MINC meeting 2003
Registration techniques issues

D. Louis Collins

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MINC
Medical Image NetCDF

REPRIC Regroupement Provincial de Recherche en Imagerie Cérébrale

Outline

- **Introduction to registration**
  - definitions
  - motivation
- **Stereotaxic Space**
- **Registration**
  - similarity measures
  - transform types
  - optimization procedures
- **Methods**
  - Talairach, SPM, AIR, MRITOTAL
- **Applications**

Registration

Registration is the process of alignment of medical imaging data (usually for the purpose of comparison).

Intra-subject:	between data volumes from the same subject
Inter-subject:	between data volumes from different subjects

Motivation / Uses

- image guided surgery
- analysis of functional images
- characterization of normal and abnormal anatomical variability
- detection of change in disease state over time
- visualization of multimodality data
- modeling anatomy in the process of segmentation
- atlas guidance for anatomical interpretation

VIPER

T Peters, K Finnis, D. Gobbi, Y Starreveld - RRI

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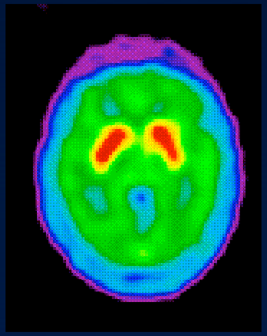

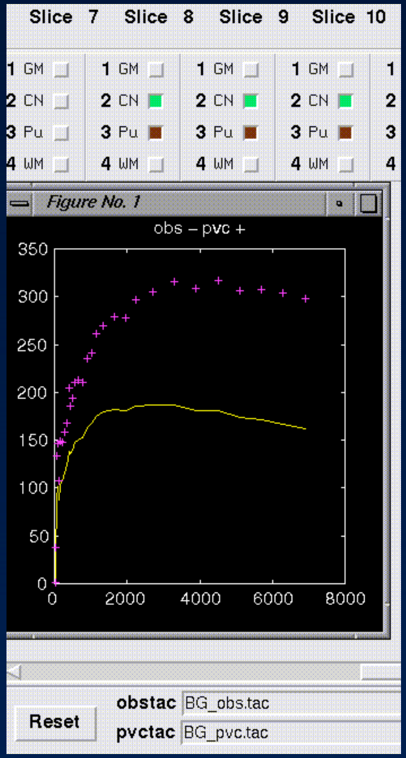

O. Rousset, A Evans - MNI

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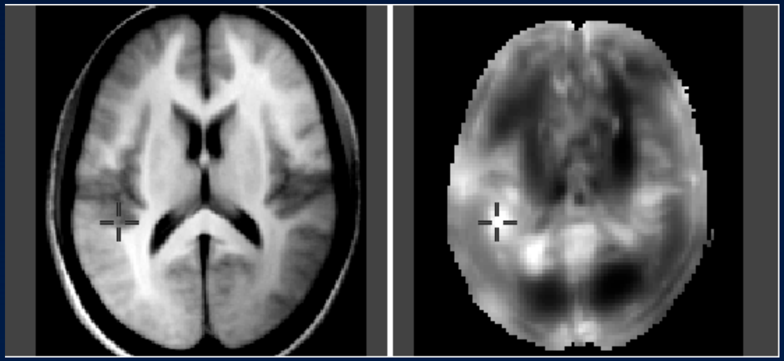

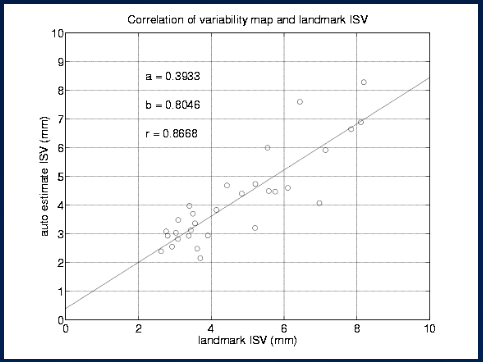

L Collins (94) - MNI

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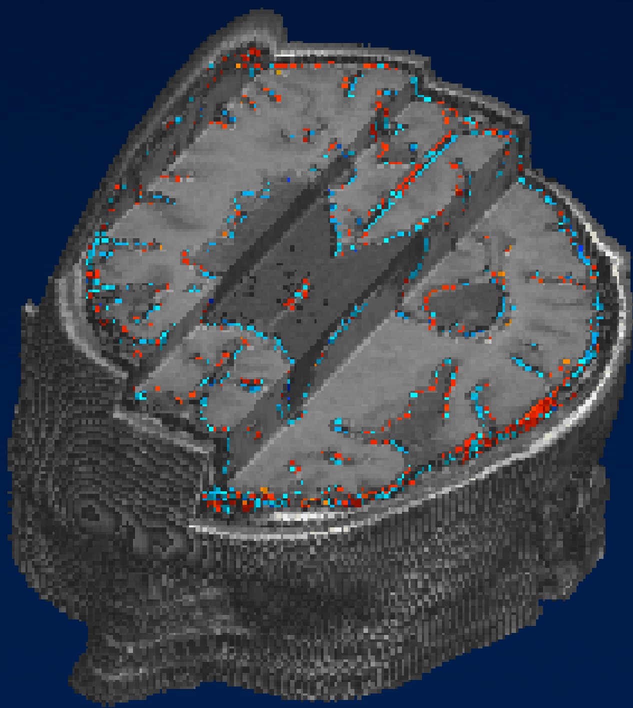

S Smith, P Matthews - Oxford

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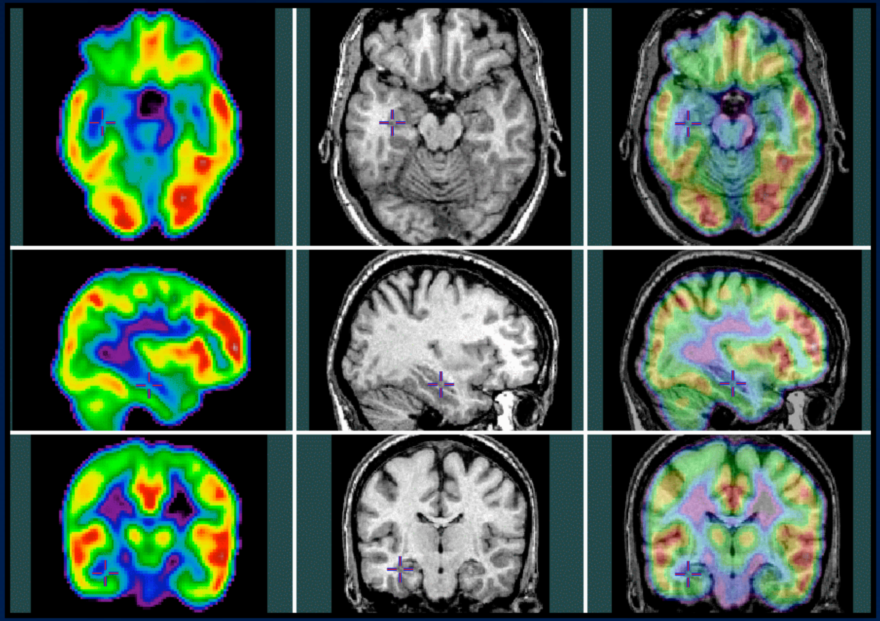

register program - MNI

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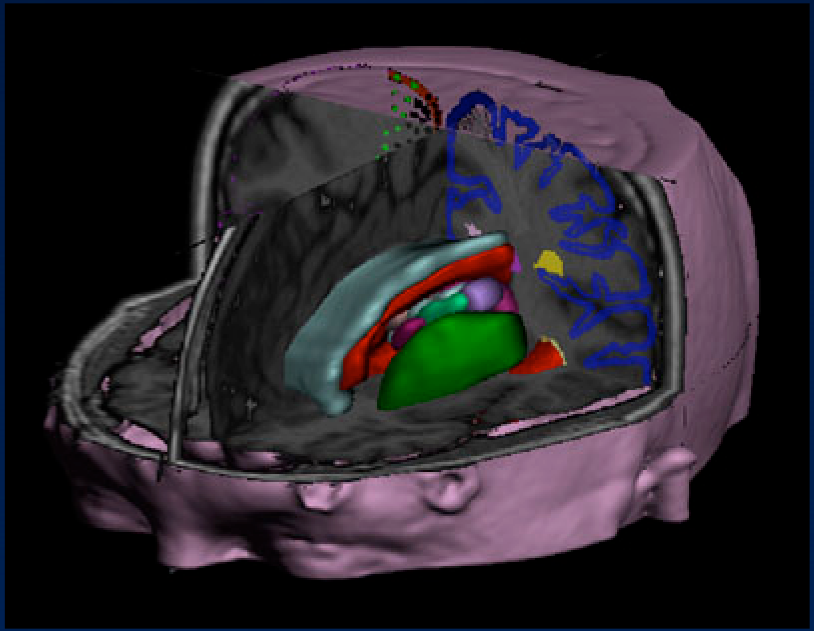

W. Nowinski - KRDL

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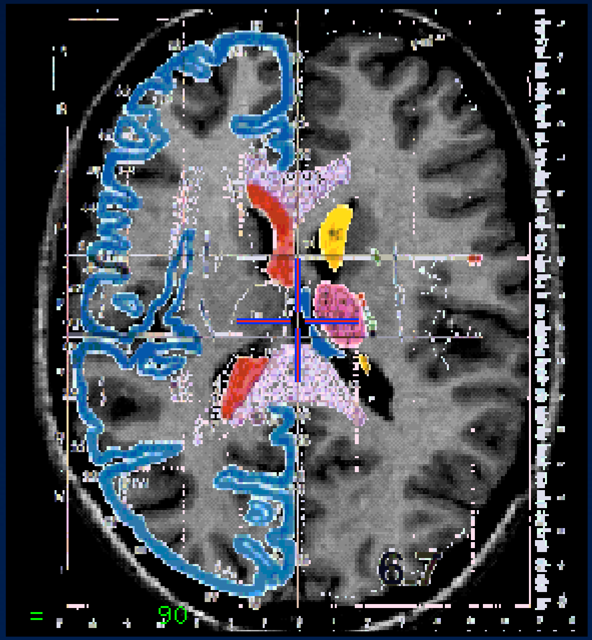


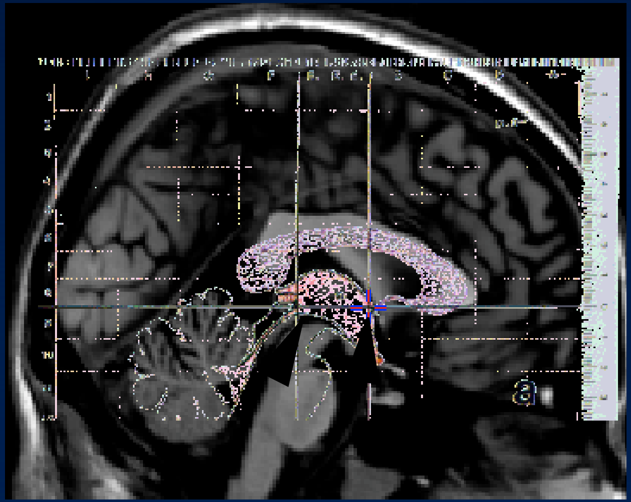
Talairach Atlas overlaid on MRI

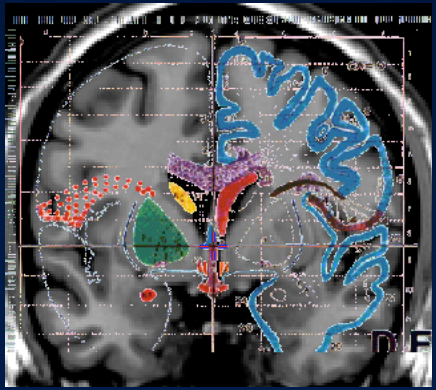
Inter-subject registration requires a well defined target space.

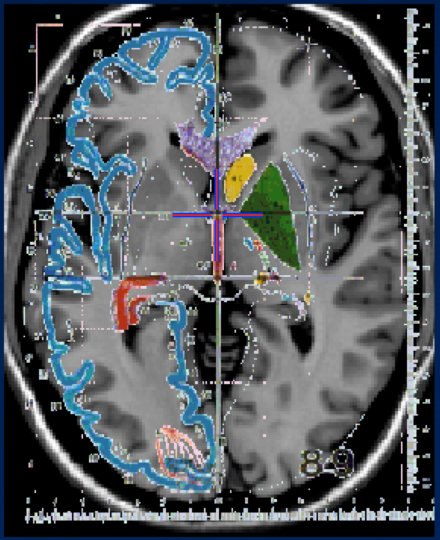
Stereotaxic Space

J. Talairach and P. Tournoux, Co-planar stereotactic atlas of the human brain: 3-Dimensional proportional system: an approach to cerebral imaging, Stuttgart, Georg Thieme Verlag, 1988

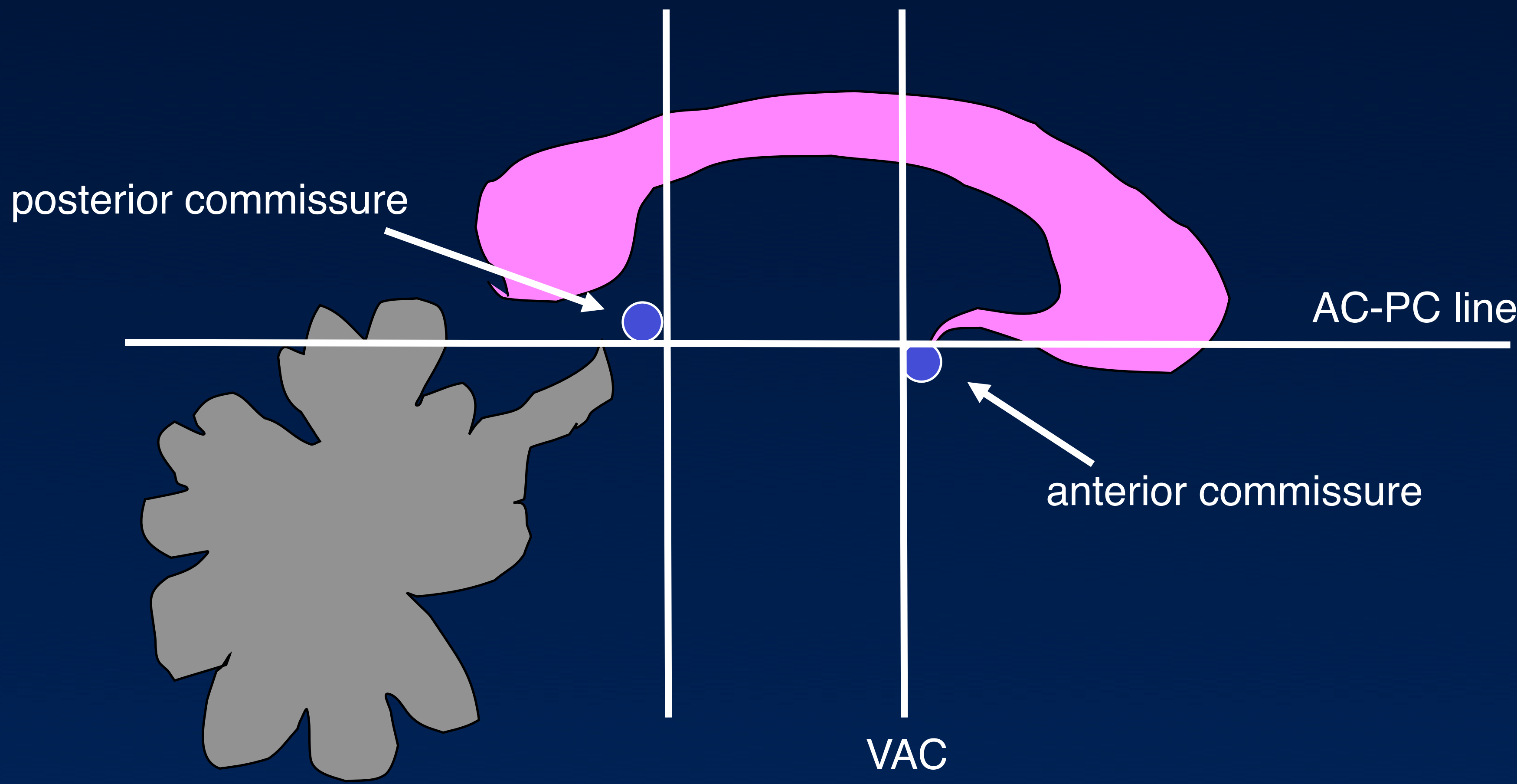
- **based on anatomical landmarks (anterior and posterior commissures)**
- **originally used to guide blind stereotaxic neurosurgical procedures (thalamotomy, pallidotomy)**
- **now used by NeuroScientific community for interpretation and comparison of results**



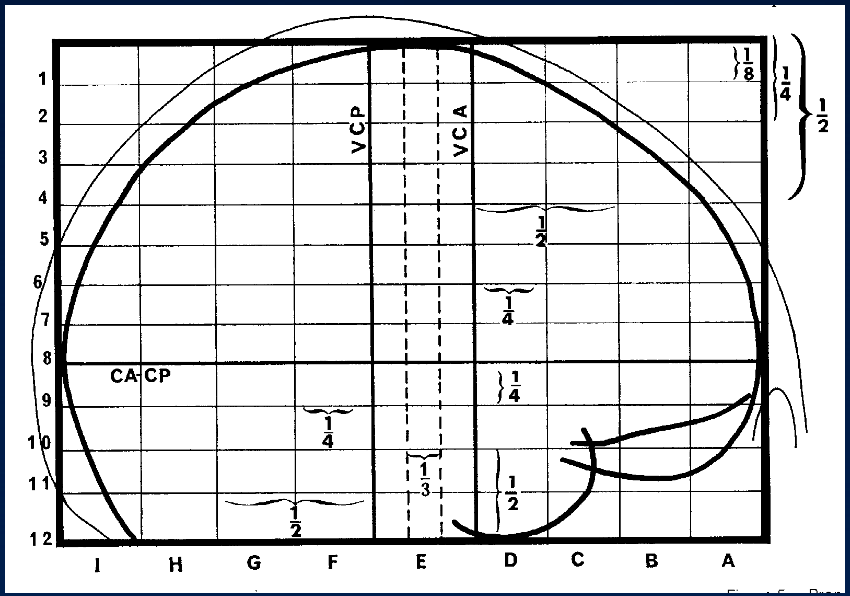


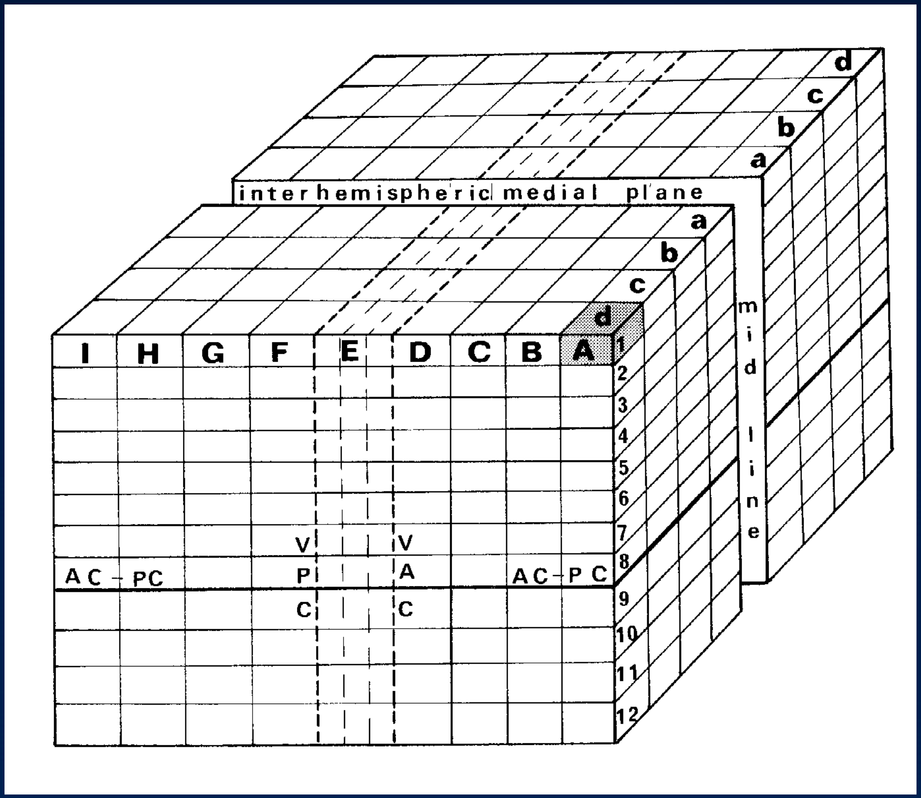


AC-PC line



Stereotaxic Space





J Talairach & P Tournoux,
Co-planar stereotaxic atlas of the human brain,
Georg Thieme, 1988

Stereotaxic Space

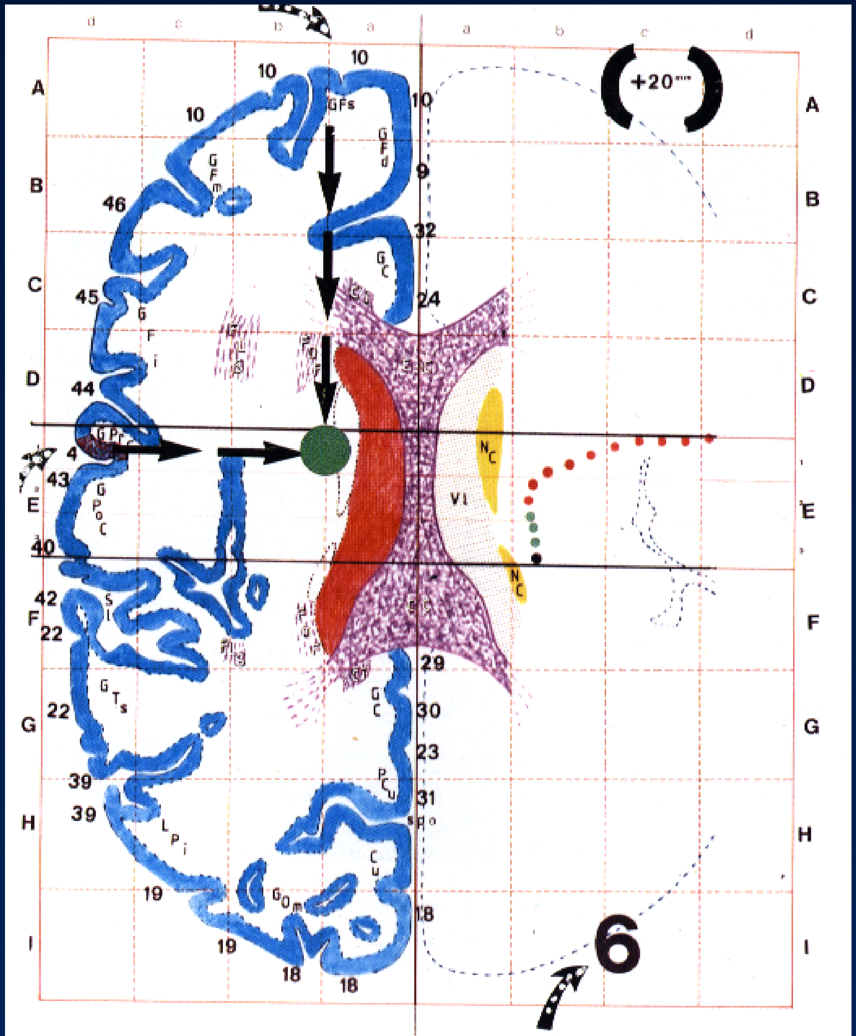
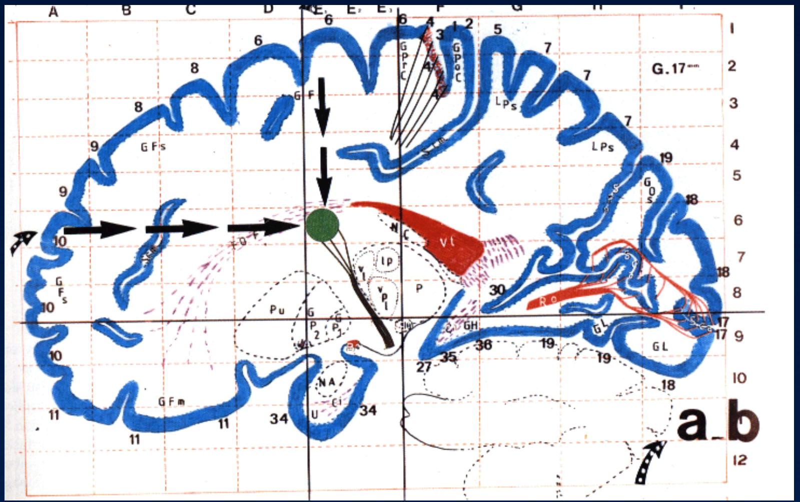


Figure 19 Horizontal Atlas section. Section of the Atlas 20 mm from the CA-CP line.



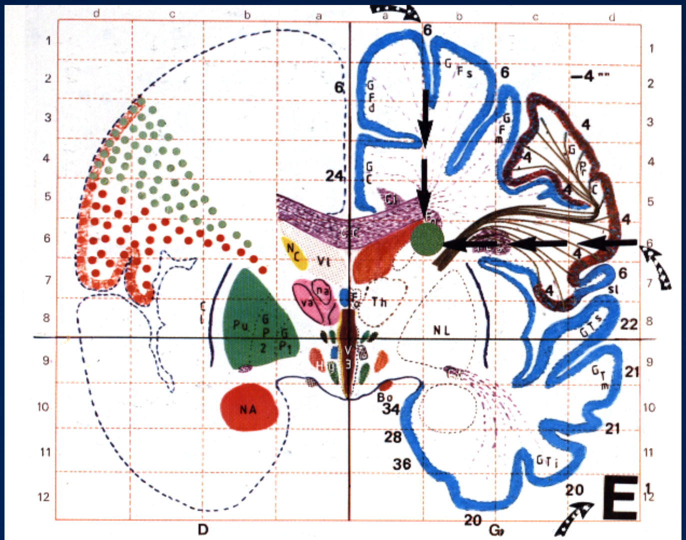


Figure 21 Verticofrontal section of the Atlas corresponding to Figures 19 and 20.

Talairach Atlas

Drawbacks for functional imaging:

- is derived from an unrepresentative single 60-yr old female cadaver brain (when most functional activation studies are done on young living subjects!)
- ignores left-right hemispheric differences
- has variable slice separation, up to 4mm
- while it contains transverse, coronal and sagittal slices, it is not contiguous in 3D

Stereotaxic Space

Advantages for functional imaging:

- **Provides a conceptual framework for the completely automated, 3D analysis across subjects.**
- **Facilitate intra/inter-subject comparisons across**
  - time points, subjects, groups, sites
- **Extrapolate findings to the population as a whole**
- **Increase activation signal above that obtained from single subject**
- **Increase number of possible degrees of freedom allowed in statistical model**
- **Enable reporting of activations as co-ordinates within a known standard space**
  - e.g. the space described by Talairach & Tournoux

Stereotaxic Space

Advantages (continued):

- **Allows the use of spatial masks for post-processing (anatomically driven hypothesis testing)**
- **allows the use of spatial priors (classification)**
- **allows the use of anatomical models (segmentation)**
- **provides a framework for statistical analysis with well-established random field models**
- **Allows the rapid re-analysis using different criteria**

Registration

Requirements:

1- similarity measure

→ how to define the match? what is the goal?

2- well defined transformation

→ how to define the mapping?

3- method to find transformation

→ how to find the mapping given the similarity constraint?

Similarity Measures

- Extrinsic

    frames, moulds, masks, markers

- Intrinsic

    anatomical landmarks

- Non-image data

    acquisition based

0D - points

1D - lines

2D - surfaces

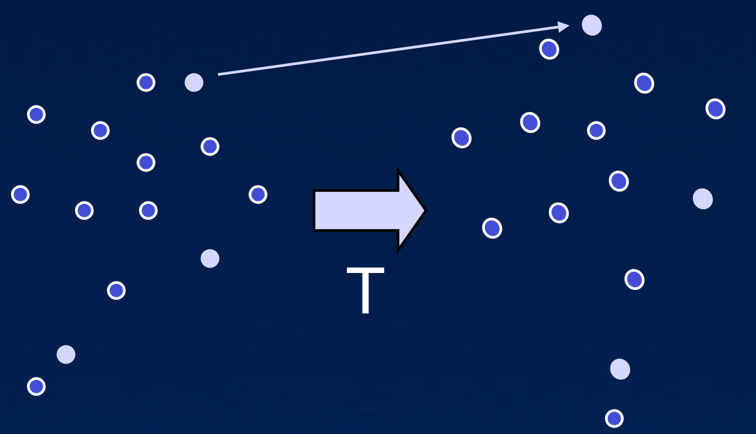
3D - volumes

nD - data over time

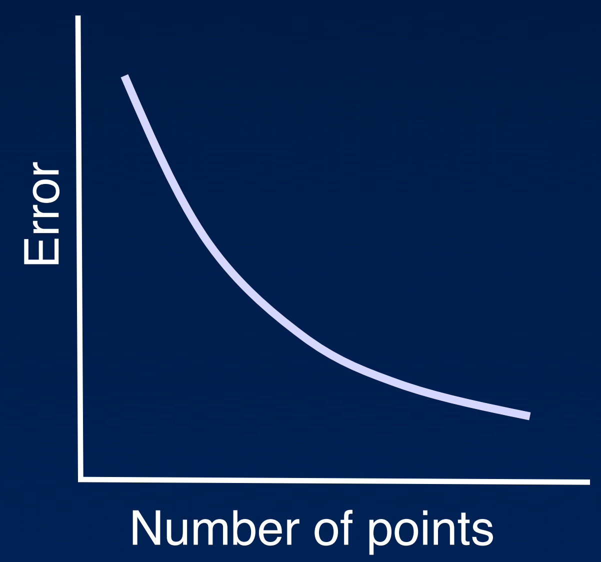
Review: P. van den Elsen, "Medical Image registration: a review with classification", IEEE Eng in Med & Biol, 1993 12(1):26-39

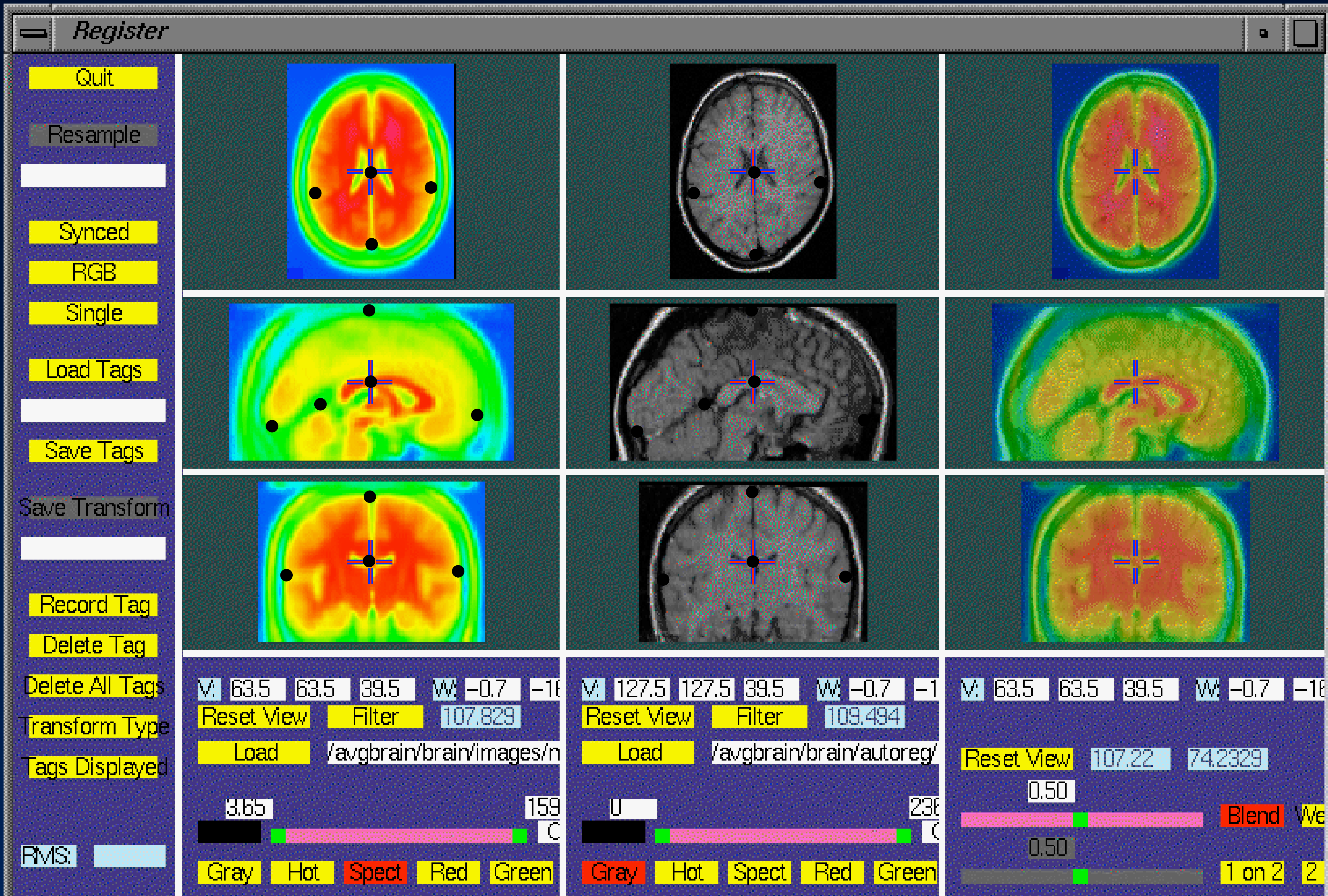
Point Similarity Measures

- **Requires identification of homologous landmark points**
- **Based on minimization of distance between points**



T found by SVD or Procrustes




Register
Quit
Resample
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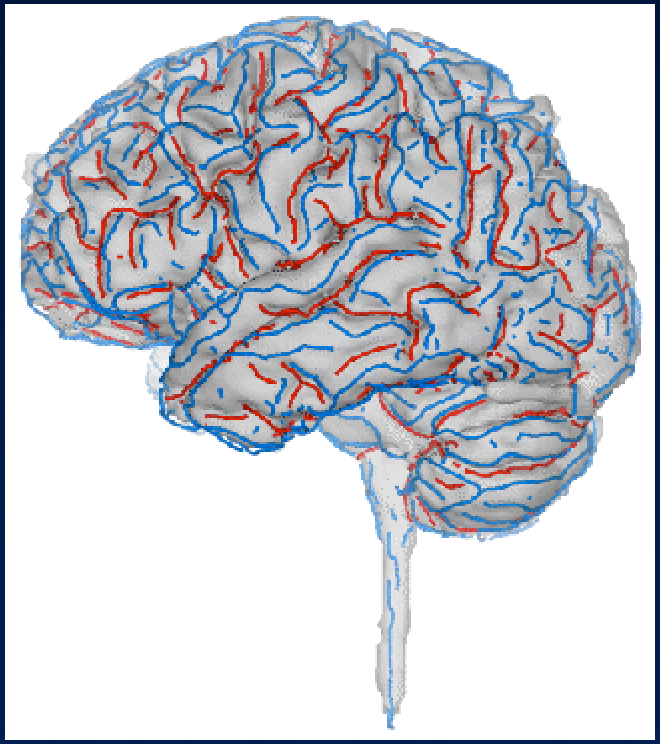
Single
Load Tags
Save Tags
Save Transform
Record Tag
Delete Tag
Delete All Tags
Transform Type
Tags Displayed
RMS:
V: 63.5 63.5 39.5 W: -0.7
Reset View Filter 107.829
Load /avgbrain/brain/images/n
3.65 159
Gray Hot Spect Red Green
V: 127.5 127.5 39.5 W: -0.7
Reset View Filter 109.494
Load /avgbrain/brain/autoreg/
Gray Hot Spect Red Green
V: 63.5 63.5 39.5 W: -0.7
Reset View 107.22 74.2329
0.50
Blend
0.50
1 on 2
2

Line Similarity Measures

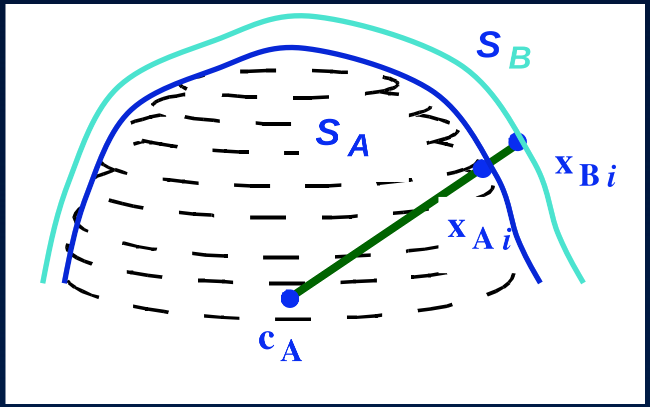
- Based on distance between homologous lines
- Used for intra-subject registration
- Difficult to use in inter-subject registration due to (lack of) homology



G. Subsol, INRIA

Surface Similarity Measures

- **Based on distance between surfaces**
- **need to ensure that the same anatomical surface is extracted from both data sets**

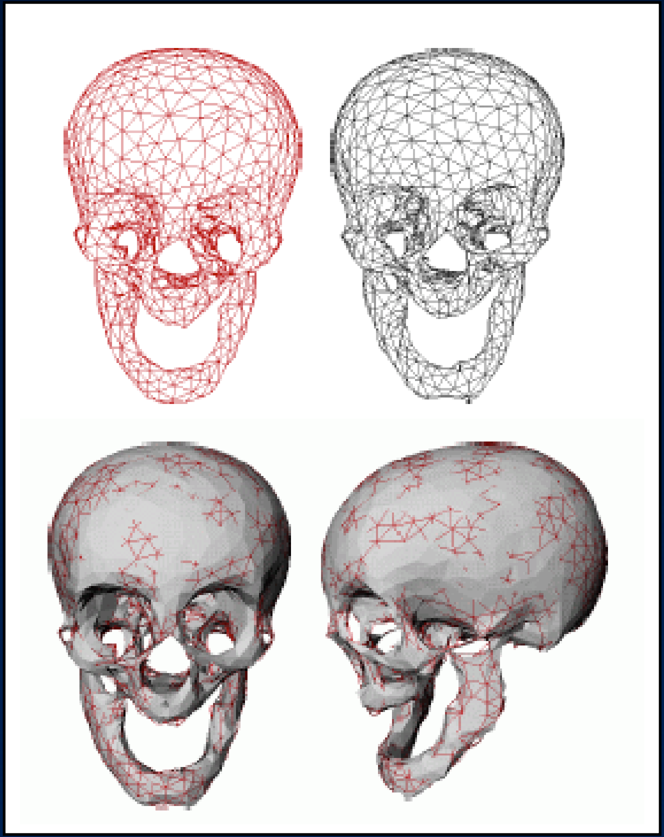


"Head-and-hat"

1. Segment slices to get S_A contours. Compute centroid of S_A: c_A.
2. For each x_{Bi}, find inter section x_{Ai} along path to c_A.
3. $\min_{T} D = \sum_{i} d_S [x_{Ai}, T(x_{Bi})]$

Pelizzari CA, Chen GTY, Spelbring DR, Weichselbaum RR, Chen C-T. Accurate three-dimensional registration of CT, PET, and/or MR images of the brain. J Comput Assist Tomogr 1989;13(1):20-26

Surface based registration

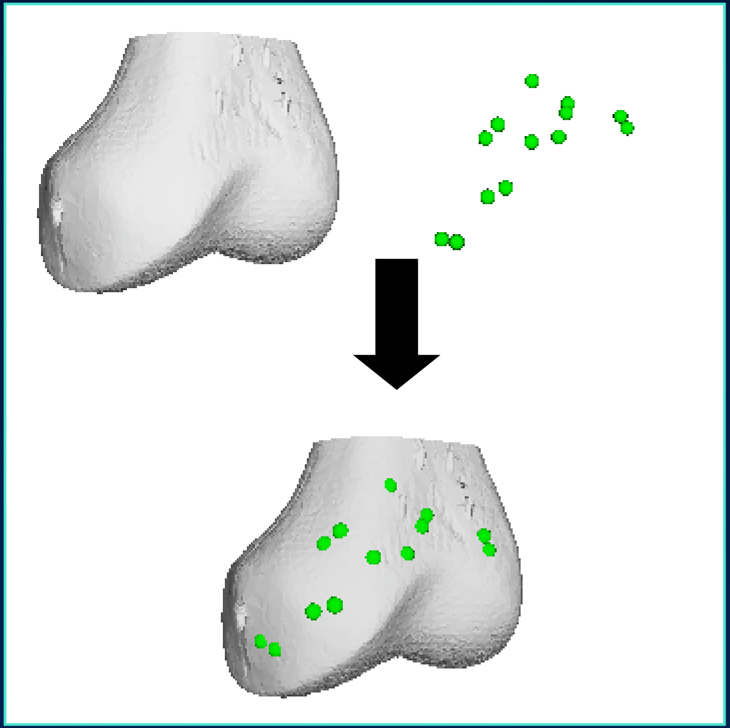


Local geometry constraints

A Johnson, Robotic Inst., CMU

Surface model

Surface data



Surface data matched to model

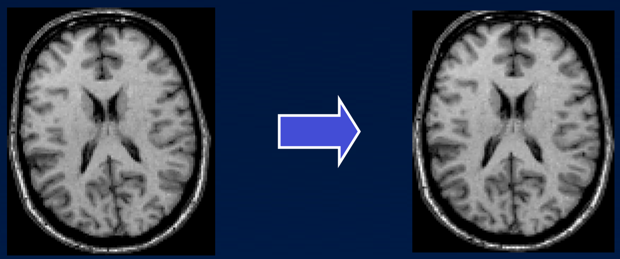
Randy Ellis, Queens U.

Volume Similarity Measures

The pixel/voxel intensities are used directly
to compute the similarity measure

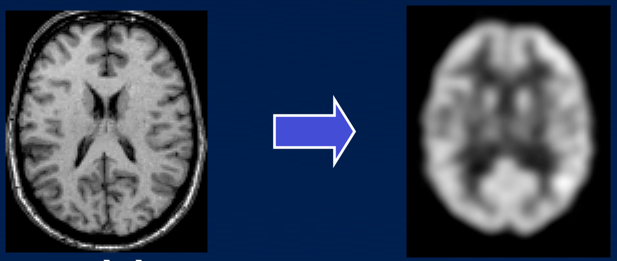
Intra-modality (same modality)

- similar contrast
- similar resolution
- similar sampling (pixel/voxel size)
- similar structures have similar intensities



Inter-modality

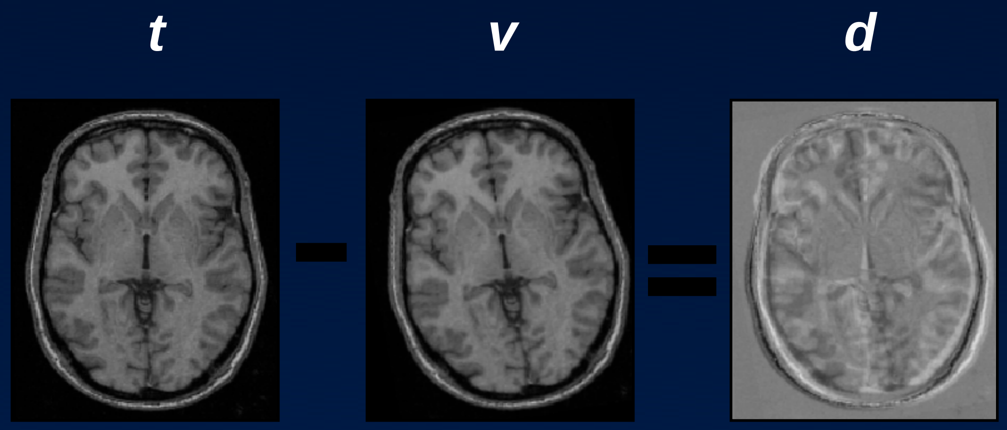
- different contrast
- different resolution
- different sampling (pixel/voxel size)
- different structures may have similar intensities, and similar structures may have the same intensity



Volume Similarity Measures

INTRA-MODALITY

- ***Absolute or squared difference***
  - Hoh93, Lange93, Christensen95, Hajnal95, Kruggel95
- ***Stochastic Sign Change (SSC), Deterministic Sign Change (DSC)***
  - Venot83, Minoshima92, Hua93, Hoh93
- ***Cross Correlation***
  - Junck90, van den Elsen93, Hill93, Collins94, Lemieux94, Studholme95
- ***Fourier Domain Correlation***
  - de Castro87, Leclerc87, Chen93, Lehmann96
- ***Optic Flow Field***
  - Barber95, Meunier96



$$S_{\min} = \sum_i \left| (v_i - t_i) \right|$$

- Very simple (fast) to compute
- Must have similar intensities
- Unbounded maximum value

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t

-

v

=

d

$$S_{max} = \sum_{\substack{rows,\\ cols,\\ slices}} z(d_i - d_{i-1})$$

- Very simple (fast) to compute
- Must have similar intensities
- Unbounded maximum value
- Can add artificial noise if needed

Volume Similarity Measures

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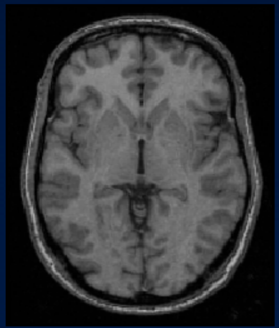
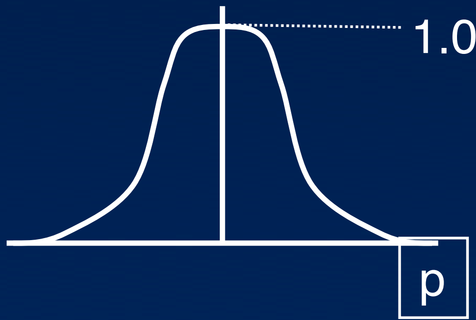


*

v

$$S_{\max} = \frac{\sum_i v_i t_i}{\sqrt{\sum_i (v_i)^2}\sqrt{\sum_i (t_i)^2}}$$

- Must have linear relation between intensities
- Bounded value [0..1]

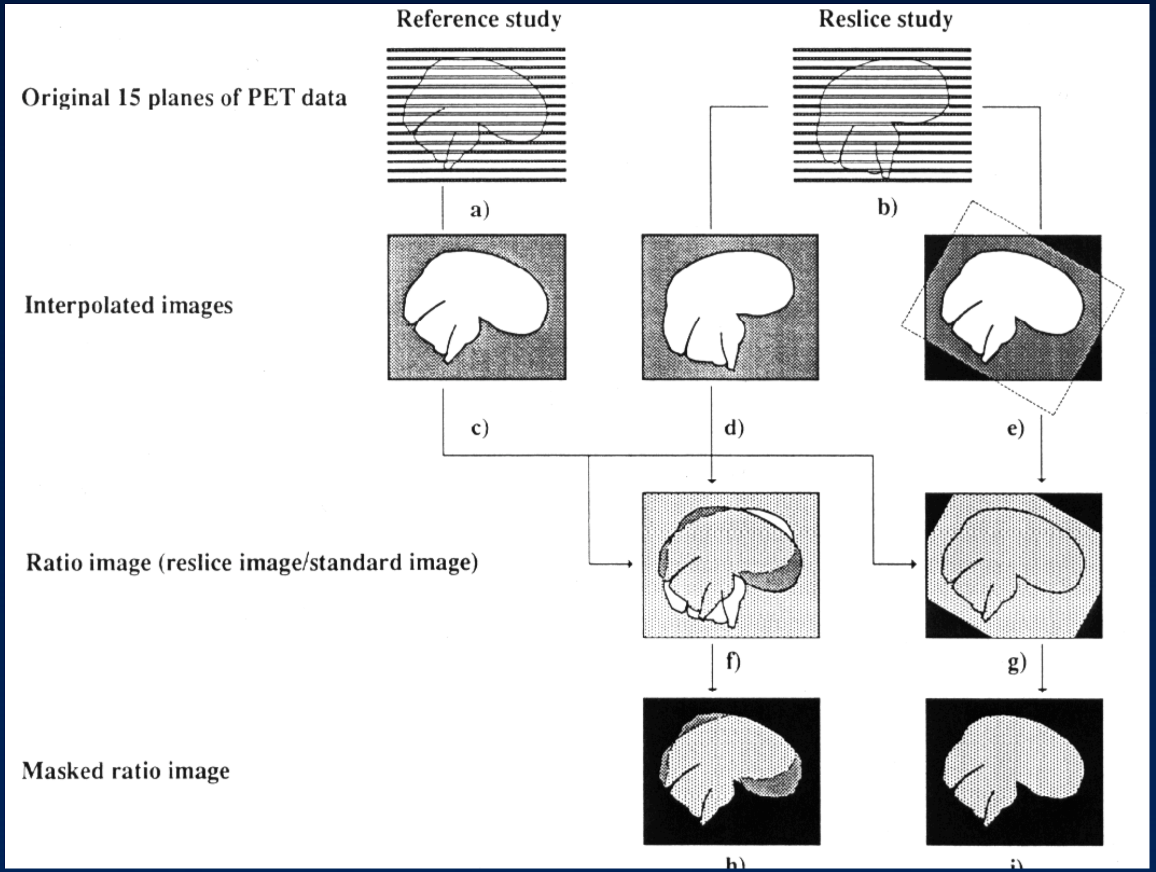


Volume Similarity Measures

INTER-MODALITY

- ***Variance of Ratios***
  - Woods92,93, Hill93, Zuo96
- ***Min. variance of ratios in segments***
  - Cox94, Ardekani95
- ***Mutual Information/ Entropy***
  - Collignon93, Studholme94
- ***Correlation Ratio***
  - Roche98

$$\underset{\min}{S} = \mathrm{var}\left(v_i / t_i\right)$$



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$$S_{\max} = \sum_{v,t} p_{AB}(a,b)\log\frac{p_{AB}(a,b)}{p_A(a)p_B(b)}$$

Where:

$p_A(a) \& p_B(b)$ - marginal probability distributions

$p_{AB}(a,b)$ - joint probability distribution

$p_{AB}(a,b) = p_A(a)p_B(b)$ If statistically independent

$p_A(a) = p_B(T(a)) = p_{AB}(a,T(a))$ If related by 1:1 mapping T().

Transformation Types

Linear

rigid body:	3 rotations, 3 translations
Procrustes:	3 rotations, 3 translations, 1 scale
affine:	3 rotations, 3 translations, 3 scale, 3 skew

Piecewise Linear

Talairach:	12 regions defined by 2 points + 6 scales

Nonlinear

polynomial:	f(x) = ax^3 + bx^2 + cx + d
basis functions:	cosine, Fourier, wavelet
physical model:	elastic, fluid with dense deformation field

mni_autoreg

- **Volumetric registration with minctracc**
- **Linear**
  - lsq6 (rigid body)
  - lsq7 (rigid + isotropic scale)
  - lsq9 (rigid + 3 scales)
  - Lsq12 (full affine)
- **Non-linear**
  - Deformation field

mni_autoreg: mritoself

mritoself scan1.mnc scan2.mnc t1-2.xfm

-veryclose	*same session*
-close	*simplex 3*
-far	*same scanner, diff sessions*

-xcorr, -vr, -mi (default)

-lsq6,-lsq7,-lsq9

-mask

mni_autoreg: mritoself

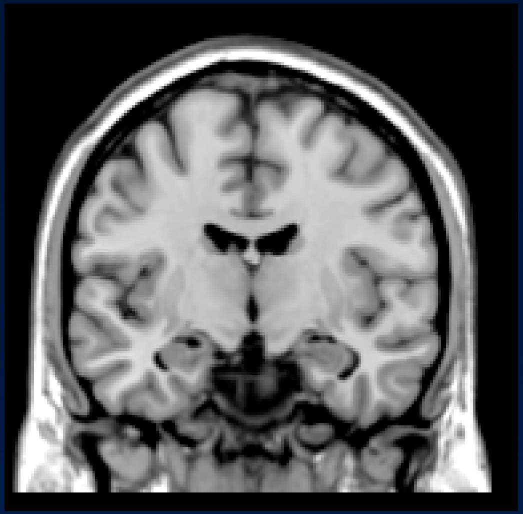
```
mritoself scan1.mnc scan2.mnc t1-2.xfm

mincresample scan1.mnc scan1-like2.mnc \
  -transformation t1-2.xfm \
  -like scan2.mnc
```

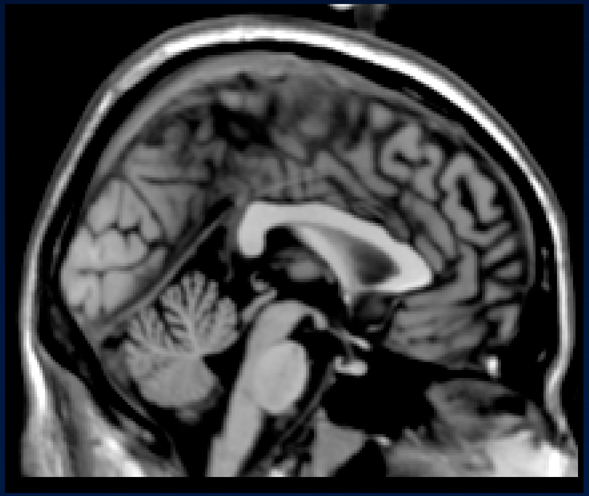
Stereotaxic Registration methods

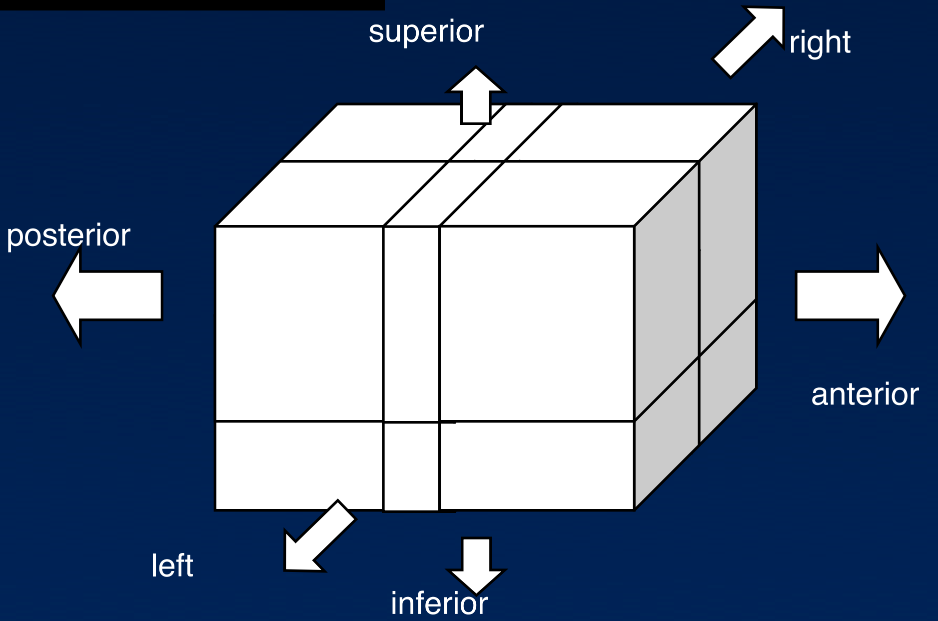
• Talairach	Talairach and Tournoux
• mritotal	Collins
• SPM	Friston, Ashburner
• FLIRT,FSL	Jenkinson, Smith

Talairach

- **identify AC/PC on mid-sagittal**
- **define vertical, lateral and anterior-posterior extents**
- **define 12 piecewise linear transformations:**
  - left / right
  - above / below AC-PC
  - anterior-AC / AC-PC / PC-posterior

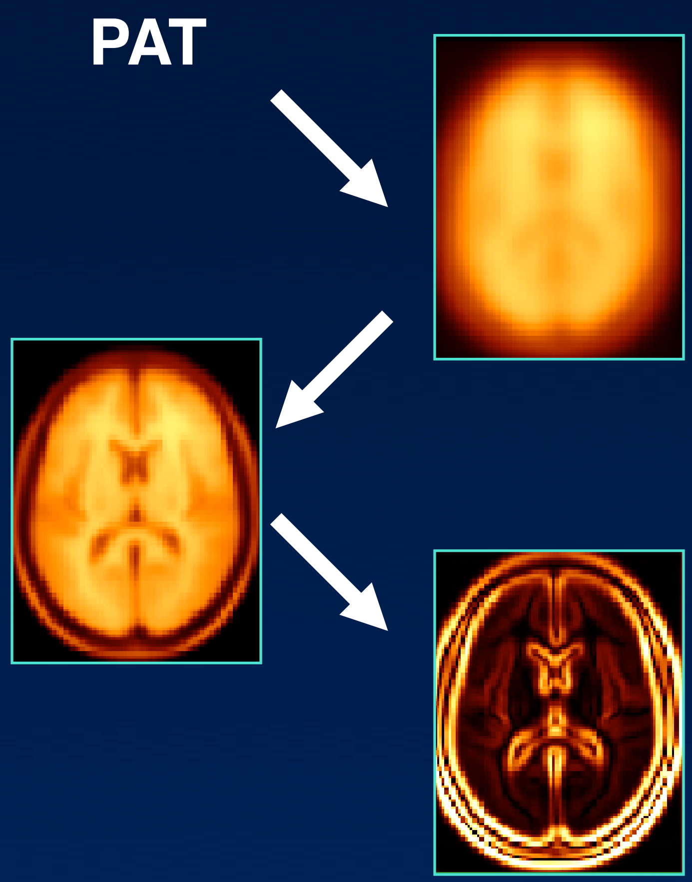






mritotal

- **Principal axis transformation**
- **correlation of 16mm fwhm blurred data**
- **correlation of 8mm fwhm blurred data**
- **correlation of 8mm gradient magnitude data**



http://www.bic.mni.mcgill.ca/software/mni_autoreg/
Collins et al, JCAT 1994

mni_autoreg: mritotal

mritotal scan1.mnc t_stx.xfm

-crops, blurs

-transformation

-model

```
mincresample scan1.mnc scan_stx.mnc \
  -transformation t_stx.xfm \
  -like stx_target.mnc
```

FLIRT

- **Correlation ratio**
- **Multi-resolution procedure**
- **Powell's search for optimmization**

Jenkinson, M. and Smith, S. (2001a).
A global optimisation method for robust affine registration of brain images.
Medical Image Analysis, 5(2):143-156

SPM: Statistical Parametric Mapping

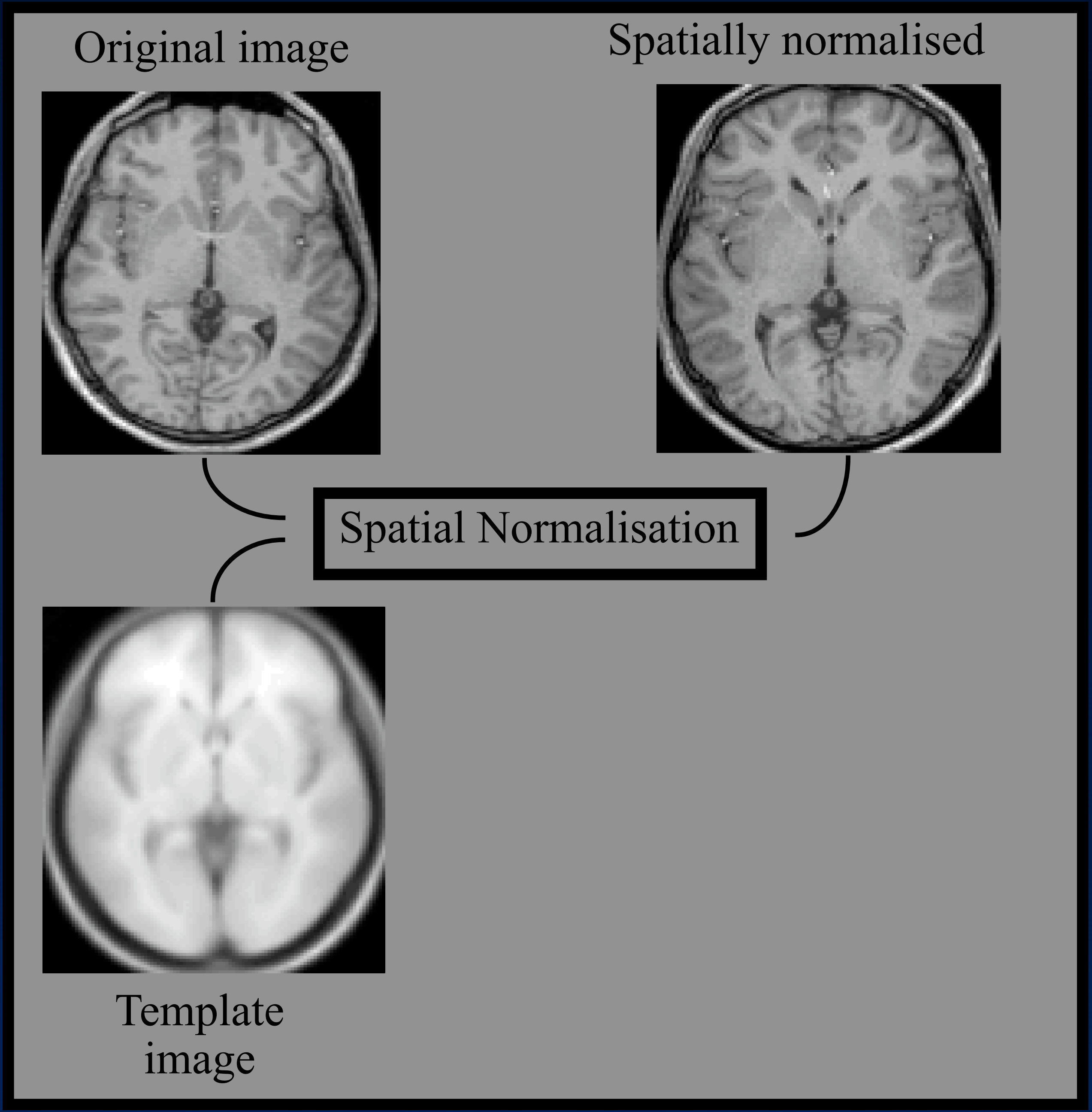
Spatial Normalisation

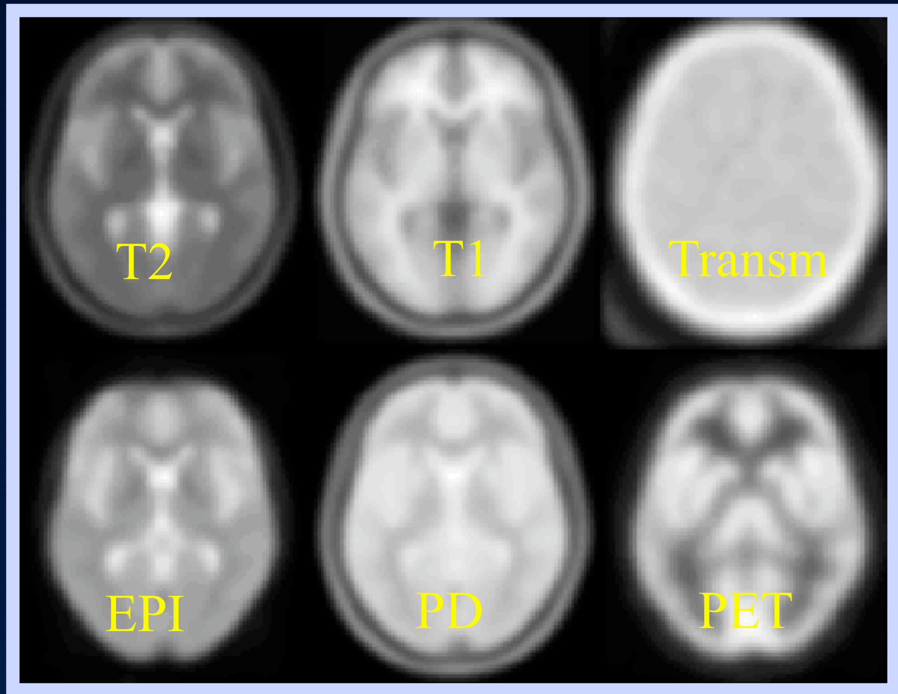
Determine the spatial transformation that minimises the sum of squared difference between an image and a linear combination of one or more templates.

Begins with an affine registration to match the size and position of the image.

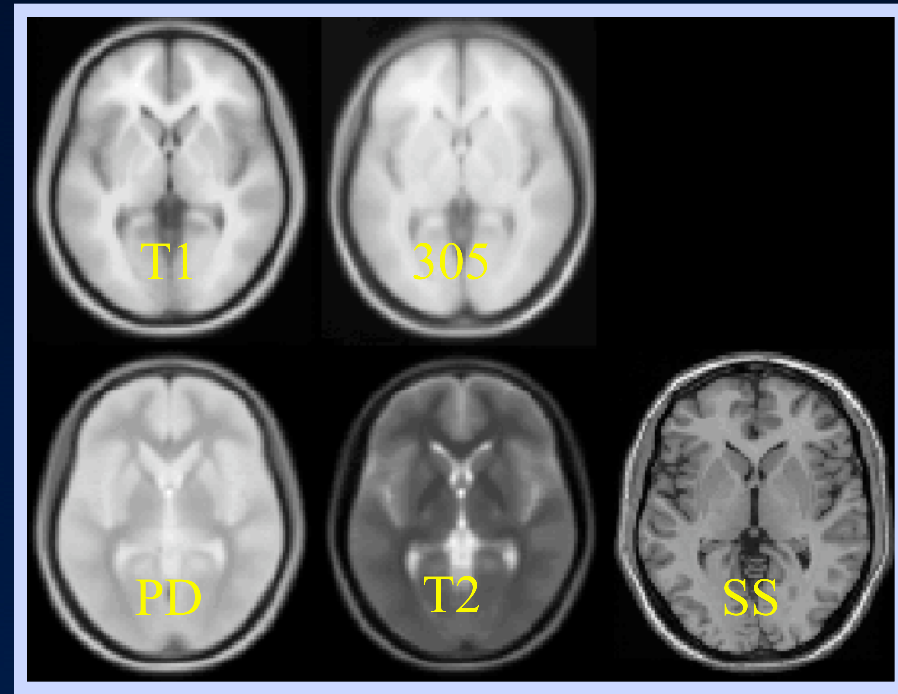
Followed by a global non-linear warping to match the overall brain shape.

Uses a Bayesian framework to simultaneously maximise the smoothness of the warps.

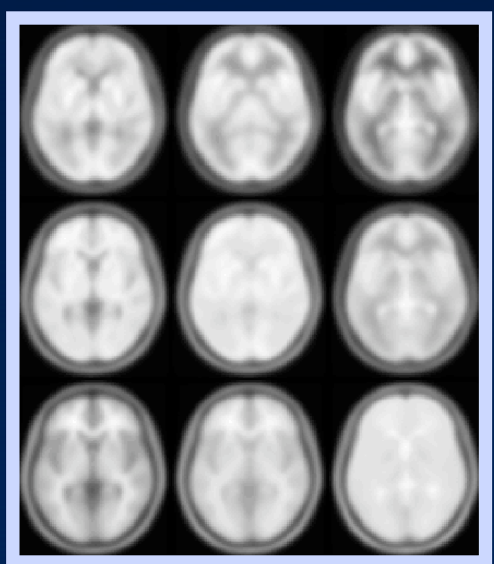




Template Images



"Canonical" images



A wider range of different contrasts can be normalised by registering to a linear combination of template images.

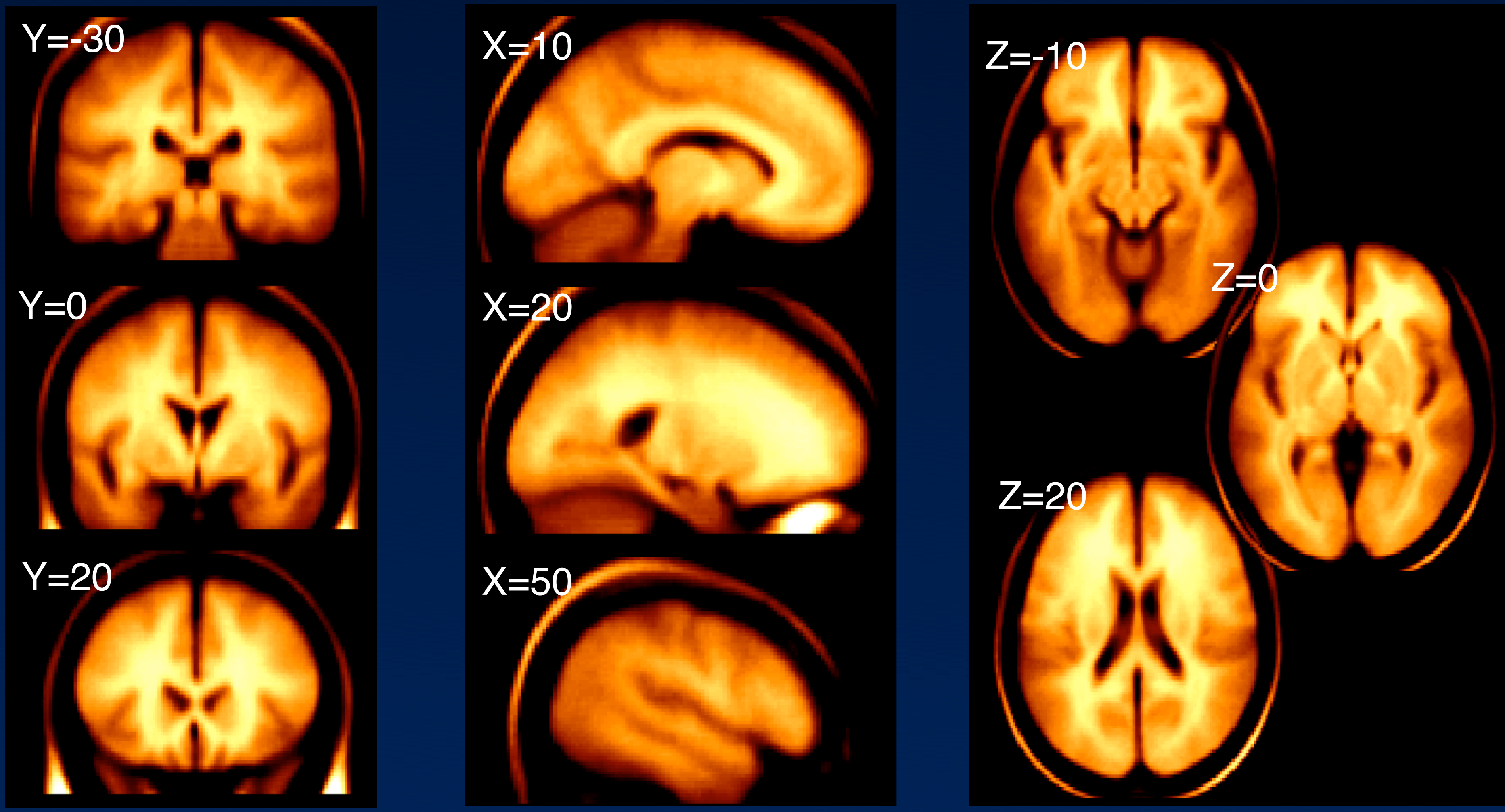
Spatial normalisation can be weighted so that out of brain voxels do not influence the result.

Similar weighting masks can be used for normalising lesioned brains.

Canonical Images

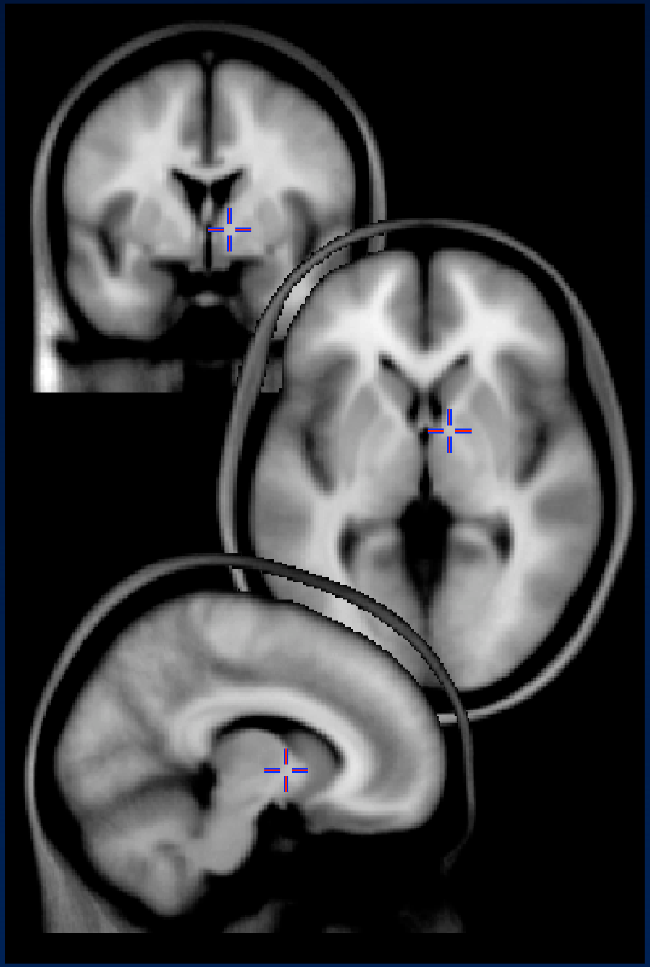
- **SPM**
  - SPM96: average of 12 manually transformed vols
  - SPM97: blurred colin27, mni305 if downloaded
  - SPM99: mni305; colin27 option
  - SPM2b11RC: icbm152
- **mritotal**
  - mni305
  - icbm152
- **Flirt**
  - mni305

Examples: MNI305 average brain

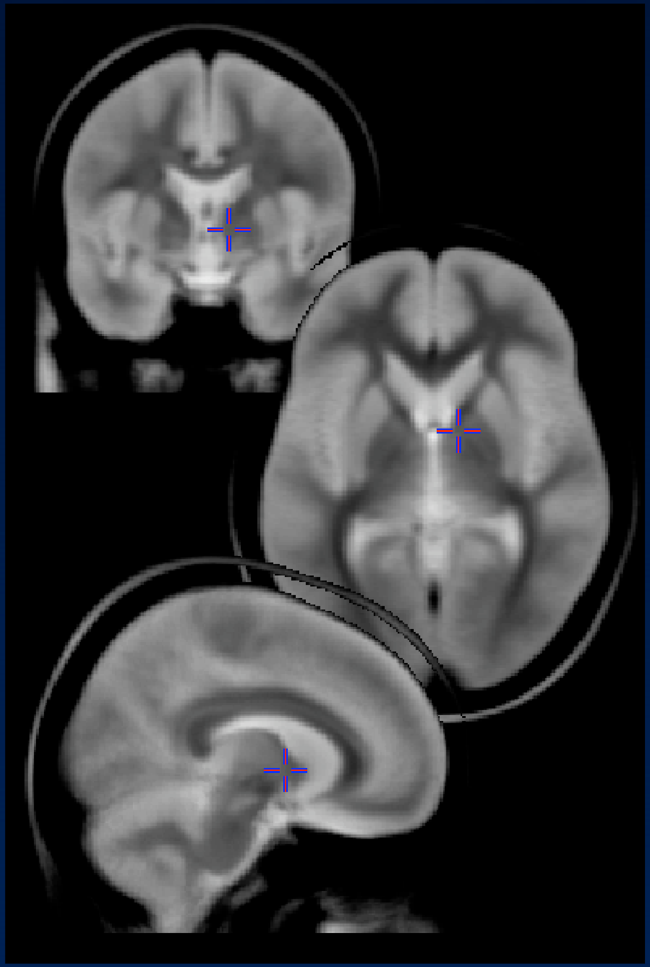


A.C. Evans et al, 1992

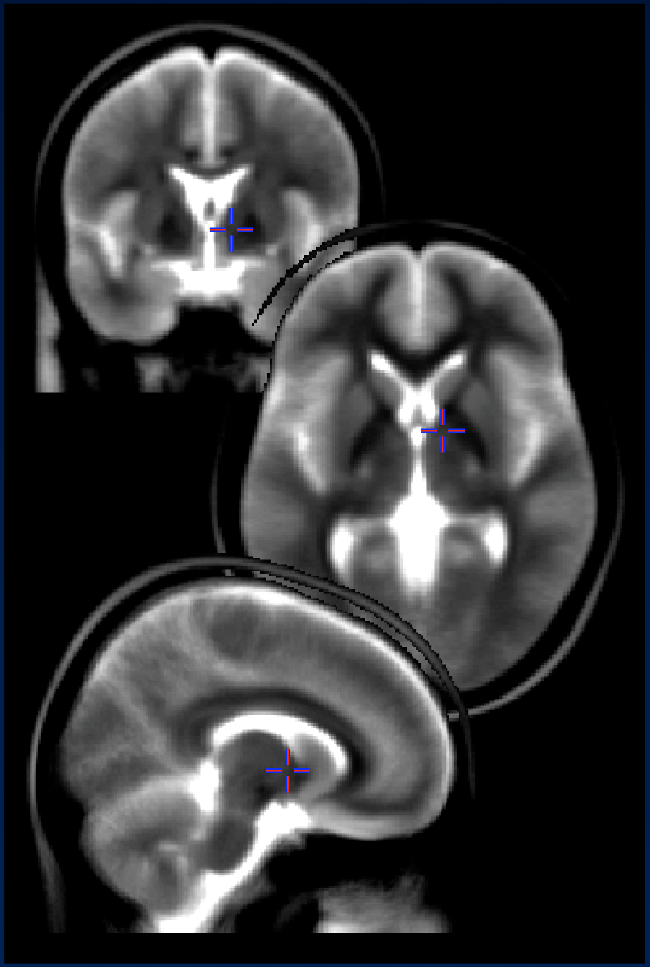
Examples: ICBM152 averages



Average T1

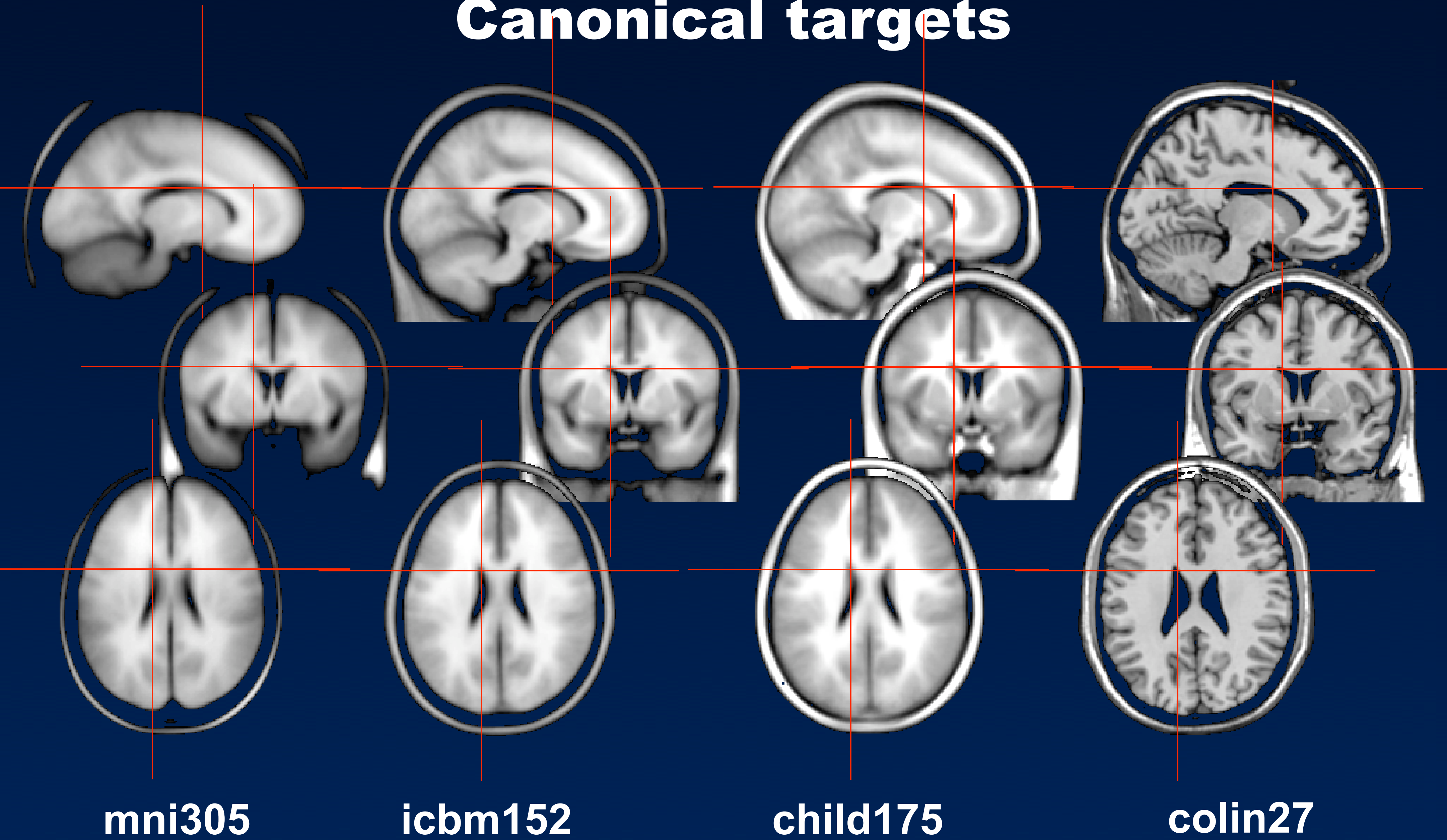


Average PD



Average T2

Canonical targets



www.bic.mni.mcgill.ca/icbmview

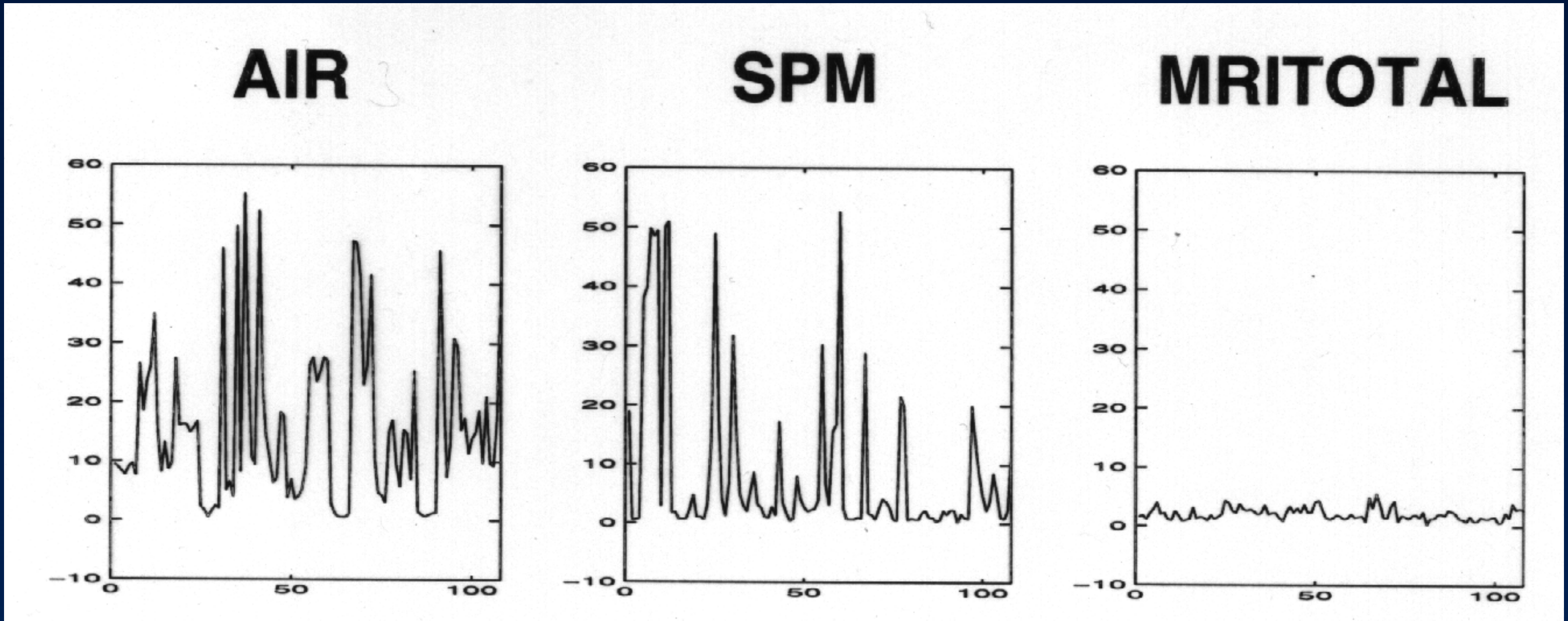
Things to take home

- **Mapping depends on**
  - Similarity function
  - Target model
  - Optimization function/strategy
- **Use a standard model!**

fin

Comparison

Preliminary results from consistency study reveals differences in robustness



In each graph the average rms error (in mm) is plotted over a set of initially rotated image volumes

Steve Smith, FMRIB, Oxford