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Can we learn from coupling EEG-fMRI to enhance neuro-feedback in EEG only?

C. Cury$^{1,2}$, P. Maurel$^1$, R. Gribonval$^2$ and C. Barillot$^1$

1– CNRS, Inserm, Inria, Univ Rennes, IRISA, Empenn team
2– CNRS, Inria, Univ Rennes, IRISA, Panama team

INTRODUCTION

**Neuro-feedback (NF):** Learn to control your brain with your brain.

EEG and fMRI, grounds solutions in the context of brain rehabilitation protocols.

EEG and fMRI provide complementary information.

EEG is easy to use, fMRI is a costly and exhausting for patients modality.

**Bi-modal NF:**
- Records and synchronises EEG and fMRI signals, in real time (Mano et al).
- Combines NF-EEG and NF-fMRI advantages
- Improve the quality of NF sessions (Perronnet et al).
- It is not portable or easy to use, due to the fMRI modality.

→ Can we enhance NF in EEG only, from a previous bi-modal NF session?

METHOD

- **Design and strategy:** Machine learning mechanism based on bimodal NF scores and EEG signals.

- **Model:** Non-linear structured design matrix $X$

  \[ X(t) = [X_0; X_3; X_4; X_5] \in \mathbb{R}^{T \times 4 \times B} \text{, with } X_i \in \mathbb{R}^{T \times E \times B} \]

  \[ X_0(t, e, b) = Freq(EEG(e, l), F_b) \quad \forall t \in \{1, ..., T\} \text{ and } \forall b \in \{1, ..., B\} \]

  \[ X_3(t, e, b) = X_0(t, e, b) \ast HRF(3) \quad \forall e \in \{1, ..., E\} \]

  \[ X_4(t, e, b) = X_0(t, e, b) \ast HRF(4) \quad \forall e \in \{1, ..., E\} \]

  \[ X_5(t, e, b) = X_0(t, e, b) \ast HRF(5) \quad \forall e \in \{1, ..., E\} \]

- **Optimisation:** Structured sparse regularisation following 3 conditions:
  1. Spatial sparsity
  2. Smooth across frequency bands

\[
\hat{\alpha} = \arg \min_{\alpha} \sum_{t=1}^{T} \frac{1}{2} \| NF(t) - \langle X(t), \alpha \rangle \|^2 + \lambda \| \alpha \|_1 + \rho \| \alpha \|_2
\]

Cond 1. and 2. Cond 3.

RESULTS

- **Significant information from NF-fMRI can be captured by the model, and enhance EEG only neurofeedback.**
- **Prediction with NF-predictor S with a median correlation of 0.74**

  - Method tested on 17 subjects with 3 bimodal neuro-feedback sessions of motor imagery tasks.
  - We tested 5 NF-predictors:
    1. $\hat{y}_{NF}(t) = \langle X, \hat{\alpha}_c \rangle$, learned from $X$ and $NF_c = NF-EEG + NF-fMRI$
    2. $\hat{y}_{NF}(t) = \langle X, \hat{\alpha}_c \rangle$, learned from $X_c$ and EEG
    3. $\hat{y}_{NF}(t) = \langle X, \hat{\alpha}_c \rangle$, learned from $X_c$ and NF-fMRI
    4. $\hat{y}_{NF}(t) + \hat{y}_{NF}(t) + \hat{y}_{NF}(t)$
    5. $\hat{y}_{EEG}(t) + \hat{y}_{EEG}(t)$, with $\hat{y}_{EEG}(t) = NF-EEG(t)$

   ![Example of prediction](image)

   ![Average and absolute activation patterns](image)

References:


