Keypoint extraction: Corners

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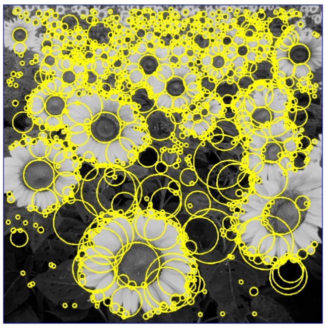
Lecture Layout

- Image features
  - Edges
  - Junctions & Corners
  - **Blobs**
  - Ridges
- Image descriptors
  - SIFT features



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HOG features

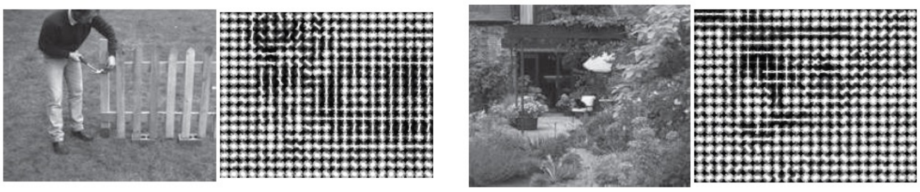

FIGURE 5.15: The HOG features for each the two images shown here have been visualized by a version of the rose diagram of Figures 5.7–5.9. Here each of the cells in which the histogram is taken is plotted with a little rose in it; the direction plotted is at right angles to the gradient, so you should visualize the overlaid line segments as edge directions. Notice that in the textured regions the edge directions are fairly uniformly distributed, but strong contours (the gardener, the fence on the **left**; the vertical edges of the french windows on the **right**) are very clear. This figure was plotted using the toolbox of Dollár and Rabaud. *Left: © Dorling Kindersley, used with permission. Right: Geoff Brightling © Dorling Kindersley, used with permission.*

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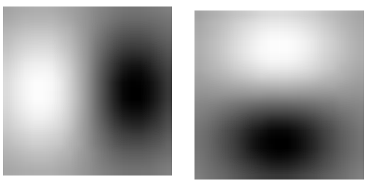
Note: Filters are Templates

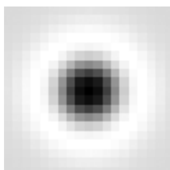
- Applying a filter at some point can be seen as taking a dot-product between an image patch and a vector.
- Filtering the image is forming a set of dot products.
- Large product: small distance

$$
\begin{aligned}
|I - f| &= < I - f, I - f > \\
&= < I, I > + < f, f > -2 < I, f > \\
&= C - 2 < I, f >
\end{aligned}
$$

Derivative of Gaussian:
Edge filter/template



Laplacian of Gaussian:
Blob filter/template



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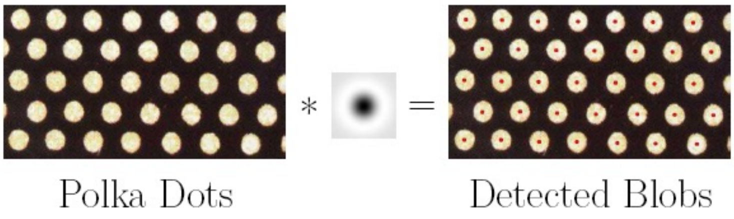
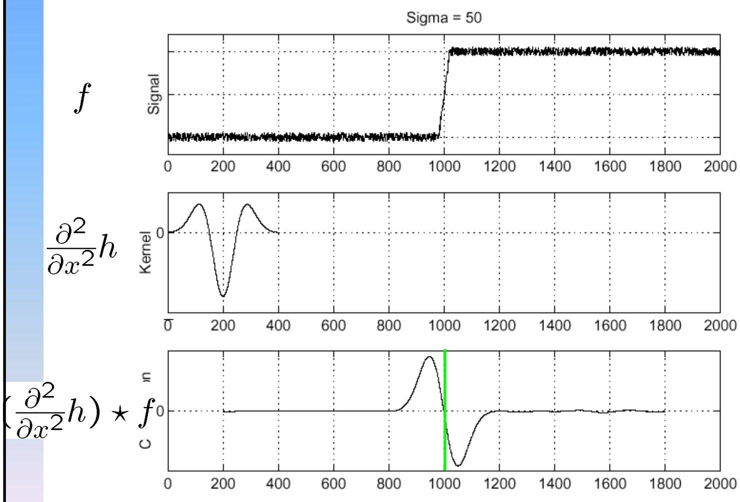
Finding blobs



Reminder: Edge detection using Laplacian

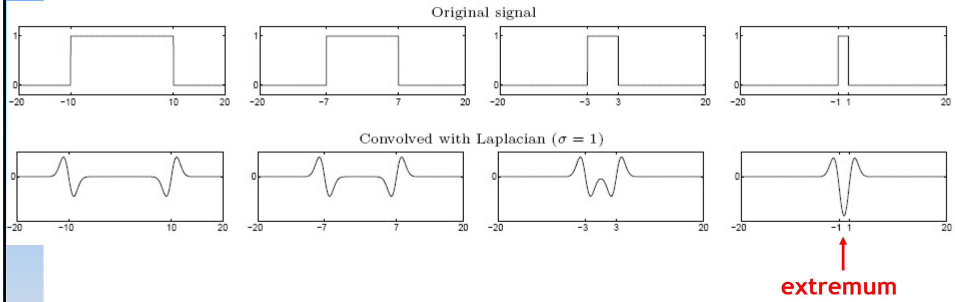


Second derivative of Gaussian (Laplacian)

Edge

From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples



Scale selection: Laplacian-of-Gaussian has extremum at the center of the blob, if the scale of the Gaussian is "matched" to the scale of the blob

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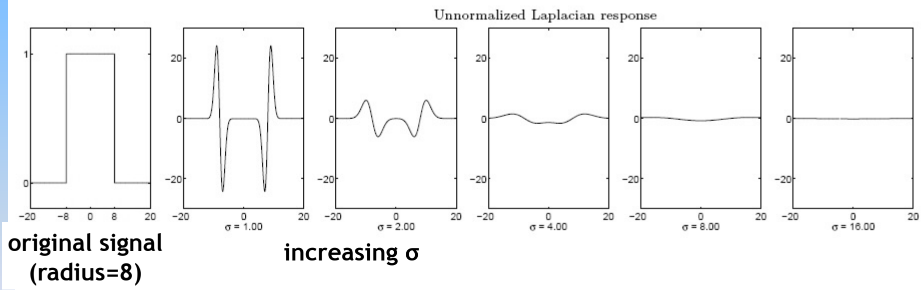
Scale selection

- First idea: convolve with Laplacians at several scales and find maximum in scale
- Observation: Laplacian decays as scale increases:



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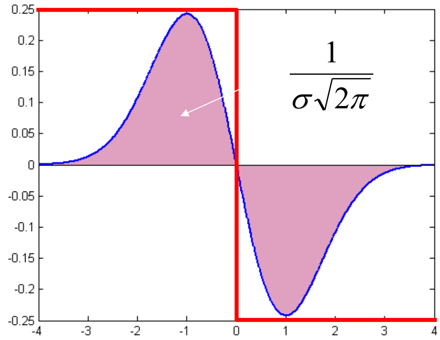
Scale normalization

- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases



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Scale normalization

- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

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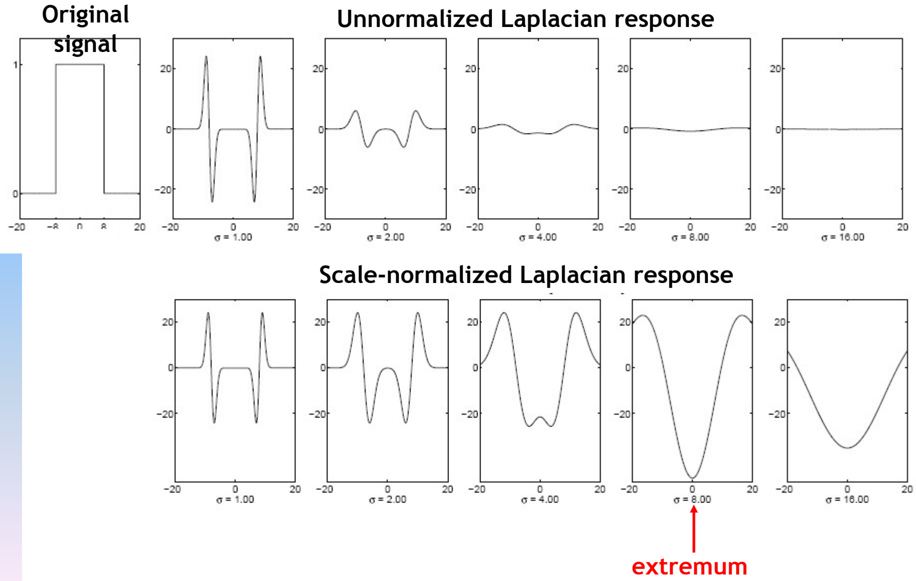
Effect of scale normalization



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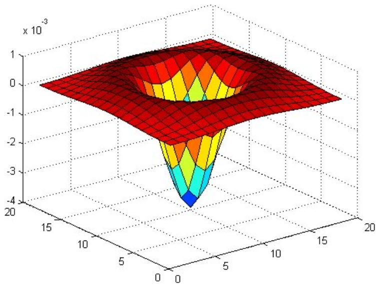
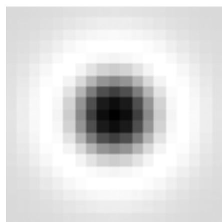
Blob detection in 2D

Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D





$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

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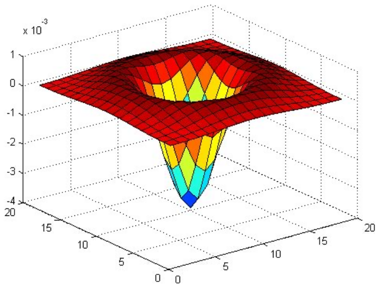
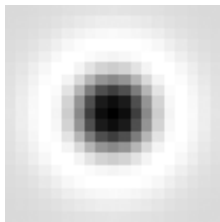
Blob detection in 2D

Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D





Scale-normalized:

$$\nabla^2_{\text{norm}} g = \sigma^2 \left(\frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \right)$$

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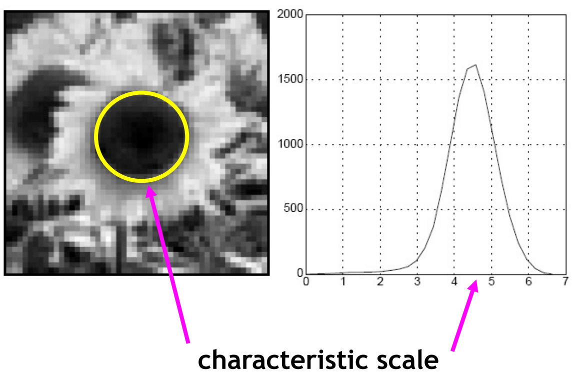
Scale selection

- Characteristic scale: peak of Laplacian response



T. Lindeberg (1998). "Feature detection with automatic scale selection." *International Journal of Computer Vision* 30 (2): pp 77--116.

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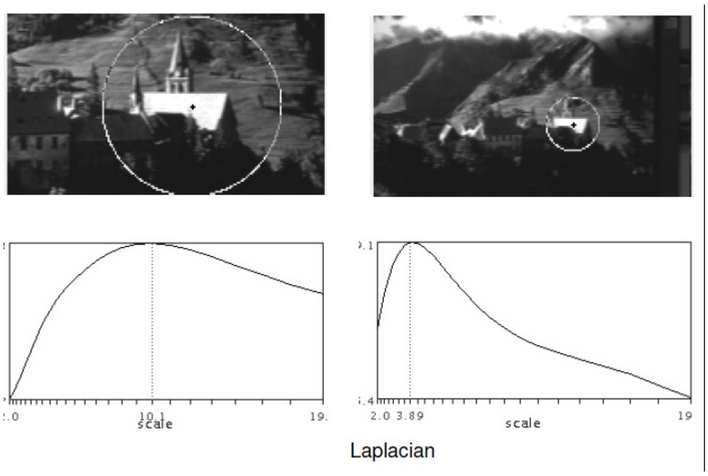
Scale invariance using scale selection



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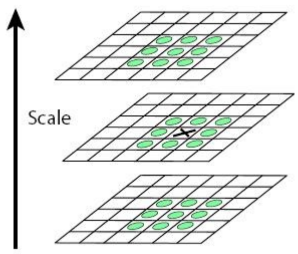
Scale-space blob detector

1. Convolve image with scale-normalized Laplacian at several scales
2. Find maxima of squared Laplacian response in scale-space



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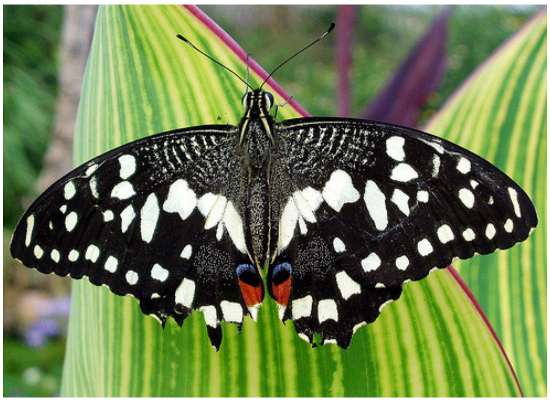
Scale-space blob detector: Example



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Scale-space blob detector: Example

sigma = 3.1296

sigma = 4.8972

sigma = 7.6631

sigma = 11.9912

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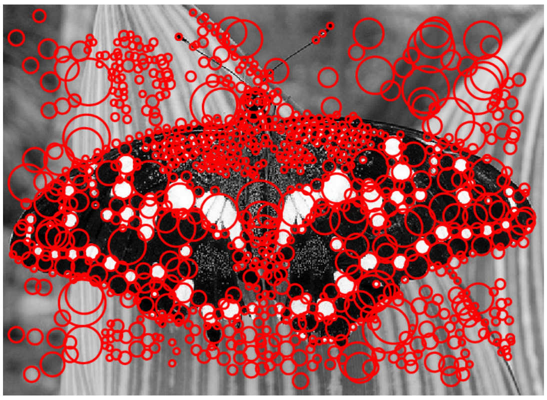
Scale-space blob detector: Example



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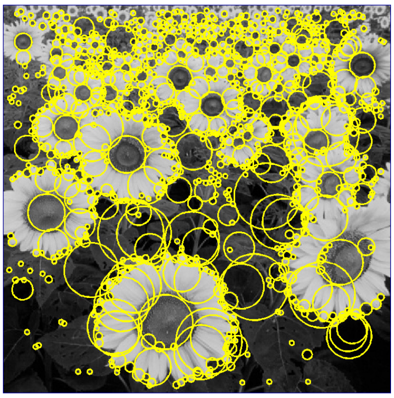
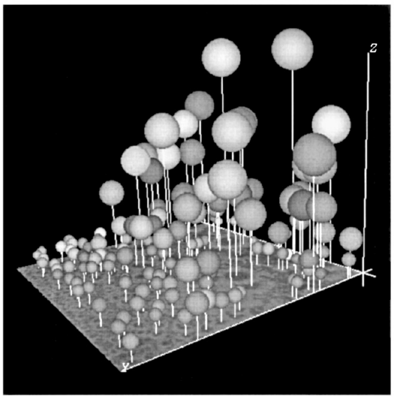
Blob coordinates: (x,y,scale)





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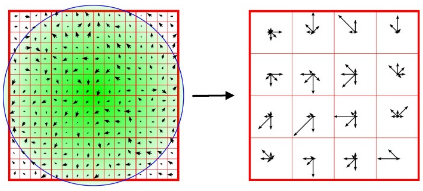
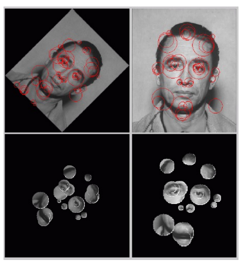
Lecture Layout

- Image features
  - Edges
  - Junctions & Corners
  - Blobs
  - Ridges
- Image descriptors
  - SIFT features



Interest point application: Image stitching

- Other applications:
  - Object recognition
  - Motion tracking
  - 3D stereo
  - Etc…



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Problem: how can you measure `similarity’?

- Patch-based similarity
  - Affected by changes in illumination
    - e.g. a cloud passing in front of the sun


Morning


Noon


Evening

- Requirement: invariance to photometric changes

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Normalized Cross-Correlation

- Make each patch zero mean:

$$\mu = \frac{1}{N}\sum_{x,y} I(x,y)$$

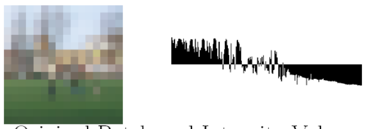
$$Z(x,y) = I(x,y) - \mu$$

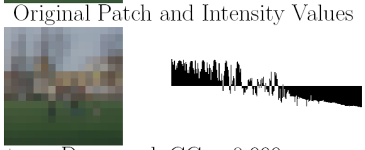
- Then make unit variance:

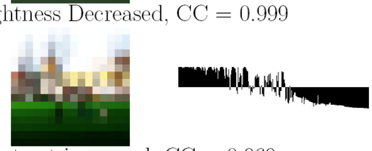
$$\sigma^2 = \frac{1}{N}\sum_{x,y} Z(x,y)^2$$

$$ZN(x,y) = \frac{Z(x,y)}{\sigma}$$

Affine photometric transformation:
I → a I + b


Original Patch and Intensity Values


Brightness Decreased, CC = 0.999


Contrast increased, CC = 0.969

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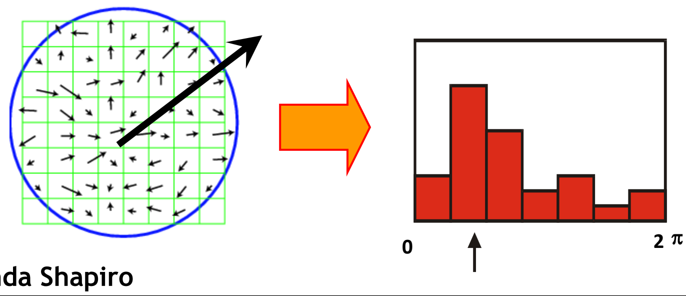
SIFT descriptor

- Alternative representation for image patches
- Location and characteristic scale given by Blob detector
- Find orientation from orientation histogram



Slide: Linda Shapiro

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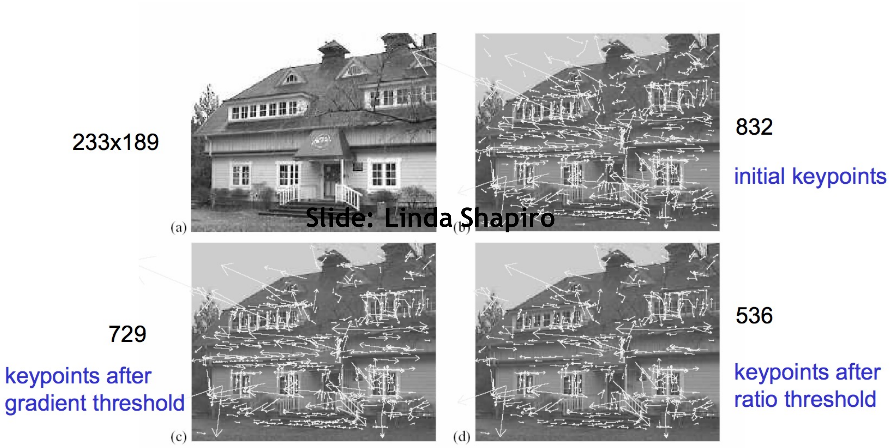
Keypoint Localization with Orientation



Slide: Linda Shapiro

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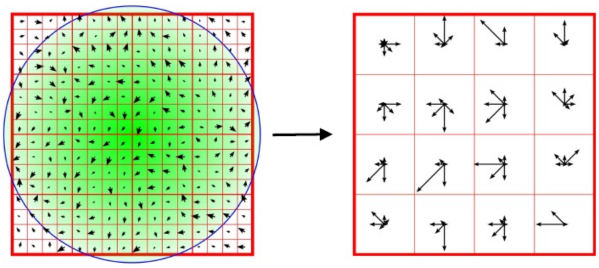
Orientation Histogram

- 4x4 spatial bins (16 bins total)
- 8-bin orientation histogram per bin
- 8 x 16 = 128 dimensions total
- Normalized to unit norm



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SIFT invariances

- Spatial binning: tolerance to small shifts in location
- Orientation normalization
- Photometric normalization by making all vectors unit norm
- Orientation histogram: robustness to small local deformations

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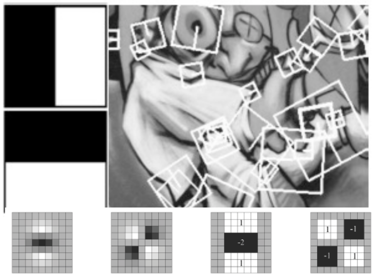
Local Descriptors: SURF



Fast approximation of SIFT idea

Efficient computation by 2D box filters & integral images
⇒ 6 times faster than SIFT

Equivalent quality for object identification

GPU implementation available

Feature extraction @ 200Hz
(detector + descriptor, 640 × 480 img)

http://www.vision.ee.ethz.ch/~surf

[Bay, ECCV'06], [Cornelis, CVGPU'08]

K. Grauman, B. Leibe

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Choosing a detector

- What do you want it for?
  - Precise localization in x-y: Harris
  - Good localization in scale: Difference of Gaussian
  - Flexible region shape: MSER
- Best choice often application dependent
  - Harris-/Hessian-Laplace/DoG work well for many natural categories
  - MSER works well for buildings and printed things
- Why choose?
  - Get more points with more detectors
- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV'05, PAMI'05]
  - All detectors/descriptors shown here work well

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Comparison of Keypoint Detectors

Table 7.1 Overview of feature detectors.

Feature Detector	Corner	Blob	Region	Rotation invariant	Scale invariant	Affine invariant	Repeatability	Localization accuracy	Robustness	Efficiency
Harris	√			√			+++	+++	+++	++
Hessian		√		√			++	++	++	+
SUSAN	√			√			++	++	++	+++
Harris-Laplace	√	(√)		√	√		+++	+++	++	+
Hessian-Laplace	(√)	√		√	√		+++	+++	+++	+
DoG	(√)	√		√	√		++	++	++	++
SURF	(√)	√		√	√		++	++	++	+++
Harris-Affine	√	(√)		√	√	√	+++	+++	++	++
Hessian-Affine	(√)	√		√	√	√	+++	+++	+++	++
Salient Regions	(√)	√		√	√	(√)	+	+	++	+
Edge-based	√			√	√	√	+++	+++	+	+
MSER			√	√	√	√	+++	+++	++	+++
Intensity-based			√	√	√	√	++	++	++	++
Superpixels			√	√	(√)	(√)	+	+	+	+

Tuytelaars Mikolajczyk 2(

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Applications of local invariant features

- Wide baseline stereo
- Motion tracking
- Panoramas
- Mobile robot navigation
- 3D reconstruction
- Recognition
- …

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Slide credit: Kristen Grauman

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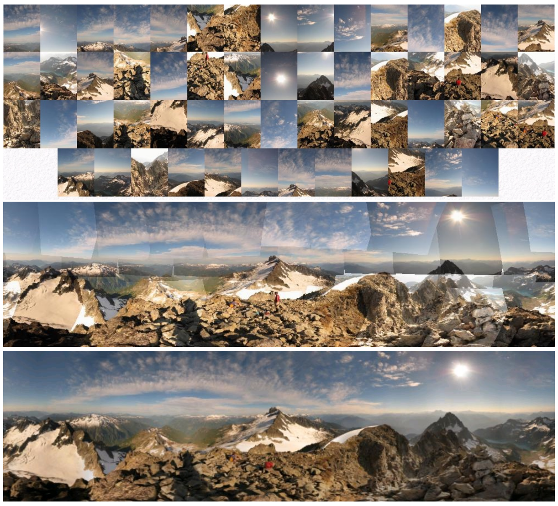
Automatic mosaicing



http://www.cs.ubc.ca/~mbrown/autostitch/autostitch.html

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Slide credit: Kristen Grauman

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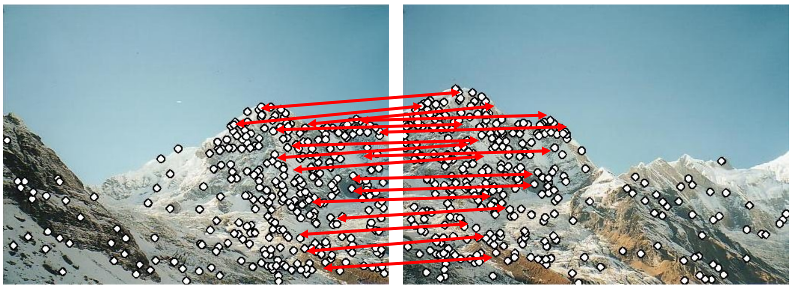
Robust feature-based alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)
  - *Verify* transformation (search for other matches consistent with *T*)

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Source: L. Lazebnik

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Robust feature-based alignment

- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)
  - *Verify* transformation (search for other matches consistent with *T*)

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Source: L. Lazebnik

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Wide baseline stereo

[Image from T. Tuytelaars ECCV 2006 tutorial]

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Recognition of specific objects, scenes

Schmid and Mohr 1997

Sivic and Zisserman, 2003

Rothganger et al. 2003

Lowe 2002

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Kristen Grauman

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