

Title: Exploiting task constraints for self-calibrated brain-machine interface control using error-related potentials

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We thank the reviewers for the valuable comments and suggestions to improve the paper. We have carefully addressed their remarks and answered their questions.

Editorial Comments

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Fixed. We now provide a link in the text where both the data and the source code can be downloaded from:

https://github.com/flowersteam/self_calibration_BCI_plosOne_2015

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Reviewer #1 Comments

Potential problem: could you get more subjects? Are eight subjects enough for a proof-of-concept? I say this because there appear to be individual differences in the data (see Table 1 and Figure 4). These might be captured by grouping the existing data by one or two performance parameters, and then used to interpret the outcomes of this larger experiment.

We agree with the reviewers that more subjects could give more information about the results obtained. As it is usual in the papers of the BCI community, the analysis shows a large variability in terms of performance. Nonetheless, this variability can be mainly grouped in those that were able to obtain the so-called sufficient accuracy to have BCI control (>70% of accuracy), and those who do not have it (see for instance [1] for analyses on this matter). The results for eight subjects show a similar behavior to [1] where 2 subjects perform poorly and the rest were around usual BCI performance.

More subjects and sessions would be required to assess usability aspects and to analyze learning curves over time.

[1] Vidaurre, Carmen, and Benjamin Blankertz. "Towards a cure for BCI illiteracy." *Brain topography* 23.2 (2010): 194-198.

The focus of this approach addresses minimizes the time needed to calibrate BCIs. The presentation of this is clear enough. The formatting is adequate. However, a few points on the text and approach in general:

*** for the first instance of "train ErrP classifier", define ErrP using the full name and cite a reference to the method.**

Fixed.

*** are the learning curves (percent accuracy) shown in Figure 6 different due to individual differences or features of the algorithmic approach? If it is due to individual differences, then are these features of the signal or behavioral performance? See my point above about acquiring more subject data.**

The learning curves represent solely inter-subject variability. This variability, which is very common in BCI-based control, is mainly due to individual differences in the features extracted from the recorded EEG. As pointed out by reviewer #2, we have also labeled the subjects in Figure 4 so they can be easily compared.

Reviewer #2 Comments

1. Since the procedure relies on the constraints from a grid reaching task, the title would be more informative if it mentioned that. As is, it seems a bit misleading that it can be applied to any brain-machine interface paradigm.

Although we have use a reaching task to illustrate the self-supervised approach, the latter is not tied to this type of tasks. Indeed, it can be applied whenever we can define a fixed number of behaviors (or policies) that impose different labels on the actions of the device. For instance, it would be possible to design a collection task where the device has to catch some items and avoid others using exactly the same approach. The common part of both cases is the use of error potentials to evaluate actions.

Therefore, we have made explicit the need of task constraints and changed the title to:

Exploiting task constraints for self-calibrated brain-machine interface control using error-related potentials

2. Authors mention data is fully available, but I only saw a link to the open source codes on github. This should be made clearer, as to adhere to PLOS One's open data policy.

Fixed. We now provide a link in the text where both the data and the source code can be downloaded from:

https://github.com/flowersteam/self_calibration_BCI_plosOne_2015

3. The authors mention in line 39 that preliminary results have been presented in [19,20]. In order to clarify the novelty of the present paper relative to these previous works, a couple of sentences could be added to that effect.

Fixed. We have summarized our previous works and differenced them from the current manuscript, as follows:

In our preliminary works, we have performed: i) an alternative algorithm that only allows to reach the first target but that had a higher failure rate due to it [19], and ii) offline computational analysis of the proposed algorithm to analyze different exploration methods [20].

With respect to our preliminary works, the current study proposes an alternative algorithm that does not suffer from the limitations of [19], namely failures due to overconfident estimates. Furthermore, it shows the applicability to online scenarios of the planning techniques described and evaluated in [20].

4. Line 77-78, it is mentioned that data is bandpass filtered from 1-10Hz, then they mention downsampling to 32Hz. I am assuming the 10Hz is a typo and should in fact read 100Hz; correct?

The description of the feature extraction was correct, but we understand that it may lead to confusion. The downsampling by a factor of 8 is simply used to reduce the number of features extracted from the proposed time window. Instead of taking 154 features from a window of length 600 ms, we took 19 (154/8) features per channel. We have also fixed the number of features, as text read 58 instead of 57. We have rewritten the phrase as follows:

In this work, ErrP features were extracted from channels Fz, FCz and Cz within a time window of [200,800] ms downsampled by a factor of 8 (being 0 ms the action onset), forming a vector of 57 features [17].

5. One claim in line 138 is that the calibration procedure seems to be sensitive to the coherence of the EEG patterns for the same sets of labels. This was not given enough attention in the paper, and could strengthen the "practicality" aspect of the proposed calibration. Can the authors quantify the effect that breaking this assumption has on the results?

With that phrase we simply wanted to reinforce the fact that one limitation of the algorithm is that users should not change the target to reach in the middle of one reaching operation. If this happens, then this could affect the quality of the labelling obtained. However, a quantitative effect of this assumption is difficult to calculate, since it depends on many free parameters, such as: the number of steps that the user was focusing on each target position; the distance to each of the target positions; or the number of target changes desired by the user.

Nonetheless, we agree with the reviewer that this issue should be reviewed further in the paper, and thus we now address it in the discussion it as follows:

Another influential limitation of the proposed approach is that, with the current algorithm implementation, the users cannot (or should not) switch the desired target during one reaching operation. Under this circumstance, the system could be affected in two ways depending on the relative distance between targets or number of switches among others: first, it could increase the convergence time exponentially; and second, it may severely affect the labeling quality obtained once the system converges to one target. As a possible solution, a target reset function could be implemented by explicitly modeling two possible target locations instead of one. Nonetheless, further work will be needed to understand the impact that this target switches may have on the proposed system and its usability.

6. Figure 4b would be enhanced if the subject numbers were overlaid with the points. I would be interested in seeing whose points correspond to the curves on figure 6. Subjects 4 and 7, for example, have very similar curves - where are they in figure 4b?

Fixed. We have added the subject numbers to the Figure.

7. Authors argue that the two curves in figure 5 are the same in line 373. Maybe a better claim is "insignificantly different"? There seems to be a clear latency difference between the two curves of about 25ms. Any potential explanation?

We have added the term insignificantly different in the discussion. Now it reads:

Although the unsupervised approach attains similar results in terms of accuracy, and insignificantly different grand average signals when compared to those obtained using supervised calibration [...]

Regarding the latency, this difference in latency cannot be considered as a result of the two protocols, since it is below our current resolution for event synchronization which is 62.50 ms. Rather, the difference is mainly caused by noise. We have added a phrase in the results explaining this:

Despite small variations of around 20 ms were found in the peak latencies, these values are below our current event synchronization resolution of 62.50 ms, and thus were mainly due to noise.

Regarding the text:

1. line 7, remove "the" from the large subject specificity

Fixed.

2. line 11, out-of-the-box use of *the* BCI

Fixed.

3. line 12: medical applications*, such* as those

Fixed.

4. line 31: have also achieved control (i.e., remove 'a')

Fixed.

5. line 56: replace 'and as incorrect' by 'or as incorrect'

Fixed.

6. line 336: replace 'have demonstrated' with 'having demonstrated'

Fixed.

7. line 373: careful with 'same' in 'same accuracy and grand average signals' (see comment 7 in section above)

Fixed. We have replaced the phrase for:

Although the unsupervised approach attains similar results in terms of accuracy and grand average signals to those obtained using supervised calibration [...]

Reviewer #3 Comments

The authors claim that their method could be employed in any other reaching task as long as the number of reaching positions is finite. The mathematical formulation seems to support the claim but practical issues relating convergence and complexity of the task should be discussed.

- p3, 194: equally probable label a priori. Couldn't any further information about this a priori be gathered from the task? In fact, in the task analysed in the experiments, this does not seem to be the case.

The reviewer is right. Each task does not only offer information about the labelling, but also about their a priori probabilities. However, exploiting this information is not easy as the actual ration of labels depends on the policy followed by the system. More precisely, the planner uses signal and task uncertainty to decide which action to execute. In order to avoid any possible complication on this matter and to be on the safe side, we decided to keep non-informative priors.

- p4, 1109: it is assumed that the user follows optimal policies to reach the task but this is not consistent with the affirmation of the previous item ("we do not have a priori knowledge of the user intended assessment of the action"). Besides, will this also be true for more complicated tasks?

The sentence states that the user evaluates the device according to the optimal policy of the task he intends to solve. This is not in contradiction with the label prior which is the result, as mentioned in the previous point, of the behavior of the system. Since the actual target is not known, the prior knowledge about labels should average over all targets and take into account the planner. Instead, we use a non-informative prior. We agree with the reviewer that these statements can lead to misunderstandings and changed it as follows:

Under the assumption that the user follows optimal policies, the ErrP detector can be used to identify the user intended task $\xi_i = t$ among a finite set of tasks $t = 1, \dots, T$. Note that this assumption does not contradict the fact that we also assume a non-informative priori for the labels, as the latter will vary among optimal policies and will depend on the planner.

In principle, this should also be true for more complicated tasks as long as: i) it is possible to compute the corresponding set of optimal policies; and ii) the user is able to evaluate the actions according to one of them (or another one that closely resembles a policy among the calculated set).

- p2, l59: how do blinks and eyes motion affect the system? Is this related with the differences in performance observed for different subjects?

These artifacts are a usual problem in current BCI systems. In our case, we performed a post-hoc test to ensure that no artifact was contaminating the signals. Additionally, we instructed the users not to blink or move the eyes during periods of movements. Notice, however, that even when ocular artifacts might be present in some trials, these artifacts are in principle not correlated with the error signal since eye movements or blinks do occur both for right and wrong actions. Therefore, the protocol would not generate stable patterns to be differentiated by the self-calibration algorithm. Also, if these artifacts were present and used for the first target, they will definitely fail when changing to the second target and the system will not be able to reach it.

- p3, l86: 'one' should be 'an'.

Fixed.

- p3, l100: the variable 'r' is not defined. Does it stand for 'reward'?

Fixed. We have added a description in the text.

- p4, l117: rephrase the sentence. Do you mean 'candidate tasks' versus 'the target task'?

We have rephrased the sentence as follows.

The previous estimate simply assigns a higher likelihood to those tasks with whom the brain signals are more coherent.

- p3, l88, p5. l152, p6. l196: k multiple times defined.

Fixed.

- References should be fully revised. There are many errors related to missing information such as volumes, pages, capital letters (for example, 'EEG' instead of 'eeg').

Fixed.

- fig. 4a: vertical axis does not reflect percentages as the label states.

Fixed.