Common Spatial Pattern Patches: online evaluation on BCI-naive users

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***Abstract*— Brain-Computer Interfaces (BCI) based on the voluntary modulation of sensorimotor rhythms (SMRs) induced by motor imagery are very prominent because allow a continuous control of the external device. Nevertheless, the design of a SMR-based BCI system that provides every user with a reliable BCI control from the first session, i.e., without extensive training, is still a big challenge. Considerable advances in this direction have been made by the machine learning co-adaptive calibration approach, which combines online adaptation techniques with subject learning in order to offer the user a feedback from the beginning of the experiment. Recently, based on offline analyses, we proposed the novel Common Spatial Patterns Patches (CSPP) technique as a good candidate to improve the co-adaptive calibration. CSPP is an ensemble of localized spatial filters, each of them optimized on subject-specific data by CSP analysis. Here, the evaluation of CSPP in online operation is presented for the first time. Results on three BCI-naive participants show indeed promising results. All three users reach the threshold criterion of 70% accuracy within one session, even one candidate for whom the weak SMR at rest predicted deficient BCI control. Concurrent recordings of the SMR during a relax condition as well as the course of BCI performance indicate a clear learning effect.**

I. INTRODUCTION

Brain Computer Interfaces (BCI) based on sensorimotor rhythms (SMRs), make use of the voluntary modulation in the alpha (8-12 Hz) or beta (13-20 Hz) frequency band of the electroencephalography (EEG) activity over sensorimotor areas during limb movement imagination to obtain, by proper real time processing of the brain activity, a control signal for an external device. Despite a great progress in BCI research (see [1] for a review), still 20-30% of the healthy population is not able to reach the level criterion of 70% of accuracy, above which users feel to have obtained BCI control, as assessed in [2] by a psychological study for two-class BCI with communication applications. A significant contribution to this research field comes from the machine learning (ML) approach, which utilizes newly developed algorithms to learn subject-specific parameters and adapt automatically to the user's brain signals (see [3]). In particular, Common Spatial Patterns (CSP), spatial filters which are optimized specifically for each user, successfully enhanced the performance for two-class BCIs (see [4] for a review). Furthermore, thanks to the new ML-based co-adaptive calibration [5] techniques, feedback can be provided from the beginning of the experiment so that the user is helped to find an appropriate strategy to modulate his/her SMR. Recently, Common Spatial Patterns Patches (CSPP) have been proposed [6], an ensemble of CSP filters which are a compromise between Laplacian filters (LAP) and CSP. Due to its simplicity, CSPP algorithm is more robust against overfitting than CSP, because it is applied to fewer number of electrodes. Additionally, thanks to its locality, CSPP is very suitable to be used in combination with co-adaptive calibration techniques. CSPP is also global and complex, because it takes into account all channels available and requires a feature selection among all patch forms and positions. In comparison to LAP, used in [5], CSPP employs the class information and thus is more optimized to subject and task. These properties have been already demonstrated in our previous works: in [6] performance accuracy of CSPP have been offline compared to LAP, CSP and a regularized CSP version ([7]), while in [8] CSPP were shown to outperform LAP in a simulation of online adaptation in combination with a subject-independent classifier. Here, the application of CSPP in an online study is presented for the first time, in order to effectively assess the suitability of the algorithm to BCI experiment and its performance. Additionally to the methods used for the offline analyses in [6] and [8], the combination of CSPP with unsupervised online adaptation is exploits in the last run of the experiment, necessary to assess the real classification accuracy as it would be in a real life application. The resulting is a complex and very flexible BCI system, which proves to optimally adapt to the user's brain actity.

II. EXPERIMENTAL SETUP

Three volunteers participated to a single session of motor imagery (MI) BCI. All three were novice SMR-based BCI users. For the class combination *left/right*, in each trial, an arrow directed either to left or to right appears in the center of the screen, together with a cross. The participant has to imagine respectively the left hand or the right hand movement. The brain activity is online processed and classified and the cross moves depending on the classifier output either to the left or to the right. A trial is correctly classified, if at the end of the trial the cross lies in the part of the screen indicated by the arrow. The class combinations *left/foot* and *foot/right* are also possible, where for the foot movement imagination the arrow is directed to the bottom of the screen.

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Five runs were acquired in total. Except for the first run, where 80 trials per class combination were recorded, one class combination was chosen based on the first run and used for the succeeding runs (100 trials each). For online classification, every 40 ms features are calculated as the log-variance of the band-pass and spatially filtered data (last 750 ms) and classified by Linear Discriminant Analysis (LDA). After each run, the algorithm training procedure described in Sec. III-E.1 was carried out, to eventually adjust subject-specific parameters and spatial filters. Methods used in each run are described in the following section.
At the beginning, after three runs and at the end of the experiment, a relax measurement was carried out, where the user had to relax and open or close the eyes depending on a vocal instruction. This measurement contained 10 trials per condition (eyes open/closed). EEG was recorded by 62 Ag/AgCl electrodes concentrated on the central areas were recorded.

III. Methods

A. CSP

CSP is a discriminative algorithm (see [4]) which determines spatial filters $\mathbf{W}$ from band-pass filtered EEG data $\mathbf{X}$ such that the difference between the variances of the filtered data $\mathbf{X}_{CSP} = \mathbf{X} \cdot \mathbf{W}$ for the two classes is maximized. This is done by solving the following generalized eigenvalue problem:

$$\Sigma_2 \mathbf{W} = (\Sigma_1 + \Sigma_2)\mathbf{W}\Lambda \tag{1}$$

where Σ_1 and Σ_2 are the covariance matrices of data belonging to class 1 and class 2, respectively. Each column of $\mathbf{W}$ is a spatial filter w_i corresponding to the eigenvalue λ_i, the $i-$th element of Λ, with $i = 1, 2, ..., N_c$ where N_c is the number of channels in $\mathbf{X}$. Choosing N filters, the filtered data $\mathbf{X_{CSP}}' = \mathbf{X} \cdot \mathbf{W}'$ will have smaller dimensionality $N < N_c$ and the two classes will be maximally separated by their variance. The filters are chosen as described in section III-G.

B. CSPP

CSPP is the application of CSP analysis to small sets of channels (patches), and the concatenation of the resulting features. Applying CSP analysis on just few channels, the risk of overfitting is reduced in comparison to usual CSP because the number of parameters to fit for each patch is less. In comparison to LAP, CSPP has the benefit to use the class information, hence to likely obtain a better performance. The patches can include a different number of surrounding channels (see Fig. 1 for the patches used in this study). Also the position of the centers of the patches can be selected, depending on the number of channels available and on the task. For each patch/center, a number of filters equal to the number of the involved channels results by CSP analysis and one filter per class is selected. For N_p centers, an ensemble $2N_p$ filters is then obtained (N_p filters per class) and N filters with $N < N_p$ are selected as described in section III-G.

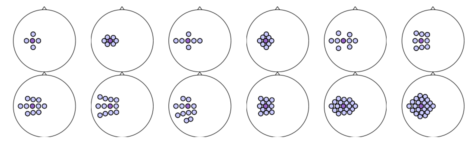

Fig. 1. Patch configurations centred on C3.

C. LDA

The decision function $D(\mathbf{x})$ of a LDA is reported in (2), where $\mathbf{w}$ is the vector normal to the hyperplane, $\mathbf{x}$ is the feature vector and b is the bias:

$$D(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b \tag{2}$$

For the calculation of $\mathbf{w} = \hat{\Sigma}^{-1}(\hat{\mu}_2 - \hat{\mu}_1)$, the estimated pooled covariance matrix $\hat{\Sigma}$ and the class means $\hat{\mu}_1$ and $\hat{\mu}_2$ are required. The bias $b = \mathbf{w}^T \hat{\mu}$ can be calculated without class information based on the estimated pooled mean $\hat{\mu} = (\hat{\mu}_1 + \hat{\mu}_2)/2$, if both classes can assumed to the equally sized (see [9]).

D. Run 1: subject-independent

1) Pre-trained CSPP and LDA: For each binary combination of motor imagery classes, CSPP filters were calculated from a data base of 48 successful BCI performers (data described in [11]). The data were concatenated, band-pass filtered in a broad band 8-32 Hz (previously chosen by offline analyses) and epoched in the time interval 750-3750 ms after stimulus onset. Six CSPP filters were then obtained by CSP analysis on three *small* patches (the first in Fig. 1) centered on C3, Cz and C4. A LDA classifier was trained on the six CSPP features (log-variance of the band-pass and CSPP filtered data).

2) Adaptation: After each trial, the LDA is adapted by updating the class means $\hat{\mu}_1$ and $\hat{\mu}_2$ and the inverse of the pooled covariance matrix $\hat{\Sigma}^{-1}$ in the calculation of the normal vector $\mathbf{w}$ and pooled mean $\hat{\mu}$ (see [5] for more details). Note that this adaptation method is supervised, i.e., exploits the information on the true target.

E. Runs 2-3-4: re-training

1) Algorithm training procedure: A semi-automatic procedure selected a subject-specific frequency band and time interval were the classes are maximally separated (see [4] for details). Data are band-pass filtered and epoched using these subject-specific parameters. Twenty-four centers distributed in the motor areas were used. For each patch form in Fig. 1, a generalization error is calculated by 5-fold cross validation where for each fold: 1) two to six CSP features and two to six CSPP features (out of 48) were calculated on the training set and used to train a LDA corrected by shrinkage and 2) the test set was spatially filtered by the up to twelve selected CSP+CSPP filters and the resulting features classified by the trained LDA. The patch form with the best generalization error was selected. Finally, CSP, CSPP (with the chosen patch form) and LDA were trained on the whole data set. For run 2, just 24 channels concentrated on the motor area were used for CSP training. For run 3 and 4, 48 channels were used, since it was found to be the optimal number of channels from a large database study [10]. Furthermore, while the training preceding run 2 and 3 used all previous trials, i.e. 80 and 180 respectively, for run 4 the trials of run 2 and run 3 were used, i.e. 200 trials.

2) Adaptation: After each trial, CSPP was recalculated using just the last 60 trials, resulting in new spatial filters and eventually new positions and number of features. The new CSPP features were concatenated to the fixed CSP features. The LDA classifier was then re-trained on the new features. This adaptation, which is still supervised, provides flexibility by CSPP with respect to spatial location of modulated brain activity, but also robustness by the fixed CSP. Offline analysis on a large database showed that the combination of CSP and CSPP gives better performance than CSP or CSPP alone.

F. Runs 5: unsupervised

Training was done as described in section III-E.1, using the trials of runs 2, 3 and 4, i.e. 300 trials. The bias of the LDA in (2) was adapted by updating the pooled mean $\hat{\mu}$ after each trial. For more information on LDA unsupervised adaptation see [9].

G. Feature Selection

The same feature selection procedure is applied for CSP, CSPP and CSPP feature ensemble. In particular, the variance $v_{i,j} = {w_j}^T \mathbf{X_i} {\mathbf{X_i}}^T w_j$ is calculated of the j-th feature within each trial i and the corresponding *ratio of medians* is taken as score s_j of that feature:

$$s_j = \frac{m_{j,2}}{m_{j,2} + m_{j,1}} \tag{3}$$

where $m_{j,1}$ and $m_{j,2}$ are the medians of $v_{i,j}$ across all trials belonging to class 1 and 2 respectively. A score s_j close to zero indicates that the corresponding feature maximizes the variance for class 1, a score close to one represents then class 2. Choosing the features with an extreme score implies that the log-variance features of the two classes will be maximally separated. This *ratio of medians* score has been suggested in the CSP review [4] as being more robust with respect to outliers than the classical eigenvalue score. Two to six features with at least 1 feature per class are selected by heuristics.

IV. Results

A. Relax measurement

Following [11], given a recording during a relax condition, it is possible to determine a prediction of the SMR-BCI performance of users. The power spectral density (PSD) at rest is modeled as $1/f$ noise spectrum with one, two or three peaks in the alpha, beta and gamma frequency bands. A higher peak gives better opportunity to voluntary suppress the respective rhythm, which is required for BCI control. The strength of the SMR (called SMR predictor) was calculated as the maximum distance between the PSD and the fit of the noise spectrum. This predictor is useful to estimate the SMR-BCI performance of BCI-naive users. If a user with exemplary spectra at rest performs poor in the BCI experiment, the chance is high that either the user used a wrong motor imagery strategy or the online algorithms did not work properly. In Fig. 2 the PSD, the corresponding fit of the noise and the value of the SMR predictor are visualized for the three users for the relax measurements acquired before (blue) and after (red) the BCI session. In particular, the Laplacian channel with the highest r^2 in the last run was selected, epochs of 2 seconds were extracted and averaged and the PSD in the frequency band 2-34 Hz was calculated. It can be clearly seen that the first user exhibits an exemplary PSD, with high SMR predictor value. After the BCI session, his SMR even improved, despite a little increase of the noise. The second user has an unusual PSD, with a large beta peak higher than the alpha peak. Moreover, the PSD of the second user is somehow noisy, because it is almost everywhere higher than the noise spectrum (this last point is not taken into account by the SMR predictor). Also for this user, the SMR improved substantially. The third user has no peak in alpha at all and a very small hump between beta and gamma with a consequent small SMR predictor. Even this user shows an improvement in the SMR, since the noise is smaller and the hump sharper after the BCI session. The chance for this user to control a BCI, especially in the very first session, is very low.

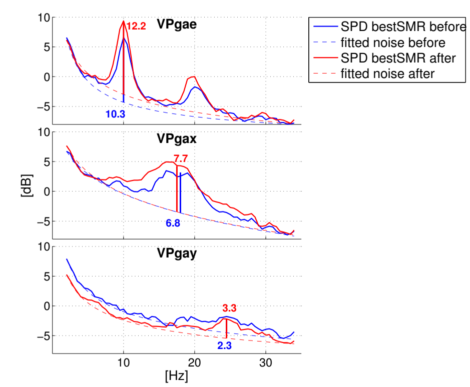

Fig. 2. PSD at rest (solid lines) and corresponding fitted noise spectrum (dashed lines) the relax measurements before (blue) and after (red) the BCI session. The number indicates the corresponding SMR predictor values, i.e. a measure of the user's potentiality to obtain BCI control.

B. Performance

The online performance is depicted in Fig. 3. The performance is computed in percentage of correct trials. The black dashed line marks the performance threshold of 70%. The red dashed line marks the performance level of 50% (random performance in two-class systems). The performance of the first run, with subject-independent methods, is shown in pink. The performance of runs 2, 3 and 4, with re-training of CSPP and LDA is depicted in orange, while the last run with unsupervised adaptation is coded in green. The first user, with high SMR predictor, reached the 70% already in the first 20 trials, because his SMR is exemplary and thus similar to those of the data used for the subject-independent classifier. Moreover, his performance increases rapidly, thanks to the co-adaptive approach, and reached 100% in two consecutive blocks in run 3. A drop in the performance happened in one block in run 4, whose causes need a detailed analysis of the data. The second user, with middle SMR value, improved the performance from block to block within the first run, reaching 75% in the last block. In the successive two runs, his performance continues to increase reaching 95% of accuracy. It then decreases a bit, probably also because of tiredness, as reported by the user himself. The third user, with very low chance of successful BCI control, shows a continuous improvement in the performance and was able to reach 75% in one block of the last run (the average accuracy of the last run is 68%).

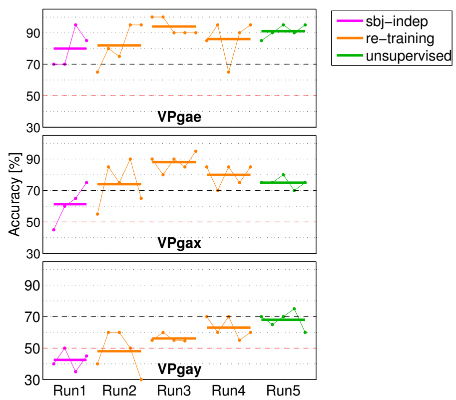

Fig. 3. Performance within each run. One dot for each group of 20 trials, each horizontal bar is the mean accuracy of the run. Colors indicare the different adaptation levels: magenta for subject-independent (run 1), orange for re-training (runs 1-3) and green for unsupervised (run 5).

V. Discussion

A first comparison of the performance with the results in the previous co-adaptation studies [5] and [12] allows to observe that, with CSPP, the first user started already by 70%, while the average of good performing users (already BCI experienced) in [5] started from 60% and novice participants in [12], which resulted also to be good performing users, also did not perform on average so well in the first run (first block accuracy was 62%, first run accuracy was 73% against 80% in this study). Neither in [5] nor in [12] middle performing users were able to reach 70% in the first run as in this study happened. More importantly, the unsupervised adaptation with CSPP was not affected by a drop in performance as in the previous co-adaptive studies and as expected since no re-training is employed. Finally, the clear learning effect visible in the performance of the third user, it has never been shown before for a BCI novice with no peak in the alpha band.

It is important to note that part of the performance increase in the third user is probably due to the continuous adaptation of the algorithms, since the SMR improvement cannot be considered enough to explain it. The drop in performance in run 4 for subject VPgae is a starting point for further improvement of the CSPP. In fact, the cause of this drop should be probably searched in a sensitivity of CSPP to artifacts. This problem affects in general the co-adaptive calibration system, because the system is adapted after each trial, even if it contains artifacts. From this point of view, CSPP is more sensitive than Laplacian, because it uses class information and adapts faster.

A very similar study with CSPP has been already conducted with 17 volunteers who previously participated to BCI standard (i.e. with calibration session and without online adaptation) as well as to co-adaptation studies. All users except for one reached better performance than the previous studies (which were conducted at least 2 years before). The authors preferred to report here just the results on BCI naive users because the analysis and the discussion of the other results require a comparison with the previous studies and thus more space. Moreover, a large number of subjects would not allow the analysis of each single subject, as done in this contribution.

Future work will analyze in particular the robustness of our proposed novel CSPP method with respect to non-stationarity in experimental conditions; here we expect a higher overall stability. In addition it will be interesting to understand the differences in the brain reorganization that happens during co-adaptive training for different subject types and to explore possible changes in the user brain plasticity.

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