Proceedings of the ASME 2012 International Design Engineering Technical Conference & Computers and Information in Engineering Conference
IDETC/CIE 2012
August 12-15, 2012, Chicago, IL, USA

DETC2012-71608

EVALUATION OF SSVEP AS PASSIVE FEEDBACK FOR IMPROVING THE PERFORMANCE OF BRAIN MACHINE INTERFACES

Shaocheng Wang*
Department of Mechanical Engineering
University of California Riverside
Riverside, CA, USA

Ehsan Tarkesh Esfahani*
Department of Mechanical Engineering
University of California Riverside
Riverside, CA, USA

Sundararajan V.
Department of Mechanical Engineering
University of California Riverside
Riverside, CA, USA

ABSTRACT

Research in brain-computer interfaces have focused primarily on motor imagery tasks such as those involving movement of a cursor or other objects on a computer screen. In such applications, it is important to detect when the user is interested in moving an object and when the user is not active in this task. This paper evaluates the steady state visual evoked potential (SSVEP) as a feedback mechanism to confirm the mental state of the user during motor imagery. These potentials are evoked when a subject looks at a flashing objects of interest. Four different experiments are conducted in this paper. Subjects are asked to imagine the movement of flashing object in a given direction. If the subject is involved in this task, the SSVEP signal will be detectable in the visual cortex and therefore the motor imagery task is confirmed. During the experiment, EEG signal is recorded at 4 locations near visual cortex. Using a weighting scheme, the best combination of the recorded signal is selected to evaluate the presence of flashing frequency. The experimental result shows that the SSVEP can be detected even in complex motor imagery of flickering objects. The detection rate of 85% is achieved while the refreshing time for SSVEP feedback is set to 0.5 seconds.

INTRODUCTION

Brain-computer interfaces (BCIs) have gained greater attention in the past several years because they provide the possibility to directly create a communication channel between the human brain and the computer by translating human intentions into control signals for the computer. In non-invasive BCIs, electroencephalography (EEG) is commonly used due to its excellent time resolution, ease of data acquisition, portability and lower system cost. Other brain monitoring mechanisms such as positron emission tomography (PET) and magnetic resonance imagery (MRI) find only restricted application in brain-computer interfaces although they are widely used in medical and research settings [1].

Brain-computer interfaces have been primarily used to provide assistance to severely disabled people [1,2]. However, BCIs can also be used as an alternative interface for regular human computer interaction. New developments in BCIs have already enabled users to navigate in virtual scenes, manipulate virtual objects or play games just by means of their cerebral activity [3]. BCIs are also being considered as effective tools in future computer aided design systems by engaging visual imagery in design process [4] or helping the selection of geometries in virtual environments[5].

Motor imagery i.e. the imagery involved in motion has been the primary focus of most BCIs [2, 3]. Here signals are obtained during imagined sensorimotor rhythms (SMR). Typically, the SMRs are detected based on features of the μ and β rhythms (8–12 and 18–26Hz) [1]. Changes in the amplitudes of these frequency bands are referred to as event-related desynchronization (ERD) (i.e. decrease) and event-related synchronization (ERS) (i.e. increase). The rhythms decrease or desynchronize with movement or its preparation, and increase or synchronize after movement and with relaxation [6].

BCIs based on sensorimotor rhythms (SMR) are the basic elements for movement control in virtual environments. It has been shown that using SMR based BCI, it is possible to control the 2D motion of a cursor [7], [8].

The main advantage of motor imagery classification is that it requires no external stimuli and the ongoing EED is used to classify the mental task. However, its implementation in continuous human computer interaction is subjected to false

* These authors have equal contributions to this manuscript.

detection of movement because certain brain activities involved even in an idle state can mimic motor imagery.

Moreover, while BCI research efforts have succeeded in providing communication for some users, it has often been report that (very roughly) 20% of subjects do not exhibit BCI performance adequate for effective control [9].

Therefore in order to use BCI as an alternative in human computer interactions, it is critical to increase its robustness.

To overcome these problems a hybrid BCI approach has been proposed. The main idea of hybrid BCI is to use a stimulus based response such as P300 or visual evoked potential with sensorimotor rhythms to increase the robustness of the BCI [8], [10].

Similarly, to reduce the false alarm in classification of ongoing EEG signals, Pfurtscheller et al [11] have proposed a brain switch by combining visual evoked potential and event related synchronization (ERS)-based BCI. Although, they could achieve high robustness by combining SSVEP and ERS, their hybrid BCI is only designed to detect one mental task and may not have the same performance in complex situations.

In this paper, we have conducted a series of experiments to verify the robustness of hybrid BCIs in multi-mental task situations. To this end, steady state visual evoked potential (SSVEP) is used in combination with different motor imagery. The idea is that in human computer interaction, the motor imagery usually occurs when the subject is gazing on a virtual object to move or rotate. Therefore by flashing the object of interest on the screen, it may be possible to get passive confirmation about correct detection of user's intent. This passive confirmation (feedback) is achieved through SSVEP detection.

The organization of this paper is as follow: The background behind visual evoked potential and SSVEP is provided in next section. It is followed by detailed experimental methods and signal processing algorithms for detecting SSVEP. Finally, the experimental results and conclusions are presented in the final sections.

STEADY STATE VISUAL EVOKED POTENTIAL

Among different brain signals that have been employed for EEG based BCIs, VEP (Visual Evoked Potentials) based system has been studied since 1970s [12]. It is commonly accepted as a method that provides high information transfer rate and needs less user training. VEP is the response of human brain to the visual stimulus. It is categorized into transient VEP (TVEP) and steady state VEP (SSVEP) which correspond to visual stimulus with low and high frequency, respectively. TVEP arises when the stimulation frequency is less than 2 Hz, while SSVEP appears when the repetition rate of the stimulus is higher than 6 Hz [13]. It is well agreed that SSVEP has a wider area of application than TVEP because in most cases, the human's brain is considered in steady state of excitability in which the responses that elicited by the high frequency visual stimulus will overlap each other. Since the characteristics caused by two kinds of stimulus are different, researchers usually use temporal methods for TVEP analysis and frequency analysis for SSVEP case [14].

A Steady-State Visual Evoked Potential (SSVEP) is a resonance phenomenon arising mainly in the visual cortex when a person is focusing his/her visual attention on a light source flickering with a frequency above 6 Hz [13].

The SSVEP can be elicited up to at least 90 Hz [15] and could be classified into three ranges: low (up to 12 Hz), medium (12-30) and high frequency (> 30 Hz). In general, the SSVEP in low frequency range has larger amplitude responses than in the medium range. Thus, the lower frequencies are easier to detect.

The high-frequency SSVEP ranges have the advantage of a minimum visual fatigue caused by flickering, making the SSVEP-based BCI a more comfortable and stable system [16]. At a same time these frequencies experience the weakest SSVEP which make the SSVEP detection a more difficult task and requires computationally expensive algorithm.

MATERIALS AND METHODS

EEG signals were recorded using the Emotiv neuroheadset at 4 channels on the scalp. The names of channels that are used for this study are based on the international 10-20 system are: P7, O1, O2, and P8. Signals were recorded at sampling rate of 2048 Hz, and sent to the computer wirelessly after being down-sampled to 128 Hz.

The selected visual stimulation was a three-dimensional cube that flashed on the screen. The background is black while the cube had white surfaces and blue edges. All surfaces of the cube were flashing at a frequency of 13 Hz.

Four different experiments were conducted in this study. Each experiment consists of two parts: part one is conducted in only one trial during which the cube is not flashing. In this part of the experiment, subject is asked to gaze at the object and conduct an imagery movement in a given direction. This experiment only contains motor imagery and therefore can be used as the control. Part two contains 5 trials in which the subject is performing the same task as part one but with presence of the flashing stimulus. In each trial for all experiments, subject is asked to sit on a comfortable position and look at the screen. EEG data for each trial is recorded once the cube appears on the screen until it disappears.

The motor imagery task that subject is instructed to perform each experiment are shown in the Figure 1. The arrows describe how the cube is rotating or translating and its direction. The numbers denote different states during the experiment process. All the arrows and numbers in the figures are only for the convenience of description and do not exist in the experiment.

In the first experiment, the cube only rotates along the horizontal axis which passes its geometric center. In the second experiment, the cube moves from the position of initial state 1 to that of final state 2, it is also rotating along the vertical axis that passes its geometric center at the same time. The third experiment is similar to the second one, but instead of translating from right to left, it goes from top to bottom. In the fourth experiment, the cube recedes into the screen along the axis that perpendicular to the screen, rotates along the horizontal axis that passes its geometric center at the same time

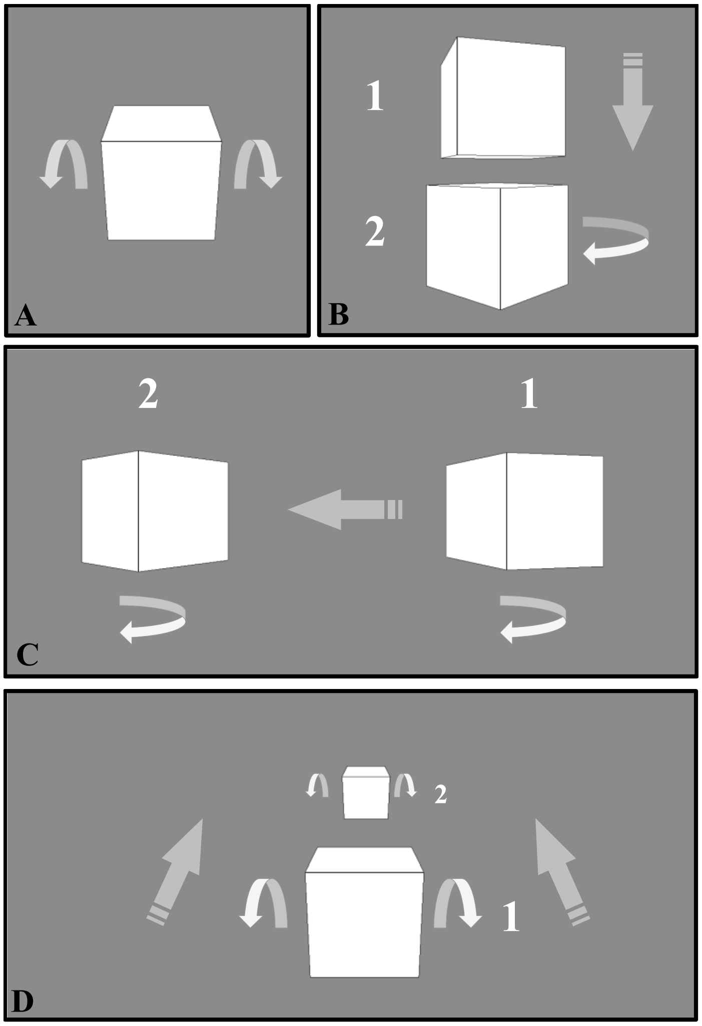

Figure 1 COMBINATION OF MOTOR IMAGERY AND SSVEP IN THREE DIFFERENT SCENARIOS A) PURE ROTATION B-D) ROTATION AND TRANSLATION AROUND X , Y AND Z AXIS.

SSVEP DETECTION

An SSVEP BCI reflects the user's attention to a visual stimulation oscillating at a constant frequency. Let consider the EEG signal recorded at N_y channels in response to a visual stimulation flickering at a frequency of f Hz. The SSVEP response recorded at each channel, $y_i(t)$, can be modeled as Equation 1.

$$y_i(t) = \sum_{n=1}^{N_h} \left[a_{in} \sin(2\pi nft) + b_{in} \cos(2\pi nft) \right] + E_i(t) \quad (1)$$

Equation 1 is a linear model which considers the dominant activity of N_h harmonics of the flickering frequency in terms of sine and cosine functions. Any other components, including all non-SSVEP cognitive process, noise and artifacts are considered in the second part ($E_i(t)$). Equation 1 can be expressed in vector form as Equation 2.

$$y_i = Xg_i + E_i \quad (2)$$

$y_i = [y_i(1) \quad \ldots \quad y_i(N_t)]^T$ is the EEG of the i^{th} electrode containing N_t data points. X is the observation matrix which contains sine and cosine components of SSVEP response. The corresponding amplitude of matrix X, (a_{in} and b_{in}) are represented with vector g_i. Equation 2 can be further generalized for N_y electrodes as Equation 3:

$$Y_{N_t \times N_y} = X_{N_t \times 2N_h} G_{2N_h \times N_y} + E_{N_t \times N_y} \quad (3)$$

where $Y = [y_1, \ldots, y_{Ny}]$ and $G = [g_1, \ldots, g_{Ny}]$ contain all the EEG data points recorded at N_y channels and their associated harmonic amplitudes respectively.

In order to enhance the SSVEP component in the recorded signal, a virtual channel is defined as a linear combination of all the electrode signals, Y.

$$s_{N_t \times 1} = Y_{N_T \times N_y} w_{N_y \times 1} \quad (4)$$

where w is a vector of weights $[w_1, \ldots, w_{Ny}]$ associated with the contribution of individual electrode signals in the enhanced SSVEP response. The weighting vector is selected to minimize the non-SSVEP components. Therefore, a linear unbiased estimator is used to estimate and thus extract the SSVEP components from the recorded signals as shown in Equation 5.

$$\tilde{Y} = Y - X(X^T X)^{-1} X^T Y \quad (5)$$

In Equation 5 the term $X(X^T X)^{-1} X^T Y$ is an estimate of SSVEP component and $\tilde{Y}$ is the remaining signal associated with noise, artifacts and background brain activity. The weighting vector w is then estimated such that it minimizes the energy of non-SSVEP component of the signal as shown in Equation 6:

$$\hat{w} = \arg\min \left\| \tilde{Y} \hat{w} \right\|^2 \quad (6)$$

Herrmann has shown that the minimal eigenvalue of matrix $\tilde{Y}^T \tilde{Y}$ will minimize the cost function in Equation 6 [17]. The weight matrix is hence chosen based on the minimum eigenvalue (λ_1) and its corresponding eigenvectors (v_1):

$$w = \frac{v_1}{\sqrt{\lambda_1}} \tag{7}$$

In SSVEP based BCI applications, the stimulation frequency should be detected as a dominant frequency in the power spectral density. Hence, to detect the presence of a frequency in the spatially filtered signals, the ratio of power of the signal (PSD) at the target frequency with respect to the maximum power of the signal is calculated as shown in Equation 8.

$$R = \frac{\max\left[PSD(s)\,|_{f-0.1}^{f+0.1}\right]}{\max\left[PSD(s)\,|_{6}^{64}\right]} \tag{8}$$

The ratio of 1 shows that flashing frequency is dominant in the signal and therefore the SSVEP is detectable.

RESULTS

A comparison between the power spectral density of the weighted signal calculated with Equation 10 and the signals recorded at different location near visual cortex are shown in Figure 2. In the actual system implementation, $N_h = 2$.

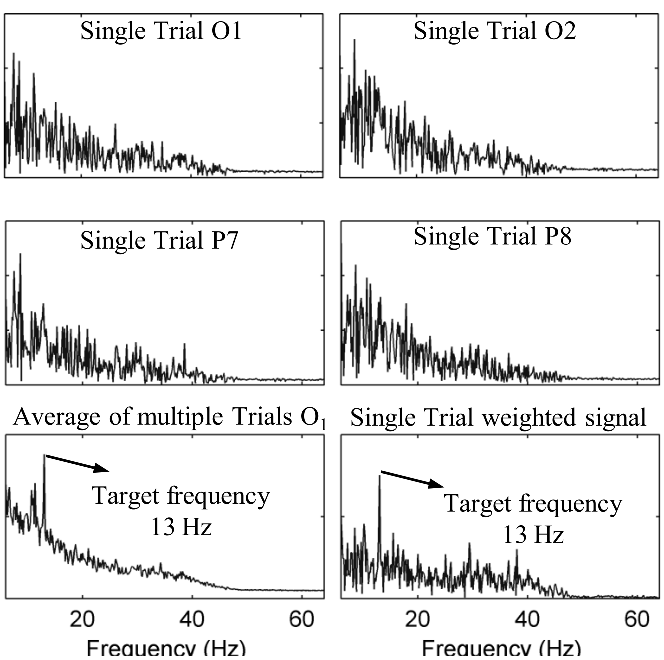

Figure 2 COMPARISON BETWEEN THE POWER OF TARGET FREQUENCY IN SINGL TRIAL SIGNAL OF EACH ELECTRODE, THE AVERAGE AND THE WEIGHTED SIGNAL

As it can be seen in Figure 2, the target frequency has a high power in the average signals of 40 trails; however it is undetectable in single trial recorded at each of the electrodes due to high activity in alpha frequency band (8-11 Hz). Finally it shows that the single trial of the weighted signal has its maximum power at the target frequency which clearly shows the effectiveness of weighting method.

Moreover, since our long-term goal is to use SSVEP as feedback to implement the motor imagery, we desire a high refreshing rate of signal in the time domain. On the other hand since the sampling rate of the signal is only 128 Hz, too short signal interval in time domain may cause fail in detection of SSVEP. Because of this trade-off, a test on the accuracy of SSVEP detection was done by selecting different subset length and shifting length for the moving window on the entire signal that recorded.

Figure 3 shows the details of how moving windows are selected. L is the length of entire signal that recorded in the time domain. The first subset has length L_w which started from the initial time. Then the subset is modified by shifting forward of d seconds.

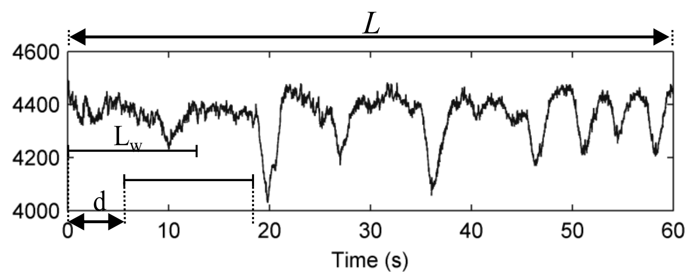

Figure 3 THE MOVING WINDOW PARAMETER FOR CALCULATING THE BEST PARAMETERS

The averaged SSVEP detection rate over all subjects, for different values of L_w and d is illustrated in Figure 4-7. Each figure compares the classification rate with the control.

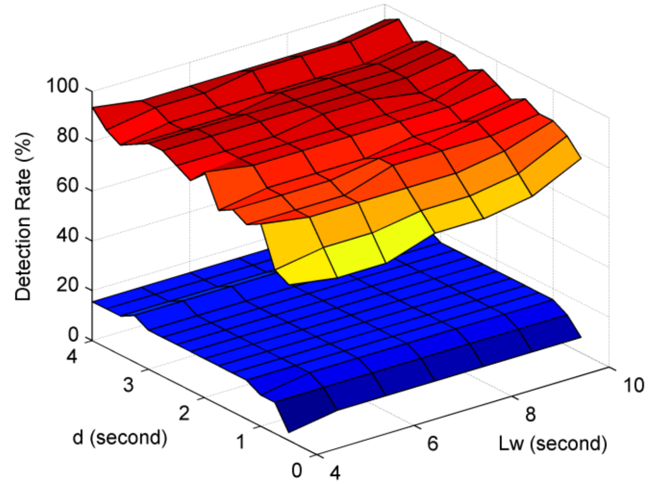

Figure 4 SSVEP DETECTION RATE FOR PURE ROTATION (EXP 1A)

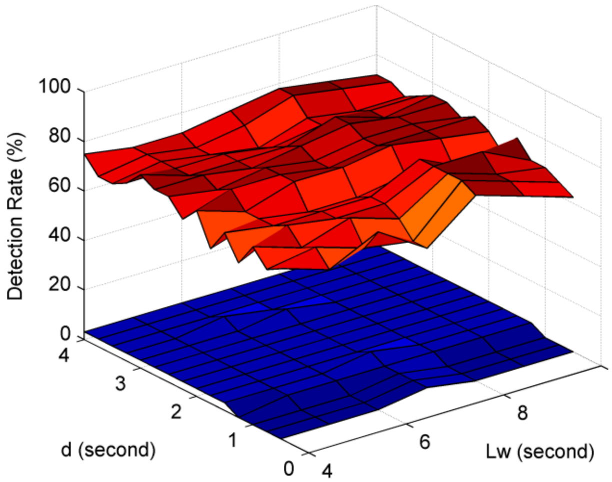

Figure 5 SSVEP DETECTION RATE FOR ROTATION AND TRANSLATION X-AXIS (EXP 1B)

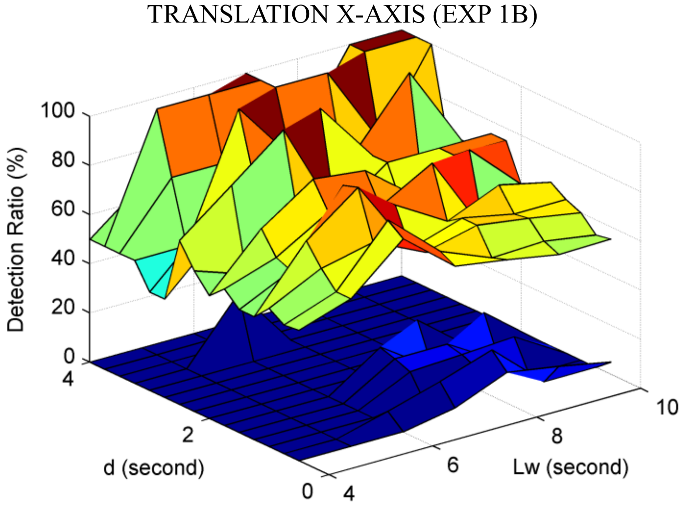

Figure 6 SSVEP DETECTION RATE FOR ROTATION AND TRANSLATION Y-AXIS (EXP 1C)

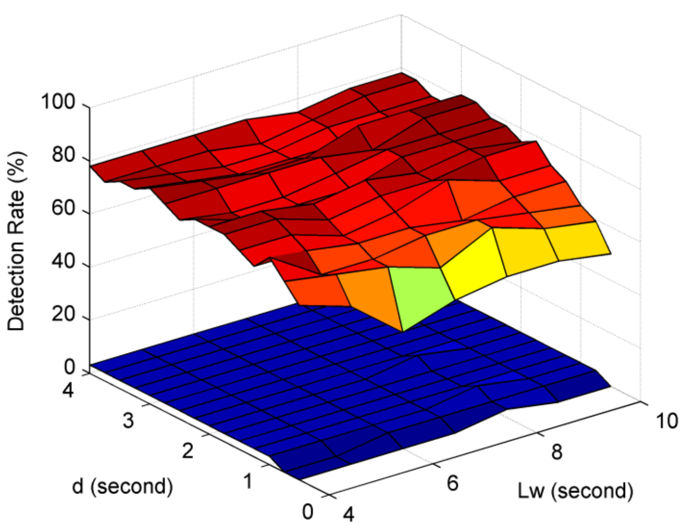

Figure 7 SSVEP DETECTION RATE FOR ROTATION AND TRANSLATION z-AXIS (EXP 1D)

As it can be seen in Figure 4-7, the minimum classification rate appears at the smallest size of the moving window where the number of available data points is relatively low.

The classification has to take the moment into account when the user does not focus on any stimuli. For this reason the SSVEP detection rate in the normal condition is also calculated. The lower surfaces in Figure 4-7 show the SSVEP detection rate in normal condition or in other words the rate of false alarm in classification. In 3 out 4 experiments, the average false alarm is less than 5%. Pure rotation with no flashing experiences the maximum misclassification of idle case as SSVEP. To further investigate the reason of false alarm and SSVEP misclassification, the normalized power of signal at flashing frequency is shown in Figure 8.

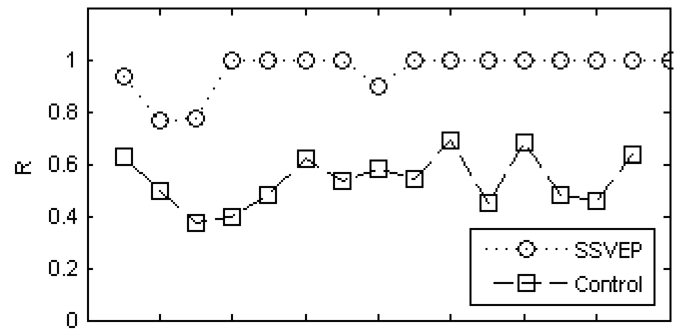

Figure 8 SSVEP DETECTION RATE FOR ROTATION AND TRANSLATION Y-AXIS (EXP 1C)

It worth nothing that the stimulation frequency is located very close to the alpha band, this could produce false classifications in the resting state or slightly reduce the normalized power of the target frequency –Equation11-. In this case the *R* value will be slightly less than one and still classify as non-SSVEP.

Such problems could easily be avoided by introducing a proper threshold for *R* value and/or using calibration session for every subject. In the calibration session, the power of the target frequency will be normalized with respect to the normal condition. However, the calibration session is avoided in this paper to eliminate the training period of the SSVEP detection to consider the worst case scenario when it is used as brain switch in a hybrid BCI.

CONCLUSION

In this paper, the steady state visual evoked potential (SSVEP) was evaluated as a feedback through conducting different experiments to confirm the mental state of the user during motor imagery. In each experiment, subjects were asked to imagine the movement of flashing object in a given direction.

Using a weighting scheme the best combination of the recorded signal is selected to evaluate the presence of flashing frequency. The presence of SSVEP implies that the subject was involved in the motor imagery and therefore, the ERD/ERS classifier should be actively applied to the signal.

It is worth noting that SSVEP detection method is considered as a brain switch. Upon detection of the target frequency, the motor imagery classifier is engaged. In other words, SSVEP detection is implemented to reduce the false alarm rate of motor imagery classifier. This paper only focused on the evaluation of SSVEP as a brain switch in BCIs. However, in future works, we are looking forward to synchronized it with an active ERD/ERS classifier

REFERENCES

[1] Mak, JN and Wolpaw, JR, 2009 "Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects". *IEEE reviews in biomedical engineering*, **2**(1), pp. 187-199.

[2] Pfurtscheller, G., Müller-Putz, G., Scherer, R. and Neuper, C., 2008. "Rehabilitation with brain-computer interface systems". *Computer*, **41**(10), pp. 58-65.

[3] Lecuyer, A., Lotte, F., Reilly, RB., Leeb, R., Hirose, M., and Slater, M., 2008. "Brain–computer interfaces, virtual reality, and videogames". *Computer*, **41**(10), pp. 66-72.

[4] Esfahani, ET., and Sundararajan, V., 2011. "Classification of primitive shapes using brain–computer interfaces". *Computer Aided Design*, doi:10.1016/j.cad.2011.04.008, (In press).

[5] Esfahani, ET., and V. Sundararajan, "Using Brain Computer Interfaces for Geometry Selection in CAD Systems: P300 Detection Approach," *ASME 2011 Design Engineering Technical Conference*, pp. 1-6.

[6] Pfurtscheller, G., 1999. "EEG event-related desynchronizeation (ERD) and event-related synchronization (ERS)". *Electroencephalography: Basic Principles, Clinical Applications and Related Fields*, 4th ed., Niedermeyer, E., and Lopes da Silva, F., Eds. Baltimore, MD: Williams and Wilkins, pp. 958-967.

[7] Trejo, LJ., Rosipal, R., and Matthews, B., 2006. "Brain–computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or steady-state visual evoked potentials". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, **14**(2), pp. 225–229.

[8] Long, J., Li, Y., Yu, T., and Gu, Z., 2012. "Target Selection With Hybrid Feature for BCI-Based 2-D Cursor Control". *IEEE Ttansactions on Biomedical Engineering*, **59**(1), pp. 132-140.

[9] Kubler, A., and Muller, KR, 2007. "An introduction to brain–computer interfacing". *Toward Brain–Computer Interfacing*, MIT Press., Dornhedge, G., Millan. J, Hinterberger, T., McFarland, DJ., and Muller, KR., Eds. Cambridge, MA, pp. 1-25.

[10] Allison, B., Brunner, C., Kaiser, V., Muller-Putz, GR., Neuper, C., and Pfurtschelle, G., 2010 "Toward a hybrid brain–computer interface based on imagined movement and visual attention". *Journal of neural engineering*, **7**(2), pp. 1-9.

[11] Pfurtscheller, G., Solis-Escalante, T., Ortner, R., Linortner, P., and Müller-Putz, GR., 2010. "Self-Paced Operation of an SSVEP-Based Orthosis With and Without an Imagery-Based Brain Switch: A Feasibility Study Towards a Hybrid BCI," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. **18**(4), pp. 409-414.

[12] Vidal, JJ., 1977. "Real-time Detection of Brain Events in EEG". *Proceedings of the IEEE*, **65**(5), pp. 633-641.

[13] Cheng, M., Gao, X., Gao, S., and Xu, D., 2002. "Design and implementation of a brain-computer interface with high transfer rates.," *IEEE Transactions on Biomedical Engineering*, **49**(10), pp. 1181-6.

[14] Wang, Y., Gao, X., Hong, B., Jia, C., and Gao, S., 2008. "Brain-computer interfaces based on visual evoked potentials". *IEEE Engineering in Medicine and Biology Magazine*, **27**(5), pp. 64–71.

[15] Herrmann, CS., 2001. "Human EEG responses to 1-100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena". *Experimental Brain Research*, **137**(3-4), pp. 346-353.

[16] Diez, PF., Mut, VA., Perona, E., and Leber, EL., 2011. "Asynchronous BCI control using high-frequency SSVEP," *Journal of Neural Engineering and Rehabilitation*, **8**(39), pp. 1-8.

[17] Friman, O., Volosyak, I., and Graser, A., 2007. "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces". *IEEE Trnsactions on Biomedical Engineering*, **54**(4), pp. 742–750.

[18] Volosyak, I., 2011. "SSVEP-based Bremen-BCI interface--boosting information transfer rates". *Journal of neural engineering*, **8**(3), p. 036020.