

An Approximation Approach for Rendering Visual Flickers in SSVEP-Based BCI Using Monitor Refresh Rate

Masaki Nakanishi, *Student Member, IEEE*, Yijun Wang*, *Member, IEEE*, Yu-Te Wang, *Student Member, IEEE*, Yasue Mitsukura, *Member, IEEE*, and Tzzy-Ping Jung, *Senior Member, IEEE*

Abstract—Steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) have potential to realize a direct communication between the human brain and the external environment in practical situations. In the conventional stimulus presentation approach, which requires a constant period of stimulation, the number of frequencies that can be presented on a computer monitor is always limited by the refresh rate of a monitor. Although an alternative approach that uses a variable on/off frame number to approximate a target flickering stimulus has been proposed in our recent study, a direct comparison between SSVEPs elicited by the conventional constant period approach and the approximation approach is still missing. This study aims to compare the amplitude, signal-to-noise ratio (SNR) and target identification accuracy of SSVEPs elicited using these two approaches with a monitor at two refresh rates (75Hz and 120Hz). Results of this study suggest that the SSVEPs elicited by the approximation approach are mostly comparable with those elicited by the constant period approach.

I. INTRODUCTION

Visual evoked potentials (VEPs) are the electrical responses of brain elicited by visual stimuli, and are widely used in electroencephalogram (EEG) based brain-computer interfaces (BCI) due to its advantages of little user training, ease of use, and high information transfer rate (ITR) [1]–[5]. In a VEP-based BCI, users are asked to fixate on one of multiple visual stimuli modulated by different sequences, and the visual stimulus, which a user is fixating at, can be identified as the command of an interface through analyzing the VEP. Stimulus sequence design plays an important role in a VEP-based BCI. The current VEP-based BCIs can be classified into three categories including time modulated VEP (t-VEP), frequency modulated VEP (f-VEP), and code modulated VEP (c-VEP) [6]. In the f-VEP-based BCI, each visual stimulus is modulated by a different stimulating frequency. In particular, the f-VEP elicited by visual stimuli modulated at a frequency higher than 6Hz is referred to as steady-state visual evoked potential (SSVEP), and it has been commonly used in practical BCI applications [7].

*Research is supported in part by a gift fund from Swartz Foundation, US Army Research Laboratory, Army Research Office, DARPA and Office of Naval Research.

M. Nakanishi and Y. Mitsukura are with Graduate School of Science and Technology, Keio University, 3-14-1, Hiyoshi, Kohoku, Yokohama, Kanagawa, 223-8522 Japan. (e-mail: nakanishi@mitsu.sd.keio.ac.jp, mitsukura@sd.keio.ac.jp)

*Y. Wang, Y. -T. Wang and T. -P. Jung are with Swartz Center for Computational Neuroscience, Institute for Neural Computation, University of California, San Diego, La Jolla, CA92093 USA. (e-mail: yijun@scn.ucsd.edu, ytwang@ucsd.edu, jung@scn.ucsd.edu)

Visual stimuli can be presented using flashing light-emitting diodes (LEDs) or flickers on a computer screen. The stimulation parameters such as the amount, color, pattern, size, and position of visual stimuli can be configured flexibly when using a computer monitor. However, the number of frequencies that can be presented is always limited by the refresh rate of a computer monitor. For instance, a monitor with a 60Hz refresh rate can only present the flickering stimulus at 7.5Hz (8 frames per period), 8.57Hz (7 frames per period), 10Hz (6 frames per period), 12Hz (5 frames per period) and 15Hz (4 frames per period) around the EEG alpha frequency band (8-13Hz). In this case, some applications such as a phone-dialing program, which requires at least 12 targets (10 digits, Backspace, and Enter), cannot be implemented. Currently, the visual stimulus design is a major factor that limits the practical applications of an SSVEP-based BCI. In addition, generally, the increase of the number of commands can lead to an increase of the ITR [3]. Therefore, it is of great importance to find a solution to realize a high resolution of stimulus frequency on a computer monitor.

Recently, Wang et al. proposed a new method to realize visual stimulus presentation for eliciting SSVEPs with a high frequency resolution using a computer monitor by approximating a stimulus flickering rate [8]. They implemented a 16-target SSVEP-based BCI system with a frequency resolution of 0.25Hz and obtained an average ITR of 75.4 bits/min in online tests [8], [9]. However, although the approximation approach was proved feasible, no direct comparison between the SSVEPs elicited by conventional approach and the approximation approach has been reported. This study aims to compare the amplitude, signal-to-noise ratio (SNR) and offline classification accuracy of SSVEPs elicited using the two approaches by using the fast Fourier transform (FFT) and canonical correlation analysis (CCA) algorithms.

II. METHODS

A. Visual Stimulus Presentation Approach

In the conventional approach, the number of frames in a period is a constant. For instance, the 10Hz visual stimulus with a 60Hz refresh rate can be realized by the reversing stimulus pattern between black and white every three frames. However, a flickering frequency by which the refresh rate is not dividable (i.e., 11Hz) cannot be realized. However, the approximation approach can realize such flickering frequency by using a varying number of frames in a period [8]. For example, 11Hz can be realized by mixing five and

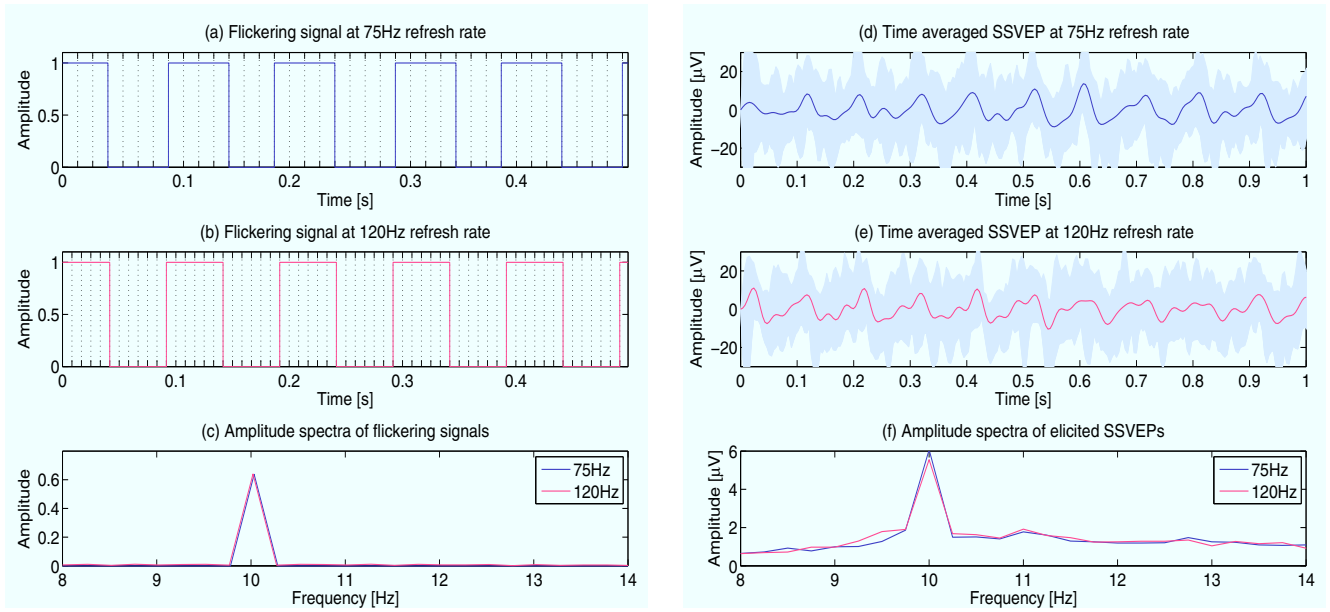


Fig. 1. (a)-(c) Time series and power spectra of stimulus sequences at 10Hz presented on a computer screen with 75Hz and 120Hz refresh rate, and (d)-(f) elicited SSVEPs and their power spectra of SSVEPs at 10Hz for a sample subject.

six frames in a period as '1110001110011100011000111...', where '1' and '0' represents a 'black' and 'white' frame respectively. Based on this approach, the stimulus sequences $c(f, i)$ corresponding to frequency f can be generated by the following equation:

$$c(f, i) = \text{square}\left[2\pi f \frac{i}{\text{RefreshRate}}\right] \quad (1)$$

where i indicates the frame index. In this way, a stimulus sequence can be generated at any frequency up to half of the refresh rate of a monitor.

B. Data Acquisition

The visual stimulus was a 5×5 cm square modulated and rendered at the center of a 21-inch CRT monitor. Two refresh rates (75Hz and 120Hz) were used to present the two stimulus presentation approaches. The stimulus frequencies ranged from 9Hz to 13Hz with an interval of 1Hz. Here, the visual stimuli at 10Hz and 12Hz can be generated by the constant period approach when using the 120Hz refresh rate. The visual stimuli at other frequencies under the 120Hz refresh rate and at any frequency under the 75Hz refresh rate need to be generated using the approximation approach. The stimulus program was developed in Microsoft Visual C++ using the Microsoft DirectX 9.0 framework and rendered on Windows XP platform.

Ten healthy subjects with normal or corrected-to-normal vision participated in this experiment. Each subject was seated in a comfortable chair in front of the monitor and asked to fixate on the visual stimulus presented at the center of a monitor for 30 seconds. The experiment consisted of four sessions, each including ten 30s-long trials for the five different stimulus frequencies under the two refresh rates. To avoid visual fatigue, there was a several-second

break between two consecutive trials and a several-minute break between two sessions. The order of the frequencies was randomized. EEG data were recorded using Ag/AgCl electrodes from 256 locations distributed over the entire head using a BioSemi ActiveTwo EEG system (Biosemi, Inc.). Electrode locations were measured with a 3-D digitizer system (Polhemus, Inc.). All signals were amplified and digitized at a sampling rate of 2048Hz. All electrodes were referred to the CMS electrode close to Cz.

C. EEG Analysis

The 256-channel EEG data were first down-sampled to 256Hz. For each 30s-long trial, six 4s-long EEG epochs were extracted according to event triggers generated by the stimulus program. For each stimulus frequency under each refresh rate, the epochs from all sessions were put together to form a dataset comprising around 24 epochs.

This study first employs the amplitude calculated by FFT and the SNR of single-channel SSVEPs at 10Hz and 12Hz to compare the approximation approach with the constant period approach. The resolution of the amplitude spectrum was 0.25Hz. The SNR was defined as follows:

$$\text{SNR} = \frac{n \times x(f)}{\sum_{k=1}^{n/2} (x(f + 0.25k) + x(f - 0.25k))} \quad (2)$$

where $x(f)$ is the amplitude spectrum calculated by a 1024-point FFT, f is the stimulus frequency, and n is set to 8 in this study. This study used EEG signals from the bipolar electrode between Oz and FPz to calculate the power spectra for the comparison study.

To compare the BCI performance under different refresh rates, in addition to the comparison of the amplitude and the SNR of SSVEPs, this study also calculates the offline SSVEP

TABLE I
THE COMPARISON OF AMPLITUDE AND SIGNAL-TO-NOISE RATIO OF SSVEPs

Subject	SSVEP amplitude [μV]				SNR							
	10Hz		12Hz		10Hz		12Hz					
	AP	CP	AP	CP	AP	CP	AP	CP				
s1	2.97	1.75	**	1.50	1.90	4.65	2.60	**	2.06	2.82	*	
s2	2.13	2.44		1.03	1.06	3.82	4.30		1.97	1.99		
s3	2.68	2.46		3.79	4.54	5.14	4.37		4.66	6.06	*	
s4	3.16	3.27		1.81	2.25	4.54	4.62		2.34	3.35	*	
s5	1.95	1.44	*	3.36	4.23	**	3.10	2.14	*	4.54	6.14	**
s6	2.10	2.72		2.92	3.51		3.41	3.61		4.06	4.43	
s7	4.04	4.26		4.48	5.19	*	6.02	6.87		5.55	6.75	**
s8	2.34	3.62	**	3.65	4.22	*	3.01	4.91	**	4.56	5.29	*
s9	2.73	2.83		2.53	2.78		2.92	3.27		2.14	1.77	
s10	2.96	3.39		2.62	3.21	*	4.00	4.92	*	3.76	5.04	**
Mean	2.71	2.84		2.77	3.31	**	4.07	4.16		3.55	4.38	*

*AP stands for approximation approach using a monitor of 75Hz refresh rate, and *CP stands for constant period approach using a monitor of 120Hz refresh rate. The significant difference between AP and CP for each subject was tested by t-test (* $p < 0.05$, ** $p < 0.005$)

TABLE II
OFFLINE PEAK DETECTION ACCURACY [%]

Subject	FFT		CCA	
	75Hz	120Hz	75Hz	120Hz
s1	68.80	71.55	77.60	92.68
s2	64.57	76.00	88.98	92.00
s3	86.72	93.33	100.00	100.00
s4	64.34	84.38	63.57	80.47
s5	95.20	92.74	94.40	98.39
s6	87.10	87.20	98.39	93.60
s7	100.00	100.00	100.00	100.00
s8	87.60	96.09	75.97	91.41
s9	66.40	65.04	80.00	86.18
s10	96.77	96.03	67.74	71.43
Mean	81.75	86.55	84.66	90.62

detection accuracy for all five stimulus frequencies using FFT and CCA-based methods. Note that, the 9Hz, 11Hz, and 13Hz stimuli were all rendered using the approximation approach under the 75Hz and 120Hz refresh rates. CCA has been successfully used in the SSVEP-based BCIs [9]–[11]. CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation. Considering two multidimensional variables X , Y and their linear combinations $x = X^T W_x$ and $y = Y^T W_y$, CCA finds the weight vectors, W_x and W_y , which maximize the correlation between x and y by solving the following problem:

$$\max_{W_x, W_y} \rho(x, y) = \frac{E[W_x^T X Y^T X_y]}{\sqrt{E[W_x^T X X^T W_x] E[W_y^T Y Y^T W_y]}}. \quad (3)$$

The maximum of ρ with respect to W_x and W_y is the maximum canonical correlation. Projections onto W_x and W_y are called canonical variants. Here, X refers to the set of 4s-long multi-channel EEG signals and Y refers to the set of reference signals that have the same length as X . The reference signals Y_f is set as

$$Y_f = \begin{bmatrix} \sin(2\pi ft) \\ \cos(2\pi ft) \end{bmatrix} \quad (4)$$

To detect the frequency of SSVEPs, CCA calculates the

canonical correlation between multi-channel EEG signals and the reference signals at each stimulus frequency. The frequency of the reference signals with the maximal correlation was selected as the SSVEP frequency.

III. RESULTS

Fig.1 illustrates the stimulus sequences, elicited SSVEPs and their power spectra at 10Hz under the 75Hz and 120Hz refresh rate. The sequence of 10Hz under a 120Hz refresh rate comprises constant periods (12 frames per period). Under a 75Hz refresh rate, 10Hz can only be implemented using the approximation approach (i.e., a varying period comprising 7 or 8 frames). As shown in Fig.1 (c), although the stimulus signals are slightly different under the two conditions, the power spectra show equivalent amplitude at 10Hz. The power spectra of SSVEPs (Fig.1 (f)) also show comparable amplitudes under both conditions, which is consistent with the result of stimulus signals.

Table I shows the averaged amplitudes and SNRs of SSVEPs for all the subjects. The averaged amplitudes of SSVEPs for all the subjects at 10Hz using the approximation approach and the constant period approach were 2.71 μV and 2.84 μV , and those at 12Hz were 2.77 μV and 3.31 μV , respectively. There was a significant difference between the amplitudes of SSVEPs elicited by the two approaches in five subjects. The averaged SNRs of the SSVEPs for all subjects were comparable under the two conditions (10Hz: 4.07 vs. 4.16, 12Hz: 3.55 vs. 4.38). A paired t-test shows a significant difference of the amplitude and SNR at 12Hz (amplitude: $p < 10^{-4}$, SNR: $p < 0.01$) across subjects under the two conditions. However, there is no significant difference at 10Hz (amplitude: $p = 0.61$, SNR: $p = 0.78$).

Table II lists the offline detection accuracy from five stimulus frequencies for ten subjects using the FFT- and CCA-based method. The FFT-based method obtained averaged accuracy of 81.75% and 86.55% ($p = 0.08$) under the 75Hz and 120Hz refresh rate respectively. The averaged accuracy increased when using the CCA-based method (75Hz: 84.66%, 120Hz: 90.62%, $p = 0.03$). This result is in line with the fact that CCA can significantly improve

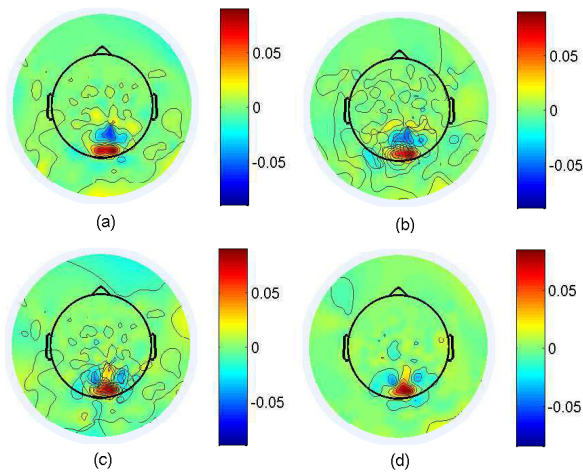


Fig. 2. Scalp topographies based on canonical coefficients of SSVEPs (a) at 10Hz under 75Hz, (b) at 10Hz under 120Hz, (c) at 12Hz under 75Hz and (d) at 12Hz under 120Hz for subject 3.

the SNR of SSVEPs through spatial filtering. Fig.2 shows the scalp maps of CCA coefficients obtained from SSVEPs and 10/12Hz reference signals for subject 3. Electrodes at the occipital area have the highest coefficients under all conditions, indicating the source locations of the SSVEPs. For different stimulus frequencies and refresh rates, similar maps were obtained for all subjects. Since high canonical coefficients were obtained from the occipital area under both the 75Hz and 120Hz refresh rates, the electrodes for classification in an online BCI system could be selected from the electrodes over the occipital area.

IV. DISCUSSIONS AND CONCLUSIONS

The stimulus presentation based on the approximation approach is efficient to elicit the SSVEPs with high frequency resolution for the SSVEP-based BCI. However, since no study has directly compared the amplitude and the SNR of SSVEPs elicited by the constant period approach and the approximation approach, the exact efficacy of the approximation approach remains unknown. This study calculated the amplitudes and SNRs of SSVEPs elicited by 10Hz and 12Hz stimuli implemented by the constant period and the approximation approaches on a CRT monitor with 75Hz and 120Hz refresh rate. The amplitudes of SSVEPs are comparable under the two conditions (75Hz vs. 120Hz, 10Hz: $2.71\mu V$ vs. $2.77\mu V$, 12Hz: $2.84\mu V$ vs. $3.31\mu V$). There is no significant difference at 10Hz across subjects. However, the amplitude of the 12Hz SSVEP under the 120Hz refresh rate is significantly higher than that of the 75Hz refresh rate ($p < 10^{-4}$). It might be caused by the resonance effect between 12Hz and 120Hz that enhances the amplitude of the SSVEP at 12Hz. Further investigations are required to explore the underlying mechanism of this finding.

In the offline analysis, this study classified the SSVEP signals into five classes corresponding to the stimulus frequencies ranged from 9Hz to 13Hz with an interval of 1Hz,

and compared the classification performance between 75Hz and 120Hz refresh rates. The averaged classification accuracy under 75Hz was lower than that under 120Hz when using the FFT-based method (81.75% vs. 86.65%), but the difference is not statistically significant ($p = 0.08$). CCA obtained better performance under 120Hz than 75Hz with a significant difference (90.62% vs. 84.66%, $p = 0.03$). Although the approximation approach and the constant period approach were mixed in the implementation of the five stimulus frequencies under the 120Hz refresh rate, these results still indicate that the two methods can achieve comparable BCI performance. The approximation approach can satisfy the requirement of a large number of visual stimuli in an SSVEP-based BCI. Interestingly, the 120Hz refresh rate seems to be able to enhance the 12Hz SSVEP, and thus leads to higher classification accuracy. From this point of view, the frequencies that can be realized using the constant period approach should be first considered in an SSVEP-based BCI.

The approximation approach for rendering SSVEP stimulus can lead to a practical BCI system that requires a large number of user selections (e.g., a spelling system with more than 30 targets including 26 alphabetical characters, Space, Shift, Backspace, and Enter) and has potential to achieve a high ITR. The main concern in future work will be the implementation of a multi-command, real-time, and portable BCI system using the approximation approach with different display technologies.

REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, pp. 767–791, 2002.
- [2] M. Cheng, X. Gao, S. Gao, and D. Xu, "Design and Implementation of a Brain-Computer Interface With High Transfer Rates," *IEEE Transactions on Biomedical Engineering*, vol. 49, pp. 1181–1186, 2002.
- [3] Y. Wang, X. Gao, B. Hong, C. Jia, and S. Gao, "Brain-computer interfaces based on visual evoked potentials: feasibility of practical system design," *IEEE Engineering in Medicine and Biology Magazine*, vol. 27, no. 5, pp. 64–71, 2008.
- [4] P.-L. Lee, C.-H. Wu, J.-C. Hsieh, and Y.-T. Wu, "Visual evoked potential actuated brain computer interface: a brain-actuated cursor system," *Electronics Letters*, vol. 41, pp. 832–834, 2005.
- [5] A. Materka and N. Byezuk, "Alternate half-field stimulation technique for SSVEP-based brain-computer interfaces," *Electronics Letters*, vol. 42, pp. 321–322, 2006.
- [6] G. Bin, X. Gao, Y. Wang, B. Hong, and S. Gao, "Research frontier: VEP-based brain-computer interfaces: time, frequency, and code modulations," *IEEE Computational Intelligence Magazine*, vol. 4, no. 4, pp. 22–26, 2009.
- [7] Y. Wang, R. Wang, X. Gao, B. Hong, and S. Gao, "A practical VEP-based brain-computer interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 14, no. 2, pp. 234–240, 2006.
- [8] Y. Wang, Y.-T. Wang, and T.-P. Jung, "Visual stimulus design for high-rate SSVEP," *Electronics letters*, vol. 46, no. 15, pp. 1057–1058, 2010.
- [9] Y.-T. Wang, Y. Wang, and T.-P. Jung, "A Cell-phone-based Brain Computer Interface for Communication in Daily Life," *Journal of Neural Engineering*, vol. 8, p. 025018, 2011.
- [10] G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," *Journal of Neural Engineering*, vol. 6, p. 046002, 2009.
- [11] G. Bin, X. Gao, Y. Wang, Y. Li, B. Hong, and S. Gao, "A high-speed BCI based on code modulation VEP," *Journal of Neural Engineering*, vol. 8, p. 025015, 2011.