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BRAIN CONTROL OF ROBOTIC ARM USING AFFECTIVE STEADY-STATE VISUAL EVOKED POTENTIALS

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ABSTRACT
The recent emergence of successfully performing Brain-Computer Interfaces (BCI) has given new hope to the disabled and elderly populations for improvements in quality of life. However, most non-invasive BCI systems which allow direct brain-to-machine control still have rather limited capabilities. Visual-flicker-based SSVEP-BCI systems have received increased attention due to their potential capability to provide a large number of commands with high reliability. Yet, researchers have had limited success improving further the single-trial extraction of the weak SSVEP oscillations buried in strong brain 'noise'. In a previous study we have shown that the optimization of the stimulus properties is essential for the enhanced performance of SSVEP–based BCI designs. This paper presents substantial enhancements in the brain response and the processing algorithms necessary for reliable multi-command SSVEP-BCI systems. The visual perception of flickering emotional video, instead of neutral checkerboards, enhanced substantially the measurable SSVEP responses of the brain. Furthermore, a single-trial phase-locking gradient measure was found to be more reliable and resulted in decreased variability when compared to wavelet energy changes. When BCI users operated a robotic arm with this Hybrid BCI platform, the speed, reliability, and information transfer rates were substantially improved when utilizing the proposed affective flicker paradigm.

KEY WORDS
Emotions, Affective, SSVEP, BCI, BMI, Extraction

1. Introduction

The fundamental task of a Brain-Computer Interfaces (BCI) platform is to identify the user's intentions from a limited set of brain activities in near-real-time. Such capability enables direct human-computer interfacing without the use of muscles, and allows brain-based control of executive devices such as a robotic arm. However, current recording and analyzing techniques are unable to deliver unique patterns for each free intention, so that not all available pattern properties are uniquely identifiable. Currently, this basic BCI problem is solved through limiting the set of expected brain activities and using specific tasks by the user during a BCI session. Among the various BCI paradigms which offer a large number of independent commands, the Steady-State Visual Evoked Potentials (SSVEP)-based approach is especially attractive with its potential for flexibility and high reliability. Quickly flickering lights or patterns evoke precisely synchronized responses in the brain (SSVEP), which makes them identifiable. SSVEP responses are dependent on attention [1], stimulus size, as well as temporal and spatial frequencies [2, 3, 4].

Previously, we designed and evaluated a dynamic 8-command SSVEP-based BCI platform which enabled the two-dimensional control of moving objects on a computer monitor [3, 4]. This system introduced substantial advantages such as a high information transfer rate (mean 50 bits/min), using a large number of commands with minimal occlusion of the user visual field, moving stimuli clustered close to each other to minimize eye movements, and flicker stimulus optimization. The frequency dependence and the time dynamics of the brain responses for these small patterned SSVEP-BCI stimuli were investigated for single-trial responses. The results of that study showed that the optimization of stimulus properties is as essential for enhancing BCI performance, as is the development of better online analysis algorithms.

The work presented here improved and extended these previous BCI results using a hybrid brain response paradigm combining visual and emotional responses. A new phase-reset-based method for rapid detection of the onset of weak SSVEP oscillations in single trials was shown to be more sensitive and robust than classic wavelet energy changes.

2. Influence of Emotions on Visual Brain Activity – An Overview

According to the emotional priming model [5], emotions exert a modulatory influence on other relevant brain systems through motivational priming, so that these systems receive a higher probability of access and strength of activation. Emotion circuits in the brain are involved not only in controlling the motor output and primitive reflexes but also modulate systems such as memory, verbal output, attention, and early sensory responses, especially in the visual cortex [6, 7, 8].

When viewing emotionally charged static images (such as the International Affective Picture System IAPS [9]), affective modulations have been observed at multiple stages of the visual evoked potential ranging from 120ms to 600 ms [10, 11]. However, in a more complex stimulation setting using flicker, a technique referred to as Steady-State Probe Topography (SSPT) has produced the opposite effect – reduction of the occipital brain response amplitude [12] during emotional face processing. In SSPT experiments users wear goggles with flickering 13 Hz semi-transparent white light superimposed on the static images. Other experiments with small flickering (7.5Hz) and moving white squares superimposed on affective images have also shown a decrease in SSVEP amplitudes, as brain resources were withdrawn from the visual system to process the background emotional pictures [13]. Yet, in spite of this brain-resource sharing hypothesis, there is initial evidence pointing that when the entire affectively arousing images were set to flicker at 10Hz while viewed, the resulting parieto-occipital SSVEP amplitudes were enhanced as compared to viewing neutral flickering pictures [14]. Based on these previous studies, in this work, we performed basic experiments using affective SSVEP (aSSVEP) to investigate further the enhancing effect of emotions on vision.

3. Experiment 1: Affective Steady-State Visual Evoked Potential (aSSVEP) Responses to Emotional Face Video

The main goal of this experiment was to explore the properties of the brain responses to affective flickering video stimuli and to compare them to cortical activity evoked by neutral patterns without emotional content.

3.1 Experimental Design

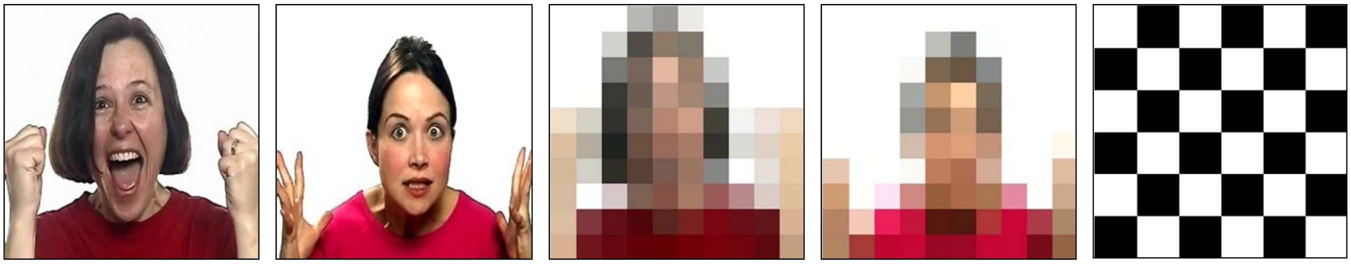
Eight subjects (four male and four female, with an average age of 26 ± 9 years) participated in this study. All had normal or corrected-to-normal vision, as well as no prior history of neurological disorders. Before each experiment the subjects were briefly tested for photosensitive epilepsy, and during the experimental sessions their EEG patterns were continuously monitored for epileptic spikes. They were seated 1m from a 40” LCD display with a vertical refresh rate of 60Hz (measured 59.7 ± 0.35Hz). Five different stimuli were shown to each subject – two short video clips (4s, 320x240 pixels) with actors depicting emotions [15] on the opposite ends of the affective valence scale (joy/happiness and anger), as well as their block-blurred versions, and a reversing 6x6 checkerboard (Figure 1). Each stimulus was shown at five flickering frequencies ranging from 5Hz to 12Hz, which are not discussed further in this paper. The blank periods in the video stimuli were replaced with 50% gray squares of the same size. Each video clip stimulus was replayed continuously until the end of the trial. Each trial was 10s long with a 2s blank-screen baseline. The brain signal acquisition was performed using a Biosemi EEG system (Biosemi Inc, Amsterdam, The Netherlands) with 128 whole-head active electrodes, and a sampling rate of 512Hz. The study was approved by the Riken Institute Ethics Committee.

After the original EEG was re-referenced to the central electrode CZ, all ocular artifacts were removed using Independent Component Analysis (ICA) employing the Unbiased Quasi-Newton Algorithm for ICA (UNICA) [16]. UNICA was selected after testing the performance of more than 20 ICA algorithms [17]. Its advantage for this application consisted in the reliable separation of ocular independent components by performing unbiased ICA in the presence of strongly correlated Gaussian noise in the mixture. UNICA performs a quasi-Newton iteration for the estimation of the mixing system with a minimum variance distortion response criterion which eliminates from the outputs the interfering components and all the noise that is outside the extracted signal subspace.

Previously, we performed the estimation of the single-trial SSVEP responses in the brain using modified quadrature amplitude demodulation [3]. In the present aSSVEP estimations, we calculated and compared the performance of two other measures – a single-trial phase-locking gradient and a wavelet energy gradient.

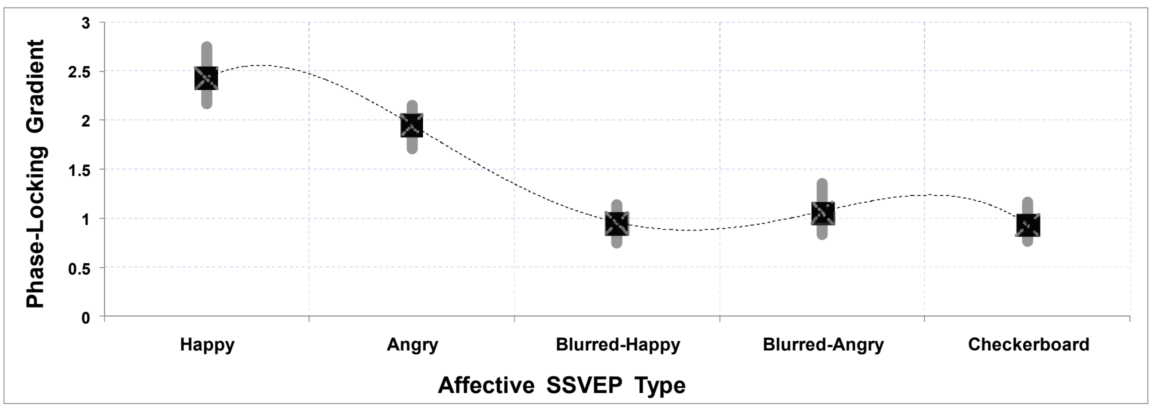
3.2 Phase-Locking Value Variability Measure

The phase-locking value (PLV) [18] represents the degree of phase stability at the flicker frequency. Previous studies have often computed the PLV measure over multiple trials, but here only single trials were evaluated. Furthermore, calculating the PLV over multiple time windows [19] would be also inappropriate in this case since it is important to associate the PLV changes with the exact time of the SSVEP onset. That is why in this study the single-trial phase-locking variability represents a normalized measure of the phase-locking value variability/increase (PLVV) in the 1^{st} second following the SSVEP onset. PLVV was estimated by measuring the degree of wavelet phase stability over a block of 12 occipital channels, when compared to an artificial sine wave of the exact same frequency as the SSVEP flicker.

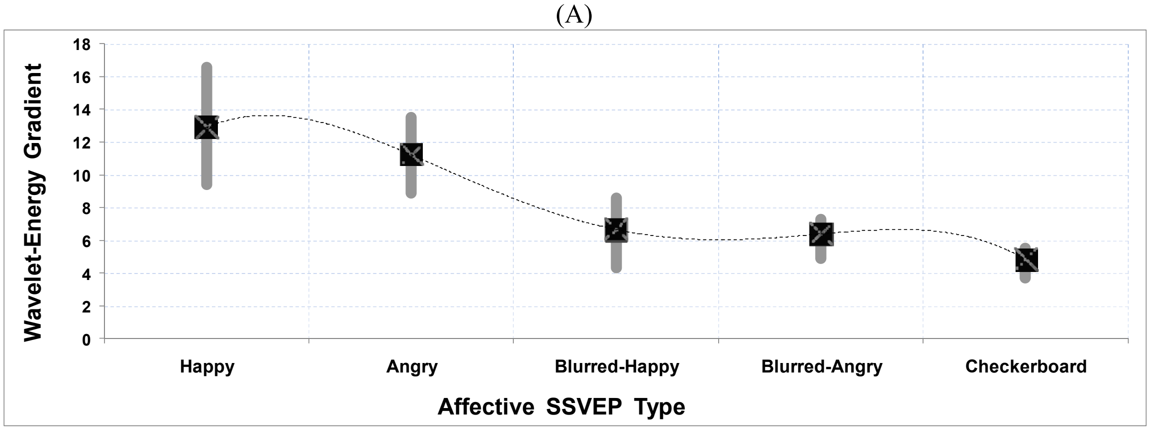


(A) (B) (C) (D) (E)

Figure 1. Affective SSVEP stimuli. (A) and (B) Two short video clips interrupted with gray flicker with actors depicting emotions on the opposite ends of the affective valence scale (joy/happiness and anger); (C) and (D) The same videos blurred to preserve the general image properties but to conceal the emotions and facial features; (E) A neutral reversing checkerboard for control.



(A)



(B)

Figure 2. Brain responses to affective and neutral video SSVEP stimuli (average of all measured frequencies). (A) Strength of the response using a normalized single-trial phase-locking gradient measure. This phase measure was more stable and sensitive to weak SSVEP oscillations than the wavelet energy. (B) Strength of the response using a normalized single-trial wavelet energy gradient measure. Affective SSVEP video stimuli evoked significantly stronger responses than their blurred versions or the neutral checkerboard.

The initial single-trial phase-locking values used here were computed for each fixed SSVEP frequency f over time t as follows:

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

where $N=12$ was the number of EEG channels (over the occipital cortex, in this case), $j^2 = -1$, and $\Phi^{i}_{\mathrm{EEG}}(\mathrm{f})$ and $\Phi^{i}_{\mathrm{ref}}(\mathrm{f})$ were the phases of the normalized EEG signal s^{i}_{EEG} ($i=1..N$) and the flicker reference signal s^{i}_{ref}, respectively. The reference s^{i}_{ref}, was a sine wave corresponding exactly to the flicker frequency f of the visual stimulus. The phase Φ for SSVEP frequency f was calculated using the imaginary and real components of the convolution of an input signal s^i with a complex Gabor wavelet $W(f)$:

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

Using these definitions, the normalized single-trial phase-locking value variability measure $PLVV^f$ was defined as the ratio:

$$PLVV^f(t) = \frac{\Delta SPLV^f(t)}{SPLV^f(t_0)} , \quad (3)$$

And the phase-reset change $\Delta SPLV^f(t)$ as calculated for each SSVEP frequency f was:

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

where $SPLV^f(t_{max}^{1s})$ was the maximum phase-locking value reached within one second after the onset of the SSVEP stimulation, while $SPLV^f(t_0)$ was the baseline phase-locking value at SSVEP onset t_0, driven by the flicker phase reset of the occipital brain activity.

3.3 Wavelet Energy Variability Measure

The second measure, a single-trial Gabor wavelet energy gradient, represented the normalized energy increase of the brain response at the flicker frequency in the first second following the SSVEP onset:

$$WTV^f(t) = \frac{\Delta SWT^f(t)}{SWT^f(t_0)} , \quad (5)$$

where:

$$\Delta SWT^f(t) = SWT^f(t_{max}^{1s}) - SWT^f(t_0) , \quad (6)$$

$SWT^f(t_{max}^{1s})$ 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.

3.4 Experimental Results

The results from the brain response changes after stimulus onset (all frequencies) showed that both for the phase-locking measure (Figure 2A), and for the wavelet energy measure (Figure 2B), the affective video clips evoked significantly stronger activity in the occipital cortex than their blurred versions or the checkerboard. In average, the video with the positive valence (joy/happiness) performed slightly better than the negative one (anger), while the blurred-face videos and the checkerboard performed comparably well but worse than the affective stimuli.

The normalized single-trial phase-locking gradient measure exhibited lower variability and better performance than the wavelet energy measure.

We recorded also behavioural measures regarding the experiences of each subject. After each EEG experiments, the subjects answered a questionnaire with 3 questions regarding a self-estimate of their trait emotionality, as well as the degree to which they felt the same emotion as the actor depicting joy, and the actor depicting anger. The degree of admitted emotionality (from 1 to 10) for all subjects was 6.3 $\pm$ 2.1. The degree to which they identified with the depicted positive emotion (from 1 to 10) was 7 $\pm$ 1.9, while for the negative emotion the score was 5.7 $\pm$ 2.2.

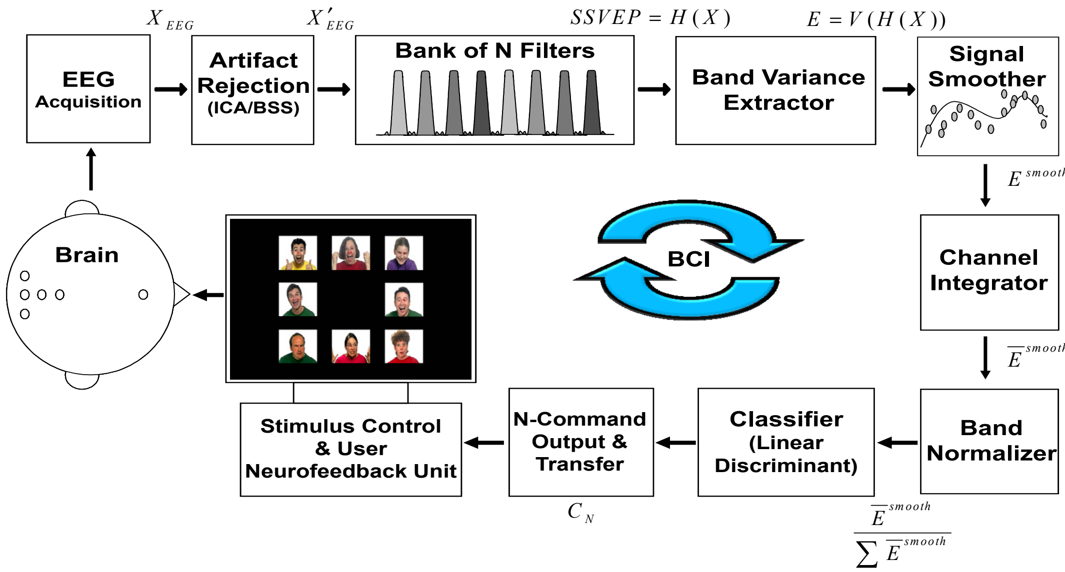
4. Experiment 2: BCI Evaluation using Affective Steady-State Visual Evoked Potentials (aSSVEP-BCI)

In a second experiment, the subjects operated an aSSVEP-based BCI system controlling a robotic arm. The goal of this experiment was to verify the efficiency of the Hybrid (emotional-visual) BCI paradigm to achieve improvement in performance and information transfer rates.

4.1 Experimental Design

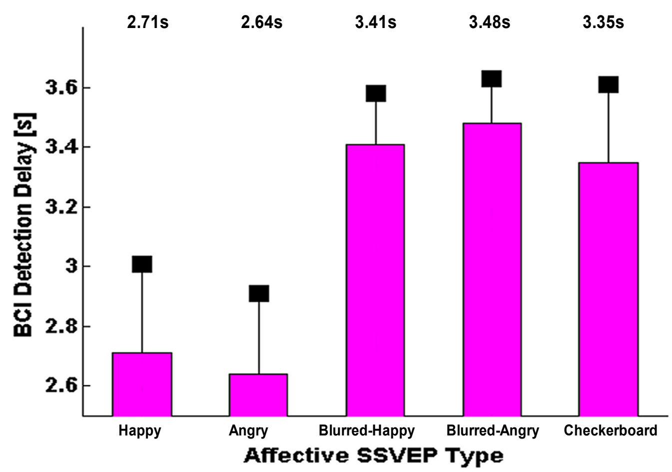
The general experimental setup was similar to that in the previous experiment, with the exceptions of several important details. The computer display used for BCI was a more readily-available compact 17” notebook PC screen. Eight different emotion-loaded face video clips flickered at different frequencies (5, 5.4, 6, 6.7, 7.5, 8.5, 10, 12 Hz). Each affective video was assigned as an independent command. The subjects directed their attention to a selected video to evoke an affective-SSVEP response and a corresponding movement of the robotic arm (Figure 3B).

The aSSVEP-based BCI platform consisted of the following main modules (Figure 3A): EEG data acquisition (Biosemi, Biosemi Inc, the Netherlands), a signal processing and evaluation unit, a neurofeedback and stimulus control user interface, and a multi-joint robotic arm executive device (iARM, Exact Dynamics Inc, The Netherlands). The online BCI data analysis module of the system was based on a multi-stage frequency band classification algorithm [3, 4, 20] with the following work flow:



(A)

(B)



(C)

Figure 3: An eight-command aSSVEP-BCI platform based on affective steady-state visual evoked potentials, and controlling a multi-joint robotic arm device in 3-D space. (A) Block diagram of the core BCI system. (B) User control of the robotic arm; (C) Shorter BCI command delays for affective and neutral video SSVEP stimuli. Emotion stimuli enhanced the speed of BCI command recognition as the signal-to-noise ratio was higher for affective SSVEP.

1) Automatic artifact removal based on ICA/BSS (eye and muscle movement artifacts)
2) Bank of narrow band-pass filters
3) Variance analyzer
4) Smoothing filter (Savitzky-Golay)
5) Channel Integrator
6) Individual band normalization
7) BCI command release / classification

4.2 Experimental Results

The mean BCI command delay and success rate were measured for all 5 types of stimuli used in the previous aSSVEP experiment, for 10Hz flicker. The BCI delay was defined as the time between issuing a request for a specific command till the time this command was recognized from the user's EEG by the signal analysis module. As shown in Figure 3C, and in agreement with the results of our first experiment, the affective SSVEP responses were faster and exhibited less transient properties than in neutral checkerboards or blurred video.

The mean BCI delay using emotional stimuli was 2.7s, while the mean neutral delay was 3.4s. In that way, 8-command BCI information transfer rate was increased from 50 bits/min for neutral stimuli to 64 bits/min for affective SSVEP.

5. Discussion

5.1 Affective SSVEP Stimuli

In this study, we used relatively simple visual-affective stimuli (actors depicting emotions on a white background) in order to reduce extraneous factors and inter-subject variability during elicitation of SSVEP brain responses for multi-command BCI. Even though emotions may be experienced in radically different ways depending on culture [21], gender [22], or even individual hormonal levels [23], the cognitive influences were maximally reduced in our experimental setup and all subjects reported empathic feelings when observing affective face videos. The time-dependent video stimuli employed in this paper are arguably more efficient than static pictures in evoking emotions reliably, quickly, and with minimal habituation on continuous use. Only a moderately strong mix of positive and negative emotions was selected here, since a BCI system is meant for daily use and the user should be as highly motivated to operate it for as long as possible. If more intensive emotions were employed, the SSVEP enhancements could be even more powerful, but this may also lead to stronger fatigue after prolonged exposure.

5.2 Phase-based and Energy-based Algorithms for the Detection of SSVEP Onset

Single-trial steady-state visual evoked responses to small flickering stimuli are more difficult to extract from the background EEG, as the signal-to-noise ratio is lower. Yet, small stimuli are essential in practical applications such as BCI, in order to let the user have as much visual space available for other activities as possible. This means that successful extraction of the SSVEP oscillations can be achieved either by more powerful signal processing algorithms, or by boosting the brain response through stimulus optimization, or using both approaches. Although we have utilized successfully signal energy measures in our previous studies [3, 4, 20], as well in the current paper, we found that a properly defined phase locking measure can be more efficient in a single-trial setting. One of the difficulties in increasing further the already high recognition rate of SSVEP-based BCI systems is that the brain does operate independent background activities whose time-frequency fingerprints may well coincide at times with BCI flicker rates, thus causing a false positive. The traditional SSVEP estimation measures such as FFT, bandpass filtering or wavelet energy are rather susceptible to this phenomenon.

However, in this paper we propose the idea and proof that a strong phase reset in the occipital cortex at one of the BCI flicker frequencies followed by an increase in the phase stability over an entire brain area is a more efficient indicator of SSVEP lock-in or visual attention shift than the oscillation energy. A rapid and robust SSVEP phase-reset measure is particularly suitable for a SSVEP-BCI platform where it is more important to detect the SSVEP onset reliably than to measure its strength continuously, as the user is switching attention quickly from one flickering stimulus (BCI command) to another. Yet, in a practical BCI implementation the PLVV procedure should be always combined with a wavelet energy measure to avoid possible false positives during unrelated brain activities which may also involve phase resets in the SSVEP frequency bands.

6. Conclusion

The goal of this study was to enhance substantially the information transfer rates in our SSVEP-based BCI system. The results of our first experiment showed that affective videos of joy and anger enhanced substantially the visual SSVEP activity in the occipital cortex as compared to emotionally neutral stimuli. It was also shown that a new single-trial phase synchrony measure, the phase-locking value variability (PLVV) is more sensitive and robust for detection of SSVEP onset than an energy variability measure. In a second experiment, we evaluated the performance of our Affective-SSVEP BCI system which controlled a multi-joint robotic arm with high reliability. We demonstrated that replacing the neutral stimuli with simple affective video clips boosted the speed of BCI command recognition by 0.7s and increased the mean information transfer rate to 64 bits/min. ASSVEP-BCI platforms, if fully implemented as proposed here, and then refined even further, would be particular useful for disabled users confined daily to wheelchair- or bed settings, who would benefit most from direct brain control of a robotic arm with complex movements.

In conclusion, the presented results indicate that it may be highly advantageous to use transient phase-based measures, and flickering emotional video stimuli in SSVEP-based practical applications such as brain-computer interfaces, or in clinical settings which rely on SSVEP for diagnosis and probing other brain functions.

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