

Computational caudate morphometry for Huntington's disease

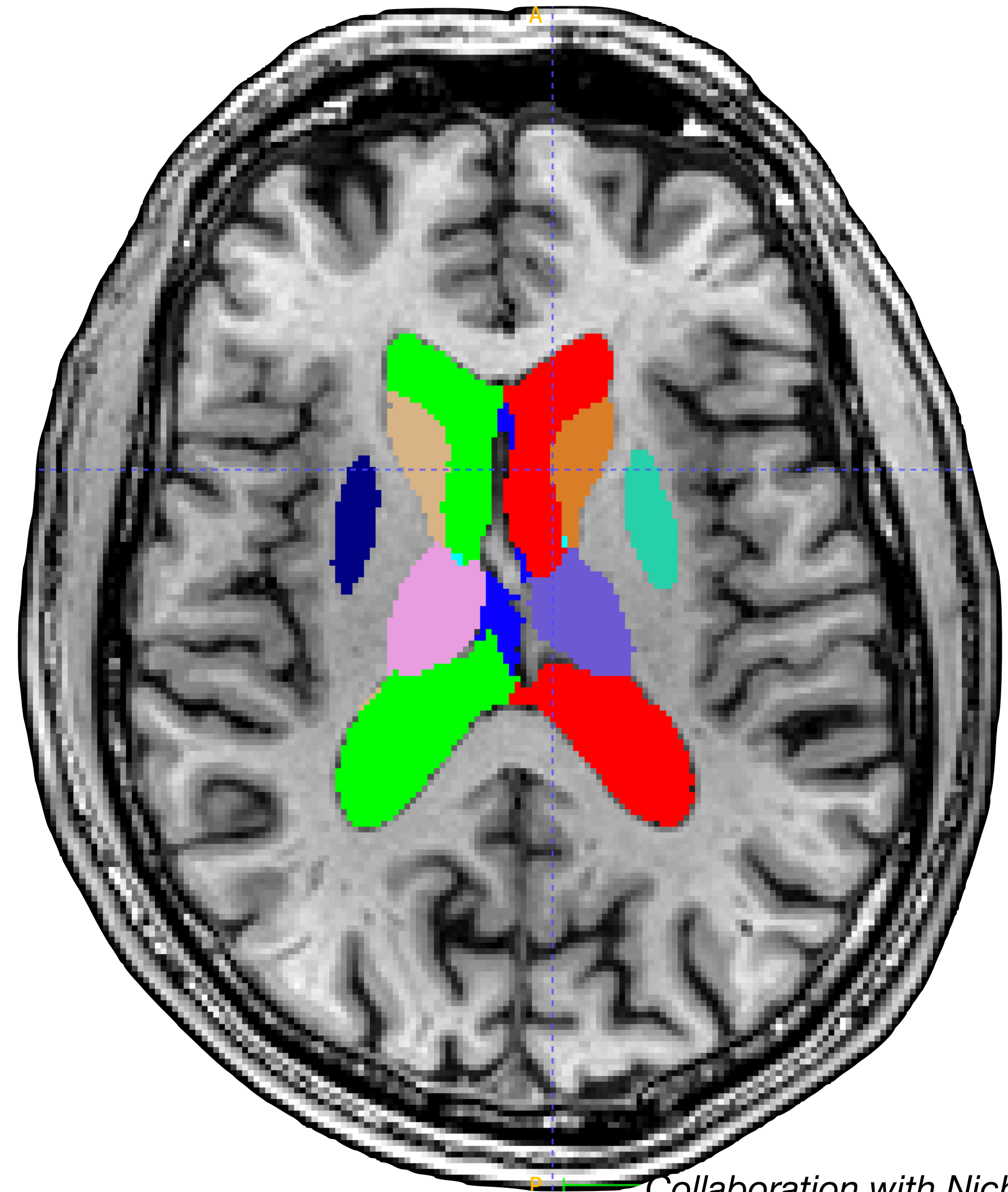
Software for quantifying anatomical shape from medical images

Overview of progress toward automated caudate morphometry from MR neuroimaging

- Basic framework in place
 - Task-based software design
 - Initial framework for testing is in place
 - Several algorithmic innovations (following slides)
- Tabular metrics from regional parcellations
 - Parcellations are restricted to the medial subdivision of the caudate nucleus (medial/lateral division is automatically calculated)
 - Mean curvature based on the shape operator applied to the distance transform of a caudate nucleus
 - Higher order shape: flatness, elongation, eccentricity
 - Basic Geometry: Volume, thickness, area
- Dense metrics
 - Log-jacobian of the mapping from the target caudate to a template caudate
 - DiReCT based thickness of the medial portion of the caudate nucleus from its skeleton
 - Mean curvature (as above)

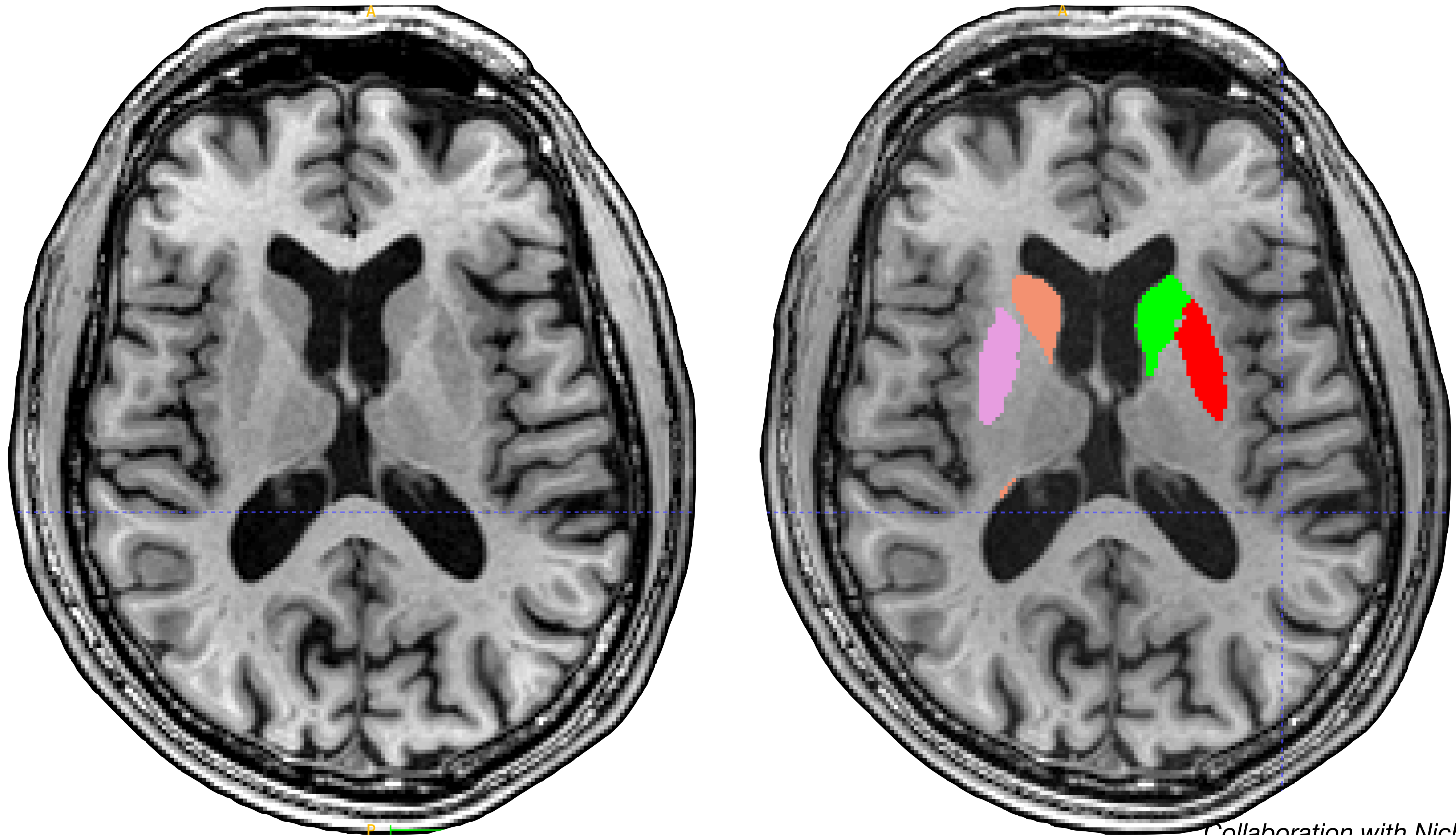
Automated caudate segmentation

Deep Learning based on the Harvard Oxford Atlas; ANTPD example data



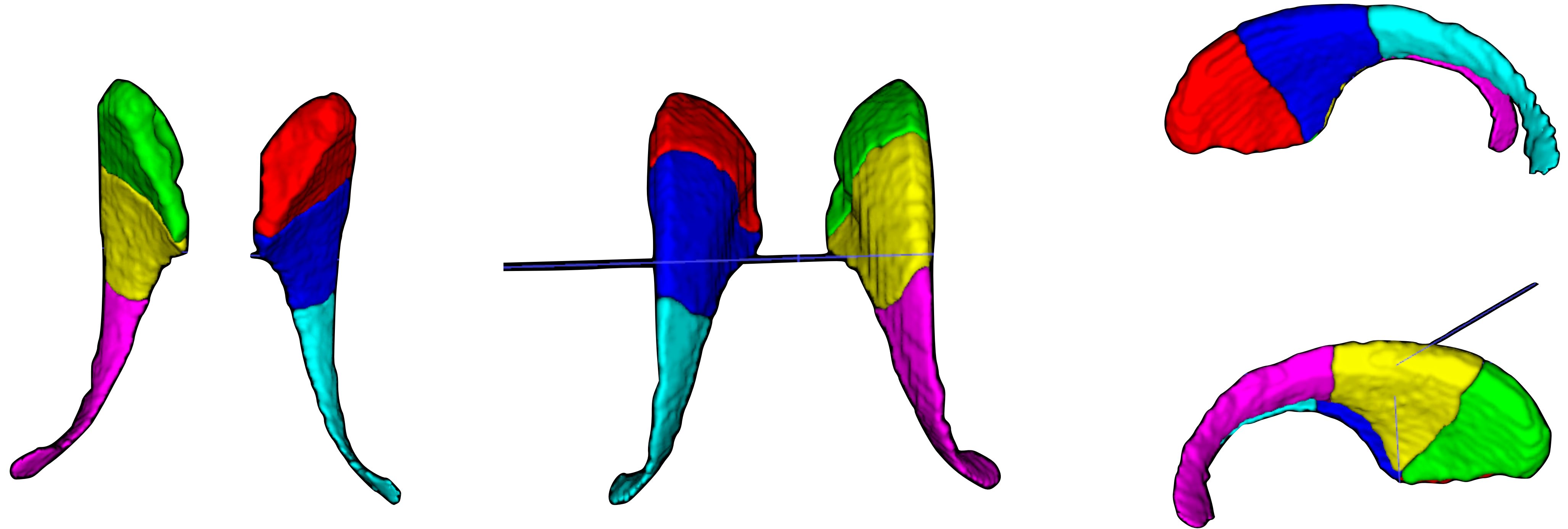
Automated caudate segmentation

Deep Learning based on the CIT168 Atlas; ANTPD example data



Collaboration with Nicholas J. Tustison

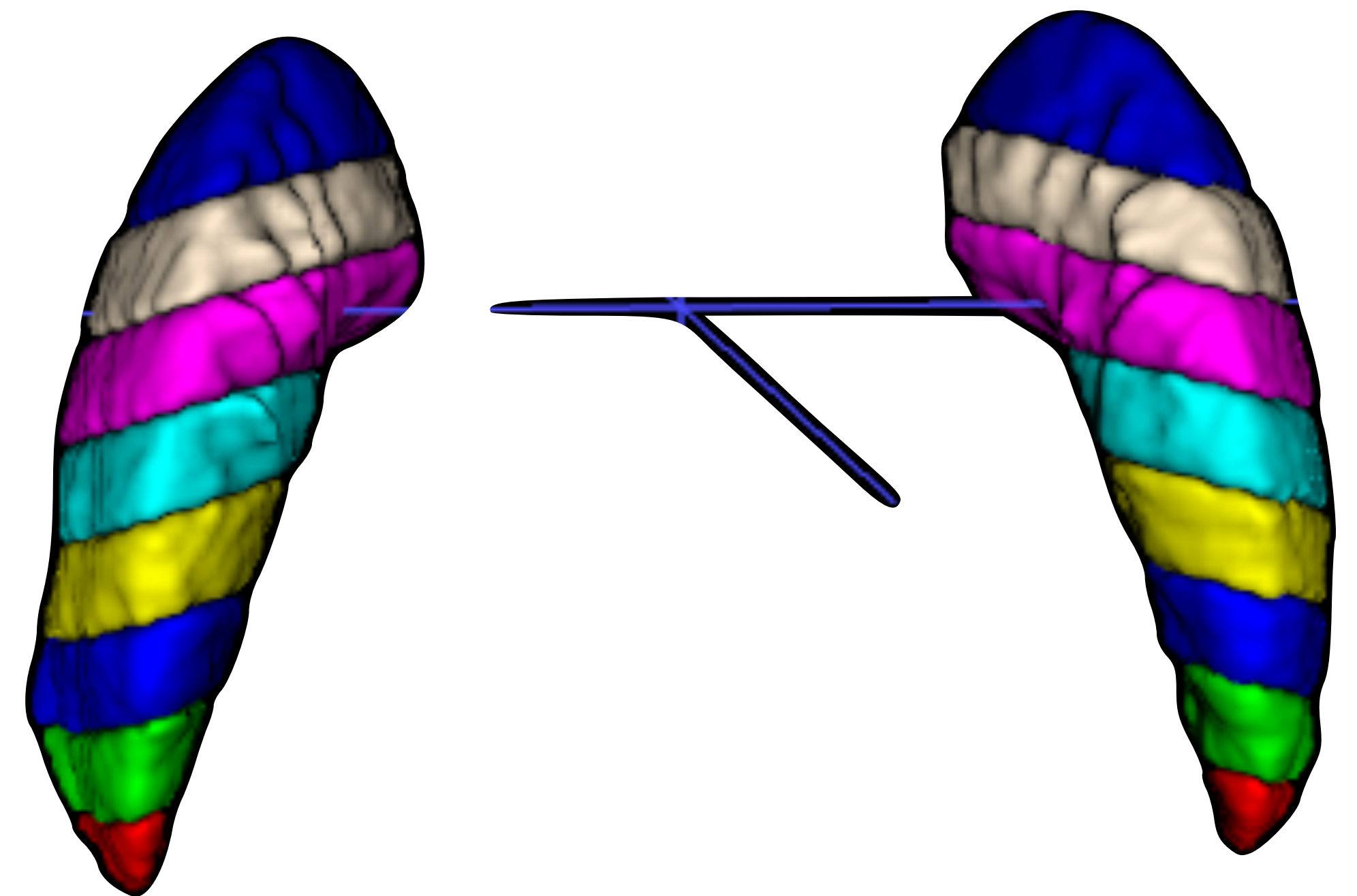
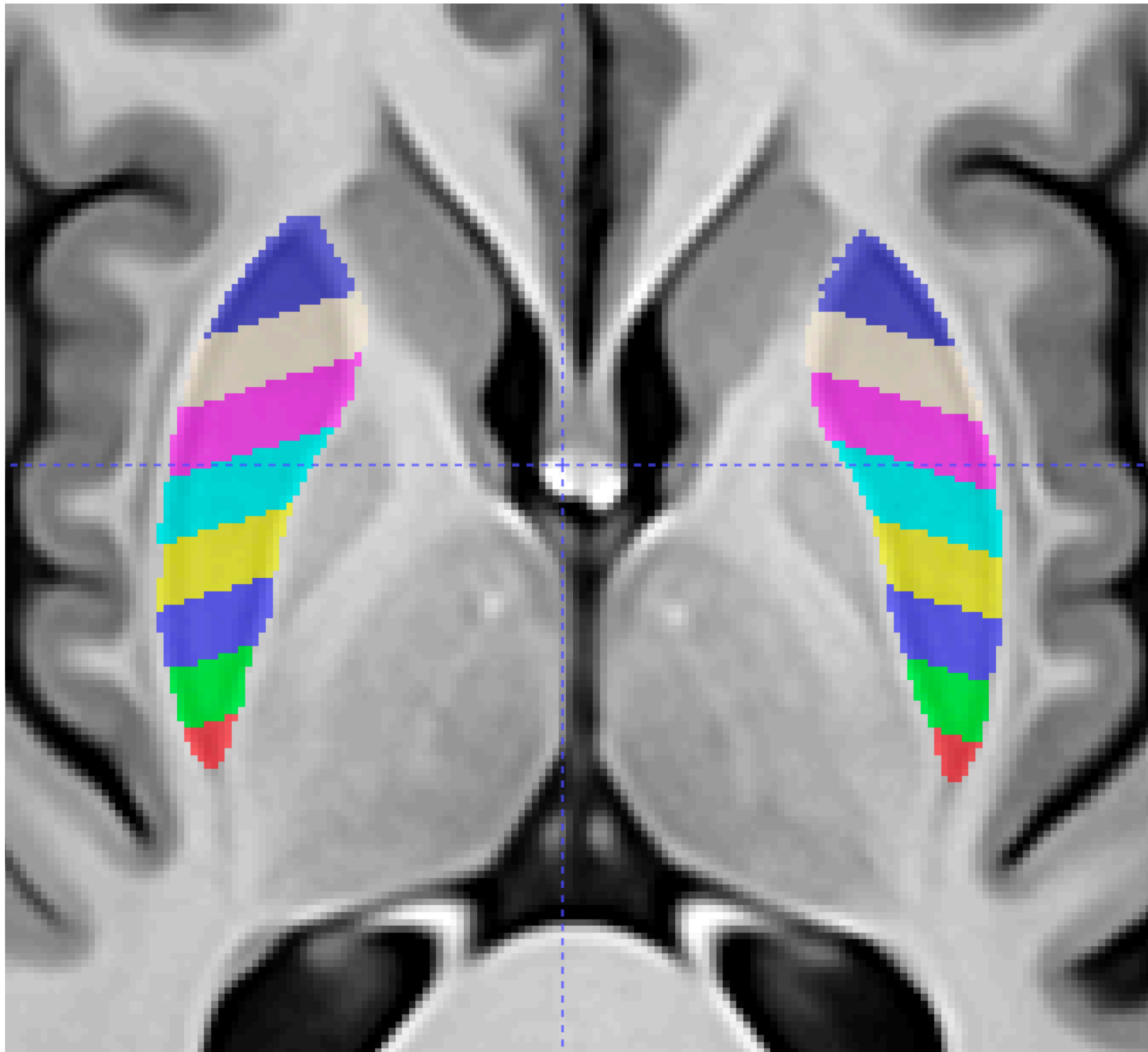
Manual caudate parcellations (template)



Parcellation performed by B. Avants in ITK-SNAP

Generic automated parcellations (k=8) putamen

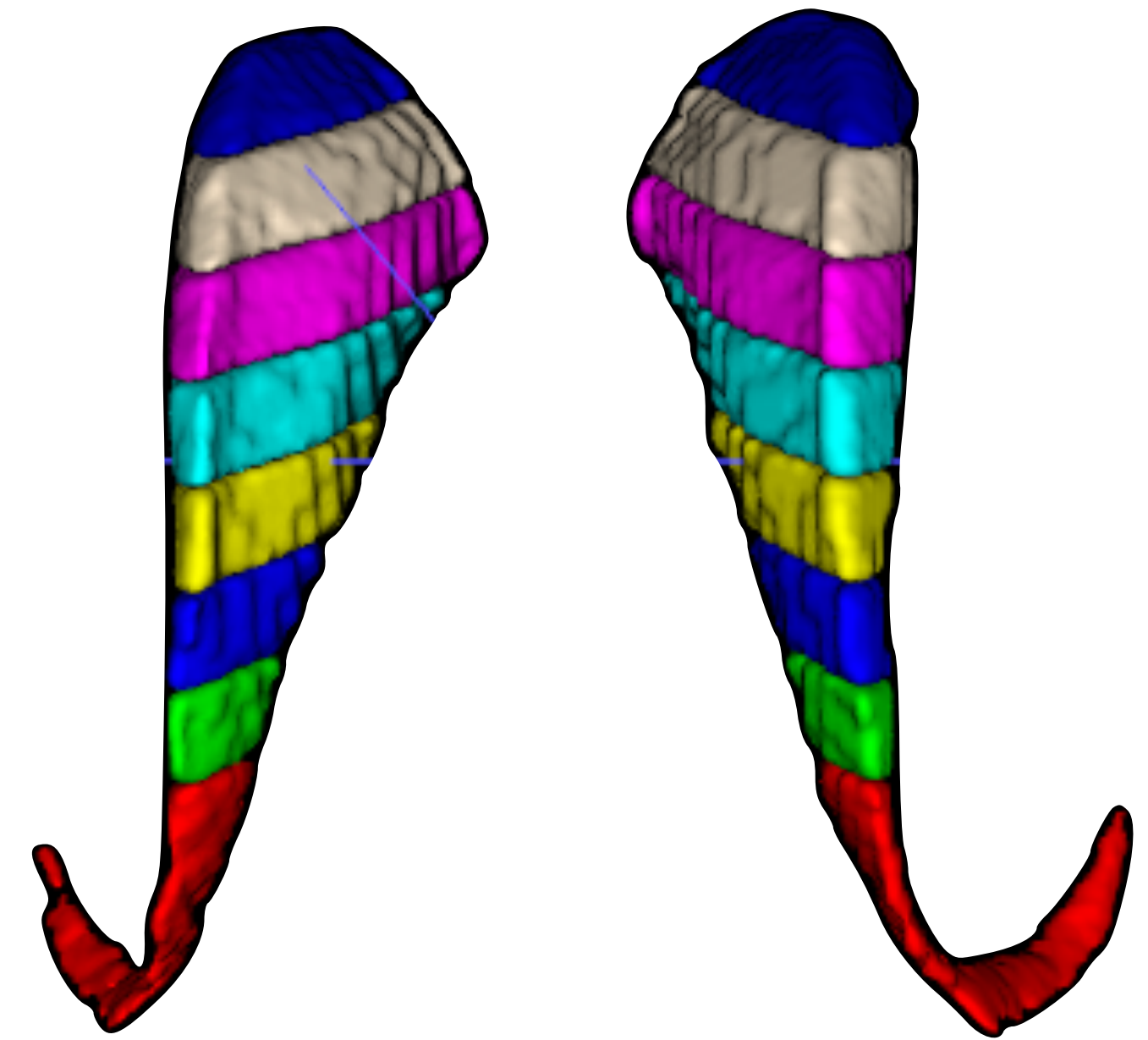
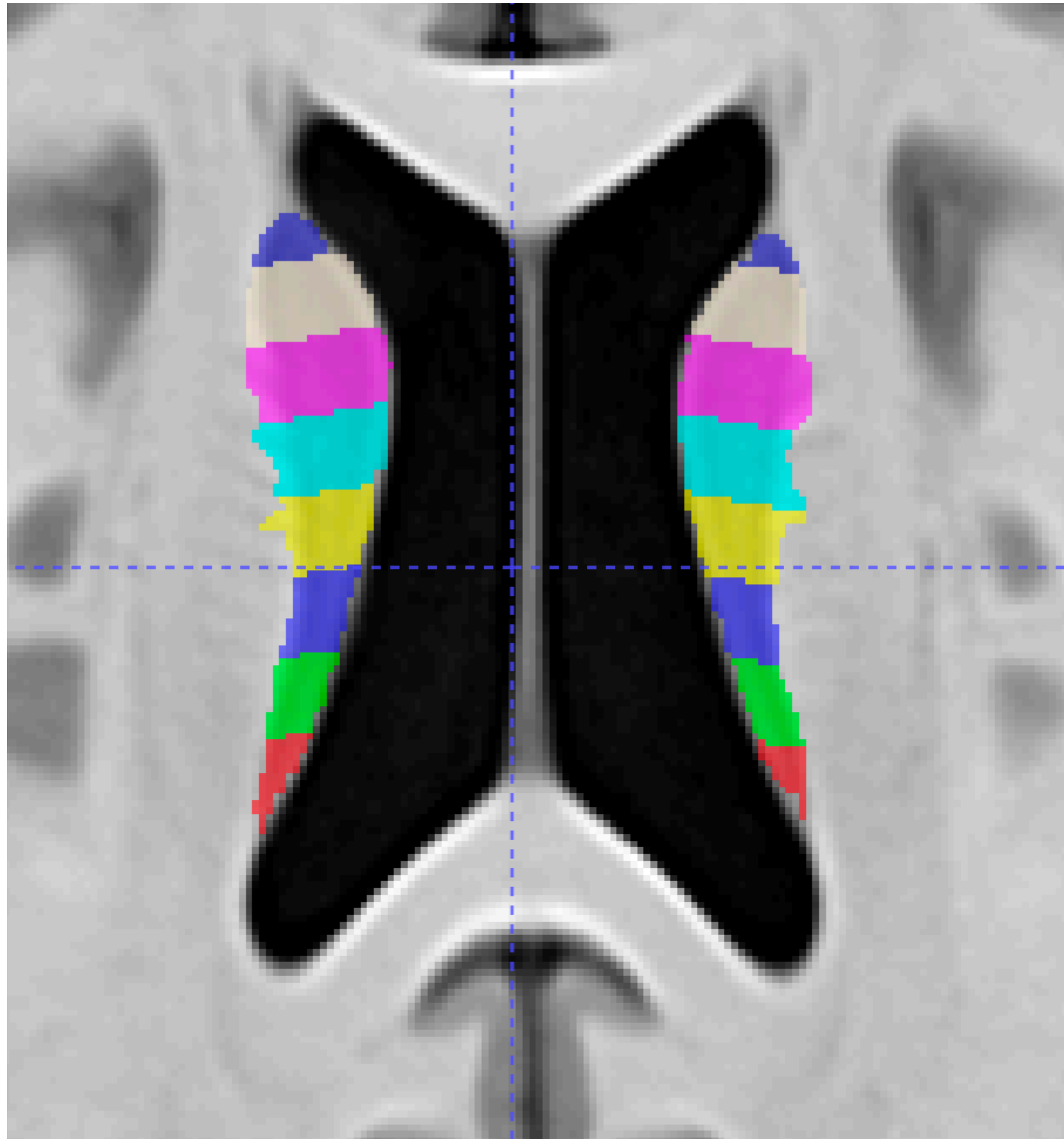
Methodology for any roughly linear structure



Parcellation performed by B. Avants with the software under discussion

Generic automated parcellations (k=8) caudate

Methodology for any roughly linear structure



Parcellation performed by B. Avants with the software under discussion

Flatness calculation

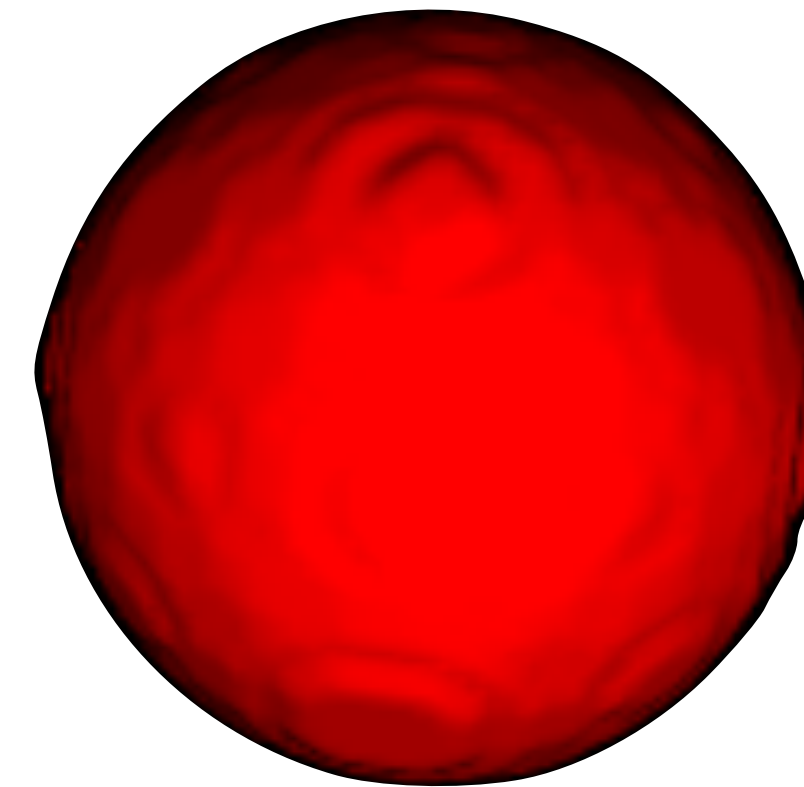
Somewhat novel definition but very classical mathematics involved

Extract voxel positions where the intensity is greater than a threshold:

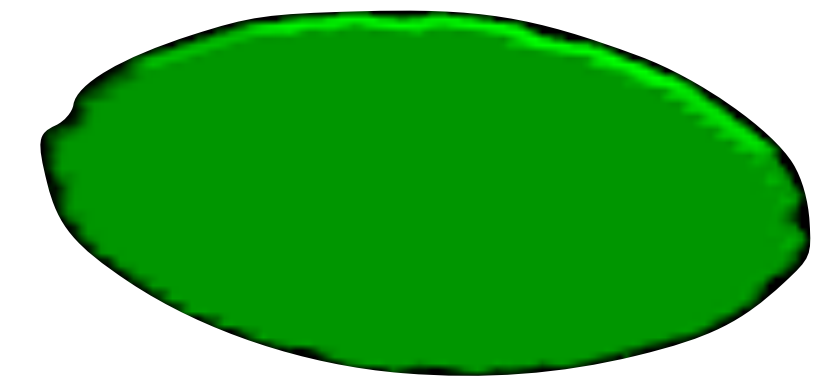
$$\mathbf{V} = \{\mathbf{v}_i \in \mathbb{R}^3 \mid I(\mathbf{v}_i) > T\}$$

Perform Principal Component Analysis (PCA) on the set of voxel positions

$$\Sigma = \frac{1}{N} \sum_{i=1}^N (\mathbf{v}_i - \bar{\mathbf{v}})(\mathbf{v}_i - \bar{\mathbf{v}})^T$$



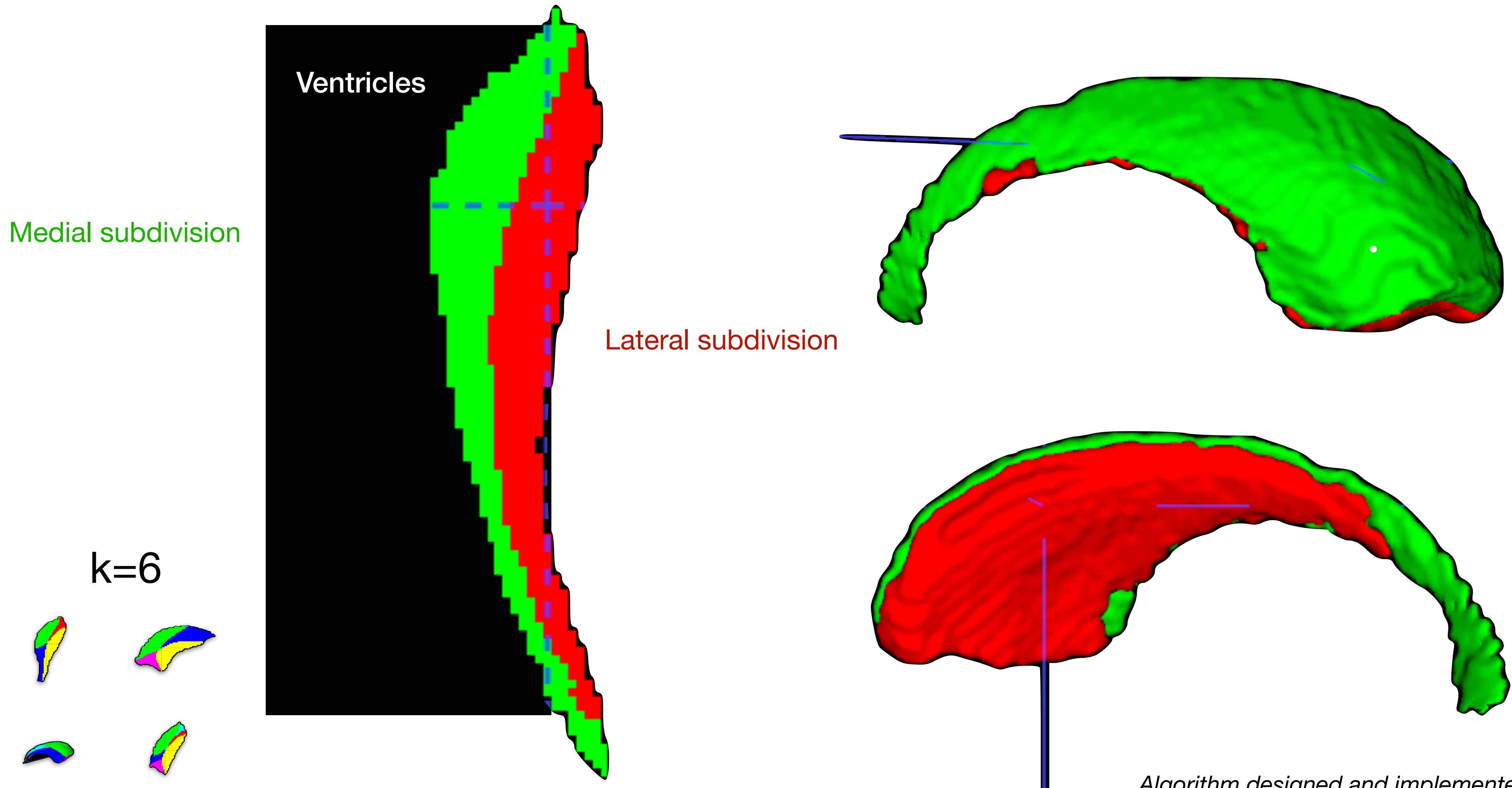
Sphere = 0



Disk = 1

Compute the flatness ratio: $F = 1 - \frac{\lambda_1}{\lambda_3}$
from the eigenvalues $\lambda_1, \lambda_2, \lambda_3$

Automated gradient-based laterality division



Algorithm designed and implemented by B. Avants

The curvature calculation

1. Input binary segmentation and template-based parcellation
2. Calculate the distance map of the segmentation
3. Calculate the curvature from the level sets of the distance map
4. Restrict the parcellation to the medial division of the structure
5. Remove the curvature “spine” before quantification with parcellation

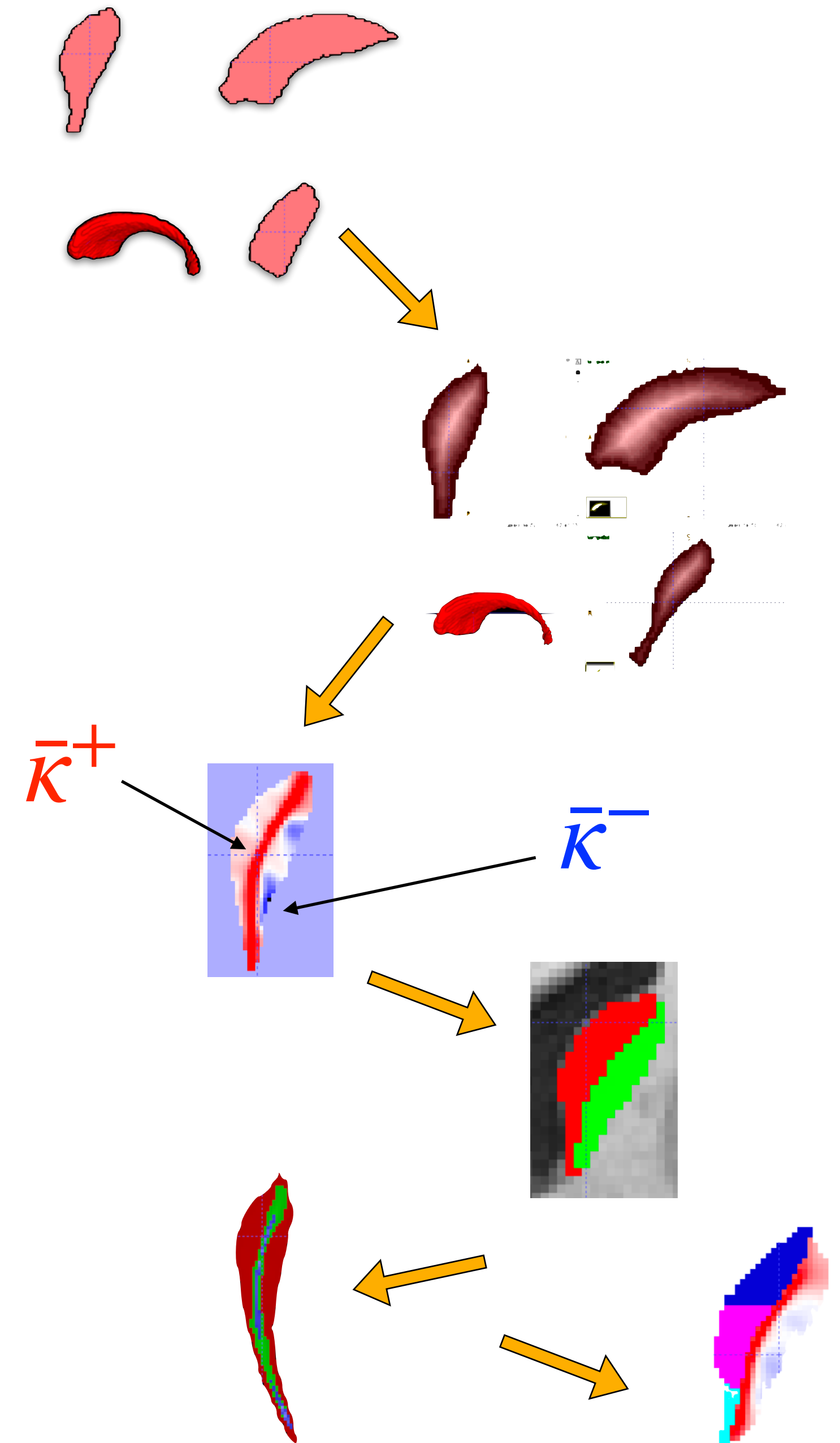
1

2

3

4

5



The curvature calculation: technical notes

Avants & Gee in “the shape operator for differential analysis of images” introduce a novel method for analyzing volumetric images using the **shape operator** to estimate surface curvature and principal directions directly from image data. Unlike traditional mesh-based methods, this approach avoids topological assumptions, using local surface patches constructed from image gradients.

Here, this method is applied to the level sets of the distance transform of a binary object. This enables the curvature calculation to be informed by both local and global shape and enables more robust summary data to be derived from labeled regions of interest or parcellations of the segmentation. Our software implementation, here, uses only the mean curvature as a summary.

Key Contributions:

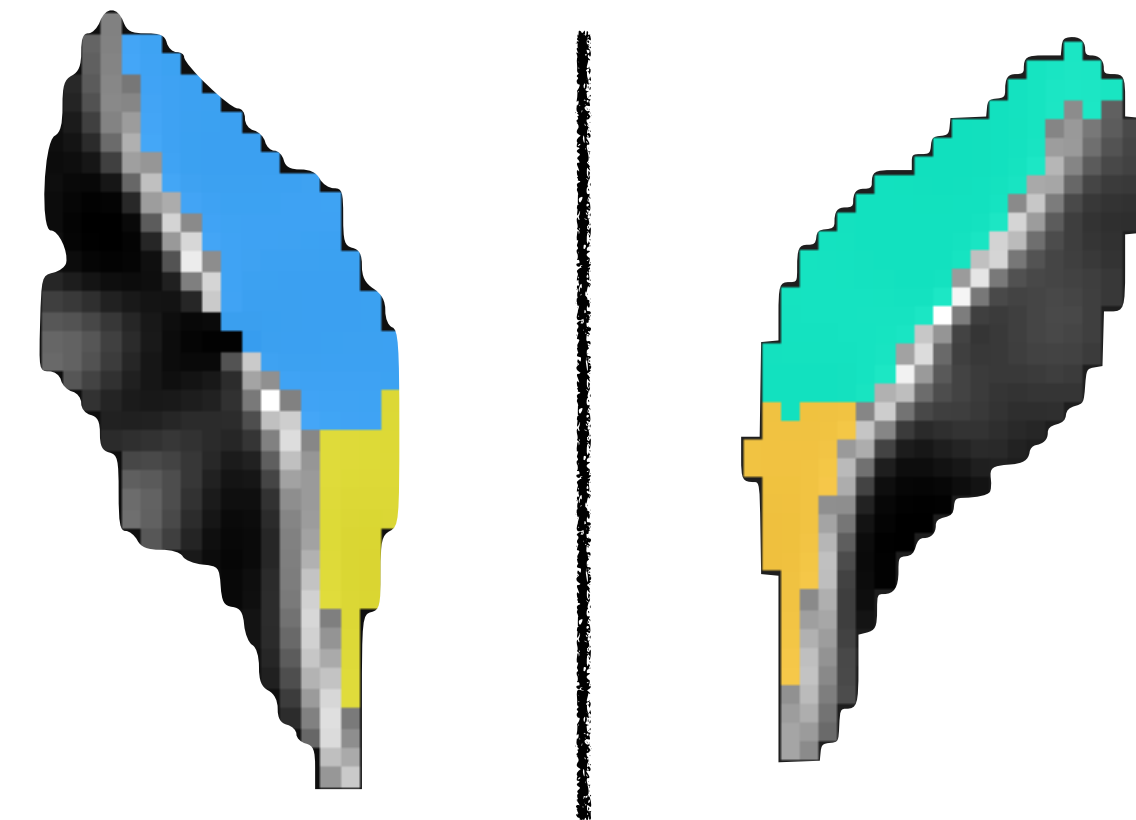
1. Surface Representation:

- Local surface patches derived from gradients in segmentation or edge maps.
- Extrinsic (Euclidean) and intrinsic (geodesic) distances define neighborhoods for analysis.

2. Shape Operator:

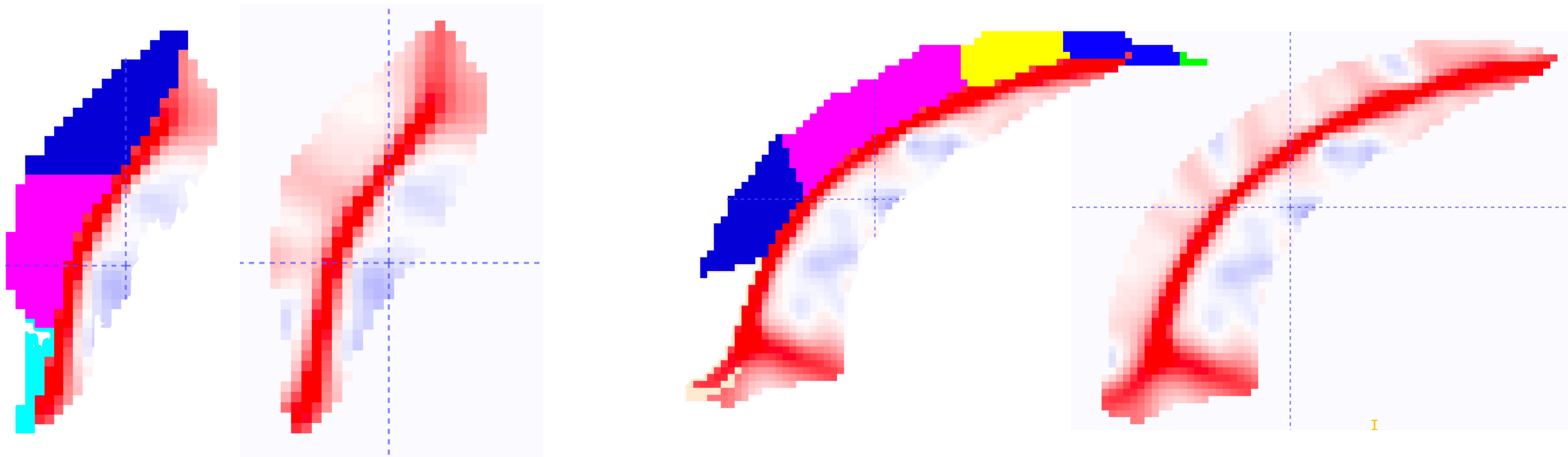
- Efficiently estimates mean and Gaussian curvature from first-order derivatives, enhancing stability.
- Principal curvatures and directions derived from eigenanalysis of the shape operator.

Algorithm designed and implemented by B. Avants

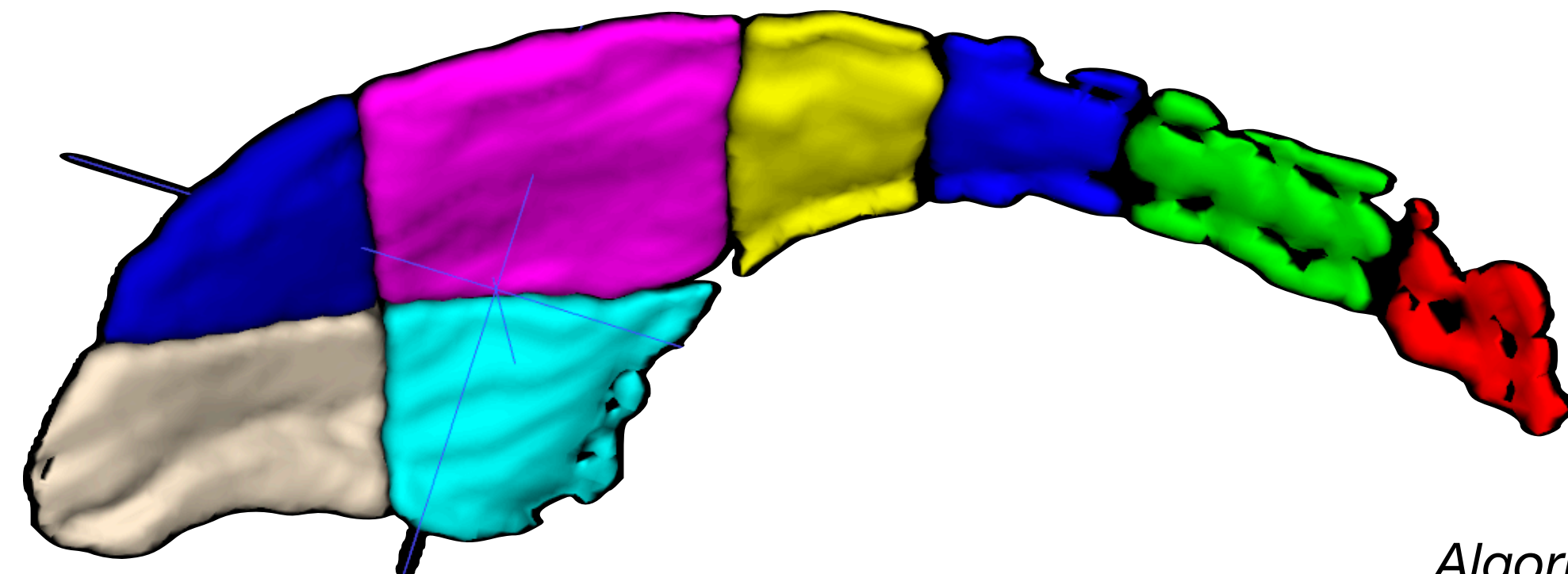


Left and right caudate with a medial partition merged with a HMT parcellation. The labels are overlaid on the voxelwise mean curvature. Darker values are negative curvatures.

Curvature map and parcellation



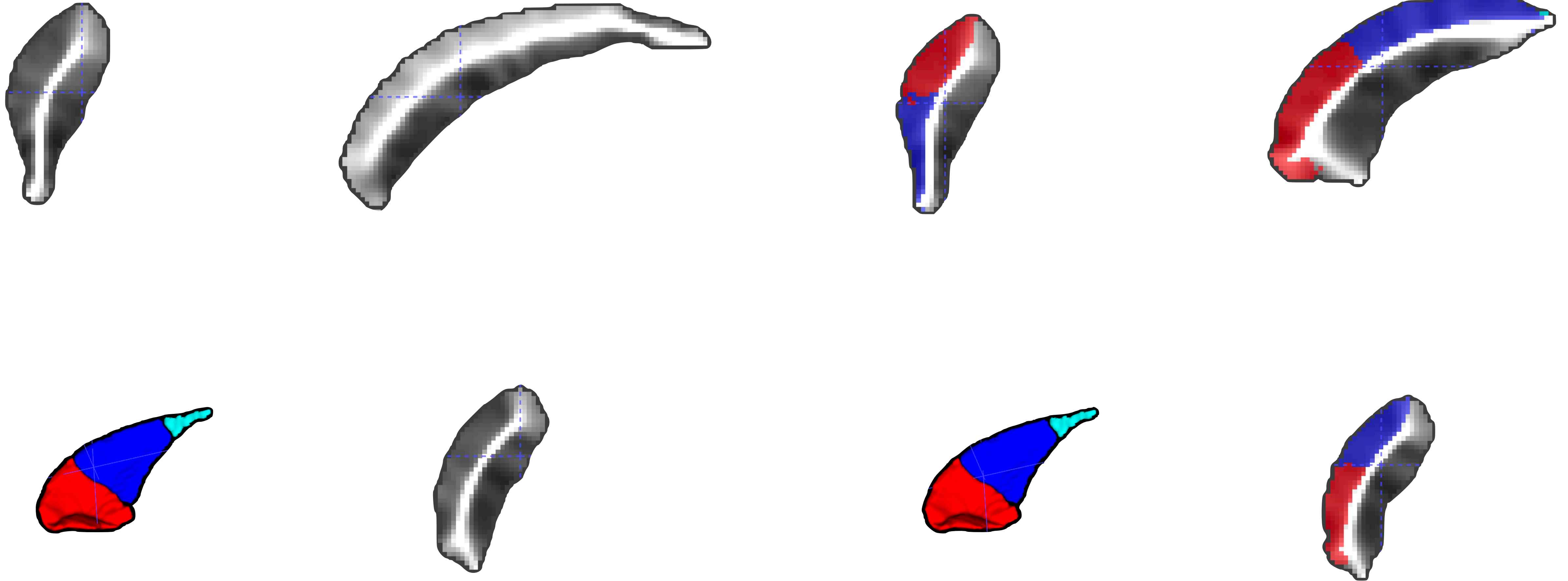
Automated grid-based subdivision of a caudate segmentation



Algorithm designed and implemented by B. Avants

Curvature map and HMT† parcellation

Manual parcellation mapped from template to target and restricted to the medial subdivision of the caudate nucleus ie the side by the ventricles

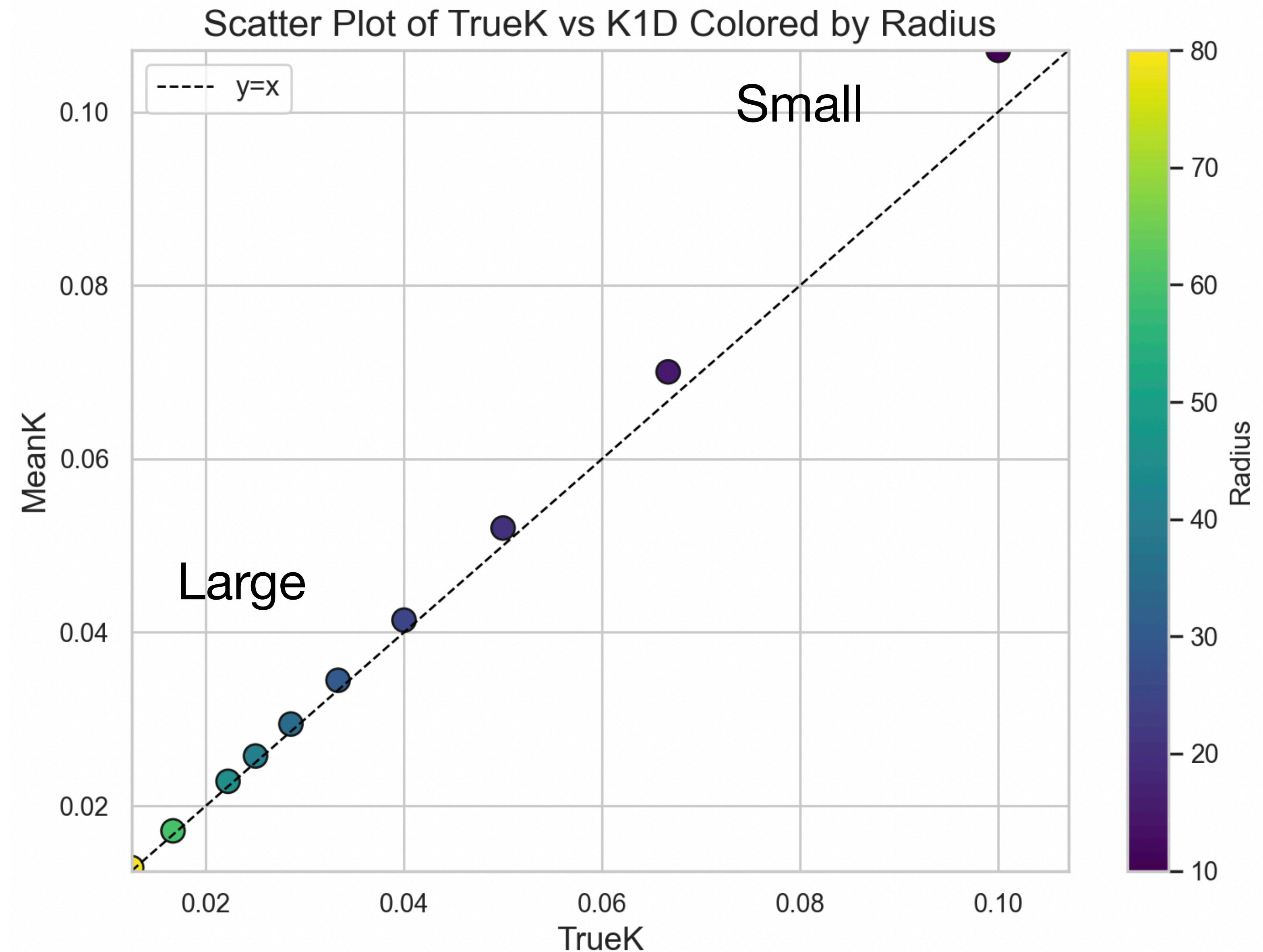


Algorithm designed and implemented by B. Avants

† HMT = head, midbody, tail

Evaluation against known spherical curvature

- Small structure curvature is overestimated†
- Larger structures are very accurate
- Average % error over this graph is 2.5%
- Correlation is >0.999

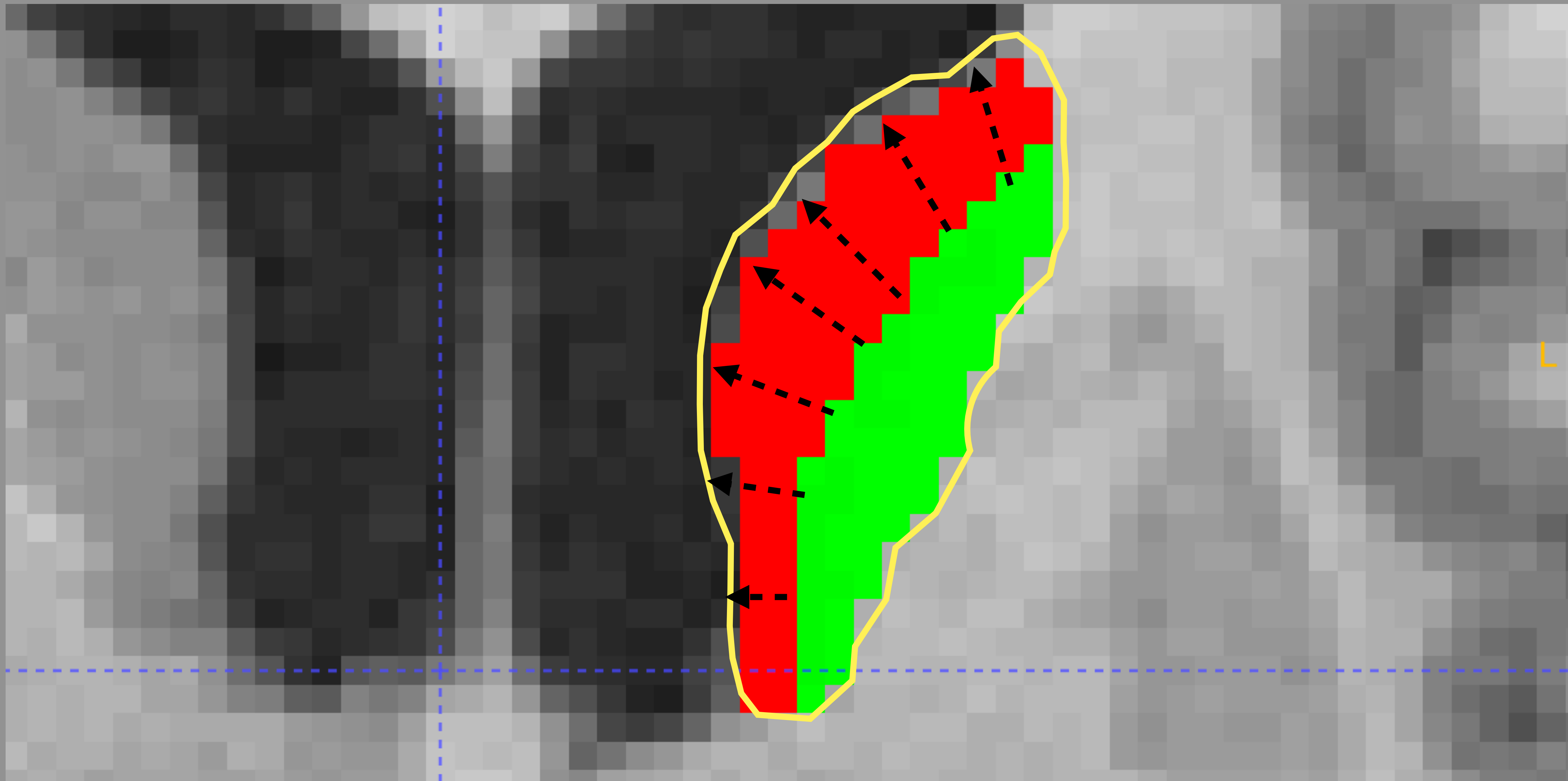


Underestimation may occur as well depending on methods

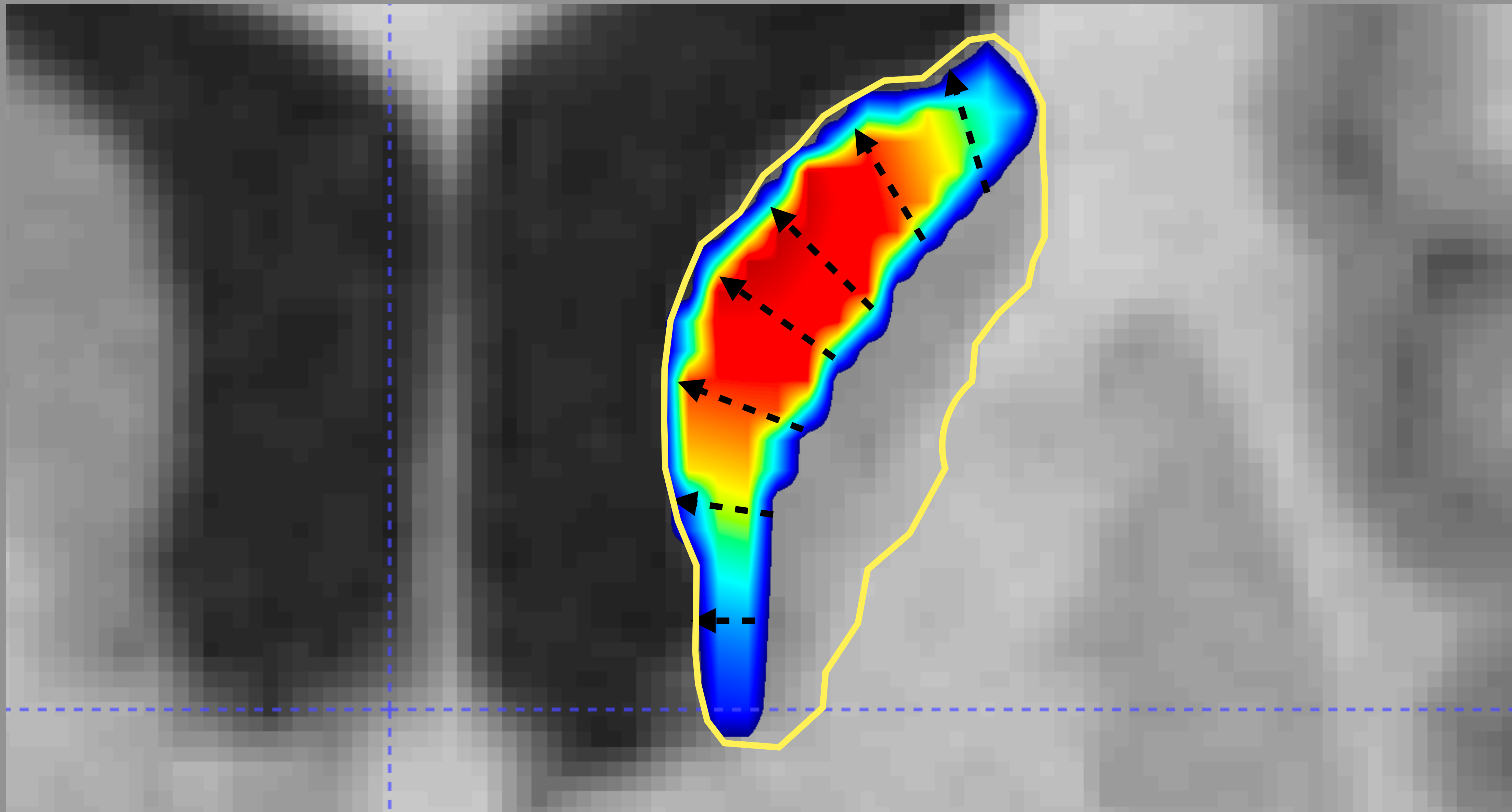
$$\bar{k} = 1/r$$

Note: this test alone took 6+ hours to design

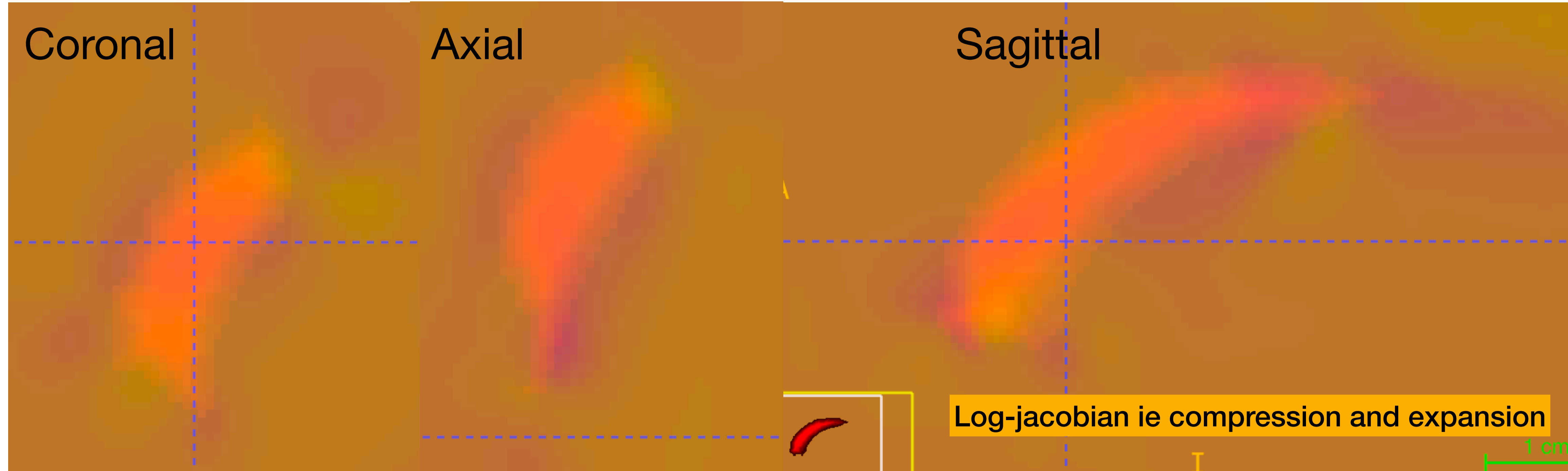
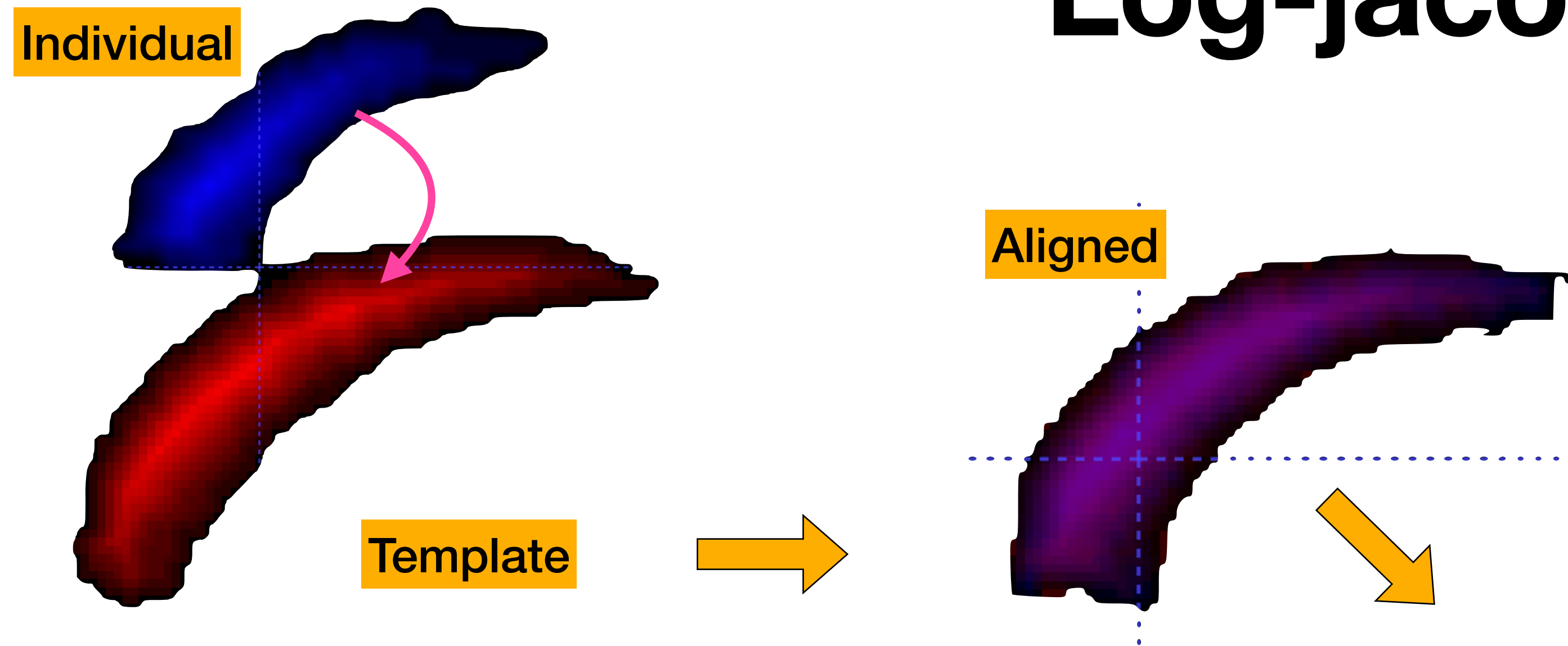
Voxelwise DiReCT thickness map: medial partition of the caudate nucleus



Voxelwise DiReCT thickness map: The output mapping



Log-jacobian measurement



Summary and next steps

- Demonstrated the current status of the CSC software (python-based)
- Software needs more testing
- Needs more work before submission to pypi
- Tested on n=364 example PPMI data with a scalable approach — high success rate (100%)
- Performed a “sanity-check” analysis on these PPMI population level data
 - Do trends in the derived measures ‘make sense’? *Yes - age-related and disease-related effects*
 - Could also perform this analysis on the putamen and/or globus pallidus (both segments)
- Additional documentation and performance details that are beyond the scope to explain here.