Content Based Image Retrieval

III

Dr. Bassam Kurdy

Tutorial outline

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- Lecture 3
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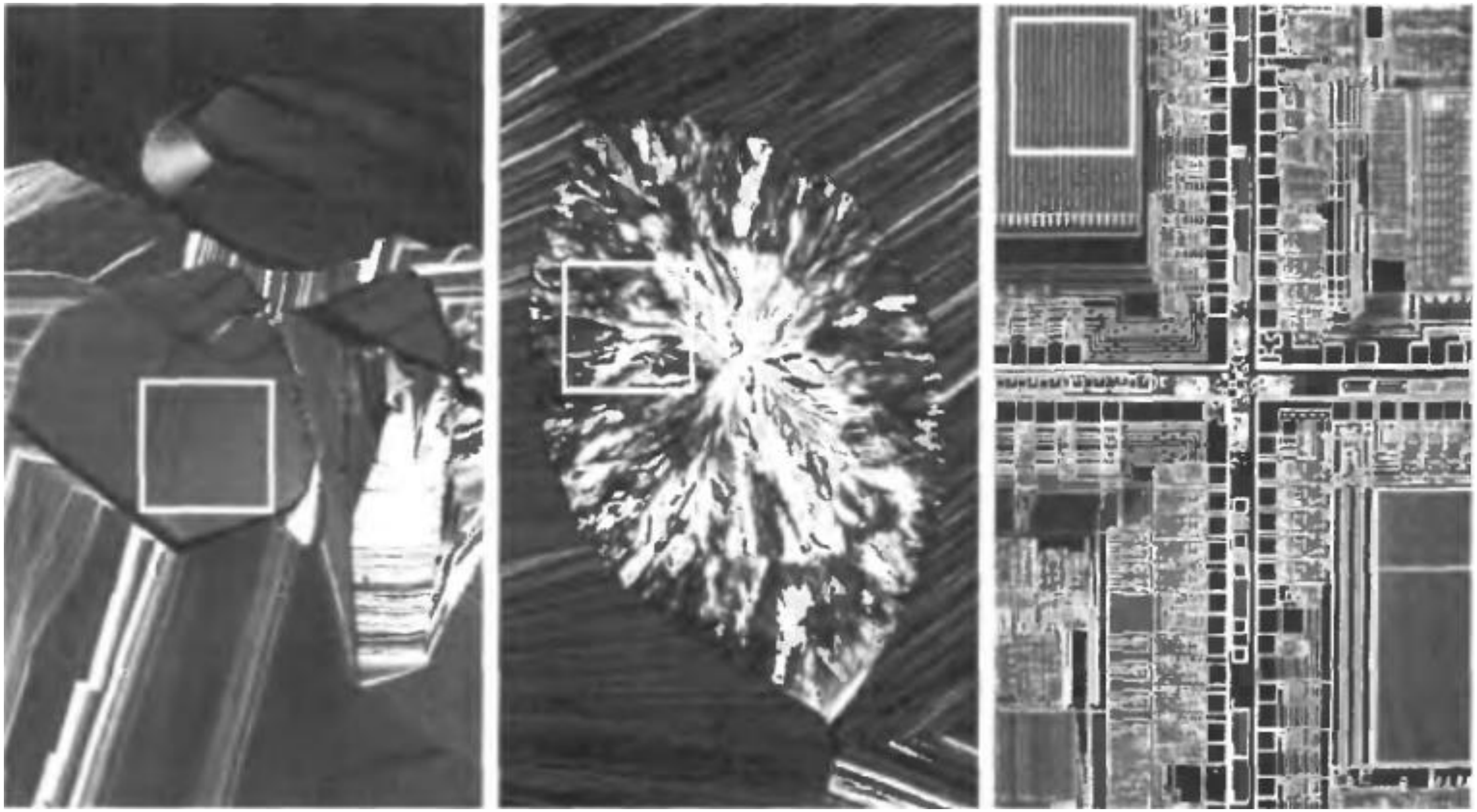
Lecture 3
Texture features
Shape features
Fusion methods

Lecture 3: Outline

- Texture features
  - Statistical
  - Spectral
- Shape features
  - Boundary based
  - Region based
- Fusion methods

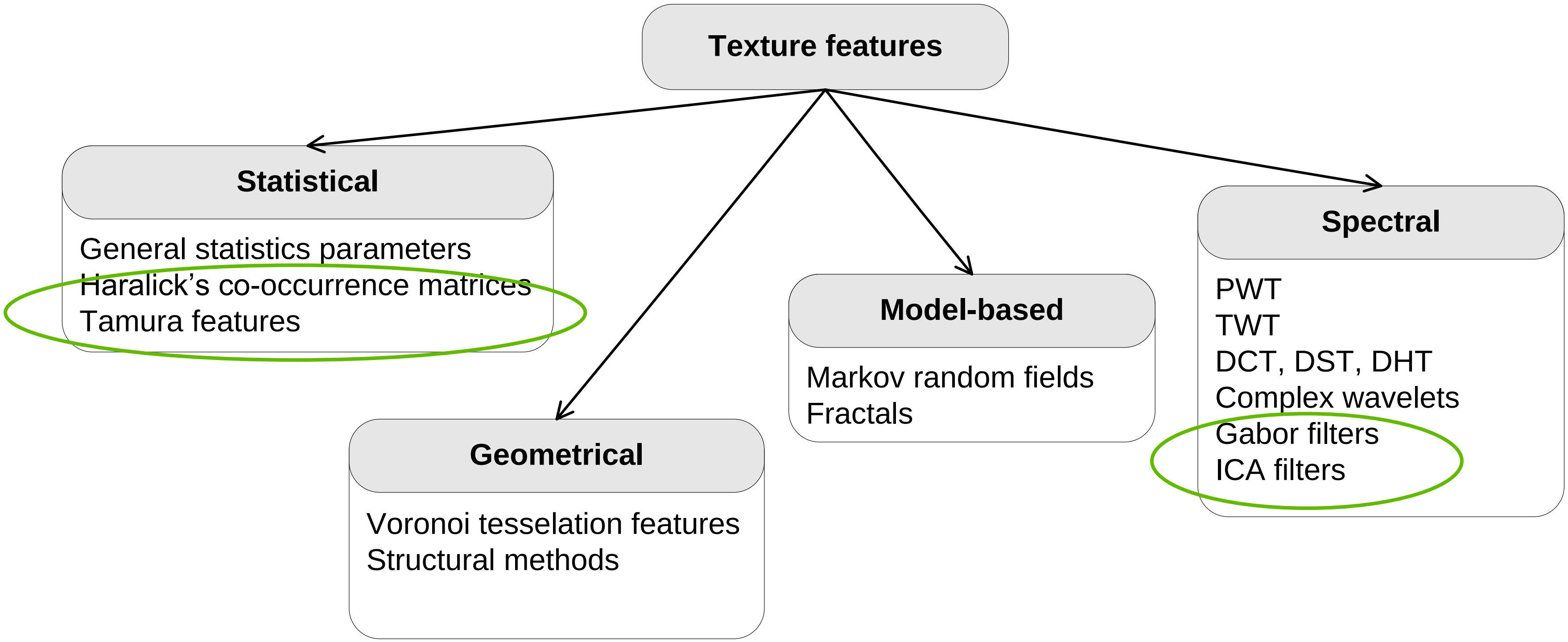
Texture features

- What is texture?



Smooth Rough Regular

Texture features



Texture features

- General statistics

Based on intensity histogram of the whole image or its regions:

$p(z_i),\ i = 0, 1, 2, \ldots, L-1$ • histogram of intensity, L = number of intensity levels

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i)$$ • central moment of order n

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$$m = \sum_{i=0}^{L-1} z_i\, p(z_i)$$ • average intensity

$$\sigma^2(z) = \mu_2(z)$$ • variance, is a measure of contrast

$$R = 1 - \frac{1}{1 + \sigma^2(z)}$$, R=0 where intensity is equal.

$$\mu_3(z) = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i)$$ • a measure of histogram assimetry

Texture features

- General statistics (2)

$$U = \sum_{i=0}^{L-1} p^2(z_i)$$

- a measure of contrast of homogeneity (max for homogeneous areas)

$$e = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i)$$

- entropy, a measure of variability (0 for homogeneous areas)

Texture	Average	Deviation	R	μ_3	U	Entropy
Smooth	82,64	11,79	0,002	–0,105	0,026	5,434
Rough	143,56	74,63	0,079	–0,151	0,005	7,783
Regular	99,72	33,73	0,017	0,750	0,013	6,674

Texture features

Grey Level Co-occurrence Matrices (GLCM):

GLCM - matrix of frequencies at which two pixels, separated by a certain vector, occur in the image.

$$C(i,\, j) = \sum_{p=1}^{N} \sum_{q=1}^{M} \begin{cases} 1, \ if \ \ I(p,q) = i, \ I(p+\Delta x, q+\Delta y) = \ j \\ 0, \ otherwise \end{cases}$$

$(\Delta x, \Delta y)$ • separation vector;

I(p,q) • intensity of a pixel in position (p, q)

GLCM – an example

original image

image pixel values

211	191	71	53	48	44	43	44
212	191	76	60	52	52	53	52
212	180	75	75	75	76	76	75
212	140	53	46	49	49	46	44
211	115	53	44	44	43	43	46
211	115	54	44	44	46	37	43
211	123	55	52	52	52	44	44
211	141	76	74	75	75	71	70

quantisation
4 levels

3	2	1	0	0	0	0	0
3	2	1	0	0	0	0	0
3	2	1	1	1	1	1	1
3	2	0	0	0	0	0	0
3	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0
3	2	1	1	1	1	1	1

quantised image

vector – length 1 pixel, direction horizontal

28	0	0	0
5	10	0	0
1	4	0	0
0	3	5	0

co-occurrence matrix

$$(\Delta x, \Delta y) = (1,0)$$

GLCM – descriptors

Statistical parameters calculated from GLCM values:

$$Energy = \sum_i \sum_j C^2(i, j)$$

- is minimal when all elements are equal

$$Entropy = -\sum_i \sum_j C(i, j) \log C(i, j)$$

- a measure of chaos, is maximal when all elements are equal

$$Contrast = \sum_i \sum_j (i - j)^2 C(i, j)$$

- has small values when big elements are near the main diagonal

$$Inverse\ Difference\ Moment = \sum_i \sum_j \frac{C(i, j)}{1 + (i - j)^2}$$

- has small values when big elements are far from the main diagonal

Texture features: Tamura features

Features, which are important for visual perception:

- Coarseness
- Contrast
- Directionality
- Line-likeness
- Regularity
- Roughness

Tamura image:

Coarseness-coNtrast-Directionality – points in 3-D space CND

Features:

- Euclidean distance in 3D (QBIC)
- 3D histogram (Mars)

Texture features: spectral

- **Texture features**
  - **Statistical**
    - General statistics parameters
    - Haralick’s co-occurrence matrices
    - Tamura features
  - **Geometrical**
    - Voronoi tesselation features
    - Structural methods
  - **Model-based**
    - Markov random fields
    - Fractals
  - **Spectral**
    - PWT
    - TWT
    - DCT, DST, DHT
    - Complex wavelets
    - Gabor filters
    - ICA filters

Texture features: wavelet based

Wavelet analysis – decomposition of a signal:

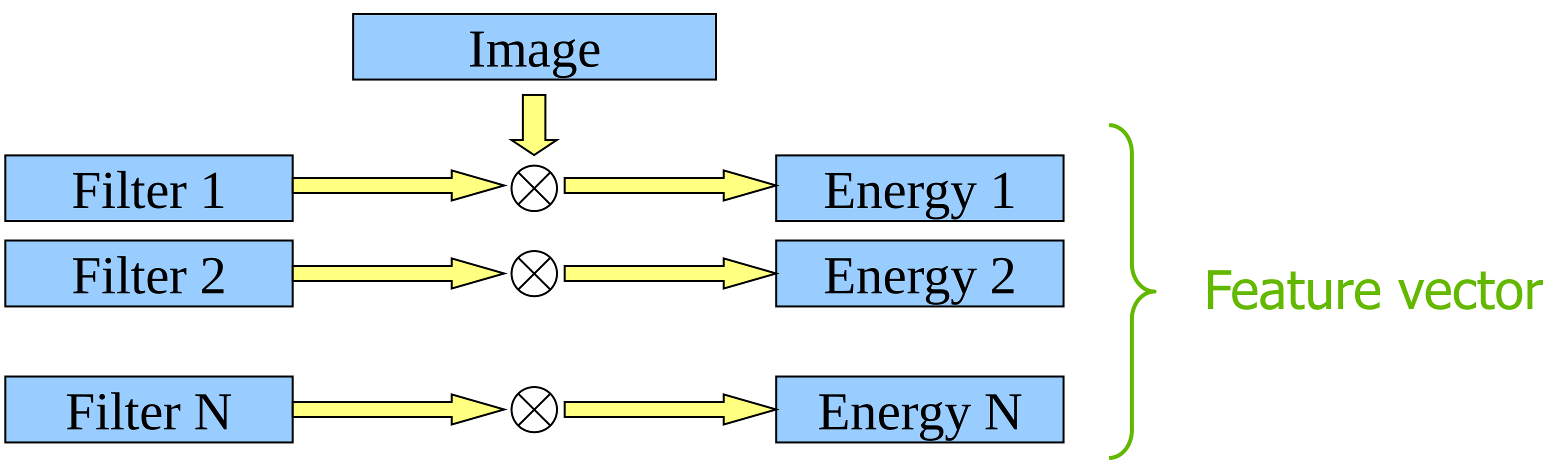
$$f(x) = \sum_{j,k} \alpha_k \psi_{j,k}(x)$$

Basis functions:

$$\psi_{j,k} = 2^{j/2} \varphi(2^j x - k)$$ – scaling function

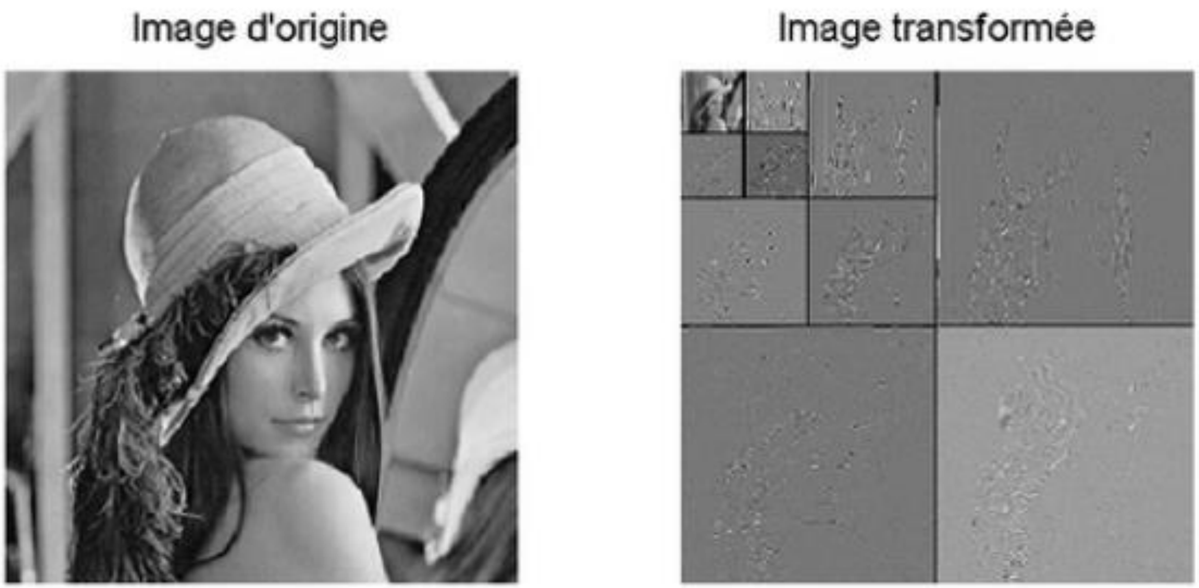
$$j,k \in Z, \quad \varphi(x) \in L^2(R)$$ – mother wavelet

A set of basis functions – filters bank



Texture features: wavelet based

Wavelet transform

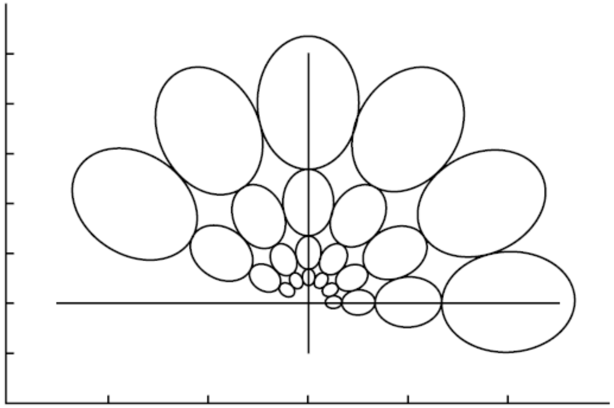


From: http://www.mathworks.com/matlabcentral/files/9554/content/wavelets/tp2.html

Texture features: Gabor filters

Mother wavelet: Gabor function

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right]$$



Filters bank:

$$g_{mn}(x,y)=a^{-m}g(x',y'),\quad a>1,\quad m,n=\text{integer},\quad \mathrm{m}=0,1,\ldots,\mathrm{S}-1,$$

$$x'=a^{-m}(x\cos\Theta+y\sin\Theta),$$

$$y'=a^{-m}(-x\sin\Theta+y\cos\Theta),$$

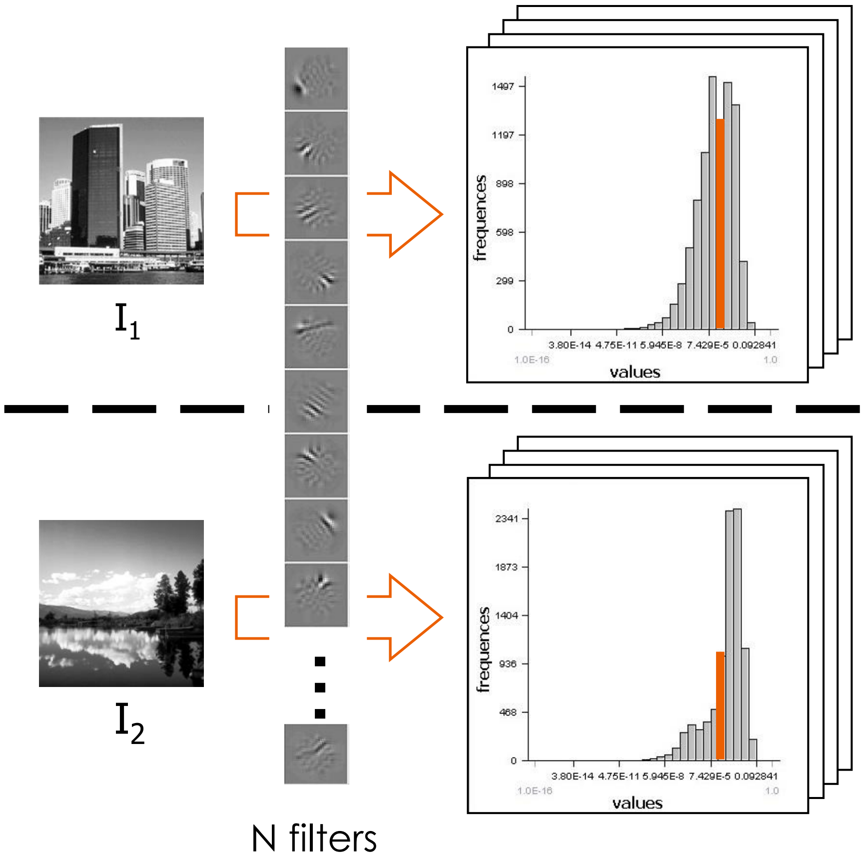
$$\Theta=n\pi/K$$

$$a=(U_h/U_l)^{-1/(S-1)}$$

K – a number of directions,
S – a number of scales,
U_h, U_l – max and min of frequencies taken into consideration.

Texture features: ICA filters

Filters are obtained using Independent Component Analysis

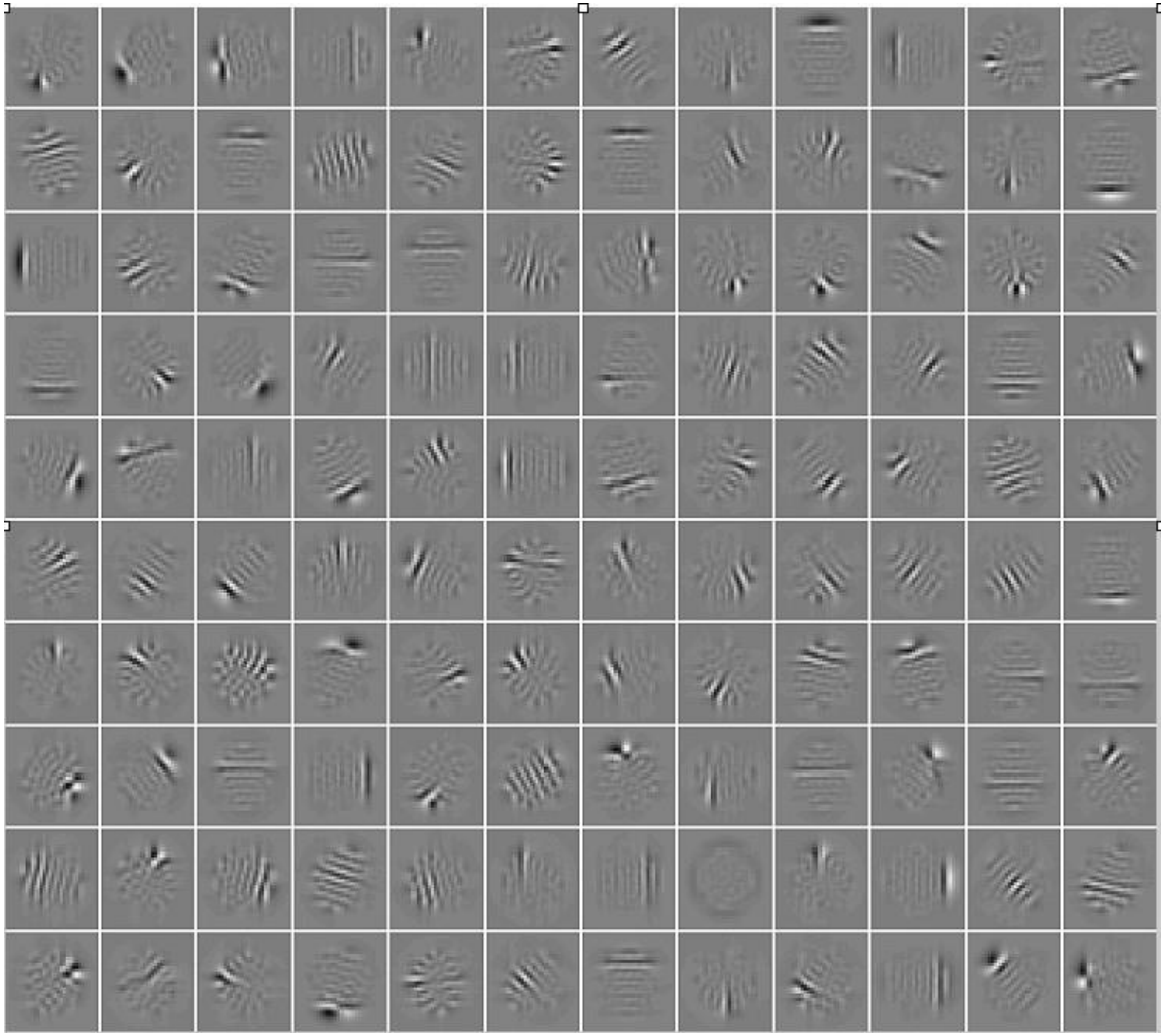


$$KL_H(H_1,H_2)=\sum_{b=1}^{B}(H_1(b)-H_2(b))\log\frac{H_1(b)}{H_2(b)}$$

$$dist(I_1,I_2) = \sum_{i=1}^{N} KL_H(H_{1i}, H_{2i})$$

H. Borgne, A. Guerin-Dugue, A. Antoniadis. Representation of images for classification with independent features. Pattern Recognition Letters, vol. 25, p. 141-154, 2004

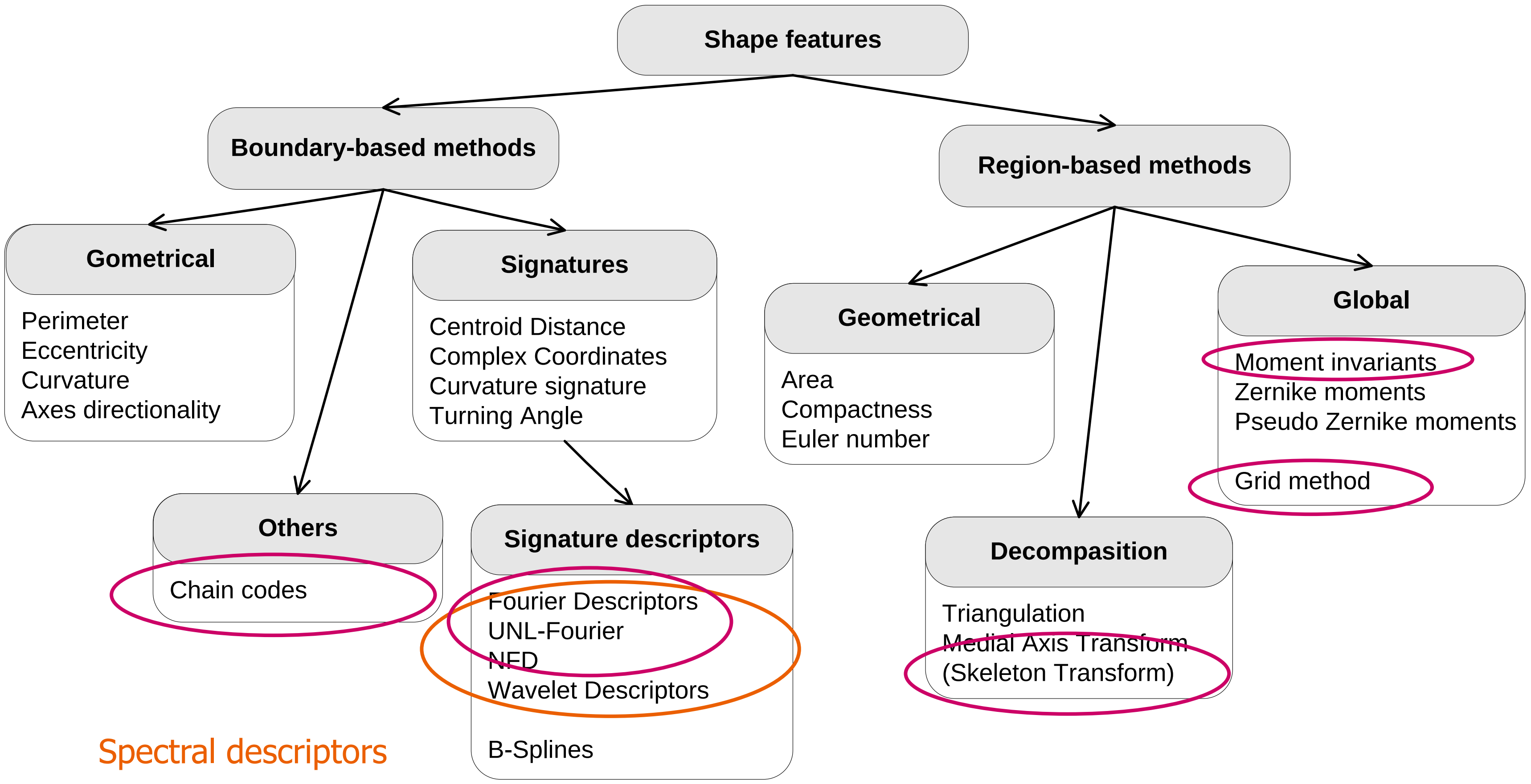
ICA Filters



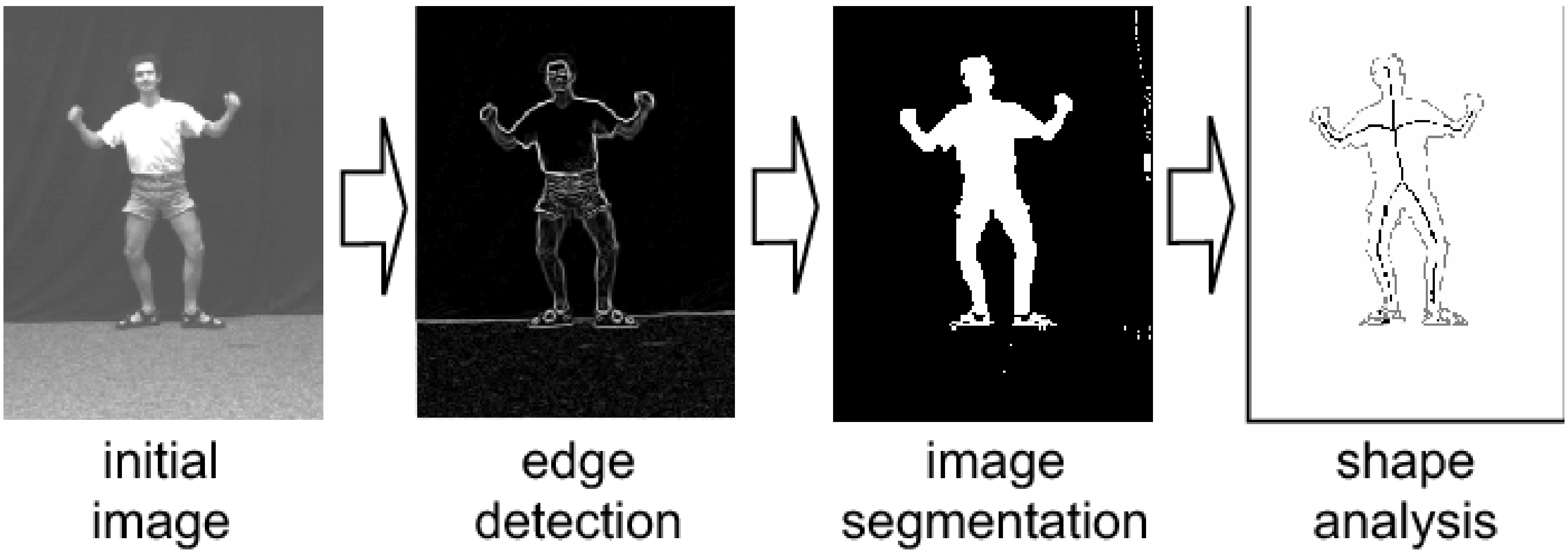
Lecture 3: Outline

- Texture features
  - Statistical
  - Spectral
- Shape features
  - Boundary based
  - Region based
- Fusion methods

Shape features



Shape Representation and Analysis

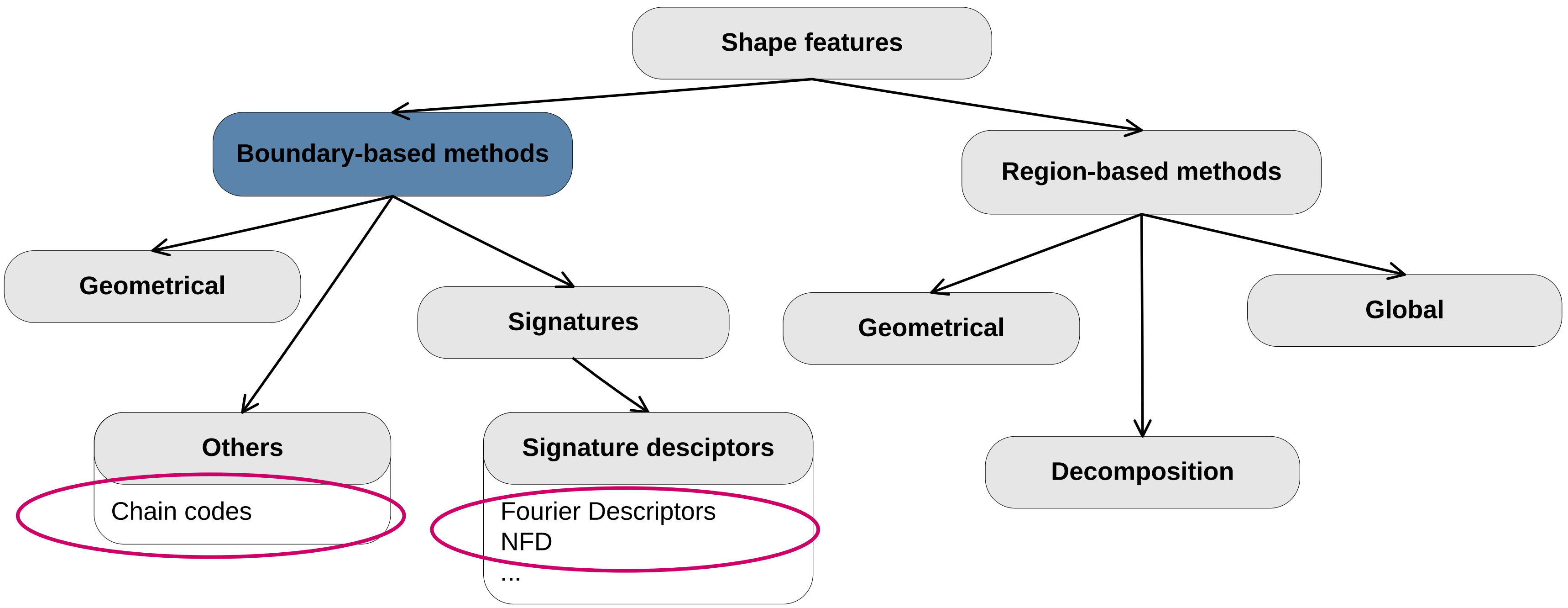


Shape Analysis Pipeline

Requirements to the shape features

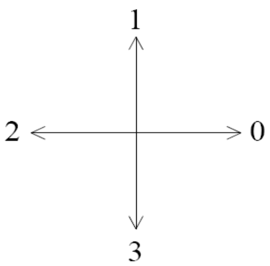
- Translation invariance
- Scale invariance
- Rotational invariance
- Stability against small form changes
- Low computation complexity
- Low comparison complexity

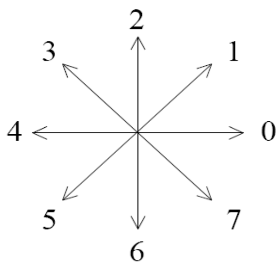
Boundary-based features



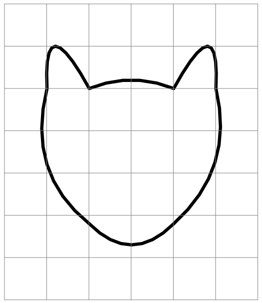
Chain codes

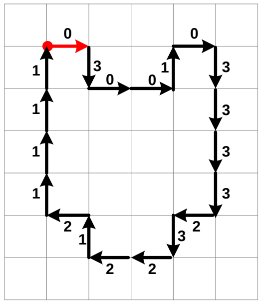
Directions for 4-connected and 8-connected chain codes:



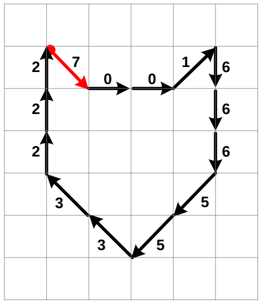


Example:





A



B

A: 03001033332322121111

B: 70016665533222

Starting point invariance: minimal code

70016665533222 -> 00166655332227

Rotation invariance: codes subtraction

00166655332227 -> 01500706070051

Fourier descriptors

1. Signature calculation (2D -> 1D):
   - Centroid – contour distance
   - Complex coordinates: z(t) = x(t) + iy(t)
   - …
2. Perform the discrete Fourier transform, take coefficients (s(t) – signature):

$$u_n = \frac{1}{N}\sum_{t=0}^{N-1} s(t) e^{-j2\pi nt/N}$$

3. Normalization (NFD – Normalized Fourier Descriptors):

$$\frac{|u_1|}{|u_0|}, \frac{|u_2|}{|u_0|}, \ldots, \frac{|u_{N-1}|}{|u_0|}$$

4. Comparison:

$$d = \left(\sum_{n=0}^{N_c} \left| f_I^n - f_J^n \right|^2\right)^{\frac{1}{2}}$$

Fourier Series

- For any continuous function f(x) with period T (or x=[0,T]), the Fourier series expansion are:

$$f(x) = a_0 + \sum_{n=1}^{\infty} a_n \sin(w_n x) + \sum_{n=1}^{\infty} b_n \cos(w_n x)$$

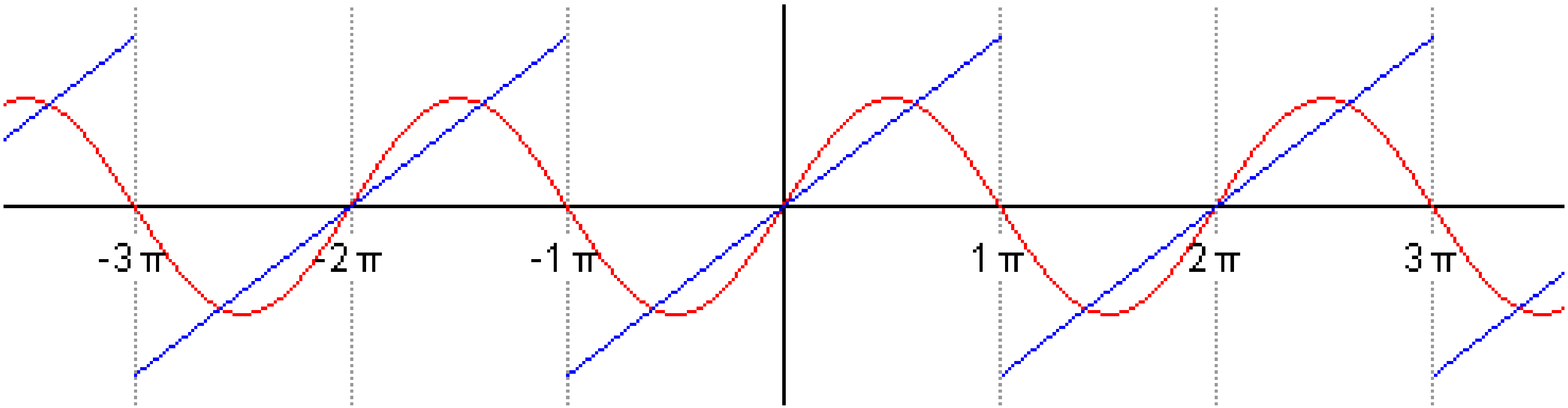
$$w_n = n\frac{2\pi}{T}$$

$$a_n = \frac{2}{T}\int_0^T f(t)\sin(w_n t)dt$$

$$b_n = \frac{2}{T}\int_0^T f(t)\cos(w_n t)dt$$

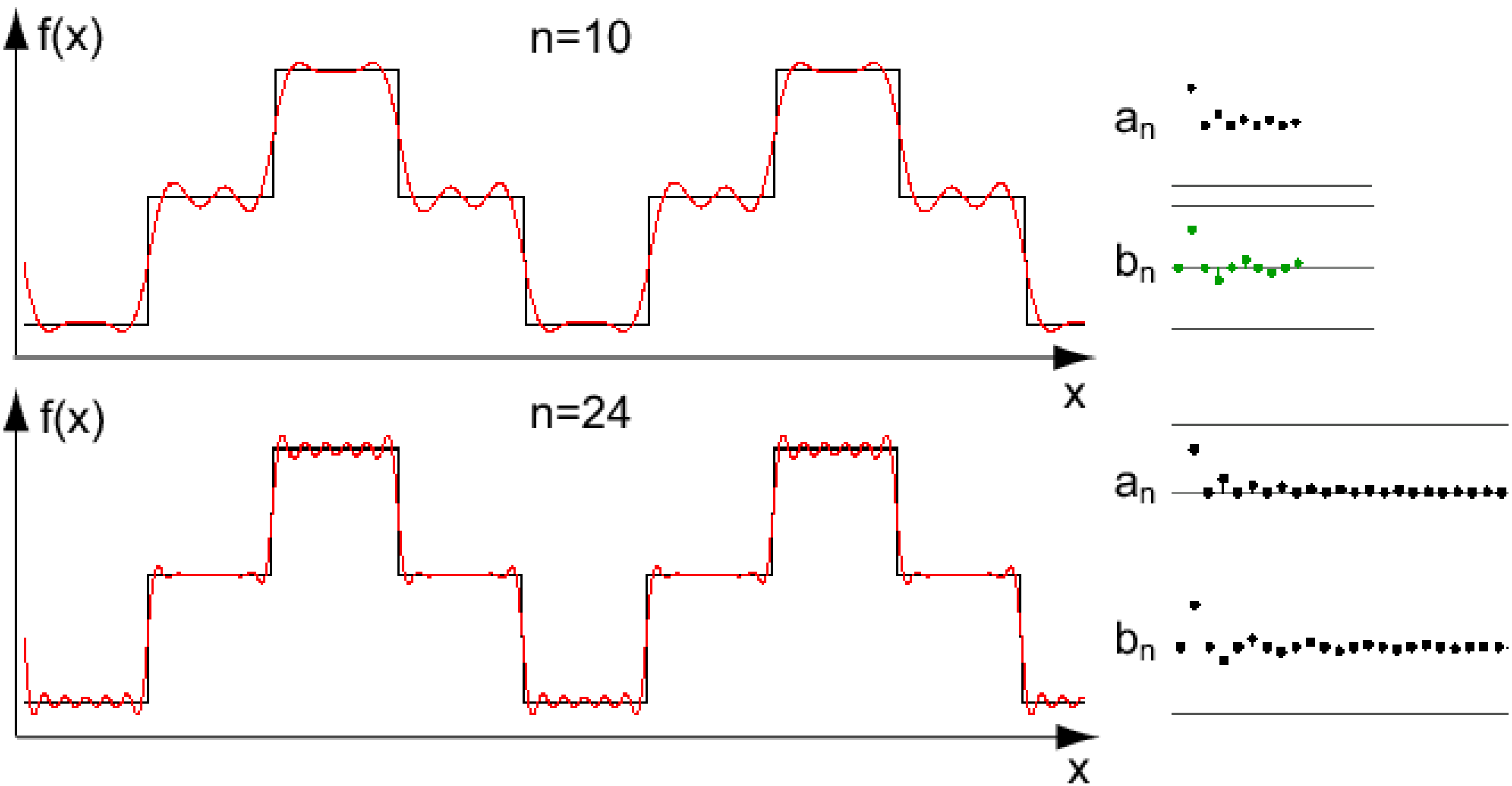
The higher the order n or the frequency, the smaller the amplitudes a_n and b_n

Fourier Series



http://en.wikipedia.org/wiki/Fourier_series

Fourier Series



Fourier Transform

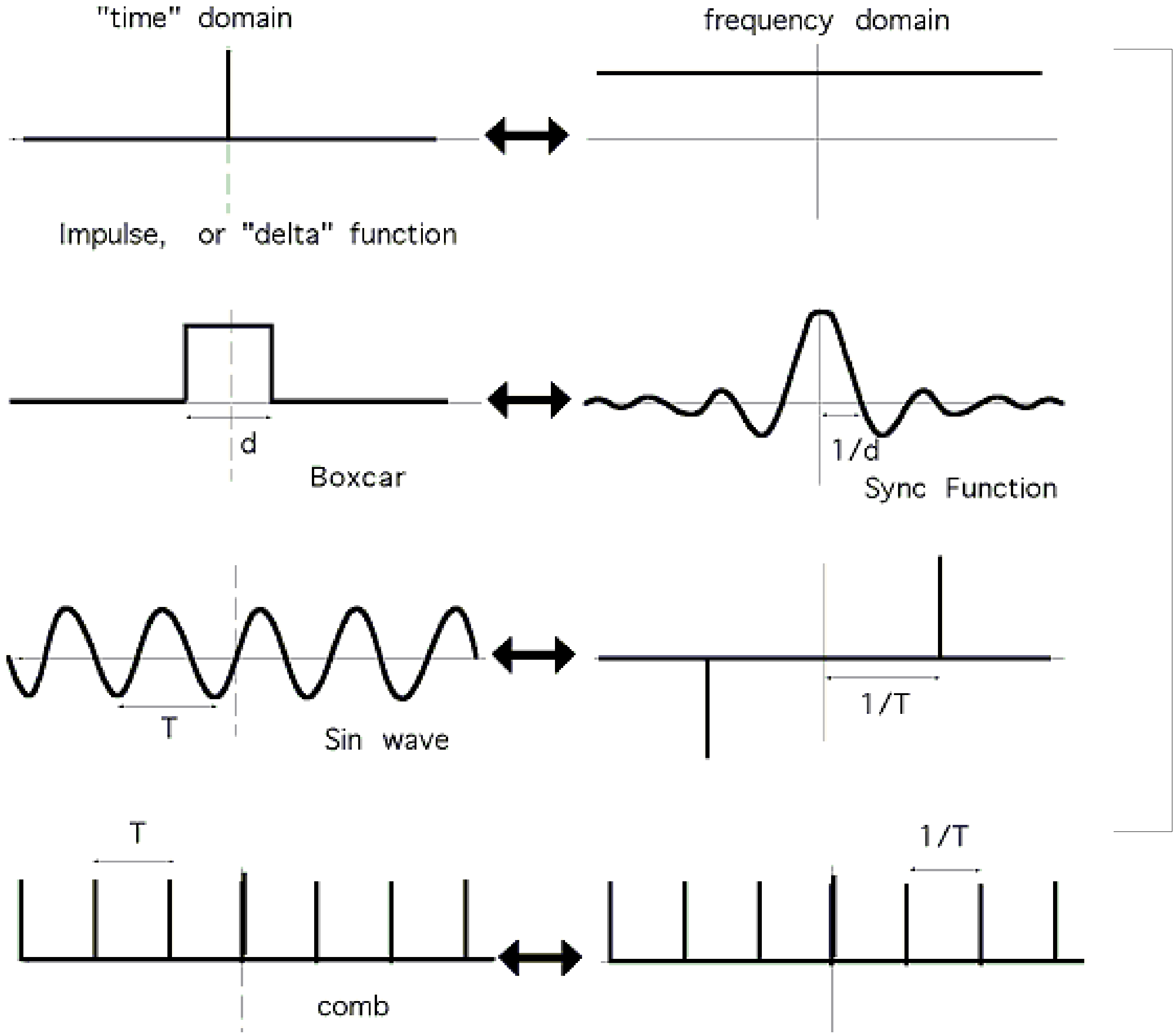
When $\mathrm{T} \rightarrow \infty$, w is continuous, amplitudes are also continuous.

$$A(w) = \int_0^\infty f(t)\sin(wt)dt$$

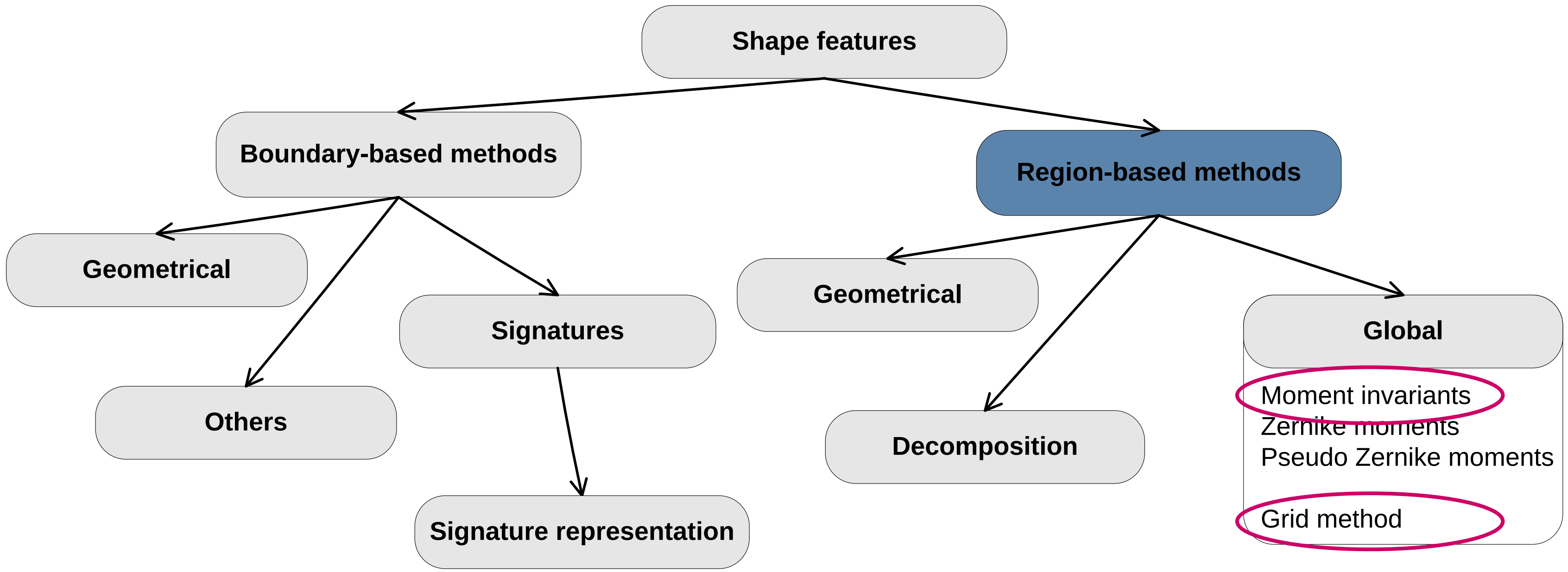
$$B(w) = \int_0^\infty f(t)\cos(wt)dt B$$

$$F(w) = (A(w), B(w))$$

Fourier Transform

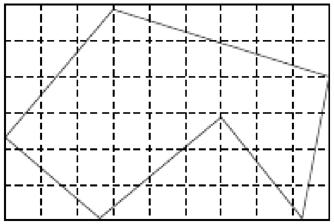


Region-based features



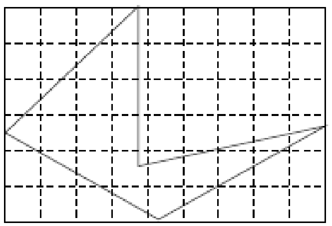
Grid-method

A



A: 001111000 011111111 111111111 111111111 111110111 0111000011

B

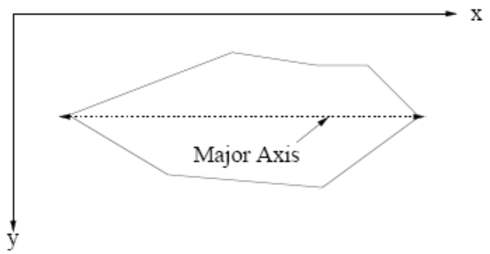


B: 001100000 011100000 111100000 111101111 111111110 001111000

Invariance:

Normalization by major axe:

- direction;
- scale;
- position.



Moment invariants

The moment of order (p+q) for a two-dimension continuous function:

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

Central moments for f(x,y) – discrete image:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y), \quad \bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}}$$

Feature vector:

Seven scale, translation and rotation invariant moments were derived based on central normalized moments of order p + q = 2; 3.

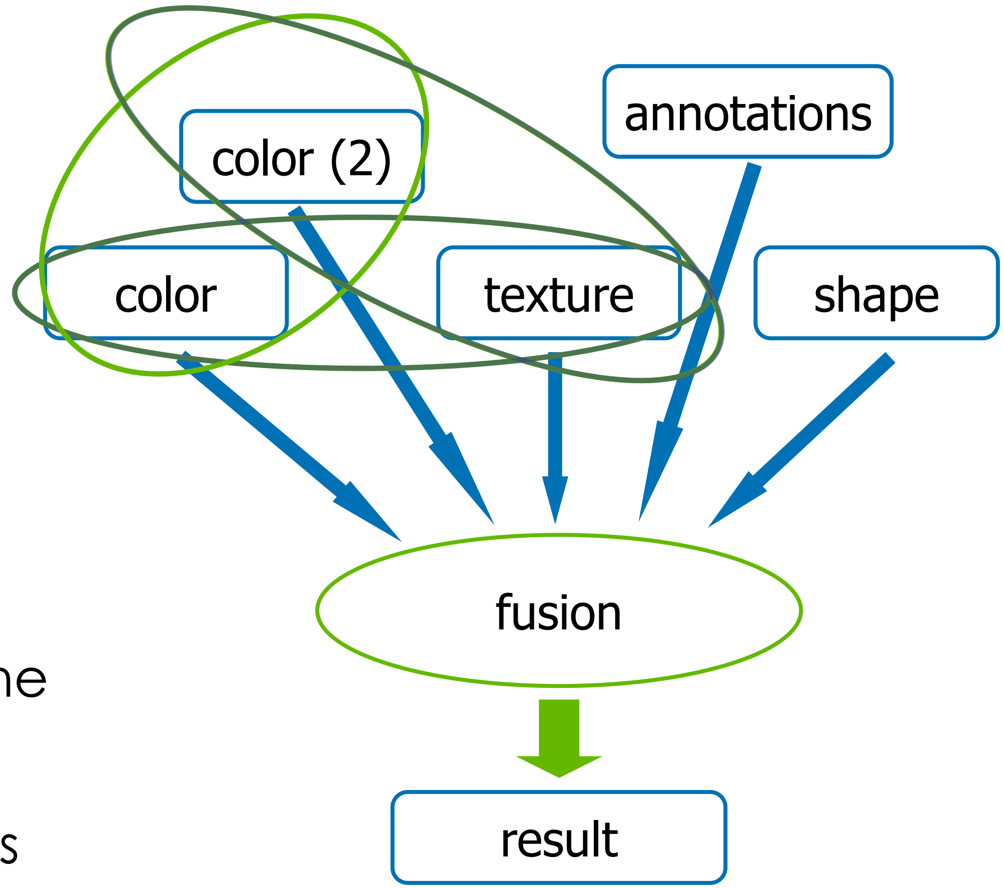
Lecture 3: Outline

- Texture features
  - Statistical
  - Spectral

- Shape features
  - Boundary based
  - Region based

- Fusion methods

Data fusion in cbIR



- Combined search (different features)
- Refine search results (different algorithms for the same feature)
- Supplement search results (different datasets)

Fusion of retrieval result sets

Fusion of weighted lists with ranked elements:

ω_1 $\boxed{(x^1_1, r^1_1), (x^1_2, r^1_2), \ldots , (x^1_n, r^1_n)}$

ω_2 $\boxed{(x^2_1, r^2_1), (x^2_2, r^2_2), \ldots , (x^2_k, r^2_n)}$

...

ω_m $\boxed{(x^m_1, r^m_1), (x^m_2, r^m_2), \ldots , (x^m_l, r^m_l)}$

?

Existing approaches in text retrieval:

- CombMax, CombMin, CombSum
- CombAVG
- CombMNZ = CombSUM * number of nonzero similarities
- ProbFuse
- HSC3D

Fusion function: properties

1) Depend on both weight and rank
2) Symmetric
3) Monotony by weight and rank
4) MinMax condition /CombMin, CombMax, CombAVG/:

$$\min\{r_x^{(\alpha_1)}, r_x^{(\alpha_2)}, \ldots, r_x^{(\alpha_N)}\} \le r_x^{(0)} \le \max\{r_x^{(\alpha_1)}, r_x^{(\alpha_2)}, \ldots, r_x^{(\alpha_N)}\}$$

5) Additional property – "conic" property: non-linear dependency from weight and rank; high weight, high rank – influence bigger to the result than several inputs with low weight, low rank.

$$\forall\sigma \quad \exists\epsilon_1, \epsilon_2 : |1 - r_x^{(\alpha_1)}| < \epsilon_1 \wedge |1 - w^{(\alpha_1)}| < \epsilon_2 \quad \Longrightarrow \quad |1 - r_x^{(0)}| < \sigma$$

for merging any N rank lists

Adaptive merge: color and texture

$Dist(I, Q) = \alpha * C(I, Q) + (1 - \alpha) * T(I, Q)$,

$C(I, Q)$ – color distance between I and Q;

$T(I, Q)$ – texture distance between I and Q;

$0 \leq \alpha \leq 1$

Hypothesis:

Optimal α depends on features of query Q. It is possible to distinguish common features for images that have the same “best” α.

Ilya Markov, Natalia Vassilieva, Alexander Yaremchuk. Image retrieval. Optimal weights for color and texture fusion based on query object. In Proceedings of the Ninth National Russian Research Conference RCDL'2007

Example: texture search

Example: color search

Mixed metrics: semantic groups

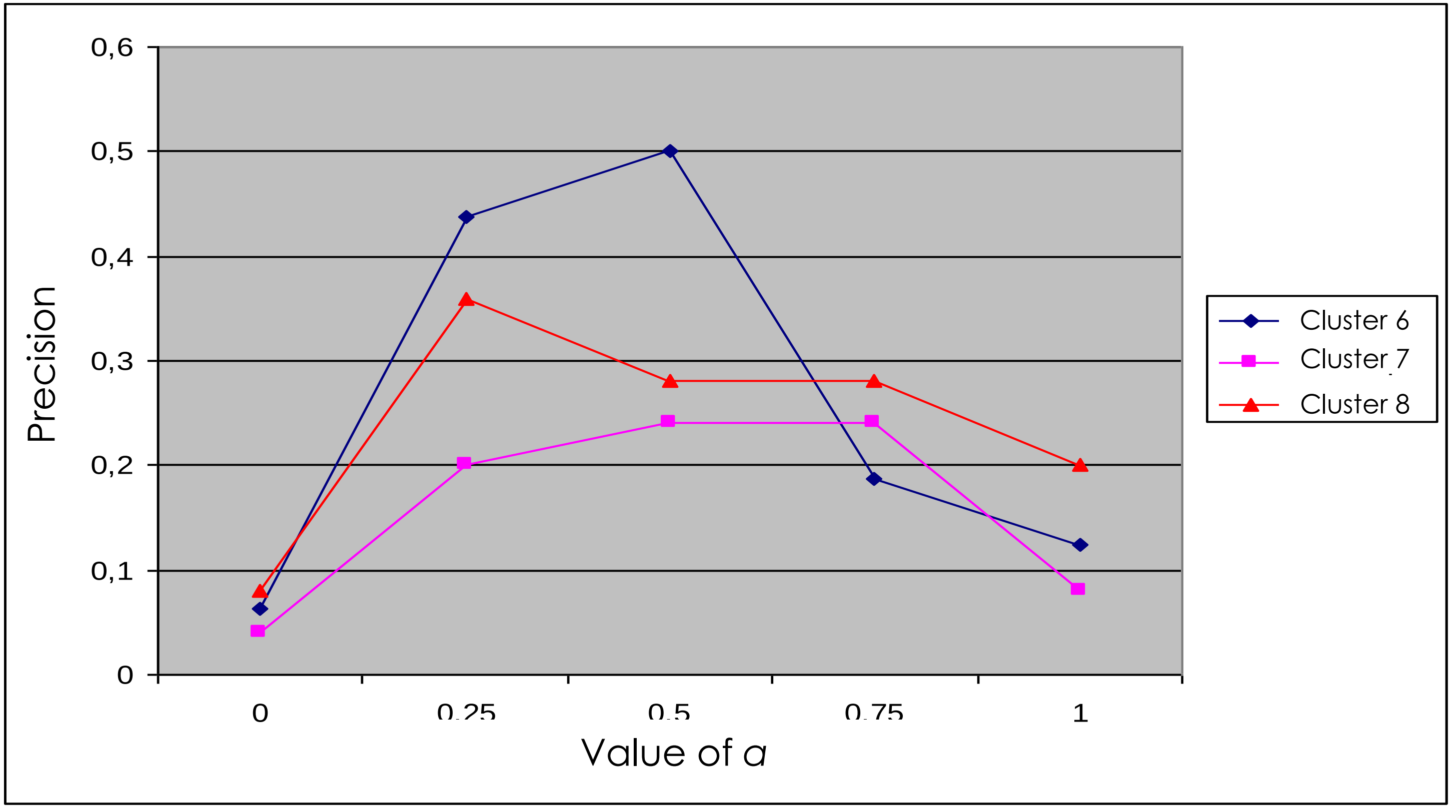
a_1

a_2

a_3

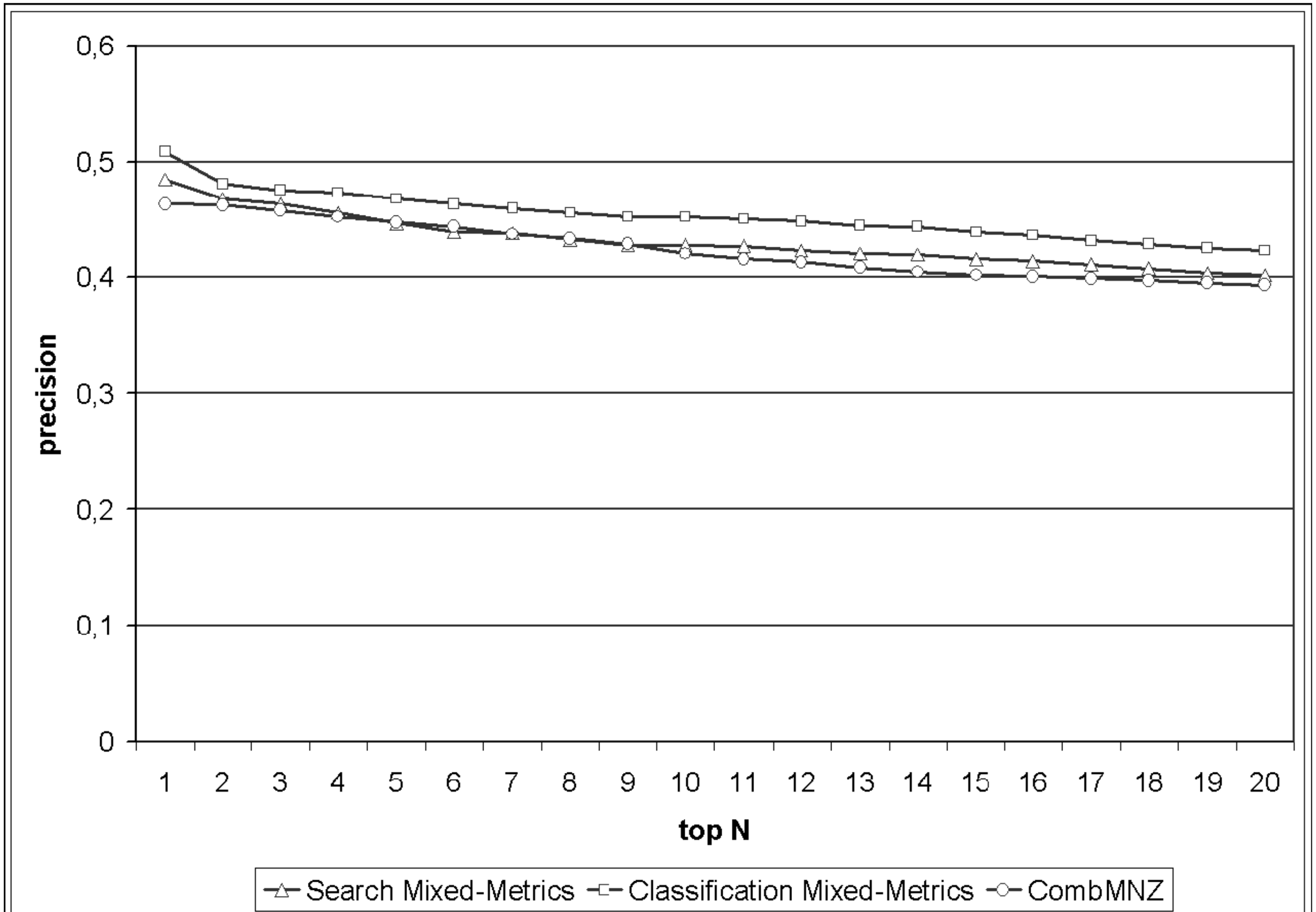
Experimental results 1

- It is possible to select the best value of *a*

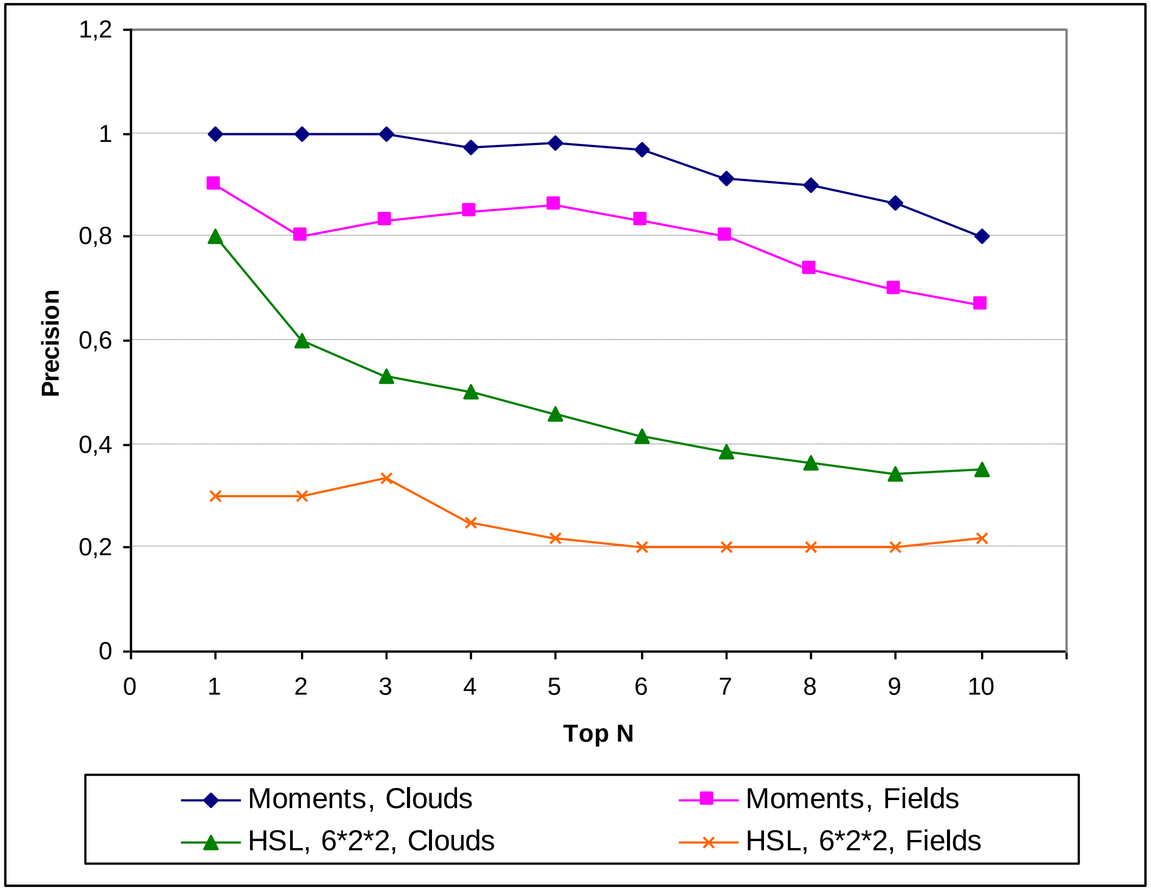


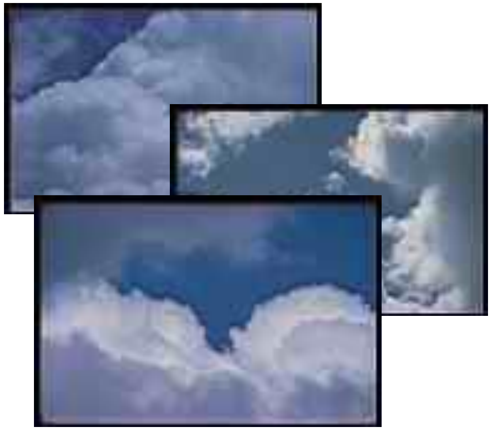
Experimental results 2

- Adaptive mixed-metrics increase precision

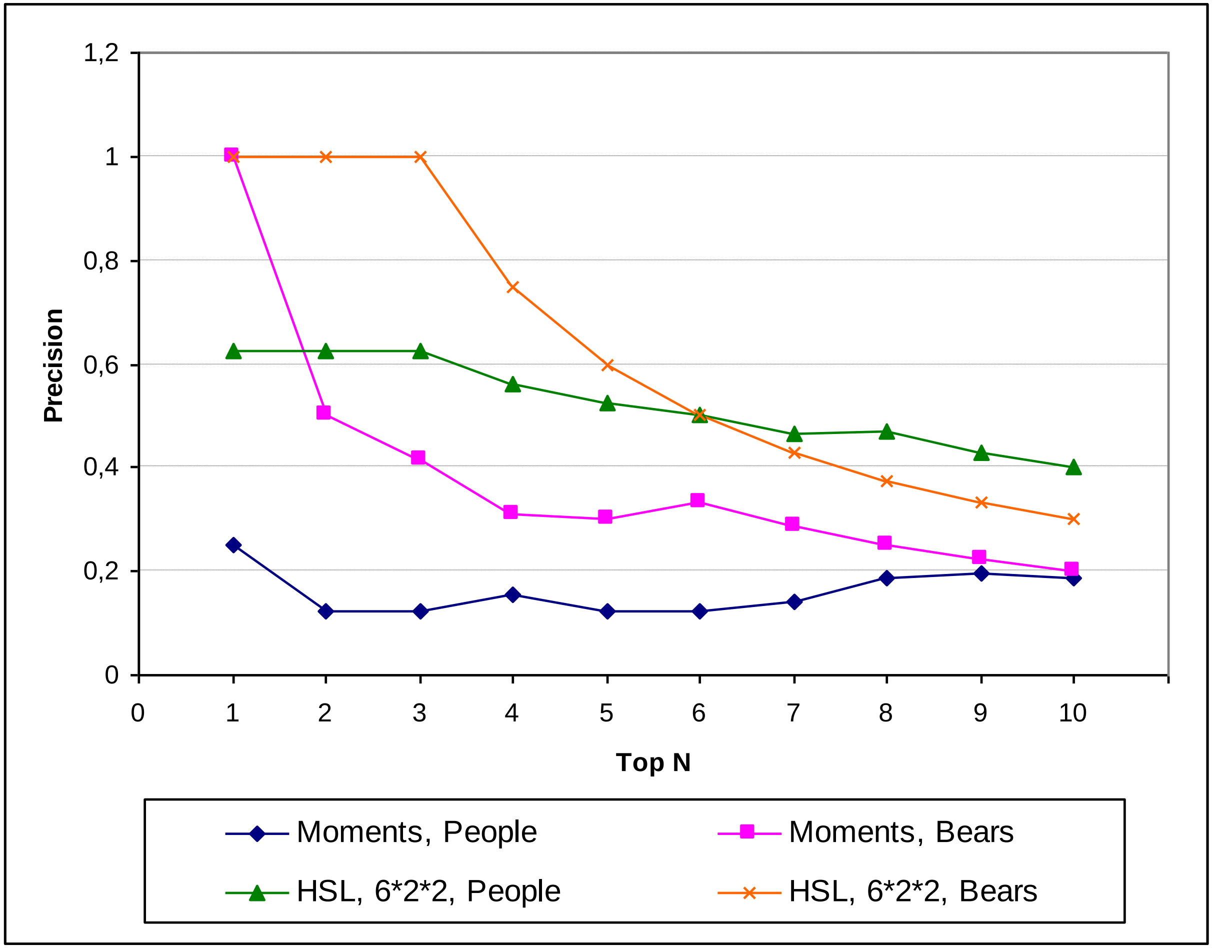


Adaptive merge: color and color



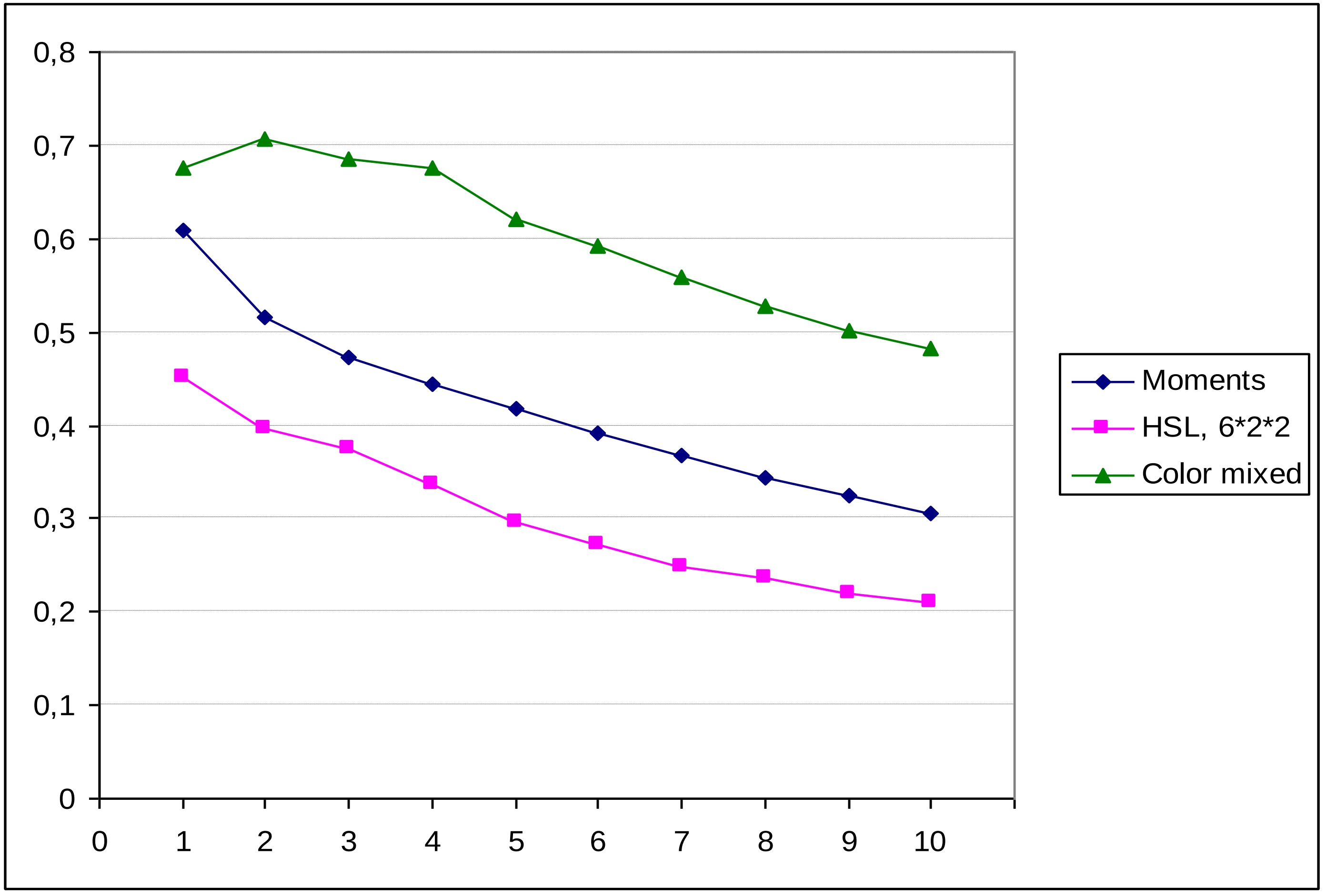


Adaptive merge: color and color



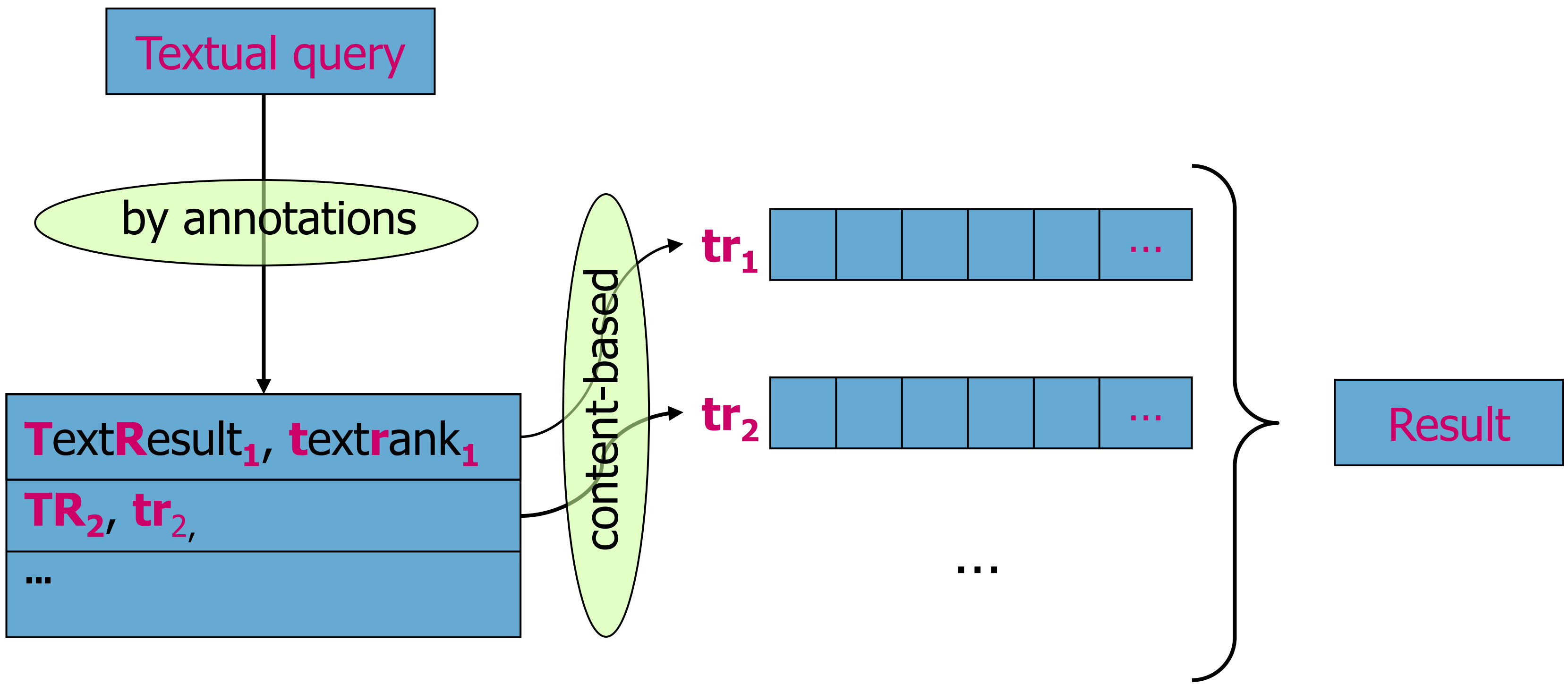
Color fusion

CombMNZ (Moments + HSL histogram)



Ranked lists fusion: application area

- Search by textual query in semi annotated image collection



Lecture 3: Resume

- Texture features
  - Statistics (Haralik’s co-occurance matrices, Tamura features)
  - Spectral features are more efficient (Gabor filters, ICA filters)

- Shape features
  - Boundary-based (Fourier descriptors)
  - Region-based (Moment invariants)

- Fusion methods
  - Are very important
  - Need to choose based on a particular fusion task

Lecture 3: Bibliography

- Haralick R. M., Shanmugam K., Dienstein I. Textural features for image classification. In IEEE Transactions on Systems, Man and Cybernetics, vol. 3(6), pp. 610 – 621, Nov. 1973.
- Tamura H., Mori S., Yamawaki T. Textural features corresponding to visual perception. In IEEE Transactions on Systems, Man and Cybernetics, vol. 8, pp. 460 – 472, 1978.
- Tuceryan M., Jain A. K. Texture analysis. The Handbook of Pattern Recognition and Computer Vision (2nd Edition), by C. H. Chen, L. F. Pau, P. S. P. Wang (eds.), pp. 207-248, World Scientific Publishing Co., 1998.
- Tuceryan M., Jain A. Texture segmentation using Voronoi polygons. In IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, No 2, pp. 211 – 216, February 1990.
- Walker R., Jackway P., Longstaff I. D. Improving co-occurrence matrix feature discrimination. In Proc. of DICTA'95, The 3rd Conference on Digital Image Computing: Techniques and Applications, pp. 643 – 648, 6-8 December, 1995.

Lecture 3: Bibliography

- Li B., Ma S. D. On the relation between region and contour representation. In Proc. of the IEEE International Conference on Pattern Recognition, vol. 1, pp. 352 – 355, 1994.
- Lin T.-W., Chou Y.-F. A Comparative Study of Zernike Moments for Image Retrieval. In Proc. of 16th IPPR Conference on Computer Vision, Graphics and Image Processing (CVGIP 2003), pp. 621 – 629, 2003.
- Loncaric S. A survey of shape analysis techniques. In Pattern Recognition, vol. 31(8), pp. 983 – 1001, 1998.
- Luren Y., Fritz A. Fast computation of invariant geometric moments: A new method giving correct results. In Proc. of IEEE International Conference on Image Processing, 1994.
- Zakaria M. F., Vroomen L. J., Zsombor-Murray P. J. A., van Kessel J. M. H. M. Fast algorithm for the computation of moment invariants. In Pattern Recognition, vol. 20(6), pp. 639 – 643, 1987.
- Zernike polynomials. Wikipedia, the free encyclopedia. http://en.wikipedia.org/wiki/Zernike_polynomials
- Zhang D., Lu G. Shape-based image retrieval using generic Fourier descriptor. In Signal Processing: Image Communication, vol. 17, pp. 825 – 848, 2002.
- Zhang D., Lu G. A Comparative Study on Shape Retrieval Using Fourier Descriptors with Different Shape Signatures. In Proc. of the International Conference on Multimedia, 2001.