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# Impact of the baseline temporal selection on the ERD/ERS analysis for Motor Imagery-based BCI

Sébastien Rimbart<sup>1</sup>, David Trocellier<sup>1</sup> and Fabien Lotte<sup>1</sup>

**Abstract**—Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) are neurotechnologies that exploit the modulation of sensorimotor rhythms over the motor cortices, respectively known as Event-Related Desynchronization (ERD) and Synchronization (ERS). The interpretation of ERD/ERS is directly related to the selection of the baseline used to estimate them, and might result in a misleading ERD/ERS visualization. In fact, in BCI paradigms, if two trials are separated by a few seconds, taking a baseline close to the end of the previous trial could result in an over-estimation of the ERD, while taking a baseline too close to the upcoming trial could result in an under-estimation of the ERD. This phenomenon may cause a functional misinterpretation of the ERD/ERS phenomena in MI-BCI studies. This may also impair BCI performances for MI vs Rest classification, since such baselines are often used as resting states. In this paper, we propose to investigate the effect of several baseline time window selections on ERD/ERS modulations and BCI performances. Our results show that considering the selected temporal baseline effect is essential to analyze the modulations of ERD/ERS during MI-BCI use.

## I. INTRODUCTION

Motor Imagery-based Brain-Computer Interfaces (MI-BCIs) are communication and control systems that enable end-users to interact with a computer by performing motor imagery tasks only, e.g., by imagining hand movements, usually measured with electroencephalography (EEG) signals [1]. Indeed, movements and imagination of movements activate similar neural networks [2], enabling MI-based BCIs to exploit the modulations of sensorimotor rhythms (SMR) over the motor cortices [3] for control purposes. Such modulations are respectively known as Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS), and are coming from the mu (7-13 Hz) and beta (15-30 Hz) frequency bands [3]. MI-BCIs are very promising neurotechnologies for many applications, particularly to control assistive technologies, for sport training or even for post-stroke motor rehabilitation [1].

Many articles have described the robustness of the ERD and its relevance to design efficient BCIs. Typically, most MI-BCI designs are based on the ERD motor pattern generated during MI. Indeed, it is well known that MI generates a contralateral [3] ERD during the task followed by a contralateral ERS afterwards with respect to the requested limb, thereby enabling MI to be detected. Motor imagery generates a gradual decrease in power which starts in the

preparatory phase of the motor task in the mu and beta rhythms and reaches a maximum during its execution. In general, the ERD has a larger amplitude in the mu-band than in the beta-band, and seems to be modulated according to the experimental criteria (e.g., type of MI performed [4], level of consciousness [5], type of feedback received [6] or user's traits [7]). We believe that a better understanding of the ERD/ERS modulations during MI-BCI tasks is crucial for developing effective interfaces.

ERD/ERS modulations are often very well described in the literature but appearances can be deceptive, particularly because of the baseline used in ERD estimations. Indeed, ERD/ERS are computed as a change of band power during MI with respect to such a baseline without MI, using a ratio of band powers (e.g., [8]). The term 'baseline' thus usually refers to a resting condition of a few seconds before MI that would maximize the ERD phase occurring during MI. Since ERD is a ratio, the estimation of ERD is directly related to the selection of the baseline used to compute it [3], [9]. Several studies have already shown that the selection of the nature of the baseline is significant and could affect the visualization of ERD/ERS [10], [9]. In particular, Tangwiriyasakul et al., used five different baseline movies in a motion imagery task and showed that the majority of the subjects had significantly higher mu power for particular baseline conditions, thus resulting in more pronounced mu ERD [9]. Another study showed that a baseline taken during a static image seems better (i.e., lead to a larger ERD) compared to a baseline taken during a period of stillness [10]. While the selection of the nature of the baseline seems to affect the visualized ERD, the effect of the time at which the baseline is selected is not well-documented.

There are several possible choices of baselines to visualize the ERD during a motor task: before each trial, at the beginning of a run or a session, or by averaging the complete EEG signal over a session [11]. The most common practice in BCI is to use a baseline taken before each trial, thus providing a baseline that corresponds to the user's state at that moment (with the same level of fatigue, workload or concentration which are known to affect the EEG signal [12], [11]). However, BCI paradigms are typically designed in such a way that each trial follows the other very quickly, i.e., there are only a few seconds between the moment when an MI is completed and when the next MI begins. Consequently, the time window for choosing which baseline to use is often limited and might result in a misleading ERD visualization due to the ERD amplitude variation associated with specific periods of the trial [6]. For example, choosing a baseline

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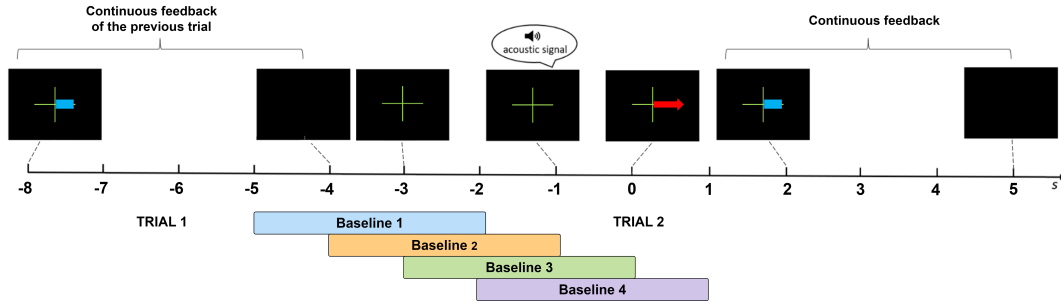


Fig. 1: Detailed steps of two MIs trial with the corresponding visual feedback. 4 different baseline time windows were selected ( $[-5;-2]$ s,  $[-4;-1]$ s,  $[-3;0]$ s,  $[-2;+1]$ s), all of the same length (3 seconds).

close to the end of the previous MI could result in a selected baseline occurring during the ERS phase (e.g., which occurs one to two seconds after the end of the previous MI), thus significantly increasing the probability of visualizing an ERD, even if there is no absolute power decrease during MI.

Therefore, we believe that the inter-subject variability of ERD/ERS previously described by numerous studies [13], [4] could be partly explained by the temporal baseline selection used. Such temporal baseline selection would influence the ERD visualization and understanding but could also be crucial in terms of BCI classification performances of resting state versus MI, since the resting state class is often selected similarly to the baseline. Consequently, a better understanding of the effect of temporal baseline selection may also lead to better BCI classification performance. In this paper, we thus propose to investigate and quantify the effects of several baseline time window selections on both ERD/ERS modulations and BCI performances. Our results show that the choice of the baseline is essential to understand and analyze the ERD/ERS modulations during MI-BCI use.

## II. MATERIAL AND METHODS

### A. Participants

Our analyses were performed on a data base of 71 right-handed healthy and MI-BCI-naive subjects (35 women;  $25.83 \pm 9.52$  y.o.), coming from two previous experiments [14], [15]. These experiments followed the statements of the WMA declaration of Helsinki on ethical principles for medical research involving human subjects, and were approved by Inria ethical committee (COERLE, approval number: 2018-13). All participants signed an informed consent form.

### B. Experimental BCI protocol

Each participant completed one MI-BCI session which comprised six 7-minutes runs during which they had to learn to perform left and right hand MI tasks with the BCI. The Graz training protocol was used and was divided into two steps: first, the training of the system (i.e., calibration phase, collecting data to train the EEG machine learning classifier) and second, the training of the user with online feedback (see Figure 1). The EEG data of the first two runs were used as calibration data for the MI-BCI machine learning algorithms. More precisely, EEG signals were first band-pass

filtered in a data-driven user-specific frequency band (5-35 Hz), then spatially filtered using Common Spatial Patterns (CSP) filters. Finally, the resulting features were classified using a Linear Discriminant Analysis (LDA) classifier (see [14], [15] for details). The trained MI-BCI was used to provide online feedback based on right-hand vs. left-hand MI discrimination during the four subsequent runs.

During the first two runs (calibration phase), users were provided with a sham feedback, i.e., a blue bar randomly appearing and varying in length. Such feedback (whether sham here, or real during the next phase) represents the BCI classifier decision (left or right hand MI when the bar goes left or right) and its associated confidence in such decision (i.e., the longer the bar the more confident). During each run (see Figure 1), users had to perform 40 trials (20 per MI-task, presented in a random order), each trial lasted 8s. At  $t = -3$ s, a cross was displayed on the screen. At  $t = -1$ s, an acoustic signal announced the appearance of a red arrow, which appeared one second later (at  $t = 0$ s) and remained displayed for 1.25s. The arrow pointed in the direction of the task to be performed. Participants were instructed to start performing the corresponding MI-task as soon as the arrow appeared, and to keep doing so until the cross disappeared. Finally, from  $t = 1.25$ s, a visual feedback was continuously provided in the shape of a blue bar, the length of which varied proportionally to the BCI classifier output, i.e., the distance to the LDA hyperplane (for run 3 to 6) or randomly (for the first two runs). The feedback was provided for 3.75s and was updated at 16Hz (1s sliding window). After 8 seconds, the screen turned black again until the beginning of the next trial. The participant could then rest for a few seconds: from 1.5s to 3.5s, randomly chosen.

### C. Electrophysiological recordings

EEG signals were recorded with two g.USBamp amplifiers (g.tec, Austria), sampled at 512 Hz, from 27 electrodes around the primary motor, the motor and the somatosensory cortices (for more details see [7]).

1) *Topographic ERD/ERS map*: All offline analyses of ERD/ERS modulations were performed using the EEGLAB toolbox 22.1 and MATLAB 2016a. The EEG data was divided into 13 second long epochs corresponding to 5 seconds before the MI-cue ( $t = 0$ s; see Figure 1) until 8 seconds after,

for each trial. Then, we have selected 4 different baseline time windows ( $[-5;-2]$ s,  $[-4;-1]$ s,  $[-3;0]$ s,  $[-2;+1]$ s) all of the same length (3 seconds) in accordance with our hypotheses to compute the ERD/ERS modulations (see Figure 1).

Brain topographies allow us to display the possible changes over different electrodes on the scalp in order to localize which part of the brain was involved when the subject performed the MI. In this article, we computed the topographic Event-Related Spectral Perturbations (ERSP; which is equivalent to ERD and ERS) in the  $\mu + \beta$  (8-30 Hz) band during the left-hand and right-hand MI tasks for both the calibration and user training phases in the time window  $[0;+5]$ s according to 4 different baseline time windows ( $[-5;-2]$ s,  $[-4;-1]$ s,  $[-3;0]$ s,  $[-2;+1]$ s (Figure 2).

2) *Offline BCI performances*: We computed offline BCI performances for classifying resting state EEG signals from a single hand MI task EEG (either left-hand or right-hand MI): rest VS left hand MI and rest VS right hand MI classification accuracies. All offline analyses of classification were performed using the MNE and Scikit-learn package in Python 3.9. These performance metrics were estimated offline by first band-pass filtering EEG signals in 8-30Hz and then extracting 3 second long MI and rest epochs from each trial. The MI corresponding to  $[0.5;3.5]$ s and the rest phase is identical to the different baseline time windows i.e. ( $[-5;-2]$ s,  $[-4;-1]$ s,  $[-3;0]$ s,  $[-2;+1]$ s (Figure 1). For each baseline/rest paradigm, a left hand MI vs rest and a right MI vs rest classifiers were built using CSP spatial filters and an LDA classifier, as done online for left-hand VS right-hand MI classification. Such classifiers were also trained on the first two calibration runs and tested on the four subsequent runs to obtain (offline) classification accuracies.

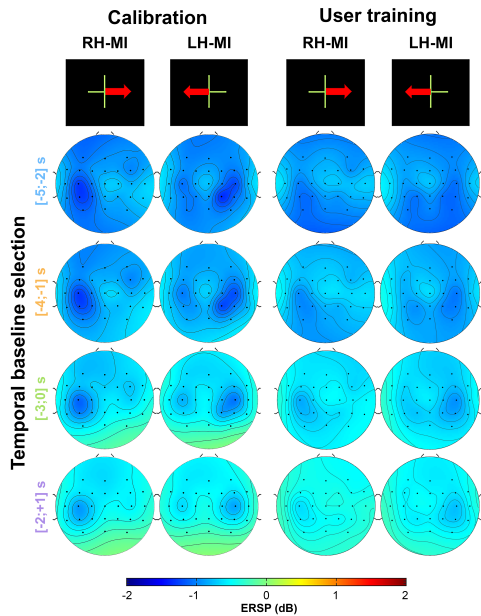


Fig. 2: Topographic map of ERD/ERS% (grand average,  $n=71$ ) in the  $\alpha/\mu + \beta$  band during the right-hand and left-hand MIs for both calibration and user training phases.

### III. RESULTS

#### A. ERD modulations according to baseline time selection

As expected, and as previously described [7], [16], our results showed an activation of the motor cortex with a contralateral ERD, i.e., covering either right and left-hand motor areas depending on the task, during the 5s when the MI task was performed (Figure 2). This result is in harmony with the literature: the ERD phase is mainly observed during the MI task and represents an activation of the motor cortex.

The comparison of ERDs across baselines shows that the closer the baseline used is to the preceding trial (e.g., Baseline 1 or Baseline 2), i.e. after the end of the previous MI, the more global the ERD is (more electrodes show an ERD) and the stronger its amplitude ( $p < 0.01$ ). This is true both for right and left-hand MIs, but also for both calibration and user training phases (Figure 2).

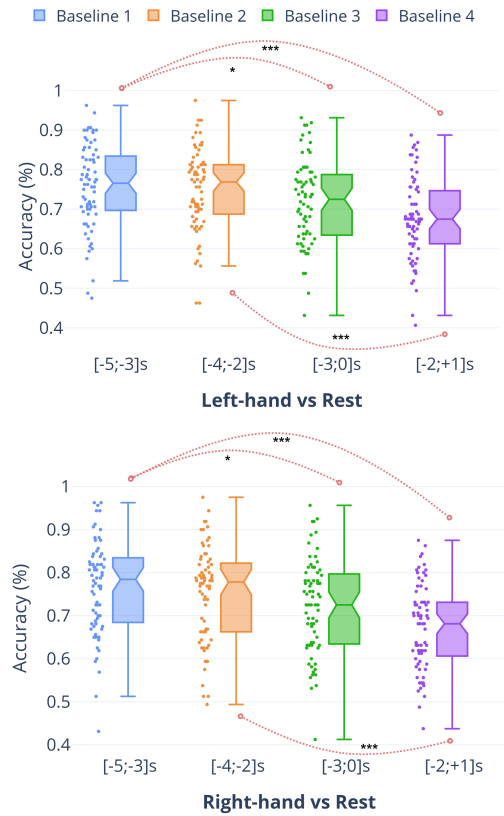


Fig. 3: Boxplots showing the distribution of classification accuracies ( $N=71$ ) for the Left-hand MI vs. Rest and Right-hand MI vs. Rest classes according to 4 different resting state times selected ( $[-5;-2]$ s,  $[-4;-1]$ s,  $[-3;0]$ s,  $[-2;+1]$ s). \*corresponds to a p-value  $< 0.05$ , \*\* to a p-value  $< 0.01$  and \*\*\* to a p-value  $< 0.001$ .

#### B. BCI performances according to baseline time selection

Regarding classification performances for MI vs Rest for various baseline/rest time windows, Figure 3 shows that the closer the selected baseline/rest time window to the preceding trial, i.e. to the end of the previous MI, the

higher the BCI performance. In contrast, if the selected resting time is close to the MI cue, the BCI performance is worse. BCI performance is significantly better for Baseline 1 compared to Baseline 3 (+4%,  $p < 0.05$ ) or Baseline 4 (+8%,  $p < 0.001$ ) for both right-hand MI and left-hand MI tasks. Interestingly, Baseline 2 is an interesting alternative since it improves the classification comparing to Baseline 4 (+7%,  $p < 0.001$ ). Although the use of baseline 4 in a practical case is rare since the person has already started to perform the MI, it provides a perspective on the impact of having a BCI paradigm designed in such a way that the participant anticipates task performance or does not follow instructions.

#### IV. DISCUSSION AND CONCLUSION

##### A. Functional interpretation of the ERD

Our results show that the baseline selected can have an impact on the interpretation of the ERD. If a baseline is selected closely to the cue of the following trial, it is possible that the subject's concentration and anticipation will decrease the SMR power, resulting in an under-representation of the ERD. In contrast, our results suggest that the selection of a baseline close to the end of the preceding MI, probably in the middle of the ERS phase, results in an over-representation of a global ERD on many electrodes (Figure 2). This suggests that it is necessary to be careful in interpreting results related to SMR activity, especially because the baseline temporal selection can possibly affect the identification of task-related SMR modulations. This may be an issue for studies pre-selecting participants or channels based on ERD modulations or simply to enable comparisons between different studies.

##### B. Implications for MI-BCIs

When designing an experiment to measure SMR, it is important to know what the ideal baseline measurement is and when it should be presented, which is rarely a priority in the BCI field. Indeed, BCI paradigms are typically designed in such a way that each trial follows the other very quickly, i.e., there are only a few seconds between the moment when an MI task is completed and when the next one begins. Our result suggested that this situation can make the baseline choice having a strong impact on the overall results, both in terms of neurophysiological interpretation and BCI performance (for rest VS MI classification). This mostly depends on whether the post-MI ERS from the previous trial affects the baseline measurement of the current trial. Thus, we would recommend designing MI-BCI protocols that either comprise dedicated resting state trials (i.e., with no MI) or that have an inter-trial duration that is long enough to ensure that baselines taken in that period are not contaminated by post-MI ERS from the previous trial. For the later point, since post-movement ERS typically peak 1.5s after the movement end [6], we recommend at least 3s in addition to the baseline duration for the inter-trial length, e.g., 6s between trials for a 3s long baseline/rest. For the same reasons, to enable between-studies comparisons between ERD/ERS, we encourage authors to carefully report

the timing and length of the baselines they use for ERD/ERS estimation, notably with respect to previous trials.

##### C. Baseline selection variability

In previous studies [10], [9], the optimal baseline was found to be subject-dependent, with no common preferred baseline for all subjects. Such a time-specific analysis of the ERD should be performed on our data and could confirm these inter-subject variability findings. Additional analysis showed that a majority of subjects has the best BCI performance with either Baseline 1 (for 55% of subjects for left-hand MI vs rest and for 52% of subjects for right-hand MI vs rest) or Baseline 2 (for 30% of subjects for left-hand MI vs rest and for 22% of subjects for right-hand MI vs rest). However, using a subject specific baseline only improved the classification performance (+2%) non significantly.

Overall, we hope this study showed the need to carefully study and report the ERD/ERS baselines for MI-BCI design.

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