SIFT - The Scale Invariant Feature Transform

Distinctive image features from scale-invariant keypoints. David G. Lowe, International Journal of Computer Vision, 60, 2 (2004), pp. 91-110

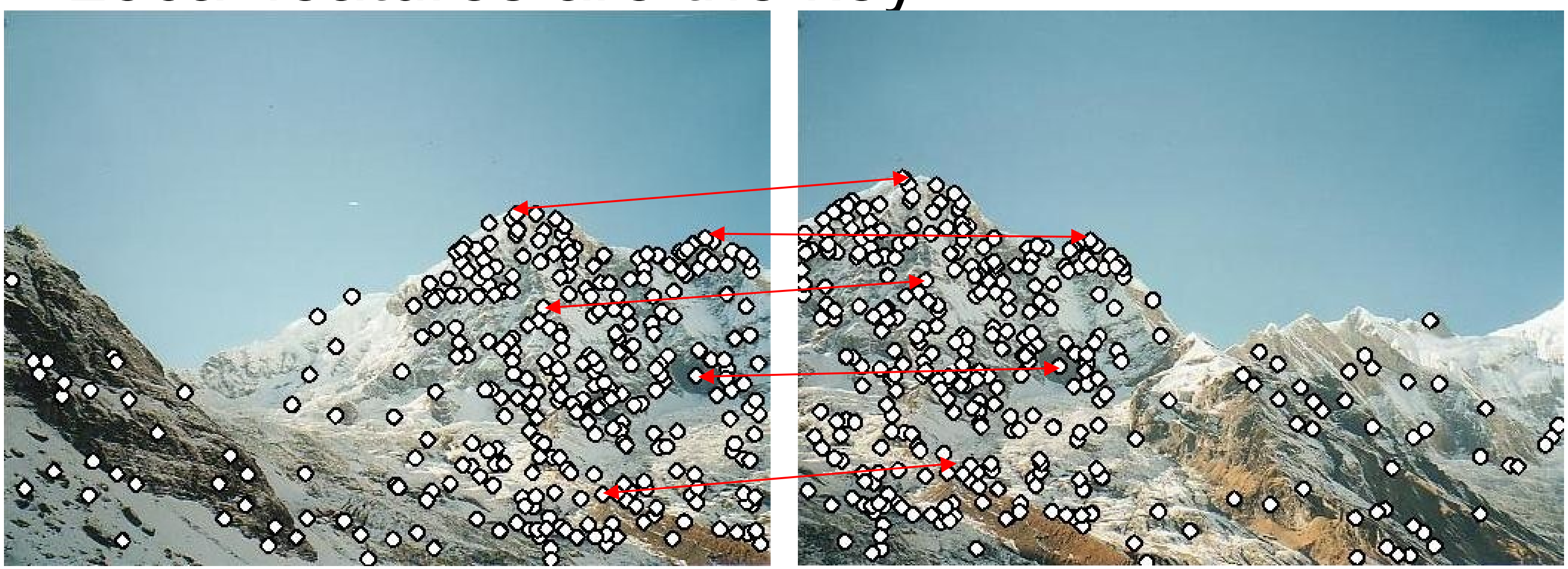
Presented by Ofir Pele.

Based upon slides from:

- Sebastian Thrun and Jana Košecká
- Neeraj Kumar

Correspondence

- Fundamental to many of the core vision problems
  - Recognition
  - Motion tracking
  - Multiview geometry
- Local features are the key

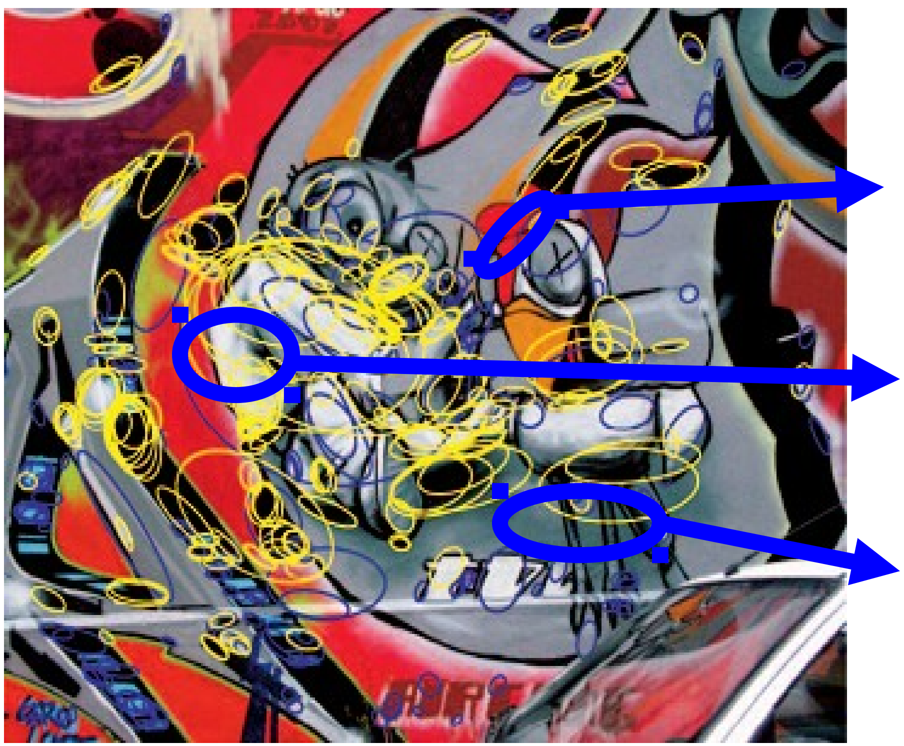


Images from: M. Brown and D. G. Lowe. Recognising Panoramas. In Proceedings of the the International Conference on Computer Vision (ICCV2003)

Local Features: Detectors & Descriptors

Detected Interest Points/Regions

Descriptors



<0 12 31 0 0 23 …>

<5 0 0 11 37 15 …>

<14 21 10 0 3 22 …>

Ideal Interest Points/Regions

- Lots of them
- Repeatable
- Representative orientation/scale
- Fast to extract and match



SIFT Overview

Detector

1. Find Scale-Space Extrema
2. Keypoint Localization & Filtering
   - Improve keypoints and throw out bad ones

3. Orientation Assignment
   - Remove effects of rotation and scale
4. Create descriptor
   - Using histograms of orientations

Descriptor

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Descriptor

Scale Space

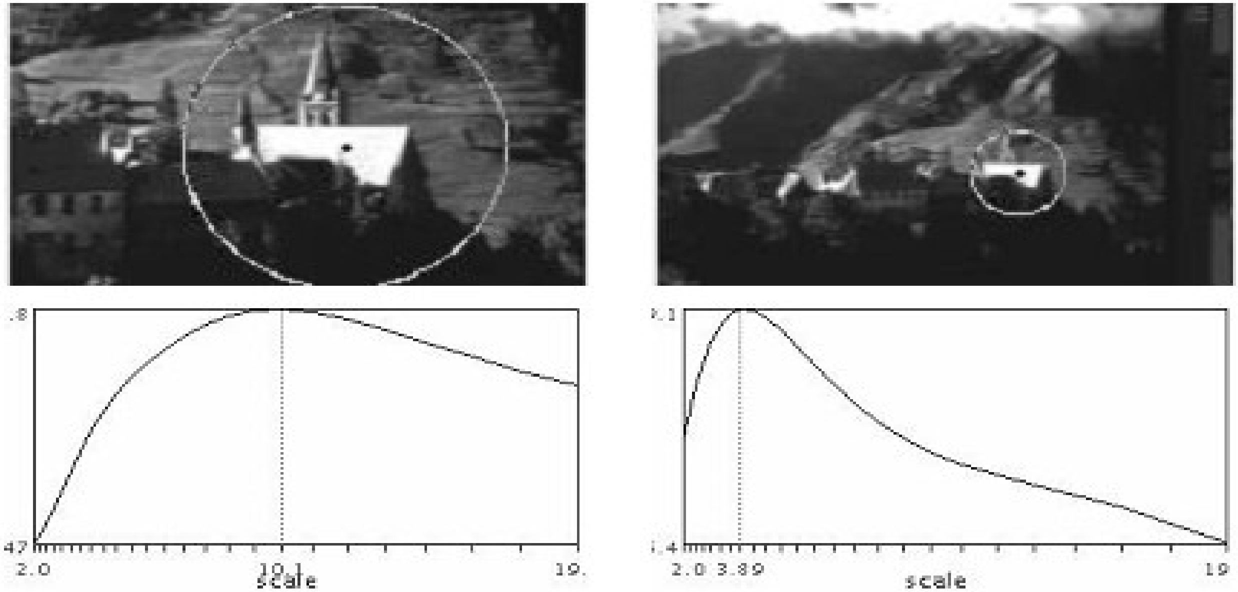
- Need to find 'characteristic scale' for feature
- Scale-Space: Continuous function of scale σ
  - Only reasonable kernel is Gaussian:

$$L(x, y, \sigma_D) = G(x, y, \sigma_D) * I(x, y)$$

[Koenderink 1984, Lindeberg 1994]

Scale Selection

- Experimentally, Maxima of Laplacian-of-Gaussian gives best notion of scale:



- Thus use Laplacian-of-Gaussian (LoG) operator:

$$\sigma^2 \nabla^2 G$$

Mikolajczyk 2002

Approximate LoG

- LoG is expensive, so let's approximate it
- Using the heat-diffusion equation:

$$\sigma \nabla^2 G = \frac{\partial G}{\partial \sigma} \approx \frac{G(k\sigma) - G(\sigma)}{k\sigma - \sigma}$$

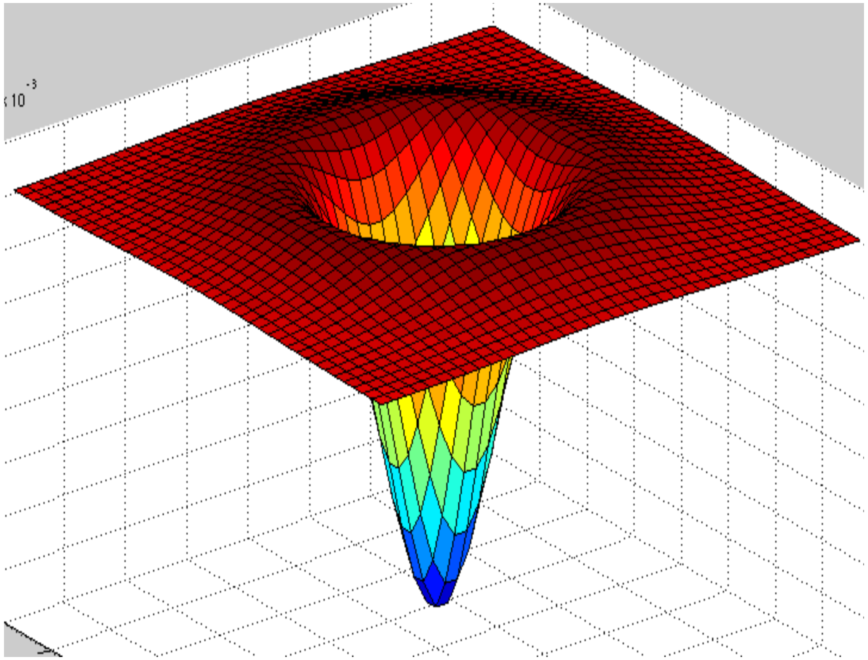
- Define Difference-of-Gaussians (DoG):

$$(k-1)\sigma^2 \nabla^2 G \approx G(k\sigma) - G(\sigma)$$

$$D(\sigma) \equiv (G(k\sigma) - G(\sigma)) * I$$

DoG efficiency

- The smoothed images need to be computed in any case for feature description.
- We need only to subtract two images.



DoB filter (`Difference of Boxes')

- Even faster approximation is using box filters (by integral image)

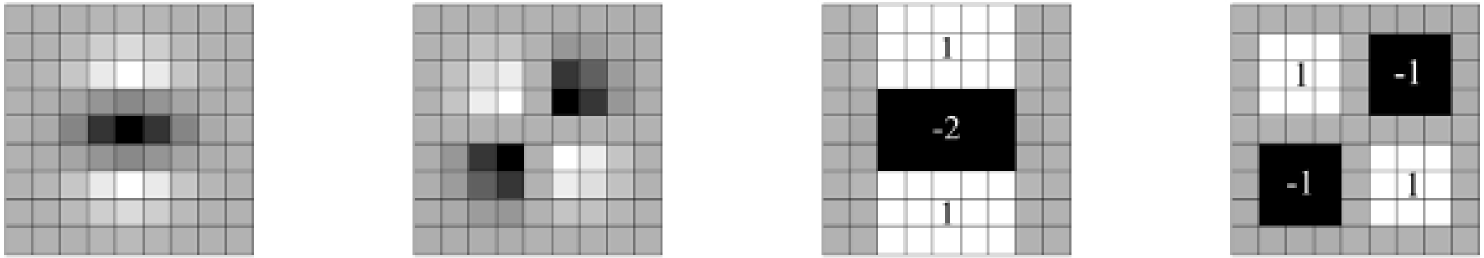
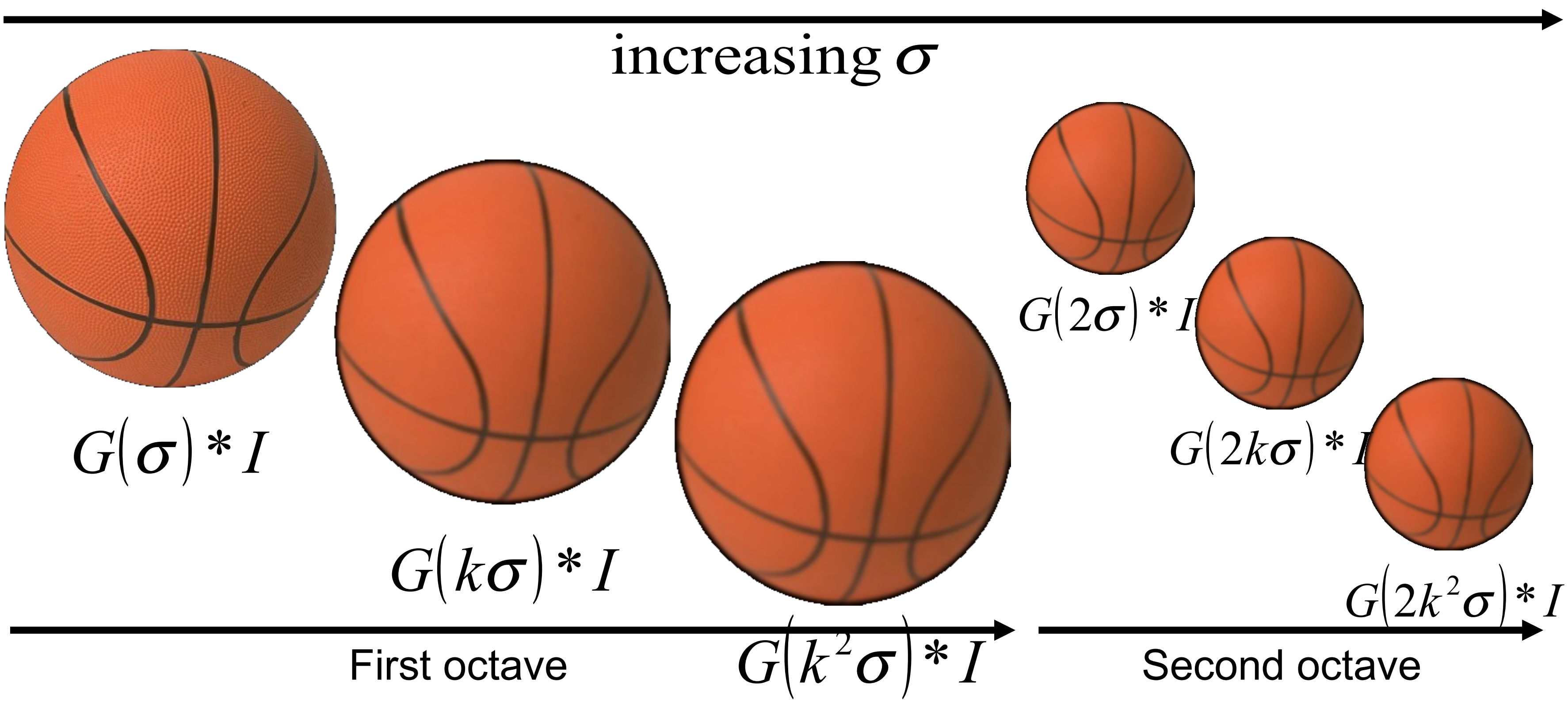


Fig. 1. Left to right: the (discretised and cropped) Gaussian second order partial derivatives in y-direction and xy-direction, and our approximations thereof using box filters. The grey regions are equal to zero.

Bay, ECCV 2006

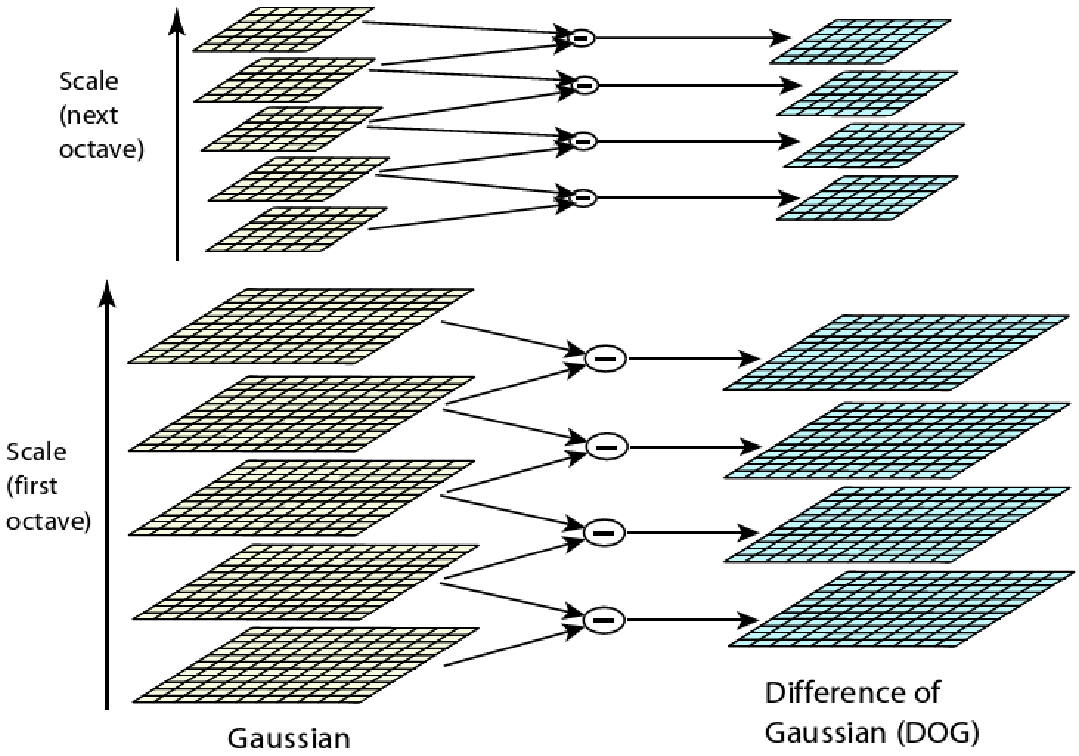
Scale-Space Construction

- First construct scale-space:



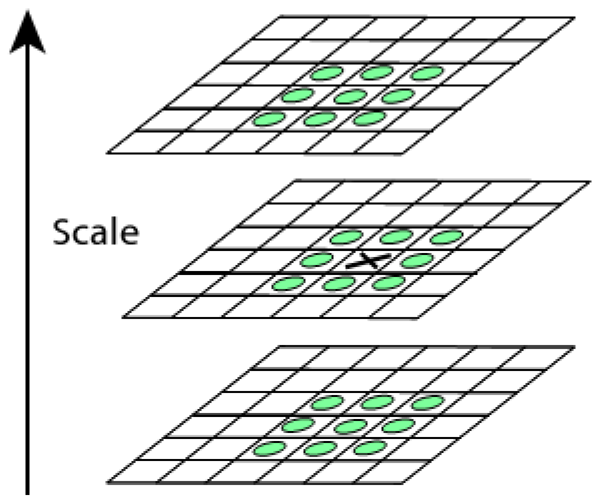
Difference-of-Gaussianss

- Now take differences:



Scale-Space Extrema

- Choose all extrema within 3x3x3 neighborhood.
- Low cost – only several usually checked



$D(k^2\sigma)$

$D(k\sigma)$

$D(\sigma)$

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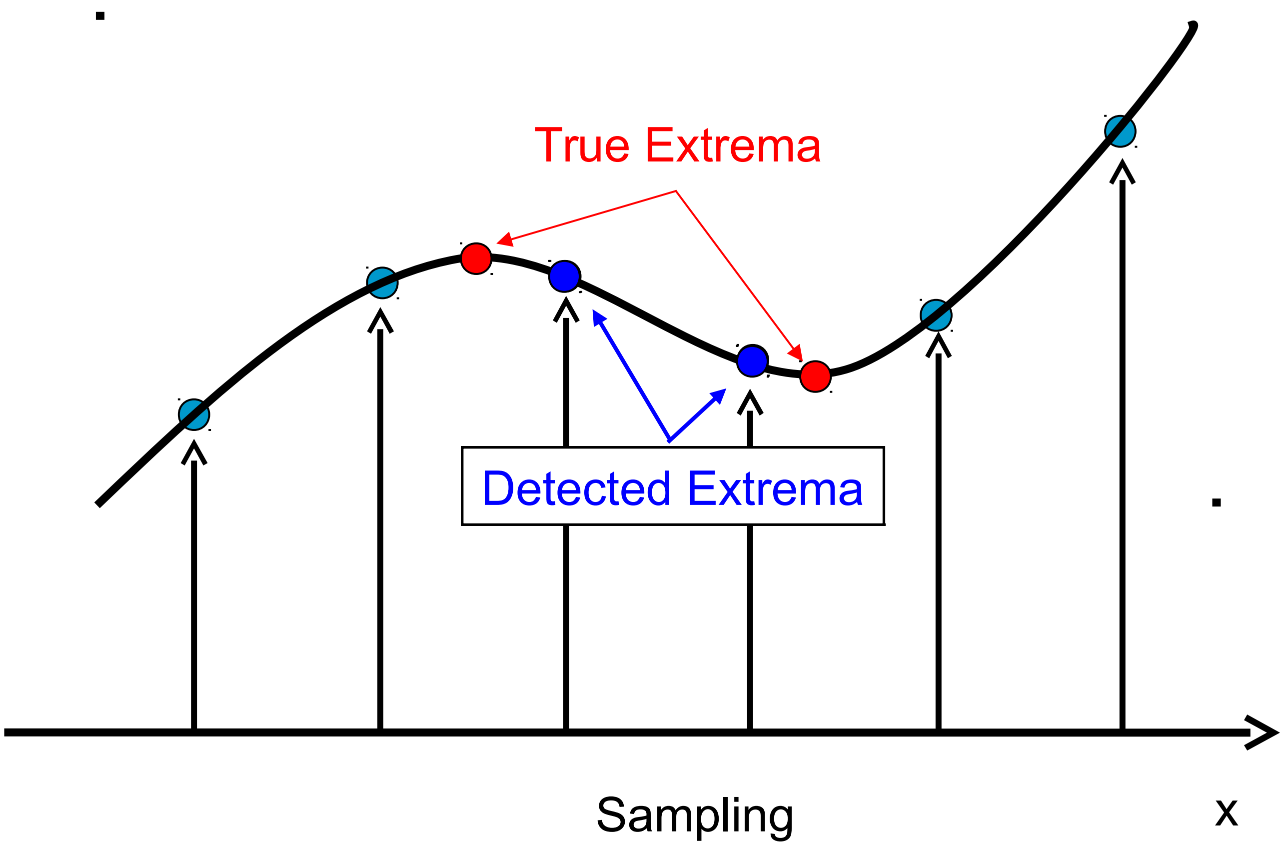
Keypoint Localization & Filtering

- Now we have much less points than pixels.
- However, still lots of points (~1000s)…
  - With only pixel-accuracy at best
    - At higher scales, this corresponds to several pixels in base image
  - And this includes many bad points

Brown & Lowe 2002

Keypoint Localization

- The problem:



Keypoint Localization

- The Solution:
  - Take Taylor series expansion:

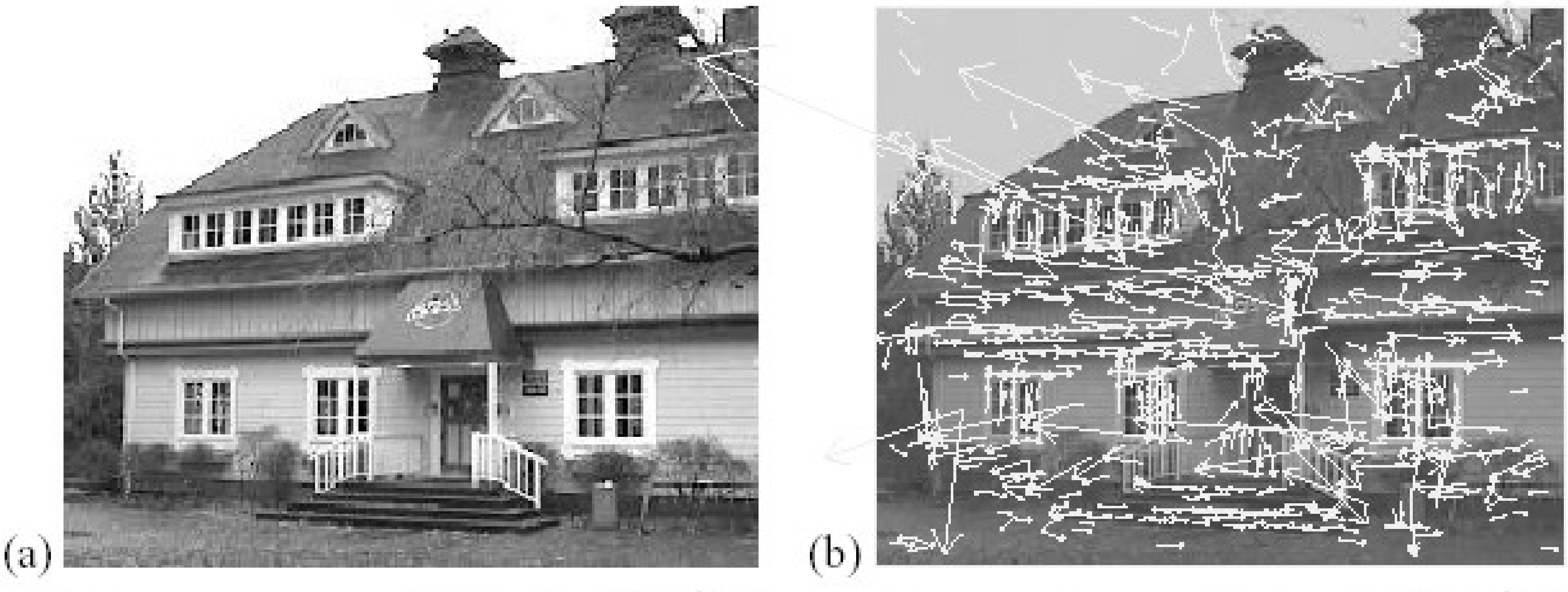
$$D(\vec{x}) = D + \frac{\partial D^T}{\partial \vec{x}} \vec{x} + \frac{1}{2} \vec{x}^T \frac{\partial^2 D^T}{\partial \vec{x}^2} \vec{x}$$

  - Minimize to get true location of extrema:

$$\hat{x} = -\frac{\partial^2 D}{\partial \vec{x}^2}^{-1} \frac{\partial D}{\partial \vec{x}}$$

Brown & Lowe 2002

Keypoints



(a) 233x189 image
(b) 832 DOG extrema

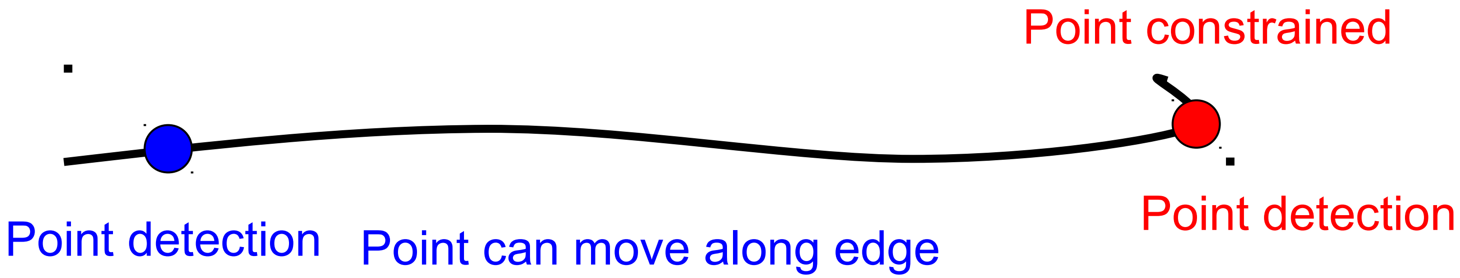
Keypoint Filtering - Low Contrast

- Reject points with bad contrast

  $D\left(\hat{x}\right)$ is smaller than 0.03 (image values in [0,1])

Keypoint Filtering - Edges

- Reject points with strong edge response in one direction only
- Like Harris - using Trace and Determinant of Hessian



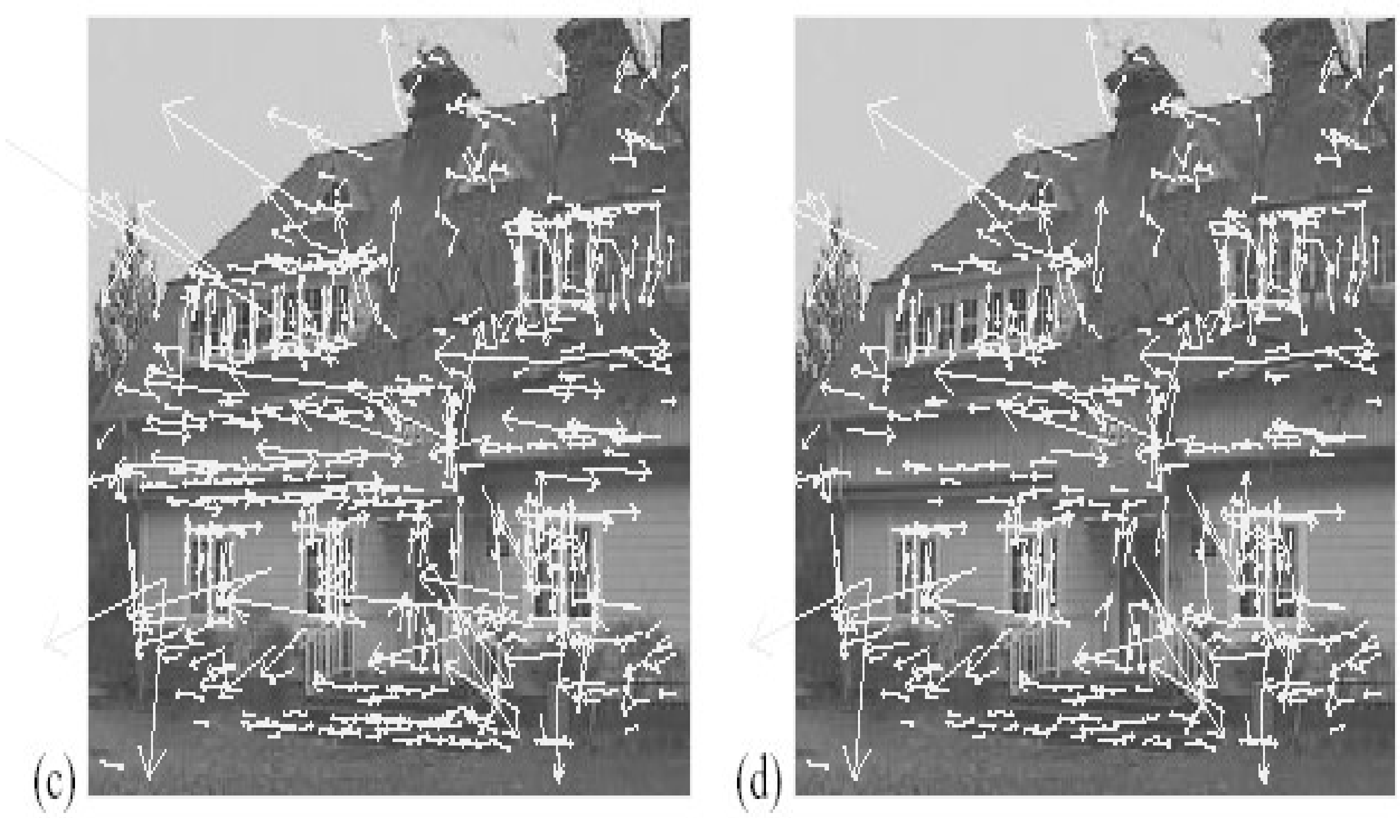
Keypoint Filtering - Edges

- To check if ratio of principal curvatures is below some threshold, r, check:

$$\frac{Tr(H)^2}{Det(H)} < \frac{(r+1)^2}{r}$$

- r=10
- Only 20 floating points operations to test each keypoint

Keypoint Filtering



(c) 729 left after peak value threshold (from 832)
(d) 536 left after testing ratio of principle curvatures

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Descriptor

Ideal Descriptors

- Robust to:
  - Affine transformation
  - Lighting
  - Noise
- Distinctive
- Fast to match
  - Not too large
  - Usually L1 or L2 matching

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Orientation Assignment

- Now we have set of good points
- Choose a region around each point
  - Remove effects of scale and rotation

Orientation Assignment

- Use scale of point to choose correct image:

$$L(x,y) = G(x,y,\sigma) * I(x,y)$$

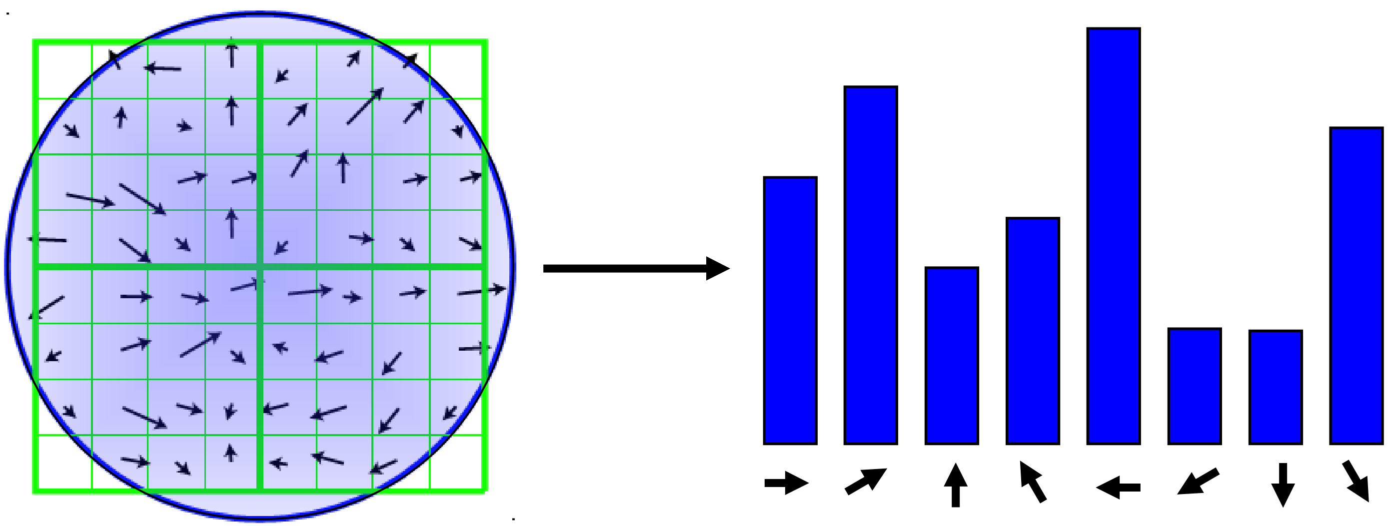
- Compute gradient magnitude and orientation using finite differences:

$$m(x,y) = \sqrt{\left(L(x+1,y) - L(x-1,y)\right)^2 + \left(L(x,y+1) - L(x,y-1)\right)^2}$$

$$\theta(x,y) = \tan^{-1}\left(\frac{\left(L(x,y+1) - L(x,y-1)\right)}{\left(L(x+1,y) - L(x-1,y)\right)}\right)$$

Orientation Assignment

- Create gradient histogram (36 bins)
  - Weighted by magnitude and Gaussian window (σ is 1.5 times that of the scale of a keypoint)



Orientation Assignment

- Any peak within 80% of the highest peak is used to create a keypoint with that orientation
- ~15% assigned multiplied orientations, but contribute significantly to the stability
- Finally a parabola is fit to the 3 histogram values closest to each peak to interpolate the peak position for better accuracy

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Descriptor

SIFT Descriptor

- Each point so far has x, y, σ, m, θ
- Now we need a descriptor for the region
  - Could sample intensities around point, but…
    - Sensitive to lighting changes
    - Sensitive to slight errors in x, y, θ
- Look to biological vision
  - Neurons respond to gradients at certain frequency and orientation
    - But location of gradient can shift slightly!

Edelman et al. 1997

SIFT Descriptor

- 4x4 Gradient window
- Histogram of 4x4 samples per window in 8 directions
- Gaussian weighting around center(σ is 0.5 times that of the scale of a keypoint)
- 4x4x8 = 128 dimensional feature vector

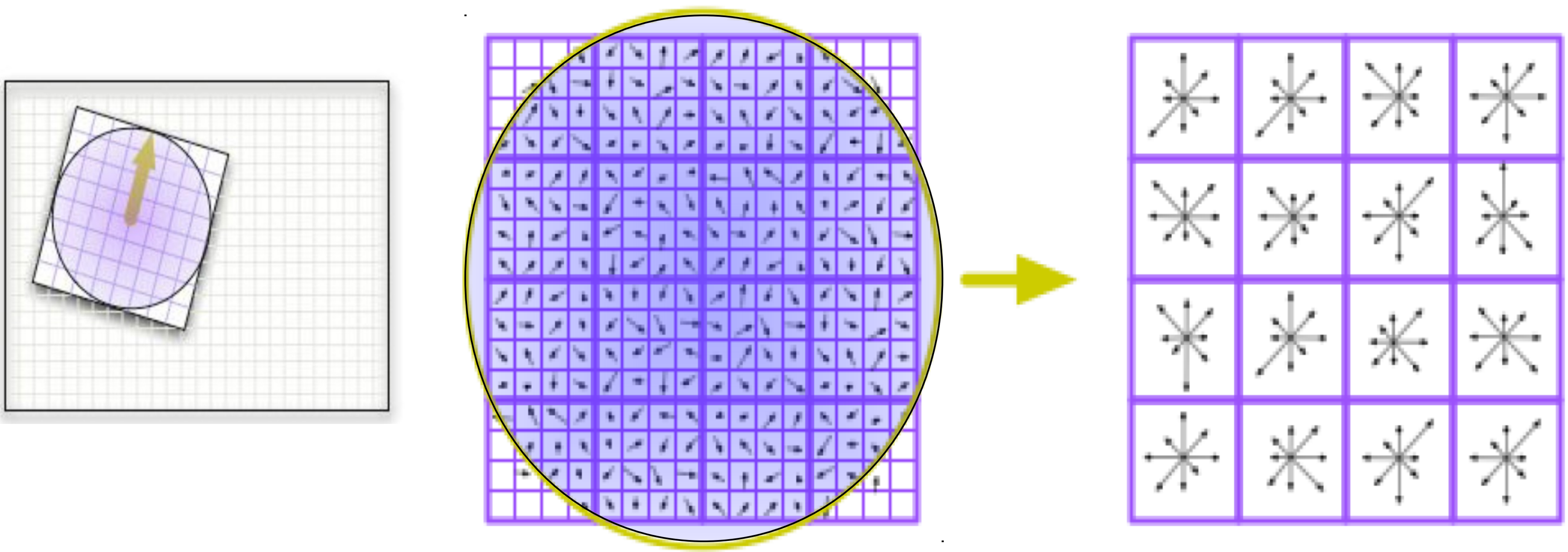


Image gradients Keypoint descriptor

Image from: Jonas Hurreımann

SIFT Descriptor – Lighting changes

- Gains do not affect gradients
- Normalization to unit length removes contrast
- Saturation affects magnitudes much more than orientation
- Threshold gradient magnitudes to 0.2 and renormalize

Performance

- Very robust
  - 80% Repeatability at:
    - 10% image noise
    - 45° viewing angle
    - 1k-100k keypoints in database
- Best descriptor in [Mikolajczyk & Schmid 2005]'s extensive survey
- 606+ citations on Google Scholar already for [2004] paper

Typical Usage

- For set of database images:
  1. Compute SIFT features
  2. Save descriptors to database
- For query image:
  1. Compute SIFT features
  2. For each descriptor:
     - Find closest descriptors (L2 distance) in database
  3. Verify matches
     - Geometry
     - Hough transform

Nearest-neighbor matching to feature database

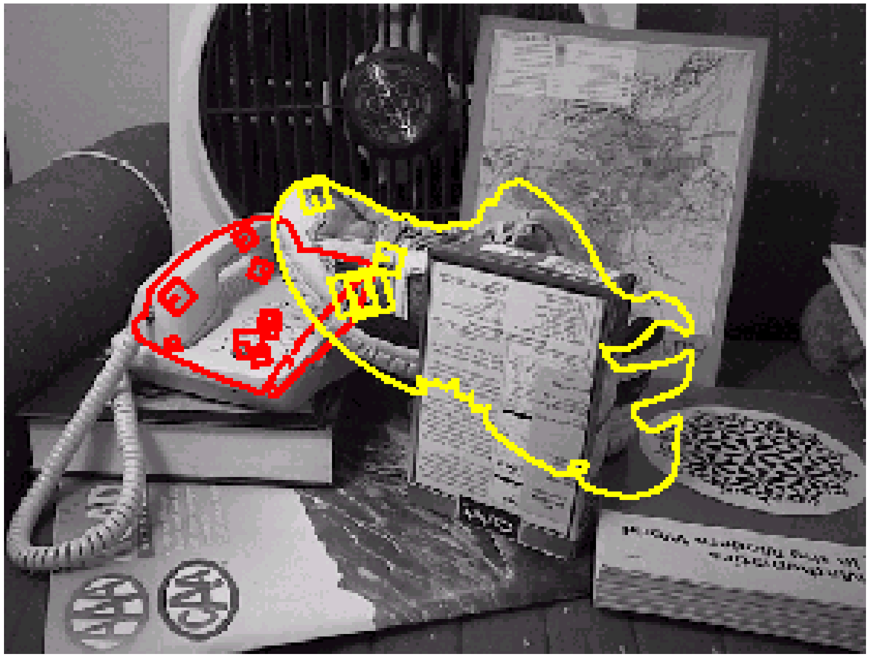
- Hypotheses are generated by **approximate nearest neighbor** matching of each feature to vectors in the database
  - SIFT use best-bin-first (Beis & Lowe, 97) modification to k-d tree algorithm
  - Use heap data structure to identify bins in order by their distance from query point

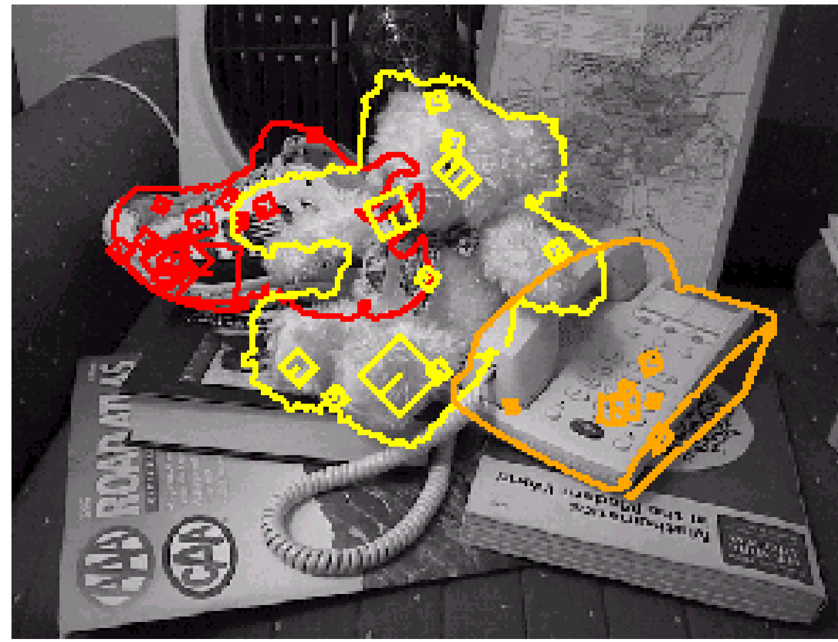
- **Result:** Can give speedup by factor of 1000 while finding nearest neighbor (of interest) 95% of the time

3D Object Recognition

- Only 3 keys are needed for recognition, so extra keys provide robustness

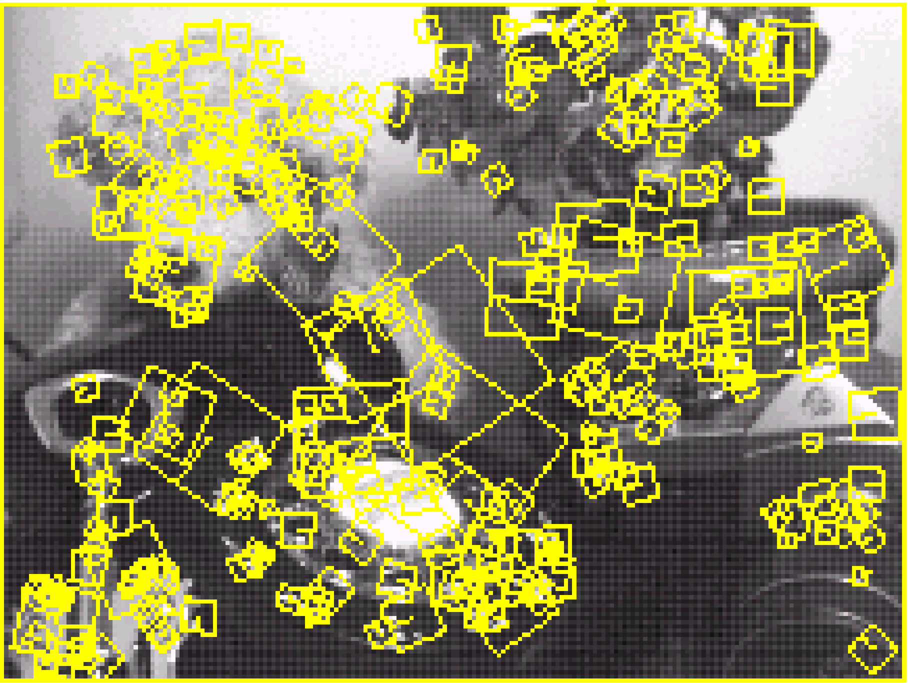
Recognition under occlusion





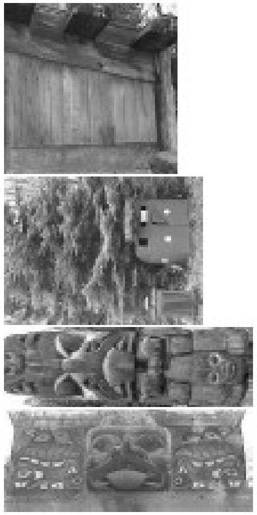
Test of illumination Robustness

- Same **image** under differing illumination



273 keys verified in final match

Location recognition



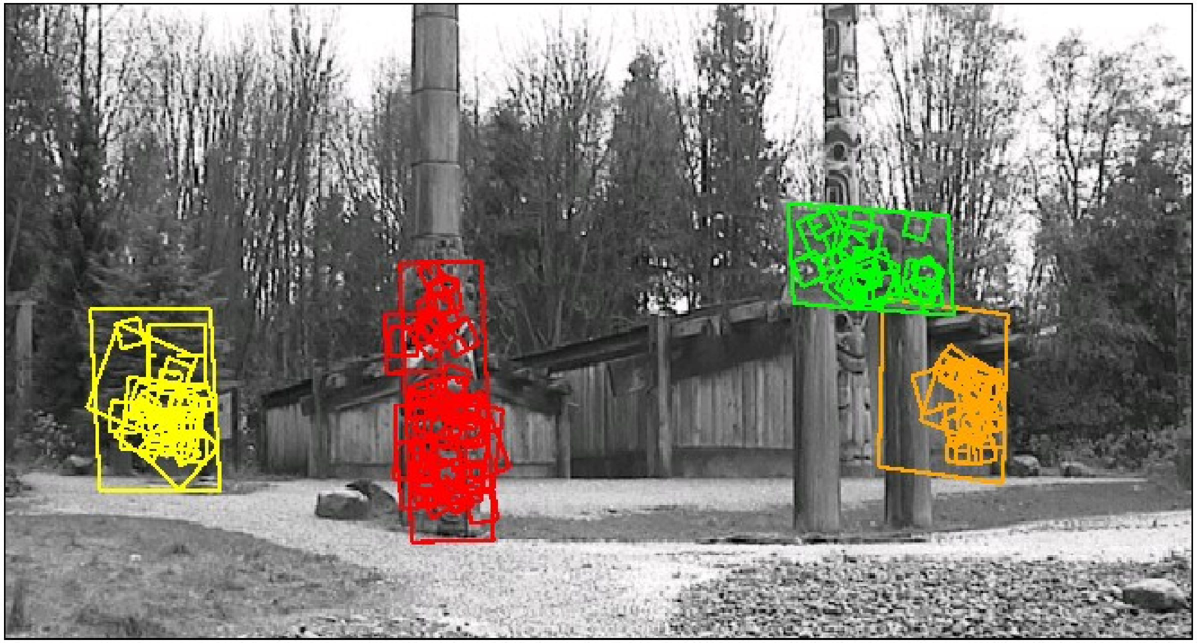


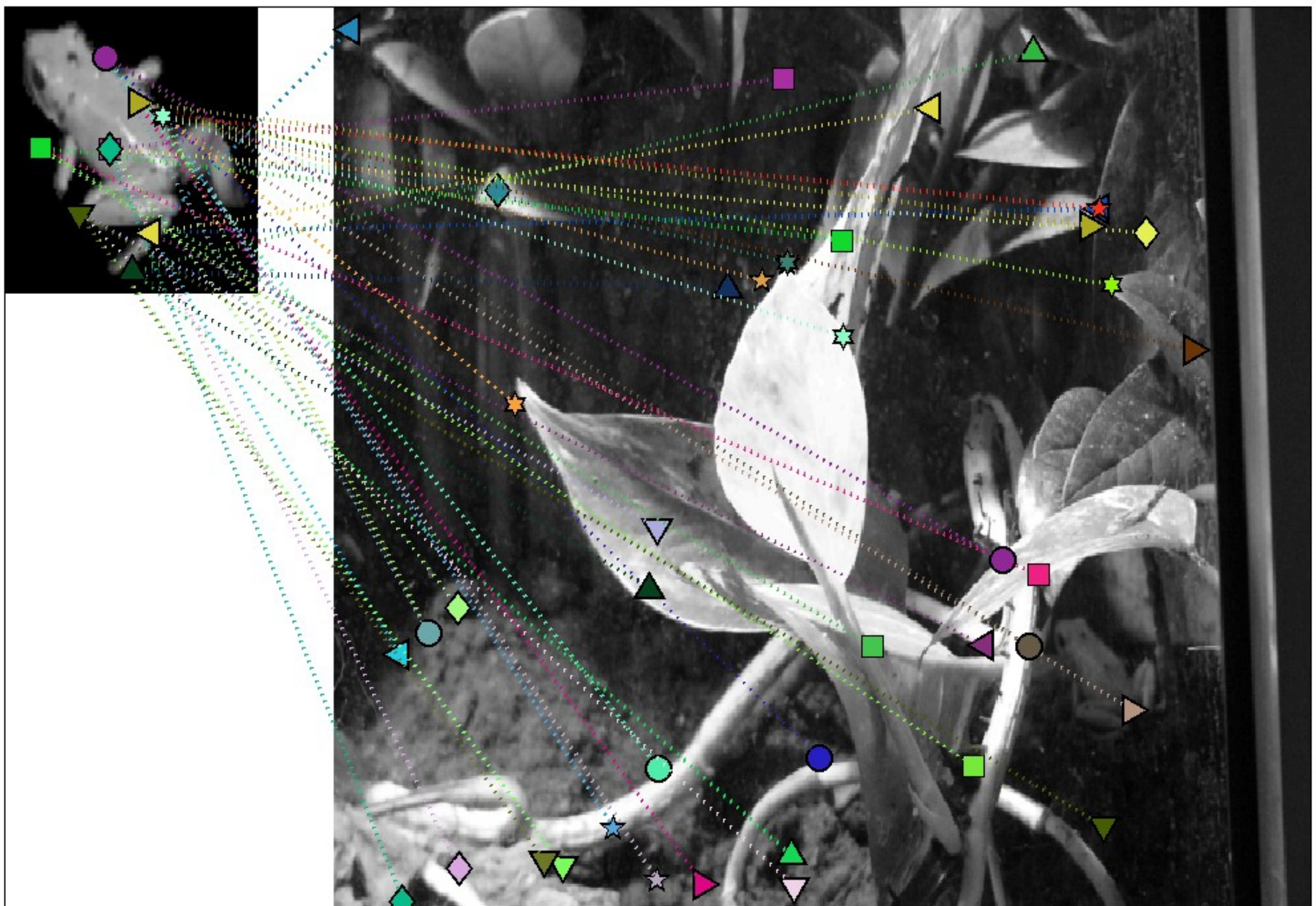
Image Registration Results

[Brown & Lowe 2003]

Cases where SIFT didn't work

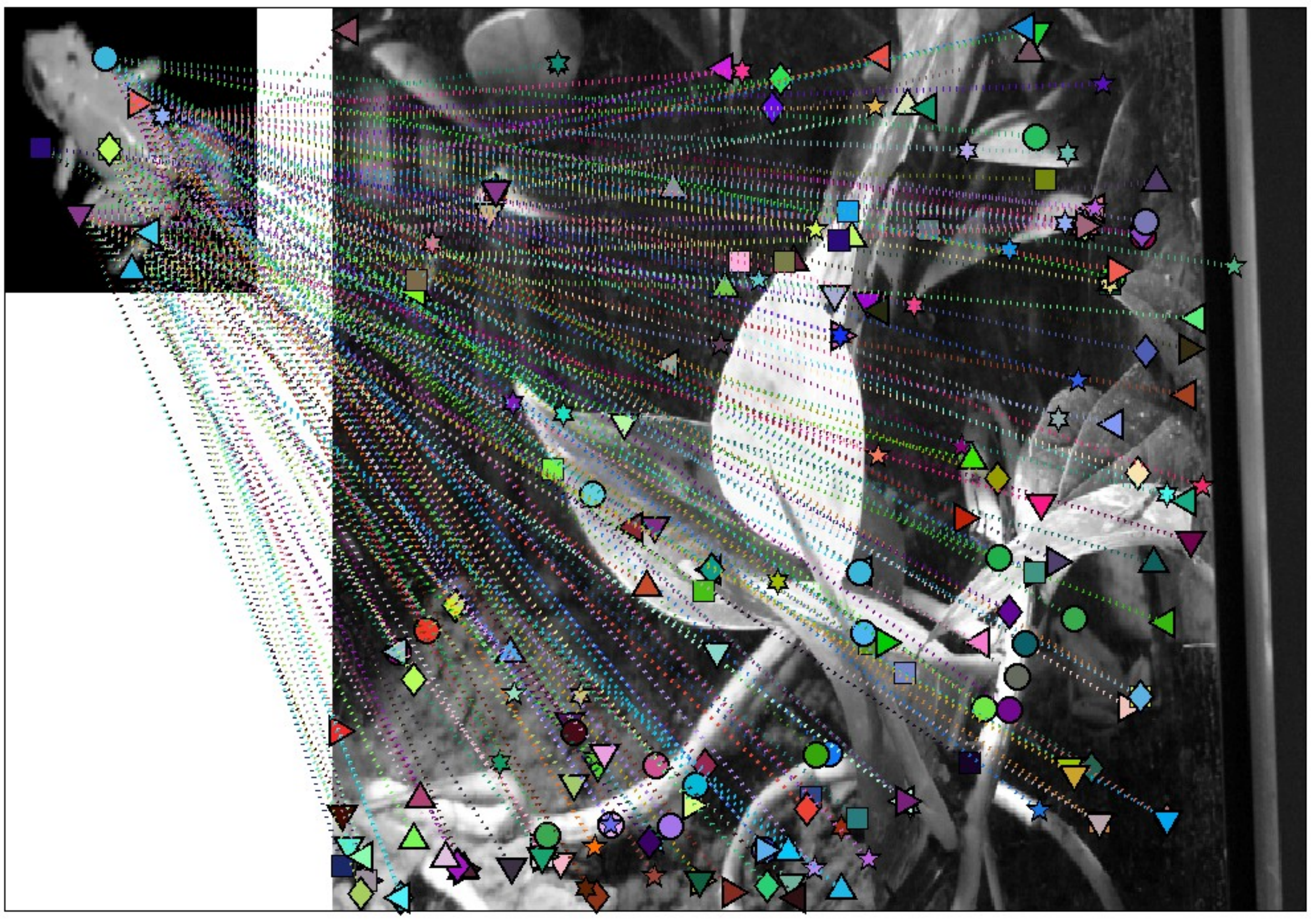
Large illumination change

- Same **object** under differing illumination
- 43 keypoints in left image and the corresponding closest keypoints on the right (1 for each)



Large illumination change

- Same **object** under differing illumination
- 43 keypoints in left image and the corresponding closest keypoints on the right (5 for each)

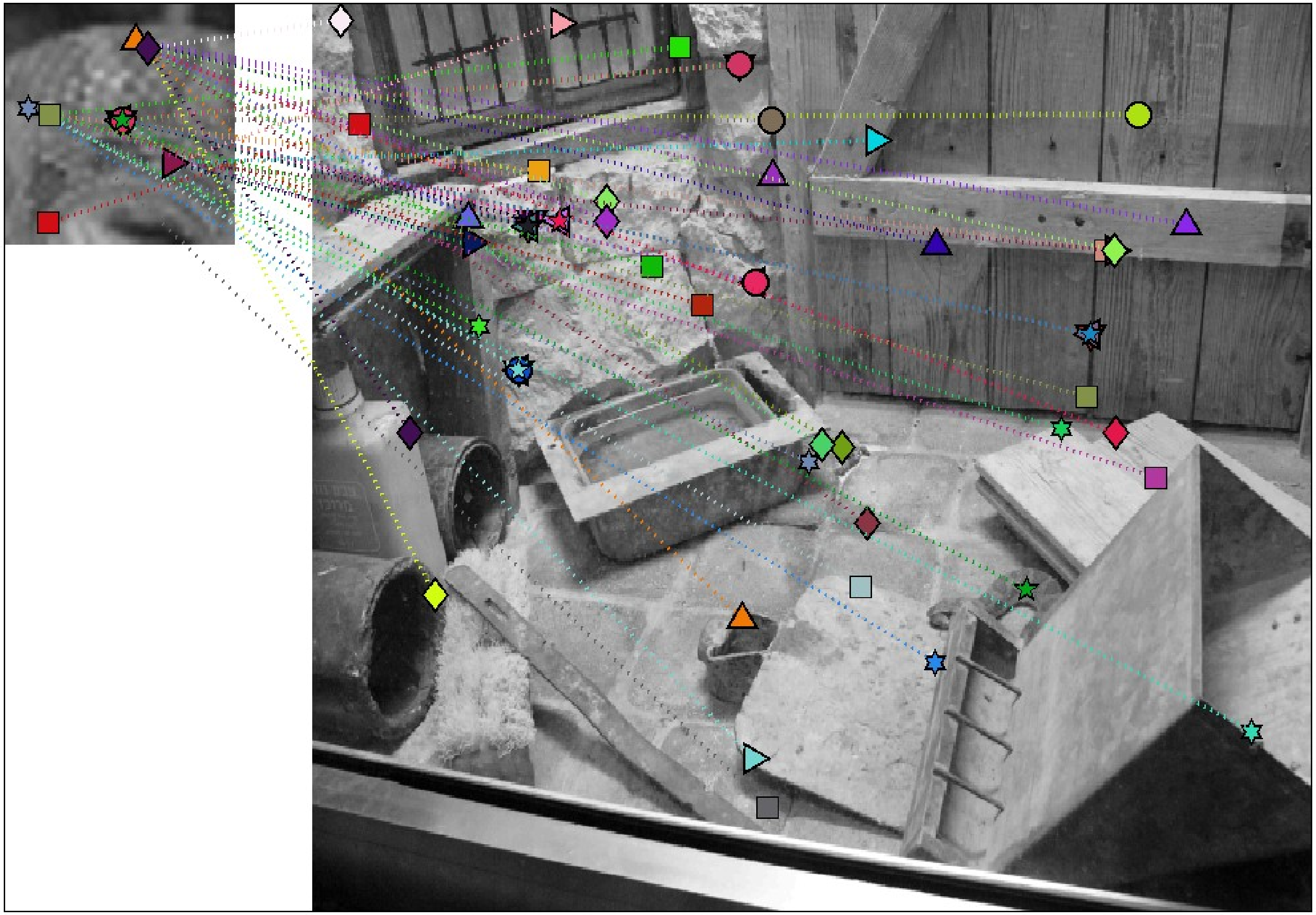


Non rigid deformations

- 11 keypoints in left image and the corresponding closest keypoints on the right (1 for each)

Non rigid deformations

- 11 keypoints in left image and the corresponding closest keypoints on the right (5 for each)



Conclusion: SIFT

- Built on strong foundations
  - First principles (LoG and DoG)
  - Biological vision (Descriptor)
  - Empirical results
- Many heuristic optimizations
  - Rejection of bad points
  - Sub-pixel level fitting
  - Thresholds carefully chosen

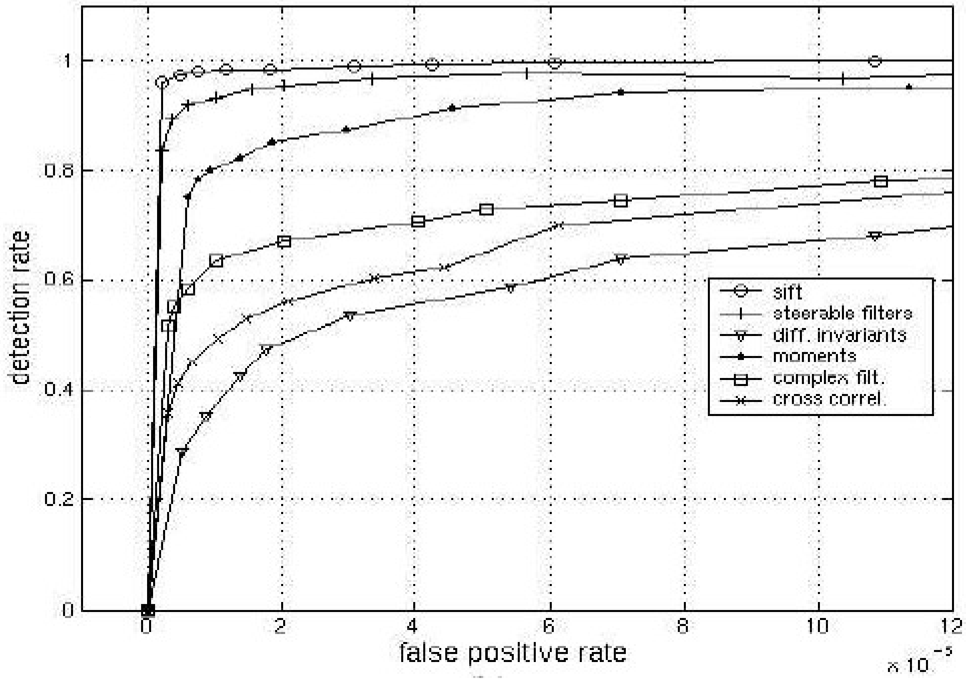
Conclusion: SIFT

- In wide use both in academia and industry
- Many available implementations:
  - Binaries available at Lowe's website
  - C/C++ open source by A. Vedaldi (UCLA)
  - C# library by S. Nowozin (Tu-Berlin)
- Protected by a patent

Conclusion: SIFT

- Empirically found[2] to show very good performance, invariant to *image rotation*, *scale*, *intensity change*, and to moderate *affine* transformations

Scale = 2.5
Rotation = 45^0



[1] Mikolajczyk & Schmid 2005

Conclusion: Local features

- Much work left to be done
  - Efficient search and matching
  - Combining with global methods
  - Finding better features

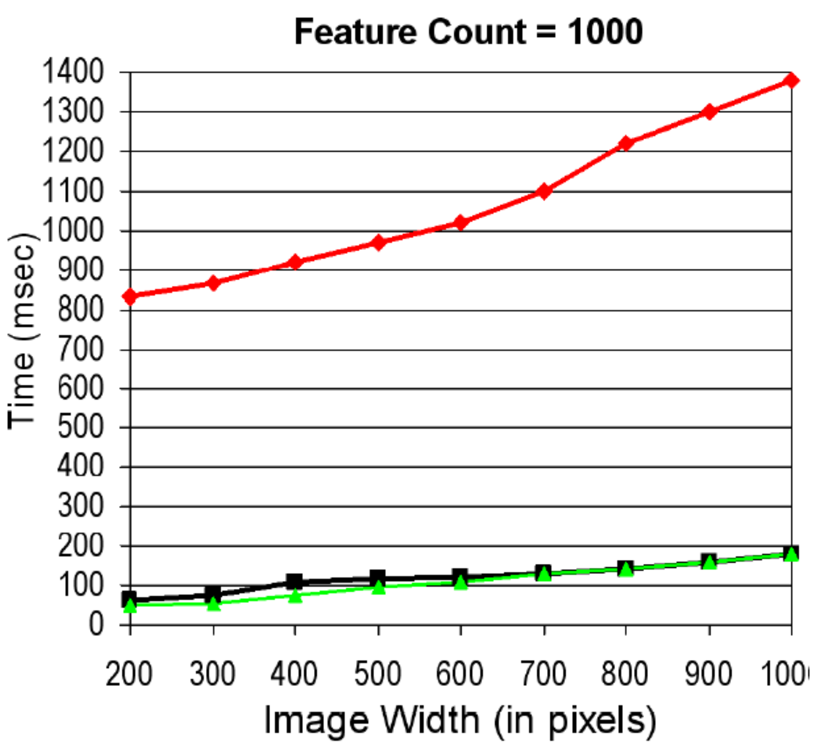
SIFT extensions

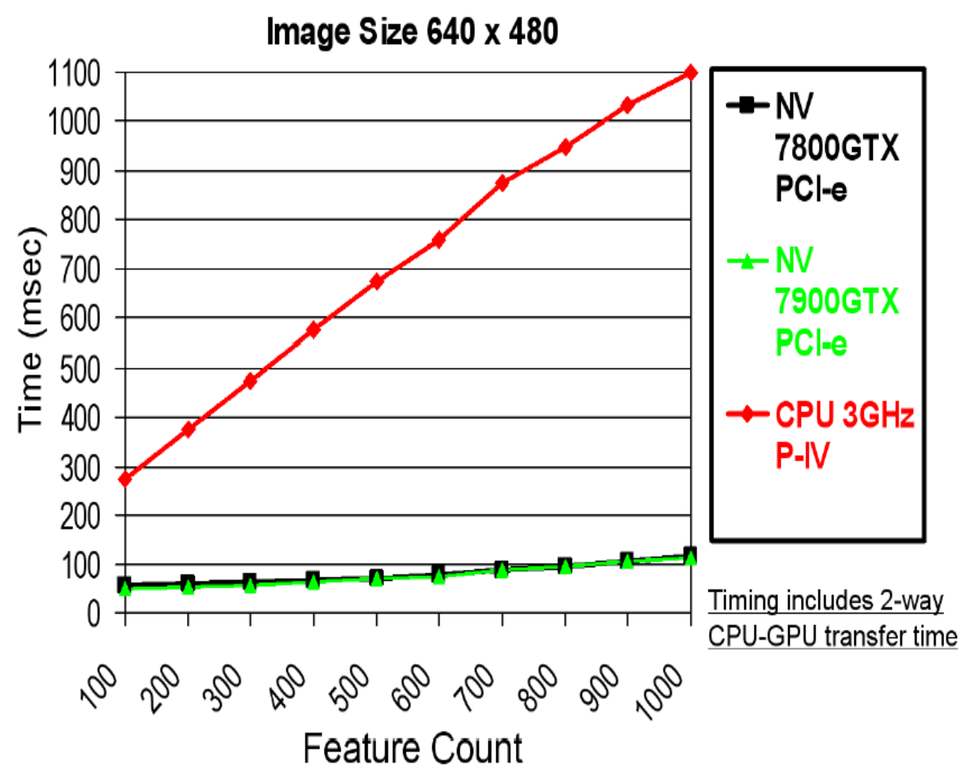
PCA-SIFT

- Only change step 4 (creation of descriptor)
- Pre-compute an eigen-space for local gradient patches of size 41x41
- 2x39x39=3042 elements
- Only keep 20 components
- A more compact descriptor
- In K.Mikolajczyk, C.Schmid 2005 PCA-SIFT tested inferior to original SIFT

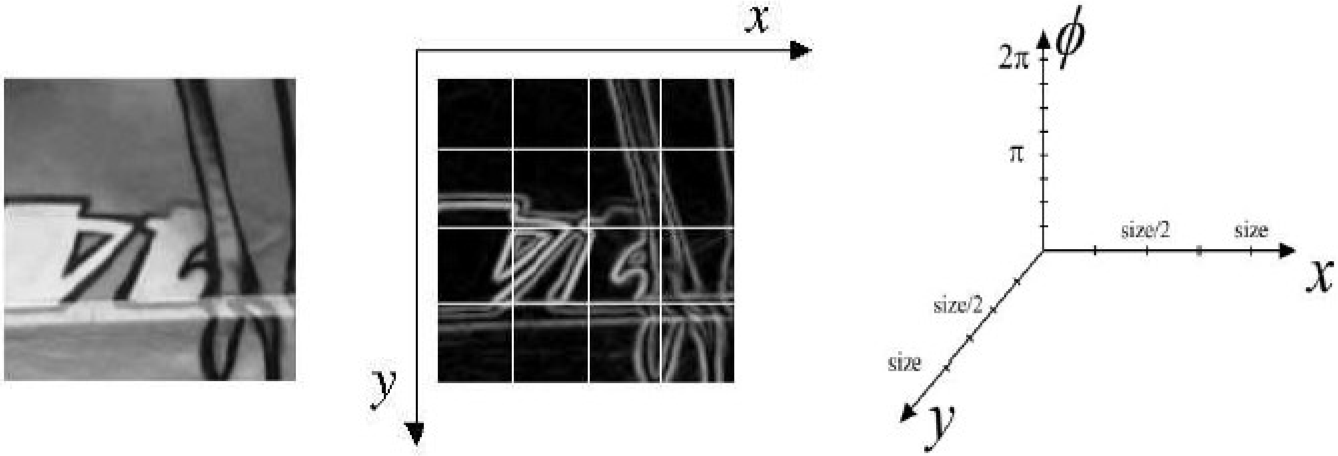
Speed Improvements

- SURF - Bay et al. 2006
- Approx SIFT - Grabner et al. 2006
- GPU implementation - Sudipta N. Sinha et al. 2006

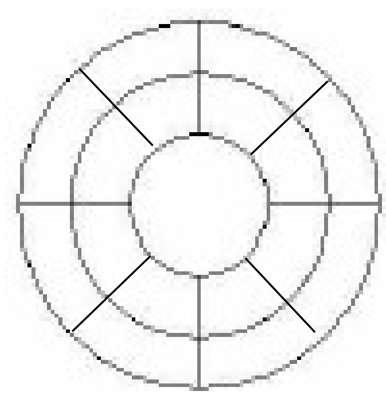




GLOH (Gradient location-orientation histogram)



SIFT



17 location bins
16 orientation bins
Analyze the 17x16=272-d
eigen-space, keep 128 components