An Ear-EEG-based Brain-Computer Interface using Concentration Level for Control

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Abstract—**Ear-EEG is an alternative EEG acquisition method to the scalp-EEG conventionally used in Brain-Computer Interface (BCI). It is a more comfortable, discreet, and fashionable method comparing to the scalp-EEG. This work proposes an Ear-EEG-based BCI system that detects and utilizes the concentration level as the BCI signal. The experiments conducted in this study shows that the concentration level can be detected from the Ear-EEG acquiring around the user's ears. In the online experiment, our BCI system achieve the average true positive rate of 83% with the performance time of 3.98 seconds and false discovery rate of 16%. This study serves as another proof that Ear-EEG is a reliable EEG acquisition method especially for the BCI system that aims for the daily-life applications for normal healthy users.**

Keywords-Brain-Computer Interface; Ear-EEG; Concentration level;

I. INTRODUCTION

Data acquisition is one of the main steps in Brain-Computer Interfaces (BCI), the technology that translate brain waves into computer command. Electroencephalography (EEG) is the most popular data acquisition method in BCI due to its conveniences and positive results. Conventional EEG acquisition method acquire EEG by attaching electrodes with electrolyte gel or electrical conductive pastes (so-called wet-electrodes) to the subject's scalp together with a cap or other wearable equipment [1]. Although BCIs with conventional scalp-EEG acquisition method have been proved to be very successful in helping patients with neurological diseases or motor impairment to regain their ability to perform daily-life activities [2][3], it is not yet to be a technology that is suitable for normal people to use in real life. BCI has so much potential to be much more than the technology for patients with disability. The concept of controlling electrical devices with human's mind can be seen in all form of media including literatures and visual media throughout different cultures around the world. Except for good signal processing algorithm, feature extraction methods, and machine learning techniques, BCI systems and the EEG acquisition method should also be easy, convenient, discreet and fashionable for normal people to use in their daily-life activities.

This issue cannot be solved by the BCI system with conventional scalp-EEG acquisition method. No matter how good the design is, wearing a cap with wet-electrode on one's head is not easy and convenient. The electrolyte gel that stick on the subject's scalp and hair could discomfort the subject and might produces an unpleasant smell depending on the product. It also requires preparation time and it is definitely not discreet or fashionable. We can replace wet-electrodes with dry-electrodes to get rid of the need to apply the electrolyte gel, which could reduce the preparation time making the whole system more convenient and user-friendly although some designs of dry electrode such as spike-shaped electrode could hurt the users when wearing for a long period of time [4]. Since putting electrodes on the scalp (with or without a cap) could be socially awkward, one of the obvious solution is to acquire EEG from other places. Commercial grade EEG acquisition device such as NeuroSky (www.NeuroSky.com) acquires EEG from the user's forehead with one active dry-electrode, which could detects simple neuro-activities such as user's concentration level and meditation level.

Ear-EEG is another EEG acquisition method that acquire EEG from around the user's ear [5] or inside the user's ear [6]. Ear-EEG is more discreet than the forehead-EEG method and the design for the device could be made in the shape of existing daily-life wearable device such as headphone and earphone. Starting from the study in [7], many research have been conducted to prove the reliability of the Ear-EEG. It has been shown that many signal types in BCIs including alpha activity, steady state visually evoked potential (SSVEP), auditory steady state response (ASSR) and event-related potential (ERP) can be acquire from the Ear-EEG [7][8].

In this work, we design an active binary-class BCI system that provide users an alternative way to operate the environment such as home-appliances. The proposed system is simple, convenient and suitable for normal people to use in real life. The proposed BCI system utilizes Ear-EEG recording from around user's ears to measure the user's concentration level. The users can voluntary send out a binary command to the computer in real-time by increasing their concentration level thus, the system acts as a "switch" to the external environments. The Ear-EEG acquisition tool is designed and made using the 3D-printer with low-cost materials. The proposed BCI system was successfully able to detect user's

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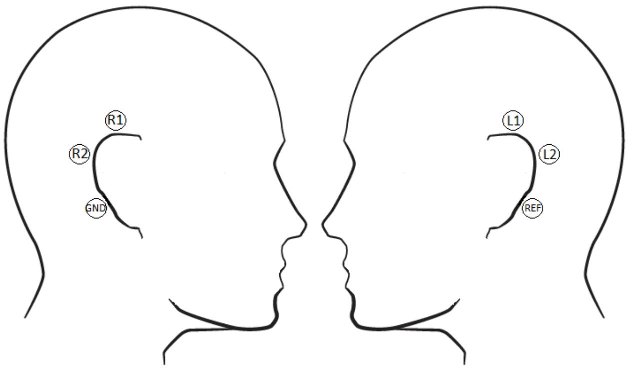

Figure 1. Position of the Ear-EEG electrodes

concentration level and gave a good performance in the experiment conducted in this study.

II. METHOD

A. Ear-EEG data acquisition

In our work, the Ear-EEG acquisition tool contains six electrodes, three on each side of the ear, where one electrode from each side is use as the reference/ground channel giving four channels of Ear-EEG (named L1, L2, R1 and R2). The position of each electrode is illustrated in Fi. 1. The Ear-EEG acquisition tool is designed in the shape similar to a headband that could be wear around the ear and wrap around the back of the user head. The frame of our device is made using 3D printer with polylactic acid (PLA), a default filament for 3D printer, which is sturdy yet flexible. Custom-made foam-type snap electrodes are used as the sensor. Electrode snap sockets are planted in the silicone (Dragon Skin 30) that is attached to the PLA frame. The foam-type snap electrodes can be easily connect and disconnect from the sockets in the Ear-EEG device. The silicone base together with foam type give a soft touch to the user's skin which make the device comfortably wearable. The device is then connected to the OpenBCI 32bit board (www.OpenBCI.com) inside a 3D-printed hard case that can be hooked to the user's clothes. A portable battery is also included in the case. The sampling rate of EEG was 250 Hz. The final design of the Ear-EEG acquisition tool is shown in Fig. 3 (left). With the black design, the device is very discreet when the subject is wearing it (Fig. 2 right).

Figure 2. (left) The Ear-EEG acquisition device.
(right) A subject wearing the device.

Figure 3. (left) black screen for rest task, and (right) living room scenario for concentration task

B. Concentration level

EEG can be separated into different bands according to their frequency: delta (<4 Hz), theta (4-7 Hz), alpha (8-15 Hz), beta (15-30 Hz) and gamma (30-100 Hz). Each frequency band has it owns functions. Theta band corresponds to the drowsy, meditative or sleep state of the adult human. In contrast to theta band, beta band correspond to the active thinking, focusing, motor activities, and attentive state of mind [1]. Concentration (or as some studies simply refer as attention) is the action of focusing one's attention or mental effort. With the distinctive function of theta and beta EEG frequency band, many researches have use the ratio of the power of beta band to the power of theta band (β/θ) to define the concentration level in subject's mind [9][10]. This BCI system presented in this work uses concentration level as the signal for the interface. Details on signal processing and how to determine the threshold for the concentration level will be discussed in the following sections.

C. Experimental setup

Two experiments were conducted in this study. The objective of the first experiment is to determine whether the concentration level can be detected from the EEG acquired around the subject's ears and to calculate the threshold for the concentration level. After that had been confirmed, we conducted the second online experiment to determine the performance of the concentration level-based binary-class BCI system in real time.

In the first experiment, subjects were ask to wear the Ear-EEG acquisition device and sit in front of a computer screen. An instruction was then given on the computer screen for user to read. In each trial of the experiment, the screen will show a black screen with an instruction reminding the subject to stay relax with his eyes open (Fig. 3, left) alternating with a picture of a living room scenario with three home-appliances: television, air-conditioner, and refrigerator (Fig. 3, right), which subject has to concentrate on each of the home-appliance. The black screen and living room scenario are shown alternately for 10 seconds until the living room scenario is shown for three times starting and finishing with the black screen. Since the word "concentration" can be ambiguous, subjects were guided to (1) visually focus on the object and (2) repeating the word "activate" in their mind. This experiment were repeated ten times for each subject.

In the second experiment, the same setup was made for the subjects and the living room picture was constantly shown on the screen. In this experiment, subjects were asked to voluntary choose the time to concentrate and give out the "activate" command on their own. To measure the performance of the system, users have to press the ENTER key on the laptop before concentrating. The BCI system will speak "Activated!" if the concentration level exceed the threshold, which send out the activate command. The time from the moment the subject presses the ENTER key and when the activate command occurs is also measured as the system's performance time. If the subject fails to activate the command within 10 seconds after the ENTER key is pressed, the system will speak "Failed" indicating that the sub-trial of the experiment is failed. No matter what the outcome after subjects press the ENTER key is, the subjects has to bring their mind back to the resting state and be ready to send out the activate command again. The subjects have to send out the total of five activate commands in one trial. We conduct this experiment for ten trials. Performance time together with the true positive rate (TPR, how many time the activate command is sent out correctly after the ENTER key is pressed) and the false discovery rate (FDR, how many time the activate command is sent out when the ENTER key has not been pressed) were used to evaluate the system.

D. Signal processing and active threshold-based method

To confirm that our system can detect the concentration level, the raw EEG data from the first experiment is first segmented and separated between the rest and concentration state. We further segment the 10-seconds data from both states into 3-seconds epochs with 4-ms step. Fast Fourier Transform (FFT) is then applied to the EEG epochs to obtain the power spectrum of the theta and beta band. The power spectrums are then averaged across the four EEG channels. Finally we calculate the concentration level according to the formula β/θ where β is the power of the beta band and θ is the power of the theta band. For each rest state and its consequence concentration state, we use the 95-percentile value (to eliminate the chance of outliner of the highest concentration level in the concentration state to find the ratio between that value and the average concentration level in rest state. This ratio value is calculated for all of the 30 rest-concentrate sequences. The 75 percent of the average ratio value between all 30 samples is then used as the initial threshold to send out the activate command in the second part of the experiment.

In the online experiment, because our system uses the increment in concentration level from the rest state to the concentration state as the trigger to send out the activate command, the system keeps tracking two values: the current concentration level and the base concentration level. The current concentration level is calculated from the current 3-seconds EEG epochs and the base concentration level is the average value of the concentration level in the first 10 seconds of the last 15 seconds before the current concentration level. The reason that we omit the last 5 seconds is that the result of the experiment showed that the concentration does not suddenly raise up but rather gradually elevates as the subject keep concentrating.

In addition, EEG is not a stationary biosignal and constantly changes depending on the subject physical and mental state, therefore, it is necessary for the system to keep updating the threshold of concentration level. Our system updating the threshold value by the following formula:

$$T_{new} = T_{old} + \alpha(T_{current} - T_{old}) \quad (1)$$

where T is the threshold value for the concentration level and $T_{current}$ can be calculated by finding the ratio of maximum current concentration level after the activate command has been sent and the base concentration level, and α is the learning rate which is set to 0.05 in this experiment.

E. Participants

Five male and one female healthy students (aged 24±4 years) from Korea Advance Institute of Science and Technology (KAIST) voluntarily participated as the subjects in our experiment. All subjects gave written informed consents. The KAIST Institutional Review Board approved the proposed experimental protocol of this study. All of the subjects were free from any neurological disorders, visual and hearing impairment.

III. RESULTS AND DISCUSSION

A. Experiment I: Concentration level

The grand average of the concentration level of the concentration state (red plot) and rest state (blue plot) across all subjects and trials are shown and compared in Fig. 4. From the results, we found that the concentration level in concentration state (1.116 ± 0.016) is significantly higher than one in the rest state (1.064 ± 0.007) with t-test ($p < 0.01$). This result shows that the concentration level, β/θ, is increased

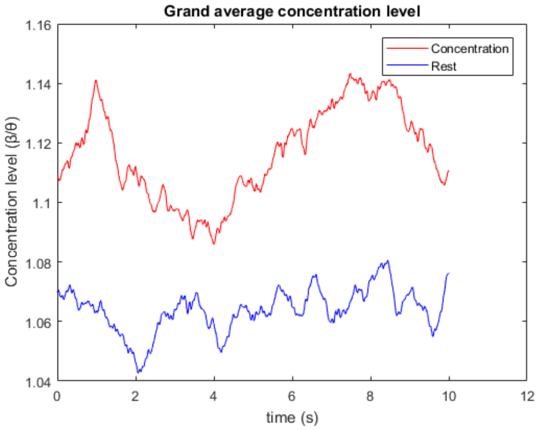

Figure 4. The grand-average concentration level across all subjects and trials obtained during the concentration state (red) and the rest state (blue)

when subjects concentrate on the object in the screen and the Ear-EEG acquisition device made in this work was able to detect these changes. The threshold level calculated from this grand-average data is equal to 1.054 meaning that the activate command will be send out when the concentration level of the subject is increased by 5.4% from this grand average data. Since the method If the number of the subjects participated in the experiment is enough, we might be able to use this threshold value as the default value and increase the learning rate α for the new user without having any training sessions.

B. *Experiment II: Online binary BCI*

We evaluated out BCI system in three aspects: TPR, FDR, and performance time. TPR is defined as:

$$\mathrm{TPR} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{2}$$

where TP is the number of true positive and FN is the false negative, which the summation TP + FN is equals to 50 in the second experiment. FDR measures the error of the system and it is defined as:

$$\mathrm{FDR} = \mathrm{FP}/(\mathrm{FP} + \mathrm{TP}) \tag{3}$$

where FP is the number of false positives. The results of the online experiment is concluded in Table 1 below.

TABLE I. EXPERIMENT II NUMBERICAL RESULTS

Subject	TPR	FDR	Performance time (s)
AR	0.84	0.19	3.02
AT	0.80	0.11	4.79
BS	0.92	0.18	3.32
ET	0.64	0.24	4.57
GP	0.80	0.18	4.53
NT	0.96	0.04	3.67
Average	0.83	0.16	3.98

As we can see in Table 1, the average TPR, FDR and performance time is 0.83, 0.16, and 3.98 seconds, respectively. Apart from the Subject ET, all subjects have achieved the TPR of more than 80%. Subject ET also shows the highest value of FDR.

In addition, according to the survey given to the subjects after the experiment, no subjects report any discomfort wearing the around-Ear-EEG acquisition tool made in this study.

IV. CONCLUSION

The results from the experiments conducted in this study have shown that the concentration level can be detected from the Ear-EEG acquiring from the tool made in this study. Even with the simplest BCI classification method such as threshold level used in the proposed system, we were able to achieve the TPR of more than 80%. The problem of FDR could be solved by applying a real-time artifact removing techniques or other noise cancelling techniques. The further improvement of the system could be done by adding a camera together with the image recognition algorithm to specify the target in the environment for the BCI system to send the command to. The preparation of the Ear-EEG device is easy and fast. The device is comfortable, discreet, and could be fashionable making it not socially awkward. In conclusion, the BCI system based on the concentration level detected from the Ear-EEG is feasible and has potential to be used, especially, for normal people in daily-life.

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