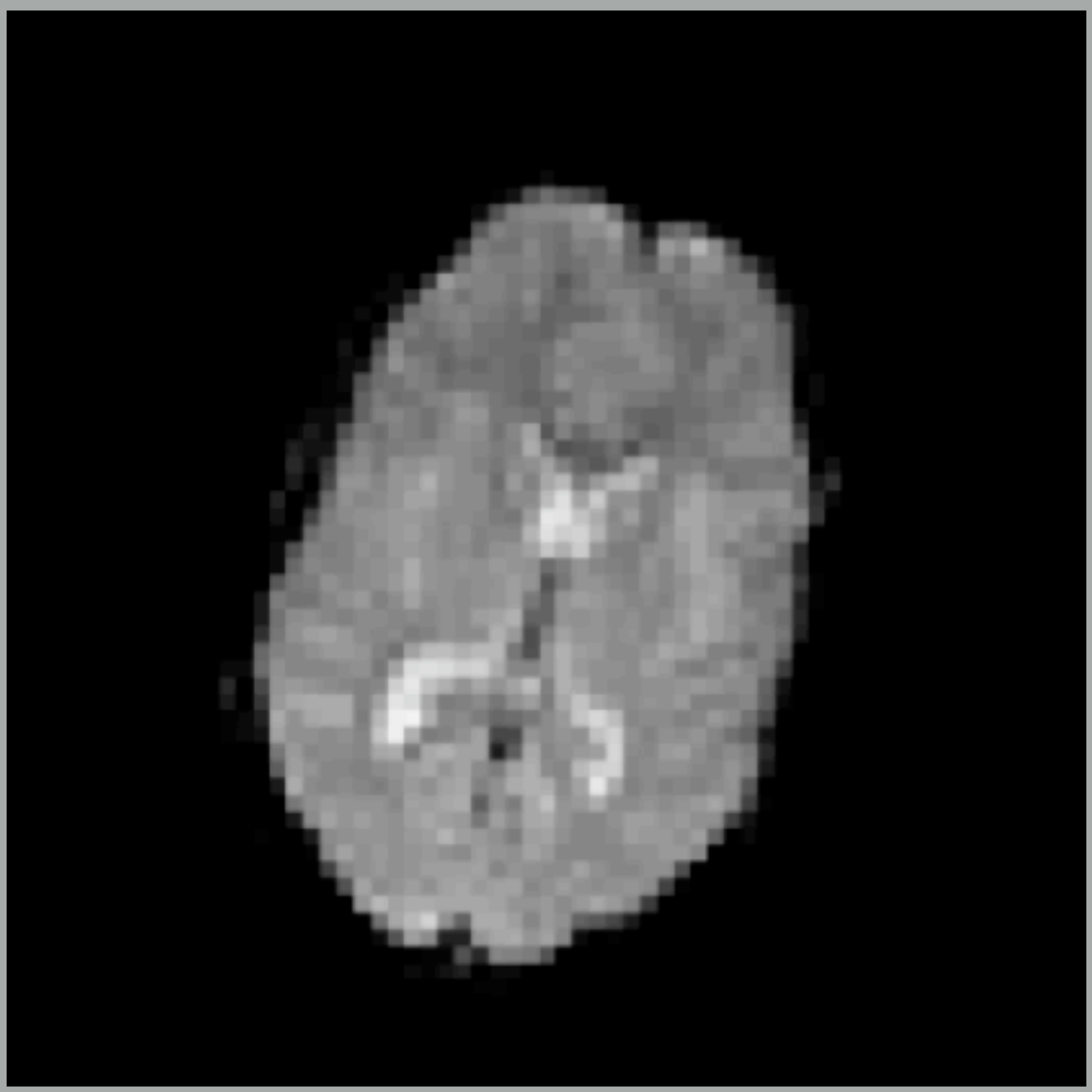
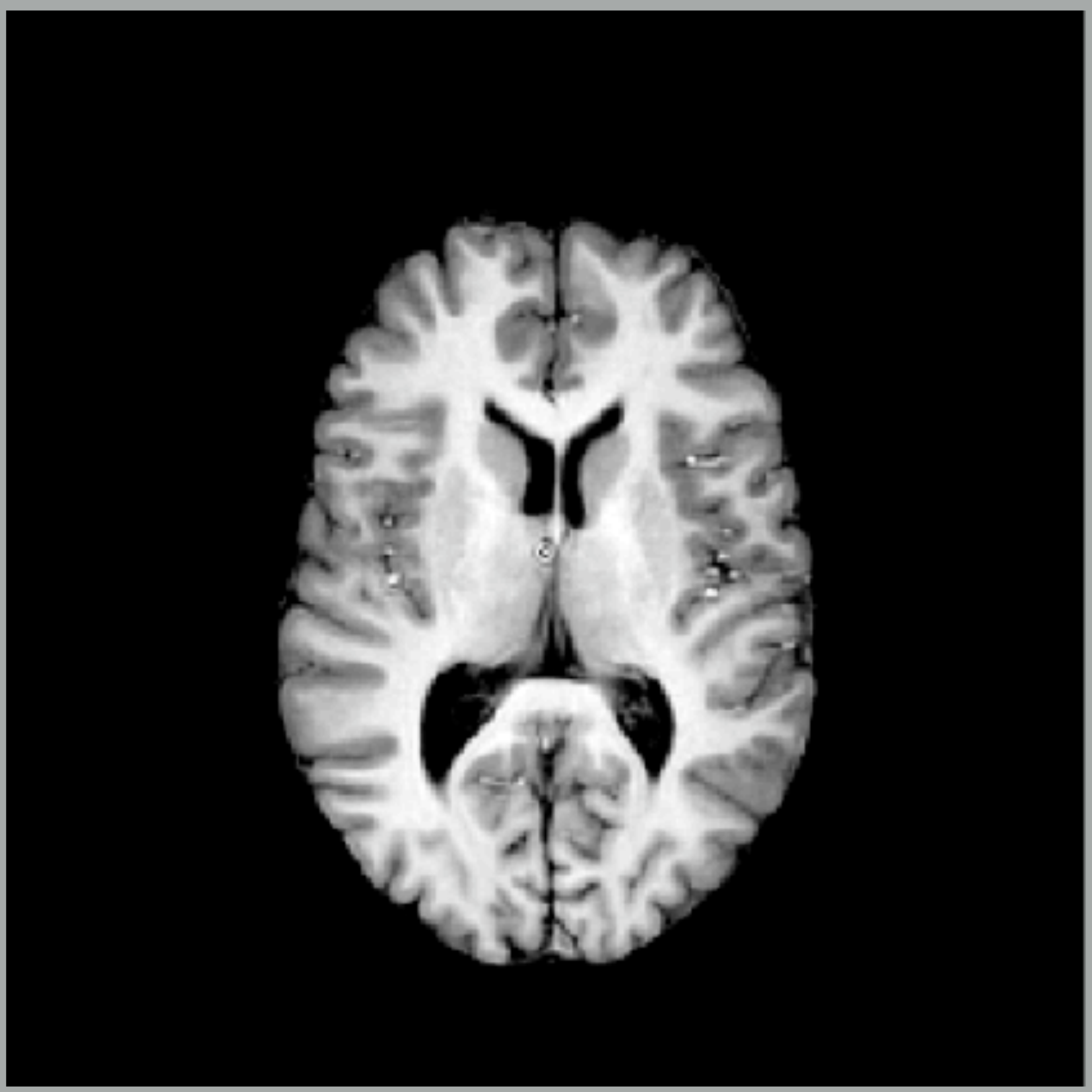
Lecture 14
Spatial Normalization and Group Comparisons of DTI data

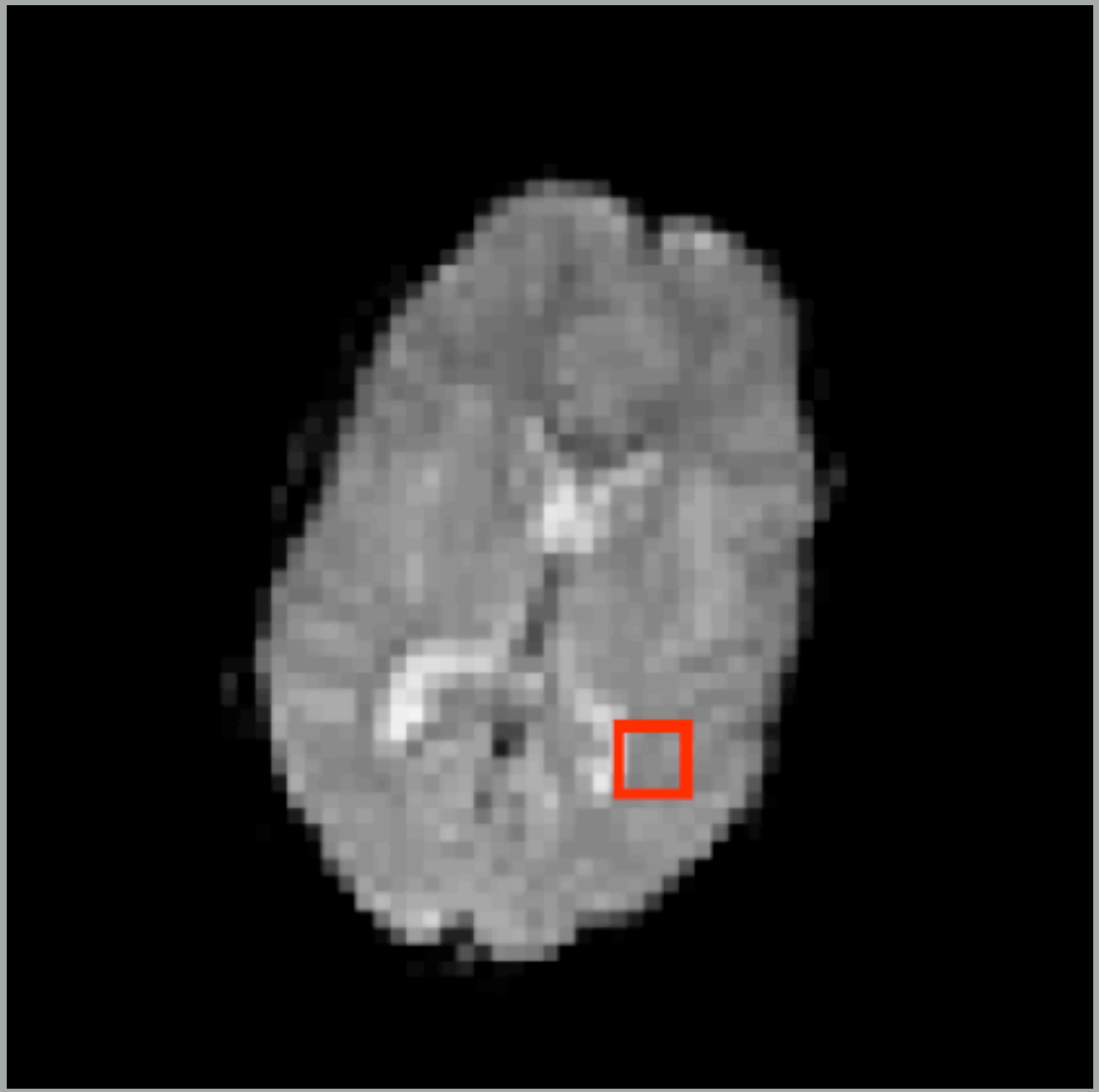
Registration





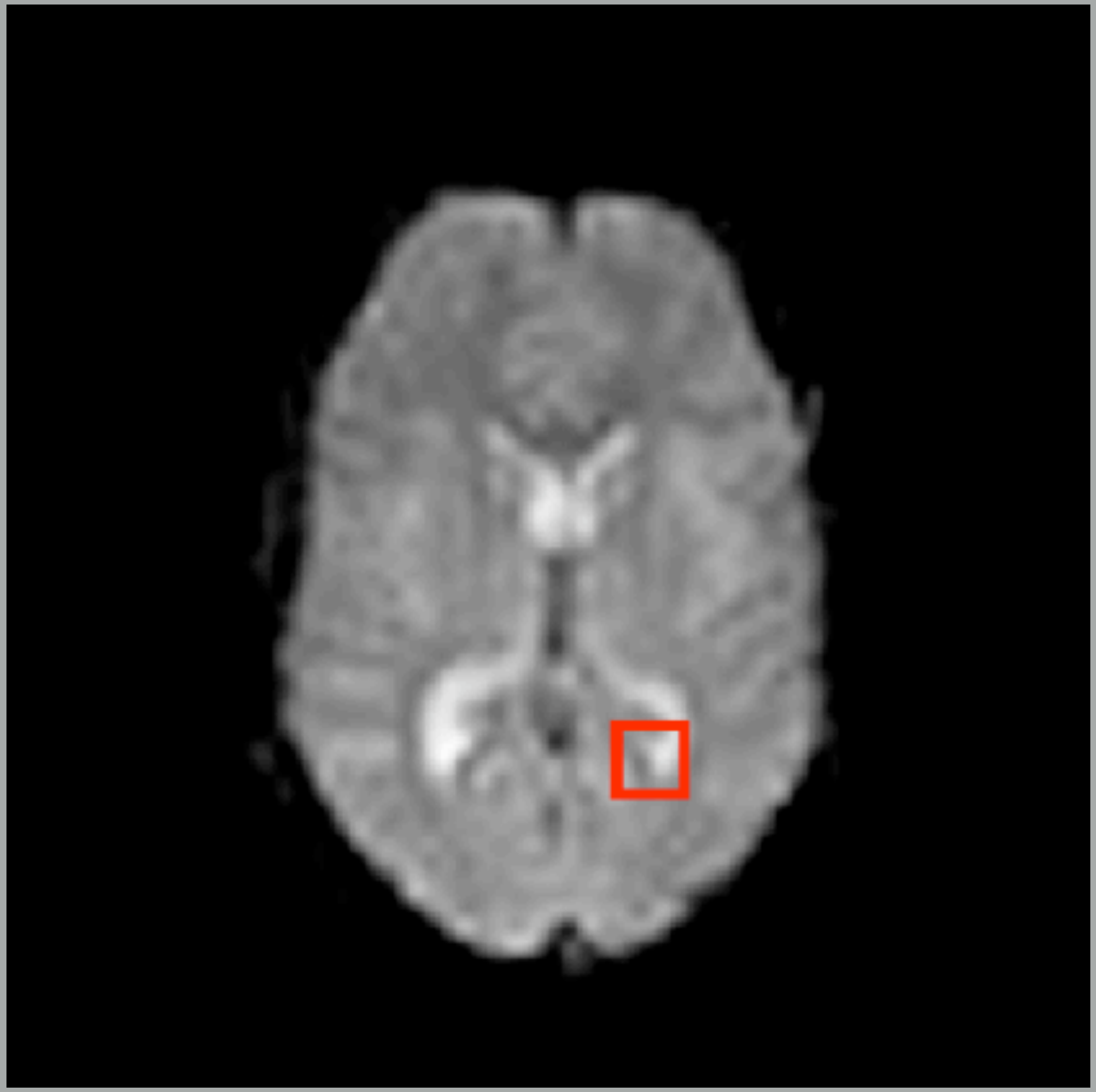
FSL: http://www.fmrib.ox.ac.uk/fsl

Registration



FSL: http://www.fmrib.ox.ac.uk/fsl

Registration



FSL: http://www.fmrib.ox.ac.uk/fsl

Registration

1. Rigid Body registration: 6 DOF
2. Affine registration: 12 DOF
3. Non-linear registration: DOF>12

DOF = "Degrees of Freedom"
The number of independent parameters

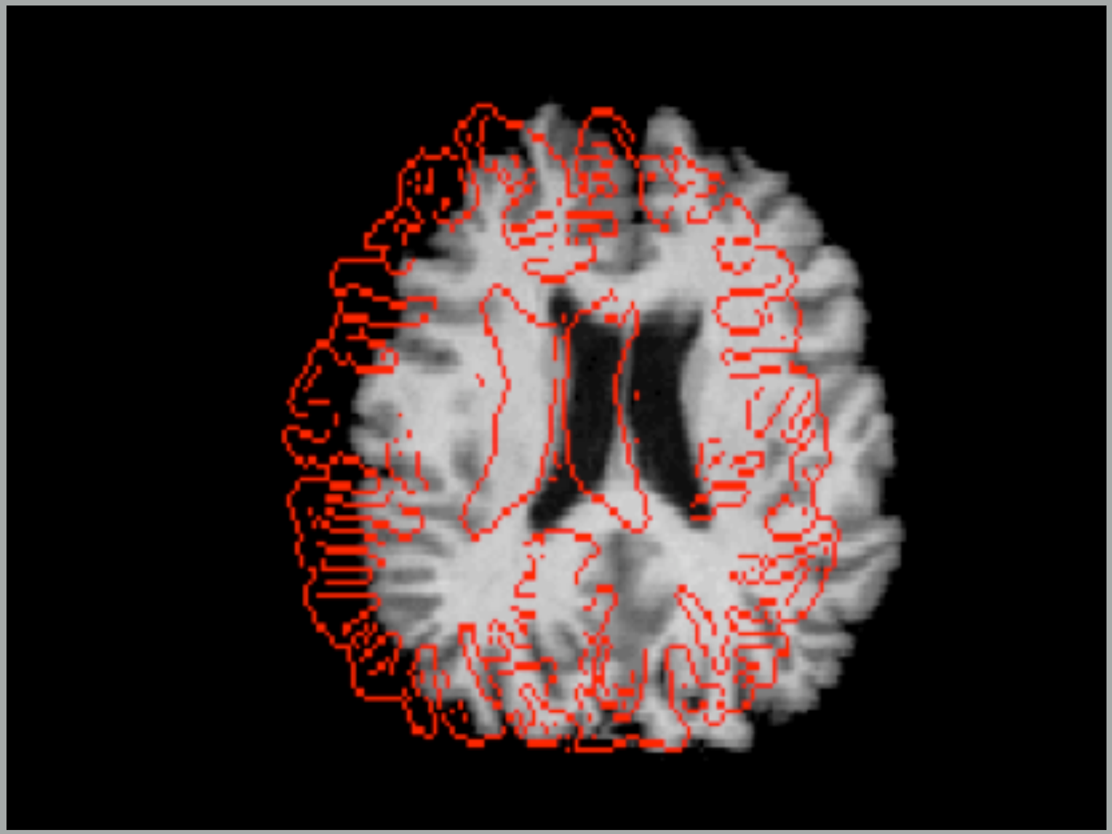
Rigid Body Registration

A rigid body in d dimensions has
$d(d + 1)/2$ degrees of freedom:

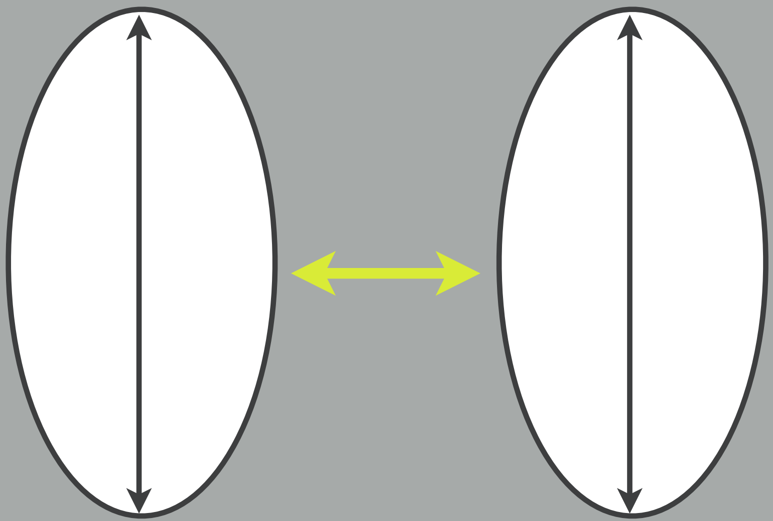
d translations
$d(d - 1)/2$ rotations

Example:
In 3-dimensions,
3 translations (x,y,z)
3 rotations (Euler angles)

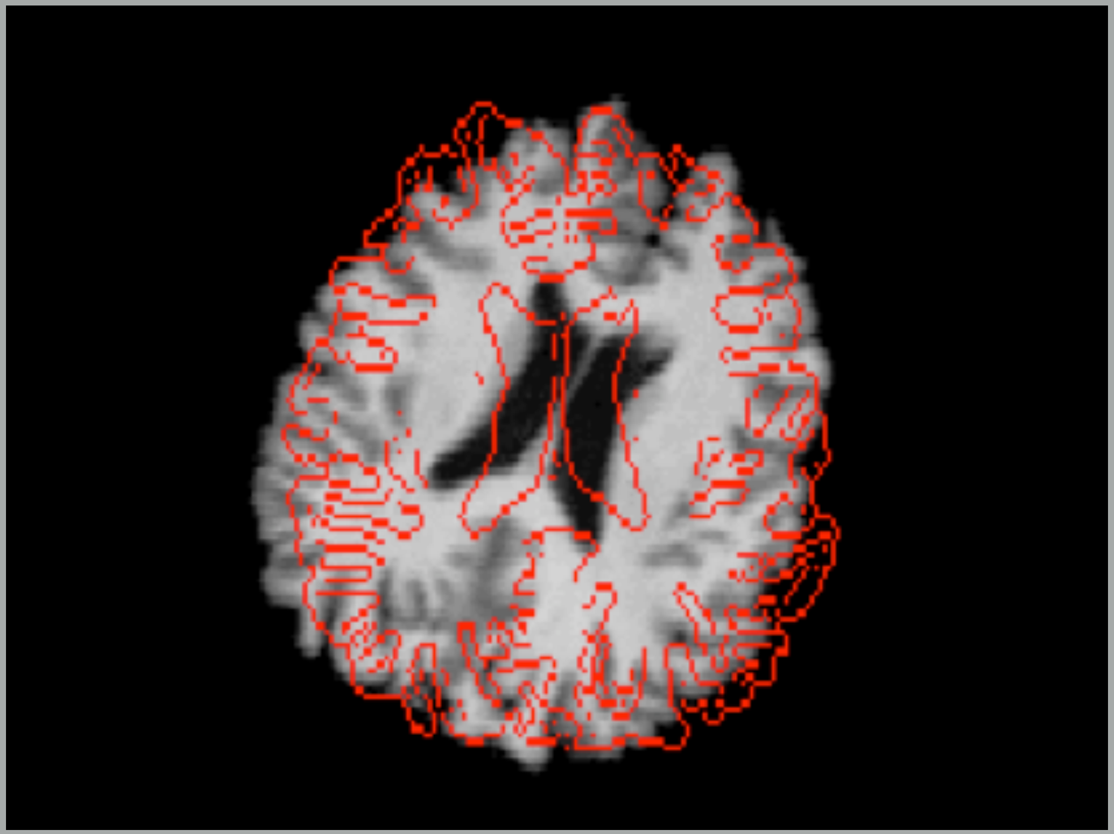
Rigid Body Registration



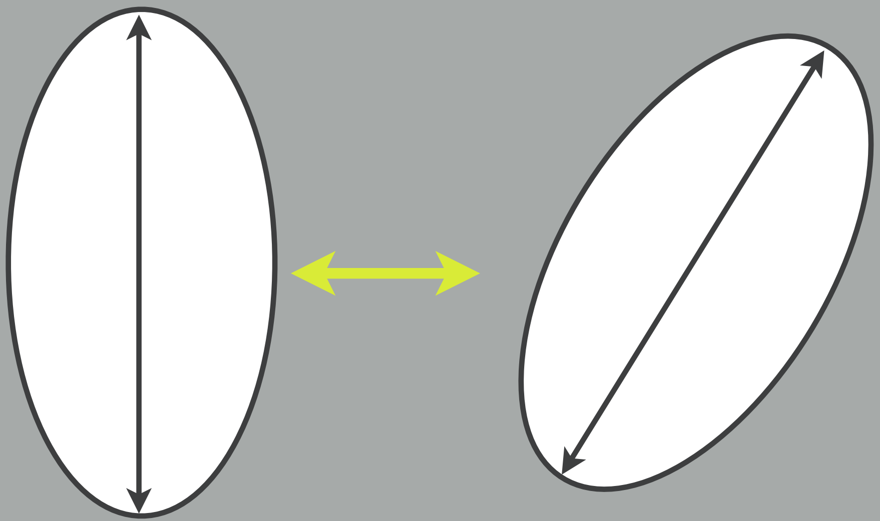
3 translations
(x,y,z)



Rigid Body Registration



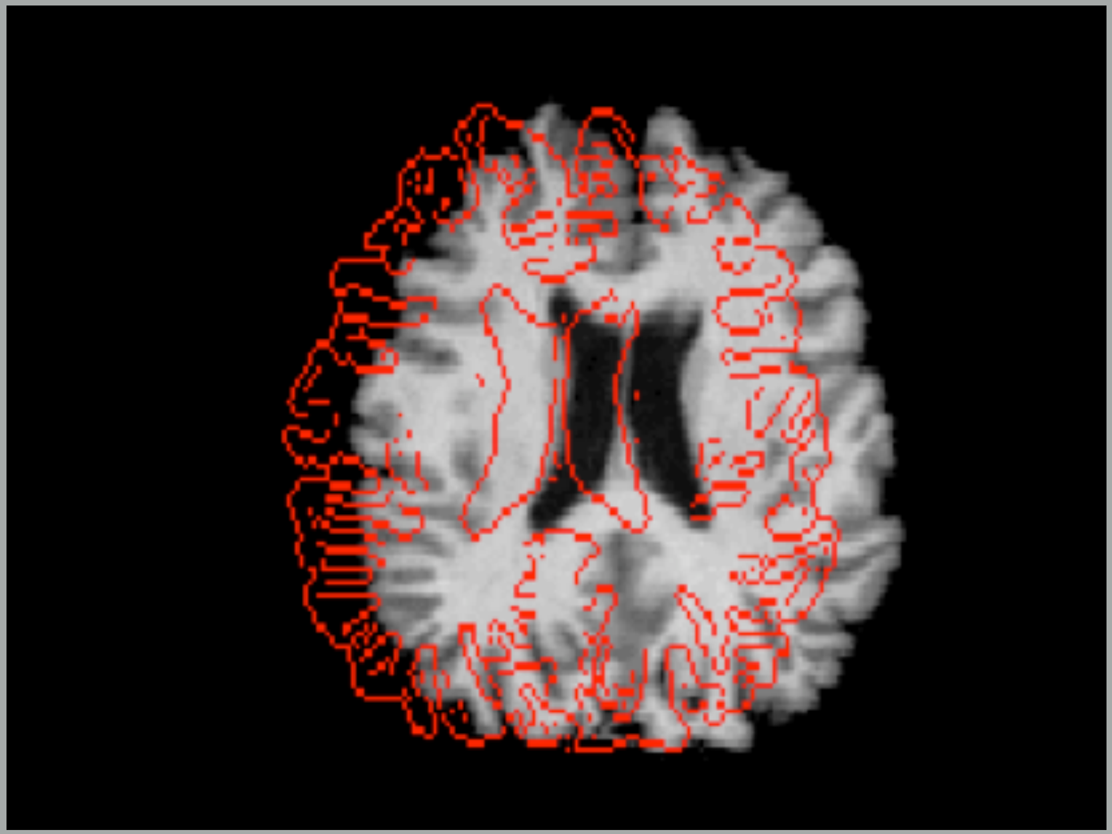
3 rotations
(x,y,z)



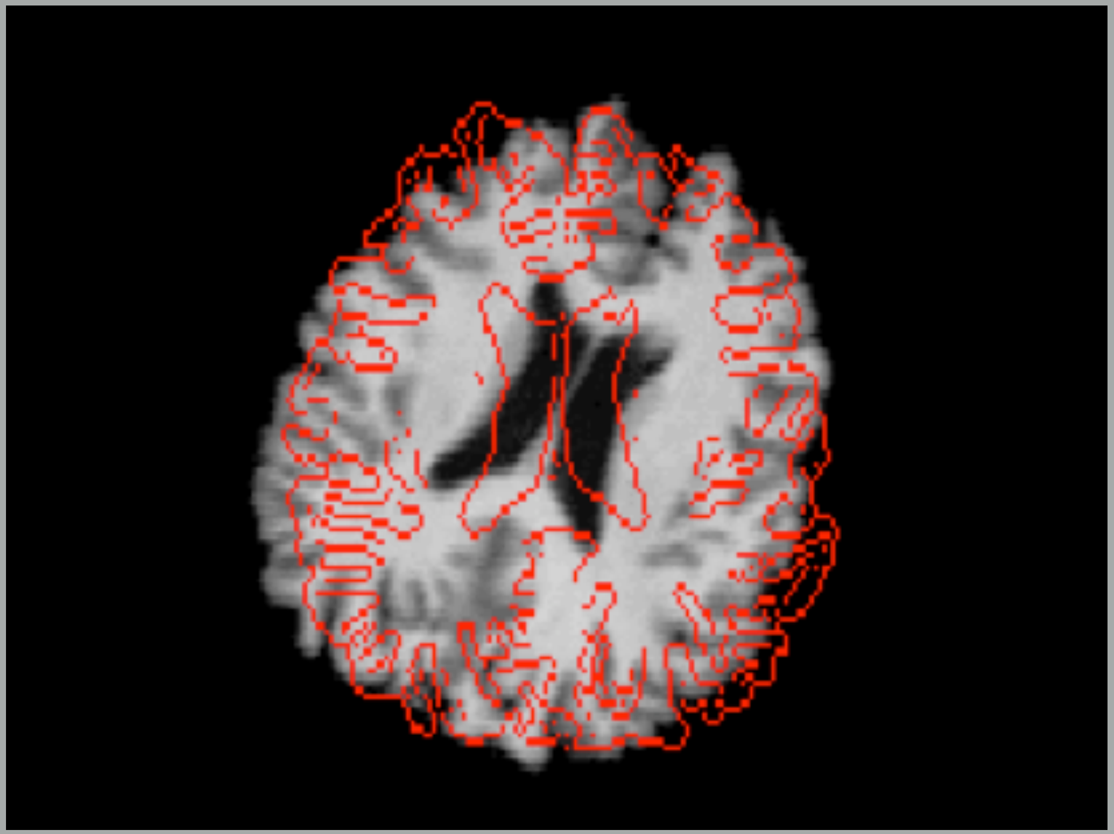
$$D' = RDR^t$$

Affine Registration

Rigid Body Registration



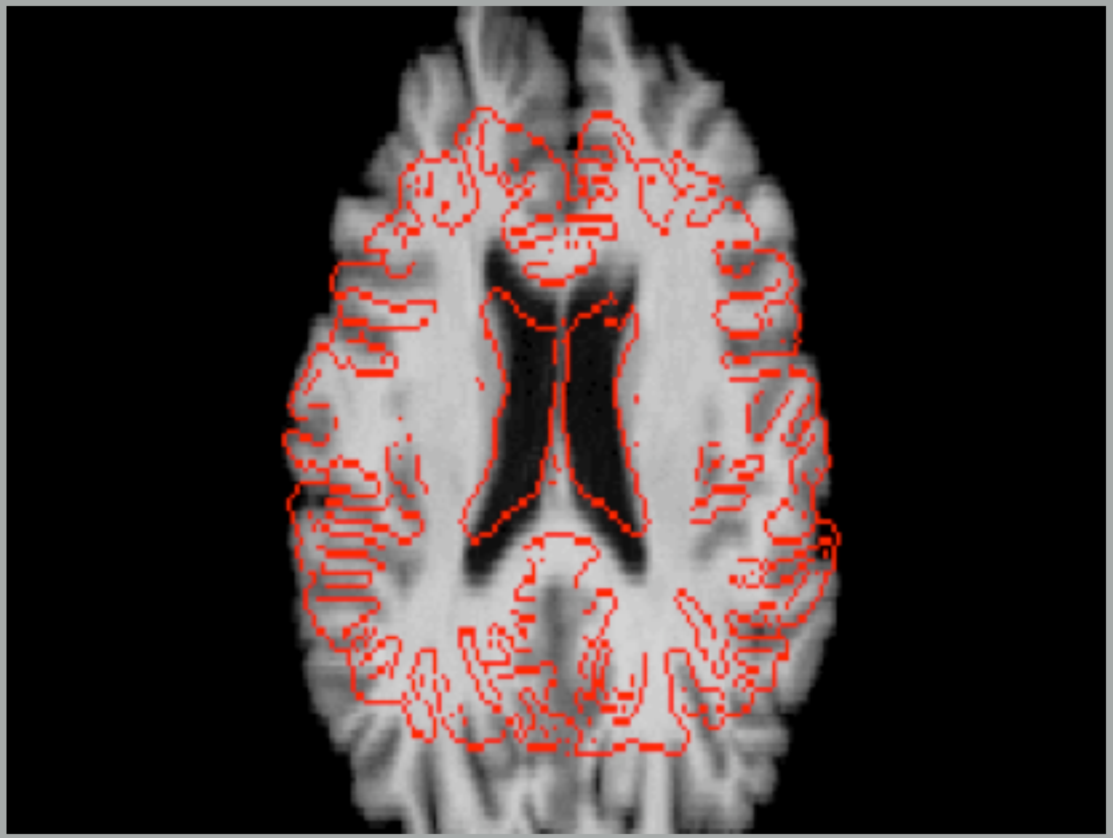
3 translations
(x,y,z)



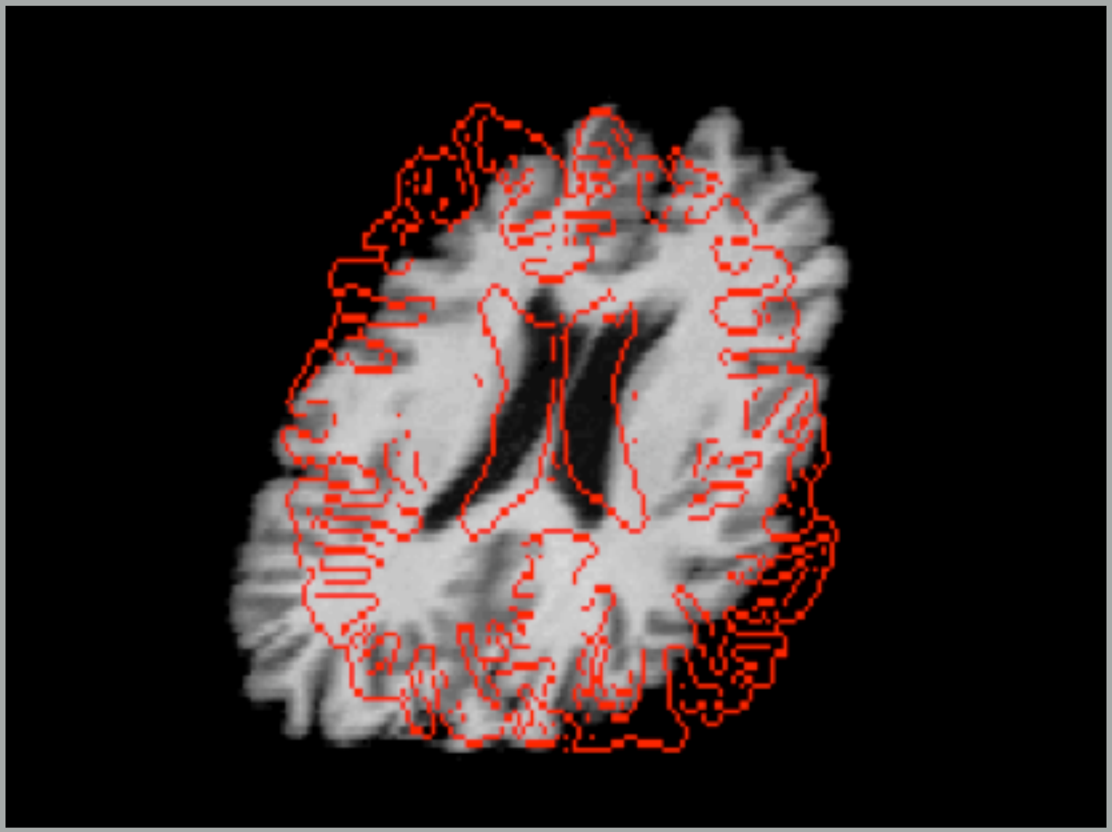
3 rotations
(x,y,z)

FSL: http://www.fmrib.ox.ac.uk/fsl

Affine Registration



3 scalings
(x,y,z)

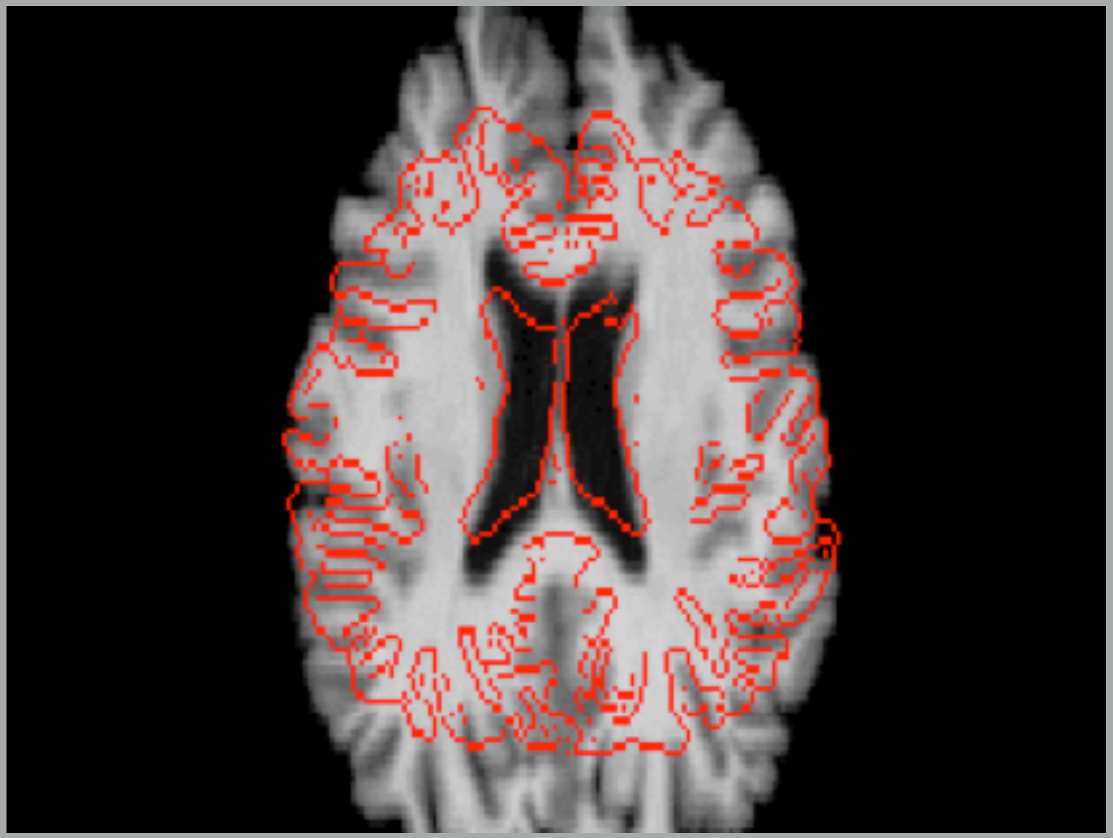


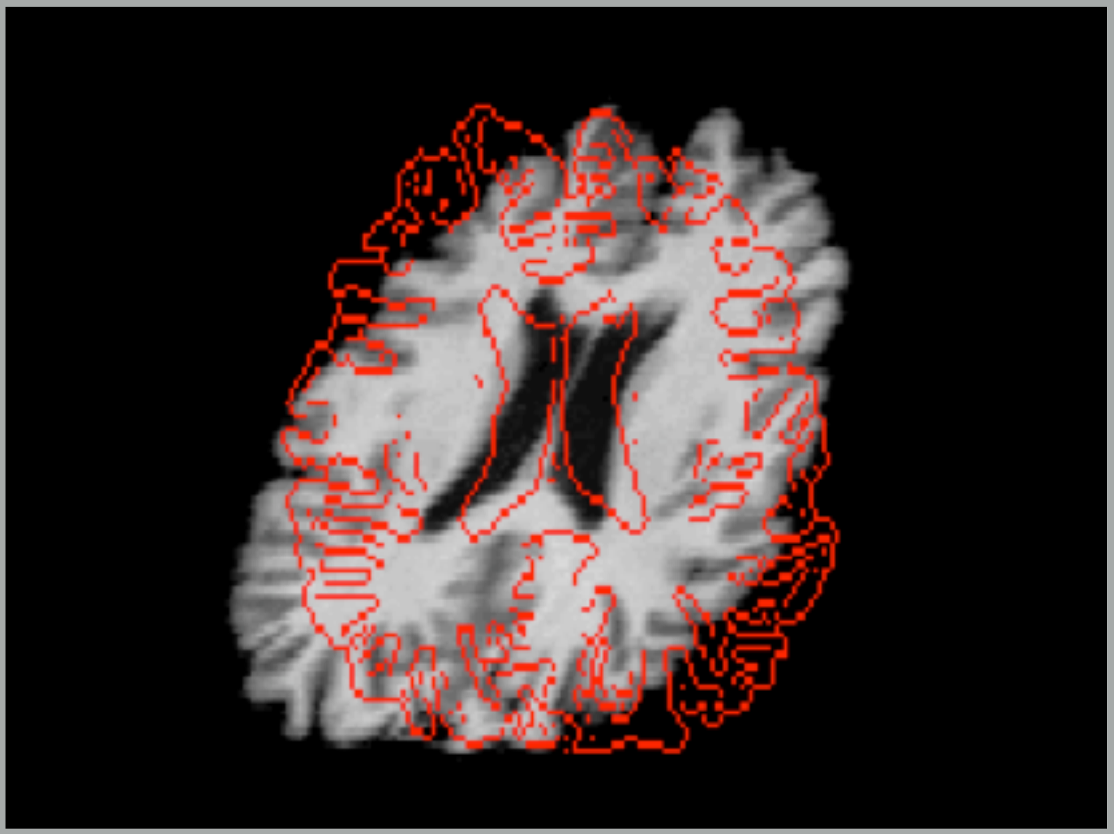
3 shears
(x,y,z)

FSL: FLIRT (affine registration)

FSL: http://www.fmrib.ox.ac.uk/fsl

Affine Transformation





3 scalings
(x,y,z)

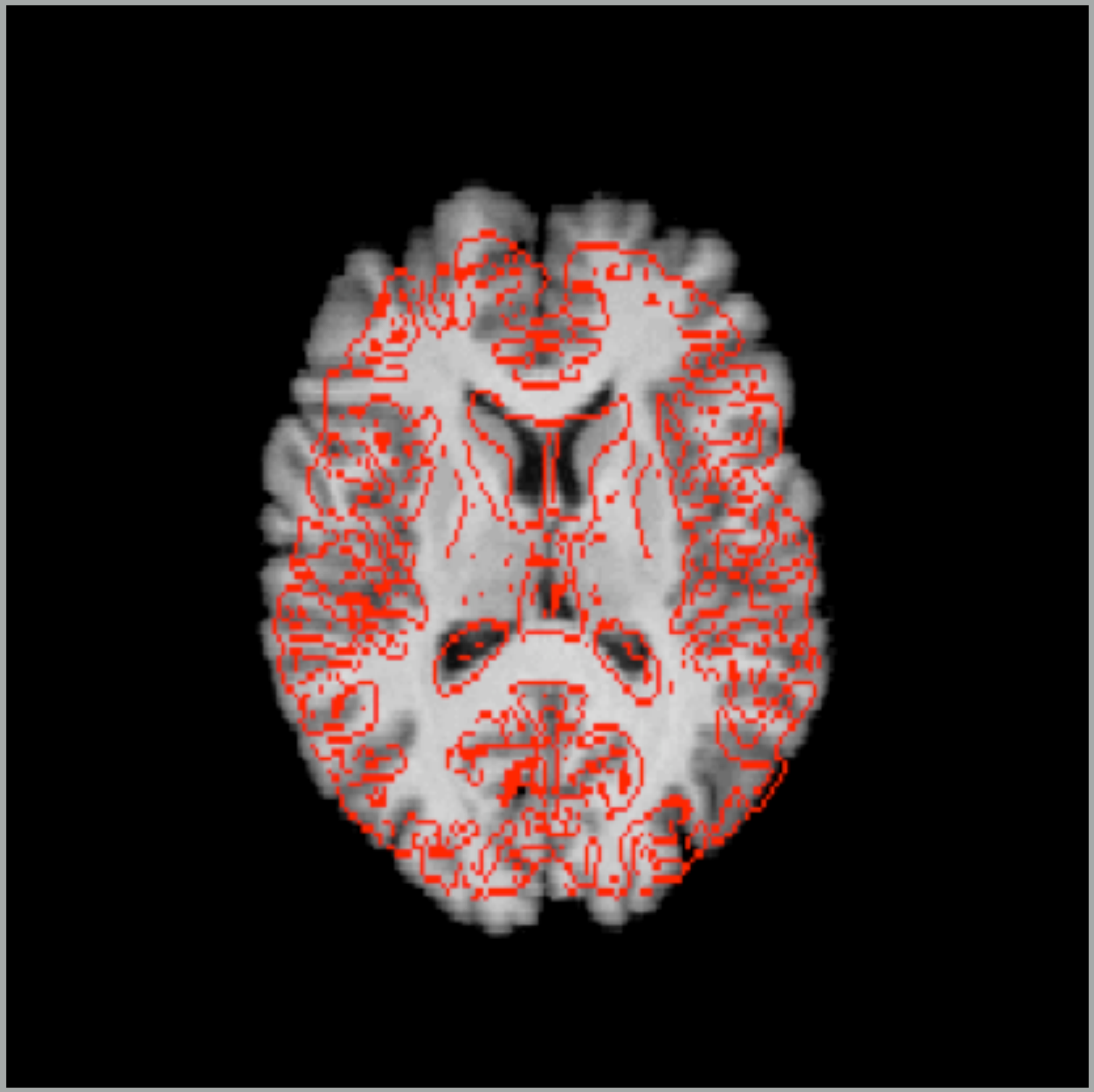
3 shears
(x,y,z)

Shape of region changes, but tissue microstructure doesn't.

Only the orientation changes, so want that part of the affine transformation

Non-linear Registration

Mean FA images are created using non-linear registration



FSL: http://www.fmrib.ox.ac.uk/fsl

Registration

1. Rigid body transformation used for **intra-subject** registration

2. Affine transformations used for **subject-standard** registration (e.g., Talairach) and for **eddy current correction**

3. Non-linear transformation used for **inter-subject** registration

AFNI's 3dQwarp

AFNI's 3dQwarp

$$S(W(X)) \approx B(X)$$

$$S(x) = \text{source image}$$

$$B(x) = \text{base image}$$

$$W(x) = \text{warp function}$$

AFNI's 3dAllineate

$$W(x) = \mathbf{M}x$$

$$\mathbf{M} = 4 \times 3 \text{ matrix}$$

$$\mathbf{M} \text{ has 12 parameters to optimize}$$

AFNI's 3dQwarp

$$W(x) = W_1(W_2(\ldots W_{n-1}(W_n)))\ldots))$$

- Each $W_k(x)$ a polynomial warp over a "patch"
- Patches start with big $W_1(x)$ and shrink
- Cubic patch = 24 parameters ; Quintic = 81 params
- By the end, 1000's of parameters have been used

AFNI's 3dQwarp
Pros and Cons

<u>Pros:</u>

- Nonlinear warping can match anatomical structures between subjects more closely than linear transformation
- Can also be used for intra-subject warping for high accuracy matching (e.g., pre- and post-surgery)

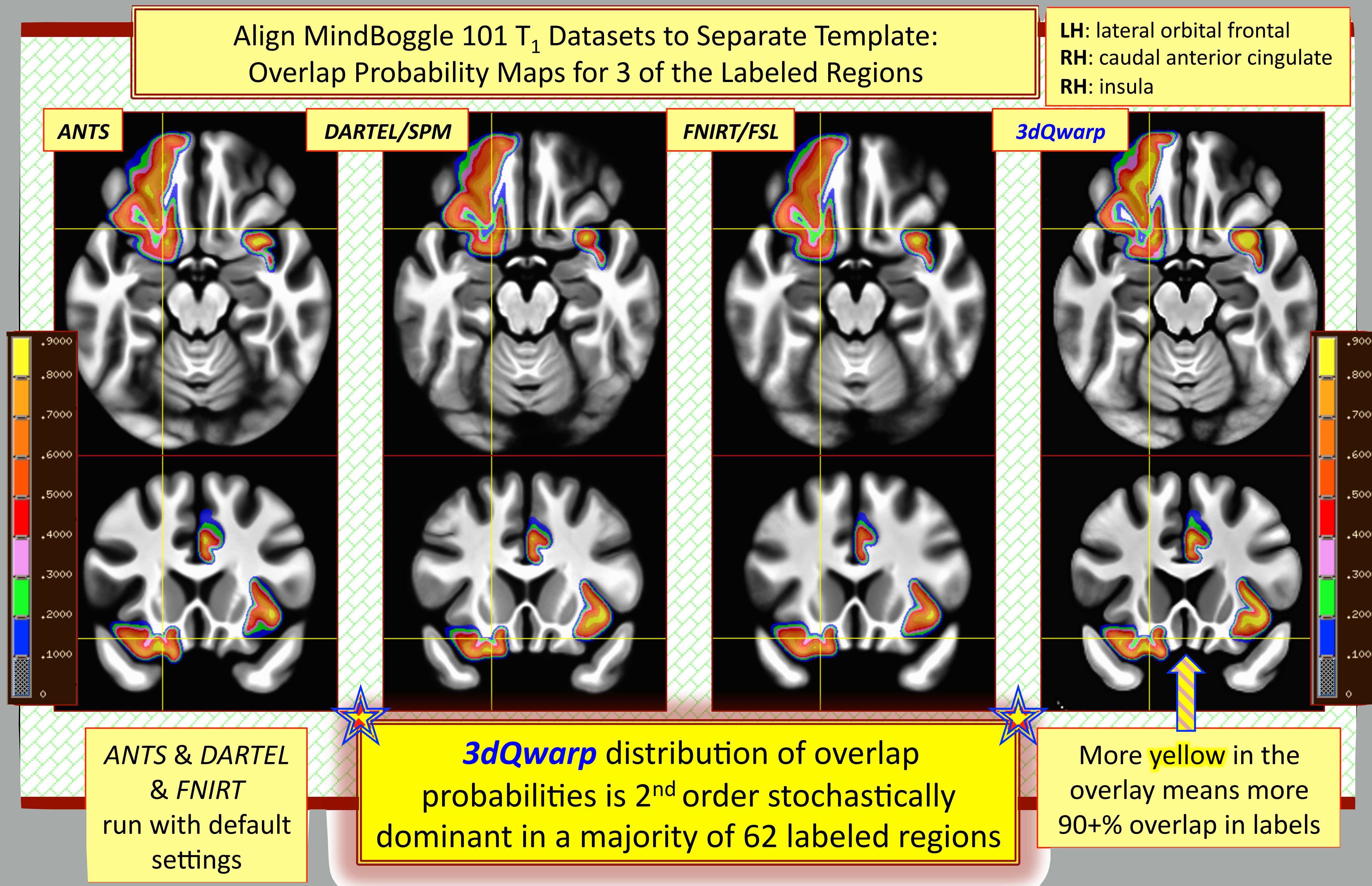
AFNI's 3dQwarp
Pros and Cons

Cons:

- Nonlinear warping can seriously distort when it tries to match in regions that don't really "fit together" (e.g., 2 gyri in one person, 1 gyrus in another)
- Extraneous small features can drive warping in strange ways (unlike linear transformation)
- Partial brain coverage is a problem

AFNI's 3dQwarp

Good match to anatomical labels



DTI warping

In order to compare DTI data across individuals, brains must be co-registered to a common coordinate, or *template*, space.

This is called *spatial normalization*

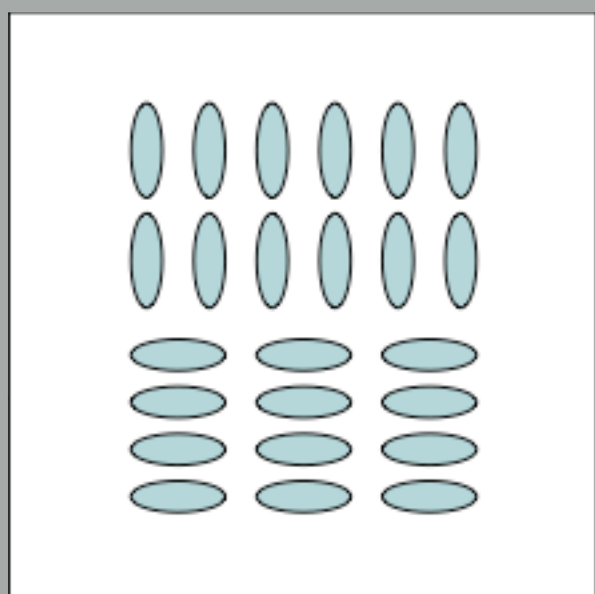
The problem

This requires:

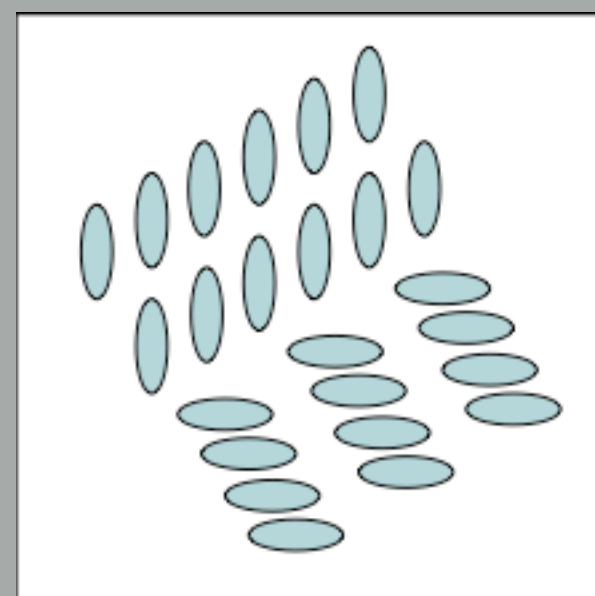
1. Voxels are moved to the correct location in template space

2. Diffusion tensor is moved to be consistent with voxel displacement while retaining its shape and orientation

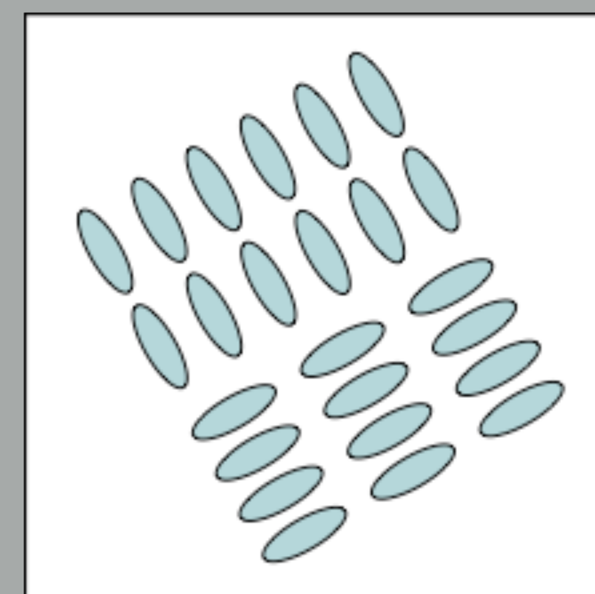
The problem



Original image



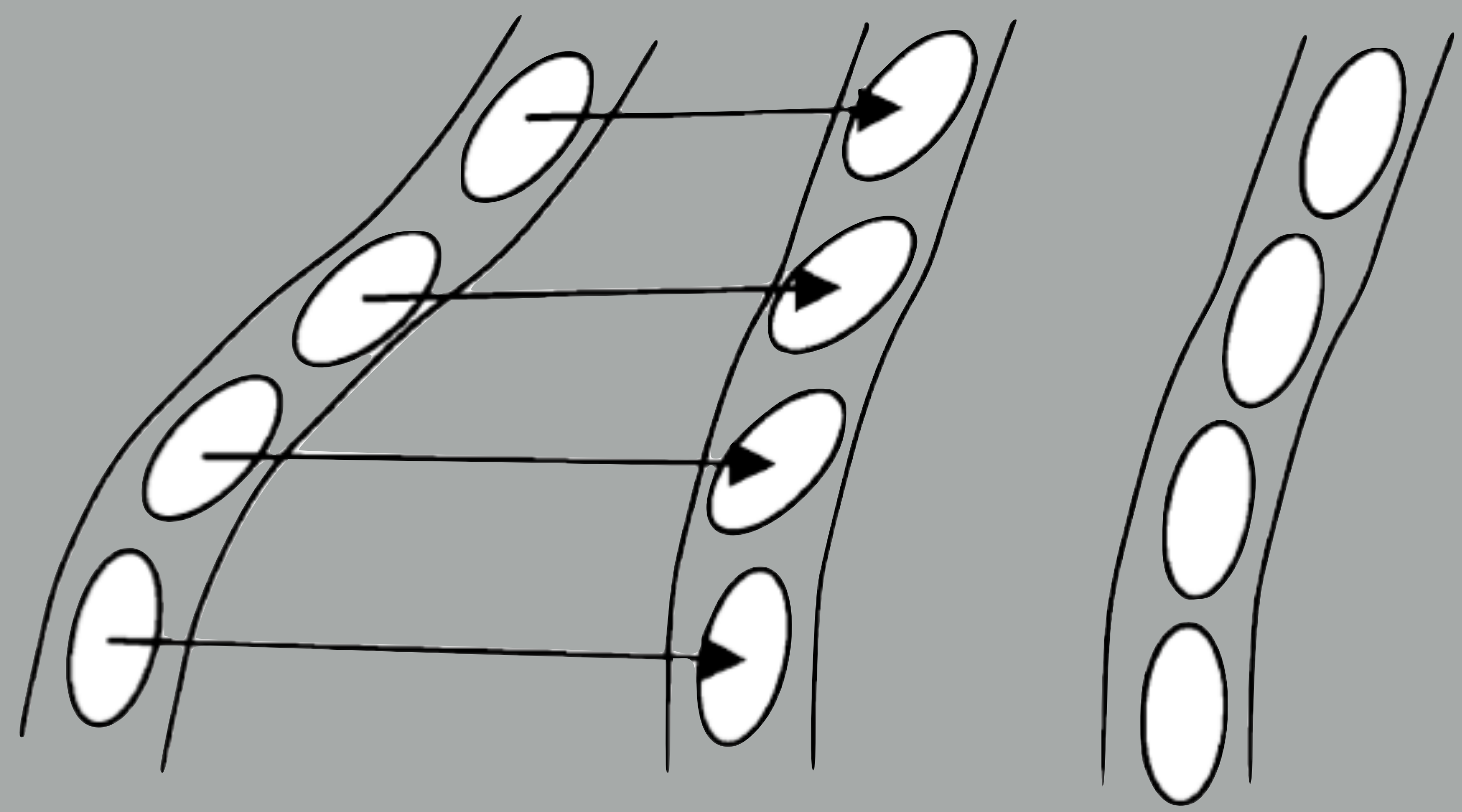
Rotated image
w/o reorienting tensors



Rotated image
with tensors reoriented

Zhang, et. al., Med. Image Analysis 10,764:2008

Tensor Warping



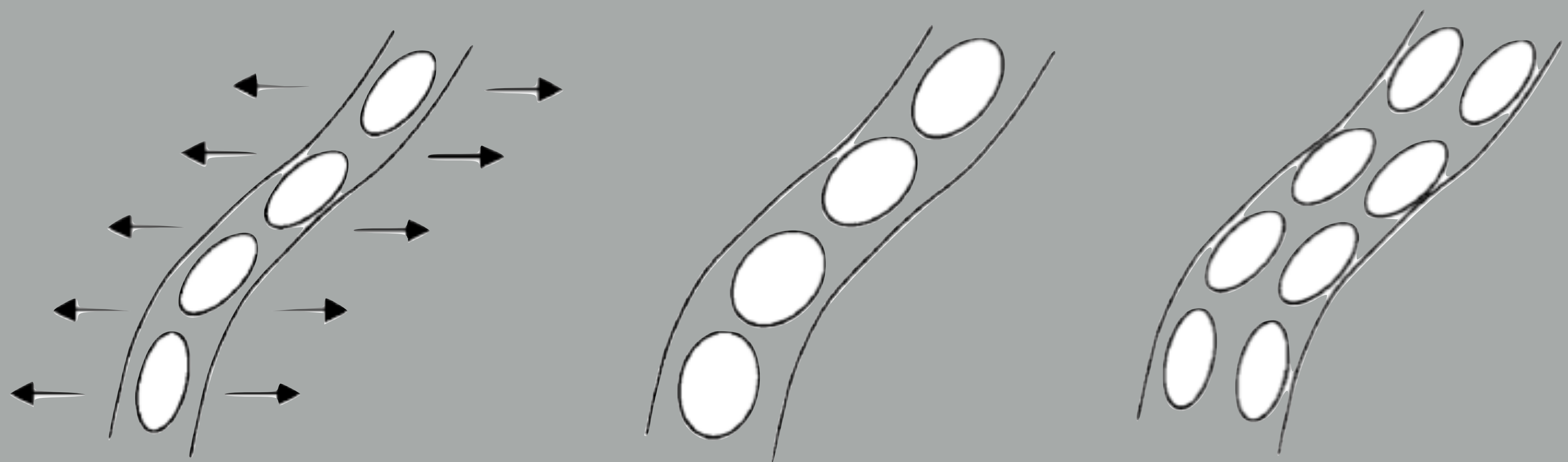
original image

tensor moved but not reoriented

tensor moved and reoriented along fiber direction

Xu, et. al., IEEE TMI 27(3):2008

Tensor Warping



original image

image warping incorrectly scales the tensors

correct warping with tensor shape preserved

Xu, et. al., IEEE TMI 27(3):2008

Affine Transformation

Affine transformation $\boldsymbol{F}$ of tensor can be written

$$\boldsymbol{D}' = \boldsymbol{F}\boldsymbol{D}\boldsymbol{F}^t$$

but this is incorrect because of the aforementioned problem: only want the rotational component of $\boldsymbol{F}$

Affine Transformation

However, $\boldsymbol{F}$ can be decomposed into

$$\boldsymbol{F} = \boldsymbol{U}\boldsymbol{R}$$

$$\boldsymbol{U} = \text{deformation}$$
$$\boldsymbol{R} = \text{rotation}$$

The rotation can be found from

$$\boldsymbol{R} = (\boldsymbol{F}\boldsymbol{F}^t)^{-\frac{1}{2}}\boldsymbol{F}$$

Affine Transformation

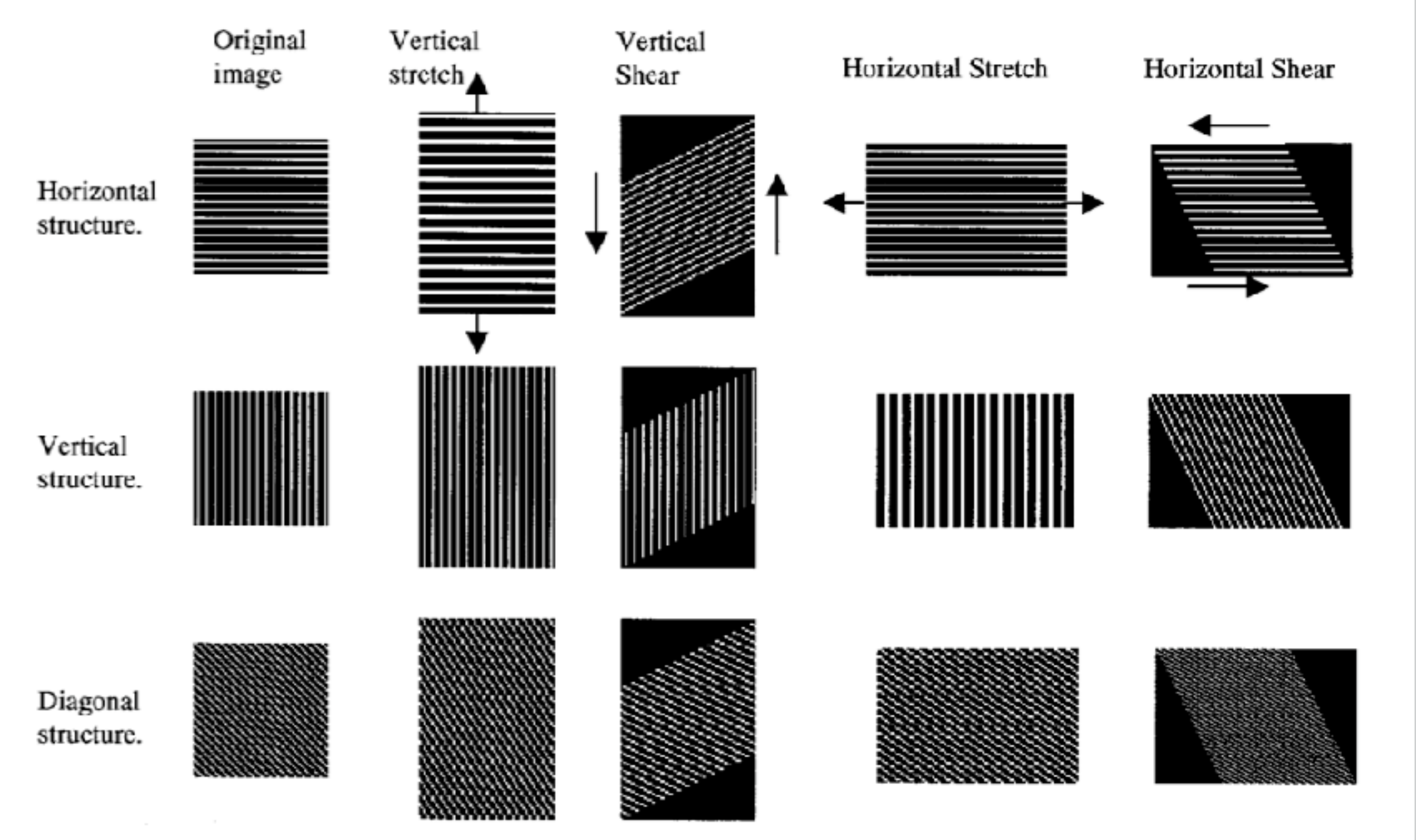
Then just rotate the tensor according to the usual

$$\boldsymbol{D}' = \boldsymbol{R}\boldsymbol{D}\boldsymbol{R}^t$$

$\boldsymbol{R}$ is constant across the entire image, and just needs to be computed once

However, shearing and stretching transformations change the orientation and we've thrown that part of F away!

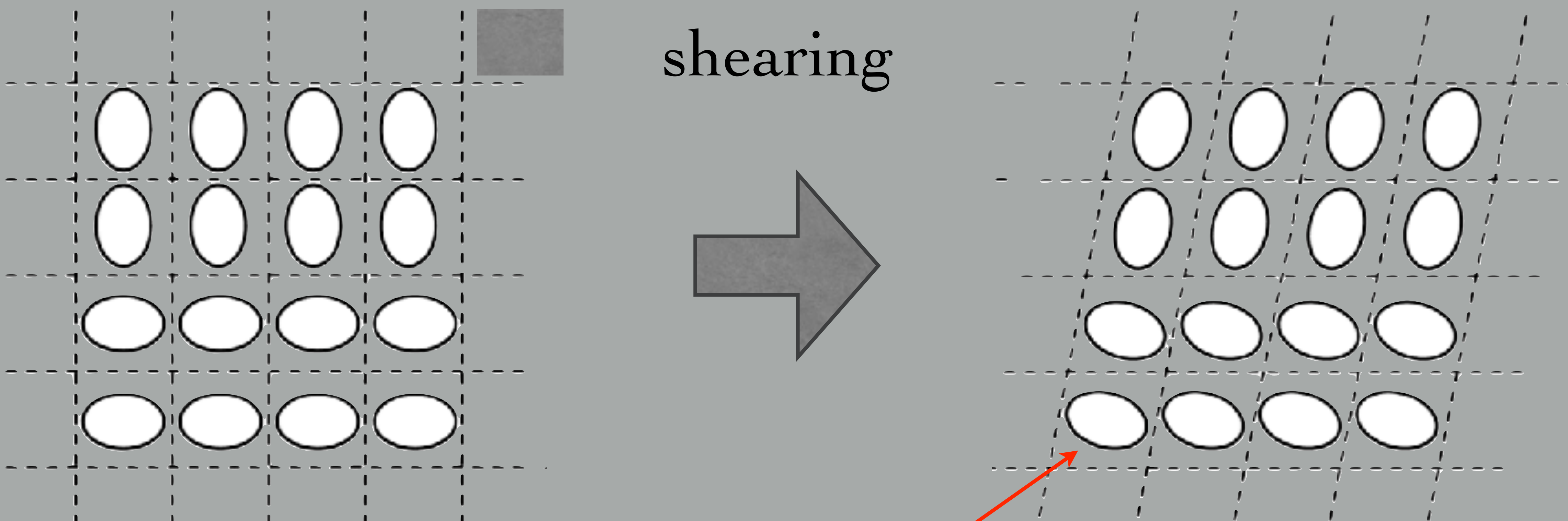
Affine Transformation



Reorientation depends on image structure

Alexander, et. al., IEEE TMI 20(11):2001

Tensor Warping

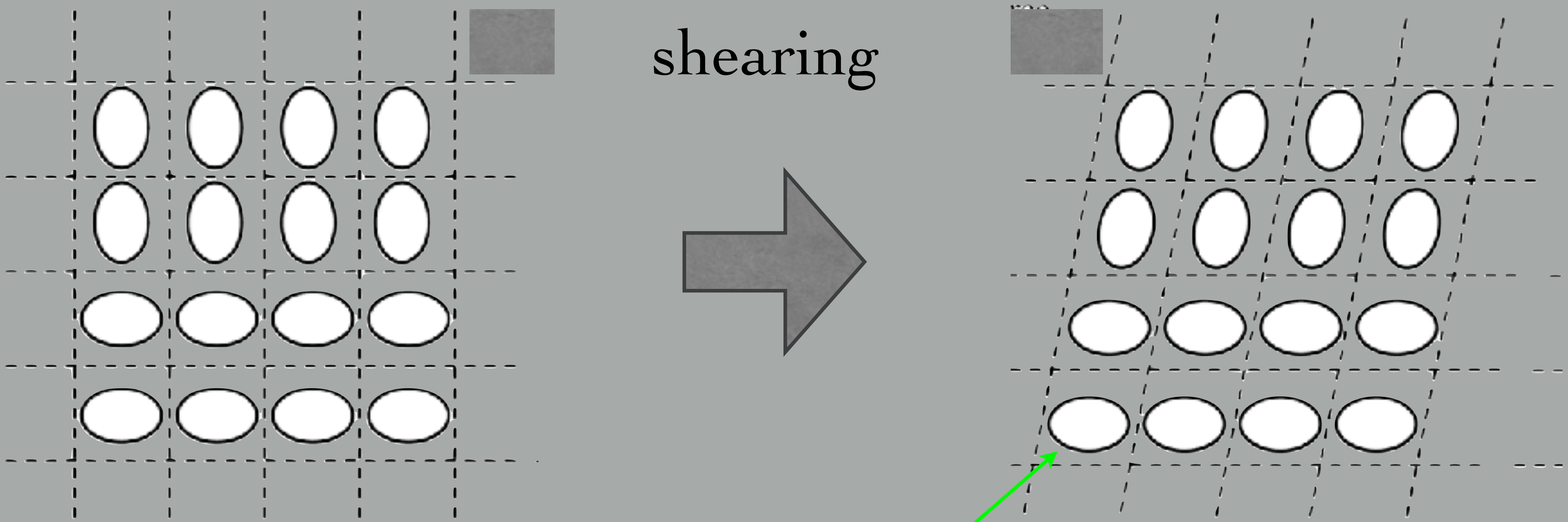


non-rigid registration methods produce this

Incorrect: shearing parallel to orientation should have no effect, but introduces rotation if not done properly

Xu, et. al., IEEE TMI 27(3):2008

Tensor Warping



Correct: shearing parallel to orientation
has no effect

Xu, et. al., IEEE TMI 27(3):2008

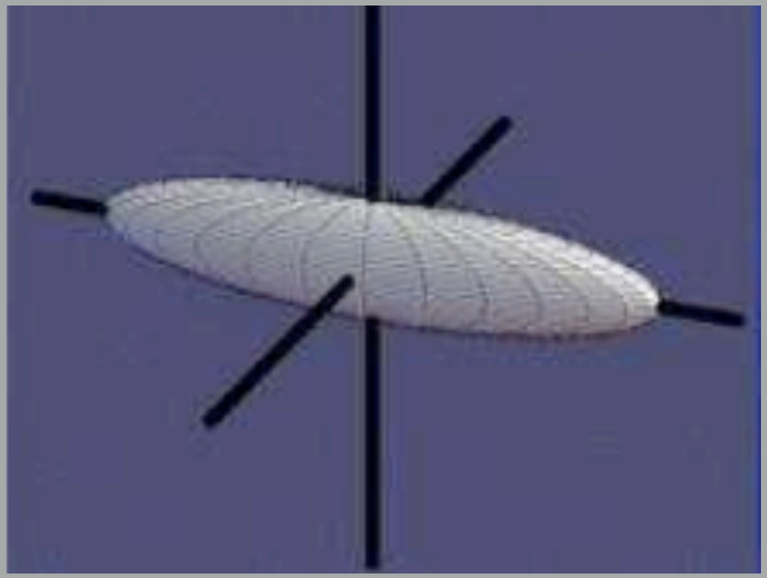
Preservation of Principal Direction (PPD)

Change in fiber direction therefore depends upon its original direction within the image

One method to take into account effect of affine transformation is Preservation of Principal Direction (PPD)

Alexander, et. al., IEEE TMI 20(11):2001

Anisotropy Indices



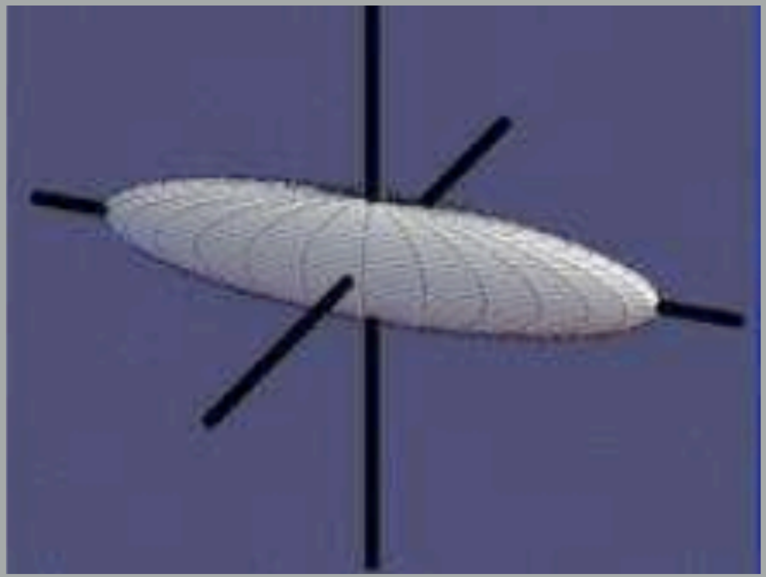
prolate

oblate

$$\lambda_1 \gg \lambda_2 = \lambda_3$$

$$\lambda_1 = \lambda_2 \gg \lambda_3$$

Prolate



Apply affine transformation to principle eigenvector, which rotates it, and define unit vector in rotated direction

$$\boldsymbol{n}_1 = \frac{F\boldsymbol{e}_1}{|F\boldsymbol{e}_1|}$$

Oblate

Plane spanned by $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$ transformed to plane spanned by $F\boldsymbol{e}_1$ and $F\boldsymbol{e}_2$ so need to find rotation that rotates $\boldsymbol{D}$ so that its new $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$ are in this plane.

PPD algorithm

Compute

$$\boldsymbol{n}_1 = \frac{F\boldsymbol{e}_1}{|F\boldsymbol{e}_1|} \qquad \boldsymbol{n}_2 = \frac{F\boldsymbol{e}_2}{|F\boldsymbol{e}_2|}$$

Then find rotation that maps

$$\boldsymbol{e}_1 \rightarrow \boldsymbol{n}_1 \qquad \boldsymbol{e}_2 \rightarrow \boldsymbol{n}_2$$

A separate R is computed for each voxel

Group Comparisons

Structure specific techniques

1. Tract-Based Spatial Statistics (TBSS)
Smith, et. al., Neuroimage 31(4),1487:2006

2. Structure-specific statistical mapping (SSSM)
Yushkevich, et. al., Neuroimage 41,448:2008

These methods used the previously discussed image co-registration methods to generate "average" parameter maps from which to work

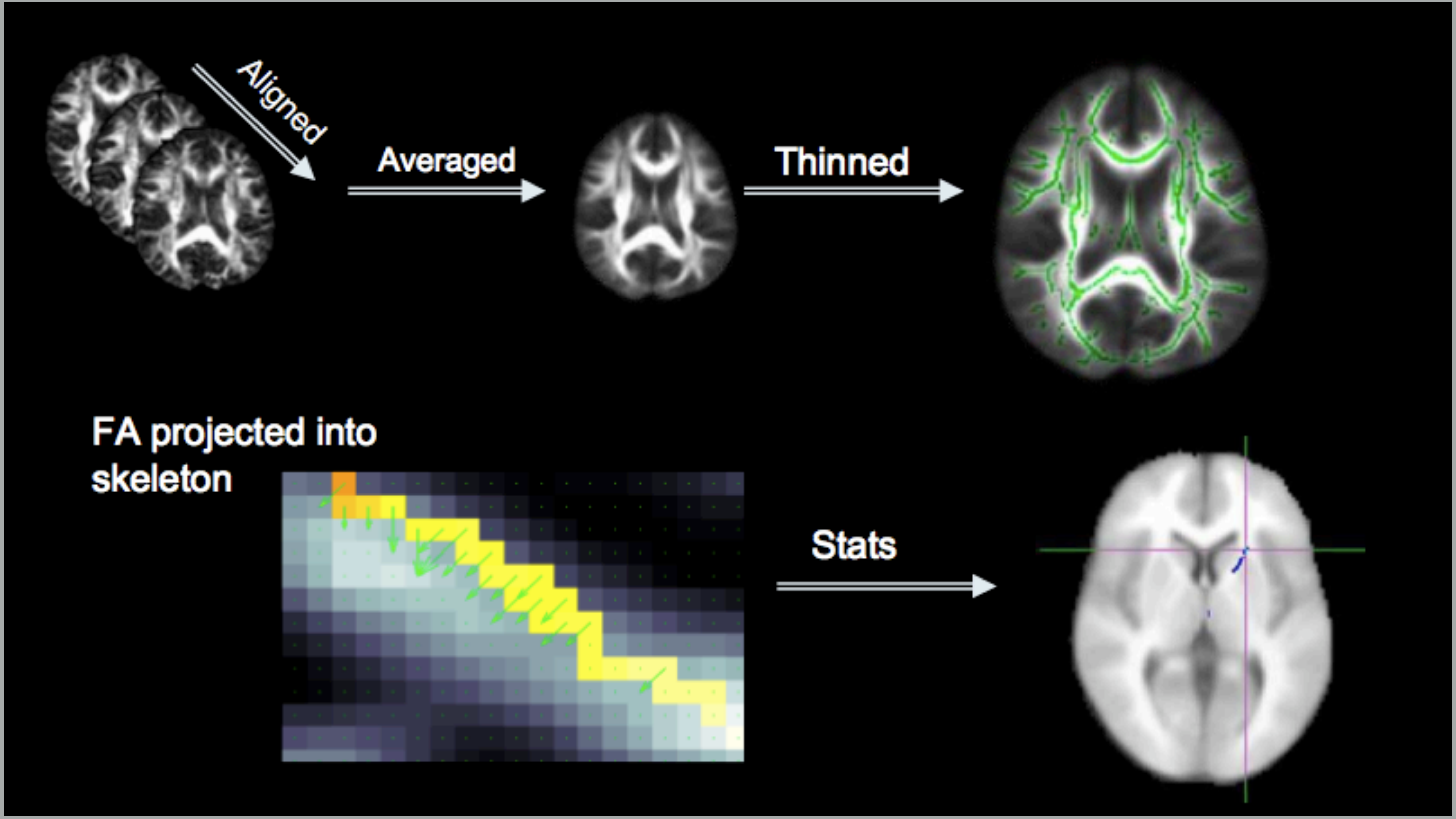
Tract-Based Spatial Statistics (TBSS)

Smith, et. al., Neuroimage 31(4),1487:2006

Structure is represented by a “skeleton” derived from the FA and which forms the backbone for the statistical analysis

Tract-Based Spatial Statistics (TBSS)

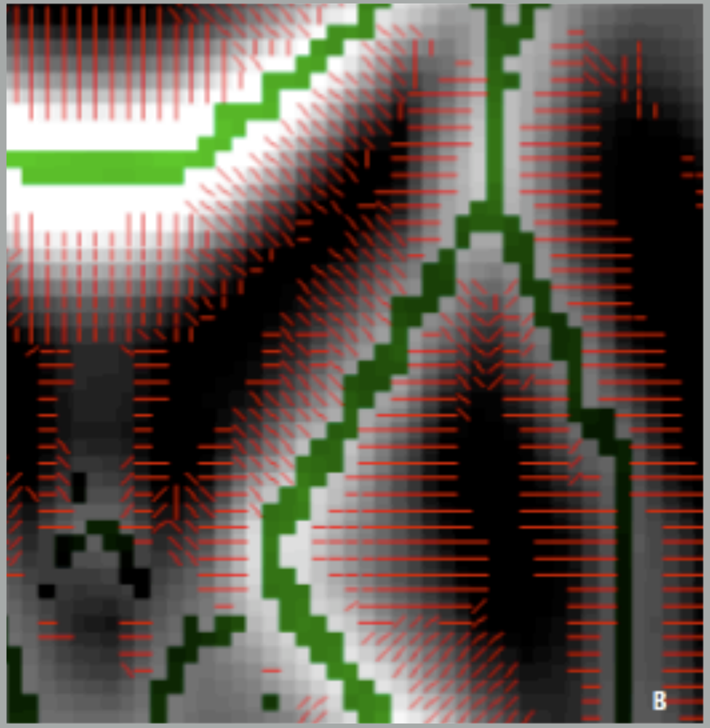
Smith, et. al., Neuroimage 31(4),1487:2006



Maniega and Bastin

TBSS Skeletonization Stages

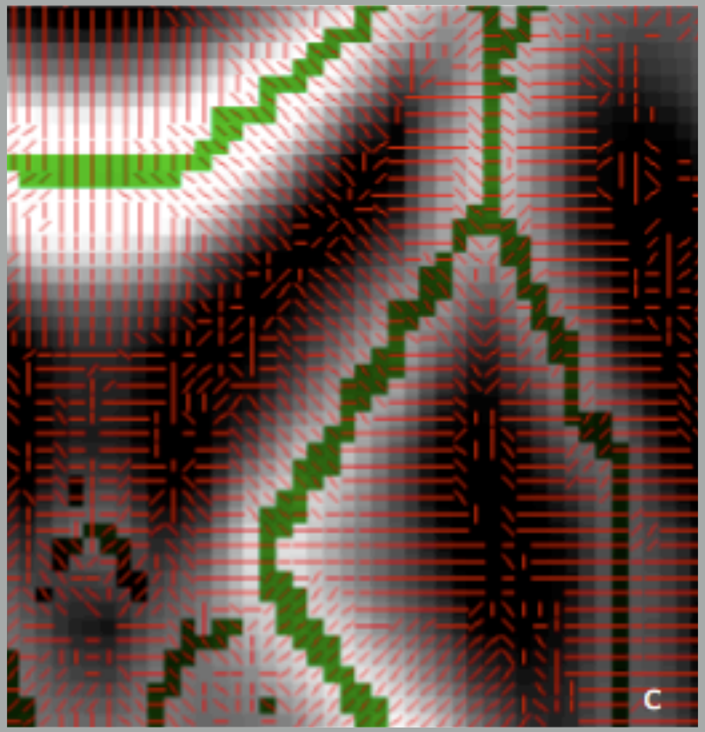
original mean FA image
and final skeleton



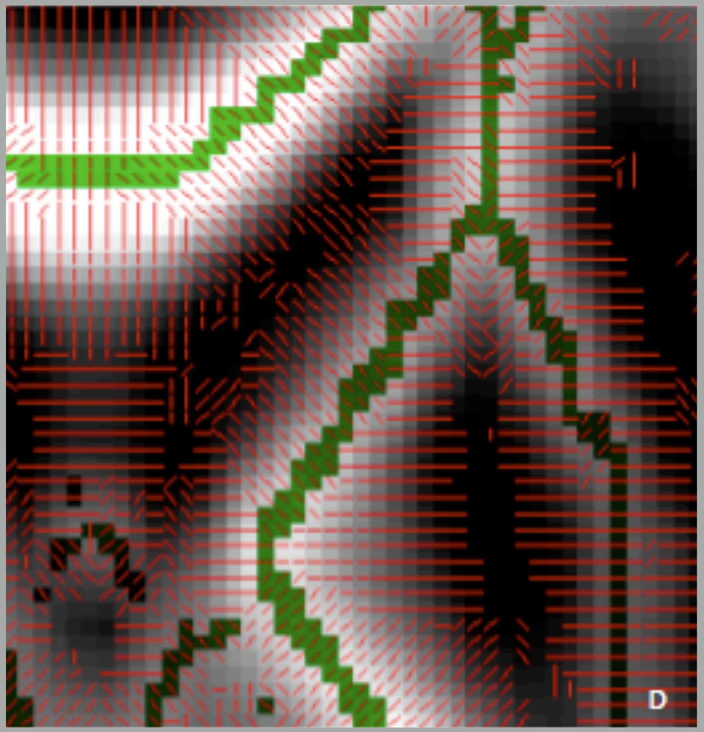
local FA center of gravity
to find tract perpendiculars

Smith, et. al., Neuroimage 31(4),1487:2006

TBSS Skeletonization Stages



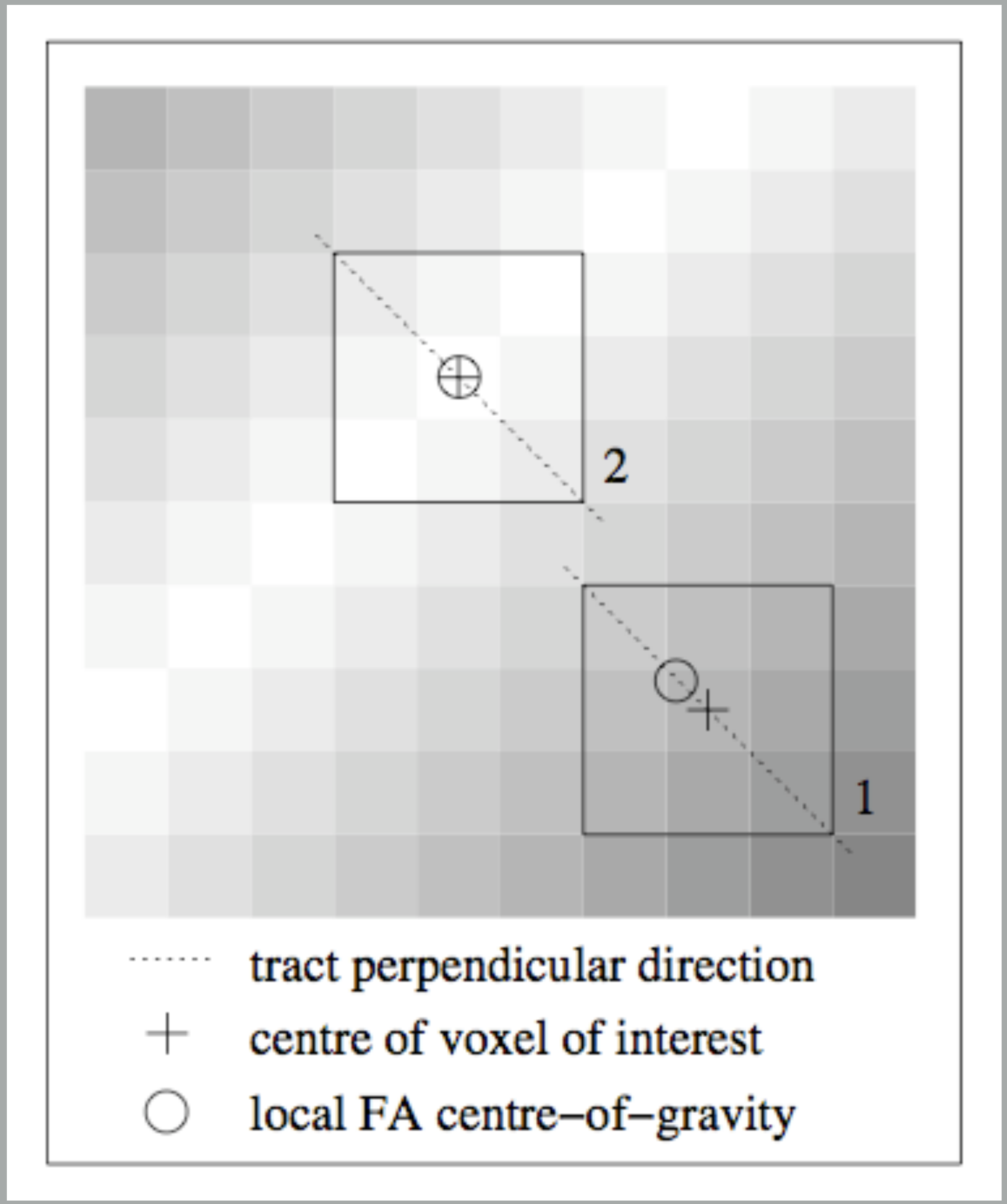
stage 2:
FA second derivative to find
remaining perpendiculars



stage 3:
Smoothing of perpendicular
direction vector image

Smith, et. al., Neuroimage 31(4),1487:2006

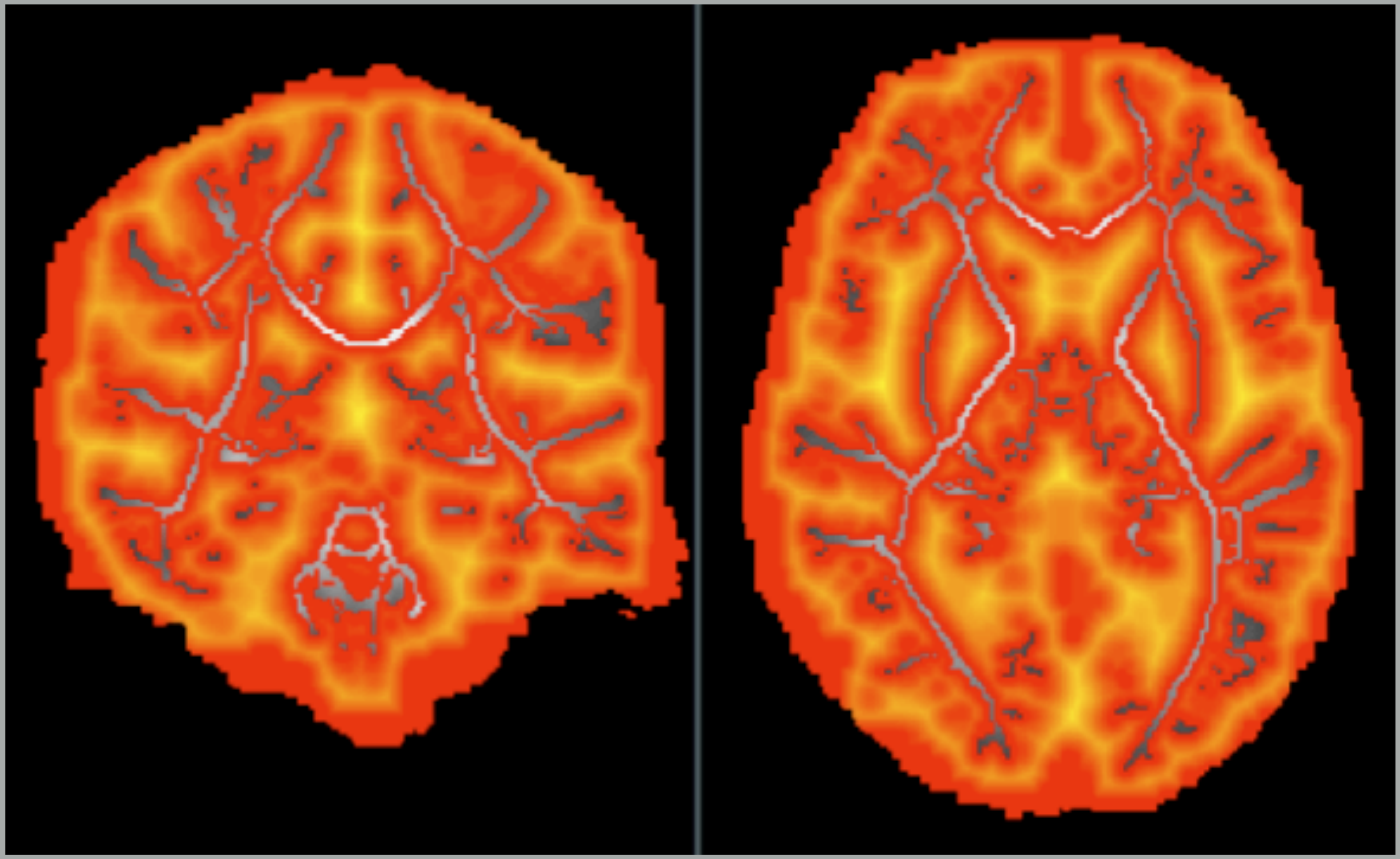
TBSS surface orientation determination



1. Voxel CoG points in the local tract perpendicular direction
2. Voxel lies direction on tract center

Smith, et. al., Neuroimage 31(4),1487:2006

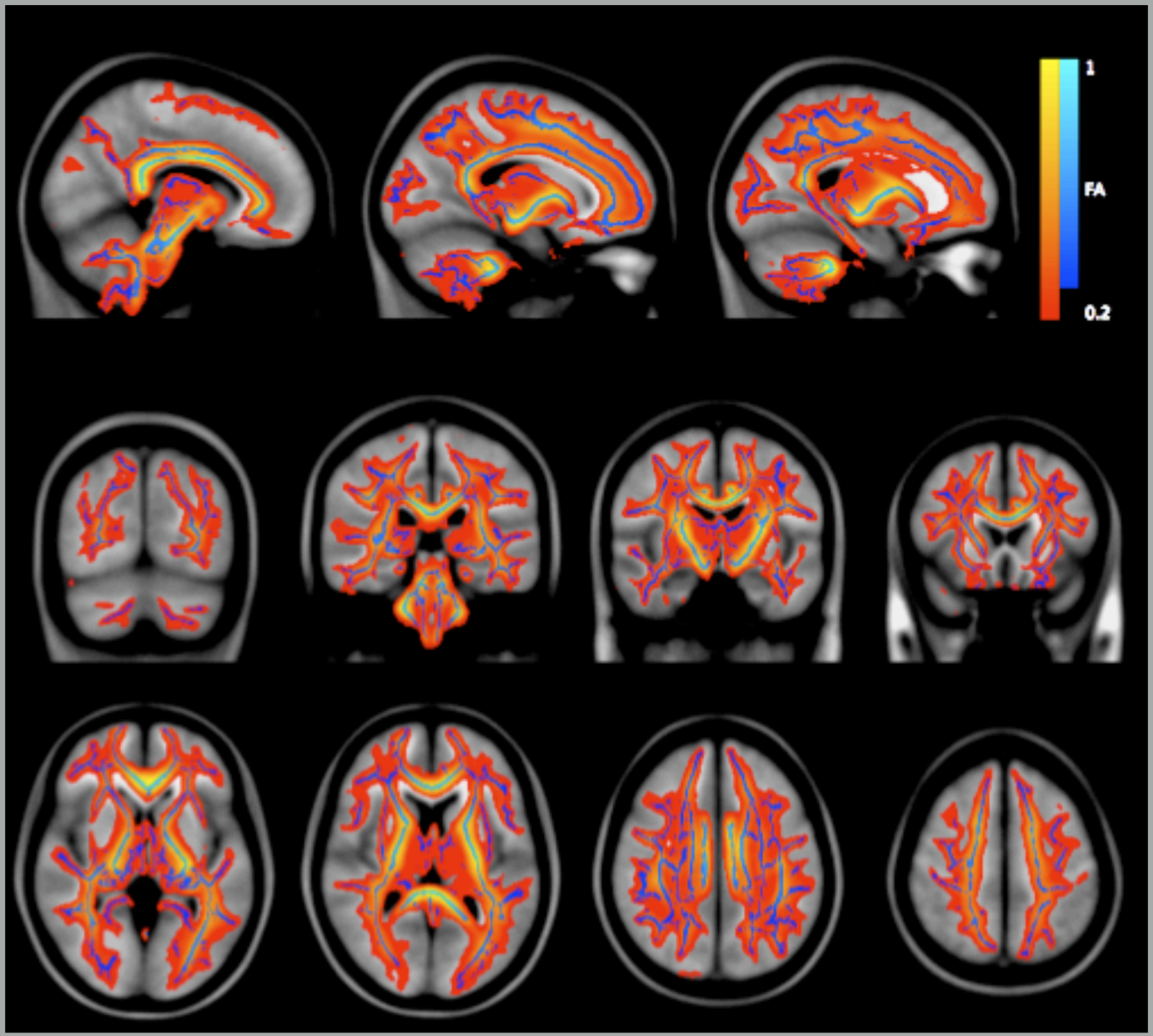
TBSS: Projecting subjects' FA onto skeleton



Red-yellow encodes how far voxels are from nearest skeleton voxel. This is used in projecting individual FA maps to ensure only voxels close to skeleton are used

Smith, et. al., Neuroimage 31(4),1487:2006

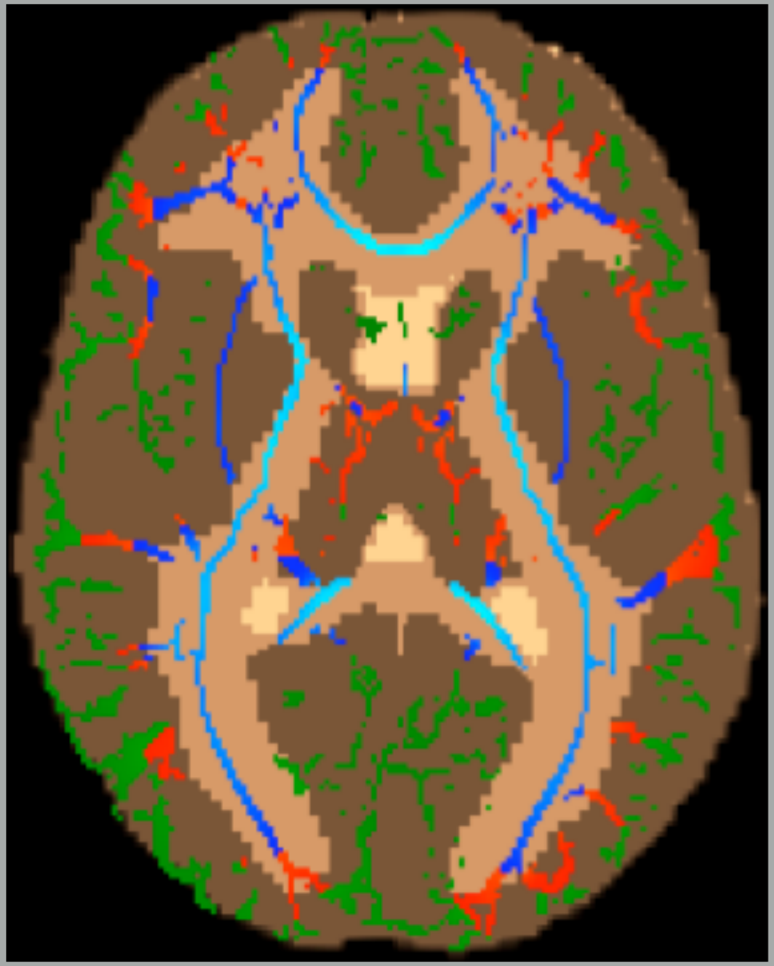
Tract-Based Spatial Statistics (TBSS)



Overlay of mean FA map from 33 subjects

Smith, et. al., Neuroimage 31(4),1487:2006

Tract-Based Spatial Statistics (TBSS)



green: $0 \leq \mathrm{FA} \leq 0.2$

red: $0.2 \leq \mathrm{FA} \leq 0.3$

blue: $0.3 \leq \mathrm{FA} \leq 1.0$

Mean FA map from 69 subjects thresholded into 3 ranges

Smith, et. al., Neuroimage 31(4),1487:2006

Tract-Based Spatial Statistics (TBSS)

TBSS ignores orientation information
since it uses a mean FA image.

This can lead to fasciculi that have different
orientation but similar anisotropy
being combined together into a single structure

Thus TBSS skeleton may not correspond to the
skeletons of the individual fasciculi in these locations

Structure-specific statistical mapping (SSSM)

Yushkevich, et. al., Neuroimage 41,448:2008

Segment major tracts then fit them with
deformable geometric medial models
i.e., *continuous medial representation (CM-Reps)*

Structure is represented by a parametric surface
which allows manifold-based statistical analysis
similar to what is used in cortical flat-mapping

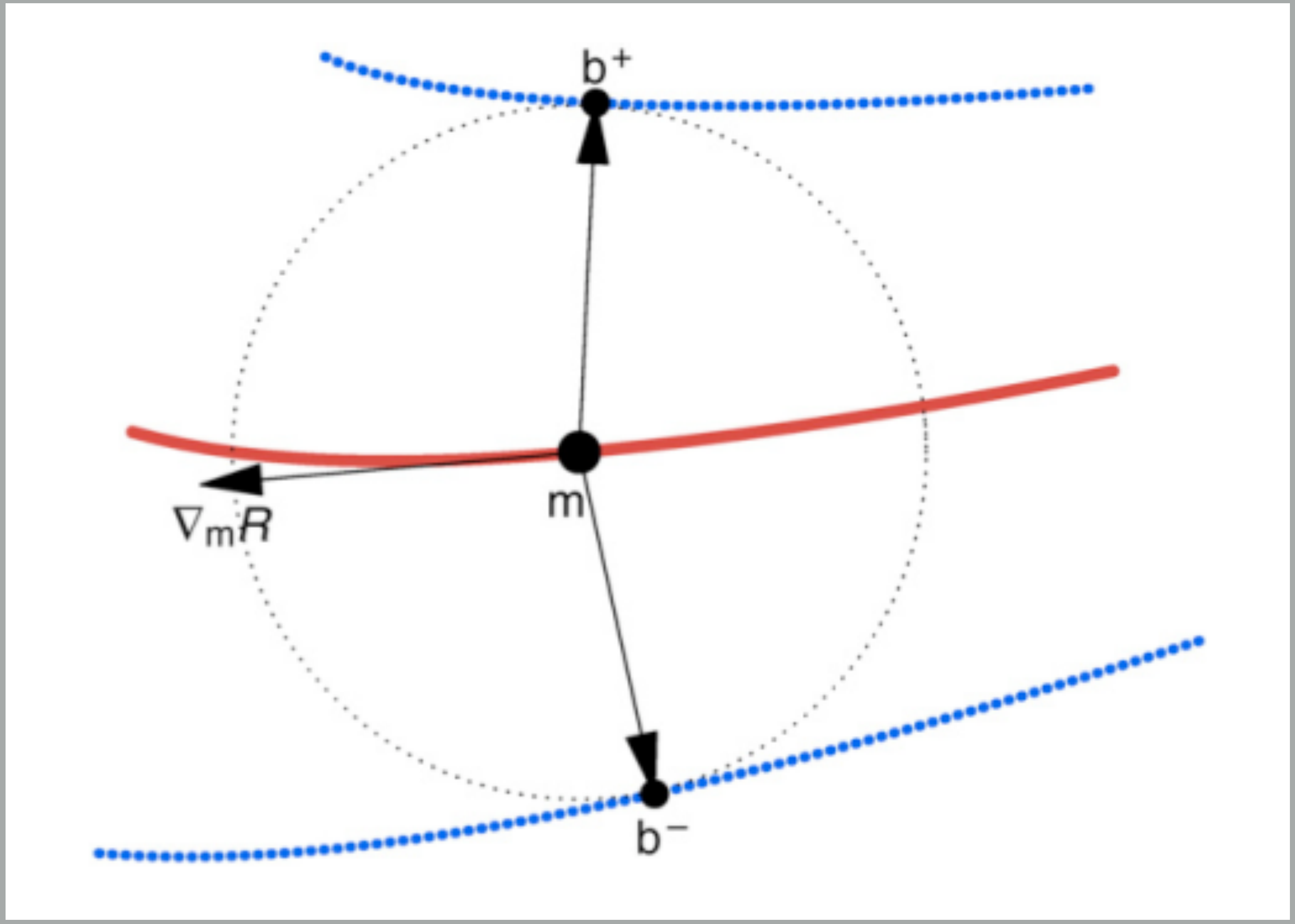
Motivated by sheet-like structure of many brain organs

Structure-specific statistical mapping (SSSM)

Basic procedure:

1. Spatially normalize all DTI data to a single "average" data set using deformable DTI registration (Zhang, 2006).
2. Since orientation information is preserved, fiber tract mapping can be done on the "average" brain
3. Segment fiber tracts from individual regions to create a representation of that region.
4. Create CM representation of that region (skeleton and boundary)
5. Generate statistics over volume along spokes to skeleton for each subject.
6. Map statistics onto boundary surface and now can compare amongst subjects

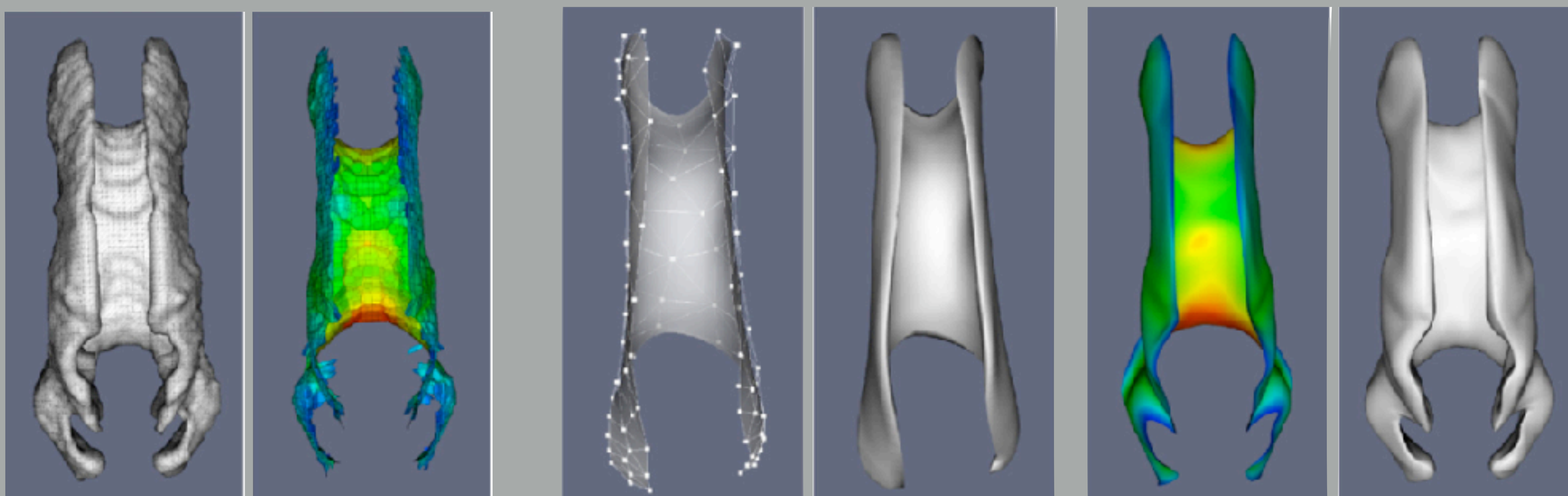
SSSM: Medial Geometry



Red curve is medial surface (skeleton)
Blue boundaries
"b" vectors are called "spokes"

Yushkevich, et. al., Neuroimage 41,448:2008

Structure-specific statistical mapping (SSSM)



a) Boundary and pruned skeleton. Color is distance to skeleton

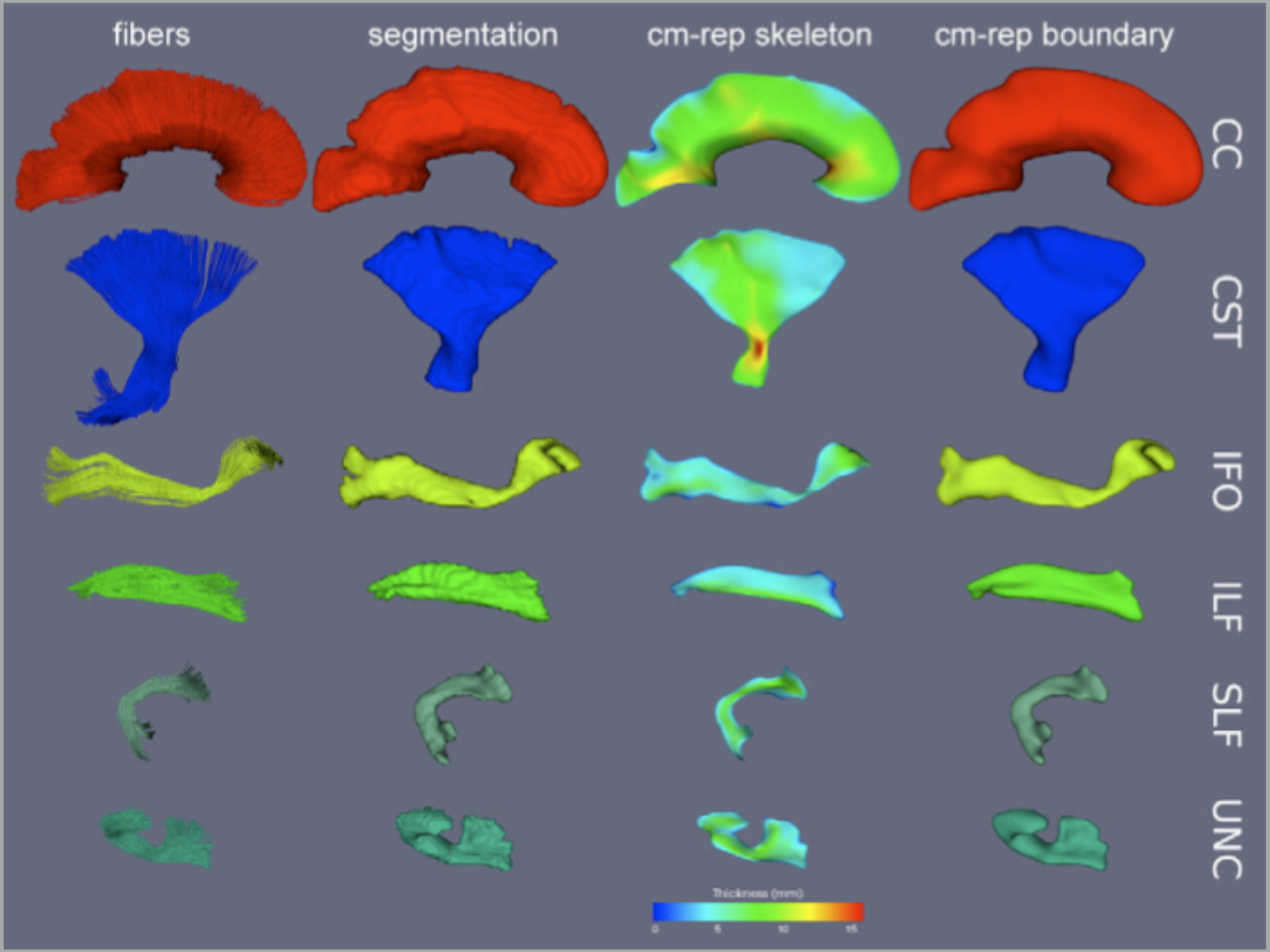
b) Continuous medial representation following triangulation, and boundary surface (right)

c) Fit of CM-Rep model to binary segmentation (skeleton and boundary)

Yushkevich, et. al., Neuroimage 41,448:2008

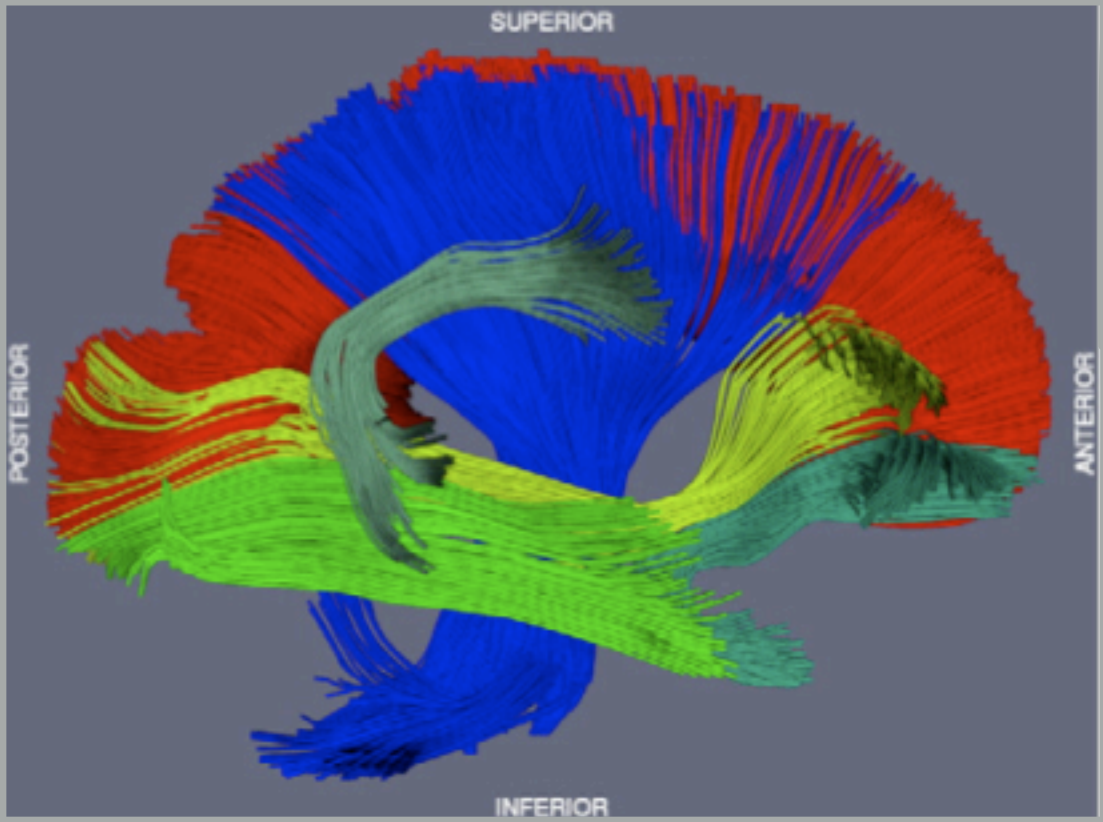
Yushkevich, et. al., Neuroimage 41,448:2008

SSSM: Model fits for 6 tracks

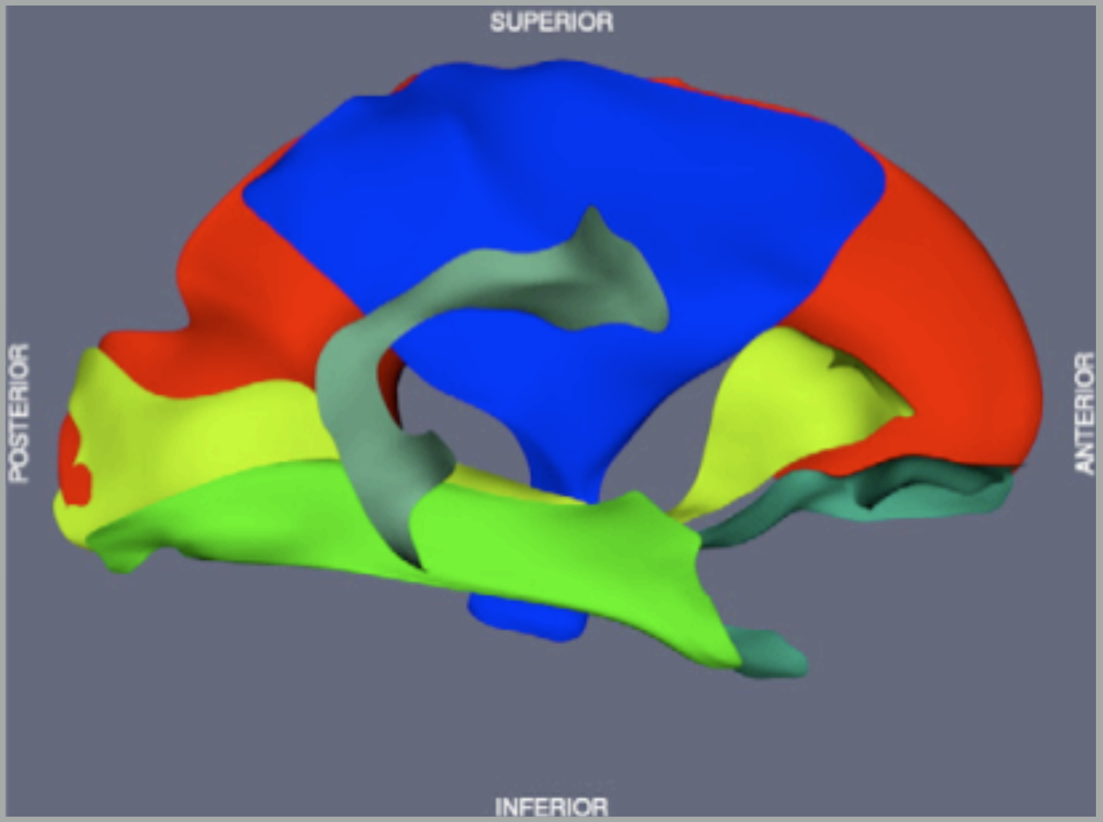


Colors mark different regions (except in Column 3, which is a t-map)

SSSM: Combined model fits



Fiber tracts

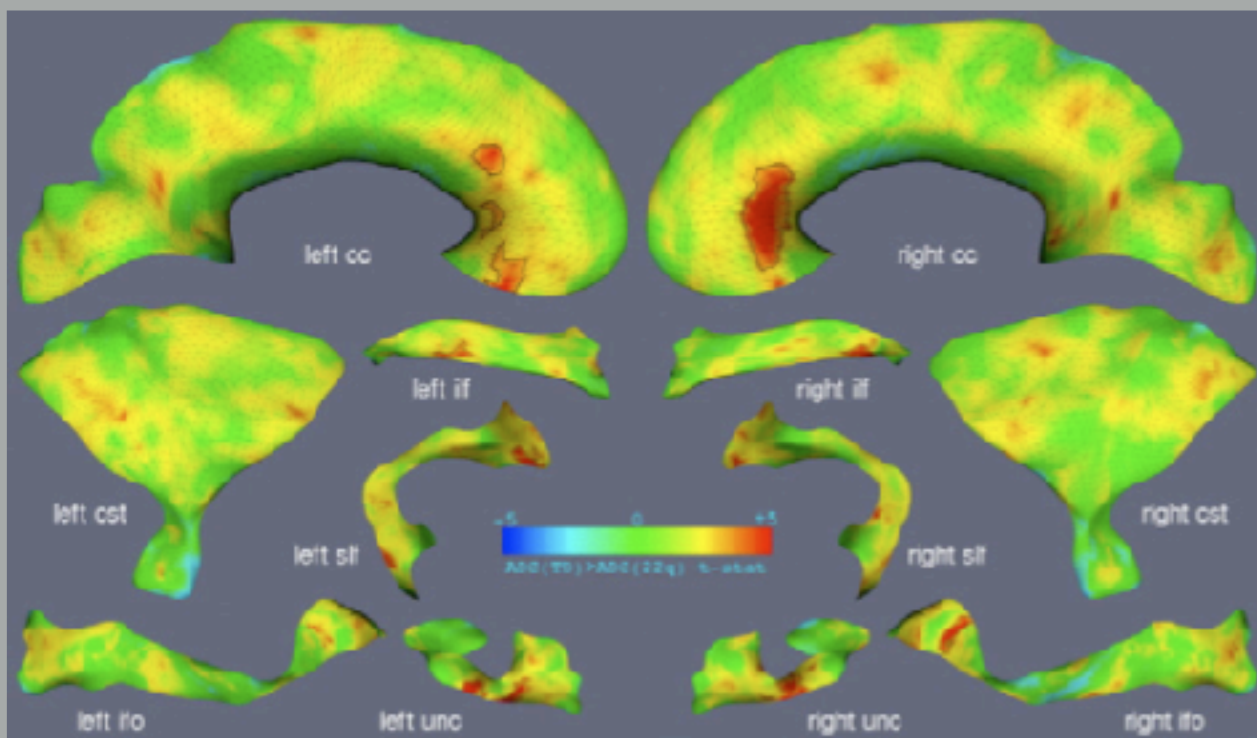


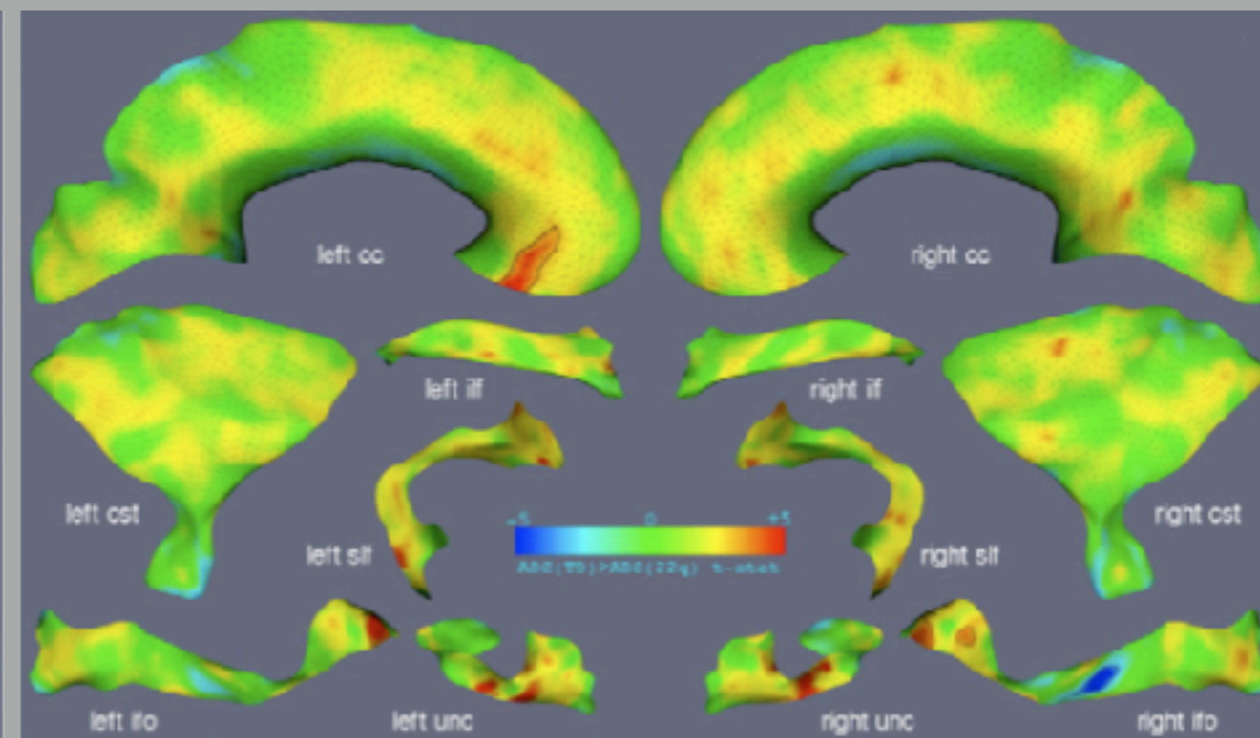
CM-Rep skeletons

Yushkevich, et. al., Neuroimage 41,448:2008

SSSM: Cluster analysis of ADC

Tensors in volume summarized along spokes according to two strategies





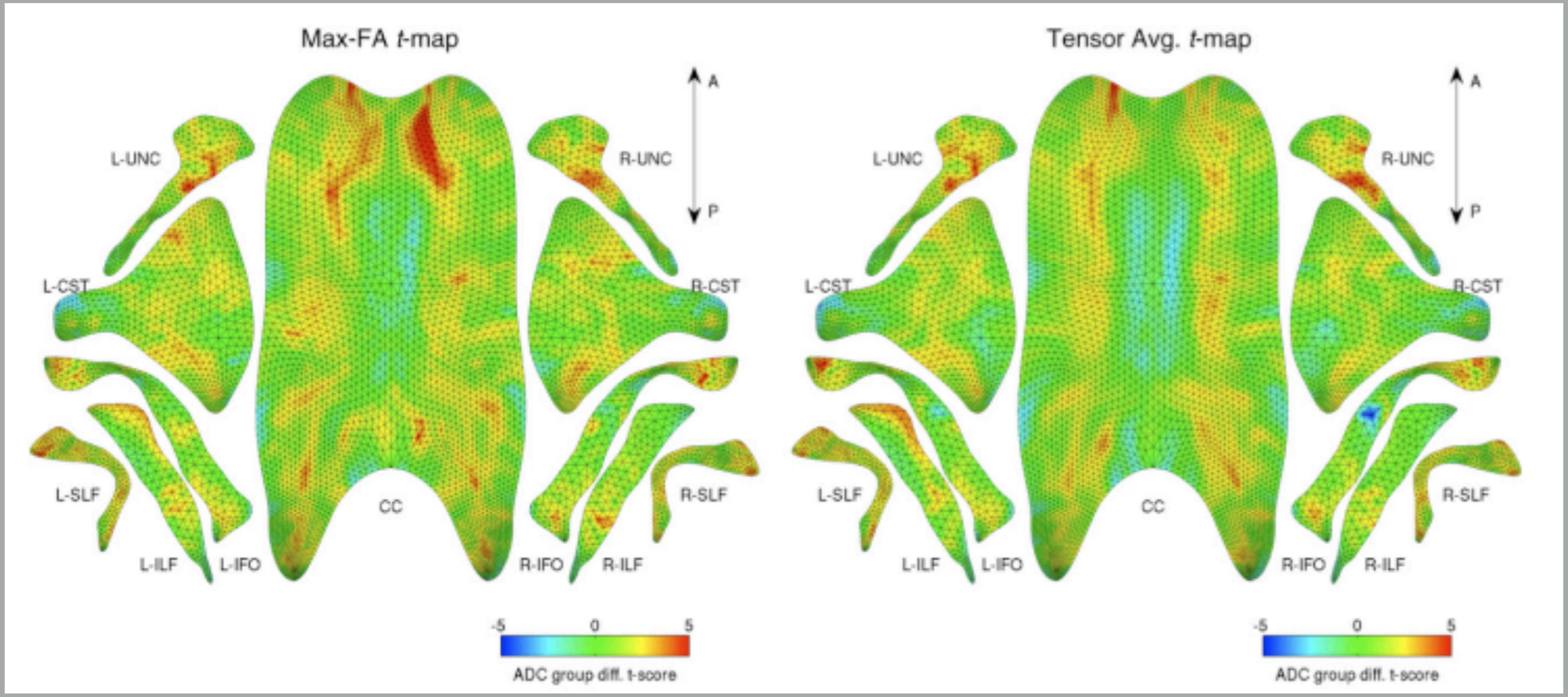
Max FA strategy

Tensor averaging strategy

Color represents t-score for hypothesis ADC(control)>ADC(abnormal)

Yushkevich, et. al., Neuroimage 41,448:2008

SSSM: Statistical Analysis of ADC



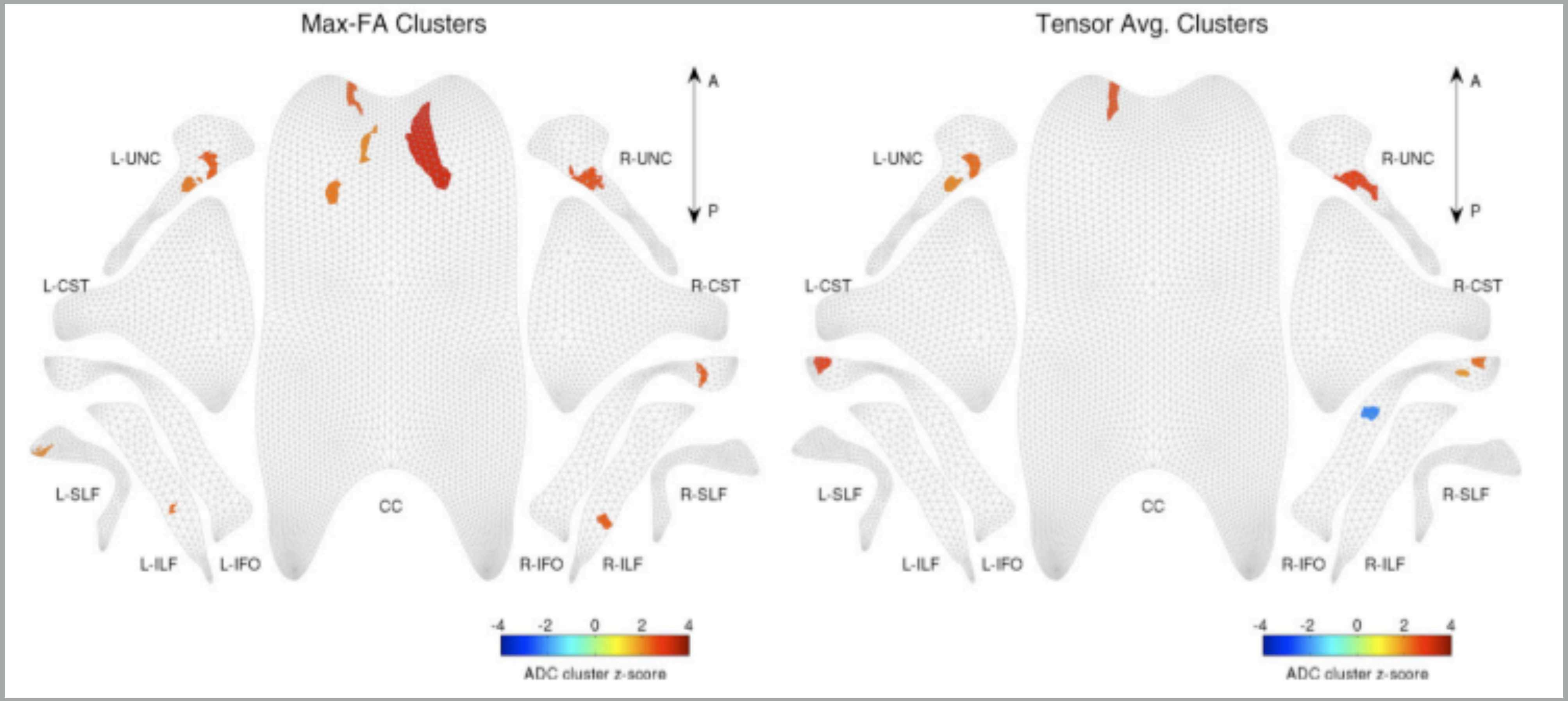
Max FA strategy

Tensor averaging strategy

Color represents t-score for hypothesis ADC(control)>ADC(abnormal)

Yushkevich, et. al., Neuroimage 41,448:2008

SSSM: Statistical Analysis of ADC



Max FA strategy Tensor averaging strategy

Color represents t-score for hypothesis ADC(control)>ADC(abnormal)

Thresholded at t+- 3.4

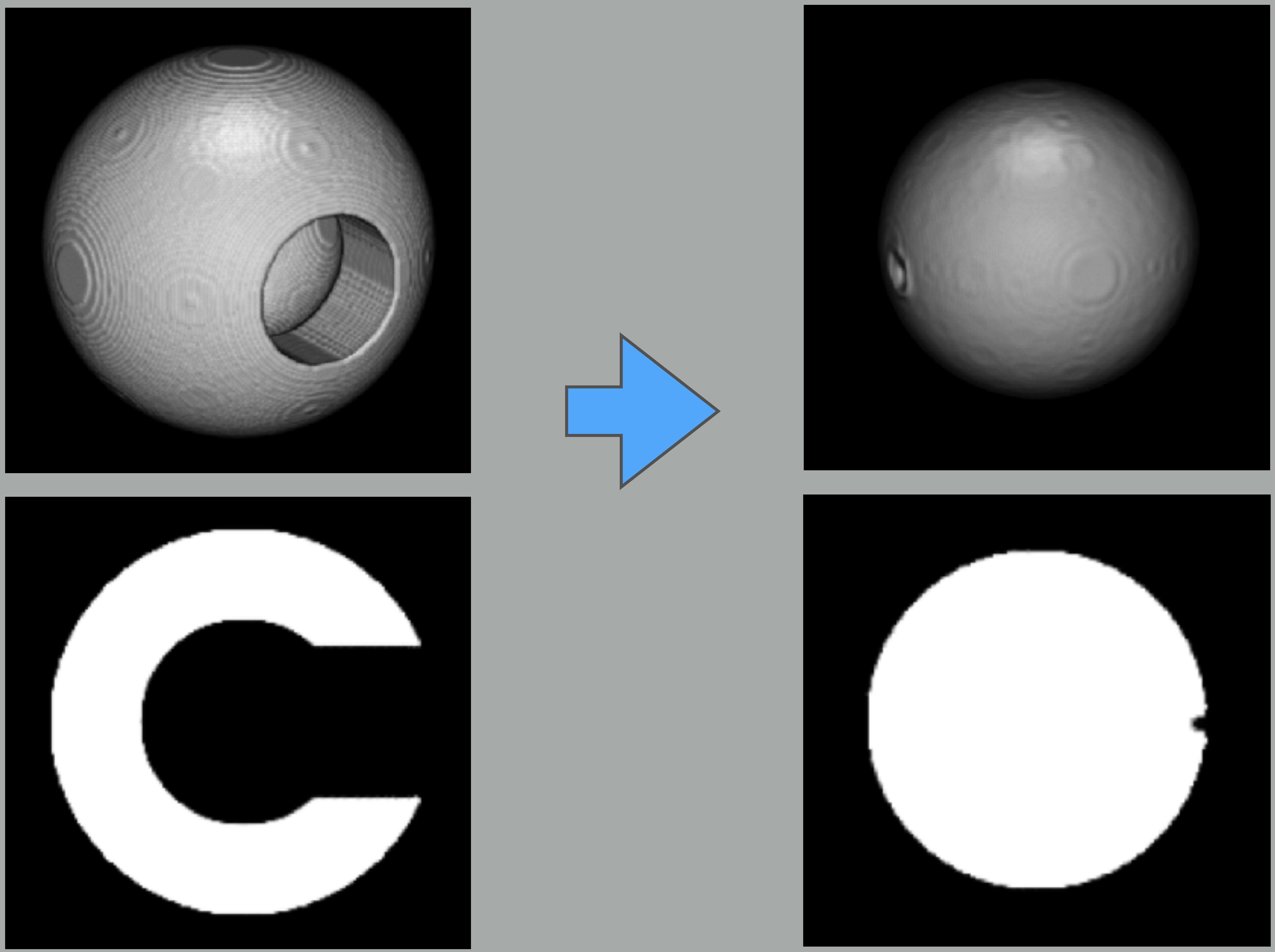
Yushkevich, et. al., Neuroimage 41,448:2008

Fast and Accurate Registration of multi-modality Neuro-MRI data

New Method:
Symplectomorphic Registration (Sym-Reg)

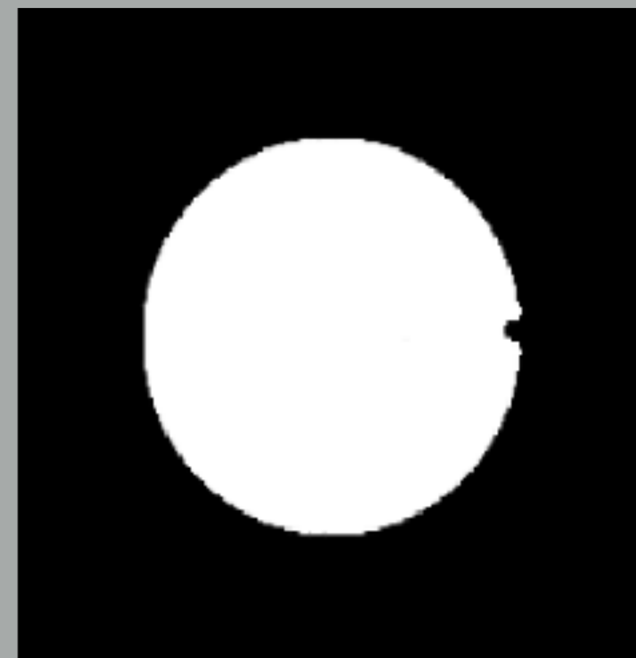
Galinsky and Frank, *NI TMI* 2016 (submitted)

Standard Warping Tools



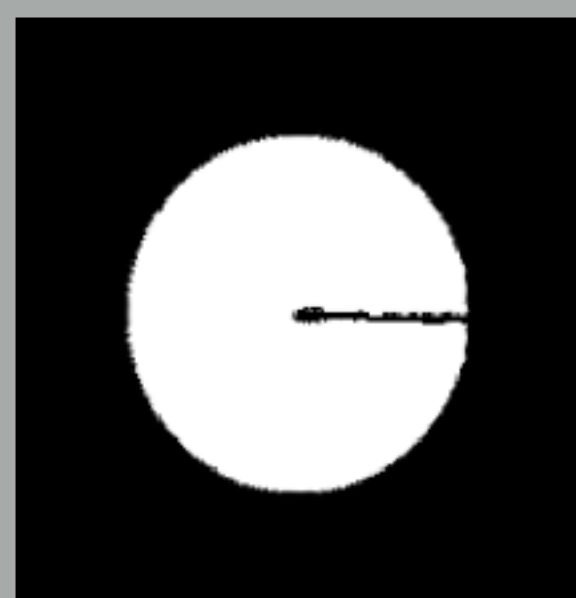
Standard Warping Tools

Ideal Result



Warping Results (slow and failed)

Ants 1
10 min

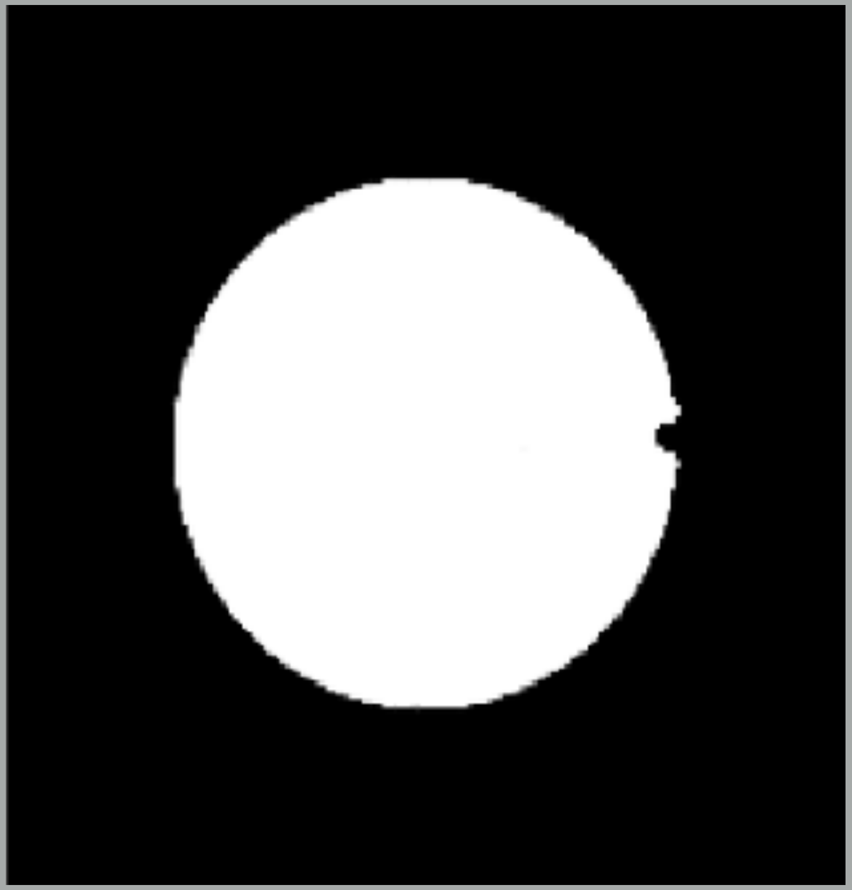


Ants 2
1 hr 20 min

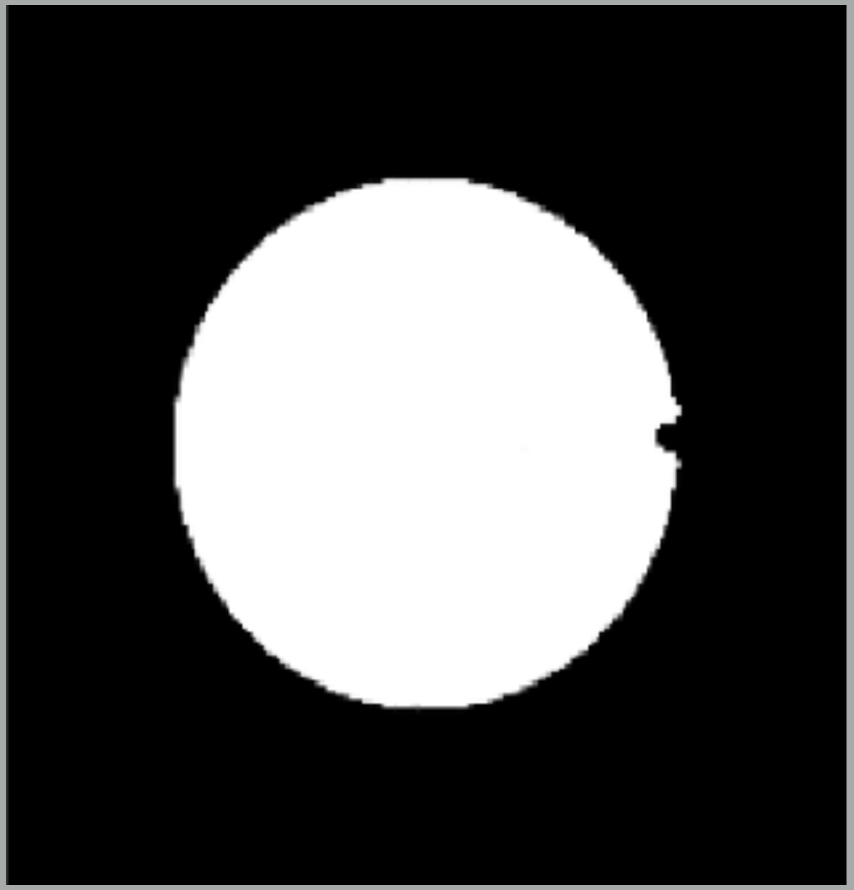
FSL
12 min

AFNI
45 min

Sym-Reg

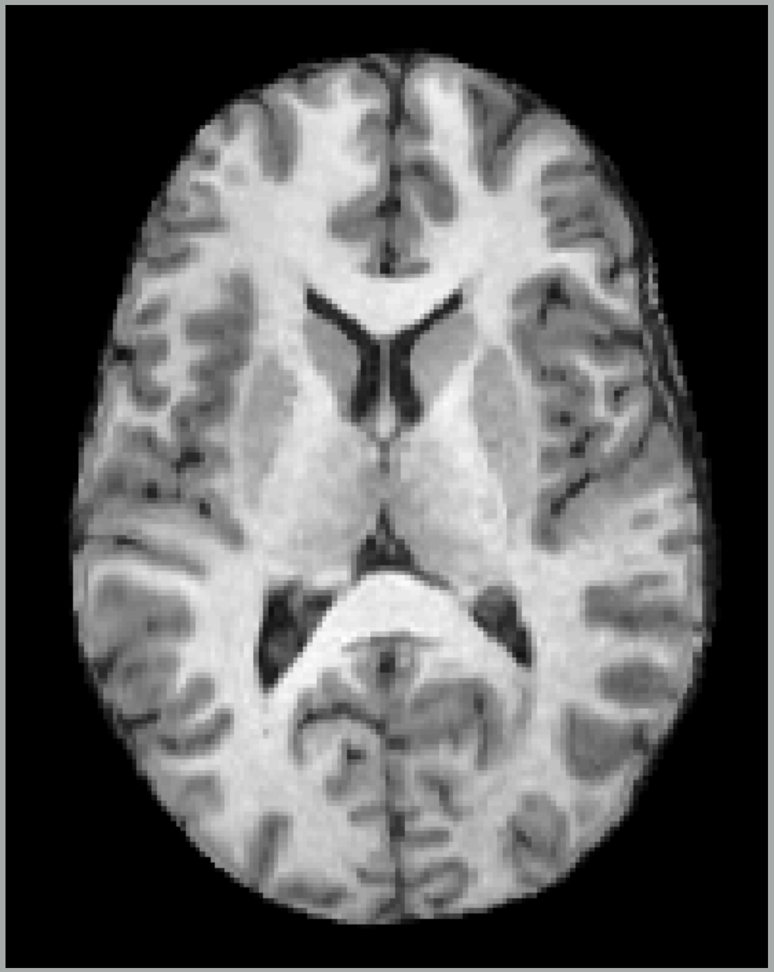


Actual object



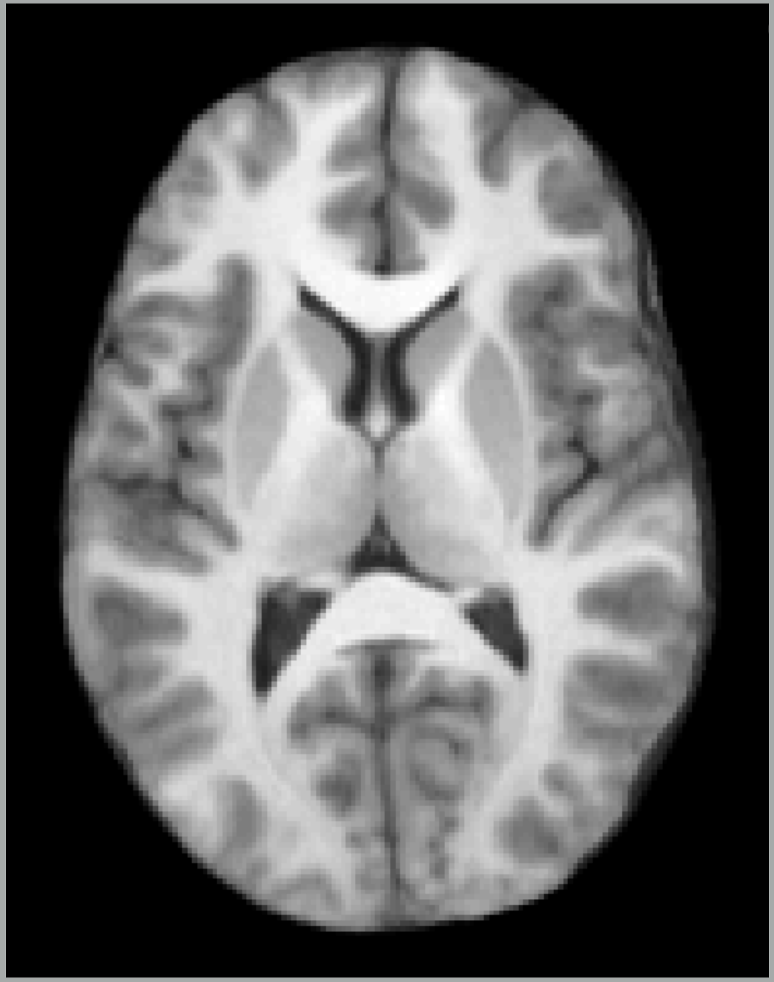
Sym-Reg
38 sec

Sym-Reg Anatomical Registration



Reference

average of 10



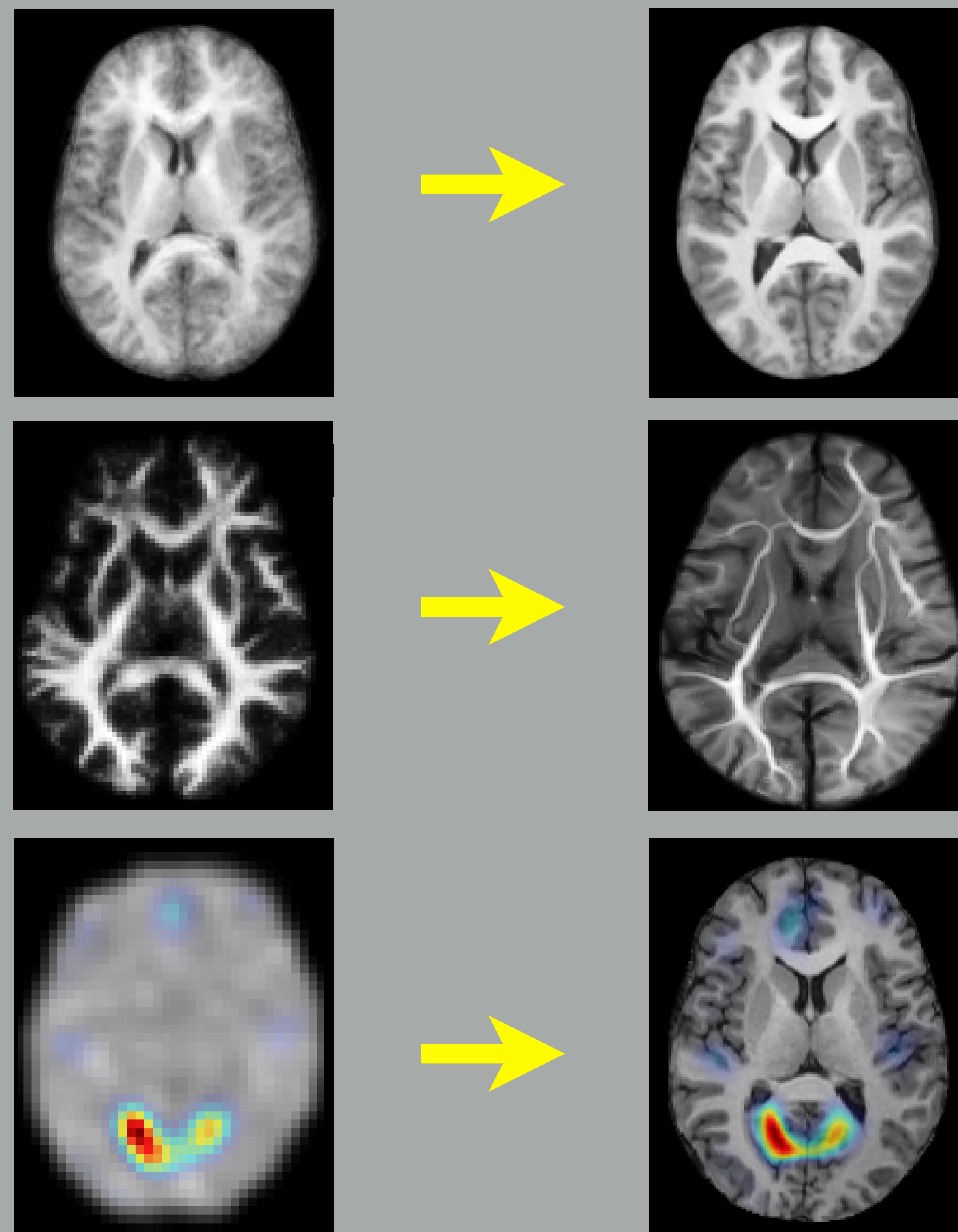
Registered Average

Symplectomorphic Registration with ESP

Anatomical
(average of 10)

DTI
(anisotropy)

FMRI
(EFD mode power)



Galinsky and Frank (*in review*)