

Hierarchical Segmentation of Thalamic Nuclei from DTI Using Spectral Clustering

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Background – Diffusion tensor imaging (DTI) can resolve thalamic nuclei based on the characteristic fiber orientation of the corticothalamic/thalamocortical striations within each nucleus (1). Delineation of the nuclei from DTI requires a segmentation procedure however. The k-means algorithm can extract the gross structure of the nuclei (1), but the k-means approach has a number of weaknesses including susceptibility to local minima and geometric bias towards spherical clusters. Here, we describe a novel clustering algorithm based on the spectral clustering framework (2) which addresses the main shortcomings of the k-means approach. The spectral clustering algorithm has no geometric bias, no initialization requirements, and a probabilistic framework. Using the spectral clustering algorithm, we resolve the hierarchical organization of the thalamic nuclei into groups and subgroups. The identification of nuclear subdivisions using the spectral clustering algorithm will facilitate localization of functional activation and pathology to individual nuclear subgroups.

Theory –The hierarchical spectral clustering algorithm constructs the clustering hierarchy from the eigensystem of the voxel affinity graph (2). The voxel affinity matrix for a diffusion tensor image is defined here as $\mathbf{W}=[W_{ij}]=[\exp\{-\beta\angle(\mathbf{v}_i,\mathbf{v}_j) + d(\mathbf{x}_i,\mathbf{x}_j)\}]$ where i and j index over the voxels, β is a trade-off parameter, $\angle(\mathbf{v}_i,\mathbf{v}_j)$ is the angle between the diffusion tensor principal eigenvectors and $d(\mathbf{x}_i,\mathbf{x}_j)$ is the spatial distance between voxels i and j . The affinity matrix is then row-normalized. Markovian relaxation is performed until an information bottleneck is reached (3). The matrix is reordered according to the ordering of the second eigenvector (i.e., Fiedler ordering (4)), and a two-way cut is identified based on the minimum conductance variable (MCV). The Fiedler reordering and matrix partitioning is performed successively until the MCV criterion is satisfied. The clustering hierarchy is obtained by varying the conductance threshold.

Methods – Single-shot EPI DTI was acquired on 3 healthy participants on a 3T Siemens Trio MRI with TR/TE=8400/82ms, b=700s/mm², 60 diffusion gradient directions, 10 T2 images, 2 mm resolution. Masks for each thalamic hemisphere were obtained from the FA map by manual segmentation. The tensor maps were smoothed element-wise using a Gaussian kernel (3.3mm FWHM, 6mm extent). The hierarchical spectral clustering algorithm was applied to each individual thalamic hemisphere. Anatomic labels for the clusters were assigned based on the anatomic location and fiber orientation of the cluster.

Results – For all thalamic data sets, spectral reordering of the voxel affinity matrix revealed significant clustering structure. Fig. 1 shows the spectral clustering results for an individual thalamic hemisphere. Fig. 1c shows the hierarchical segmentation results with the nuclear assignments. The highest segmentation division reflected the pulvinar, medial, and ventral groups. The ventral group further subdivided into the ventral anterior and ventral lateral nuclei. The medial group further subdivided into the mediodorsal, centromedian, and centrolateral nuclei.

Conclusions – Hierarchical spectral clustering of DTI in the thalamus can identify nuclear groups and subgroups based solely on the voxel affinity matrix. The hierarchical framework allows for the exploration of nuclear organization over a range of anatomical scales. Future work will investigate the application of the spectral clustering algorithm to other white matter anatomical structures including white matter fascicles.

References – 1. Wiegell, M.R. et al. *Neuroimage*. 19:391-401, 2003. 2. Kannan R. et. al. *J ACM*. 51:497-515, 2004W. 3. Tishby, M. et. al. *NIPS*. 640:646, 2000. 4. Juvan, M. et al. *Disc. Appl. Math.* 36, 153-168, 1992. **Acknowledgments** – Supported in part by Glaxo Smith Kline, NCRR RR14075, the Athinoula A. Martinos Foundation, and the MIND Institute.

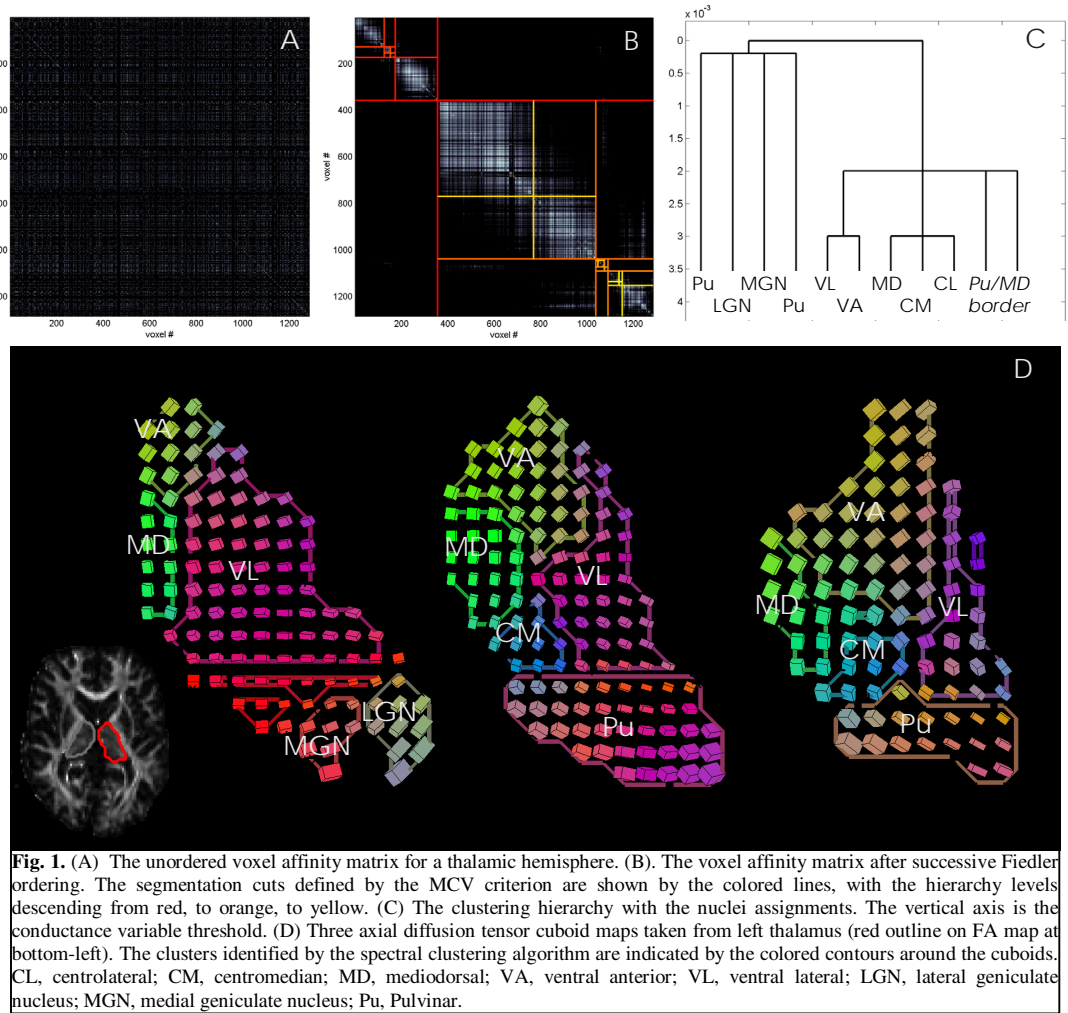


Fig. 1. (A) The unordered voxel affinity matrix for a thalamic hemisphere. (B) The voxel affinity matrix after successive Fiedler ordering. The segmentation cuts defined by the MCV criterion are shown by the colored lines, with the hierarchy levels descending from red, to orange, to yellow. (C) The clustering hierarchy with the nuclei assignments. The vertical axis is the conductance variable threshold. (D) Three axial diffusion tensor cuboid maps taken from left thalamus (red outline on FA map at bottom-left). The clusters identified by the spectral clustering algorithm are indicated by the colored contours around the cuboids. CL, centrolateral; CM, centromedian; MD, mediodorsal; VA, ventral anterior; VL, ventral lateral; LGN, lateral geniculate nucleus; MGN, medial geniculate nucleus; Pu, Pulvinar.