Medical Image Retrieval / Visual Features

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Features

two important questions for content-based image retrieval:

- **how are images represented $\Rightarrow$ features**
- **how are image representations compared $\Rightarrow$ distance/similarity measures**

two views on the concept of 'feature':

- **features are numerical values computed from each image**
  view connected to image classification (IRMA)
  learn from classification and machine learning
- **features are image properties that are present or absent**
  view connected to text retrieval (medGIFT)
  learn from text retrieval

Topics

visual features
- color, texture, shape, ...

statistical features
- histograms, invariant features, ...

model-based approaches
- image comparison, holistic, active shapes, active contours

distance or similarity measures

Visual Features

color:
- only limited applicability in medical images
  (but e.g. good to distinguish color photographs from X-rays)
- very good feature for general images
- different color spaces can be used: RGB, HSV/HSI, L*a*b,...
- colors are values at pixel level
  $\Rightarrow$ need to combine colors into a feature vector for most distance measures

texture:
- different representations possible
- global / local texture descriptors

shape:
- difficult (impossible?) to determine for general images
- same holds for general medical images
- with additional knowledge $\Rightarrow$ more possibilities
- alternative: local shape parts

Color Histograms

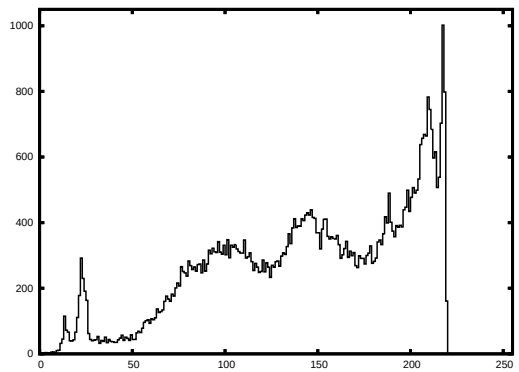
idea:

partition feature space $\mathcal{S}$ into M regions: $\mathcal{S}^m \subset \mathcal{S}$ **with** $\dot{\bigcup}_{m=0}^{M-1} \mathcal{S}^m = \mathcal{S}$

$$P(x \in \mathcal{S}^m) = \frac{K^m}{N}$$

usually regularly spaced grid ('bins')

example:



for vector-valued pixels we obtain a multi-dimensional histogram

Tamura Texture Features

proposed by Tamura et al. 1978:

- **features corresponding to human perception**
- **examined 6 different features, three correspond strongly to human perception**
  - **coarseness – coarse vs. fine**
  - **contrast – high vs. low**
  - **directionality – directional vs. non-directional**
  - **line-likeness – line-like vs. blob-like**
  - **regularity – regular vs. irregular**
  - **roughness – rough vs. smooth**
- **calculate the first three features pixel-wise**
- **create a 3d histogram of these features**

Gabor Texture Features

Definition Gabor Filter

windowed Fourier transform with Gaussian $g_\alpha(t)$ as window function:

$$g_\alpha(t) = \frac{1}{2\sqrt{\pi\alpha}} e^{-\frac{t^2}{4\alpha}}$$

$$\begin{aligned} G_f(\omega,\tau) &= \int_{-\infty}^{+\infty} f(t) g_\alpha(t-\tau) e^{i\omega t} dt \\ &= e^{-i\omega\tau}(f(\tau) * h(\tau)) \end{aligned}$$

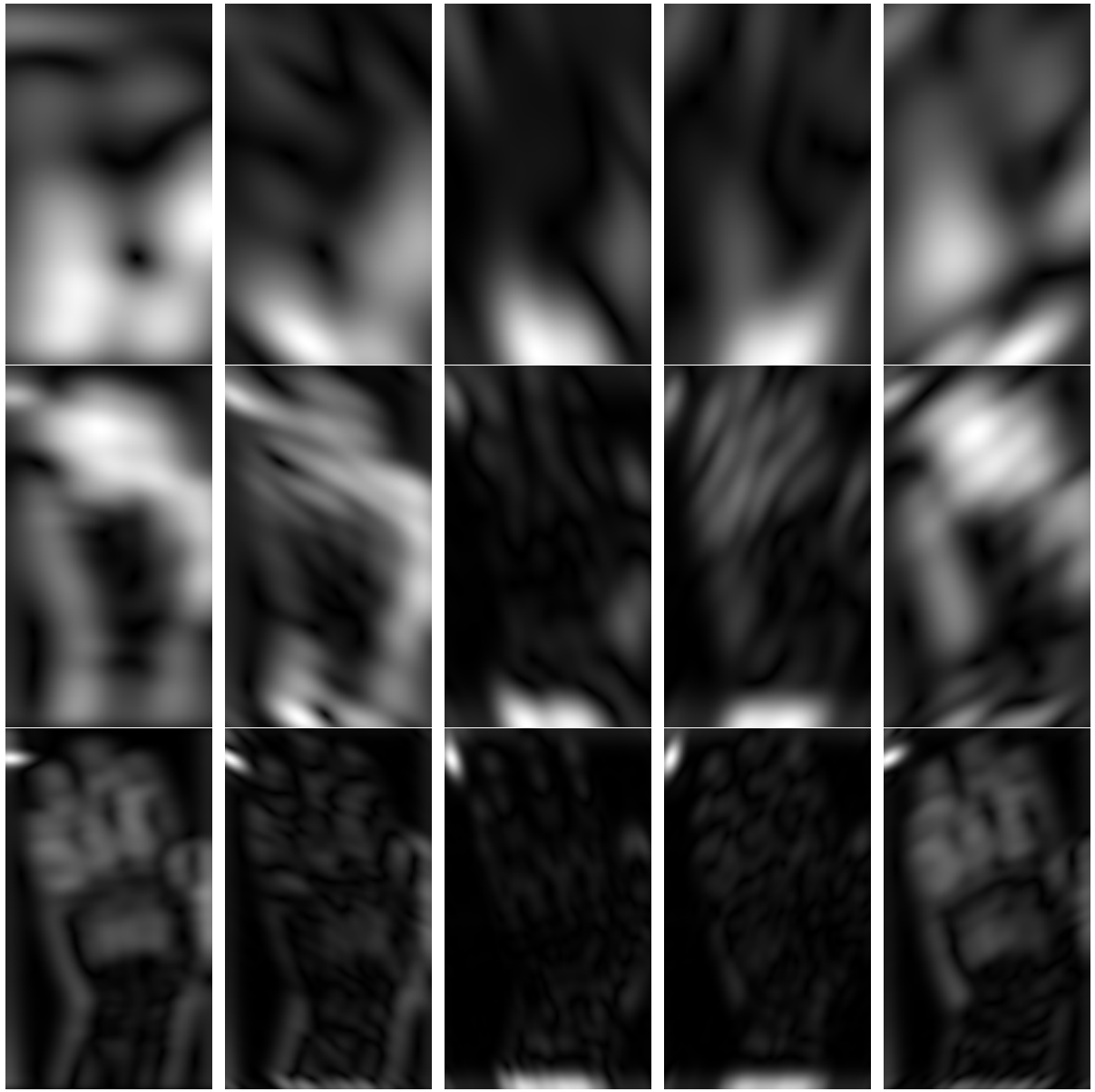
Gabor Features

yield one value per pixel (for grey value images)
for color images use a transformed HSV color space
use different phases and frequencies to obtain a vector of values per pixel:

$$(G_f(\omega_1,\tau_1)\ldots(G_f(\omega_n,\tau_m))$$

compute global (histogram) or local features from Gabor responses

Gabor Texture Features – Example



Invariant Features

invariances desired:
- **rotation**
- **translation**
- **scaling**
- **...**

invariant features can be obtained by:
- **normalization**
- **solving differential equations**
- **integration**

Theory of Invariant Features by Integration

given:

image X**,** $X(n_0, n_1)$ **= gray value at position** (n_0, n_1)

$g \in G$**: transformation from a group of transformations**

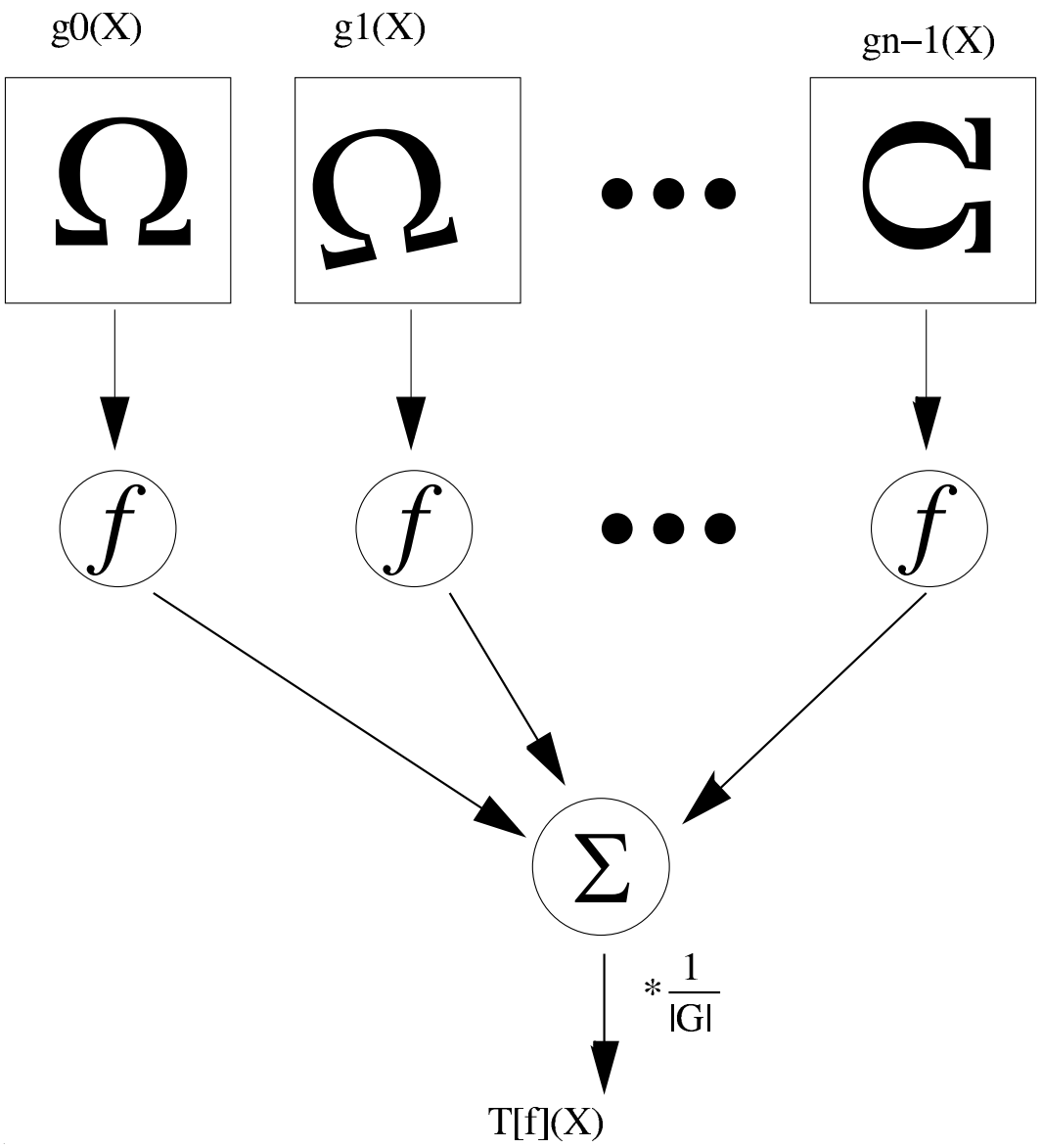
gX**: image** X **transformed by** g

f**: function from the image to a number:** $f(X) : \mathbb{X} \mapsto \mathbb{R}$

then:

$F(X) = \frac{1}{|G|} \int_{g \in G} f(gX)$ **is invariant against any transformation from** G

Invariant Features – Illustration



Invariant Features in Practice

settings

let $G_{t,r}$ be the group of translations and rotations:

$g_{t_0,t_1,\phi} \in G_{t,r}$ **transforms the image by** $(g_{t_0,t_1,\phi}X)(n_0,n_1) = X(n_0',n_1')$

with $\left(n_0',n_1'\right) = \left(\begin{smallmatrix}\cos\varphi & -\sin\varphi \\ \sin\varphi & \cos\varphi\end{smallmatrix}\right)\left(n_0,n_1\right) + \left(t_0,t_1\right)$

the image $X(n_0,n_1)$ **is discrete** $\Rightarrow$ **discretization and interpolation**

choose e.g. $f(X) = \sqrt{X(1,0)X(0,2)}$

result

$$F(X) = \frac{1}{2\pi N_0 N_1} \sum_{t_0=1}^{N_0} \sum_{t_1=1}^{N_1} \sum_{r=1}^{R} \sqrt{X(\sin\tfrac{2\pi r}{R} + t_0, \cos\tfrac{2\pi r}{R} + t_1) X(2\cos\tfrac{2\pi r}{R} + t_0, -2\sin\tfrac{2\pi r}{R} + t_1)}$$

problem

just one value $\Rightarrow$ **not enough discriminative power**

Invariant Feature Histograms

solution to the problem of insufficient data:

replace one or more sums by histogramization $\Rightarrow$ preserves invariance

$$H_F(X) = \underset{t_0=1,t_1=1}{\overset{N_0,N_1}{\text{hist}}} \frac{1}{R} \sum_{r=1}^{R} f\left(g_{t_0,t_1,\frac{2\pi r}{R}} X \right)$$

Direct Image Features

straightforward way to compare images

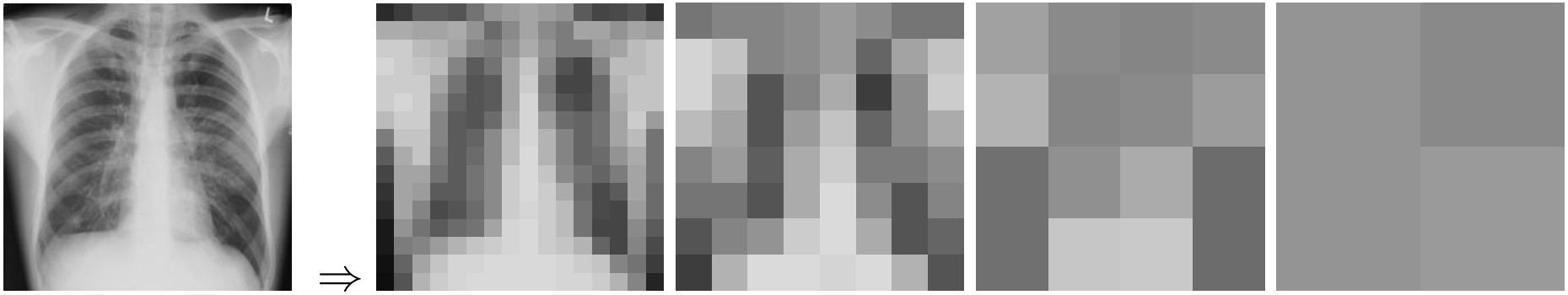
use the pixel values as features

achieves very good results for some (medical!) tasks

different comparison measures can compensate different transformations

Multi-scale Representations

⇒ **see MedGIFT part**



Local Features/Patches

definition

- small sub images extracted at different relevant positions of original image
- position determined by local variance or entropy
- known to achieve good results in various classification tasks

classification method

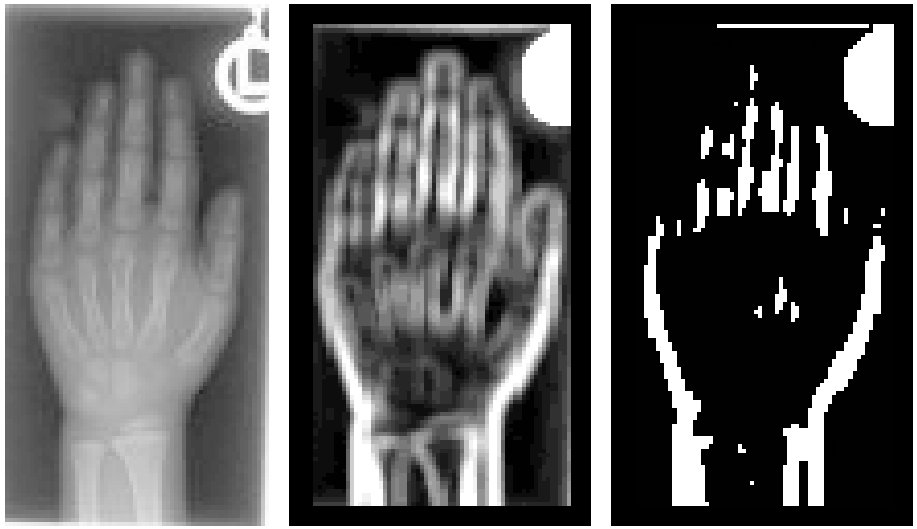
training:

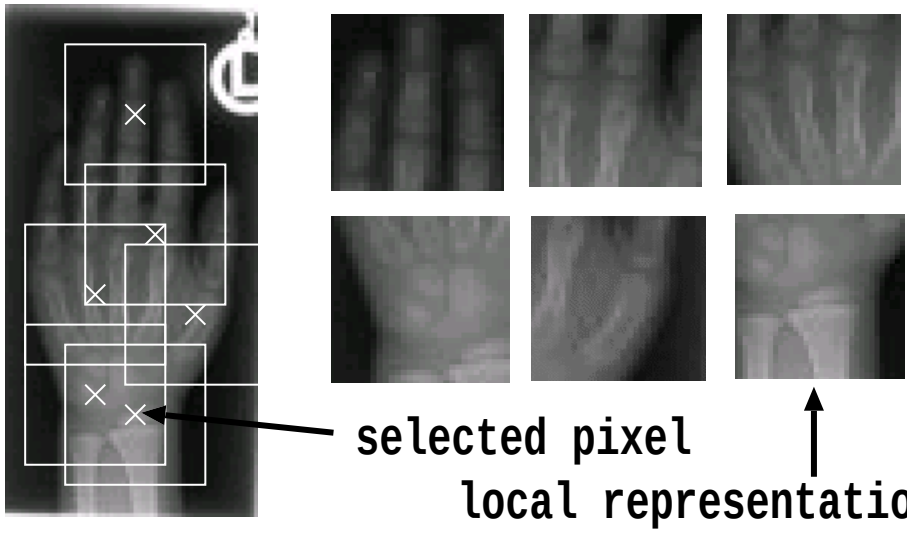
- extract local features from all training images
- build KD-Tree of this large set of local features

testing:

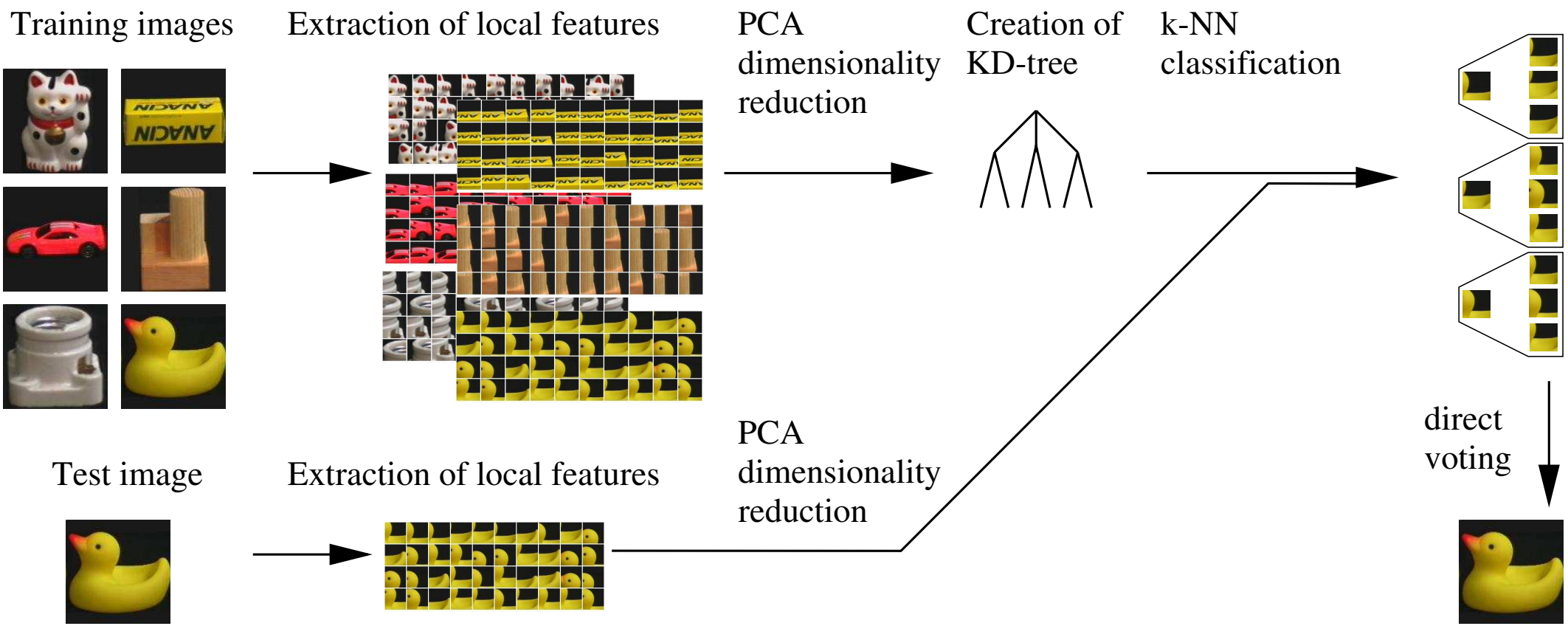
- extract local features from the test image
- query the KD-Tree about these local features
- use a direct voting scheme for classification

Local Features/Patches





Local Representations for Classification



Local Features for Image Retrieval

3 possibilities:

comparison of images based on local features

- extract local features from images Q and X_i
- create KD-tree from local features from X_i
- query KD-tree for each local feature from Q
  - get distance between query-LF and it's nearest neighbor
  - sum up distances

querying directly using local features

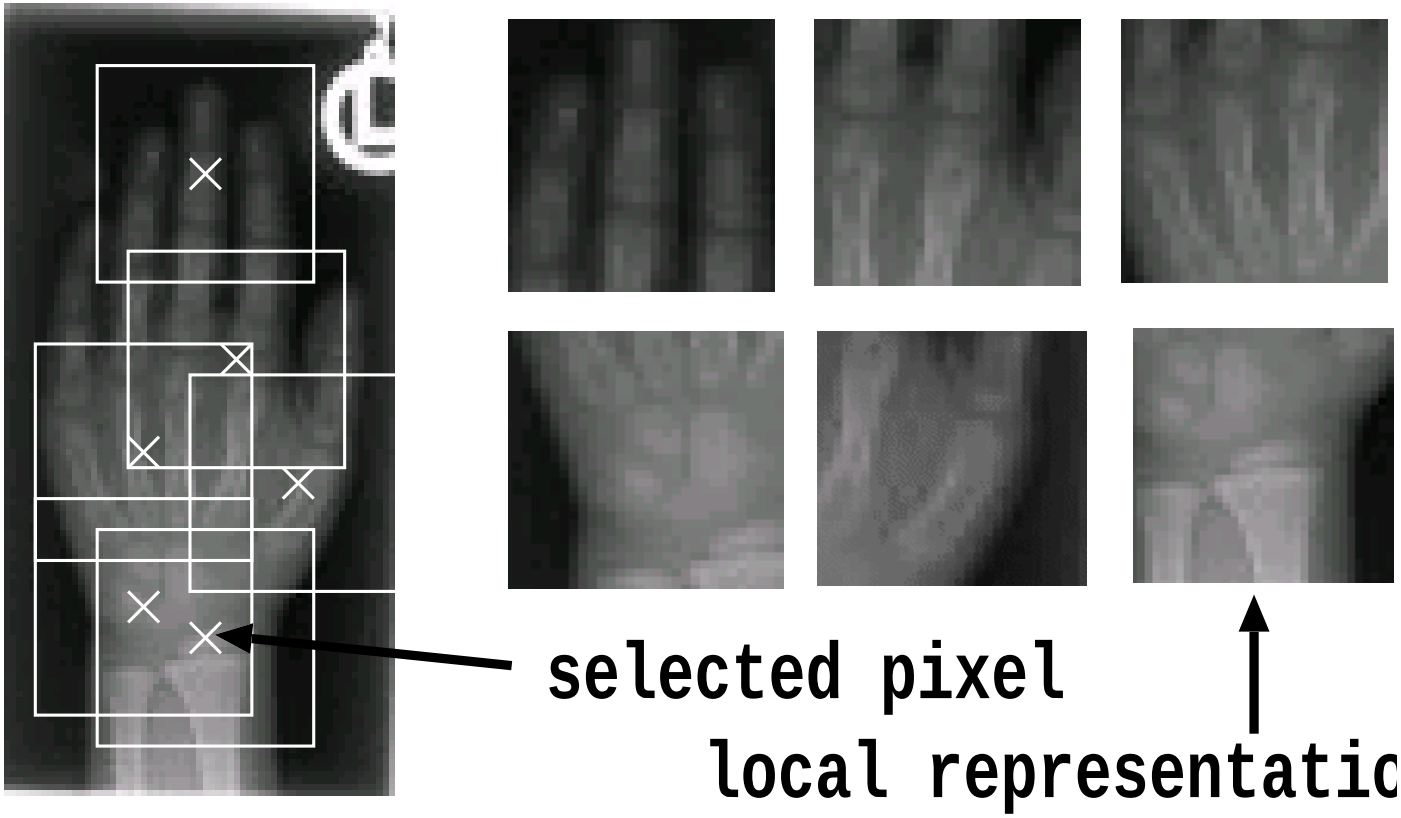
- extract local features from all images in the database
- create KD-tree from all the local features
- query KD-tree for each local feature from query image Q
- count "votes" for database images
- return those images from the database with highest number of votes

creating histograms of local features

- extract local features from all images in the database
- cluster these local features to a reasonable number of clusters (e.g. 512)
- save for each image how many features are in which cluster

Image Distance: Distortion Model

- nonlinear image distortion models
- very low error rates for medical image categorization
- most important aspect: include gradient and image parts for each pixel
- difference to image registration: discrimination



Distortion Models

local image context

- pixel neighborhoods of e.g. 3×3 or 5×5
- image gradient horizontal and vertical (Sobel)

dependencies between displacements

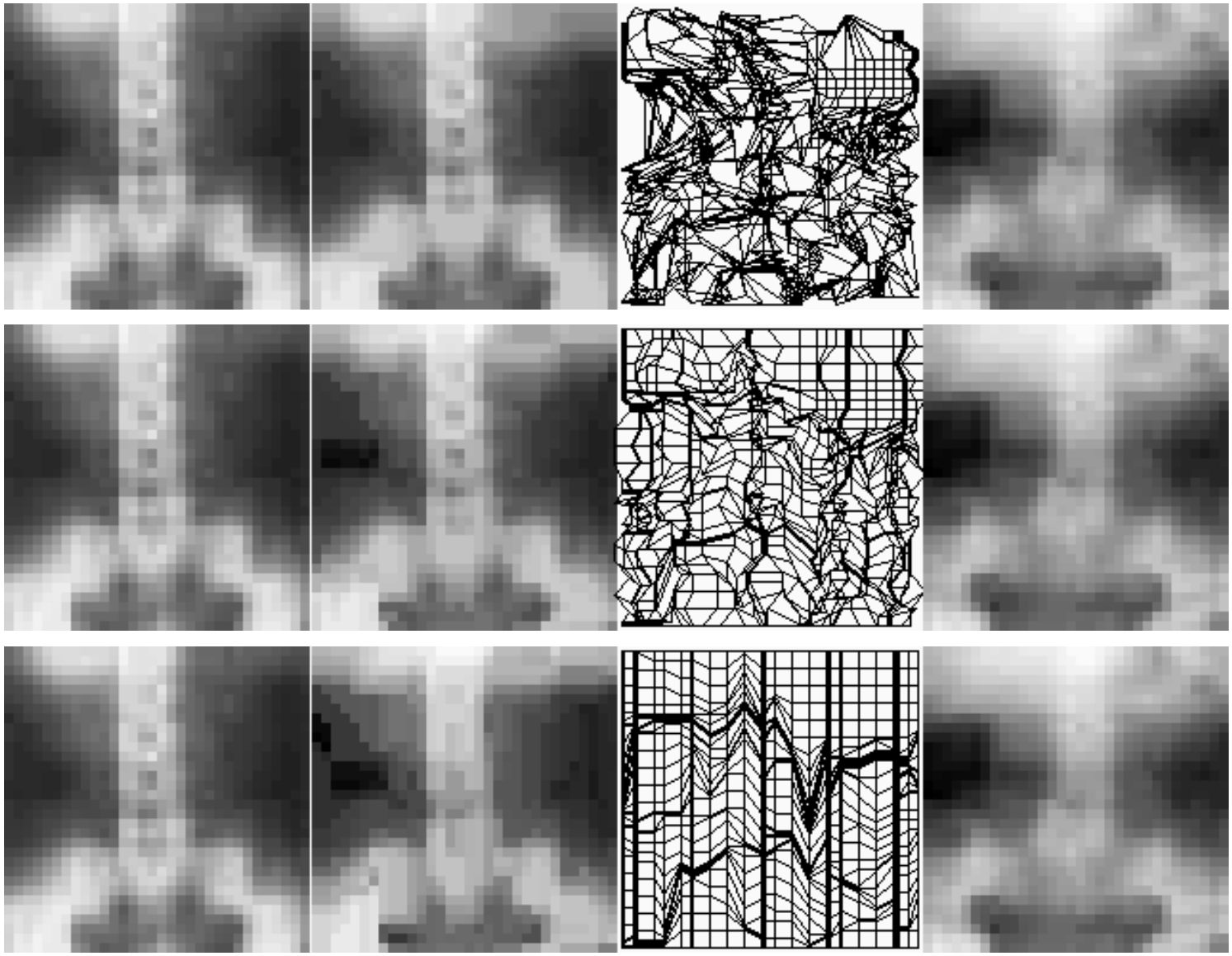
- restrict pixel mappings w.r.t. mappings of neighboring pixels
- continuity and monotonicity
- two-dimensional restrictions
  $\Rightarrow$ NP-complete and approximations difficult
- relax in one dimension
  $\Rightarrow$ pseudo two-dimensional hidden Markov model (P2DHMM)
- additionally allow deviations from the column assignment
  $\Rightarrow$ P2DHM distortion model (P2DHMDM)

Examples

IDM

P2DHMDM

P2DHMM



Examples

IDM

P2DHMDM

P2DHMM

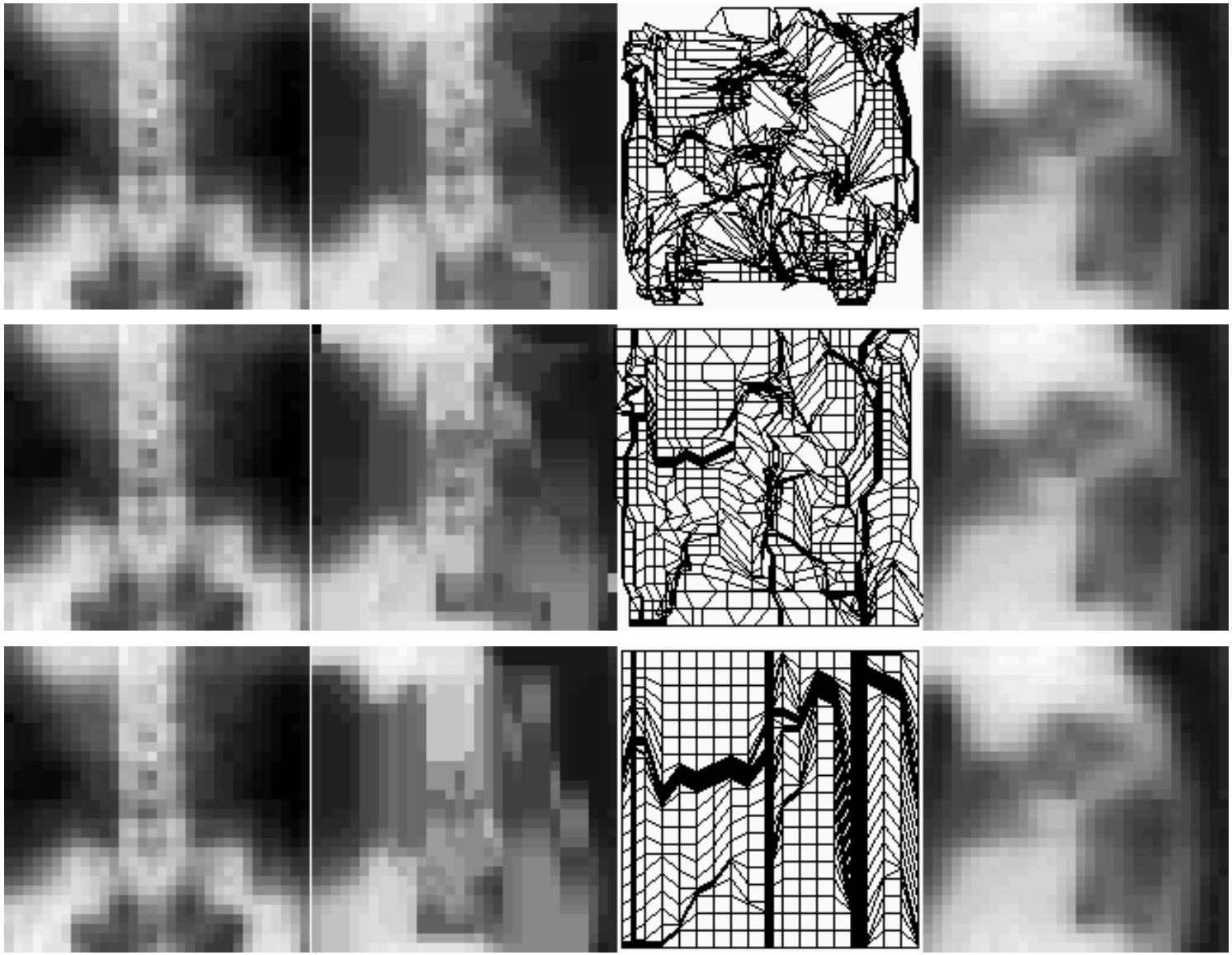
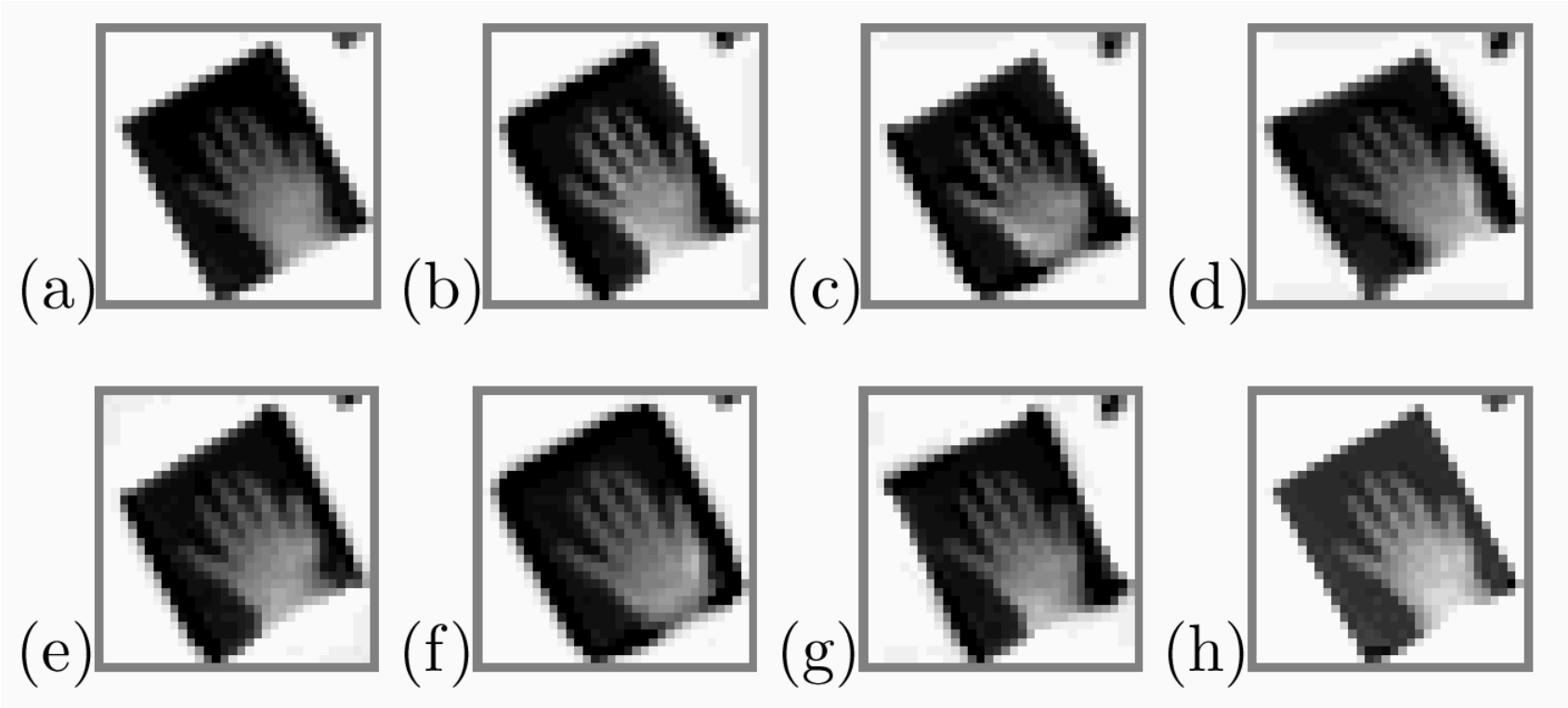


Image Distance: Tangent Distance

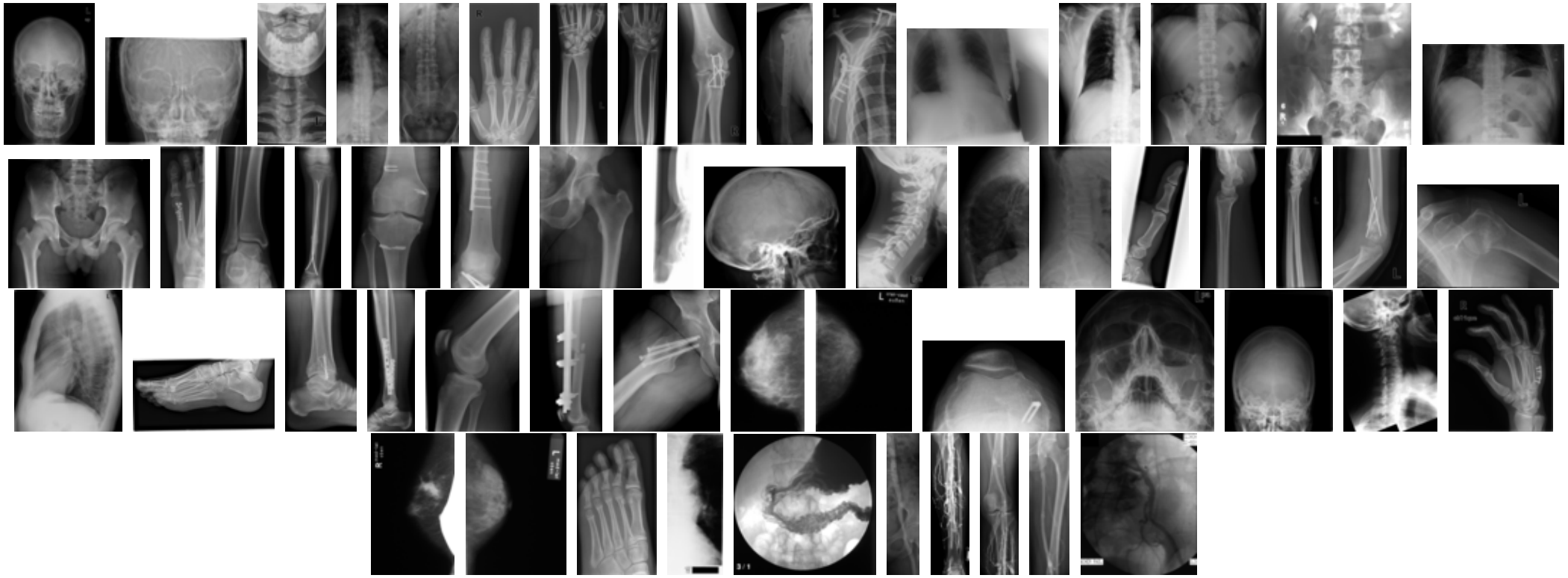


examples: linear approximations of affine transforms and image brightness

(a) original image, (b) left shift, (c) down shift (d) hyperbolic diagonal deformation, (e) hyperbolic axis deformation, (f) scaling, (g) rotation, (h) increased brightness

Comparison on IRMA Database

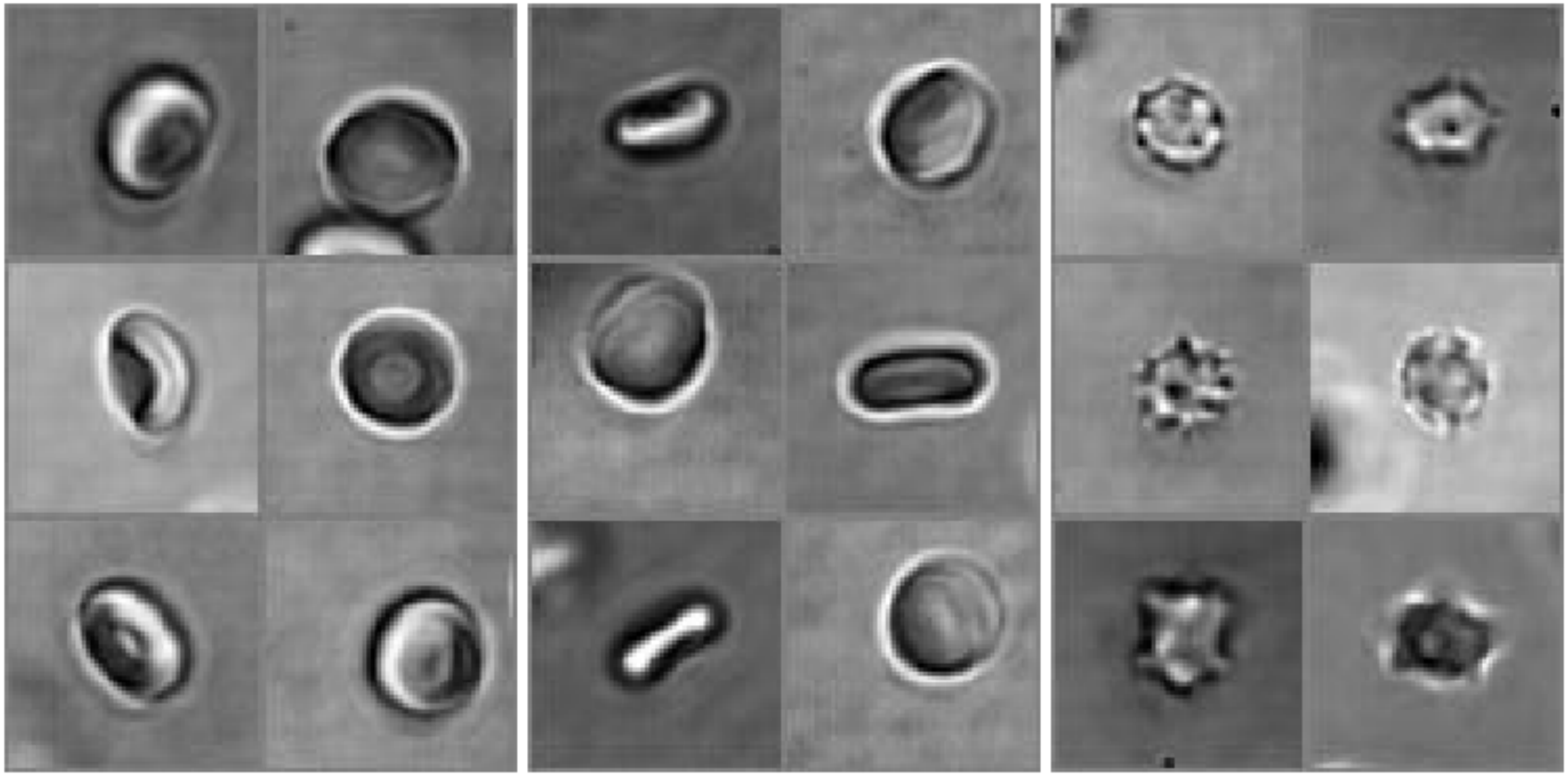
RWTH Aachen University IRMA data
- 10,000 medical radiographs
- 57 classes describing body regions,...
- subset of larger IRMA database with >15000 images and detailed code
- reference results available



Comparison on IRMA Database

method	error rate [%]
1-NN, Image Distortioin Model	12.6
image patch histograms, disc. training	13.9
image patches, decision trees	14.1
1-NN, 32x32, cross-correlation	17.4
medGIFT	20.6
1-NN, Tamura Texture Histograms	33.1
1-NN, Euclidean distance	36.8
1-NN, Gray Value Histograms	45.2
1-NN, cooccurrence matrices	65.8

Another Medical Task: Red Blood Cells



good results using:
- tangent distance
- invariant features based on Fourier transform
- local patches

Other Features

invariant feature histograms with different kernels

Tamura texture feature histogram

Gabor features, Gabor feature histograms

local features, local feature histograms

color histograms (1D, multi-D, pseudo-multi-D)

texture feature based on cooccurrence matrices

Fourier-Mellin feature

region features

pixel values / direct image features

transformed features: PCA, LDA, ...

aspect ratio / image size

Different features: Examples

$X(4,0)X(0,8)$

$X(4,0)X(0,8)$ **with scaling**

Different features: Examples

$rel(X(0,0) - X(0,4))$

$rel(X(0,0) - X(0,4)$
& $X(4,0)X(0,8)$

Different features: Examples

Tamura
coarseness, contrast, directionality

Tamura & $X(4,0)X(0,8)$

Different features: Examples

Local features

Local features
& $X(4,0)X(0,8)$

Different features: Examples

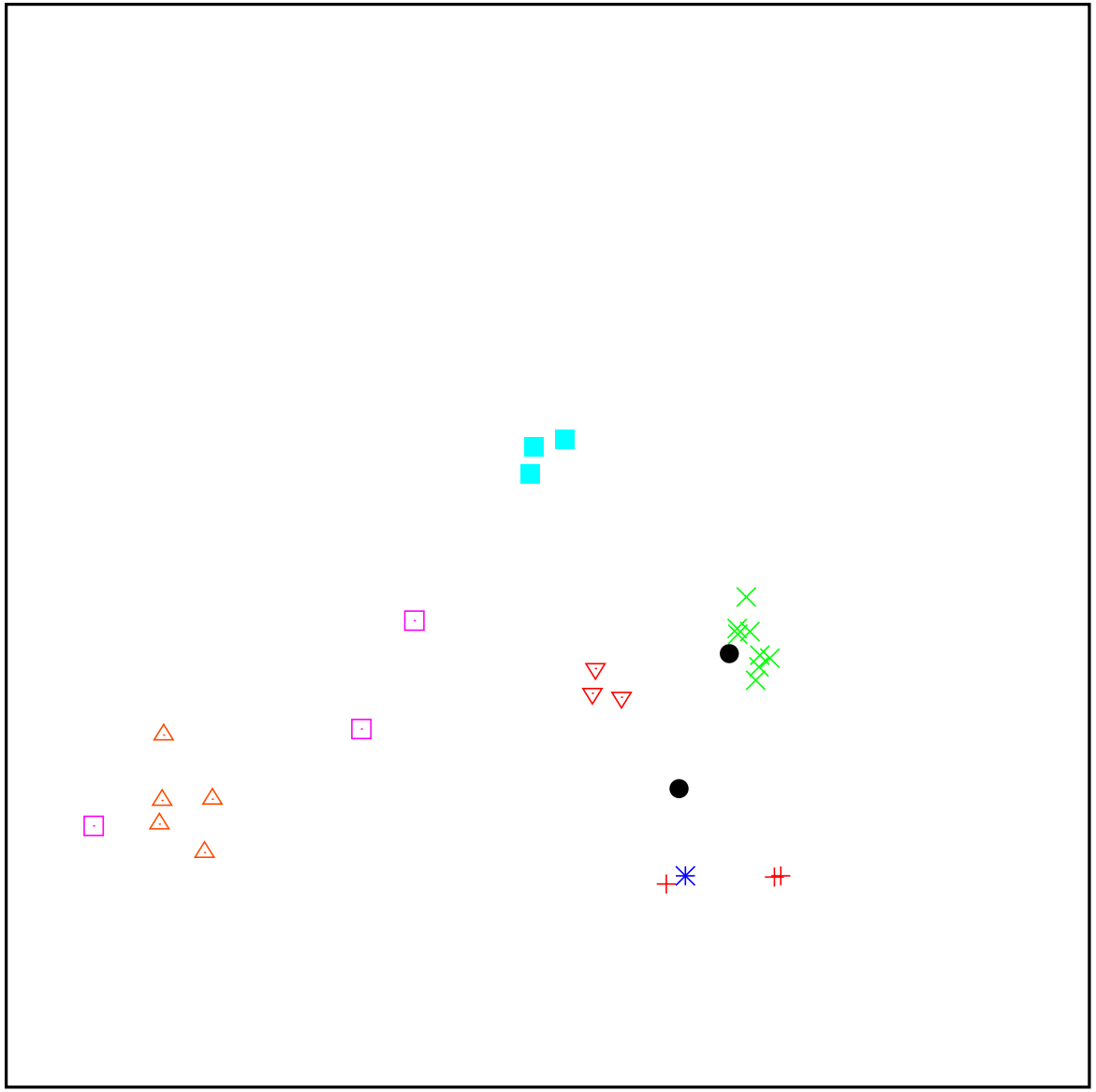
3D color histogram

Texture features
cooccurrence matrices

Different features: Examples

3D color histogram & texture feature

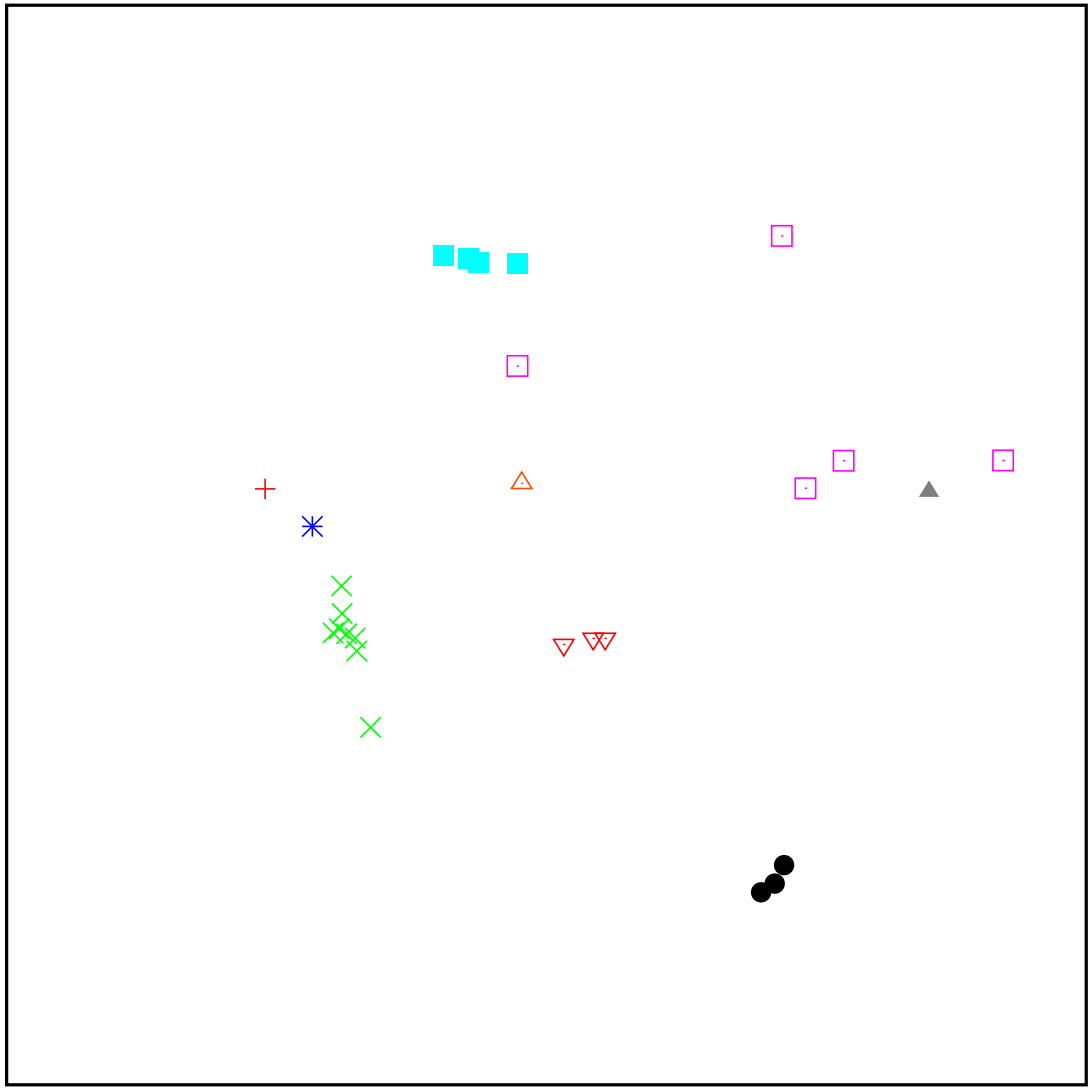
Correlation Between Features: WANG



- Image features
- Inv. feat. histogram
- Inv. feat. vector
- Texture features
- Gabor histogram
- LF histogram
- Color histogram
- Region features

Graph from multi-dimensional scaling of $1 - |\mathbf{cor}(\cdot,\cdot)|$.

Correlation Between Features: IRMA



- Image features
- Inv. feat. histogram
- Inv. feat. vector
- Texture features
- Gabor histogram
- LF histogram
- Local features
- Fourier Mellin feature
- Image size

Graph from multi-dimensional scaling of $1 - |\mathbf{cor}(\cdot,\cdot)|$.

Distance Measures

Histogram comparison measures

- Minkowski: Euclidean, L_1
- Histogram intersection
- Relative deviation
  Relative bin deviation
- χ^2 distance
- Kullback-Leibler divergence,
  Jensen-Shannon divergence
- Bhattacharyya based distances
- Quadratic forms
- Earth movers distance
- Time warp distance

Image comparison measures

- Euclidean distance
- Tangent distance
- Image distortion model

Local feature comparison measures

- Direct transfer
- Image based

Region comparison measures

- Integrated region matching
- Quantized Hungarian matching

Distance Measures

Minkowski Distances: $D_p(H,H') = \left(\sum_{m=0}^{M-1}(H_m - H'_m)^p\right)^{\frac{1}{p}}$.

Histogram Intersection: $\cap(H,H') = \sum_{m=0}^{M-1} min(H_m, H'_m)$

Relative Deviation: $D(H,H') = \frac{\sqrt{\sum_{m=0}^{M-1}(H_m - H'_m)^2}}{\frac{1}{2}(\sqrt{\sum_{m=0}^{M-1} H_m^2} + \sqrt{\sum_{m=0}^{M-1} {H'_m}^2})}$

Relative Bin Deviation: $D(H,H') = \sum_{m=0}^{M-1} \frac{\sqrt{(H_m - H'_m)^2}}{\frac{1}{2}(\sqrt{H_m^2} + \sqrt{{H'_m}^2})}$

χ^2**-Distance:** $\chi^2(H,H') = \sum_{m=0}^{M-1} \frac{H_m - H'_m}{H_m + H'_m}$

Kullback Leibler Divergence: $KL(H,H') = \sum_{m=0}^{M-1} H_m \log \frac{H_m}{H'_m}$

Jensen Shannon Divergence: $JD(H,H') = \sum_{m=0}^{M-1} H_m \log \frac{2H_m}{H_m + H'_m} + H'_m \log \frac{2H'_m}{H'_m + H_m}$

Fidelity based distance measures: $F(H,H') = \sum_{m=0}^{M-1} \sqrt{H_m}\sqrt{H'_m}, \quad \overline{F}(H,H') = 1 - F(H,H'),$

$F_{\sqrt{-}}(H,H') = \sqrt{1 - F(H,H')}, \quad F_{\log}(H,H') = \log(2 - F(H,H')),$

$F_{\arccos}(H,H') = \frac{2}{\pi} \arccos F(H,H'), \quad F_{\sin}(H,H') = \sqrt{1 - F^2(H,H')}$