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Hybrid EEG-EOG Brain-Computer Interface System for Practical Machine Control

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Abstract—**Practical issues such as accuracy with various subjects, number of sensors, and time for training are important problems of existing brain-computer interface (BCI) systems. In this paper, we propose a hybrid framework for the BCI system that can make machine control more practical. The electrooculogram (EOG) is employed to control the machine in the left and right directions while the electroencephalogram (EEG) is employed to control the forword, no action, and complete stop motions of the machine. By using only 2-channel biosignals, the average classification accuracy of more than 95% can be achieved.**

I. Introduction

The study on the brain-computer interface (BCI) raises a lot of signal processing issues to be solved [1]. Some of the issues include accuracy with respect to various subjects, number of sensors, and time for training.

One of the classical problems in BCI is how to distinguish between the left and right motor imagery signals and correctly classify them. The possible applications include controlling robots, wheelchairs, or a mouse by using EEG. Distinguishing the left and right motor imagery EEGs is possible since the event-related desynchronization and synchronization (ERD/ERS) patterns usually occur on the opposite sides of the imagination of a movement [2]. This observation regarding the ERD/ERS patterns motivates many researchers to explore novel theories and algorithms for left/right motor imagery EEG classification. In [3], a time-frequency based approach is proposed by filtering the fixed time windows in order to obtain band powers (BP) and classifying the resulting BP with the learning vector quantization (LVQ). Automated approach to adjust the influence of the BP during the learning process can be done using the distinction-sensitive learning vector quantization (DLVQ) instead of the LVQ [4]. An alternative way to obtain useful features for the classification is by employing parameters of the autoregressive (AR) model over uniformly short intervals [5]. To further improve [5], AR parameters are designed to be time dependent by using the model called adaptive autoregressive (AAR) [6]. Since the ERD/ERS patterns might not uniformly occur in time, the classification accuracy might be degraded in some cases. This problem can be efficiently solved by extracting the features of channels C3 and C4 of a multi-channel EEG based on the local discriminant bases (LDB) procedure derived from the local cosine packets (LCP) [7] over nonuniform time-segments [8], [9]. Even though the above systems employ complicated feature extraction methods, they still suffer from the average classification accuracy of approximately 80-90% which is still unsatisfactory in practice. Since, in reality, the movement control needs more than left and right movements, multi-directional BCI systems are invented e.g. in [10]-[14]. The features used in those algorithms are from both motor imagery (ERD/ERS) signals and the patterns that naturally obtained from the users via the various frequency information of EEGs. As we increase the classes (more than 2 classes), the classification accuracy is also decreased. This is one of the problems that make BCI systems difficult to use efficiently used in practice.

Therefore, in this paper, we propose a hybrid BCI system that employs the electrooculogram (EOG) together with the EEG as the signals used to control the BCI system. With no cue needed, the system can classify the motions into five classes, i.e. right, left, forward, completely stop, and no action. The proposed system yields a classification accuracy of more than 95% while employing only 2-channel biosignals. Furthermore, the results among 3 subjects illustrate that with less than 20 minutes of training, all subjects can efficiently use the proposed system regardless of the experience in BCI.

II. Proposed hybrid EEG-EOG BCI System

In order to solve the problem metioned above, we design the hybrid EEG-EOG BCI system. The algorithm can be divided into two parts (Sections II*A* and II*B*), i.e. EOG and EEG detection algorithms, respectively. Both algorithms are combined to obtain the complete system which is described in Section II*C*.

A. Electrooculogram (EOG) Detection Algorithms

Since most completely paralyzed people can still move their eyes, EOG is a signal that can be practically used for controlling the prosthetic devices. Unlike EEG, EOG is in the scale of micro volts, therefore it can be easily detected with higher accuracy than EEG. In order to capture the EOG, i.e. the right/left eye gazing patterns, we put the

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positive electrode at the right side of the right eye, and put the negative electrode at the left side of the left eye. The ground electrode is placed at the forehead. This pattern of electrode placement is insensitive to eye blinking. Hence, it makes the system more robust to the eye-blink artifact. The Ag/AgCl electrodes and the EOG BIOPAC MP100 amplifier with the sampling rate of 200 Hz are employed in the system.

Before using the proposed system, the user needs to perform a quick software calibration as follows:

1) Make a maximum right eye gazing (look to the right by 90^o) and record the maximum positive potential denoted as V_{Rmax}.
2) Make a maximum left eye gazing (look to the left by 90^o) and record the minimum negative potential denoted as V_{Lmax}.

The overall algorithm for the right/left eye gazing detection via EOG can be summarized as follows:

1) Define V_R as the maximum amplitude of V_{EOG},
2) Define V_L as the minimum amplitude of V_{EOG},
3) If $V_R \geq T_R$ then make the decision as TURN RIGHT,
4) ElseIf $|V_L| \geq T_L$ then make the decision as TURN LEFT,
5) Else, i.e. $V_R < T_R$ and $|V_L| < T_L$, make the decision as NO ACTION.

V_{EOG} is denoted as the acquired EOG signals. T_R and T_L are denoted as the right and left thresholds used for EOG detection and can be automatically calculated as

$$T_R = V_{Rmax} - (V_{Rmax}/4),$$

$$T_L = |V_{Lmax}| - (|V_{Lmax}|/4),$$

that is, the thresholds are selected as 75% of the recorded EOG amplitudes from the calibration.

B. Electroencephalogram (EEG) Detection Algorithm

Besides the left/right control via EOG, in order to control the other motions, i.e. forward, completely stop, and no action, a single channel EEG is employed. In the proposed system, according to the 10-20 system, we put the positive and negative electrodes at the Pz and Cz positions, respectively, and use the same ground electrode as the EOG. The Ag/AgCl electrodes and the EEG BIOPAC MP100 amplifier with the sampling rate of 200 Hz are employed.

Similarly, before using the proposed system, the user needs to perform a quick software calibration by closing the eyes and record the maximum power spectral density (PSD) in alpha band (8-13 Hz). This recorded parameter is denoted as P_{Smax}. The overall algorithm for the EEG detection can be summarized as follows:

1) Define P_α as the maximum power spectral density (PSD) in alpha band (8-13 Hz).
2) Define P_β as the maximum power spectral density (PSD) in beta band (18-26 Hz).
3) If $P_\alpha \geq T_s$ then make the decision as COMPLETELY STOP
4) ElseIf $P_\beta \geq P_\alpha$ then make the decision as FORWARD,
5) Else, i.e. $P_\beta < P_\alpha$ and $P_\alpha < T_s$, make the decision as NO ACTION.

T_s is denoted as the threshold for checking the completely stop motion and can be automatically calculated as

$$T_S = P_{Smax} - (P_{Smax}/4).$$

The forward movment is detected when the beta activity is greater than the alpha activity, i.e. the subjects need to think about something. In this experiment, we have the subjects think that they are moving forward. To completely stop, we have the subjects close their eyes so that we can obtain a higher amount of alpha activity than when their eyes are open.

C. Process Summary of the Overall System

Since we employ both EEG and EOG, the system needs to acquire and process both signals simultaneously. The overall process of the hybrid BCI system can be summarized as the flowchart in Fig.1. One second of EEG and EOG signals are acquired so that the system can deliver the command every one second. For security reasons, the system will first check the condition for completely stop. After that it will check for the right movement, left movement, forward movement, and no action accordingly. Right and left movements are decided via EOG. Forward movement and completely stop movement are decided via EEG. Finally, no action of movement is decided using the information from both EEG and EOG. It should be noted that COMPLETELY STOP means that if the machine is moving, after the completely stop command, it will be stopped immediately, while NO ACTION means that if the machine is moving, after the no action command, the system will not put any force to the machine and let it be as it is.

III. Test Results

In this paper, we tested our proposed framework with 3 subjects. The first subject (Subject1) has experience with the BCI system while the rest are new to the BCI system. Each subject performed 3 trials. Each trial randomly contained 10 times of each motion, i.e. left, right, forward, completely stop, and no action. Hence, in total, we have 50 commands per trial. Each motion needs to be performed within 2 seconds to be marked as correct. The results are summarized in Table I.

According to Table I, the right and left motions can be perfectly detected via EOG for all subjects. Another practical result is that we can perfectly detect the completely stop motion via eye closing through the EEG alpha activity.

This result makes the hybrid BCI system more practical in reality. Furthermore, approximately 87% and 95% accuracies can be detected for the forward movement and no action, respectively. In overall, the proposed system can lead to approximately 96% classification accuracy which is much higher than the recently developed BCI algorithm [12] which yields a maximum classification accuracy of approximately 86% with synchronized mode performance.

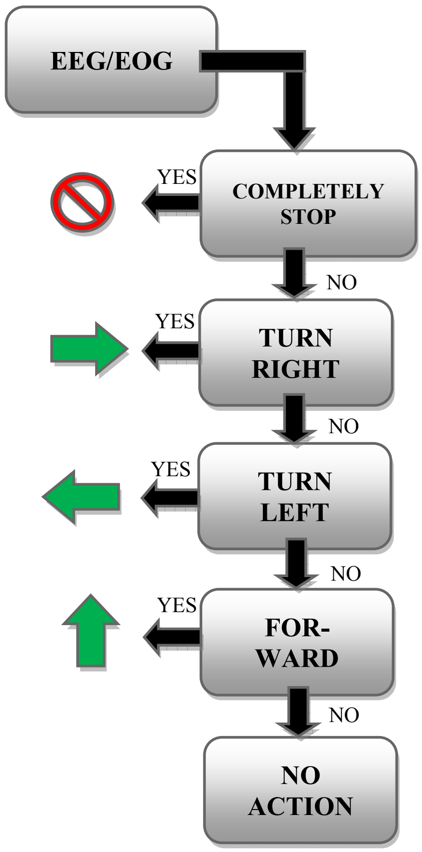

Fig.1 Overall process of the hybrid BCI system

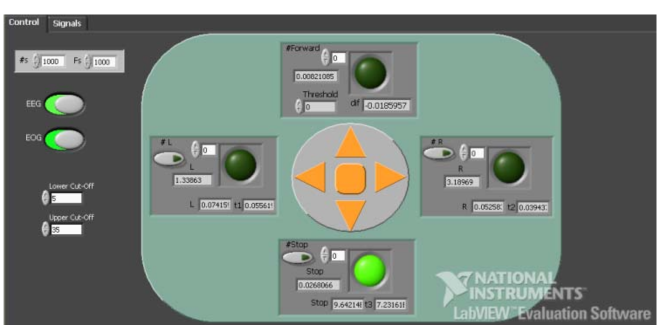

Fig.2 GUI of the proposed system: Calibration and control page.

IV. DISCUSSIONS

The proposed hybrid system contains both software and hardware parts. Regarding the software, we use LABVIEW 8.5 for implementing the graphical user interface (GUI). The first page of the GUI is used for calibration and giving the LED feedback to the subjects for the period of using the machine (Fig.2). Figs.3(a)-3(e) illustrate another page of the software which can visualize the acquired signals. The upper image of Figs.3(a)-3(e) show the acquired EOG signals while the two lower images illustrate the time and frequency (PSD) information of the acquired EEG signals. Figs.3(a)-3(e) demonstrate the right movement, left movement, forward movement, no action, and completely stop actions. It should be noted that the scale of Fig.3(e) is almost 10 times larger than Figs.3(a)-3(d) since the alpha activity obtained from the eye closing are much larger than the eye openning. Regarding the hardware, a toy truck is used as the machine that we employ to test our hybrid BCI system. Fig.4(a) shows the scenario during the experiment and Fig.4(b) illustrates the hardware used in the system which consists of the EEG/EOG amplifiers, data acquisition card, radio transmitter, toy truck, laptop, and electrodes.

In addition, according to the results in Section III, by with less than 20 minutes for each subject to get used to the system, all subjects can perform very well regardless of BCI experience. Furthermore, the system employs only 2 bio-amplifiers and 5 electrodes. These issues make the proposed system practical in reality.

TABLE I
AVERAGE CLASSIFICATION ACCURACY (%) OF THE HYBRID BCI SYSTEM OVER THREE TRIALS.

	Subject 1	**Subject 2**	**Subject 3**
Left	100%	100%	100%
Right	100%	100%	100%
Forward	86.67%	76.67%	96.67%
Completely Stop	100%	100%	100%
No Action	90%	96.67%	100%
Average Accuracy	**95.33%**	**94.67%**	**99.33%**

V. CONCLUSIONS

In this paper, we have proposed a hybrid BCI framework that uses the combination of EEG and EOG for machine control. The proposed system can solve three main problems, i.e. training time, classification accuracy, and number of electrodes. The system employs the simple automatic thresholding method for the EOG detection and uses the simple periodogram PSD as the features for the EEG detection. The performance is justified via 3 subjects and yields the synchronized results. This makes the framework of the proposed system practical and useful in reality.

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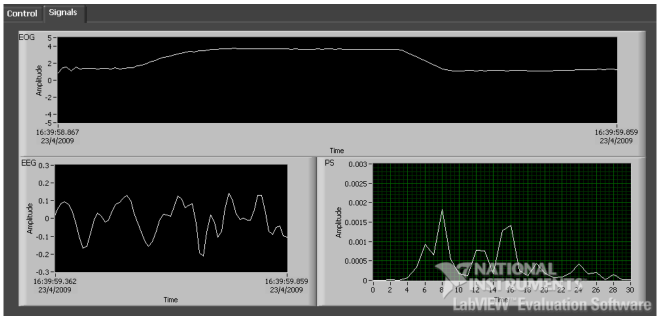
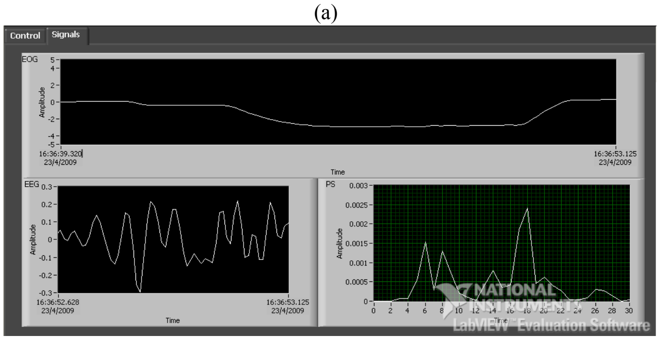


(a)



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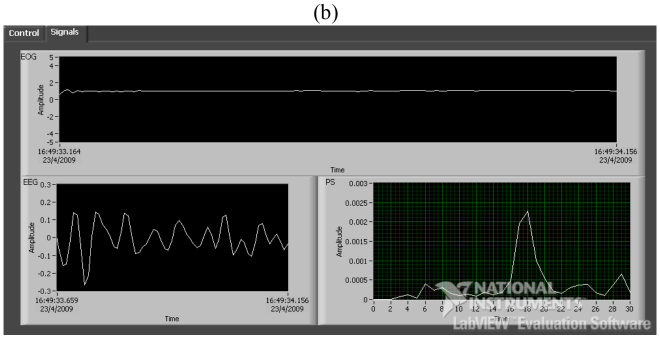
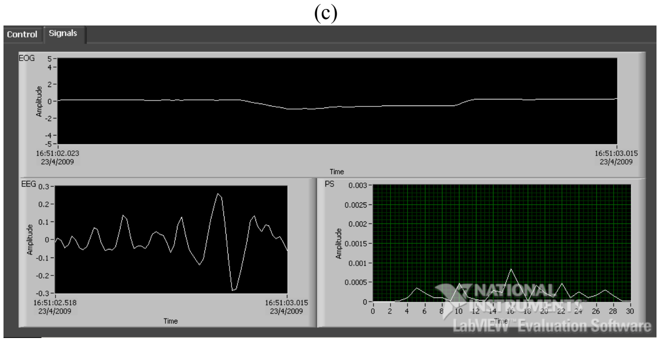
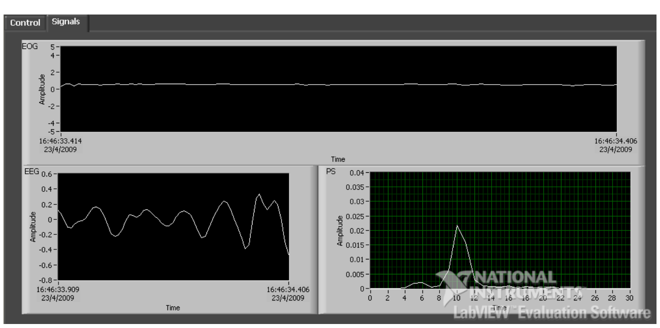


(c)



(d)



(e)

Fig.3 GUI of the proposed system: Waveform analysis page of (a) Right motion, (b) Left motion, (c) Forward, (d) No action, and (e) Completely stop.

(a)

(b)

Fig.4 (a) Scenario during the experiment, and (b) Equipment used in the experiment.

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