图像处理技术讲座（17）
Digital Image Processing (17)

Image Registration(1)
图像配准技术（1）

顾 力栩

上海交通大学生物医学工程学院

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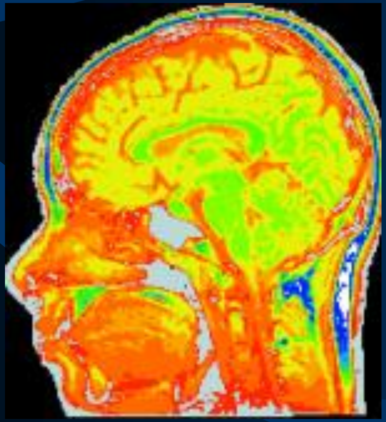
Image Registration Overview

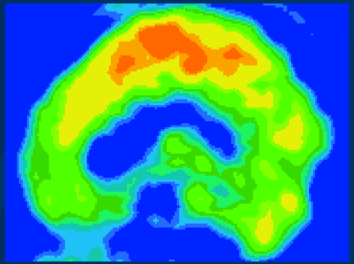
Image registration

- 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



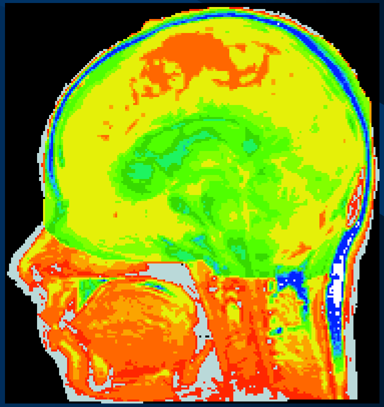
MR

+



SPECT

=



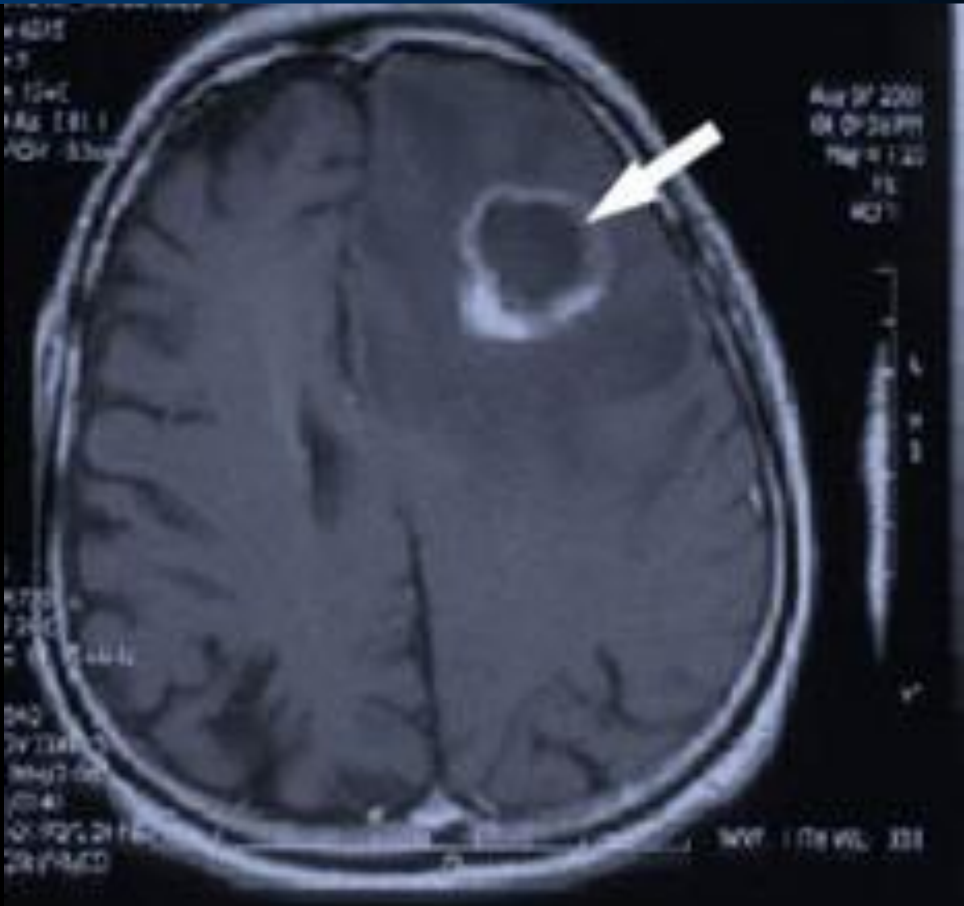
registered

What is image registration

Moving image

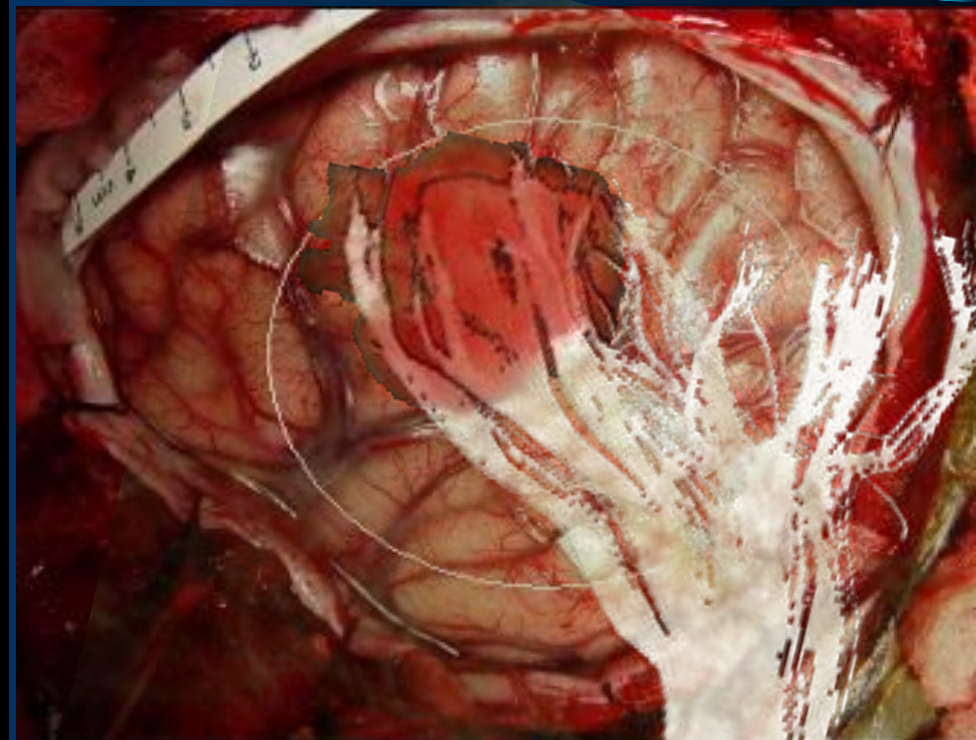
Fixed image

Moving image

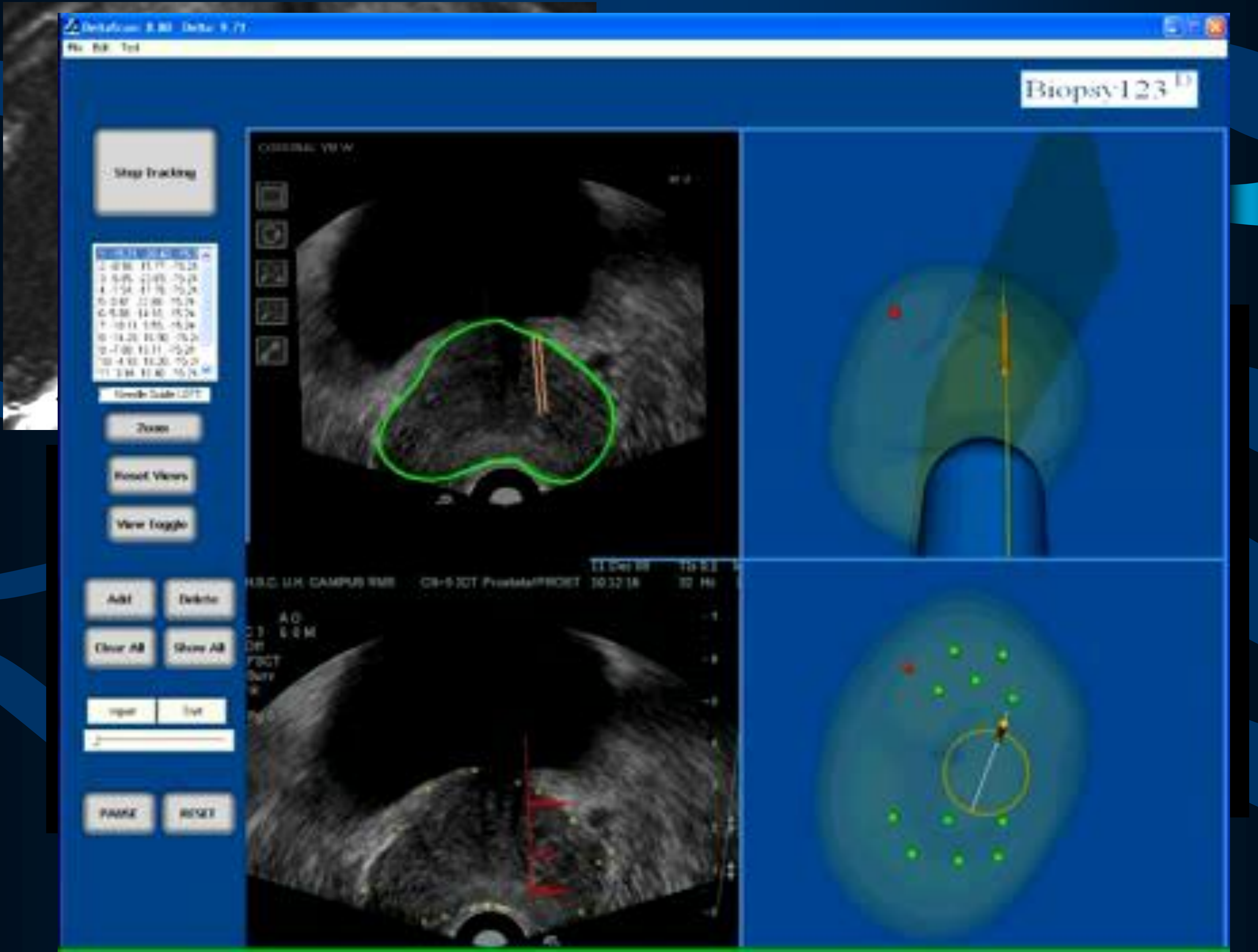


Fixed image

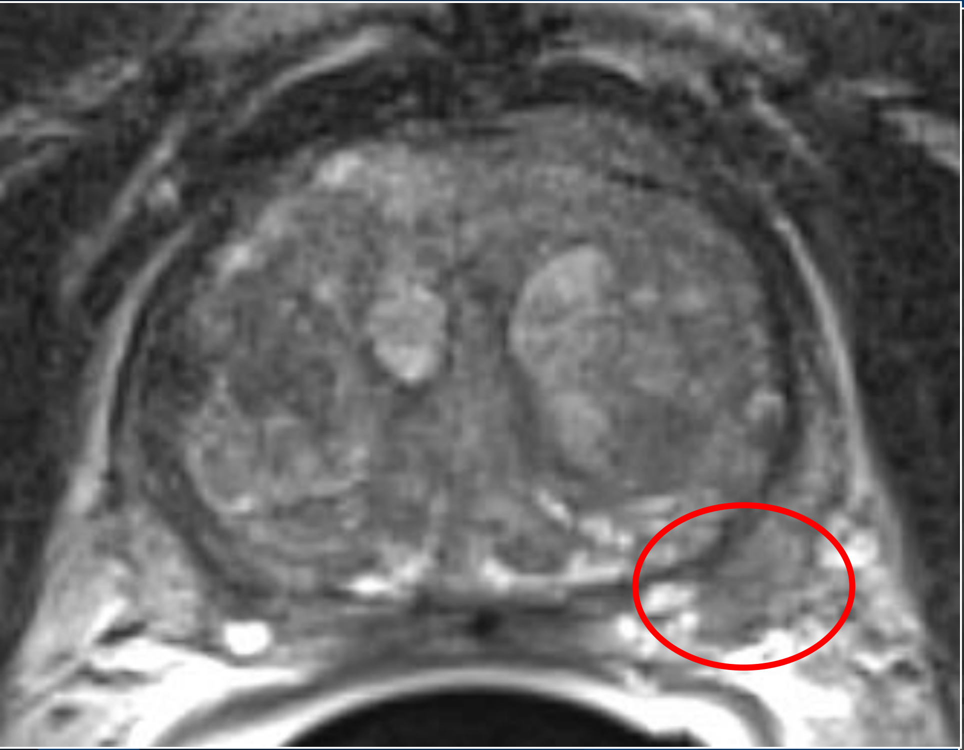
Moving image



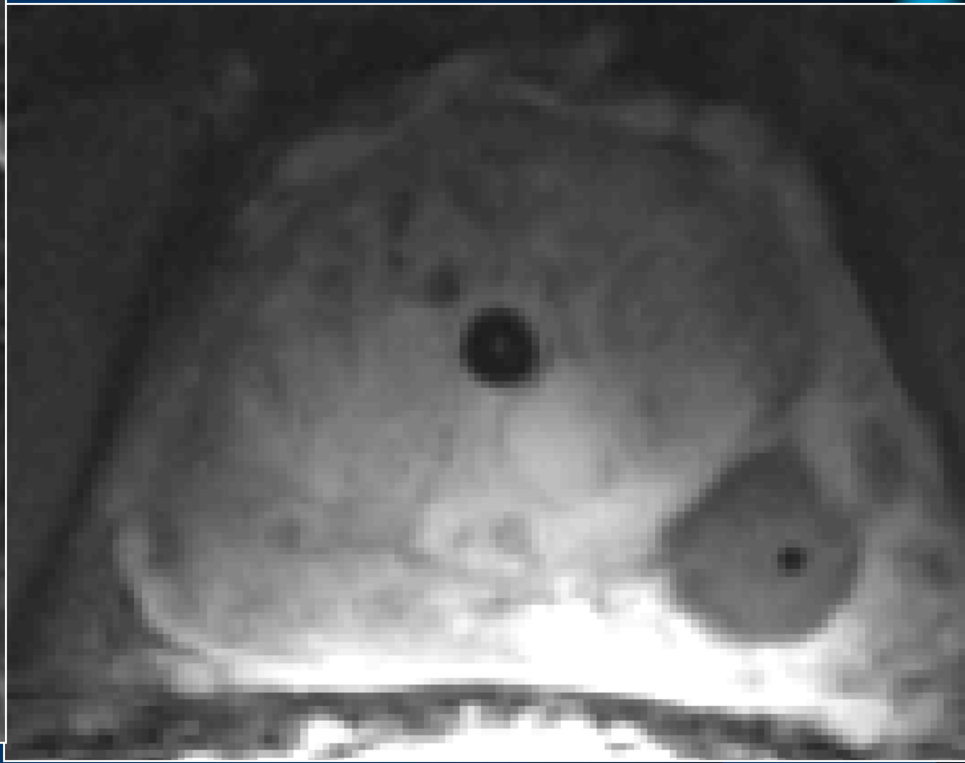
Fixed image



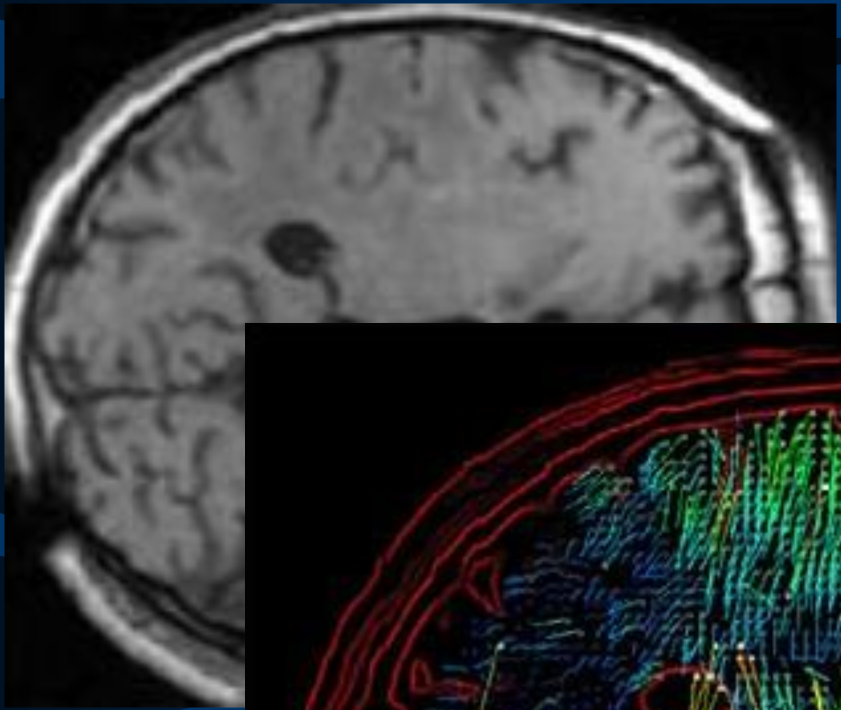
Biopsy123
Stop Tracking
Zoom
Reset Views
View Toggle
Add
Delete
Clear All
Show All
PAUSE
RESET

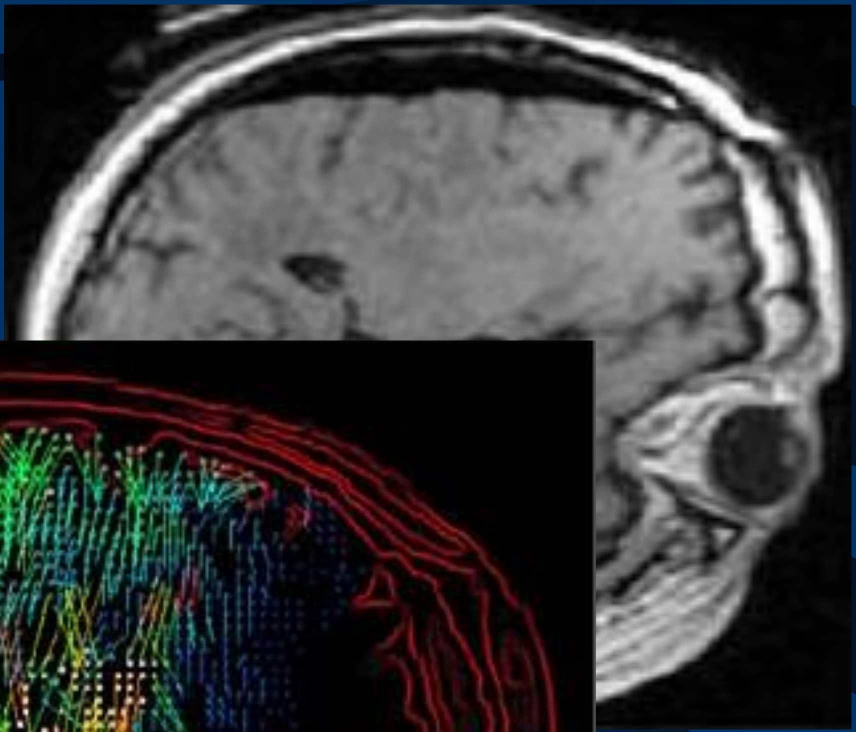


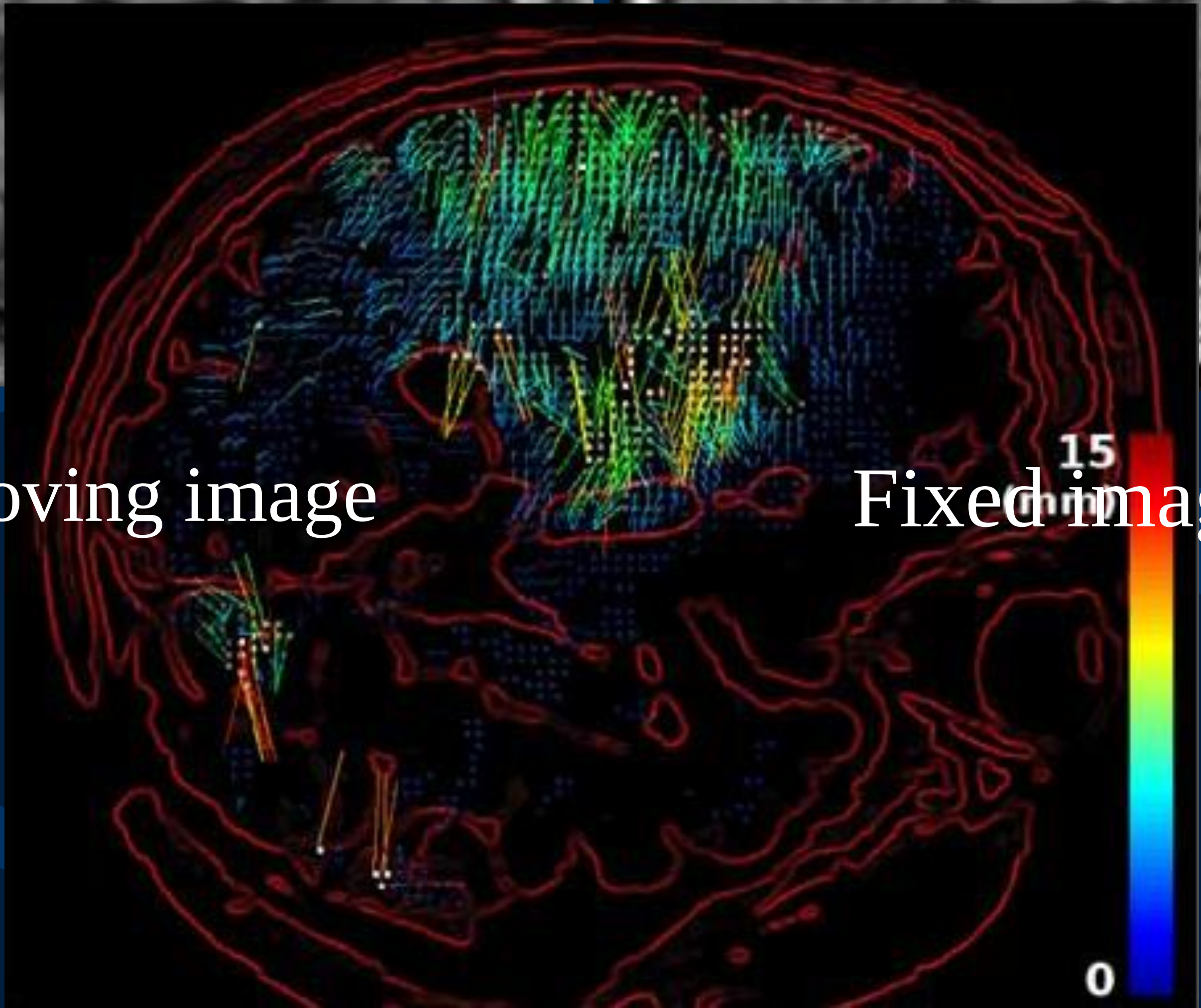
Moving image



Fixed image

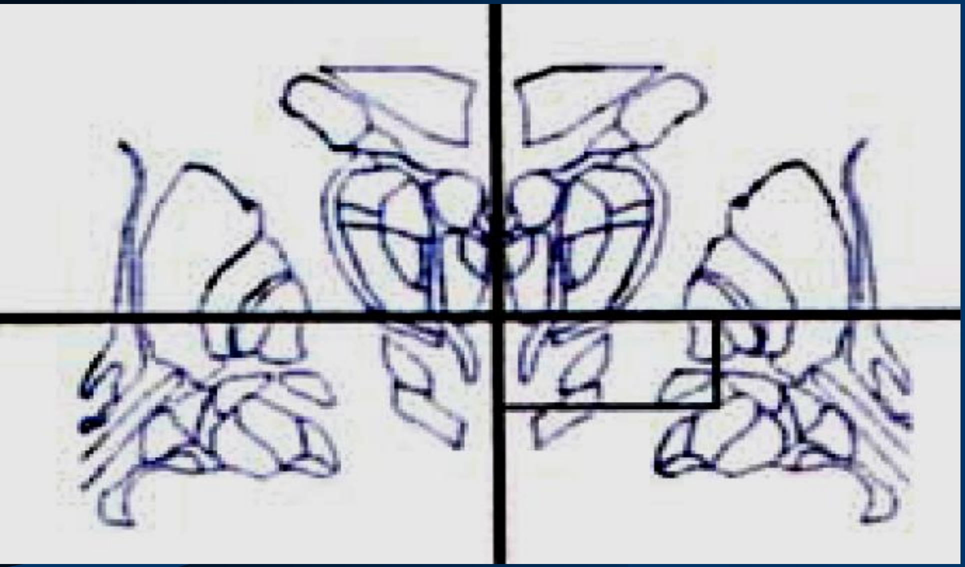




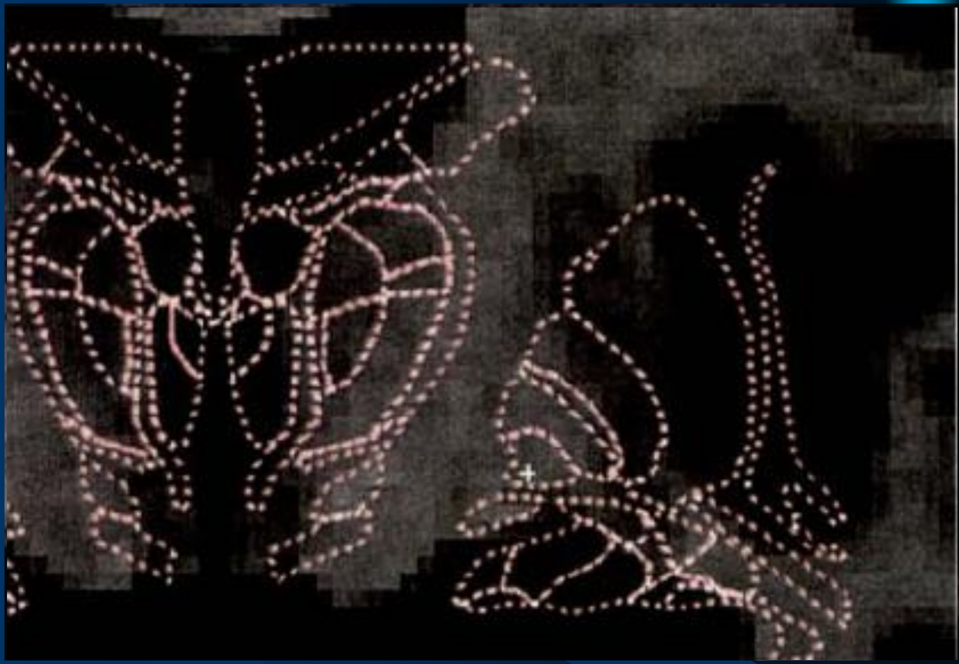


Moving image

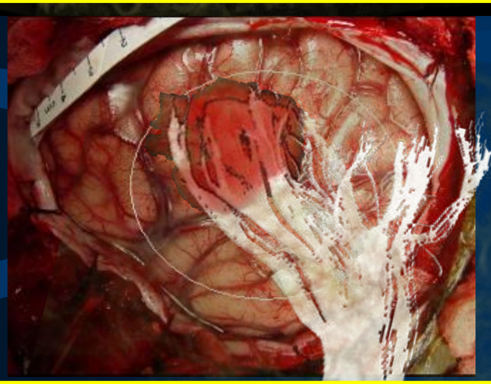
Fixed image

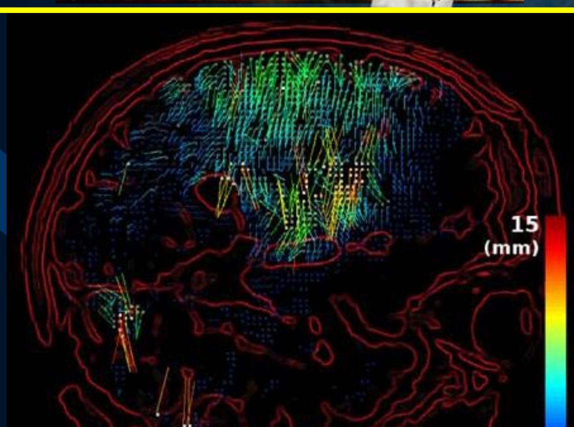


Moving image



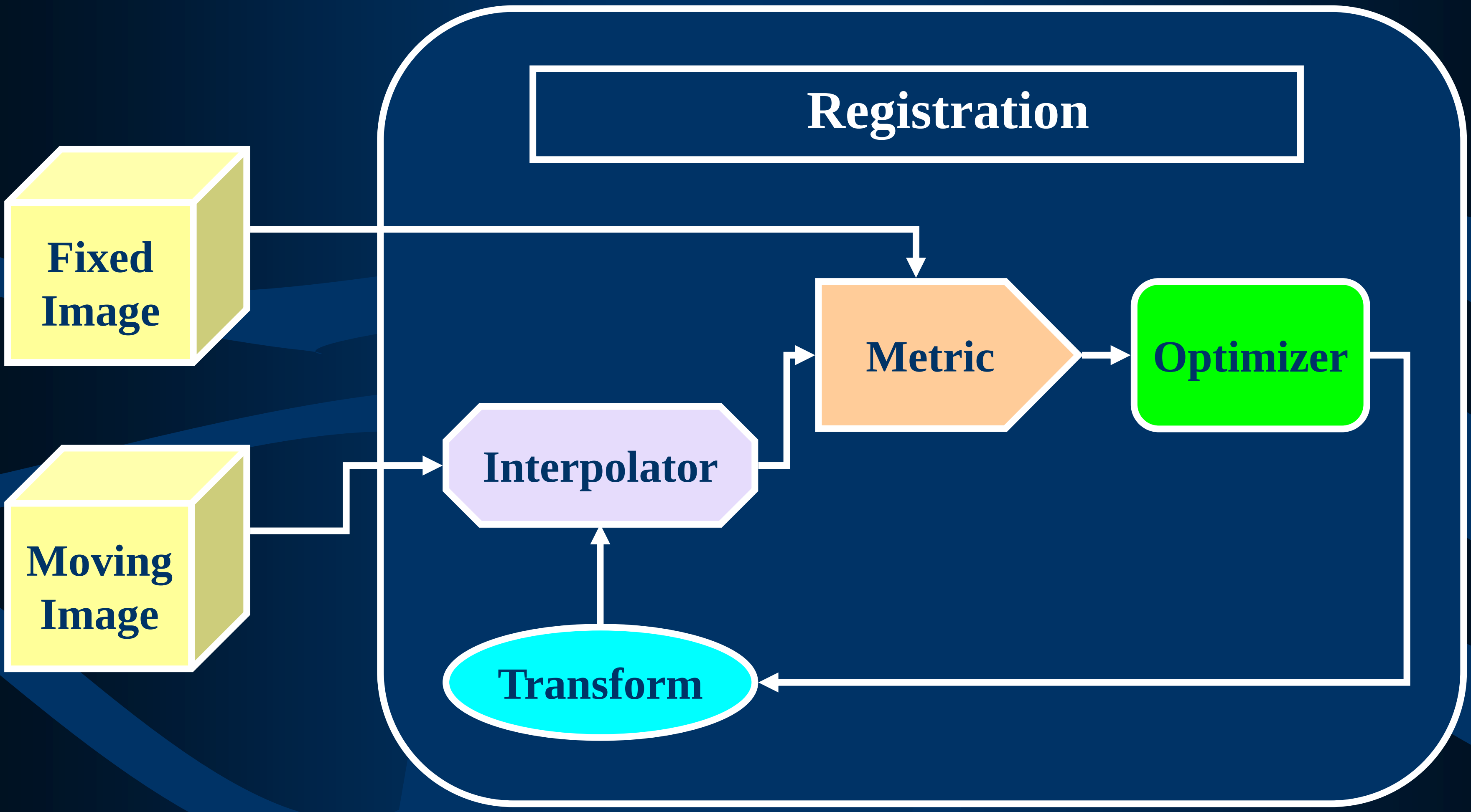
Fixed image




15
(mm)


ATL

Registration Framework



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

Classification

- 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
  - Monomodal, Multimodal, Modality to model

- Subject:

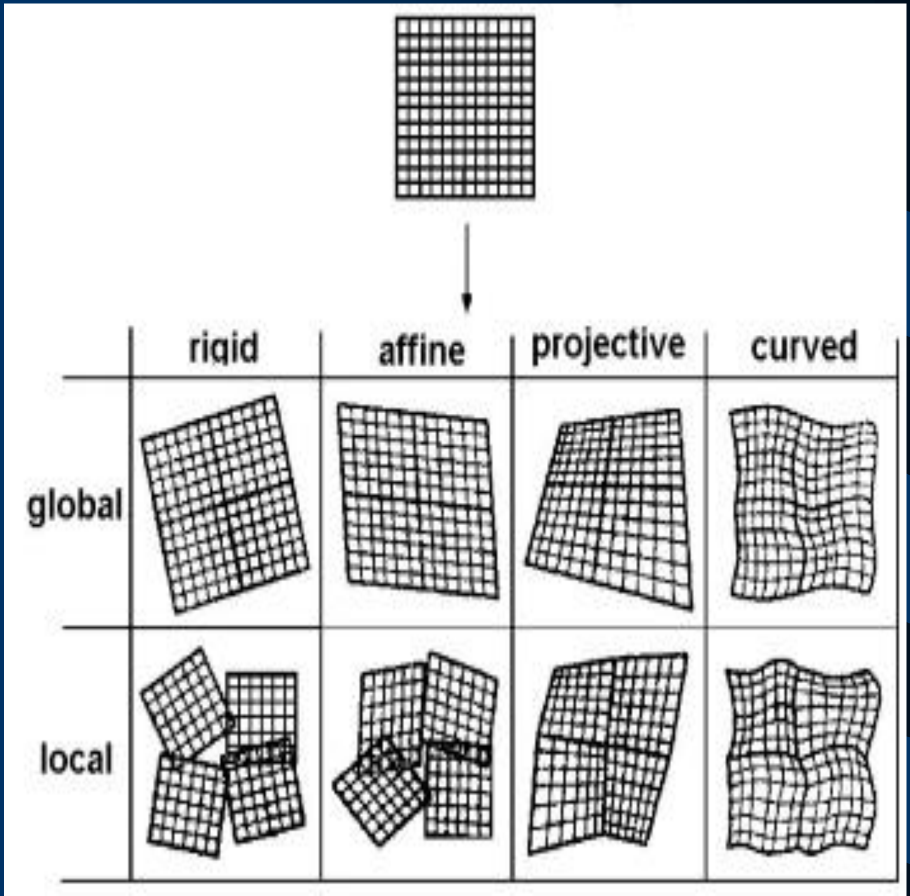
  Intra-subject

  Inter-subject

  Atlas
- Domain of transformation
  - Local, global
- Optimization procedure
- Object

Transformation

- Relates the position of features in two images
  - Rigid
    - translations and rotations
  - Affine
    - Also allows scaling and shearing
  - curved
    - Allows the mapping of straight lines to curves
  - perspective
    - The parallelism of lines need not be preserved

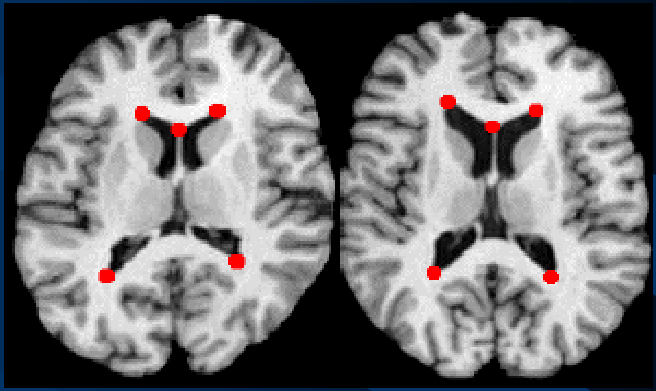


Registration algorithms

- Method used to find the transformation
- Rigid & affine
  - Landmark based
  - Edge based
  - Information theory based
  - Voxel intensity based
- Non-rigid
  - Registration using basis functions
  - Registration using splines
  - Physics based
    - Elastic, Fluid, Optical flow, etc.

Landmark based

- Identifying corresponding points in the images and inferring the image transformation



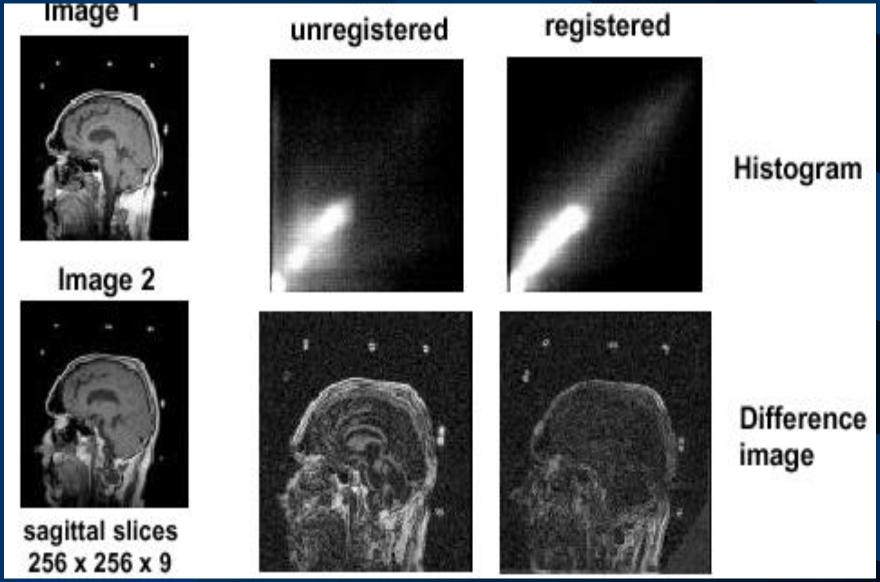
- Types of landmarks
  - Intrinsic
    - internal anatomical structure
  - Extrinsic
    - artificial objects attached to the patients
- Computing the average or "centroid" of each set of points → translation
- Rotated this point set about the new centroid until the sum of the squared distances between each corresponding point pair is minimized

Surfaced based

- Method
  - Extracting corresponding surfaces
  - Computing the transformation by minimizing some measure of distance between the two surfaces
- Algorithms used
  - The “Head and Hat” Algorithm
  - The Iterative Closest Point Algorithm
  - Registration using crest lines

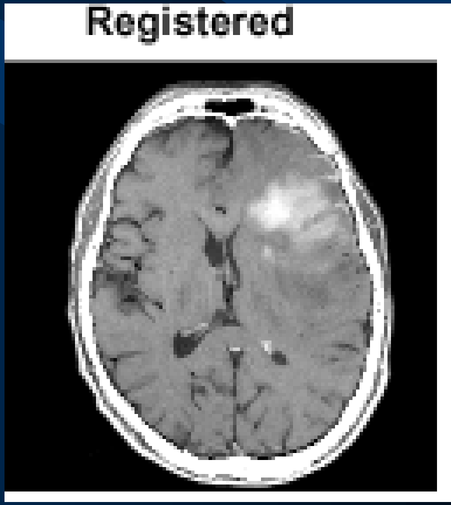
Voxel intensity based

- 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



Information theory based

- 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



Registration using basis functions

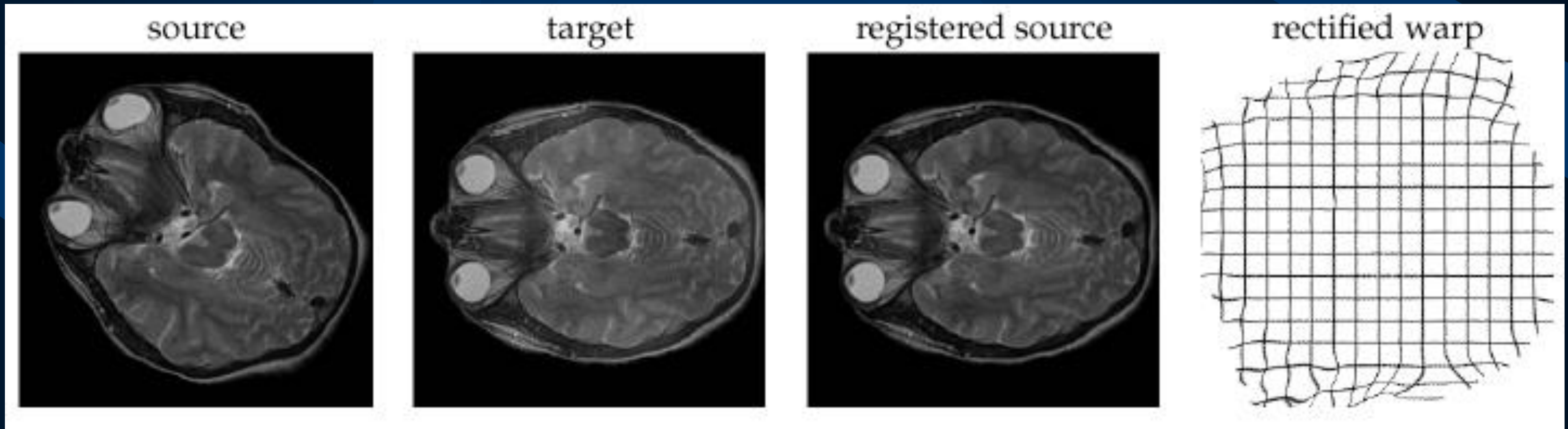
- Represent the deformation field using a set of basis functions
  - Fourier (trigonometric) basis functions or wavelet basis functions.
  - Implement smoothness constraint by linear combination of basis functions
  - The trigonometric basis functions corresponds to a spectral representation of the deformation field where each basis function describes a particular frequency of the deformation.

Registration using splines

- Assumption
  - a set of corresponding points or landmarks (*control points*) can be identified
- At control points, interpolate or approximate the displacements to map the location of the control points in both images
- Between control points, they provide a smoothly varying displacement field

Elastic registration

- Model the deformation as a physical process resembling the stretching of an elastic material
  - The physical process is governed by the internal force & external force
  - described by the Navier linear elastic partial differential equation
- The external force drives the registration process
  - The external force can be the gradient of a similarity measure
    - e.g. local correlation measure based on intensities, intensity differences or intensity features such as edge and curvature
  - Or the distance between the curves and surfaces of corresponding anatomical structures.



Other physics based registration

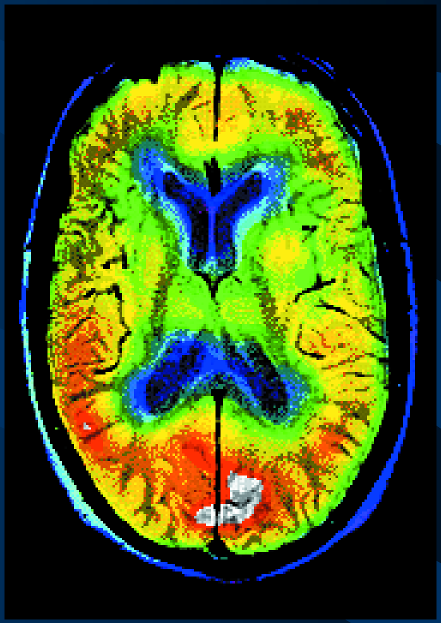
- Fluid registration
  - The image was modeled as a highly viscous fluid
- Registration using mechanical models
  - using a three-component model to simulate the properties of rigid, elastic and fluid structures.
- Registration using optical flow

Optimization

- Many registration algorithms require an iterative approach
  - an initial estimate of the transformation is gradually refined
  - In each iteration, the current estimate of the transformation is used to calculate a similarity measure
  - makes another estimate of the transformation, evaluates the similarity measure again, and continues until the algorithm converges
    - no transformation can be found that results in a better value of the similarity measure, to within a preset tolerance.

Visualization

- Color overlay
- Interleaved pixel or chessboard fusion
- Dynamic alternating display
- Split view displays
- Subtraction images
- Etc.



registrated SPECT-MRI image

Validation

- Measurements using computer generated models, images of physical phantoms of accurately known construction and dimensions and images of patients or volunteers.
  - robustness
  - Accuracy
- Assessment of accuracy
  - estimate of some geometrical measure of alignment error
  - compare the system to be validated against a gold standard
  - Visual assessment
- Benefit to the patient and cost

Image Resampling

Image Origin & Spacing

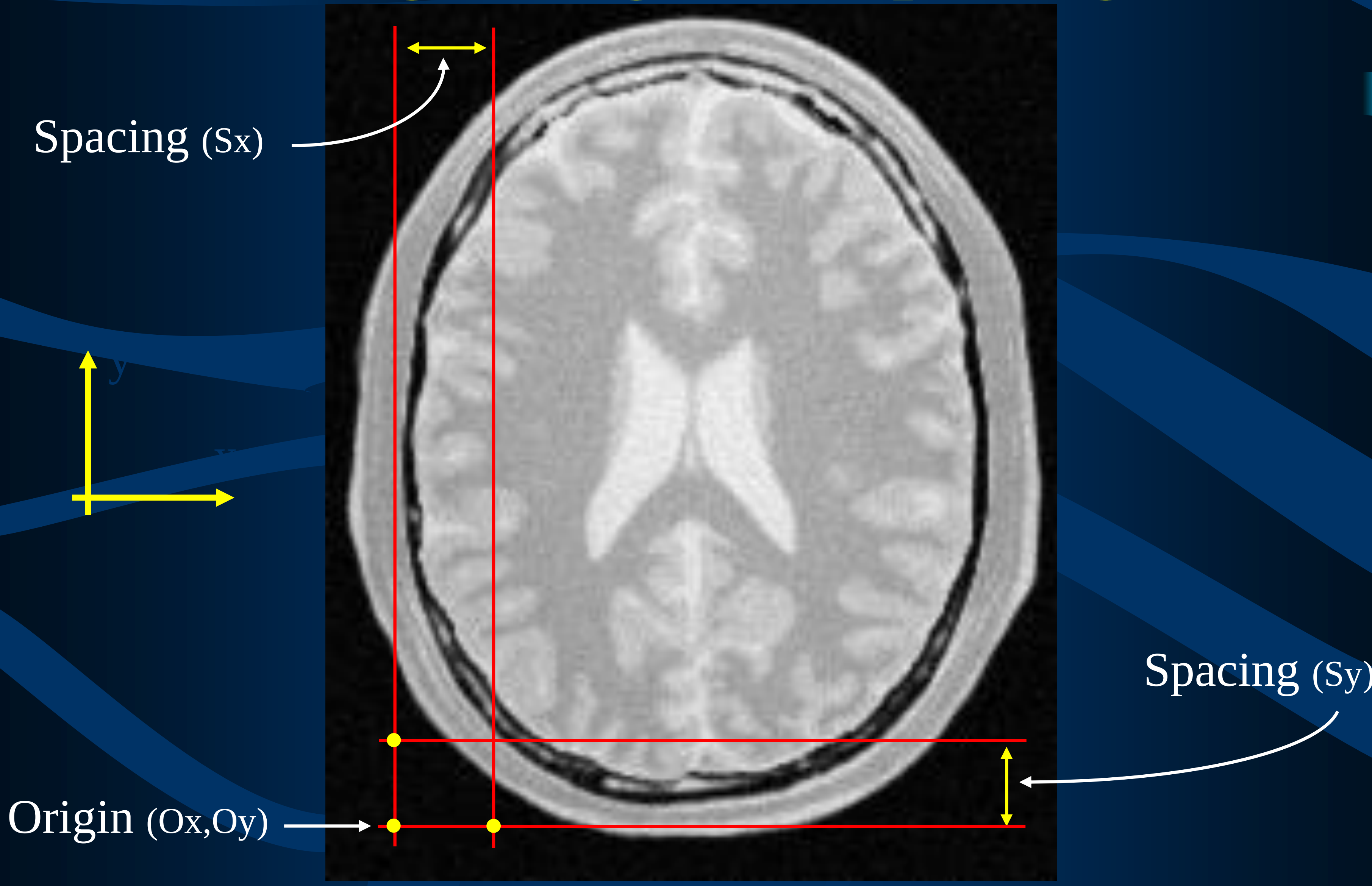


Image Sampling Grid

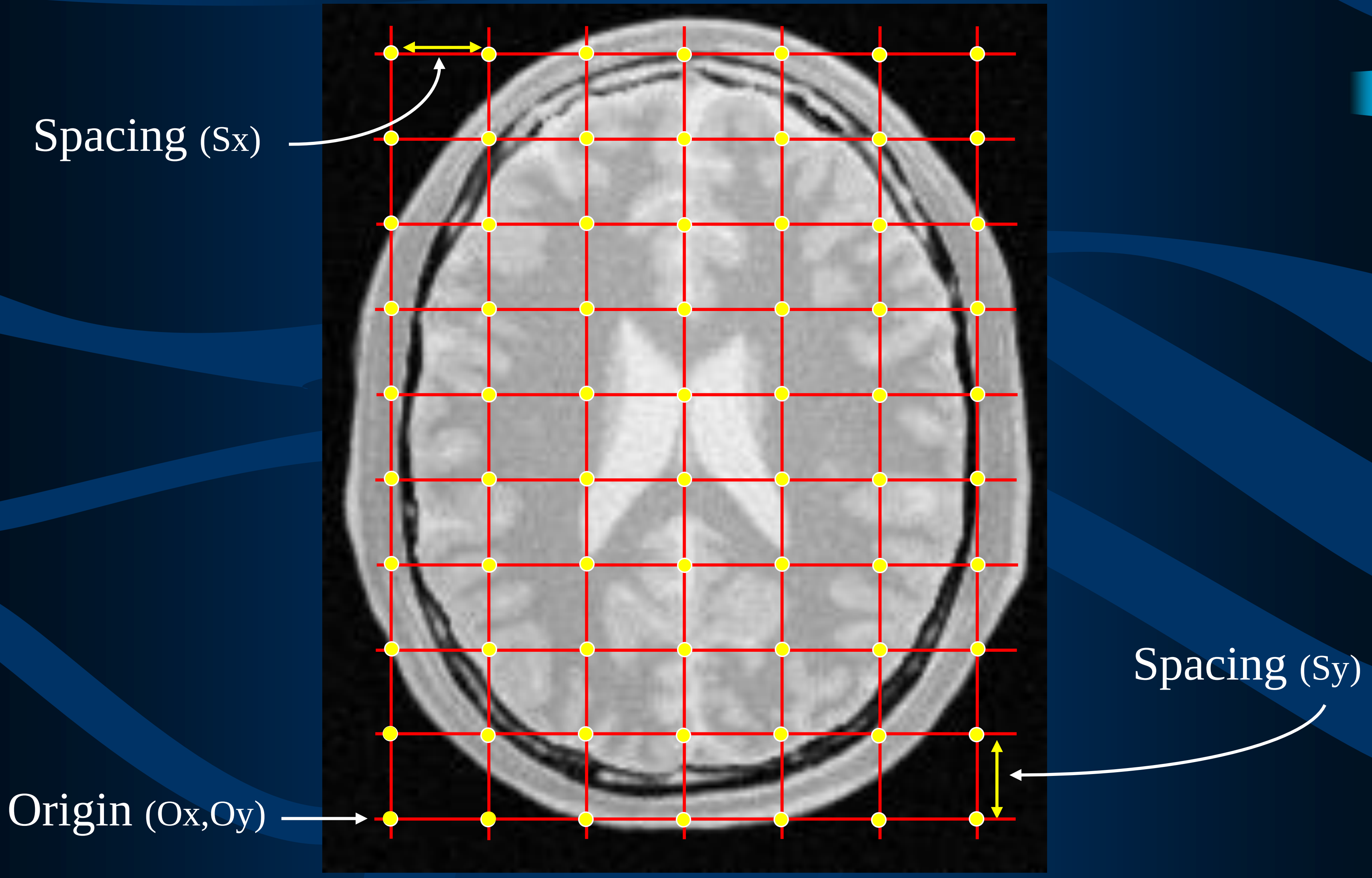


Image Pixel

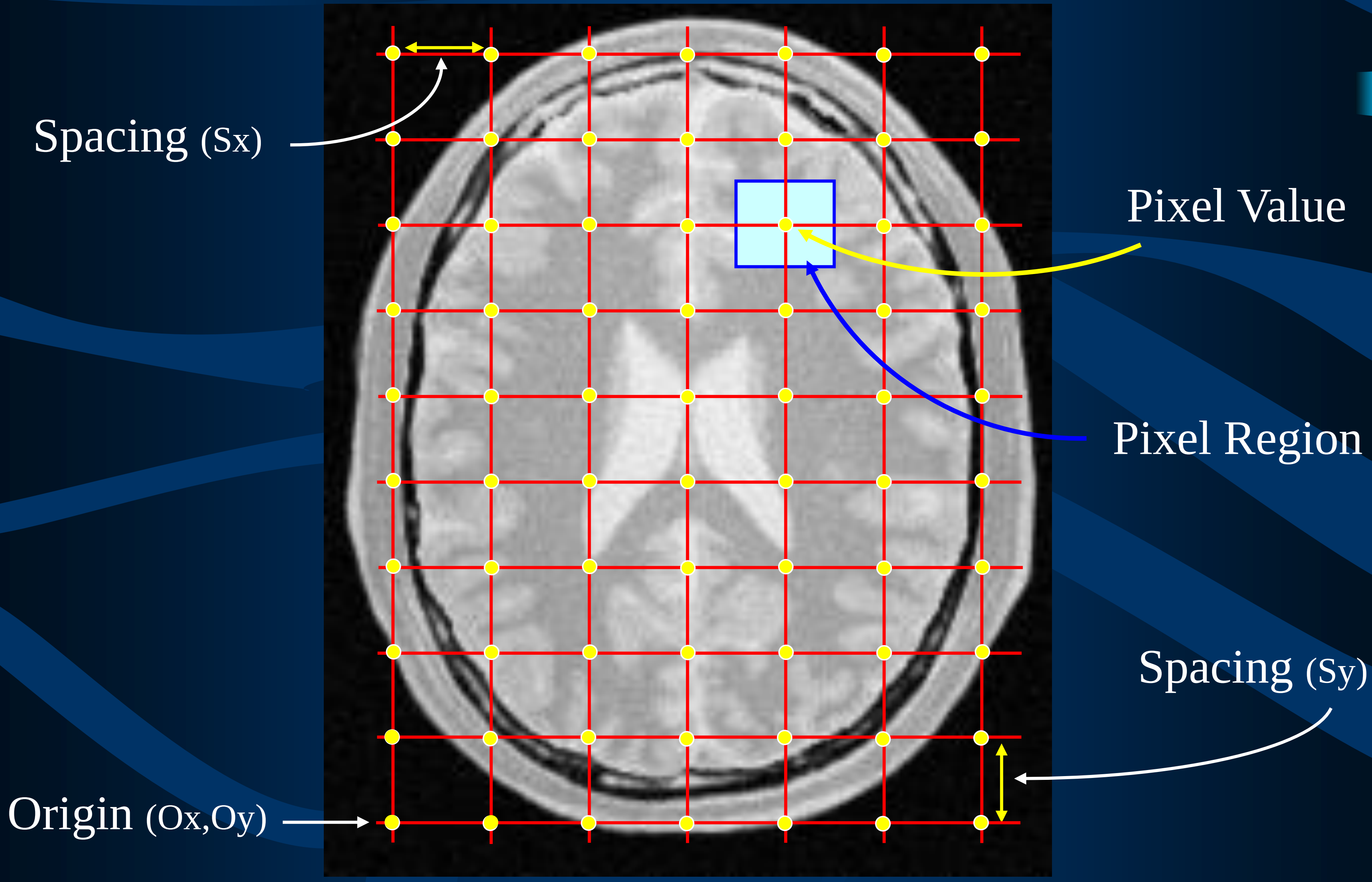
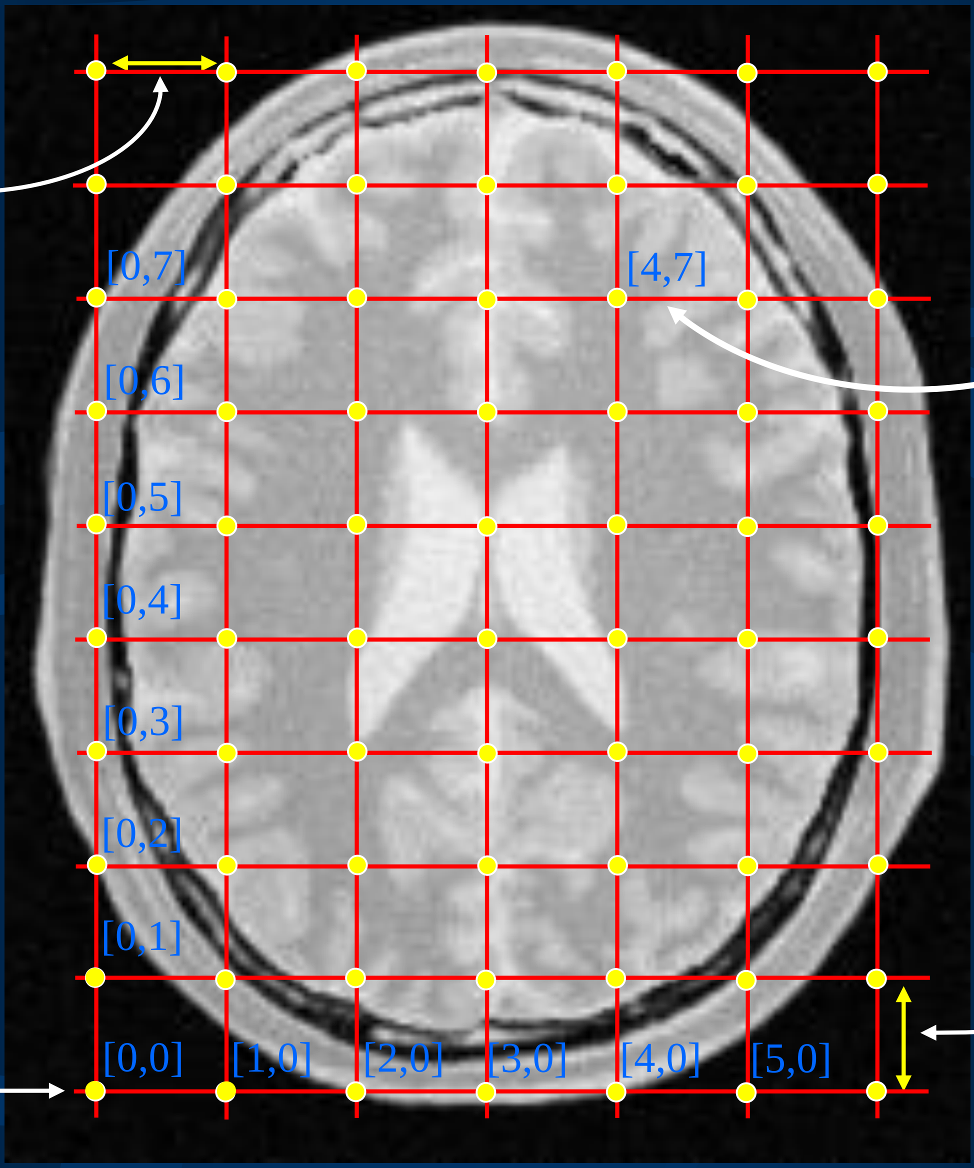


Image Indices

Spacing (Sx)

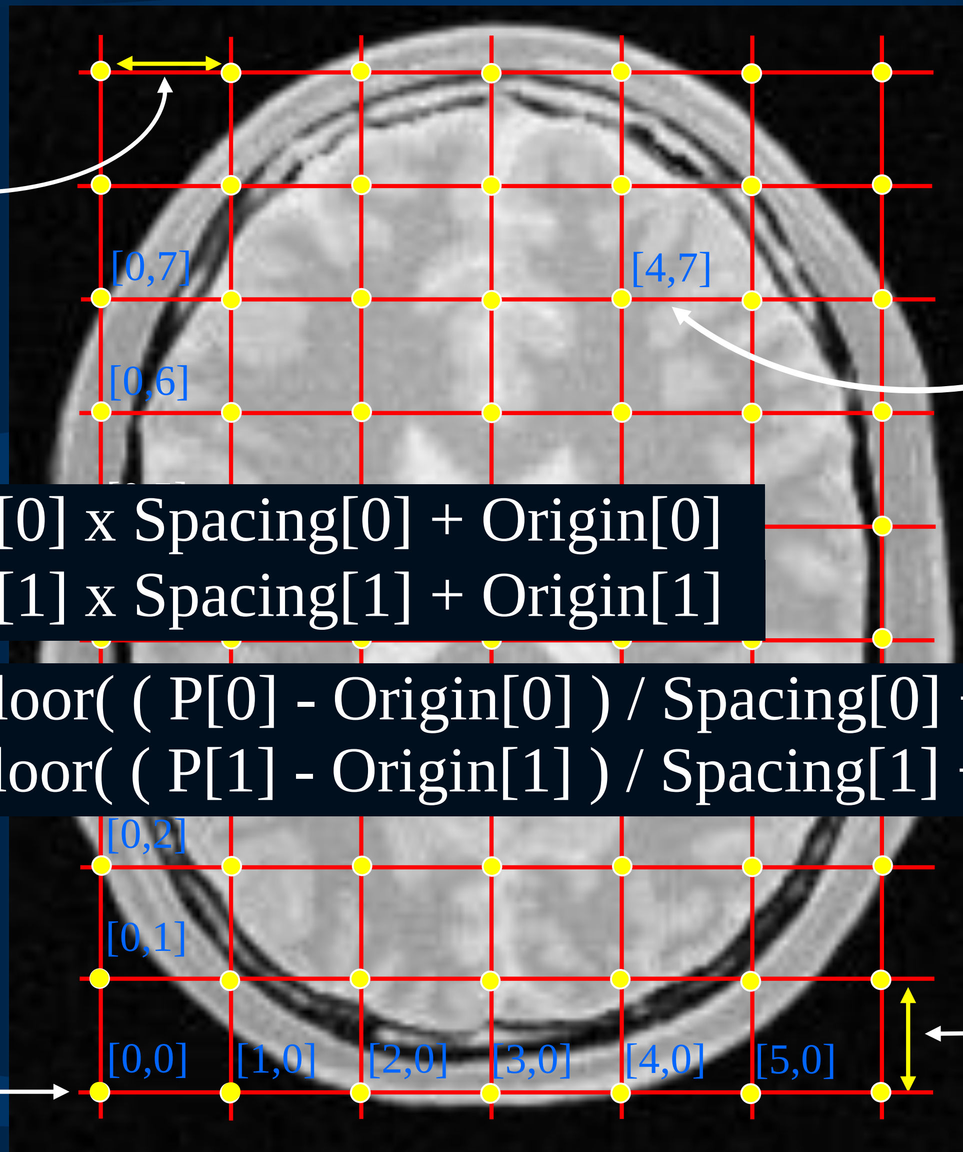
Pixel Index



Spacing (Sy)

Origin (Ox,Oy)

Index to Physical Coordinates



P[0] = Index[0] x Spacing[0] + Origin[0]
P[1] = Index[1] x Spacing[1] + Origin[1]

Index[0] = floor((P[0] - Origin[0]) / Spacing[0] + 0.5)
Index[1] = floor((P[1] - Origin[1]) / Spacing[1] + 0.5)

Image Region

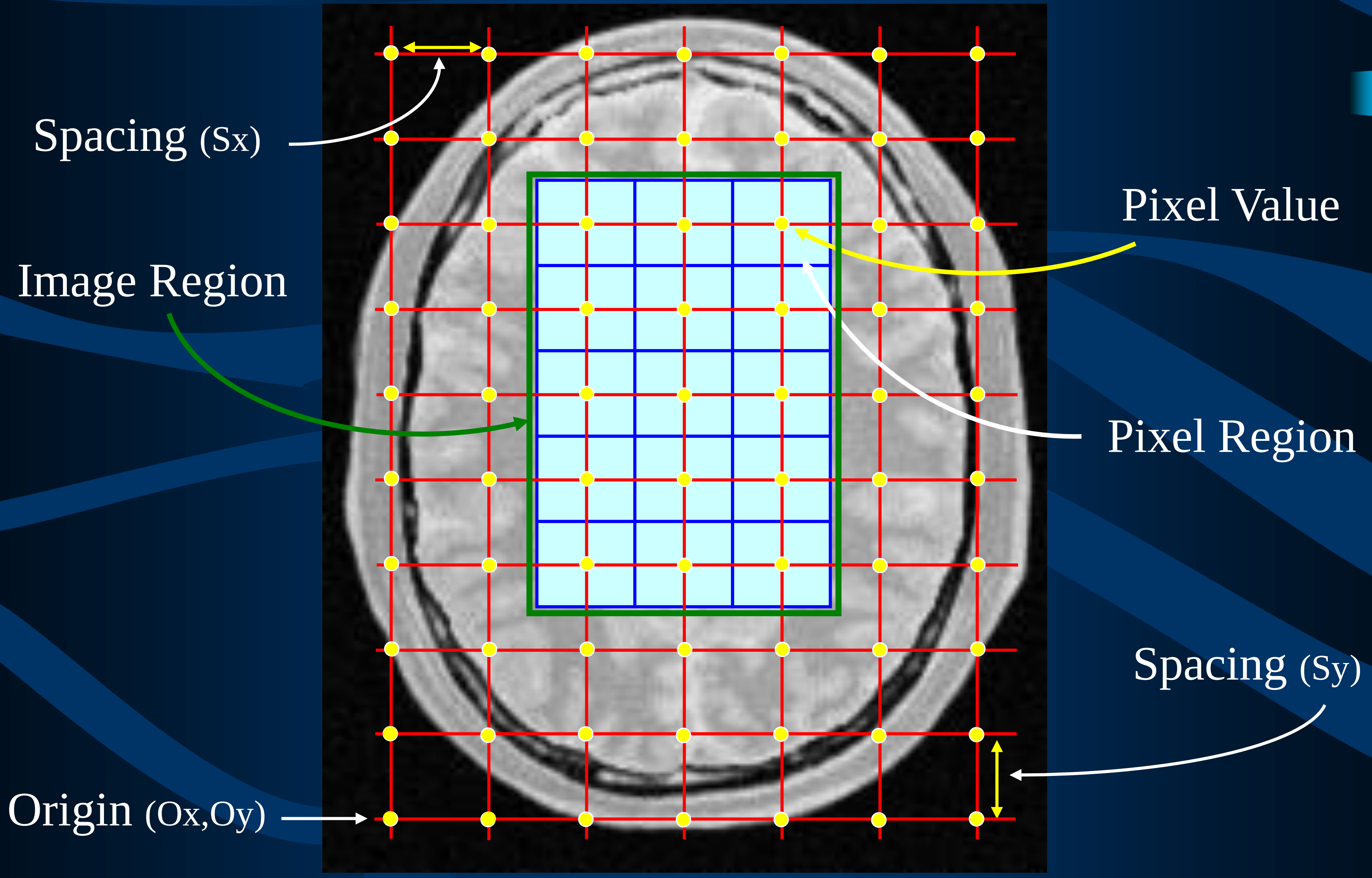
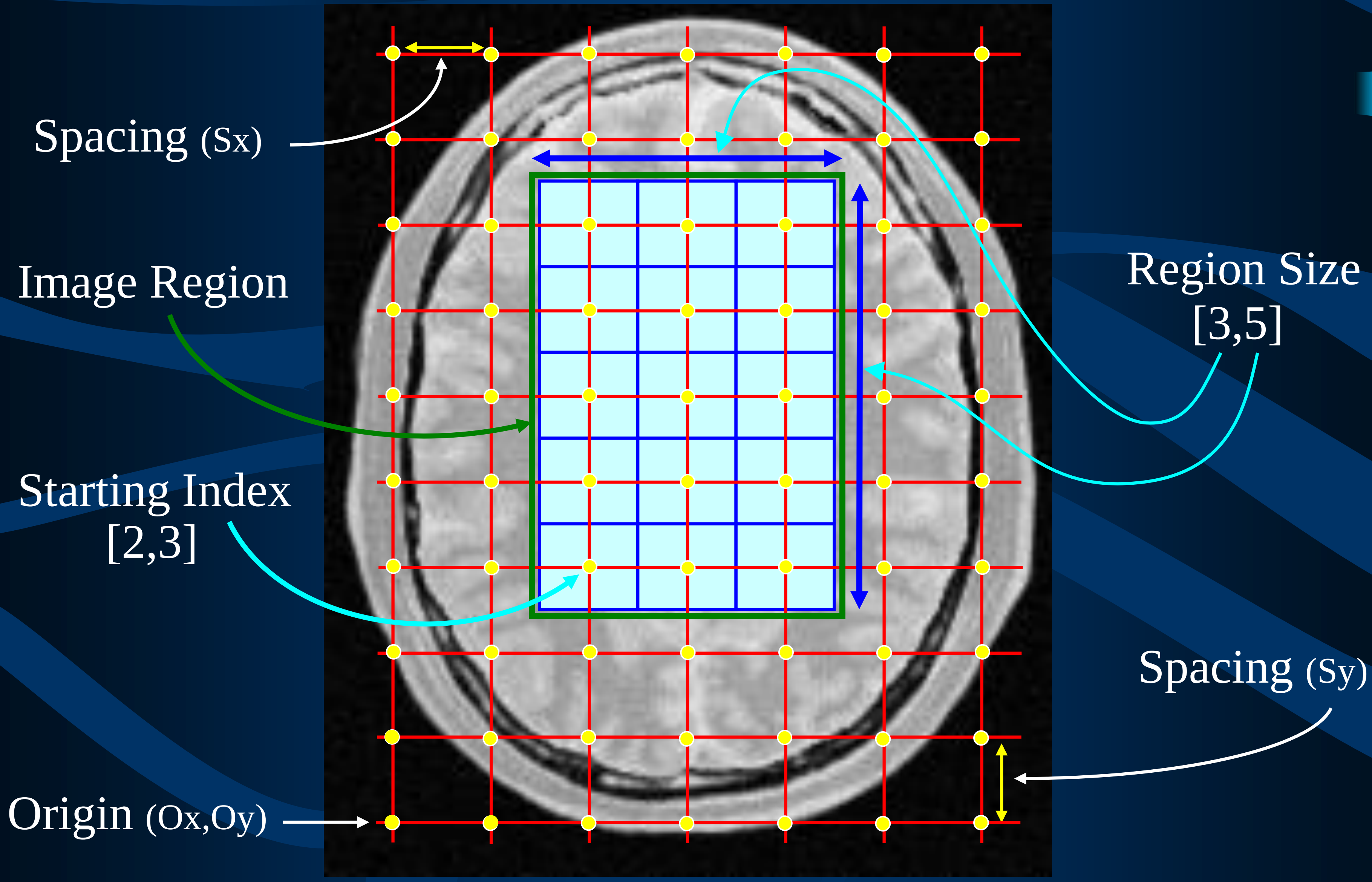
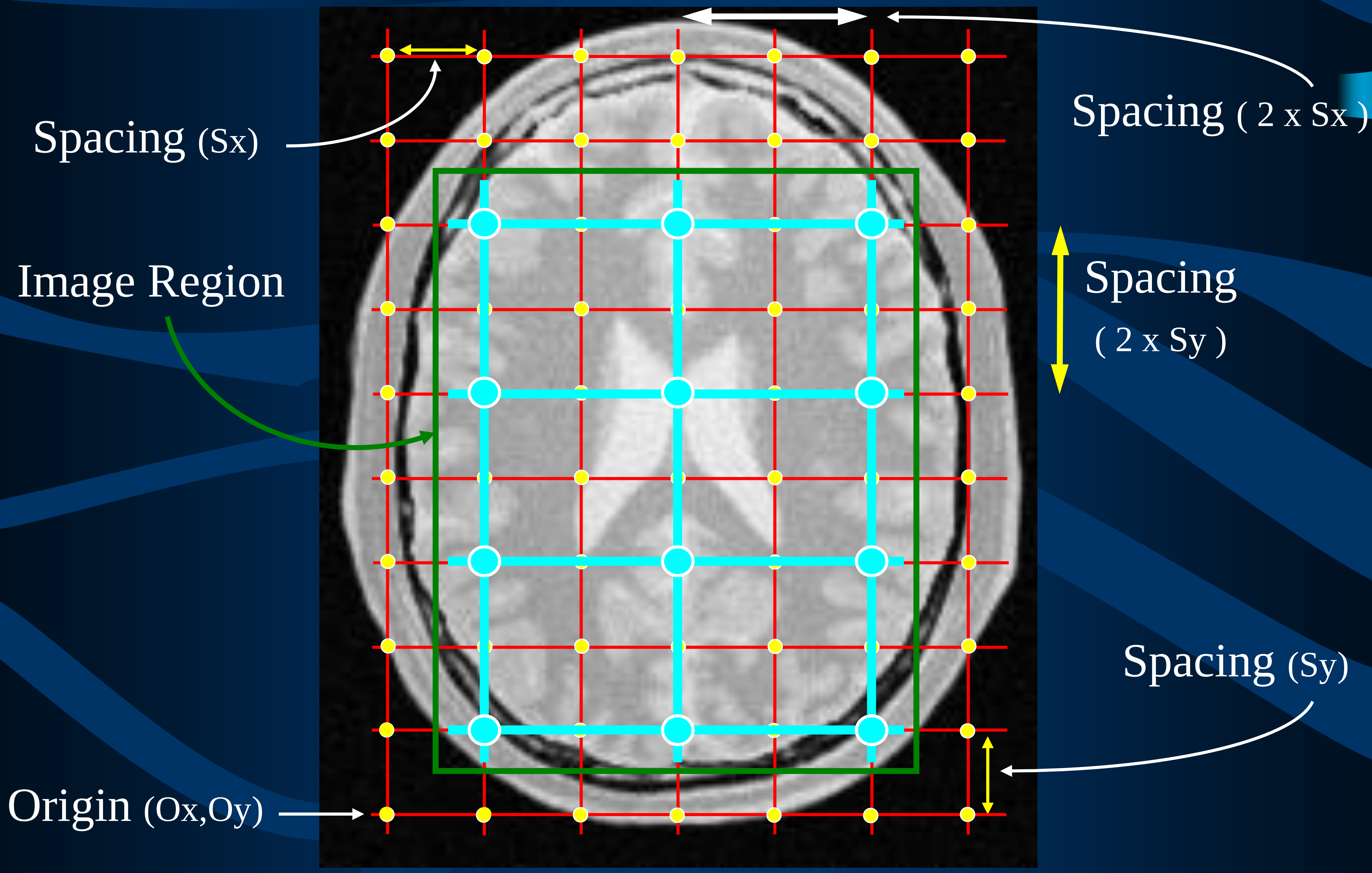


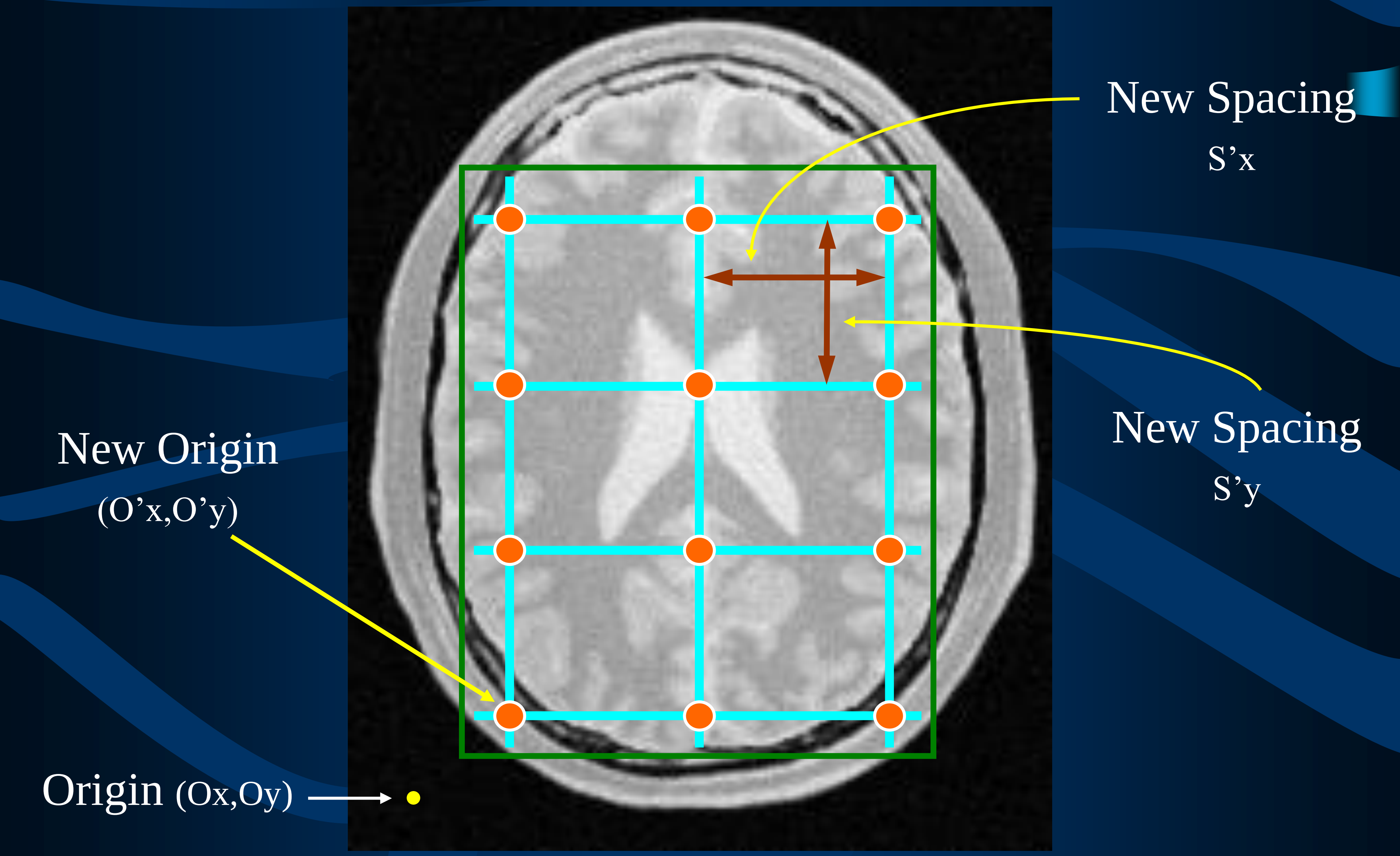
Image Region



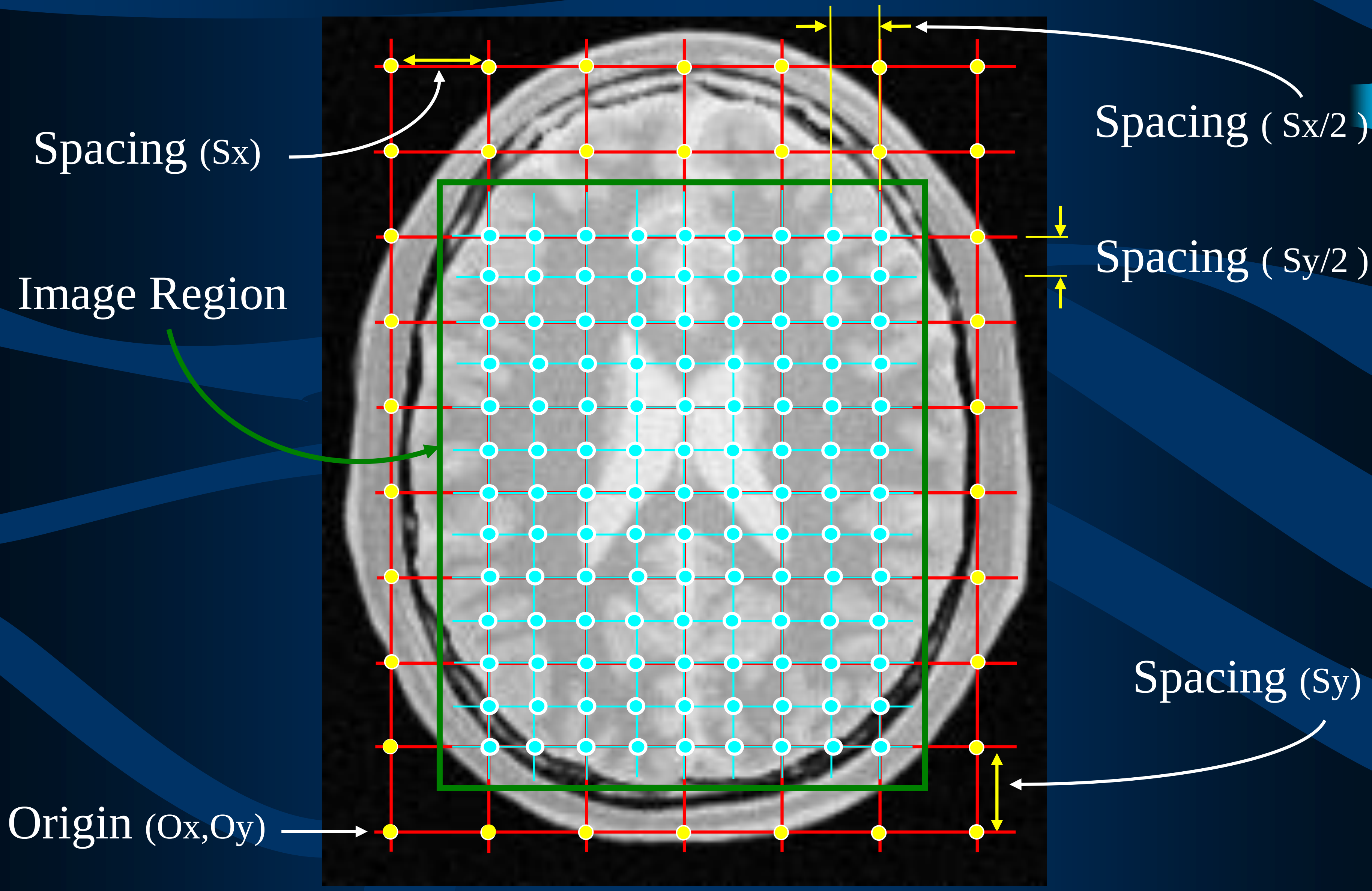
Sub-Sampling by Half



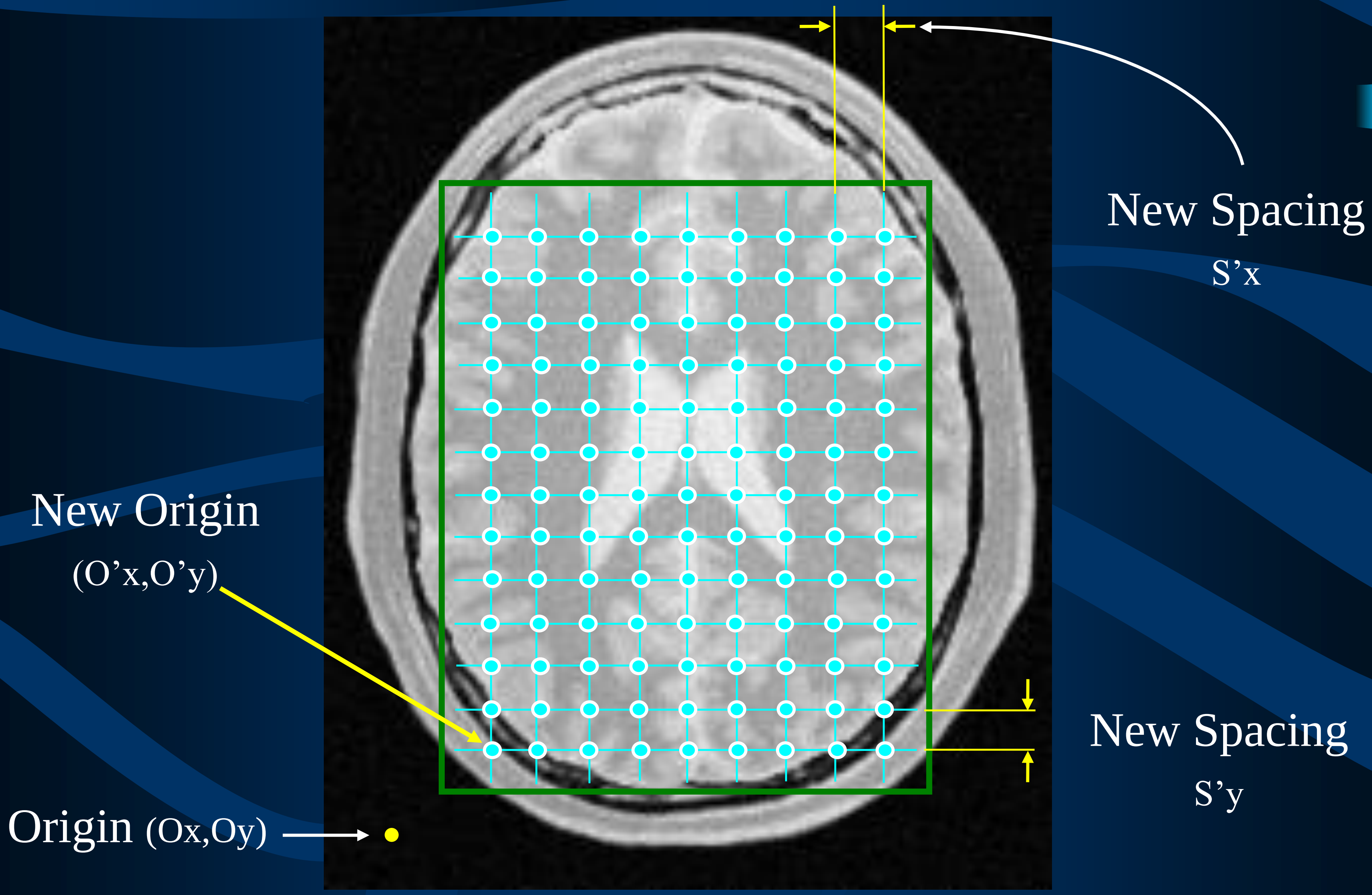
Sub-Sampling by Half



Super-Sampling by Double



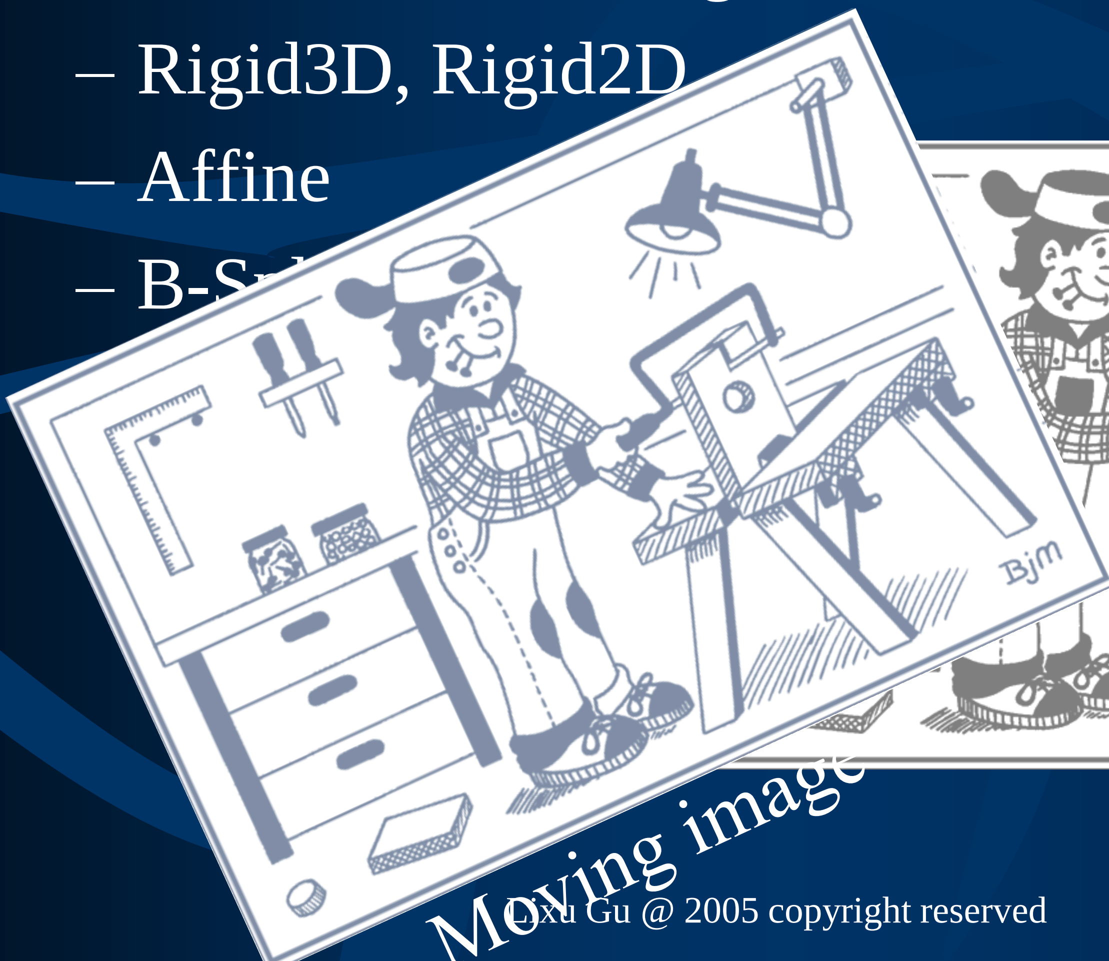
Super-Sampling by Double



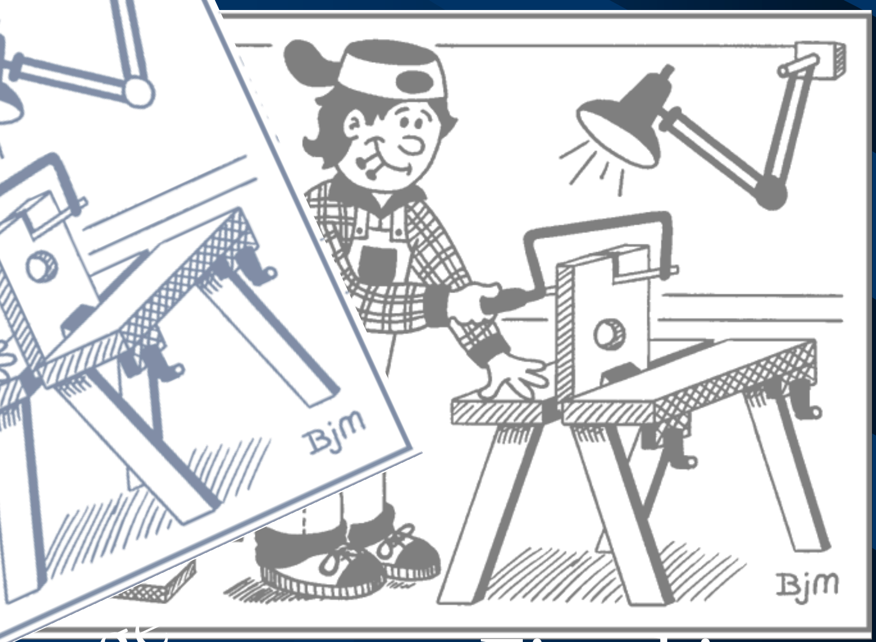
Linear Registration

Rigid Body

- Linear Registration
  - Translation, Scaling, Rotation
  - Rigid3D, Rigid2D
  - Affine
  - B-Spl

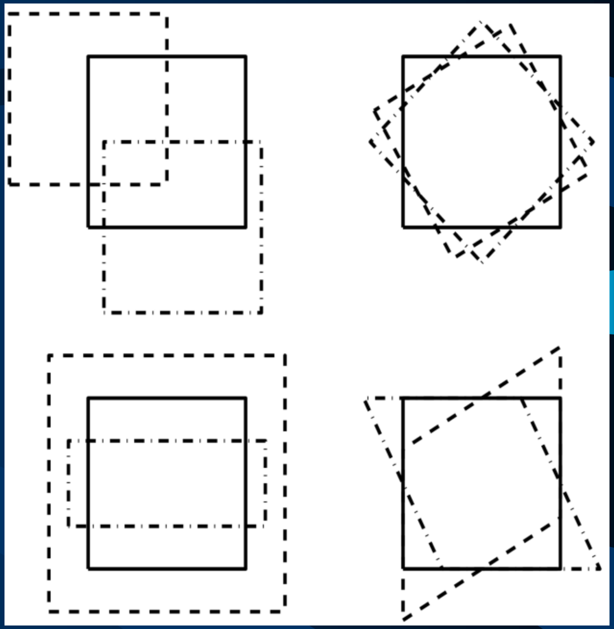


Moving image



Fixed image

2D Affine Transforms



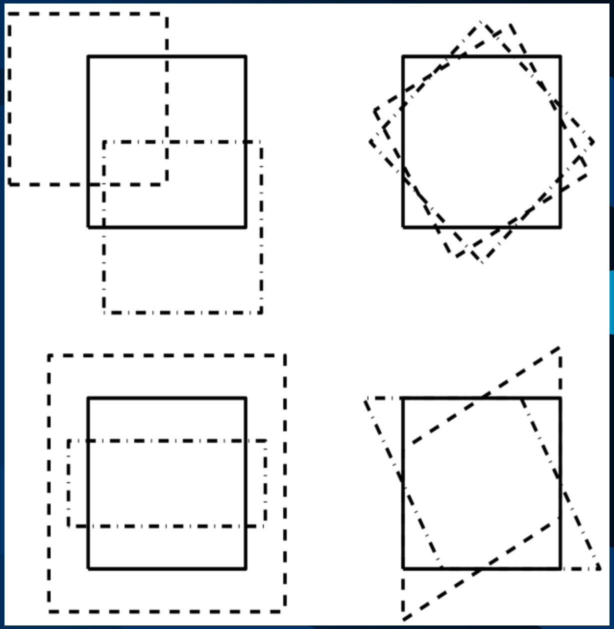
- Translations by t_x and t_y
  - $x_1 = x_0 + t_x$
  - $y_1 = y_0 + t_y$
- Rotation around the origin by Θ radians
  - $x_1 = \cos(\Theta)\, x_0 + \sin(\Theta)\, y_0$
  - $y_1 = -\sin(\Theta)\, x_0 + \cos(\Theta)\, y_0$
- Zooms by s_x and s_y
  - $x_1 = s_x\, x_0$
  - $y_1 = s_y\, y_0$

Shear

$x1 = x0 + h\ y0$

$y1 = y0$

2D Affine Transforms



- Translations by t_x and t_y
  - $x_1 = 1\ x_0 + 0\ y_0 + t_x$
  - $y_1 = 0\ x_0 + 1\ y_0 + t_y$
- Rotation around the origin by Θ radians
  - $x_1 = \cos(\Theta)\ x_0 + \sin(\Theta)\ y_0 + 0$
  - $y_1 = -\sin(\Theta)\ x_0 + \cos(\Theta)\ y_0 + 0$
- Zooms by s_x and s_y:
  - $x_1 = s_x\ x_0 + 0\ y_0 + 0$
  - $y_1 = 0\ x_0 + s_y\ y_0 + 0$

Shear

$x1 = 1\ x0 + h\ y0 + 0$

$y1 = 0\ x0 + 1\ y0 + 0$

3D Rigid-body Transformations

- A 3D rigid body transform is defined by:
  - 3 translations - in X, Y & Z directions
  - 3 rotations - about X, Y & Z axes
- The order of the operations matters

$$\begin{pmatrix} 1 & 0 & 0 & X_{trans} \\ 0 & 1 & 0 & Y_{trans} \\ 0 & 0 & 1 & Z_{trans} \\ 0 & 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\Phi & \sin\Phi & 0 \\ 0 & -\sin\Phi & \cos\Phi & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} \cos\Theta & 0 & \sin\Theta & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\Theta & 0 & \cos\Theta & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \times \begin{pmatrix} \cos\Omega & \sin\Omega & 0 & 0 \\ -\sin\Omega & \cos\Omega & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

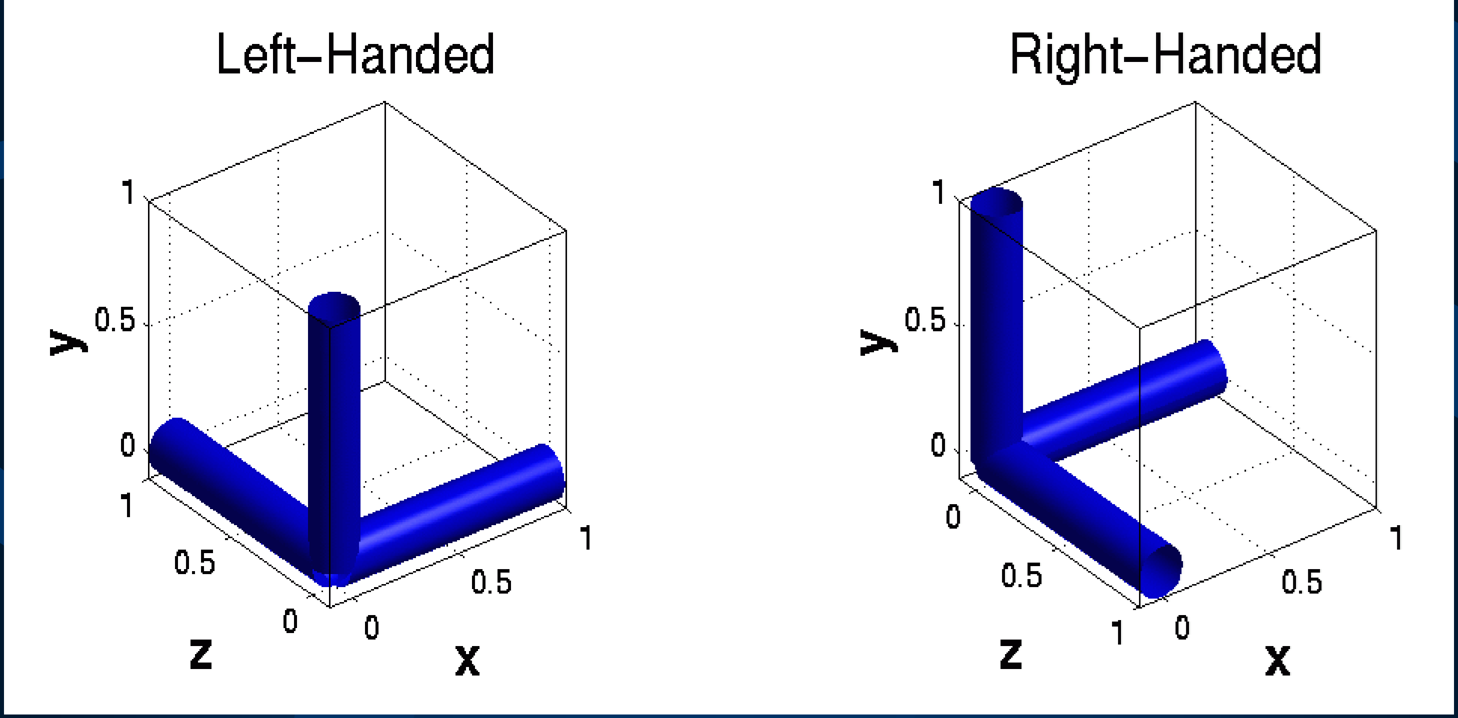
Translations	Pitch	Roll	Yaw
	about x axis	about y axis	about z axis

Voxel-to-world Transforms

- 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}
    - $M_B^{-1} M_A$

Left- and Right-handed Coordinate Systems

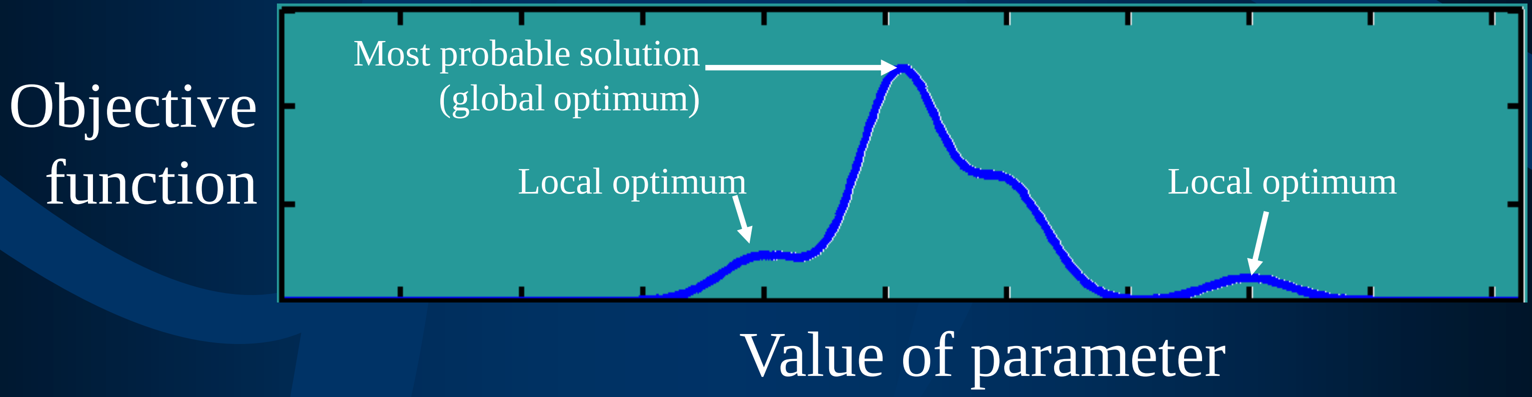
- Analyze™ files are stored in a left-handed system
- Talairach & Tournoux uses a right-handed system
- Mapping between them requires a flip
  - Affine transform with a negative determinant



Optimization

Optimisation

- Optimisation involves finding some “best” parameters according to an “objective function”, which is either minimised or maximised
- The “objective function” is often related to a probability based on some model



Objective Functions (Metrics)

- Intra-modal
  - Mean squared difference (minimise)
  - Normalised cross correlation (maximise)
  - Entropy of difference (minimise)
- Inter-modal (or intra-modal)
  - Mutual information (maximise)
  - Normalised mutual information (maximise)
  - Entropy correlation coefficient (maximise)
  - AIR cost function (minimise)

Mean Squared Differences

For each pixel in A

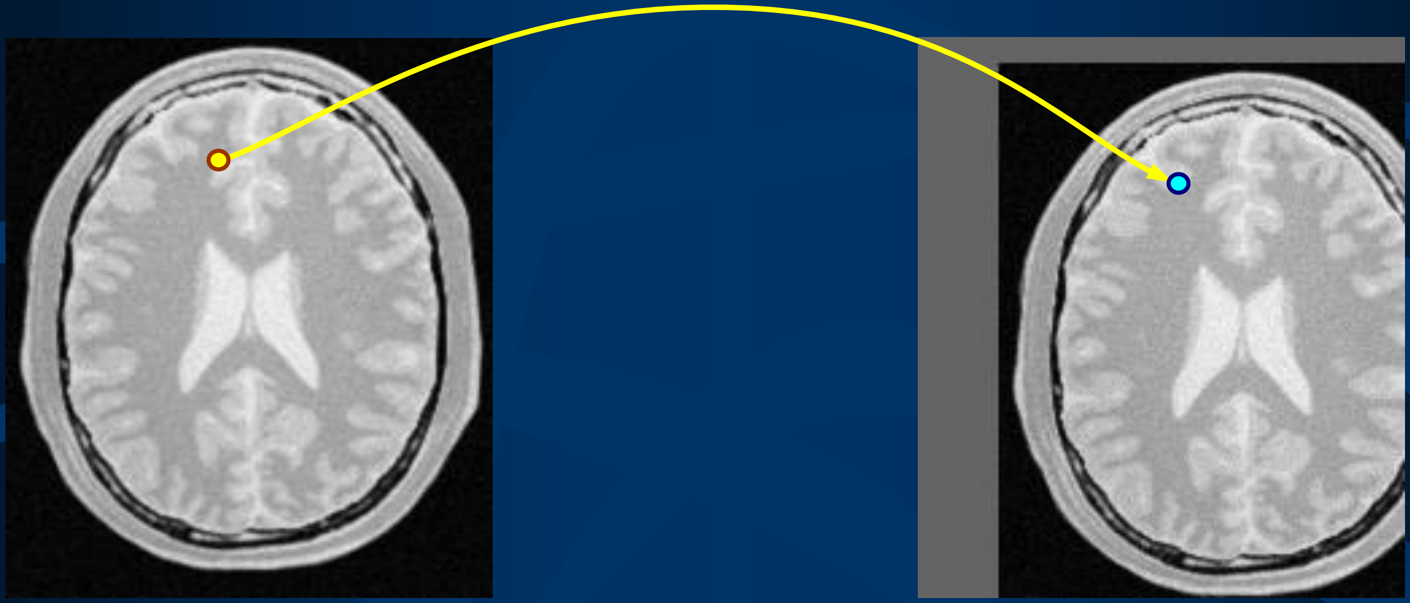


Image A

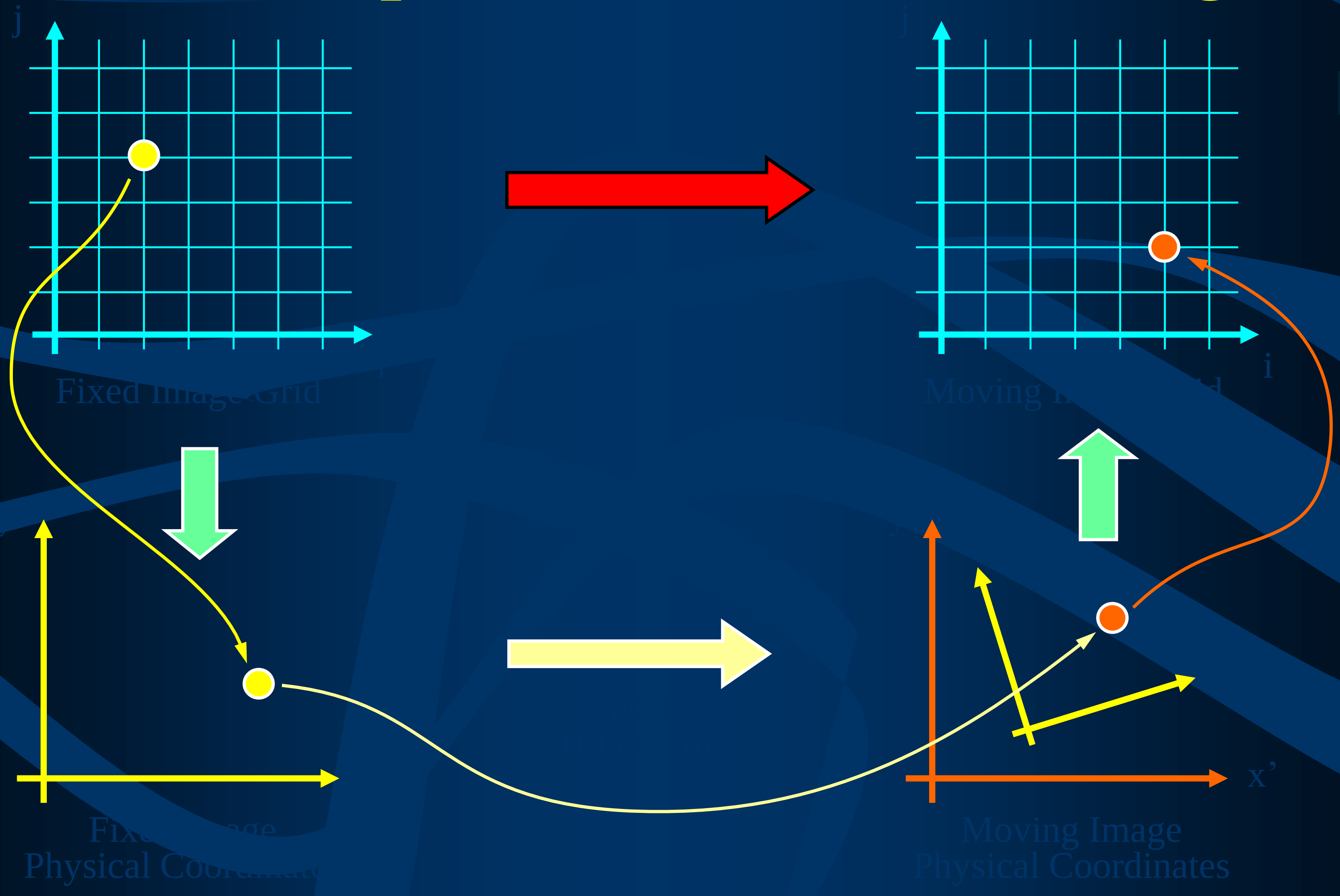
Image B

Difference(index) = A(index) – B(index)

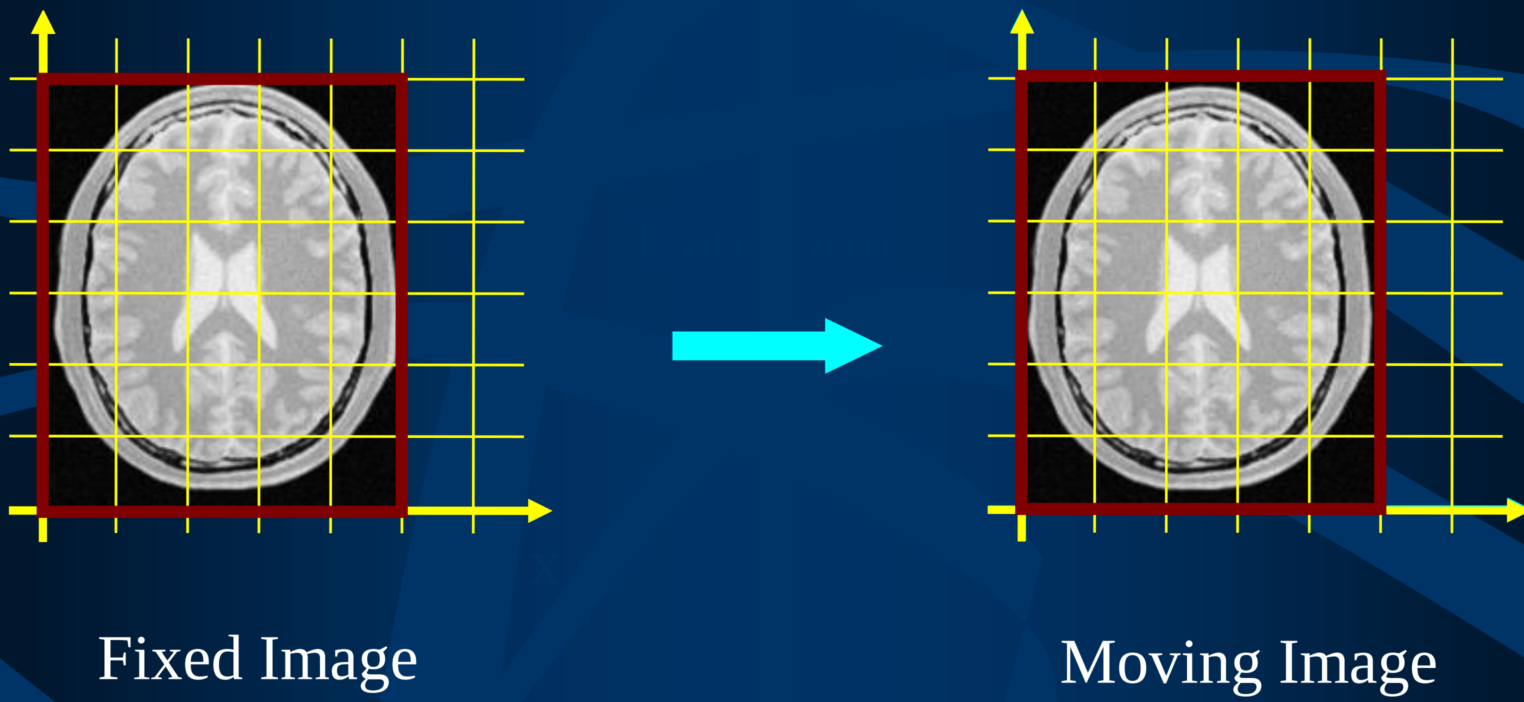
Sum += Difference(index) ^{2}

Match(A , B) = Sum / numberOfPixels

For each pixel in the Fixed Image

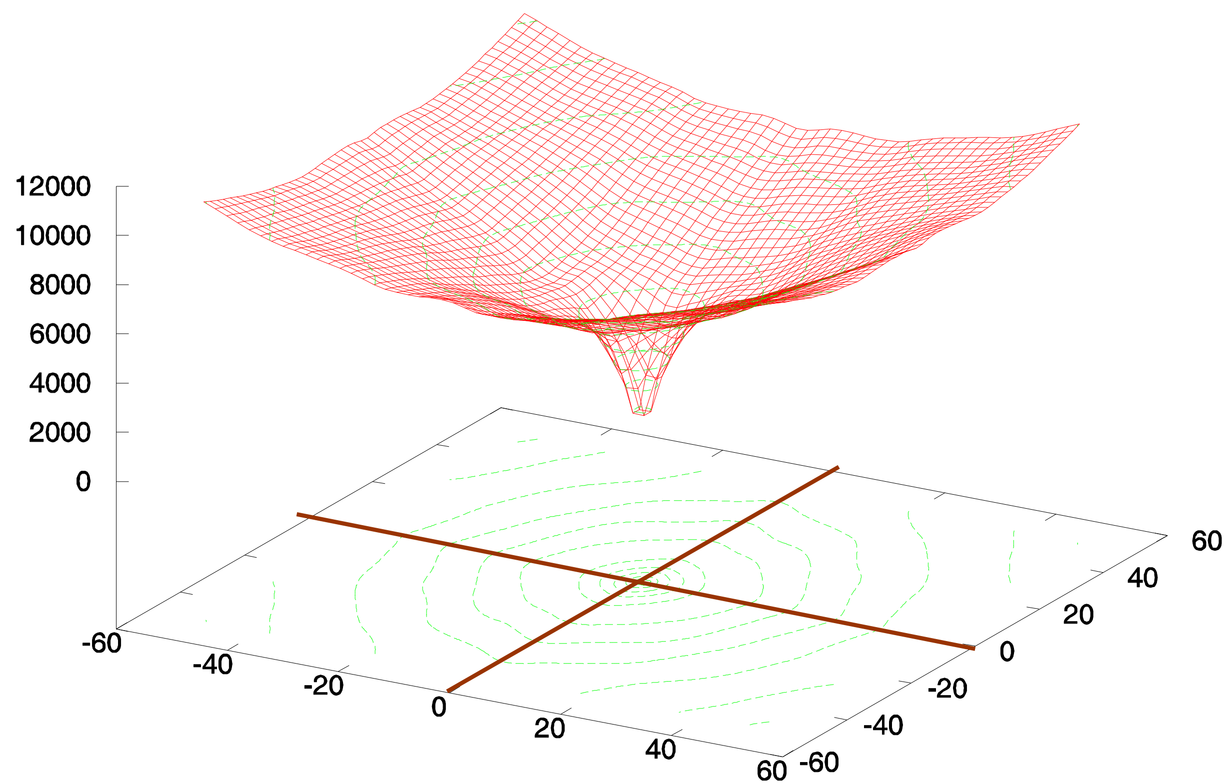


Evaluating many matches



Plotting the Metric

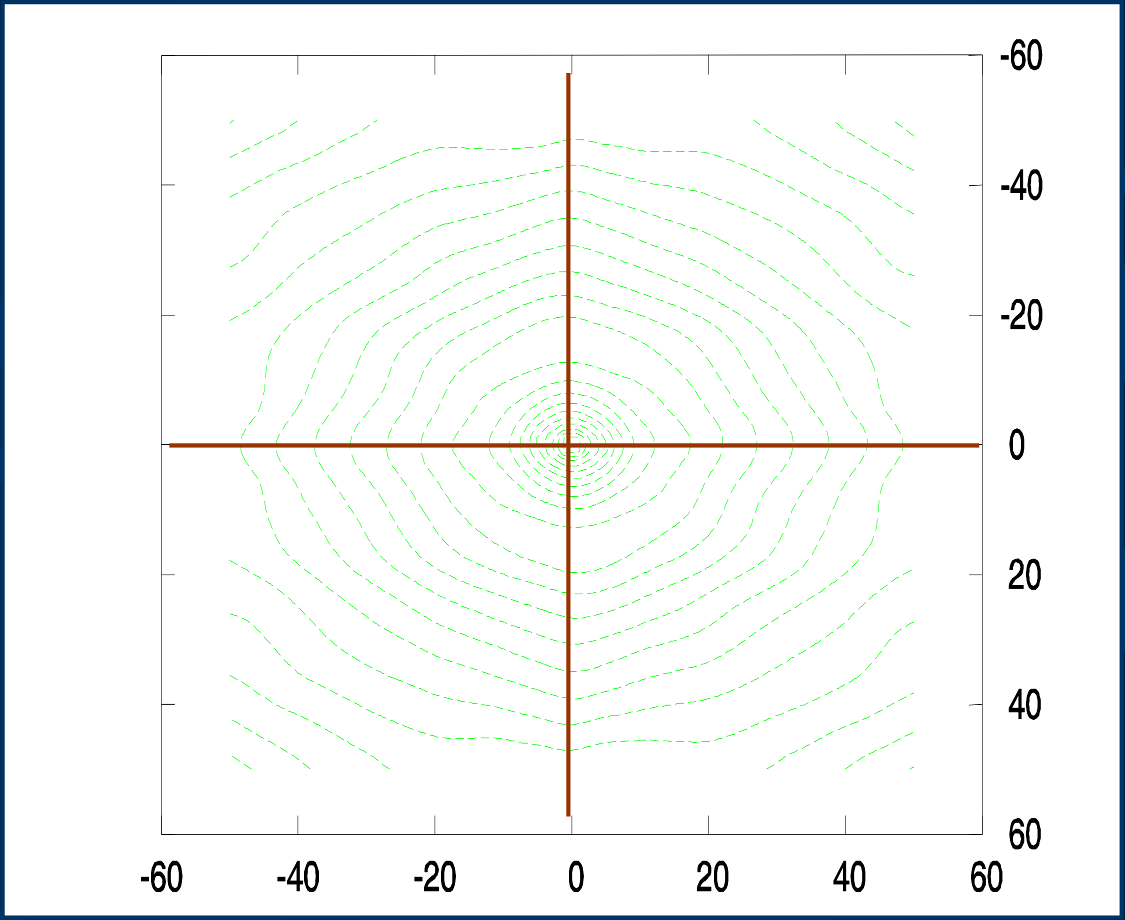
Mean Squared Differences



Transform Parametric Space

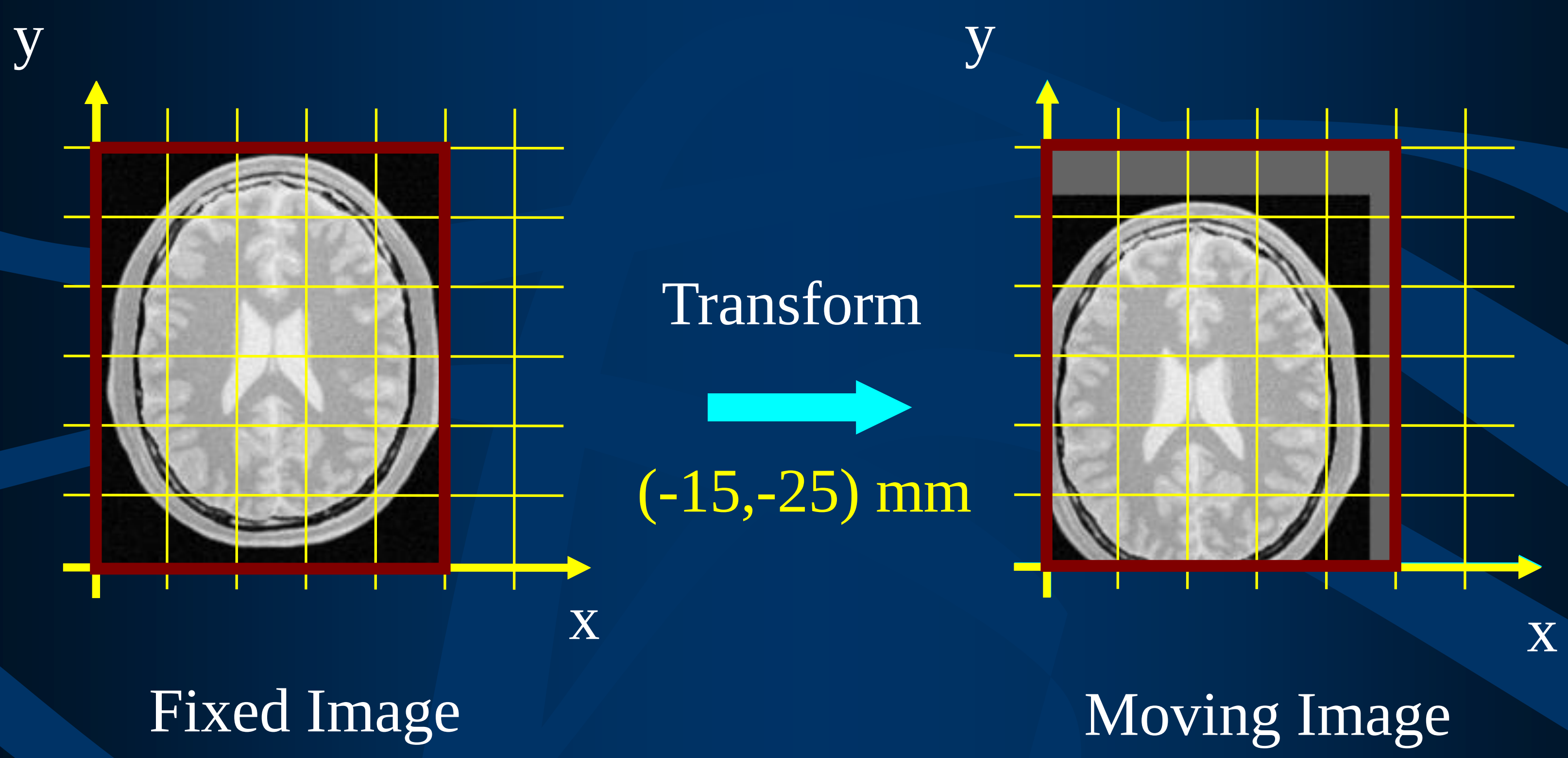
Plotting the Metric

Mean Squared Differences



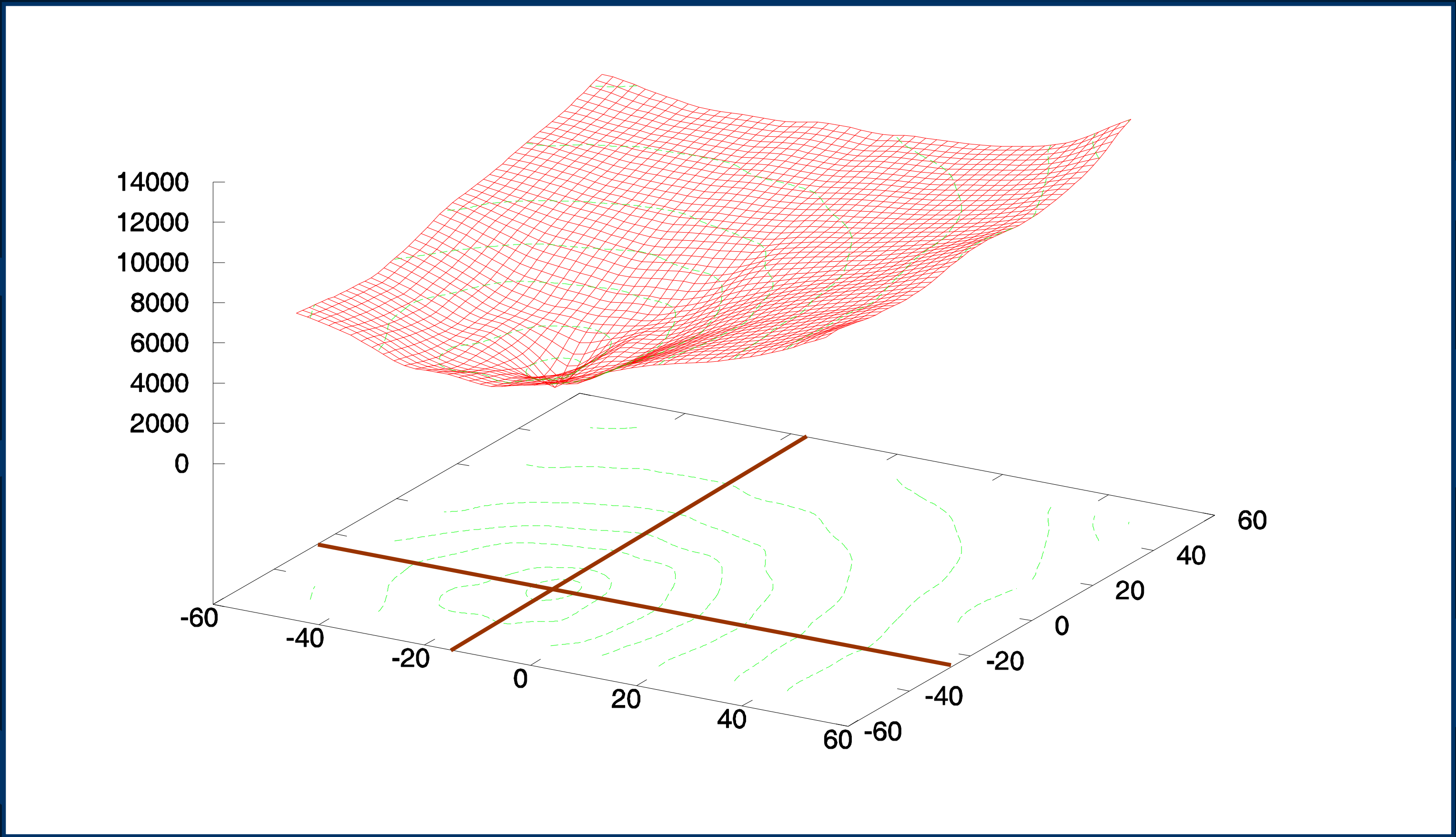
Transform Parametric Space

Evaluating many matches



Plotting the Metric

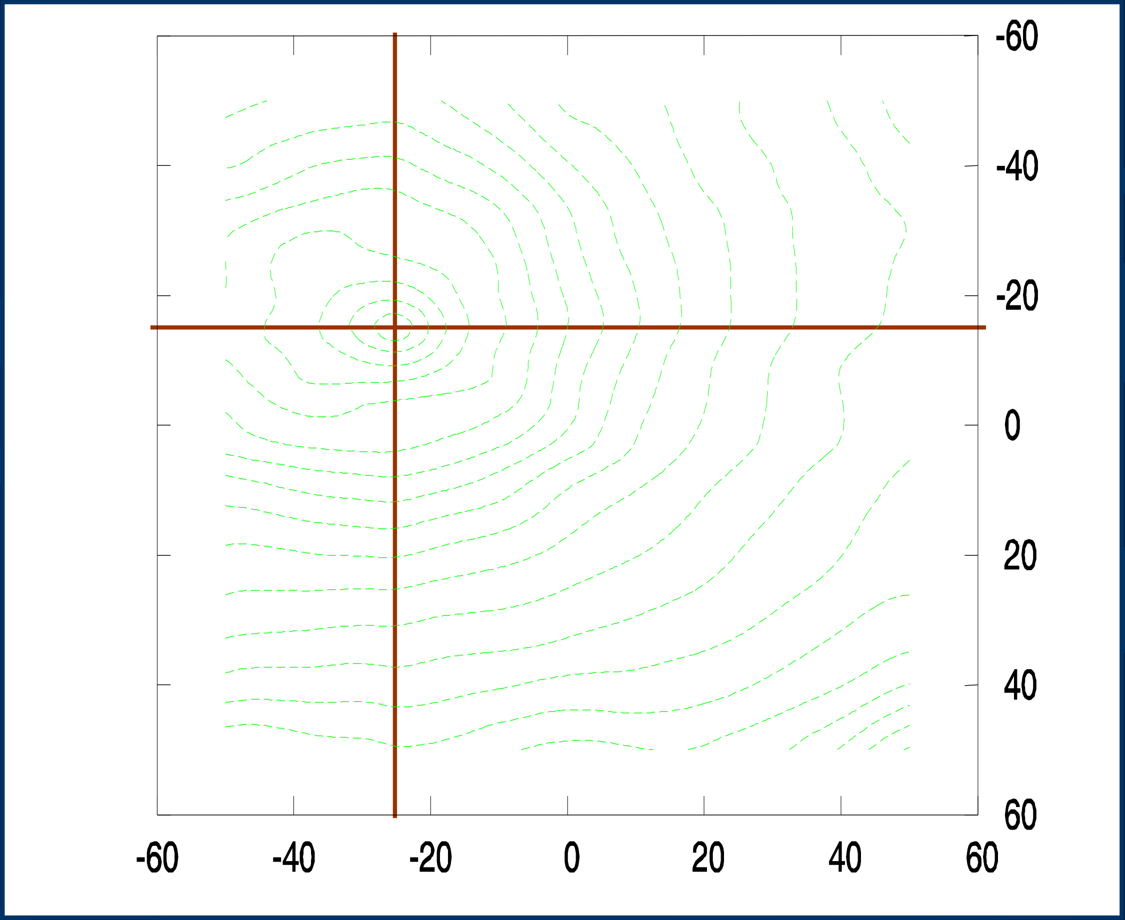
Mean Squared Differences



Transform Parametric Space

Plotting the Metric

Mean Squared Differences



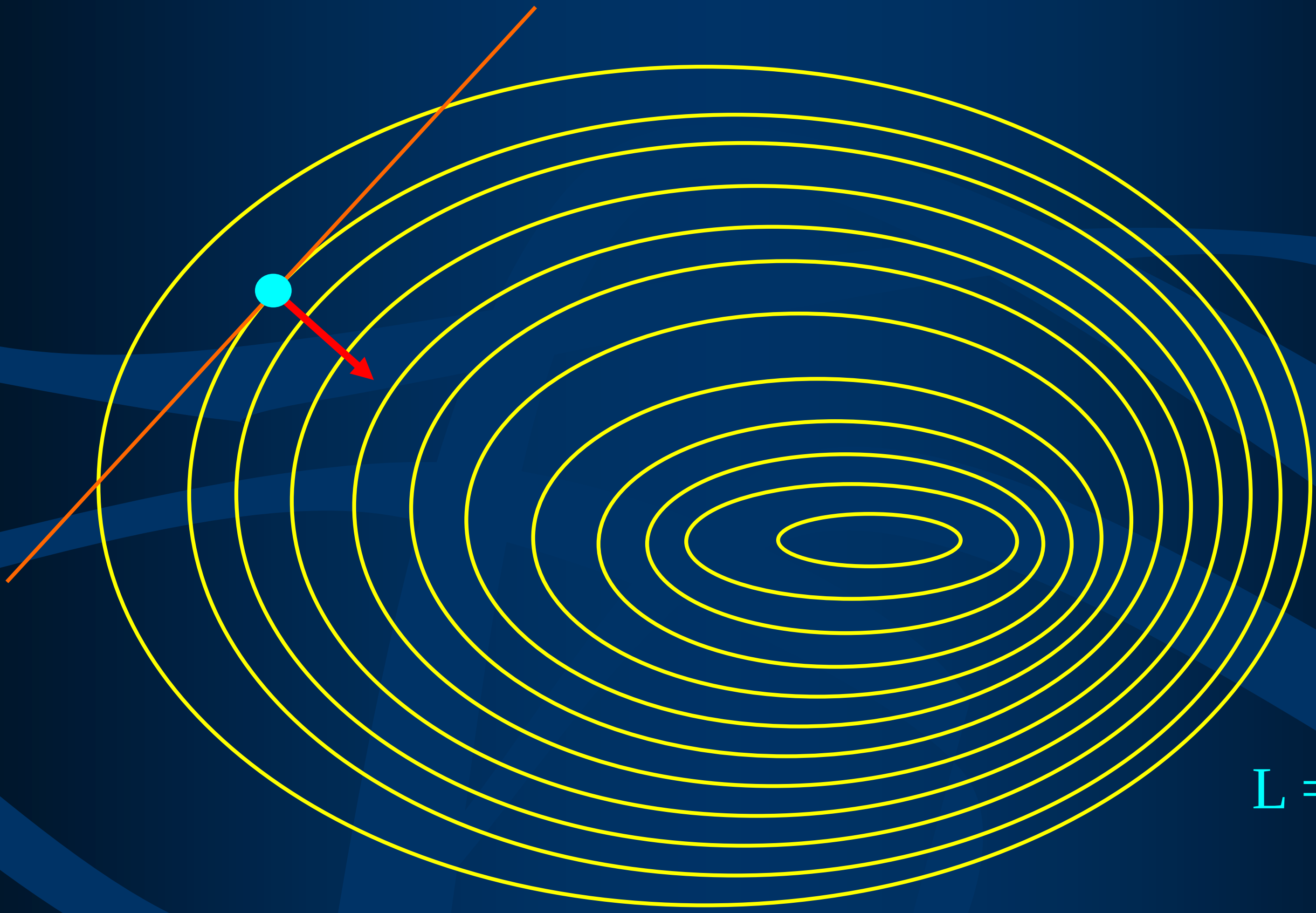
Transform Parametric Space

Best Transformation Parameter

- Evaluation of the full parameter space is equivalent to performing optimization by exhaustive search
- Very Safe but Very Slow
- Better Optimization Methods
  - Gradient Descent
  - Regular Step Gradient Descent
  - Conjugate Gradient
  - Levenberg-Marquardt

Gradient Descent Optimizer

f(x , y)



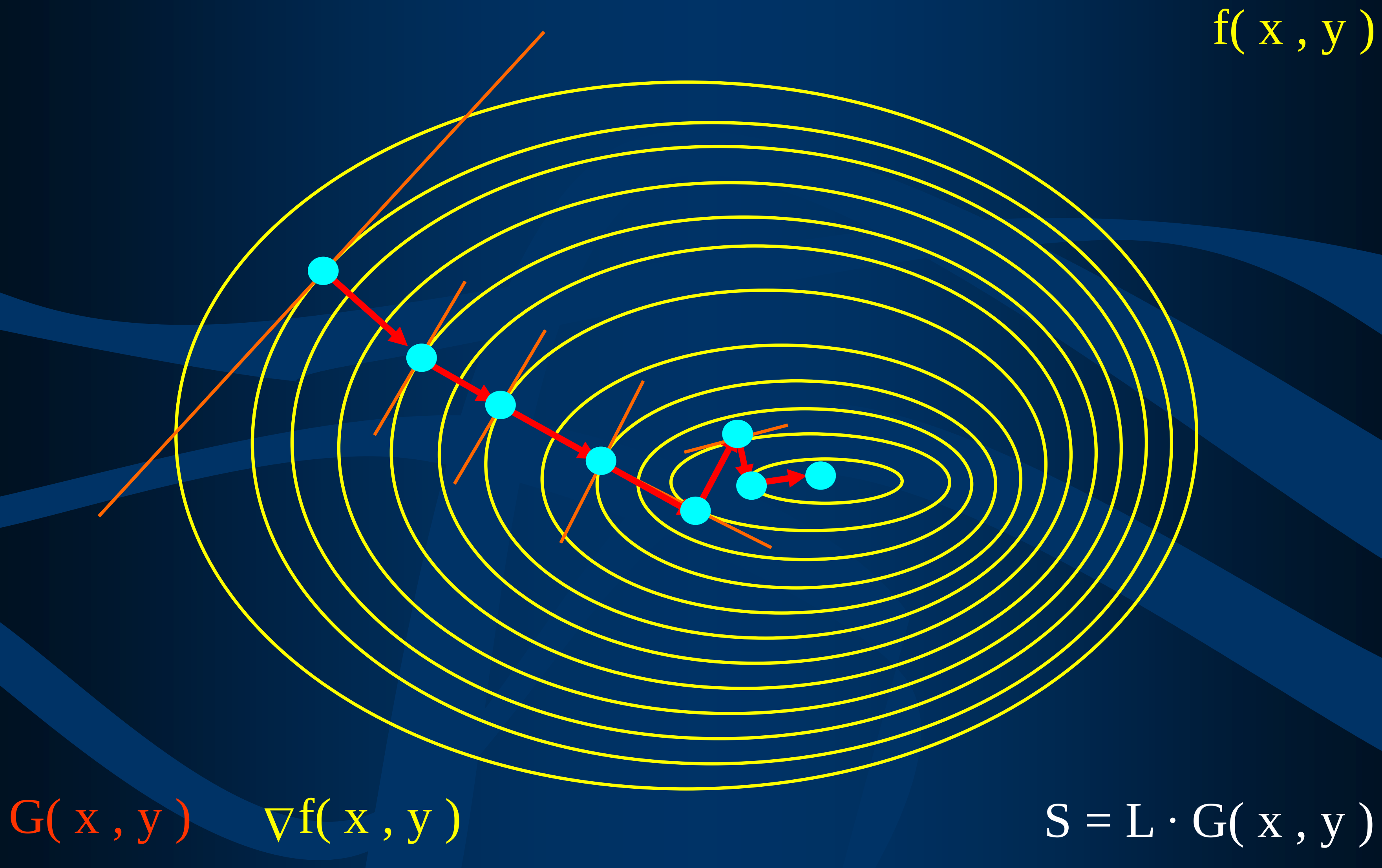
S = Step

L = Learning Rate

G(x , y) ∇f(x , y)

S = L · G(x , y)

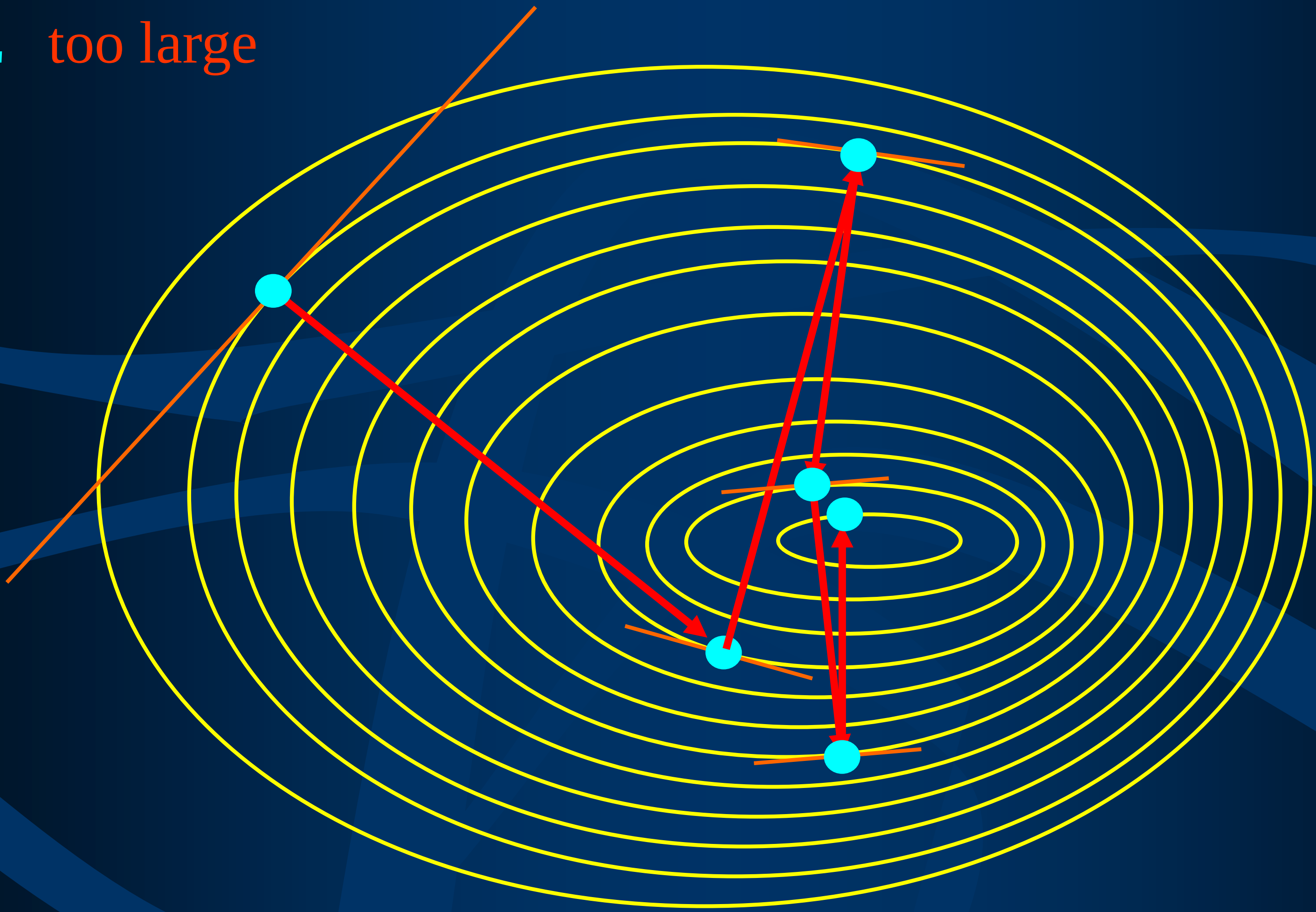
Gradient Descent Optimizer



Gradient Descent Optimizer

f(x , y)

L too large



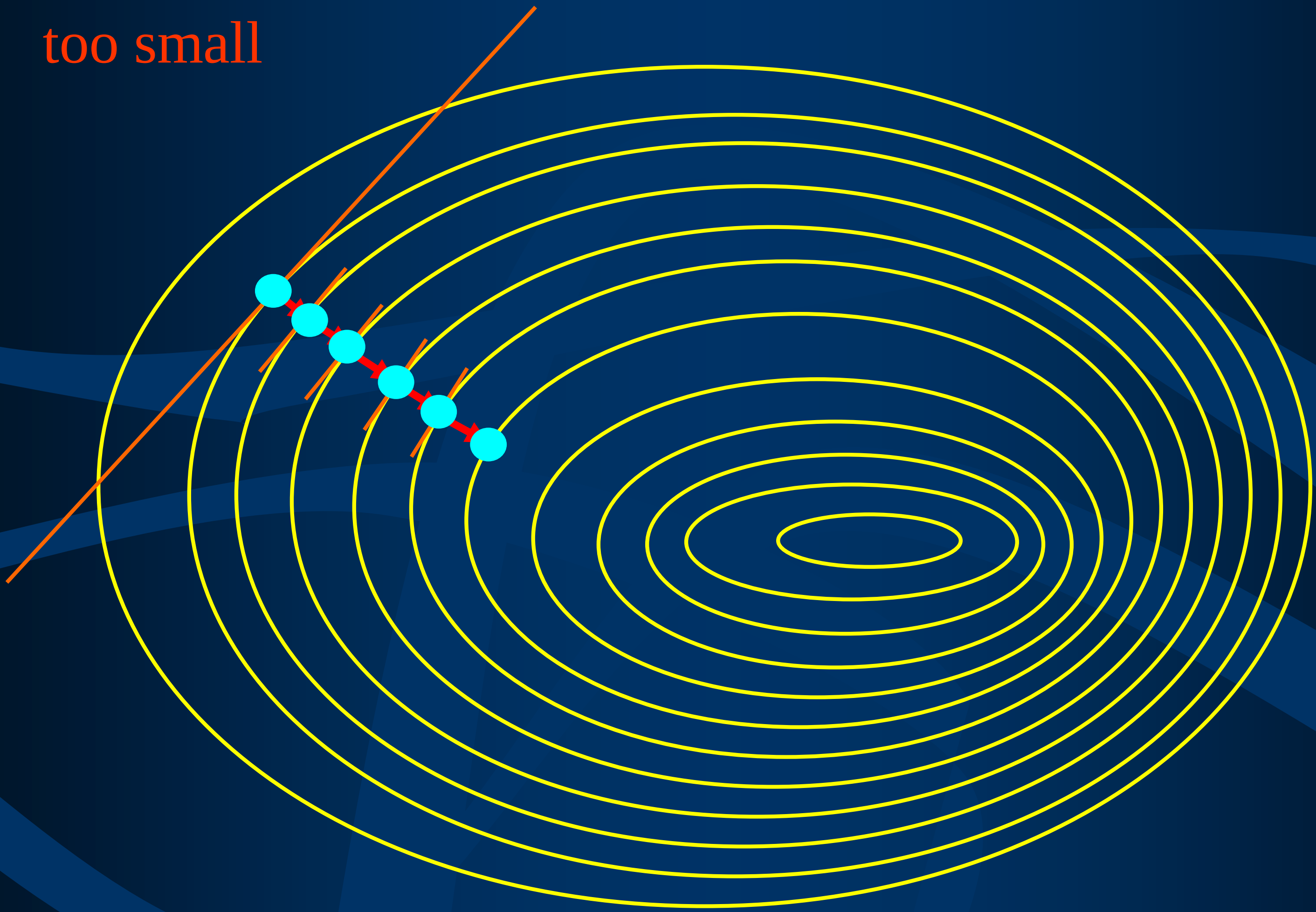
G(x , y) $\nabla f(x, y)$

$S = L \cdot G(x, y)$

Gradient Descent Optimizer

$f(x, y)$

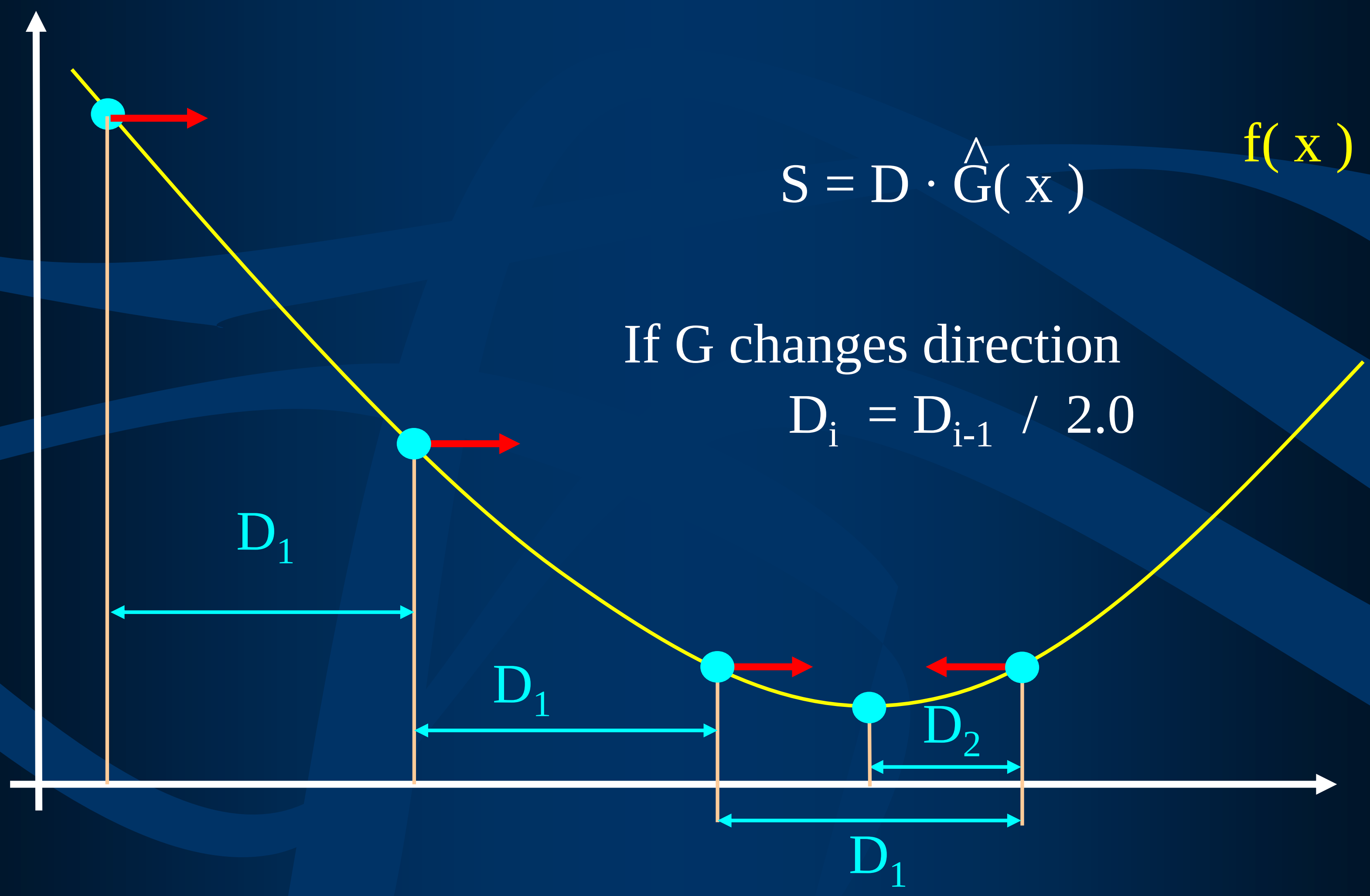
L too small



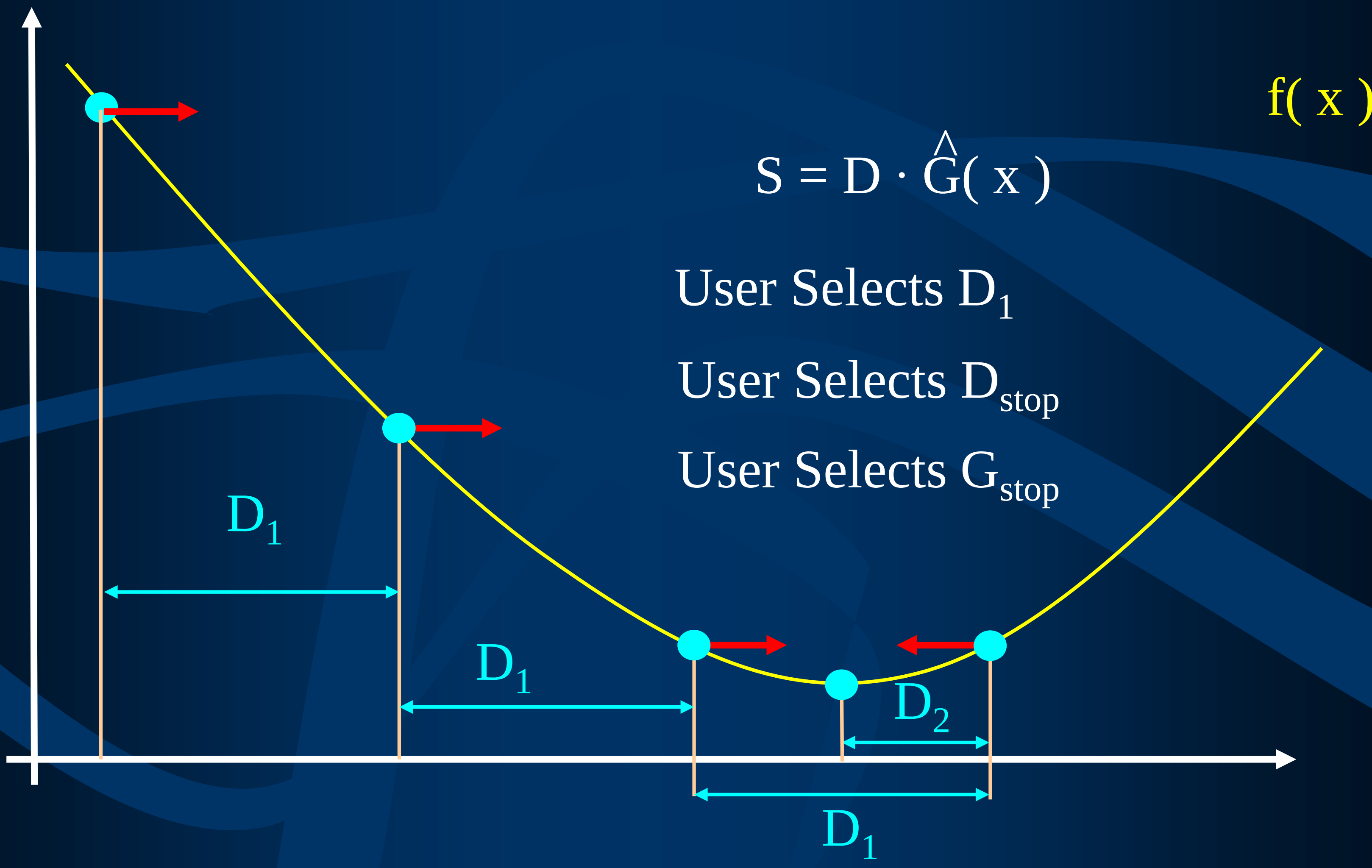
$G(x, y)$ $\nabla f(x, y)$

$S = L \cdot G(x, y)$

Regular Step Gradient Descent



Regular Step Gradient Descent



$$S = D \cdot \hat{G}(x)$$

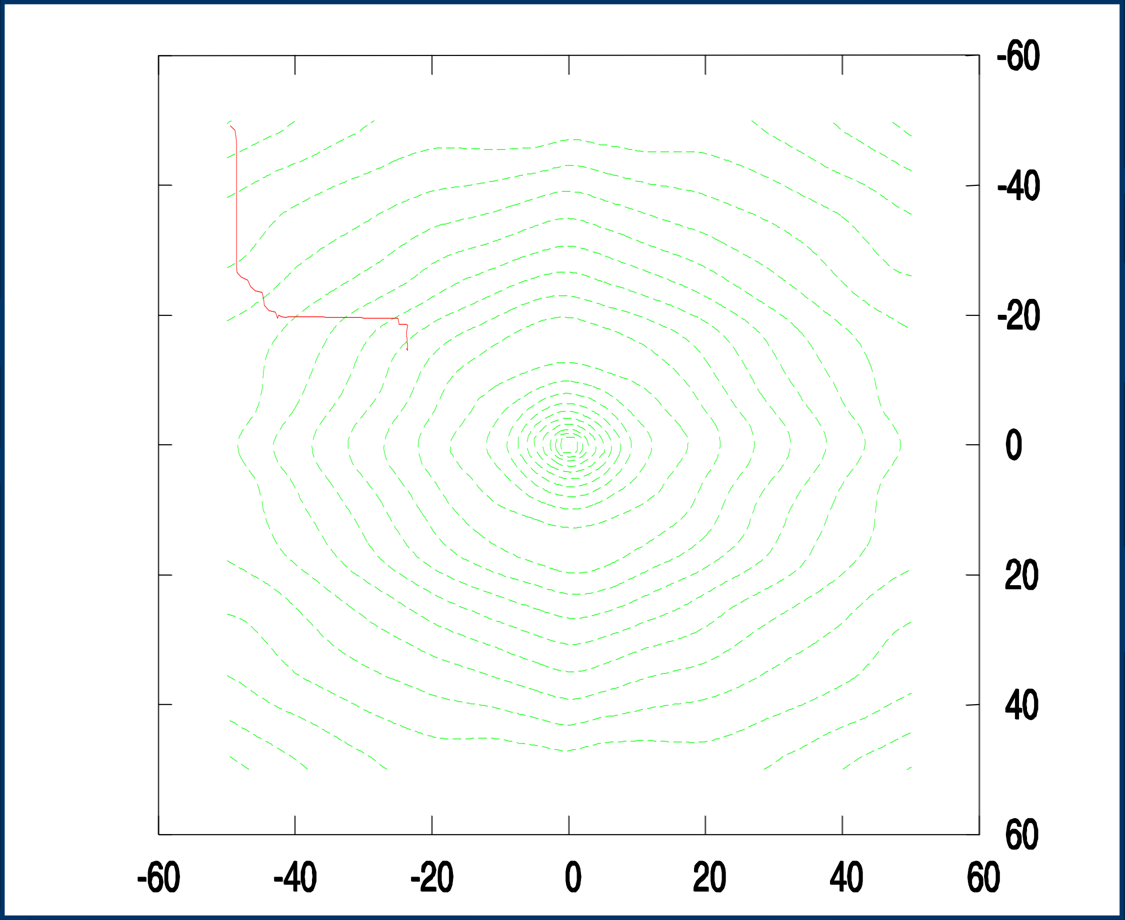
User Selects D_1

User Selects D_{stop}

User Selects G_{stop}

Plotting the Optimizer's Path

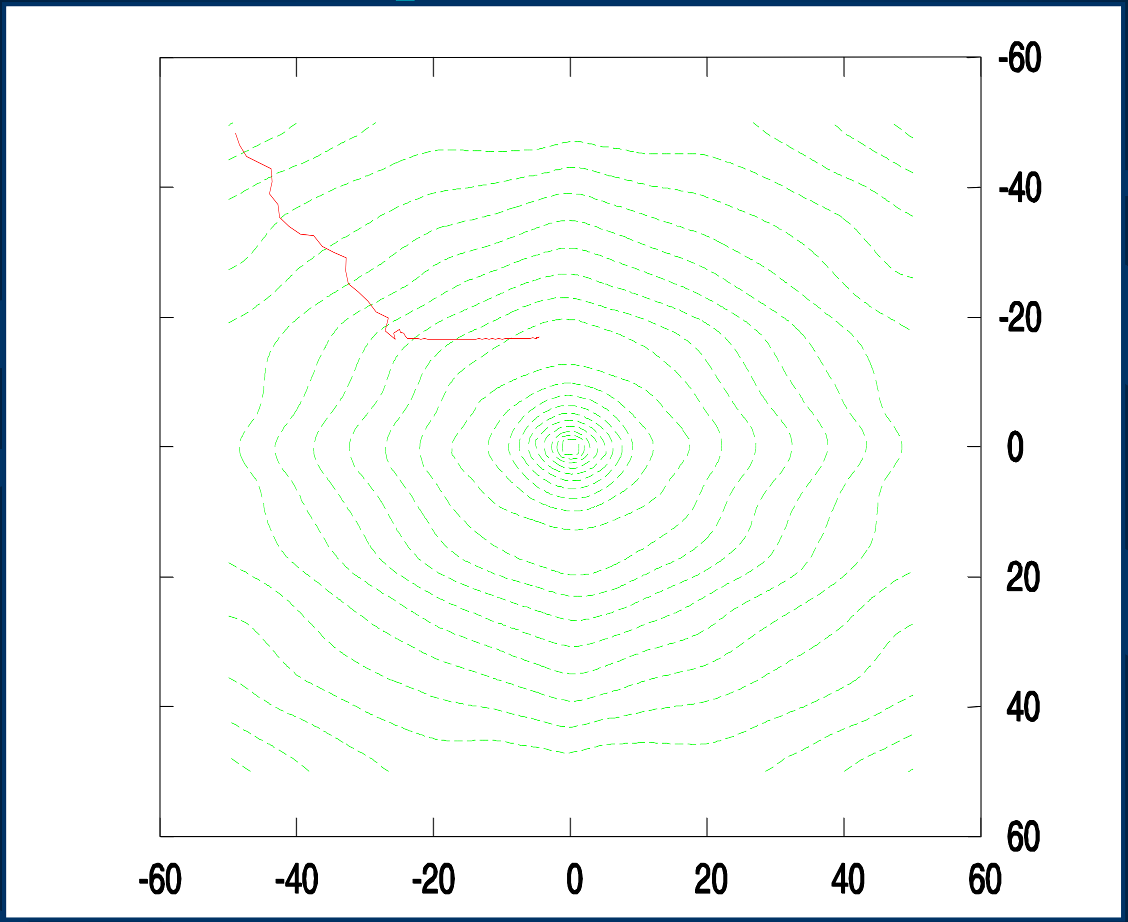
Mean Squared Differences



Step Length = 1.0 mm

Plotting the Optimizer's Path

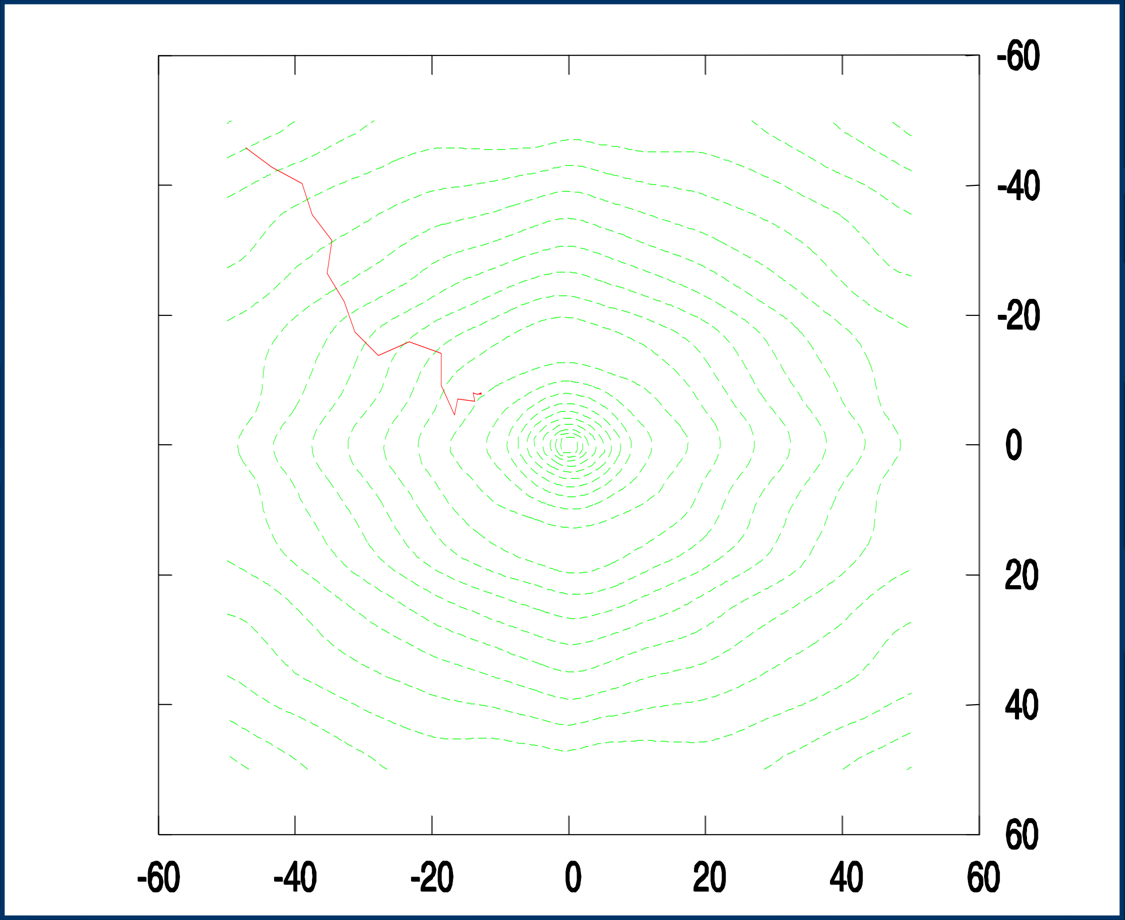
Mean Squared Differences



Step Length = 2.0 mm

Plotting the Optimizer's Path

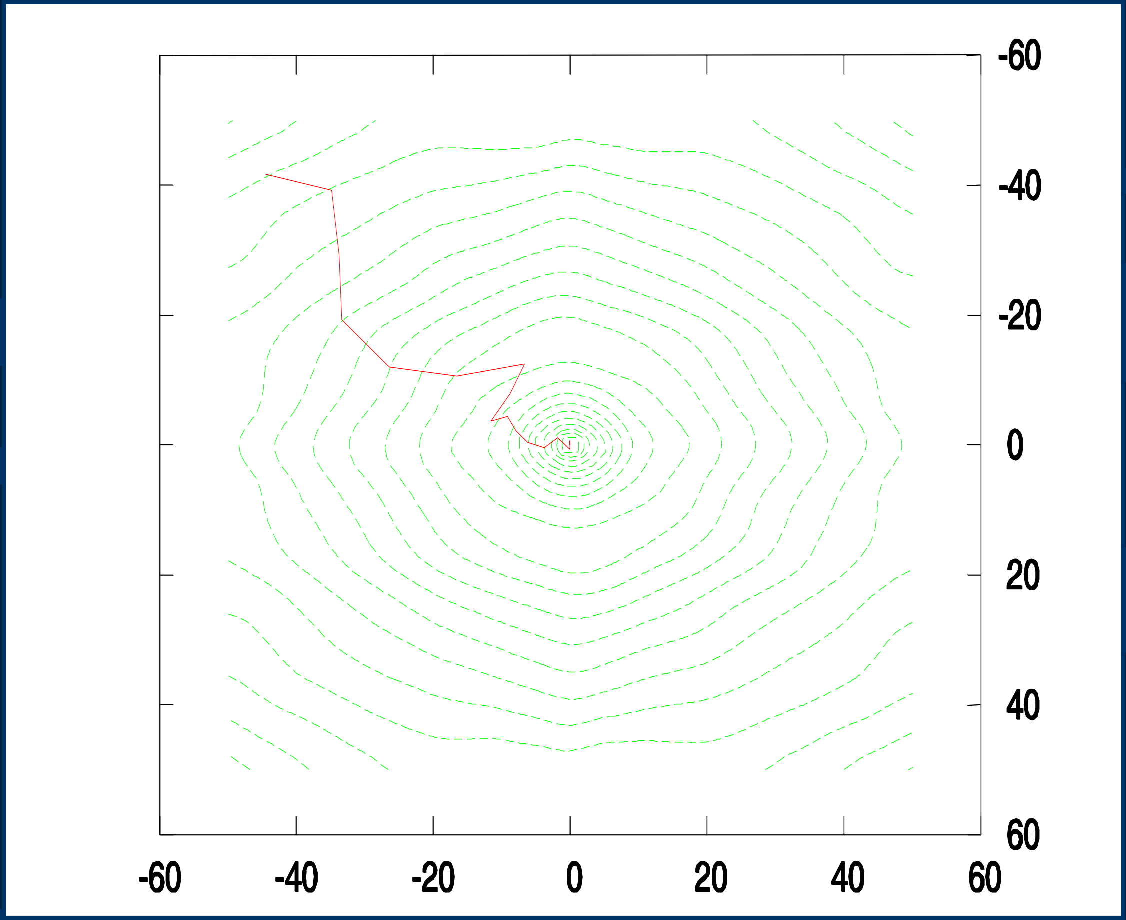
Mean Squared Differences



Step Length = 5.0 mm

Plotting the Optimizer's Path

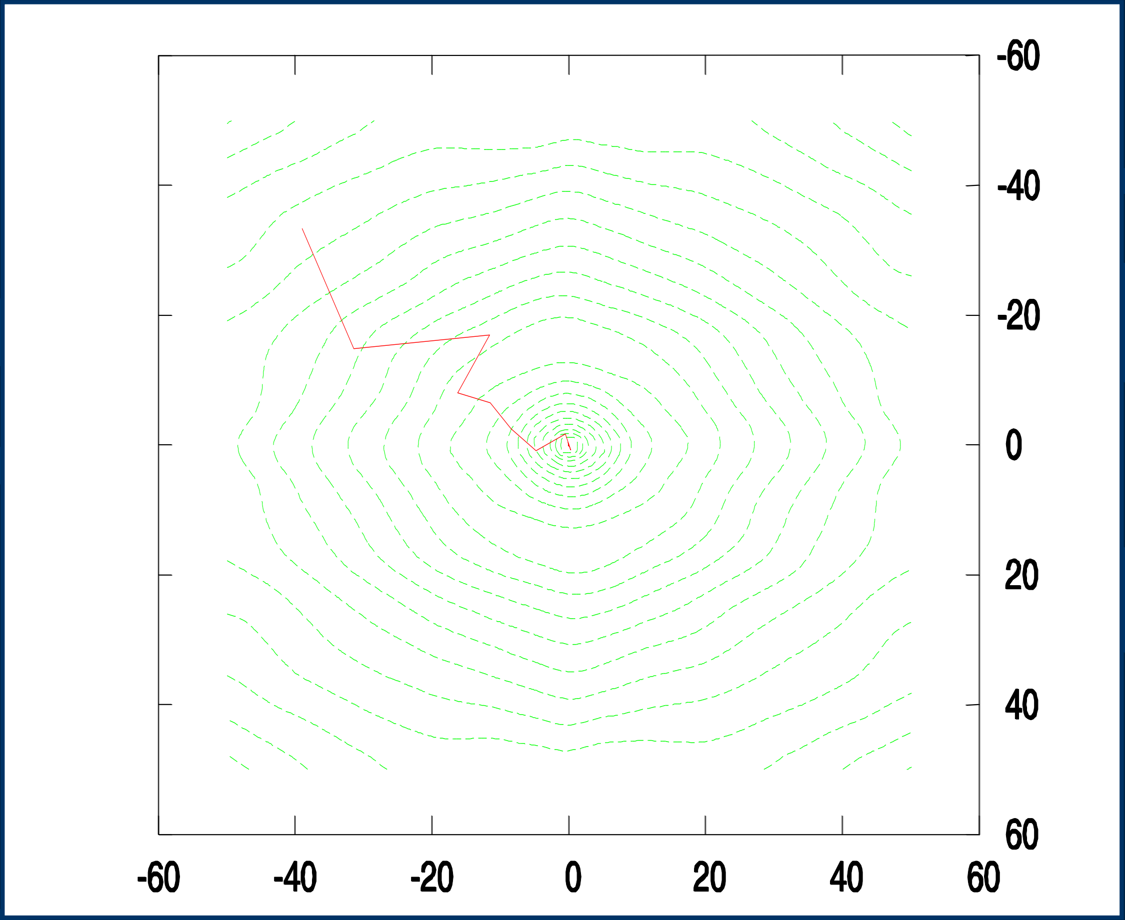
Mean Squared Differences



Step Length = 10.0 mm

Plotting the Optimizer's Path

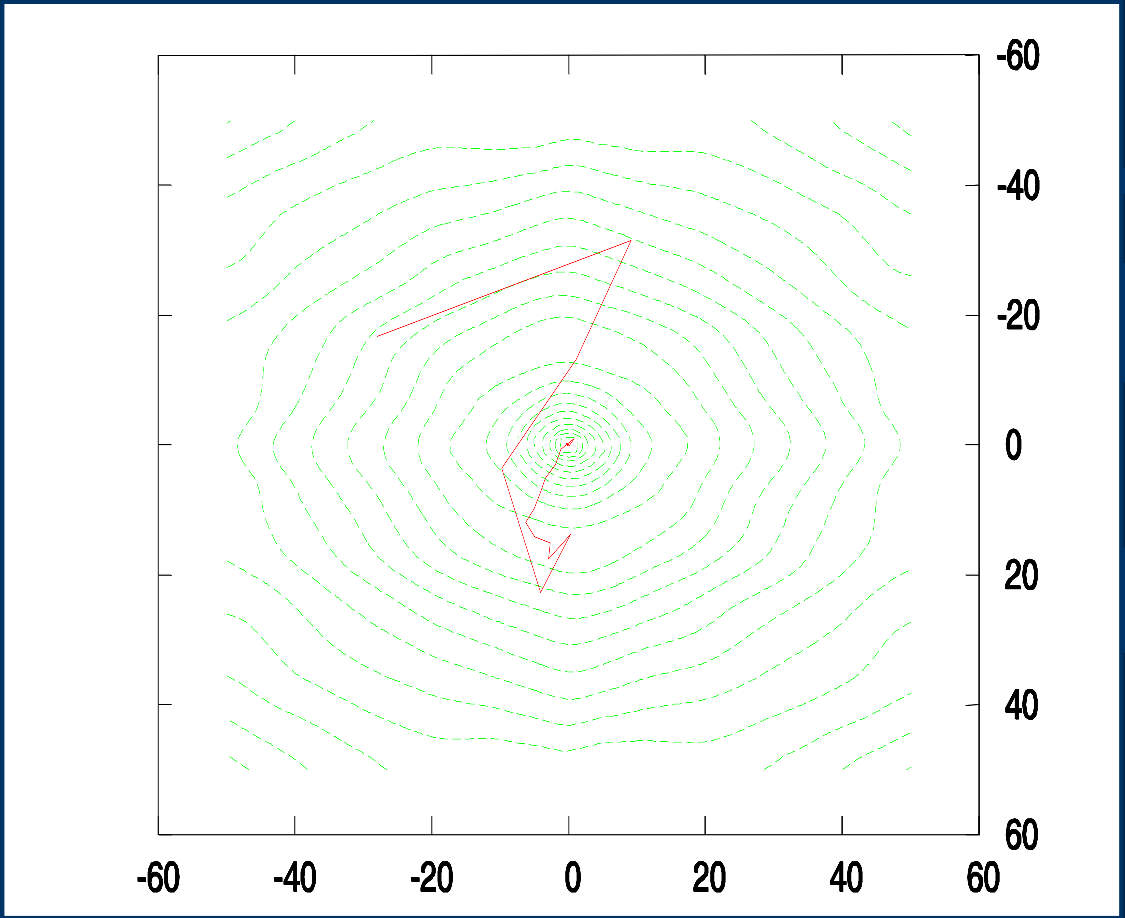
Mean Squared Differences



Step Length = 20.0 mm

Plotting the Optimizer's Path

Mean Squared Differences



Step Length = 40.0 mm

Conclusion

- Rigid body registration is now used routinely
  - image guided surgery systems for neurosurgery and orthopaedic surgery
- Challenges:
  - validation methodologies for non-rigid registration algorithms
  - More robust similarity measures
  - distinguish between rigid and deformable structures
  - Optimization: accuracy *vs.* efficiency

Discussion