Non-Rigid Registration and Atlases in Medical Image Analysis

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Non-Rigid Registration in Medical Image Analysis

- Where is Non rigid registration needed in Medical Imaging?
- How do we describe image deformations?
  - Global Parametric Approaches
  - Dense Fields Approaches:
  - 'Physical' Models
  - Large Deformation Models:

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Uses for Non-Rigid Registration

- Correcting/Accounting for Imaging Distortions
  - Scanner Induced Geometric changes
- Correcting Tissue Deformations
  - Subject Related Anatomical Changes
- Capturing Tissue Growth or Loss within a Subject
  - Studying Dementia or Tissue Growth: Deformation Based Morphometry
- Resolving Differences Between Subjects:
  - Spatial Normalization to Compare Image Data Across Populations

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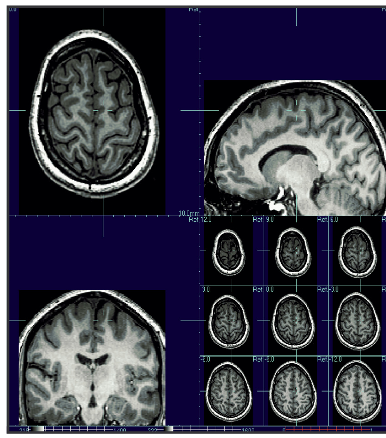

GE 3T Control Subject
Time 1

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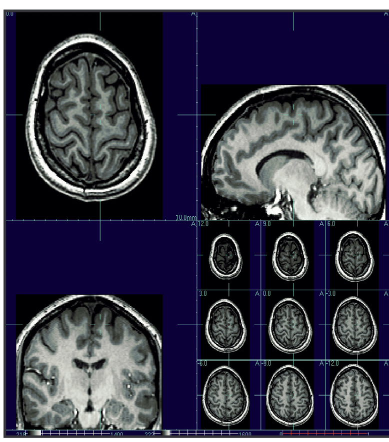

GE 3T Control Subject
Time 2

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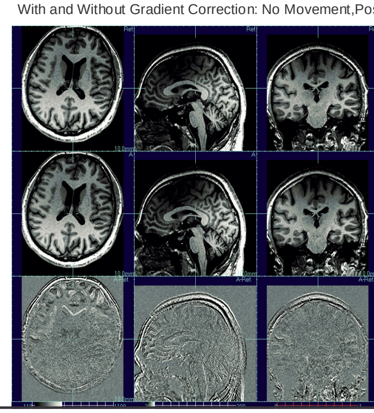
With and Without Gradient Correction: No Movement,Positioned Centrally in Magnet



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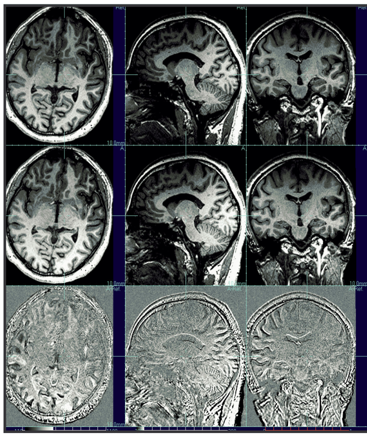
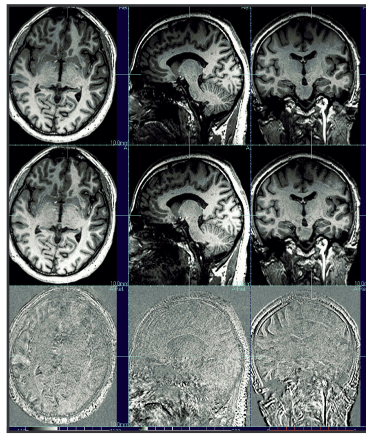
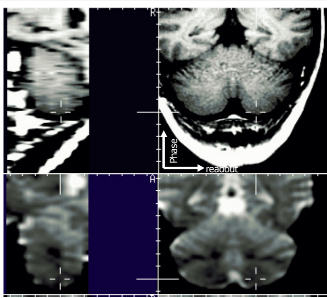


Change in Positioning
(Approx 3.4cm shift along bore
No Gradient Correction



Change in Positioning
(Approx 3.4cm shift along bore
With Gradient Correction
For Both Images
(2D Console Only)

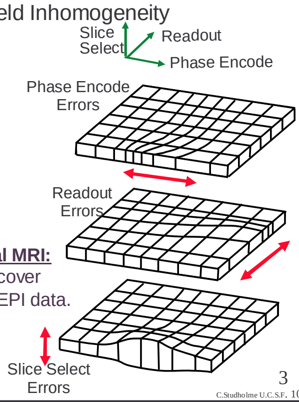
Correction of Larger Scale Geometric and Intensity Distortion



Reference T1
Anatomical MRI

Spin Echo EPI
(Rigid Registration)

Components of Spatial Distortion Induced by Magnetic Field Inhomogeneity

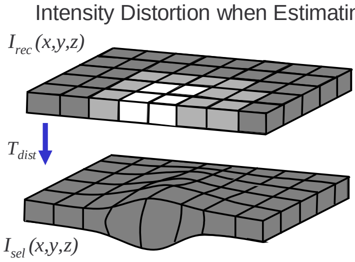


Conventional Spin Echo MRI:
Displacements occur in the readout and slice select axes

In Mapping EPI to Anatomical MRI:
The primary *relative* error to recover is along phase encode axis of EPI data.

3

Using a Model of Spin Echo Signal Conservation and Intensity Distortion when Estimating Registration



Reconstructed
Spin Echo Image with
Intensity Distortion

Distorted Voxel
Selection
Due to Magnetic Field
Inhomogeneity

$$I_{rec}(x,y,z) = I_{sel}(x,y,z)/J_{dist}(x,y,z)$$

So, if we have a spatial registration estimate of EPI to anatomy, we can use its Jacobian to estimate an EPI intensity correction.

C. Studholme, T.C. Constable, J.S. Duncan, Non-Rigid Spin Echo MRI Registration Incorporating an Image Distortion Model: Application to Accurate Alignment of fMRI to Conventional MRI, IEEE Trans. Med. Imaging, Vol 19, No 11, Nov 2000.

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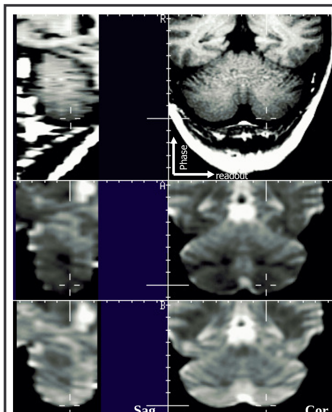
Correction of Larger Scale Geometric and Intensity Distortion



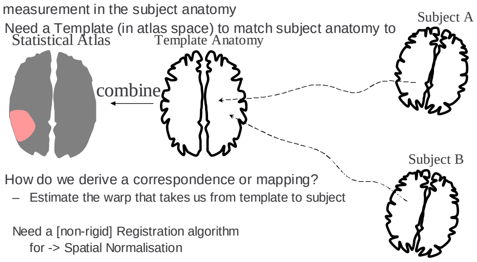
Reference T1
Anatomical MRI

Spin Echo EPI
(Rigid Registration)

Spin Echo EPI
(10mm Spline Estimate)
incorporating Jacobian
Intensity Correction

Spatial Normalisation: Bringing Image data into a Common Coordinate System

- Collecting data from different individual anatomies not trivial
- Need to locate corresponding location in atlas for a given measurement in the subject anatomy
- Need a Template (in atlas space) to match subject anatomy to

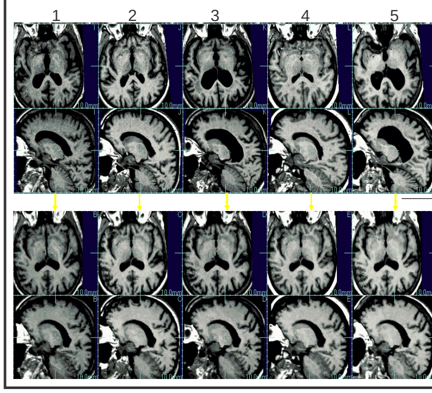


- How do we derive a correspondence or mapping?
  - Estimate the warp that takes us from template to subject

Need a [non-rigid] Registration algorithm for -> Spatial Normalisation

Example Group Spatial Normalization

(Studholme et al, proc. SPIE medical imaging 2001)

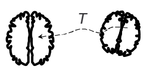


Global Normalized Mutual Information driven B-Spline Spatial Normalisation of Brain Anatomy

Compare Transformations

Non Rigid Registration

- Components of a non-rigid registration algorithm
  - Model or parameterization of the Transformation *T*
    - What structural differences we can resolve
  - Registration (similarity) measure $S(T)$
    - provide an absolute or relative measure of the quality of match
  - [Geometric Constraints] $C(T)$
    - prevent unwanted or physically meaningless deformations



so... need to vary *T* to find Optimum (here maximum) value for

$$F=S(T)-\alpha C(T)$$

  - Optimization Method
    - Continuous refinement of many parameters
    - Often high dimensional search space
    - Constrained by corresponding spatial structures

Image Warping: How to model deformations between Images?

Mathematical Models for Spatial Transformations of Image Data

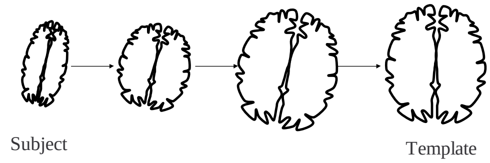
- Global Affine
- Non-Linear Global Parameterizations
- Spatially Local Parameterizations
- Dense Field Techniques

Deformation Models For Non-Rigid Registration

- Simplest Methods:
  - Use Global Linear or Affine model
  - Describing only global
    - Translations, Rotations,
    - Scaling and Skew

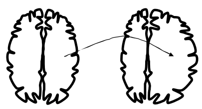
$$x' = a*x+t$$

$$\begin{pmatrix} x' \\ y' \\ z' \\ 1 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & tx \\ a_{21} & a_{22} & a_{23} & ty \\ a_{31} & a_{32} & a_{33} & tz \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$$



Deformation Models For Non-Rigid Registration

- More complex deformations:
  Globally Parameterize the Deformation Field:
  e.g. Polynomial function of location (here 1D)
  `T(x)=a.x³ +b.x² + cx + d`



- Modify Parameters *a, b, c* and *d* so global similarity *F(T)* maximized

[Woods et al, Automated Image registration,JCAT 1998.]

Deformation Models For Non-Rigid Registration

Cosine Basis Functions

$T(x_i)=x_i- \sum_{j=1..J} t_{jd}\, b_{ij}(x_i)$

$T(y_i)=y_i- \sum_{j=1..J} t_{jd}\, b_{ij}(y_i)$

$T(z_i)=z_i- \sum_{j=1..J} t_{jd}\, b_{ij}(z_i)$

where:

$b_{m1}(x_i)=1/\sqrt{M}$ for $m=1... M$

$b_{mj}(x_i)= \sqrt{2}/\sqrt{M} \cos[\pi(2m-1)(j-1)/2M]$

$j=2....J, m=1..M$

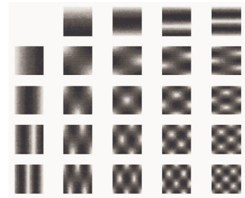
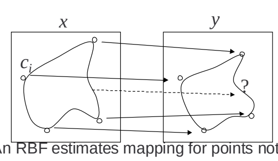


Figure 1.
The lowest-frequency basis functions of a two-dimensional discrete cosine transform.

[Ashburner and Friston, Nonlinear Spatial Normalisation Using Basis Functions, Human Brain Mapping, 7:254-266, 1999]

Radial Basis Functions

- Given a set of corresponding landmarks, what happens between?



- An RBF estimates mapping for points not at landmarks
- For a given point x, it combines mappings from neighboring landmarks c_i weighted by a function of distance

$$y(\mathbf{x}) = \sum_{i=1}^{N} w_i\, \phi(\|\mathbf{x} - \mathbf{c}_i\|),$$

- Where the basis function determines the form of the warp:

$$\phi : \mathbb{R}^+ \rightarrow \mathbb{R}$$

F. L. Bookstein. Principal Warps: Thin-Plate Splines and the Decomposition of Deformations. ***IEEE Trans.*** on ***Pattern Anal. and Machine Intell.***, 11(6):567-585, 1989.

Different forms of Radial Basis Function:

- Thin Plate Spline:

$$\phi(r) = r^2 \log(r)$$

- Gaussian:

$$\phi(r) = \exp(-cr^2)$$

- Multiquadric

$$\phi(r) = \sqrt{r^2 + c^2}$$

D. Ruprecht and H. Muller. Free form deformation with scattered data interpolation methods. *Comp. Suppl.*, 8:267-281, 1993.

J. A. Little, D. L. G. Hill, and D. J. Hawkes. Deformations Incorporating Rigid Structures. *Computer Vision and Image Understanding*, 66(2):223-232,1997.

Properties of RBF

- Many of the common forms (eg thin plate) provide optimally smooth deformations
- Generally stable to estimate weights for many different configurations of points.
- Change location of any landmark and whole deformation field changes:
  - Expensive to re-evaluate whole image match

Limitations of Global Parameterizations

T(x)=f(x,a,b,c)

- Each Parameter a,b,c... Modifies entire image
  - Expensive to evaluate gradients of T wrt parameters
- Complex Brain shape differences requires a fine scale deformation
- Fine Scale deformation requires MANY parameters
  - High spatial frequencies for Cosine parameters
  - or: high order polynomial

So.. Need a way to simplify problem

Alternatives: Local Models

- Rather than have:
  - Many parameters
  - Where each influences the image deformation over the whole space:
- Need parameters that have localized influence on the deformation
  - Faster to Evaluate Image Match
- Forms of Spline can provide spatially localized deformation control

Spline Based Deformations with local support

- Thin-Plate splines can be adapted to have local support:

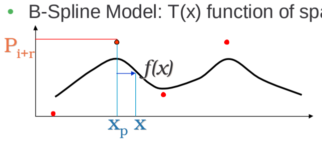
  Mike Fornefett, Karl Rohr, and H. Siegfried Stiehl, Elastic Registration of Medical Images Using Radial Basis Functions with Compact Support, Computer Vision and Pattern Recognition, 1999

- Other forms using Specialized regular control knots can provide faster evaluation:

  S. Lee, G. Wolberg, K.Y. Chwa and S.Y. Shin IEEE Trans Vis. Comp. Graph., 1996 and 1997

B-Spline Models For Registration

- B-Spline Model: T(x) function of sparse knot values



$f(x) = \Sigma_{r=0,N} P_{i+r} B_r(x-x_p)$

Sum of contributions from local knots r=0..N only

The Basis functions $B_r()$ are specific polynomials eg Cubic B-Spline with 4 controlling knots:

$B_0(t)=(1-t)^3/6$

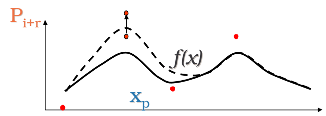
$B_1(t)=(3t^3-6t^2+4)/6$

$B_2(t)=(-3t^3+3t^2+3t+1)/6$

$B_3(t)=t^3/6$

S. Lee, G. Wolberg, K.Y. Chwa and S.Y. Shin IEEE Trans Vis. Comp. Graph., 1996 and 1997

B-Spline Models For Registration



$f(x) = \Sigma_{r=0,N} P_{i+r} B_r(x-x_p)$

Move one knot and deformation changes only within A given range of knot locations.

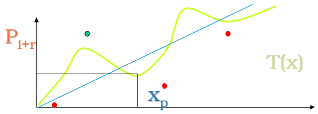
A B-Spline Approximates: it does not interpolate! Functions does not have to pass through knot values

B-Spline Models For Registration

- B-Spline Transformation Model

$T(x) = x + \Sigma_{r=0,N} P_{i+r} B_r(x-x_p)$

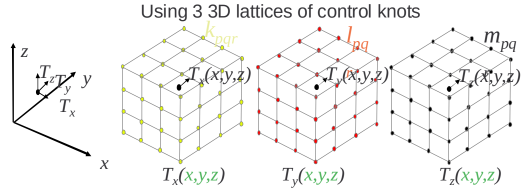
B-Spline can Still Fold! (e.g. multiple x's map to the same value of T(x)



Can Test for Folding based on distance between knot values.

Can Prevent folding by adding a smoothness penalty term

Extend to 3D Displacement Along 3 Axes Using 3 3D lattices of control knots

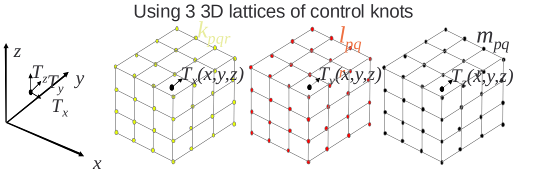


•Describe Transformation $T()$ in directions x , y and z for each point in $\{x,y,z\}$

•Parameterized by a Lattice of control parameters (knots)

$\mathbf{Q}_{pqr}=\{k_{pqr},l_{pqr},m_{pqr}\}$

Extend to 3D Displacement Along 3 Axes
Using 3 3D lattices of control knots

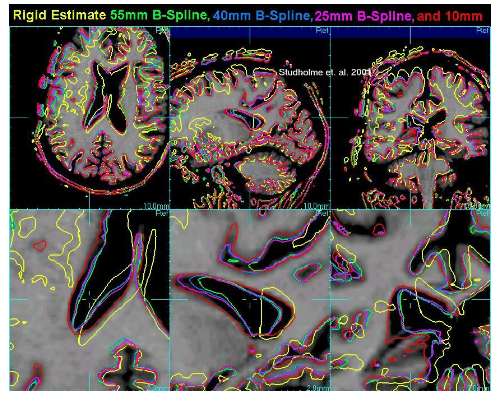


Maximize Image Similarity Y() w.r.t. $\mathbf{Q}_{pqr}$

$$R(\mathbf{Q}_{pqr}) = Y(\mathbf{Q}_{pqr}) - \lambda \sum_x \frac{\partial^2 T(x,Q_{pqr})}{\partial^2 x}$$

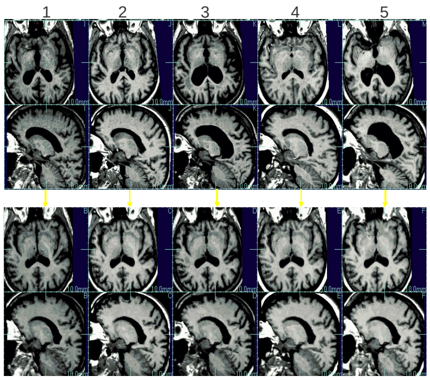
Registration Criteria Regularization Penalty

Ruckert, Hayes, Studholme, Leach, Hawkes, Non-rigid registration of Breast MR images using Mutual Information Proc. MICCAI, 1998 pp1144-1152, Springer, eds Wells, Colchester, Delp



Example Group Spatial Normalization

(Studholme et al, proc. SPIE medical imaging 2001)



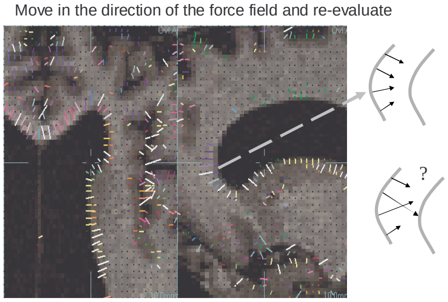
Global Normalized Mutual Information driven B-Spline Spatial Normalisatio of Brain Anatomy

Capturing More Detail...

Dense Field Models

Dense Field Methods

- Derive a voxel by voxel force field making images more similar
  - (local gradient of similarity measure with respect to individual voxel location)
- Move in the direction of the force field and re-evaluate

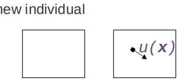


Need a model to describe how image responds to registration force

Deformation Models for Registration

- Early approach applied to 3D brain images: Elastic Registration [Bajcsy, JCAT, 1983]
  - Applying a marked template to a new individual

$T(\mathbf{x}) = \mathbf{x} + u(\mathbf{x})$



- Find a displacement field u(x) which balances the elastic energy of u(x) with the registration criteria S(x)
- So the Elastic Deformation Model then is given by:

  $\mu \nabla^2 u(x) + (\lambda+\mu)\, \nabla(\nabla^T u(x)) = S(x)$

  μ and λ are Lame's elasticity constants

Deformation Models for Registration

- $\mu\nabla^2 u(x) + (\lambda+\mu)\ \nabla(\nabla^T u(x)) = S(x)$

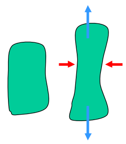
  μ and λ relate applied forces to the resulting strains, by the Poisson's Ratio:

  $\sigma = \lambda/(\lambda+\mu)$

  -> Ratio of Lateral Shrink to Extensional Strain.

  Generally for registration $\lambda=0$

  So registration force in one axis does not influence other axes



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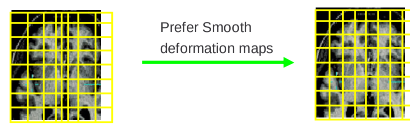
Elastic Deformation for Registration

$\mu\nabla^2 u(x) + (\lambda+\mu)\ \nabla(\nabla^T u(x)) = S(x)$

Key Idea: The Force balancing registration Criteria is a function of the derivatives of the deformation field

[$\nabla^T u(x)$ etc].

..Rates of Change of displacements *u(x)* w.r.t. location *x*:



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Elastic Deformation for Registration

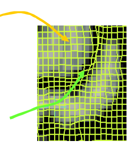
$\mu\nabla^2 u(x) + (\lambda+\mu)\ \nabla(\nabla^T u(x)) = S(x)$

If neighboring displacements are similar:

Local relative size is similar across image.

If neighboring displacements are different:

local relative size is changing.



When anatomical differences very localized (e.g. voxels in cortex) Registration Force balancing smoothness may under-estimate local contractions

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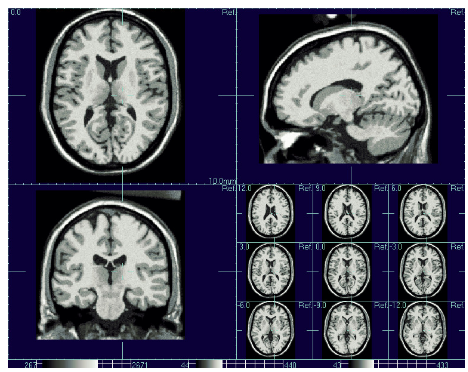
Example Elastic Warping of Brain Anatomy: Template (MNI)



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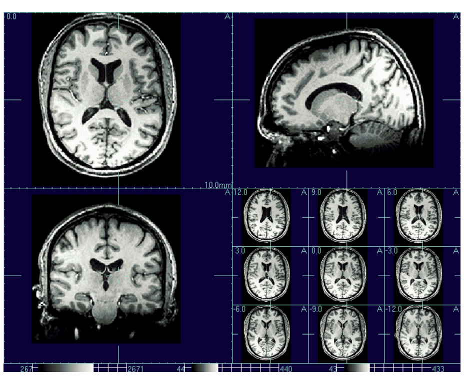
Example Elastic Warping of Brain Anatomy: Subject (affine)



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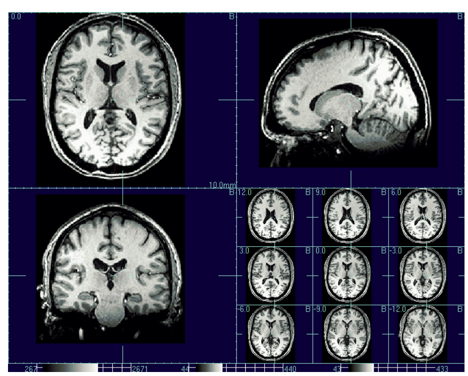
Example Elastic Warping of Brain Anatomy: Subject (Elastic Warp)



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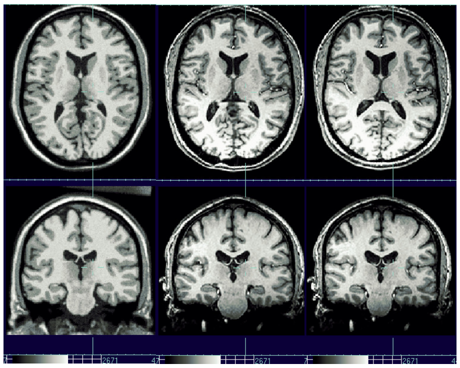
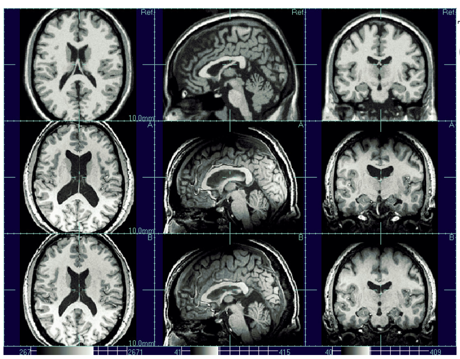
template(MNI) Warped Subject Subject (affine alignment)



Elastic Deformation for Registration

- Can be used to prevent Singularities or Folding…
- But as displacement field evolves:
  - Deformation Energy builds up
- For extreme differences in anatomies:
  - deformation energy will prevent complete registration

Limits of Elastic Matching



Template (MNI27)

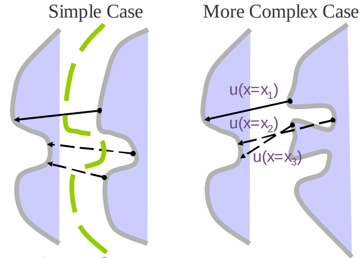
Subject

Elastic Warp of Subject to Template

Regularization and Large Deformations

$\mu\nabla^2 u(x) + (\lambda+\mu)\ \nabla(\nabla^T u(x)) = S(x)$

Simple Case More Complex Case

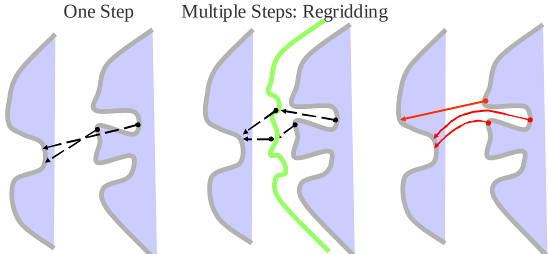


Intermediate Anatomy

For "Large Deformations" When Evaluating "Distance" of deformation for regularization: linear distance can fail or limit our shape alignment

Regularization and Large Deformations

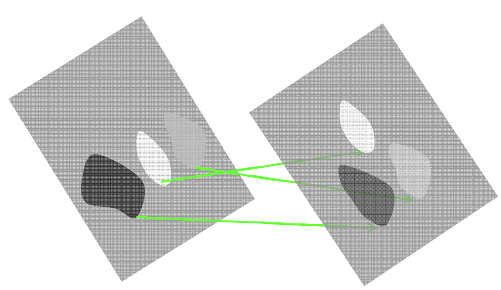
One Step Multiple Steps: Regridding



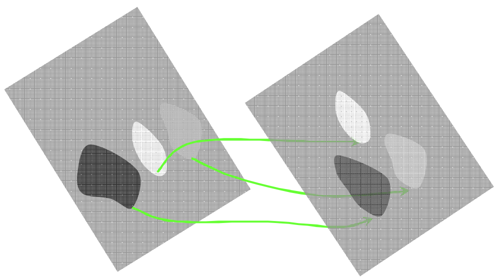
Christensen, Miller et al,
IEEE trans Image Processing, 1996

Track Evolution over Curved Manifold

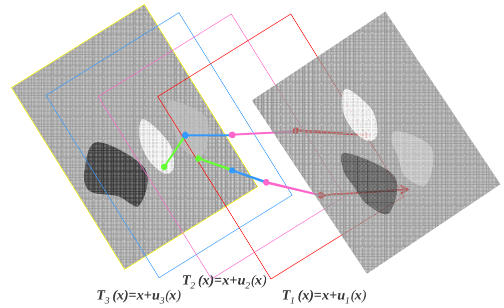
Mapping between Anatomies: Describing Correspondence



Curved Diffeomorphic Mapping: Describing Large Deformations



Discrete Large Diffeomorphic Mapping: Composing Sequences of Small deformations



$$T_{TOT}(x)=T_3(T(_2(T_1(x))))$$

Christensen, Miller et al, IEEE trans Image Processing, 1996

Deformation Models For Registration

- Best known approach is a Viscous Fluid Deformation Model [Christensen,TIP,1996] and (Freeborough&Fox98]
- For current deformation, evaluate Velocity Field:

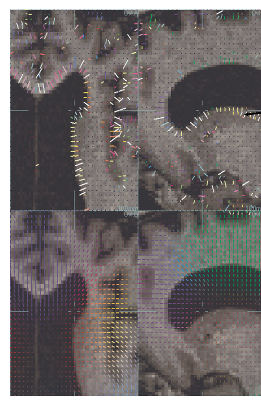
  $\mu\nabla^2 v(x) + (\lambda+\mu)\, \nabla(\nabla^T v(x)) = S(u(t,x))$

  μ is Shear Modulus, λ is Lame's Modulus
- Evaluate a fractional update (Δt 'seconds') of the displacement field along current velocity field:

  $u'(x)=u(x)+R\,\Delta t$

where

  $R=v(x)-v(x).[\partial u/\partial x]^T$
- Then update the Force Field $S(u(x,t))$ and iterate



Sparse Registration Force Field
Driving Points into Better Alignment

In Regions of misaligned Tissue Force->0

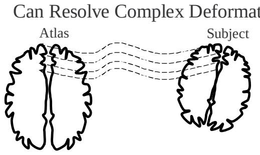
'Velocity' Field
Smooth and Well Behaved
i.e. no singularity points or folding

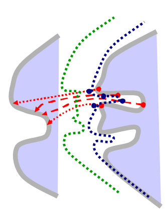
Then: Update displacement estimate u(x) along v(x)

Deformation Models For Registration

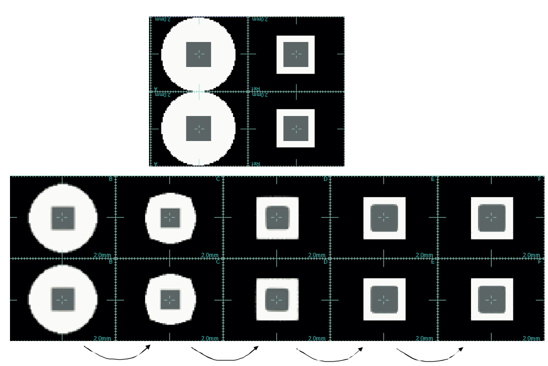
i) Evaluate Velocity Field $v(x)$ for Current Force
ii) Propagate mapping along Velocity Field (update $u(x)$)
iii) Update Force Field $F(u(t,x))$ for Current Deformation
Key Idea: The fluid model ensures that the deformation preserves topology at each step:
i.e. two points don't map to one point.

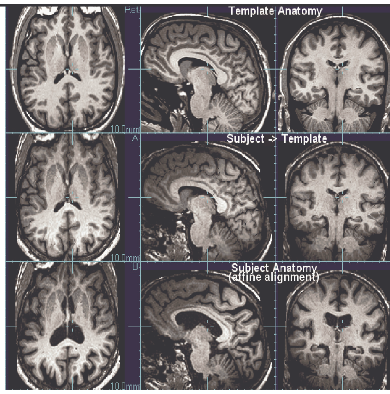
Can Resolve Complex Deformations:





Example Large Deformation





Viscous Fluid Registration

Even Many Cortical Structures Deformed (intensities/tissue... look the same)
BUT: not necessarily registered!

Derived from: Studholme et al, IEEE transactions on medical imaging, 2006

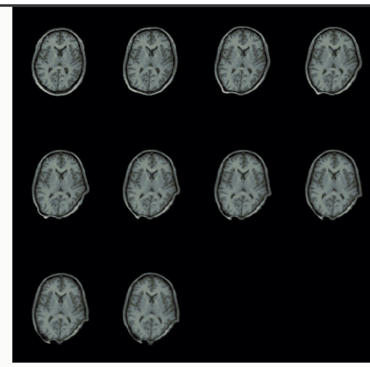


Fig. 5. The first 8 timesteps in a fluid registration of test image head2B to head2A showing misregistration of scalp to cortex.

Fluid registration can be dangerous..

Can be critically dependent on initialization: pre-registration and constraints on region applied to.

Key factor:
Lots of engineering rather than mathematics

H. Lester, S. Arridge, A survey of hierarchical nonlinear medical image registration., Pattern recognition, vol 32(1), 1999, page 129-149.

Atlases and Templates for Spatial Normalization of Anatomies

Overview

- What is an Atlas?
- Templates for Spatial Normalisation

An Atlas

In practice we might say an Atlas is:
A map or spatial record of what we know about a region

Types of Atlas

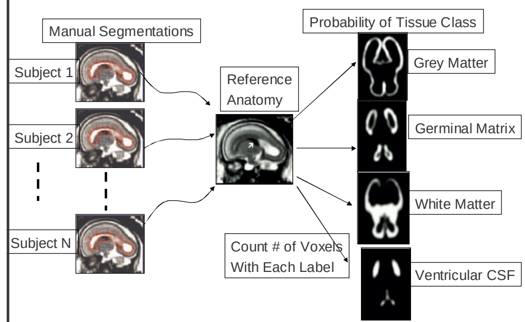
Characteristics of an Atlas:

1. The type information we record in it
2. How we place that information within the atlas
3. How we display/project/extract that information

Atlases in Medical Imaging

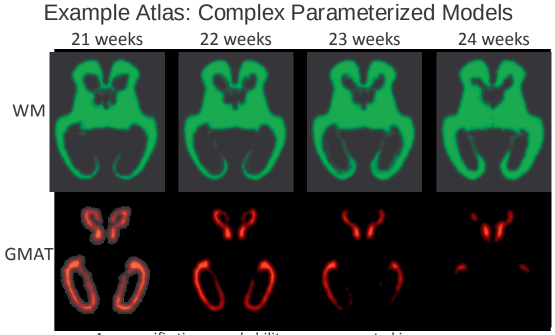
1. An Atlas usually refers to an (often probabilistic) model of a population of spatial data (images).
2. Parameters determining the model are learned from a set of training data.
   - One or more subjects: eg atlas of brain regions
3. Simplest form is a template or average intensity.
   - Eg: Mean grey matter density, Mean PET tracer uptake
4. More complex forms capture
   - Higher order statistics: Variance, or other Model of Distribution
   - Complex parameterized models: eg Age

Example Atlases: Statistical Model of Brain Tissue Distribution in fetal brain



P. A. Habas,et al, "Atlas-based segmentation of the germinal matrix from in utero clinical MRI of the fetal brain," in Medical Image Computing and Computer-Assisted Intervention, LNCS, vol. 5241, part I, pp. 351-358, September 2008.

Example Atlas: Complex Parameterized Models

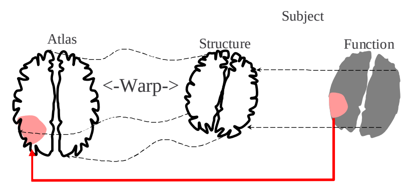


Age-specific tissue probability maps generated in average space

P. A. Habas, et al "A spatio-temporal atlas of the human fetal brain with application to tissue segmentation," in Medical Image Computing and Computer-Assisted Intervention, LNCS, vol. 5761, part I, pp. 289-296, September 2009.

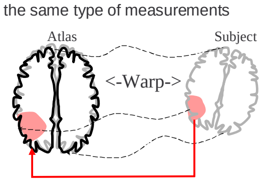
How do we place information into an atlas?
Independent Modalities

eg: Use 'structure' to place 'functional' measurements within the atlas
- Use MRI to normalize subject anatomy to a template anatomy
- Apply anatomical transformations to bring functional measurements in a subject into the atlas



How do we place information into an atlas?
Same Modality

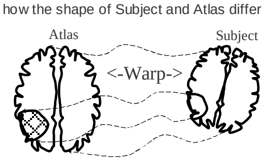
- Use neighboring structure to locate and place measurements within an atlas of the same type of measurements



- How accurately do we place that information?
- How does that neighboring information influence placement?

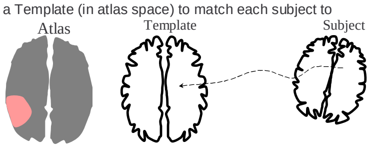
How do we place information into an atlas?
Shape Mapping: Morphometric Atlases

- Do not record imaging measurements in subject:
  BUT: record how subject was spatially re-arranged to fit the atlas
  - Record how the shape of Subject and Atlas differ



Warping in Atlas Mapping

- Collecting data from different individual anatomies not trivial
- Need to locate corresponding points in atlas for a give measurement in the subject
- Need a Template (in atlas space) to match each subject to

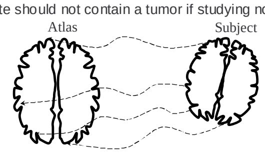


- How do we derive a correspondence or mapping?
  - Warp from template to subject?

Need a [non-rigid] Registration algorithm
for -> Spatial Normalisation

Templates for Atlas Mapping

- What structure do we use as a target or template?
- Needs to contain information relevant to problem
  - Where are the ports along a coastline?
  - Where are the gyri delineating functional brain regions?
- Needs to Exclude irrelevant information:
  - Template should not contain a tumor if studying normal anatomy



- Need to have a representative shape:
  - Don't use a brain with rare sulcal patterns to study normal anatomy

Templates and Atlases

- Early Atlases for presentation/visualization:
  - Were often manually drawn
    - Broadmann[1]
  - 'Idealized' anatomies created by sketching features of interest
  - Difficult to compare results
- Modern Templates -> for Spatial normalisation:
  - Can be optimized for use with registration method

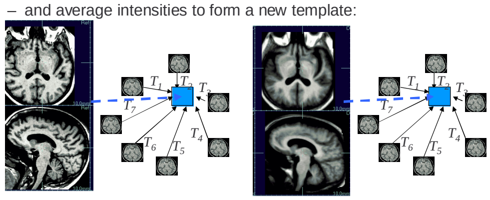
1. Broadmann, K: On the Comparative Localization of the Cortex 201-230.

Optimizing Templates

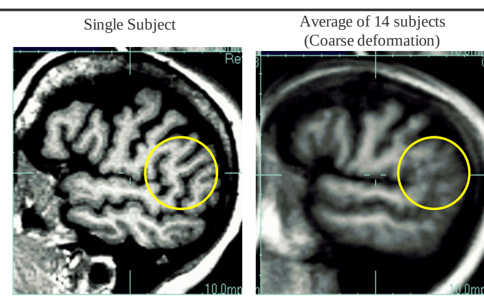
- Contrast/Intensity Properties
  - High signal to noise (average brain of MNI colin27?)
  - Show Imaging structures of interest:
    - T1W template for T1W matching -> structure
    - T2W template for T2W matching -> fMRI?
- Resolution
  - High isotropic resolution
    - Minimize loss of fine structure/tissue boundary
- Spatial Mathematical Properties:
  - Average 'Shape' of Anatomies studied
    - Aid in visualization of results
    - Improve registration algorithm?

Optimal Templates for Matching

- Average Intensity? (older SPM/VBM analyses)
  - Register a set of MRI's to a single subject MRI:
  - and average intensities to form a new template:

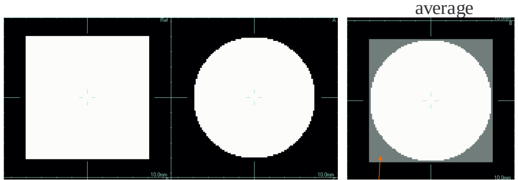


Single subject MRI 'Average' subject MRI



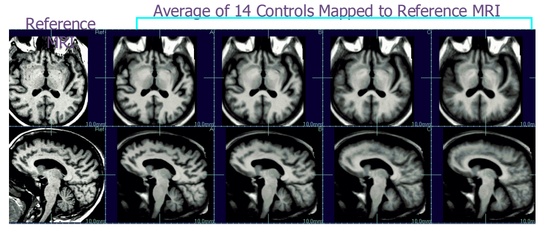
- Since images imperfectly aligned:
  there is a Fundamental problem:
- Resulting 'average' image is not necessarily an example of a real anatomy which has been blurred.
- May even be topologically different: (eg sulci covered over)
- So... deforming an individual to it may be impossible!

Average Shape Between a Cube and a Sphere:
The need for local deformations



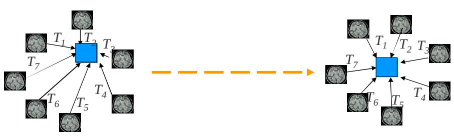
Optimal Templates for Matching

- Improving Average through fine scale registration



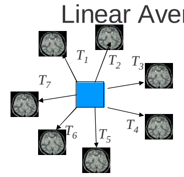
Optimal Templates for Matching

- Average Geometry?
  - Template is most similar in shape to a given group being studied
  - Makes registration easier?



- How to define Average anatomical geometry??
  - need a definition of *distance* between anatomies

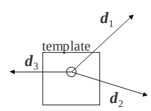
Linear Averaging: 'Unbiased Atlases'



Evaluate a common space such that the average displacements of a given point to a set of subjects is zero.

Can do this

1) Group-Iteratively during registration:
   - register group to template
   - warp template to linear average
   - re-warp subject to template
   - Guimond, A., Meunier, J., Thirion, J.P.: Average brain models: a convergence study. Comput. Vis. Image Underst. 77(2) (2000) 192–210
2) Collectively during group-wize registration
   - Use distance as a constraint



$$\sum_{x} \sum_{n=1..N} d_n \rightarrow 0$$

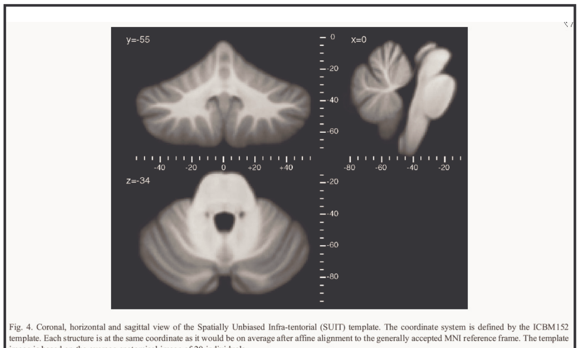
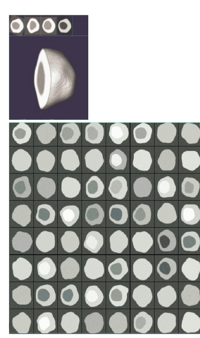


Fig. 4. Coronal, horizontal and sagittal view of the Spatially Unbiased Infra-tentorial (SUIT) template. The coordinate system is defined by the ICBM152 template. Each structure is at the same coordinate as it would be on average after affine alignment to the generally accepted MNI reference frame. The template image is based on the average anatomical image of 20 individuals.

A spatially unbiased atlas template of the human cerebellum, Jörn Diedrichsen , Neuroimage vol 33, issue 1, 2006

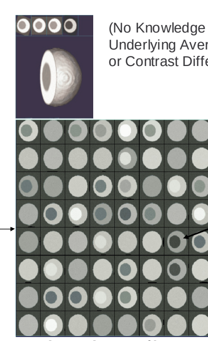
Elastic averaging of group (driven by entropy)

Starting Population



Populations Deformed Toward Each other

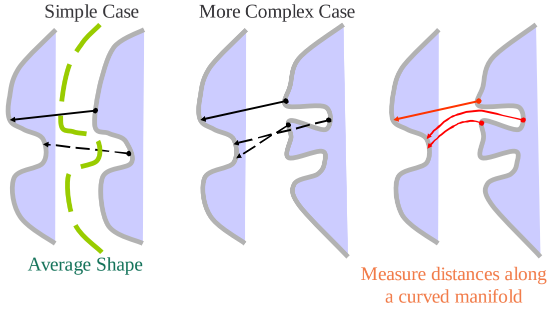
(No Knowledge of Underlying Average Shape or Contrast Differences)



Studholme et al, A template free approach to spatial normalisation of brain anatomy Pattern Recognition Letters, vol 25(10), July. 2005

Non-Linear Shape Averaging

- The shape distance problem (same as in regularization):



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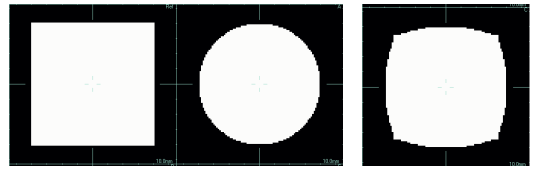
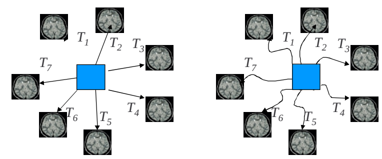
Large Deformation Non-Linear Average Shape Between a Cube and a Sphere





Distance measured along curved Manifold: Then Averaged Over Population

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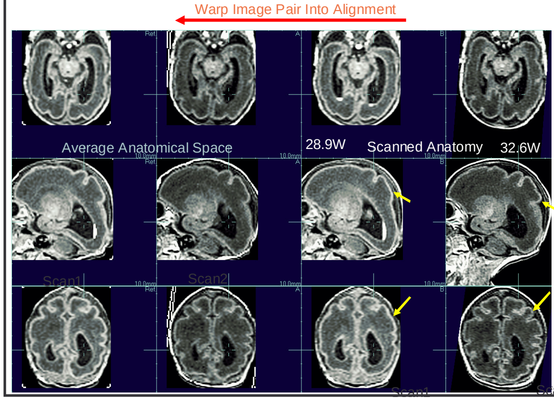
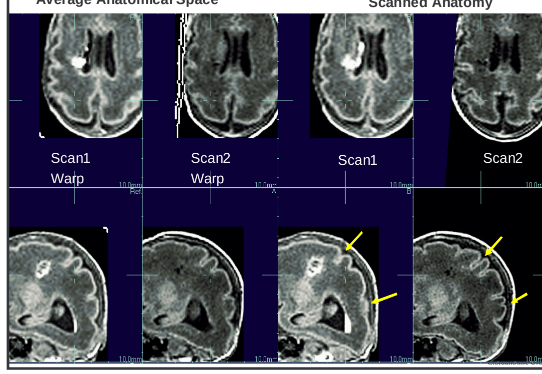
Example Symmetric Warping between Developing Anatomies



Example Symmetric Warping between Developing Anatomies



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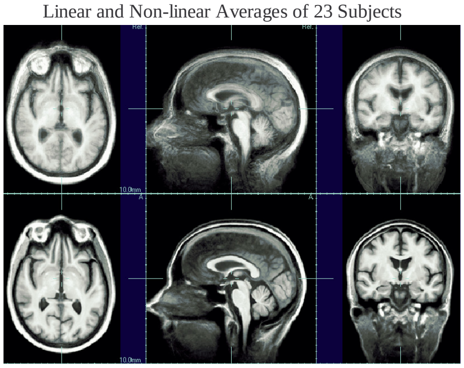
Linear and Non-linear Averages of 23 Subjects



S. Joshi, B. Davis, M. Jomier, and G. Gerig, "Unbiased Diffeomorphic Atlas Construction for Computational Anatomy", NeuroImage; Supplement issue on Mathematics in Brain Imaging, Volume 23, Supplement 1, Pages S151-S160, Elsevier, 2004.

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Summary

- Many Different factors in atlas based analysis
- Critical issues is registration algorithm
  - how accurately can you relate individuals to atlas?
    - for atlas construction and atlas use
  - importance depends on application.
- Very active area of research

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