Implementation of SSVEP Based BCI with Emotiv EPOC

Yue Liu, Xiao Jiang, Teng Cao, Feng Wan, Peng Un Mak, Pui-In Mak, Mang I Vai
Department of Electrical and Computer Engineering
Faculty of Science and Technology
University of Macau, Av. Padre Tomás Pereira Taipa, Macau, China
E-mail: fwan@umac.mo

Abstract—**In recent years, steady-state visual evoked potential (SSVEP) based brain-computer interface (BCI) has received much attentions. However, most SSVEP based BCI devices are not portable and have high price, which are not suitable to be used for clinical and commercial purpose. Thanks to the low cost and portable Emotiv EPOC, it brings BCI into daily life. In this paper, SSVEP based BCI through Emotiv EPOC is implemented. BCI 2000 is employed to connect Emotiv EPOC and Matlab to implement the online system. The online experiments have the accuracy of 95.83±3.59 %, information transfer rate (ITR) with 22.85±1.85 bits/min and detection duration of 5.25±2.14 sec.**

Keywords-brain-computer interfaces (BCI); steady-state visual evoked potential (SSVEP); Emotiv EPOC; canonical correlation cnalysis (CCA)

I. INTRODUCTION

Brain-computer interface (BCI) systems establish direct communication connections between human brain and external devices, which skip peripheral nerves and muscular tissues [1], [2]. For example, invasive BCI have been used to treat non-congenital (acquired) blindness in vision science [3]. For patients suffering from amyotrophic lateral sclerosis or brain stem stroke, BCI provide an alternative way to connect with external environments. Therefore, BCI lead to an improved quality of life and reduced social costs.

In recent years, non-invasive BCI such as Electroencephalography (EEG) have been widely developed. Steady-state visual evoked potential (SSVEP) attracts more and more attentions because of its high signal-to-noise ratio (SNR) and higher information transfer rate (ITR) [4]-[6]. SSVEP presents natural responses to visual stimulation at specific frequencies in a range larger than 6Hz, that is, when the retina is excited by a visual stimulus, the brain can produce relevant electrical signals with the same frequency as the stimulus signal as well as its harmonics [7]. The SSVEP can be recorded from the surface of the scalp over the visual cortex.

In our previous work [8], [9], SSVEP based BCI has been implemented by using g.USBamp (from Guger Technologies, Graz, Austria) and the system has very good performances. However, there are also some drawbacks in the previous system based on g.tec platform. Firstly, using the previous system needs longer preparation time. Subjects have to clean their hair before the experiments in order to remove oil or dirt on scalp. In addition, the subjects have to wear an electrode cap filled with conductive gel to ensure the conductivity, which may increase the workload and make the subjects feel uncomfortable. Secondly, the high financial cost of g.tec (about USD $23,215) in the market greatly restricts to use it as commercial purpose. The longer preparation time and high price determine that g.tec is suitable for research purpose but not common people and disabled people.

Compared with g.tec, Emotiv EPOC is an epoch-making wireless BCI device with a low price (USD $299 for an EPOC neuro-headset and USD $500 for the Developer edition) and it has shorter preparation time to use. Before the experiments, subjects only need to drop some special solution (contact lenses protection solution) on the sponge in electrodes on the headset and directly wear it. With Emotiv EPOC it does not need to clean the scalp and other after-care work, so it is much more eco-friendly. Another advantage is that, the operation of Emotiv EPOC is very easy to be understood, so that even customers without much BCI knowledge could learn to use its basic functions easily. The Emotiv EPOC has already been used by other research groups, for instance, they use it to play video games [10]. Since the purpose is to bring BCI technique into our daily life and improve life quality, especially for disables, therefore, Emotiv EPOC is a promising device for BCI.

However, the Emotiv EPOC does not have much open source and has some limitations on Matlab programming. Hence, it is difficult to implement it on SSVEP BCI system. Therefore, the objective of this study was to solve the above problem. Firstly, to achieve offline signal processing, the Emotiv TestBench (software provided by Emotiv) is used to record and convert the EEG data to the format that Matlab can acquire. Then canonical correlation analysis (CCA) is employed for feature detection on EEG data and the performance of g.tec and Emotiv EPOC is compared. Secondly, due to the difficulty in direct connection, BCI2000

978-1-4577-1759-8/12/$26.00 ©2012 IEEE

is employed to connect Emotiv EPOC and Matlab to implement the online system.

II. METHODS

A. Visual Stimulator

The visual stimulator can be presented by using light-emitting diode (LED) or liquid crystal display (LCD)/ cathode ray tube (CRT) monitors [11]. The LEDs need extra elaborate hardware to generate a constant frequency and it is also not easy to configure. Therefore, we prefer to use LCD/CRT monitors.

Based on traditional frame method, stimuli frequencies on a LCD/CRT monitor could be limited by the monitor refresh rate to some extent. That is to say, the refresh rate should be multiple times of the stimulus frequencies. For example, for a monitor with 60 Hz refresh rate in practical design of visual stimulator, 6.67 Hz, 7.5 Hz, 8.57 Hz, 10 Hz, 12 Hz, 15 Hz and 20 Hz are usually used. However, the number of stimulus frequencies and the system performance are largely limited. What is worse, in SSVEP response, the amplitude of harmonic frequency could be larger or even stronger than that of the theoretical response frequency. This may lead to a result that the system cannot distinguish between the fundamental frequency and the harmonic frequency (e.g. 7.5 Hz and 15 Hz). On the other hand, the limited stimulus frequencies could affect later online work. In a 60 Hz refresh rate monitor, there are 60 frames per second and the frame number per cycle is a constant. For 10 Hz flicker, it reverses between black and white every three frames; for 12 Hz flicker, it states in black for three frames and reverses to white for two frames. Therefore, the sequences of a certain two frequencies could be combined to get three frequencies with a varying number of frames in each cycle (e.g. 10 Hz and 12 Hz produce 10.5 Hz, 11 Hz and 11.5 Hz). In our experiment, it could be verified that 11 Hz could also make stable SSVEP response (see Fig.1).

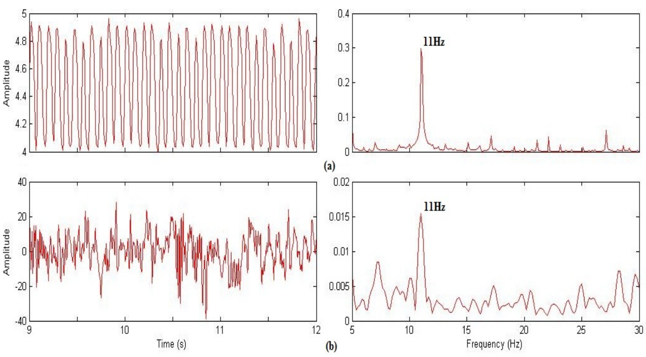

Figure 1. Time series and frequency spectrum of stimulus signal and elicited SSVEP at 11Hz.

For offline experiments, 16 frequencies stimulator is used and the distribution is shown in Fig. 2 (a). Its frequencies are from 8 to 15.5 Hz with 0.5 Hz interval between each two. The stimulus interface for online experiment is shown in Fig. 2 (b), which contains 6 stimulus frequencies. The stimulus frequencies are 6.67 Hz, 7.5 Hz, 8.57 Hz, 10 Hz, 12 Hz and 15 Hz. These visual stimulators are programmed in Microsoft Visual C++ 6.0 and DirectX DirectDraw 7.

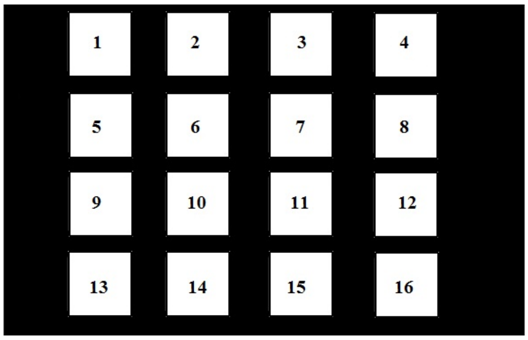

Figure 2 (a). The distribution of 16 flickers in the visual stimulator.

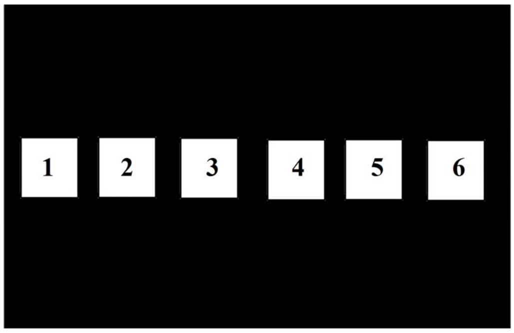

Figure 2 (b). The distribution of 6 flickers in the visual stimulator.

B. Algorithms

In this paper, canonical correlation analysis (CCA) is used to extract frequency information from the multiple channel EEG signals. CCA is a multivariable statistical method used when there are two sets of data, which may have some underlying correlation. It finds a pair of linear combinations, for two sets, such that the correlation between the two canonical variables is maximized. CCA extends ordinary correlation to two sets of variables and is widely used in statistical and information mining. Consider two multidimensional random variables X, Y and their linear combinations $x = X^T W_x$ and $y = Y^T W_y$, respectively. CCA finds the weight vectors, W_x and W_y, which maximize the correlation between x and y, by solving the following problem:

$$\max_{W_x, W_y} p(X,Y) = \frac{E[X^T Y]}{\sqrt{E[X^T X]E[Y^T Y]}} = \frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_y]E[W_x^T Y Y^T W_y]}} \qquad (1)$$

The user' command C is recognized as

$$C = \arg\max_i \rho_i \qquad i = 1,2,...,k \qquad (2)$$

where ρ_i is the CCA coefficient, and command C is used to make a determination, more details please refer to [12].

Information transfer rate (ITR) is a very important index to evaluate a BCI system. ITR is represented by the information transmitted given in bits per minute. The formula is defined as:

$$ITR = \frac{60}{S} \times [\log_2 N + p \log_2 p + (1-p)\log_2(\frac{(1-p)}{N-1})] \quad (3)$$

S is calculated as the detection speed which is valued as 6 in our experiment; p represents the probability to input characters correctly, or in other words p is the CCA accuracy; N is the number of the possible characters which equals to 16 in offline experiments and 6 in online experiments. N is the detective speed (gaze length 6s in offline experiment and variable in online experiment) and p means the accuracy.

C. *Signal Processing*

The CCA is used for extraction of frequency information of SSVEP signals. In our experiments, CCA method is implemented for 3s length data, and then the coefficient is calculated every 0.25s. For example, 24 correlation coefficients will be obtained in a 6s length gazing interval in offline experiments. The corresponding command will be selected only when more than 2 commands C of them are the same, otherwise the EEGs should be detected again. Then the corresponding correlation coefficients ρ_i are picked up to calculate the mean. If it is larger than the threshold value which is equal to 0.3, the selected command C will be chosen as the final result and the system will output a selection command.

III. Experimental Results and Discussion

A. *Experimental Setup*

In our experiment, a LCD monitor was used as visual stimulator (ViewSonic 22", refresh rate 60 Hz, 1680×1080 pixel resolution). There were four subjects with experience in BCI experiments. The subjects sat in a comfortable chair facing the screen and kept the distance about 60cm. Due to the special characteristics of Emotiv EPOC, we did our best to build the system setting in the same conditions. Since Emotiv EPOC only had static electrode locations: AF_3, F_7, F_3, FC_5, T_7, P_7, O_1, O_2, P_8, T_8, FC_6, F_4, F_8 and AF_4, 4 standard EEG electrodes placed on P_8, P_7, O_1, and O_2 were used as input channels in both devices (g.USBamp and Emotiv EPOC). Oz was the ground electrode and the sampling rate in g.USBamp was set as 128 bits/s since Emotiv EPOC could only offer 128 bit/s sampling rate. In g.USBamp, EEG signals were collected and data was saved through Matlab Simulink. While Emotiv EPOC data was saved in Emotiv Test Bench and then converted to mat files. The dominant frequency was detected every 0.25s and the threshold value in CCA was 0.3. During our offline experiment, the gaze length was 6s and the rest length was 4s so that the subjects could change their sights to the next target and will not feel uncomfortable for their eyes. Each subject needs to do 3 trials for each amplifier, a total of 8 groups, 24 trials. In our online experiments, the detection duration is variable and there is no rest time. Each subject needs to do 3 trials in Emotiv, totally 12 trails.

B. *Offline Experimental Results*

TABLE I presents the average accuracy and the average ITR of the 4 subjects using g.USBamp. Subject S1 and S2 presented prefect performance in the experiments with 100 % accuracy and 40 bits/min ITR. Subject S3 presented 93.75±1.74 % accuracy which was also good. However, 85.41±2.13 % accuracy for subject S4 demonstrated there was individual difference in SSVEP experiments. The mean accuracy of all the four subjects was 94.79±1.94 %.

TABLE II demonstrates the results from Emotiv EPOC group. Subject S1 had the best performance 94.55±3.34 %, which was acceptable but still with a little difference from his control group result. For Subject S2 and S3, their average accuracies were reduced to 85.14±7.21% and 83.13±5.11% respectively, with over 10 % off compared with their control group results. Subject S4 had accuracy around 70 %, also with nearly 25 % difference from his control group result. Finally, the average accuracy for Emotiv EPOC group presented 11.8 % decrease from that of control group.

Based on 4 of 6 trials of S4, he had worse performance especially when gazing 8-13 Hz range stimulus signals. The corresponding frequency band was overlapped with alpha band. Fig.3 demonstrates one FFT plot of his EEG signal when gazing at 13 Hz stimulus. It is obvious that, the highest amplitude was not located on 13 Hz, but in alpha wave band, which leaded to false detection by the system. The result verifies that some subjects with stronger alpha wave may lead to worse performance in SSVEP experiments.

TABLE I. ACCURACY & ITR OF G.USBAMP

Subject	Average Accuracy (%)	Average ITR (bpm)
S1	100±0	40±0
S2	100±0	40±0
S3	93.75±1.74	33.12±5.23
S4	85.41±2.13	29.50±6.18
Mean	94.79±1.94	35.66±5.71

TABLE II. ACCURACY & ITR OF EMOTIV

Subject	Average Accuracy (%)	Average ITR (bpm)
S1	94.55±3.34	36.44±8.85
S2	85.14±7.21	28.88±2.40
S3	83.13±5.11	26.97±7.43
S4	69.15±4.26	19.95±7.13
Mean	82.99±4.98	28.06±6.45

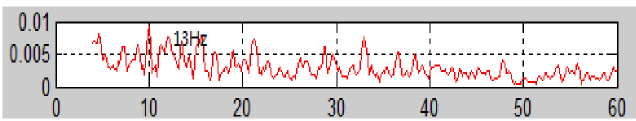

Figure 3. 13Hz SSVEP response.

C. *Online Experimental Results*

We use software BCI2000 to connect Emotiv and Matlab. BCI2000 is a multi-functional system for BCI research, which contains main functions of data acquisition, stimulus presentation, and brain monitoring applications. After launching the BCI2000 while it has already linked with Matlab, then the Matlab command window can be seen. The brain signal is sent to MATLAB workspace as a matrix. Therefore, we could directly apply m-file to analyze the online result. BCI2000 will send a block with 128 samples per second to Matlab. In Matlab, we divide the block into 4 frames, leading to per detection each 0.25 sec (no rest time). In theory, the shortest detection duration per target is 4 sec. For each result, 4 detections are needed. TABLE III shows the result of our experiment. The average accuracy was 95.83±3.59 %, which was high in online SSVEP experiment. And the average detection duration per target was 5.25±2.14 sec, which was still acceptable.

TABLE III. ACCURACY, ITR AND DETECTION DURATION

Subject	Average Accuracy (%)	Average ITR (bpm)	Average detection duration per target (sec)
S1	100±0	22.57±0	4.78±2.62
S2	94.44±7.84	20.44±0.61	5.56±1.86
S3	100±0	23.98±0	5.27±2.42
S4	88.89±6.54	16.88±0.88	5.38±1.68
Mean	95.83±3.59	20.97±0.37	5.25±2.14

Then we use the online system to implement an environment controller, which aims to control the states of electrical devices. In reality, users could control the environment without extra body movements.

IV. CONCLUSION

In this paper, SSVEP based BCI based on a market-aimed platform Emotiv EPOC is implemented. Compared with g.tec, Emotiv EPOC is an epoch-making wireless BCI device with a low price and it has shorter preparation time for use. However, the Emotiv EPOC does not have much open source and has some limitations on Matlab programming. To overcome these difficulties, firstly, for offline signal processing, the Emotiv TestBench (software provided by Emotiv) is used to record and convert the EEG data to the format that Matlab can acquire. Then canonical correlation analysis (CCA) is employed for feature detection on EEG data and the performance of g.tec and Emotiv EPOC is compared. The accuracy and ITR of g.tec are 94.79±1.94 % and 35.66±5.71 bits/min. For the Emotiv, the average accuracy is 82.99±4.98 % and the ITR is 28.06±6.45 bits/min. Secondly, due to the difficulty in direct connection, BCI2000 is employed to connect Emotiv EPOC and Matlab to implement the online system. The online system achieves an average accuracy of 95.83±3.59 %, an average ITR of 18.99±1.68 bits/min and detection time is 5.25±2.14 sec. Finally, the online system is used and tested for environment control which will help the users especially people with disabilities to control home appliances without any body movements and thus enhance their life quality.

The future work may include further improvements on the online implementation of Emotiv SSVEP and some other types of BCI based on Emotiv EPOC such as motor imagery (MI). Furthermore, in this work, it is found that using existing software for connection to Matlab with Emotiv is troublesome and inconvenient to some extent. A better solution to build a stable or flexible connection between Emotiv EPOC and Matlab would be desirable and deserve more investigations.

ACKNOWLEDGMENT

This work was supported in part by the Macau Science and Technology Development Fund (Grant FDCT/036/2009/A), the University of Macau Research Fund (Grants RG059/08-09S/FW/FST and RG080/09- 10S/WF/FST) and the University of Macau Research Committee under Grant MYRG139(Y1-L2)-FST11-WF.

REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," Clin. Neurophysiol., vol. 113, no. 2, pp. 767-791, Jun. 2002.

[2] M. A. Lebedev and M. A. L. Nicolelis, "Brain-machine interfaces: past, present and future," Trends Neurosci., vol. 29, no. 9, pp. 536-546, Sep. 2006.

[3] S. Kotler, "Vision Quest," Wired Magazine, Sep. 2002.

[4] Y. J. Wang, X. R. Gao, B. Hong, C. Jia, and S. K. Gao, "Brain-computer interfaces based on visual evoked potentials-feasibility of practical system design," IEEE Eng. Med. Biol. Mag., vol. 27, no. 5, pp. 64-71, Sep. 2008.

[5] G. Y. Bin, X. R. Gao, Z. Yan, B. Hong, and S. K. Gao, "An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method," J. Neural Eng., vol. 6, no. 4, Jun. 2009.

[6] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," Electroenceph. Clin. Neurophysiol., vol. 70, no. 6, pp. 510–523, Apr. 1988.

[7] H. A. Baseler, E. E. Sutter, S. A. Klein, and T. Carney, "The topography of visual evoked response properties across the visual field," Electroencephalogr. Clin. Neurophysiol., vol. 90, no. 1, pp. 65-81, Jan. 1994.

[8] C. M. Wong, B. Y. Wang, F. Wan, P. U. Mak, P. I. Mak, M. I. Vai, "An improved phase-tagged stimuli generation method in steady-state visual evoked potential based brain-computer interface," Proc. of 3rd Int. Conf. on Biomed. Eng. and Inform. (BMEI'10), Yantai, vol. 2, pp. 745- 749, Oct. 2010.

[9] T. Cao, X. Wang, B. Y. Wang, C. M. Wong, F. Wan, P. U. Mak, P. I. Mak, M. I. Vai, "A high rate online SSVEP based brain-computer interface speller," Proc. of 5th Int. IEEE/EMBS Conf. on Neural Eng. (NER'11), Cancun, pp. 465- 468, May. 2011.

[10] A. Nijholt, D. P. Bos, and B. Reuderink, "Turning shortcomings into challenges: Brain-computer interfaces for games," Entertainment Computing, vol. 1, no. 2, pp. 85-94, Sep. 2009.

[11] Z. H. Wu, Y. X. Lai, Y. Xia, D. Wu, and D. Z. Yao, "Stimulator selection in SSVEP-based BCI," Med. Eng. Phys., vol. 30, no. 8, pp. 1079-1088, Jan. 2008.

[12] Y. J. Wang, R. P. Wang, X. R. Gao, B. Hong, and S. K. Gao, "A practical VEP-based brain-computer interface," IEEE Trans. on Neural Syst. Rehabil. Eng., vol. 14, no. 2, pp. 234-240, Jun. 2006.