RELATING EEG MICROSTATES TO THE DEFAULT MODE NETWORK

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ABSTRACT

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

1. INTRODUCTION

1.1. Microstates

Microstates are unique topographic distributions of the electrical field potential in the brain [1]. They are transient, patterned and quasi stable ($\tilde{1}$00 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. Motivation

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. This research aims to find a correlation between microstates derived from EEG data and DMN from fMRI. This may allow the use of EEG as a cheaper and more portable tool for diagnosis of neurological diseases.

1.4. Problem

2. DATA

The EEG data contains 10 minutes probes from 20 subjects, recorded in free different settings: in atmospheric, increased CO_2 and increased O_2 conditions. The data 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 moment 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. METHODS FOR GENERATING MICROSTATES

3.1. GFP

Following Yuan et al., we calculated the global field power time course (GFP), and 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. FastICA

We concatenated the topographies 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].

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.

4. FINDING RELATION BETWEEN MICROSTATES AND DMN

4.1. Independent Components from fMRI

4.2. Elastic net

4.3. Cross-validation

5. EXPERIMENTS

5.1. Adjusting pick 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. ILLUSTRATIONS, GRAPHS, AND PHOTOGRAPHS

Illustrations must appear within the designated margins. They may span the two columns. If possible, position illustrations at the top of columns, rather than in the middle or at the bottom. Caption and number every illustration. All halftone illustrations must be clear black and white prints. Colors may be used, but they should be selected so as to be readable when printed on a black-only printer.

Since there are many ways, often incompatible, of including images (e.g., with experimental results) in a LaTeX document, below is an example of how to do this [**?**].

(a) Result 1

(b) Results 3 (c) Result 4

Fig. 1. Example of placing a figure with experimental results.

9. CONCLUSIONS

10. ACKNOWLEDGEMENTS

11. REFERENCES

[1] Arjun Khanna, Alvaro Pascual-Leone, Christoph M. Michel, and Faranak Farzan, "Microstates in resting-state eeg: Current status and future directions," *Neuroscience & Biobehavioral Reviews*, vol. 49, no. 0, pp. 105 – 113, 2015.

[2] R. L. Buckner, J. R. Andrews-Hanna, and D. L Schacter, "The brain's default network: Anatomy, function, and relevance to disease," *Annals of the New York Academy of Sciences 1124 (1): 138*, 2008.

[3] Han Yuan, Vadim Zotev, Raquel Phillips, Wayne C. Drevets, and Jerzy Bodurka, "Spatiotemporal dynamics of the brain at rest exploring {EEG} microstates as electrophysiological signatures of {BOLD} resting state networks," *NeuroImage*, vol. 60, no. 4, pp. 2062 – 2072, 2012.

[4] A. Hyvarinen, "Fast and robust fixed-point algorithms for independent component analysis," *Neural Networks, IEEE Transactions on*, vol. 10, no. 3, pp. 626–634, May 1999.

[5] Trevor Hastie, Robert Tibshirani, and Jerome Friedman, *The Elements of Statistical Learning. Data Mining, Inference, and Prediction, Second Edition*, Springer-Verlag New York, 2009.

[6] C.D. Jones, A.B. Smith, and E.F. Roberts, "Article title," in *Proceedings Title*. IEEE, 2003, vol. II, pp. 803–806.