Outside the Head Thinking: A Novel Approach for Detecting Human Brain Cognition

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Abstract. Electroencephalography (EEG) is one of the most commonly used measures in neuroscience and psychophysiology research for studying functional information of brain activity such as cognition and emotion. However, because of lack of convenient methods to measure EEG, it is difficult to use in everyday situations. The electrodermal potential (EDP) can be used to monitor brain activities. This study investigated the correlation between scalp acquired EEG and EDP from the body below the head, for two distinctive cognitive statuses of relaxation and attention. The results showed that theta power decreases while beta power increases in the attention state compared to relaxation from EDP. We also obtained 84.2 % of classification accuracy to discriminate attention-relaxation states using EDP signals, while obtaining 83.9 ∼ 89.3 % of the classification accuracy using a single channel EEG.

Keywords: Electroencephalography · Electrodermal potential · Brain-machine interfaces · Relaxation · Attention · Cognition

1 Introduction

EEG (Electroencephalogram) often provides interfaces for controlling machines or computers due to recent developments in inexpensive, easy-to-wear, and low power acquisition systems [1, 2]. Thus, EEG-based Brain Computer Interface (BCI) is one of the most promising technologies for device interaction and detection of cognitive and emotional activities. As a result, abundant studies have been performed to investigate the BCI-based interfaces: event-related synchronization/desynchronization (ERS/ERD), steady-state visual evoked potentials (SSVEP), slow cortical potentials (SCP), visually evoked P300 potentials, movement-related potentials (MRPs), and changes in brain rhythms [3, 4].

However, current EEG-based BCI headsets are ill-suited for daily use owing to challenges with hardware positioning/placement, requisite device knowledge, training, and skills. In fact, the current EEG-based BCI technology usually takes anywhere from a few minutes up to 45 min to configure EEG electrodes on a person's scalp depending on the types of electrodes (e.g., dry and wet electrodes) used, which is one of major obstacles for the technology to be widely adapted in daily living. Additionally, consumer based EEG headsets have not been widely accepted by the public due to design and their obtrusive nature.

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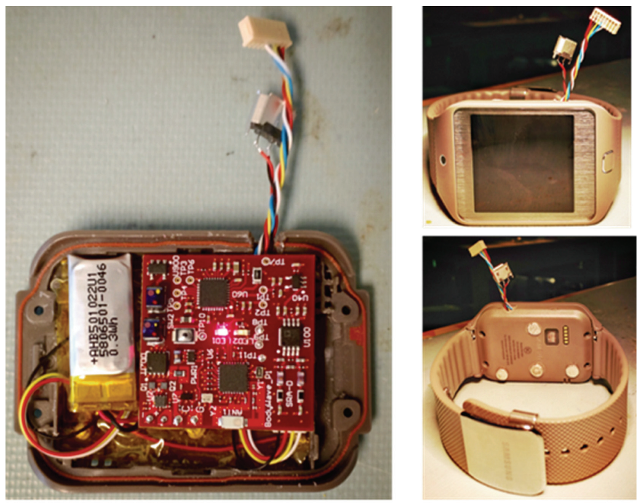
To overcome these issues, we explored the possibility of estimating the brain's cognitive states using electrodermal potentials (EDP), which characterize the skin's electrical activity by measuring potential differences between two separate electrodes similar to measuring surface electromyogram, from non-scalp areas in the body. In this study, we developed a wrist-worn device (Fig. 1) by collaboration with Freer Logic (Skyland, NC, U.S.A.), and verified the feasibility of classifying an individual's attention and relaxation states by comparison with EEG.



(a) (b)

Fig. 1. The proposed wrist-worn device to measure EDP. The printed circuit board (a) measures 1 × 1 inch in size and the device has four electrodes in the back (b); two electrodes are for signal sensing, one is for ground and the other one is for electrode-off detection.

2 Methods

2.1 Signal Acquisition

Simultaneous EDP and EEG recordings were performed in 5 healthy subjects (4 males, 1 female) using the proposed device and commercially available EEG recording system as shown in Fig. 2. The EDP device incorporating two recording electrodes and one reference electrodes was positioned in the middle of anterior left forearm where brachioradialis and flexor carpi radialis muscles reside. For the EEG recording, an Avatar EEG recording amplifier (Electrical Geodesics Inc., OR, U.S.A.) with g. SAHARA dry electrodes (g.tec Medical Engineering, Gmbh, Austria) was used. Six electrodes (Fz, Cz, C5, C6, PO3, and PO4) were positioned based on the international 10–20 system, while the reference and ground were placed at the right and left mastoids, respectively. The recorded data were transmitted to the same host computer for signal processing via on-board microcontrollers and Bluetooth modules.

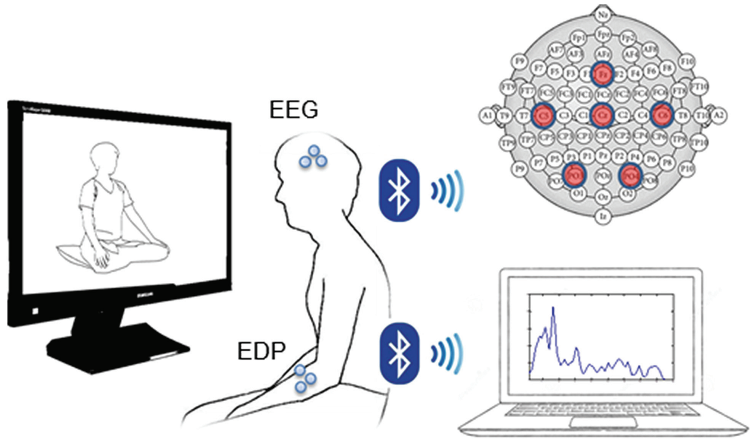


Fig. 2. Two acquisition systems were used: EEG and EDP. An electrode cap was positioned as International 10–20 electrode placement, and the activity was recorded at Fz, Cz, C5, C6, PO3, and PO4. EDP was collected via the wrist-worn device.

2.2 Experimental Protocol

Participants were tested in multiple sessions over 40 min. They were requested to avoid any stimulants such as coffee, tea, and cigarettes in the 2 h preceding the recording period. We educated the participants on the entire experimental procedure and guided them during the recordings. No training and/or calibration were provided to the subjects prior to the recordings. The participants sat down in a comfortable chair wearing both EDP and EEG recording systems described in Sect. 2.1 during the recording. A host computer was connected to both, the EDP and the EEG recording systems for simultaneous data storage.

The participants were asked to be comfortable and to refrain from moving to minimize motion and EMG artifacts during recording. The experiments were conducted with the following protocol: First, a monitoring session was performed for eyes-closed resting EEG with no stimulus. Second, the participants were asked to relax while closing their eyes to obtain the status of relaxation. Third, for the attention state, the Continuous Performance Test (CPT) was used to induce sustained attention level of the participants. The CPT was designed to present the randomized sequence of letters on the computer screen for 0.5 s with 1-s intervals. Participants were instructed to continuously pay attention to the computer screen for about 2 min and mentally count the total number of appearances of a designated target letter (e.g. 'G') (Fig. 3). At the end of the CPT session, the participant was required to input the total number of such appearances. We assessed the attentiveness of each participant by verifying the correctness of the answer.

2.3 Signal Processing

The recorded EEG and EDP data were analyzed using MATLAB (MathWorks Inc., Natick, MA). The EEG signal was low-pass filtered under 45 Hz (with digital Butter-worth filter) and 5th-order band-pass filtered with 0.5 to 50 Hz. Under human

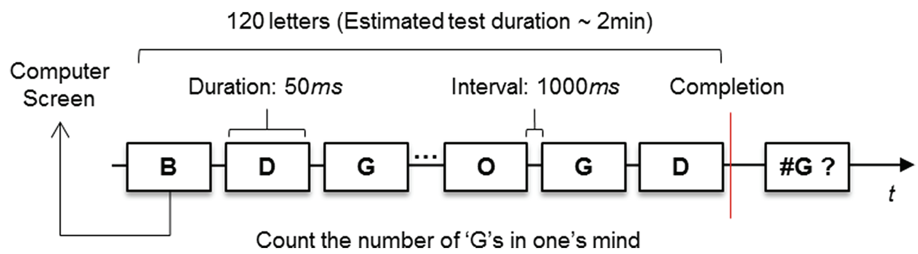


Fig. 3. Continuous Performance test devised for the attention state.

supervision, the EDP and EEG data were synchronized with time stamps generated during the recording. Each dataset was analyzed in 5-s epochs without overlap. The Power spectral density (PSD) and the averaged power were calculated for four frequency bands: theta (4 ~ 8 Hz), alpha (8 ~ 12 Hz), beta1 (12 ~ 15 Hz), and beta2 (15 ~ 20 Hz).

For the attention classification analysis, we extracted a more diversified set of features from both the spectral domain and the time domain. A total of 80 features were composed of the statistical variables in time-domain signals (e.g. mean, standard deviation of amplitude), the spectral powers (both absolute and relative) of each frequency bin (e.g. theta, relative theta, theta/alpha, 4 ~ 12 Hz, 12 ~ 20 Hz), and signal entropy and complexity (e.g. permutation entropy, Higuchi fractal). The classification between the relaxation and attention states was analyzed with the linear kernel Support Vector Machine (SVM) in a 10-fold cross-validation for each subject. We balanced the number of samples of the relaxation and attention states by resampling for unbiased error estimation.

3 Results

Figure 4 represents the signal trend analysis results from the EDPs. We compared average powers of each frequency band when the subjects were asked to change their cognitive states (e.g., attention to relax, quiet attention to relax, and attention to quiet attention). In the comparison between attention and relax states, we observed theta power decreases in 14 epochs (93.3 %) out of 15 epochs and an increase in beta2 power in 12 out of 15 epochs (80 %). On the other hand, for comparisons between attention and quiet attention states, no significant difference was observed.

We carried out 10-fold cross-validation to estimate classification accuracy in each subject (Fig. 5). As expected, the 8-channel EEG showed the highest accuracy (91.1 %). However, the classification performance varied in single EEG channel analysis, ranging from 83.9 ~ 89.3 %. EDP achieved 84.2 % of classification accuracy on average, which is comparable to that of any single EEG channel, but with large standard deviation (17.0 %) relative to EEG (3.3 ~ 7.8 %). We believe EDP is a valuable signal for studying an individual's attentional state, although it requires improvements in signal reliability for general use.

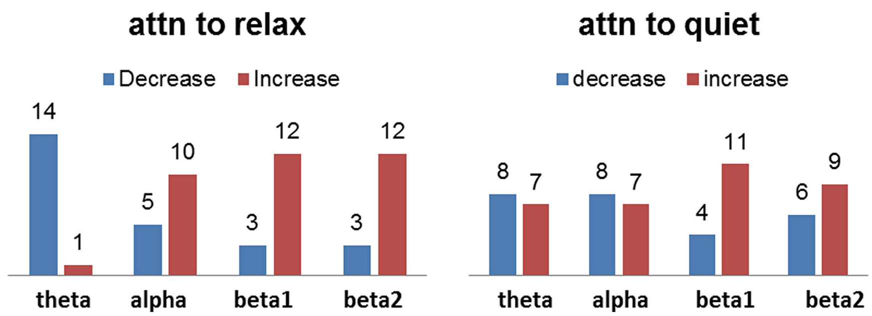


Fig. 4. Comparisons of the average power of each frequency band with different cognitive states. (Color figure online)

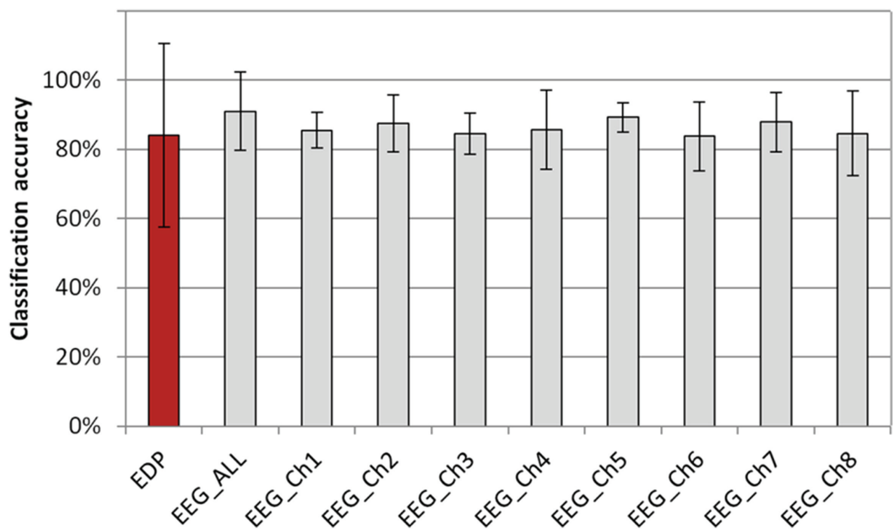


Fig. 5. Comparative analysis of the EDP and EEG in classification accuracy of attention-relaxation state (N = 5). (Color figure online)

4 Conclusion

We have introduced a technique for unobtrusive measurements of cognitive responsiveness in the body. We hypothesized that body locations other than the traditional scalp area can also represent a cognitive activity in bio-potentials such as EDP. To verify this hypothesis, we performed simultaneous EDP and EEG recording at six scalp locations of Fz, Cz, C5, C6, PO3, and PO4 and the body location of the middle of the anterior left forearm. As shown in the results, there are similar trends in EDP and EEG responses to the cognitive status of relaxation and attention. Although many challenges exist in the field, our results illustrate the considerable potential of this technology. Further investigation on EDP and development of the acquisition system will enhance usability of the EEG-based BCI system. In addition, this study initiates further investigation to unveil EDP and EEG correlation for other brain functionalities such as event-related potentials responding to sensory, cognitive, or motor events.

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