RELATING EEG MICROSTATES TO THE DEFAULT MODE NETWORK

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ABSTRACT

Index Terms— machine learning, EEG, fMRI, microstates, Default Mode Network

1. INTRODUCTION

The aim of this project is to find relation between EEG-derived microstates and Default Mode Network (DMN) from fMRI, using methods described in [3].

Alterations in DMN have been connected to various neurological diseases, like Alzheimers or schizophrenia [3], [1]. DMN can be easily detected by fMRI scanning, but it is an expensive procedure requiring a visit to the hospital. If correlation between EEG and DMN from fMRI can be found, it may allow the use of EEG as a cheaper and more portable tool for diagnosis of neurological diseases.

1.1. Microstates

Microstates are unique topographic distributions of the electrical field potential in the brain [1]. They are transient, patterned and quasi stable (1̃00 ms). They are derived from EEG signal using either temporal clustering or temporal ICA. Microstate analysis has been used for assessing the function of large-scale brain networks.

1.2. Default Mode Network

Resting State Networks (RSNs) are networks of brain regions, that are active when a person is resting (but not sleeping). Default Mode Network (DMN) is one of the most researched RSNs. It is becoming active when one mind is ”wandering”. Its subsystems include part of the medial temporal lobe for memory, part of the medial prefrontal cortex for theory of mind, and the posterior cingulate cortex for integration, along with the adjacent ventral precuneus and the medial, lateral and inferior parietal cortex [2].

1.3. Research topic

The topic of this article consists of few subproblems:

- **artefact removal** - simultaneous recording of EEG and fMRI is causing a lot of noises in EEG signal. EEG is also very sensitive to heartbeat and eye and body movements. Removing artefacts is important part of feature engineering.

- **retrieving microstates** - different methods can be used to retrieve microstates from EEG [1]. Establishing proper pipeline for retrieving microstates allows them to be robust and valuable features.

- **finding correlation** - once we obtain a features from EEG and values from fMRI, there are various tools that can be used to find correlation. Choosing a right one allows for finding hopefully high correlation with low bias.

1.4. Current status in literature

2. DATA

The EEG and fMRI data were recorded simultaneously.

The data contains 10 minutes probes from 20 subjects, recorded in free different settings: in atmospheric, increased CO_2 and increased O_2 conditions. It was recorded in Glostrup Hospital by Egill Rostrup and Ulrich Lindberg as a simultaneous EEG/fMRI. The recording included 30 electrodes for brain activity measurement, one for eye movement and one for heartbeat. The sampling frequency was 500 Hz. The time stamp of launching the fMRI is recorded for each sample, so the data can be trimmed appropriately.

2.1. Artefact removal

Initial cleaning of the data, especially removing the fMRI artefacts, has been performed by Glostrup Hospital staff, followed by further artefact removal performed by Andreas Trier Poulsen. This process included notch- and low-pass filtering, as well as using ECG and EOG to get rid of eye blinks and heart beat artefacts. The data from only 5 subjects (in all conditions) remained.

3. GENERATING MICROSTATES

The input data for this process is artefact-free data from five subjects in all conditions, from 30 electrodes. At the end, we have 30 microstates, from which some will be chosen as regressors in correlation task.

3.1. Global Field Power

Following Yuan et al., we calculated the Global Field Power time course (GFP), which is a standard deviation across electrodes. Then we found topographies corresponding to peaks in the GFP. The parameters of the peak detection algorithm were selected for highest correlation with the fMRI data via a grid search.

3.2. Independent Component Analysis

We concatenated the topographies from peaks across subjects, and run ICA. Our algorithm of choice was FastICA [4] with the cubic non-linearity function. The resulting separation matrix was applied to the continuous EEG to obtain time courses of the microstates.

3.3. Hemodynamic response function

We constructed a binary matrix which encodes which microstate has the highest activation at each time, and convolved it with the hemodynamic response function to adjust for the time-delay of the BOLD fMRI response. These were used as regressors in the elastic net model [5].

4. CORRELATION OF MICROSTATES AND DMN

4.1. Independent Components from fMRI

4.2. Elastic net

4.3. Cross-validation

5. EXPERIMENTS

In order to evaluate the robustness of the algorithm of finding microstates, we altered the minimum peak width and height in the peak detection and performed 5-fold cross validation omitting one subject at each fold. In each fold, for a specific set of parameters in the peak detection, we found a set of microstates ordered by the power explained. We aligned the matrices to be of the same sign using correlation of the first column of the mixing matrices with respect to the first fold. We calculated the sum of the Frobenius norm of the deviation from the mean of the mixing matrices. We found that the robustness decreased in both directions. Hence, no restrictions should be given for the peak detection algorithm for the maximum robustness.

5.1. Adjusting peak sizes

We performed 5-fold cross-validation with log-spaced in the interval [10^{-4} - 10^{2}] by randomly dividing the data into the 5 folds to adjust of the fact that the behaviour of a subject might 'change' over time in the scanner e.g. fall asleep. Since we did not have an independent test set, we couldn't assess the generalization error. Instead, we estimated the error on the validation set.

6. RESULTS

7. DISCUSSION

8. CONCLUSIONS

9. ACKNOWLEDGEMENTS

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