ANATOMICALLY-INFORMED MULTIPLE LINEAR ASSIGNMENT PROBLEMS FOR WHITE MATTER BUNDLE SEGMENTATION

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Background

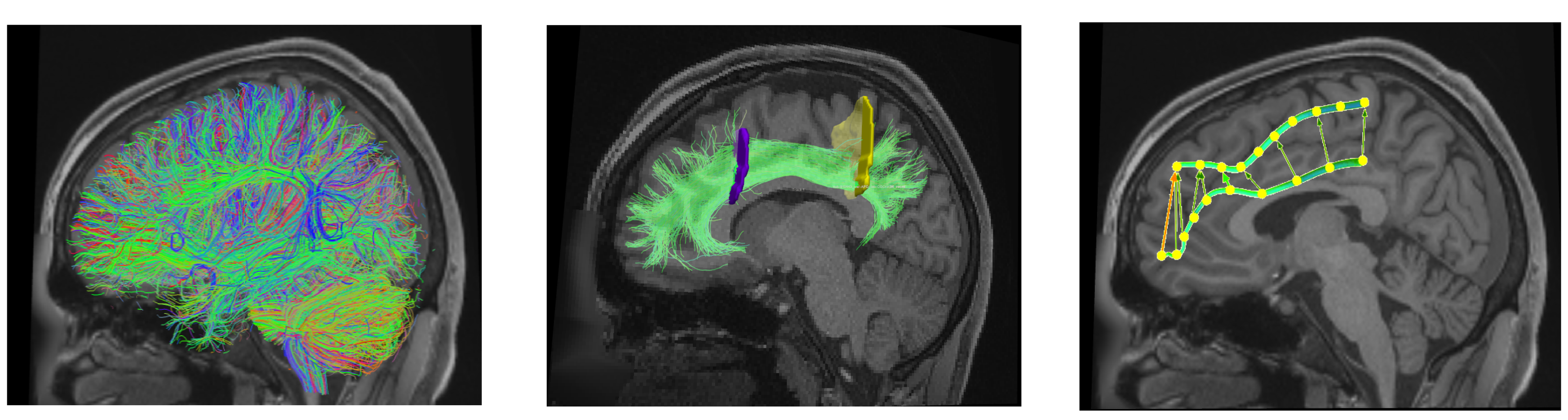
Segmenting anatomical structures in the white matter of the human brain is useful in many different applications. The information about the orientation of the fibers composing such anatomical structures can be estimated in-vivo by diffusion Magnetic Resonance Imaging (dMRI) techniques. By means of tractography, the paths of millions of these fibers can be mathematically represented by 3D polylines, called streamlines.

White matter **bundle segmentation** aims to group together streamlines into anatomically meaningful structures, known as bundles.

Introduction

Main automatic methods for white matter bundle segmentation:

1. **Connectivity-based** (based on *anatomy*)
   - Region of Interest (ROI)-based
2. **Streamline-based** (based on *geometry*)
   - clustering-based
   - example-based (Sharmin et al., 2018)



whole-brain tractogram | connectivity-based approach | streamline-based approach

AIM: **improve the results of bundle segmentation by considering *anatomy* and *geometry* at the same time**

HOW: extending the example-based method proposed in (Sharmin et al., 2018) by including additional anatomical information within the optimization process of the Linear Assignment Problem (LAP) (Bijsterbosch and Volgenant, 2010).

Methods

Let $s = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ be a streamline with n points, where $\mathbf{x}_i \in \mathbb{R}^3, \forall i$.

Given the following two sets of objects:

- the example bundle of a subject A, $b^A = \{s_1^A, \dots, s_k^A\}$
- the tractogram of a subject B, $T^B = \{s_1^B, \dots, s_M^B\}$

the aim of example-based bundle segmentation is to find the optimal correspondence of all the streamlines in b^A with those of T^B by solving the following LAP:

$$P^* = \underset{P \in \mathcal{P}}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{j=1}^{M} c_{ij} p_{ij} \tag{1}$$

Original formulation of LAP (Sharmin et al., 2018)
Cost matrix: $\mathbf{C} = \mathbf{D}$ = distance matrix

Proposed formulation of LAP
Cost matrix: $\mathbf{C} = \lambda_D \mathbf{D} + \lambda_E \mathbf{E} + \lambda_R \mathbf{R}$

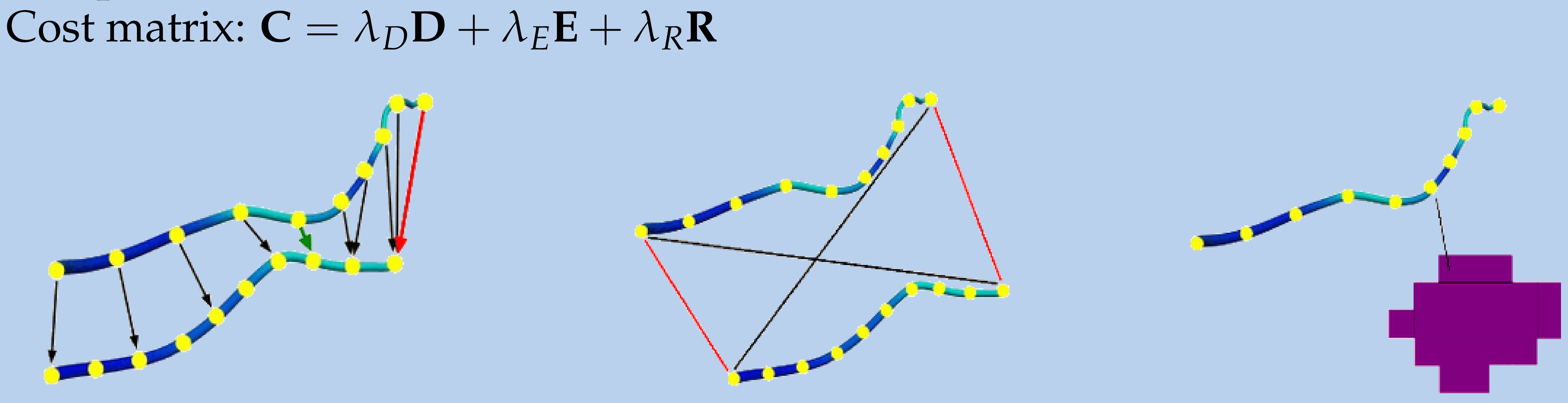


Figure 1: Visual interpretation about how the three distance matrices are computed.

Experiments

Dataset - Human Connectome Project (HCP) dMRI dataset (90 gradients; b=2000, voxel size=1.25mm isotropic) with ensemble probabilistic tracking (750k streamlines, step size=0.625mm, curvature parameters=0.25, 0.5, 1, 2 and 4mm)

Ground truth - 30 segmentations per bundle to use both as examples and ground truth, obtained with the Automated Fiber Quantification (AFQ) algorithm (Yeatman et al., 2012)

- 6 small bundles: Cingulum Cingulate (CGCl and CGCr), Cingulum Hippocampus (CGHl and CGHr) and Uncinate Fasciculus (UFl and UFr)
- 6 large bundles: Thalamic Radiation (TRl and TRr), Corticospinal tract (CSTl and CSTr) and Arcuate Fasciculus (AFl and AFr)

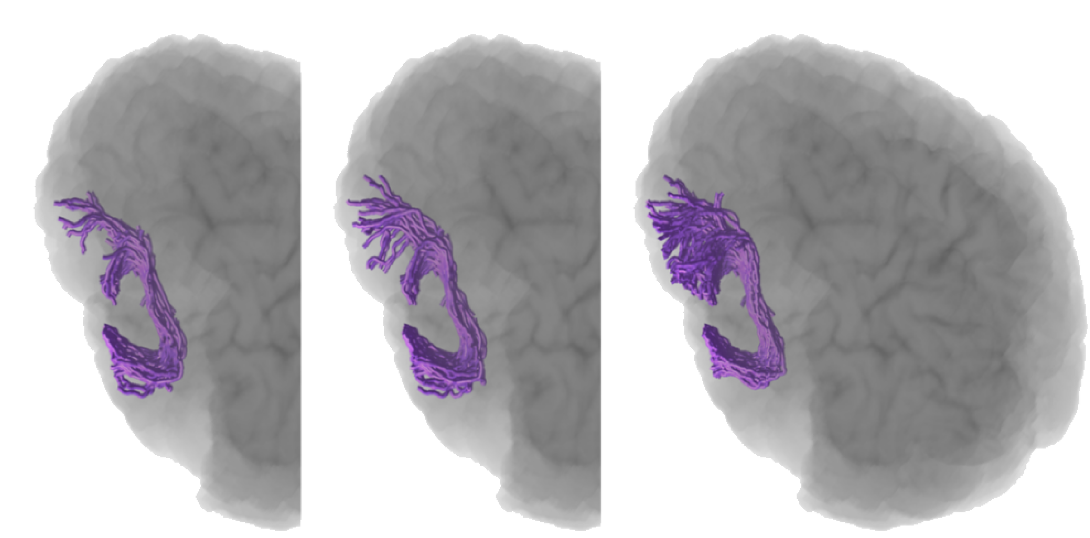
Experimental design - We ran multiple experiments with multiple examples using the LAP method of (Sharmin et al., 2018) (multi-LAP) and the proposed method (multi-LAP-anat). We then compared their performances through the Dice Similarity Coefficient (DSC) score, which measures the degree of overlap with the ground truth bundle (the higher the better).

Results

	CGCl	CGCr	CGHl	CGHr	UFl	UFr	mean
multi-LAP	0.81	0.82	0.77	0.76	0.74	0.76	0.77
multi-LAP-anat	**0.83**	**0.86**	**0.83**	**0.80**	**0.80**	**0.81**	**0.82**

	TRl	TRr	CSTl	CSTr	AFl	AFr	mean
multi-LAP	0.85	0.85	0.84	0.85	0.83	0.80	0.84
multi-LAP-anat	**0.87**	**0.87**	**0.86**	**0.87**	**0.86**	**0.84**	**0.86**

Table 1: Mean DSC across 30 subjects for the 6 small bundles (top) and the 6 large bundles (bottom).



Conclusions

Table 1 shows that the proposed multi-LAP-anat method outperforms the multi-LAP method of (Sharmin et al., 2018), for all the bundles considered. Higher improvements were obtained in particular for smaller bundles.
These results confirm the assumption that considering information about both the geometry and the relative position of the bundle of interest helps to improve the results of example-based bundle segmentation.

References

Bijsterbosch, J. and Volgenant, A. (2010). Solving the Rectangular assignment problem and applications. *Annals of Operations Research*, 181:443–462.

Sharmin, N., Olivetti, E., and Avesani, P. (2018). White Matter Tract Segmentation as Multiple Linear Assignment Problems. *Frontiers in Neuroscience*, 11.

Yeatman, J. D., Dougherty, R. F., Myall, N. J., Wandell, B. A., and Feldman, H. M. (2012). Tract Profiles of White Matter Properties: Automating Fiber-Tract Quantification. *PLoS ONE*, 7(11):e49790+.

Acknowledgments

This work was partially supported by NSF IIS-1636893, NSF BCS-1734853, NIH NIMH ULTTR001108, a Microsoft Research Award, a Google Cloud Award, the Indiana University Areas of Emergent Research initiative Learning: Brains, Machines, Children, and Indiana University Pervasive Technology Institute to F.P.

The code is freely available for reproducibility on the platform BrainLife.io at https://doi.org/10.25663/brainlife.app.122.