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Hubert Cecotti

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H. Cecotti [1,2]
[1] GIPSA-lab CNRS UMR 5216
38402, Saint Martin d'Hères, France
[2]Institute of Automation (IAT) - University of Bremen
Otto-Hahn-Allee, NW1
28359 Bremen, Germany

Abstract

The detection of Steady State Visual Evoked Potentials (SSVEP) in the eletecroencephalogram (EEG) is one way to create efficient non-invasive Brain-Computer Interfaces (BCIs). A visual stimulus shall be presented to the user to produce an SSVEP response. This stimulus is usually a flickering light at a particular frequency. One issue for an SSVEP based BCI can be the flickering stimuli. We propose to evaluate the impact of the duty cycle of the flickering lights for evoking SSVEP responses. Three paradigms based on different duty cycles over six subjects are evaluated and compared. The offline classification of the obtained SSVEP responses is performed with spatial filters based on the Principal Component Analysis.

Keywords

Brain-Computer Interface, Steady-State Visual Evoked Potentials, Signal detection.

1. Introduction

A Brain-Computer Interface (BCI) allows people to communicate through direct neural activity measurements [2, 18]. BCIs based on non-invasive scalp electroencephalography (EEG) have become a promising and active research area during this decade. Different BCI paradigms are available, they mostly differ in the type of brain activity to detect. Event-related potentials, event-related desynchronization/synchronization (ERD/ERS), sensory based evoked potentials and slow cortical potentials are commonly used for tailoring an EEG-based BCI. Current BCIs suffer from several drawbacks. The main drawback is the information transfer rate (ITR). While the ITR is often described as the most important criteria, other features are also relevant. The system shall be convenient for the user and facilitate the subject's adaptation to a new communication device. For BCIs that require special external stimuli, their quality and their sources are a bottleneck for increasing the number of basic commands in a BCI. These stimuli should be reliable and not involve any risk or inconvenience like visual fatigue for the user. This last point is particularly relevant when patients have to use a BCI daily. For these persons, a BCI shall be convenient as much as possible.

In this paper, we focus on Steady State Visual Evoked Potentials (SSVEP). Compared to other BCIs, SSVEP-BCIs are described as more accessible. They have been used for several applications [12, 15, 13]. They include several advantages among a high information transfer rate (ITR) and almost no user training [7, 5]. However, BCIs based on SSVEP or P300 are not considered as independent BCIs: the generation of the VEP depends on the gaze control via extraocular muscles and particular nerves. For these BCIs, the only requirement is the possibility to control the eye movements.

SSVEP-BCIs use the response of the user attention to an oscillating visual stimulus. When a person is looking at one particular oscillating object, then the subject's brain response can provide a way for tailoring a BCI. Usually, the stimuli that are considered for inducing SSVEP responses are flickering lights at different frequencies. When an object flickers at a frequency *f*, then a response occurs in the visual cortex. This response corresponds to the frequency of the stimulus and its higher harmonics [16]. Therefore, it is possible to obtain different responses in relation to different frequencies. In relation to these responses, it is possible to create a BCI where each response is related to a command (selecting a symbol, using a device,...). The detection of SSVEP responses is described as reliable in the literature [6, 10, 9].

One first issue is to select the best frequencies for obtaining the best responses. This question has been largely discussed in the literature, the frequency choice can depend on the subject [9, 15]. The amplitude and the phase that define an SSVEP response depend on three main parameters [19]:

- The frequency. The SSVEP responses with maximum amplitude are usually obtained in three frequency bands: 5-12Hz, 12-25Hz and 30-50Hz [17].
- The intensity of the flickering light.

- The structure of the repetitive visual pattern. This point is the main focus of this paper, which deals with the effect of the stimulus duty cycle over the produced SSVEP responses. The goal here is to determine the effect of the duty cycle on the detection.

The paper is organized as follows. First, the different methods for processing the signal are described. Second, the protocol experiment is detailed in the third section. Finally, the results are presented and analyzed in the last sections.

2. Methods

2.1 Signal structure

Visual stimuli are usually presented on a set of LEDs or on an LCD screen. We consider the visual stimulation on a classical LCD screen with a vertical refresh rate of 60Hz. With visual stimuli on a screen, the graphical user interface (GUI) of the BCI application and the stimuli can be both on the same screen. When the visual stimuli and the application share the same screen, the subject does not need to shift her/his gaze too much between the stimuli and the GUI [5]. Monitors can also provide easily a display of the neurofeedbacks. The repetitive visual pattern is composed of n frames with $n > 1$. Thus, the frequency of a stimulus based on n frames is $60/n\ Hz$. A visual stimulus is represented on the screen by a flickering box (white/black). We define the duty cycle by $D = \tau/T$ where τ is the duration when the function is non-zero, *i.e.*, the number of black frames and T is the period of the function, *i.e.*, the number of frames describing a period of the visual stimulus. The duty cycle of the visual stimuli is usually not mentioned in the literature for SSVEP experiments. The structure of the signal was however specified in [11]. Kelly et al. consider two frequencies at 10.03Hz and 12.04Hz with duty cycles of 0.16 and 0.2, respectively.

2.2 Spatial filters

In a real BCI application, several types of SSVEP responses must be taken into account. Each type of SSVEP response corresponds to a particular frequency. In this multi-class classification task, we consider N_f classes where each class corresponds to an SSVEP response, *i.e.* a particular frequency. We consider a visual stimulation with a flicker-frequency of f Hz is applied. We use the following description for the signal $y_i(t)$ as the voltage between the electrode i and a reference electrode at a time t:

$$y_i(t) \quad = \quad \sum_{k=1}^{N_h} a_{i,k}\ sin(2\pi kft + \Phi_{i,k}) + B_{i,t} \quad (1)$$

where N_h is the number of considered harmonics h. The signal is decomposed into the SSVEP response and the noise. The first part corresponds to the evoked SSVEP response signal. The estimated responses are composed of a number of sinusoids with frequencies in relation to the stimulus frequency and a number of N_h harmonic frequencies. Thus each sinusoid is defined by its amplitude $a_{i,k}$ and its phase $\Phi_{i,k}$. The second part $B_{i,t}$ is dedicated to the noise.

The online detection of an SSVEP response on an EEG signal requires a time segment for the signal analysis. We consider a time segment of N_t samples of the signals, with a sampling frequency of F_s Hz.

$$y_i \quad = \quad Xa_i + B_i \quad (2)$$

where $y_i = [y_i(1), \ldots, y_i(N_t)]^T$ contains the EEG signal for the electrode i in one time segment. The SSVEP information matrix X is of size $N_t \times 2N_h$. For N_y electrodes, the signal is defined as:

$$Y \quad = \quad XA + B \quad (3)$$

where $Y = [y_1, \ldots, y_{N_y}]$ contains the sampled EEG signals from all the electrodes. A contains all the amplitudes for all the expected sinusoids for all electrode signals.

For enhancing discriminant features from the signal, the signals from the electrodes must be combined. A channel is used for a combination of the signals measured by different electrodes. A vector of channel data is denoted by s. Its purpose is to enhance the information contained in the EEG while reducing the nuisance signals. A channel is defined as a linear combination of y_i.

$$s \quad = \quad \sum_{i=1}^{N_y} w_i y_i = Yw \quad (4)$$

where w_i is the weight for the i^{th} electrode.

Several channels can be created by using several sets of weights w. We note N_s the number of channels. The channel creation is an essential step for enhancing the relevant signal [16, 3, 4]. In this work, we consider the minimum energy combination, which is based on the principal component analysis (PCA) [9]. Its purpose is to have an optimal combination of the electrode signals, which cancels the nuisance signals as much as possible. The technique removes any potential discriminant components from all the electrode signals, by projecting them onto the orthogonal complement of the formal model of the signal X. It can generate a frequency power estimation of any frequency. The method assumes for each frequency that it is the right frequency to detect. Then it removes the noise considering this hypothesis. Thus, channels are set in relation to hypotheses of the expected frequency to observe. This method allows the combination of a fixed number of electrodes that minimizes the nuisance signals. Once the channels are created, the power of the expected frequencies and their harmonics are calculated for each channel. For each frequency, the evaluation of the SSVEP response is defined by:

$$R = \frac{1}{N_s N_h} \sum_{i=1}^{N_s} \sum_{j=1}^{N_h} |P(i,j)| \quad (5)$$

where $|P(i,j)|$ is the amplitude of the frequency power in the channel i at the harmonic j. N_s, the number of channels, is equal to the number of electrodes. N_h is the number of considered harmonics. $N_h = 1$ is equivalent of using only the frequency of the visual stimulus. For the classification in the next sections, we set $N_h = 4$.

For the classification of SSVEP responses corresponding to different frequencies, we consider the N_f frequencies to detect and some other noisy frequencies that improve the robustness of the decision during the classification [14]. During online processing, the detected frequency may be different than the N_f expected frequencies. For the classification, we consider the stimulating frequencies: 6.66, 7.50 and 8.57Hz, which belong to the same frequency band. For the noisy frequencies, we also consider two additional frequencies for improving the reliability of the outputs: 7.08, 8.03Hz. These frequencies are selected between two target frequencies. 7.08Hz and 8.03Hz are between 6.66 and 7.50, 7.50 and 8.57, respectively. The time segment used for the signal analysis is 2s.

The frequency F is detected if its response has the highest signal value.

$$F = argmax_i R(i) \tag{6}$$

where $1 \leq i \leq N_f$, $N_f = 5$. If the best frequency power does not correspond to the expected frequency, then it is considered as an error.

3 Experiments

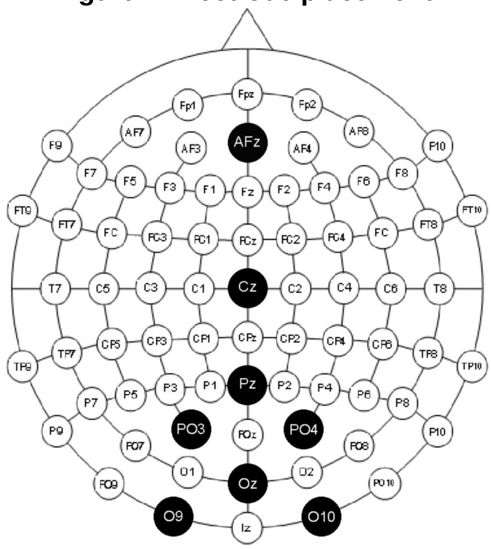
3.1 Materials

In the conducted experiments, we use sensors with contact on the surface of the scalp via eight standard EEG electrodes (EEG are usually used for non-invasive BCIs). The location of the electrodes are described in Figure 1. The electrodes are AF_Z for ground, C_Z for the reference and $PO_3, PO_4, P_Z, O_{10}, O_9, O_Z$ for the input electrodes [8]. The impedances below $5k\Omega$ were achieved by using an abrasive electrode gel. The EEG signal was acquired with an amplifier from the G.tec company [1], the sampling frequency was 128Hz. During the EEG acquisition, an analog bandpass filter between 2 and 35Hz, and a notch filter around 50Hz (main frequency in Europe) were applied directly inside the amplifier. For the stimuli display, a laptop LCD screen with a resolution of 1680 × 1050 pixels and a vertical refresh rate of 60Hz was used. The luminance is about $180.0 cd/m^2$ with an estimated contrast of 280 : 1. The stimulus is centered on the screen with a luminance equivalent to about $0.27cd$.

3.2 Subjects

Six healthy male subjects participated in this study. These subjects had no risk of epileptic seizure. The average age of the subjects was 28.5 years, with a standard deviation of 1.22 years. Subjects are not BCI-naive and are aware of the system principle. They have all already tested some SSVEP-BCI systems and they know how disturbing the lights can be after long sessions. Therefore, their experience could be an advantage for estimating and qualifying the impact of the duty cycle. However, the subjects were not aware about the purpose of the experiment.

Figure 1. Electrode placement.



3.3 Paradigms

During the experiments, three paradigms were tested. Each paradigm corresponds to a different duty cycle. For the first paradigm (A), the number of black frames is equal to the number of white frames in the repetitive visual stimulation (except when the number of frames in one period is odd). In the second and third paradigm, B and C, the number of black frames is equal to 2 and 1, respectively. Table 1 presents the signal structure for each paradigm and each frequency (1 for rendering a black box, 0 for for a white box).

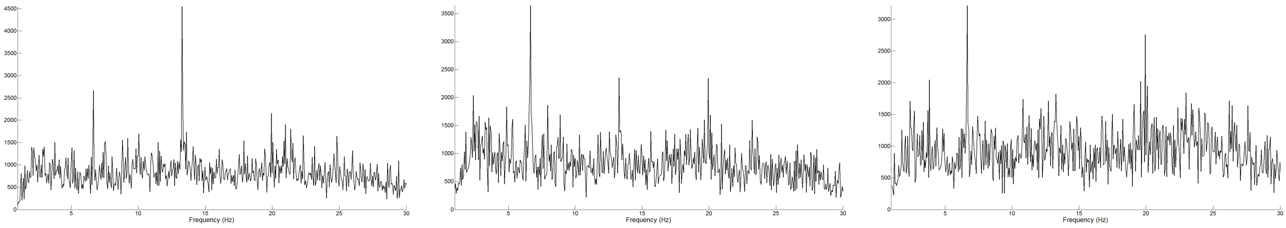
The protocol experiment is identical for each paradigm. Each subject had to look for 20s at one particular stimulus. The task was to focus on the flickering box on the screen. Subjects were instructed to gaze at the flashing targets. If the subject was not focusing on the screen, the session was restarted. The order of the trials was randomized. The lighting conditions and the subject position were identical for all experiments. For each frequency, six sessions were recorded. Subjects were sitting in a comfortable chair, wearing an EEG cap as described previously (cf. section 3.1.

4 Results

4.1 Amplitude analysis

Figure 2 presents the amplitude of frequencies till 30Hz for two subjects. For each paradigm, the am-

Figure 2. Frequency amplitude during one trial of 20s for a stimulus at 6.66Hz.



D=0.458 D=0.253 D=0.126

Subject 6

Table 1. Parameters for the each paradigm.

Paradigm	Frequency (Hz)	D	Structure
A	6.66	0.444	111100000
	7.50	0.500	11110000
	8.57	0.429	1110000
B	6.66	0.222	110000000
	7.50	0.250	11000000
	8.57	0.286	1100000
C	6.66	0.111	100000000
	7.50	0.125	10000000
	8.57	0.143	1000000

plitude was determined on a whole trial of 20s. The channel combination was achieved with a Laplacian filter instead of the minimum energy combination. The amplitude corresponds to the sum of the amplitude for the six channels (one channel per electrode). This evaluation over 20s does not translate the SSVEP detection like it should be done with a BCI. It enhances the overall peaks that can be expected during the SSVEP detection.

For every subject, we can observe a difference in the amplitude of the frequencies in relation to the duty cycle. Indeed, the frequency of the visual stimulus (6.66Hz) and its first harmonic (13.33Hz) have a high amplitude in the first paradigm (A). Furthermore, the first harmonic has higher amplitude than the fundamental frequency of the stimulus. In the second paradigm (B), the distribution of the amplitude is different: the second and third harmonics (20 and 26.66Hz) have clearly a peak. The SSVEP response seems more reliable in this paradigm. In the last paradigm (C), which has the lowest duty cycle, the amplitude of the first harmonic is very low compared to the others. The amplitude at 20Hz remains high and reliable for the detection. The low accuracy in the third paradigm can be explained by the low amplitude of the first harmonic and by consequence its low discriminant power in the detection. This harmonic can involve confusion in the detection. These distributions of the amplitude between the different harmonics are also detected for the two other frequencies. The different amplitudes suggest that the signal processing method could be tuned in relation to the duty cycle.

4.2 SSVEP classification

The effect of the duty cycle on the SSVEP responses is evaluated thanks to the accuracy of their detection. The signal detection technique is applied on the signal every 100ms. As the considered time segment length is 2s, the signal processing parameters simulate conditions that are close to what shall be used with a BCI. Table 2 presents the detailed results for the three methods for rendering the SSVEP stimuli. For each frequency the average signal value for the expected frequency, its standard deviation (S.D.) and the accuracy (Acc.), in %, are given. The part of table 2 presenting the results of paradigm A represents the classical setup for SSVEP experiments where the duty cycle is about $D = 0.5$. In this case, the average accuracy is 97.66% and the average signal value is 7.47. In the paradigm B, the average accuracy is 96.73% with an average power of 5.94. The duty cycle has more an impact on the average signal value when it decreases from 0.5 to 0.25. Between 0.25 and 0.12, the impact of the duty cycle is translated in the accuracy. With the paradigm C, the frequency power still decreases like in the previous paradigms but the accuracy clearly drops. It shows that the frequency power values and the accuracy are not completely related. Indeed, it is possible to achieve a high accuracy while lowering the power of the frequencies to detect. As expected, the quality of the SSVEP response is not homogeneous among the subjects. This variability exists also for the duty cycle effect as we notice some clear performance drops and some stable situations. For subject 2, there is a clear performance drop between the two first paradigms from 95.34% to 83.49%. At the opposite, subject 4 gains about 5% in the second paradigm. Among all subjects, only subjects 4 and 5 can allow keeping a high accuracy while decreasing the duty cycle.

5. Conclusion

The effect of the duty cycle, *i.e.* the structure of the periodic signal, of the visual stimuli has been tested and evaluated on the offline classification of SSVEP responses. Three duty cycles and three flickering frequencies have been tested over six subjects. The offline classification of the SSVEP responses has

Table 2. Detailed results for the three methods.

	f=6.66Hz			f=7.50Hz			f=8.57Hz			Total		
	SNR			SNR			SNR			SNR		
	Mean	S.D.	Acc.	Mean	S.D.	Acc.	Mean	S.D.	Acc.	Mean	S.D.	Acc.
(A) MEAN	7.03	1.77	99.68	7.32	2.04	95.57	8.07	1.68	97.74	**7.47**	1.37	**97.66**
(A) S.D.	1.70	1.02	0.31	2.51	1.18	6.21	3.04	0.71	5.20	2.42	0.73	3.91
(B) MEAN	6.21	1.17	97.75	5.66	1.30	93.62	5.97	1.42	98.82	**5.94**	0.97	**96.73**
(B) S.D.	1.19	0.57	5.37	1.13	0.48	13.24	1.40	0.68	1.37	1.11	0.43	6.52
(C) MEAN	5.88	1.14	94.90	4.87	1.06	86.93	4.57	1.13	77.31	**5.10**	0.83	**86.38**
(C) S.D.	1.33	0.41	11.01	0.93	0.41	15.94	1.18	0.61	17.82	0.93	0.36	12.27

been successfully achieved with a time segment of 2s. In addition, flickering lights with a low duty cycle seem to improve the user comfort improvement during the sessions. Future studies could be carried out towards understanding and measuring the visual fatigue in relation to the duty cycle.

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