Fundamentals of Image Processing

▶ Lecture 9: Characterization of image primitives ◀

Master of Computer Science
Sorbonne University

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Outline

Introduction

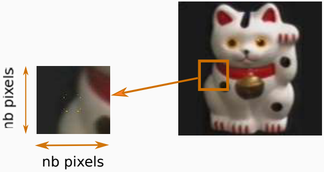
Back to classical detectors

- Several POI/ROI detectors are robust to changes in scale and point of view

  - MSER well suited for structured scenes
  - Harris and Hessian well suited to textured scenes
  - SIFT (DoG), and variants such as SURF, are very robust
- The algorithmic processing chain:
  - Detection of extrema in the space volume scale with possibly fine relocation of POI
  - Extraction of the area of interest (affine inv., rotation inv....)
  - Descriptor calculation

Introduction on feature descriptors

- Depending on the type of primitives
- Usual attributes:
  - Colorimetry
  - Calculations in a neighborhood: texture, curvature, shape
- Specialized attributes
  - Face images: distance between eyes...



Introduction on feature descriptors

- Why compute descriptors?
  - Registration: image alignment (homography, fundamental matrix)
  - 3D reconstruction
  - Motion tracking
  - Object recognition
  - Indexing and database retrieval
  - Navigation (robotics)
  - Classification
  - ...

Introduction on feature descriptors

- What are the expected properties?
  - Patches with similar content must have similar descriptors
  - The requirements of invariance (or robustness) in relation to transformations are multiple: image rotation, scale transformation, change of view point, change of brightness, change of objects in the category...

Issues

- Image transformations (rotation, scale)
- Brightness change
- Partial visibility / occlusions
- Additional objects, background
- Field of view for 3D objects

$\downarrow ?$

Introduction on feature descriptors

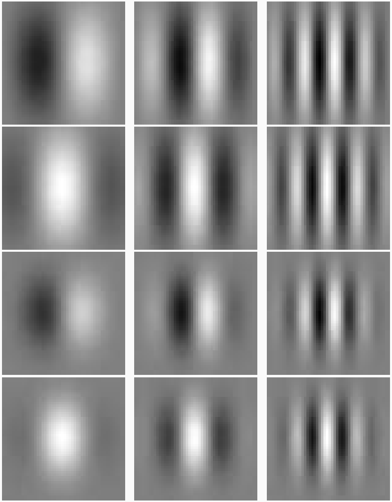
- What are the expected properties?
    - **Robustness** $\Rightarrow$ Invariance to changes in illumination, scale, rotation, affine transformations, perspective
    - **Distinctive** $\Rightarrow$ useful for inquiring large databases
    - **Efficient** $\Rightarrow$ easy and quick to calculate (real-time)
    - **Representative** $\Rightarrow$ many points/regions detected even on small areas/objects
- Local primitive descriptors (ROI, POI, edge):
    - **Local** $\Rightarrow$ therefore intrinsically robust to occlusions and (background) noise
    - **Modular** $\Rightarrow$ easily complemented by other types of descriptors to gain in robustness

Introduction on feature descriptors

- Typology of local descriptors:
  - Texture, filter banks
  - Derivatives of the gray level function
  - Differential invariants [van Gool et al., 1996]
  - SIFT descriptor [Lowe, 1999]
  - Moment invariant [van Gool et al., 1996]
  - Shape context analysis [Belongie et al., 2002]
  - Gray-scale - Centering, normalization (MOPS) [Brown et al., 2005]

Image descriptors

Descriptors based on Gabor filter banks

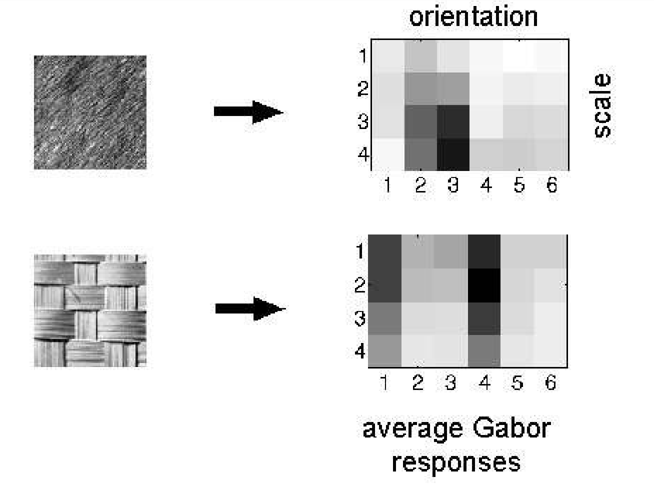


- Gabor filters at different spatial scales and frequencies
- Anti-symmetrical (odd) or symmetrical (even) filters

- Symmetrical: $\cos(k_x x + k_y y)e^{-\frac{x^2+y^2}{2\sigma^2}}$
- Anti-symmetrical: $\sin(k_x x + k_y y)e^{-\frac{x^2+y^2}{2\sigma^2}}$

Descriptors based on Gabor filter banks

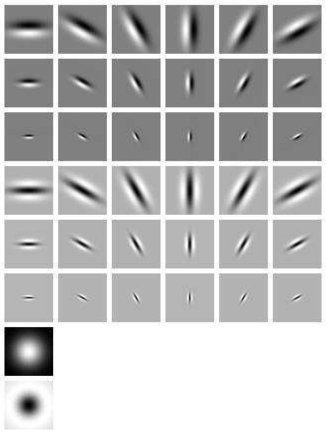
- Vector of dimension 6×4



darkest is the highest response

What does human use?

- Gabor filters!



- ... and many other things.

Descriptors based on Gaussian derivative filter banks

- Steerable filters [Freeman and Adelson, 1991], dim 13.

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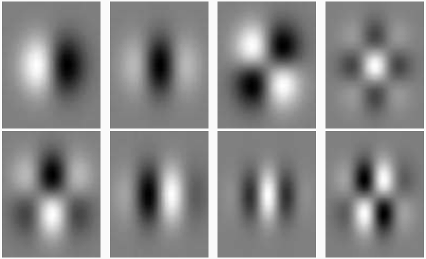


Local descriptors based on image intensity derivatives

- Convolution with Gaussian derivatives

$$\mathbf{v}(x,y) = \begin{pmatrix} I \star G(\sigma) \\ I \star G_x(\sigma) \\ I \star G_y(\sigma) \\ I \star G_{xx}(\sigma) \\ I \star G_{xy}(\sigma) \\ I \star G_{yy}(\sigma) \\ \vdots \end{pmatrix}$$

- Reminder:
  - $I \star G(\sigma)(x,y) = \int_{\mathbb{R}} \int_{\mathbb{R}} G(x', y', \sigma) I(x - x', y - y') dx' dy'$
  - $G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$

Reminder: derivation and convolution commute

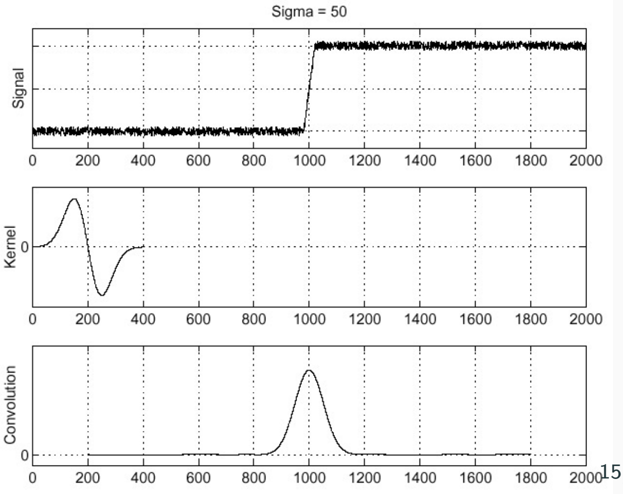
- As linear operators, derivation and convolution commute, i.e.:

$$\frac{\partial}{\partial x}(f \star g) = f \star \frac{\partial g}{\partial x}$$

f

$\frac{\partial g}{\partial x}$

$f \star \frac{\partial g}{\partial x}$



Local derivative descriptors

- Notation:

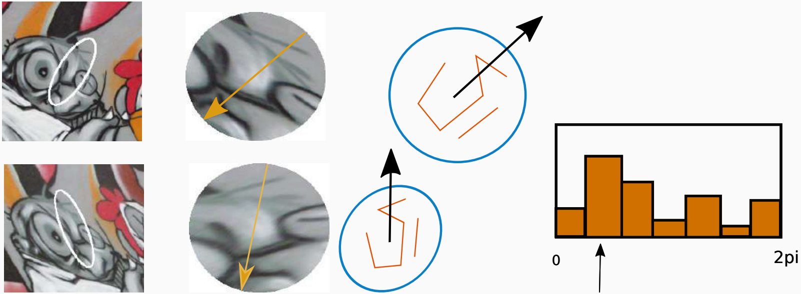
$$\mathbf{v}(x,y) = \begin{pmatrix} I \star G(\sigma) \\ I \star G_x(\sigma) \\ I \star G_y(\sigma) \\ I \star G_{xx}(\sigma) \\ I \star G_{xy}(\sigma) \\ I \star G_{yy}(\sigma) \\ \vdots \end{pmatrix} = \begin{pmatrix} L(x,y) \\ L_x(x,y) \\ L_y(x,y) \\ L_{xx}(x,y) \\ L_{xy}(x,y) \\ L_{yy}(x,y) \\ \vdots \end{pmatrix}$$

Local derivative descriptors: rotation invariance

- Rotation invariance: differential invariants

$$
\begin{array}{rl}
 & \\
\text{Gradient norm} \longrightarrow & \\
 & \\
\text{Laplacian} \longrightarrow & \\
 & \\
 &
\end{array}
\begin{pmatrix}
L \\
L_x L_x + L_y L_y \\
L_{xx} L_x L_x + 2 L_{xy} L_x L_y + L_{yy} L_{yy} \\
L_{xx} + L_{yy} \\
L_{xx} L_{xx} + 2 L_{xy} L_{xy} + L_{yy} L_{yy} \\
\vdots
\end{pmatrix}
$$

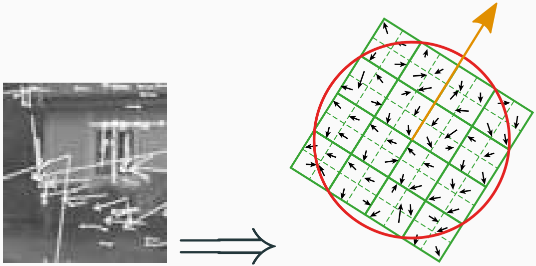
Alternative: normalization of the analysis window



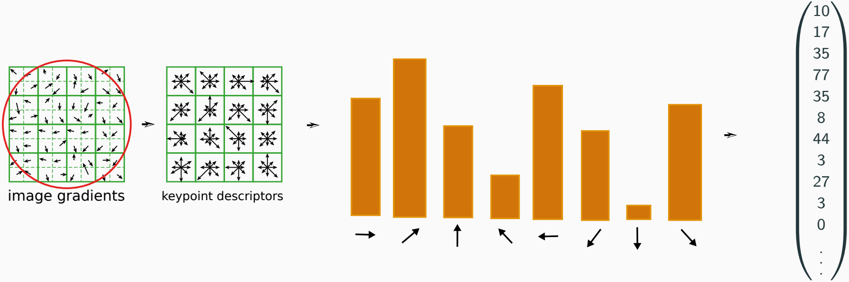
- Computation of orientations histogram
- Selection of the dominant orientation
- Normalization: rotation according to dominant orientation

SIFT descriptor

- Scale Invariant Feature Transform
- Principle:
  1. Square window shifted in the direction of the main gradient
  2. Gaussian weighting
  3. Histogram of gradient orientations image computed in each quadrant



- Creation of 16 gradient histograms (8 bins)
  - Gaussian weighting (centred on a POI, σ set to half of the window size)

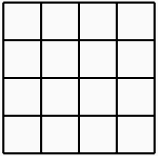


$\Rightarrow$ vector of size 128

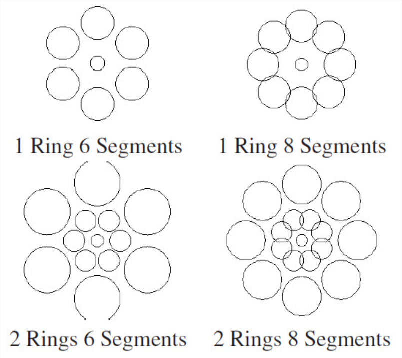
SIFT descriptor

- Invariance to affine illumination changes: $I \mapsto a \times I + b$:
  - Gradients unaffected by a bias ($I \mapsto I + b$, gain change)
  - Normalization of the histogram $\Rightarrow$ insures robustness to contrast change ($I \mapsto a \times I$)
- Compared to non-linear changes:
  - Saturation affects more amplitude than orientation
  - Thresholds on amplitude (empirically set to 0.2) and normalization

Other methods: Daisy



SIFT



DAISY

Other methods: BRIEF

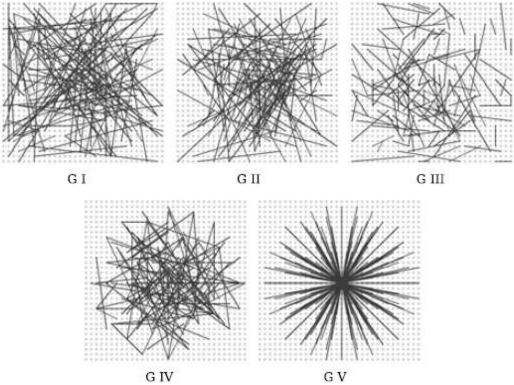
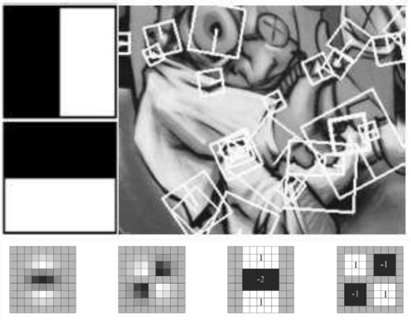


Fig. 2. Different approaches to choosing the test locations. All except the righmost one are selected by random sampling. Showing 128 tests in every image.

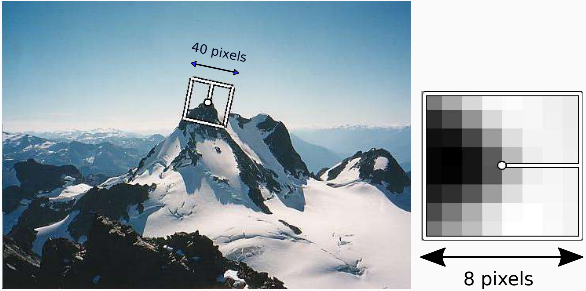
SURF: a faster SIFT



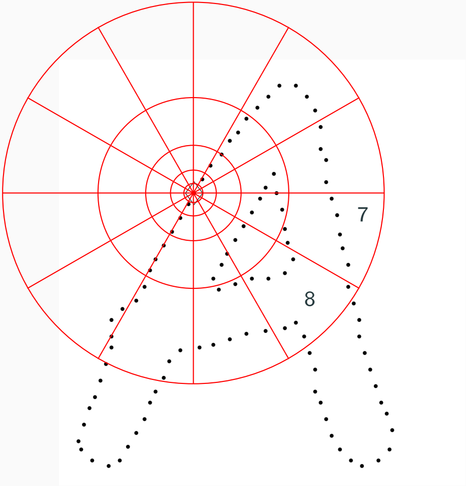
- Fast approximation of SIFT
    - Efficient computation with 2D filters and integral images
    - 6 times faster than SIFT with similar quality for object identification

MOPS: normalized patch type descriptor

- Compute multiscale Harris corners, first eigenvector gives orientation.
- Build 8x8 patches with orientation normalization (64 values)
  - Sampled with step 5 and using anti-aliasing filtering
- Renormalization (bias/gain): $I' = (I - \mu)/\sigma$



Shape-based descriptors [Belongie et al., 2002]



- Log-polar histogram
  - 5 bins in distance
  - 12 bins in orientation
- Count edges for all sub-domains

Conclusion on descriptors

- Many descriptors
- Many evaluations/comparisons
    - Presentation of top performers: SIFT
- Best choice often depends on the application
- Often better results by combining them
- How do we use these descriptors?

Applications

Image matching

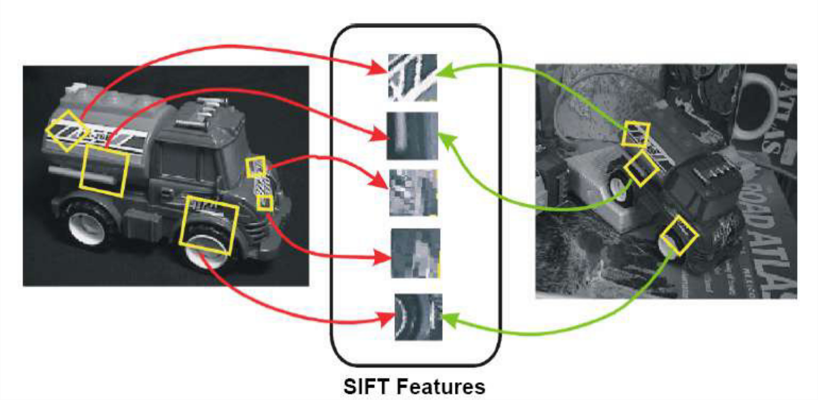
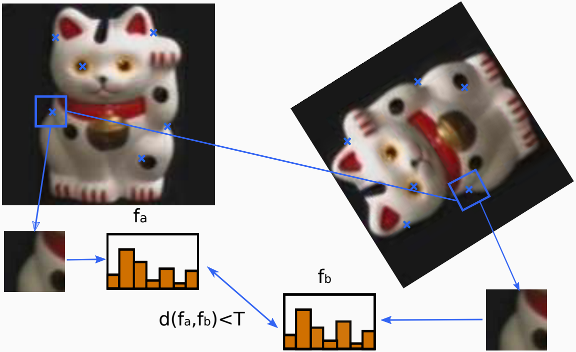


Image matching



1. Detection
2. Define a region of interest
3. Extraction / normalization
4. Descriptor computation
5. Matching

Image matching

Image matching

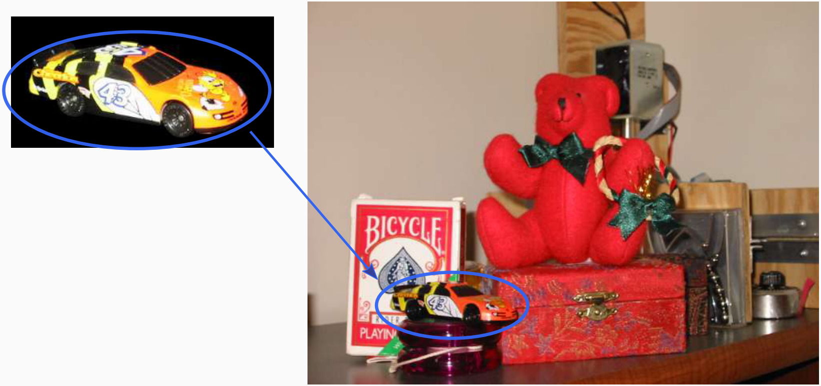
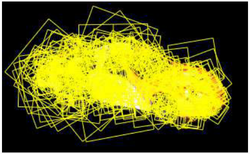


Image matching



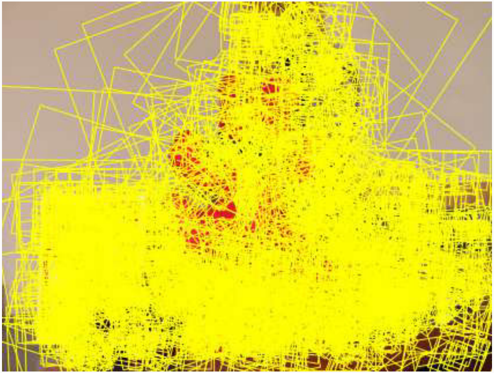


Image matching

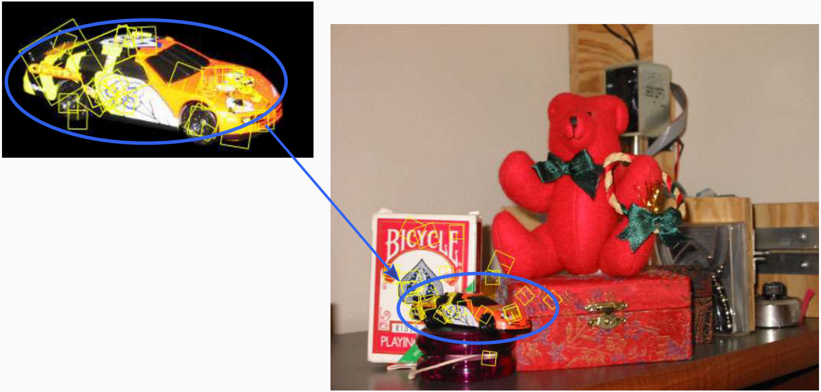


Image matching: localization of patches

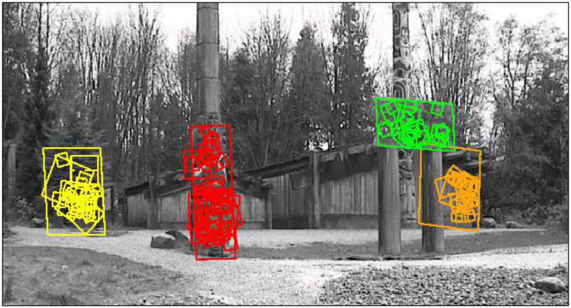


Image matching: change of point of view

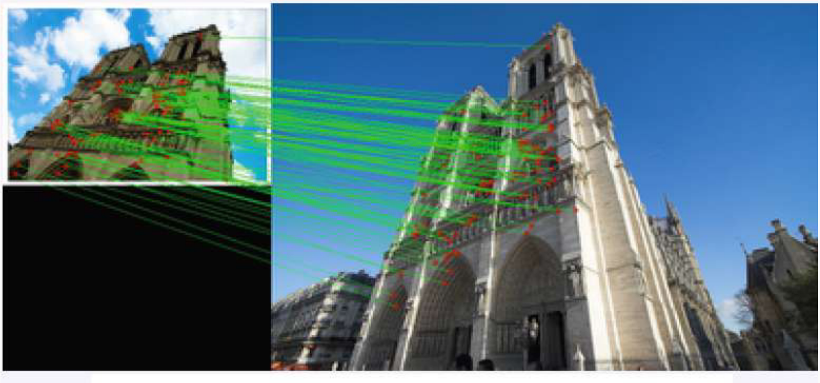
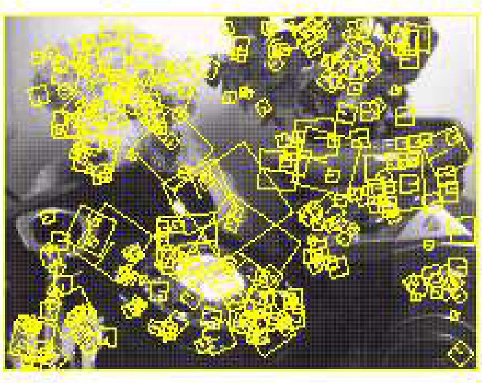


Image matching: robustness to occlusions

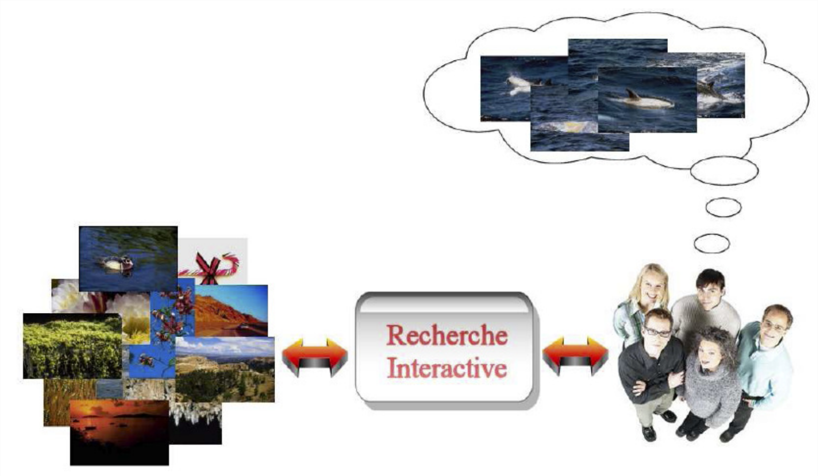


Image matching: robustness to change of illumination



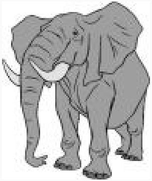
Generation of panoramas by registration

Indexing and searching in a database

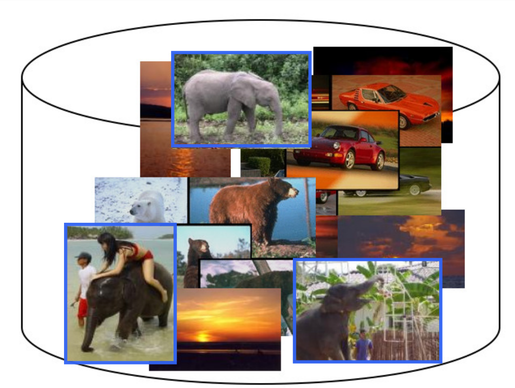


Search for image classes

- Query a category of objects



Query



Database

Search for image classes

- Query by semantics
  - Search for high level scene types or descriptors

Query

Database

Search engine architecture

- Off-line:
  1. Base of images
  2. Indexation (computation of image signatures)
  3. Indexed base
- On-line:
  1. User query
  2. Computation of image signature
  3. Find in the indexed base the most similar signatures (define a metric)
  4. Display results
  5. Optional: user feedback and back to 3.

Indexing: image signatures

- local signature:
  - set of descriptors (bag of vectors)
  - typical choice for images: SIFT
- global signature: dictionary-based approaches
  - construction of a dictionary of visual patterns (words)
  - projection on the dictionary and count words

Example of global signature: color histogram

- Codebook color

- Image signature: histogram computed on codebook

$[8, 27, 35, 48, 1, 10, 32, 9, 1, 4, 26, 6, 19, 7, 3, 8, 3, 7, 2, 0, 0, 0, 3, 0, 2]$

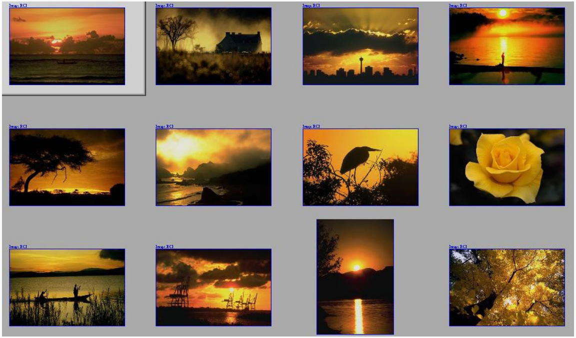
Measure of similarity

Measure of similarity: scalar product, L_1, L_2 norms...
Principle:

1. Pre-processing: centering, normalization...
2. Fusion of features: for a model i, compute on I a vector of features $F_i(I)$
3. Final vector of features: $F(I) = (F_1(I), F_2(I), \cdots, F_n(I))$
4. Similarity between I_A and I_B: $\mathrm{Sim}(F(I_A), F(I_B))$

Example (practical work)

- Example of semantic search based on similarity between color histograms



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