NARROW BAND SPECTRAL ANALYSIS FOR ONSET DETECTION IN ASYNCHRONOUS BCI

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SUMMARY: Asynchronous Brain-Computer Interfaces (BCI) offer more natural mode of human-machine interaction, allowing users to make voluntary and self-paced mental activities. However, it is difficult to discriminate intentional user control from idle with this approach. In this paper, we propose an approach that requires minimal user training for accurate onset detection of real movements using optimal spectral features from selected electrodes. We obtained true positive rates of 100%, 88%, and 73% for 3 subjects respectively. The results also indicate a potential of the approach for detecting onset of imagery movements.

INTRODUCTION

In recent years, there has been active research on techniques for detecting mental activities in asynchronous BCI designs [1][2][3]. In our approach here, narrow band spectral analysis of the electroencephalogram (EEG) from 8~45Hz is conducted, because it covers mu, beta, and lower gamma frequency components, each having its own distinctive characteristics during real and imagery movements [4]. The onset detector presented in this paper has combined EEG spectral feature extraction, feature selection to reduce feature space dimension, and a decision mechanism to detect onset from classification results within a moving window. We present the methodology in the following section, followed by results and discussions, and a brief conclusion.

MATERALS AND METHODS

Subjects and motor task: 3 right-handed subjects (2 males and 1 female) were sitting in an arm-chair with right arm resting on the arm rest. They were asked to perform the same real movements 40 times on their own pace in one session (session lasted 534, 338 and 400 seconds for Subject 1, 2, and 3, respectively). The subjects were asked to leave at least 4 seconds between two movements. There was no prior training session, and the subjects had no experience of similar experiments. The designed movements were: extending right wrist, holding for about 1~2 seconds, and relaxing.

EEG and EMG Acquisition: EEG signals were recorded with 64 electrodes according to the International 10-20 Standard (ActiveTwo, Biosemi, The Netherlands). We used electromyogram (EMG) to record muscle activities for establishing correct onset and offset time points for self-paced movements. This allows training data to be correctly labelled according to the real movement activities. EMG was recorded bipolar, from extensor carpi radialis muscle. Both EEG and EMG were sampled at 1024Hz, but downsampled to 256Hz for offline analysis. No artefact rejection or EOG correction was employed.

EEG data labelling: The continuous EEG data were labelled into 4 classes. Samples of 1.5 seconds prior to EMG onset were labelled as “preparation”. Samples between an EMG onset and offset of one movement were labelled as “execution”. Samples of 1.5 seconds after an EMG offset were labelled as “after execution”. Samples that did not fall into one of the above classes were labelled as “baseline”, because these samples should indicate no EEG activity with respect to the right wrist movement.

Feature extraction and selection: First, EEG data were filtered with common average reference method. To extract features for narrow band spectral analysis, the Thomson Multitaper Method was used to estimate the power spectral density (PSD) of each EEG channels over a 1 second moving window with an overlap of 7/8 seconds (i.e., the moving window is shifted 1/8 of a second each time). The PSD over 8~45Hz was sampled. Over 8~27Hz it was sampled and averaged every 2Hz, and over 28~45Hz it was sampled and averaged every 3Hz, resulting in a vector of 16 features. For 64 channels, there are 1024 features in total.

Davis Bouldin Index (DBI) [5] was used to select a subset of the best features. N features (with smallest DBI values) that maximise the validity of “preparation” against other classes were selected, and another N features that maximise the validity of “execution” against other classes were also selected. Therefore, $2N$ features were used for classification and evaluation.

Classification and onset recognition: A naïve Bayes classifier was used to deal with the 4 class problem, which classifies each sample in the testing data as either “preparation”, “execution”, “after execution” or “baseline”. To find an EEG onset, a 1.375 second (11 samples in feature space) moving decision window was applied on the classified results. In the moving window, if there were 2 (for Subjects 1 & 2) or 3 (for Subject 3) predicted “preparation”, followed by 3 “execution”, then the current position of this window was recognised to be an EEG onset. In performance evaluation this predicted EEG onset is considered correct, if there is a real movement onset that occurs either 2 seconds before or after this predicted point.

The evaluation was conducted by 10-fold cross-validation. Each fold had 4 trials for testing and 36 trials for training. The number of true-positive (TP) detections and the number of false-positive (FP) detections from all the folds were combined to produce true-false difference (TF%) that is an event-by-event measurement. Given that E is the total number of movements or events, TF% is defined by TF% = (TP/E–FP/(E+FP))*100 [1][*].

RESULTS AND DISCUSSIONS

Classification performance depends on the number of selected features. For each subject, the method was evaluated by cross-validation, with $2N$ (total number of selected features) ranging from 2 to 100. The optimal values of $2N$ are shown in Tab. 1, where the features were selected from 64 channels (1024 features). Subject 1 produced the best overall result, with only 2 FP detections and no missed event. Subjects 2 and 3 produced similar results: though Subject 2 had a higher TF%, whilst Subject 3 had less FP detection. Tab. 1 also shows the averaged time deviation.

The selected channels and frequency components (i.e., features) are also explicitly given in Tab. 3. It is interesting to note that some features selected for Subjects 1 and 2 are from lower gamma band, which dominate the "preparation". Although rarely found in the human EEG, study in [4] has shown the existence of gamma band activities shortly before movement onset, which is then followed by mu rhythm activities.

Previous ERD/ERS research [6] showed that during real movements, EEG activity can be found in both contralateral and ipsilateral hemispheres, but in the case of imaginary movements only contralateral hemisphere gets activated. In order to make the conditions similar to imaginary movements, classification was performed not only on all channels but also on chontralateral channels alone. Tab. 2 shows the results with features selected only from the contralateral hemisphere. With fewer available features, it can be expected that the evaluation performance would be worse. As a matter of fact, only a slight drop in TF% was found for Subject 3, but almost a 10% drop for Subject 1. This is because for Subject 1, the best selected features that optimise the detection of "execution" are from ipsilateral hemisphere which gets activated after the contralateral one during real movements. The results in Tab. 2 indicate a potential of our method for detecting onset of imagery movements.

Table 1: Performance with the optimal number of features selected from 64 channels. Dev is the averaged time between correctly detected onset and real movement onset.

Subject	$2N$	TF%	TP/E	FP	Dev(ms)
1	16	95.24	40/40	2	325
2	10	69.13	35/40	9	788
3	28	59.46	29/40	6	688

[*] Townsend et al. [1] counted multiple detections during an event as a single TP. However, in this paper we counted M detections during an event as a single TP, and add $M-1$ to total number of FP.

Table 2: Performance with the optimal number of features selected from 37 channels on contralateral hemisphere.

Subject	$2N$	TF%	TP/E	FP	Dev(ms)
1	14	86.39	39/40	5	556
2	30	70.91	32/40	4	922
3	40	57.61	29/40	7	575

Table 3: Selected features that give the results as shown in Tab. 1. In each sub-table, left column shows features that optimise the detection of "preparation" and right column shows features that optimise the detection of "execution".

Subject 1 ($2N$=16)	
CP1 34-36Hz	CP4 10-11Hz
FC1 31-33Hz	P4 10-11Hz
CPz 34-36Hz	CP2 10-11Hz
FC1 28-30Hz	P4 8-9Hz
P3 8-9Hz	CP4 12-13Hz
P3 16-17Hz	P2 10-11Hz
FCz 31-33Hz	P4 12-13Hz
P1 10-11Hz	Pz 10-11Hz

Subject 2 ($2N$=10)	
Cz 28-30Hz	CP3 10-11Hz
Cz 26-27Hz	CP1 10-11Hz
FCz 28-30Hz	CP3 8-9Hz
C1 28-30Hz	CP3 12-13Hz
C1 18-19Hz	P1 10-11Hz

Subject 3 ($2N$=28)	
CPz 20-21Hz	P5 18-19Hz
CP3 18-19Hz	CP5 16-17Hz
P2 20-21Hz	P5 16-17Hz
CP3 22-23Hz	Pz 20-21Hz
CP3 16-17Hz	CP3 20-21Hz
CP5 14-15Hz	CP1 20-21Hz
CP5 18-19Hz	CPz 22-23Hz
C3 22-23Hz	CP3 14-15Hz
P5 14-15Hz	CP2 22-23Hz
CP5 12-13Hz	P2 22-23Hz
P5 20-21Hz	CPz 18-19Hz
P5 12-13Hz	CP2 20-21Hz
CP5 10-11Hz	CP1 22-23Hz
P7 18-19Hz	P5 22-23Hz

CONCLUSION

An onset detection method for asynchronous BCI is presented in this paper, which shows some promise for detection of self-paced real movements, and potentially of imagery movements. New experimental protocol and extension to deal with imagery movements will be investigated in our future research. There is also much room for improving the feature selection method.

REFERENCES

[1] Townsend G, Graimann B, Pfurtscheller G. Continuous EEG classification during motor imagery – Simulation of an asynchronous BCI. IEEE Trans. Neural Sys. Rehab. Eng. 2004; 12(2): 258-265

[2] Borisoff JF, Mason SG, Bashashati A, Birch GE. Brain-computer interface design for asynchronous control applications: Improvements to the LF-ASD asynchronous brain switch. IEEE Trans. Biomed. Eng., 2004; 51(6): 985-992

[3] Millan J del R. Adaptive brain interfaces. Communications of the ACM, 2003; 46(3): 74-80

[4] Pfurtscheller G, Neuper C. Motor imagery and direct brain-computer communication. Proc. IEEE, 2001; 89(7): 1123-1134

[5] Bezdek JC, Pal NR. Some new indexes of cluster validity. IEEE Trans. Systems, Man and Cybernetics, 1998; 28(3): 301-315

[6] Neuper C, Pfurtsheller G. Motor imagery and ERD. In: Pfurtscheller G, Lopes da Silva FH. Handbook of Electroencephalography and Clinical Neurophysiology- Event-related Desynchronization, Elsevier, Netherlands 1999, pp. 303-325