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# A Self-paced Hybrid BCI based on EEG and EOG

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**Abstract.** Daily-used BCIs should provide users the freedom to realize the control through all possible physiological functions and to turn on/off the control system independently. Thus, we propose a hybrid BCI (hBCI) that combines ocular-based control with a self-paced on/off brain switch. The proposed system involves the detection of  $\alpha$ -rhythm in EEG and ocular activities in EOG data. Experiments carried out on four subjects illustrate the interest of the proposed method.

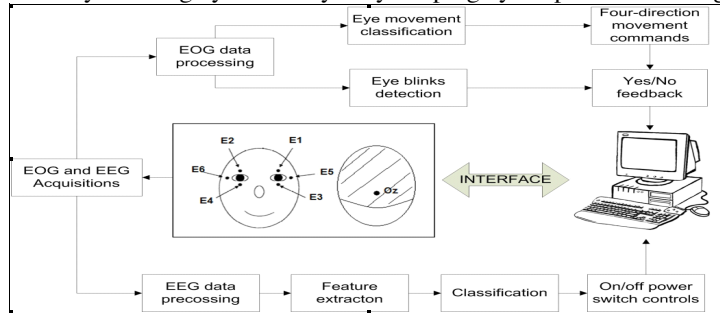
**Keywords:** Hybrid BCI, Self-paced BCI, EOG, EEG,  $\alpha$ -rhythm,

## 1. Introduction

Daily-used BCIs should give users the freedom to realize the control through all possible physiological functions [Leeb et al., 2011] and to turn on/off the control system independently. We propose a hybrid BCI (hBCI) that combines ocular-based control with a self-paced on/off brain switch, which provides users possibilities to communicate through ocular activities and to independently switch the system.

## 2. Methods

In the proposed hBCI, electroencephalography (EEG) was recorded over Oz while electrooculographic (EOG) data were recorded above (E1, E2) and below (E3, E4) the left and right eye, respectively, and from the outer canthi of the left (E5) and right (E6) eyes (see Fig. 1). Data are recorded by g.tec EEG system using the right earlobe as reference (sample rate: 512Hz). EEG is processed to identify the mental state of the user. If active  $\alpha$ -rhythm (8-13Hz EEG) is detected, which means that the user is in the wakeful relaxation (WR) with closed eyes (CE), then the whole system is in the waiting state. When the active  $\alpha$ -rhythm disappears, the system will be activated and EOG processing is triggered. The user can control the direction of the object movement by saccades (simultaneous movements of both eyes). When a saccade is detected, the system will classify its direction. Then, a message will be given to ask the user whether the detection is correct and intentional. The user can confirm it by blinking eyes or deny it by keeping eyes open within the given time.



**Figure 1.** Framework of the proposed self-paced BCI system.

### 2.1. EEG processing

The activity of  $\alpha$ -rhythm  $\Sigma[i]$  is defined as the standard deviation of signal square inside a 4-second sliding window at time  $i$ . Thus, a subject-specific threshold  $T_\alpha$  for detecting active  $\alpha$ -rhythm is set to

$$T_\alpha = \frac{1}{2} [\min(\Sigma_{close}[i]) + \max(\Sigma_{open}[i])] \quad (1)$$

where  $\sum_{close}[i]$  and  $\sum_{open}[i]$  represent  $\sum[i]$  of the learning data under the WR with CE and open eyes (OE) condition, respectively. When  $\sum[i]$  is lower than  $T_a$ , the system considers that the active  $\alpha$ -rhythm disappeared and triggers EOG processing.

## 2.2. EOG processing

The vertical EOG ( $\overline{VEOG} = E1 - E3 + E2 - E4$ ) and horizontal EOG ( $\overline{HEOG} = E5 - E6$ ) are computed from original EOG, and then smoothed by a Gaussian filter ( $\sigma = 3$ ) to remove the glitches. The vertical saccades (*up* and *down*) and eye blinks are classified from  $\overline{VEOG}$  while horizontal saccades (*left* and *right*) are identified from  $\overline{HEOG}$  through a 600ms sliding window using a waveform detector, and subject-specific amplitude/duration ranges, which are  $1 \pm 0.15$  of mean values of amplitude/duration in learning data. The waveform detector relies on two criteria in the sliding window to identify saccades (rectangular wave) and eye blinks (triangular wave) [Bulling et al., 2011]: 1) the presence of symmetric positive and negative extrema of the time derivative of the data (common criterion for both waveforms); 2) the number of zero crossings between them (eye blink: one, saccade: multiple and successive).

## 3. Experimental results

The experiments are carried out on four healthy individuals, including: 1) *the learning section*, where the subjects were in states of WR with CE and OE, 2min, respectively, and repeated 20 times of eye blinks and different saccades at  $[10^\circ, 15^\circ, 26^\circ, 30^\circ, 45^\circ]$  in the directions of *left*, *right*, *up* and *down* for learning the subject-specific thresholds; 2) *the testing section*, where the testing data were recorded for the same subjects who executed 2mins WR with CE, 1min WR with OE, then 6 different saccades guided by audio cues during 1.5mins. Eye blink was performed after each saccade to serve as confirm signal as described in Section 2. Subject-specific threshold  $T_a$  estimated by Eq.1 (see Table 1) can successfully switch the system according to the subject's mental states with a few seconds delay (D). A linear relation was observed between EOG amplitudes and saccade angles for all subjects from the learning data, and applied to set the amplitude ranges for detecting different degree saccades. The ranges (unit:  $\mu V$ ) vary with different subjects (e.g.,  $[15^\circ]$  left saccade: [328, 445] for subject A but [144, 195] for subject C). The system wrongly detected two vertical saccades as eye blinks for subject B due to his eyelids movements during the saccades. This problem can be solved by training subjects to avoid eyelids movements during saccades.

**Table 1.** Preliminary results of brain switch and saccade, eye blink detection for all subjects during the test. TP/FP is true/false positive.

Subject	Brain switch		Saccade	Blink
	$T_a$	D(s)	TP/FP	TP/FP
A	31.1	2.11	1.00/0	1.00/0
B	27.0	2.07	0.67/0	1.00/0.33
C	58.8	1.81	1.00/0	1.00/0
D	9.9	3.13	1.00/0	1.00/0

## 4. Conclusion

This study proposes a hBCI that combines ocular-based control with a self-paced on/off brain switch. As ocular activities can be measured with EOG electrodes via ordinary EEG recording system, only one recording system is required while allowing a multi-function hBCI, which reduces the hardware cost in hBCI experience. Repeatability and long-term stability of the system will be tested in the future experiments to proof its feasibility for daily use.

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