Automatic Anatomical & Functional Labeling of Brain Activity Maps

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Abstract

Your abstract.

1 Introduction

[group ICA]

[falff and dyn range]

[REST toolbox masks]

2 Methods

2.1 Data

2.1.1 FBIRN

2.1.2 COBRE

2.1.3 BSNIP

2.1.4 NeuroMark

2.2 Group ICA

The simplest way to use the autolabeller is to run it with the group independent component analysis (ICA) session information file as the input. Prior to that we need to ensure that the group ICA on the given functional magnetic resonance imaging (fMRI) dataset has finished successfully, and the ICA post-processing step has been completed. The ICA post-processing step generates the fractional amplitude of low frequency fluctuation (fALFF) and dynamic range values of the independent components (ICs) time courses (TCs) as well as the mean static functional network connectivity (FNC) matrix across all subjects. In the group ICA for fMRI toolbox (GIFT) toolbox, generating the HTML report will ensure that the post-processing step has been run.

2.3 Identifying Resting-State Networks

We trained a logistic regression model with different IC characteristics or features in order to separate resting-state network (RSN) from artifacts. Five different features were used. Two of those are based on the IC TC characteristics, such as fALFF and dynamic range. The other three features are based on the IC spatial map characteristics, such as correlations with edge motion mask, cerebrospinal fluid (CSF) mask and white matter mask.

[the masks come from REST toolbox]

[use Matthew's corelation]

The output of the model is either 0 or 1, indicating artifact or RSN respectively. We obtained the logistic regression model parameters by training on the Function Biomedical Informatics Research Network (FBIRN) dataset features, which could be used on any testing dataset to identify those.

2.3.1 Training Data

We trained a logistic regression model with different IC characteristics in order to separate RSN from artifacts. We obtained these training ICs and their labels from the FBIRN dataset Damaraju et al. (2014).

2.3.2 Testing Data

We ran two separate group ICA analysis on Bipolar-Schizophrenia Network on Intermediate Phenotypes (BSNIP) and Centers of Biomedical Research Excellence (COBRE) datasets and tested the autolabeller on the resulting IC spatial maps.

2.4 Anatomical Labeling of Spatial Maps

We determined the anatomical label of a region of activation by correlating the spatial map with known regions in a given anatomical atlas. A number of anatomical atlas are available. We first used the Automated Anatomical Labeling (AAL) atlas which is probably the most widely used cortical parcellation map in the literature Tzourio-Mazoyer et al. (2002). As we develop the autolabeller, we will add more choices of anatomical atlases.

2.5 Functional Labeling of Spatial Maps

We determined the functional label of a region of activation by correlating the spatial map with known regions in a given functional parcellation of the brain. Several functional parcellations are available. We first used the Yeo 2011 functional parcellations (17 networks version) in conjunction with the Buckner functional cerebellar parcellation Yeo et al. (2011); Buckner et al. (2011). As we develop the autolabeller, we will add more choices of functional parcellations.

2.6 Reordering of FNC Matrix

3 Results

4 Discussion

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