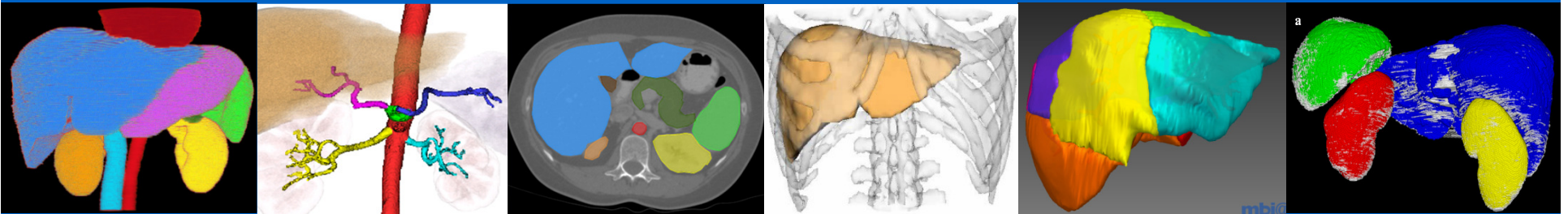


Computational Anatomy: Multi-organ Modeling and Analysis in Abdominal CT



Marius George Linguraru, D.Phil.

GLOBAL HEALTH – 22nd October 2012



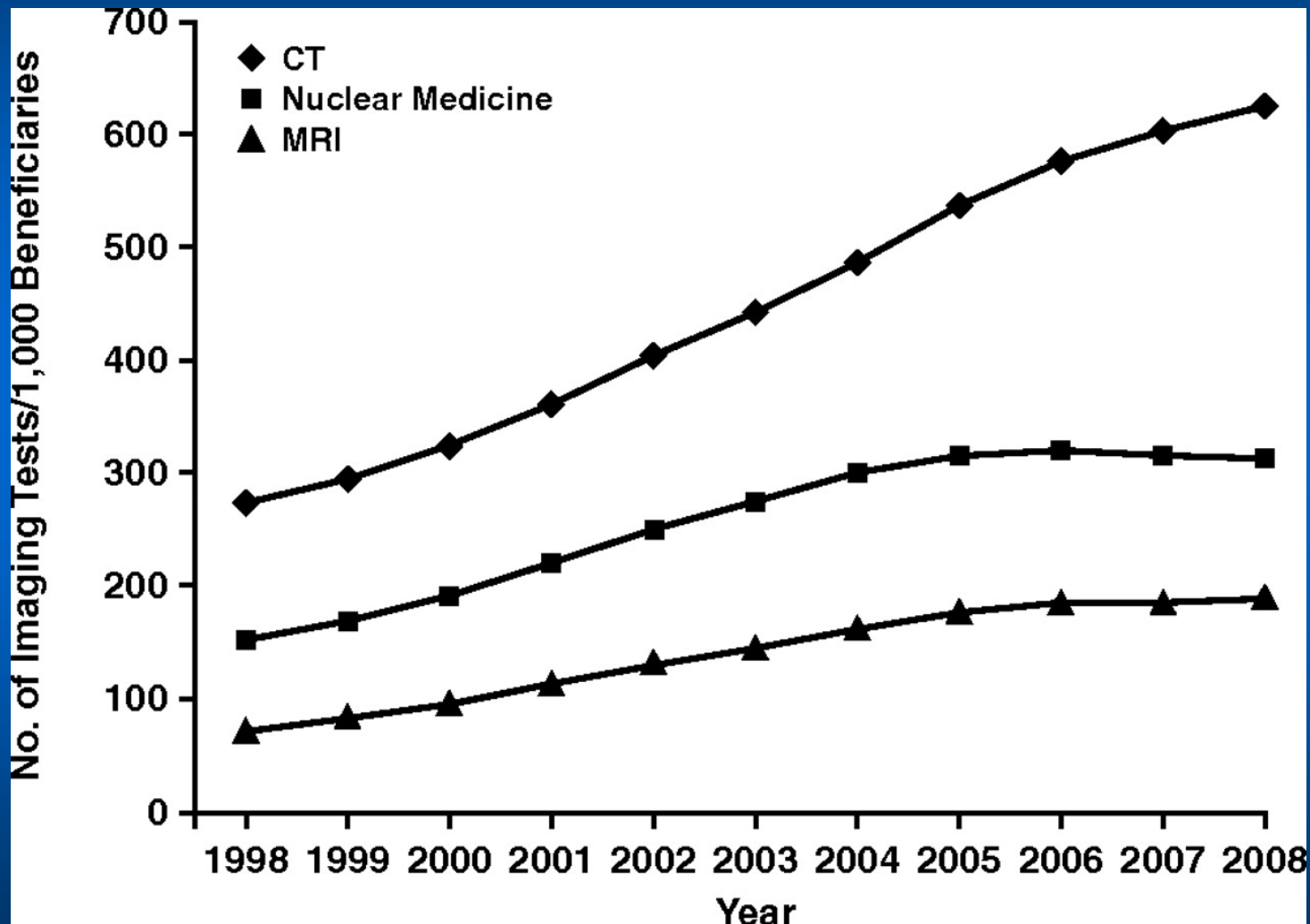
Children's National

SHEIKH ZAYED INSTITUTE *for* Pediatric Surgical Innovation

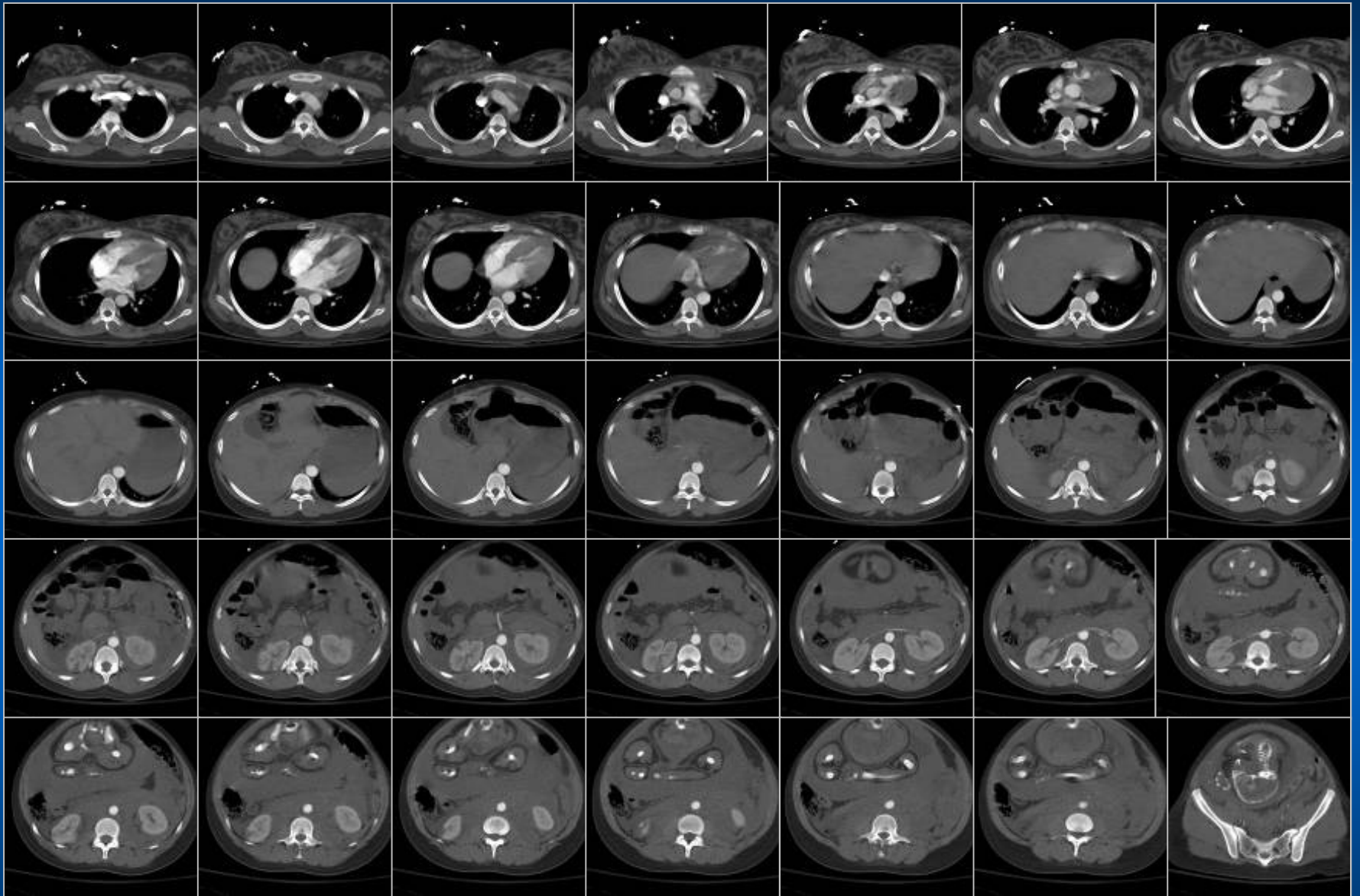
Site Map

- **Introduction**
- Established Segmentation
- Priors in Medical Image Data
- Segmentation and Simulation

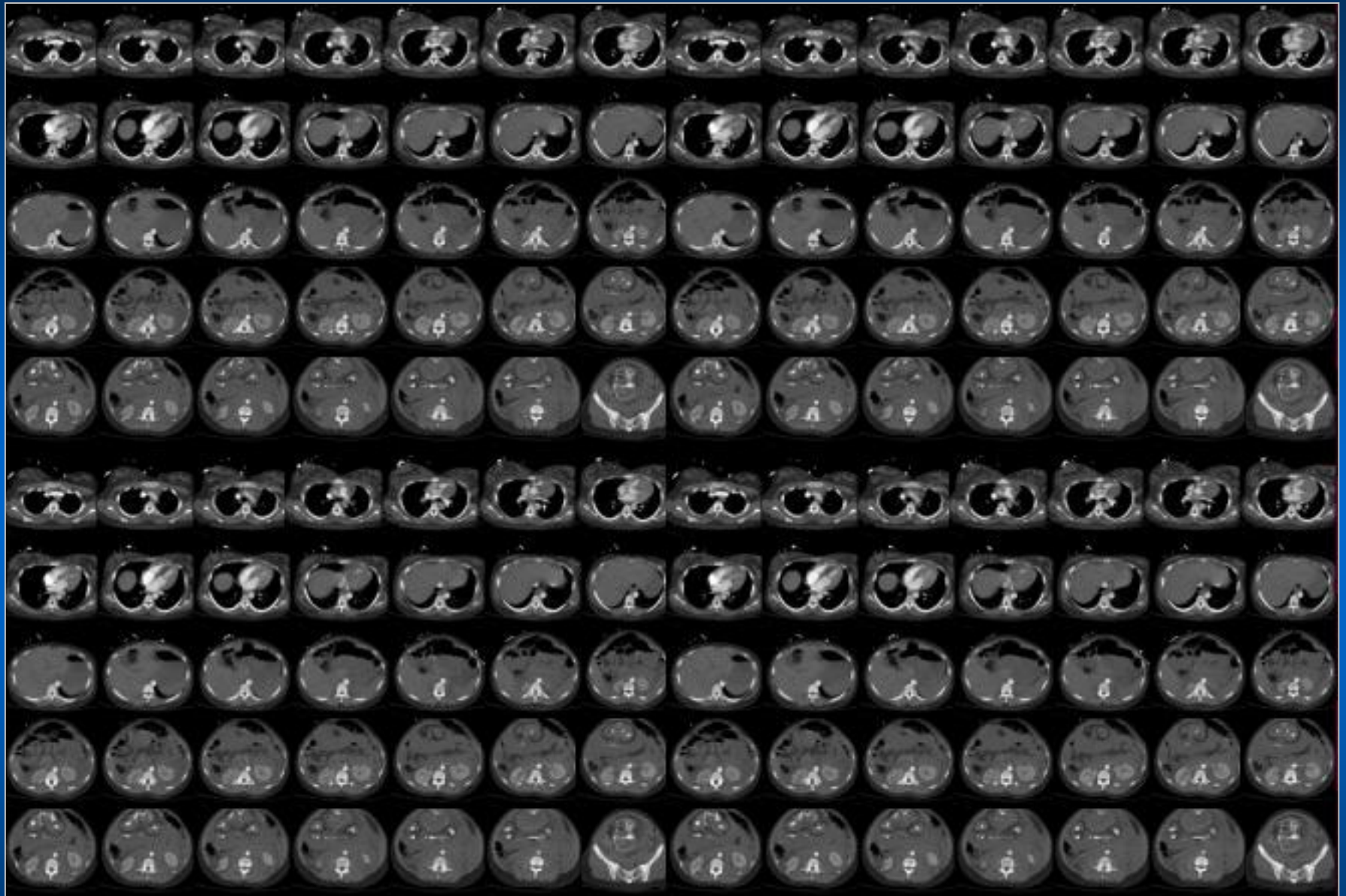
Utilization rates of CT (◆); nuclear medicine (■); and MRI (▲) in Medicare fee-for-service population, 1998–2008.



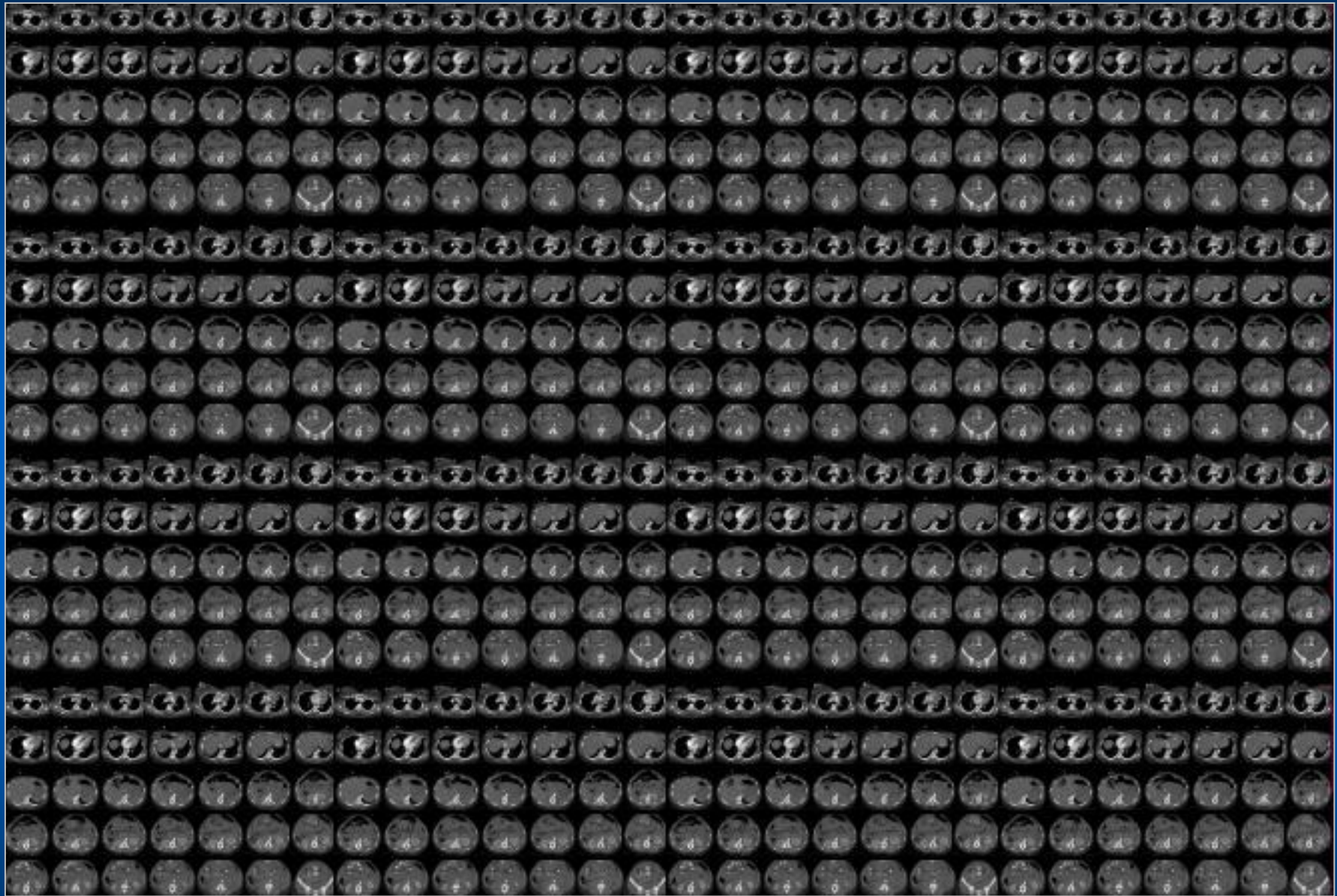
[Levin D C et al. AJR 2011]



Courtesy of Reuben Mezrich MD, Ph.D.



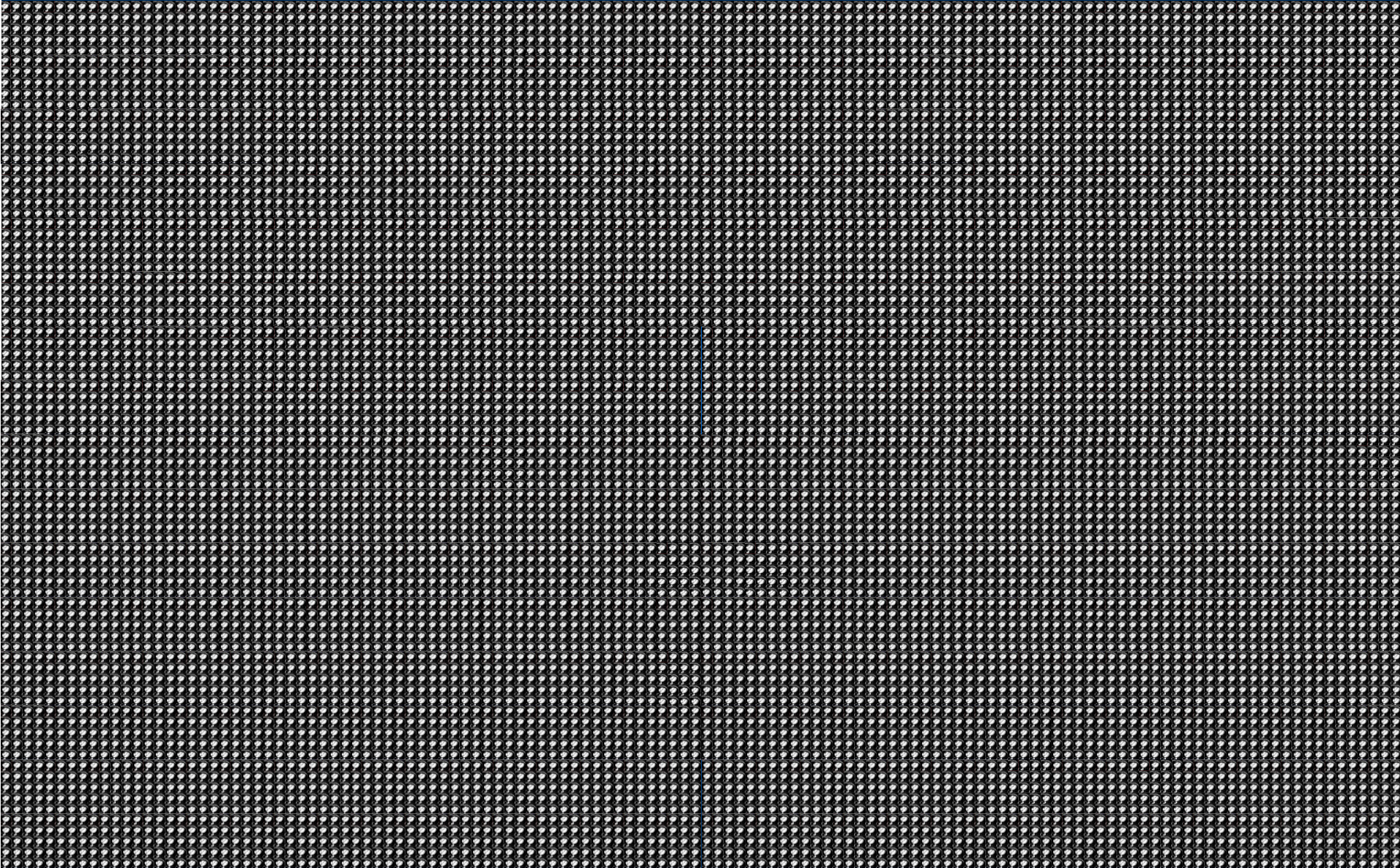
Courtesy of Reuben Mezrich MD, Ph.D.



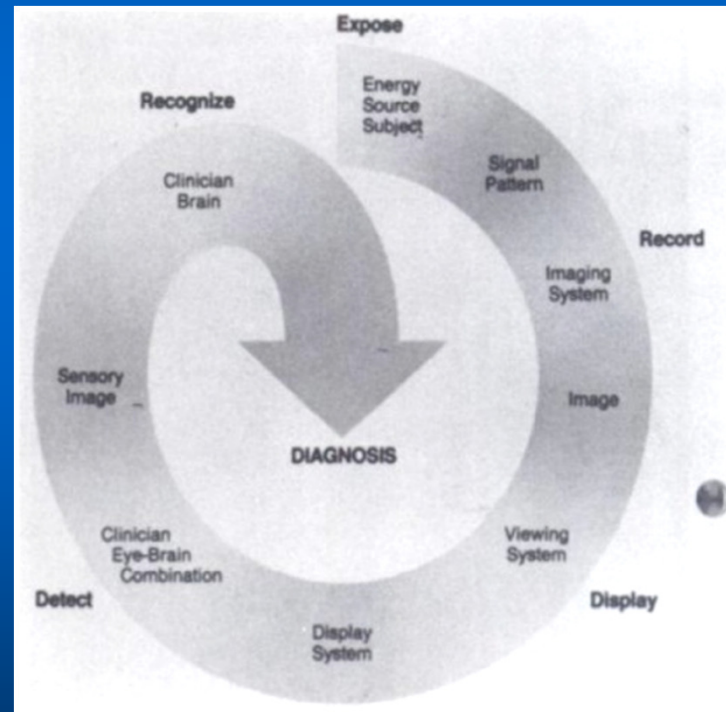
Courtesy of Reuben Mezrich MD, Ph.D.

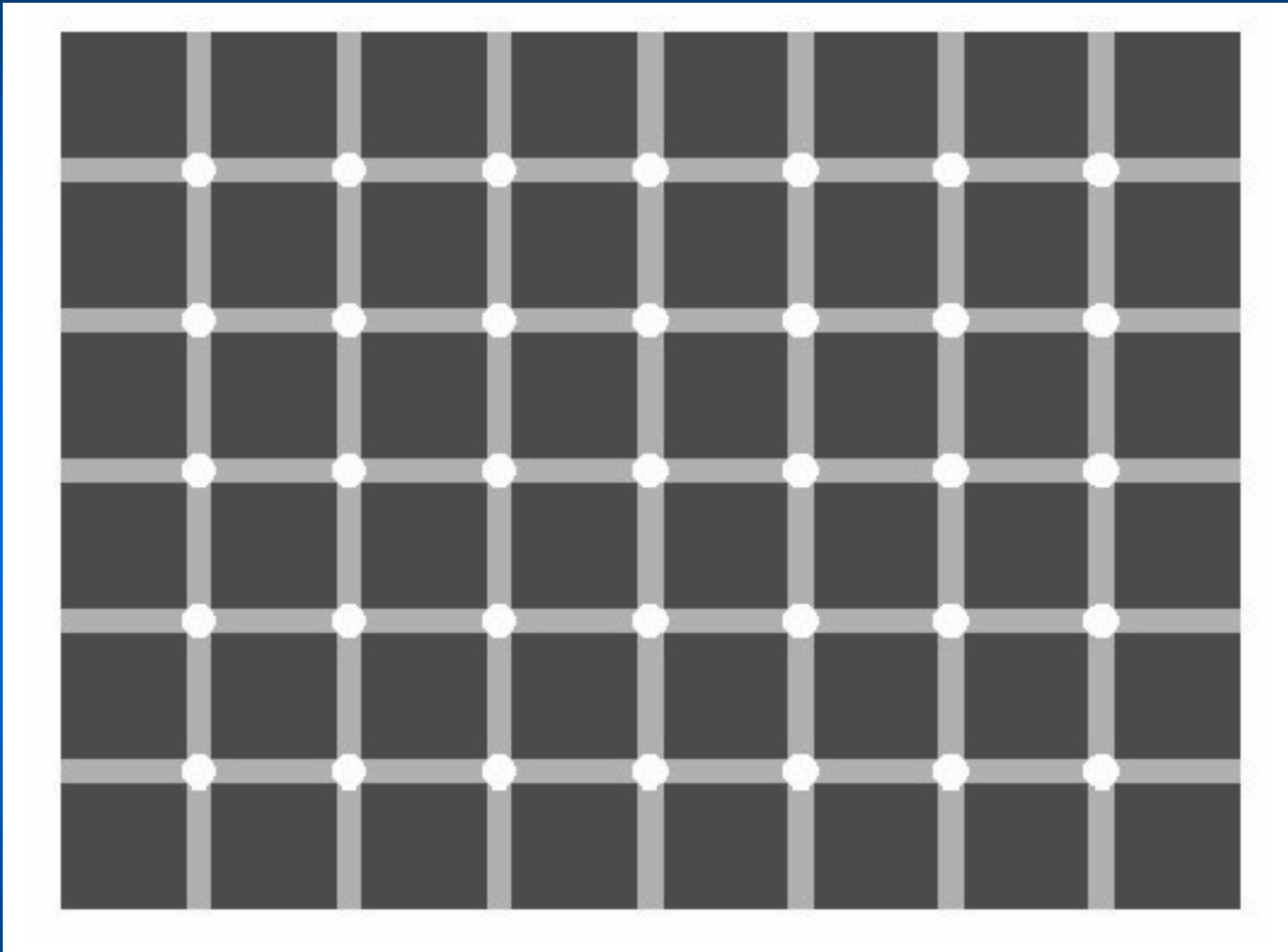


Courtesy of Reuben Mezrich MD, Ph.D.

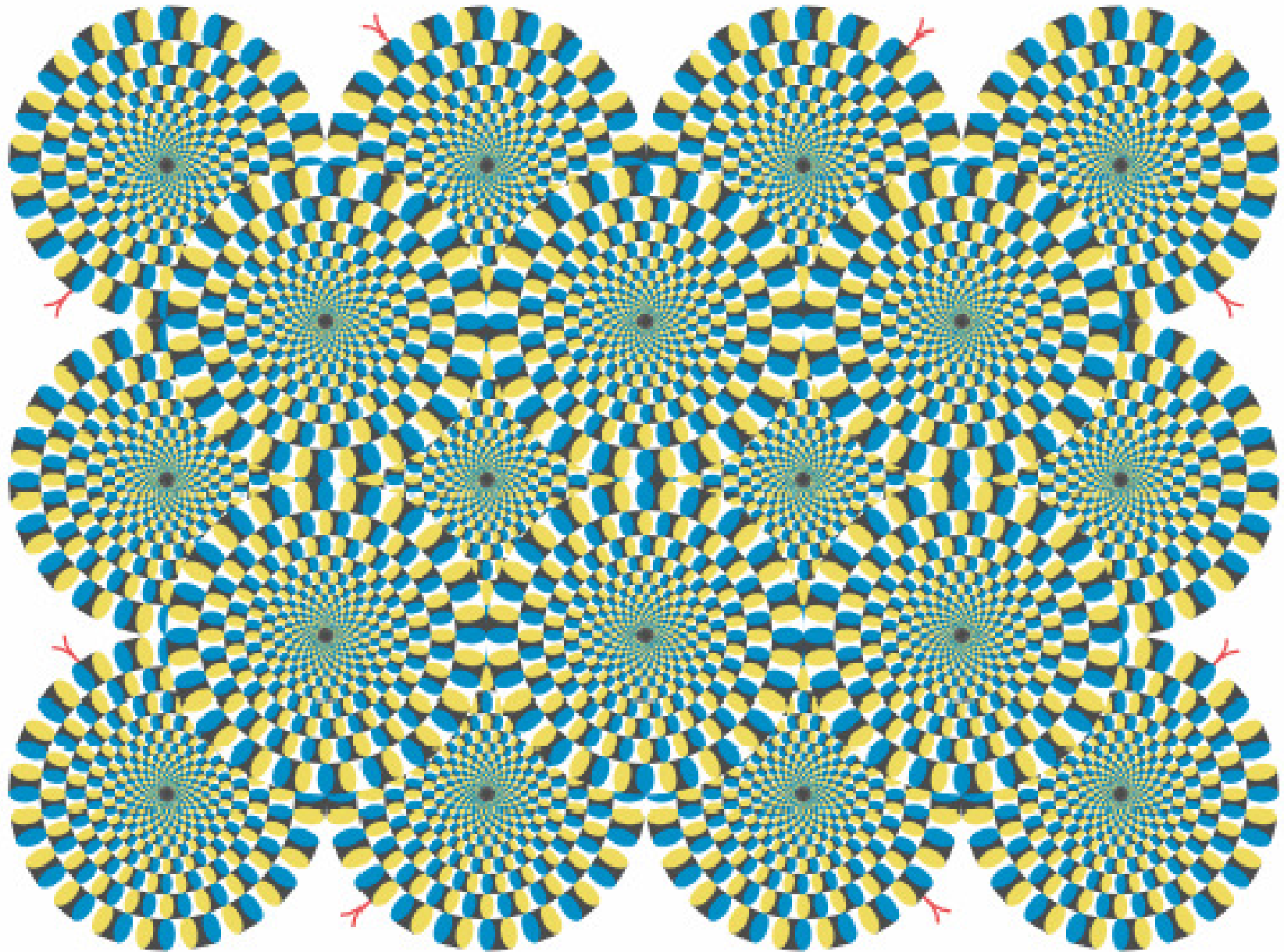


- The human observer may be the greatest source of variability in the image interpretation chain



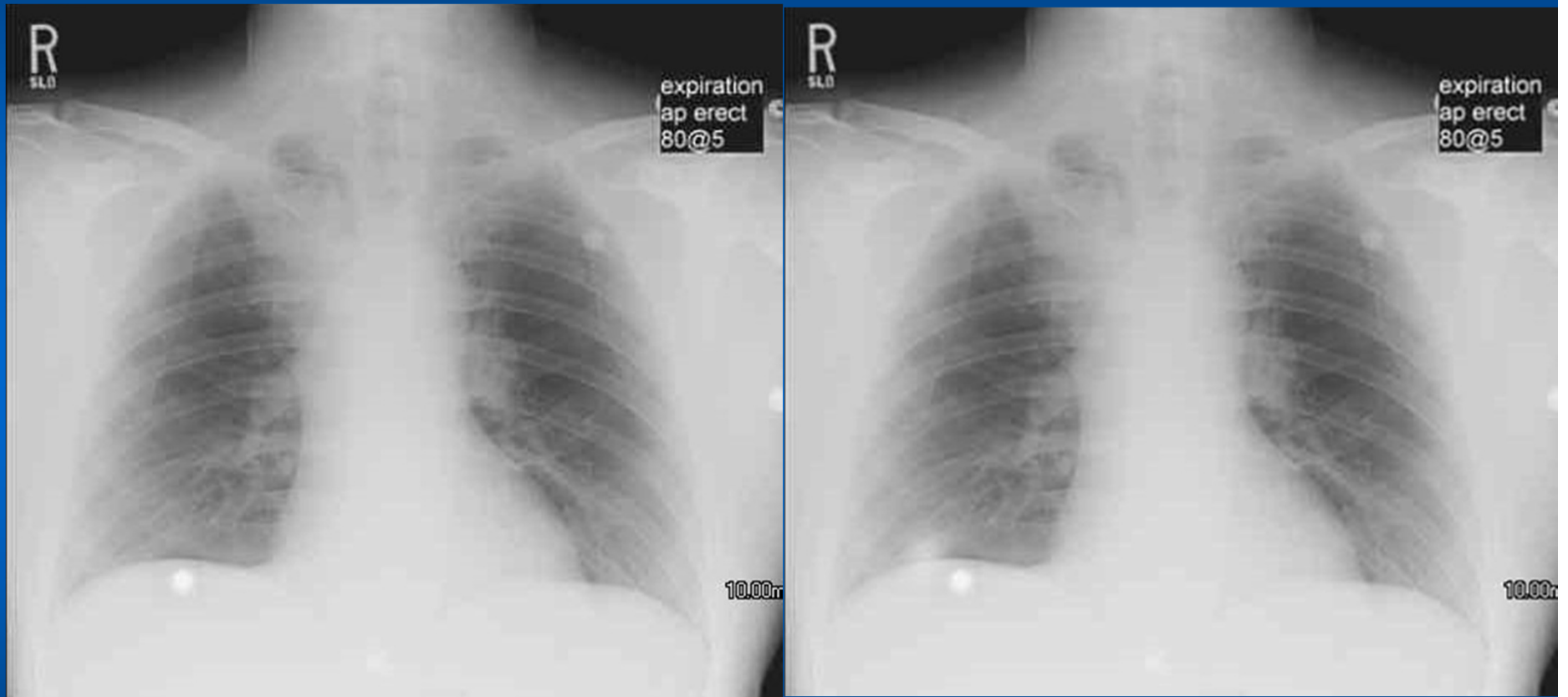


Courtesy of Nabile, Safdar, MD



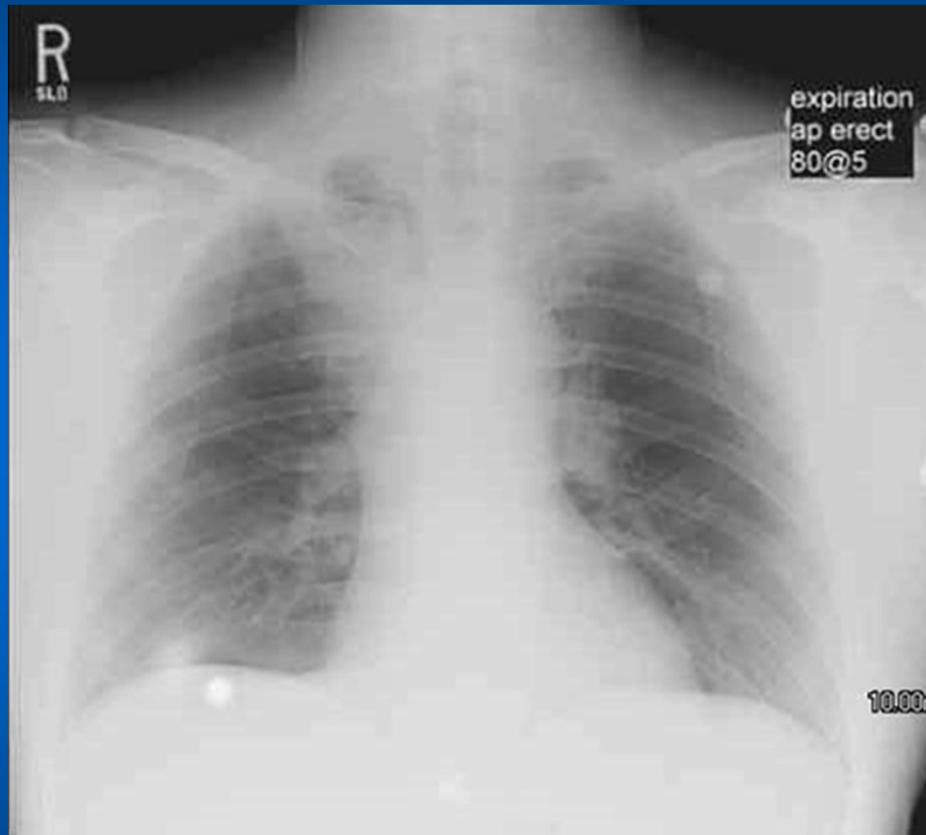
Courtesy of Nabile, Safdar, MD

Vision, Light, Luminance, Motion



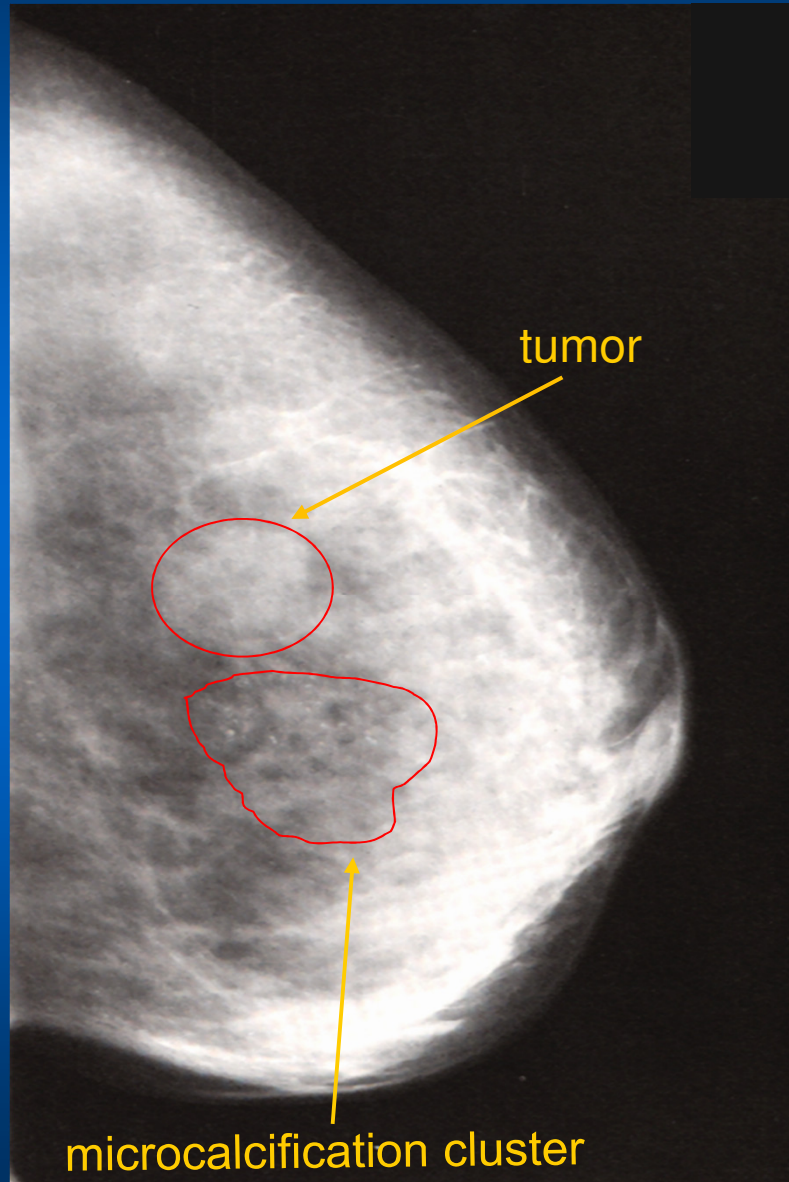
Courtesy of Nabile, Safdar, MD

Vision, Light, Luminance, Motion



Courtesy of Nabile, Safdar, MD

Mammography





TERMINATOR 3
RISE OF THE MACHINES

Clinical Challenges of Segmentation

- In clinical practice - **manual measurements** (often 2D)
 - high intra- and inter-operator variability.
 - time consuming – expensive.
- **Loads of data!**
- **Need:** quantitative, robust, accurate, repeatable.

- Large **variations** on organ shape, size, location.
- **Similar** appearance.
- **Unusual/abnormal** anatomy.
- Fast **motion**.

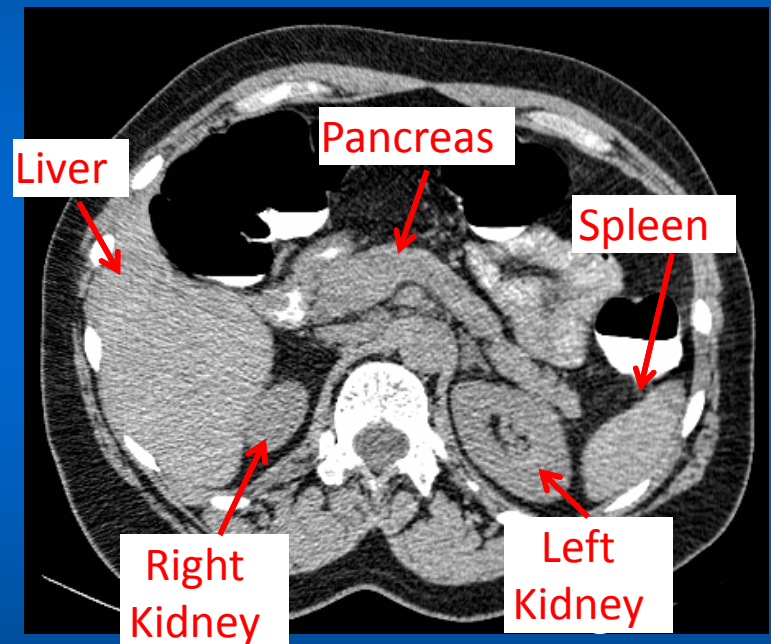
- Use **anatomical and physiological constraints** typical to medical image data.

Computer-Assisted Radiology

- Radiologists analyze the entire image data.

- Organ-by-organ.
- Slice-by-slice.

- CAD applications focused on organ- or disease-based applications.

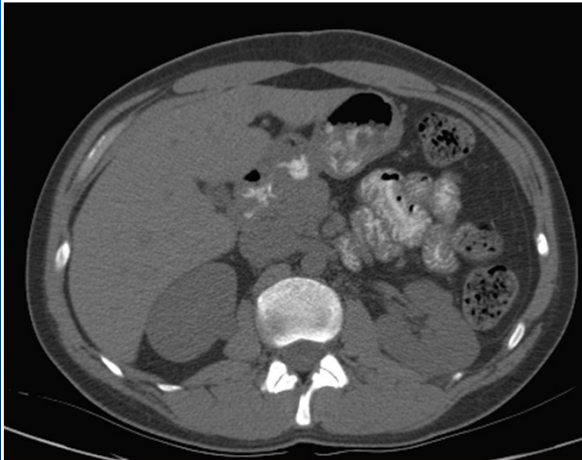


- Migration toward the automated simultaneous analysis of multiple organs for comprehensive diagnosis.

Clinical Protocol

- Diagnostic
 - Contrast enhanced CT – 3 Phases
- Serial Monitoring
 - Manual measurements
 - Limitations

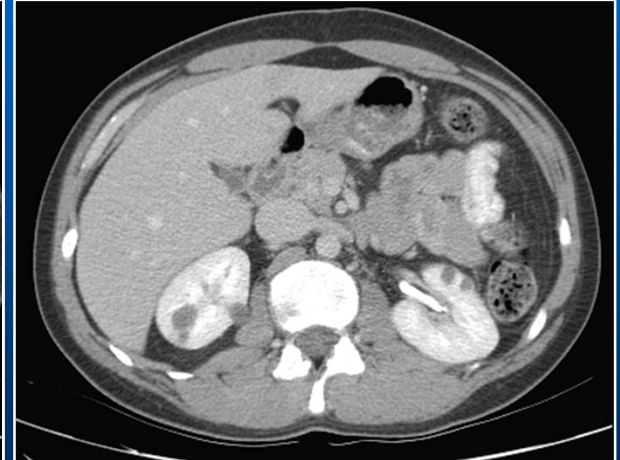
Pre-Contrast



Arterial Phase



Venous Phase

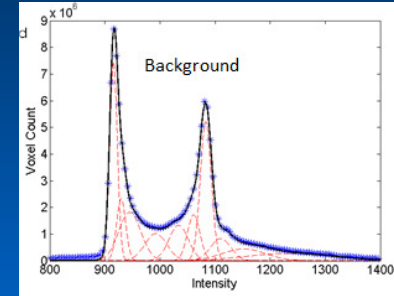


Site Map

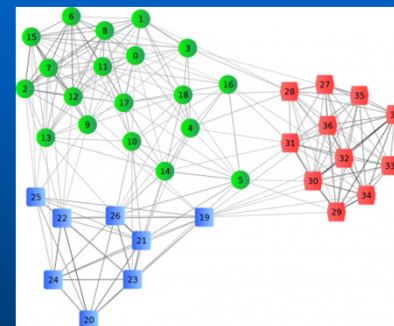
- Introduction
- **Established Segmentation**
- Priors in Medical Image Data
- Segmentation and Simulation

Segmentation Techniques

- Lower level
 - Pixel-based
 - Intensity, gradients.
 - Region-based
- Thresholding.
- Edge detection.
- Histogram-based.
- Mathematical morphology.
- Region growing/clustering.
- Cannot handle variability!



[Linguraru et al., Med Imag Anal 2012]



[espin086.wordpress.com]

Higher Level Segmentation

■ Partial Differential Equations

- Snakes

[Kass and Terzopoulos, IJCV 1987]

- Splines

- Deformable models

- Level sets

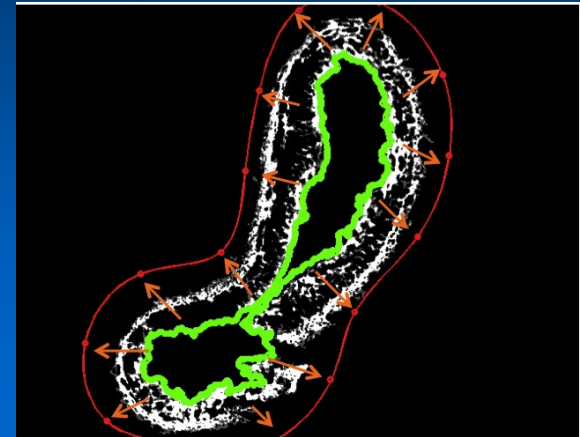
[Osher and Sethian, J Comput Phys 1988]

■ Need initialization.

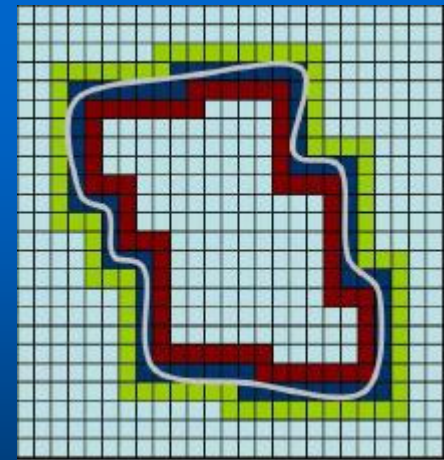
■ Computationally (in)efficient.

■ Parametric.

■ Handle topological changes.



<http://www.tnt.uni-hannover.de>



<http://www.mathworks.com>

Higher Level Segmentation

■ Graph- based Partitioning

- Min-cut (graph-cut)

[Wu and Leahy, IEEE TPAMI 1993]

- Random walker

[Grady, IEEE TPAMI 2006]

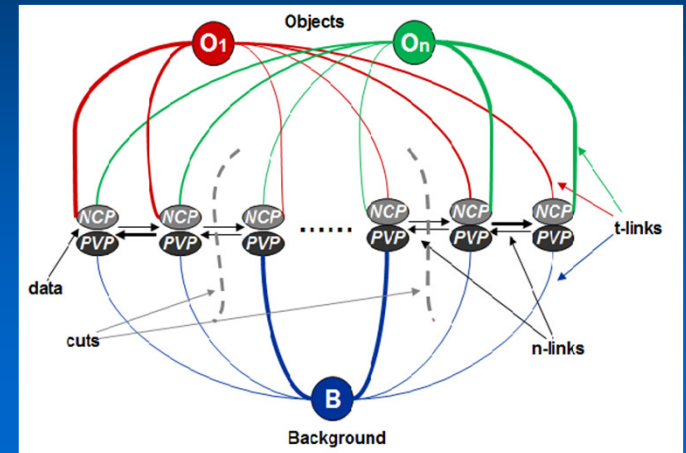
■ Need initialization.

■ Computationally efficient.

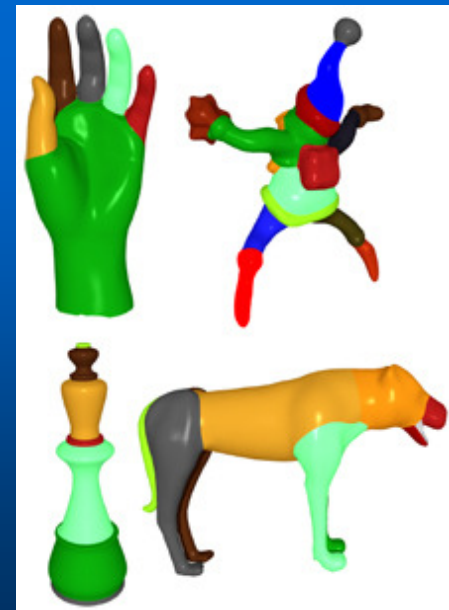
■ Globally optimal.

■ Any topology.

■ Multiple objects.



[Linguraru et al., Med Imag Anal 2012]

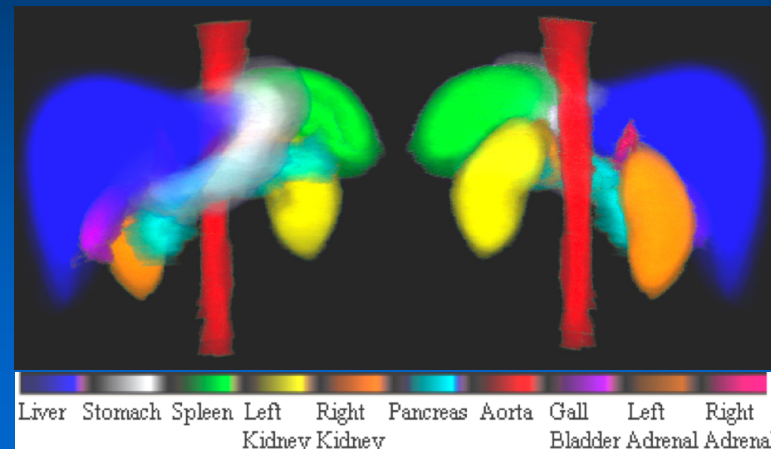


[Lai et al., Comp Aid Geom Design 2009]

Higher Level Segmentation

- Model-based
 - Atlas-based
 - Active Shape Models
 - Active Appearance Models

[Cootes and Taylor, BMVC 2006]



[Linguraru et al., Med Phys 2010]

- Need point correspondences.
 - Sensitive to training set.
 - Match to a new topology.
 - Multiple objects.
-
- Hybrids!



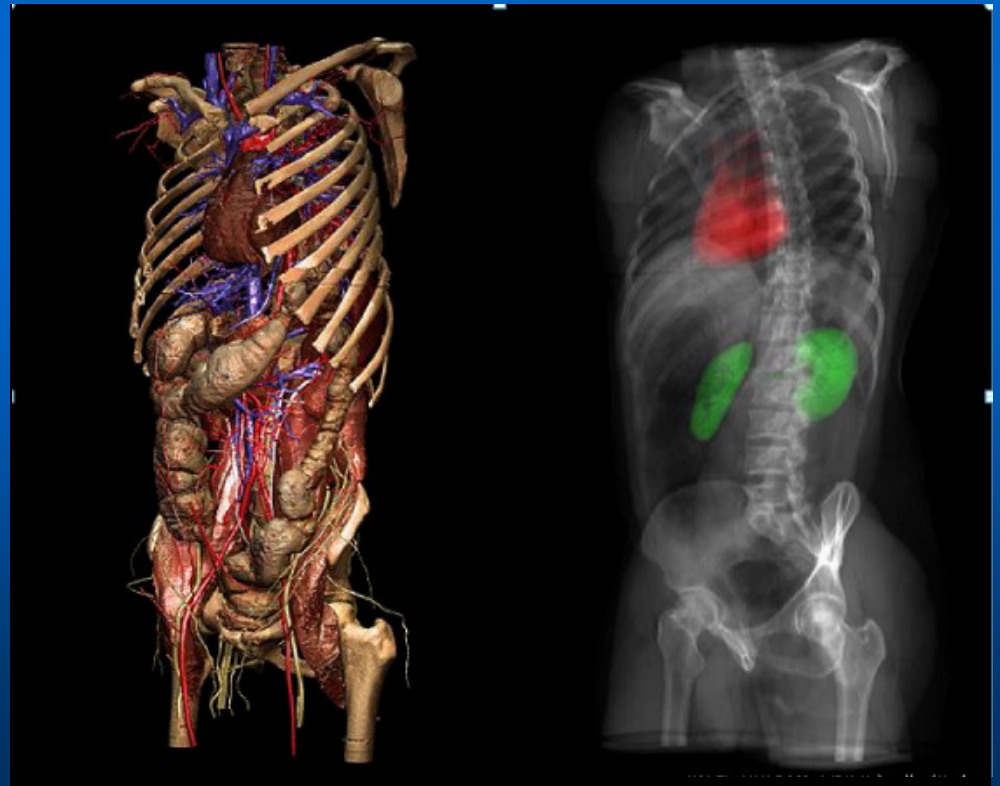
[Ionita and Cootes. IEEE ICCV Workshop 2011]

Site Map

- Introduction
- Established Segmentation
- **Priors in Medical Image Data**
- Segmentation and Simulation

Visible Human Project (NLM)

- Image library of volumetric data representing complete, normal adult male and female anatomy.
- MRI/CT/anatomical images.
- Models of the body.
- Insight Toolkit (ITK).
- Columbia University found several errors in anatomy textbooks.



Anatomical Analysis

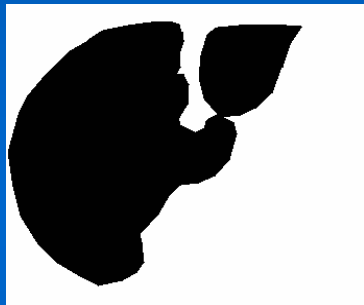
- Organ size is an indicator of disorders.
- Shape is locally variable in organs – global constraints.
- Soft tissue enhancement helps detecting abnormality.
- Organ geometry and enhancement are 3D.

Priors in Medical Data

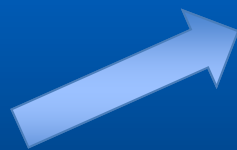
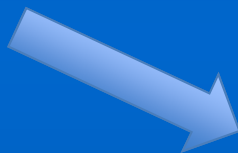
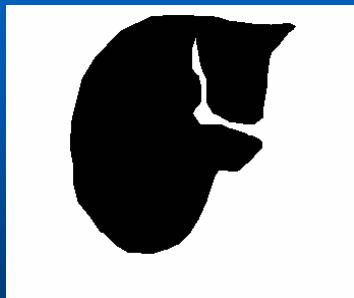
- Location
- Shape
- Appearance
- Interaction
- Training data.
- Integration.

Probabilistic Atlas

- Organ positions normalized to anatomical landmarks.
- Linear transformation: translation, rotation.
- Probabilities of liver in the abdominal cavity.



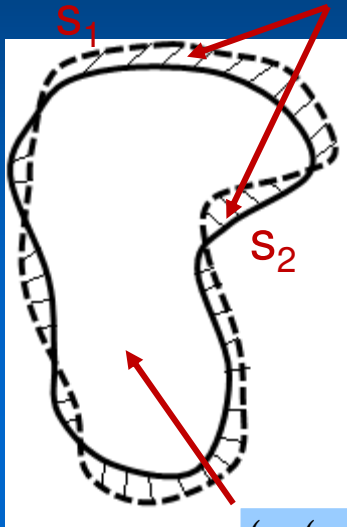
...



$$E_{location}(A) = - \sum_{p \in P} \ln(S_p(p|O))$$

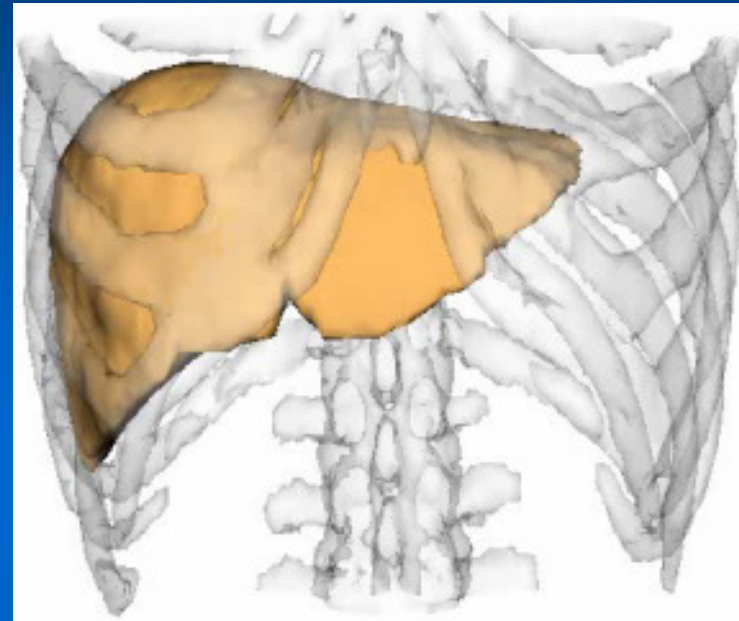
Shape Distribution

$$(H(s_1) - H(s_2))^2 = 1$$



$$(H(s_1) - H(s_2))^2 = 0$$

[Linguraru et al., MICCAI 2010]



[Okada et al. , MICCAI 2008]

$$D(s_1, s_2) = \int (H(s_1) - H(s_2))^2 H(s_1) dx / \int H(s_1) dx$$

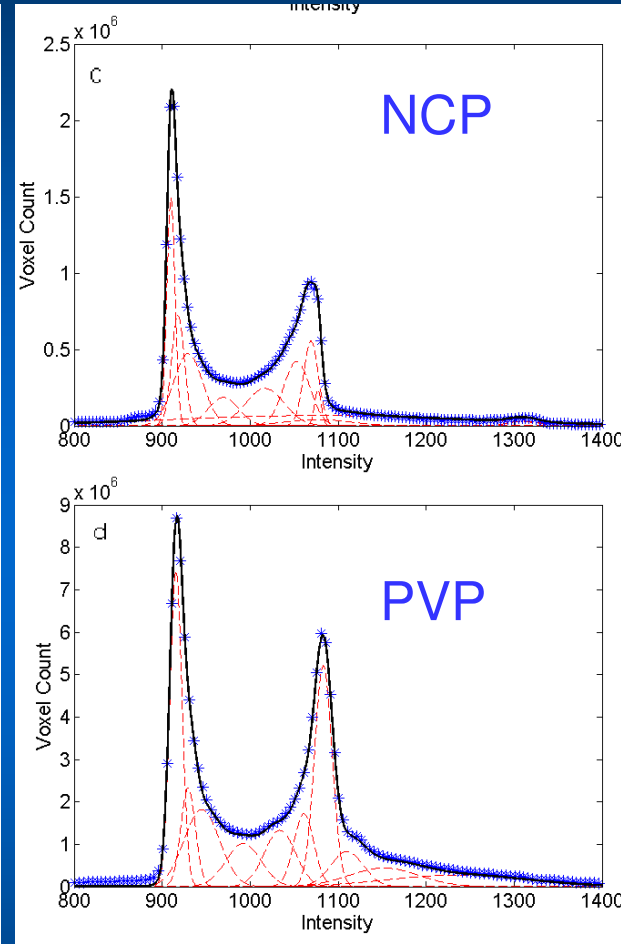
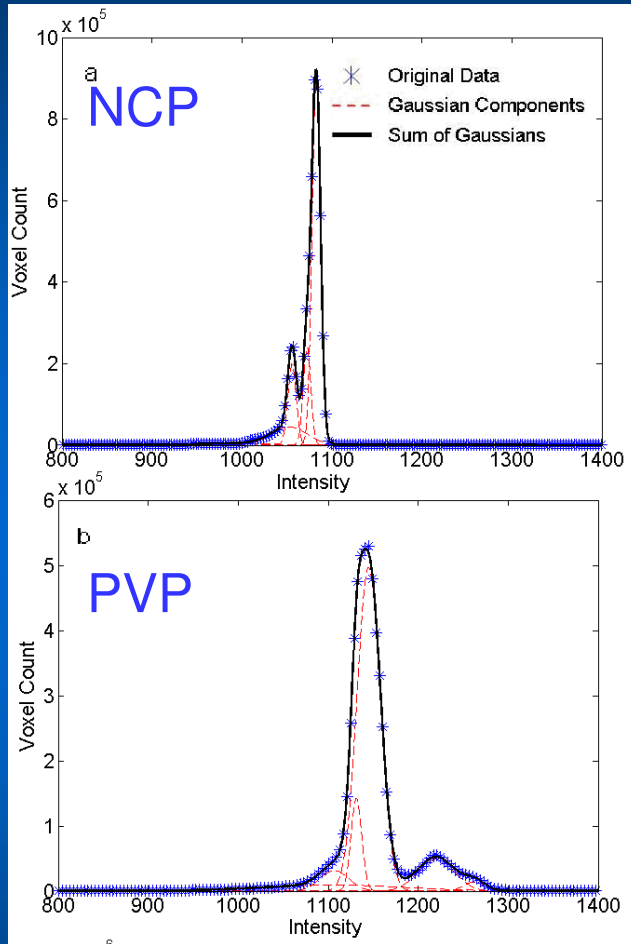
Dissimilarity Metric

- Linear transformation: translation, rotation, scaling. Preserves **shape**.
- Statistical Shape Models – from a population.

Intensity Model

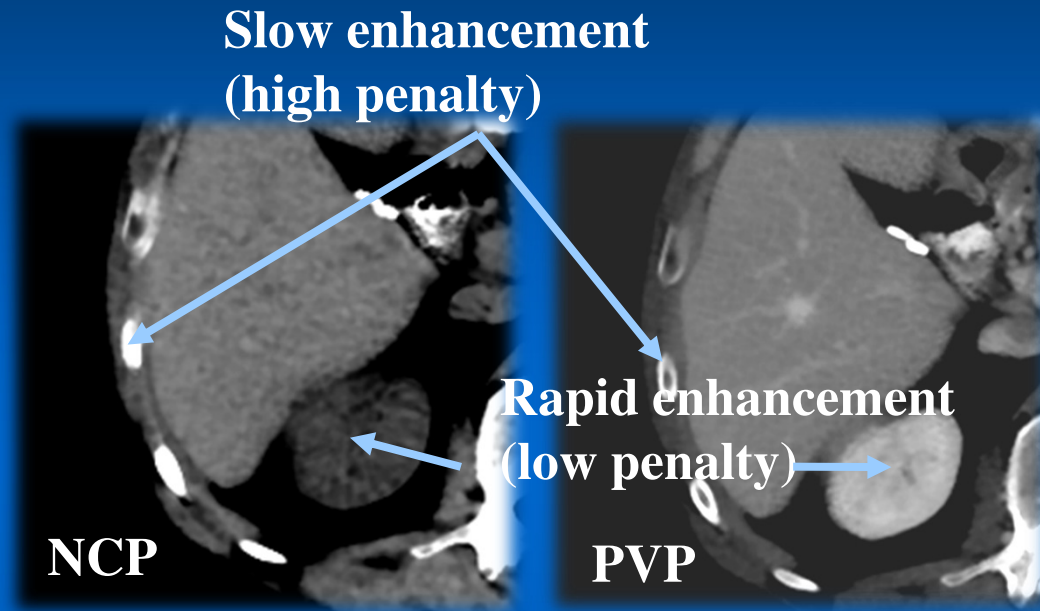
Organ

Background



$$R_p(O) = -\ln \left(\frac{\sqrt{P_{ncp}(I_{ncp}^p | O) P_{pvp}(I_{pvp}^p | O)}}{\sqrt{P_{ncp}(I_{ncp}^p | O) P_{pvp}(I_{pvp}^p | O) + P_{ncp}(I_{ncp}^p | B) P_{pvp}(I_{pvp}^p | B)}} \right)$$

Enhancement Model



$$E_p = \frac{(I_{pvp}^p - I_{ncp}^p)^2}{2\sigma_{ncp}\sigma_{pvp}}$$

Model Integration - Energy

- Appearance
- Location
- Shape

$$E(A) = E_{intensity}(A) + E_{enhance}(A) + E_{location}(A) + E_{shape}(A)$$

- Graph

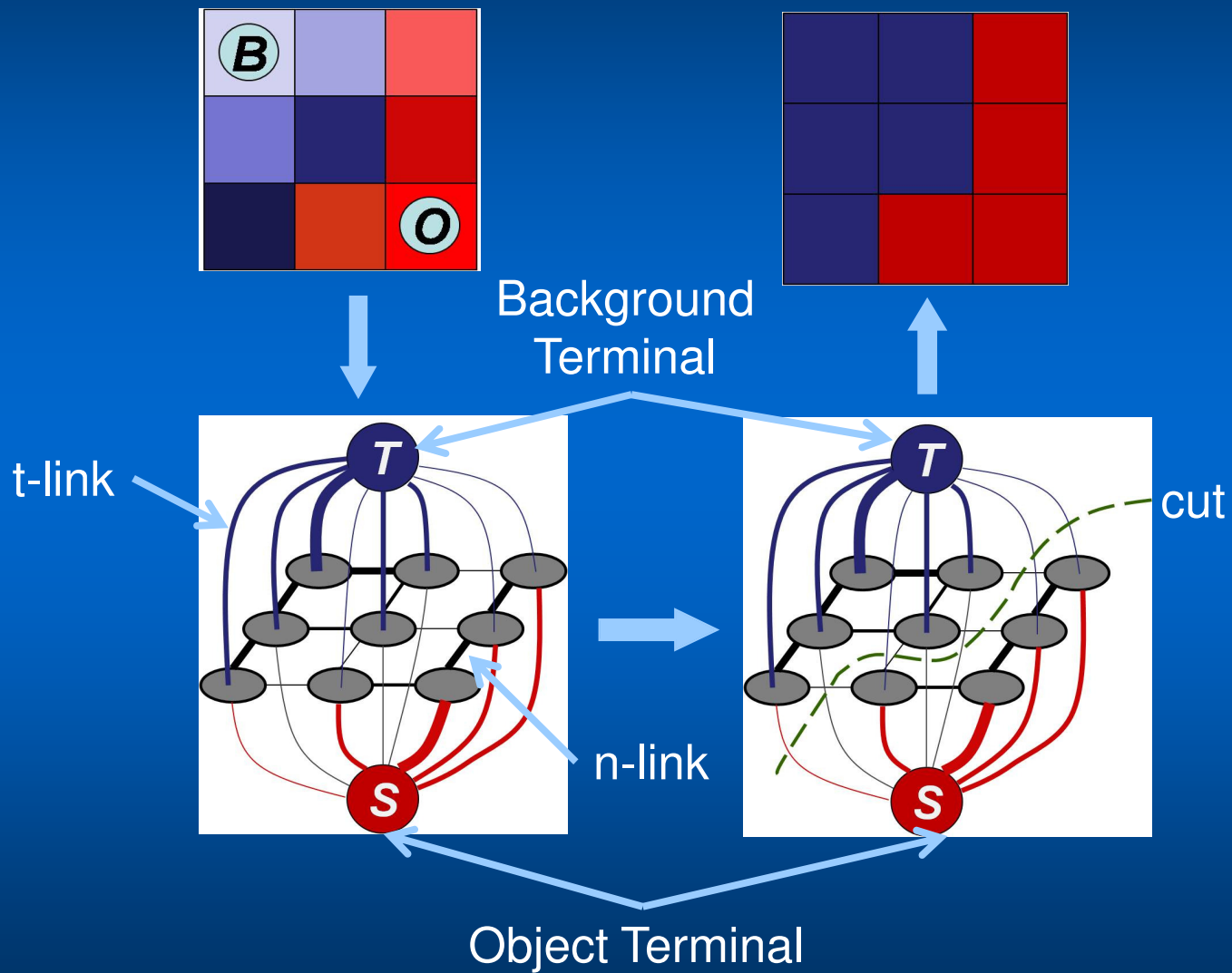
Graph Cuts

1. Image can be decomposed into a graph of **nodes** and **edges**.
2. **Background** (B) and **Object** (O) seeds initialize a segmentation.
3. Node are connected to terminals and are inter-connected.
4. Node connections have **costs**.
5. A cut corresponds to the minimum cost/maximum flow of the total segmentation energy.

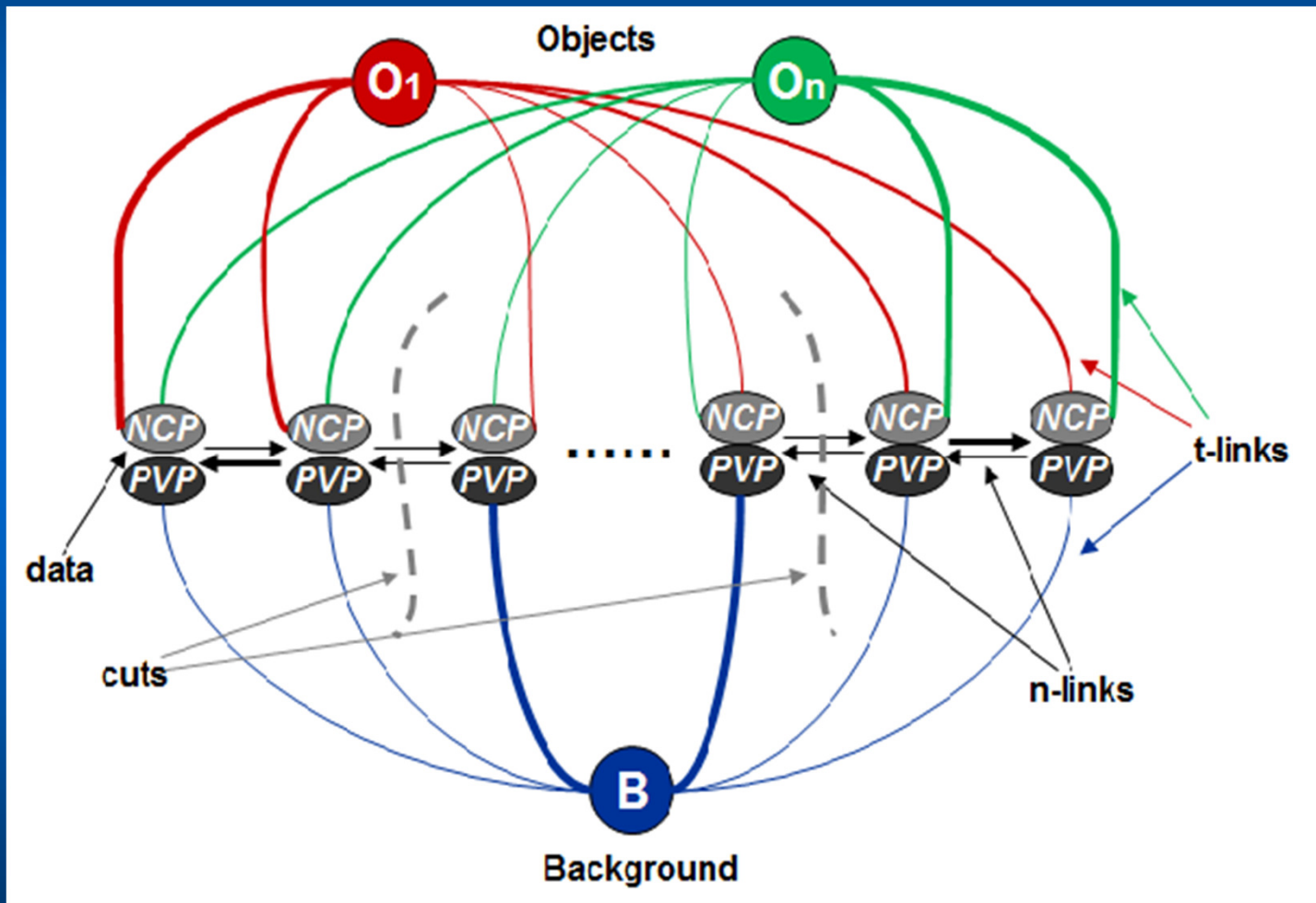
$$E(A) = E_{region}(A) + E_{boundary}(A)$$

[Boykov and Jolly: ICCV 2001]

Graph Cuts

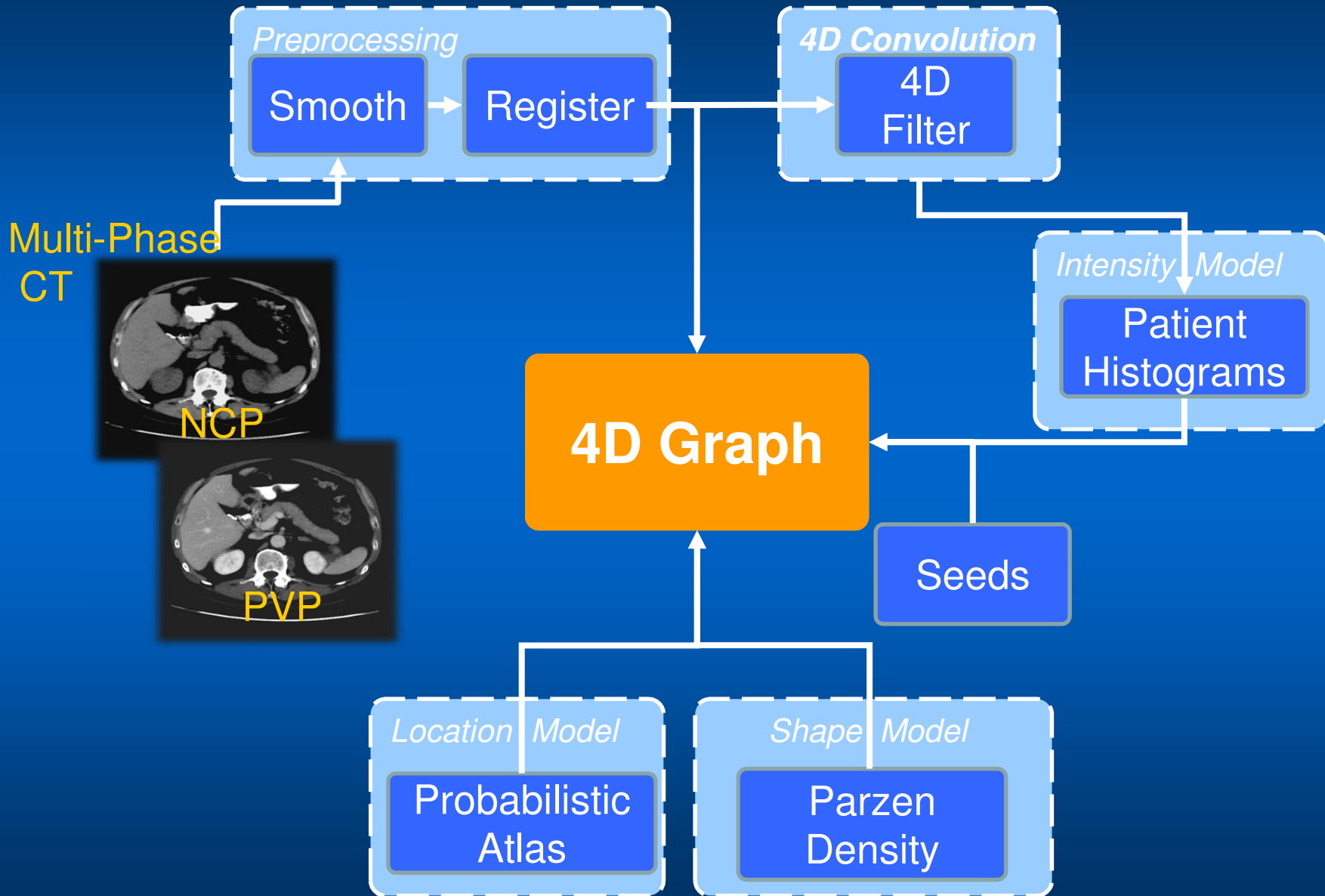


Multi-objects – Multi-phase



[Linguraru et al., Med Imag Anal 2012]

Integration - 4D Graph

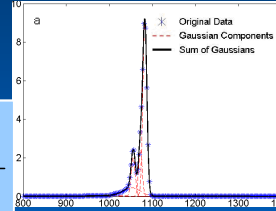


[Linguraru et al., Medical Image Analysis 2012]

Integration – 4D Graph

$$E(A) = E_{data}(A) + E_{enhance}(A) + E_{location}(A) + \sum_{i=1}^4 (E_{boundary}(A) + E_{shape}(A))$$

$$E_{data}(A) = \lambda \sum_{p \in O} R_p(O) + (1 - \lambda) \sum_{p \in B} R_p(B)$$



$$E_{enhance}(A) = \sum_{p \in P} 1 / (1 + E_p^2)$$

$$E_p = \frac{(I_{pvp}^p - I_{ncp}^p)^2}{2\sigma_{ncp}\sigma_{pvp}}$$

$$E_{location}(A) = -\sum_{p \in P} \ln(S_p(p|O))$$

$$D(s_1, s_2) = \int (H(s_1) - H(s_2))^2 H(s_1) dx / \int H(s_1) dx$$

$$E_{shape}(A) = \delta \sum_{\{p,q\} \in N_p} v_{\{p \rightarrow q\}} + (1 - \delta) \sum_{\{p,q\} \in N_p} v_{\{q \rightarrow p\}}$$

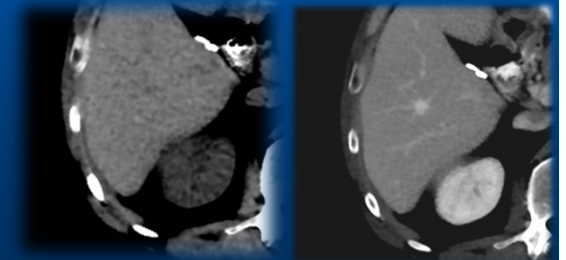
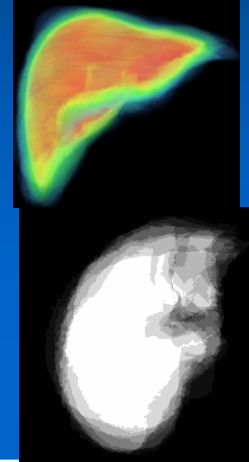
$$v_{\{p \rightarrow q\}} = v_{\{q \rightarrow p\}} = \begin{cases} 0 & , \text{if } A_p = A_q \text{ or } PS(s)^p = PS(s)^q \\ \max(PS(s)^p, PS(s)^q) / \text{dist}(p, q) & , \text{otherwise} \end{cases}$$

$$\text{IF } (PS(s)^p > PS(s)^q), \text{ THEN } v_{\{q \rightarrow p\}} = 1 \text{ ELSE } v_{\{p \rightarrow q\}} = 1$$

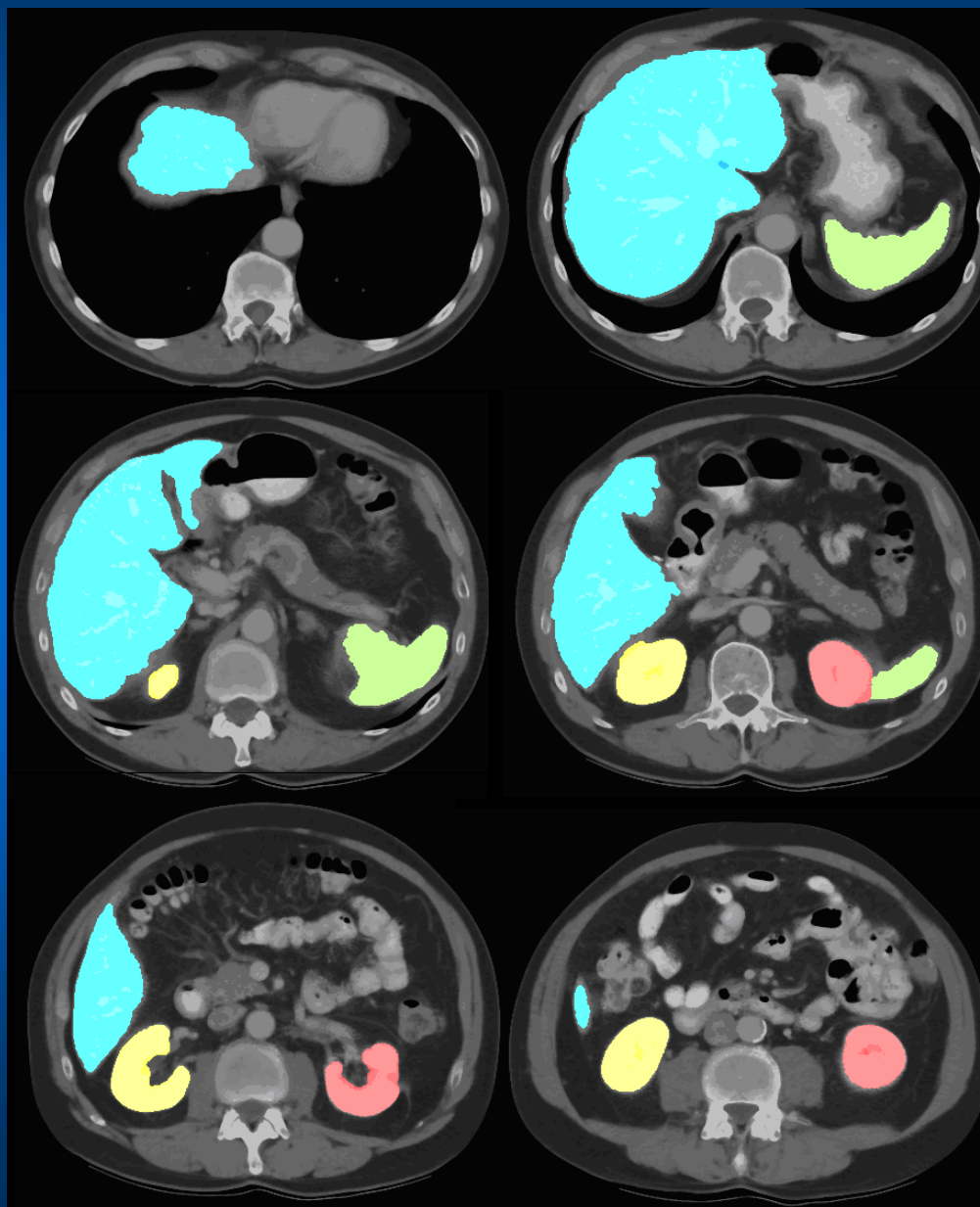
$$E_{boundary}(A) = \mu \sum_{\{p,q\} \in N_p} w_{\{p \rightarrow q\}} + (1 - \mu) \sum_{\{p,q\} \in N_p} w_{\{q \rightarrow p\}}$$

$$\text{Initialize } w_{\{p \rightarrow q\}} = w_{\{q \rightarrow p\}} = \begin{cases} 0 & , \text{if } A_p = A_q \\ \exp\left(-\frac{|I_{ncp}^p - I_{ncp}^q| \cdot |I_{pvp}^p - I_{pvp}^q|}{2\sigma_{ncp}\sigma_{pvp}}\right) \frac{1}{\text{dist}(p, q)} & , \text{otherwise} \end{cases}$$

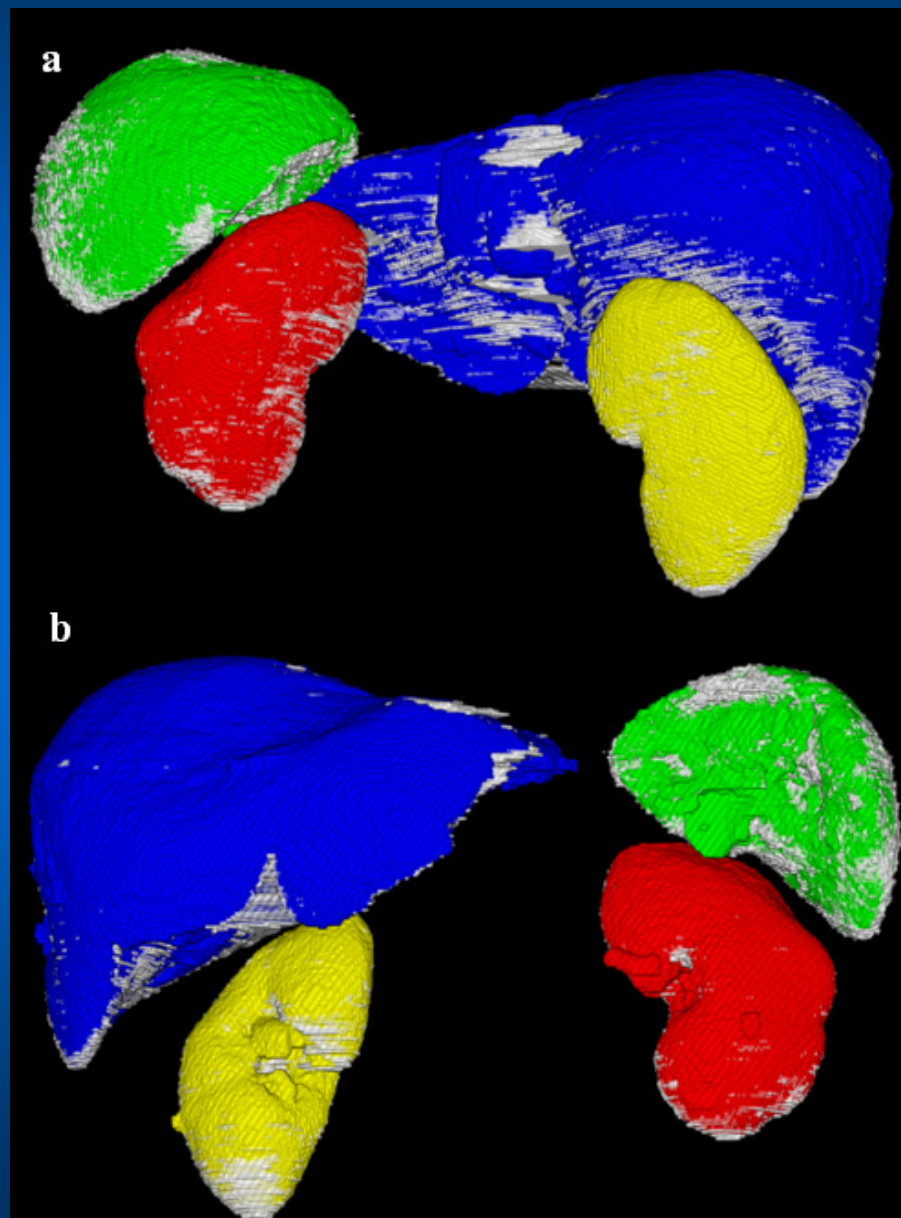
$$\text{IF } ((I_{pvp}^p - I_{pvp}^q) > \sigma_{pvp} \text{ OR } (I_{ncp}^p - I_{ncp}^q) > \sigma_{ncp}), \text{ THEN } w_{\{q \rightarrow p\}} = 1, \text{ ELSE } w_{\{p \rightarrow q\}} = 1$$



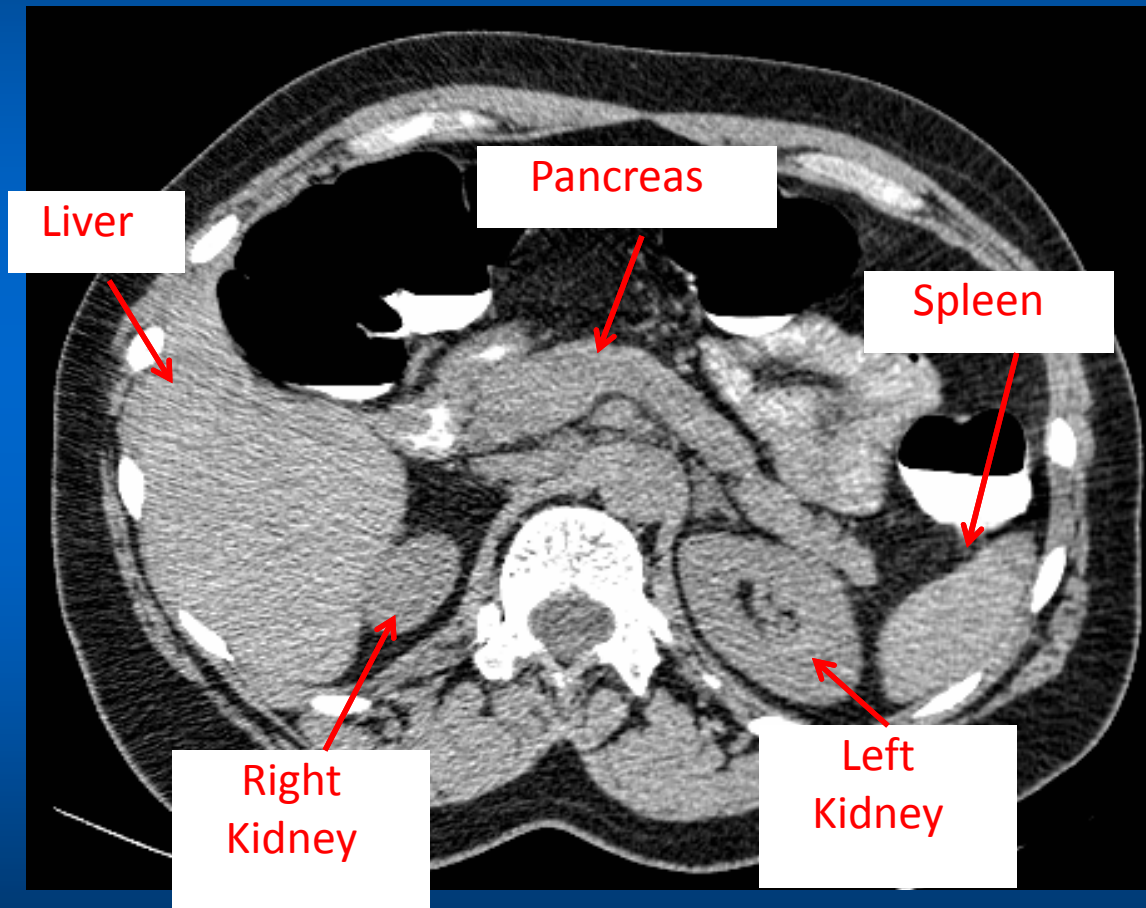
Results



Results

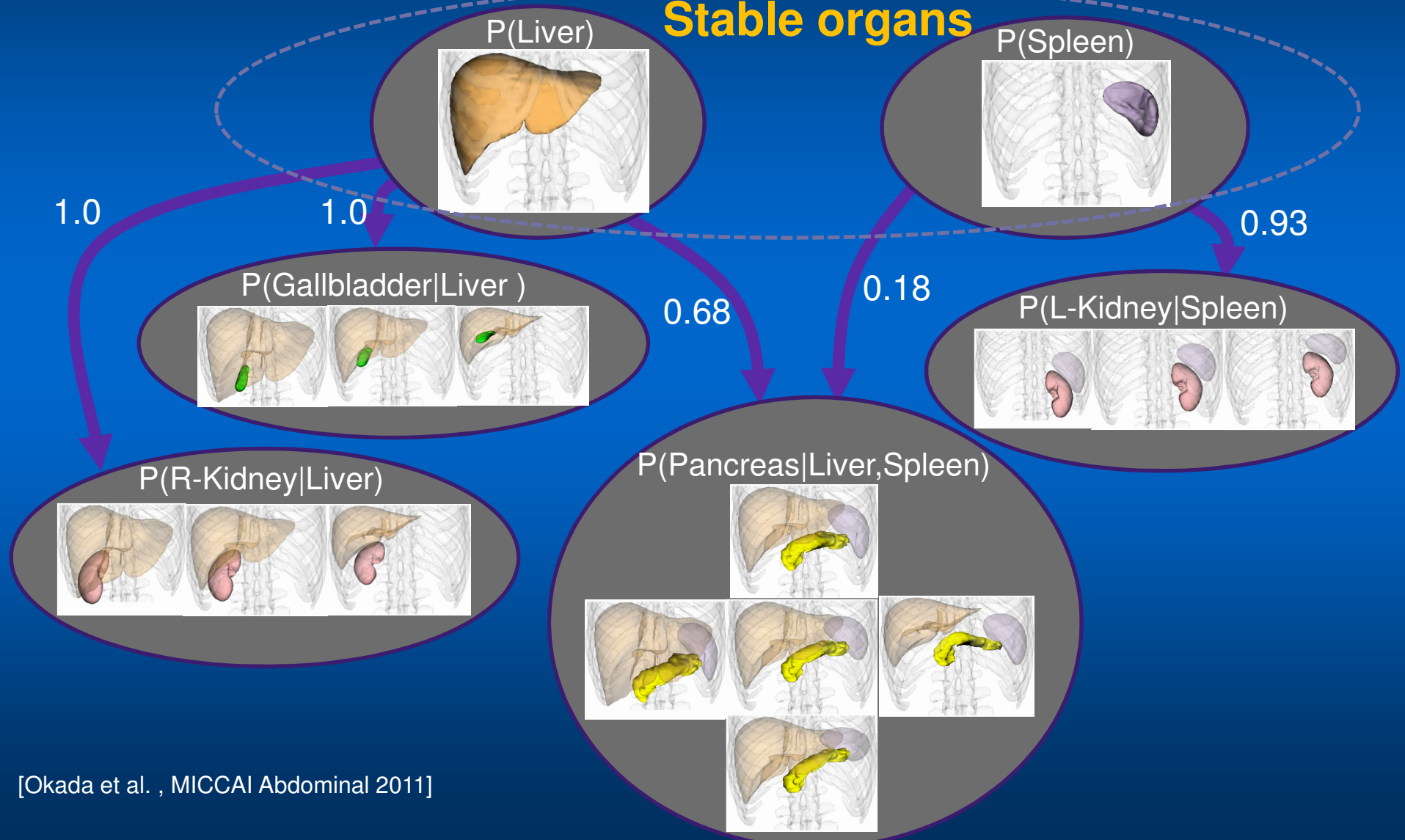


Some Organs are More Challenging!



Hierarchical Inter-Patient Anatomical Variability

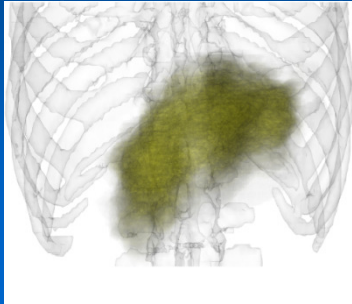
Stable organs



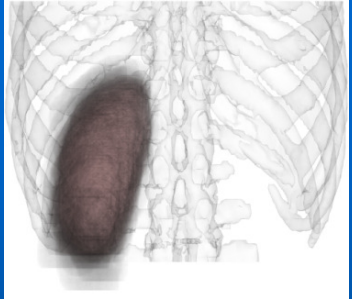
Prediction-based Probabilistic Atlas

Conventional

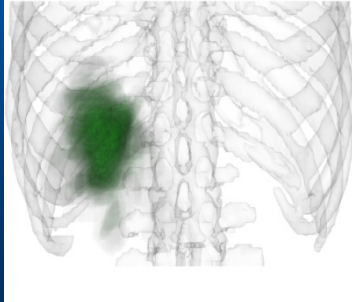
$P(\text{Pancreas})$



$P(\text{R-Kidney})$



$P(\text{Gallbladder})$



Hierarchical

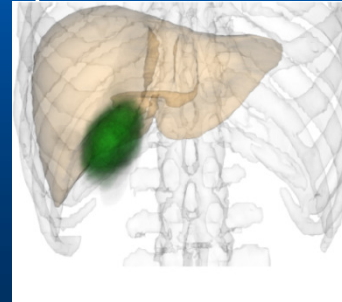
$P(\text{Pancreas}|\text{Liver,Spleen})$



$P(\text{R-Kidney}|\text{Liver})$

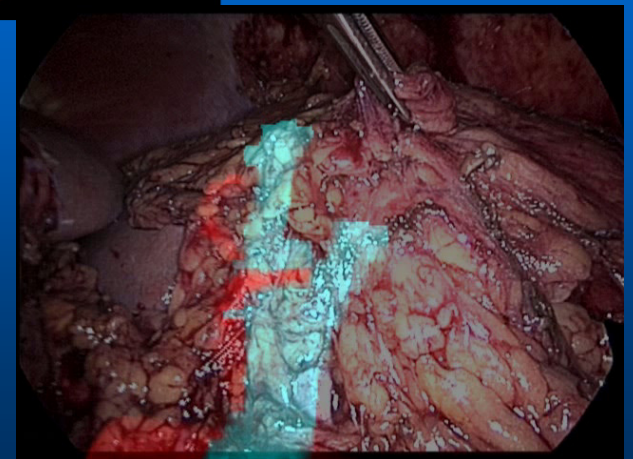
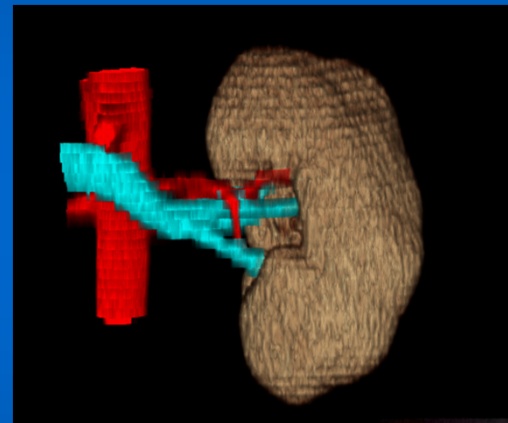
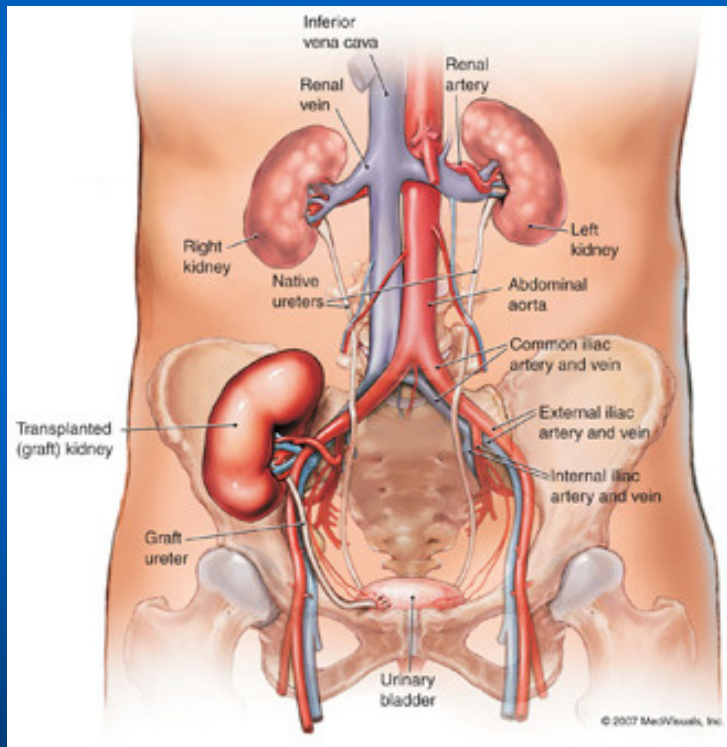


$P(\text{Gallbladder}|\text{Liver})$



Abdominal Vessels

- Anatomical constraints
- Important in surgical planning and guidance.



Courtesy of Yoshinobu Sato, PhD

Vessel Models



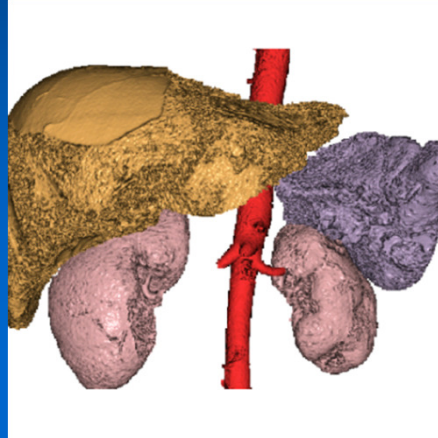
Courtesy of Yoshinobu Sato, PhD

Vessel Models

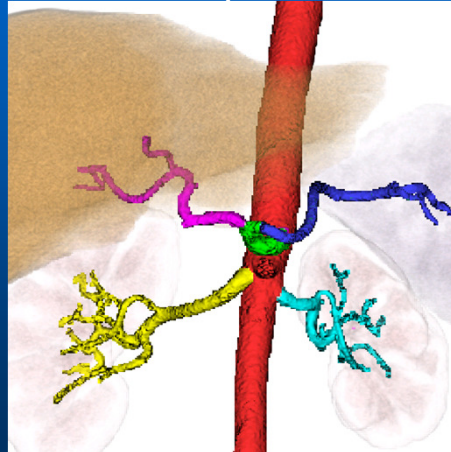
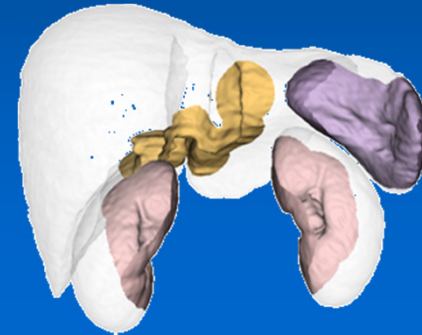
Original CT



Extracted organ & aorta



Flow-in-region atlas



[Suzuki et al., MICCAI CLIP 2002]

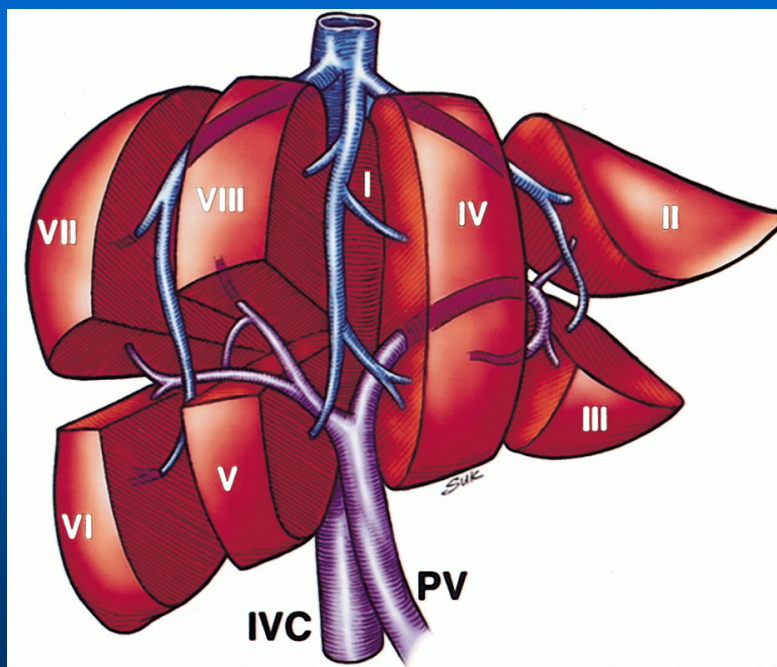
Courtesy of Yoshinobu Sato, PhD

Site Map

- Introduction
- Established Segmentation
- Priors in Medical Image Data
- **Segmentation and Simulation**

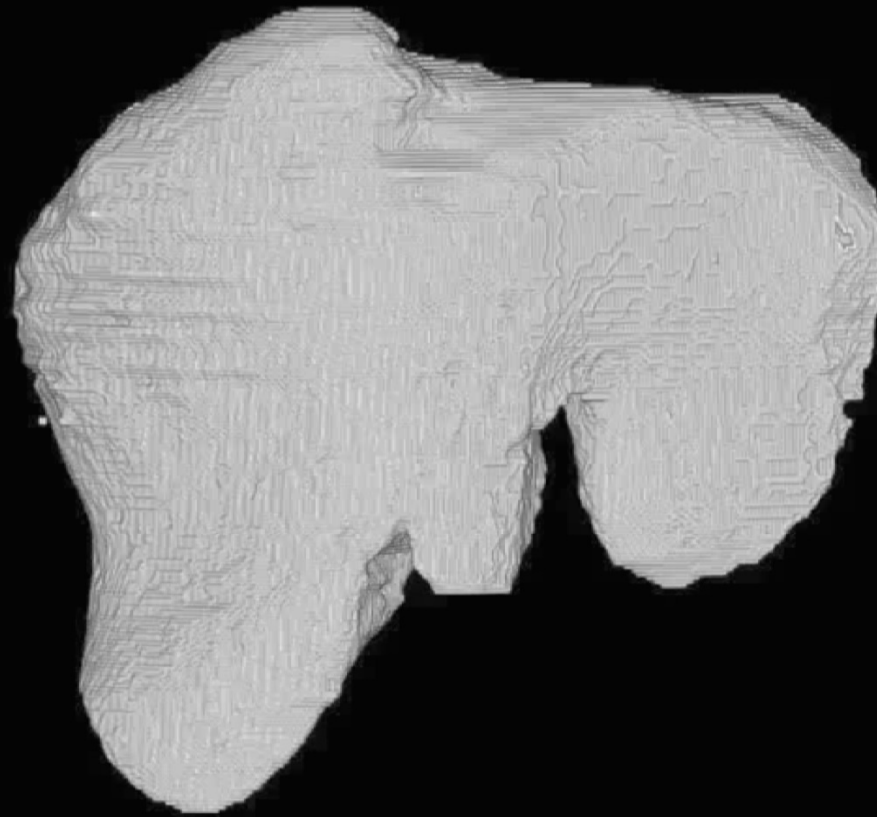
Segmentation to Intervention

- Proximity of tumors to intrahepatic veins - patient's suitability for surgery/intervention.
- Minimally invasive therapies – minimize healthy tissue damage.
- Living donor liver transplant – segmental anatomy.



[Madoff DC, et al 2002]

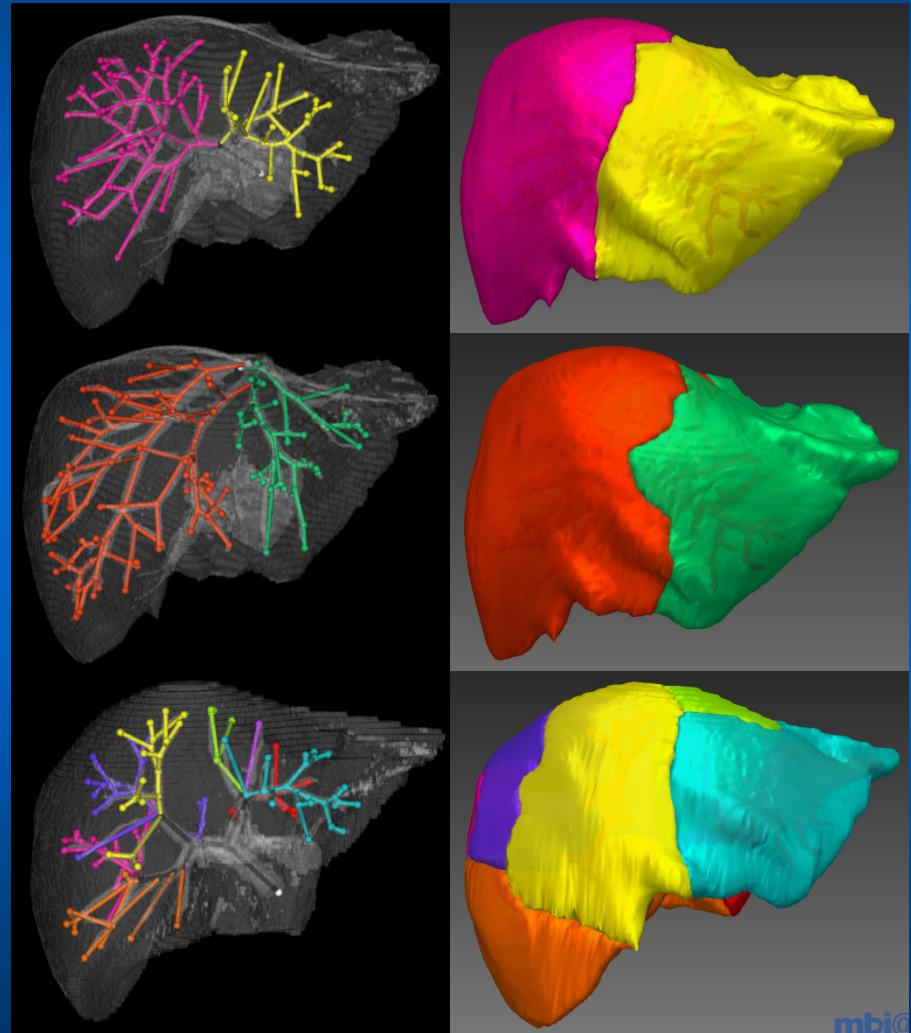
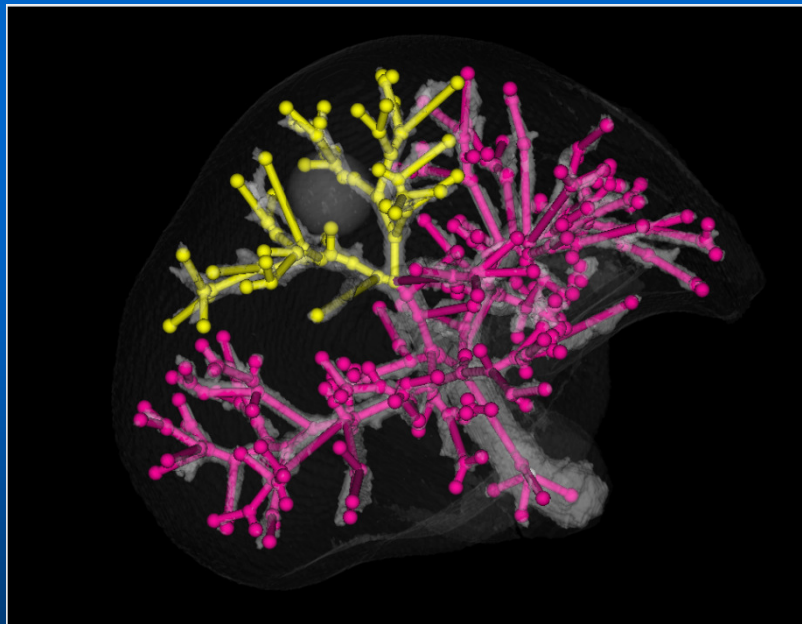
Segmental Anatomy



[Pamulapati et al., MICCAI Abdominal 2011]

Vein Clamping

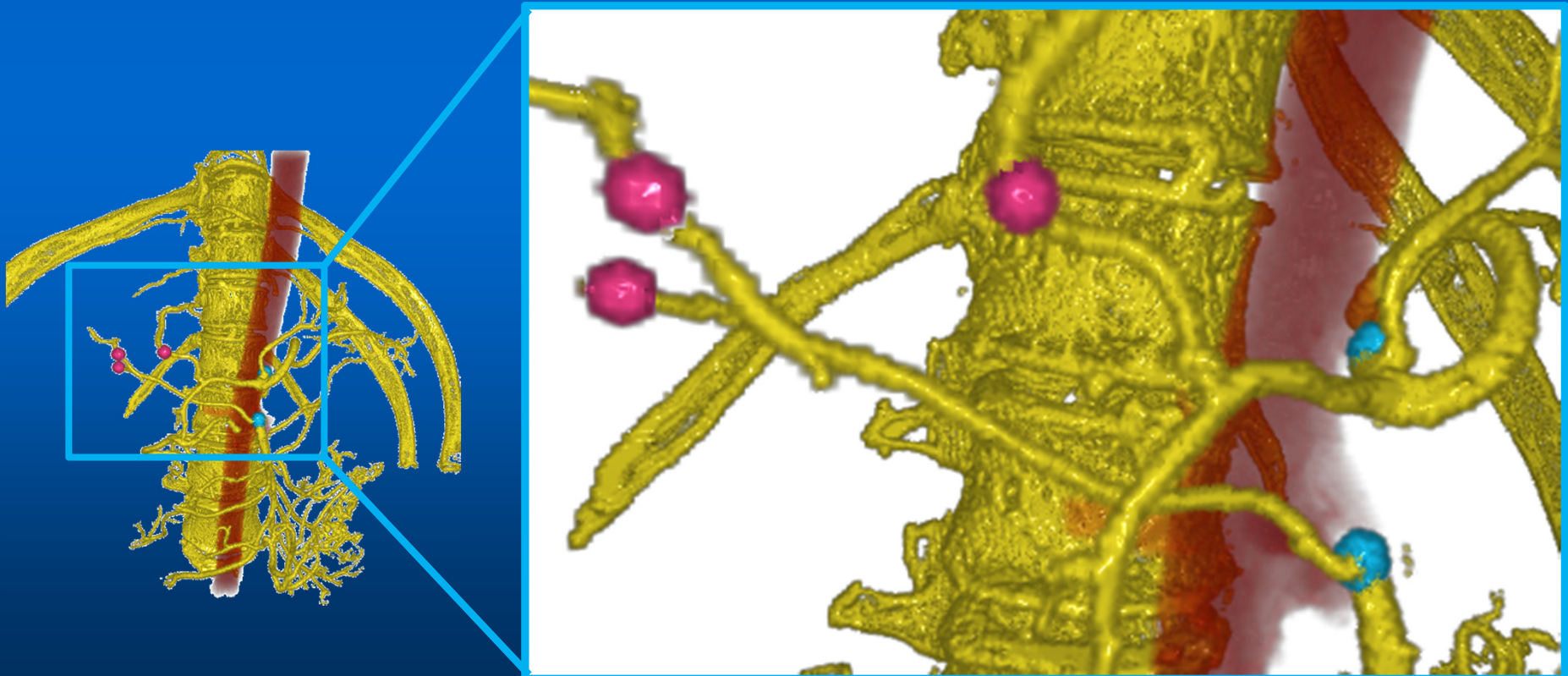
- Simulate effect of vein clamping
 - Training
 - Planning
 - Safety margins



[Drechsler et al., MICCAI Abdominal 2011]

Simulate Catheterization

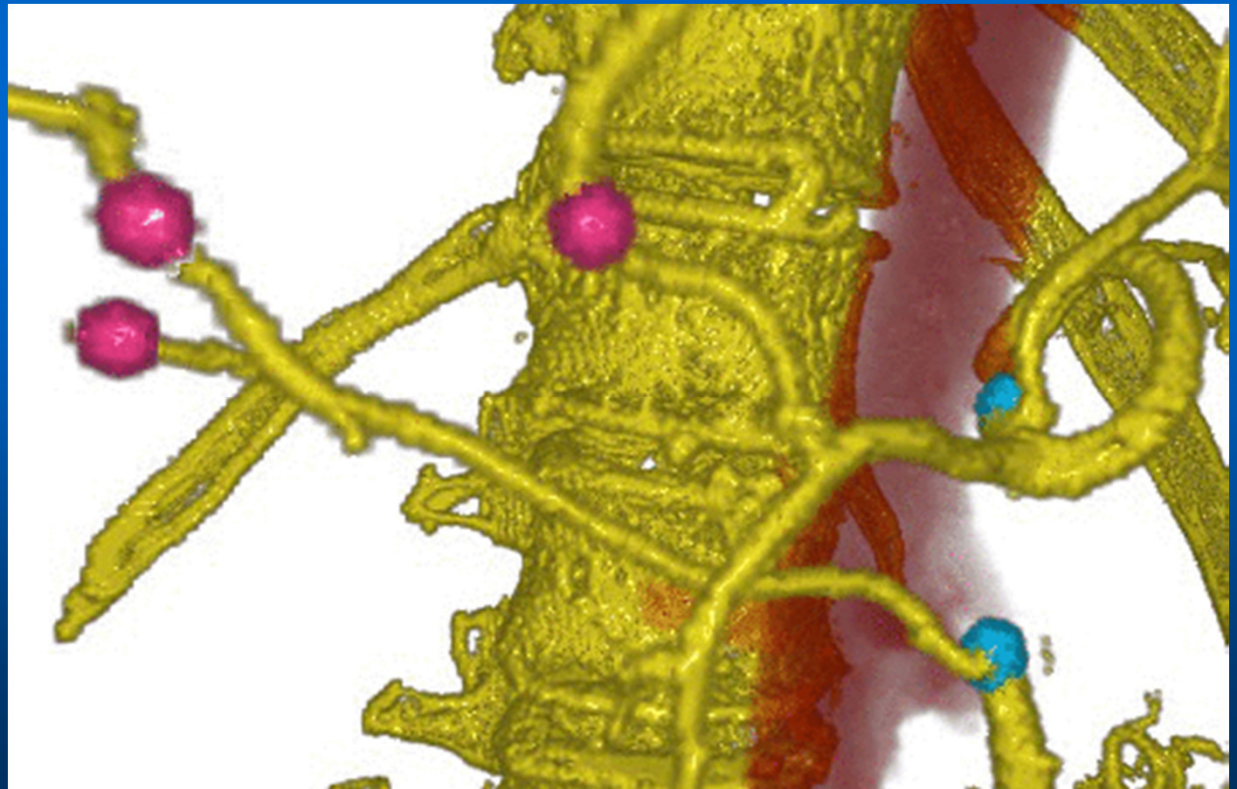
- Localized root and leaf nodes are shown below.



Courtesy of Yoshinobu Sato, PhD

Simulate Catheterization

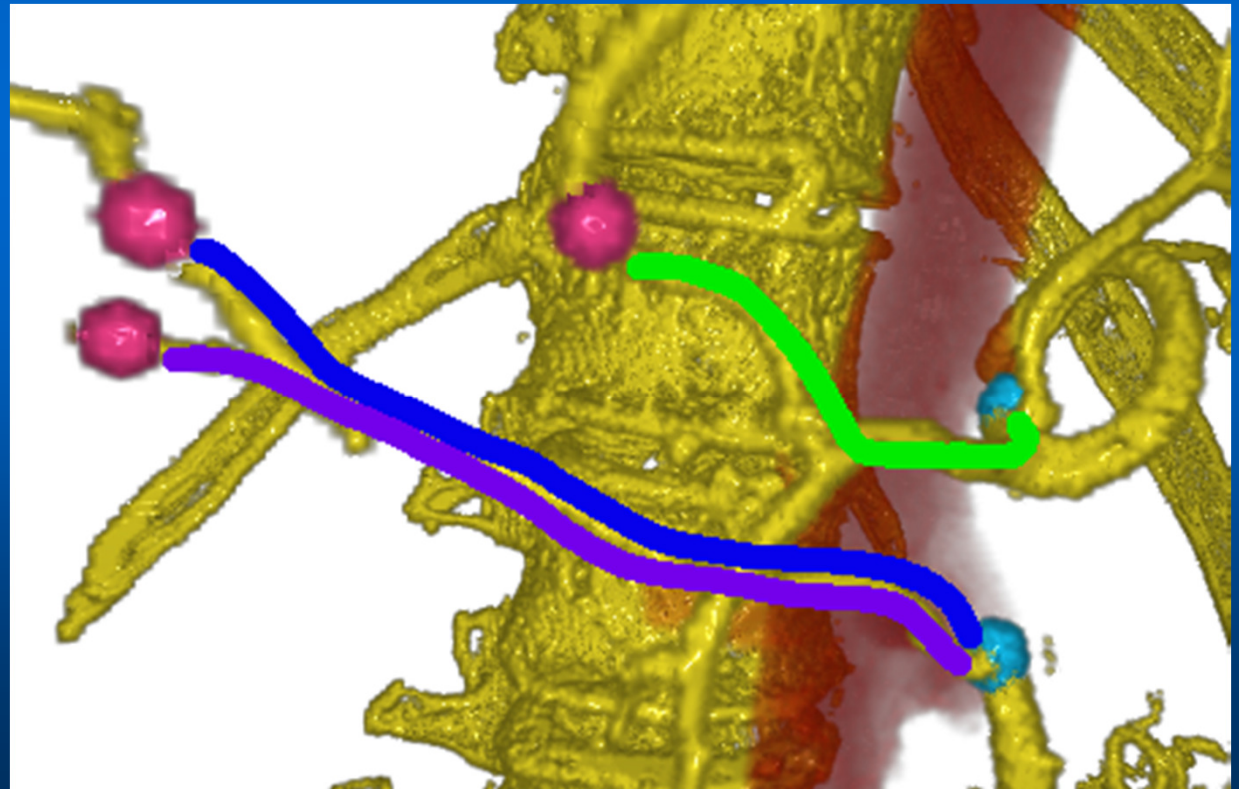
Shortest path findings are performed from all nodes



Courtesy of Yoshinobu Sato, PhD

Simulate Catheterization

Shortest path findings are performed from all nodes



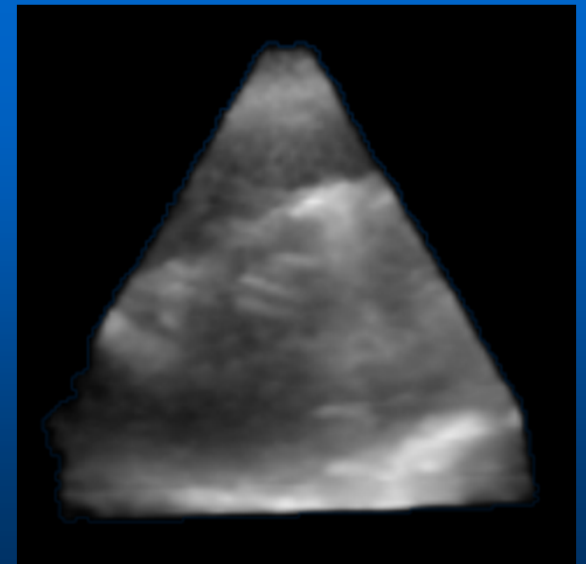
Courtesy of Yoshinobu Sato, PhD

Consider

- Speed – motion modeling
(US 25 frames/s + heart 80 b/min)
- Size – for pediatrics
- Interactive segmentation
– more accurate/preferable
- Machine learning
- learn from large data
- Human body is well studied
(multiple organs)



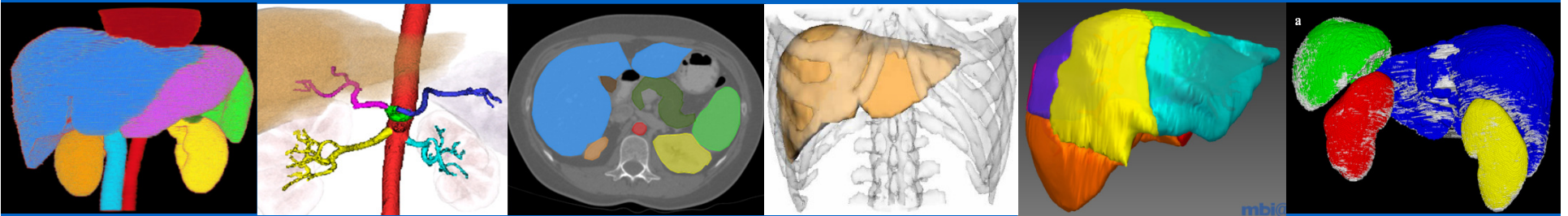
[Harvard University]



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