DISCOVERING VOXEL-LEVEL FUNCTIONAL CONNECTIVITY BETWEEN CORTICAL REGIONS

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Connectivity

**Subregion Connectivity**

Precuneus
Amygdala
Thalamus
Lateral occipital complex LOC

Zhang et al. 2008
Kim et al. 2010
Roy et al. 2009
Margulies et al. 2007
Margulies et al. 2009
Heinzle & Haynes 2011
GOAL: Fine-Grained Connectivity

Voxel-level Maps
Symmetrical
Few Data Points Needed

Subregion Connectivity
Precuneus
Amygdala
Thalamus
Lateral occipital complex LOC

Zhang et al. 2008
Kim et al. 2010
Roy et al. 2009
Margulies et al. 2007
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Heinzle & Haynes 2011
Previous Work

Area 1
Area 2

Traditional
- no voxel-level connectivity
- cannot identify novel subregions

CCRF / FF
- treats areas asymmetrically
- no continuous maps
- post-hoc clustering often needed

CCA
- # voxels < # timepoints
- cannot identify multiple correlated correspondences

Rogers et al. 2007
Kim et al. 2010
Margulies et al. 2007
Margulies et al. 2009
Haak et al. 2011
Cohen et al. 2007
Deleus & Van Hulle 2011
Previous Work

Our Method:
Jointly Learn Continuous Maps over 2 Areas
Multiple Solutions, Even If Correlated

Traditional
- no voxel-level connectivity
- cannot identify novel subregions

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Optimization Problem

Traditional

\[ \underset{w}{\text{minimize}} \| w \cdot \text{mean}_v(A^1) - \text{mean}_v(A^2) \|_2^2 \]

\[ w \rightarrow \text{scalar} \]
\[ \text{mean}_v \rightarrow \text{mean across voxels} \]

\[ A = \begin{bmatrix} \#\text{timepoints} \\ \#\text{voxels} & \ldots \end{bmatrix} \]

\[ \text{minimize} \| a^{1^T} A^1 - a^{2^T} A^2 \|_2^2 \]

\[ a^1 = \frac{w}{N_{A^1}} \cdot 1, \ a^2 = \frac{1}{N_{A^2}} \cdot 1 \]

constant connectivity map

\[ a^T = \begin{bmatrix} \ldots \end{bmatrix} \]

\[ N_{A} \text{ voxels} \]
Optimization Problem

**Traditional**

constant map

\[
\begin{align*}
\text{minimize} & \quad \|a^1 A^1 - a^2 A^2\|_2^2 \\
\text{subject to} & \quad a^1 = \frac{w}{N_{A^1}} \cdot 1, \quad a^2 = \frac{1}{N_{A^2}} \cdot 1
\end{align*}
\]

**CCRF / FF**

one non-constant connectivity maps

\[
\begin{align*}
\text{minimize} & \quad \|a^1 A^1 - a^2 A^2\|_2^2 \\
\text{subject to} & \quad a^1 = \frac{w}{N_{A^1}} \cdot 1, \quad a^2 = \frac{1}{N_{A^2}} \cdot 1
\end{align*}
\]

**Our Method**

two non-constant connectivity maps

\[
\begin{align*}
\text{minimize} & \quad \|a^1 A^1 - a^2 A^2\|_2^2 \\
\text{subject to} & \quad a^1 = \frac{w}{N_{A^1}} \cdot 1, \quad a^2 = \frac{1}{N_{A^2}} \cdot 1
\end{align*}
\]
Optimization Problem

$$\min_{a^1, a^2, w} \| a^1^T A^1 - a^2^T A^2 \|_2^2 + \lambda \left[ \sum_{i \in v_1} \sum_{j \in n(i)} \frac{1}{|n(i)|} (a^1_i - a^1_j)^2 + \sum_{i \in v_2} \sum_{j \in n(i)} \frac{1}{|n(i)|} (a^2_i - a^2_j)^2 \right]$$

Hyperparameter

Regularization term

Graph $D_k$

Sparse Connectivity Graph
Optimization Problem

\[
\begin{align*}
\text{minimize} & \quad a_1^T A^1 - a_2^T A^2 \quad \text{subject to} \quad \|\beta\|_2 = 1, \quad \beta \succeq 0 \\
& \quad a_1, a_2, w
\end{align*}
\]

\[
\begin{align*}
& \quad \min_{a^1, a^2, w} \quad \|a_1^T A^1 - a_2^T A^2\|_2^2 + \lambda \left[ \sum_{i \in v_1} \sum_{j \in n(i)} \frac{1}{n(i)} (a^1_i - a^1_j)^2 + \sum_{i \in v_2} \sum_{j \in n(i)} \frac{1}{n(i)} (a^2_i - a^2_j)^2 \right] \\
& \quad = \quad \|X \lambda \cdot \beta\|_2^2
\end{align*}
\]

Our Method

Not Convex

Use trust region approach and multiple initializations
Datasets

Meridian and Eccentricity Mapping
256 timepoints

Isolated Objects & Objects in Context
306 timepoints
V1 – VP Connectivity

Expected Connectivity
V1 – VP Connectivity
V1 – VP Connectivity
V1 – VP Connectivity
V1 – VP Connectivity

Solution Maps Consistent with Retinotopic Organization

Regularization Improves RF Localization

256 Timepoints
Expected Connectivity
Left LOC – Right LOC Connectivity

CCRF / FF

Our Method
No Regularization

Our Method
With Regularization

Regularized Method Recovers Anterior-Posterior Connectivity

Timecourse Correlation
\( r = 0.8 \)

Correlation Between Left and Right Posterior-Anterior Profiles (Z-Transformed)

**

Clustering NR R

Our Method
Summary

Jointly Learns Continuous Connectivity Maps

Can Recover Retinotopic Organization and Anterior-Posterior Differences in LOC

No Specialized Datasets, Fewer Timepoints than Voxels!

Can Recover Correlated Distinct Solutions

Implementation Available at: vision.stanford.edu/resources_links.html
Acknowledgements: NSF, SGF, NIH

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