A Feature-Based Approach To Combine Multimodal Brain Imaging Data

V. Calhoun[1]

[1]Institute of Living/Yale University, Hartford, CT, United States

Synopsis

Approaches for combining or fusing data in brain imaging can be put on a spectrum with meta-analysis (highly distilled data) to examine convergent evidence at one end and large-scale computational modeling (highly detailed theoretical modeling) at the other end. In between are methods that attempt to do direct data fusion. In this study, we present a general ICA fusion framework and introduce a method to assess the value of combining different types of data by using a discrimination metric based on the Kullback-Leibler (KL) divergence to evaluate the joint distributions. The data types we focus on in this paper are fMRI, structural MRI (sMRI), and EEG. We show that by combining modalities in certain ways, performance (ability to distinguish schizophrenia patients from controls) is improved.

Introduction

Many studies currently collect multiple types of imaging information from the same participants. Each imaging method reports on a limited domain and likely provides some common information and some unique information. This motivates the need for a joint analysis of these data. Most commonly, each type of image is analyzed independently and then perhaps overlaid to demonstrate its relationship with other data types (*e.g.* structural and functional images)-this process we define as *data integration*. A second approach, called *data fusion*, utilizes multiple images types together in order to take advantage of the 'cross'-information. We have recently done work showing the value of combining multi-task fMRI data [1], fMRI and sMRI data [2], and fMRI and event-related potential (ERP) data [3]. One important aspect of our approach is that we believe it is important to allow for the possibility that a change in a certain location in one modality is associated with a change in a *different* location in another modality (or, in the case of ERP one is associating time in ERP with space in fMRI). Each data-type gives information about a different aspect of the brain. FMRI and EEG provide dynamic information about brain function during a particular task (or rest) and can be collected in multiple experiments with different tasks, and sMRI provide information about tissue type [gray matter, white matter, cerebrospinal fluid (CSF)].

Joint ICA

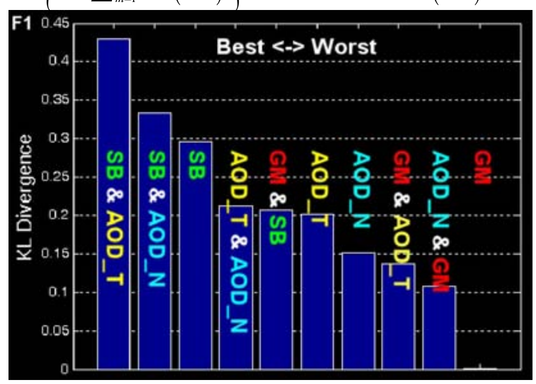
Independent component analysis is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals [4]. Specifically, ICA is an application of blind source separation that attempts to decompose a data set into maximally independent components. ICA has demonstrated considerable promise for the analysis of fMRI [5], EEG [6], and sMRI [7] data. ICA provides a theoretically rich, extendable approach that takes advantage of higher-order statistical information in the data and can reveal hidden associations between variables whose explicit relationship is not well understood.

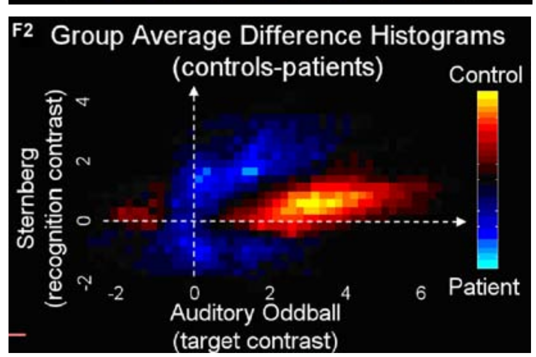
Each data type is first reduced to a *feature* (e.g. activation image, segmented tissue image, stimulus-averaged time courses) using standard processing methods. For data fusion of multiple modalities, we assume joint spatial or temporal independence of each modality, using the following generative model for the data: $\mathbf{X}^{(m)} = \mathbf{A}\mathbf{S}^{(m)},\ m = 1:M$ Here, m is the modality index, $\mathbf{S}^{(m)}$ and $\mathbf{X}^{(m)}$ are the $S \times V$ source and data matrix for modality m, respectively, and M is the total number of modalities being fused. Without loss of generality, we assume each modality has V data points and each modality is collected for each of the S subjects. We use an algorithm based upon information maximization, and thus maximize the logarithm of the likelihood given above to estimate $\mathbf{W}$ given data from all modalities using natural gradient updates to write the update rule for two modalities as $\Delta\mathbf{W} = \eta\left\{\mathbf{I} - 2\sum_{m=1}^{M}\mathbf{y}^{(m)}\left(\mathbf{u}^{(m)}\right)^T\right\}\mathbf{W}$, where $\mathbf{y}^{(m)} = g\left(\mathbf{u}^{(m)}\right)$ and $g(x) = 1/(1+e^{-x})$ is the nonlinearity chosen as the sigmoid function [8].

Methods

Twenty healthy participants and twenty patients with schizophrenia each provided written, informed, IRB approved consent at Hartford Hospital. Each received fMRI for auditory oddball and Sternbern working memory paradigms, and a structural scan. Scans were acquired at the Olin Neuropsychiatry Research Center on a Siemens Allegra 3T scanner equipped with 40mT/m gradients and a standard quadrature head coil. Functional (GE-EPI, TR=1.5s, TE=30ms, 4mm^3,s 30 slices) and structural (MPRAGE, 1mm^3) scans were acquired. Scans were motion corrected, spatially normalized, and smoothed using SPM2. Activation maps for each task, and segmented gray matter images were created in SPM2. EEG data was collected in a separate session for the auditory oddball task and event-related potentials were generated for target and novel stimuli.

We compute features for 1) Auditory oddball target-related fMRI activity (AOD_T), 2) auditory oddball novel-related fMRI activity (AOD_N), 3) Sternberg recognition fMRI activity (SB), and 4) gray matter sMRI values (GM). We then perform a 2-way joint ICA analysis for all combination of features and select the components which show the greatest difference in their ICA loading parameter. The estimated distributions for these components are computed separately for each group and the KL divergence is computed between the patient (sz) and control (hc) distributions (e.g. $\mathbf{D}\left(p_{sz}(\mathbf{f}) \,\|\, p_{hc}(\mathbf{f})\right)$ where $\mathbf{f}$ is an N-dimensional feature/modality vector). The results are then ranked according to this measure in order to determine which combination of feature/modality provides the largest separation.





Results

The plot in Figure F1 illustrates how we can assess the added value of a data fusion approach. For example, it shows us that combining the SB feature combined with the AOD_N or AOD_T features provides increased separation beyond SB or AOD_T alone. It also suggests that the incorporation of GM tends to decrease the separation (and thus in this particular case would mean it is better not to include the GM feature). Note that though we have demonstrated above a comparison of patients and controls these methods are using for addressing questions for healthy controls as well. For example, we could just as well have examined e.g. age-related activity in healthy controls only.

Results from a joint analysis of fMRI data collected from a Sternberg task and an auditory oddball task. Additional details of the tasks are provided in [2]. A joint histogram was computed by ranking voxels surviving the threshold for the AOD and SB parts of the joint source in descending order and pairing these two voxel sets. Group-averaged joint histograms are presented in Figure F2. The patient and controls are better separated for the 2D histogram than for the 1D histograms (for either task alone).

Discussion

We present a general framework for combining different types of brain imaging data at the group level via features computed from each data type. We also show that by combining modalities in certain ways performance is improved. This approach enables us to take advantages of the strengths and limitations of various modalities in a unified analytic framework and demonstrates that data fusion techniques can be successfully applied to joint brain imaging data to reveal unique information that cannot be evaluated in any one modality.

References

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