Latency correction of error-related potentials reduces BCI calibration time

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Abstract

Calibration of brain-machine interfaces exploiting event-related potentials has to be performed for each experimental paradigm. Even if these signals have been used in previous experiments with different protocols. We show that use of signals from previous experiments can reduce the calibration time for single-trial classification of error-related potentials. Compensating latency variations across tasks yield up to a 50% reduction the training period in new experiments without decrease in online performance compared to the standard training.

1 Introduction

Successful decoding of event-related potentials (ERP) for brain-machine interfacing requires adequate models of the signal of interest. Considering the variability of EEG signals, calibration of these models is done through the acquisition of a large number of trials. Therefore, a considerable amount of time has to be spent before a system can be operated in online manner. Different approaches have been proposed to overcome this issue by applying adaptive classifiers [7] or using previous information from multiple subjects [5, 6].

Remarkably, the recalibration process has to be performed for every protocol, even if ERPs elicited by the same cognitive processes have previously been used with other experimental setups (e.g. different feedback stimuli or final application). Recent works have tried to exploit ERP similarities in these cases [2, 4]. For instance, it has been shown that variations of error-related potentials (ErrP) across different experimental protocols can be largely explained by changes in their latency [2]. We claim that these variations can be compensated in order to exploit available data from previous experiments for the calibration of new experimental protocols. This work reports an online evaluation of this approach, showing that it can effectively reduce the calibration time with respect to the standard practice without degrading the online recognition performance.

2 Methods

2.1 Experimental protocols

Twelve participants performed three experimental protocols of increasing complexity as shown in Fig. 1. They were seated on a comfortable chair facing the visual displays of the protocols approximately one meter away and asked to restrict eye movements and blinks to specific

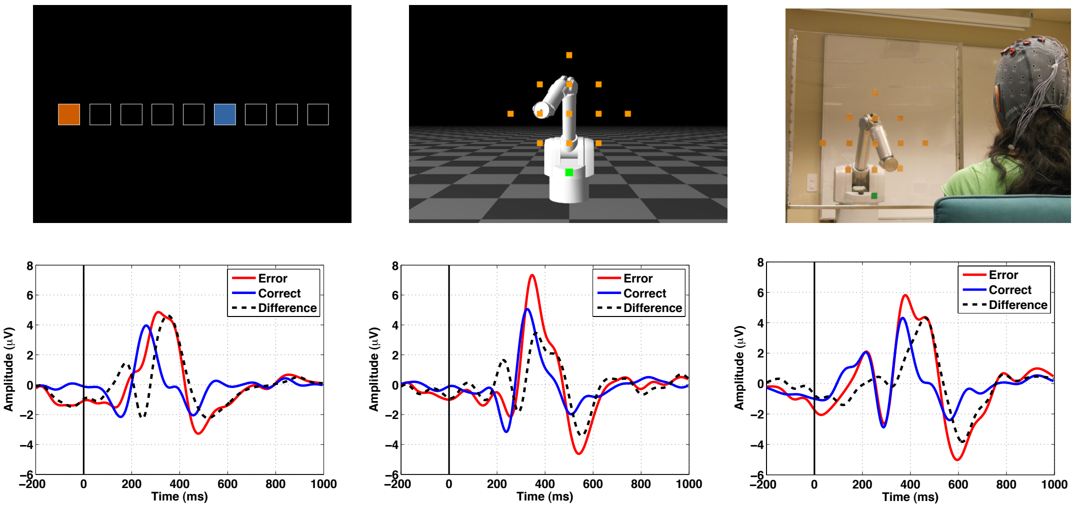

Figure 1: (Top) Experimental protocols. (Bottom) ErrPs at the FCz electrode obtained in each experimental protocol. (Left) One-dimensional cursor movement ($E1$). (Center) Two-dimensional movements of a simulated robotic arm ($E2$). (Right) Real robotic arm ($E3$).

resting periods. In all experiments they were asked to evaluate whether a device moves towards a given target location. The device moved in discrete steps and the time between movements was randomly chosen within the range [1.7 4.0] s. There was a probability of moving in the wrong direction of about 30%. Experiments were always performed in the same order from the simplest to the most complex one. The first experiment, E_1, consists of a cursor that moves in discrete steps (either left or right) towards a target [1]. In the second protocol, E_2, the user monitors a simulated robotic arm that moves on a 2D plane (allowed movement directions were left, right, up and down). The third experiment, E_3, consists of the same task using a real robotic arm. A detailed explanation of the protocols and methods is provided in [2].

Each experiment started by a calibration phase. This phase had a variable length depending on the obtained performance. Calibration stopped whenever the mean accuracy (ten-fold cross-validation) on the training data exceed 75%. Then the classifier parameters were fixed, and performance was tested on an online phase lasting 400 trials.

EEG was recorded at 256 Hz with a gUSBAmp amplifier (gTec GmbH, Austria) with 16 active electrodes (Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, and CP4 according to the 10-10 system). Ground and reference were placed on the forehead and the left earlobe. Data was notch filtered at 50 Hz, and zero-phase band-pass filtered at [1, 10] Hz. Prior to classification, we applied common-average reference and downsampled the signal to 64 Hz. Features from eight fronto-central channels were selected in the window [200 800] ms using a spatiotemporal filter [3]. On average 45 ± 10 features were selected based on their r^2 score. Single-trials were classified as erroneous or correct using linear discriminant analysis (LDA).

2.2 Training paradigm using latency-correction

As mentioned above, differences between ErrPs elicited in different experiments can be largely explained by latency variations. These variations can be easily estimated by computing the

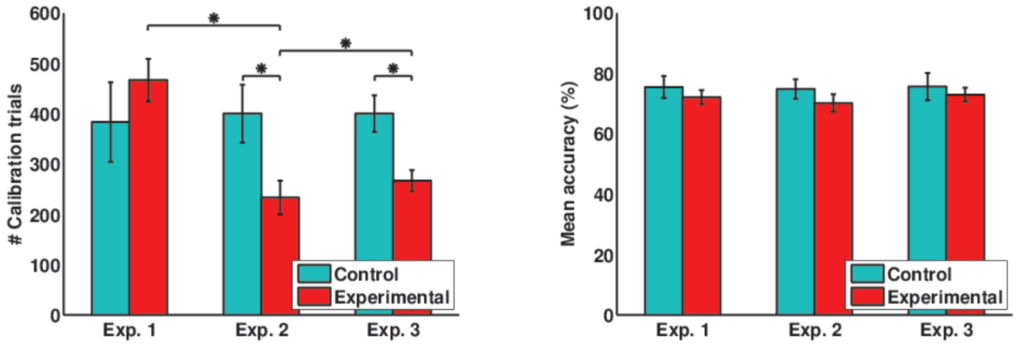

Figure 2: (Left) Number of calibration trials (mean ± SEM) required to reach the calibration criterion (*: $p < 0.05$). (Right) Mean classifier accuracy during the online control phase.

cross-correlation between the grand-average ERPs for each experiment. In brief, given a previous experiment E_i, from which data is available, and a new experiment E_j, the ERP latency variation $d_{E_iE_j}$ will correspond to the shift that yields the maximum cross-correlation. Then, ERP data from E_i can be shifted in time by $d_{E_iE_j}$ and used along the available (few) trials from the new experiment E_j to train a classifier.

Complementing previous reports [2], we compare whether this latency correction mechanism effectively reduces the calibration time. To that end, we defined two groups of participants depending on the training procedure. The *control* group (N=6, one female, mean age 27.33±2.73 years) followed a standard calibration approach, i.e., based only on data from the current experiment. The *experimental* group (N=6; two females, mean age 27.17 ± 4.07 years) used latency-corrected trials from the previous experiment to build the classifier for the current task. That is, standard calibration was followed for E_1, while data from that experiment was used during the calibration period of E_2. Similarly, during calibration for E_3 the data from E_2 was used. The latency between experiments was estimated based on the cross-correlation of the difference ERP (error minus correct condition) of channel FCz within the window $[0, 500]$ ms.

Mixed two-way ANOVAs (within factor: experiments; between factor: group of subjects) were performed to test whether (*i*) the number of calibration trials in the experimental group decreased across experiments; (*ii*) the number of calibration trials was significantly different between groups; and (*iii*) the online accuracies of both groups were not different. Post-hoc one-tailed Bonferroni-corrected t-tests were performed to assess statistically significant differences.

3 Results

The obtained ErrPs can be seen in Figure 1. Latency variations were about 60± 25ms between E_1 and E_2, and about 41±13 ms between E_2 and E_3 Figure 2 shows the number of calibration trials needed in each experiment to reach the stopping criteria. The calibration period for the control group was similar for all experiments. In contrast, the experimental group exhibit a large reduction on the required calibration trials in E_2 and E_3 when previous information was re-used. The ANOVA test revealed a significant interaction between the experiment and group ($F_{2,20} = 8.65, p = 0.002$). Post-hoc tests showed that significant differences were found between groups in experiments 2 and 3 (one-tailed unpaired t-tests, $p < 0.05$), and also significant differences within the experimental group between experiments 1 and 2 (one-tailed paired ttest, $p = 0.004$), and between experiments 1 and 3 ($p = 0.004$).

No significant difference was found in the accuracies for all the experiments and subjects ($p > 0.85$). These results indicate that, provided data from previous experiments, knowledge from these protocols can be transferred to the new task using the latency correction algorithm.

4 Conclusion

Our results confirm that compensating for latency variations across protocols allows the use of previous data to shorten the calibration phase in new applications. In the reported experiments the use of data from the first experiment enabled users to reach the training criteria for the second one in about half of the trials required with the standard approach. Importantly, no significant difference was observed between the two training paradigms in the online performance. Similar reductions were also observed for the third experiment with the real robot.

The latency correction mechanism used in this work relied on a simple measure based on the cross-correlation in a single channel. However, ERP variations across experiments may follow more complex patterns both spatially (i.e. across channels) and temporally (i.e. individual ERP components). Multiple factors affect the ERP waveforms including the feedback modality, the inter-stimulus interval, as well as subject dependent variability. It remains to be validated how suitable this correction mechanism is to other experimental paradigms and signals. Moreover, further research is required to explore more sophisticated techniques to better model these ERP variations (e.g. dynamic time warping).

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