

# EFFECT OF THE VISUAL SIGNAL STRUCTURE ON STEADY-STATE VISUAL EVOKED POTENTIALS DETECTION

*Hubert Cecotti and Bertrand Rivet*

GIPSA-lab CNRS UMR 5216  
Grenoble Universities  
38402 Saint Martin d’Heres, France

## ABSTRACT

The detection of Steady-State Visual Evoked Potential (SSVEP) responses in the Electroencephalogram (EEG) is a current challenge in signal processing applied on Brain-Computer Interfaces (BCI). BCI based on SSVEP requires visual stimuli. When these stimuli are displayed on an LCD screen, the number of frequencies for flickering object on the screen is limited. We propose to extend the number of frequencies by composing different visual patterns. We evaluate the relationship in the frequency domain between the visual stimuli and the recorded EEG signal. The signal detection across seven types of SSVEP responses is achieved by considering spatial filters based on the generalized Rayleigh quotient. The mean detection accuracy across three subjects is 89.58%.

*Index Terms*— SSVEP, EEG, BCI, Signal structure, Signal detection.

## 1. INTRODUCTION

Brain-Computer Interfaces (BCI) based on non-invasive scalp electroencephalography (EEG) is a multidisciplinary research area where signal processing is one of the major aspect for processing brain signals. The main purpose of BCI is to allow the communication through direct neural activity measurements [1]. Among the different existing paradigms for creating a BCI, several rely on external stimuli. These stimuli are often visual like for the detection of event related potential like the P300 or for steady-state visual evoked potentials (SSVEP). One of main challenges in the BCI community is to increase the information transfer rate (ITR) while keeping a convenient interface. The ITR depends on the number of available commands in the BCI and the detection accuracy for these commands. Furthermore, the ITR is directly related to visual stimuli. Indeed, the accuracy of the commands depends on the reliability of the visual stimuli [2]. In addition, the device that presents visual stimuli can be a bottleneck for enabling a large number of different commands. The reli-

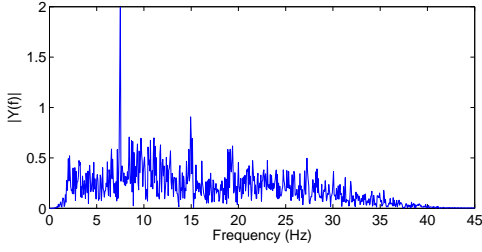
ability of the visual stimuli presentation is therefore a critical parameter for BCI based on external stimuli like P300 or SSVEP-BCI. While the required precision of the flashing time is not so crucial for the detection of the P300, the detection of an SSVEP response requires reliable stimuli due to its particular characteristics.

In this study, we focus on the detection of SSVEP responses [3]. BCIs based on SSVEP are presented in the literature as more accessible than other BCI systems: they allow a high information transfer rate (ITR) and little or no user training [4, 5]. SSVEP responses are also easier to detect in the EEG [6, 7]. The visual stimuli that are used for inducing SSVEP responses are flickering lights at different frequencies. When someone looks at a particular flickering object 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, as depicted in Figure 1, [8]. It is then possible to detect different responses for different frequencies in the EEG signal.

The amplitude and the phase that define an SSVEP response depend on three main parameters [9]: the frequency, the intensity of the flickering light, and the structure of the repetitive visual pattern (phase, duty cycle, ...). For the frequencies, SSVEP responses are usually obtained with frequencies between 5 and 50Hz [10]. If it is not possible to detect a Dirac delta function at a frequency  $f$  and its harmonics on the visual stimuli, then it will become harder to detect a Dirac delta function for  $f$  and its harmonics in the EEG signal [2]. Therefore, the visual stimuli presented to the user has a direct impact on the efficiency of an SSVEP response detection method. This statement implies some problems for the choice of the display device. It is possible to use old CRT monitors, LEDs, or to adjust to some extend the frequency of some LCD screens in relation to the resolution of the screen. The usual refresh rate of LCD screens in the mass market is currently limited to 60Hz. Due to the limit of the vertical refresh rate in current LCD screens, the number of frequencies for displaying flickering objects is limited. Such limitation can represent a drawback for commercial and clinical applications using SSVEP. Monitors possess advantages for pre-

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**Fig. 1.** Frequency amplitude in the EEG (bipolar combination of electrodes  $O_1$  and  $O_2$ ) for a visual stimulus flickering at 7.5Hz during 13s.

senting together visual stimuli, monitoring the EEG activity and other information to the user. We propose a new strategy for enabling different frequencies on a screen. We evaluate the relationship between the amplitudes in the visual stimuli and the EEG signal. Then, the produced SSVEP responses are detected by considering spatial filters obtained through the generalized Rayleigh quotient. The paper is organized as follows. The visual stimuli are described in the second section. The method for signal detection is presented in the third section. Then, the experimental protocol is given in section four. Finally, the accuracy of the signal detection and its relationship with the visual stimuli are presented in the last section.

## 2. VISUAL STIMULI

Visual stimuli for generating an SSVEP response are usually presented on a set of LEDs or on an LCD screen [11]. We consider here visual stimulation on a classical LCD screen with a vertical refresh rate of 60Hz. The repetitive visual pattern is composed of  $n$  frames with  $n \geq 2$  (black+white). Hence, the frequency of a stimulus based on  $n$  frames is  $60/n$  Hz. Besides, we are limited to a maximum of 30Hz due to the Shannon theorem. A visual stimulus is represented on the screen by a flickering box (white/black). We define a basic flickering pattern  $P_b$  by  $i$  white frames followed by  $j$  black frames where  $i + j \geq 2$ . Combined patterns  $P$  can be obtained by concatenating different patterns  $P_b$ . We denote by  $N_P$  and  $S_P$ , the number of undecomposable (basic) patterns and the size (the number of frames on the screen) of the combined pattern  $P$ . Thus, a repetitive pattern  $P$  will have peaks at  $60/S_P$  Hz and its harmonics. It will have a higher peak especially at the frequency  $60 * N_P / S_P$  Hz. Table 1 presents different frequencies and the corresponding structure of the flickering pattern. The frequencies are given for the higher peak. These frequencies are obtained by concatenating basic patterns representing 8.671 and 7.500Hz.

**Table 1.** Frequency of the structure different visual stimuli.

$f$ (Hz)	$(N_P, S_P)$	Signal structure (P)
8.571	(1,7)	00001111
8.276	(4,29)	0000111000011110000111000011111
8.182	(3,22)	000011100001111000011111
8.000	(2,15)	0000111100011111
7.826	(3,23)	0000111100001111100011111
7.742	(4,31)	0000111100001111100001111100011111
7.500	(1,8)	00001111

## 3. SIGNAL DETECTION

The detection of several SSVEP responses corresponds to a multi-class classification problem. We consider  $N_f$  classes. Each class corresponds to an SSVEP response, *i.e.* a particular frequency, a visual stimulus. We consider a visual stimulation flickering at  $f$  Hz. We consider the following description for the signal  $y_i(t)$  as the voltage between the electrode  $i$  and a reference electrode at a time  $t$ :

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

where  $N_h$  is the number of considered harmonics. The signal is decomposed into two parts: the SSVEP response and the remaining EEG activity, which is considered as noise. The first part corresponds to the evoked SSVEP response signal, which is composed of a number of sinusoids with frequencies in relation to the stimulus frequency and a number of  $N_h$  harmonic frequencies. Each sinusoid is defined by its amplitude and phase:  $a_{i,k}$  and  $\Phi_{i,k}$ .  $b_{i,t}$  corresponds to the background EEG activity.

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:

$$y_i = X_f a_{i,f} + B_i \quad (2)$$

where  $y_i = [y_i(1), \dots, y_i(N_t)]^T$  contains the EEG signal for the  $i^{th}$  electrode in one time segment. The SSVEP model of the frequency  $f$ ,  $X_f$ , is contained in a matrix  $N_t \times 2N_h$  defined by

$$X_f(t, 2k-1) = \sin(2\pi kft) \quad (3)$$

$$X_f(t, 2k) = \cos(2\pi kft) \quad (4)$$

with  $1 \leq k \leq N_h$ . For  $N_y$  electrodes, the signal is defined as:

$$Y = X_f A_f + B \quad (5)$$

where  $Y = [y_1, \dots, y_{N_y}]$  contained the sampled EEG signals from all the electrodes.  $A_f$  contains all the amplitudes for all

the expected sinusoids for every electrode signal related the the expected frequency to detect.

Spatial filters shall be consider to enhance the SSVEP response in the signal. A spatial filter is represented by a linear combination of the signals measured by different electrodes. We denote by  $s$ , a linear combination of  $y_i$ , the EEG after a spatial filter. Its purpose is to enhance the information contained in the EEG while reducing the nuisance signals.

$$s = \sum_{i=1}^{N_y} w_i y_i = Yw \quad (6)$$

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

Several components can be created by using several sets of weights  $w$ . We note  $N_s$  the number of channels. We first estimate the background activity by removing the potential SSVEP components from the signal. It is achieved by projecting the signal onto the orthogonal complement of the SSVEP model matrix ( $X$ ).

$$\check{Y}_f = Y - X_f(X_f^T X_f)^{-1} X_f^T Y \quad (7)$$

Spatial filters  $\hat{W}_f$  that maximize the Signal-to-Noise Ratio are obtained though determining the generalized Rayleigh quotient that maximizes the following expression:

$$\hat{W}_f = \operatorname{argmax}_W \frac{\operatorname{Tr}(W^T Y^T Y W)}{\operatorname{Tr}(W^T \check{Y}_f^T \check{Y}_f W)} \quad (8)$$

We denote by  $\hat{Y}_f = X_f^T Y \hat{W}_f$  the signal after spatial filtering. The power of the expected frequencies and their harmonics are calculated for the  $N_s$  components. For each frequency, the evaluation of the SSVEP response is defined by:

$$R(f) = \frac{1}{N_s N_h} \sum_{i=1}^{N_s} \sum_{k=1}^{N_h} \left( \hat{Y}_f(i, 2k-1)^2 + \hat{Y}_f(i, 2k)^2 \right) \quad (9)$$

In the next sections,  $N_s$  is equal to the number of electrodes and  $N_h = 4$ . The detection of an SSVEP response is simply performed by selecting the frequency with the maximum associated value  $R(f)$ .

#### 4. EXPERIMENTAL PROTOCOL

The EEG signal was recorded on three healthy subjects (average age= 26.3 years). Subjects were wearing an EEG cap with 10 electrodes [12]. The location of these electrodes are depicted in Figure 2.  $F7$  and  $F8$  were dedicated to the ground and the reference, respectively. The signal was recorded on  $O_1, O_2, P_3, P_4, P_7, P_8, P_Z$  and  $FC_z$ . The amplifier was a FirstAmp (Brain Products GmbH) with a sampling frequency of 2kHz. The signal was bandpassed filtered (Butterworth filter of order 4) with cut-off frequencies at 4 and 45Hz. Each subject looked at a box on the screen flickering at one of the seven frequencies presented previously (Table 1). For each

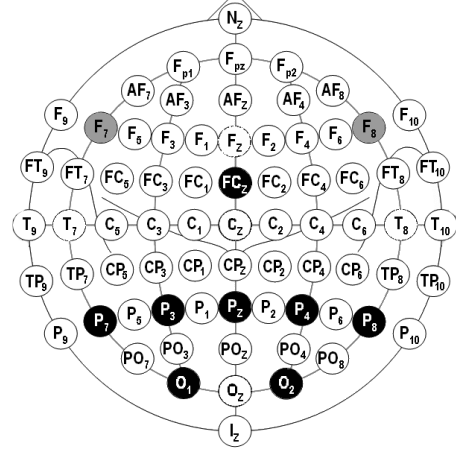


Fig. 2. Location of the electrodes in the system 10-20.

frequency and for each subject, we record the equivalent of 20s of EEG signal. The detection procedure of the SSVEP responses is applied every 250ms by considering a sliding window of 3s, *i.e.*, the signal detection is only performed on 3s of EEG data.

#### 5. RESULTS

Table 2 presents the detection accuracy across three subjects for the seven types of SSVEP responses, *i.e.*, seven different visual stimuli. The average accuracy of the SSVEP detection is 89.58%. This result is interesting as it shows that with only two basic frequencies, it is possible to create five other frequencies and to obtain a reliable accuracy for the detection. Indeed, the only difference between two SSVEP responses can correspond to only one frame on the screen, *i.e.* a difference of only 16.7ms in the observed visual stimulus. It is worth mentioning that the accuracy can be increased by considering only a limited number of basic patterns. In the current evaluation, up to four basic patterns were combined. Decreasing the number of basic patterns naturally leads to the improvement of the accuracy. Table 3 presents the results in relation to the number of basic patterns that can be considered. With only two types of SSVEP responses, it is possible to reach 98.07%. The amplitudes between the harmonics is different between the visual stimuli and the estimated amplitude in the EEG. Table 4 presents the mean and standard deviation of the amplitude ratio between the main frequency ( $60 * N_P / S_P$ ) and its higher harmonics ( $H * 60 * N_P / S_P$ ), across the three subjects and seven frequencies. These results show a stable behavior between the amplitudes in the EEG, in spite of the different methods for enabling these frequencies.

**Table 2.** SSVEP detection accuracy (in %) across 3 subjects.

Subject	$f$ (Hz)							Mean	SD
	8.57	8.28	8.18	8.00	7.83	7.74	7.50		
1	88.40	65.21	97.10	79.71	84.05	100.0	100.0	87.78	11.8
2	81.16	84.06	97.10	89.85	86.96	79.71	82.60	85.92	5.57
3	98.55	94.20	94.20	91.30	100.0	86.96	100.0	95.03	4.51
Mean	89.37	81.16	96.13	86.95	90.34	88.89	94.2	89.58	4.52

**Table 3.** SSVEP detection accuracy (in %) across 3 subjects (S1,S2,S3).

$N_P$ max	$N_f$	S1	S2	S3	Mean
4	7	87.78	85.92	95.03	89.58
3	5	93.04	91.01	97.10	93.72
2	3	95.17	93.72	97.58	95.49
1	2	96.38	97.83	100.0	98.07

**Table 4.** Amplitude ratio based on the main frequency.

H	S1		S2		S3		Mean
	Mean	SD	Mean	SD	Mean	SD	
2	0.53	0.13	0.39	0.12	0.34	0.03	0.42
3	0.24	0.04	0.20	0.03	0.17	0.02	0.20
4	0.16	0.03	0.16	0.03	0.11	0.02	0.15

## 6. CONCLUSION

With a device like an LCD screen, which has a low frequency for enabling flashing patterns at a particular frequency, it is difficult to enable a large number of different frequencies. We have proposed an efficient way for solving this problem. The proposed detection method was sufficient for detecting the SSVEP responses at the different frequencies across three subjects. Such method for providing visual stimuli on a screen could be considered for BCI based on the detection on SSVEP. A large number of frequencies implies a large number of possible BCI commands, hence increasing the information transfer rate. While the choice of LEDs can be judicious for displaying visual stimuli, the graphical user interface will be separated from the visual stimuli. Enabling efficient visual stimuli on an LCD screen can be an advantage for rehabilitation, spelling applications, applications combining neurofeedbacks... As low frequencies (below 20Hz) can be disturbing for the user, further works will extend the proposed strategy with new materials, which are initially dedicated for nvidia 3D vision, *i.e.*, a screen with a vertical refresh rate of 120Hz and an nvidia graphic card.

## 7. REFERENCES

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