

Lectures 1 & 2: Basic Image Analysis

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Tuesday 10th March 2020
11:15am – 13:15pm

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Basic Image Analysis

- Limited to simple 2D scenes
 - Adequately described as background and objects
- Good contrast between objects and background

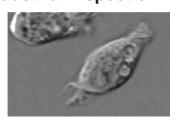
staining or backlighting

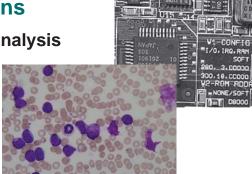
Constrained applications

■ microscopic materials analysis

■ biomedical microscopy

industrial inspection





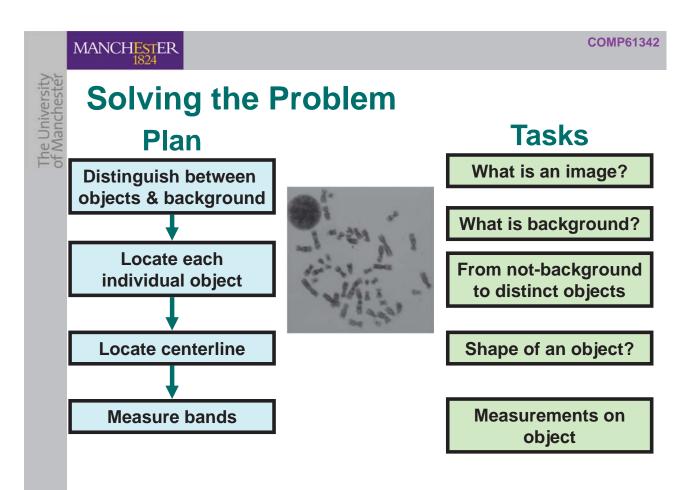
Sample Problem:





- Stained preparation, light microscope
- Chromosomes, with bands
- Measure banding pattern

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Overview:

- Image Representation
 - What is an image?
- Grey-Level Processing
 - Improving the starting image
- Segmentation
 - Background pixels and object pixels
- Binary Image Processing
 - Improved background/object binary image
- Measurement
 - Object as connected region

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Image Representation

Image Representation

- Isn't it totally obvious? We all know what an image is!
- Various ways of representing an image, depending on the task in hand
 - Image function
 - Landscape
 - Array of pixels
 - Image histogram
 - In another space entirely!

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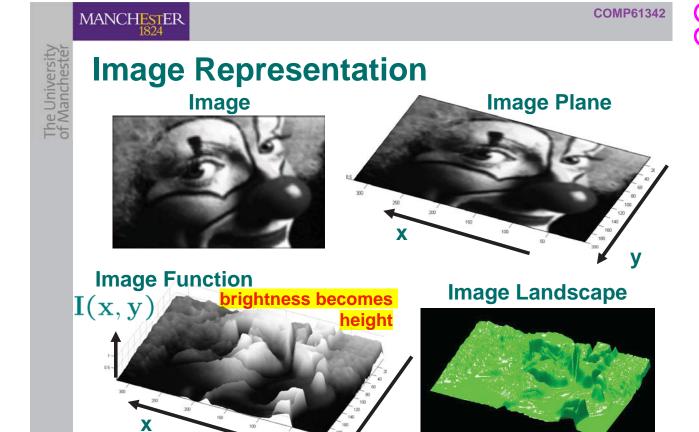
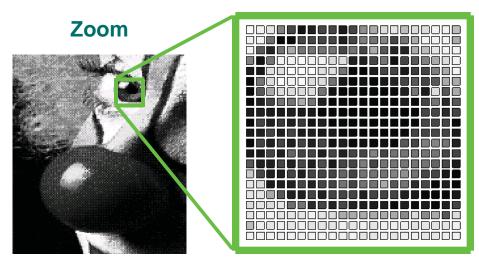
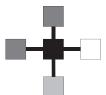


Image Representation



Array of Pixels:
Values and spatial relationship



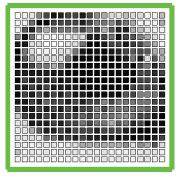
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Image Representation



 Sort pixels by grayscale value/colour and stack them up

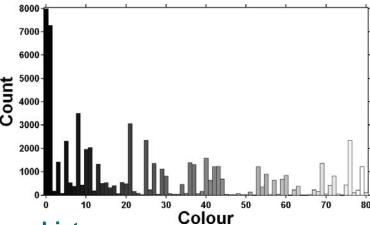
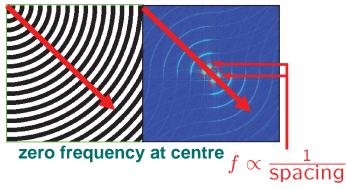


Image histogram:
Kept values but lost spatial information

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Image Representation

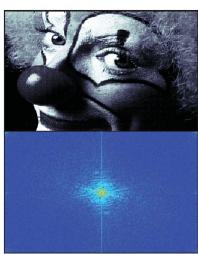
- 傅立叶分析 Fourier Analysis:
 - any signal can be decomposed into a sum of sinusoids (FFT)
 - low frequencies, general shape, high frequencies details





NOTE:

zero frequency removed by subtracting mean value across image from image before doing FFT



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Image Representation

- Frequency Space:
- Integrate over the image, weighted by complex exponentials

$$\mathcal{F}_I(u,v) \propto \iint I(x,y) \exp(iux + ivy) dxdy$$

■ Compact vector form:

$$\mathcal{F}_I(\underline{k}) \propto \iint I(\underline{r}) \exp(i\underline{k} \cdot \underline{r}) d\underline{r}$$

Inverse:

$$I(\underline{r}) \propto \iint \mathcal{F}_I(\underline{k}) \exp(-i\underline{k} \cdot \underline{r}) d\underline{k}$$

NOTE: $e^{i\theta} \equiv \cos\theta + i\sin\theta$ \Rightarrow $\mathcal{F}_{\mathbf{I}}$ complex, $\mathbf{I}(\underline{r})$ real

so $\mathcal{F}_{\mathbf{I}}(-\underline{k}) \equiv \overline{\mathcal{F}}_{\mathbf{I}}(\underline{k})$



Grey-Level Processing

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Grey-Level Processing

Restoration:

- What is noise, what is signal?
- Remove blurring

Enhancement

- Emphasize required features (e.g., linear features)
- Emphasize change (e.g., surveillance)



Grey-Level Processing: Overview

- Point processing
 - Transform global gray-level scale
- Neighbourhood Processing
 - Values and their context (local context & processing)
- Image Arithmetic
 - Using a sequence/pair of images
- Image Transforms
 - Images in a different space (frequency space)

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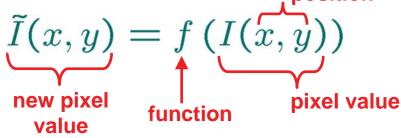


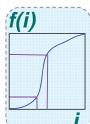
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Grey-Level Processing: Point Processing

Grey-Level Processing: Point Processing

- Point = Pixel
- Transforms image based on single pixel value alone: position





- Various choices for monotonic function f(i)
 - Increase/decrease/stretch brightness and contrast
 - lacksquare Gamma correction, power law : $f(i)=i^{\gamma}$
 - Histogram matching between images
 - Histogram equalization

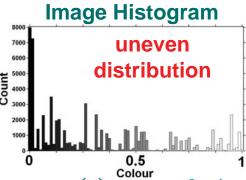
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Point Processing: Histogram Equalisation





- Re-assign colours, keep ordering (light to dark)
- Increase contrast
- n(i): no of pixels with colour i,

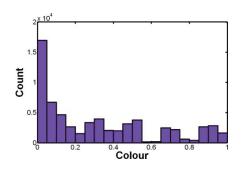
N: Total number

New Colour:
$$f(i) = \frac{1}{N} \sum_{j \le i} n(j)$$

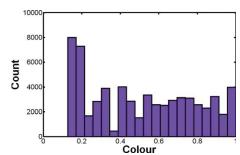
f(i) = 0.75,75% darker than this

Point Processing: Histogram Equalisation





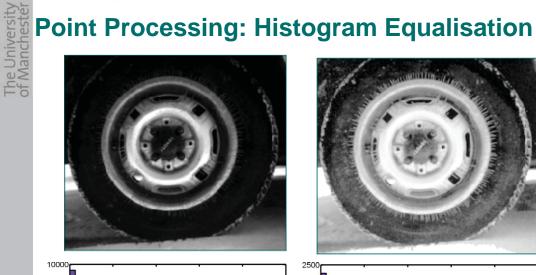




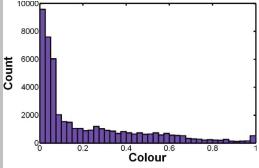
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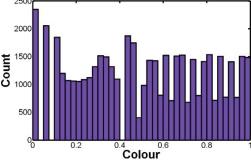
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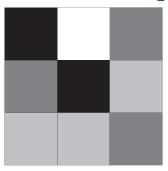


Grey-Level Processing: Neighbourhood Processing

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Neighbourhood Processing

single black pixel

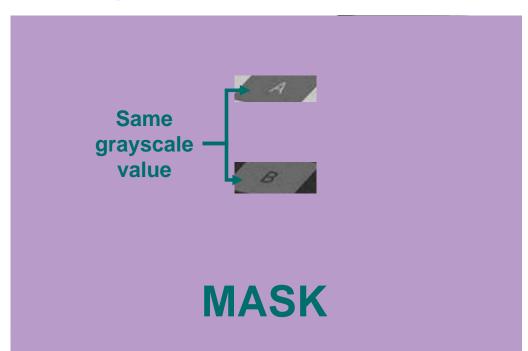


Noisy dark area

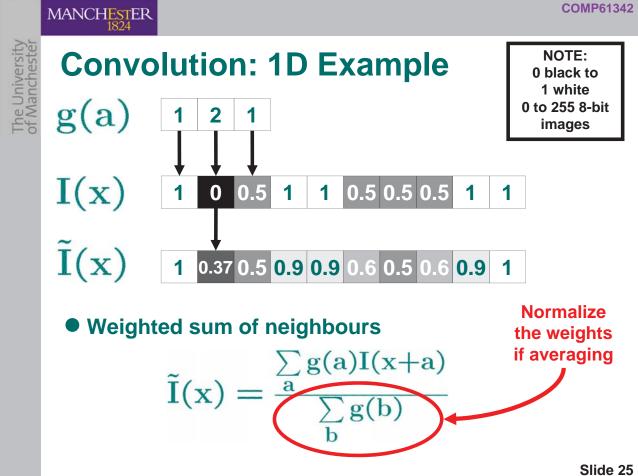
Just noise

- Consider a single pixel value in context of neighbours
- Neighbourhood (e.g. 3 x 3), structuring element (SE)
- Two methods:
 - Convolution
 - Rank Filtering

Aside: Context in Human Vision

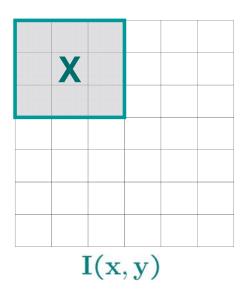


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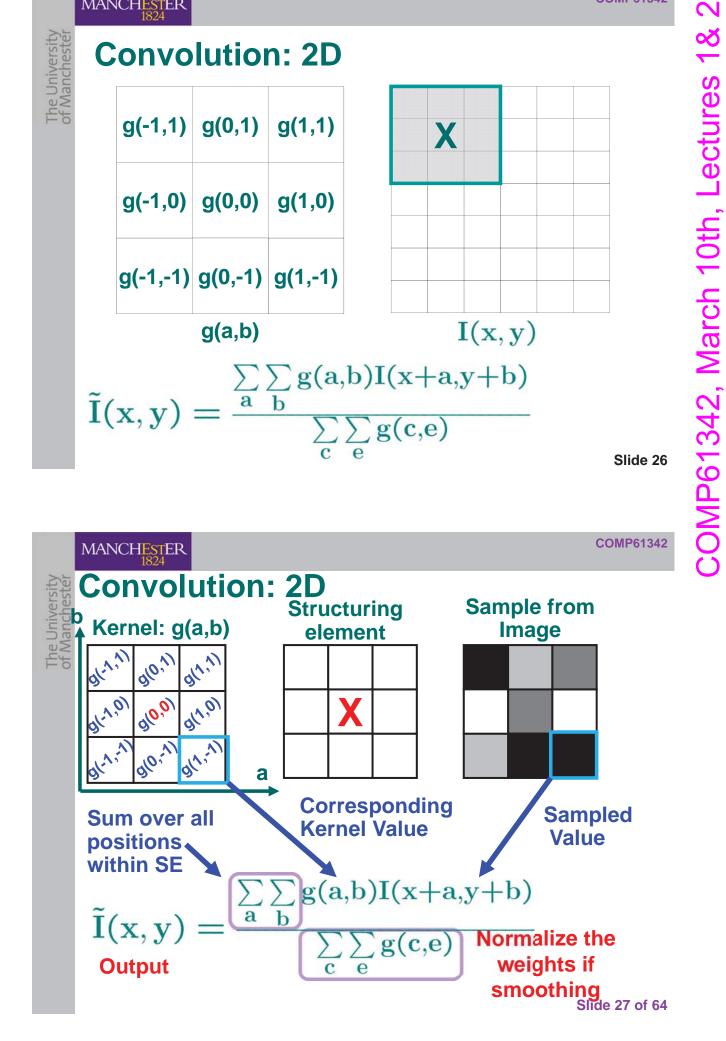
Convolution: 2D

| g(a,b) | | |
|---------|---------|---------|
| (-1,-1) | g(0,-1) | g(1,-1) |
| g(-1,0) | g(0,0) | g(1,0) |
| g(-1,1) | g(0,1) | g(1,1) |
| g(-1,1) | g(0,1) | g(1,1) |



$$\tilde{I}(x,y) = \frac{\sum\limits_{a}\sum\limits_{b}g(a,b)I(x+a,y+b)}{\sum\limits_{c}\sum\limits_{e}g(c,e)}$$

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Convolution: 2D

- Asterisk notation:
 - (but NOT in MATLAB!) $ilde{
 m I}={
 m g}*{
 m I}$
- Discrete form: $\tilde{I}(x,y) = \frac{\sum\limits_{a}\sum\limits_{b}g(a,b)I(x+a,y+b)}{\sum\limits_{c}\sum\limits_{e}g(c,e)}$
- Integral form: $\tilde{I}(x,y) = \frac{\iint g(a,b) I(x+a,y+b) dadb}{\iint g(c,e) dcde}$
- Integral form (vector notation)

$$\underline{r} = (\mathbf{x}, \mathbf{y}), \ \tilde{\mathbf{I}}(\underline{r}) = \frac{\iint \mathbf{g}(\underline{z})\mathbf{I}(\underline{r} + \underline{z})\mathbf{d}\underline{z}}{\iint \mathbf{g}(\underline{y})\mathbf{d}\underline{y}}$$

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Convolution: Common Kernels

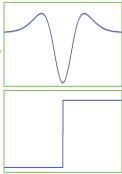
- Gaussian: $g(x,y) = A \exp(-(x^2 + y^2)/2\sigma^2) \sigma$ width
 - Smoothing kernel
 - Any unimodal kernel smoothes the image
- Difference of Gaussian (DoG)

$$g(x, y) = A \exp(-(x^2 + y^2)/2\sigma^2) - B \exp(-(x^2 + y^2)/2\sigma^2)$$

- Laplacian (or Laplacian of Gaussian)
 - similar shape to DoG, second-derivative filter



Give ridges/troughs at edge positions



Convolution Theorem

 $\begin{array}{c} \text{NOTE:} \\ e^{i\theta} \equiv \cos\theta + i\sin\theta \\ \Rightarrow \ \mathcal{F}_{\mathbf{I}} \ \text{complex,} \ \mathbf{I}(\underline{r}) \ \text{real} \\ \text{so} \ \mathcal{F}_{\mathbf{I}}(-\underline{k}) \equiv \overline{\mathcal{F}}_{\mathbf{I}}(\underline{k}) \end{array}$

Frequency space (see Image Representation):

$$\mathcal{F}_I(\underline{k}) \propto \iint I(\underline{r}) \exp(i\underline{k} \cdot \underline{r}) d\underline{r}$$

- Look at it in frequency space or real space:
 - convolution in real space ⇔ multiplication in frequency space

$$\mathbf{g} * \mathbf{I} \iff \mathcal{F}_{\mathbf{g}} \times \mathcal{F}_{\mathbf{I}}, \quad \mathbf{g} * \mathbf{I} \equiv \mathcal{F}^{-1} \left(\mathcal{F}_{\mathbf{g}} \times \mathcal{F}_{\mathbf{I}} \right)$$

■ convolution in frequency space ⇔ multiplication in real space

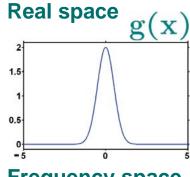
$$\mathcal{F}_{g} * \mathcal{F}_{I} \quad \Longleftrightarrow \quad g \times I, \quad \mathcal{F}_{g} * \mathcal{F}_{I} \equiv \mathcal{F} \left(g \times I \right)$$

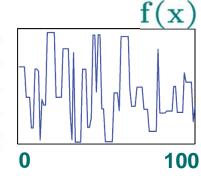
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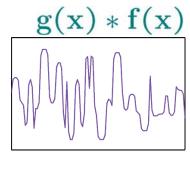
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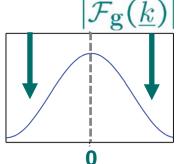
Convolution Theorem: Gaussian

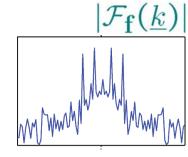


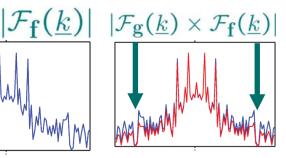






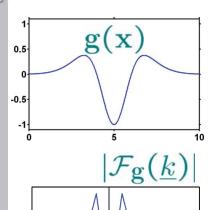






Convolution Theorem: Difference of Gaussians

 $g(x, y) = A \exp(-(x^2 + y^2)/2\sigma^2) - B \exp(-(x^2 + y^2)/2\sigma^2)$



- band-pass filter, enhances edges
- Laplacian and LoG similar





signal at edges

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Convolution Theorem: Laplacian of Gaussian & Difference of Gaussians

Gaussian and FT of Gaussian

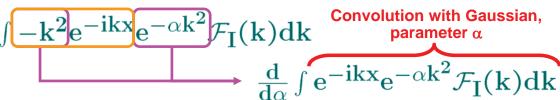
Convolution Theorem

$$\mathbf{g}(\mathbf{x}) \propto \mathrm{e}^{-eta \mathbf{x^2}}, \mathcal{F}_{\mathbf{g}}(\mathbf{k}) \propto \mathrm{e}^{-lpha \mathbf{k^2}} \mathbf{g} * \mathbf{I} \equiv \mathcal{F}^{-1} \left(\mathcal{F}_{\mathbf{g}} imes \mathcal{F}_{\mathbf{I}}
ight)$$

Laplacian of gaussian:

$$\begin{array}{c} \frac{\partial^2}{\partial x^2} \left(\int e^{-ikx} e^{-\alpha k^2} \mathcal{F}_I(k) dk \right) \\ \text{Laplacian} & \text{Inverse FT} \quad \text{Gaussian} & \text{FT of Image} \end{array}$$

Do the derivative:



- LoG: difference of infinitesimally-separated gaussians
- DoG: difference of finitely-separated gaussians



Neighbourhood Processing: Rank Filtering

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Neighbourhood Processing: Rank Filtering

- Output is rank function of neighbourhood:
 - median (smoothes and preserves edges)
 - max and/or min (mathematical morphology)
 - rank number (seven of nine)
- Harder to analyse than convolution



Noisy Image



3x3 mean



3x3 median



Rank Filtering & Edges: Example

Smooth Mean:

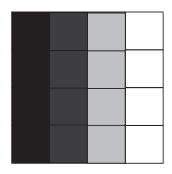
sharp **Median:**

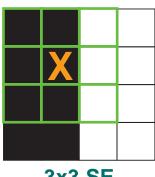
2/3 + 1/3

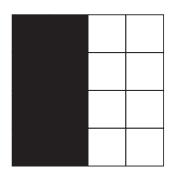
6 8 3

1/3 + 2/3

& 3







3x3 SE

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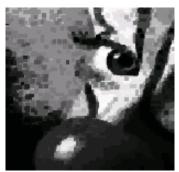
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Neighbourhood Processing: Rank Filtering

- **Rank Number**
 - 3 x 3 structure element





Original

maximum

7th of nine

blocky, impressionistic effect



Grey-Level Processing: Image Arithmetic

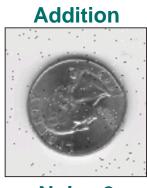
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Image Arithmetic: Addition

- Take average over images in sequence
- Reduces noise





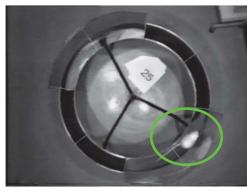


Noisy 1

Noisy 2

Image Arithmetic: Subtraction

- Take difference:
 - Negative values?Shift and scale to get back to [0:255]
 - Or take absolute difference
- Static background, detects change
- Object, shadows & reflections in realworld scenes





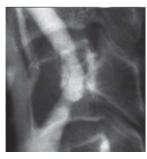
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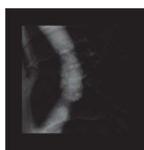
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Image Arithmetic: Subtraction

- Digital subtraction angiography (DSA)
- Pre-study radiograph
- Contrast agent injection
- Post-contrast radiograph
- Difference









Introduction to Segmentation

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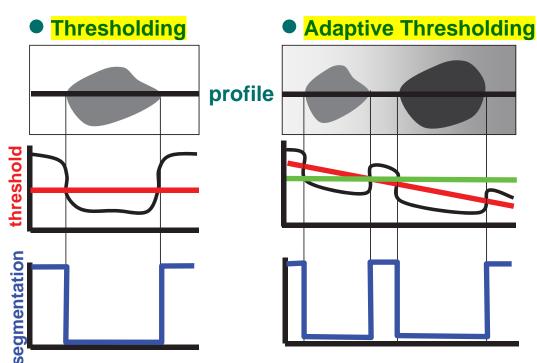
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Segmentation:

Task: label each pixel as either object or background

- Grayscale image → binary label image
- Thresholding
 - simple, high-contrast images
- Adaptive thresholding
 - simple images with shaded background
- Advanced Segmentation
 - open research problem

Segmentation: Thresholding



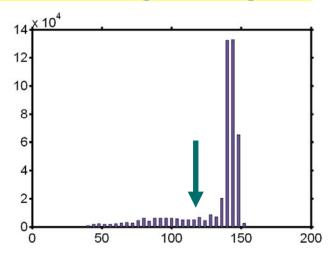
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Segmentation: Thresholding, Histogram





Segmentation: Thresholding

Varying the Threshold







Threshold 110



Threshold 140

- Need to choose threshold with care,
- How to improve the binary image

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Segmentation: Adaptive Thresholding

Original Image

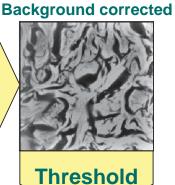


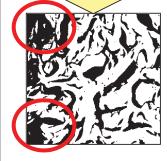
Smoothing

Threshold

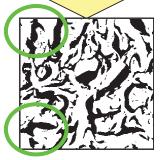


Estimate of varying background





Adaptive thresholding works provided you can obtain reasonable estimate of background shading





Binary Processing

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Binary Processing

Aim: Improved binary image

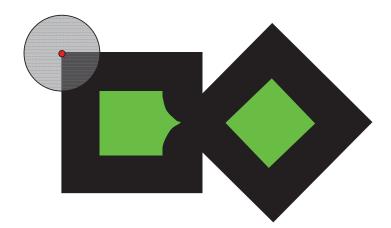
- Restoration or enhancement
- Neighbourhood Processing:
 - binary morphology (erosion & dilation)
 - skeletonization
- Image Logic:
 - combining binary images for more complicated processing

Binary Morphology: Erosion





- Binary object:
- Sweep SE along boundary, and delete region covered



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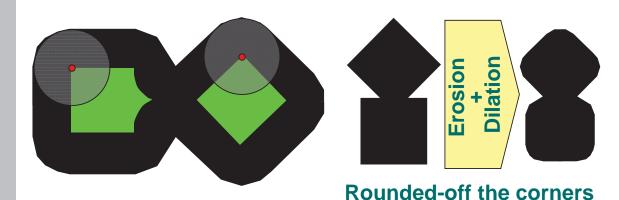
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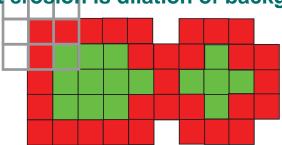
Binary Morphology: Dilation

- Structure element (centre marked):
- Binary object:
- Reverse of erosion
- Sweep SE along boundary, and add region covered



Binary Morphology: Dilation, Implementation via Neighbourhood Processing

- Pixellated structuring element
- Pixellated image object
- Scan SE over image, and add pixel at defined centre if any object pixel lies within SE
- Object erosion is dilation of background, so similar



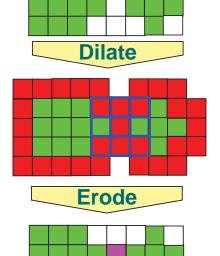
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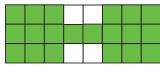
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Binary Morphology: Closing & Opening

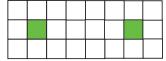
Closing: reconnection



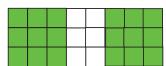
Opening: disconnection



Erode



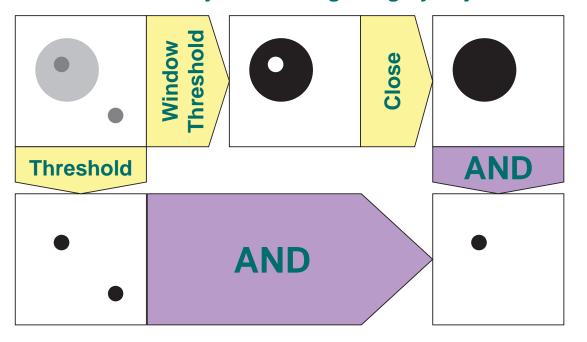
Dilate



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Image Logic:

Want dark object within lighter grey object



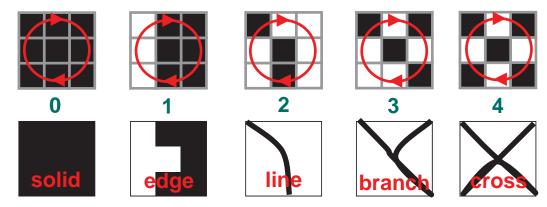
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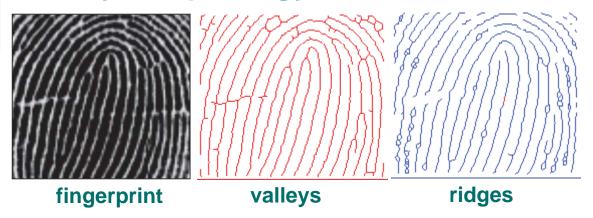
Binary Morphology: Skeletonisation

- Erosion that preserves connections
- Rutovitz Crossing Number: (3x3 SE)
 - loop and half the number of times value changes



- Remove centre pixel if 1: nibble at edge, but leave crossings
- Repeat until no further change

Binary Morphology: Skeletonisation



Feng Zhao and Xiaoou Tang

PREPROCESSING FOR SKELETON-BASED FINGERPRINT MINUTIAE EXTRACTION

CISST'02 International Conference

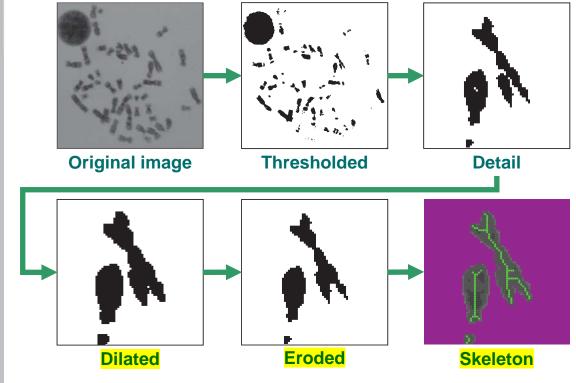
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Chromosome Results:



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Measurement

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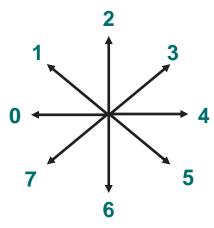
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Simple Measurements on Objects

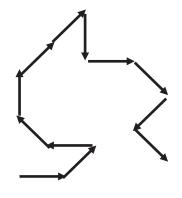
- Extracted objects as above
- Representing Objects:
 - Boundary representation
 - Area representation
- Simple geometric measurements
 - Area
 - Perimeter
 - Circularity

Representing Objects: Boundary

Boundary Representation: chain code



Pick a set of directions



chain code: 4 3 0 1 2 3 3 6 4 5 7 5

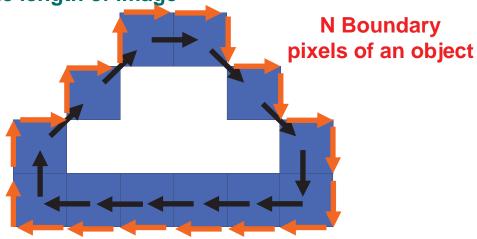
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Representing Objects: Boundary

Positions of boundary pixels: 2N times (one from L)

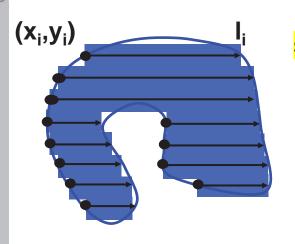
L: side length of image



- Chain code: N times (one of eight)
- OR: ~1.5 N times (one of four)

Representing Objects: Area

Area Representation: Chord List



chord (x_i,y_i,l_i): start position and length

Chord list represents the shape of the pixelated object

Much more efficient representation of data compared to storing position of every pixel within the region!

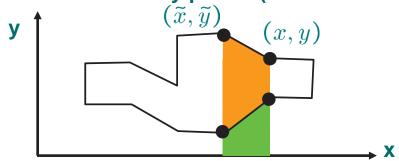
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Measurement: Area

List of all boundary points (derived from chord list)

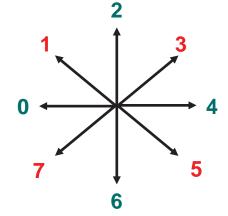


- Trapezoidal rule Area = $\frac{(y+\tilde{y})(x-\tilde{x})}{2}$
- Take difference to find area of strip of shape

Measurement: Perimeter

- 8-piece Chain Code:
- Diagonals are longer!

$$P = N_{even} + \sqrt{2}N_{odd}$$



- 4-piece chain code: P = N, all equal length
- Circularity: $C = \frac{4\pi \text{Area}}{P^2}$,
- C=1 for circle, C<1 for anything else</p>

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Summary

Basic Image Analysis:

- Mostly straightforward and fairly intuitive
- Can give good results on suitable images
- Have to grasp basics before can move on to more sophisticated methods