Medical Image Retrieval / Visual Features

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Features

two important questions for content-based image retrieval:
– how are images represented ⇒ features
– how are image representations compared ⇒ 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
  ⇒ 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 ⇒ more possibilities
- alternative: local shape parts
Color Histograms

idea:

partition feature space $S$ into $M$ regions: $S^m \subset S$ with $\bigcup_{m=0}^{M-1} S^m = S$

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

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
examed 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:

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

$$G_f(\omega, \tau) = \int_{-\infty}^{+\infty} f(t)g_\alpha(t - \tau)e^{i\omega t}dt$$

$$= e^{-i\omega\tau}(f(\tau) \ast h(\tau))$$

**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: \( f(X) : X \mapsto \mathbb{R} \)

then:

\[
F(X) = \frac{1}{|G|} \int_{g \in G} f(gX)
\]

is invariant against any transformation from \( G \)
Invariant Features – Illustration

\[ \Omega \xrightarrow{f} \Omega \xrightarrow{f} \ldots \xrightarrow{f} \mathbb{C} \]

\[ \sum_{i=0}^{n-1} \frac{1}{|G_i|} \]

\[ T[f(X)] \]
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

$(n'_0, n'_1) = (\cos \phi - \sin \phi, \sin \phi \cos \phi)(n_0, n_1) + (t_0, t_1)$

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

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

problem

just one value $\Rightarrow$ not enough discriminative power
solution to the problem of insufficient data:
replace one or more sums by histogramization \( \Rightarrow \) preserves invariance

\[
H_F(X) = N_{0,1,1}^{\text{hist}} \sum_{r=1}^{R} \frac{1}{R} f\left(g_{t_0,t_1,\frac{2\pi r}{R},X}\right)
\]
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:
exttract local features from the test image
query the KD-Tree about these local features
use a direct voting scheme for classification
Local Features/Patches

selected pixel
local representation

selected pixel
local representation
Local Representations for Classification

Training images

Extraction of local features

PCA dimensionality reduction

Creation of KD-tree

k-NN classification

direct
voting

Test image

Extraction of local features

PCA dimensionality reduction

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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

selected pixel
local representation

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Distortion Models

local image context
- pixel neighborhoods of e.g. $3 \times 3$ or $5 \times 5$
- 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
  ⇒ NP-complete and approximations difficult
- relax in one dimension
  ⇒ pseudo two-dimensional hidden Markov model (P2DHMM)
- additionally allow deviations from the column assignment
  ⇒ 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

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<th>error rate [%]</th>
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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

\[ \text{rel}(X(0, 0) - X(0, 4)) \]

\[ \text{rel}(X(0, 0) - X(0, 4)) \quad & \quad X(4, 0)X(0, 8) \]
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
coooccurrence matrices
Different features: Examples

3D color histogram & texture feature
Correlation Between Features: WANG

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

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Correlation Between Features: IRMA

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

Histogram comparison measures
- Minkowski: Euclidean, $L_1$
- Histogram intersection
- Relative deviation
  Relative bin deviation
- $\chi^2$ 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: \(D(H, H') = \sum_{m=0}^{M-1} \frac{\sqrt{(H_m - H'_m)^2}}{\frac{1}{2}(\sqrt{H_m^2} + \sqrt{H'_m^2})}\)

\(\chi^2\)-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:
- \(F(H, H') = \sum_{m=0}^{M-1} \sqrt{H_m} \sqrt{H'_m}\), \(\overline{F}(H, H') = 1 - F(H, H')\),
- \(F_{\sqrt{}}(H, H') = \sqrt{1 - F(H, H')}\), \(F_{\log}(H, H') = \log(2 - F(H, H'))\),
- \(F_{\arccos}(H, H') = \frac{2}{\pi} \arccos F(H, H')\), \(F_{\sin}(H, H') = \sqrt{1 - F^2(H, H')}\)