Computer Vision for HCI

2-D Shape

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Region Representations/Properties

- Once regions have been identified, properties of regions can be input to higher-level decisionmaking procedures
 - Recognition or inspection
- Common geometric properties of region useful for simple shape description
 - Boundary, bounding box, extremal points, area, perimeter, compactness/circularity, moments, etc.
- We will examine geometric and shape representation/properties for <u>binary</u> images [(0,1) or (0, 255)]
 - Assumes have segmented out pixels for the object of interest

Boundary Coding

- Regions can be represented by their boundaries instead of an image
- Simplest form is linear list of border pixels of each region



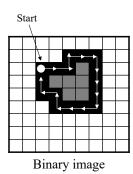


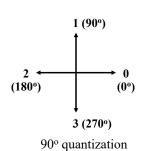
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Chain Code Representation

- Simple technique for representing shape of contour
- Each directed line segment is assigned code
- Chain code is string of those ordered codes





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Shape Number

- Chain codes dependent upon:
 - Orientation and start point of contour
- Invariance to rotation by integer multiples of quantization (90°)
 - Take "circular" first-difference of chain code: f(x)-f(x-1)

Chain code: 0010033332221211

First-diff: 3013030003003130 (1-2=3!)

- Could also align grid to main axes of object
- Invariance to starting point
 - Circular shift first-diff number to be minimal integer

First-diff: **301303**0003003130 Shape #: 0003003130**301303**

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Internal/External Boundaries

- When region has one or more hole boundaries, represented by chain code for each of them
 - Spatial relation between contours?





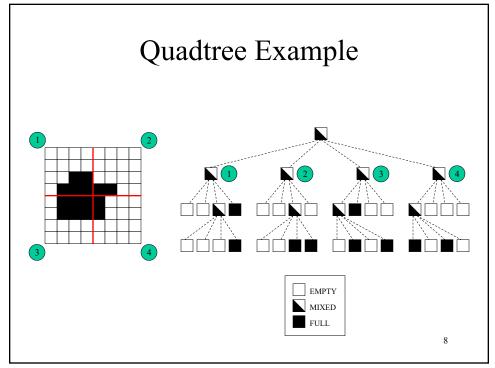
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Quadtree Representation

- Quadtree encodes entire region (not just boundary)
 - Binary image
- Each node of quadtree represents a square region in the image
 - Has one of 3 labels: FULL, EMPTY, MIXED
- Subdivide nodes until either FULL or EMPTY

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Quadtree

- Tree/graph matching for recognition
- Previous example is "blocky"
 - Small image grid
 - Need many more levels/cells (resolution) to approximate curves
- Quadtrees have been used to represent map regions in geographic information systems (GIS)

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Medial Axis Transform

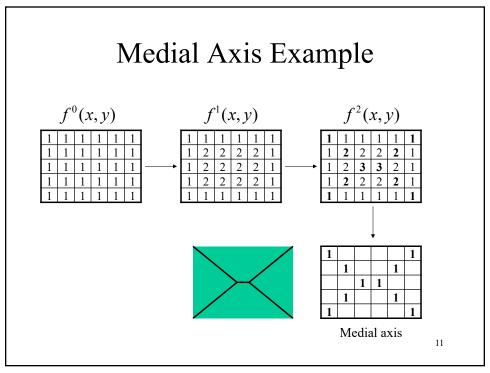
- "Skeleton" representation of binary region
- Steps
 - Original binary image is f^0
 - Iteratively compute (until no change):

$$f^{k}(x,y) = f^{0}(x,y) + \min(f^{k-1}(p,q))$$

\(\forall (p,q) \) 4-connected to (x,y)

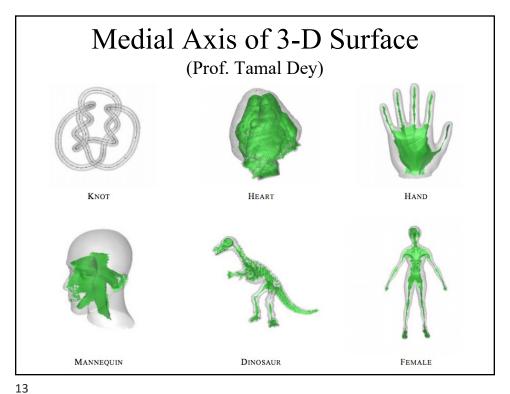
– Medial axis given by all points (x,y) such that:

$$f^k(x,y) \ge f^k(p,q)$$



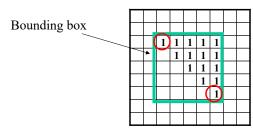
Medial Axis Extras

- Also can recover shape from medial axis with iterative algorithm
- Matlab code available for skeletonization
 - Skel function (bwmorph)
 - Also has morphological functions



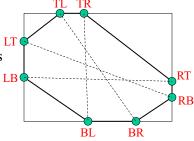
Bounding Box

- Often useful to have rough idea of where region located (e.g., for tracking)
- Bounding box is enclosing rectangle that touches topmost, bottommost, leftmost, and rightmost points in region
- As shown, can include much of background



Extremal Points

- Examine where region touches bounding box
- At most 8 distinct "extremal" points/pixels for region on bounding box
 - Topmost left/right
 - Rightmost top/bottom
 - Leftmost top/bottom
 - Bottommost left/right
- Extremals occur in opposite pairs
 - Defines axis for each pair
- Compute approximations of
 - Axis length
 - Axis orientation



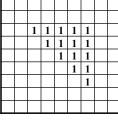
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Area

• Area A of binary region R simply defined as:

$$A = \sum_{(x,y)\in R} 1$$



Binary image

Area =
$$15$$
 (pixels)

Perimeter and Compactness

- Perimeter *P* of binary region *R* is sum of its border pixels
 - Border pixel has at least 1 background pixel in its neighborhood
- <u>Compactness/Circularity</u> C of region is defined as follows:

Circle:
$$A = \pi r^2$$
 $P = 2\pi r$

$$C = 4\pi \frac{A}{P^2}$$

Square:
$$A = L^2$$
 $P = 4L$

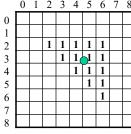
$$C = \frac{\pi}{4}$$

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Centroid

• Centroid of binary region is <u>average location</u> of pixels in *R*:

$$x_c = \bar{x} = \frac{1}{N} \sum_{(x,y) \in R} x$$
 $y_c = \bar{y} = \frac{1}{N} \sum_{(x,y) \in R} y$



Binary image

 $x_c = \frac{1}{15} [2 + (2 \cdot 3) + (3 \cdot 4) + (4 \cdot 5) + (5 \cdot 6)]$

= 4.67

 $y_c = \frac{1}{15} [(5 \cdot 2) + (4 \cdot 3) + (3 \cdot 4) + (2 \cdot 5) + 6]$

Useful for target tracking!

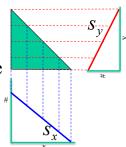
Signatures

- Useful for finding preliminary landmarks
- Horizontal signature of binary image
 - Projection of image onto the x-axis

$$S_x = \sum_{y} B[x, y]$$

• Vertical signature of binary image

- Projection of image onto the y-axis #



(consider figure-8 shape)

$$S_y = \sum_x B[x, y]$$

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Spatial Moments

• Spatial moments often used to describe region shape

$$m_{pq} = \sum \sum x^{p} y^{q} I[x, y]$$

$$A = m_{00} = \sum \sum x^{0} y^{0} I[x, y]$$
 "Zeroth order"
$$m_{10} = \sum \sum x^{1} y^{0} I[x, y]$$
 "First order"
$$m_{01} = \sum \sum x^{0} y^{1} I[x, y]$$
 "First order"

"Centroid"
$$\overline{x} = \frac{m_{10}}{m_{00}}$$
 $\overline{y} = \frac{m_{01}}{m_{00}}$

Central Moments

• Central moments (translation invariant)

$$\mu_{pq} = \sum \sum (x - \overline{x})^p (y - \overline{y})^q I[x, y]$$

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

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Second-Order Central Moments

• Three second-order central moments

$$\mu_{20} = \sum \sum (x - \overline{x})^2 (y - \overline{y})^0 I[x, y]$$

$$\mu_{11} = \sum \sum (x - \overline{x})^1 (y - \overline{y})^1 I[x, y]$$

$$\mu_{02} = \sum \sum (x - \overline{x})^0 (y - \overline{y})^2 I[x, y]$$

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Moment Ellipse Orientation

• If region is ellipse, second-order central moments have useful algebraic description of orientation

Let,

$$a = \mu_{20} = \sum \sum (x - \overline{x})^2 (y - \overline{y})^0 I[x, y]$$

$$b = \mu_{11} = \sum \sum (x - \overline{x})^1 (y - \overline{y})^1 I[x, y]$$

$$c = \mu_{02} = \sum \sum (x - \overline{x})^0 (y - \overline{y})^2 I[x, y]$$

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Moment Ellipse Orientation

• Resulting orientation relationship

$$\tan(2\theta) = \frac{2b}{a-c}$$

- If (b = 0) and (a = c)
 - Object is too symmetric to allow definition of axis
- Can also use eigenvalues and eigenvectors to determine ellipse [more on this later...]

Similitude Moments

(Invariant to translation and scale)

$$\eta_{ij} = \frac{\mu_{ij}}{\left(m_{00}\right)^{\frac{i+j}{2}+1}} = \frac{\sum \sum (x - \overline{x})^{i} (y - \overline{y})^{j} I[x, y]}{\left(\sum \sum I[x, y]\right)^{\frac{i+j}{2}+1}}$$

Not integer division operator

for $2 \le (i+j) \le 3$:

$$N = \begin{bmatrix} \eta_{02} & \eta_{03} & \eta_{11} & \eta_{12} & \eta_{20} & \eta_{21} & \eta_{30} \end{bmatrix}$$

M.K. Hu, "Visual pattern recognition by moment invariants", Information Theory, IRE Transactions, 1962, pp. 179-187

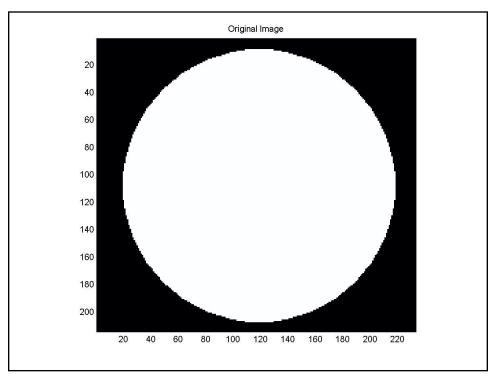
http://www.sci.utah.edu/~gerig/CS7960-S2010/handouts/CS7960-AdvImProc-MomentInvariants.pdf

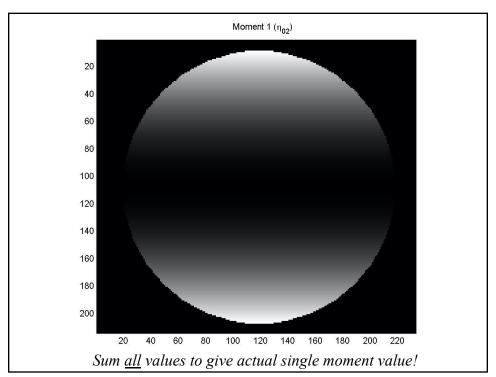
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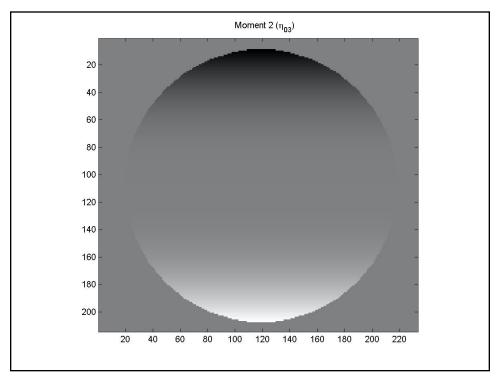
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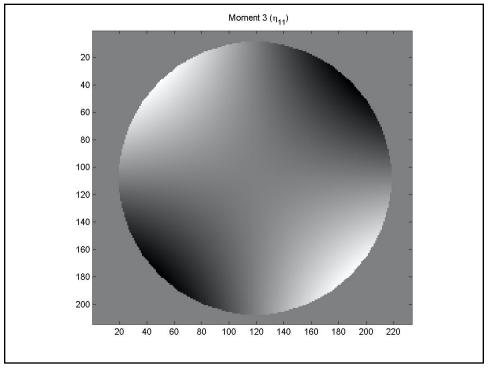
"Per-pixel" Moment Visualization ONLY...

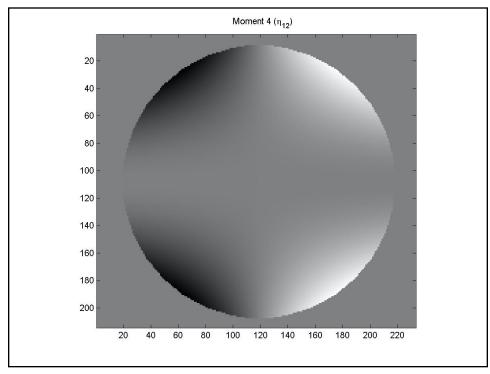
Would need to sum all of these values across the image to get the actual moment value for the image

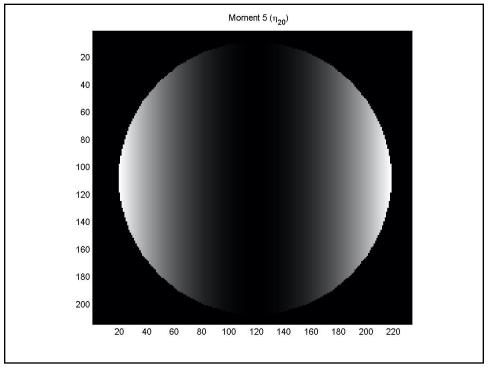


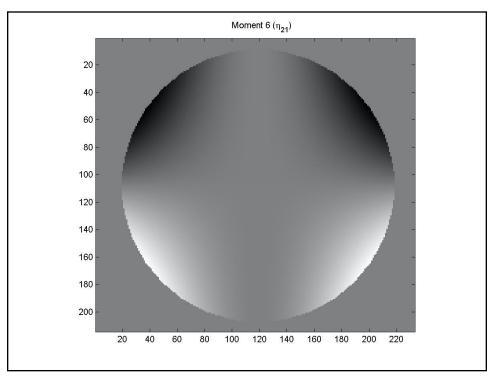


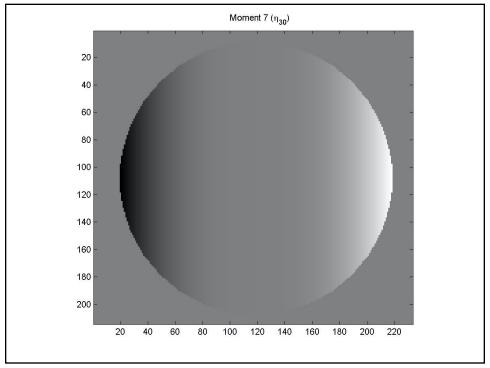












Works for Binary Images Only?

- NO!
- Can use equations for <u>grayscale</u> (or real-valued) image

use grayscale value

$$\eta_{ij} = \frac{\mu_{ij}}{\left(m_{00}\right)^{\frac{i+j}{2}+1}} = \frac{\sum \sum (x-\overline{x})^{i} (y-\overline{y})^{j} I[x,y]}{\left(\sum \sum I[x,y]\right)^{\frac{i+j}{2}+1}}$$

for
$$2 \le (i+j) \le 3$$
:

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Summary

- Given a 2-D binary shape, use representations/properties to characterize the region
 - Recognition or matching
- Methods
 - Chain code
 - Quadtree
 - Medial axis
 - Bounding box, extremal points
 - Area, centroid
 - Perimeter, compactness, circularity
 - Signatures
 - Moments