FEASIBILITY ANALYSIS AND ADAPTIVE THRESHOLDING FOR MOBILE APPLICATIONS CONTROLLED BY EEG SIGNALS

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ABSTRACT

Given the availability of EEG technology and existing studies, this paper discusses the feasibility of development of mobile applications controlled by brainwaves using a low-cost, non-invasive, headband type of device that collects two-channel EEG signals at frontal lobe. We have performed temporal, spectral and spatial analysis on EEG signals collected during game-playing and found particular trends of EEG signals at certain brain (mental) states for all subjects, and some variations of the trends among different subjects. The analysis results motivate us to design an adaptive thresholding mechanism to find user-specific thresholds for a classifier that controls mobile applications.

***Index Terms*—** Brainwaves, Classification, Mobile application

1. INTRODUCTION

Analyzing electroencephalogram (EEG) signals is one of the promising approaches to understand physical, physiological, and psychological activities of human beings [1]. The recent bio-sensor technologies make it possible to develop low-cost, non-invasive, wireless devices with dry-contact electrodes to capture EEG signals detected at the scalp.

Typically, rhythmic activity of EEG signals is divided into five main frequency bands such as delta (0.5-4 Hz), theta (4-7Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (31Hz and up). Existing studies [2] showed that the brainwaves with different frequencies can be observed due to different brain (mental) states such as deep sleep (delta), drowsiness (theta), relaxed awareness (alpha), attention (beta), and fast activity binding (gamma).

In brainwave research, EEG recordings are mainly used to diagnose brain diseases such as Alzheimer's disease. It has potential to aid patients in their early diagnosis [3] by investigating the difference between normal signals and abnormal signals. EEG signals are also applied to evaluate sleep quality [4], learning effect [5], and attentional disorders [6]. Besides, motor imagery applications can identify movement intentions, and differentiate right and left body parts movements. Therefore, those applications can help people do mental practice, and rehabilitate motor deficits [7, 8]. Preference recognition applications, such as music [9, 10] and smell [11], are potentially useful, since they can provide personalized recommendations integrating current recommendation systems.

Most research work have been done with invasive, wired, multi-channel devices with wet-gel electrodes. Rather, we try to show the practicality of using a cheaper, non-invasive device with fewer channels. There are some tentative works with such portable devices, e.g., negative/positive emotion tracking during game-playing [12] and studies of attention and memory enhancement [13]. Utilizing the knowledge from existing work, we develop mobile applications controlled by brainwaves.

Given the availability of EEG technology and studies, this paper discusses the feasibility of development of mobile applications controlled by brainwaves using a low-cost, non-invasive, headband type of device that collects EEG signals at frontal lobe. The spectral and spatial analysis are performed on EEG signals collected during game-playing. The analysis results motivate us to design an adaptive thresholding mechanism to find user-specific thresholds for a classifier that controls mobile applications.

Main contributions of the paper are as follows.

- We have investigated spectral and spatial features of EEG signals during game-playing and found a) particular trends of EEG signals at certain brain (mental) states for all subjects, and b) some variations of the trends among different subjects.
- Based on the finding a), we have developed mobile applications controlled by brainwaves.
- According to the finding b), we have designed a user-specific adaptive thresholding mechanism for a classifier.

The reminder of the paper is organized as follow. Section 2 describes our experiment method for data collection and feature extraction. Section 3 presents data analytics results of the experiment. Section 4 introduces feasibility and usability of EEG-based mobile applications and controls, followed by conclusion.

2. DATA COLLECTION

2.1. Method

We use a wireless headband device named InteraXon MUSE [14] for recording frontal lobe EEG, including 4 scalp electrodes and 2 reference electrode. According to the international 10-20 system, the location for these 4 electrodes are FP1, FP2, TP9, TP10. All 4-channel data were sampled at 3520Hz, and down sampled to 220Hz. In this work, we use 2 channels FP1 and FP2.

We have collected EEG signals for playing a game, named "Where is Wally?". As illustrated in Figure 1-(a), a subject finds and clicks "Wally" in a given picture on screen. 15 subjects (11 male and 4 female) are participated this experiment. Subjects are asked to play 3 games (i.e., 3 different pictures) with no time limit (Game 1), 60 seconds limit (Game 2) and 40 seconds limit (Game 3), respectively, in sequence with 20 seconds break between games as described in Figure 1-(b). For Games 2 and 3, if subjects could not find Wally within the time limits, then we ask them to play the same game again until they find. During Game 3, subjects will hear an alarm sound per sec for last 10 seconds while they will not here it

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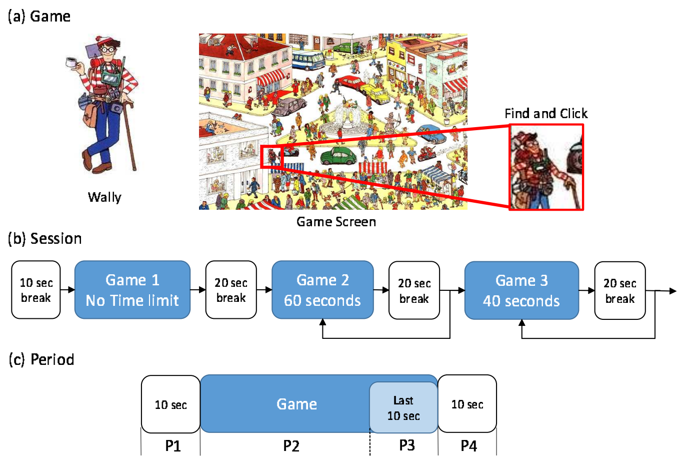

Fig. 1. Instruction of Experiment.

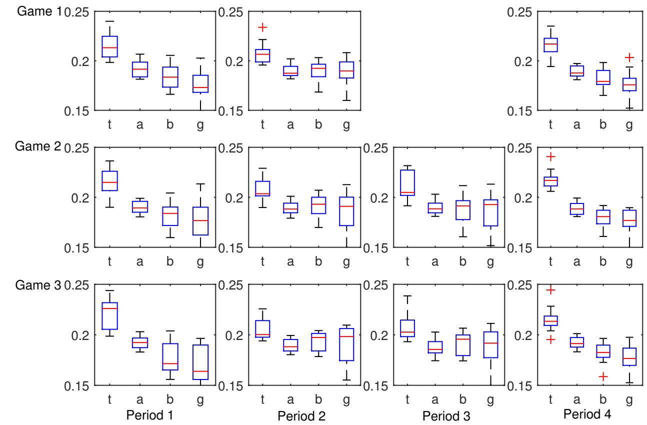

Fig. 2. Comparison of periods (FP1).

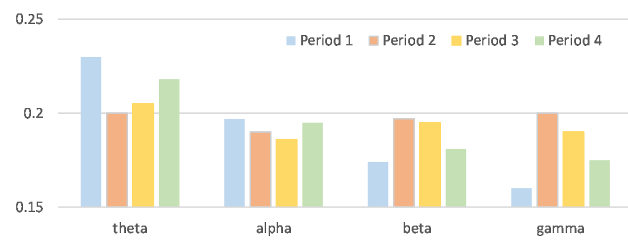

Fig. 3. Comparison of medians for Game 3 (FP1).

in Game 2. Besides, we intentionally remove Wally from the picture for Game 3. We let subjects play a few trials of Game 3 until they want to quit.

We define a term called Period in Figure 1-(c). Each game has 3 (Game 1) or 4 (Games 2 and 3) periods such as "Before a game" (Period 1), "During a game" (Period 2), "Last 10 seconds" (Period 3), "After a game" (Period 4). Thus, Game 1 does not have Period 3.

2.2. Feature Extraction

We consider EEG signals within a window of 1 second with 50% of overlap-shifting. Thus, at every half second, we retrieve twelve features of two types as follows:

- As spectral features, we apply a Hanning window function to the windowed EEG signals followed by FFT to retrieve average log power P_b of frequency bands such as theta (4-7Hz), alpha (8-13Hz), beta (14-30Hz) and gamma (31-50Hz). Then, we compute the log power ratio R_b defined by

$$P_b = \sum_{f=F_b^{min}}^{F_b^{max}} \frac{V_f}{F_b^{max} - F_b^{min}} \quad (1)$$

$$R_b = P_b / \sum_{\forall b} P_b \quad (2)$$

where V_f is the log power of the frequency f and $b \in \{theta, alpha, beta, gamma\}$.

- As spatial features, we compute asymmetry of average log power of the aforementioned frequency bands by subtracting P_b of FP1 (left) from P_b of FP2 (right) for all b.

3. DATA ANALYSIS

This section discusses the analysis results in terms of (i) EEG features among different games, periods and trials (ii) cluster analysis, (iii) subject similarity, and (iv) classification accuracy.

3.1. Feature analysis

3.1.1. Comparison of Periods

Figure 2 shows the percentiles of average log power ratio of four bands over periods at FP1 for all subjects. Each row of the figures indicates Game, and each column indicates Period. Red line indicates median value, and red plus sign indicates outlier. Here are some remarkable observations in the figures.

- Medians and means of alpha in Periods 1 and 4 are higher than those of beta/gamma while medians and means of alpha in Periods 2 and 3 become smaller than those of beta/gamma.
- Medians of theta/alpha decrease in Periods 2 and 3 and increase again in Period 4. In contrast, medians of beta/gamma increase in Periods 2 and 3 and decrease again in Period 4.
- Considering the log power ratio of frequency bands, we observe the difference between game-playing periods (i.e., P2 and P3) and non-game-playing periods (i.e., P1 and P4). Those trends are clearly shown in Game 3 as summarized in Figure 3. It seems that EEG signals are well-modulated between game-playing and non-game-playing due to subjects being used to play games and take a break.

Note that we have observed similar trends at FP2, whose figure is omitted due to page limitation.

3.1.2. Comparison of Trials

Figure 4 shows the percentiles of log power ratio of four bands at FP1 for all subjects. In this figure, each row indicates trial of Game3, and each column does Period. As we expect, we have observed the same trends over different trials as discussed in *3.1.1*.

However, we have found the different trend in Beta and Gamma asymmetry in different trials. Figure 5 shows Beta and Gamma asymmetry of (i) the first trial of different Games and (ii) different trials of Game 3 during Period 2. Red lines indicate median, and blue circles indicate mean values.

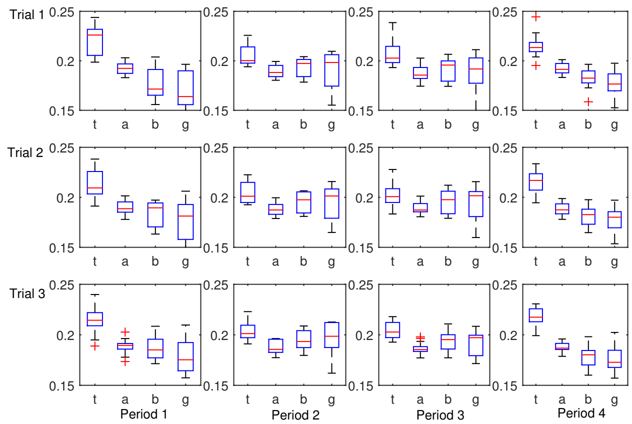

Fig. 4. Comparison of trials of Game 3 (FP1).

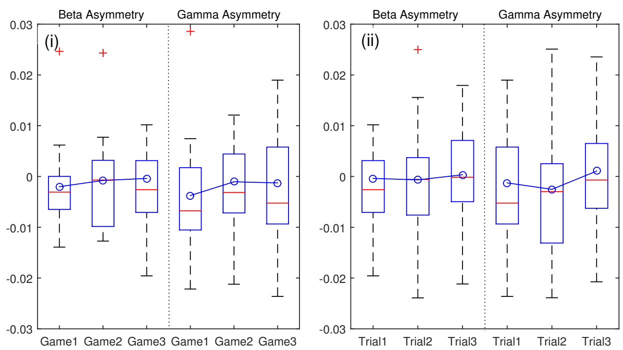

Fig. 5. Beta and Gamma asymmetry during Period 2 of (i) the first trials of different Games, and (ii) different trials of Game 3.

- In Figure 5(i), medians of both Beta and Gamma asymmetry values increase at Game 2 and drop at Game 3. It seems that subjects feel less focus due to familiarity with the game.
- In Figure 5(ii), median values keep increasing as subjects play Game 3 more and more, especially for Gamma asymmetry. This seems to contradict the above observation. We claim that this is an indication of frustration.
- Variances of both Beta and Gamma asymmetry values increase with trials. This might be an indication of subject-specific response to the game-playing. That is, some subjects feel bored or frustrated while the others still get excited to find Wally.

3.2. Cluster Analysis

Based on the observation above, we refine features into the followings: the sum of log power ratio of theta and alpha, the sum of log power ratio of beta and gamma, beta asymmetry, and gamma asymmetry; i.e., eight features.

Figure 6 plots cluster centroids of four Periods (for the first trial of Game 3) in a subspace with three principal components. As you see, game-playing period (P2 and P3) and non-game-playing period (P1 and P4) are clearly differentiated. In this experiment, we could not see significant difference between P2 and P3 by t-test, except some subjects (e.g., Subjects 3, 10, 11). We understand that those subjects played in a hurry and felt tense due to alarm sounds.

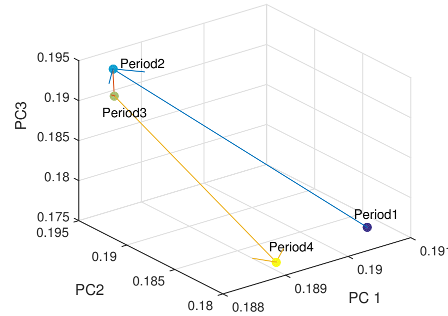

Fig. 6. Plot of cluster centroids over different periods.

3.3. Subject Similarity

As we realized from the feature and cluster analysis, EEG signals are subject-specific. In order to verify that, we compute self-similarity and cross-similarity for each period as suggested in [15]. Here, the self-similarity and cross-similarity are defined by an average distance of signals within a single subject and an average distance of signals between different subjects, respectively, using standardized Euclidean distance. The small value implies high similarity.

Table 1 shows that self-similarity is higher than cross-similarity for all subjects. This result motivates us to design a user-specific adaptive thresholding mechanism. It also shows us the feasibility of subject identification.

Table 1. Subject self-similarity and cross-similarity

	Period 2		Period 4	
SID	self	cross	self	cross
1	3.858	3.964	3.809	4.169
2	3.707	4.069	3.757	4.478
3	3.549	6.762	3.766	5.788
4	3.679	4.601	3.739	4.651
5	3.827	4.577	3.807	4.748
6	3.768	4.219	3.743	4.296
7	3.846	4.486	3.805	4.568
8	3.580	4.469	3.724	4.388
9	3.858	3.928	3.806	4.864
10	3.735	5.831	3.660	5.199
11	3.837	5.536	3.757	5.684
12	3.734	4.300	3.818	4.589
13	3.794	4.465	3.589	5.312
14	3.767	4.118	3.759	4.517
15	3.785	4.554	3.832	5.048

3.4. Classification

This subsection compares the classification accuracy of four approaches using a common centroid for all subjects (CC), a user-specific centroid (UC), a user-specific k-nearest-neighbor (kNN), and a user-specific threshold with the minimum error rate (ME). As training data, we take samples for 10 seconds of each period of the first trial of Game 3, and we use samples from the second trial of Game 3 as testing data.

CC: As a baseline classifier, we compute centroids of classes (i.e. periods) from the training data of all subjects. Each testing data is labeled by one of the classes, whose centroid is the closest to it.

UC: The second classifier is similar to the first one except that we compute centroids of classes from the training data of each subject. Thus, we classify testing data of each subject based on the user-specific centroid.

kNN: With this classifier, each testing data is classified by a majority class of its k-closest training data of each subject in terms of standardized Euclidean distance. Note that we ignore to evaluate kNN using training data of all subjects due to high time complexity.

ME: For this classifier, we compute threshold with the minimum classification error as follows:

[Step 1]: For each class c, compute medoid $\vec{m}_c$ from N_c training samples for class c.

[Step 2]: For each class, compute standardized Euclidean distances between N_c samples and the corresponding medoid by $d_c^k = dist(\vec{s}_c^k, \vec{m}_c)$, $k = 1, \ldots, N_c$ where $\vec{s}_c^k$ is the k-th sample of class c.

[Step 3]: Consider $\{d_c^k\}$ as a set of tentative thresholds for class c. Based on each of the thresholds, compute FPR_c^k, the number of false positive samples over the total number of samples of all classes except class c, and TNR_c^k, the number of true negative samples over the total number of samples of class c.

[Step 4]: Compute error rates defined by

$$\text{e}_c^k = (\text{FPR}_c^k + \text{TNR}_c^k)/2 \quad (3)$$

and generate an error rate set, ER$= \cup_{\forall c, \forall k}\{\text{e}_c^k\}$.

[Step 5]: For each testing sample $\vec{t}$, compute distances from the sample to medoids, i.e., $\{dist(\vec{t}, \vec{m}_c)\}$ for all classes.

[Step 6]: Select d_c^k as a threshold, whose corresponding error rate is the smallest in ER.

[Step 7]: Check if d_c^k exceeds the corresponding $dist(\vec{t}, \vec{m}_c)$. If it is true, then label the testing sample as class c. Otherwise, select another d_c^k with the next smallest error rate in ER and repeat Step 7.

We evaluate 4-class (4 periods) classification and 2-class (P2 and P4) classification. Table 2 shows the 2-class classification accuracy because we develop mobile applications based on the 2-class classifier. As expected, the proposed ME classifier outperforms the other approaches. Some subjects (e.g., Subject 2, 3, 8, 13, 15) show relatively high accuracy of around 80%. Some studies claim that subjects are intentionally able to relax through daily or repeated training. Training subjects to improve the accuracy is left for the future work.

Table 2. Classification Accuracy (%)

SID	Common Centroid	User Centroid	k-NN (k = 5)	Minimum Error
1	67.80	69.46	70.37	74.64
2	71.41	75.14	77.28	77.28
3	67.52	76.97	79.12	82.41
4	65.52	65.97	67.24	71.21
5	64.63	68.52	70.12	72.14
6	70.33	72.99	73.68	75.31
7	55.13	65.92	66.71	68.97
8	77.11	77.27	78.64	78.64
9	72.91	72.50	74.51	75.10
10	57.96	60.67	61.33	65.45
11	60.52	65.03	67.15	72.42
12	65.44	74.99	75.23	77.74
13	70.51	77.37	77.37	81.37
14	67.00	74.73	75.82	77.45
15	73.15	76.27	78.37	78.93
Avg	67.13	71.59	72.86	75.27

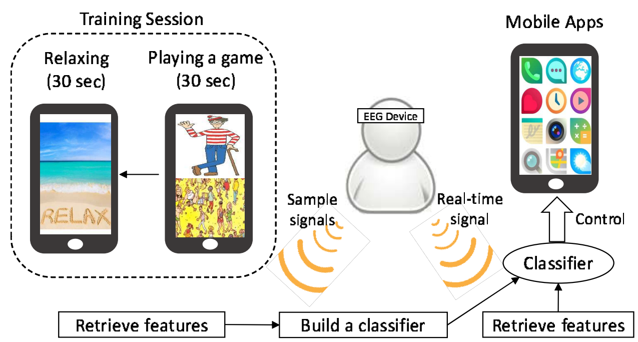

Fig. 7. A system flow for controlling mobile applications.

4. MOBILE APPLICATION

The previous section shows us the feasibility of building a classifier based on user brainwaves. Utilizing the classification capability, we try to control mobile applications. EEG signals are retrieved from MUSE to a mobilephone via Bluetooth.

4.1. State Evaluation

In this paper, we focus on a 2-states classifier. At the beginning of application use, a user is asked to go through a 1-minute training session. As illustrated in Figure 7, the session includes 30 seconds of game-playing and 30 seconds of relaxing. We expect that a user stays an attention state (A) for the first 30 seconds, and a relaxation state (R) for the later 30 seconds. From the session, we collect 120 samples (i.e., feature vectors), i.e., 60 from A state and 60 from R state. Based on these training samples, we build a ME classifier with user-specific thresholds as explained in the previous section.

Then, we start collecting and classifying the real-time EEG signals. In order to make up for the classification error, we utilize a winner-take-all scheme to determine which state a user is in. Also, this scheme can avoid possible fluctuation of classified states. For example, given the recent h real-time samples $\vec{r}_{t-h+1}, \vec{r}_{t-h+2}, \ldots \vec{r}_t$, we obtain h state values $c_{t-h+1}, c_{t-h+2}, \ldots, c_t$ by a classifier. c_t is a classified state of a sample $\vec{r}_t$, e.g., $c_t \in \{1(\text{A}), 2(\text{R})\}$ The current user state S_t is computed as a weighted majority among the state values, which is defined by

$$S_t = \begin{cases} 1 & \text{if } \sum_{i=t-h+1}^{t} w_i * c_i \leq \frac{1+2}{2} * \sum_{i=t-h+1}^{t} w_i \\ 2 & \text{otherwise} \end{cases} \quad (4)$$

where $w_{t-h+1} \leq w_{t-h+2} \leq \ldots \leq w_t$.

4.2. Example Applications

This subsection introduces three mobile applications that we develop and a few other example applications.

- Toggle: A simple light-on/off is controlled by the current user state S_t. Once a user enters one state from another state, a switch will be toggled. Other possible applications might be camera shutter control, app start-up, etc.

- Continuous action: A sound volume is controlled by the duration a user stays in the same state. The volume keeps increasing/decreasing as long as a user is in an attention/relaxation state more than the pre-defined time. This type of control can be used for the speed control of a car-racing game or the power control in "Angry Bird". For example, the power level can be increased by focusing, and a bird can be released once a user enters a relaxation state.
- Pattern: A screen unlock application is constructed by registering a user-specific pattern that is a set of state-duration pairs. For example, a user stays in an attention state for 3 sec followed by staying in a relaxation state for 2 sec. In this case, the user's pattern will be $\{(A,3),(R,2)\}$. Once the pattern is found, the screen will be unlocked. As an alternative way, the pattern might be generated by a user's response to images. An application tries to monitor brain states when a user looks at a particular set of images in a given image pool. For example, a user looks at images of "friend", "cake", and "car" in order, and then attention, relaxation, and attention states are monitored, respectively. In this case, the user's pattern will be $\{(A,i1),(R,i2),(A,i3)\}$.

5. CONCLUSION

Given the availability of EEG technology, this paper discusses the feasibility of development of mobile applications controlled by brainwaves using a low-cost, non-invasive, headband type of device that collects two-channel EEG signals at frontal lobe. We have investigated spectral and spatial features of EEG signals during game-playing and designed a user-specific adaptive thresholding mechanism for a classifier. Using the proposed classifier, we have developed a few mobile applications controlled by brainwaves to verify the feasibility and practicality.

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