Lecture #10

Biomedical Image Registration

Acknowledgement
In preparing the Lecture 10 presentation, Dr. Ulaş Bağcı's lecture notes were used.

Outline

- Introduction to the medical image registration
- Transformation types
  - Rigid, affine, non-rigid
- Mono-modal, multi-modal image registration
- Similarity metrics
- Mutual Information

Image Registration Taxonomy

- **Dimensionality**
  - 2D-2D, 3D-3D, 2D-3D
- **Nature of registration basis**
  - Image based
    - Extrinsic, Intrinsic
  - Non-image based
- **Nature of the transformation**
  - Rigid, Affine, Projective, Curved
- **Interaction**
  - Interactive, Semi-automatic, Automatic
- **Modalities involved**
  - Mono-modal, Multi-modal, Modality to model
- **Subject:**
  - Intra-subject
  - Inter-subject
  - Atlas
- **Domain of transformation**
  - Local, global
- **Optimization procedure**
  - Gradient Descent, SGD,
  - …
- **Object**
  - Whole body, organ, …

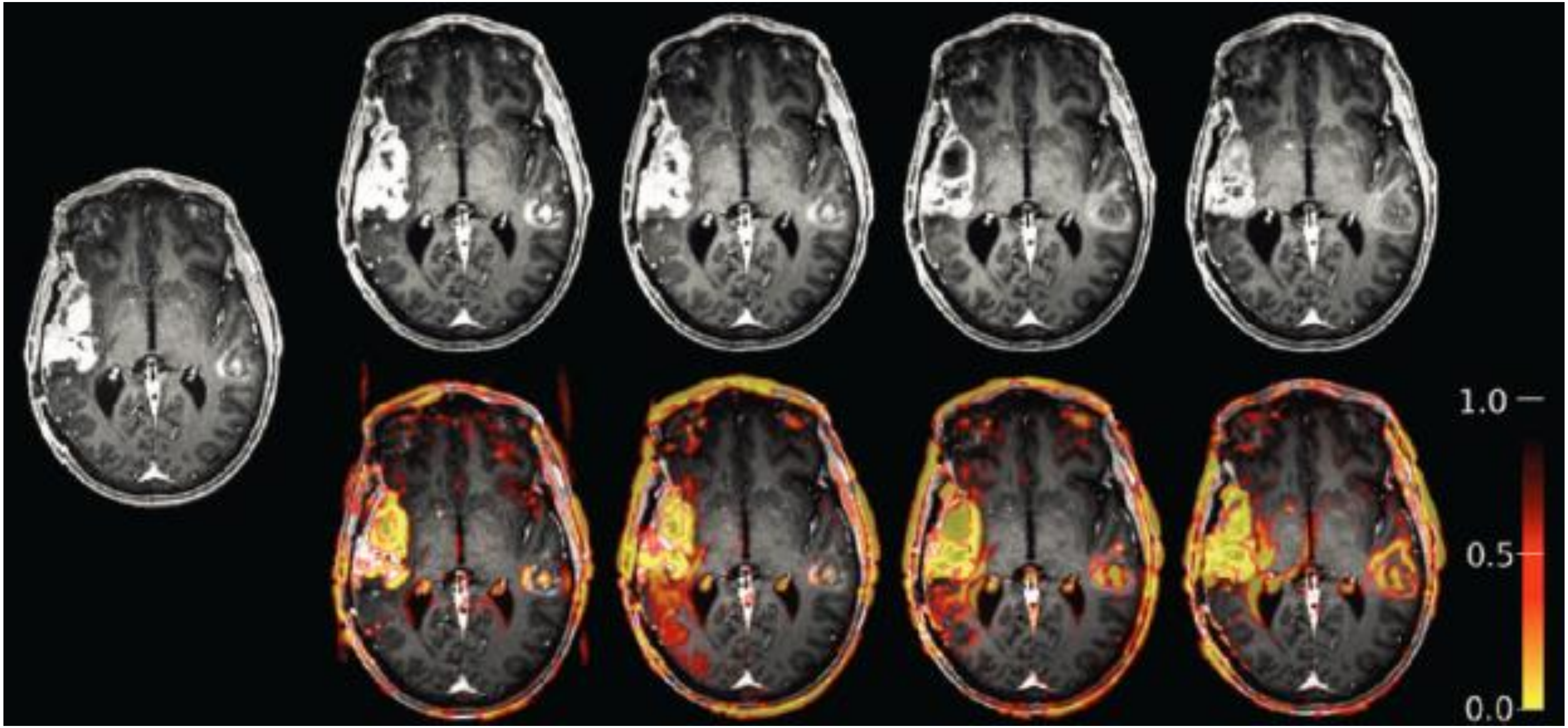
Open Sources for Implementation

- ITK
- ANTS (advanced normalization tools) (PICSL of Upenn)
- CAVASS (MIPG of Upenn)
- Nifty Reg (UCL)
- Elastix (www.elastix.isi.uu.nl)
- FAIR (Modersitzki 2009), mostly matlab.
- 3D Slicer
- FSL
- …

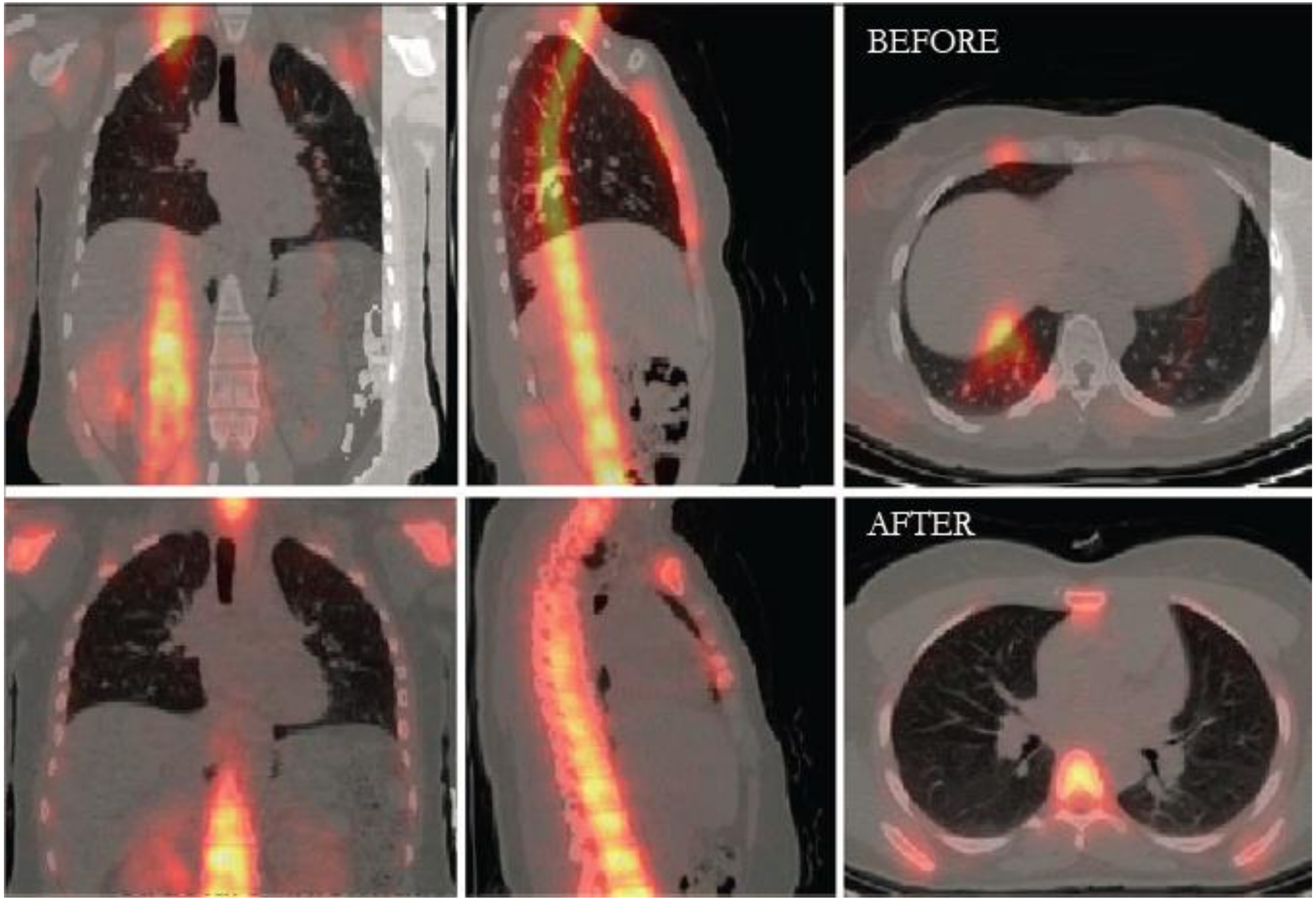
Modalities in Medical Imaging

- **Mono-modality:**
  - A series of same modality images (CT/CT, MR/MR, Mammogram pairs,…).
  - Images may be acquired weeks or months apart; taken from different viewpoints.
  - Aligning images in order to detect subtle changes in intensity or shape
- **Multi-modality:**
  - Complementary anatomic and functional information from multiple modalities can be obtained for the precise diagnosis and treatment.

Modalities in Medical Imaging

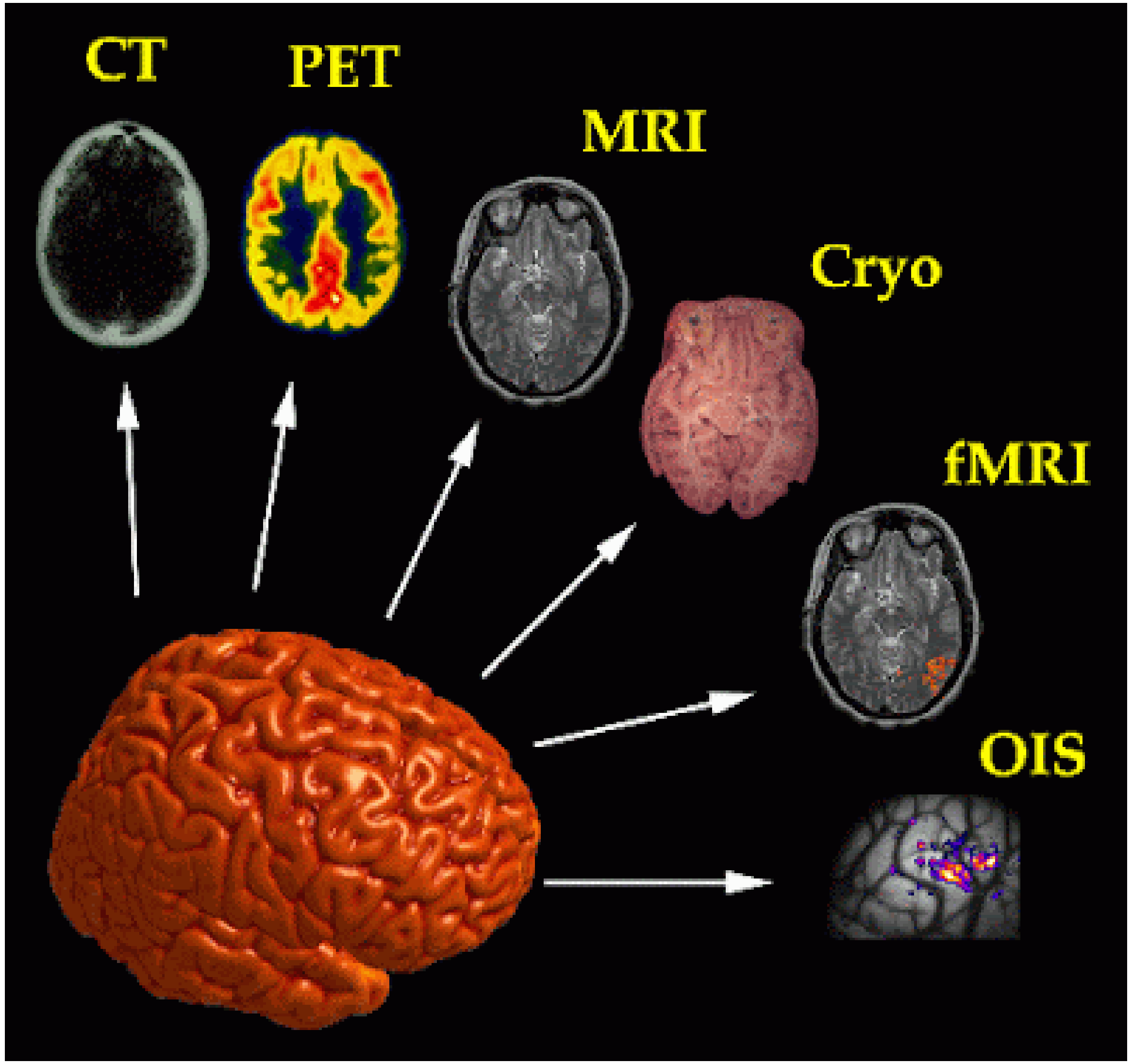


PET/CT Example

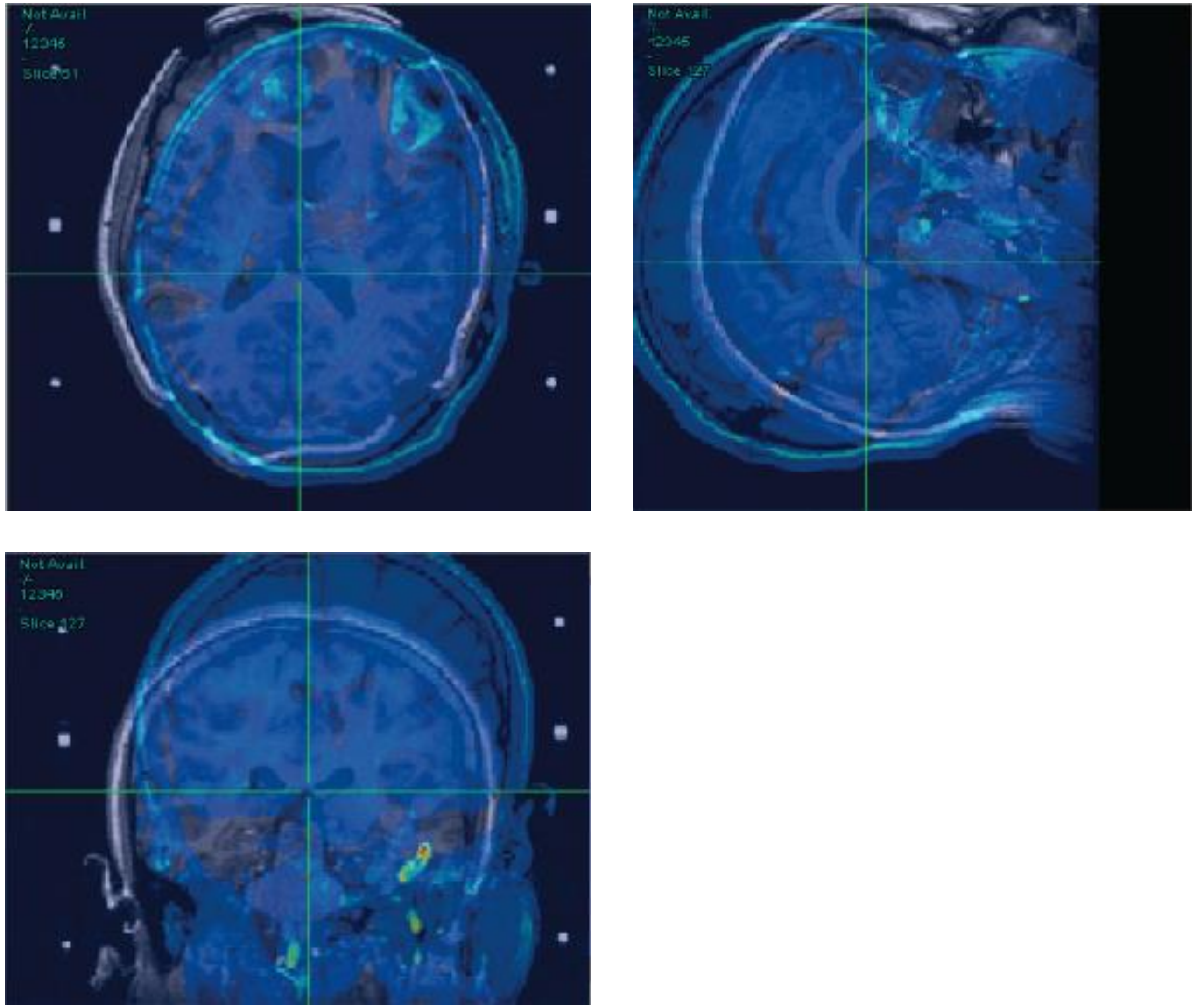


Why We Register Medical Images?

- Combining modalities (**inter modality**) gives extra information.
- Repeated imaging over time same modality, e.g. MRI, (**intra modality**) equally important.
- Have to spatially register the images.

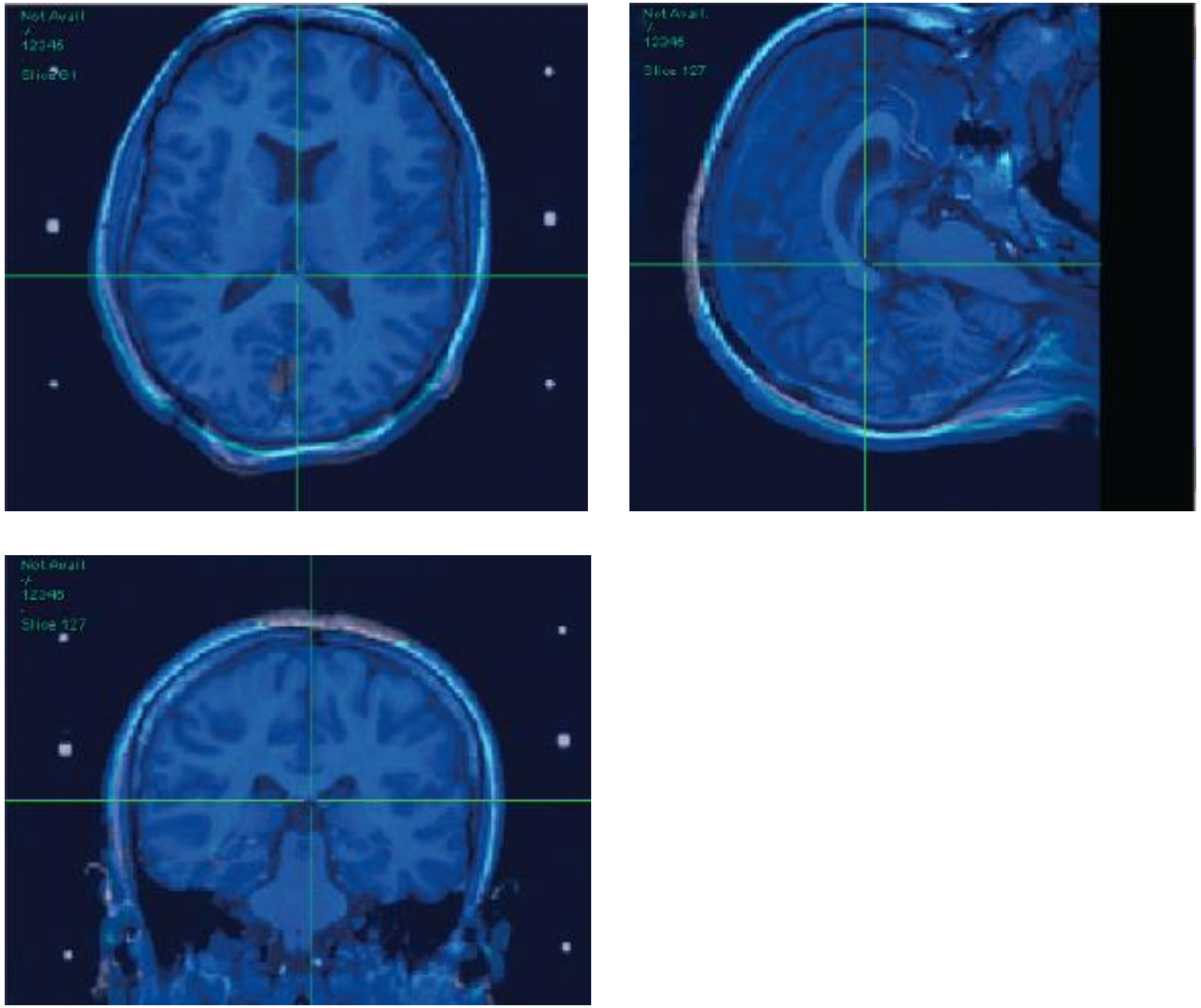


Before Registration



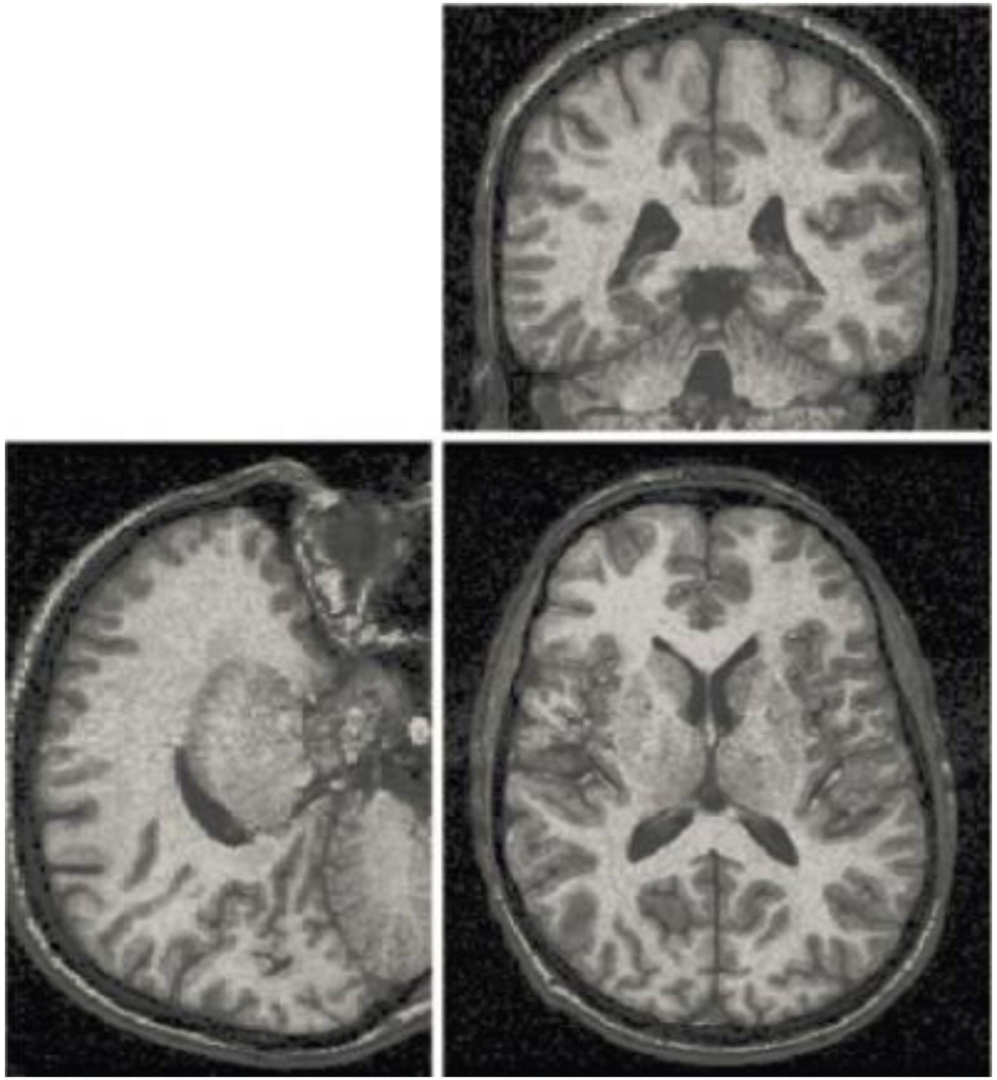
- Two brain MRI images of the same patient (3 orthogonal views)
- One of the images is taken prior to the operation, in order to plan it; the second while the patient is having the operation: the 6 white dots are the stereotactic frame screwed into the patient’s skull.
- In this case, a rigid transform suffices

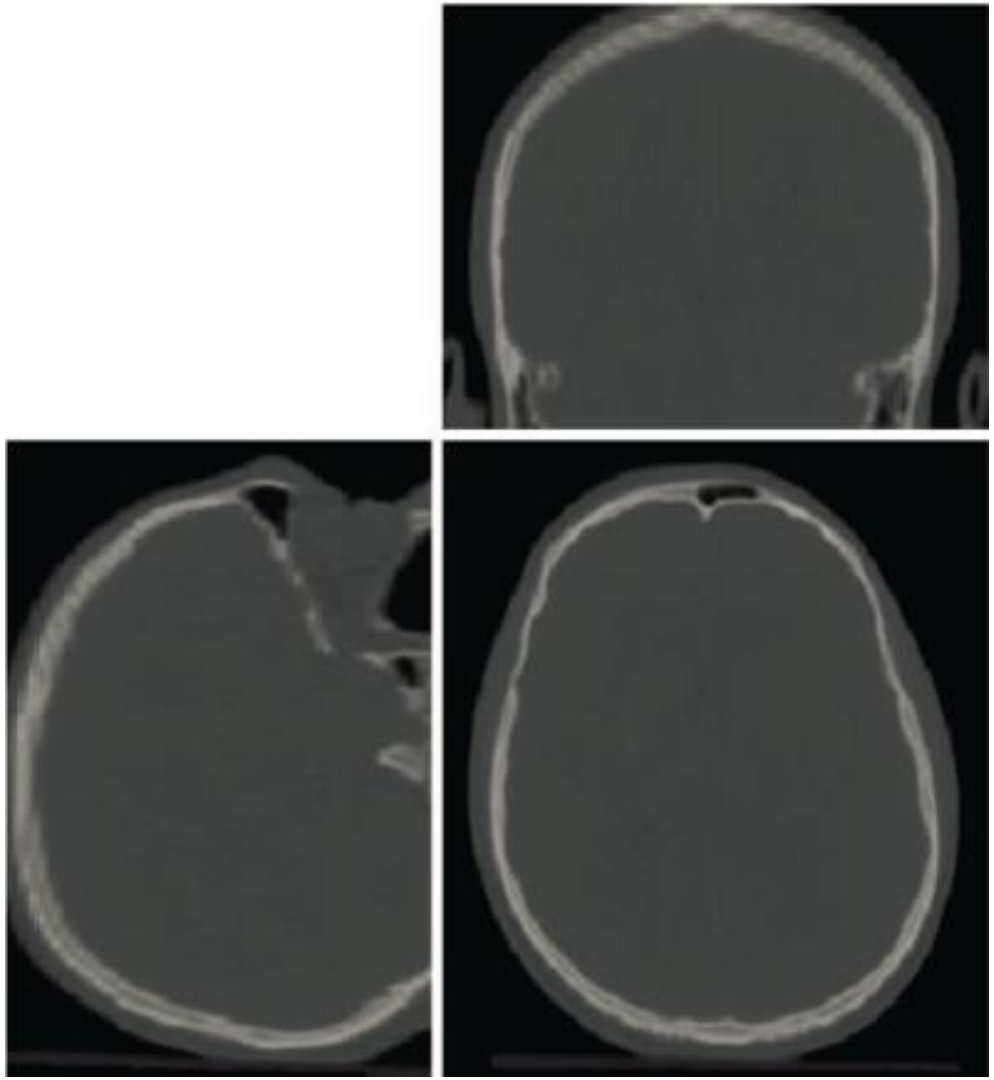
After Registration



- This shows the situation after the pre-op and inter-op images have been aligned.
- Typically, a rigid registration algorithm applied to brain images will be accurate to 1/10 of a voxel and 0.1 degrees of rotation.

Example: Rigid CT/MR Registration





Multiple Fusion Algorithms

- **Rigid fusion**: No compensation for motion or patient movement
- **Deformable fusion**: Crucial when structures have changed position or shape between or during scans due to voluntary or physiological motion or imperfect scanning protocols

Figure 1

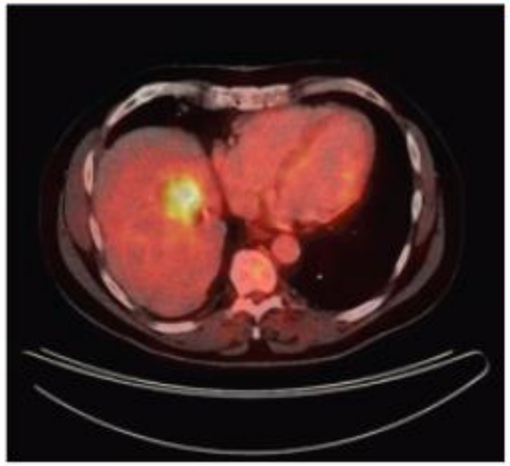


Figure 2

Rigid fusion (fig 1) can be ambiguous- the active growth identified on PET might be either one of two CT lesions, However, deformable fusion (fig 2) identifies the PET activity with the anterior lesion on CT

Multiple Fusion Algorithms

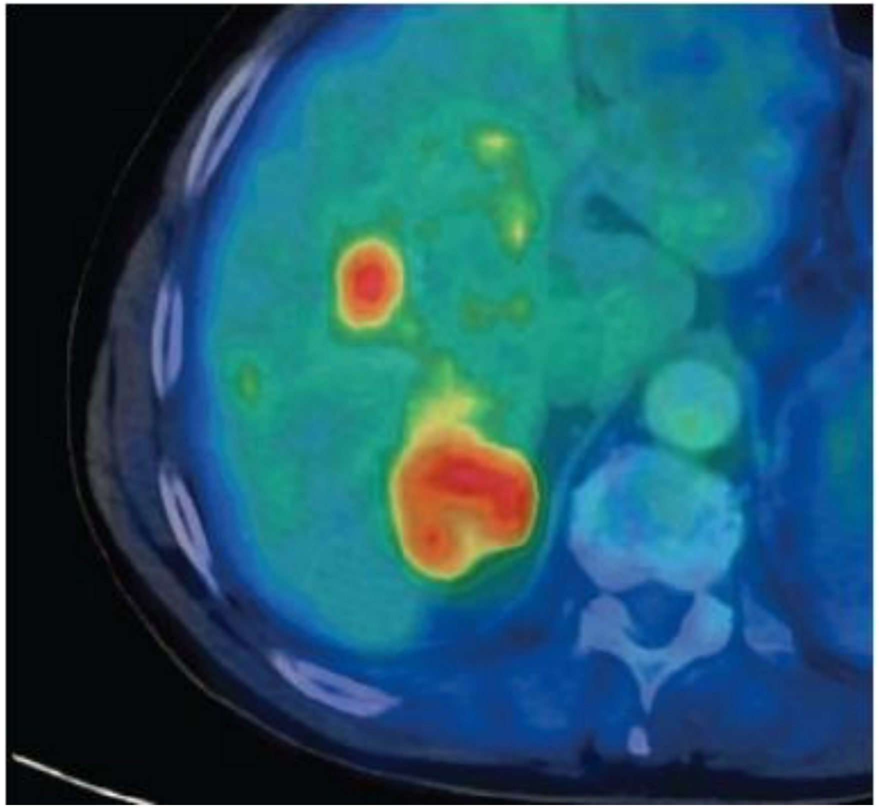
- **Fusion** of information = Registration + Combination in a single representation: PET/CT

CT

Deformable fusion: PET shows increased metabolism in lesions identified on CT, consistent with active tumour growth rather than necrosis post-radiotheraphy

PET

Multiple Fusion Algorithms



Deformable fusion: PET shows increased metabolism in lesions identified on CT, consistent with active tumour growth rather than necrosis post-radiotheraphy

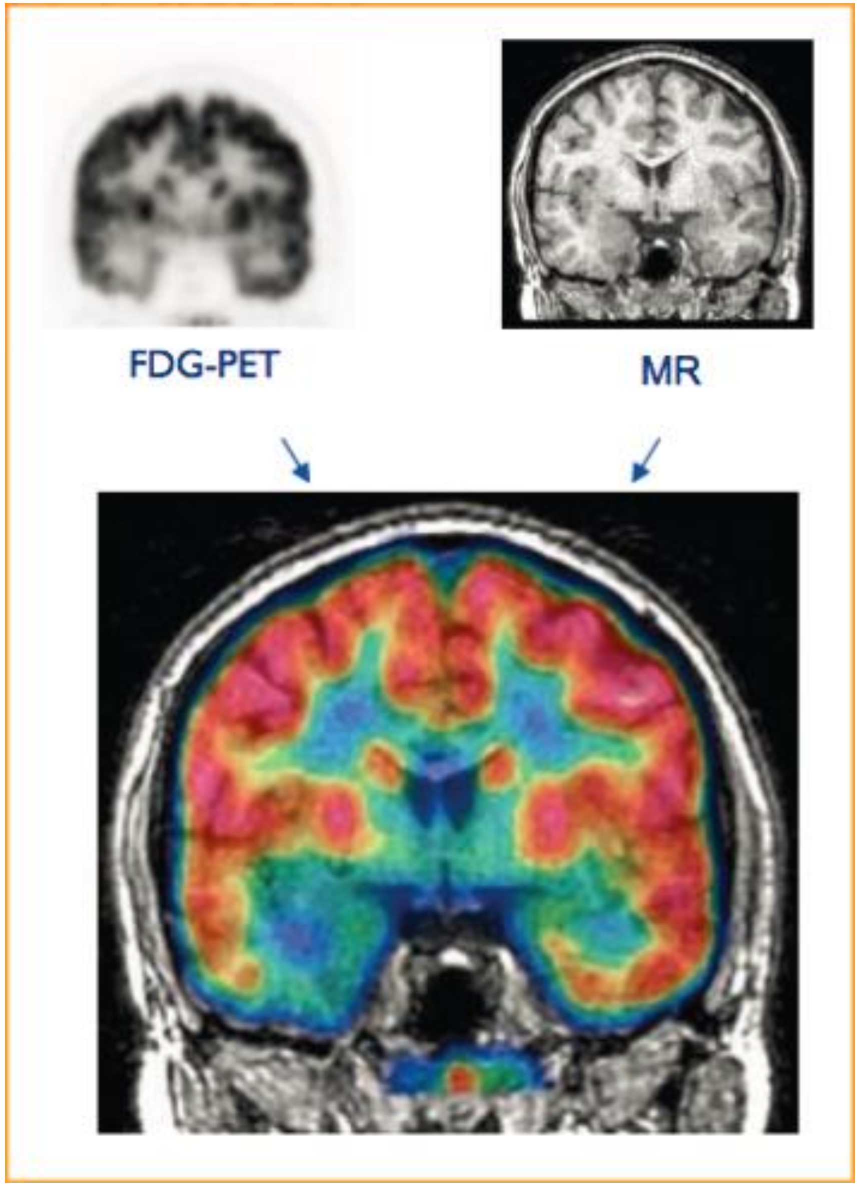
CT

PET

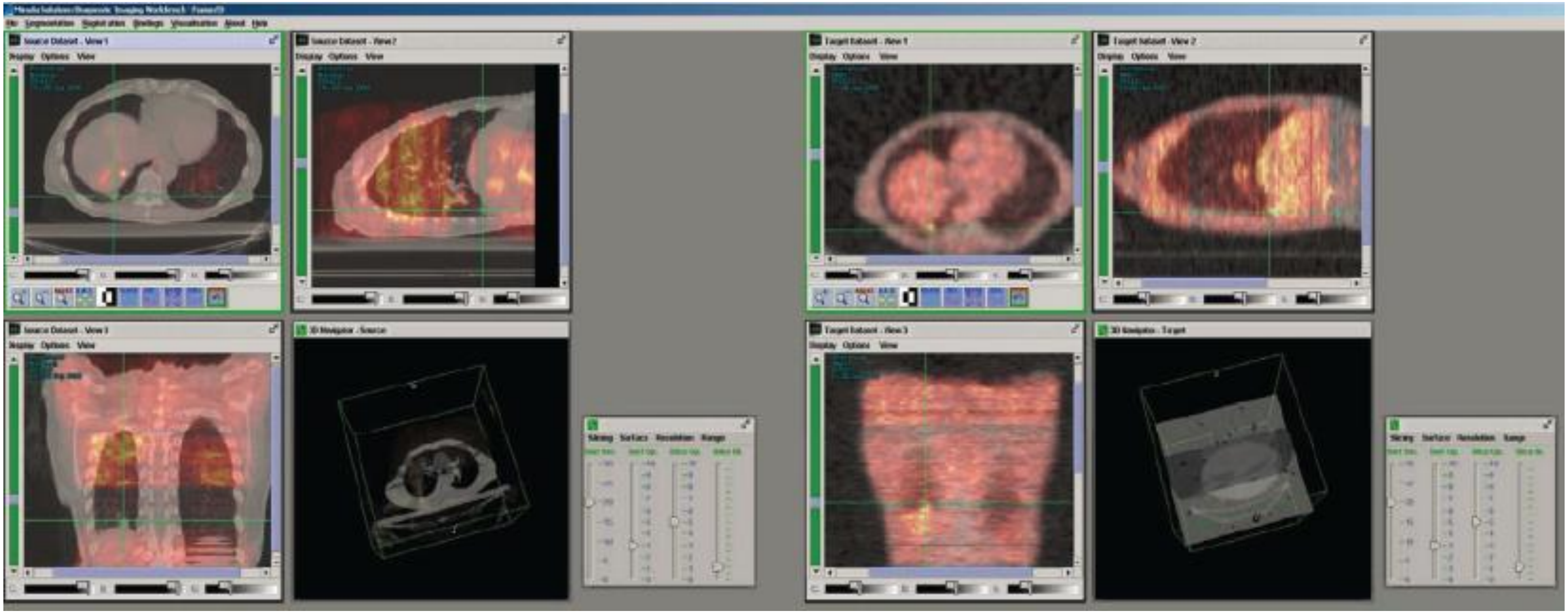
Many Clinical Applications of Fusion

- Cancer staging
- Biopsy planning
- Radiotherapy treatment planning
- Quantitative assessment of treatment response
- Pre-surgical assessment of other conditions e.g. epilepsy
- As an effective communication tool when reporting to clinical meetings, referring physicians or to patients
- Whenever multiple data sources may be better assessed together

PET data identifies a region of hypometabolism due to epilepsy. Fusion with MRI localizes the damage to the anterior and medial areas of the right temporal gyrus.



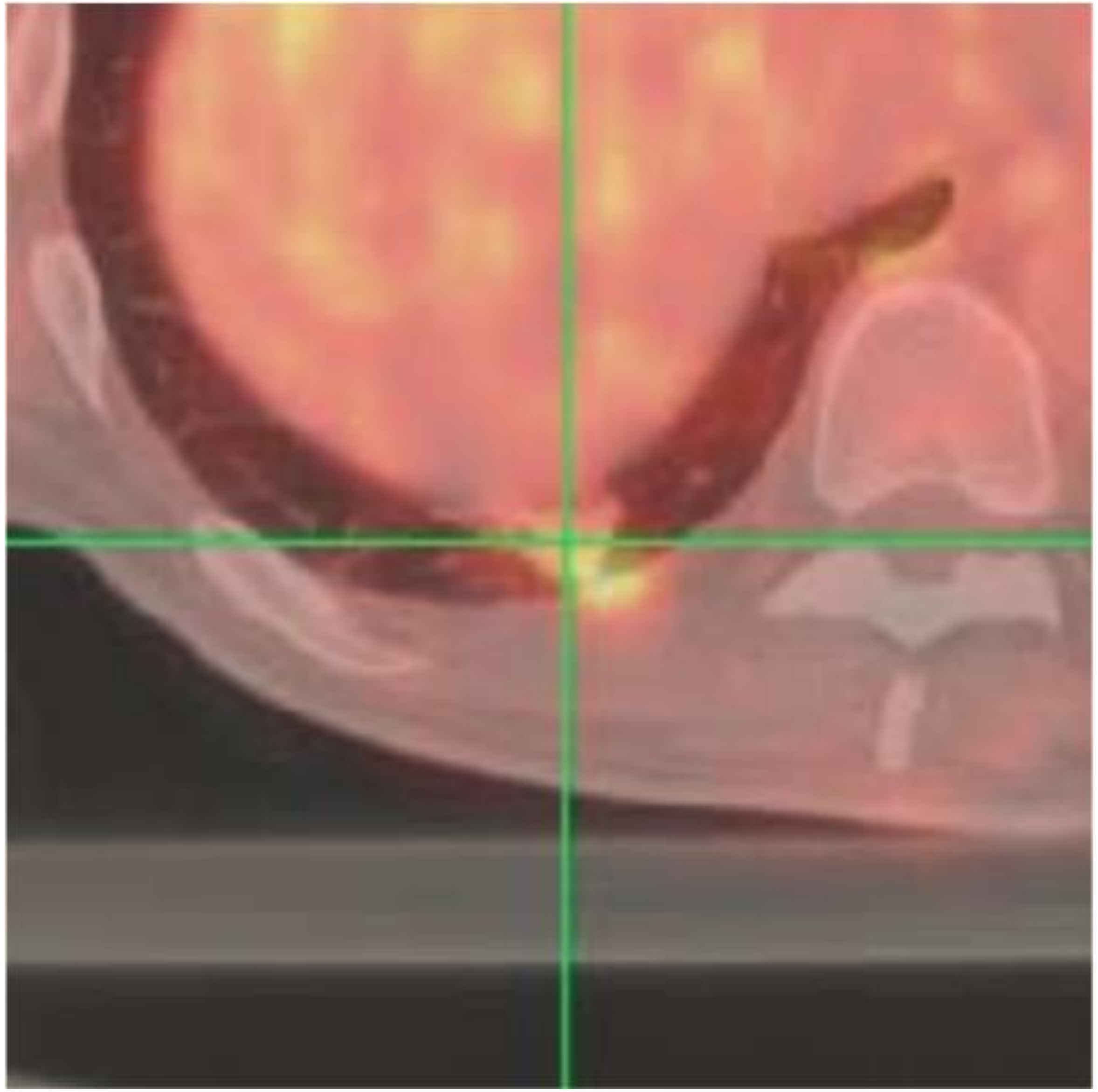
CT – PET Registration



Non-rigid registration is necessary

CT – PET Registration

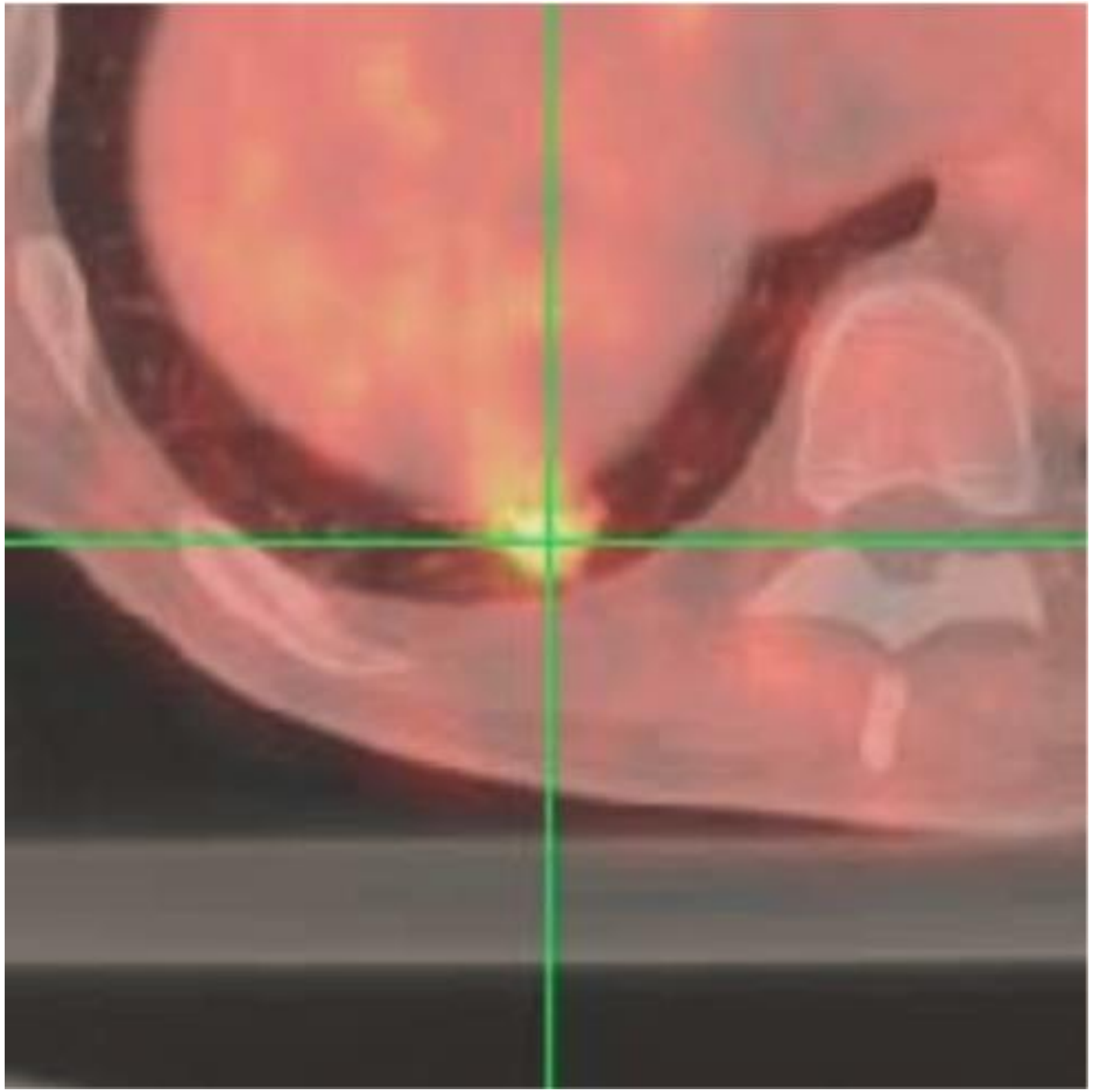
- **Rigid registration is poor!**



Is the tumor in the lungs or the stomach?

CT – PET Registration

- **Nonrigid registration**



Looks plausible; but how could you be sure?

Are you prepared to risk your software against getting sued?

Summary of Mostly Used Applications

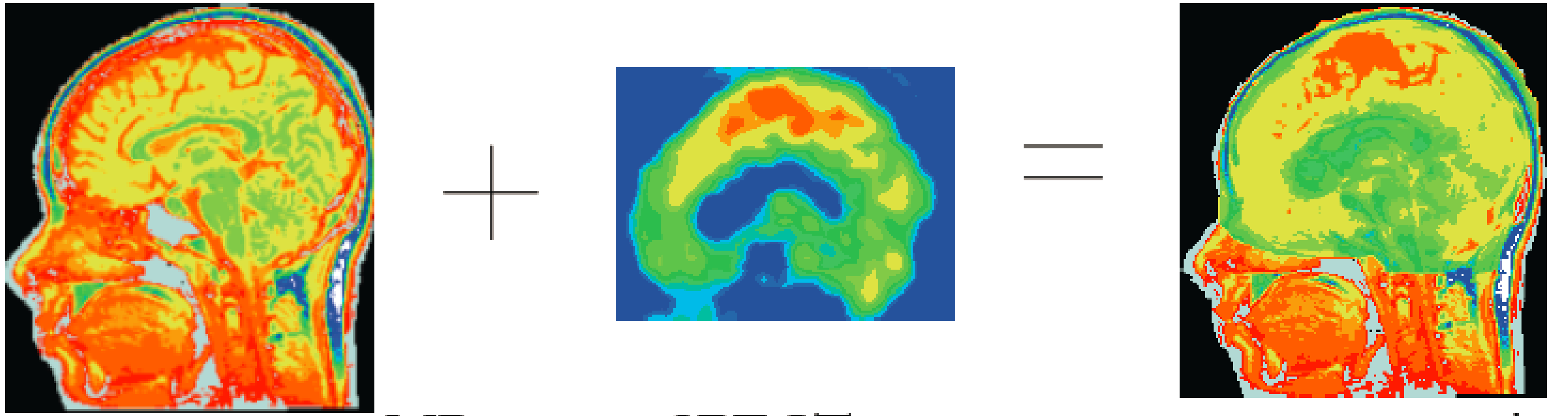
- Diagnosis
  - Combining information from multiple imaging modalities
- Studying disease progression
  - Monitoring changes in size, shape, position or image intensity over time
- Image guided surgery or radiotherapy
  - Relating pre-operative images and surgical plans to the physical reality of the patient
- Patient comparison or atlas construction
  - Relating one individual's anatomy to a standardized atlas

Then, What is Image Registration (formally)?

Image Registration is a

- Spatial transformation that maps points from one image to corresponding points in another image

  matching two images so that corresponding coordinate points in the two images correspond to the same physical region of the scene being imaged also referred to as image fusion, superimposition, matching or merge



MR SPECT registered

Then, What is Image Registration (formally)?

Image Registration is a

- Spatial transform that maps points from one image to corresponding points in another image
  - **Rigid**
    - Rotations and translations
  - **Affine**
    - Also, skew and scaling
  - **Deformable**
    - Free-form mapping

Registration Framework

Deformation Model

Matching Criteria (Objective Function)

Optimization Method

Image Registration Taxonomy

- **Dimensionality**
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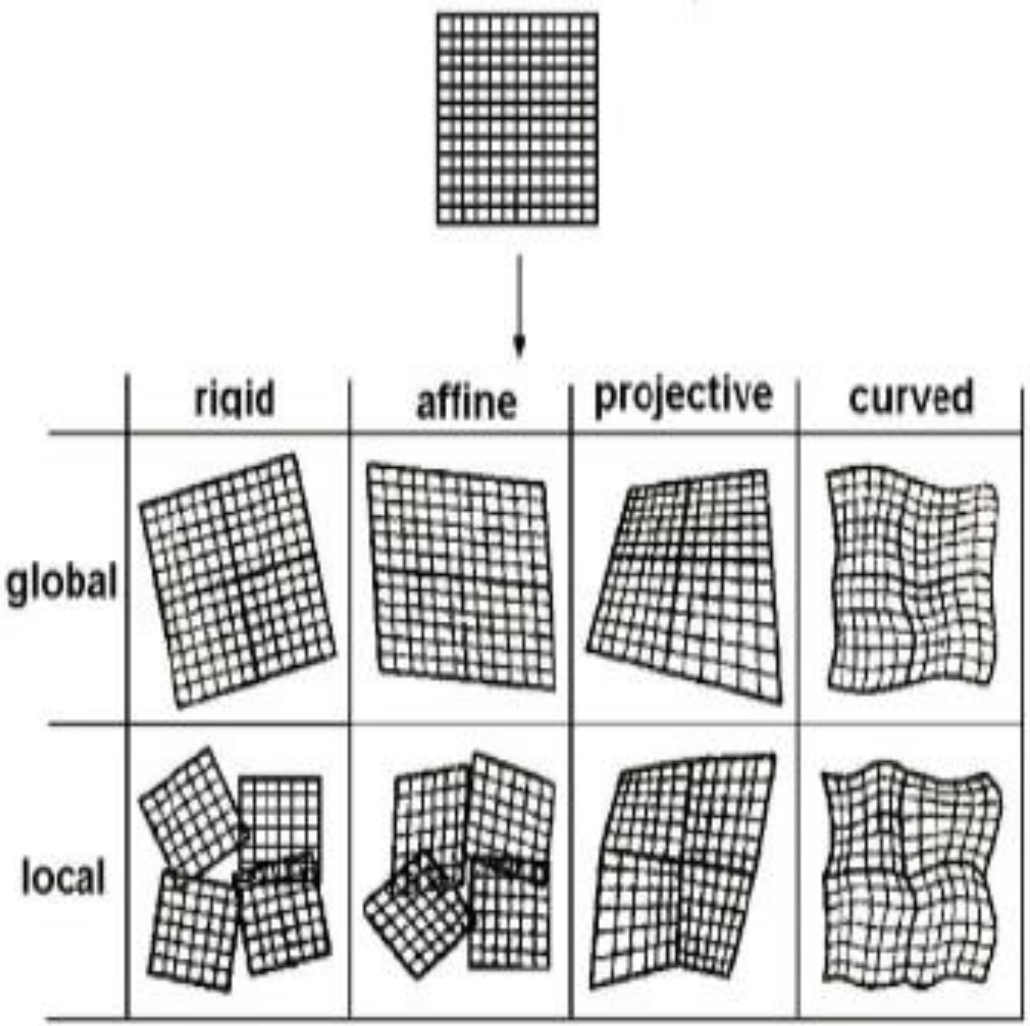
Deformation Models

Method used to find the transformation

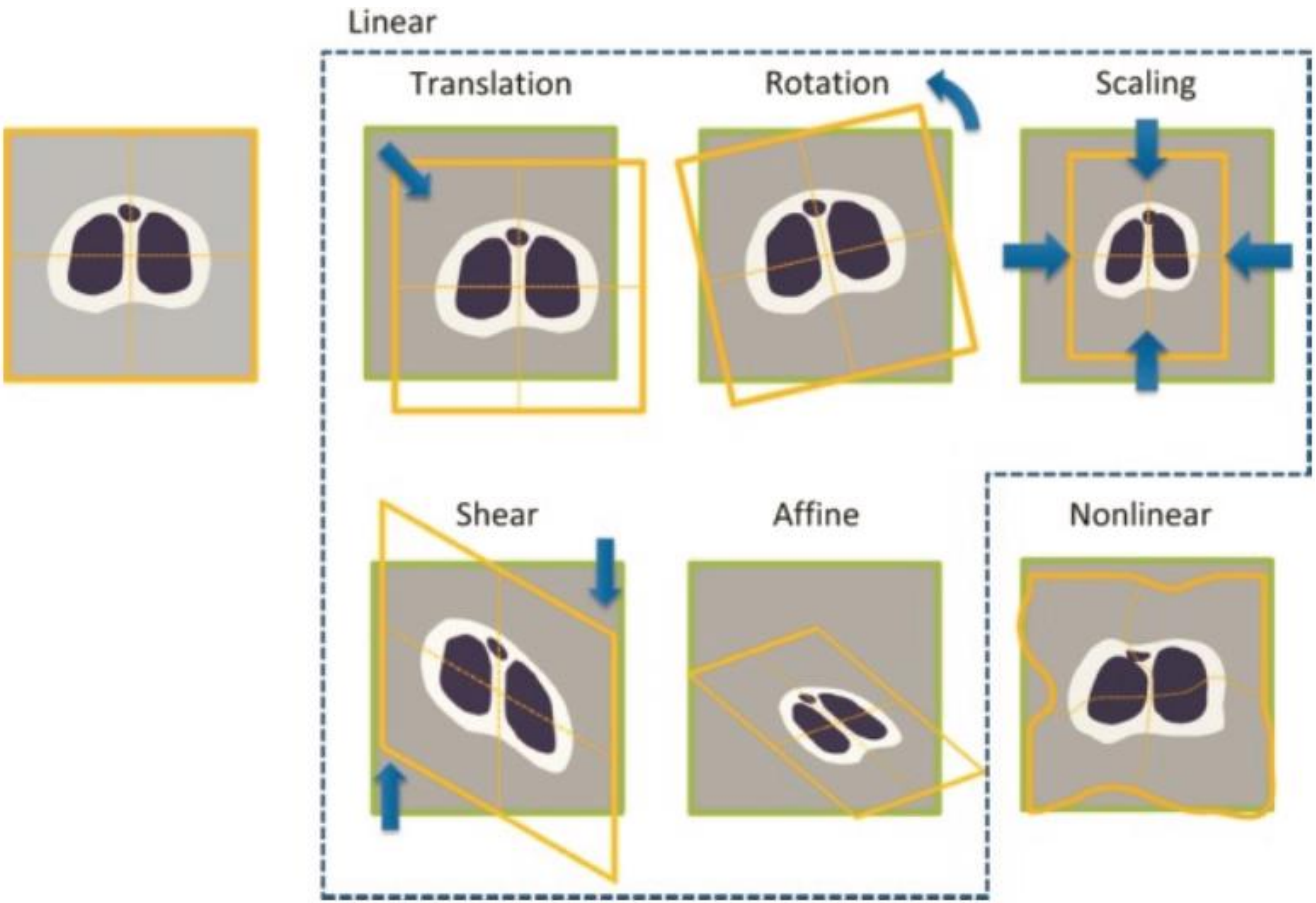
- **Rigid & affine**
  - Landmark based
  - Edge based
  - Voxel intensity based
  - Information theory based
- **Non-rigid**
  - Registration using basis functions
  - Registration using splines
  - Physics based
  - Elastic, Fluid, Optical flow, etc.



Deformation Model (Transformation)

- Rigid
  - Rotation, translation
- Affine
  - Rigid + scaling
- Deformable
  - Affine + vector field
- ….

Deformation Model (Linear vs Nonlinear)



Linear Registration → Separable

$$T(a\mathbf{x}_1 + \mathbf{x}_2) = aT(\mathbf{x}_1) + T(\mathbf{x}_2)$$

Rigid Transformation

The dimensionality can be adapted

- 2D/2D → 3 parameters (2 translations, 1 rotation)
- 3D/3D → 6 parameters (3 rotations, 3 translations)

Linear Registration → Separable

$$T(a\mathbf{x}_1 + \mathbf{x}_2) = aT(\mathbf{x}_1) + T(\mathbf{x}_2)$$

Rigid Transformation

The dimensionality can be adapted

- 2D/2D → 3 parameters (2 translations, 1 rotation)
- 3D/3D → 6 parameters (3 rotations, 3 translations)

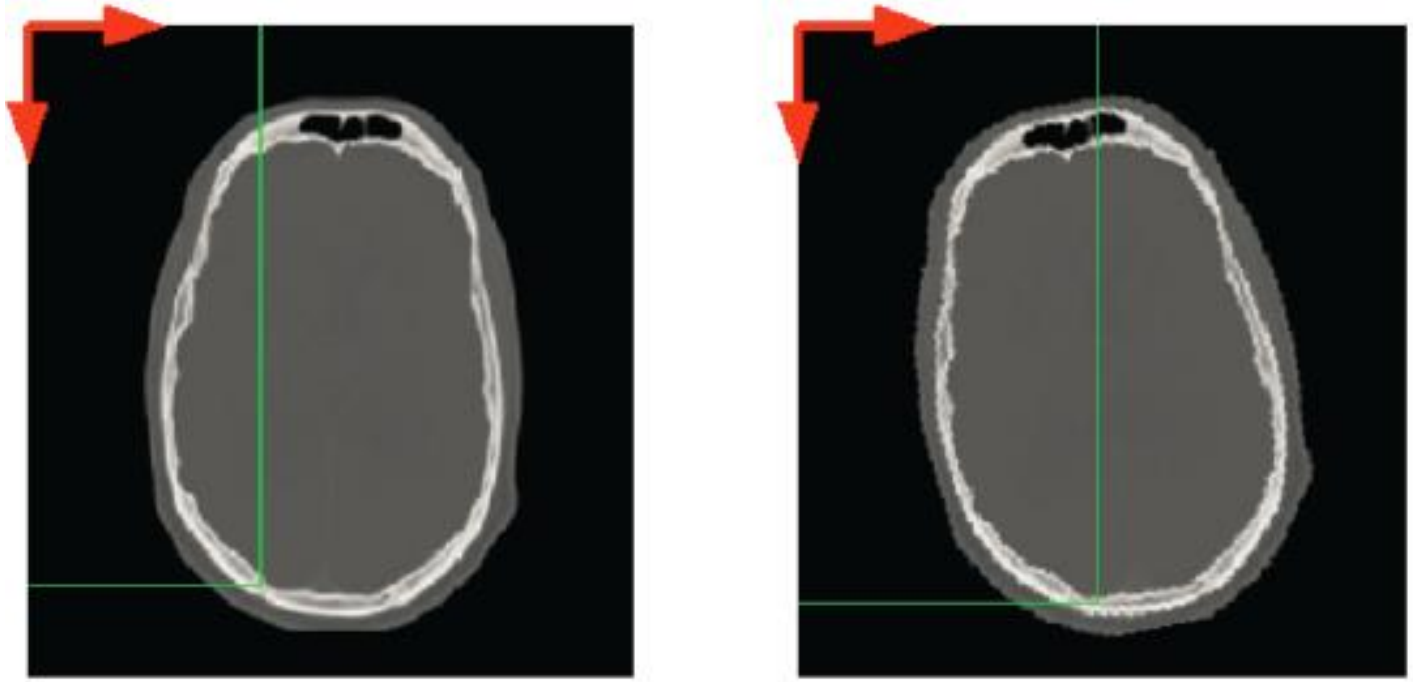
In 3D, 3 translation parameters

$$\boldsymbol{M} = \begin{bmatrix} 1 & 0 & 0 & t_0 \\ 0 & 1 & 0 & t_1 \\ 0 & 0 & 1 & t_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

In 2D, 2 translation parameters

$$\boldsymbol{M} = \begin{bmatrix} 1 & 0 & t_0 \\ 0 & 1 & t_1 \\ 0 & 0 & 1 \end{bmatrix}$$

Rigid Registration - Rotation



One parameter, the angle θ:

$$\boldsymbol{R} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Example Rigid Transformation Formulation

- **Goal**: Find parameter values (i.e., t_x, t_y, θ) that optimize some image similarity metric

$$\mathbf{x}' = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

$$\mathbf{x}' = \mathbf{T}(\mathbf{x}|\mathbf{p}) = \mathbf{T}(x, y | t_x, t_y, \theta)$$

New location

Old location

Linear Registration → Separable

$$T(a\mathbf{x}_1 + \mathbf{x}_2) = aT(\mathbf{x}_1) + T(\mathbf{x}_2)$$

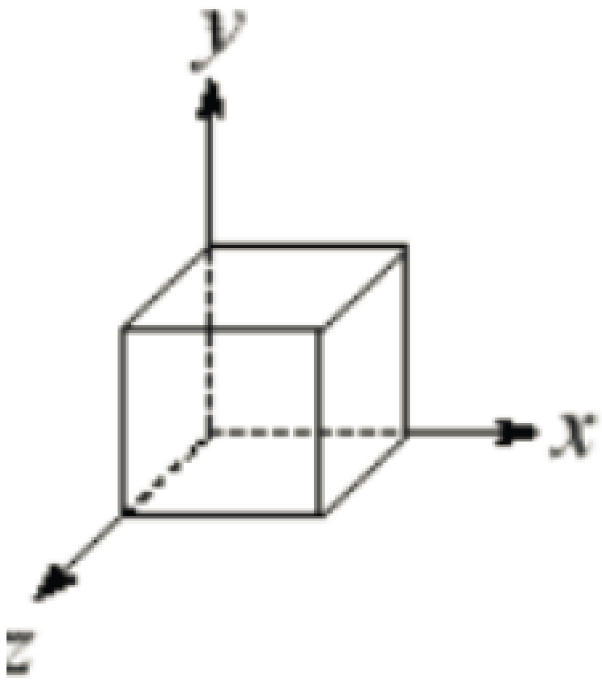
Affine Transformation (Rigid + Scaling (+ skew))

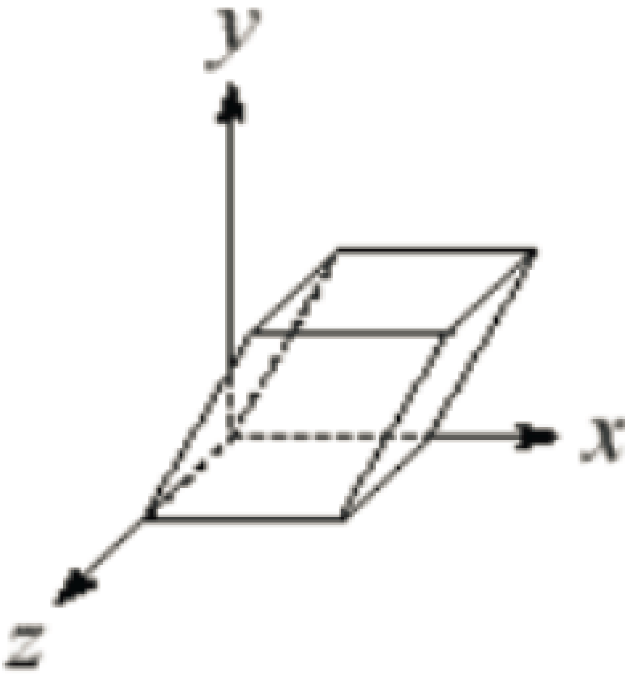
In 3D, 3 parameters: s_x, s_y, s_z

$$= \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & s_z \end{bmatrix}$$

- 9 parameters, Affine = 6 parameters (rotation + translation) + 3 parameters (scaling)
- 12 parameters, Affine = …+ 3 parameters (skew)

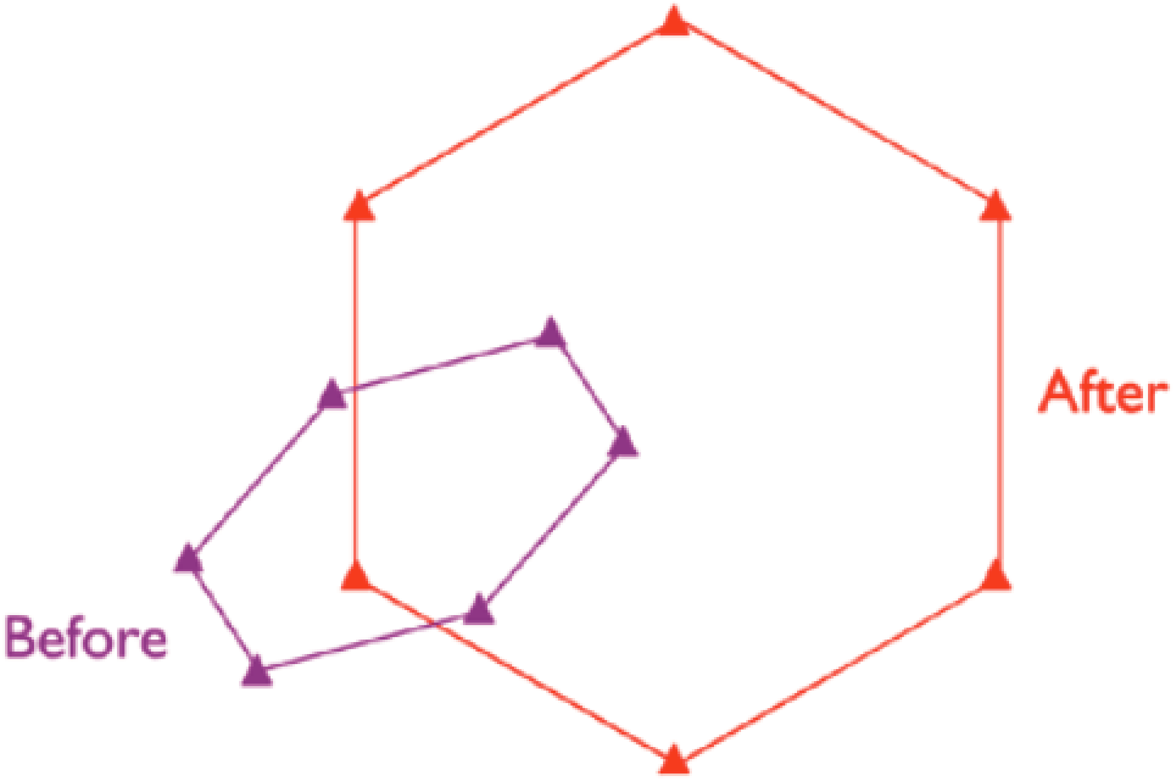
Shear in 3D





$$\begin{bmatrix} x' \\ y' \\ z' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & b & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

Affine Transformation



$$\mathbf{p'} = \mathbf{M}\,\mathbf{p} + \mathbf{t}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$x' = ax + by$$
$$y' = cx + dy$$

Homogenous Coordinates for Transformations

$$\mathbf{p}' = \mathbf{M}\mathbf{p} = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} \mathbf{u} & \mathbf{v} & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$= x \cdot \mathbf{u} + y \cdot \mathbf{v} + 1 \cdot \mathbf{t}$$

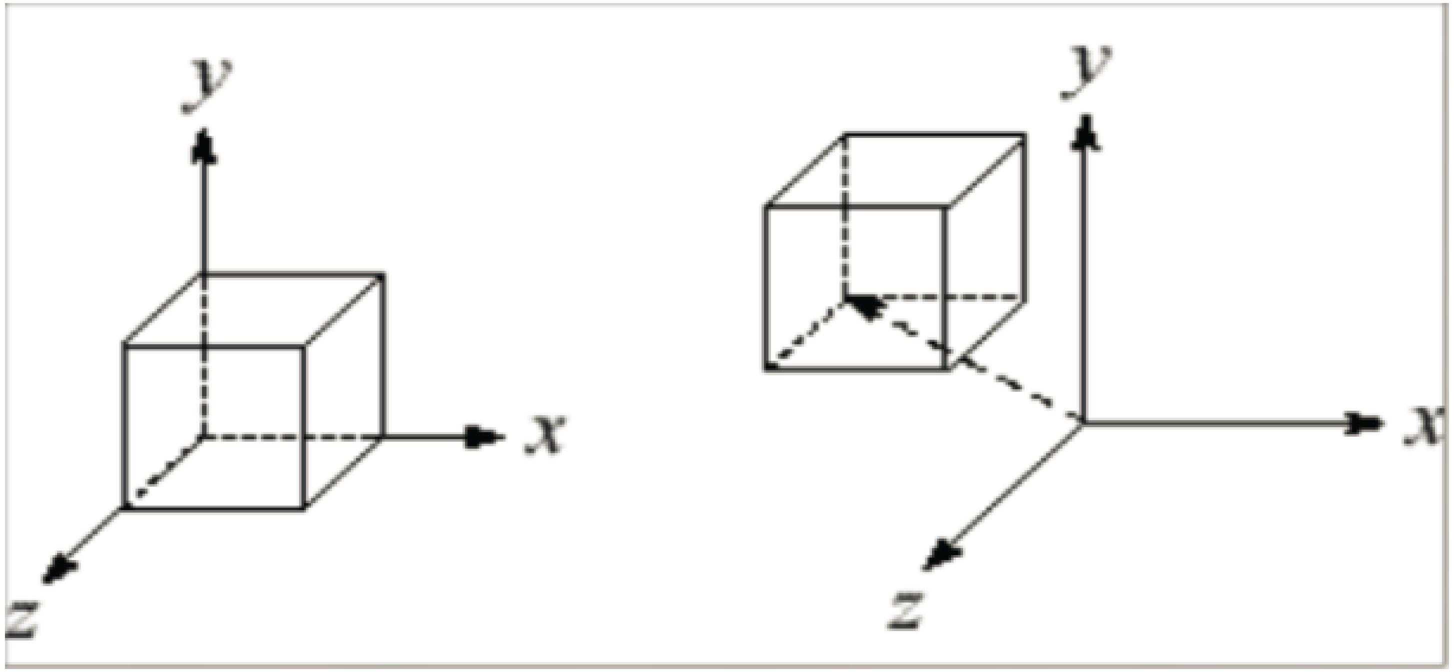
Homogenous Coordinates for Transformations

$$\mathbf{p}' = \mathbf{M}\mathbf{p} = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ \boxed{1} \end{bmatrix}$$

$$= \begin{bmatrix} \mathbf{u} & \mathbf{v} & \mathbf{t} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

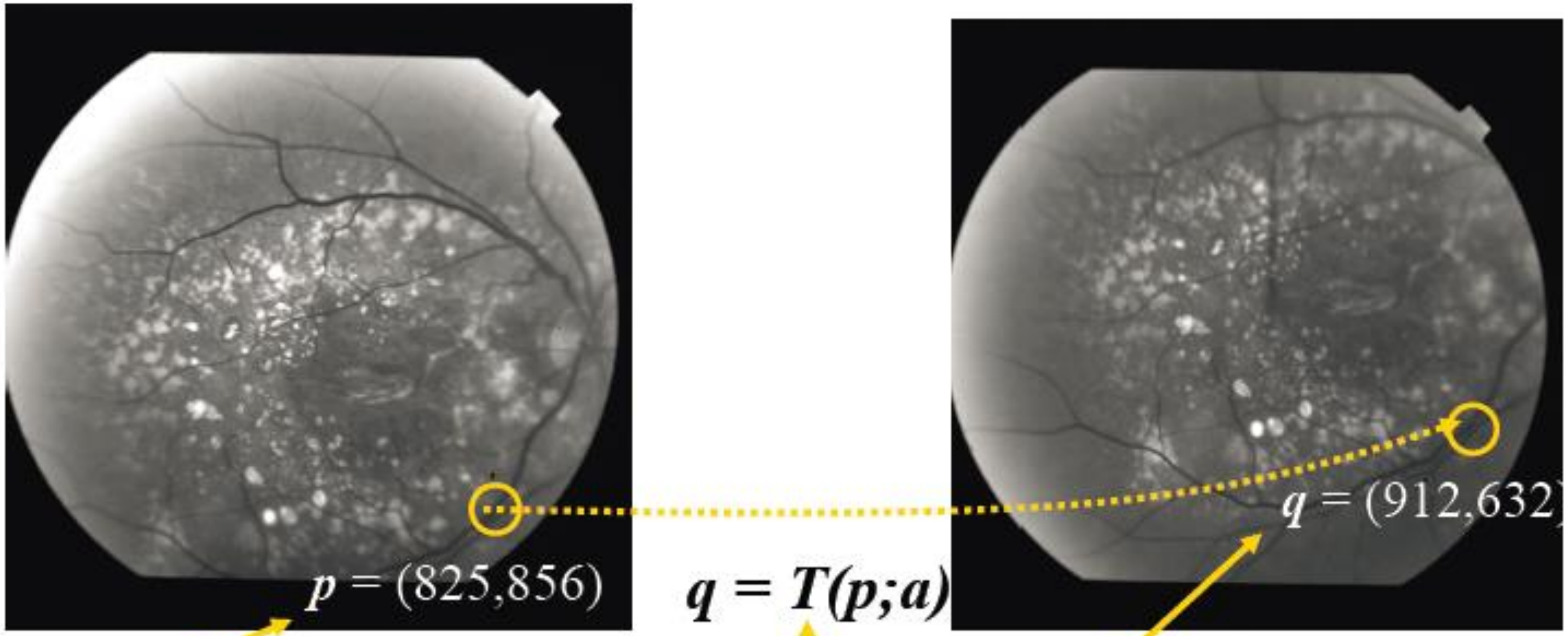
$$= x \cdot \mathbf{u} + y \cdot \mathbf{v} + 1 \cdot \mathbf{t}$$

Translation in Homogenous Coordinate System



$$\begin{bmatrix} x' \\ y' \\ z' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & t_x \\ 0 & 1 & 0 & t_y \\ 0 & 0 & 1 & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

Registration is an alignment problem



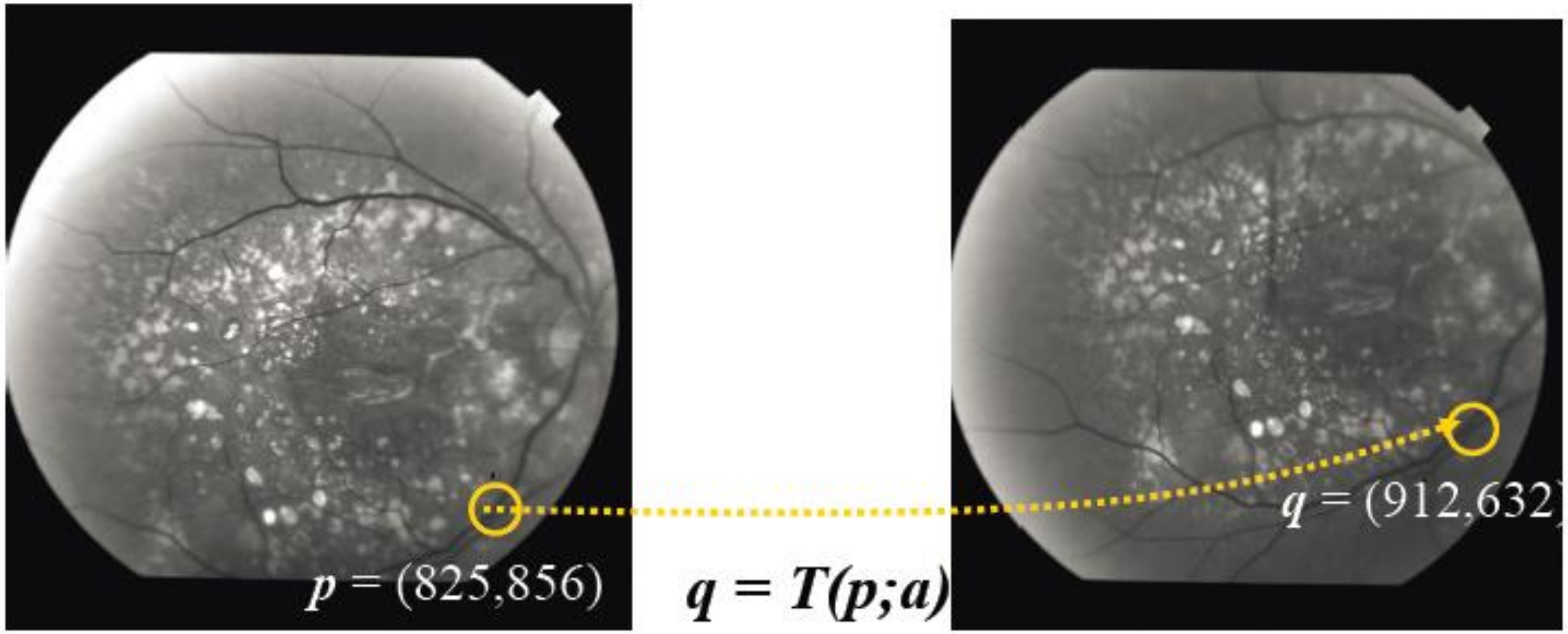
$$q = T(p;a)$$

Pixel location in first image

Homologous pixel location in second image

Pixel location mapping function

Registration is an alignment problem



$$\mathrm{p} = (x, y)^T$$

$$\mathbf{\Theta} = (s, t_x, t_y)^T$$

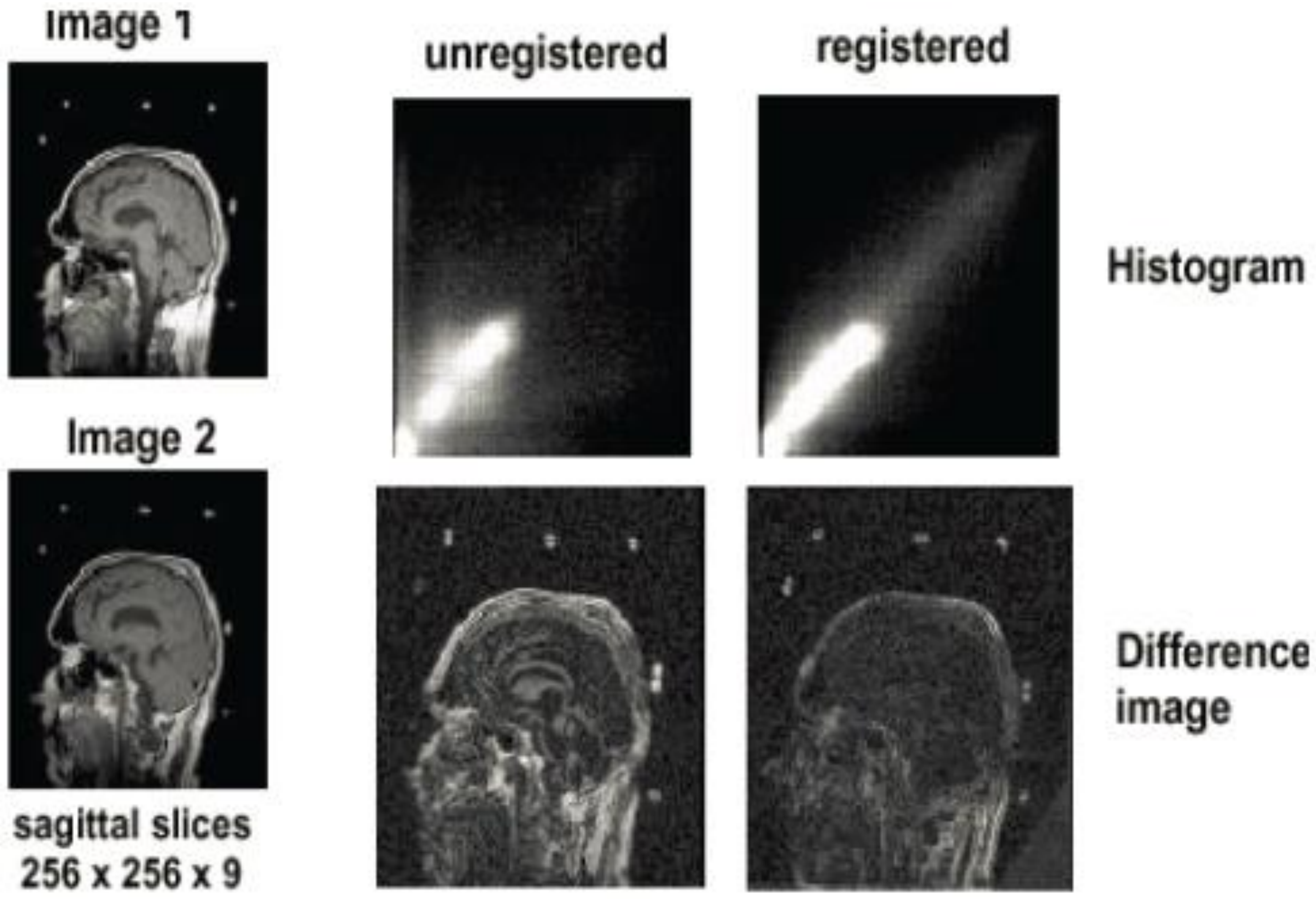
$$\mathrm{T}(\mathrm{p}; \mathbf{\Theta}) = \begin{pmatrix} sx + t_x \\ sy + t_y \end{pmatrix}$$

Pixel scaling and translation

Similarity Criteria

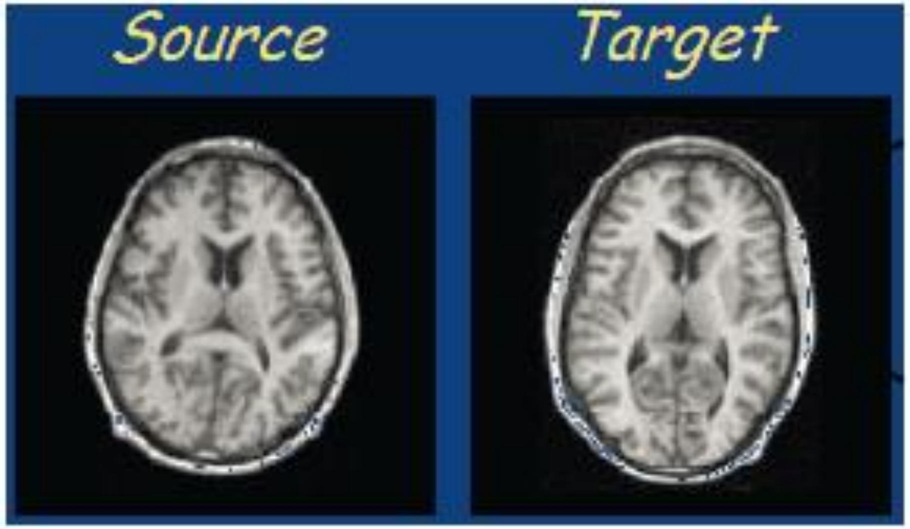
Intensity Based

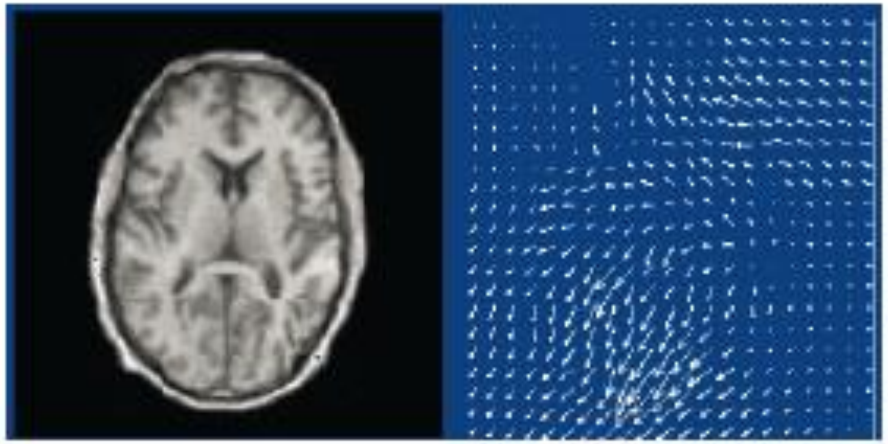
- Method
  - Calculating the registration transformation by optimizing some measure calculated directly from the voxel values in the images
- Algorithms used
  - Registration by minimizing intensity difference
  - Correlation techniques
  - Ratio image uniformity
  - Partitioned Intensity Uniformity



Intensity Based

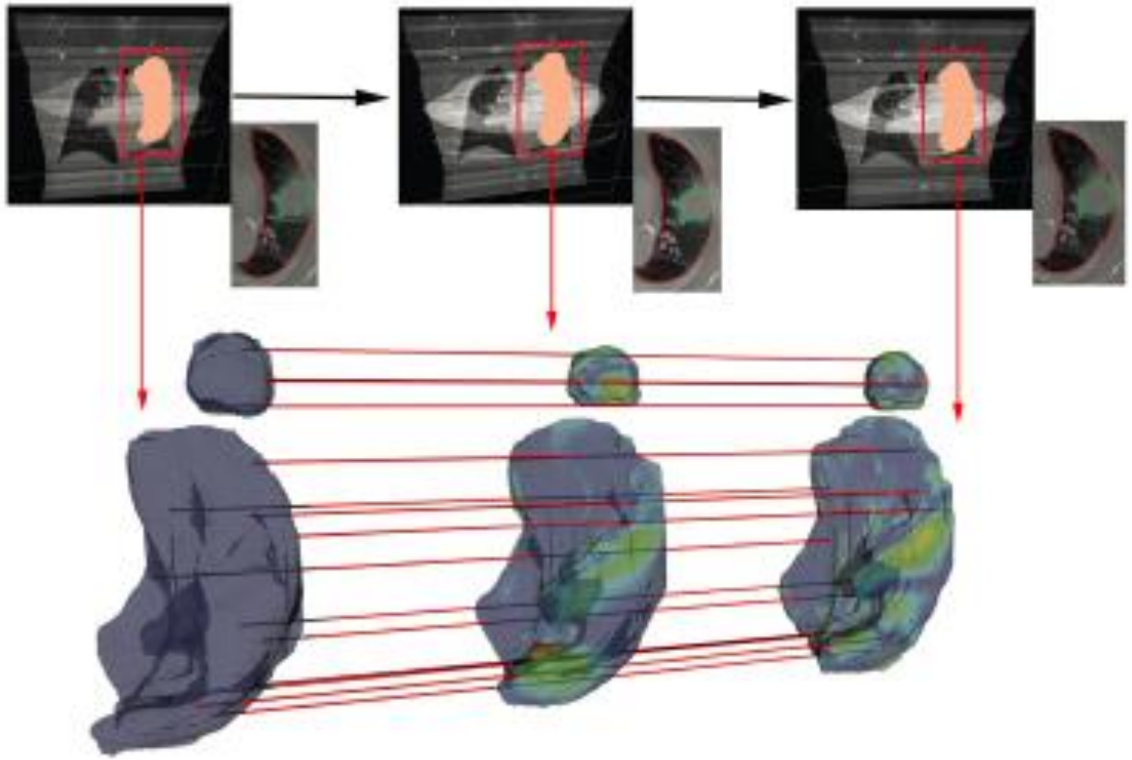
- Intensity-based methods compare intensity patterns in images via some similarity metrics
  - Sum of Squared Differences
  - Normalized Cross-Correlation
  - Mutual Information





Feature Based

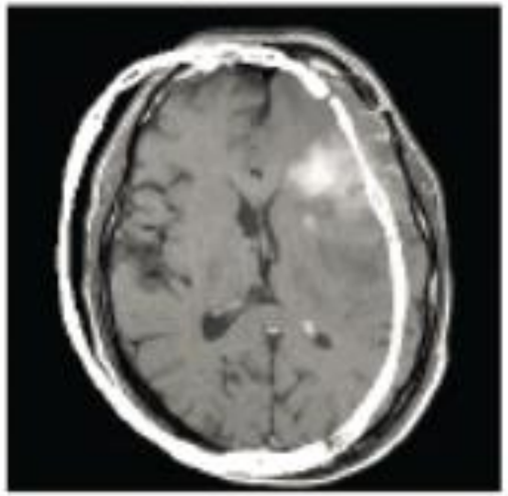
- Feature-based methods find correspondence between image features such as points, lines, and contours.
  - Distance between corresponding points
  - Similarity metric between feature values
    - e.g. curvature-based registration



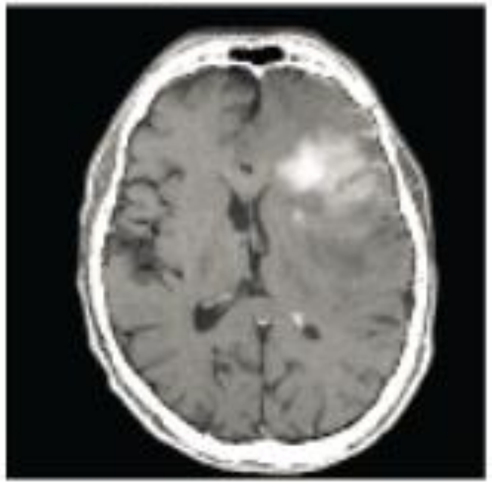
Information Theory Based

- Image registration is considered as to maximize the amount of shared information in two images
  - reducing the amount of information in the combined image
- Algorithms used
  - Joint entropy
    - Joint entropy measures the amount of information in the two images combined
  - Mutual information
    - A measure of how well one image explains the other, and is maximized at the optimal alignment
  - Normalized Mutual Information

Not registered



Registered

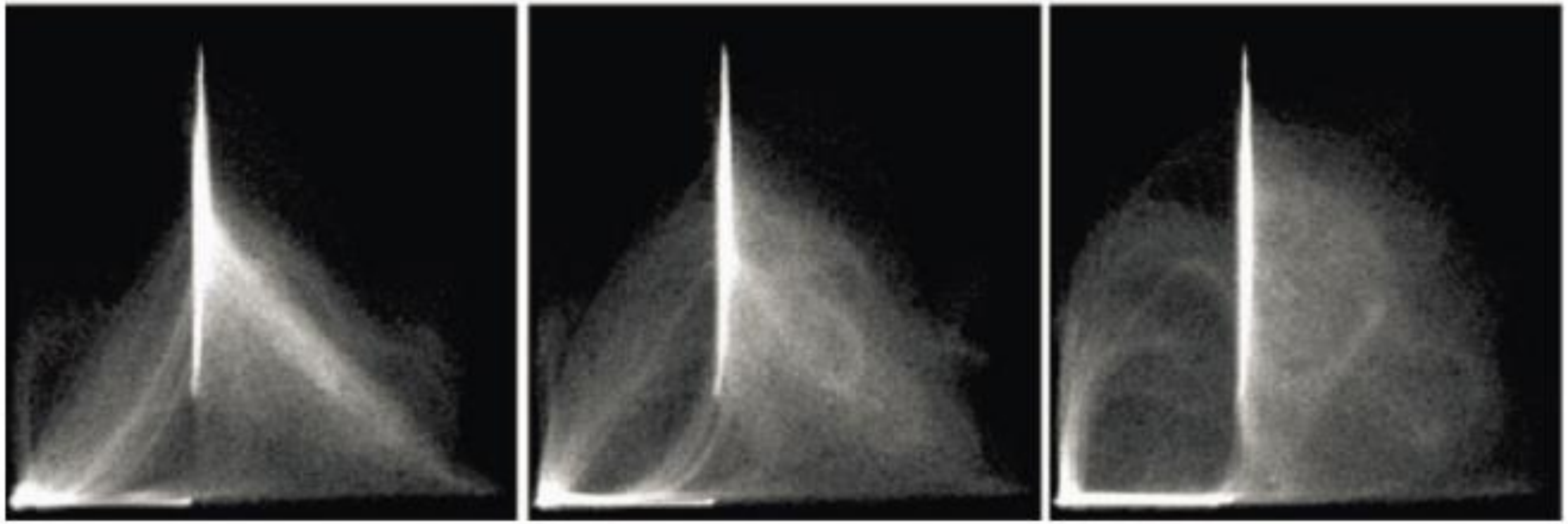


Mutual Information

$$MI(I,J\,|\,T) = \sum_{i,j} p_{i,j} \log \frac{p_{i,j}}{p_i p_j}$$

- Algorithms for maximizing mutual information (between intensities) have been the most popular for medical image registration to date.
- There are many refinements underway … not least using measurements of local phase instead of intensity

Roger Wood’s Heuristic Observation



Images perfectly aligned

2mm displacement of one image to the side

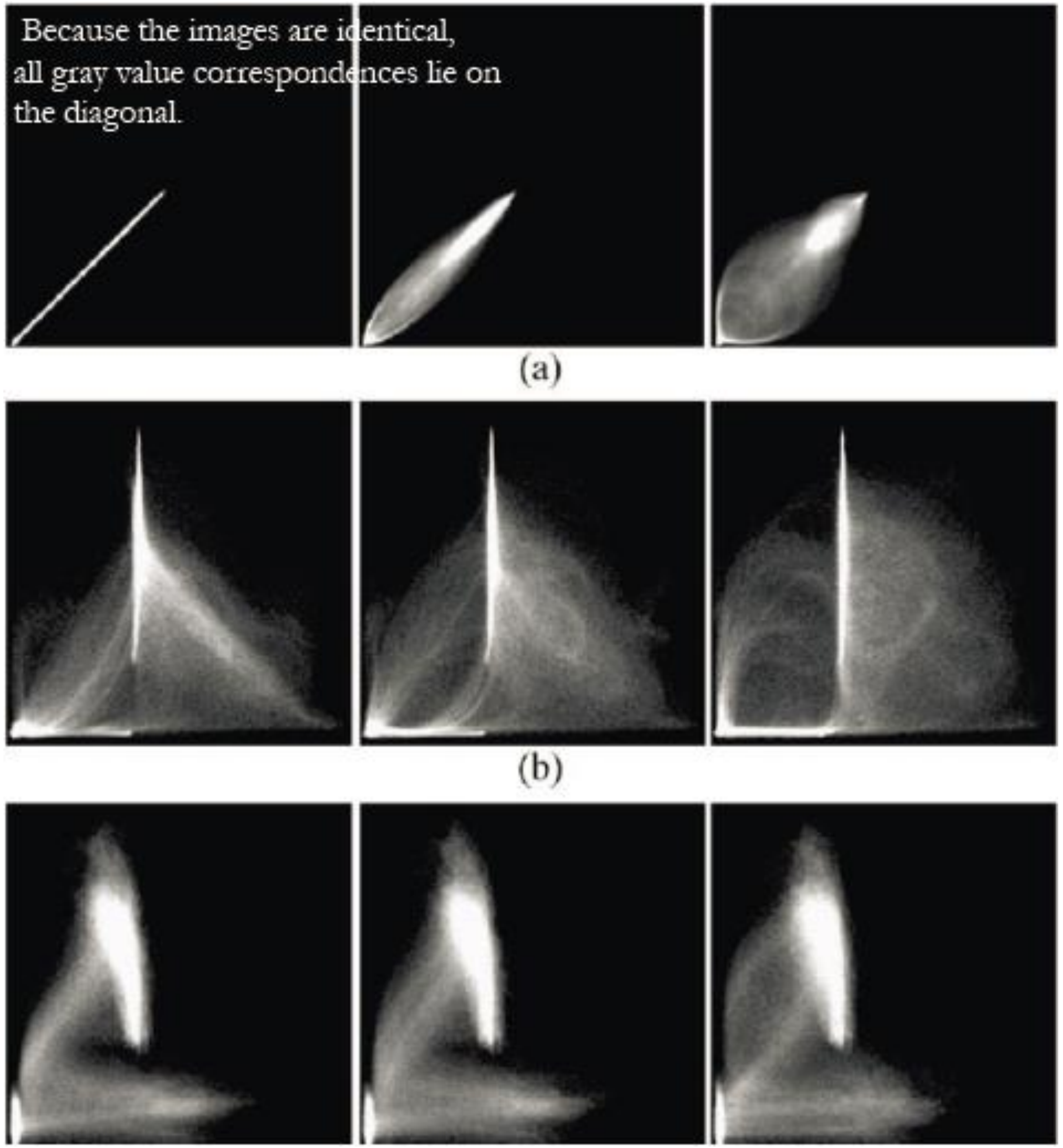
5mm displacement of one image to the side

- Heuristic observation is that when the images are aligned, the joint histogram appears “sharpest” : “Wood’s criterion”
- Why this should be the case is still not certain!

Simple Code for Joint Entropy Computation

```
rows=size(x,1);
cols=size(y,2);
N=256;
h=zeros(N,N);
        for i=1:rows;
                for j=1:cols;
                h(x(i,j)+1,y(i,j)+1)= h(x(i,j)+1,y(i,j)+1)+1;
                end
        end
imshow(h)
end
```

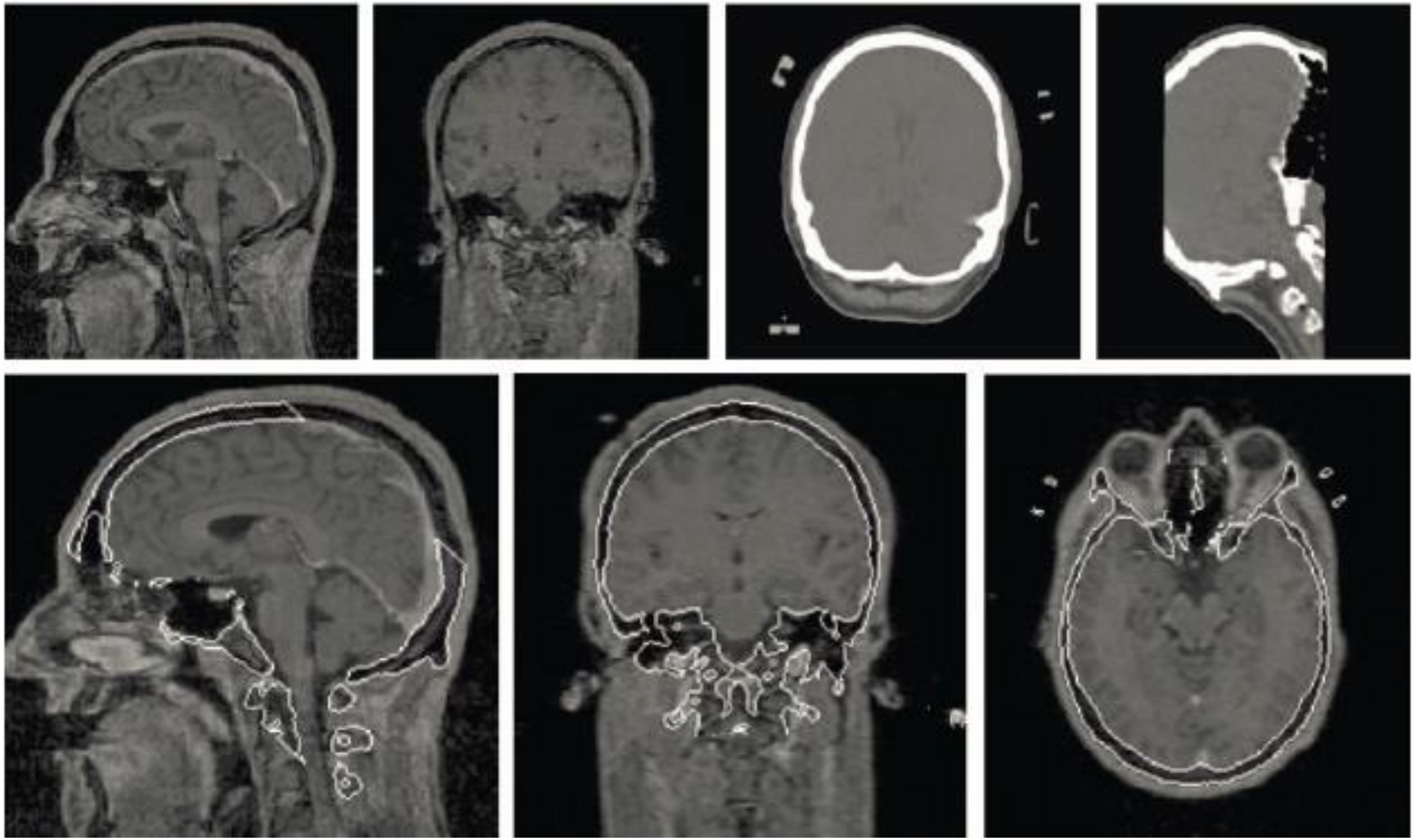
Simple Code for Joint Entropy Computation



- Top: MR-MR (head)
- Middle: MR-CT
- Bottom: MR-PET
- Left: Aligned
- Middle: 2mm translation
- Right: 5mm translation

Heuristic observation is that when the images are aligned, the joint histogram appears “sharpest”

Registration by Maximizing Mutual Information



Registration by Maximizing Mutual Information

986 IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 22, NO. 8, AUGUST 2003

Mutual-Information-Based Registration of Medical Images: A Survey

Josien P. W. Pluim*, *Member, IEEE*, J. B. Antoine Maintz, and Max A. Viergever, *Member, IEEE*

$$I(A,B) = H(A) + H(B) - H(A,B)$$

- Maximizing mutual information is related to minimizing joint entropy

$$\mathrm{NMI}(A,B) = \frac{H(A) + H(B)}{H(A,B)}$$

Less sensitive to changes in overlap!

Registration Algorithm

- Fixed and Moving Images (target and source, …)
- Preprocessing
- Define Similarity Measure (NMI, CC, MSE, …)
- Define Spatial Transformation (Rigid, Affine, Deformable)
- Implementation
    1. Initialize
    2. Transform (and Interpolate) moving image
    3. Measure similarity
    4. Optimize (decide parameters of the transform)
    5. If converged

        STOP
    6. Else
    7. Go to Transform Step 2. Repeat