18ECE340T- MACHINE PERCEPTION WITH COGNITION
UNIT-2

Topics Covered: Boundary descriptors and Region descriptors

Reference Book

Computer and Machine Vision
by E.R.Davies

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BOUNDARY DISCRIPTORS AND REGION DISCRIPTORS

BOUNDARY DISCRIPTORS :

- Simple Descriptors. q Length of a Contour.

- By counting the number of pixels along the contour.

- For a chain coded curve with unit spacing in both directions, the number of vertical and horizontal components plus 21/2 times the number of components give the exact length of curve.

REGION DISCRIPTORS

- **REGION DISCRIPTORS:**

- In computer vision, visual descriptors or image descriptors are descriptions of the visual features of the contents in images, videos, or algorithms or applications that produce such descriptions.

- They describe elementary characteristics such as the shape, the color, the texture or the motion, among others.

Shape Analysis & Measurement

- The extraction of quantitative feature information from images is the objective of image analysis.

- The objective may be:
  - shape quantification
  - count the number of structures
  - characterize the shape of structures

Shape Measures

- The most common object measurements made are those that describe shape.
    - 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.

Shape Measures

- The performance of any shape measurements depends on the quality of the original image and how well objects are pre-processed.

  - Object degradations such as small gaps, spurs, and noise can lead to poor measurement results, and ultimately to misclassifications.

  - Shape information is what remains once location, orientation, and size features of an object have been extracted.

  - The term pose is often used to refer to location, orientation, and size.

Shape Descriptors

- What are shape descriptors?
    - Shape descriptors describe specific characteristics regarding the geometry of a particular feature.
    - In general, shape descriptors or shape features are some set of numbers that are produced to describe a given shape.

Shape Descriptors

– 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.

– Shape features can be grouped into two classes: *boundary features* and *region features*.

Distances

- The simplest of all distance measurements is that between two specified pixels (x_1, y_1) and (x_2, y_2).

- There are several ways in which distances can be defined:

  - *Euclidean*
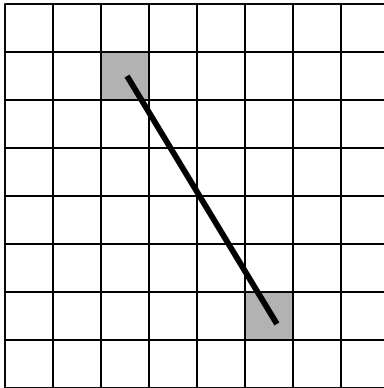 $$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

  - *Chessboard*
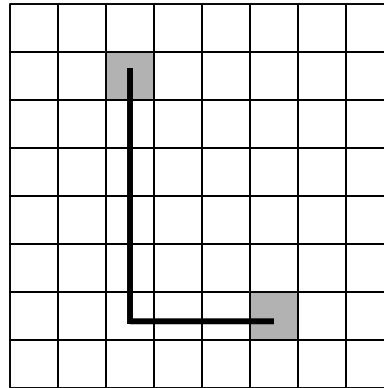 $$d = \max\left(\left|x_1 - x_2\right|, \left|y_1 - y_2\right|\right)$$

Distances

– *City-block*

$$d = \left| x_1 - x_2 \right| + \left| y_1 - y_2 \right|$$
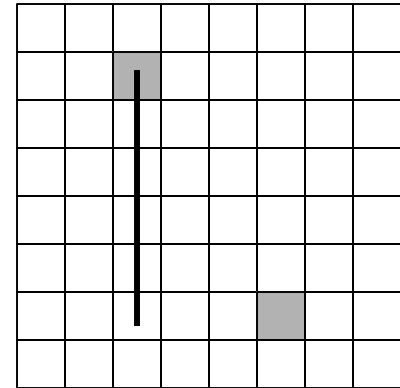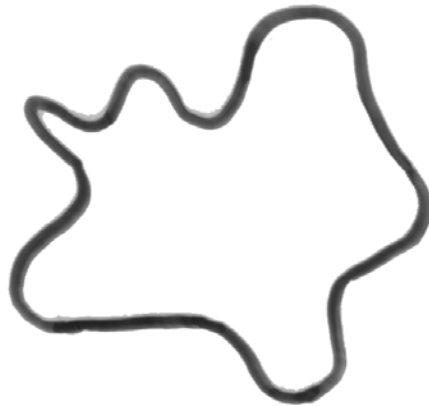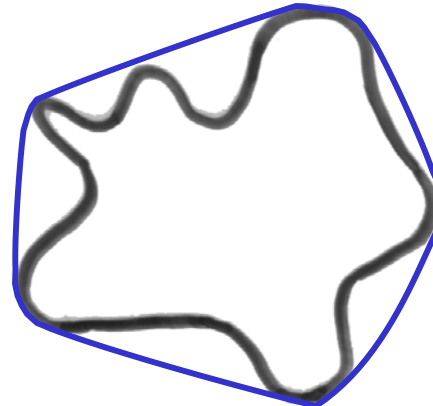
Euclidean
Chessboard

City-block

Area

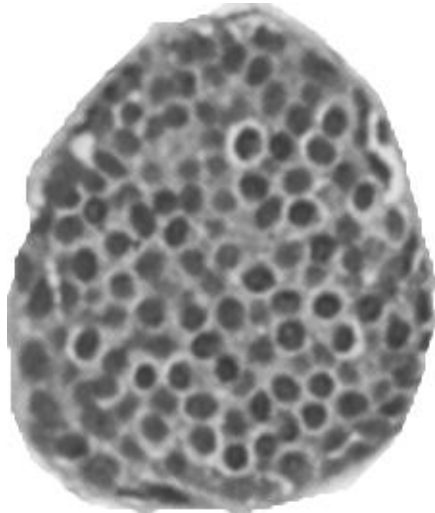- The area is the number of pixels in a shape.
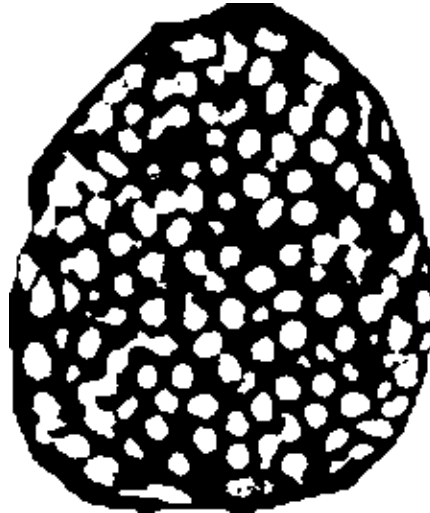

Net Area

Convex Area

- The convex area of an object is the area of the convex hull that encloses the object.

Area

Original Image   Net Area   Filled Area

Perimeter

- The perimeter [length] is the number of pixels in the boundary of the object.

    – If $x_1,\ldots,x_N$ is a boundary list, the perimeter is given by:

    $$\text{perimeter} = \sum_{i=1}^{N-1} d_i = \sum_{i=1}^{N-1} \left| x_i - x_{i+1} \right|$$

    – The distances d_i are equal to 1 for 4-connected boundaries and 1 or $\sqrt{2}$ for 8-connected boundaries.

Perimeter

- For instance in an 8-connected boundary, the distance between diagonally adjacent pixels is the Euclidean measure $\sqrt{2}$

  – The number of diagonal links in N_4–N_8, and the remaining N_8–(N_4–N_8) links in the 8-connected boundary are of one pixel unit in length. Therefore the total perimeter is:

$$\text{perimeter} = (\sqrt{2} - 1)N_4 + (2 - \sqrt{2})N_8$$

Perimeter

- The convex perimeter of an object is the perimeter of the convex hull that encloses the object.

object perimeter

convex perimeter
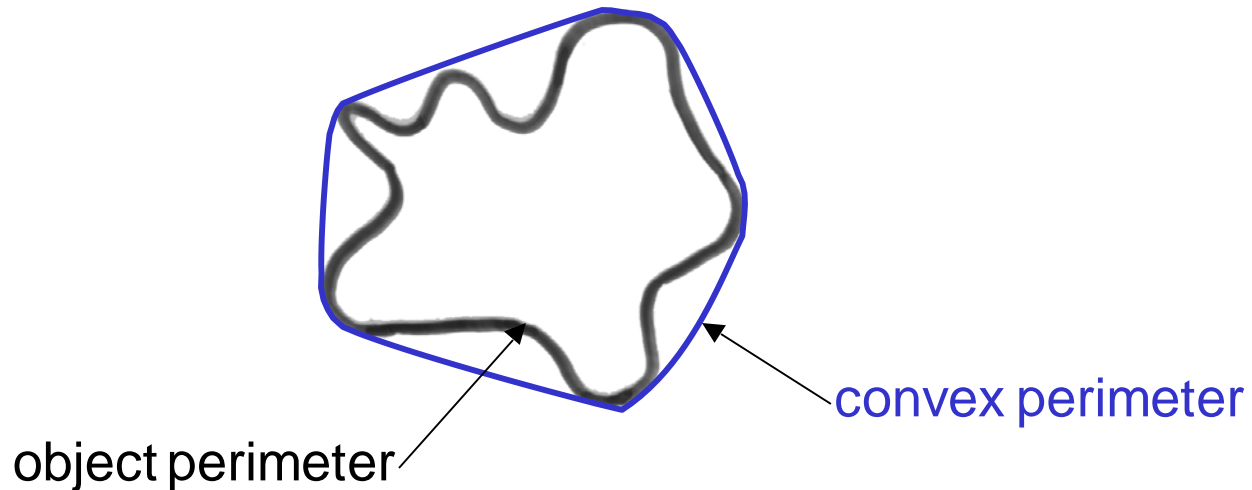
Major Axis

- The major axis is the (x,y) endpoints of the longest line that can be drawn through the object.

  - The major axis endpoints (x_1,y_1) and (x_2,y_2) are found by computing the pixel distance between every combination of border pixels in the object boundary and finding the pair with the maximum length.

Major Axis Length

- The major-axis length of an object is the pixel distance between the major-axis endpoints and is given by the relation:

$$\text{major-axis length} = \sqrt{\left(x_2 - x_1\right)^2 + \left(y_2 - y_1\right)^2}$$

  – The result is measure of object length.

Major Axis Angle

- The major-axis angle is the angle between the major-axis and the x-axis of the image:

$$\text{major-axis angle} = \tan^{-1}\left(\frac{y_2 - y_1}{x_2 - x_1}\right)$$

  - The angle can range from 0° to 360°.
  - The result is a measure of object orientation.

Minor Axis

- The minor axis is the (x,y) endpoints of the longest line that can be drawn through the object whilst remaining perpendicular with the major-axis.

  - The minor axis endpoints (x_1,y_1) and (x_2,y_2) are found by computing the pixel distance between the two border pixel endpoints.
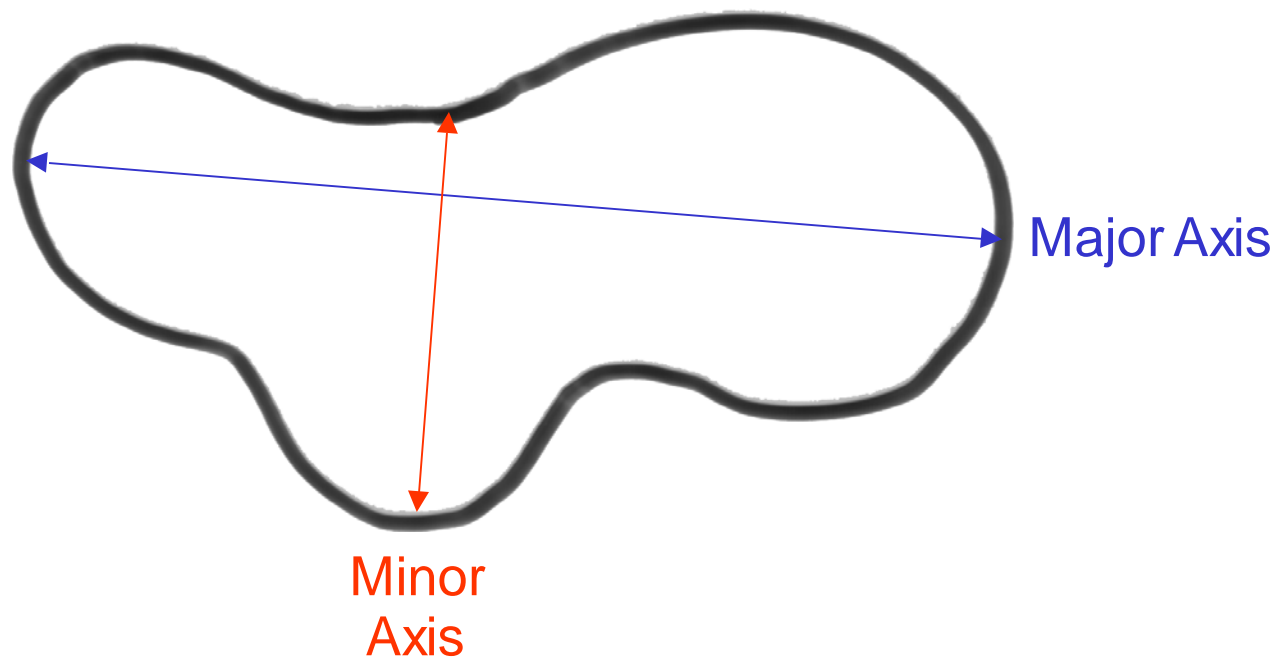
Minor Axis Length

- The minor-axis length of an object is the pixel distance between the minor-axis endpoints and is given by the relation:

$$\text{minor-axis length} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

  – The result is measure of object width.

Major and Minor Axes

Major Axis

Minor Axis

Compactness

- Compactness is defined as the ratio of the area of an object to the area of a circle with the same perimeter.

$$\text{compactness} = \frac{4\pi \cdot area}{(perimeter)^2}$$

  - A circle is used as it is the object with the most compact shape.
  - The measure takes a maximum value of 1 for a circle
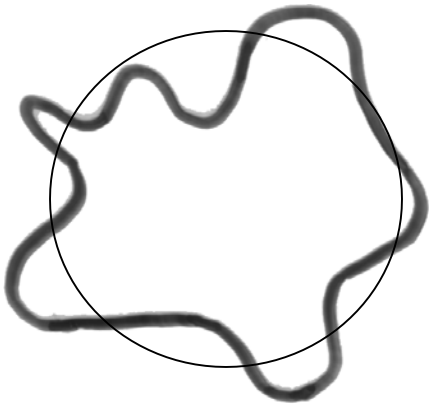 - A square has compactness $= \quad \pi/4$

Compactness

- Objects which have an elliptical shape, or a boundary that is irregular rather than smooth, will decrease the measure.

- An alternate formulation:

$$\text{compactness} \;=\; \frac{(perimeter)^2}{4\pi \cdot area}$$

- The measure takes a minimum value of 1 for a circle

- Objects that have complicated, irregular boundaries have larger compactness.

Compactness

low compactness   compactness=0.764   compactness=0.668

Elongation

- In its simplest form elongation is the ratio between the length and width of the object bounding box:

$$\text{elongation} \quad = \quad \frac{\text{width}_{\text{bounding-box}}}{\text{length}_{\text{bounding-box}}}$$

   - The result is a measure of object elongation, given as a value between 0 and 1.
   - If the ratio is equal to 1, the object is roughly square or circularly shaped. As the ratio decreases from 1, the object becomes more elongated.
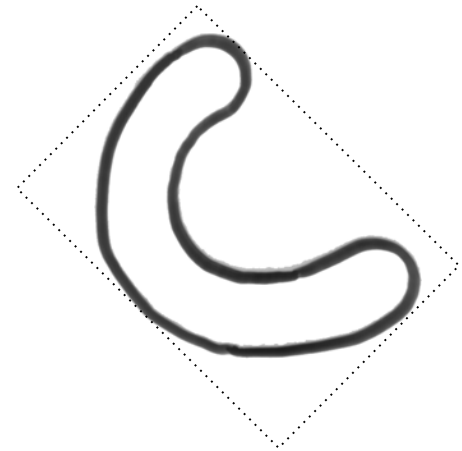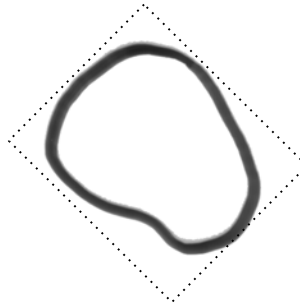
Elongation

- This criterion cannot succeed in curved regions, for which the evaluation of elongatedness must be based on maximum region thickness.

  – Elongatedness can be evaluated as a ratio of the region area and the square of its thickness.

  – The maximum region thickness (holes must be filled if present) can be determined as the number **d** of erosion steps that may be applied before the region totally disappears.

$$elongation = \frac{area}{2\mathbf{d}^2}$$

26
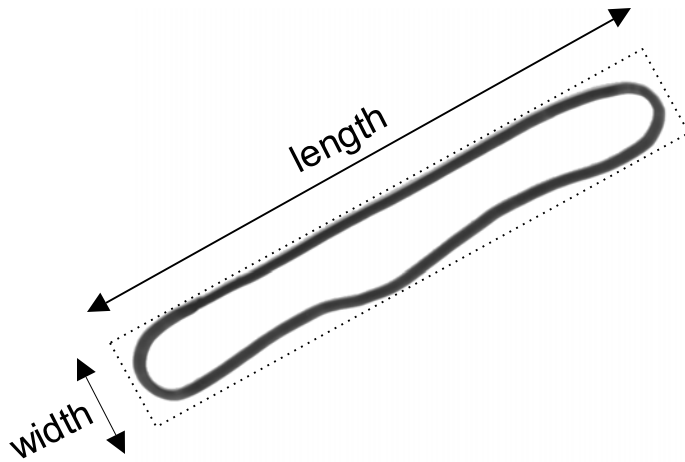
Elongation

high elongation   low elongation

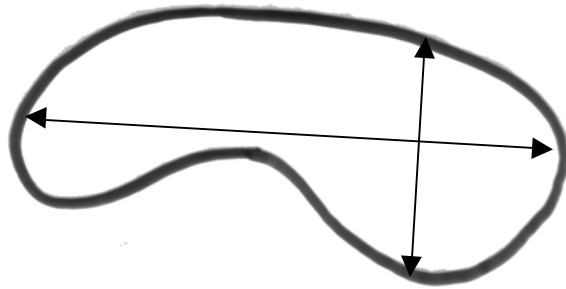# Eccentricity

- Eccentricity is the ratio of the length of the short (minor) axis to the length of the long (major) axis of an object:

$$\text{eccentricity} = \frac{\text{axislength}_{short}}{\text{axislength}_{long}}$$

- The result is a measure of object eccentricity, given as a value between 0 and 1.
- Sometimes known as ellipticity.

Eccentricity
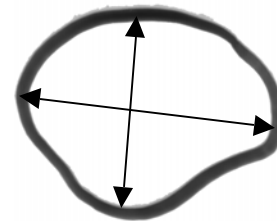
high eccentricity　　　　　low eccentricity

Eccentricity

- Eccentricity can also be calculated using central moments:

$$\text{eccentricity} = \frac{\left(\mu_{02} - \mu_{20}\right)^2 + 4\mu_{11}}{\text{area}}$$

Measures of "Circularity"

- Sometimes it is useful to have measures that are sensitive only to departures of a certain type of circularity:

    e.g.   convexity (measures irregularities)

                 roundness (excludes local irregularities)

Circularity or Roundness

- A measure of roundness or circularity (area-to-perimeter ratio) which excludes local irregularities can be obtained as the ratio of the area of an object to the area of a circle with the same convex perimeter:

$$\text{roundness} \ = \ \frac{4\pi \cdot area}{(convex \ perimeter)^2}$$

  - This statistic equals 1 for a circular object and less than 1 for an object that departs from circularity, except that it is relatively insensitive to irregular boundaries.

Circularity
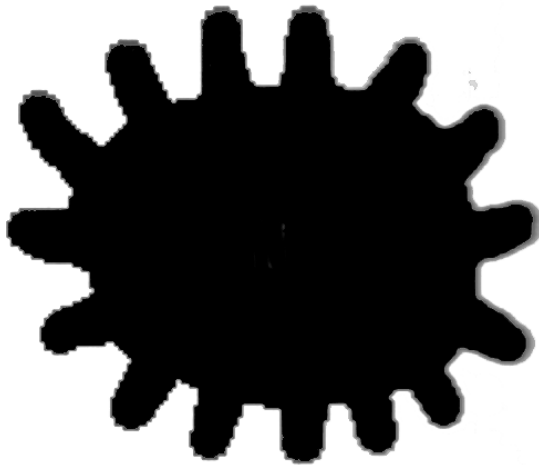
roundness=0.584   roundness=0.447

Sphericity

- Sphericity measures the degree to which an object approaches the shape of a "sphere".

$$\text{sphericity} = \frac{R_{inscribing}}{R_{circumscribing}}$$

Center of mass

$R_{circumscribing}$

$R_{inscribing}$
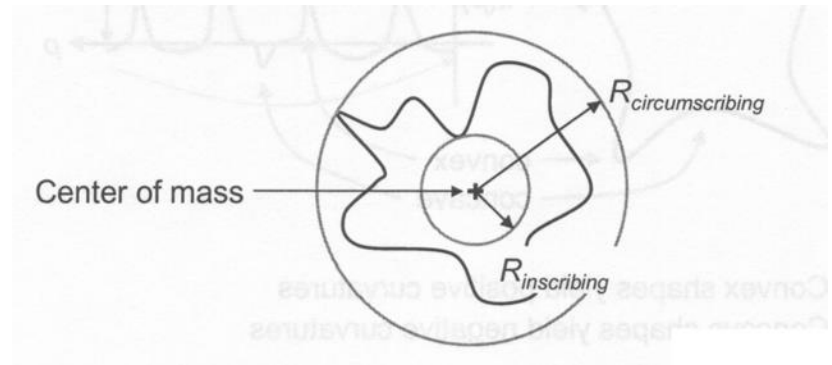
– For a circle, the value is the maximum of 1.0

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 object's convex hull to the perimeter of the object itself:

$$\text{convexity} = \frac{\text{convex perimeter}}{\text{perimeter}}$$

Convexity

– This will take the value of 1 for a convex object, and will be less than 1 if the object is not convex, such as one having an irregular boundary.
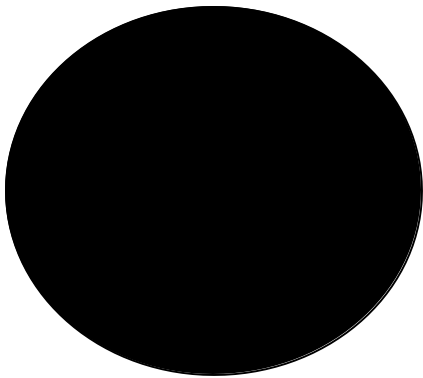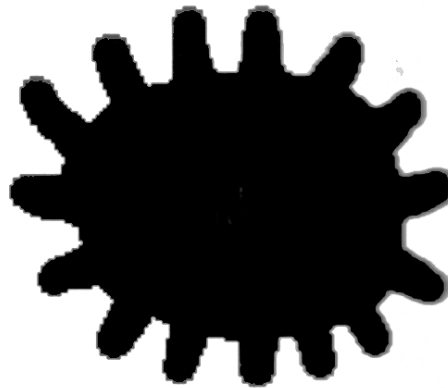
convexity=1.0   convexity=0.483   convexity=0.349

Aspect Ratio

- The aspect ratio measures the ratio of the objects height to its width.

$$\text{aspect ratio} \;=\; \frac{\text{height}}{\text{width}}$$

Caliper Dimensions

- Caliper or feret diameters are the distances between parallel tangents touching oppoisite sides of an object.

  - At orientation θ, the caliper diameter is:

  $$\max_{(x,y)\in A}(x\sin\theta + y\cos\theta) - \min_{(xy)\in A}(x\sin\theta + y\cos\theta)$$

  - Certain caliper diameters are of special interest:

    - The width of an object ($\theta = 0°$)

    $$\max_{(x,y)\in A}(y) - \min_{(x,y)\in A}(y)$$

Caliper Dimensions

- The height of an object ($\theta = 90°$)

$$\max_{(x,y) \in A}(x) - \min_{(x,y) \in A}(x)$$

- The maximum caliper diameter is one definition of an objects length.

Curl

- The curl of an object measures the degree to which an object is "curled up".

$$curl = \frac{length}{fibre\ length}$$

length

breadth

fibre width

fiber length
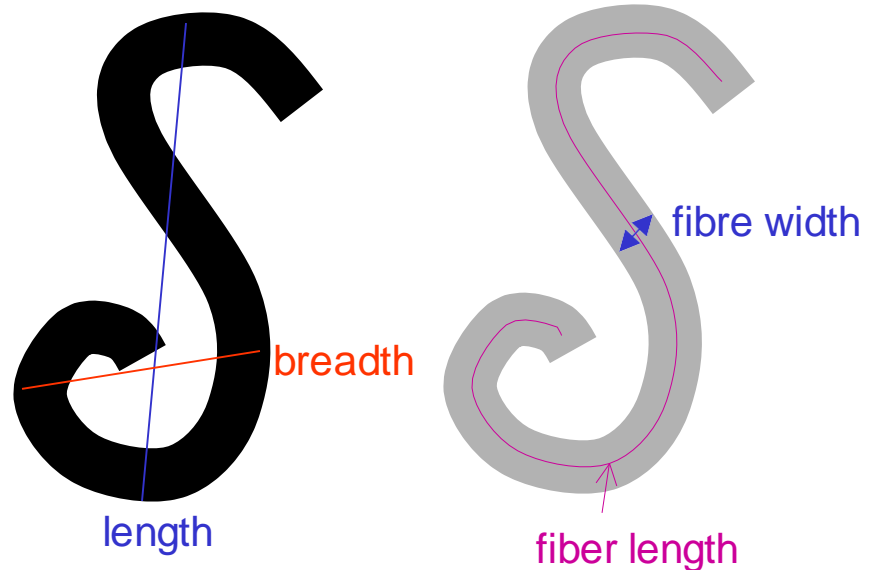
Curl

- As the measure of curl decreases, the degree to which they are "curled up" increases.

$$\text{fibre length} \ = \ \frac{\text{perimeter-} \sqrt{(\text{perimeter})^2 - 16 \cdot \text{area}}}{4}$$

$$\text{fibre width} \ = \ \frac{\text{area}}{\text{fibre length}}$$

Convex Hull

- The convex hull of an object is defined to be the smallest convex shape that contains the object.
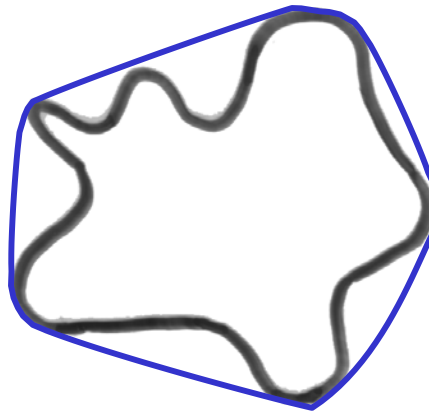
Solidity

- 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:

$$\text{solidity} = \frac{\text{area}}{\text{convex area}}$$

Solidity

– A value of 1 signifies a solid object, and a value less than 1 will signify an object having an irregular boundary, or containing holes.
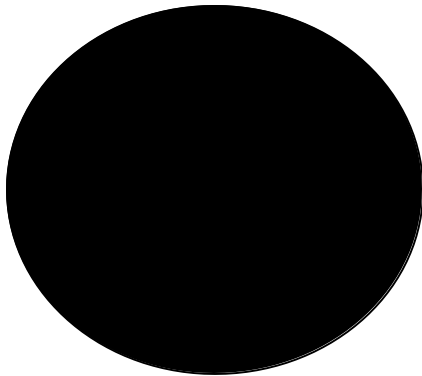
solidity=1.0   solidity=0.782   solidity=0.592

Shape Variances

- Sometimes a shape should be compared against a template.

    - A circle is an obvious and general template choice. The circular variance is the proportional mean-squared error with respect to solid circle.

    - It gives zero for a perfect circle and increases along shape complexity and elongation.
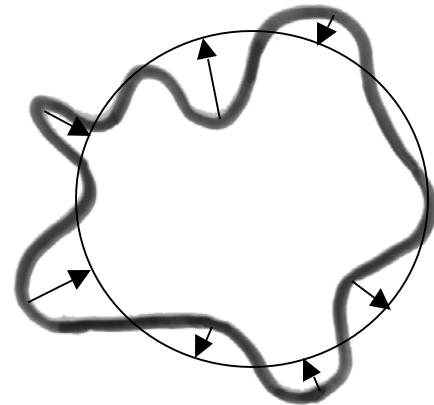
Shape Variances

- Elliptic variance is defined similarly to the circular variance. An ellipse is fitted to the shape (instead of a circle) and the mean-squared error is measured.

Rectangularity

- Rectangularity is the ratio of the object to the area of the minimum bounding rectangle.
  - Let F_k be the ratio of region area and the area of a bounding rectangle, the rectangle having the direction k. The rectangle direction is turned in discrete steps as before, and rectangularity measured as a maximum of this ratio F_k

$$\text{rectangularity} = \max_k(F_k)$$

  - Rectangularity has a value of 1 for perfectly rectangular object

Bounding Box

- The bounding box or bounding rectangle of an object is a rectangle which circumscribes the object. The dimensions of the bounding box are those of the major and minor axes.

  - The area of the bounding box is:

    $$\text{area} \;=\; (\text{major axis length}) * (\text{minor axis length})$$

  - The minimum bounding box is the minimum area that bounds the shape.

Bounding Box
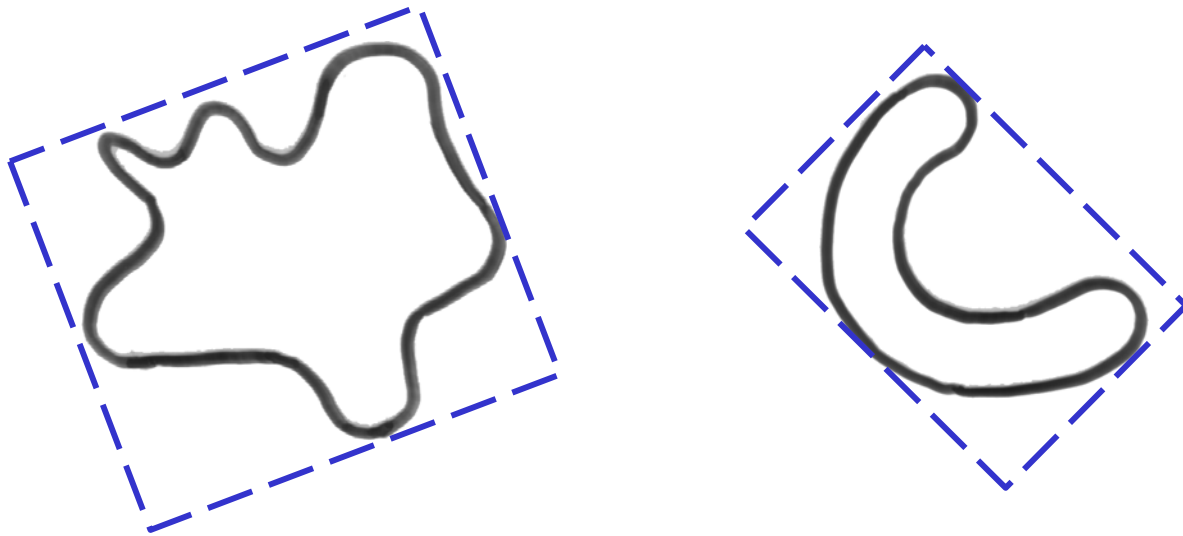
bounding boxes

Direction

- Direction is a property which makes sense in elongated regions only. If the region is elongated, direction is the direction of the longer side of a minimum bounding rectangle.
  - If the shape moments are known, the direction θ can be computed as:

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

Direction

- Elongatedness and rectangularity are independent of linear transformations translation, rotation, and scaling.

- Direction is independent on all linear transformations which do not include rotation.

- Mutual direction of two rotating objects is rotation invariant.

Orientation

- The overall direction of the shape.

Topological Descriptors

- Topological properties are useful for global descriptions of objects in an image.

  - Features that do not change with elastic deformation of the object.

  - For binary regions, topological features include the number of holes in a region, and the number of indentations, or protrusions.

  - One topological property is the number of connected components.

Topological Descriptors
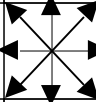
- The number of holes **H** and connected components **C** in an image can be used to define the Euler number.

    - The Euler number is defined as the number of components minus the number of holes:

    $$\text{Euler number} \ = \ \textbf{C} - \textbf{H}$$

    - This simple topological feature is invariant to translation, rotation and scaling.

Boundary Descriptors

- The shape of a region can be represented by quantifying the relative position of consecutive points on its boundary.

- A chain code consists of a starting location and a list of directions $d_1, d_2, \ldots, d_N$ provides a compact representation of all the information in a boundary.

    - The directions d_i are estimates of the slope of the boundary.

Boundary Descriptors

- Chain codes are based on 4- or 8-connectivity:

3	2	1
4		0
5	6	7

e.g.

2,1,0,7,7,0,1,1
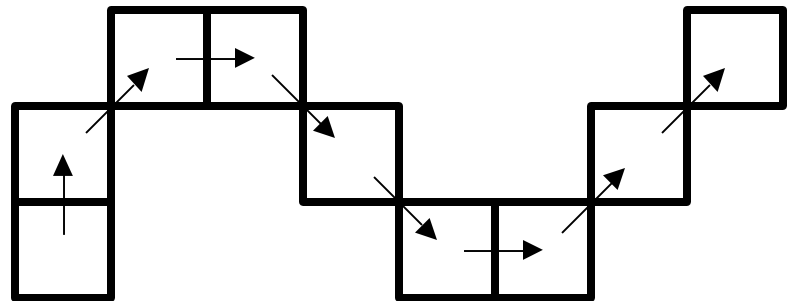
Boundary Descriptors

- The *k-slope* of the boundary at (x_i, y_i) can be estimated from the slope of the line joining $(x_{i-k/2}, y_{i-k/2})$ and $(x_{i+k/2}, y_{i+k/2})$ for some small, even value of k. Calculated as an angle of:

$$\tan^{-1}\left(\frac{y_{i+k/2} - y_{i-k/2}}{x_{i+k/2} - x_{i-k/2}}\right)$$

measured in a clockwise direction, with a horizontal slope taken to be zero.

Boundary Descriptors: Curvature

- The *k-curvature* of the boundary at (x_i, y_i) can be estimated from the change in the *k-slope*:

$$\left\{ \tan^{-1}\left(\frac{y_{i+k} - y_i}{x_{i+k} - x_i} \right) - \tan^{-1}\left(\frac{y_i - y_{i-k}}{x_i - x_{i-k}} \right) \right\} \quad (\mathrm{mod}\, 2\pi)$$

Boundary Descriptors: Curvature

- The curvature (κ) of an object is a local shape attribute.
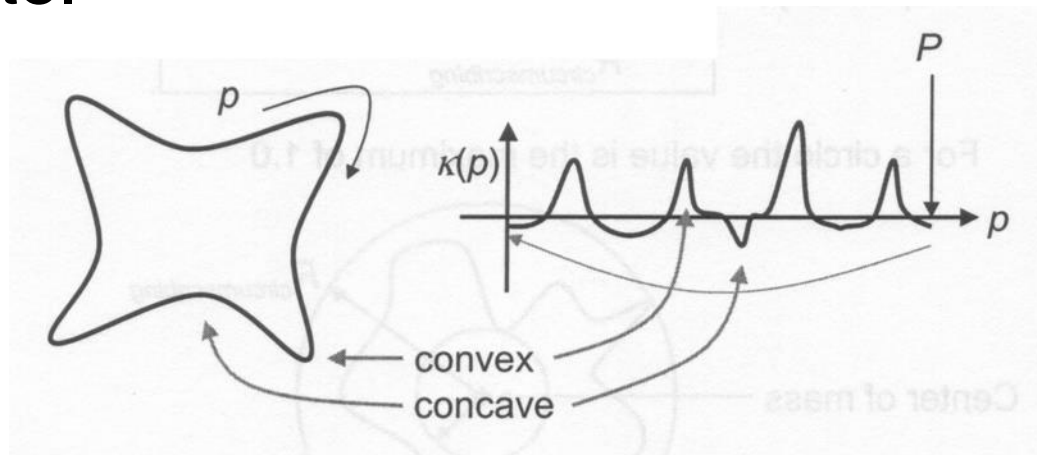
- – Convex shapes yield positive curvatures
- – Concave shapes yield negative curvatures

Boundary Descriptors: Bending Energy

- The total bending energy E_C is a robust global shape descriptor.

  - The bending energy of a boundary may be understood as the energy necessary to bend a rod to the desired shape and can be calculated as a sum-of-squares of the boundary curvature $\kappa(p)$ over the boundary length L.

$$E_c = \frac{1}{L}\sum_{p=1}^{L}\kappa(p)^2 \qquad \frac{2\pi}{R} \leq E_c \leq \infty$$

  - The minimum value $2\pi/R$ is obtained for a circle of radius R.

Boundary Descriptors: Bending Energy

- For example:
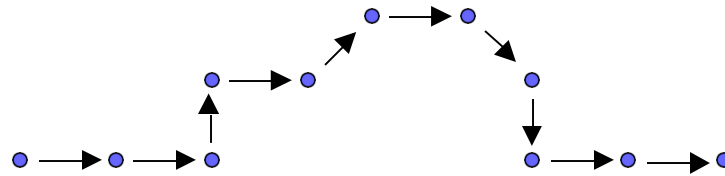
chain-code: 0 0 2 0 1 0 7 6 0 0

curvature: 0 2 −2 1 −1 −1 −1 2 0

sum of squares: 0 4 4 1 1 1 1 4 0

Bending Energy = 16

Total Absolute Curvature

- This descriptor is a measure of the total absolute curvature in an object:

$$\kappa_{total} = \frac{1}{L} \sum_{p=1}^{L} |\kappa(p)| \quad 2\pi \leq \kappa_{total} \leq \infty$$

  – The minimum value is found for all convex objects.

Moment Analysis

- The evaluation of moments represents a systematic method of shape analysis.

  - The most commonly used region attributes are calculated from the three low-order moments.

  - Knowledge of the low-order moments allows the calculation of the central moments, normalised central moments, and moment invariants.

Spatial Moments

- To define the $(p,q)^{\text{th}}$-order moment:

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p\, y^q \quad \text{for} \quad p,q = 0,1,2,...$$

- The zero$^{\text{th}}$-order moment m_{00} simply represents the sum of the pixels contained in an object and gives a measure of the area (because $x^0 = y^0 = 1$)

Spatial Moments

- The first-order moments in x (m_{10}) and y (m_{01}) normalised by the area can be used to specify the location of an object:

  - The *centre of gravity*, or *centroid* of an object is a measure of the object's location in the image.

  - It has two components, denoting the row and column positions of the point of balance of the object.

$$\text{centroid} = (\bar{x}, \bar{y}) = \left(\frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}} \right)$$

Spatial Moments
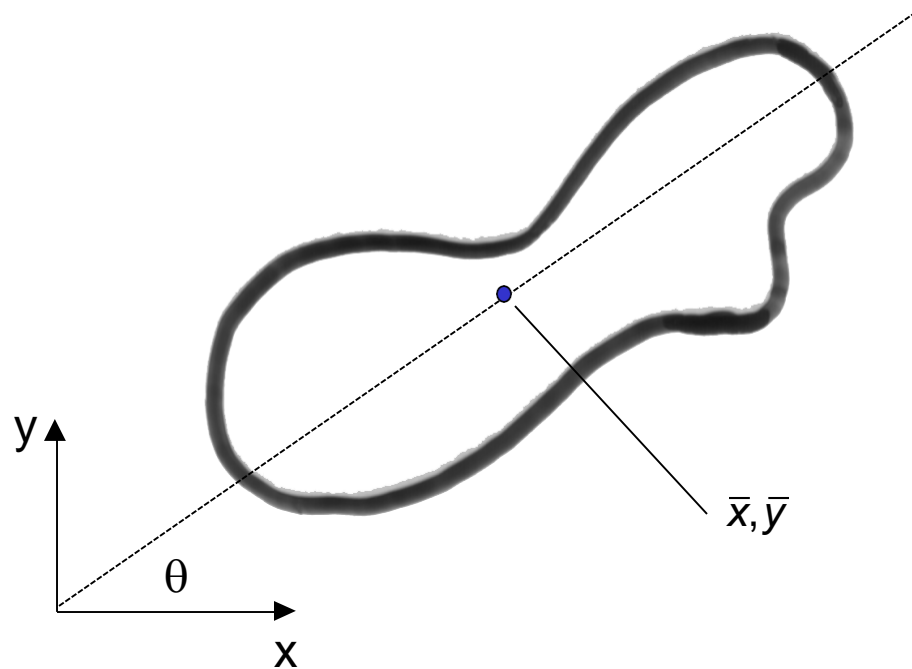
Central Moments

- The central moments μ_{pq} (i.e. $p+q > 1$) represent descriptors of a region that are normalised with respect to location.

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x - \bar{x})^p (y - \bar{y})^q \quad \text{for } p + q > 1$$

Normalised Central Moments

- The central moments can be normalised with respect to the zero[th] moment to yield the normalised central moment:

$$\eta_{pq} = \mu_{pq} \big/ \mu_{00}^{\gamma}$$

$$\gamma = (p + q)\big/2 + 1$$

- The most commonly normalised central moment is η_{11}, the first central moment in x and y.

  – This provides a measure of the deviation from a circular region shape. A value close to zero describes a region that is close to circular.

Central Moments

- Central moments are translation invariant:
  - i.e. two objects that are identical except for having different centroids, will have identical values of
  - Central moments are not rotationally invariant μ_{pq}
- Central moments are not rotationally invariant – they will change if an object is rotated.

Central Moments

- The second-order central moments:

$$\mu_{20} = m_{20} - \frac{m_{10}^2}{m_{00}} \qquad \mu_{02} = m_{02} - \frac{m_{01}^2}{m_{00}} \qquad \mu_{11} = m_{11} - \frac{m_{10}\,m_{01}}{m_{00}}$$

- The second-order moments measure how dispersed the pixels in an object are from their centroid:
  - μ_{20} measures the object's spread over rows
  - μ_{02} measures the object's spread over columns
  - μ_{11} is a cross-product term representing spread in the direction in which both row and column indices increase.

Principal Axes

- Principal axes of an object can be uniquely defined as segments of lines crossing each other orthogonally in the centroid of the object and representing the directions with zero cross-correlation. This way, a contour is seen as an realization of a statistical distribution.

Principal Axes

- Principal (major and minor) axes are defined to be those axes that pass through the centroid, about which the moment of inertia of the region is, respectively maximal or minimal.

  – The orientation of the major axis:

  $$\theta = \tfrac{1}{2} \tan^{-1}\left[\frac{2\mu_{11}}{\mu_{20} - \mu_{02}} \right]$$

  which is measured clockwise, with the horizontal direction taken as zero.

  – This can be used to find the minimum bounding box.

Moment Invariants

- Normalisation with respect to orientation results in rotationally invariant moments.
  - The first two are the following functions of the second-order central moments:

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = \left(\eta_{20} - \eta_{02} \right)^2 + 4\eta_{11}^2$$

  - The first of these statistics is the moment of inertia, a measure of how dispersed, in any direction, the pixels in an object are from their centroid.
  - The second statistic measures whether this dispersion is isotropic or directional.

Moment Invariants

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = \left(\eta_{20} - \eta_{02}\right)^2 + 4\eta_{11}^2$$

$$\phi_3 = \left(\eta_{30} - 3\eta_{12}\right)^2 + \left(3\eta_{21} - \eta_{03}\right)^2$$

$$\phi_4 = \left(\eta_{03} + \eta_{12}\right)^2 + \left(\eta_{21} + \eta_{03}\right)^2$$

Central Moments

$$\mu_{10} = \mu_{01} = 0$$

$$\mu_{11} = m_{11} - m_{10}\,m_{01}\,/\,m_{00}$$

$$\mu_{20} = m_{20} - m_{10}^2\,/\,m_{00}$$

$$\mu_{02} = m_{02} - m_{01}^2\,/\,m_{00}$$

$$\mu_{30} = m_{30} - 3\bar{x}m_{20} + 2m_{10}\;\bar{x}^2$$

$$\mu_{03} = m_{03} - 3\bar{y}m_{02} + 2m_{01}\bar{y}^2$$

$$\mu_{12} = m_{12} - 2\bar{y}m_{11} - \bar{x}m_{02} + 2m_{10}\;\bar{y}^2$$

$$\mu_{21} = m_{21} - 2\bar{x}m_{11} - \bar{y}m_{20} + 2m_{01}\bar{x}^2$$
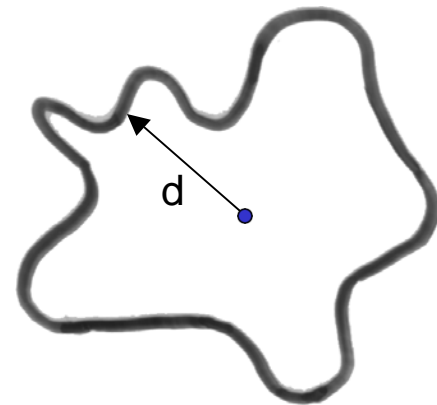
Radial Distance Measures

- The shape of a structure of interest can be determined by analysing its boundary, the variations and curvature of which constitute the information to be quantified.

  - Transform the boundary into a 1D signal and analysing its structure.

  - The radial distance is measured from the central point (centroid) in the object to each pixel x(n), y(n) on the boundary.

Radial Distance Measures

- Generally the centroid is used as the central point, and the radial distance:

$$d(n) = \sqrt{\left[x(n) - \bar{x}\right]^2 + \left[y(n) - \bar{y}\right]^2} \qquad n = 0, 1, \ldots, N - 1$$

is obtained by tracing all
N pixels of the boundary.

d

Radial Distance Measures

- To achieve scale invariance, the normalised radial distance $r(n)$ is obtained by normalising $d(n)$ with the maximal distance

- The number of times the signal $r(n)$ crosses its mean and other similar metrics can be used as a measure of boundary roughness.

  – Kilday, J., Palmieri, F., and Fox, M.D., "Classifying mammographic lesions using computerized image analysis", *IEEE Transactions on Medical Imaging,* 1993, **12**: pp.664-669

Radial Distance Measures

- The sequence $r(n)$ is further analysed to extract shape metrics such as the entropy:

$$E = \sum_{k=1}^{K} h_k \log h_k$$

where h_k is the k-bin probability histogram that represents the distribution of $r(n)$ as well as the statistical moments:

$$m_p = \frac{1}{N} \sum_{n=0}^{N-1} \left[r(n) \right]^p$$

Radial Distance Measures

- The central moment:

$$\mu_p = \tfrac{1}{N} \sum_{n=0}^{N-1} \left[r(n) - m_1 \right]^p$$

- Normalised moments invariant to translation, rotation and scaling:

$$\bar{m}_p = \frac{m_p}{\mu_2^{p/2}} \qquad\qquad \bar{\mu}_p = \frac{\mu_p}{\mu_2^{p/2}} \qquad p \neq 2$$

Fourier Descriptor

- The information in the $r(n)$ signal can be further analysed in the spectral domain using the discrete Fourier transform (DFT):

$$a(u) = \frac{1}{N} \sum_{n=0}^{N-1} r(n) e^{-j2\pi nu/N} \qquad u = 0, 1, \ldots, N-1$$

  - The "low-frequency" terms, correspond to the smooth behavior.
 - The "high-frequency" terms correspond to the jagged, bumpy behavior ◎   roughness

References:
Radial Distance Measures

1. Pohlman, K.A., Powell, K.A., Obuchowski, N.A., Chilcote, W.A., Grunfest-Bronlatowski, S., "Quantitative classification of breast tumours in digitized mammograms", *Medical Physics,* 1996, **23**: pp.1337-1345 **(masses)**

2. Bruce, L.M., Kallergi, M., "Effects of image resolution and segmentation method on automated mammographic mass shape classification", *Proceedings of the SPIE*, 1999, **3661**: pp.940-947 **(masses)**

3. Kilday, J., Palmieri, F., and Fox, M.D., "Classifying mammographic lesions using computerized image analysis", *IEEE Transactions on Medical Imaging,* 1993, **12**: pp.664-669 **(masses)**

4. Shen, L., Rangayyan, R.M., and Desautels, J.E.L., "Application of shape analysis to mammographic calcifications", *IEEE Transactions on Medical Imaging,* 1994, **13**: pp.263-274 **(calcifications)**

Contour-based Shape Representation & Description

- Object boundaries must be expressed in some mathematical form:
  - Rectangular (Cartesian) coordinates
  - Polar coordinates (in which boundary elements are represented as pairs of angle ϕ and distance r.
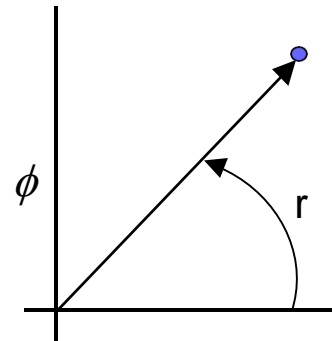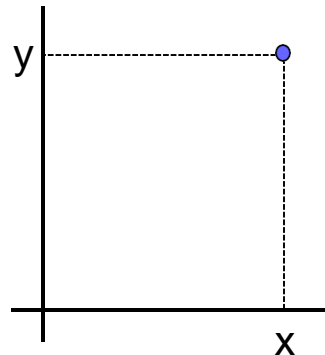
Fractal Dimension

- The fractal dimension is the rate at which the perimeter of an object increases as the measurement scale is reduced.

  – The fractal dimension produces a single numeric value that summarizes the irregularity of "roughness" of the feature boundary

Fractal Dimension

- Richardson dimension
  - Counting the number of strides needed to "walk" along the boundary, as a function of stride length.

    number of steps $\times$ stride-length = perimeter measurement

  - As the stride length is reduced, the path follows more of the local irregularities of the boundary and the measured parameter increases.
  - The result, plotted on log-log axes is a straight line whose slope gives the fractal dimension.
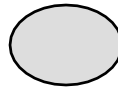
Mammogram Features

- Shape descriptors can be used to characterise features extracted from mammograms.
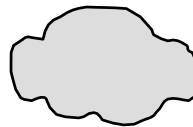
Round

Oval

Lobulated

Cell Image Features

- When dealing with images containing numerous objects, such as histological or cytological cell images, shape descriptors are calculated for all the individual cells.
  - Global shape measures can be calculated from the individual image descriptors:
    - Standard deviation ⓞ   area, short-axis, long-axis, perimeter, circularity,
    - Mean ⓞ   compactness, elongation, perimeter, area

Profile

- The profile of a binary image analyses the binary image in terms of its projections.

  – Projections can be vertical, horizontal, diagonal, circular, radial, spiral.

  e.g. used in determining a region of highest density

  – A profile is the sum of the pixel values in a specified direction
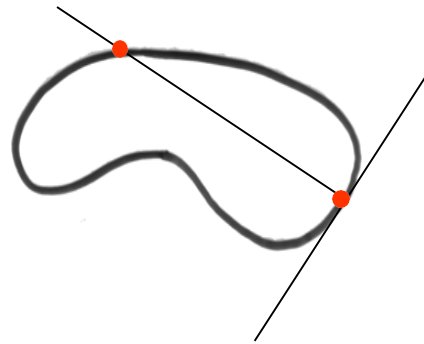
Signature Analysis

- A signature is a one-dimensional representation of the boundary.

    - Computing the distance from the centroid of an object to the boundary as a function of angles, from 0° ⓪ 360° in any chosen increment.

    - Harmonic analysis, or shape unrolling

    - The plot repeats every 2π g