UBC SPM Course 2010

Spatial Preprocessing

Ged Ridgway

Wellcome Trust Centre
for Neuroimaging

Preprocessing overview

REALIGN

COREG

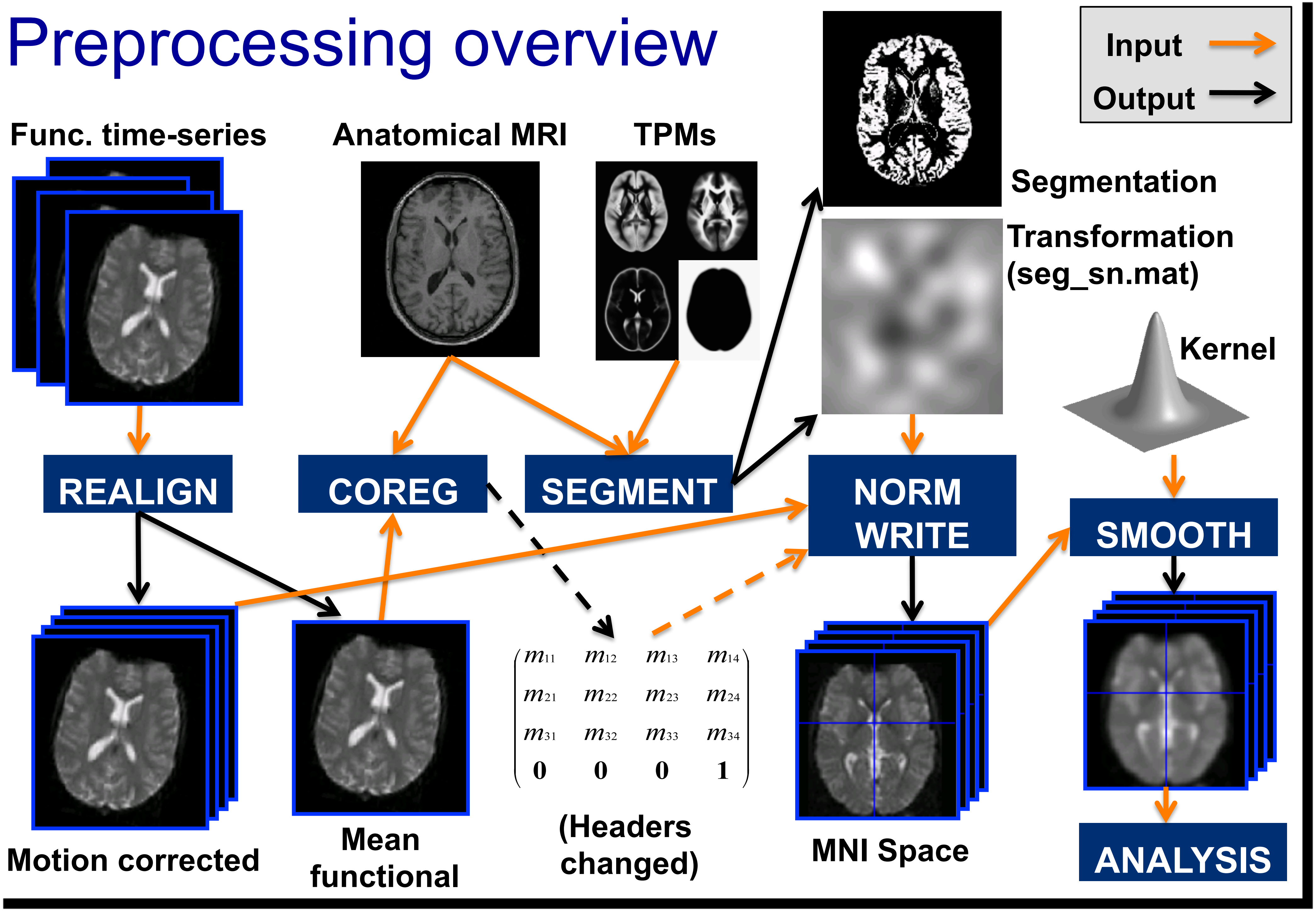
SEGMENT

NORM WRITE

SMOOTH

ANALYSIS

Preprocessing overview



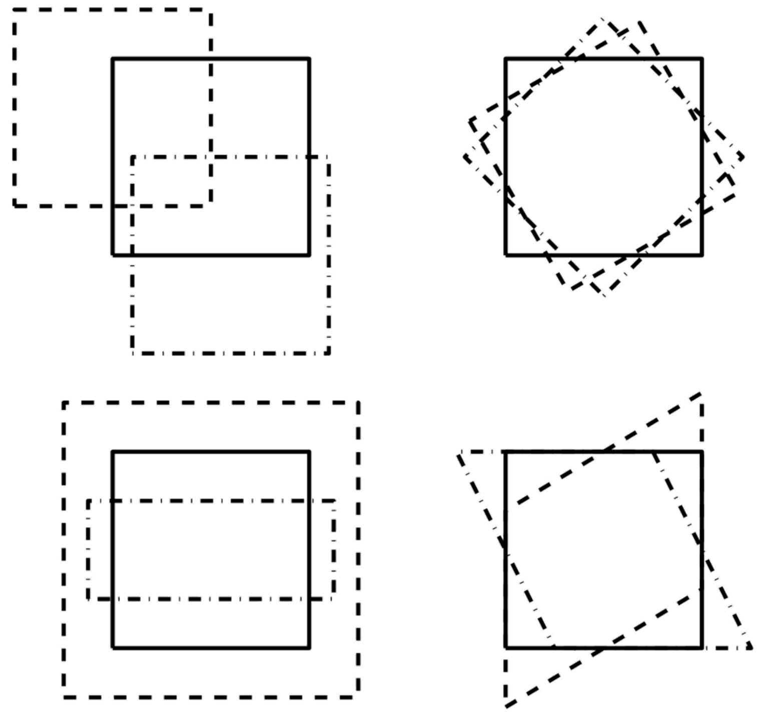
Contents

Special cases of affine registration

* Manual reorientation
* Rigid intra-modal realignment
  * **Motion correction of functional time-series**
  * Within-subject longitudinal registration of serial sMRI
* Rigid inter-modal coregistration
  * **Aligning structural and (mean) functional images**
  * Multimodal structural registration, e.g. T1-T2
* Affine inter-subject registration
  * First stage of non-linear spatial normalisation
  * Approximate alignment of tissue probability maps

Affine transformations

* Rigid rotations have six degrees of freedom (DF)
  * Three translations and a 3D rotation (e.g. 3 axis rots.)
* Voxel-world mappings usually include three scaling DF (for a possible total of 9 DF)
* General 3D affine transformations add three shears (12 DF total)
* Affine transform properties
  * Parallel lines remain parallel
  * Transformations form a group



Other types of registration in SPM

* Non-linear spatial normalisation
  * Registering different subjects to a standard template
* Unified segmentation and normalisation
  * Warping standard-space tissue probability maps to a particular subject (can normalise using the inverse)
* High-dimensional warping
  * Modelling small longitudinal deformations (e.g. AD)
* DARTEL
  * Smooth large-deformation warps using flows
  * Normalisation to group's average *shape* template

Voxel-to-world mapping

* Affine transform associated with each image
  * Maps from voxels ($x=1..n_x$, $y=1..n_y$, $z=1..n_z$) to some world co-ordinate system. e.g.,
    * Scanner co-ordinates - images from DICOM toolbox
    * T&T/MNI coordinates - spatially normalised
* Registering image B (source) to image A (target) will update B's voxel-to-world mapping
  * Mapping from voxels in A to voxels in B is by
    * A-to-world using M_A, then world-to-B using M_B^{-1} : $M_B^{-1} M_A$

Manual reorientation

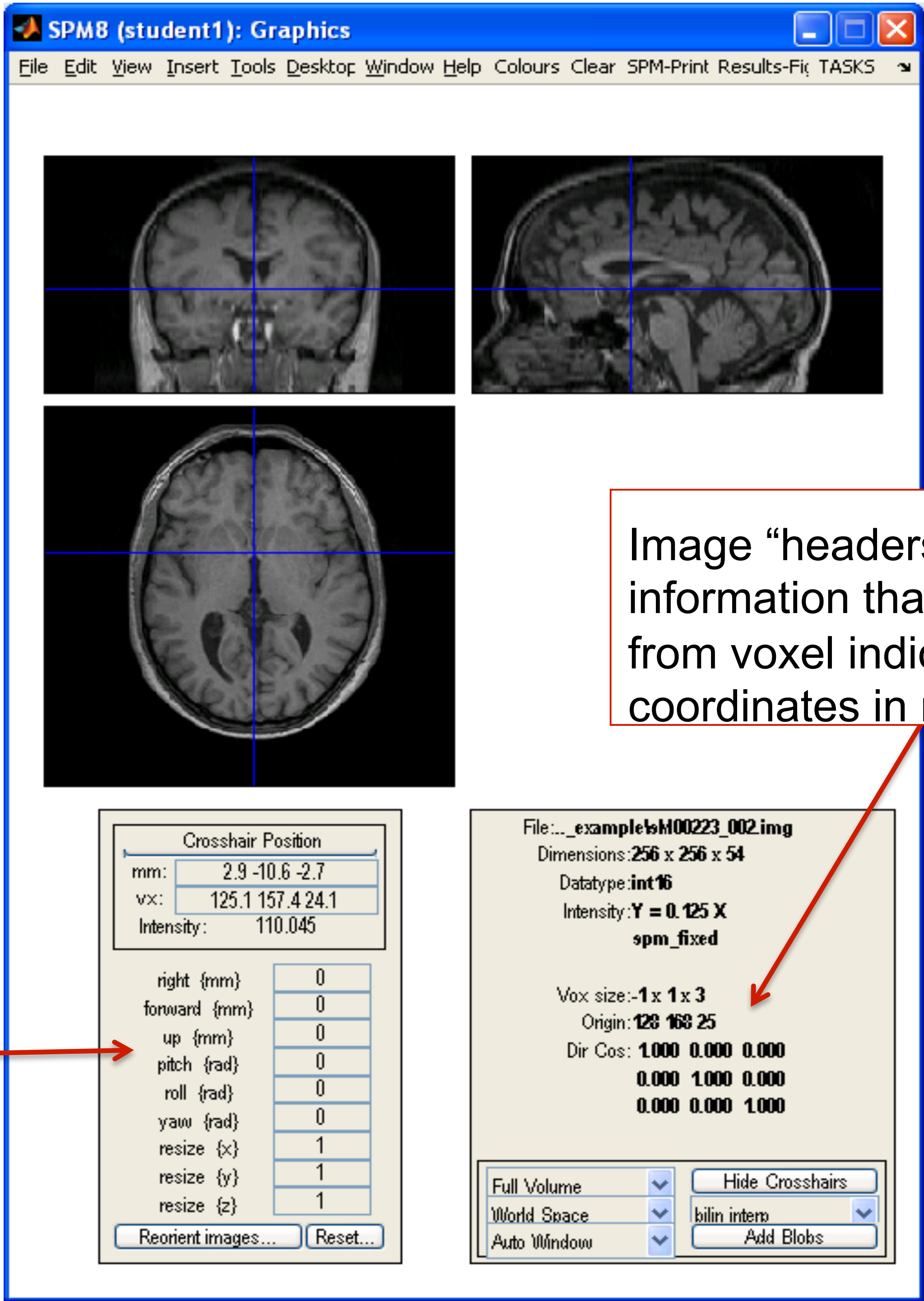
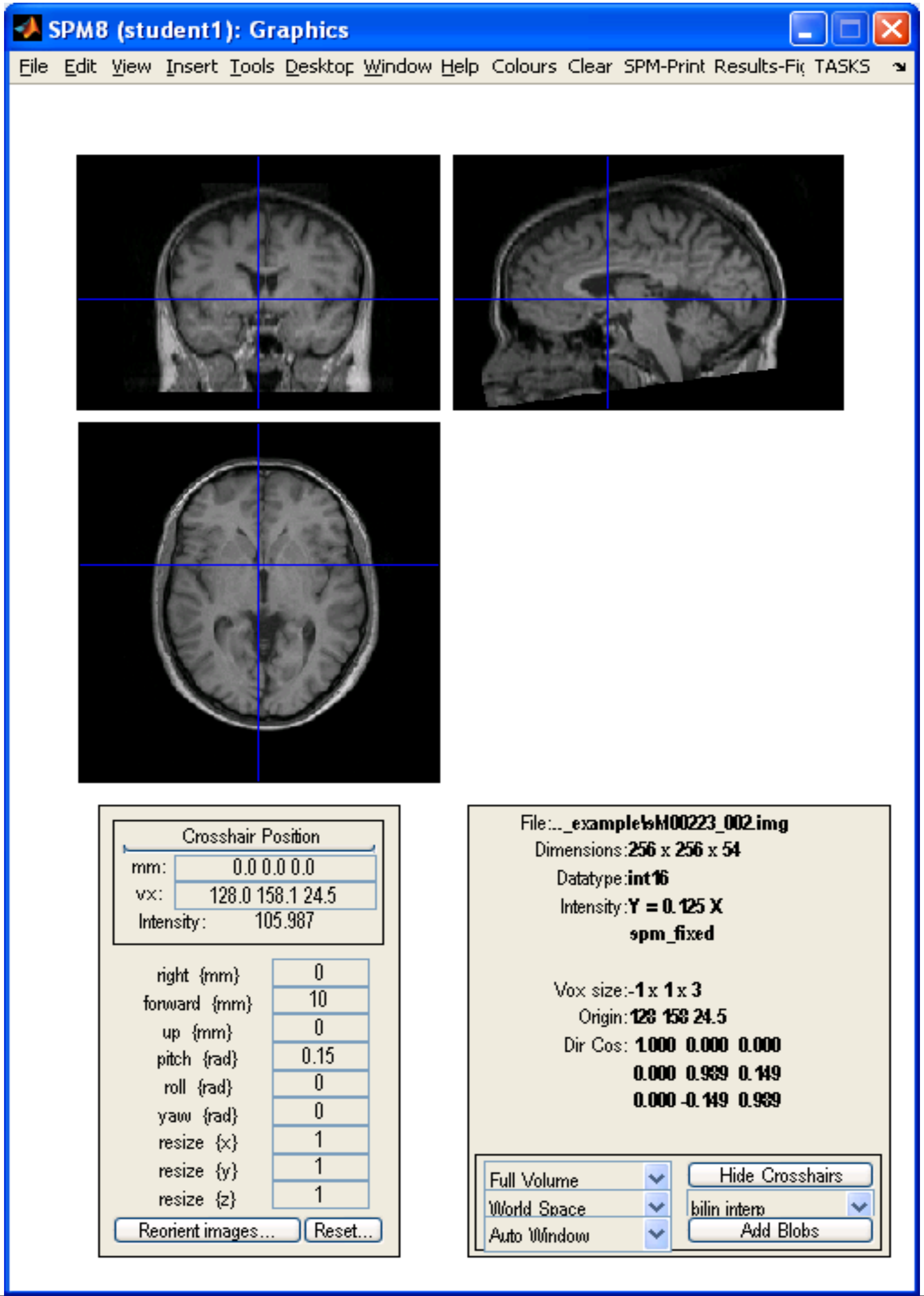


Image "headers" contain information that lets us map from voxel indices to "world" coordinates in mm

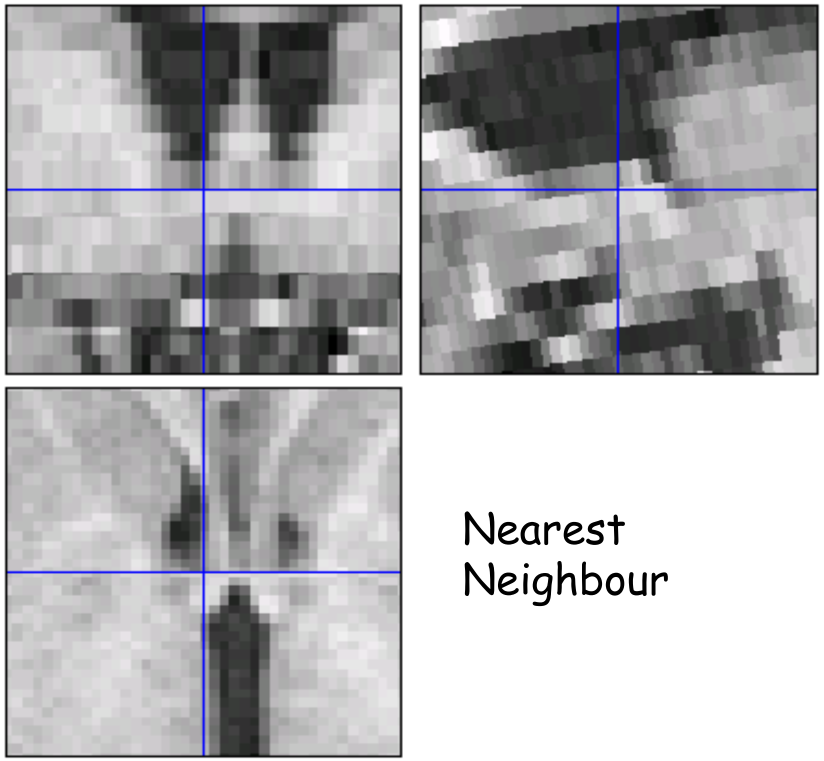
Modifying this mapping lets us reorient (and realign or coregister) the image(s)

Manual reorientation

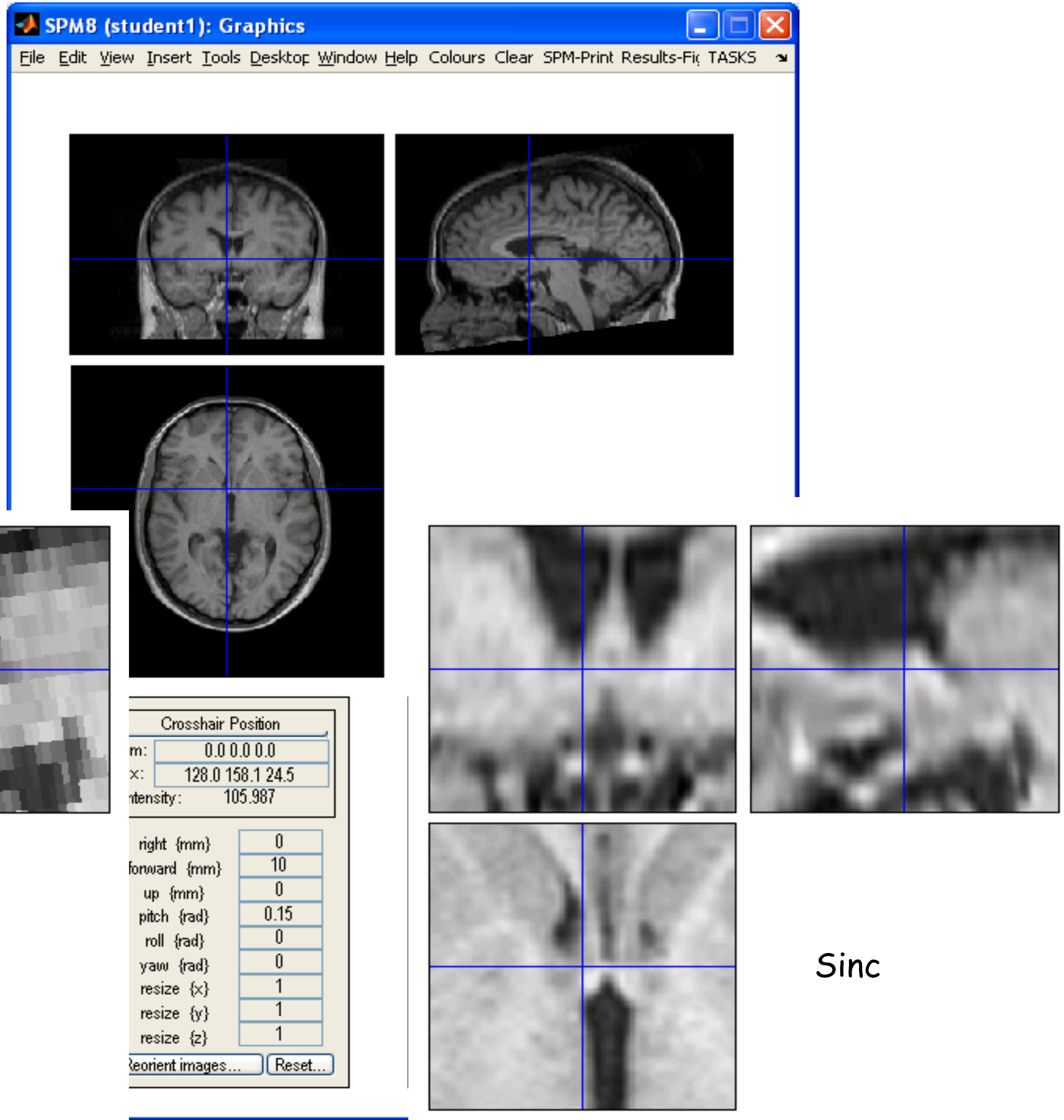


Manual reorientation

Interpolation



Nearest Neighbour

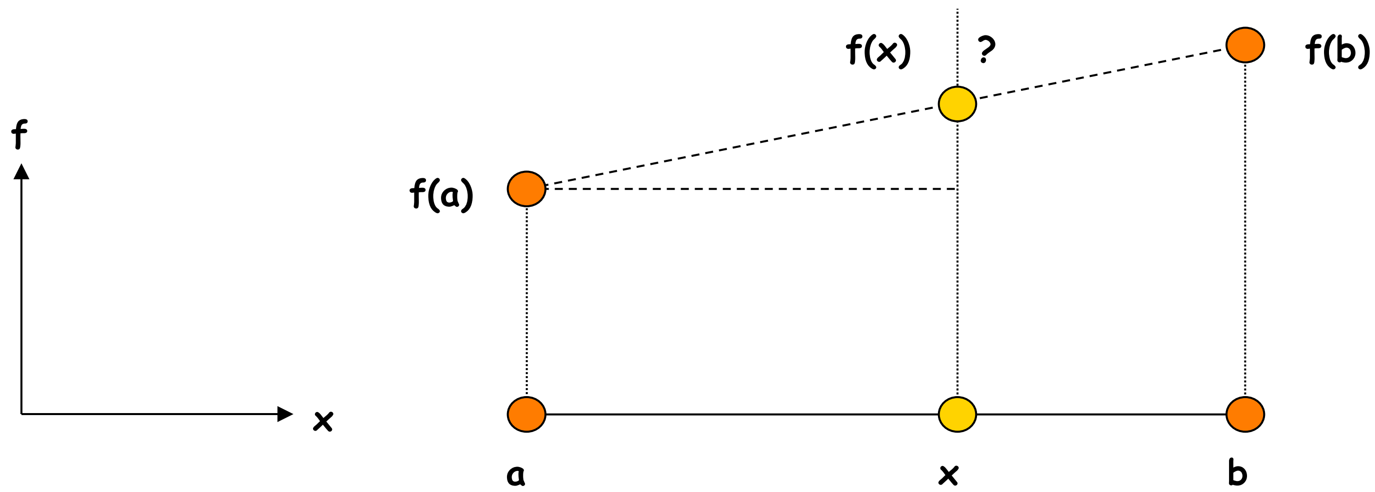


Sinc

Interpolation

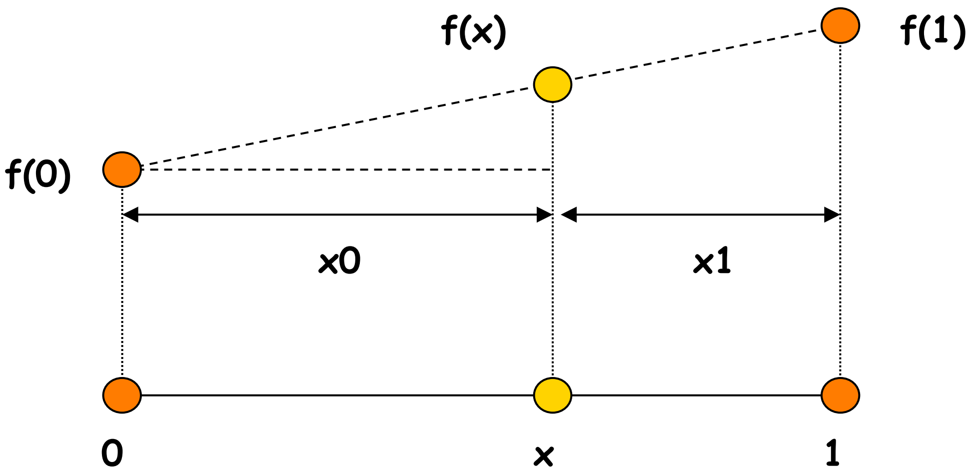
* Applying the transformation parameters, and re-sampling the data onto the same grid of voxels as the target image
  * AKA reslicing, regridding, transformation, and writing (as in **normalise - write**)
* Nearest neighbour gives the new voxel the value of the closest corresponding voxel in the source
* Linear interpolation uses information from all immediate neighbours (2 in 1D, 4 in 2D, 8 in 3D)
* NN and linear interp. correspond to zeroth and first order B-spline interpolation, higher orders use more information in the hope of improving results
  * (Sinc interpolation is an alternative to B-spline)

Linear interpolation – 1D



$$f(x) = f(a) + \frac{f(b) - f(a)}{b - a}(x - a) = f(a)\frac{b - x}{b - a} + f(b)\frac{x - a}{b - a}$$

Linear interpolation – 1D

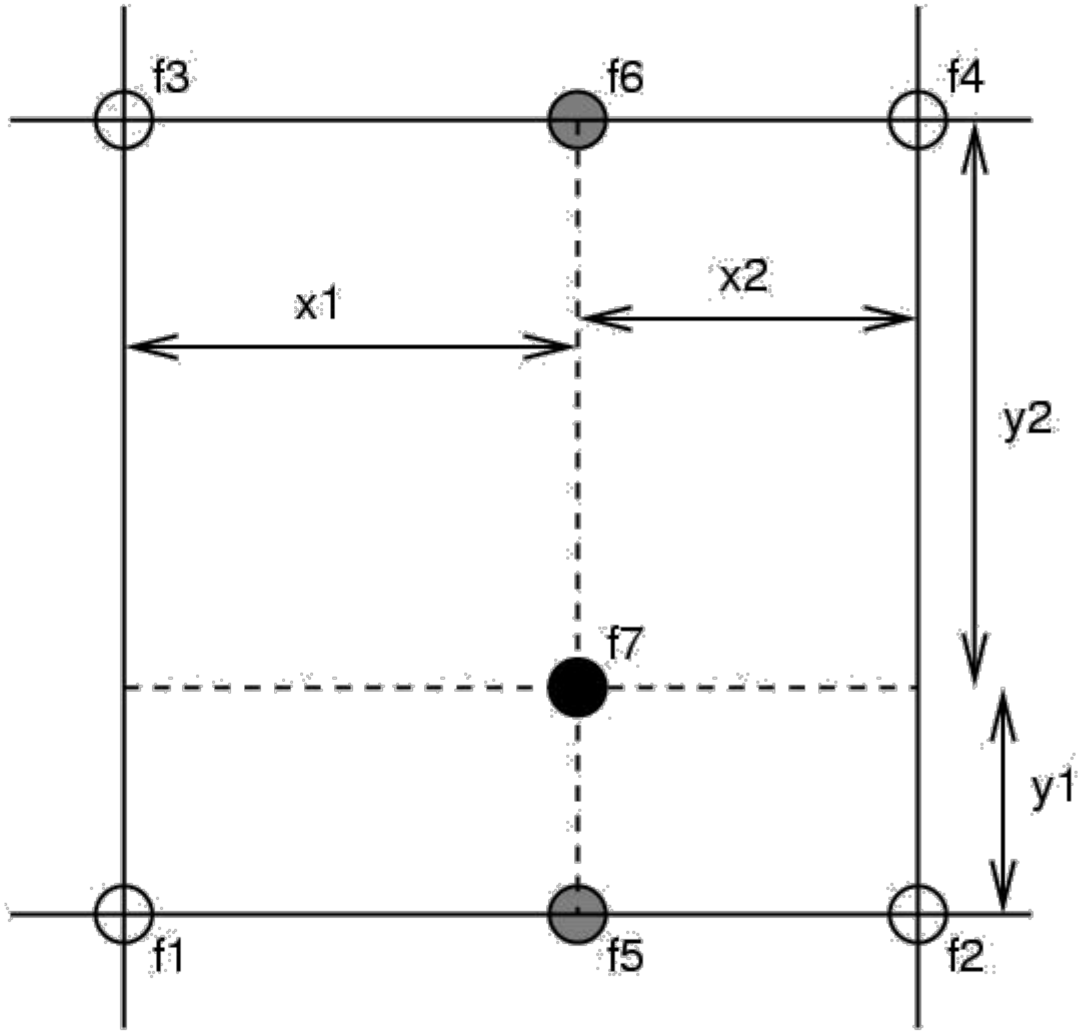


$$f(x) = f(0) + (f(1) - f(0))x = f(0)(1 - x) + f(1)x$$

$$= f(0)x_1 + f(1)x_0$$

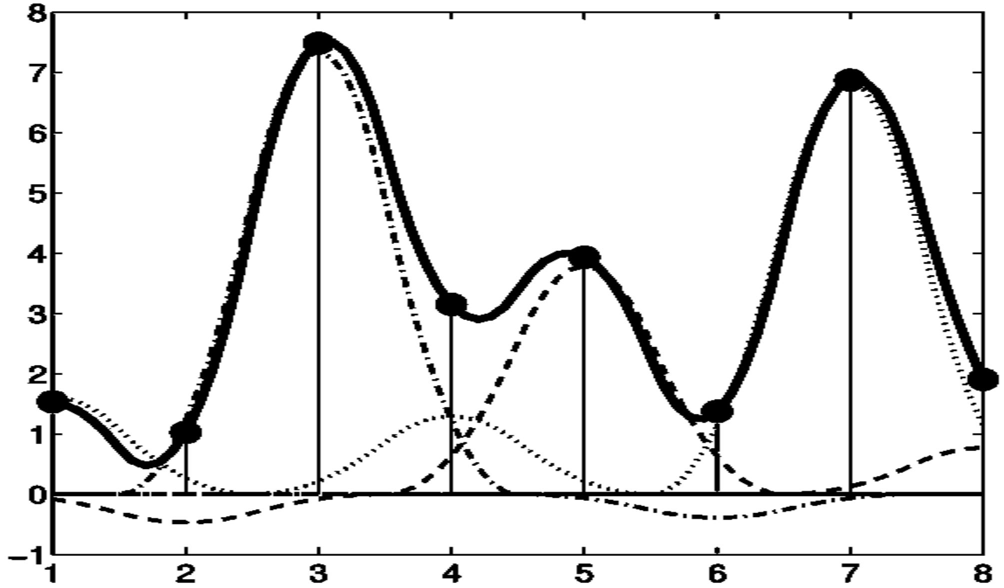
Linear interpolation – 2D

* Nearest neighbour
  * Take the value of the closest voxel
* Tri-linear
  * Just a weighted average of the neighbouring voxels
  * $f_5 = f_1 x_2 + f_2 x_1$
  * $f_6 = f_3 x_2 + f_4 x_1$
  * $f_7 = f_5 y_2 + f_6 y_1$

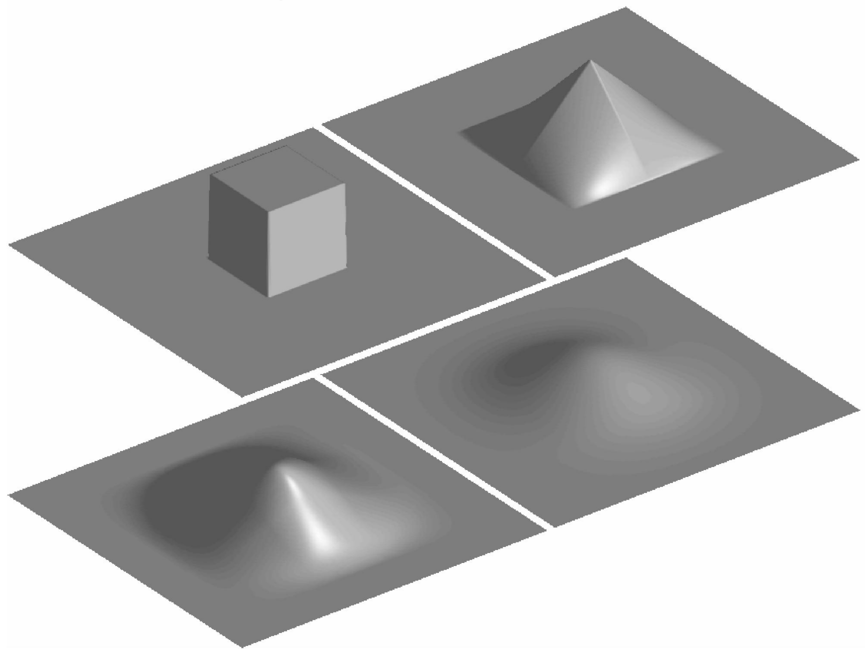


B-spline Interpolation

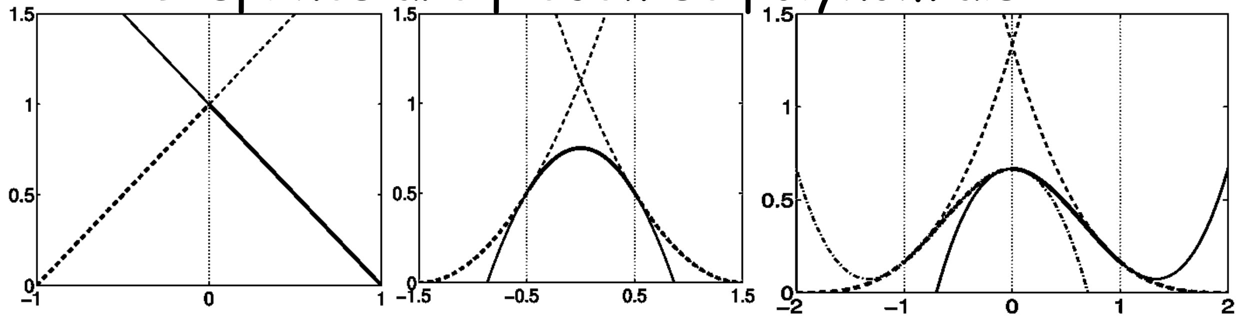
A continuous function is represented by a linear combination of basis functions



2D B-spline basis functions of degrees 0, 1, 2 and 3

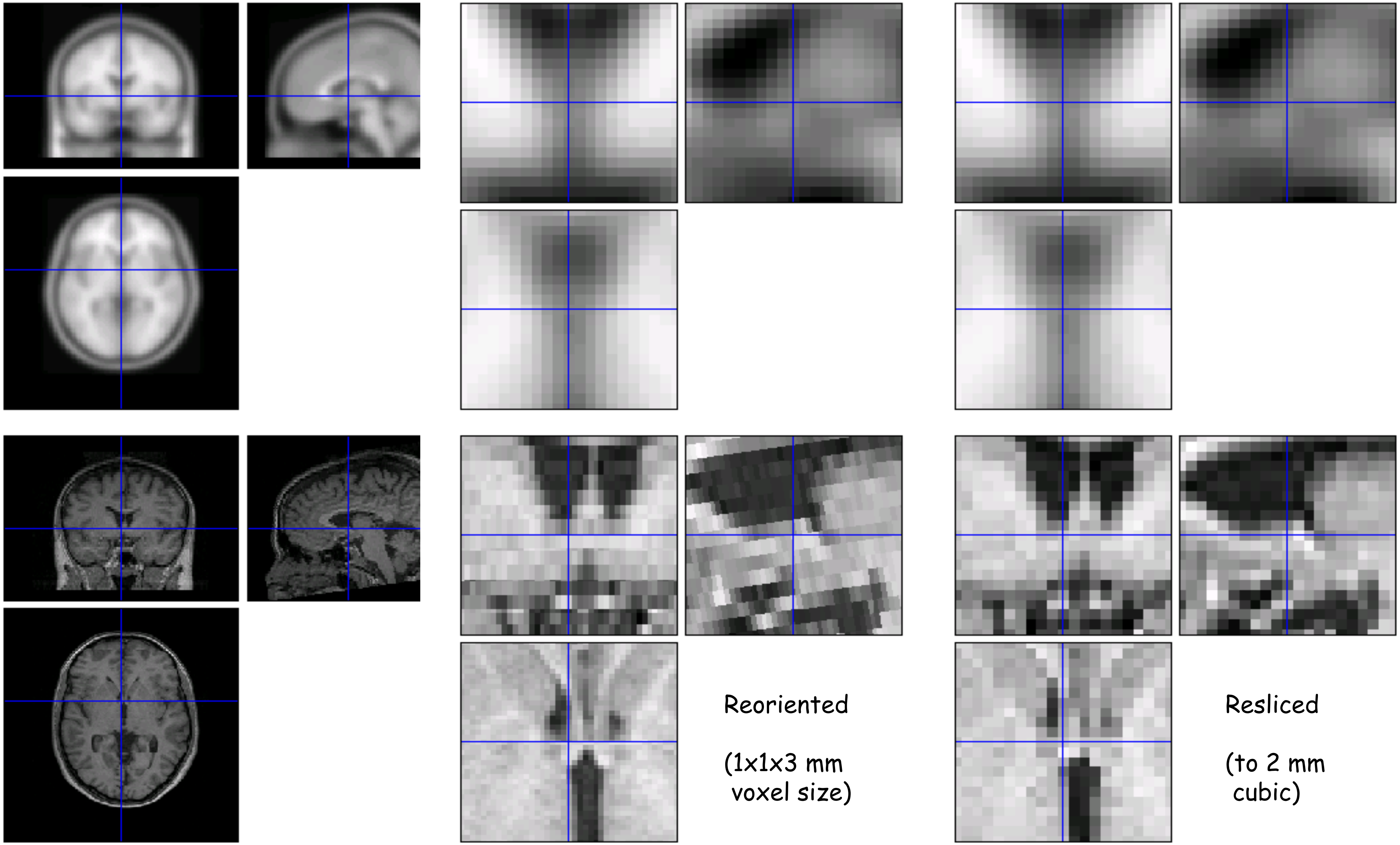


B-splines are piecewise polynomials



Nearest neighbour and trilinear interpolation are the same as B-spline interpolation with degrees 0 and 1.

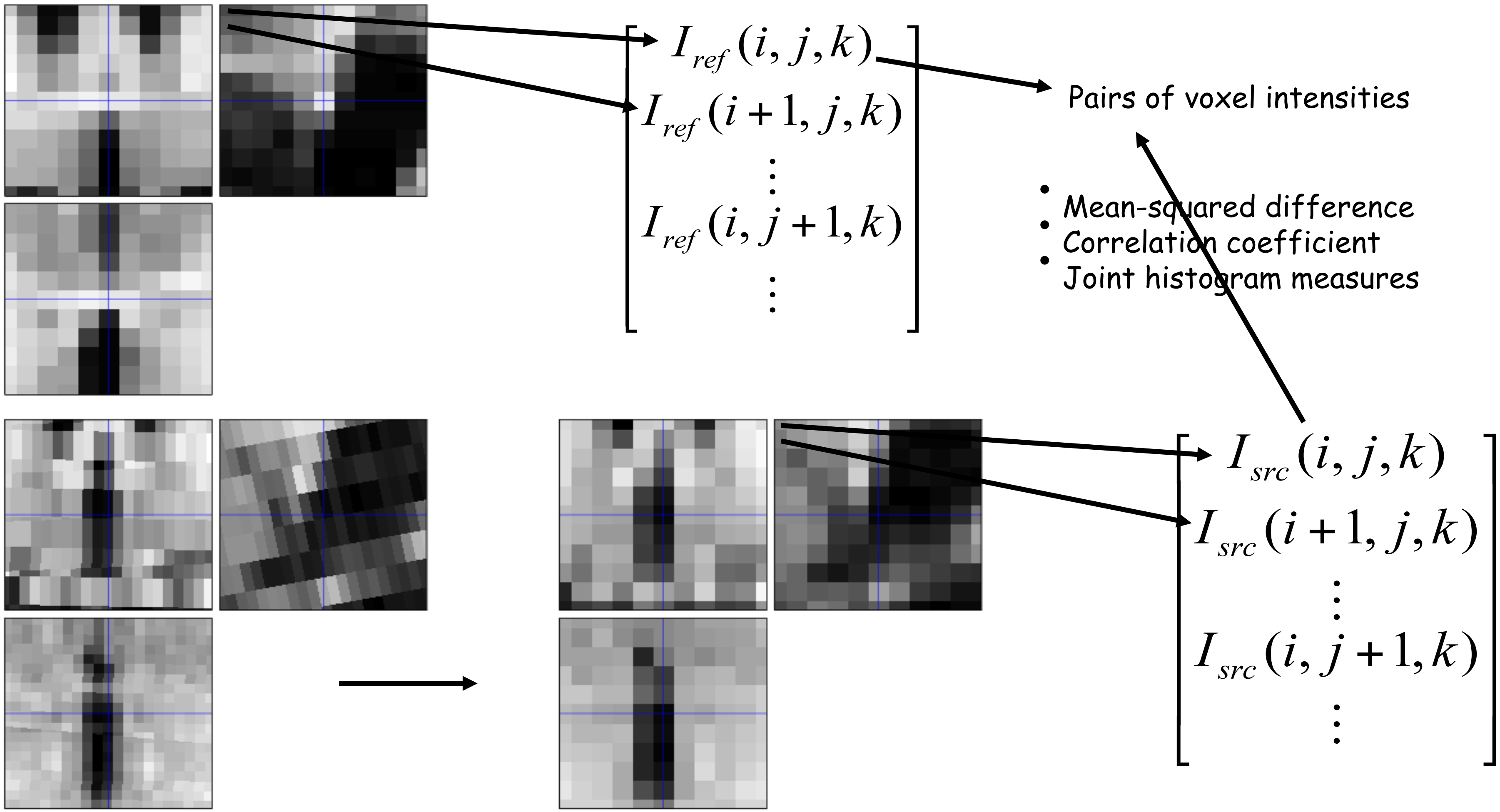
Manual reorientation – Reslicing



Quantifying image alignment

* Registration intuitively relies on the concept of aligning images to increase their similarity
  * This needs to be mathematically formalised
  * We need practical way(s) of measuring similarity
* Using interpolation we can find the intensity at equivalent voxels
  * (equivalent according to the current transformation parameter estimates)

Voxel similarity measures



Intra-modal similarity measures

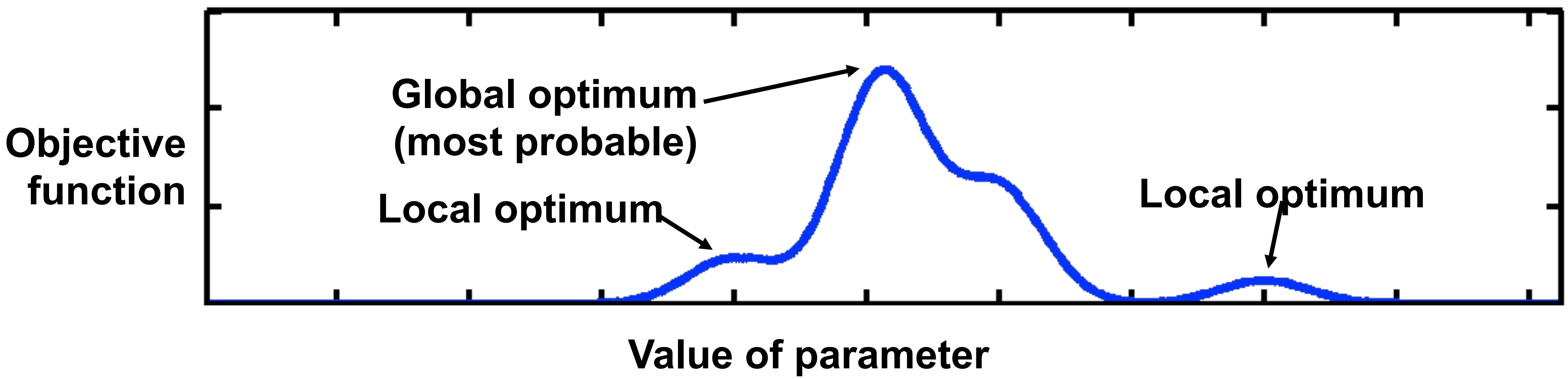
* Mean squared error (minimise)
  * AKA sum-squared error, RMS error, etc.
  * Assumes simple relationship between intensities
  * Optimal (only) if differences are i.i.d. Gaussian
  * Okay for realignment or sMRI-sMRI coreg
* Correlation-coefficient (maximise)
  * AKA Normalised Cross-Correlation, Zero-NCC
  * Slightly more general, e.g. T1-T1 inter-scanner
  * Invariant under affine transformation of intensities

Automatic image registration

* Quantifying the quality of the alignment with a measure of image similarity allows computational estimation of transformation parameters
* This is the basis of both realignment and coregistration in SPM
  * Allowing more complex geometric transformations or warps leads to more flexible spatial normalisation
* Automating registration requires optimisation...

Optimisation

* Find the “best” parameters according to an “objective function” (minimised or maximised)
* Objective functions can often be related to a probabilistic model (Bayes -> MAP -> ML -> LSQ)



Contents

Motion in fMRI

* Can be a major problem
  * Increase residual variance and reduce sensitivity
  * Data may get completely lost with sudden movements
  * Movements may be correlated with the task
  * Try to minimise movement (don’t scan for too long!)
* Motion correction using realignment
  * Each volume rigidly registered to reference
  * Least squares objective function
* Realigned images must be resliced for analysis
  * Not necessary if they will be normalised anyway

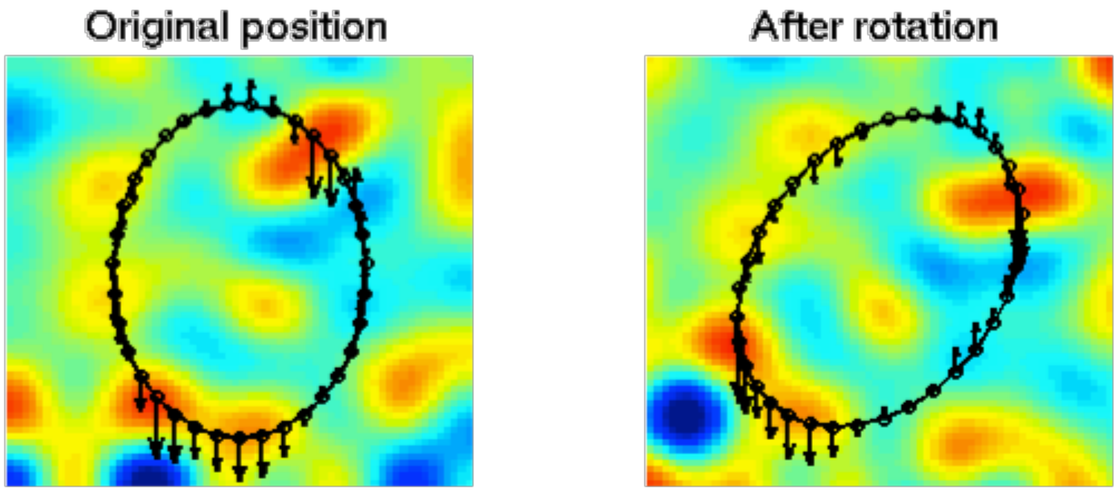
Residual Errors from aligned fMRI

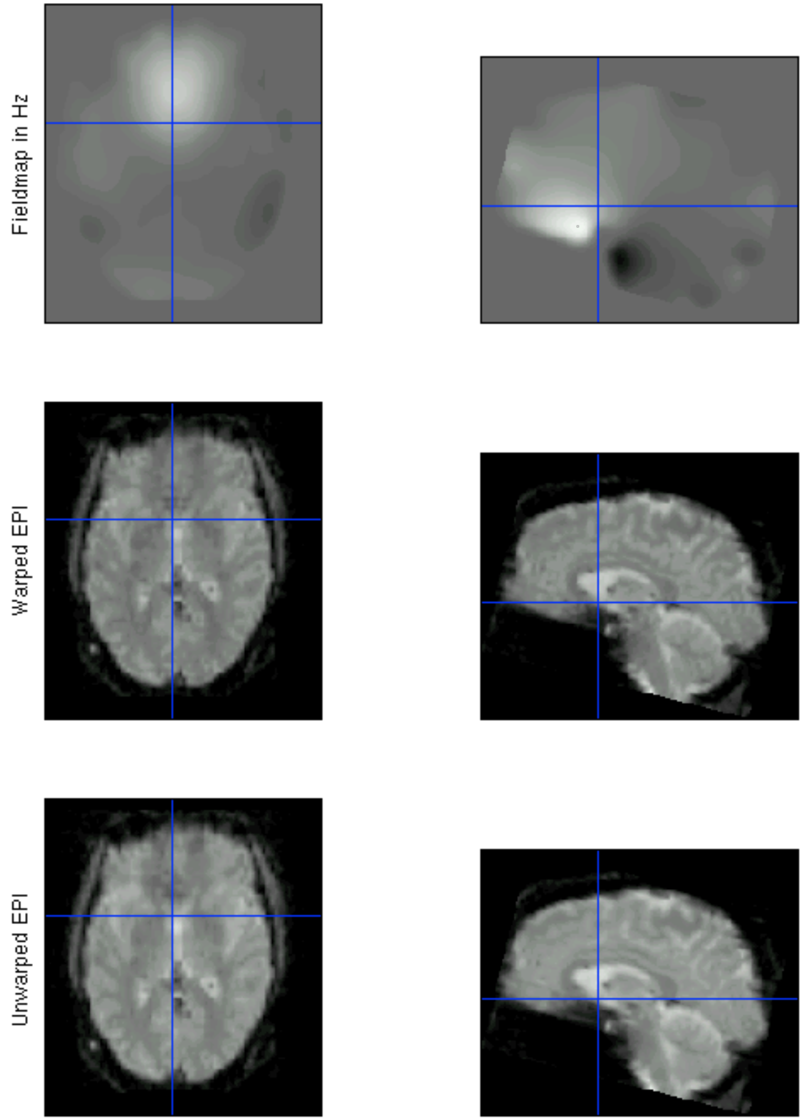
* Slices are not acquired simultaneously
    * rapid movements not accounted for by rigid body model
* Image artefacts may not move according to a rigid body model
    * image distortion, image dropout, Nyquist ghost
* Gaps between slices can cause aliasing artefacts
* Re-sampling can introduce interpolation errors
    * especially tri-linear interpolation

* Functions of the estimated motion parameters can be modelled as confounds in subsequent analyses

fMRI movement by distortion interaction

* Subject disrupts B0 field, rendering it inhomogeneous
  * distortions occur along the phase-encoding direction
* Subject moves during EPI time series
  * Distortions vary with subject position
  * shape varies (non-rigidly)



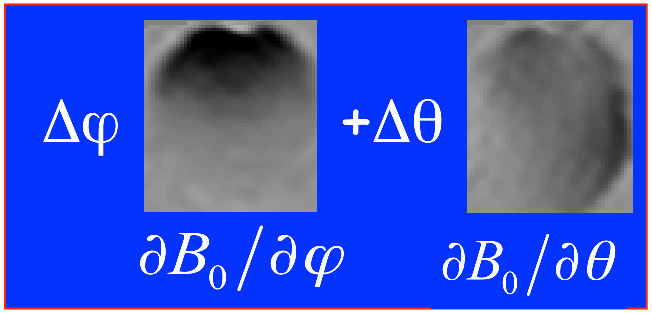


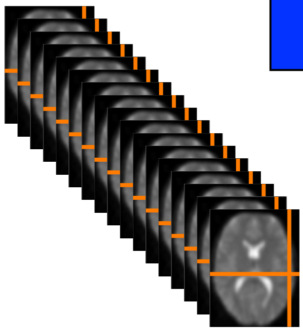
Correcting for distortion changes using Unwarp

Estimate reference from mean of all scans.

Estimate new distortion fields for each image:

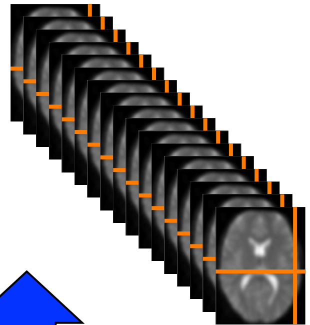
- estimate rate of change of field with respect to the current estimate of movement parameters in **pitch** and **roll**.





Estimate movement parameters.

Unwarp time series.



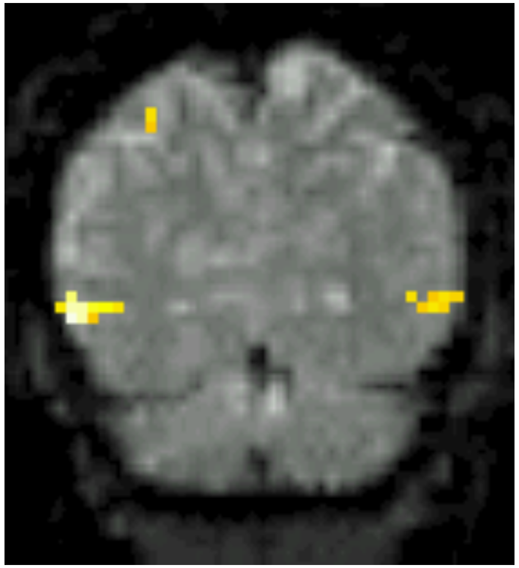
Andersson et al, 2001

Contents

1. Registration basics
2. Motion and realignment
3. **Inter-modal coregistration**
4. Spatial normalisation
5. Unified segmentation
6. Gaussian smoothing

Inter-modal coregistration

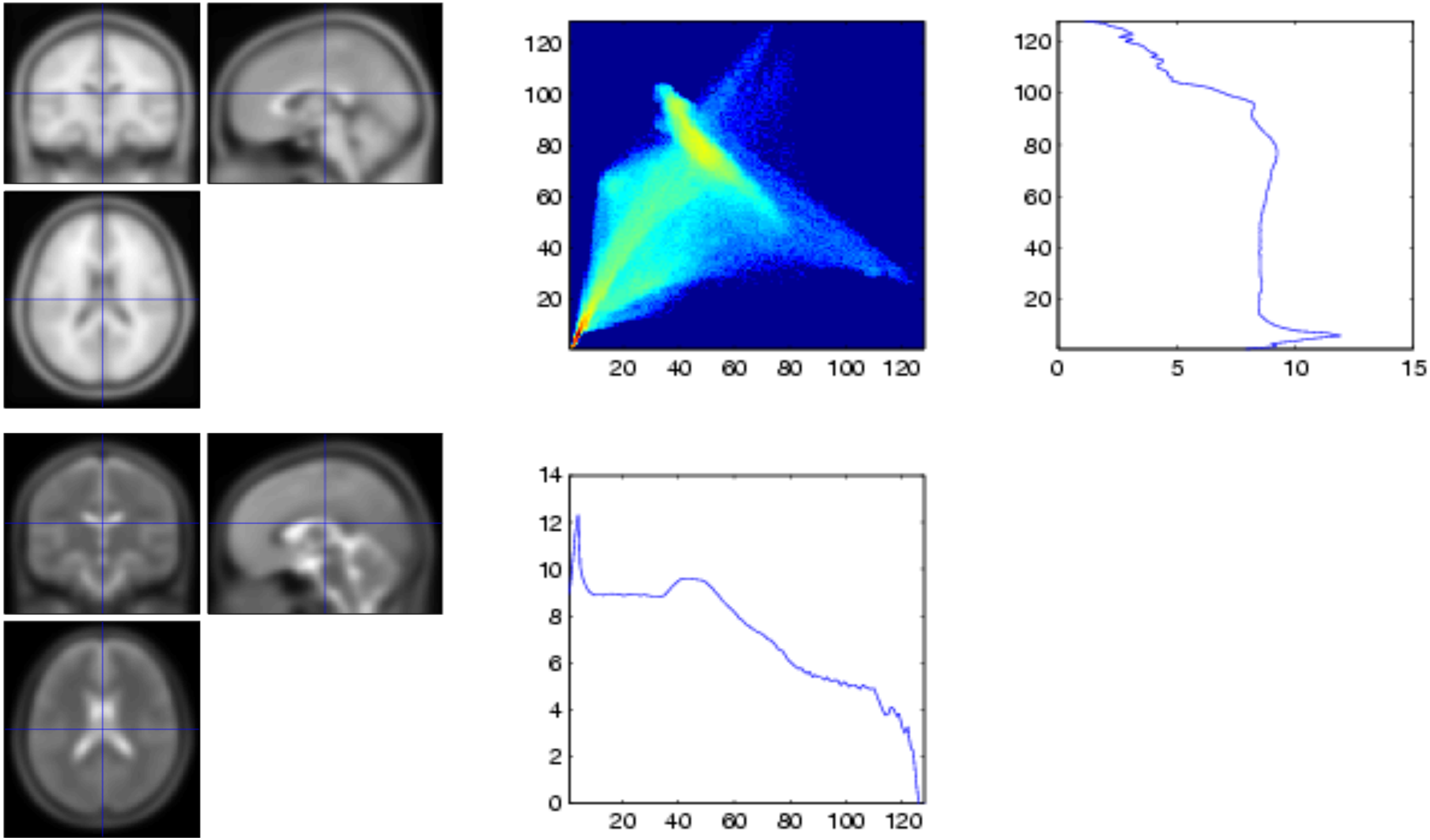
- Match images from same subject but different modalities:
  - anatomical localisation of single subject activations
  - achieve more precise spatial normalisation of functional image using anatomical image.



Inter-modal similarity measures

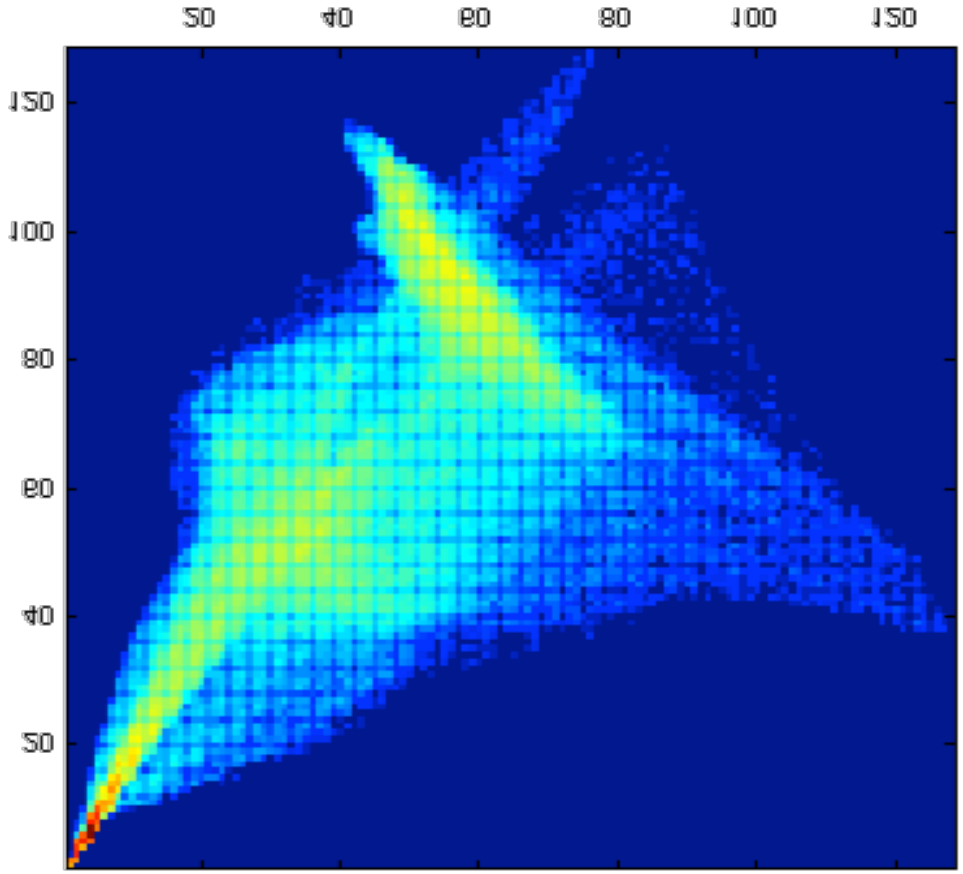
* Commonly derived from joint and marginal entropies
  * Entropies via probabilities, from histograms
  * $H(a) = -\int a\ P(a) \log_2 P(a)$
  * $H(a,b) = -\int a\ P(a,b) \log_2 P(a,b)$
* Minimise joint entropy H(a,b)
* Maximise mutual Information
  * $MI = H(a) + H(b) - H(a,b)$
* Maximise normalised MI
  * $NMI = (H(a) + H(b)) / H(a,b)$

Joint and marginal histograms

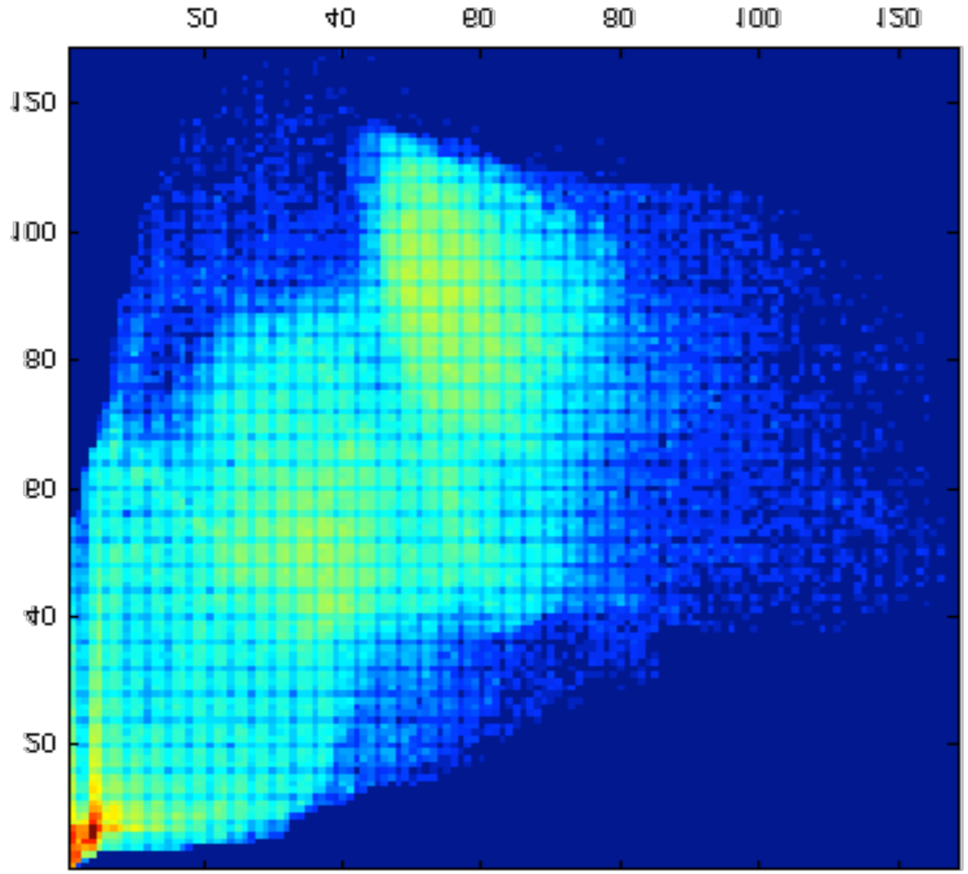


Joint histogram based registration

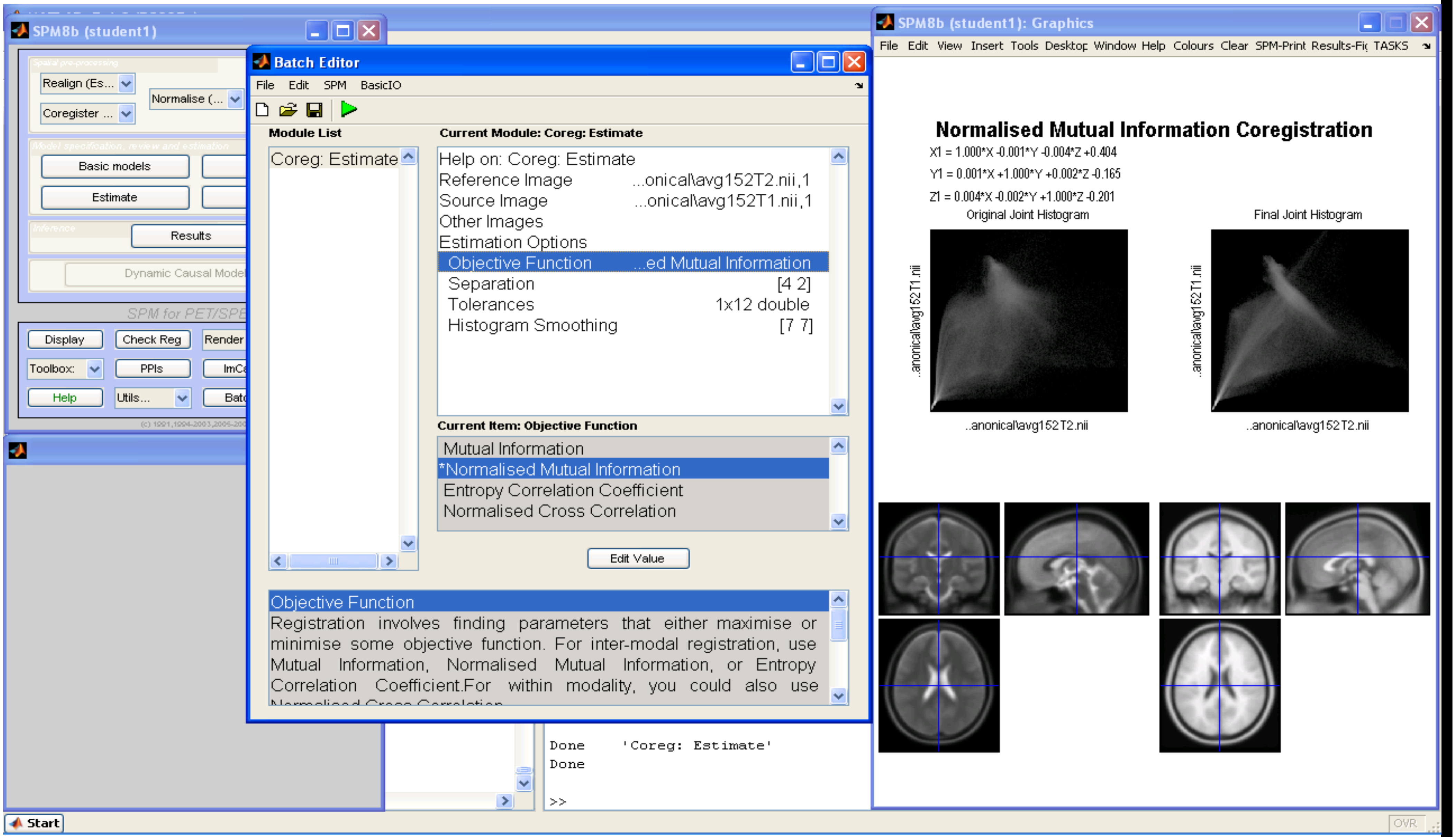
Initially registered T1 and T2 templates



After deliberate misregistration
(10mm relative x-translation)

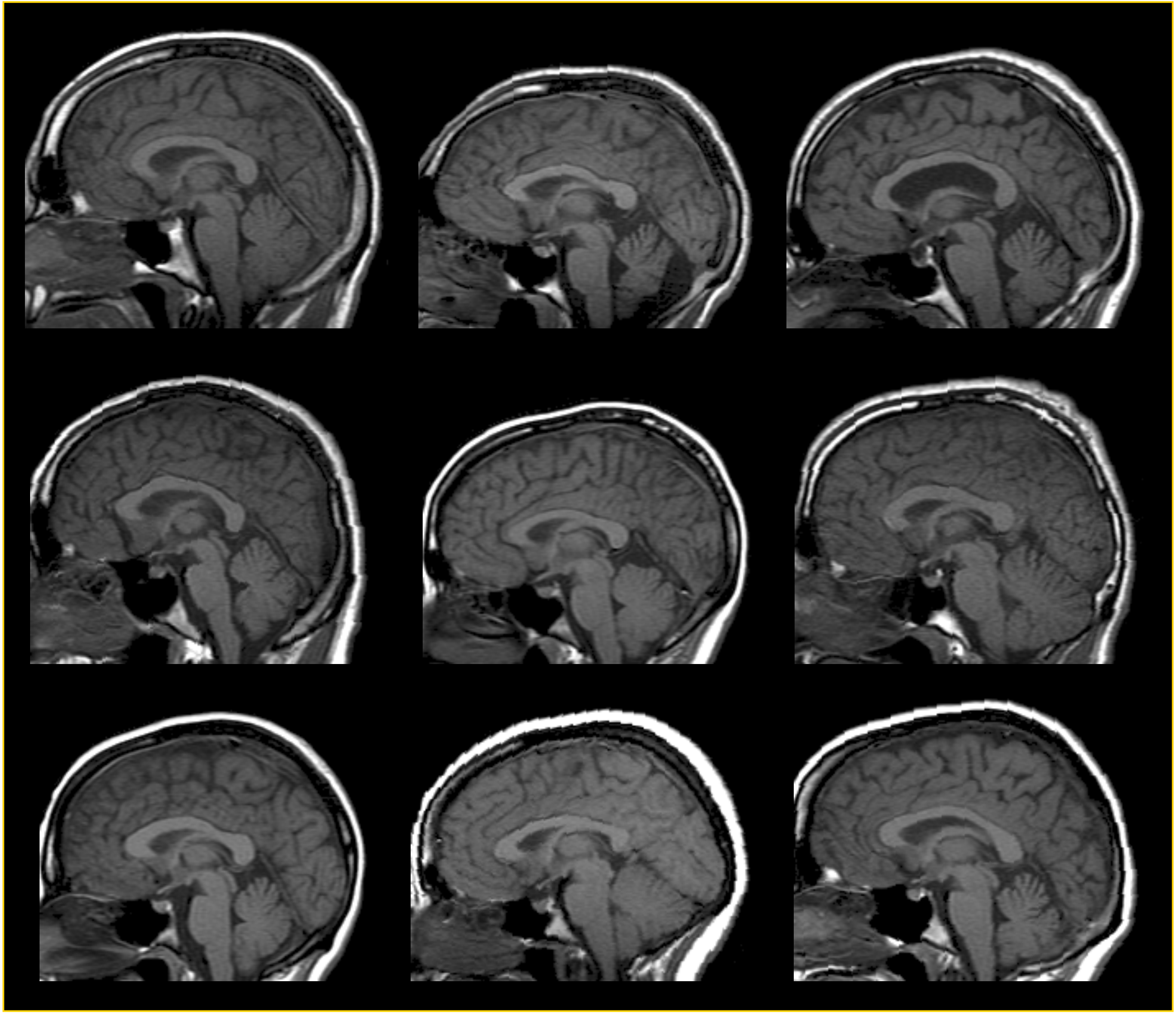


Joint histogram sharpness correlates with image alignment
Mutual information and related measures attempt to quantify this


SPM8b (student1)
Realign (Es...
Normalise (...
Coregister ...
Basic models
Estimate
Results
Dynamic Causal Model
SPM for PET/SPE
Display
Check Reg
Render
Toolbox:
PPIs
Help
Utils...
Batch Editor
File Edit SPM BasicIO
Module List
Coreg: Estimate
Current Module: Coreg: Estimate
Help on: Coreg: Estimate
Reference Image ...onical\avg152T2.nii,1
Source Image ...onical\avg152T1.nii,1
Other Images
Estimation Options
Objective Function ...ed Mutual Information
Separation [4 2]
Tolerances 1x12 double
Histogram Smoothing [7 7]
Current Item: Objective Function
Mutual Information
*Normalised Mutual Information
Entropy Correlation Coefficient
Normalised Cross Correlation
Edit Value
Objective Function
Registration involves finding parameters that either maximise or minimise some objective function. For inter-modal registration, use Mutual Information, Normalised Mutual Information, or Entropy Correlation Coefficient.For within modality, you could also use
Done 'Coreg: Estimate'
Done
>>
Start
SPM8b (student1): Graphics
File Edit View Insert Tools Desktop Window Help Colours Clear SPM-Print Results-Fig TASKS
Normalised Mutual Information Coregistration
X1 = 1.000*X -0.001*Y -0.004*Z +0.404
Y1 = 0.001*X +1.000*Y +0.002*Z -0.165
Z1 = 0.004*X -0.002*Y +1.000*Z -0.201
Original Joint Histogram
Final Joint Histogram
..anonical\avg152T1.nii
..anonical\avg152T2.nii

Contents

Spatial Normalisation



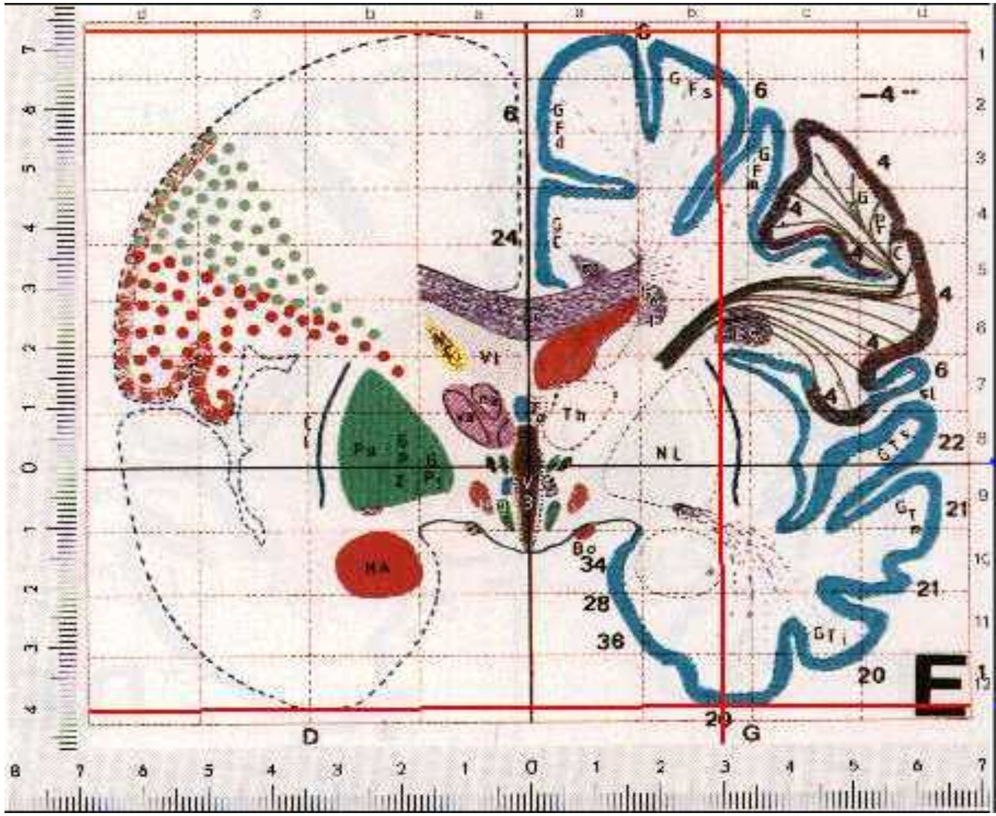
Spatial Normalisation - Reasons

* Inter-subject averaging
  * Increase sensitivity with more subjects
    * Fixed-effects analysis
  * Extrapolate findings to the population as a whole
    * Mixed-effects analysis

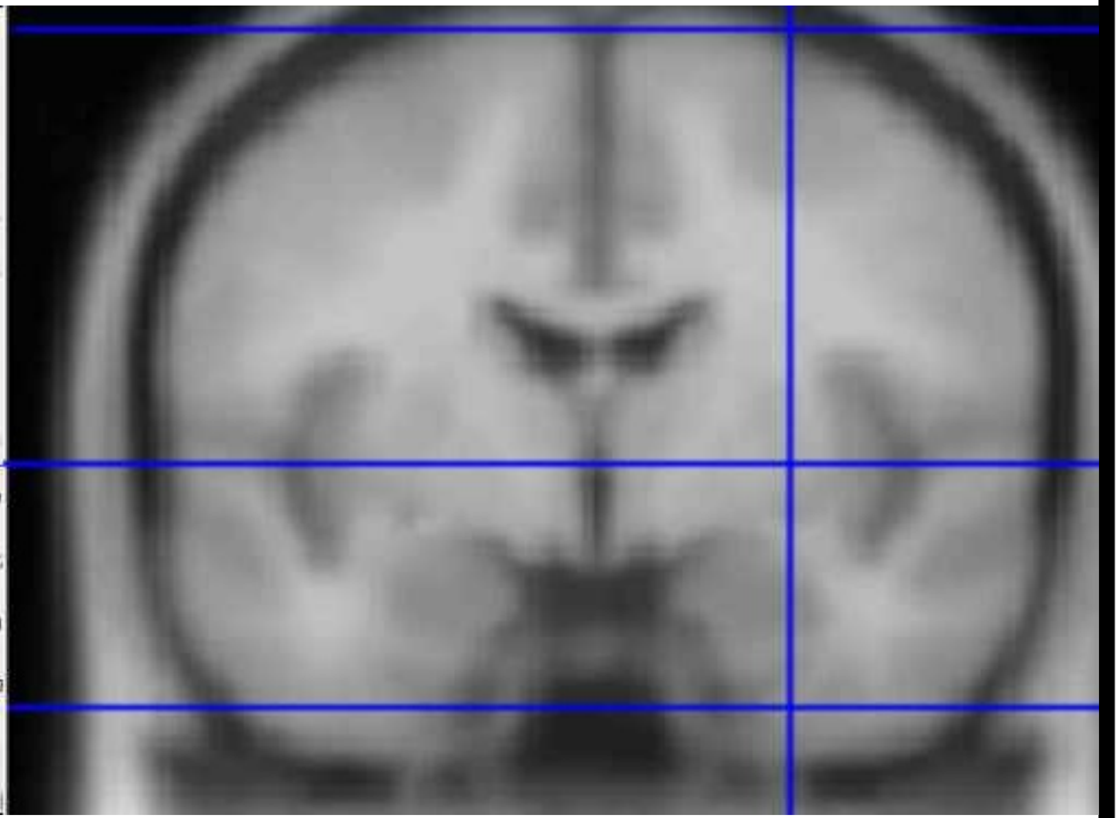
* Make results from different studies comparable by aligning them to standard space
  * e.g. The T&T convention, using the MNI template

Standard spaces

The Talairach Atlas



The MNI/ICBM AVG152 Template

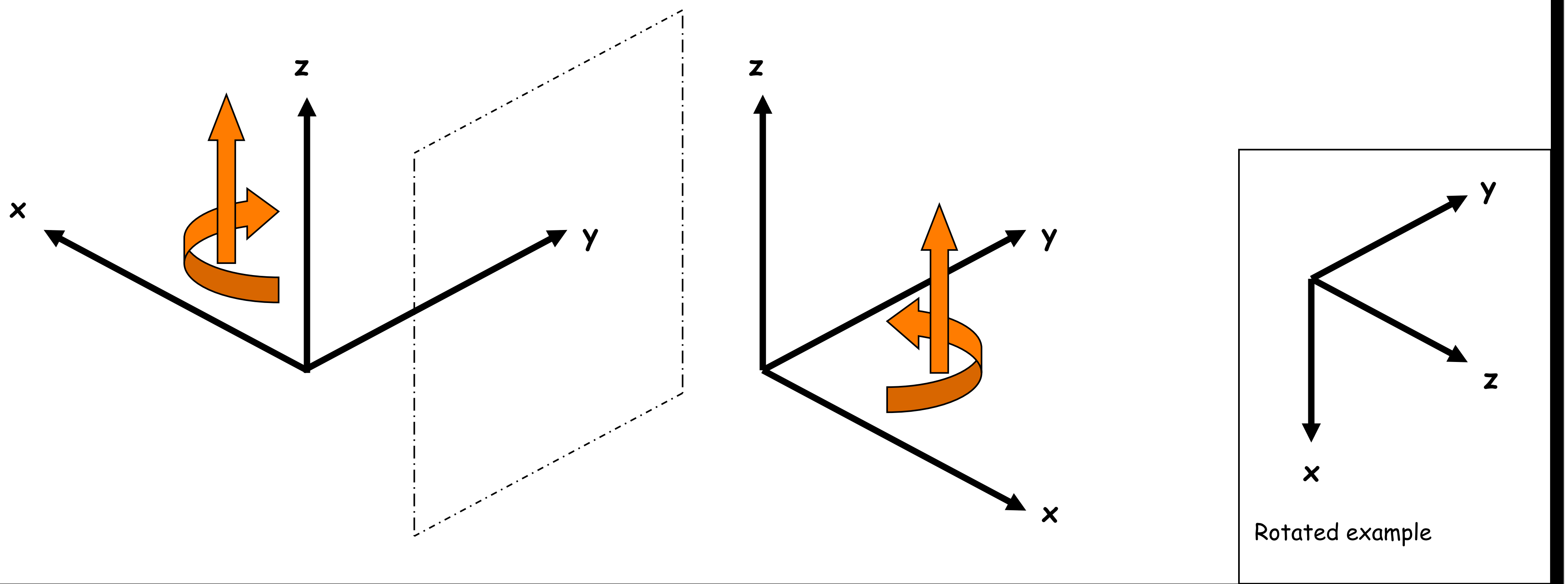


The MNI template follows the *convention* of T&T, but doesn't match the *particular brain*

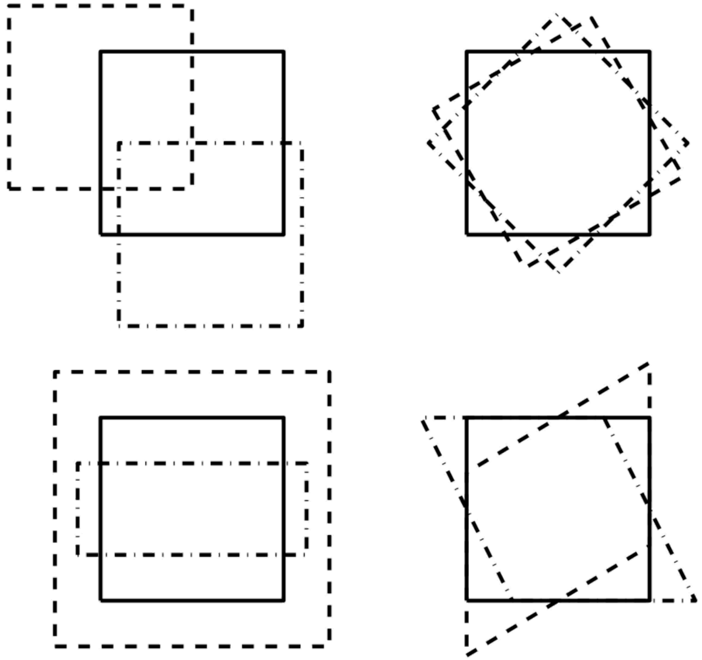
Recommended reading: http://imaging.mrc-cbu.cam.ac.uk/imaging/MniTalairach

Coordinate system sense

* Analyze™ files are stored in a left-handed system
* Talairach space has the opposite (right-handed) *sense*
* Mapping between them requires a reflection or "flip"
  * Affine transform with a negative determinant

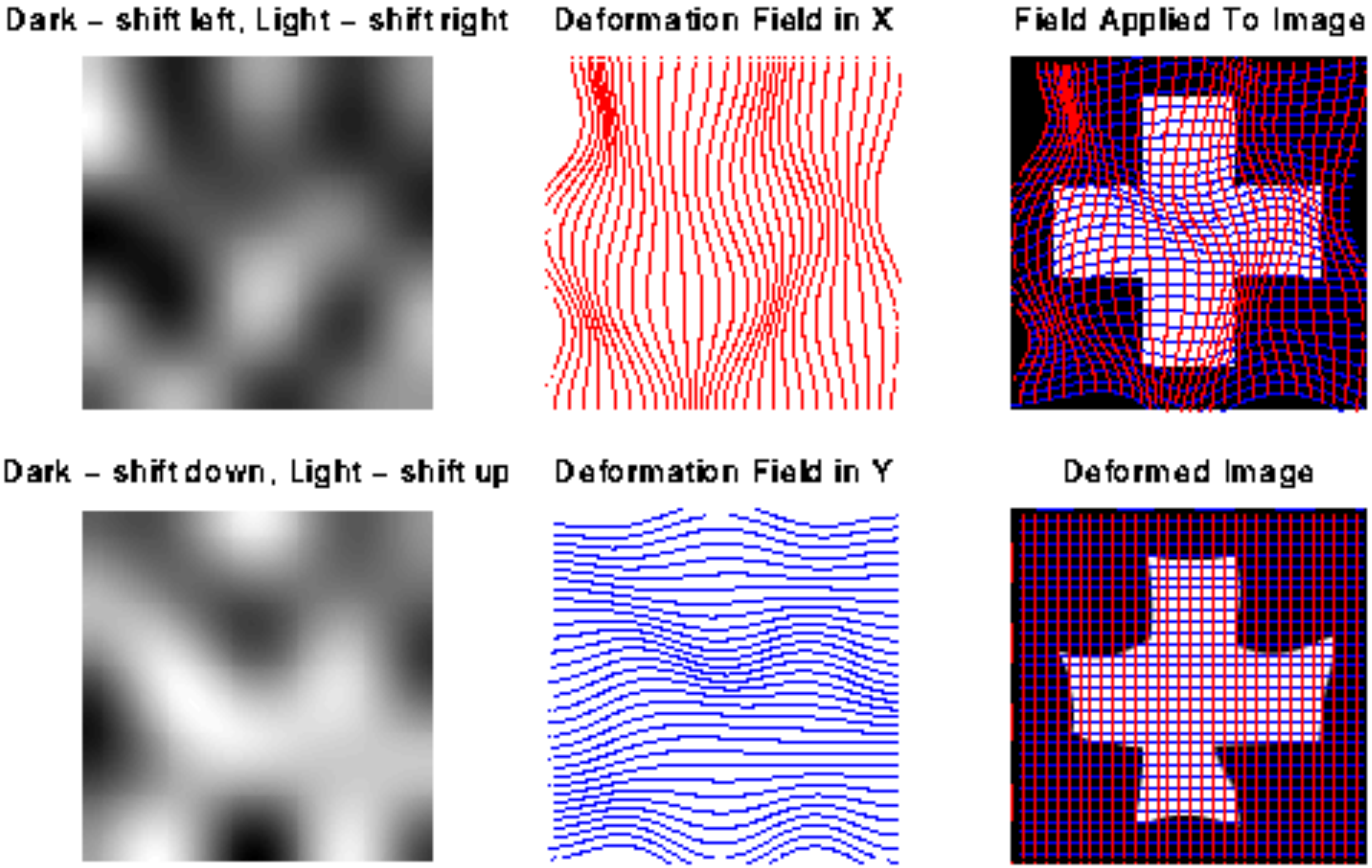


Spatial Normalisation – Procedure



* Start with a 12 DF affine registration
  * 3 translations, 3 rotations
    3 zooms, 3 shears
  * Fits overall shape and size
* Refine the registration with non-linear deformations
* Algorithm simultaneously minimises
  * Mean-squared difference (Gaussian likelihood)
  * Squared distance between parameters and their expected values (regularisation with Gaussian prior)

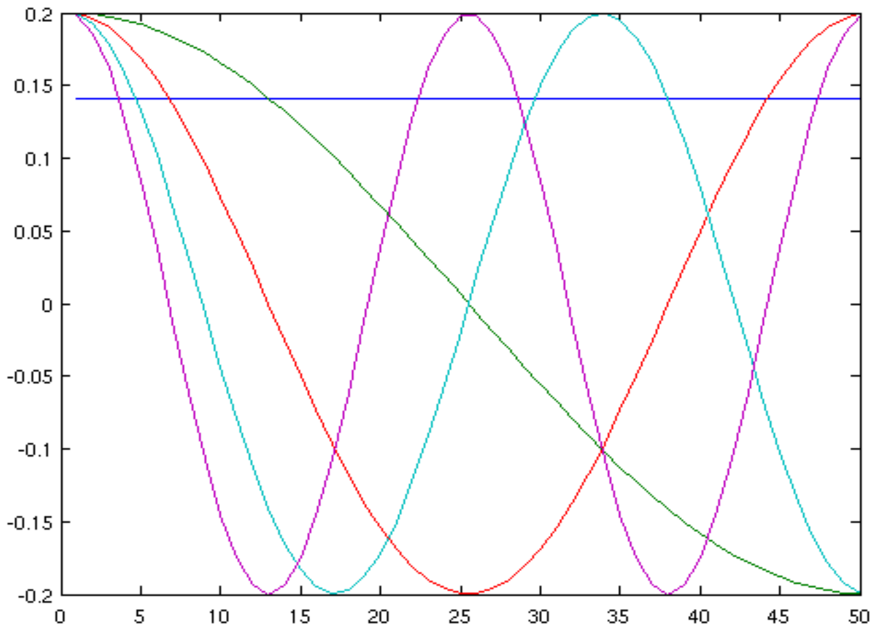
Spatial Normalisation – Warping



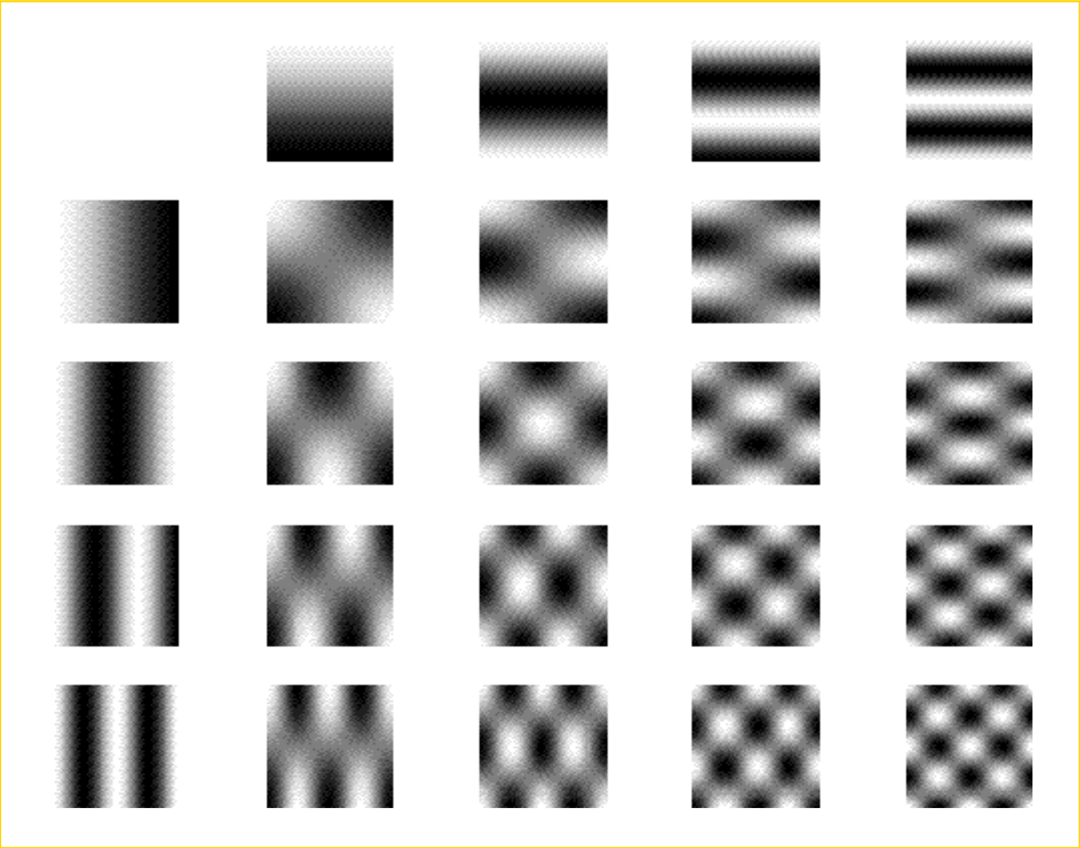
Deformations are modelled with a linear combination of non-linear basis functions

Spatial Normalisation – DCT basis

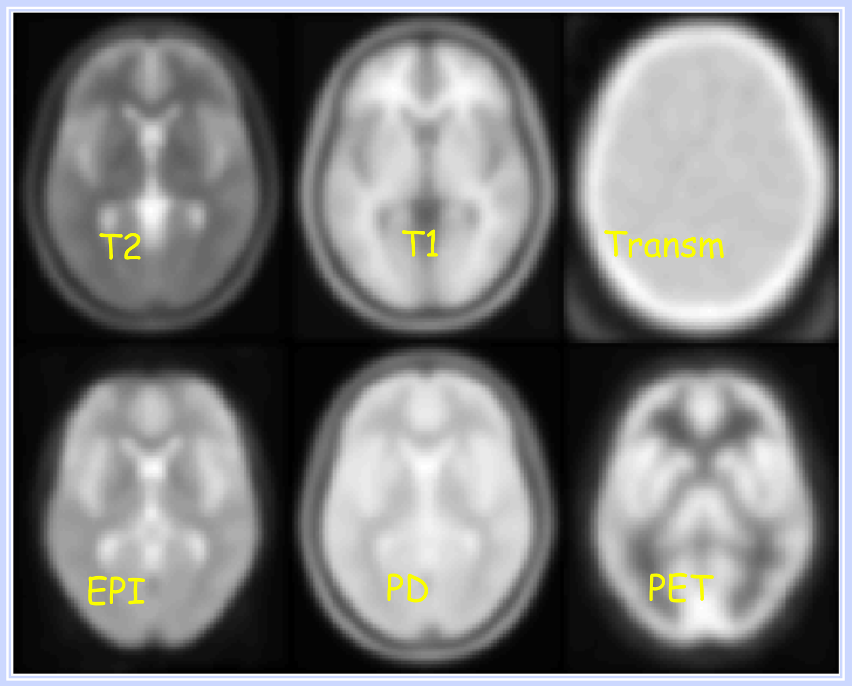
The lowest frequencies of a 3D discrete cosine transform (DCT) provide a smooth basis



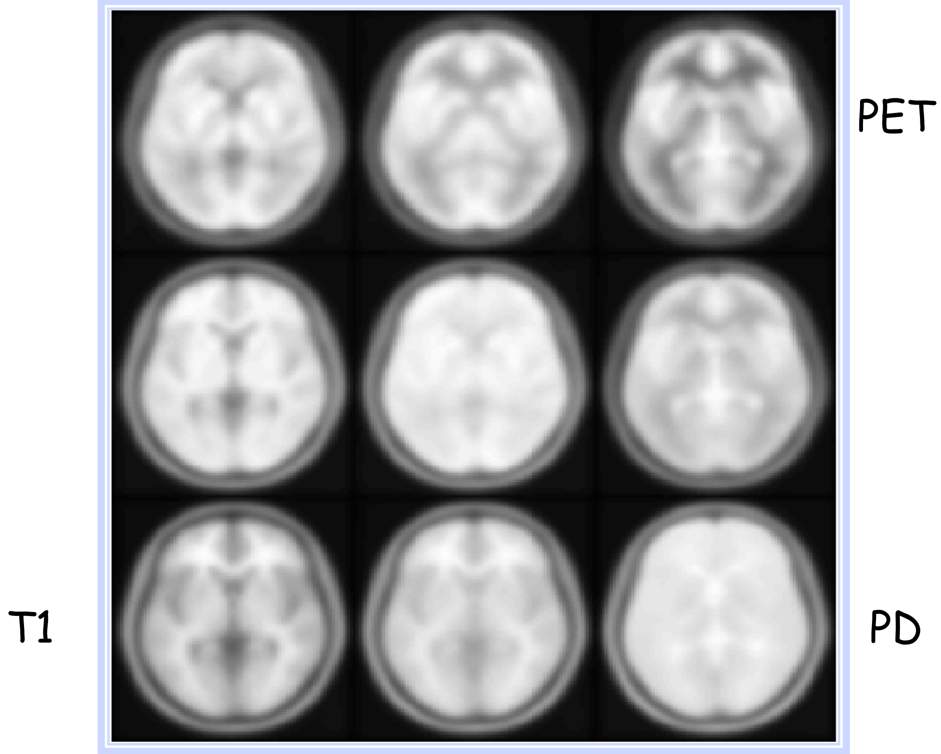

```
plot(spm_dctmtx(50, 5))
```



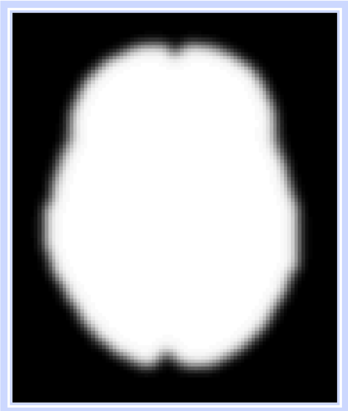
Spatial Normalisation – Templates and masks



A wider range of contrasts can be registered to a linear combination of template images.

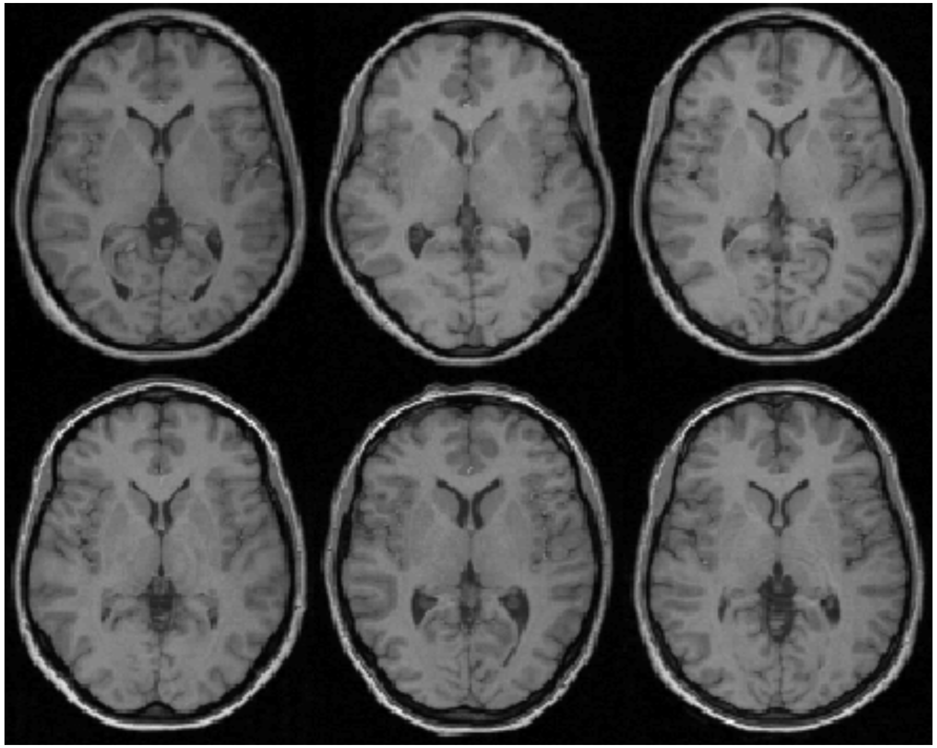


Spatial normalisation can be weighted so that non-brain voxels do not influence the result.

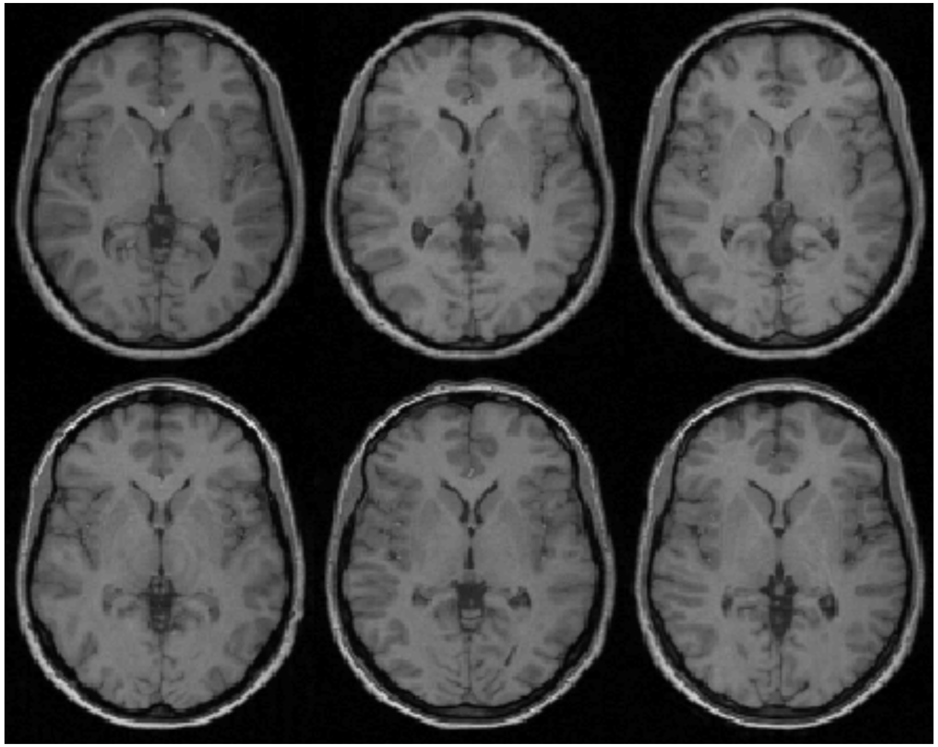


More specific weighting masks can be used to improve normalisation of lesioned brains.

Spatial Normalisation – Results



Affine registration



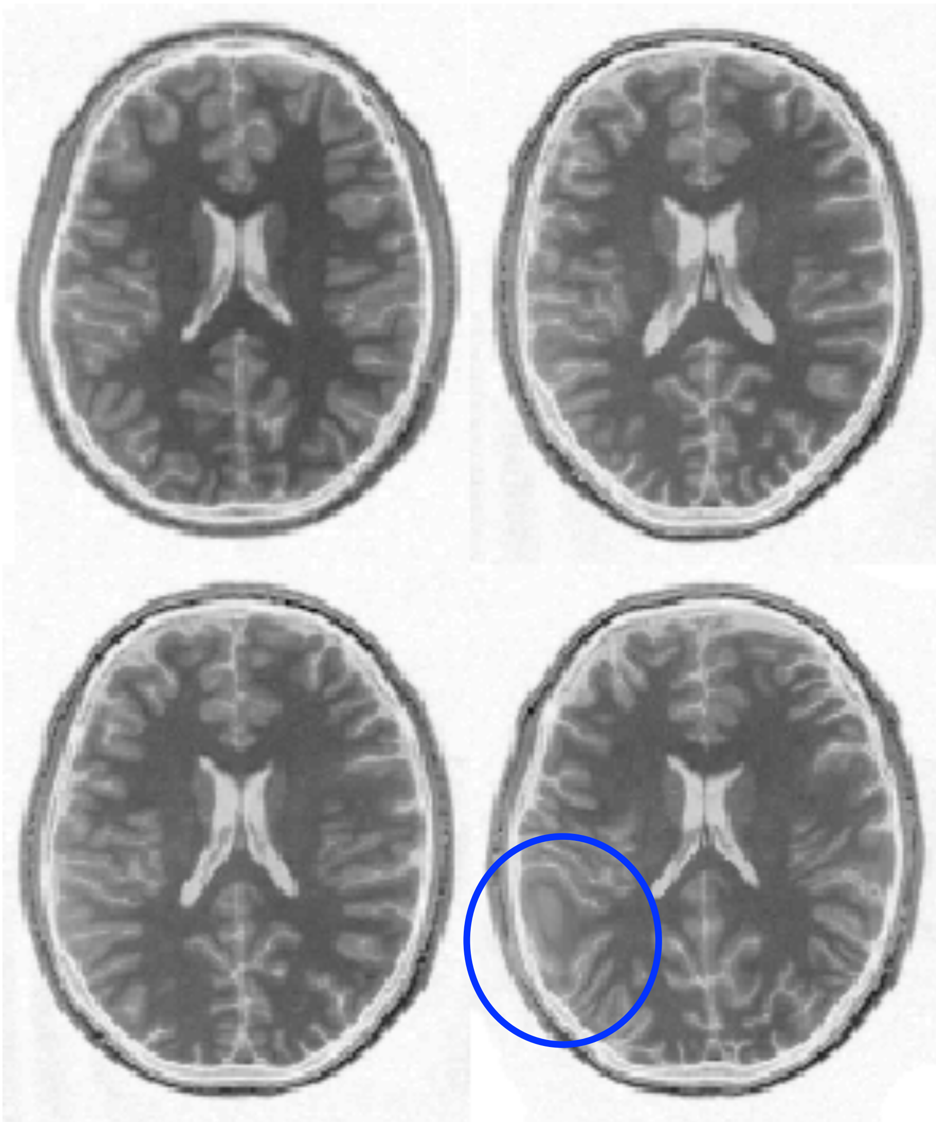
Non-linear registration

Optimisation – regularisation

* The “best” parameters according to the objective function may not be realistic
* In addition to similarity, regularisation terms or constraints are often needed to ensure a reasonable solution is found
  * Also helps avoid poor local optima
  * These can be considered as priors in a Bayesian framework, e.g. converting ML to MAP:
    * log(posterior) = log(likelihood) + log(prior) + c

Spatial Normalisation – Overfitting

Without regularisation, the non-linear normalisation can introduce unnecessary deformation



Spatial Normalisation – Issues

* Seek to match **functionally** homologous regions, but...
  * No exact match between structure and function
  * Different cortices can have different folding patterns
  * Challenging high-dimensional optimisation
    * Many local optima
* Compromise
  * Correct relatively large-scale variability (sizes of structures)
  * Smooth over finer-scale residual differences

Contents

Unified segmentation and normalisation

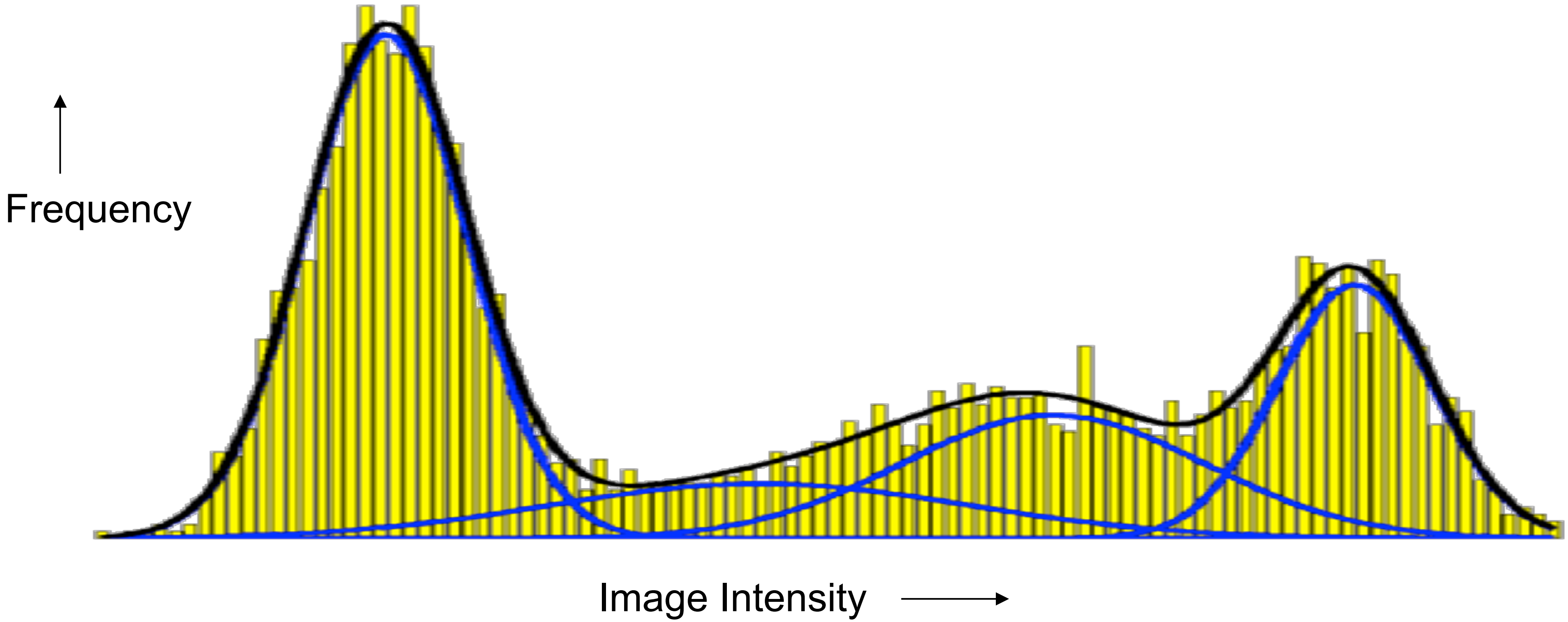
* MRI imperfections make normalisation harder
  * Noise, artefacts, partial volume effect
  * Intensity inhomogeneity or “bias” field
  * Differences between sequences
* Normalising segmented tissue maps should be more robust and precise than using the original images ...
* … Tissue segmentation benefits from spatially-aligned prior tissue probability maps (from other segmentations)
* This circularity motivates simultaneous segmentation and normalisation in a unified model

Summary of the unified model

* SPM8 implements a **generative model**
  * Principled Bayesian probabilistic formulation
* Gaussian mixture model segmentation with deformable tissue probability maps (priors)
  * The inverse of the transformation that aligns the TPMs can be used to normalise the original image
* Bias correction is included within the model

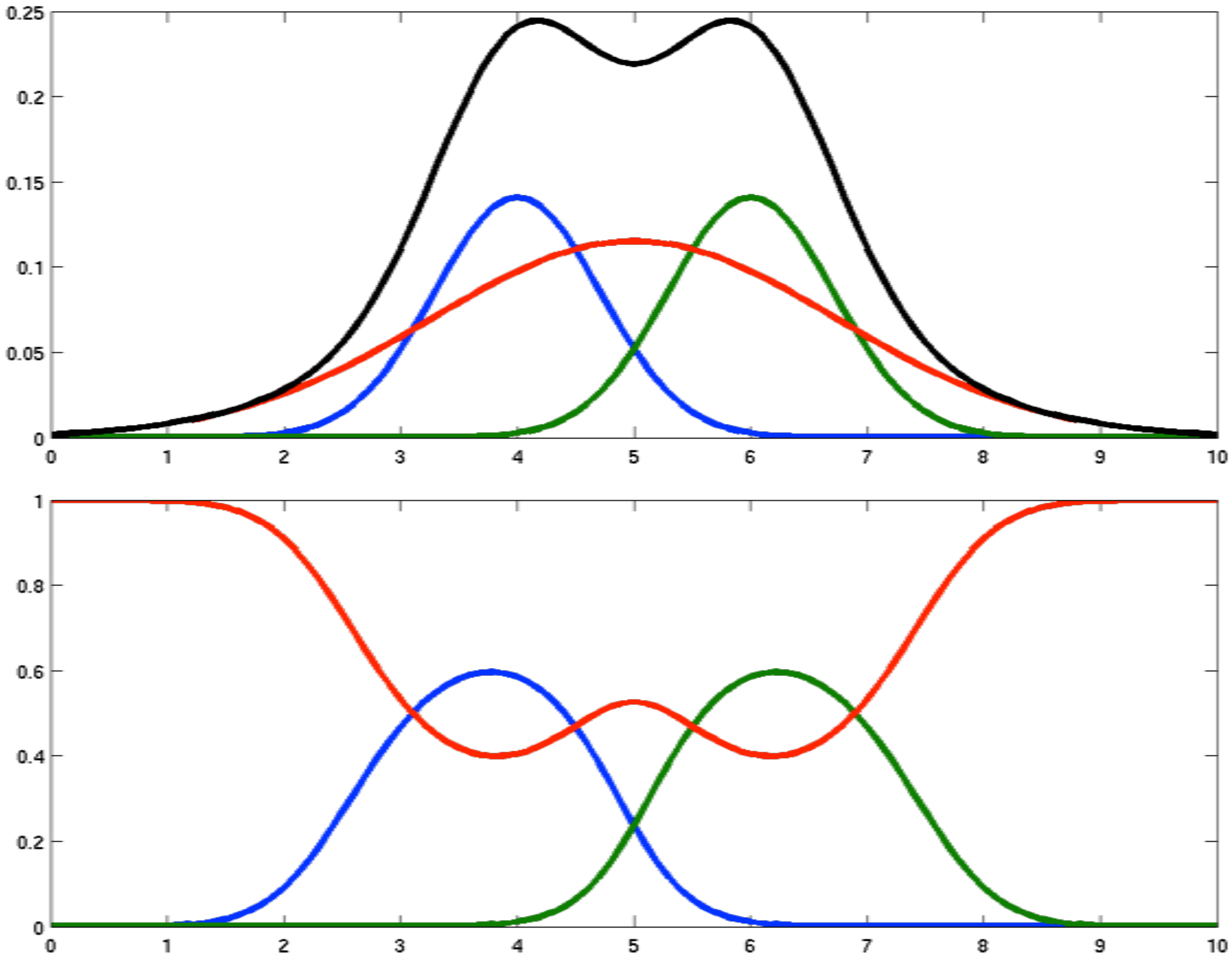
Mixture of Gaussians (MOG)

* Classification is based on a Mixture of Gaussians model (MOG), which represents the intensity probability density by a number of Gaussian distributions.

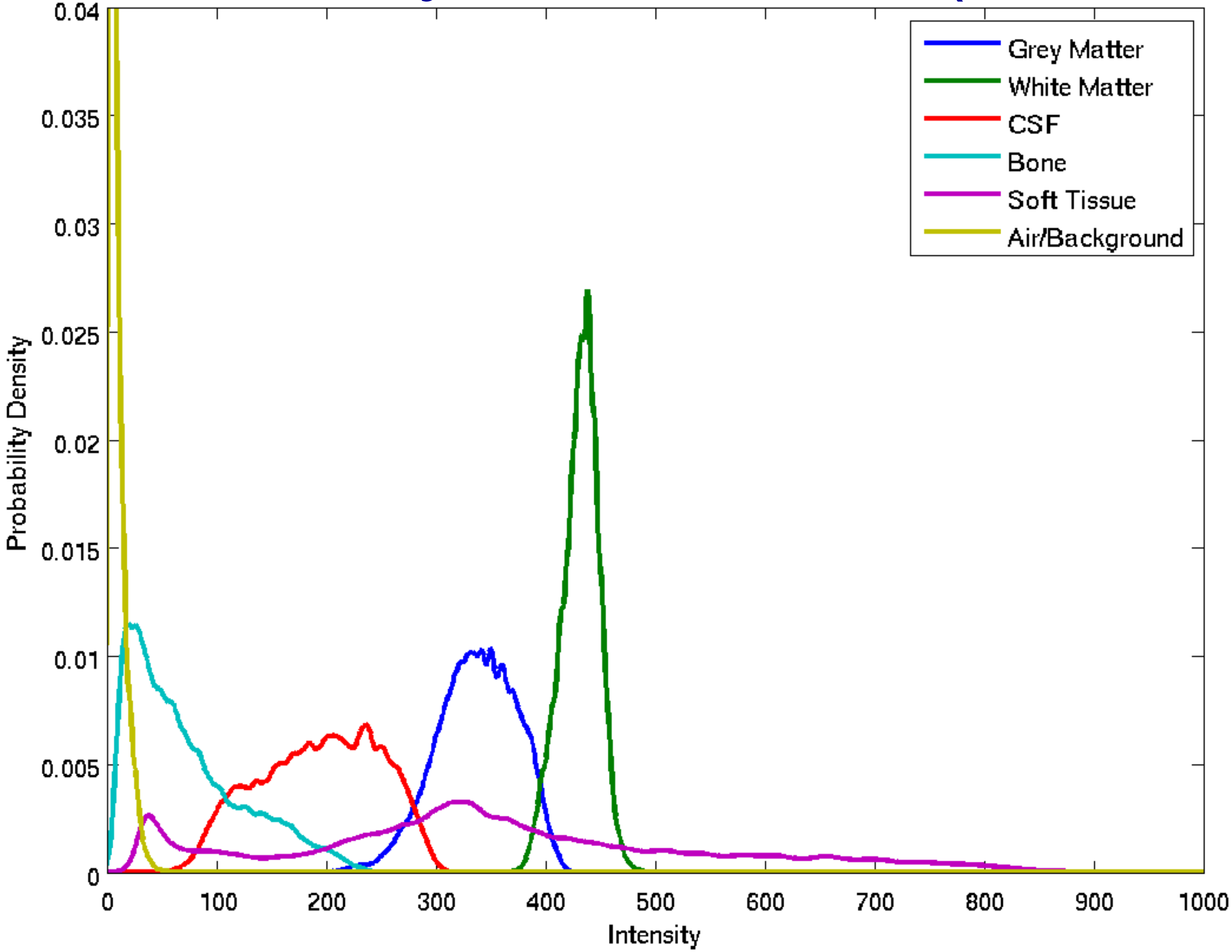


Belonging Probabilities

Belonging probabilities are assigned by normalising to one.

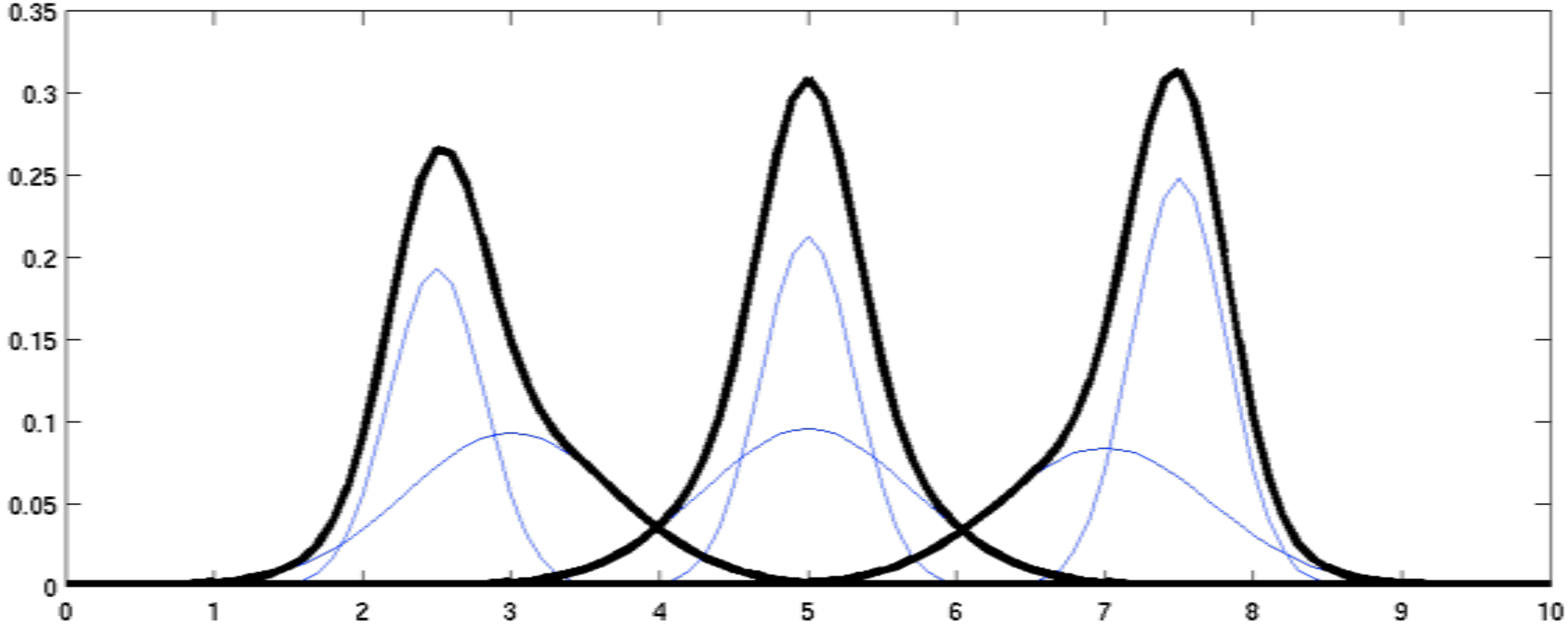


Tissue intensity distributions (T1-w MRI)

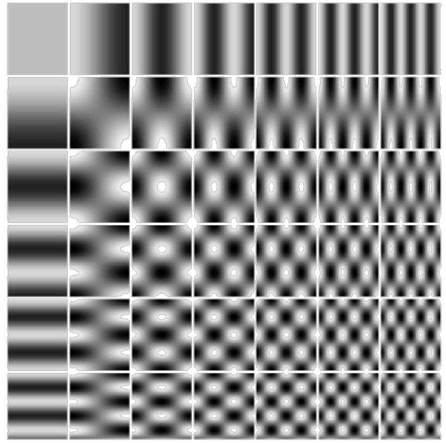


Non-Gaussian Intensity Distributions

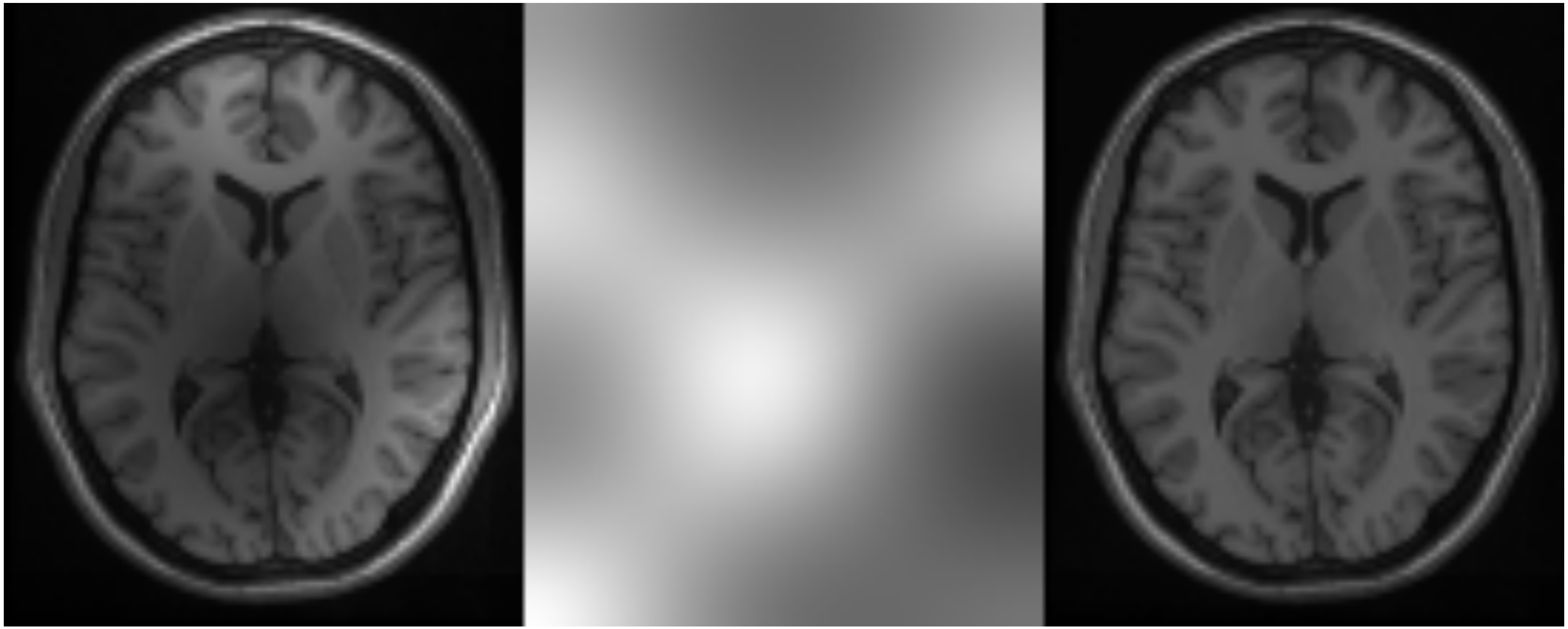
* Multiple Gaussians per tissue class allow non-Gaussian intensity distributions to be modelled.
  * E.g. accounting for partial volume effects



Modelling inhomogeneity



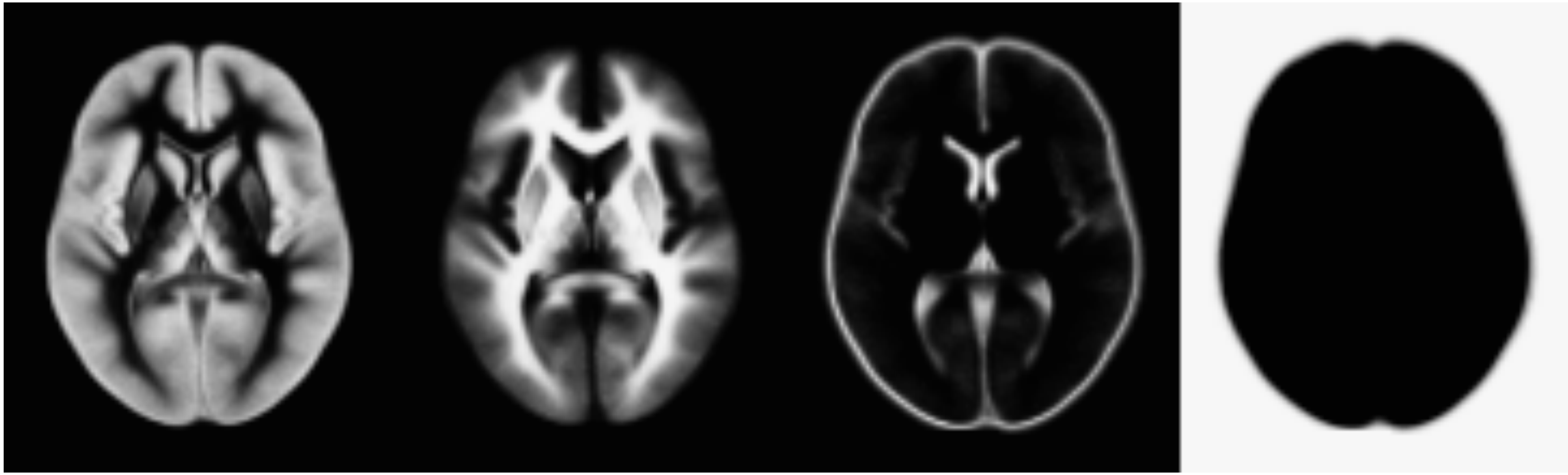
* A multiplicative bias field is modelled as a linear combination of basis functions.



Corrupted image Bias Field Corrected image

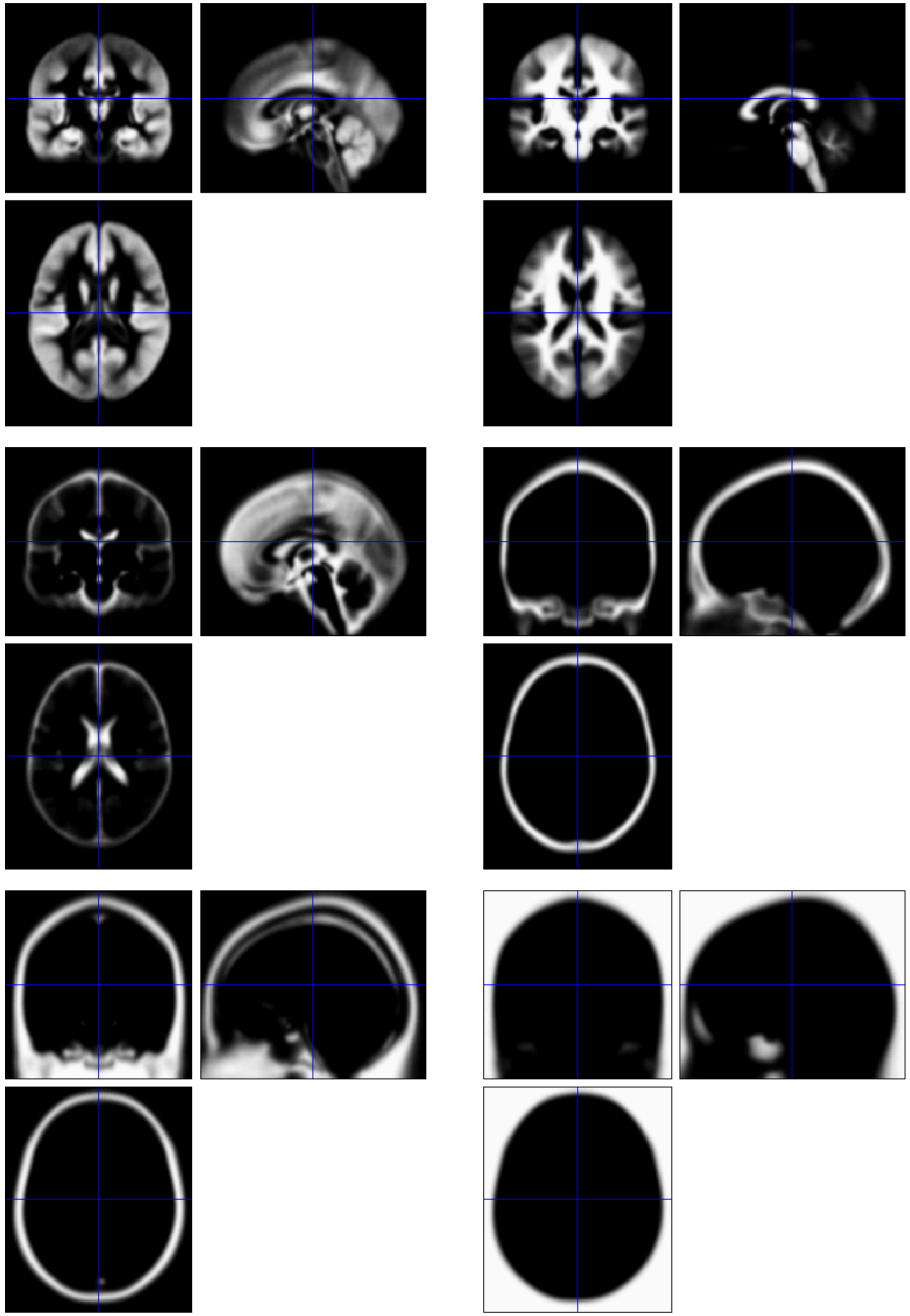
Tissue Probability Maps

* Tissue probability maps (TPMs) are used as the prior, instead of the proportion of voxels in each class

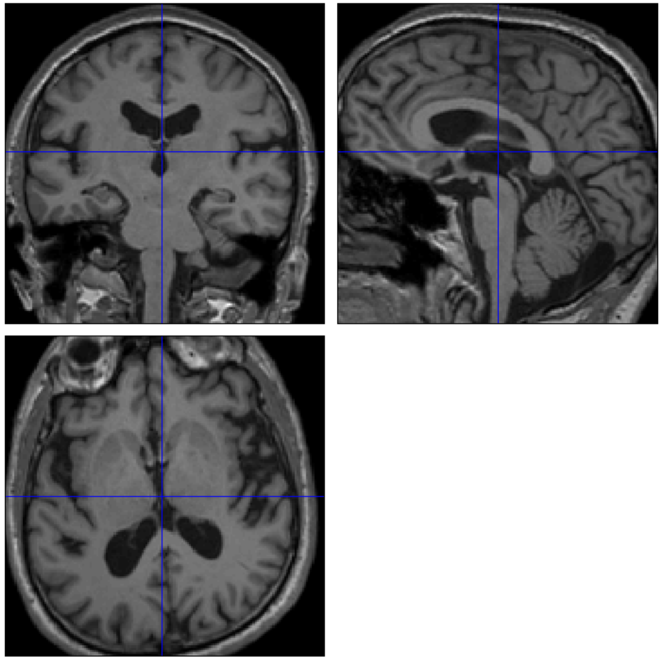


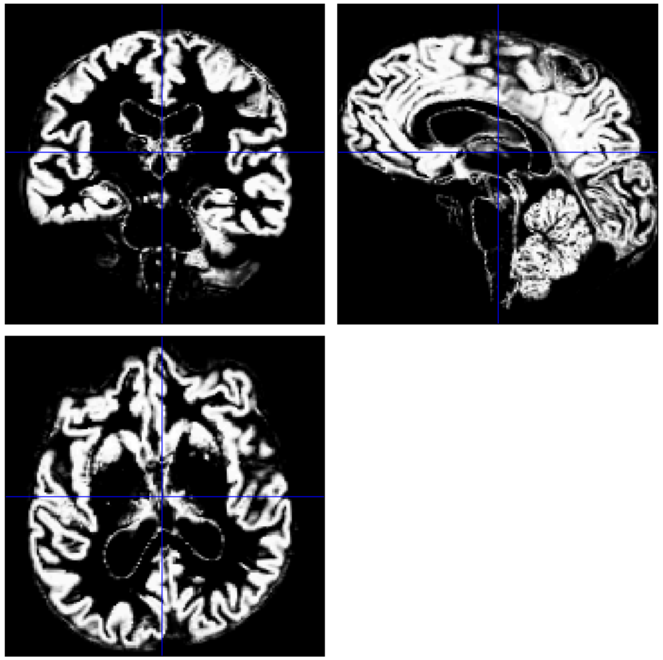
ICBM Tissue Probabilistic Atlases. These tissue probability maps are kindly provided by the **International Consortium for Brain Mapping**, John C. Mazziotta and Arthur W. Toga.

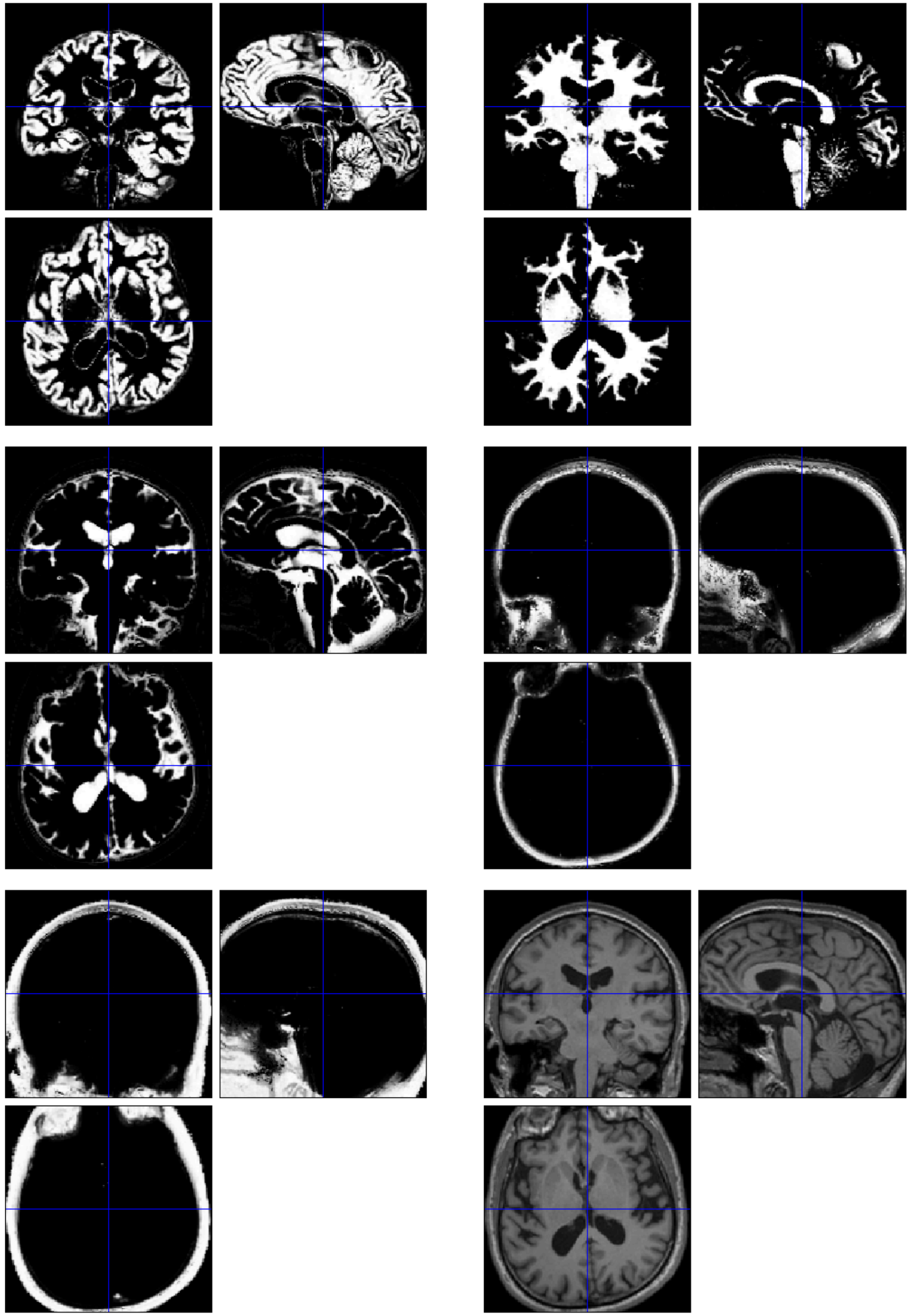
Tissue Probability Maps for "New Segment"



Includes additional non-brain tissue classes (bone, and soft tissue)

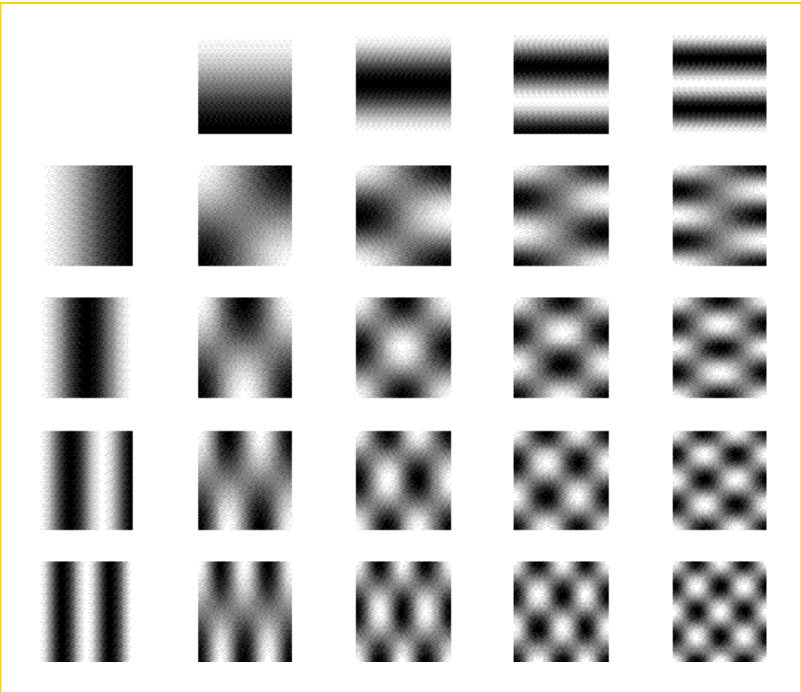


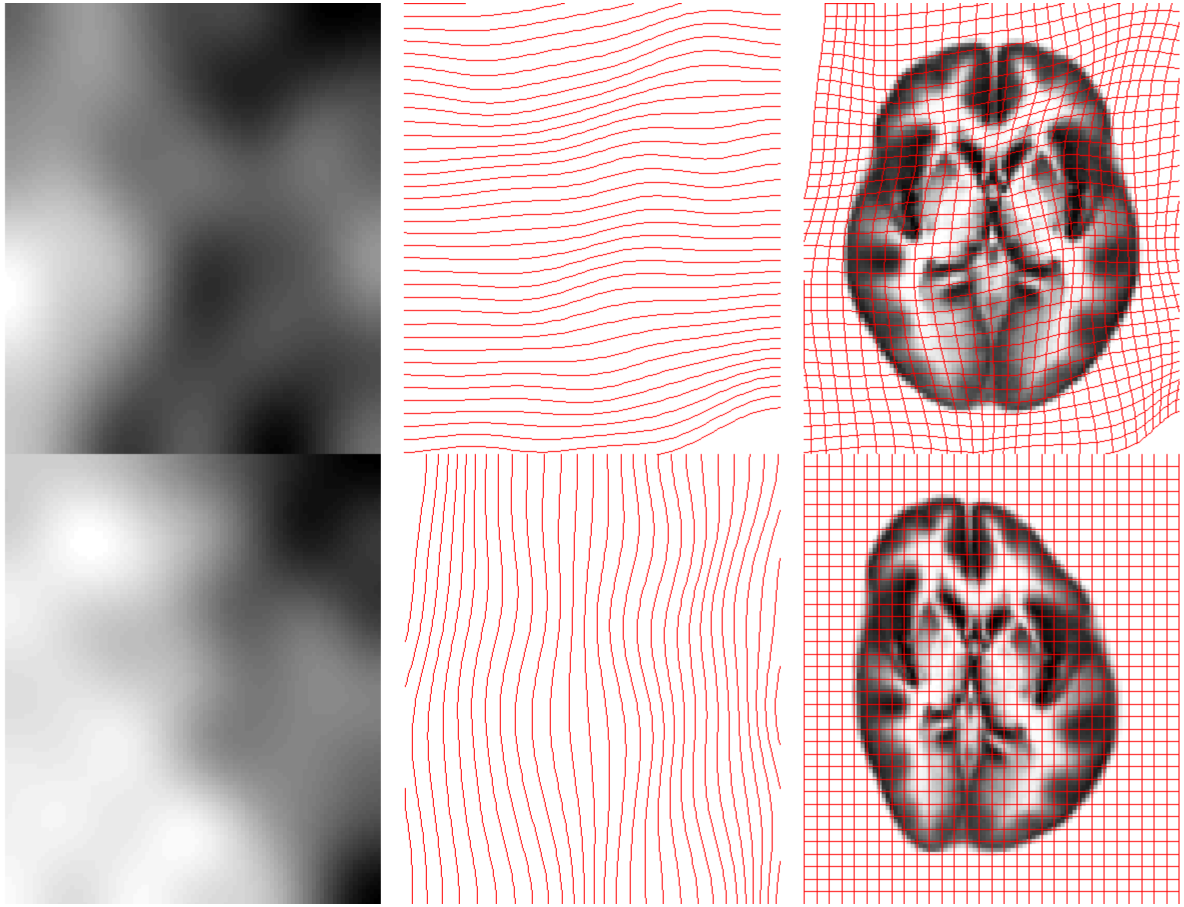




Deforming the Tissue Probability Maps

- Tissue probability images are warped to match the subject
- The inverse transform warps to the TPMs



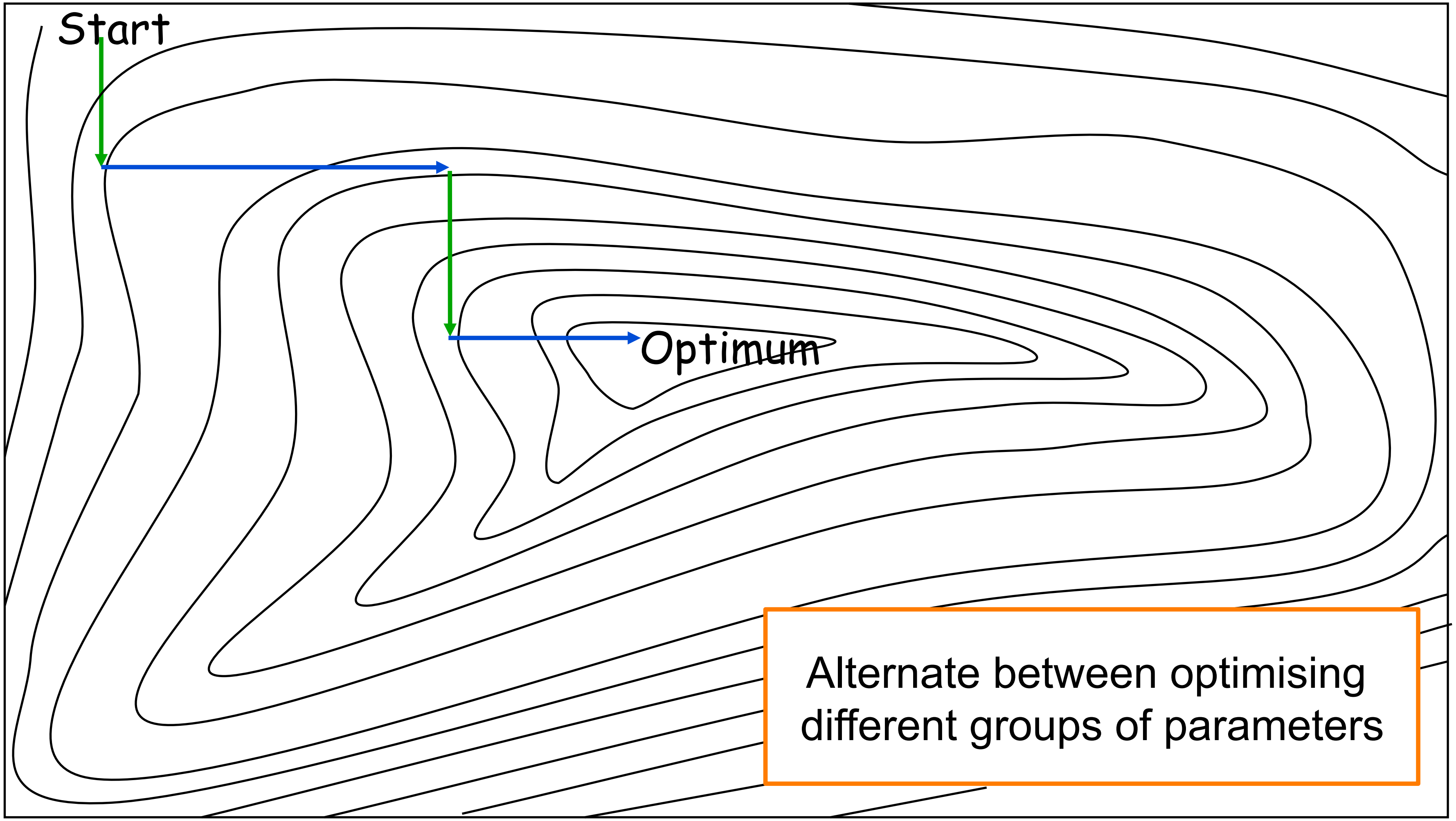


Fitting the unified model

* Model fitting involves optimising an objective function as with respect to its parameters
* Begin with starting estimates, and repeatedly change them so that the objective function decreases each time
* The unified model has one overall objective function
* Sets of parameters are repeatedly optimised in turn

$$E = -\sum_{i=1}^{I} \log \left[\rho_i(\beta) \sum_{k=1}^{K} \frac{\gamma_k b_{ik}(\alpha)}{\sum_{j=1}^{K} \gamma_j b_{ij}(\alpha)} \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(\rho_i(\beta) y_i - \mu_k)^2}{2\sigma_k^2} \right) \right]$$

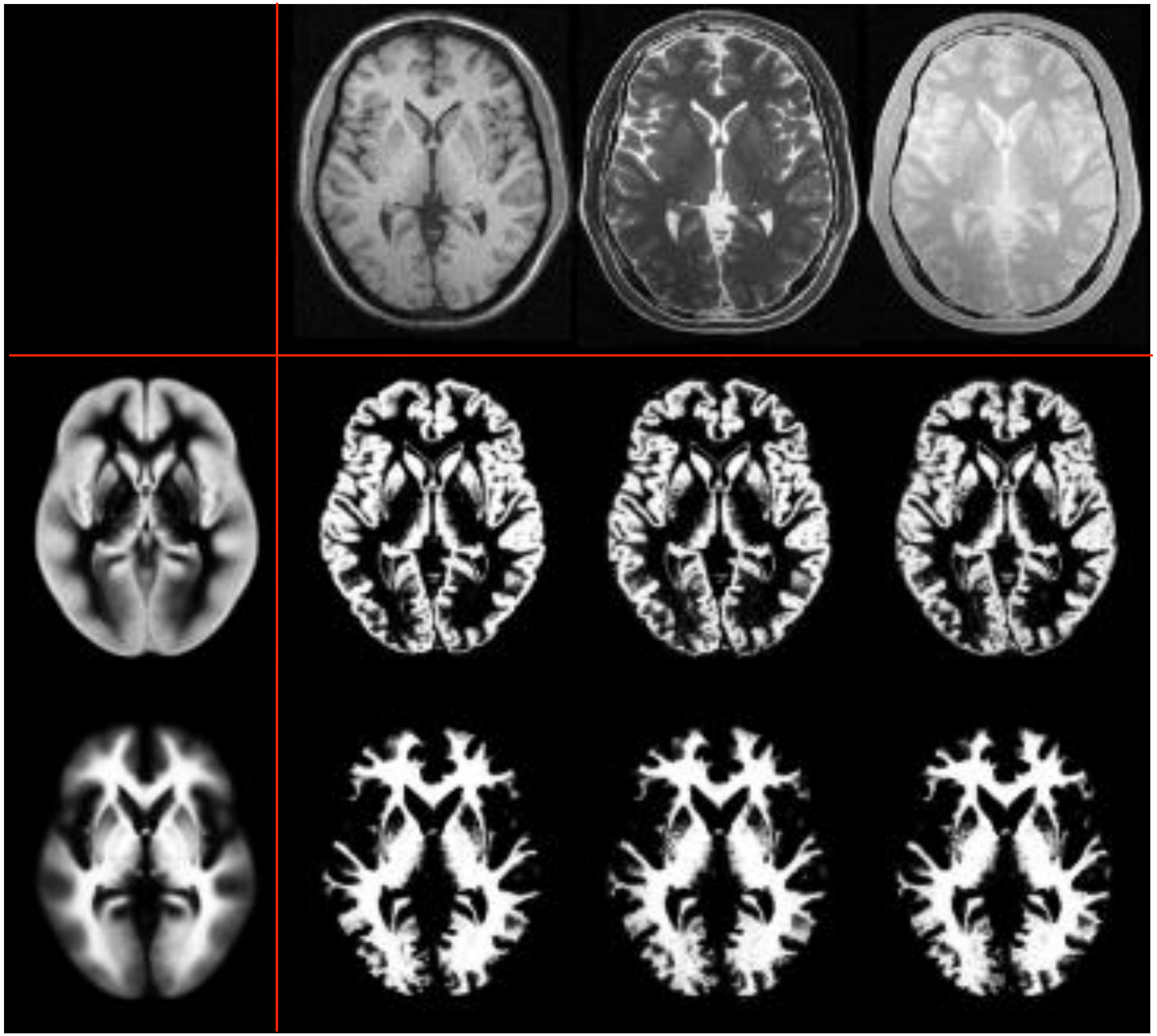
Steepest Descent



Alternate between optimising different groups of parameters

Spatially normalised BrainWeb phantoms (T1, T2 and PD)

Tissue probability maps of GM and WM

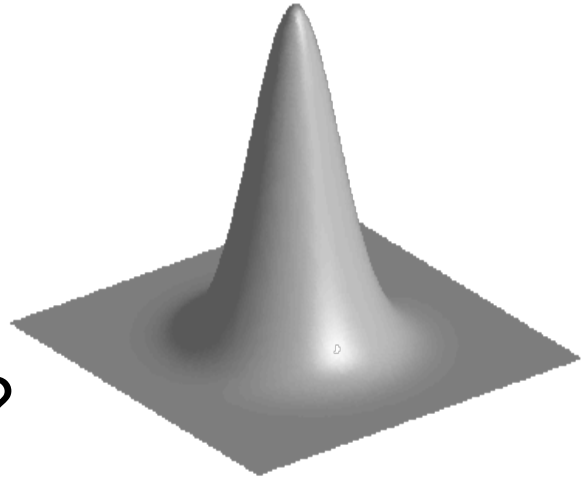


Cocosco, Kollokian, Kwan & Evans. "*BrainWeb: Online Interface to a 3D MRI Simulated Brain Database*". NeuroImage 5(4):S425 (1997)

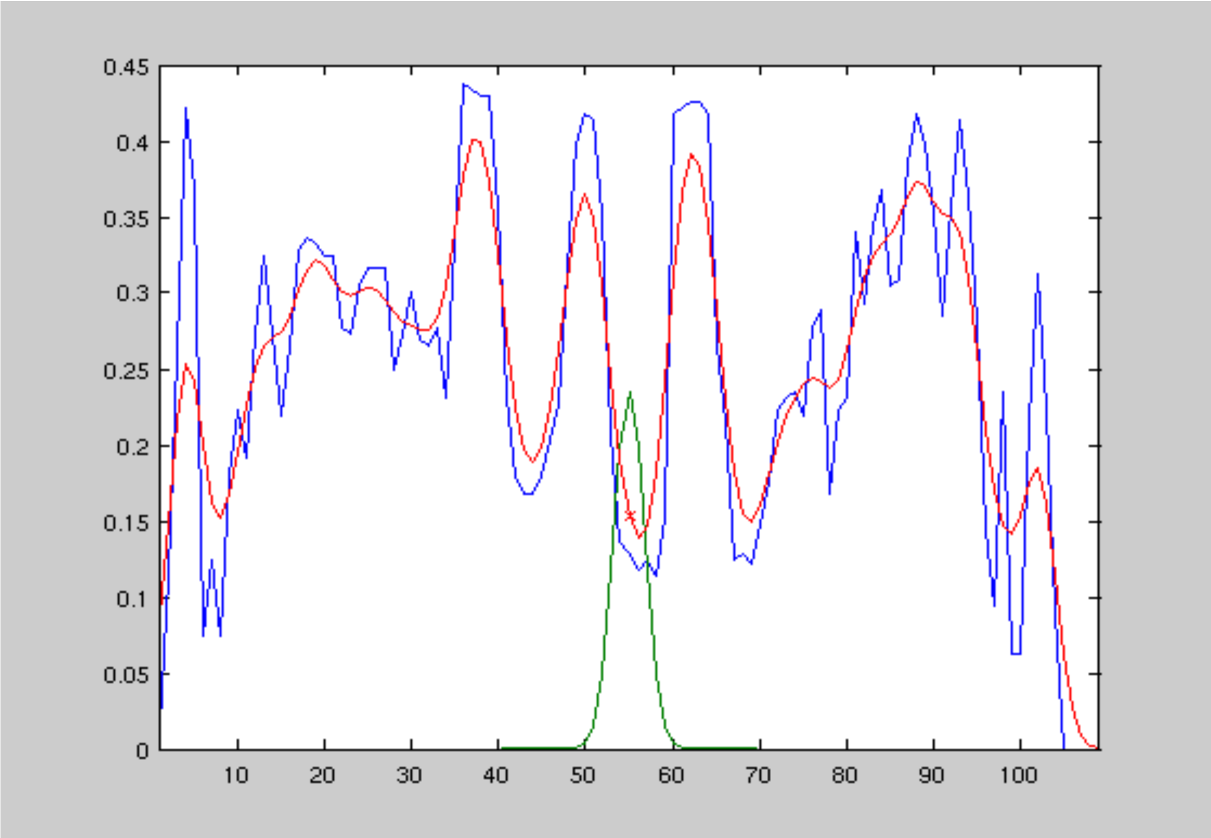
Contents

1. Registration basics
2. Motion and realignment
3. Inter-modal coregistration
4. Spatial normalisation
5. Unified segmentation
6. **Gaussian smoothing**

Smoothing



* Why would we deliberately blur the data?
  * Averaging neighbouring voxels suppresses noise
  * Makes data more normally distributed (central limit theorem)
  * Increases sensitivity to effects of similar scale to kernel (matched filter theorem)
  * Reduces the effective number of multiple comparisons
  * Improves spatial overlap by blurring over minor anatomical differences and registration errors
* How is it implemented?
  * Convolution with a 3D Gaussian kernel, of specified full-width at half-maximum (FWHM) in mm

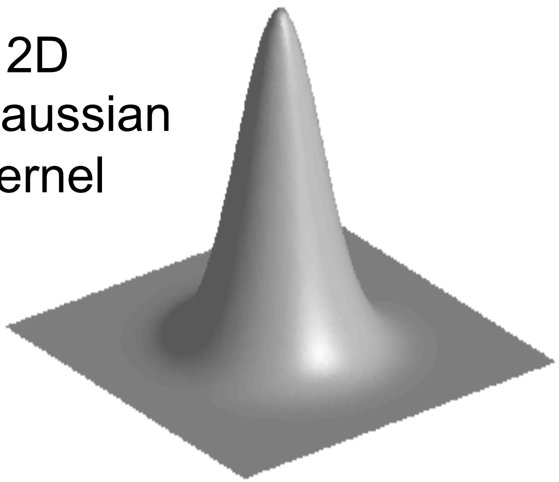


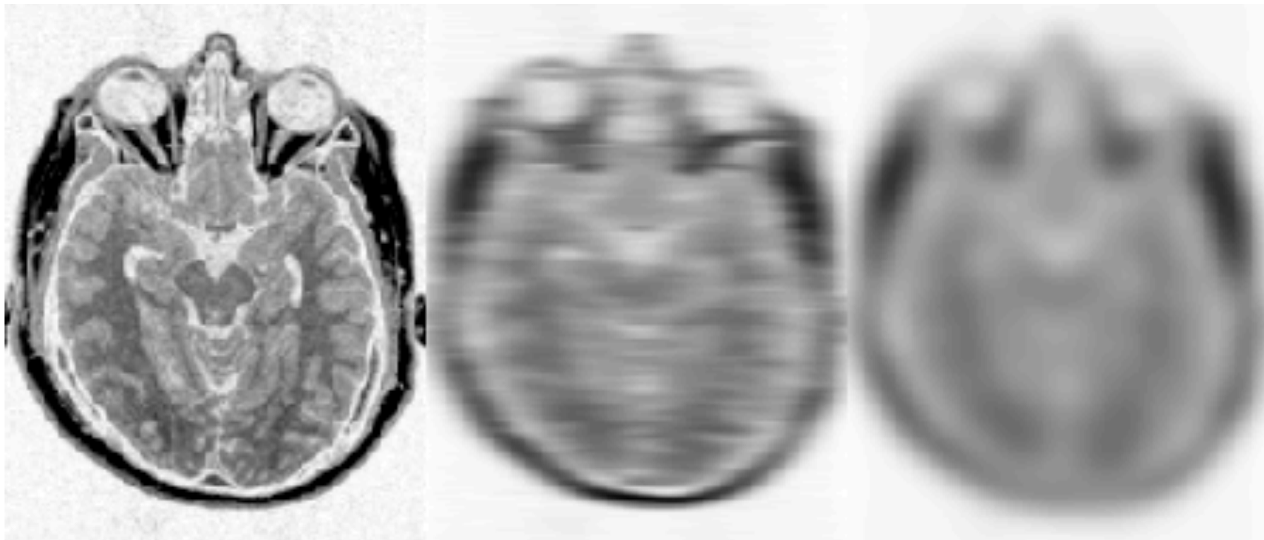
Example of Gaussian smoothing in one-dimension

The Gaussian kernel is **separable** we can smooth 2D data with two 1D convolutions.

Generalisation to 3D is simple and efficient

A 2D Gaussian Kernel

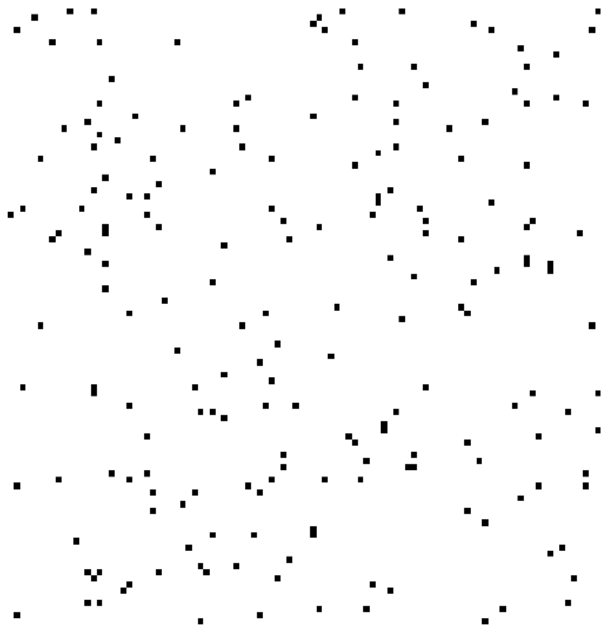




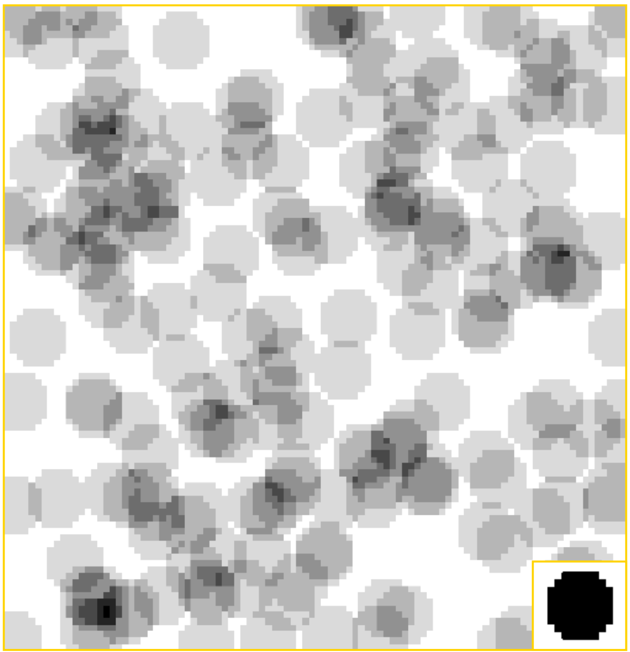
Smoothing – a link to ROI analysis

Each voxel after smoothing effectively represents a weighted average over its local region of interest (ROI)

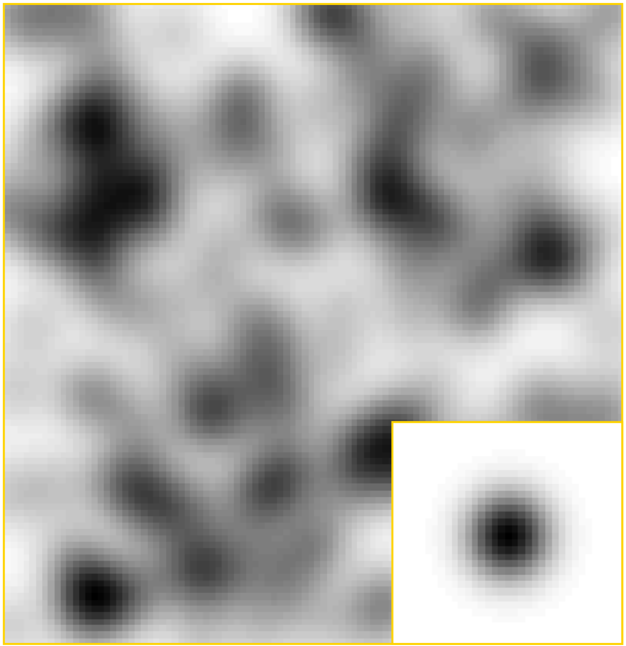
Before convolution



Convolved with a circle



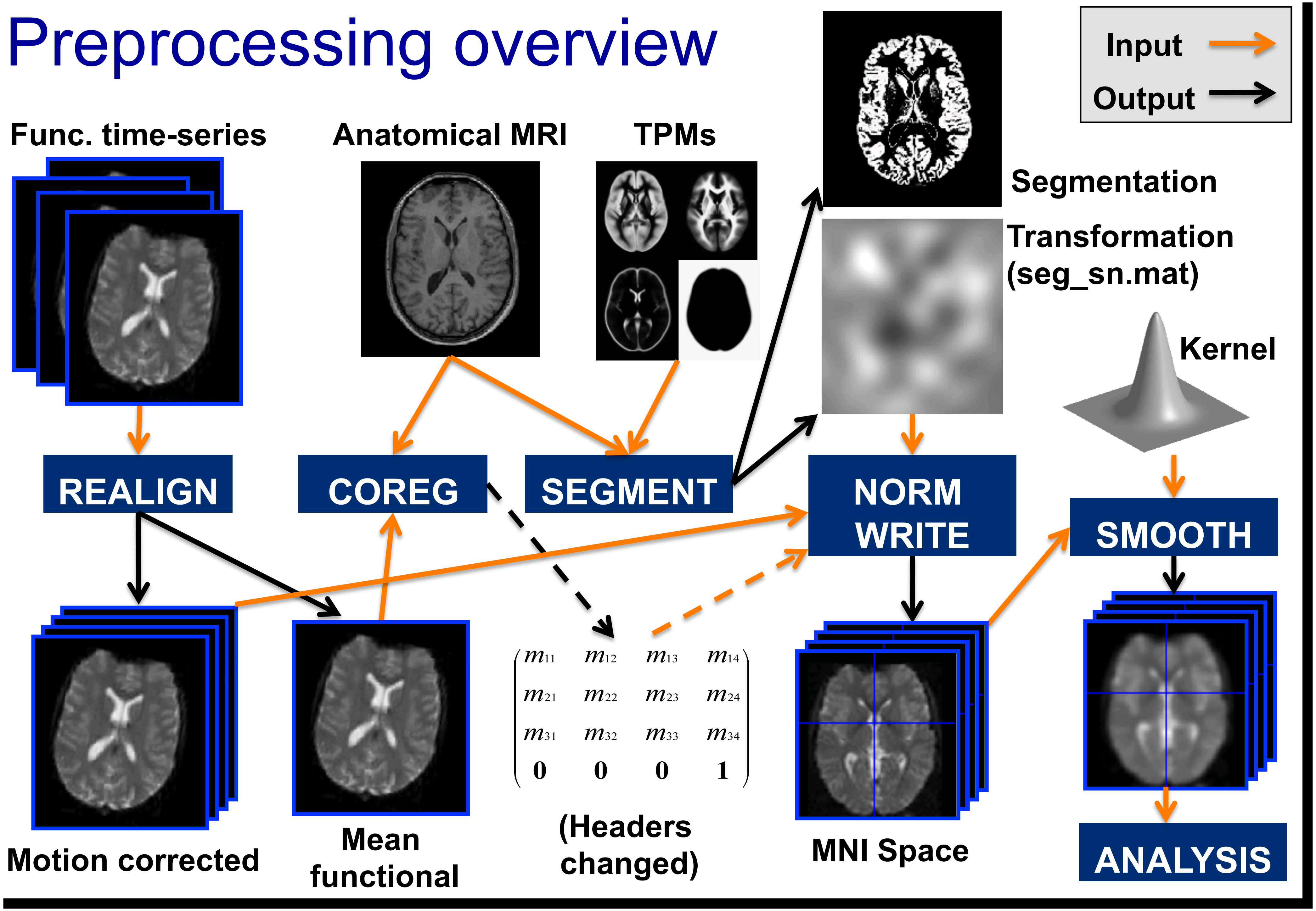
Gaussian convolution



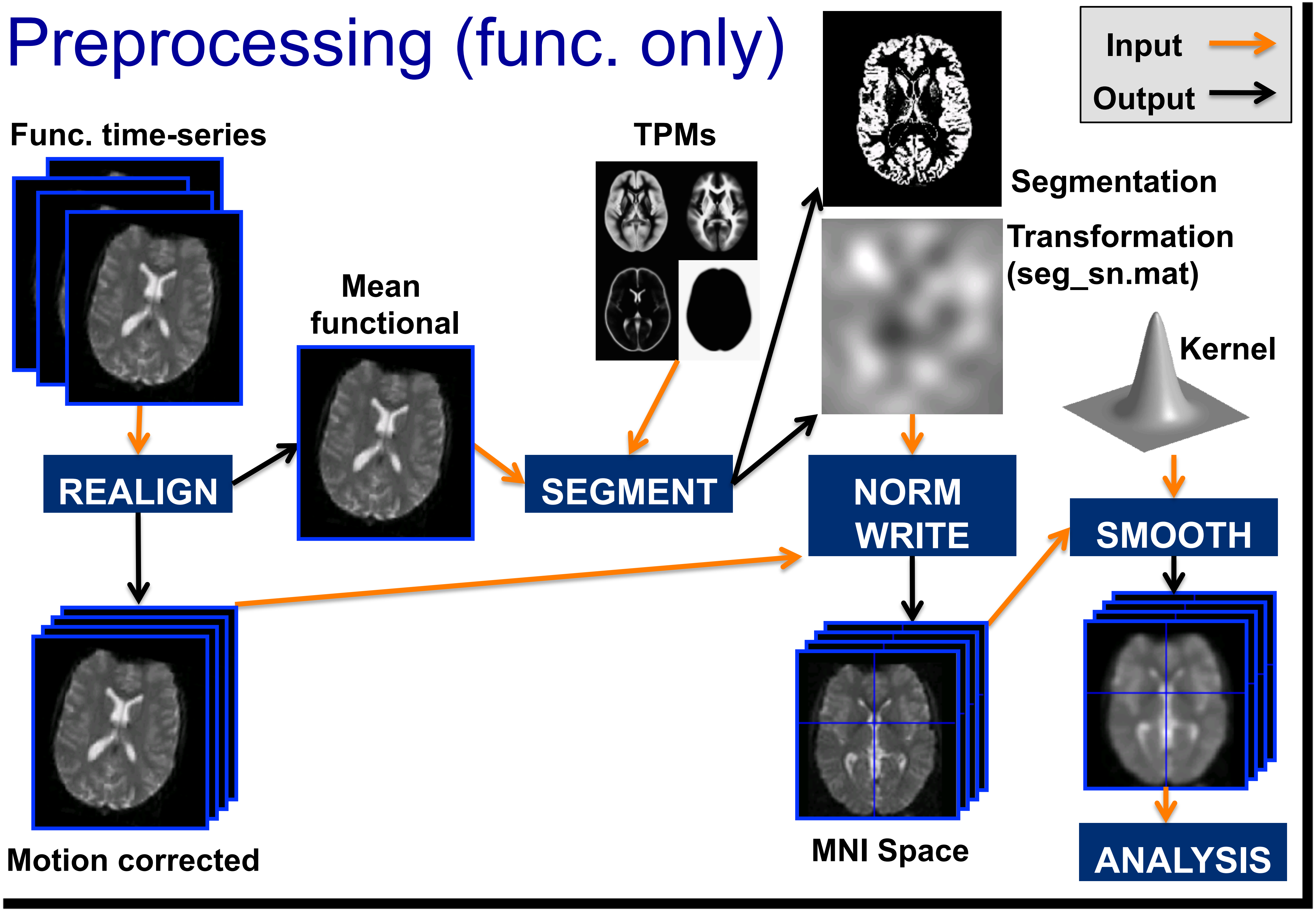
References

* Friston et al. *Spatial registration and normalisation of images*. Human Brain Mapping 3:165-189 (1995).
* Collignon et al. *Automated multi-modality image registration based on information theory*. IPMI'95 pp 263-274 (1995).
* Ashburner et al. *Incorporating prior knowledge into image registration*. NeuroImage 6:344-352 (1997).
* Ashburner & Friston. *Nonlinear spatial normalisation using basis functions*. Human Brain Mapping 7:254-266 (1999).
* Thévenaz et al. *Interpolation revisited*. IEEE Trans. Med. Imaging 19:739-758 (2000).
* Andersson et al. *Modeling geometric deformations in EPI time series*. Neuroimage 13:903-919 (2001).
* Ashburner & Friston. *Unified Segmentation*. NeuroImage 26:839-851 (2005).
* Ashburner. *A Fast Diffeomorphic Image Registration Algorithm*. NeuroImage 38:95-113 (2007).

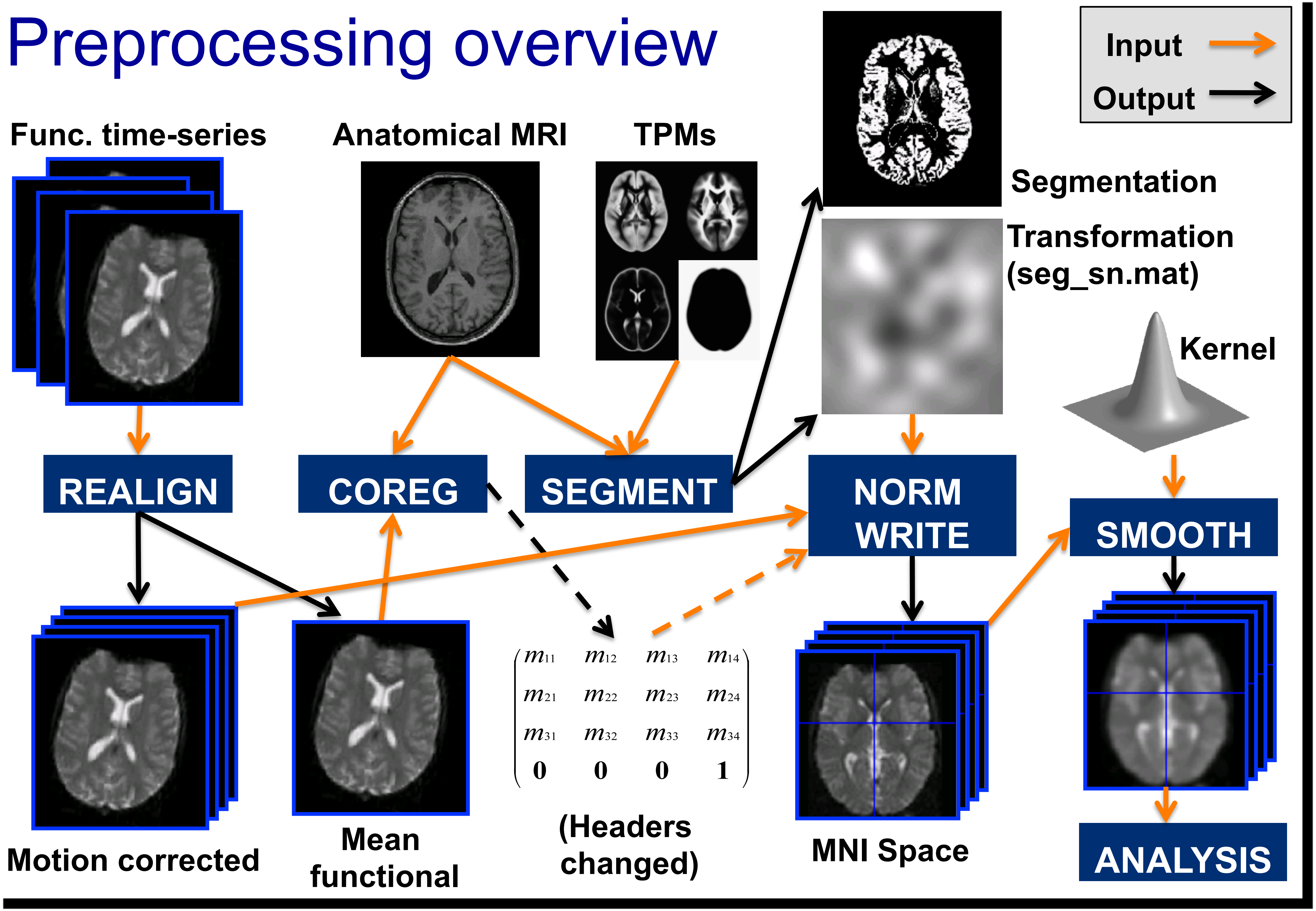
Preprocessing overview



Preprocessing (func. only)



Preprocessing overview



Preprocessing with Dartel