Calibration-Free BCI based Control using Error Related Potentials

Jonathan Grizou
Inria Bordeaux Sud-Ouest, France
jonathan.grizou@inria.fr

Iñaki Iturrate
CNBI, EPFL, Switzerland
inaki.iturrate@epfl.ch

Pierre-Yves Oudeyer
Inria Bordeaux Sud-Ouest, France
pierre-yves.oudeyer@inria.fr

Manuel Lopes
Inria Bordeaux Sud-Ouest, France
manuel.lopes@inria.fr

Luis Montesano
I3A, Univ. of Zaragoza, Spain
montesano@unizar.es

1 Introduction

EEG-based brain-computer interfaces have been used successfully to control different devices, such as robotic arms and simulated agents, using self-generated (e.g. motor imagery) and event-related potentials signals (see [1] for a review). Error-related potentials (ErrPs) are one kind of event-related potential appearing when the user's expectation diverges from the actual outcome. Recently, they have been used as feedback instructions for devices to solve a user's intended task [2, 3].

As in most BCI applications, ErrP-based BCI requires a calibration phase to learn a decoder that translates raw EEG signals from the brain of each user into meaningful instructions. This calibration is required due to specific characteristics of the EEG signals: non-stationary nature, large intra- and inter-subject variability, and variations induced by the task. The presence of an explicit calibration phase, whose length and frequency is hard to tune and is often tedious and impractical for users, hinders the deployments of BCI applications out of the lab. Thus, calibration free methods are an important step to apply this technology in real applications [1].

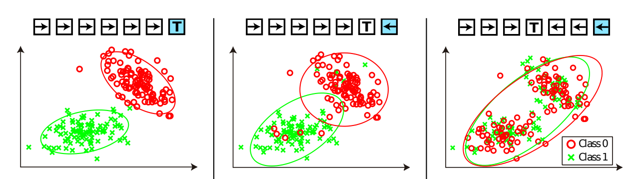
We propose a new methodological approach that removes the need for a calibration phase, this allows to simultaneously and seamlessly learn an EEG decoder of error-related potentials while controlling a device to achieve a sequential task. Contrary to other approaches [4], our method learns the specific sequence of actions that fulfills the user's desired task. The proposed method assumes a distribution of possible tasks, and infers the interpretation of EEG signals and the task by selecting the hypothesis which best explains the history of interaction. This inference can be continuously run and updated as new data comes in, which removes the need for an explicit calibration. We report online experiments where four users use BCI to control in real time an agent on a virtual world to reach a desired target by following a trajectory without any previous calibration process.

2 Principle

BCI control based on feedback signals differs from classical brain-computer interfaces in the sense that the user does not actively deliver commands to the device, but only delivers feedback about actions performed by the device [2, 3]. Essentially, this BCI control follows an iterative sequential process where the device performs an action which is in turn assessed by the user. This assessment will elicit ErrPs into the user's brain that can be recorded using EEG and will be different for "correct" and "incorrect" assessments.

This process can be exemplified for a reaching task, where the user wants to reach a target position unknown by the system. The device performs several discrete actions (e.g. moving left or right), and learns from the feedback given by the user. To solve this problem, the usual methods require a calibration phase to train a usable decoder of brain signals. Once the brain signals can be translated into binary feedback, the device can infer which sequence of actions can lead to the user's desired position.

We explain how we can achieve similar performances without knowing the brain signal decoder beforehand. The intuition for our method is that the classification of the brain signals is easier when they are interpreted according to the task desired by the user [5]. The method assumes a distribution of possible tasks and relies on finding which pair of decoder-task has the highest expected classification rate on the brain signals.



(a) (b) (c)

Figure 1: Interpretation hypothesis for a 1D grid world.

The main idea is depicted in Figure 1 for a toy 1D example. The user wants the device to reach the right-most state (shaded in blue). For each device's action, the user provides a feedback signal which encodes whether the action executed is "correct" or "incorrect" according to the intended target (represented in a 2D feature space). Such signals are generated from an underlying model which maps a binary label to a continuous signal. However, neither the user's desired target nor the labels associated to the user's feedback signals are known.

Considering that we can define a finite set of target state hypothesis (marked with a T letter), we can infer the labels that should be provided by the user with respect to each hypothesis. Given a particular interaction history, it is possible to compute a different signal decoder for each task hypothesis. The key point is that only the correct hypothesis will assign the correct labels to all feedback signals (Figure 1a), while the other hypotheses will gradually mix both classes as the hypothetic target gradually differs more from the correct one (Figure 1b and 1c).

Therefore, the hypothesis which provides the decoder with best accuracy and compactness can be selected as the most probable one. This property can be exploited by measuring the overlap between the distributions of each class [5], by using for example the Bhattacharyya coefficient. The task intended by the user being the one whose associated signal models overlap the less.

3 Method

Control task We consider a 5x5 grid world, where an agent can perform five different discrete actions: move up, down, left, right, or a target-reached action. The user wants to command the system to move to a particular location (i.e. to reach one of the 25 discrete states) following a trajectory and for this he/she can only use the brain feedback.

EEG-based feedback signals During operation, the role of the users was to mentally assess the agent's actions as correct or incorrect with respect to a selected target, obtaining this way error-related potentials. EEG signals were recorded with a gTec system (2 gUSBamp amplifiers) with 32 electrodes distributed according to the 10/10 international system, with the ground on FPz and the reference on the left earlobe. The EEG signals were digitized with a sampling frequency of 256 Hz, common-average-reference filtered and band-pass filtered at $[0.5, 10]$ Hz.

4 Results

Comparison with calibration method Figure 2 shows one particular run of 500 steps comparing our self-calibration method with a calibration procedure of 400 steps in simulation and using a pre-recorded dataset of ErrP signals. As our algorithm is operational from the first step, it can identify the correct task when sufficient evidence has been collected. On the other hand, a calibration approach collects signal-label pairs for a fixed number of steps and use the resulting classifier. During the calibration phase no tasks can be learned, substantially delaying the user's online operation. Importantly after the 500 steps the decoders of each methods are of similar qualities.

Calibration-Free Online BCI Control The experiments were conducted with four subjects (aged between 25 and 28). Each subject was asked to mentally assess the agent's actions with respect to a given target. Each subject performed 5 runs, for each run a new target, unknown to our

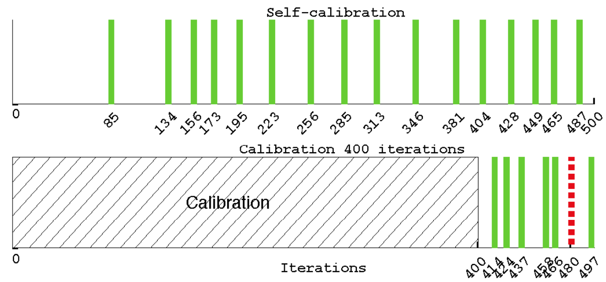


Figure 2: Time-line of one simulated experiment using an EEG dataset, self-calibration (top) versus calibration (bottom). Green (filled) and red (dashed) bars represents respectively correct and incorrect task achievement.

system, was selected by the user. The system was not calibrated to decode the user EEG signals beforehand. There was an agent's action every three seconds. Each run lasted 200 actions, and the time between runs was around one minute.

Table 1 shows for each subject and run the number of iterations needed to reach the confidence threshold for the subject selected target. The algorithm was able to identify the correct target for all runs of all the subjects. On average, the number of iterations needed to identify the target was of 85 $\pm$ 32. We note that our system identified each task in less iterations than a normal calibration phase requires (between 300 and 600 examples depending on the user performance [2, 3]).

	Run1	Run2	Run3	Run4	Run5	mean$\pm$std
S1	95	62	56	60	64	67 $\pm$ 16
S2	89	77	98	60	62	77 $\pm$ 17
S3	68	80	118	76	157	100 $\pm$ 37
S4	98	142	57	142	47	97 $\pm$ 45

Table 1: Number of iterations needed to identify the target for each subject and run.

References

[1] J. Millán, R. Rupp, G. R. Müller-Putz, R. Murray-Smith, C. Giugliemma, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb, *et al.*, "Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges," *Frontiers in neuroscience*, vol. 4, 2010.

[2] R. Chavarriaga and J. Millán, "Learning from EEG error-related potentials in noninvasive brain-computer interfaces," *IEEE Trans. on Neural Systems and Rehab. Eng.*, 2010.

[3] I. Iturrate, L. Montesano, and J. Minguez, "Single trial recognition of error-related potentials during observation of robot operation," in *EMBC*, 2010.

[4] P.-J. Kindermans, D. Verstraeten, and B. Schrauwen, "A bayesian model for exploiting application constraints to enable unsupervised training of a P300-based BCI," *PloS one*, 2012.

[5] J. Grizou, I. Iturrate, L. Montesano, P.-Y. Oudeyer, and M. Lopes, "Calibration-Free BCI Based Control," in *AAAI*, 2014.