Automatic method for thalamus parcellation using multi-modal feature classification

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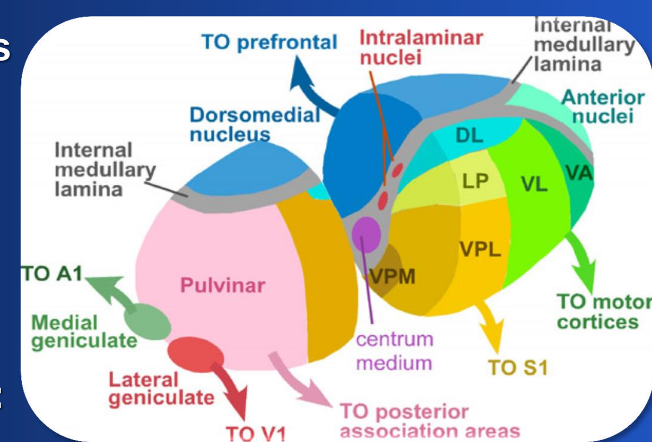
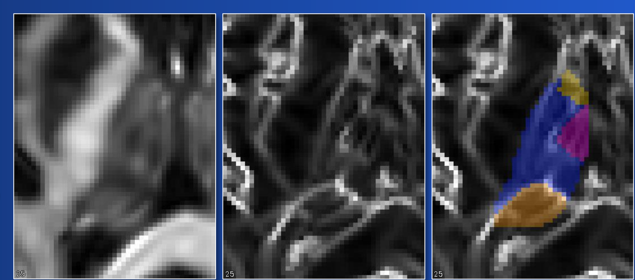
Goal: Fully automatic thalamus segmentation and nuclear parcellation from random forest learning on MR/DTI – derived features.

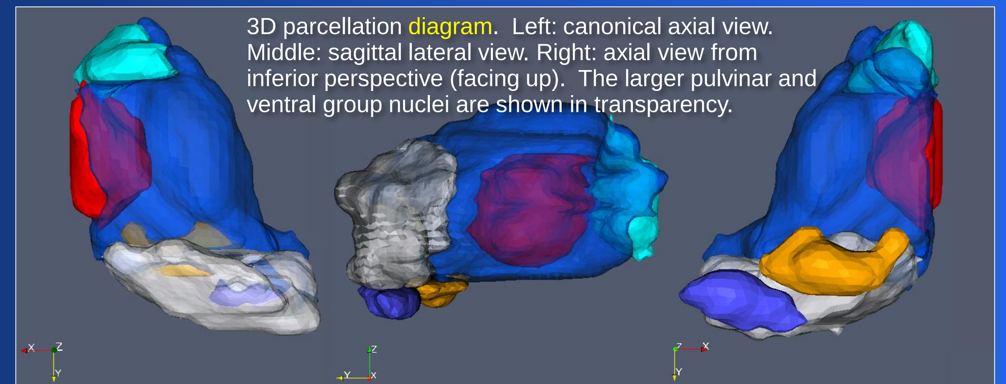
1. Motivation

- The thalamus is implicated in numerous neurodegenerative diseases (Alzheimer's, Multiple Sclerosis, Parkinson's).
- It is composed of neuronal clusters called nuclei, responsible for communication between various cerebral cortex and midbrain regions. The nuclei are *differentially affected* in disease.
- Minimal contrast in conventional MR. DTI (diffusion tensor imaging):
  - Fractional Anisotropy (FA) shows thalamus boundary
  - Changes in Principal Eigenvector (PEV) through Knutsson edge map show inter-nuclear boundaries
- Previous work relies on tensor statistics or connectivity, and requires some manual interaction..
- Our method is first:
  - Combining many modalities
  - Fully automatic





Left: FA of left thalamux Middle: Knutsson map, showing changes in PEV. Right: thalamus nuclear delineation (manual) from the Knutsson edge map image: anterior nucleus [yellow], medialdorsal [red], ventral group [blue], and pulvinar [orange].



3D parcellation diagram. Left: canonical axial view. Middle: sagittal lateral view. Right: axial view from inferior perspective (facing up). The larger pulvinar and ventral group nuclei are shown in transparency.

2. Method

- Goal is fully-automatic segmentation and parcellation of the thalamus using learned patterns in multi-modal features. We integrate potentially discriminating features used in prior work, such as spatial coordinates, the Knutsson map, cortical connectivity, and other DTI-based and structural MRI information.
- ROI Identification: atlas-based, topology-preserving fuzzy classification—TOADS [Bazin and Pham]—provides gross thalamus. Axis-aligned circumscribing box provides ROI.
- Feature Selection: spatial coordinates, the Knutsson map, cortical connectivity, and other DTI-based and structural MRI information, associated with a nucleus label (or background) from a manual rater.
- Random Forest (RF): classification to discriminate thalamus from background and separately thalamic nuclei from each other, using all modalities available, per voxel.
- Target case:
  - Find ROI using TOADS.
  - Segment thalamus versus background with first RF, smooth with simple morphology
  - Parcellate previous result using second (nucleus-nucleus) RF.

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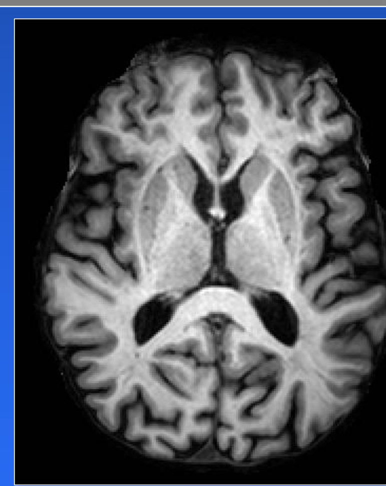
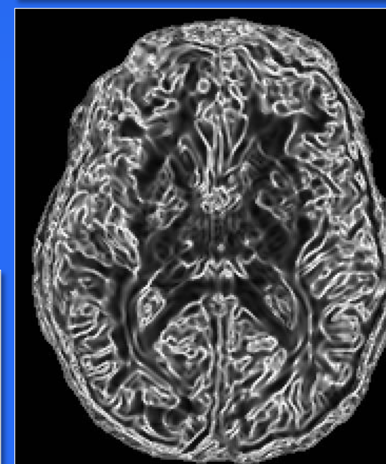
2.2 Feature Selection

- 18 discriminating features from structural and diffusion-derived imaging data.
  - MP-RAGE (magnetization-prepared rapid acq. with grad. echo) – improved contrast for MS lesions.
  - FA (fractional anisotropy) – non-uniformity of diffusion computed using the eigenvalues of the diffusion tensor.
  - MD (mean diffusivity) – average eigenvalue of tensor.
  - KN: Knutsson (5D) mapping accounts for orientation ambiguity in the principal eigenvector [Knutsson]:

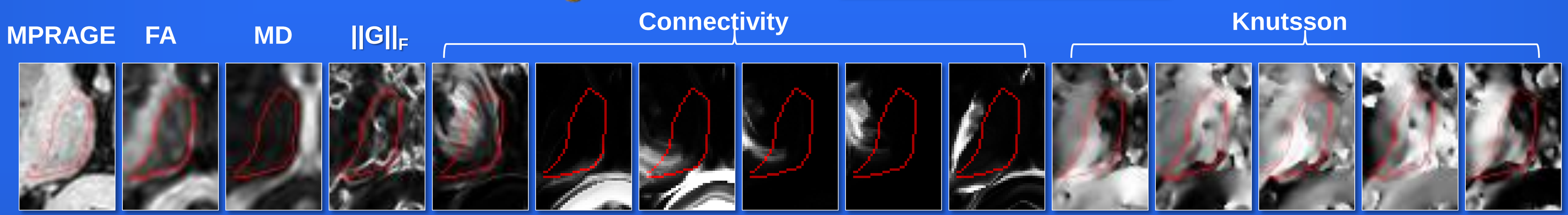
$$M([x,y,z]) = \{x^2 - y^2, 2xy, 2xz, 2yz, (2z^2 - x^2 - 2y^2)/\sqrt{3}\}$$

  - Knutsson edge map $||G||_F$ – orientation gradient
  - Spatial location (3D)
  - Cortical Connectivity (6D) through FSL Diffusion Toolbox: frontal precentral postcentral parietal occipital temporal



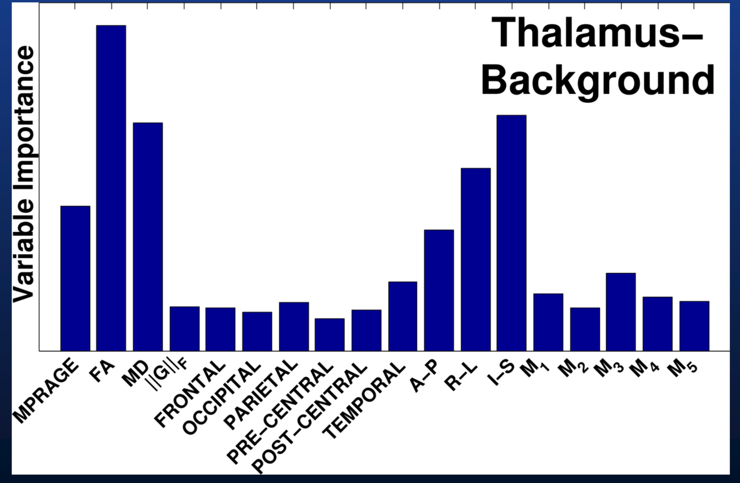


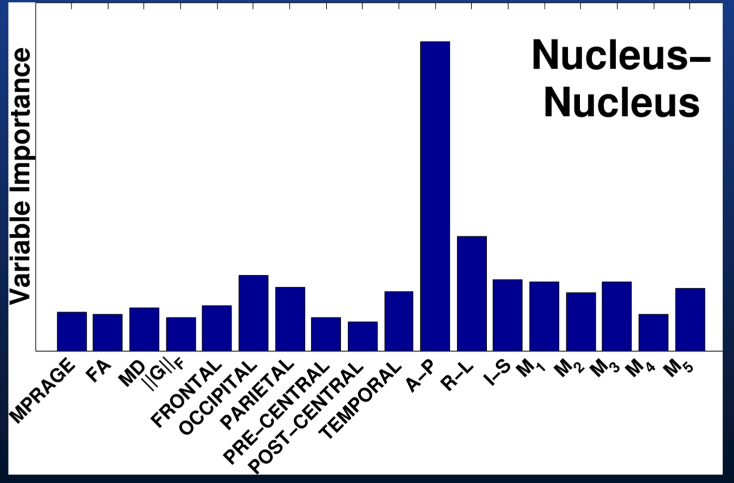
Above: whole brain axial view of MP-RAGE (top) and Knutsson edge map (bottom). Left: cortical labels (left), and (right) axial view of fiber counts given seeding within the thalamus.



2.3 Random Forest Learning

- Decision trees are constructed through random subsampling of the data and features [Breiman]. Here: single feature, minimum misclassification decision
- Train separate thalamus-background and nucleus-nucleus random forest ensembles
- Test: Apply thalamus-background RF on ROI, morphological correct
  Apply nucleus-nucleus

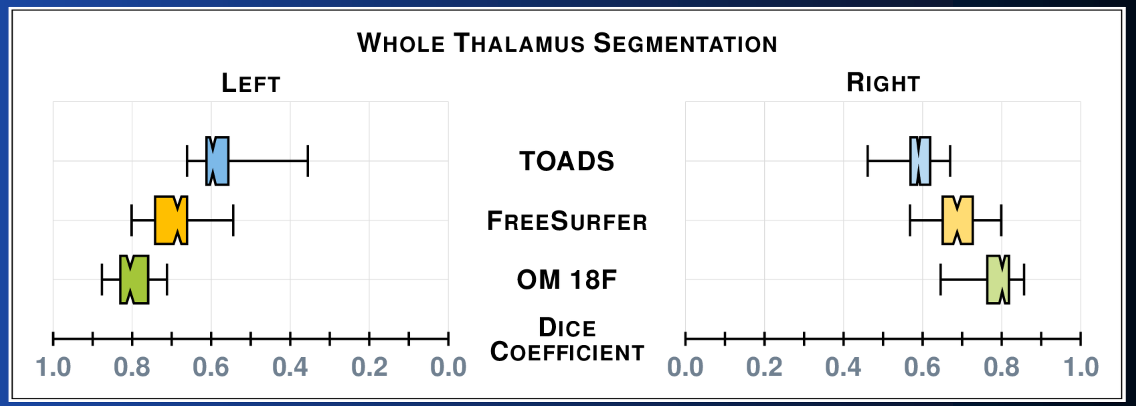


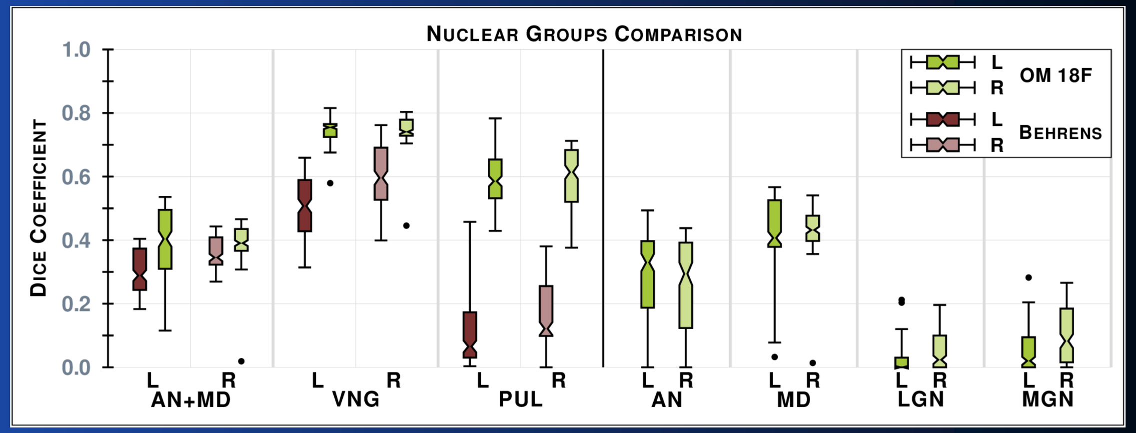


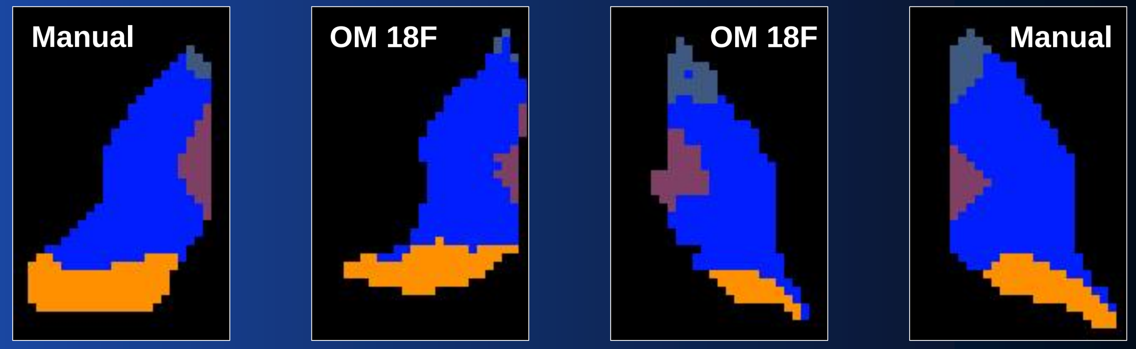
Variable importance in the Random Forest classification for thalamus-background (left), and nucleus-nucleus (right).

3. Experimental Results

- 21 MP-RAGE and DTI on 3T MR scanner, resampled to .83mm isotropic
- Leave-one-out validation against manual delineations
- Significant improvement in thalamus segmentation vs. [FreeSurfer] and TOADS. two-sample Wilcoxon rank sum
- Results are achieved without any manual interaction.
- Parcellation: we do well on nuclear groups comparable to those in [Behrens].
- Large variability in Dice for smaller nuclei







4. Conclusions, Future Directions

- Goal is large-scale study of thalamic neuropathology using automated methods. In this paper we have extended thalamic parcellation to place us closer to that goal.
- Needed for improved accuracy:
  - Individual nucleus random forest learners
  - Pool results over a larger number of training cases.
  - Incorporate deformable model or a priori shape, topology constraints. Per-voxel decision leads to significant noise
- Compare Knutsson to other tensor/PEV dissimilarity measures.

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