

## II. Segmentation: from shades of gray to black and white

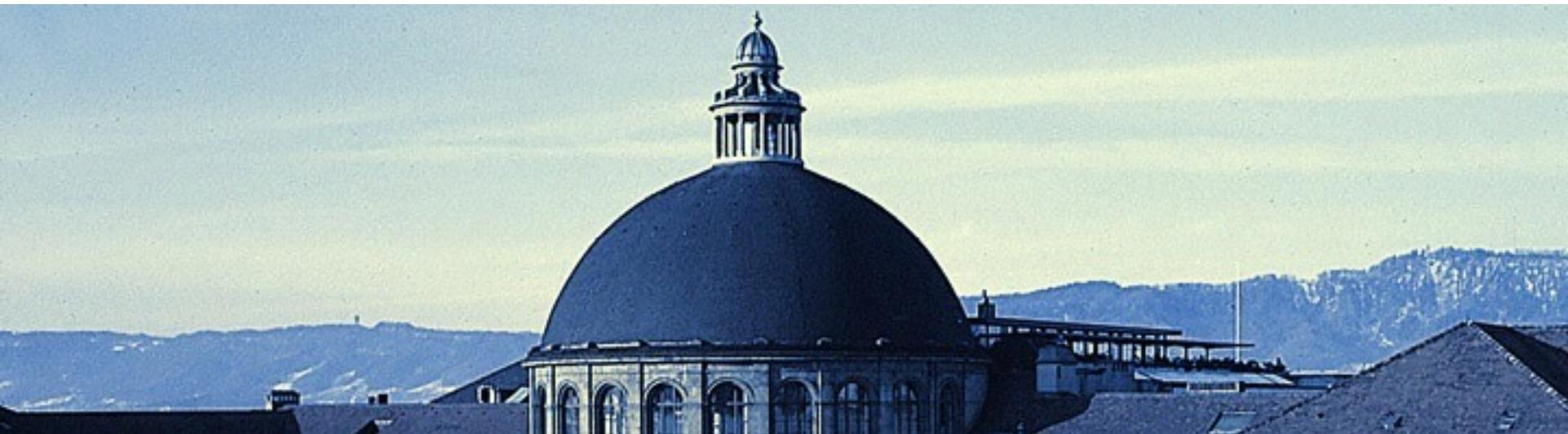
Kevin Mader, Philipp Schneider, and  
Marco Stampanoni

[mader@biomed.ee.ethz.ch](mailto:mader@biomed.ee.ethz.ch)



# Topics

1. Segmentation and thresholding
2. Processing binary images
3. Demonstration



# Literature

John C. Russ, “The Image Processing Handbook”,

Available online within domain ethz.ch (or proxy.ethz.ch / public VPN)

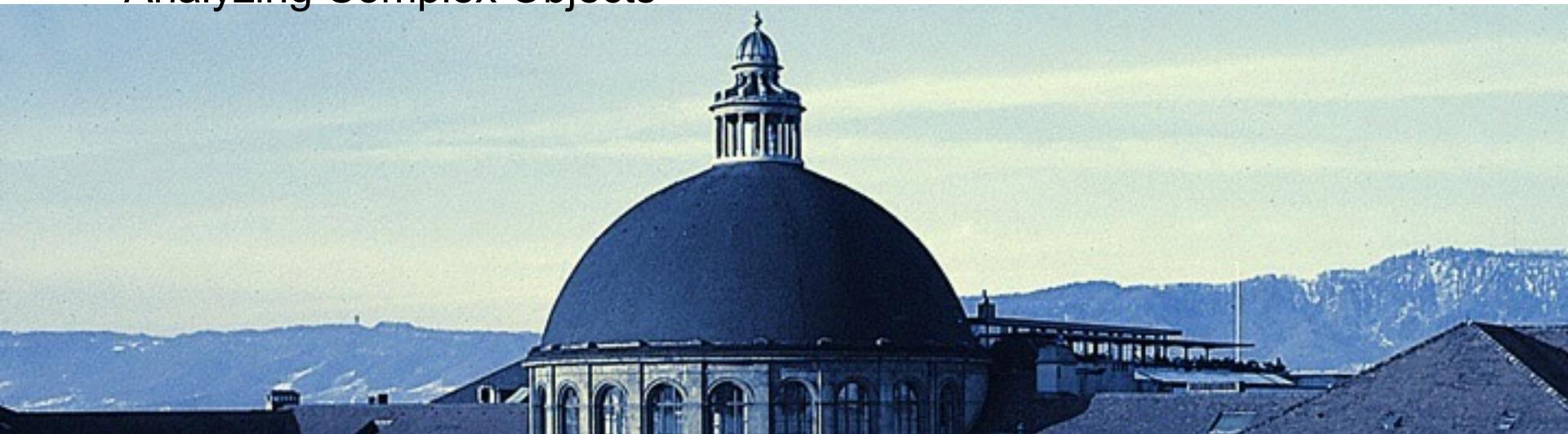
<http://dx.doi.org/10.1201/9780203881095>

Machine Learning Stanford: <http://cs231n.github.io/>

More detailed Slides: Quantitative Big Imaging Course

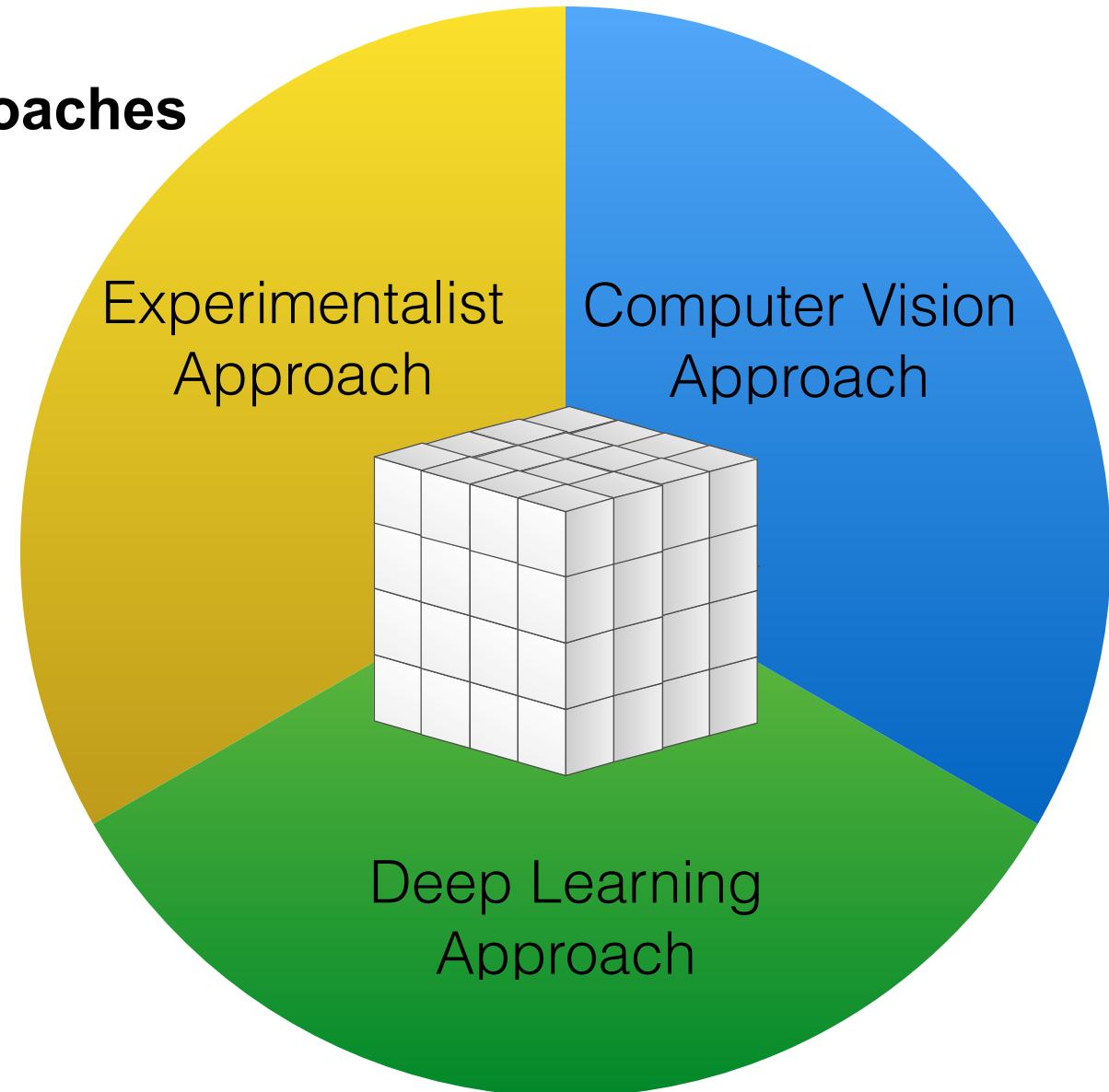
[kmader.github.io/Quantitative-Big-Imaging-2015/](http://kmader.github.io/Quantitative-Big-Imaging-2015/)

- Basic Segmentation, Discrete Binary Structures
- Advanced Segmentation
- Analyzing Complex Objects



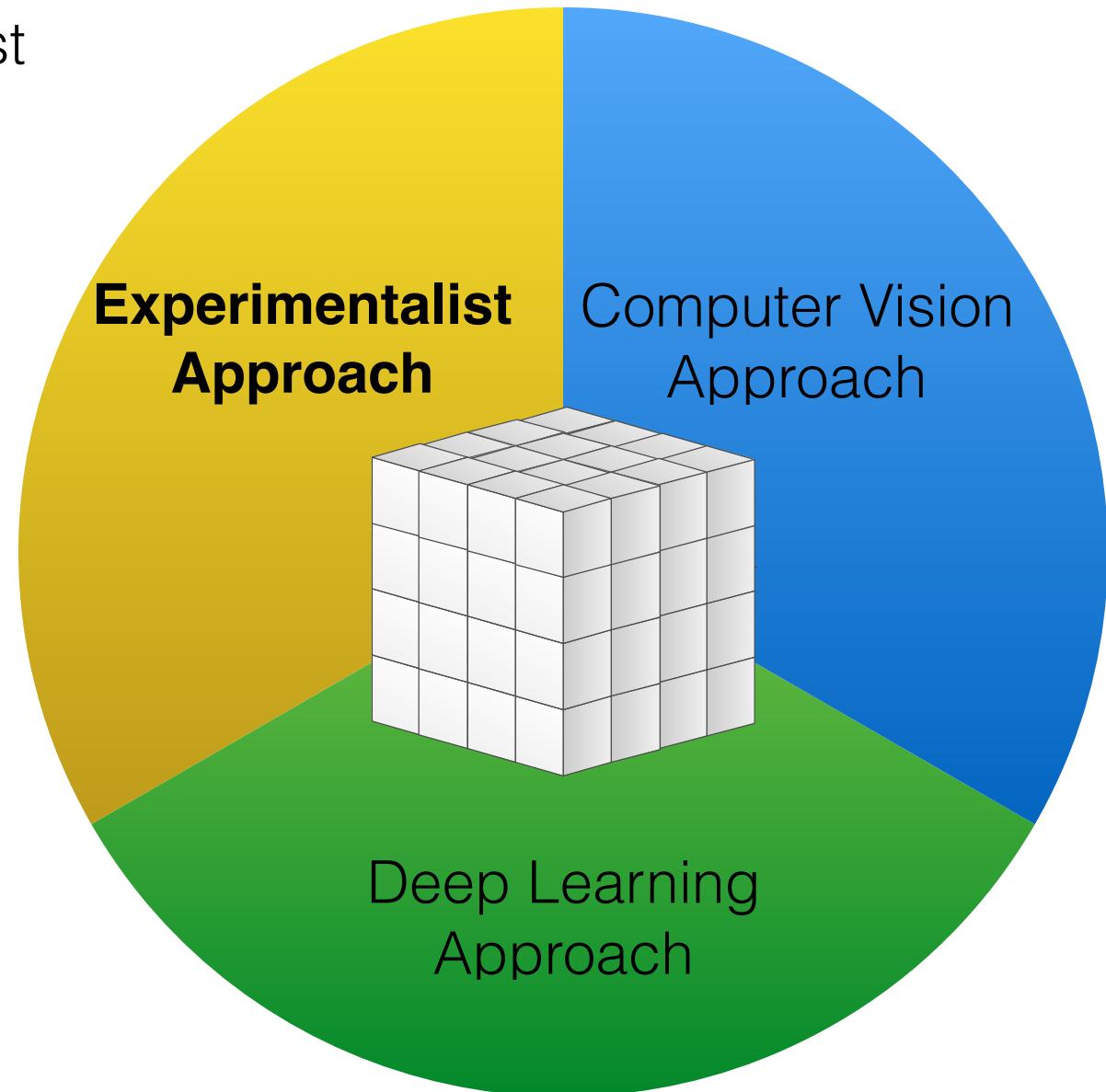
# Image Analyst Approaches

- An image is a bucket of pixels.
- How you choose to turn it into useful information is strongly dependent on your background



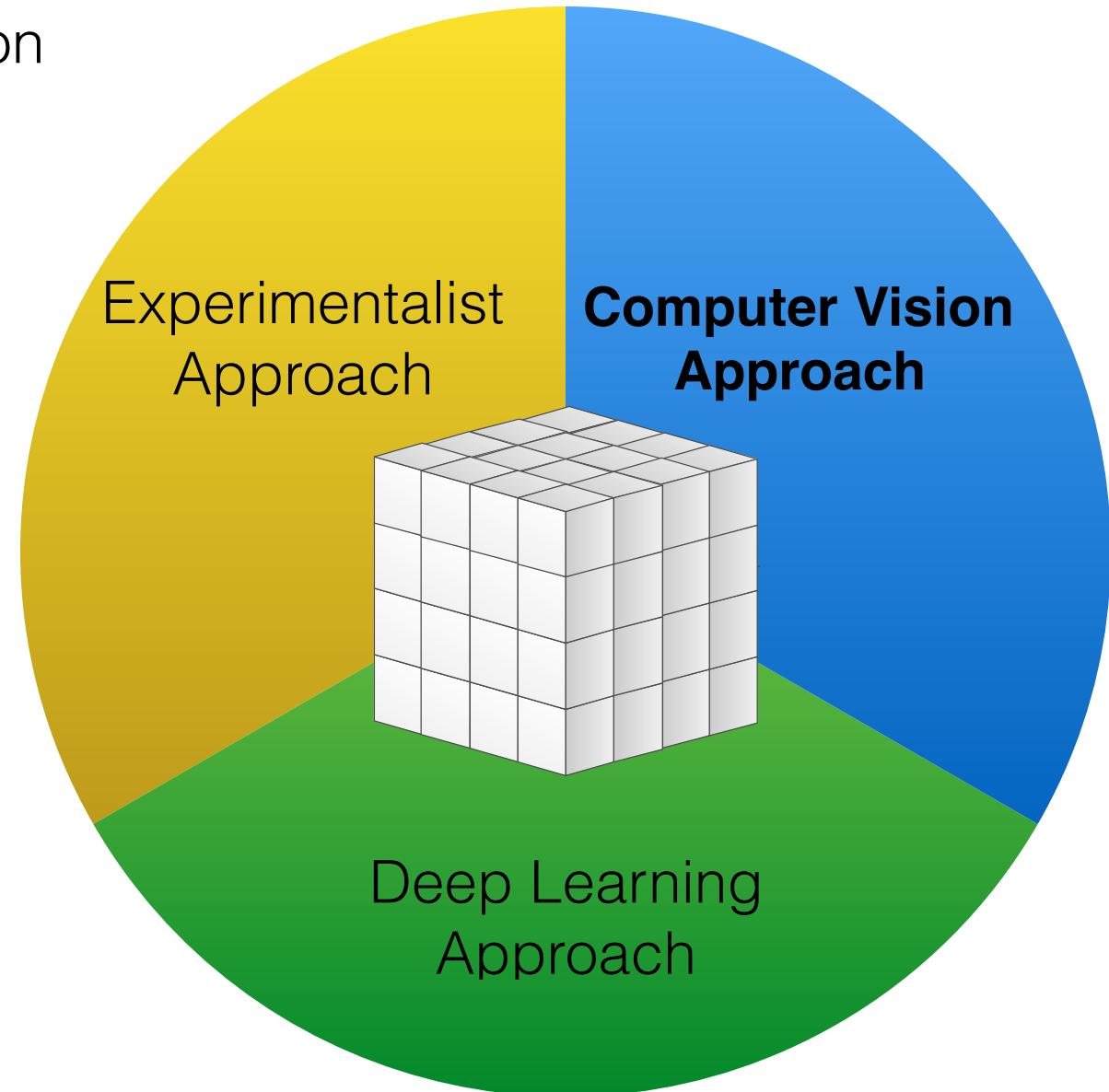
## Experimentalist Approach

- Problem-driven
  - Top-down
  - ‘Reality’ Model-based
- cell counting
- porosity



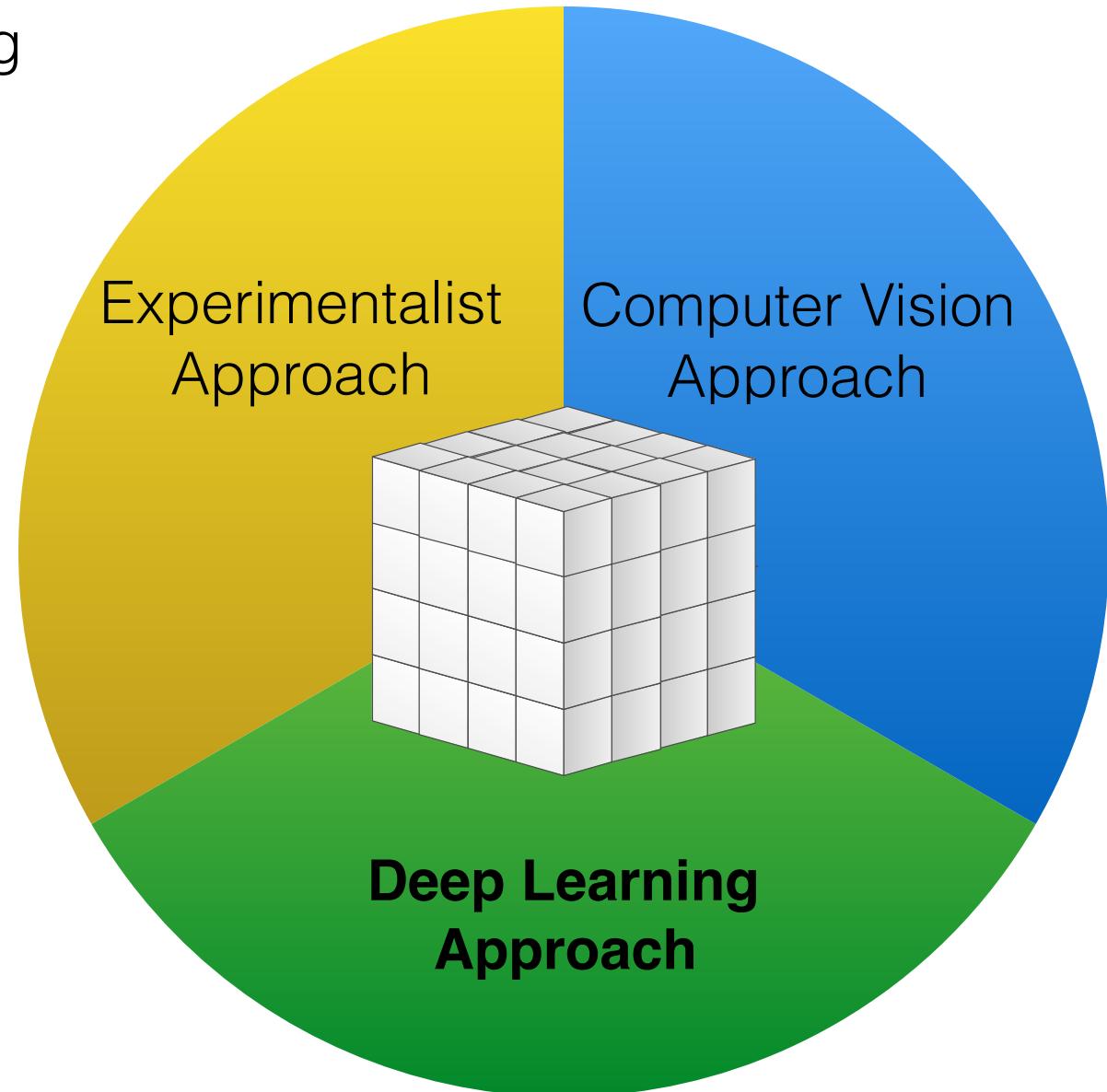
## Computer Vision Approach

- Method-driven
  - Feature-based
  - ‘Image’ Model-based
- Engineer features for solving problems
- edge detection
- face detection



## Deep Learning Approach

- Results-driven
  - Biology ‘inspired’
- Build both image processing and analysis from scratch
- Captioning images
- Identifying unusual events

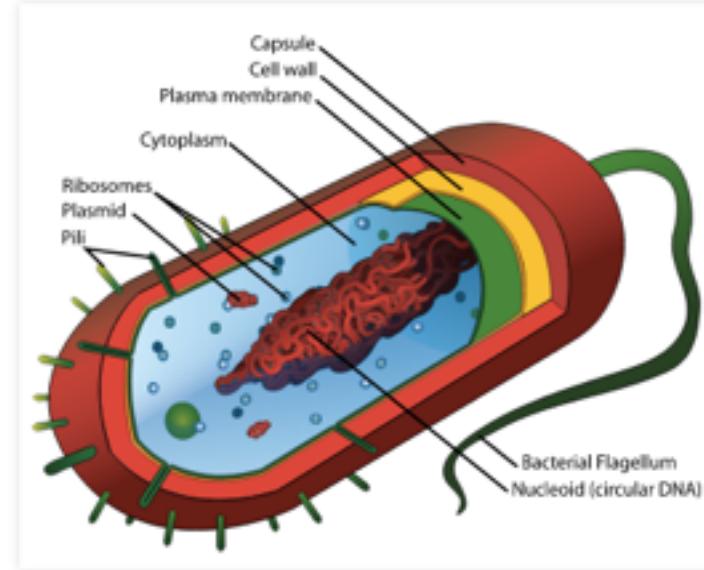


# 1. Motivation

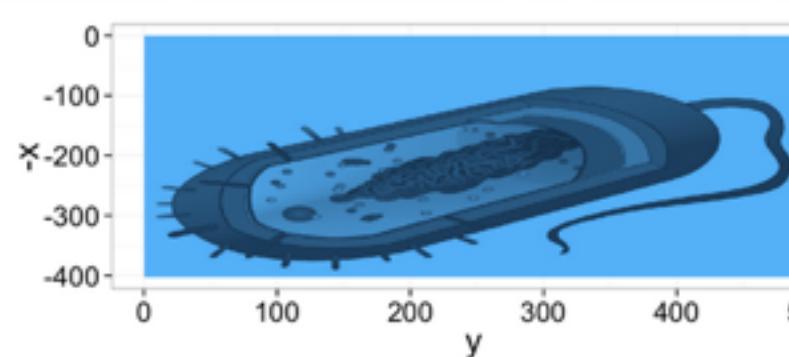
## Why do we do experiments?

1. To get an idea of what is going on
2. To test a hypothesis
  1. Does temperature affect bubble size?
  2. Is this gene important for cell shape and thus mechanosensation in bone?
  3. Does higher canal volume make bones weaker?
  4. Does the granule shape affect battery life expectancy?

- What we are looking at



- What we get from the imaging modality



# 1. Motivation

## Why do we do experiments?

### 1. To test a hypothesis

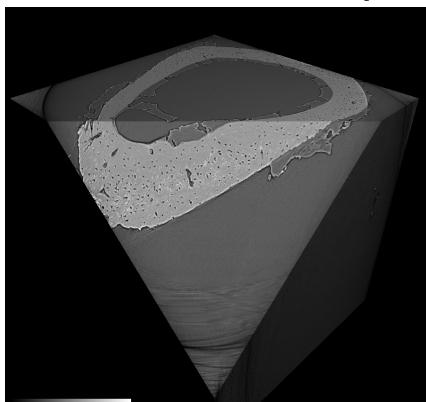
2560 (pixels in x)

x 2560 (pixels in y)

x 2160 (pixels in z)

x 32 bit

= 56GB / sample

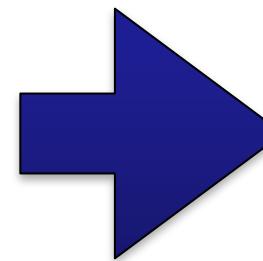


Highly Weakly  
Absorbing Absorbing  
Regions Regions

Filtering /  
Preprocessing

Same exact  
size :(

....



Way too much,  
need to reduce

Single number:  
volume  
fraction,  
cell count,  
average cell  
stretch,  
cell volume  
variability

# 1. Motivation

## Why do we do experiments?

### 1. To test a hypothesis

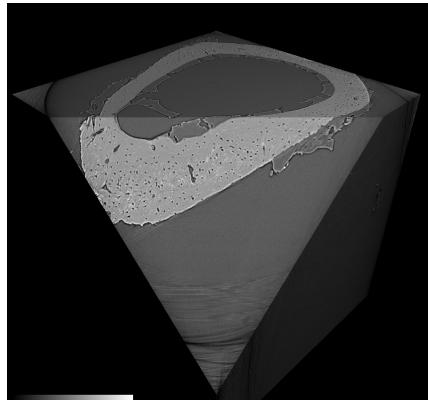
2560 (pixels in x)

x 2560 (pixels in y)

x 2160 (pixels in z)

x 32 bit

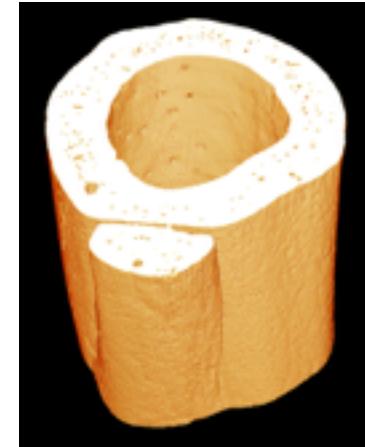
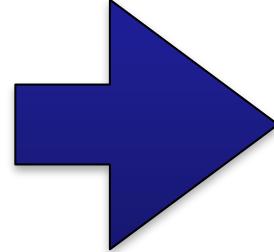
= 56GB / sample



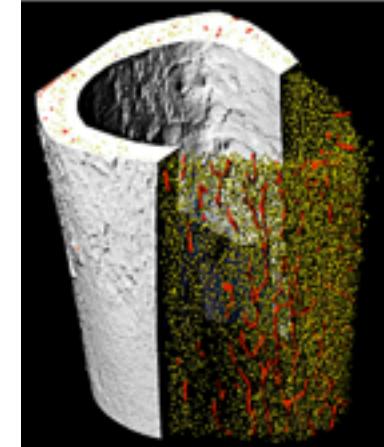
Highly  
Absorbing  
Regions

Weakly  
Absorbing  
Regions

Segmentation

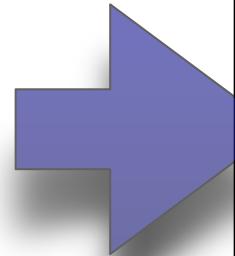


...  
x 1-2 bit  
~ 2GB / sample



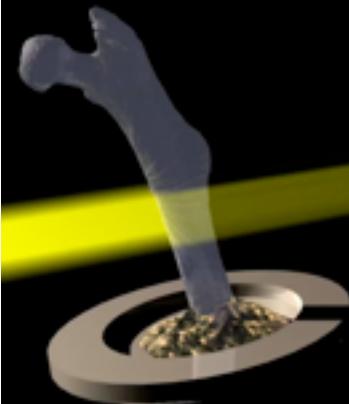
still a long  
way to go

....



# 1. Segmentation and thresholding

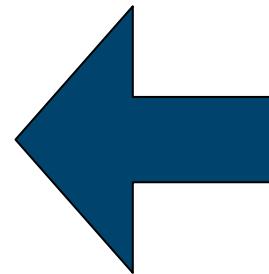
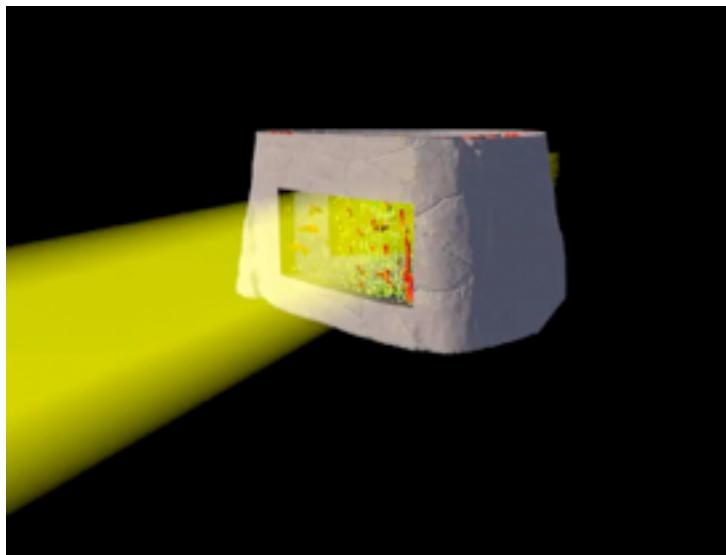
Goal



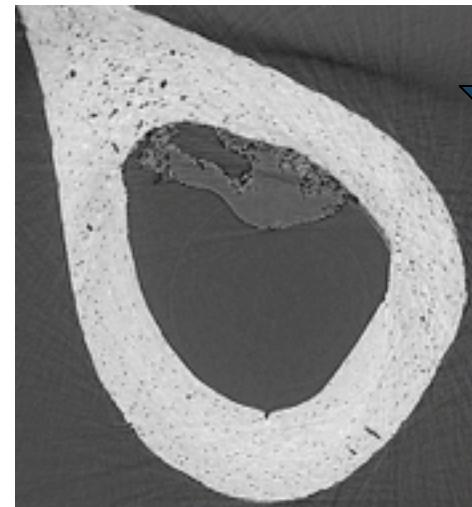
Visible Light



Reconstruction



Segmentation



# 1. Motivation

## Review: Filtering and Image Enhancement

- This was a noise process which was added to otherwise clean imaging data

$$I_{measured}(x, y) = I_{sample}(x, y) + \text{Noise}(x, y)$$

- What would the perfect filter be

- $\text{Filter} * I_{sample}(x, y) = I_{sample}(x, y)$

- $\text{Filter} * \text{Noise}(x, y) = 0$

- $\text{Filter} * I_{measured}(x, y) = \text{Filter} * I_{real}(x, y) + \text{Filter} * \text{Noise}(x, y) \rightarrow I_{sample}(x, y)$

- What most filters end up doing

$$\text{Filter} * I_{measured}(x, y) = 90\%I_{real}(x, y) + 10\%\text{Noise}(x, y)$$

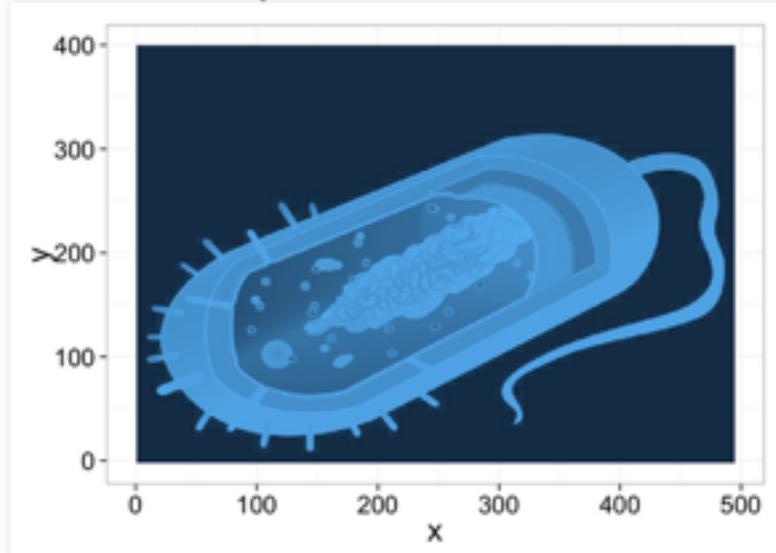
- What bad filters do

$$\text{Filter} * I_{measured}(x, y) = 10\%I_{real}(x, y) + 90\%\text{Noise}(x, y)$$

# 1. Motivation

## What did people used to do?

- What comes out of our detector / enhancement process

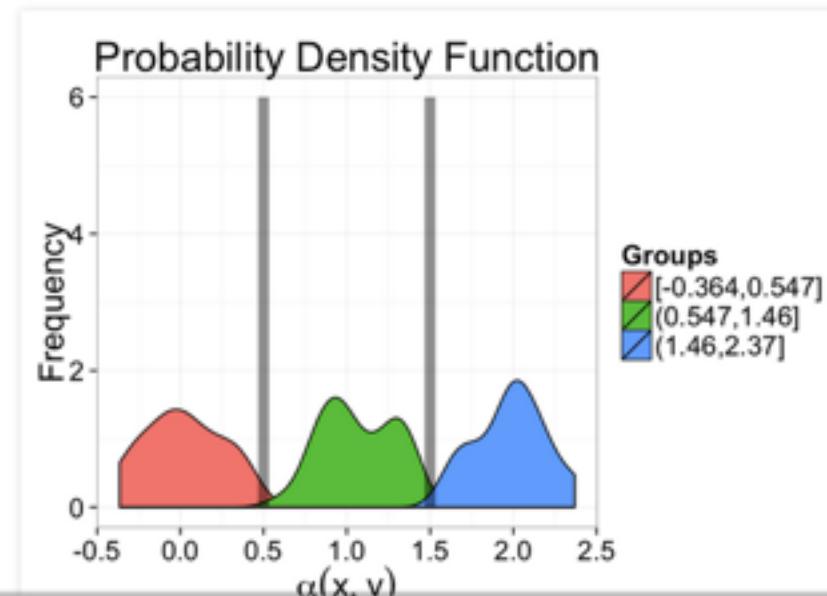
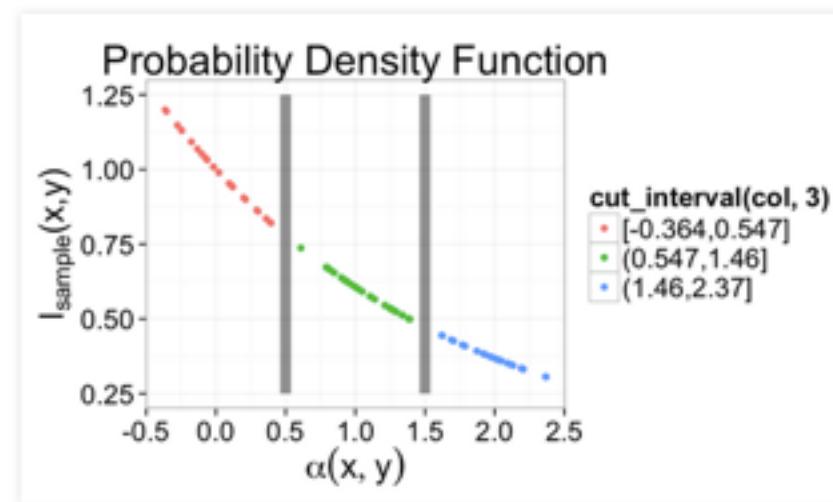


- Identify objects by eye
  - Count, describe qualitatively: "many little cilia on surface", "long curly flagellum", "elongated nuclear structure"
- Morphometrics
  - Trace the outline of the object (or sub-structures)
  - Can calculate the area by using equal-weight-paper and employing the "**cut-and-weigh**" method

# Quantitative Analysis

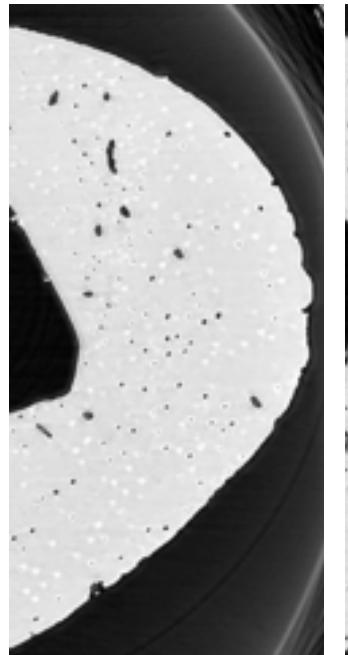
- For segmentation this model is:
  - there are 2 (or more) distinct components that make up the image
  - these components are distinguishable by their values (or vectors, colors, tensors, ...)
- For absorption/attenuation microscopy, **Beer-Lambert Law**
$$I_{detector} = I_{source} \exp(-\alpha d)$$
- Different components have a different  $\alpha$  based on the strength of the interaction between the light and the chemical / nuclear structure of the material
$$I_{sample}(x, y) = I_{source} \exp(-\alpha(x, y)d)$$

$$\alpha = f(N, Z, \sigma, \dots)$$



# 1. Segmentation and thresholding

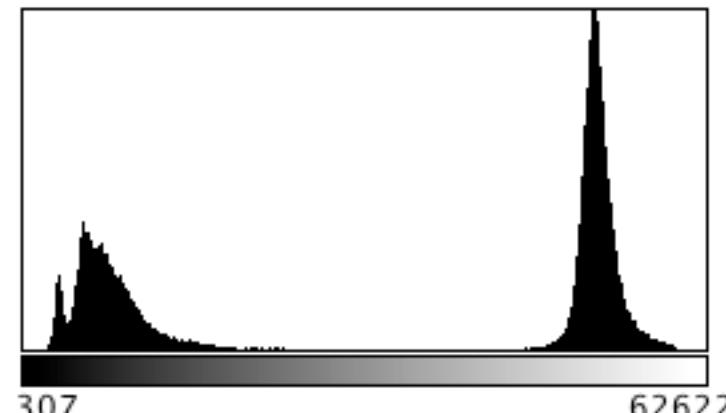
## Thresholding Histogram



Slices of Cortical Bone Tissue  
from a mouse

100µm

Original



Count: 70089 Min: 307  
Mean: 34408.424 Max: 62622  
StdDev: 21994.130 Mode: 52654 (3220)  
Bins: 256 Bin Width: 243.418

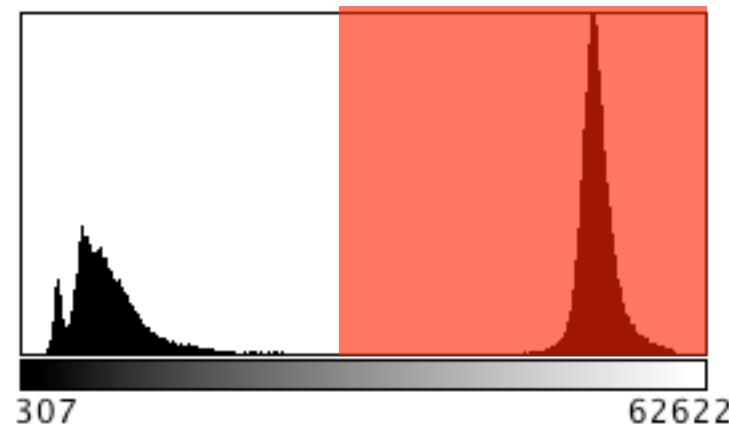
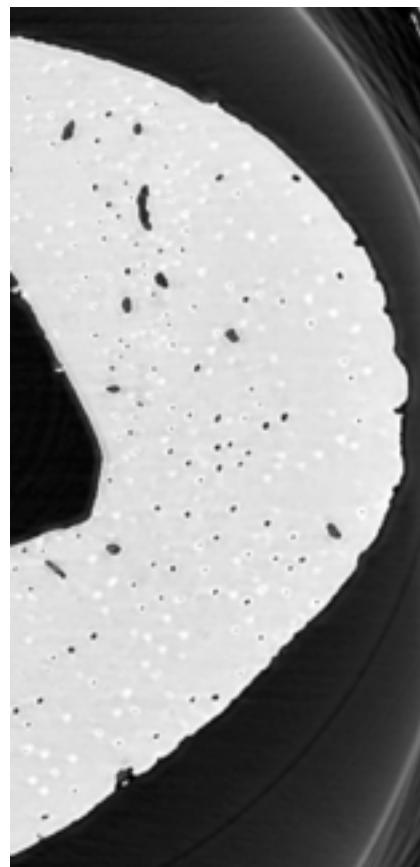
Histogram

# 1. Segmentation and thresholding

## Thresholding

### Histogram

=> Brightness peak corresponds to a bone



Count: 70089      Min: 307  
Mean: 34408.424      Max: 62622  
StdDev: 21994.130      Mode: 52654 (3220)  
Bins: 256      Bin Width: 243.418

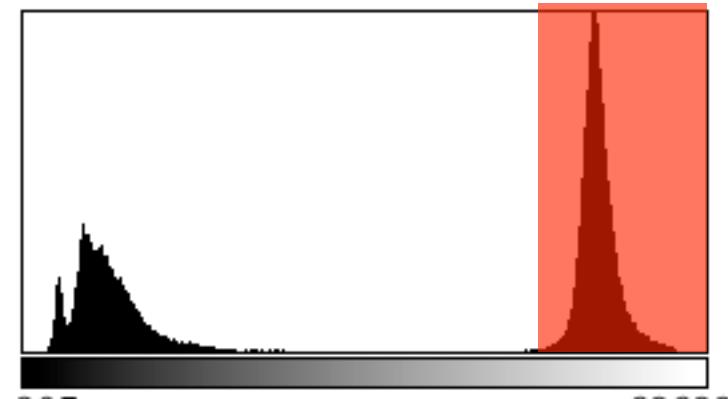
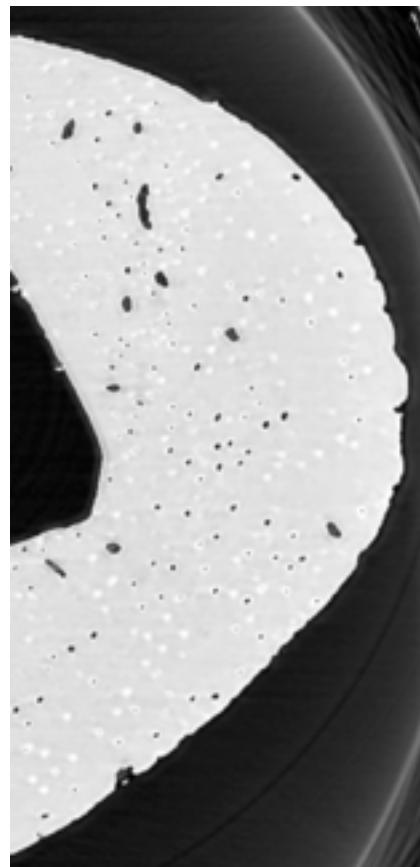
Threshold



# 1. Segmentation and thresholding

## Thresholding

### Histogram



Count: 70089      Min: 307  
Mean: 34408.424      Max: 62622  
StdDev: 21994.130      Mode: 52654 (3220)  
Bins: 256      Bin Width: 243.418

Threshold

Highly mineralized bone only

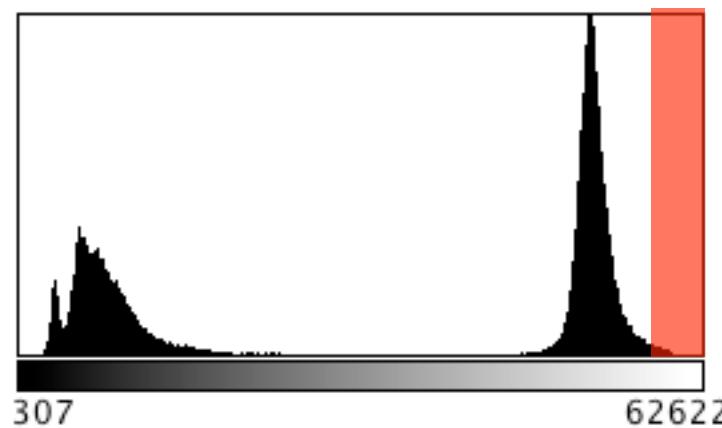
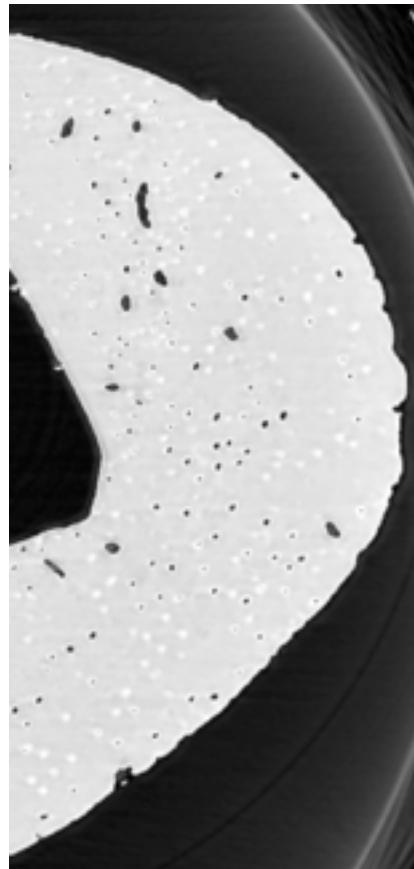


# 1. Segmentation and thresholding

## Thresholding

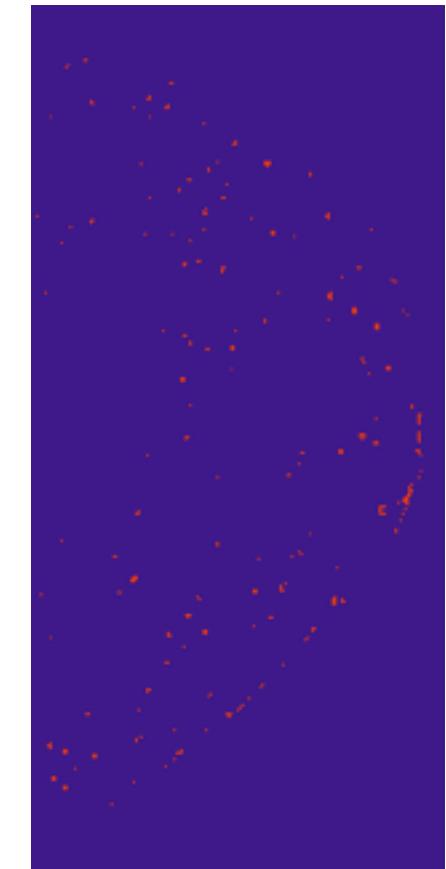
### Histogram

Very Highly mineralized  
spots only



Count: 70089          Min: 307  
Mean: 34408.424      Max: 62622  
StdDev: 21994.130      Mode: 52654 (3220)  
Bins: 256                Bin Width: 243.418

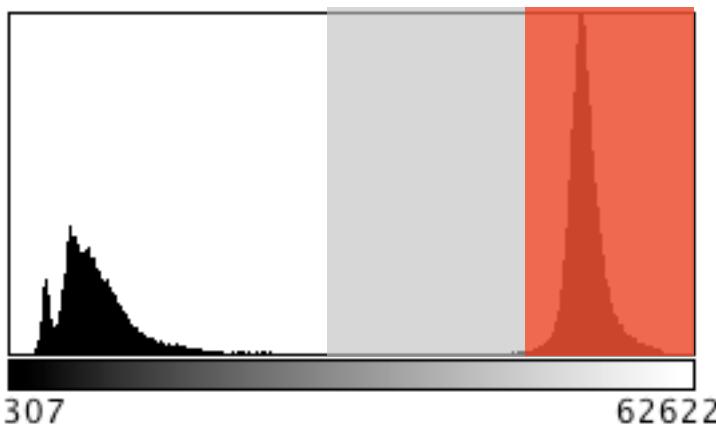
Threshold



# 1. Segmentation and thresholding

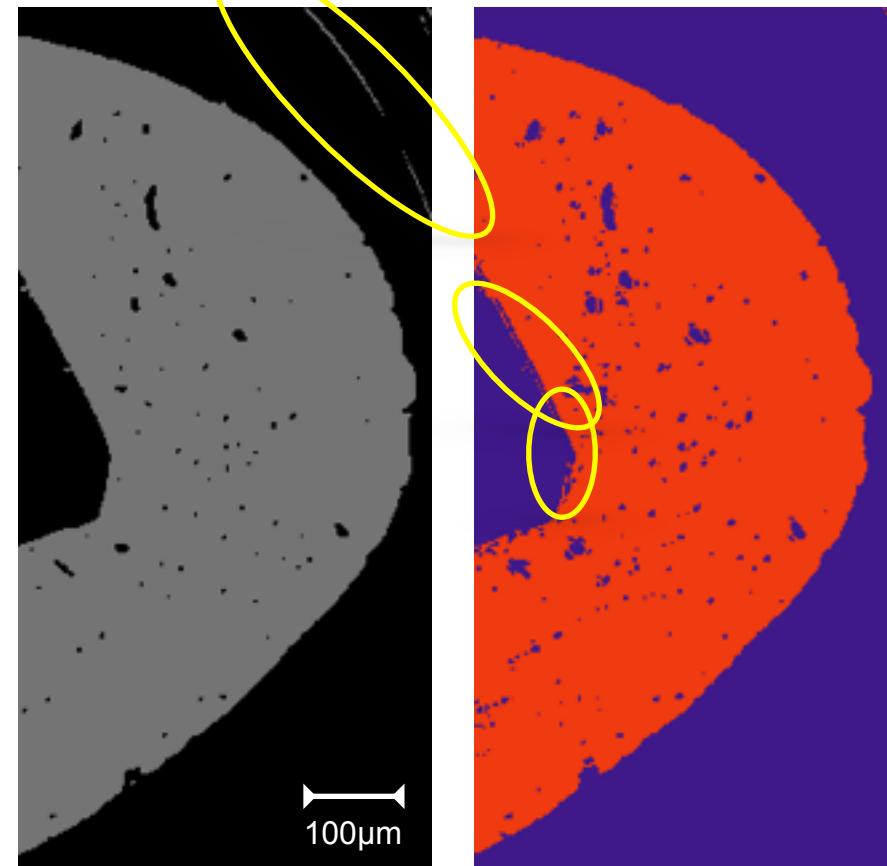
## Selecting a Threshold

Histogram



Count: 70089      Min: 307  
Mean: 34408.424    Max: 62622  
StdDev: 21994.130   Mode: 52654 (3220)  
Bins: 256            Bin Width: 243.418

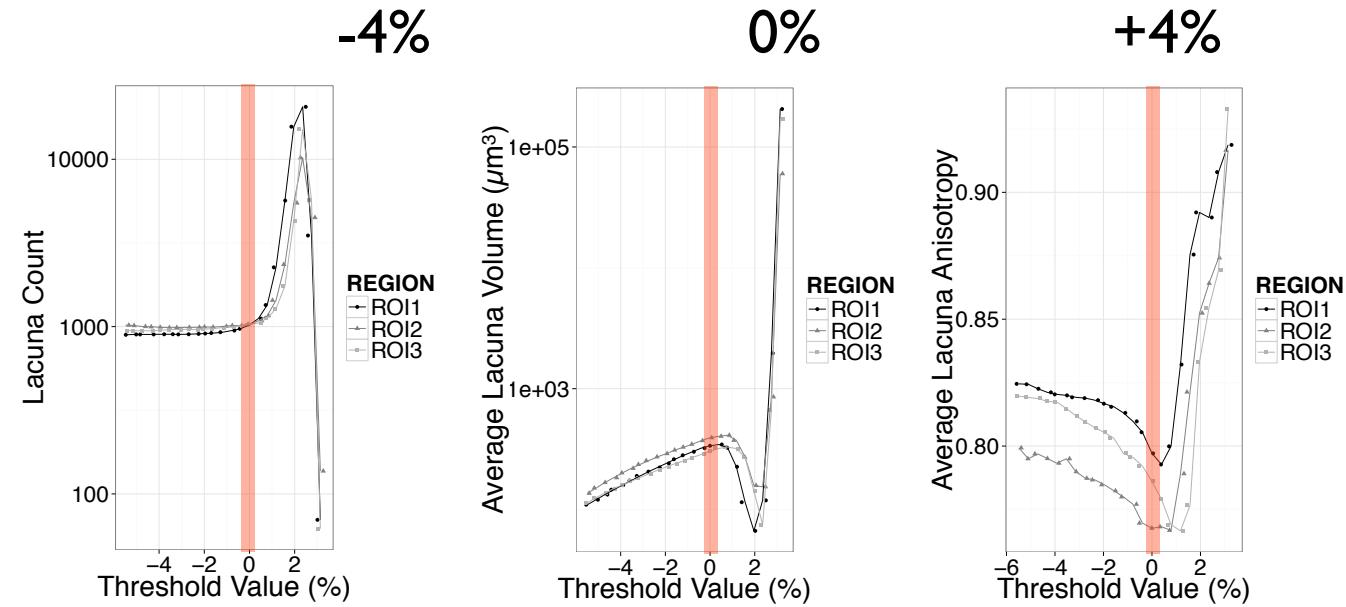
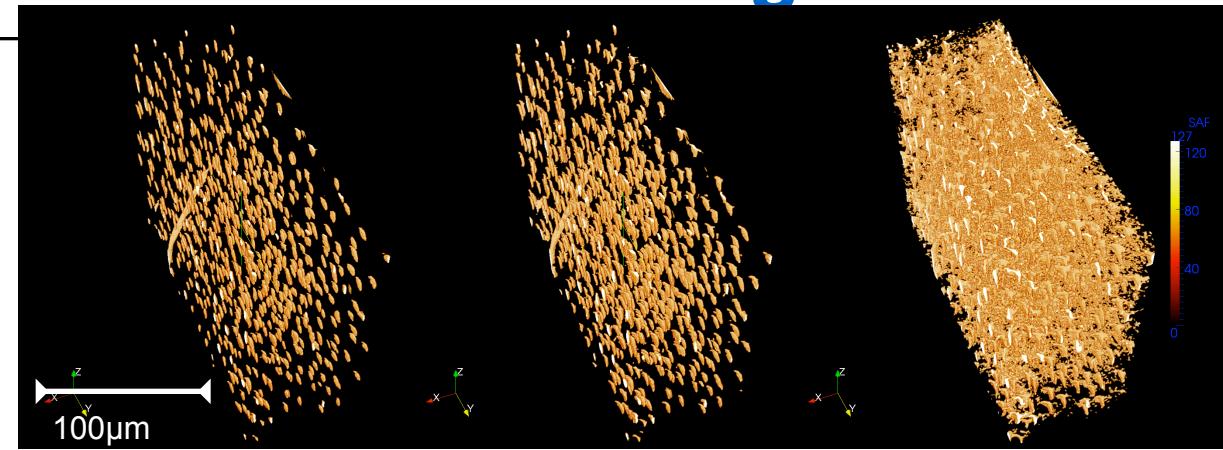
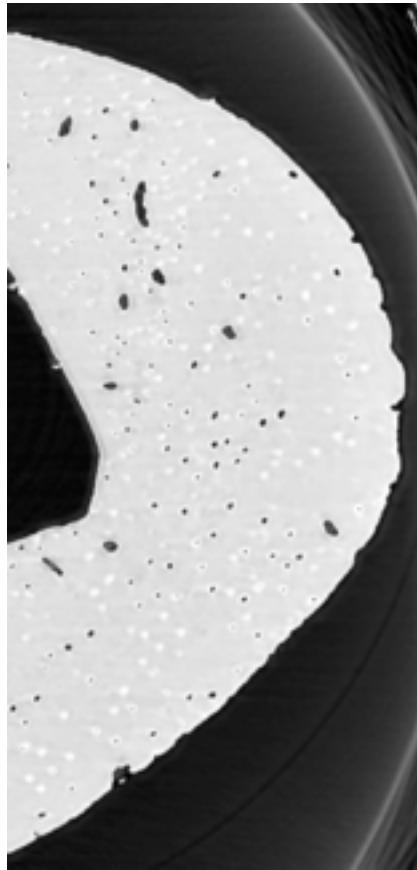
How do you pick a threshold?  
What is “real”?



# 1. Segmentation and thresholding

## Thresholding

Picking a threshold



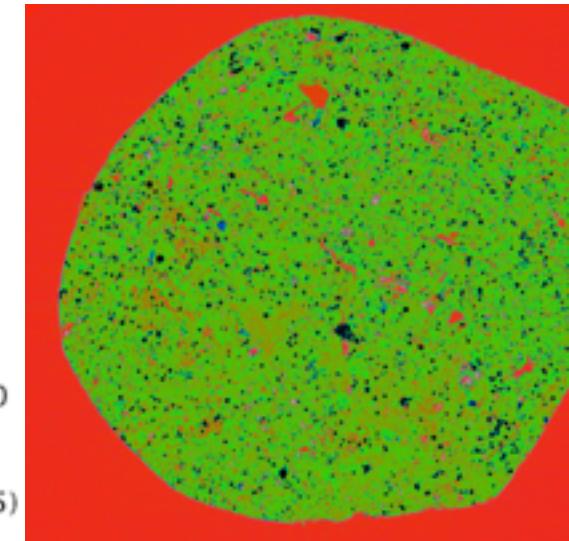
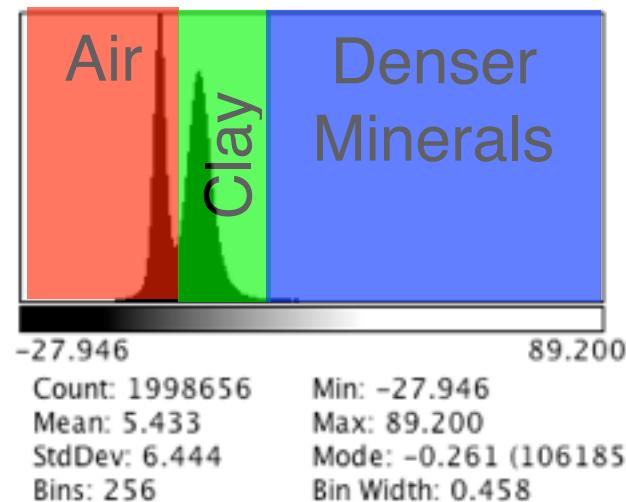
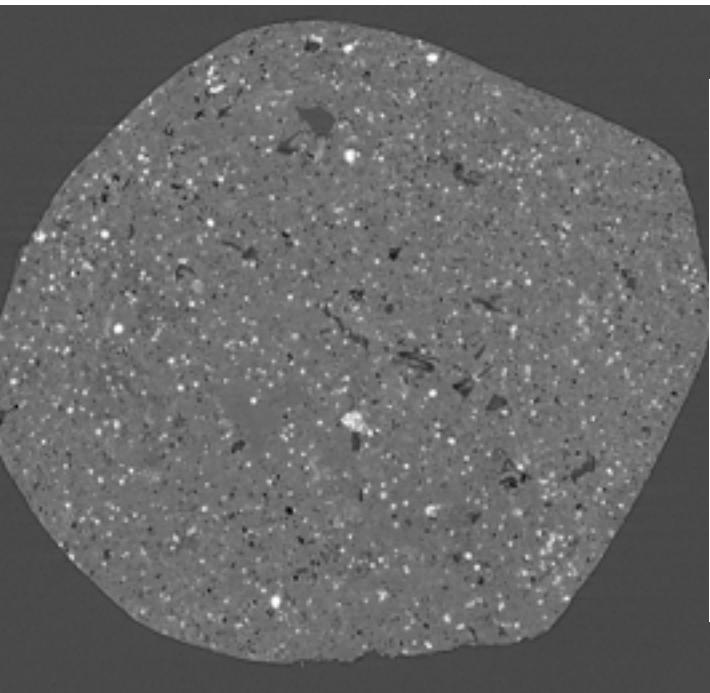
Mader, K. S., Schneider, P., Müller, R., & Stampanoni, M. (2013). A quantitative framework for the 3D characterization of the osteocyte lacunar system. *Bone*, 57(1), 142–154. doi:10.1016/j.bone.2013.06.026

# 1. Segmentation and thresholding

## Thresholding

### Histogram

All three materials identified



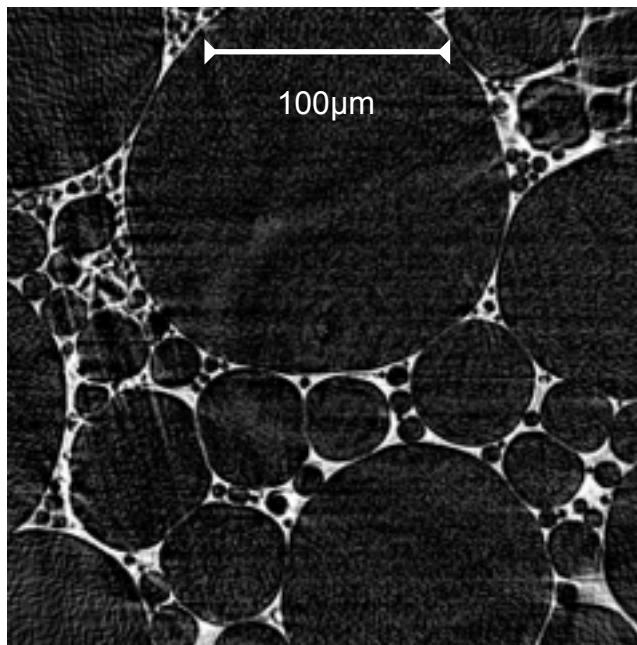
Apply Each Threshold

Shale provided from Kanitpanyacharoen, W. (2012). Synchrotron X-ray Applications Toward an Understanding of Elastic Anisotropy.

# 1. Segmentation and thresholding

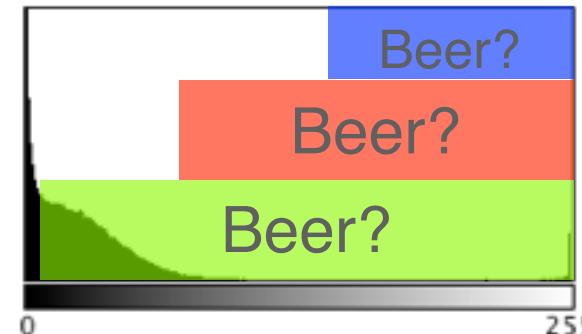
## Thresholding

### Histogram

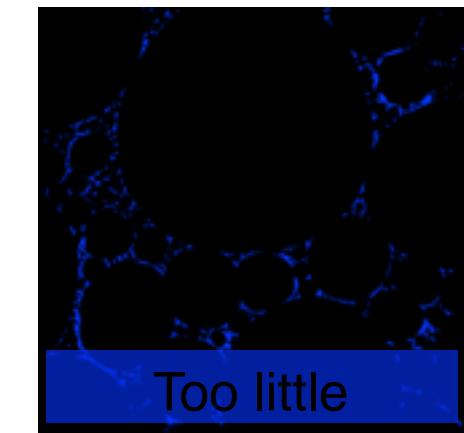
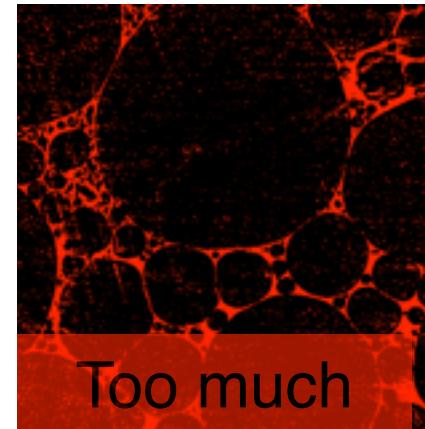


Beer foam  
Courtesy of R. Mokso

More difficult histogram  
to interpret



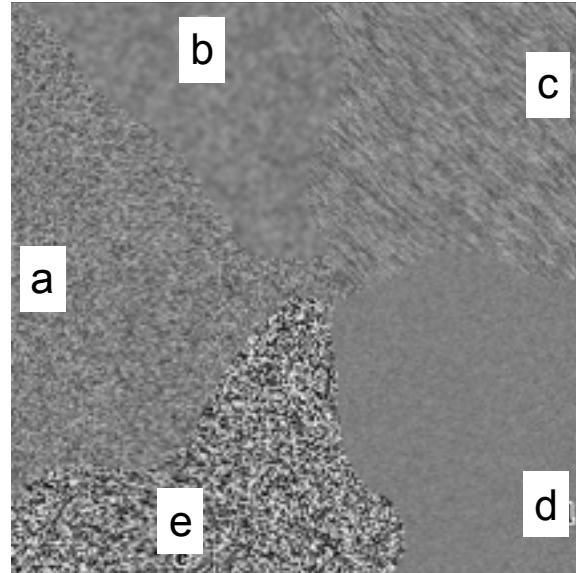
Count: 254016      Min: 0  
Mean: 31.100      Max: 255  
StdDev: 47.902      Mode: 0 (49739)



# 1. Segmentation and thresholding

## Thresholding

### Texture



- a) Gaussian brightness variation
- b) Gaussian filtered a)
- c) Directionally averaged a)
- d) Gaussian brightness variation
- e) Uniformly random brightness distribution

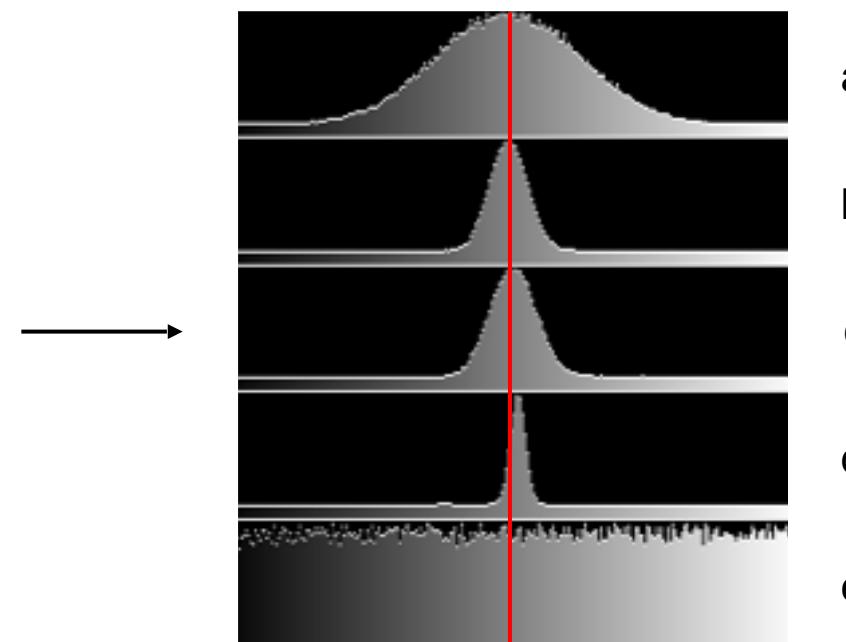
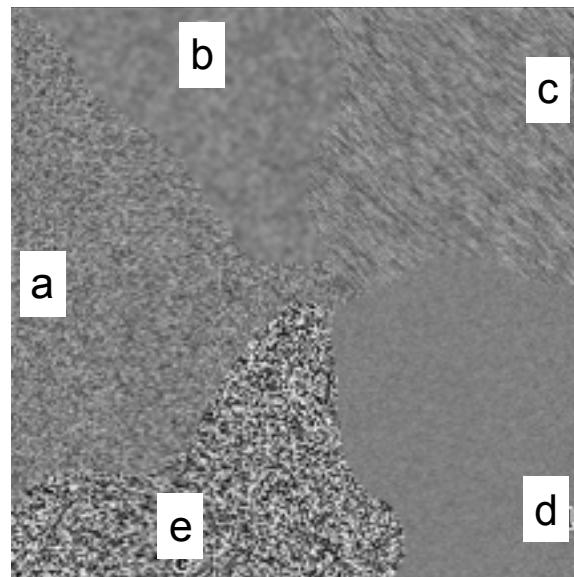
[Image Processing Handbook, J. C. Russ](#)

Different textures

# 1. Segmentation and thresholding

## Thresholding

Texture



[Image Processing Handbook, J. C. Russ](#)

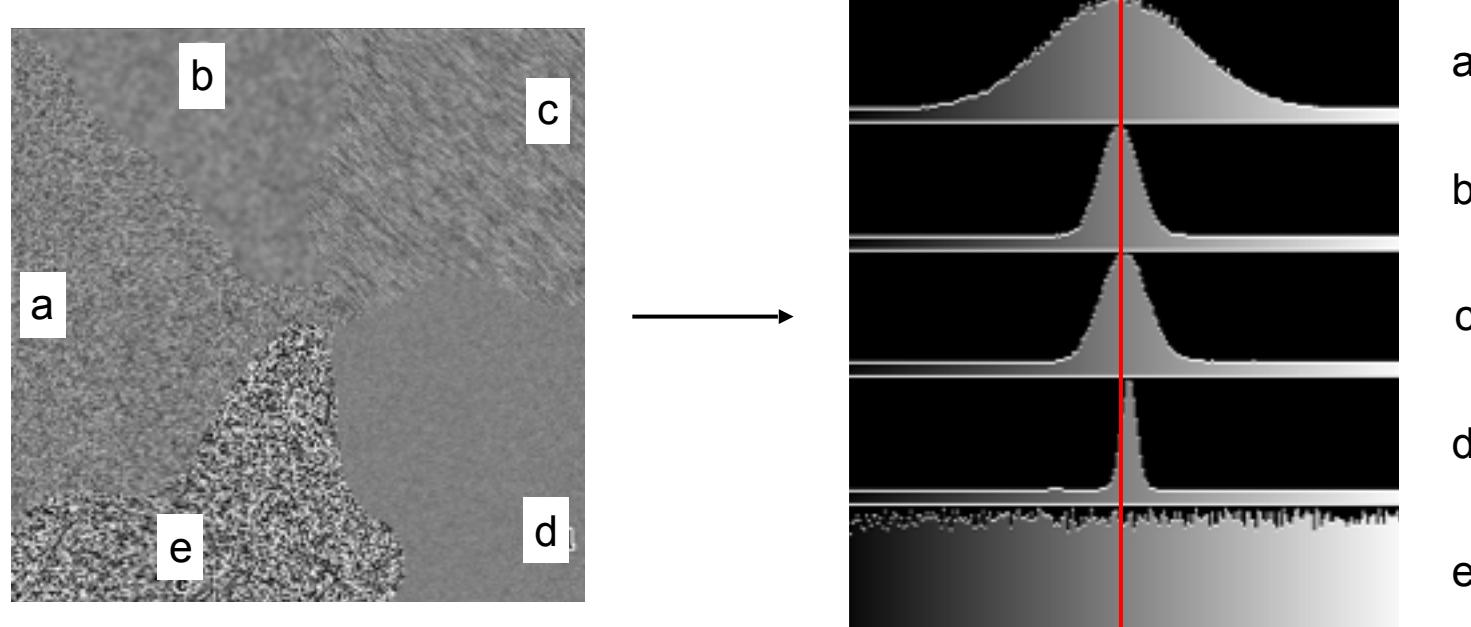
Different textures

Histograms

# 1. Segmentation and thresholding

## Thresholding

### Texture



[Image Processing Handbook](#), J. C. Russ

Different textures

=> Average brightnesses identical  
=> Histogram-based thresholding unfeasible

# 1. Segmentation and thresholding

## Thresholding

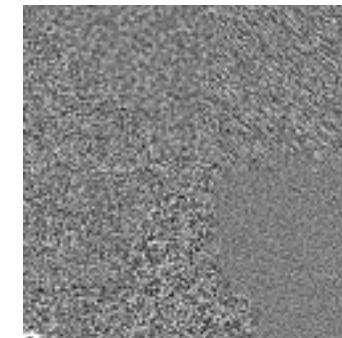
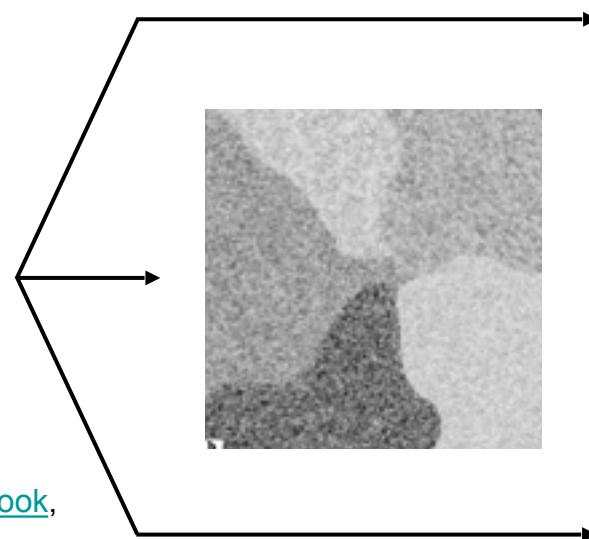
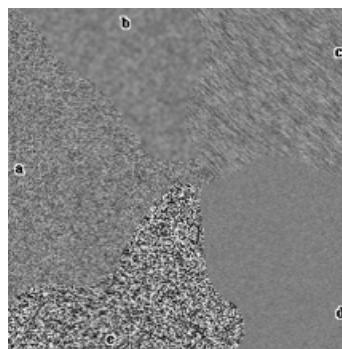
### Texture-sensitive operators

- Laplacian
  - Frei and Chen
  - Variance
  - Haralick
  - Hurst
  - Range
  - ...
- } Already discussed for sharpening and finding edges (within block I. Preprocessing)

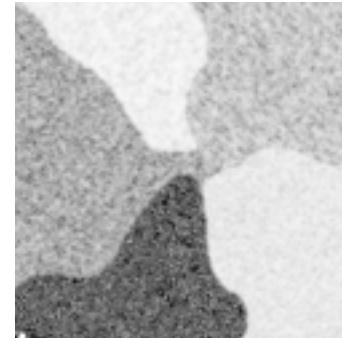
# 1. Segmentation and thresholding

## Thresholding

Texture-sensitive operators



Frei and Chen



Laplacian

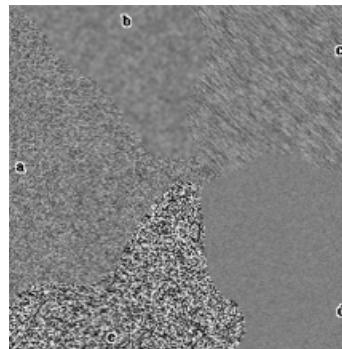
Variance

[Image Processing Handbook](#),  
J. C. Russ

# 1. Segmentation and thresholding

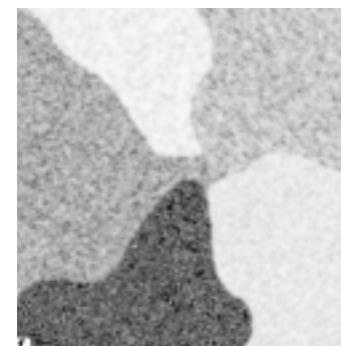
## Thresholding

Thresholding from texture



Original

Variance



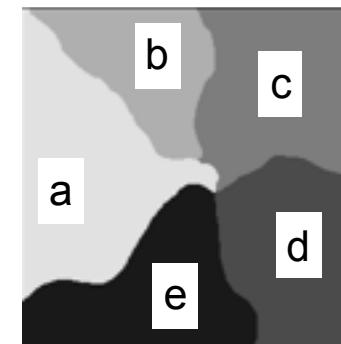
Variance

Gaussian

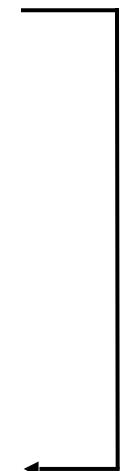


Gaussian

Multiple thresholds



Segmented



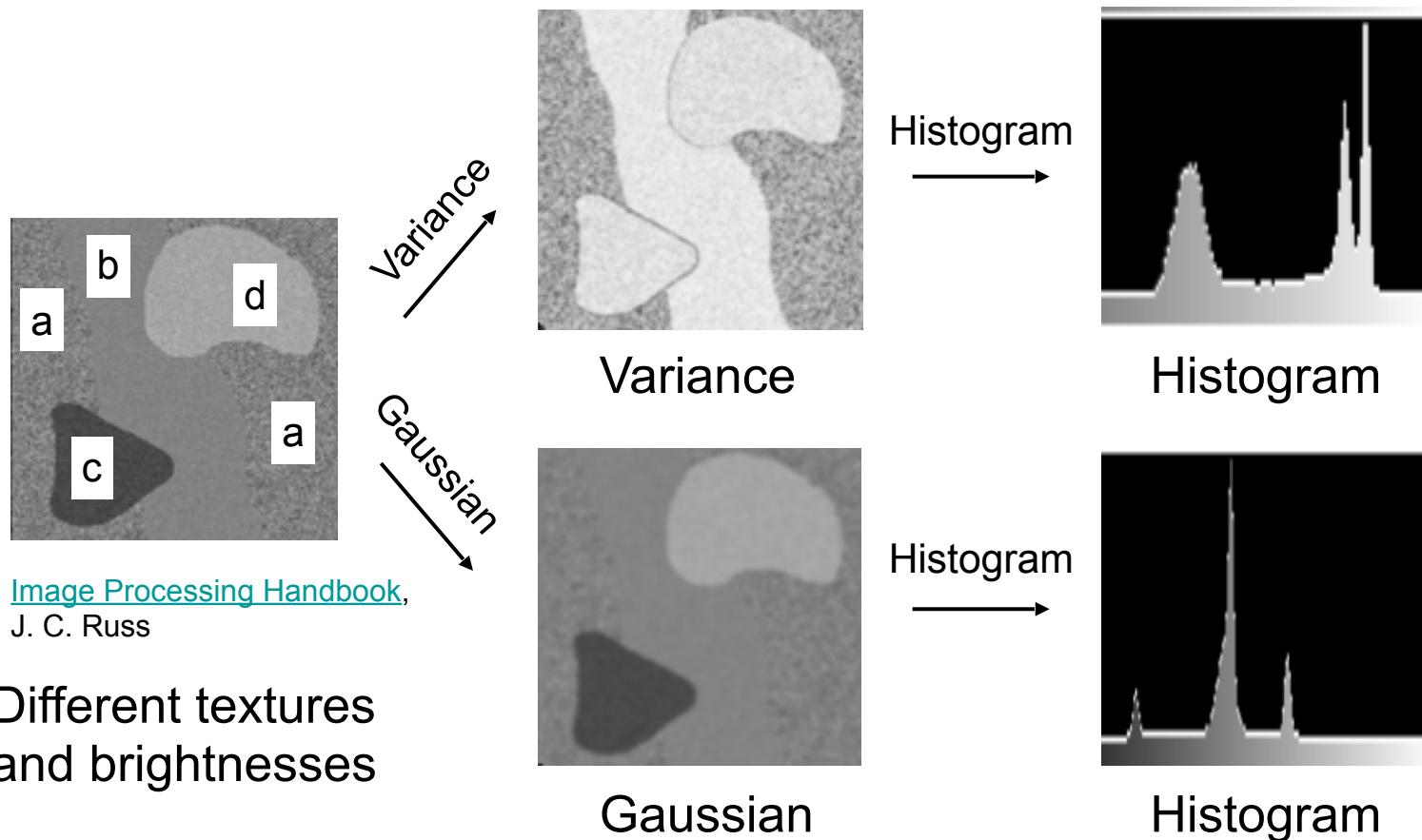
Histogram

[Image Processing Handbook](#),  
J. C. Russ

# 1. Segmentation and thresholding

## Thresholding

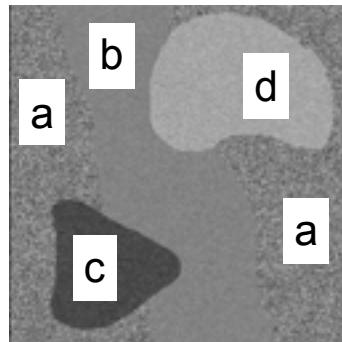
Multiple thresholding criteria



# 1. Segmentation and thresholding

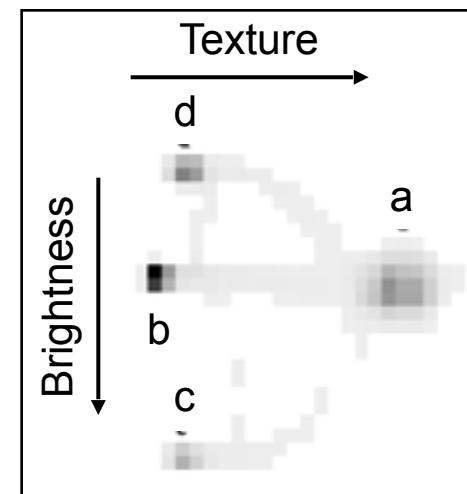
## Thresholding

Multiple thresholding criteria



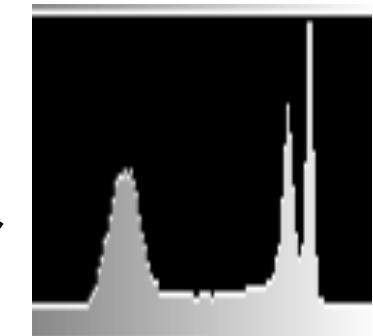
[Image Processing Handbook](#),  
J. C. Russ

Different textures  
and brightnesses

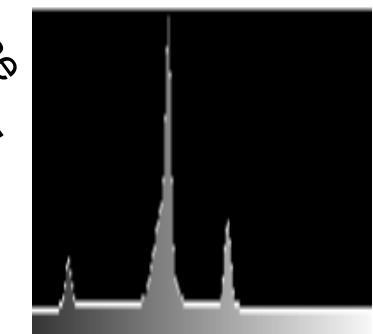


Texture-brightness  
histogram

Combine  
Combine



Histogram

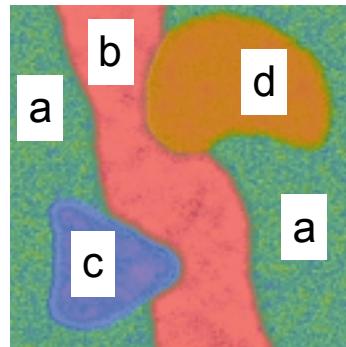


Histogram

# 1. Segmentation and thresholding

## Thresholding

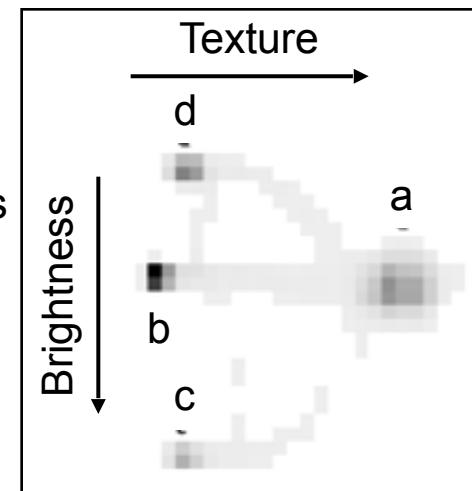
Multiple thresholding criteria



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J. C. Russ

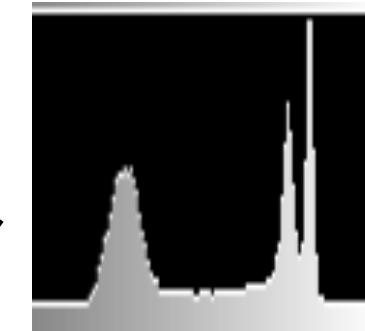
Segmented

2D thresholds

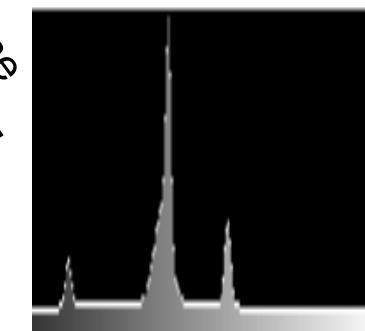


Texture-brightness  
histogram

Combine  
Combine



Histogram

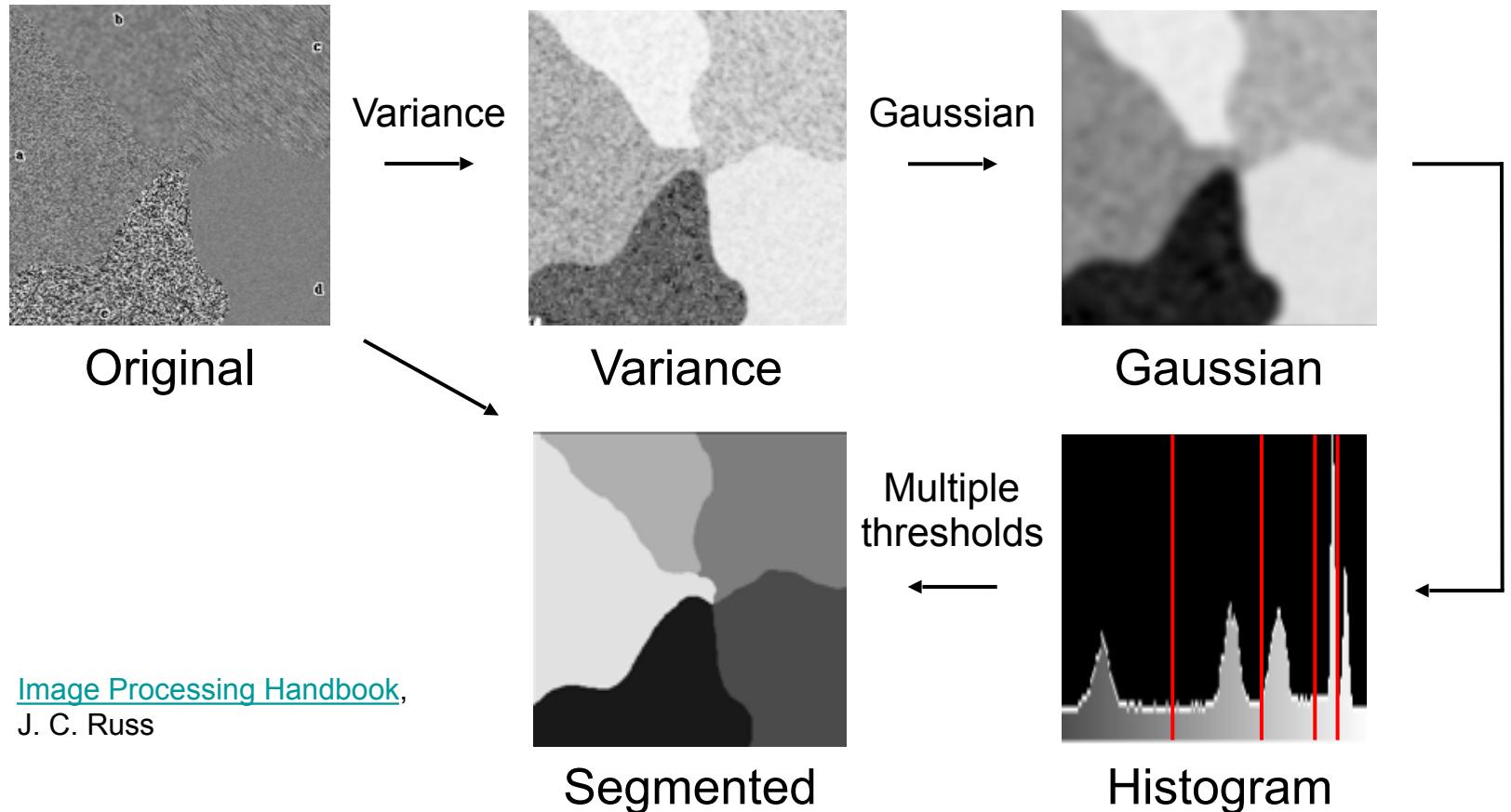


Histogram

## 2. Processing binary images

### Masks

#### Creation

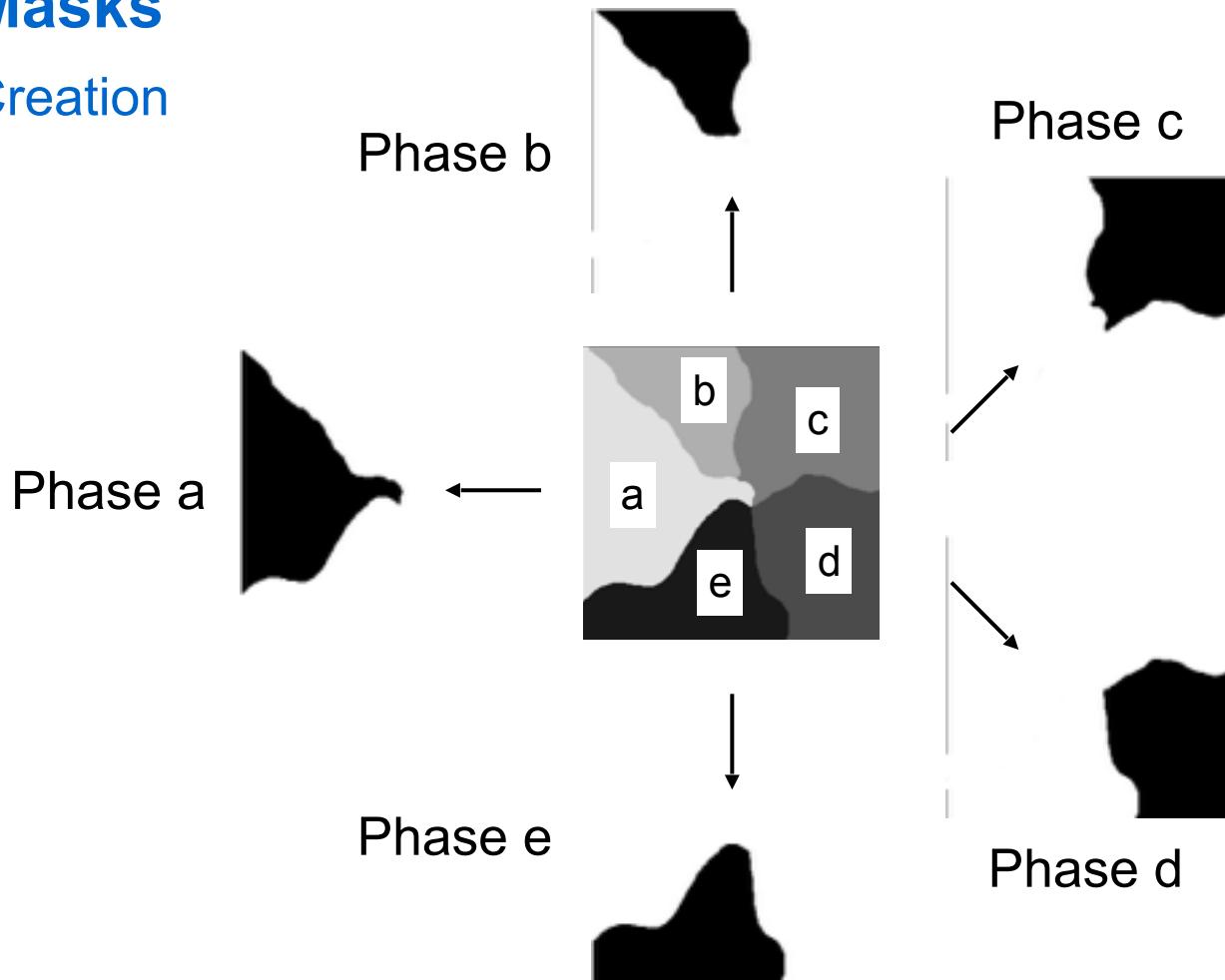


[Image Processing Handbook](#),  
J. C. Russ

## 2. Processing binary images

### Masks

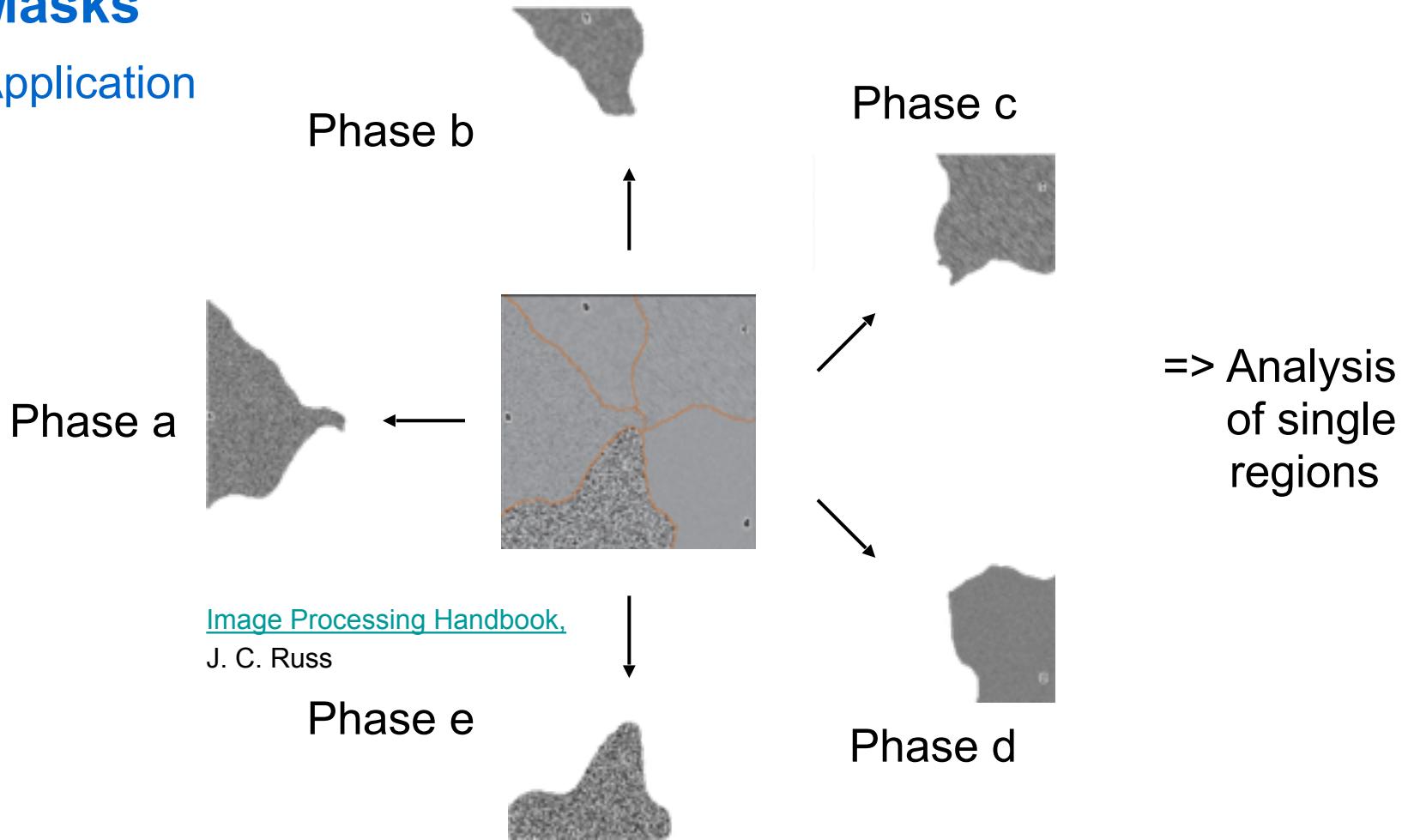
#### Creation



## 2. Processing binary images

### Masks

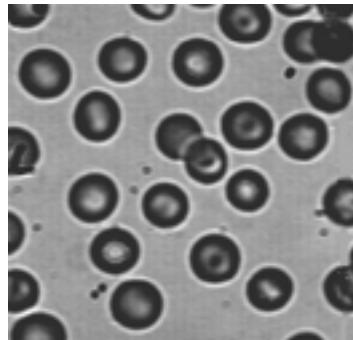
#### Application



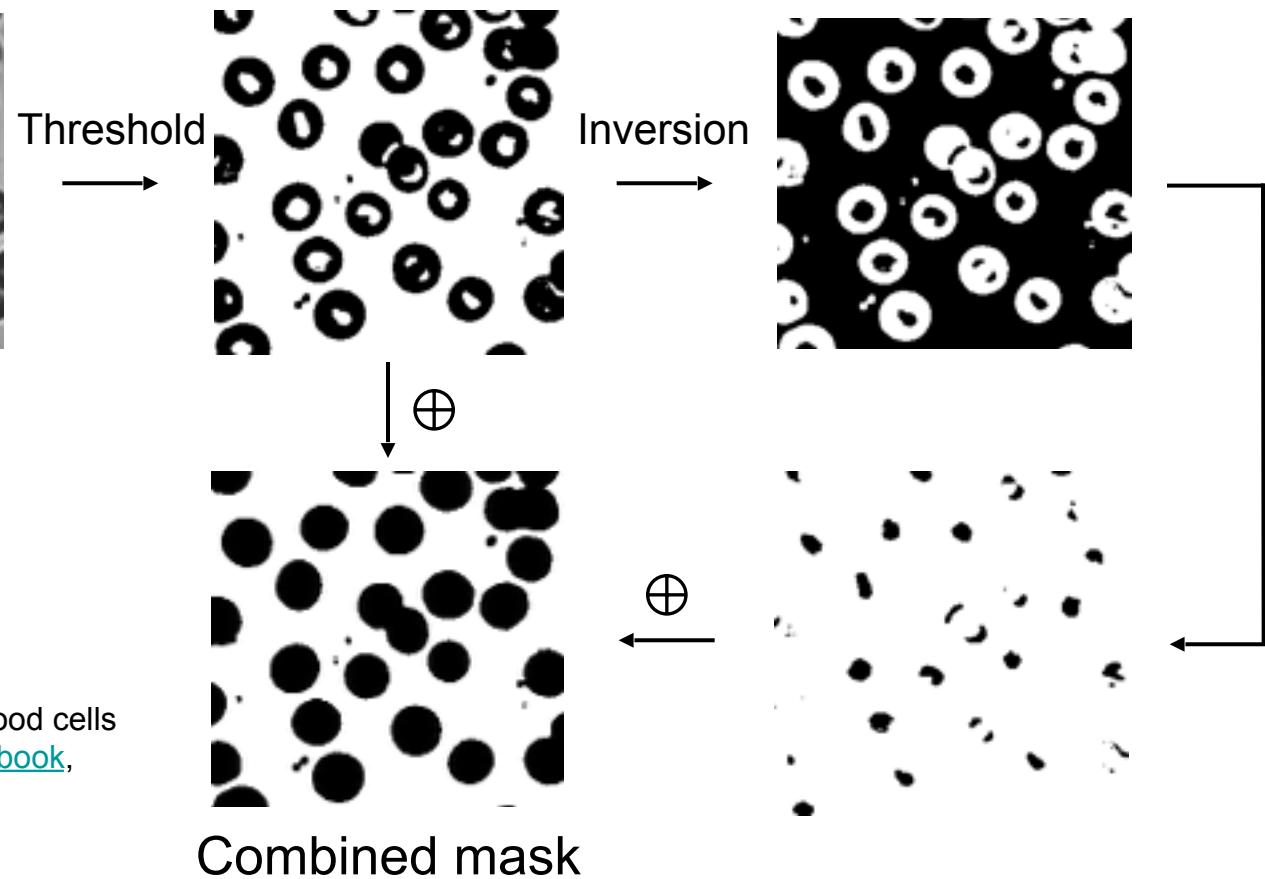
## 2. Processing binary images

### Masks

#### Combining masks



Original

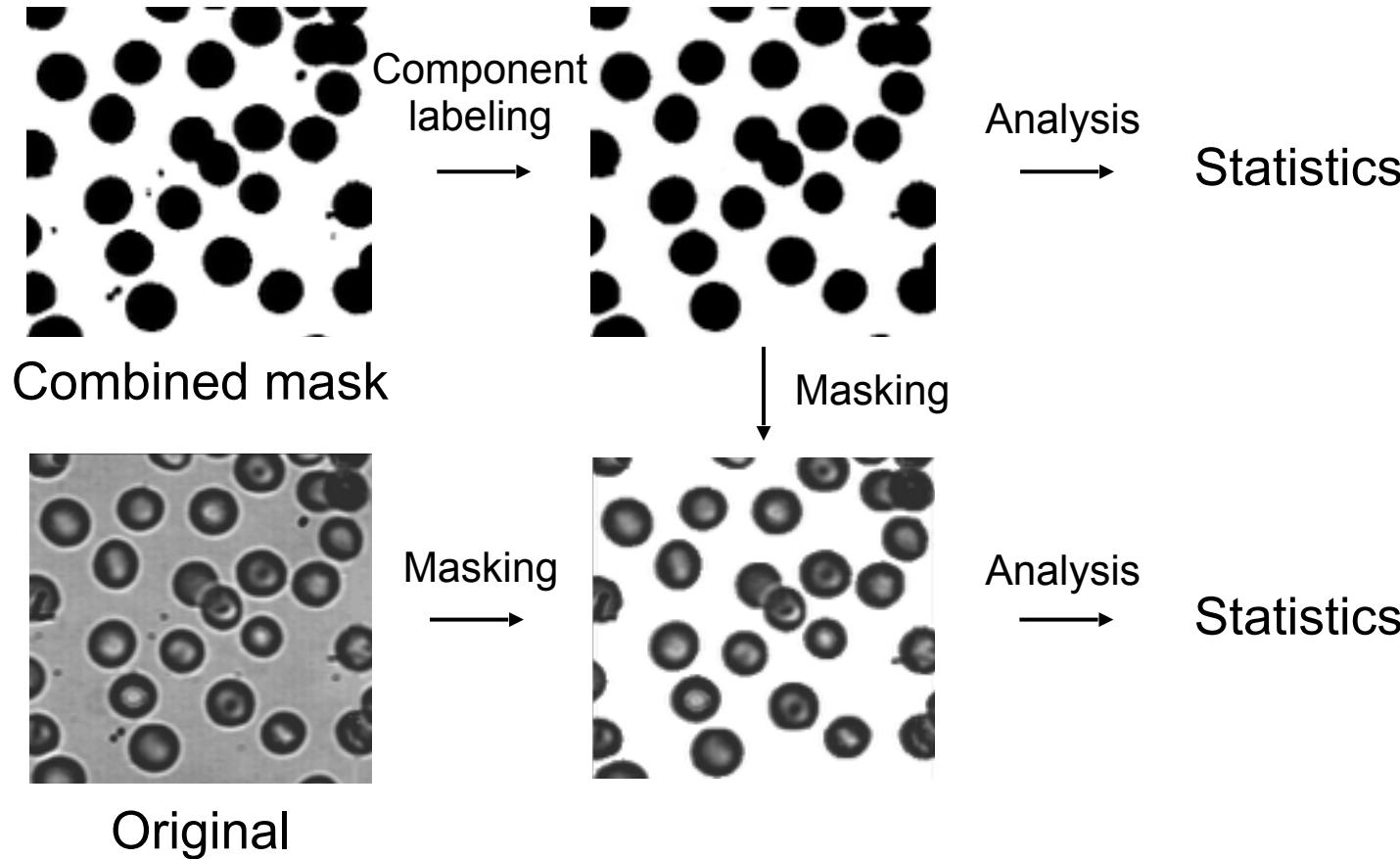


Light micrograph: red blood cells  
[Image Processing Handbook](#),  
J. C. Russ

## 2. Processing binary images

### Masks

#### Combining masks



## 2. Processing binary images

### Morphological operations

Foreground and background



- 1) Definition of foreground and background is arbitrary
- 2) Human vision interprets an image in terms of relationships between structures  
 $\Leftrightarrow$   
For computer-based image analysis systems, classification of foreground-background must be made at the level of individual pixels/voxels

[Image Processing Handbook](#), J. C. Russ

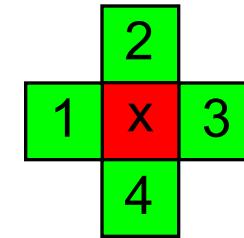
## 2. Processing binary images

### Morphological operations

Neighborhood in 2D

2	3	4
1	x	5
8	7	6

8-adjacent

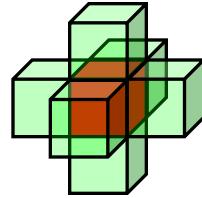


4-adjacent

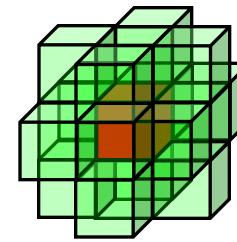
## 2. Processing binary images

### Morphological operations

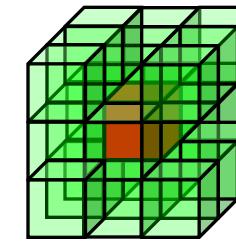
Neighborhood in 3D



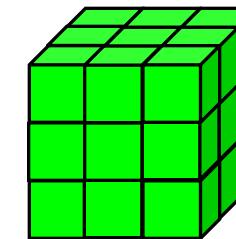
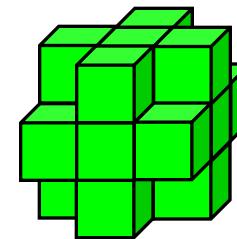
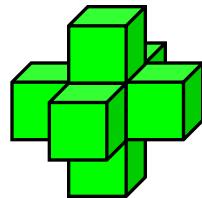
6-adjacent  
(faces shared)



18-adjacent  
(faces or edges  
shared)



26-adjacent  
(faces or edges or  
corners shared)



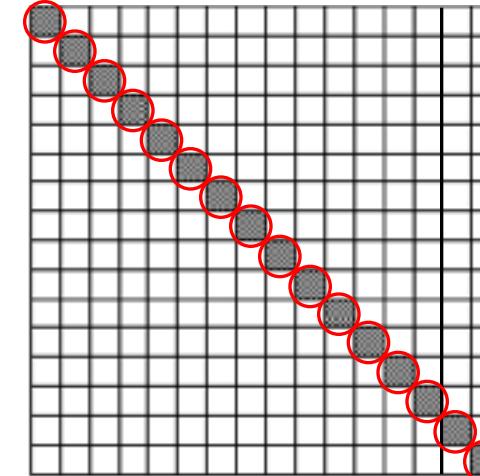
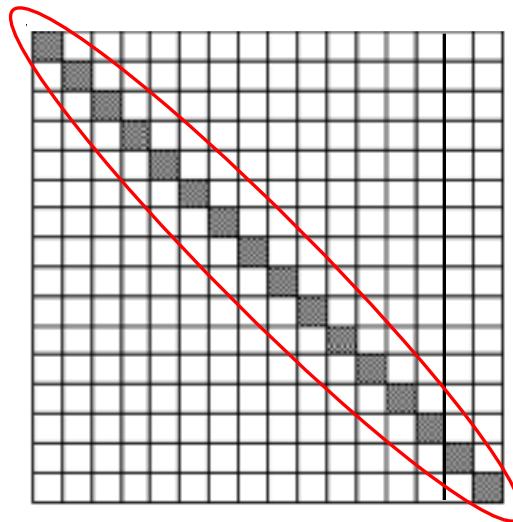
Cubic voxels: standard

## 2. Processing binary images

### Morphological operations

#### Foreground/background-connectivity dualism

- Foreground: 8-adjacent
  - Background: 4-adjacent
- => 1 object (○)  
background separated
- Foreground: 4-adjacent
  - Background: 8-adjacent
- => 16 objects (○)  
background connected



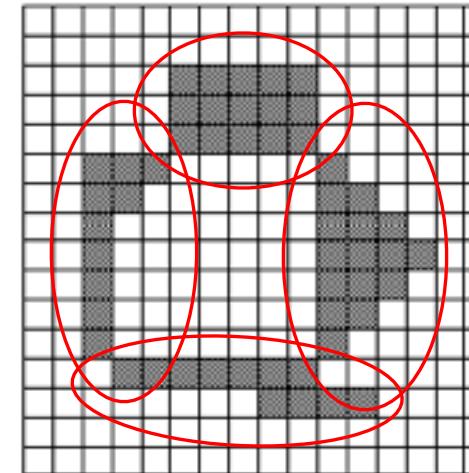
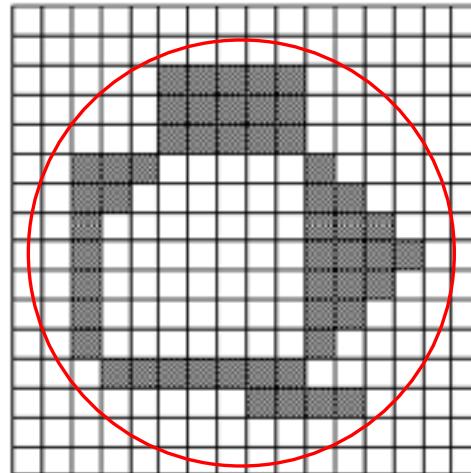
[Image Processing Handbook](#), J. C. Russ

## 2. Processing binary images

### Morphological operations

#### Foreground/background-connectivity dualism

- Foreground: 8-adjacent
  - Background: 4-adjacent
- => 1 object (○)  
background separated
- Foreground: 4-adjacent
  - Background: 8-adjacent
- => 4 objects (○,○)  
background connected

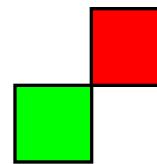


[Image Processing Handbook](#), J. C. Russ

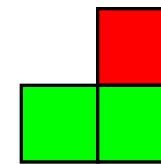
## 2. Processing binary images

### Morphological operations

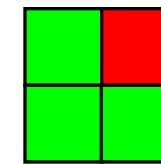
Neighbor coefficient



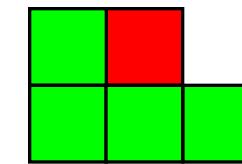
1



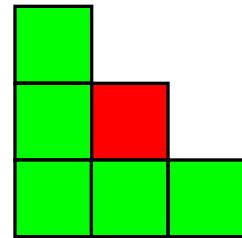
2



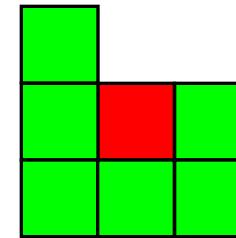
3



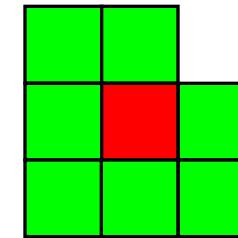
4



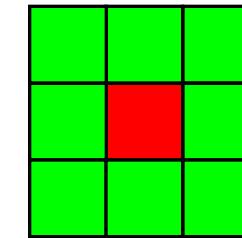
5



6



7



8

## 2. Processing binary images

### Morphological operations

#### Erosion and dilation / opening and closing

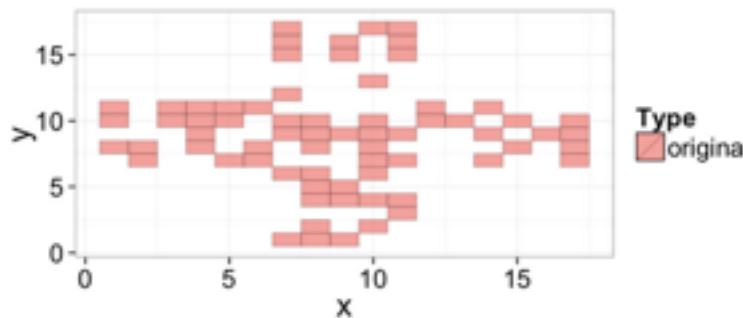
- Erosion:
  - Turn pixel off (foreground -> background)  
if touching any background pixel (neighborhood coefficient > 0)
- Dilation:
  - Turn pixel on (background -> foreground)  
if touching any foreground pixel (neighborhood coefficient > 0)
- Opening:
  - Erosion followed by dilation
- Closing:
  - Dilation followed by erosion

## 2. Processing binary images

### Applied Erosion and Dilation

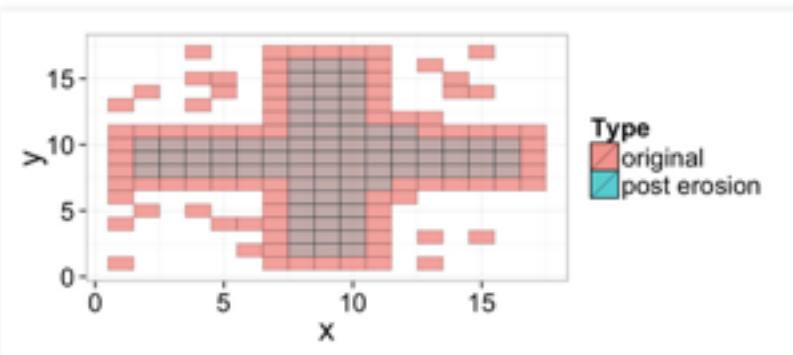
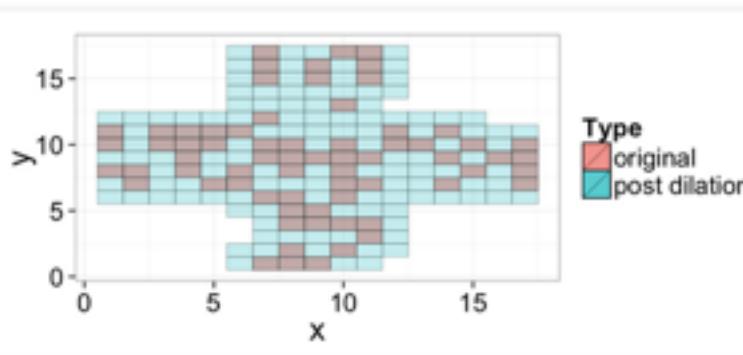
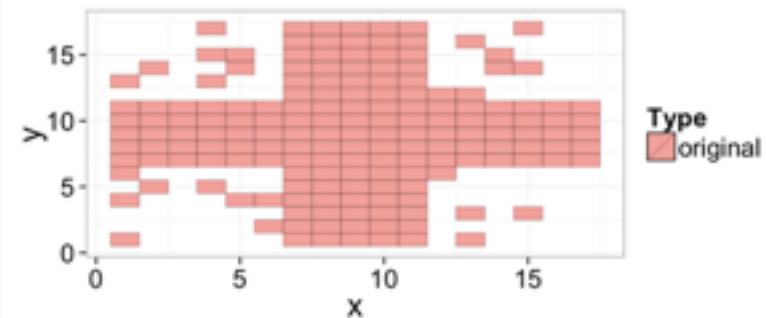
#### Erosion

Taking an image of the cross at a too-high threshold, we show how dilation can be used to recover some of the missing pixels



#### Dilation

Taking an image of the cross at a too-low threshold, we show how erosion can be used to remove some of the extra pixels

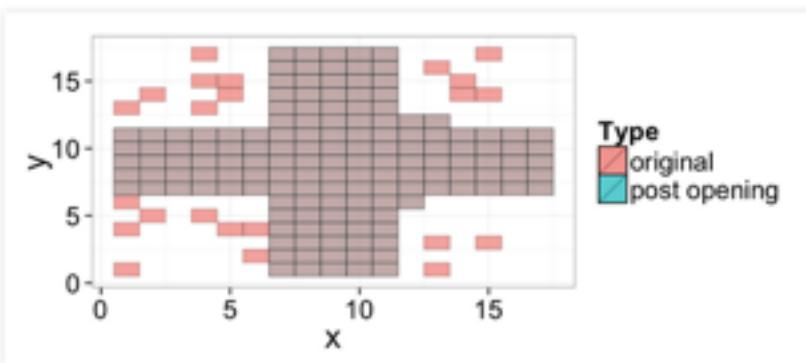
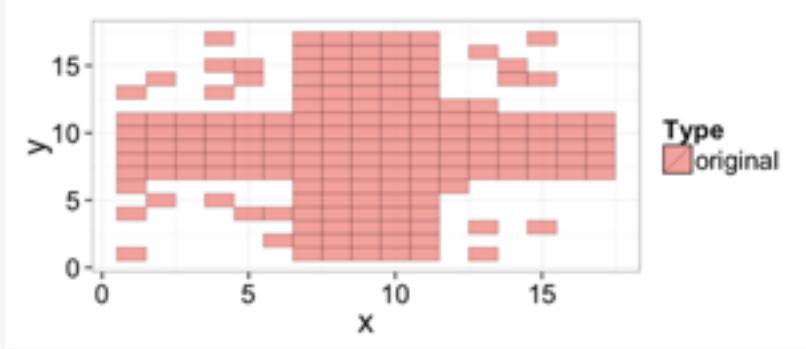


## 2. Processing binary images

### Applied Opening and Closing

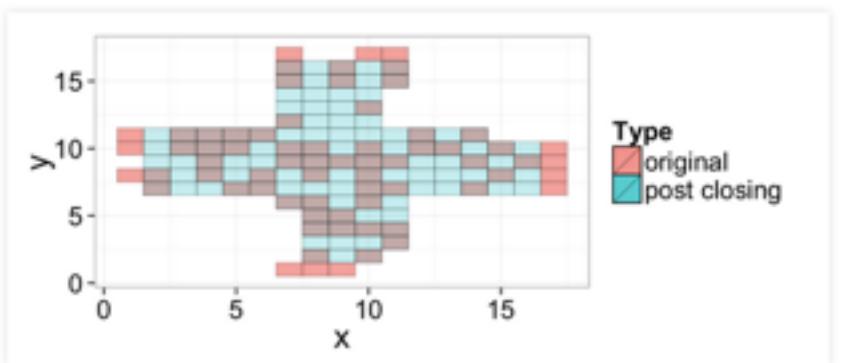
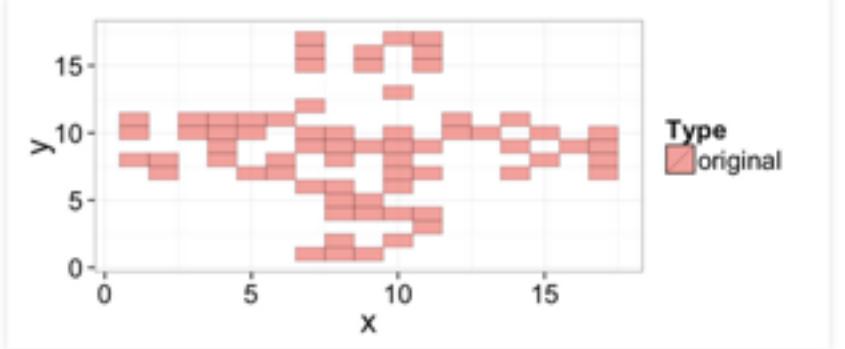
#### Opening

Taking an image of the cross at a too-low threshold, we show how opening can be used to remove some of the extra pixels



#### Closing

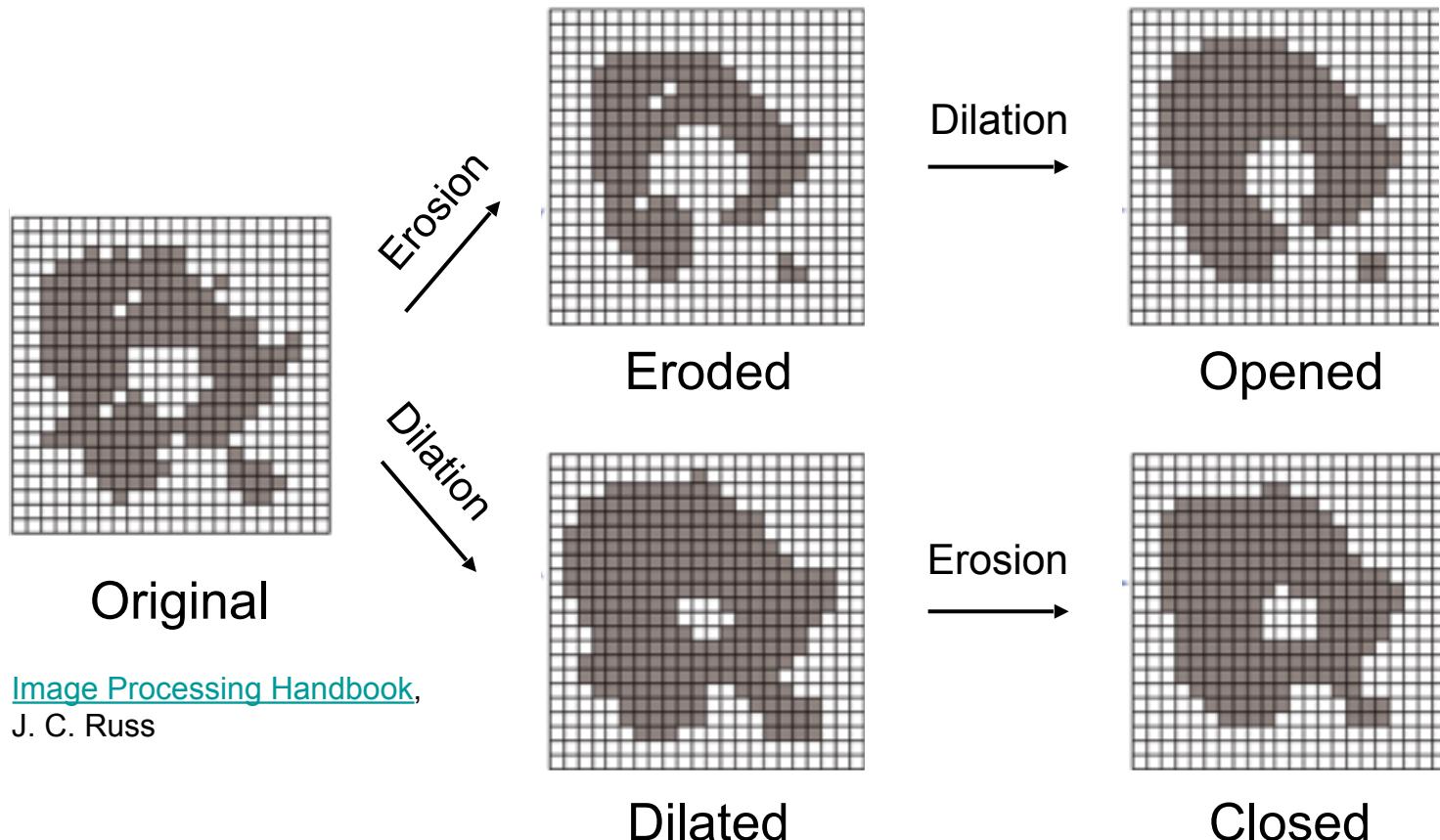
Taking an image of the cross at a too-high threshold, we show how closing can be used to recover some of the missing pixels



## 2. Processing binary images

### Morphological operations

Erosion and dilation / opening and closing

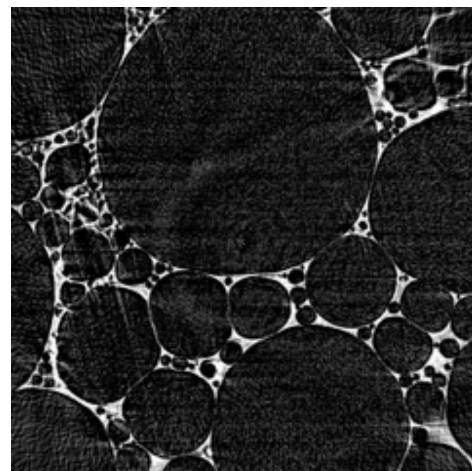


[Image Processing Handbook](#),  
J. C. Russ

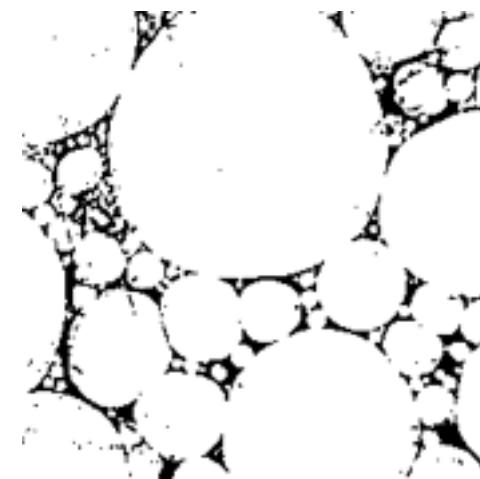
## 2. Processing binary images

### Morphological operations

#### Closing



Threshold



Original

Thresholded

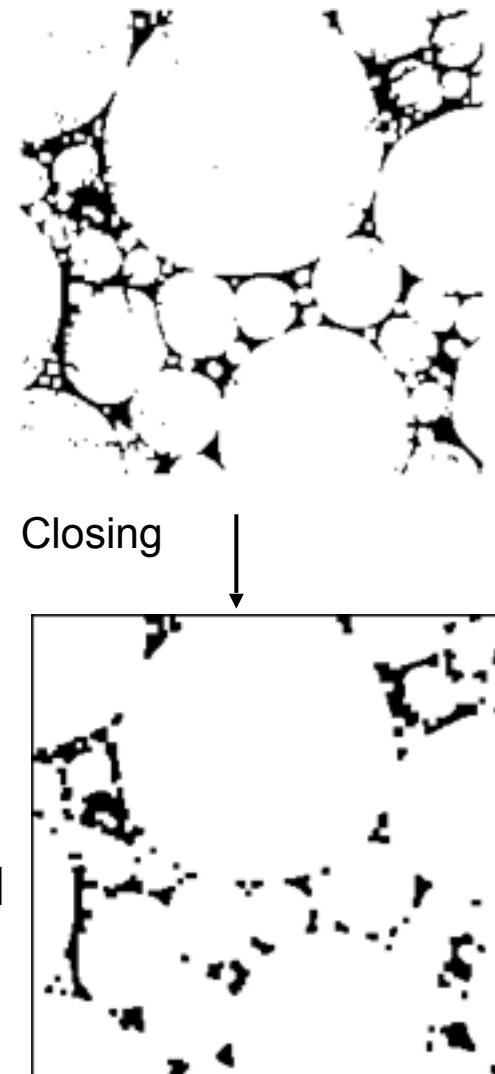
Beer foam, courtesy of R. Mokso

Closed

Closing

Closing

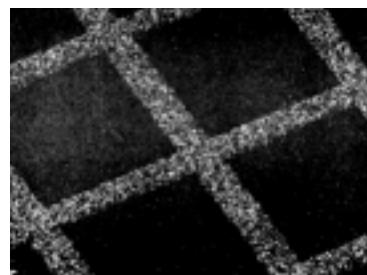
Closed  
2x



## 2. Processing binary images

### Morphological operations

#### Masking

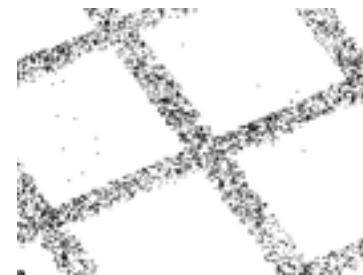


X-ray dot map:  
gold grid above aluminum stub  
[Image Processing Handbook](#),  
J. C. Russ

#### Originals

Scanning electron micrograph:  
gold grid above aluminum stub  
[Image Processing Handbook](#),  
J. C. Russ

Threshold

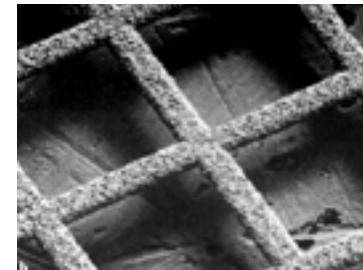


#### Thresholded

2 x closing



#### Closed



Masking



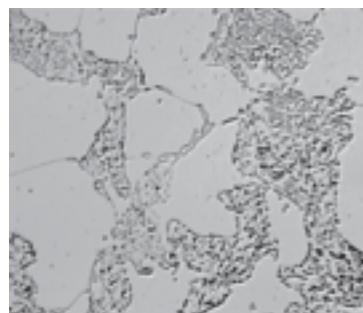
#### Masked SEM original

Masking

## 2. Processing binary images

### Morphological operations

#### Segmentation



Original

Threshold



Thresholded

Closing



Closed

Opening



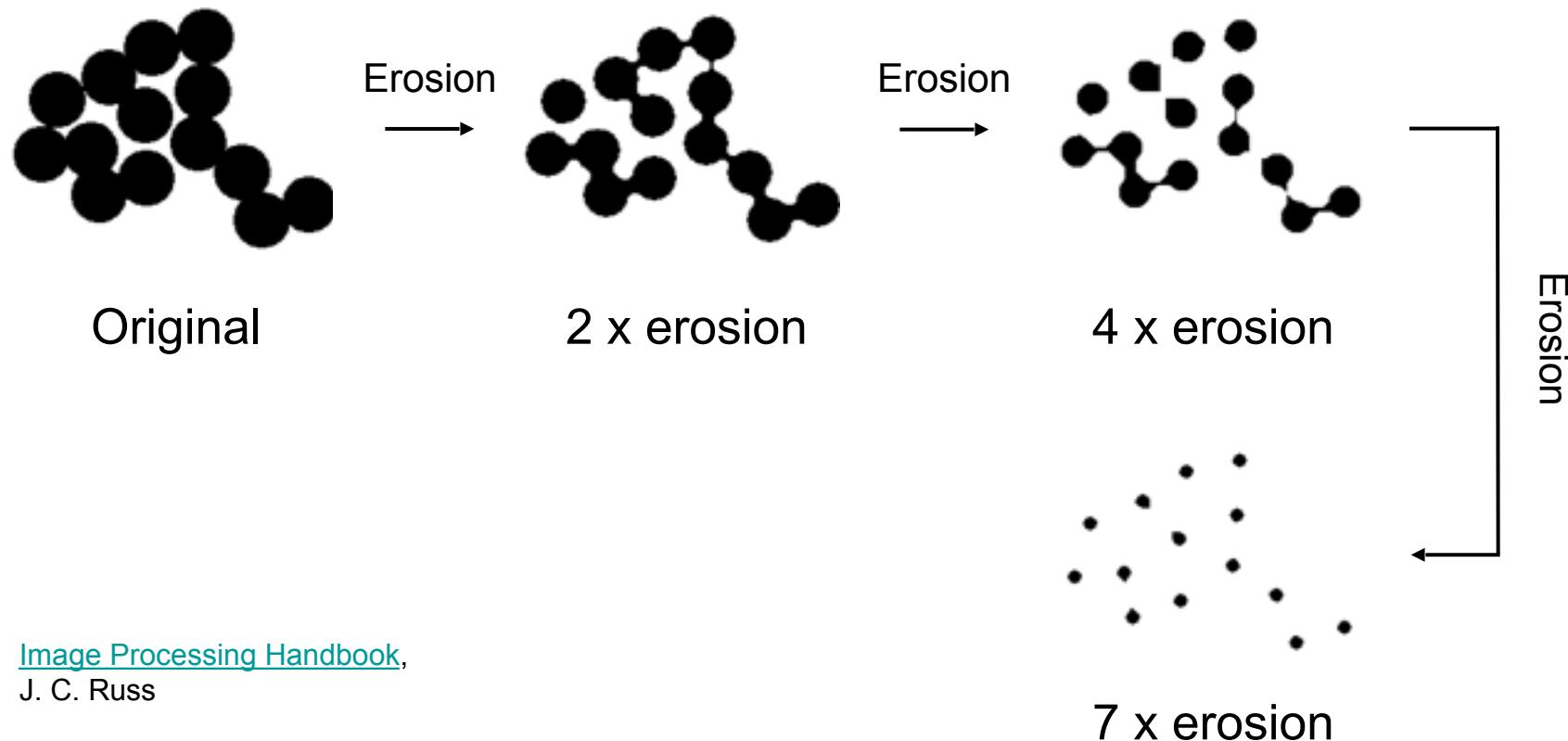
Opened

Light micrograph: iron carbide  
particles (dark) in a steel specimen  
[Image Processing Handbook](#),  
J. C. Russ

## 2. Processing binary images

### Morphological operations

#### Component separation



[Image Processing Handbook](#),  
J. C. Russ

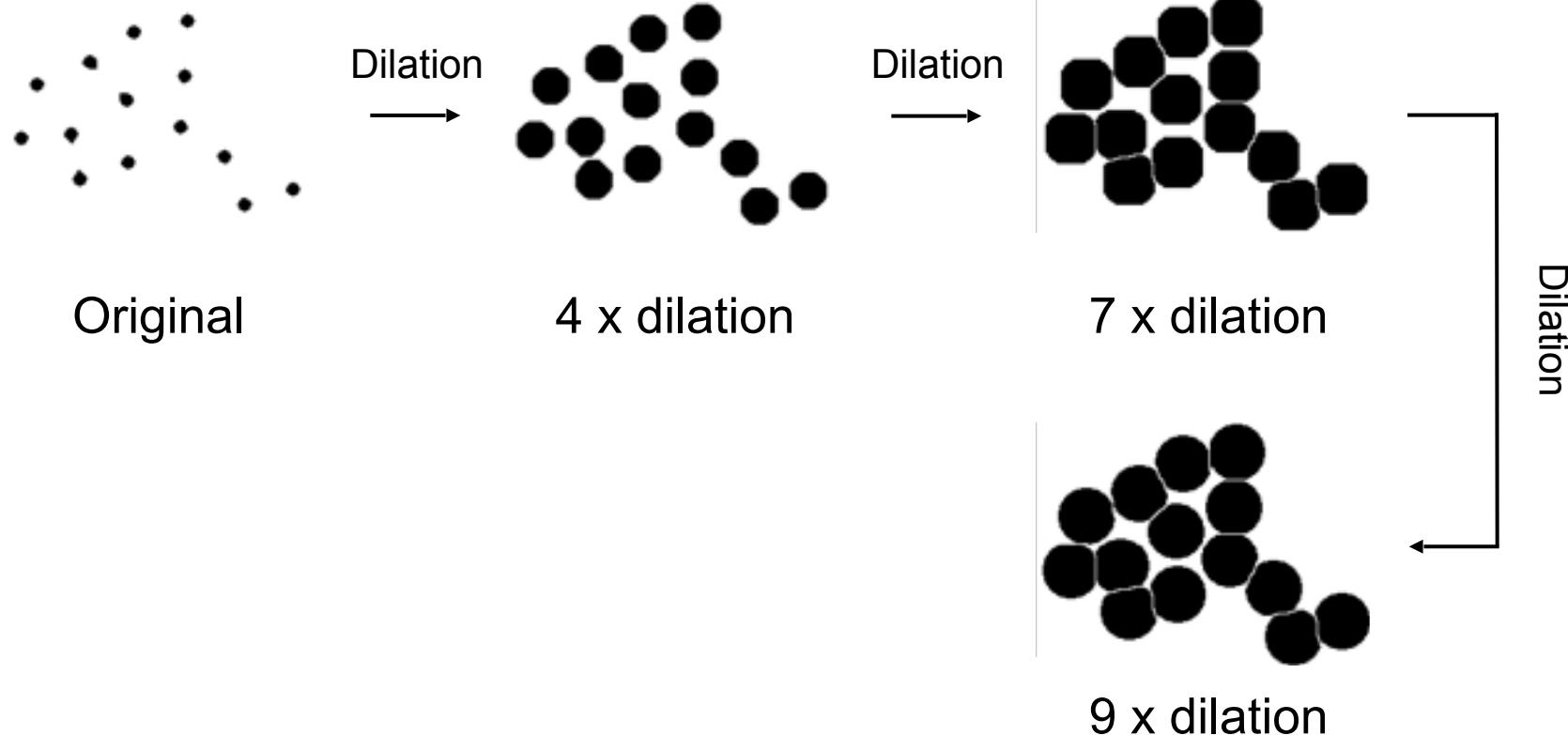
## 2. Processing binary images

### Morphological operations

#### Component separation

Additional rules applied here:

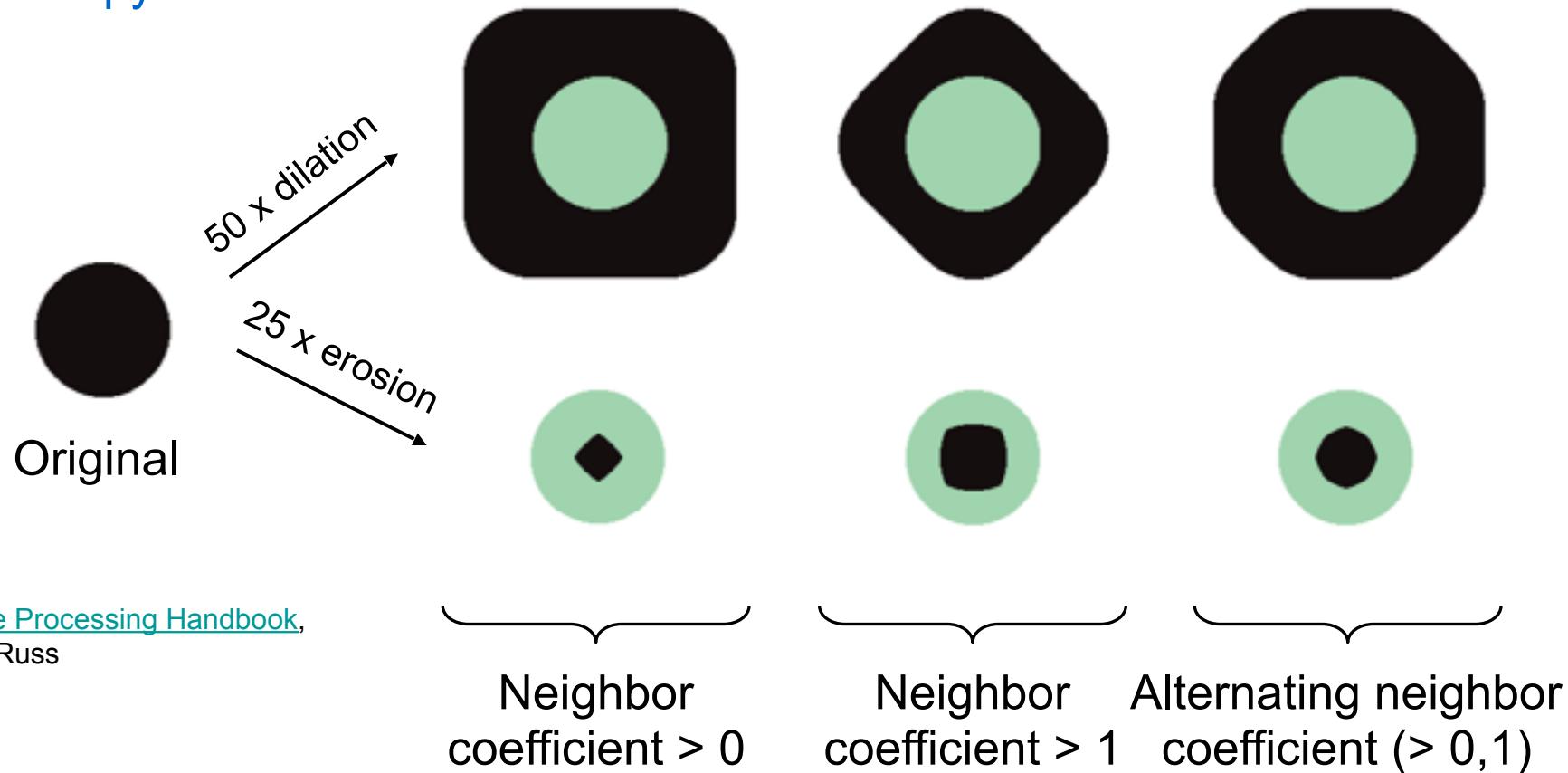
- Do not merge distinct structures
- Structures restricted to original size



## 2. Processing binary images

### Morphological operations

#### Anisotropy

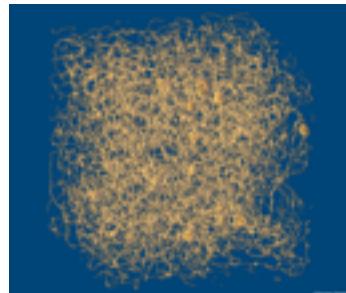


## 2. Processing binary images

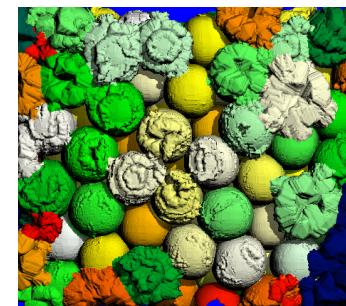
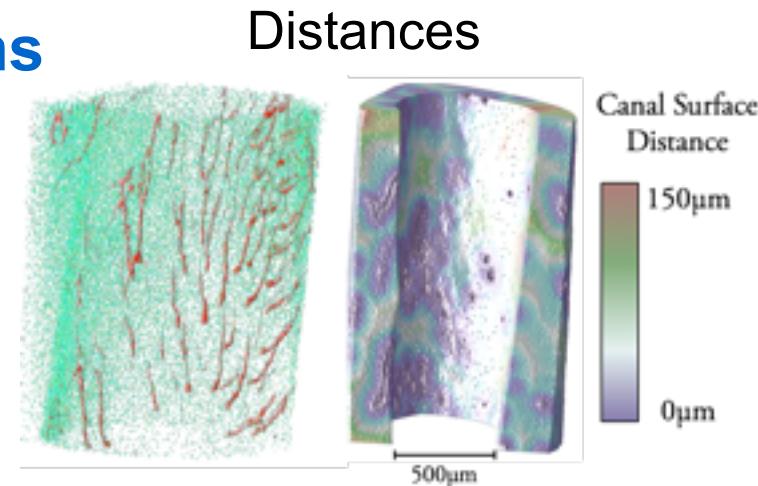
### Distance Map / Distance Transforms

#### Motivation

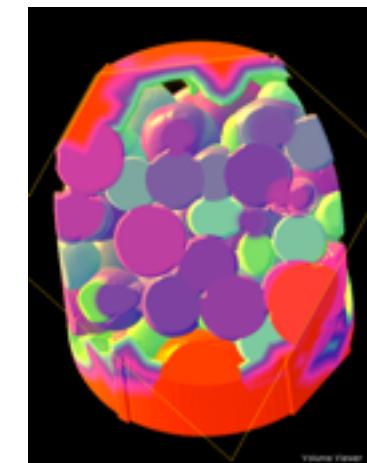
1. Measuring distances between structures
2. Characterizing the thickness of structures
3. Labeling touching structures
4. Identifying skeleton / backbone of structures



Calculating Skeleton



Labeling Connected Structures



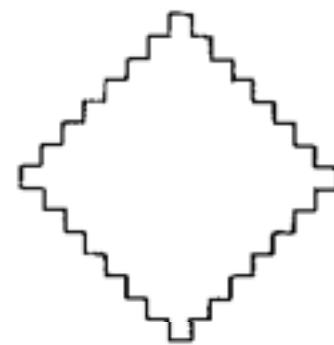
Thickness

## 2. Processing binary images

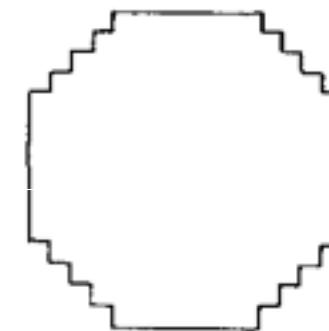
### Euclidean distance transformation (EDT)

Distance

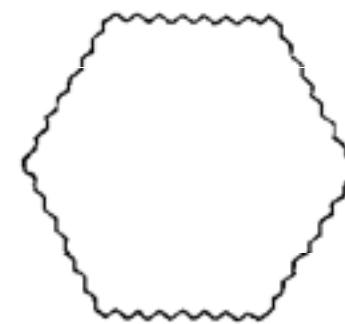
4-neighbor  
distance



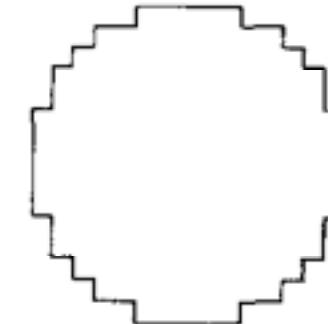
Octagonal  
distance



Hexagonal  
distance



Euclidean  
distance

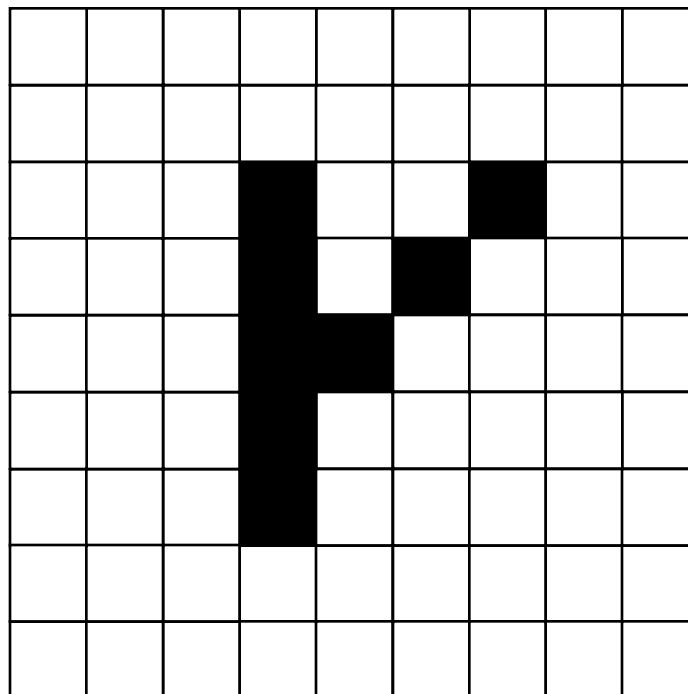


G. Borgefors, [Computer Vision, Graphics,  
and Image Processing](#) 27:321-45 (1984)

## 2. Processing binary images

### Euclidean distance transformation (EDT) / map (EDM)

#### Definition



EDT  
→

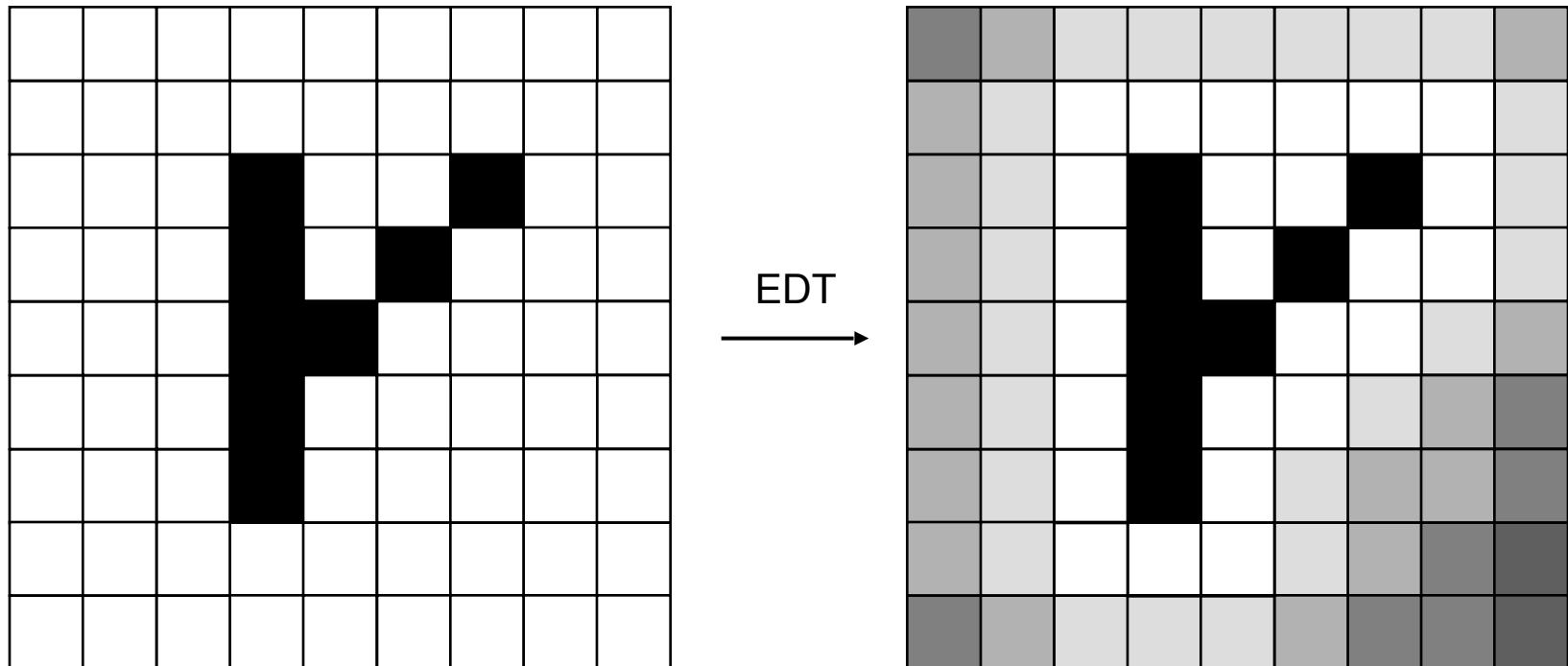
4	3	2	2	2	2	2	2	3
3	2	1	1	1	1	1	1	2
3	2	1		1	1		1	2
3	2	1		1		1	1	2
3	2	1			1	1	2	3
3	2	1		1	1	2	3	4
3	2	1		1	2	3	3	4
3	2	1	1	1	2	3	4	5
4	3	2	2	2	3	4	4	5

Adapted from G. Borgefors, [Computer Vision, Graphics, and Image Processing](#) 27:321-45 (1984)

## 2. Processing binary images

### Euclidean distance transformation (EDT) / map (EDM)

Definition

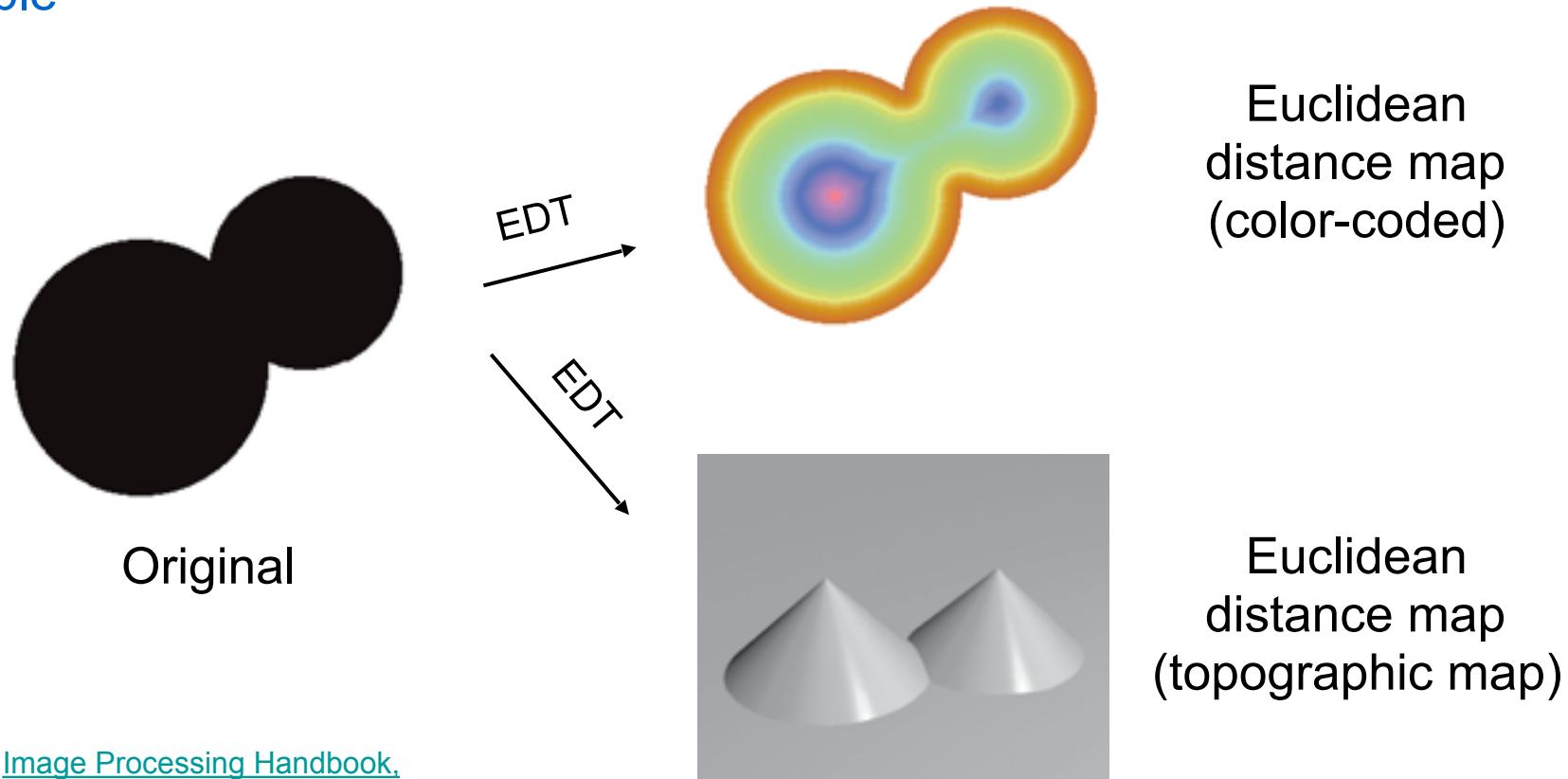


Adapted from G. Borgefors, [Computer Vision, Graphics, and Image Processing](#) 27:321-45 (1984)

## 2. Processing binary images

### Euclidean distance map (EDM)

Example



[Image Processing Handbook,](#)  
J. C. Russ

## 2. Processing binary images

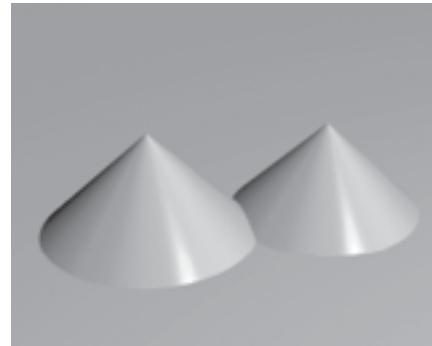
Rain drops -> in which basin do they collect

### Watershed Transformation

Example

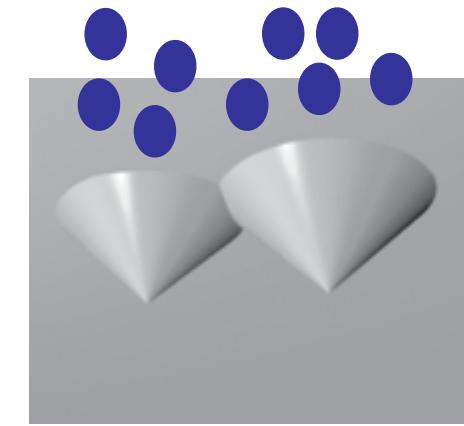
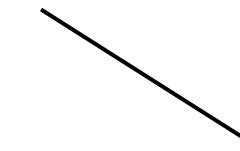


EDT  
→

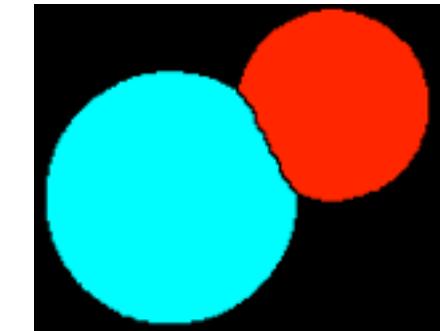


Euclidean  
distance map  
(topographic map)

Watershed  
Transformation



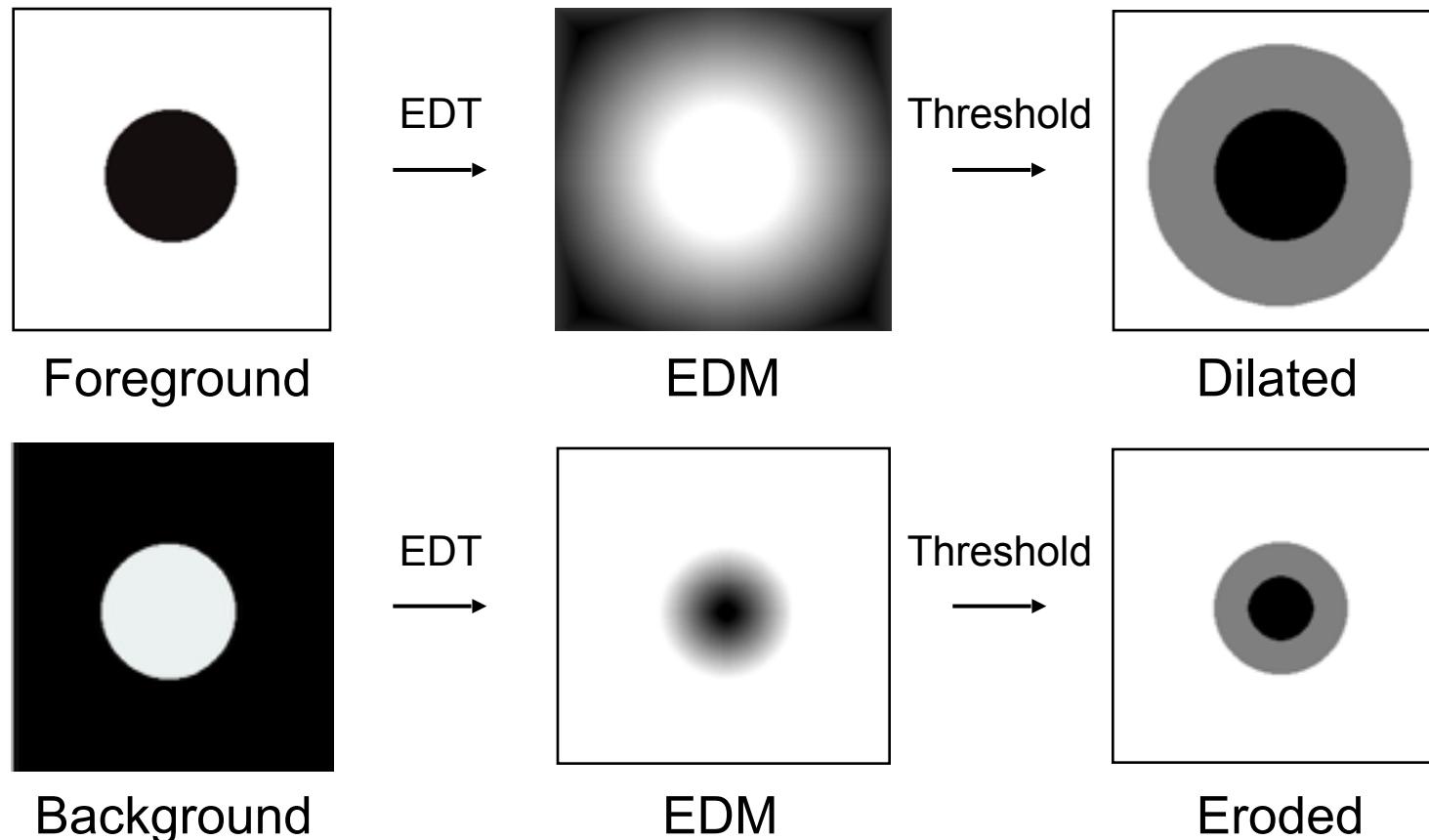
Original



## 2. Processing binary images

### Euclidean distance map (EDM)

Erosion and dilation

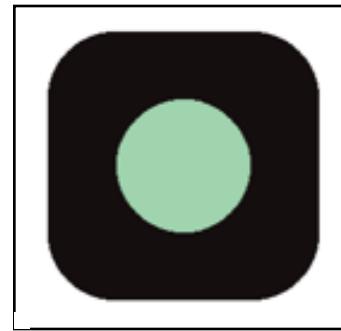


## 2. Processing binary images

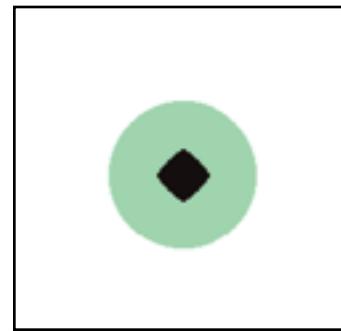
### Euclidean distance map (EDM)

#### Erosion and dilation

Conventional erosion and dilation



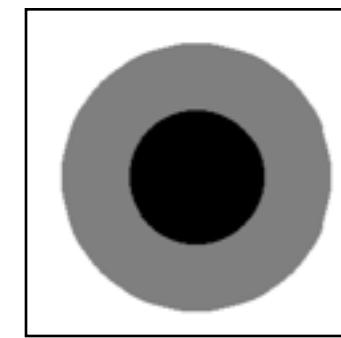
Dilated



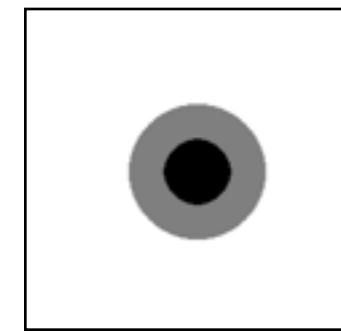
Eroded

=> Erosion and dilation  
more isotropic  
when using EDM

Erosion and dilation using EDM



Dilated



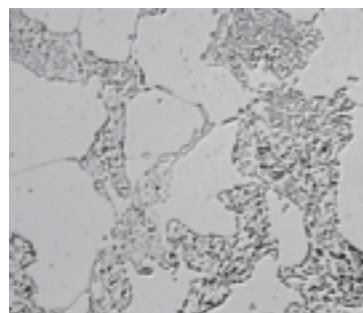
Eroded

[Image Processing Handbook](#), J. C. Russ

## 2. Processing binary images

### Euclidean distance map (EDM)

#### Segmentation



Original

Threshold



Thresholded

Closing  
using EDM



Closed

Opening using EDM



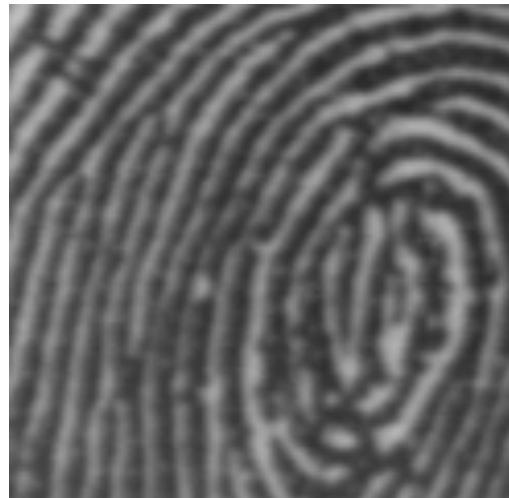
Opened

Light micrograph: iron carbide  
particles (dark) in a steel specimen  
[Image Processing Handbook](#),  
J. C. Russ

## 2. Processing binary images

### Skeletonization

#### Examples



Original



Skeleton

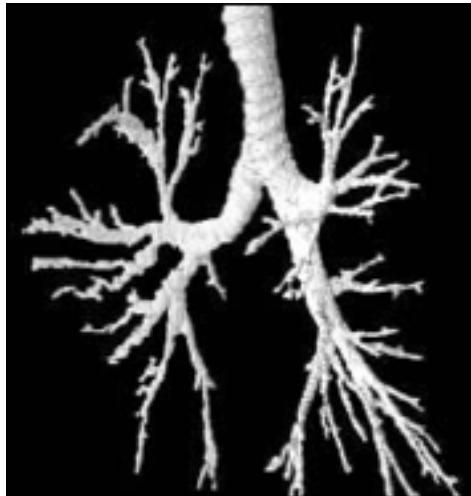
Light micrograph: fingerprint  
[Image Processing Handbook](#), J. C. Russ

- Reflects topology
- Has a compact form

## 2. Processing binary images

### Skeletonization

#### Examples



Original



Skeleton

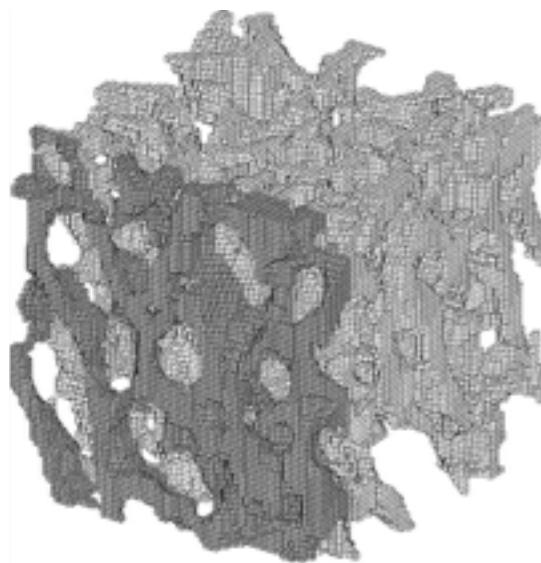
Computed tomography: human bronchus

J. Toriwaki and K. Mori, [Digital and Image Geometry, Advanced Lectures \(Lecture Notes in Computer Science\) 2243 \(2001\)](#)

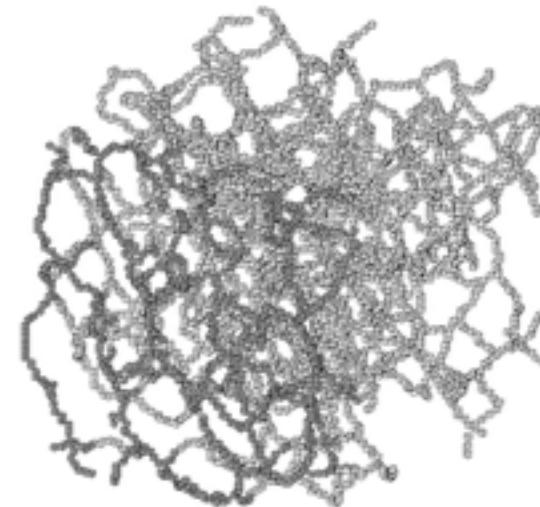
## 2. Processing binary images

### Skeletonization

#### Examples



Original



Skeleton

Computed tomography: human iliac crest specimen  
W. Xie et al., *Pattern recognition* 36:1529-44 (2003)

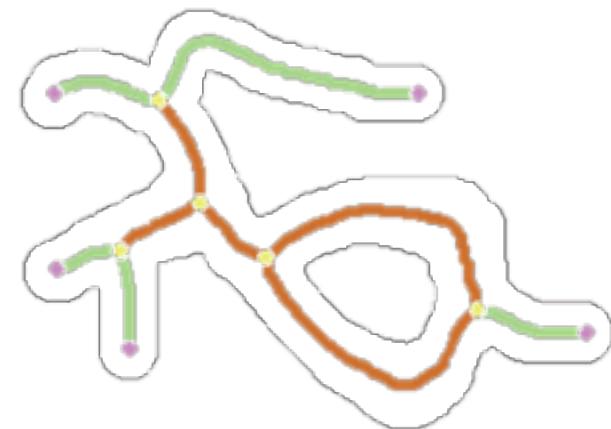
## 2. Processing binary images

### Skeletonization

Elements of a skeleton



Original



Skeleton

[Image Processing Handbook](#), J. C. Russ

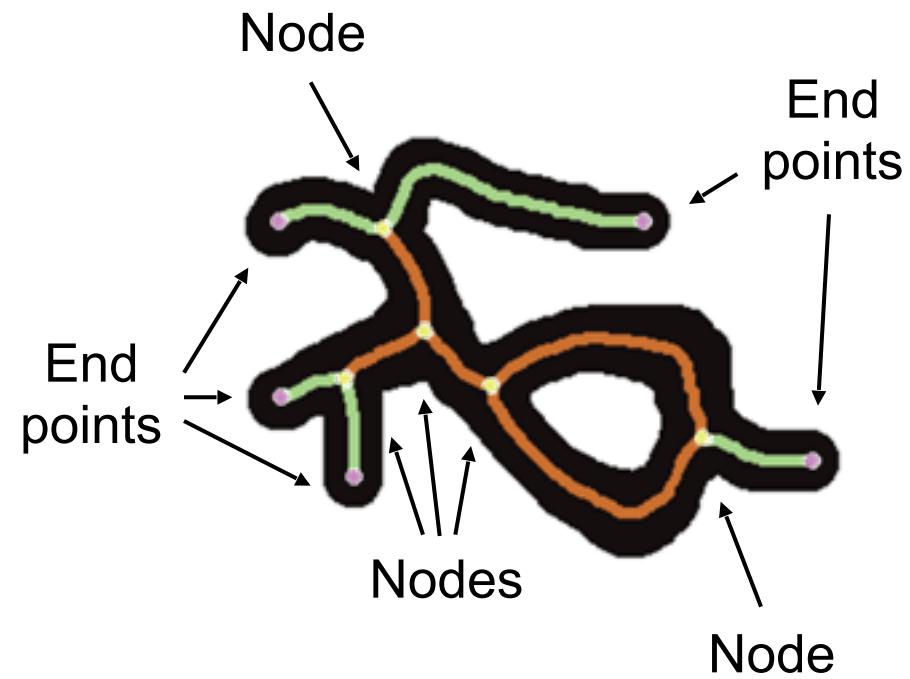
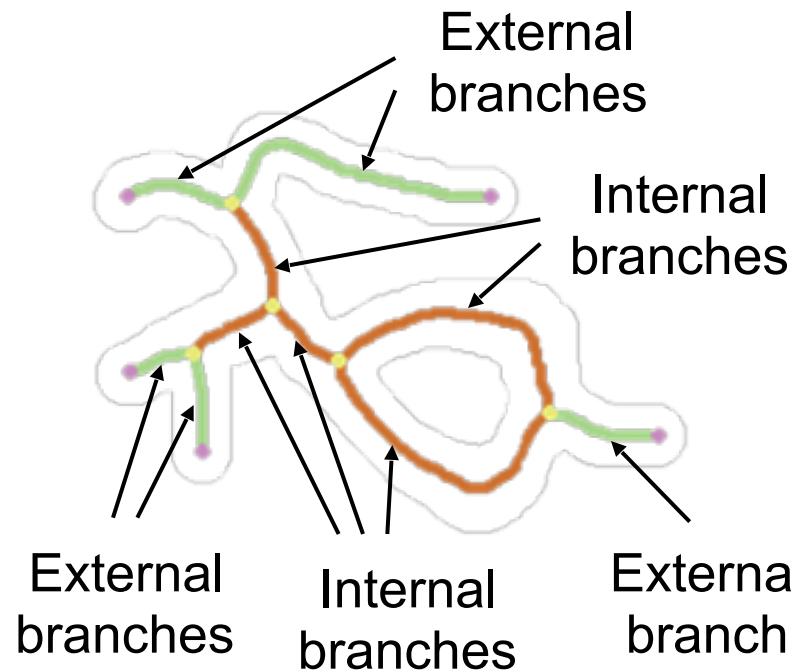
## 2. Processing binary images

# Skeletonization

## Euler-Poincaré characteristics

$$\chi = \# \text{Nodes} + \# \text{Ends} - \# \text{Branches}$$

$$\#Loops = 1 - \chi$$



## 2. Processing binary images

### Skeletonization

#### Requirements for ideal skeleton

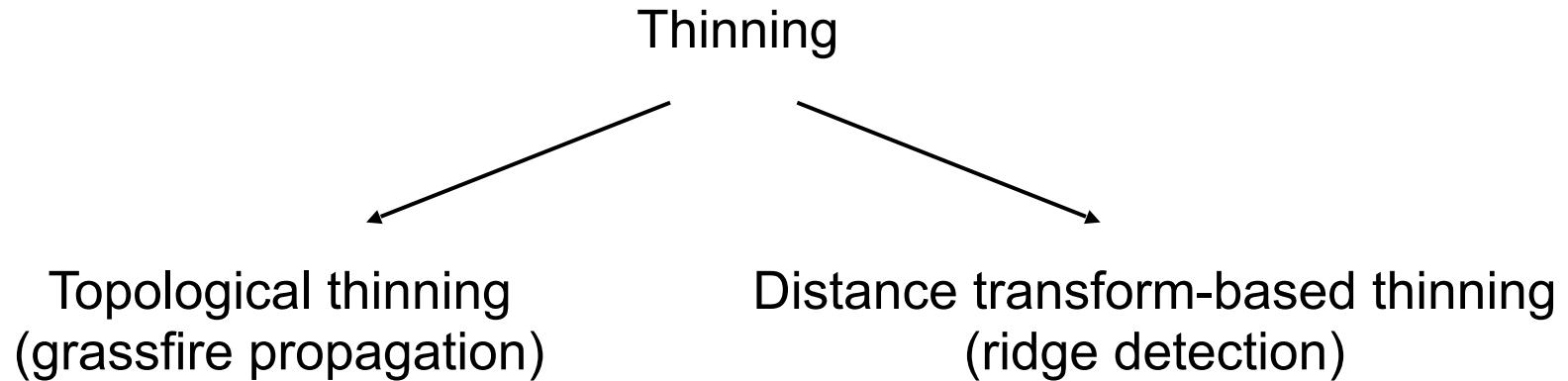
- Homotopic (topology preserving): skeleton topologically equivalent to the object (same Euler-Poincaré characteristic)
- Invariant under isometric transformations (distance-preserving transformations): skeleton of transformed object equal to transformed skeleton of original object
- Thin: one-dimensional skeleton (except at nodes)
- Centered: skeleton centered within the object
- Reliable: every boundary point visible from at least one skeleton point
- Robust: insensitive to noise on the boundary of the object
- Smooth
- Others

N. D. Cornea et al., [IEEE Transactions on Visualization and Computer Graphics 13\(3\):530-48 \(2007\)](#)

## 2. Processing binary images

### Skeletonization

Thinning classification for discrete data sets



N. D. Cornea et al., *IEEE Transactions on Visualization and Computer Graphics* 13(3):530-48 (2007)

## 2. Processing binary images

### Skeletonization

#### Simple points

Human vision interprets an image in terms of relationships between structures

<=>

For computer-based image analysis systems, classification of structures must be made at the level of individual pixels/voxels

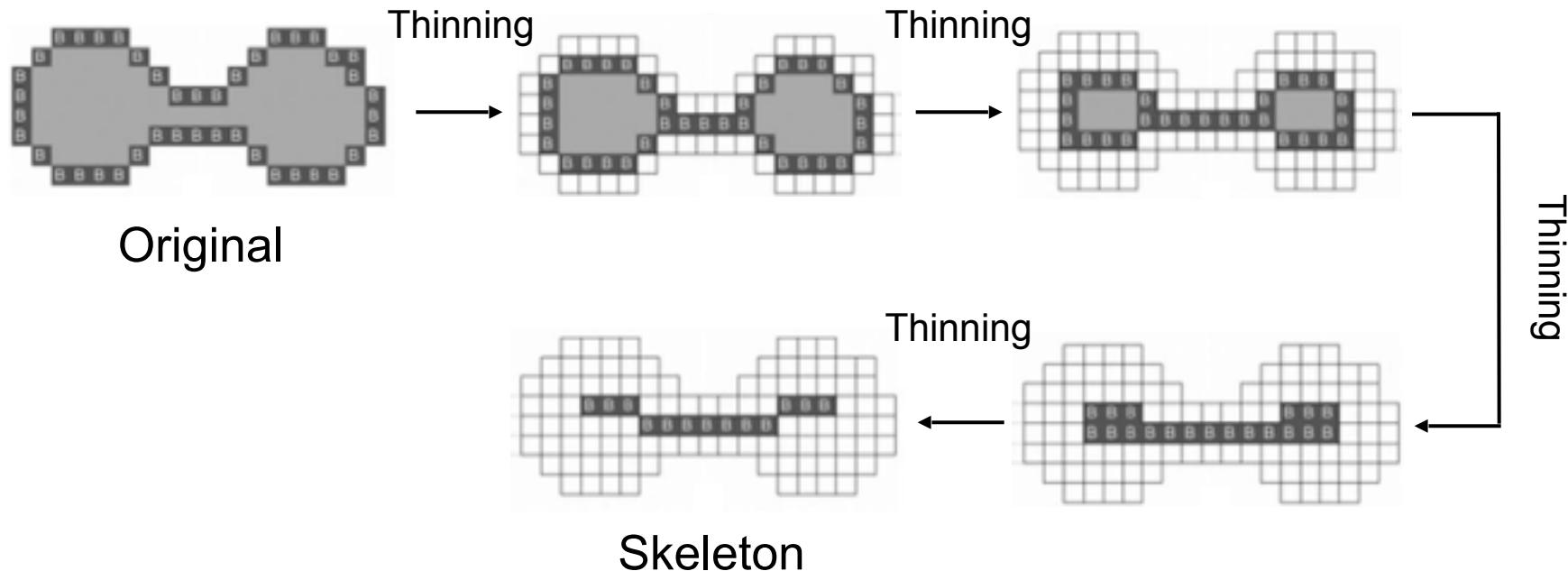
- Thinning algorithms operate in the discrete (pixel/voxel) space and rely on the concept of simple points
- Simple point: object point (pixel/voxel) that can be removed without changing the topology of the object
- Simple points can be locally characterized (-> efficient thinning algorithm)

N. D. Cornea et al., [IEEE Transactions on Visualization and Computer Graphics 13\(3\):530-48 \(2007\)](#)

## 2. Processing binary images

### Skeletonization

#### Topological thinning



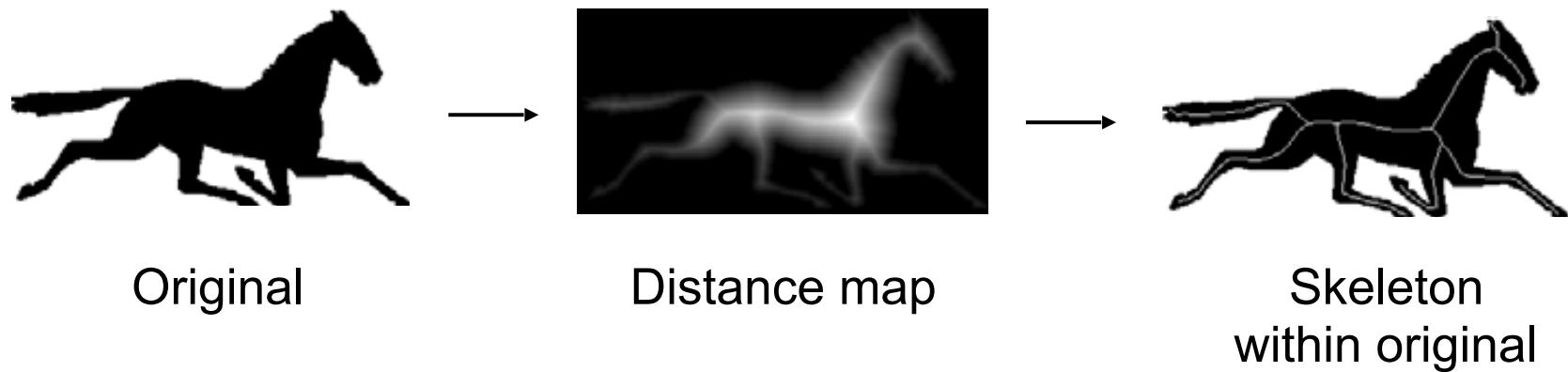
=> Erosion with special rule (remove simple boundary points only)

N. D. Cornea et al., *IEEE Transactions on Visualization and Computer Graphics* 13(3):530-48 (2007)

## 2. Processing binary images

### Skeletonization

Distance transform-based thinning



L. J. Latecki et al., [IEEE International Conference  
on Image Processing V:349-52 \(2007\)](#)

## 2. Processing binary images

### Skeletonization

Distance transform-based thinning

1) Find ridge points (detection)



2) Pruning



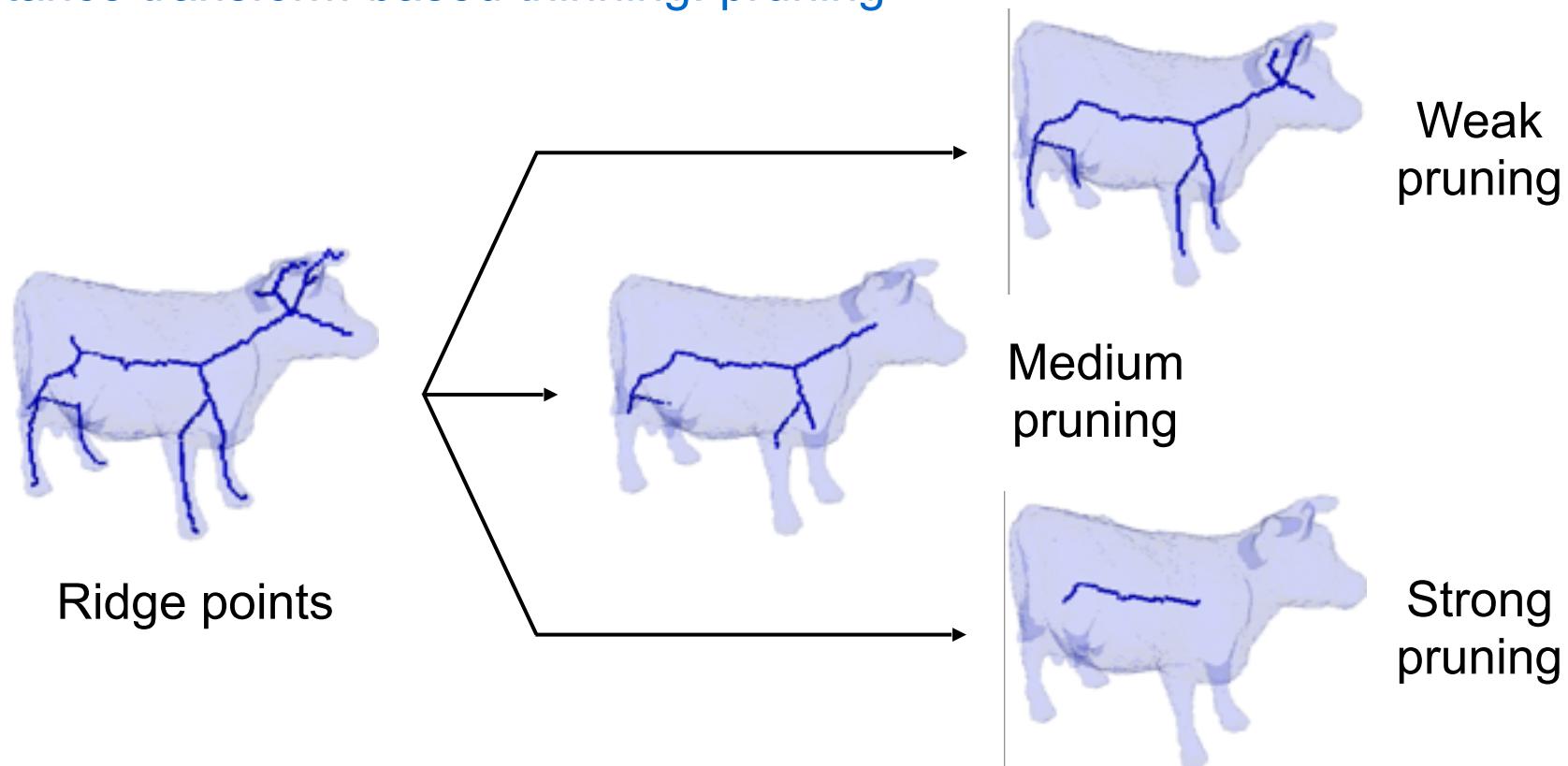
3) Connecting

N. D. Cornea et al., [IEEE Transactions on Visualization and Computer Graphics](#) 13(3):530-48 (2007)

## 2. Processing binary images

### Skeletonization

Distance transform-based thinning: pruning

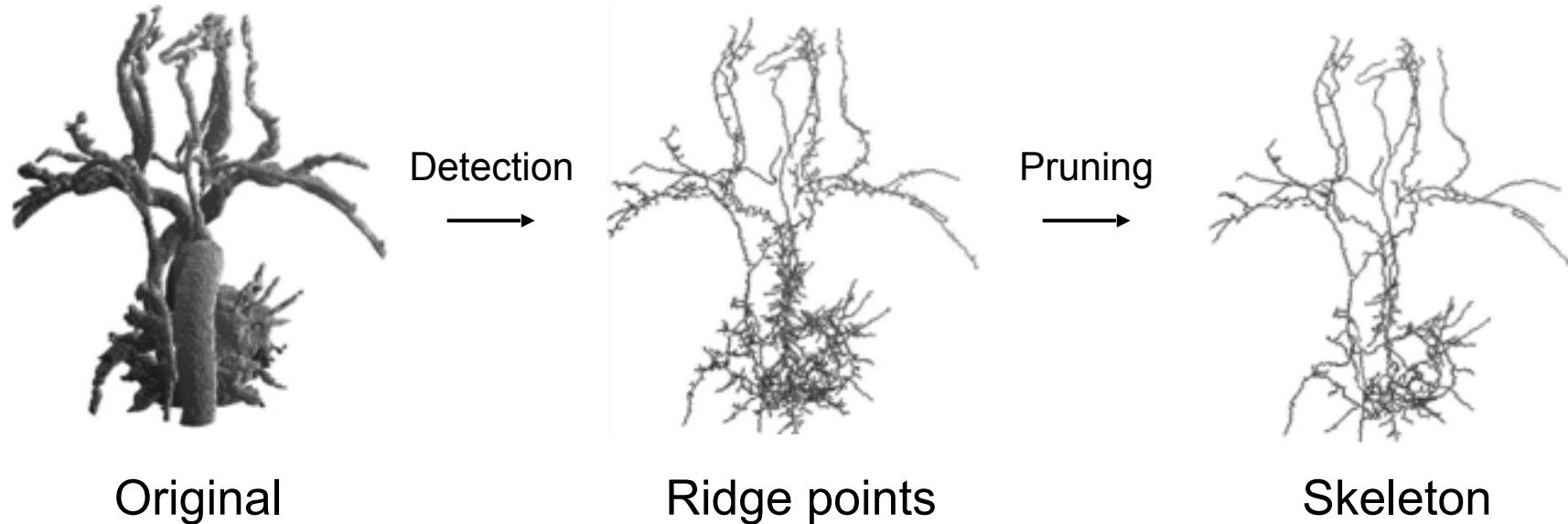


A. Telea et al., *Proceedings of the Symposium on Data Visualisation* 40:185-94 (2003)

## 2. Processing binary images

### Skeletonization

Distance transform-based thinning: pruning



Magnetic resonance angiography: thoracic vessel system

S. Svensson *et al.*, [\*Computer Vision and Image Understanding\* 90:242-57 \(2003\)](#)

I. Nyström *et al.*, [\*Proceedings of the 11<sup>th</sup> International Conference on Image Analysis and Processing\*: 495-500 \(2001\)](#)

## 2. Processing binary images

### Skeletonization

Distance transform-based thinning: connecting

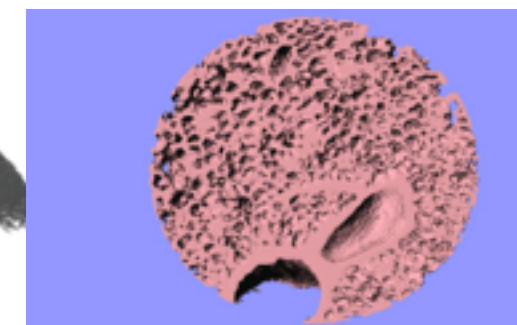
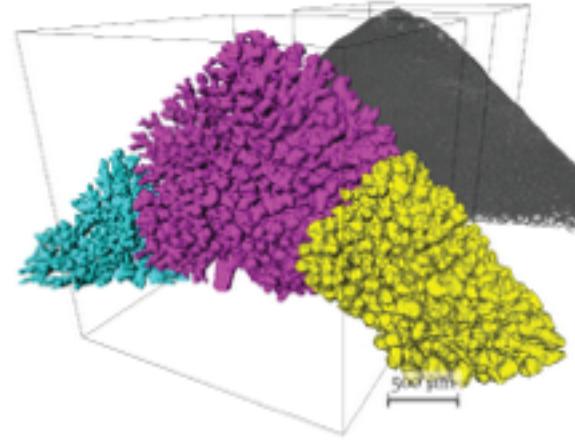
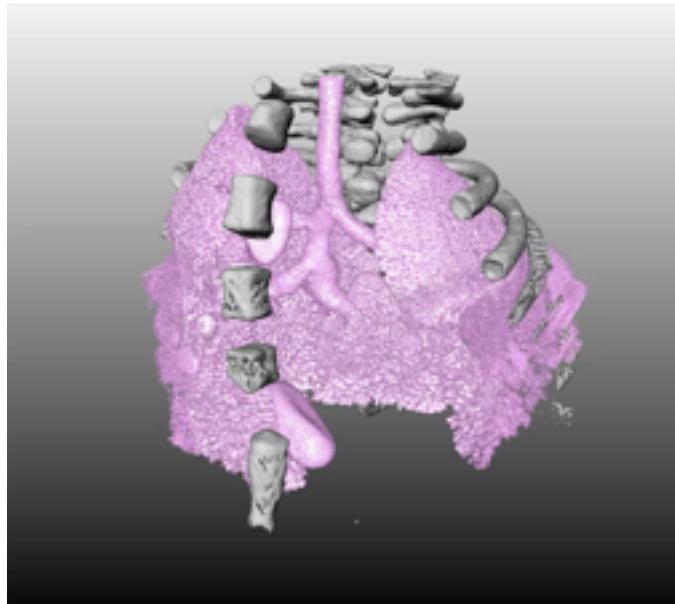


A. Telea et al., *Proceedings of the Symposium on Data Visualization* 40:185-94 (2003)

### 3. Demonstration

#### Baby Rat Lung Structure

Micron-scale aveolar structure



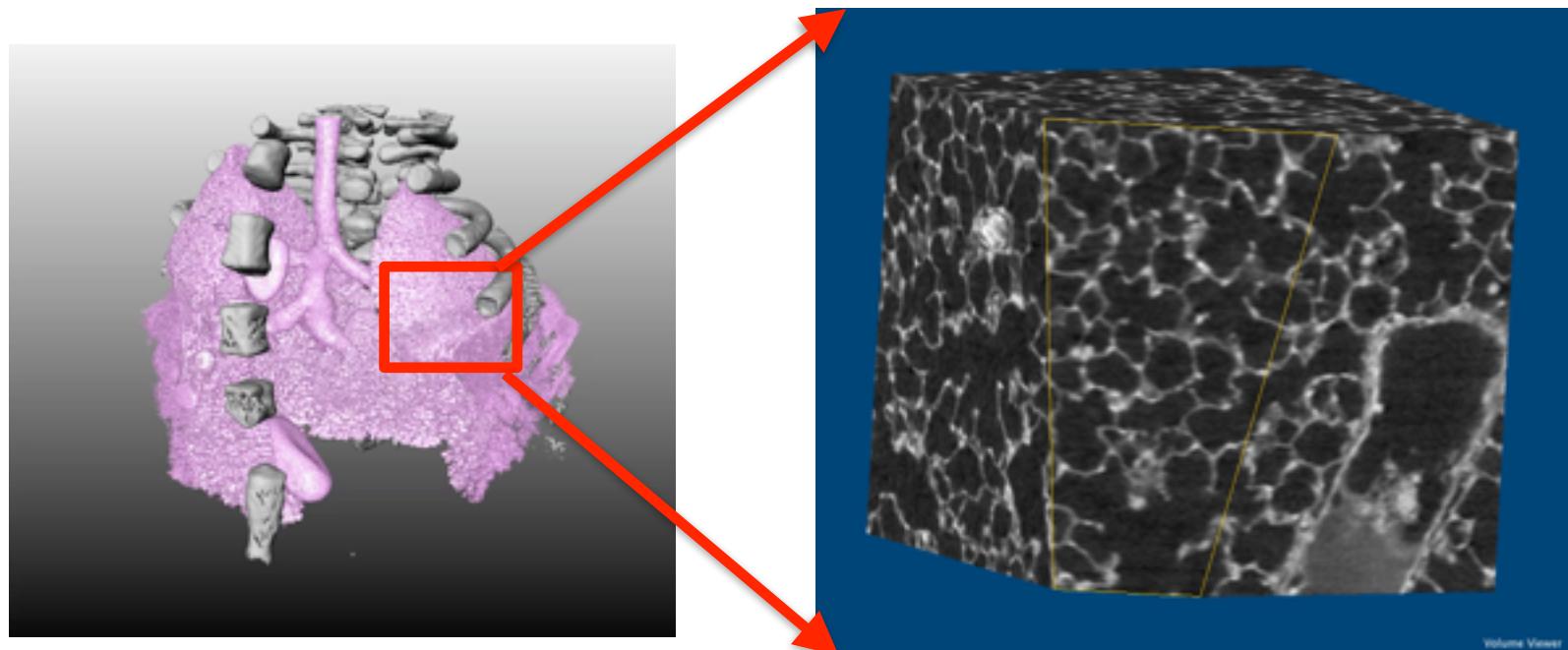
##### Morphology of lung acini

Haberthür et al., Journal of Synchrotron Radiation, 17(5), 2010  
Schittny et al., American Journal of Physiology 294 (L246), 2008

### 3. Demonstration

#### Baby Rat Lung Structure

Micron-scale aveolar structure

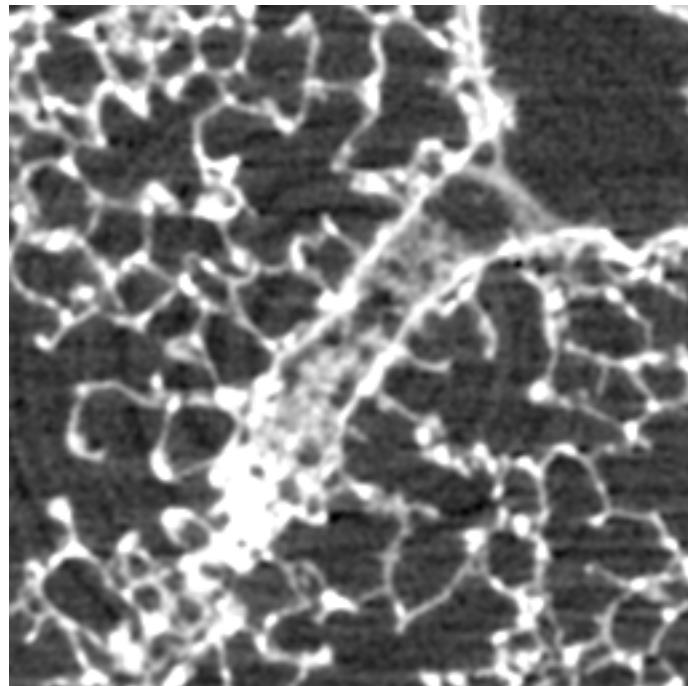


Lung measurement  
courtesy of G. Lovric

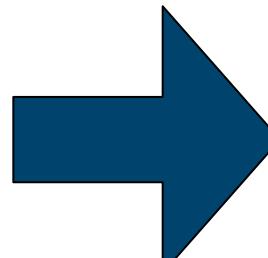
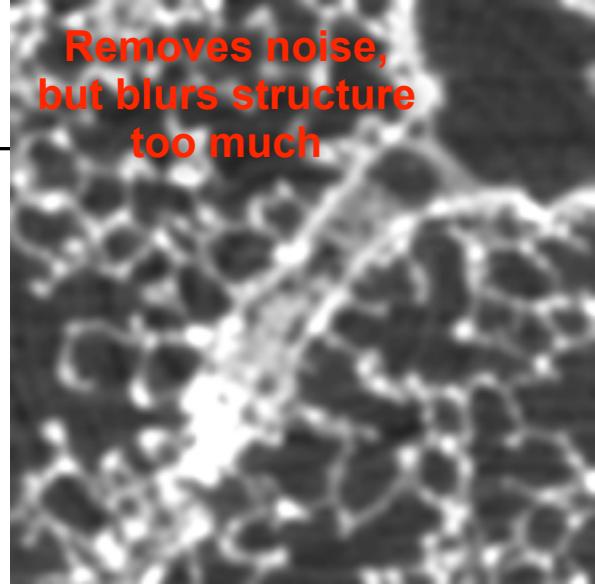
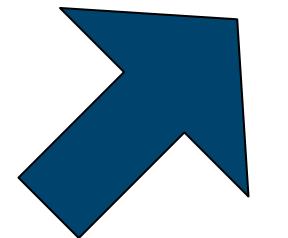
### 3. Demonstration

#### Baby Rat Lung Structure

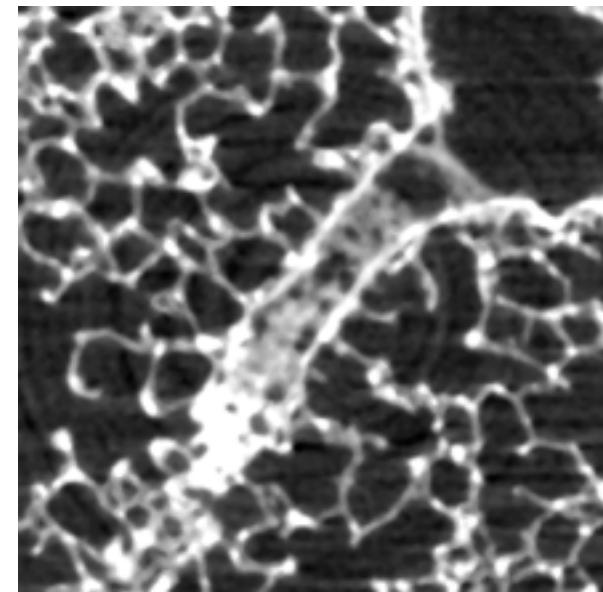
Micron-scale aveolar structure



Gaussian  
Filtering



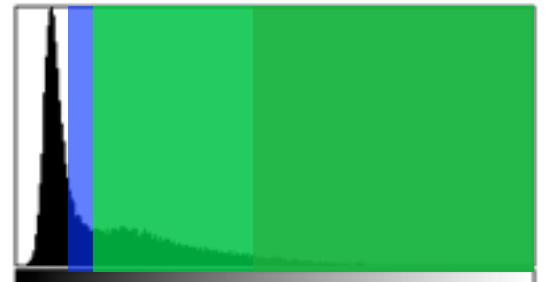
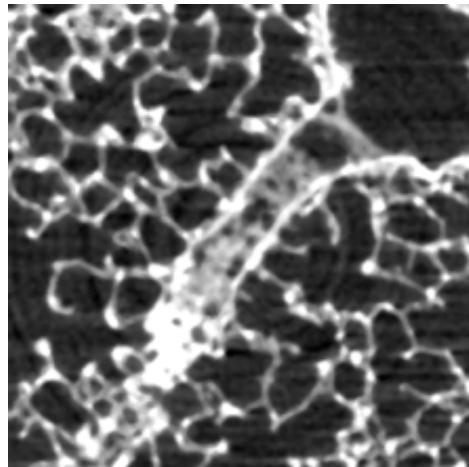
Median  
Filtering



### 3. Demonstration

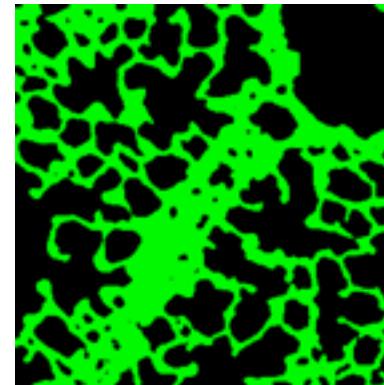
#### Baby Rat Lung Structure

Micron-scale aveolar structure

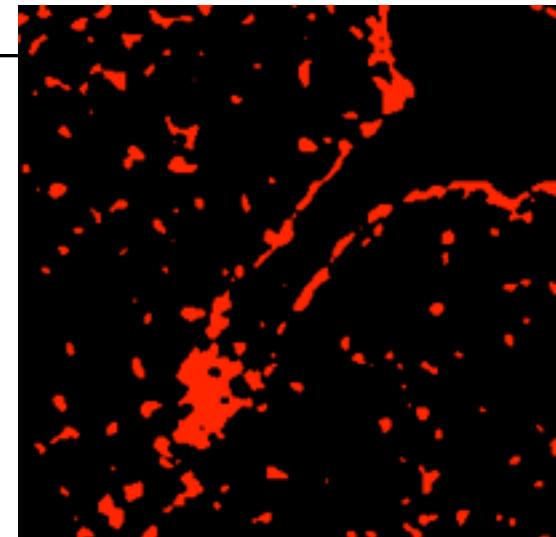


Count: 65536	Min: 14850
Mean: 21165.189	Max: 51245
StdDev: 5219.193	Mode: 17182 (3017)
Bins: 256	Bin Width: 142.168

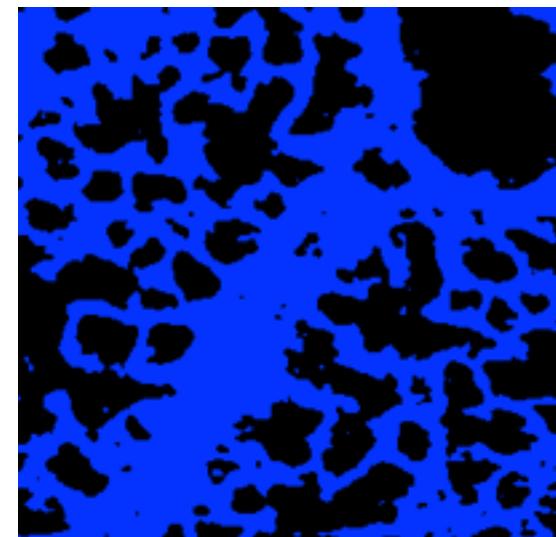
Just right



Too strict a threshold



Too lax

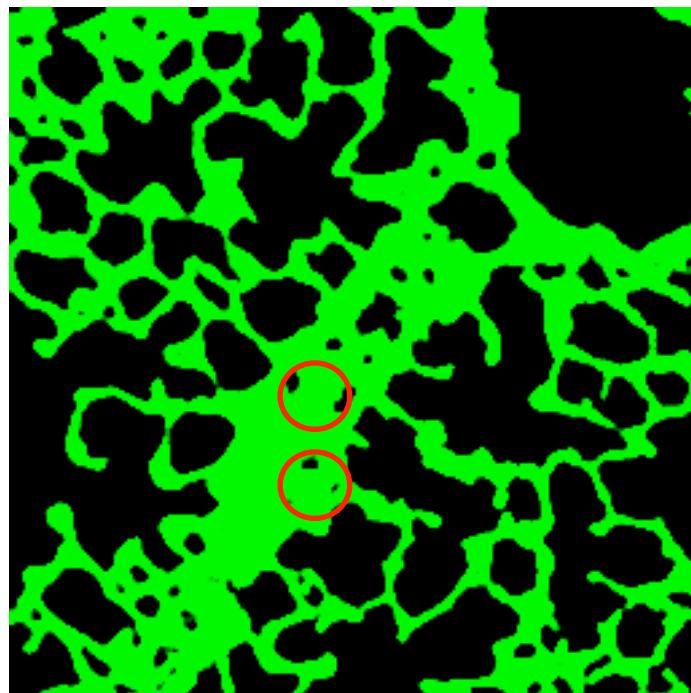


### 3. Demonstration

#### Baby Rat Lung Structure

Micron-scale aveolar structure

Some detail is lost!



Threshold

Remove Small Holes

3x Dilation  
3x Erosion  
= 3x Close

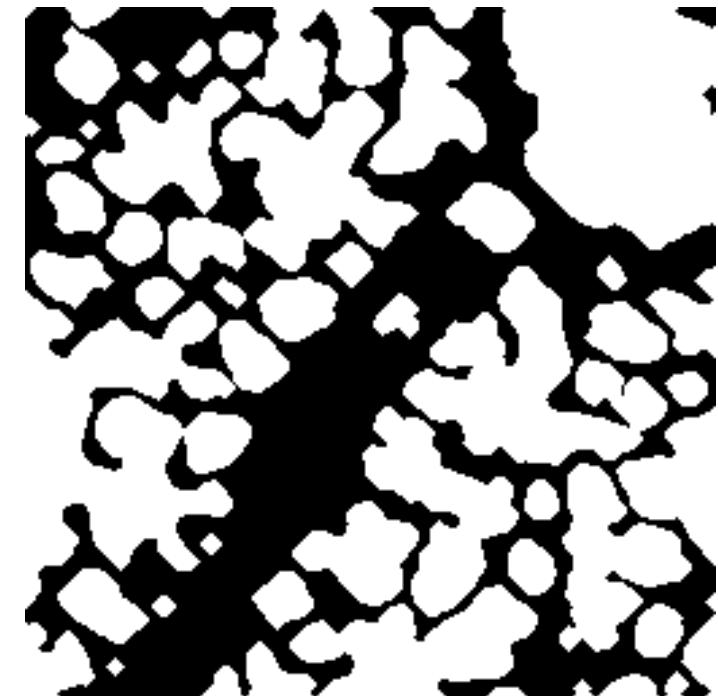
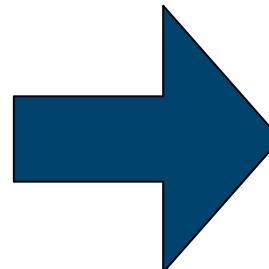
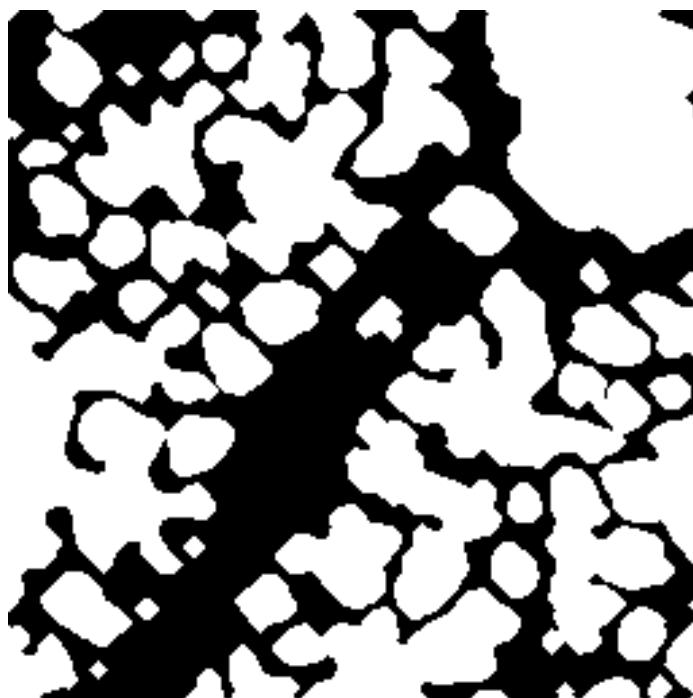


Image without small holes

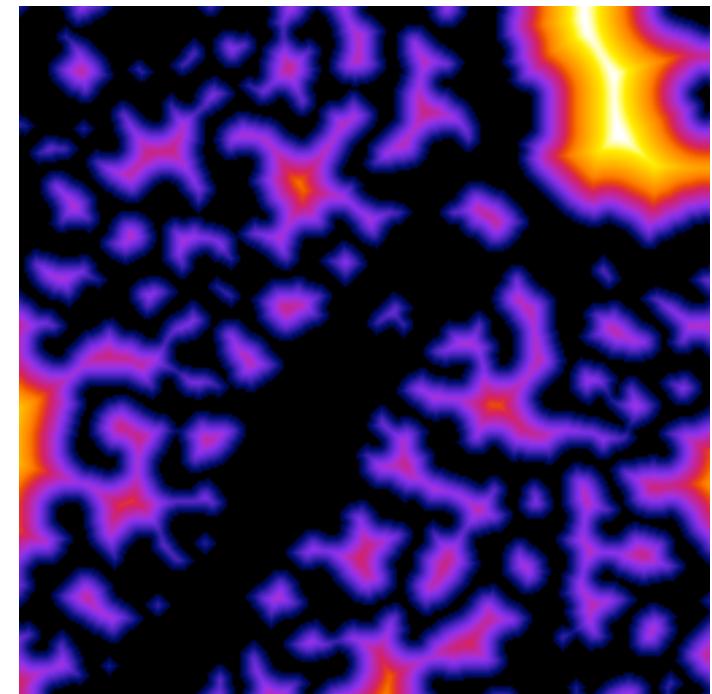
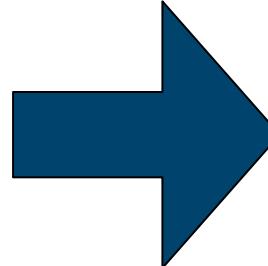
### 3. Demonstration

#### Baby Rat Lung Structure

Micron-scale aveolar structure



Euclidean Distance Transform

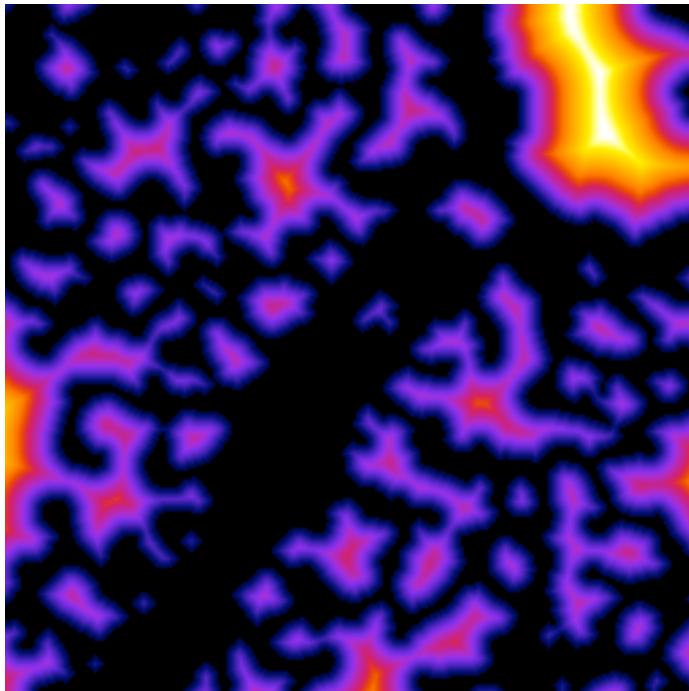


Distance to nearest  
aveolar structures

### 3. Demonstration

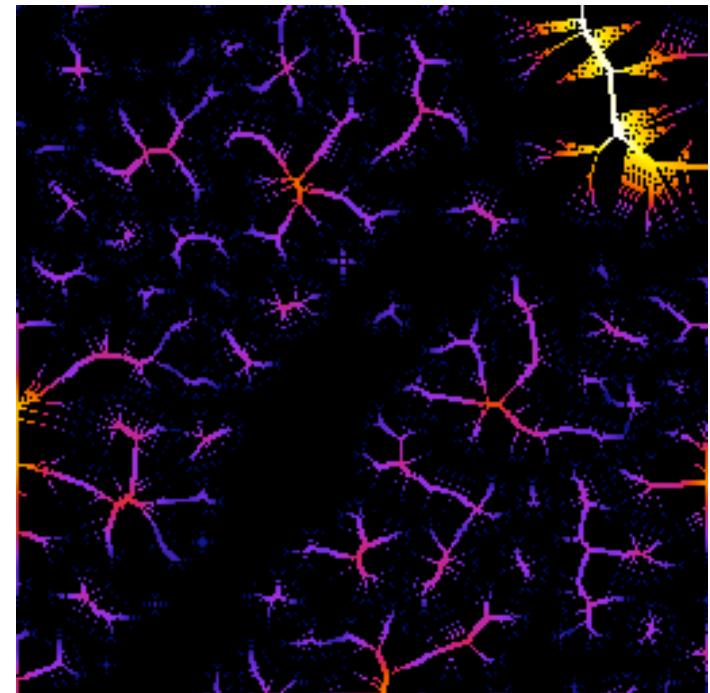
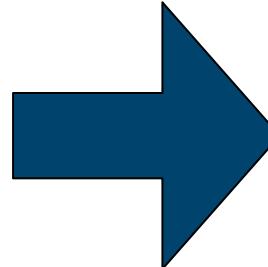
#### Baby Rat Lung Structure

Micron-scale aveolar structure



Distance Map

Gradient = 0

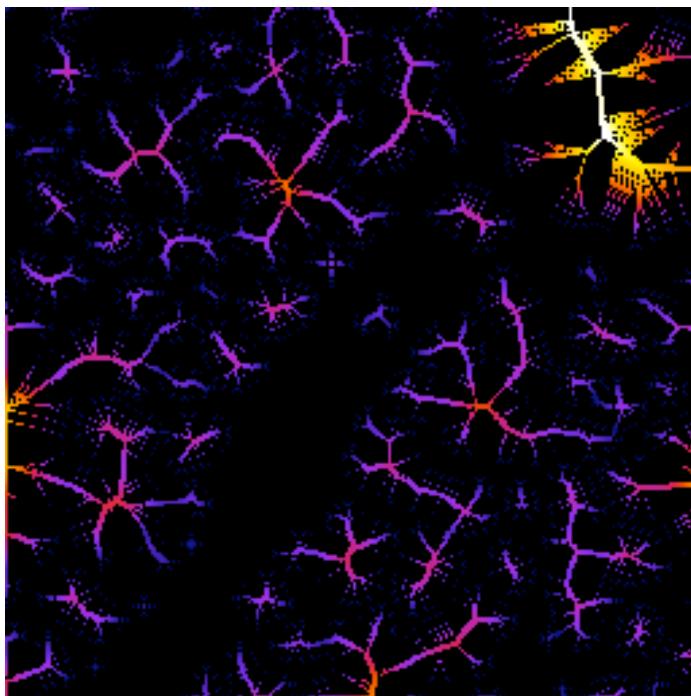


Ridge Map

### 3. Demonstration

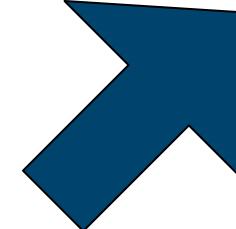
#### Baby Rat Lung Structure

Micron-scale aveolar structure

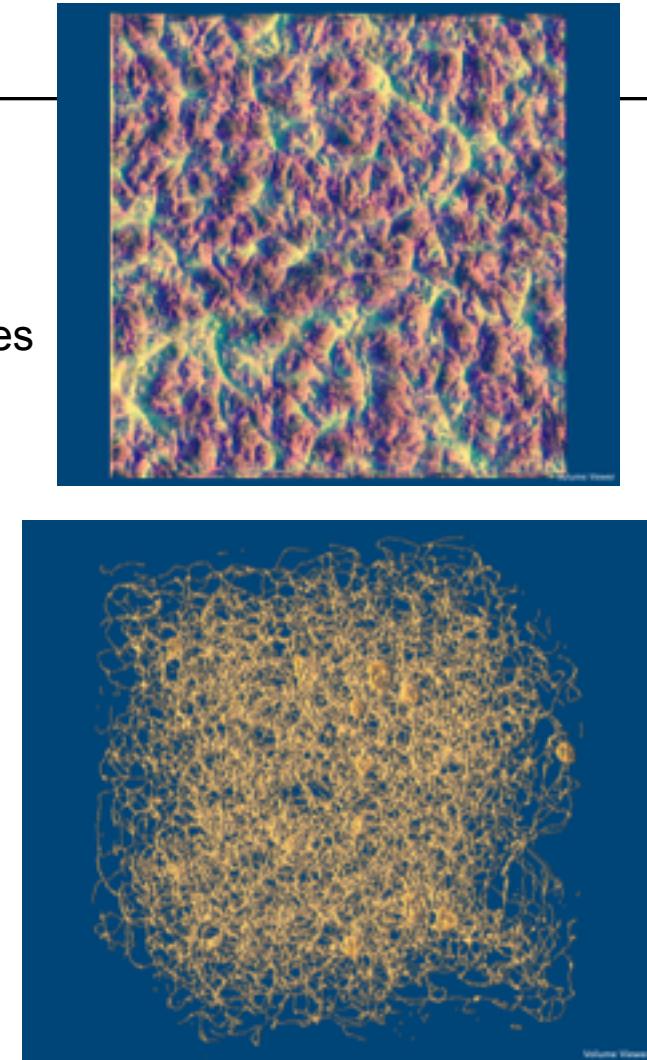


Ridge Map

All structures



Only structures  
larger than  
5 voxels

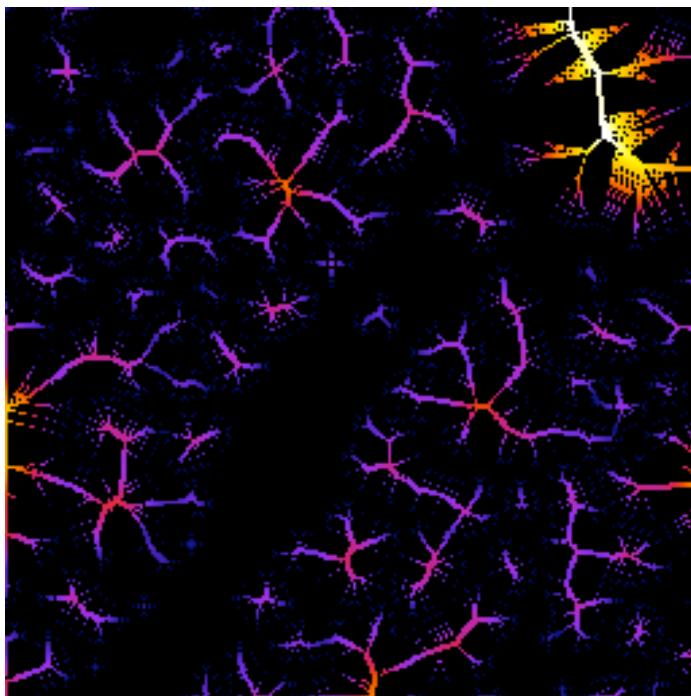


Lung Skeleton / Network

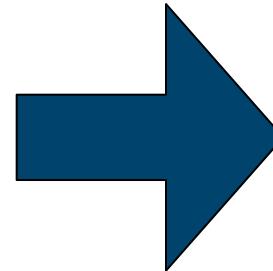
### 3. Demonstration

#### Baby Rat Lung Structure

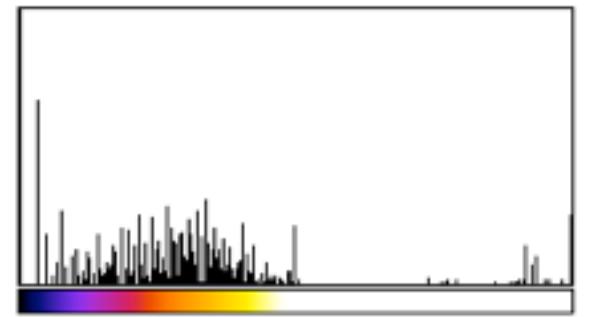
Micron-scale aveolar structure



Ridge Map

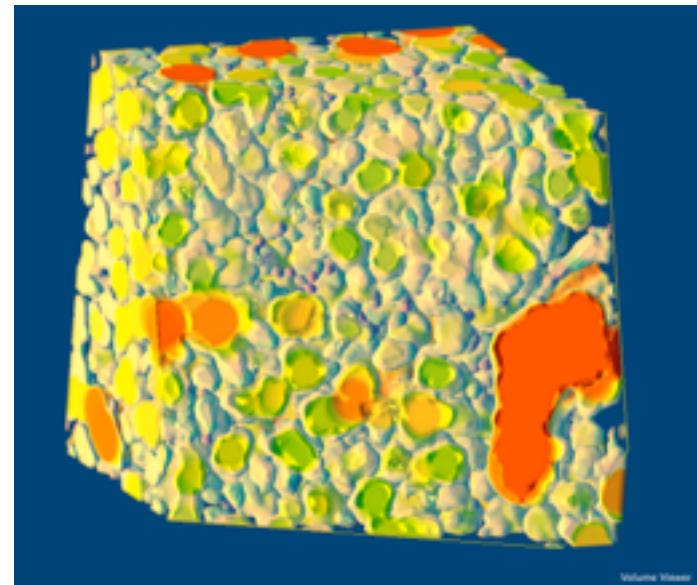


Thickness Filling



Count: 65536  
Mean: 14.113  
StdDev: 13.545  
Bins: 256

Min: 0  
Max: 58.549  
Mode: 0.114 (15479)  
Bin Width: 0.229



Thickness map of alveoli

# 3. Demonstration

## Baby Rat Lung Structure

### Reproducibility?

- For this analysis all steps performed with ImageJ / FIJI
- Provides built-in Macro-recording feature
- Acts like a log-book of all the steps done

```
run("Median (3D)");
//run("Threshold...");  
setAutoThreshold("Default dark");
setAutoThreshold("Default dark");

run("Dilate (3D)", "iso=255");
run("Dilate (3D)", "iso=255");
run("Dilate (3D)", "iso=255");
run("Erode (3D)", "iso=255");
run("Erode (3D)", "iso=255");
run("Erode (3D)", "iso=255");
run("Geometry to Distance Map", "threshold=128 inverse");
run("Distance Map to Distance Ridge");

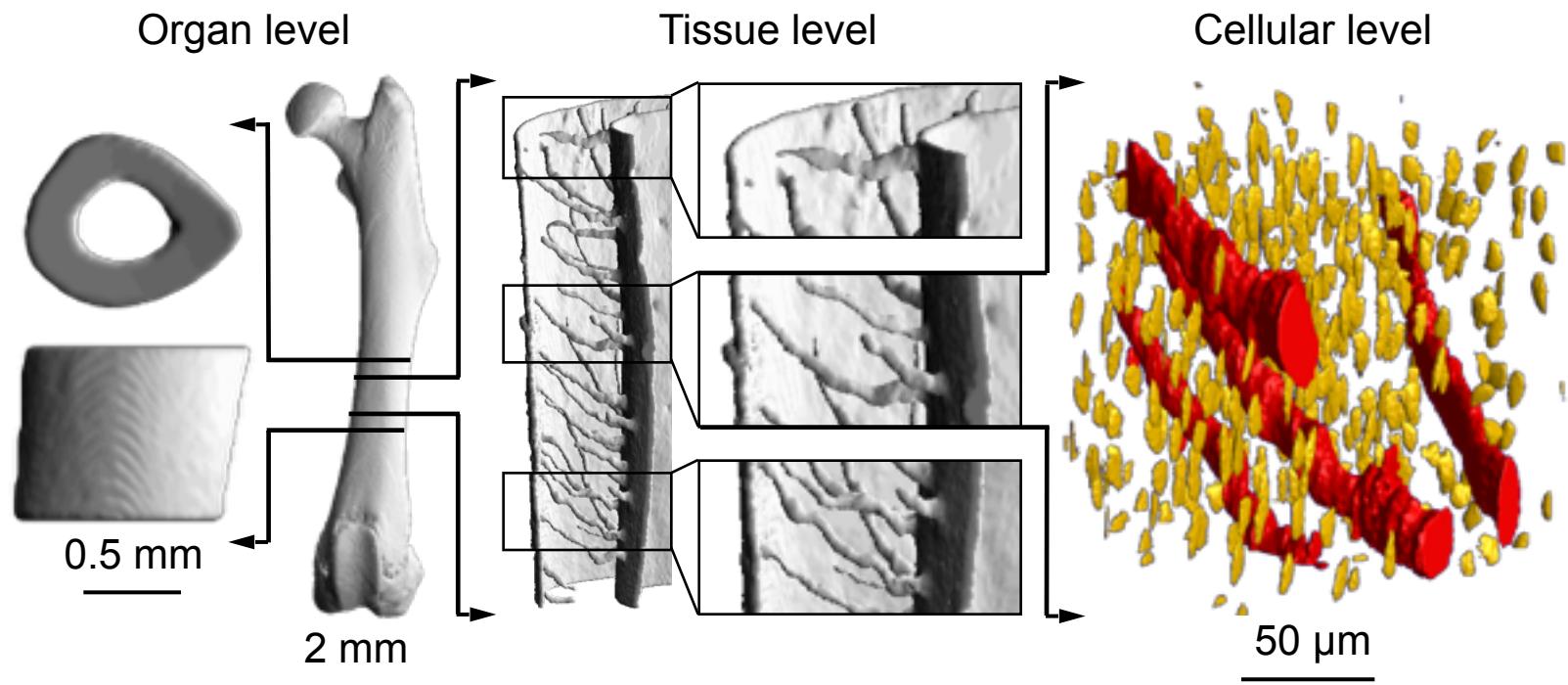
run("Distance Ridge to Local Thickness");
run("Histogram", "bins=256 use x_min=0 x_max=29.27 y_max=Auto");
```

<http://fiji.sc/Fiji>

### 3. Demonstration

#### Lacuno-canicular network

##### Murine bone microstructure

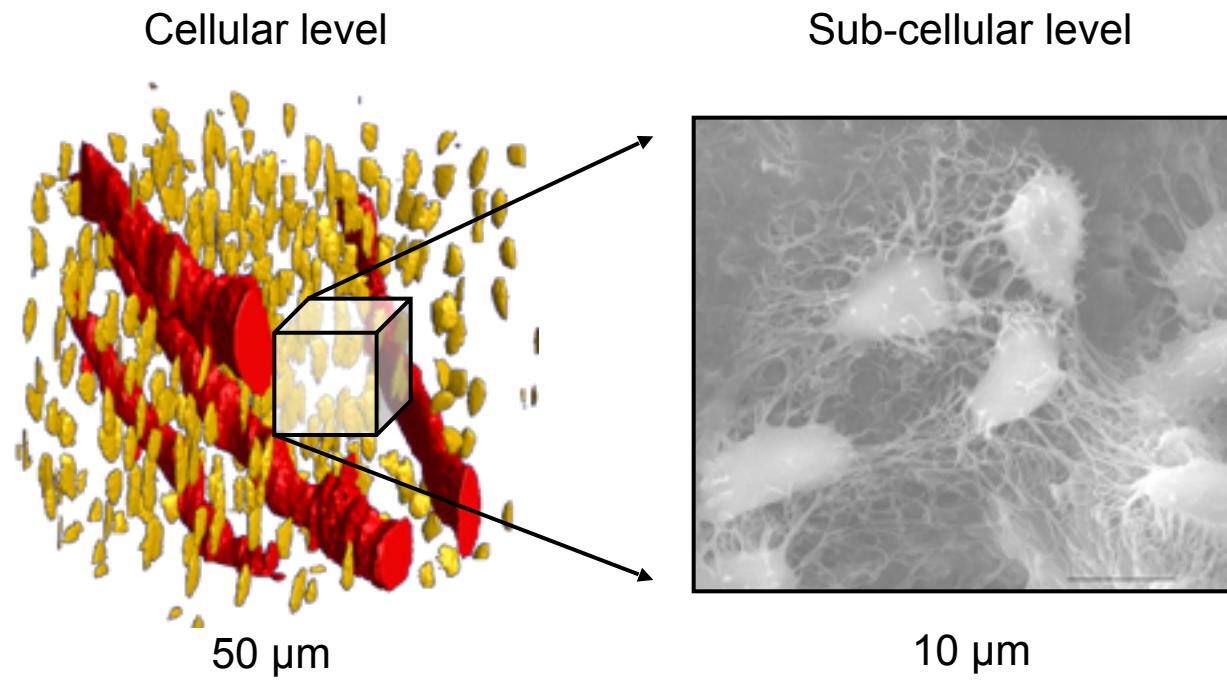


Synchrotron radiation CT: murine cortical bone ultrastructure  
P. Schneider *et al.*, [Proceedings of SPIE 6916:19-1–19-12 \(2008\)](#)

### 3. Demonstration

#### Lacuno-canicular network

Osteocytes and canaliculi

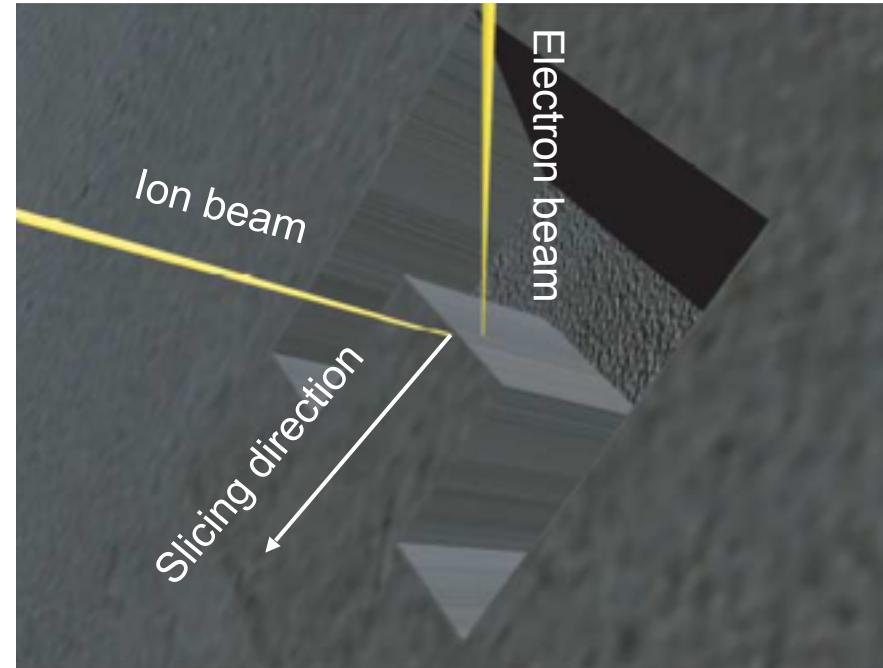


Scanning electron micrograph: murine lacuno-canicular network  
S. C. Cowin, [Journal of Biomechanics 40:S105-S109 \(2007\)](#)

### 3. Demonstration

#### Lacuno-canicular network

Focused ion beam

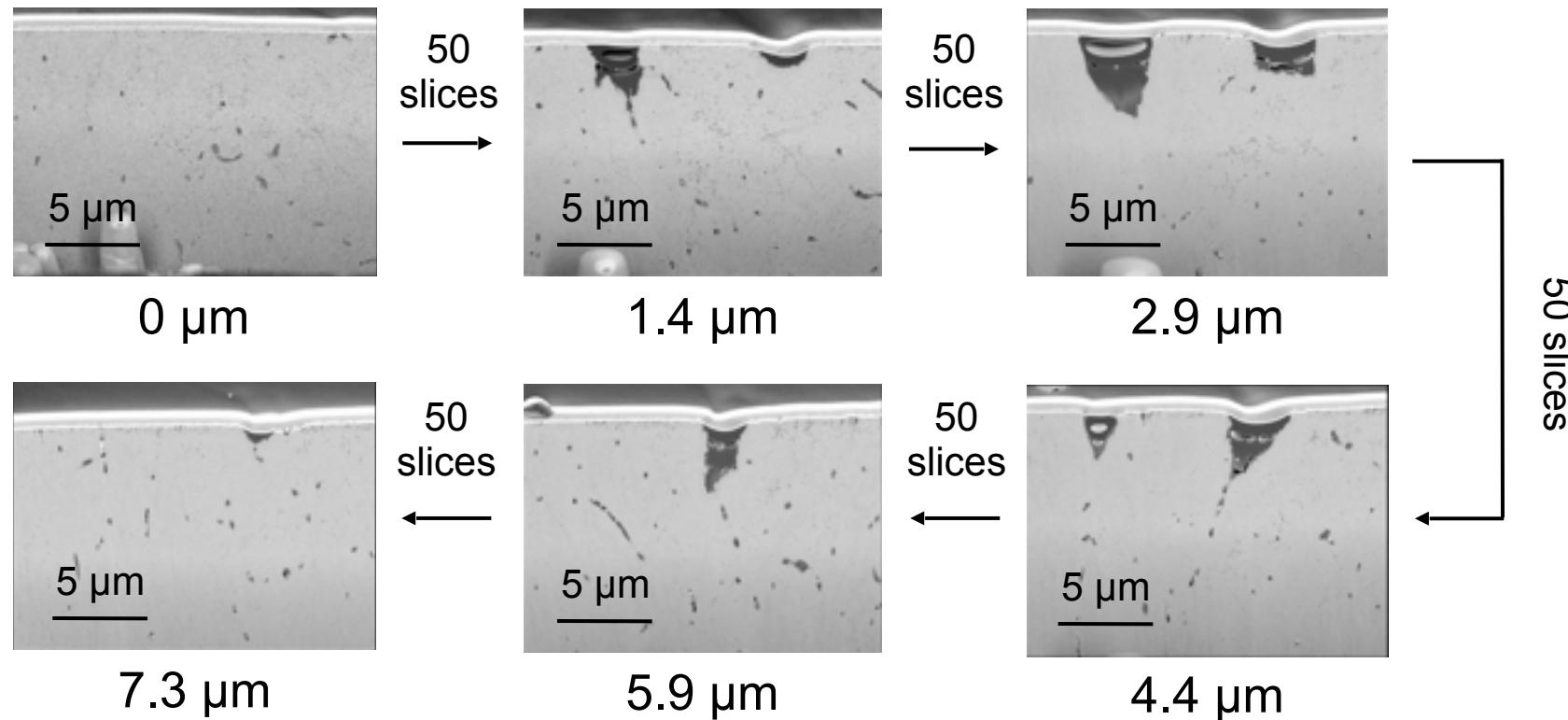


Dual focused ion beam-scanning electron microscopy: serial sectioning and imaging procedure  
L. Holzer et al., [Journal of Microscopy 216\(1\):84-95 \(2004\)](#)

### 3. Demonstration

#### Lacuno-canicular network

Raw data

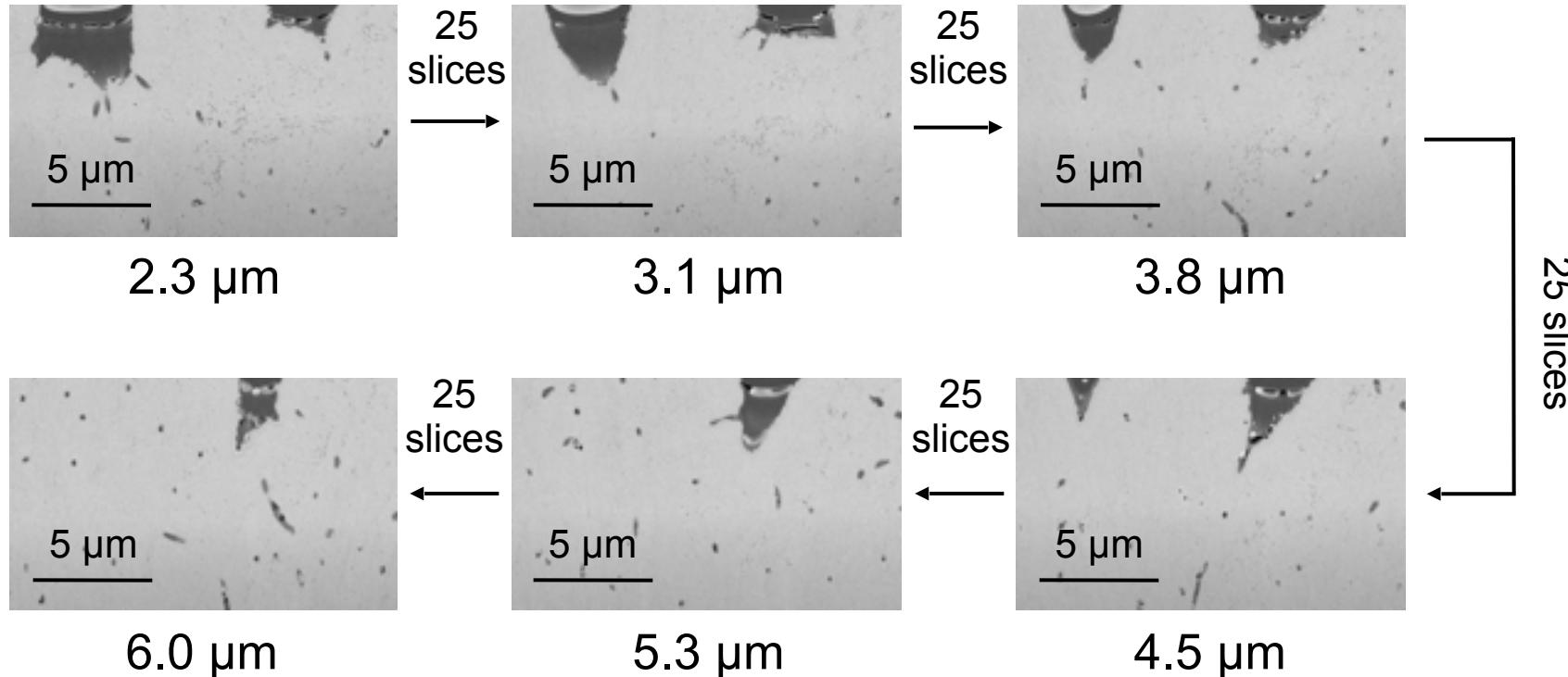


P. Schneider and M. Meier *et al.*, [Bone 49:304-11 \(2011\)](#)

### 3. Demonstration

#### Lacuno-canicular network

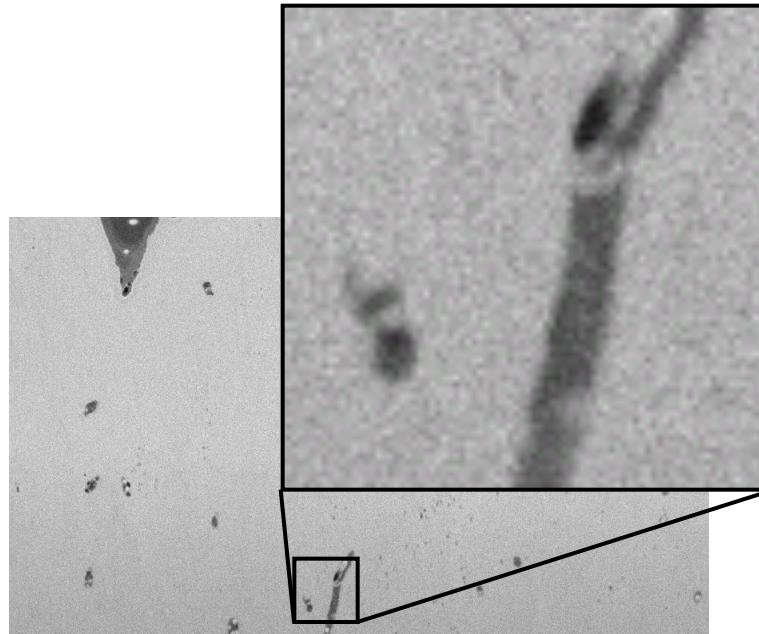
Cutting: define volume of interest



### 3. Demonstration

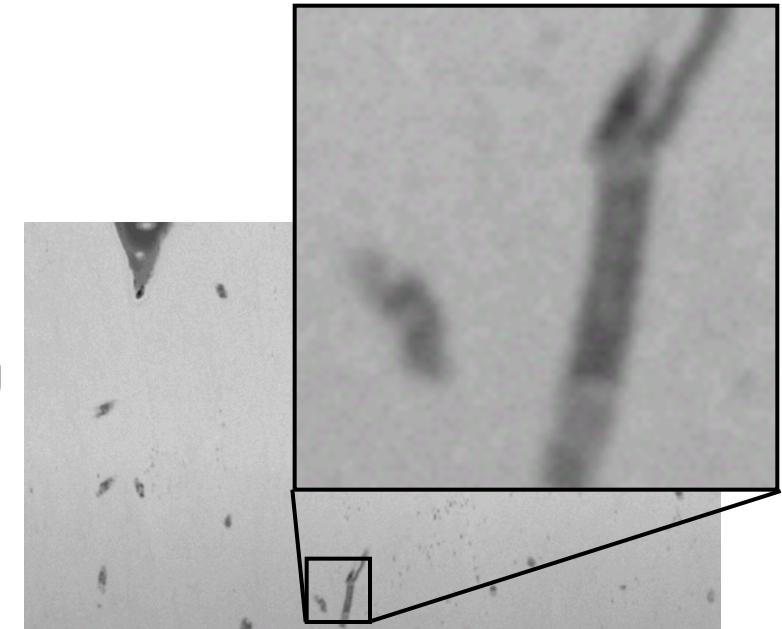
#### Lacuno-canicular network

Gaussian filtration: reduce noise



Original

Filtering

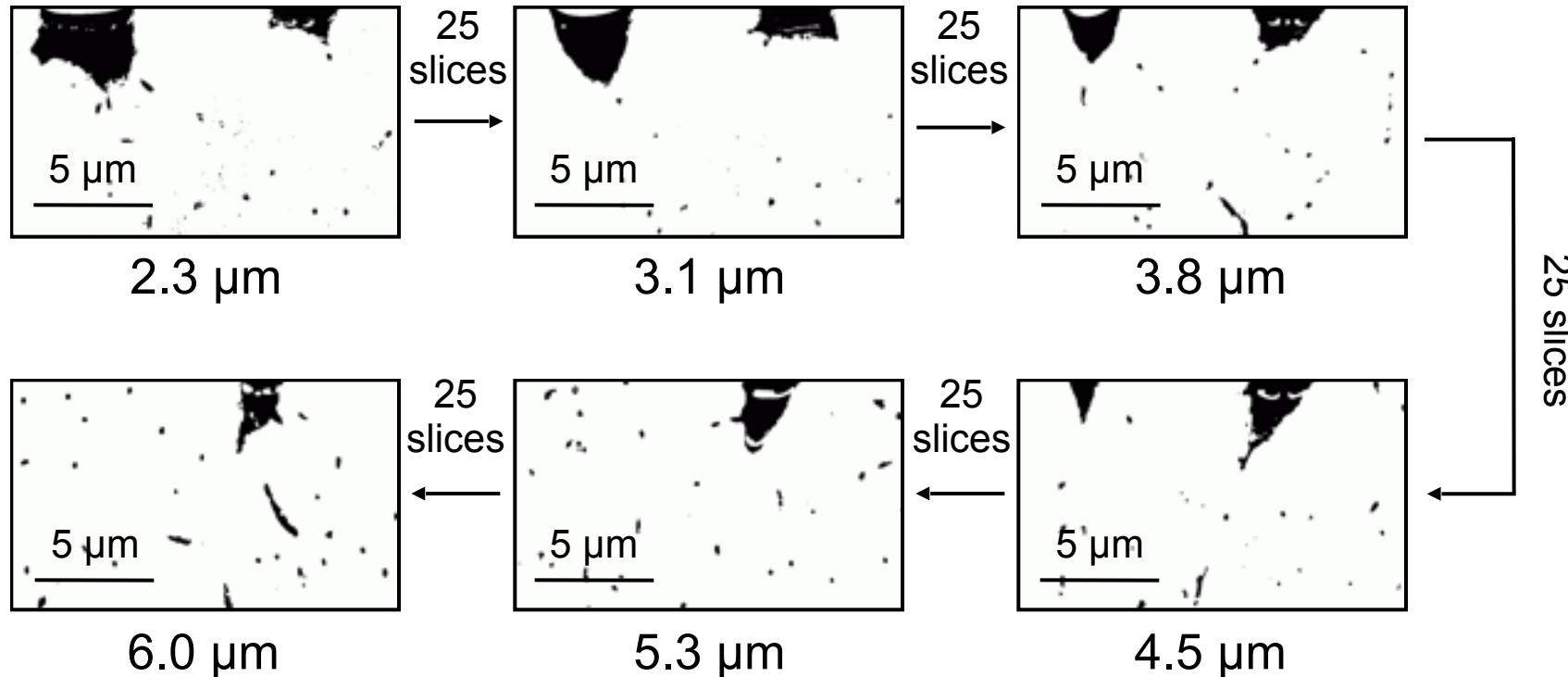


Gaussian filtered

### 3. Demonstration

#### Lacuno-canicular network

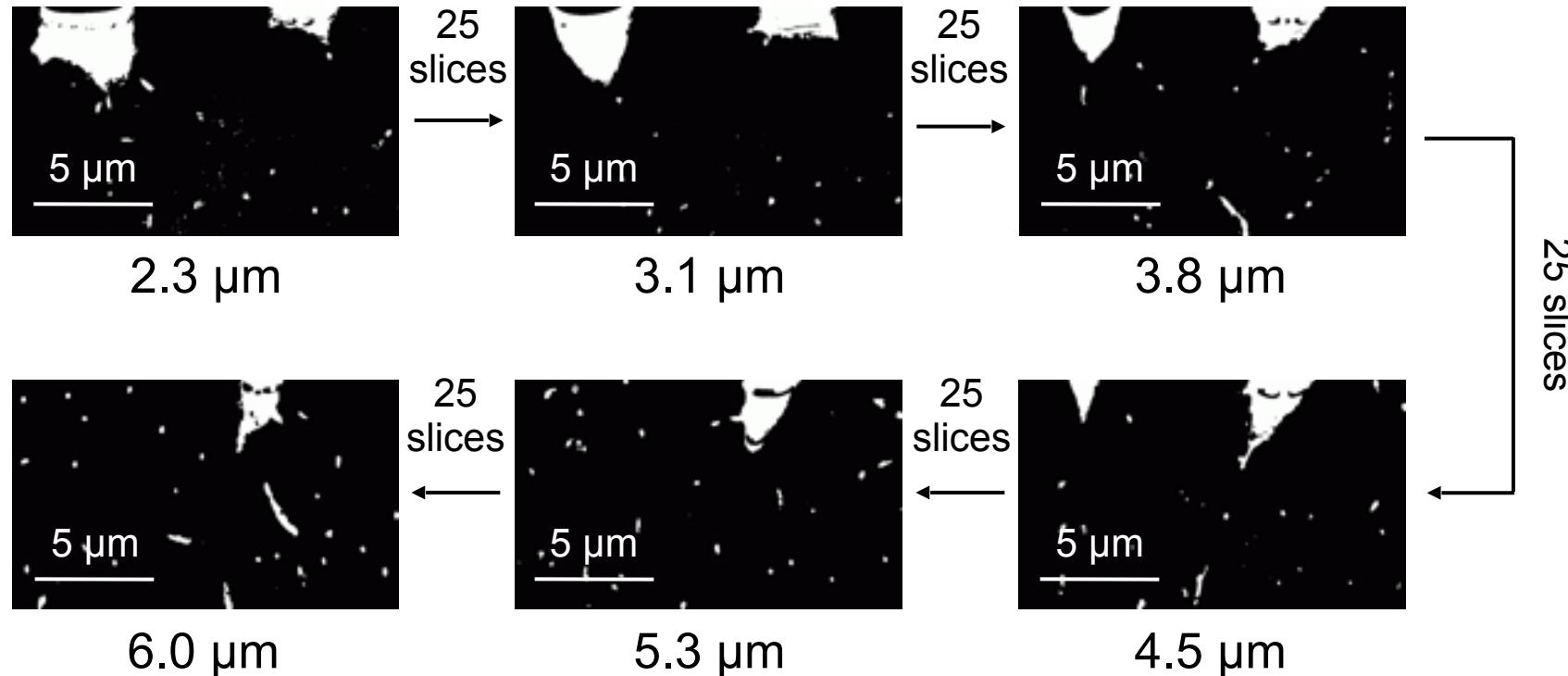
Thresholding: segment data



### 3. Demonstration

#### Lacuno-canicular network

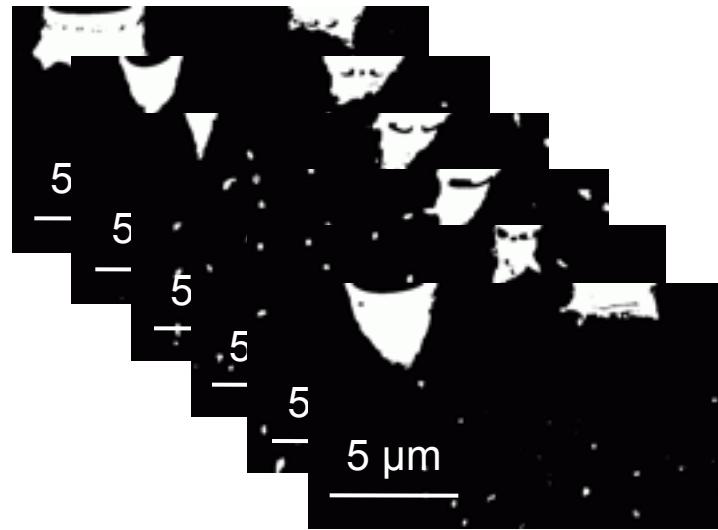
Inverting: access porosity



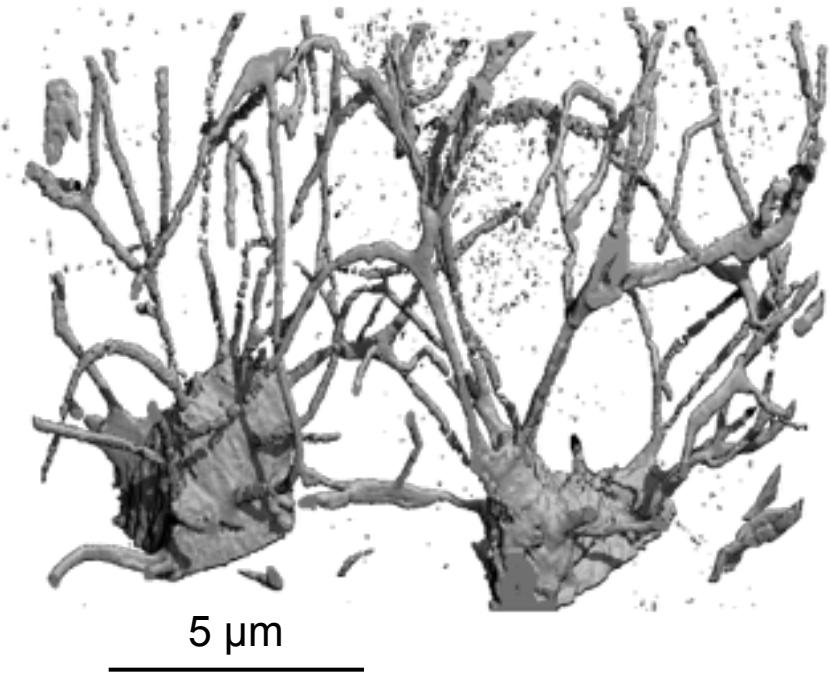
### 3. Demonstration

#### Lacuno-canicular network

Visualization: 2D → 3D



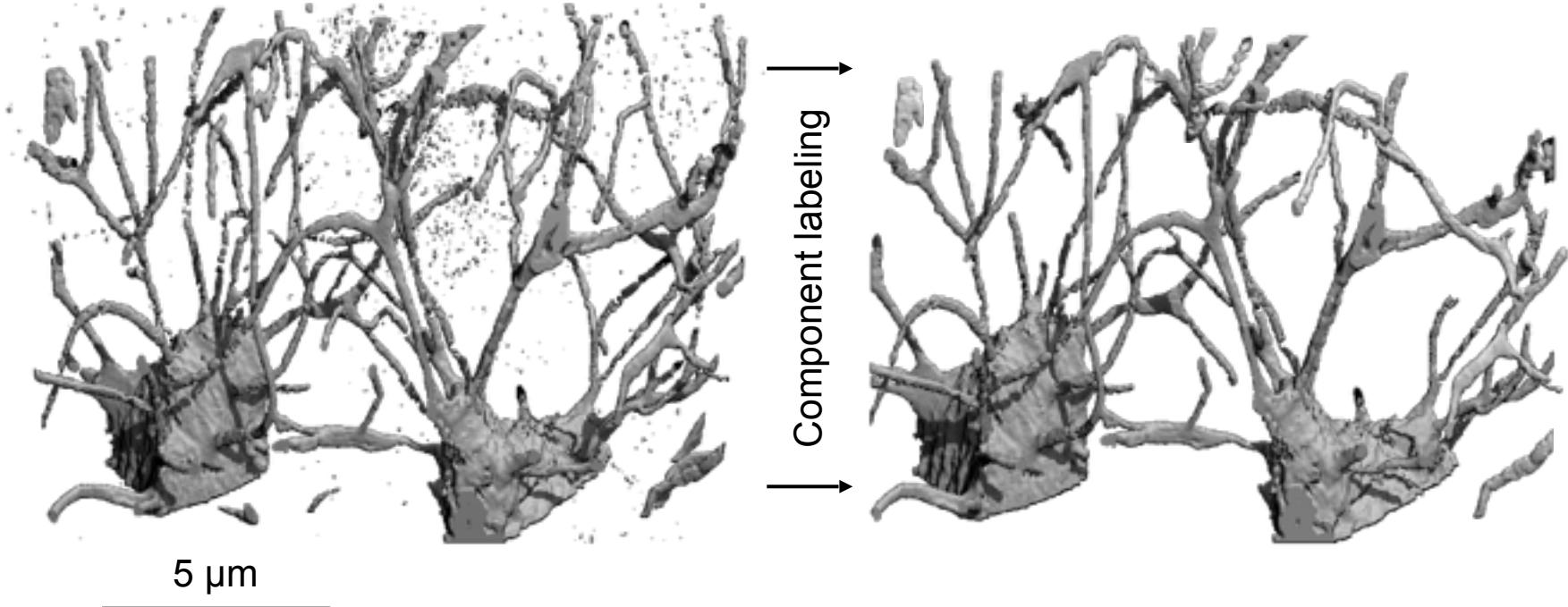
Stacking



### 3. Demonstration

#### Lacuno-canicular network

Component labeling: remove noise and small fragments



### 3. Demonstration

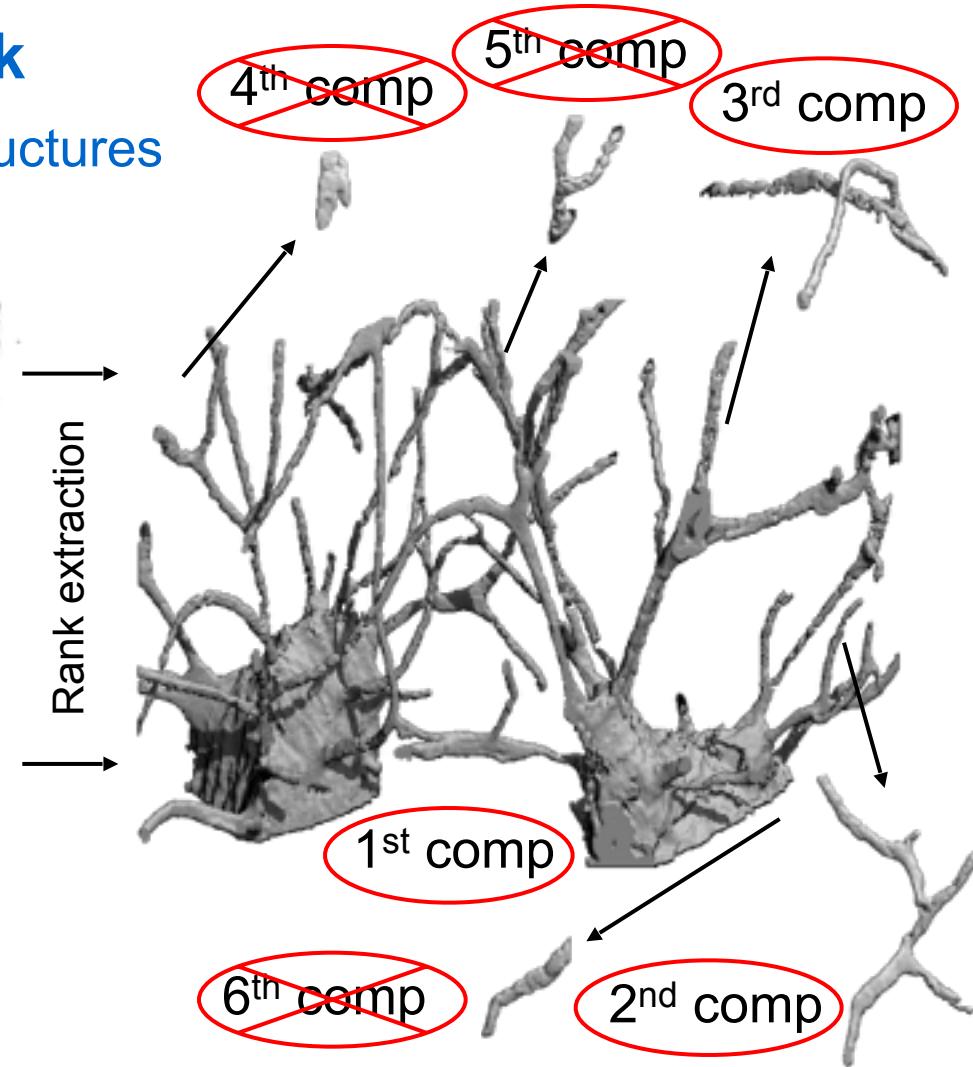
#### Lacuno-canicular network

Rank extraction: focus on main structures



5 μm

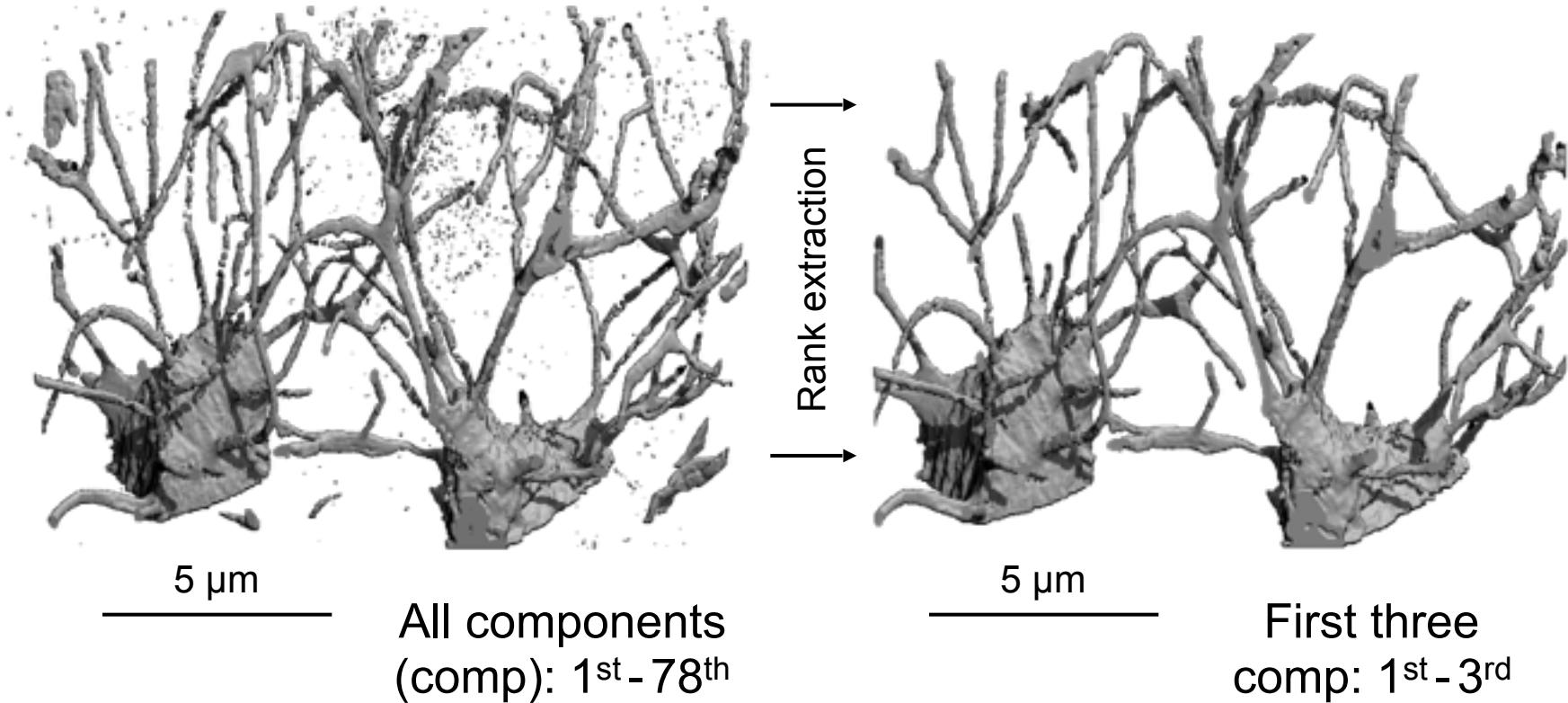
All components  
(comp): 1<sup>st</sup> - 78<sup>th</sup>



### 3. Demonstration

#### Lacuno-canicular network

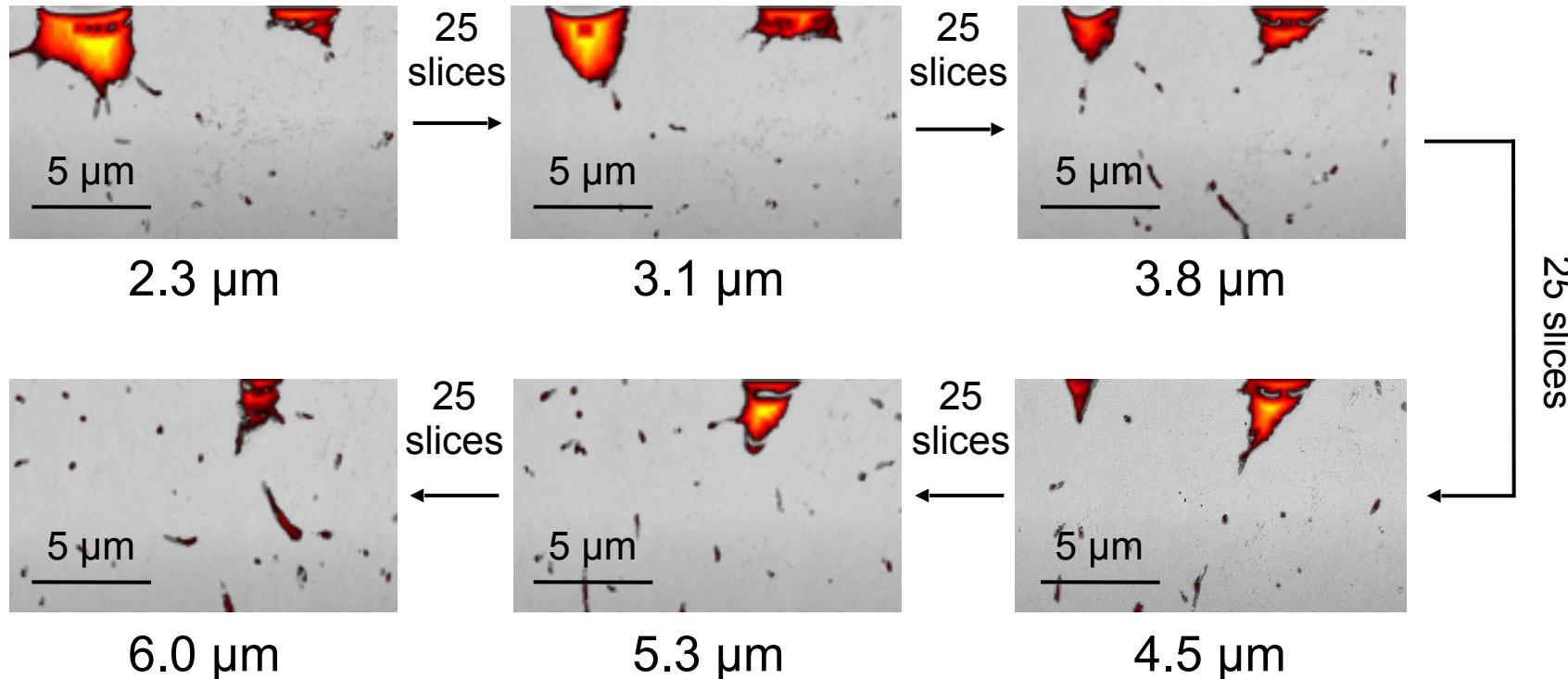
Rank extraction: focus on main structures



### 3. Demonstration

#### Lacuno-canicular network

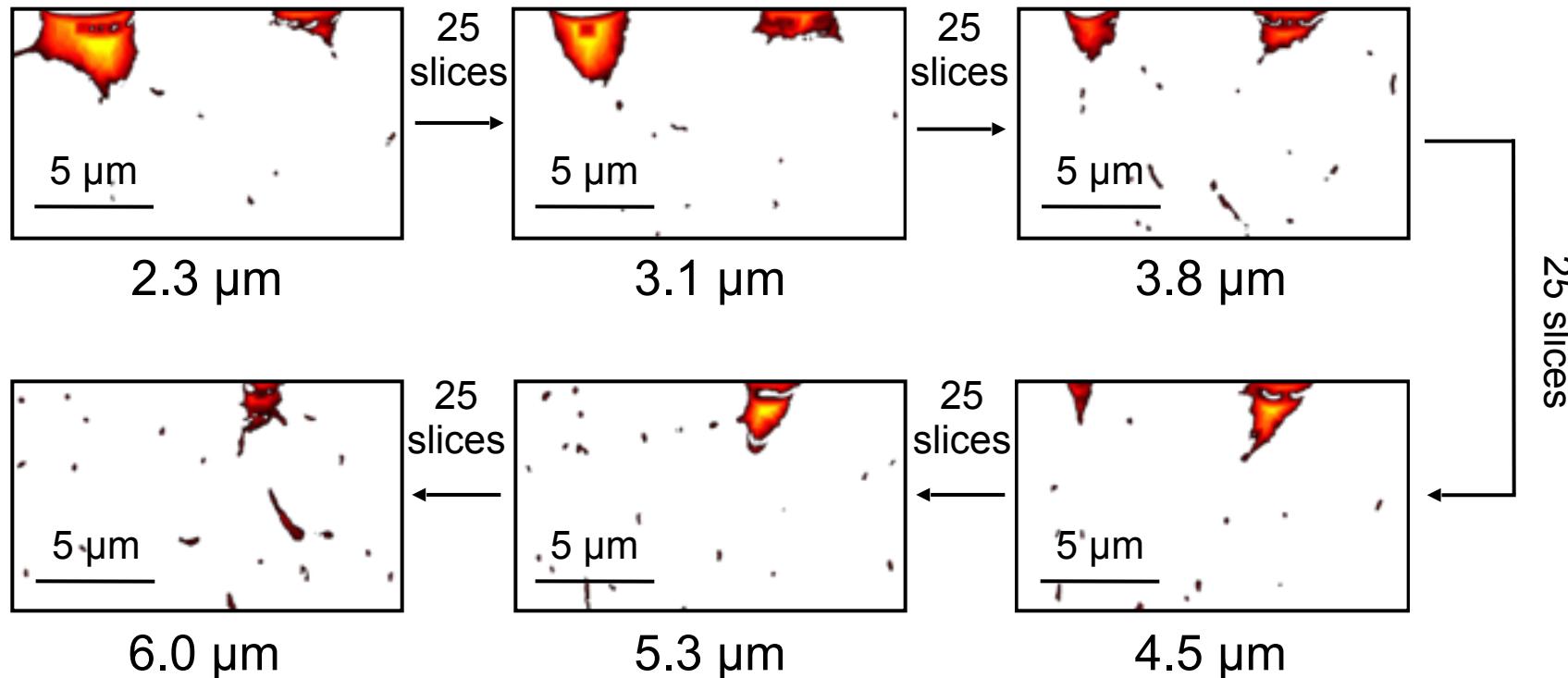
Distance map: extract osteocyte lacunae



### 3. Demonstration

#### Lacuno-canicular network

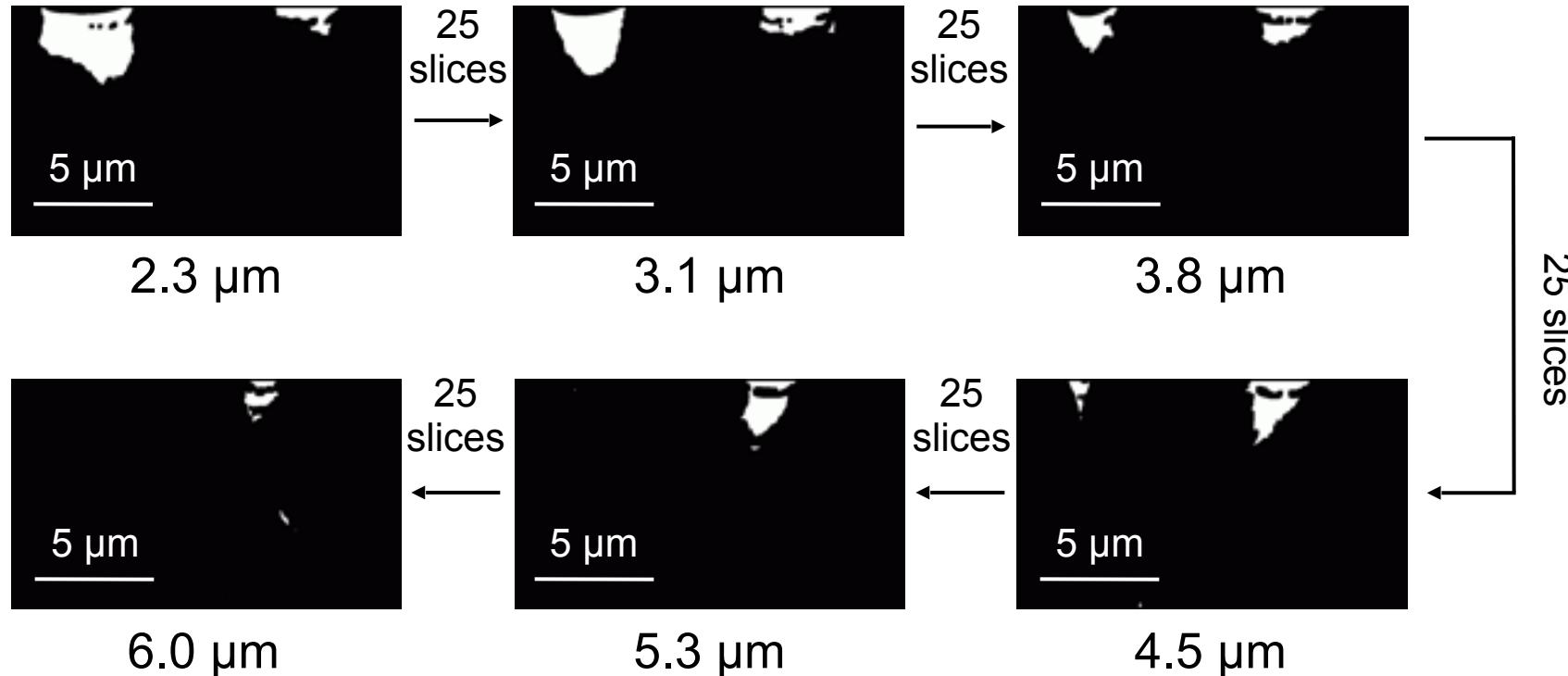
Distance map: extract osteocyte lacunae



### 3. Demonstration

#### Lacuno-canicular network

Thresholding distance map: extract osteocyte lacunae



### 3. Demonstration

#### Lacuno-canicular network

Erosion by thresholding distance map: extract osteocyte lacunae



First three  
comp: 1<sup>st</sup> - 3<sup>rd</sup>

→  
Erosion  
→

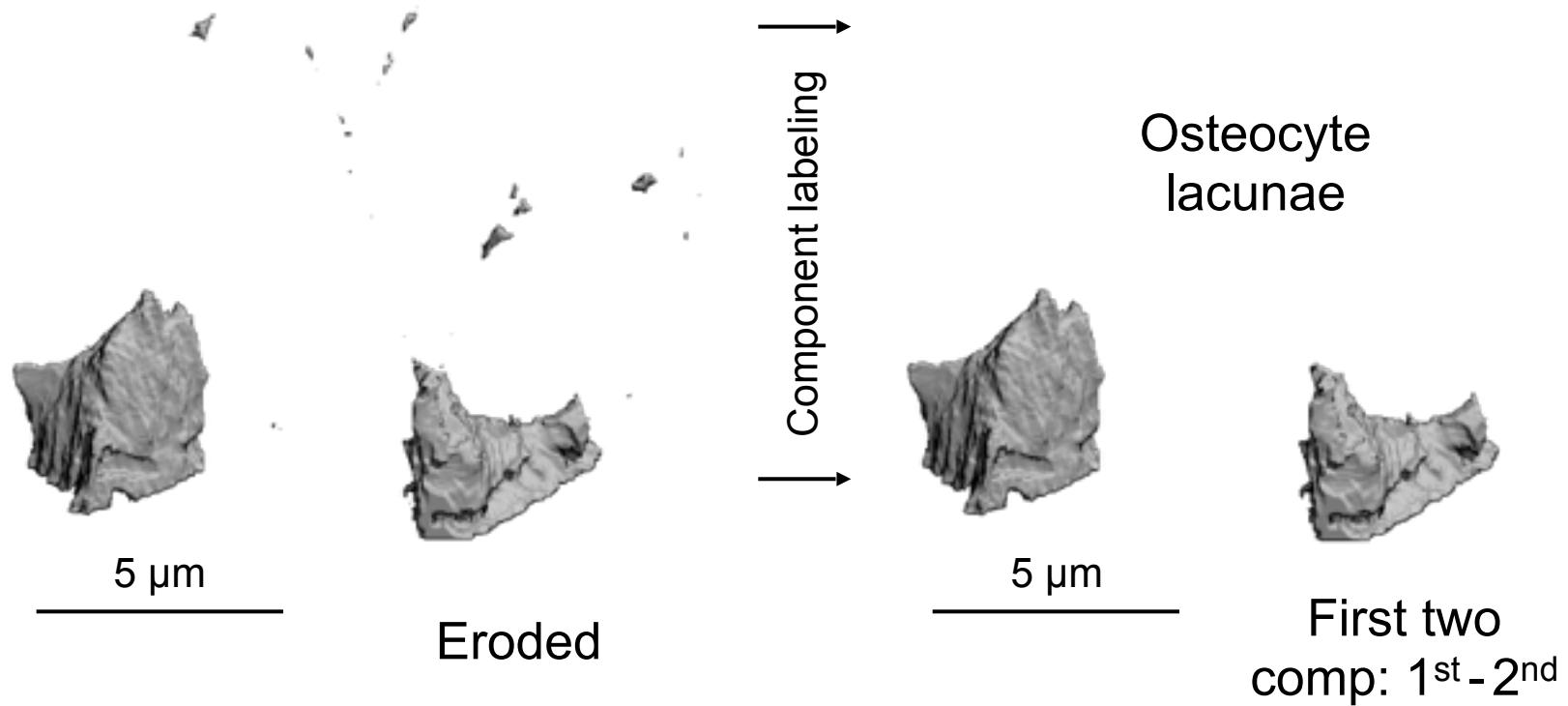


Eroded

### 3. Demonstration

#### Lacuno-canicular network

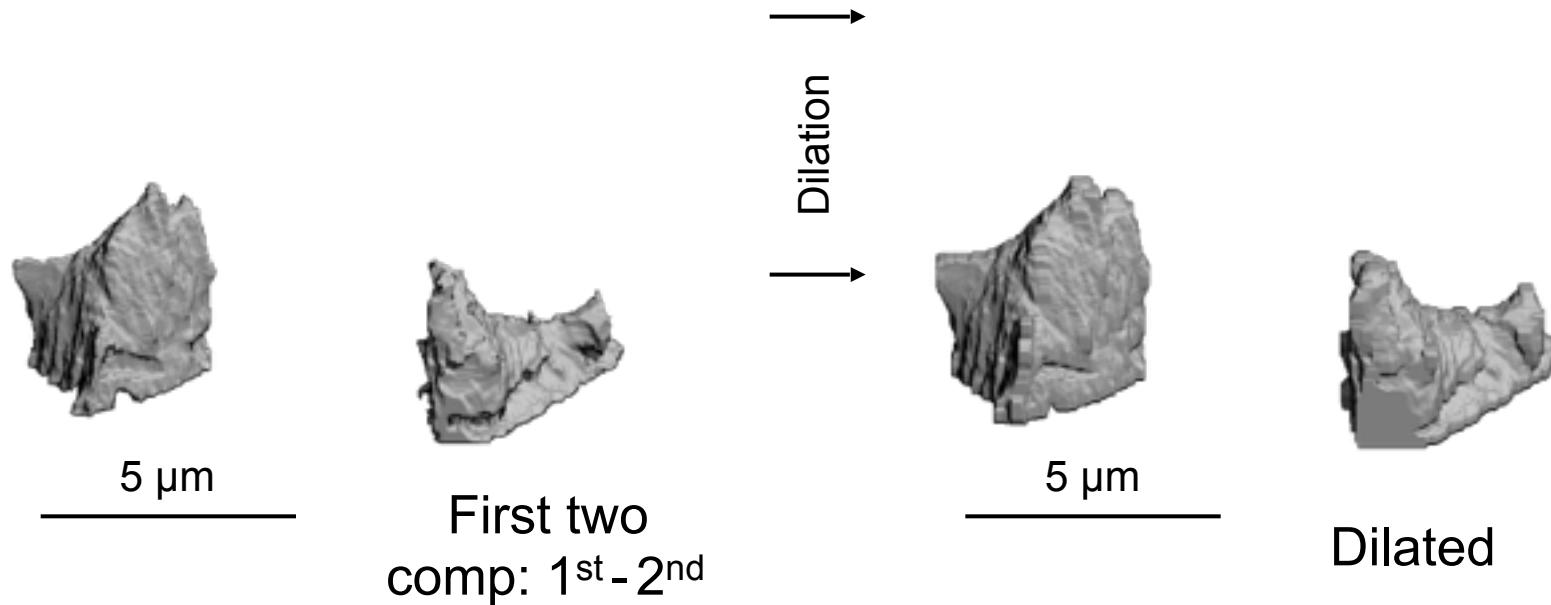
Component labeling: remove remaining canaliculi



### 3. Demonstration

#### Lacuno-canicular network

Dilation: recover original extent of osteocyte lacunae



### 3. Demonstration

#### Lacuno-canicular network

Inversion: create mask to extract canaliculi



5 μm



Dilated

→  
Inversion  
→



5 μm

Inverted

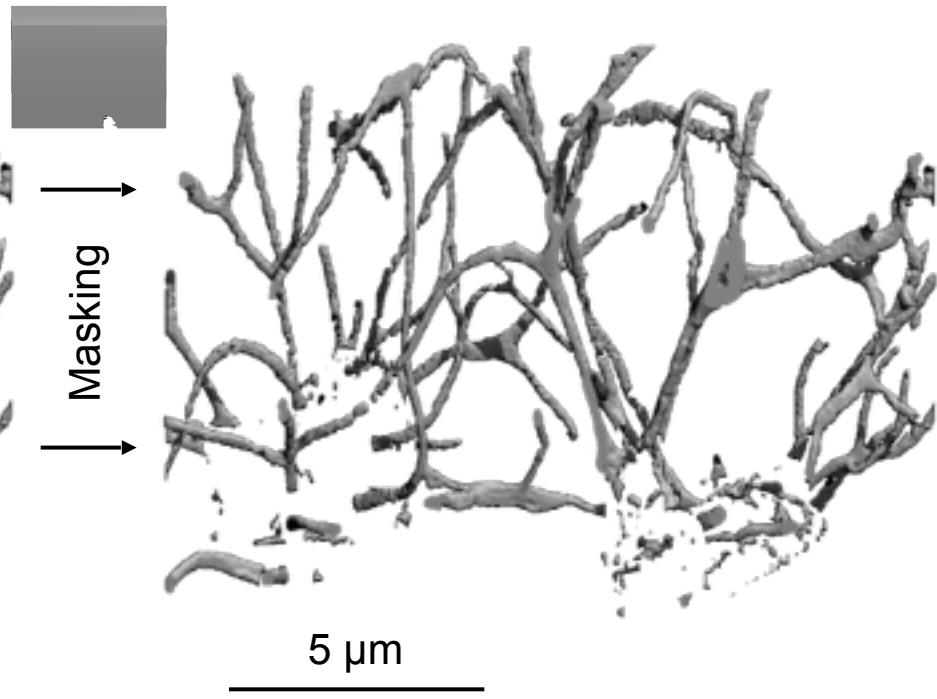
### 3. Demonstration

#### Lacuno-canicular network

Masking: extract canaliculi



First three  
comp: 1<sup>st</sup> - 3<sup>rd</sup>

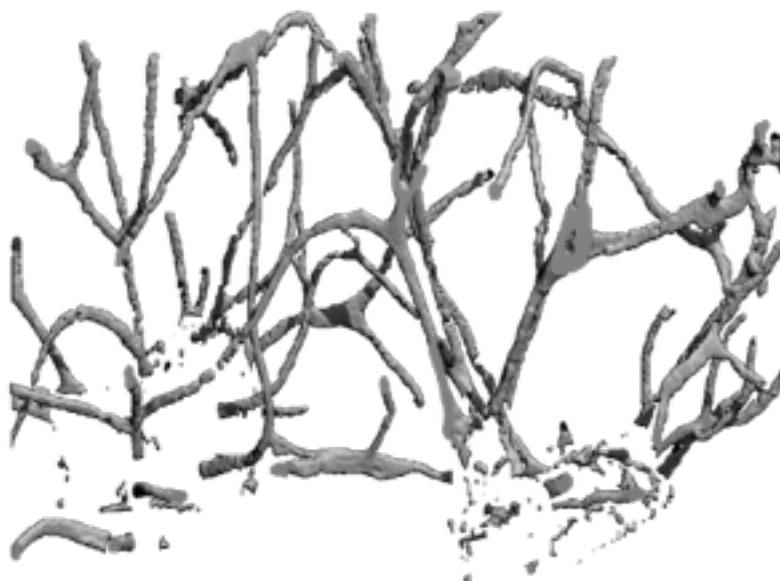


Masked canalliculi

### 3. Demonstration

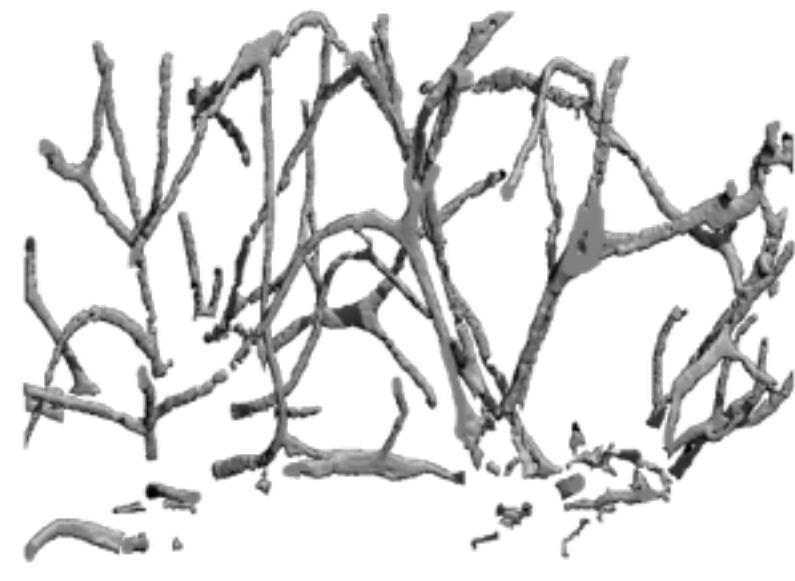
#### Lacuno-canicular network

Component labeling: remove small fragments to extract canaliculi



Masked canaliculi

Component labeling  
→  
→

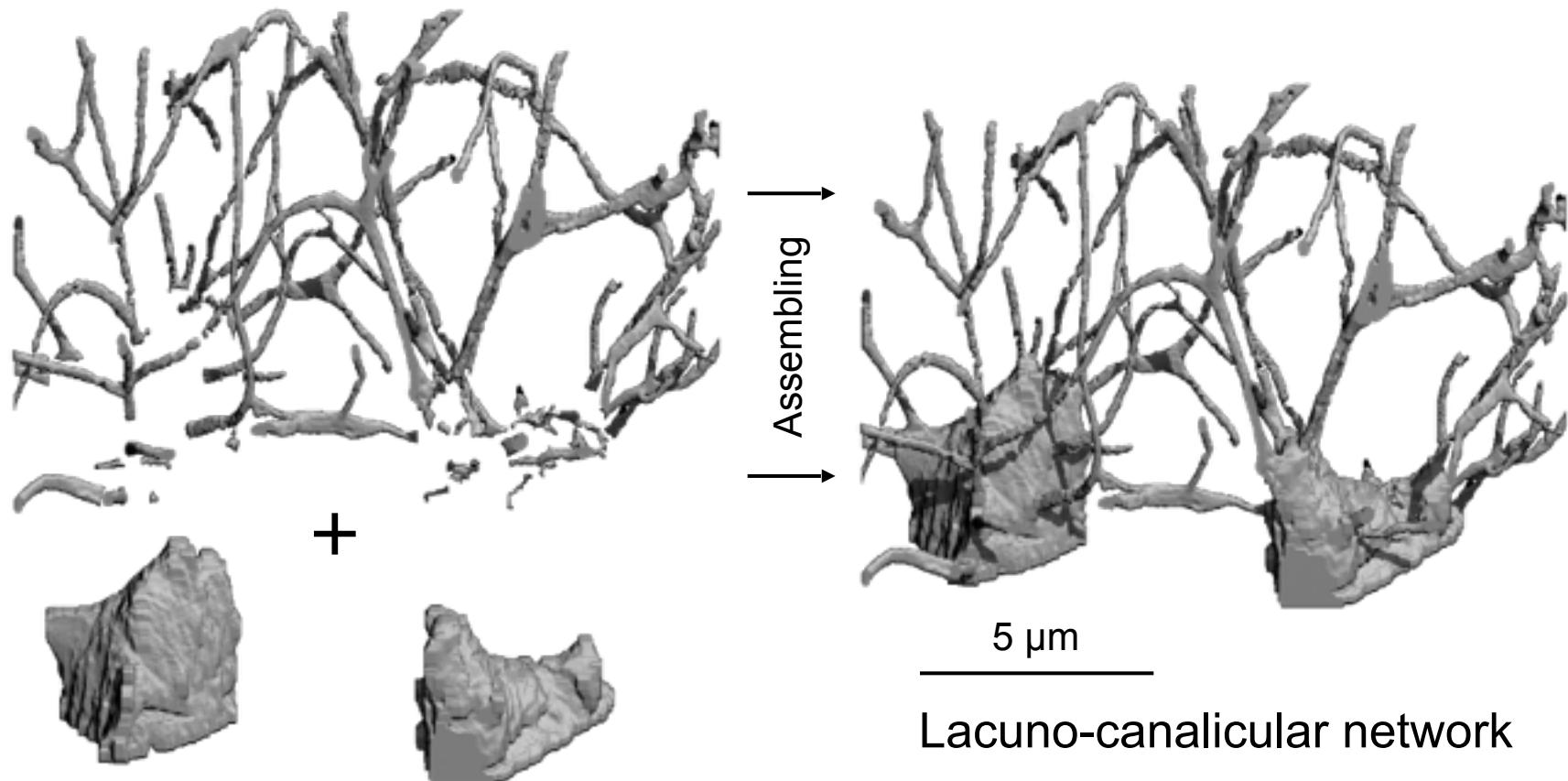


Osteocyte lacunae rests removed

### 3. Demonstration

#### Lacuno-canicular network

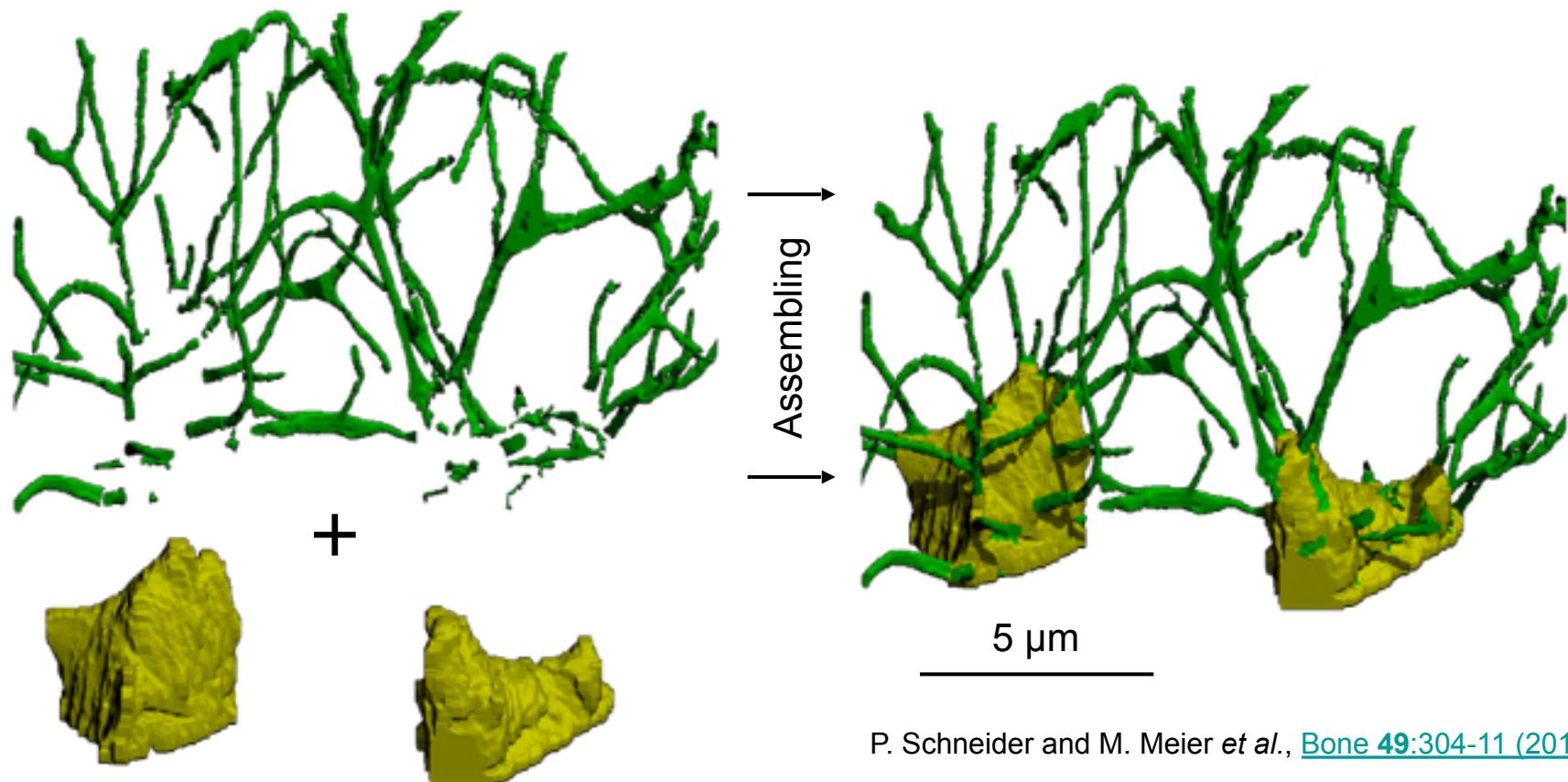
Addition: assemble osteocyte lacunae and canaliculi



### 3. Demonstration

#### Lacuno-canicular network

Visualization: distinguish components optically

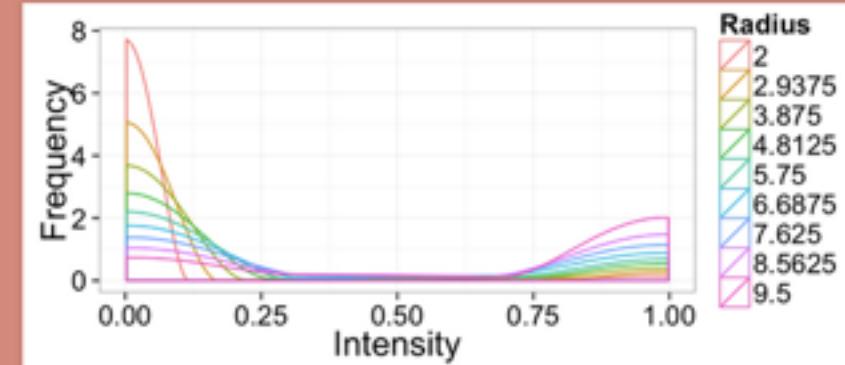
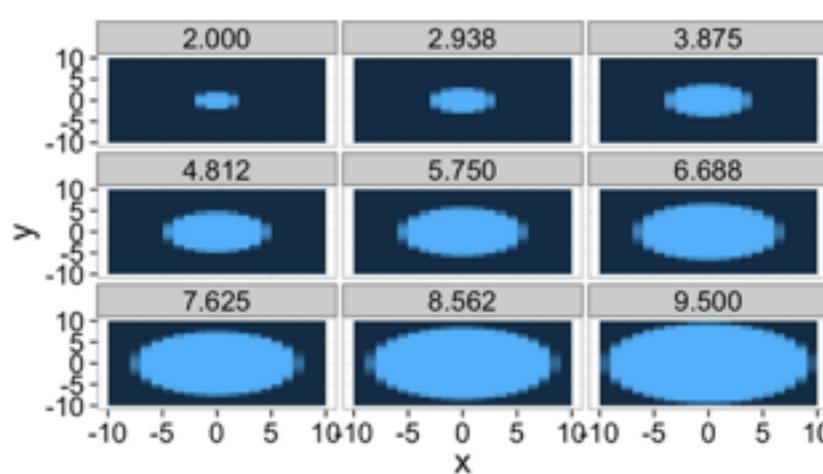


P. Schneider and M. Meier et al., [Bone 49:304-11 \(2011\)](#)

# Pitfalls with Segmentation

## Partial Volume Effect

- The **partial volume effect** is the name for the effect of discretization on the image into pixels or voxels.
- Surfaces are complicated, voxels are simple boxes which make poor representations
- Many voxels are only partially filled, but only the voxels on the surface
- Removing the first layer alleviates issue



- Shown as a function of radius

Radius	Mean Intensity	Sd Intensity
2.000	0.0311	0.1623
2.938	0.0677	0.2370
3.875	0.1177	0.3061
4.812	0.1822	0.3688
5.750	0.2601	0.4196
6.688	0.3511	0.4567
7.625	0.4569	0.4763
8.562	0.5761	0.4690
9.500	0.7073	0.4259