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Optimization of SSVEP brain responses with application to eight-command Brain–Computer Interface

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ABSTRACT

This study pursues the optimization of the brain responses to small reversing patterns in a Steady-State Visual Evoked Potentials (SSVEP) paradigm, which could be used to maximize the efficiency of applications such as Brain–Computer Interfaces (BCI). We investigated the SSVEP frequency response for 32 frequencies (5–84 Hz), and the time dynamics of the brain response at 8, 14 and 28 Hz, to aid the definition of the optimal neurophysiological parameters and to outline the onset-delay and other limitations of SSVEP stimuli in applications such as our previously described four-command BCI system. Our results showed that the 5.6–15.3 Hz pattern reversal stimulation evoked the strongest responses, peaking at 12 Hz, and exhibiting weaker local maxima at 28 and 42 Hz. After stimulation onset, the long-term SSVEP response was highly non-stationary and the dynamics, including the first peak, was frequency-dependent. The evaluation of the performance of a frequency-optimized eight-command BCI system with dynamic neurofeedback showed a mean success rate of 98%, and a time delay of 3.4 s. Robust BCI performance was achieved by all subjects even when using numerous small patterns clustered very close to each other and moving rapidly in 2D space. These results emphasize the need for SSVEP applications to optimize not only the analysis algorithms but also the stimuli in order to maximize the brain responses they rely on.

The ability of the human brain to control directly objects other than its own body has become reality in the past few decades with the success of the interdisciplinary Brain–Computer Interface (BCI) paradigm [5,13,16,18]. BCI offers disabled and healthy users an important alternative channel of communication and control by conveying intent through premeditated modification of the brain activity, instead of using muscles. Recent studies have indicated an increased interest in BCI systems which are based on conscious modification of natural brain responses to external stimuli with various sensory modalities [2,16]. Such BCI methods, in spite of the necessity for stimulation equipment and increased attention efforts by the user, allow advantages such as a very large number of commands, high reliability, shorter or no subject training, and higher resistance to artifact contamination, when compared to BCI approaches based only on mental imagery. In the Steady-State Visual Evoked Potential (SSVEP) BCI paradigm [10], the user focuses attention selectively on one of multiple patterns/lights which reverse/flicker repetitively at slightly different frequencies. This continuous visual stimulation evokes a precisely synchronized, recognizable "steady-state" brain activity which depends on the user's choice of a target, as each reverse or flicker at its own unique frequency. SSVEP BCI systems have been used, for example, as a two-command flight simulator control device [10], or the BCI NASA Earth viewer in which large stationary patterns on the edges of the screen reversing at 5–7 Hz enabled four-command control of the scrolling direction of a satellite map of the Earth [17]. Reportedly, BCI systems based on SSVEP stimulation have been tested successfully for up to 48 commands, even though with just one user [6]. In a previous report [9] we showed a four-command BCI design with pre-selected stimulation frequencies, mean success rate of 94.7%, and mean command delay of 3.7 s. In the present study we aimed to increase the number of commands to 8, while improving the BCI performance. In addition, we decreased substantially the size of the checkerboard stimuli in order to free up screen space for application purposes. To minimize visual occlusion, all 8 patterns were assembled in a very tight but simultaneously moving spatial configuration around a controlled object, in a novel dynamic paradigm for pattern SSVEP BCI [3]. Even though relatively robust, the cortical SSVEP oscillations depend strongly on stimulation characteristics, including repetition rate, stimulus size, spatial frequency, contrast and color [14], as well as attention [12] and proximity of other simultaneous stimuli. In this study, we investigated the effect of

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the stimulation frequency on the SSVEP response (Experiment 1), as well as its time dynamics (Experiment 2). These results were used to construct, evaluate and account for the performance of an eight-command SSVEP-based BCI system (Experiment 3), featuring a robust optimized stimulation which is extendable to higher number of commands.

Brain signal acquisition in SSVEP Experiments 1 and 2 was performed with 128 active electrodes at a sampling rate of 2048 Hz (Biosemi Inc., Amsterdam). In BCI Experiment 3, a lower sampling rate of 256 Hz was used, and 5 occipital electrodes were placed in an inverted T-shape configuration (with OZ at the crossing point). An additional electrode was placed in an anterior location (FZ) to aid the automated removal of ocular artifacts. Four healthy subjects with normal or corrected-to-normal vision participated in this conceptual study. The subjects were fully informed of all procedures and signed an informed consent agreement, in accordance with the Declaration of Helsinki, and including a statement that they have no known neurological disorders. Before each experiment they were briefly tested for photosensitive epilepsy. Subjects, who did not have any prior training except for a short practice run during the briefing, were seated 0.9 m from a 21″ CRT computer display operated at a high vertical refresh rate (setting 170 Hz, measured 168 ± 0.4 Hz). SSVEP stimulation was achieved using small reversing black and white checkerboards with 6×6 checks. The checkerboards had dimensions $1.8^\circ \times 1.8^\circ$ arc, so that the diameter (2.5° arc) would just cover the size of the fovea.

Experiment 1 was designed to expose the brain frequency responses for our small patterned stimuli. A single reversing checkerboard was presented on a black background in the middle of the screen in this experiment. The rate of reversal of the pattern was changed every 6 s and increased stepwise, with larger steps at higher stimulation frequencies due to the limitations imposed by the discrete refresh cycle of the computer display. Overall, 32 reversal frequencies were shown: 5.1, 5.25, 5.4, 5.6, 5.8, 6.0, 6.2, 6.5, 6.7, 7.0, 7.3, 7.6, 8.0, 8.4, 8.85, 9.3, 9.9, 10.5, 11.2, 12.0, 12.9, 14.0, 15.3, 16.8, 18.7, 21.0, 24.0, 28.0, 33.6, 42.0, 56.0, 84.0 Hz. Due to the discrete vertical refresh rate of the computer monitor and to avoid improper partial display, these frequencies were obtained by dividing the measured refresh rate of 168 Hz by integer values (33, 32, ..., 2). After re-referencing the original EEG data to the central CZ electrode, eye blink and muscle artifacts were extracted and removed using a blind source separation (BSS) approach utilizing modified Robust Second Order Blind Identification with Joint Approximate Diagonalization (SOBI) and automatic Hoyer sparsity ranking of the components [4]. This pre-processing procedure served to increase the success rate of the system by reducing the probability for false positive recognition of BCI commands. Artifact-free responses for each of the 32 stimulation frequencies were band-passed at their individual stimulation frequencies (± 0.1 Hz) using a zero-phase finite impulse response (FIR) filter configured for a 0-dB magnitude response at the center frequency of the passband. The response strength for each band and subject were estimated as the mean *z*-score of the band power throughout the stimulation interval. The average *z*-score across all subjects was calculated for each pattern reversal rate as a measure of the frequency response of the brain.

In Experiment 2, a single small checkerboard stimulus was displayed for three reversal frequencies sequentially (8, 14 and 28 Hz), covering each of the three SSVEP response regions (low-, medium-, and high-frequency) as defined by Regan [14]. Six trial repetitions were used for each frequency. Each trial consisted of 5 s baseline rest (black screen) and 15 s stimulation. To remove the interference caused by the synchronous SSVEP response oscillations, and to observe their envelope, we applied a demodulation procedure [12]. Our modified quadrature amplitude demodulation (QAD) method recovered the amplitudes of phase-shifted messages Y_1 and Y_2 in a modulated carrier input signal X (SSVEP):

$$Y_1 = X\cos(2\pi ft), \quad Y_2 = X\sin(2\pi ft) \tag{1}$$

and reconstructed the original modulating signal using the following equation:

$$Z = |H^f(Y_1)| + |H^f(Y_2)|, \tag{2}$$

where f is the counterphase modulation frequency, and H^f is a low-pass Butterworth filter at cutoff frequency f applied to filter out the carrier signal. The QAD model output Z represented the recovered single-trial SSVEP response envelope, which could be used further to measure the characteristics of the signal dynamics. The demodulated, squared and normalized SSVEP brain response signals were subjected to peak analysis for each frequency, trial and subject. The onset was defined as the envelope value on a rising slope for which the baseline oscillation maximum was exceeded by 10%. The first peak was defined as the first extremum of the signal following the onset point. Single-trial latencies for the SSVEP onset and first-peak delays were measured and evaluated through two-factor ANOVA statistical analysis. Data series were considered significantly different if the 95% probability threshold ($p < 0.05$) was passed, indicating that they do not belong to the same sample populations.

The goal of Experiment 3 was to evaluate an online eight-command SSVEP BCI system with frequency-optimized stimuli. The system consisted of the following basic modules: (1) data acquisition module, (2) user neurofeedback and stimulation module, and (3) data analysis/command recognition module. Eight checkerboard patterns were displayed simultaneously, each allowing control of one independent BCI command (Fig. 2). The patterns, reversing at optimized frequencies of 6.0, 7.3, 8.4, 11.2, 12.9, 14, 15.3, 16.8 Hz, were fixed very close to a moving controllable object, and allowed its spatial translation in 8 directions with 45° resolution in 2D space. Shortly after a subject's attention was directed to a selected pattern, the synchronized SSVEP brain responses were identified by the BCI analysis module, and the online visual neurofeedback enabled the movement of the controlled object (a small car in this case) in the desired direction: UP, RIGHT, DOWN, LEFT, UPPER-LEFT, UPPER-RIGHT, LOWER-RIGHT, LOWER-LEFT, as well as IDLE. In addition, the first byte of the transmitted command data indicated the strength of the current EEG command feature, so that the speed of the car object moving on screen was higher for stronger brain responses. Three different modes of operation were enabled in BCI Experiment 3: (a) short classifier training mode, (b) performance evaluation mode, and (c) self-paced free roaming mode, which are not discussed further in this report. For all modes of operation the user's neural commands were detected and sent for visual feedback every 120 ms. During the classifier training mode (~2 min duration), each of the eight BCI commands was requested three times in random order, in addition to a no-stimulation command. After hearing a command request, the subject switched attention as soon as possible to the corresponding reversing pattern, or, in case of a no-stimulation request, to the controlled object between them. The voice requests were short pre-recorded messages asking the user to attend a specific pattern. Each command request was also accompanied by a thin red frame appearing around the requested pattern to minimize the searching delay. Neurofeedback was disabled during the training mode, and all user interface objects remained stationary. The second, evaluation mode served the purpose of measuring objectively the mean success rate and time delay of the BCI system. Six repetitions for each of the eight commands were presented to the user in random order, after which the success rate was measured, as well as the recognition time delay. The dynamic neurofeedback was fully enabled in evaluation mode. A thin red frame aided the user to find the requested command pattern quickly, while a green frame showed which command was recognized. The BCI data analysis module utilized

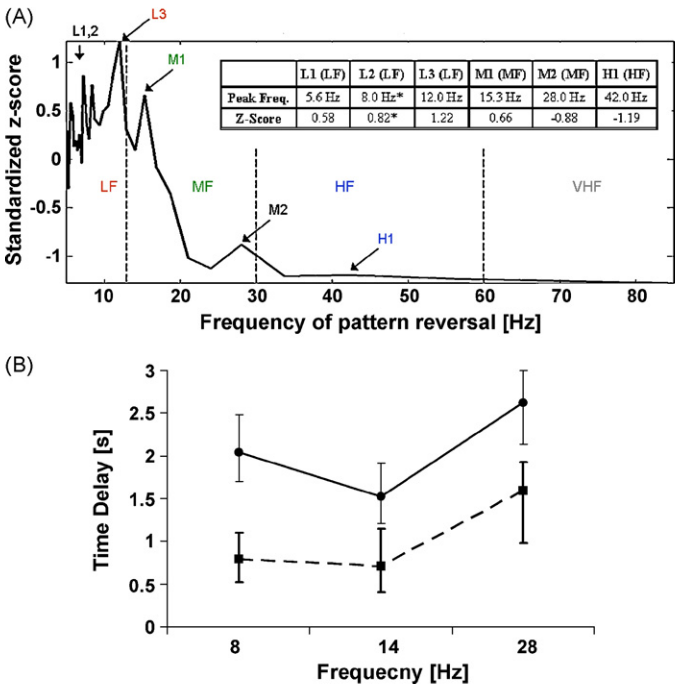

Fig. 1. (A) Brain frequency response to small-pattern reversal for 32 frequencies. The mean *z*-scores exceeded 0.5 in the 5.6–15.3 Hz frequency range; the strongest response was observed at 12 Hz. Here, the SSVEP frequency region definitions by Regan [14] were adopted and extended: low-frequency (LF: 5–13 Hz), medium-frequency (MF: 13–30 Hz), high-frequency (HF: 30–60 Hz), and very-high-frequency (VHF: >60 Hz); (B) SSVEP response delays for 8, 14, and 28 Hz stimulation with small patterns: (dashed line) SSVEP onset exceeding the baseline by 10% and (solid line) 1st peak following the onset.

the following work flow (Fig. 2): (a) artifact removal based on a modified fast BSS AMUSE procedure [4], which ranked the signal components so that the undesired first and last components were rejected automatically (the first component extracted the slowest brain activity due to eye blinks, eye movements, or other slow artifacts, while the last component contained the fastest activity due to muscle artifacts or other high-frequency noise); (b) bank of elliptic narrow-band IIR filters $H(X'_{EEG})$ of 3rd order with center frequencies corresponding to the reversal rates of the command patterns and a bandwidth of 0.2 Hz; (c) variance analyzer calculating the variance of the band-power signals $E = V(H(X'_{EEG}))$ for all pattern reversal frequencies and all EEG channels; (d) 2nd-order polynomial smoothing filter (Savitzky-Golay); (e) Channel integrator to obtain the estimated energy per band; (f) Individual inter-band normalization for improved performance which generated $N = 8$ time series describing the percentage of the estimated normalized energy per band for each user, and (g) Linear discriminant analysis classifier, which used the relative band energies to identify the user's target of attention every 120 ms.

Fig. 1A shows the occipital SSVEP frequency dependency results from Experiment 1 in the full stimulation frequency range 5.1–84 Hz we studied. The table in Fig. 1A lists the frequencies and strengths of the main mean peak responses in the occipital area of the brain. These frequency characteristics indicated that during SSVEP stimulation with small checkerboards the strongest response was around 12 Hz. We observed also LF response peaks at 5.6 Hz and around 8 Hz (7.6–8.8 Hz). In the MF range, the strongest response was detected at 15.3 Hz, while a much weaker peak was observed for 28 Hz stimulation. The HF region presented a small local enhancement at 42 Hz, while the VHF was characterized by a linear inverse relationship between frequency and brain responses up to the highest tested frequency of 84 Hz. The highest inter-subject variability was observed at 5.6 Hz and 9.9 Hz. According to these results, and assuming a *z*-score threshold value of 0.5, we propose that the peak responses to SSVEP stimulation in the range 5.6–15.3 Hz are optimal for use in applications such as multi-command SSVEP-based BCI systems.

In Experiment 2, investigating the 8, 14 and 28 Hz SSVEP dynamics, we observed highly non-stationary SSVEP responses in all 15-s trials, depending on frequency. The occipital SSVEP onset- and 1st-peak delays both showed statistically significant dependency on the stimulation frequency (Fig. 1B), $p = 0.00001$ for onsets, and $p = 0.002$ for first peaks). In most trials, the 14 Hz onset and 1st-peak activity was the fastest among the three measured frequencies, with the strongest, most stationary, and most global brain response. The 28 Hz activity onset and 1st-peak were the slowest and the oscillations most non-stationary. Statistical testing did not show significant inter-trial differences among all available trials ($p = 0.85$ for onsets, and $p = 0.94$ for first peaks). There was, however, frequency-dependent variability between individual subject responses, as also pointed out in other studies [7]. The inter-subject variability almost reached significance ($p = 0.07$) for the onset-delay measurements, but was not significant for the first peaks ($p = 0.29$). Furthermore, a slow SSVEP modulation with a 2–3 s period was observed in most trials, which may be due to natural fluctuations in selective attention, habituation or other phenomena such as fatigue-prevention processes (Fig. 2).

In Experiment 3 we measured the performance of the eight-command BCI system in evaluation mode (using voice request-responses) with checkerboard patterns reversing in the 6.0–16.8 Hz range. The BCI system reached a mean command success rate of 98% and mean command recognition delay of 3.4 ± 0.7 s, with information transfer rate (ITR) of 50 bits/min.

In this study, we investigated the SSVEP frequency characteristics and time dynamics of the brain responses to small reversing checkerboard patterns, which could be used to optimize the performance of SSVEP-based BCI systems. Specifically, this study found the following:

1. Stimulation frequencies in the range 5.6–15.3 Hz were optimal for small patterned stimuli.
2. Maximal brain response was elicited at 12 Hz stimulation, with peaks at 5.6–8 Hz, as well as weaker local maxima at 15.3, 28.0 and 42.0 Hz. In general, these results agreed with previous reports. Srinivasan [15] showed that random dot patterns elicited occipital response peaks at 8 and 12 Hz. Koch [8] experimented with red flash stimulation using goggles and found EEG response peaks at 5 and 11 Hz. Furthermore, in agreement with our findings, a study using transcranial magnetic stimulation (TMS) demonstrated strongest suppression of the brain's flash response when the lag between the stimulus and the magnetic pulse was 80–100 ms [1].
3. The first single-trial SSVEP local maxima after start of stimulation were measured at 1.5–2.5 s. The trial maxima usually followed the first peak by several seconds. The initial SSVEP onsets were considerably frequency-dependent, gradually starting 0.5 s or more after the start of stimulation. One of the reasons to account for these time delays may be that attentional switching mechanisms could expend up to 0.6–0.8 s between cue onset and SSVEP facilitation [11].
4. Among three studied reversal frequencies, 8 Hz (LF), 14 Hz (MF), and 28 Hz (HF), the 14 Hz response was strongest and its first peak was the fastest (except for one subject who exhibited an 8 Hz preference).
5. The dynamics of extended SSVEP responses (15 s in duration) were found to be essentially non-stationary, especially for higher stimulation frequencies (28 Hz). Recent EEG studies often examine relatively short-term SSVEP oscillations or otherwise ignore the oscillation envelope changes, which could be substantial at

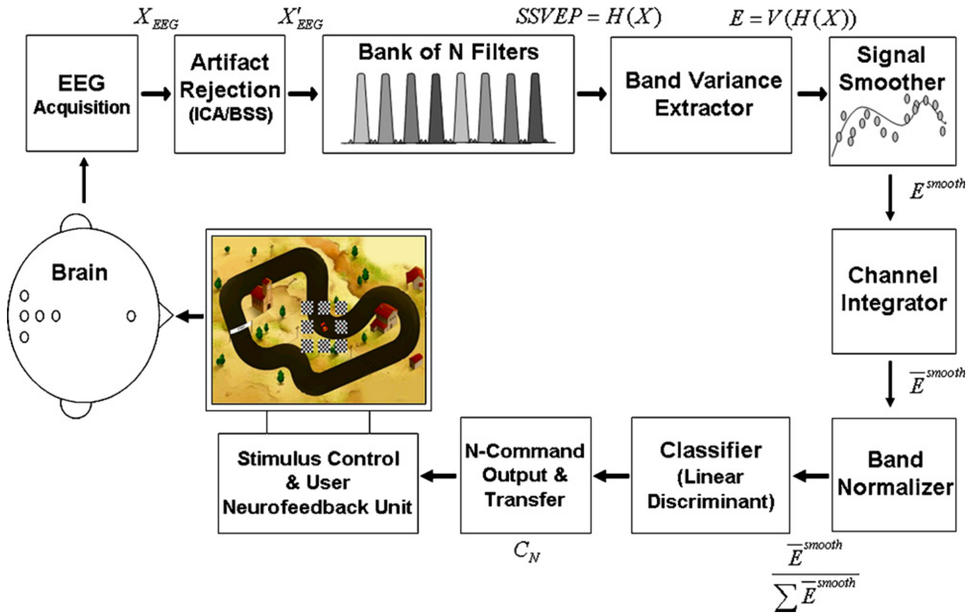

Fig. 2. Block diagram of the online eight-command BCI system.

higher frequencies. In our Experiment 2, we noted also common slow envelope modulations with a period of roughly 2–3 s. We hypothesize that they might be due either to natural fluctuations in attention, or to inhibition feedback in order to prevent fatigue and preserve concentration, or possibly due to another unknown mechanism.

6. BCI evaluation showed high performance for eight commands, with mean command success rate of 98% (96–100%) and mean command recognition delay of 3.4 s (2.5–4.2 s). Although low-frequency preference was observed for one subject, the inter-subject variability of the BCI measures was relatively small, if provided sufficient attention, lack of anxiety and short initial practice.
7. Close aggregation, small size and rapid movement of the 8 reversing patterns did not affect BCI performance negatively, and users were able to attend successfully to each selected pattern. The small size of the patterns and their attachment to the moving controllable object served to reduce the time and distraction from large eye movements necessary for patterns fixed to the edges of the screen [17]. This robust mode of stimulation improved user performance and reduced fatigue by scaling down the demands on attention, especially over longer periods of operation.

In the past decade, many online SSVEP BCI communication studies relied on signal processing approaches based on the fast Fourier transformation (FFT) [6,17] to extract the rhythmic visual responses in the brain. The success of such systems depended to a large extent on striking the right balance between the fundamental and harmonic frequencies of the evoked oscillations. Other reports were based on data processing methods such as Bayesian decision making with recursive outlier rejection [18], template matching [16], 'lock-in' techniques and autoregressive spectral analysis. However, progress in analyzing non-stationary signals with very low brain signal-to-noise ratios is just one of the factors to consider in the fundamental challenge in the pursuit of the 'perfect' stimulus-dependent BCI. Another essential set of factors involves presenting stimulation which is optimal for most users, considering the differences in their brain neuroanatomy, attention levels, and flicker preferences. The present study is an attempt to integrate these requirements in order to achieve robust SSVEP responses for clinical applications and improved BCI performance.

In conclusion, the optimization of the experimental parameters to evoke maximal visual brain responses is necessary to allow the highest efficiency of any SSVEP application, including the eight-command BCI system presented in this study. Further development of the multi-disciplinary approach holds the promise to lead to BCI applications for a very large number of commands with enhanced reliability and robustness, such as direct brain control of e-Home appliances, operation of preset command sequences for TV, radio, vehicle navigation systems, and integrated robotics.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.neulet.2009.11.039.

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