EEG band powers for characterizing user engagement in P300-BCI

Yichuan Liu, *Student Member, IEEE*, Hasan Ayaz, *Member, IEEE*, Banu Onaral, *Fellow, IEEE* and Patricia A. Shewokis, *Member, IEEE*

***Abstract*—An asynchronous P300-based brain computer interface (BCI) allows users to operate the BCI at their own pace by being able to detect a user's engagement. In our previous work, band powers has been shown to be able to provide additional information for characterizing user engagement and yielded better performance compared to the use of only the amplitudes of event-related potentials. In this follow up study, 19 subjects participated in an experiment which was designed to further evaluate additional predictors of user engagement using band powers. In addition to the regular P300 attended condition, two not-engaged conditions were considered: one with the P300 stimulus matrix still shown (control 1) and the other with stimulus covered by a blank screen (control 2). Alpha and beta band activities decreased in the order of control 2, control 1 and attended. Furthermore, the attended condition had lower delta activity compared to the control conditions. Classification results indicated that band powers were better at differentiating attended and control 2 conditions. Using band powers as additional features resulted in a moderate to moderately large (dz= 0.52 to 0.74) improvement over the classification of the two conditions.**

I. Introduction

Brain-computer interface (BCI) interprets brain signals and translates them into output commands for direct communication between the brain and the external world [1]. The P300 paradigm is among the most popular BCI paradigm for its high performance and ease of use. The classic P300-BCI proposed by Farwell and Donchin in the 1980s [2] shows the participants a matrix of icons and the row and column of the matrix would be intensified randomly. The participants were asked to focus attention on the icons they want to choose. As in a typical oddball paradigm, the rare events of intensification of the target row and column would elicit an event-related potential (ERP) which can be detected by proper signal processing. This ERP contains the P300 component which mainly contributed to the differentiation of the target and non-target intensification though studies showed that other components such as N200 also contributed to the control of the BCI [3].

The classic P300-BCI works in a synchronized mode which requires the user to follow the pace of the BCI. A practical BCI should be able to detect user engagement for allowing them to operate the BCI with the pace of their own. Several asynchronous P300-BCIs have been proposed in the literature [4-7]. They detect user engagement either by the statistics of the EEG amplitudes [4-6] or incorporating another paradigm such as steady state visually evoked potentials (SSVEP) [7]. In [8], we proposed using band powers for characterizing user engagement. The preliminary results from 9 subjects showed a significant difference in the delta and beta band for engaged sequences of intensifications compared to not being engaged. Additionally, combining features extracted from the EEG amplitudes and band powers yielded higher prediction accuracy which indicated band powers contains additional information for characterizing user engagement.

In this study, 19 subjects were recruited for a follow up study using band power for user engagement characterization. For further testing the robustness of the proposed approach, two different types of non-engagement situations were considered: one with a stimulus shown and the other with stimulus not shown. The former case represents the situation when the subjects were looking at the stimulus screen but not actively engaged with the BCI whereas the latter case represents when the subjects were not looking at the screen.

II. Materials and methods

A. Participants

Nineteen volunteers (12 males, 7 females, ages between 18 and 27 years) participated the study. All participants reported no previous experience with BCIs and no history of neurological disorders. In addition, the participants self-reported that they were not taking any medication known to affect alertness and/or brain activity. Three subjects (10, 13 and 19) with BCI accuracy scores lower than 70% were rejected from the study due to possible P300-BCI illiteracy.

B. Recording

EEG data were recorded using Neuroscan NuAmps from 9 locations (FCz, Cz, CP3, CPz, CP4, P3, Pz, P4, and Oz) according to 10-20 international system. Left and right mastoid was used as ground and reference, respectively. Data were sampled at 250Hz and filtered from 0.5 to 40Hz.

C. P300 stimulus

A 3×3 matrix of spatial navigation icons was used for P300 stimulus presentation as we described before in [9] using standard row and column stimulus [2]. The stimulus duration (StD) was 80ms and the inter-stimulus-interval (ISI) was 160ms. For each stimuli, there is a corresponding data epoch,

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Y. Liu, H. Ayaz, and B. Onaral are with the School of Biomedical Engineering, Science and Health Systems, Drexel University, Philadelphia, PA 19104 USA (e-mail: yl565@drexel.edu, ayaz@drexel.edu, banu.onaral@drexel.edu)

P. A.Shewokis is with the College of Nursing and Health Professions & School of Biomedical Engineering, Science and Health Systems, Drexel University, Philadelphia, PA 19104 , (USA phone: 215-571-3709; fax: 215-571-3718; e-mail: pas38@drexel.edu)

which is from 0 to 800ms (200 samples) after the onset of each stimulus. In a *sequence* of stimuli, each row and column stimulus was presented exactly once in a pseudo random order. Each sequence included 6 epochs, which is a total of (160+80)*5+800=2000ms. In a *run*, 10 sequences of stimuli (or 60) were presented to the subjects, which is a total of (160+80)*59+800=14960ms.

D. *Protocol*

Subjects sat comfortably in front of a LED monitor in a dimly lighted room. Each subject participated in 3 sessions. Each session included 16 runs. Figure 1 shows the time line of a run.

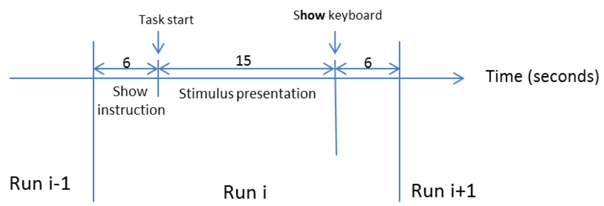

Figure 1. Timeline of a run

There are three types of runs: *attended*, *control 1* and *control 2*:

- For *attended* runs, subjects were instructed to attend to an icon and mentally count the number of times it flashes.
- For *control 1* runs, P300 stimulus was still shown. In addition, a red plus sign was shown randomly at one of the four locations between the icons around the center icon. Subjects were instructed to fix their gaze at a red plus sign, ignore the flashes and relax.
- For *control 2* runs, the P300 stimulus was covered by a blank screen and subjects were instructed to fix their eye gaze at a red plus sign appeared at the center and relax. This condition is representing the case when the subjects were not looking at the stimulus screen.

Each session included 8 *attended*, 4 *control 1* and *4 control 2* runs which were presented in a pseudo random order.

III. Data Analysis

For each *sequence* of data, we considered the problem of determining which type of run (*attended*, *control 1* or *control 2*) the data best matched. Since the classification of *control 1 vs. control 2* was not of interest for detecting user engagement, we considered the following three binary classification problems: *attended vs. control 1*, *attended vs. control 2*, and *attended vs. both control 1 and control 2*. In addition, three approaches were considered: P300 scores, band powers and hybrid in which both P300 scores and band powers are used in the feature level.

A. *P300 scores*

EEG signals were band-pass filtered 0.5 to 12 Hz using 200 order finite impulse response (FIR) filter. The data epoch for each stimulus were concatenated to form a single feature vector for each channel. For reducing the dimension of the feature vector, EEGs were down sampled to 41.7Hz by taking one sample for every six samples. Epochs of target stimulus from *attended* runs were labeled as 1. All the other epochs were labeled as 0. Step-wise linear discriminant analysis (SWLDA) was used to train classifiers. The P300 score which was used for estimating the presence of P300 wave is defined as follows:

$$s_{ERP} = \max_{i=1,2,3} s^{i}_{row} + \max_{i=1,2,3} s^{i}_{col}$$

Where s^{i}_{row} and s^{i}_{col} were scores given by the classifiers for the ith row and column stimulus, respectively.

B. *Band powers*

For each *sequence*, we estimated the periodogram (Hann window applied) of each channel. The band power of delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz) and beta (13-30Hz) activities were then extracted as features. A SWLDA was applied for classification. Statistical analysis has been conducted for testing the effect of band (4 levels: delta, theta, alpha and beta), condition (3 levels: Attended, Control 1and Control 2) and their interaction on band powers. For the main analysis, linear mixed models (LMM) have been employed for each channel with band, condition and their interaction as fixed effects, band power as observations and a random intercept for capturing between-subject variations. For post hoc analysis, dependent samples pair-wise comparisons has been employed to compare the means of band powers for different conditions. A significance criterion α= 0.05 was used for all analyses. To control for Type I error rate, False Detection Rate (FDR) was applied [10]. Cohen's dz effect size index is used to interpret the findings.

C. *Hybrid*

The P300 scores and band powers features were both used for characterization. The two approaches were combined at the feature level. A SWLDA was employed for classification for selecting only those features that significantly improved classification.

IV. Results

Table I-IV summarizes the significant results from the statistical analysis. Although we tested the nine channel, results are reported for the primary midline channels of FCz, Cz, CPz, Pz and Oz. Results indicated significant fixed effects of condition, band and band by condition interaction. Post hoc analysis revealed significantly higher delta and beta activity for *control 1* compared to *attended*, significantly higher delta, alpha and beta activity for *control 2* compared to *attended* and significantly higher alpha and beta activity for *control 2* compared to *control 1*. Figure 4 shows the grand average power spectral density (PSD) for the three conditions at Pz.

Table V-VII shows the leave-one-run-out cross-validation results in terms of area under the receiver operating characteristic curve (AUC). Bold values shows the highest AUC among the three approaches for each row.

TABLE I. MAIN ANALYSIS

Channel	Fixed effect		
	Condition $F_{(2,30693)}$	Band $F_{(3, 30693)}$	Interaction $F_{(6, 30693)}$
FCz	112.2*	4272.5*	23.8*
Cz	99.3*	3325.4*	21.7*
CPz	85.8*	4368.3*	20.7*
Pz	90.9*	4717.8*	32.8*
Oz	68.5*	4600.2*	18.8*

Note: *p<0.0005, Benjamini-Hochberg corrected

TABLE II. CONTRAST, CONTROL 1 VS. ATTENDED

Channel	$t_{(7662)} = (X_{control1} - X_{attended})/SE$			
	delta	theta	alpha	beta
FCz	5.8*	-2.8^	NS	10.2*
Cz	4.2*	-3.3#	NS	9.7*
CPz	3.9*	-4.8*	3.2#	8.3*
Pz	6.0*	2.1^	NS	8.1*
Oz	NS	-2.9^	NS	5.0*

Note: *p<0.0005, #p<0.005, ^p<0.05, Benjamini-Hochberg corrected

TABLE III. CONTRAST, CONTROL 2 VS. ATTENDED

Channel	$t_{(7662)} = (X_{control2} - X_{attended})/SE$			
	delta	theta	alpha	beta
FCz	9.4*	NS	15.0*	20.6*
Cz	7.7*	NS	14.2*	19.4*
CPz	5.4*	NS	14.3*	18.5*
Pz	6.3*	-4.6*	16.2*	21.0*
Oz	4.9*	-2.9*	14.2*	18.1*

Note: *p<0.0005, #p<0.005, ^p<0.05, Benjamini-Hochberg corrected

TABLE IV. CONTRAST, CONTROL 2 VS. CONTROL 1

Channel	$t_{(7662)} = (X_{control2} - X_{control1})/SE$			
	delta	theta	alpha	beta
FCz	3.2#	NS	13.7*	9.0*
Cz	3.0#	NS	12.6*	8.4*
CPz	NS	3.1#	9.6*	8.9*
Pz	NS	-5.8*	12.6*	11.2*
Oz	3.5#	NS	13.2*	11.3*

Note: *p<0.0005, #p<0.005, ^p<0.05, Benjamini-Hochberg corrected

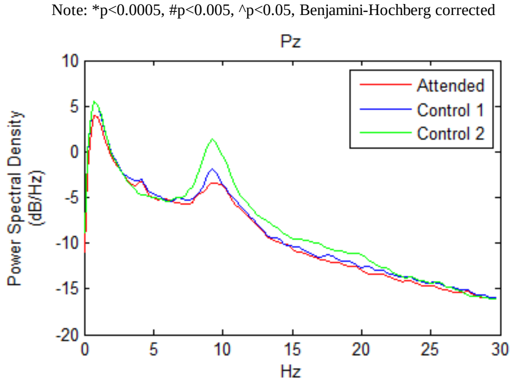

Figure 2. Grand average PSD for Pz.

Paired t-tests revealed that there are significant differences in AUC values between hybrid and P300 approach for *attended vs. control 2* (t(15)=3.264, p<0.005, Cohen's dz=0.74 [11]) and *attended vs. both control 1 and control 2* (t(15)=2.160, p<0.05, Cohen's dz=0.52). These results indicated significant improved performance of the hybrid approach compared to the P300 approach for differentiating between attended and control 2. No significant differences were found between hybrid and P300 approach for the attended vs. control 1 case.

TABLE V. AUC VALUE FOR ATTENDED VS. CONTROL 1

Subject	**P300 +BandP**	**P300**	**BandP**
1	0.74	**0.82**	0.63
2	0.65	**0.66**	0.46
3	**0.94**	0.92	0.79
4	**0.85**	0.80	0.74
5	**0.85**	0.84	0.76
6	**0.74**	0.67	0.67
7	0.90	**0.91**	0.75
8	**0.83**	0.81	0.76
9	0.85	**0.86**	0.60
11	0.85	**0.85**	0.69
12	0.90	**0.92**	0.76
14	0.79	**0.83**	0.56
15	0.83	**0.87**	0.67
16	**0.77**	0.75	0.68
17	0.75	**0.76**	0.53
18	0.67	**0.74**	0.56
Avg.	0.81	**0.81**	0.66
Std.	0.08	0.08	0.10

TABLE VI. AUC VALUE FOR ATTENDED VS. CONTROL 2

Subject	**P300 +BandP**	**P300**	**BandP**
1	**0.93**	0.91	0.74
2	0.95	**0.96**	0.79
3	**0.98**	0.89	0.95
4	**0.91**	0.86	0.86
5	**0.95**	0.88	0.89
6	**0.90**	0.78	0.89
7	0.97	0.97	0.90
8	**0.99**	0.92	0.97
9	0.93	**0.94**	0.84
11	0.80	**0.84**	0.67
12	**0.95**	0.94	0.90
14	**0.91**	0.87	0.76
15	**0.99**	0.94	0.96
16	**0.96**	0.78	0.94
17	**0.79**	0.79	0.69
18	**0.98**	0.93	0.84
Avg.	**0.93**	0.89	0.85
Std.	0.06	0.06	0.09

TABLE VII. AUC VALUE FOR ATTENDED VS. CONTROL 1 & CONTROL 2

Subject	P300 +BandP	P300	BandP
1	0.86	**0.86**	0.69
2	**0.77**	0.76	0.63
3	**0.95**	0.91	0.84
4	**0.89**	0.85	0.76
5	**0.89**	0.84	0.79
6	**0.81**	0.73	0.80
7	**0.94**	0.94	0.81
8	**0.89**	0.84	0.85
9	0.87	**0.90**	0.70
11	0.83	**0.83**	0.73
12	0.92	**0.92**	0.78
14	**0.83**	0.82	0.58
15	**0.91**	0.91	0.73
16	**0.85**	0.77	0.81
17	0.72	**0.75**	0.59
18	0.80	**0.83**	0.65
Avg.	**0.86**	0.84	0.73
Std.	0.06	0.06	0.09

V. DISCUSSION

In this study, band powers were evaluated as predictors for P300-BCI user engagement detection. Two different resting conditions, one with a stimulus shown (control 1) and the other with a stimulus not shown (control 2) were considered. For all channels, alpha and beta activities were decreasing in the order of control 2, control 1 and attended. Attended condition also has lower delta activity compared to the control conditions. The lower rhythmic activity in attended condition may be due to the high level of mental workload, attention and information processing [12-14].

For user engagement detection, attended vs. control 2 comparison shows higher AUC values compared to the attended vs. control 1 comparison for all three approaches. This indicates the influence of the stimulus presentation on both the P300 score and band power characterization. However, band power seems to be more severely affected.

Utilizing band power features as additional predictors showed significantly higher performance compared to using only P300 scores (which were extracted from the amplitudes of the ERPs) for differentiating *attended* and *control 2* with a moderate to moderately large effect size (dz=0.74). For attended vs. control 1 case, no significant difference in performance was detected.

The idea of using only band power for user engagement is tempting since it has the potential of working independent of a P300-BCI and without the stimulus timing information. For using only the band power for classification, only the attended vs. control 2 case showed comparable performance (AUC=0.85) to using P300 score (AUC=0.89). These results imply that band powers are better at differentiating the non-engaged condition during which a blank screen has been shown to the subjects.

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