Computers in Biology and Medicine 64 (2015) 155–162

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

Evaluation of the continuous detection of mental calculation episodes as a BCI control input

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ARTICLE INFO

Article history:
Received 19 October 2014
Accepted 17 June 2015

Keywords:
Mental calculation
Scaling exponent
PSD
BCI
SVM

ABSTRACT

This paper presents an evaluation of the continuous detection of mental calculation episodes, which may be useful for users who strive to operate current BCI paradigms or even for augmenting degrees of freedom. The experimentation consisted in the alternated realization of basic arithmetic mental calculations and resting periods. EEG data were analyzed using sliding windows of 2s length. The experimental population was comprised of fifteen healthy subjects who participated in three sessions on different days. The features used for the classification process were the power spectral density over the beta band ([14–35] Hz) and the scaling exponent obtained via detrended fluctuation analysis. Both indices were estimated over four channels, specifically selected for each subject. The performance was evaluated using the Area Under the ROC Curve (AUC) by measuring the overall classification performance of each experimental session with a cross-validation procedure, and by transferring the model obtained from one session to the others called inter Session Validation (iSV). The best AUC values computed in each cross-validation session were: 0.87 ± 0.067, 0.89 ± 0.056 and 0.88 ± 0.040 respectively; and the iSV provided a value of 0.67 ± 0.122. These high values indicate that a mental calculation paradigm and a combination of features can efficiently control a BCI system. Notwithstanding that several days passed between sessions, the AUC mean value estimated for the iSV is similar to the performance of a motor imagery-BCI calibrated on the same day.

1. Introduction

Brain Computer Interfaces (BCI) can be divided into two major categories, depending on the instant when instructions from the user are received by the system [1]. The synchronous BCI, exemplified by the traditional P300 Speller, covers implementations that cue up when the mental activity must be executed. For the second class, asynchronous BCI, the operation is completely paced by the user. Event Related Desynchronization/Synchronization (ERD/ERS) paradigms become dominant for such type of applications [2]. The operation of an asynchronous BCI takes into consideration that the subject can activate the BCI at any moment; thereby, the system must be capable of changing from *standby* to *active* states according to the user's willing. The use of mechanisms like Motor Imagery (MI), which produce changes on ERD/ERS, has been proposed to control this type of BCI, because changes of the EEG dynamics can be modulated entirely by the subject without needing stimulation to elicit them. Several factors play important roles for a good operation of such paradigms. For instance, the power on the *mu* band achieved by the user during resting periods [3,4], or the relationship between the power over the *alpha* and *theta* bands [5]. The use of the ERD/ERS paradigm then supposes that the subject is actually performing the imagination of a motor task. But the correct execution of such task is not verifiable by an external element, because only the feedback is actually related to the execution of the corresponding task. Yet, a bad calibration will produce a poor performance. In principle, improvements may be achieved by changing feedback strategies [6], and/or modifying the resting paradigm [3]. Nonetheless, it is considered that between 10 and 30% of the population is not able to control a BCI based on this paradigm [4]. A study presented by Guger et al. [7] shows that in about 48% of sessions subjects achieved an accuracy between 50 and 69%. Additionally, proficient subjects may need several training sessions before reaching a reliable level. The selection of other mental tasks that elicit detectable changes on the ongoing EEG could then be useful for those subjects that cannot control reliably a MI-BCI, like it happens to subjects with cerebral palsy or other neural diseases that affect the motor cortex

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http://dx.doi.org/10.1016/j.compbiomed.2015.06.014
0010-4825/

[8], perhaps accelerating the adaptation to its use or even increasing the degrees of freedom of the system [9,10].

Paradigms that elicit Steady State Potentials (either visual, auditory or somatosensory [11]) could also be used as inputs for an asynchronous system, but an exogenous stimuli is still unavoidable by demanding the subjects to attend it. This condition is not possible for subjects affected with some kind of neural disabilities like palsy or Parkinson's disease. Some other paradigms like silent reading, imagining a 3D figure rotation, mental calculation or even silent singing, also elicit changes on the dynamics of the EEG signals and on the cortical networks as occurs with MI [12–14]. Given that these tasks are endogenous and self-controlled by the user, any of them could be used to control an asynchronous BCI, without the need of an exogenous stimuli.

For instance, mental arithmetic as a task to control a BCI was first suggested by Keirn and Aunon [13], who classified segments of EEG recordings associated with the execution of one of five different tasks. Their experiments were performed without interleaving tasks and each paradigm was repeated five consecutive times. In a posterior work, Anderson et al. [15] classified the data obtained by Keirn and Aunon using a neural network, and Obermaier et al. [16] experimented with a similar paradigm including again an arithmetic task. Another approach was followed by Penny et al. [17], identifying either mental arithmetic versus MI or baseline versus MI. Their paradigm consisted in successive interleaved periods to perform any of these tasks; features extracted from an AR model and power spectral analysis were used again as input for the classification. Roberts et al. [18] used an experimental paradigm similar to that used by Penny, but changed the duration of the block size. In a later work, the same group suggested that the use of non-linear characteristic could improve the classification performance [19]. These two experimental setups (either Penny et al. [17] or Roberts et al. [18]) indicate that mental calculation is easier to detect in combination with MI. These four studies use the same mental calculation task: ‘the serial subtractions of seven from a large number’, and the classification was obtained using artifact-free segments, which are not possible in an actual BCI system. Yet, the utilization of more complex arithmetic operations has not been explored. Experiments led by Fernández et al. [20], showed that the execution of mental arithmetic produces significant changes on spectral power in all bands and on several sites. Dehane et al. [21,22] have demonstrated that the execution of an arithmetic task involves several networks, located mainly on the parietal lobe and angular gyrus and that, depending of the operation that is presented, different mechanisms can be activated in order to solve the task. Furthermore, an advantage of assessing a mental calculation task as control of BCI systems relies, first, on the possibility of verifying that the users are actually doing the calculation, which is important to perform a good calibration process; and second, on the fact that any person with basic arithmetic training may be able to participate (even BCI naive subjects). Both are characteristics that the classical MI paradigm lacks, and that may speed up the process of setting a BCI with a new user.

This paper evaluates the performance of a continuous detection of mental computation versus resting episodes, simulating the conditions for an online BCI, by using short analysis windows (two seconds length) and few EEG channels (four), which could be useful to build a switch and/or add a degree of freedom to an actual system. The mental task suggested here involves a broader approach than those previously presented, using four basic operations in a scheme that involves both, remembering results, and combining operations with and without carry. Several evaluations were attained, first, a cross-validation test (during the same session), and second, by transferring the model generated with data from one session to analyze recordings from different sessions. This last evaluation, which has not been reported before, helps to identify if it is possible to start a BCI session by avoiding a set up procedure for the system. Additionally, the classification performance using linear (PSD) and non-linear (Scaling Exponent) features, either individually or in combination, was also evaluated.

2. Data

2.1. Subjects

For the mental calculation experiments fifteen volunteers were recruited (eight female), aged 25.3 ± 3.47 years old, all with high school studies completed. The volunteers participated during three experimental sessions on different days according to their time availability (the elapsed time between consecutive sessions ranged from 6 to 110 days). In each session, two or three runs of the mental calculation paradigm were completed depending on the fatigue that each subject expressed. An experimental run involved the solution of fourteen series of three to five mental calculation operations, previously defined and randomly selected. For all operations, the results and operands were integers lower than 100. A detailed explanation of the paradigm is presented in the next section.

A 32 channel EEG montage was used; the electrodes were located at the positions: 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], PO[3,4], P[7,3,z,4,8] and O[1,2,z]; using the right mastoid as ground and linked-ears as reference. All recordings were acquired using a g.USBamp system (from g.tec medical engineering, Austria), with a sampling rate of 512 sps, a bandpass filter between 0.1 and 60 Hz and a notch filter centered at 60 Hz. These parameters are in accordance with standard practices to reduce contamination from several artifacts, like EOG [23,1].

2.2. Paradigm description

Subjects were seated in front of a monitor and instructed to mentally solve the operations indicated, avoiding movements as much as possible. Subjects verbalized the final results at specific times and their answers were contrasted against the correct value. Those episodes with a mismatched response were discarded for the analysis (4–36% of the trials were rejected by this criterion); thereby ensuring that subjects completed the task and were not guessing the answer. This decision was taken to avoid periods of “false” task realization similar to those that may occur within the MI paradigm.

An entire run was composed of an initial period of 20 s with a blank screen, 14 sets of interleaved operation-resting and 20 additional seconds of a blank screen, a complete run duration ranged between 406 and 425 s. The operation-resting sets consisted in the presentation of five different type of stimuli, always in same order, intending to generate periods of activation (mental calculation) and resting states (idle). These stimuli were grouped as follows: *Cue* (“X” on screen, ready), *Begin* (one number between 1 and 20), *Operate* (mental calculation, operation and number), *Answer* (“=” on screen, verbalize answer) and *Rest* (blank screen, idle). All stimuli had a duration of two seconds and the interstimulus interval was randomly selected between 625 and 725 ms ($625 \leq \mathrm{ISI} \leq 725$). A set of operations was defined from the appearance of a *Cue* screen until the last *Rest* screen (just before the next *Cue*). A screen sequence used for these experiments is exemplified in Fig. 1.

The operands of each calculation were: the previous result or the number at the *Begin* stimulus, and the actual one shown on the current screen (it means that the subject must concatenate consecutive operations as depicted in Fig. 1). In each run of the