Computer Vision
(CSE 40535 / 60535)

Image features

[Part III: Pattern recognition]

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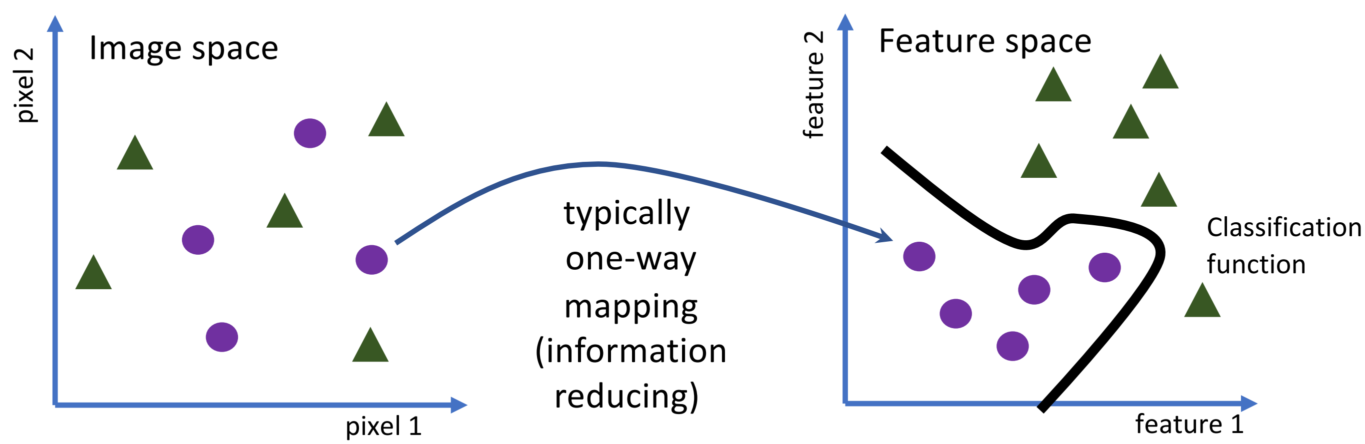
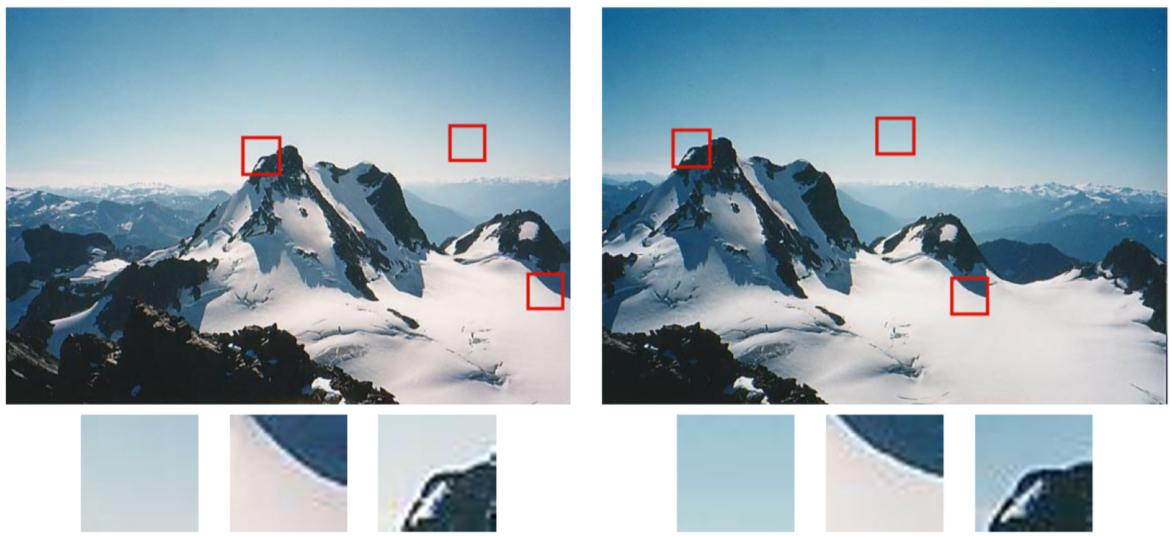
Why we need features?

1. Object classification
   - representation (typically: simplified, when compared to the image) of the objects in a feature space
   - classification (grouping) of points in a feature space with the use of classifiers



Why we need features?

2. Solving image correspondence problem
    - calculation of camera pose, stereo matching
    - image stitching, video stabilization
    - object tracking, recognition in presence of occlusions



R. Szeliski (2010), Computer Vision: Algorithms and Applications, Springer

Features

- Geometric features
  - global and local properties of shapes
- Intensity-based features
  - global and local properties of image intensity
  - often based on image filtering
  - statistical descriptors
  - key points

Geometric features

Global and local properties of shapes

Geometric features

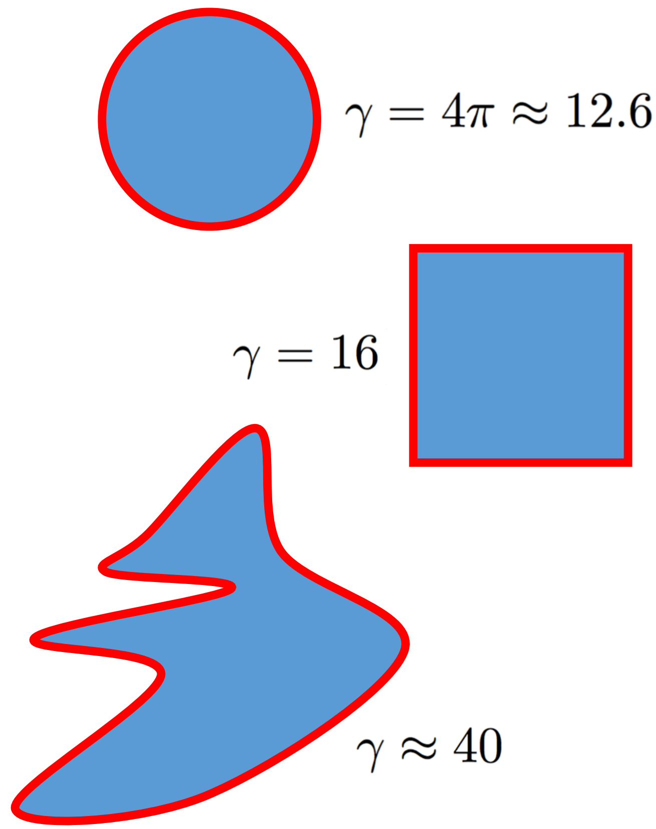
Global shape properties

- Area (A) and perimeter (L)
- Height and width
- Mass center
- Compactness

$$\gamma = \frac{L^2}{A}$$

- Normalized compactness

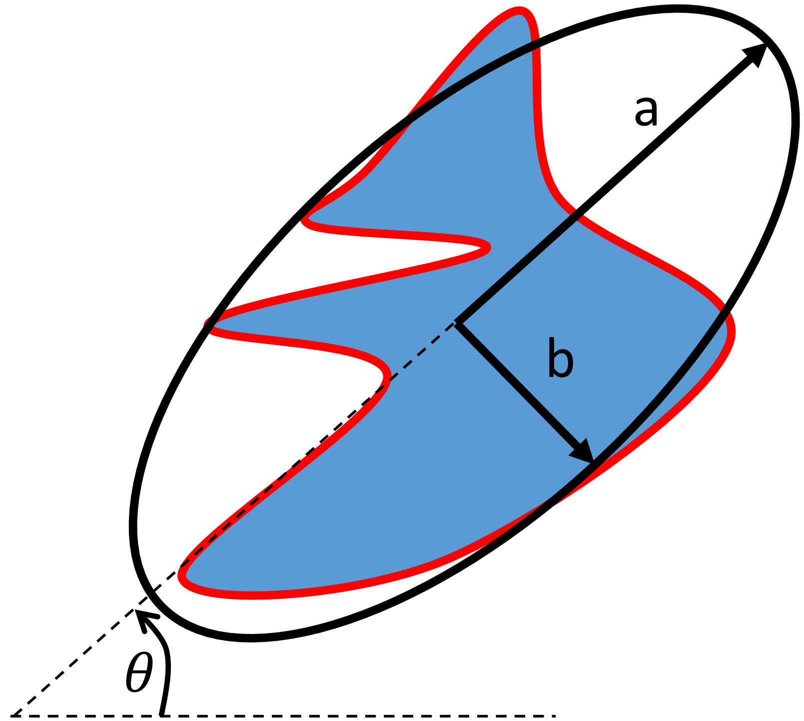
$$\gamma_{\mathrm{norm}} = 1 - \frac{4\pi A}{L^2}$$



Geometric features

Global shape properties

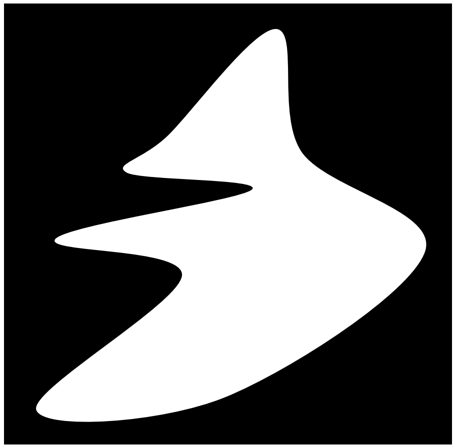
- Major (a) /minor (b) axis length
- Orientation (θ)
- Eccentricity (a/b)
  - yet another measure of deviation from circularity

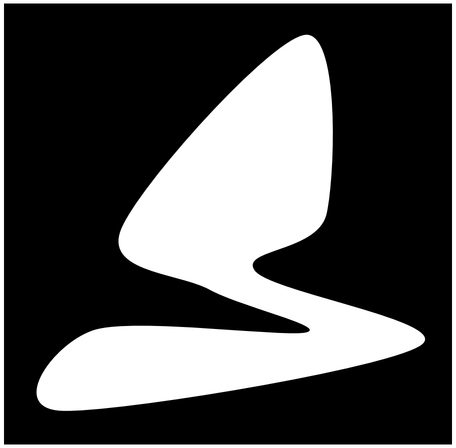


Geometric features

Geometric moments

- Assume that our shape is represented by a binary image I
- Global (m) and central (μ) moments:





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

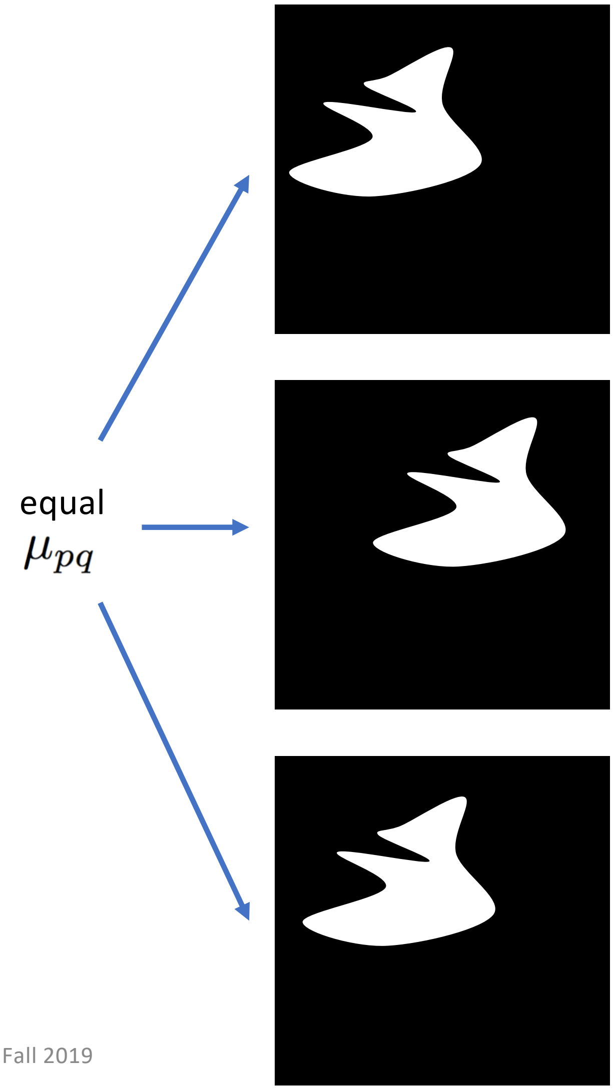
$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q I(x,y)$$

where: $\bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}}$

Geometric features

Geometric moments

- All central moments are translation-invariant
- Not the case for global moments



Geometric features

Moment-based functions: “Hu moments”

The following moment-based functions are
translation-, rotation- and scale-invariant:

$$
\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + \\
&\quad (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + \\
&\quad 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - \\
&\quad (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned}
$$

Originally proposed by Hu Ming-Kuei: "Visual pattern recognition by moment invariants," *Information Theory, IRE Transactions,* vol. 8, pp. 179-187, 1962

where:

$$\eta_{rs} = \frac{\mu_{rs}}{\mu_{00}^t} \qquad t = \frac{r+s}{2} + 1$$

Geometric features

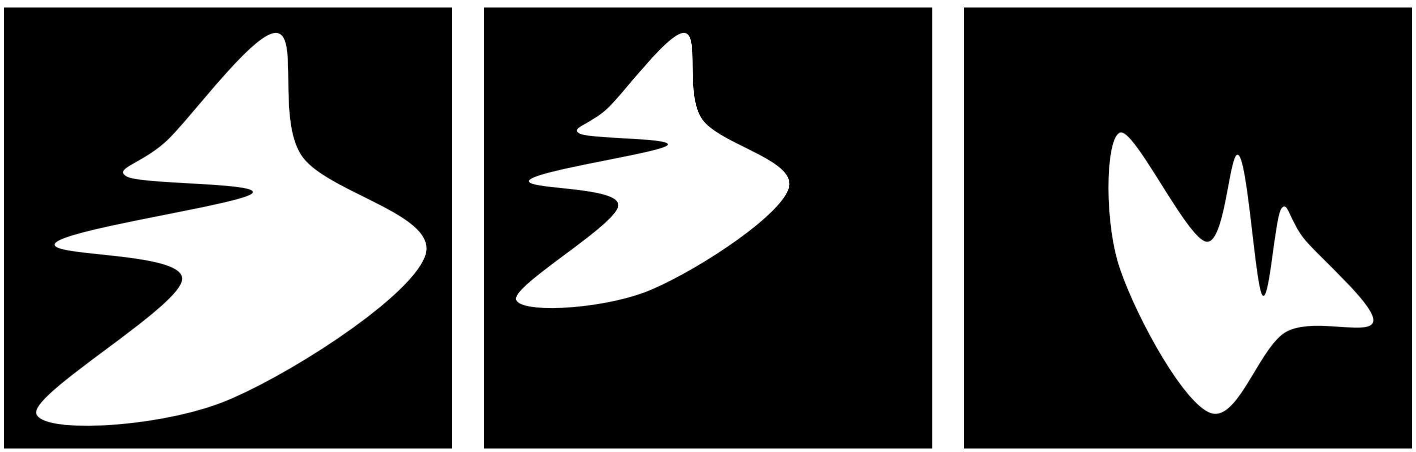
Moment-based functions: "Hu moments"

- The moment functions $\phi_1, \ldots, \phi_6$ are also reflection (mirroring) invariant
- In case of ϕ_7 its magnitude is reflection invariant but its sign changes after reflection

Geometric features

Moment-based functions: "Hu moments"

These shapes have similar $\phi_1,\ldots,\phi_7$



Geometric features

Moment-based functions: “Hu moments”

These shapes have also similar $\phi_1,\ldots,\phi_7$

Geometric features

Moment-based functions: “Hu moments”

But it should be possible to distinguish these shapes calculating their $\phi_1, \ldots, \phi_7$