mainly targeted for disabled users.

Our experiments indicated that natural, dynamic video stimuli may be more efficient than static pictures in evoking emotions reliably and quickly, and in enhancing the selective attention during stimulus perception [16]. The affective stimuli we used in this study featured visually simplified white backgrounds and actor's faces depicting emotions in a moderate way, so that extraneous brain responses [17], inter-participant variability, and fatigue because of long-term exposure were reduced. We are currently performing further experiments to evaluate the contributions of face-processing and attentional components of the affective SSVEP brain response. We may investigate the effects of stronger emotion stimuli in our future research, as they could either enhance the SSVEP, or suppress it by diverting attentional and other brain resources.

Although we have used signal energy measures successfully in our earlier studies [6,18-21] and in the BCI research presented here, we show in this paper that a properly defined single-trial phase-locking measurement is an important alternative tool to detect reliably SSVEP in a BCI setting. A strong phase reset in the cortex at the observed flicker frequency followed by an increase in the phase stability is a faster and more sensitive indicator of SSVEP lock-in than the oscillation energy increase. Nevertheless, for an optimal robust SSVEP BCI design, a classification mechanism based on a parallel implementation of both phase-locking and energy variability tools will offer best results in terms of signal sensitivity, elimination of competing brain transients in the critical SSVEP frequency bands, and lower inter-participant variability.

#### Conclusion

Flickering video clips of joyful and angry human faces were evaluated as novel affective SSVEP stimuli for multicommand BCI, and compared with neutral blurred faces and standard checkerboards. Our results show that flickering emotional face videos may offer a more efficient visual stimulation mode for neural applications such as robust SSVEP BCI for the disabled and healthy populations, neurofeedback-based rehabilitation, and advanced clinical tests that rely on SSVEP for diagnosis and probing of brain functions.

## References

- Cichocki A, Washizawa Y, Rutkowski T, Bakardjian H, Phan A-H, Choi S, et al. Noninvasive BCIs: multiway signal-processing array decompositions. Computer 2008: 41:34-42.
- Sutter EE. The visual evoked response as a communication channel. Proc of the IEEE/NSF Symp Biosensors 1984; 95-100.
- Middendorf M McMillan G Calhoun G Jones KS Brain-computer interfaces based on the steady-state visual-evoked response. IEEE Trans Rehabil Eng 2000; 8:211-214.
- Regan D. Steady-state evoked potentials. J Opt Soc Am 1977; 67:1475-1489.

- 5 Müller MM, Hillyard S. Concurrent recording of steady-state and transient event-related potentials as indices of visual-spatial selective attention. Clin Neurophysiol 2000; 111:1544-1552.
- Bakardjian H, Tanaka T, Cichocki A. Optimization of SSVEP brain responses with application to eight-command brain-computer interface. Neurosci Lett 2010; 469:34-38. (http://dx.doi.org/10.1016/j.neulet.2009.11.039)
- Schupp HT, Junghoefer M, Weike AI, Hamm AO. Emotional facilitation of sensory processing in the visual cortex. Psychol Sci 2003;
- 8 Peyk P, Schupp HT, Elbert T, Junghöfer M. Emotion processing in the visual brain: a MEG analysis. Brain Topogr 2008; 20:205-215.
- Lang PJ, Bradley MM, Cuthbert BN. International affective picture system: technical manual and affective ratings. Gainesville, FL: NIMH Center for the Study of Emotion and Attention; 2005.
- Keil A, Gruber T, Müller MM, Moratti S, Stolarova M, Bradley MM, Lang PJ. Early modulation of visual perception by emotional arousal: evidence from steady-state visual evoked brain potentials. Cogn Affect Behav Neurosci 2003; 3:195-206.
- 11 Baron-Cohen S, Golan O, Wheelwright S, Hill J. Mind reading: the interactive guide to emotions [Computer software]. London: Jessica Kingsley Publishers UK; 2004. http://www.jkp.com/mindreading
- 12 De Cesarei A, Codispoti M. Fuzzy picture processing: effects of size reduction and blurring on emotional processing. Emotion 2008; 8:352-363
- 13 Cruces S, Cichocki A, Castedo L. Blind source extraction in gaussian noise. Proc Intern Workshop Independent Component Anal Blind Signal Separation 2000; 63-68.
- Cichocki A, Amari S. Adaptive blind signal and image processing: learning algorithms and applications. Chichester: Wiley; 2003.
- Lachaux JP, Rodriguez E, Martinerie J, Varela FJ. Measuring phase synchrony in brain signals. Hum Brain Mapp 1999; 8:194-208.
- Flaisch T, Schupp HT, Renner B, Junghöfer M. Neural systems of visual attention responding to emotional gestures. Neuroimage 2009; **45**:1339-1346.
- Müller MM, Andersen SK, Keil A. Time course of competition for visual processing resources between emotional pictures and foreground task. Cereb Cortex 2008; 18:1892-1899.
- Bakardjian H, Martinez P, Cichocki A. Dynamic online target control of SSVEPbased brain-computer interface with multiple commands. Neurosci Res 2007: **58**:S70. (http://dx.doi.org/10.1016/j.neures.2007.06.410)
- Martinez P, Bakardjian H, Cichocki A. Fully-online, multi-command brain computer interface with visual neurofeedback using SSVEP paradigm. J Comp Intell Neurosci 2007; 2007. Online article ID 94561. (http:// www.hindawi.com/journals/cin/contents.10.html)
- 20 Martinez P, Bakardjian H, Vallverdu M, Cichocki A. Fast multi-command SSVEP brain machine interface without training. Lect Notes Comput Sci 2008; **5164**:300–307. (http://dx.doi.org/10.1007/978-3-540-87559-8\_31)
- Bakardjian H, Tanaka T, Cichocki A. Brain control of robotic arm using affective steady-state visual evoked potentials. IASTED Intern Conf Human-Comp Interact 2010; 264-270.