Learning Macroscopic Brain Connectomes via Group-Sparse Factorization

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Abstract

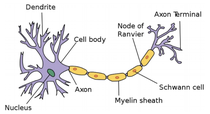
We propose **a data driven framework to determine tracts within a brain** from diffusion-weighted magnetic resonance imaging data. Applying tensor encoding enables us to **design an objective function with a group regularizer that captures the biologically plausible fascicle structure** in order to extract connectomes automatically as **a fully unsupervised** method. Moreover, we proved that this objective is convex and **has a unique solution** ensuring identifiable connectomes for an individual. We develop an **efficient optimization strategy** for this extremely high-dimensional sparse problem by **designing a greedy algorithm** that significantly improves the standard one, called OMP.

BACKGROUND & SETTINGS

1. Motivations

Goal:

- Map structural brain connectomes from dMRI data:
  - Neuronal axon bundles travelling through white matter



Applications:

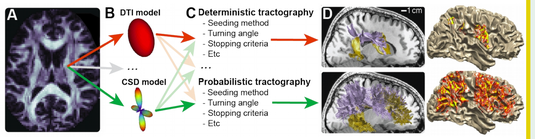
- Investigating white matter health and disease, development and aging of brain, tumors and preoperative planning, psychiatric disorders, and many more!

Problem statement:

- No unique result for different models, algorithms and parameter sets.

Previous Work:

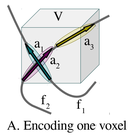
- Supervised learning
  - Requires labelled data
- Regularized learning
  - To remove false connections



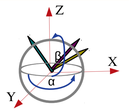
2. Encoding Brain Connectomes as Tensors

ENCODE:

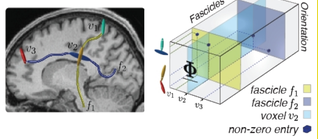
- Encodes natural brain space → 3D sparse tensor
  - Tensor of brain structure, $\mathbf{\Phi} \in R^{Na \times Nv \times Nf}$
    - N_a: #orientations, fascicles orientation at each position
    - N_v: #voxels, fascicles spatial position
    - N_f: #fascicles, indices of each fascicle
- Unified dMRI signal with connectome structure
  - Matrix of dMRI signal $Y \in R^{N\theta \times Nvd}$, θ is gradient direction
  - Factorizing **Y** into **Φ** and dictinary **D**
    - $D \in R^{N\theta \times Na}$
    - $Y \approx \mathbf{\Phi} \times_1 D \times_3 W$, where $W \in R^{Nf}$



A. Encoding one voxel



B. Discretizing space

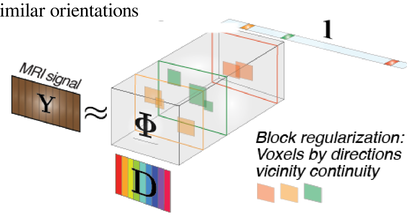


C. Natural brain space and tensor encoding

THEORIES & ALGORITHMS

3. A Tractography Objective for Learning Brain Connectomes

- Unconstrained objective to learn **Φ**
  - $\mathbf{\Phi} = argmin_{\mathbf{\Phi}} \|Y - \mathbf{\Phi} \times_1 D \times_3 I\|^2$, where $I \in R^{Nf}$
- Designing a group regularizer to enforce continuity and smoothness of fascicles
  - Neighbouring voxels are more likely to share similar orientations
    - $\mathcal{G}_V \subseteq V$, group of neighbouring voxels
    - $\mathcal{G}_A \subseteq \mathcal{A}$, group of similar orientations
    - We want either all-zero or more than one none-zero entries in $\mathbf{\Phi}(\mathcal{G}_A, \mathcal{G}_V, :)$
- Constrained objective to learn **Φ**
  - $min_{\mathbf{\Phi}} \|Y - \mathbf{\Phi} \times_1 D \times_3 I\|^2 + \lambda R(\mathbf{\Phi})$,
  - $R(\mathbf{\Phi}) = \sum_{f \in F} \sum_{\mathcal{G}_V \in \mathcal{V}} \sum_{\mathcal{G}_A \in \mathcal{A}} \sqrt{\sum_{v \in \mathcal{G}_V} \left(\sum_{a \in \mathcal{G}_A} |\mathbf{\Phi}_{a,v,f}| \right)^2}$



Model formulation and block regularizer

4. An Efficient Algorithm for the Tractography Objective

- Challenge: number of optimization parameters is large: $N_f \times N_v \times N_a$

Screening Algorithms:

- Orthogonal Matching Pursuit (OMP)
  - Issue: it selects orthogonal or dissimilar orientations for the fascicles in an individual voxel!
- Proposed Orientation Greedy Strategy:
  - Goal: Select similar orientations to reconstruct diffusion information, **Y**.
  - Selection criterion: $\bar{g}(S) \stackrel{def}{=} g(S) + \sum_{s \in S} g(s)$
  - $g(S)$ is squared multiple correlation
  - $\bar{g}(S)$ prefers S with **high multiple correlation** & ensures **usefulness of each orientation** itself.

Full Algorithm:

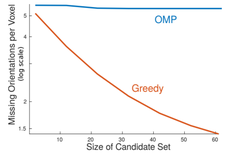
- Screen the orientations using GreedyOrientation, $|S| \leq k$
- Optimize the tractography objective using subgradient descent

EMPIRICAL RESULTS

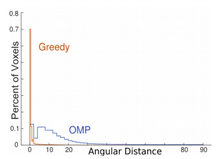
5. Reconstructing the anatomical structure of tracts

Data:

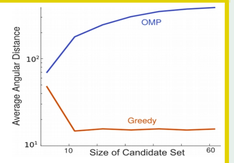
- Arcuate
  - $N_a = 1057$,
  - $N_v = 11823$,
  - $N_f = 868$



A. Screening: missing orientations vs. k



B. Screening: pdf of voxels' angular distance



C. Screening: avg. angular distance by k

Evaluating:

- Screening
- Optimization

Comparing:

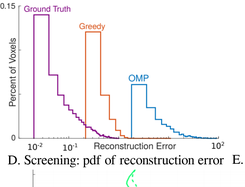
- OMP
- Greedy

Resources:

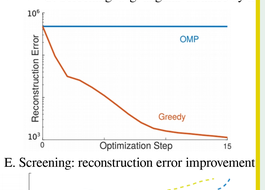
- ≃13 GB RAM
- CPU Core i7,
- 2.4 GHz

Opt. Time:

- ≃ 15 hrs



D. Screening: pdf of reconstruction error



E. Screening: reconstruction error improvement

F. Optimization: visualization of **Φ**

G. Optimization

6. Conclusion and Future Work

- This fully unsupervised learning approach does not require any labelled data and is able to capture brain structures beyond the expert's settings and tractography results.
- In the future: do more experiments on different brains & learn fascicles as well.