In-Vivo Parcellation of the Human Thalamus Using Multimodal Microstructural Data

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INTRODUCTION

Brain parcellation - the act of dividing the brain into sub-regions - has intrigued neuroanatomists since the dawn of the discipline. Here, we explore a *de novo*, data-driven, unsupervised method of parcellation the thalamus - a subcortical neuroanatomical hub essential for information relay and integration [1].

Unlike most thalamic parcellations, which typically use a single type of data (e.g. histology), our method allows for multiple modalites of information to be considered collectively in determining patterns of covariance and result in highly interpretable decompositions of the original data [2; 3].

METHODS

Data Acquisition and Pre-Processing

Structural and diffusion data (T1-weighted, T2-weighted, Mean Diffusivity, Fractional Anisotropy) of 100 unrelated subjects were obtained from the Human Connectome Project [4]. Voxel intensities for each subject / image type combination from the L. thalamus are extracted and represented as row vectors.

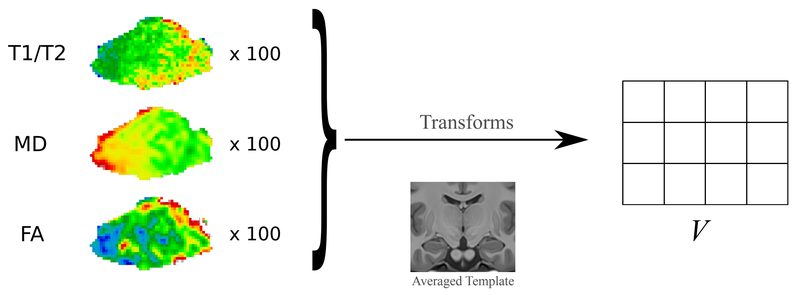
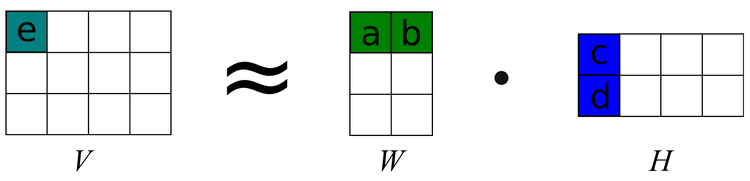


Image Decomposition & Parcellation

Non-Negative Matrix Factorization (NMF) is used to decompose the input matrix (V) with a user specified component quantity (r).



Where a*c + b*d ≈ e , and:

- The matrix W describes each component;
- The matrix H describes the weighing of each voxel on each component.

Parcellation is generated via running a k-means algorithm using the H matrix weights as parameters to generate k clusters of voxels.

Tractography

As a way of validation, we seed from each pacel to compute streamlines, and label each voxel with the dominant tract.

RESULTS

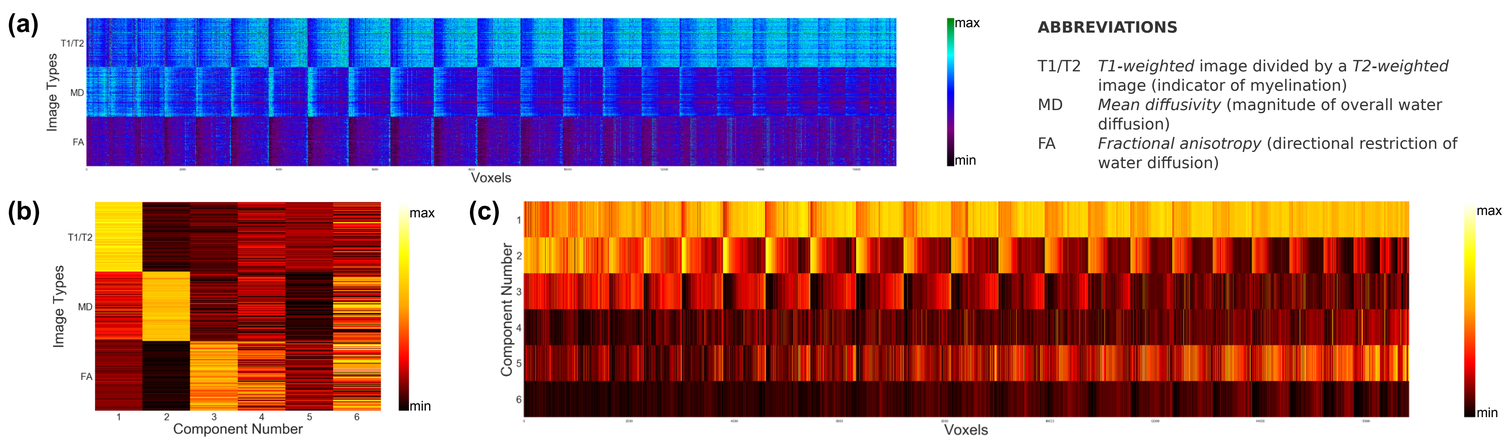


Figure 1. NMF decomposition with $r=6$, where $V \approx W \bullet H$ **(a)** Input matrix (V), where each row depicts a subject / image type combination, and each column depicts a voxel; **(b)** Component matrix (W), where each column depicts the characteristics of a single decomposed component; **(c)** Weight matrix (H), where each row depicts the weights of voxels loading onto that particular component. For instance, voxels with hot colours in row 1 (of matrix H) have strong component 1 (column 1 of matrix W) characteristics.

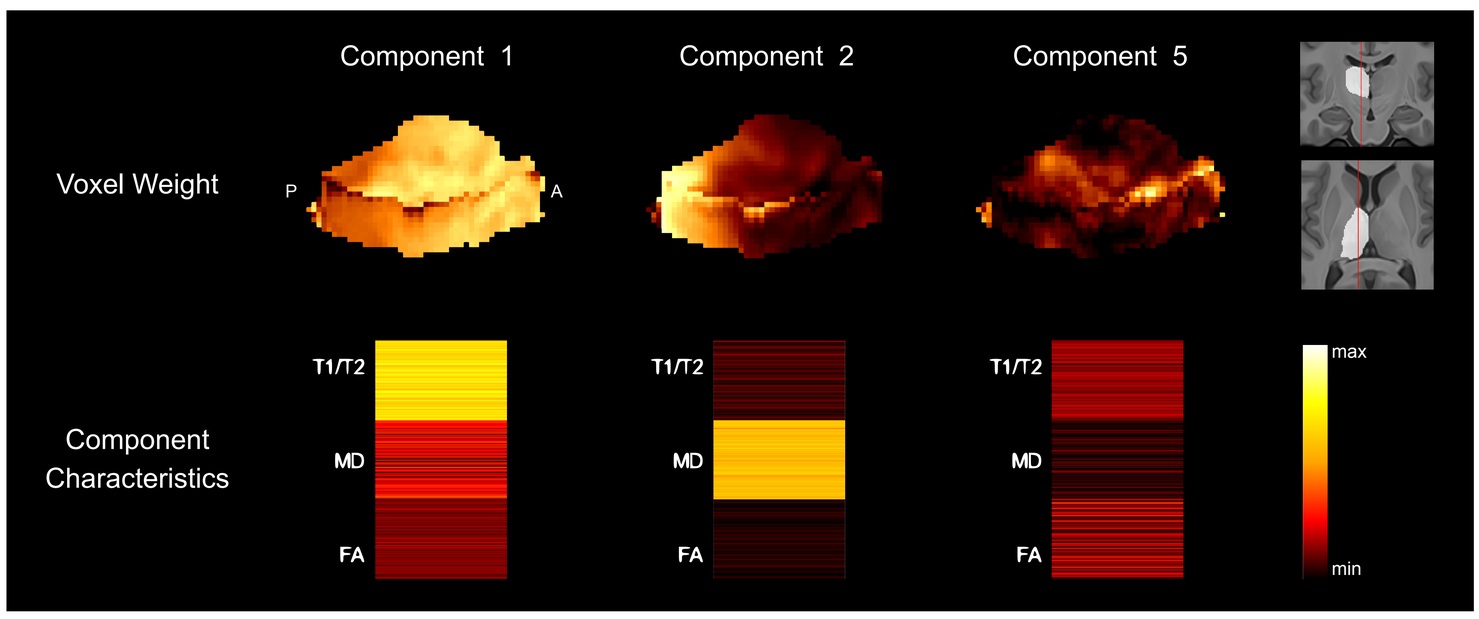


Figure 2. ***(Top row)*** Sagittal view of the left thalamus. Colour range depicts each voxel's weight (as represented in the weight matrix, H) loading onto components 1, 2 and 5. Hotter colours indicate that a voxel is more strongly dependent on the particular component. ***(Bottom row)***: Each component's characteristics (from the component matrix, W). Hotter colours indicate stronger representation of a particular image modality. For instance, combining the two rows, we see that the posterior thalamus has strong component 2 characteristics: high *mean diffusivity* (MD), low T1/T2 and low *fractional anisotropy* (FA) measures.

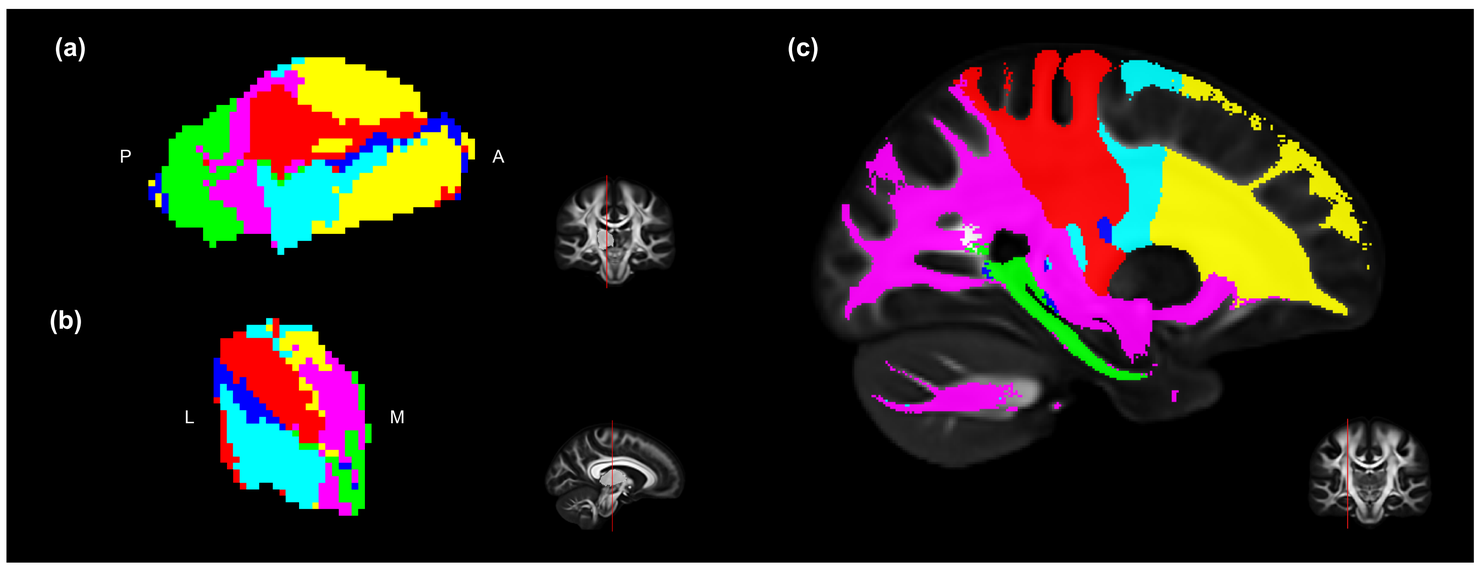


Figure 3. K-means clustering ($k=6$) with weights from matrix H as input parameters for each voxel. **(a)** Sagittal view of the k-means generated left thalamus parcellation labels; **(b)** Coronal view of the thalamus labels; **(c)** Tractography analysis using the k-means generated labels as seeds. The label value for a voxel is determined by the seed with the highest number of tracts innervating that voxel. Interestingly, we observe preferential connectivity to distinctive cortical regions.

CONCLUSION

NMF is shown to produce spatially continuous components that captures prominant, interpretable variations, making it a useful tool in interpreting and analyzing multimodal, heterogeneous data.

Furthermore, prelimary work on discrete thalamic parcellation via *k*-means shows promise. As a next step, further optimization of the algorithms and improvements in the input data should be considered.

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