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Introduction

In neurofeedback (NF), a new kind of data are available: electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) acquired simultaneously during bi-modal EEG-fMRI neurofeedback. These two complementary techniques have only recently been integrated in the context of NF for brain rehabilitation protocols. Bi-modal NF (NF-EEG-fMRI) combines information coming from two modalities sensitive to different aspect of brain activity, therefore providing a higher NF quality [1]. However, the use of the MRI scanner is cumbersome and exhausting for patients.

We present, a novel methodological development, able to reduce the use of fMRI while providing to subjects NF-EEG sessions of quality comparable to the bi-modal NF sessions [2]. We propose an original alternative to the ill-posed problem of source reconstruction. We designed a non-linear model considering different frequency bands, electrodes and temporal delays, with a structured sparse regularisation. Results show that our model is able to significantly improve the quality of NF sessions over what EEG could provide alone. We tested our method on 17 subjects that performed three NF-EEG-fMRI sessions each.

Materials and Methods

Participants and Data acquisition.

We used 17 right-handed healthy volunteers that were scanned using a hybrid Neurofeedback platform coupling EEG and fMRI signal [3]. A 64-channel MR-compatible EEG solution from Brain Products has been used, with a 3T Verio Siemens MRI scanner with a 12 channels head coil. All 17 subjects had 3 NF-EEG-fMRI motor imagery sessions of 8 blocks each. One block alters between 20 seconds of rest, eyes open, and 20 seconds of motor imagery of their right hand. Complementary information about ethic and data acquisition can be found in [1].

General procedure and study design.

The approach is based on a machine learning mechanism. One NF-EEG-fMRI session is used to learn the model, and the two others, unseen by the model, are used to test the model. Our approach directly intents to predict NF-EEG-fMRI scores ($y_c = y_e + y_f$, with y_e NF-EEG scores, y_f NF-fMRI scores), without source reconstruction nor estimation of the BOLD-fMRI signal as proposed by methods reviewed in [4]. First, each time interval t of EEG signals are summarised into a design matrix $\boldsymbol{X_0}$, from different frequency bands and electrodes. Second, different delays are applied to $\boldsymbol{X_0}$ by a non-linear transformation, the hemodynamic response function (HRF), inducing a potential linearity to the NF-fMRI scores estimated from BOLD signal. The new design matrices are noted $\boldsymbol{X_3}$, $\boldsymbol{X_4}$ and $\boldsymbol{X_5}$, for delays of 3 4 and 5 seconds. We note $\boldsymbol{X_c} = [\boldsymbol{X_0}\,; \boldsymbol{X_3}\,; \boldsymbol{X_4}\,; \boldsymbol{X_5}\,]$. Finally, the model, called NF-predictor, learns optimal activation patterns $\widehat{\boldsymbol{\alpha_c}}$ minimising: $\sum_t \frac{1}{2}(y_c(t) - \langle \boldsymbol{X_c}(t), \boldsymbol{\alpha_c}\,\rangle)^2 + \phi(\boldsymbol{\alpha_c})$ with $y_c(t)$ the reference NF score, and $\phi(\boldsymbol{\alpha_c}) = \lambda \|\boldsymbol{\alpha_c}\|_{21} +$

$\rho\|\boldsymbol{\alpha_c}\|_1$ a mixed norm giving a structured sparsity to the activation patterns : spatially selecting electrodes and smoothing the corresponding frequency bands. ρ is a fixed parameter.

Data analysis.
We built different NF-predictors for each subject: $\tilde{y}_{\widehat{\boldsymbol{\alpha_c}}}$ predicts y_c with the design matrix $\boldsymbol{X_c}$, and $\tilde{y}_{\widehat{\boldsymbol{\alpha_f}}}$ predicts y_f with $[\boldsymbol{X_3}; \boldsymbol{X_4}; \boldsymbol{X_5}]$. We assessed, for all subjects, the quality of the proposed model on the validation set, and assessed the quality of prediction on the testing set. Finally, to estimate the dispersion between models across subjects j and pair of learning/testing sessions (s_1, s_2), we visualised the absolute activation pattern: $\widehat{\zeta_c} = \sum_j^{17} \sum_{s_1=1,s_2=1}^{3} \left|\widehat{\boldsymbol{\alpha_c}}^{(j,s_1,s_2)}\right|$.

Results and Conclusions
On the validation set, the NF-predictors have a correlation of 0.83 in median for $\tilde{y}_{\widehat{\boldsymbol{\alpha_c}}}$ vs y_c and 0.80 for $\tilde{y}_{\widehat{\boldsymbol{\alpha_f}}}$ vs y_f, confirming that the design of the proposed model is adapted to the problem. On the testing set, the correlation to the reference score for $\tilde{y}_{\widehat{\boldsymbol{\alpha_c}}}$ vs y_c is 0.52 in median. However, the correlation of $y_e + \tilde{y}_{\widehat{\boldsymbol{\alpha_f}}}$ vs y_c is 0.74 in median, which is significantly better (one sided paired t-test; p=0.01) than y_e vs y_c (so without learning from fMRI). Figure 1 shows the prediction of y_c by the model on a testing set of a subject. Figure 1 also shows that the absolute patterns over all subjects and sessions consistently finds the C3 electrode when no delay is induced in this part of the model, which coincide with the motor area of the right hand. It also highlights that activation patterns have complementary information and are consistent across subjects and sessions.

To conclude, the NF-predictor we proposed is able to extract, using EEG signals, significant information from NF-fMRI to overcome the absence of NF-fMRI and increases the quality of the estimation of bi-modal NF when using EEG only.

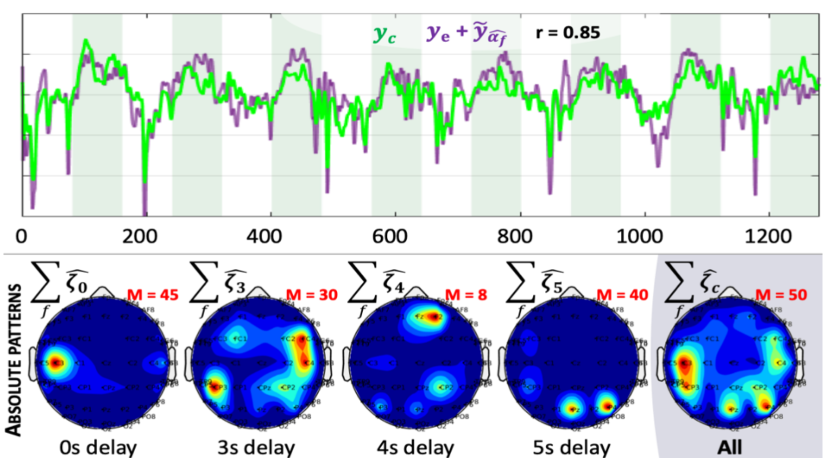

Figure 1, Results*:*

Top: Prediction of the NF-EEG-fMRI scores with $y_e + \tilde{y}_{\widehat{\boldsymbol{\alpha_f}}}$ *(purple) and the reference* y_c *(green).*

Bottom: absolute activation patterns (from $\widehat{\boldsymbol{\alpha_c}}$*) over all subjects and sessions, split-back into the different considered delays.*

References

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