Self-organizing group level Independent Component Analysis reveals task-related activity as well as resting state networks during auditory stimulation

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Purpose

Although numerous fMRI studies have examined visual processing, less work has focused on the auditory system. With the exception of sparse sampling techniques, interference from scanner noise has hindered the study of auditory processing with fMRI. Independent component analysis (ICA) can isolate and remove components in the data representing extraneous sources of noise, thereby facilitating auditory data analysis. Until recently, however, ICA has been limited to analyzing single subject data. A relatively new technique for group-level ICA analysis proposed by Esposito et al., 2005, Self-organizing group ICA (SogICA), classifies individual-level decompositions into group-level clusters of components by contrasting inter- to intra-subject similarities. The average components generated from these self-organized clusters represent functional connectivity patterns common to the group. We applied SogICA to the data from a simple auditory passive listening fMRI study to compare the results with a standard random effects multi-subject general linear model (GLM) analysis.

Method

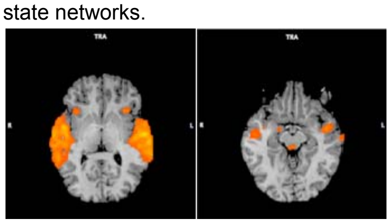
18 healthy subjects (9 male, 9 female, ages 19-39, mean 27.5 years) were scanned with Siemens 3T TrioTim scanner. EPI was used to acquire BOLD functional images (TR=1500ms, matrix=64x64, voxel size=3.4x3.4x3.5mm3). A high-resolution structural volume was acquired via a 3d MPRAGE sequence to provide the anatomical reference for fMRI data. Each 5 minute fMRI run consisted of 7 pleasant and 7 unpleasant sounds selected from the International Digital Affective Sound library (4.5s on/15s off). FMRI data were analyzed using BrainVoyager QX version 2.0 software. Preprocessing of the fMRI data included slice timing correction, 3D motion correction, spatial smoothing (Gaussian kernel of full-width-at-half-maximum of 6 mm) and normalization to standard Talairach anatomical space. Individual spatial ICA was first performed to decompose the fMRI time-series into brain activity patterns. After data reduction by means of principle component analysis (PCA), 30 ICs were estimated for each subject using the deflation approach of the FastICA algorithm. To display voxels contributing most strongly to a particular IC, the intensity values in each map were converted to z scores. Voxels with absolute z scores >2.0 were considered to be IC active voxels. For group level ICA analysis, the ICs estimated from each subject were clustered with the self-organizing group ICA (SogICA) method, according to their mutual similarities (inter-subject similarities). The reconstructed time courses across subjects in every cluster were averaged and correlated to a reference function (generated by the design matrix with an estimate of the HRF) to identify whether the cluster was task-related. A random effects group level GLM analysis was performed for comparison purposes.

Results

The clusters of components from SogICA are ranked by their mean similarities. The first cluster (Cluster 1) with highest similarity measurement includes widespread and predominantly peripheral brain areas. This cluster most likely represents noise or “residual” components from unexplained variance and is therefore disregarded. The cluster with the second highest similarity (Cluster 2) has an average time course that highly correlates with the reference function (Pearson’s correlation, r=0.922. p<0.0001, Fig 2) and is identified as the expected task-related components (Fig 1, t map, p≤ 0.002, FDR corrected, degree of freedom (df) =17). A comparison of the SogICA map to the GLM t-map (Fig 3, t map threshold is set to the same level as the ICA map for comparison, df =17) reveals that ICA captures task-related activity in the right amygdala and in more widespread auditory areas than the GLM analysis. Only diffuse bilateral areas in the thalamus and brainstem were more significant in the GLM analysis. Cluster 5 reveals correlated signal in the medial prefrontal cortex and posterior cingulate region consistent with the resting state default network (Fig 4). Additional clusters suggestive of other resting-state related networks include patterns of activity identified as the visual, dorsal attention, ventral attention and motor networks (Fig 4).

Conclusions

SogICA uses a data driven approach for classifying ICA components into group clusters representing patterns of activity common to the group. When applied to an auditory passive listening study, SogICA readily isolates the task-related components and identifies additional meaningful activations within the network of task-related activity not seen with traditional GLM analysis. SogICA also distinguishes patterns of activity consistent with known resting state networks.



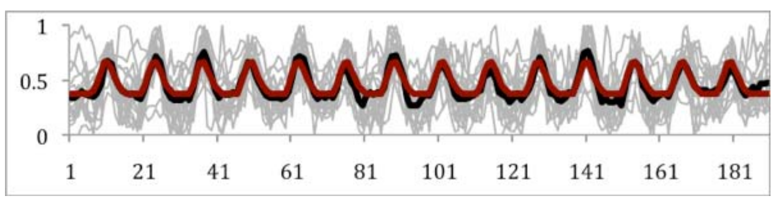
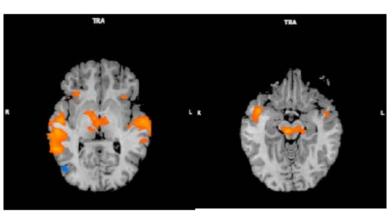


Fig. 1 (upper left, two images). Cluster 2 map (random effect, t= 3.55, p≤ 0.002, FDR corrected, degree of freedom (df) =17) demonstrates bilateral auditory cortex, anterior insula and right amygdala activation (right image). **Fig. 2** (upper right). Time courses of the task-related auditory components (Cluster 2). Time points (unit: TR). The mean time course averaged across subjects is depicted in red, the reference function in bold black, and each subject individually in light black.



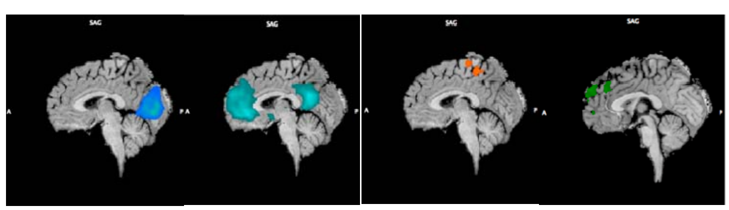


Fig. 3 (lower left, two images). Group GLM result reveals the bilateral auditory cortex, anterior insula and thalamus. No amygdala activation is apparent (random effect, t =3.55, p≤ 0.002, degree of freedom (df) =17). **Fig. 4** (lower right, 4 images). Networks from SogICA (random effect, t= 3.55, p≤ 0.002, FDR corrected, degree of freedom (df) =17). Blue: visual. Teal: default mode. Red: motor, Green: ventral attention.

References: 1. Fabrizio Esposito et al. NeuroImage 25 (2005) 193-205. 2. D.Mantini et al. PNAS August 7, 2007, 13170-13175.