Introduction

- The practice of modern medicine incorporates an enormous amount of image data
- Traditional computational vision relies on cameras and, more recently, range finders
- Medicine uses, to name a few:
  - Computed Tomography (CT)
  - Magnetic Resonance Imaging (MRI)
  - X-ray fluoroscopy
  - Ultrasound

Medical Physics and Imaging Fundamentals

Imaging Modalities

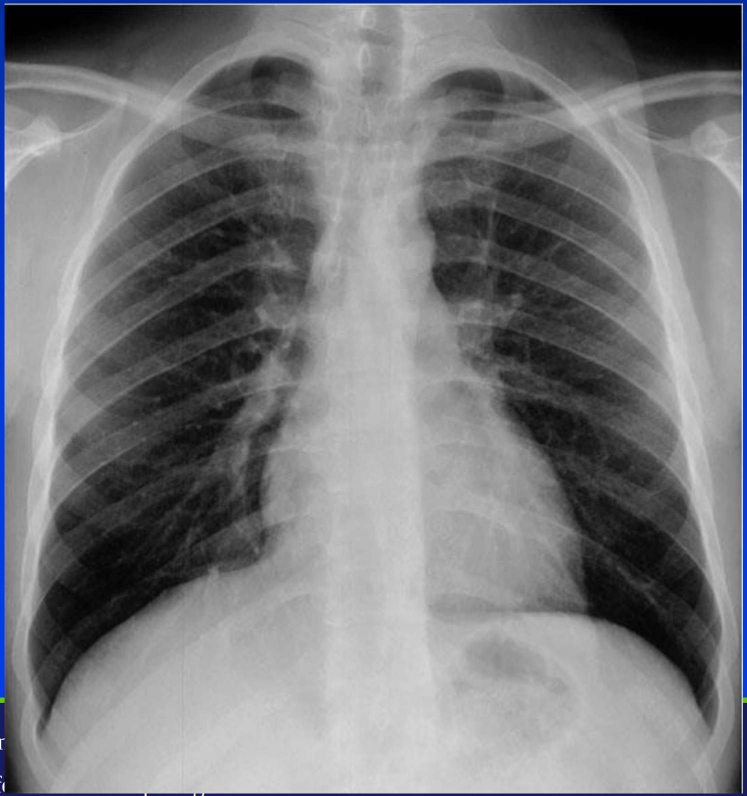
- **Diagnostic Radiography** ionizing radiation or x-rays to produce images of various parts of the body.
- **Magnetic Resonance Imaging (MRI)** uses radio frequency waves and magnetic forces to provide images of internal organs and tissues.
- **Sonography** uses high frequency sound waves to create images of tissues, organs, and vessels.
- **Computed Tomography (CT)** provides cross-sectional or "3D" images of the anatomy.

Diagnostic Radiography ("X-Ray")

- Uses ionizing radiation to study anatomy and physical structures in human or veterinary medicine.
- Other modalities build on the foundation of diagnostic radiography.

Diagnostic Radiography

- The first image is a normal chest x-ray
- The second image shows a chest x-ray of a person who swallowed a whistle



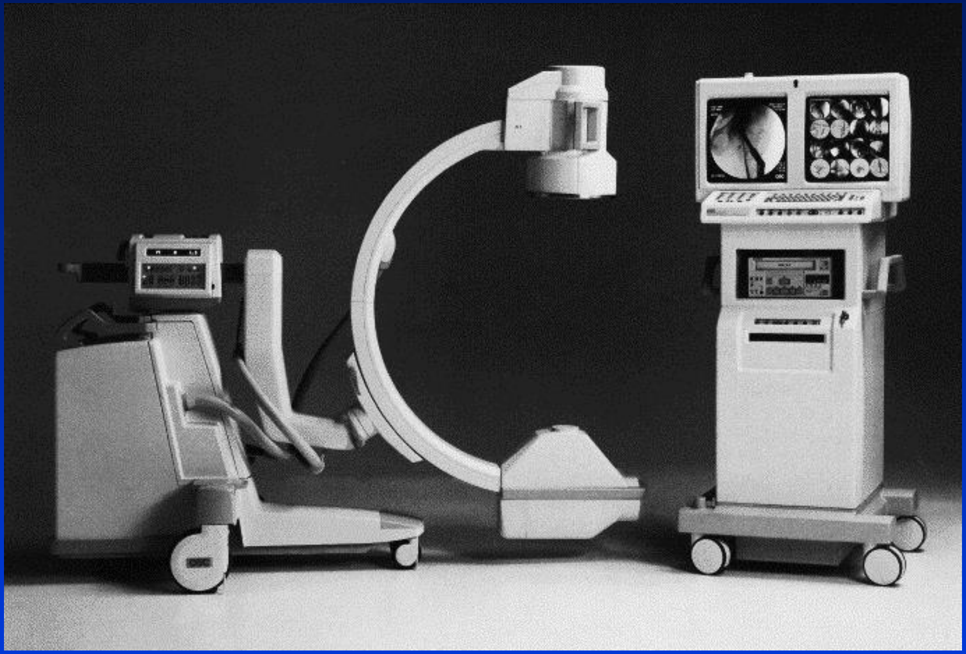
Diagnostic Radiography

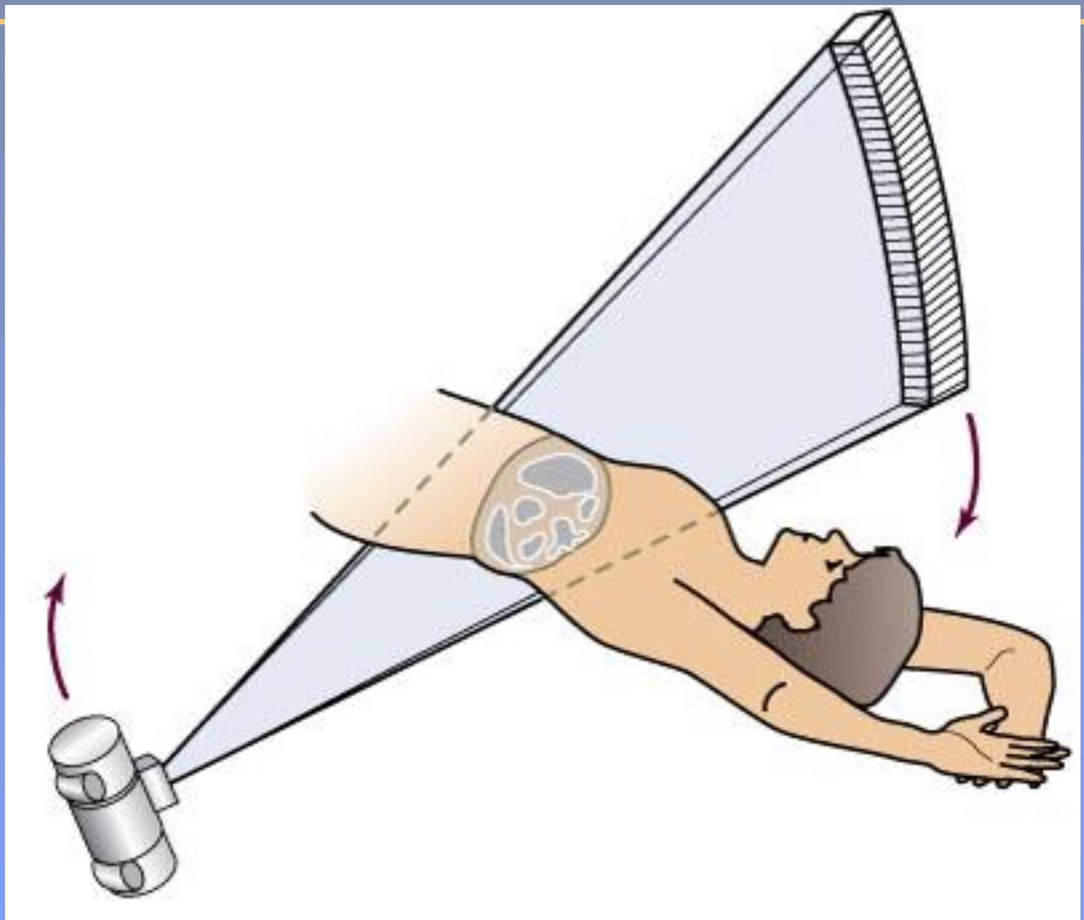
- A Radiologic technologist must master the subjects of anatomy and physiology. They are the foundations for diagnostic radiography.

Diagnostic Radiography

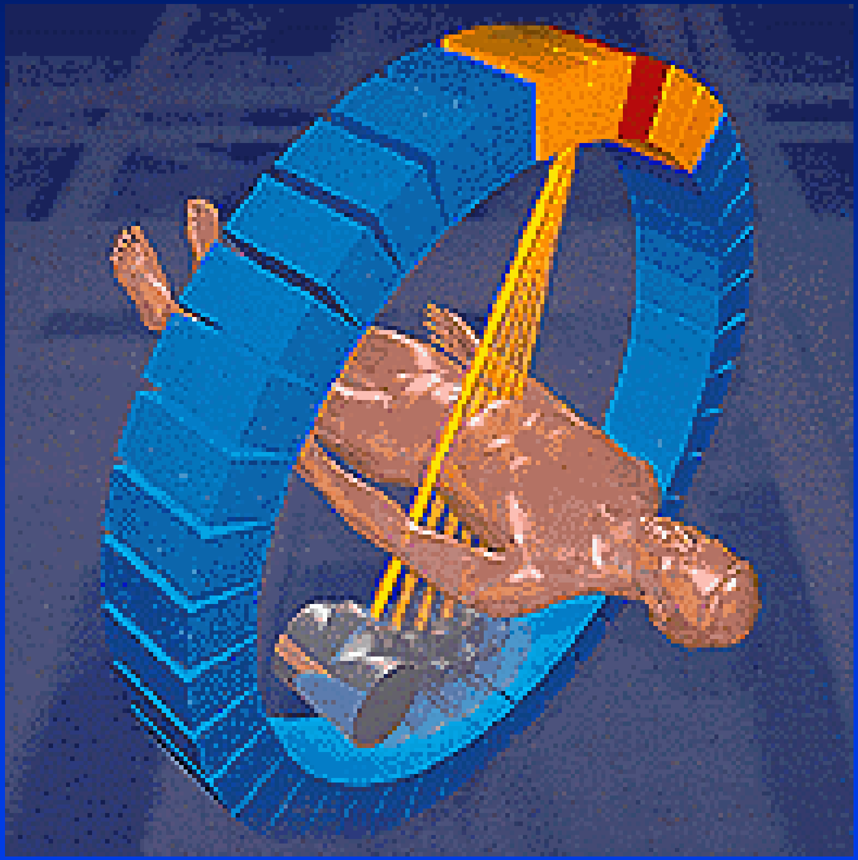
- The following image shows an x-ray of a hand with a middle broken finger. A Radiologic technologist must know every bone in the body! Can you identify the broken bone?

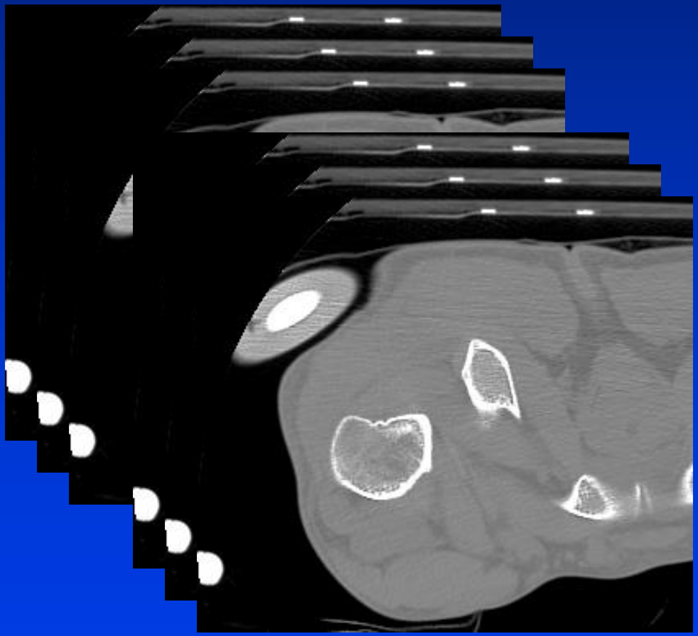
Modalities: X-ray Fluoroscopy





Modalities: CT





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Medical Image Examples – CT

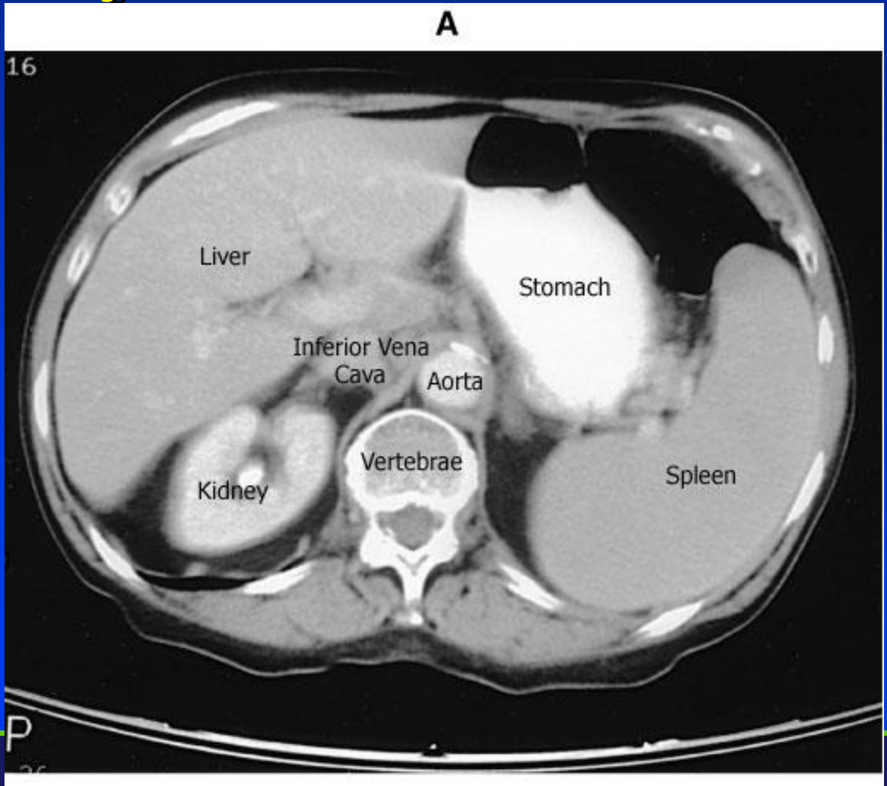
- Bones has high value level
- Soft tissues has relatively low contrast

Computed Tomography (CT Scan)

- CT uses a rotating x-ray machine to obtain cross-sectional images or “slices” of the anatomy to observe a wide range of angles within the body.
- CT can be used to image brain, neck, chest, abdomen, pelvis and extremities.
- CT provides “3D” imaging to diagnose fractures, strokes, cancer and other abnormalities.

CT Scan

- The next slide shows a CT of the abdomen. A CT "slice" is a cross sectional image that provides a great deal of information. Many slices are reviewed to make a diagnosis

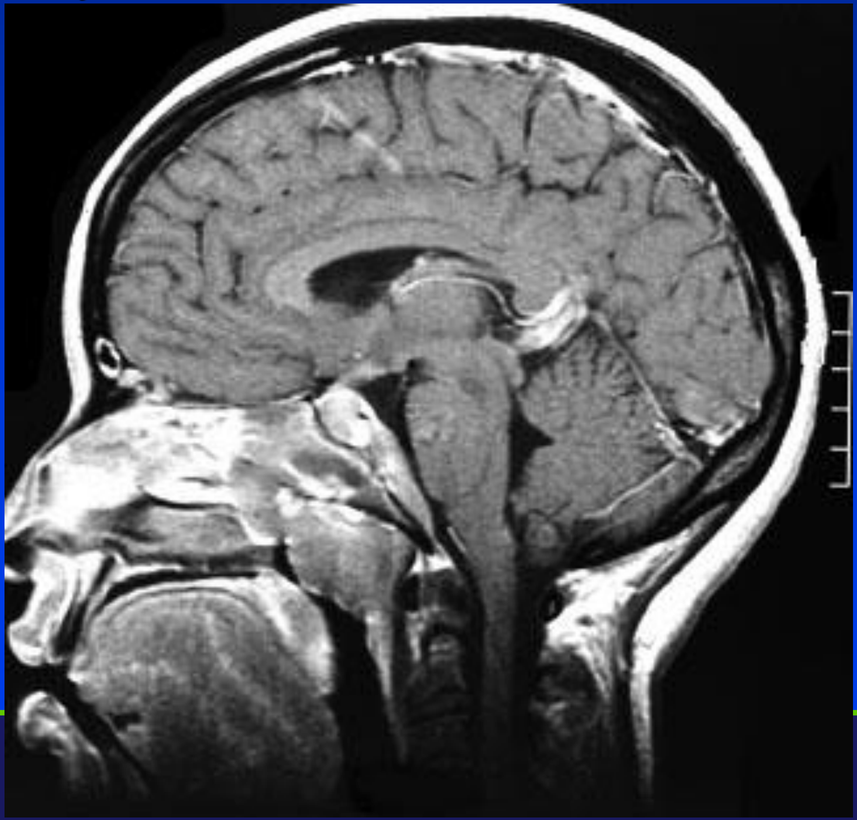


Magnetic Resonance Imaging(MRI)

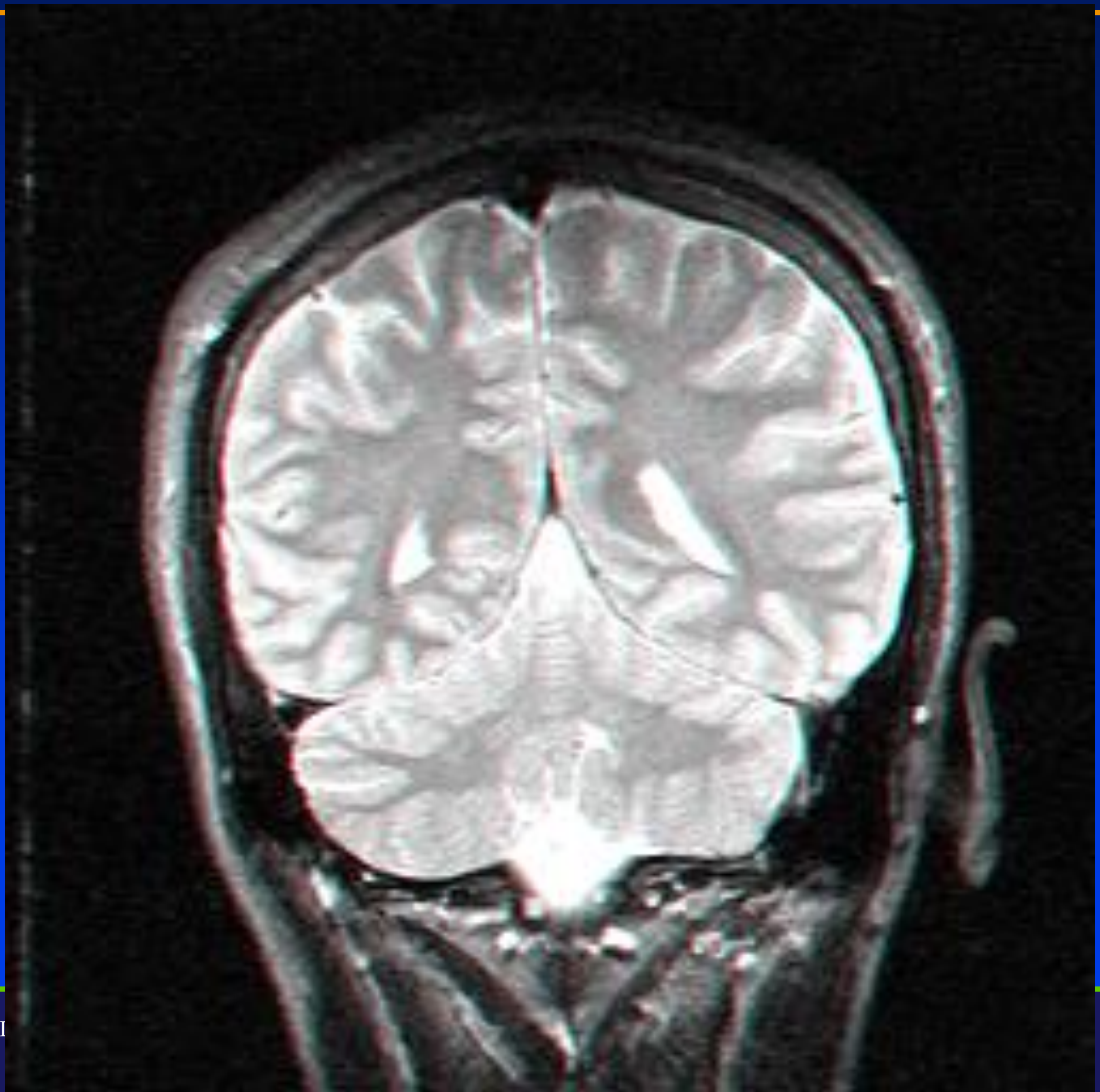
- Uses the magnetic properties of hydrogen to produce an image.
- Uses a very powerful, super-conducting magnet.
- All planes in a body can be viewed.
- MRI is an effective diagnostic tool that demonstrates tissue, muscle, cartilage, and fat using no ionizing radiation.

MRI

- The next slide is an image of a human brain taken with magnetic resonance imaging.
- You can actually see the sections of the brain in the image.

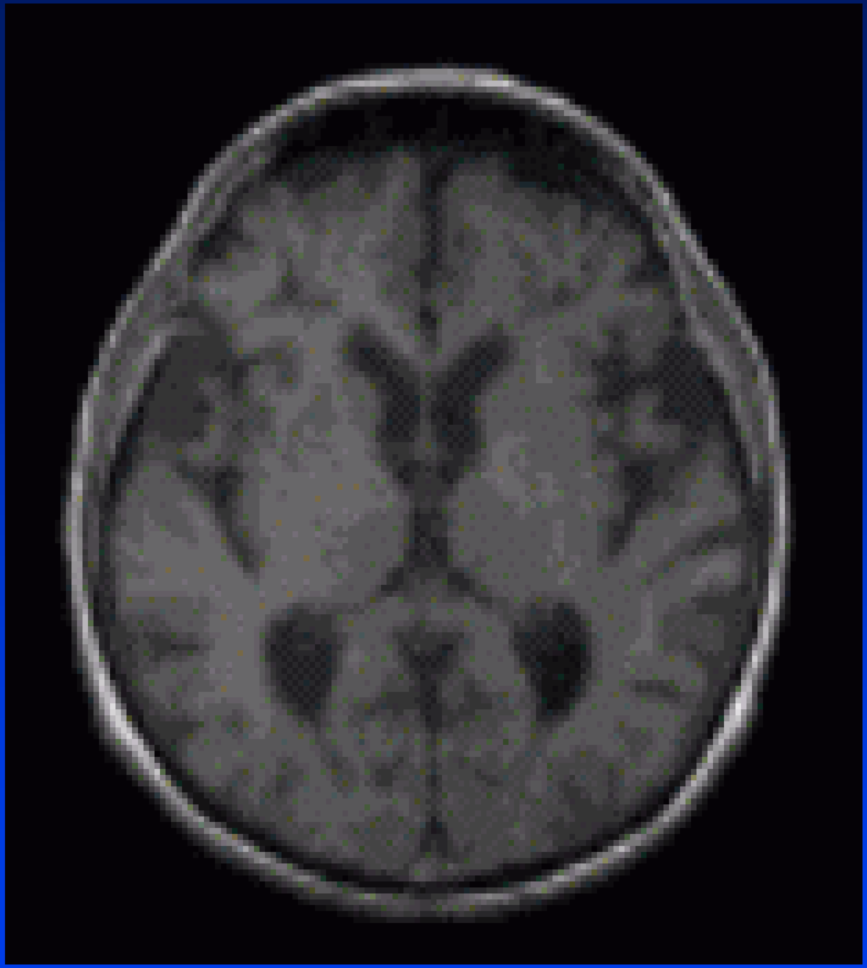


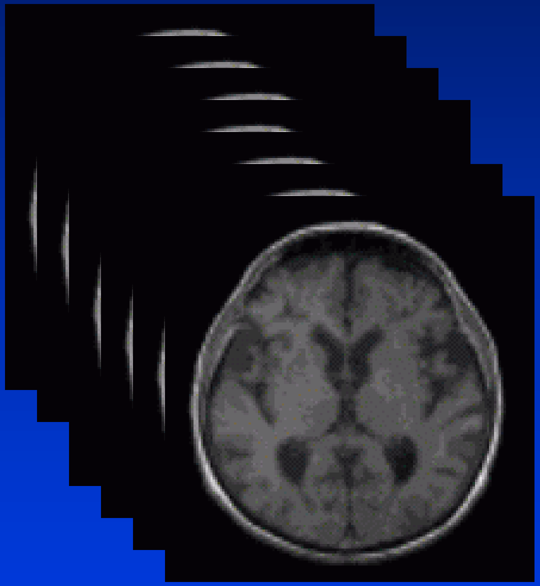
Medical Image Examples – MR



- Soft tissues has high contrast
- Bones are “black”, with no signal.

Modalities: MRI





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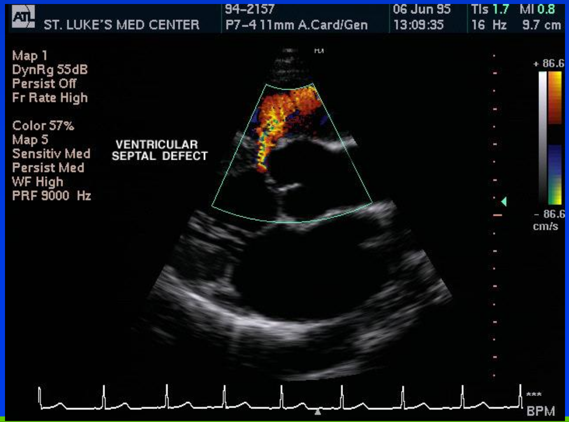
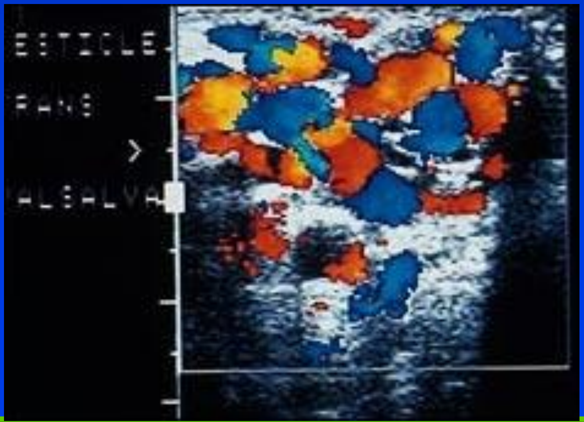
Modalities: Ultrasound

Medical Image Examples – US

- 2D, planar
- 3D, space
- 4D, dynamic space
- Dopler, blood flow





Ultrasound, or Sonography

- Uses sound waves to study, treat and to reach a body area.
- High frequency sound waves are transmitted to the areas of interest and the returning echo is recorded.
- It is non-invasive and involves no radiation.
- Ultrasound is used in the diagnosis and treatment of organ malfunctions.
- Sonographers work in hospital rooms, emergency rooms, operating rooms and clinics assisting with many complicated diagnostic procedures.

Obstetrical Ultrasound

- Diagnoses an assessment of early pregnancies.
- Determines gestational age and fetal size.
- Determines multiple pregnancies.
- Determines sex.
- Observes a fetal image as observed in the next slide.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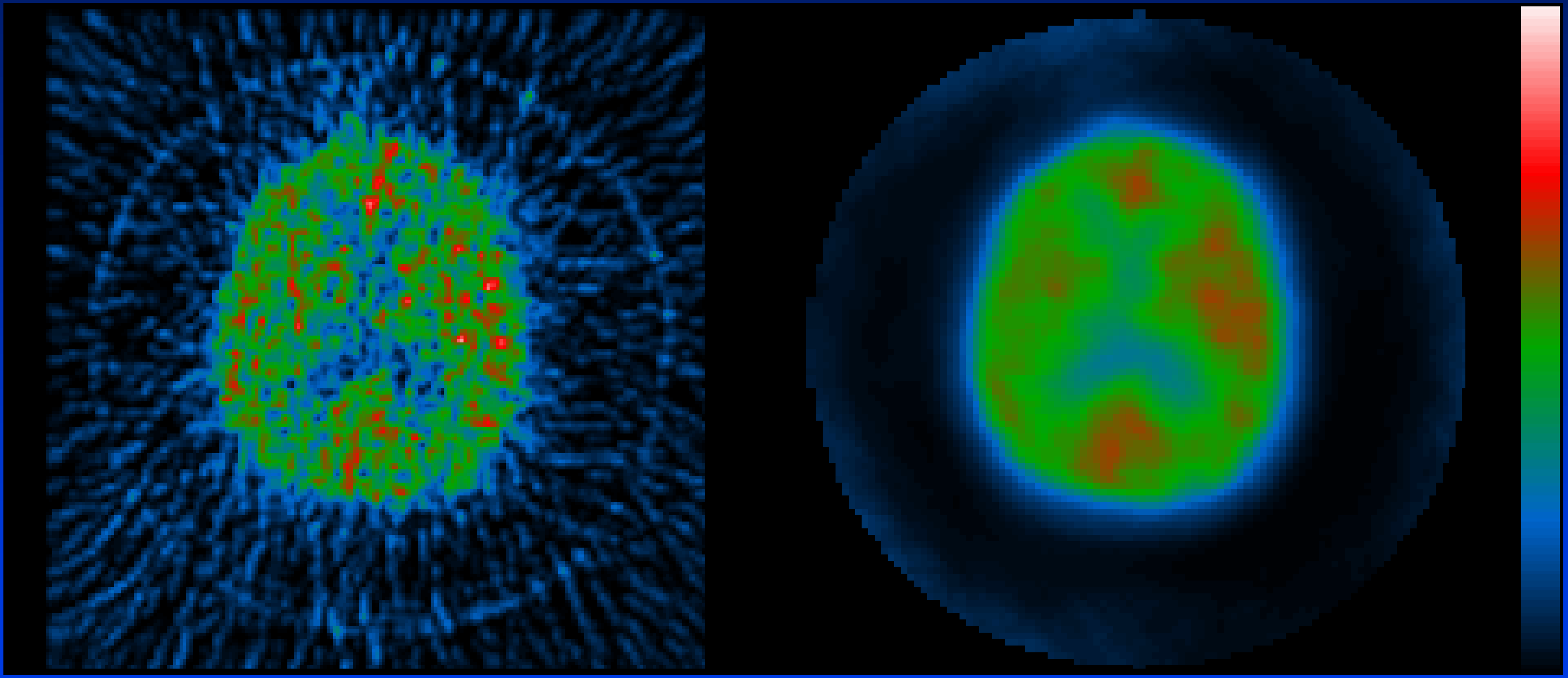
Data Sources

- Computer tomography (CT):
  - X-ray
  - Structural information, diagnostic
  - Axial, Spiral
  - Housfield units (HU, CTU), air = –1000 HU, water = 0 HU
- Magnetic resonance (MR):
  - Magnetic nuclear resonance
  - Density of hydrogen nucleuses
  - Structural information, diagnostic
  - Functional MR
  - MR spectroscopy
- Ultrasound (US):
  - Reflection of ultrasound waves on tissue boundaries
  - 2D, 3D, 4D - structural information, diagnostic
  - Dopler – functional information, blood flow
- Positron emission tomography (PET):
  - Positron emitter is put inside of body
  - Space positron emission is scanned, in plane slices
  - Functional information
- Nuclear medicine (NM):
  - Gamma emitter in put inside of body
  - Plane gamma emision is scaned by gamma camera
  - Functional information

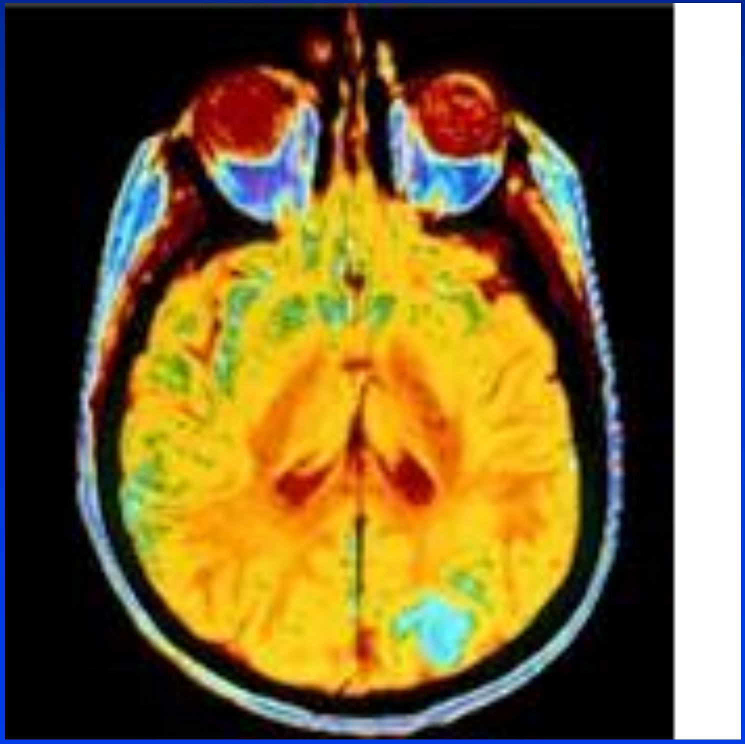
Data Sources

- These medical diagnostic methods produce images
- The methods are not invasive
- We can look inside without cuts
- Some of the methods make patients radiation stress (CT, NM, PET)
- The methods are based on several physical principles (medical physics)
- The images describe geometry, structure, and physical behaviors of tissues (density, chemical composition, …)

Medical image examples – PET

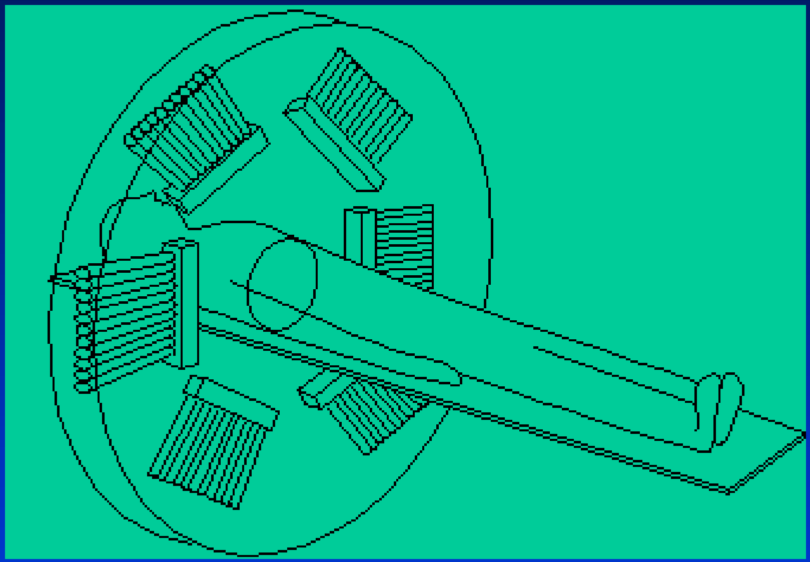


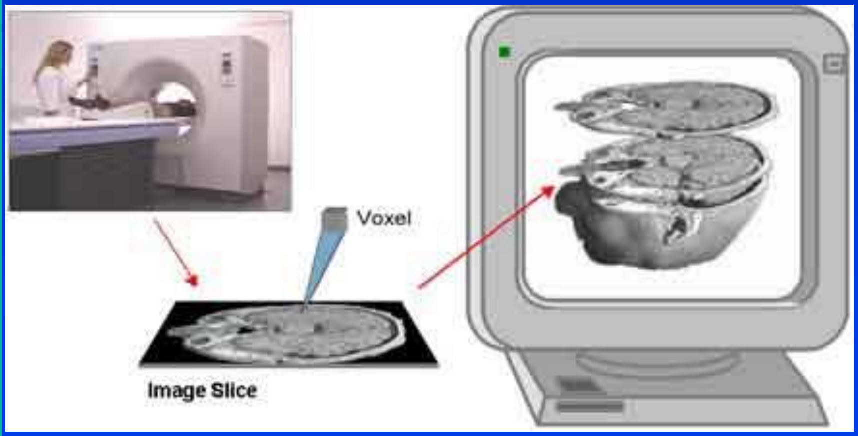
Medical Image Examples – NM



STONY BROOK
STATE UNIVERSITY OF NEW YORK

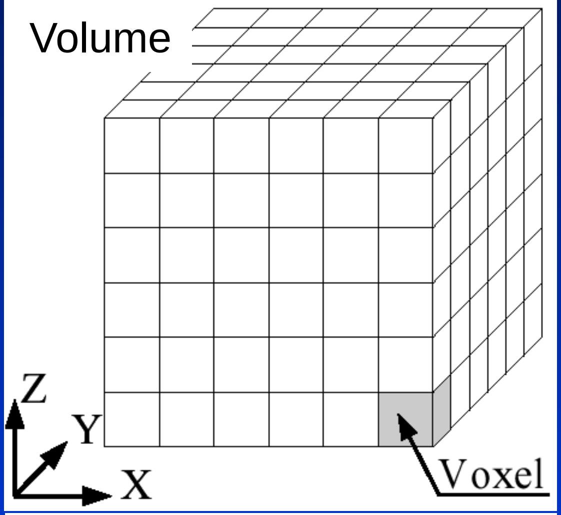
Data Properties

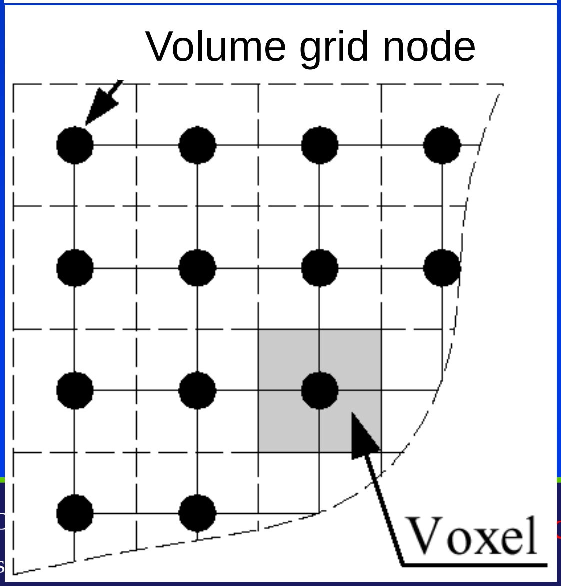




- Focused on CT/MR data
- CT/MR data have defined geometry (cubed homog. grid) and good resolution (~0.5 mm)
- One CT/MR exploration consists of several planar sections (slices)
- Each slice is defined by 2D orthogonal matrix
- Therefore, the exploration is defined by 3D orthogonal grid
- The grid is described by discrete distribution of physical scalar values (HU) in volume.

Data Properties



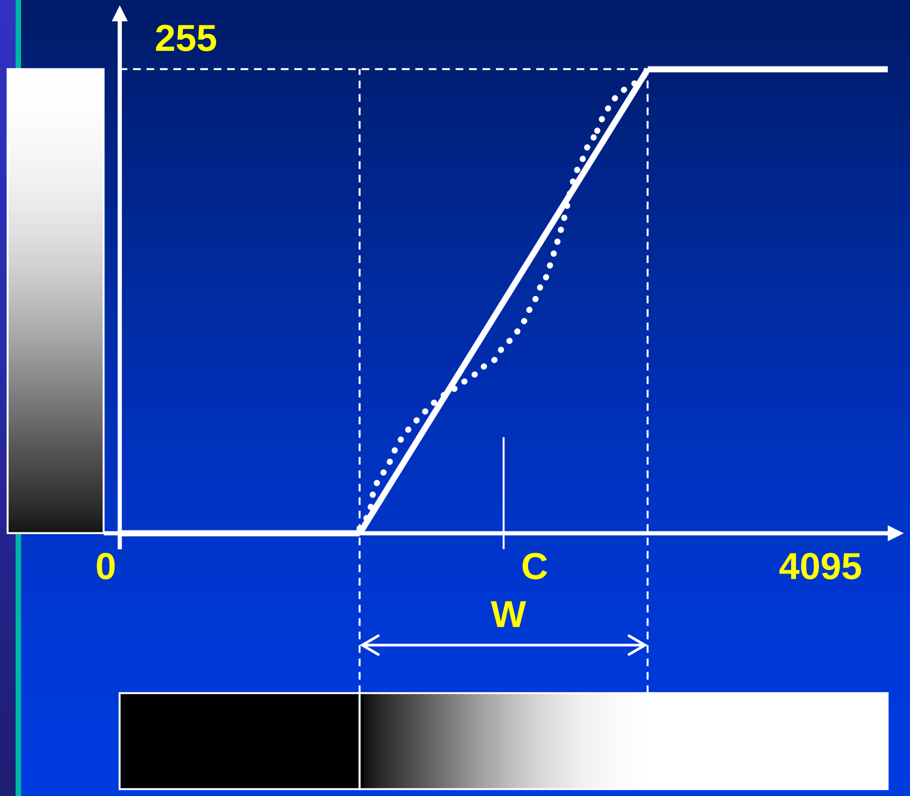


- In graphics/visualization we can call the data grid also: “volume (voxel) data”
- An image is cross section through volume, with color mapping
- We can use three basic image planes (xy, xz, yz)
- Scalar values are stored in 12 bits information, but are saved in 16 bits
- Typical exploration have ~ 100 - 200 slices, typical matrix size is 512^2, data has ~ 52 - 104 MB.

Medical Image Processing/Analysis and Geometric Models

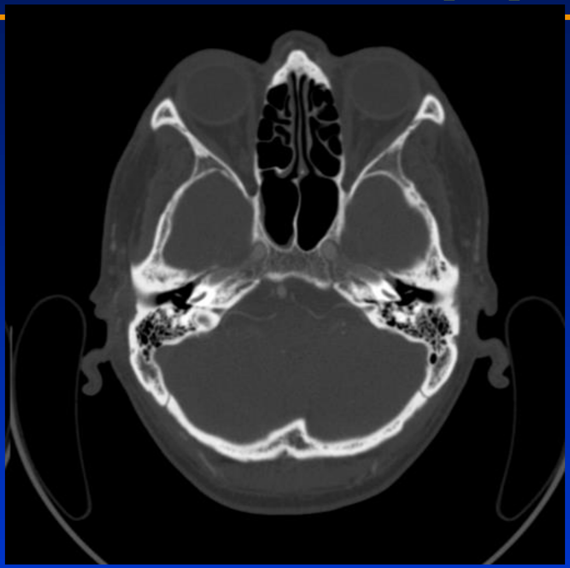
- Data acquisition
- Image generation
- Image processing/analysis
- Tissue geometric models

Color Mapping



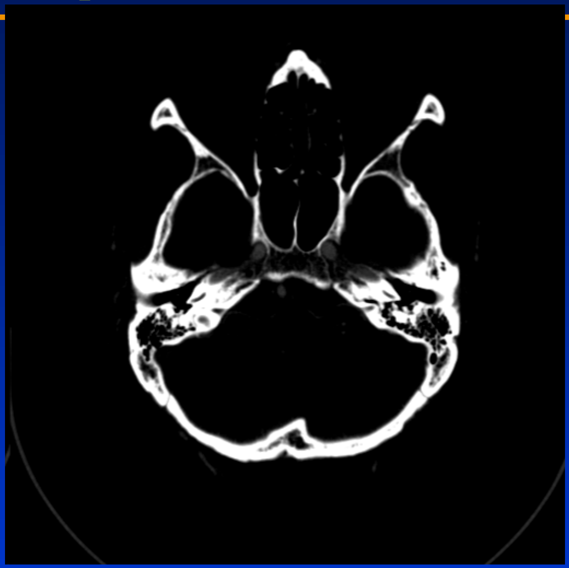
- Volume data describe discrete distribution of physical scalar values
- We need to display grayscale image (medical standard)
- Therefore, we have to make color mapping of physical values
- 12 bits value have 4096 levels
- 8 bits grayscale color have 256 levels
- Density window:
  - Defined by values of window center and width
  - Linear interpolation (or equalization) of window values, from black to white

Color Mapping, Examples



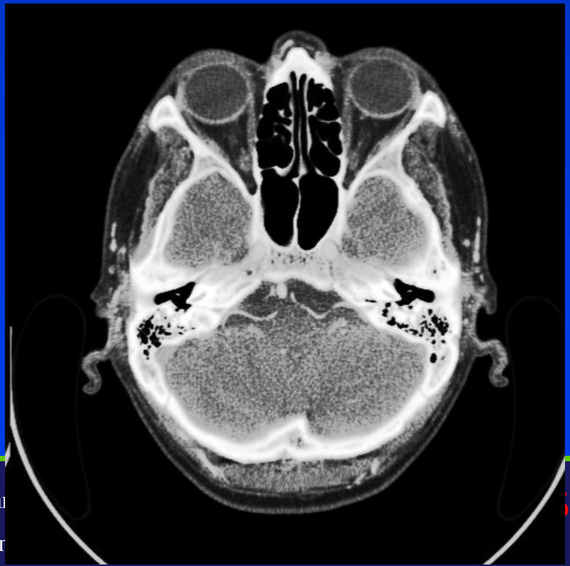
C – 500

W - 2000



C – 500

W - 1000



C – 500

W – 2000

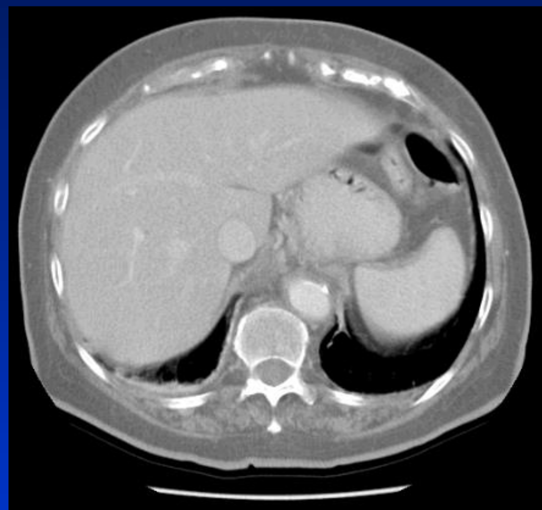
equalization

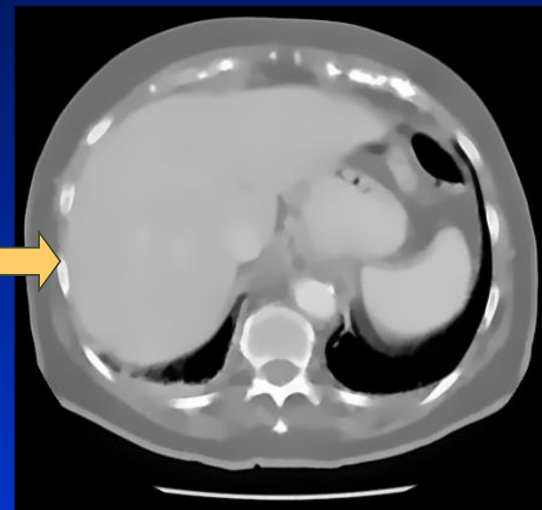
C – 100

W – 300

Image-based Computing Pipeline

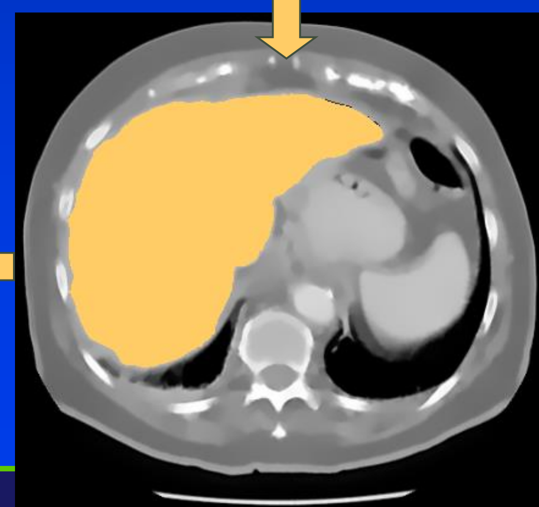
Image Acquisition

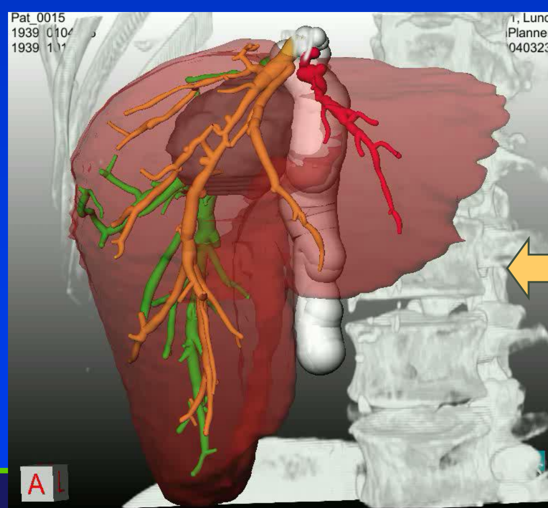




De-noising/ Enhancement

Segmentation





- PDE model/ Simulation
  - Electric potential
  - Heat distribution

Medical Image Analysis: Overview

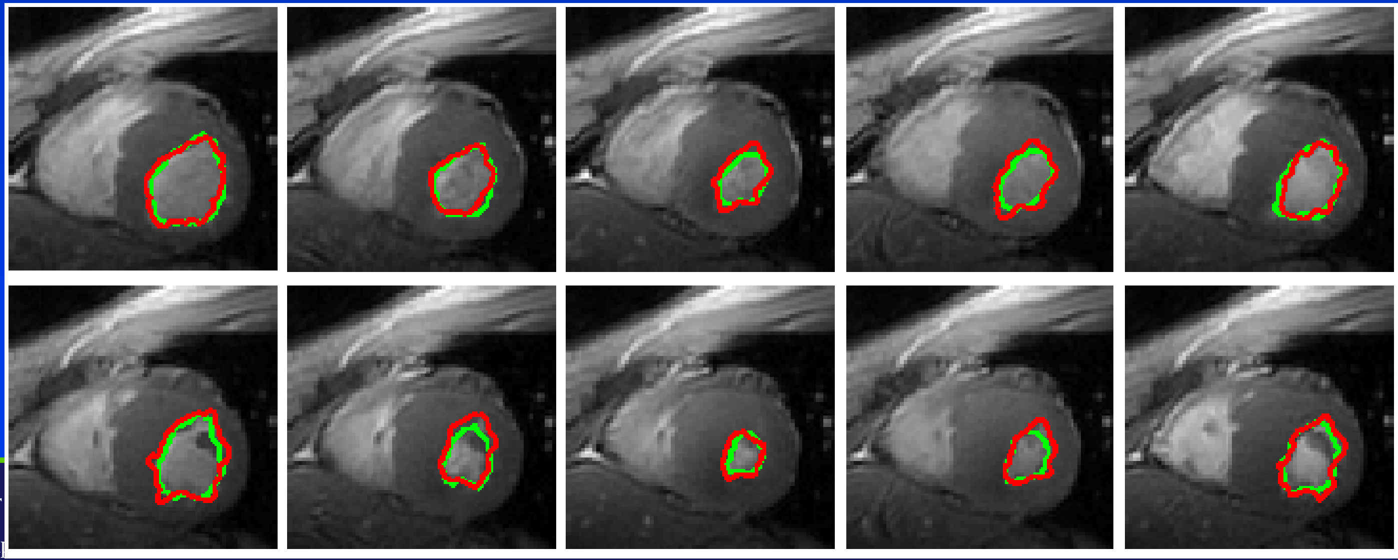
- The practice of modern medicine incorporates an enormous amount of image data
- Traditional computational vision relies on cameras and, more recently, range finders
- Medicine uses, to name a few:
  - Computed Tomography (CT)
  - Magnetic Resonance Imaging (MRI)
  - X-ray fluoroscopy
  - Ultrasound

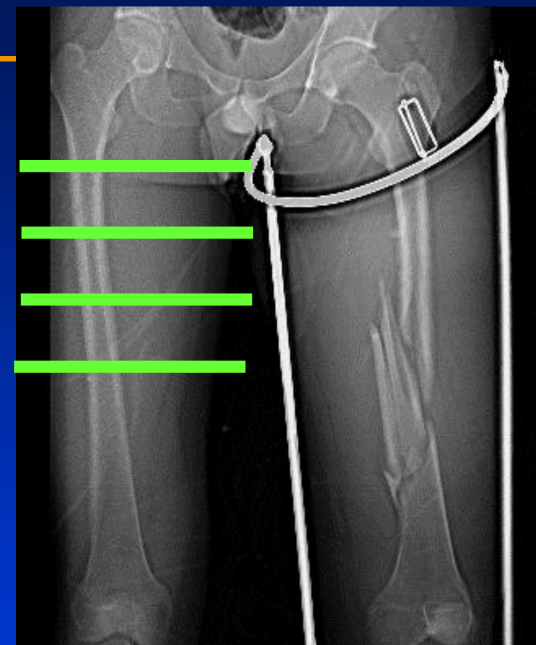
Segmentation

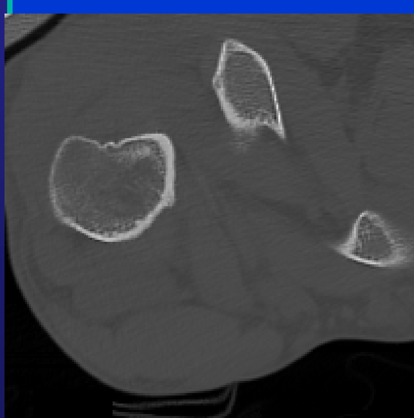
- Thresholding (normal and adaptive)
- Level sets (2D and 3D)
- Shape models
- Level sets + shape models
- And beyond…

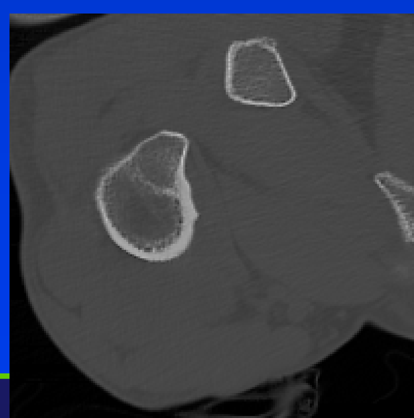
Segmentation

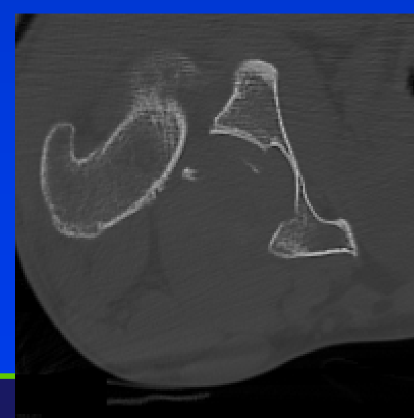
- In medicine, 3D segmentation often proceeds as a boundary propagation problem along the 2D slices of the data
- Starting point for contour in new slice comes from the final contour in the previous slice

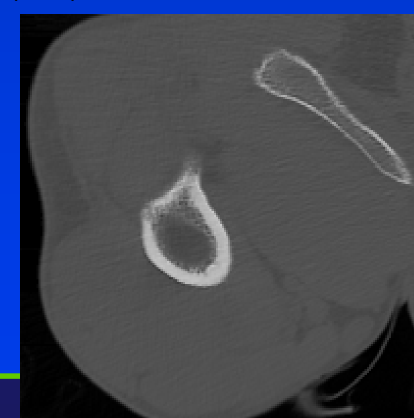








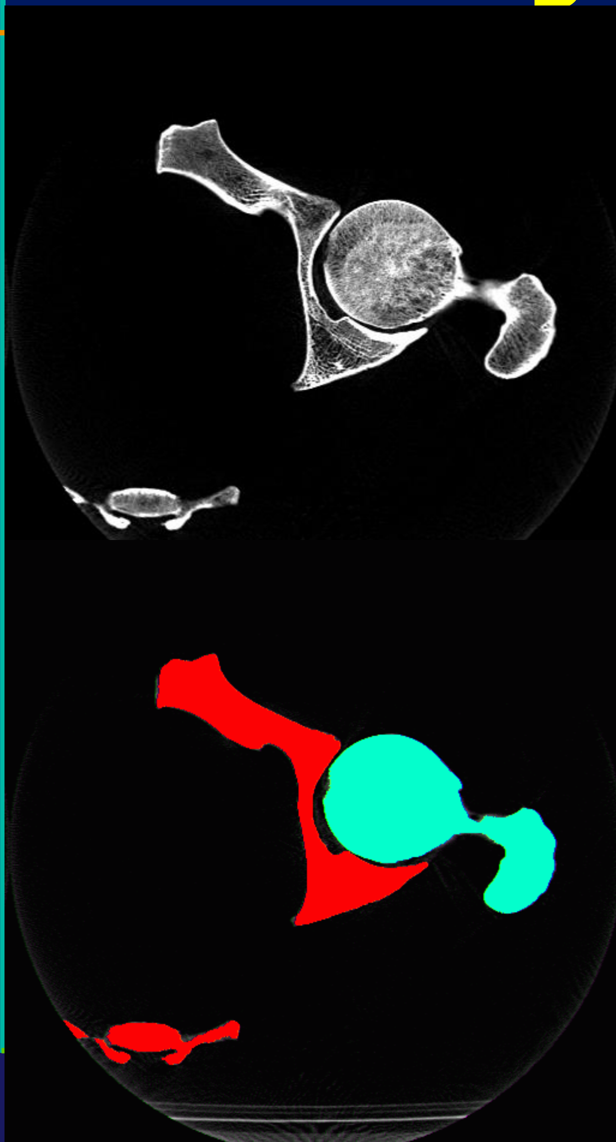




3D Segmentation

- Can think of this problem as one of tracking a moving interface in time
- What happens as the interface splits and rejoins?

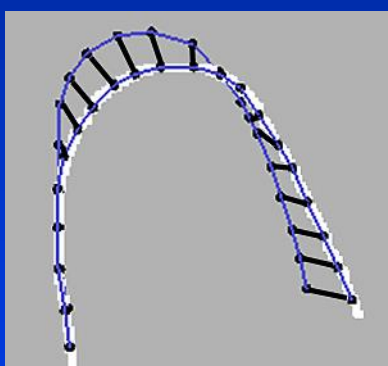
Tissue Segmentation

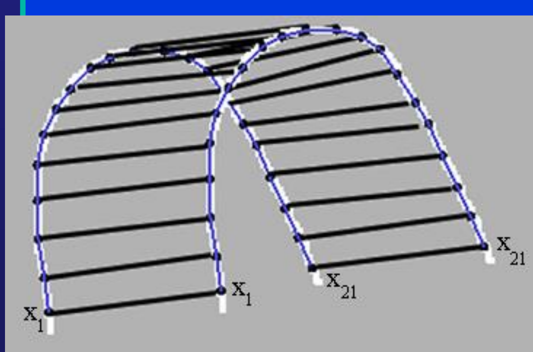


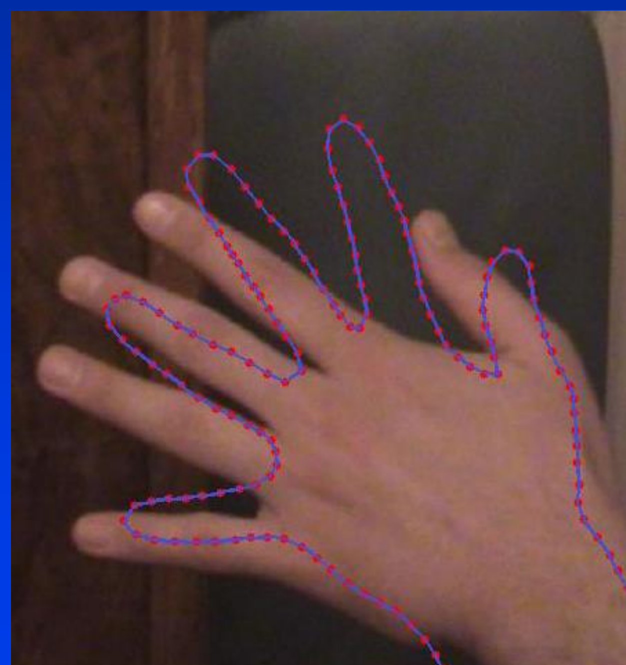
- Volume data describe discrete distribution of physical scalar values
- We need tissues distribution
- Segmentation process:
  - It is not trivial, thresholding is not enough, values overlapping.
  - It is not yet fully automatic
  - It is still an open problem
- Practice:
  - Semi-automatic preprocessing:
    - Active contouring, PCA, ICA, Watershed, Implicit surfaces …
    - Combination of methods by probability
  - Manual corrections are needed
  - Multiplanar, 2.5D (three planes)
  - Raster based x vector based segmentation
- Produce tissue voxel models

Non-rigid Shape Modeling

- Solve for correct correspondences between two or more shapes
- Difficult due to the shape variations (pose, deformation noise,…)

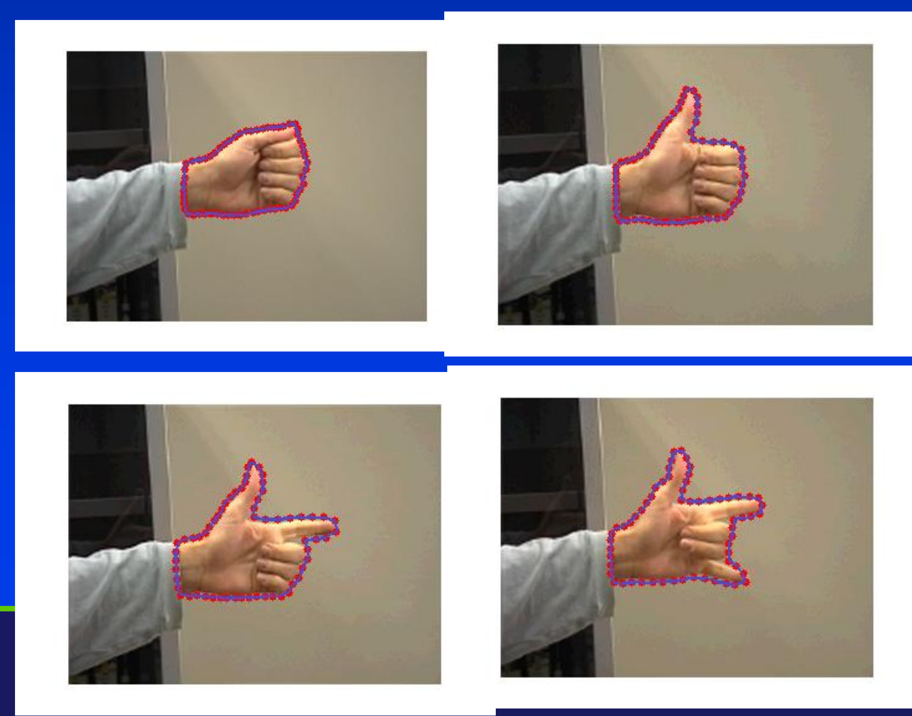






Tracking

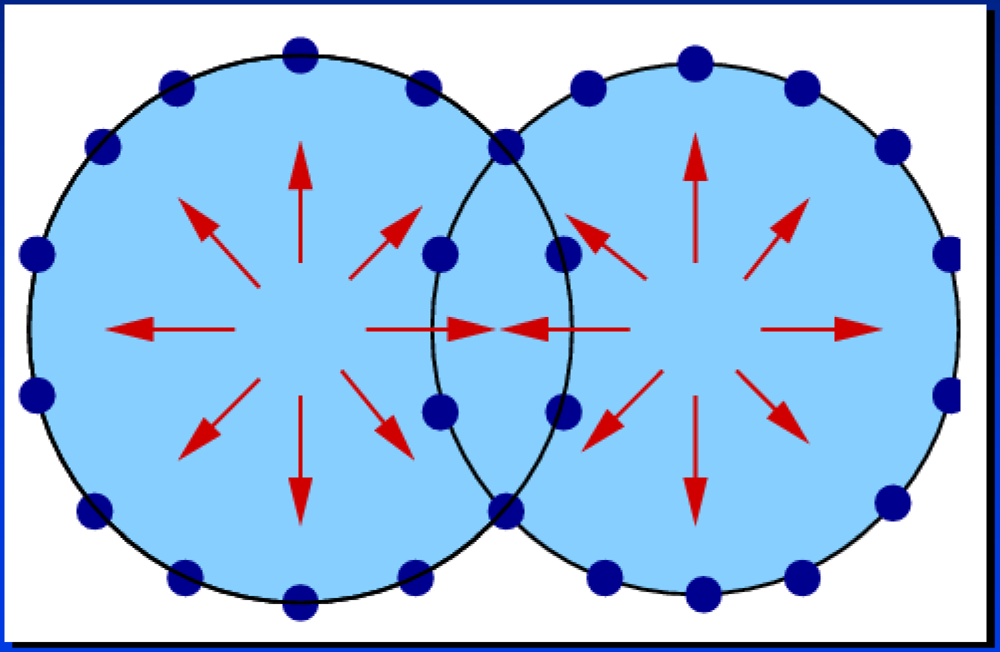
- Tracking objects in motion, 3D morphing in virtual reality,
- Nonlinear registration,…



Level Sets

- Snakes have difficulty dealing with changing topology
- Requires messy bookkeeping of control points

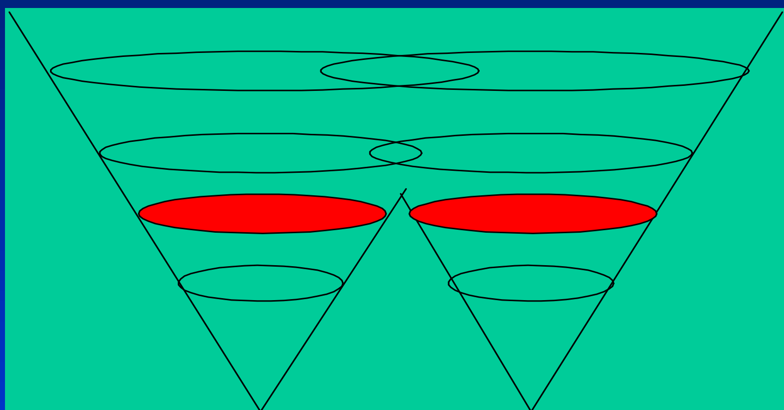
Level Sets

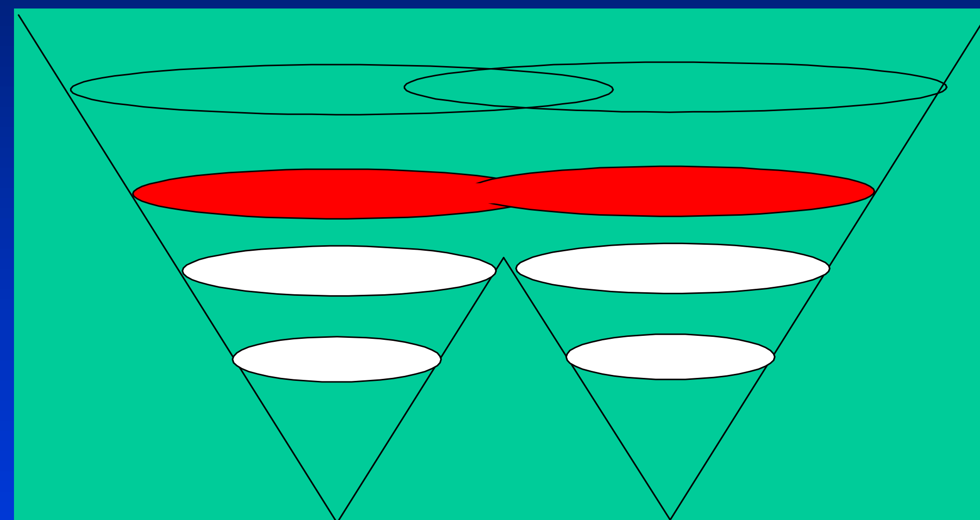


Level Sets

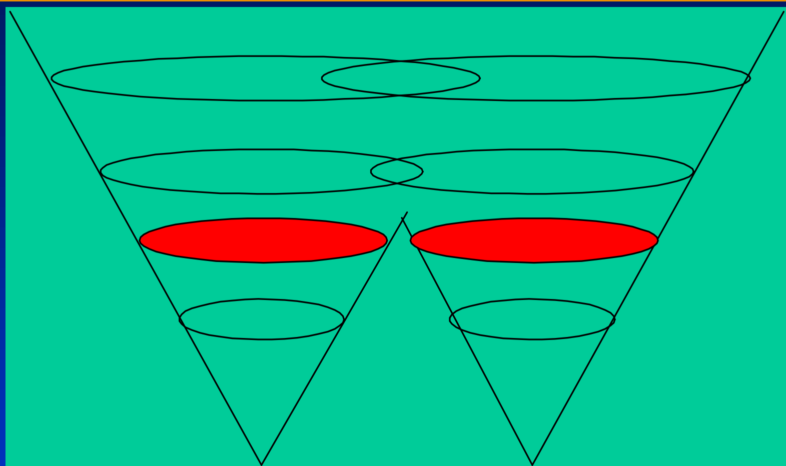
- Level sets deal with this in a very clever way.
- We add a dimension to the problem and propagate the "level set surface" instead of the curve
- The boundary becomes the "zero level set"

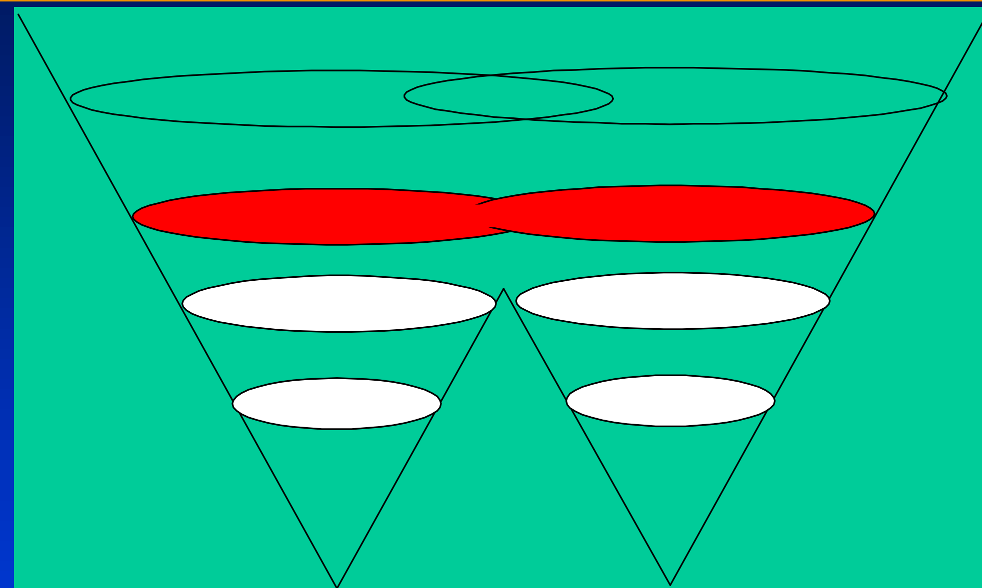
Level Sets

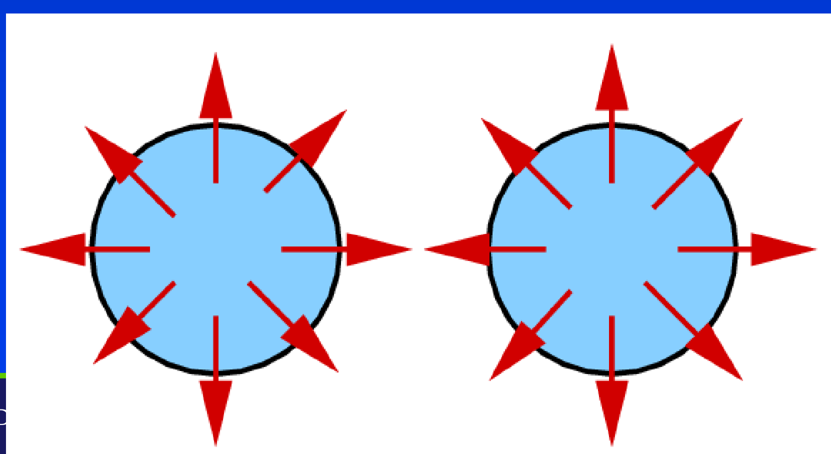


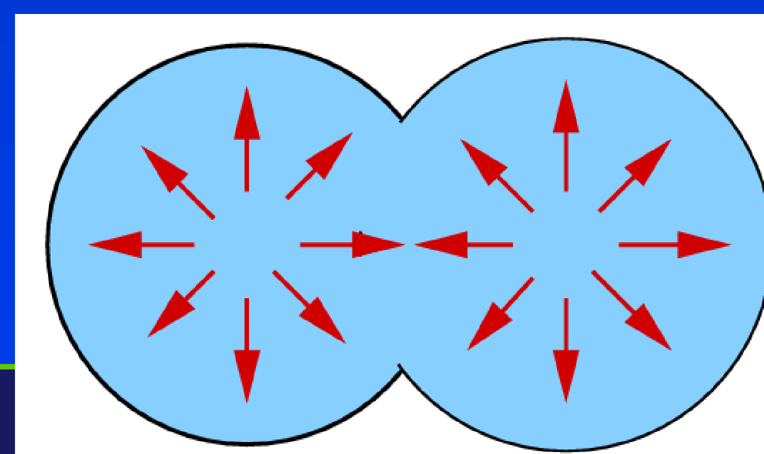


Level Sets

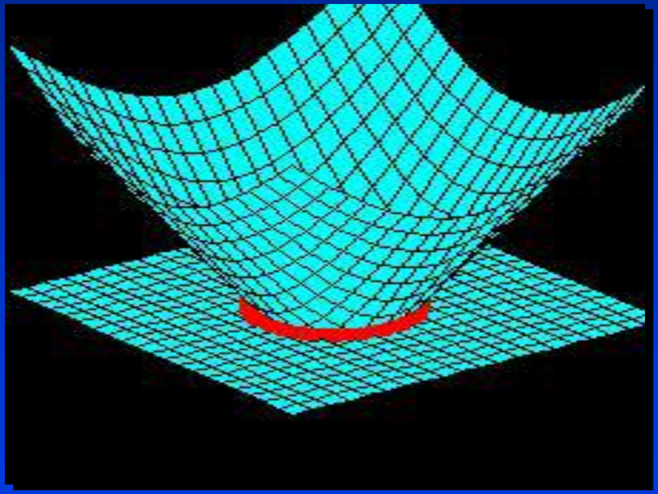








Level Sets



Level Sets

- Now the question remains, how do we propagate the level set function?

$$\phi(C) = 0$$

$$\frac{d\phi(C)}{dt} = \frac{\partial C}{\partial t} \cdot \nabla \phi + \frac{\partial \phi}{\partial t} = 0$$

$$\therefore \frac{\partial \phi}{\partial t} = -F\left|\nabla \phi\right|$$

- F is a term representing the speed of motion

Level Sets Formulation

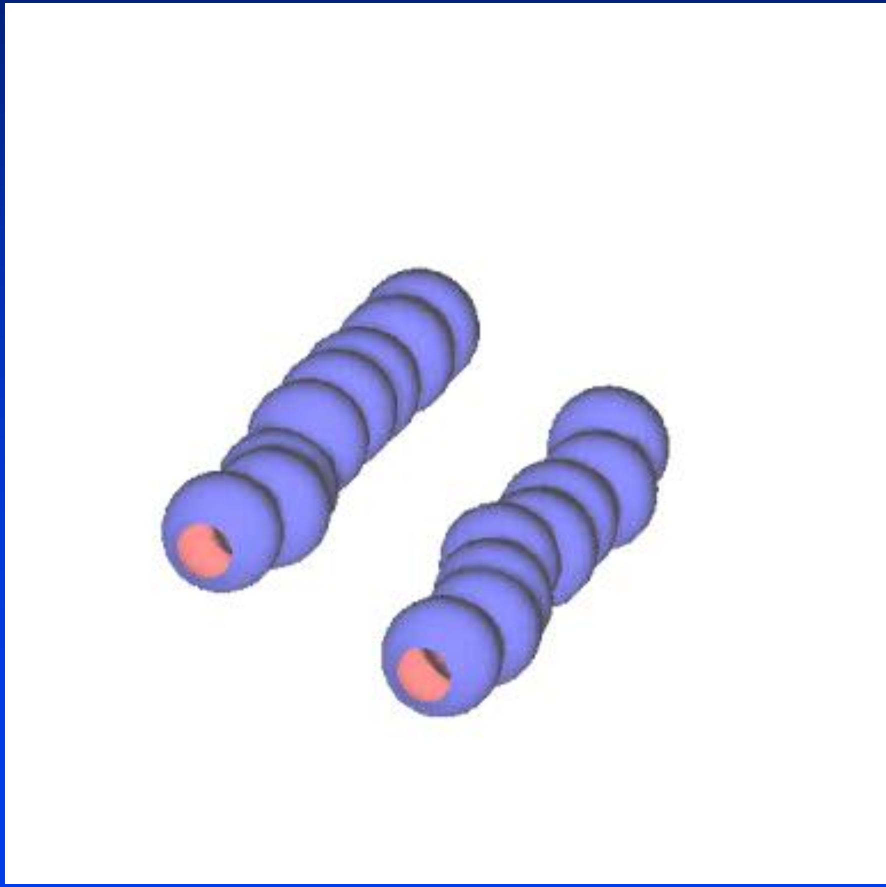
$$F = 1 - \varepsilon\kappa + \beta\left(\nabla\phi \cdot \nabla\left|\nabla I\right|\right)$$

- Typical level set speed function ***F***

- The *1* causes the contour to expand in the object
- The -$\varepsilon\kappa$ (viscosity) term reduces the curvature of the contour
- The final term (edge attraction) pulls the contour to the edges
- Other terms possible depending on your application
- Level sets trivially extend to 3D segmentation

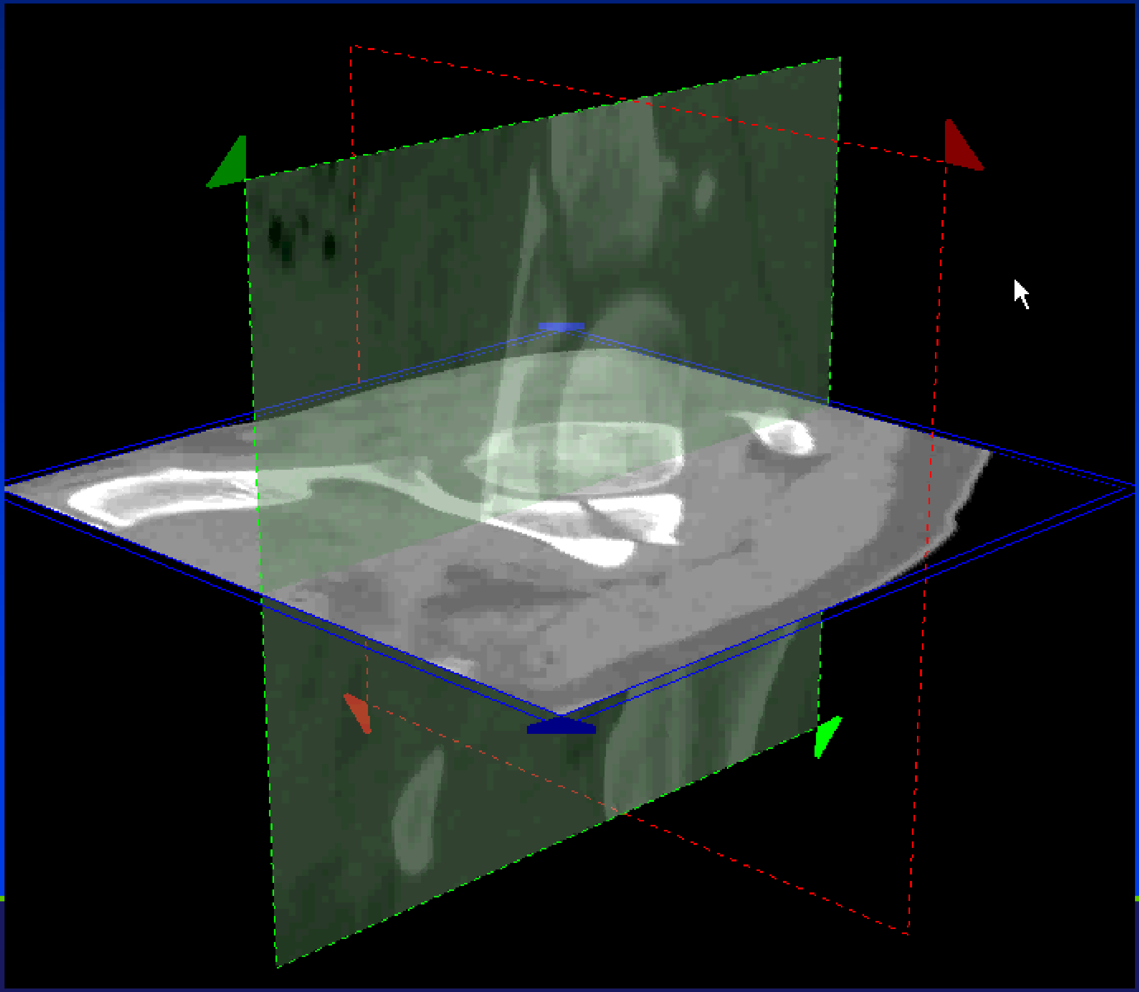
Level Sets

- Results: femur segmentation



Other Technologies

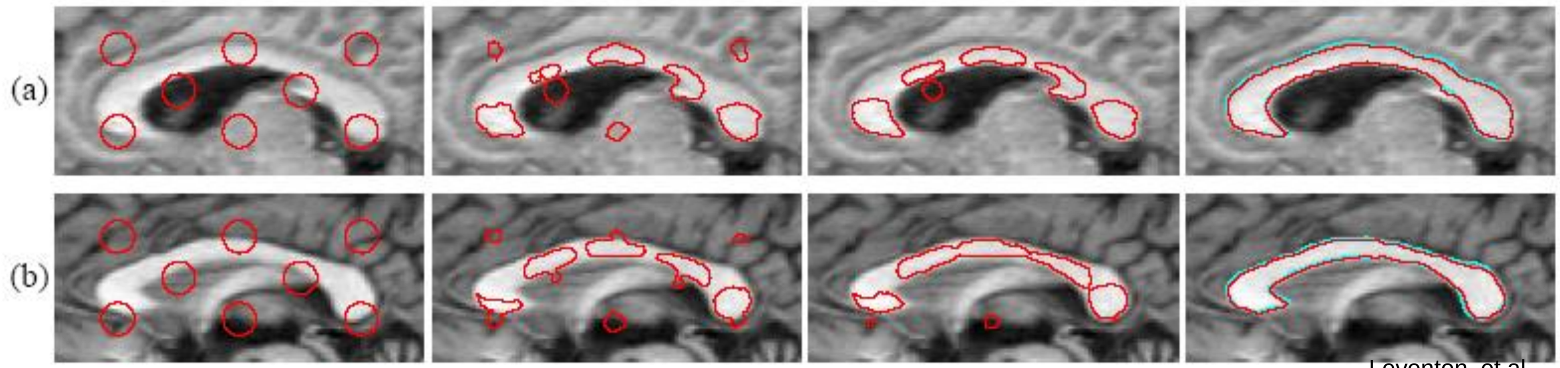
- ICCV 2003: Geodesic contours + Min Cuts



Boykov, et al.

Shape Models and Level Sets

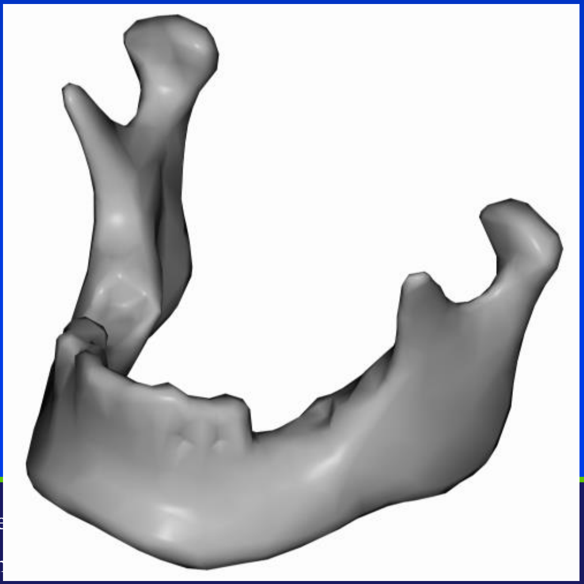
- Can incorporate priors based on shape models into the F term in the level set equation.
- Leads to robust segmentations of challenging objects without much initialization

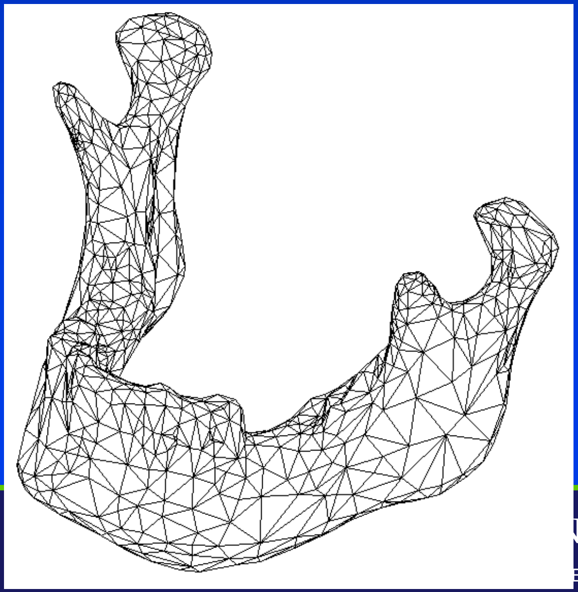


Leventon, et al.

Tissue Geometry Modeling

- Practically oriented
- Focused on human tissue geometry models creation, based on CT/MR volume data
- On input are segmented CT/MR data – tissue voxel models
- Some basic problems in the models creation process



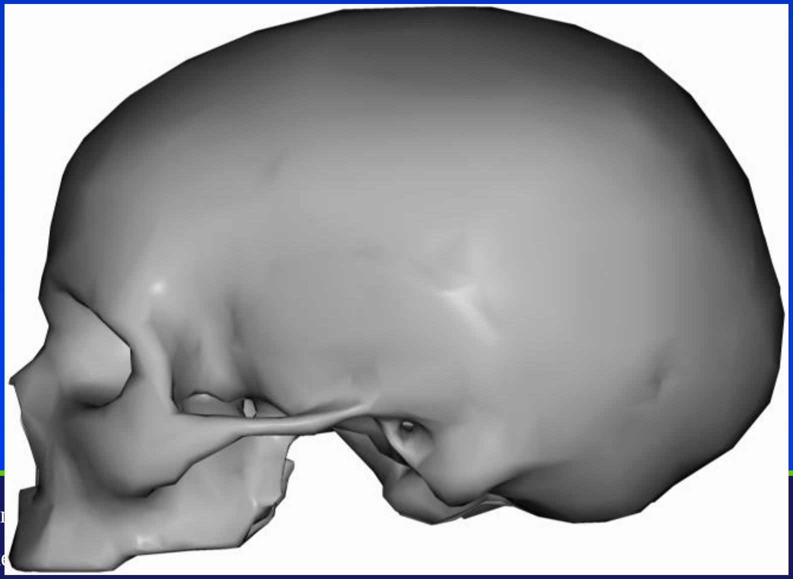


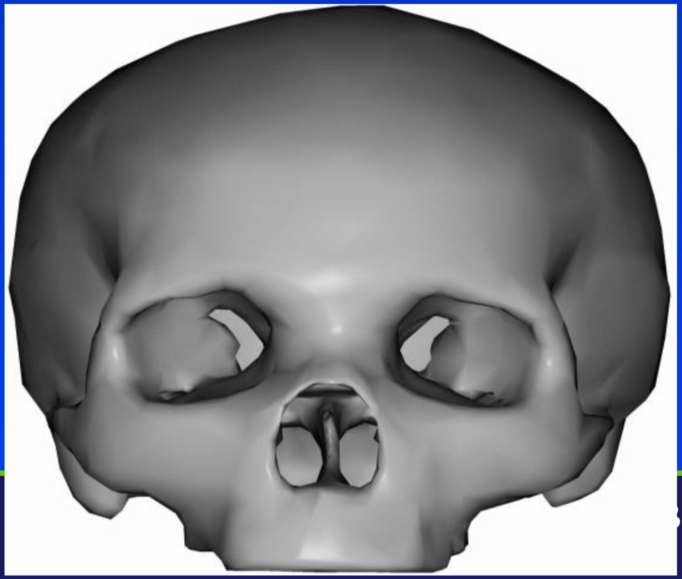
The Problems

- Each medical subject is individual, nothing is exactly the same
- Tissues has complex geometry and small details

- We need to create special geometry model for each tissue
- Manual tissues geometry models creating process is not possible

Therefore, used methods have to be geometry and topology independent and fully automatic

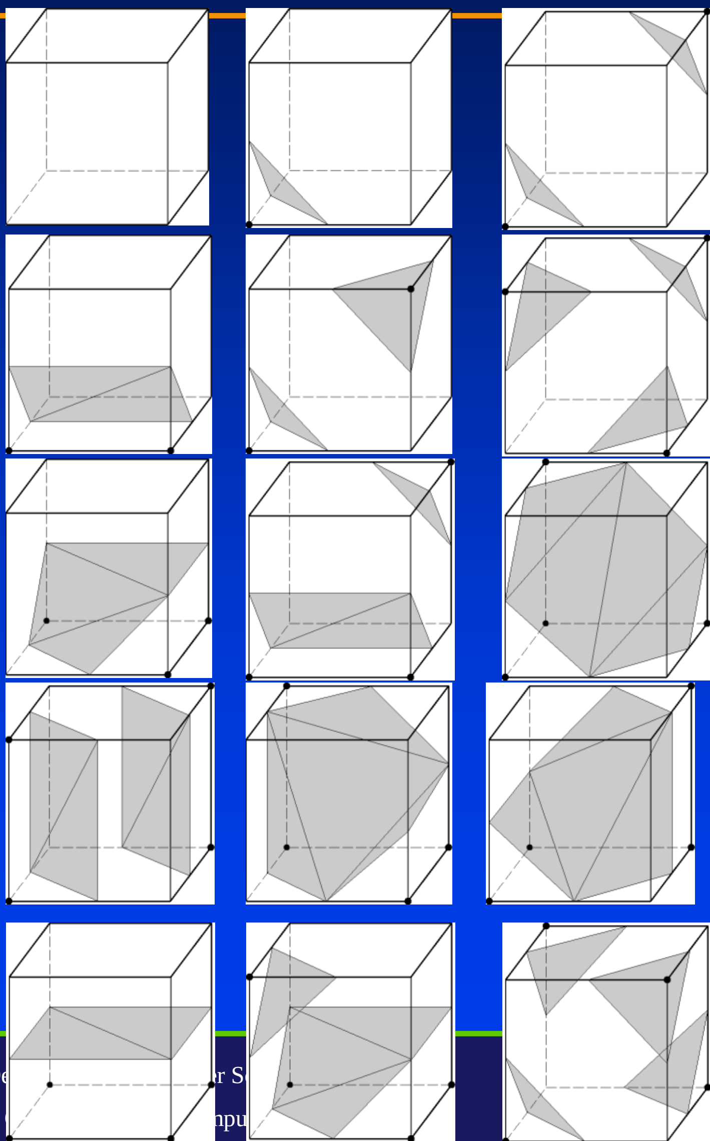




Tissue Models Creation Process

- Input data are volume discrete data, voxel models
- Output data have to be vector based models
- Therefore, creating process consist of several steps:
  - Vectorization, transformation from discrete to vector data representation
  - Vector model modification
    - Vector model smoothing
    - Vector model elements number reduction (decimation)
    - Quality optimization
  - Export for particular application
    - Data format (VRML, STL, DXF, IGES, ….)
    - NURBS surface
    - Finite element method (FEM) model

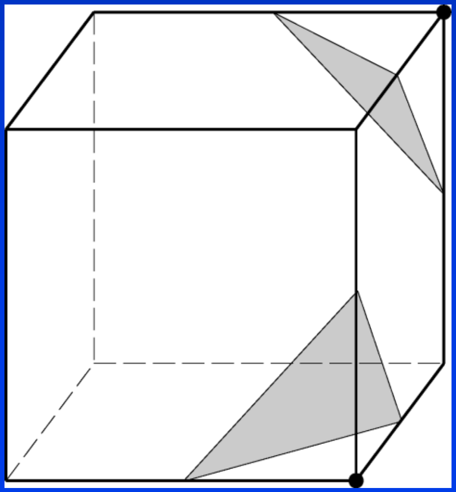
Vectorization – Marching Cubes

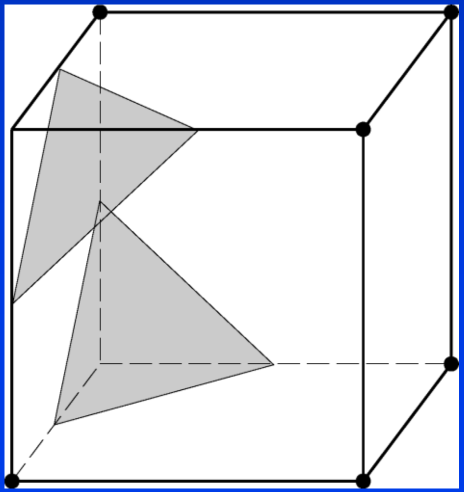


- Famous, classical vectorization algorithm, Lorensen, Cline, 1987
- Take 8 neighbor voxels in cube position and evaluate state
- March through all volume
- Fully automatic
- Geometry independent
- Produce closed (almost) and oriented boundary triangular meshes
- High level of detail, in resolution of input discrete grid

Marching Cubes - Holes

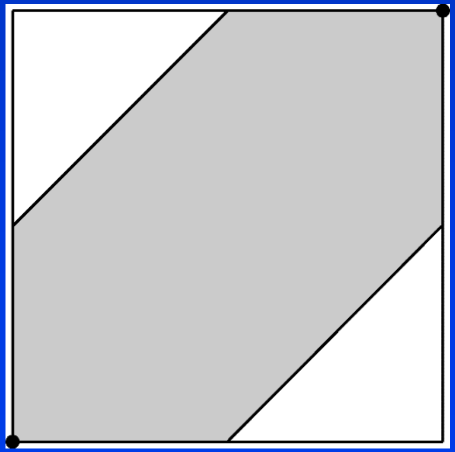
- In case of neighbor state complement it sometimes produce squared hole
- It is necessary to detect and correct the errors (patch holes) during vectorization process

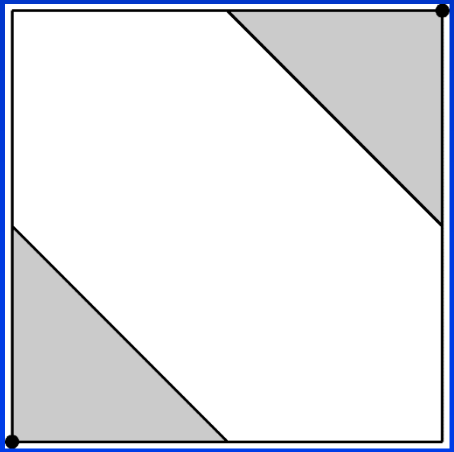




Marching Cubes - Ambiguities

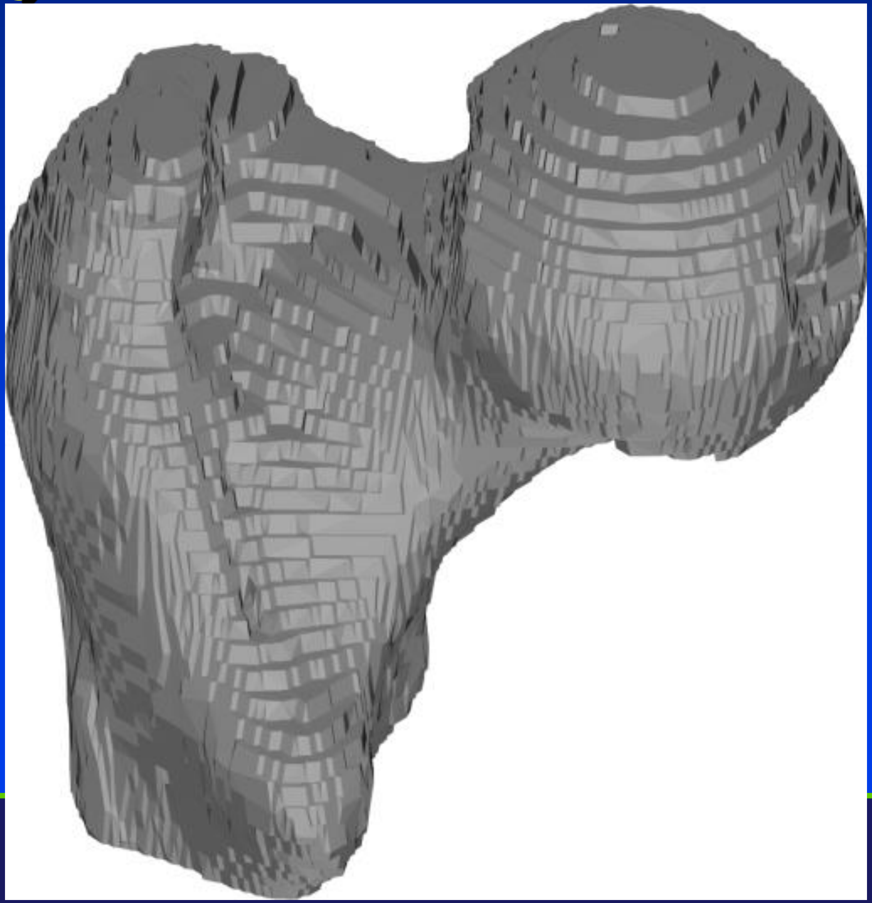
- In case diagonal position of full voxel it is possible evaluate it in two ways
- It is necessary make choice of only one interpretation (based on vertex unique identification) and use it strictly





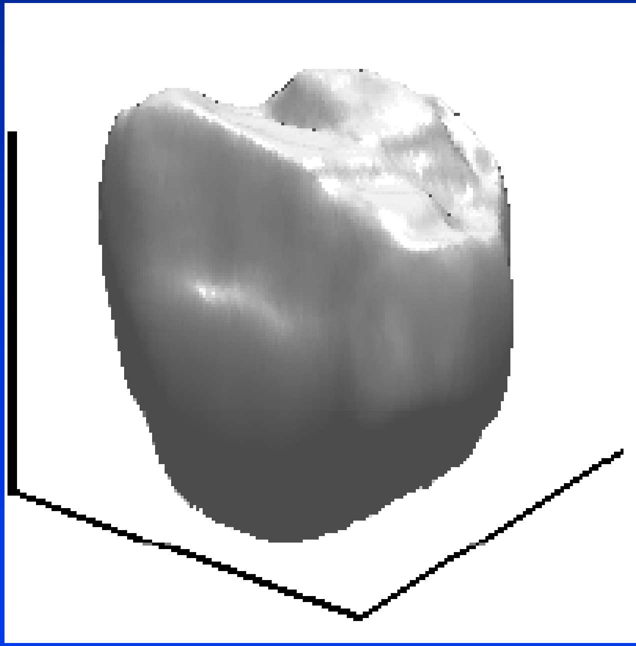
Marching Cubes - Surface

- Resulted meshes has a lot of small elements and edgy and layered character

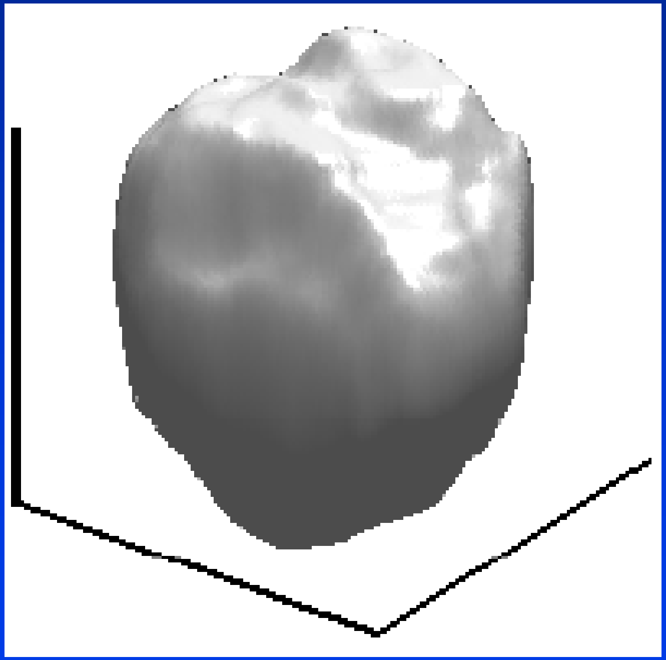


Shape Models

- New shape can be seen as a linear combination of the basis shapes



Patient A

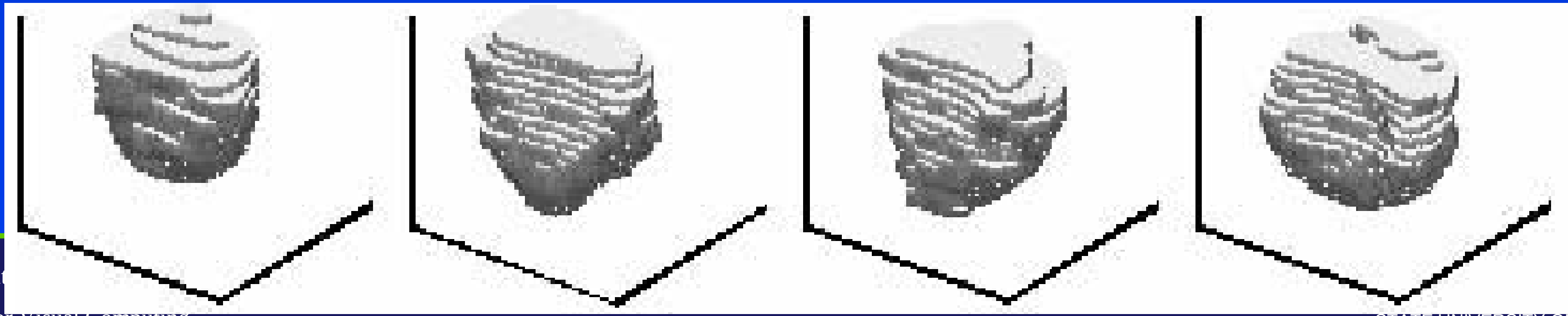


Patient B

Tsai, et al.

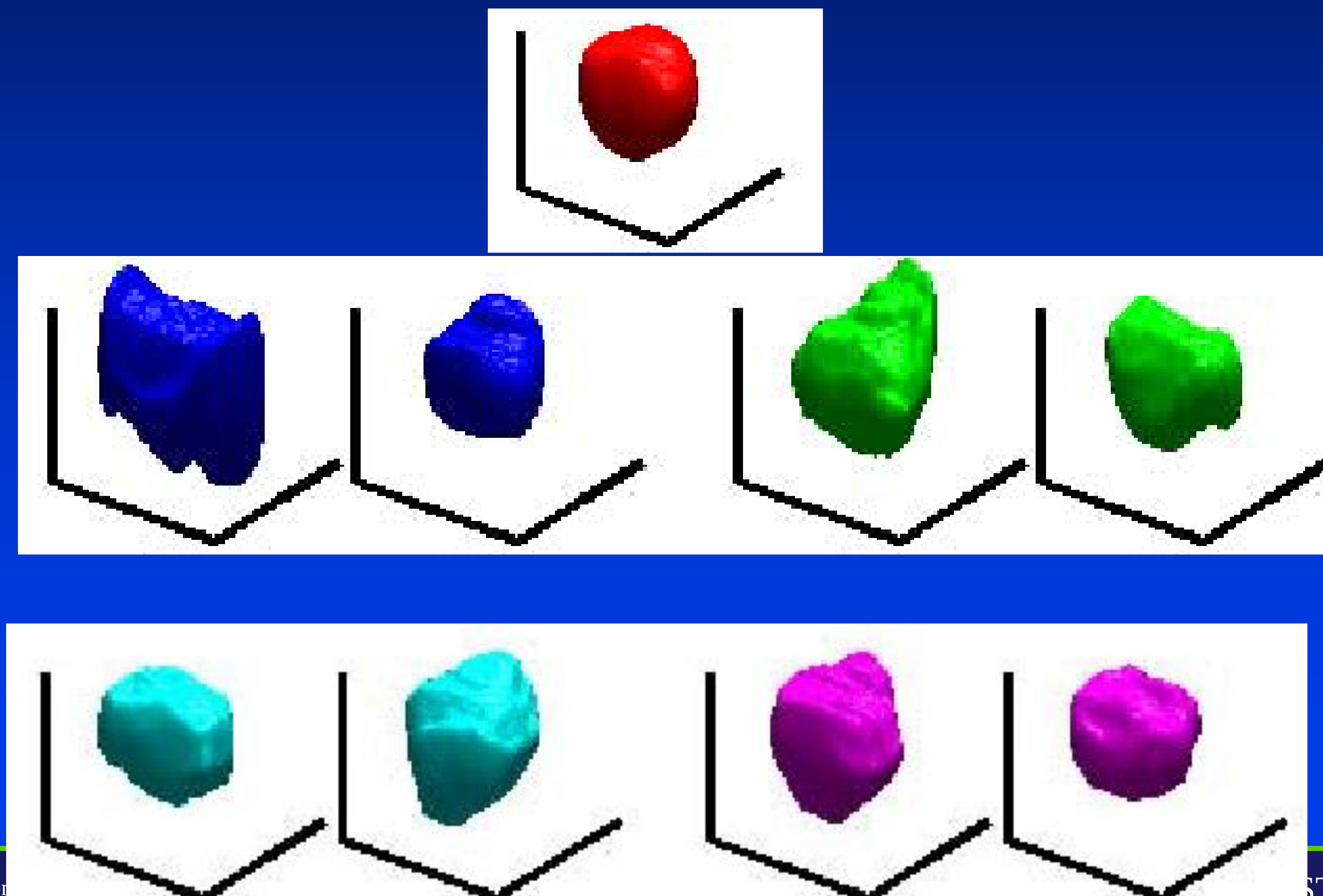
Shape Models as Priors

- Learn modes of variation of a structure
- Use PCA to generate orthonormal basis of variation
- Example: prostate segmentation
- Start with a training set of segmented prostates



Statistical Analysis on Shape Models

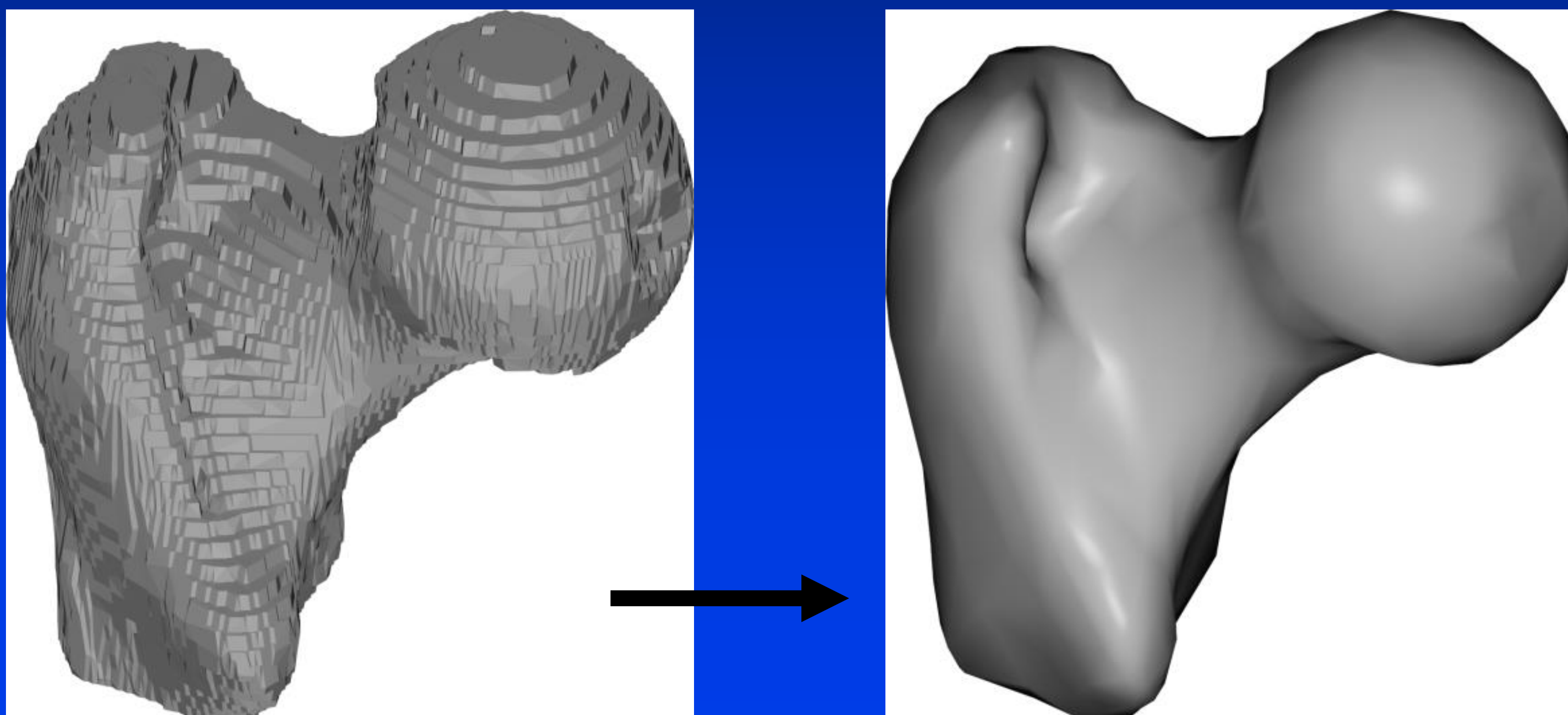
- Mean shape and □□ of 1st 4 principal modes of variation



Tsai, et al.

Smoothing

- Edgy and layered surfaces produced by MC is needed to be smooth



Smoothing – Laplacian Operator

$$V^* = V + \delta \cdot \frac{1}{n} \cdot \sum_{i=1}^{n} (V_i - V)$$

V^* – new vertex position

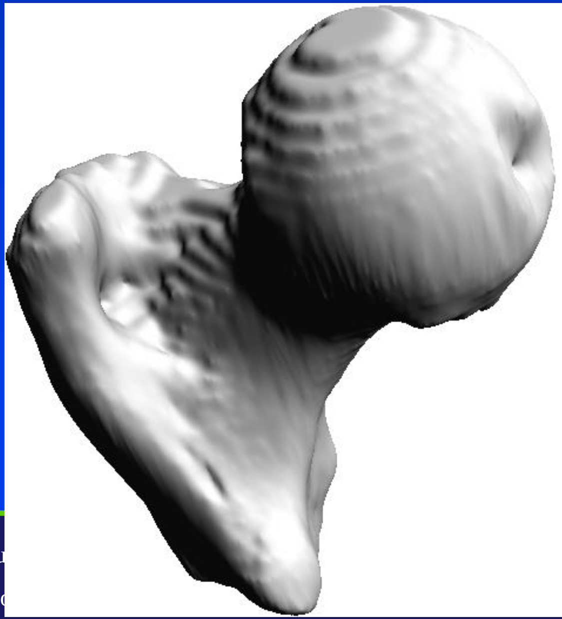
V – original vertex position

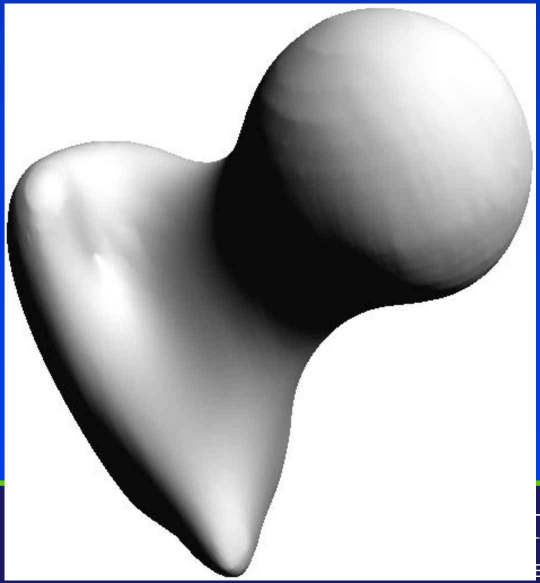
V_i – adjacent vertex

n – nuber of adjacent vertexes

δ – smoothing factor

- Laplacian filtering – averaging vertex position
- A very simply method
- Volume shrinking problem
- Geometry distortion
- Is hard to find accurate level





Smoothing – Taubin

$$V^* = V + \left|\frac{\lambda}{\mu}\right| \cdot \delta \cdot \frac{1}{n} \cdot \sum_{i=1}^{n} (V_i - V)$$

V^* – *new vertex position*

V – *original vertex position*

V_i – *adjacent vertex*

n – *nuber of adjacent vertexes*

λ, μ – *smoothing factors*

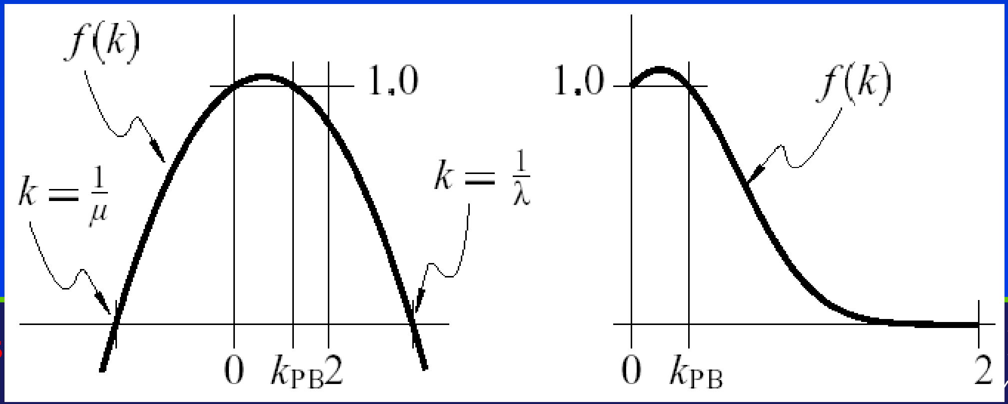
$$f(k) = (1 - \lambda \cdot k) \cdot (1 - \mu \cdot k)$$

$$f(k) = ((1 - \lambda \cdot k) \cdot (1 - \mu \cdot k))^{N/2}$$

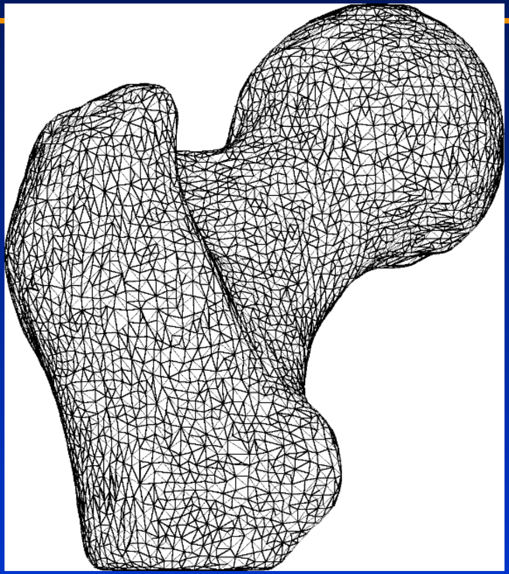
$$\mu < -\lambda < 0$$

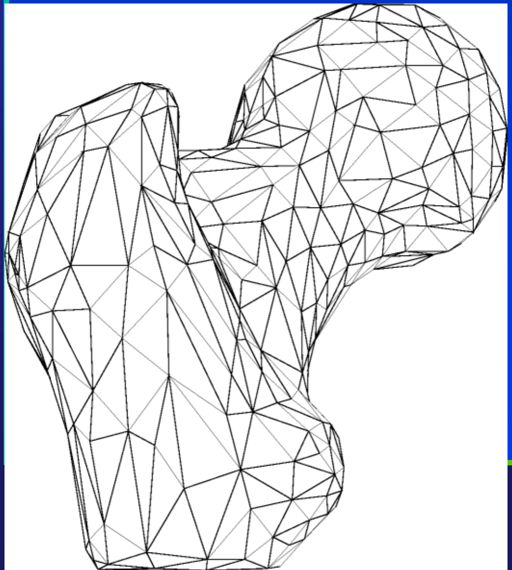
$$k_{PB} = \frac{1}{\lambda} + \frac{1}{\mu} > 0$$

- Taubin G., Geometry signal processing on polygonal meshes
- Low pass filtering
- Shrinking problem solution
- Laplacian filtering in two steps:
  - Shrinking with factor λ
  - Unshrinking with factor μ



Triangle Number Reduction



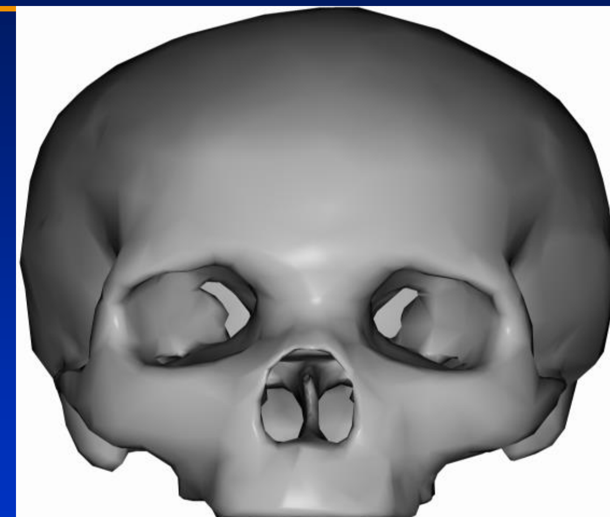


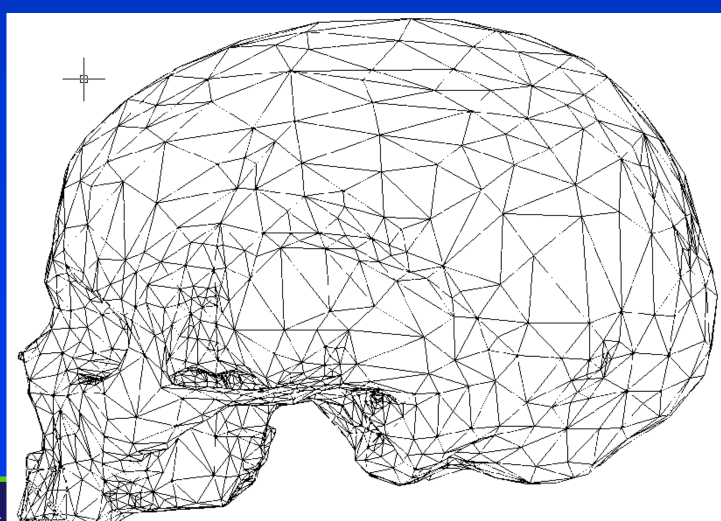
- Triangle number of meshes produced by MC need reduction
- Because of applications mesh quality have to by saved
- Need ~ 99% reduction
- Tested algorithm:
  - Schroeder W. Decimation of triangle meshes
  - Garland M. Surface simplification using quadric error metrics
- Our algorithm:
  - Polygonal models simplification with volume error metrics
  - Version of edge collapsing algorithm

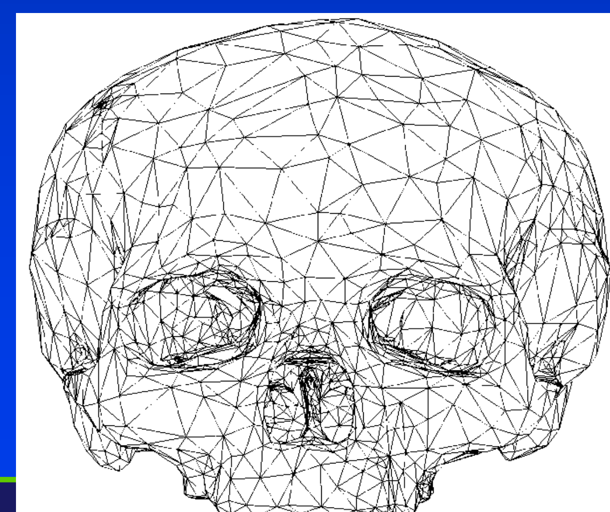
Applications

- Medicine:
  - Diagnostic tissue visualization (VRML, OpenGL)
  - Implants design (CAD), producing (CAM) and simulations (FEM)
  - Surgery planning and simulations (VRML, OpenGL, CAD, CAS)
  - Used formats: VRML, STL, DXF (triangular polygonal surfaces), IGES (NURBS polysurfaces)
- Biomechanics:
  - Computational modeling of tissues (bones, muscles) behaviour (stress and deformation)
  - Automatic creating of tissue FEM models from boundary triangular meshes:
  - Creating process:
    - 3D Delaunay triangulations based on boundary triangular meshes
    - Tetrahedral mesh quality optimization
    - Direct import into some FEM system (ANSYS)

FEM Models - Skull

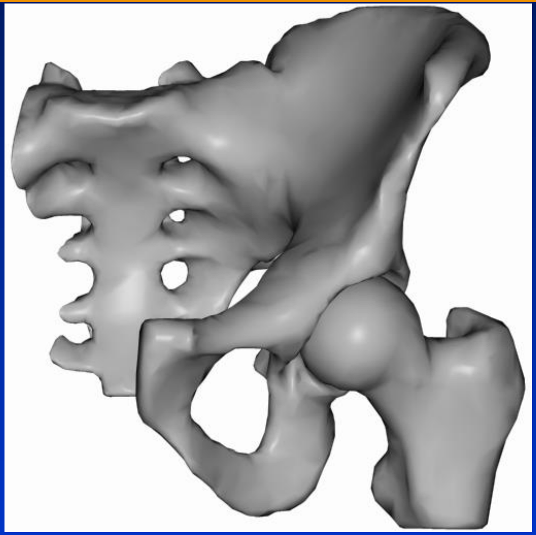


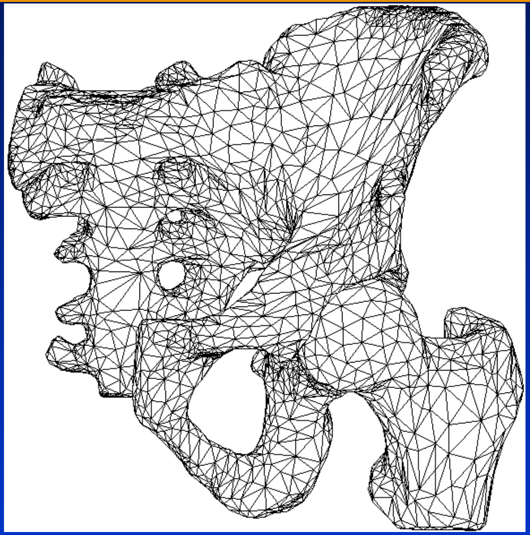


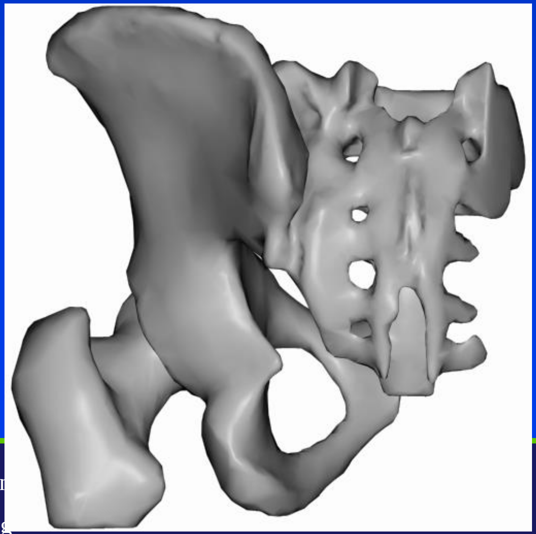


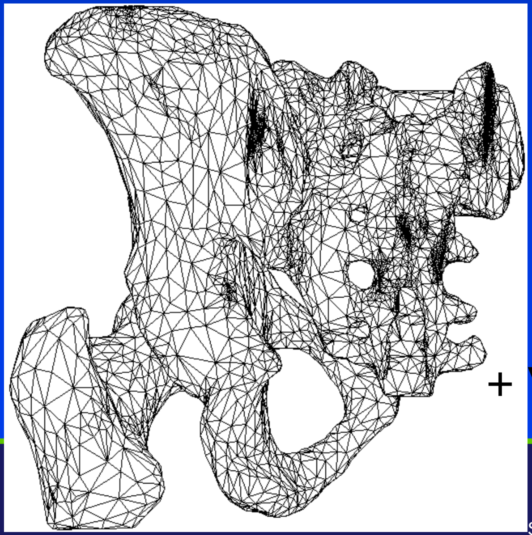
+ VRML models

FEM Models - Pelvis



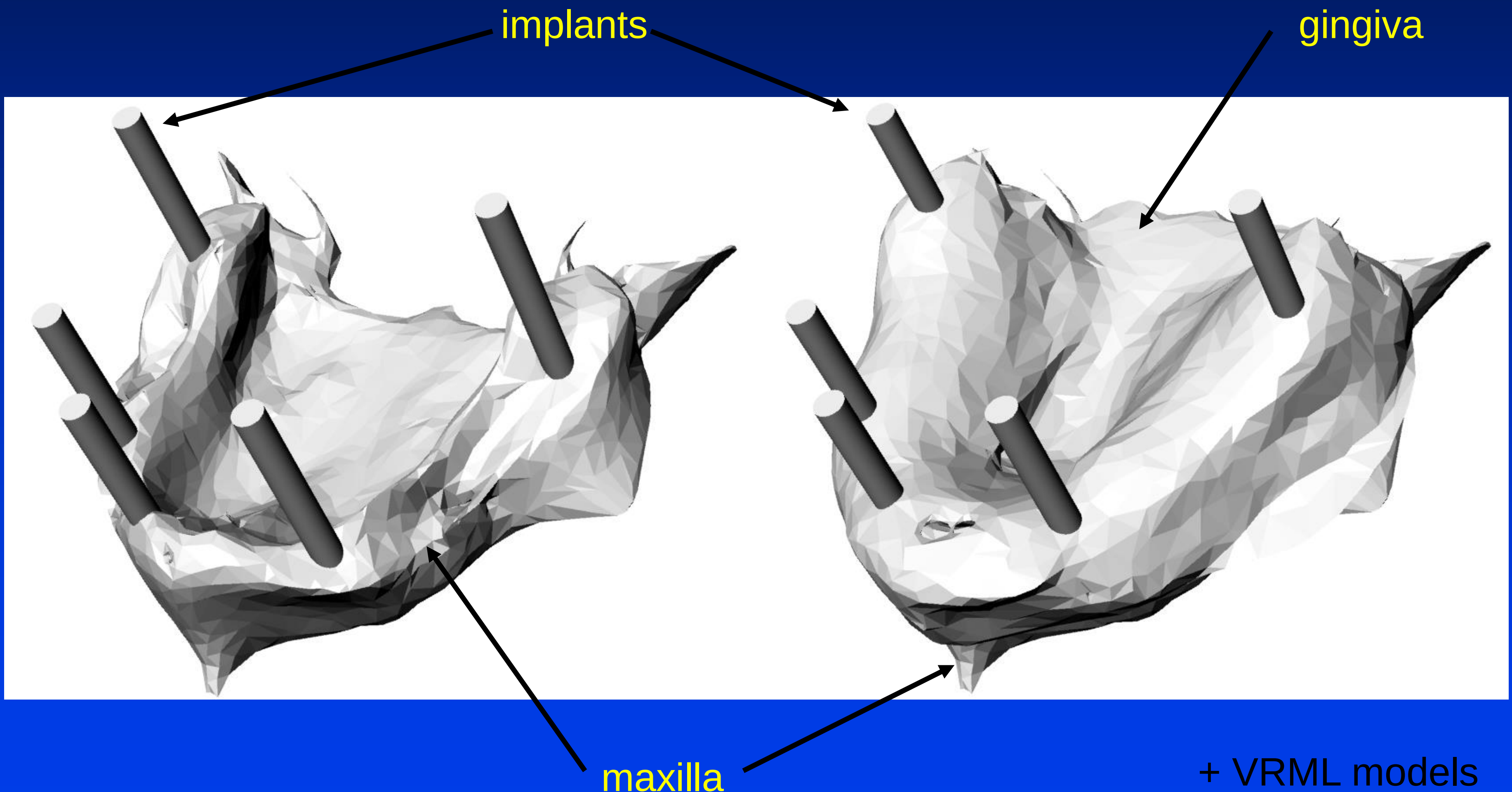






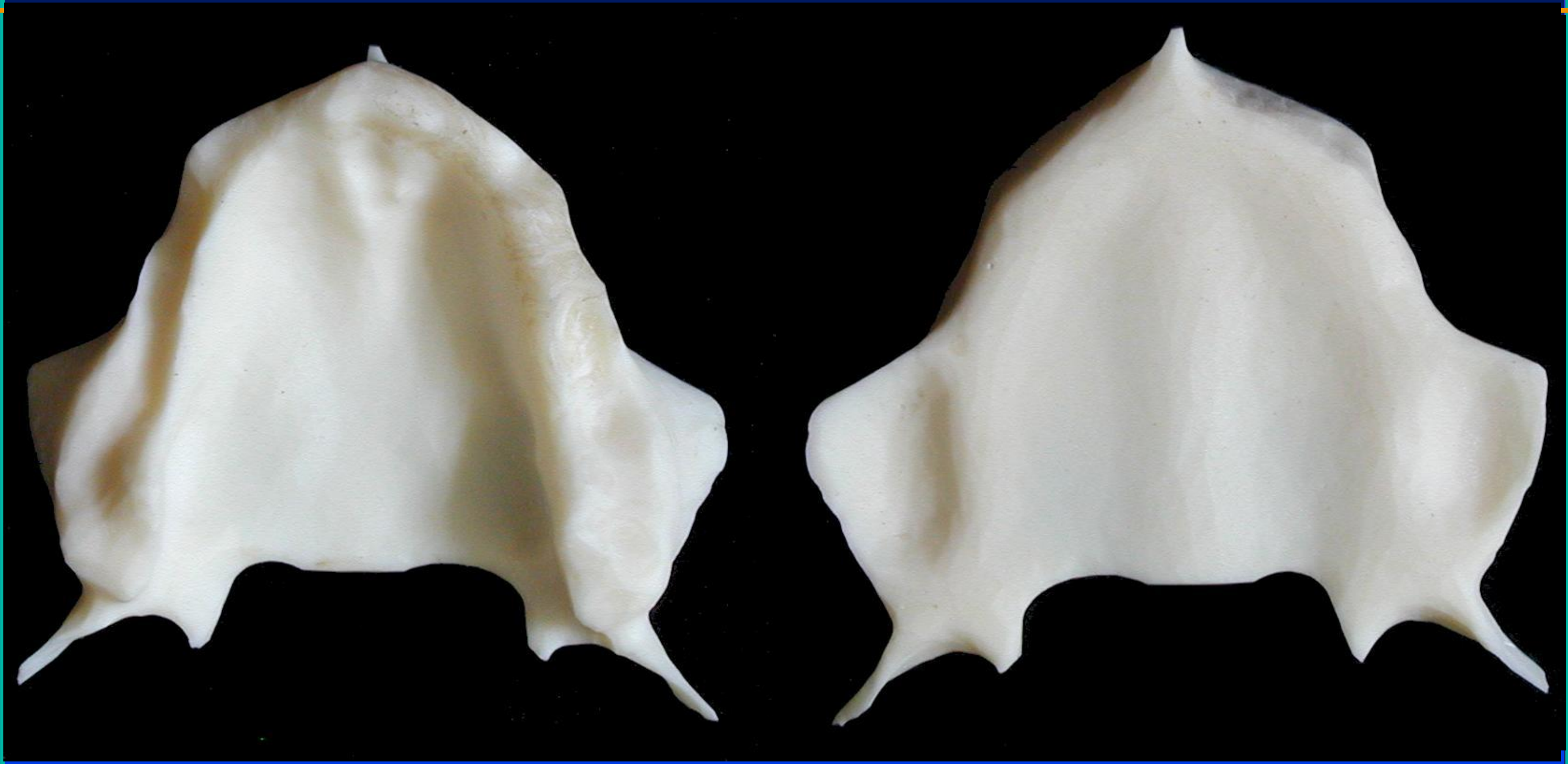
+ VRML models

Dental Surgery



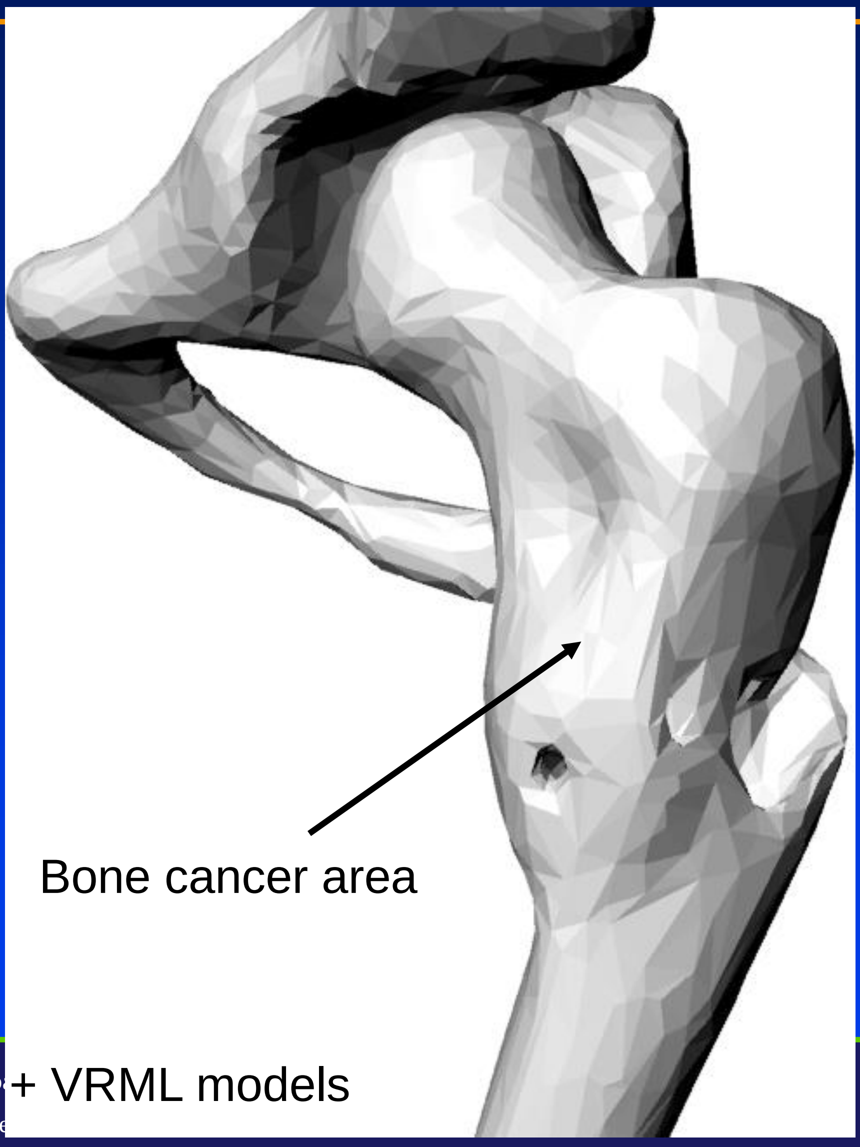
+ VRML models

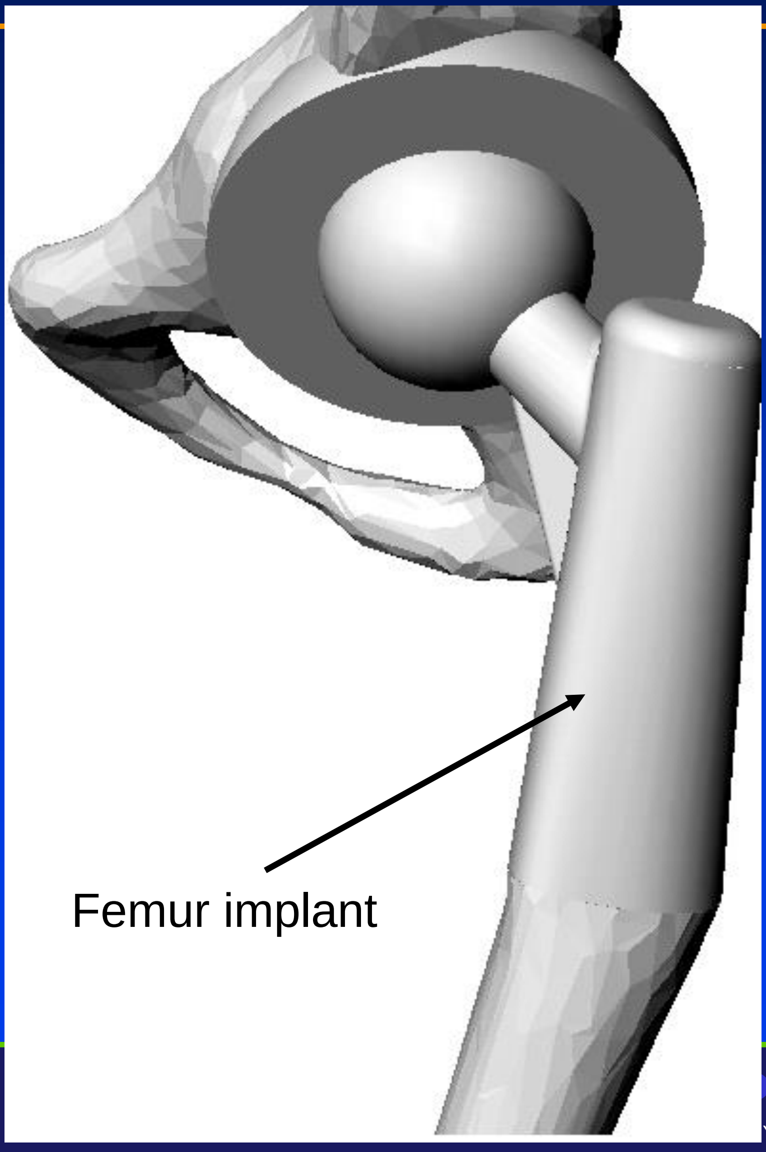
Dental Surgery – Physical Output



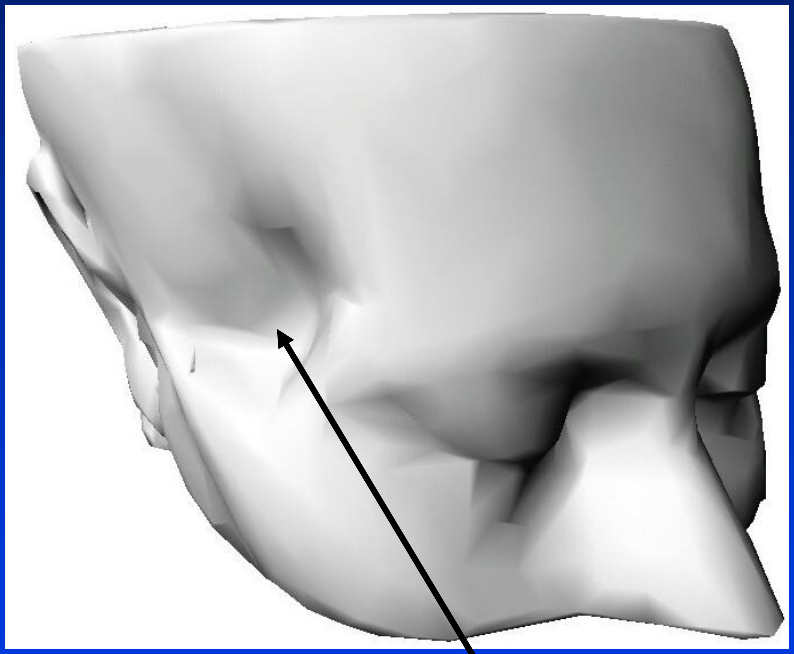
Made maxilla model

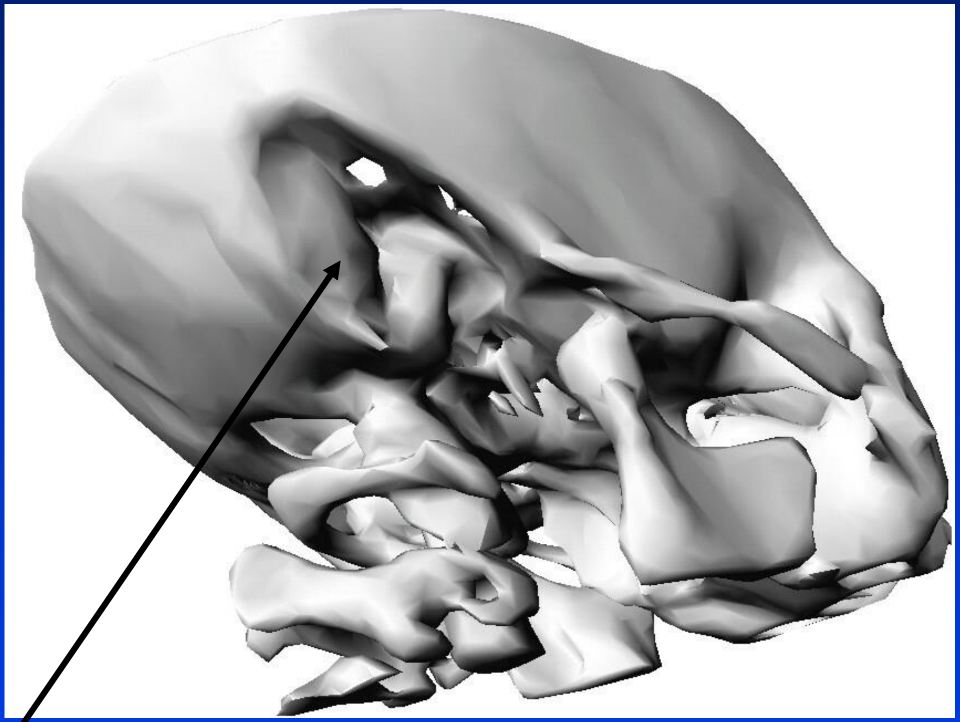
Orthopedic





Aesthetic Surgery



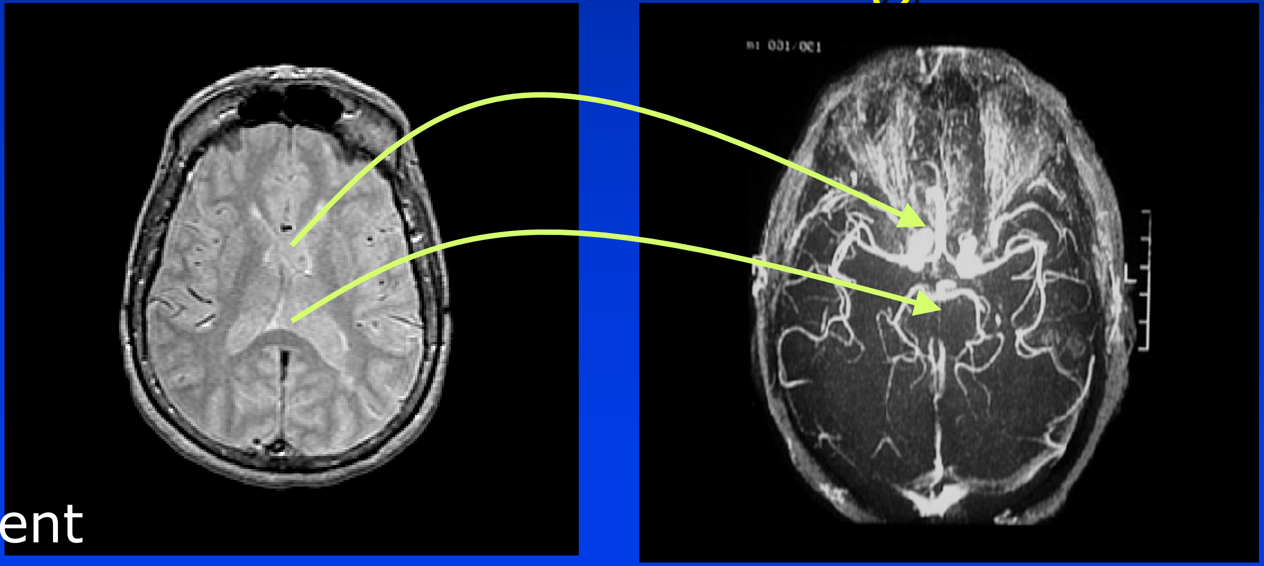


resections

+ VRML models

Image Registration: Overview

- Image registration aims to determine a spatial transformation (T), or mapping, that can map positions in one image, to corresponding positions in one or more other images



Source image Target image

- 3D - 3D
- 3D - 2D
- 3D/2D - patient

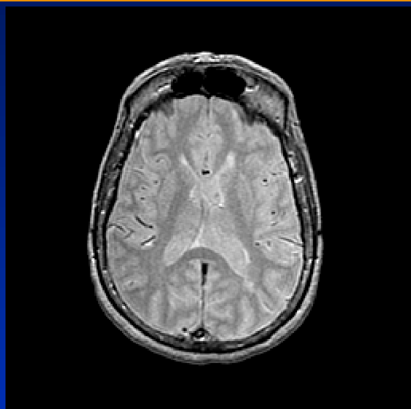
Registration

- "The process of establishing a common, geometric reference frame between two data sets."
- Previously used in vision to align satellite images, generate image mosaics, etc.

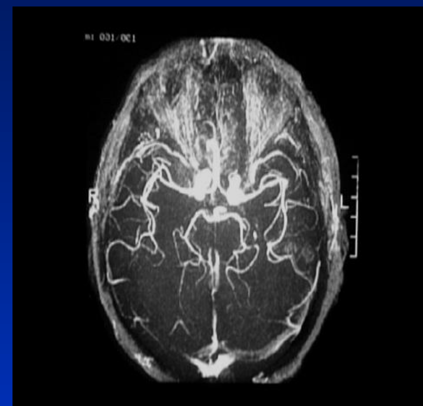
Data Registration in Medical Imaging

- Explosion of data, both 2D and 3D from many different imaging modalities have made registration a very important and challenging problem in medicine

Different Imaging Modalities

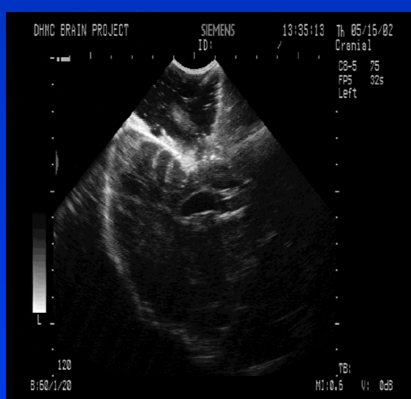


MRI

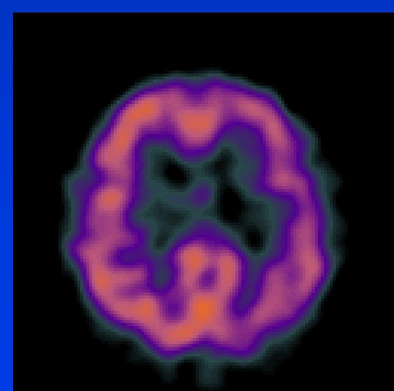


Angiography

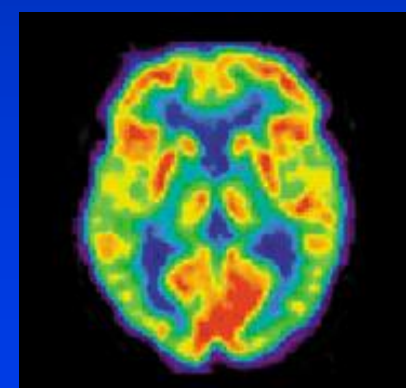
X-rays CT



Ultrasound



SPECT



PET

Multi-modal Registration

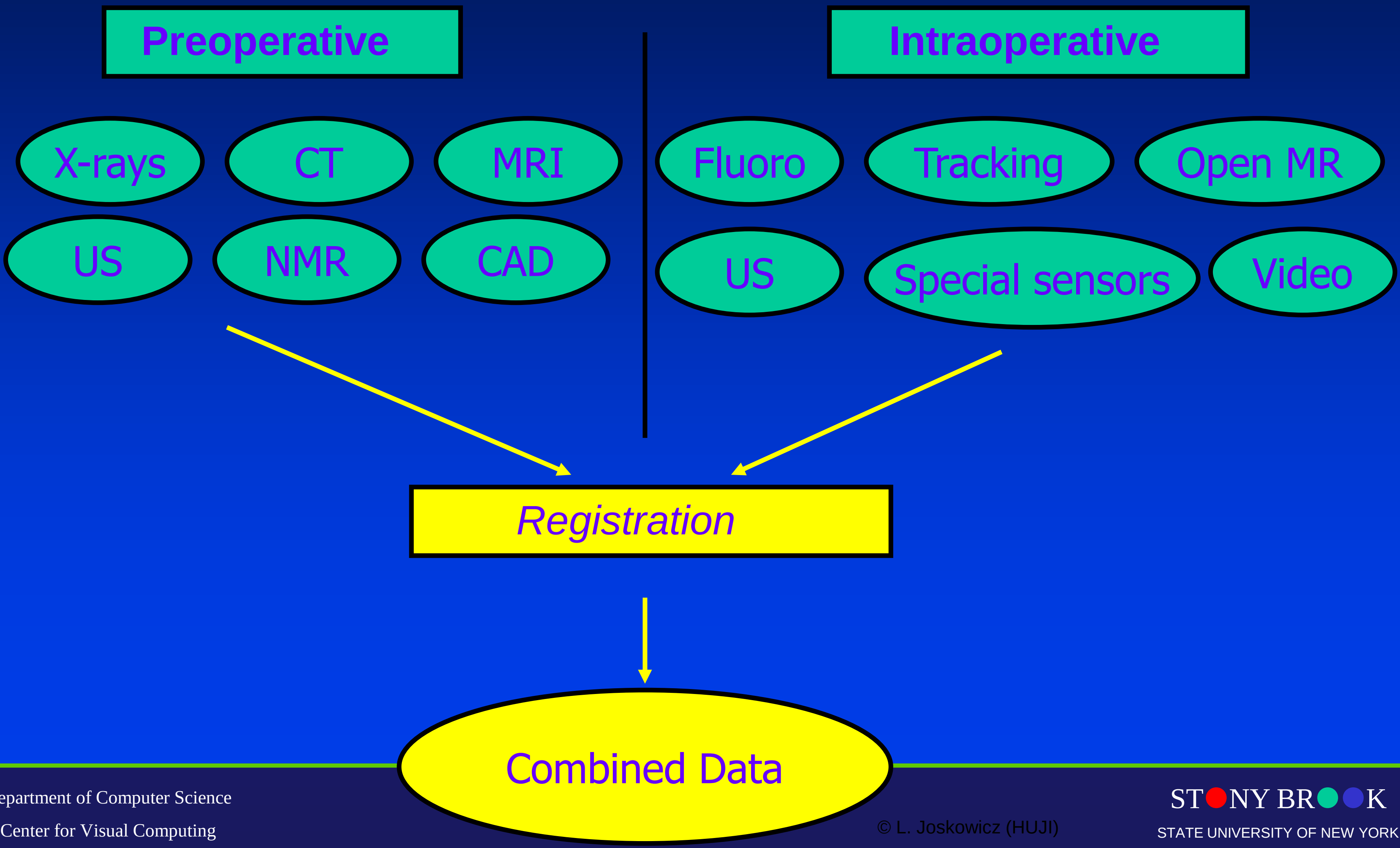


Image Registration: Categories

- Same modality, same patient

  - monitor and quantify disease progression over time,

  - evaluate intraoperative brain deformation, etc.

- Different modalities, same patient

  - correction for different patient position between scans,

  - link between structural and functional images, etc.

- Same modality, different patients

  - Atlas construction,

  - studies of variability between subjects, etc.

Image Registration

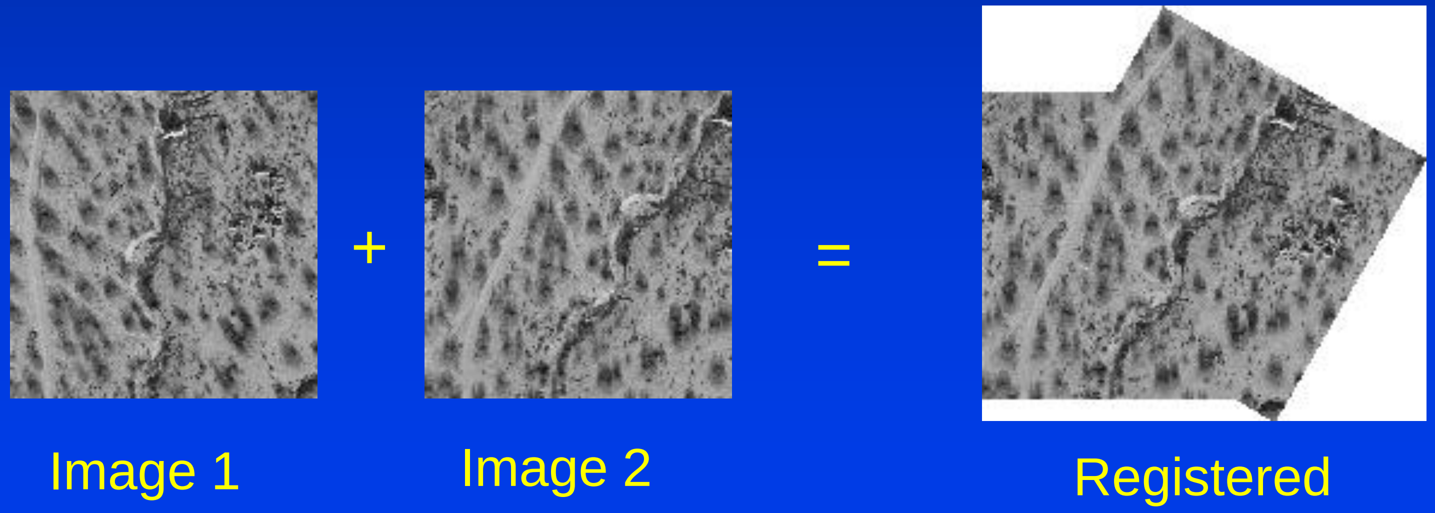


Image Registration Basics

- Task of calculating the transformation between two or more data sets…..
- Transformation – Rigid-body, Linear affine, Non-linear
- Data sets – 2D or 3D

Illustrating the Registration Process

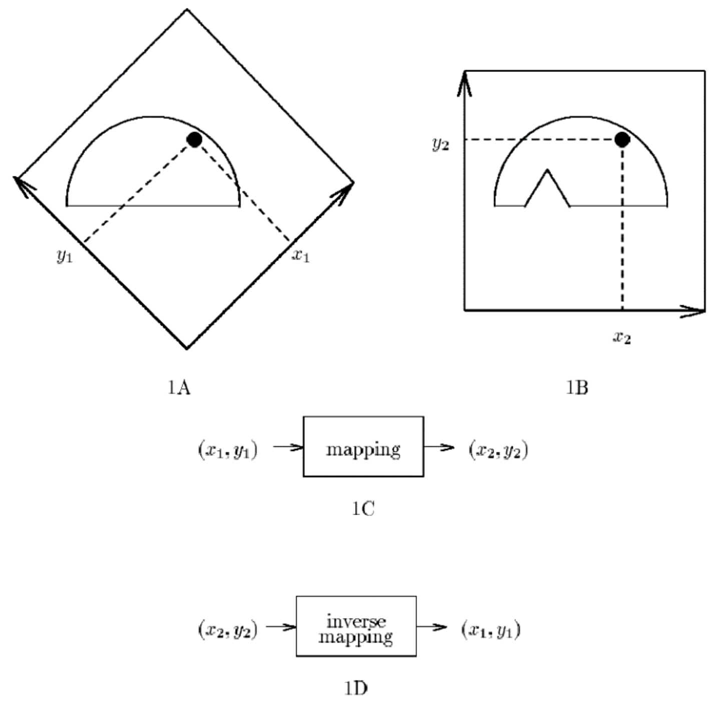


Figure 1: *Registration.* 1A: An image of some object. 1B: A second image of the same object acquired at a different orientation. Image 1A has been rotated so that the object appears in the same orientation as in 1B. Image 1B reveals that part of the object has been removed between image acquisitions. The black dot in each image corresponds to the same anatomical point in the object. The origin of the x, y coordinate system is at the bottom corner in 1A and at the lower left corner in 1B. 1C: Schematic illustration of the process of mapping in two-dimensional space. Each point (x_1, y_1) in the space of image 1A is mapped into a unique point (x_2, y_2) in the space of image 1B. 1D: The equivalent inverse mapping in which points in space two are mapped into points in space one.

Basic Types of Transformations

- Rigid-body:- consisting of only rotation and translation

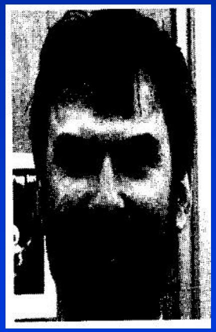
Original Image

Same after a rigid transformation

Basic Types of Transformations

- Linear affine:- scaling, translation, rotation, reflection

Original Image



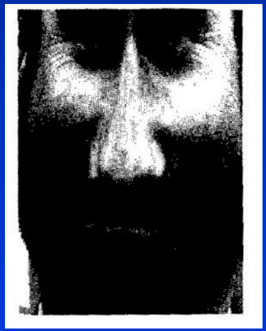
Same after a linear affine transform

Basic Types of Transformations

- Non-linear transformation – changes shape of an object. e.g. warping, morphing etc.

Image of a person

Image of a mandrill



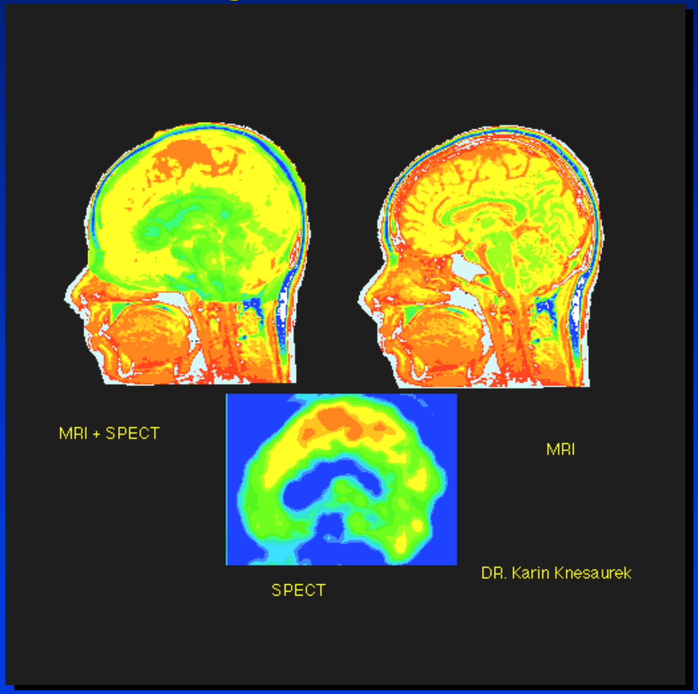
Result of warping

Data Registration is Ubiquitous

- Medical imaging – brain tumors, lung cancer, cardiac studies, complex surgery …..
- Scene analysis
- Object recognition
- Remote sensing
- Automated monitoring
- Industrial inspection
- Robot vision

Image Registration in Medical Imaging

- **<u>Illustration 1</u>:- Study of Brain tumor**



knowledge from Single Photon Emission Computed Tomography (SPECT)

Registered to have both types of knowledge simuAnatomical knowledge from Magnetic Resonance Imaging (MRI)

Physiological/functional simultaneously

Illustration 2:- Extracranial Study of Thorax

- The top row shows Positron Emission Tomography (PET) images
- The bottom row shows MRI with a contour
- The middle row shows image registration using both MRI and PET

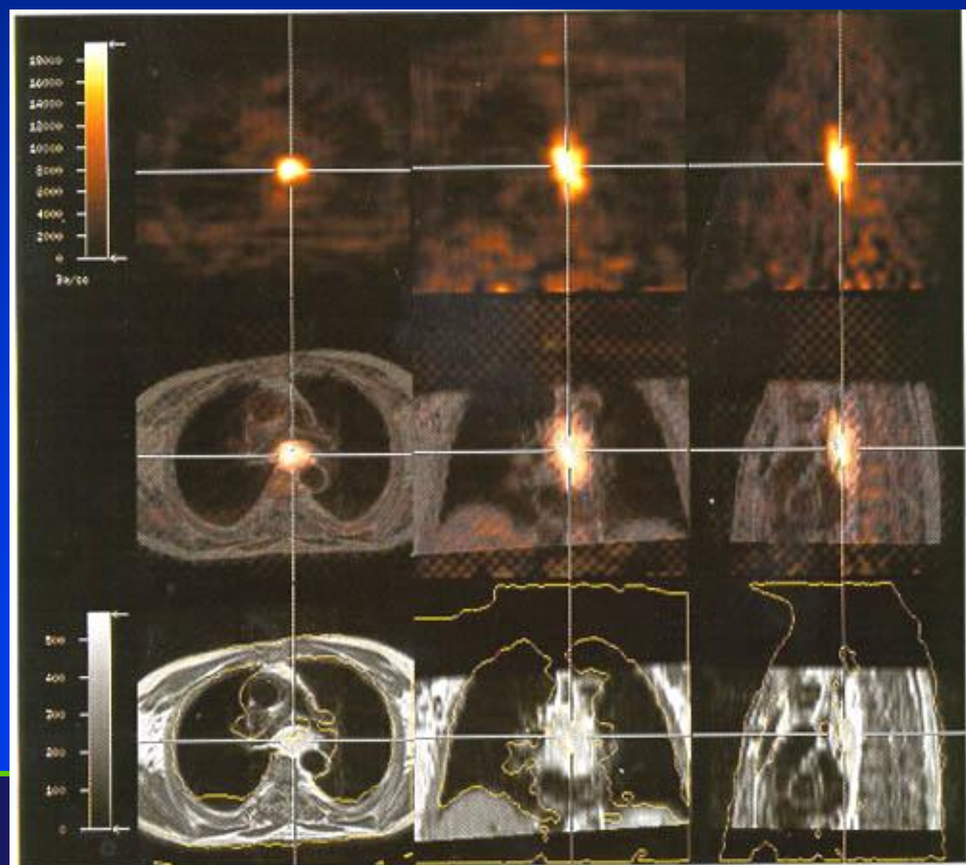
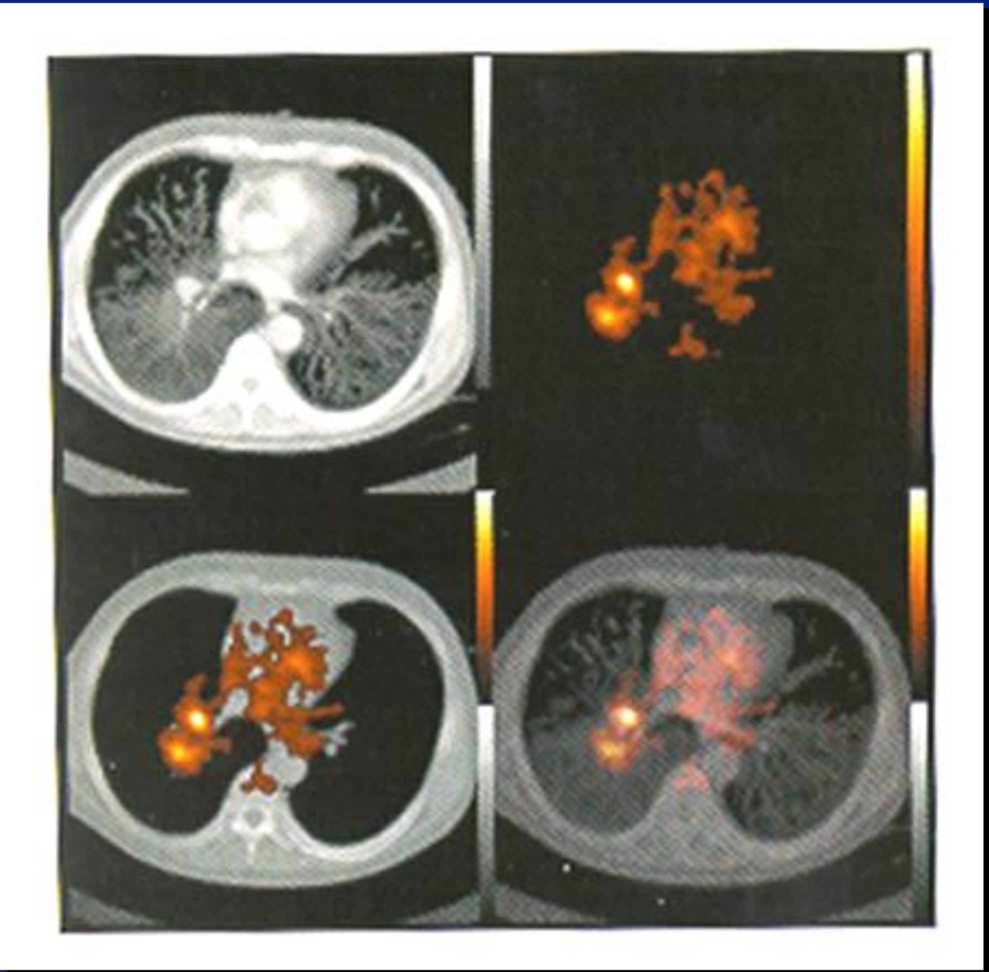
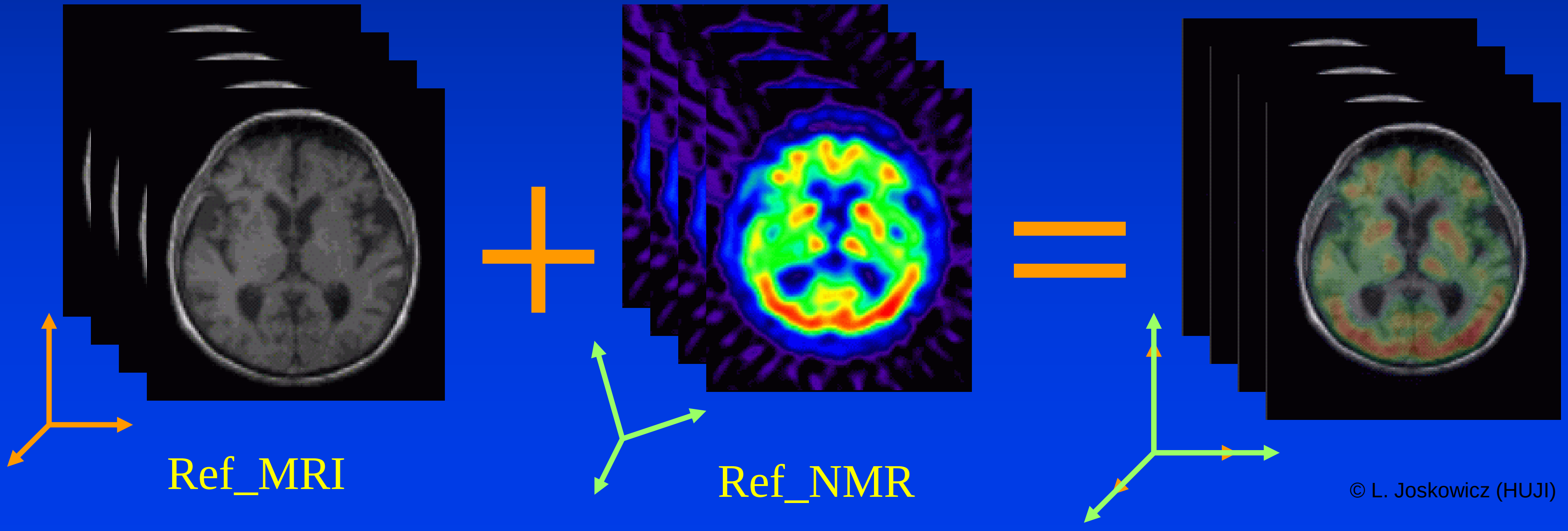


Illustration 3:- Detecting Lung Cancer

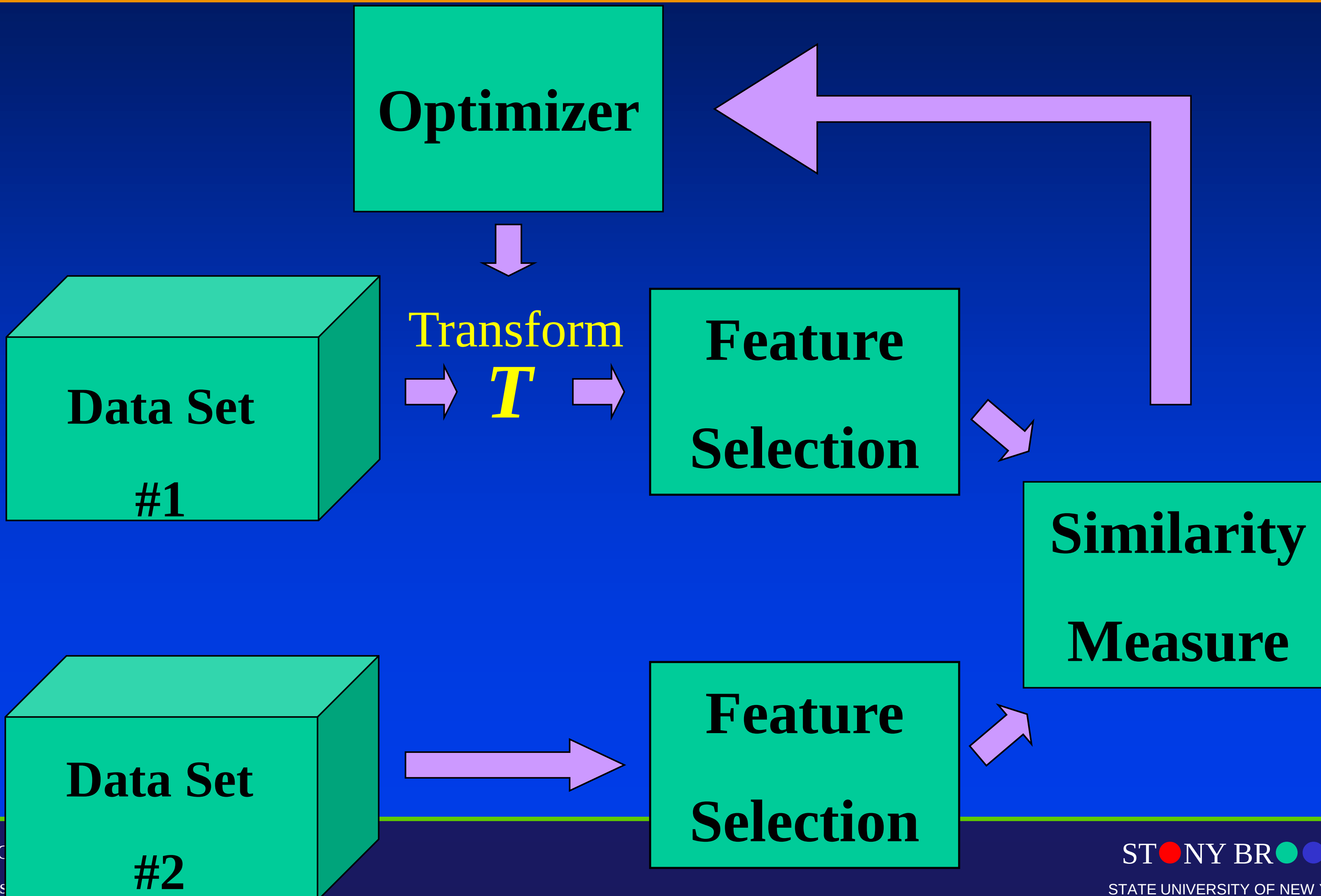
- The top-left shows a PET image of the thorax, the top-right hows the x-ray CT scan of the same. The bottom images are results of PET-CT registration.



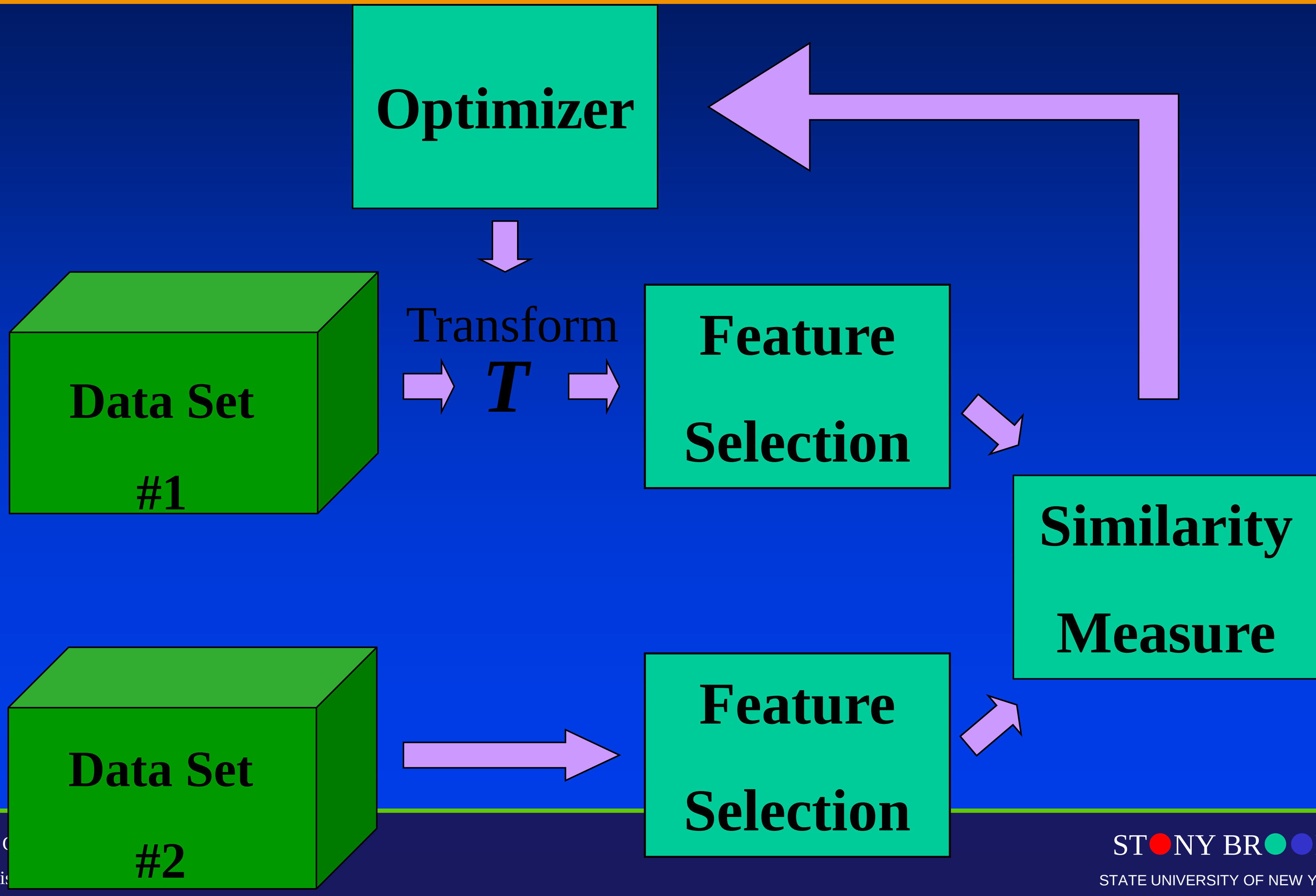
Another Illustration



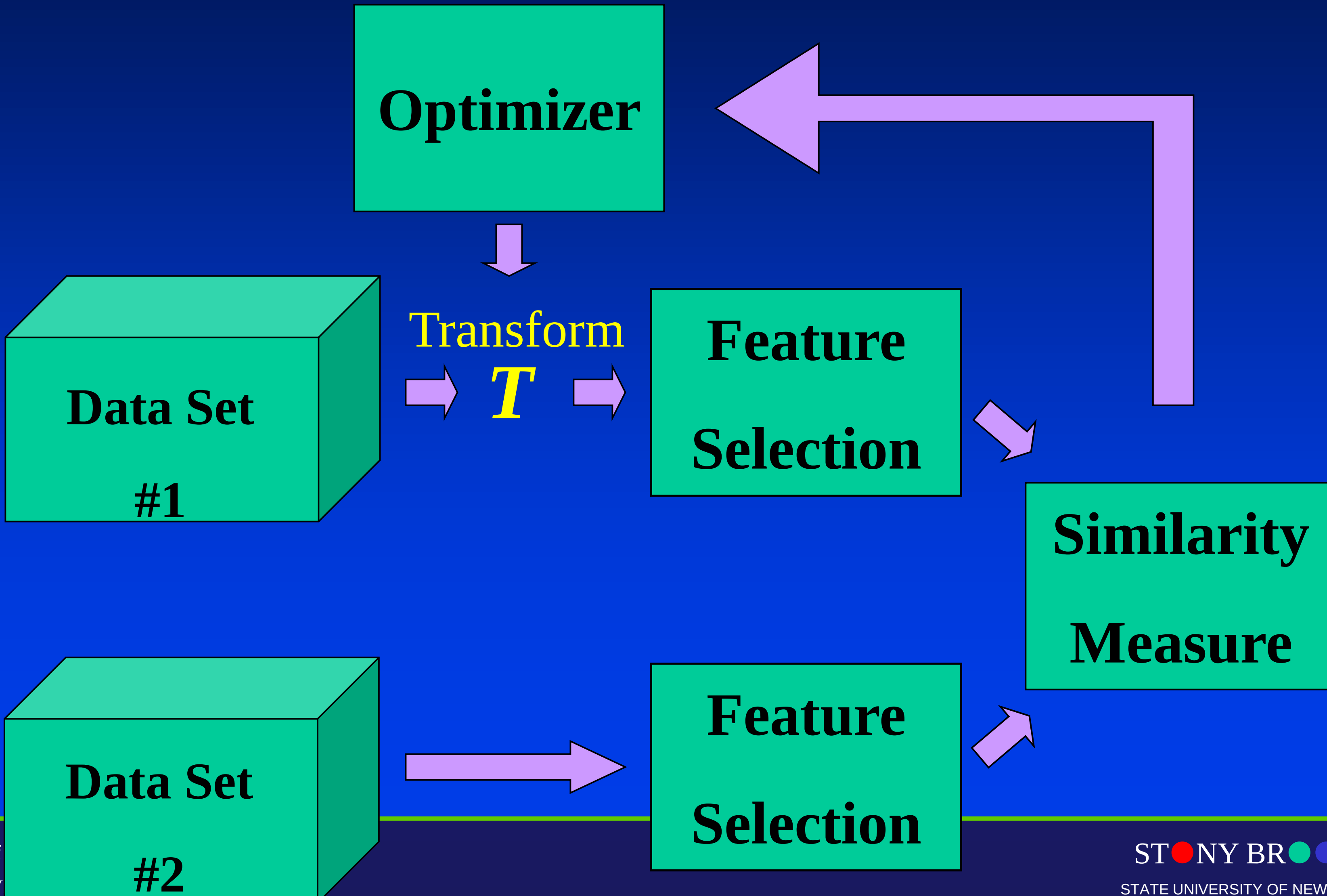
Multi-modal Registration Pipeline



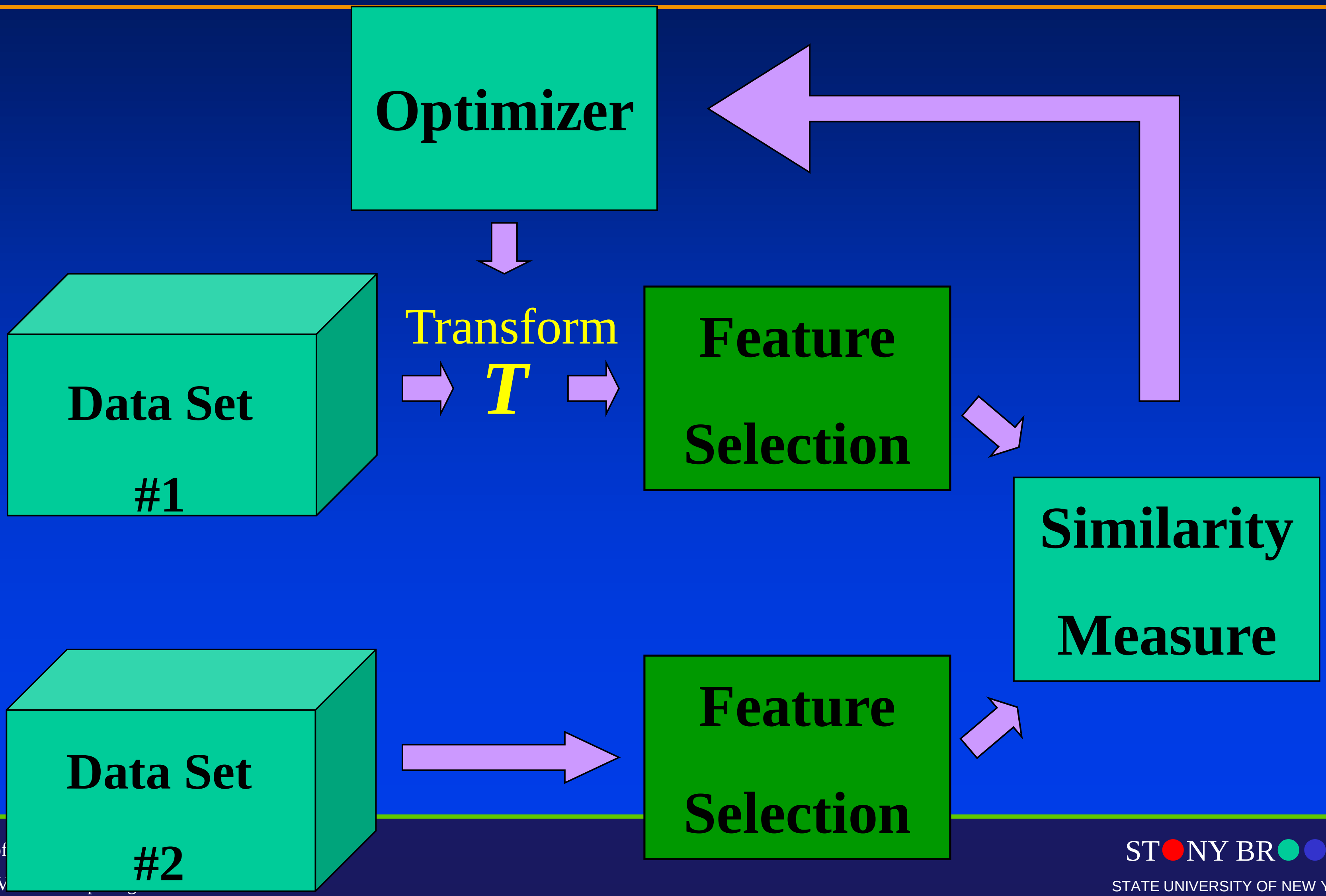
Multi-modal registration Pipeline



Multi-modal Registration



Multi-modal Registration



Feature Selection

- Points-based
  - 3D points calculated using an optical tracker

- Surfaces
  - Extracted from images using segmentation algorithms
- Intensities
  - Uses the raw voxel data itself

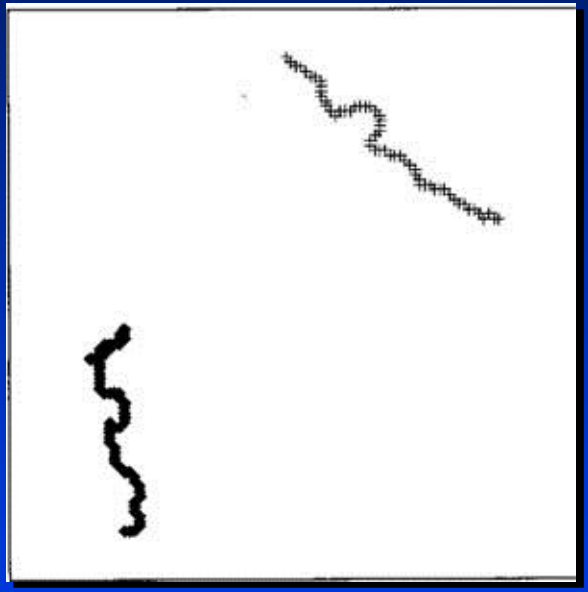
Feature Selection and Registration Schemes

- Landmark based –
- Surface based –
- Registration based on voxel intensities –
- 2D-3D registration –
- Intersubject registration –
- Intrasubject registration -

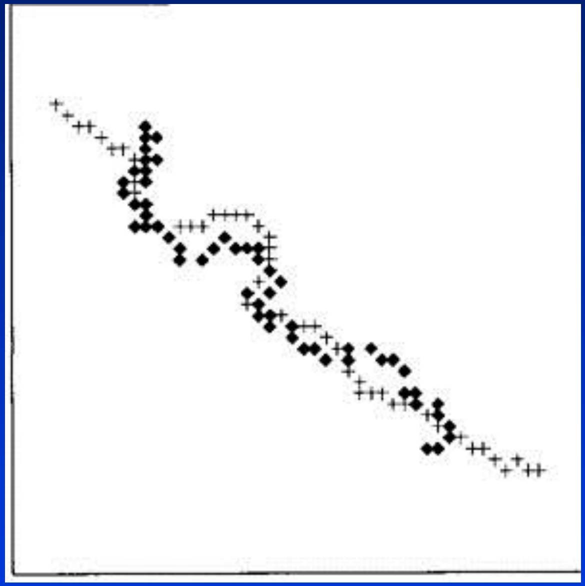
Registration Algorithm Types

- Control-point based – Involves identification of corresponding landmark points
- Moment based – Uses information like centre of gravity, principal axis and moments of inertia
- Edge-based – Takes advantage of an existing neat contour
- Optimization of a similarity measurement – Aims at achieving best fit between two images using some sort of similarity like correlation coefficient etc.

Iterative Closest Point



Two data sets before ICP



Two data sets after ICP

Brief Mathematical Foundations

- Centroid of a data set :-The centroid of a data set is the weighted mean of all data points present in the set. For a data set A having N points, each denoted by a_i the centroid is given by:-

  $$\mu_A = (1/N) \Sigma a_i$$

- Covariance Matrix :- This gives a measure of similarity between 2 data sets to be matched. If μ_A and μ_B are the centroids of the data sets A and B respectively then, the Covariance Matrix between the two sets is given by:-

  $$\Sigma_{AB} = \Sigma (a_i - \mu_A) (b_i - \mu_B)^T$$

Mathematical Foundations

- Eigenvalues :- A given N x N matrix C is said to have an eigenvector x and corresponding eigenvalue λ if the following equation holds:-

  $C.x = \lambda x$

  The above equation can hold iff $| C - \lambda I | = 0$.

  where $| P |$ denotes determinant of the matrix P.

  It is to be noted that the last equation if expanded out, is an Nth degree polynomial in λ, whose roots are the eigenvalues of the matrix C.

- Mean Square Error :- The Mean Square error (MSE) between 2 data sets A and B having N points each is given by :-

  $MSE = (1/N) \Sigma \|a_i - b_i\|^2$

  where $\| \|$ denotes the L2 -Norm/Euclidean Norm between 2 data points.

Mathematical Foundations

- Quaternions:-

  A Quaternion (q) is a 4-dimensional vector consisting of a scalar component (q_0) and a vector part (q_1, q_2 , q_3). So, we can write :-

  $q = q_0 + q_1 \mathbf{i} + q_2 \mathbf{j} + q_3 \mathbf{k}$

- Quaternions and Rotation Sequences:-

  Rotations are represented by a special class of quaternions having the property $q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$.

  Rotation by an angle θ about an unit vector (q_1 , q_2 , q_3) can be represented by a quaternion q_R as:-

  $q_R = \cos(\theta/2) + q_1 \sin(\theta/2) \mathbf{i} + q_2 \sin(\theta/2) \mathbf{j} + q_3 \sin(\theta/2) \mathbf{k}$

  We can have also have a 3x3 Rotation Matrix from a given q_R

Singular Value Decomposition

Basic Features -

- Prior knowledge of correspondence is required between two sets to be matched. It is a non-iterative algorithm.

SVD algorithm :-

Input :- Two sets of points A and B containing N points each.

Output :- R and T needed to match the two sets.

Steps :- a) Compute the centroid of each data set as μ_A and μ_B

b) Calculate the co-variance matrix Σ_{AB}

c) Do the SVD decomposition of the $\Sigma_{AB} = U \Lambda V^T$

d) Calculate the matrix $X = VU^T$

e) If determinant of X = 1, then X = R, R being the rotation matrix.

f) Finally figure out T from the equation:- $T = \mu_B - R\mu_A$

Iterative Closest Point

Basic Features -

- No prior knowledge of correspondence is required between two sets to be matched. Moreover, these two sets in most cases don't have same number of points to begin with. It is an iterative algorithm.

ICP algorithm :-

Input :- Two sets of points A and B containing say K and N points.

Output :- R and T needed to match the two sets.

Steps:- a) Compute the closest set C. Note that C is a sub-set of B.

b) Compute the centroid of each data set as μ_A and μ_C

c) Calculate the co-variance matrix Σ_{AC}

d) Determine a 4x4 symmetric matrix Q from Σ_{AC}

e) Unit eigenvector that corresponds to the maximum eigenvalue of Q is the optimal rotation quaternion q_R. Then calculate R.

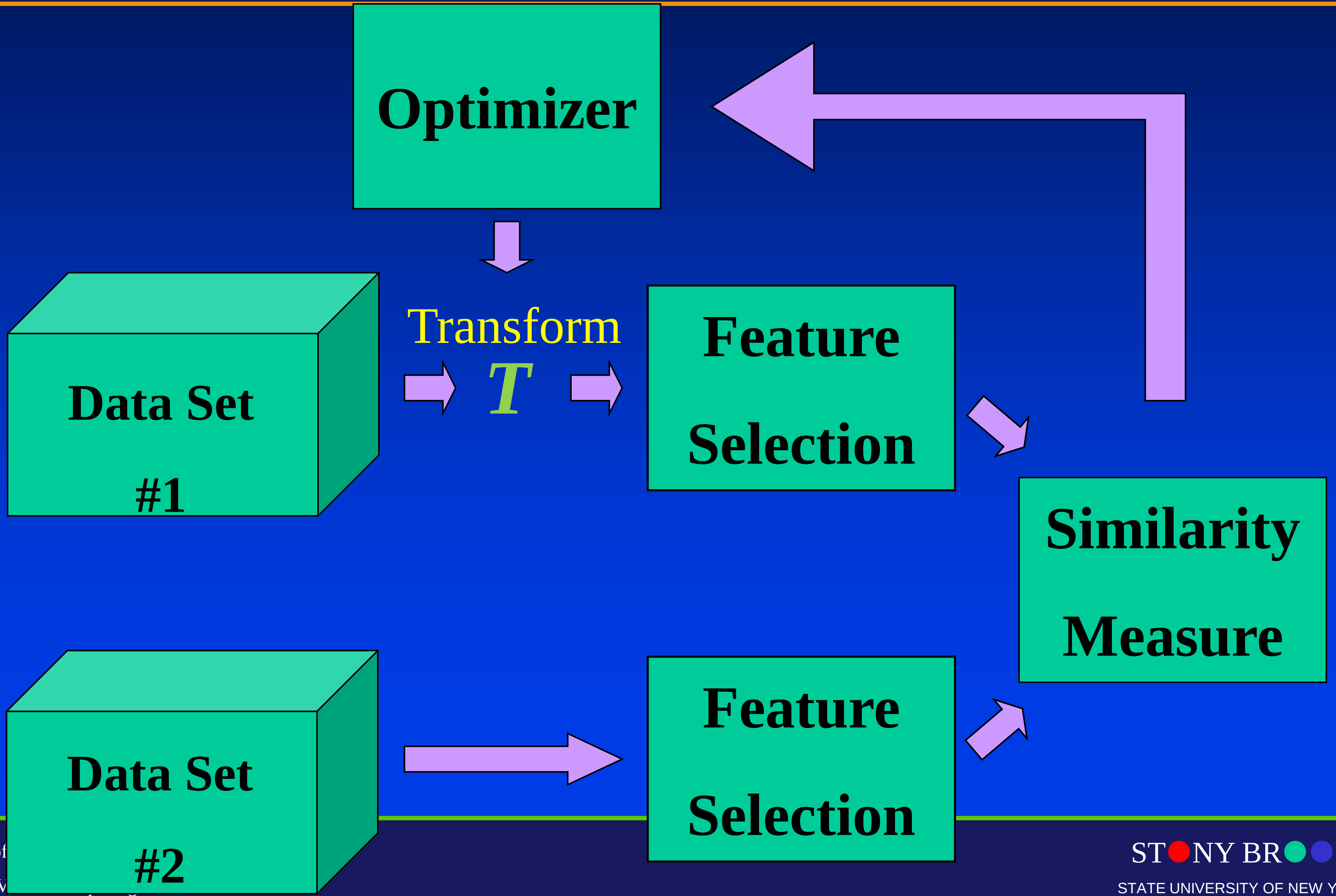
f) Obtain T from the equation:- $T = \mu_C - R\mu_A$

g) Update set A with the R and T i.e. get a new A say A_1 from the original A say A_0

h) Calculate the MSE between C and A_1

i) If the MSE falls below a certain threshold, stop else go back to a) with $A = A_1$

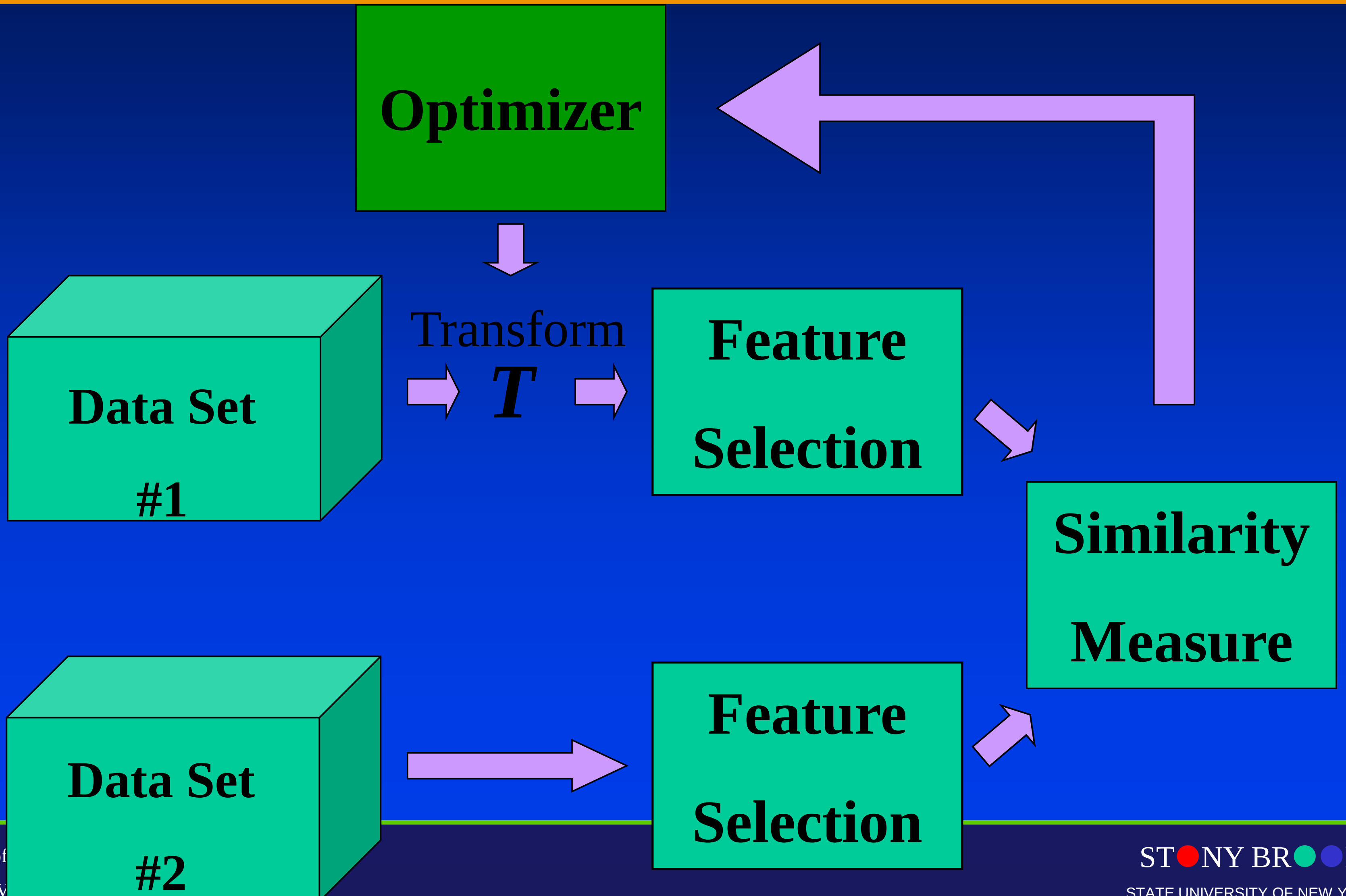
Multi-modal Registration



Algorithmic Components

- Similarity: the similarity criterion measures how well 2 images match
- Transformation: The transformation specifies the way in which the source image can be matched the target image. A number of numerical parameters specify a particular instance of the transformation
- Optimization: The optimization process varies the parameters of the transformation model to maximize the matching criterion

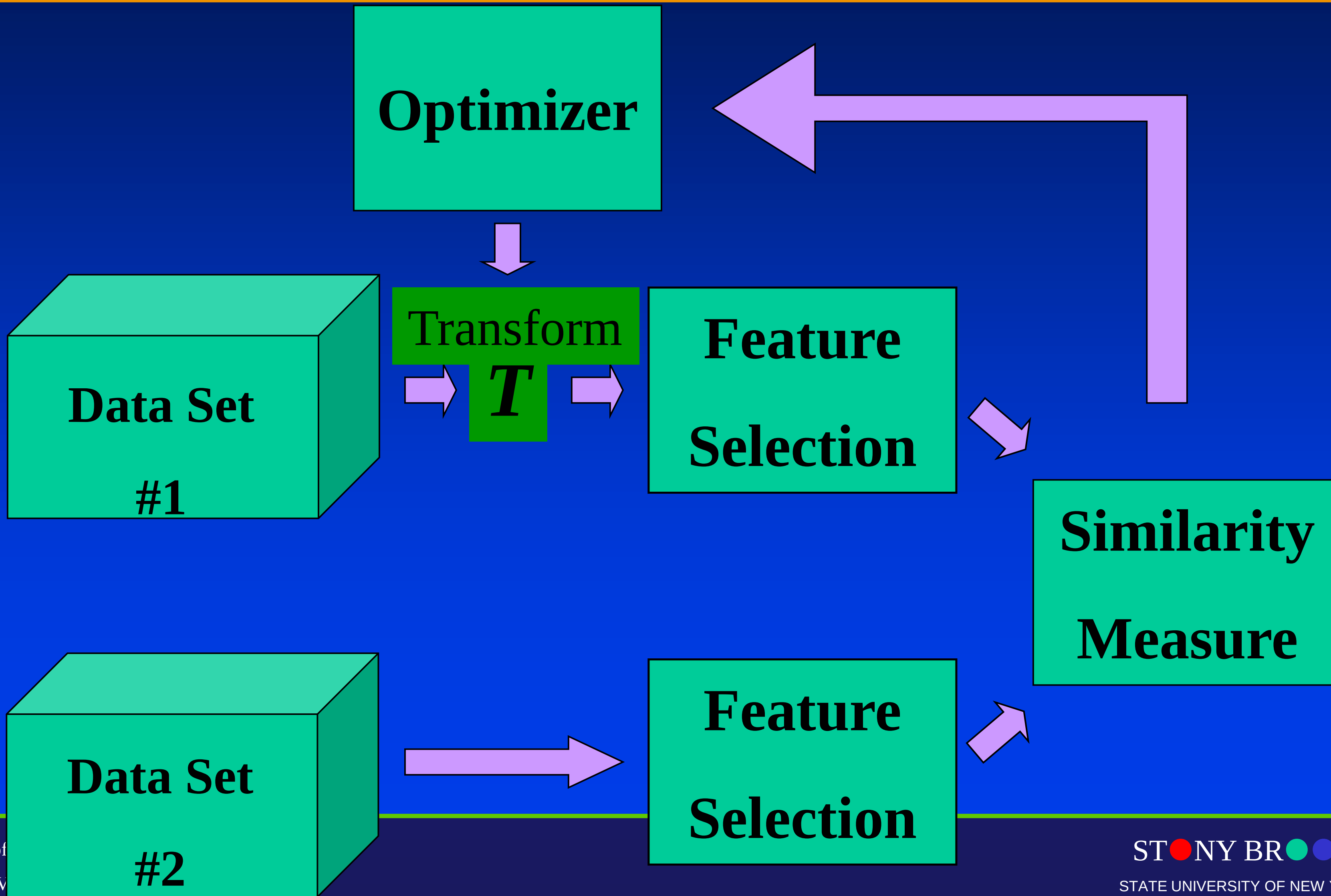
Multi-modal Registration

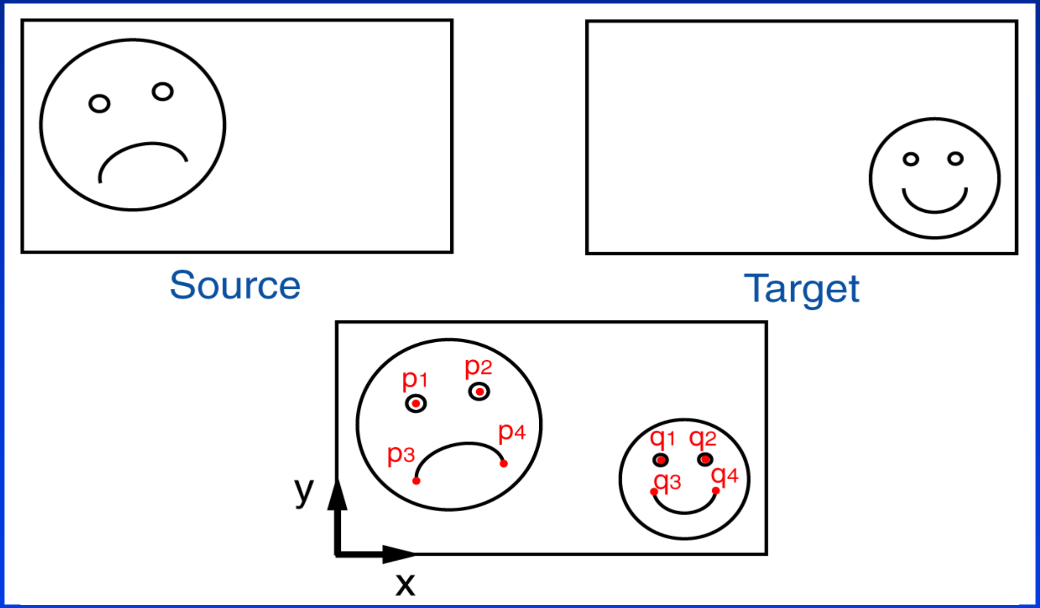


Optimization

- Gradients
  - Gradient descent
  - Conjugate-gradient
  - Levenburg-Marquardt
- No gradients
  - Finite-difference gradient + above
  - Best-neighbor search
  - Nelder-Mead
  - Simulated annealing

Multi-modal Registration




Source
Target
p1
p2
p3
p4
q1
q2
q3
q4
y
x

Transformations

- Rigid (6 DOF)
  - 3 rotation
  - 3 translation
- Affine (12 DOF)
  - 6 from before
  - 3 scale
  - 3 skew
- Non-rigid (? DOF)
  - As many control points as your favorite supercomputer can handle

- Rigid transformation: 6 parameters

T depends of t_x, t_y, t_z ,θ_x, θ_y, θ_z

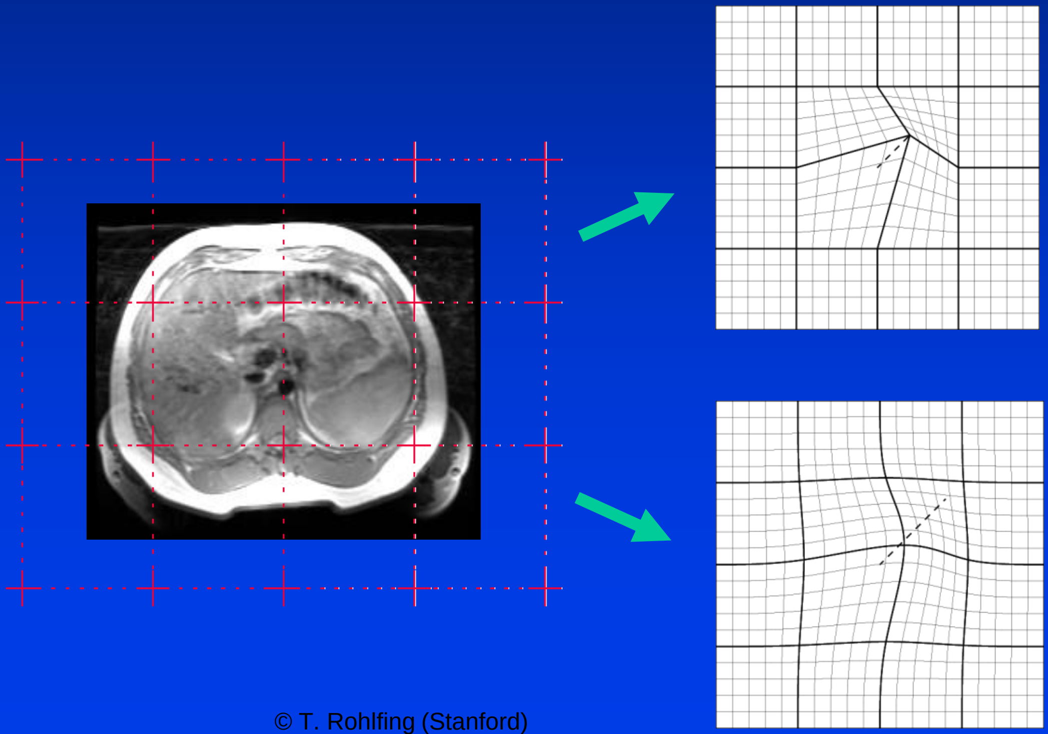
- Affine transformation: 12 parameters

T depends of t_x, t_y, t_z ,θ_x, θ_y, θ_z ,s_x, s_y, s_z ,c_x, c_y, c_z

- Nonrigid transformation: number of parameters $\{\alpha_i\}$

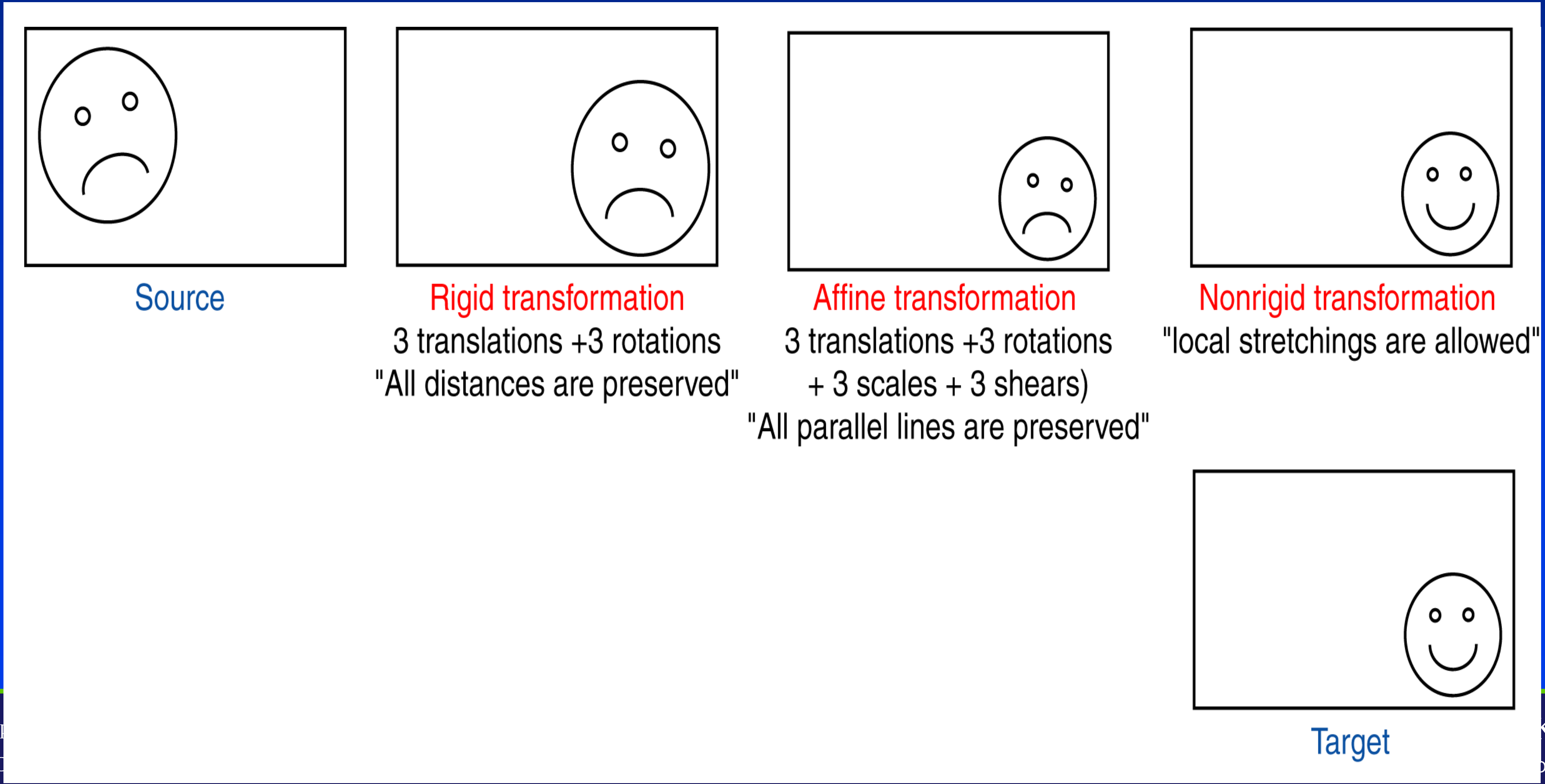
T depends of $\alpha_1, \alpha_2, \ldots ,\alpha_{n-1}, \alpha_n$

Transformations

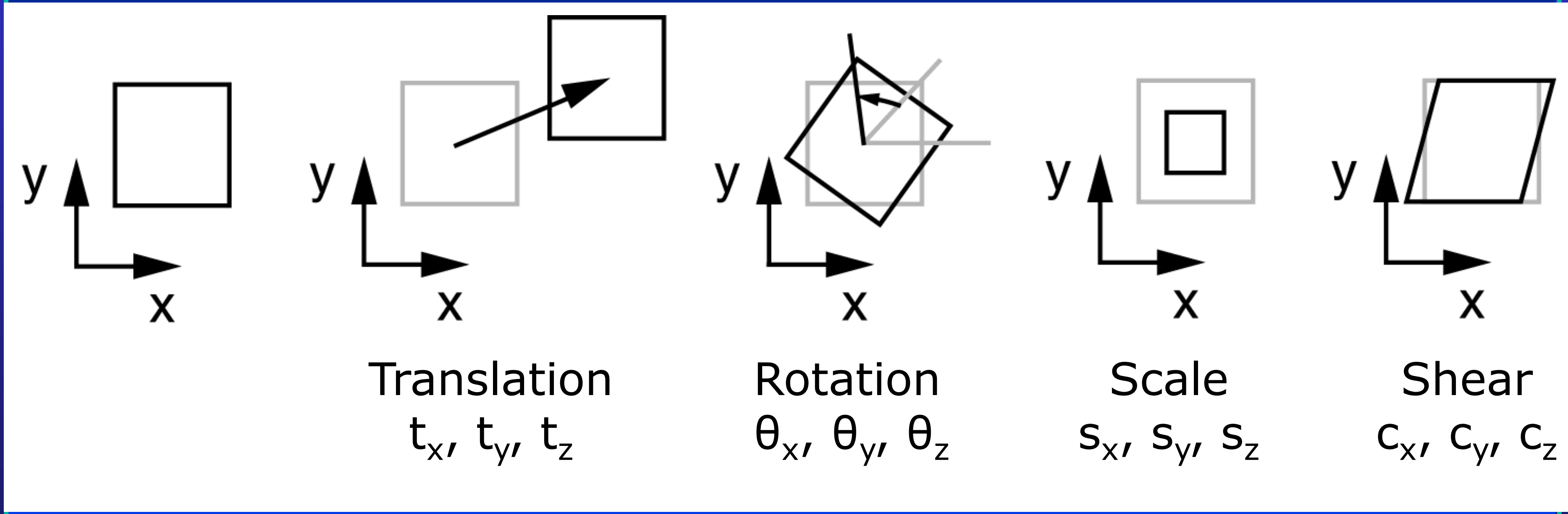


© T. Rohlfing (Stanford)

Different Types of Transformation



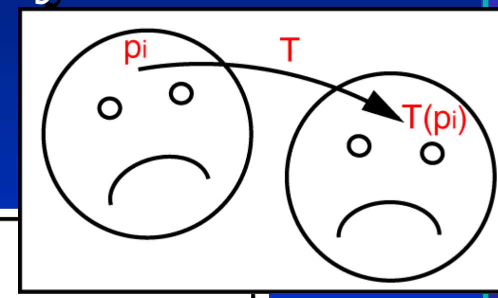
Rigid, Affine, and Nonrigid Transformations

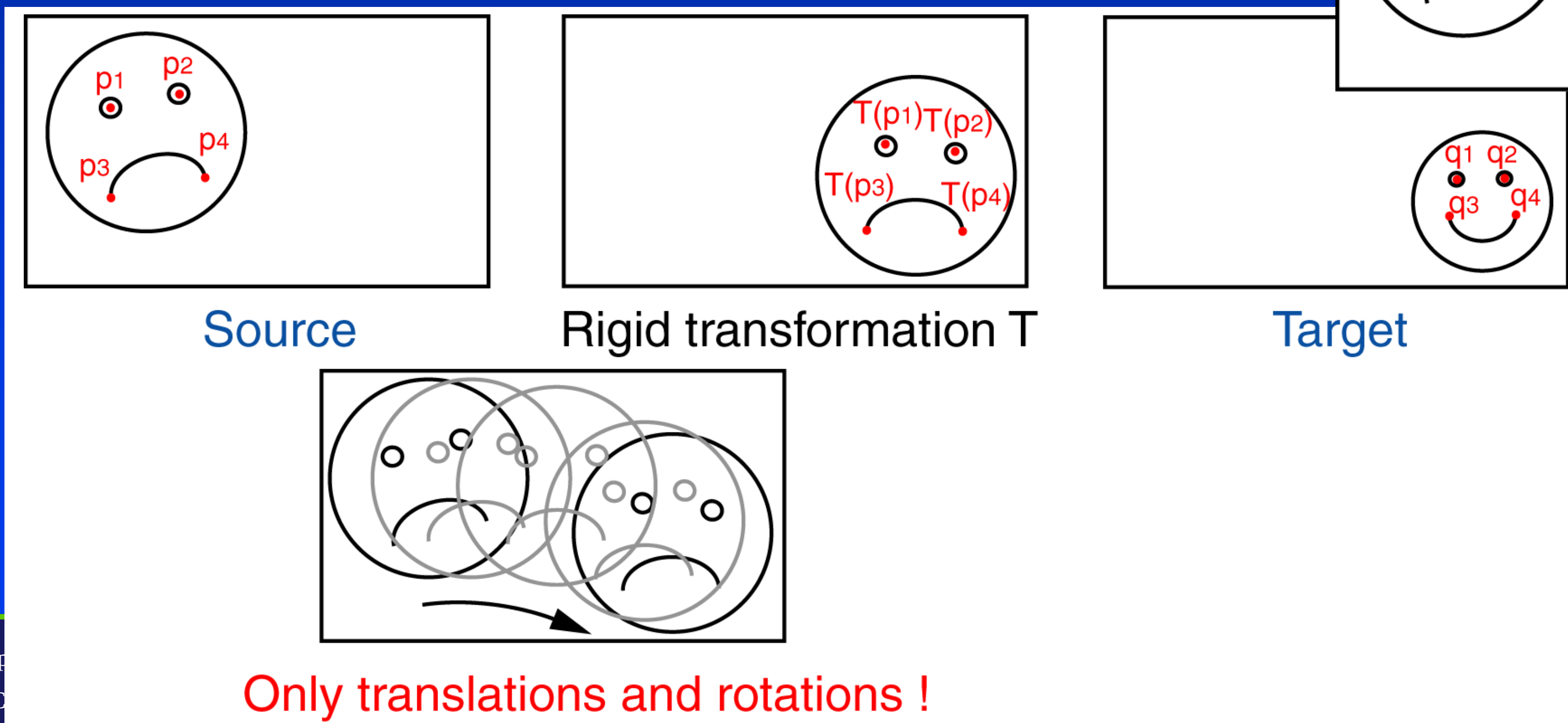


Transformation Serves 2 Purposes

1) Controls how image features can be moved relative to one another to improve the image similarity
   example: $G(T)=\sum_i |T(p_i)-q_i|^2$ is minimum

2) Interpolates between those features





Different Components

1) Similarity

The similarity criterion measures how well 2 images match

2) Transformation

The transformation specifies the way in which the source image can be changed to match the target. A number of numerical parameters specify a particular instance of the transformation

3) Optimization

The optimization process varies the parameters of the transformation model to maximize the matching criterion

Transformation + Optimization

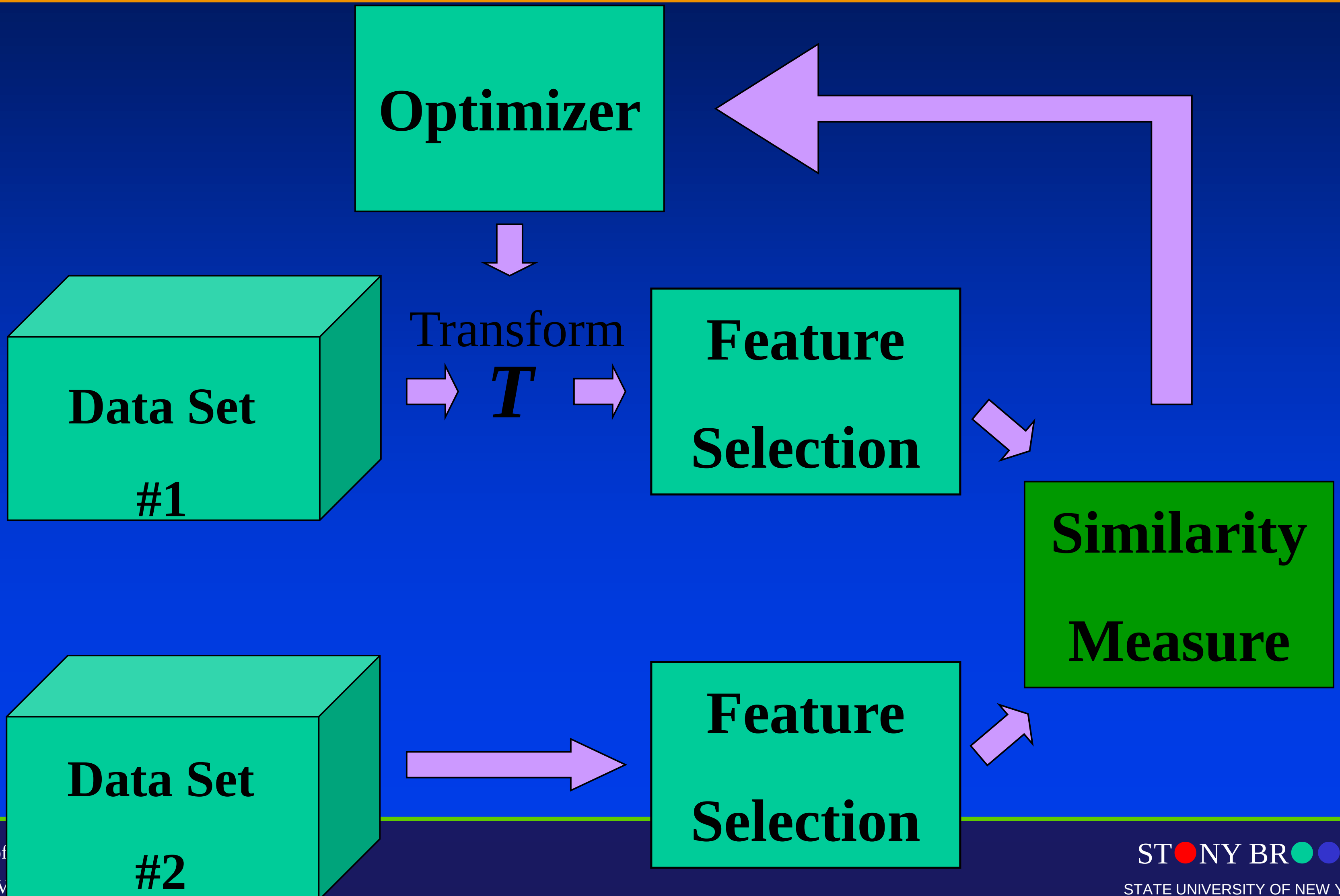
2) Transformation

The transformation specifies the way in which the source image can be changed to match the target. A number of numerical parameters specify a particular instance of the transformation

3) Optimization

The optimization process varies the parameters of the transformation model to maximize the matching criterion

Multi-modal Registration



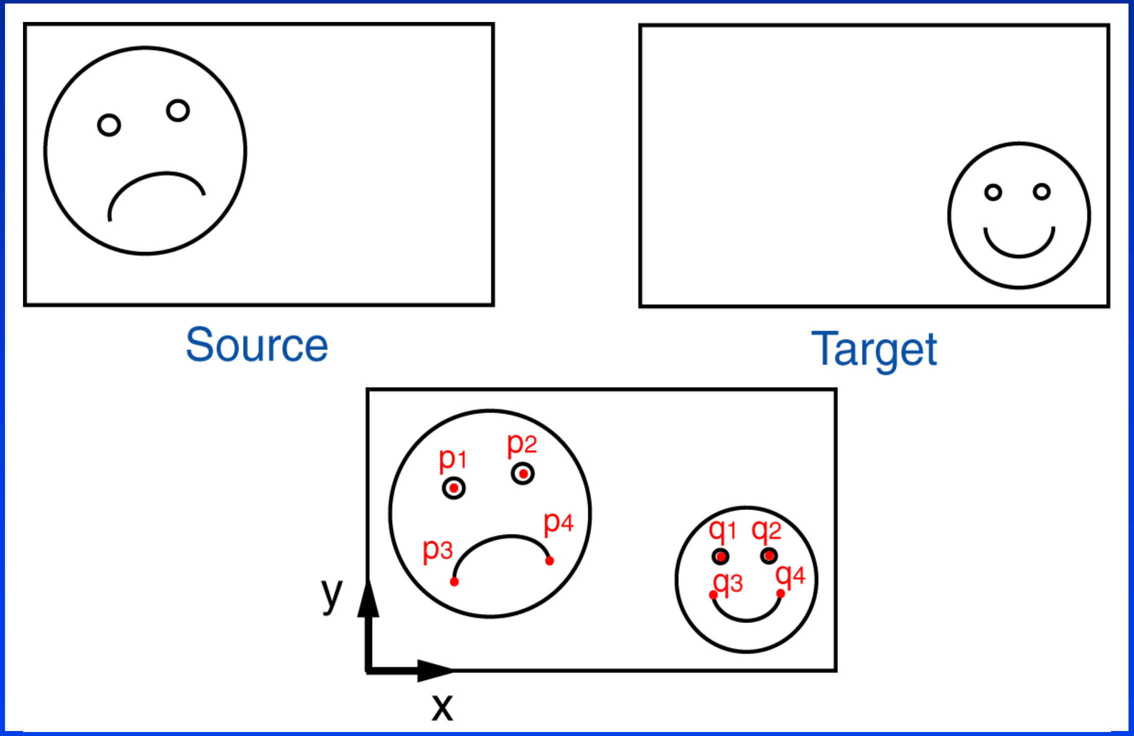
Similarity Measurement

- Geometry-based, or
- Intensity-based

Similarity Measures

- Intra-modality
  - normalized cross-correlation
  - gradient correlation
  - pattern intensity
  - sum of squared differences
- Inter-modality
  - mutual information (the industry standard)

Geometry-based Similarity Measures



Geometry-based Similarity Measures

1) Point-based similarity measures (Procrustes problem): Given 2 configurations of N points in D dimensions $P=\{p_i\}$ and $Q=\{q_i\}$ extracted from source image A and target image B, the transformed source and target images will be most similar when

   $G(T)=|T(P)-Q|^2$ is minimum. The notation is P, Q are N-by-D matrices whose rows are the coordinates of the points p_i, q_i, that correspond, and T(P) the matrix of transformed points p_i.

Geometry-based Similarity Measures

2) Surface-based similarity measure: closest point

Given 2 surfaces S_p and S_q extracted from source image A and target image B, the transformed source and target images will be most similar when $G(T)=\sum_i |T(p_i)-q_i|^2$ is minimum. The notation is $P=\{p_i\}$ is the set of points representing S_p and $Q=\{q_i\}$ is the set of points such that q_i is the closest point of p_i on S_q

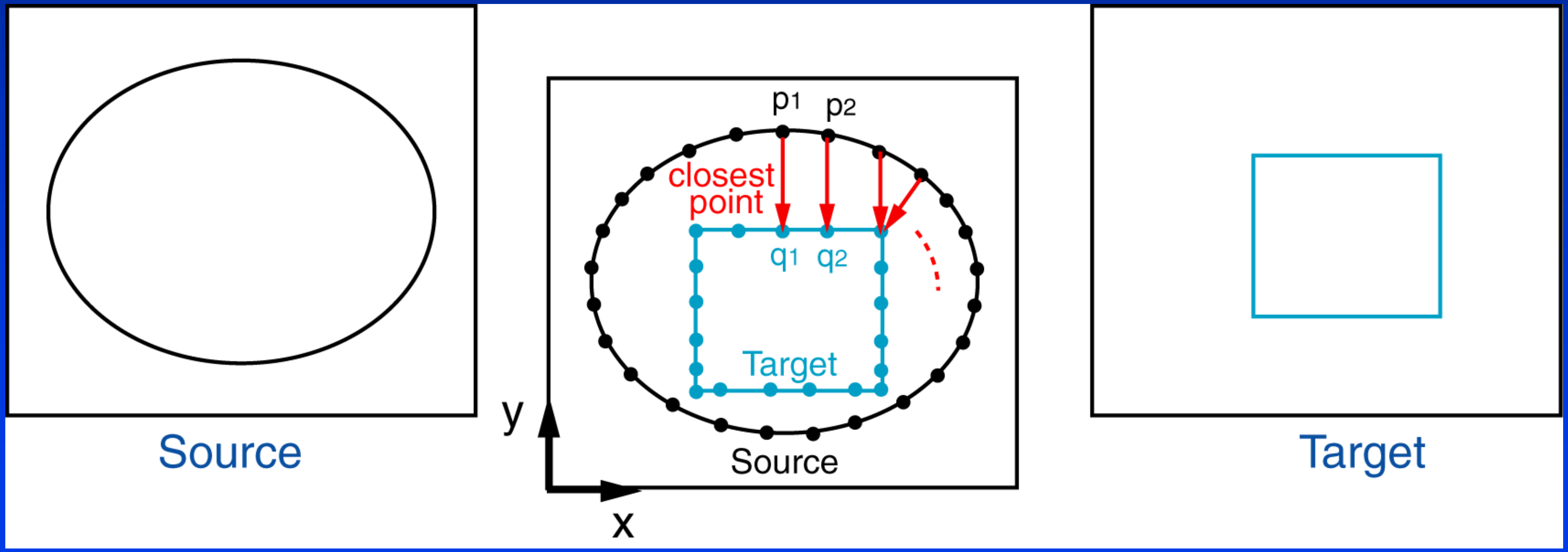
Note: A lot of other geometric-based similarity measures exist

Geometry-driven Approach

- Matches identifiable anatomical features, like points or surfaces, extracted from source and target images.

  example bifurcation of blood vessels, center of orbit of the eyes, ….

  Advantage: the use of structural information ensures that the mapping has biological validity and allows the transformation to be interpreted in terms of the underlying anatomy or physiology

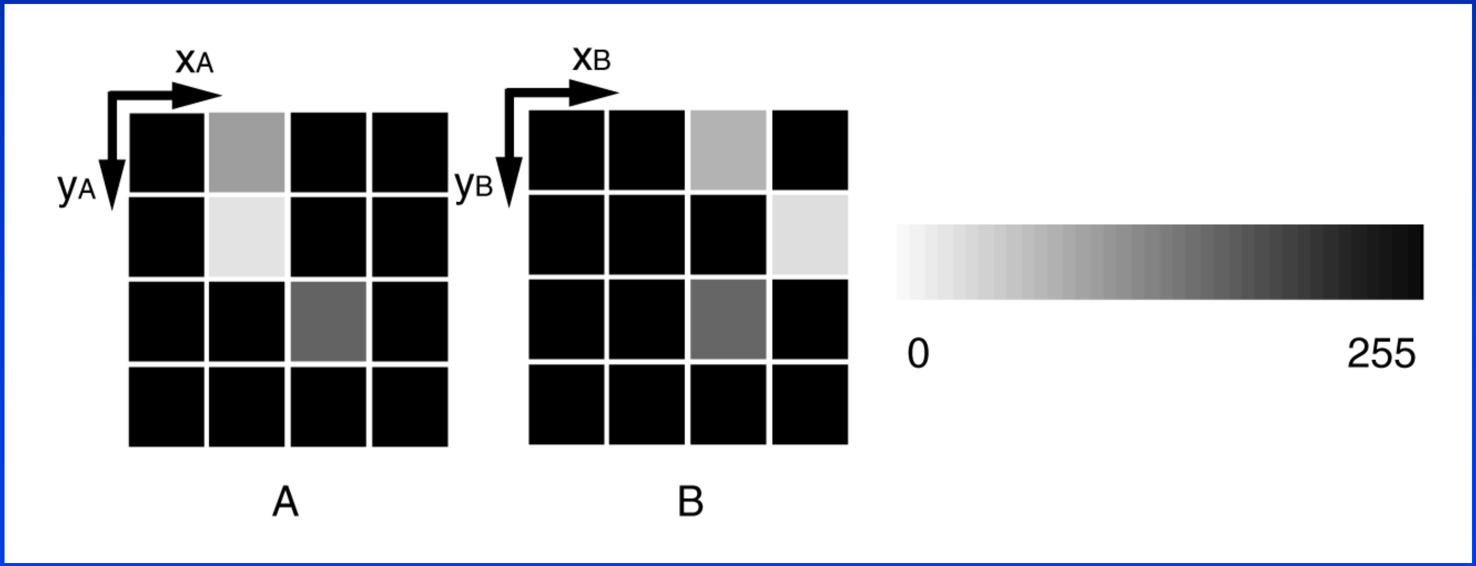

Source
y
p1
p2
closest
point
q1
q2
Target
Source
x
Target

Intensity-Driven Approach

- Matches intensity patterns in each image using mathematical or statistical criteria

Advantage: all (or a large proportion of) data is used in source

and target images


xA
yA
xB
yB
0
255
A
B

Intensity-based Similarity Measure

1) Sum of square intensity difference (SSD)

Given the voxel location $\underline{x}_B$ of the target image B, and the overlapping domain Ω, comprising N voxels, between the transformed source image and target image, these two images will be most similar when

$$SSD=(1/N) \sum_{\underline{x}_B \in \Omega} |T(A(\underline{x}_B))-B(\underline{x}_B)|^2 \text{ is minimum}$$

where $A(\underline{x}_B)$ and $B(\underline{x}_B)$ are the intensity value of respectively image A and B at the voxel location $\underline{x}_B$

Intensity-based similarity measure (Cross Correlation)

With the same notation than for SSD, the transformed source image and target image will be most similar when

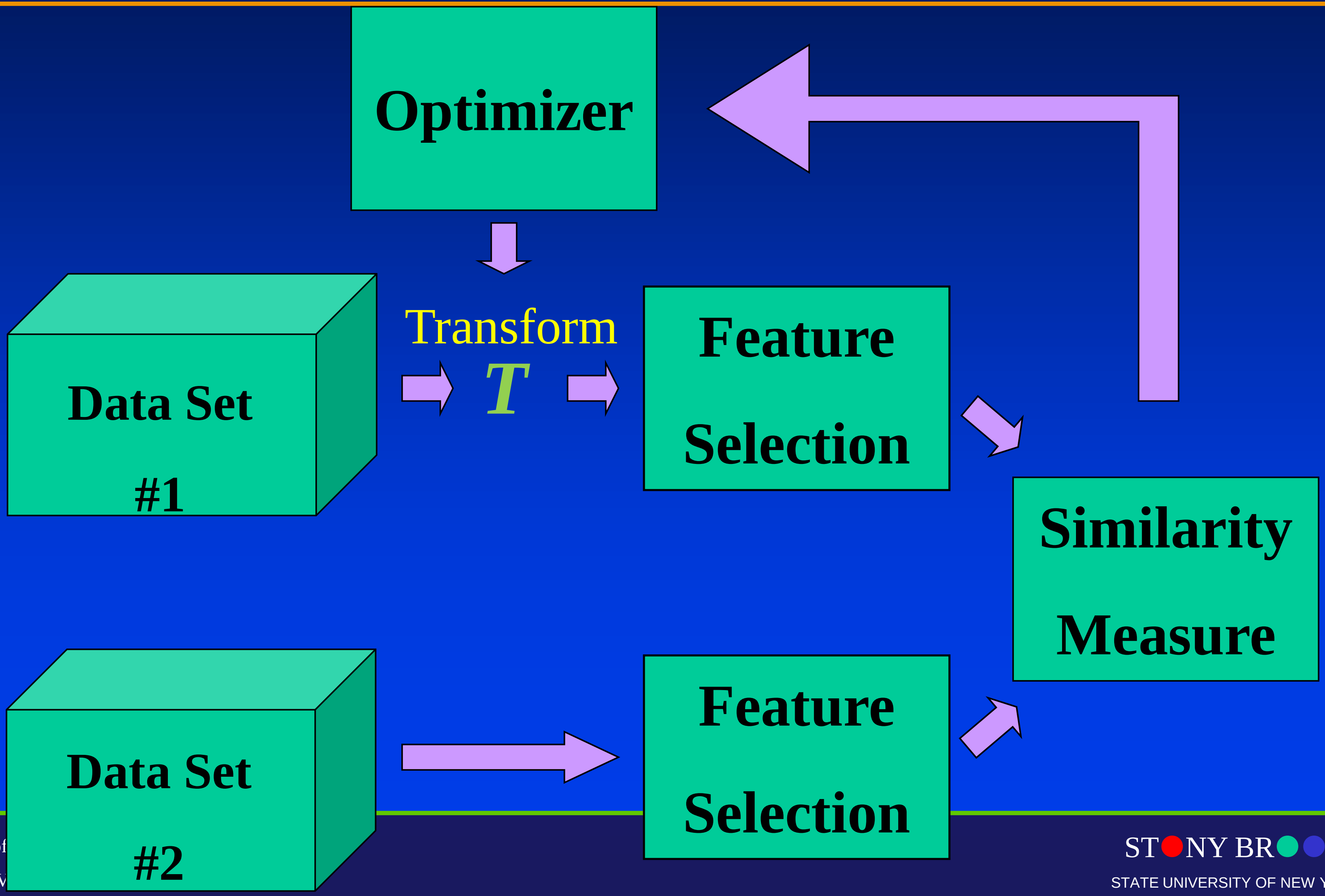
$$CC = \frac{\sum_{x_B \in \Omega} (B(x_B) - \overline{B}) \cdot (T(A(x_B)) - \overline{A})}{\sum_{x_B \in \Omega} (B(x_B) - \overline{B})^2 \cdot \sum_{x_B \in \Omega} (T(A(x_B)) - \overline{A})^2}$$

is maximum

where $\overline{A}$ ($\overline{B}$) are the mean voxel value in image A (B) within Ω

Note: SSD and CC are 2 similarity measures that are suitable for monomodal registration where intensity characteristics are very similar in the images. For multimodal registration, similarity measures have been developed, such as correlation ratio or mutual information, which define weaker relationships between intensities

Multi-modal Registration



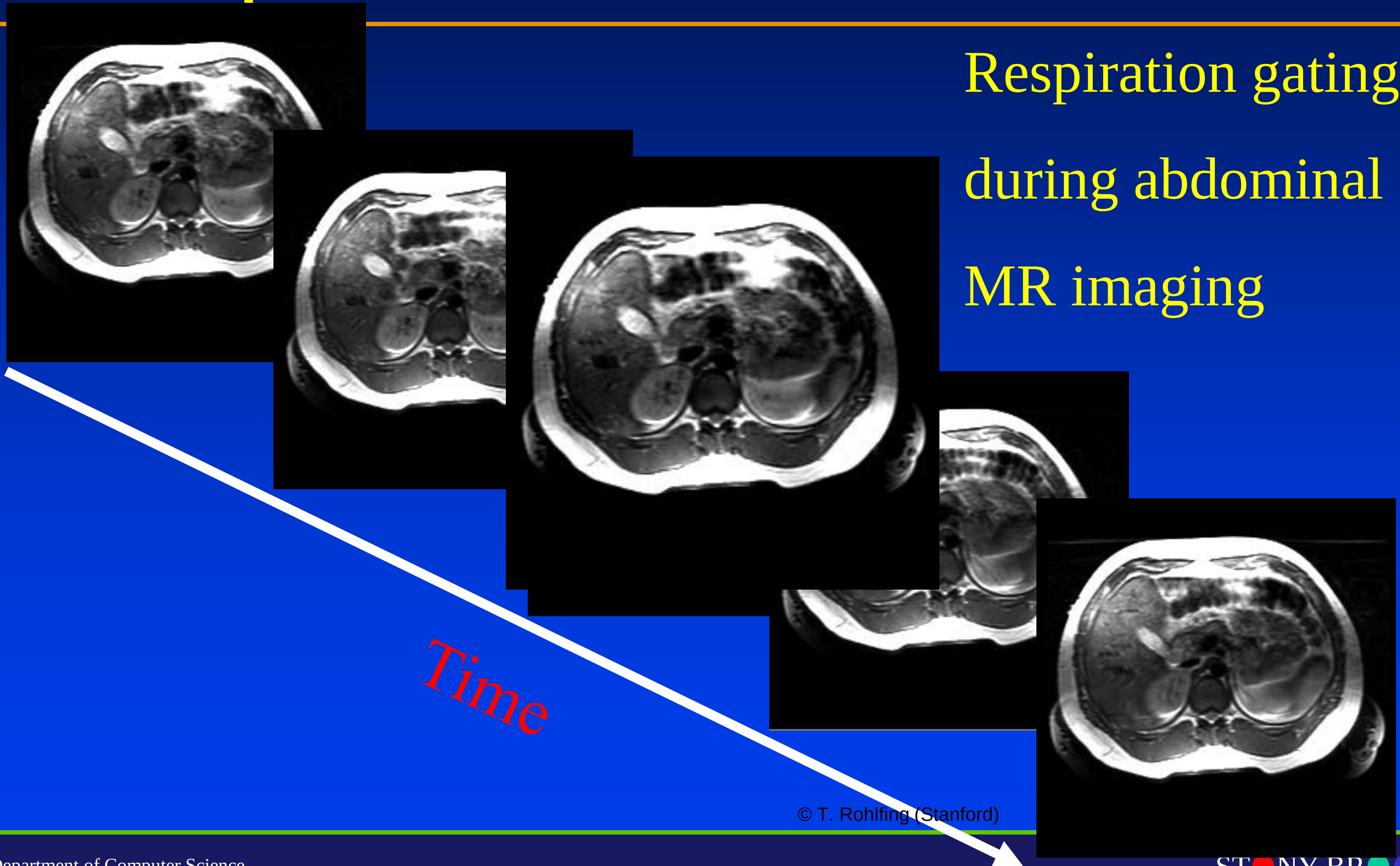
Example of Optimization: Iterative Closest Point (ICP)

- Hypothesis:
  - Similarity measure:
    Procrustes problem
    $G(T)=|T(P)-Q|^2$ is minimum
  - Rigid transformation
- Solution:

Iteration

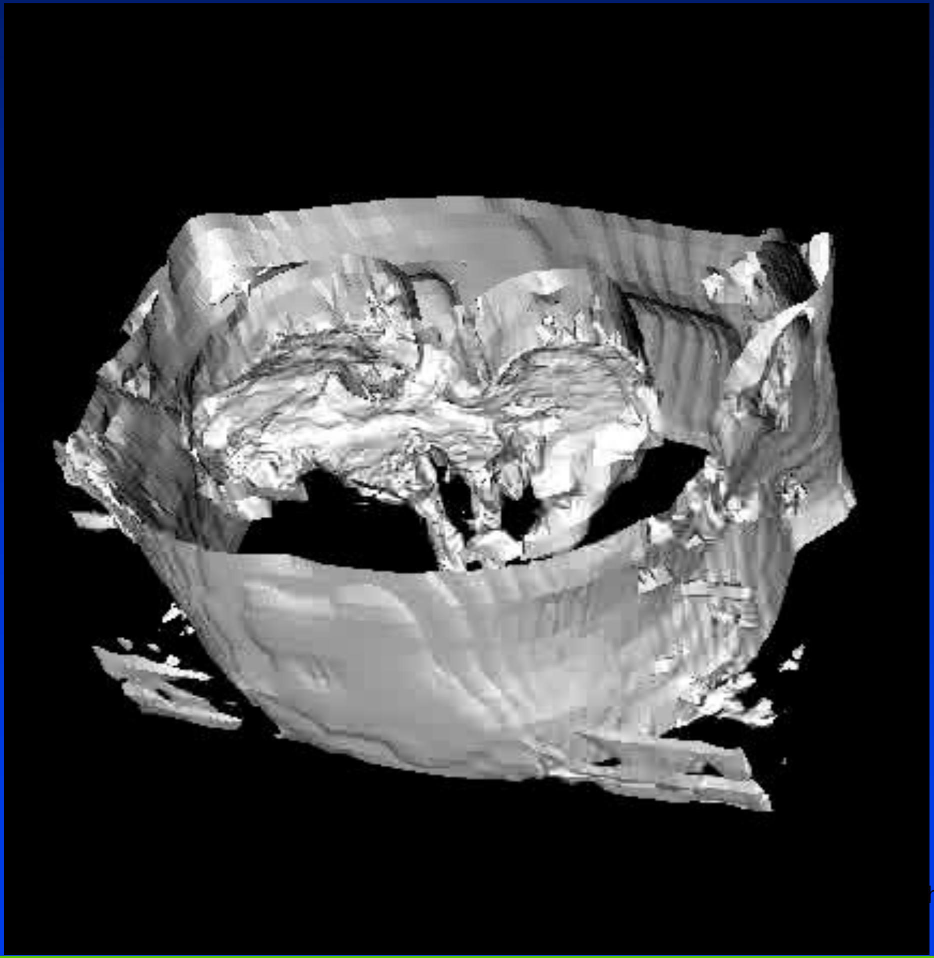
1) - Computation of the centroid of each set of points
   - Translation (= difference of centroid position) is applied
2) - Computation of the sum of square distances between each corresponding point pair
   - Rotation to apply is the one mimizing this value. It is computed with the method of Singular Value Decomposition

Example: Liver Motion



Respiration gating during abdominal MR imaging

Example: Liver Motion



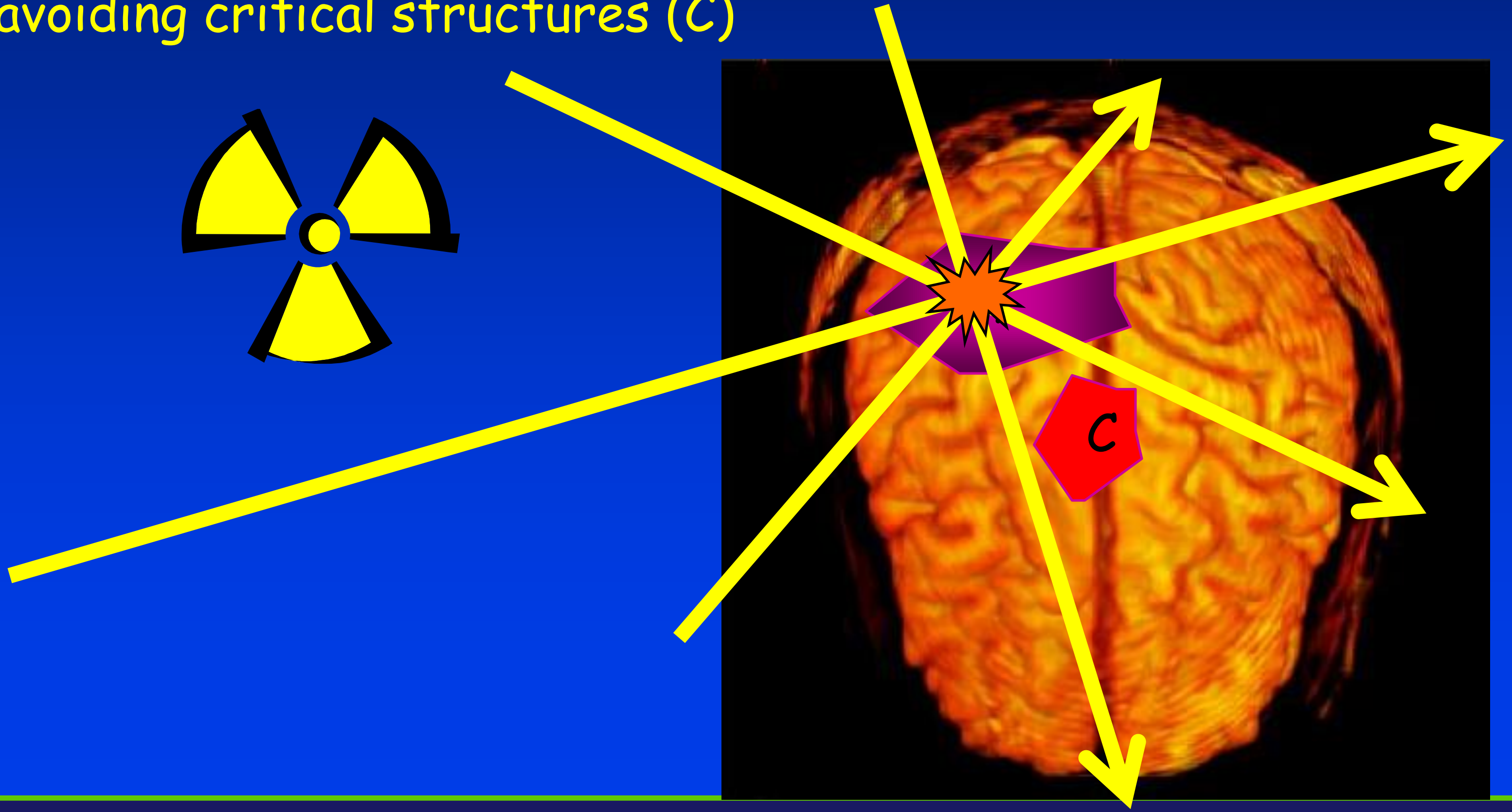
hlfing (Stanford)

Applications

- What do we gain with multi-modal registration?

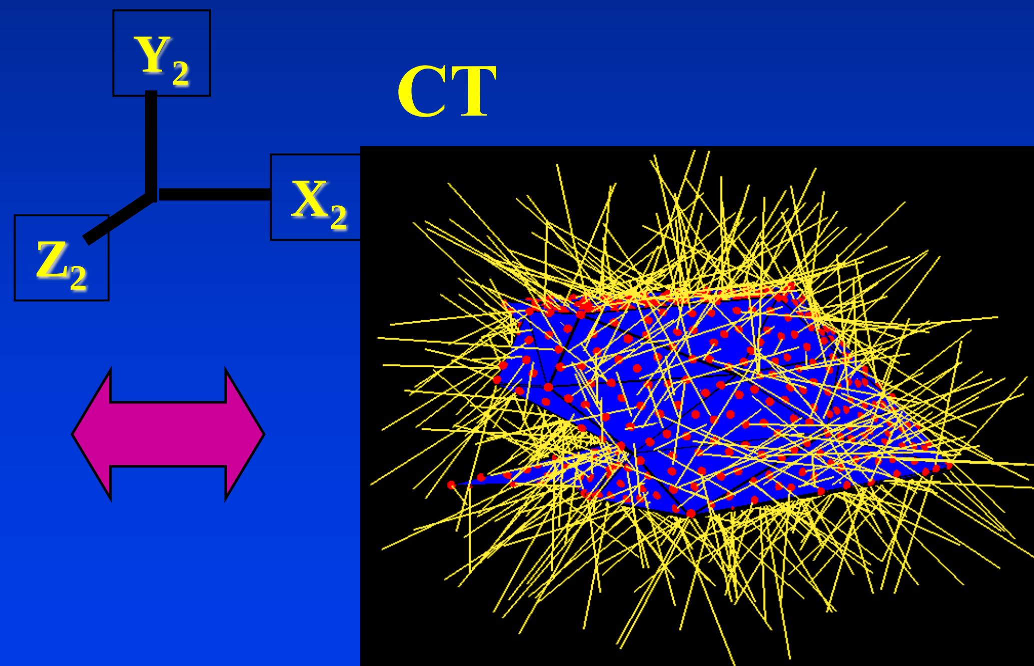
Example: CyberKnife

Irradiate tumor (T) with a series of directed beams avoiding critical structures (C)



Example: CyberKnife

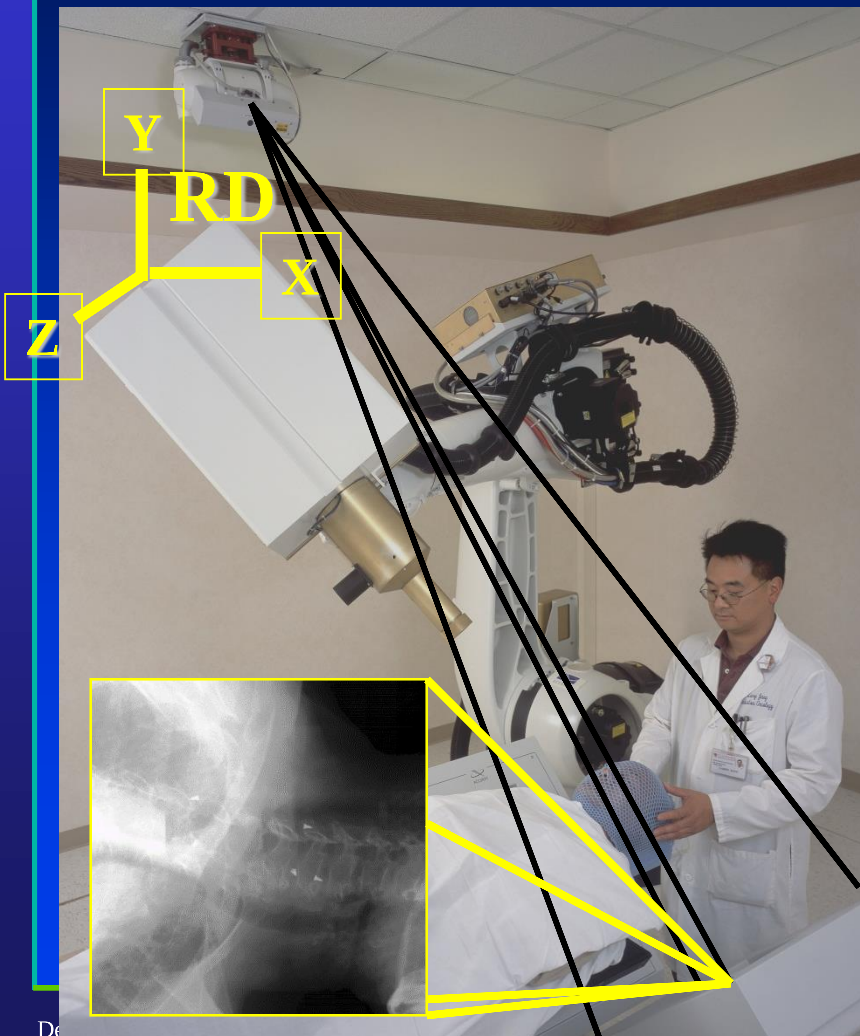
The crux of the problem is to match up the coordinate frames of the CT and the radiation delivery device

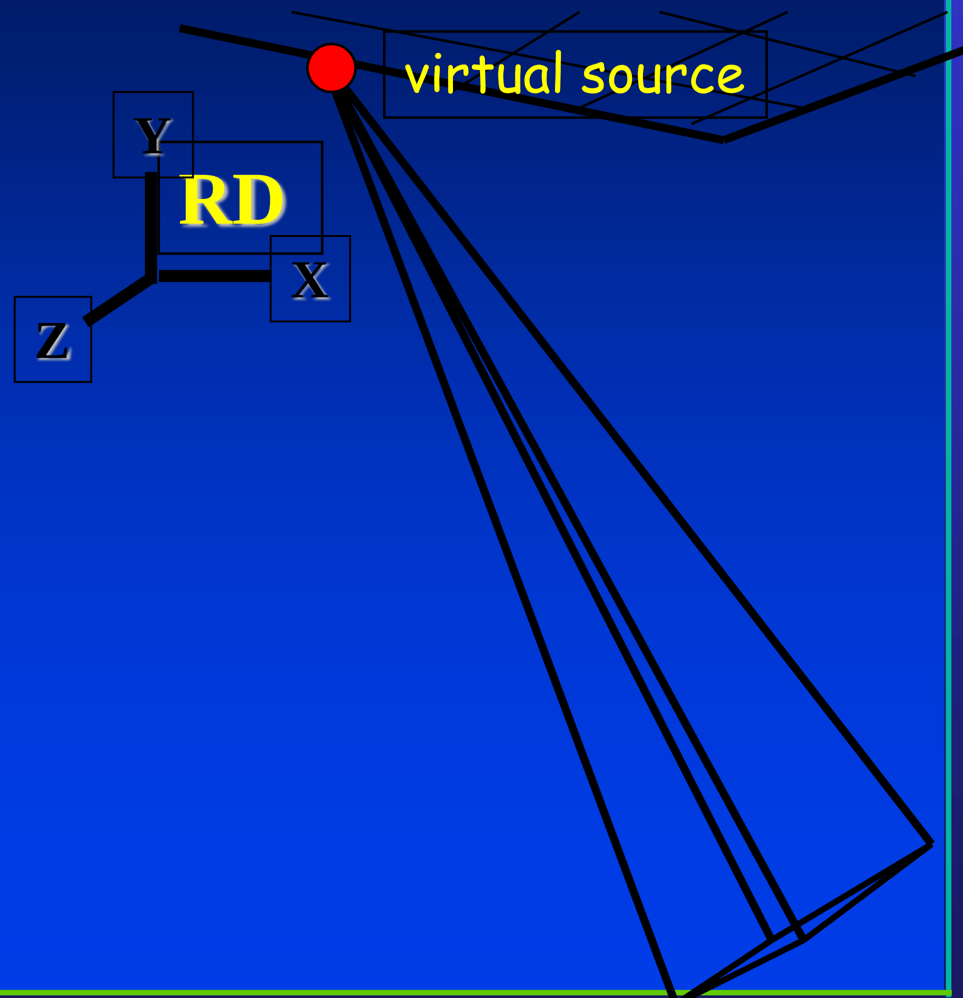


Example: CyberKnife

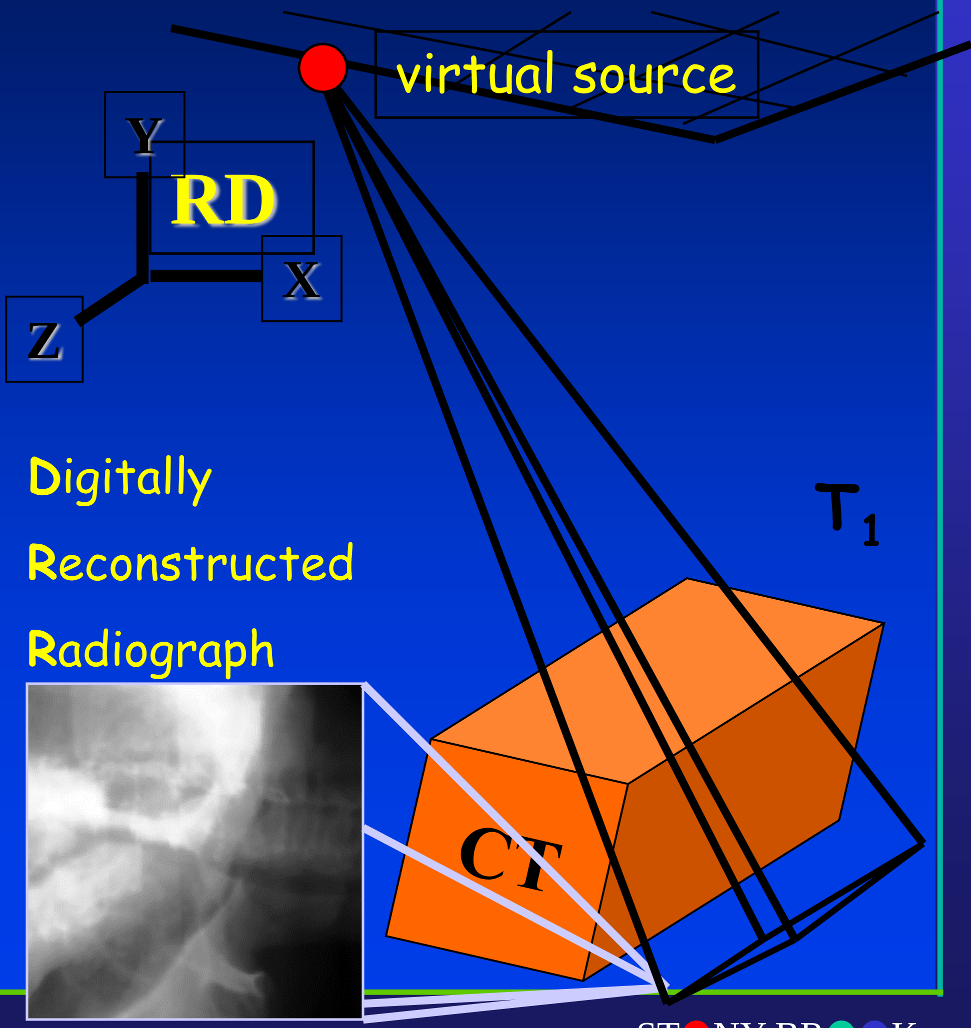
Using only 2D projection images!

Example: CyberKnife

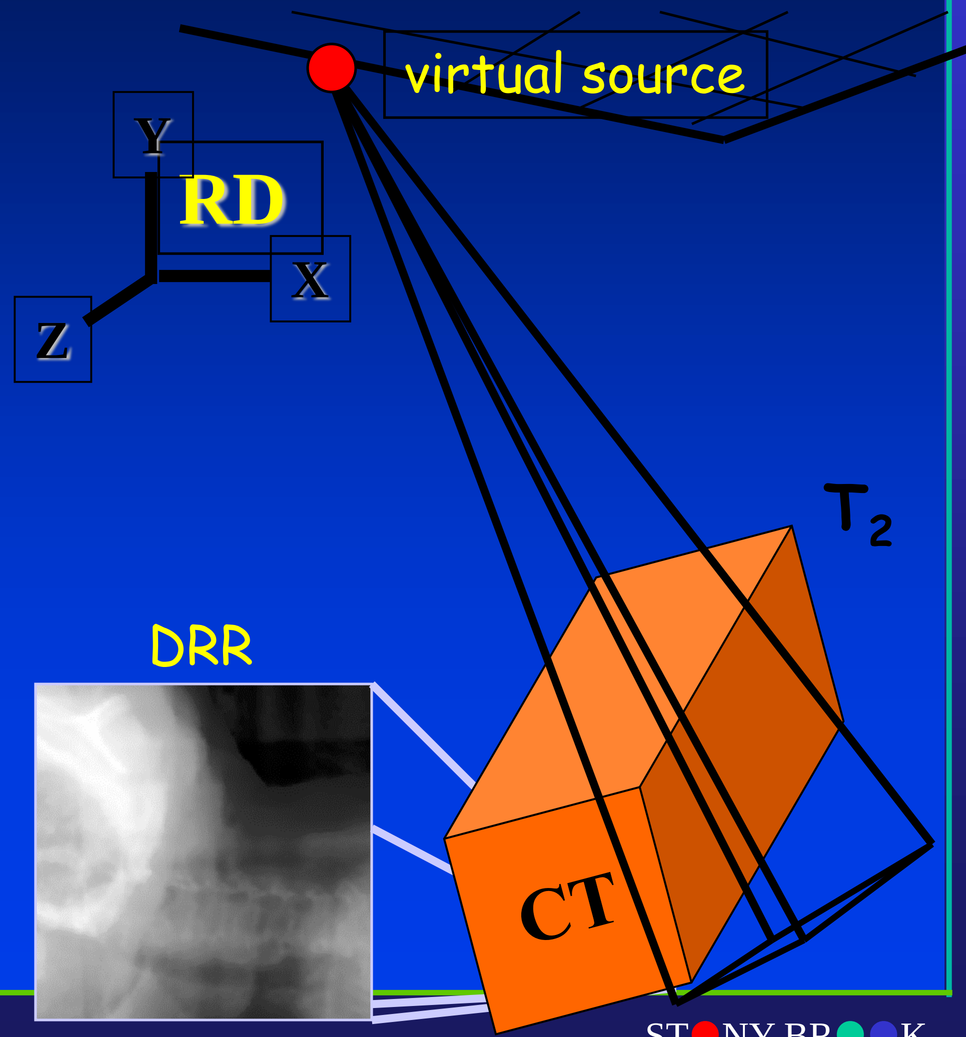




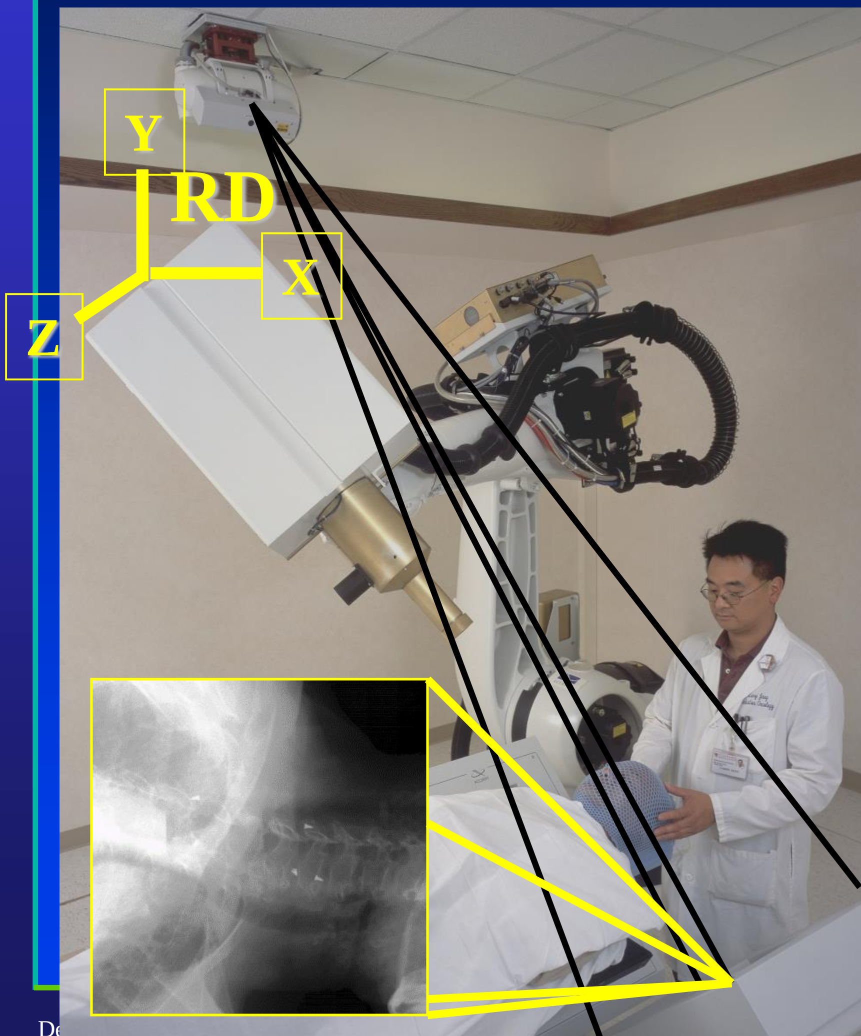
Example: CyberKnife



Example: CyberKnife



Example: CyberKnife



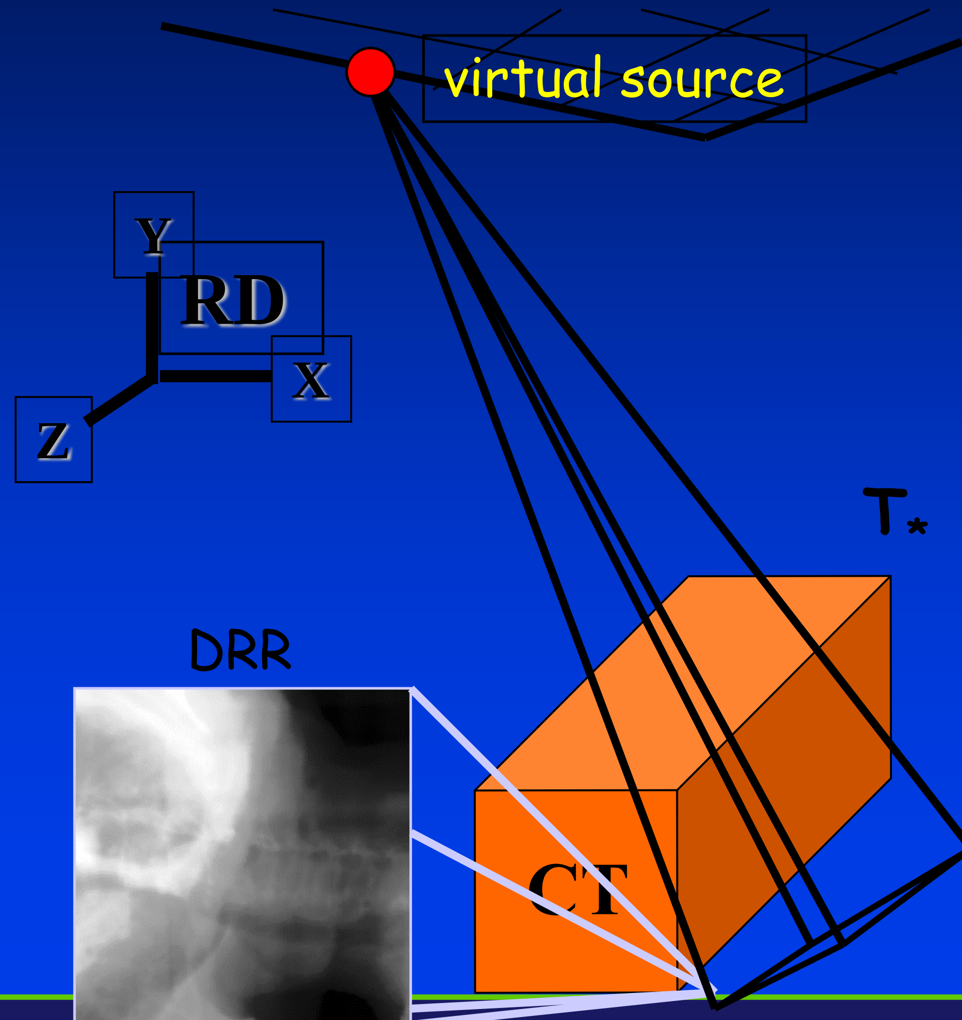


Image Registration Application to Image-guided neurosurgery

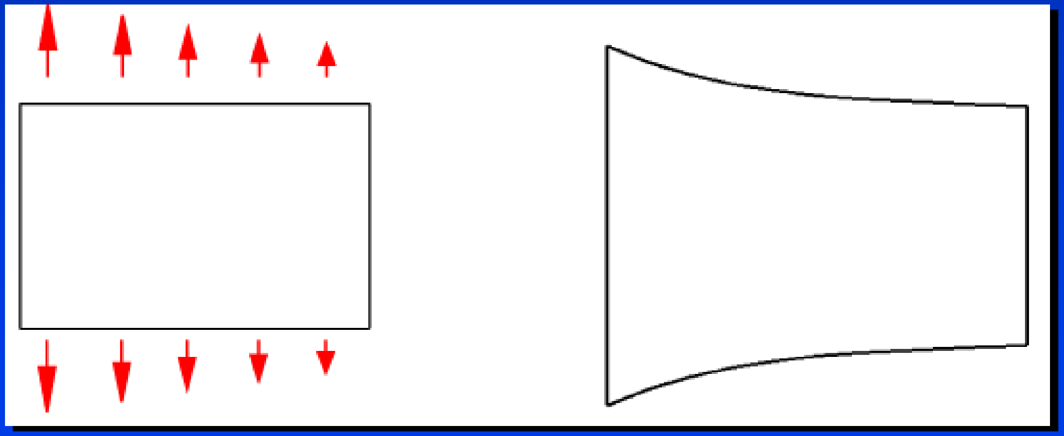
Nonrigid transformation: Example of deformable mechanical model

As seen before, T controls how image features can be moved, such as translations, rotations for rigid transformation. For T based on deformable mechanical model, we decide the objects, and image features to register, which can be moved accordingly to mechanics laws.

Solution ?

Find the displacement field which minimize the total deformation energy of the object

Little problem in mechanics…



Steps of nonrigid registration based on a deformable mechanical model

Characteristic of this algorithm of nonrigid registration: the transformation used to control the similarity criterion is different from the tranformation used to interpolate the deformation to the entire object. So this algorithm can be seen as 2 nonrigid registrations (surface and volume)

Steps of nonrigid registration based on a deformable mechanical model

1) Computation of the "controlling transformation"

based on a surface similarity criterion

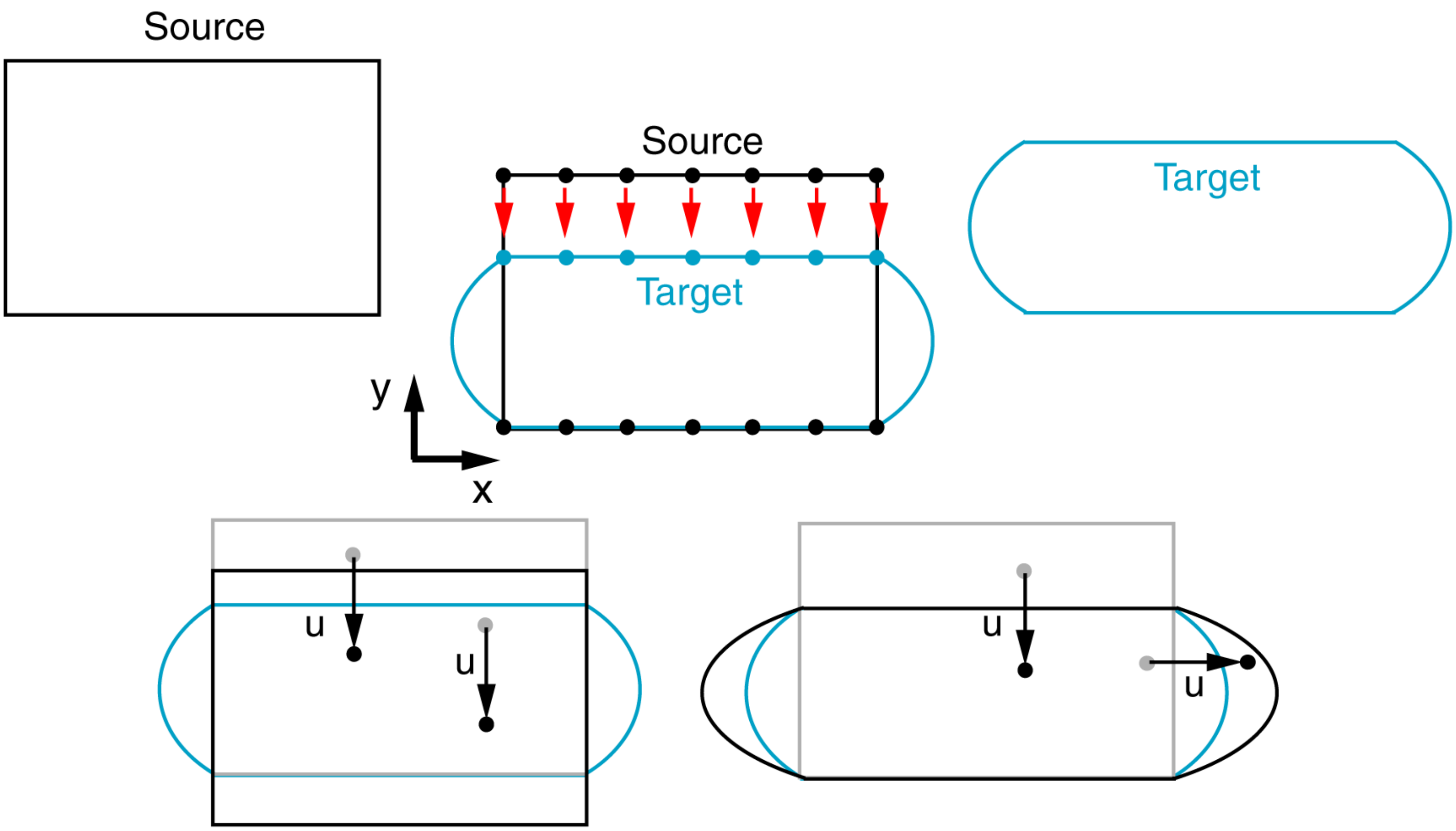
- Extraction of brain, ventricles, and tumor surfaces
- Computation of surface transformation

2) Computation of the "interpolating transformation"

based on a deformable mechanical model

- Building of the model
- Computation of volume transformation

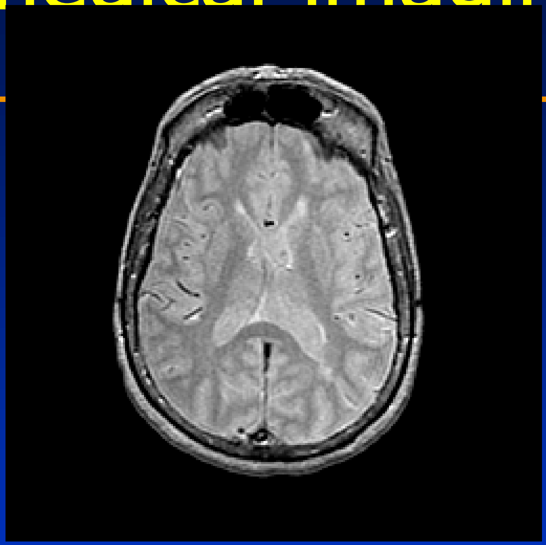
Deformable Bio-mechanical Model



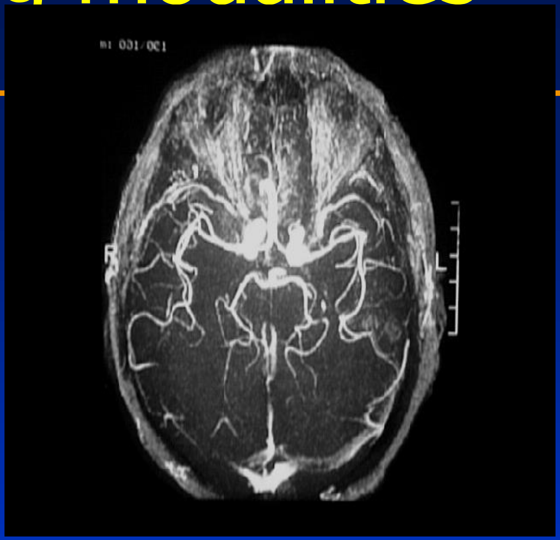
Rigid transformation T
displacement u:
translation and rotation

Nonrigid transformation T
displacement u :
deformable energy is minimum

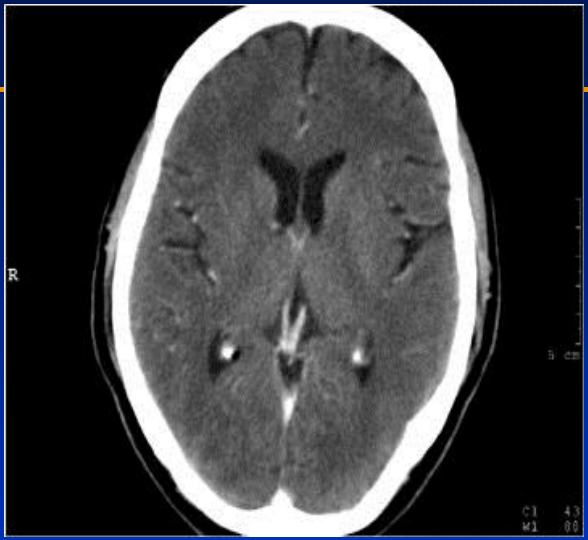
Surgery is planned on multiple medical-imaging modalities



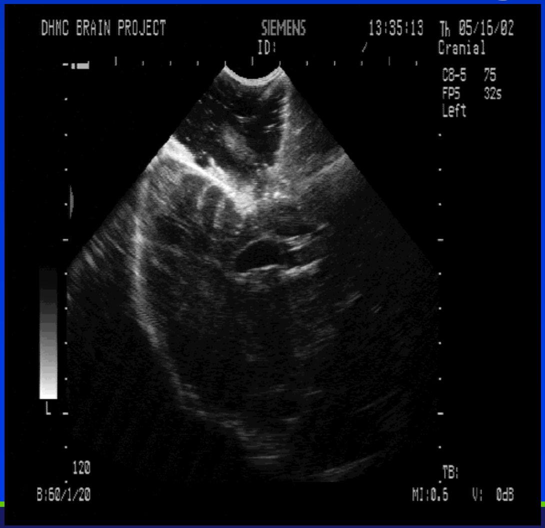
MRI



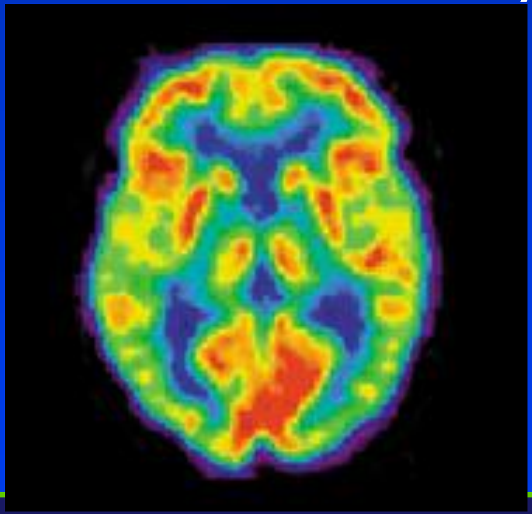
Angiography



X-rays CT



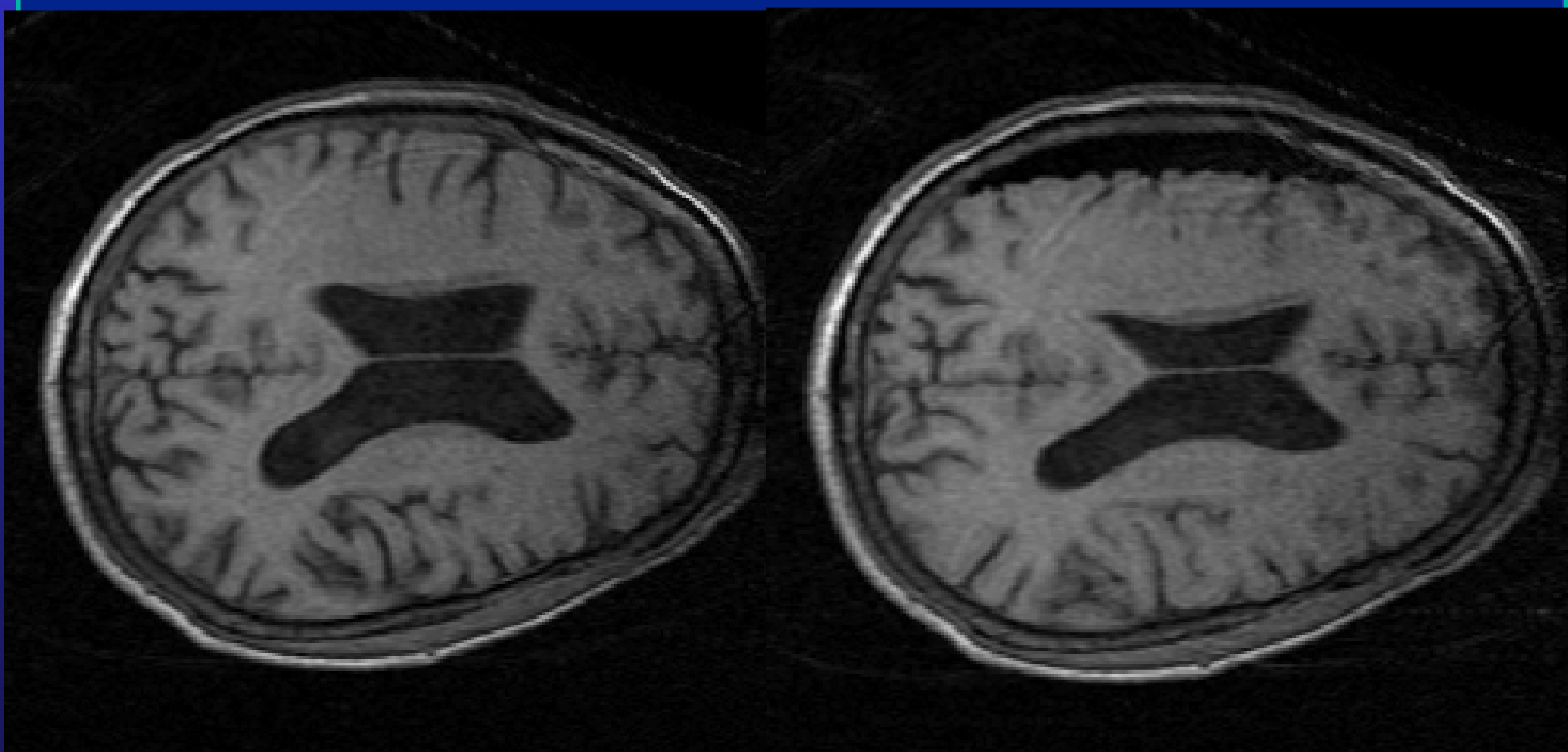
Ultrasound



PET

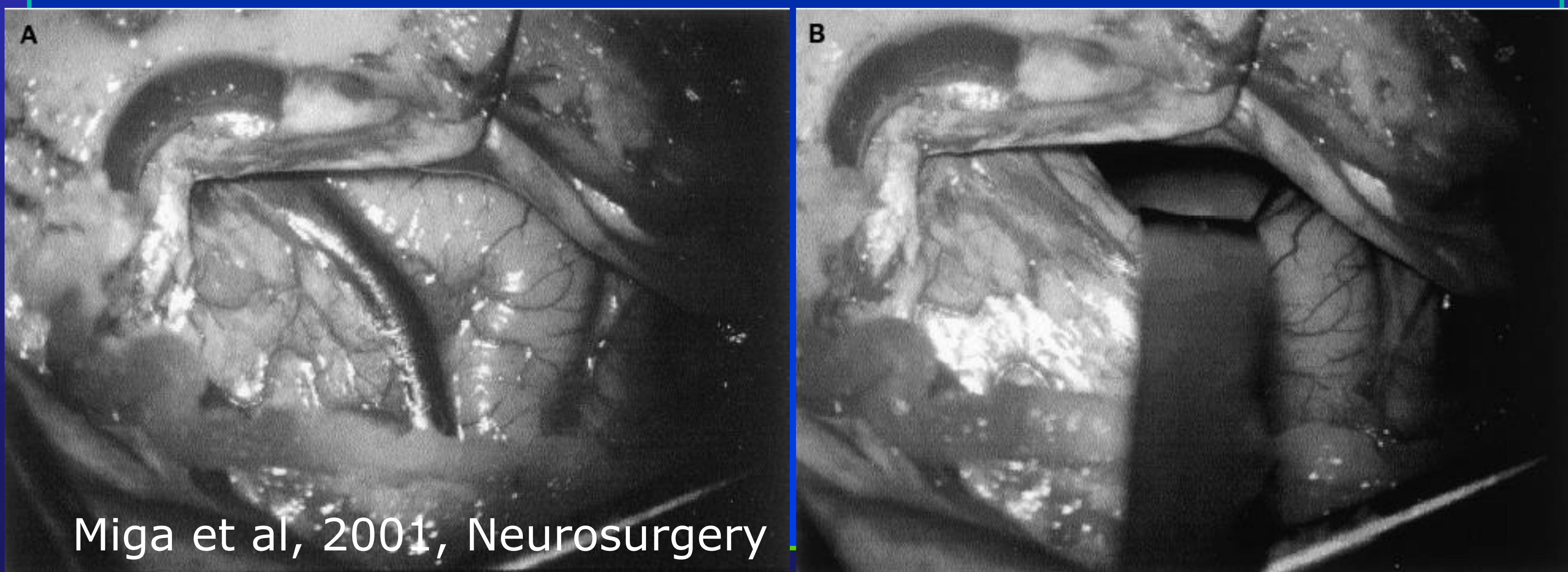
Brain Deformation during Surgery

- Skull Opening



Brain Deformation during Surgery

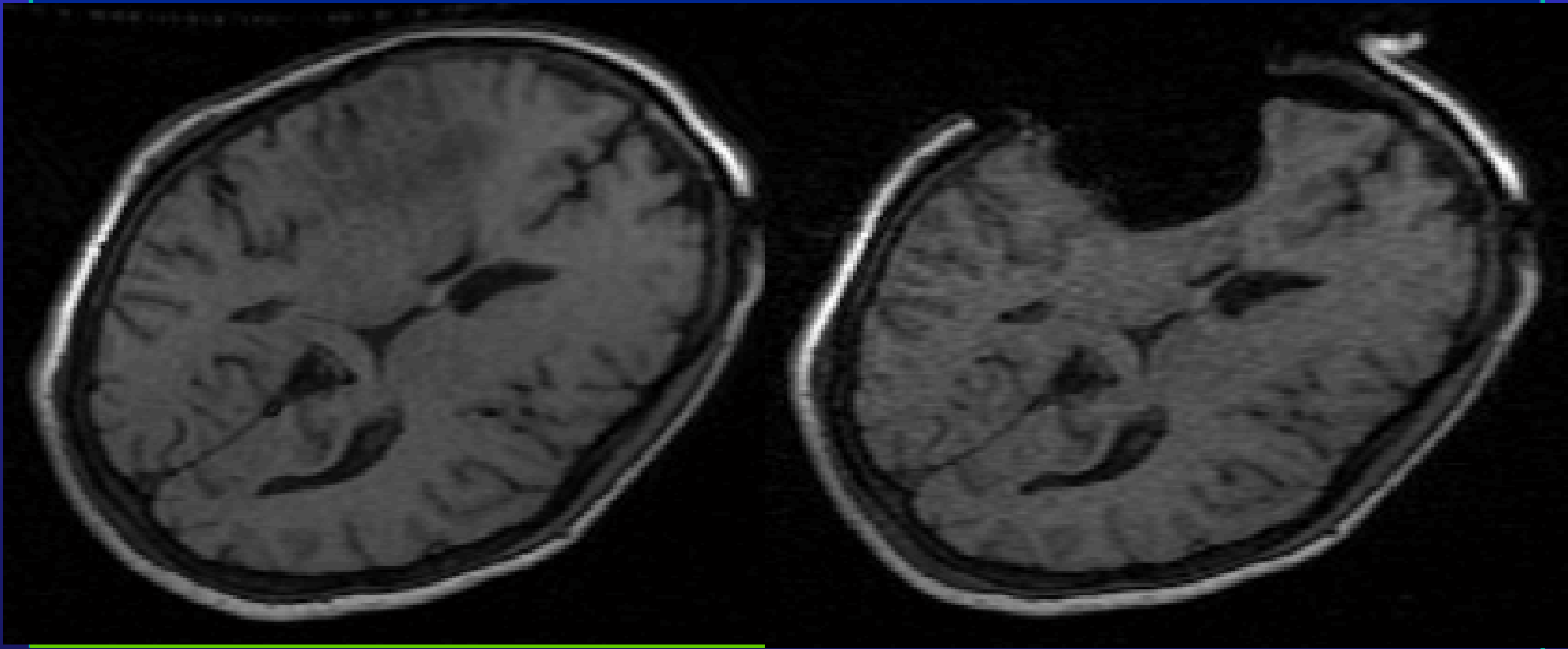
- Retractor insertion



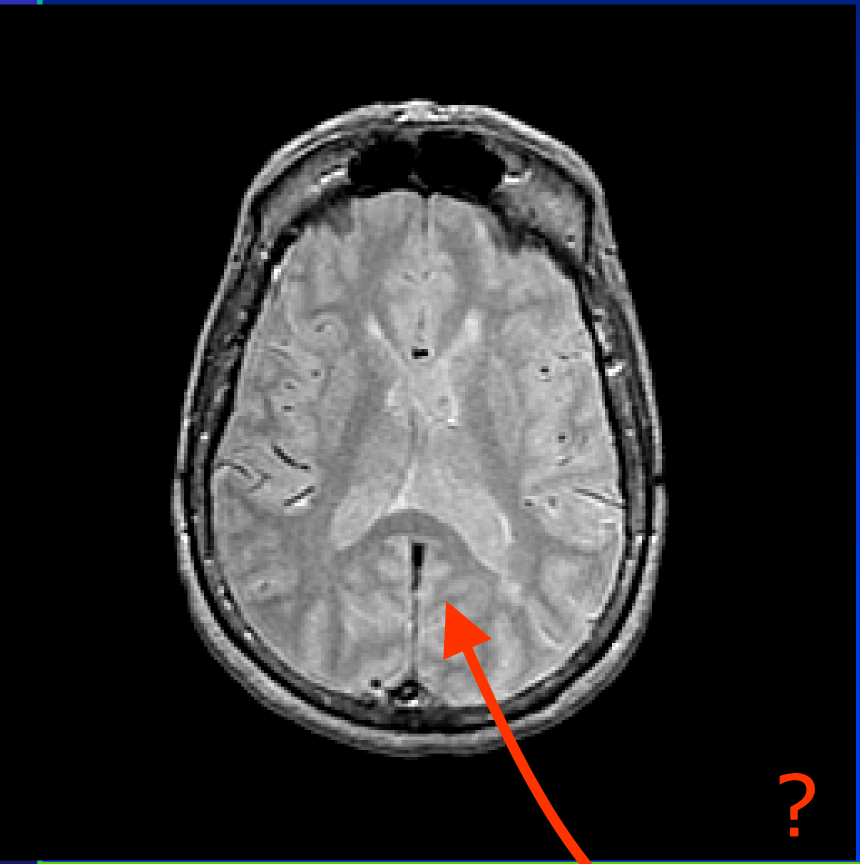
Miga et al, 2001, Neurosurgery

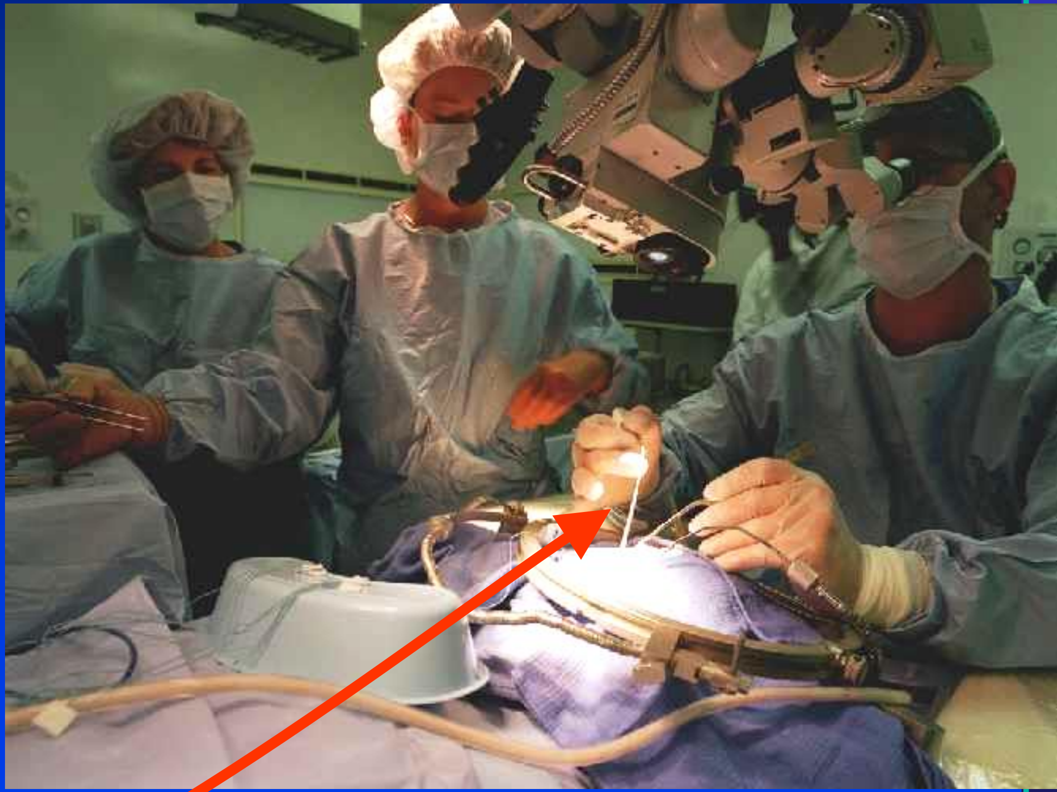
Brain Deforms during Surgery

- Tumor resection



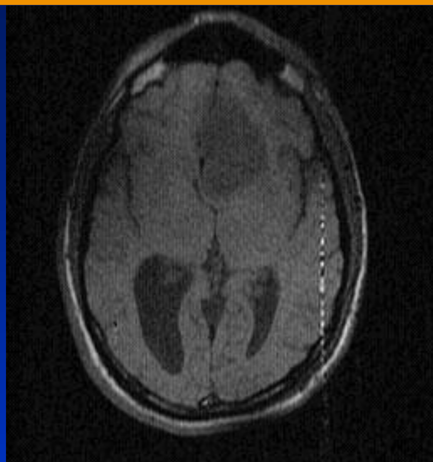
Preoperative images are no longer representative during surgery





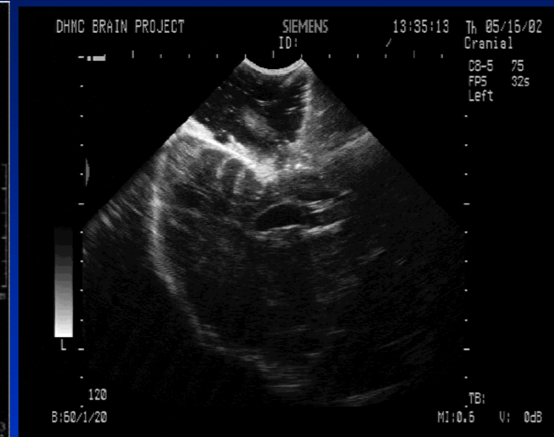
Only a few intraoperative modalities are available and can be acquired in real-time

So far:



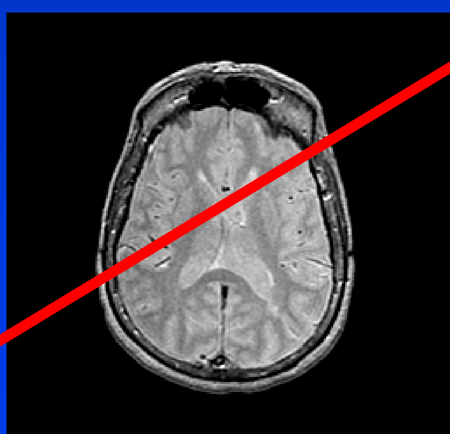
Low-res MRI

X-rays CT

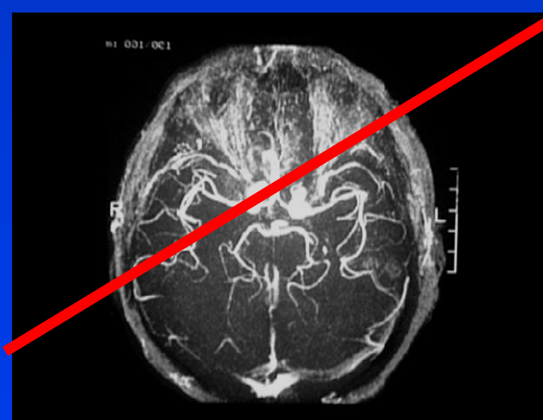


Ultrasound

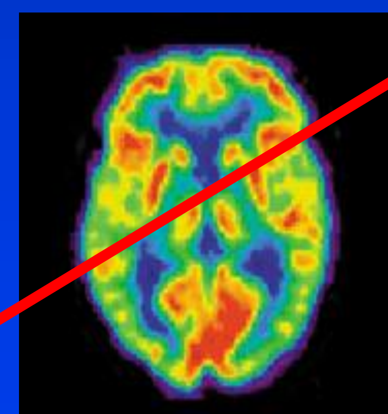
...



High-res MRI



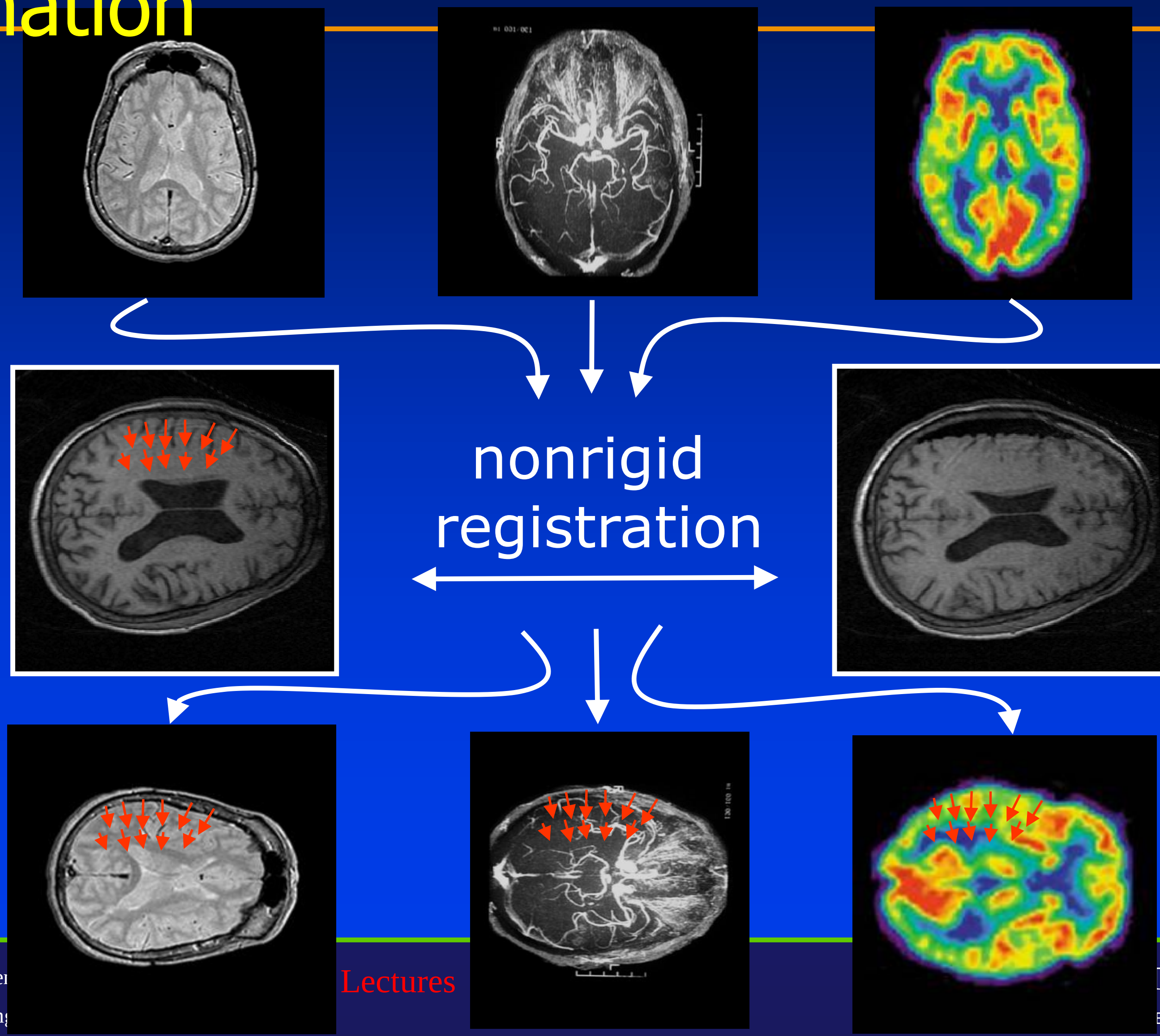
Angiography



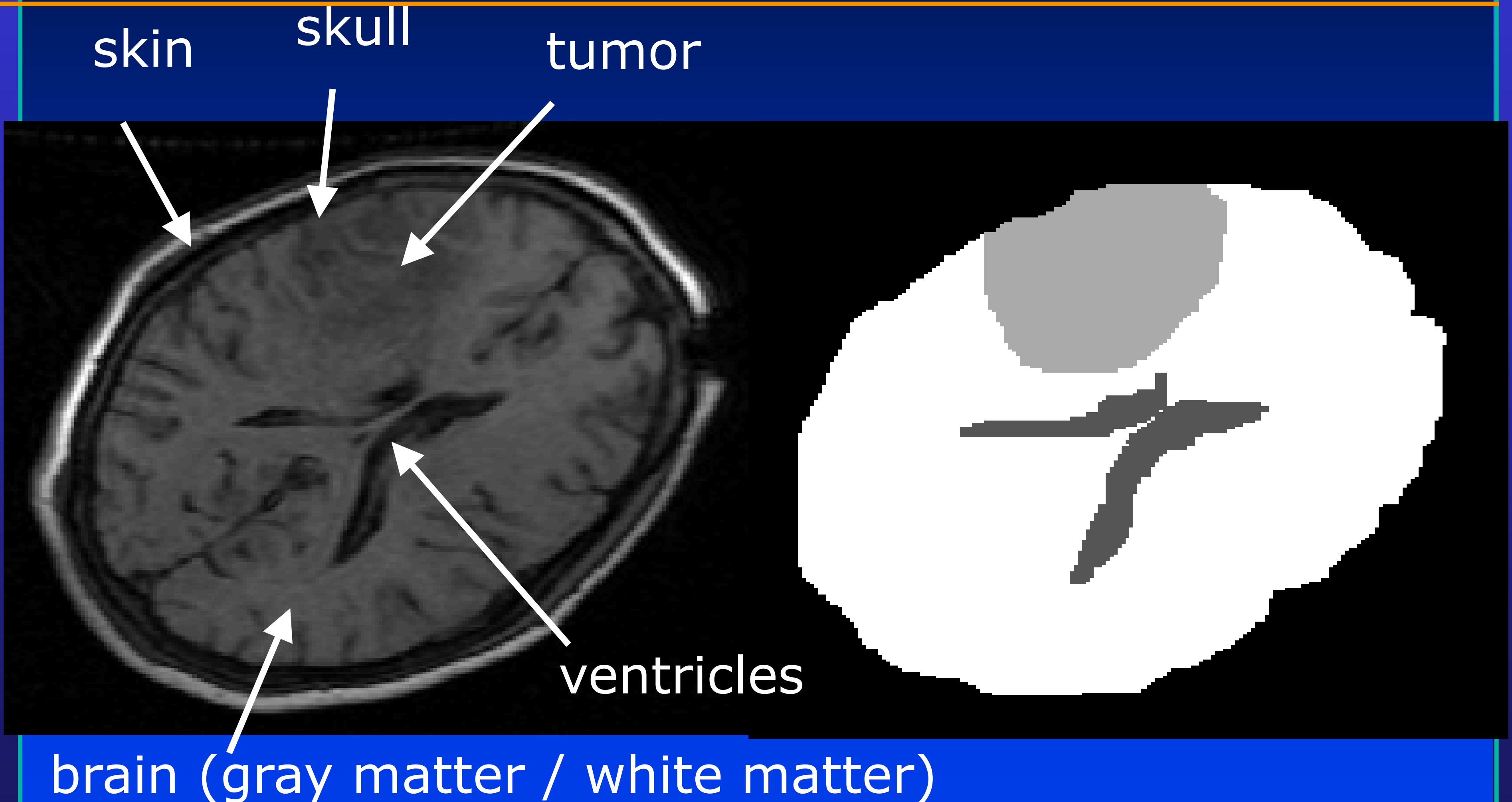
PET

...

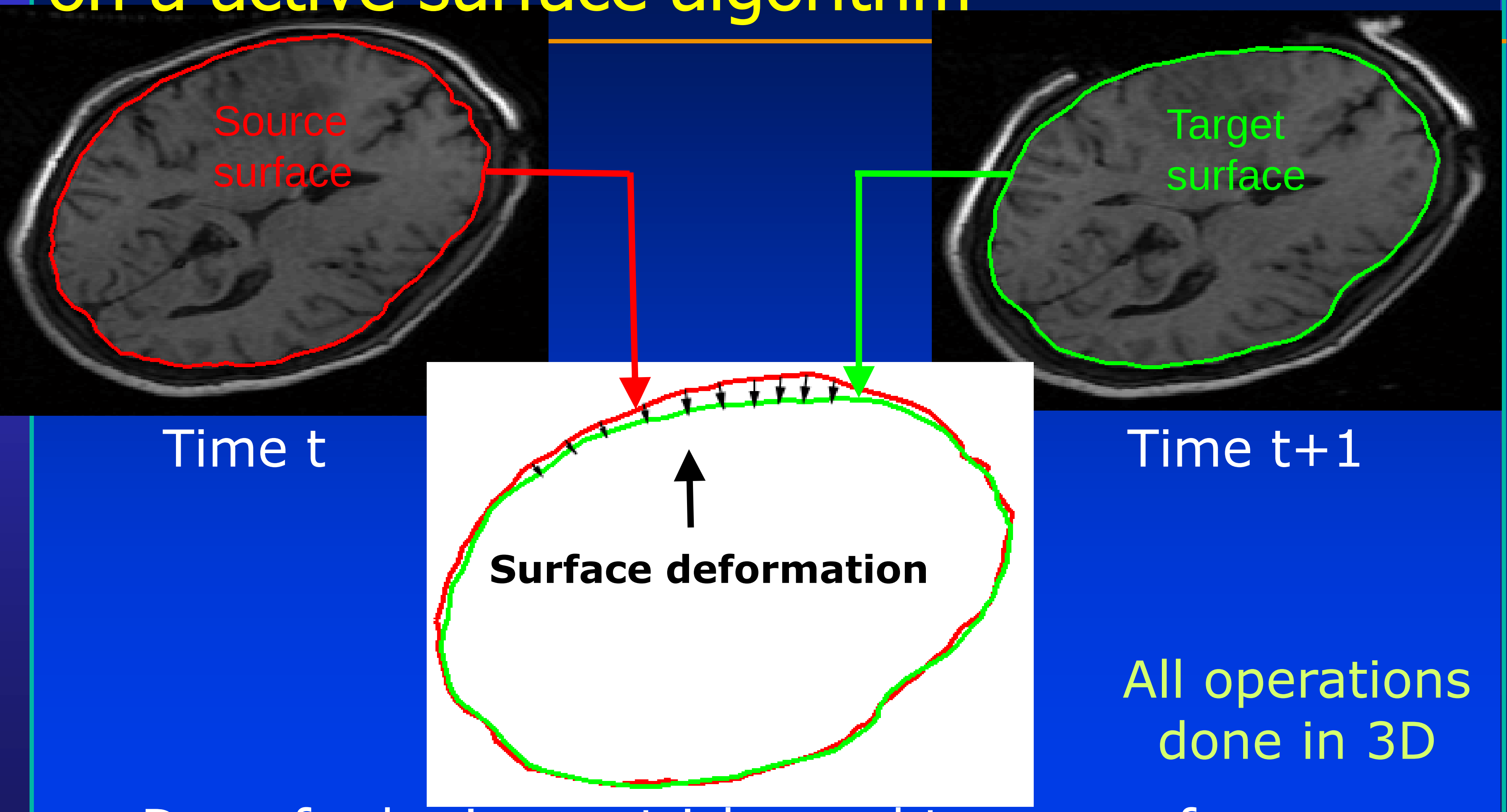
How to bring the most information together? Update preop imagery with intraoperative deformation



Extraction of brain, ventricles, and tumor surfaces is done by segmentation



Computation of surface transformation based on a active surface algorithm



Time t

Time t+1

All operations done in 3D

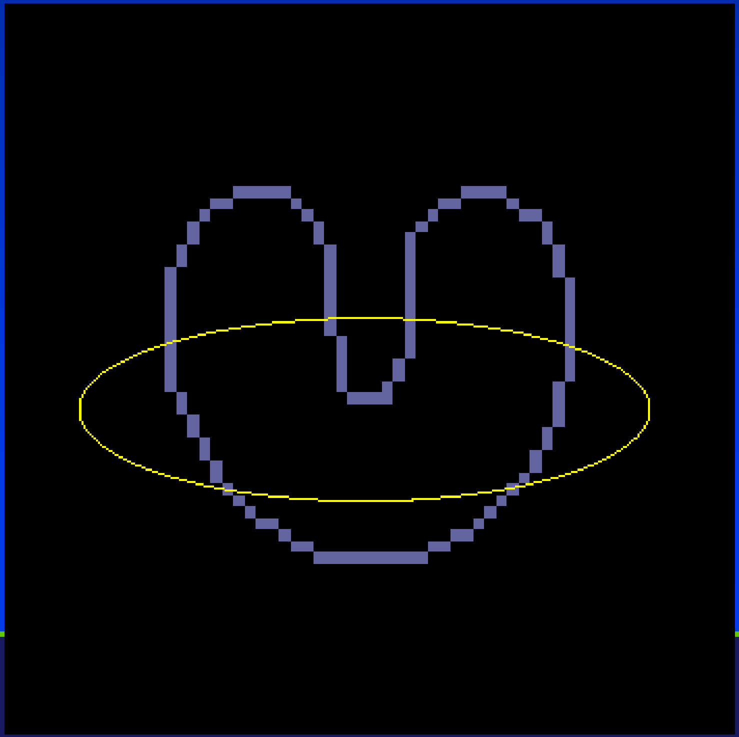
Done for brain, ventricles and tumor surfaces

Computation of surface transformation based on an active surface algorithm

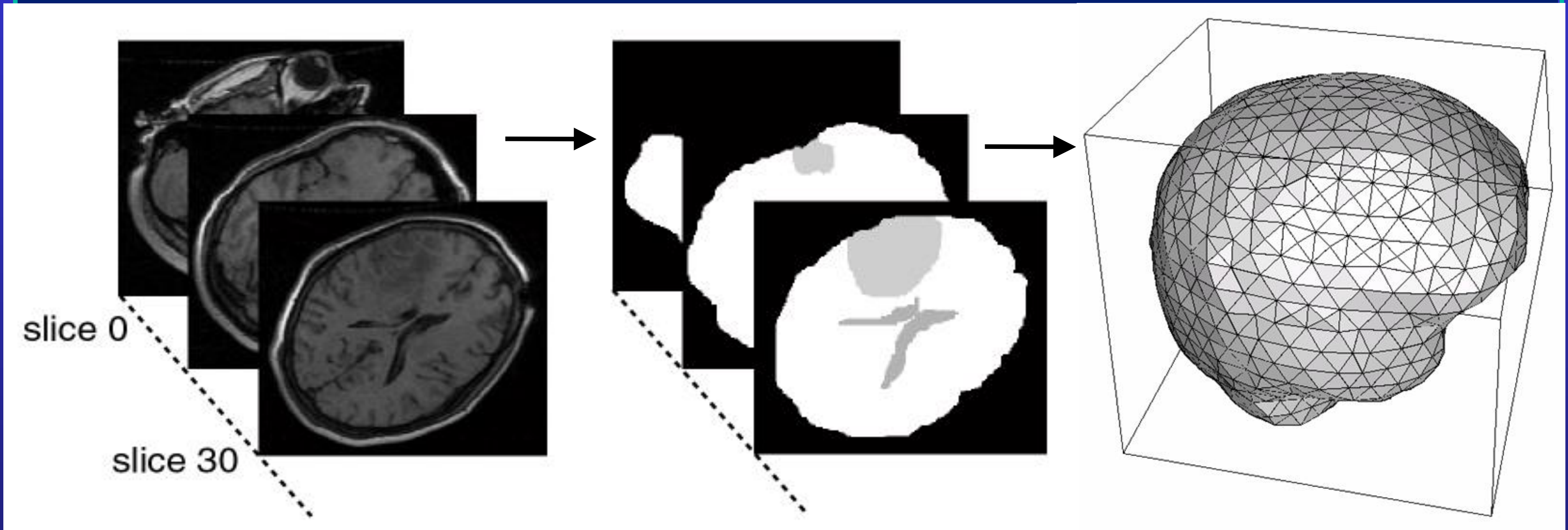
Active surface algorithm: trade-off between

- Constraints of smoothness on surface shape

- Attraction of source surface by target surface



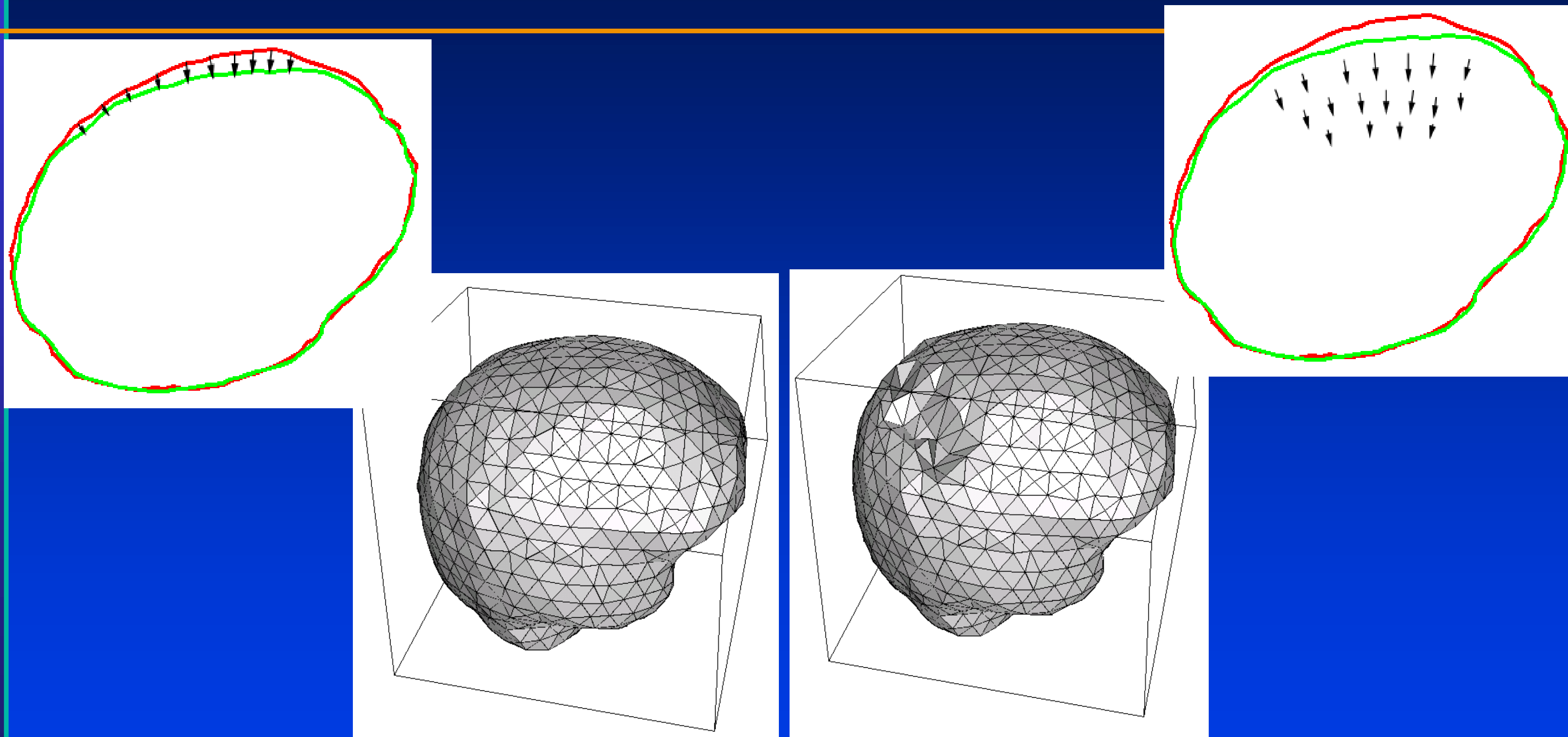
From Data Scans to Volumetric Meshes



Behavior law for deformable bio-mechanical models: linear elastic, etc…

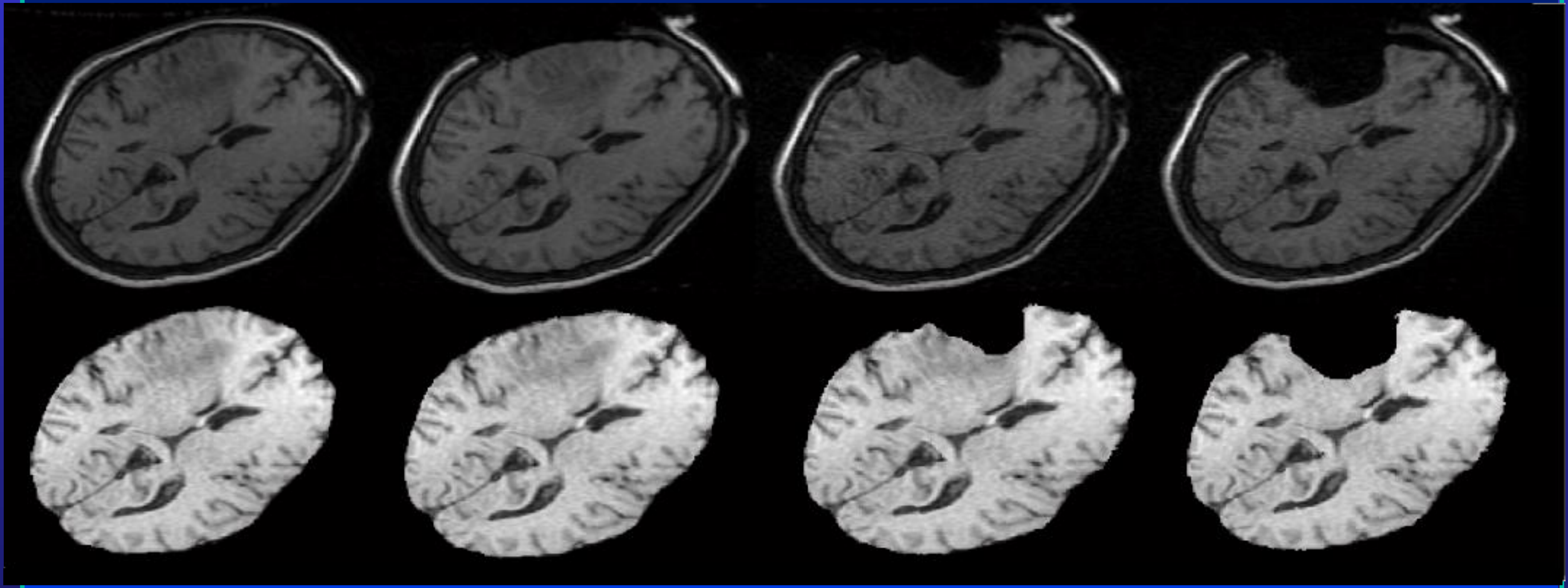
Reminder: the transformation T is such that the deformable energy is minimum

Deformable Bio-Mechanical Model



The calculation is based on Finite Element Method (FEM) for bio-mechanical model, such that the surface deformation leads to nonrigid registration for the volume.

Results



Computer-aided Detection

- Computer-aided diagnosis

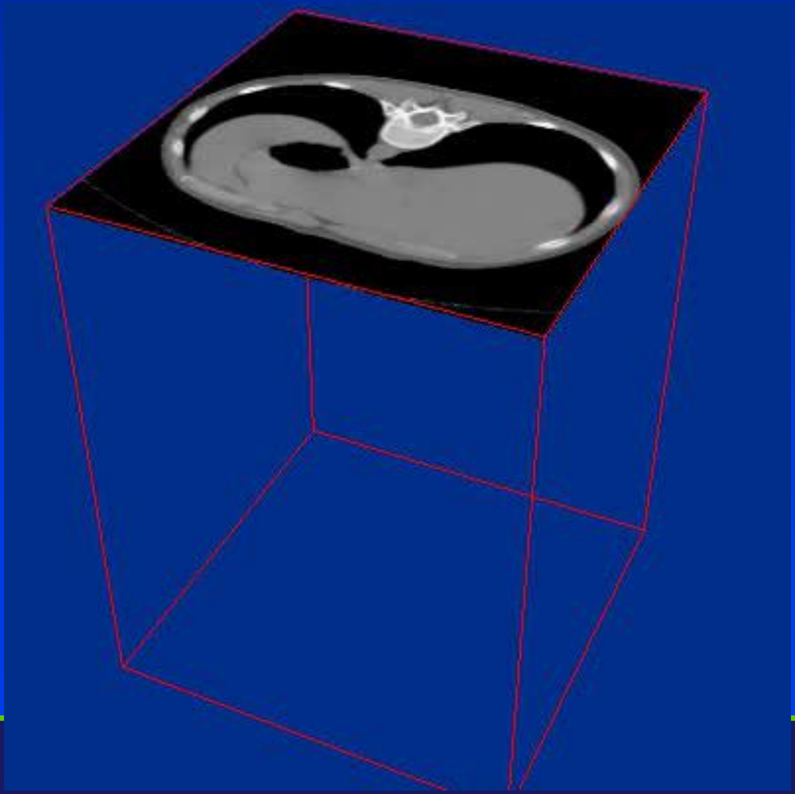
Computer-aided Detection (CAD)

- "CAD may be defined as a diagnosis made by a physician who takes into account the computer output as a second opinion"

  -Dr. Kunio Doi (U. Chicago)
- Currently in use for early detection of breast cancer in mammography (FDA approved)
- On the way for lung nodule detection and colon polyp detection

Case Study: Polyp Detection

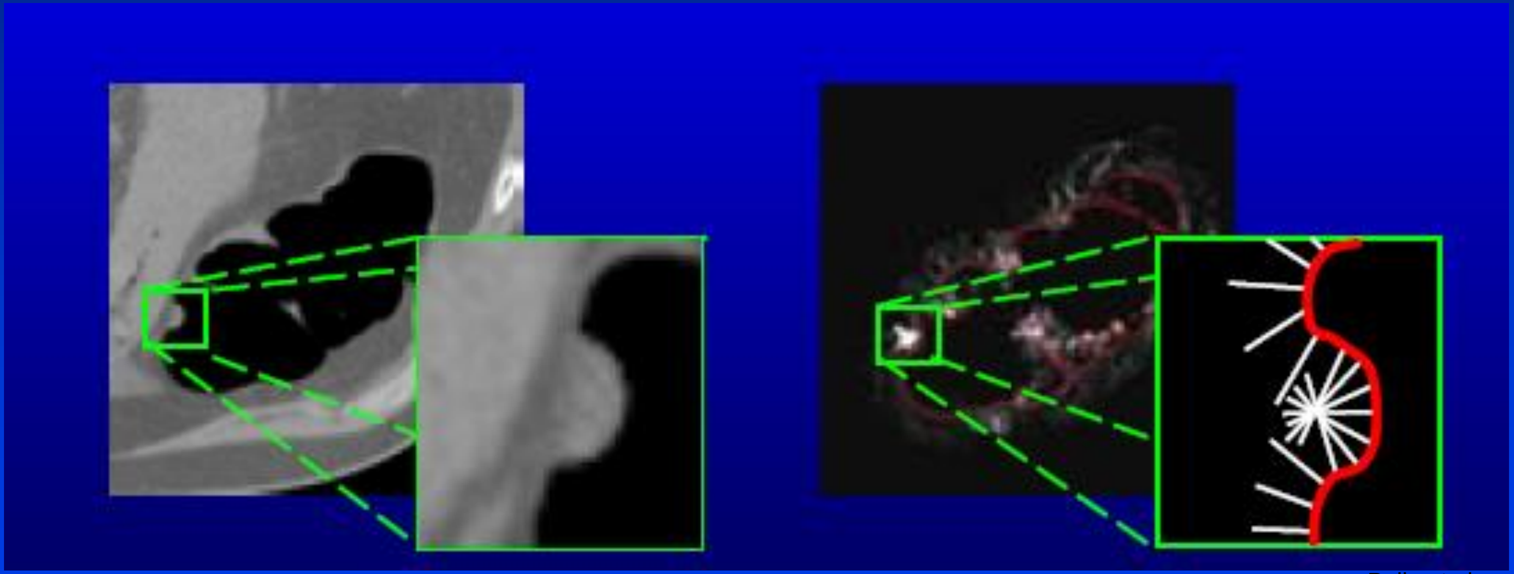
- Step 1: CT scan of patient
- Step 2: Segmentation of colon



Paik, et al.

Case Study: Polyp Detection

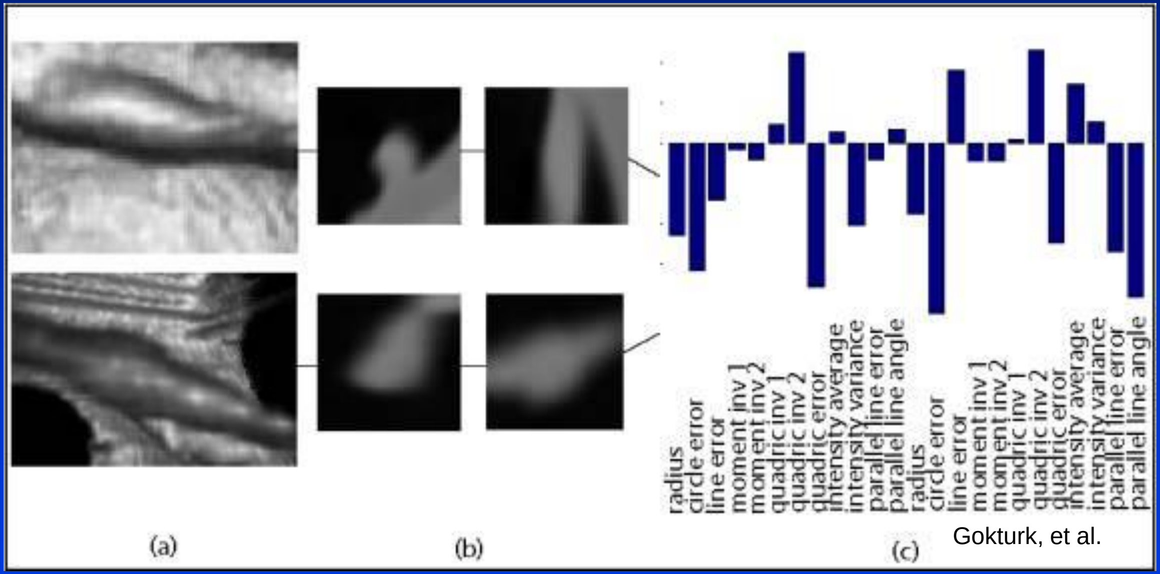
- Step 3: detection of polyp candidates
  - Hough transform (looking for spheres)



Paik, et al.

Case Study: Polyp Detection

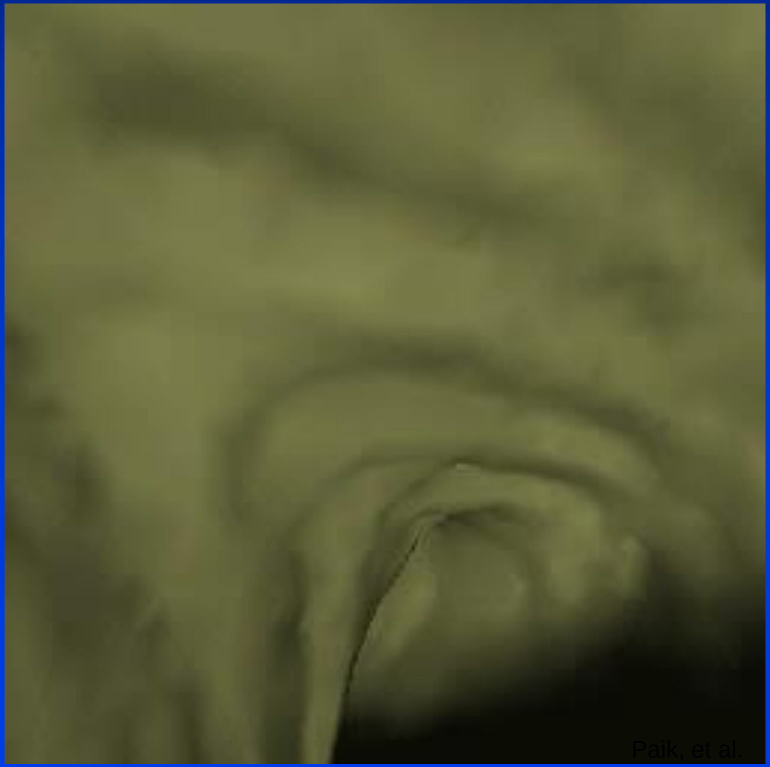
- Step 4: feature extraction



- Step 5: classification
  - Take your pick of algorithms (SVM, ANN, etc.)

Case Study: Polyp Detection

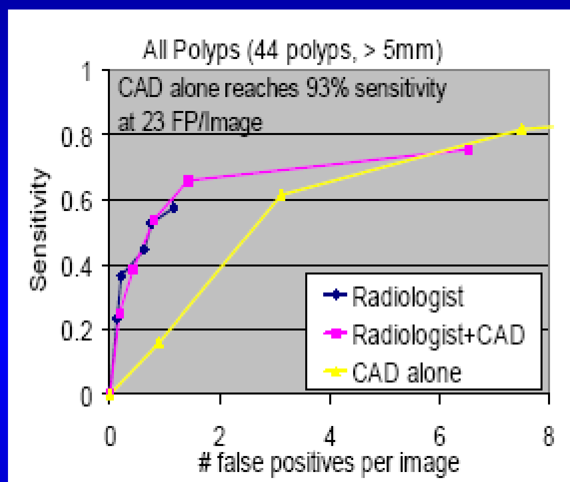
- Step 6: Flythrough colon giving information to physician for final diagnosis (not yet realized)

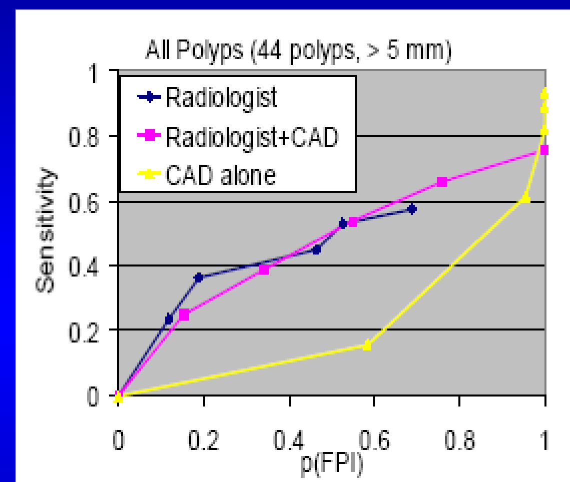


Case Study: Polyp Detection

RAD vs. CAD

FROC, AFROC, Time Results



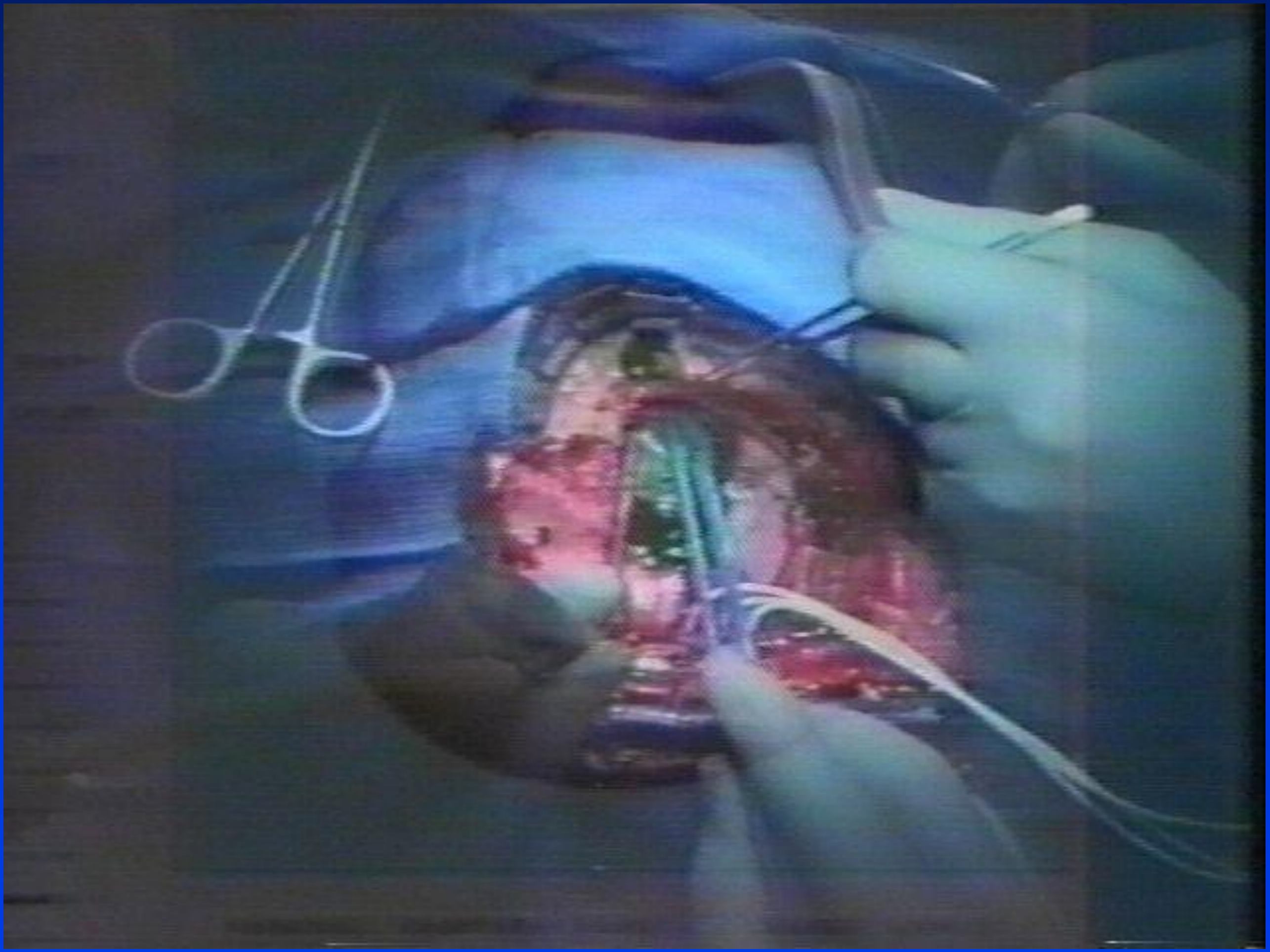


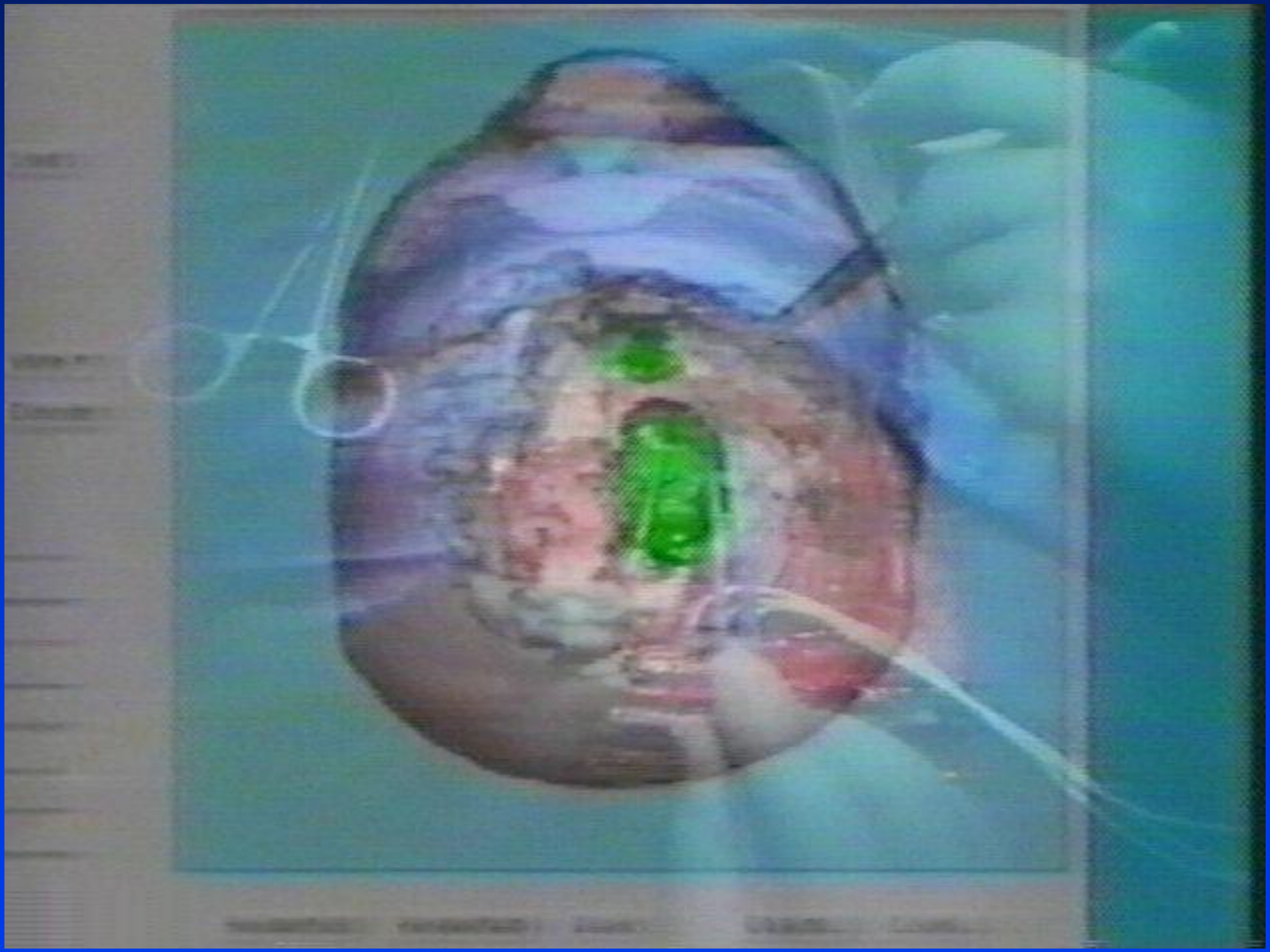
	Radiologist	Radiologist+CAD	CAD alone
t_1 (min)	3.5	1.6	N/A
t_{total} (min)	9.7	7.7	N/A

Adding CAD to radiologist significantly decreases both t_1 and t_{total} ($p<0.01$)

Paik, et al.

AR/VR for Medical Image Analysis





Summary

- Applications of standard computer graphics and visualization (also including vision) techniques into the medical domain
  - Segmentation
  - Computer-Aided Detection
  - 3D Reconstruction
  - Multi-modal registration

- New techniques for medical image analysis

Conclusions

- Medicine is a fertile and active area for computer graphics and vision research
- Application of existing graphics and vision tools to new, challenging domains
- Development of new graphics and vision tools to assist in the practice of medicine

The End