Quantitative Neuro-Anatomic and Functional Image Assessment

Recent progress on image registration and its applications

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Applications of image registration in neuroimaging

- Atlas construction
  - Probabilistic atlases
  - Statistical atlases
  - Unbiased atlases

- Atlas-based segmentation
  - Atlases are used as prior knowledge
  - Tissue and/or anatomical segmentation

- Quantification of anatomical and functional differences
  - across time ⇒ longitudinal studies
  - across groups ⇒ cross-sectional studies
Motivation: A Natural Question

- Given a collection of Anatomical Images what is the Image of the “Average Anatomy”.

Courtesy S. Joshi
Population Variability

• How to compare and measure structures across different subjects?
Average after linear alignment (affine)

Adult brain MRI atlas (Montreal Neurological Institute):
- 152 adult subjects
- Affine registration
- Superposition
- Serves as probabilistic template for brain mapping
- Blurry, does not look like a real image
Motivation: A Natural Question

Consider two simple images of circles:

What is the Average?
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Average considering “Geometric Structure”

A circle with “average radius”

Courtesy S. Joshi
Mathematical Foundations of Computational Anatomy

• Structural variation with in a population represented by transformation groups:
  – For circles simple multiplicative group of positive reals ($\mathbb{R}^+$)
  – Scale and Orientation: Finite dimensional Lie Groups such as Rotations, Similarity and Affine Transforms.
  – High dimensional anatomical structural variation: Infinite dimensional Group of Diffeomorphisms.
Unbiased Diffeomorphic Atlas Construction for Computational Anatomy (Joshi, Davis, Lorenzen)
Atlas Formation: Symmetric Registration

\[ g = h_1 \circ h_2^{-1} \]
\[ f = h_2 \circ h_1^{-1} \]

Symmetric Registration Framework

\[ f \circ g = h_2 \circ h_1^{-1} \circ h_1 \circ h_2^{-1} = \text{Id} \]
Averaging Anatomies

Motivation:
- Map population into common coordinate space
- Learn about normal variability
- Describe difference from normal
- Use as normative atlas for segmentation

Figure 1. Template Construction Framework

Group-wise Atlas Building

Minimize total distance between population and template
(Gee & Avants, Joshi & Fletcher)
More than Pairs: Sample of 16 Bull’s eye Images

Courtesy S. Joshi
Group-wise Image Averaging

Courtesy S. Joshi
Averaging of 16 Bull’s eye images

Numerical geometric average of the radii of the individual circles forming the bulls eye sample.

Courtesy S. Joshi
Averages in Metric Spaces

- Recall the linear average:
  \[ \mu = \frac{1}{N} \sum_{i=1}^{N} x_i \]

- The space of diffeomorphisms is not a vector space

- Need a more general notion of "average"

- Frechet mean:
  \[ \mu = \text{argmin}_{x \in \mathcal{M}} \sum_{i=1}^{N} d(x, x_i)^2 \]
Large deformation diffeomorphisms.

- $\text{Diff}(\Omega)$ infinite dimensional “Lie Group”.
- Tangent space: The space of smooth vector valued velocity fields on $\Omega$.
- Construct deformations by integrating flows of velocity fields.
- Induce a metric via a differential norm on velocity fields.

\[
\frac{d}{dt} h(x, t) = v(h(x, t), t) \quad h(x, 0) = x.
\]
Atlas Building – Population Average (Infant 2 yr)
Atlas Builder – Atlas with 14 images
Averaging Brain Images
• Brain atlases is central to the understanding of the variability of brain anatomy.
• How to study statistical shape properties from nonlinear deformation fields of atlases?
Embedded Objects: Voxel Representation

To evaluate shape variability

• reliable user-supervised voxel segmentations by geodesic snakes

• probability map in atlas space
Voxel-based Representation: Linear vs. Nonlinear Atlas

- Single population
- Linear averaging of voxel objects — blurry probability maps
- Nonlinear average appears sharper
- Notion of probabilistic label atlas: centered & population-based
Atlas-based segmentation: Atlas Building

**Step 1**
- Template image created from several cases

**Step 2**
- Probabilistic maps of the 12 ROIs
Pipeline

Atlas with segmented structures

1. Transformation $T$
   From the atlas to the case i

2. transformation $T$

Case i

- Putamen
- Pallidus
- Amygdala
- Lat
- Ventricle Caudate
- Hippocampus
Segmented ROIs

Axial View

Coronal View

Sagittal View

Segmented case
Without ROIs    With ROIs
Automatic segmentation (N=130)

UNC Chapel Hill pediatric autism study (J. Piven, H. Cody, G. Gerig et al.)
DTI: Population-based analysis of fiber tracts

Example: 150 neonate DTI mapped to unbiased atlas

Casey Goodlett, Sarang Joshi, Sylvain Gouttard, Guido Gerig,
(MICCAI’06, MICCAI’08, NeuroImage 2009)
Atlas Building for DTI Tensor Fields

Atlas

$\hat{I}_1$

[Joshi et al 2004]
[Goodlett et al 2006, 2009]
Backdrop: FA
Color: RGB(e₁)
G. Kindlmann
Unbiased atlas-building by deformable registration

Structural Average Deformation Fields (1:N)

Structural Operator Transformation (Affine, Fluid) H-fields (1:N)

[Goodlett et al. MICCAI 06, ISMRM 06]

[Goodlett et al., NeuroImage, in print]
Co-registration: From linear to nonlinear

Linear registration (affine)  Nonlinear registration (fluid)
Atlas Building: FA of average tensor field

raw  linear  nonlinear
Concept: Group statistics of fiber tracts

Images
Atlas
Atlas Tract
Mapped Tracts
Sampled Functions
Functional Statistics

Goodlett et al., NeuroImage March 2009
Pediatric Example: Genu Tract 1-2yrs

- Working example of 1 year vs. 2 year subjects
- Significance expected
- Discrimination provides interpretation

(b) All FA curves
(c) All norm curves
Towards 4D Atlases: Study of Healthy Aging

Elizabeth Bullitt, UNC

- MRI Aging Study
- 100 volunteers (50 male, 50 female). 20 subjects, equally divided by sex, were imaged by decade (20-29, 30-39, 40-49, 50-59, and 60-72).
- Images (T1 and T2 sequences) 3T MR
- Automatic EM Segmentation (Marcel Prastawa, Gerig)
- Atlas formation (Peter Lorenzen, Sarang Joshi, Brad Davis)

T1 of female subjects, per decade
Manifold Kernel Regression (B. Davis)

- What are we looking for: A weighted Fréchet mean image as a function of age!
- Weights depend on the age
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Aging Brain via Population Shape: Manifold Kernel Regression

- B. Davis, E. Bullitt, (UNC)
- S. Joshi, T. Fletcher (Utah)
- D. Marr Prize, ICCV’07 best paper award
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Conclusions

• Image registration has become one of the most important tools for medical image analysis

• Powerful packages available to the scientific community:
  – RVIEW, ITK, Demons, SPM, AIR, FSL, FreeSurfer, SLICER-3, etc.

• Important issue: Choice of appropriate methodology (linear versus nonlinear, type of nonlinear method, image match metric, cascading of transformations)

• Community needs: Platform for validation and cross-method comparison -> Users can choose most appropriate, best techniques