Inter-subject Image Registration

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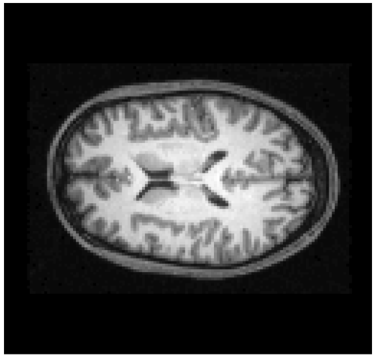
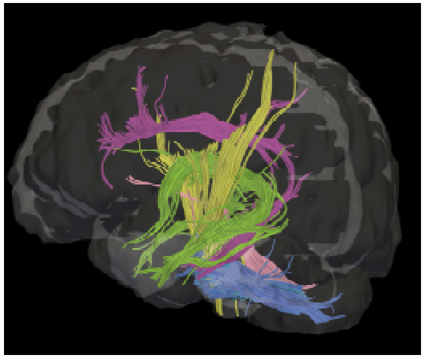
Image Registration

- Image: 2,3,4 D function of spatial variables
- Registration: Spatial alignment
- Goal: Point-wise *correspondence*
- Modality: MRI, fMRI, DTI, US, CT, X-ray

Images from Ben Singer (CSBMB, Princeton) and Lauren O'Donnell (BWH, Harvard)

Inter-subject Image Registration

- Goal: Compare and/or fuse information from multiple subjects
- Scenes are slightly different
- Sophisticated warp models (Nonlinear)

Rigid $\longrightarrow$ Affine $\longrightarrow$ B-splines $\longrightarrow$ Dense

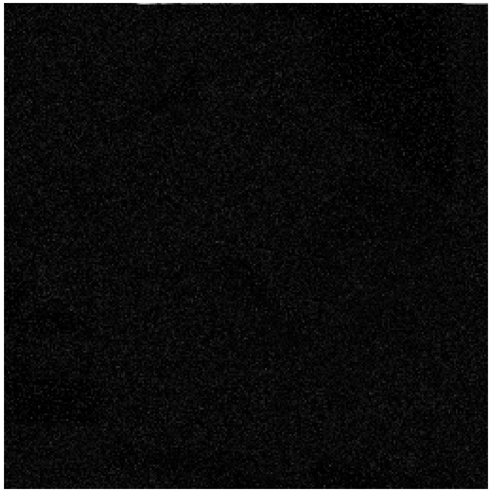
- Applications: surgery planning, disease monitoring, brain mapping, morphometry

Typical Registration Algorithm

- Warp space: e.g. rotate around image center
- Alignment measure: e.g. mean absolute difference
- Optimization: e.g. exhaustive search

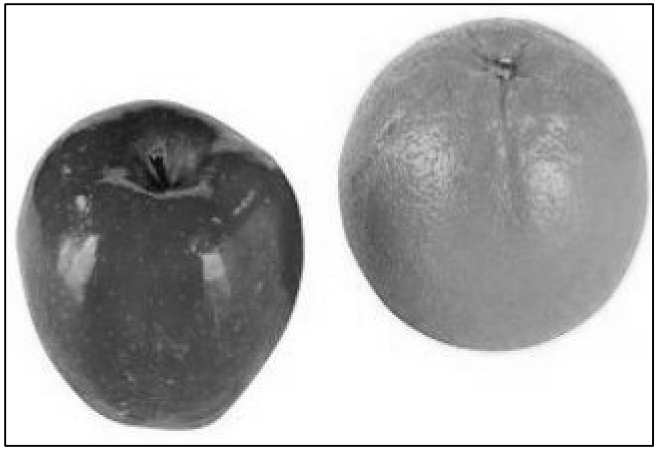
Fixed Image

Floating Image



Absolute Difference

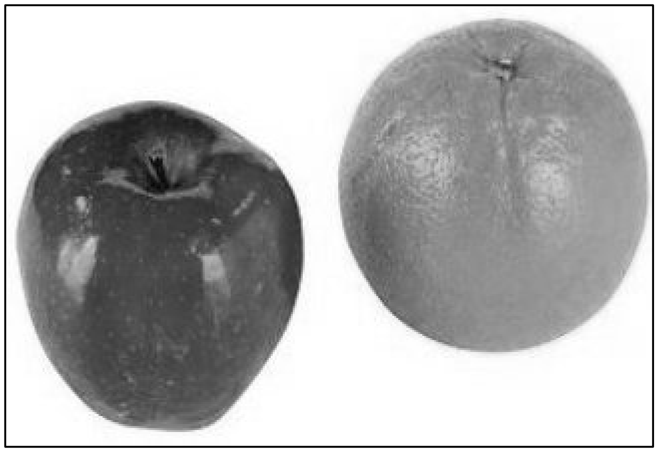
Toy example: apple and orange



Original Picture

Flipped Picture

Apple and orange registered



Original Picture

Flipped Picture

"Level-set Entropy as a fast and simple alignment measure," Sabuncu and Ramadge, *submitted to* ICIP'07

You can't compare apples and oranges

- Correspondence depends on context
- Typical alignment measures use local image features, e.g. pixel intensities
- Warp models should be motivated by application
- Warps are typically very (!) high dimensional
- Optimizer usually guarantees local convergence
- Registration is a tool
- Keep in mind the real question !

Three Applications

- Functional registration of the cerebral cortex
- DTI-tract based inter-subject registration
- Atlas-based parcellation of the cerebral cortex

- Current and future work

Functional Registration of the Human Cerebral Cortex

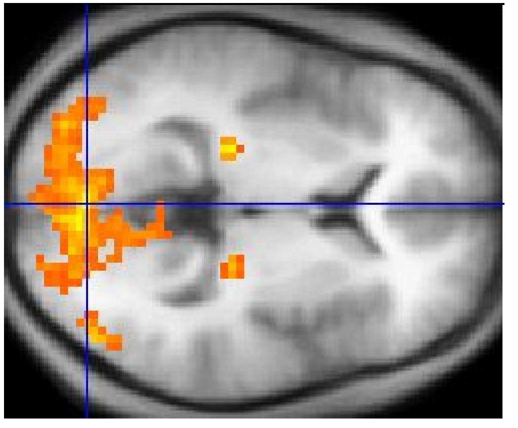
- Cerebral Cortex: 2-4 mm thick sheet of tissue - outer portion of the brain.
- Convoluted: gyri and sulci
- Responsible for many brain functions inc. memory, attention, perceptual awareness, etc.

http://www.toosmarttostart.samhsa.gov/InteractiveBody/html/cerebral.htm

"Function-based inter-subject alignment of cortical anatomy," M Sabuncu, Singer B, Bryan R, Ramadge P and Haxby J

MRI

- Structural MRI: Displays tissues, e.g. gray, white matter and CSF.
- Functional MRI: Displays neural activity. Typically of 3mm spatial resolution and 2-4 sec. temporal resolution.



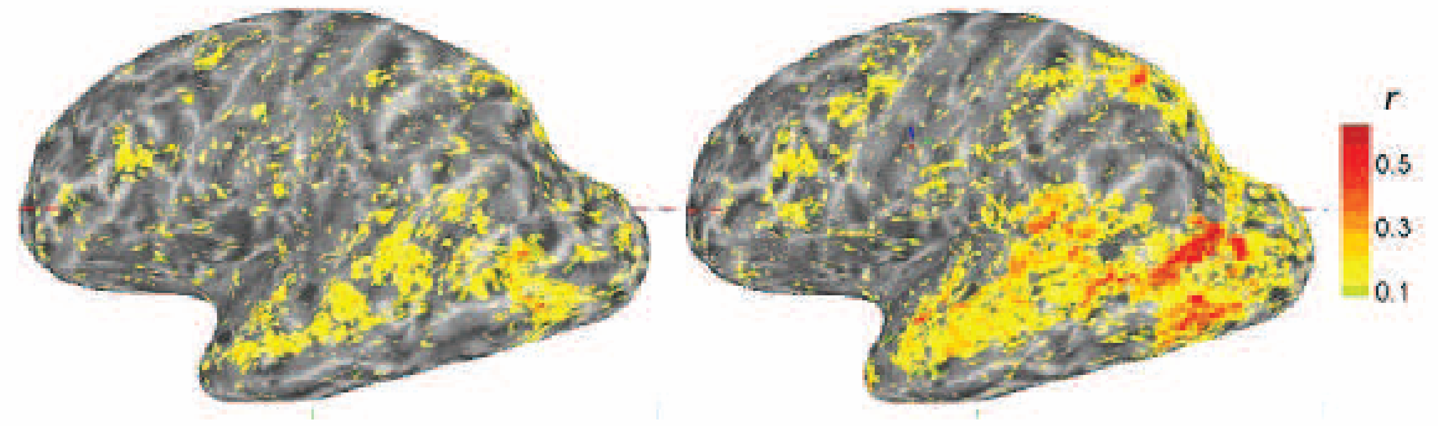
Images from http://en.wikipedia.org/wiki/MRI

Motivation

- A method to determine inter-subject *functional correspondence* based on MRI.
- The “Movie” experiment (Hasson et al. *Science* 2004)

Inter-subject correlations

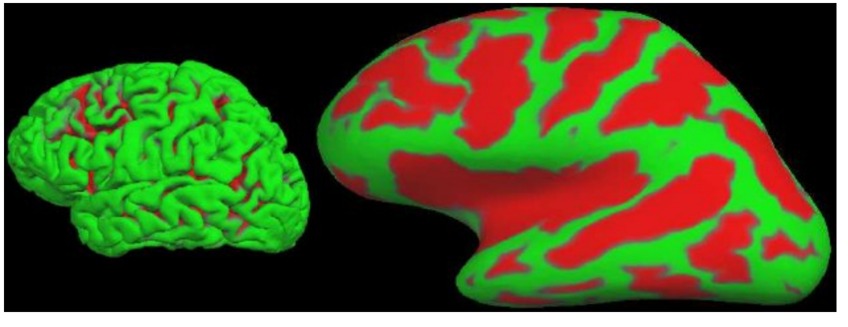
Anatomical correspondence   Functional correspondence



Method: Pre-processing

Tools from AFNI and FreeSurfer to:

- Extract and triangulate inner and outer boundaries of the cortex based on sMRI.
- Inflate to smooth these surfaces.
- Universal representation on a sphere.
- Non-linear anatomical registration on sphere.
- Uniform re-sampling of mesh.

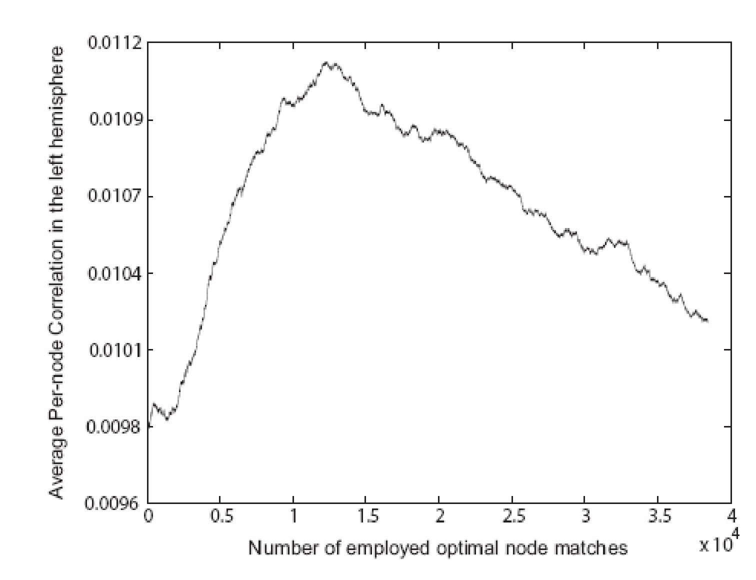


Method: Correlation as an Alignment Measure

- With fMRI, at each mesh node we have long time-series, $Y(x,t)$.
- The inter-subject correlation between these time-series measures linear dependency.
- GLM: $Y = X b + \varepsilon$
- So, we're assuming: functionally equivalent point: $b_1 = a\, b_2$

Method: Regularizing the warp

- W/o regularization, risk of *overfitting*.



- Mildest form of regularization: *invertibility*.

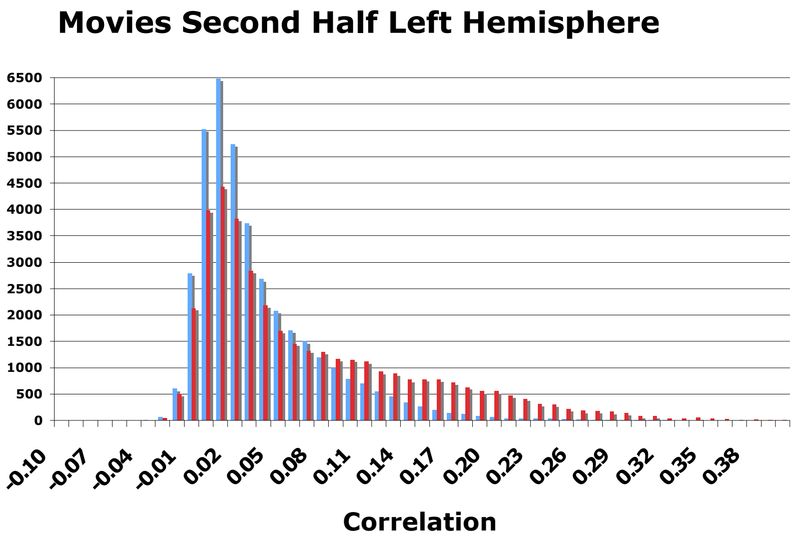
Implementation

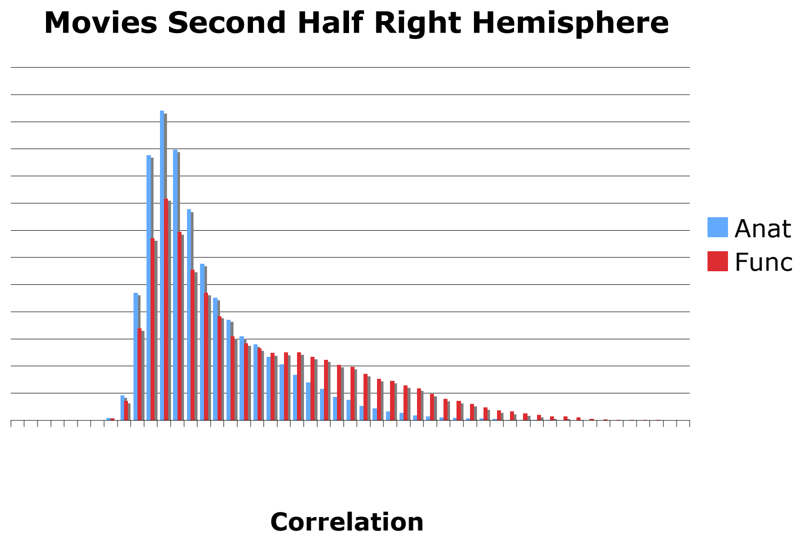
- Iterative gradient-ascent to maximize a functional:

  Total Correlation – λ Warp Penalty
- To initialize:
  - Raw warp field from exhaustive search within a 3 cm radius from anatomical correspondence. Use nodes with a correlation higher than a threshold (0.3).
  - Smooth raw field w/ a Gaussian.

Empirical Results

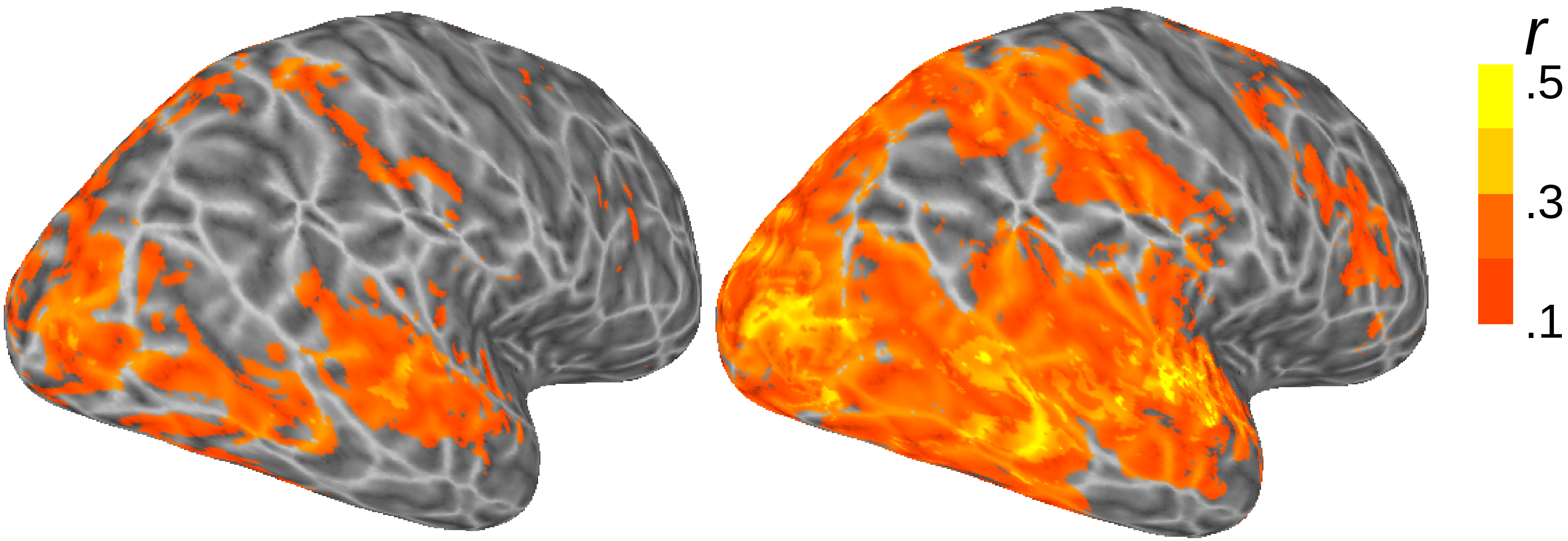
- Functionally register based on first half of movie experiment. Test on second half of movie.





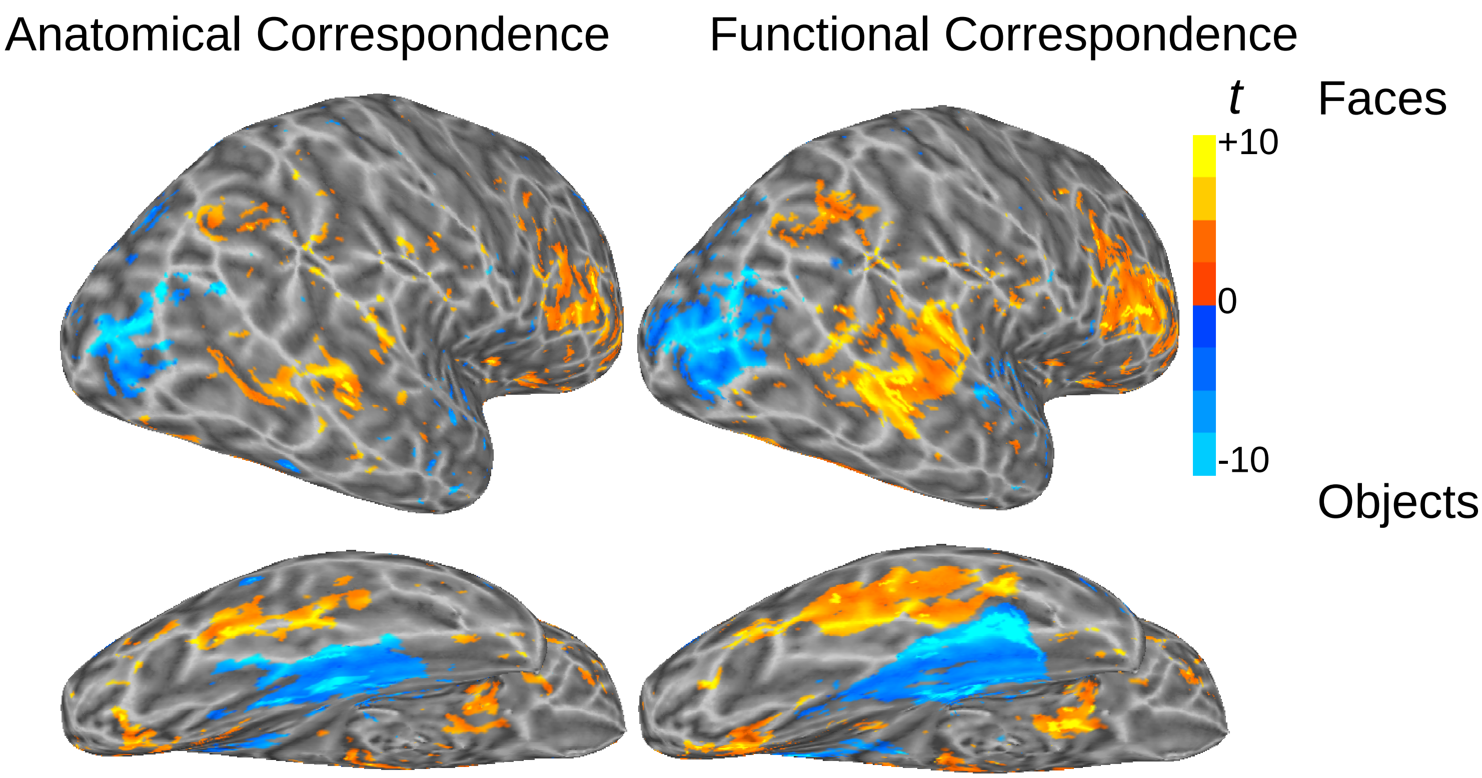
Empirical Results (cont'd)

Correlations on the brain



Generalization to a Visual Category Experiment

GLM Results on 7 subjects

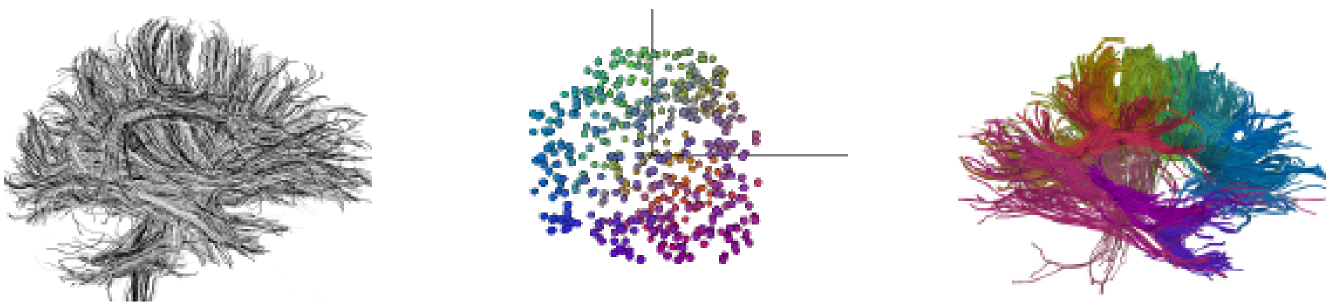


Discussion

- Promising results that support the plausibility to perform functional registration based on fMRI
- Further experimentation required for validation
- Other approaches should be tested
- The effect of functional normalization should be tested in different analyses, e.g. MVPA

DTI-tract based Registration

- DTI measures water diffusion
- Tractography aims at reconstructing white matter tracts
  - Our resolution is too low to identify individual axons
  - Tractography bundles similar to white matter tracts
- Using atlas-based "clustering" we can identify these bundles (O'Donnell, MIT PhD Thesis, 2006)



Whole-Brain Tractography ⇒ Spectral Embedding (Single Subject or Multiple Subject) ⇒ Selected Clusters

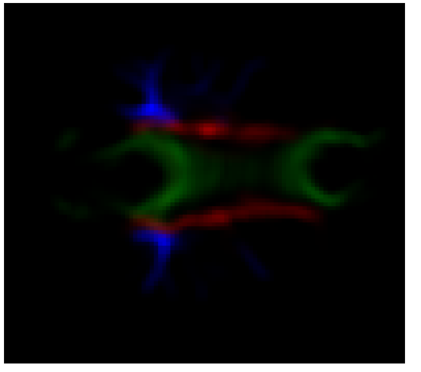
DTI-tract based Registration

- Goal: Perform group studies on DTI-tracts.
- Requires correspondence between tracts.
- Tract-based registration is not well-studied.
  - Leemans et al. 2006
- Problem: Too many tracts. Too noisy data.

Our Approach

- We define the spatial distribution of bundles:

$$P_{b_i}(\boldsymbol{x}) = \frac{1}{Z} \sum_{t_j \in b_i} \sum_{\boldsymbol{x}_k \in t_j} \kappa(\boldsymbol{x} - \boldsymbol{x}_k)$$



Red: Corona Radiata

Green: Corpus Collosum

Blue: Arcuate

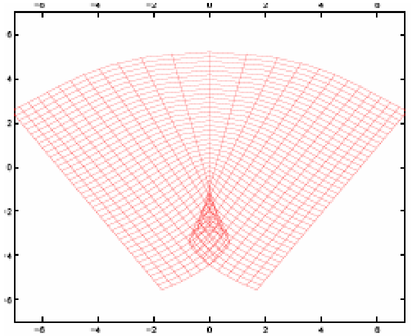
- Discretize to a voxel-based image – can use existing methods to register medical data
- Find affine registration for each bundle, e.g. by maximizing correlation

"Fiber bundle-based nonlinear registration of diffusion MR images," U Ziyan, Sabuncu M, O'Donnell L, Westin C-F, *submitted.*

Polyaffine Framework

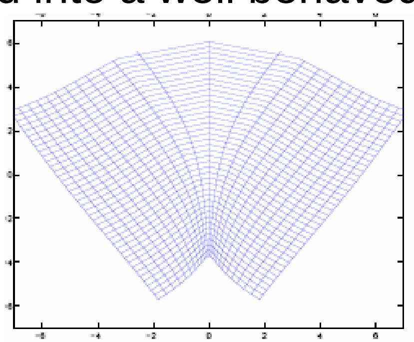
(Arsigny et al. 2006)

- We have a set of affine parameters **A(x)** along with a spatial distribution of each structure. How do we fuse them into one well behaved warp field?
- Obvious Solution: A weighted summation of the affine transformations:



$$\Phi(\boldsymbol{x}) = \sum_i w_i(\boldsymbol{x}) \boldsymbol{A}_i(\boldsymbol{x})$$

- A weighted summation of the speed vectors lead into a well behaved transformation:



$$\frac{d}{dt}\boldsymbol{x}(t) = \sum_{i=1}^{S} w_i(\boldsymbol{x}(t)) \log(\boldsymbol{A}_i)(\boldsymbol{x}(t))$$

with $\boldsymbol{x}(0) = \boldsymbol{x}_0$

$\log(\boldsymbol{A}_i) \in \mathbb{R}^{4\times 4}$ is the principal logarithm of $\boldsymbol{A}_i$

$\Phi(\boldsymbol{x}_0) = \boldsymbol{x}(1)$

Tensor Rotation

- The Diffusion Tensor (D) Field needs to be reoriented after a warp:
  - $D' = R^T D R$, where R is the rotational component of the warp.
  - The rotational component is usually not readily available for a non-linear transformation
  - R can be estimated from the **Jacobian**

$$\boldsymbol{R} = (\boldsymbol{J}\boldsymbol{J}^T)^{-1/2}\boldsymbol{J}$$

- We showed: the **Jacobian** of the polyaffine can be calculated analytically

Quantification (FiT measure)

- We want to quantify how well the transformed tracts fit to the DTI data of the other subject
  - Or, equivalently the fit of transformed DTI data to the tracts of the other subject
- ODF is defined as:

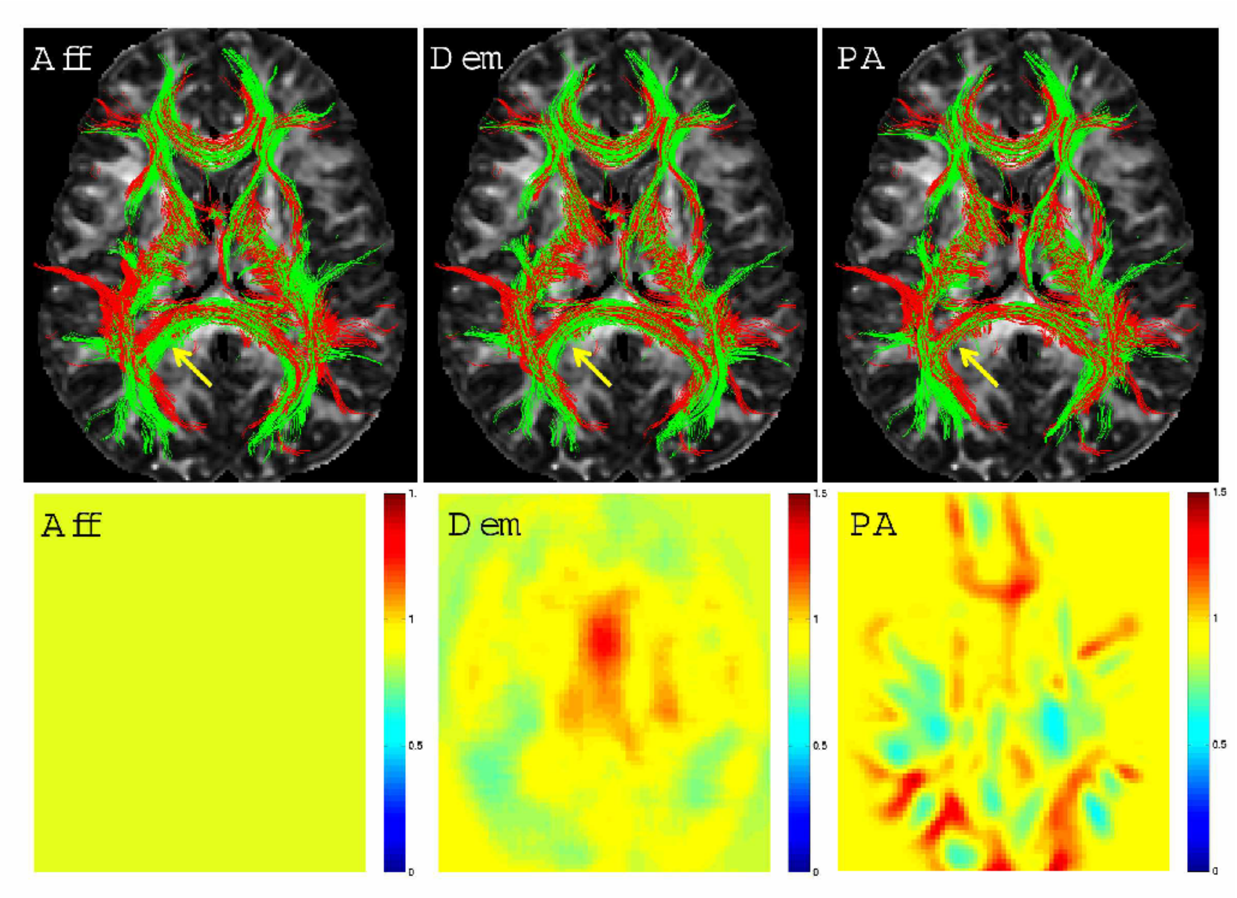
$$\psi(\boldsymbol{u}) = \int_0^\infty p(\boldsymbol{u}r)dr$$

$$\psi(\boldsymbol{u}(\boldsymbol{x})) = \frac{1}{\sqrt{(4\pi)^2|\boldsymbol{D}(\boldsymbol{x})|}} \frac{1}{\sqrt{\boldsymbol{u}(\boldsymbol{x})^T \boldsymbol{D}^{-1}(\boldsymbol{x})\boldsymbol{u}(\boldsymbol{x})}}$$

- We define FiT:

$$\varphi(t_i; \boldsymbol{D}) = -(\sum_{\boldsymbol{x}\in t_i} \log(\boldsymbol{t}_i(\boldsymbol{x})^T \boldsymbol{D}^{-1}(\boldsymbol{x})\boldsymbol{t}_i(\boldsymbol{x})) + \log(\lambda_1(\boldsymbol{x})))$$

Results

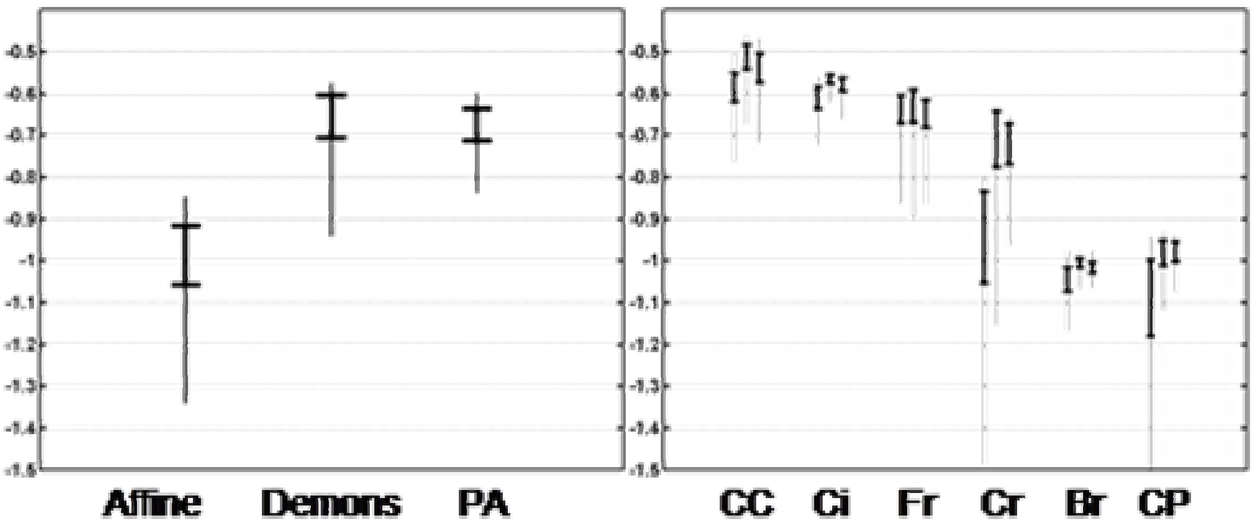


Aff: Global affine registration on FA volumes

Dem: The “Demons Algorithm” on FA volumes (Park et al. NeuroImage 2003)

PA: Proposed Algorithm

Results: FiT values



CC: Corpus Collosum

Ci: Cingulum

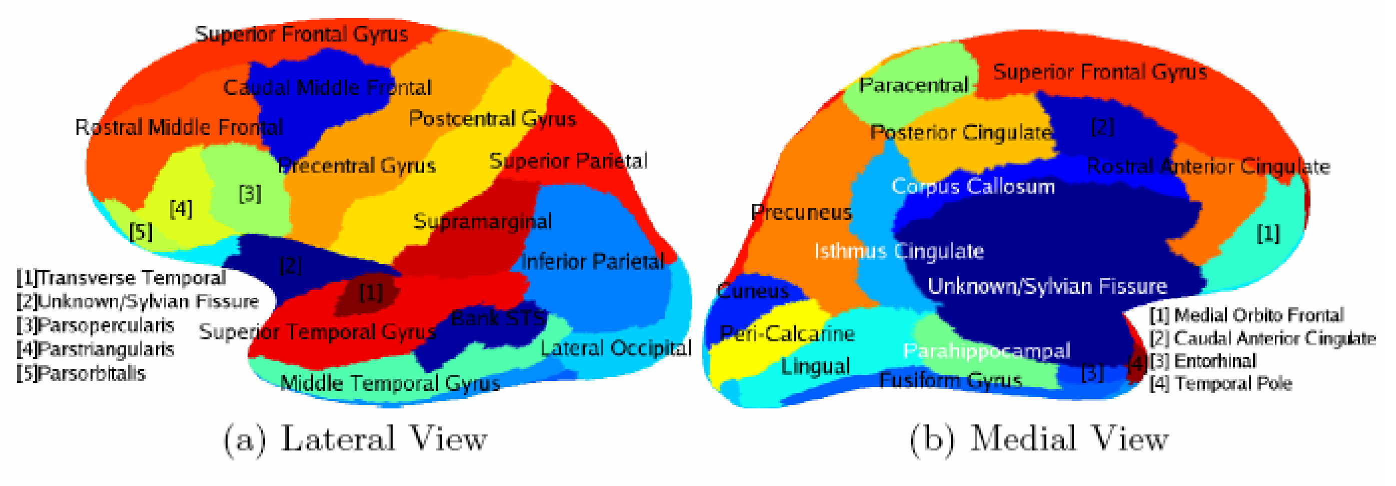
Fr: Fornix

CR: Corona Radiata

Br: Brainstem

CP: Cerebellar Peduncle

Parcellation of the Cerebral Cortex



"Effects of Registration Regularization and Atlas Sharpness on Segmentation Accuracy," T Yeo, Sabuncu M, Fischl B, and Golland P. *submitted*

Approach

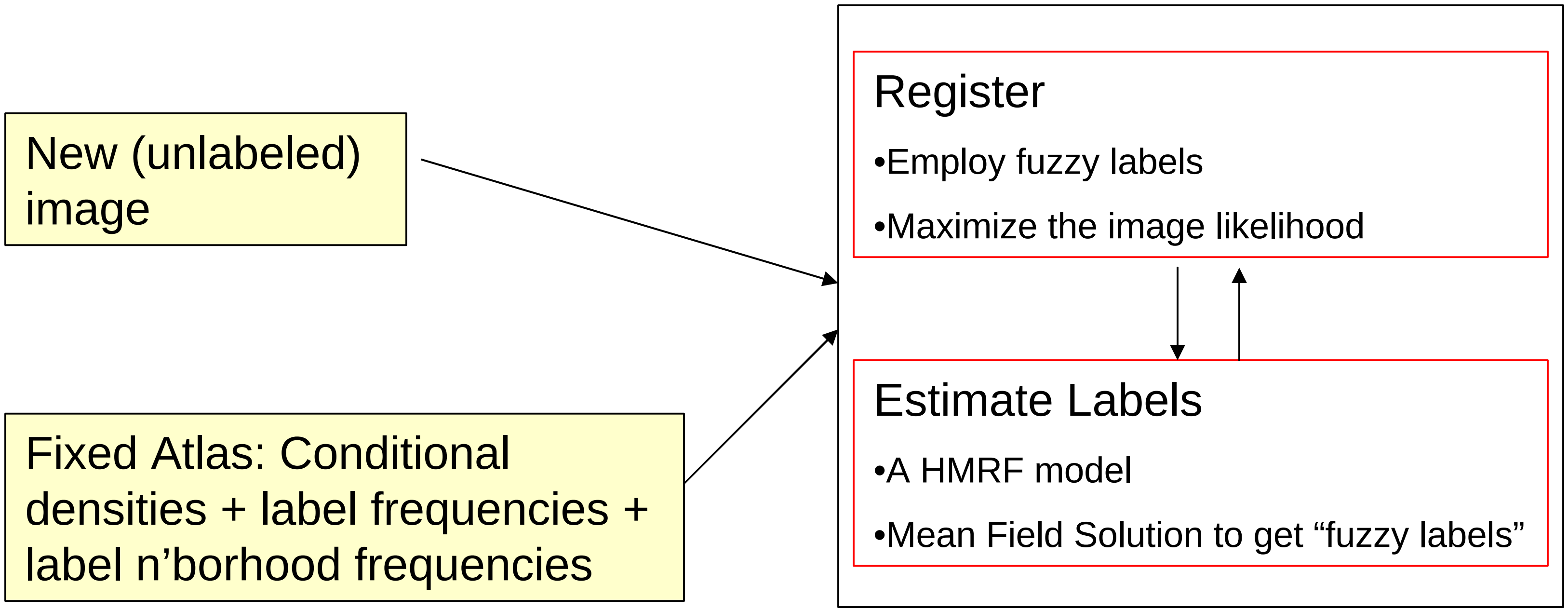
- Build an atlas from manually labeled data sets.
  - Jointly register the images. How? Using labels? Image features? Or both?
  - How much warp should be allowed? A sharp atlas or a blurry atlas?
- Register a new image to the atlas AND infer the labels.

Joint registration and segmentation

- Atlas-based segmentation quality is determined by registration quality.
- Registration quality can be improved if we had the labels.
- So, do registration and segmentation together. (iteratively, using EM)

  (Extended the ideas of Killian et al. 2006)

An EM Algorithm



Building an atlas

Manually labeled images

"Rigidly" co-register (FreeSurfer)

Compute "rigid" atlas:

- Count labels at each location
- Count label neighborhood instances
- Compute conditional means and variances

N Iterations

- Initialize Atlas from previous iteration
- Decrease Warp constraint

Manually labeled images

- Employ manual labels
- Maximize the image likelihood

Register

Atlas

Update Atlas

Stack of Atlases (Multi-scale Atlas)

Fuzzy Atlas:

•Manual labels are not lined up perfectly

•Conditional distributions are fat

→

Sharp Atlas:

•Manual labels are lined up.

•Conditional distributions are tight

Built with a highly constrained warp

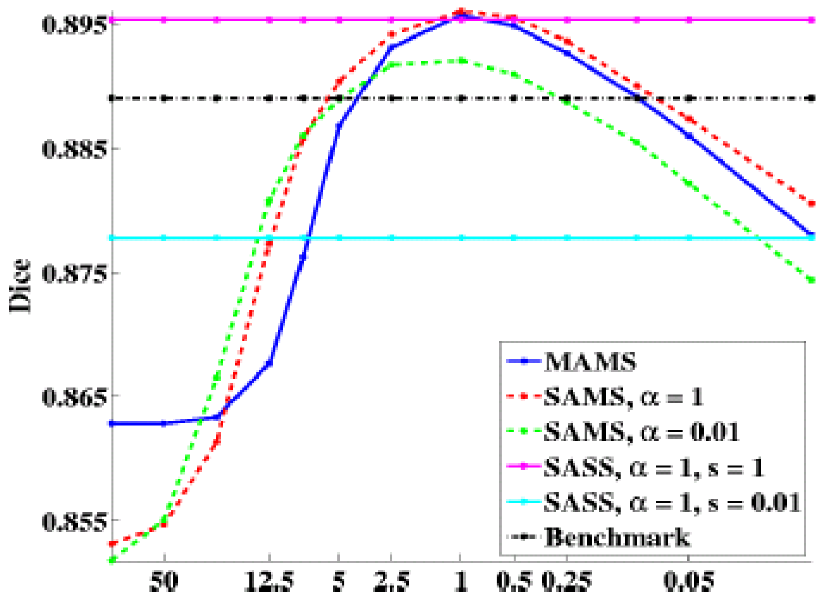
Built with a highly non-linear warp

Three Implementations

- SASS: Single Atlas scale, Single warp Scale
- SAMS: Single Atlas scale, multiple warp Scales
- MAMS: Multiple Atlas scales, Multiple warp Scales

Results

Quality of Segmentation vs. Function of Warp Scale



Conclusion

- Joint registration segmentation improves segmentation accuracy.
- In this context, optimal MAMS, SAMS and SASS have similar performance
- Picking the optimal warp scale is important

Other Work

- Joint registration and segmentation in the volume
  - Warp definition using poly-affine on structure-specific affines
  - PCA on the warp space
  - Morphometry on the warp space
- Extend the idea of multiple atlases
- Functional Registration