

# Lecture 5

## Image Characterization

ch. 4 of *Machine Vision* by Wesley E. Snyder & Hairong Qi

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16-725 (CMU RI) : BioE 2630 (Pitt)

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# Digital Images

- How are they formed?
- How can they be represented?

# Image Representation

- Hardware
  - Storage
  - Manipulation
- Human
  - Conceptual
  - Mathematical

# Iconic Representation

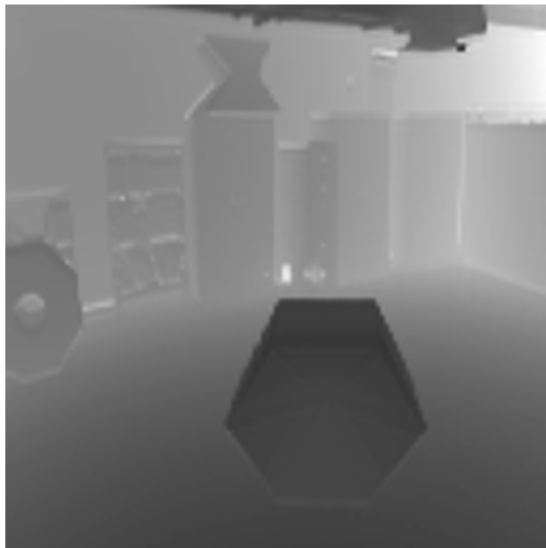
- What you think of as an image, ...
  - Camera
  - X-Ray
  - CT
  - MRI
  - Ultrasound
  - 2D, 3D, ...
  - etc



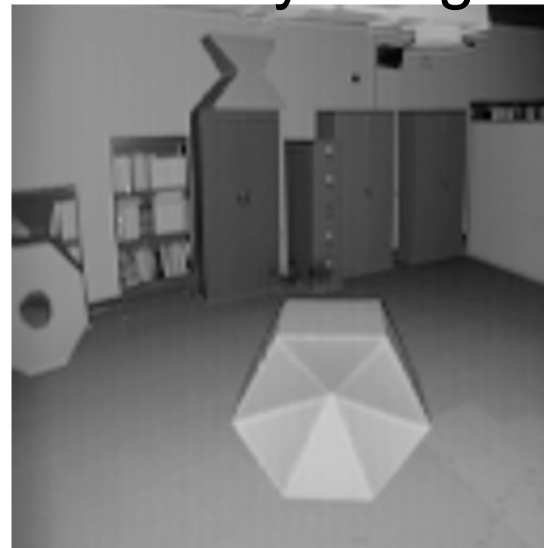
# Iconic Representation

- And what you might not

Range Image



Corresponding  
Intensity Image



Images from CESAR lab at Oak Ridge National Laboratory,  
Sourced from the USF Range Image Database:  
<http://marathon.csee.usf.edu/range/DataBase.html>  
Acknowledgement thereof requested with redistribution.

# Functional Representation

- An Equation

- Typically continuous

- Fit to the image data

- Sometimes the entire image
  - Usually just a small piece of it

- Examples (Quadratic Surfaces):

- Explicit:  $z = ax^2 + by^2 + cxy + dx + ey + f$

- Implicit:  $0 = ax^2 + by^2 + cz^2 + dxy + exz + fyz + gx + hy + iz + j$

# Linear Representation

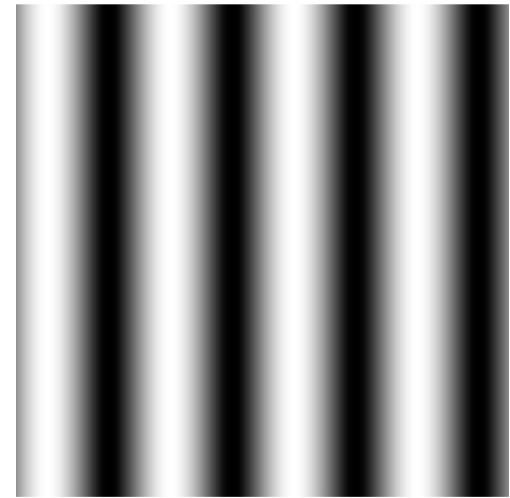
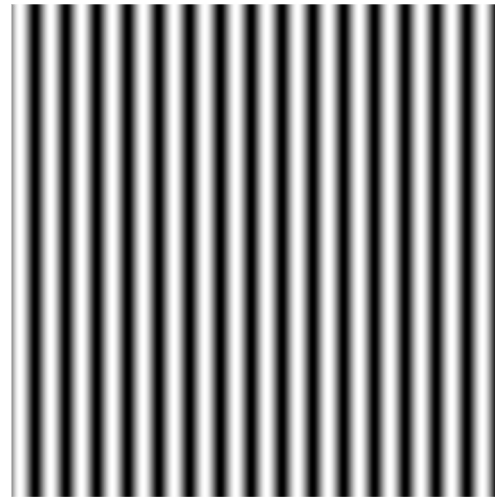
- Unwind the image
  - “Raster-scan” it
- Entire image is now a vector
  - Now we can do matrix operations on it!
  - Often used in research papers

# Probabilistic & Relational Representations

- Probability & Graphs
- Discussed later (if at all)

# Spatial Frequency Representation

- Think “Fourier Transform”
- Multiple Dimensions!
- Varies greatly across different image regions
- High Freq. = Sharpness



- More examples & details:  
<https://www.cs.unm.edu/~brayer/vision/fourier.html>



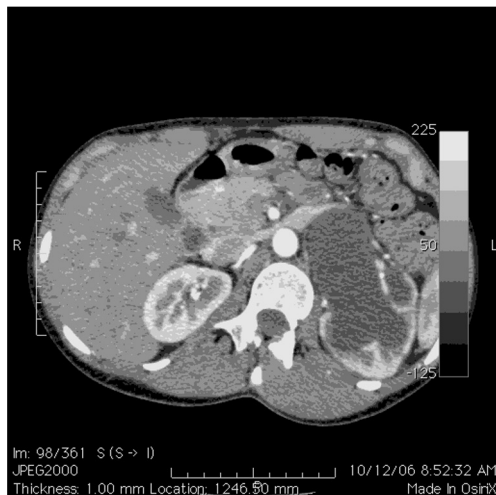
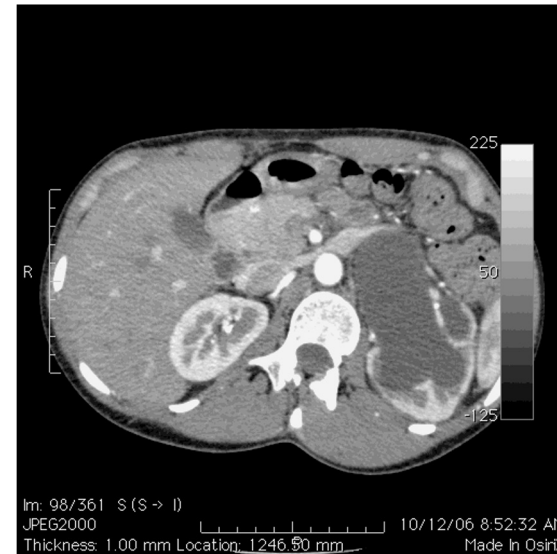
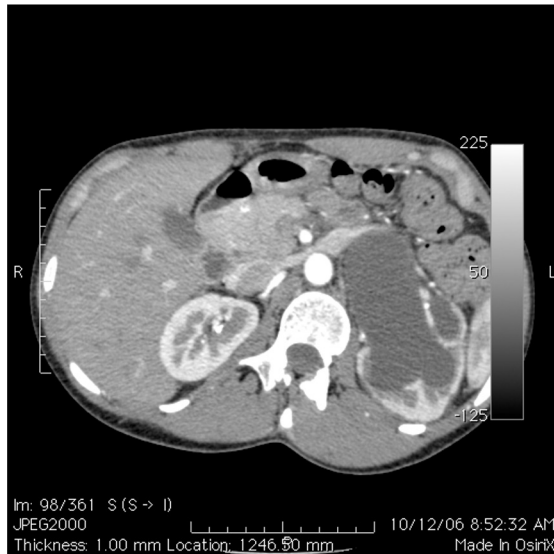


# Image Formation

- Sampling an analog signal
- Resolution
  - # Samples per dimension, OR
  - Smallest clearly discernable physical object
- Dynamic Range
  - # bits / pixel (quantization accuracy), OR
  - Range of measurable intensities
    - Physical meaning of min & max pixel values
    - light, density, etc.

# Dynamic Range Example

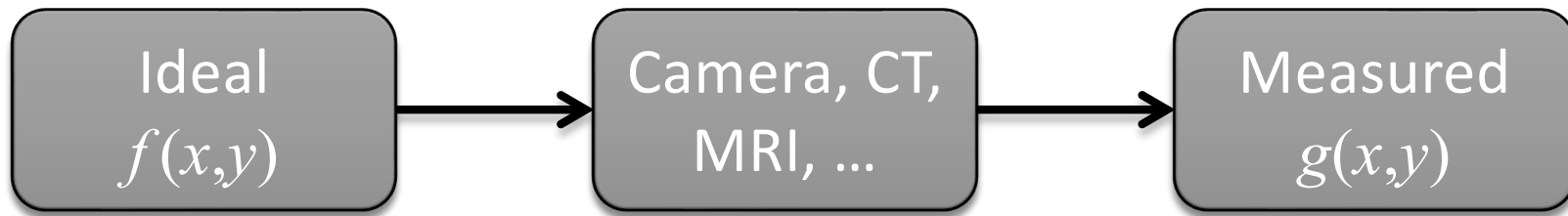
(A slice from a Renal Angio CT: 8 bits, 4 bits, 3 bits, 2 bits)



# An Aside: The Correspondence Problem

- My Definition:
  - Given two different images of the same (or similar) objects,  
for any point in one image  
determine the exact corresponding point in the other image
- Similar (identical?) to registration
- Quite possibly, it is THE problem in computer vision

# Image Formation: Corruption



- There is an ideal image
  - It is what we are physically measuring
- No measuring device is perfect
  - Measuring introduces noise
  - $g(x,y) = D( f(x,y) )$ , where  $D$  is the distortion function
- Often, noise is additive and independent of the ideal image

# Image Formation: Corruption

- Noise is usually not the only distortion
- If the other distortions are:
  - linear &
  - space-invariant

then they can *always* be represented with the convolution integral!

- Total corruption:

$$g(x, y) = \iint_{-\infty \dots \infty} f(\alpha, \beta) h(x - \alpha, y - \beta) d\alpha d\beta + n(x, y)$$

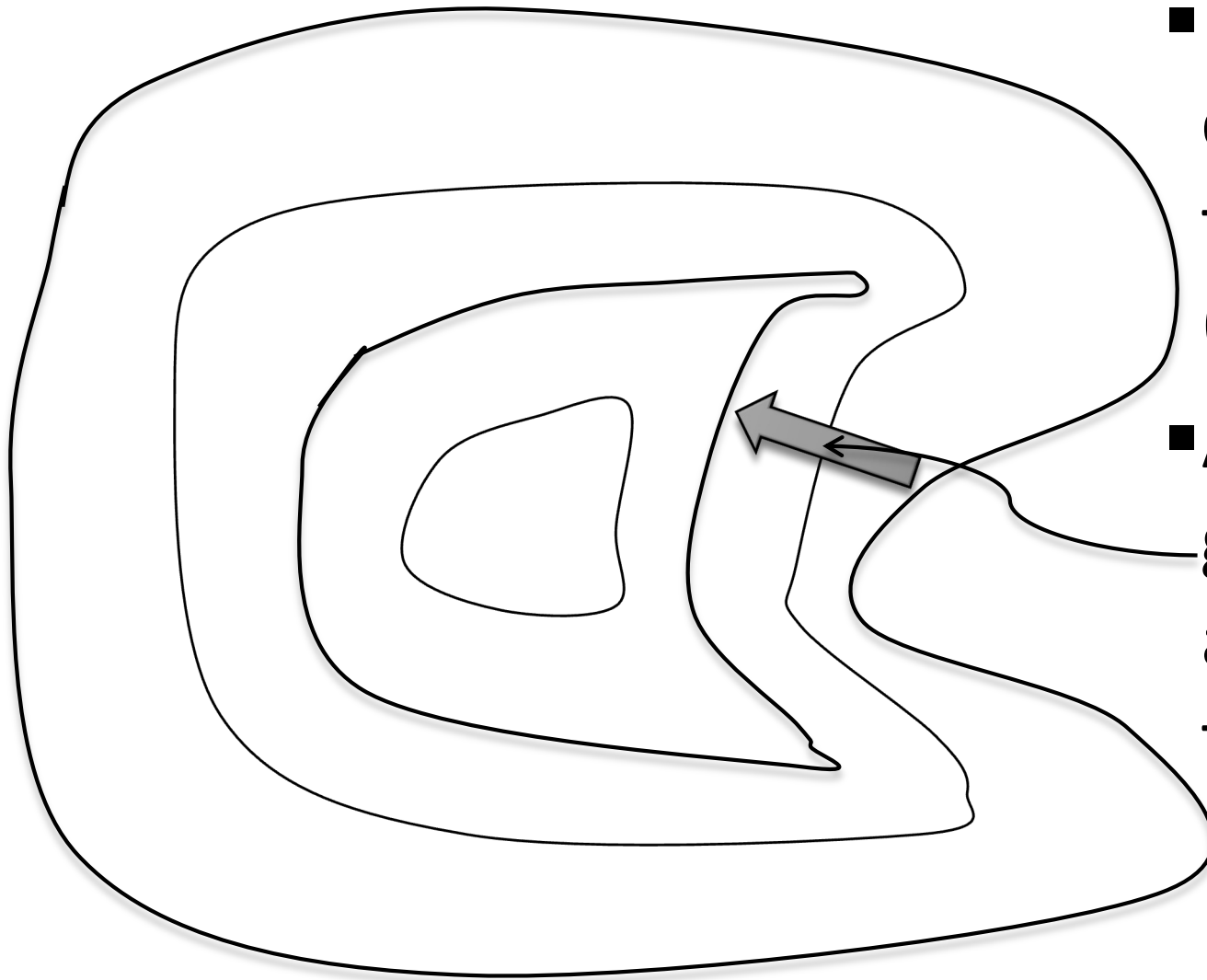
# The image as a surface

- Intensity  $\rightarrow$  height
  - In 2D case, but concepts extend to ND
- $z = f(x, y)$
- Describes a surface in space
  - Because only one  $z$  value for each  $x, y$  pair
  - Assume surface is continuous (interpolate pixels)

# Isophote

- “Uniform brightness”
- $C = f(x, y)$
- A curve (2D) or surface (3D) in space
- Always perpendicular to image gradient
  - Why?

# Isophotes & Gradient



- Isophotes are like contour lines on a topography (elevation) map.
- At any point, the gradient is always at a right angle to the isophote!

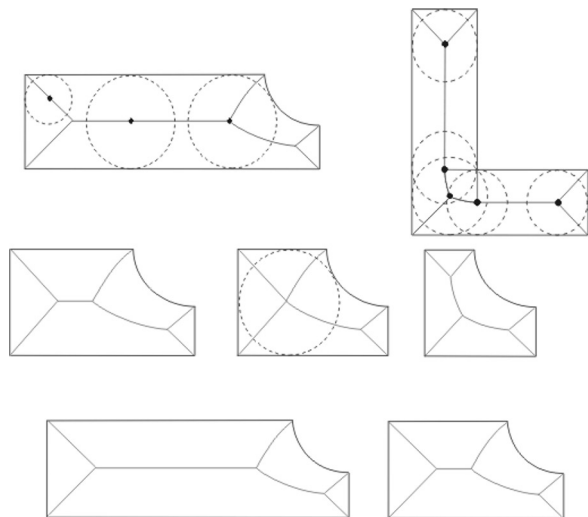


# Ridges

- One definition:
  - Local maxima of the rate of change of gradient direction
  - Sound confusing?
  - Just think of ridge lines along a mountain
  - If you need it, look it up
    - Snyder references Maintz

# Medial Axis

- Skeletal representation
- Defined for binary images
  - This includes segmented images!
- “Ridges in scale-space”
  - Details have to wait (ch. 9)



<http://sog1.me.qub.ac.uk/Research/medial/medial.php>

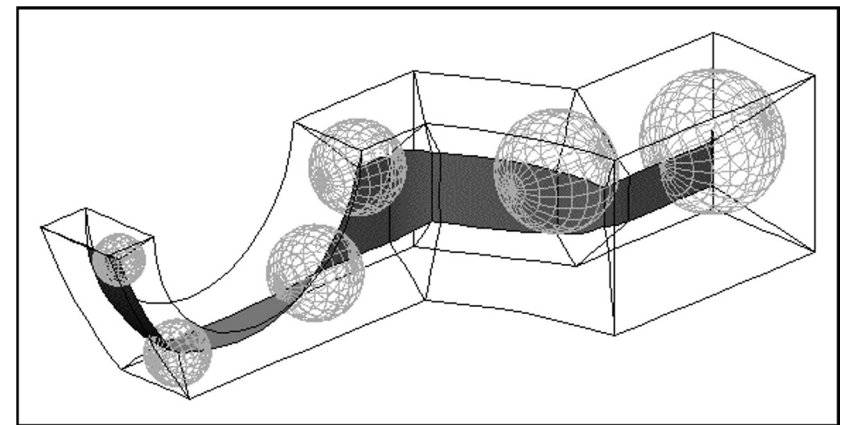
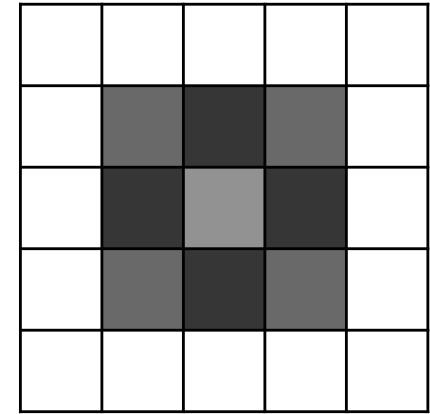


Image courtesy of TranscenData Europe  
<http://www.fegs.co.uk/motech.html>

# Neighborhoods

- Terminology

- 4-connected vs. 8-connected
- Side/Face-connected vs. vertex-connected
- Maximally-connected vs. minimally-connected (ND)

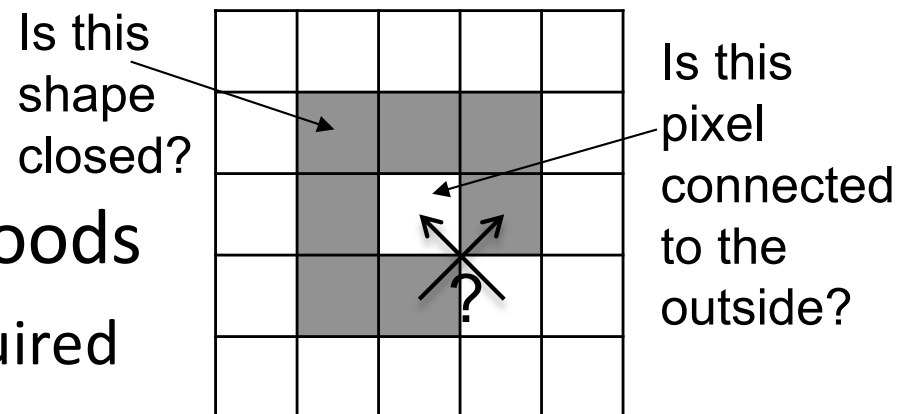


- Connectivity paradox

- Due to discretization

- Can define other neighborhoods

- Adjacency not necessarily required



# Curvature

- Compute curvature at every point in a (range) image
  - (Or on a segmented 3D surface)
- Based on differential geometry
- Formulas are in your book
- 2 scalar measures of curvature that are invariant to viewpoint, derived from the 2 principal curvatures,  $(K_1, K_2)$ :
  - Mean curvature (arithmetic mean)
  - Gauss curvature (product)
    - =0 if either  $K_1=0$  or  $K_2=0$