



flusser@utia.cas.cz

www.utia.cas.cz/people/flusser

Prof. Ing. Jan Flusser, DrSc.

Lecture 1 – 2D Features

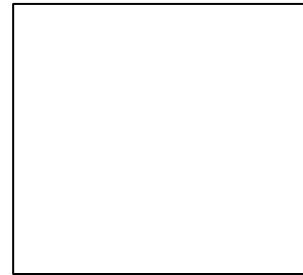
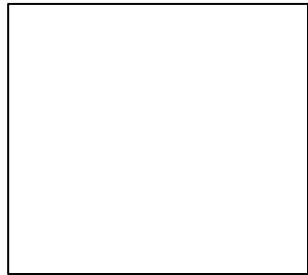
Digital Image Processing

- Digitization (sampling + quantizing)
- Preprocessing (contrast and brightness changes, denoising, sharpening, ...)
- Image analysis (object detection and recognition, scene understanding)
- Image coding (compression)

Topics of ROZ2

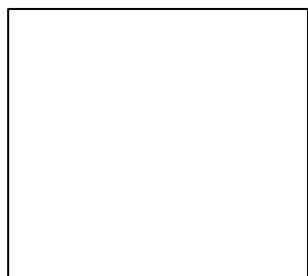
- Digitization (sampling + quantizing)
- Preprocessing (contrast and brightness changes, denoising, sharpening, ...)
- Image analysis (object detection and recognition, scene understanding)
- Image coding (compression)

Image (pre)processing



Image

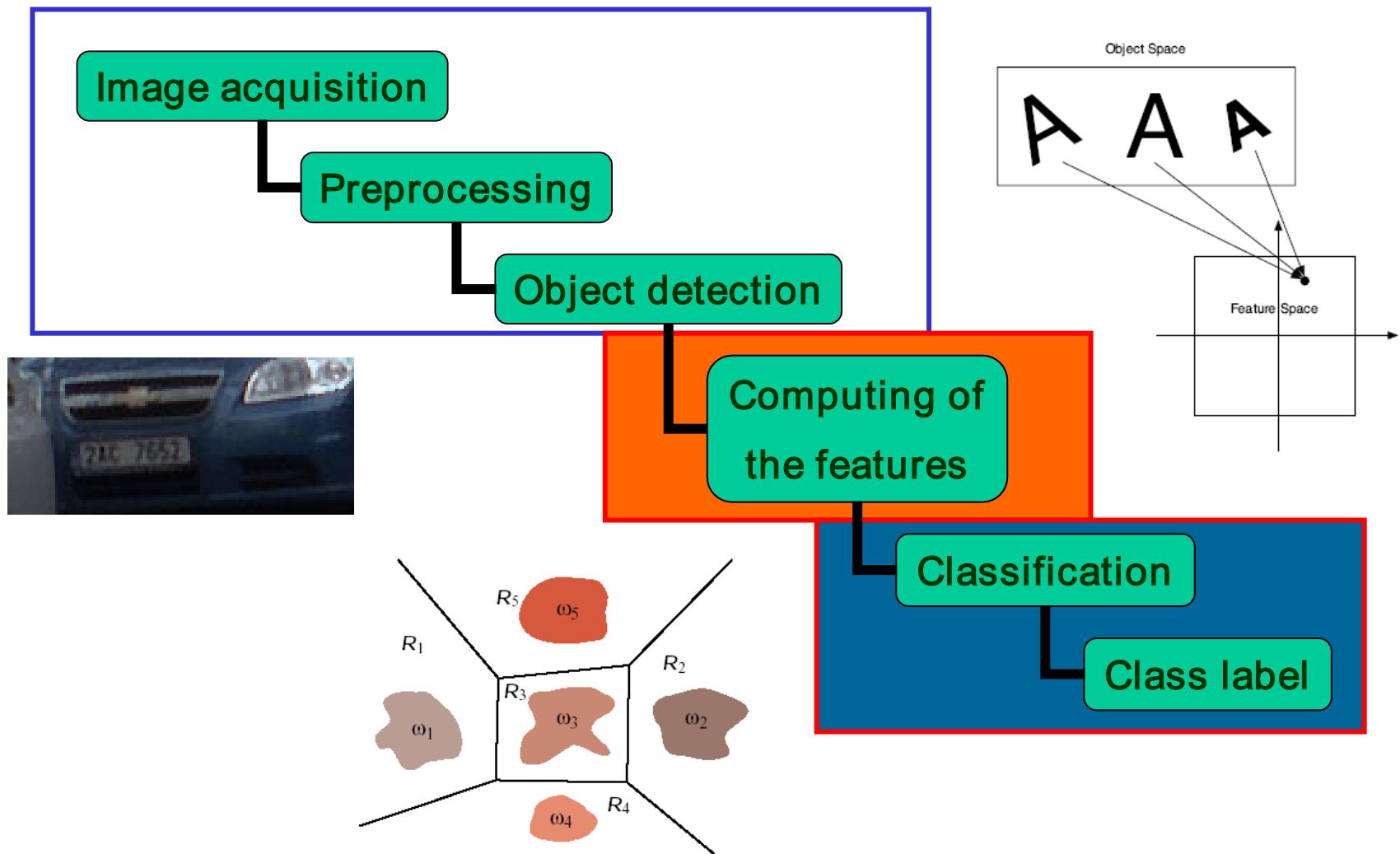
Image analysis



(d_1, d_2, \dots)

Non-
image

Object Recognition System





(F_1, F_2, \dots, F_n)

2AC 7652

Why is visual object recognition so difficult for machines?

Human beings

- use their lifetime experience as a prior

Why is visual object recognition so difficult for machines?

Human beings

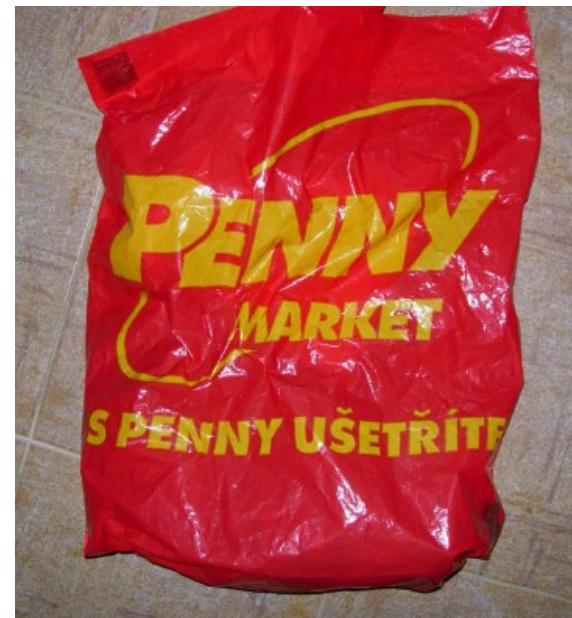
- use supplementary information (sound, touch)



Why is visual object recognition so difficult for machines?

Human beings

- are very robust to object degradations



Why is visual object recognition so difficult for machines?

Human beings

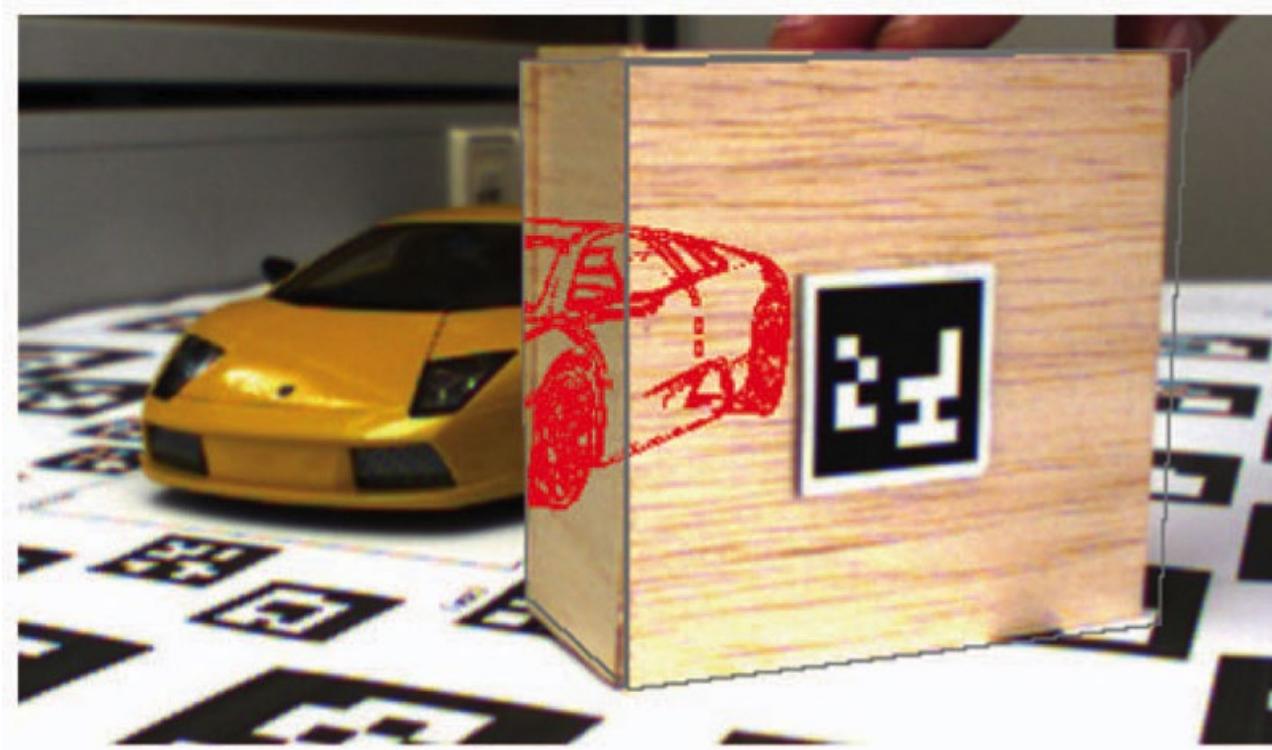
- learn not only from the previous results but also from the recognition process itself



Why is visual object recognition so difficult for machines?

Human beings

- can efficiently work with incomplete information



Why is visual object recognition so difficult for machines?

Human beings

- can use a broad context



Features for description and recognition of 2D objects

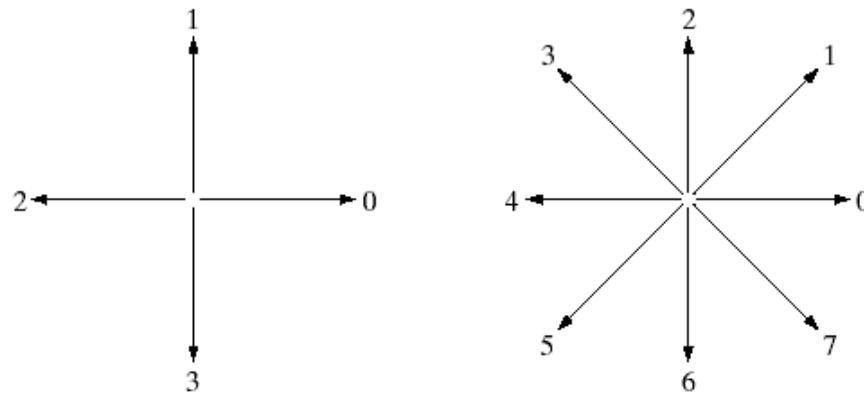
Feature = a point in a metric space (usually in n -D Euclidean space) that describes the object

What is a 2-D object?

- **Binary**
- **Finite**
- **Boundary** – a simple closed curve or a finite set of them

What is a (discrete) boundary?

- Boundary pixel – an object pixel having a background neighbor
- What is a neighbor? (Definition of discrete topology)



How to detect objects in the image? (Image segmentation)

- Thresholding
- Edge linking
- Region growing

Thresholding

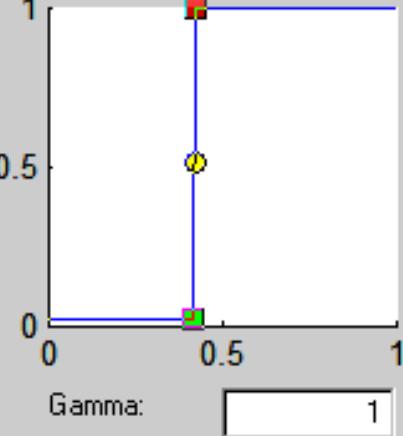
Select an Image:

Rice

Adjusted Image

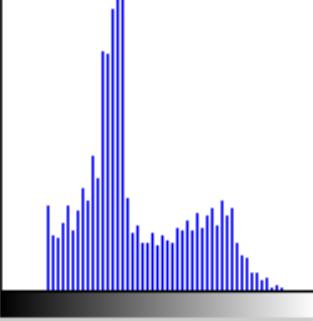


Output vs. Input Intensity

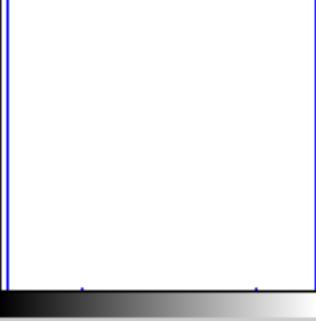


Gamma: 1

Histogram



Histogram



Operations:

Intensity Adjustment

+ Brightness - Brightness

+ Contrast - Contrast

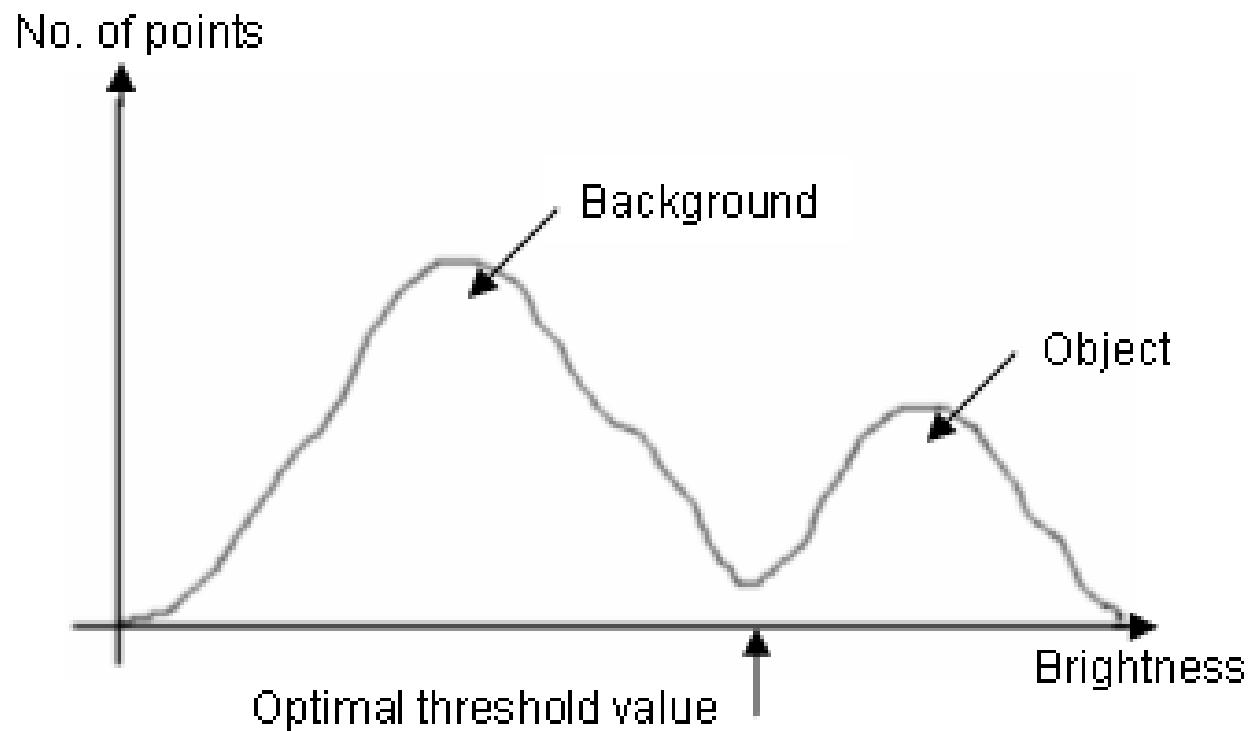
+ Gamma - Gamma

Info Close

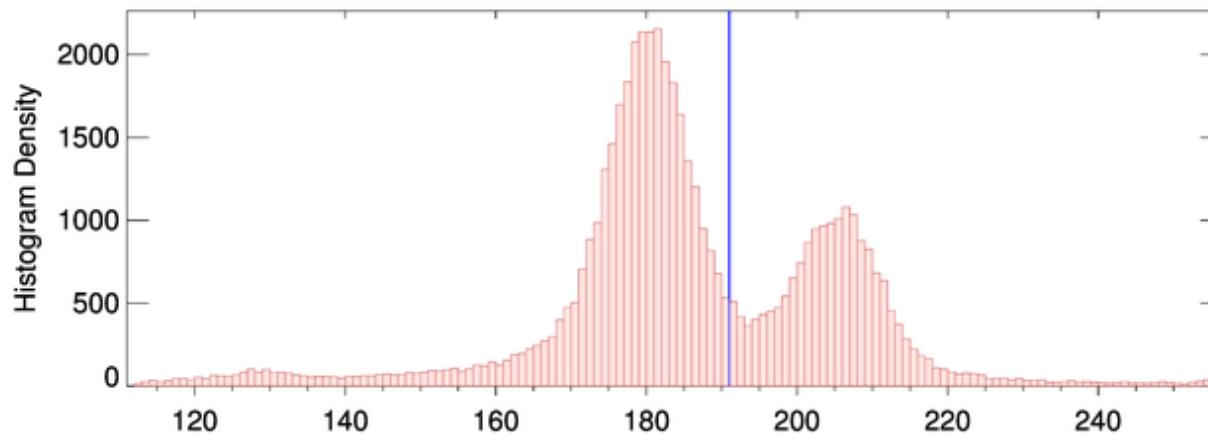
The Otsu's threshold

$$\sigma_w^2(t) = \omega_1(t)\sigma_1^2(t) + \omega_2(t)\sigma_2^2(t)$$

$$\sigma_b^2(t) = \sigma^2 - \sigma_w^2(t) = \omega_1(t)\omega_2(t) [\mu_1(t) - \mu_2(t)]^2$$



The Otsu's threshold



Between Class Variance Threshold: 191.00

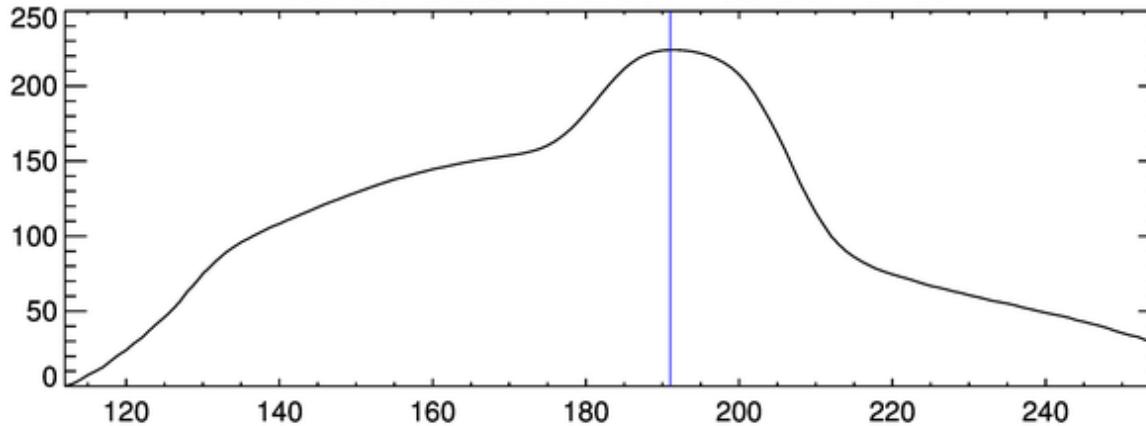
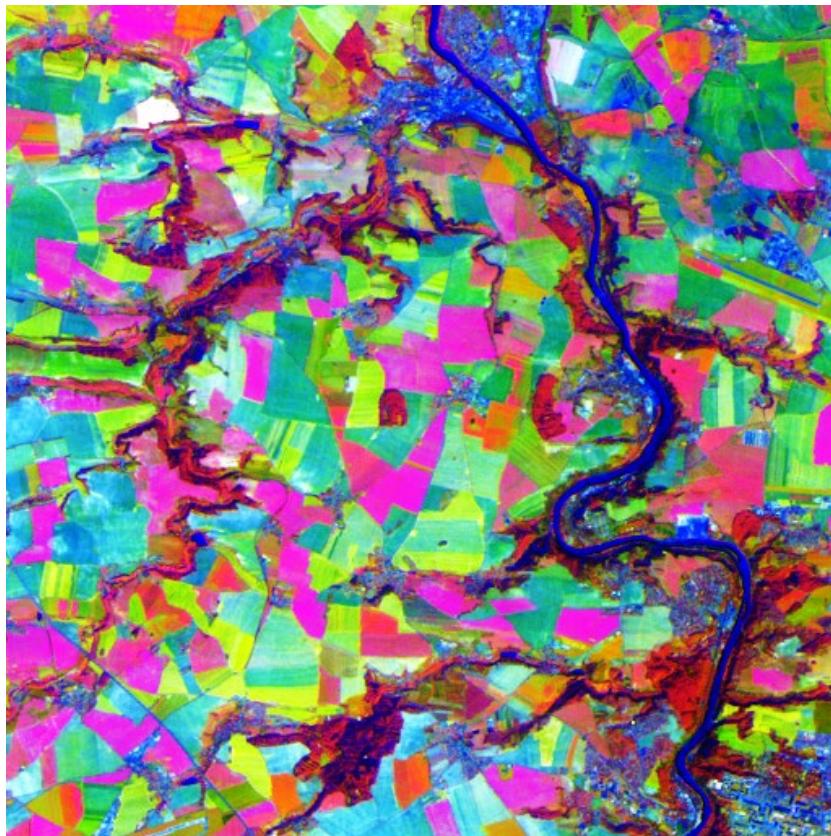
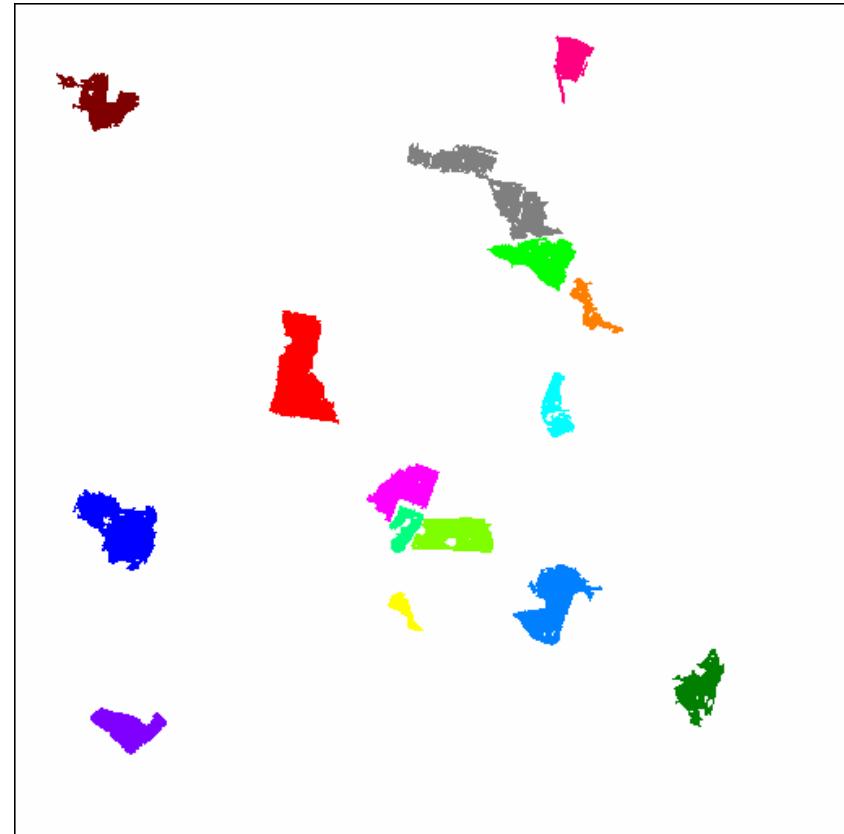


Image segmentation

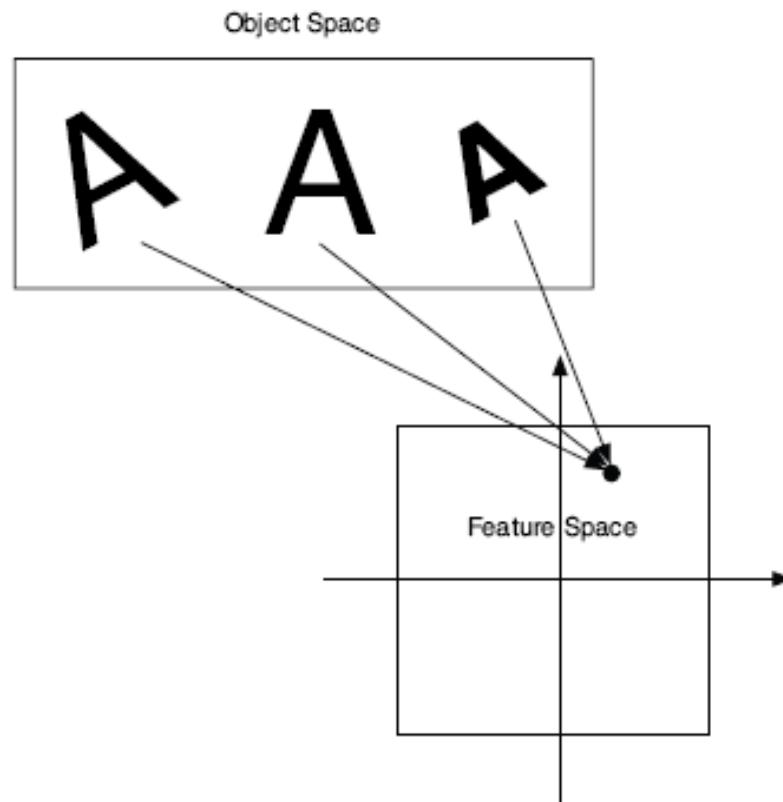


Original

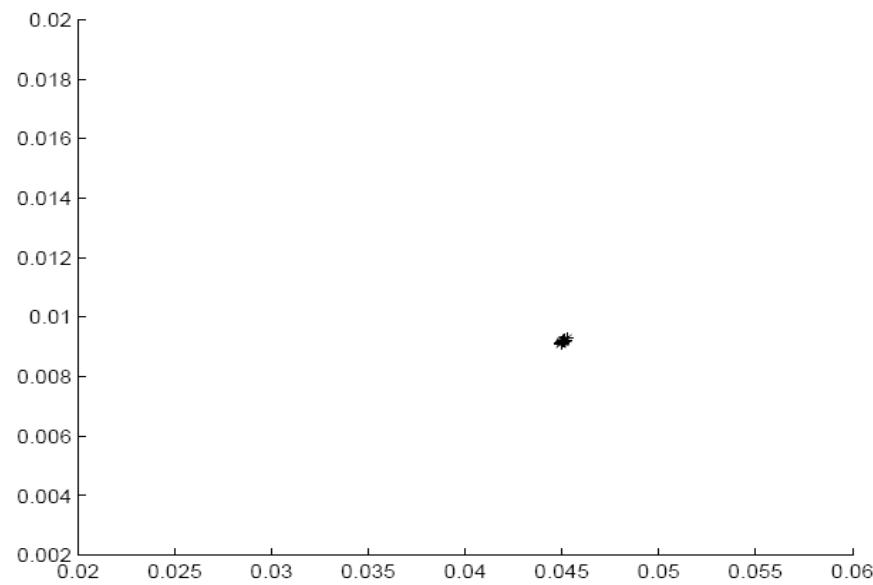


Partial segmentation

What are features?



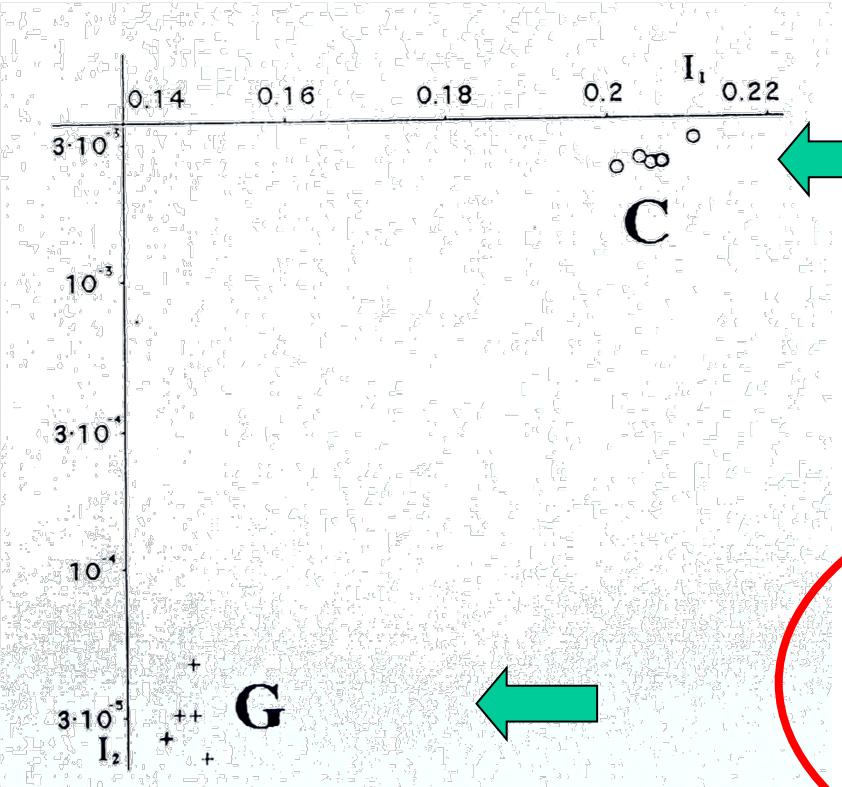
Example: TRS



Desirable properties of the features

- Invariance
- Discriminability
- Robustness
- Efficiency, independence, completeness

Discrimination power



C C C C C C C C C C

G G G G G G G G G G

Major categories of invariants

Simple “visual” shape descriptors

- compactness, convexity, elongation, ...

Transform coefficient invariants

- Fourier descriptors, wavelet features, ...

Point set invariants

- positions of dominant points

Differential invariants

- derivatives of the boundary

Moment invariants

Visual features for binary objects

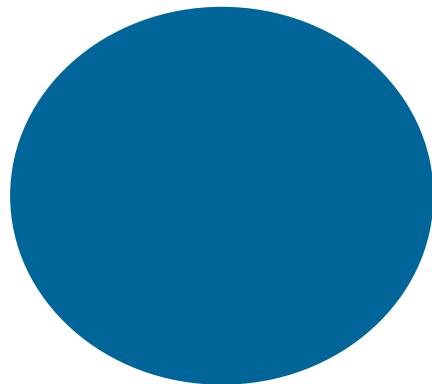
Simple features

- Compactness

$$\frac{4\pi P}{O^2}$$

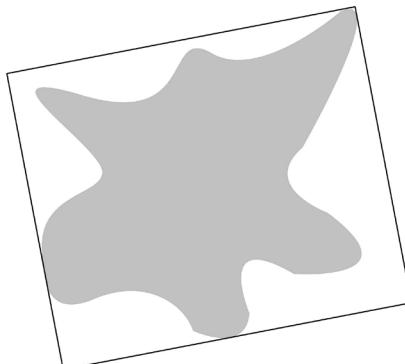
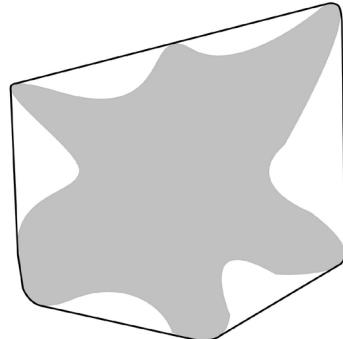
- Convexity

$$\frac{P(A)}{P(C_A)}$$



Visual features for binary objects

Simple features



- Compactness

$$\frac{4\pi P}{O^2}$$

- Convexity

$$\frac{P(A)}{P(C_A)}$$

- Elongation

- Rectangularity

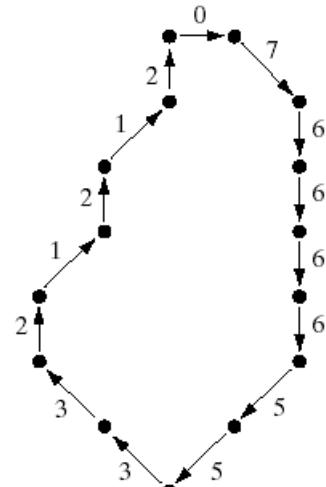
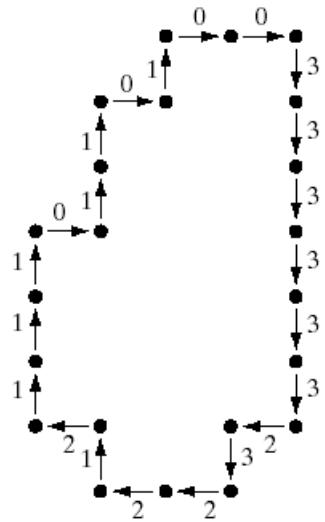
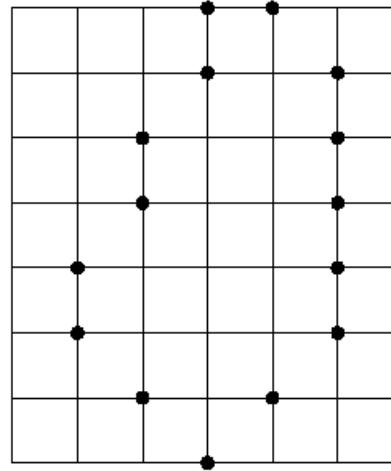
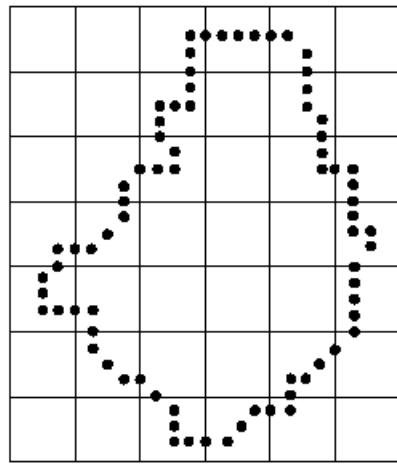
- Euler number

Visual features for binary objects

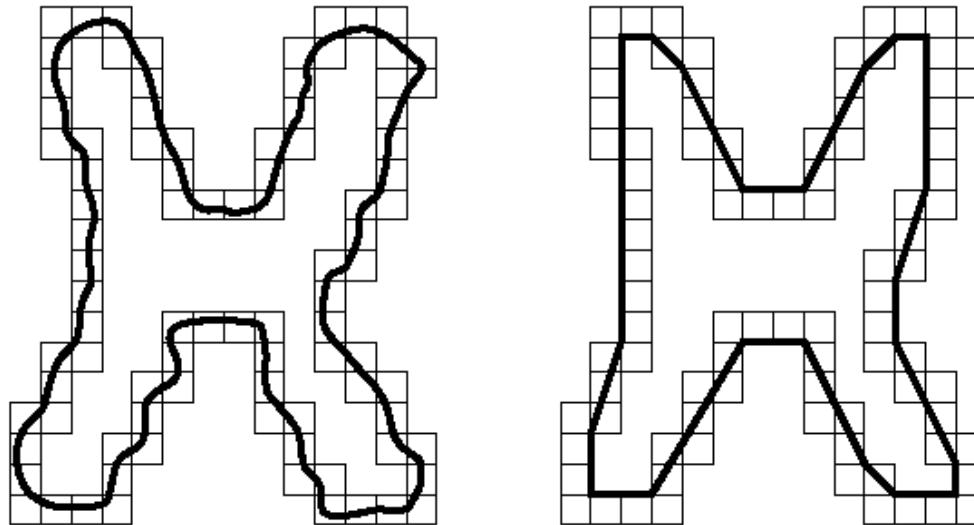
“Complete” features

- Chain code
- Polygonal approximation
- Shape vector
- Shape matrix
- Other encodings of the radial function

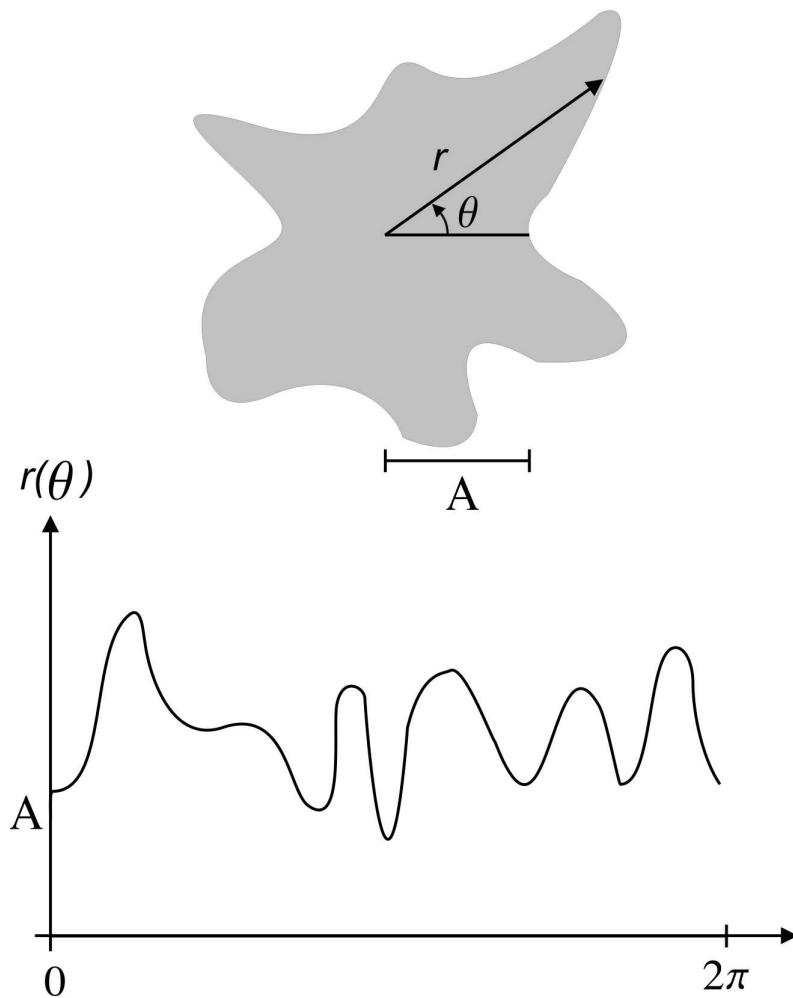
Chain code



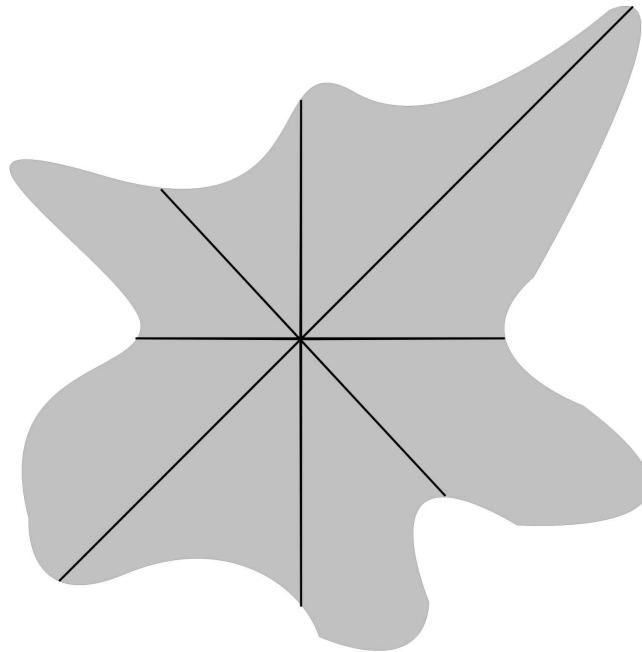
Polygonal approximation



Radial function



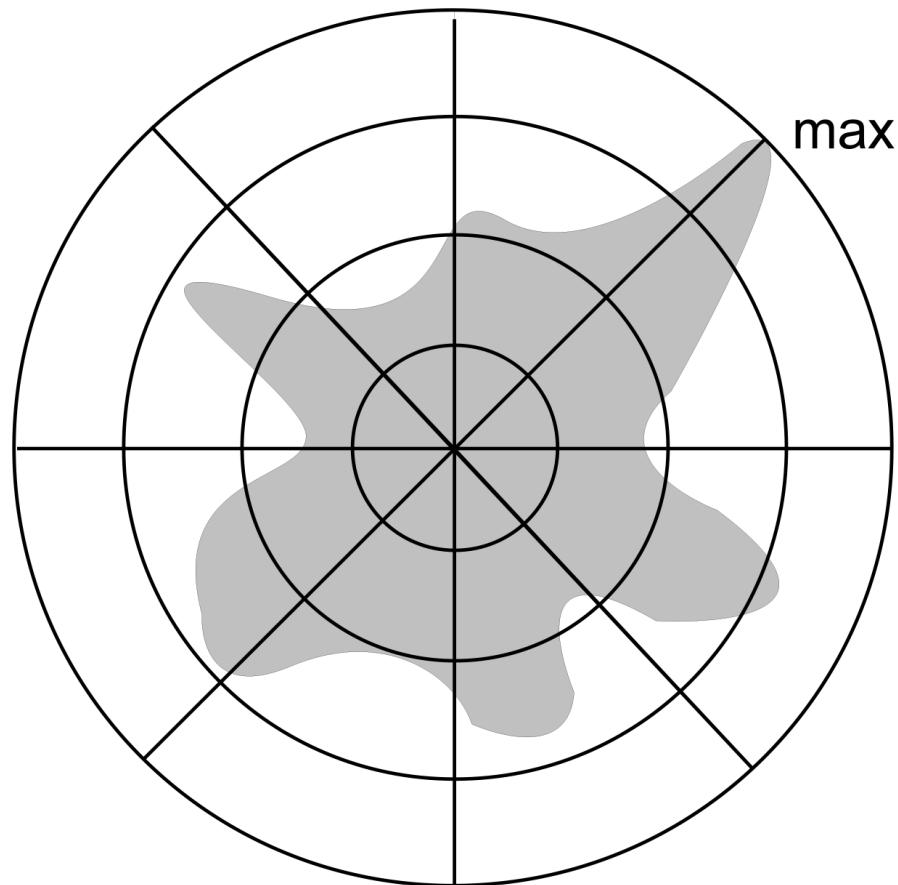
Shape vector



$$v = (d_1, d_2, \dots, d_n)$$

$$n = 8$$

Shape matrix

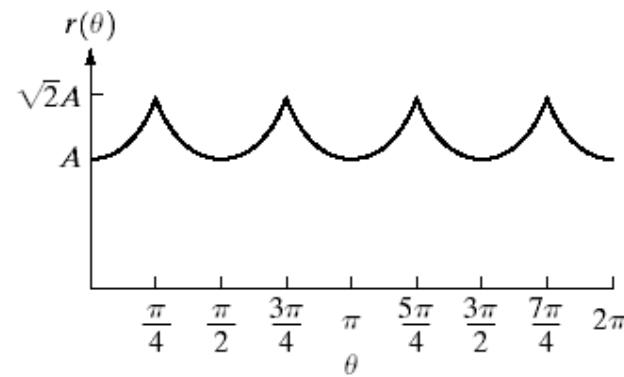
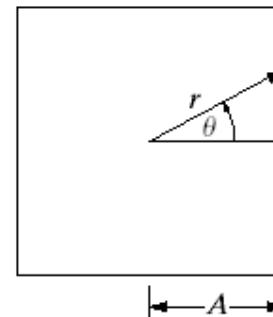
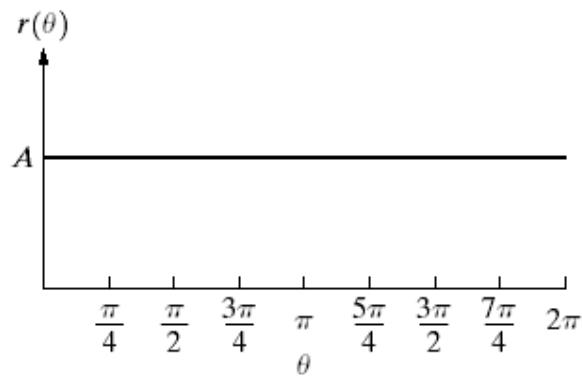
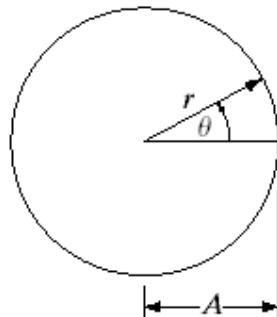


$$B = \begin{vmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{vmatrix}$$

Transform coefficient features

- Fourier descriptors
- Wavelet-based features
- Other transform coefficients

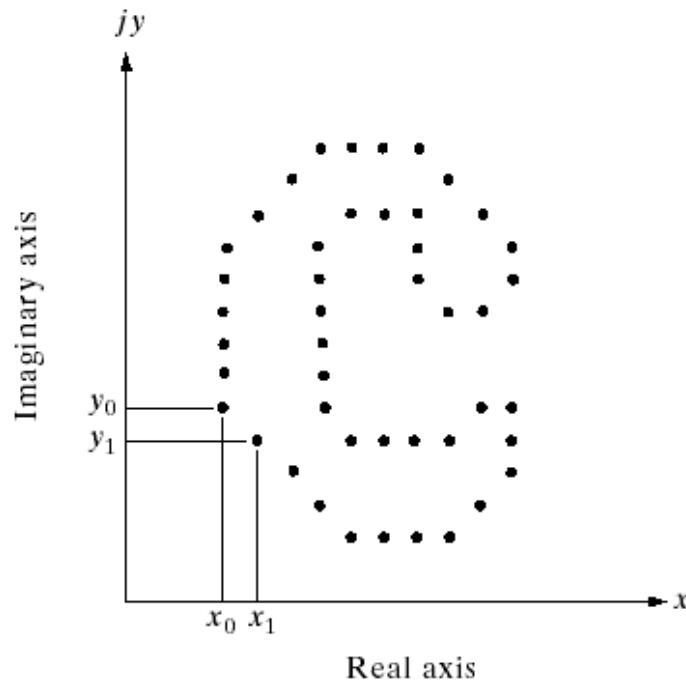
Fourier descriptors



$$f(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2}$$

Fourier descriptors

$$z_n = x_n + i \cdot y_n$$



$$Z_k = \sum_{n=0}^{N-1} z_n e^{-2\pi i kn/N}$$

$$C_k = |Z_k|/|Z_1|, k = 2, 3, \dots$$

Shift invariance

$$\sum_{n=0}^{N-1} (z_n - z) e^{-2\pi i k n / N} = \sum_{n=0}^{N-1} z_n e^{-2\pi i k n / N} + z \sum_{n=0}^{N-1} e^{-2\pi i k n / N}$$

$$\sum_{n=0}^{N-1} e^{-2\pi i k n / N} = 0, \quad k \neq 0$$

$$\sum_{n=0}^{N-1} e^{-2\pi i k n / N} = N, \quad k = 0$$

Rotation invariance

$$\sum_{n=0}^{N-1} (z_n e^{\varphi i}) e^{-2\pi i k n / N} = e^{\varphi i} \sum_{n=0}^{N-1} z_n e^{-2\pi i k n / N}$$

Scaling invariance

$$\sum_{n=0}^{N-1} (cz_n) e^{-2\pi i kn/N} = c \sum_{n=0}^{N-1} z_n e^{-2\pi i kn/N}$$

Invariance to the starting point

- Fourier Shift Theorem

Wavelet features



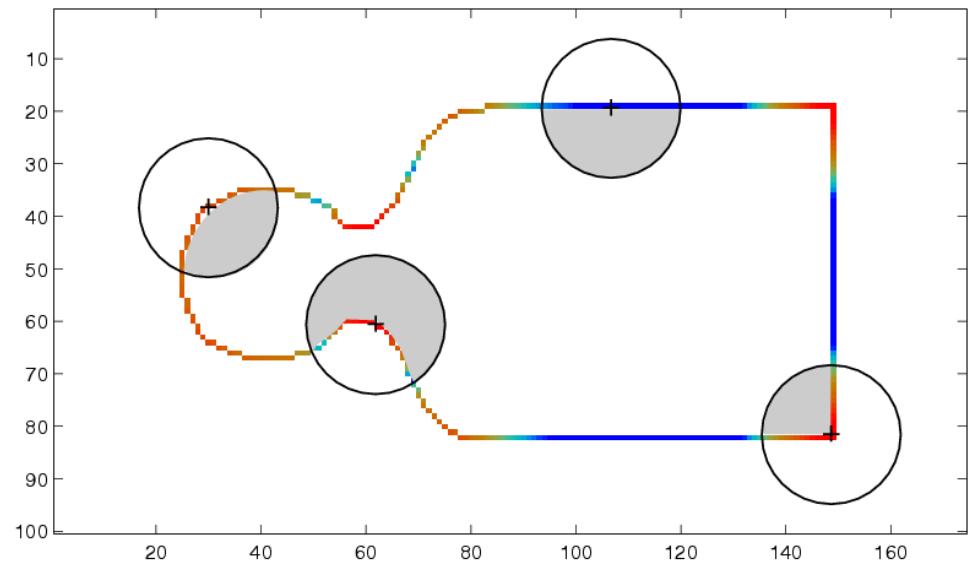
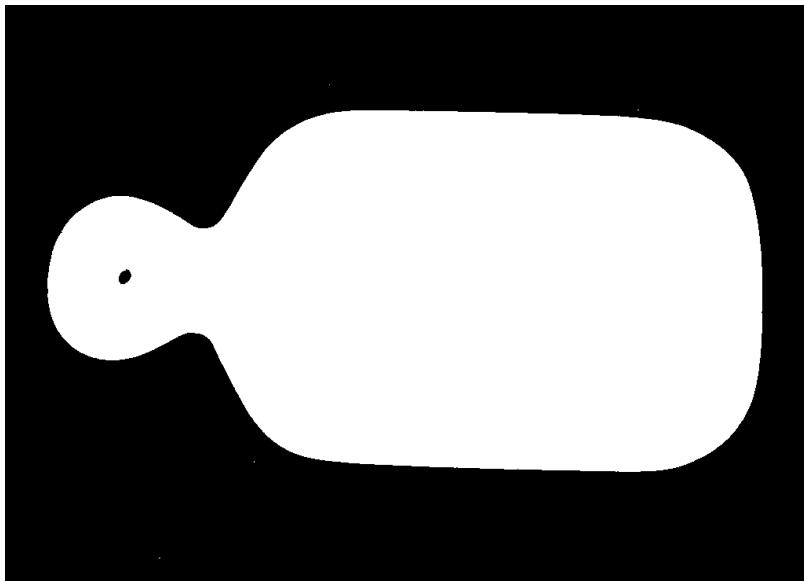
Differential invariants

Motivation: recognition of occluded objects
→ Features must be local

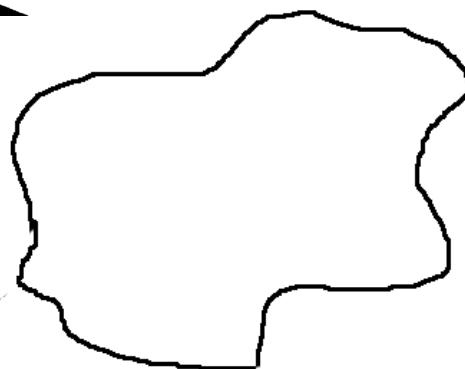
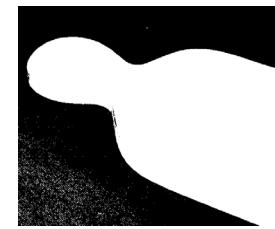
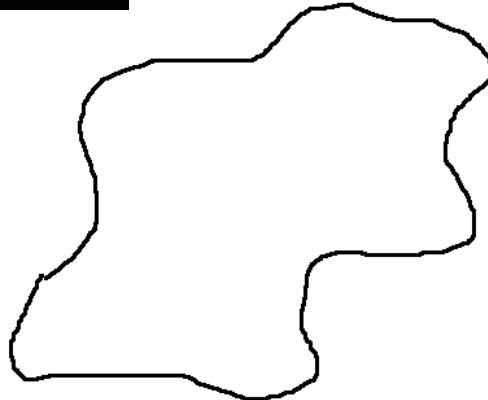
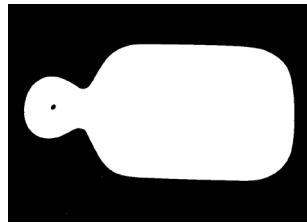
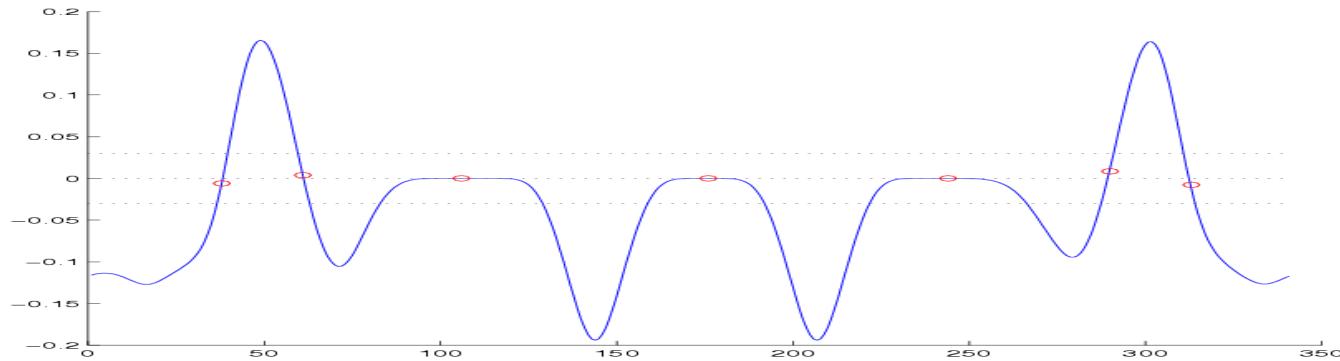


Differential invariants – an example

$$c(t) = \frac{\dot{x}\ddot{y} - \ddot{x}\dot{y}}{(\dot{x}^2 + \dot{y}^2)^{3/2}}$$



Differential invariants – an example



Differential invariants

DI's are composed from higher-order derivatives of the boundary

DI's are invariant to affine and even to projective transform but are extremely unstable

Semi-differential invariants

**Motivation: avoiding high-order derivatives
while preserving the locality**

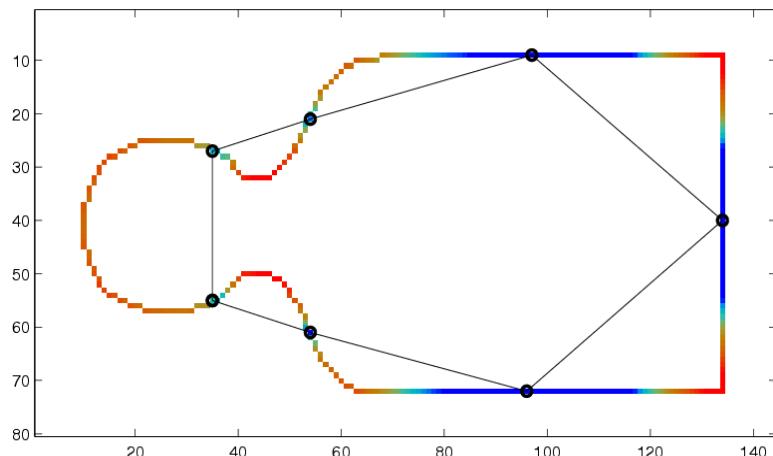
Decomposition of the object into parts, each part is then described by global invariants

The decomposition is often based on inflection points (they are affine- and projective-invariant)

$$\dot{x}\ddot{y} - \ddot{x}\dot{y} = 0$$

Dividing the object into invariant parts

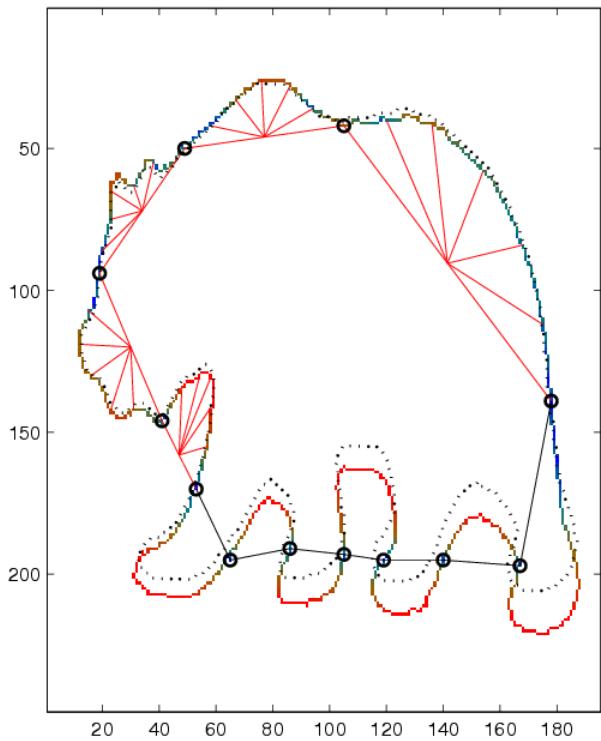
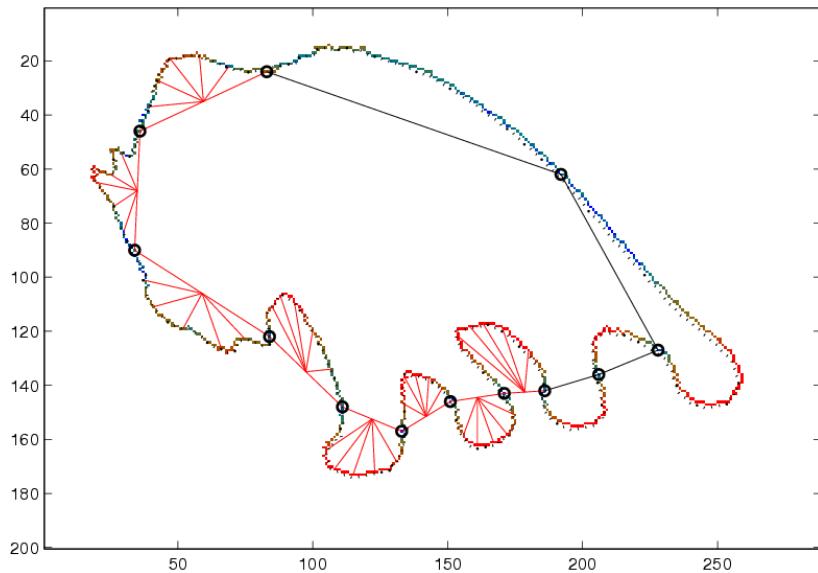
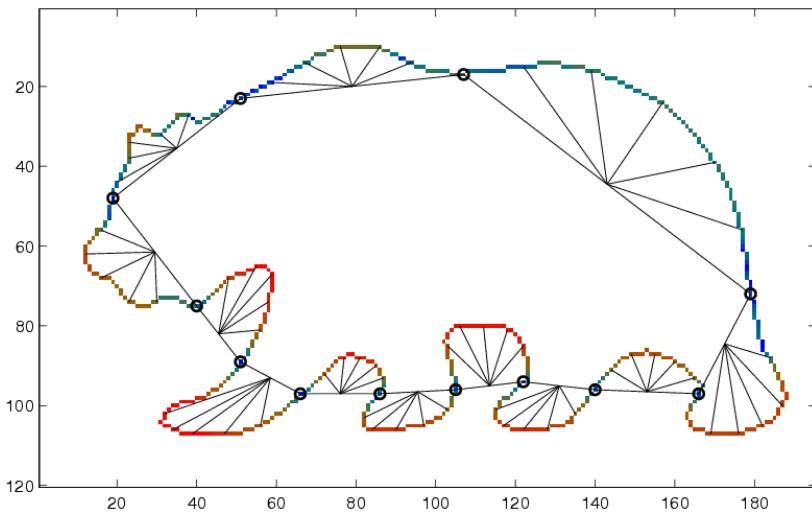
- Inflection points and centers of straight lines



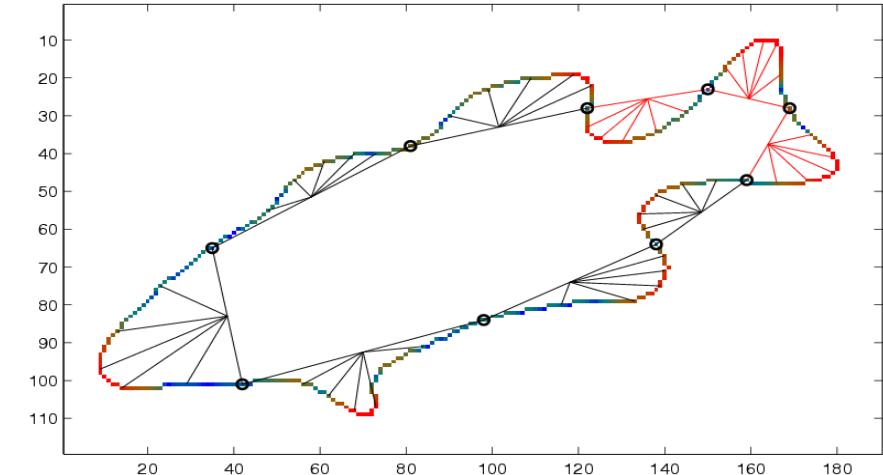
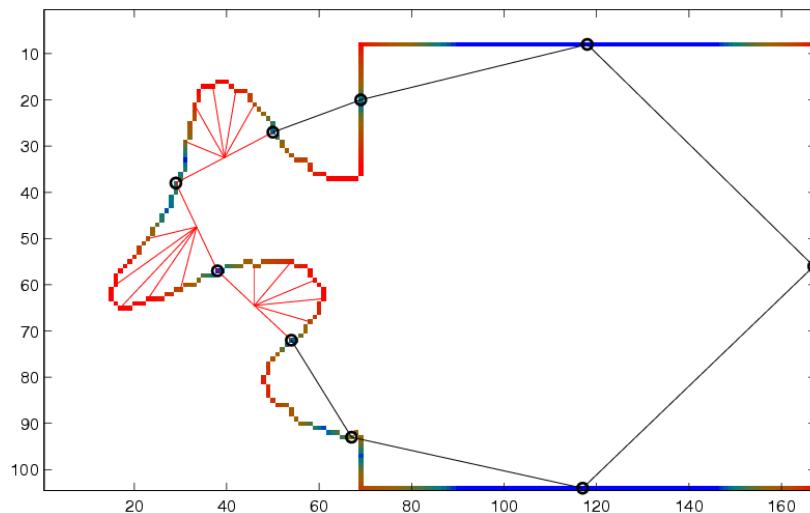
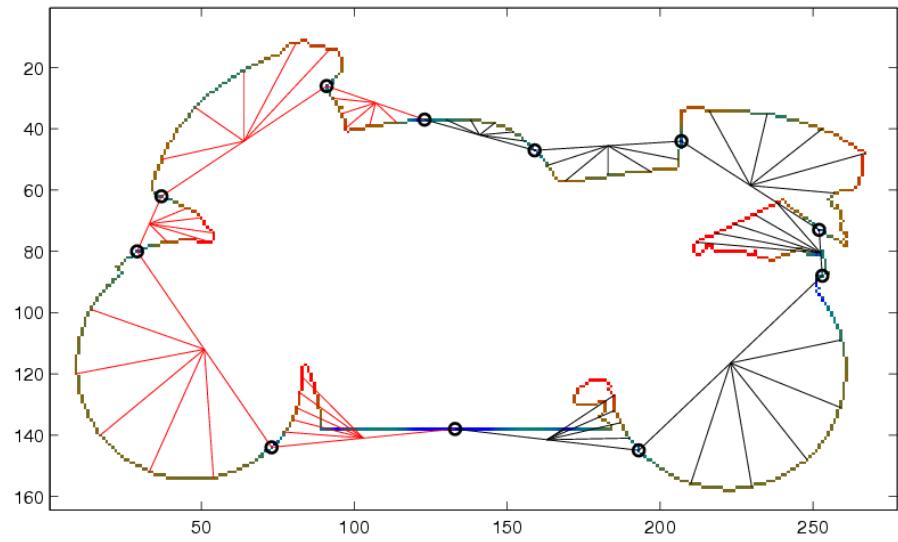
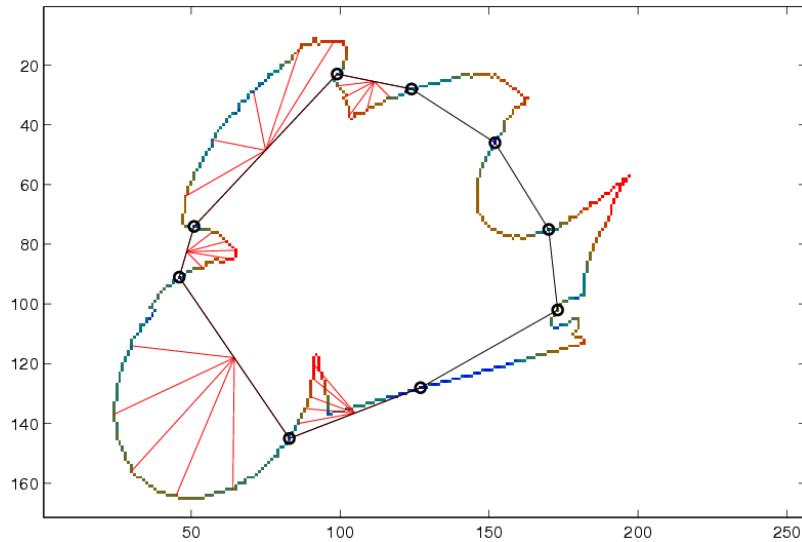
$$\dot{x}\ddot{y} - \dot{y}\ddot{x} = 0$$

- Computing invariants of each part

Affine-invariant radial vectors

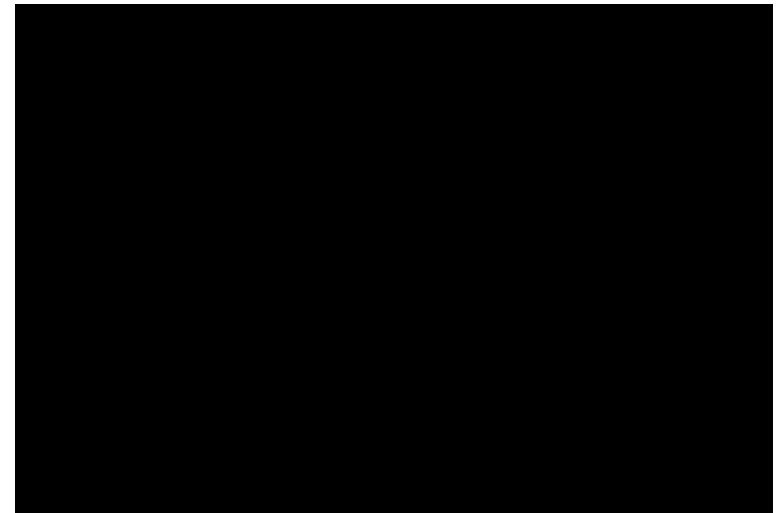
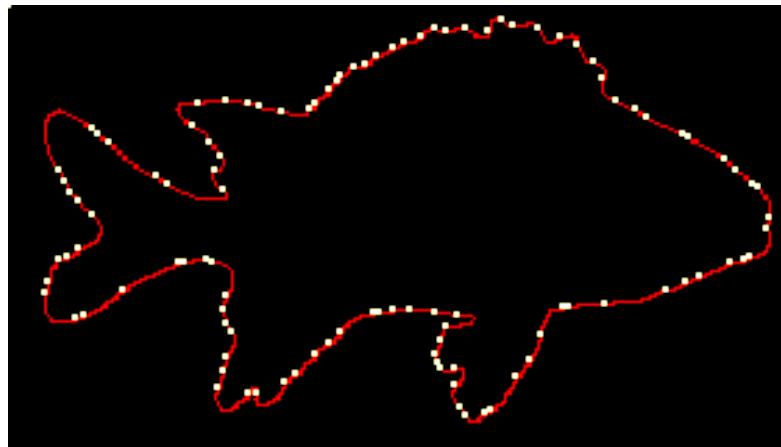


Recognition of occluded objects

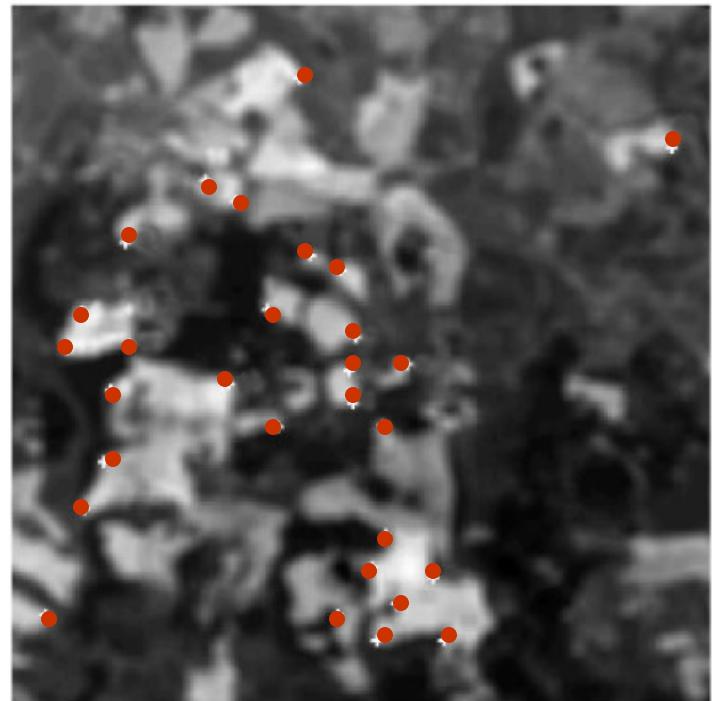
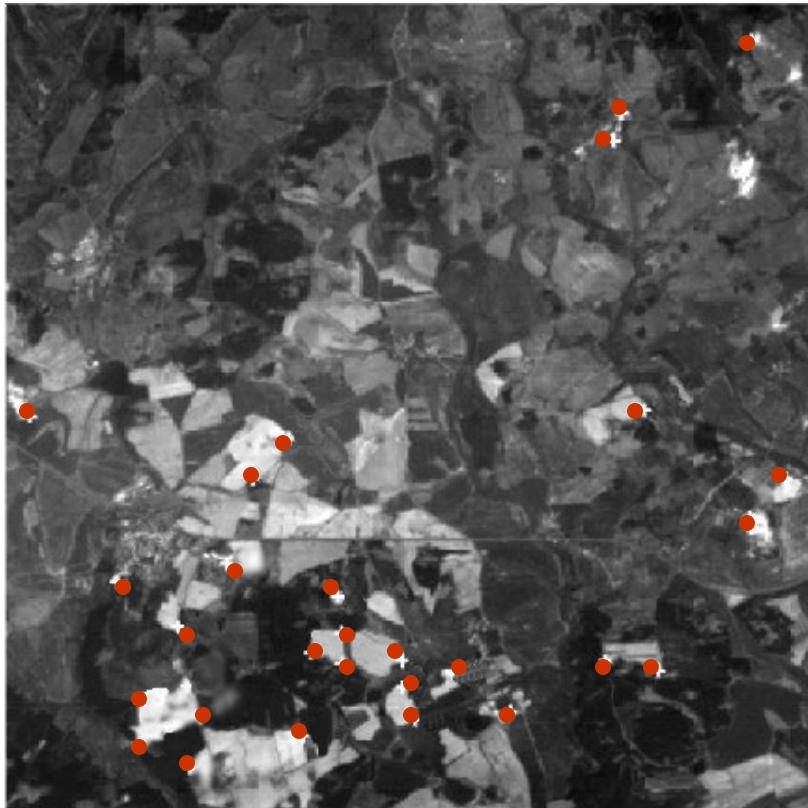


CSS – Curvature Scale Space

Evolution of inflection points at different scales



Local invariants of graylevel images

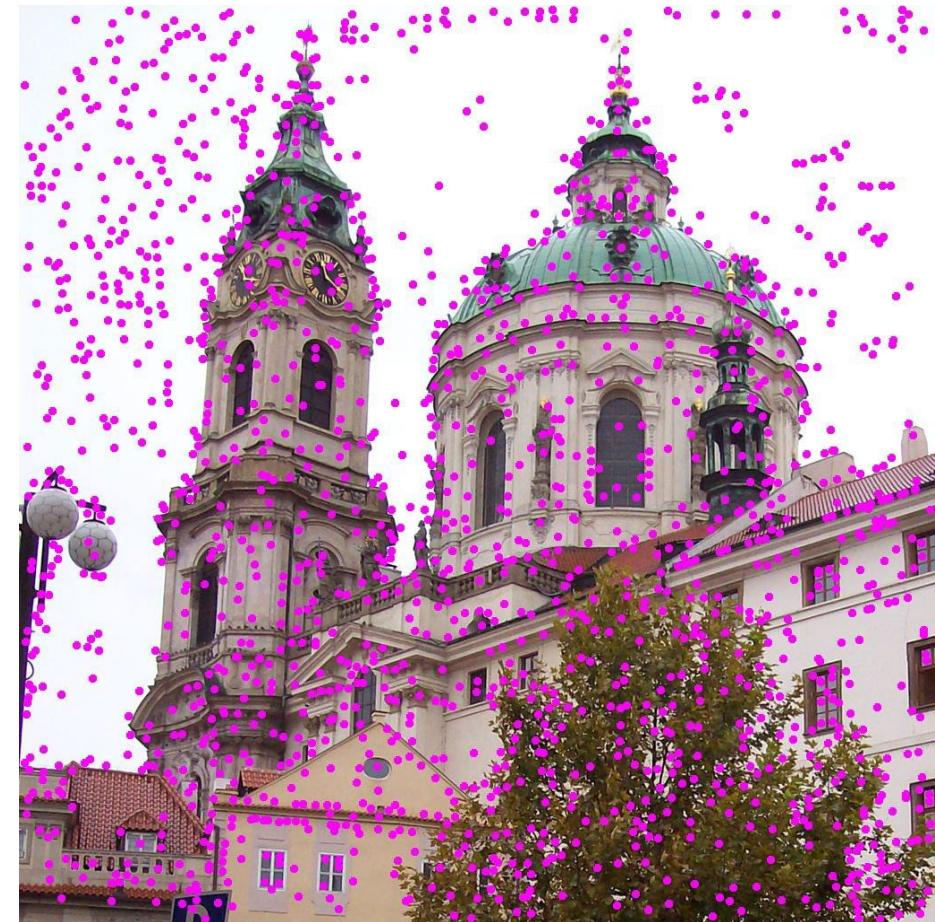
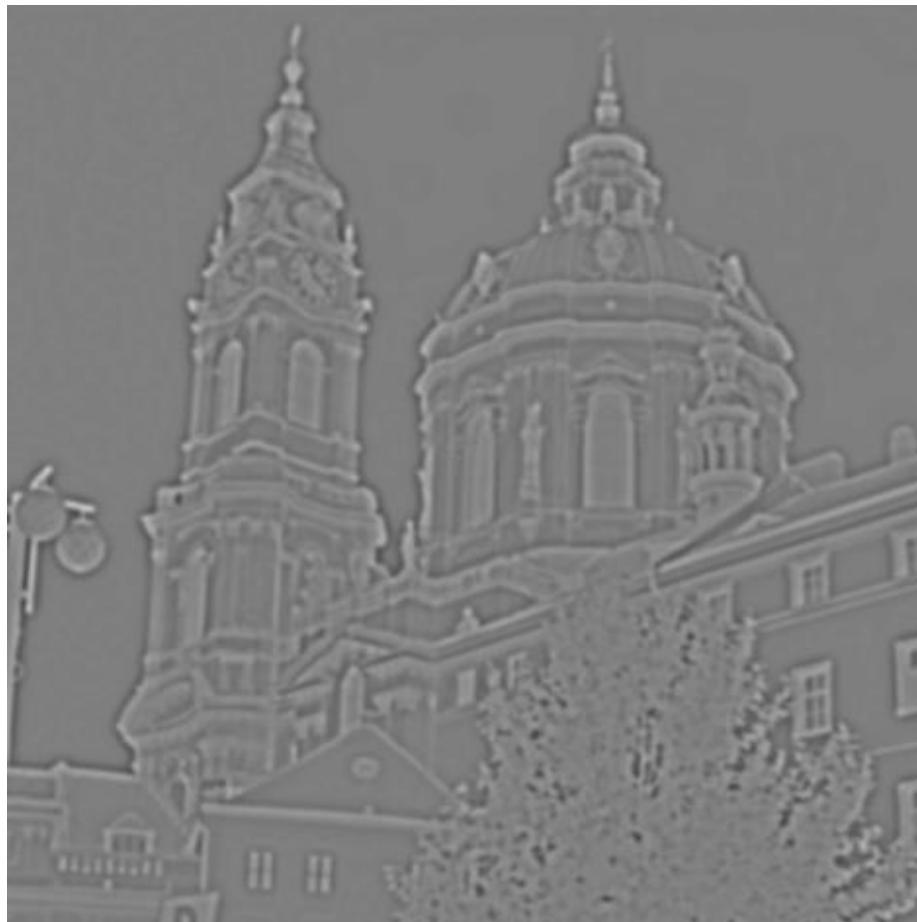


$$\min_{k,m} \text{distance}((v1_k, v2_k, v3_k, \dots), (\overline{v1}_m, \overline{v2}_m, \overline{v3}_m, \dots))$$

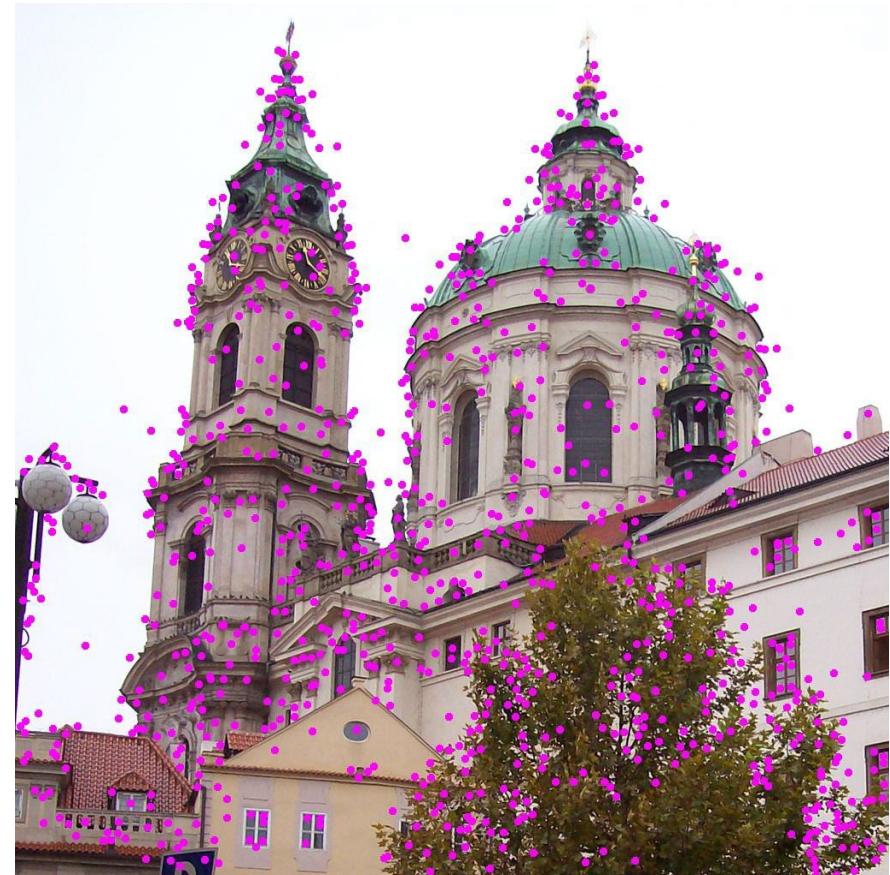
SIFT (D.G. Lowe, 1999)



Find local extrema in the difference image



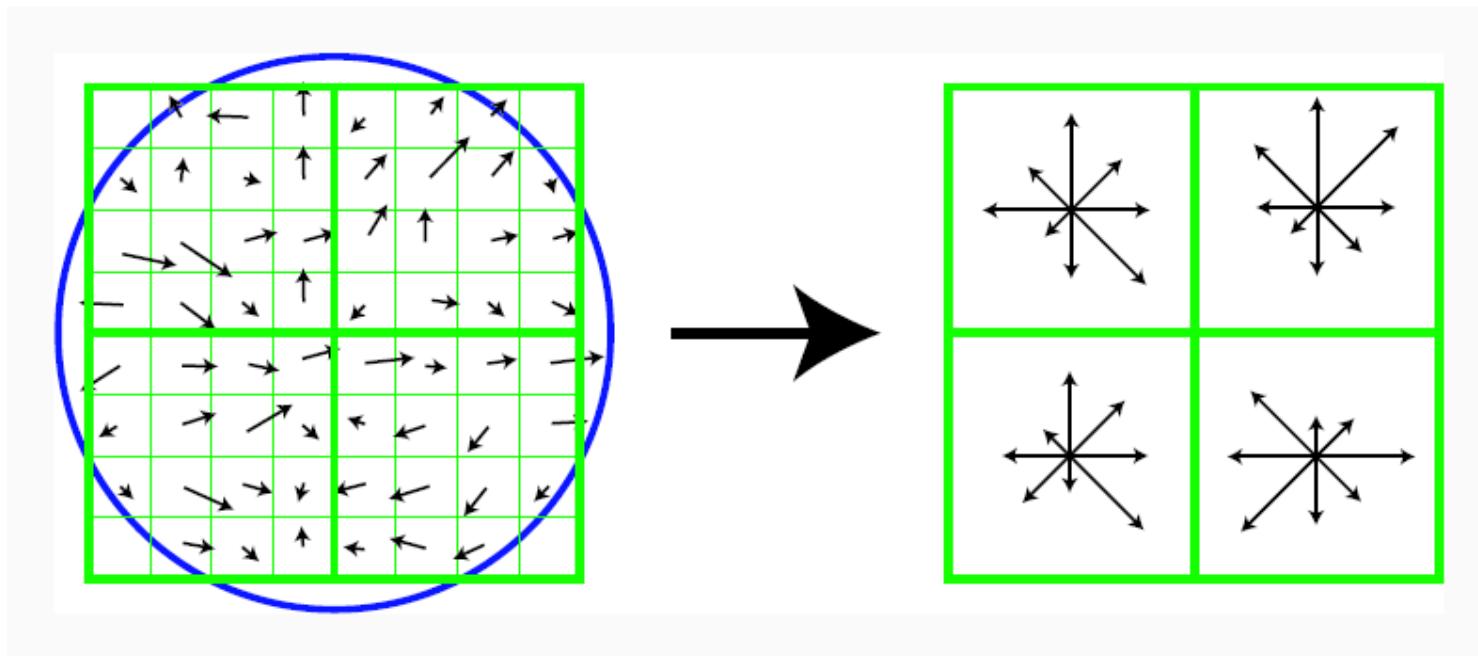
Delete local extrema with low contrast and those on edges



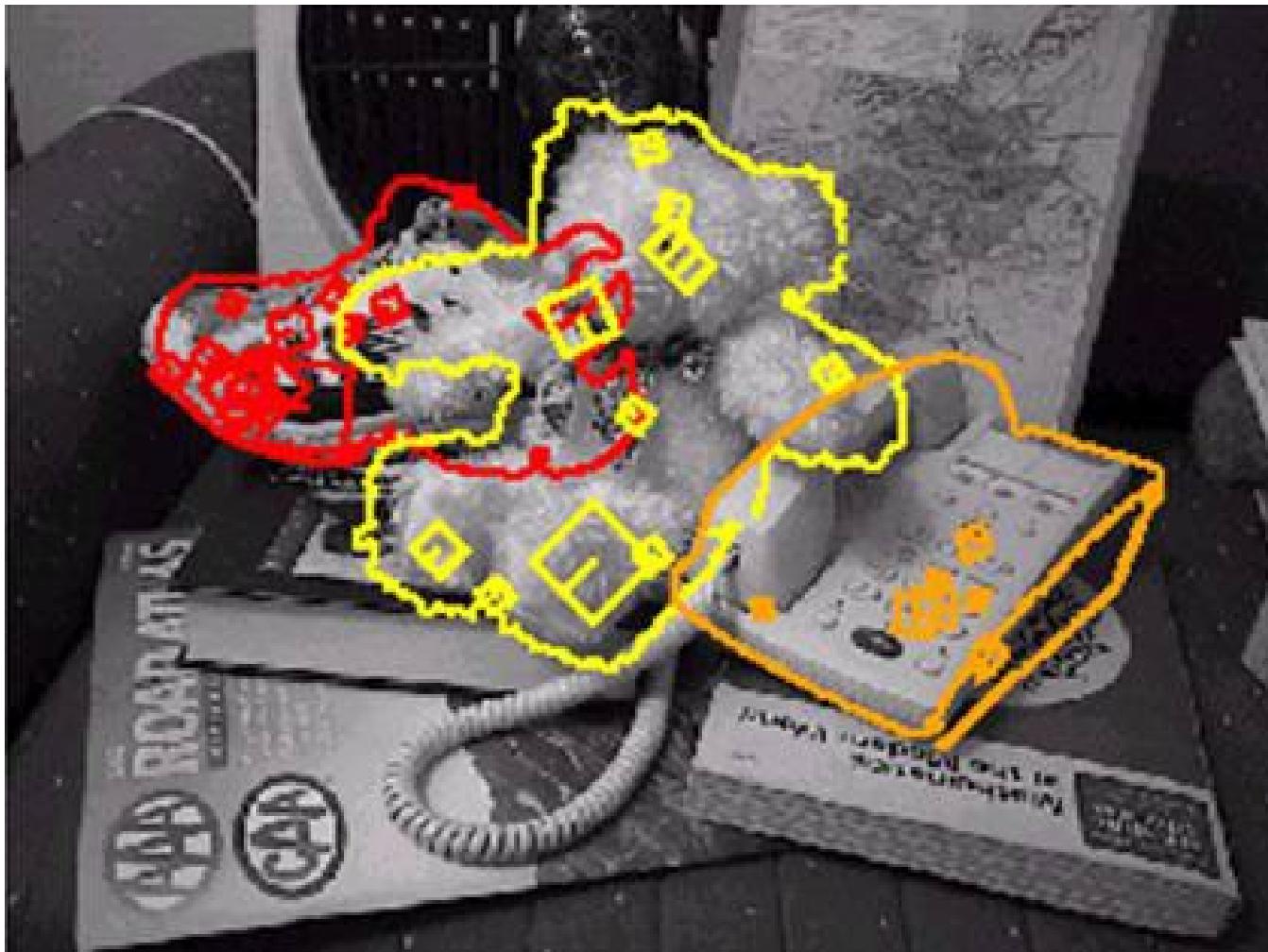
Gradient-based neighborhood



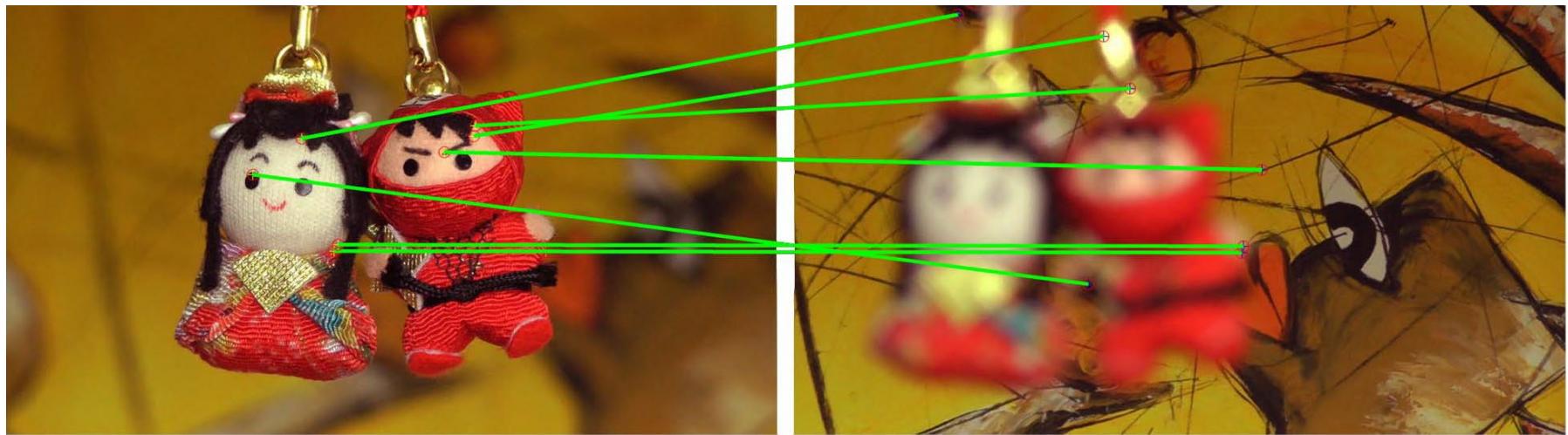
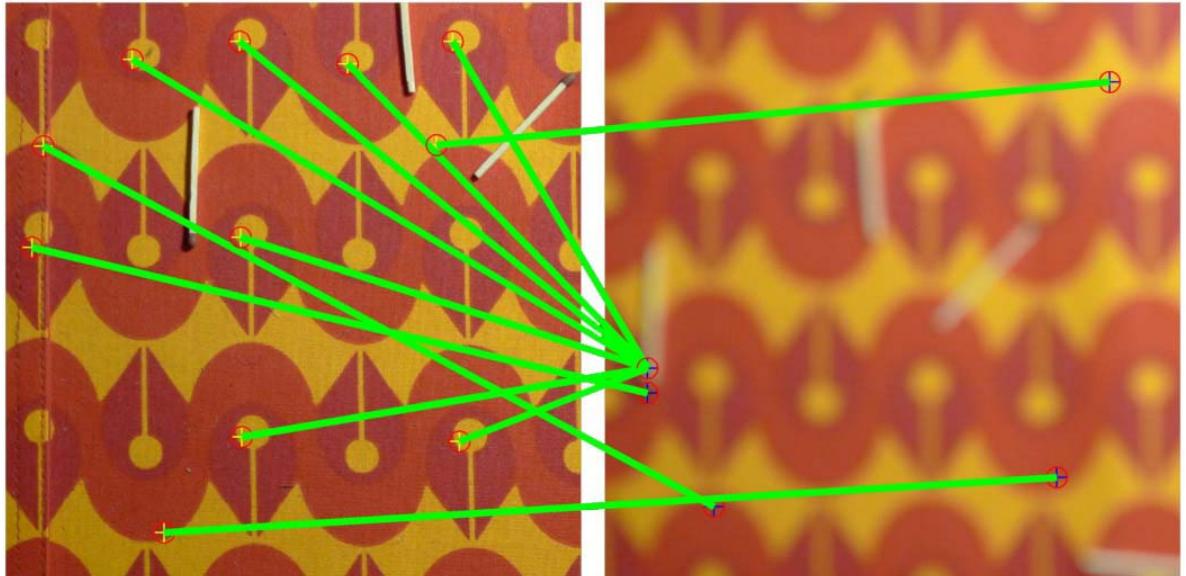
Feature vector: histogram of gradients In the neighborhood



Recognition of occluded objects



Problems



Moment invariants

Moments are “projections” of the image function into a polynomial basis

$f(x, y)$ – piecewise continuous image function defined on bounded $\Omega \subset \mathcal{R} \times \mathcal{R}$

$\{\mathcal{P}_{pq}(x, y)\}$ – set of polynomials defined on Ω

$$M_{pq} = \iint \mathcal{P}_{pq}(x, y) f(x, y) dx dy$$

Common types of moments

Geometric moments

$$m_{pq}^{(f)} = \int_{R^2} x^p y^q f(x, y) dx dy$$

Central moments

$$\mu_{pq}^{(f)} = \int_{R^2} (x - x_t)^p (y - y_t)^q f(x, y) dx dy$$

What are moment invariants?

Functions of moments, invariant to certain class of image degradations

- Rotation, translation, scaling
- Affine transform
- Convolution/blurring
- Combined invariants

Invariants to translation and scaling

Normalized central moments

$$\nu_{pq} = \frac{\mu_{pq}}{\mu_{00}^w} \quad w = \frac{p+q}{2} + 1$$

Invariants to rotation

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

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

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

$$\phi_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2$$



Thank you !

Any questions ?