Overview of quantitative neuroimaging—MRI

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Disclosure: Funded ADNI investigator, NIH support

Overview

- Introduction to imaging
  - Image Acquisition
  - Artifacts
  - Quality control
- Analyses

Medical images

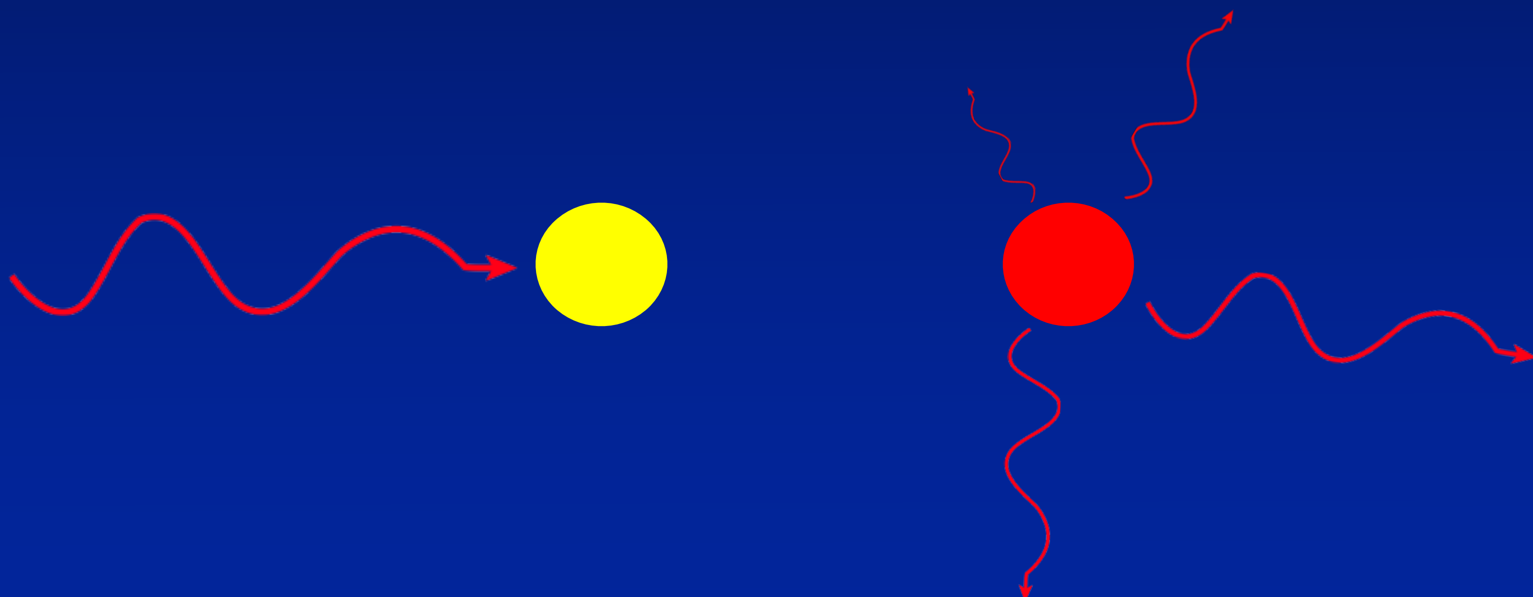
- **The key distinguishing characteristic of medical images is that you get to look at the interior of objects**
  - **Instead of a 2D array of data (like photos)...**
  - **You get a full 3D volume of data: for each (x,y,z) location in space you have a measurement of some aspect of the material at (x,y,z)**
  - **The images are referred to as** volumetric images **or** tomographs

Medical image acquisition

- Scientific principles that underlie MRI and PET:
  - If you shoot beams of electromagnetic energy into biological tissue, the amount of time it takes for the tissue to release that energy depends on the type of material
  - If you inject biological tissue with a radioactive substance, you can tell where the substance goes by detecting the radioactive decay

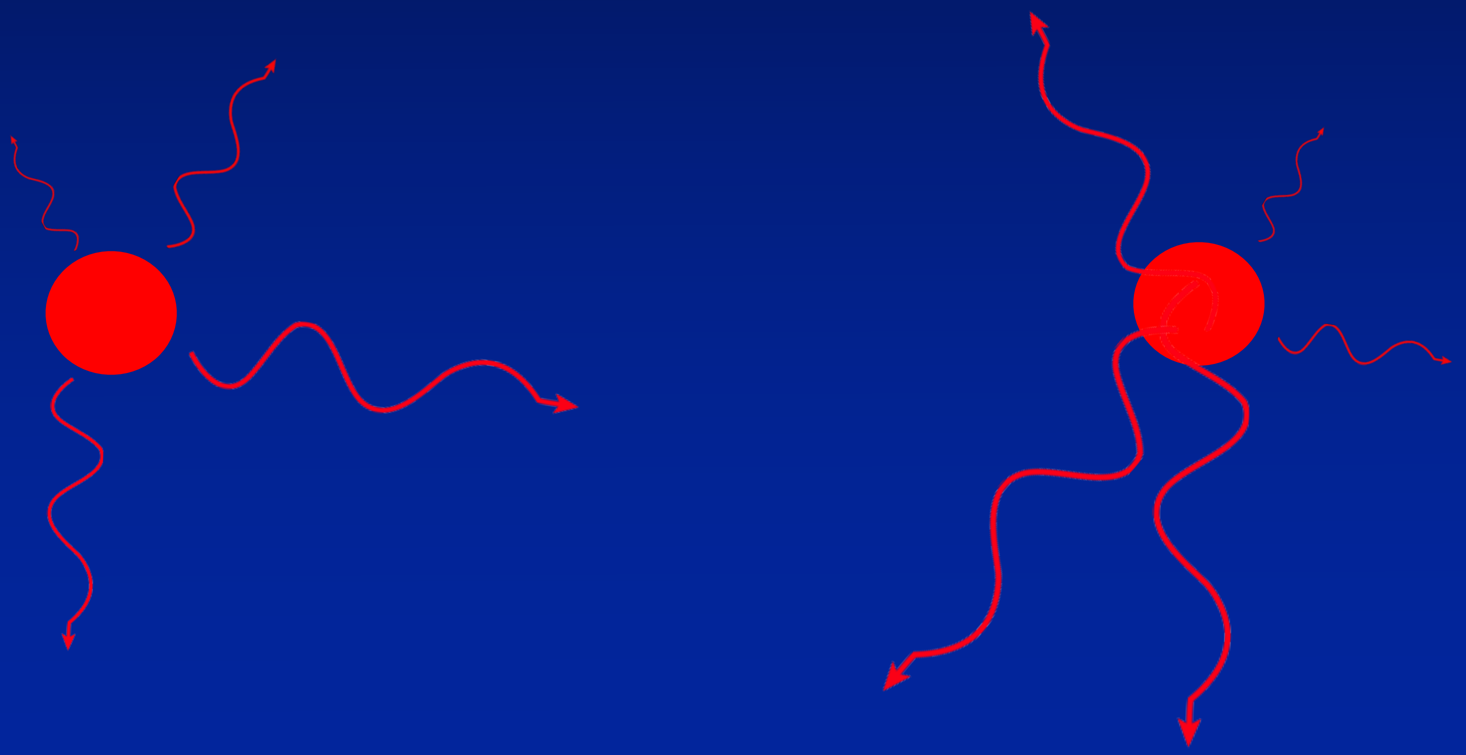
Magnetic Resonance Imaging

- Basics:
  - If you excite atoms (beam energy into them) they gradually relax (let off the energy over time)
  - How quickly they let off the energy depends on the structure of the atom and the organization of the atoms surrounding them: so if you can record how quickly a set of atoms lets off the energy you beam into it, you can figure out what material the atoms are in



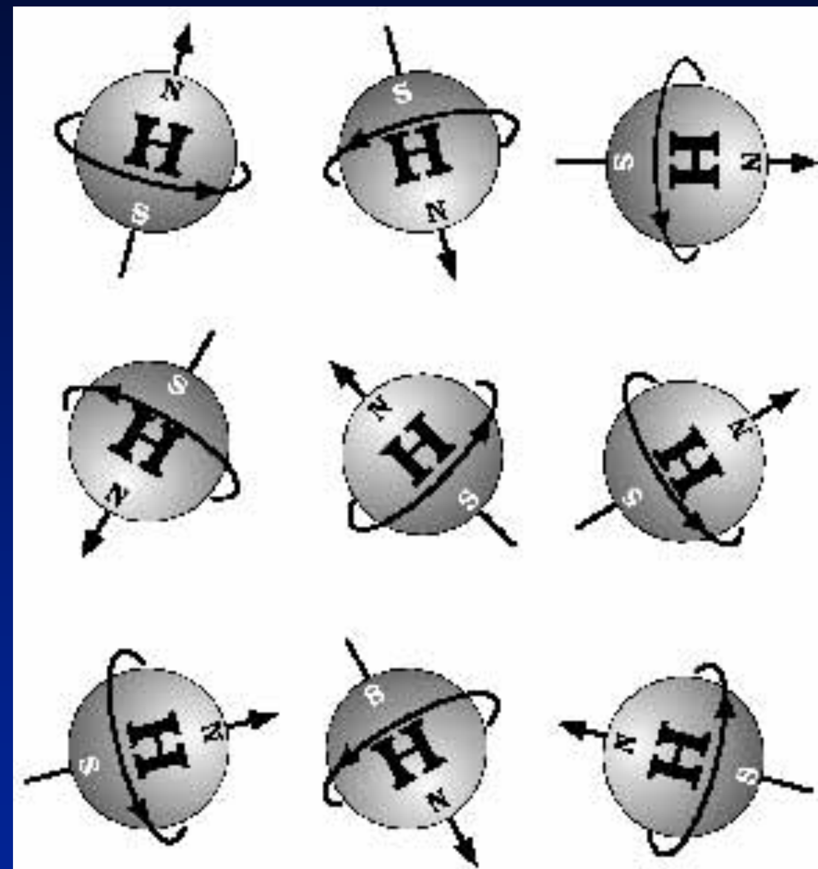
Magnetic Resonance Imaging

- Generally, they let varying amounts of energy off in all directions
- So if you beam energy into a bunch of atoms and set up detectors all around it to detect the energy being let off, the signal going into the detectors will be somewhat random



Magnetic resonance imaging (MRI)

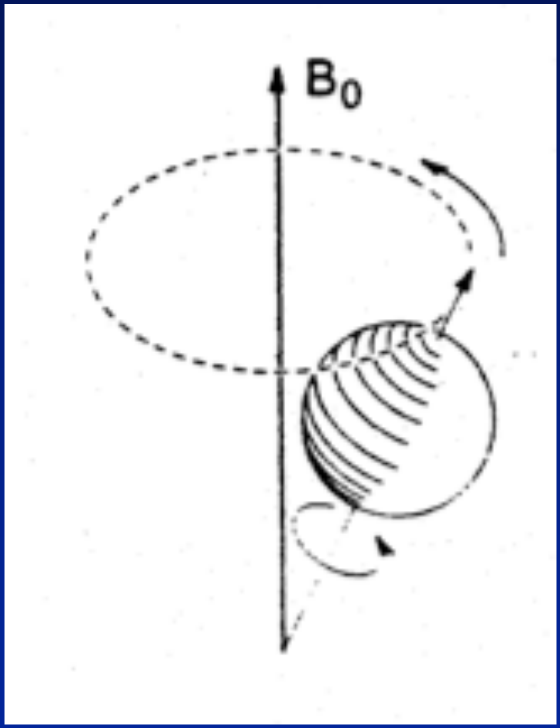
- However, some atoms have asymmetries: atoms like ^{1}H, ^{31}P, ^{13}C, ^{19}F have a non-zero nuclear spin
- Valence electrons spin around the nucleus in a particular orbit and induce a tiny magnetic field along the atomic pole
- Normally, these poles are oriented at arbitrary orientations

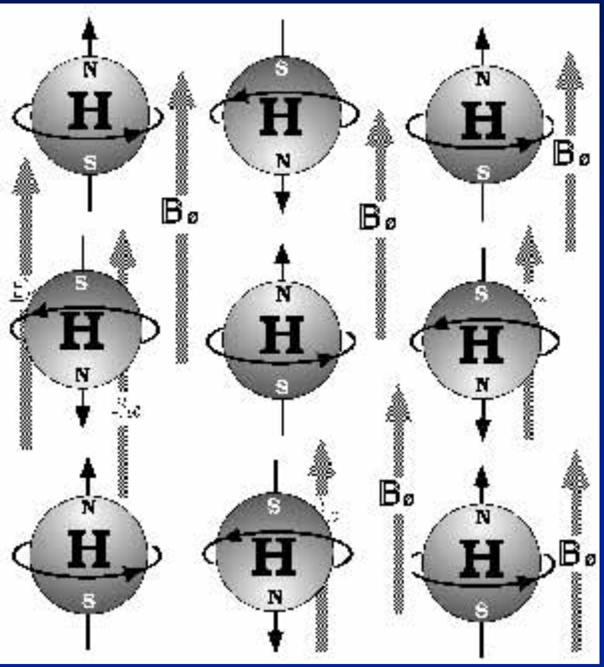


http://www.simplyphysics.com

Magnetic resonance imaging (MRI)

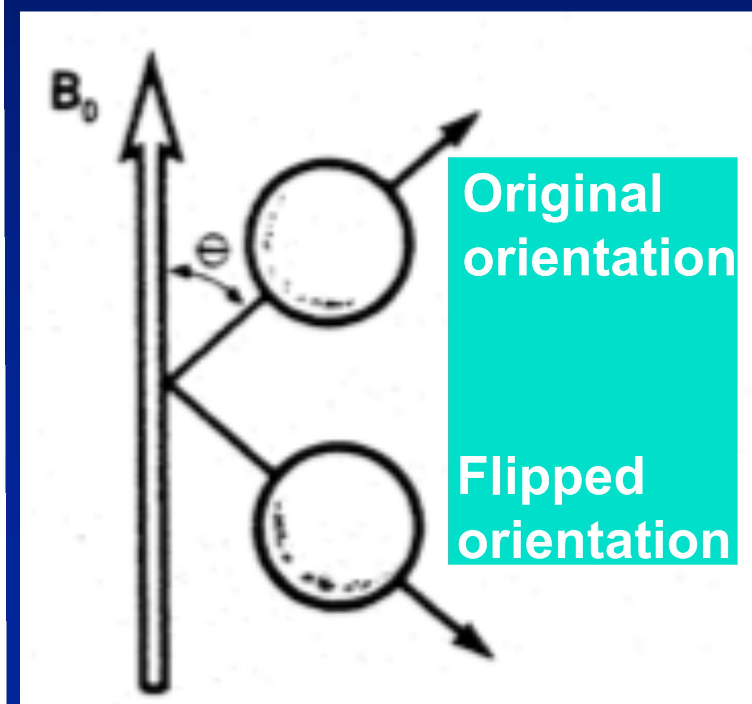
- But if you apply an external magnetic field (B0), the atomic poles tend to line up along the direction of that field. They spin at some angle with respect to the B0 direction; the stronger B0 is, the more they align with B0

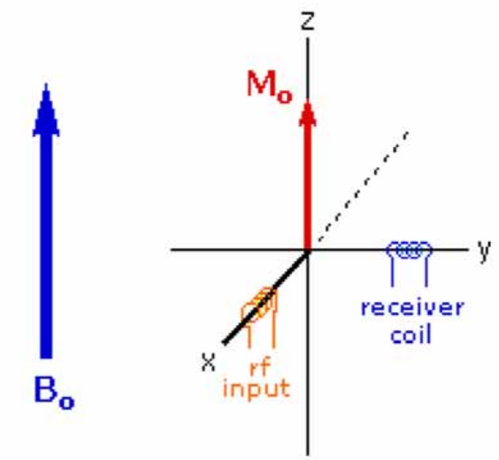




Magnetic resonance imaging (MRI)

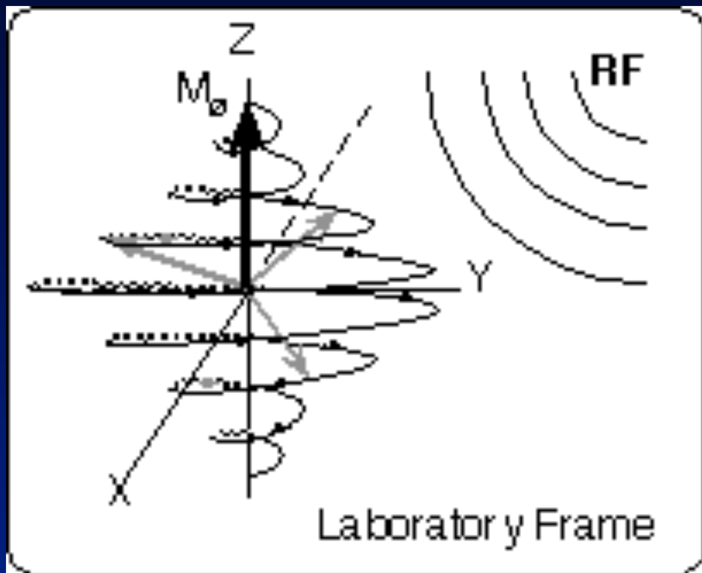
- The radio-frequency (RF) pulse
  - Perturbs the spin and
  - They gradually release their energy in predictable directions while reorienting themselves toward B0
- Energy is released orthogonal to B0
- By having a detector orthogonal to B0, we can record how quickly the pre-cessing atoms release their energy, and thus back out the material properties of the atoms

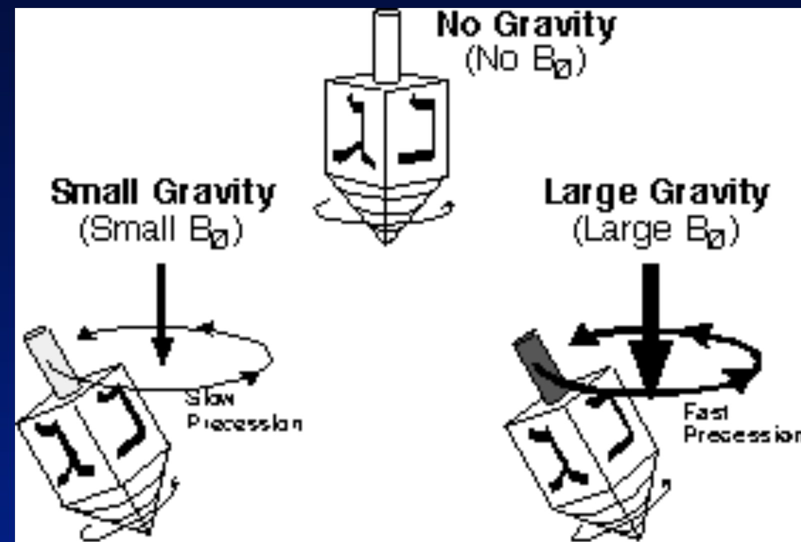


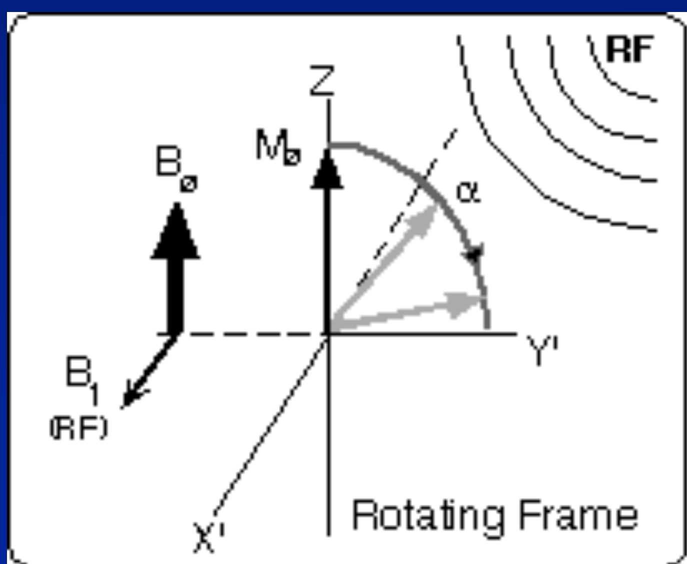


Jolinda Smith

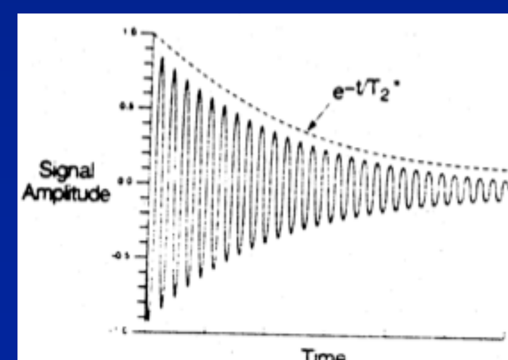
T1 and T2



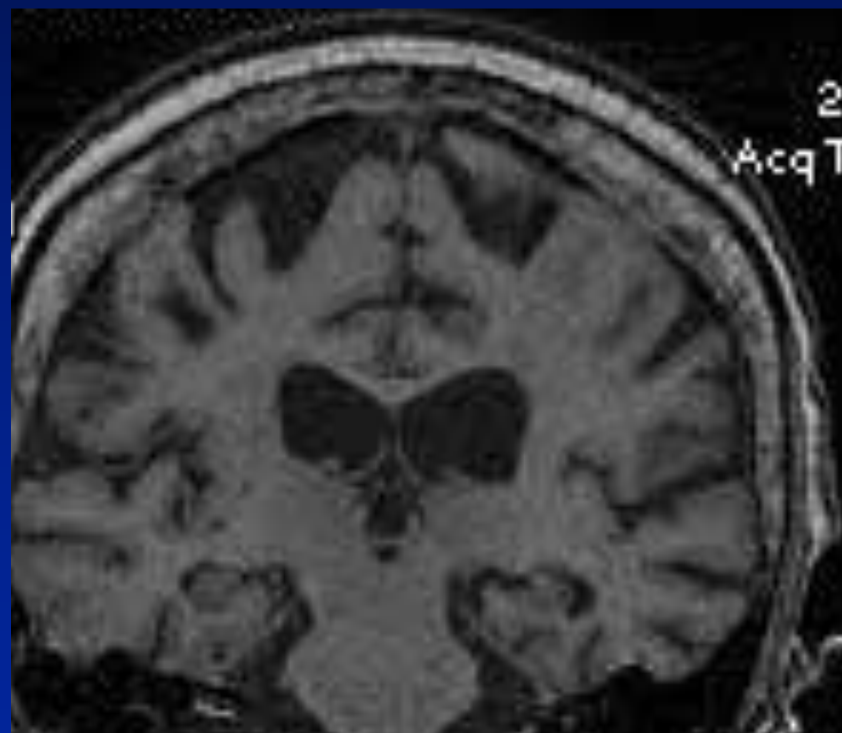




T1-exponential recovery of Mz in time
T2-exponentia decay of signal

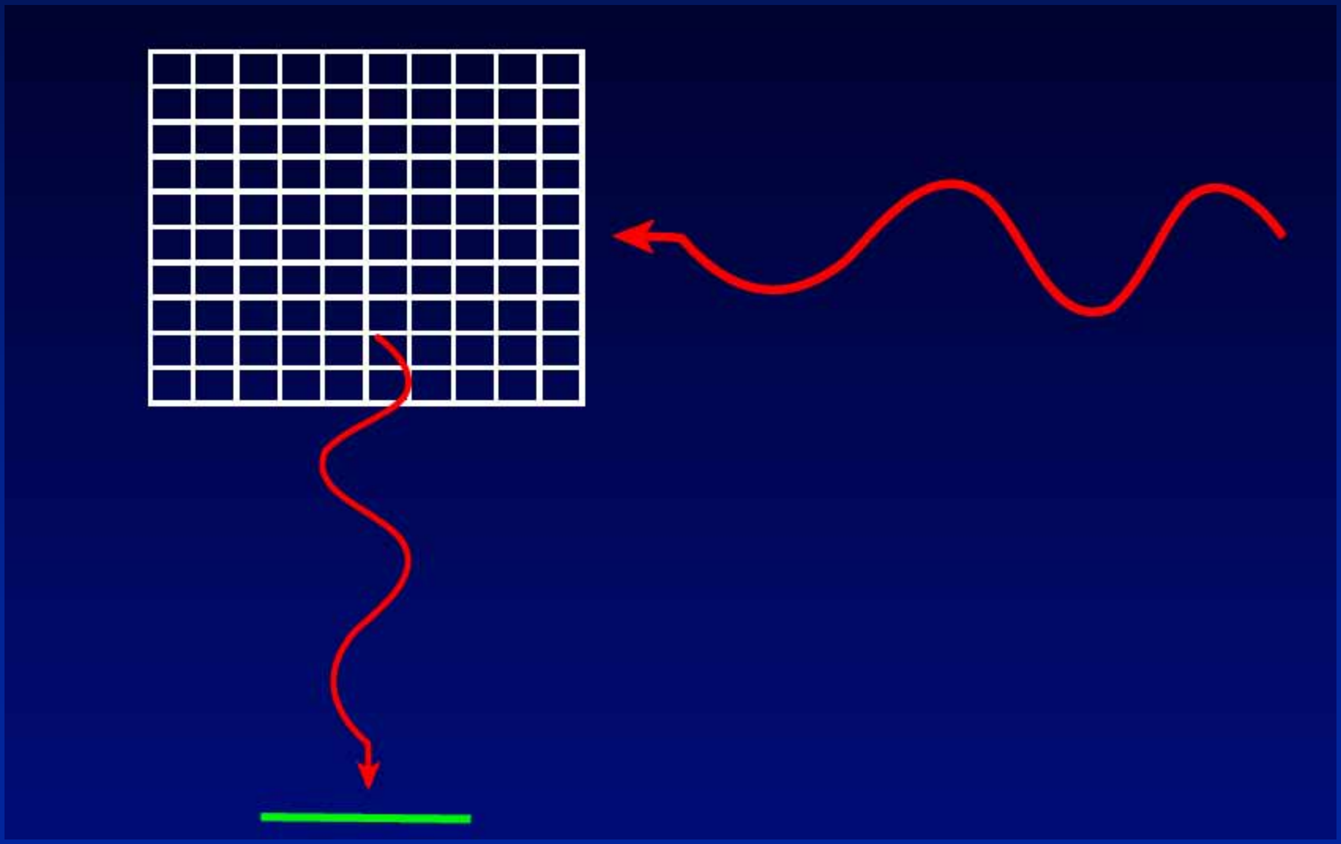


Tissue Specific T1/T2



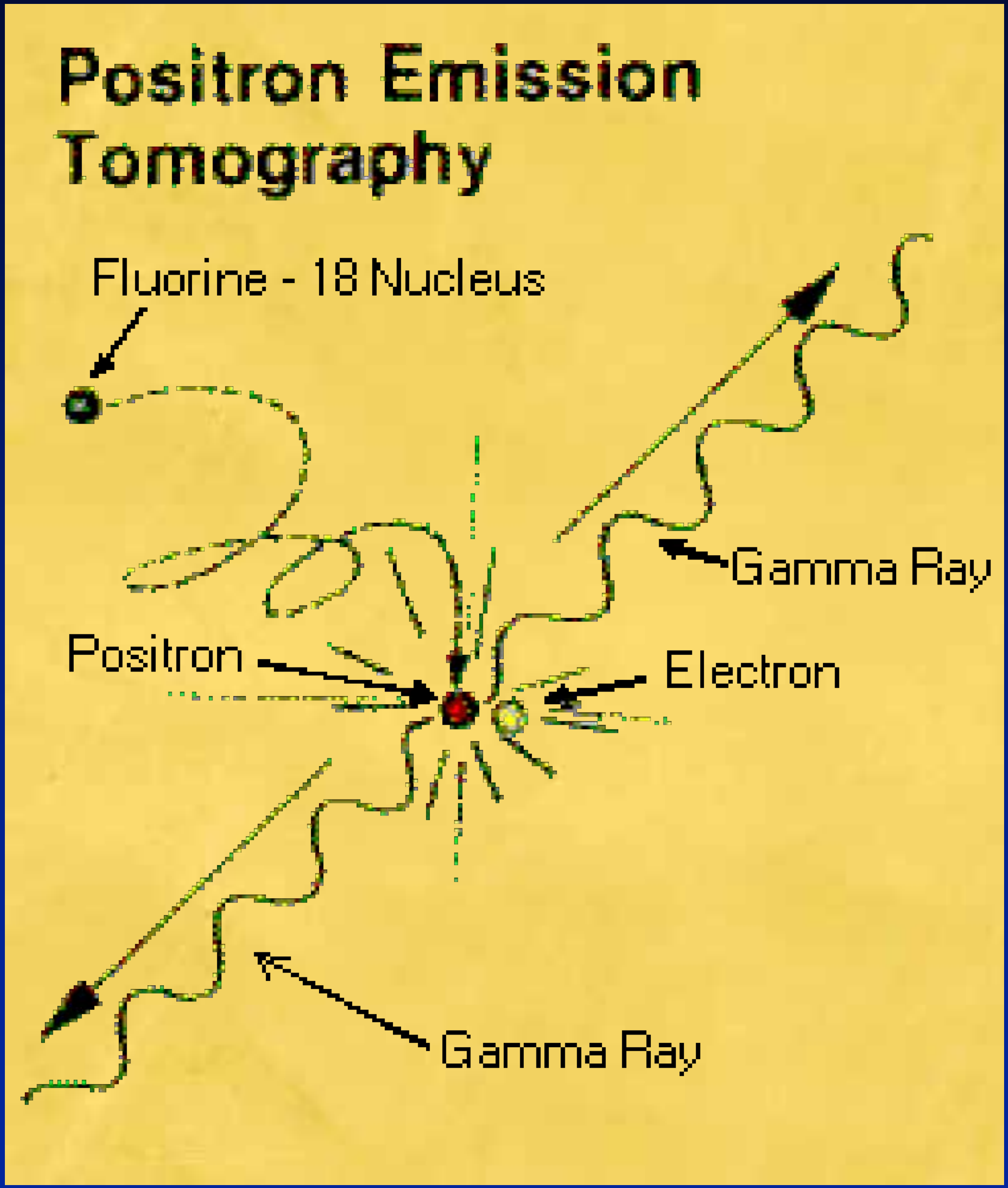
Magnetic resonance imaging

- A receiver picks up this emitted energy after the RF pulse is administered.
- Based on the time course of energy captured by the receiver, we back out material properties at each spatial location that is consistent with all the receiver data.



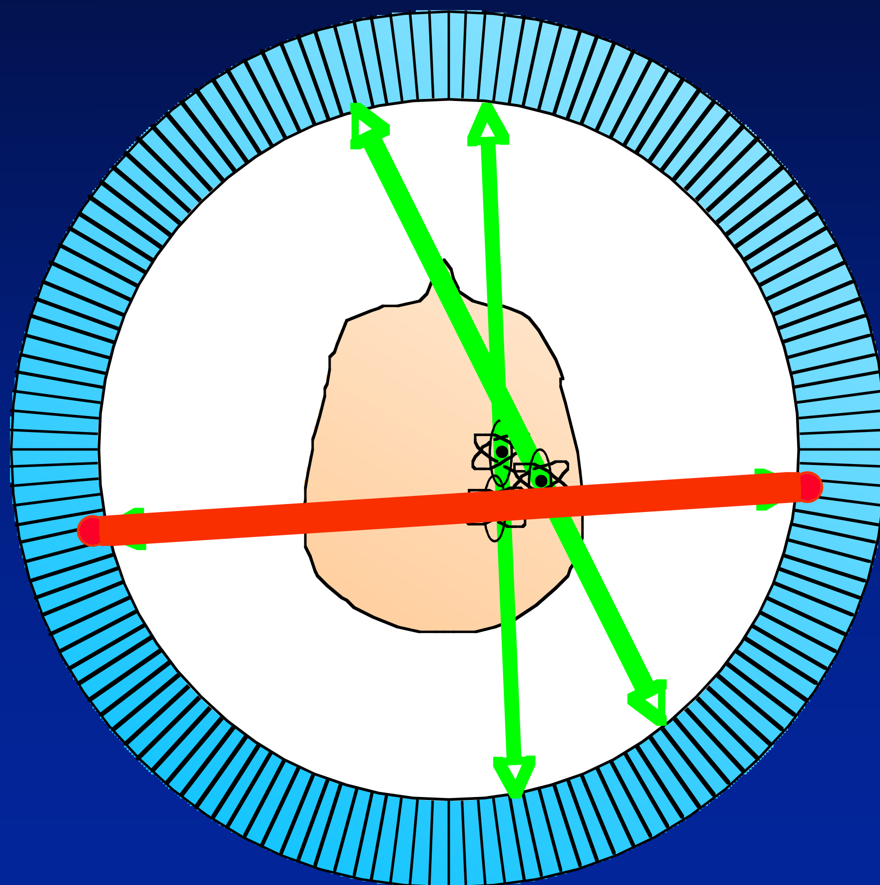
Positron Emission Tomography

- Let's say you have a radioactive substance (a radioisotope) at some point in space
- "Radioactive" means it decays by emitting high-energy charged particles
- When it emits a positively-charged particle-- a positron-- it smashes into an electron, which annihilates both of them
- The by-product of this reaction is a pair of high-energy photons (gamma rays) that shoot off 180 degrees apart from each other



Positron Emission Tomography

- If we can detect two emitted gamma rays that are 180 degrees apart from each other and hit the detectors at the same time, we know that a positron must have been emitted somewhere along the line between them: the **line of response**
- The radioisotope emits many, many positrons that cause gamma rays to shoot off in all directions
- Intersect all the lines of response to determine where in space the radioisotope is
- In this way the gamma rays act as a sort of “homing beacon” for the radioisotope



William Moses

Positron emission tomography

- Specific Uses
  - Attach radioisotopes to molecules that are used in normal metabolism (e.g. F18)
    - Radiation is emitted during metabolism
  - Attach radioisotopes to drugs acting at specific receptors
    - Radiation is emitted during interaction with receptor
  - Attach radioisotopes to molecules that interact with specific protein confirmations (e.g. PiB)
    - Radiation is emitted when molecule interacts with protein

Key problem with PET

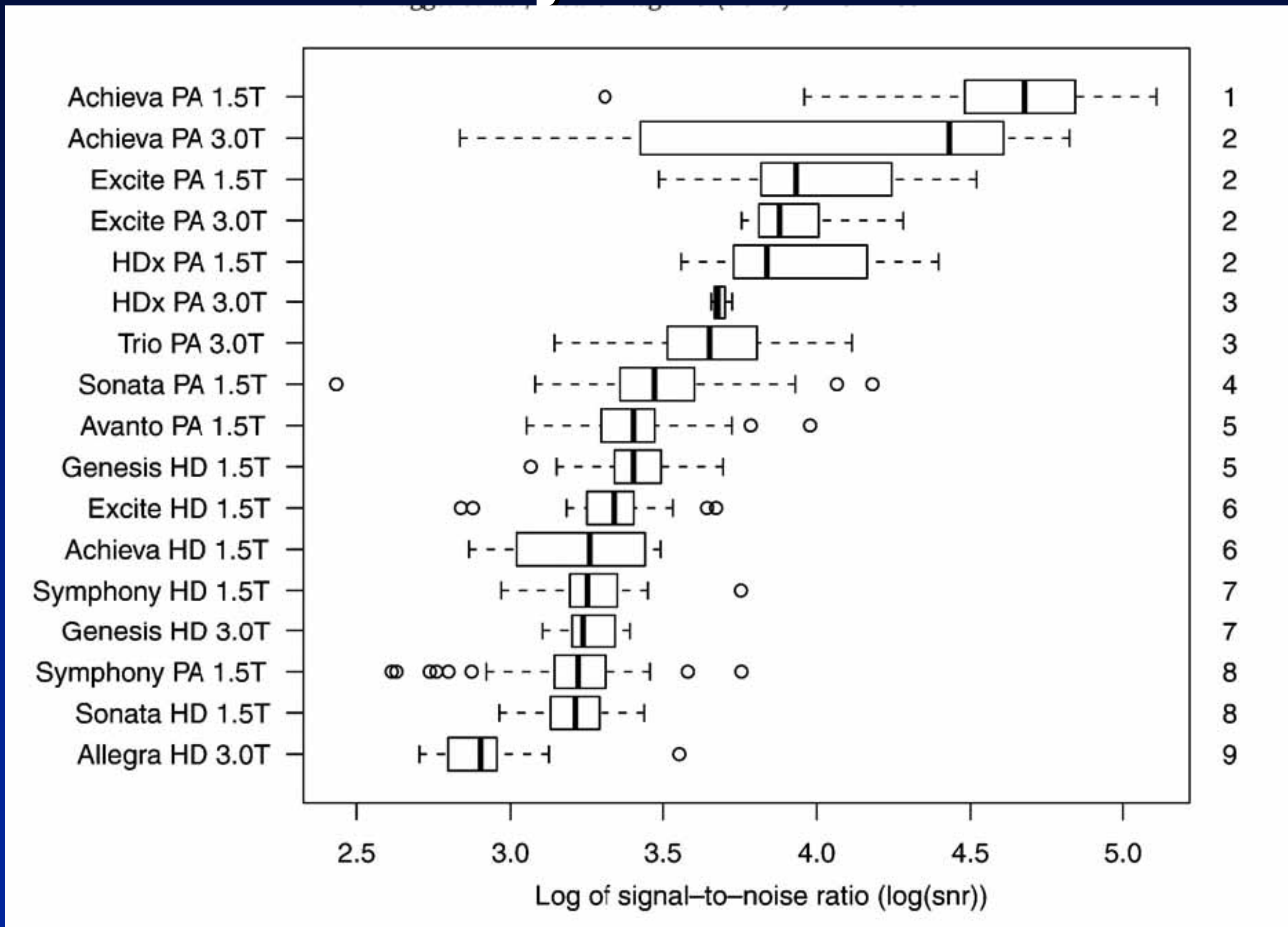
- Each radioisotope has a half-life: it only spits out positrons for a short period of time
- Fluorine has a half life of 2 hours
- Heavy oxygen is more like 20 minutes
- Meaning you better be VERY close to a cyclotron to use 15O.

Summary

- MRI examines how magnetic-field-aligned materials give off RF energy
  - High spatial resolution
  - High tissue contract that can be varied
- PET attaches radioactive isotopes to molecules used in metabolism, receptors and even protein-protein interaction

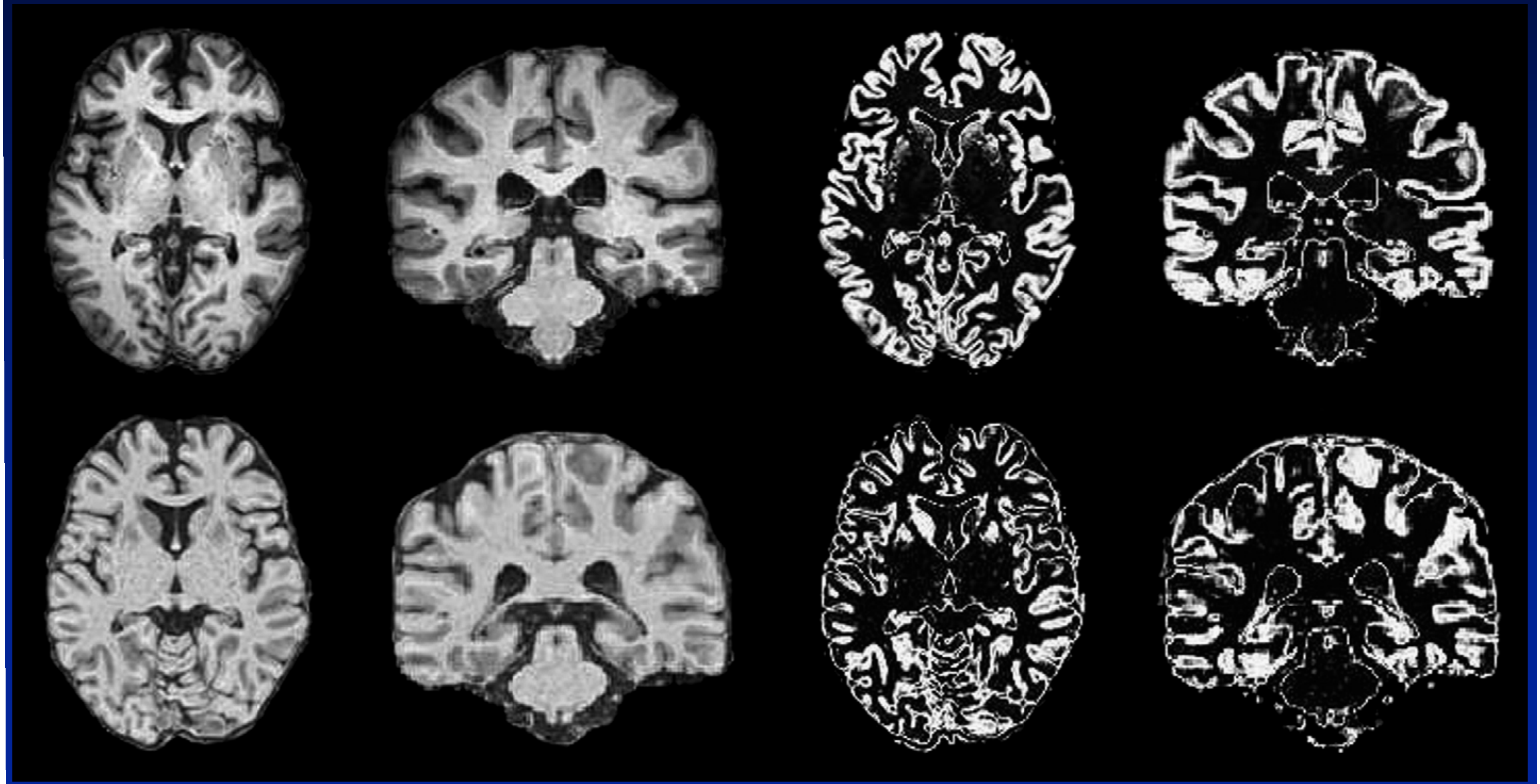
Issues of Image Quality

Signal to Noise of Various Systems



NeuroImage 49 (2010) 2123–2133

Effect of SNR on Segmentation



NeuroImage 49 (2010) 2123–2133

Artifacts

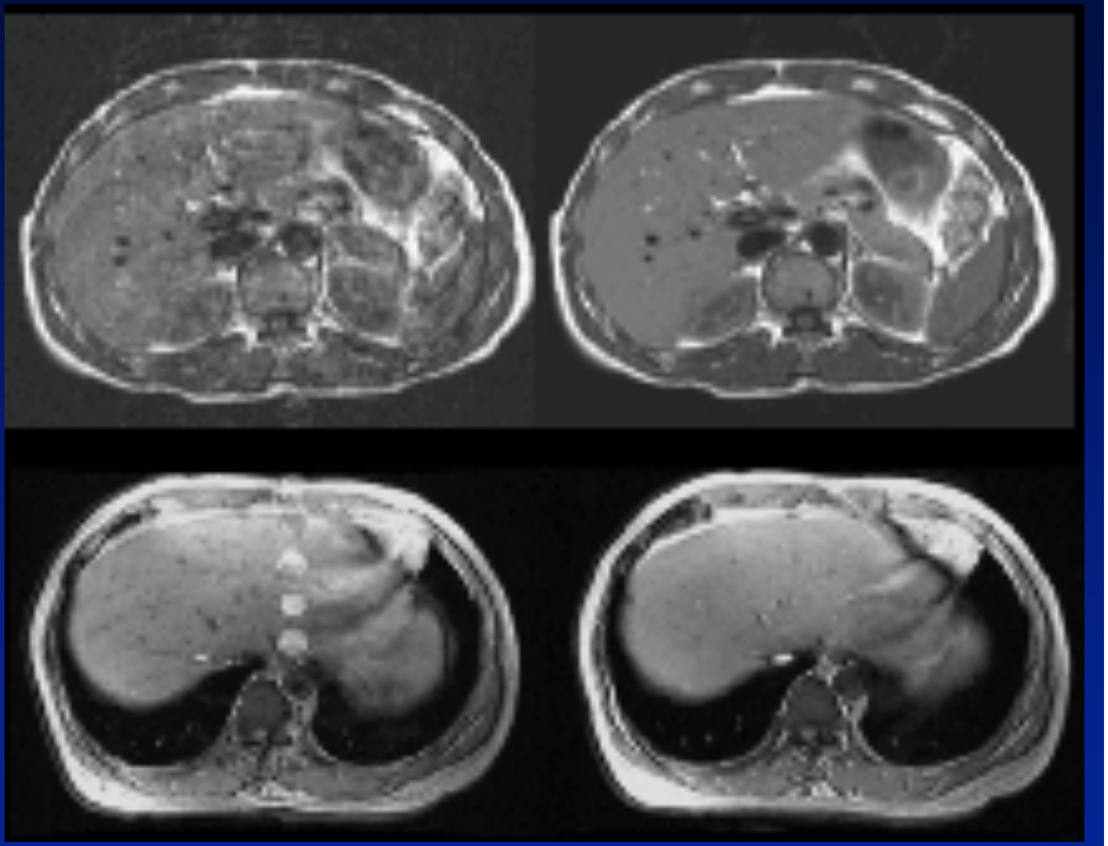
- Movement
- Foreign bodies
- Field Inhomogeneity
  - B0:Geometric Distortion
  - B1: Intensity inhomogeneity

MR Artifacts: Motion

- MR image reconstruction methods assume the patient is sitting still. Here is an abdominal MR image taken while the subject is breathing
- Motion is a problem for all imaging modalities; they all assume the subject is sitting perfectly still

Raw image

Image after correction for motion



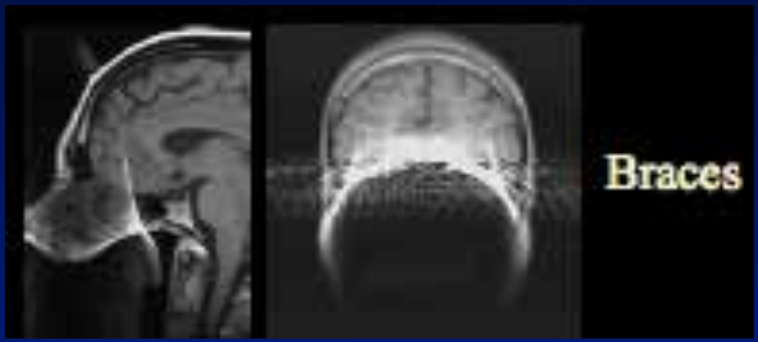
E.F. Jacksc

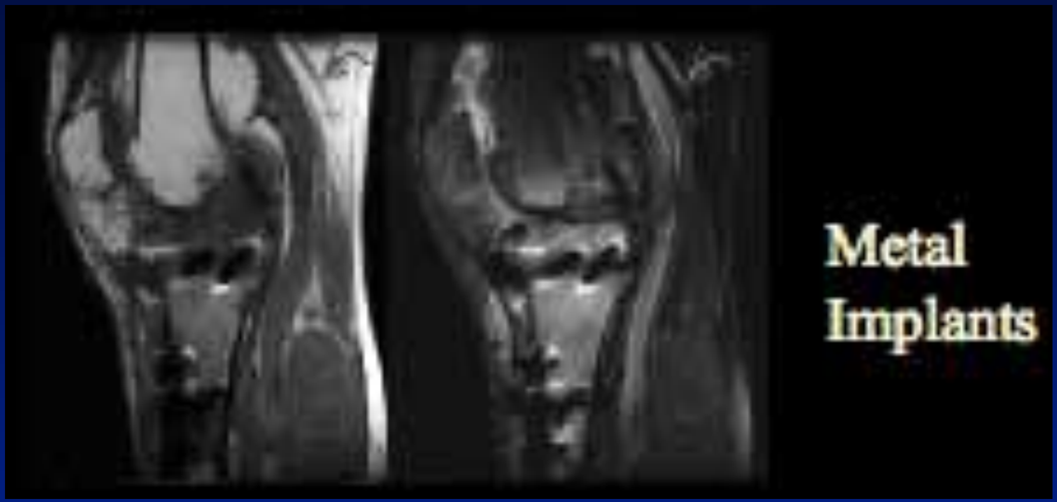
MR Artifacts: Motion

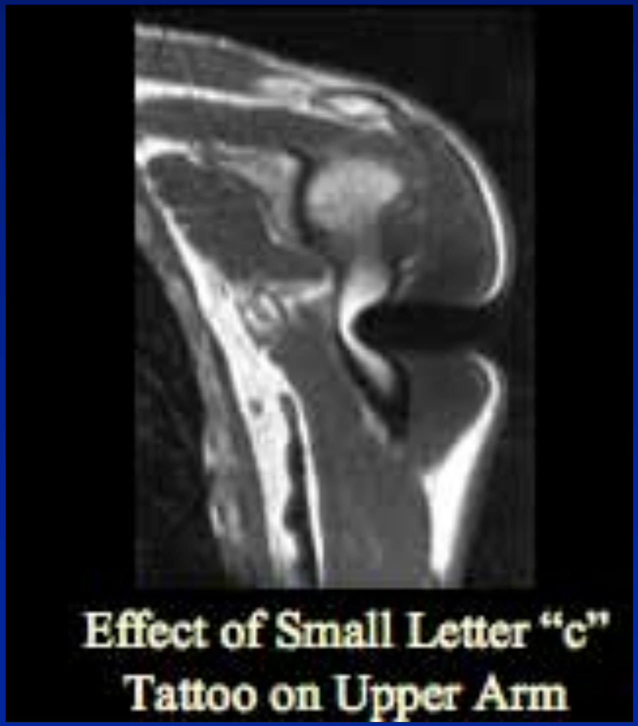
- Correct for respiratory motion by:
  - Telling the subject to hold his/her breath
  - Respiratory gating: Take repeated scans at the same point in the subject's respiratory cycle
- Increasing scanning speed
  - Taking many fast scans, aligning them, and averaging helps to average out the noise while compensating for motion

MR Artifacts: Metal

- Pieces of metal can distort the magnetic field and cause all sorts of problems







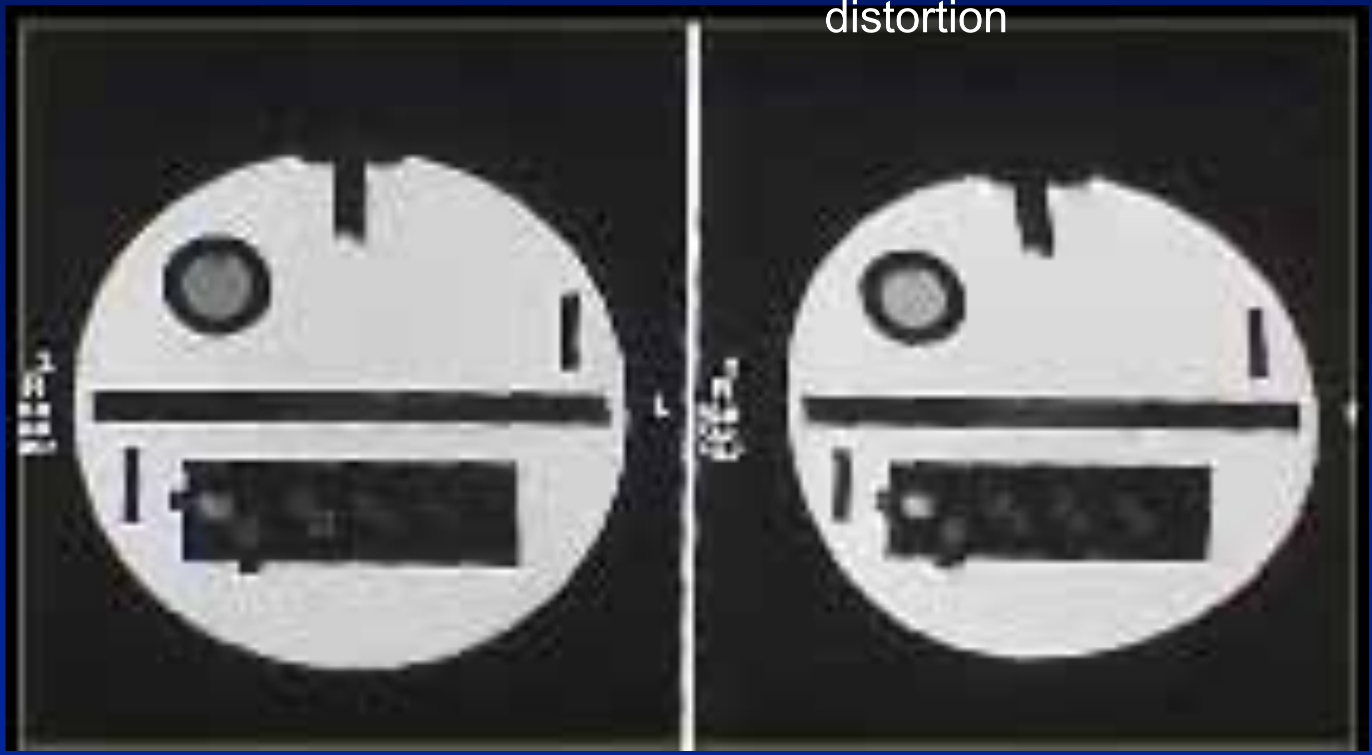
wwwrad.pulmonary.ubc.ca/stpaulsstuff/MRartifacts.html

MR Artifacts: Geometric Distortion

- We start out assuming that our magnet generates a magnetic field (B0) that is constant (same direction and magnitude) throughout the 3D space.

What it looks like without geometric distortion

What it looks like with geometric distortion



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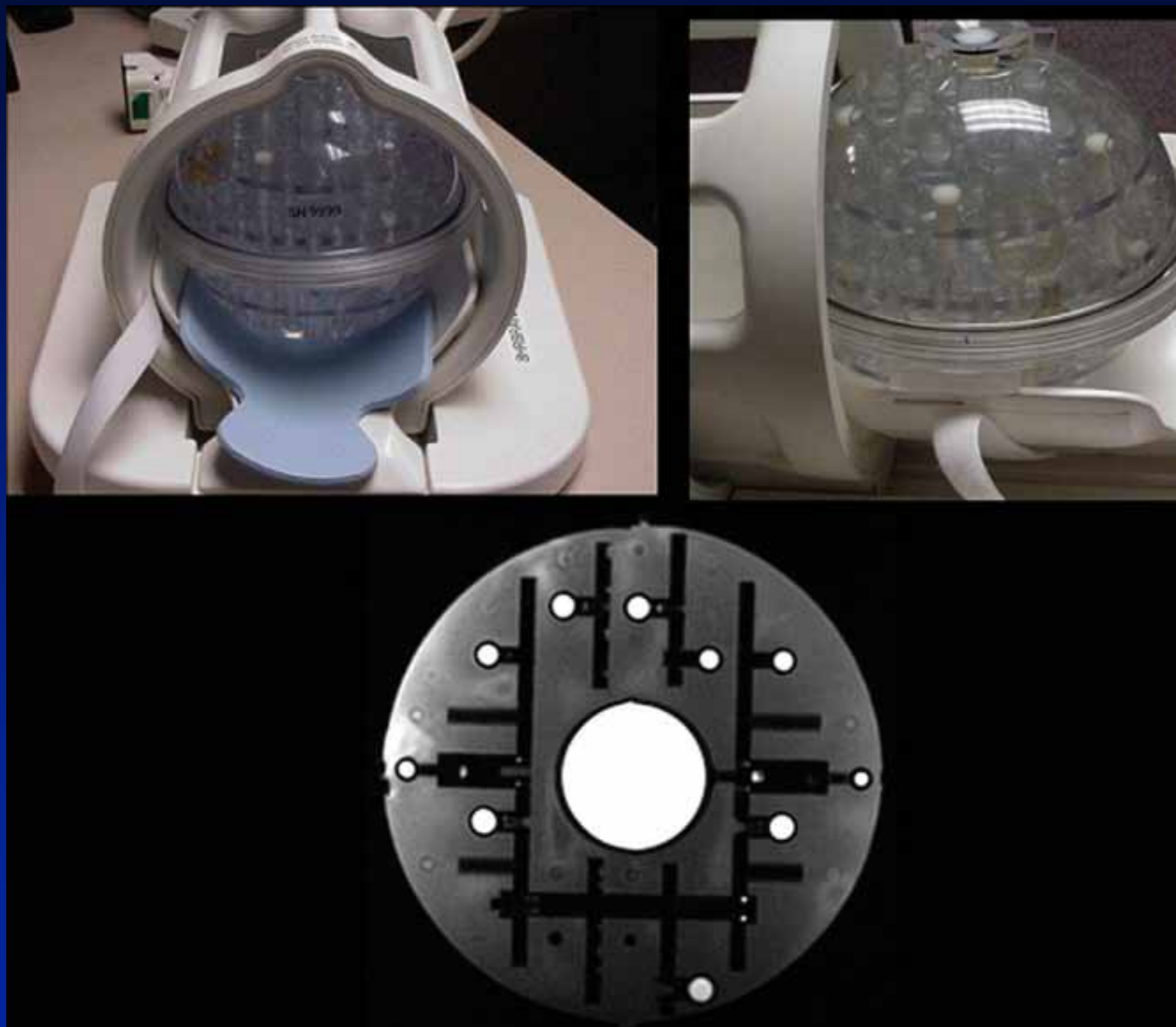
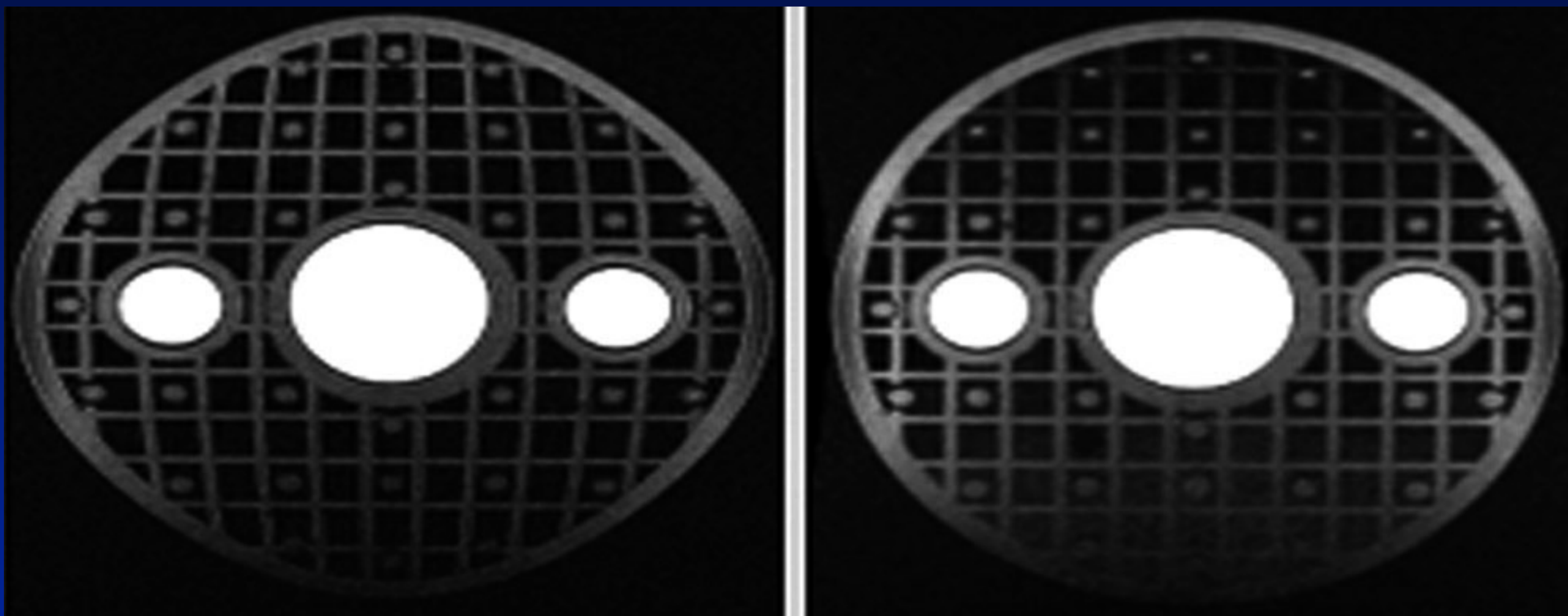
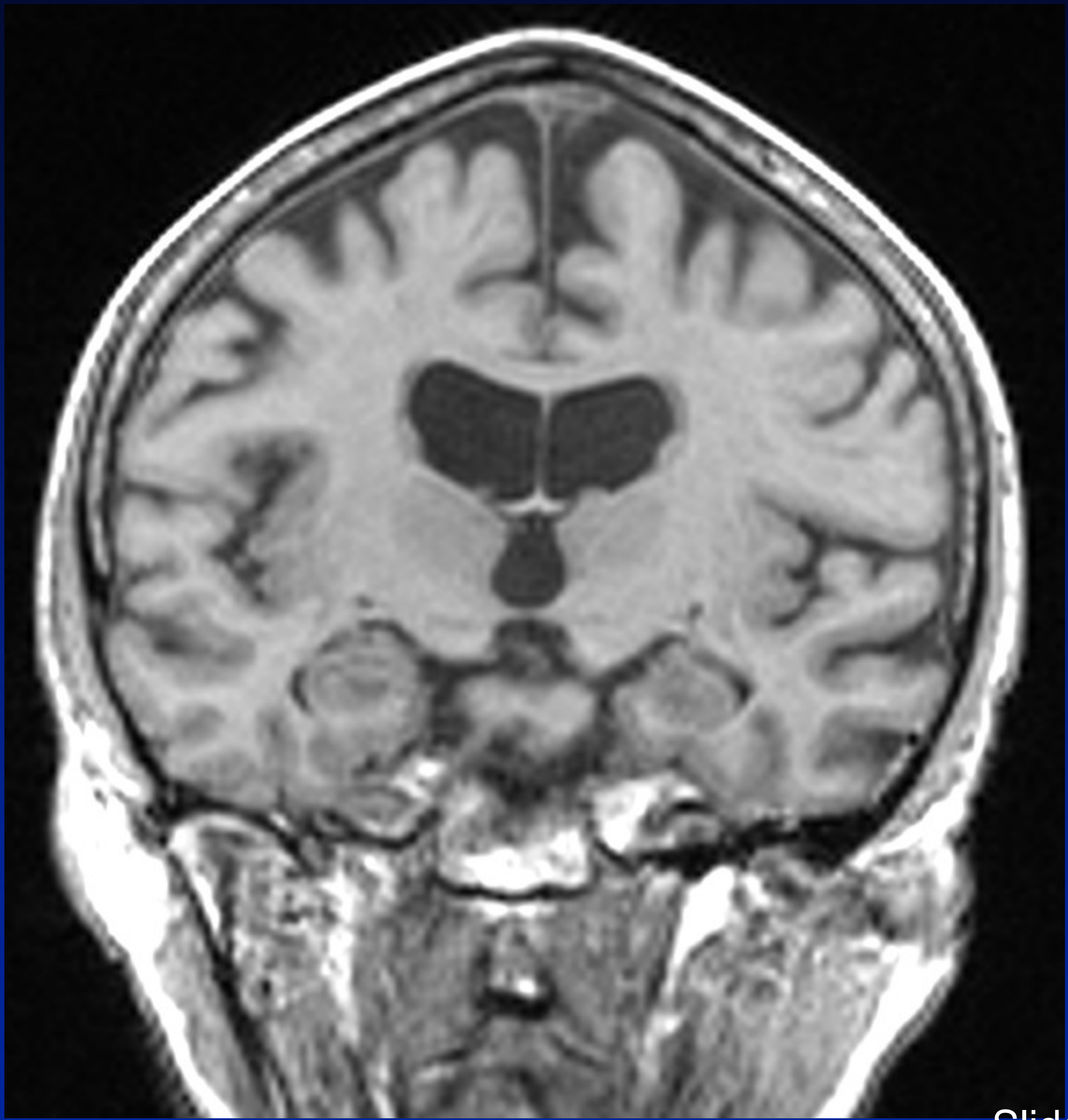
ADNI Phantom



Distortion Correction



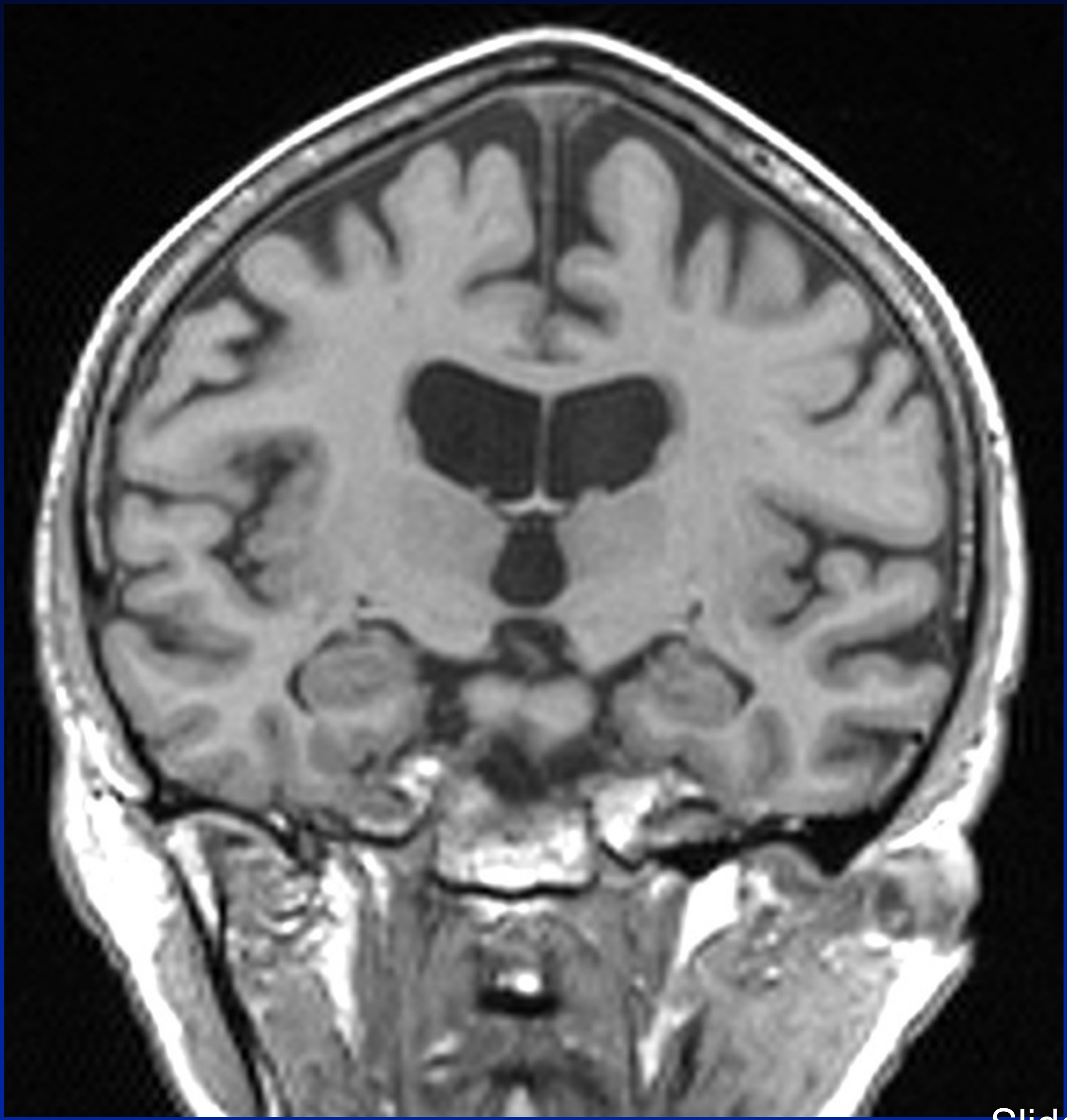


SPGR

Phased Array

Baseline

Slide courtesy Nick Fox, UCL



SPGR

Phased Array

Repeat

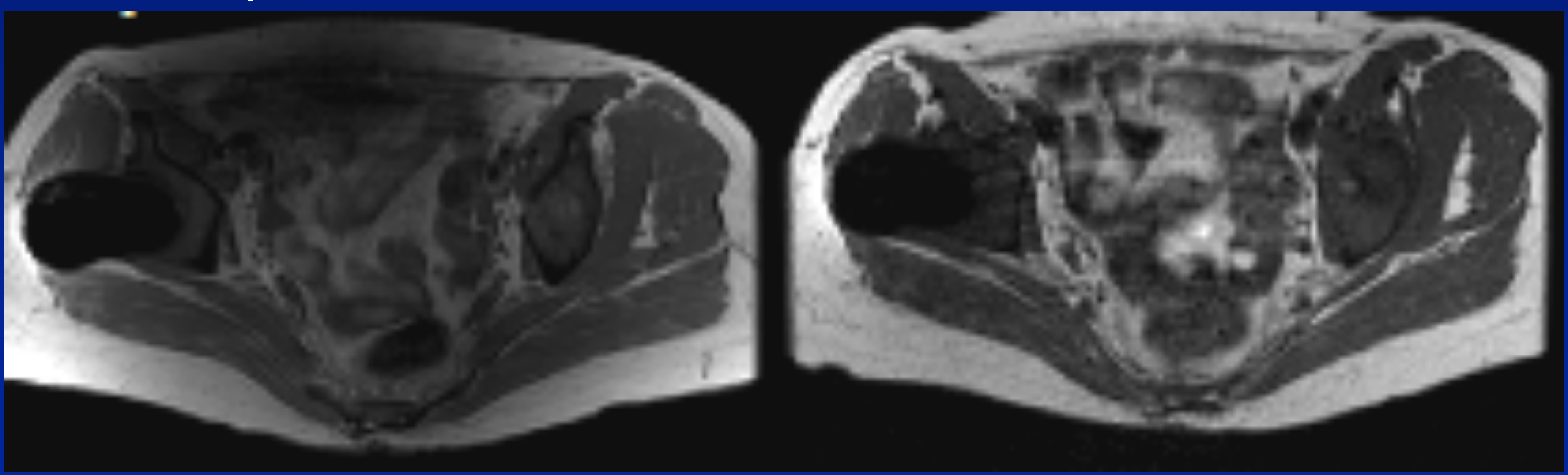
Slide courtesy Nick Fox, UCL

MR Artifacts: Intensity distortion

- Magnetic field irregularities in the gradient coil (B1) can also cause intensity distortions in parts of the image

What the image looks like with intensity distortion

What it looks like without it



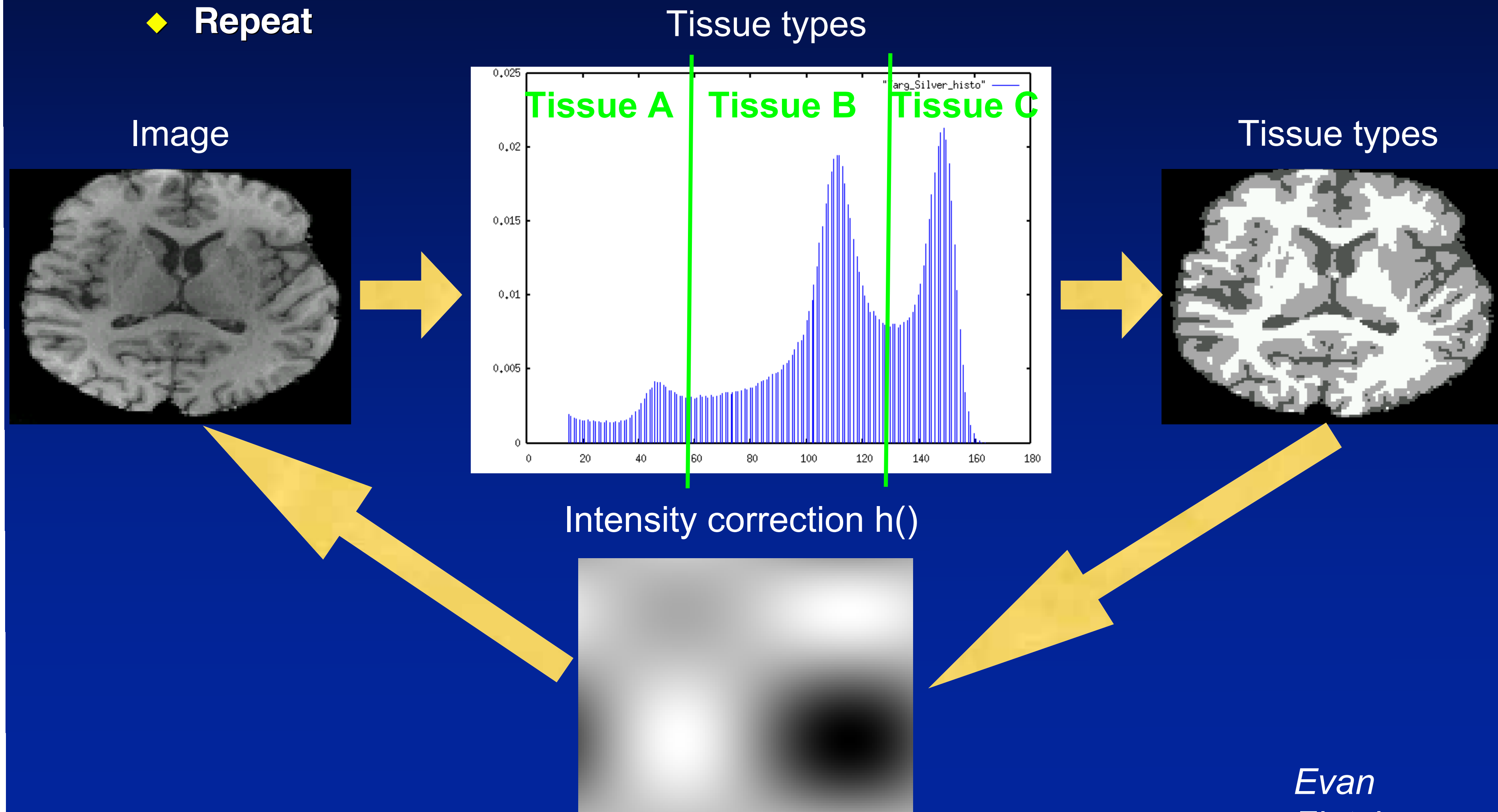
E.F. Jackson

Correcting intensity distortion

- Assume that all voxels that belong to the same tissue type have the same intensity
- Assume h() is the function that defines image inhomogeneities
  - IF we know the tissue type of all voxels, we can estimate what h() is
    - All the voxels of type T should have the same intensity I_T
    - If [x,y,z] is of tissue type T, $h([x,y,z])=I'([x,y,z])-I_T$
    - h is usually assumed to be a smoothly-varying, low-dimensional function, so these initial guesses at h([x,y,z]) can be fit to a parametric model

Correcting intensity distortion

- One common solution:
  - Estimate the tissue types by simple thresholding of the image intensity
  - Use those tissue types to estimate h
  - Update the image intensity based on the current h
  - Repeat



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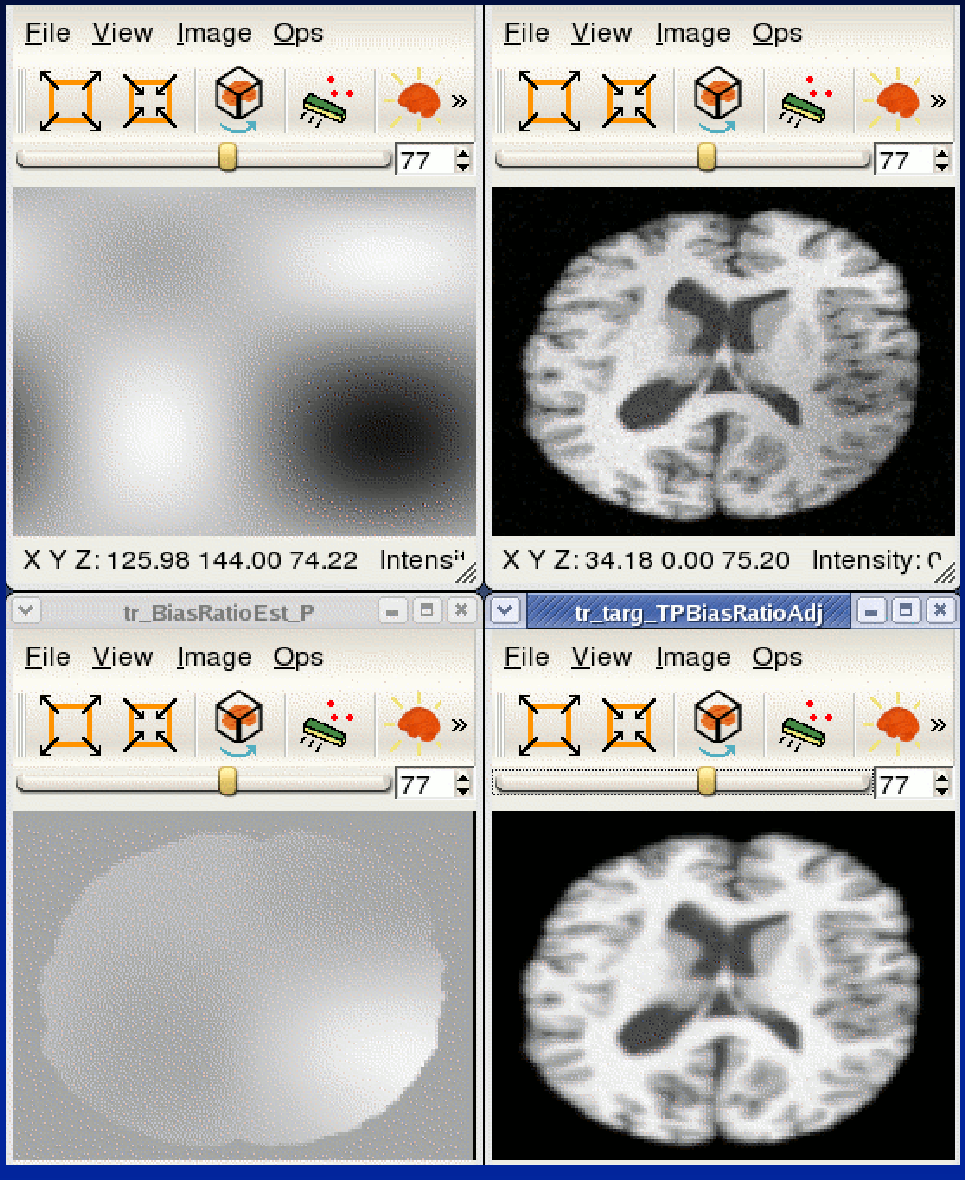
Correcting intensity distortions: examples

Intensity distortion: h()



Distorted image

Intensity correction: - h()

Corrected image

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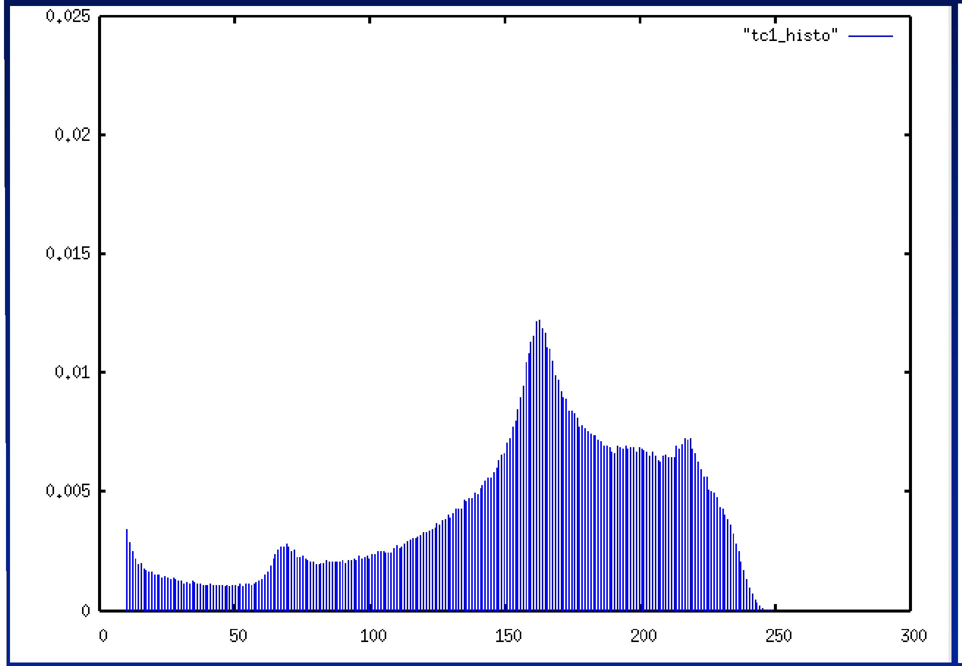
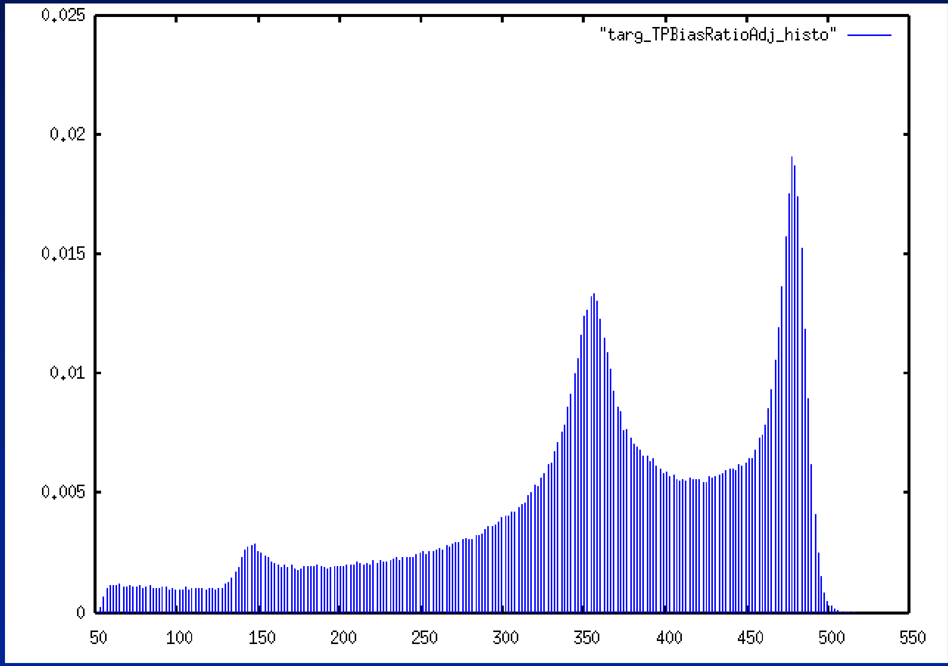
Correcting intensity distortions: examples

Intensity histogram before correction:



Intensity histogram after correction:



The intensity histogram should have sharp peaks corresponding to the different tissue types

Evan Fletcher

Image Analysis

- Manual ROIs
- Segmentation
- Alignment
- SPM
- Free-Surfer

Regions of Interest (ROI)

- Manual
  - Anatomically defined, usually by expert
  - Detailed discussion of boundaries
  - Documented procedure with high precision

Hippocampus

Differences of anatomical landmarks among protocols after semantic harmonization.

Plane of tracing			
Axis of hippocampus [B,C,dTM,J,L,S,W]	AC-PC line [H,K,M,Pa,Pr]		
Most posterior slice			
Where inferior and superior colliculi are jointly visualized [B]	Where crus/crura of fornix/ces is/are visible in full profile [C,dTM,J,K,L,S,W]	Where gray matter is visible inferomedially to the trigone of the lateral ventricle [H,M,Pa,Pr]	
Superior border			
Lower border of alveus/fimbria [B,H,K,Pa,S]		Upper border of alveus/fimbria [C,dTM,J,L,M,Pr,W]	
Separation subiculum/enthorinal cortex			
vertical line from the CA to the WM of the parahippocampal gyrus [C]	Oblique line with same inclination of parahippocampal WM, connecting the inferior part of the subiculum to the quadrigeminal cistern [K,L,M,Pr,W]	Horizontal line from the highest medial point of the parahippocampal WM to the cistern [B,dTM,H]	Line outlining the contour of white matter of parahippocampal gyrus [J,Pa,S]

AC= anterior commissure; PC= posterior commissure; CA=cornu Ammonis; WM=white matter.
[B] Bartzokis et al., 1998, [C] Convit et al., 1997, [dTM] deToledo-Morrell et al., 2004, [H] Haller et al., 1997, [J] Jack et al., 1994, [K] Killiany et al., 1993, [L] Lehericy et al., 1994, [M] Malykhin et al., 2007, [Pa] Pantel et al., 2000, [Pr] Pruessner et al., 2000, [S] Soininen et al., 1994, [W] Watson et al., 1992.

BACKGROUND
The effect of segmentation protocols on hippocampal volume

Ref.	Med border	Lat border	Inf border	Norm. hippo vol (cm^3)	
				Left	Right
Watson et al.	Mesial edge of temporal lobe	Temp horn of lat ventr	Incl subicular complex & uncal cleft w/ border separating subicular complex from parahippo gyrus	**4.903**	**5.264**
Zipursky et al.	Regional outline at choroidal fissure	Not mentioned	The interface of hippocampal tissue and parahippocampal gyrus white matter	**1.990**	**2.070**

Geuze et al., Mol Psychiatry 2005;10:147-59

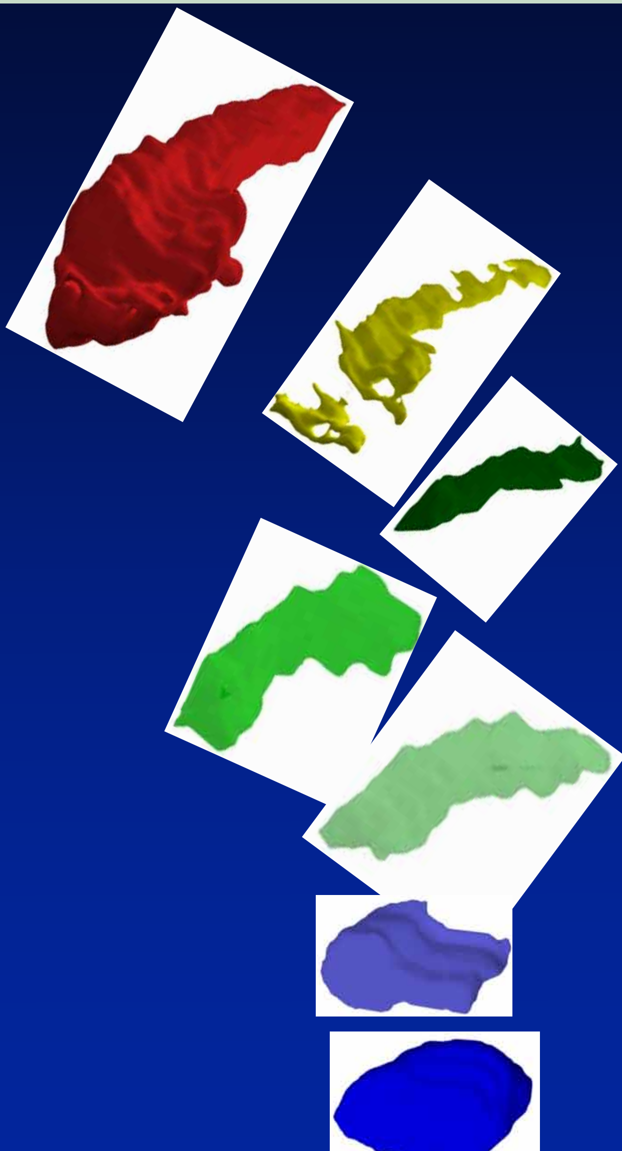
3D RENDERING & COMPUTATIONS

Rendering by
Simon Duchesne and **Nicolas Robitaille**
Université Laval and Centre de Recherche
Université Laval – Robert Giffard
Québec City, Canada

LENITEM

MEDICS Laboratory Laboratoire

Preliminary ICC values by Segmentation Unit



	Intra-rater
MinHB	0.992
Alveus/fimbria	0.863
MinHB+Alveus/fimbria	0.993
Subiculum	
Oblique line	0.964
Morphology	0.981
Horizontal line	0.980
Tail	
Crus/crura	0.998
Most caudal	0.988

A few words about precision

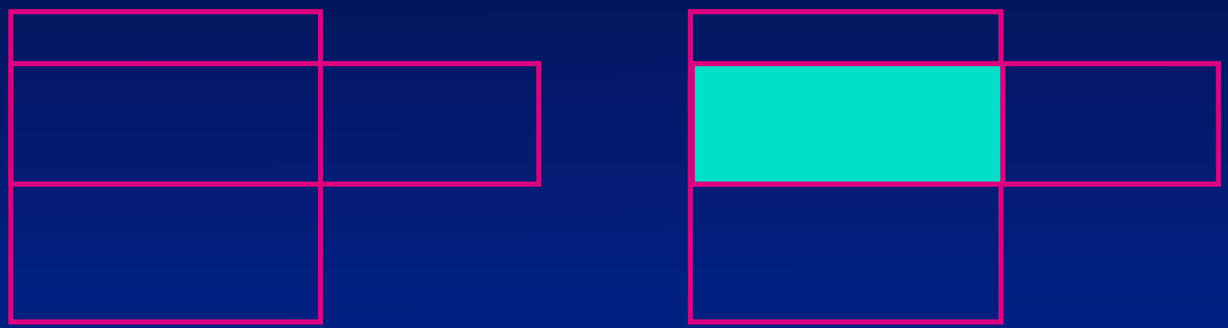
- Reliability of measurement
  - Intra-rater
  - Inter-rater
- Inter-class correlation

<u>Between measure variance</u>

Within group variance

Another word about precision

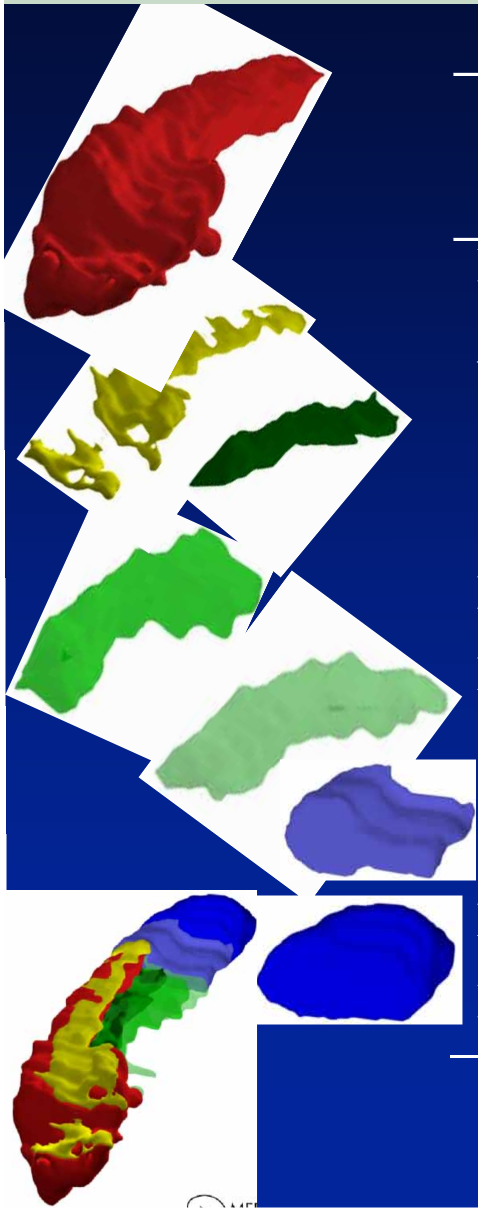
More words about precision



ROIa and ROIb have the same area, but are measuring different Things!

Real measure of precision is overlap

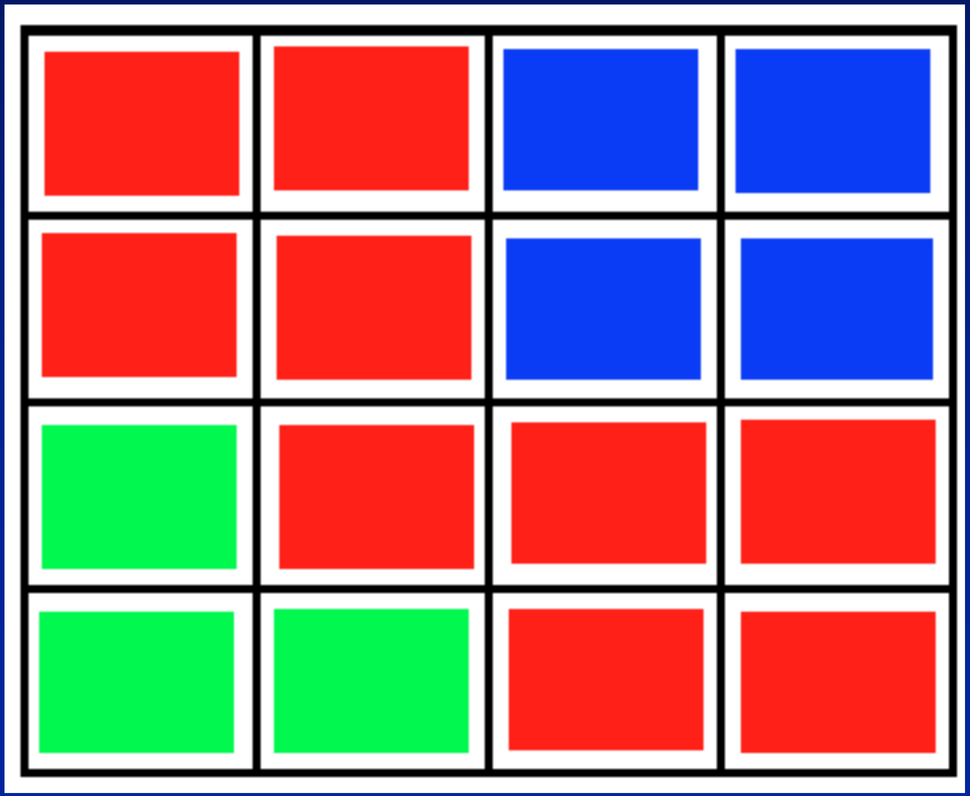
Measurements in prototypical control and AD



	Control	AD	% diff from CTR
MinHB	1888 (65%)	1126 (56%)	-40%
Alveus/fimbria	249 (9%)	236 (12%)	-5%
Subiculum	355 (12%)	261 (13%)	-26%
Oblique line	199 (7%)	231 (12%)	+16%
Morphology	335 (11%)	258 (13%)	-23%
Horizontal line	355 (12%)	261 (13%)	-26%
Tail	430 (15%)	373 (19%)	-13%
Crus/crura	122 (4%)	145 (7%)	+19%
Most caudal	308 (11%)	228 (11%)	-26%
MaxHV	2922	1997	-32%

Segmentation

- Reliable determination of voxels associated with distinct tissue types
  - Gray matter
  - White matter
  - CSF
  - +/- White matter hyperintensities

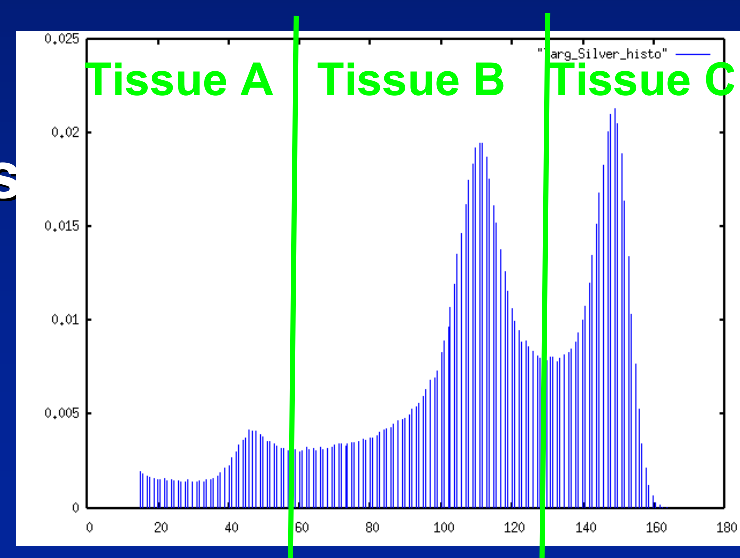


Expectation Maximization

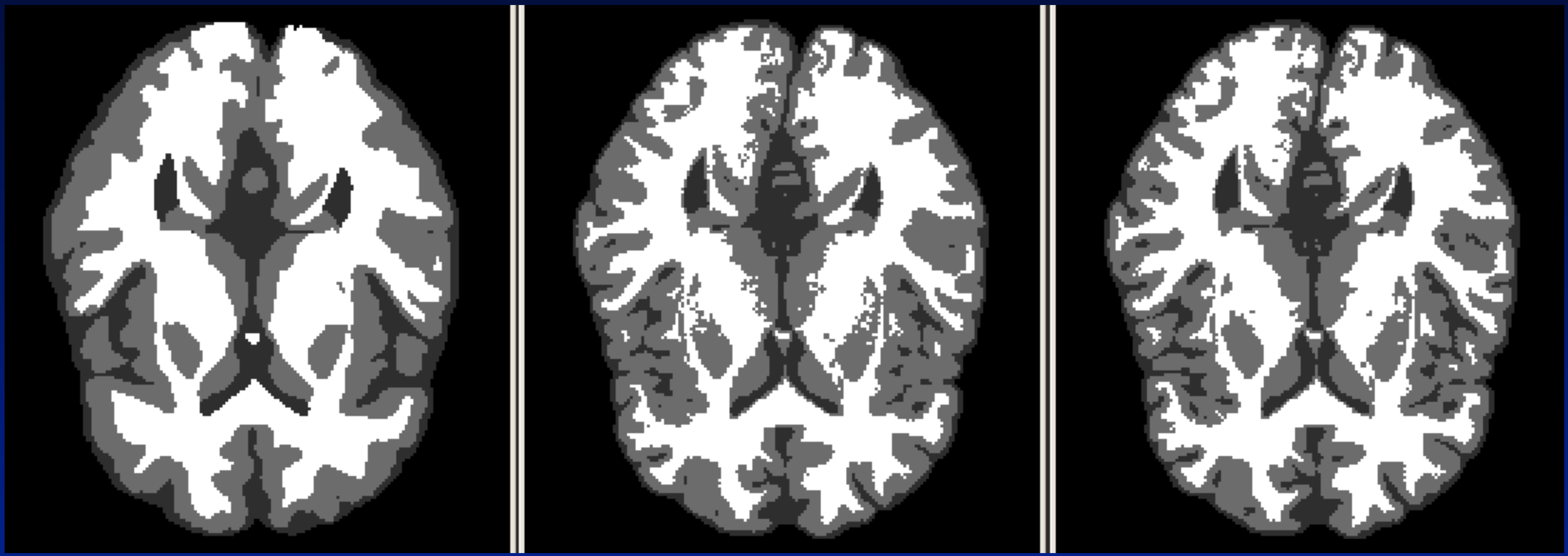
- Image consists of an array of y intensities
- Each voxel (y_i) has a single intensity
- Segmented image is an array of labels x drawn from a small set of labels k.
- Given a conditional probability density, p we seek optimal labeling x* such that:
  - $x^* = \arg\max_x p(x|y)$

Bayesian Theory

- x^{*} = arg $\max_x p(y/x)\ p(x)$
- Where $p(y/x)$ is the measurement model (pixel intensity distribution)
- $p(x)$= priors
  - Local
    - Markov-random fields



Steps in Segmentation



Model to estimate initial tissue distributions
Initial segmentation based on assignment
Results of iterations

Segmentation based on MRF Adaptation

Assumptions

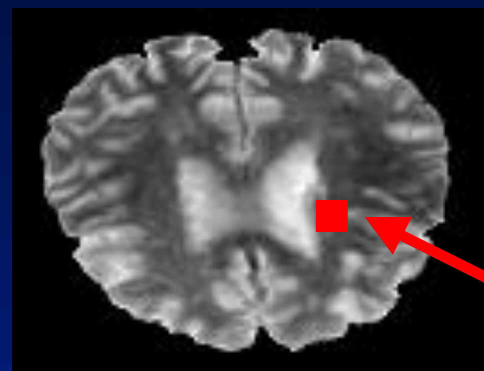
- Voxel intensity (the most common type of image segmentation) reflects differences in tissue classes
- The underlying distribution of each tissue type has a known mean and standard deviation
- The distribution of intensities about the mean is assumed to be gaussian

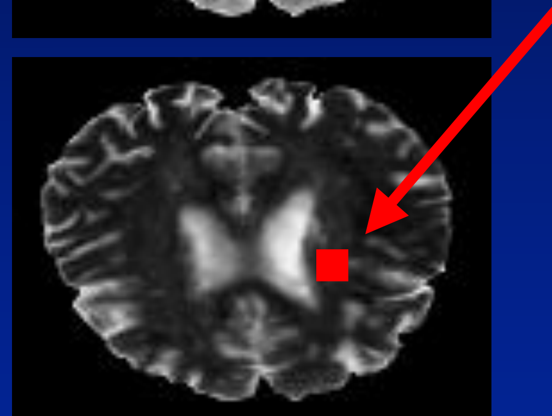
WMH Detection from MRI
Bayesian Inference Model

Use two key sources of information to determine whether there is a white matter hyperintensity at each voxel:

Prior knowledge

Do WMHs tend to occur at this voxel in general?





The image signal

Does it look like a WMH on PD, T1, and T2 MRI?

Combine these two sources of information in a **Bayesian inference framework.**

Image Alignment

- Fundamental to image processing
  - Places two images in common location
    - Target
    - To each other
  - Look at similar areas across multiple images
  - Look at differences in same individual over time

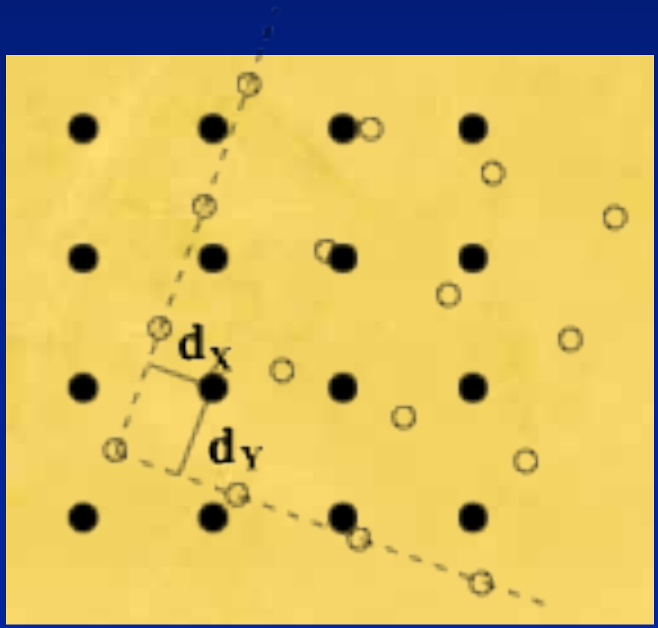
Principles of image alignment

- Given 2 images I_1 and I_2 as volumetric images $I([x\ y\ z])$
- Estimate a geometric transformation of I_1 that aligns it to I_2: $g([x\ y\ z]) \to [x'\ y'\ z']$
- g should align corresponding parts of the objects shown in I_1 and I_2 to each other:
  - If I_1 and I_2 are images of the same instance of the same object, $I_1([x\ y])$ and $I_2(g([x\ y]))$ should be pixels covering the same part of the same object
  - If I_1 and I_2 are images of the same *type of* object, $I_1([x\ y])$ and $I_2(g([x\ y]))$ should be pixels covering the same general part of the object shown

Components of image registration

- **Transformation model:** The functional form of g(), which is parameterized by a vector of parameters θ.
- **Metric:** A function M(I_1([x y z]) , I_2(g([x y z]))) that is low when g aligns I_1 and I_2 well and high when it does not
- **Interpolation scheme:** Given an image I_1 where I_1([x y z]) is only defined at integer [x y z], the interpolation scheme assigns intensities to I_1 at floating point [x y z]
- **Optimizer:** Iteratively finds θ that minimize M
  - Initial conditions: **A starting guess at θ**
  - Stopping conditions: **Criterion for determining when to stop trying to find better values of θ**

Interpolation example:
Out transformation gives us this alignment between I_1 and I_2, and to measure goodness-of-fit we need to evaluate I_1 (black dots) at the in-between-pixel positions (clear dots) where I_2's pixels get transformed to



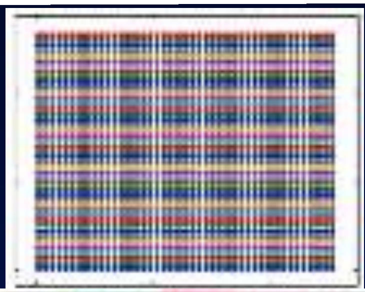
Transformation models

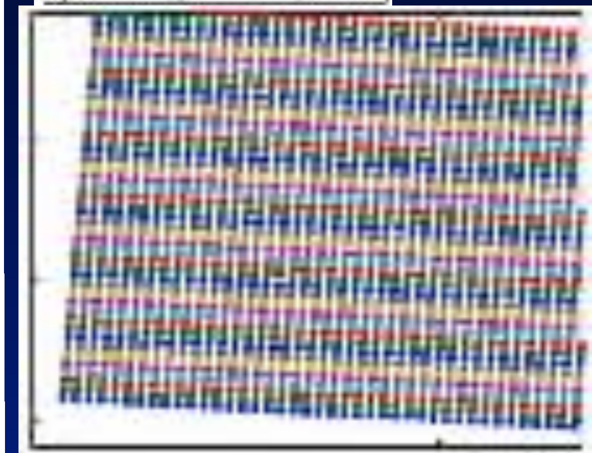
- Rigid **transformations rotate and translate I_1 to align it with I_2**
- Similarity **transformations add isotropically scaling to this (e.g., a*x,b*y,c*z)**
- Affine **transformations add anisotropic scaling and shearing**

Above assume a single transformation function applied to all voxels in the image

- Deformable **transformations**
  - **Local tranformation in voxel locations based on regional comparisons (e.g. control points) allowing for different shape**

Transformation models





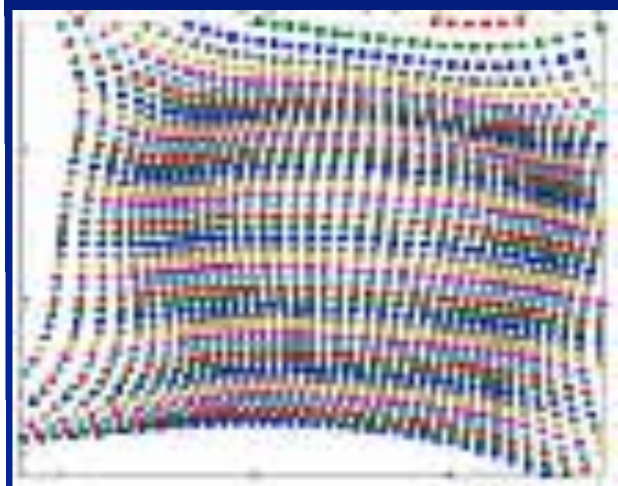
$$g_{\phi}(x,y,z) = T * [x\ y\ z]$$

Affine model: T is a 4x4 matrix of constants

12 parameters: 3 rotations, translations, scalings, and shears

Global transformation: each pixel is moved the same amount

No local expansions or contractions



$$g_{\phi}(x,y,z) = \sum_{p=0}^{K}\sum_{q=0}^{K}\sum_{r=0}^{K}[a_{pqr1}, a_{pqr2}, a_{pqr3}] \cdot x^p y^q z^r$$

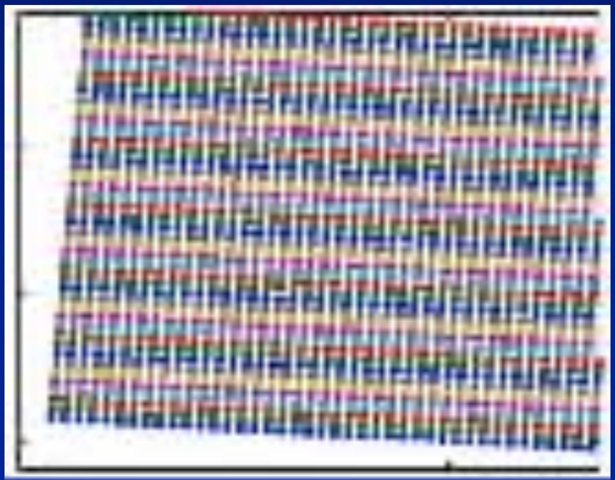
Polynomial model: the a coefficients are the parameters

The number of parameters depends on your choice of K: the degree of the highest polynomial in your model

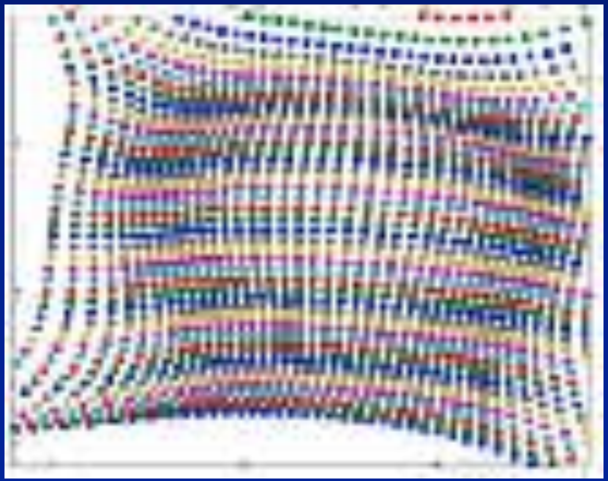
More polynomials means a higher degree of possible deformation

Nonrigid transformations

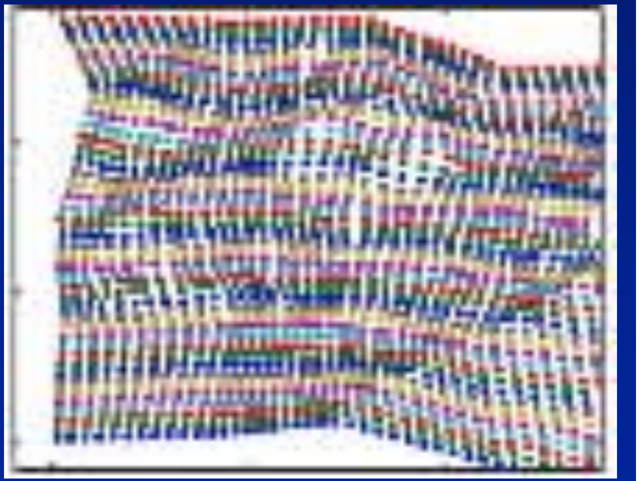
- **Semi-deformable models** allow the image to deform in more constrained, smooth ways
- **Fully-deformable models** allow each pixel to move around arbitrarily, in an unconstrained way
- Because they constrain the deformation less, fully-deformable methods have the potential to more accurately align the images together, even when one is a highly deformed version of the other
- But higher degrees of deformation usually imply more parameters that need to be estimated and the possibility of non-biological transformations



Affine

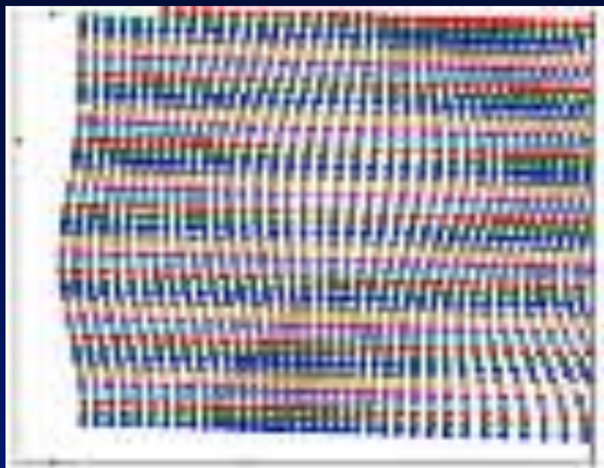


Semi-deformable



Fully-deformable

Transformation models



$$g_\phi(x,y,z) = [x,y,z] + \sum_{p=0}^{K} [a_{p1}, a_{p2}, a_{p3}] \cdot d_p(x,y,z)$$

Discrete cosine transform model:

The coefficients (a_p) are the parameters; d_p() is the pth DCT basis function

The number of parameters depends on the number of DCT basis functions you include

Higher-order DCT basis functions corresponds to higher-frequency sinusoids: therefore higher degrees of deformation

$$g_\phi(x,y,z) = [x,y,z] + [\delta x, \delta y, \delta z]$$

Fully-deformable model:

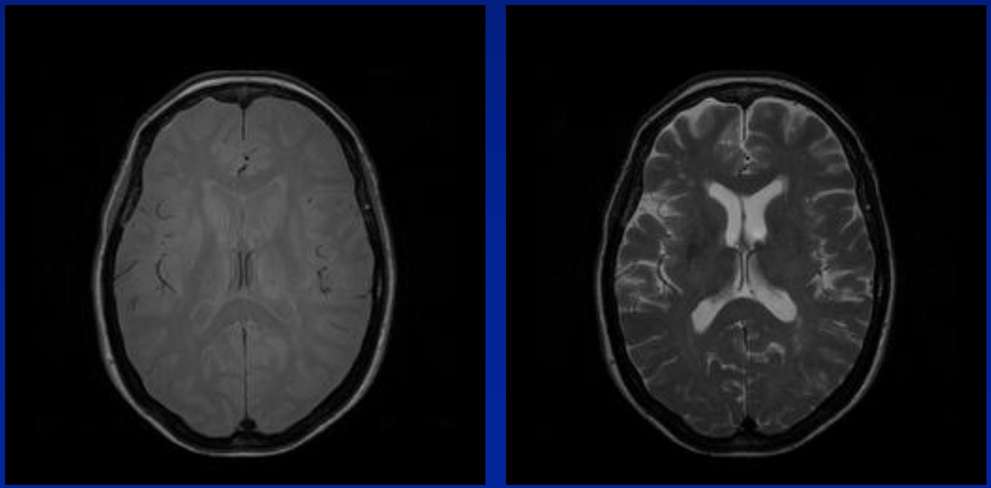
Each voxel is translated by its own individual displacement vector [dx,dy,dz]

The number of parameters is high-- 3 per pixel!

The degree of deformation is arbitrary

The metric

- The relationship between intensities in I_1 and intensities in I_2 can be complex, even if they are images of the same object
  - Consider two images of the same face in different lighting: parts of the face that are bright in one image may look dark in another
  - Two MR images of the same brain may look entirely different if the scanner or scanning parameters differ
- Therefore we use geometric and intensity transformations to model the relationship between I_1 and I_2 : $I_1([x\ y\ z]) = h(I_2(g([x\ y\ z])))$
- Different metrics make different assumptions about the relationship



2 MR scans of the same brain with different scan parameters

CMU PIE Database

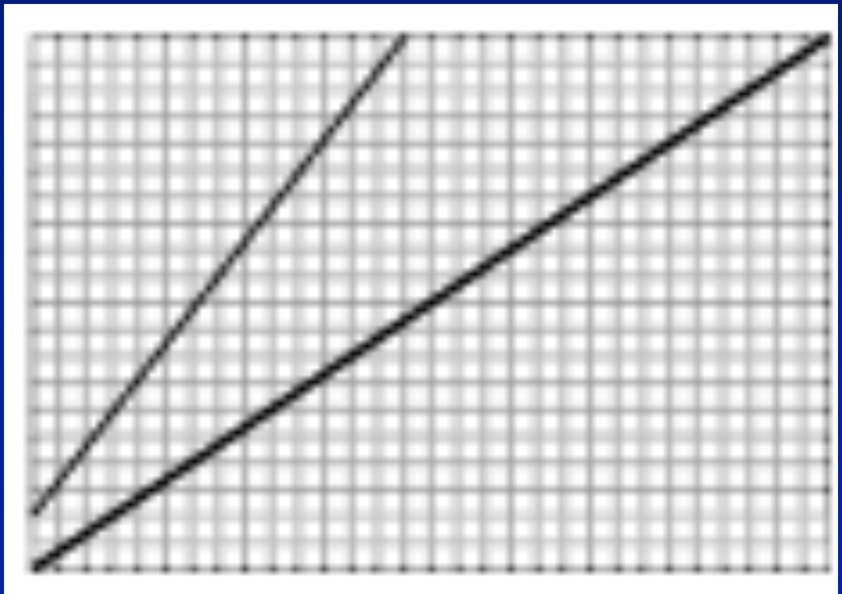
Linear intensity transformations

- Let's say that instead of assuming the two images have identical intensities, you assume that there is a linear relationship between them: h(x) = m*x+b
- The intensity differences between the two images will be high even if they are aligned perfectly
- Two Common Approaches:
  - Try to rectify the images to remove m and b: for example, set the means and variances of the images to the same constant values: $I_1 \rightarrow (I_1 - \mathrm{mean}(I_1)) / \mathrm{variance}(I_1)$
    - Not possible if Image A and Image B have different Tissue contrasts
  - Use a metric that rewards $I_1([x\ y\ z])$ and $I_2(g([x\ y\ z]))$ if there is a consistent linear relationship between intensities in $I_1([x\ y\ z])$ and in $I_2(g([x\ y\ z]))$

Linear intensity transformations

- **Normalized correlation rewards the two images for having a consistent linear relationship in intensities:**

$$\frac{\sum_{x,y,z} I_1(x,y,z) * I_2(g(x,y,z))}{\sqrt{\sum_{x,y,z} I_1(x,y,z) * I_1(x,y,z) + \sum_{x,y,z} I_2(g(x,y,z)) * I_2(g(x,y,z))}}$$



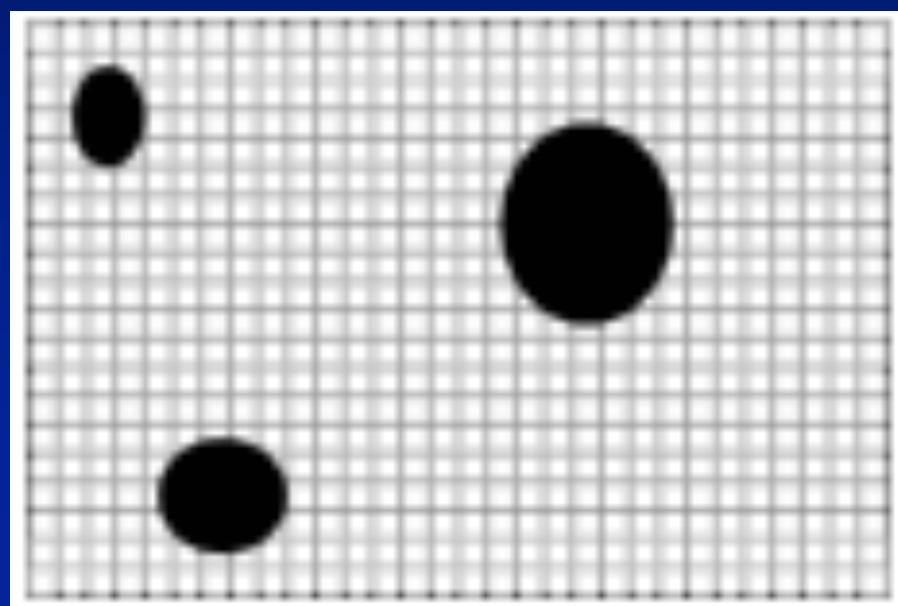
$I_1([x\ y\ z])$

$I_2(g([x\ y\ z]))$

Mutual information

- Mutual information is a way of rewarding images when they have an intensity relationship that is consistent in any way-- regardless of what that relationship is (linear, non-linear, etc.)
- Very simple requirement: If h() transforms intensity x to intensity y for **one** pixel, it should transform **all** pixels of intensity x to intensity y
- In other words, the distribution of h(x), given x, should be highly peaked around y
- Note that this says nothing about the functional form of h()-- whether it is linear, quadratic, etc. Just that it should be consistent, transforming all of the x pixels to y no matter where they are in the image

I_1([x y z])



I_2(g([x y z]))

Ideal case for MI: A tightly-clustered joint histogram of I_1 and I_2

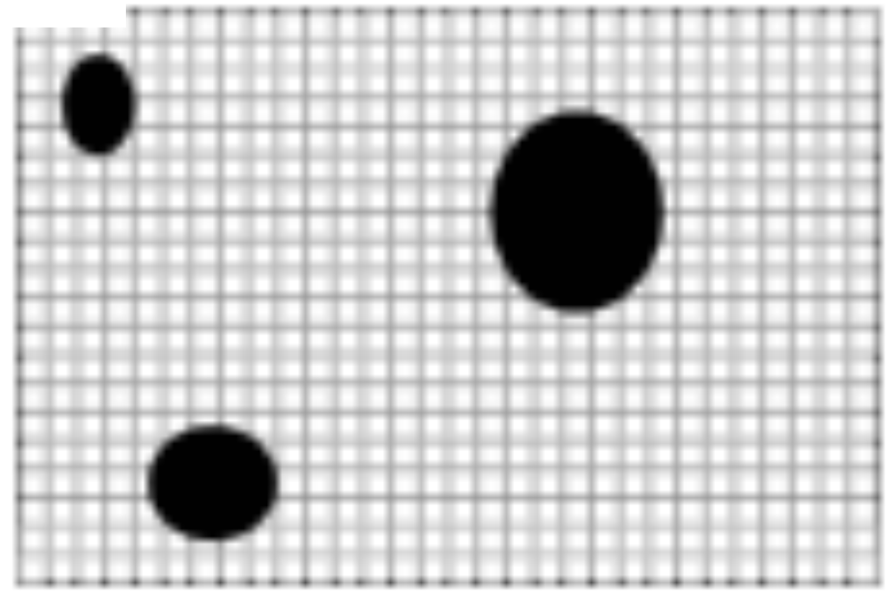
Each intensity level in I_1 gets mapped to a small number of intensities in I_2

Mutual information

- The idea that h should be as one-to-one as possible is formalized by looking at the joint distribution of I_1 and I_2 intensities -- $P_{AB}(a,b)$ -- and the marginal distributions of intensities in I_1 and I_2 : $P_A(a)$ and $P_B(b)$
- The entropy of these distributions is H(A,B), H(A), and H(B)

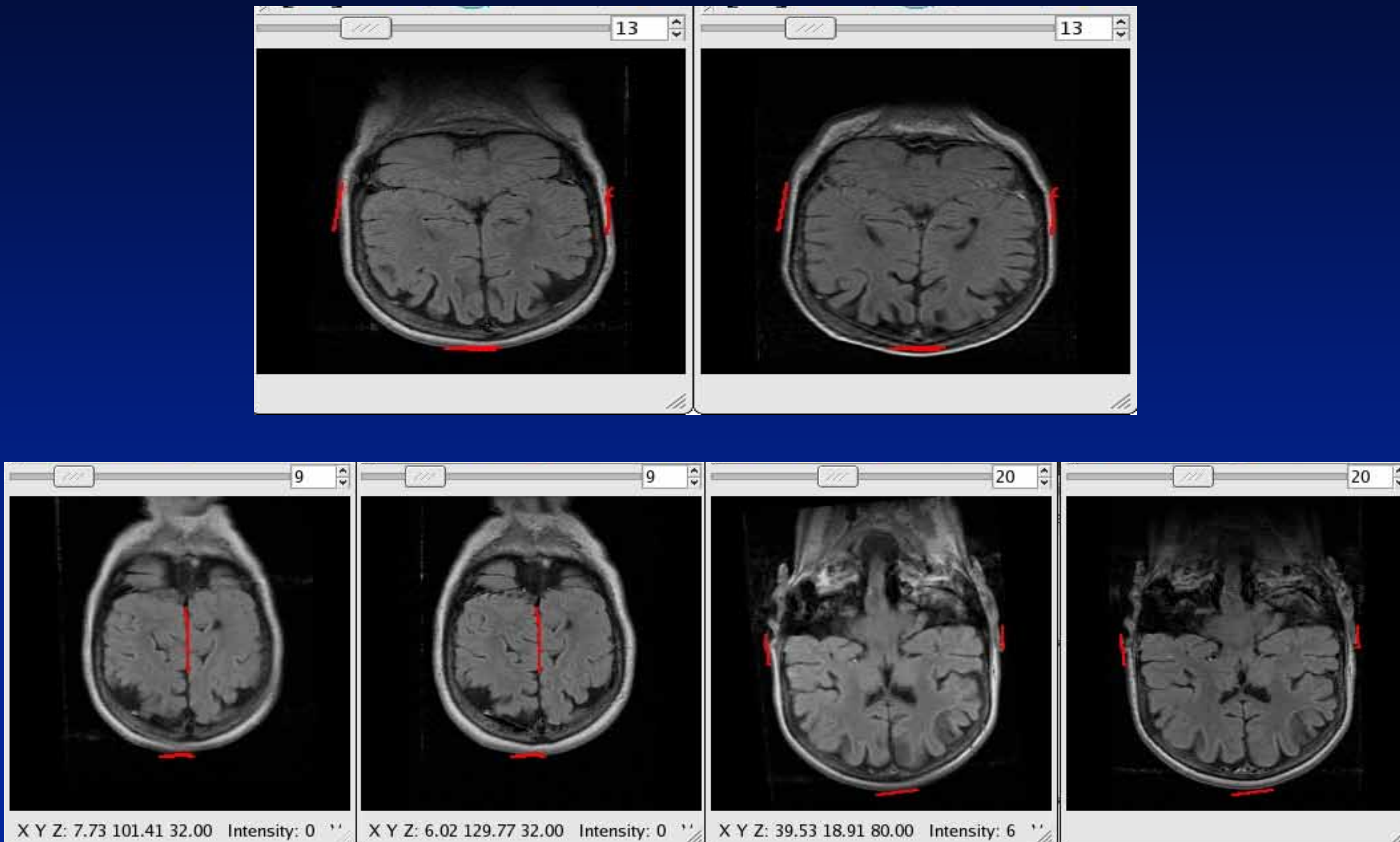
$$I(A,B) = \sum_a \sum_b P_{AB}(a,b) \log \frac{P_{AB}(a,b)}{P_A(a) P_B(b)}$$

$I_1([x\ y\ z])$ intensities

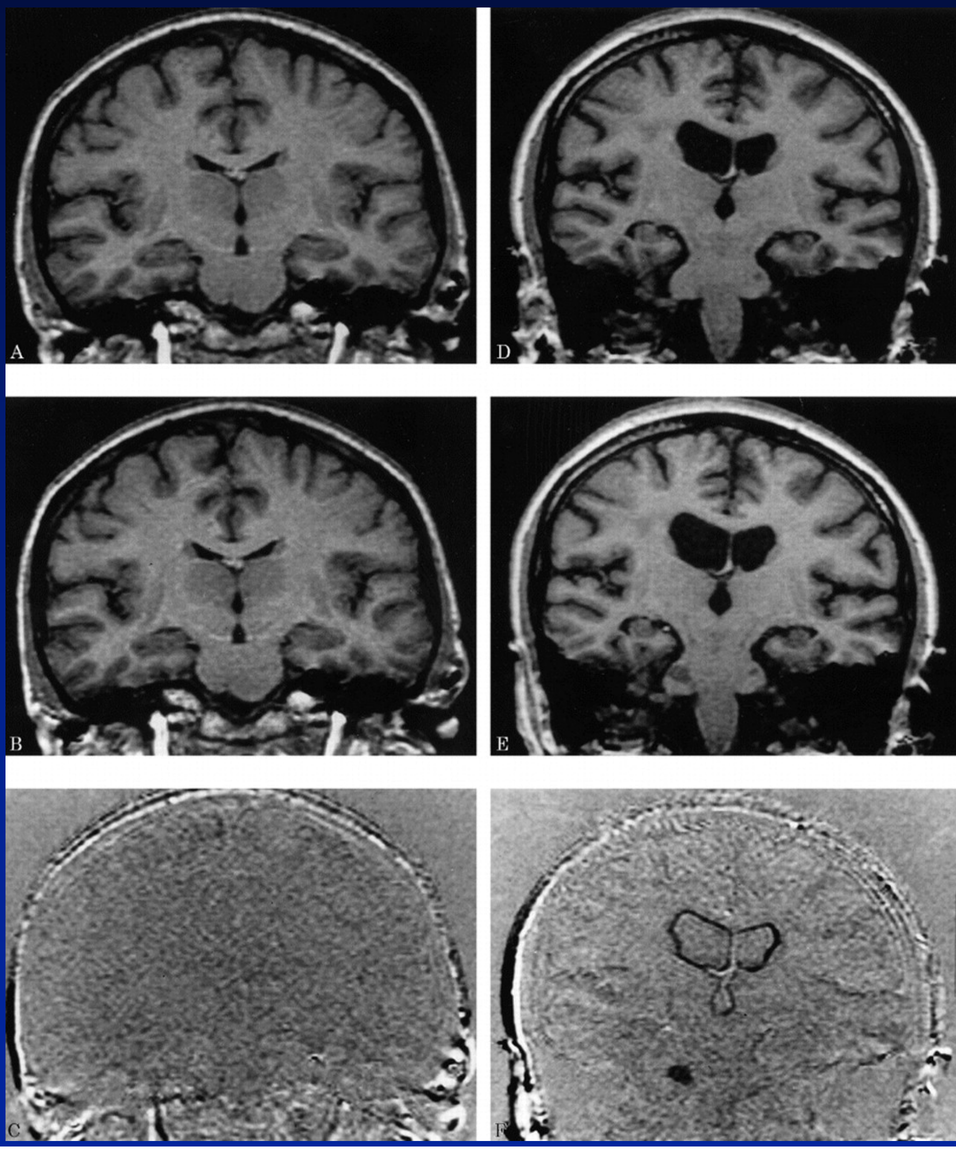


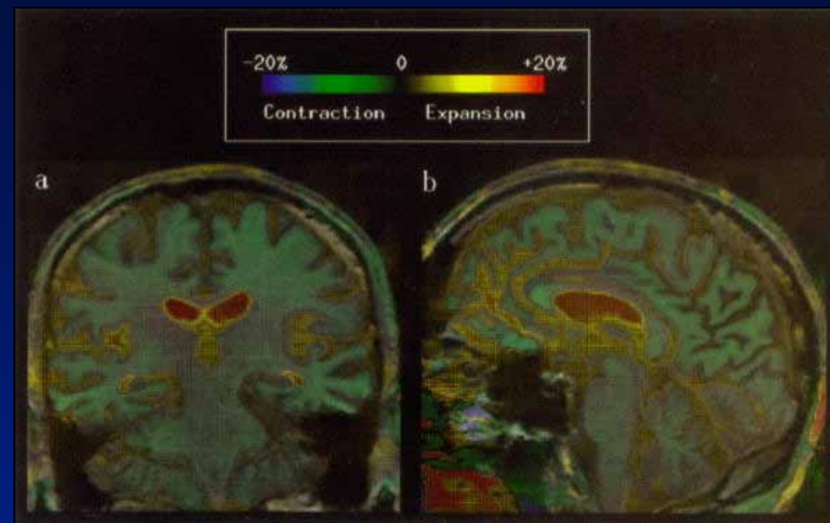
$I_2(g([x\ y\ z]))$ intensities

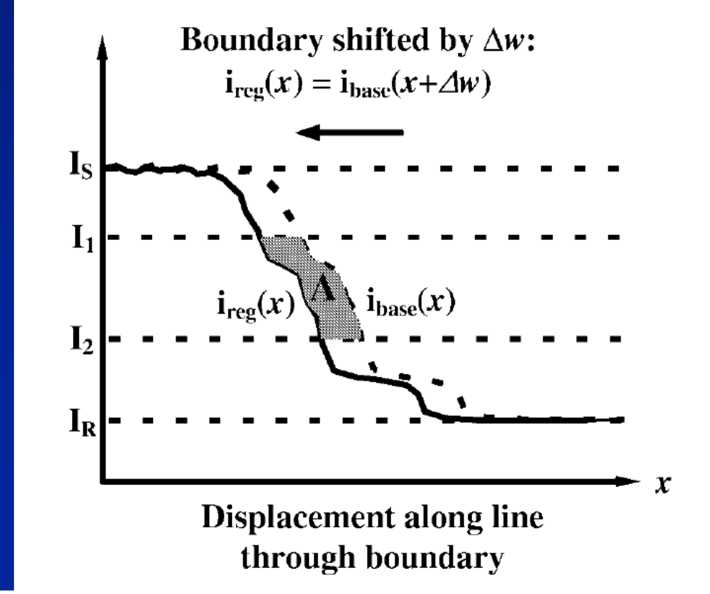
Example of Linear Alignment



Brain Boundary Shift Integral

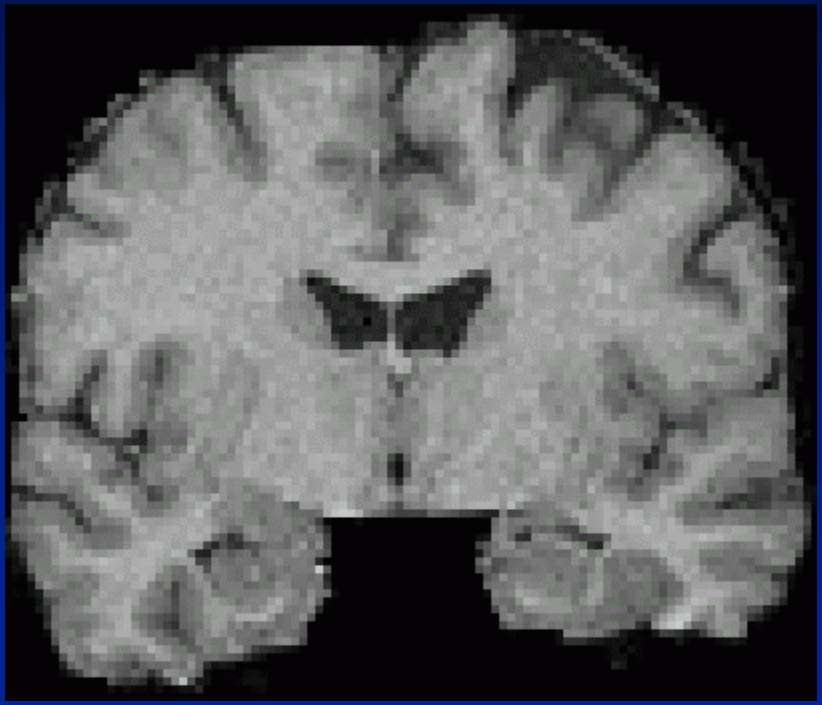




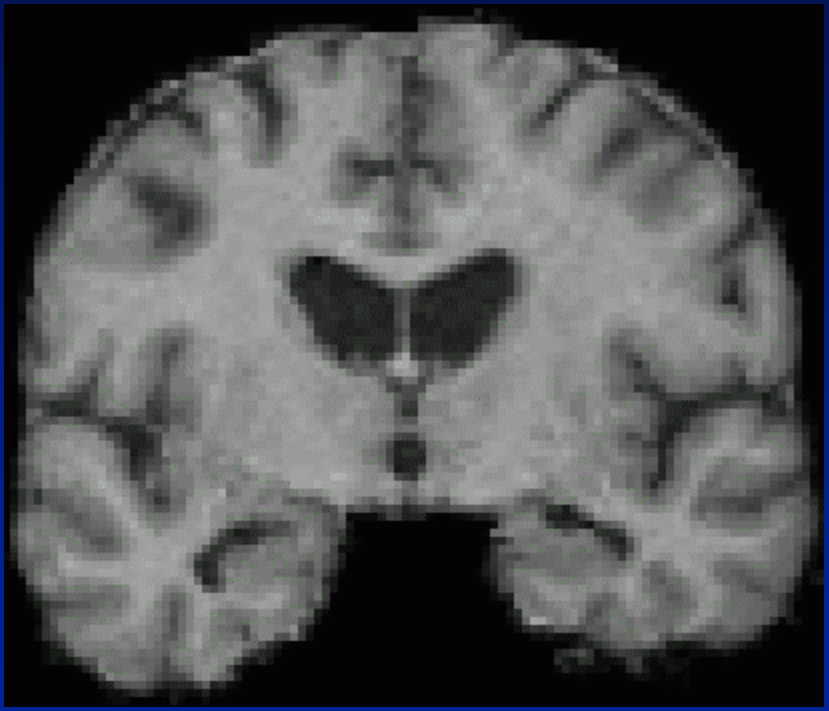


Non-linear Alignment

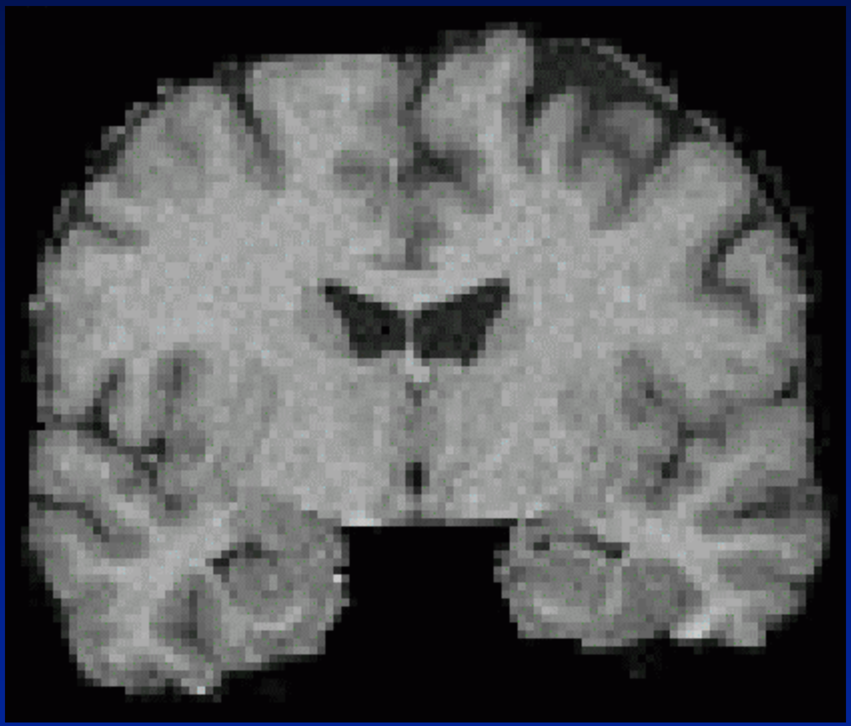
Starting Subject Brain

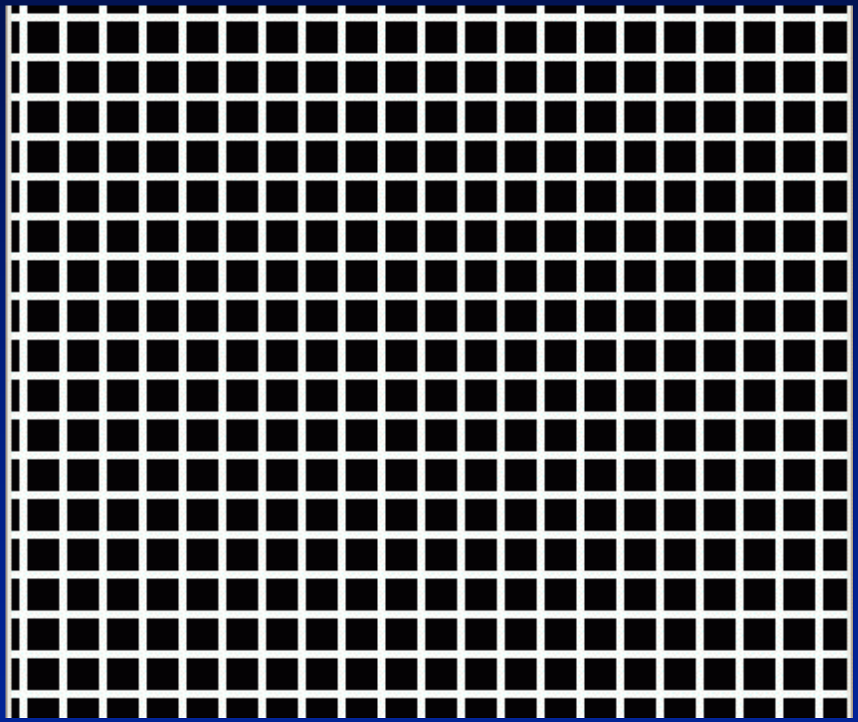


Target Brain to Warp onto

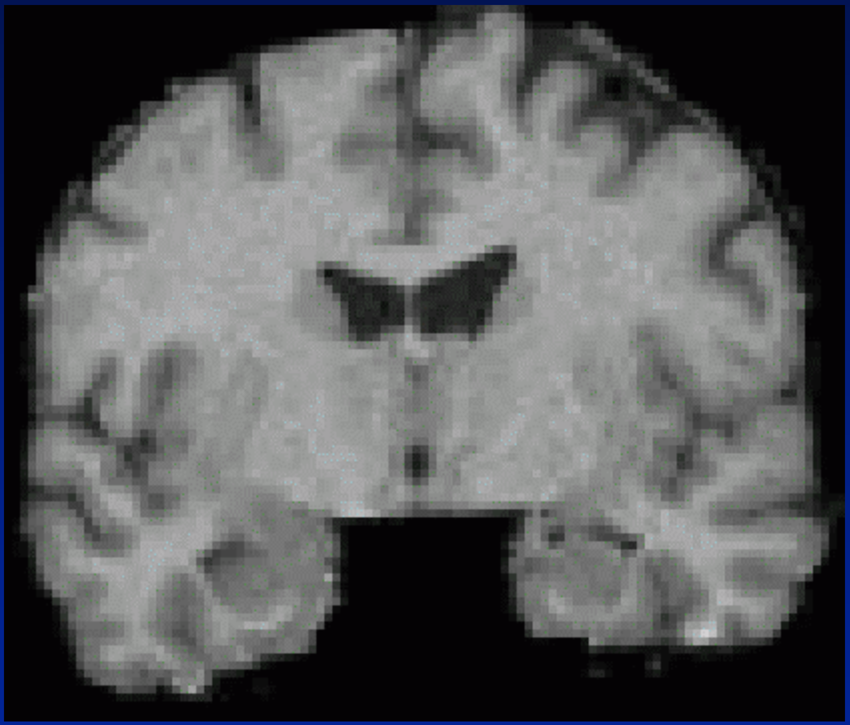


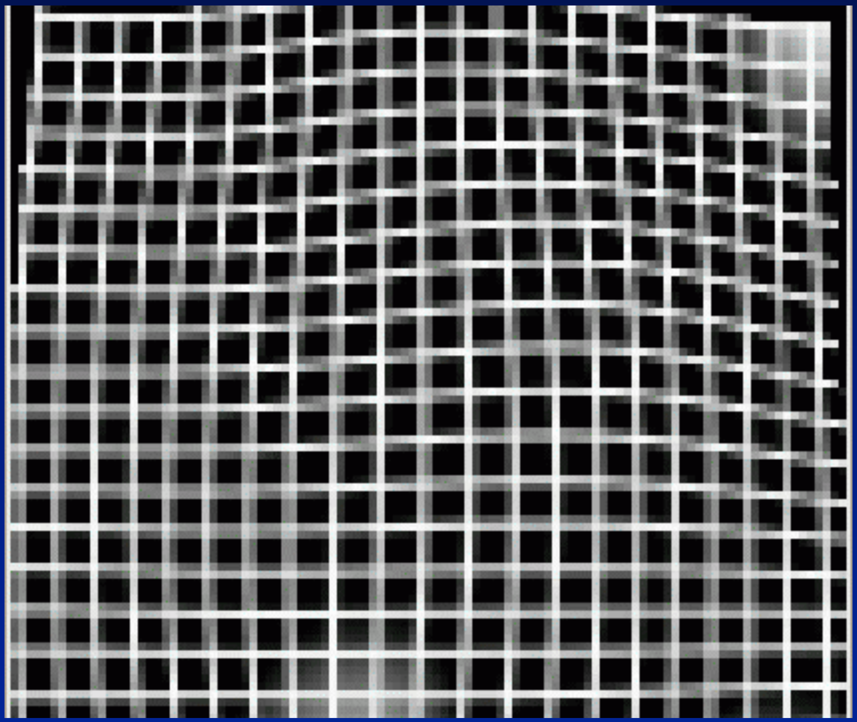
The Method in Action: Left hand image starts with subject, right with unwarped grid



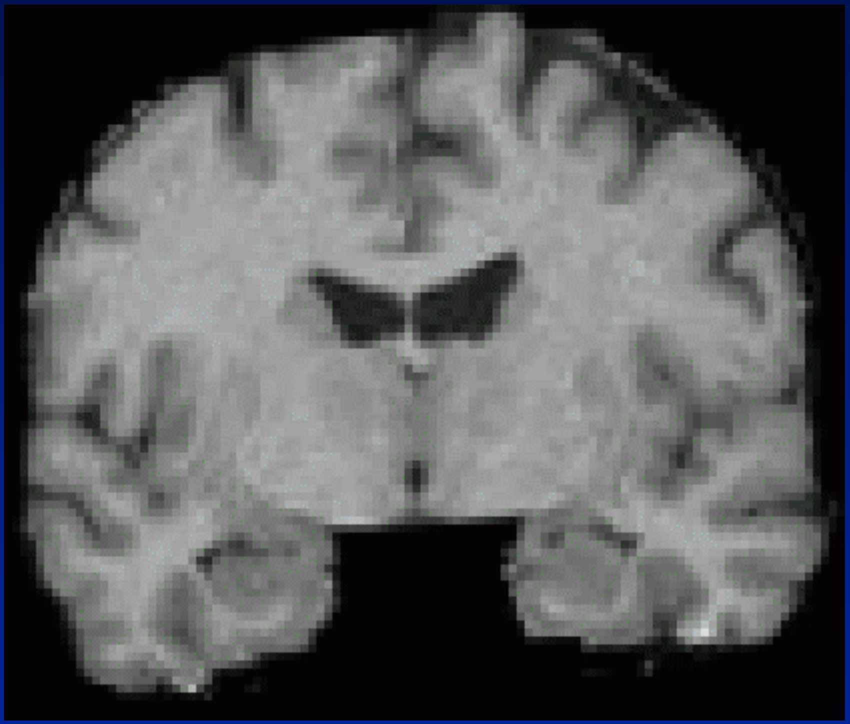


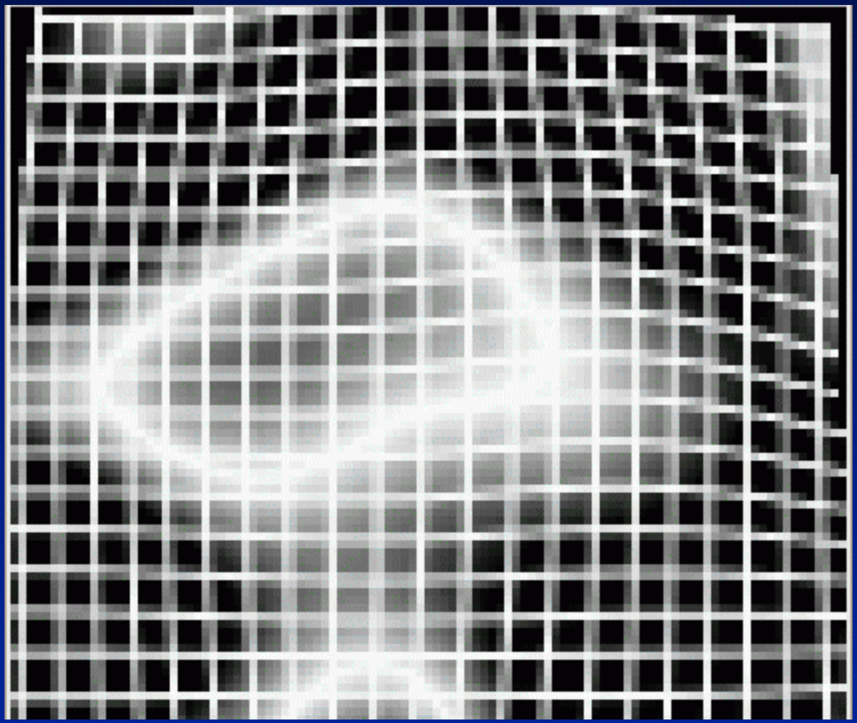
Initial large-scale warps



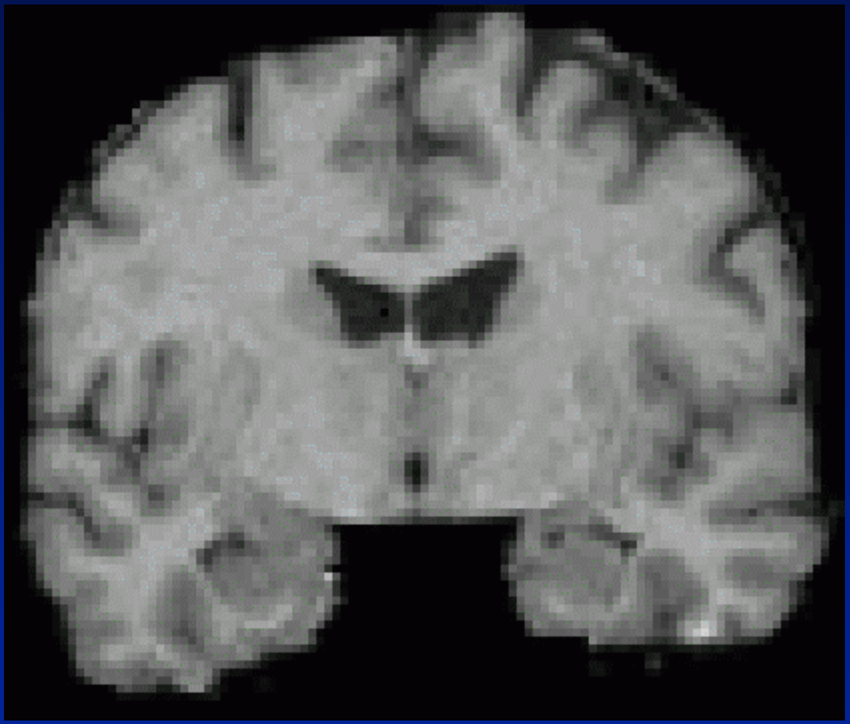


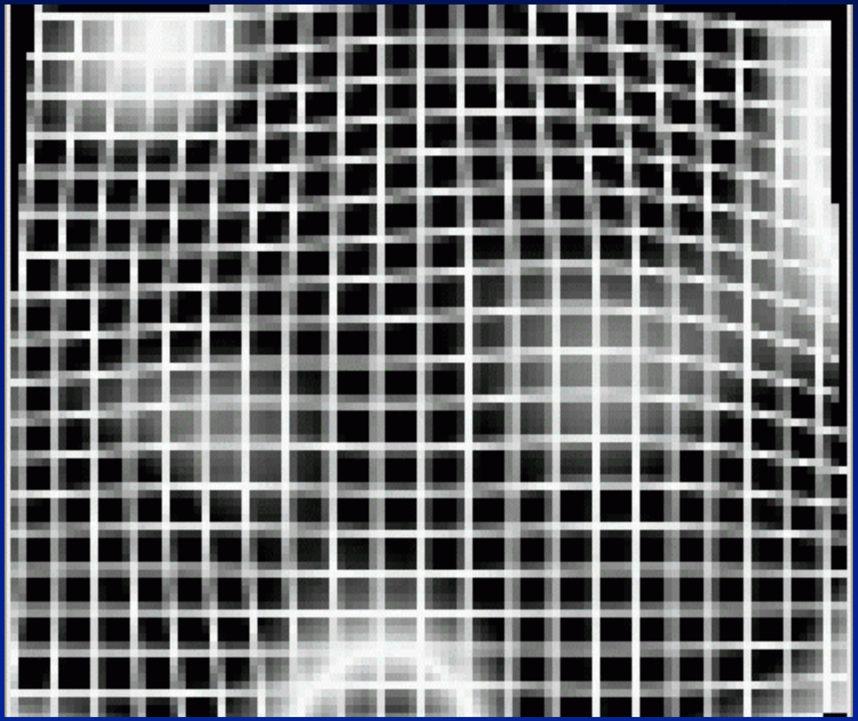
Further warping including out-of-slice warps





The Method in Action





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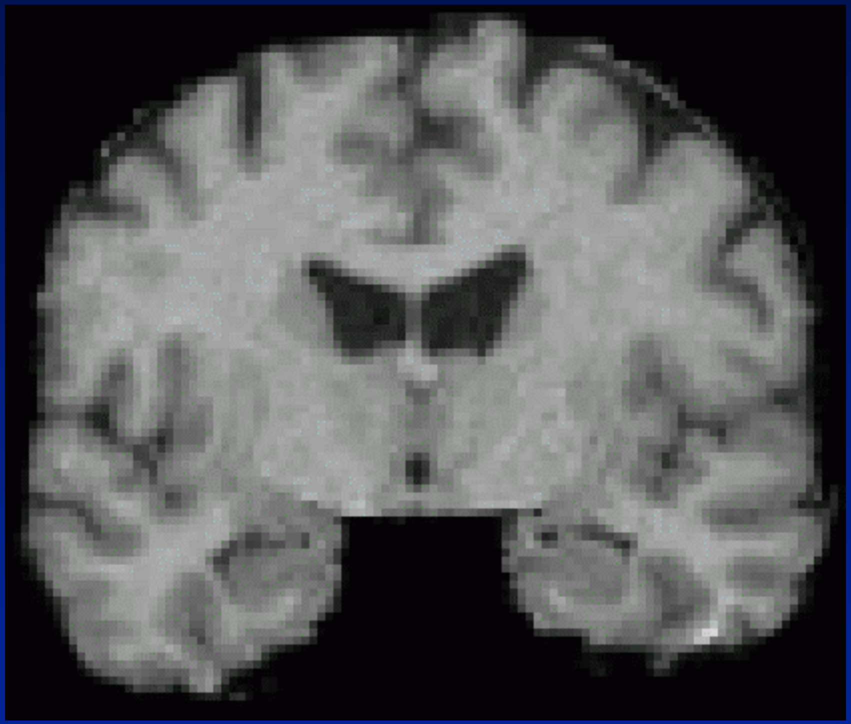

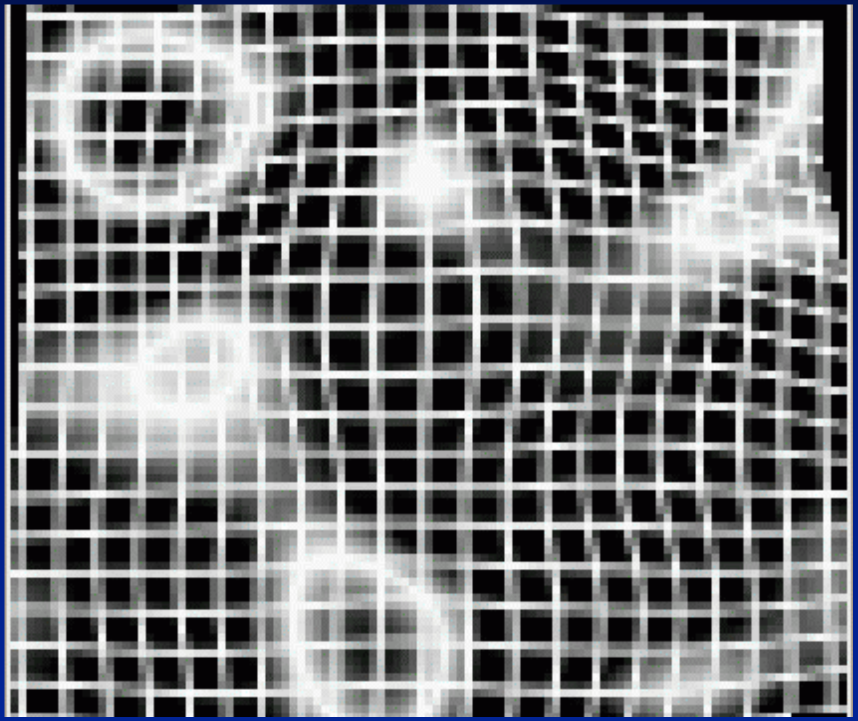

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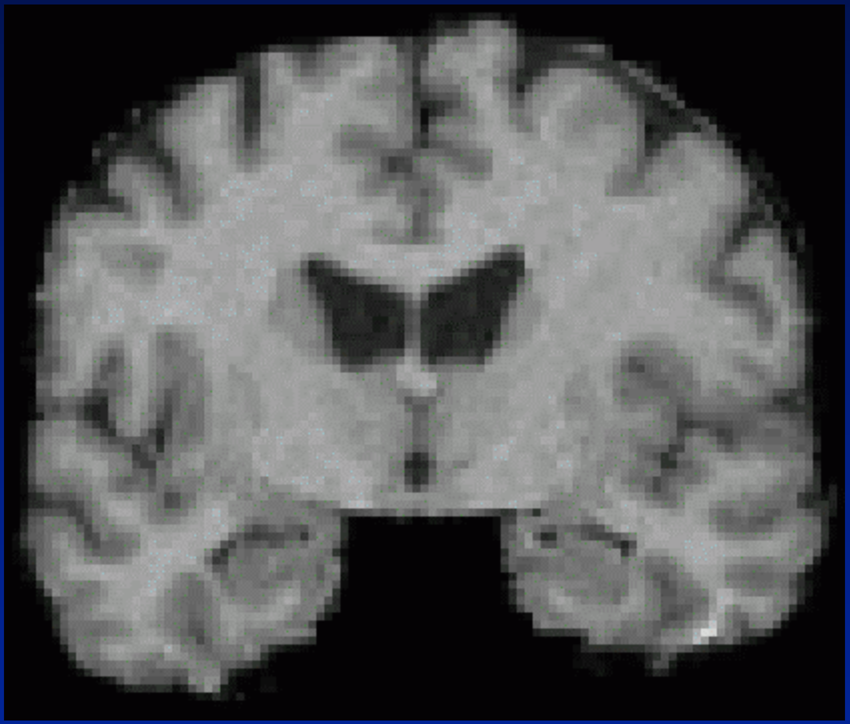

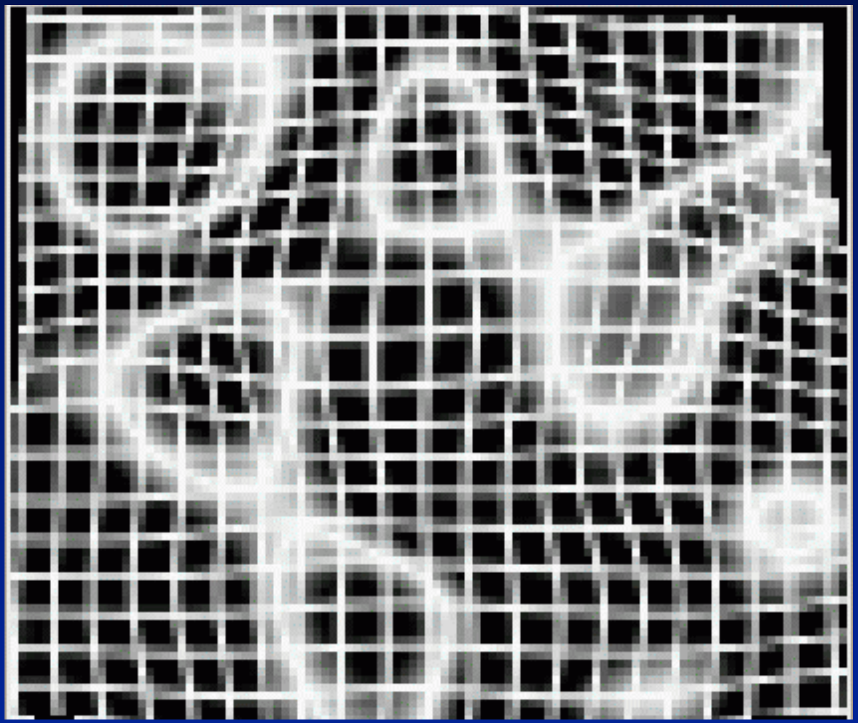

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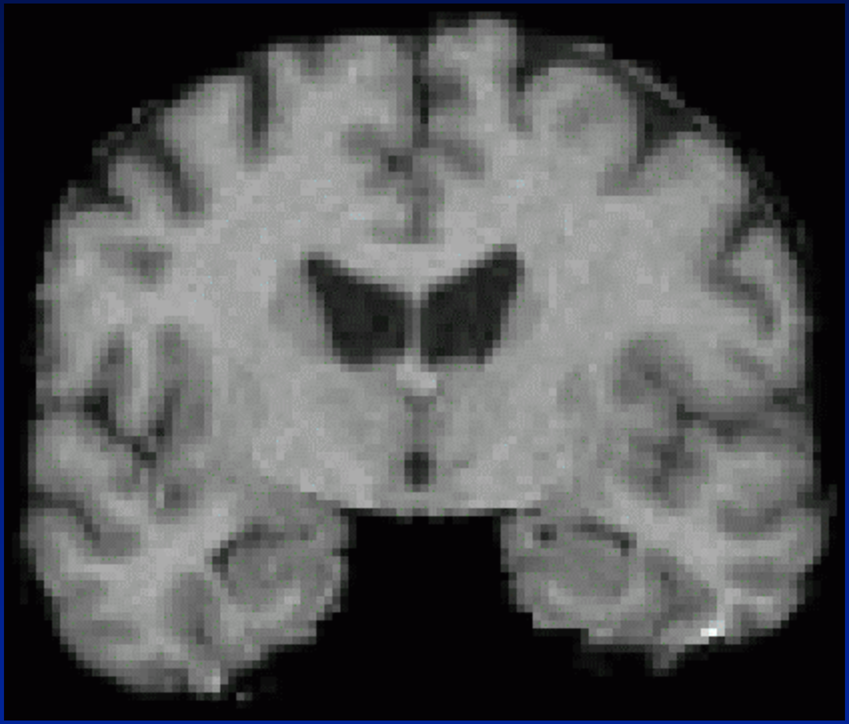

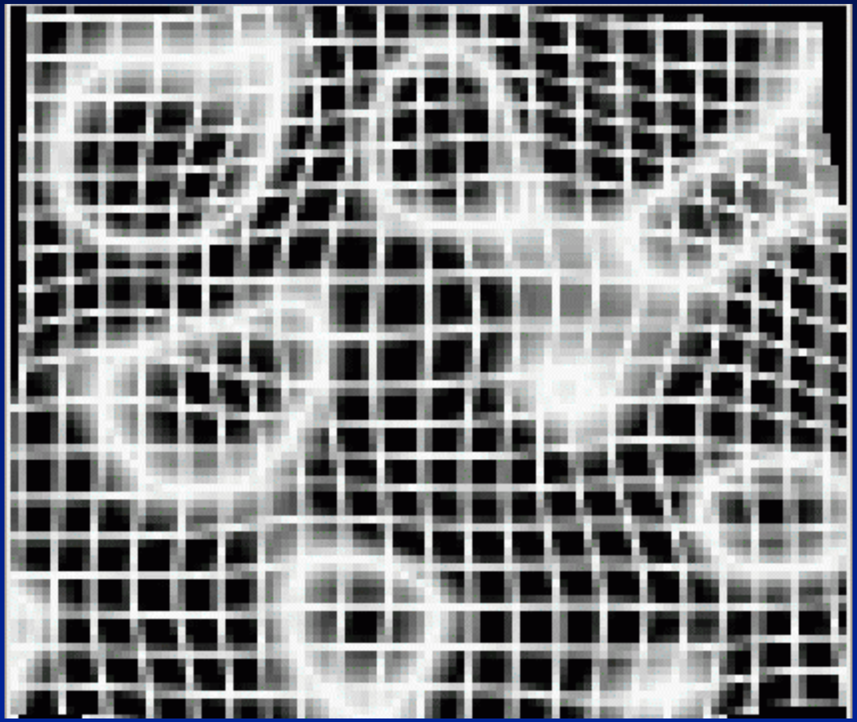

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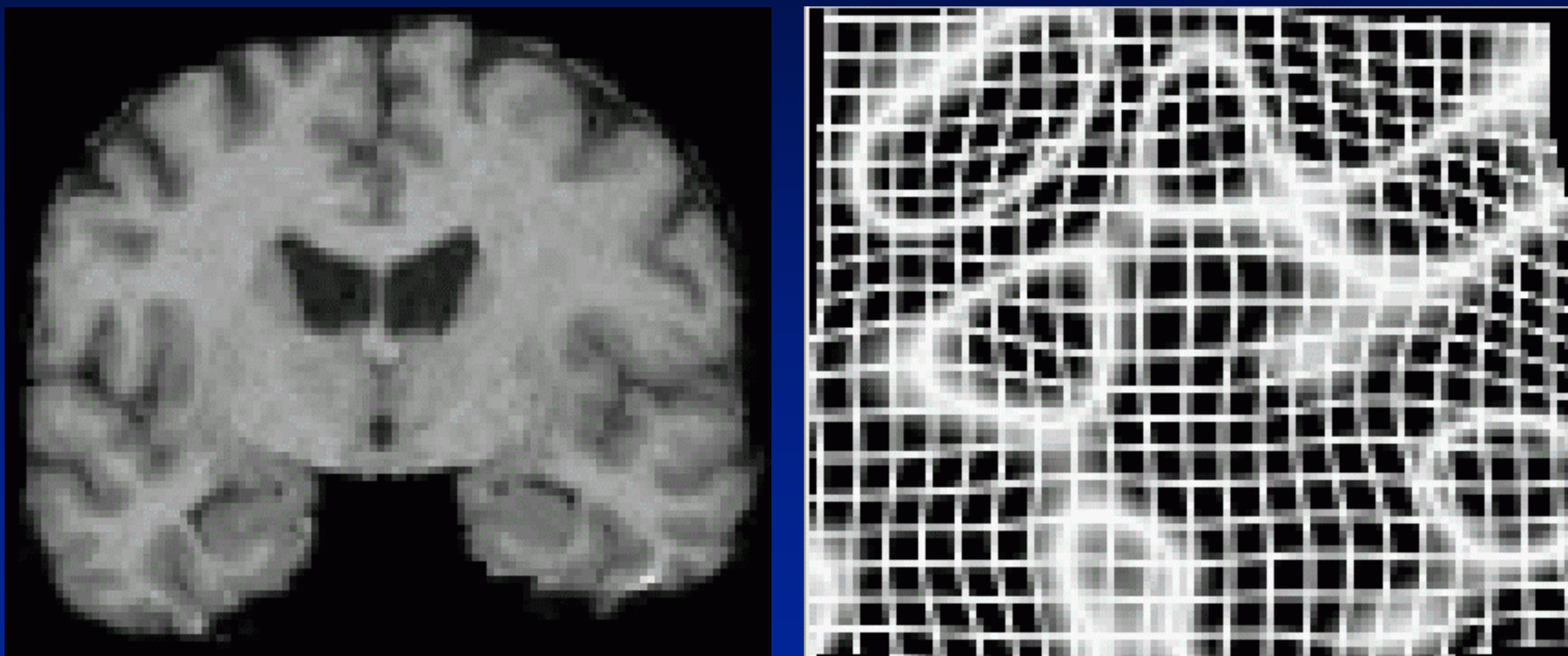

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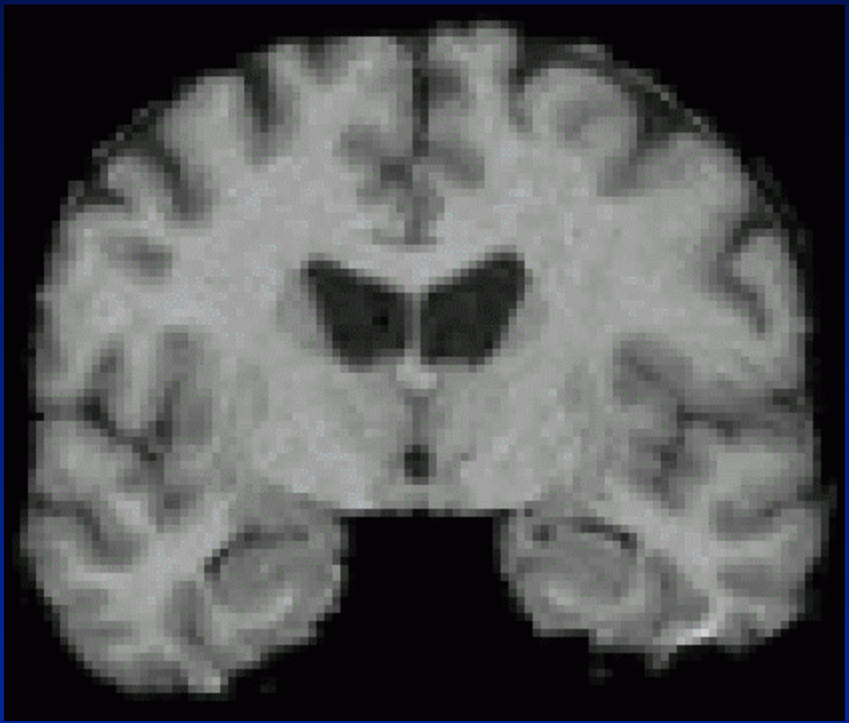

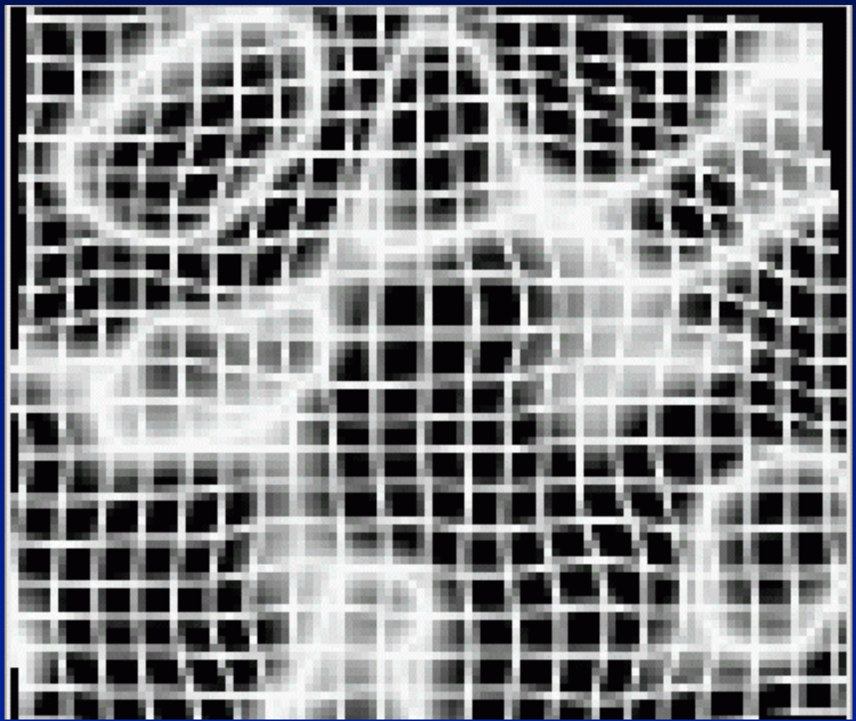

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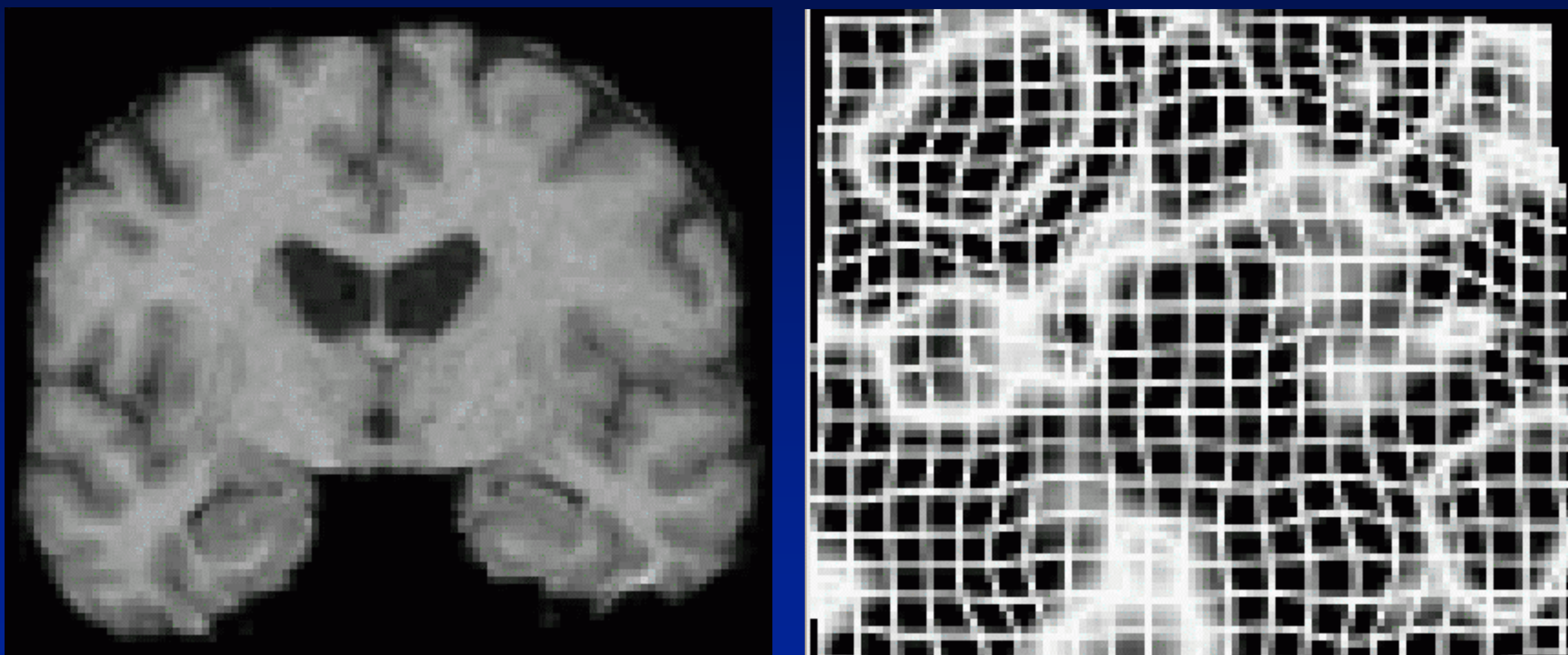

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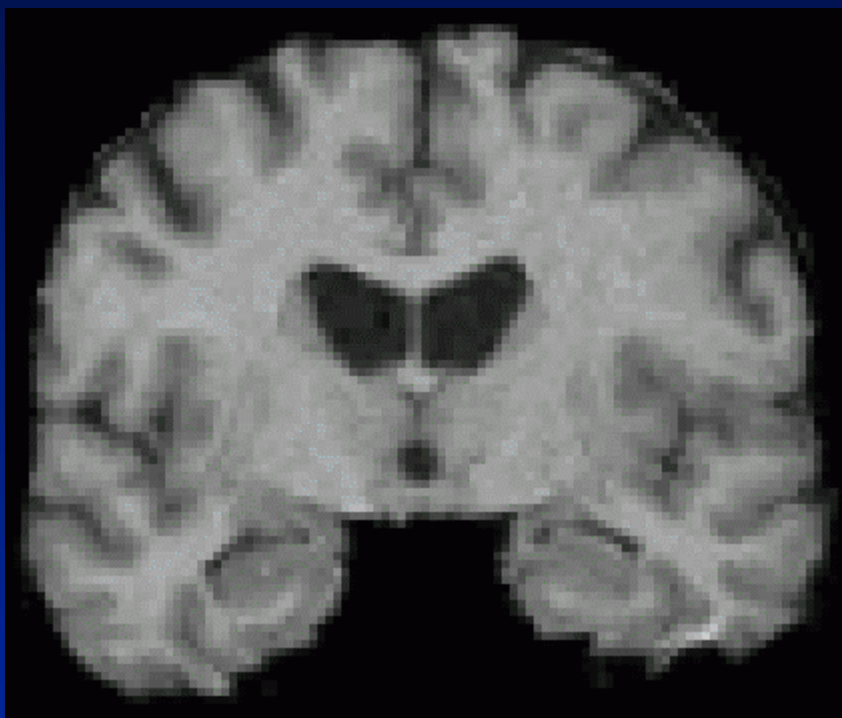

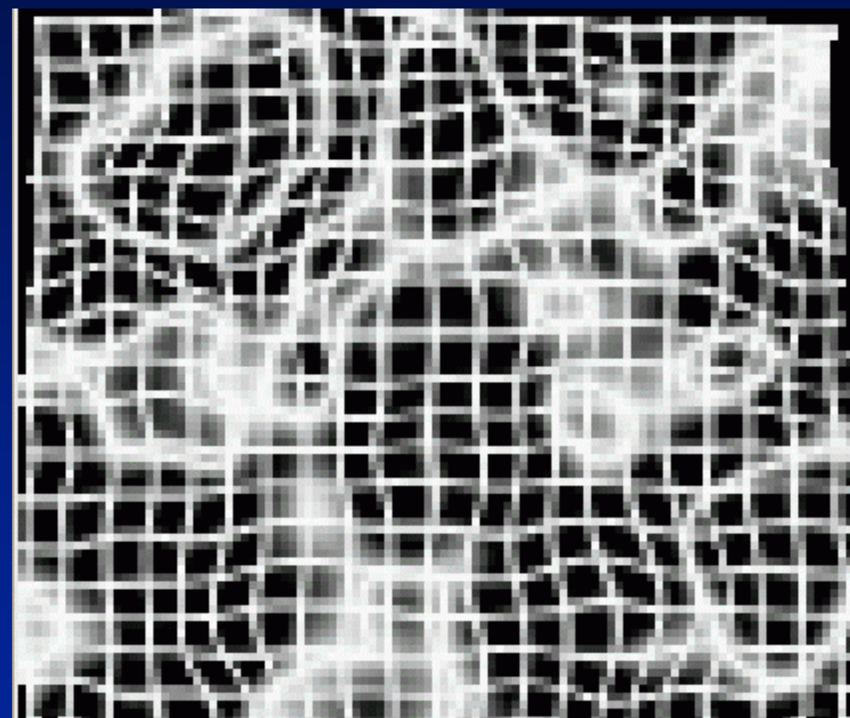

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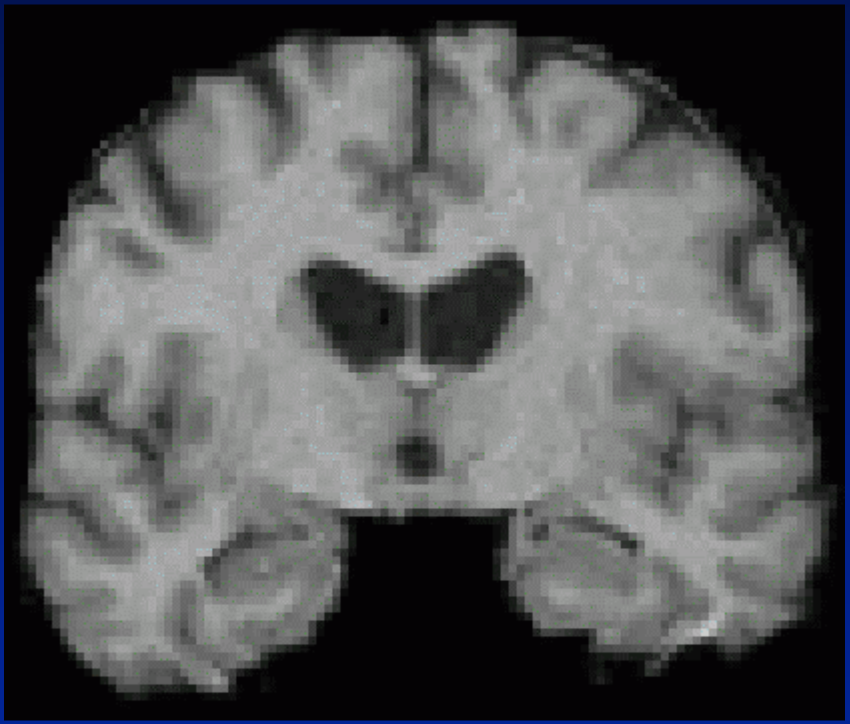

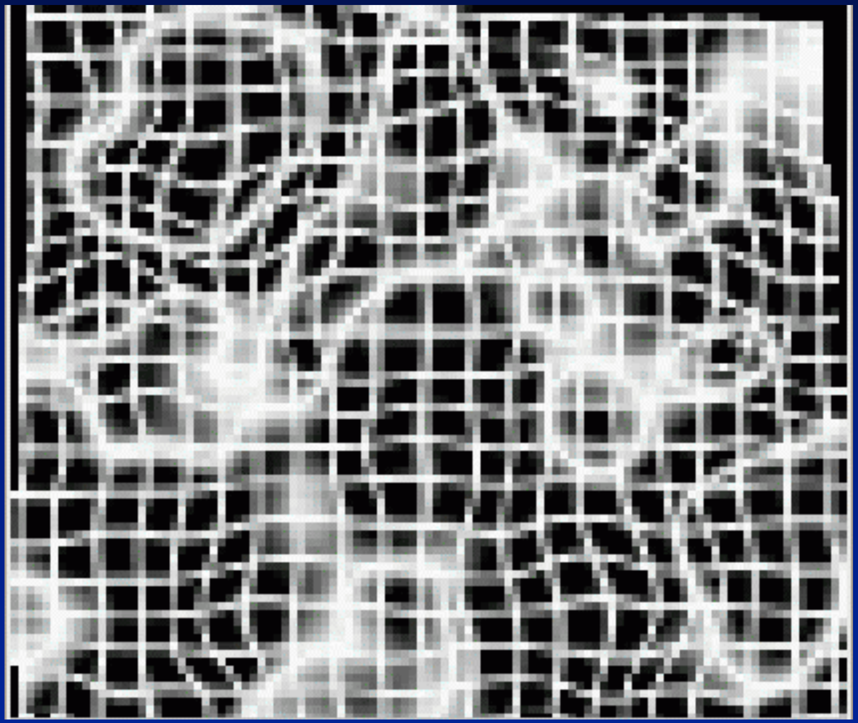

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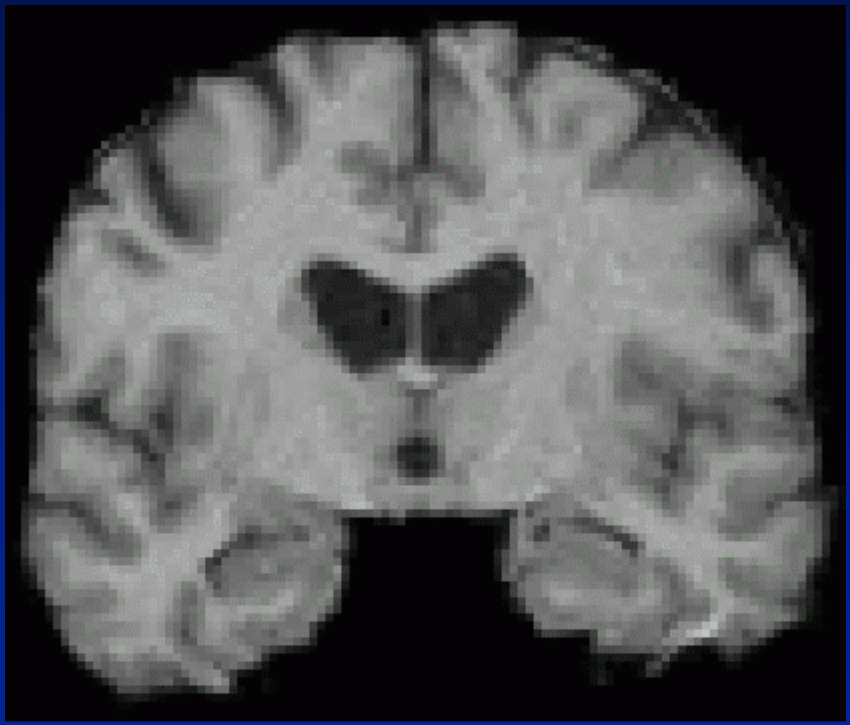

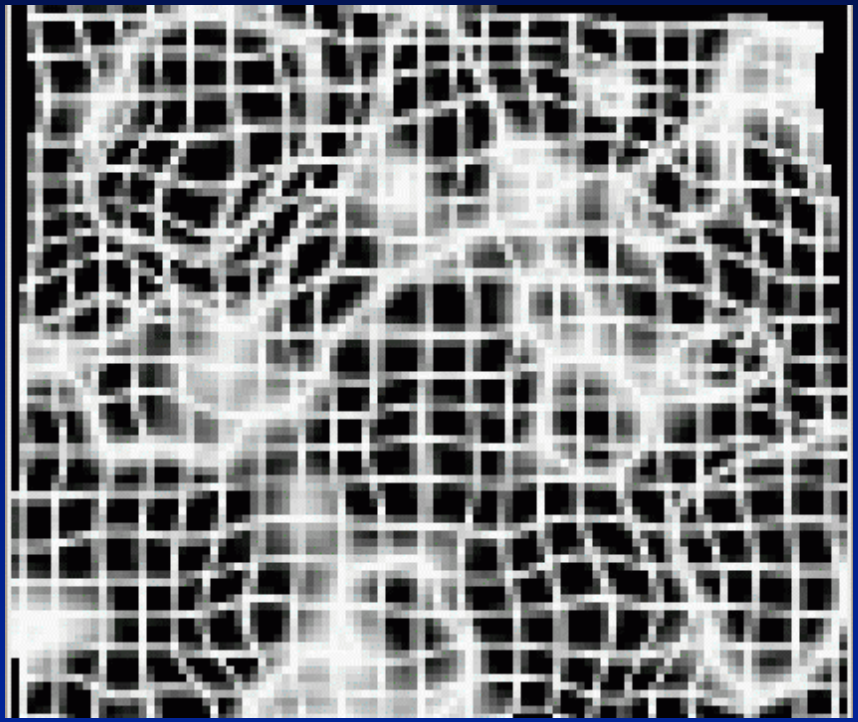

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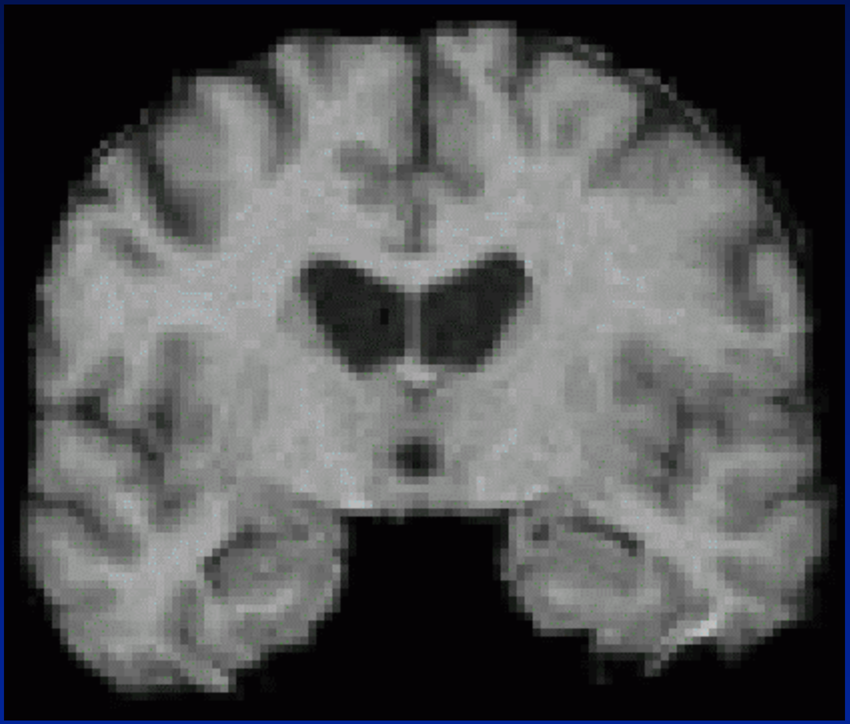

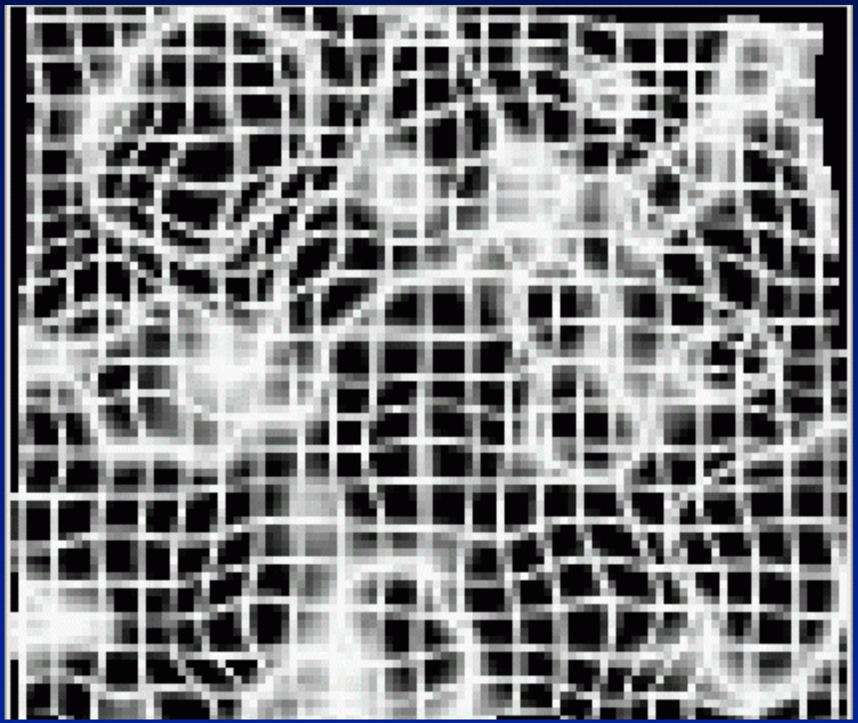

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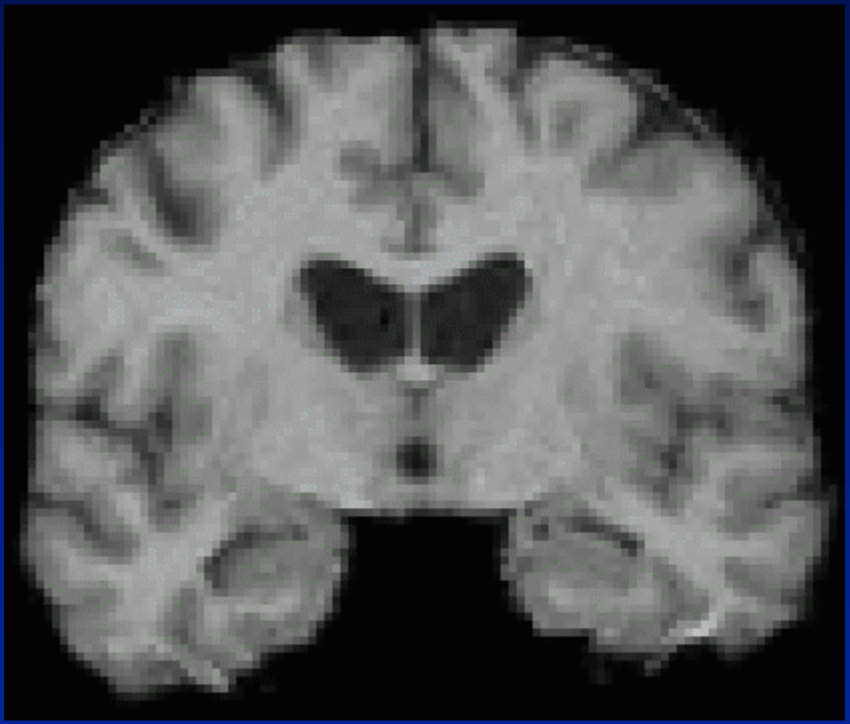

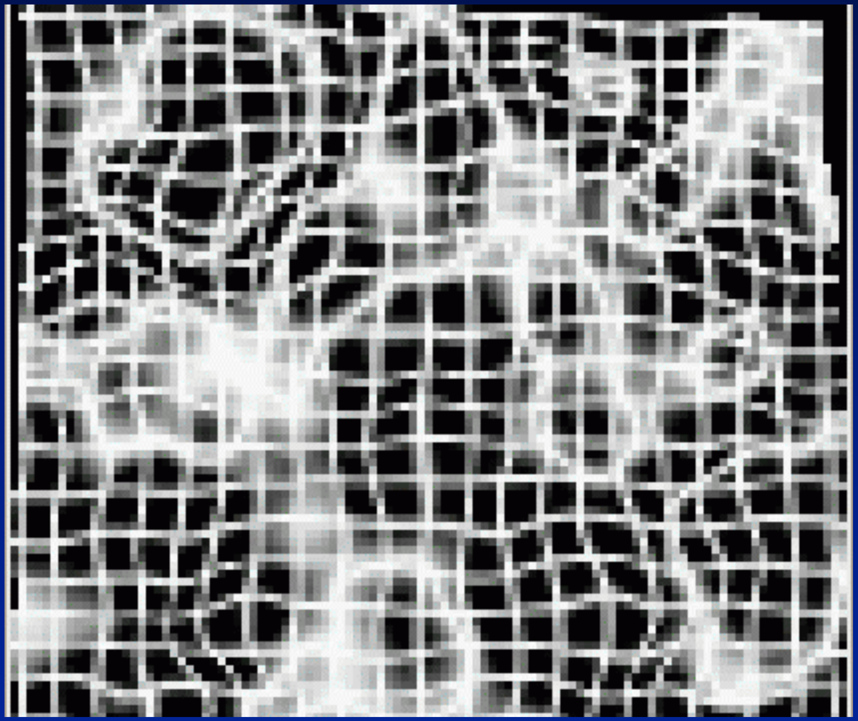

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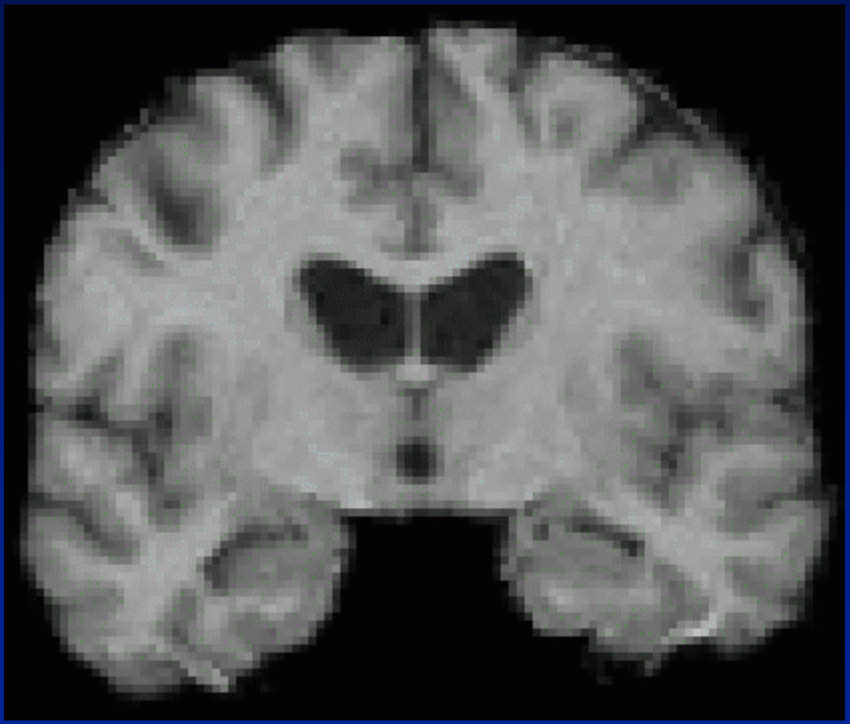

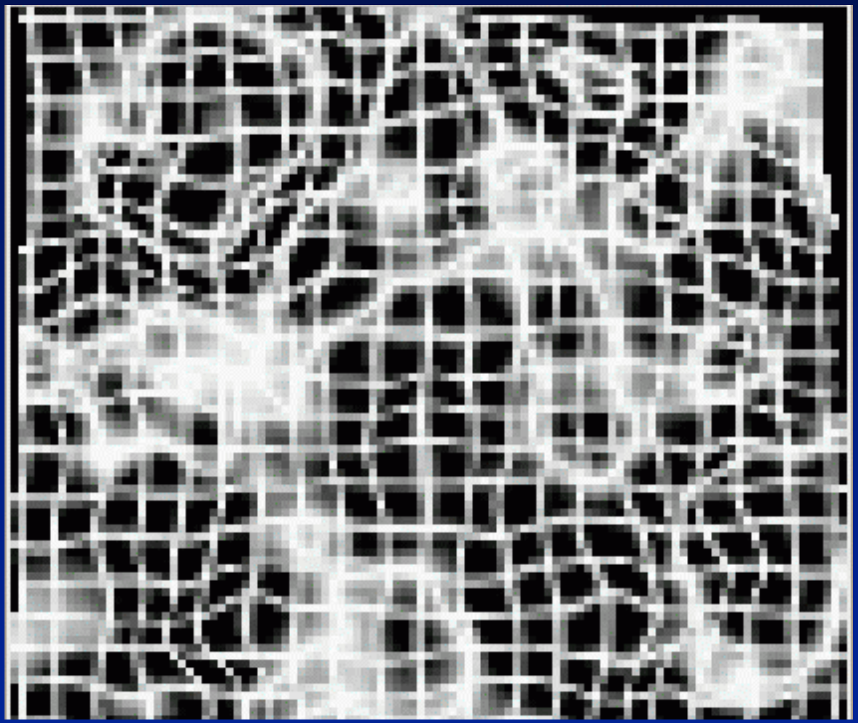

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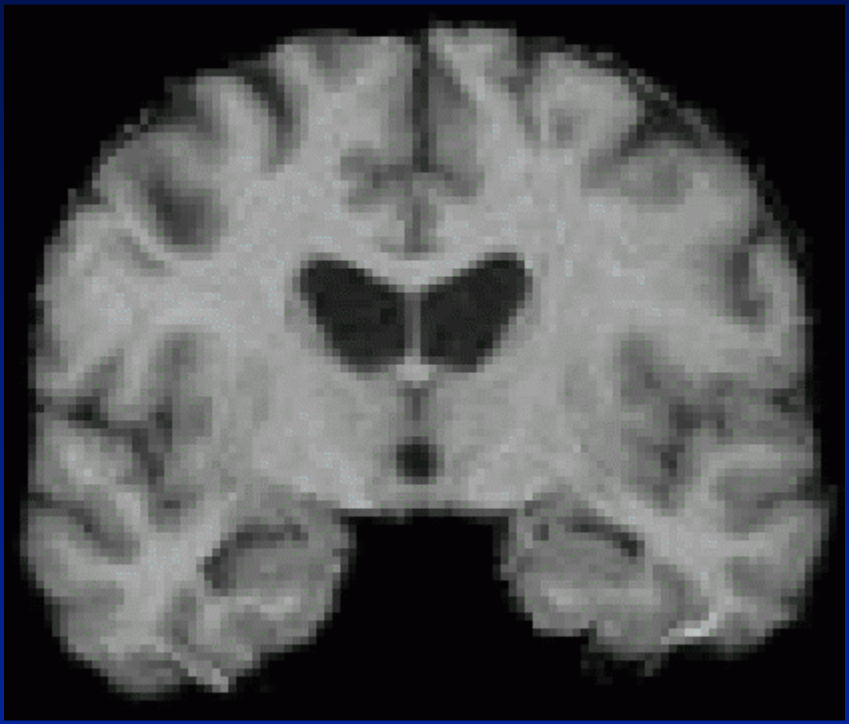
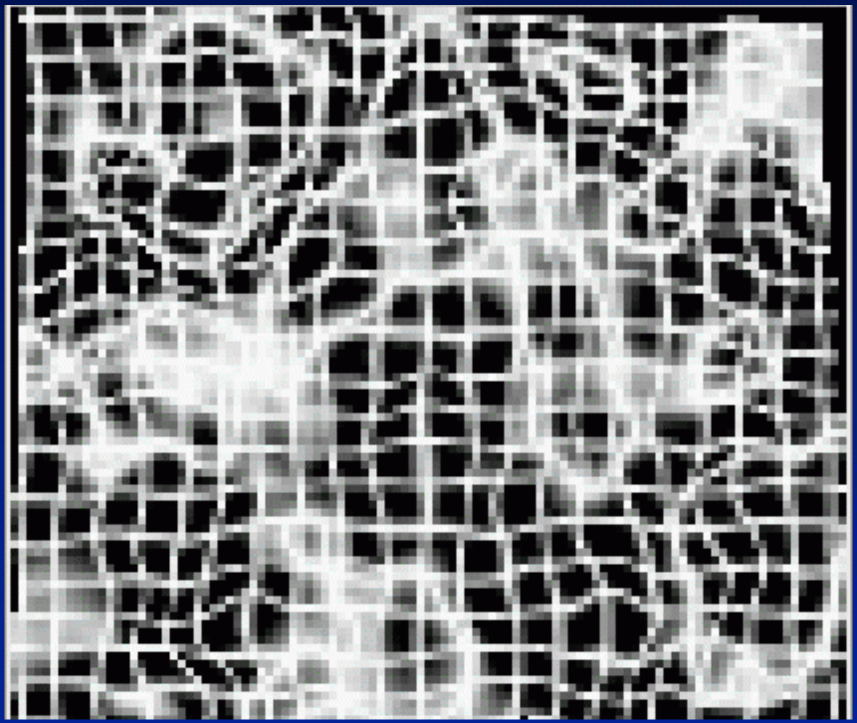
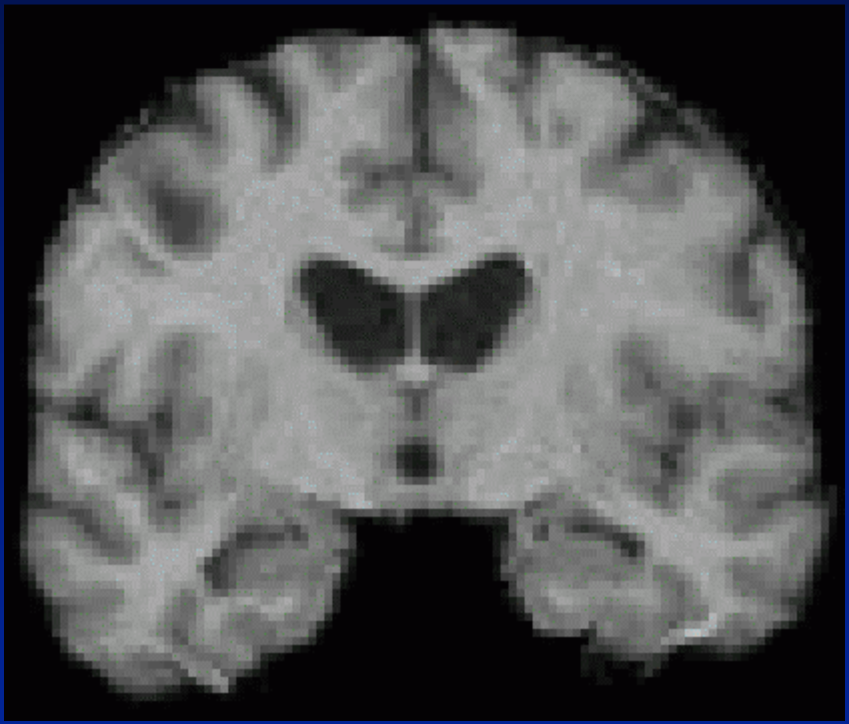
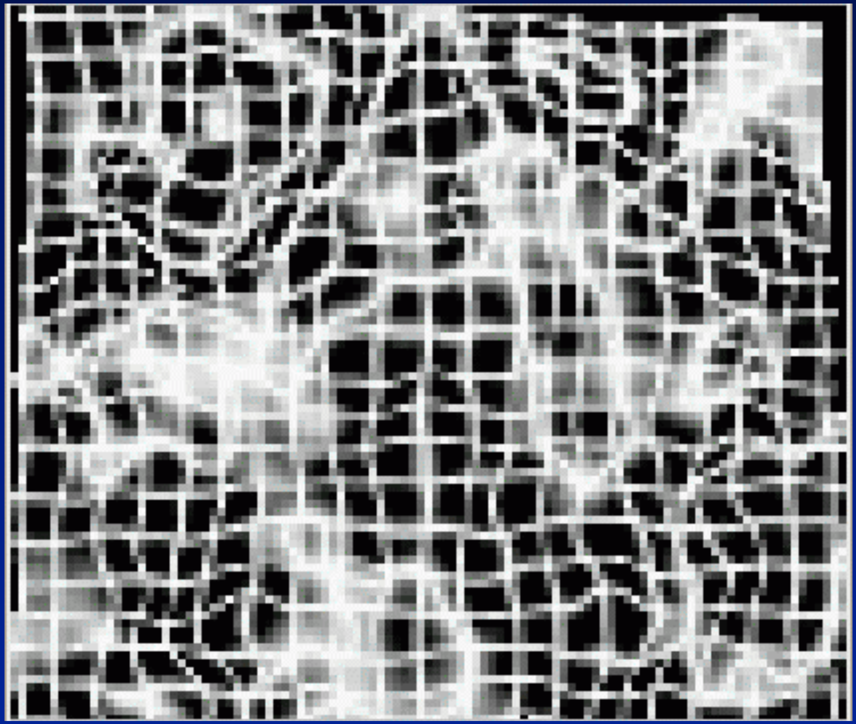




The Method in Action





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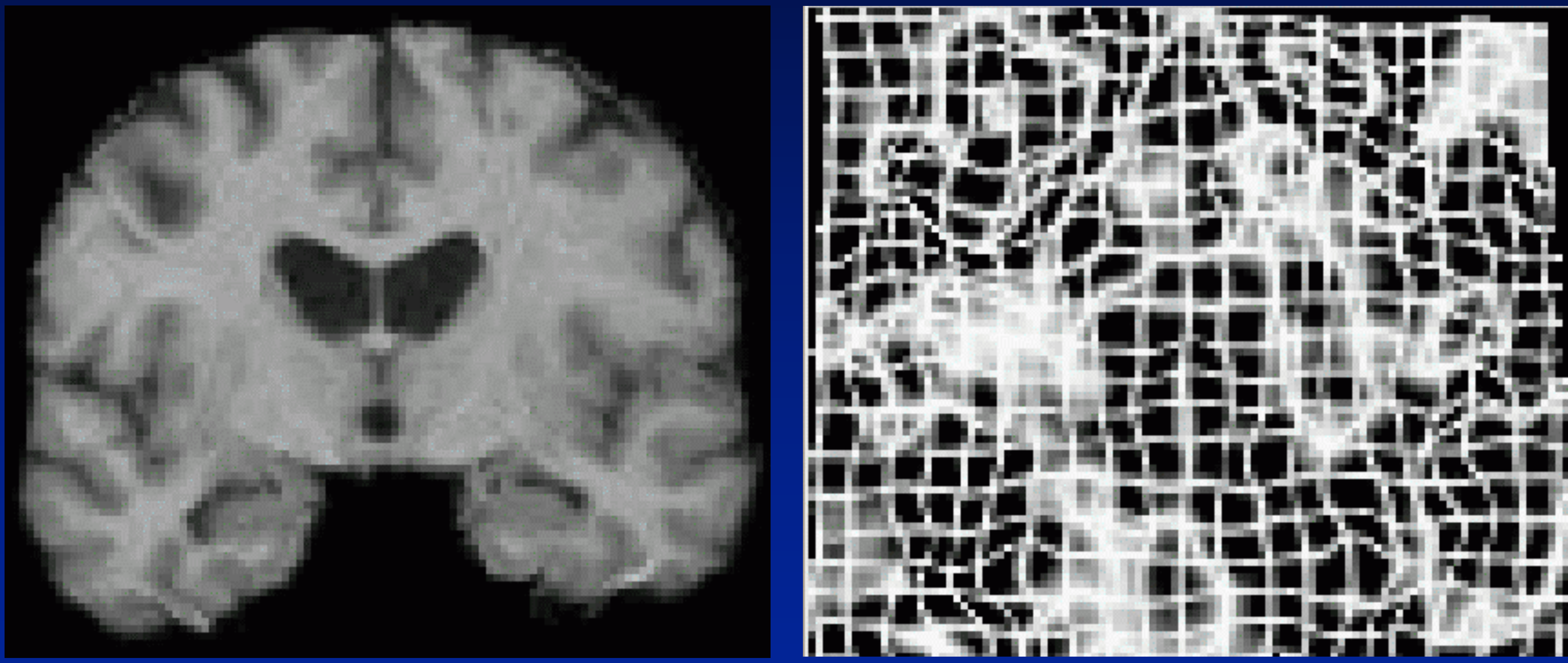
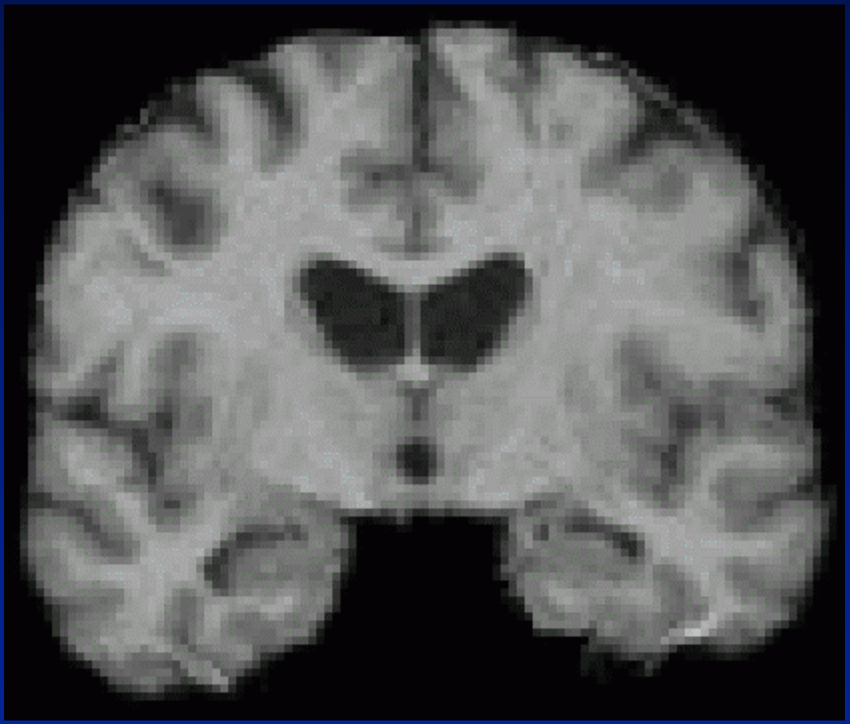
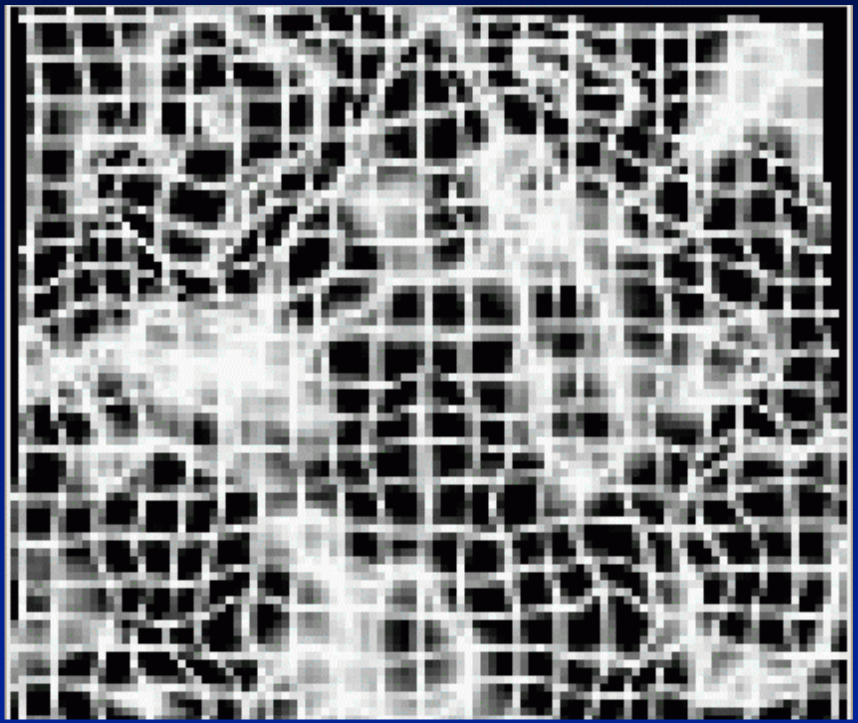


The Method in Action





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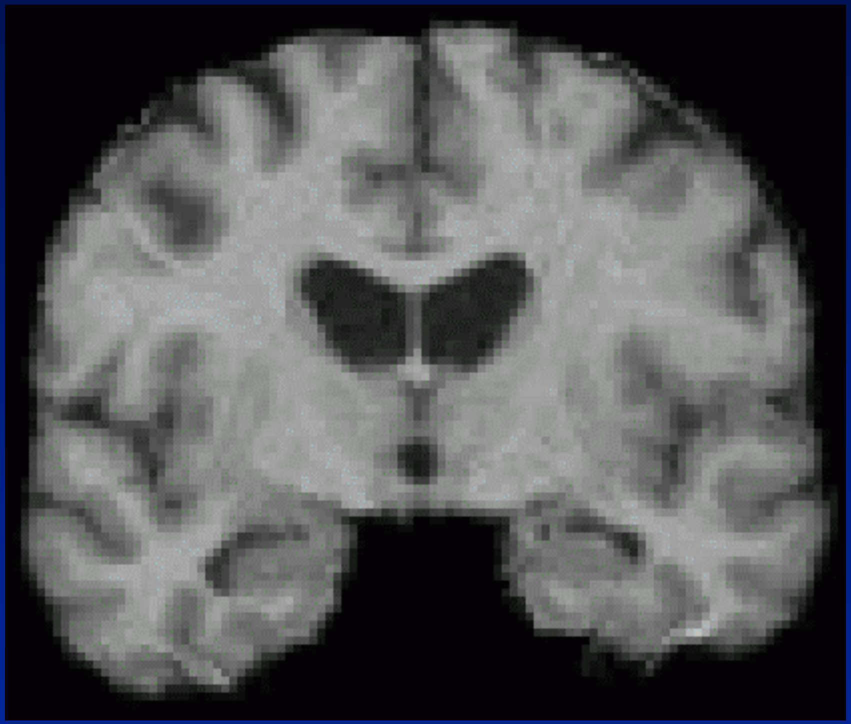
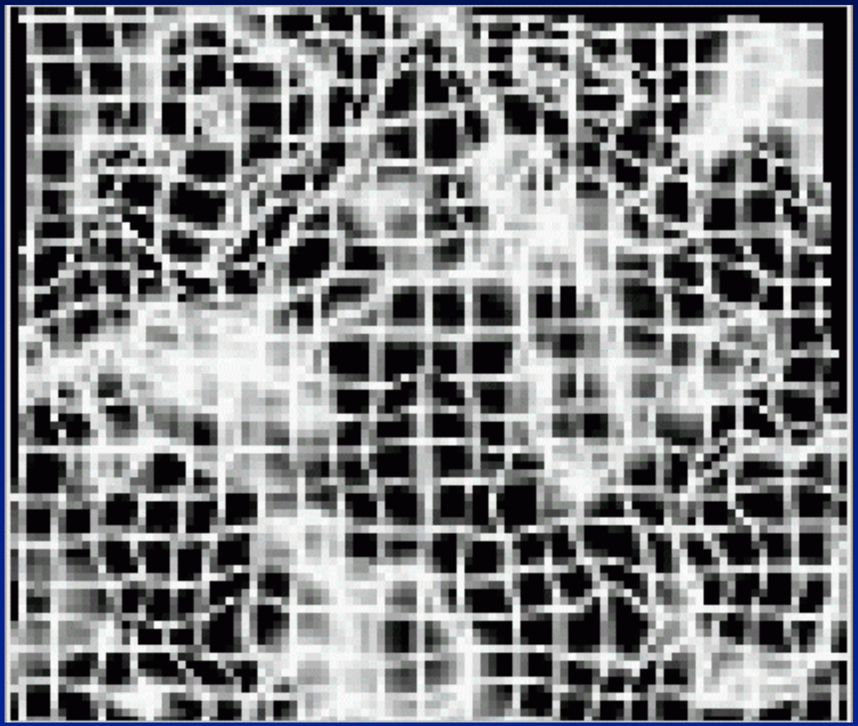
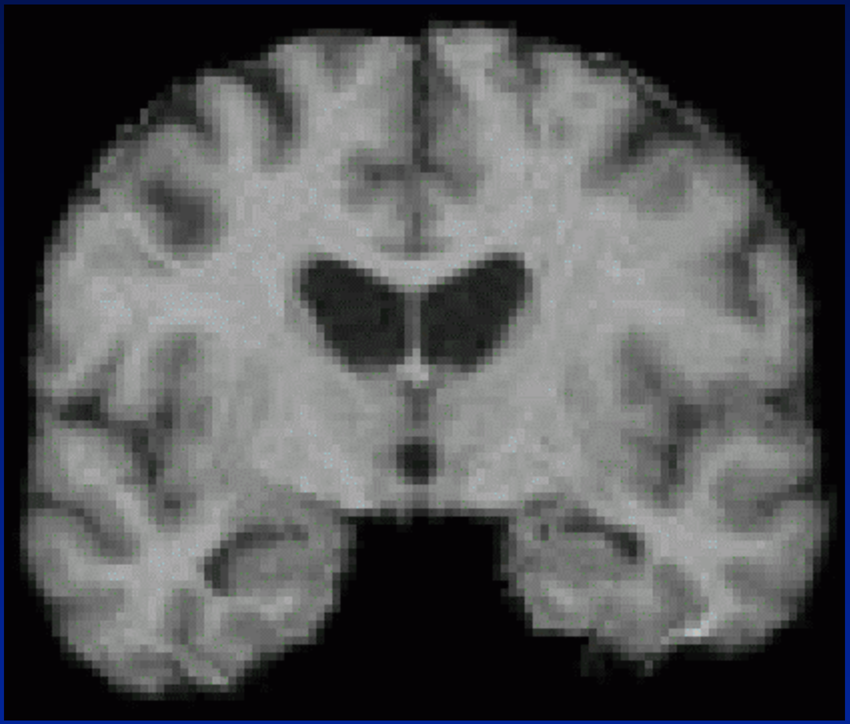
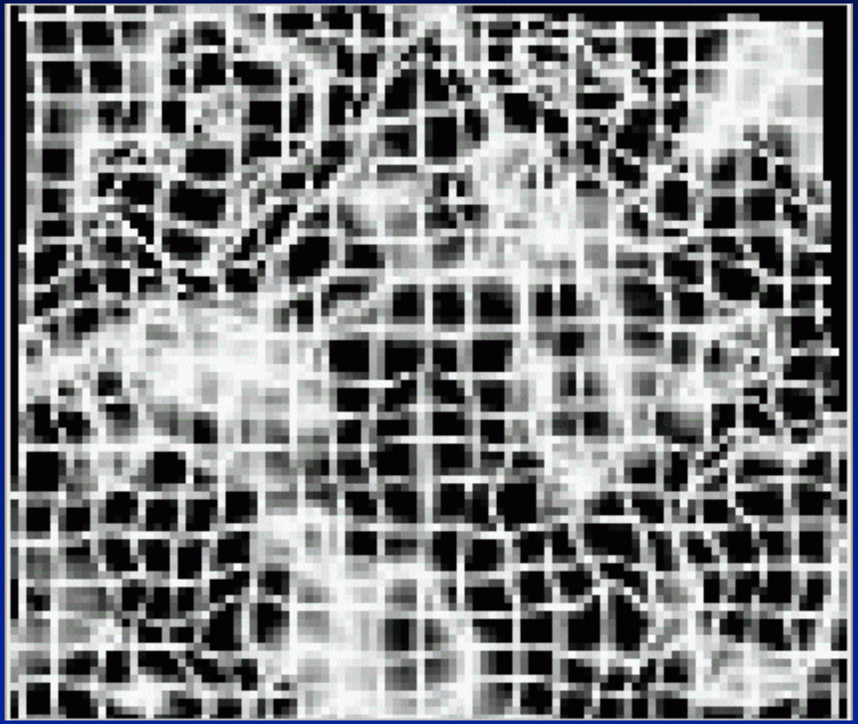


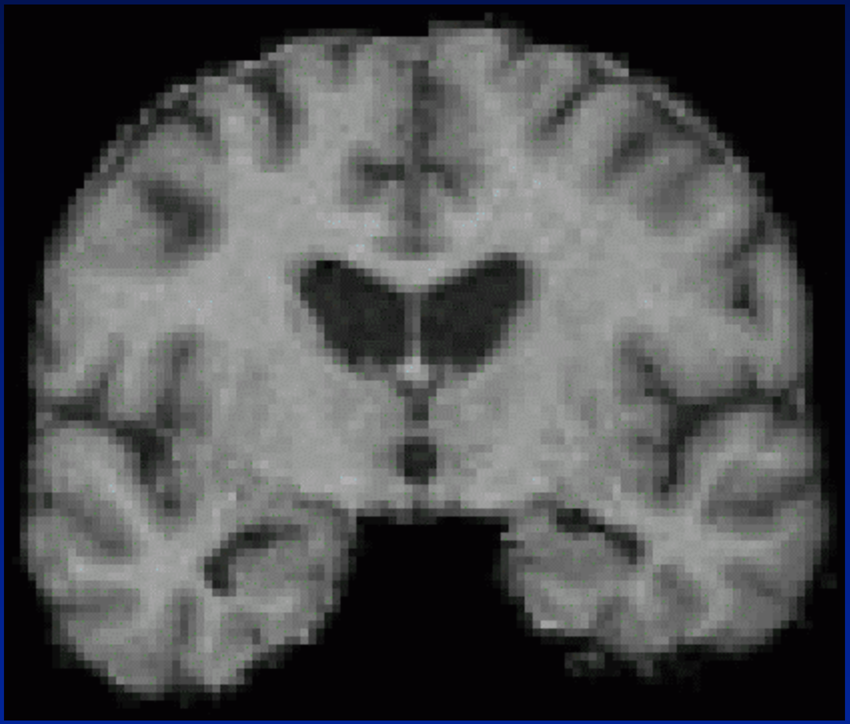


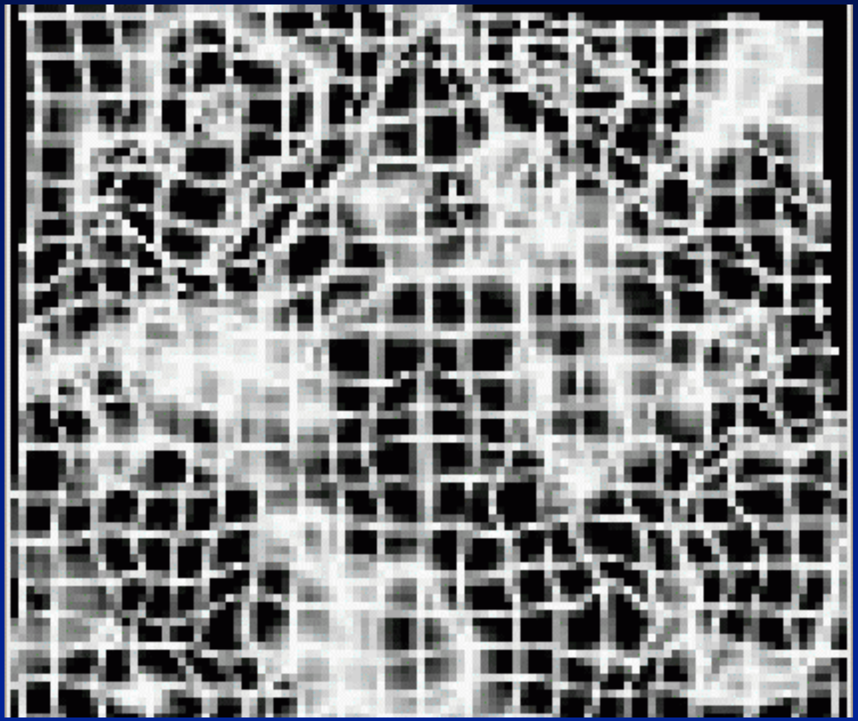
The Method in Action





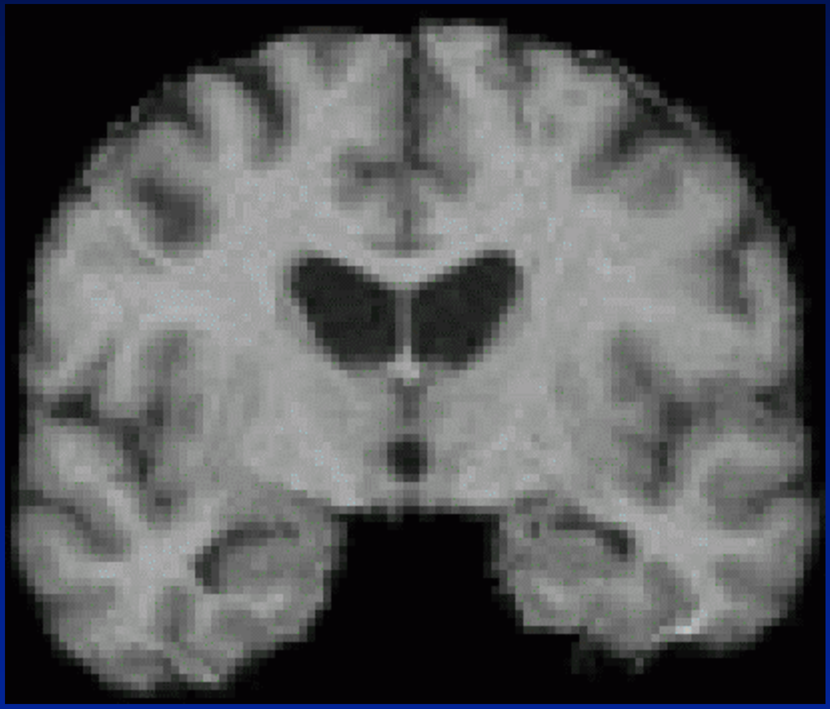
The Method in Action



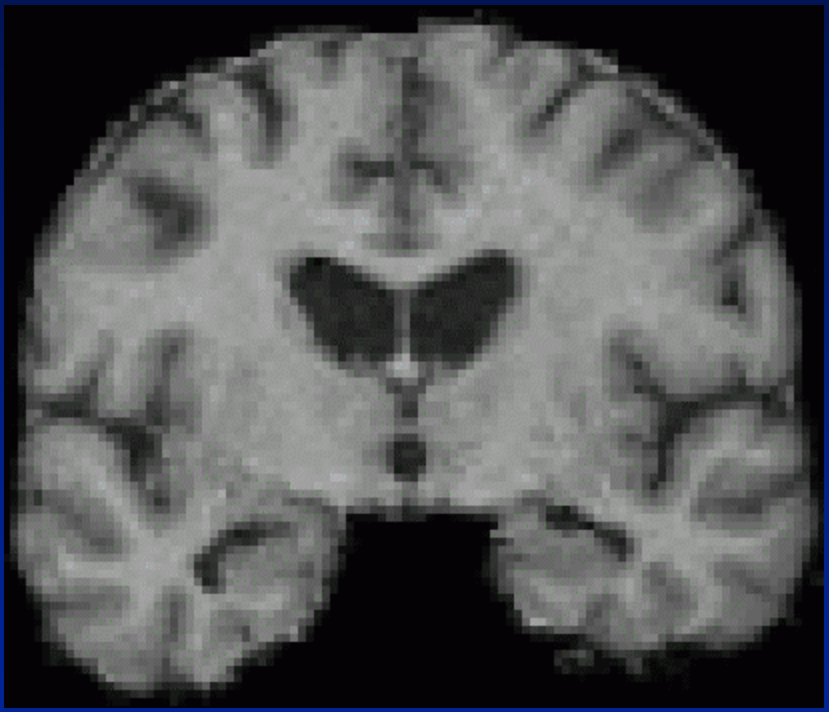


Now Brains are in a Common Space

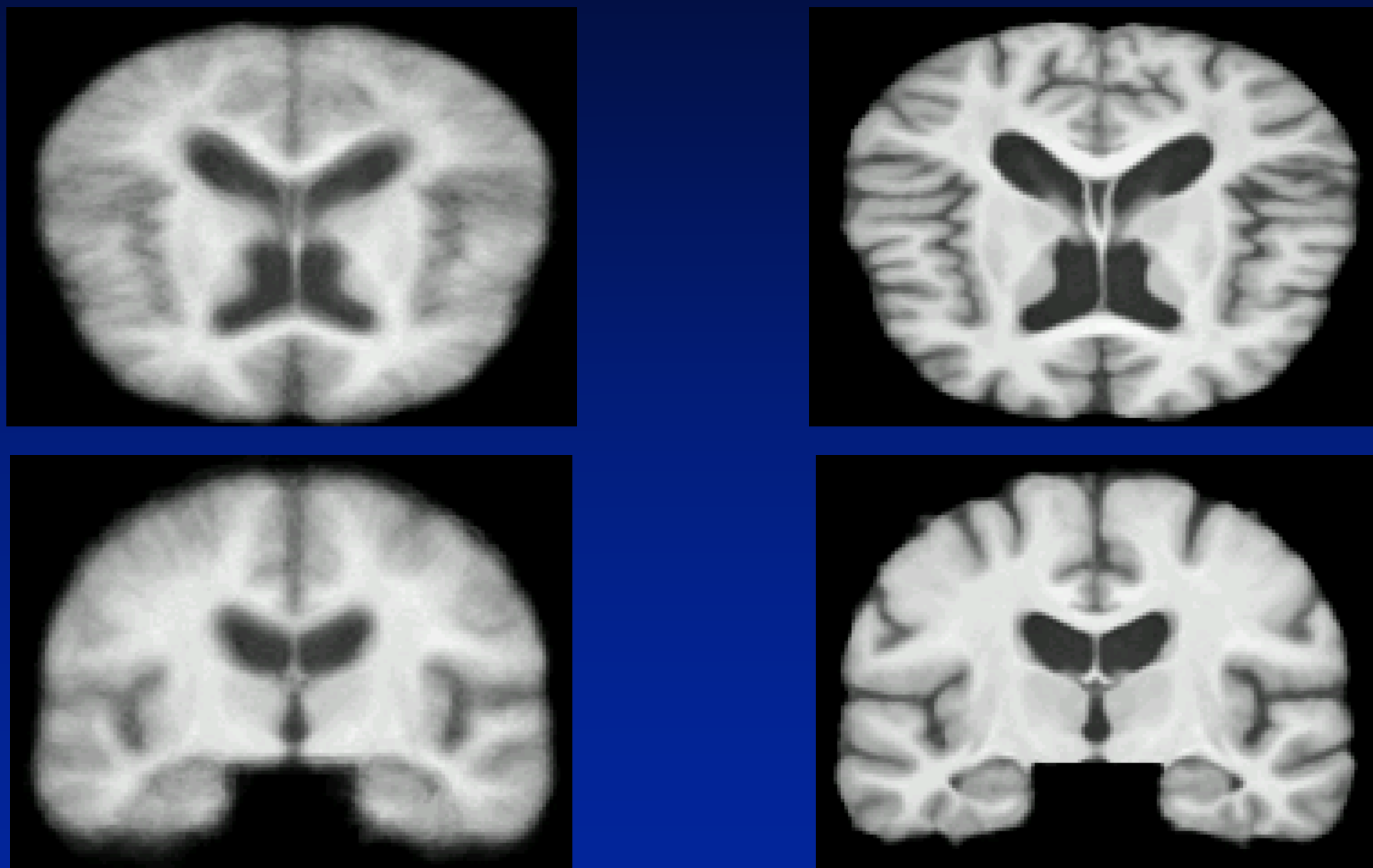
Subject Brain After Transformation

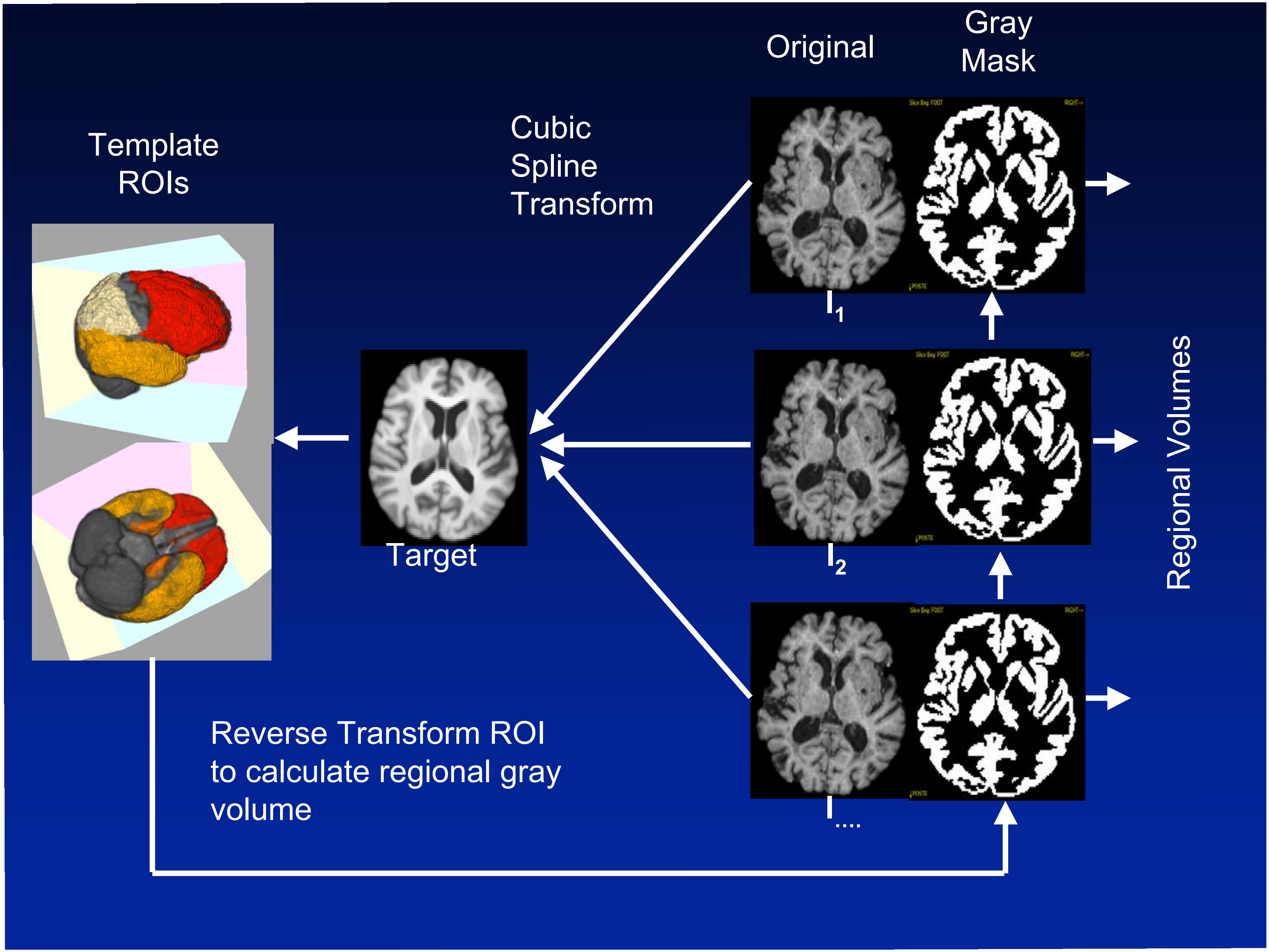


Target Brain



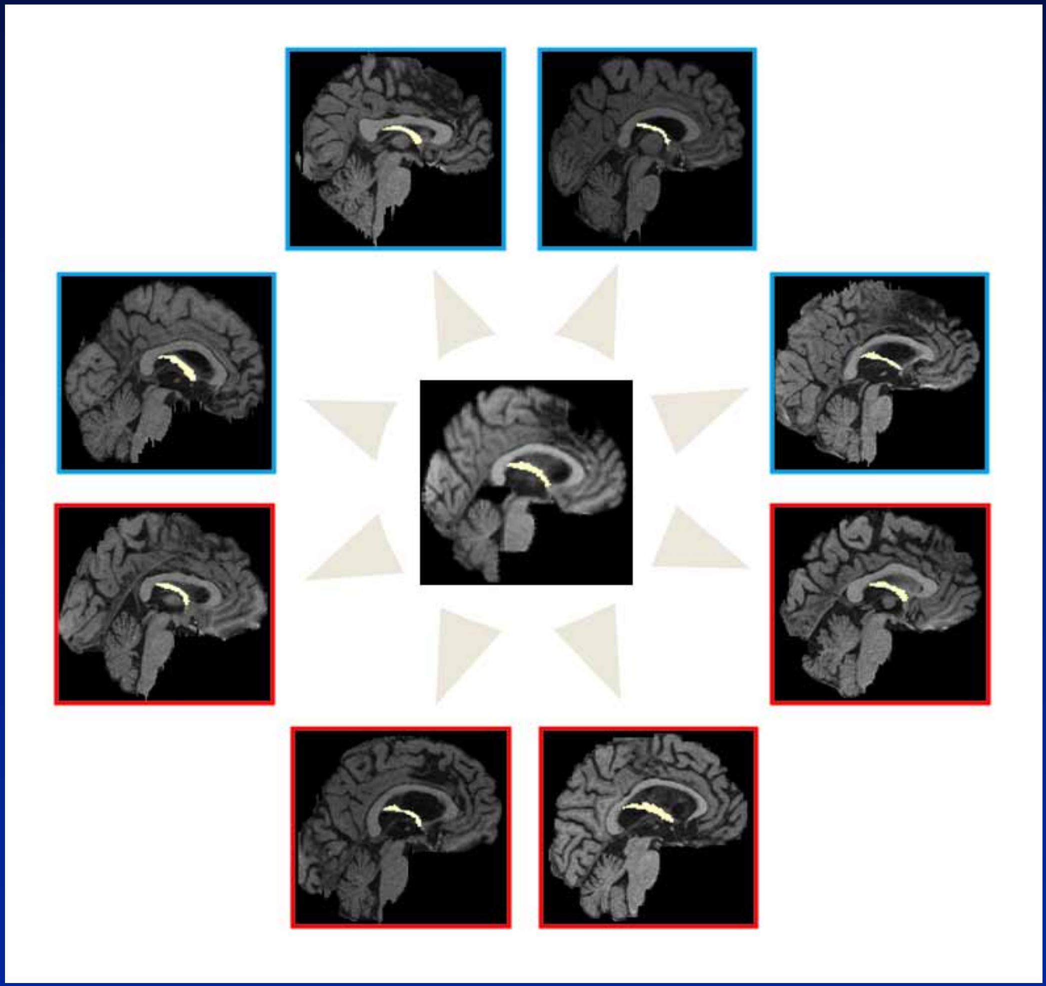
Linear v Non-linear Alignment



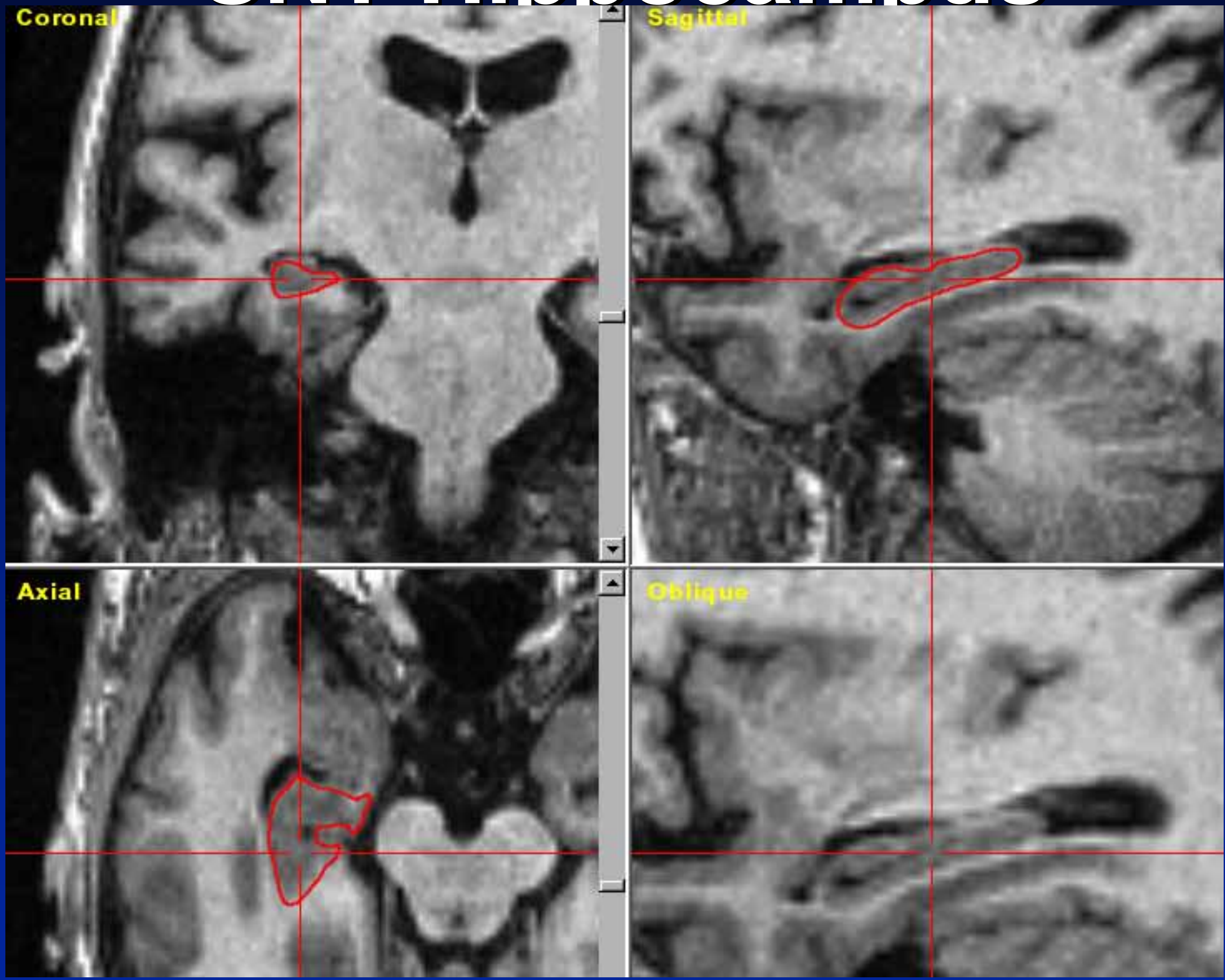


Template ROIs
Cubic Spline Transform
Original
Gray Mask
Target
I_1
I_2
I....
Regional Volumes
Reverse Transform ROI to calculate regional gray volume

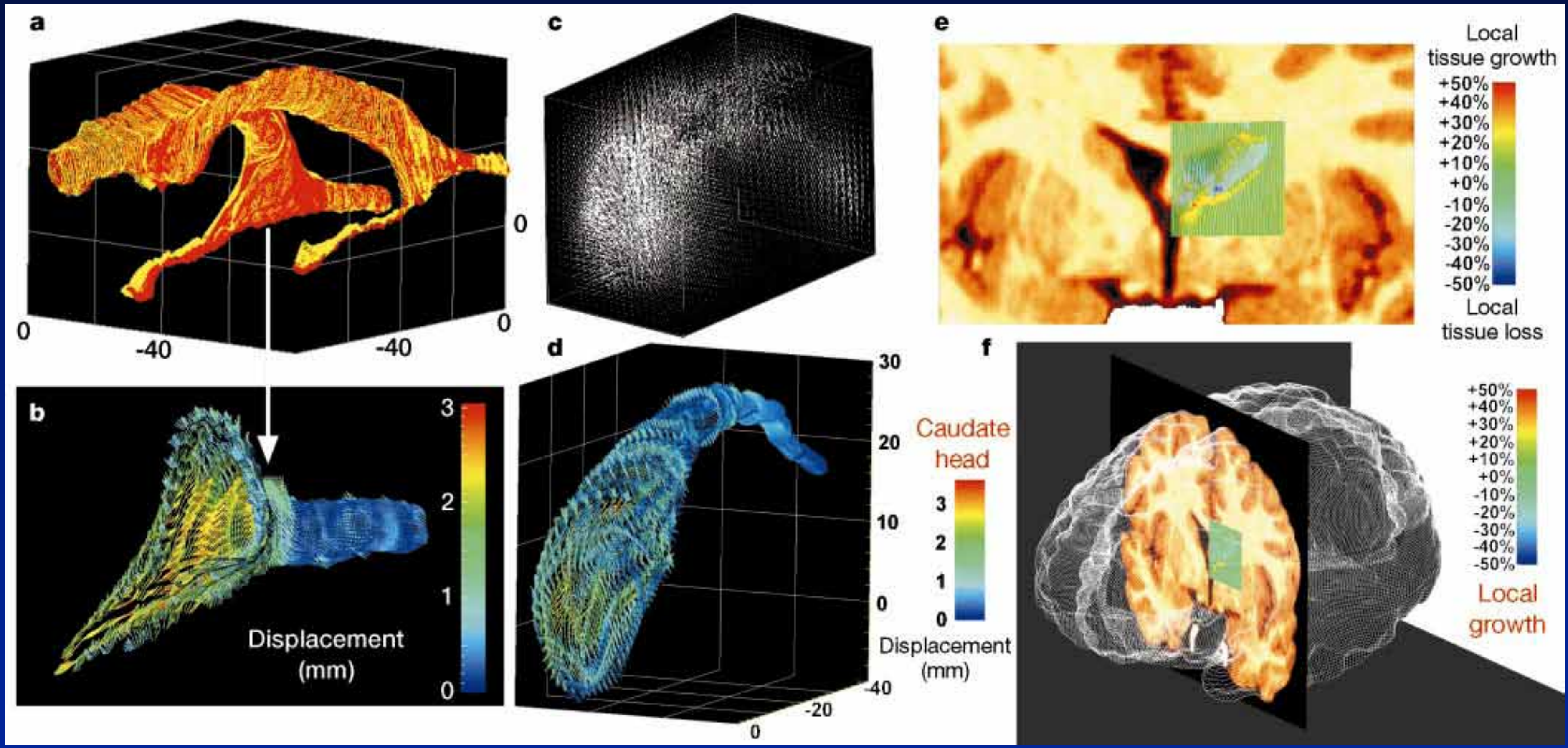
Automatic ROI



Assisted ROI
SNT Hippocampus



Tensor Morphometry



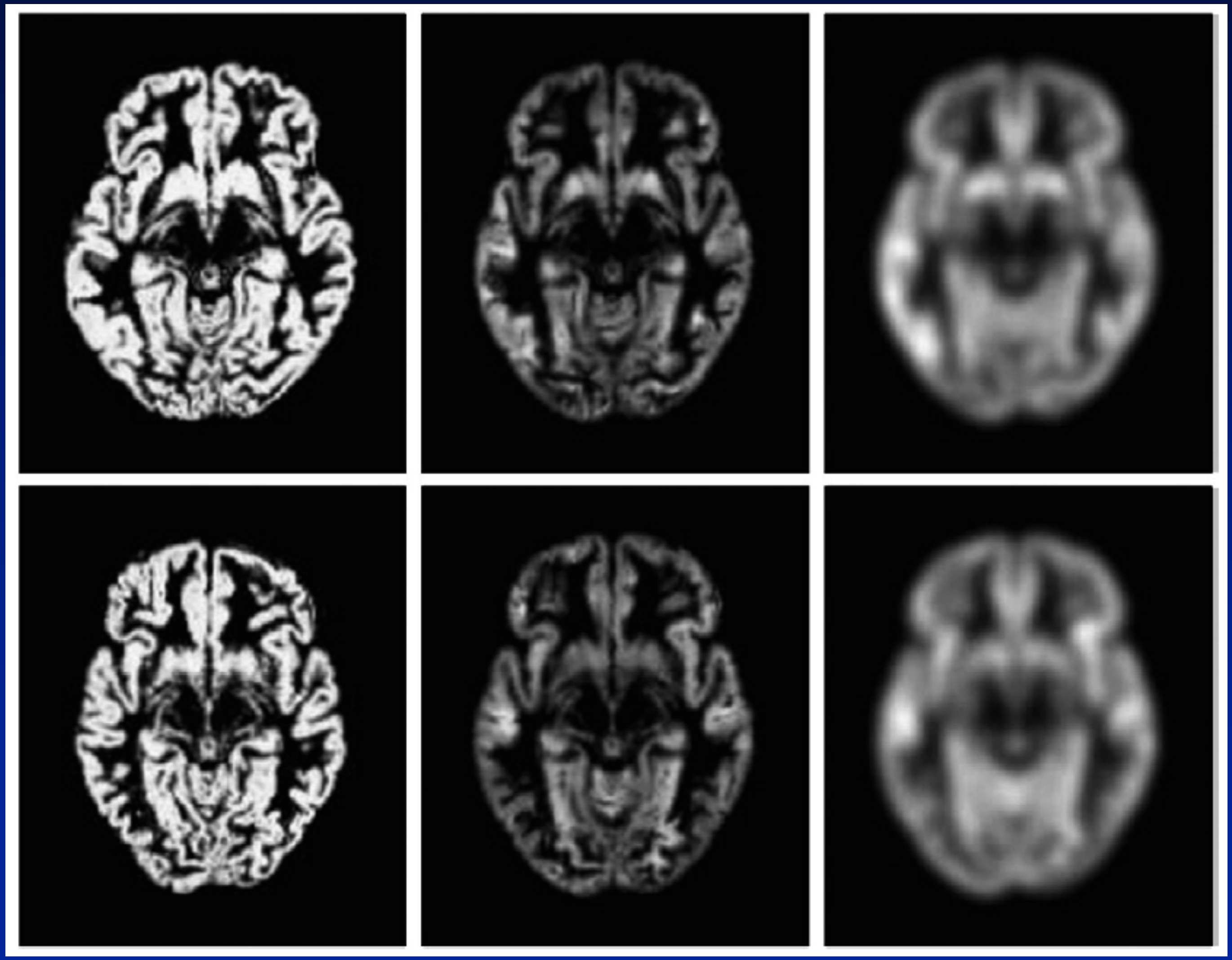
SPM

- Affine Alignment to template
  - Discreet cosign model
- Image segmentation based on template and EM
- Smoothing kernel to create tissue “density”

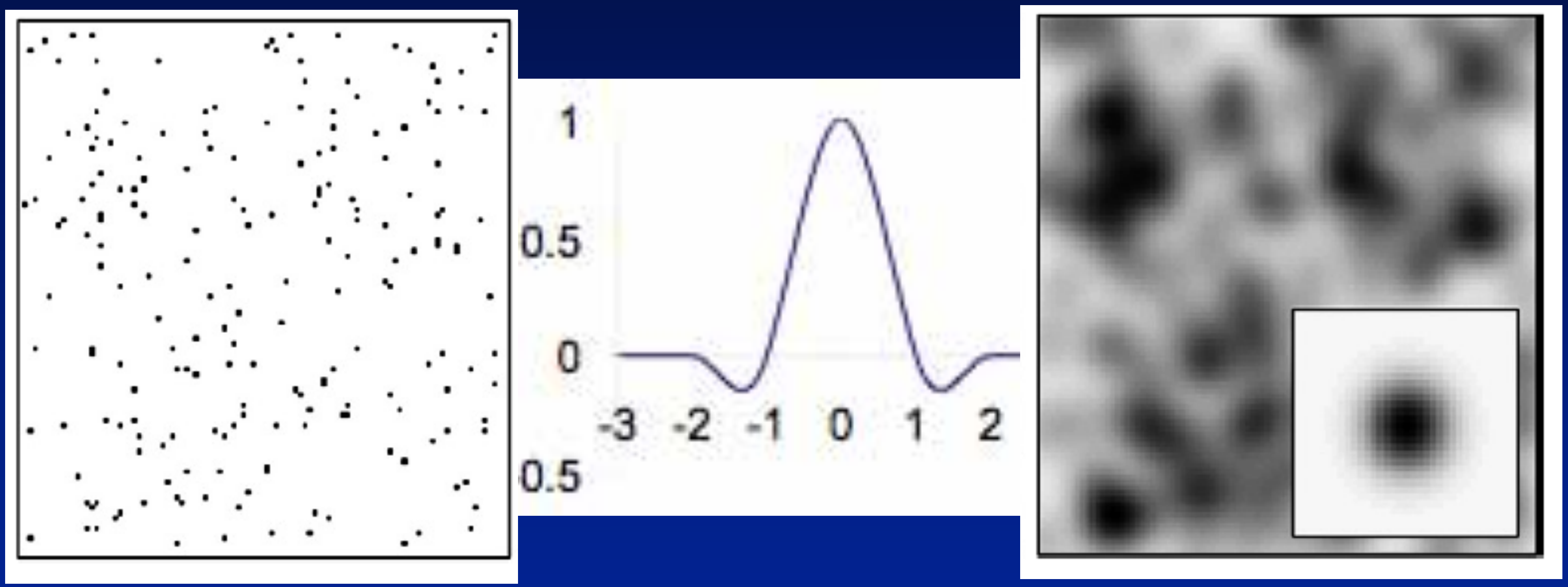
SPM Preprocessing

Subject A

Subject B

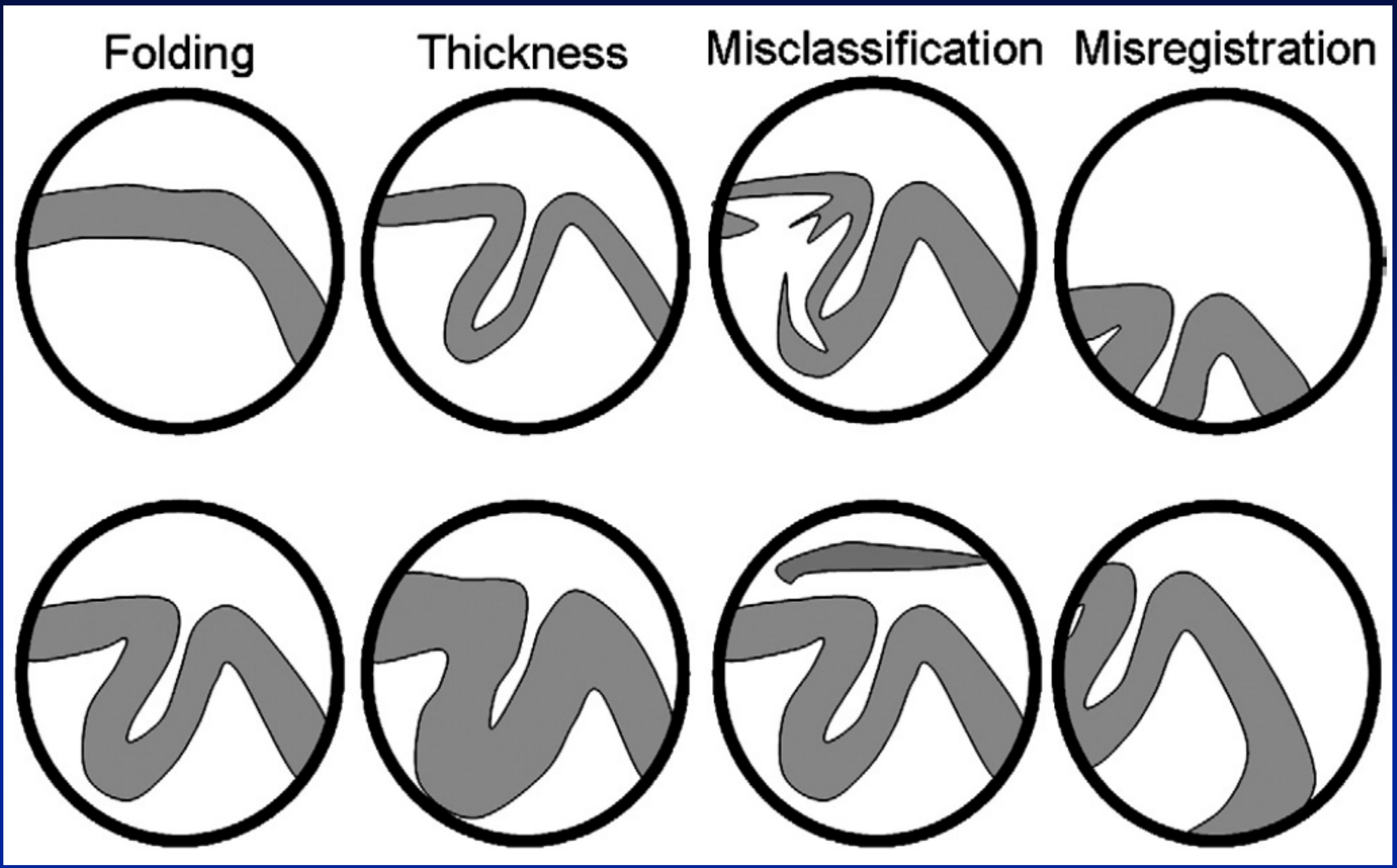


Gaussian Convolution

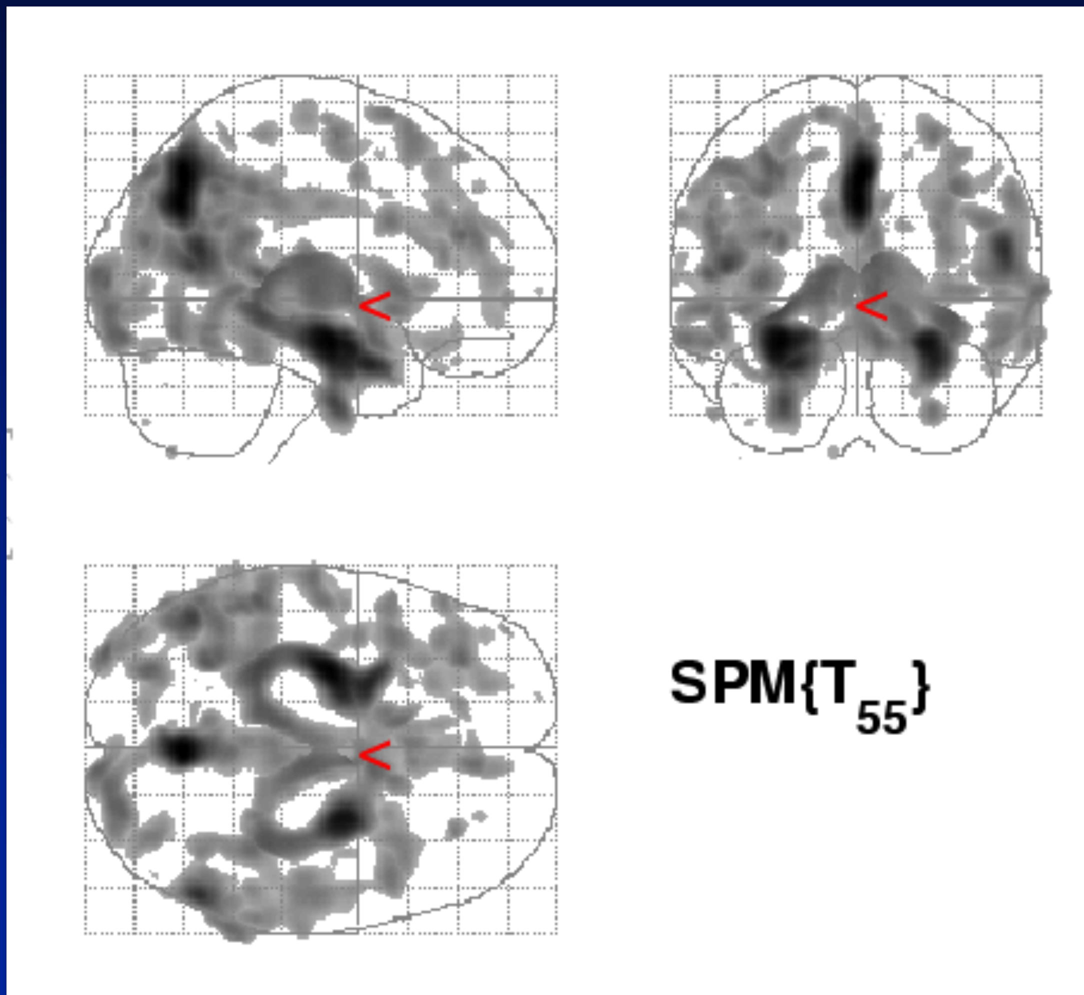


Black is Tissue A on background of Tissue B

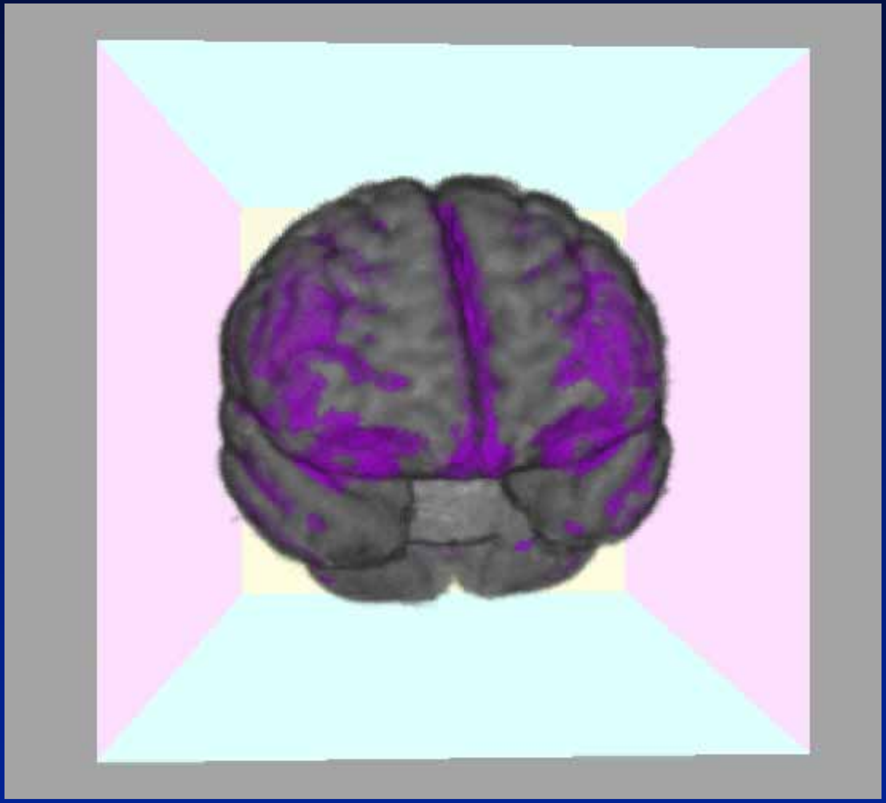
SPM Interpretation



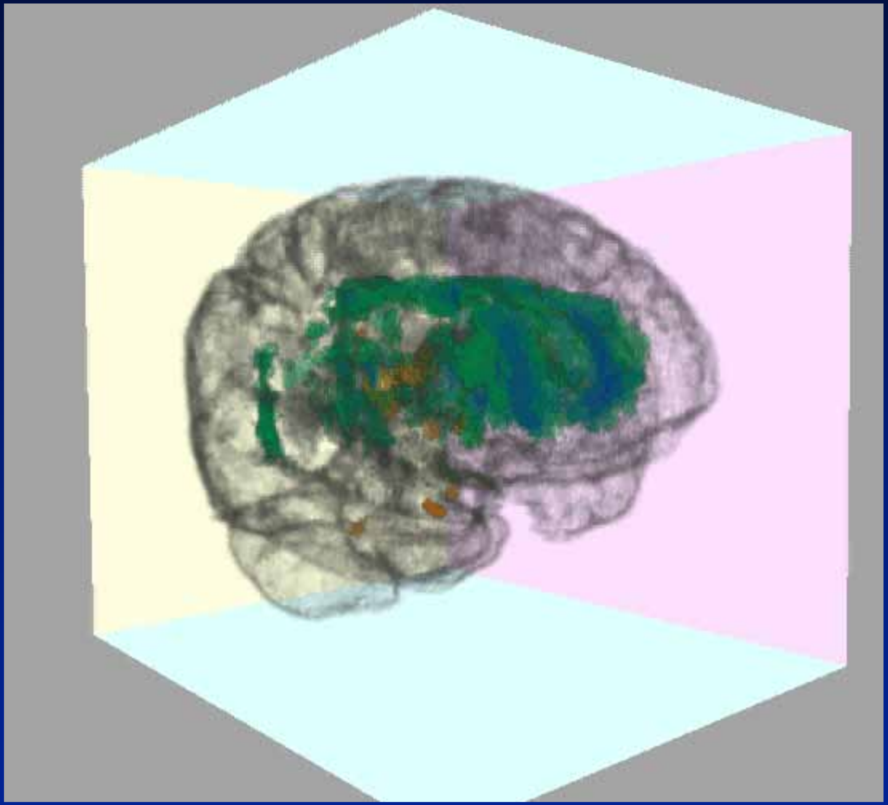
ADNI AD vs Normal SPM



Voxel Based Regression on Age

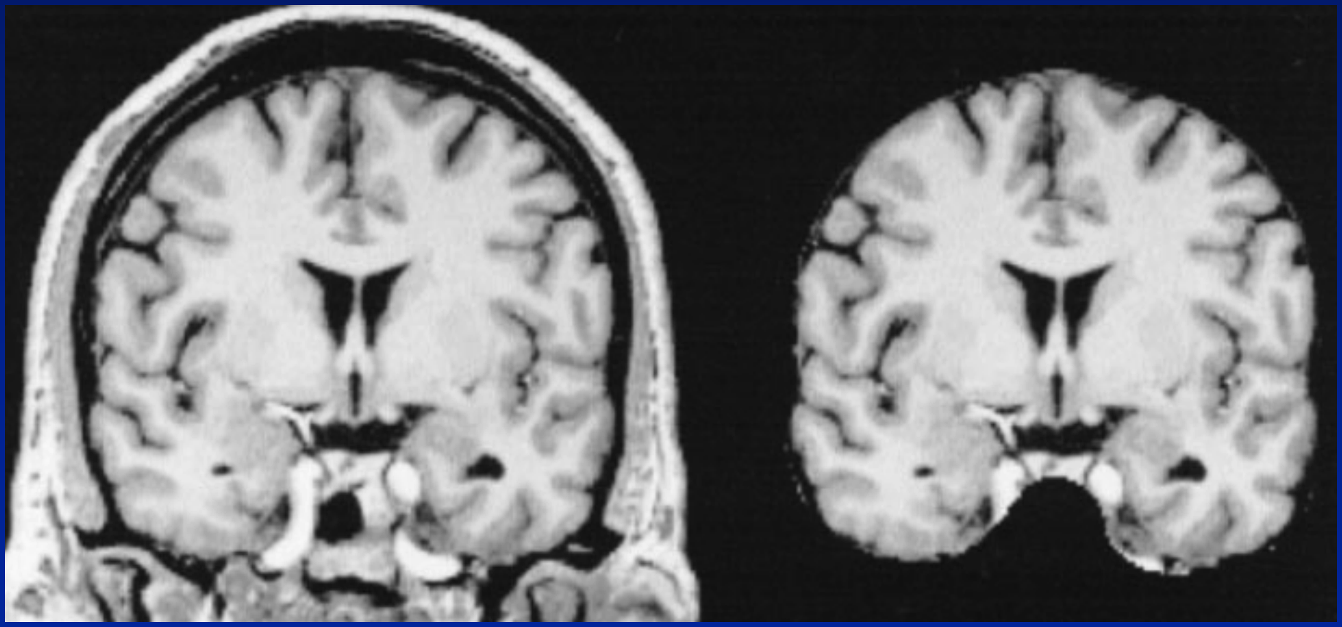


Gray Matter Density



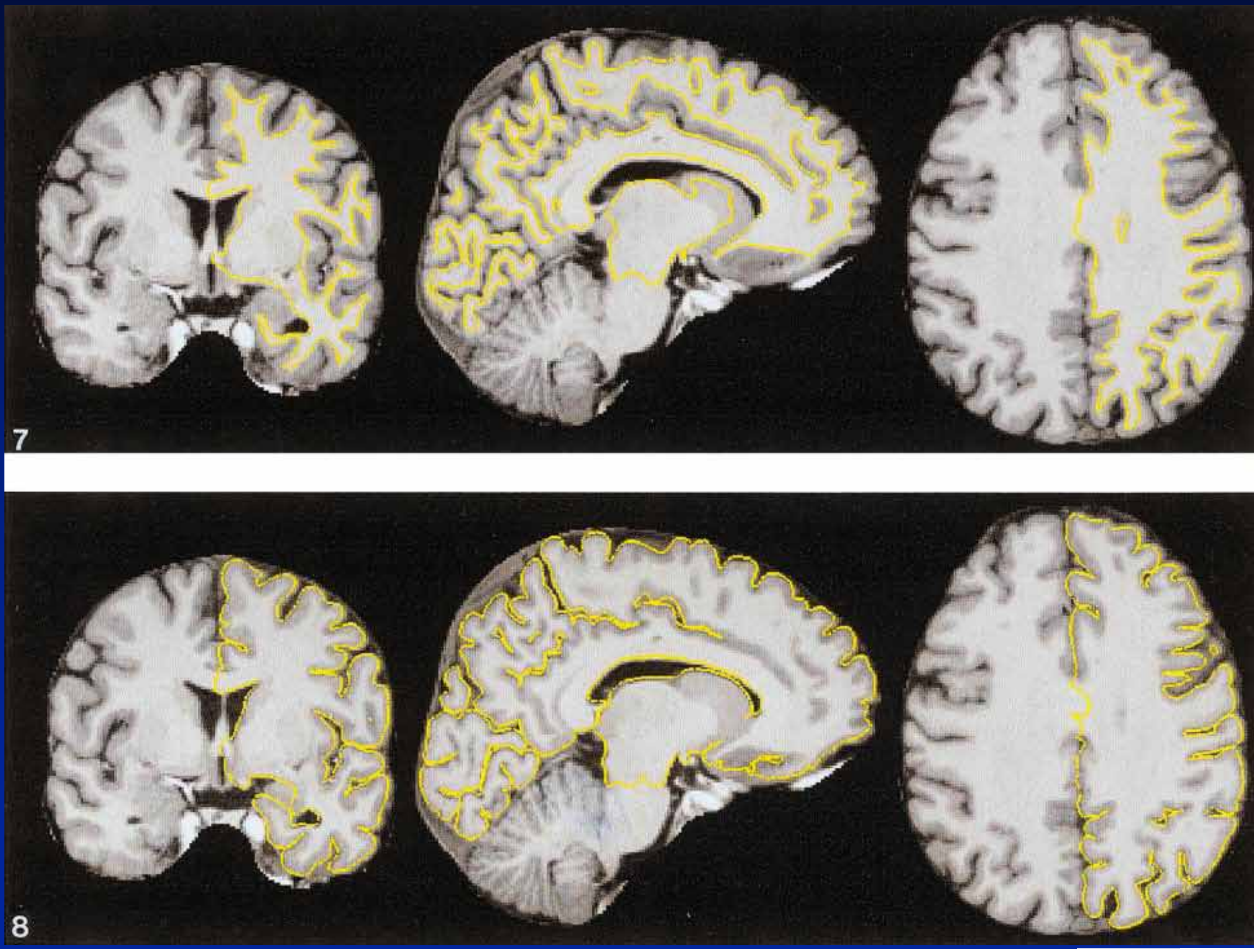
FA

Free-Surfer

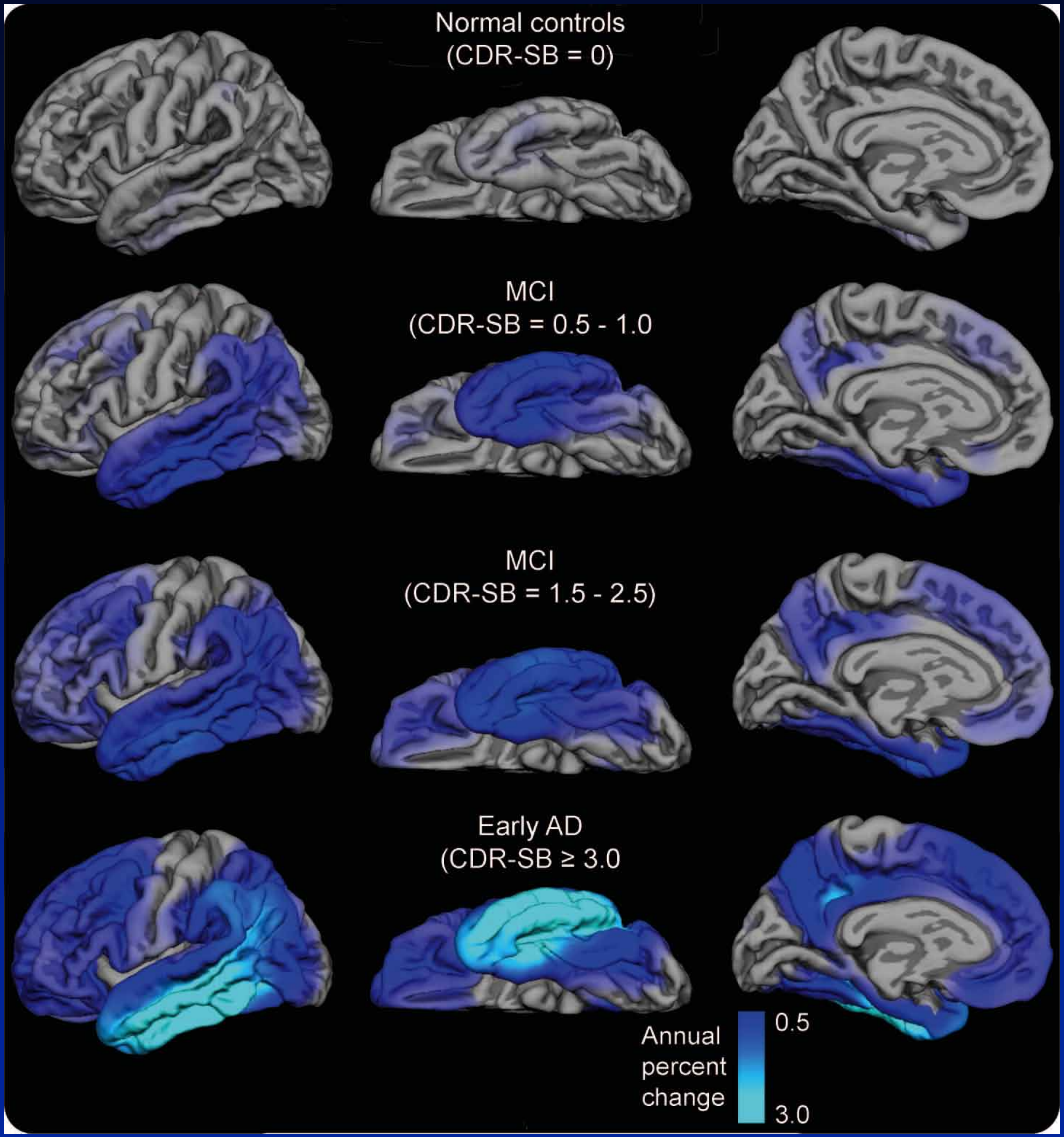


Skull stripping based on deformation template

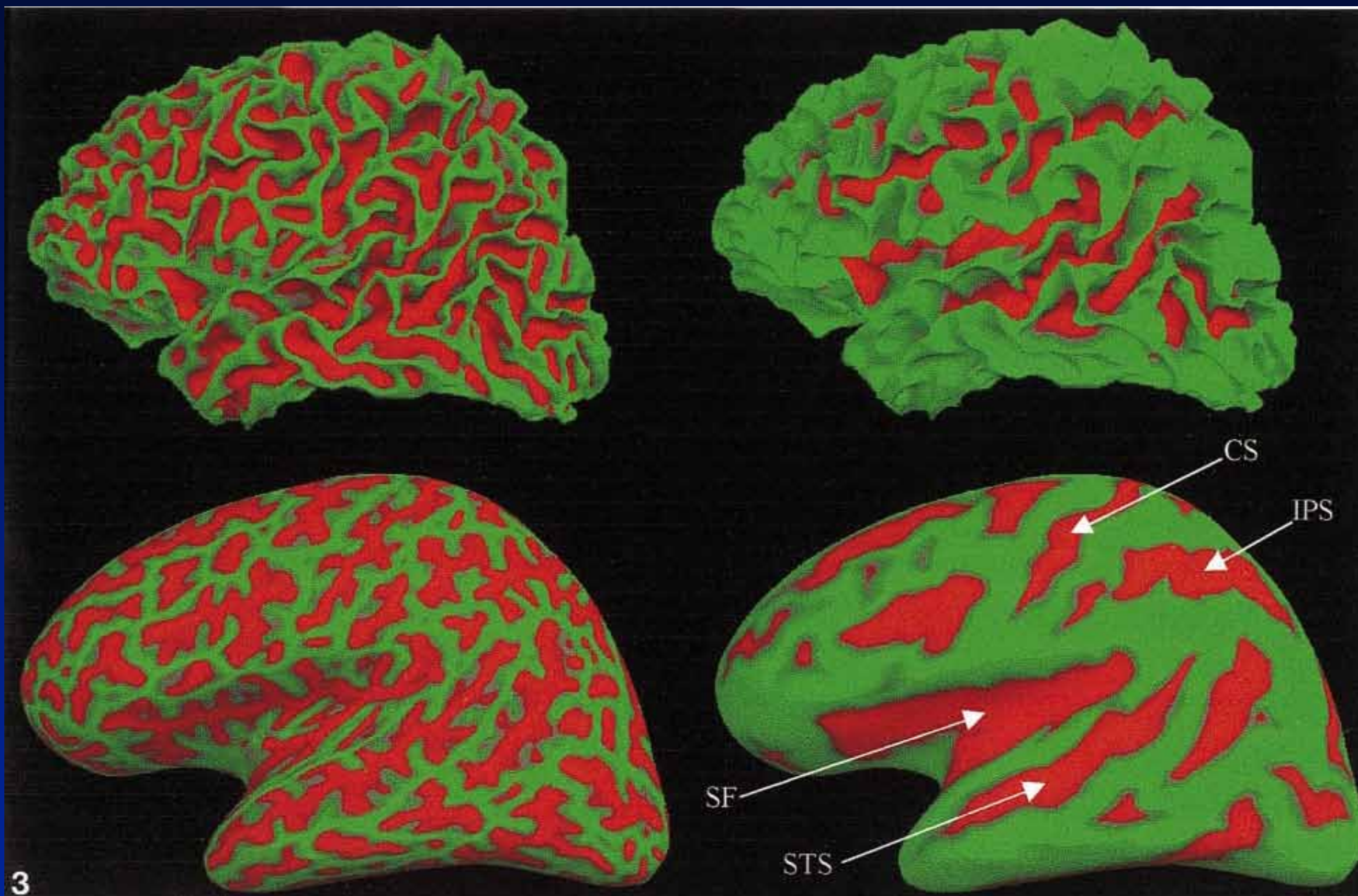
White Matter, Pial Surface Detection

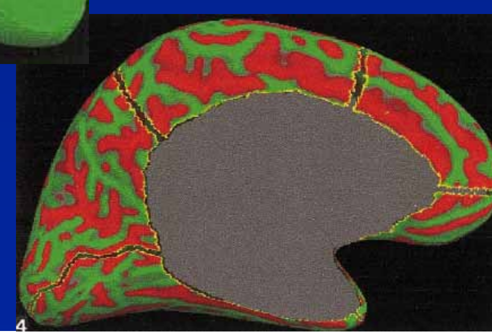


FreeSurfer Cortical Thickness

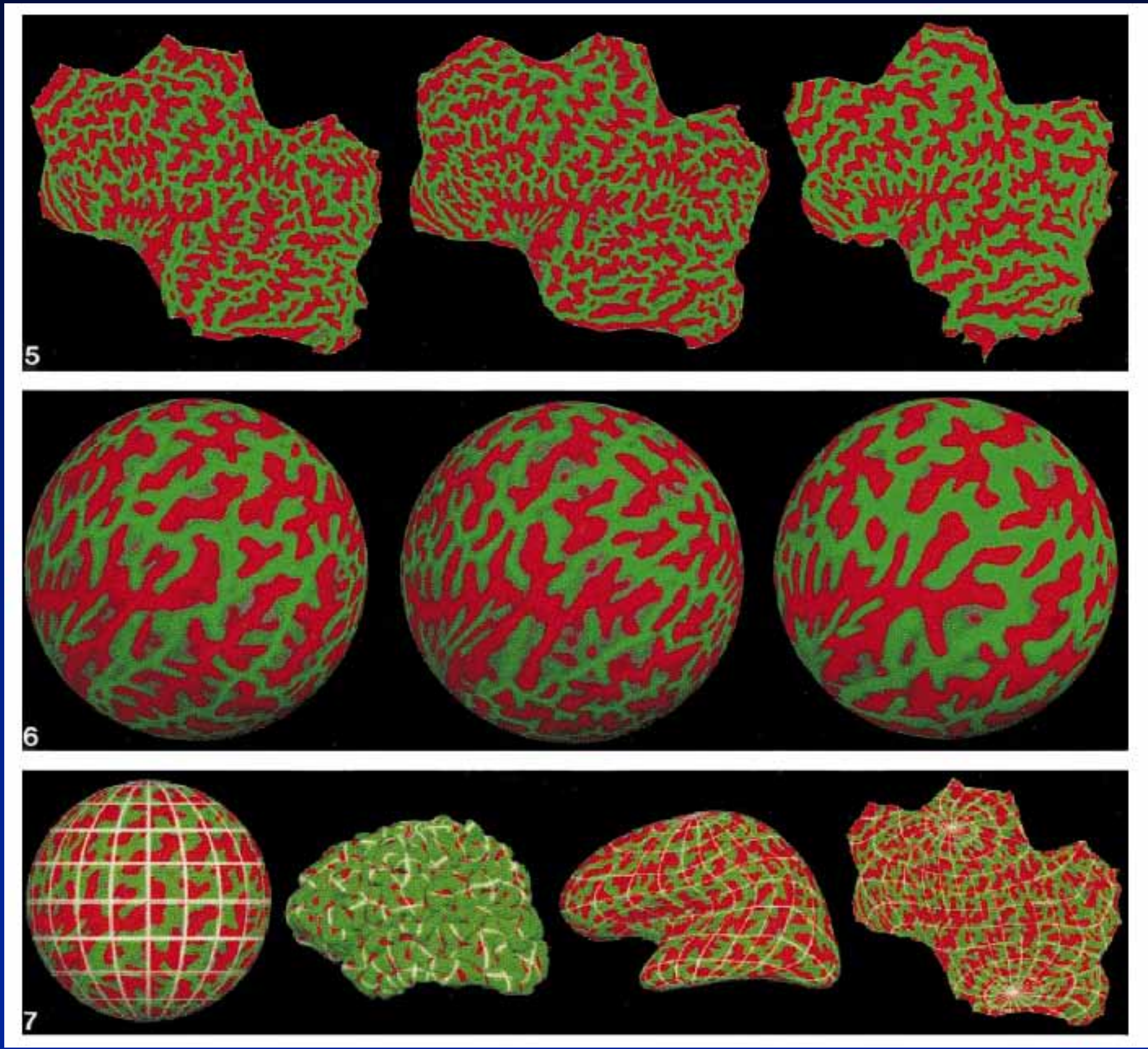


Inflated Surface

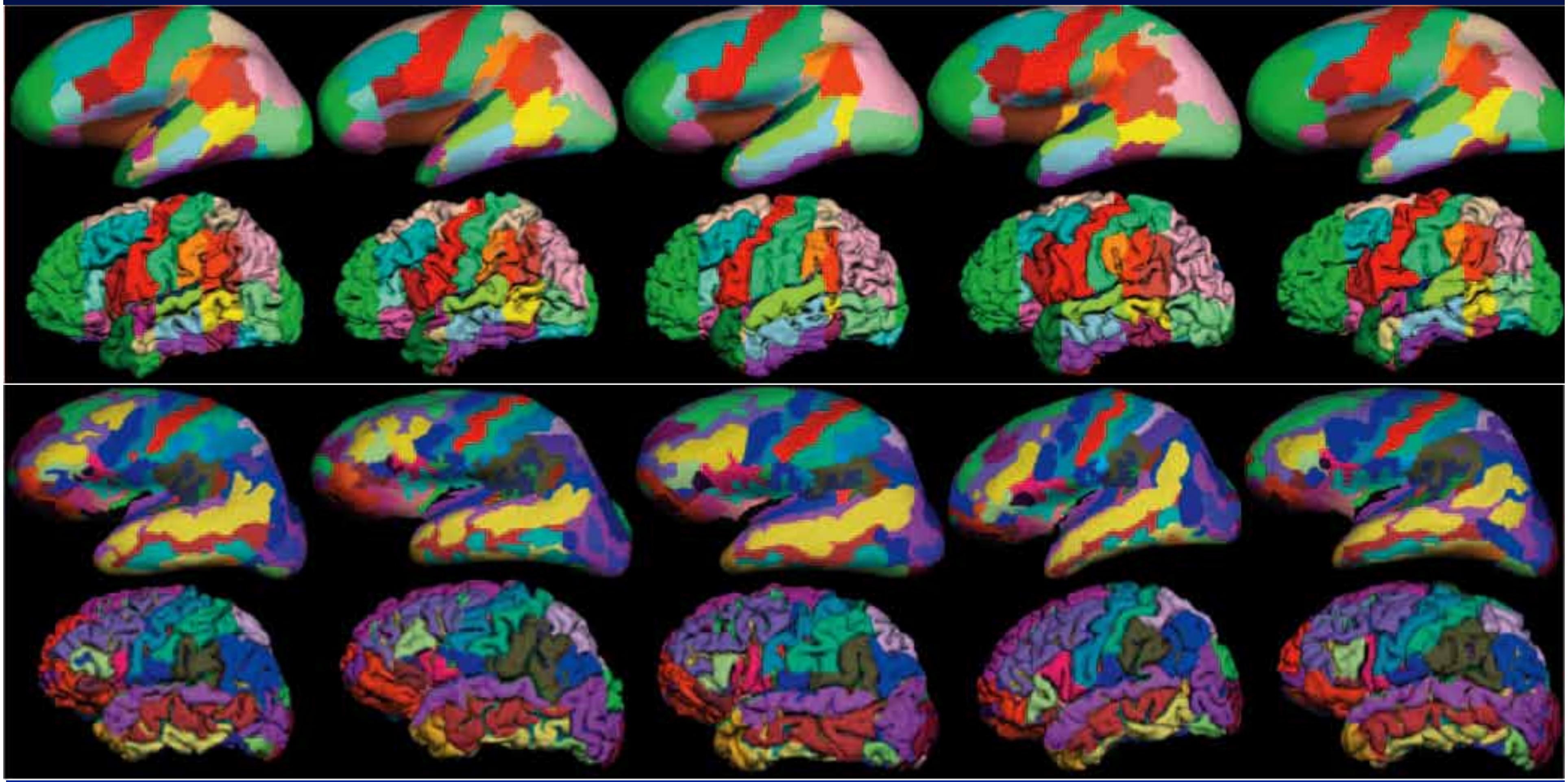




World Geometry



Parcellation



ADNI MRI

- Aims:
  - Ease of implementation
    - Standard sequences
    - Short sequence times
  - Reliability
    - Stable products
  - Quality control
    - Phantom

ADNI MRI Methods

- Sequence selection
  - Standard prescan and scouting procedure recommended by the manufacturer
  - Sagittal 3D MP-RAGE
  - Sagittal 3D MP-RAGE repeat
  - Sagittal *B1-calibration scan (phased array)*
  - Sagittal *B1-calibration scan (body coil)*
  - Axial proton density *T2 dual contrast FSE/TSE*
- ADNI Phantom

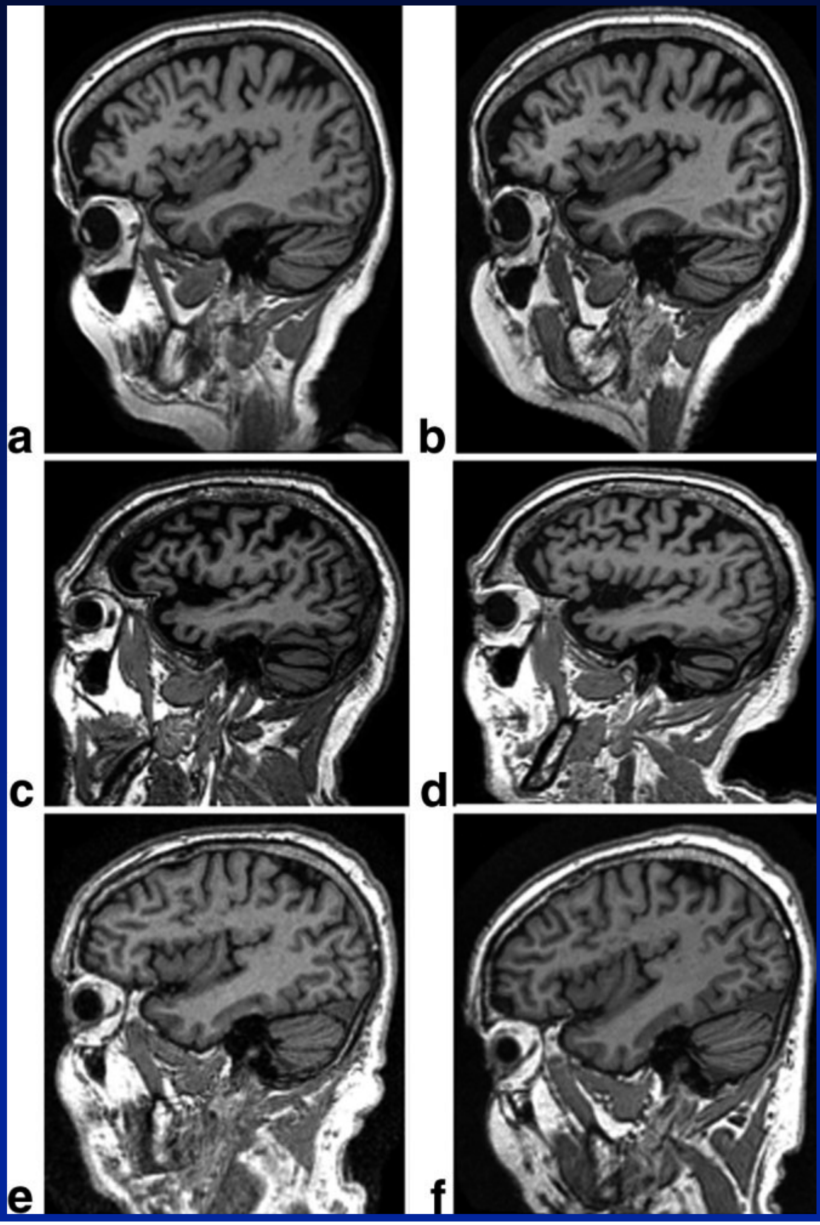
Available MRI Systems

General Electric (GE) Healthcare	Philips Medical Systems	Siemens Medical Solutions
GE 1.5T	**Philips 1.5T**	**Siemens 1.5T**
• 9.1M4 BC	• Multi-Channel Scan List ASO	• Avanto VB11
• 9.1M4 BC Phantom	• R103 Multi-Channel	• Avanto VB13
• 11.00M4 BRM 8Ch	• R122 Multi-Channel	• Avanto VB15
• 11.0M4 BRM 8Ch Phantom	• Quad Head Scan List ASO	• Avanto VB15 Phantom
• 11.0M4 TwinSpeed BC	• R103 Quad Head	• Espree VB15
• 11.0M4 TwinSpeed BC Phantom	• R122 Quad Head	• Espree VB15 Phantom
• 11.0M4 TwinSpeed 8Ch		• Sonata VA21 CP
• 11.0M4 TwinSpeed 8Ch Phantom		• Sonata VA25 8Ch
• 12.0M3 TwinSpeed 8Ch		• Sonata VA25 CP
• 12.0M3 TwinSpeed 8Ch Phantom		• Symphony Ultra VA21 CP
• 12.0M4 TwinSpeed 8Ch		• Symphony Sprint VA25
• 12.0M4 TwinSpeed 8Ch Phantom		• Symphony VA21 VA25 CP Phantom
• 14.0M4 TwinSpeed 8Ch		• Symphony VA30 CP
• 14.0M4 TwinSpeed 8Ch Phantom		
• 14.0M4 TwinSpeed BC		
• 14.0M4 TwinSpeed BC Phantom		
GE 3.0T	**Philips 3.0T**	**Siemens 3.0T**
• E2M4 CRM 8Ch	• Multi-Channel Scan List	• Allegra VA25
• E2M4 CRM 8Ch Phantom	• R104 Multi-Channel	• Trio VA25 8Ch
• VH3M4 CRM BC	• R122 Multi-Channel	• Trio VB12T
• VH3M4 CRM BC Phantom		• TrioTim VB13
• G3M4 TwinSpeed 8Ch		• Trio VB15
• G3M4 TwinSpeed 8Ch Phantom		• Trio VB15 Phantom
• 12.0M4 TwinSpeed 8Ch		
• 12.0M4 TwinSpeed 8Ch Phantom		
• 14.0M4 TwinSpeed 8Ch		
• 14.0M4 TwinSpeed 8Ch Phantom		

http://adni.loni.ucla.edu/research/protocols/mri-protocols/

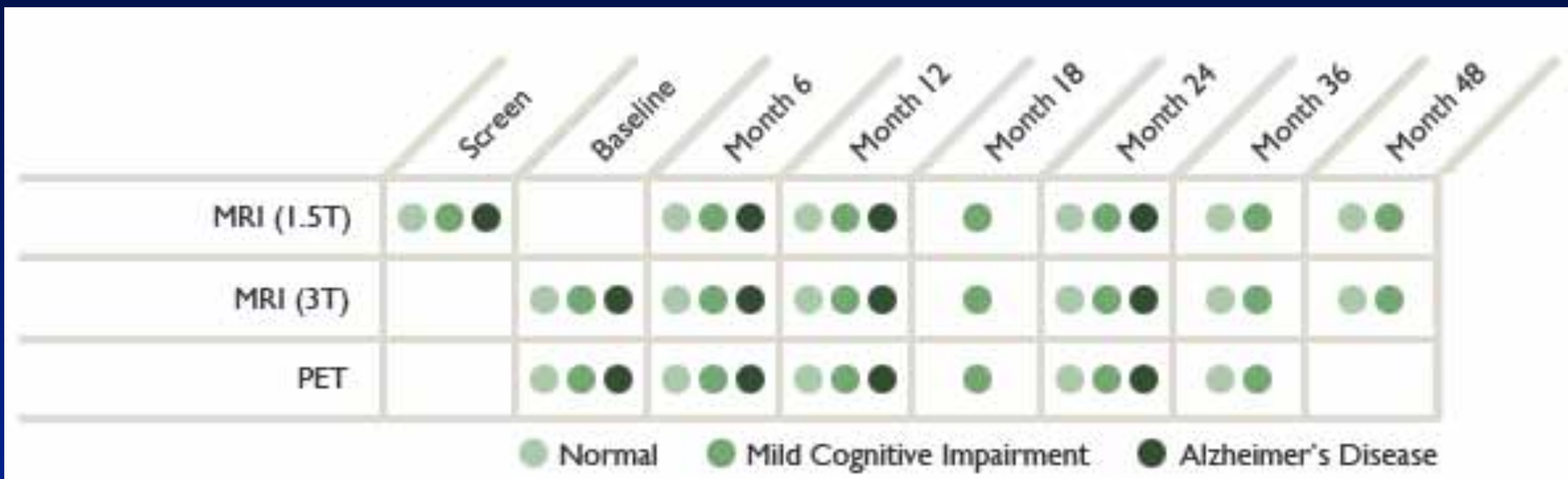
Examples

1.5 T



3.0 T

Number of MRI Acquisitions



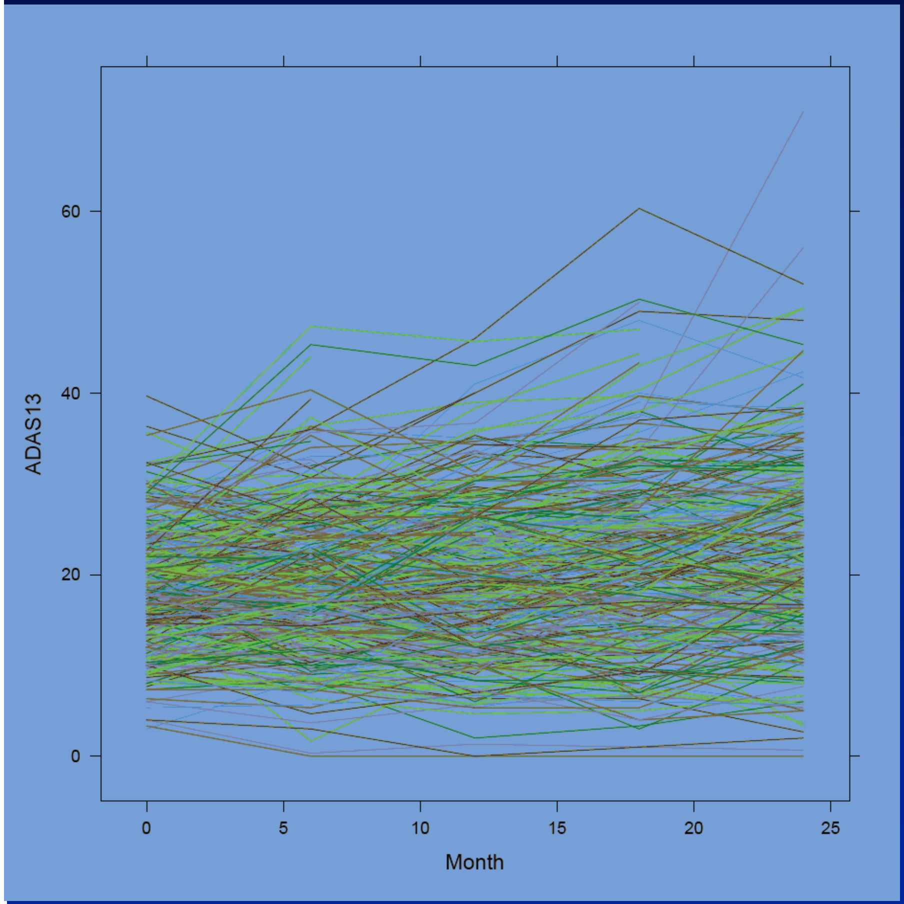
Everyone received 1.5 T MRI and 50% received an additional 3T for comparison

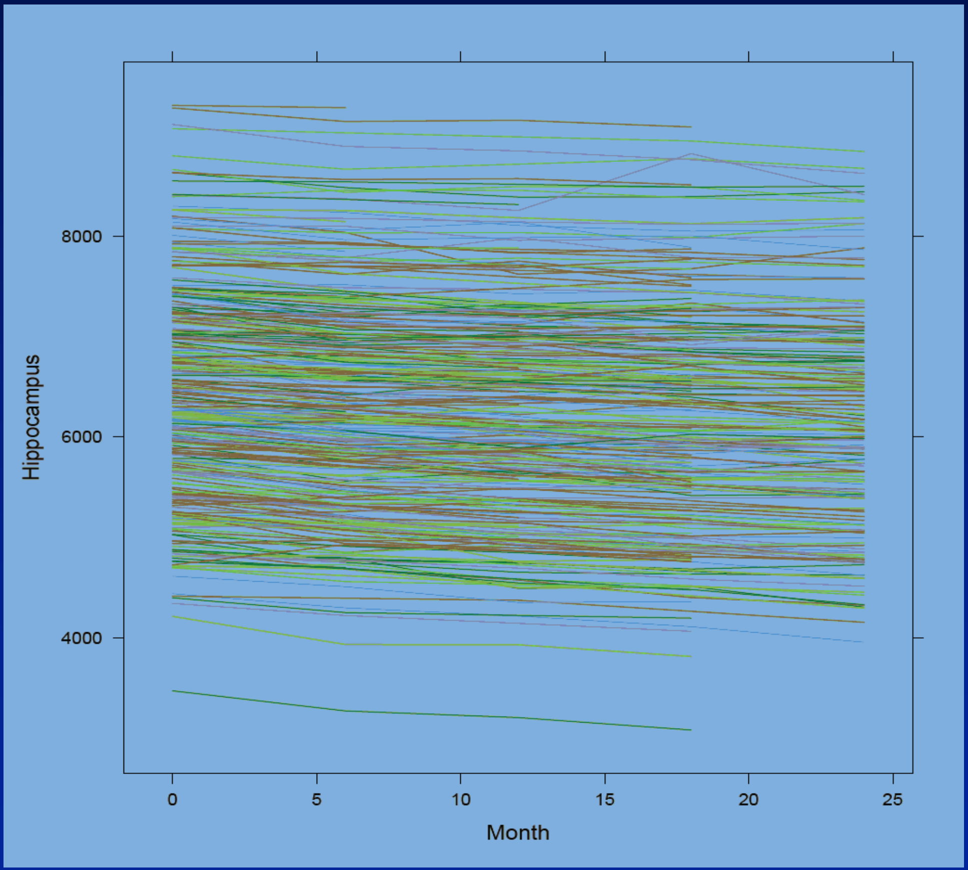
Analysis Groups

- UCSF—Norbert Schuff
  - SNT hippocampus
  - Freesurfer
- UCLA—Paul Thompson
  - Tensor morphometry
- UCD—DeCarli/Carmichael
  - White matter disease/infarcts
- UCSD—Anders Dale
  - Modified Freesurfer
- University College of London—Nick Fox
  - BBSI

Summary Results

Measures of Change in MCI: ADAScog13 vs Hippocampal Volume





ADNI, unpublished data.

Mean ± (SD) of ADNI Variables

Variable name	Annualized mean change by diagnosis		
	NC	MCI	AD
CSF Aβ_{42}	−0.94 (18)	−1.4 (17)	−0.1 (14)
CSF Tau	3.45 (13)	2.34 (21)	1.24 (24)
PIB	0.098 (0.18)	−0.008 (0.18)	−0.004 (0.25)
FDG-PET: SumZ2PNS	−177 (1532)	752 (2950)	2993 (4040)
FDG-PET: ROI-avg	−0.006 (0.06)	−0.015 (0.064)	−0.055 (0.067)
FDG-PET: DD-fROI	−0.019 (0.037)	−0.047 (0.030)	−0.081 (0.047)
Hippocampus	−40 (84)	−80 (91)	−116 (93)
Ventricles	848 (973)	1551 (1520)	2540 (1861)
ADAS-cog total	−0.54 (3.05)	1.05 (4.40)	4.37 (6.60)
MMSE	0.0095 (1.14)	−0.64 (2.5)	−2.4 (4.1)
CDR-SB	0.07 (0.33)	0.63 (1.16)	1.62 (2.20)
RAVLT 5-trial total	0.29 (7.8)	−1.37 (6.6)	−3.62 (5.6)

Baseline MRI Measures

FreeSurfer	NC	MCI	AD
Hippocampus	3631 ± 440	3240 ± 521	2902 ± 501
Brain	999417 ± 96951	992133 ± 10104	942935 ± 100330
Ventricles	37994 ± 20449	44727 ± 21454	49489 ± 22971

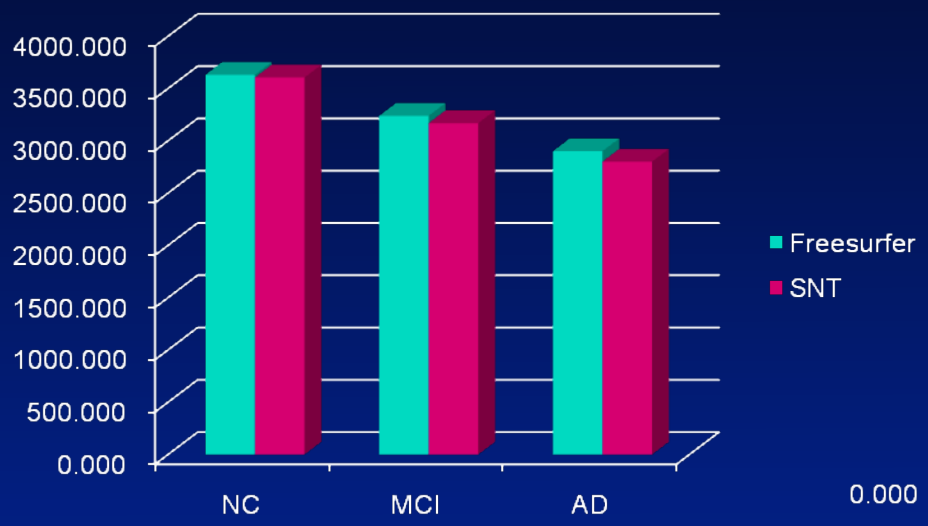
UCD			
WMH Volume (cm^3)	0.745 ± 2.27	0.838 ± 2.53	1.05 ± 1.90

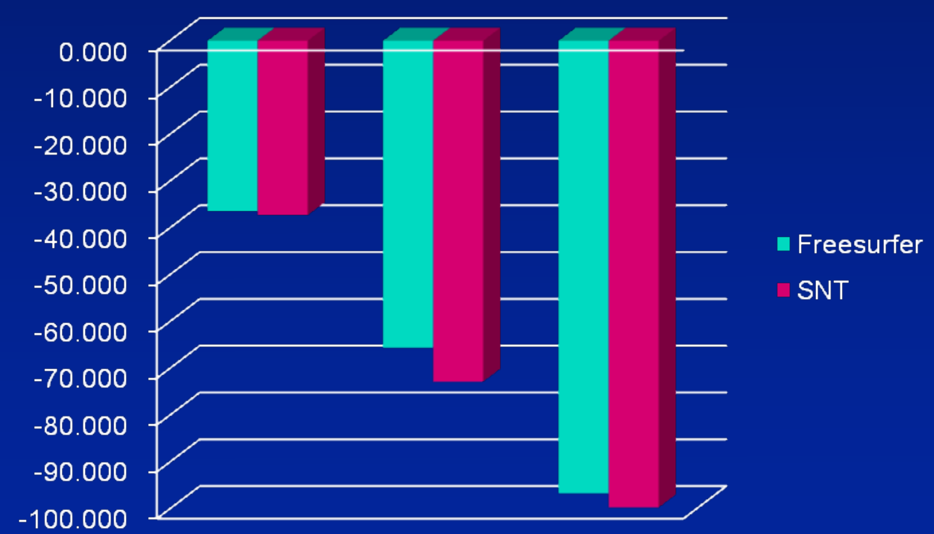
SNT			
hippocampus	3606 ± 446	3170 ± 533	2802 ± 526
ventricles	17934 ± 10192	22348 ± 12150	25815 ± 13417

Longitudinal Change

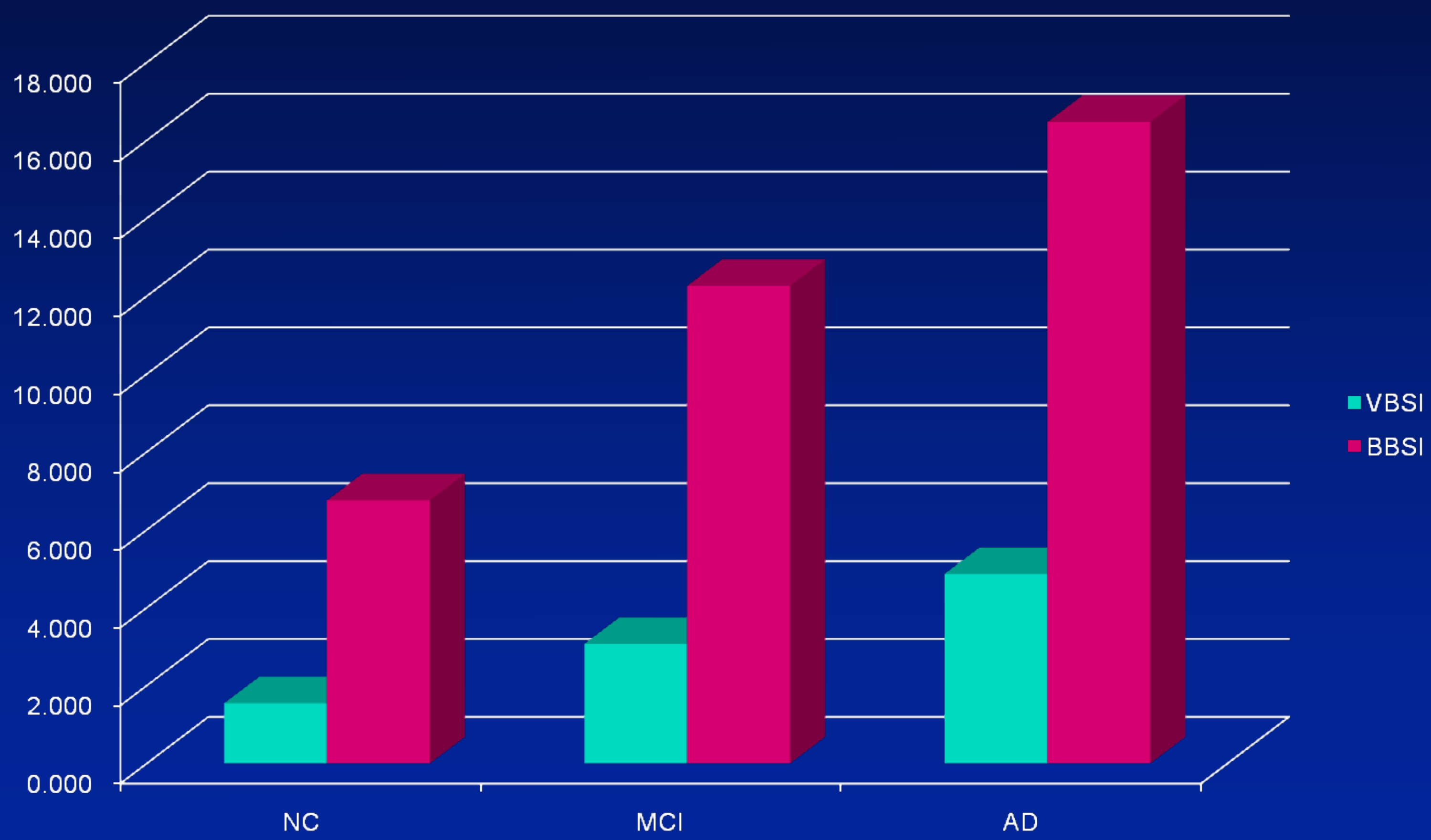
FreeSurfer	NC	MCI	AD
Hippocampus	-36.4 ± 2.0	-65.6 ± 2.5	-96.7 ± 4.2
Brain	-5580 ± 258	-9309 ± 346	-13328 ± 637
Ventricles	1486 ± 99	2935 ± 146	4775 ± 277
UCD			
WMH Volume	0.028 ± 0.048	0.085 ± 0.052	0.155 ± 0.106
BSI			
VBSI	1.55 ± 1.79	3.07 ± 3.0	4.87 ± 3.4
BBSI	6.76 ± 6.7	12.27 ± 9.4	16.47 ± 9.5
SNT			
hippocampus	-37.3 ± 3.7	-72.8 ± 3.3	-99.7 ± 4.9
ventricles	824 ± 52	1517 ± 73	2524 ± 141

Hippocampus Cross-Sectional v Longitudinal

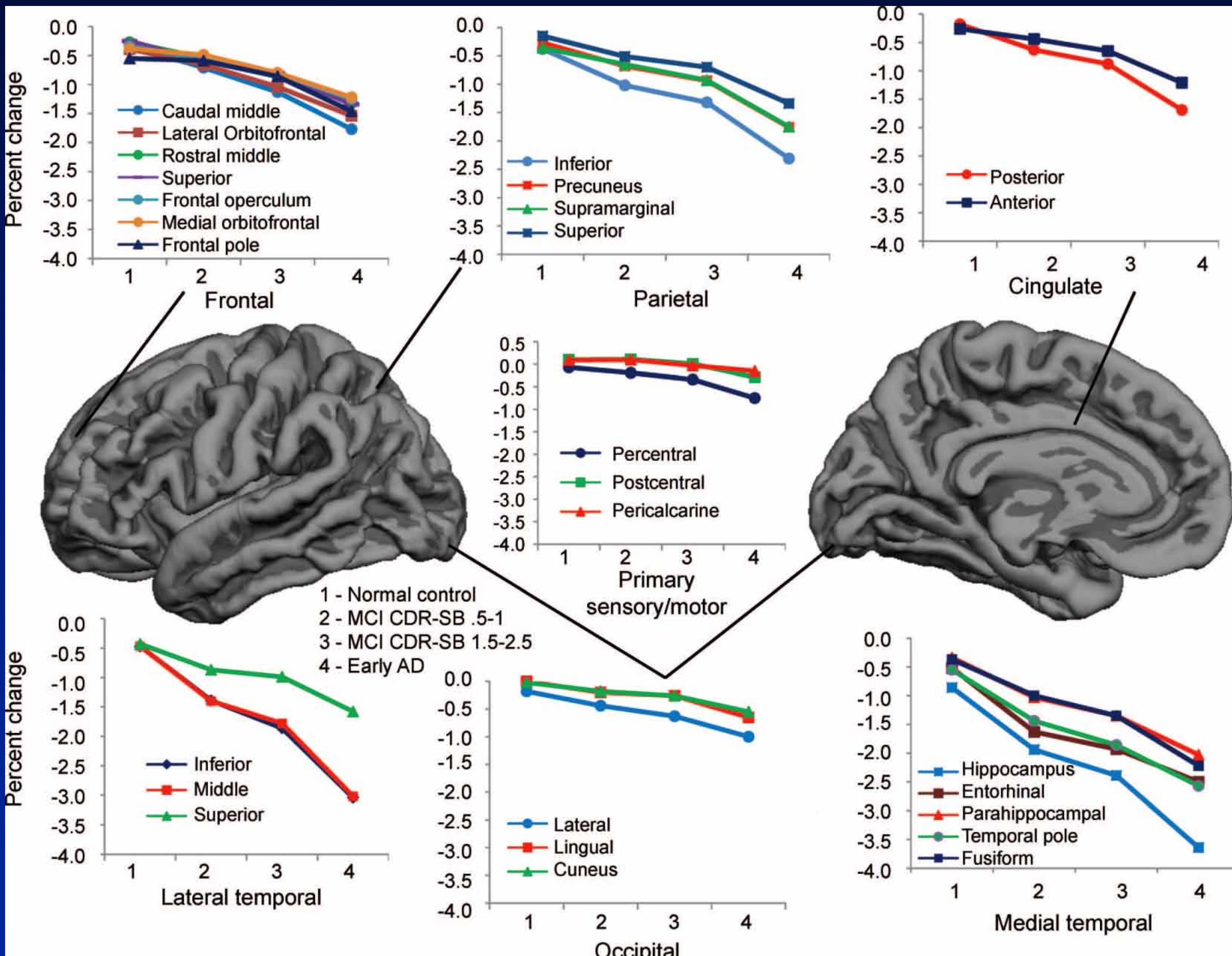




Boundary Shift Integral



FreeSurfer Rates of Change



Neurology® 2009;73:457-465