



University of Pennsylvania School of Engineering and Applied Science¹; Georgia Institute of Technology²; University of Pennsylvania, Perelman School of Medicine³; Department of Bioengineering⁴; Department of Neurology⁵

SUMMARY

- Goal: Improve use of language task fMRI to inform diagnosis and treatment of drug-resistant epilepsy
- Motive: Language task fMRI is common in presurgical evaluation for epilepsy; repurposing the data can provide new insights and improve performance of established methods
- **Results:** Language task shows activation in expected regions but visual subject-wise variation; deriving resting state functional connectivity from language task data shows some canonical networks

METHODS

Dataset Summary and Preprocessing

- Initial dataset has language fMRI scans from 35 patients with epilepsy from the Hospital of the University of Pennsylvania
- Localization and Lateralization of Epilepsy: 30 Temporal, 4 Frontal, 1 Generalized; 13 Left, 16 Right, 6 Both, 1 Generalized
- Tasks: Sentence Completion, Word Generation, Verb Generation, Scene Memory, Object Naming, Auditory, Picture
- Heudiconv-based script converted data to Brain Imaging Data Structure (BIDS) [4]
- Data processed with fMRIprep with synthetic field-map correction [2]

Language Activation

- Python package nilearn [1] used to apply General Linear Model (GLM) regression on time series for each voxel and visualize results
- Confound Signals Applied: Translation and Rotation along x, y, and z axes, Cerebrospinal Fluid, Global Signal, White Matter
- Contrast maps derived from regression results to detail voxel participation in task

Deriving Resting State Approximation from Task-Based fMRI

- Residual voxel time series from GLM regression were concatenated to approximate resting state fMRI scans, similar to methods described in Fair et al. 2007 [3]
- Group level "resting state" networks were generated using the Collaborative Brain Decomposition pipeline [5]



Figure 1 - Methods Outline: Pipeline for processing analyzing task-based fMRI deriving resting state fMRI and identifying activated language regions; for visualization, contrast maps are thresholded with a z-score corresponding to a p-value of 0.001

Resting State Approximation and Language Network Characterization with Language Task fMRI

Eric Zou¹, Kian Zendehrouh Kermani², Alfredo Lucas^{3,4}, Kathryn A. Davis^{4,5}

Center for Neuroengineering and Therapeutics (CNT)

RESULTS

Regression on Language Task fMRI

- Activation maps show activity in areas of the brain commonly associated with language (Broca's area, Inferior Frontal Gyrus)
- Some tasks also show strong activation of visual networks in the brain, such as the object and sentence tasks
- Some subjects have visually sparse activations, though statistical significance was not calculated
- A laterality index of (L R)/(L + R) ranging from -1 (right) to 1 (left), with L and R the sum of all positive, significant voxels on that side



Figure 2 - Language Task Activation Maps: Only positively valued voxels are shown. Figures are maximum intensity projections of activation maps of different tasks (word generation, sentence, and rhyme respectively) with a single subject. Language regions are highlighted in blue, visual regions in green.

Resting State Approximation from Task Data Shows Canonical Networks

- With Dice similarity coefficient, group-level components from the brain decomposition method were compared to 7 resting state networks described by Yeo et al. 2011 [6]
- Components of the Visual, Limbic, and Somatomotor networks were most visible with combined subject residual fMRI
- Portions of other networks (Default Mode, Salient Ventral Attention, Control, Dorsal Ventral Attention) seen in other components
- Noticeable overlap in some components, with components sharing high similarity with the same networks



Figure 3 - Dice Similarity Plots: Dice similarity plots between the 7 canonical Yeo networks and the component being analyzed, thresholded to voxels with values of 1 standard deviation above the mean. 7 components were generated; component 3 is omitted due to zero or near zero similarities with all networks.

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LIMITATIONS

• Subjects do not all have the same tasks; uniform approaches difficult • Methods for resting state estimation not fully explored, such as using interleaved resting blocks and excluding or including certain tasks • Task activation may have interfered with residual signal (visual for example)

• Resting state approximations not compared with null models or patient-specific resting state

 Ground-truth language lateralization for subjects not available • Multiple ways to calculate laterality index and inform lateralization that have not been tested

CONCLUSIONS AND FUTURE WORK

Language Task Activation Analysis

• Regression of language task fMRI shows activation in known language regions like Broca's area and the inferior frontal gyrus Subject data exhibits differences in the visual appearance of networks that may be significant and clinically useful for informing diagnoses and evaluation

• Future work could expand on language network lateralization and characterization, and differences in language networks between patients with epilepsy and controls or across epilepsy types

Resting State Estimation from Task fMRI Data Holds Promise • Canonical resting state networks (and elements of others) are visible from decomposition using task-based residuals

• Would enable use of large amounts of preexisting language task data to generate extra resting-state fMRI or possibly substitute the need to collect resting state scans

• Future work could involve finding the tasks and the time series extraction methods to achieve most comparable results to subjectspecific resting state and reduce redundancy and mixing of networks in components from decomposition

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