## Introduction

Computer vision is the analysis of digital images by a computer for such applications as:

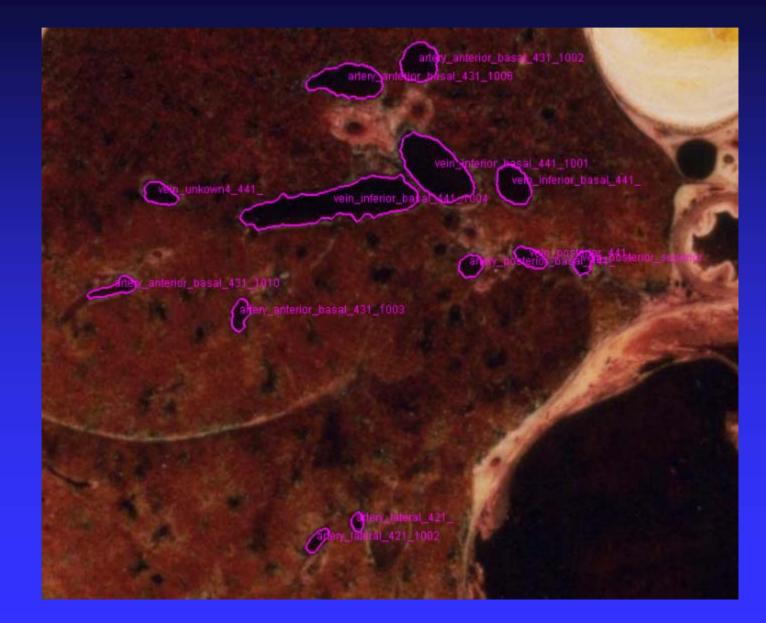
- Industrial: part localization and inspection, robotics
- Medical: disease classification, screening, planning
- Military: autonomous vehicles, tank recognition
- Intelligence Gathering: face recognition, video analysis
- Security: video analysis
- Science: classification, measurement
- Document Processing: text recognition, diagram conversion

## Medical Applications

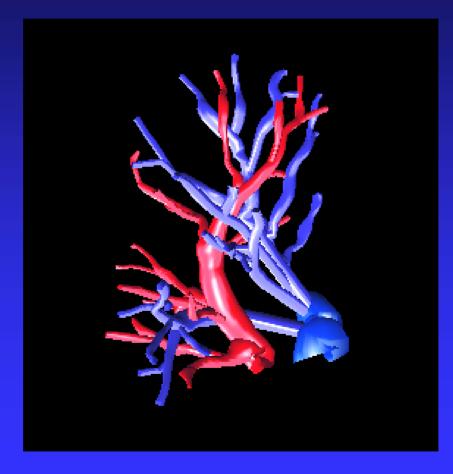
# CT image of a patient's abdomen



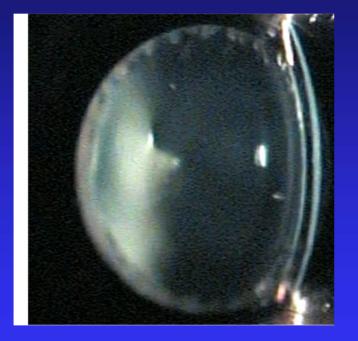
## Visible Man Slice Through Lung



### 3D Reconstruction of the Blood Vessel Tree



### **CBIR of Mouse Eye Images for Genetic Studies**





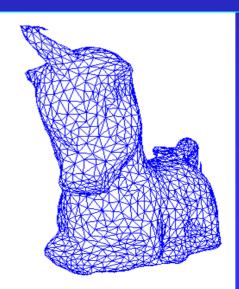
### Robotics

### • 2D Gray-tone or Color Images

### "Mars" rover

### • 3D Range Images

### What am I?



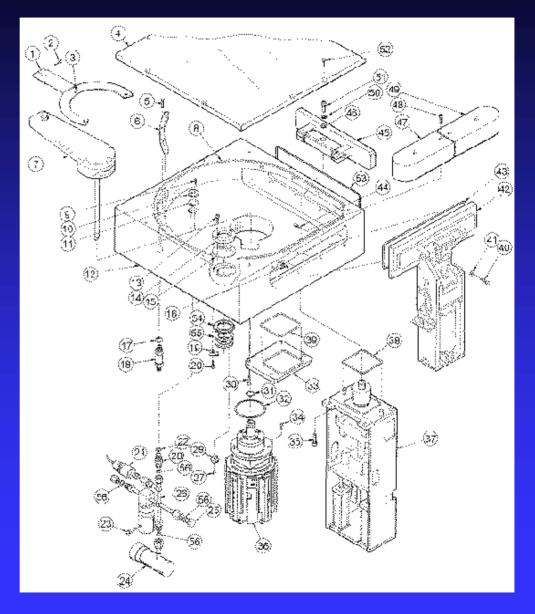
### Image Databases:

### Images from my Ground-Truth collection.



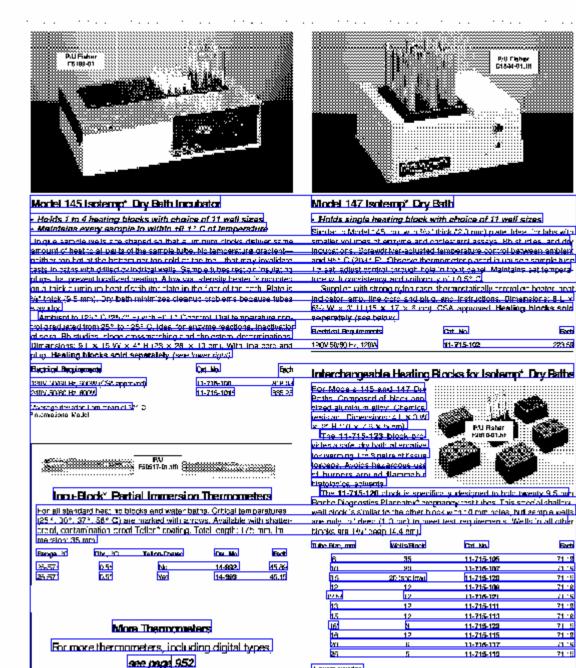
- Retrieve all images that have trees.
- Retrieve all images that have buildings.
- Retrieve all images that have antelope.

### Documents:









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Each

Each

71 12

*(*1.15

71.15

71.18

71.15

71 . 2 71.18

71.9

71 12

71.15

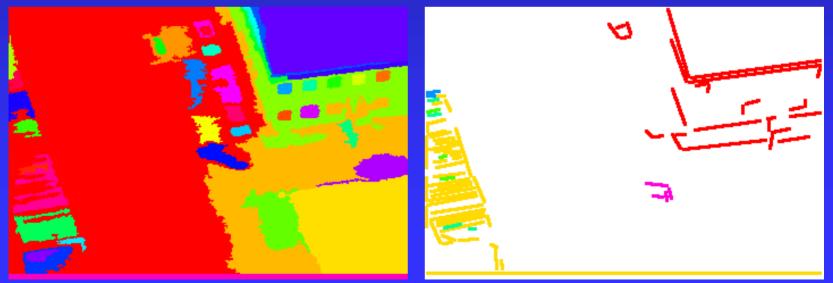
71.19

223.58

### **Surveillance: Object and Event Recognition in Aerial Videos**



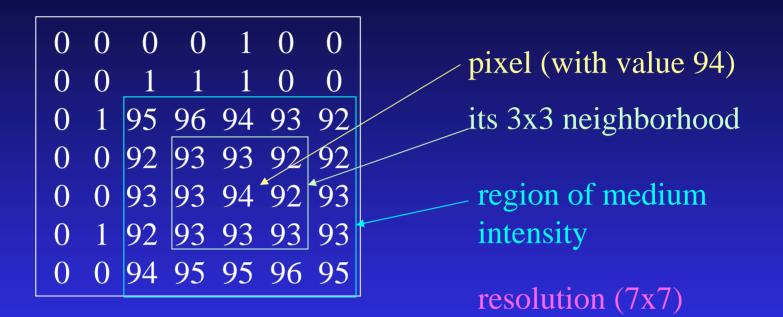
Original Video Frame



#### Color Regions

**Structure Regions** 

## Digital Image Terminology:



- binary image
- gray-scale (or gray-tone) image
- color image
- multi-spectral image
- range image
- labeled image

## Goals of Image and Video Analysis

- Segment an image into useful regions
- Perform measurements on certain areas
- Determine what object(s) are in the scene
- Calculate the precise location(s) of objects
- Visually inspect a manufactured object
- Construct a 3D model of the imaged object
- Find "interesting" events in a video







### •The Three Stages of Computer Vision

• low-level

image → image

• mid-level

image — features

• high-level

features —— analysis

### Low-Level

### sharpening



blurring



### Low-Level



Canny edge operator



original image

edge image

### Mid-Level (Lines and Curves)



ORT line & circle extraction data structure



circular arcs and line segments<sup>15</sup>

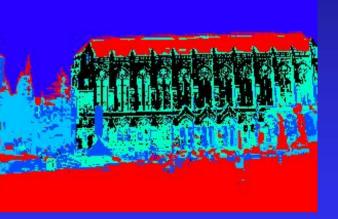
edge image

## Mid-level (Regions)



### original color image

K-means clustering (followed by connected component analysis)

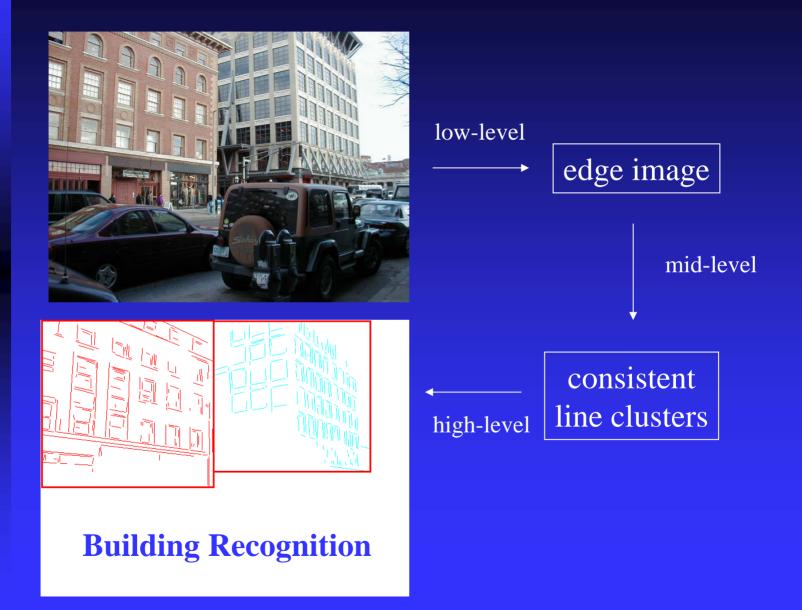


### regions of homogeneous color

data structure



### Low- to High-Level



## Filtering Operations Use Masks

- Masks operate on a neighborhood of pixels.
- A mask of coefficients is centered on a pixel.
- The mask coefficients are multiplied by the pixel values in its neighborhood and the products are summed.
- The result goes into the corresponding pixel position in the output image.

3636363636364545364545453645545445455454

Input Image

1/9 1/9 1/9 1/9 1/9 1/9 1/9 1/9 1/9

3x3 Mask (mean filter)

** **	: **	**	**
** 39	**	**	**
** **	: **	**	**
** **	: **	**	**
** **	: **	**	**

Output Image

## Comparison: salt and pepper noise



## Comparison: Gaussian noise

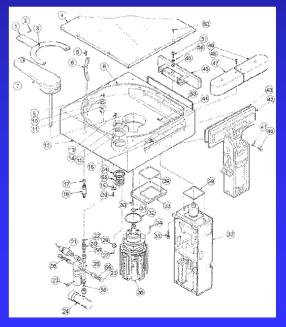


# Lines and Arcs Segmentation

In some image sets, lines, curves, and circular arcs are more useful than regions or helpful in addition to regions.

Lines and arcs are often used in

- object recognition
- stereo matching
- document analysis



## **Edge Detection**

Basic idea: look for a neighborhood with strong signs of change.

Problems:

• neighborhood size

818226248233252581822624

• how to detect change

## **Differential Operators**

**Differential operators** 

• attempt to approximate the gradient at a pixel via masks

• threshold the gradient to select the edge pixels

## **Example: Sobel Operator**

$$\mathbf{Sx} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \qquad \mathbf{Sy} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

On a pixel of the image I
let gx be the response to Sx
let gy be the response to Sy

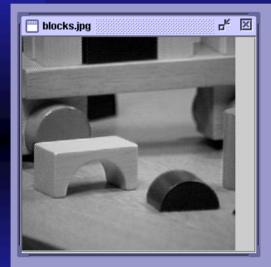
Then the gradient is  $\nabla I = [gx \ gy]^T$ 

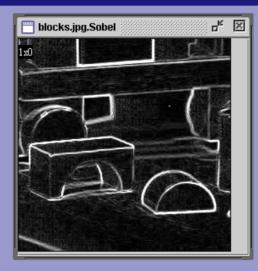
And  $g = (gx^2 + gy^2)^{1/2}$ 

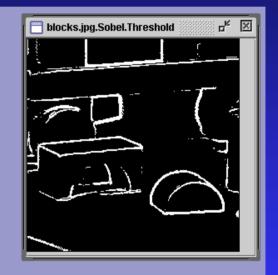
is the gradient magnitude.

 $\theta = atan2(gy,gx)$  is the gradient direction.

## Sobel Operator on the Blocks Image



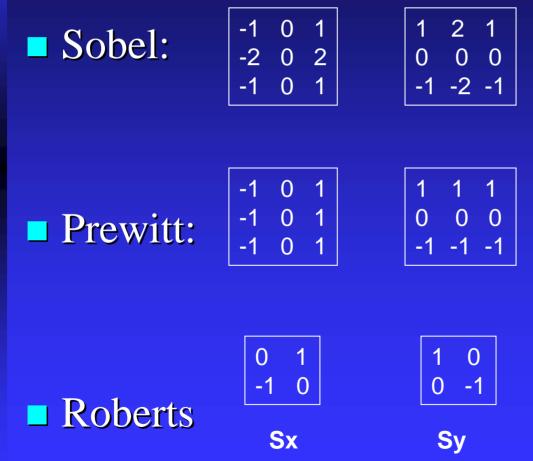




original image

gradient magnitude thresholded gradient magnitude

## Common Masks for Computing Gradient



## Canny Edge Detector

- Smooth the image with a Gaussian filter with spread  $\sigma$ .
- Compute gradient magnitude and direction at each pixel of the smoothed image.
- Zero out any pixel response ≤ the two neighboring pixels on either side of it, along the direction of the gradient.
- Track high-magnitude contours.

• Keep only pixels along these contours, so weak little segments go away.

## Canny Examples

Canny σ=1

### Canny $\sigma=4$

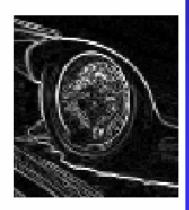








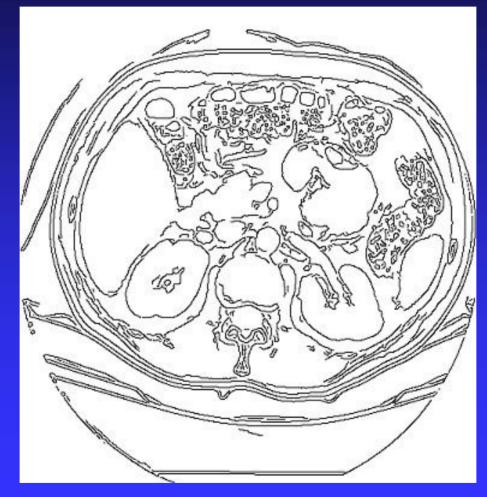




Canny σ=1

Roberts 2X2

## Canny on Kidney Image



## Canny on the Blocks image



## Canny Characteristics

The Canny operator gives single-pixel-wide images with good continuation between adjacent pixels

It is the most widely used edge operator today; no one has done better since it came out in the late 80s. Many implementations are available.

It is very sensitive to its parameters, which need to be adjusted for different application domains.

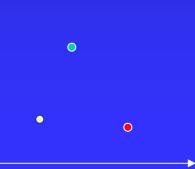
## Segmentation into Regions

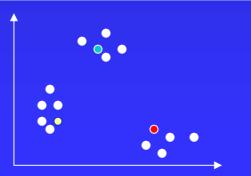
- Instead of looking for 1D features like lines and curves, some processes look for regions.
- The regions must be homogeneous in some attribute such as gray-tone, color, texture,...
- Although "region-growing" was popular in the past, clustering the pixels into subsets has become the best methodology for finding regions.

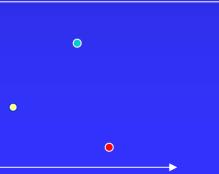
## Clustering by K-means Algorithm

Form K-means clusters from a set of *n*-dimensional feature vectors

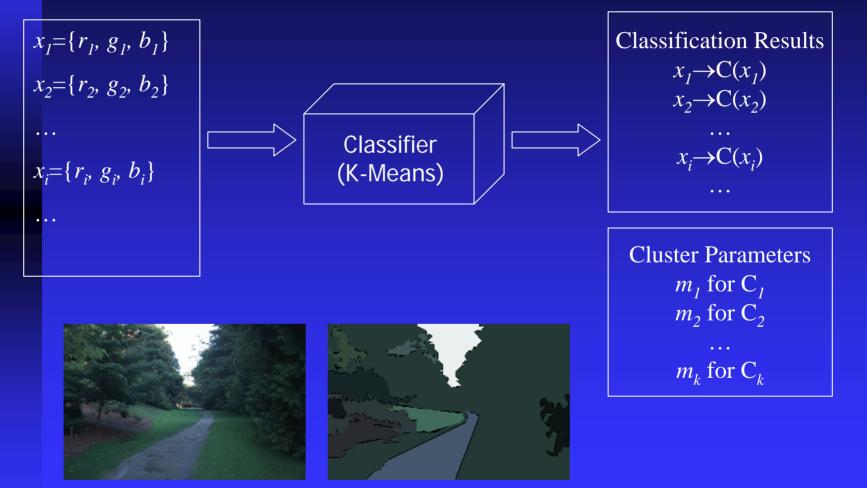
- 1. Set *ic* (iteration count) to 1
- 2. Choose randomly a set of K means  $m_1(1), ..., m_K(1)$ .
- 3. For each vector  $x_i$ , compute  $D(x_i, m_k(ic))$ , k=1, ..., Kand assign  $x_i$  to the cluster  $C_i$  with nearest mean.
- 4. Increment *ic* by 1, update the means to get  $m_1(ic), \dots, m_K(ic)$ .
- 5. Repeat steps 3 and 4 until  $C_k(ic) = C_k(ic+1)$  for all k.







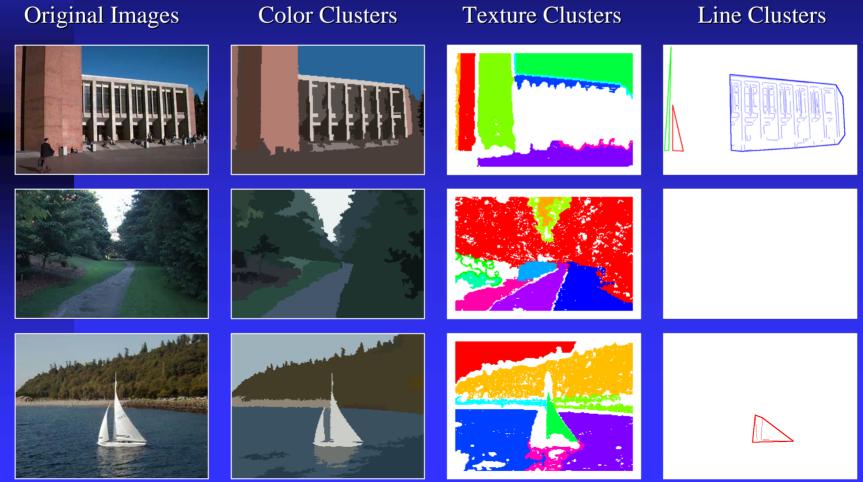
## K-Means Classifier (shown on RGB color data)



original data one RGB per pixel

color clusters

## Abstract Regions



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