

# Comp 775: Image Registration

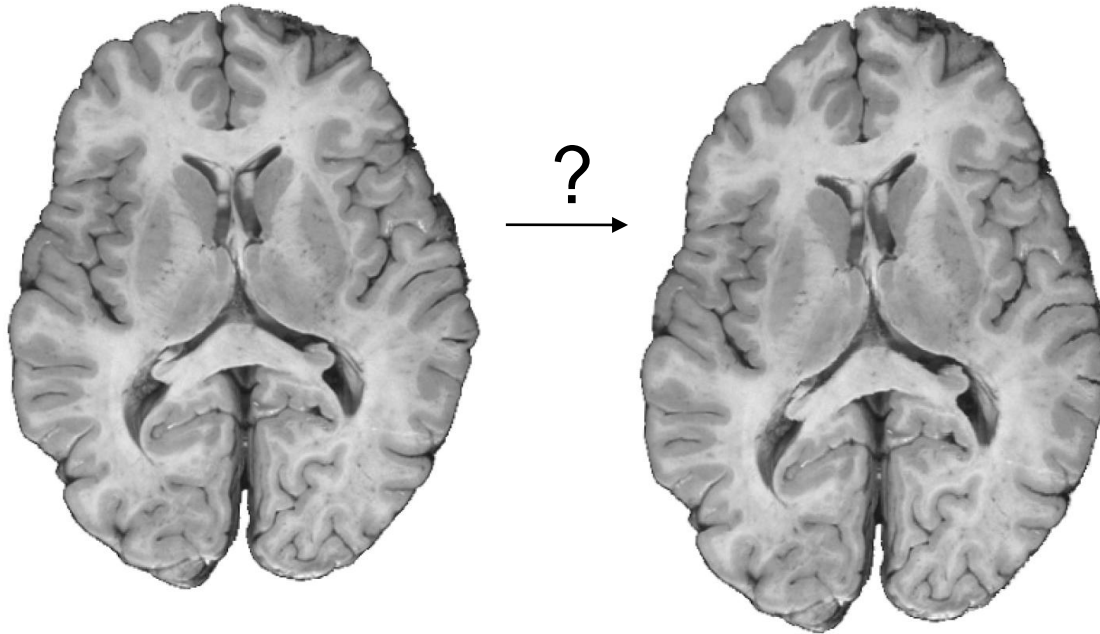
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Department of Computer Science  
University of North Carolina, Chapel Hill

# Purpose of Image Registration

Establishing a geometric transformation

$$\underline{x}' = \underline{h}(\underline{x}) = \underline{x}' = \underline{x} + \underline{\Delta x}$$

relating points in one image to points in another.



Source Image

Target Image

# Purpose of Image Registration

Establishing a geometric transformation

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relating points in one image to points in another.

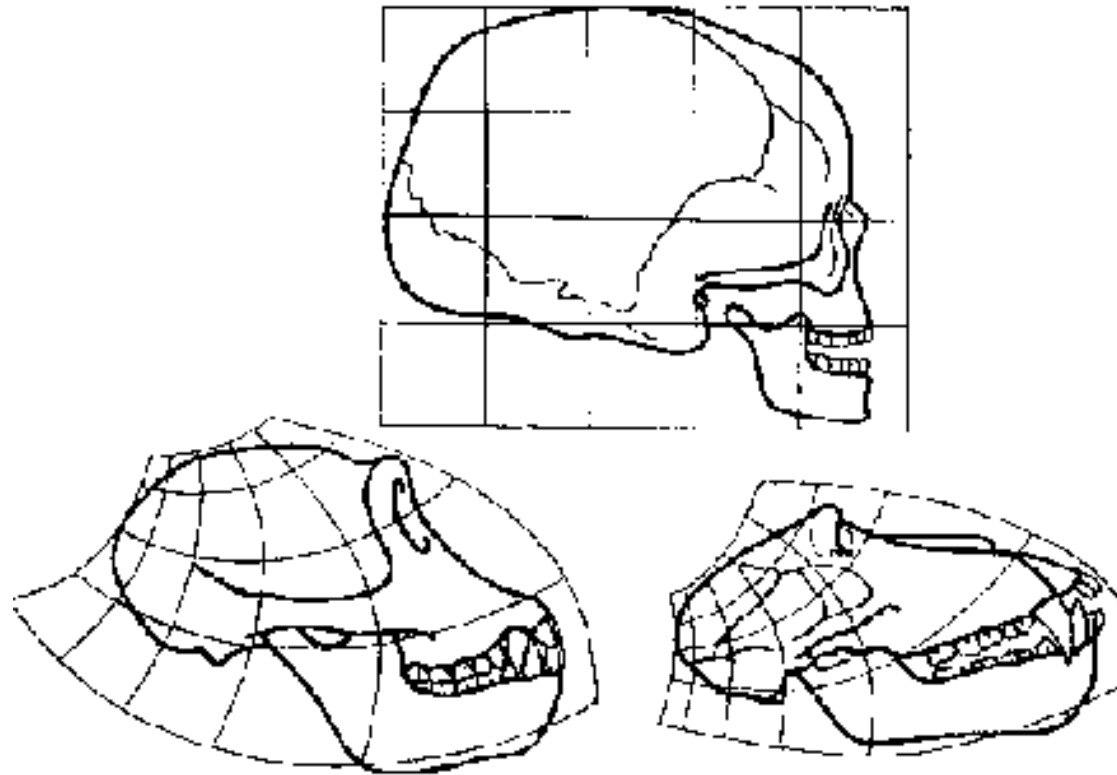
Needed (as with segmentation)

- Regularization Energy (Geometric atypicality)
- Data Similarity Measure (geometry-to-data match)
- Optimization Scheme

And also

- Transformation Model
- Interpolation Model

# Registration Example



Skulls of a human, a chimpanzee and a baboon  
and transformations between them

D'Arcy Thompson

# Coordinate Systems

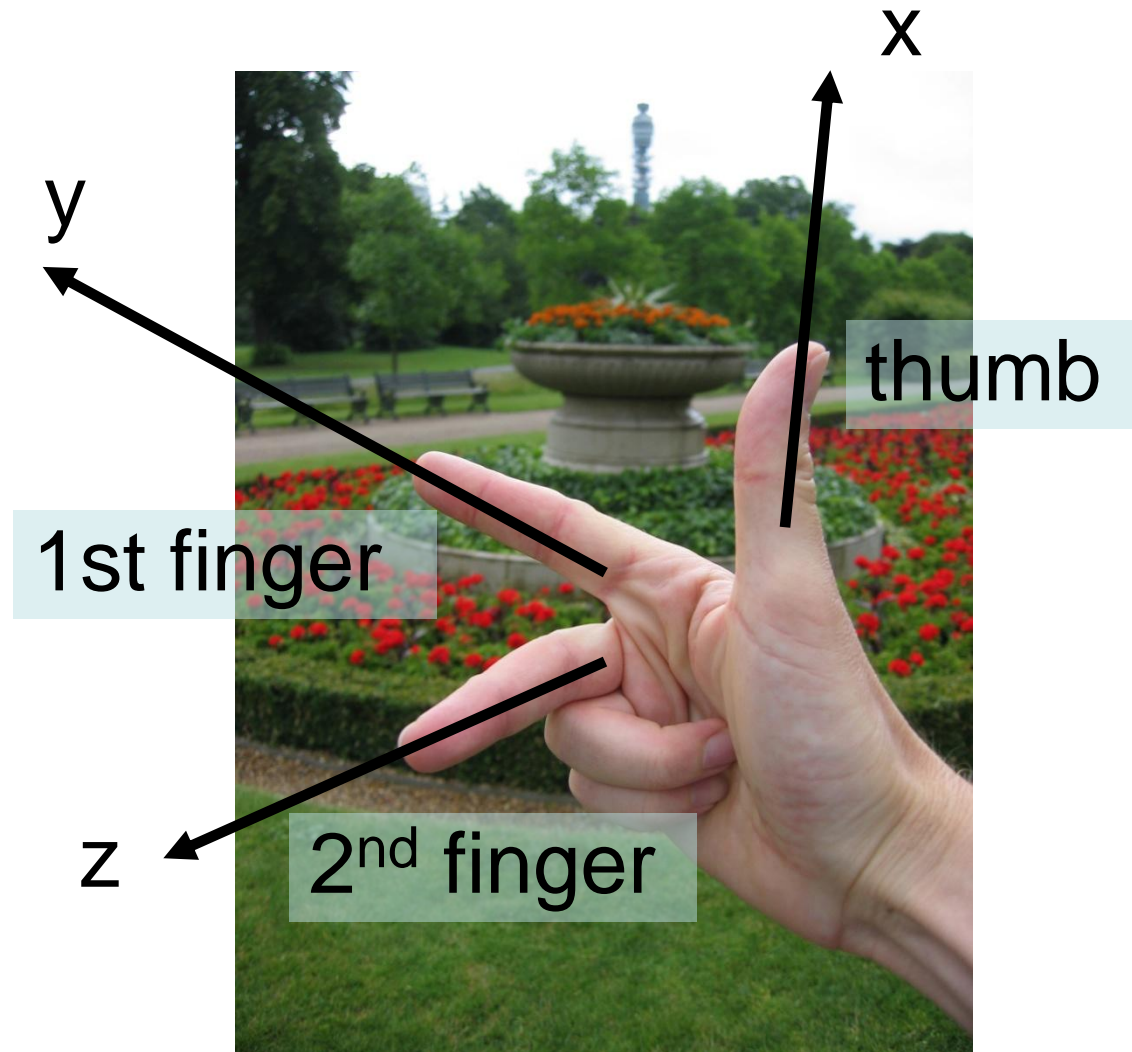
**Important: Make sure to get your coordinate systems straight.**

- Image data is more than just a 3D-array of numbers
- Images may have been acquired in different coordinates systems
- Orientationally dependent data (e.g., tensors) may have additional coordinate systems.

To be certain the alignment can work properly work in

**World coordinates**

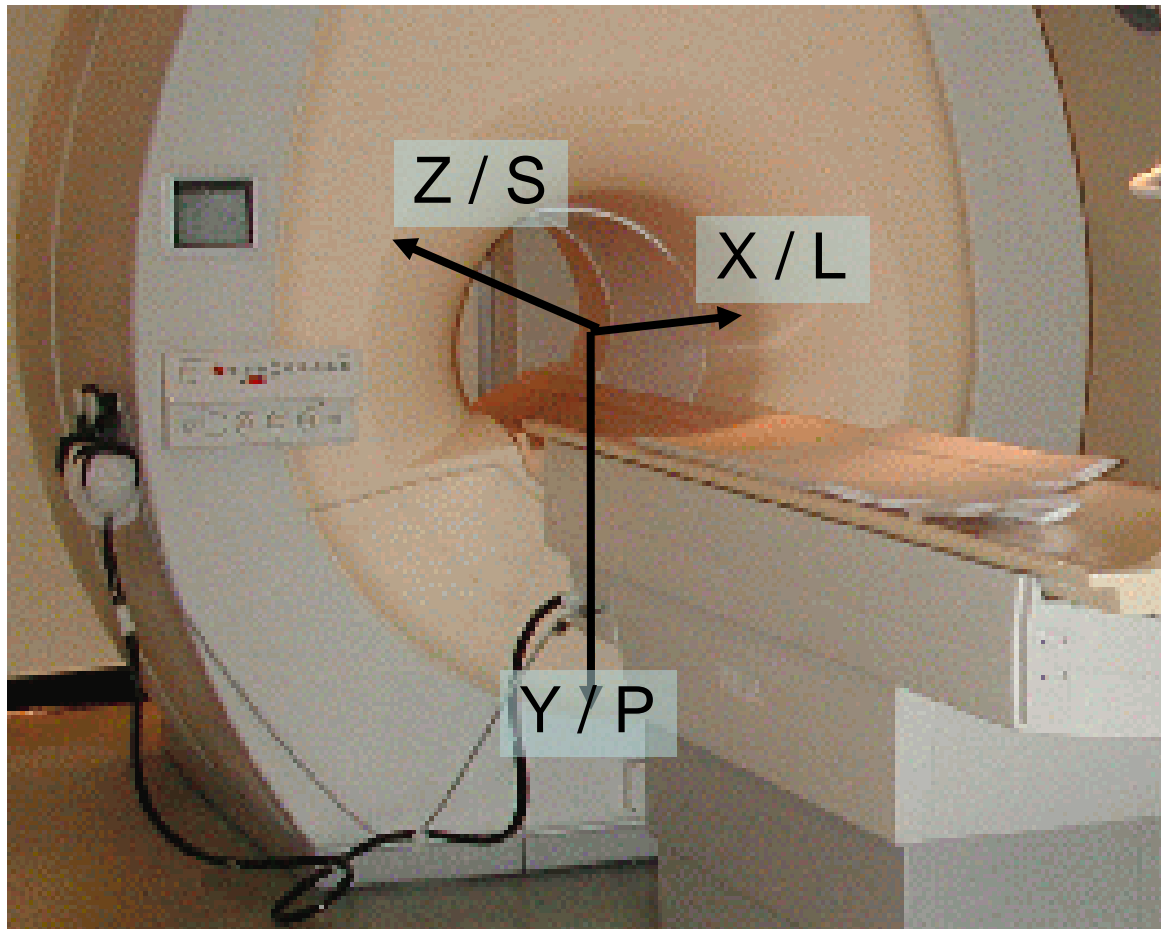
# Right-handed coordinate systems



Right handed coordinate system.

Image: Atkinson

# Coordinate Systems



L: Left  
P: Posterior  
S: Superior

R: Right  
A: Anterior  
S: Superior

Supine (face-up)  
patient.

Image: Atkinson

# Coordinate Systems

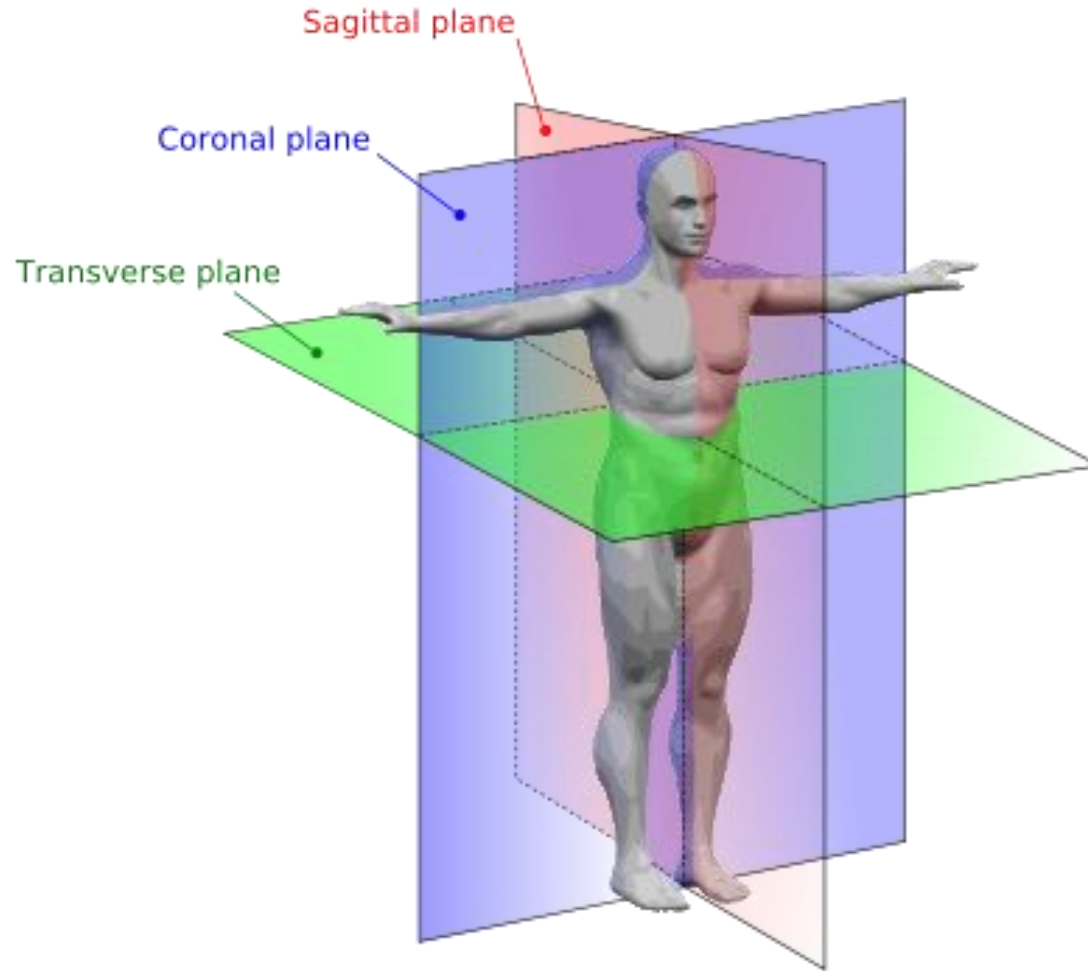
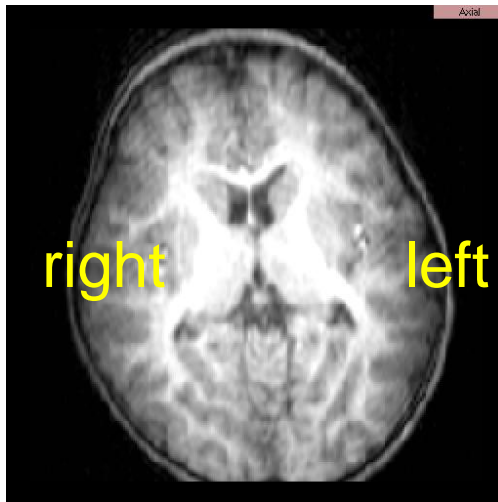


Image:Wikipedia



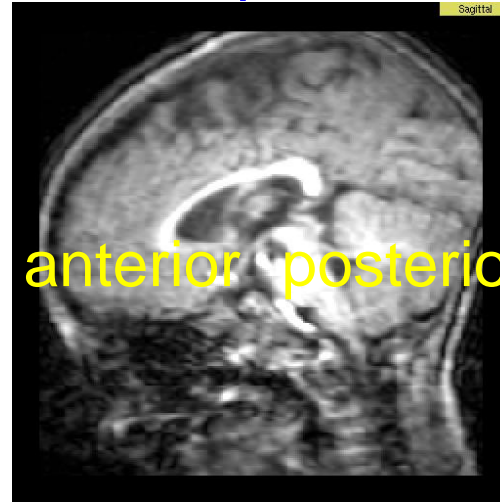
# Coordinate Systems

Axial  
anterior



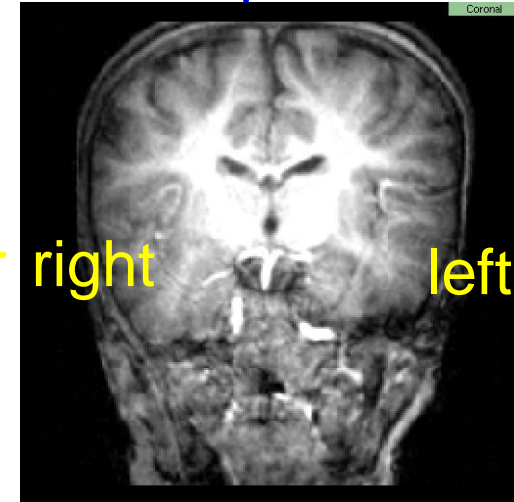
posterior

Sagittal  
superior



inferior

Coronal  
superior



inferior

Important: Make sure to get your coordinate systems straight. What is right and what is left for example?

# Coordinate Systems: Viewpoints

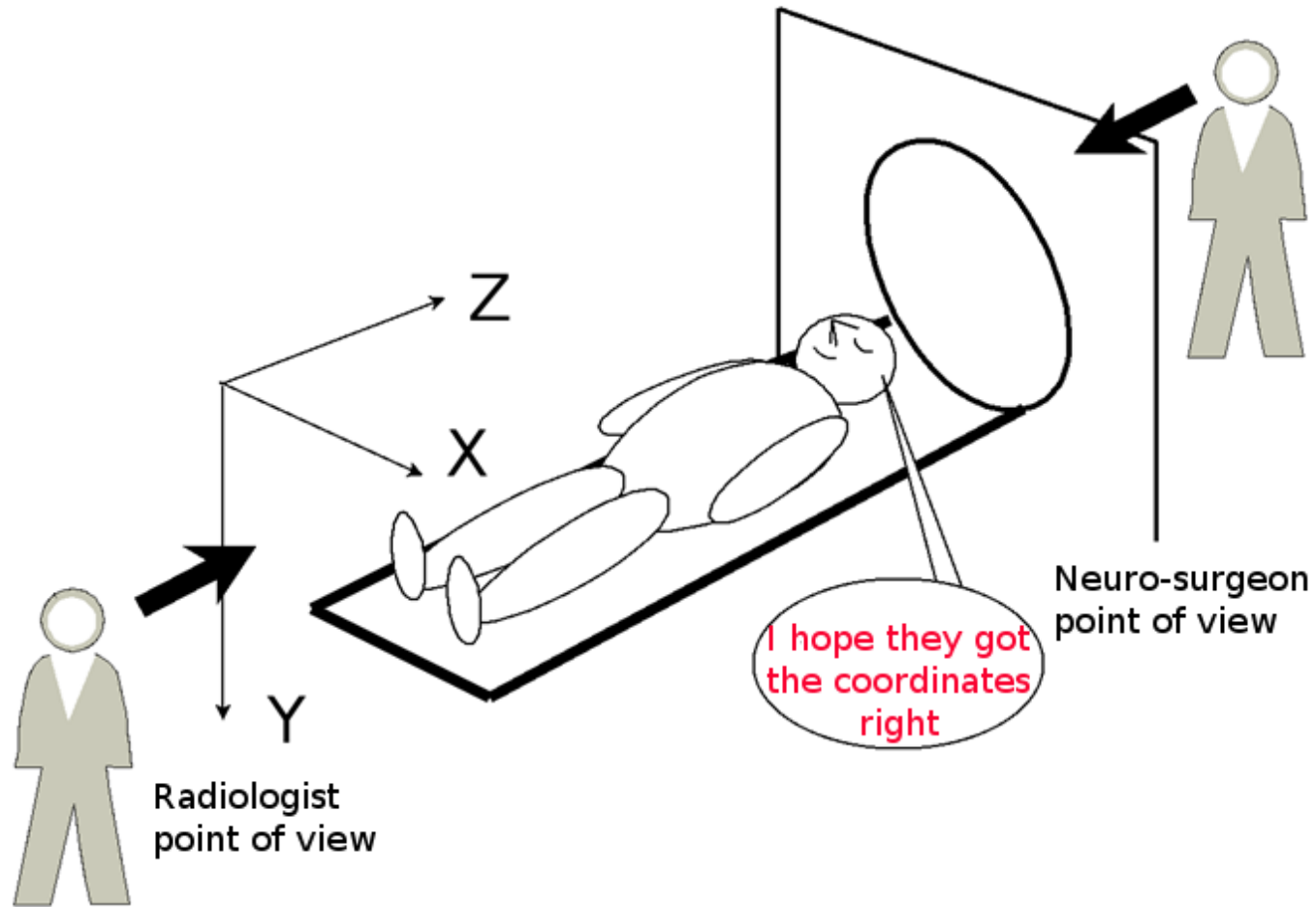


Image: Adapted from Kitware

# Pixels/Voxels vs. World Coordinates

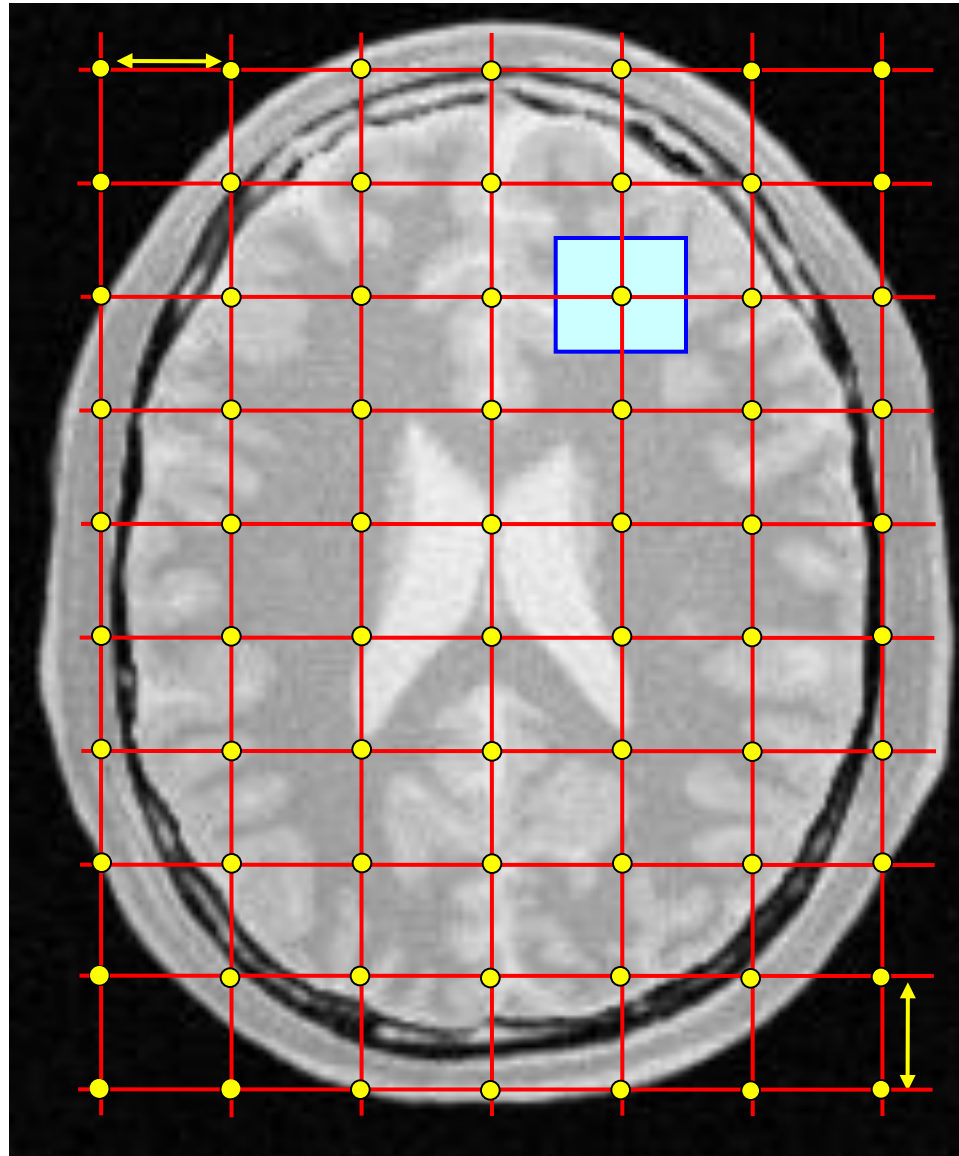


Image: ITK  
Registration  
Guide

# Image Coordinates

Spacing ( $S_x$ )

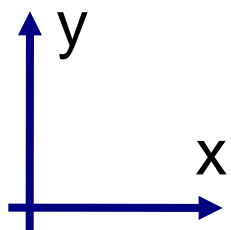


Image: ITK  
Registration  
Guide

Spacing ( $S_y$ )

Origin ( $O_x, O_y$ )

# Image coordinates

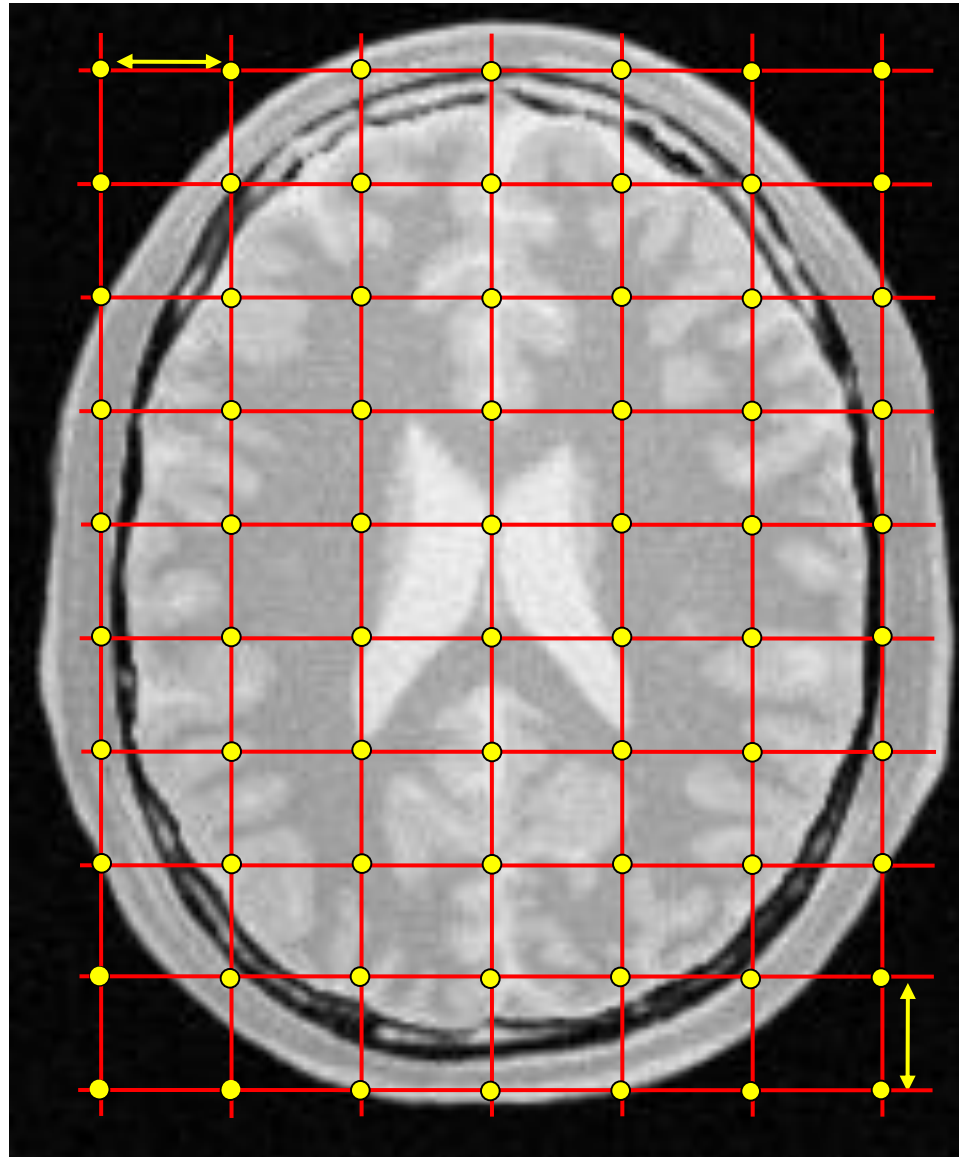
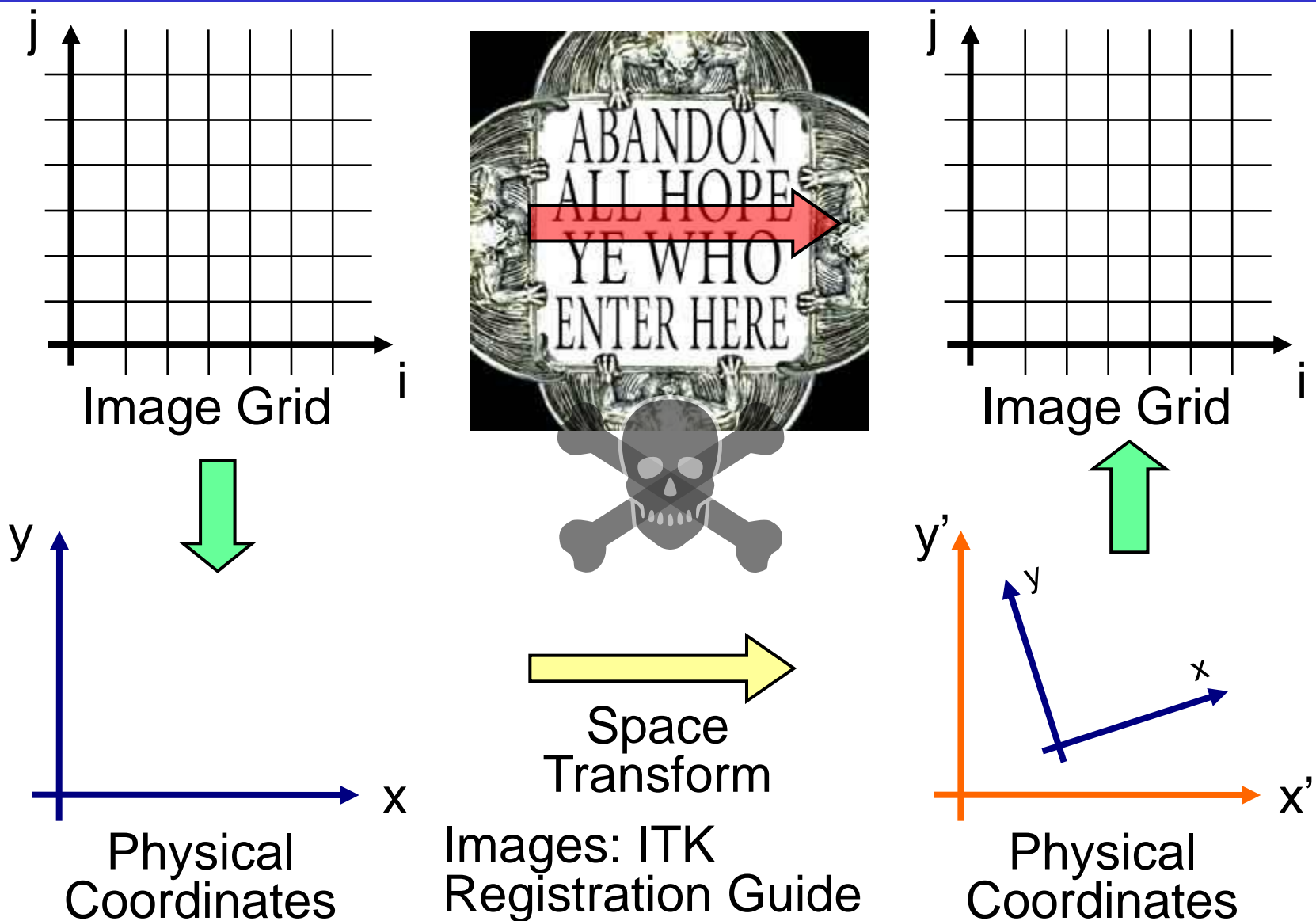
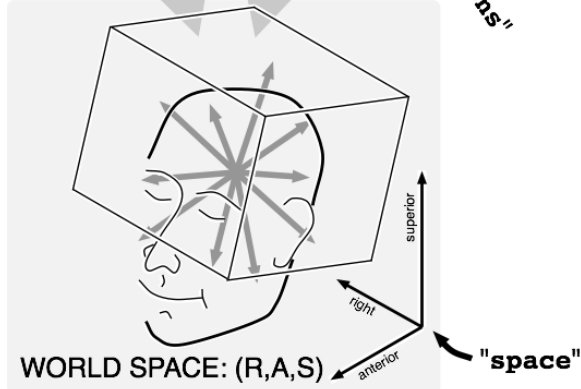
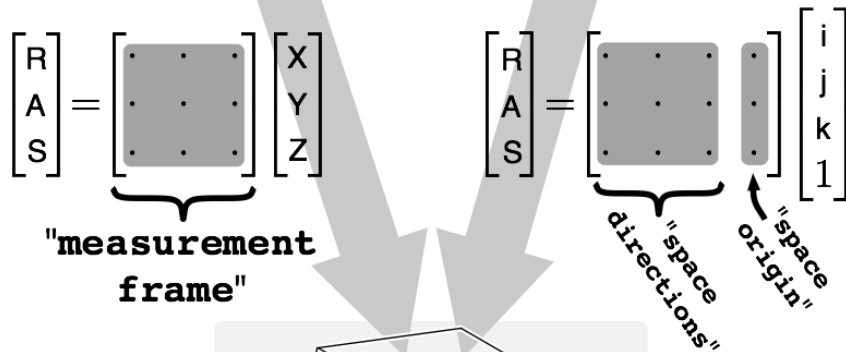
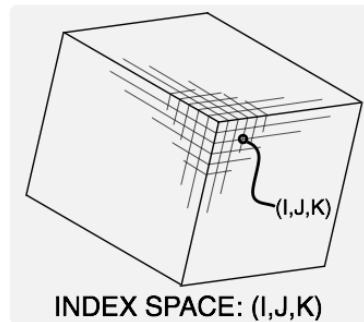
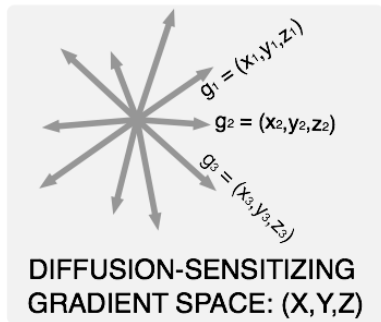


Image: ITK  
Registration  
Guide

# Coordinate System Conversions



# Coordinate Systems, Example



NRRD0005

# Complete NRRD file format specification at:  
# <http://teem.sourceforge.net/nrrd/format.html>

type: unsigned short

dimension: 4

space: right-anterior-superior

sizes: 256 256 78 59

thicknesses: NaN NaN 2 NaN

space directions: (-0.9375,0,0) (0,-0.9375,0) (0,0,1.7)

none

centerings: cell cell cell ???

kinds: space space space list

endian: little

encoding: gzip

space units: "mm" "mm" "mm"

space origin: (-136.14,-130.248,-29.8626)

measurement frame: (1,0,0) (0,1,0) (0,0,1)

data file: caseD00959-dwi-EdCor.raw.gz

modality:=DWMRI

DWMRI\_b-value:=700

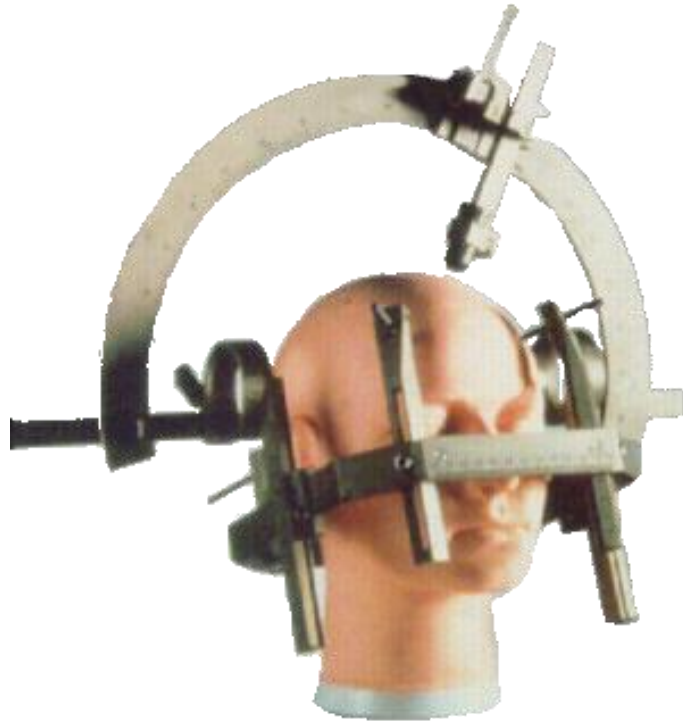
DWMRI\_gradient\_0000:= 0.000000 0.000000 0.000000

DWMRI\_gradient\_0001:= 0.000000 0.000000 0.000000

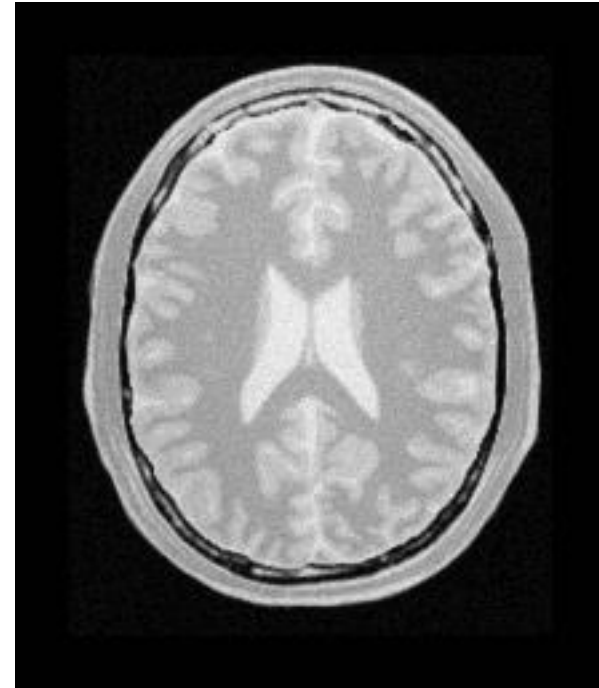
....

Image: Kindlmann

# Registering What to What?



Extrinsic

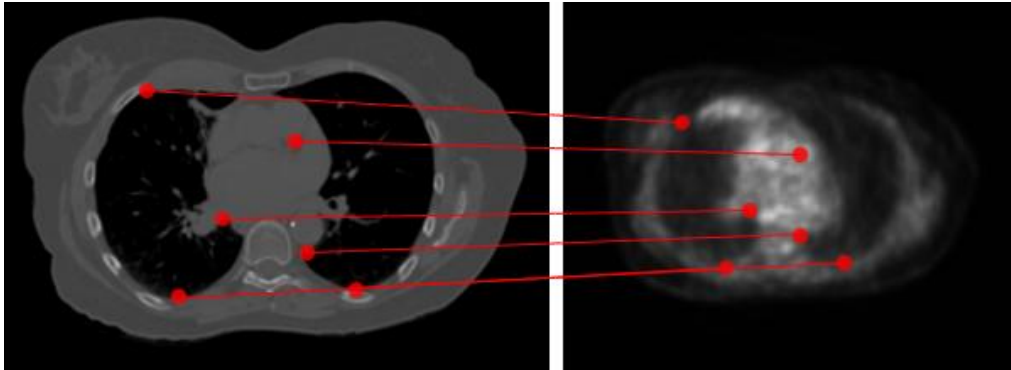


Intrinsic

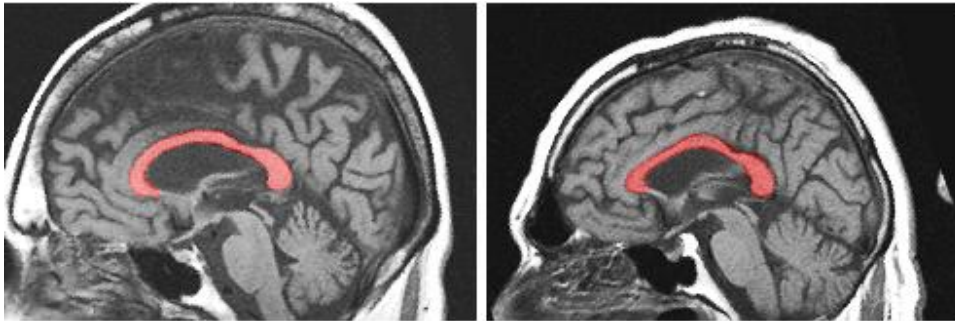
Registration features  
derived from image itself



# Registration Types



Landmark based



Segmentation based

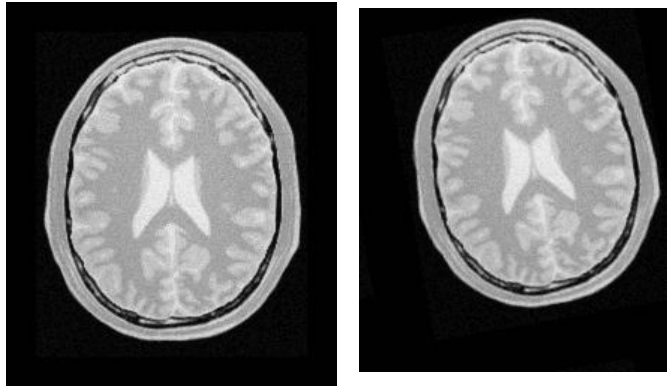
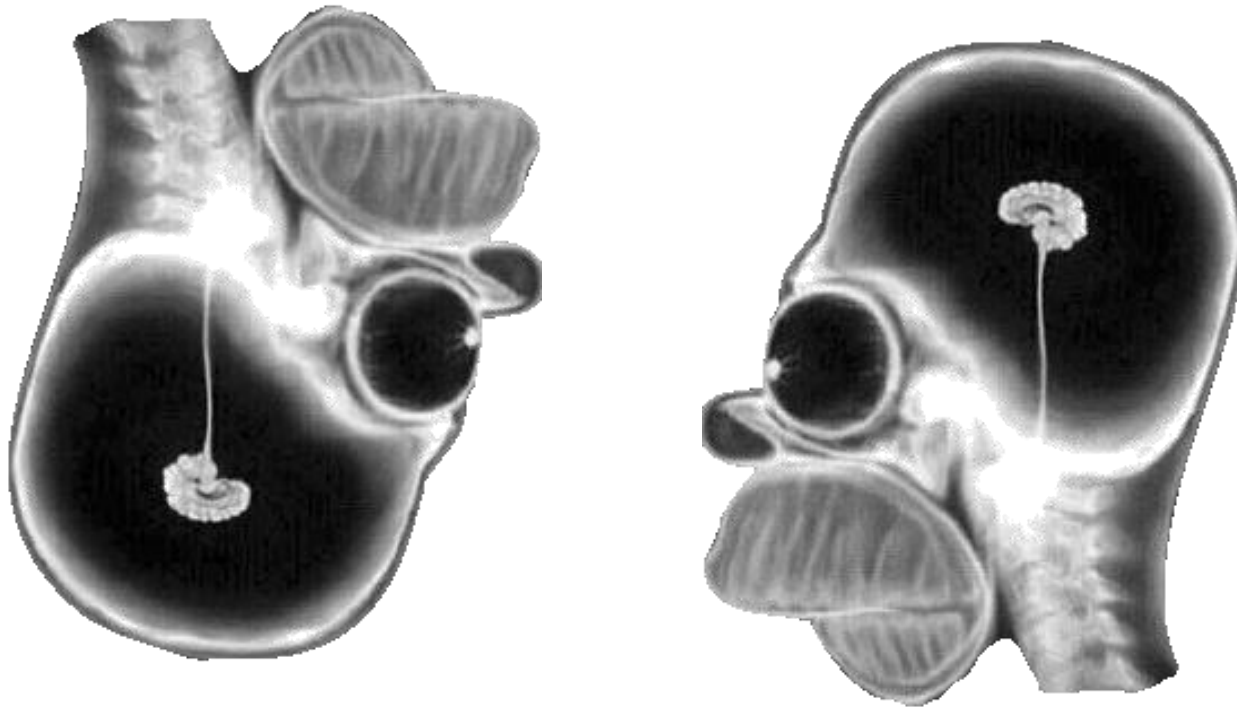


Image based

Images: Alain Pitiot

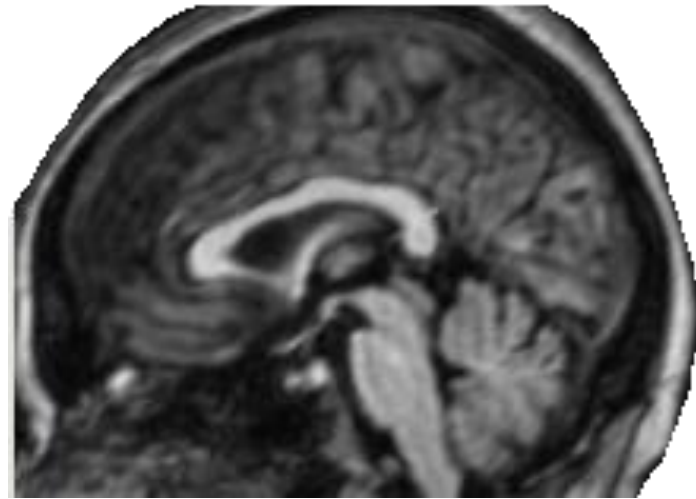
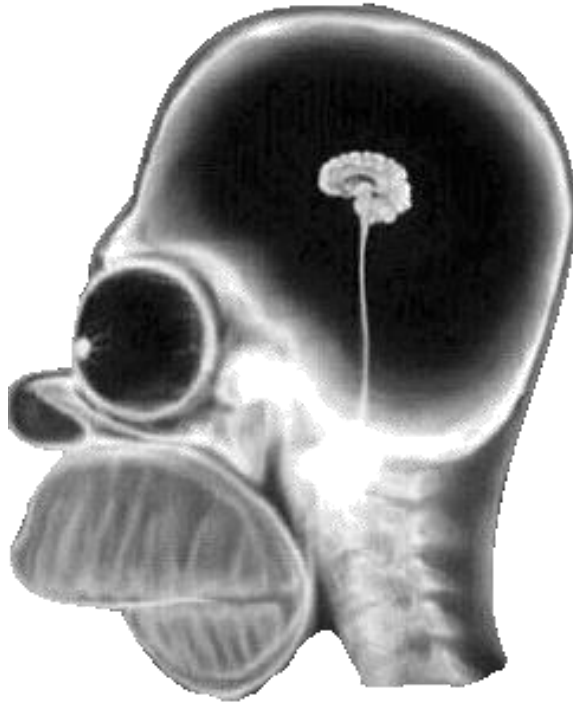
# Registration Types



Intra-subject registration  
(Within subject)

Images: Alain Pitiot

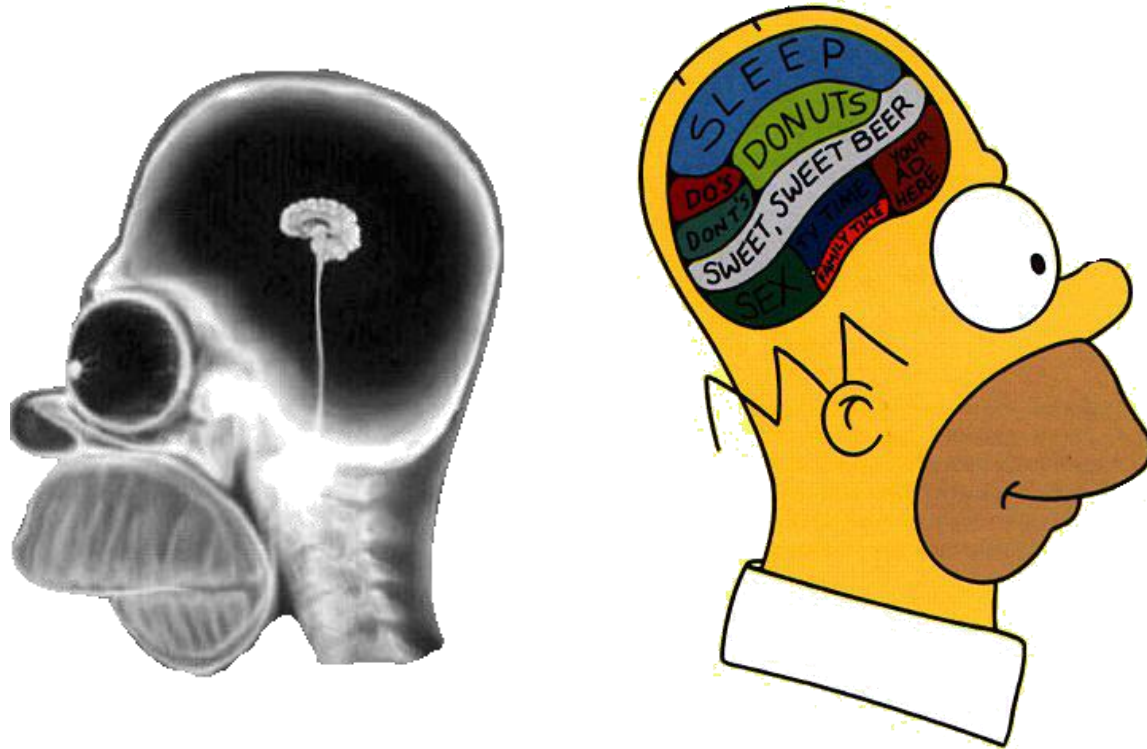
# Registration Types



Inter-subject registration  
(Between subject)

Images: Alain Pitiot

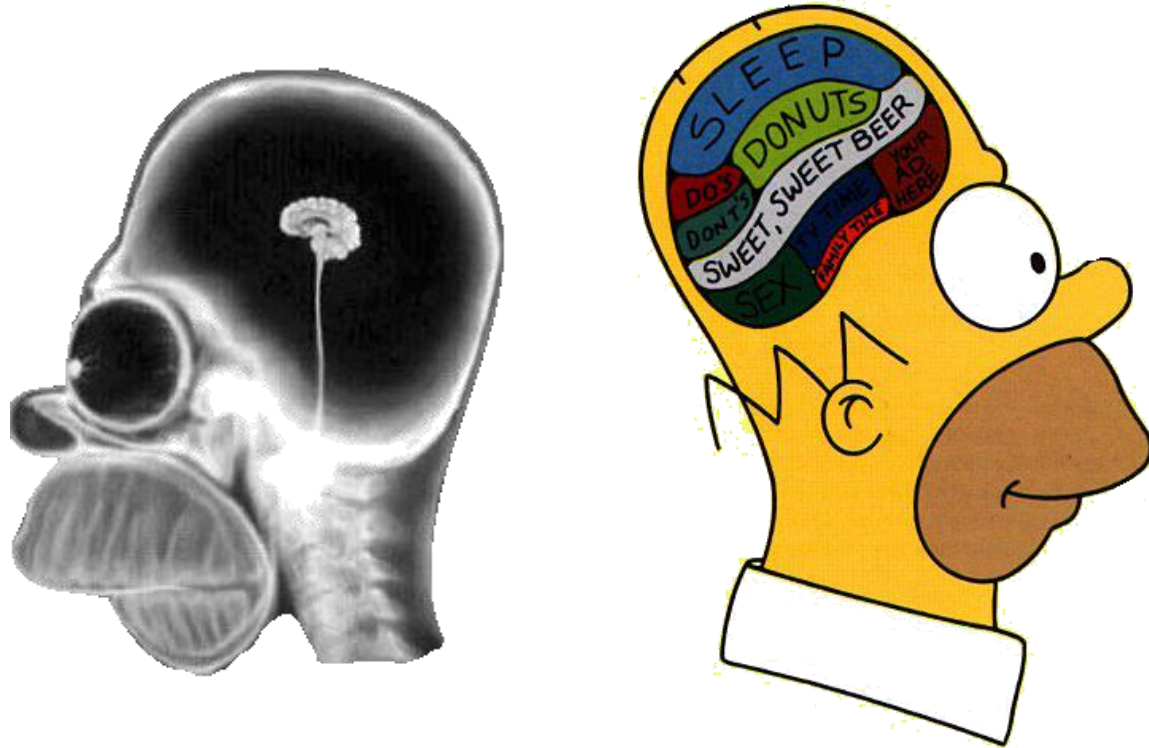
# Registration Types



Subject/Atlas Registration

Images: Alain Pitiot

# Registration Types

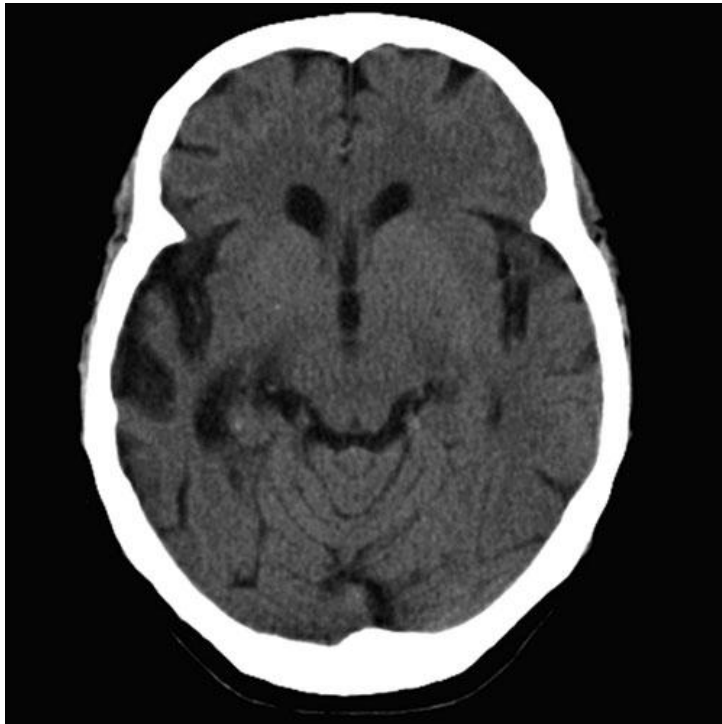


This can be used as a segmentation method  
or to add spatial prior information to a segmentation method  
= Atlas-based segmentation

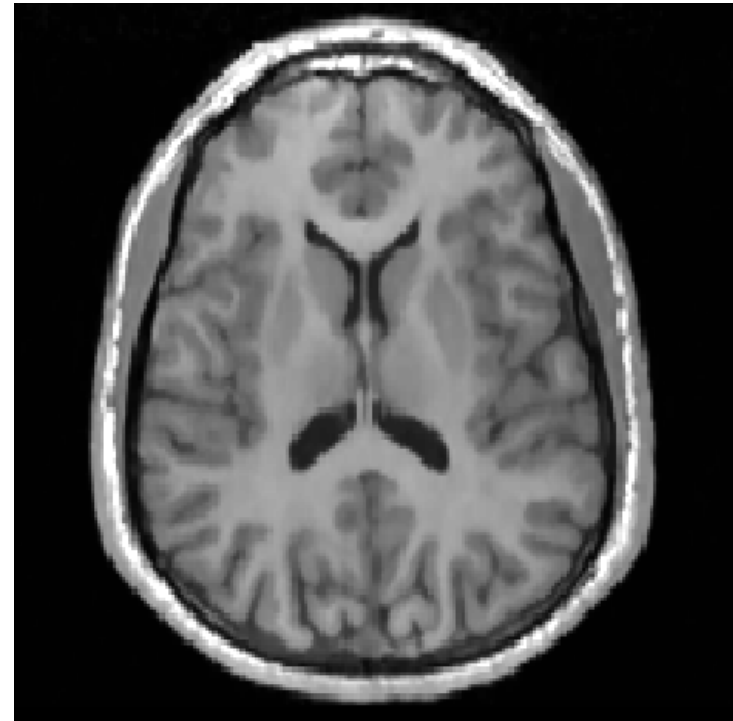
Images: Alain Pitiot

# Multi-Modality Registration

X-ray CT



MRI



Requires special care with respect to the similarity metric.  
Use for example mutual information.

# Image Registration Components

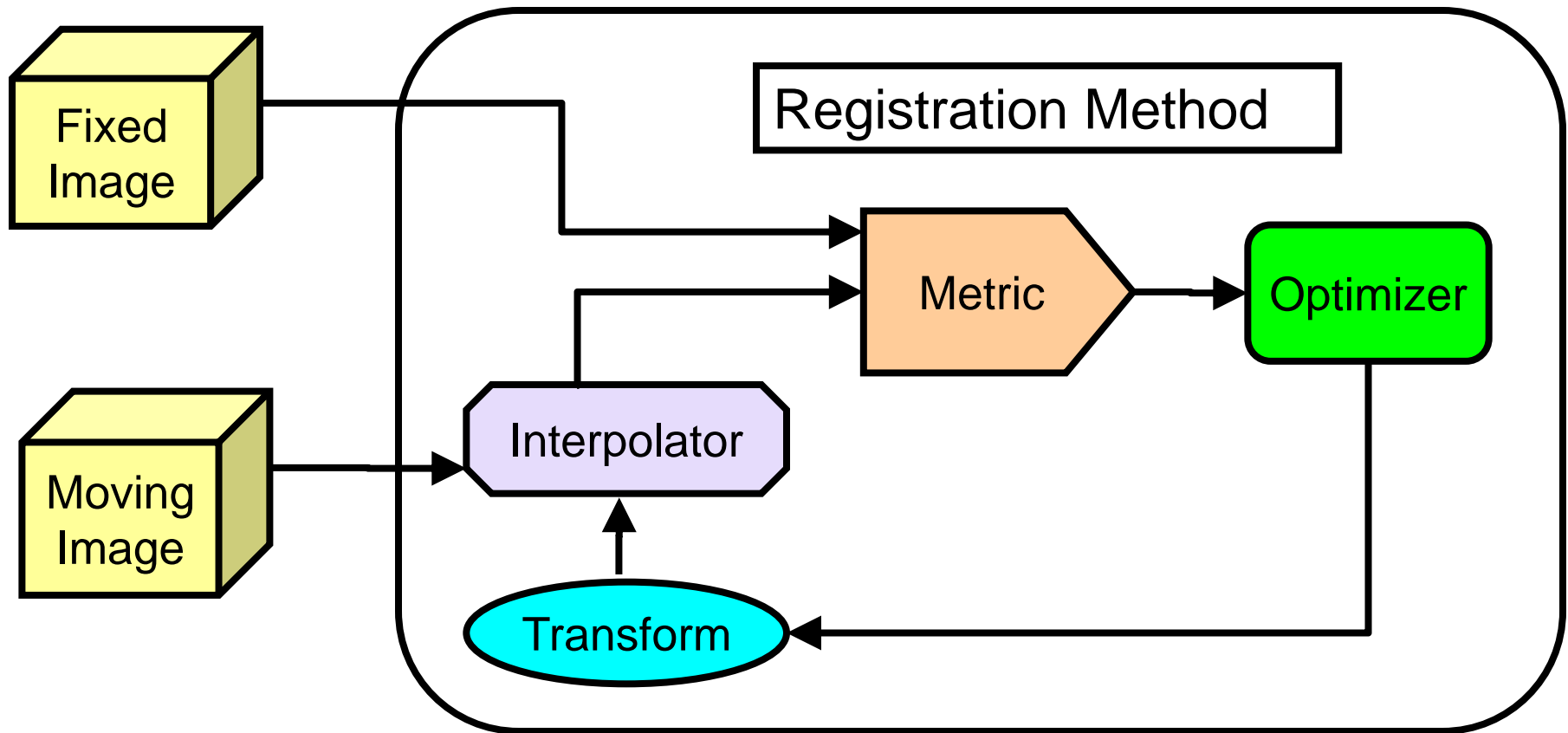


Image: ITK Registration Guide

# Interpolation

Determining function values off the grid.

Nearest Neighbor Interpolation:

Good for labelmaps (does not create any new values)

Linear Interpolation

B-Spline Interpolation

Smooth, piecewise bi(tri)-cubic

Achievable by successive subdivision, when

discrete interpolation is what is desired

Used for interpolation (but does not exact match control pts),

but also to represent spatial transformations (see later)



# Transformations

## Low-dimensional

Rigid translation + rotation

Similarity translation + rotation + scale

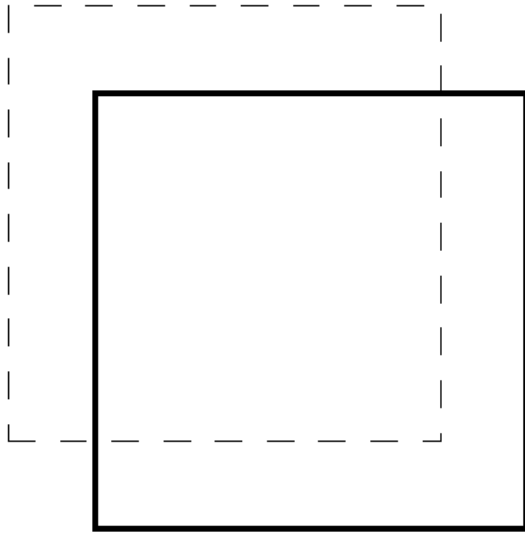
Affine translation + rotation + scale + shear

## High-dimensional

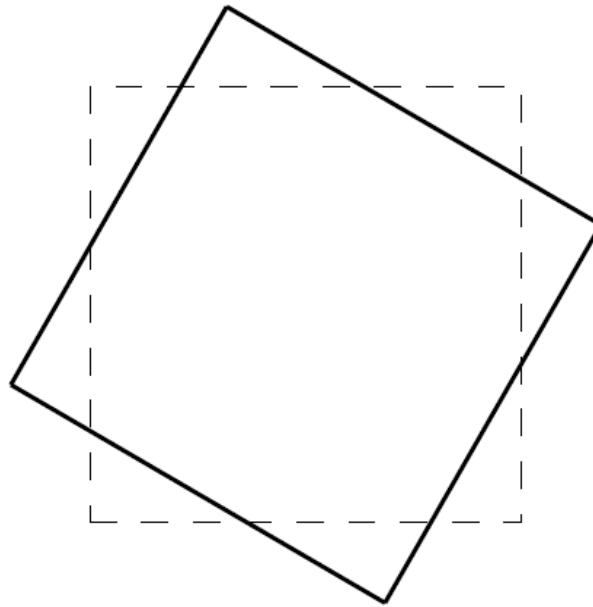
Elastic regularization of displacements (can fold)

Fluid regularization of velocities  
(can avoid folding)

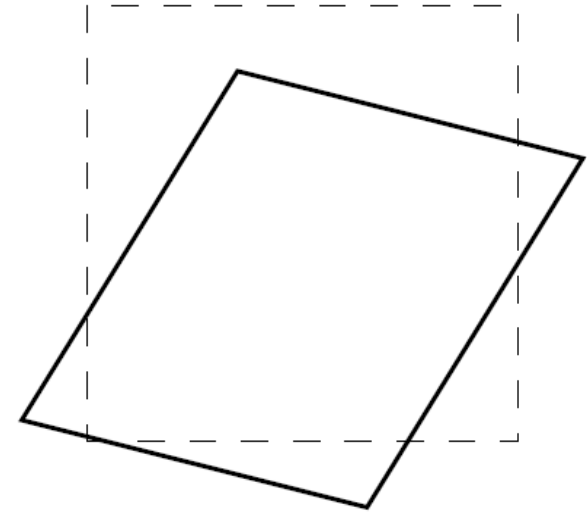
# Transformations



Translation  
 $f : \mathbf{x} \mapsto \mathbf{x} + \mathbf{t}$



Similarity Transform  
 $f : \mathbf{x} \mapsto sR\mathbf{x}$



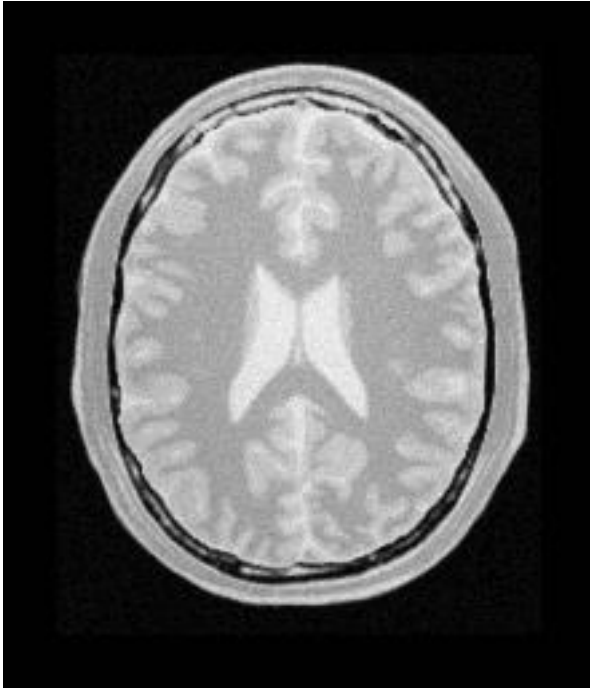
Affine Transform  
 $f : \mathbf{x} \mapsto A\mathbf{x} + \mathbf{t}$

# Example affine transformation

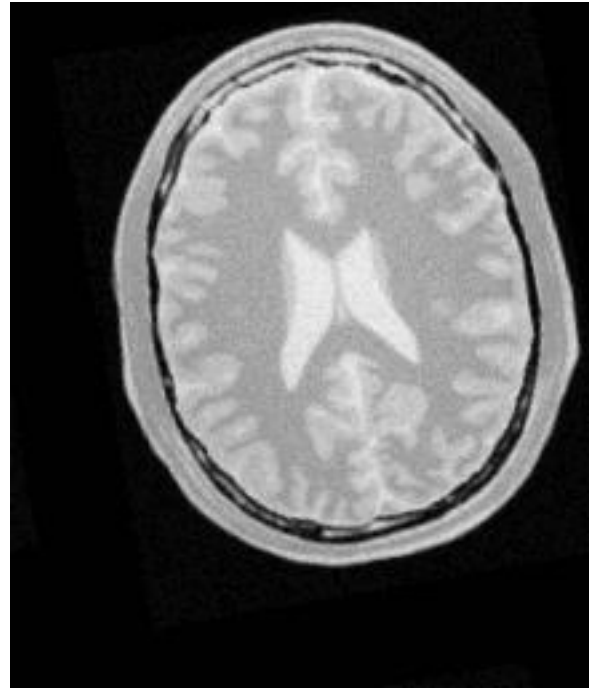


$$\underline{x}' = A\underline{x} + \underline{\Delta x}$$

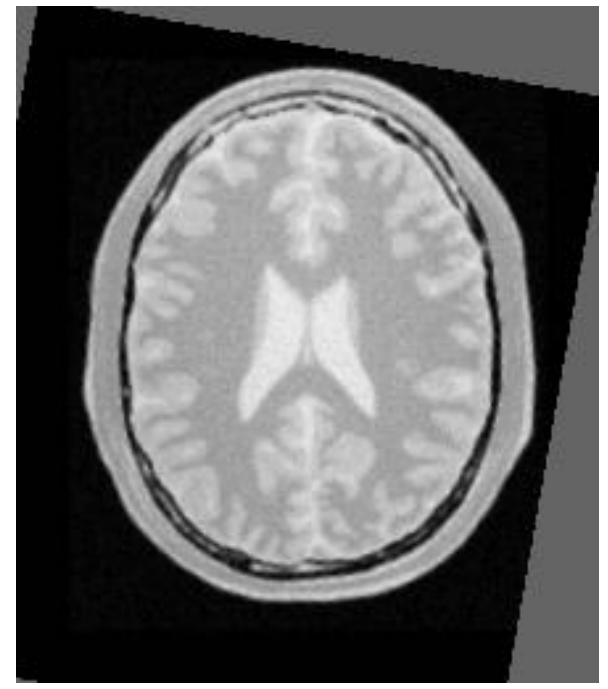
# Example Registration



Fixed Image



Moving Image



Registered  
Moving Image

Images: ITK Registration Guide

# Landmark-based registration

## Landmarks

# Parametric

**More parameters = more flexibility**

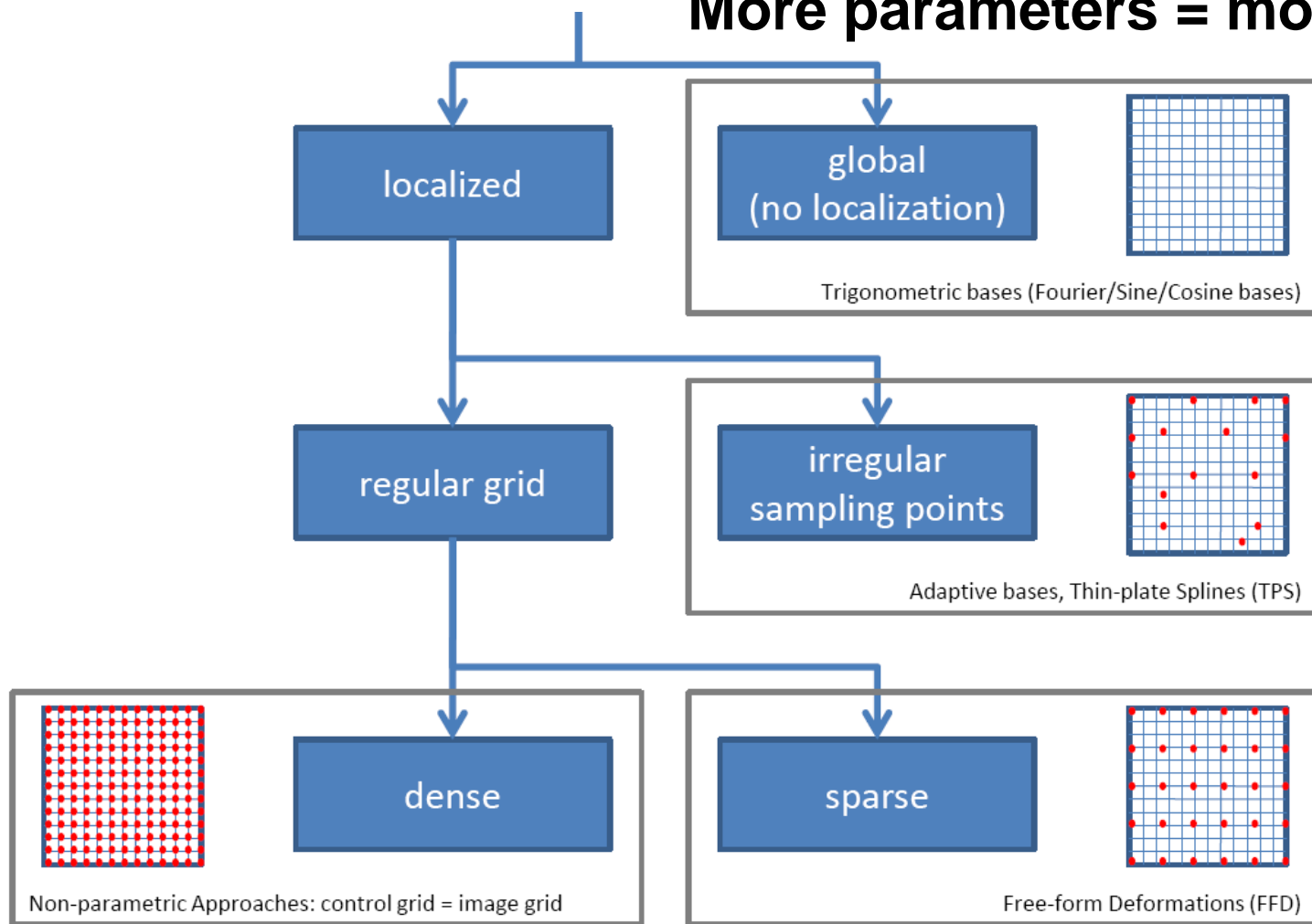


Image: Zikic

*Simplest parametric ones are of course rigid, similarity, affine, ...*

# Geometry and Warps Via Landmarks

- Compute  $\underline{\Delta x}(\underline{x})$  or a decomposition into translations, rotations, magnifications, & ellipse forming deformations
- Energy options
  - Procrustes energy: for global alignment
  - Thin plate spline bending energy: for exact matching warp, possibly incl. alignment
  - Approximate matching warps:
    - Elastic energy
    - Diffeomorphic flow, e.g., by fluid energy
    - “Freeform” (b-spline) deformations

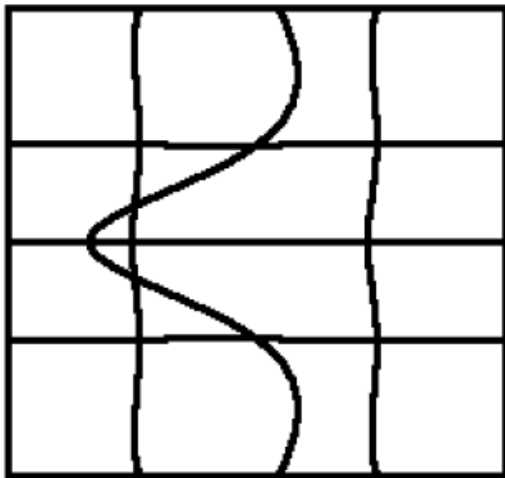
# Geometry and Warps via Landmarks: Issues

- Produces general warp?
- Limited to non-folding warps?
- Energy captures all aspects of warp?
- Symmetric re static vs. moving images?

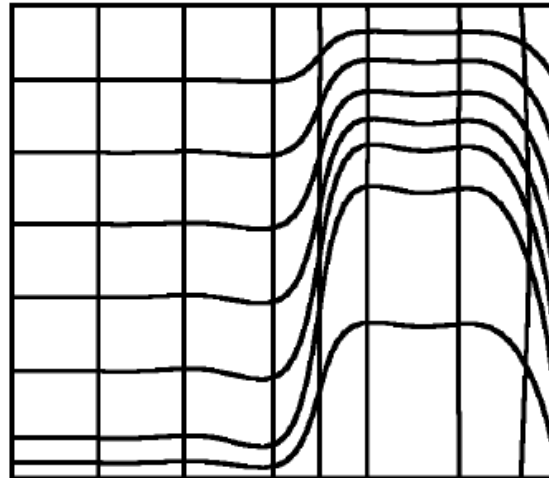


# Want to avoid implausible transformations

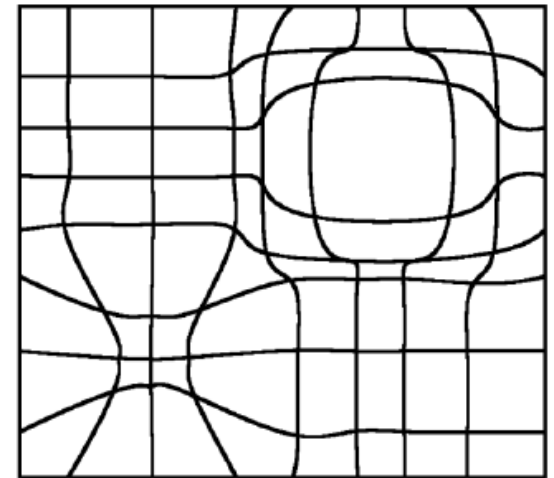
folding



irregular



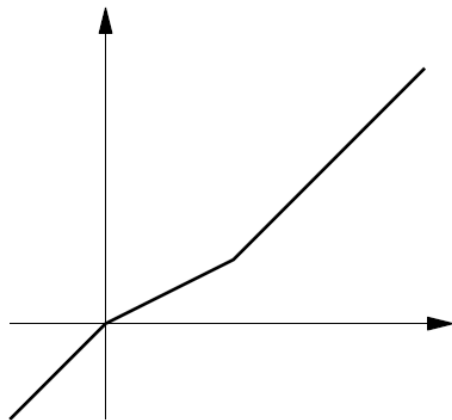
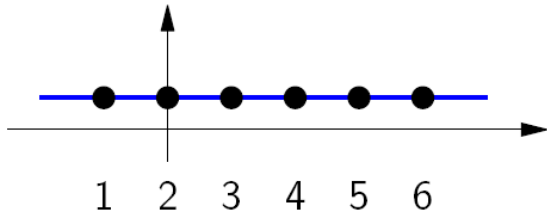
expansion / compression



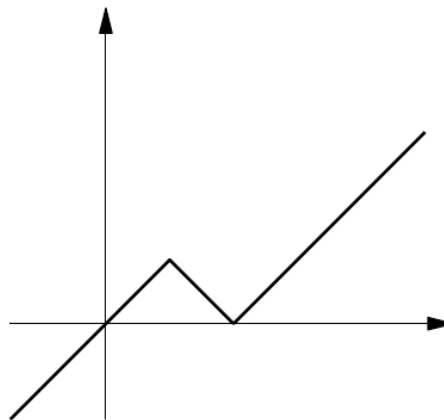
For example, diffeomorphic transformations:  
*“Bijective, smooth, with a smooth inverse”*

Image: Staring

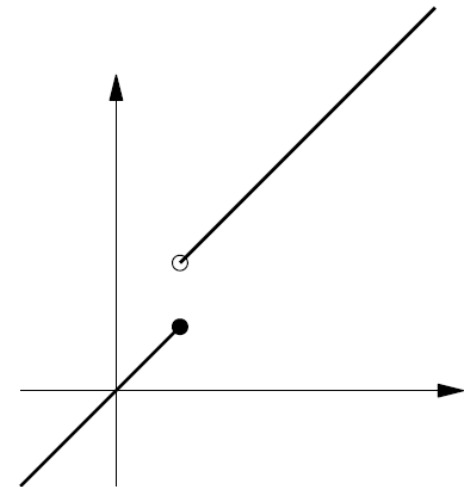
# Diffeomorphisms



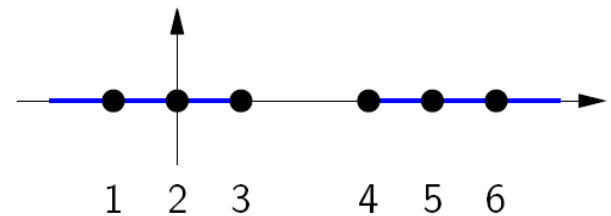
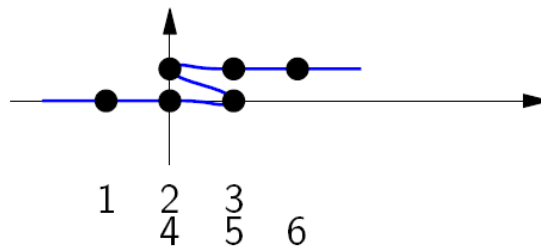
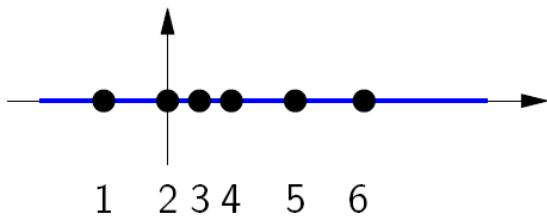
Homeomorphic mapping



Mapping is not bijective



Mapping is discontinuous



Is this all that is needed? Are we missing something?

# Diffeomorphisms

It seems like a homeomorphism is all we want. Because it

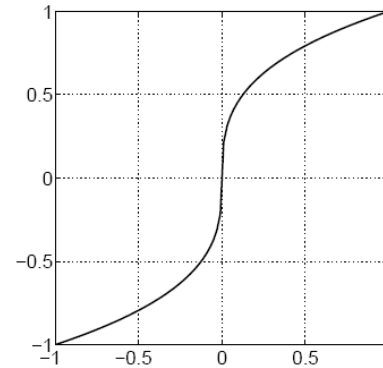
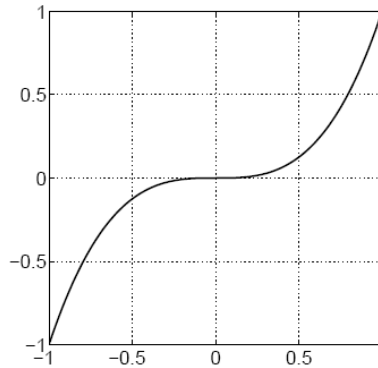
- prevents folding and
- does not allow for tearing either.

What else could we ask for?

The function

$$f : x \mapsto x^3, \quad f^{-1} : x \mapsto x^{\frac{1}{3}}, \quad x \in \mathbb{R},$$

is homeomorphic. But the derivative of  $f^{-1}$  is not defined at 0.



**A diffeomorphism is a smooth bijective mapping with a smooth inverse.**

# Geometric typicality metrics: PDM: Procrustes

- Align shape before warp transformation
  - translation, e.g., to center of mass
  - scaling(?):  $|\underline{\mathbf{x}}| = 1$
  - rotation to minimize  $|\underline{\mathbf{x}} - \underline{\mathbf{x}}_{\text{std}}|$
- Metric =  $\sum_i |\mathbf{x}^i - \mathbf{x}_{\text{std}}^i|^2$ 
  - Has statistical variant
- $O(n)$ , with  $n$  = number of points
- Symmetric

# Thin plate spline deformation energy

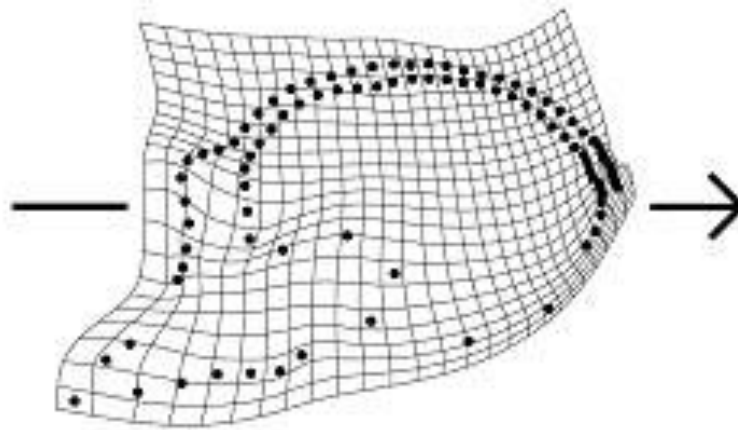
- Elastic warp in each variable
- Based on landmark primitives
- Minimizing integrated 2nd derivs<sup>2</sup>
  - So smooth
- Not necessarily diffeomorphic; may produce folding
- Not symmetric
- Due to Bookstein: Ref: [Dryden & Mardia, *Statistical Shape Analysis*]
- $O(n^2)$

# Splines w/ Landmarks



Image: Younes

# Thin-plate Splines



Images: University of Vienna

Warping a human skull into a chimpanzee skull.

# Thin plate spline deformation energy

Method of landmark matching based on finding the mapping fcn.

$$f(x, y) = a_0 + a_x x + a_y y + \sum_{i=1}^n w_i U(|p_i - (x, y)^T|)$$

$$\text{where } U(r) = -r^2 \log(r^2)$$

that matches landmark points to each other while minimizing

$$I_f = \iint \left( \left( \frac{\partial^2 f}{\partial x^2} \right)^2 + 2 \left( \frac{\partial^2 f}{\partial x \partial y} \right)^2 + \left( \frac{\partial^2 f}{\partial y^2} \right)^2 \right) dx dy$$

This mapping is not guaranteed to be diffeomorphic.



# B-Spline Transformations “Freeform Deformation” [Rueckert]

- *Grid* of control points
- Value at each control point
  - Can be scalar in general
  - For registration, a displacement vector
    - 3 scalars, each separately interpolated
- Patchwise bi(tri)-cubic; smooth at patch boundaries
- Raw form can fold; there is diffeomorphic variant
  - Successive small freeform changes

# Diffeomorphic Landmark Matching [Yoshi]

Flowing images into each other. Mapping function  $h(\mathbf{x}) = \phi(\mathbf{x}, 1)$  given through the ODE

$$\frac{d\phi(\mathbf{x}, t)}{dt} = v(\phi(\mathbf{x}, t)), \quad t \in [0, 1], \quad \phi(\mathbf{x}, 0) = \mathbf{x}.$$

Minimize smoothness cost subj. to landmark constraints ( $h(\mathbf{x}_n) = \mathbf{y}_n$ )

$$\hat{v}(\cdot) = \operatorname{argmin}_{v(\cdot)} \int_0^1 \int_{\Omega} \|Lv(\mathbf{x}, t)\|^2 d\mathbf{x} dt.$$

This is guaranteed to give a diffeomorphic  $h$  for suitable  $L$  (for example  $L = I(-\nabla^2 + c)$  works).

# Diffeomorphic Landmark Matching

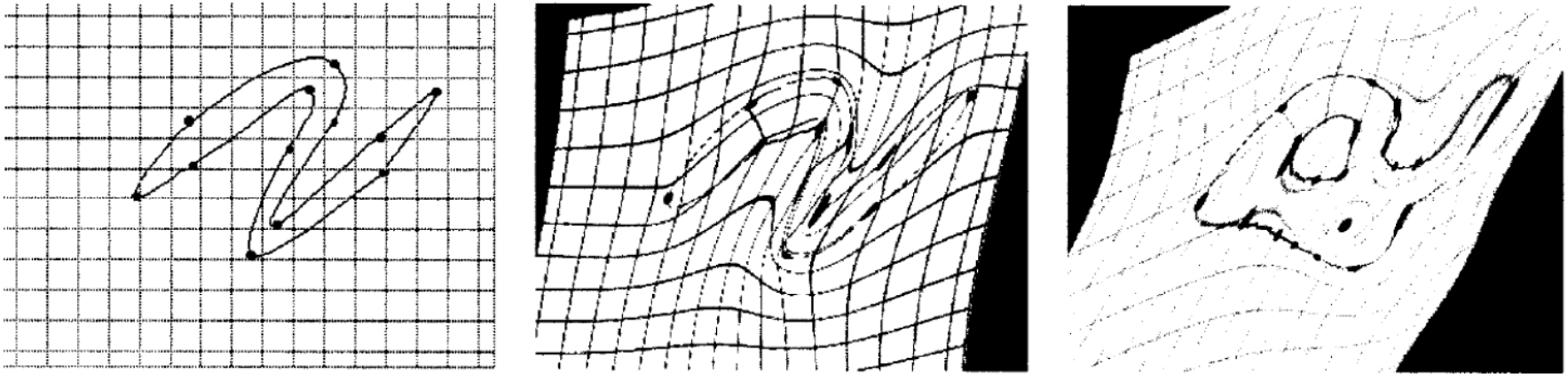


Image from Joshi.

Left: target image, middle: diff. landmark matching, right: small displacement matching.

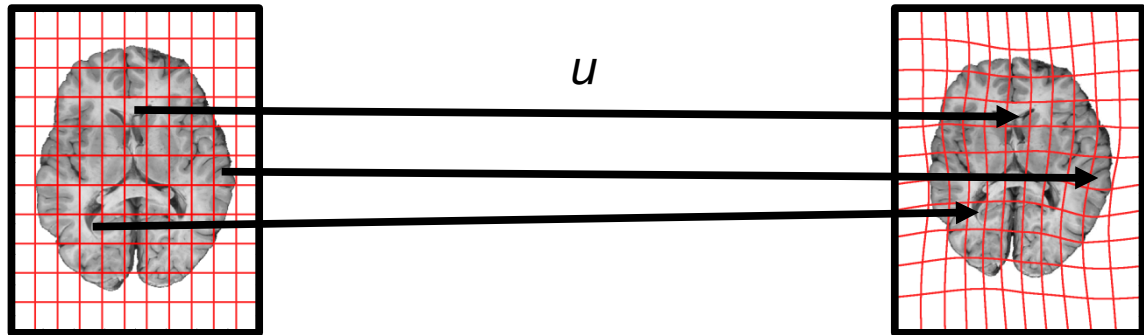
# Image-based registration

# Image-based registration

# Elastic-type versus fluid-type registration

## Elastic Registration

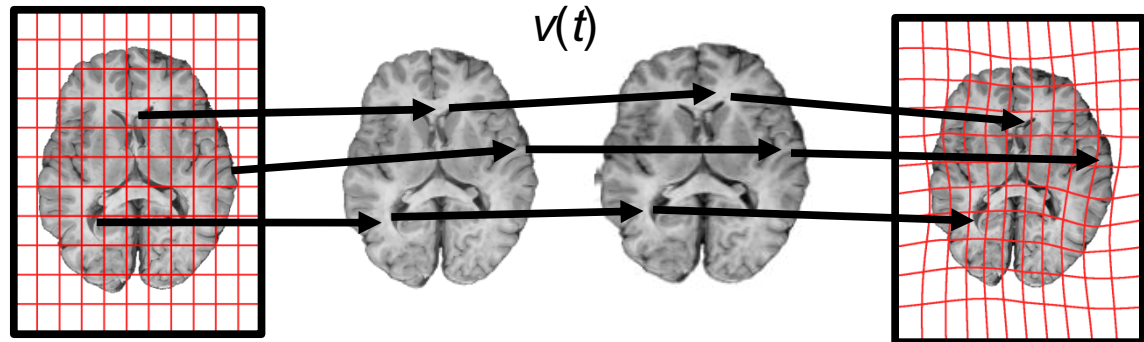
Regularization on the displacement field ( $u$ )



$$u = \operatorname{argmin}_u \int \Psi_s^u[u] + \frac{1}{\sigma^2} \Psi_d[u, I_0, I_1] d\Omega$$

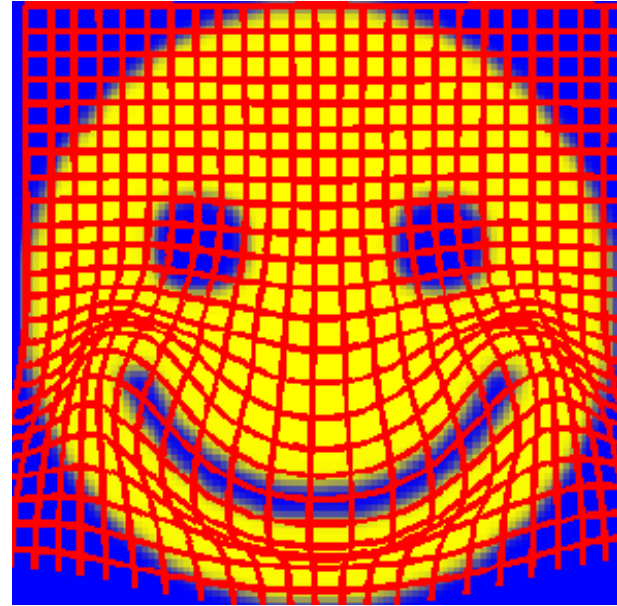
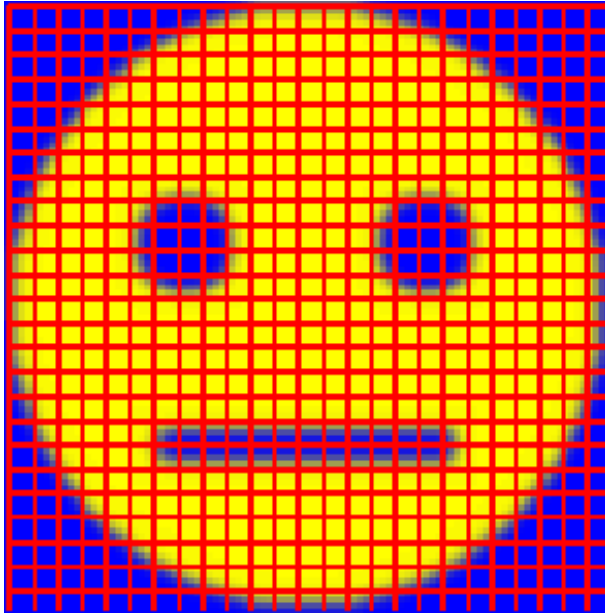
## Fluid Registration

Regularization on the time dependent velocity field ( $v$ )



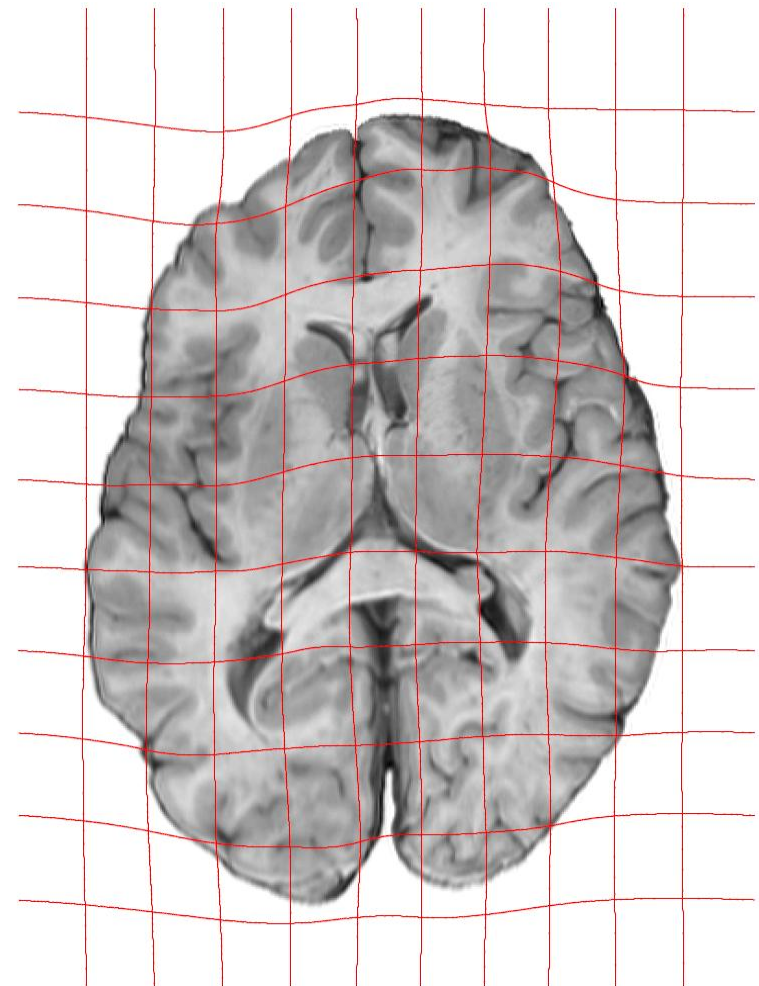
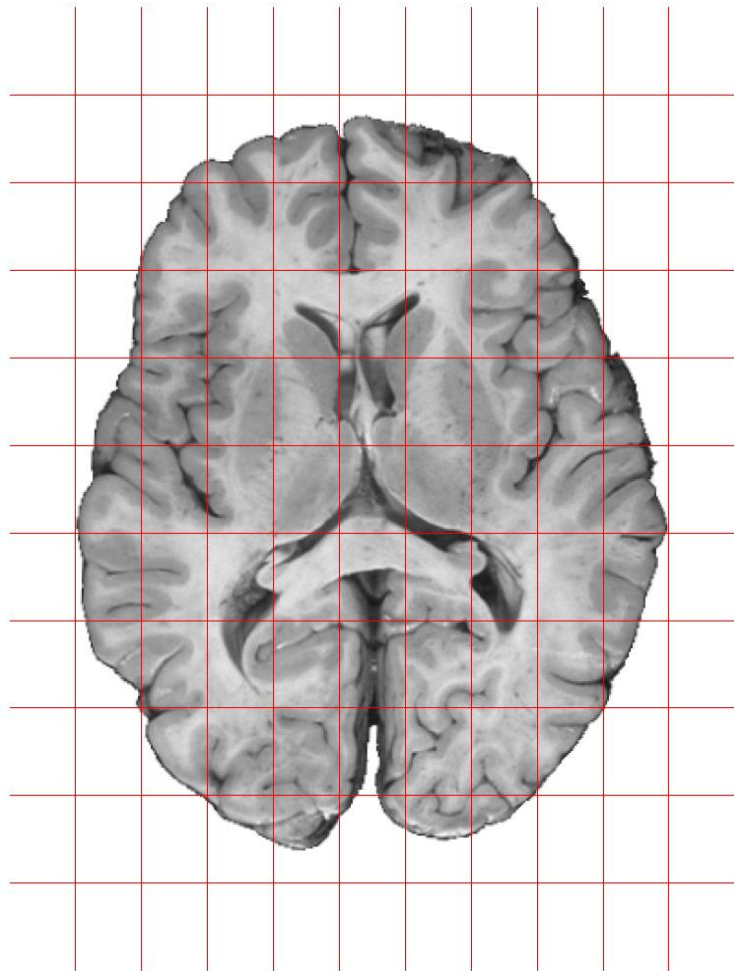
$$v = \operatorname{argmin}_v \iint \Psi_s^v[v] d\Omega dt + \frac{1}{\sigma^2} \int \Psi_d[u, I_0, I_1] d\Omega.$$

# Elastic Transformation



Images: Ashburner

# Deformable registration (dense deformation fields)



Many registration methods available.

# Displacement-regularized registration

Combination of

- regularization of displacement field  $u$  and
- image similarity measure (SSD, correlation, MI, etc.)

$$u^* = \operatorname{argmin}_u \underbrace{S[u]}_{\text{regularization}} + \underbrace{\frac{1}{\sigma^2} D[u, I_0, I_1]}_{\text{similarity measure}}$$

Multiple options for regularization also

- diffusive
- curvature
- elastic
- ...



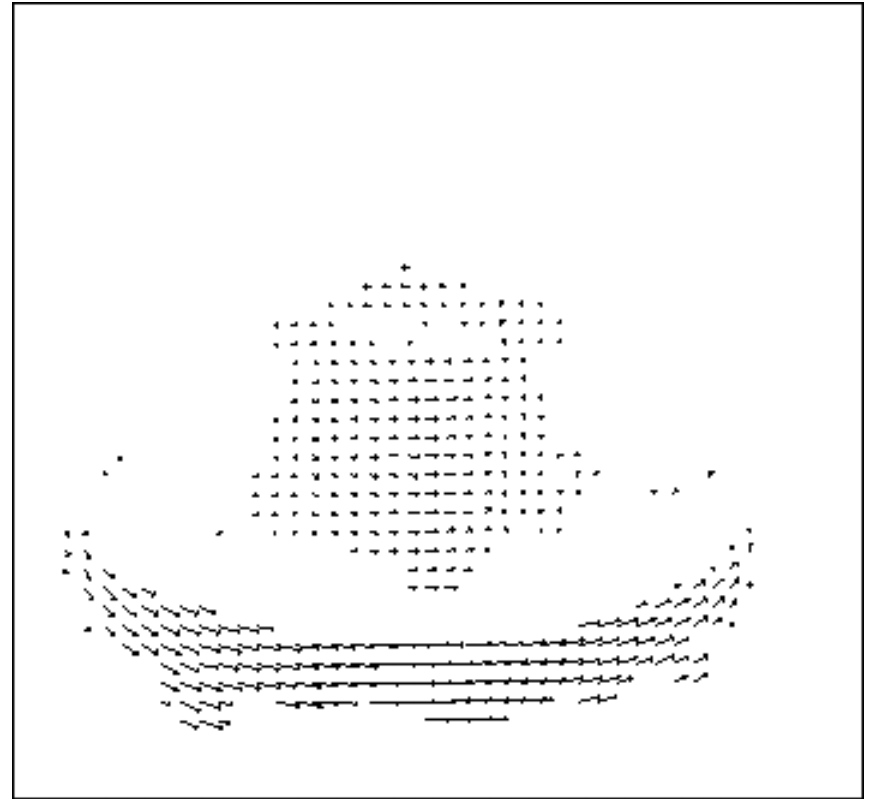
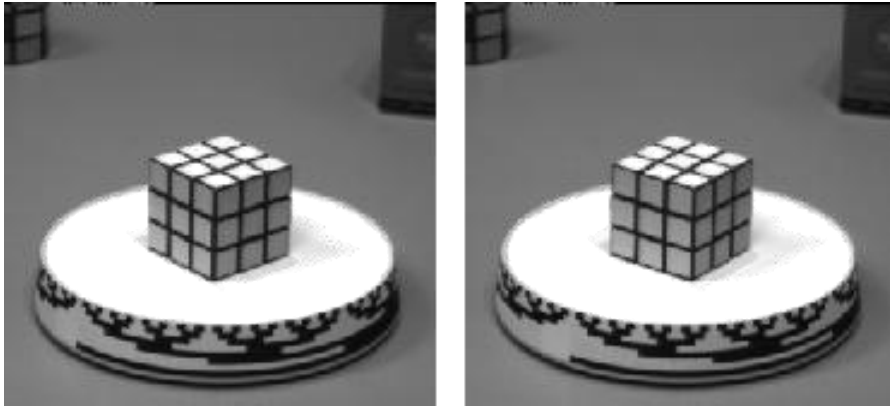
# Diffusion Regularization (=Optical Flow)

Enforces smoothness of the displacement fields  
(component by component)

$$S[u] = \frac{1}{2} \sum_{l=1}^d \int_{\Omega} \|\nabla u_l\|^2 dx \stackrel{2D}{=} \frac{1}{2} \int_{\Omega} \|\nabla u_1\|^2 + \|\nabla u_2\|^2 dx$$

Simplest model, as used for example in optical flow  
(Gradients will result in Laplacian terms -> smoothing)

# Optical Flow



$$E(v^x, v^y) = \int_{\Omega} (I_t + I_x v^x + I_y v^y)^2 + \alpha (\|\nabla v^x\|^2 + \|\nabla v^y\|^2) d\Omega$$

Images: Slides of Bill Freeman

# Curvature Regularization

Regularization based on the Laplacian of the displacements

$$S[u] = \frac{1}{2} \sum_{l=1}^d \int_{\Omega} (\Delta u_l)^2 dx \stackrel{2D}{=} \frac{1}{2} \int_{\Omega} (\Delta u_1)^2 + (\Delta u_2)^2 dx$$

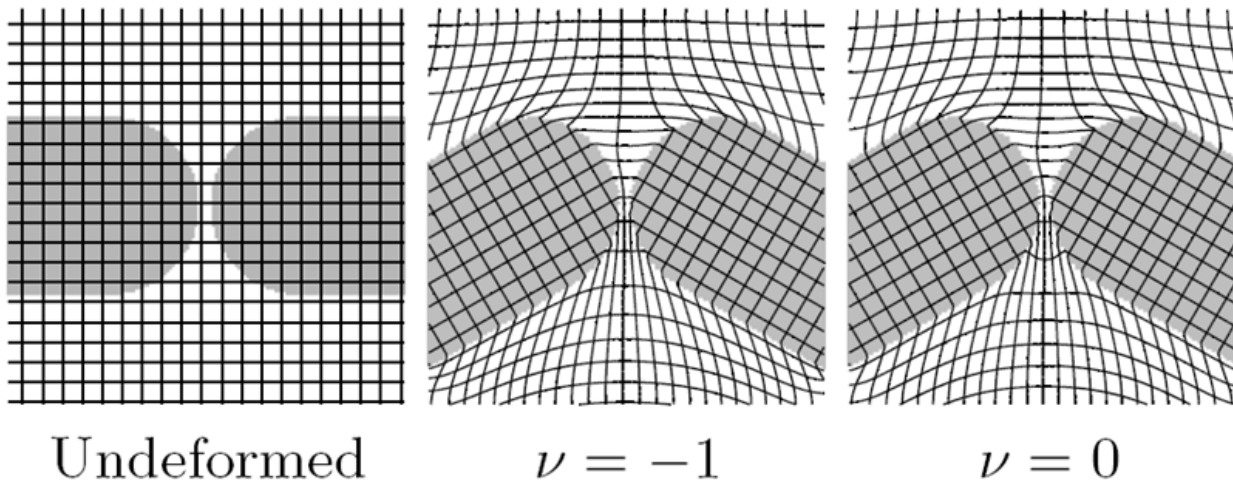
Invariant to affine transformations (due to second derivatives).

# Elastic Regularization

Based on physical model of linear elasticity

$$S[u] = \int_{\Omega} \frac{\mu}{4} \sum_{j,k=1}^d \underbrace{(\partial_{x_j} u_k + \partial_{x_k} u_j)^2}_{\text{rigidity}} + \underbrace{\frac{\lambda}{2} (\text{div } u)^2}_{\text{change in material volume}} dx = \underbrace{P[u]}_{\text{elastic potential}}$$

$\mu, \lambda$ : Lamé constants (control elastic behavior)



# Elastic Regularization

Elasticity model is the continuum mechanics equivalent to the spring model

$$E[u] = \frac{1}{2}ku^2$$

Can compute the force by differentiation

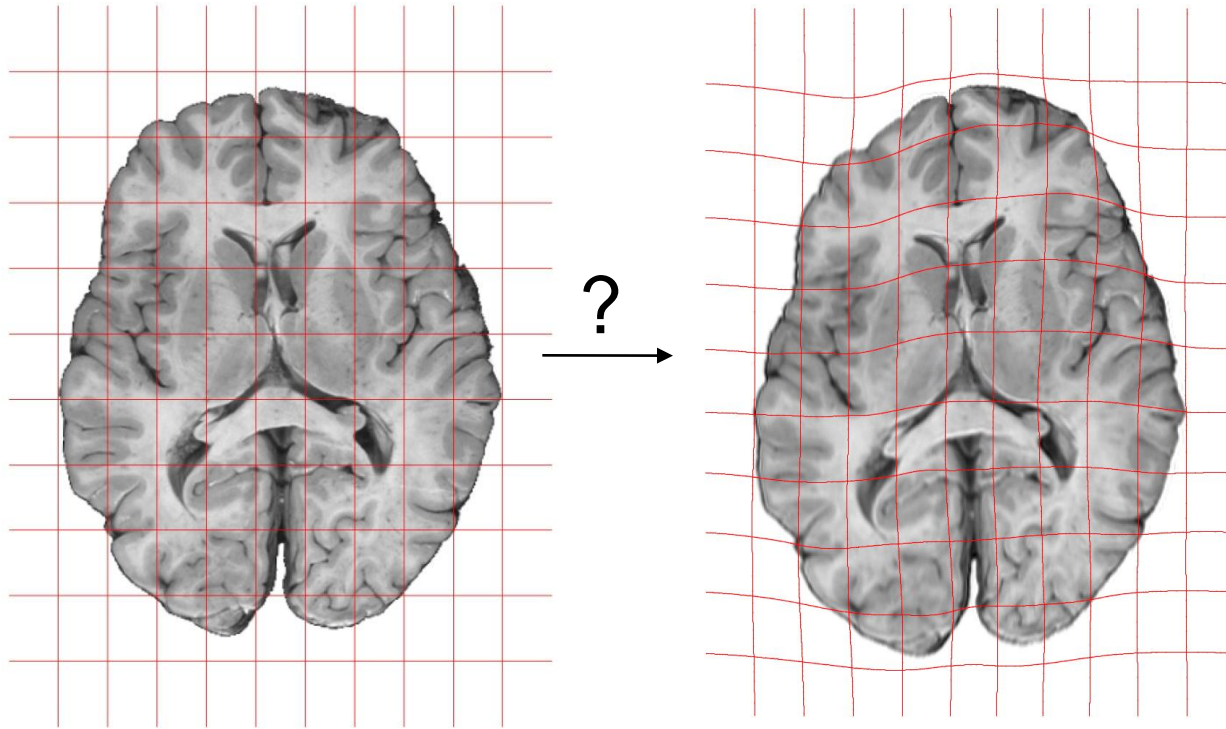
$$F[u] = -\frac{dE(u)}{du} = -ku$$

In the continuum, the force is obtained through the variation

$$f = \mu\Delta u + (\lambda + \mu)\nabla\text{div}(u)$$

which, needs to be balanced w/ force from similarity measure

# Fluid flow registration



What is the best velocity field,  $v$ , to deform one image into the other?

Fluid flow setup [Miller et al.]:

$$E(v) = \int_0^1 \|v\|_V^2 dt + \frac{1}{\sigma^2} \|I_0 \circ \Phi_{1,0} - I_1\|_{L_2}^2$$

# Fluid flow registration

Fluid flow setup [Miller et al.]:

$$E(v) = \int_0^1 \|v\|_V^2 dt + \frac{1}{\sigma^2} \|I_0 \circ \Phi_{1,0} - I_1\|_{L_2}^2$$

Complex optimization problem:

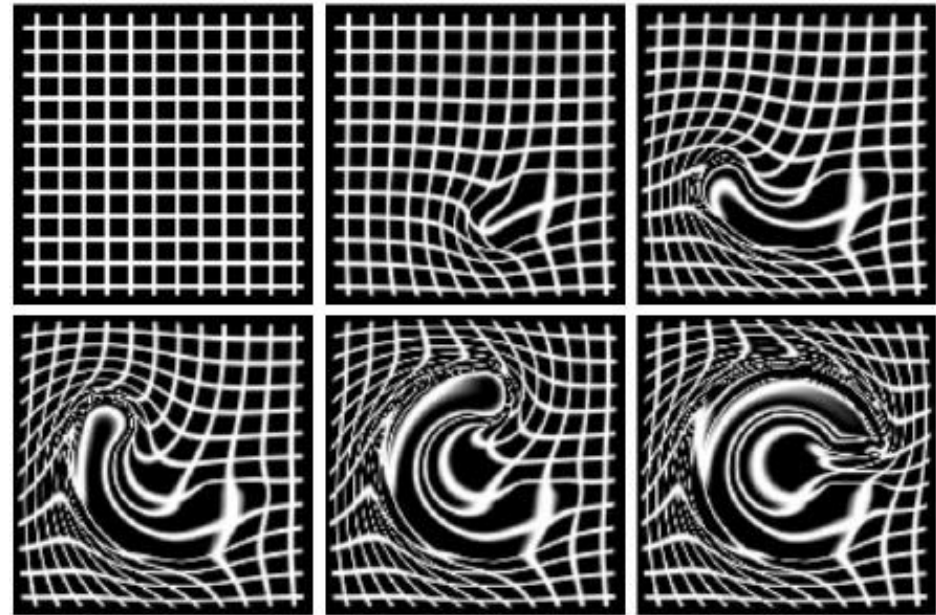
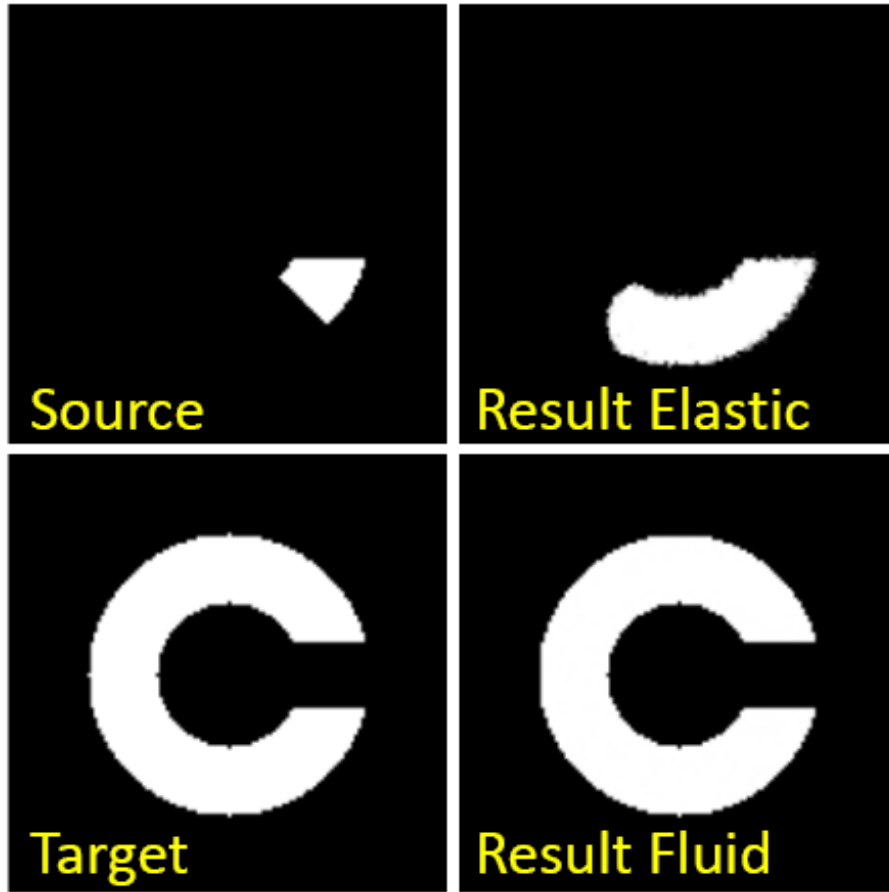
- $v$  depends on time and space
- requires solution of full space-time problem
- often approximately solved using a greedy algorithm (greedy versions of LDDMM, Demons, ...)

# Test cases

# Test cases



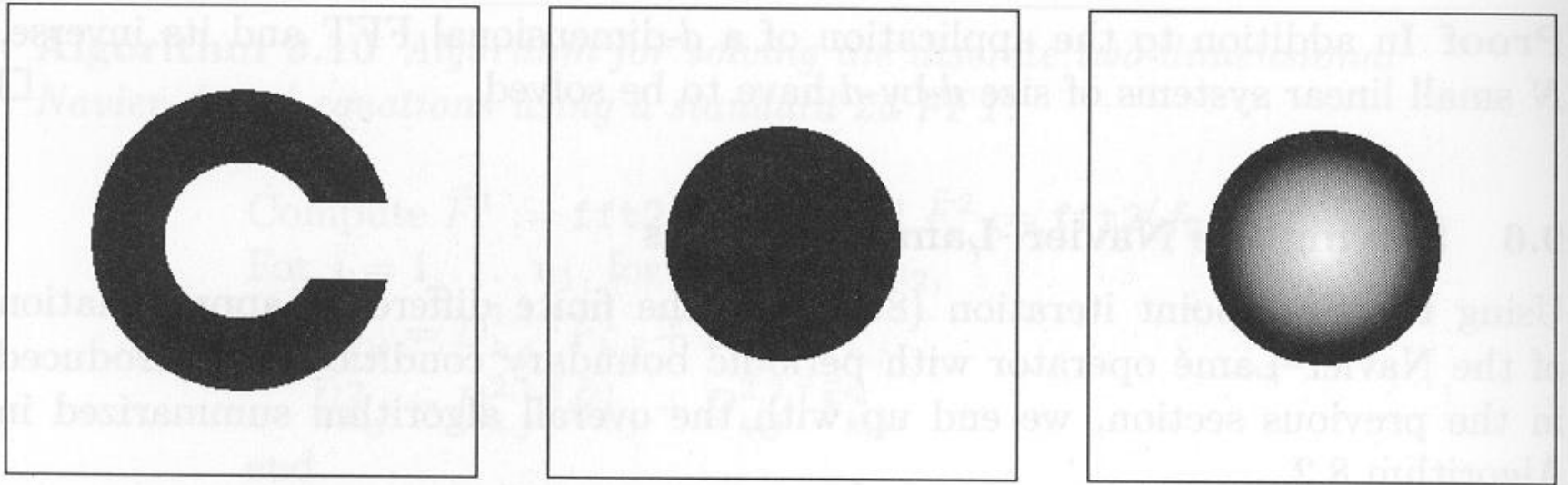
# Non-parametric: Elastic- vs. fluid-type registration



Images: Christensen

# Test Cases

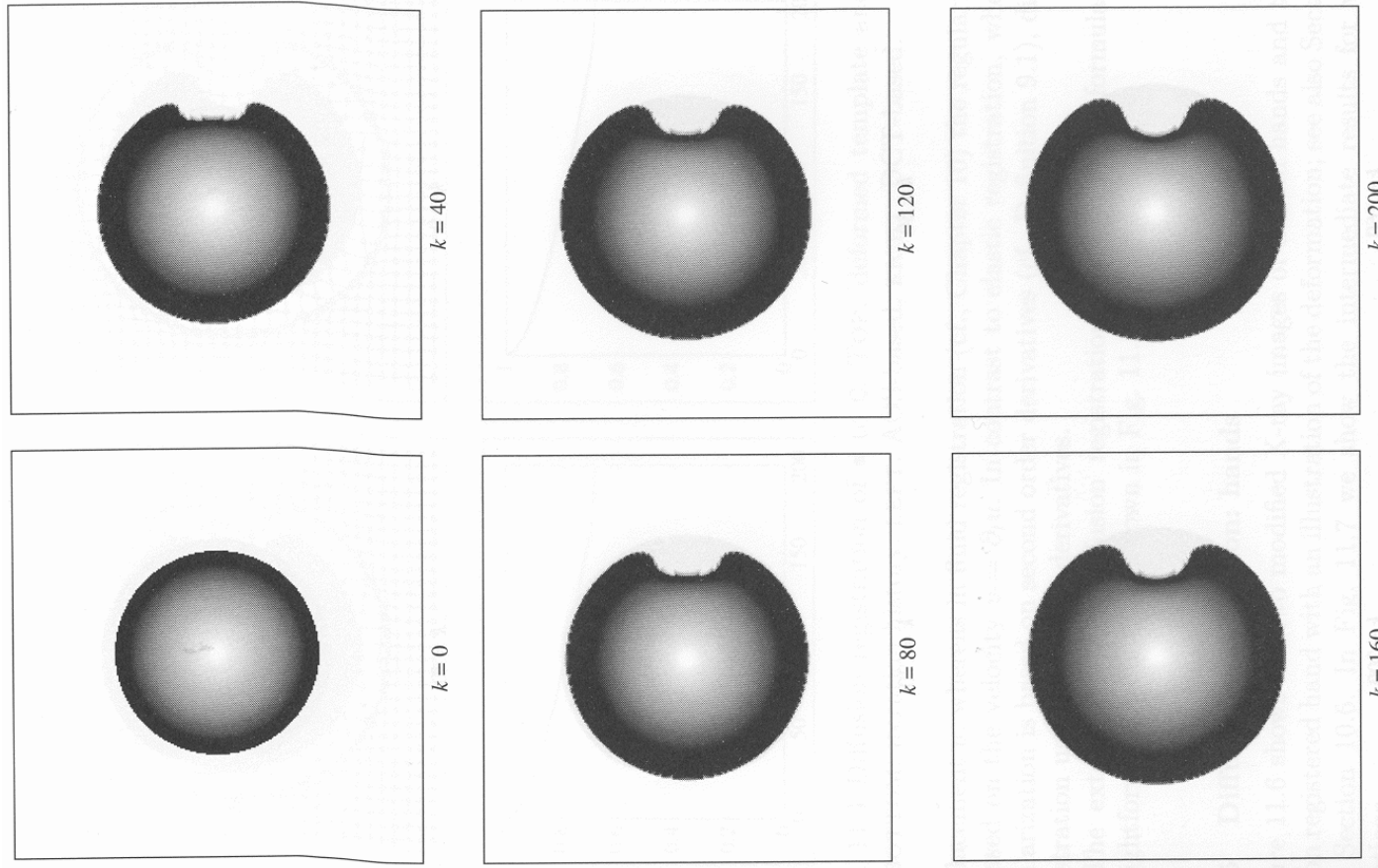
Standard test cases to assess registration behaviour for different registration algorithms



Images: Modersitzki

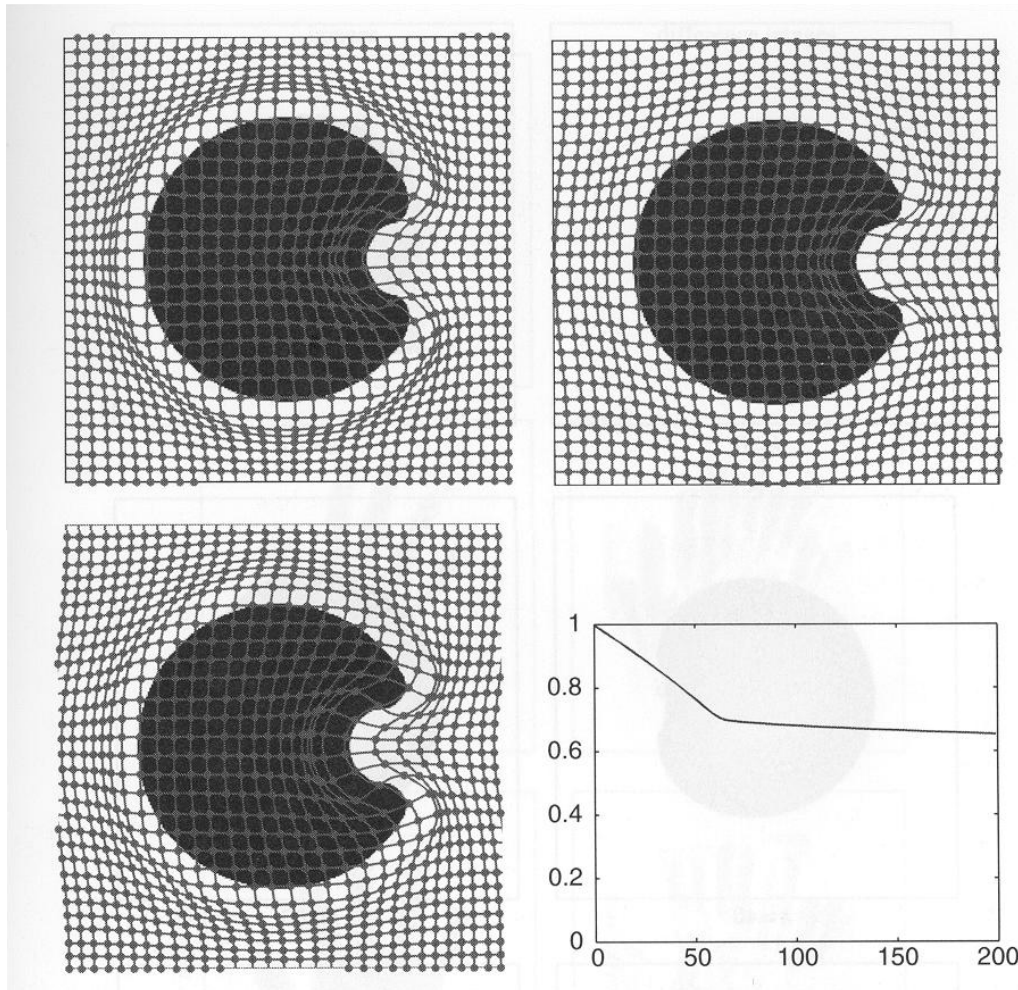
# Diffusion Registration

Regularization of displacements hinders large deformations



Images: Modersitzki

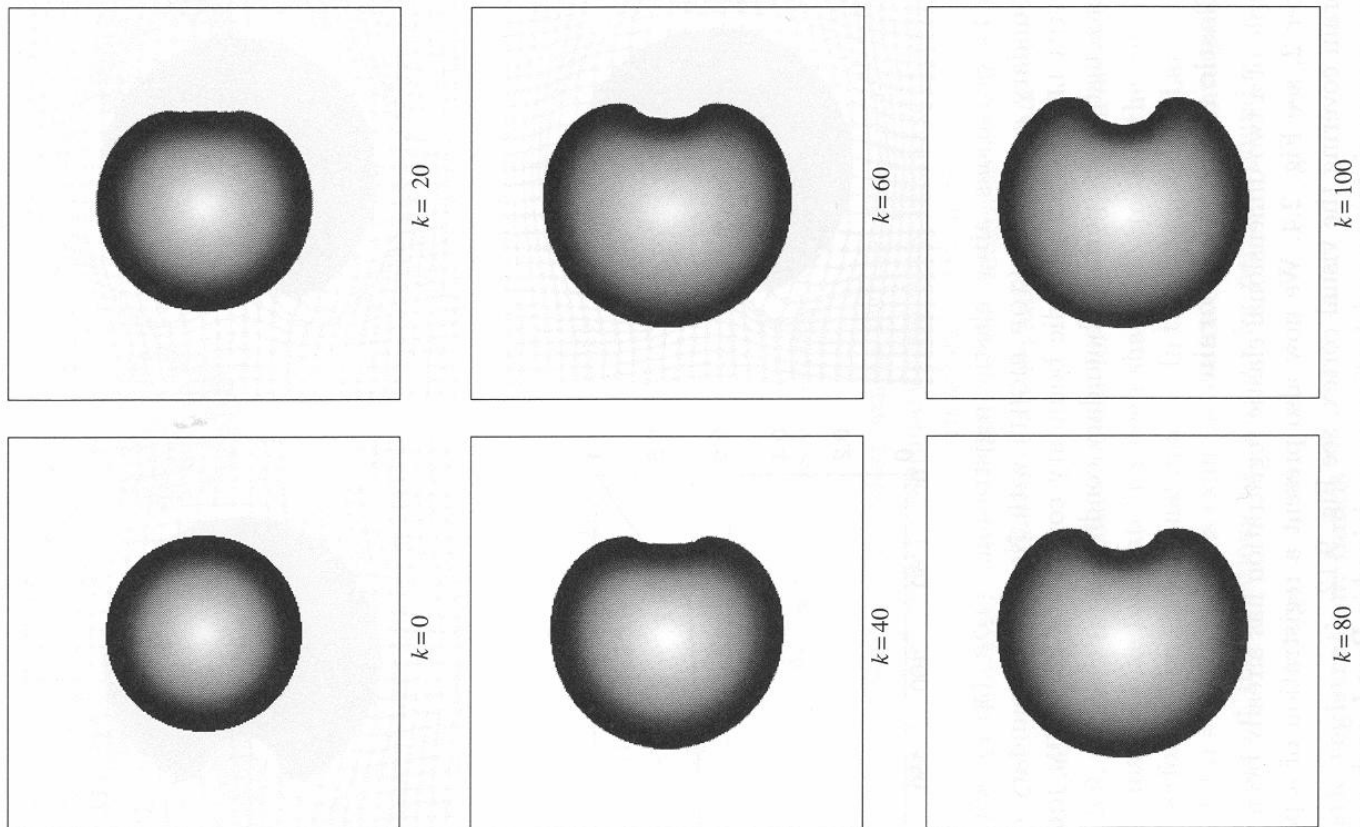
# Elastic Registration



Images: Modersitzki

# Elastic Registration

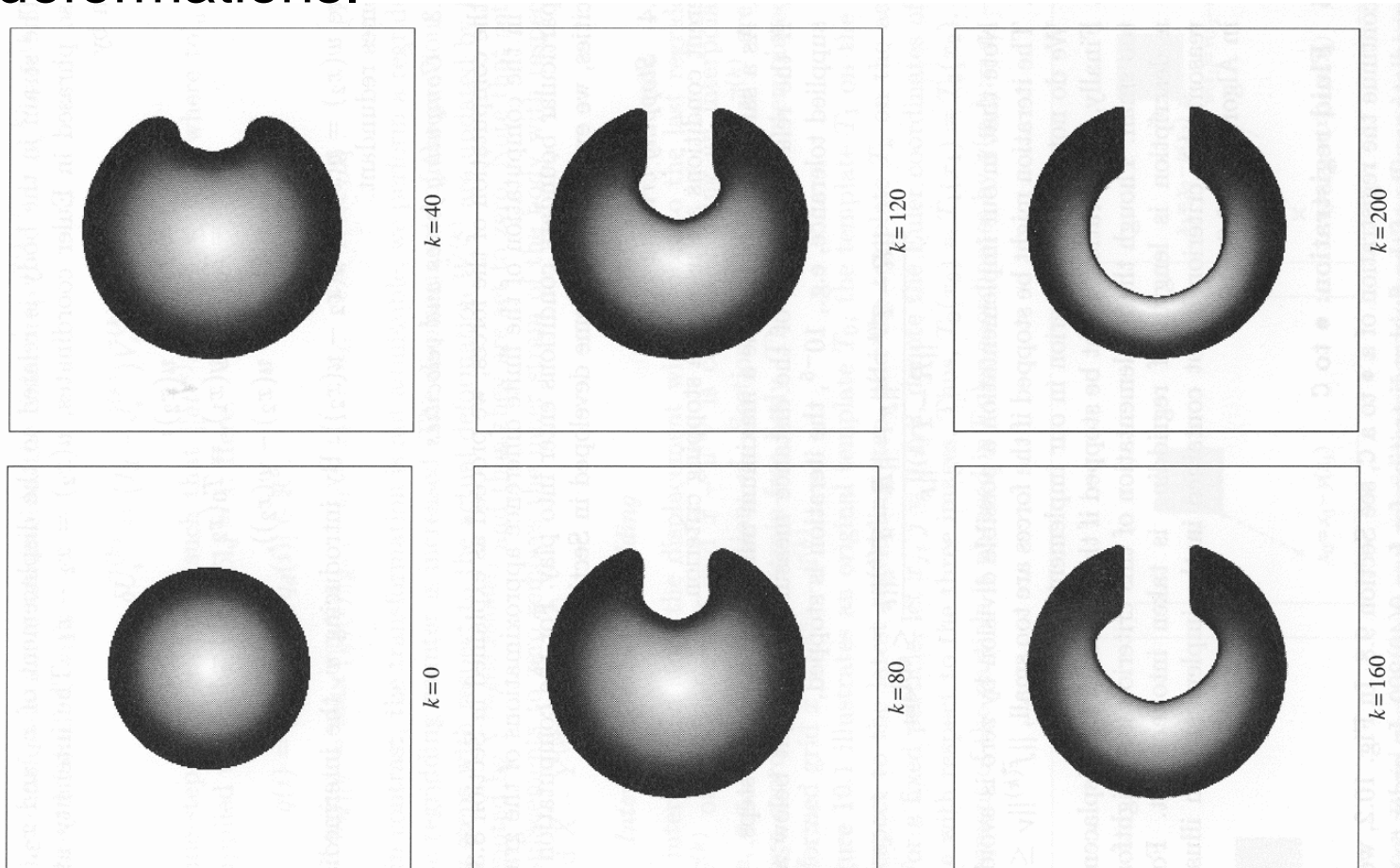
As for diffusive regularization, the regularization of displacements discourages large displacements



Images: Modersitzki

# Fluid Registration [Christensen, Joshi, Miller]

Since fluid registrations regularize velocities they allow for large deformations.



Images: Modersitzki

# General Issues

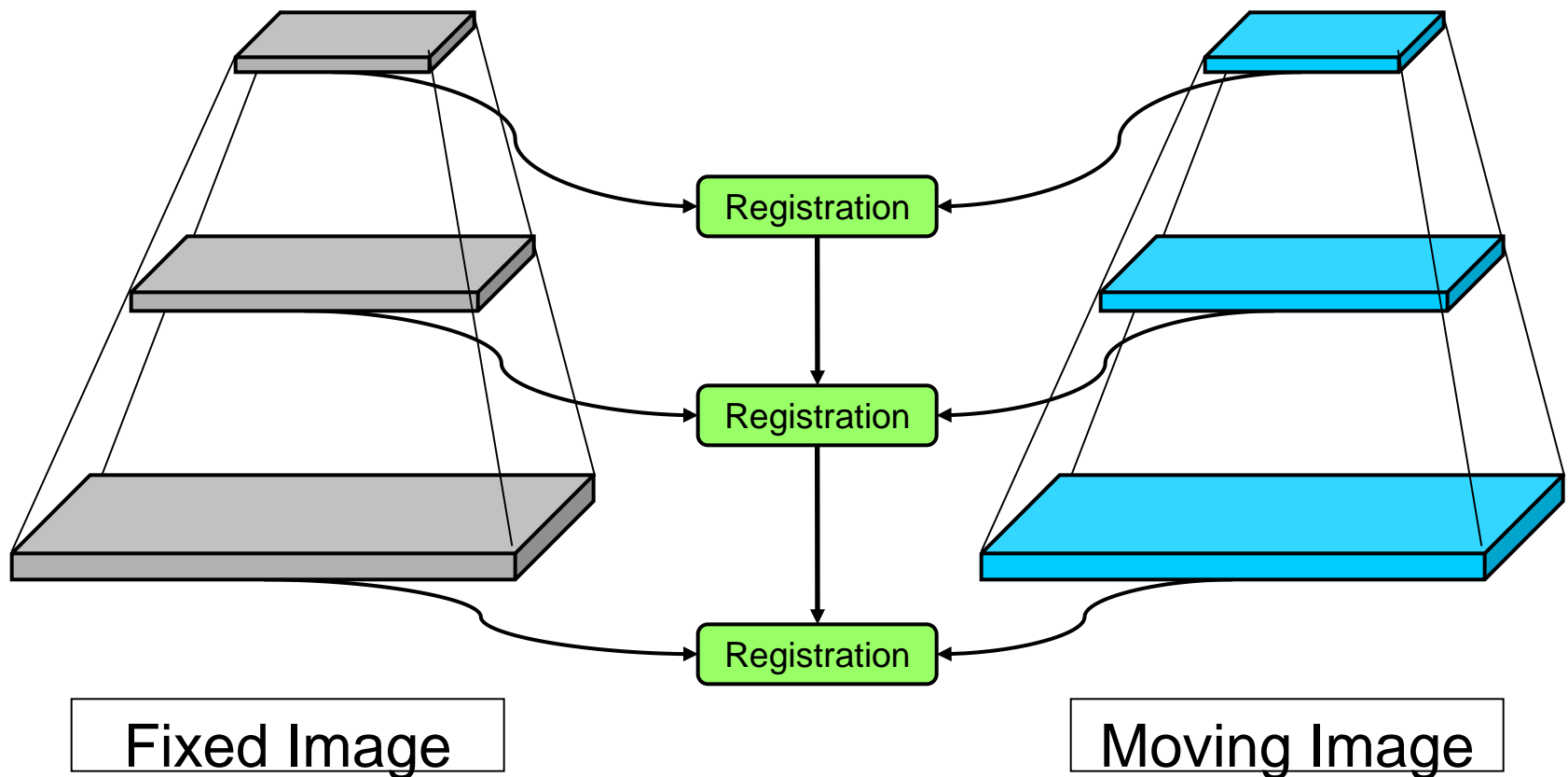
# General Issues

# Warp Transformation on Landmarks or Image Data (or both)

- Typically pre-align
  - Result is different if you don't pre-align
- Objective function terms:
  - Regularization energy
    - Weight value is hard to determine, esp. since two terms are in different units
  - Geometry-to-data match
    - For landmarks
    - For image features
- Does not give exact match due to regularization
- Often will still fall into local energy minima
  - Especially if you do not pre-align



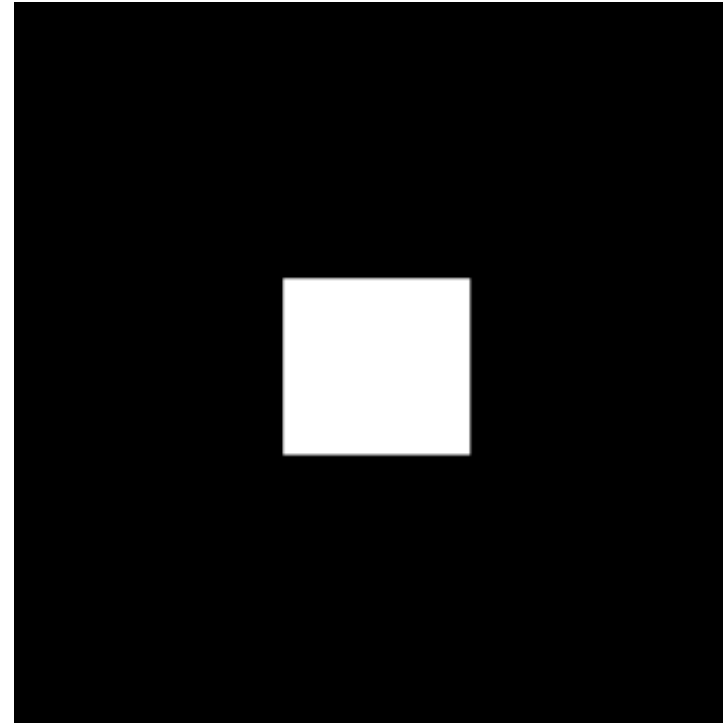
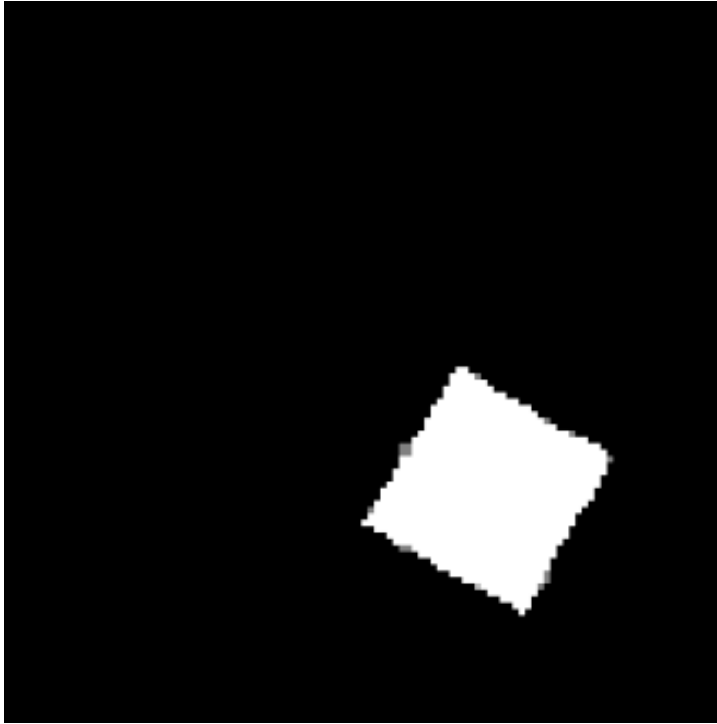
# Multi-Resolution



Speeds-up convergence  
Helps w/ local minima

Images: ITK Registration Guide

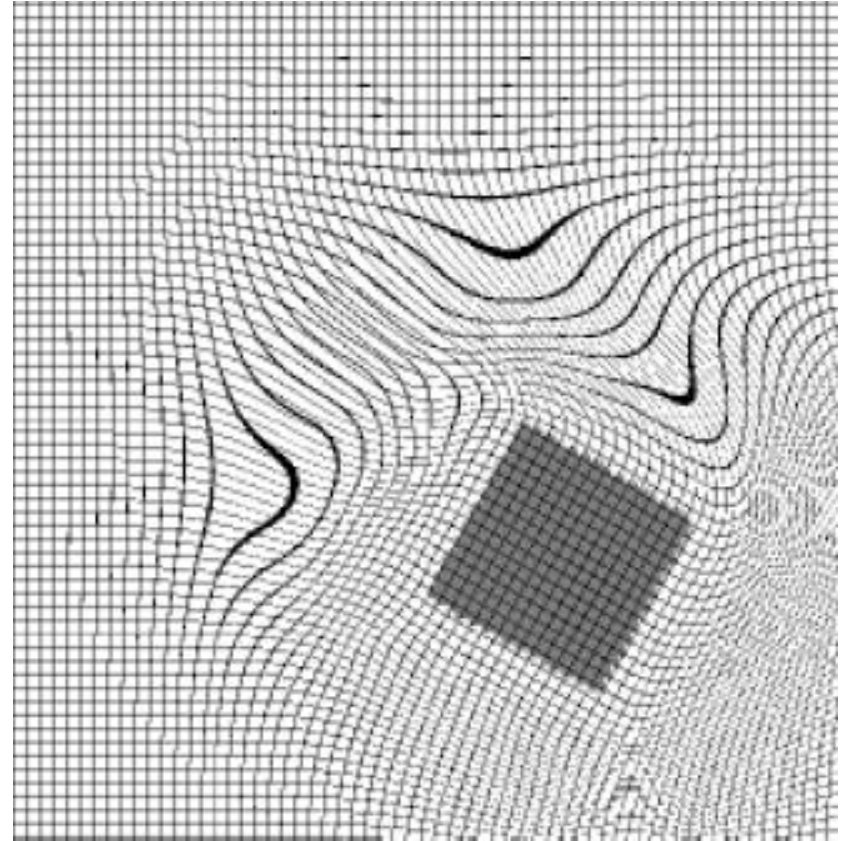
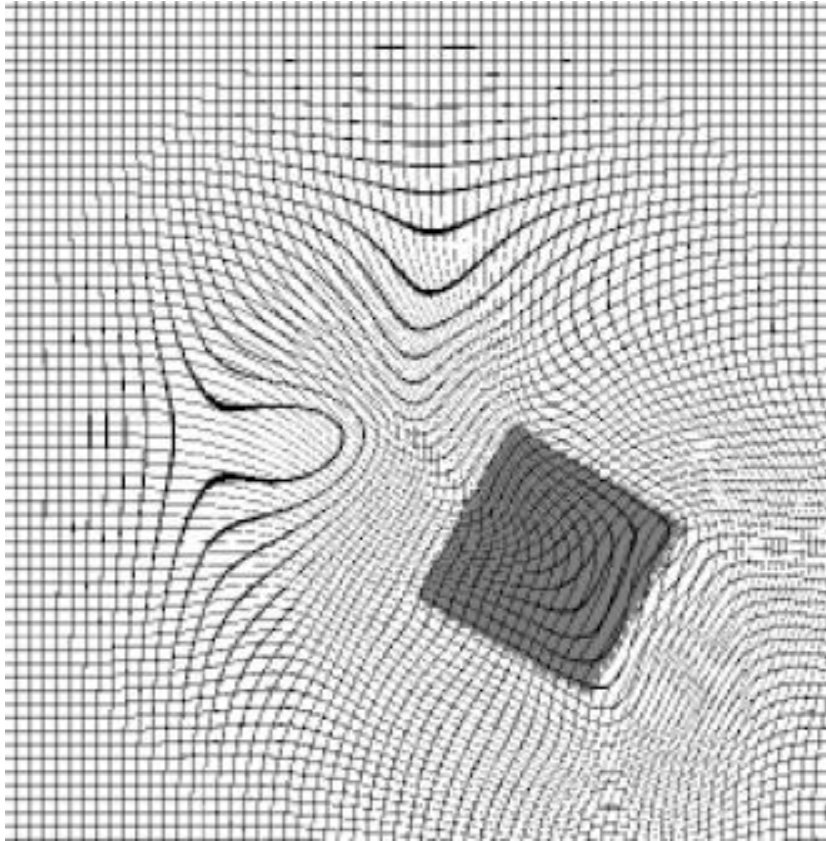
# Registration Quality $\neq$ Visual Quality



There may be more than one (visually identical) solution, depending on the transformation chosen.

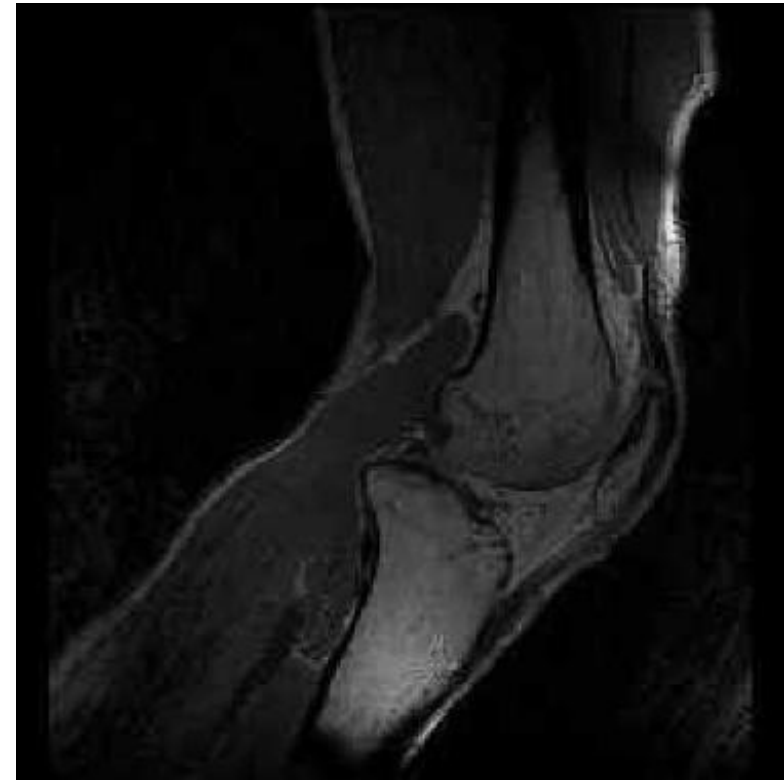
Images: Modersitzki and Haber

# Registration Quality $\neq$ Visual Quality



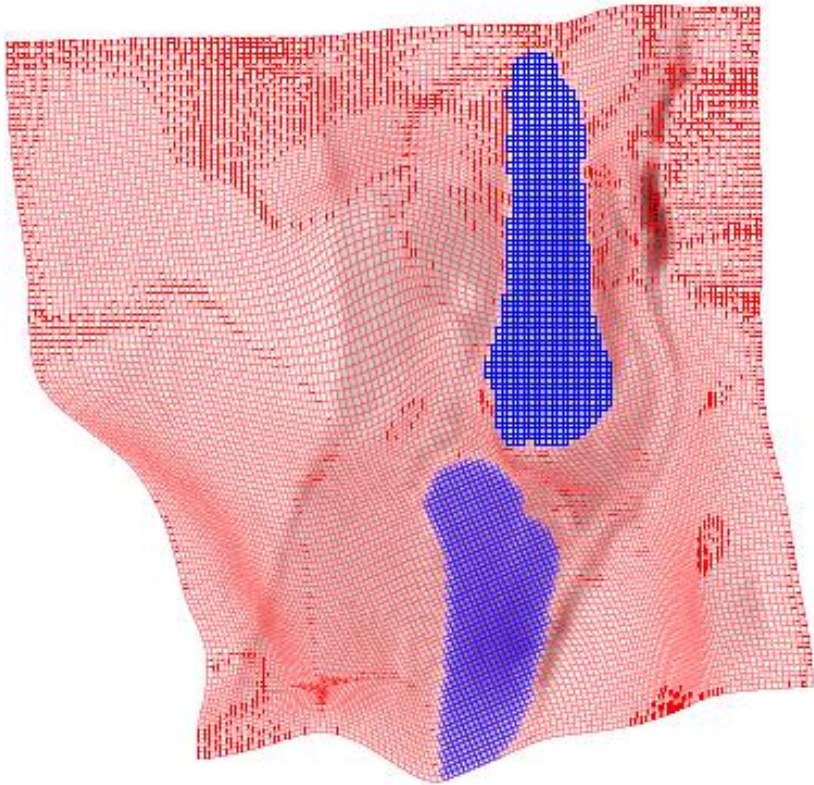
Images: Modersitzki and Haber

# Registration Quality $\neq$ Visual Quality

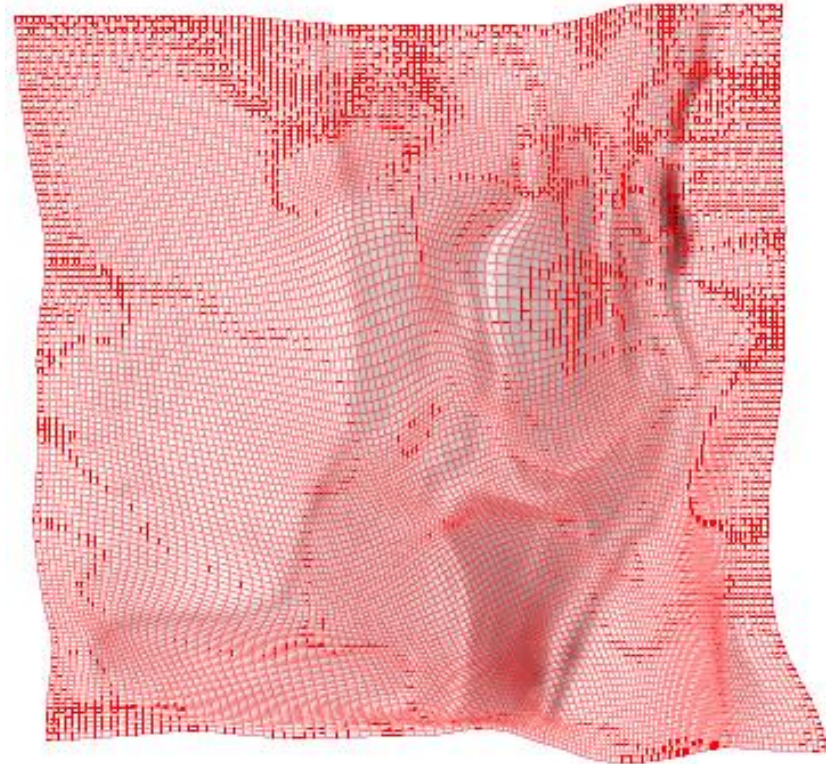


Images: Modersitzki and Haber

# Registration Quality $\neq$ Visual Quality



With constraint of bone rigidity.



Without constraint.

Images: Modersitzki and Haber

# Registration w/ Point Correspondences

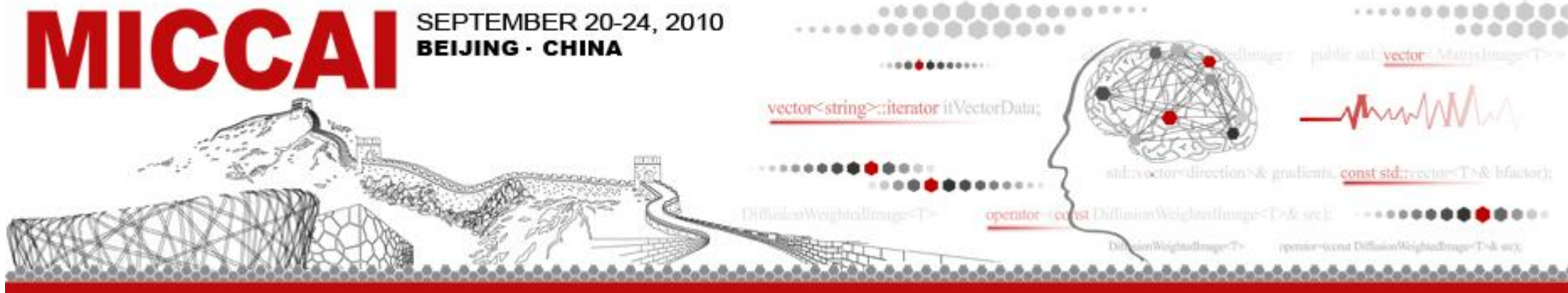
- Landmarks only
  - Sum of
    - Atypicality energy term prevents perfect correspondence
    - Landmark match: typically sum of squared distances
    - No perfect landmark match is achieved
  - Or curved diffeomorphic paths plus piecewise TPS interpolation
- Image registration with point correspondence
  - Image match + landmark match + geom energy
    - No perfect landmark match is achieved
  - Or landmark-constrained registration

# Optimization

- By gradient descent on objective function  $J(T)$  over space of possible functions  $T$
- So what is the gradient  $\nabla_T J$  of a scalar function of a function of typically many variables?
  - Calculus of variations
- With  $\nabla_T F$ , gradient descent is  $\partial l / \partial t = \nabla_T J$ 
  - Euler-Lagrange optimization

Gradient descent is simplest method. May not have fastest convergence. Other optimization methods exist.

# Some Background Material



## Registration tutorial

- Some of the slides only
- Many details on underlying theory

<http://campar.in.tum.de/DefRegTutorial/WebHome>

INTENSITY-BASED  
DEFORMABLE  
REGISTRATION  
MICCAI2010TUTORIAL





# Tools supporting parametric registration

- B-splines

- Insight Toolkit [itk.org](http://itk.org)
- Elastix [elastix.isi.uu.nl](http://elastix.isi.uu.nl)
- FAIR

<http://www.cas.mcmaster.ca/~modersit/FAIR/index.shtml>

- Image Registration Toolkit (IRTK)

<http://www.doc.ic.ac.uk/~dr/software/index.html>

- Thin-plate splines

- Elastix

The logo for the Insight Toolkit (itk) features the letters 'itk' in a stylized blue font with a yellow and blue vertical bar to the left, followed by the words 'Insight Toolkit' in a green, outlined font.

The logo for Elastix features the word 'elasti' in a bold red font, followed by a graphic of two brown ribbons crossing each other to form an 'X' shape.

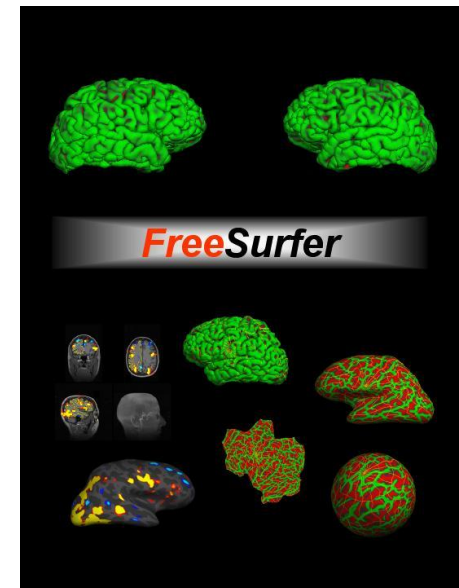


# Tools supporting non-parametric registration

- Diffusive Registration
  - FAIR
  - Free-surfer
- Curvature Registration
  - FAIR
- Membrane/Bending Energy
  - FSL <http://www.fmrib.ox.ac.uk/fsl/>
- Demons
  - ITK (Insight Journal)
- Diffeomorphic Demons
  - ITK (Insight Journal)
- Fluid flow
  - FAIR

**itk** Insight Toolkit

**elasti** 



# Tools supporting non-parametric registration

- General diffeomorphic fluid flow
  - ANTs (Advanced Normalization Tools)
    - [www.picsl.upenn.edu/ANTS/lastix.isi.uu.nl](http://www.picsl.upenn.edu/ANTS/lastix.isi.uu.nl)
  - FRAT (Fluid Registration and Atlas Toolkit)
    - [www.nitrc.org/projects/frat](http://www.nitrc.org/projects/frat)
  - SPM (recommends DARTEL)
    - <http://www.fil.ion.ucl.ac.uk/spm/>
  - AtlasWerks (has GPU implementations)
    - <http://www.sci.utah.edu/software.html>

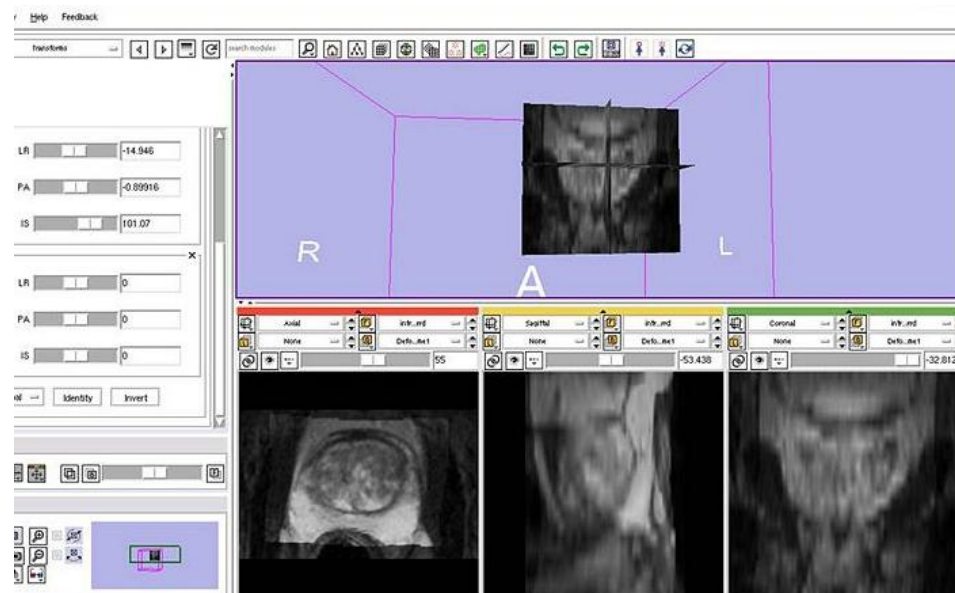


# 3D Slicer

## 3D Slicer: *slicer.org*

- Integrates a large selection of registration algorithms
- parametric and non-parametric

<http://www.slicer.org/slicerWiki/index.php/Slicer3:Registration>



Images: slicer.org

# 3D Slicer registration capabilities

Module	mode		type / DOF of motion						speed		for Brain ONLY	data-type			options			in- & output			
	automated	interactive	rigid (6 DOF)	translation (3 DOF)	similarity (7 or 9 DOF)	affine (12 DOF)	Non-rigid	Non-rigid fiducial	pipelines (affine->nonrigid)	multi-resolution		fast	robust	images	surfaces/models	fiducials	supports ROI mask	choice of cost function	supports labelmap mask	transform input	transform output (affine)
Expert Pipeline Registration	•		•		•	•	•	•			•					•	•	•	•	•	
Robust Multiresolution	•					•			•		•					•	•		•	•	
Fast Affine Registration	•					•				•								•	•		
Fast Rigid Registration	•		•															•			
Fast B-Spline Registration	•						•			•			•					•	•	•	
Transforms		•	•	•						•	•	•	•					•	•		
Fiducial Registration		•	•	•	•					•	•			•				•	•		
Surface Registration	•		•		•	•				•			•			•		•	•		
BrainsFit	•		•		•	•	•	•		•	•					•		•	•	•	
BrainsDemonWarp	•						•						•			•	•		•	•	
BrainsVectorDemonWarp	•						•						•			•	•		•	•	
Plastimatch	•		•	•		•	•	•		•			•	•							
Hammer	•						•					•									
AC-PC Transform		•	•							•	•	•							•		

Large collection of registration algorithms

Images: slicer.org

# Questions

Questions?