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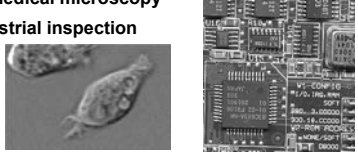
## Lectures 1 & 2: Basic Image Analysis

Dr Carole Twining  
Thursday 18th March  
10:00am – 12:00am

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## Basic Image Analysis

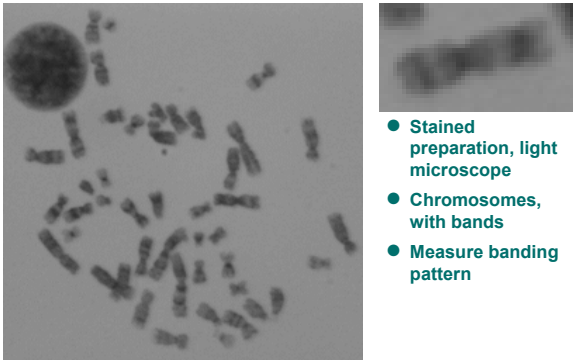
- Limited to simple 2D scenes
  - Adequately described as background and objects
- Good contrast between objects and background
  - staining or backlighting
- Constrained applications
  - microscopic materials analysis
  - biomedical microscopy
  - industrial inspection



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## Sample Problem:



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

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## Solving the Problem

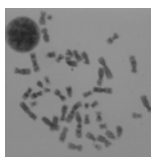
### Plan

```

graph TD
    A[Distinguish between objects & background] --> B[Locate each individual object]
    B --> C[Locate centerline]
    C --> D[Measure bands]
          
```

### Questions

- What is an image?
- What is background?
- From not-background to distinct objects
- Shape of an object?
- Measurements on object



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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

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## 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

Image

Image Plane

Image Function  $I(x, y)$  brightness becomes height

Image Landscape

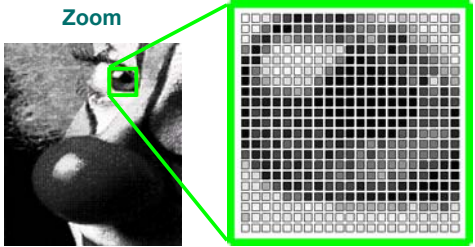
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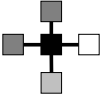
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## Image Representation

Zoom



Array of Pixels:  
Values and spatial relationship



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## Image Representation

Sort pixels by grayscale value/colour and stack them up

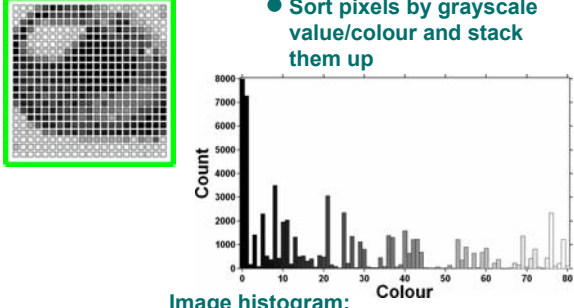


Image histogram:  
Kept values but lost spatial information

Slide 10

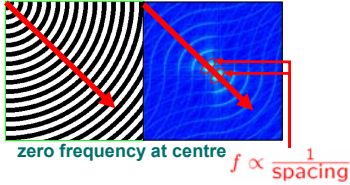
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## Image Representation

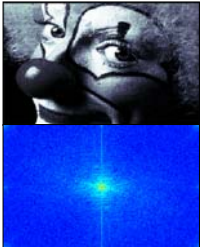
Fourier Analysis:

- any signal can be decomposed into a sum of sinusoids (FFT)
- low frequencies, general shape, high frequencies details



zero frequency at centre  $f \propto \frac{1}{\text{spacing}}$

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

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

- 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:  
 $e^{i\theta} \equiv \cos \theta + i \sin \theta$   
 $\Rightarrow \mathcal{F}_I$  complex,  $I(\underline{r})$  real  
so  $\mathcal{F}_I(-\underline{k}) \equiv \overline{\mathcal{F}_I(\underline{k})}$

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## 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)

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## Grey-Level Processing: Overview

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

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## Grey-Level Processing: Point Processing

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### Grey-Level Processing: Point Processing

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

$$\bar{I}(x, y) = f(I(x, y))$$

new pixel value      function      pixel value  
 position

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

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### Point Processing: Histogram Equalisation

Image Histogram

uneven distribution

- Re-assign colours, keep ordering (light to dark)
- Increase contrast

$n(i)$  : no of pixels with colour  $i$ ,  
 $N$  : Total number

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

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

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### Point Processing: Histogram Equalisation

Slide 19

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### Point Processing: Histogram Equalisation

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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

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## Aside: Context in Human Vision

Same grayscale value

MASK

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## Convolution: 1D Example

NOTE:  
0 black to  
1 white  
0 to 255 8-bit  
images

$g(a)$     1   2   1

$I(x)$     1   0   0.5   1   1   0.5   0.5   0.5   1   1

$\tilde{I}(x)$     1   0.37   0.5   0.9   0.9   0.6   0.5   0.6   0.9   1

- Weighted sum of neighbours

$$\tilde{I}(x) = \frac{\sum_a g(a)I(x+a)}{\sum_b g(b)}$$

Normalize the weights

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### Convolution: 2D

$g(-1,1)$	$g(0,1)$	$g(1,1)$
$g(-1,0)$	$g(0,0)$	$g(1,0)$
$g(-1,-1)$	$g(0,-1)$	$g(1,-1)$

$$\tilde{I}(x,y) = \frac{\sum_a \sum_b g(a,b) I(x+a,y+b)}{\sum_c \sum_e g(c,e)}$$

Normalize the weights

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### Convolution: 2D

- Asterisk notation:  $\tilde{I} = g * I$
- Discrete form: 
$$\tilde{I}(x,y) = \frac{\sum_a \sum_b g(a,b) I(x+a,y+b)}{\sum_c \sum_e g(c,e)}$$
- Integral form: 
$$\tilde{I}(x,y) = \frac{\iint g(a,b) I(x+a,y+b) da db}{\iint g(c,e) dc de}$$
- Integral form (vector notation)  
 $\underline{r} = (x,y), \tilde{I}(\underline{r}) = \frac{\iint g(\underline{z}) I(\underline{r}+\underline{z}) d\underline{z}}{\iint g(\underline{y}) d\underline{y}}$

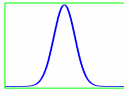
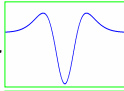
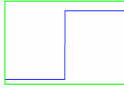
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### Convolution: Common Kernels

- **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)**  
 $g(x,y) = A \exp(-(x^2 + y^2)/2\sigma^2) - B \exp(-(x^2 + y^2)/2\alpha^2)$
- **Laplacian (or Laplacian of Gaussian)**
  - similar shape to DoG, second-derivative filter
- **First-derivative edge filters**
  - ridges at edge positions

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### Convolution Theorem

**NOTE:**  
 $e^{i\theta} \equiv \cos \theta + i \sin \theta$   
 $\Rightarrow \mathcal{F}_I$  complex,  $I(\underline{r})$  real  
 so  $\mathcal{F}_I(-\underline{k}) \equiv \overline{\mathcal{F}_I(\underline{k})}$

- **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  $\Leftrightarrow$  multiplication in frequency space  
 $g * I \Leftrightarrow \mathcal{F}_g \times \mathcal{F}_I, \quad g * I \equiv \mathcal{F}^{-1}(\mathcal{F}_g \times \mathcal{F}_I)$
  - convolution in frequency space  $\Leftrightarrow$  multiplication in real space  
 $\mathcal{F}_g * \mathcal{F}_I \Leftrightarrow g \times I, \quad \mathcal{F}_g * \mathcal{F}_I \equiv \mathcal{F}(g \times I)$

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## Convolution Theorem: Gaussian

Real space  $g(x)$   $f(x)$   $g(x) * f(x)$

Frequency space  $|\mathcal{F}_g(k)|$   $|\mathcal{F}_f(k)|$   $|\mathcal{F}_g(k) \times \mathcal{F}_f(k)|$

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## Convolution Theorem: Difference of Gaussians

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

- 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

$g(x) \propto e^{-\beta x^2}, \mathcal{F}_g(k) \propto e^{-\alpha k^2}$   $g * I \equiv \mathcal{F}^{-1}(\mathcal{F}_g \times \mathcal{F}_I)$

Laplacian of gaussian:

$$\frac{\partial^2}{\partial x^2} \left( \int e^{-ikx} e^{-\alpha k^2} \mathcal{F}_I(k) dk \right)$$

Laplacian  $\uparrow$  Inverse FT  $\uparrow$  Gaussian  $\uparrow$  FT of Image

Do the derivative:

$$\int -k^2 e^{-ikx} e^{-\alpha k^2} \mathcal{F}_I(k) dk$$

Convolution with Gaussian, parameter  $\alpha$

$$\frac{d}{d\alpha} \int e^{-ikx} e^{-\alpha k^2} \mathcal{F}_I(k) dk$$

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

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## 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

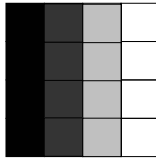
Slide 33

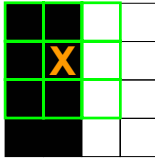
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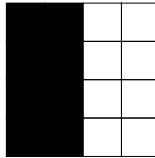
### Rank Filtering & Edges: Example

- Mean:
  - $2/3 \blacksquare + 1/3 \square = \blacksquare$
  - $1/3 \blacksquare + 2/3 \square = \square$
- Median:
  - $6 \blacksquare \& 3 \square \Rightarrow \blacksquare$
  - $6 \square \& 3 \blacksquare \Rightarrow \square$





3x3 SE




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### Neighbourhood Processing: Rank Filtering

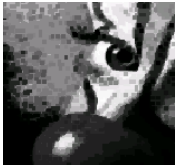
- Rank Number
  - 3 x 3 structure element



Original



maximum



7<sup>th</sup> of nine

blocky, impressionistic effect

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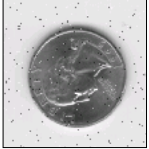

### Grey-Level Processing: Image Arithmetic

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## Image Arithmetic: Addition

- Take average over images in sequence
- Reduces noise

	
Original	Addition
	
Noisy 1	Noisy 2

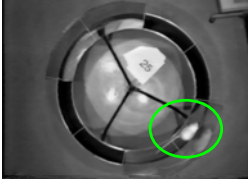
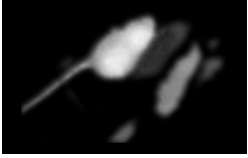
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## Image Arithmetic: Subtraction

- 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 real-world scenes




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## Image Arithmetic: Subtraction

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

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## Introduction to Segmentation

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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

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## Segmentation: Thresholding

- Thresholding
- Adaptive Thresholding

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## Segmentation: Thresholding, Histogram

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## Segmentation: Thresholding

- Varying the Threshold

Threshold 100    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

Estimate of varying background

Subtract

Background corrected

Threshold

Threshold

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

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## 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

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## Binary Morphology: Erosion


- Structure element (example, centre marked):
- Binary object:
- Sweep SE along boundary, and delete region covered

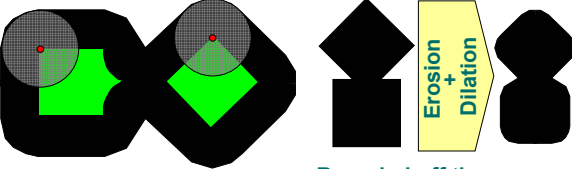
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## Binary Morphology: Dilation

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





Rounded-off the corners

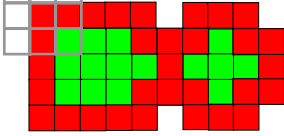
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## Binary Morphology: Dilation, Implementation via Neighbourhood Processing

- 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



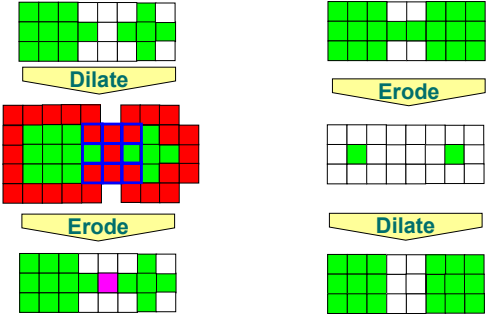
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## Binary Morphology: Closing & Opening

- Closing: reconnection
- Opening: disconnection



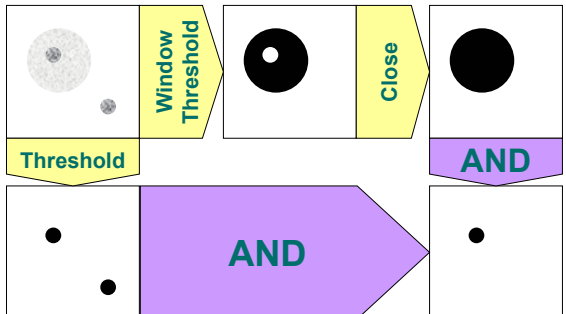
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## Image Logic:

Want dark object within grey object



Slide 52

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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

0 1 2 3 4

solid edge line branch cross

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

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## Binary Morphology: Skeletonisation

fingerprint valleys ridges

Feng Zhao and Xiaou Tang  
 PREPROCESSING FOR SKELETON-BASED  
 FINGERPRINT MINUTIAE EXTRACTION  
 CISST'02 International Conference

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## Chromosome Results:

Original image Thresholded Detail

Dilated Eroded Skeleton

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## Measurement

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## Simple Measurements on Objects

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

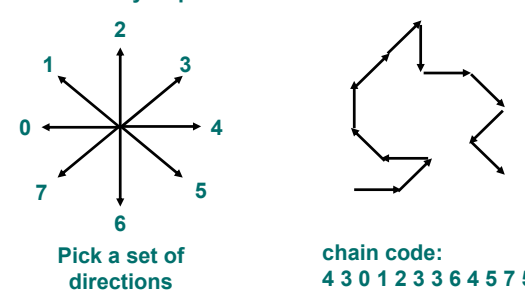
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## Representing Objects: Boundary

- Boundary Representation: chain code



Pick a set of directions

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

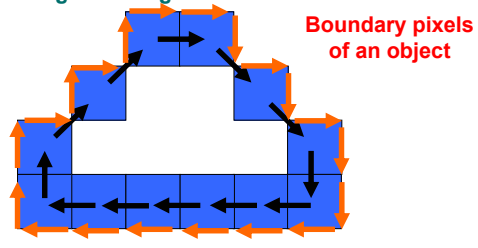
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## Representing Objects: Boundary

- Positions of boundary pixels:  $2N$  times (one from L)
- L: side length of image



Boundary pixels of an object

- Chain code:  $N$  times (one of eight)
- OR:  $\sim 1.5 N$  times (one of four)

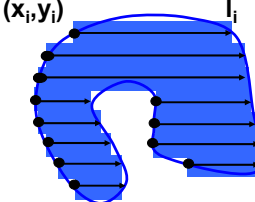
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## Representing Objects: Area

- Area Representation: Chord List



$(x_i, y_i)$   $l_i$

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!

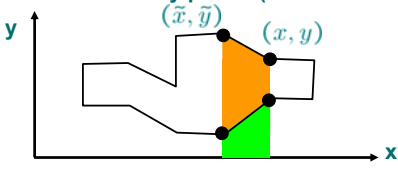
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## Measurement: Area

- List of all boundary points (derived from chord list)



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

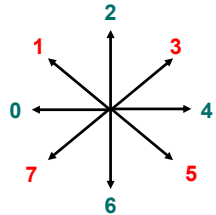
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## Measurement: Perimeter

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

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


- 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

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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

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