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Non-Linear and Spectral EEG Features during a Mental Calculation Task for Asynchronous BCI Control

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Abstract

In this paper a binary BCI control based on mental computation of arithmetic operations is evaluated. Data analysis was performed using information derived from five EEG channels, estimating the detrended fluctuation analysis scaling exponent and the power on β band. The strategy (task and data analysis) was validated on fifteen subjects realizing three experimental sessions on different days. Performance was measured using the area under receiver operating characteristic curve obtaining 0.85 ± 0.079, 0.87 ± 0.071 and 0.87 ± 0.065 for each experimental session.

1 Introduction

Despite that the mechanism used to elicit a response for an asynchronous BCI application intents to be a "natural" mental activity (i.e. imagining to move a limb) the modest proportion of population capable of achieving a satisfactory control of these systems remains as major drawback [1]. Ono et al. [2] have shown that the mean accuracy values may be improved using a more realistic feedback for the training process. ERD/ERS responses can also be elicited during the realization of other activities like imagining a cube rotation, or by another type of cognitive activities such as performing mental calculation [3]. This last activity has been proposed for controlling a BCI, combining fNIRS and EEG techniques [4, 5]. Power et al., have reported accuracy values above 70%, using EEG window lengths of 5-20 seconds. Notwithstanding that these values suggest that it is possible to use such task in a BCI paradigm, the window length used produces a low information transfer rate [6]. This paper explores the feasibility of mental calculation, during shorter time windows, to be used as control for a BCI implementation.

2 Task and Data Collection

EEG data were recorded from fifteen subjects, seven men and eight women, 25.3 ± 3.47 years old, all with completed high school studies. A 32 channel (Fp[z,1,2], AF[7,3,z,4,8], F[7,3,z,4,8], Fc[3,4], T[7,8] C[3,z,4], Cp[3,4], P[7,3,z,4,8], PO[3,4] and O[1,2,z]) montage was used and the signals were digitized at 512 sps with a g.tec USBamp amplifier system, using a bandpass filter between [0.1, 60] Hz and a notch filter at 60 Hz. All subjects were recorded for three sessions on different days (the lapse of time between sessions extended from 6-110 days, according to the time availability of volunteers); each session consisted of two or three runs. In each run the subject was instructed to pay attention to a screen and solve mentally fourteen sets of basic concatenated arithmetic operations. A set was formed by the concatenation of four to six randomly selected simple operations ("+","-","·","/"). The beginning and ending of each set was visually cued by an "X" and an "=" symbol, respectively. At the end of each set, the subject was asked to vocalize the answer.

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As illustrated on figure 1, each set consisted of five different screens: *Cue*, *Begin*, *Operate*, *Answer* and *Rest*, presenting each one for two seconds with a random ISI duration within [625,750] ms. Subjects performed periods of continuous mental solving through the *Begin* and *Operate* screens, and idle periods at the *Rest* screens.

For data analysis, signals were conditioned by removing CAR and lowpass filtered at 40 Hz. Afterwards, signals were analyzed using windows of two seconds synchronized with the screen presentation for the channel selection process, and using sliding windows for an online BCI simulation. Epochs were labeled in relation to solving or resting periods, and only those sets with a correct answer were used for estimating the model and evaluating the performance.

Five different indexes were extracted from EEG data: the power spectral density (PSD) over the four classical bands, δ_{PSD}, θ_{PSD}, α_{PSD} and β_{PSD} using the Welch Periodogram method, and the scaling exponent α_{DFA} obtained using Detrended Fluctuation Analysis (DFA) [7, 8].

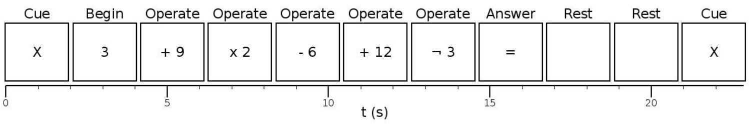

Figure 1: Example of a set of operations used for stimulation, infix notation:$((((3 + 9) \cdot 2) - 6) + 12)/3 = 10$.

3 Methods

3.1 Channel Selection

Channel selection was based on a statistical analysis applied to each electrode as follows. Valid epochs of each session, as synchronized with the screen presentation and correct arithmetic answer, were divided into two sets, *Operating* and *Idle*. To avoid including false positive channels not reflecting a real region of activity, only AF[3,z,4], F[7,3,z,4,8], FC[3,4], C[3,z,4] and CP[3,4] were considered. For each of these channels and each index (δ_{PSD}, θ_{PSD}, α_{PSD}, β_{PSD} and α_{DFA}), the area under the receiver operating characteristic (ROC) curve (AUC) was individually estimated using these two labels. The channels were sorted according to AUC value and the top five of each index were selected. Hence, the five most repeated channels were chosen as the final set.

3.2 Performance evaluation

Using α_{DFA} and β_{PSD} estimated from the five selected channels, evaluation of performance was carried out by both cross-validation (CV) and inter-session identification (iSI). In both cases, performance was measured with AUC values using a data set also labeled as subsection 3.1, but in this case epochs were extracted from sliding windows of two seconds length and overlapped by 70%. The CV process was applied to find support vector machine (SVM) parameters that optimized AUC values using repeated sub-sampling method with 20-folds. The mean and standard deviation were assessed and considered as the final CV performance value. Then, the classification model corresponding to each session was constructed and tested on the remaining two sessions. Therefore for each subject three values of CV were obtained and six related to iSI; Figure 2(a) presents box plots which summarize these results.

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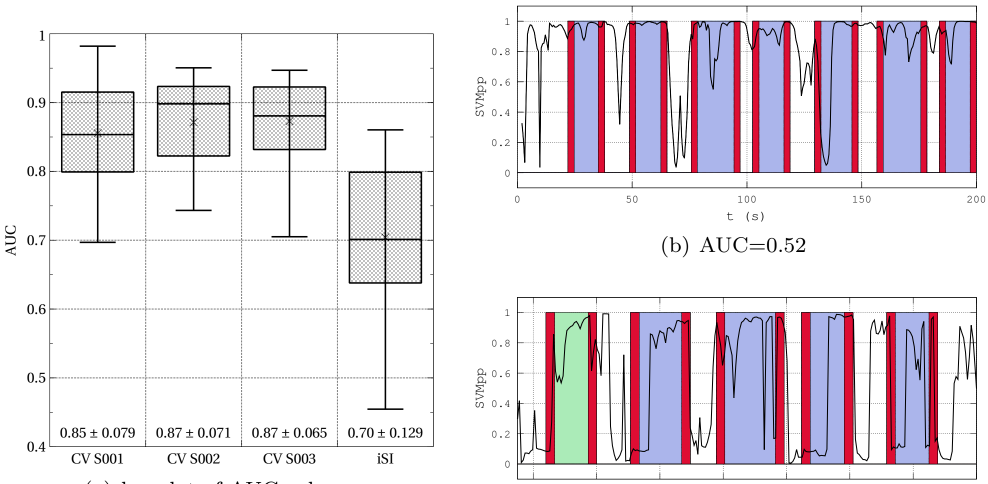
4 Results

Using sliding windows the mean AUC values for CV assessed for each session, were 0.85 ± 0.079, 0.87 ± 0.071 and 0.87 ± 0.065. The distribution of the individual values was above 0.7 for all sessions as can be seen on Figure 2(a). iSI evaluation shows a mean AUC value of 0.7 which is below the CV evaluation but acceptable for a BCI implementation; in particular when considering that for this process, the model used and data identified were recorded in different days. The individual distribution of iSI evaluation shows that about half of the population achieved a value above 0.7, and only two subjects performed below 0.6.

For illustration purposes, Figures 2(b) and 2(c) show two examples of SVM posterior probability estimates (SVMpp) and periods of mental activity. Given that SVMpp is proposed as the control signal for a BCI implementation, it should follow as is manifested in these examples the realization of the mental task, which means that it must be related with the decision to select the command or, for the case studied here, with the periods of mental activity due to mental calculation.



(a) boxplot of AUC values

(b) AUC=0.52

(c) AUC=0.81

Figure 2: The distributions of the AUC values achieved for the three CV sessions and iSI are presented in subfigure (a), the mean and standard deviation values are included over the horizontal axis. Subigures (b) and (c) depict two examples of SVMpp (black line) assessed for two subjects that achieved different AUC values, the light blue and green shadows indicate the periods of mental calculation realization with either correct or wrong answers, respectively, and the red ones indicate the periods for cue presentation and vocalization of the answer.

5 Discussion and Conclusions

Day-to-day activities could be fitted as stimulation paradigms for an asynchronous BCI. Here the utilization of mental calculation is demonstrated to be useful for such context. The results presented in this paper suggest that, for asynchronously controlling a BCI, it seems possible

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to use mental computation with overlapped EEG windows of two seconds length. More experiments are required to assess the potential interference of other factors, such as tiredness, distraction or low attention. Importantly, the AUC values achieved were above 0.8; which appear better than the performance reported on previous publications that also use mental calculation tasks but under different experimental conditions [4, 5]. As can be seen on the examples of Figure 2, the classification output shows a rapid response to the changes of mental activity which is also a desirable condition for a BCI control. This encourages the utilization of mental calculation as a BCI activation paradigm.

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