A Co-adaptive SMR-BCI Based on Common Spatial Patterns and Random Forest

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Introduction

Sensorimotor rhythm (SMR) based brain-computer interfaces (BCI) typically require lengthy user training. This can be exhausting and fatiguing for the user as data collection may be monotonous and typically without any feedback for user motivation. Hence **reducing user training and improving performance** is highly appreciated. We recently introduced a two class motor imagery BCI system which **continuously adapts** to the brain patterns of the user [1]. The system is designed to **provide visual feedback** to the user **after just five minutes**. The aim of the current work was to **improve user-specific online adaptation**, which was expected to lead to higher performances.

Methods

Methods: We combined filterbank CSP (fbCSP) [2] and random forests (RF) [3],[4] with our co-adaptive training approach [1].

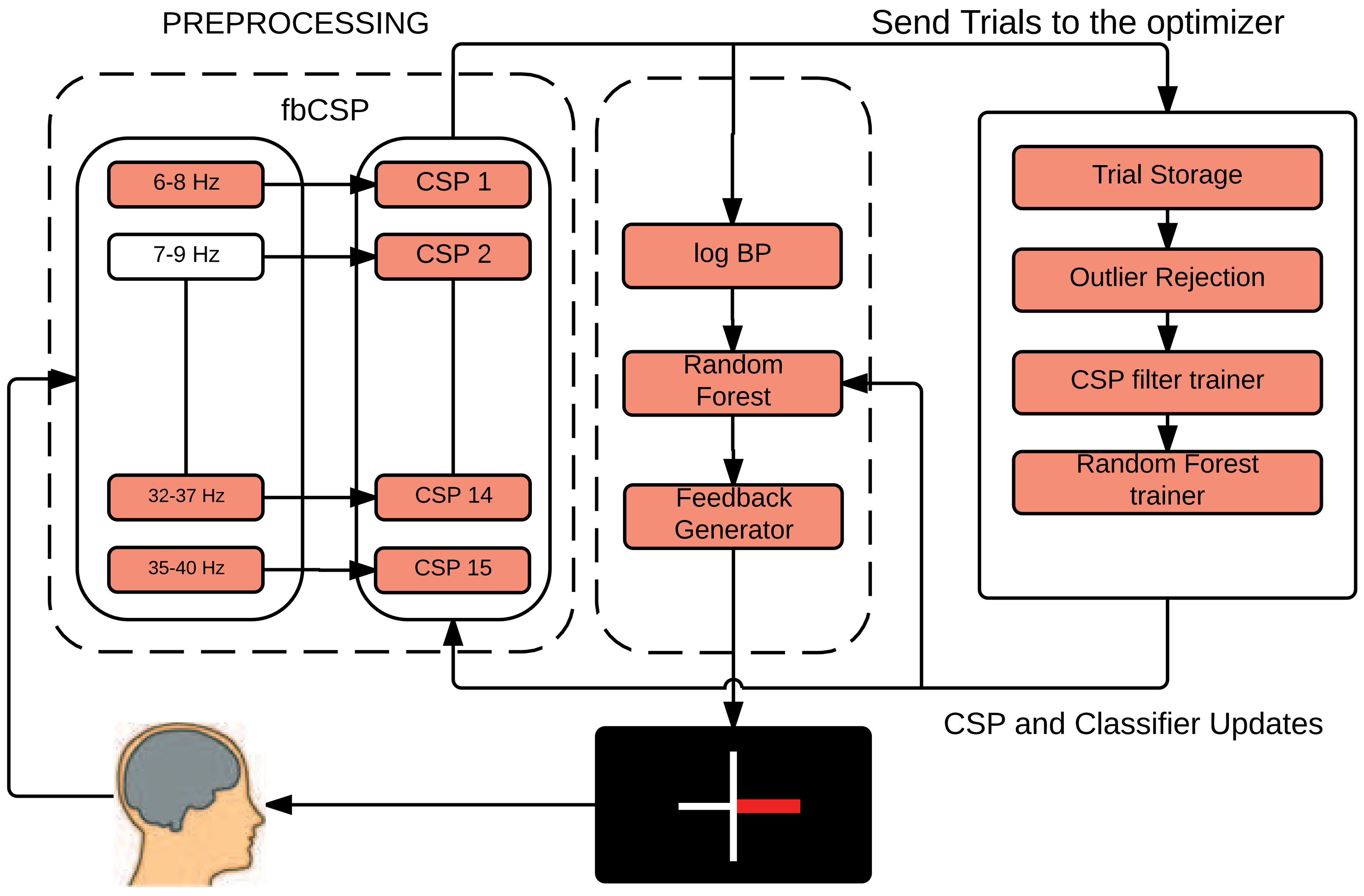


Figure 1: Multichannel EEG is preprocessed using a fbCSP [2]. Logarithmic bandpower features are extracted and classified by a random forest classifier [3][4]. The classifier output drives the feedback generator. On recurrent update points CSP filter and RF model are retrained with all available data.

Participants: 12 healthy volunteers (9 BCI naïve, mean age 27.8 years, 2 female)
Electrodes: EEG acquired from 13 active electrodes (g.Tec GammaSys) over sensori motor areas covering surrounding C3, Cz and C4.
Experiment Setup: 4 runs á 20 trials per class (TPC). The first 10 TPC of the first run were used for initial calibration of the system. Thereafter positive feedback was given.
Paradigm: Two class cue-based paradigm: Sustained MI of right hand, repeated MI of both feet.

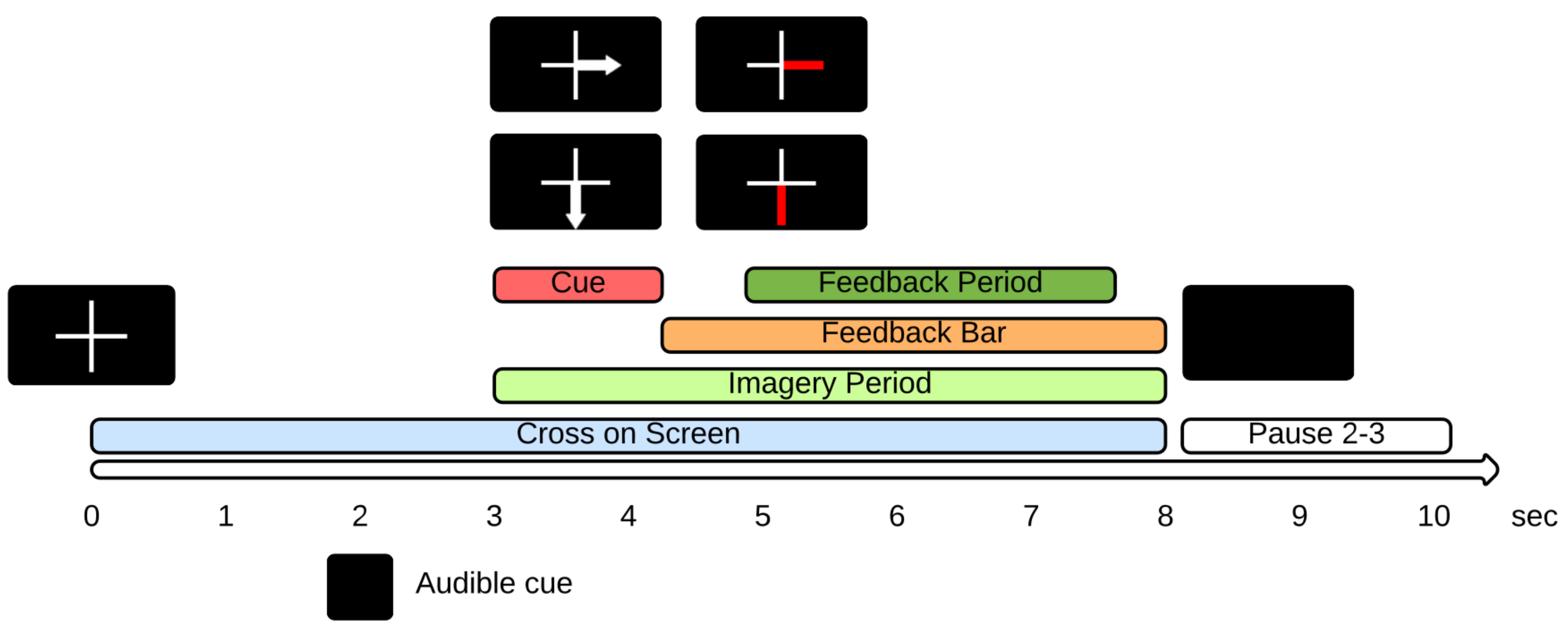
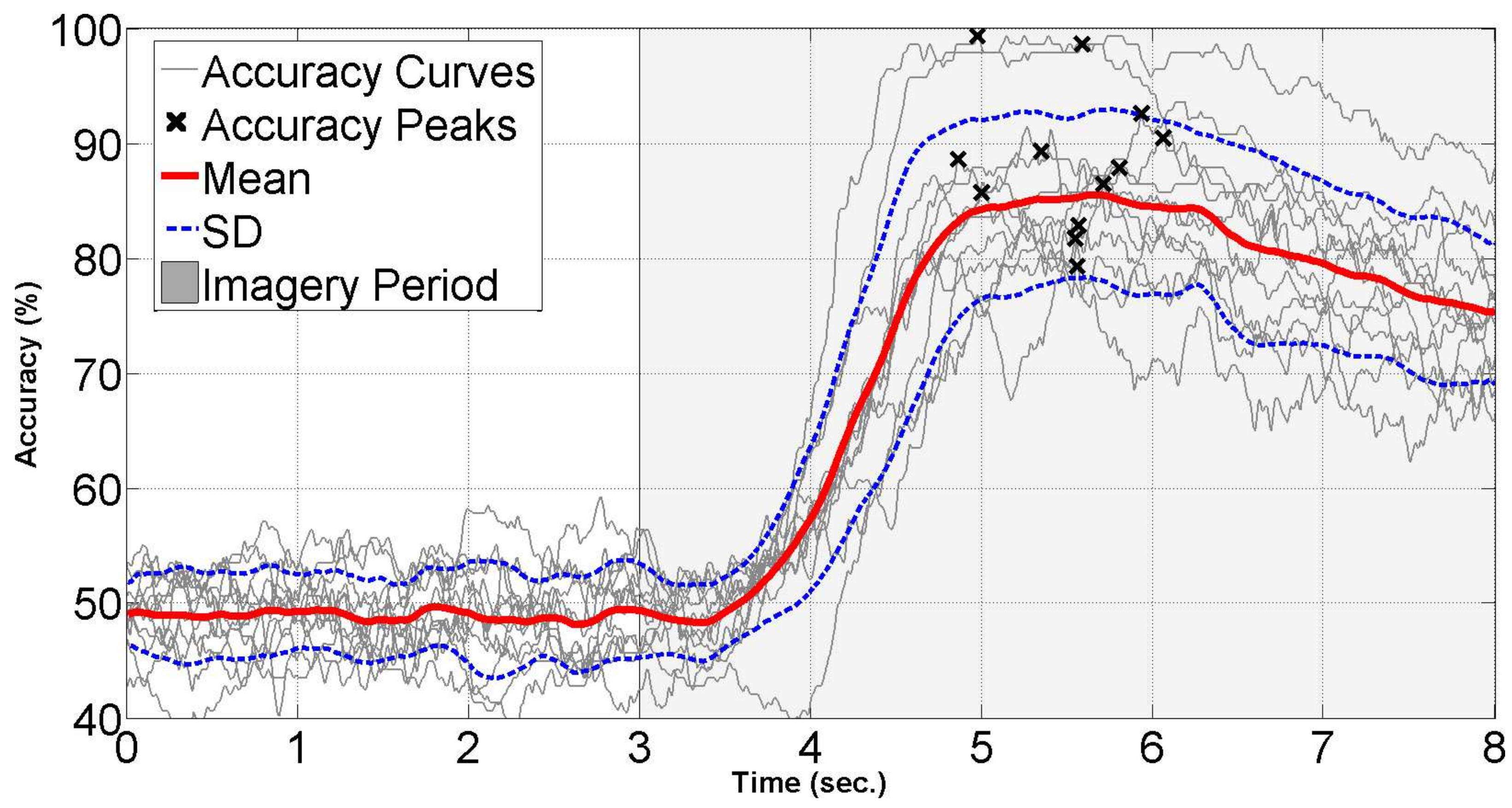


Figure 2: Two class cue based GRAZ-BCI paradigm: For CSP and RF training we took the period from 4.75s-7.75s respective time point 5.5s after trial onset.

Results



	th=50% of trials (%)	Peak (%)	Median 4.75-7.75s (%)
Mean (näive)	124 ±9	87.7 ± 5.3	81.4 ± 6.3
Mean (all)	125 ±9	88.6 ± 6.1	82.1 ± 6.9

Figure 3: Mean accuracy of all subjects over all feedback trials. Table: Column 2: If the number of correct classifications during the feedback-period (4.75s-7.75s) exceeded the threshold (th) we counted a correct selection. Column 3-4: Peak and median accuracy over the feedback-period.

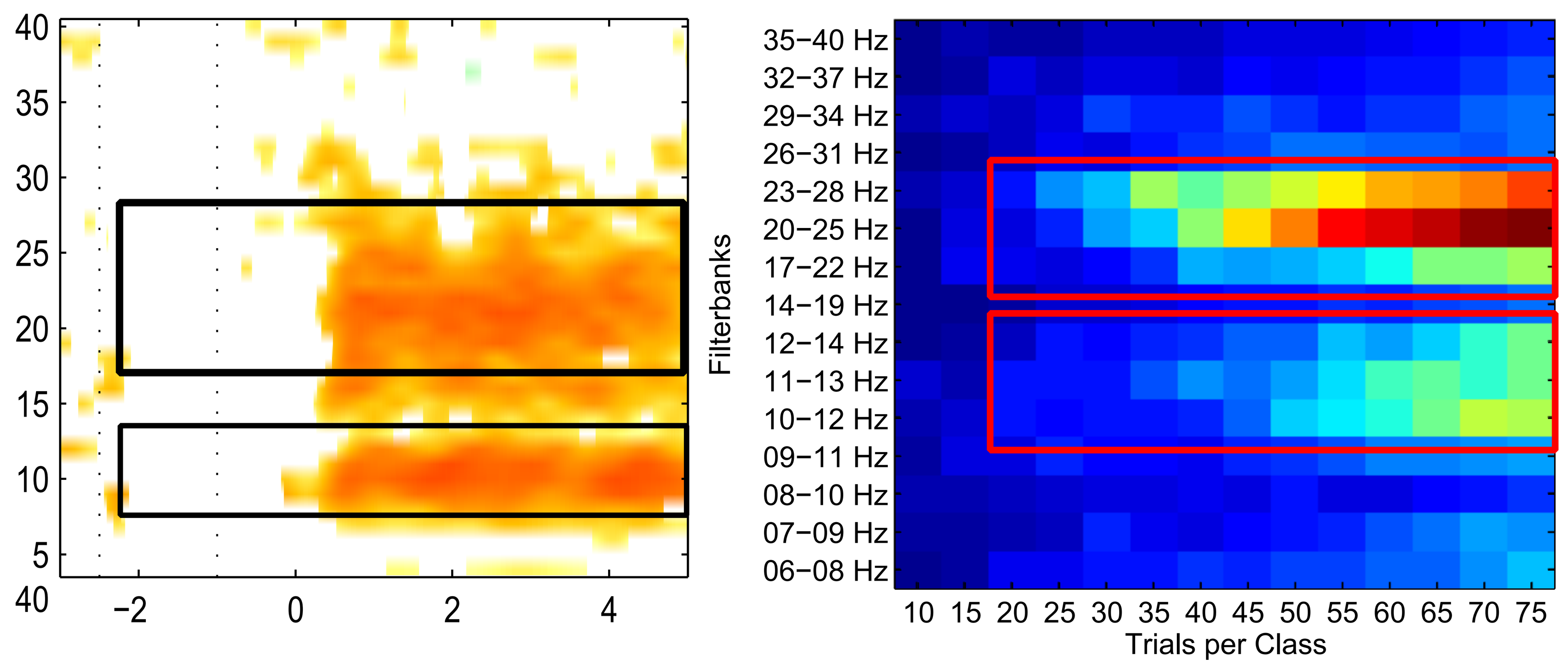


Figure 4: Comparison of an ERDS map (S12, Laplace Channel C3, MI of right hand) with the feature importance map of the RF [4]. X-axis shows every retraining step, Y-axis the importance of the fBCSP-features.

Discussion

The study indicates that the novel combination of these methods [1],[2],[3] is applicable for online use. We could show that the selection of user-specific features leads to increased performance in comparison to our previous approach [1]. Statisitical comparison between both approaches showed significant ($p < 0.05$) difference (two sided Wilcoxon rank sum test, $p = 0.015$).
The next step is to evaluate the performance in an online-control-scenario, where we stop adaptation and the user actually starts controlling applications.

References

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