Tract-Specific Analysis for DTI of Brain White Matter

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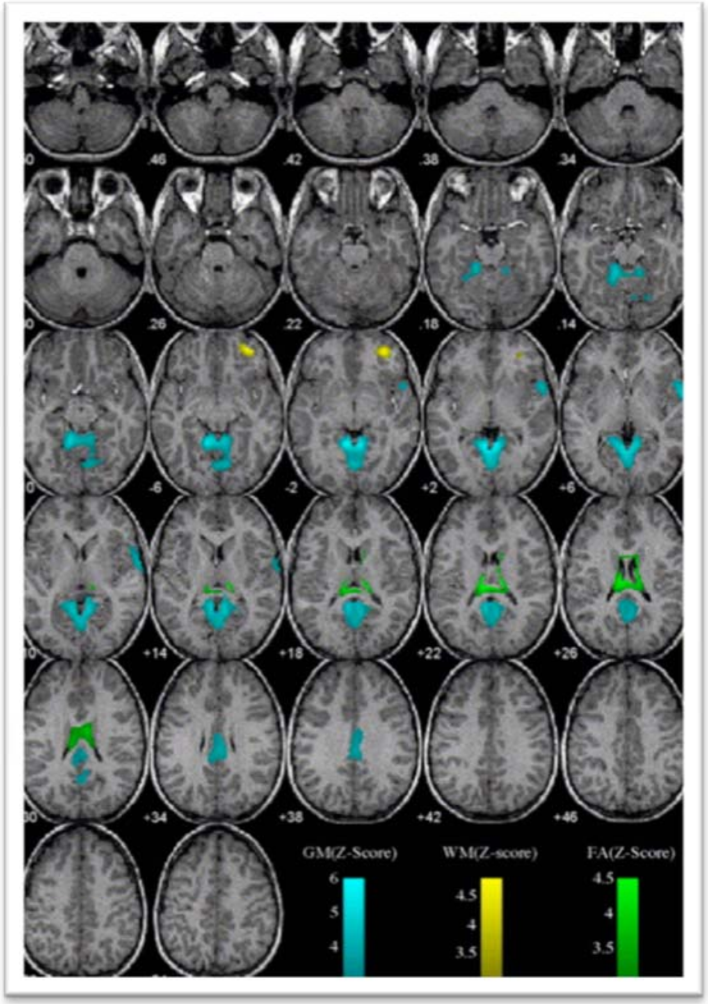
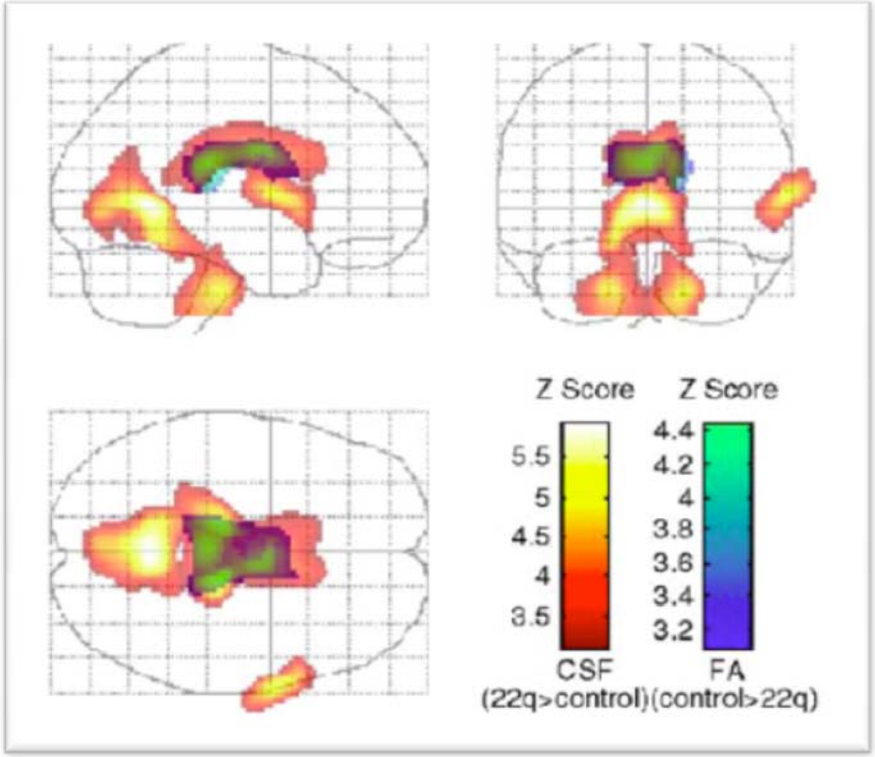
PICSL

The Whole-Brain Approach to Population Analysis

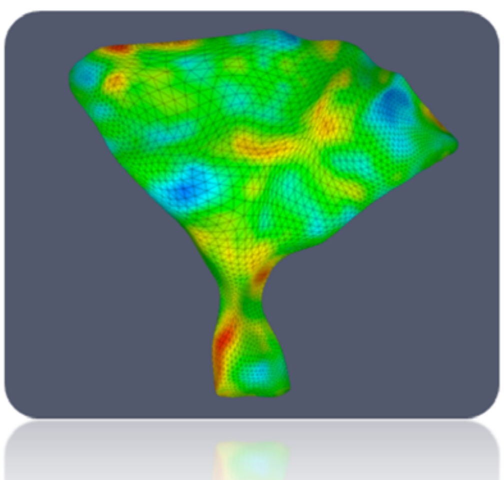


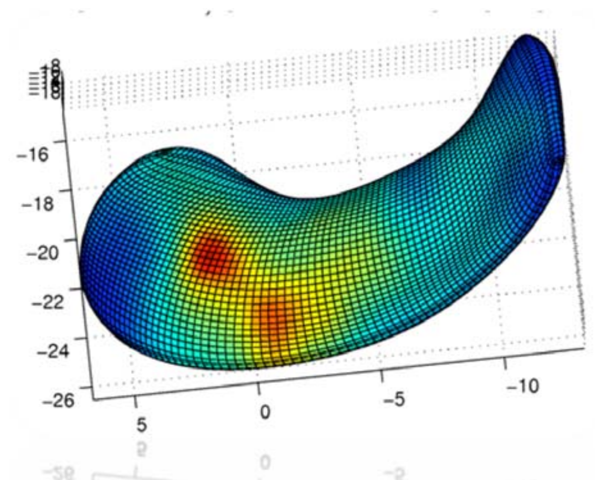


From Simon *et al.*, *Neuroimage*, 2005

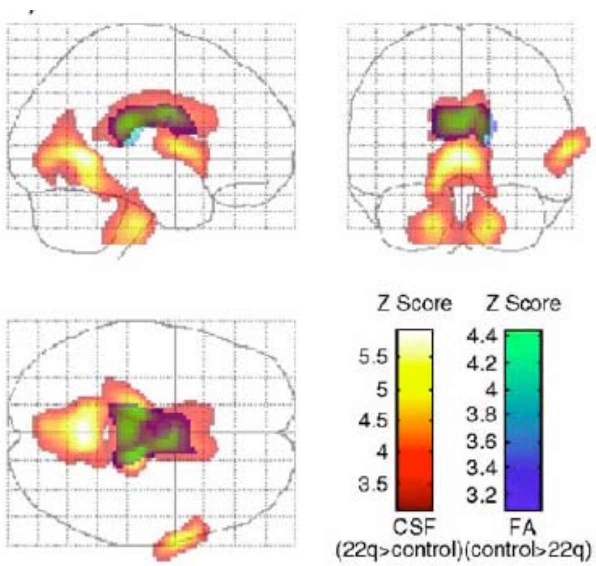
Why Focus on Structures?

- Evaluate specific *a priori* hypotheses
- Reduce confounding effects of surrounding structures
- Enable structures to be normalized independently
- Increase the level of detail
- Present findings in the context of anatomy

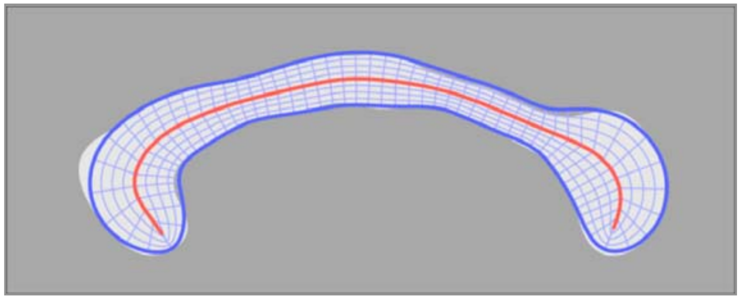




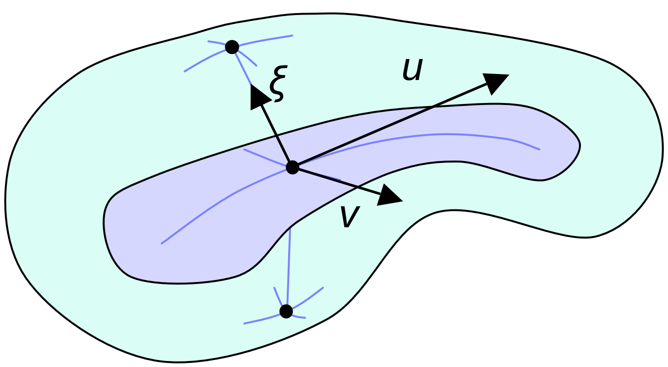
Structure-Specific Coordinate Systems



Talairach space: a coordinate system for the whole brain

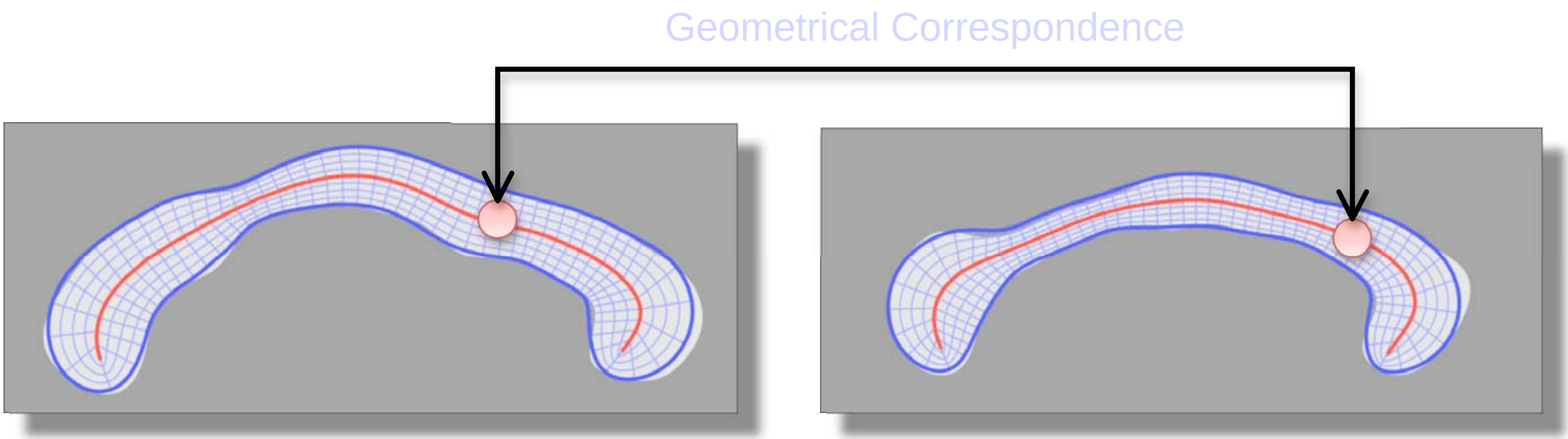


A shape-based coordinate system for the corpus callosum in 2D



A three-dimensional shape-based coordinate system

Structure-Specific Normalization



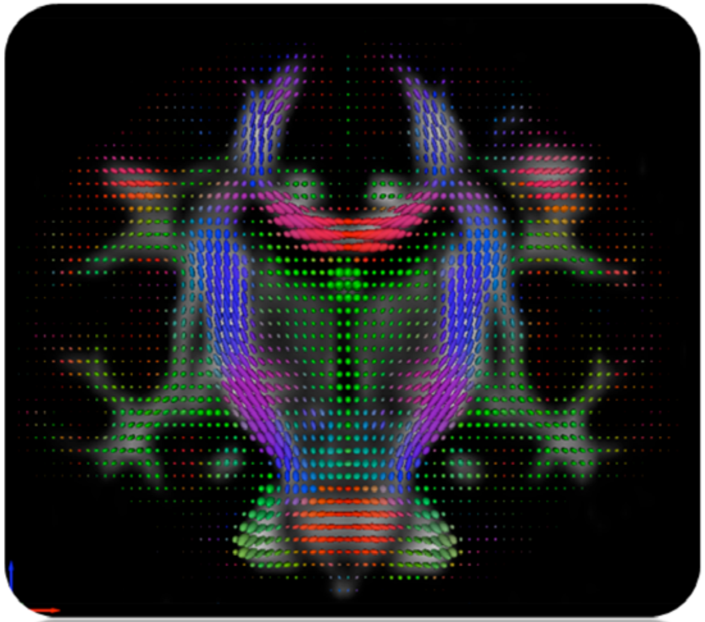
Motivation:

Anatomical correspondences may not be always continuous across structures

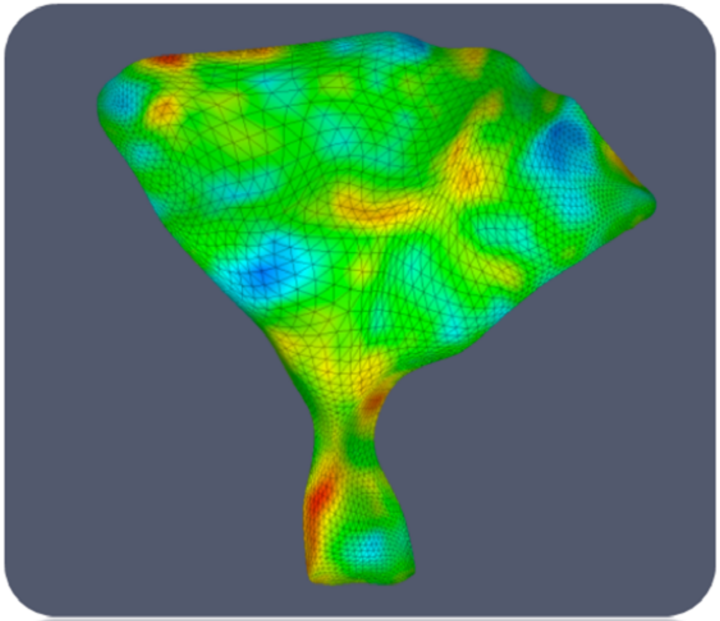
Motivation:

In the absence of strong intensity features, structures may be better normalized on the basis of shape cues

Preliminaries

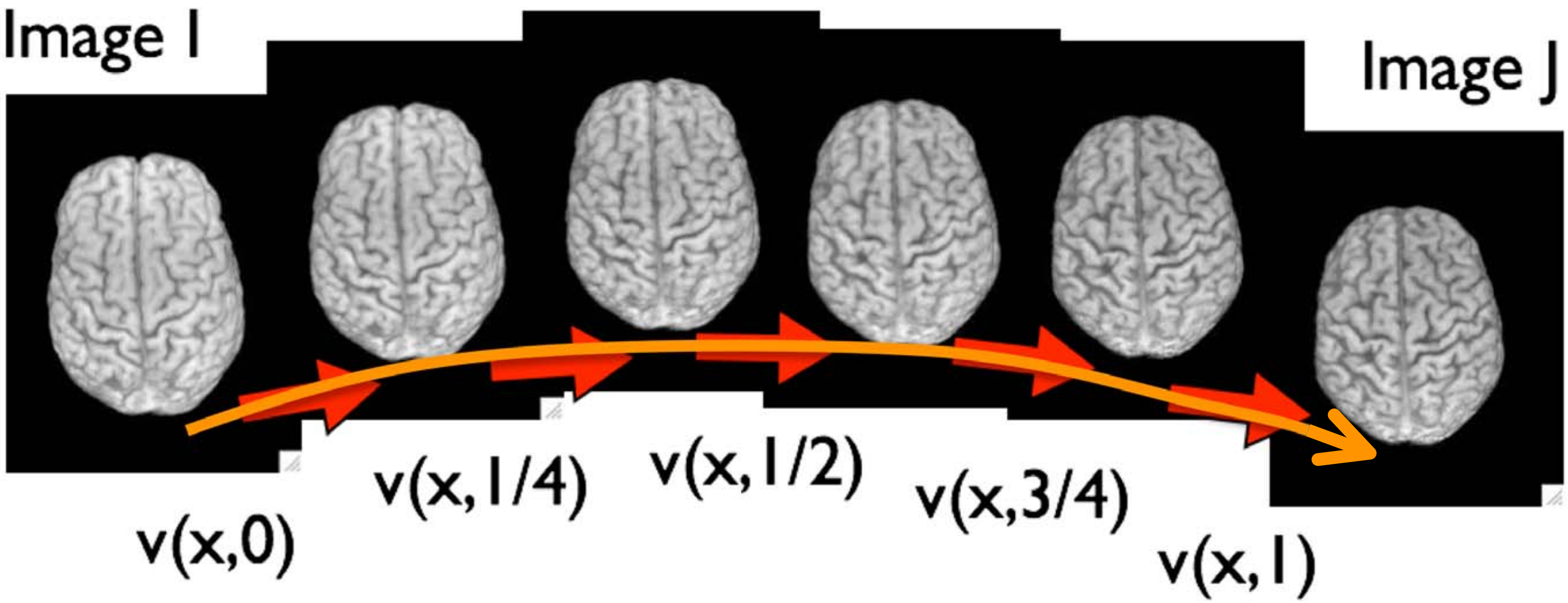


A specialized method for
DTI registration
and template-building



A surface-based
framework for
DTI population studies

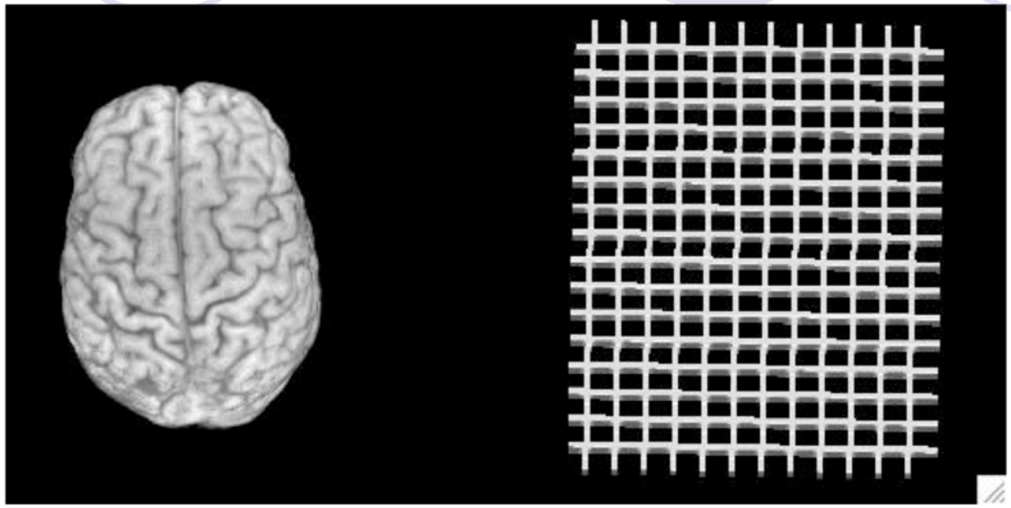
Normalization with Diffeomorphisms



Find $$\phi(\mathbf{x},t) = x + \int_0^1 v(\phi(\mathbf{x},t),t)dt$$

with $\phi(x,1)I = J$ **and** $D(\phi(\mathbf{x},0),\phi(\mathbf{x},1)) = \int_0^1 \|\boldsymbol{v}(\mathbf{x},t)\|_L dt$ **minimal.**

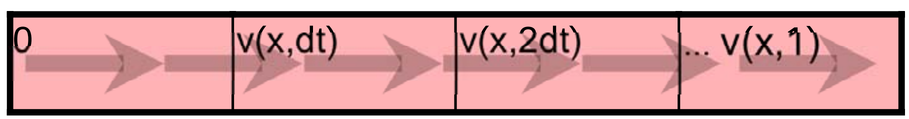
A Diffeomorphic Deformation



$$\phi(\mathbf{x}, t) = x + \int_0^1 v(\phi(\mathbf{x}, t), t)dt$$

Discretize v(x,t) and integrate at sub-voxel resolution

$$\phi(\mathbf{x}, t) = x + \int_0^1$$



$$dt$$

$\phi(x, t)$ is a *path of diffeomorphisms* and gives a smooth curve at each voxel

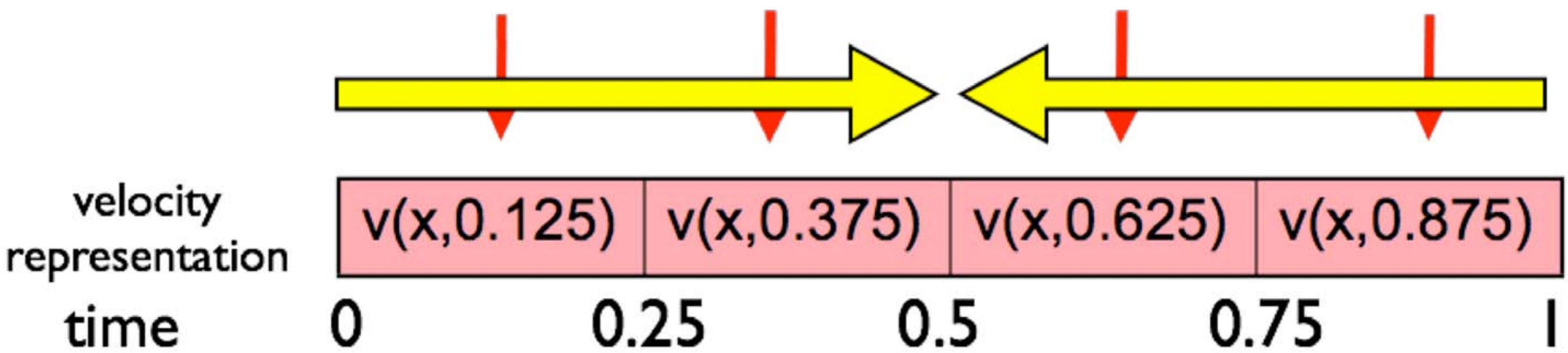
Optimization is performed by manipulating *v* at each *x* and *t*

Symmetric Normalization with Diffeomorphisms

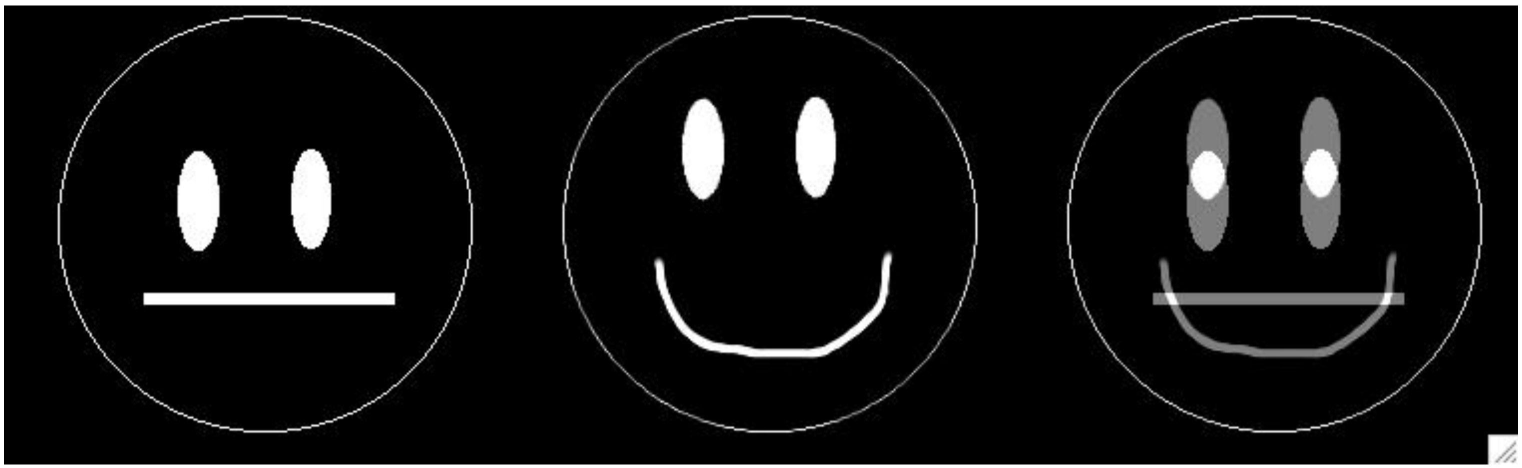
Find $\phi(x,t) = x + \int_0^{0.5} v_1(\phi(x,t),t)dt + \int_{0.5}^{1} v_2(\phi(x,t),t)dt$

gradients wrt *I* gradients wrt *J*

with $\phi_1(x,0.5)I = \phi_2(x,0.5)J$ and $\phi(x,1) = \phi_2^{-1}(\phi_1(x,0.5),0.5)$



A Symmetric Normalization Diffeomorphic Deformation



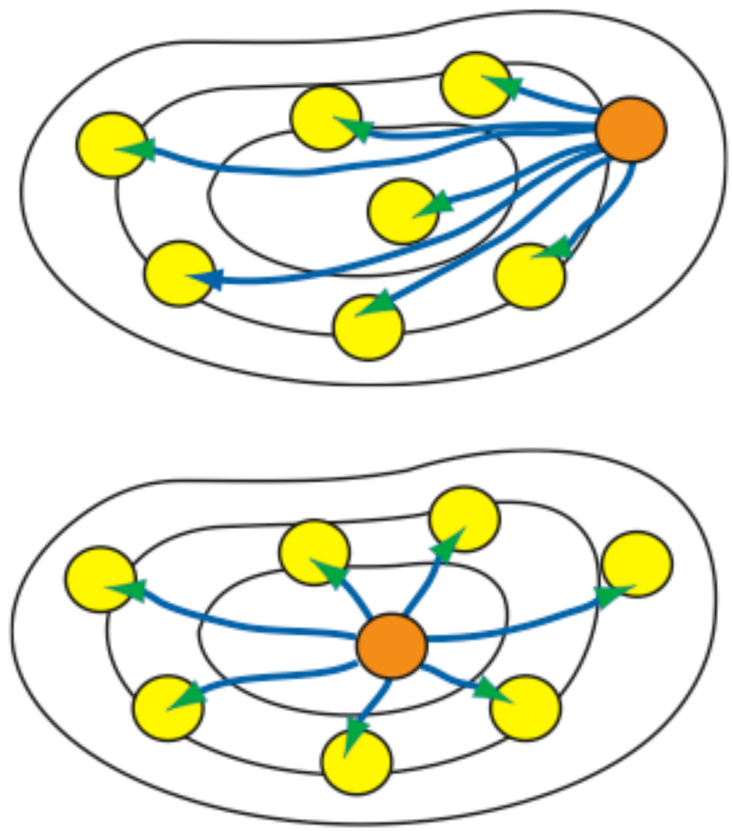
Sad Happy Overlay

Extension to Symmetric Population Studies
Optimal Template Construction

- Find the template and set of transformations that gives the "smallest" parameterization of the dataset:

$$\sum_i \inf_{\phi_1^i} \inf_{\phi_2^i} \int_{t=0}^{1} \{ \|v_1^i\|_L^2 + \|v_2^i\|_L^2 \} \, dt + \int_\Omega \omega |\bar{I}(\phi_1^i(0.5)) - J_i(\phi_2^i(0.5))|^2 d\Omega.$$

where $\forall i, \phi_1^i(0) = \psi, \bar{I}(\phi_1^i(\mathrm{x}, 1)) = J_i$, and each pairwise problem is solved with SyN (see equation 1 and 2).



Varying the geometric origin of the study is fundamental to minimizing the total distance between the template and the population

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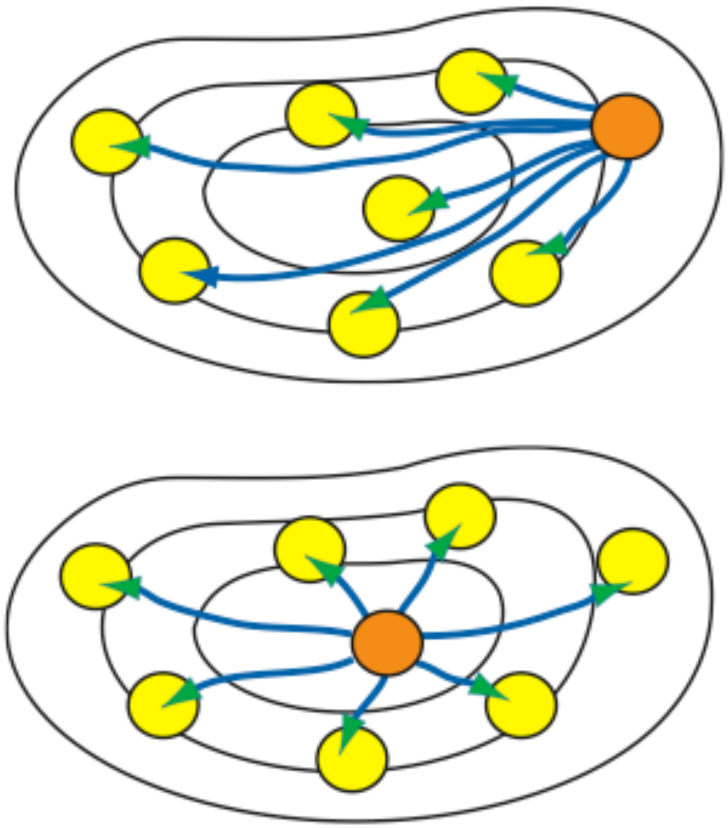

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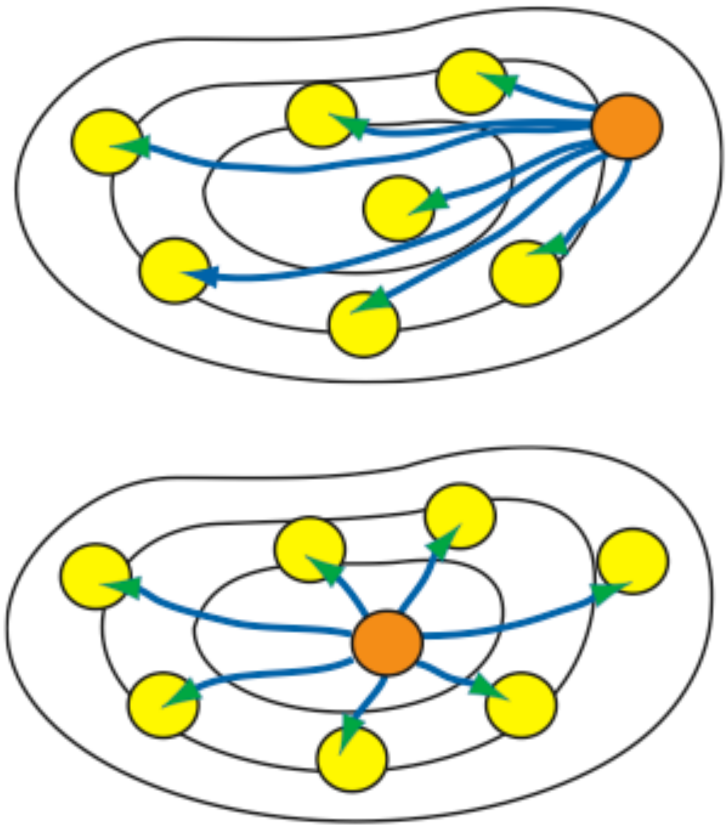

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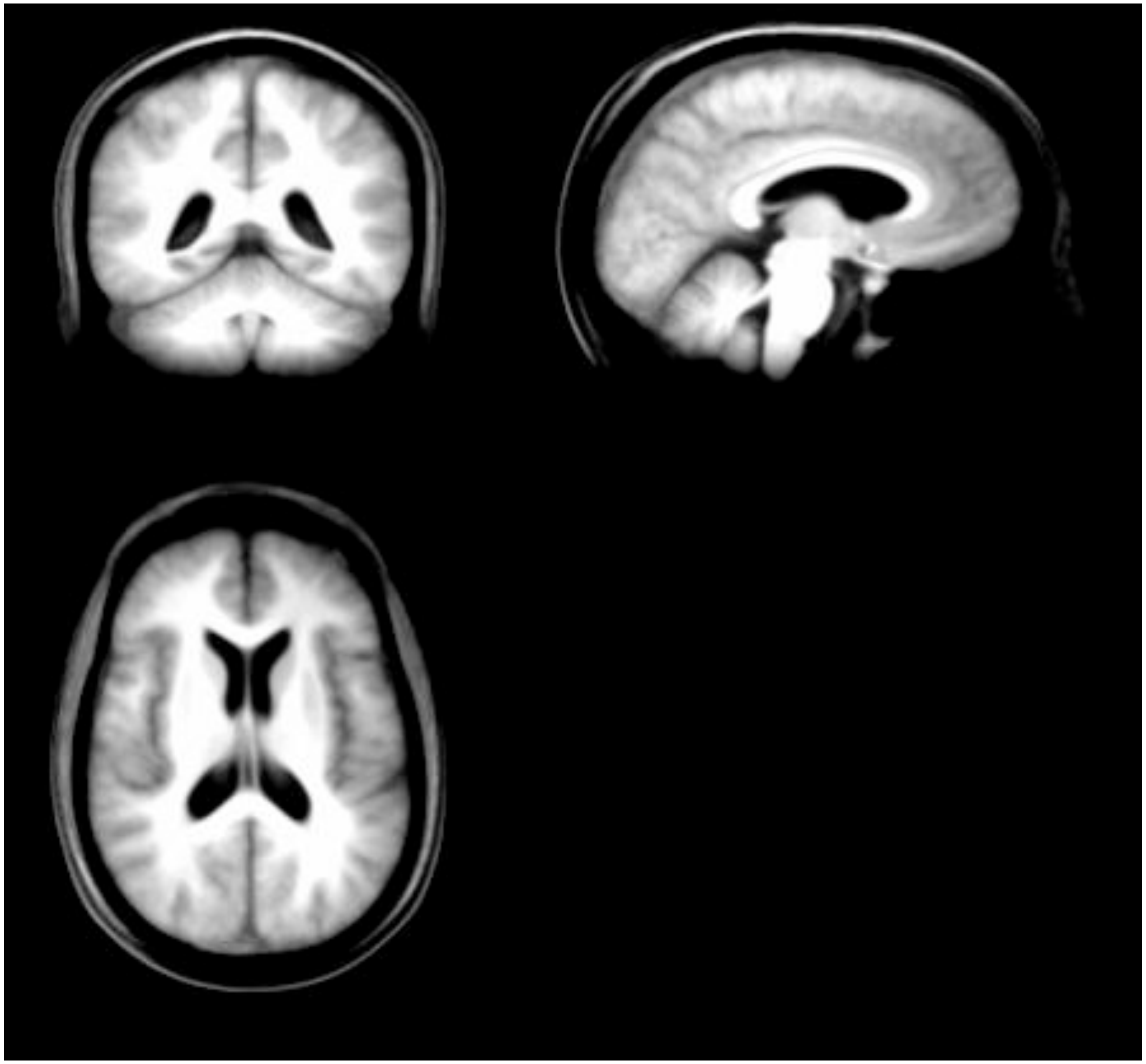
Steps in Template Construction for Lesioned Brains

Benefit of Shape Update

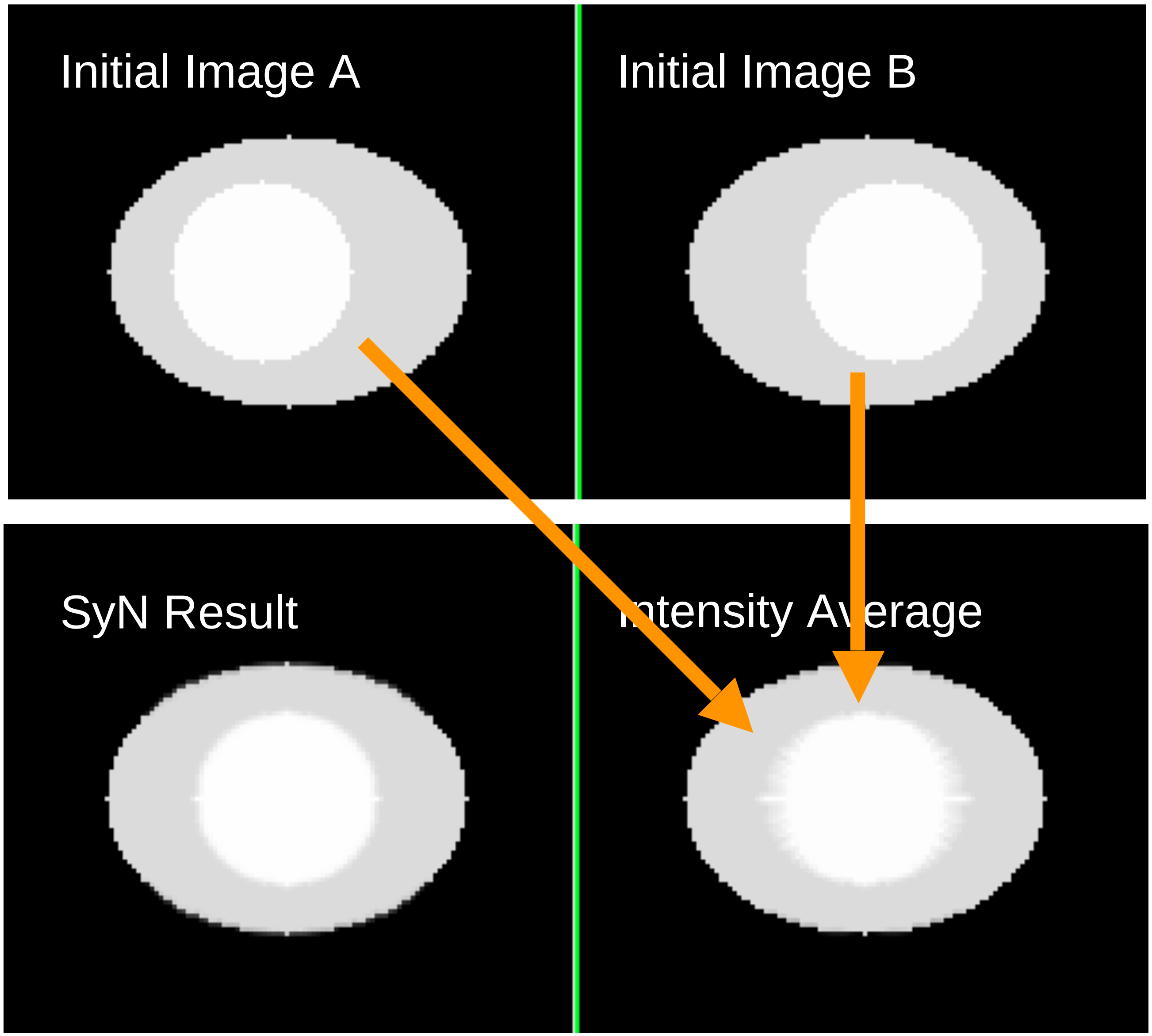


Initial Template

Later Template

Shape Update to the Previous Template

Comparison with Appearance Averaging Only
Need for Shape Update



Intensity averaging does not fully correct blurring caused by mismatch during initialization

This problem becomes more severe with more complex shapes or worse initialization

SyN finds the theoretical result for the **mean shape and appearance**

Comparison with Appearance Averaging Only
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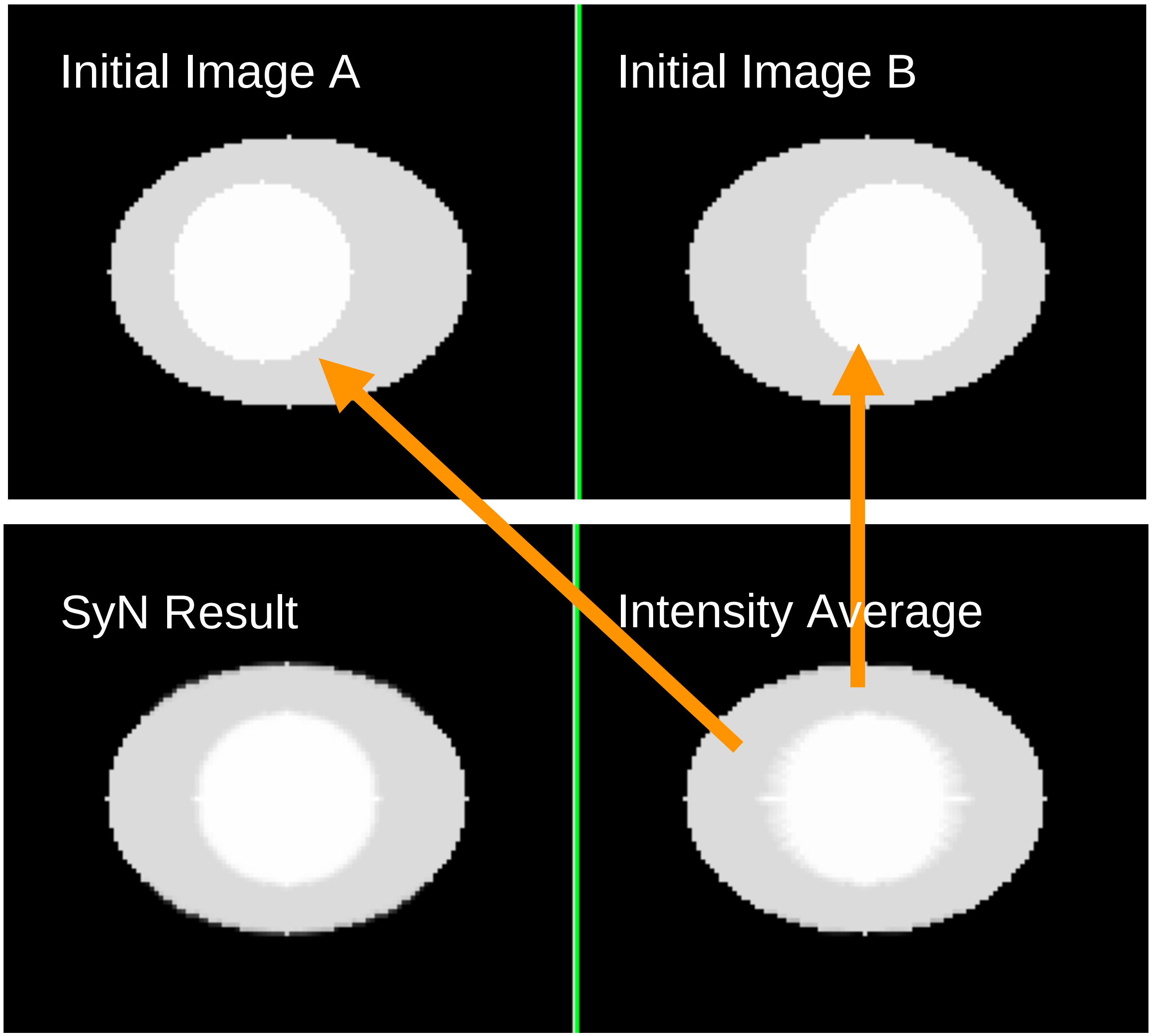

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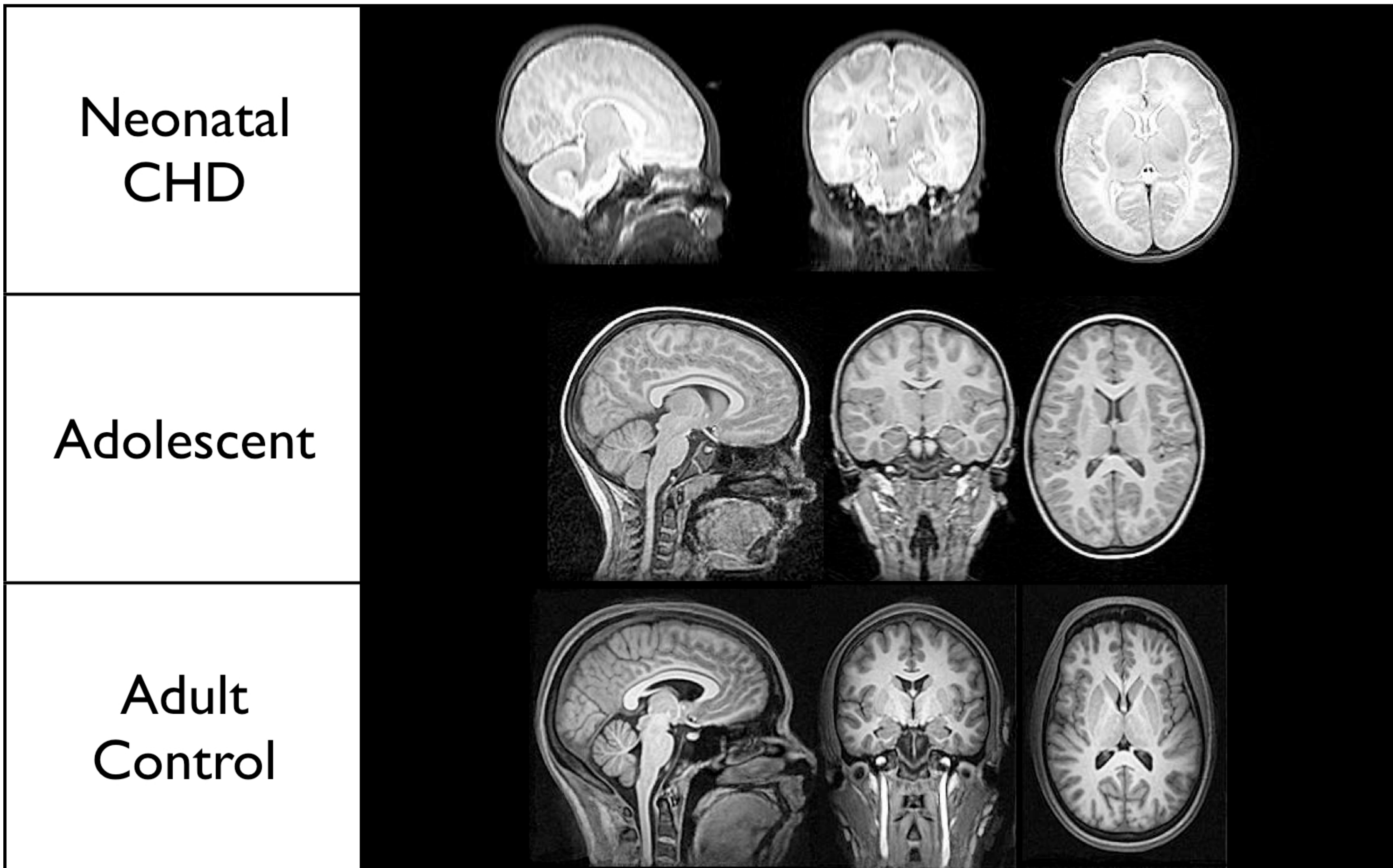
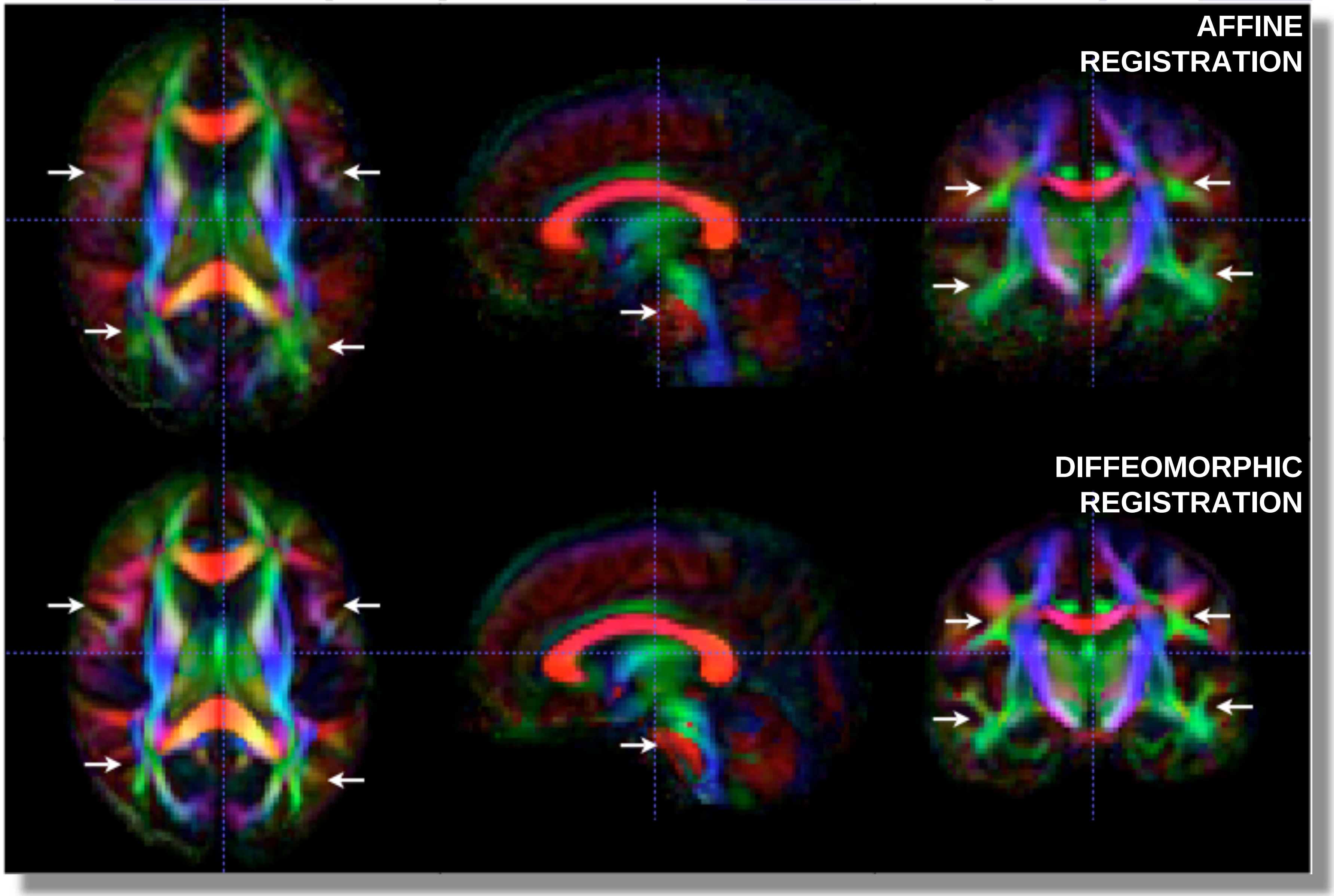
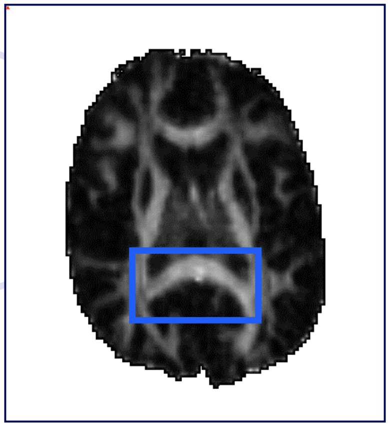
Example SyN Templates



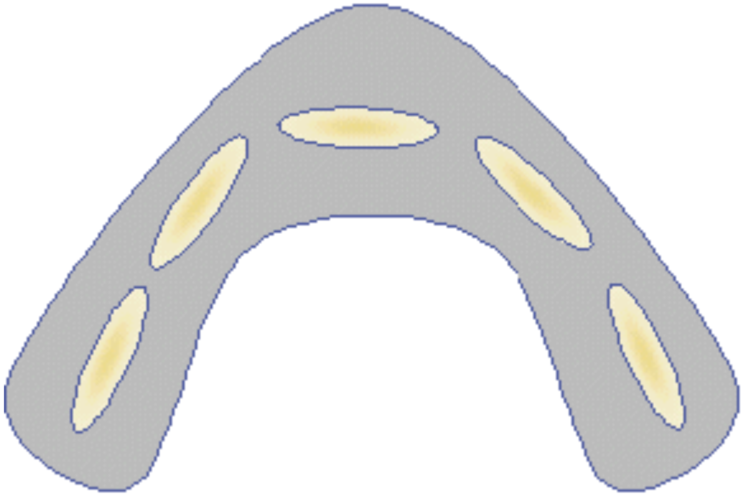
Example DTI Template



Spatial Transformations
Need for DT Reorientation

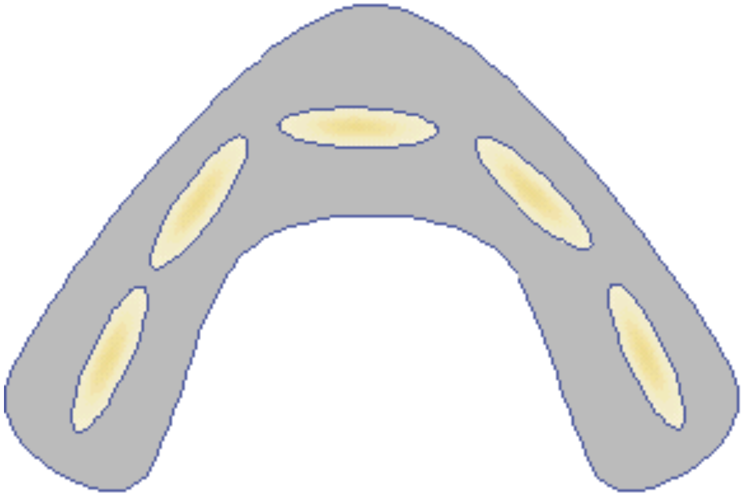


No Reorientation



Tensors are re-located
but not reoriented

With Reorientation



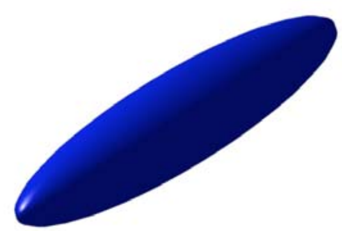
Tensors are correctly
re-located and reoriented

Affine Tensor Transformations

Original Tensor

Transformed Tensor

$D \rightarrow F \cdot D \cdot F^{\mathrm{T}}$



$D \rightarrow R \cdot D \cdot R^{\mathrm{T}}$

- We wish to preserve the shape of the DTs
- But we must reorient them appropriately
- Require R that reflects reorientation due to F

- For an affine transformation, (F,t), $D \rightarrow F \cdot D \cdot F^{\mathrm{T}}$?
- No...

Finite Strain Estimation

- Decompose F into:
  - Rigid rotation, R, and
  - Deformation, U:

    $F = R \cdot U$

    $R = F \cdot (F^T \cdot F)^{-1/2}$
- Then reorient D using R:

  $D' = R \cdot D \cdot R^T$

Affine Tensor Transformations

Original Tensor

Transformed Tensor

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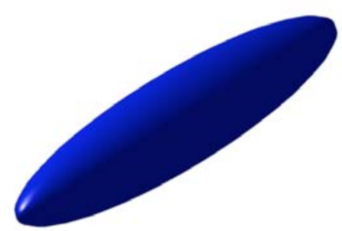

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$$\text{ø}(x,1)I = J$$

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- Then reorient D using R:

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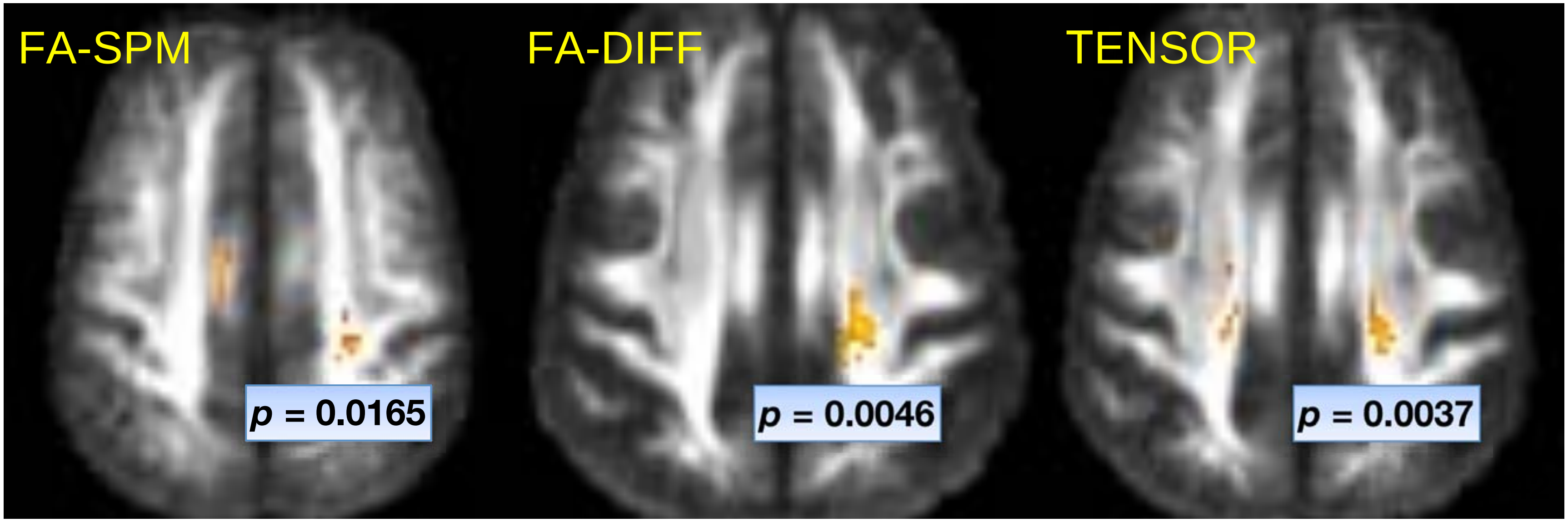
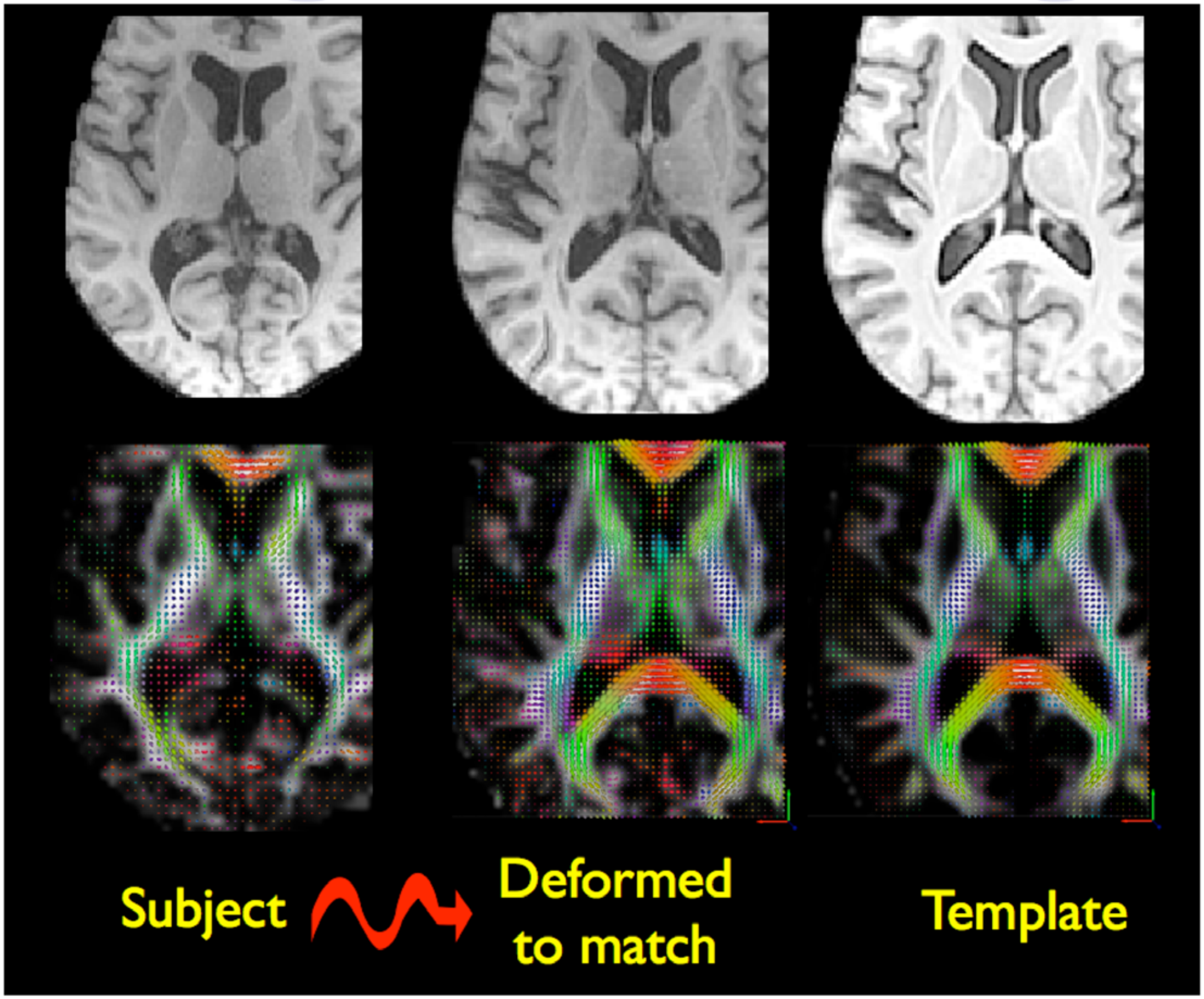
Piece-wise Affine DTI Registration

- Task-Driven Evaluation Study:
  - White matter changes in ALS
  - Cross-sectional design (8 patients, 8 controls)
- Key Findings:
  - Increased sensitivity of detected FA changes with full-tensor registration
  - Reduced susceptibility to false positives due to shape confounds

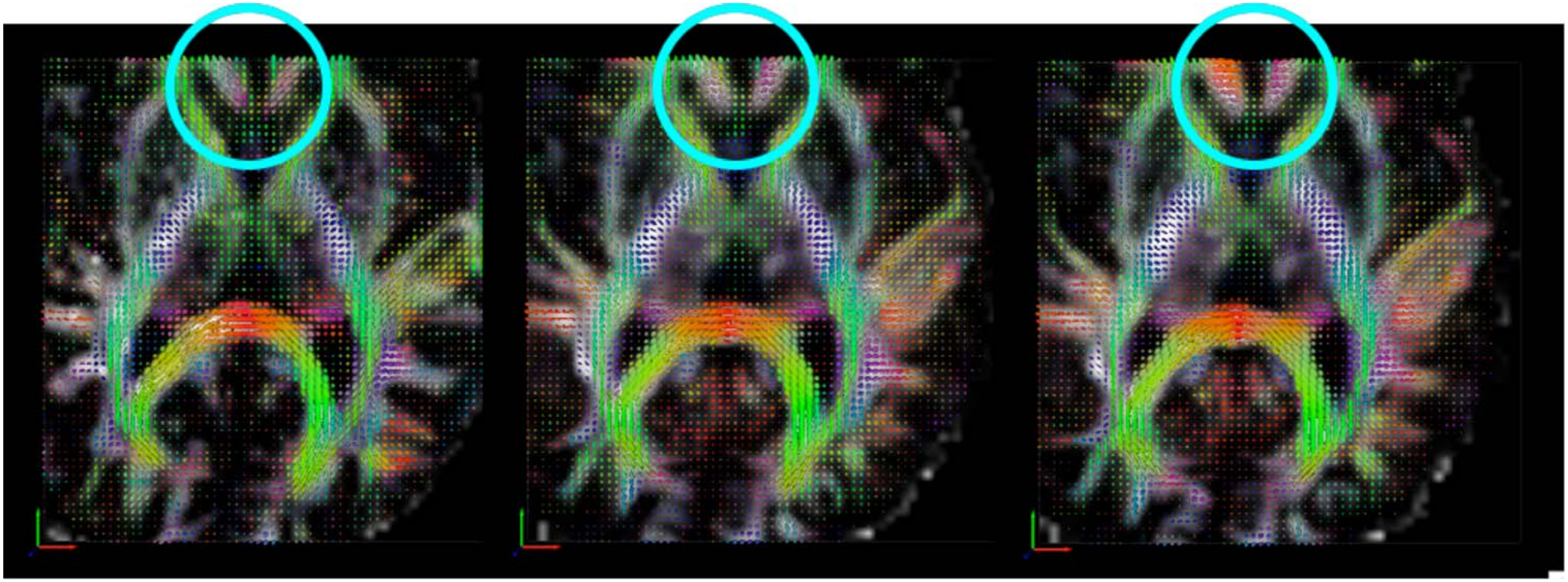


Deformable registration of FA images to an external template using SPM2	Population-Specific Atlas via diffeomorphic registration of FA images	Population-Specific Atlas via registration of full diffusion tensors

Tensor SyN Captures Large Deformations



Tensor SyN vs SyN on FA



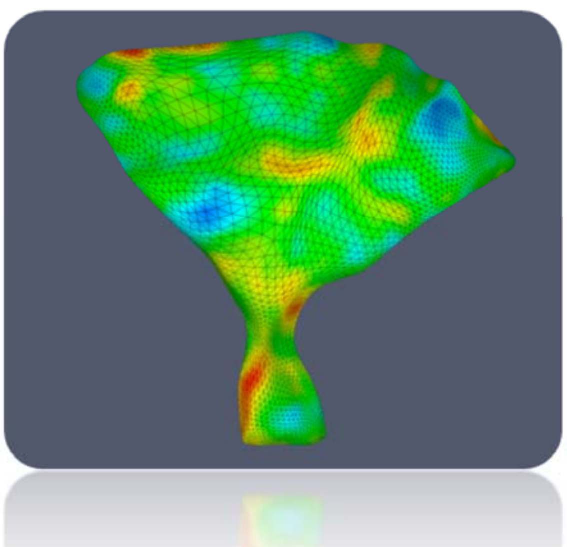
Template DT

Tensor SyN registration

SyN registration on FA

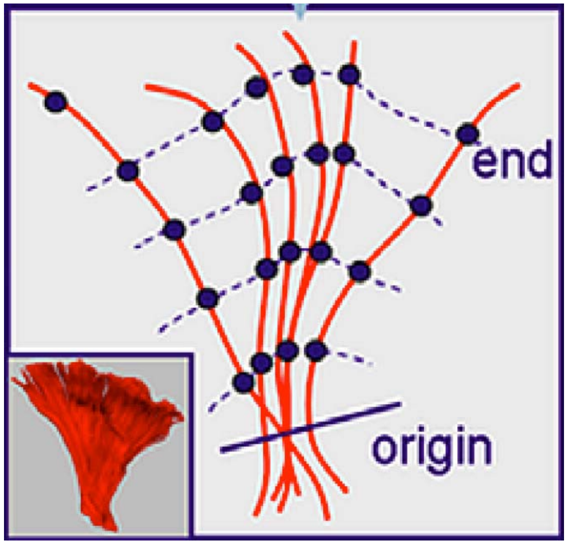
Tract-Specific Analysis Framework

Normalization	Fasciculus Segmentation	Surface-Based Modeling
Population-Specific WM Atlas	Fiber tracking	Representation via geometrical models
	Track grouping and labeling	Tract-Wise Statistical Mapping
		Visualization and Flattening

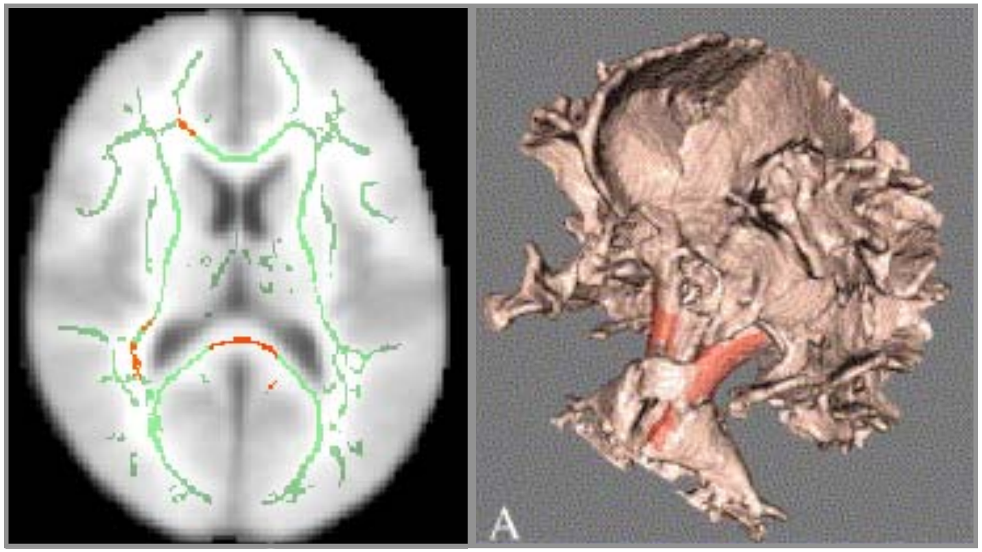


Tract-Based Analysis in the Literature

Curve-Based	Skeleton-Based

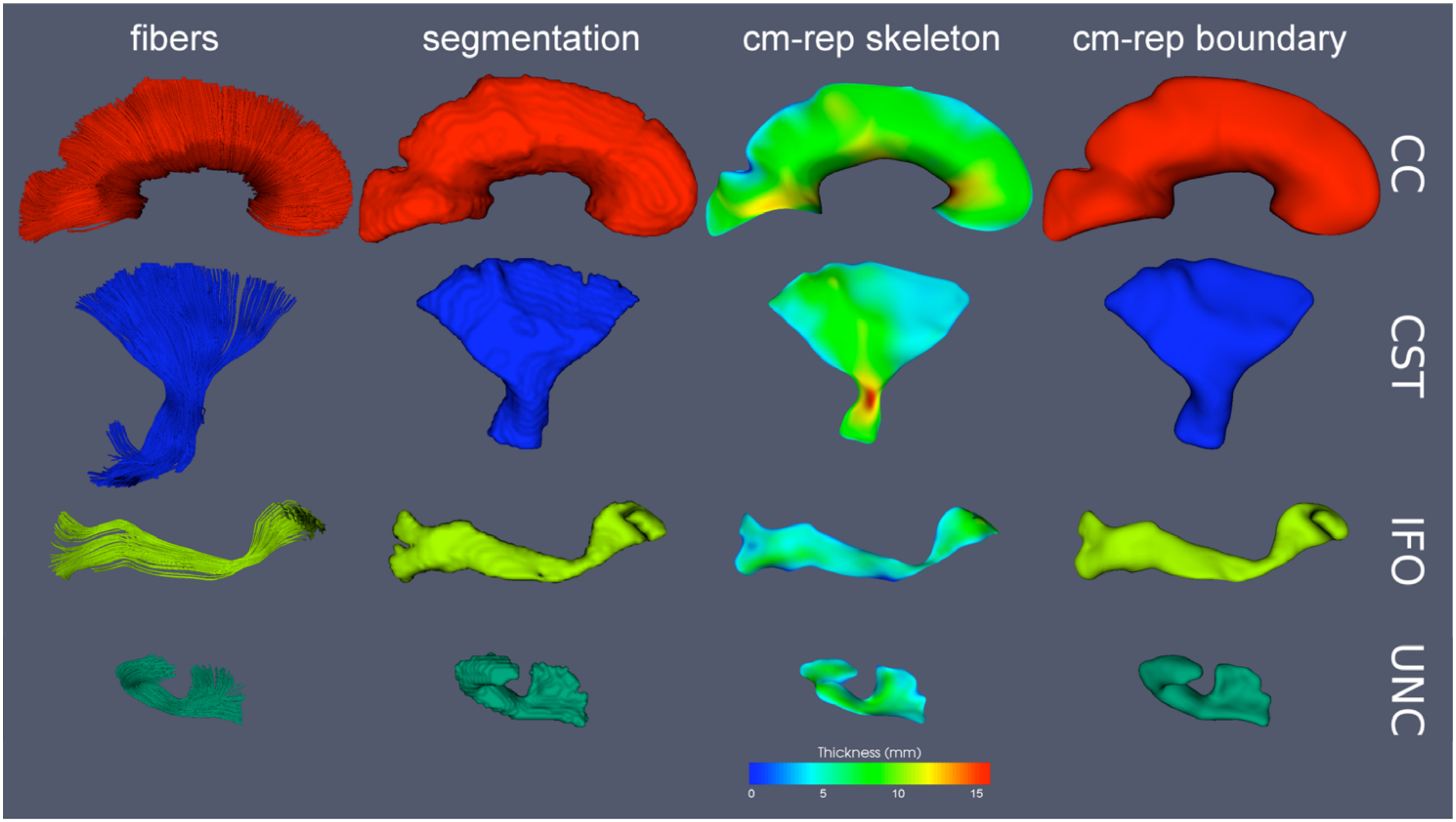


Curve-based tract representation (Corouge et al., *MedIA*, ‘06)

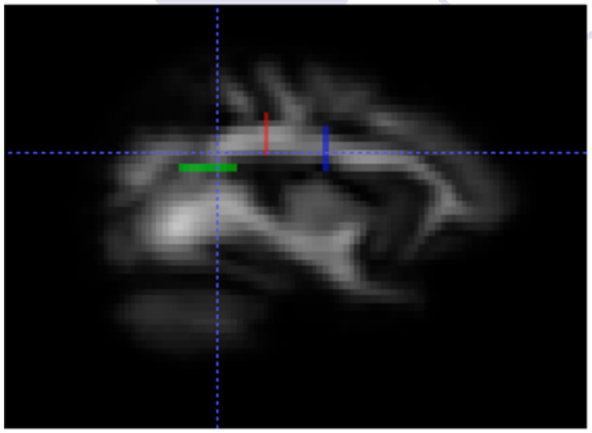


Skeleton-based white matter representation (Smith et al., *Neuroimage*, ‘06)

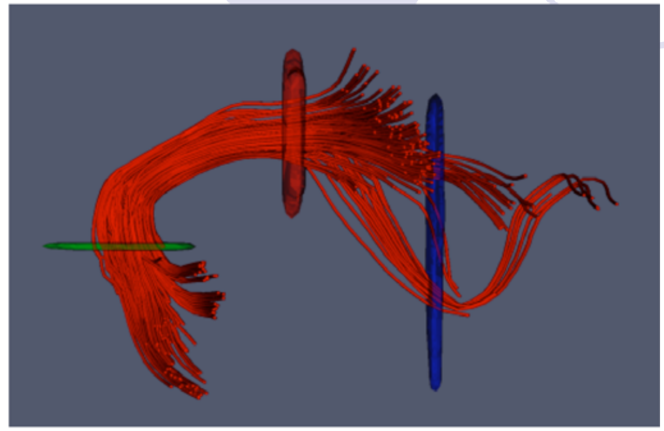
Surface-Based Tract Representation



Expert-Driven Tract Labeling

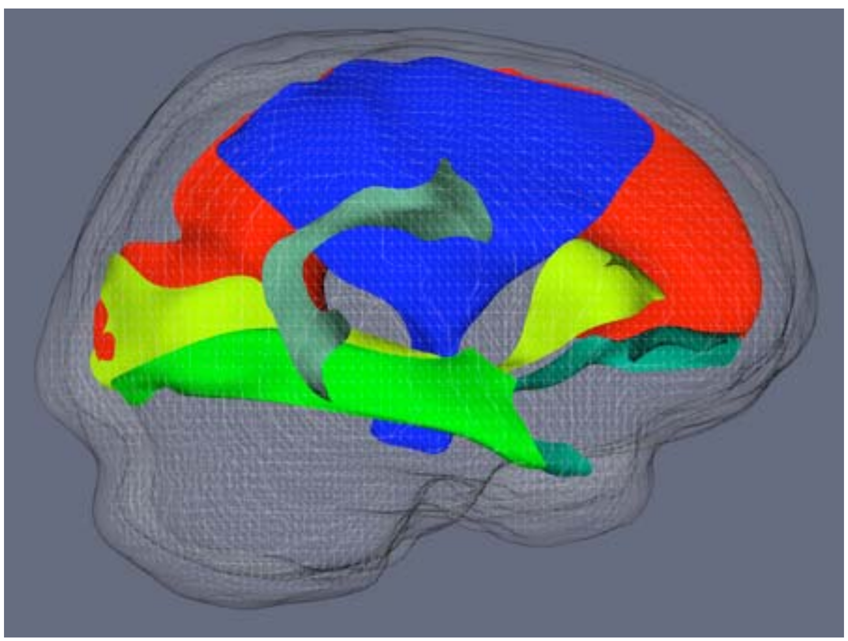


ROI delineation

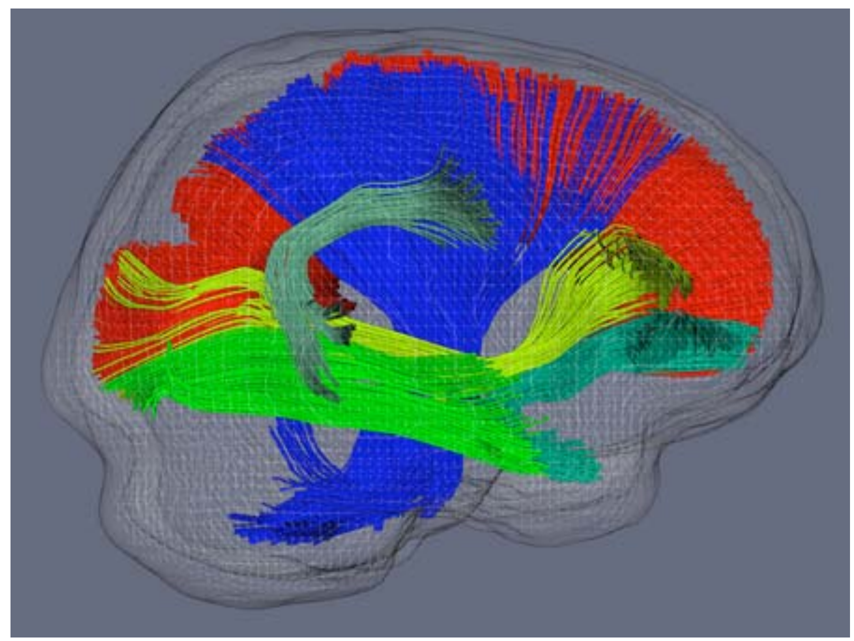


Fiber selection

corpus callosum (CC)
corticospinal tract (CST)
inferior longitudinal fasciculus (ILF)
superior longitudinal fasciculus (SLF)
inferior fronto-occipital fasciculus (IFO)
uncinate fasciculus (UNC)

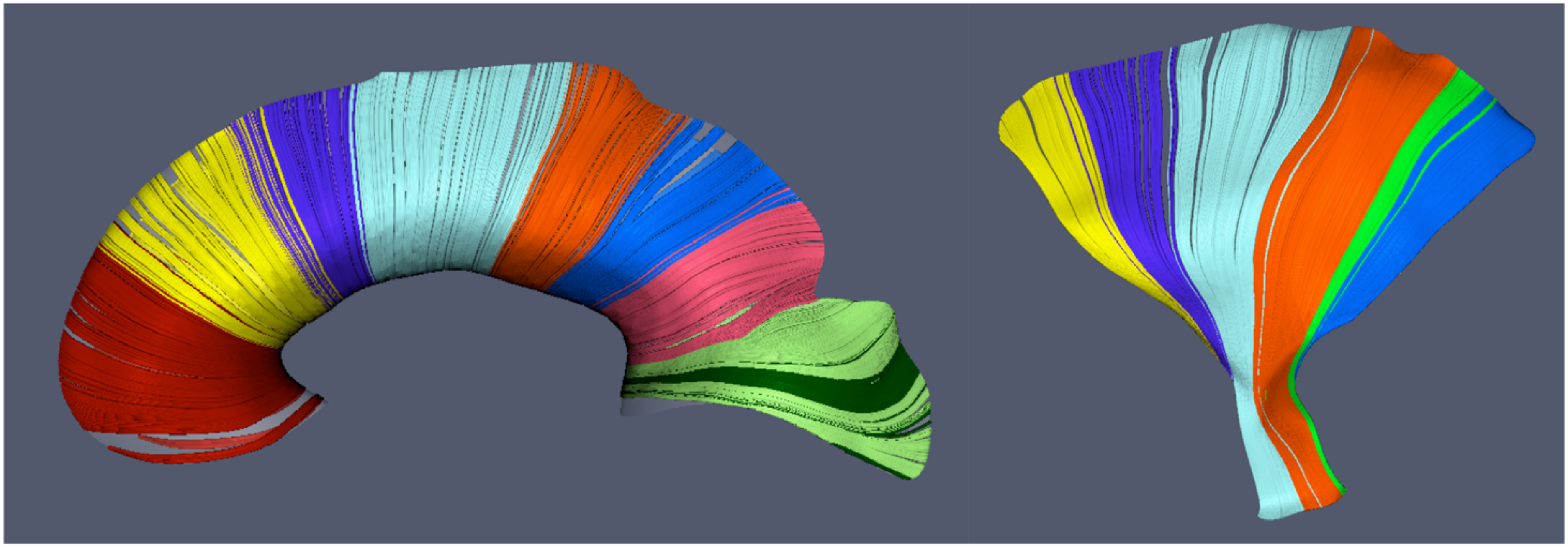


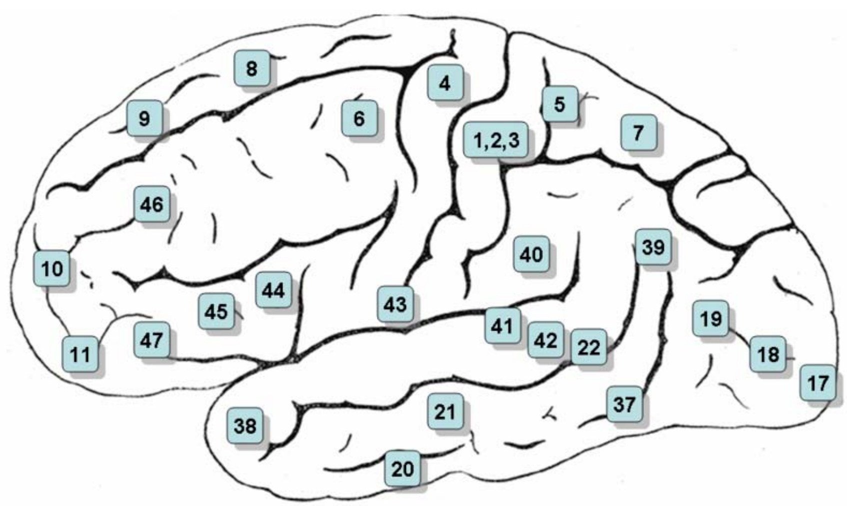
Surface representation



Six sheet-like fasciculi

Tracking and Labeling on the Surface





Brodmann Area 2

Brodmann Area 4

Brodmann Area 5

Brodmann Area 6

Brodmann Area 7

Brodmann Area 8

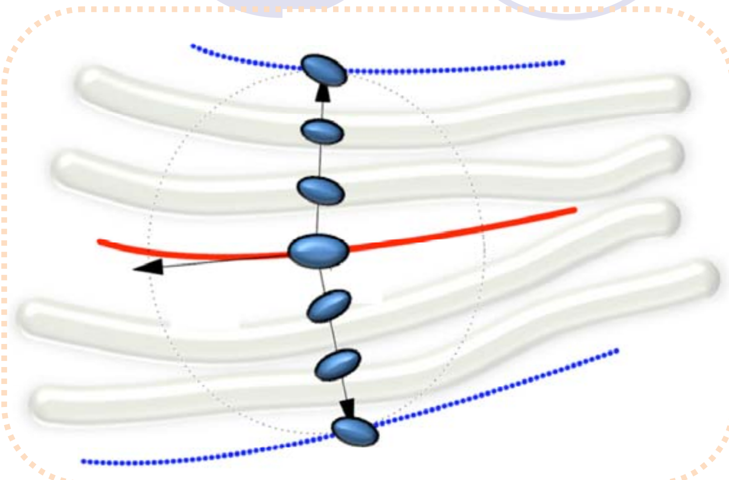
Brodmann Area 9

Brodmann Area 10

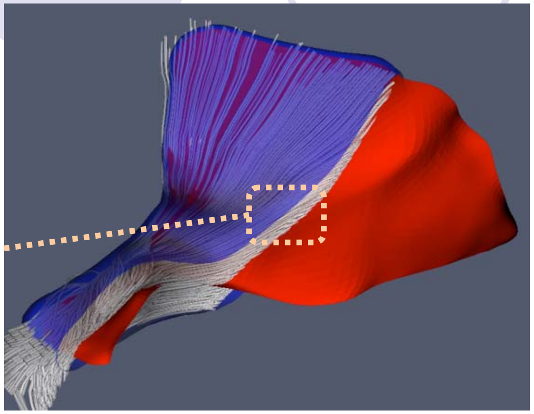
Brodmann Area 18

Brodmann Area 19

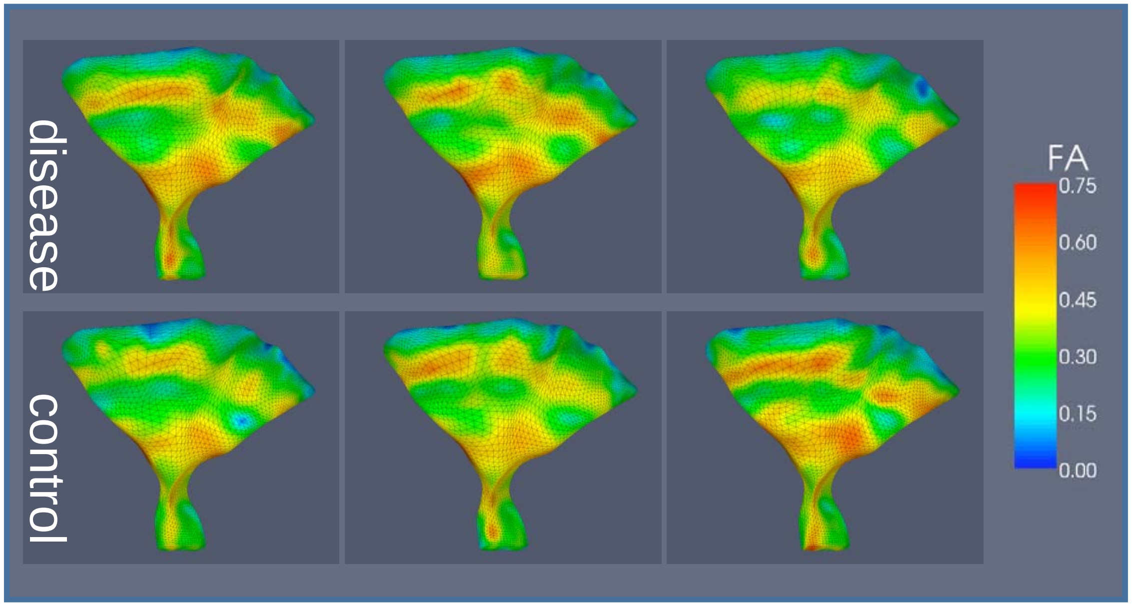
Tract-Wise Statistical Mapping



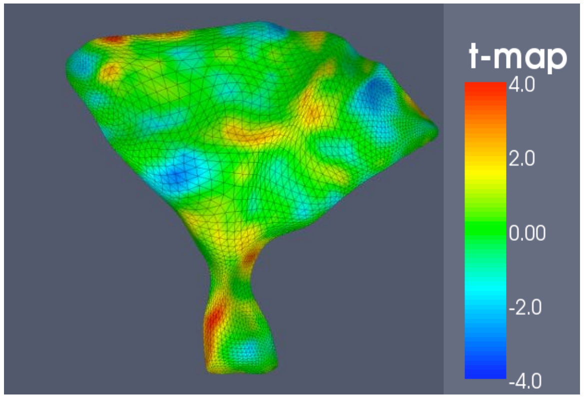
Dimensionality Reduction



Model and fibers

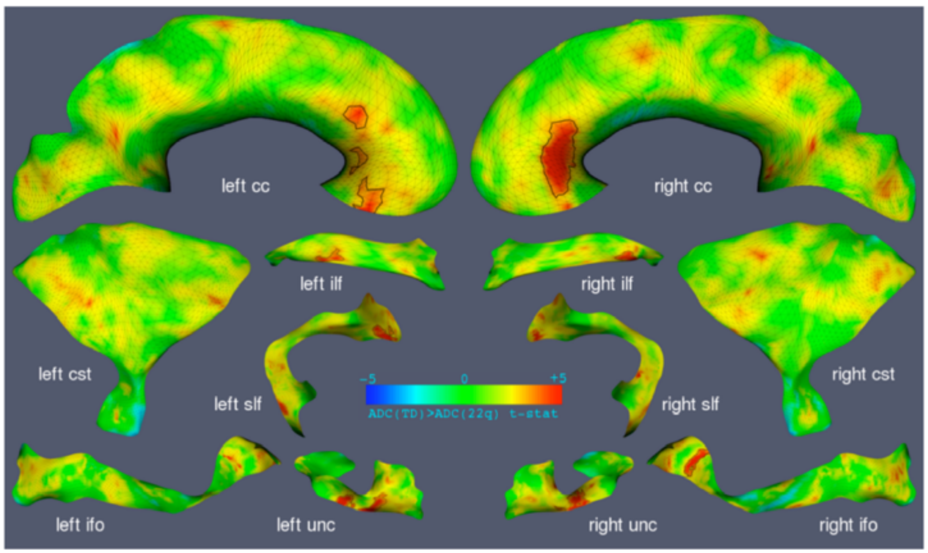


Subject FA Maps

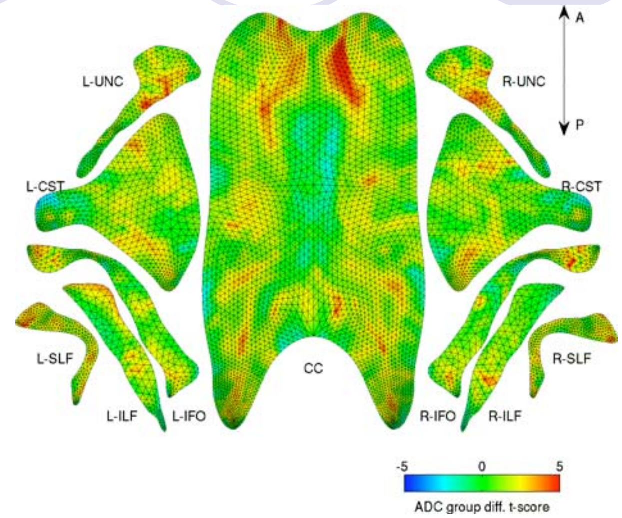


Tract-wise t-map

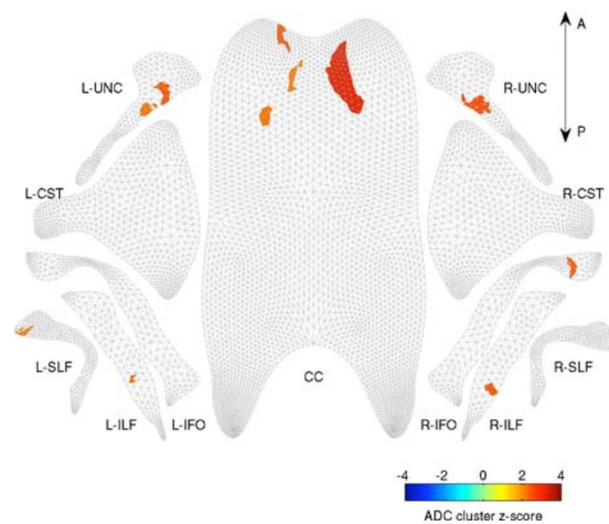
Flattening for White Matter Tracts



3D t-statistic map



2D t-statistic map



2D FWER-controlled cluster analysis

Results shown are ADC difference maps from a 22q11.2 deletion syndrome study (Tony J. Simon, PI)