Categorization and Generation of group-wide independent components in fMRI using clustering

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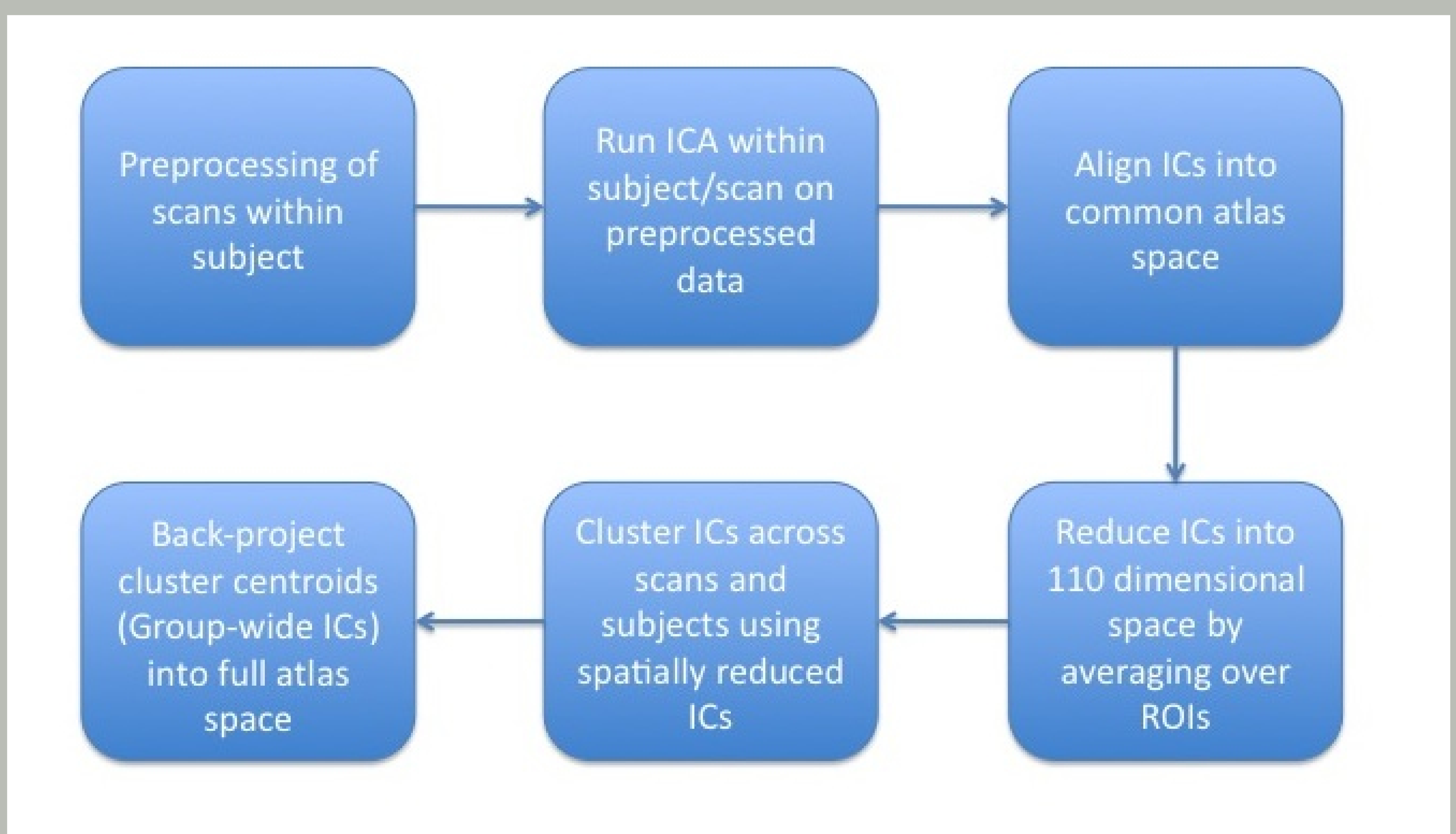
Motivation

Statistically independent spatial components (ICs) in fMRI time series may represent functionally connected brain regions marked by temporally coherent signal fluctuations [5]. We are exploring the use of these ICs as features for classification of mental states, premised on the model the such states represent the superposed activity of meaningful functional subsystems. Towards the goal of generalization of our classification strategy we seek to find ICs that are common across populations of individuals. Group Independent Components Analysis (gICA) methods identify common spatial patterns of signal change or activation across scan sessions or individuals [1, 2]. However, the high computational complexity of gICA limits the number of scans one can analyze simultaneously. These algorithms effectively assume that given components are present in all individuals, but with unique time courses. This may not be a realistic assumption in patients performing different tasks, receiving different treatments, or having different impairments (mental illnesses). We present a method to generate and categorize group-wide independent components) using clustering over thousands of single-subject ICs from hundreds of scan sessions. Computationally simpler clustering is performed over anatomically (and presumably functionally) constrained ROIs instead of voxels to generate group-wide ICs.

Procedure



Advantages of Compressing Spatial Dimensions

- Reduced spatial dimensions give the ability to analyze larger numbers of scan session results, leading to a more general estimate of group-ICs.
- By using the average IC magnitudes within regions our method is also somewhat more robust against problems of movement of misregistration than voxel-based approaches.
- The compression of spatial dimensions allows the usage of k-means clustering, which in turns allows the computation of cluster "centroids", or points that are most representative of each cluster.
- Centroids allow efficient "categorization" of future ICs with a simple nearest-neighbor distance.

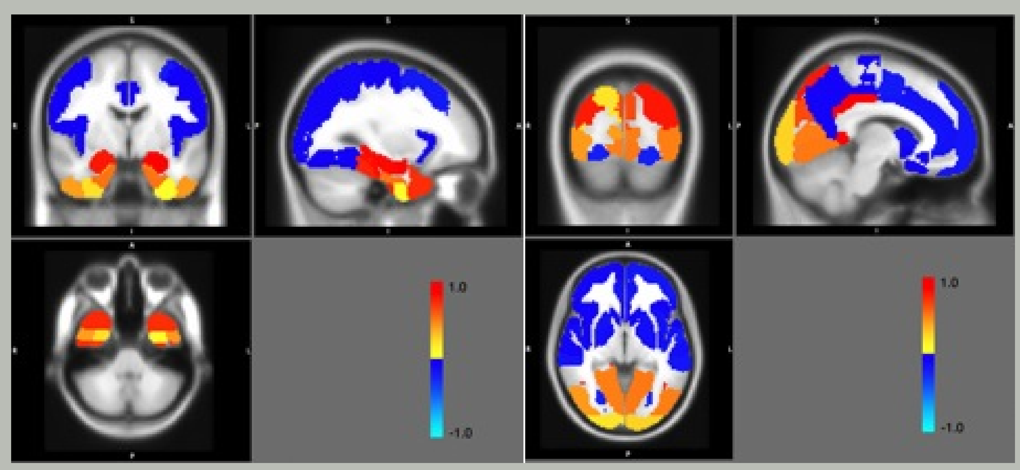
Data

- As part of a wider study aimed at understanding the treatment effects of group psychotherapy and bupropion HCl on regional brain activation, smokers were studied with fMRI scanning before and after treatment with one of these two active treatments or inactive pill placebo (random assignment).
- During fMRI scanning, participants underwent exposure to either cigarette-related cues while allowing themselves to crave, cigarette-related cues while resisting craving, or neutral cues. These cues were presented visually. [3]
- These three scanning states were taken within two sessions both prior to and post smoking cessation intervention.

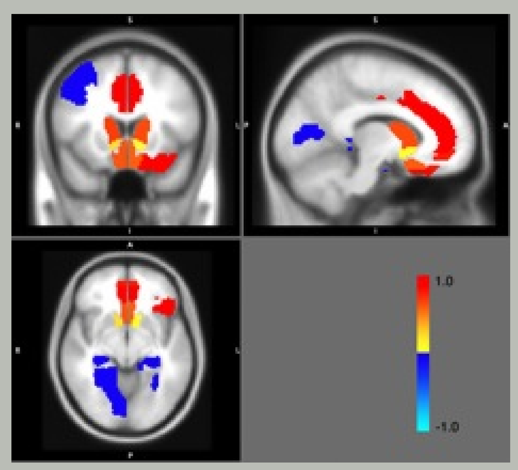
Methods

- Single-subject ICA (with number of components determined within subject by Laplacian Approximation to the model order) was performed on 304 scans of 51 subjects giving 21,256 components total
- Each IC was segmented into 110 anatomical regions of interest (ROI) specified by the Harvard-Oxford cortical and subcortical structural atlases, assigning to each ROI the average intensity in the corresponding IC maps, thereby compacting the 81,920 voxel dimensions into a compact 110 ROI dimension vector.
- The 21,256 ICs were then clustered into between 2 and 40 groups using k-means clustering.
- The "centroids" of each cluster were then backprojected into full space.

Results: Exemplar Cluster Centroids



IC1: entorhinal cortex and hippocampus (memory structures) IC2: visual cortices (visual structures)



IC3: ventromedial prefrontal cortex and parts of striatum (motor and learning structures)

Limitations

Reducing the dimensional space to these anatomical ROIs is somewhat arbitrary, as it is well accepted that some of these labeled brain regions (e.g., DLPFC) have heterogeneous functionality. ICA also give ambiguous signs to the associated regions, so that an IC labeled as "negative" may actually only appear in actual images as a positive going signal; this renders the interpretation somewhat more difficult. In order to create these dictionary elements we adopted somewhat arbitrary constraints on the number of ICs to be represented in the group, which may have resulted either in the splitting of single clusters into multiple groups or in the clustering of ROIs that may actually be formed form heterogeneous spatial components. While certain phylogenetically ancient functionally connected regions (e.g., the descending motor system, of the various sensory systems) are likely to be conserved across individuals, newer behaviors such as mathematics or language may well be represented very differently across individuals.

Conclusions

- Performing clustering on ICs whose dimensionality has been reduced enables processing of large numbers of scans
- Cluster centroids can be used to "classify" independent components from a new subject, using nearest-neighbor distances to cluster centroids.
- The components can also be used for classification of mental states by analyzing the change in component distribution with task changes, as ICs have previously been shown to be useful as features. [4][5]

References

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