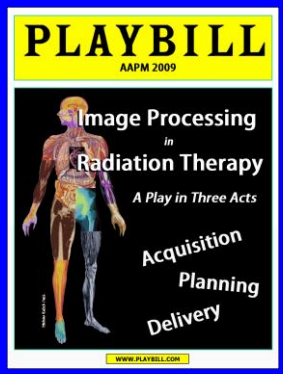
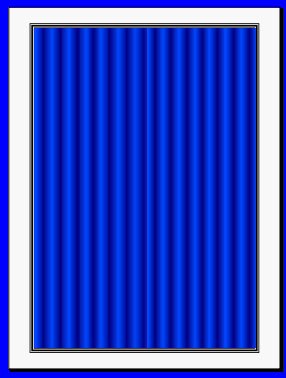


# Disclosure Statement

## I receive research funding from …

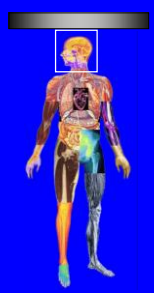
UNIVERSITY OF MICHIGAN

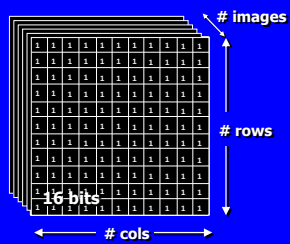
National Cancer Institute
U.S. National Institutes of Health | www.cancer.gov

VARIAN medical systems | A partner for life

# Act I

## *Turning Patients into Numbers*

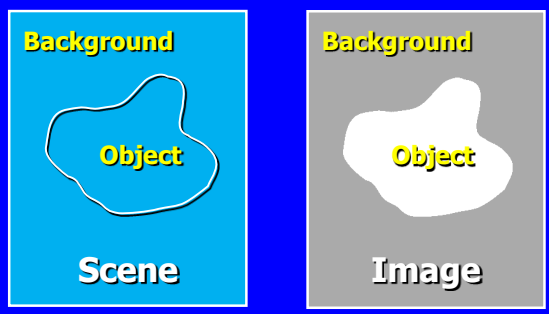




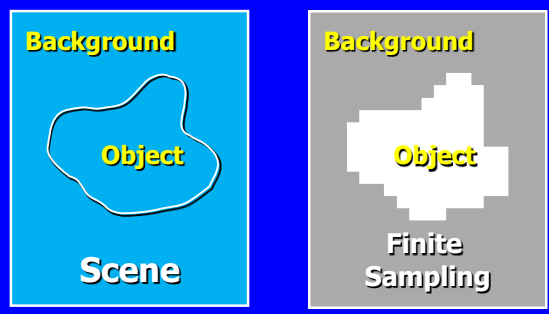

16 bits

Δx, Δy, Δz

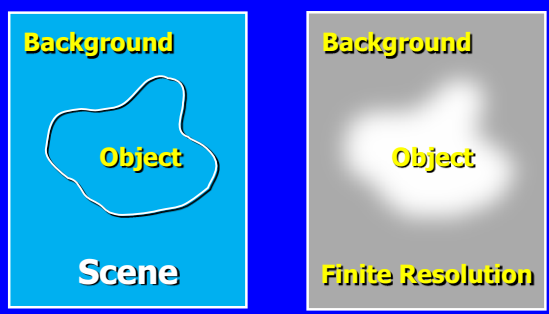
## Imaging Basics




## Imaging Basics




## Imaging Basics

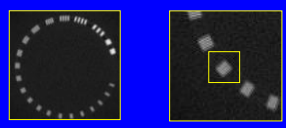



## Question 1

The best metric for image resolution is

# Question 1

**The best metric for image resolution is**



**4. Minimum resolvable line pair**

**Reference ACT I**

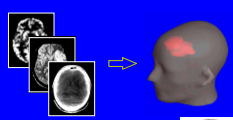
# Act I

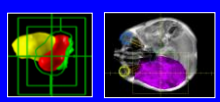
***Turning Patients into Numbers***


| Computed Tomography | Magnetic Resonance | Nuclear Medicine |
|---|---|---|
| ***Physics*** | ***Anatomy*** | ***Physiology*** |

# Act II

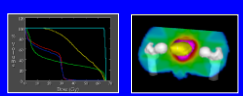
***Turning numbers into other numbers***



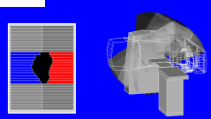


***Patient Modeli*** ***ion of Plan Geometry***

DICOM
Digital Imaging and Communications in Medicine



***Plan Evaluation***



***Implementation of Therapy***

2008

# Image Processing

**Anniversary Paper: Image processing and manipulation through the pages of *Medical Physics***

Samuel G. Armato III[a)]
*Department of Radiology, The University of Chicago, 5841 South Maryland Avenue, Chicago, Illinois 60637*
Bram van Ginneken
*Image Sciences Institute, University Medical Center Utrecht, Heidelberglaan 100, Room Q05.459, 3584 CX Utrecht, The Netherlands*

***Enhancement*** ***Visualization***

***Segmentation*** ***Registration***

***Quantification***

## Image Processing for $T_x$ Planning

**Enhancement**

*enhance / suppress features or noise for delineation*

**Visualization**

*n-D rendering for delineation, planning & evaluation*

**Segmentation**

*delineation for planning, evaluation & registration*

**Registration**

*fusion to support improved delineation*

**Quantification**

*improved delineation and dose calculations*

## Question 2

I would like you to concentrate on …

1. Enhancement
2. Segmentation
3. Registration
4. Visualization
5. Quantification

Answer Now

10

## Question 2

I would like you to concentrate on …

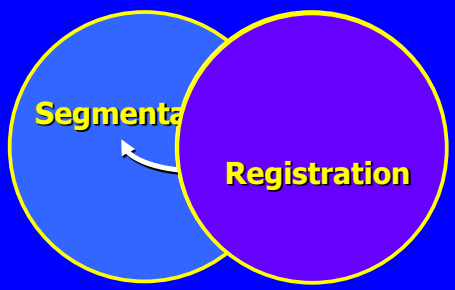
20% 1. Enhancement
21% 2. Segmentation
20% 3. Registration
19% 4. Visualization
20% 5. Quantification

## Question 2

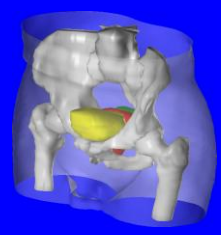
I would like you to concentrate on …

20% 1. Enhancement
21% 2. Segmentation
20% 3. Registration
19% 4. Visualization
20% 5. Quantification

## Segmentation / Registration




## Object Representation



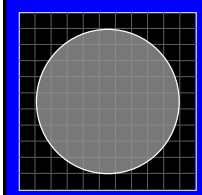
**Boundary**

Contours / Surfaces

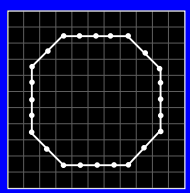
**Region**

Pixel / Voxel Masks

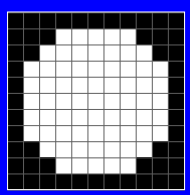
## Object Representation



**Object**



**Boundary**

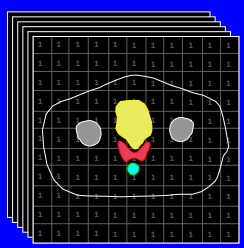


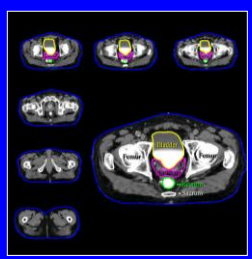
**Region**

*Each representation has pros and cons!*

## Image Segmentation

*numbers turned into other numbers*



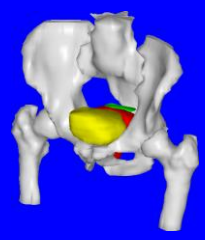


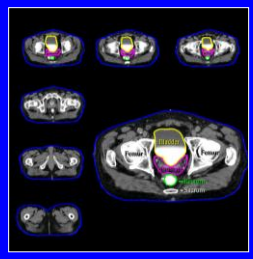
40 - 100+ images / series

5 - 10+ structures / image

## Image Segmentation

*numbers turned into other numbers*

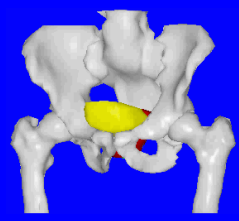


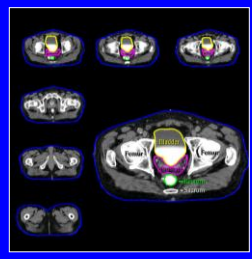


40 - 100+ images / series
5 - 10+ structures / image

## Image Segmentation

*numbers turned into other numbers*

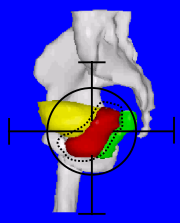




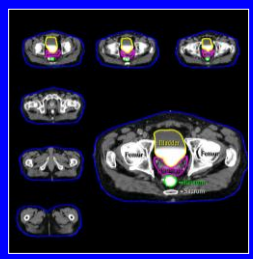
40 - 100+ images / series
5 - 10+ structures / image

## Image Segmentation

*numbers turned into other numbers*



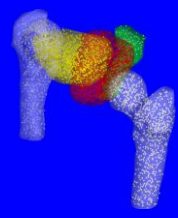
margins &
field shaping



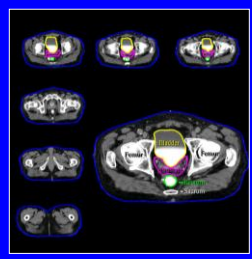
40 - 100+ images / series
5 - 10+ structures / image

## Image Segmentation

*numbers turned into other numbers*



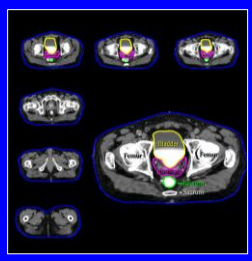
point samples
for IMRT calcs



40 - 100+ images / series
5 - 10+ structures / image

# Image Segmentation

*numbers turned into other numbers*



circa 1988 ( … 2009?)

40 - 100+ images / series
5 - 10+ structures / image

Brock/PMH

# Image Segmentation

*numbers turned into other numbers*

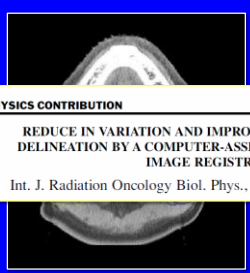
… now we also have 4D CT!

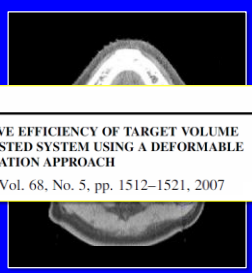
Multiple breathing states!
40 - 100+ images / phase
5 - 10+ structures / image

Chao/MDACC

# Image Segmentation

*numbers turned into other numbers*





PHYSICS CONTRIBUTION

REDUCE IN VARIATION AND IMPROVE EFFICIENCY OF TARGET VOLUME DELINEATION BY A COMPUTER-ASSISTED SYSTEM USING A DEFORMABLE IMAGE REGISTRATION APPROACH

Int. J. Radiation Oncology Biol. Phys., Vol. 68, No. 5, pp. 1512–1521, 2007

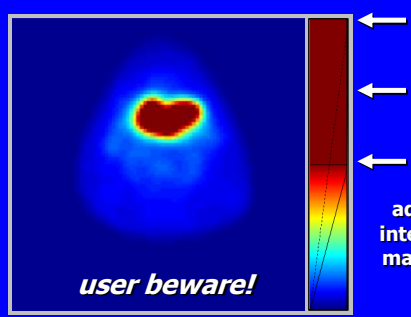
Numerous MD outlines

Couple of Experts + Image Processing

Lee /UCL

# Image Segmentation

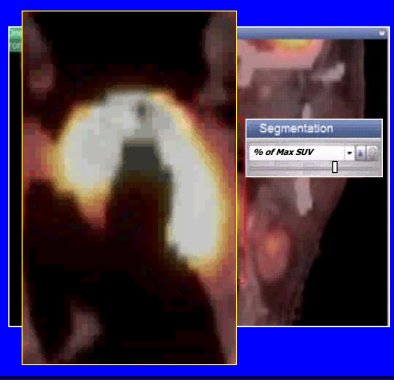
*numbers turned into other numbers*




adjust intensity mapping

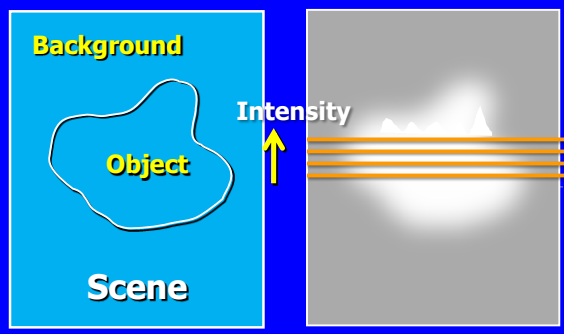
J Dawson / UCSD

## Different Thresholds

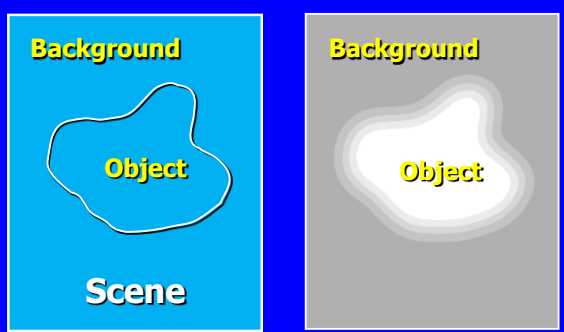



% max SUV

## Image Segmentation




## Image Segmentation




RTH / UM

## Does a *mm* make a difference?

Volume of Sphere $= 4/3\ \pi r^3 = \pi d^3 / 6$

and $\delta V = (\pi d^2 / 2)\ \delta d$

then $\delta V/V = \{(\pi d^2 / 2)\ \delta d\} / \{\pi d^3 / 6\}$

or $\delta V/V = 3\ \delta d/d$

**... adding a 1 mm margin to a 6 cm target increases the volume by 10%!**

$\delta V/V = 3\ \delta d/d = 3 \bullet 2\text{x}1\text{mm} / 60\text{ mm}$

$= 0.1 =$ **10%**

# Image Segmentation

*numbers turned into other numbers*

- We need to automate!
- We need to standardize!

***Image Processing to the Rescue***

# Question 3

Image processing is important for

| | |
|---|---|
| 19% | 1. Enhancement |
| 21% | 2. Segmentation |
| 25% | 3. Registration |
| 15% | 4. Visualization |
| 20% | 5. All of the above |

# Question 3

Anniversary Paper: Image processing and manipulation through the pages of *Medical Physics*

Samuel G. Armato III[a)]
*Department of Radiology, The University of Chicago, 5841 South Maryland Avenue, Chicago, Illinois 60637*

Bram van Ginneken
*Image Sciences Institute, University Medical Center Utrecht, Heidelberglaan 100, Room Q05.459, 3584 CX Utrecht, The Netherlands*

5. All of the above

# Image Segmentation

- Edge detection
- Clustering methods
- Histogram-based
- Region growing
- Level set methods
- Graph partitioning
- Watershed transform
- Model based

# Image Segmentation

## Boundary Methods

- simple edge detection - high contrast objects
- deformable models - active contours / surfaces

## Region Methods

- feature space - image intensity
- region growing / voxel recruitment
- morphologic techniques

# Edge Detection

## Good detection

algorithm should mark as many real edges in the image as possible

## Good localization

edges marked should be as close as possible to the edge in the real image

## Minimal response

a given edge in the image should only be marked once, and where possible, image noise should not create false edges

# Edge Detection

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

x- gradient

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

y-gradient

$$G = \sqrt{G_x^2 + G_y^2}$$

***Sobel kernel***

# Image Processing Basics

Original

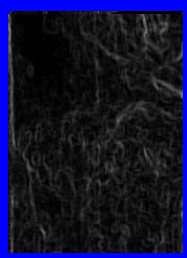
## Edge Detection

$*$

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

| | | |
|---|---|---|
| +1 | +2 | +1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

$=$

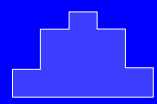


Original Filtered

*Sobel kernel*

## Smoothing

$$\frac{1}{115}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 2 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix}$$



$\sigma=1.4$

*Gaussian kernel*

## Smoothing

$*$

$=$

Original Filtered

*Gaussian kernel*

## Edge Detection

$*$

$=$


Original Filtered

*Gaussian then Sobel kernel*

# Image Segmentation

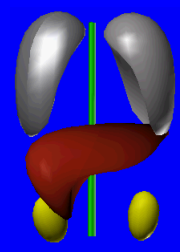
## Boundary Methods

- simple edge detection - high contrast objects
- deformable models - active contours / surfaces

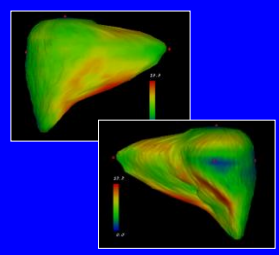
## Region Methods

- voxel recruitment - region growing
- feature space - image intensity
- morphologic techniques

# Model-based Segmentation

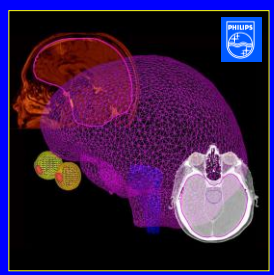


Simple analytic shapes
super-quadrics, spherical harmonics



Population averaged models
mean position and variance

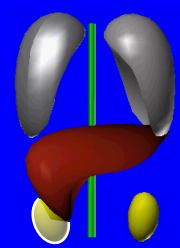
# Model-based Segmentation




3D extension of Snakes / Active Contours

Wiesmeyer/UM

# Model-based Segmentation



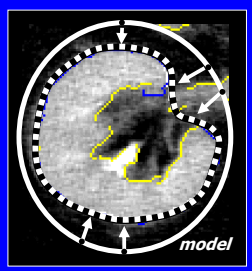
right kidney

Circa 1992

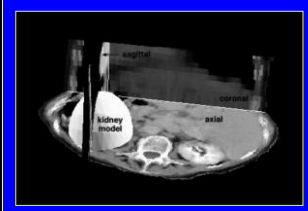

Place model *into* image volume

Wiesmeyer/UM

## Model-based Segmentation



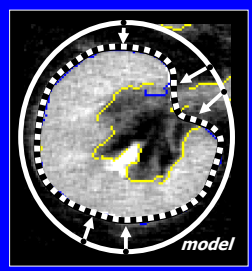

Circa 1992




Optimize model to *match* image data

Wiesmeyer/UM

## Model-based Segmentation




$E_{total} = \omega E_{int} + E_{ext}$

$E_{int}$ = model forces

curvature, elastic, population variance

$E_{ext}$ = image forces

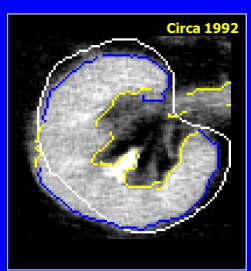
edges/ surfaces

Wiesmeyer/UM

## Model-based Segmentation

raw edges

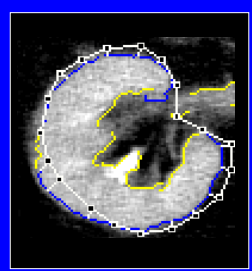
Circa 1992



filtered edges

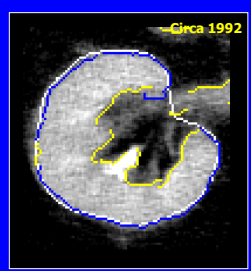
Wiesmeyer/UM

## Model-based Segmentation



optimizing

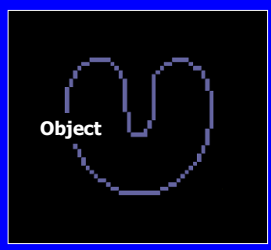
Circa 1992

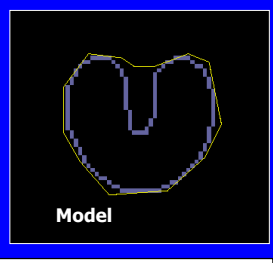


$E_{total}$ minimized

1988

## Model-based Segmentation



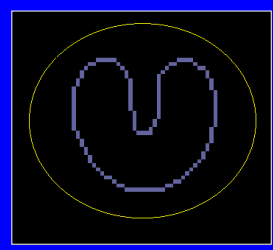



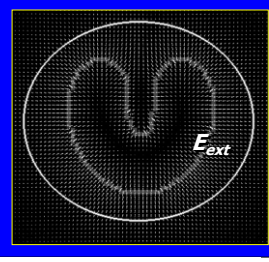

**Snakes: Active Contour Models** International Journal of Computer Vision, 321-331 (1988)

MICHAEL KASS, ANDREW WITKIN, and DEMETRI TERZOPOULOS
*Schlumberger Palo Alto Research, 3340 Hillview Ave., Palo Alto, CA 94304*

1998

## Model-based Segmentation






IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 7, NO. 3, MARCH 1998

Snakes, Shapes, and Gradient Vector Flow

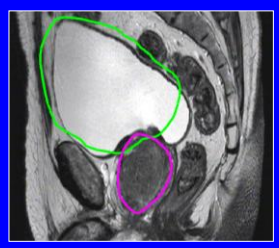
Chenyang Xu, *Student Member, IEEE,* and Jerry L. Prince, *Senior Member, IEEE*

## Segmentation Example

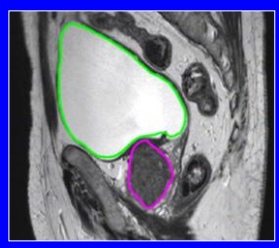

Tracking prostate during treatment using segmentation from ultrasound

## Segmentation Example

## Model-based Segmentation



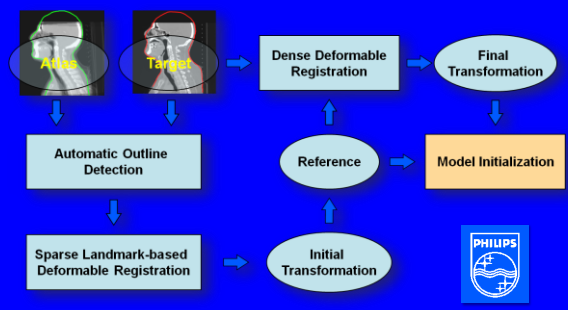
Initialized



Optimized

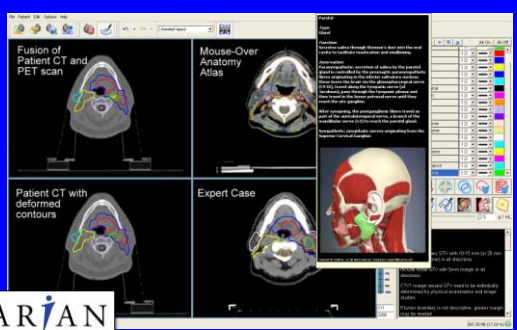
Qazi / PMH

## Model-based Segmentation




Varian

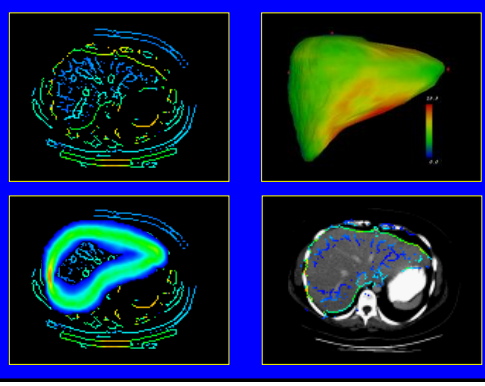
## Atlas-based Segmentation



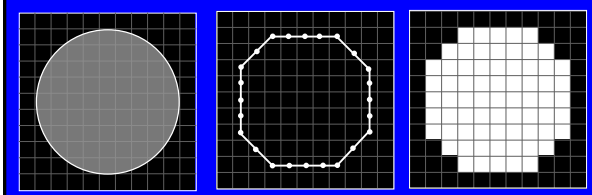

VARIAN medical systems

Meyer/UM

## Image Segmentation



## Object Representation



Object Boundary Region

*Each representation has pros and cons!*

## Image Segmentation

### Boundary Methods

- simple edge detection - high contrast objects
- deformable models - active contours / surfaces

### Region Methods

- voxel recruitment - region growing
- feature space - image intensity
- morphologic techniques

## Image Segmentation

### Boundary Methods

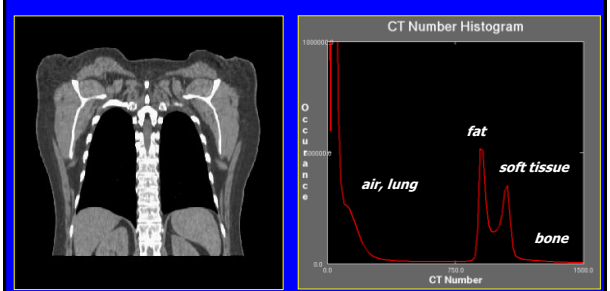
- simple edge detection - high contrast objects
- deformable models - active contours / surfaces

### Region Methods

use *some* feature of the data to determine the intrinsic grouping in a set of unlabeled data

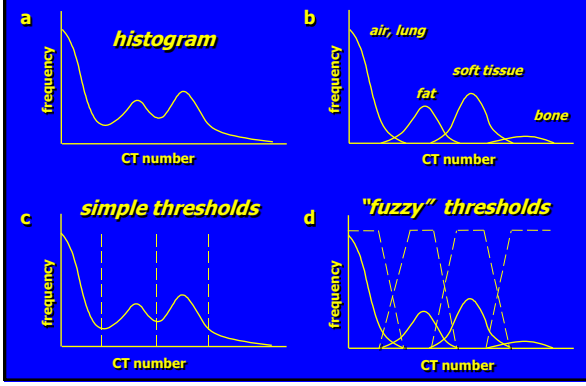
*... think "membership"*

## Intensity Feature

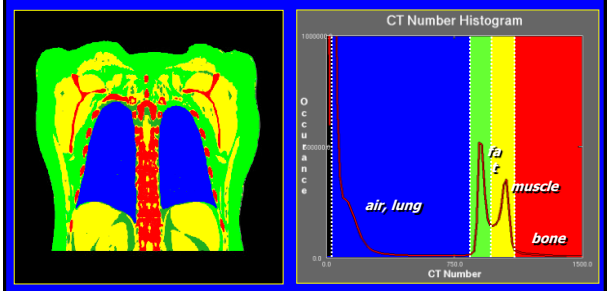



*Simple intensity thresholds*

## Intensity Feature



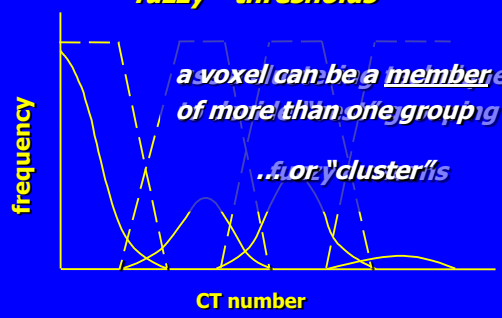

## Intensity Feature




*Simple intensity thresholds*

## Intensity Feature

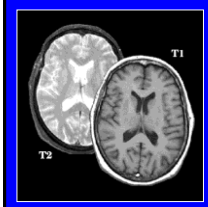
*"fuzzy" thresholds*



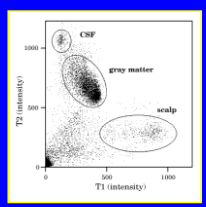

*a voxel can be a member of more than one group*

*.. or "cluster"*

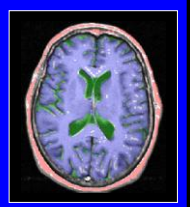
## Vector Intensity Feature




Original images
$T_1$, $T_2$



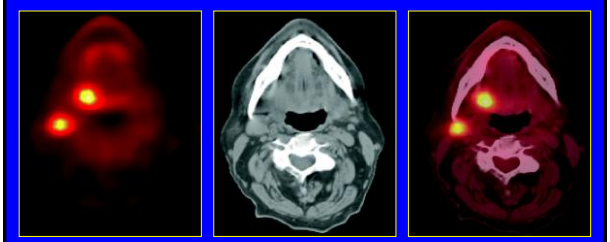

2-D feature plot
w/ clusters



Labeled image
color-coding

*... use intensity vectors*

## Vector Intensity Feature



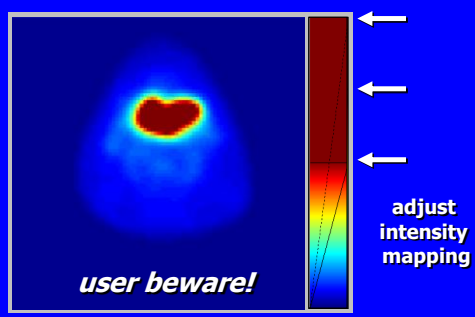
PET CT PET / CT

*... from different modalities!*

## Image Segmentation

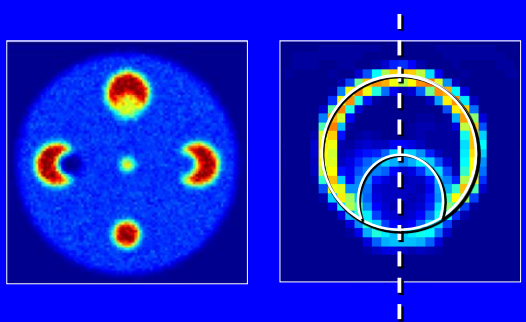
Lee /UCL

*numbers turned into other numbers*



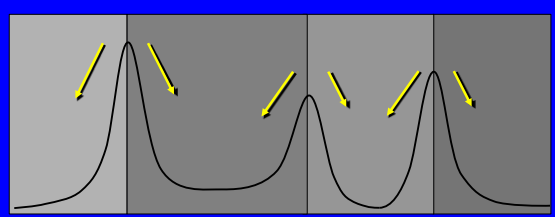

## Image Segmentation

Lee /UCL



## Image Segmentation

### Watershed Transform



*... consider gradient magnitude of an image as a topographic surface*

Lee /UCL

# Image Segmentation

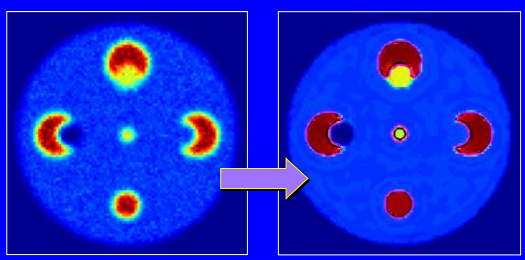


*Image Processing to the Rescue*

Lee /UCL

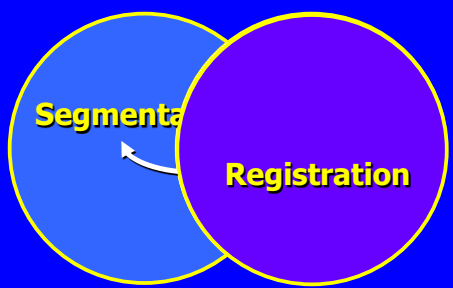
# Validation Studies

| Patient | Surgical specimen | Simple Threshold | Gradient-based method |
|---|---|---|---|
| 1 | 4.1 | 8.7 | 4.7 |
| 2 | 5.2 | 7.4 | 5.5 |
| 3 | 5.6 | 16.3 | 8.2 |
| 4 | 14.4 | 37.2 | 19.7 |
| 5 | 4.5 | 33.8 | 45.7 |
| 6 | 24.3 | 34.1 | 25 |
| 7 | 30.9 | 33.4 | 27.8 |
| mean | 14.7 | 24.7 | 16.6 |
| RMSE | 0 | 12.22 | 3.78 |

Total laryngectomy – surgical specimen is sliced, digitized, delineated, and registered*

* Daisne, Gregoire

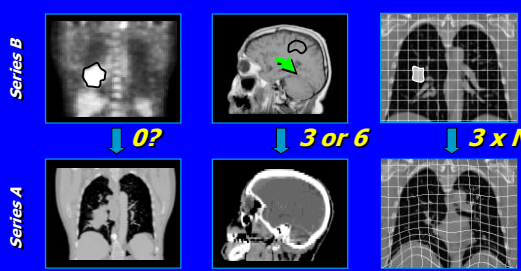
# Segmentation / Registration




# Image Registration

Transformation Models

*How many DOF?*



# Image Registration

## Geometric / Physical Methods

- Point matching
- Surface matching
- Finite element models

## Intensity Methods

- Cross correlation / SSD
- Diffusion / Demons
- Mutual information

# Registration / Segmentation

## Structure Mapping / Propagation

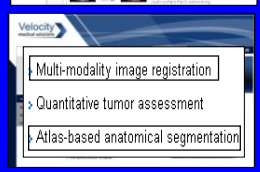

*...what about doing this for doses too?*

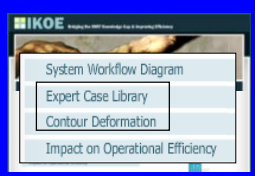
Original Segmentation

Mapped Structure

# Registration / Segmentation


Several independent products are there or *almost* there!



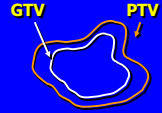




I have no commercial interest in any of these company

Ling / MSKCC

# Multimodality Targeting

**Morphology**



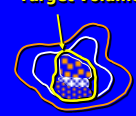

**Hypoxia**
- PET
- F-miso

**Tumor Burden**
- MRI/MRS
- choline / citrate

**Tumor Growth**
- PET
- IUDR

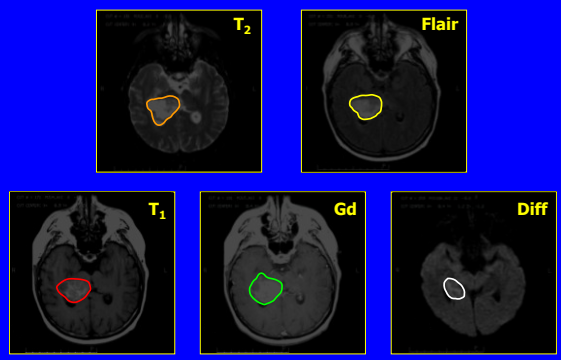
**Biology versus Morphology**

**Biological Target Volume**

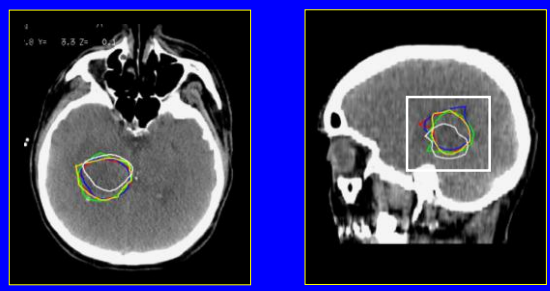


RTH / UM

## Multimodality Targeting

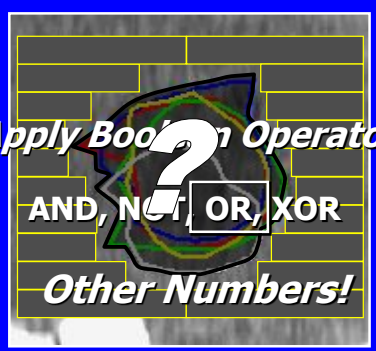



## Multimodality Targeting



MR volumes mapped to CT study

## Multimodality Targeting



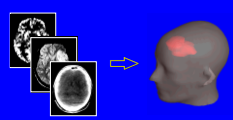
*Apply Boolean Operator*

AND, NOT, OR, XOR

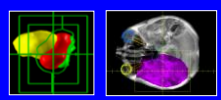
*Other Numbers!*

## Act II

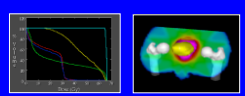
*Turning numbers into other numbers*



*Patient Modeling*



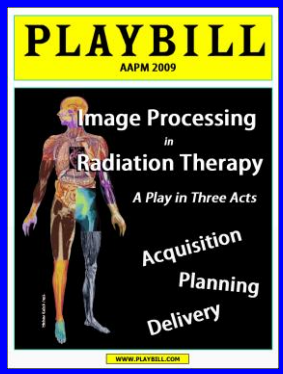
*Definition of Plan Geometry*

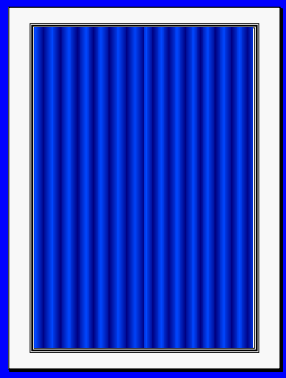


*Plan Evaluation*

DICOM
Digital Imaging and Communications in Medicine

*Implementation of Therapy*



## Image Processing Basics

$f(x) \longrightarrow$ **System H** $\longrightarrow g(x)$

$g(x) = H\,[\,f(x)\,]$

image processing is any form of signal processing for which the input is an image

## Image Processing Basics

$f(x) \longrightarrow$ **System H** $\longrightarrow g(x)$

$g(x) = H\,[\,f(x)\,]$

Correlation

Convolution

## Image Processing Basics

$f(x) \longrightarrow$ **System H** $\longrightarrow g(x)$

$$g(x) = kernel \otimes f(x)$$

**Convolution**

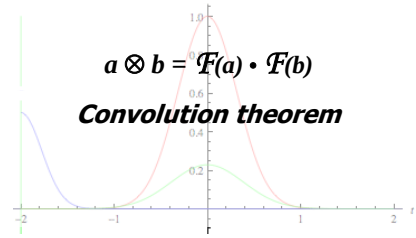
## Image Processing Basics

$$g(x) = \int kernel(\tau) \cdot f(x-\tau)\, d\tau$$

mathworld

$$a \otimes b = \mathcal{F}(a) \cdot \mathcal{F}(b)$$

***Convolution theorem***




**Convolution**

## Image Processing Basics

*kernel*

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 1 | | | | | | | |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | | | | | | | |

**Convolution**

## Image Processing Basics

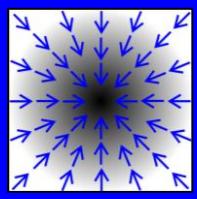
*kernel*

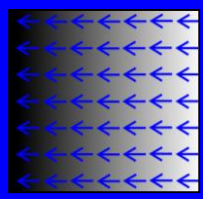
| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 1 | 1 |
| 1 | 1 | 1 |

***Did we just add a margin to the object?***

**Convolution**

## Image Processing Basics





The gradient of an image is one of the basic building blocks in image processing