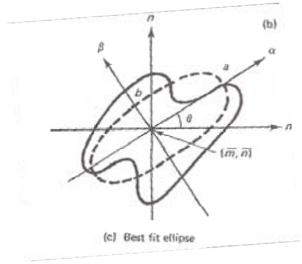
INF 4300 – Digital Image Analysis

OBJECT DESCRIPTION - FEATURE EXTRACTION



Fritz Albregtsen 19.10.2016

Today

We go through
G&W section 11.2 Boundary Descriptors
G&W section 11.3 Regional Descriptors
Curriculum includes these lecture notes.

We cover the following :
1. Introduction
2. Topological features
3. Projections
4. Geometric features
5. Statistical shape features
6. Moment-based geometric features

Also remember that texture features are regional descriptors!

What is feature extraction?

- Devijver and Kittler (1982):
  ”Extracting from the raw data the information which is most relevant for classification purposes, in the sense of minimizing the within-class pattern variability while enhancing the between-class variability”.
  - Within-class pattern variability: variance between objects belonging to the same class. AAAAAAAAAAA
  - Between-class pattern variability: variance between objects from different classes.
    A B C D E F G H I J

Feature extraction

- We will discriminate between different object classes based on a set of features.
- The features are chosen given the application.
- Normally, a large set of different features is investigated.
- Classifier design also involves feature selection
  - selecting the best subset out of a larger feature set.
- Given a training data set of a certain size, the dimensionality of the feature vector must be limited.
- Careful selection of an optimal set of features is an important step in image classification!

Feature extraction methods

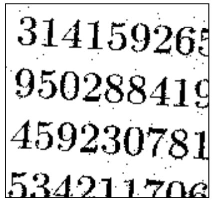
- There are a lot of different feature extraction methods, you will only learn some in this course.
- The focus of this lecture is on **features for describing the <u>shape</u> of an object**.
  - i.e., recipes to extract features characterizing object shape.
- Features can also be extracted in local windows around each pixel, e.g. using texture descriptors.
- The features will later be used for object recognition/classification.

Describing the shape of a segmented object

Assumptions:

- We have a segmented, labeled image.
- Each object that is to be described has been identified during segmentation.
  - Ideally, one region in the segmented image should correspond to one object.
  - One object should not be fragmented into several non-connected regions.
  - Some small noise objects will often occurr, but these can often be removed later.

    (… lecture on mathematical morphology)



Example 1: Recognize printed numbers

- Goal: get the series of digits, e.g. 14159265358979323846……

Steps in the program:

1. Segment the image to find digit pixels.
2. Find angle of rotation and rotate back.
3. Create region objects – one object pr. digit or connected component.
4. Compute features describing shape of objects
5. Train a classifier on many objects of each digit.
6. Assign a class label to each new object, i.e., the class with the highest probability.

Example 2: Recognize music symbols

- Goal: interpret the notes and symbols to create a MIDI-file and then play it!

Steps in the program:

1. Segment the image to find symbol pixels.
2. Find angle of rotation and rotate back.
3. Find the note lines and remove them.
4. Create regions objects for connected components.
5. Match each object with a known object class (whole note, quarter note, rest, bar, etc.) based on object features.
6. For all notes: find note height given its vertical position.
7. Create a MIDI file from this.

Typical image analysis tasks

- Preprocessing/noise filtering
- Segmentation
- Feature extraction
  - Are the original image pixel values sufficient for classification, or do we need additional features?
  - What kind of features do we use in order to discriminate between the object classes involved?
- Exploratory feature analysis and selection
  - Which features separate the object classes best?
  - How many features are needed?
- Classification (next three lectures)
  - From a set of object examples with known class, decide on a method that separates objects of different types.
  - For new objects: assign each object/pixel to the class with the highest probability
- Validation of classifier accuracy

Topologic features

- This is a group of invariant integer features
  - Invariant to position, rotation, scaling, warping
- Features based on the object skeleton
  - Number of terminations (one line from a point)
  - Number of breakpoints or corners (two lines from a point)
  - Number of branching points (three lines from a point)
  - Number of crossings (> three lines from a point)
- Region features:
  - Number of holes in the object (H)
  - Number of components (C)
  - Euler number, E = C - H
    - Number of connected components – number of holes
  - Symmetry

Region with two holes

Regions with three connected components

1D Projection histograms

- For each row in the region, count the number of object pixels.

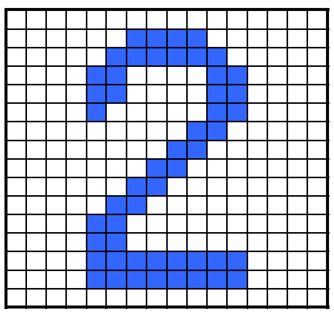
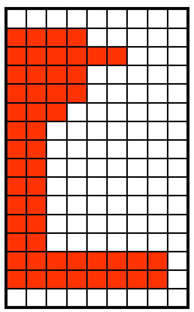


Image – binary region pixels



Row histogram

Projections

- 1D horizontal projection of the region:

$$p_h(x) = \sum_y f(x,y)$$

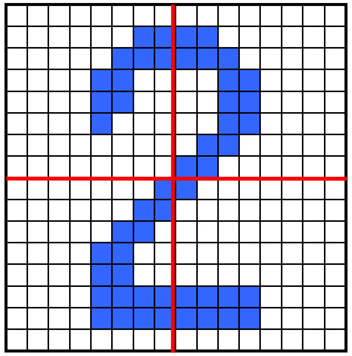
- 1D vertical projection of the region:

$$p_v(y) = \sum_x f(x,y)$$

- f(x,y) is normally the binary segmented image
- Can be made scale independent by using a fixed number of bins and normalizing the histograms.
- Radial projection in reference to centroid -> ”signature”.

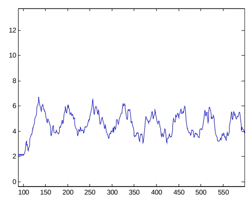
Use of projection histograms

- Divide the object into different regions and compute projection histograms for each region.
  - How can we use this to separate 6 and 9?
- Compute features from the histograms.
  - E.g. mean and variance of the histograms.
- The histograms can also be used as features directly.

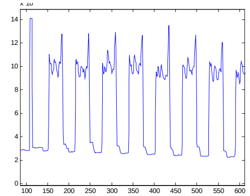


Use of projection histograms

- Check if a page with text is rotated

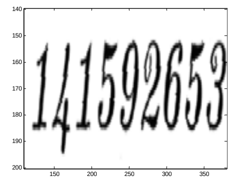


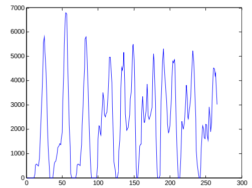
Y-axis projection of page



Y-axis projection after rotation correction

- Detecting lines, connected objects or single symbols





x-axis projection of page

Geometric features from contours

- Boundary length/perimeter
- Area
- Curvature
- Diameter/major/minor axis
- Eccentricity
- Bending energy
- Basis expansion (Fourier – last week)

Object area

- Generally, the area is defined as: $A = \int_X \int_Y I(x,y)\,dxdy$

  I(x,y) = 1 if the pixel is within the object, and 0 otherwise.
- In digital images: $A = \sum_X \sum_Y I(x,y)\,\Delta A$

  ΔA = area of one pixel. If ΔA = 1, area is simply measured in pixels.
- Area changes if we change the scale of the image
  - change is not perfectly linear, because of the discretization of the image.
- Area ≈ invariant to rotation (except small discretization errors).

Perimeter length from chain code

- Distance measure differs when using 8- or 4-neighborhood
- Using 4-neighborhood, measured length ≥ actual length.
- In 8-neighborhood, fair approximation from chain code by:

$$P_F = n_E + n_O\sqrt{2}$$

- This overestimates real perimeters systematically.
- Freeman (1970) computed the area and perimeter of the chain by

$$A_F = \sum_{i=1}^{N} c_{ix}\left(y_{i-1} + {c_{iy}}/{2}\right), \quad P_F = n_E + n_O\sqrt{2}$$

- where **N** is the length of the chain, $\mathbf{c_{ix}}$ and $\mathbf{c_{iy}}$ are the **x** and **y** components of the **i**th chain element $\mathbf{c_i}$ ($\mathbf{c_{ix}}$, $\mathbf{c_{iy}}$ = {1, 0, -1} indicate the change of the **x**- and **y**-coordinates), $\mathbf{y_{i-1}}$ is the **y**-coordinate of the start point of the chain element $\mathbf{c_i}$. $\mathbf{n_E}$ is the number of even chain elements and $\mathbf{n_O}$ the number of odd chain elements**.**

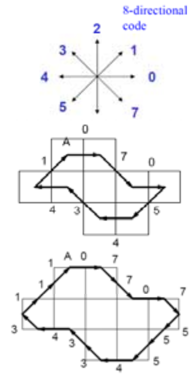
Chain code

- Vossepoel and Smeulders (1982) improved perimeter length estimate by a corner count $\mathbf{n_C}$, defined as the number of occurrences of unequal consecutive chain elements:

$$P_{VS} = 0.980\,n_E + 1.406 n_O - 0.091\,n_C$$

- Kulpa (1977) gave the perimeter as

$$P_K = \frac{\pi}{8}\left(1+\sqrt{2}\right)\left(n_E + \sqrt{2}n_O\right)$$



Pattern matching - bit quads

- Let n{Q} = number of matches between image pixels and pattern Q.
- Then area and perimeter of 4-connected object is given by:

$$A = n\{1\}, \quad P = 2n\{0 \quad 1\} + 2n\begin{Bmatrix}0\\1\end{Bmatrix}$$

Bit Quads handle 8-connected images:

$$Q_0: \begin{bmatrix}0&0\\0&0\end{bmatrix}$$
$$Q_1: \begin{bmatrix}1&0\\0&0\end{bmatrix}\begin{bmatrix}0&1\\0&0\end{bmatrix}\begin{bmatrix}0&0\\0&1\end{bmatrix}\begin{bmatrix}0&0\\1&0\end{bmatrix}$$
$$Q_2: \begin{bmatrix}1&1\\0&0\end{bmatrix}\begin{bmatrix}0&1\\0&1\end{bmatrix}\begin{bmatrix}0&0\\1&1\end{bmatrix}\begin{bmatrix}1&0\\1&0\end{bmatrix}$$
$$Q_3: \begin{bmatrix}1&1\\0&1\end{bmatrix}\begin{bmatrix}0&1\\1&1\end{bmatrix}\begin{bmatrix}1&0\\1&1\end{bmatrix}\begin{bmatrix}1&1\\1&0\end{bmatrix}$$
$$Q_4: \begin{bmatrix}1&1\\1&1\end{bmatrix}$$
$$Q_D: \begin{bmatrix}1&0\\0&1\end{bmatrix}\begin{bmatrix}0&1\\1&0\end{bmatrix}$$

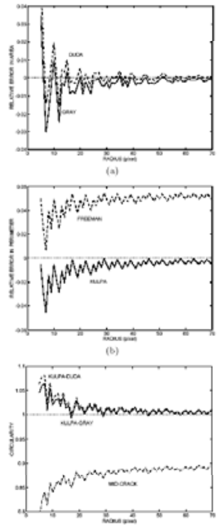
- Gray (1971) gave area and the perimeter as

$$A_G = \frac{1}{4}\left[n\{Q_1\} + 2n\{Q_2\} + 3n\{Q_3\} + 4n\{Q_4\} + 2n\{Q_D\}\right], \quad P_G = n\{Q_1\} + n\{Q_2\} + n\{Q_3\} + 2n\{Q_D\}$$

- More accurate formulas by Duda :
- $$A_D = \frac{1}{4}\left[n\{Q_1\} + 2n\{Q_2\} + \frac{7}{2}n\{Q_3\} + 4n\{Q_4\} + 3n\{Q_D\}\right], \quad P_D = n\{Q_2\} + \frac{1}{\sqrt{2}}\left[n\{Q_2\} + n\{Q_3\} + 2n\{Q_D\}\right]$$

A comparison of methods

- We have tested the methods on circles, R ={5,…,70}.
- Area estimator :
  - Duda is slightly better than Gray.
- Perimeter estimator :
  - Kulpa is more accurate than Freeman.
- Circularity :
  - Kulpa's perimeter and Gray's area gave the best result.
- Errors and variability largest when R is small.
- Best area and perimeter not computed simultaneously.
- Gray's area can be computed using discrete Green's theorem, suggesting that the two estimators can be computed simultaneously during contour following.



Object area from contour

- The surface integral over S (having contour C) is given by Green's theorem:

```
s := 0.0;
n := n + 1;

pkt[n].x := pkt[1].x;
pkt[n].y := pkt[1].y;
for i:=2 step 1 until n do
begin
        dy := pkt[i].y - pkt[i-1].y
        s := s + (pkt[i].x + pkt[i-1].x)/2 * dy;
end;
area := if (s > 0) then s else -s;
```

$$A = \iint_S dxdy = \int_C xdy$$

- The region can also be represented by n polygon vertices

where the sign of the sum reflects the polygon orientation.

$$\hat{A} = \frac{1}{2}\left|\sum_{k=0}^{N-1}(x_k\, y_{k+1} - x_{k+1}\, y_k)\right|$$

Compactness and circularity

- Compactness (very simple measure)
  - γ = $P^2/(4\pi A)$, where P = Perimeter, A = Area,
  - For a circular disc, γ is minimum and equals 1.
  - Compactness attains high value for complex object shapes, but also for very elongated simple objects, like rectangles and ellipses where a/b ratio is high.

  => Compactness is not correlated with complexity!

- Note that G&W defines
  - Compactness = P^2/A
  - Circularity ratio = $4\pi A/P^2$

Circularity and irregularity

- Circularity may be defined by C = $4\pi A/P^2$.
- C = 1 for a perfect continuous circle; betw. 0 and 1 for other shapes.
- In digital domain, C takes its smallest value for a
  - digital octagon in 8-connectivity perimeter calculation
  - digital diamond in 4-connectivity perimeter calculation
- Dispersion may be given as the major chord length to area
- Irregularity can be defined as:

$$D = \frac{\pi \max\left((x_i - \bar{x})^2 - (y_i - \bar{y})^2\right)}{A}$$

  - where the numerator is the area of the centered enclosing circle.
- Alternatively, ratio of maximum and minimum centered circles:

$$I = \frac{\max\left(\sqrt{(x_i - \bar{x})^2 - (y_i - \bar{y})^2}\right)}{\min\left(\sqrt{(x_i - \bar{x})^2 - (y_i - \bar{y})^2}\right)}$$

Curvature

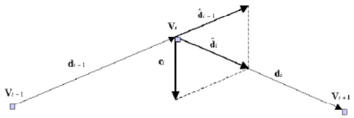
- In the continous case, curvature is the rate of change of slope.

$$|\kappa(s)|^2 = \left[\frac{d^2x}{ds^2}\right]^2 + \left[\frac{d^2y}{ds^2}\right]^2$$

- In the discrete case, difficult because boundary is locally ragged.
- Use difference between slopes of adjacent boundary segments to describe curvature at point of segment intersection.
- Curvature can be calculated from chain code.

Discrete computation of curvature

- Trace the boundary and insert vertices, at a given distance (e.g. 3 pixels apart), or by polygonization (previous lecture).



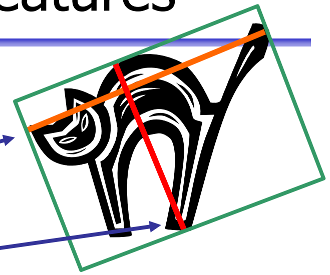
v_i: edge segment i
$d\hat{}_{t-1}$: unit vectors of edge segments d_{t-1} and dt
c_i: local curvature at point i

- Compute local curvature c_i as the difference between the directions of two edge segments joining a vertex:

$$c_i = \vec{d}_i - \vec{d}_{i-1}$$

- Curvature feature: sum all local curvature measures along the border.
- More complex regions get higher curvature.

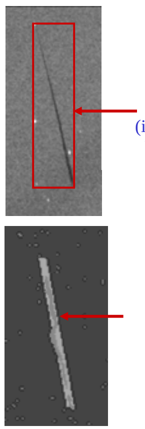
Contour based features



- Diameter = Major axis (a)
  Longest distance of a line segment
  connecting two points on the perimeter
- Minor axis (b)
  Computed along a direction perpendicular to the major axis. Largest length possible between two border points in the given direction.
- "Eccentricity" of the contour (a/b)
  - This is a very rough estimate!

Bounding box and CH features

- Regular bounding box
  - Width/height of bounding box
  - Centre of mass position in box
- If the object's orientation is known, a bounding box can also be oriented along this direction.
- Extent = Area/(Area of bounding box)
  - But which type of bounding box?
- Solidity = Area/(Area of Convex Hull) (also termed "convexity")



Moments

- Borrows ideas from physics and statistics.
- For a given continuous intensity distribution *g(x, y)* we define moments m_{pq} by

$$m_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q g(x, y) dx dy$$

- For sampled (and bounded) intensity distributions f(x, y)

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y)$$

- A moment m_{pq} is said to be of *order* p + q.

Moments from binary images

- For binary images, where
  - f (x, y) = 1 ⇒ object pixel
  - f (x, y) = 0 ⇒ background pixel
- Area

$$m_{00} = \sum_x \sum_y f(x,y)$$

- Center of mass / ”tyngdepunkt”

$$m_{10} = \sum_x \sum_y x f(x,y) = \bar{x} m_{00} \quad \Rightarrow \quad \bar{x} = \frac{m_{10}}{m_{00}}$$

$$m_{01} = \sum_x \sum_y y f(x,y) = \bar{y} m_{00} \quad \Rightarrow \quad \bar{y} = \frac{m_{01}}{m_{00}}$$

Grayscale moments

- In gray scale images, we may regard *f(x,y)* as a discrete 2-D probability distribution over (x,y)
- For probability distributions, we should have

$$m_{00} = \sum_x \sum_y f(x,y) = 1$$

  – And if this is not the case we can normalize by

$$F(x,y) = f(x,y)/m_{00}$$

Central moments

- These are position invariant moments, defined by

$$\mu_{p,q} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y)$$

- where

$$\bar{x} = \frac{m_{10}}{m_{00}}, \qquad \bar{y} = \frac{m_{01}}{m_{00}}$$

- The total mass, and the center of mass coordinates are given by

$$\mu_{00} = \sum_x \sum_y f(x,y), \qquad \mu_{10} = \mu_{01} = 0$$

- This corresponds to computing ordinary moments after having translated the object so that center of mass is in origo.
- Central moments are independent of position, but are not scaling or rotation invariant.
- Q: What is μ_{00} for a binary object?

Central moments μ_{pq} from m_{pq}

- Moments μ_{pq} (p + q ≤ 3) are given by m_{pq} by:

$$\begin{aligned}
\mu_{00} &= m_{00}, \ \mu_{10} = 0, \ \mu_{01} = 0 \\
\mu_{20} &= m_{20} - \bar{x} m_{10} \\
\mu_{02} &= m_{02} - \bar{y} m_{01} \\
\mu_{11} &= m_{11} - \bar{y} m_{10} \\
\mu_{30} &= m_{30} - 3\bar{x} m_{20} + 2\bar{x}^2 m_{10} \\
\mu_{12} &= m_{12} - 2\bar{y} m_{11} - \bar{x} m_{02} + 2\bar{y}^2 m_{10} \\
\mu_{21} &= m_{21} - 2\bar{x} m_{11} - \bar{y} m_{20} + 2\bar{x}^2 m_{01} \\
\mu_{03} &= m_{03} - 3\bar{x} m_{02} + 2\bar{y}^2 m_{01}
\end{aligned}$$

- The 3D μ_{pqr}, are expressed by m_{pqr}:

$$\mu_{pqr} = \sum_{S=0}^{p} \sum_{t=0}^{q} \sum_{u=0}^{r} -1^{[D-d]} \binom{p}{s} \binom{q}{t} \binom{r}{u} \Delta x^{p-s} \, \Delta y^{q-t} \, \Delta z^{r-u} \, m_{stu}$$

- where
- D = (p + q + r); d = (s + t + u)
- and the binomial coefficients are given by

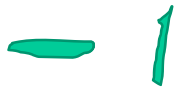
$$\binom{v}{w} = \frac{v!}{w! \, (v-w)!}, \quad w < v$$

Moments of inertia or Variance

- The two second order central moments measure the spread of points around the y- and x-axis through the centre of mass

$$\mu_{20} = \sum_x \sum_y (x-\bar{x})^2 f(x,y)$$

$$\mu_{02} = \sum_x \sum_y (y-\bar{y})^2 f(x,y)$$



- From physics: moment of inertia about an axis: how much energy is required to rotate the object about this axis:
  - Statisticans like to call this variance.
- The cross moment of intertia is given by

$$\mu_{11} = \sum_x \sum_y (x-\bar{x})(y-\bar{y}) f(x,y)$$

  - Statisticans call this covariance or correlation.
- Orientation of the object can be derived from these moments.
  - **This implies that they are not invariant to rotation.**

Moments of an ellipse

- Assume that the ellipse has semimajor and semiminor axes (*a*,*b*), a>b. An ellipse where major axis is along x-axis is given by

$$(x/a)^2 + (y/b)^2 = 1 \quad \Rightarrow y = \pm \frac{b}{a}\sqrt{a^2 - x^2}$$

The largest second order central moment (here called I_{20}) is given by

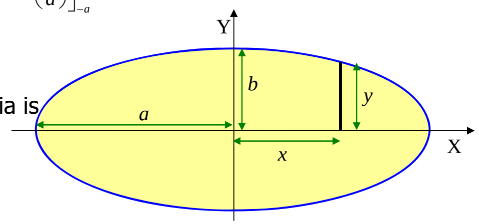
$$I_{20} = 2\int_{-a}^{a} x^2 y\, dx \; = 2\frac{b}{a}\int_{-a}^{a} x^2 \sqrt{a^2 - x^2}\, dx$$

$$I_{20} = 2\frac{b}{a}\left[\frac{x}{8}\left(2x^2 - a^2\right)\sqrt{a^2 - x^2} + \frac{a^4}{8}\sin^{-1}\left(\frac{x}{a}\right)\right]_{-a}^{a}$$

$$I_{20} = 2\frac{b}{a}\left[\frac{a^4}{8}\left(\frac{\pi}{2}+\frac{\pi}{2}\right)\right] = \underline{\underline{\frac{\pi}{4}a^3 b}}$$

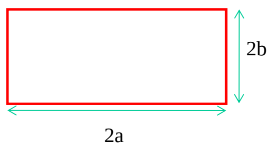
Similary, the smallest moment of inertia is

$$I_{\min} = \underline{\underline{\frac{\pi}{4}a\, b^3}}$$

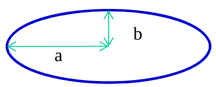


Moments of inertia for simple shapes

- Rectangular object (2a×2b):
  $I_{20} = 4a^3b/3$, $I_{02} = 4ab^3/3$



- Square (a×a):
  $I_{20} = I_{02} = a^4/12$
- Elliptical object, semi-axes (a,b):
  $I_{20} = \pi a^3 b/4$, $I_{02} = \pi a b^3/4$



- Circular object, radius R:
  $I_{20} = I_{02} = \pi R^4/4$

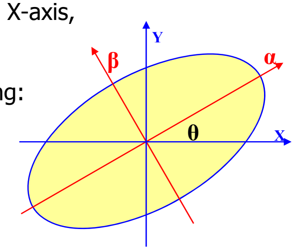
Object orientation - I

- Orientation is defined as the angle, relative to the X-axis, of an axis through the centre of mass that gives the lowest moment of inertia.
- Orientation θ relative to X-axis found by minimizing:

$$I(\theta) = \sum_\alpha \sum_\beta \beta^2 \, f(\alpha,\beta)$$

where the rotated coordinates are given by

$$\alpha = x\cos\theta + y\sin\theta, \quad \beta = -x\sin\theta + y\cos\theta$$



- The second order central moment of the object around the α-axis, expressed in terms of x, y, and the orientation angle θ of the object is:

$$I(\theta) = \sum_x \sum_y \left[y\cos\theta - x\sin\theta\right]^2 f(x,y)$$

- We take the derivative of this expression with respect to the angle θ
- Set derivative equal to zero, and find a simple expression for θ :

Object orientation - II

- Second order central moment around the α-axis:

$$I(\theta)=\sum_x\sum_y [y\cos\theta - x\sin\theta]^2 f(x,y)$$

- Derivative w.r.t. Θ = 0 =>

$$\frac{\partial}{\partial\theta} I(\theta)=\sum_x\sum_y 2f(x,y)[y\cos\theta - x\sin\theta][-y\sin\theta - x\cos\theta]=0$$

$$\Downarrow$$

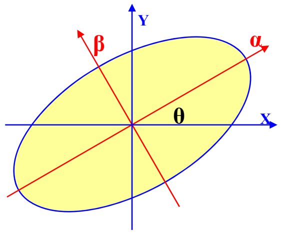
$$\sum_x\sum_y 2f(x,y)\left[xy(\cos^2\theta-\sin^2\theta)\right]=\sum_x\sum_y 2f(x,y)\left[x^2-y^2\right]\sin\theta\cos\theta$$

$$\Downarrow$$

$$2\mu_{11}(\cos^2\theta-\sin^2\theta)=2(\mu_{20}-\mu_{02})\sin\theta\cos\theta$$

$$\Downarrow$$

$$\frac{2\mu_{11}}{(\mu_{20}-\mu_{02})}=\frac{2\sin\theta\cos\theta}{(\cos^2\theta-\sin^2\theta)}=\frac{2\tan\theta}{1-\tan^2\theta}=\tan(2\theta)$$



- So the object orientation is given by:

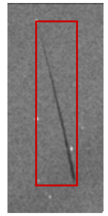
$$\theta=\frac{1}{2}\tan^{-1}\left[\frac{2\mu_{11}}{(\mu_{20}-\mu_{02})}\right],\quad \text{where}\ \ \theta\in\left[0,\pi/2\right] \text{if}\ \mu_{11}>0,\ \ \theta\in\left[\pi/2,\pi\right] \text{if}\ \mu_{11}<0$$

Bounding box - again

- Image-oriented bounding box:
  - The smallest rectangle around the object, having sides parallell to the edges of the image.
  - Found by searching for min and max x and y within the object (*xmin, ymin, xmax, ymax*)
- Object-oriented bounding box:
  - Smalles rectangle around the object, having one side parallell to the orientation of the object (θ).
  - The transformation

$$\alpha = x\cos\theta + y\sin\theta,\qquad \beta = y\cos\theta - x\sin\theta$$

    is applied to all pixels in the object (or its boundary).
  - Then search for α_{min}, β_{min}, α_{max}, β_{max}



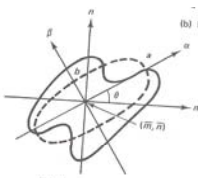
The best fitting ellipse

- Object ellipse is defined as the ellipse whose least and greatest moments of inertia equal those of the object.
- Semi-major and semi-minor axes are given by

$$(\hat{a},\hat{b})=\sqrt{\frac{2\left[\mu_{20}+\mu_{02}\pm\sqrt{(\mu_{20}+\mu_{02})^2+4\mu_{11}^2}\right]}{\mu_{00}}}$$

- Numerical eccentricity is given by

$$\hat{\varepsilon}=\sqrt{\frac{\hat{a}^2-\hat{b}^2}{\hat{a}^2}}$$



(c) Best fit ellipse

- Orientation invariant object features.
- Gray scale or binary object.

Radius of gyration, K

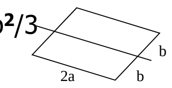
- The radius of a circle where we could concentrate all the mass of an object without altering the moment of inertia about its center of mass.

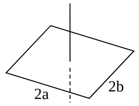
$$I=\mu_{00}\hat{K}^2 \Rightarrow \hat{K}=\sqrt{\frac{I_Z}{\mu_{00}}}=\sqrt{\frac{I_X+I_Y}{\mu_{00}}}=\sqrt{\frac{\mu_{20}+\mu_{02}}{\mu_{00}}}$$

- This feature is invariant to rotation.
- A very useful quantity because it can be determined, for homogeneous objects, entirely by their geometry.
- Squared radius of gyration, K^2, may be tabulated for simple object shapes, to help us compute the moments of inertia.

A table of K² in 2D images

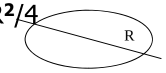
Rectangle: $K^2 = b^2/3$

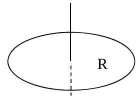




$K^2 = (a^2+b^2)/3$

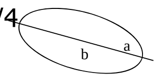
Disk: $K^2 = R^2/4$

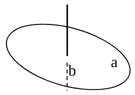




$K^2 = R^2/2$

Ellipse: $K^2 = b^2/4$

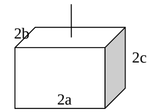




$K^2 = (a^2+b^2)/4$

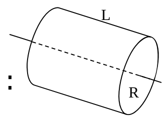
K² of some solid objects

Parallelepiped :



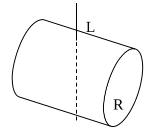
$K^2 = (a^2+b^2)/3$

Cylinder :



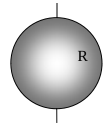
$K^2 = R^2/2$

Cylinder :



$K^2 = R^2/4 + L^2/12$

Sphere :



$K^2 = 2R^2/5$

What if we want scale-invariance?

- Changing the scale of *f(x,y)* by (α,β) gives a new image:

$$f'(x,y) = f\left(x/\alpha, y/\beta\right)$$

- The transformed central moments

$$\mu'_{pq} = \alpha^{1+p}\beta^{1+q}\mu_{pq}$$

- If $\alpha=\beta$, scale-invariant central moments are given by the normalization:

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\gamma}}, \quad \gamma = \frac{p+q}{2}+1, \quad p+q \geq 2$$

Symmetry

- To detect symmetry about center of mass, use central moments.

- For invariance of scale, use scale-normalised central moments
  - **(η_{11}, η_{20}, η_{02}, η_{21}, η_{12}, η_{30}, η_{03}).**
- Objects symmetric about either x or y axis will produce **$\eta_{11} = 0$**.
- Objects symmetric about y axis will give **$\eta_{12} = 0$** and **$\eta_{30} = 0$.**
- Objects symmetric about x axis will give **$\eta_{21} = 0$** and **$\eta_{03} = 0$.**
- X axis symmetry: **$\eta_{pq} = 0$ for all p = 0, 2, 4, … ; q = 1, 3, 5, …**

	η_{11}	η_{20}	η_{02}	η_{21}	η_{12}	η_{30}	η_{03}
M	0	+	+	-	0	0	-
C	0	+	+	0	+	+	0
O	0	+	+	0	0	0	0

Rotation invariant moments

1 Find principal axes of object, rotate and compute moments.
This can break down if object has no unique principal axes.

2 The method of absolute moment invariants:
This is a set of normalized central moment combinations, which can be used for scale, position, and rotation invariant pattern identification.

- For second order (p+q=2), there are two invariants:

$$\boldsymbol{\varphi_1 = \eta_{20} + \eta_{02} \qquad \varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2}$$

Third order Hu moments

- For third order moments, (p+q=3), the invariants are:

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

φ_7 is skew invariant, and may help distinguish between mirror images.

- These moments are not independent, and do not comprise a complete set.

Hu's moments; a bit simplified

For second order moments (p+q=2), two invariants are used:

$$\varphi_1 = \eta_{20} + \eta_{02}$$
$$\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

For third order moments, (p+q=3), we can use

$a = (\eta_{30} - 3\eta_{12})$, $b = (3\eta_{21} - \eta_{03})$,
$c = (\eta_{30} + \eta_{12})$, and $d = (\eta_{21} + \eta_{03})$

and simplify the five last invariants of the set:

$$\varphi_3 = a^2 + b^2$$
$$\varphi_4 = c^2 + d^2$$
$$\varphi_5 = ac[c^2 - 3d^2] + bd[3c^2 - d^2]$$
$$\varphi_6 = (\eta_{20} - \eta_{02})[c^2 - d^2] + 4\eta_{11}cd$$
$$\varphi_7 = bc[c^2 - 3d^2] - ad[3c^2 - d^2]$$

Hu moments of simple objects

- In the continuous case, the two first Hu moments of a binary rectangular object of size 2a by 2b, are given by

$$\phi_1 = \frac{1}{12}\left(\frac{a}{b} + \frac{b}{a}\right), \qquad \phi_2 = \left(\frac{1}{12}\right)^2\left(\frac{a}{b} - \frac{b}{a}\right)^2$$

while the remaining five Hu moments are all zero.

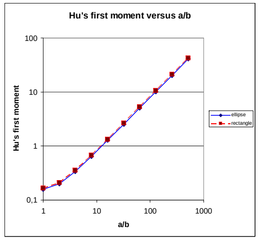
- Similarly, the two first Hu moments of a binary elliptic object with semi-axes a and b, are given by

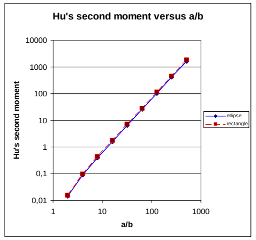
$$\phi_1 = \frac{1}{4\pi}\left(\frac{a}{b} + \frac{b}{a}\right), \qquad \phi_2 = \left(\frac{1}{4\pi}\right)^2\left(\frac{a}{b} - \frac{b}{a}\right)^2$$

while the remaining five Hu moments are all zero.

Φ_1 and φ_2 versus a/b

- Only (φ1, φ2) are useful for these simple objects.
- Notice that even in the continuous case it may be hard to distinguish between an ellipse and its bounding rectangle using these two moments.
- Relative difference in φ_1 of ellipse and its object oriented bounding rectangle is constant, 4.5%.
- Relative difference in φ_2 of ellipse and its object oriented bounding rectangle is constant, 8.8%.
- Relative differences given above are also true when comparing an ellipse with a same-area rectangle having the same a/b ratio, regardless of the size and eccentricity of the ellipse.





Moments as shape features

- The central moments are seldom used directly as shape descriptors.
- Major and minor axis are useful shape descriptors.
- Object orientation is normally not used directly, but to estimate rotation.
- The set of 7 Hu moments can be used as shape features. (Start with the first four, as the last half are often zero for simple objects).

Moments that are invariant to general affine transforms

$$
\begin{aligned}
I_1 &= \frac{\mu_{20}\mu_{02} - \mu_{11}^2}{\mu_{00}^4} \\
I_2 &= \frac{\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} + 4\mu_{30}\mu_{12}^3\mu_{03} - 3\mu_{12}^2\mu_{21}^2}{\mu_{00}^{10}} \\
I_3 &= \frac{\mu_{20}(\mu_{21}\mu_{30} - \mu_{12}^2) - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12} + \mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2)}{\mu_{00}^7} \\
I_4 &= \{\mu_{20}^3\mu_{03}^2 - 6\mu_{20}^2\mu_{02}\mu_{21}\mu_{03} + 9\mu_{20}^2\mu_{02}\mu_{12}^2 \\
&\quad +12\mu_{20}\mu_{11}^2\mu_{21}\mu_{03} + 6\mu_{20}\mu_{11}\mu_{02}\mu_{30}\mu_{03} - 18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} \\
&\quad -8\mu_{11}^3\mu_{30}\mu_{03} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} + 9\mu_{20}\mu_{02}^2\mu_{21}^2 \\
&\quad +12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} - 6\mu_{11}\mu_{02}^2\mu_{30}\mu_{21} + \mu_{02}^3\mu_{30}^2\}/\mu_{00}^{11}
\end{aligned}
$$

Contrast invariants

- Abo-Zaid *et al.* have defined a normalization that cancels both scaling and contrast.
- The normalization is given by

$$\eta'_{pq} = \frac{\mu_{pq}}{\mu_{00}} \left(\frac{\mu_{00}}{\mu_{20} + \mu_{02}} \right)^{\frac{(p+q)}{2}}$$

- This normalization also reduces the dynamic range of the moment features, so that we may use higher order moments without having to resort to logarithmic representation.
- Abo-Zaid's normalization cancels the effect of changes in contrast, but not the effect of changes in intensity:

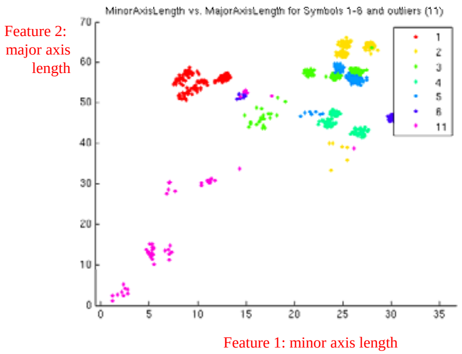
$$f'(x,y) = f(x,y) + b$$

- In practice, we often experience a combination:

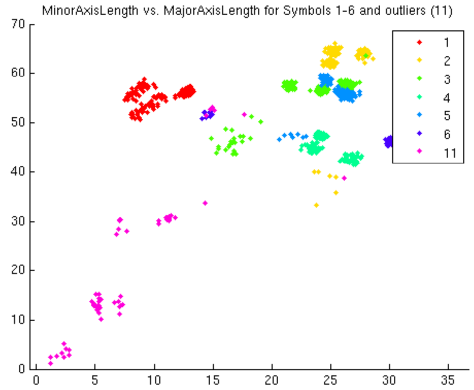
$$f'(x,y) = cf(x,y) + b$$

Scatter plots

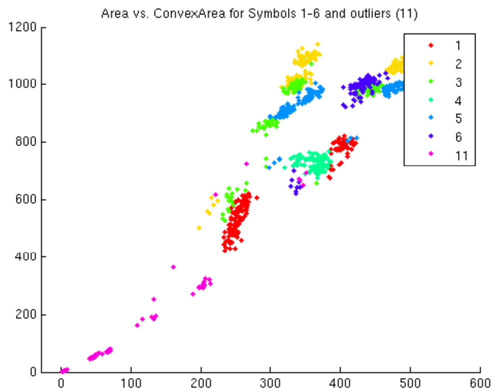
- A 2D scatter plot is a plot of feature values for two different features. Each object's feature values are plotted in the position given by the features values, and with a class label telling its object class.
- Matlab: gscatter(feature1, feature2, labelvector)
- Classification is done based on more than two features, but this is difficult to visualize.
- Features with good class separation show clusters for each class, but different clusters should ideally be separated.

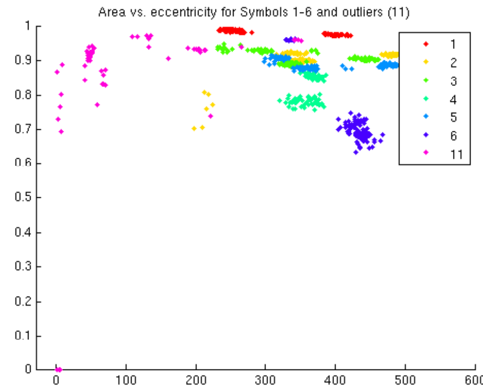


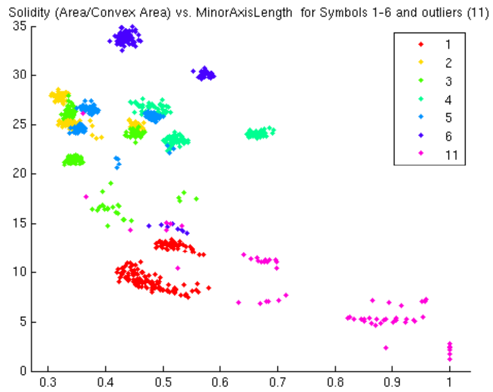
Which numbers are well separated?



Two correlated features





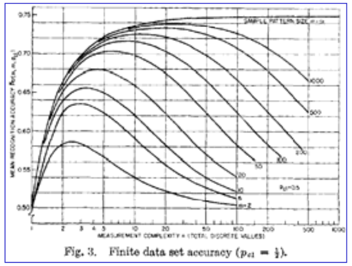


Aristotle and Occam

- Our search for models or hypotheses that describe the laws of nature is based on a "minimum complexity principle".
- Aristotle (384-322 BC), Physics, book I, chapter VI:
  'The more limited, if adequate, is always preferable'.
- William of Occam (1285-1349):
  'Pluralitas non est ponenda sine necessitate'.
- The simplest model that explains the data is the best.
- So far, "Occam's Razor" has generally motivated
  the search and selection of reduced dimensionality feature sets.
- It should also motivate us to generate
  only a few but powerful features.
- Many practitioners have forgotten the minimum complexity principle.

The "curse-of-dimensionality"

- Also called "peaking phenomenon".
- For a finite training sample size, the correct classification rate initially increases when adding new features, attains a maximum and then begins to decrease.
- The implication is that:
- For a high measurement complexity, we will need large amounts of training data in order to attain the best classification performance.
- => 5-10 samples
  per feature per class.



Correct classification rate as function of feature dimensionality, for different amounts of training data. Equal prior probabilities of the two classes is assumed.

Illustration from G.F. Hughes (1968).

Learning goals – object description

- Invariant topological features
- Projections and signatures
- Geometric features
  - Area, perimeter and circularity/compactness
  - Bounding boxes
  - Moments, binary and grayscale
    - Ordinary moments and central moments
  - Moments of objects, object orientation, and best fitting ellipse
  - Scale invariance
- Inspection of feature scatter plots
- "Curse of dimensionality" and feature selection