Image Processing in Biomedical Applications

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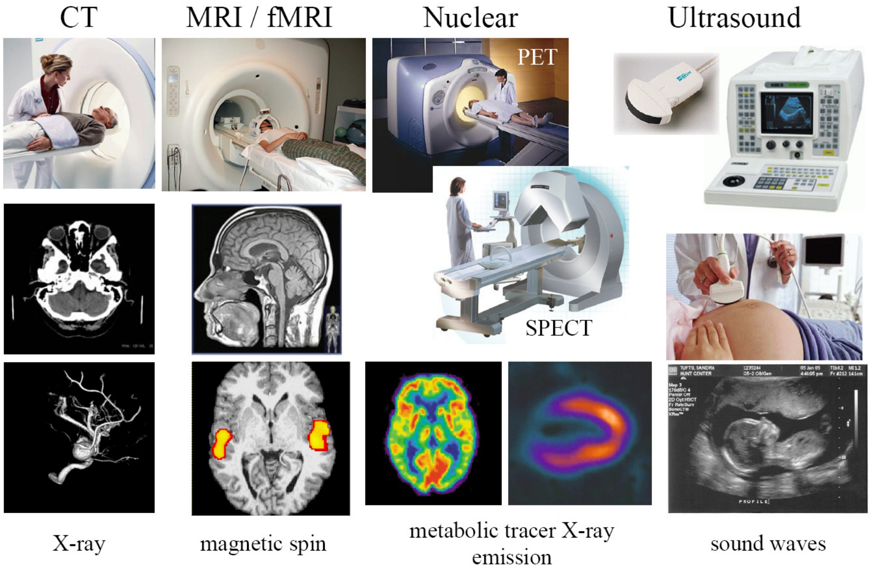
4. Image segmentation
   - Thresholding
   - Texture segmentation
   - Edge detection
   - Active contours

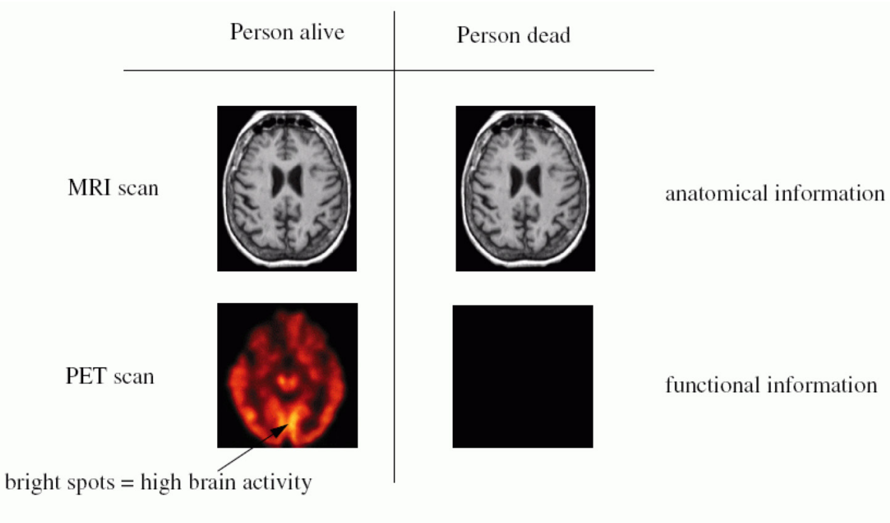
5. Image Registration
   - Basics

6. Shape analysis
   - Basics

Imaging modalities



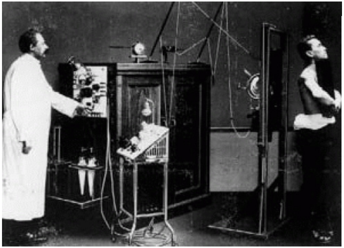
Anatomical vs. Functional Imaging

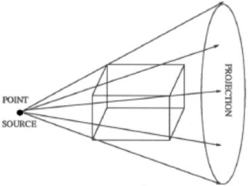


History: X-ray

Wilhelm Conrad Röntgen

- 8 November 1895: discovers X-rays
- 22 November 1895: X-rays
  Mrs. Röntgen's hand
- 1901: receives first Nobel Prize in physics





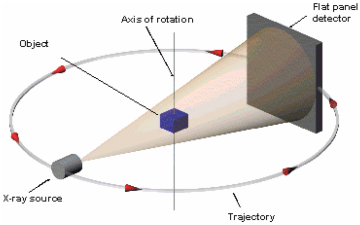
History: Computed Tomography (CT)

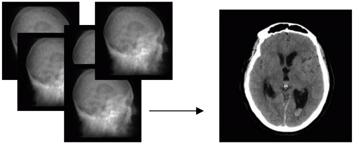
The breakthrough

- acquiring many projections around the object enables the reconstruction of the 3D object (or a cross-sectional 2D slice)

CT pioneers

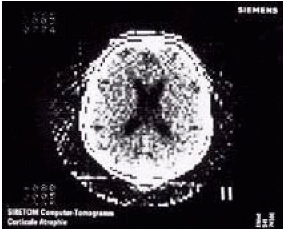
- 1917: Johann Radon establishes the mathematical framework for tomography, now called the Radon transform
- 1963: Allan Cormack publishes mathematical analysis of tomographic image reconstruction, unaware of Radons work
- 1972: Godfrey Hounsfield develops first CT system, unaware of either Radon or Cormacks work, develops his own reconstruction method
- 1979: Hounsfield and Cormack receive the Nobel Prize in Physiology or Medicine





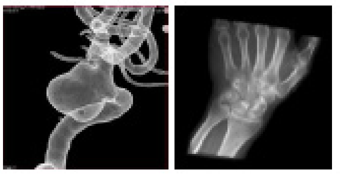
CT: past and present

1975: Siemens SIRETON CT scanner (image size 128×128)

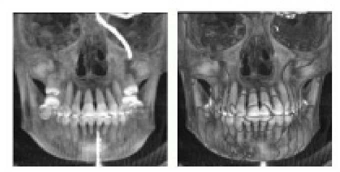



Now: Common modern CT scanner (image size 512×512)

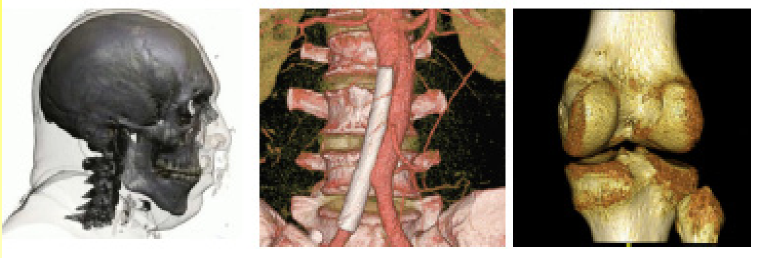

3D Visualization Capabilities



Extrapolate novel views of the structures

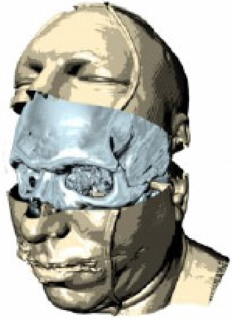


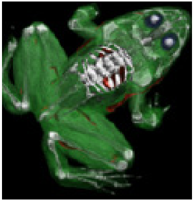
Maximum intensity visualization



Shaded structures visualization

More visualizations

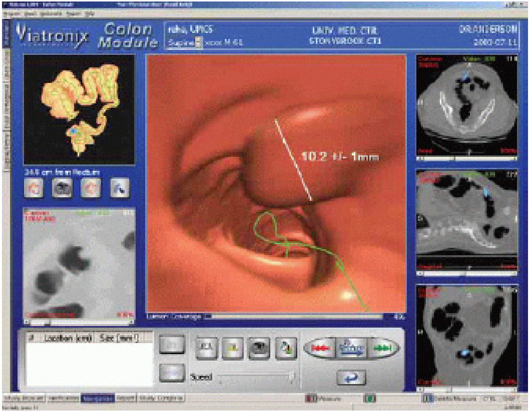




Visualization and Virtual Medicine

Offer a virtual reality environment for

- Virtual examination (e.g. virtual colonscopy)
- Surgical planning
- Medical training

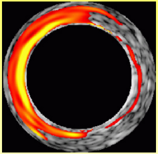


Ultrasound: past and present

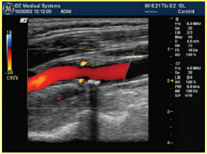
- 1942. Dr. Karl Theodore Dussik: transmission ultrasound investigation of the brain
- 1955. Holmes and Howry: Subject submerged in water tank to achieve good acoustic coupling
- 1959. Automatic scanner, Glasgow

US scanner

3D Ultrasound



Intra Vascular



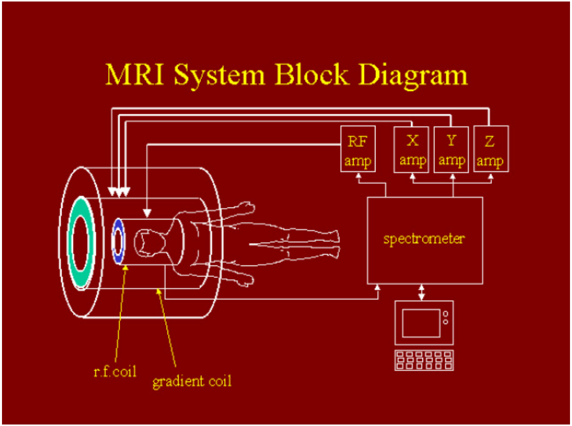
Doppler

History: MRI

- 1946: Felix Bloch (Stanford) and Edward Purcell (Harvard) demonstrate nuclear magnetic resonance (NMR)
- 1973: Paul Lauterbur (Stony Brook University, Nobel 2003) published first MRI (Magnetic Resonance Imaging) image in Nature
- Late 1970s: First human MRI images conceived
- Early 1980s: First commercial MRI systems available
- 1993: Functional MRI in humans demonstrated

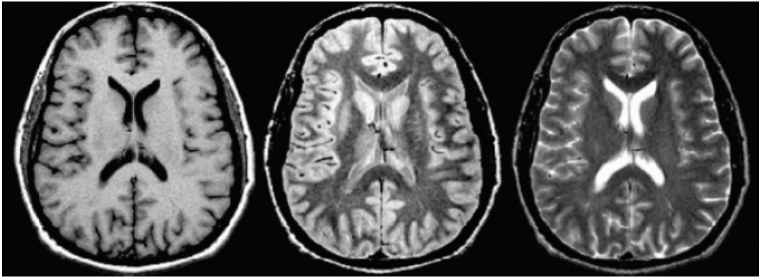
MRI: basics

- MRI measures the effects of magnetic properties of tissue
- Effects are tissue-specific
- Also specific to blood perfusion/ oxygenization (functional MRI)
- MRI is very versatile (but also more expensive than CT)



MRI: basics

Permits the acquisition of several kind of images:

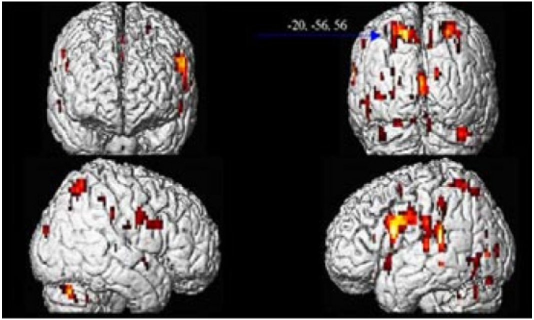


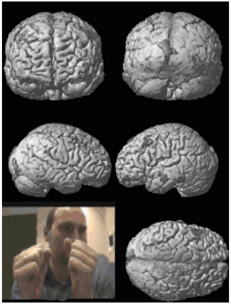
T1, density and T2 weighted MRI

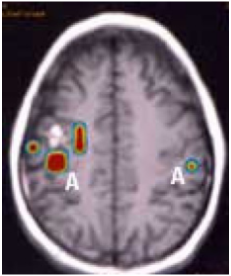
MRI: applications

Functional MRI:

- Allows to assess brain activity during certain tasks
- Valuable for brain functional studies (cognitive sciences)
- Also for surgery planning and diagnosis



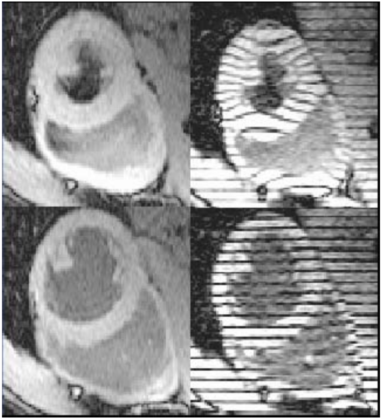




MRI: recent applications

Cardiac tagged MRI:

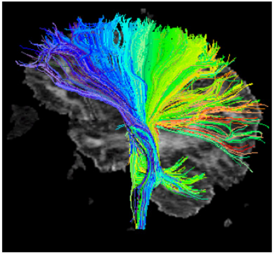
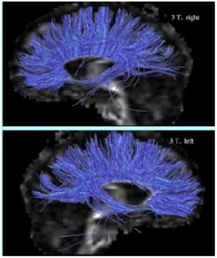
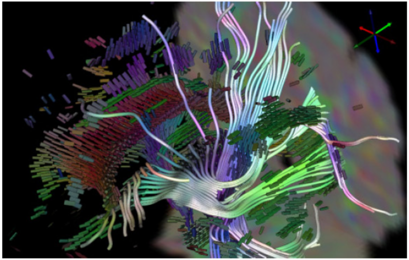
- Draw magnetic patterns in the matter
- Study how these patterns are distorted during heart contraction
- Infer information about heart dynamical behavior



MRI: very recent applications

Diffusion Tensor Imaging:

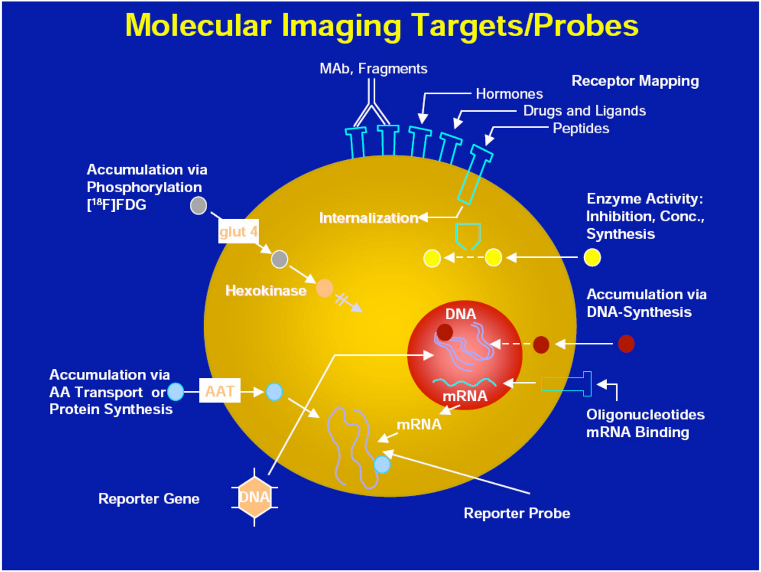
- Measures the diffusion of water
- Allows the tracking of nerve fibers in the brain (white matter)
- Visualization challenging!

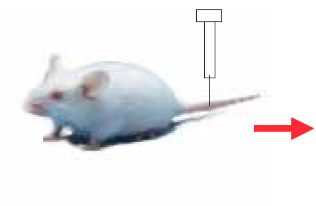
Molecular imaging

- Exotic but trendy
- Molecular imaging provides information about specific molecular processes
- Links to genomic and proteonomics
- Exploits all portions of the physical spectrum in addition to sound
- No one of the previous imaging modality is ideal so combinations must often be used
- Often in vivo

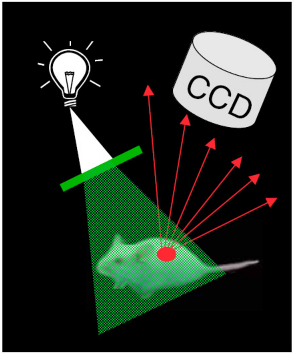
Molecular imaging



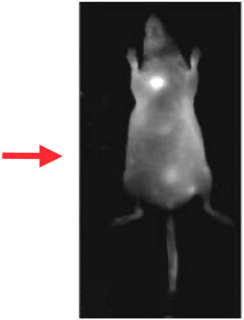
Molecular imaging



inject fluorophore or
labeled biomolecule



excite fluorophore with external light
source and image fluorescence



Weissleder et al,
Nature Biotech.
1999; 17: 375

Image processing: what for?

Image acquisition and reconstruction $\Rightarrow$ Physics, Maths, Engineer, ...

- studies how to reconstruct efficiently meaningful images from the raw data

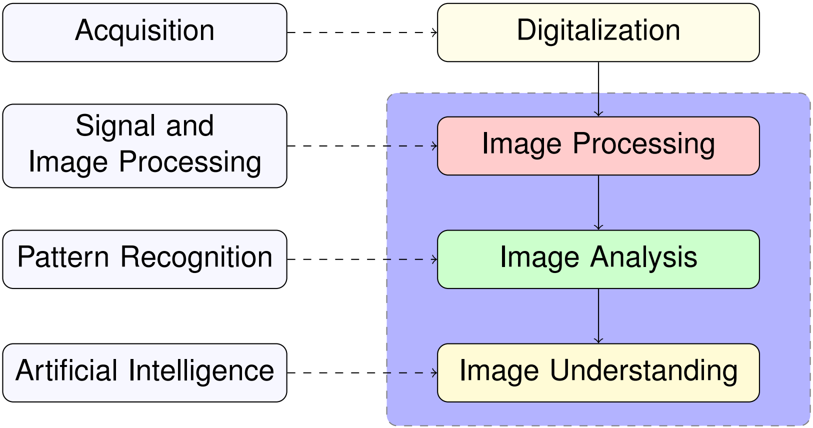
Visualization $\Rightarrow$ Computer graphics

- studies how to visualize the reconstructed images in a way that is useful for human observers

Image Analysis and Understanding $\Rightarrow$ Computer Vision

- studies how to emulate with a computer perceptual and visual behaviors similar to the biological ones
- studies models, algorithms and techniques to
  - obtain objective measurements automatically
  - recognize objects, structures and events

Processes in Computer Vision

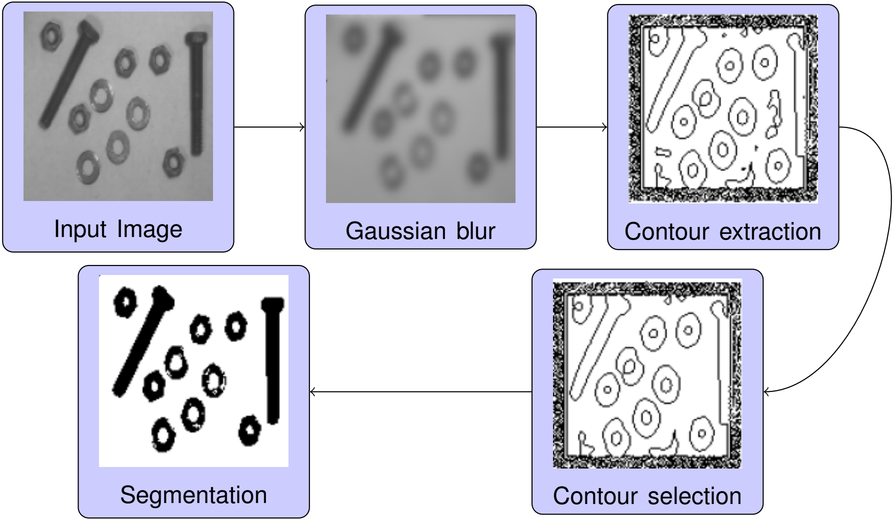


Low-Level Vision (image processing)

Image processing processes: set of operations performed on images aiming at enhancing their quality and selecting useful information, which will be processed by humans or other algorithms

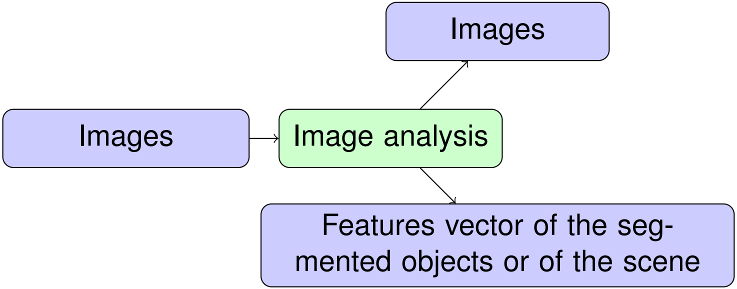
Images → Image processing → Images

Example of low-level processing



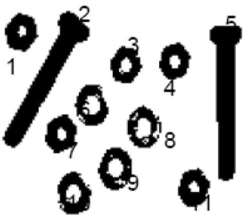
Mid-Level Vision (image analysis)

- Includes extraction of symbolic information from pre-processed images and analysis techniques of the visual characteristics of the objects that are in the images

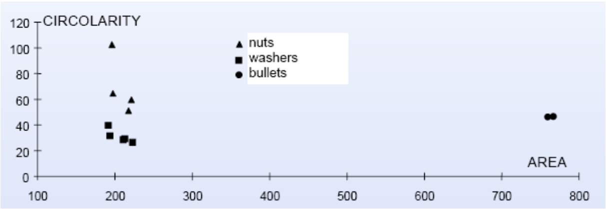


Example of mid-level processing

- Extraction of visual primitives:
  - Area
  - Circularity



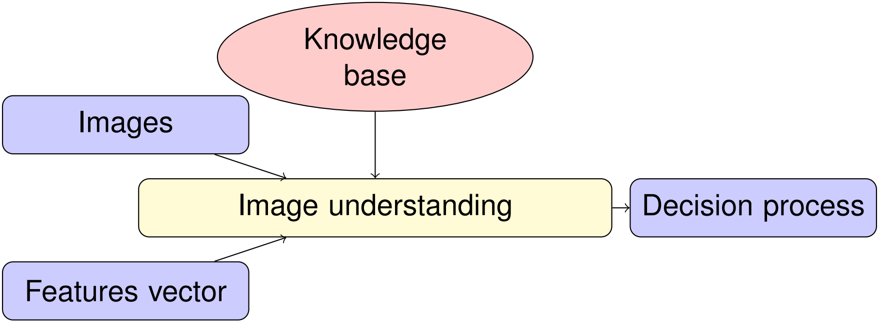
Labeling



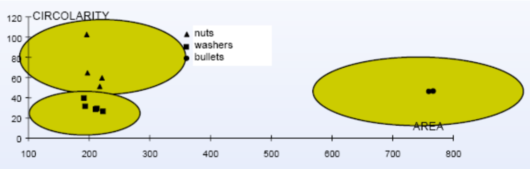
High-Level Vision (image understanding)

Aims at obtaining some “comprehension” of the observed scene, as shape recognition or spatial relationship among objects. It includes high-level abstraction processes:

- Classification
- Identification
- Localization



Example of high-level processing



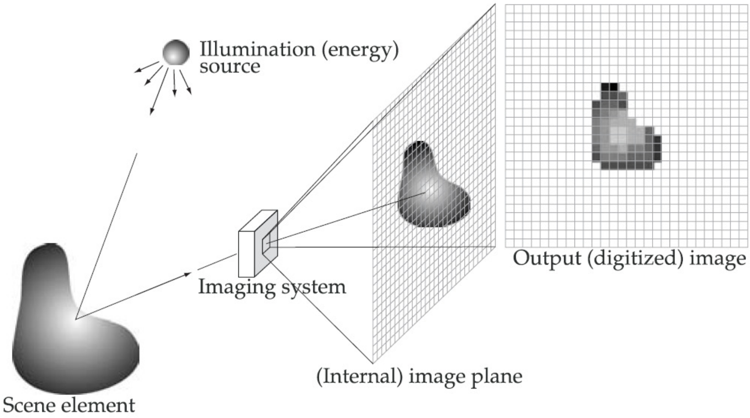
Clustering

- Classification method
- Non supervised

Outline

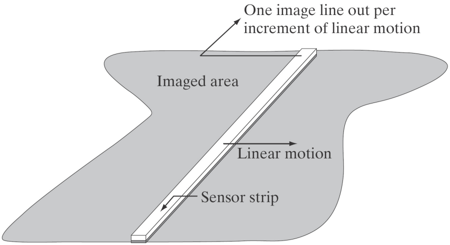
2. Digital images
   - Image acquisition and representation

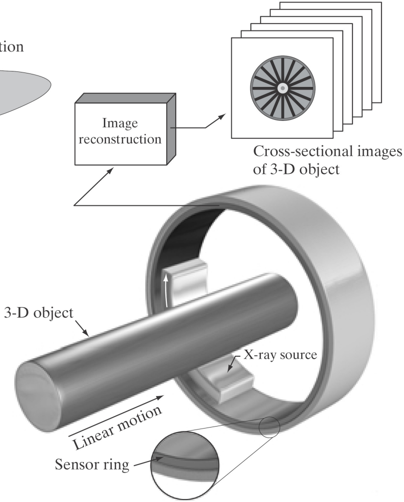
Digital Image Acquisition: sensor array



- Light source, Object reflection
- CCD sensor
- Imaging System: Lenses
- Digital Image

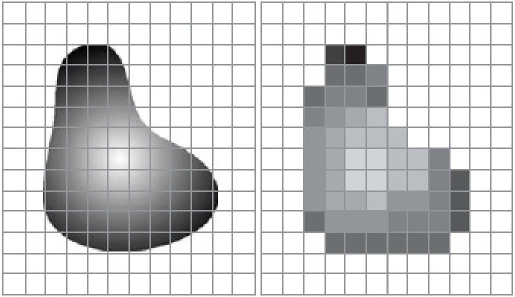
Digital Image Acquisition: sensor strip

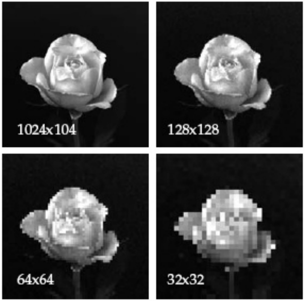




Sampling & Quantization

- Sampling produces continuous values $f[x, y]$
- Digitizing the Pixel Amplitude — Quantization
- n bits per pixel — 2^n Discrete (monochromatic)

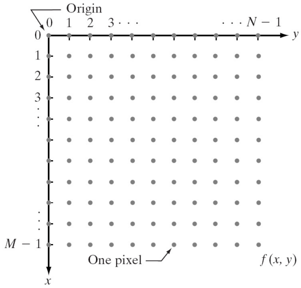




Digital Image Representation

The result of sampling and quantization is a matrix:

$$f(x,y) = \begin{pmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & \ddots & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{pmatrix}$$



Outline

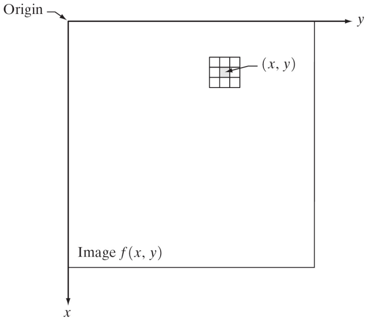
3. Image enhancement
   - Spatial Filtering
   - Intensity transformations
   - Image histograms and equalization
   - Convolution filters
   - Order-statistic filters

Spatial filtering

- The simplest way to enhance an image f
- Based on direct manipulation of the pixels

$$g(x, y) = T[f(x, y)]$$

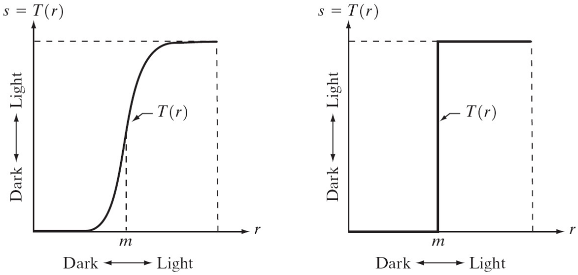
- T operator on f
- defined over a neighborhood of the pixel (x, y) (for example a small subimage centered at (x, y))



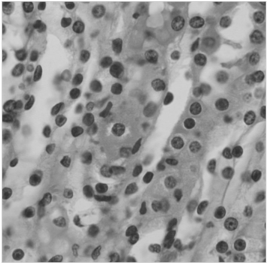
Intensity transformations

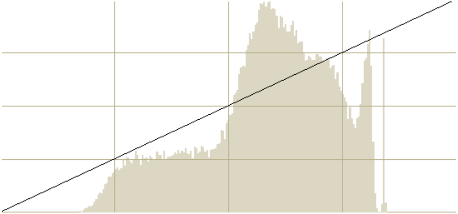
- Spatial filtering with neighborhood size 1×1
- In this case g depends only on the intensity value of f at (x, y)
- It is completely described as a function between intensity values:

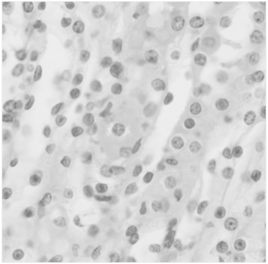
$$s = T(r)$$

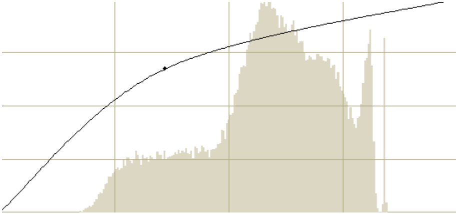


First examples

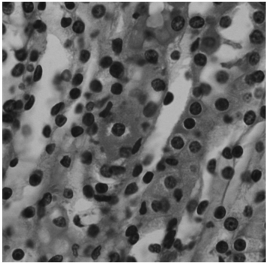


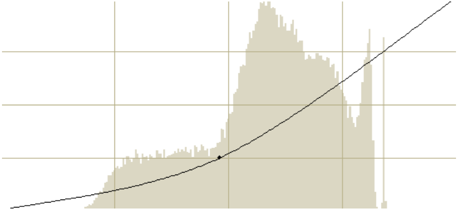


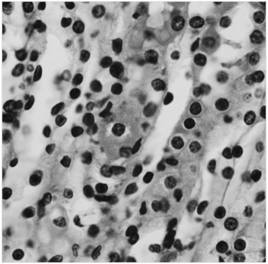


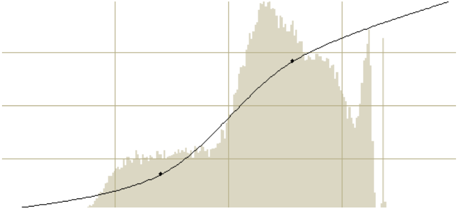


First examples



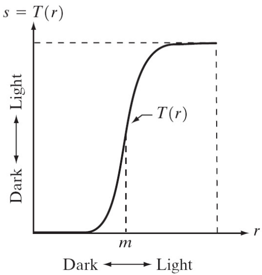






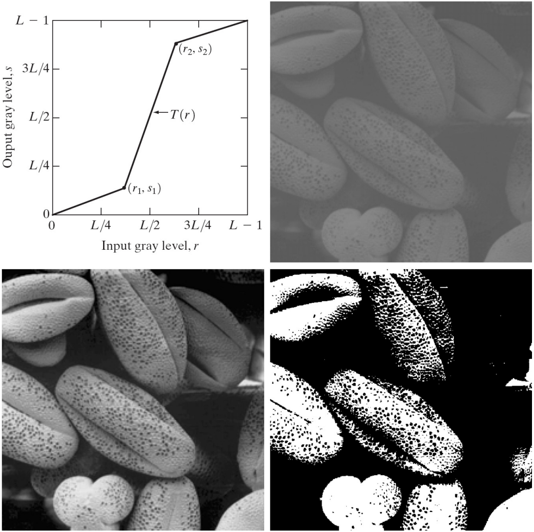
Intensity transformations: contrast enhancement

- Left plot: Contrast stretching
  - Darken gray values below m
  - Brighten gray values above
- Right plot: Thresholding
  - Limit of contrast stretching
  - Produces a binary image



Contrast enhancement

a) Intensity transform
b) Low contrast image
c) Contrast enhanced image
d) Thresholded image



Negative

- Equivalent of photographic negative
- Enhance white or gray details embedded in a black background

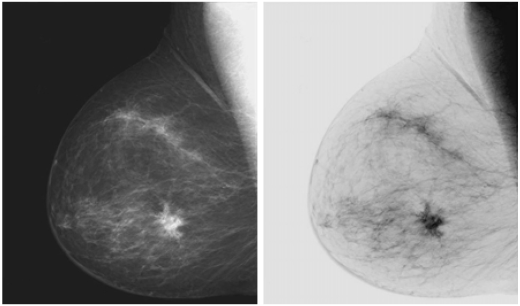


Image histograms

Image Histogram

Discrete function that associates to the gray level r the number of pixels N_r having gray value equal to r

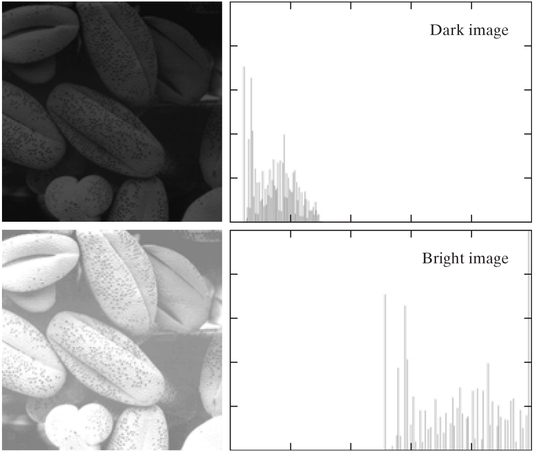
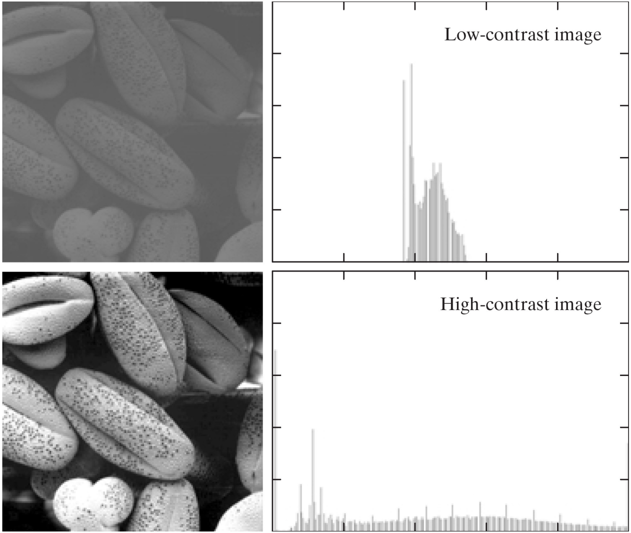


Image histograms: example



Histogram equalization

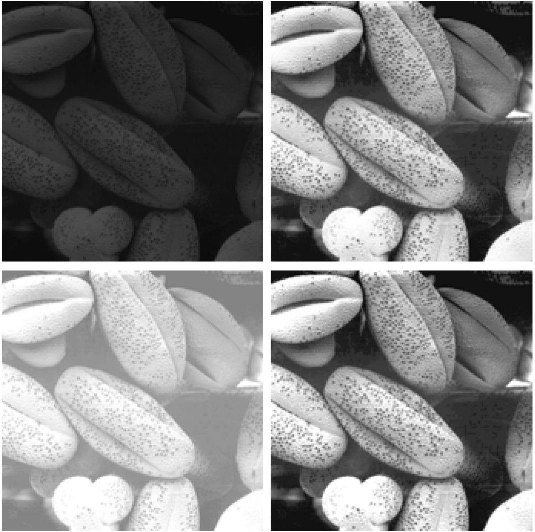
- An enhancement method based on intensity transformation
- Find a function $s = T(r)$ (strictly increasing) such that the image

$$g(x, y) = T \circ f(x, y)$$

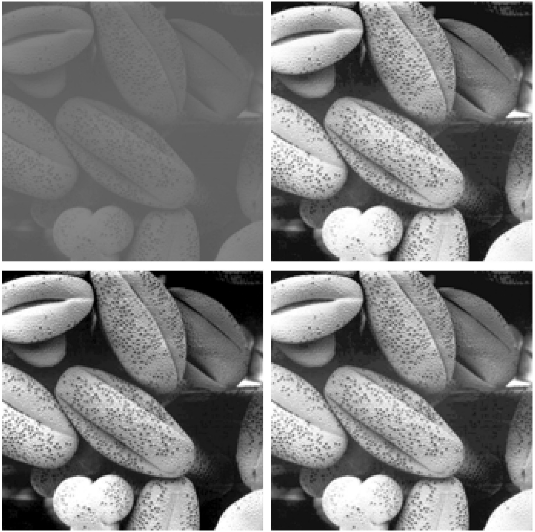
  has uniform normalized histogram
- Letting $p(r)$ be the normalized histogram of f

$$T(r) = \sum_{r' \leq r} p(r')$$

Histogram equalization: example 1



Histogram equalization: example 2



Convolution filters

Linear spatial filters based on convolution kernels

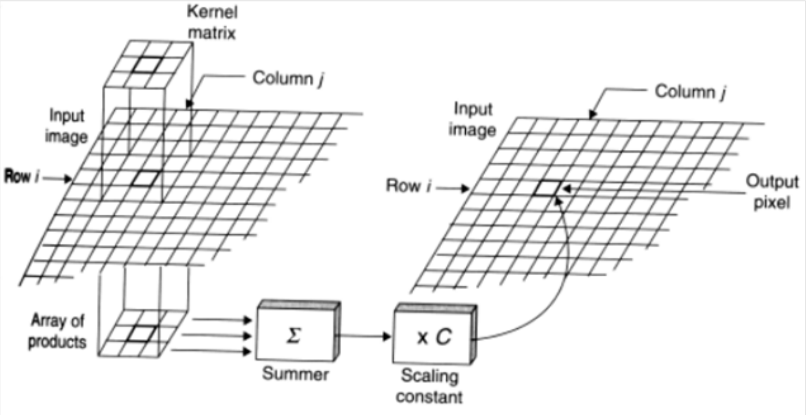


Figure 9–7 Digital convolution

Convolution filters

Different choices of h lead to very different results:

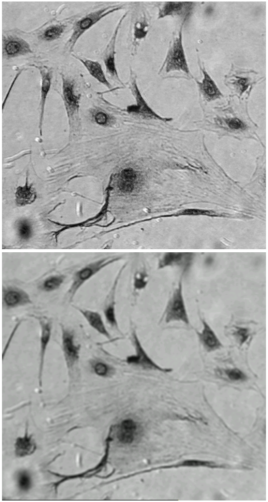
- Smoothing
- Sharpening
- Edge enhancement

Smoothing filters

Averaging matrix kernel:

1	1	1
1	1	1
1	1	1

(size 3×3)



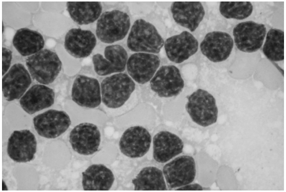
Averaging filters


Original image

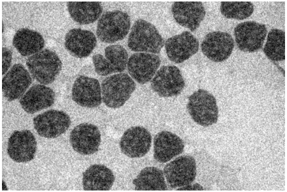

mask size $= 9 \times 9$


mask size $= 35 \times 35$

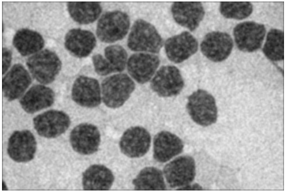
Averaging filters



Original image



Gaussian Noise added



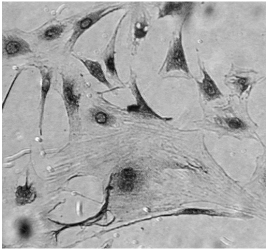
mask size $= 3 \times 3$

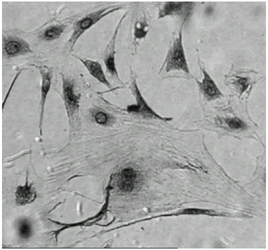
Smoothing filters

Gaussian filter:

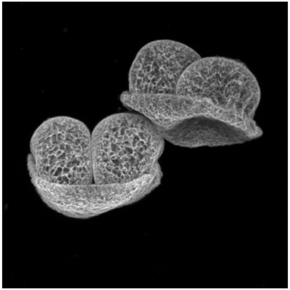
1	2	1
2	4	2
1	2	1

(size 3×3)

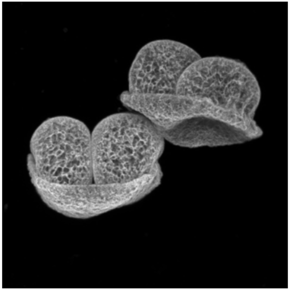




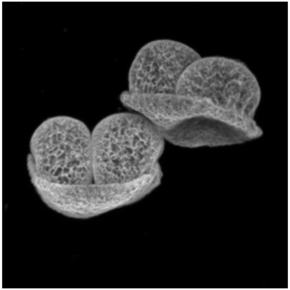
Gaussian filters



Original image



mask size $= 3 \times 3$



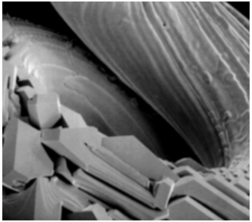
mask size $= 9 \times 9$

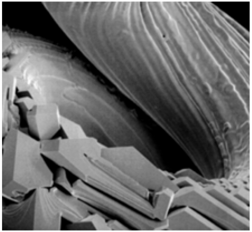
Sharpening filters

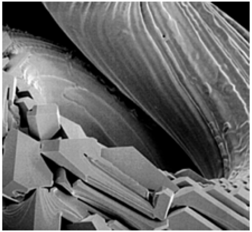
a) Two sharpening filters
b) Original image
c) Application of I filter
d) Application of II filter

0	−1	0
−1	5	−1
0	−1	0

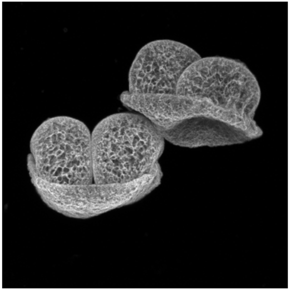
−1	−1	−1
−1	9	−1
−1	−1	−1



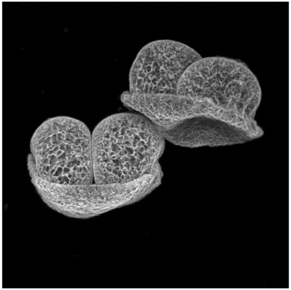




Sharpening filters



Original image



mask size $= 3 \times 3$

mask size $= 9 \times 9$

Edge enhancement: Definition

- An edge is a location in the image where there is a steep intensity variation
- Hopefully, these discontinuities correspond to boundaries of object of interest
- How do we enhance edges?
  - Determine a measure of intensity change in the pixels neighbourhood
  - First derivative of a two-variate function $\longrightarrow$ Gradient

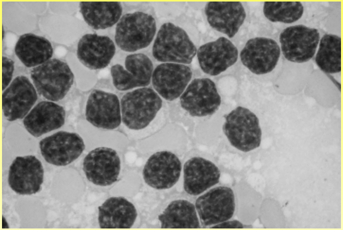
Edge enhancement: Sobel Operator

- Estimation of ∇f in 2 directions:

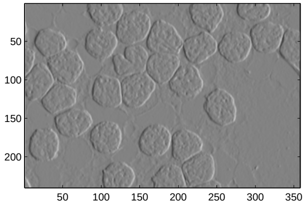
$$h_{\mathrm{hor}} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad h_{\mathrm{vert}} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

- It can be thought:
  1. First Gaussian blurring
  2. Then derivation
- Indeed, $f' * g = (f * g)' = f * g'$
- Sobel operator is separable!

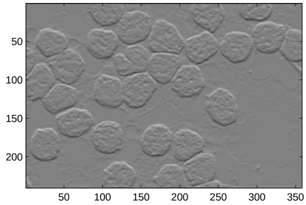
Edge enhancement: Sobel Operator



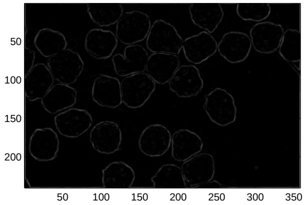
Original



Horizontal



Vertical

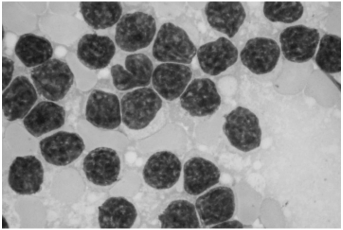


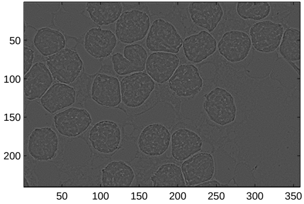
Gradient norm

Edge enhancement: Laplace operator

$$\nabla^2 = \nabla \cdot \nabla = \left(\frac{\partial^2}{\partial x^2}\right) + \left(\frac{\partial^2}{\partial y^2}\right)$$

$$\nabla^2 \approx \begin{bmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 \\ 0 & -2 & 1 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$





Order-statistic filters

- Sort pixel values inside a $m \times n$ neighborhood of pixel (x, y)

9	7	11
6	4	5
2	5	1

$$1 \leq 2 \leq 4 \leq 5 \leq 5 \leq 6 \leq 7 \leq 9 \leq 11$$

- The response of this class of filters depends on the ordering of the pixel values

Order-statistics filters: Min-filter

- Sort pixel values inside a $m \times n$ neighborhood of pixel (x, y)

9	7	11
6	4	5
2	5	1

$$1 \leq 2 \leq 4 \leq 5 \leq 5 \leq 6 \leq 7 \leq 9 \leq 11$$

- Elimination of salt noise

Order-statistics filters: Max-filter

- Sort pixel values inside a $m \times n$ neighborhood of pixel (x, y)

9	7	11
6	4	5
2	5	1

$$1 \leq 2 \leq 4 \leq 5 \leq 5 \leq 6 \leq 7 \leq 9 \leq 11$$

- Elimination of pepper noise

Order-statistics filters: Median filter

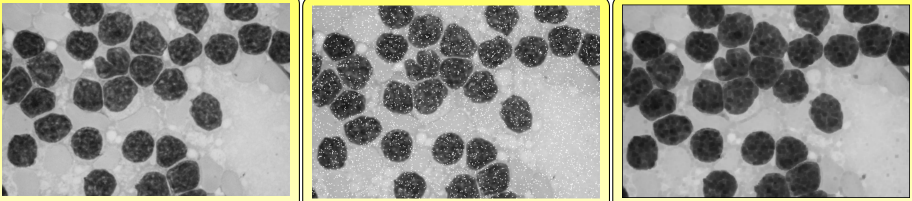
- Sort pixel values inside a $m \times n$ neighborhood of pixel (x, y)

9	7	11
6	4	5
2	5	1

$$1 \leq 2 \leq 4 \leq 5 \leq 5 \leq 6 \leq 7 \leq 9 \leq 11$$

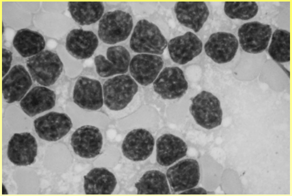
- Elimination of general impulsive noise
- Less blurring than linear smoothing filter

Applications of Order-statistics filters: Min filter

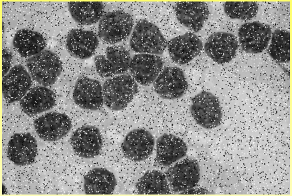


Original | Salt added | Min filter 3×3

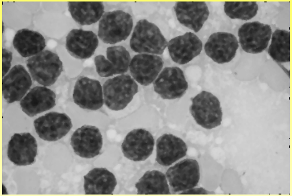
Applications of Order-statistics filters: Median filter



Original

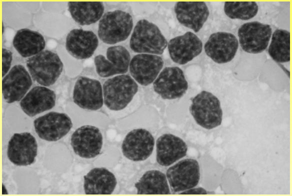


Salt & Pepper added

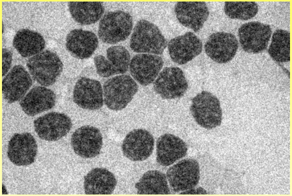


Median filter 3×3

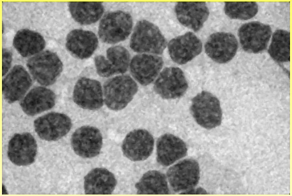
Applications of Order-statistics filters: Median filter



Original

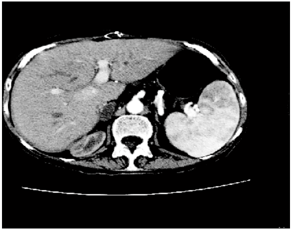


Gaussian noise added



Median filter 3×3

Further Example: Anisotropic Diffusion



Original image

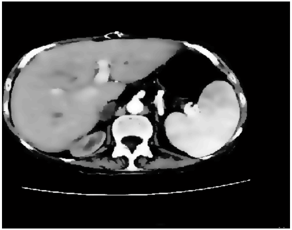
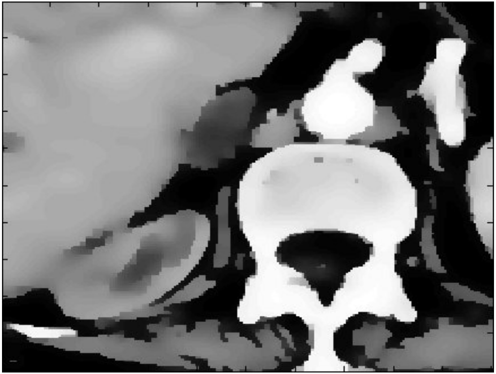


Image after evolution



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Outline

4. Image segmentation
   - Thresholding
   - Texture segmentation
   - Edge detection
   - Active contours

Image segmentation: definition

- Fundamental step in many applications
- Segmentation $=$ Partitioning of the image into homogeneous regions with respect to some visual feature (e.g. gray level value)
- Distinguishing objects from the background
- Two approaches:
  - Region based methods
  - Edge based methods

Thresholding

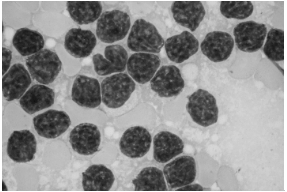
- Selection of an intensity T (called Threshold) capable to divide the image into two regions, corresponding to higher or lower intensity value
- Given an image $f(x, y)$ and a threshold T, a binary image $g(x, y)$ is produced:

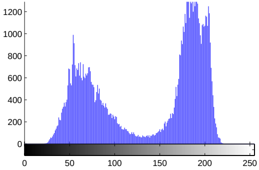
$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) \geq T \\ 0 & \text{otherwise} \end{cases}$$

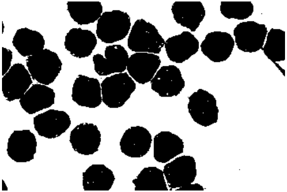
- Threshold selection depends on the intensity value of the objects of interest

Automatic Threshold selection

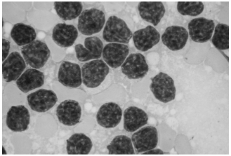
- In case no a priori information is available
- Exploiting the statistical properties of the image, e.g. its histogram
  - Histogram valleys as thresholds
  - Histogram inflection points as thresholds
  - Otsu's method (1979)
    - ★ Optimal threshold selection method
    - ★ Minimize the within-group variance





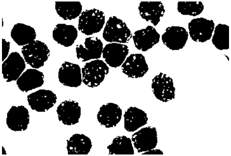


Otsu thresholding: Example

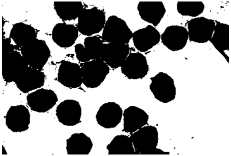


Original

Otsu ($T = 127$)

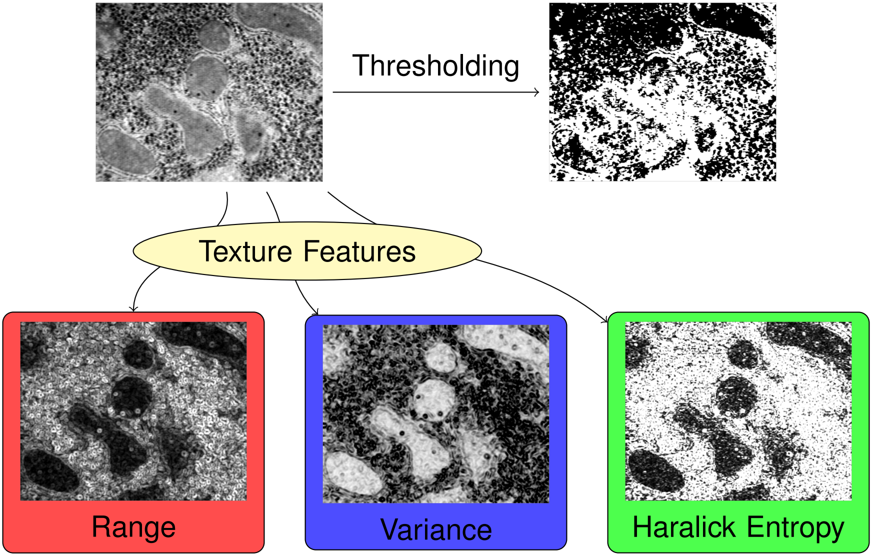


$T = 100$

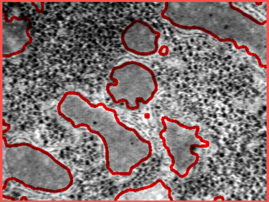


$T = 160$

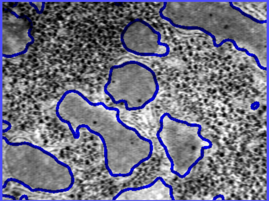
Example: Improvement via texture features



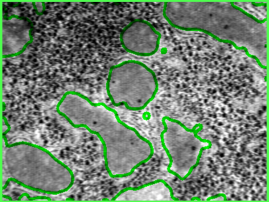
Example: Improvement via texture features



Range



Variance



Haralick Entropy

Original Image → Texture Operator → Smoothing Filter → Thresholding → Segmented Image

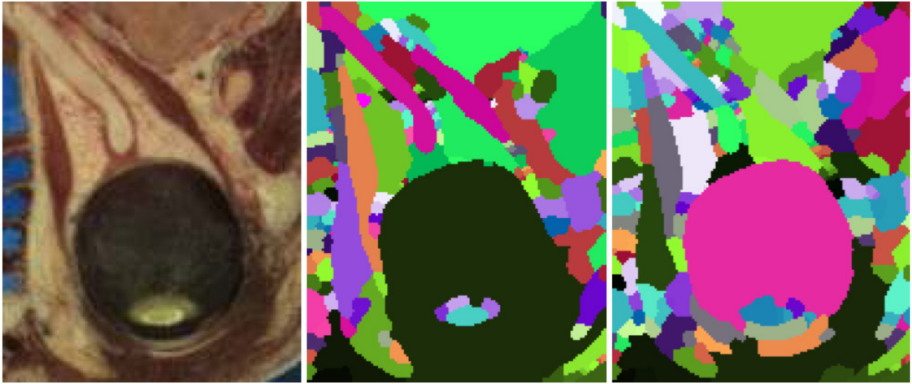
Further Example: Watershed segmentation

- Another popular region based method, like thresholding
- Boundaries are local extrema of features
- Drawback: over-segmentation

Intensity profile of input image — Intensity profile of filtered image — Watershed Segmentation

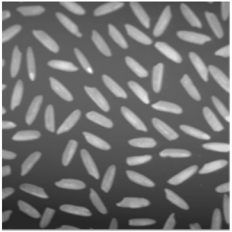
Further Example: Watershed segmentation

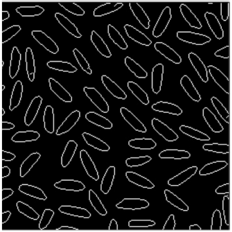
- Gradient magnitude as feature



Edge based segmentation

- This approach identifies the steep intensity variations in an image, called edges
- Uses edge operators plus binarization (e.g. thresholding)
- Hopefully these correspond to object boundaries
- Edges are extended or deleted so as to produce closed boundaries
- Only good for simple images
- Shape can then be used for recognition



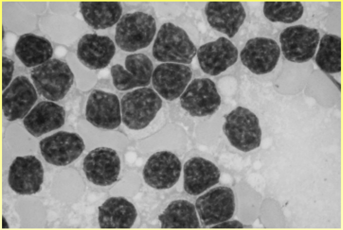


Example:Canny Edge Detector (1986)

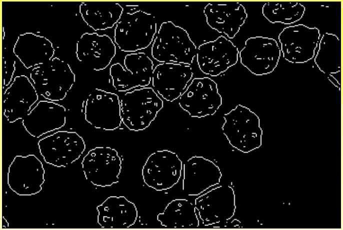
Popular but powerful edge detector

1. Gaussian smoothing
2. Gradient computation
3. Search of local maxima in the direction of the gradient, i.e. ridges in the gradient magnitude image
4. Non-maximal suppression
5. Thresholding of ridge points (actually with hysteresis)

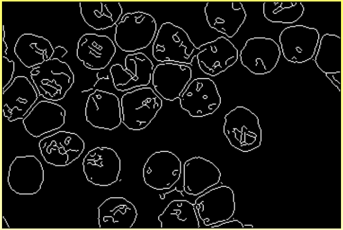
Edge detectors: examples



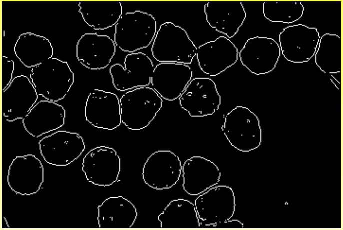
Original



Laplace



Canny

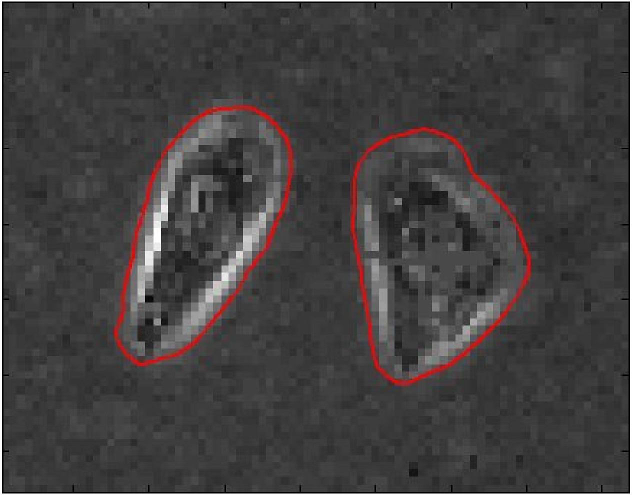


Sobel

Further Example: Active contours

- Aim: improve boundary detection
- Integrate information over distance
- Use cues from biological vision (Gestalt cues)
  - Smoothness
  - Closure
- Main ideas:
  - Insert an initial contour in the image domain
  - Stretch and bend it according to the forces defined by the image data
  - Keep the contour smooth during the evolution with a sort of internal energy
- Active contours techniques use:
  - Optimization strategies
  - Calculus of variations and PDEs

Example



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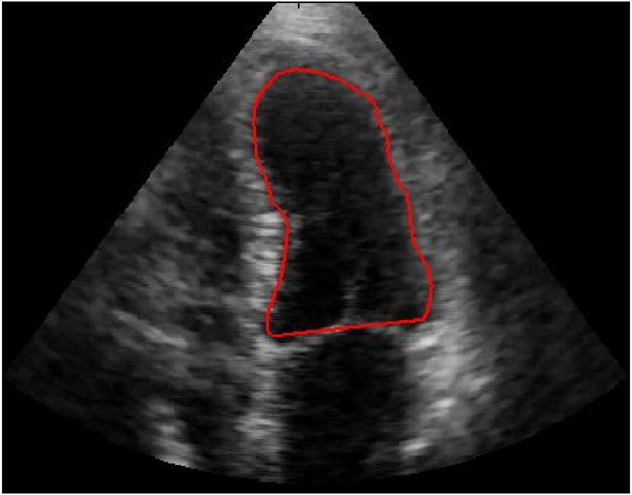
HEARTFAID project: Example of Activity



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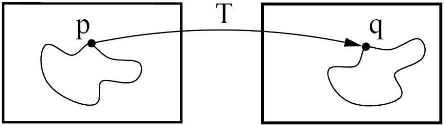
5 Image Registration

- Basics

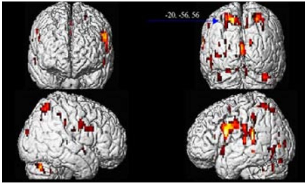
Image Registration: definition

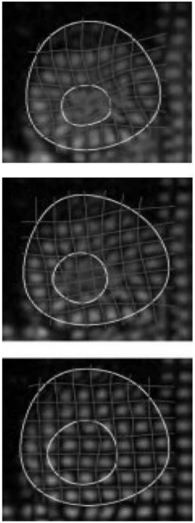
- Image registration is the process of determining the spatial transform that maps points from one image to homologous points on a object in the second image
- e.g. align if the images depict the same object, align the points corresponding to the same material point
- or match structures of interest (corners, edges,. . .)
- Generally, the criterion is prescribed by an application relying on the registration task



Registration purposes

- Data fusion (e.g. functional data to anatomical data)
- Construction of anatomical atlases
- Mapping to anatomical atlases
- Comparison of patients
- Content based image retrieval
- Motion analysis in image sequences
- ...





Registration bases

- Let f, g be images, T a geometric transformation
- $D(f, g, T)$ a criterion asserting the goodness of the matching
- Then the registration problem boils down to:

$$\bar{T} = \arg\min_{T} D(f, g, T)$$

- Thus to develop a registration framework, we may:
  - Represent somehow the geometric transformation T
  - Design a similarity measure $D(f, g, T)$
  - Devise an optimization algorithm

Representing geometric transformation

- Classical (matrix) groups
  - rotations, scaling, isometries, affine transformations,...
- Splines
- General diffeomorphisms
  - Discretized as Free Form Deformations (FFD)
  - i.e. we assign to every pixel (voxel) x a displacement vector $u(x)$ s.t.:

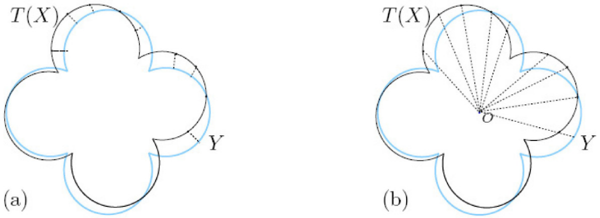
    $$T(x) = x + u(x)$$

  - Requires some regularization of the solution (e.g. Tichonov regularization)

Similarity measures

- Landmark based
  - If we now that a set of points $\{p\}$ in the first image $f$correspond to the points $\{q\}$ in the second image g
  - Remark: such points should be characteristic points of an object (a contour, corners or other easily detectable couple of points)
  - Then we may choose:

$$D(f, g, T) = \sum_{p \in \{p\}} \| Tp - q \|^2 \tag{1}$$



Similarity measures

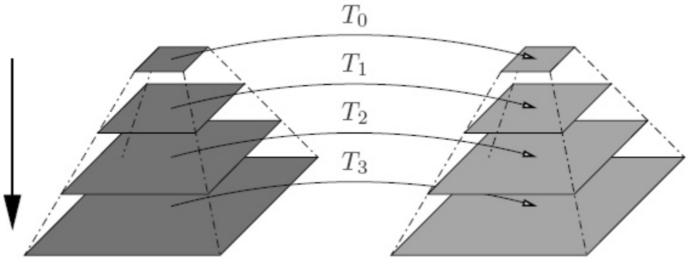
- Intensity based
  - Uses directly the intensity functions of the images
  - Remark: No point extraction or segmentation is required
  - Then we may choose some functional norm, the simplest ones being:

$$\begin{aligned} \mathrm{SSD}(f,g) &= \int_{\Omega} (f(x) - g(T(x)))^2 = \|f - g \circ T\|_2^2 \\ \mathrm{SAD}(f,g) &= \int_{\Omega} |f(x) - g(T(x))| = \|f - g \circ T\|_1 \end{aligned}$$

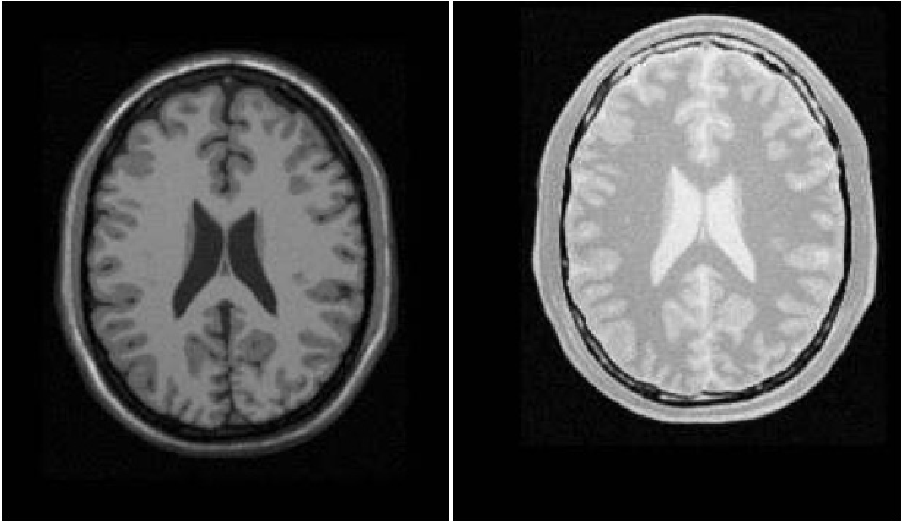
  - Also in use: mutual information, cross correlation,...
  - Depending on
    - ★ statistical hypothesis (e.g. gaussian noise)
    - ★ *a priori relation* between the intensity functions (identical, linear dependence, functional dependence,. . .)

Optimization

- Generally gradient descent
- Non convex functional $\Rightarrow$ Big dependence on the initialization
- Use the pyramid trick:

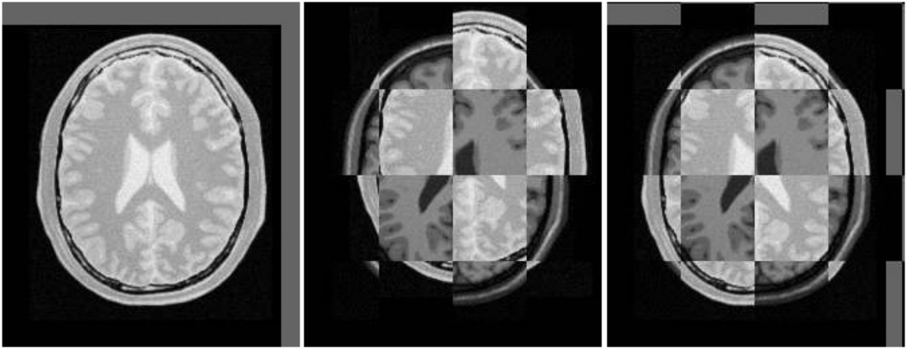


Examples



T2 weighted and proton density brain MRI

Examples



Moving image, initial and final alignment

6 Shape analysis
- Basics

Shape analysis

- Shape measurements are physical dimensional measures that characterize the appearance of an object
- The goal is to use the fewest necessary measures to characterize an object adequately so that it may be unambiguously classified
- The shape may not be entirely reconstructable from the descriptors, but the descriptors for different shapes should be different enough that the shapes can be discriminated

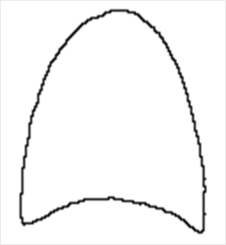
Area

- The area is the number of pixels in a shape
- The convex area of an object is the area of the convex hull that encloses the object

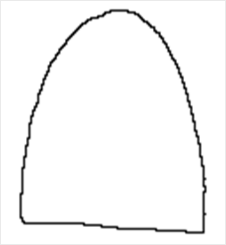
Perimeter

- The perimeter (length) is the number of pixels in the boundary of the object
- The convex perimeter of an object is the perimeter of the convex hull that encloses the object

Perimeter



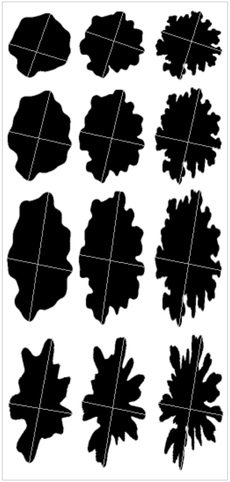
External perimeter



Convex perimeter

Axis

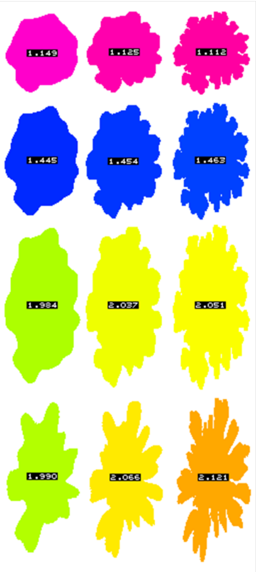
- The major axis is the longest line that can be drawn through the object
- The minor axis is the longest line that can be drawn through the object whilst remaining perpendicular with the major-axis



Aspect Ratio

- The major axis is the longest line that can be drawn through the object
- The minor axis is the longest line that can be drawn through the object whilst remaining perpendicular with the major-axis
- The aspect ratio measures the ratio of the objects height to its width:

$$\text{AspectRatio} = \frac{\text{Height}}{\text{Width}}$$



Compactness

- Compactness (also called formfactor) is defined as the ratio of the area of an object to the area of a circle with the same perimeter:

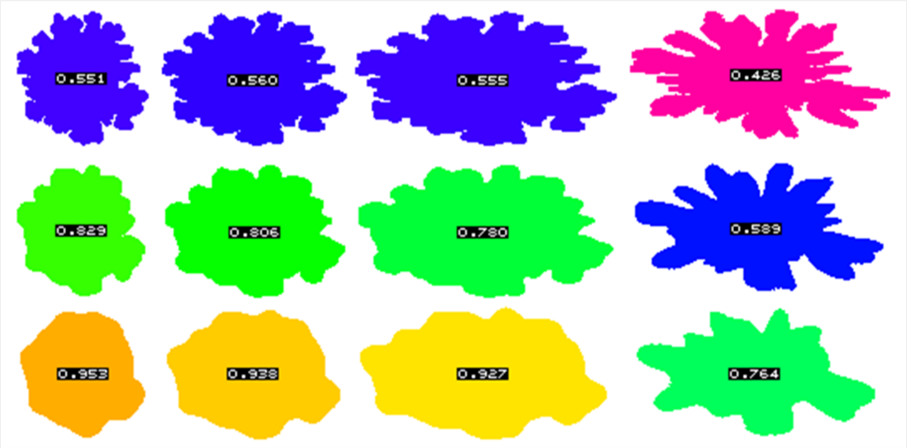
$$\text{Compactness} = \frac{4\pi \cdot \text{Area}}{\text{Perimeter}^2}$$

Convexity

- Convexity is the relative amount that an object differs from a convex object
- A measure of convexity can be obtained by forming the ratio of the perimeter of an objects convex hull to the perimeter of the object itself:

$$\text{Convexity} = \frac{\text{Perimeter}_{\text{convex}}}{\text{Perimeter}_{\text{external}}}$$

Convexity

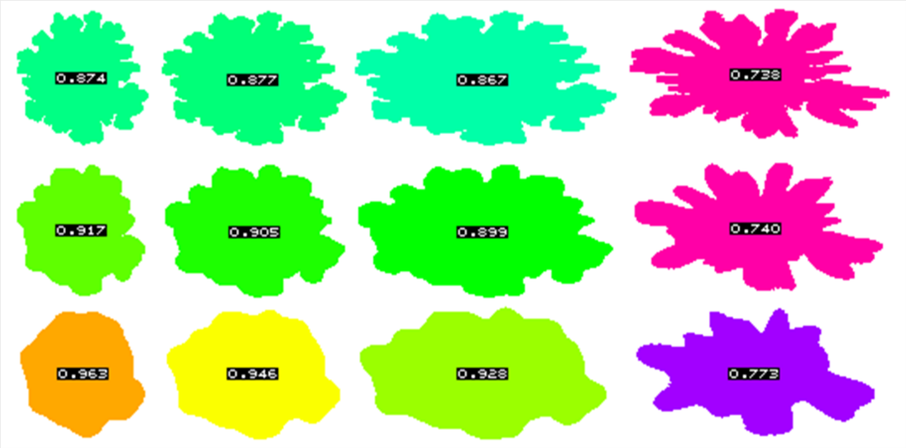


Solidity

- Solidity measures the density of an object
- A measure of solidity can be obtained as the ratio of the area of an object to the area of a convex hull of the object:

$$\text{Solidility} = \frac{\text{Area}}{\text{Area}_{\text{convex}}}$$

Solidility



Fiber length

- Fiber length gives an estimate as to the true length of a threadlike object

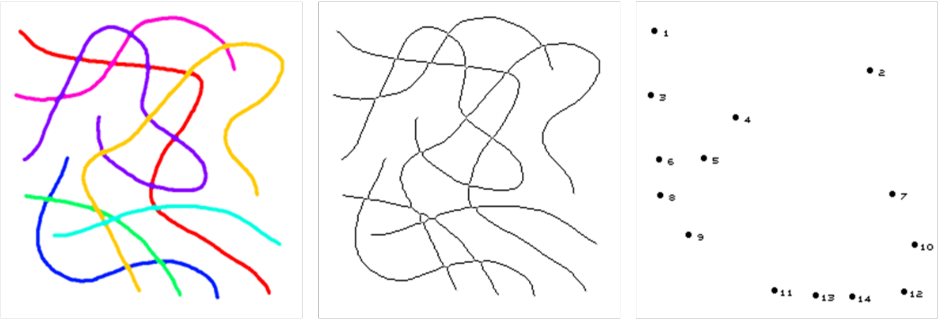
$$\text{FiberLength} = \frac{\text{Perimeter} + (\text{Perimeter}^2 - 16 \cdot \text{Area})^{1/2}}{4}$$

- The estimate is fairly accurate on threadlike objects with a formfactor that is less than 0.25 and gets worse as the formfactor increases

Average Fiber length

- The number of skeleton end-points estimates the number N of fibers (half the number of ends)

$$\text{AverageFiberLength} = \frac{\text{TotalFiberLength}}{N}$$



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1. IEEE Transaction on Pattern Analysis and Machine Intelligence
2. IEEE Transaction on Image Processing International
3. Journal of Computer Vision Image and Vision Computing
4. Pattern Recognition
5. Journal of Mathematical Imaging and Vision
6. Pattern Recognition and Image

Sotware tools

- Photoshop
- GIMP
- ImageJ
- Mathematica and Digital Image Processing Toolbox
- MATLAB: Image Processing Toolbox
- ITK
- VTK
- AVS

Credits

Some materials for this presentation have been draw from public resources available on the World Wide Web.
In particular, most historical data were taken from Klaus Mueller presentation (`http://www.cs.sunysb.edu/~mueller/`).
Some images and data were taken from:

- Gonzalez RC, Woods RE: *Digital Image processing*
- Sam Gahmbir (`http://mips.stanford.edu/public/video_lectures/index.adp`)
- Guy Gilboa, Nir Sochen and Yehoshua Y. Zeevi (`http://www.math.ucla.edu/~gilboa/PDE-based_image_filtering.html`)
- Chunming Li, Chenyang Xu, Changfeng Gui and Martin D. Fox (`http://www.engr.uconn.edu/~cmli/code/`)
- Johns Hopkins University (`http://www.jhu.edu/`)
- Philips, Siemens, GE,...

If you find any omission in the list above, please contact us.