



**HAL**  
open science

## Learning bi-modal EEG-fMRI neurofeedback to improve neurofeedback in EEG only

Claire Cury, Pierre Maurel, Giulia Lioi, Rémi Gribonval, Christian Barillot

### ► To cite this version:

Claire Cury, Pierre Maurel, Giulia Lioi, Rémi Gribonval, Christian Barillot. Learning bi-modal EEG-fMRI neurofeedback to improve neurofeedback in EEG only. *Real-Time Functional Imaging and Neurofeedback*, Dec 2019, Maastricht, Netherlands. pp.1-2, 10.1101/599589 . inserm-02368720

**HAL Id: inserm-02368720**

**<https://inserm.hal.science/inserm-02368720v1>**

Submitted on 18 Nov 2019

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

*Submitter information:*

Claire Cury, PhD, Post-doctorat, Inria Rennes Bretagne Atlantique, [claire.cury@inria.fr](mailto:claire.cury@inria.fr)

## **Learning bi-modal EEG-fMRI neurofeedback to improve neurofeedback in EEG only**

Claire Cury<sup>1,2</sup>, Pierre Maurel<sup>1</sup>, Giulia Lioi<sup>1</sup>, Rémi Gribonval<sup>2</sup> and Christian Barillot<sup>1</sup>

*1 - Univ Rennes, CNRS, Inria, Inserm, IRISA UMR 6074, Empenn, F-35000 Rennes, France.*

*2 - Univ Rennes, CNRS, Inria, IRISA UMR 6074, PANAMA team, F-35000 Rennes, France.*

### **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  $\mathbf{X}_0$ , from different frequency bands and electrodes. Second, different delays are applied to  $\mathbf{X}_0$  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  $\mathbf{X}_3$ ,  $\mathbf{X}_4$  and  $\mathbf{X}_5$ , for delays of 3 4 and 5 seconds. We note  $\mathbf{X}_c = [\mathbf{X}_0; \mathbf{X}_3; \mathbf{X}_4; \mathbf{X}_5]$ . Finally, the model, called NF-predictor, learns optimal activation patterns  $\widehat{\alpha}_c$  minimising:  $\sum_t \frac{1}{2} (y_c(t) - \langle \mathbf{X}_c(t), \alpha_c \rangle)^2 + \phi(\alpha_c)$  with  $y_c(t)$  the reference NF score, and  $\phi(\alpha_c) = \lambda \|\alpha_c\|_{21} +$

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

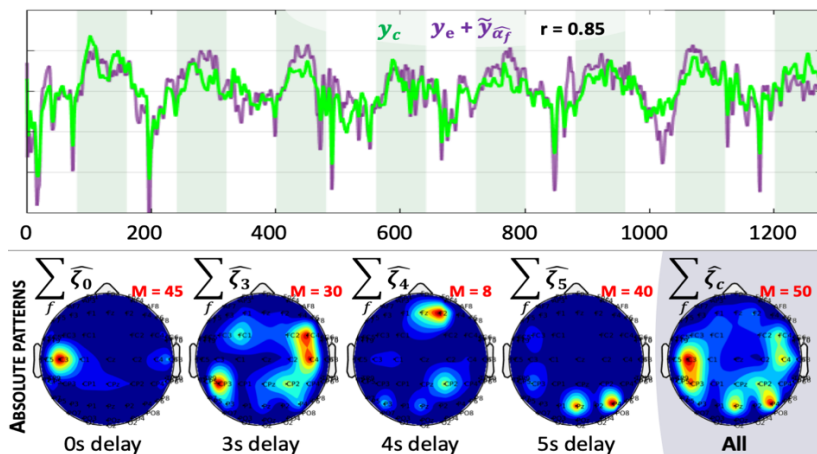
#### Data analysis.

We built different NF-predictors for each subject:  $\tilde{y}_{\hat{\alpha}_c}$  predicts  $y_c$  with the design matrix  $\mathbf{X}_c$ , and  $\tilde{y}_{\hat{\alpha}_f}$  predicts  $y_f$  with  $[\mathbf{X}_3; \mathbf{X}_4; \mathbf{X}_5]$ . 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:  $\hat{\zeta}_c = \sum_j^{17} \sum_{s_1=1, s_2=1}^3 |\hat{\alpha}_c^{(j, s_1, s_2)}|$ .

### Results and Conclusions

On the validation set, the NF-predictors have a correlation of 0.83 in median for  $\tilde{y}_{\hat{\alpha}_c}$  vs  $y_c$  and 0.80 for  $\tilde{y}_{\hat{\alpha}_f}$  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  $\tilde{y}_{\hat{\alpha}_c}$  vs  $y_c$  is 0.52 in median. However, the correlation of  $y_e + \tilde{y}_{\hat{\alpha}_f}$  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  $y_e + \tilde{y}_{\hat{\alpha}_f}$  (purple) and the reference  $y_c$  (green).*

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

### References

- [1] Perronnet, L., Lécuyer, A., Mano, M., Bannier, E., Lotte, F., Clerc, M., et al. (2017). Unimodal Versus Bimodal EEG-fMRI Neurofeedback of a Motor Imagery Task. *Frontiers in Human Neuroscience* 11
- [2] Cury, C., Maurel, P., Gribonval, R., and Barillot, C. (2019). A sparse EEG-informed fMRI model for hybrid EEG-fMRI neurofeedback prediction. *bioRxiv* doi:10.1101/599589
- [3] Mano, M., Lécuyer, A., Bannier, E., Perronnet, L., Noorzadeh, S., and Barillot, C. (2017). How to Build a Hybrid Neurofeedback Platform Combining EEG and fMRI. *Frontiers in Neuroscience* 11
- [4] Abreu, R., Leal, A., and Figueiredo, P. (2018). EEG-Informed fMRI: A Review of Data Analysis Methods. *Frontiers in Human Neuroscience* 12