Bio-Medical Materials and Engineering 24 (2014) 2919–2925 2919
DOI 10.3233/BME-141111
IOS Press

Hybrid Brain-Computer Interface (BCI) based on the EEG and EOG signals

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Abstract. Recently, the integration of different electrophysiological signals into an electroencephalogram (EEG) has become an effective approach to improve the practicality of brain-computer interface (BCI) systems, referred to as hybrid BCIs. In this paper, a hybrid BCI was designed by combining an EEG with electrocardiograph (EOG) signals and tested using a target selection experiment. Gaze direction from the EOG and the event-related (de)synchronization (ERD/ERS) induced by motor imagery from the EEG were simultaneously detected as the output of the BCI system. The target selection mechanism was based on the synthesis of the gaze direction and ERD activity. When an ERD activity was detected, the target corresponding to the gaze direction was selected; without ERD activity, no target was selected, even when a subjects gaze was directed at the target. With this mechanism, the operation of the BCI system is more flexible and voluntary. The accuracy and completion time of the target selection tasks during the online testing were 89.3% and 2.4 seconds, respectively. These results show the feasibility and practicality of this hybrid BCI system, which can potentially be used in the rehabilitation of disabled individuals.

Keywords: hybrid brain computer interface, EEG, EOG, event-related (de)synchronization, target selection

1. Introduction

Brain-computer interface (BCI) technology provides a novel communication conduit between people and the surrounding environment, and can translate mental intentions into computer commands without the participation of peripheral nerves and muscles[1]. BCI systems can serve as potential assistive tools for disabled individuals, helping to maintain or restore their lost motor function. Many BCI systems based on non-invasive techniques, such as electroencephalograms (EEG), which take readings from the scalp, have been established in recent years. A few of these systems include the computer cursor control, mind-spelling, and wheelchair actuation[2,3,4]. Although EEG-based BCI has showed an impressive progress[5,6,7], its usability in practical and real-time applications still needs continuous improvement. The primary challenge is the low spatial resolution and the signal-to-noise ratio (SNR) of EEG[8].

The most current technology is the hybrid BCI created by combining EEG with other physiological signals, which were developed to improve the performance of conventional single modal BCI systems[9,10].

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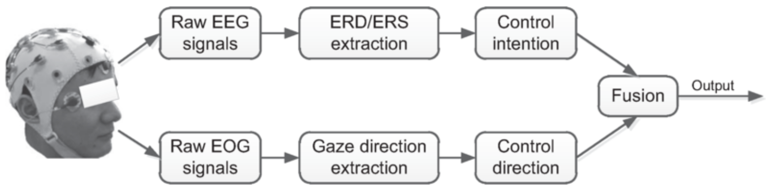

Fig. 1. Framework of the hybrid BCI paradigm based on the EEG and EOG combination.

This kind of BCI allows disabled individuals to use brain activities along with their remaining functionalities to generate more reliable control commands. Several hybrid BCI paradigms developed by incorporating the above physiological signals have been established. Additional functionalities of disabled individuals can be detected by electromyograph (EMG), electrocardiograph (ECG), or electrooculograph (EOG) *etc.*, representing muscle activities, heart beats, or eye movements, respectively[11,12,13]. Among these signals, EOG is considered an effective alternative signal because most paralyzed patients are able to move their eyes. Usakli *et al* presented a hybrid BCI based on EOG and EEG[13]. The EOG was used to select a target, such as a virtual keyboard, and then a typical P300-speller BCI paradigm was performed on the keyboard using EEG. Yan *et al* designed an EOG-EEG hybrid BCI system which can translate EOG activities into output commands, and simultaneously adjust according to the eye-close related alpha rhythm from the EEG[14]. Zhang and Punsawad also present the similar BCI systems[15,16].In the above-mentioned research, the EOG was directly translated into the control command. However, when users simply look at a target before they decide whether to trigger it, this control mode may perform erroneous operations, which could lead to accidents in some conditions.

In this paper, a novel EEG/EOG-based hybrid BCI system was designed and applied to an online target selection experiment. The gaze direction could be extracted from the EOG, which was considered the target selecting procedure, while the event-related (de)synchronization (ERD/ERS) induced by the motor imagery (MI) task could be detected from the EEG, which considered it a target triggering procedure. When the ERD was detected, the target corresponding to the current gaze direction would be triggered; otherwise, no operation was performed. With this method, the BCI system could be more flexible and voluntary. The average accuracy and time of the target selection task in the experiment was 89.3% and 2.4 seconds, respectively, which demonstrated the feasibility of our hybrid BCI system.

2. Methods

2.1. System description

In the hybrid BCI described in this paper, the EEG and EOG were synchronously processed and transmitted to output commands. The control intention (CI) of the subject was detected from the ERD activity in the EEG induced by the MI task, and the control direction was decided by the horizontal gaze direction from the EOG. If the CI was detected, the command with the corresponding gaze direction was sent; if CI was not detected, no command was sent, even if the gaze direction was detected. The framework of the hybrid BCI paradigm is shown in Figure 1.

2.2. Subjects and data acquisition

Four healthy subjects participated in this study, and were provided a detailed description of what the study entailed. During the experiments, the subjects were seated in armchairs facing a 22*in.* computer

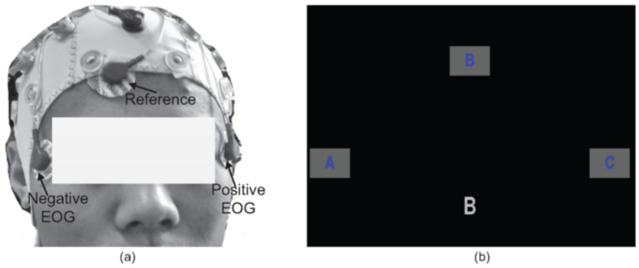

Fig. 2. (a): The locations of the two EOG electrodes. The electrode near the left eye was considered the positive channel, while the electrode near the right eye was the negative; (b): The interface of the online target selection experiment.

screen. The EEG signals were recorded from fifteen electrodes around the sensorimotor cortex and its surrounding cortices (F3, F4, FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6, P3, and P4, referenced to P8 and grounded to FPz), based on the international 1020 system. The impedances of all the electrodes were kept below 10kΩ. The EOG signals were recorded from two electrodes placed in the region adjoining the subjects eye to monitor horizontal movement, as illustrated in Figure 2(a). Both the EEG and EOG signals were acquired by a BrainAmp DC Amplifier (Brain Products, Germany) with a sampling rate of 250Hz.

2.3. Experiments

2.3.1. Calibration and training experiment

This experiment was designed to calibrate the detection algorithm parameters for ERD activity and gaze direction. In the EEG experiment, a typical cue-based training experiment for a MI task was designed, which consisted of non-feedback and feedback training procedures. In the non-feedback training, the subjects were asked to imagine left hand movement or stay relaxed, depending on cues displayed on the computer screen. Following that, a feedback training procedure was performed to train the subject and optimize the classifiers with new EEG samples. 56 MI task trials with the same number relax state trials were collected in the experiment for ERD detection calibration.

In the EOG calibration experiment, there were two signs labeled on the left and right edge of the computer screen. Subjects were asked to look at the left or right signs according to the cues displayed on the screen. 28 EOG samples of each gaze direction were collected to calibrate the algorithm parameters for gaze direction when the participants looked in the two different directions.

2.3.2. Online target selection experiment with EEG-EOG hybrid BCI

After the calibration and training experiment with the EEG and EOG, an online target selection experiment was introduced to evaluate the performance of the hybrid BCI paradigm. There were three text targets located at the left, right and top position on the screen, as illustrated in Figure 2(b). In the first 4 seconds, three text targets were displayed on the screen in random order. Subjects could look at these targets freely during this period. Then, the desired target was prompted on the screen, and subjects were asked to select the correct target with eye movement and motor imagery. For example, if the desired target was located at the left position, subjects should look at left side and perform the MI task simultaneously. For the target on the top position, subjects should look at middle to select it. The participants were asked to complete 56 target selection tasks, and the accuracy and completion time were calculated to evaluate the performance of our hybrid BCI system.

2.4. Signal processing

2.4.1. ERD calibration algorithm

All EEG channels were filtered between 8-16Hz because the broad frequency range contains mu frequency components which are important for ERD detection. The filtered signals were divided into $1000ms$ samples to serve as the training data sets. The selected MI samples and relax samples in training experiment were used to conduct the MI task classifier by the common spatial pattern (CSP) and the linear discriminant analysis (LDA) algorithms which were widely used for binary mental state discrimination in BCI research [8,17]. The detecting accuracy of ERD in the training samples was used as the criterion of calibration. If the accuracy was below 85%, the calibration experiment was repeated until the accuracy criterion was satisfied. In online detection, the ERD was classified every $100ms$. Because the classification of ERD could occasionally be mistaken by an unpredictable signal noise or other problem, a sliding window with one-second length (called filter window in this paper) was applied on the classification results. If the number of ERD results in the filter window exceeded a given threshold of 0.8, the CI was finally detected to trigger a selection.

2.4.2. EOG calibration algorithm

The EOG channels were filtered between 5-20Hz, and then down-sampled to 10Hz. In this study, the left EOG electrode was considered as the positive electrode, while the right electrode as the negative one. The difference of the two EOG channels was denoted as H_{EOG}. The maximum H_{EOG} when the subjects gazed left was denoted as H_{max} and the minimum value when subjects gazed right was denoted as H_{min}. If $H_{EOG} > f \cdot H_{max}$, the gaze direction was left; if $H_{EOG} < f \cdot H_{min}$, the gaze direction was right; otherwise the gaze direction was toward the middle. In the above formulas, $f \in (0, 1)$ can be calculated by a receiver operating characteristic (ROC) analysis[18]. However, as the EOG features can be easily discriminated, f was selected as 0.8 to avoid the false positive ratio (FPR). The accuracy of eye movements detection was calculated as the criterion to ensure a reliable calibration.

2.4.3. Fusion rule of EEG and EOG

In the proposed hybrid BCI paradigm, the output command was decided by the ERD/ERS of the EEG and the gaze direction detected by the EOG simultaneously. However, because the EOG have better quality than the EEG, and the gaze direction could be detected (0.5 seconds) faster than the ERD/ERS (1-2 seconds), a time delay was added to the EOG detection to match the different response times. When a gaze direction was detected, it would last for 3 seconds if there were no new direction detected. Subjects could execute the MI task to generate the CI during this 3-second period to produce a selection. If no CI was detected in this period, there was no operation conducted. With the above fusion rule, the ERD/ERS and gaze direction could be detected simultaneously.

To evaluate the performance of the hybrid BCI system, the information transfer rate (ITR) was calculated by the formula below[1]

$$ITR = \left\{ \log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1} \right\} /T \tag{1}$$

Where *P* denoted the accuracy and *T* was the completion time of the target selection tasks.

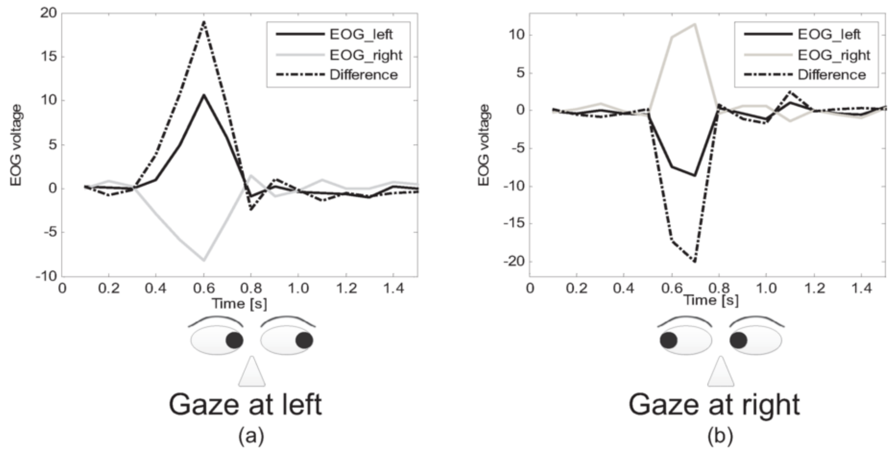

Fig. 3. Gaze direction result from EOG. (a): When subject gazed at left, the left EOG channel (*black line*) is positive while the right one (*dash-dot line*) is negative. Therefore, the difference (*gray line*) between the left and right EOG channel is positive. (b): When subject gazed at right, the voltages of the two EOG channel are inverse and their difference is negative.

Table 1
Performance of the EEG and EOG calibration.

Subject	EEG classification [%]		EOG classification [%]	
	MI task	Relax state	Left	Right
A	93.1	91.1	96.4	92.9
B	92.9	92.9	100	96.4
C	89.1	91.1	92.9	100
D	86.3	89.3	96.4	100
Avg.	90.4	91.1	96.4	97.3

3. Results

3.1. Calibration results of EEG and EOG

The results of the EEG and EOG classification are shown in Table 1. The averaged accuracy of the MI task and relax state for all the subjects was 90.4% and 91.1% respectively. The average accuracy of eye movements classification was 96.9%. Figure 3 shows the EOG voltages when the subjects gazed left and right. When the subject looked to the left, the positive EOG (near the left eye) was larger than the negative EOG (near the right eye). A distinct difference can be found between the two channels(*the dash-dot line*).

3.2. Online target selection experiment result

The averaged accuracy and completion time of the target selection tasks were calculated among 56 trials, as illustrated in Table 2. The averaged accuracy for all the participants was 89.3%, with the ITR of 24.7 bits/min. In Table 2, the finish time between the desired target on-set time (at 4 second) and the time when the target triggered was used to calculate the ITR. The duration of the first four seconds was

Table 2
Performance of the online target selection experiment

Sub.	accuracy [%]	finish time [s]	ITR [bits/min]
A	92.7	2.1	32.4
B	91.1	2.4	26.6
C	87.5	2.3	23.9
D	85.7	2.7	18.9
Avg.	89.3	2.4	24.7

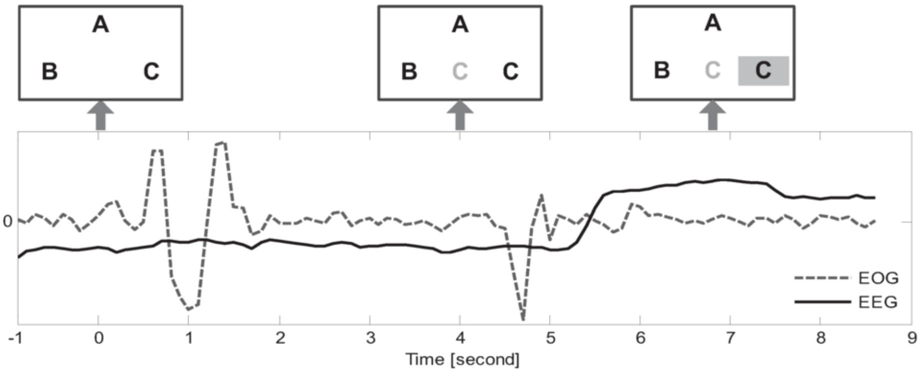

Fig. 4. Detailed process of a target selection task.

ignored because it was used to demonstrated how the system reduced the unexpected operation. In Figure 4, when the three targets displayed at the first 4 seconds, subjects could look at these targets freely and some visible eye movements could be found in the EOG curve. However, no target was triggered during this period because the ERD activity of EEG was not detected. When the desired target (“C”, located at left) was prompted, the subjects looked at left side as well as perform the MI task, and when the ERD exceeds the threshold, the target was triggered.

4. Conclusion and Discussion

In this study, a hybrid BCI system was proposed by combining EEG with EOG signal and applied to the target selection experiment. The output of the BCI system was decided by the two kinds of neural signals simultaneously. Four subjects participated in this study, and completed the online target selection experiment using the hybrid BCI paradigm. The averaged accuracy was 89.3%, with the ITR of 24.7 bits/min. The results showed the feasibility of our proposed hybrid BCI paradigm, which could be a practical rehabilitation technology for disabled individuals.

By incorporating EOG into the conventional EEG-based BCI system, a high performance and practical BCI system were constructed. Although the EEG-based BCI has a single class output (by executing one MI task), the gaze direction extracted from the EOG provided more information, producing three kinds of different output commands. Comparing to the EOG-based systems without EEG, the operation of the proposed BCI system was more flexible. Because the gaze direction from EOG was invalid if an ERD was not detected simultaneously, the subjects were able to observe the surrounding environment freely without causing erroneous operations. Additionally, subjects could voluntarily trigger the commands in our BCI system by performing the MI task, while in other EEG-EOG systems the EEG signal determined the subjects control state in a passive way.

However, as the detecting time of ERD was longer than EOG, the systems response time was increased. The EOG recorded in this study measured the relative eye movements, but gave poor accuracy of the absolute gaze direction. Therefore, the proposed system may not work well when the number of targets increased. This challenge will be addressed in our future work by integrating advanced acquisition equipments and signal processing algorithms of EOG to estimate precise of eye gaze direction[19,20]. Future efforts to improve the system performance will take into account the results of the previously mentioned programs, making the proposed hybrid BCI system a valuable assistive tool for disabled individuals.

Acknowledgements This work was supported by the National Natural Science Foundation of China (Project 61375117 and Project 91320202).

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