Improving portability of bimodal neurofeedback: predicting NF-fMRI scores from EEG signals
Caroline Pinte, Claire Cury, Pierre Maurel

HAL Id: hal-04168694
https://inria.hal.science/hal-04168694
Submitted on 21 Jul 2023

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.

Distributed under a Creative Commons Attribution 4.0 International License
Improving portability of bimodal neurofeedback: predicting NF-fMRI scores from EEG signals

Caroline Pinte
@Caroline_Pinte
caroline.pinte@irisa.fr

Introduction

• Neurofeedback (NF) training is more effective with simultaneous EEG-fMRI acquisitions [1].
• However, the use of MRI is expensive and draining for the subject.
• So, we need to reduce its use.

→ We propose a method based on a one-dimensional convolutional neural network (1D CNN). With this model, we aim to predict fMRI information from EEG recordings.

Objective

Learning a neural network model from simultaneous EEG-fMRI data to predict NF-fMRI scores from EEG signals alone.

Methods

1. Data: We acquired simultaneous EEG-fMRI data on 15 healthy subjects in a motor imagery context, described in [2]. This includes fMRI and EEG data for three NF runs of five minutes per subject, with their respective NF scores.

2. Preprocessing: We compute a supervised learning dataset, where a certain number of timesteps from a selection of EEG channels become one sample that has one NF score as target.

3. Training: We train the 1D CNN model. Since we have 15 subjects with 3 runs each, the training dataset consists of 14 subjects and 2 runs, the validation dataset of the third run from these 14 subjects, and the test dataset of the 3 runs from the 15th subject.

4. Analysis: After the model is trained, NF-fMRI scores are predicted, and compared to the ground truths with the RMSE and Pearson correlation metrics.

Discussion

We are currently working on improving the correlations, which are negatively impacted by:
• Sensitivity to the neural network hyperparameters
• Noisy nature of the EEG modality
• Lack of diversity in data

Conclusion

• The interest of this method compared to the previous modeling [3] is to train a single deep learning model for all subjects, which would eventually allow the use of the model to predict these fMRI scores directly online.

• An important aspect of the issue is to interpret this model, in order to understand links between EEG and fMRI.

Results

<table>
<thead>
<tr>
<th></th>
<th>Predicting NF-EEG scores</th>
<th>Predicting NF-fMRI scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean RMSE</td>
<td>0.23</td>
<td>0.47</td>
</tr>
<tr>
<td>Mean correlation</td>
<td>0.94</td>
<td>0.22</td>
</tr>
<tr>
<td>Min-max correlation</td>
<td>(0.62 - 0.86)</td>
<td>(0.60 - 0.44)</td>
</tr>
</tbody>
</table>

Fig. 2: Prediction of NF-EEG scores train and valid loss curves (top left) and comparison between NF-EEG ground truth and NF-fMRI prediction for the 1st run (top right), the 2nd run (bottom left) and the 3rd run (bottom right) from the test subject.

Fig. 3: Prediction of NF-fMRI scores train and valid loss curves (top left) and comparison between NF-fMRI ground truth and NF-fMRI prediction for the 1st run (top right), the 2nd run (bottom left) and the 3rd run (bottom right) from the test subject.

2. Lioi et al. "Simultaneous EEG-fMRI during a neurofeedback task, a brain imaging dataset for multimodal data integration." (2020)