Self-Calibration in an Asynchronous P300-Based BCI

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Abstract. Reliability is an important issue to use Brain Computer Interface in real life contexts. In this work we investigate whether a continuous adaptation of control parameters in P300-based BCI can improve the accuracy of the system over time and we propose an algorithm able to label unsupervised data on-line allowing for automatic recalibration of the system without the need for frequent explicit calibration sessions.

Keywords: EEG, Brain Computer Interface (BCI), P300, self-calibration

1. Introduction

In order to use Brain Computer Interfaces (BCIs) as assistive technologies outside experimental contexts they should ensure reliability and should not require complex configuration and calibration procedures. Since there are evidences about the variability of the P300 potential morphology across different sessions [Thompson et al., 2012], classification methods for partial/complete unsupervised learning in P300 based BCI were proposed in order to hide/avoid the calibration process to the user [Lu et al., 2009; Panicker et al., 2010; Kindermans et al., 2012]. However the proposed methods were tested on brief controlled BCI sessions (1-2 hours), and they are not able to recognize when the user is not attending to the stimulation (No-Control) or to dynamically adapt the speed of selection (Dynamic Stopping). In this work, i) we investigated if a continuous adjustment of the control parameters can boost P300 based BCI accuracy in repeated BCI sessions in a day and ii) we propose and evaluate a self-calibration algorithm that starting from an asynchronous classifier [Aloise et al., 2011a] can correctly label data from on-line sessions, allowing for the continuous adaptation of the classifier parameters.

2. Material and Methods

Ten healthy subjects with previous experience with P300 based BCIs were involved in this study (5 male, mean age 25 ± 3). Scalp electroencephalographic (EEG) signals were recorded (g.USBamp, g.tec, Austria, 256 Hz) from 8 scalp positions (right earlobe referenced and grounded to the left mastoid). The stimulation interface consisted in the 6 by 6 Farwell and Donchin's matrix Speller. Each subject underwent 5 recording sessions in the same day at well-defined times: 10:00 AM, 12:00 AM, 2:00 PM, 4:00 PM and 6:00 PM. A session consisted of 6 runs of 6 trials each. A trial consisted of 8 random repetitions of the 12 stimulation classes. Two additional No-Control runs were acquired for each session in order to collect data affected by artefacts.

The asynchronous classifier relies on the introduction of a set of thresholds in the classifier and defined as explained in [Aloise et al., 2011a] in order to manage the Dynamic Stopping and the No-Control features. The asynchronous classifier performance were assessed by an off-line cross-validation both in Intra-Session condition (the training and testing dataset belong to the same session) and in Inter-Session condition (the training and testing dataset belong to two different sessions). For each session we considered all the combinations of 5 runs for training (3 Control runs and the 2 No-Control runs) and 3 runs for testing. Score values were assessed by using a Stepwise Linear Discriminant Analysis (SWLDA). Finally, we compared the communication efficiency [Bianchi et al., 2007] in the inter- and intra-session condition, assuming a cost of 1 for unwanted abstentions (the users only need to repeat the trial), and a cost of 2 for misclassifications (they need to undo the selection and select again the desired symbol).

In order to collect correctly labeled data for the continuous recalibration of the asynchronous classifier we introduced a second threshold yielding error rate fixed to 0%. When the first threshold is exceeded the value of the score relating to the classified class is compared to the second threshold; if the latter is exceeded the epochs relating to the current trial are labeled according to the classification result and stored for further recalibration. We first defined the classifier and the thresholds parameters using data from the first session, and then every time we stored 5% of new data from the other sessions, we removed the same amount of the oldest data from the training dataset and we updated the classifier weights and the thresholds values. The Self Calibration (SC) communication efficiency was compared to the one obtained when no recalibration (NC) was applied during the day.

3. Results

Intra-Session cross-validation showed higher correct classification rate with respect to Inter-Session (Fig. 1A). Efficiency was significantly higher for the Intra-Session (0.30) condition with respect to Inter-Session condition (0.24) as assessed by a paired t-test ($p < .01$). On average the SC algorithm (Fig. 1B) increased the corrected classification rate from 71.7% to 78.4%. The SC Efficiency (0.30) was significantly higher with respect to NR (0.24) as assessed by a paired t-test ($p < .05$). Despite the different values for correct classifications between the Intra-Session and the SC condition, the Efficiency remains the same, since the SC allows on average to reduce stimuli repetitions with respect to Intra-Session Condition (2.36 and 3.1 respectively). The SC on average stored 41% of new data for recalibration, and only the 2% of stored data was incorrectly labeled.

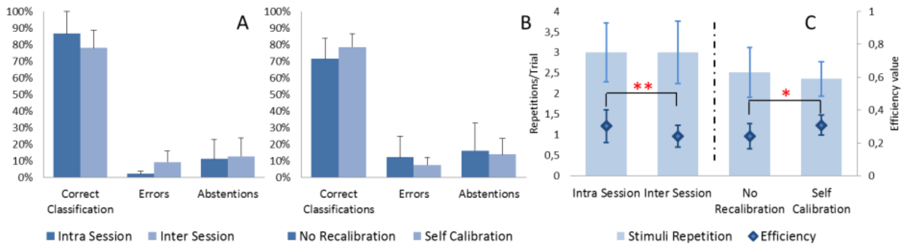

Figure 1. **A**) *Intra and Inter Session conditions mean classification performance for the asynchronous classifier. B) Mean performance of the asynchronous classifier with Self-Calibration and with No Recalibration across different sessions in a day.* *C) Mean Efficiency values (dots) and number of Stimuli Repetitions (bars) for all the considered conditions (**p< .01, *p<.05).*

4. Discussion

In this work we demonstrated that continuous update of control parameters increases the accuracy of P300 based BCI among several sessions in the same day. We improved the asynchronous classifier introducing an algorithm that can automatically perform a recalibration of the system using unlabeled data from on-line sessions and ensuring the stability of the performances. After an initial supervised calibration session, the whole recalibration procedure will be hidden to the user, which is an important point to increase the usability of BCI systems as assistive technology. Furthermore considering the higher variability exhibited by potential end users with respect to healthy subjects [Aloise et al., 2011b], we expect that the proposed system would be more effective if tested with end users.

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