A Quadcopter Controlled by Brain Concentration and Eye Blink

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***Abstract*—Brain computer interface (BCI) is a technology that enables a user to interact with the outside world by measuring and analysing signals associated with neural activity, and mapping an identified neural activity pattern to a behavior or action. In this work, an BCI system was developed where the operation of a quadcopter is controlled by identified brain concentration and eye blink patterns. A portable electroencephalography (EEG) headset is used to acquire neural signal around forehead and both eyes. Acquired EEG data are sent to a data processing computer wirelessly and processed in real-time. Identified brain concentration and eye blink patterns are associated with quadcopter operation commands and transmitted to the remote control that is modified to interface with the computer. The BCI system was evaluated by an experiment study and classification accuracy was calculated. Experimental results indicate that the system can achieve the expected performance without using EEG data from all channels and complicated data processing algorithms.**

I. Introduction

The brain computer interface (BCI) technology enables operation of an electromechanical device or computer using neural signals. A typical BCI system can acquire neural signals, identify useful neural activity patterns, and associate them with machine commands. Common applications of BCI include prosthetic limbs, robotics, exoskeletons, autonomous vehicles, computer games, and virtual keyboard [1].

BCI systems can be categorized as invasive and noninvasive, depending on where sensors are placed [2]. This study is focused on noninvasive BCI. Electroencephalography (EEG) has been widely used in noninvasive BCI systems. Since EEG data usually exhibit low signal-to-noise ratio (SNR), synchronous protocols are often used to improve SNR. A synchronous protocol is time-locked to externally paced cues repeated multiple times and the response of the BCI is the overall decision over this period [3]. The repetition of the cue significantly reduce the information transfer rate (ITR), an overall performance measurement of a BCI system [4]. In real applications, an asynchronous BCI, which is a self-paced system where the subject operates independently to decisions on when to stop a mental task and start the next one, is more practical because it can handle real-time BCI tasks and provide a higher ITR.

In this work, an asynchronous BCI system is developed to control the operation of a quadcopter. BCI-controlled quadcopter has been paid increased attention in recent years [5], [6]. A previous state-of-art approach used a 64-channel EEG to identify motor imagery patterns to control the flight of a quadcopter in three-dimensional space [5]. Conventional multi-channel EEG systems are very expensive and in recent studies, efforts have been made to use low-cost commercial EEG headsets [6], [7], [8]. Since these low-cost headsets cannot provide a full coverage of brain cortex, additional neural activity patterns are required to provide a sufficient number of control commands. For instance, an eye tracking device was used together with a low-cost EEG headset to control a quadcopter based on brain concentration and eye movement patterns [6]. In the proposed system, instead of using a supplementary eye tracking device, only a low-cost EEG headset is used based upon which brain concentration and eye blink patterns can be obtained to control the quadcopter. Experimental results indicate the effectiveness and applicability of the proposed system.

II. System Design and Implementation

Fig. 1 shows the block diagram of the proposed BCI system. EEG data are acquired using a low-cost portable headset and transmitted to a data processing computer. Data processing algorithms are implemented using computer programming to analyze the EEG data in real-time. The processing results are associated with quadcopter operation commands, and sent to an Arduino Uno microcontroller that transfers the digital computer outputs into analogue voltage signals that can be recognized by the remote control of the quadcopter. Fig. 2 shows a picture of the entire BCI system. More specific design details are elaborated in the following subsections.

A. EEG Headset

A commercial Emotiv EPOC wireless EEG headset is used in the BCI system [9], as shown in the top left panel of Fig. 1. There are fourteen EEG channels and two Common Mode Sense (CMS)/Driven Right Leg (DRL) reference channels placed around the sensorimotor cortex. In terms of the international 10-20 system, the fourteen EEG channels include AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. During an acquisition, the EEG data in each channel is

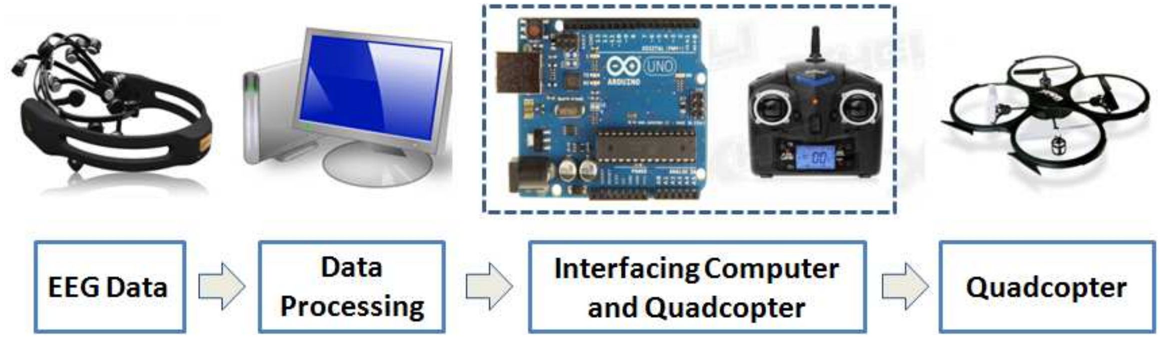

Fig. 1. Block diagram of the proposed BCI system.

Fig. 2. A picture of the proposed BCI system.

sampled at a rate of 128 Hz, and bandpass filtered between 0.2 Hz and 43 Hz. Power-line noise at 50 Hz and 60 Hz are also attenuated before the data are sent to the wireless transmitter.

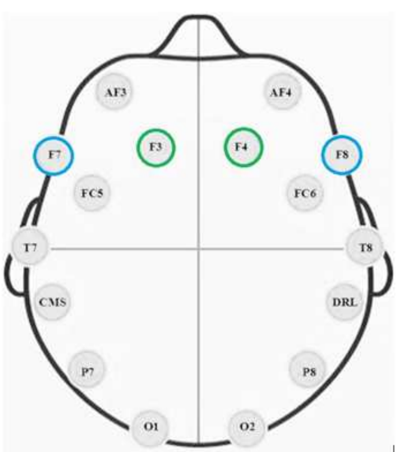

Fig. 3. Four EEG channels (F3, F4, F7, F8) used in the proposed BCI system.

B. Data Processing

EEG data acquired by the headset are transmitted to a data processing computer through a customized Wi-Fi channel at 2.4G Hz. The received data are processed to remove noise and artifacts and identify interested neural activity patterns. Instead of using data from all EEG channels, the data from only four channels, F3, F4, F7, and F8, are analyzed. Fig. 3 illustrates the locations of these four channels that are encircled with green (F3, F4) and light blue (F7, F8) lines. F3 and F4 are located above the dorsolateral prefrontal cortex and used to identify an increase of brain concentration. F7 and F8 are used to identify eye blink patterns because these two channels are close to eyes, and a significant amount of signal variations in these channels is originated from muscle movement around eyes. Four neural activity patterns of interest are identified in this study: increased brain concentration, intentional blink of left eye, right eye, and both eyes. These patterns are mapped to four quadcopter operation commands: move forward (increased concentration), turn left (left eye), turn right (right eye), and move backward (both eyes).

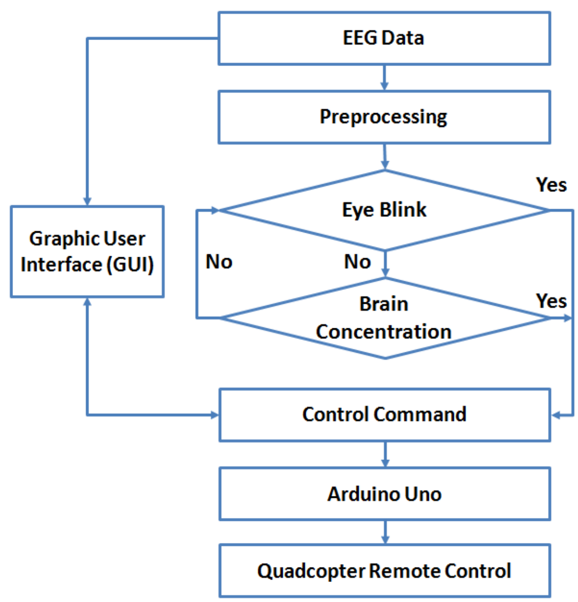

Fig. 4. Flowchart of the data processing.

Fig. 4 shows a flowchart of the data processing. In the preprocessing, a surface Laplacian is performed on all EEG channels for spatial filtering [10]. Then the EEG data from channels F3, F4, F7, and F8 are normalized between 0 and 1.

The signal magnitude from channels F7 and F8 are compared to predetermined thresholds to identify eye blink patterns. When identifying an intentional eye blink, the selected threshold should be able to differentiate it from a spontaneous eye blink. The thresholds are experimentally determined for each individual subject: First, the average signal magnitude from multiple trials are calculated for each intentional eye blink task in each channel; Second, the average magnitude of spontaneous eye blink is also computed for each channel using multiple trials of EEG data; Third, for each channel, the difference between the two average magnitudes is calculated, and the threshold is a half of the difference plus the average magnitude of spontaneous eye blink in this channel. If an intentional eye blink is detected, the corresponding command is generated and sent to the Arduino Uno microcontroller. The microcontroller transfers the digital computer output into an analogue voltage signal that can be understood by the quadcopter to control the flight. Each command is executed for one second and then the quadcopter stops to hover.

If no intentional eye blink is detected, EEG data from F3 and F4 are analyzed with the following steps: First, a linear regression is performed to remove eye movement artifacts in F3 and F4 based on EEG recordings from F7 and F8 [11]. Second, after the regression, EEG data are bandpass filtered between 8 and 32 Hz. Third, the average band power in Alpha (8-15 Hz) and Beta (16-31 Hz) bands are computed in each second, and compared to predefined thresholds to detect an increased brain concentration. An increased Beta band power and a decreased Alpha band power indicate an increase of concentration. The band power thresholds in the Alpha and Beta bands are experimentally determined by averaging the band power values in each band using multiple baseline EEG trials. If an increased concentration is identified, the related quadcopter command is sent to the Arduino board to control the quadcopter. If not, the program will go back to detect intentional eye blink.

C. Quadcopter and Arduino Interface

A UDI U818A model radio-controlled quadcopter is used in the BCI system. The remote of the quadcopter was slightly modified to interface with the Arduino Uno microcontroller. In addition to the movement direction, three additional variables are required as the inputs to the Arduino board: thrust level, movement speed, and an initialization flag. Movement speed and thrust level of quadcopter motor can be manually set through the graphic user interface (GUI) developed for this BCI system, and sent to the Arduino board to generate control signals. When starting the quadcopter remote, it is required to first undergo an initialization process to calibrates the thrust stick for use during flight. This process involves moving the thrust stick from 0% thrust to 100% and back down to 0%, and is implemented using the Arduino programming. The initialization flag triggers the Arduino board to run the initialization process. Once initialized, the remote begins to perform the flight maneuvers based on the voltage signals generated by Arduino.

D. Software

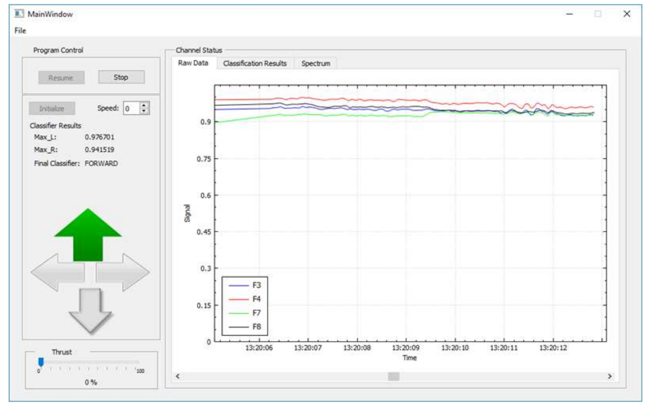

Fig. 5. A screen shot of the graphic user interface.

The commercial software for the Emotiv headset can be used to visualize the EEG data in real-time. Since the software cannot be directly used for the proposed BCI system, an in-house software was developed with a GUI to receive, analyze EEG data, and visualize processing results. Some control functions of the quadcopter, such as power thrust, movement speed, and remote initialization, are also performed through the GUI. The GUI and all data processing algorithms are implemented using C++ based Windows programming. Fig. 5 shows a screen shot of the GUI where EEG data from the four channels are shown in real-time with different colors. The frequency distribution of EEG data and BCI classification results can also be visualized in real-time. The user may initialize the remote, start, stop, or resume the quadcopter operation by a single click of the button in the GUI. The highlighted arrow in the lower left panel of GUI indicates the current movement direction of the quadcopter.

III. Experimental Study

Five healthy subjects participated in the experimental study of the proposed BCI system. Before each experiment, a randomized list of tasks was designed that consists of 150 trials of eye blink and 100 trials of brain concentration. In the 150 eye blink trials, there are 50 trials of left eye blink, 50 trials of right eye blink, and 50 trials of both eye blink. The duration of each trial was controlled by the user and ranged from 1 second to 5 seconds. In each brain concentration trial, the participant imagined to raise both arms slowly while trying to minimize eye movement by looking at an icon on the computer desktop. The thresholds for the intentional eye blink and brain concentration tasks were determined for each subject individually using EEG data collected on three different days during a two weeks' period of time before the experiment. At the beginning of each experiment, the participant was instructed to wear the headset and make sure that all electrodes achieve the best possible contact quality. During the experiment, the participant went through the list of tasks based upon the self-paced decision on when to start and stop a task. Meanwhile, the BCI classification results were recorded and compared to the designed experimental paradigm. Both indoor and outdoor experiments were performed. The quadcopter was not connected during the indoor experiments due to the limited lab space. The overall classification accuracy was calculated for each participant.

IV. Results

The thresholds for eye blink and brain concentration tasks were calculated for each individual subject, and were not used for the BCI classification of different subjects. Therefore, only the intra-subject BCI classification performance was evaluated. Table I show the classification accuracy of each individual subject on the eye blink and brain concentration tasks. The average accuracy of the eye blink task is 85.3%, and that of the brain concentration task is 79.0%. It can be seen that the accuracy varies significantly across subjects and tasks. For example, in the eye blink task, the highest accuracy is 98.9%, while the lowest one is 69.4%. The accuracies of the brain concentration task ranges from 75% to 90%. For each individual subject, the accuracy of the eye blink task could be very different to that of the brain concentration task. In general, the brain concentration task is more difficult than the eye blink because not every one can focus well in a short period of time. But there is an exception where subject 3 achieved a higher accuracy in the brain concentration task.

A major reason of these variations is that different subjects have different levels of familiarity with the EEG headset and experimental paradigms. For example, the two subjects with accuracies above 98% in the eye blink tasks are more familiar with the use of headset compared to the other subjects. In addition, EEG always exhibits nonstationarity and between-subject variation is typically significant. Despite of the observed variations in accuracies, the overall classification performance is satisfying considering that only four channels of data are used and the final decision is only made by thresholding. For instance, subjects 1 and 5 achieved an average accuracy above 91%, and the overall average accuracy of all subjects and tasks is above 82%.

TABLE I
Individual and average classification accuracies (%) of the five experiment participants.

Subjects	1	2	3	4	5	Average
Eye Blink	98.9	83.9	69.4	75.6	98.5	85.3
Brain Concentration	80.0	70.0	75.0	90.0	80.0	79.0
Average	91.2	78.4	71.6	81.4	91.1	82.7

Compared to the existing BCI-controlled quadcopter systems, less data and computational sources are used in the proposed system while a satisfying performance was achieved. Based upon the same low-cost Emotiv EPOC headset, the performance of the system can be further improved from several aspects. First, instead of the surface Laplacian, the common spatial patterns (CSP) method or its variants can be used for spatial filtering [4], [12]. Second, additional EEG channels can be included to obtain more information about brain activity and eye movement. Third, additional EEG features extracted from CSP can be added for the classification. Fourth, based on multiple EEG features, multivariate data classifiers, such as Support Vector Machine or Linear Discriminant Analysis, can be used to improve the classification performance without a significant increase in computational load. Finally, only one brain concentration and three eye blink patterns are used in this system. By including data from other EEG channels, more facial expression patterns can be identified to support additional operation commands so that the quadcopter control can be expanded to three-dimensional space.

V. Conclusion

In this work, a BCI system was developed that can identify brain concentration and eye blink patterns and use identified patterns to control the movement of a radio-controlled quadcopter in real-time. In the current system, EEG data are acquired using a low-cost fourteen-channel wireless EEG headset and sent to a data processing computer. Only four channels' data are processed to identify brain concentration and eye blink patterns. The data processing results are transferred to quadcopter operation commands through an Arduino-based interface. A graphic user interface was designed and implemented to visualize EEG data, frequency distribution, classification results, and to set up initial conditions to control the quadcopter. Experimental results indicate that the system can provide a satisfactory performance with a small amount of EEG data and low computational load.

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