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

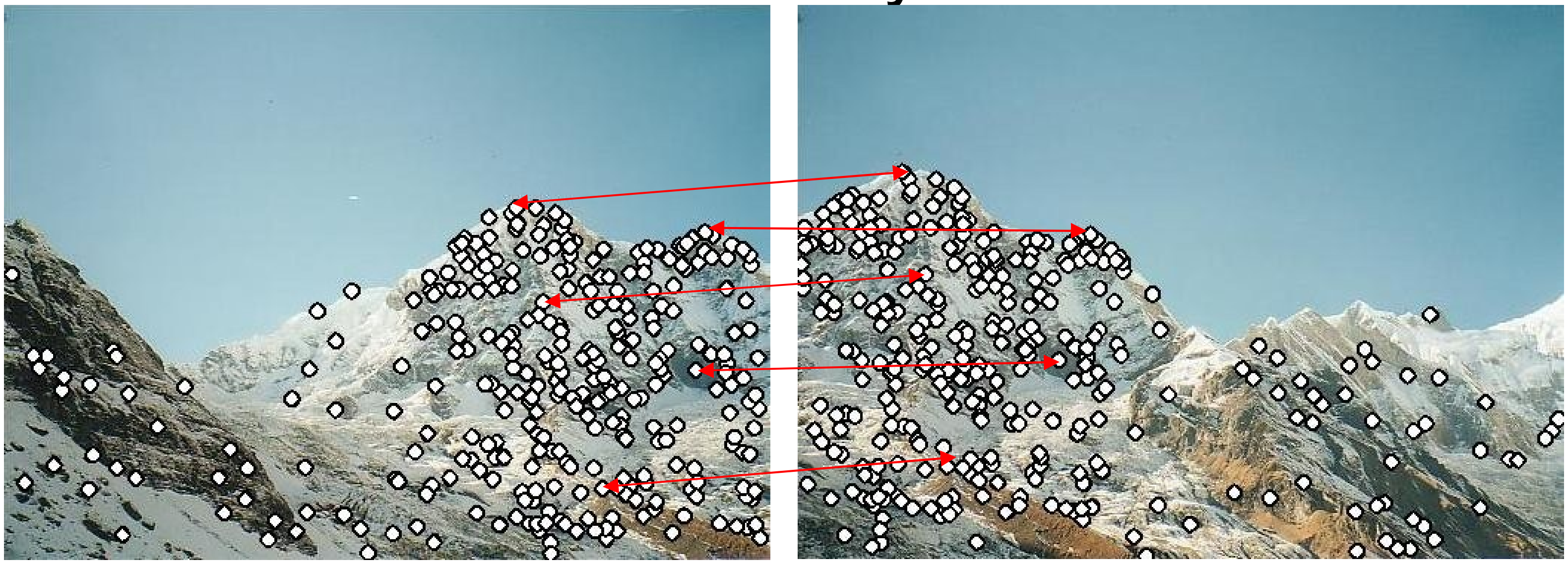
Presented by Ofir Pele.

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

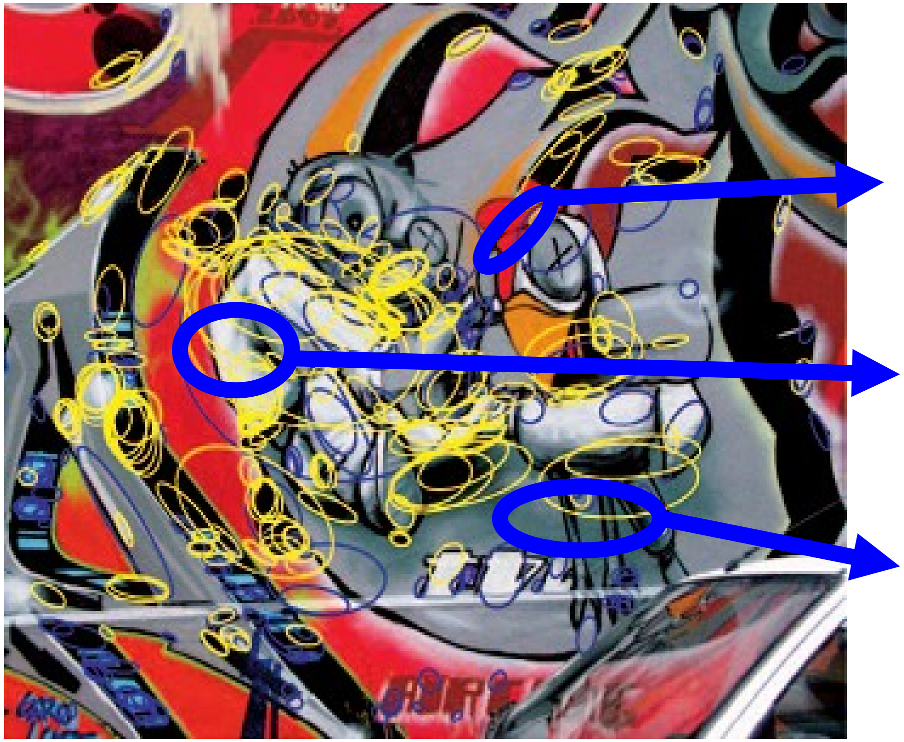


Images from: M. Brown and D. G. Lowe. Recognising Panoramas. In Proceedings of the the International Conference on Computer Vision (ICCV2003 (

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

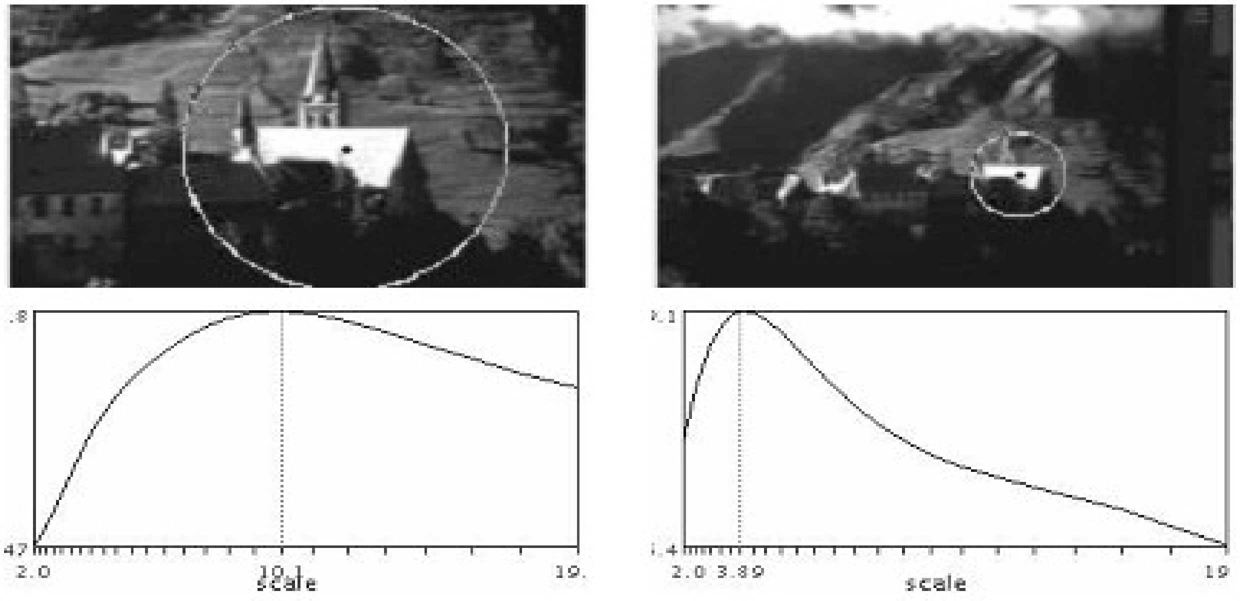
- Need to find ‘characteristic scale’ for feature
- Scale-Space: Continuous function of scale σ
  - Only reasonable kernel is Gaussian:

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

[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:

$$\sigma\nabla^{٢}G = \frac{\partial G}{\partial\sigma} \approx \frac{G(k\sigma) - G(\sigma)}{k\sigma - \sigma}$$

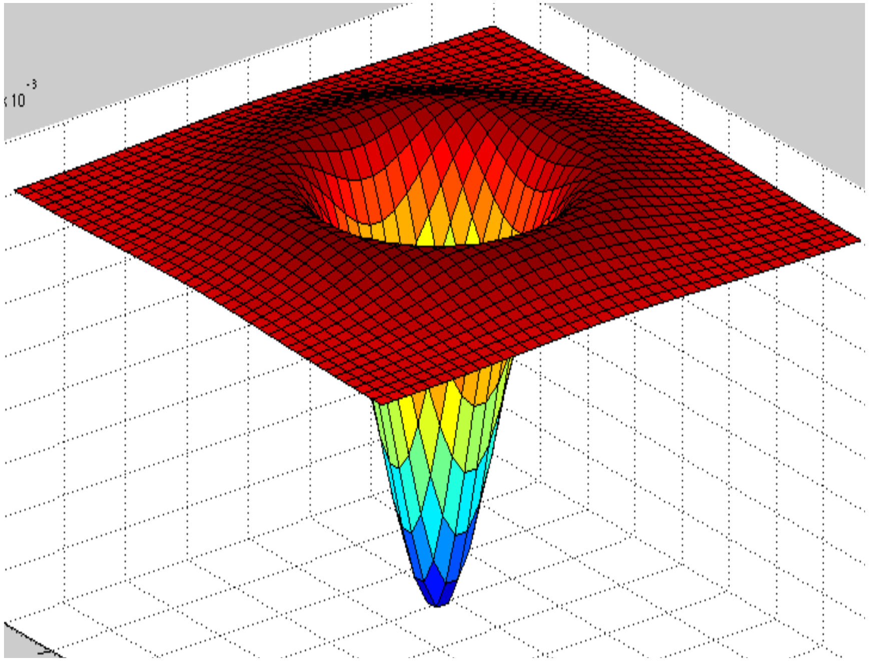
- Define Difference-of-Gaussians (DoG):

$$(k - ١)\sigma^{٢}\nabla^{٢}G \approx G(k\sigma) - G(\sigma)$$

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

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)

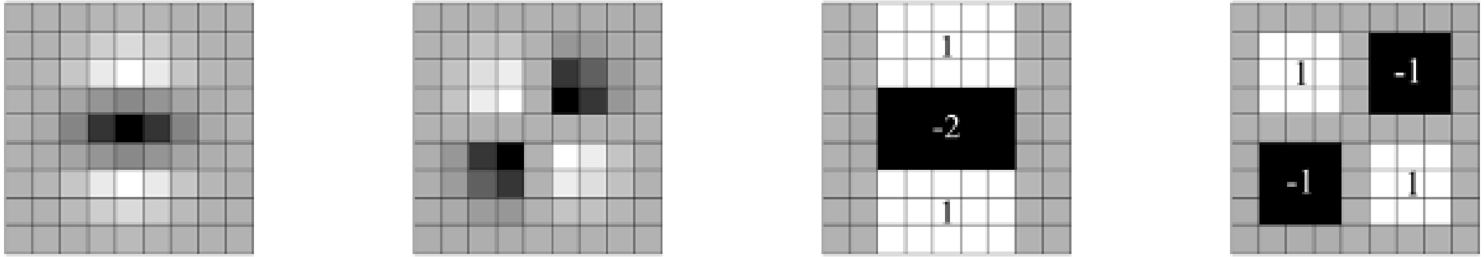
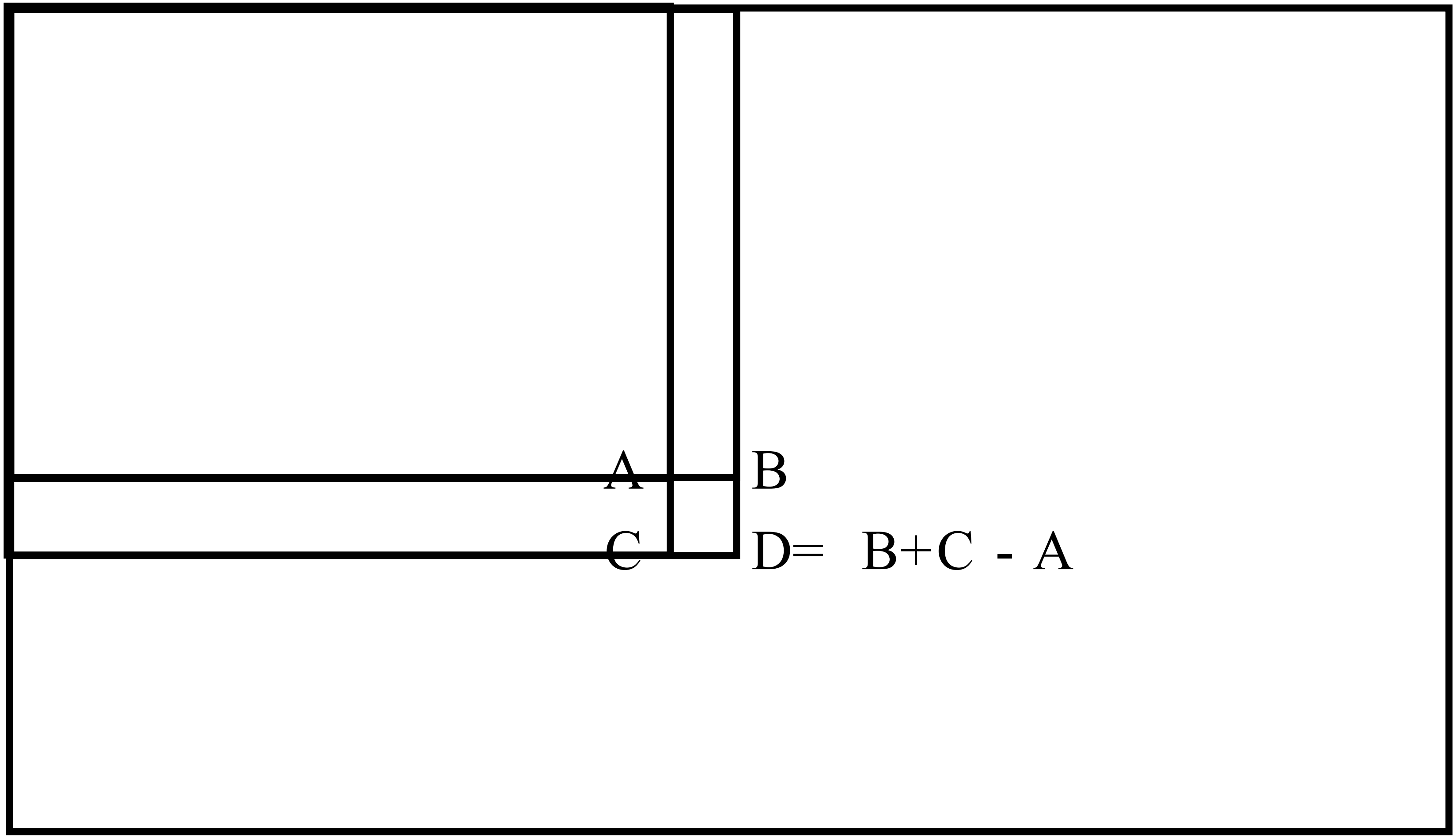


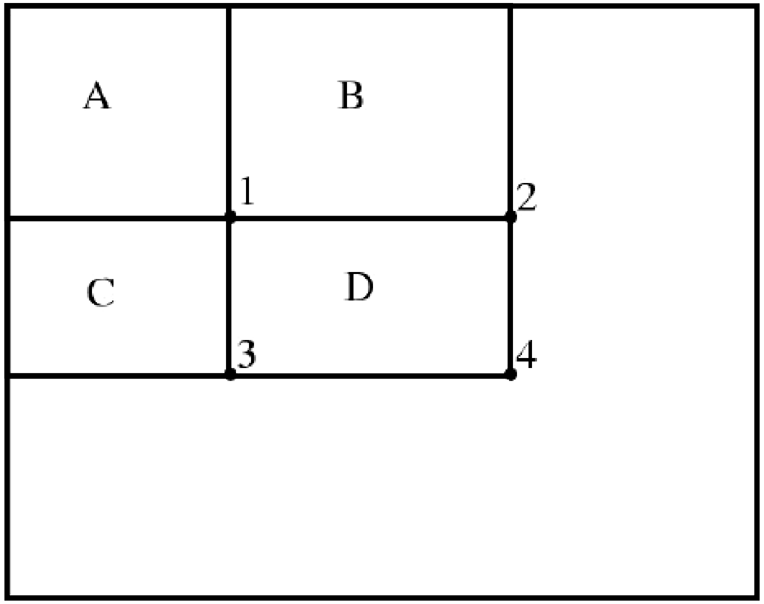
Fig. 1. Left to right: the (discretised and cropped) Gaussian second order partial derivatives in y-direction and xy-direction, and our approximations thereof using box filters. The grey regions are equal to zero.

Bay et al., ECCV 2006

Integral Image Computation



Integral Image Usage



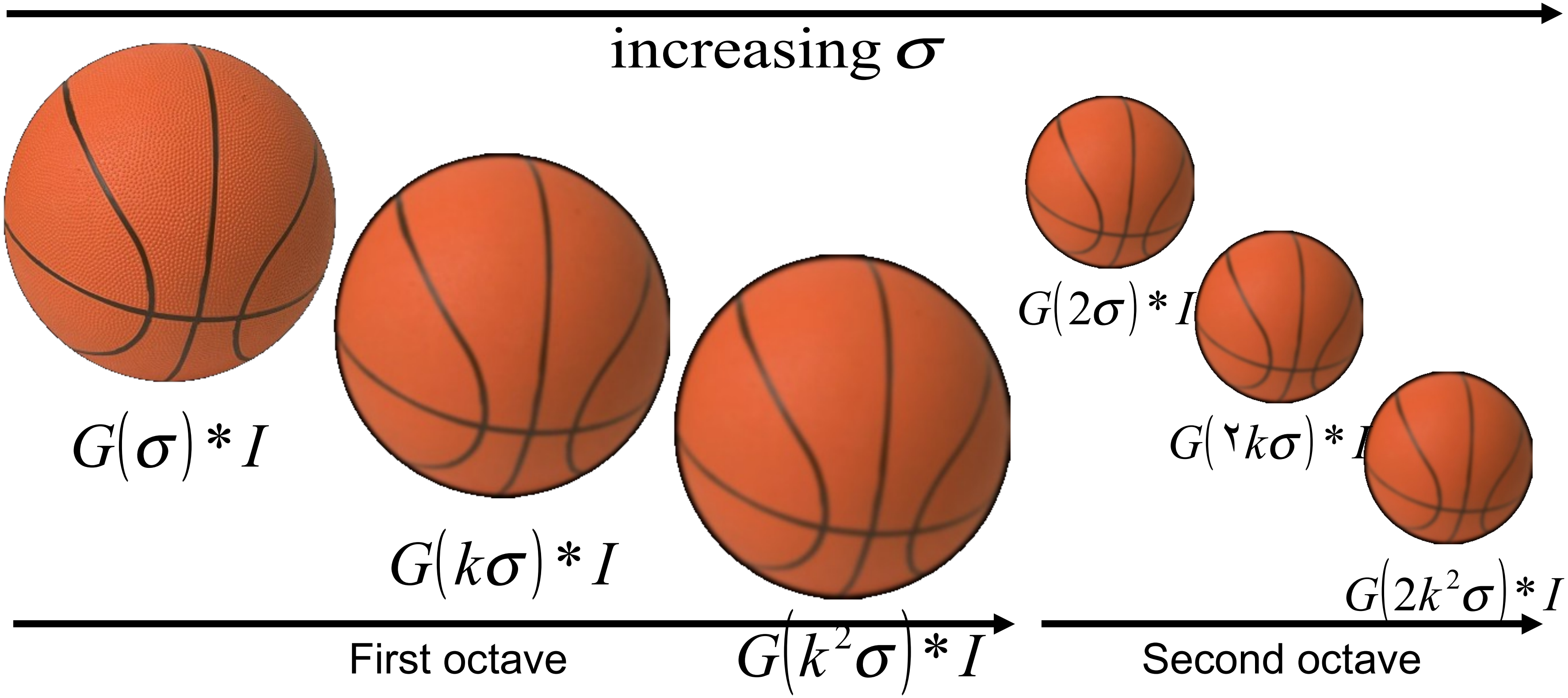
Using the integral image representation one can compute the value of any rectangular sum in constant time.

Example: Rectangle D

$$ii(4) + ii(1) - ii(2) - ii(3)$$

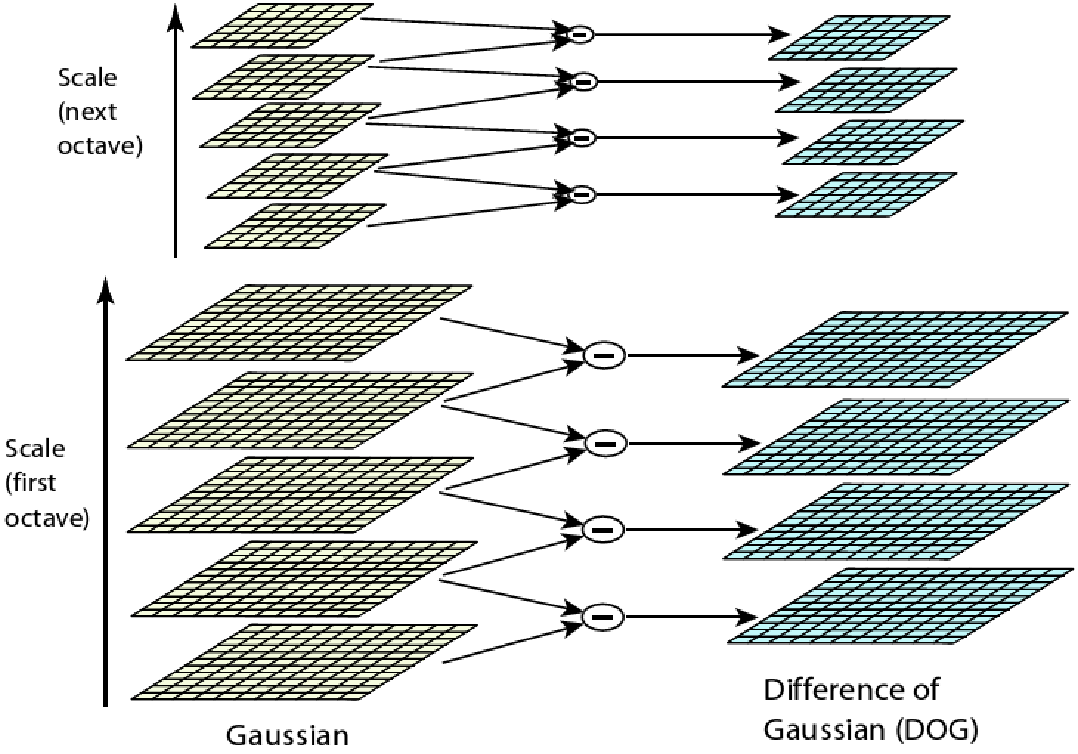
Scale-Space Construction

- First construct scale-space:



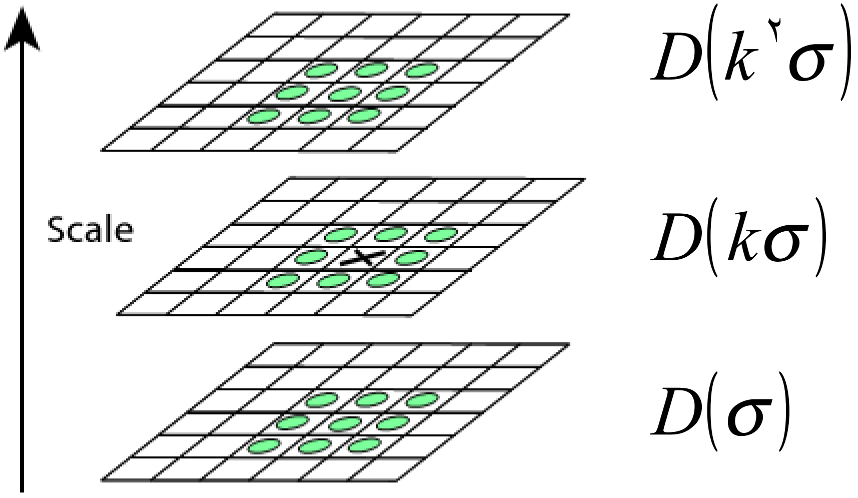
Difference-of-Gaussianss

- Now take differences:



Scale-Space Extrema

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



SIFT Overview

Detector

1. Find Scale-Space Extrema
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Descriptor

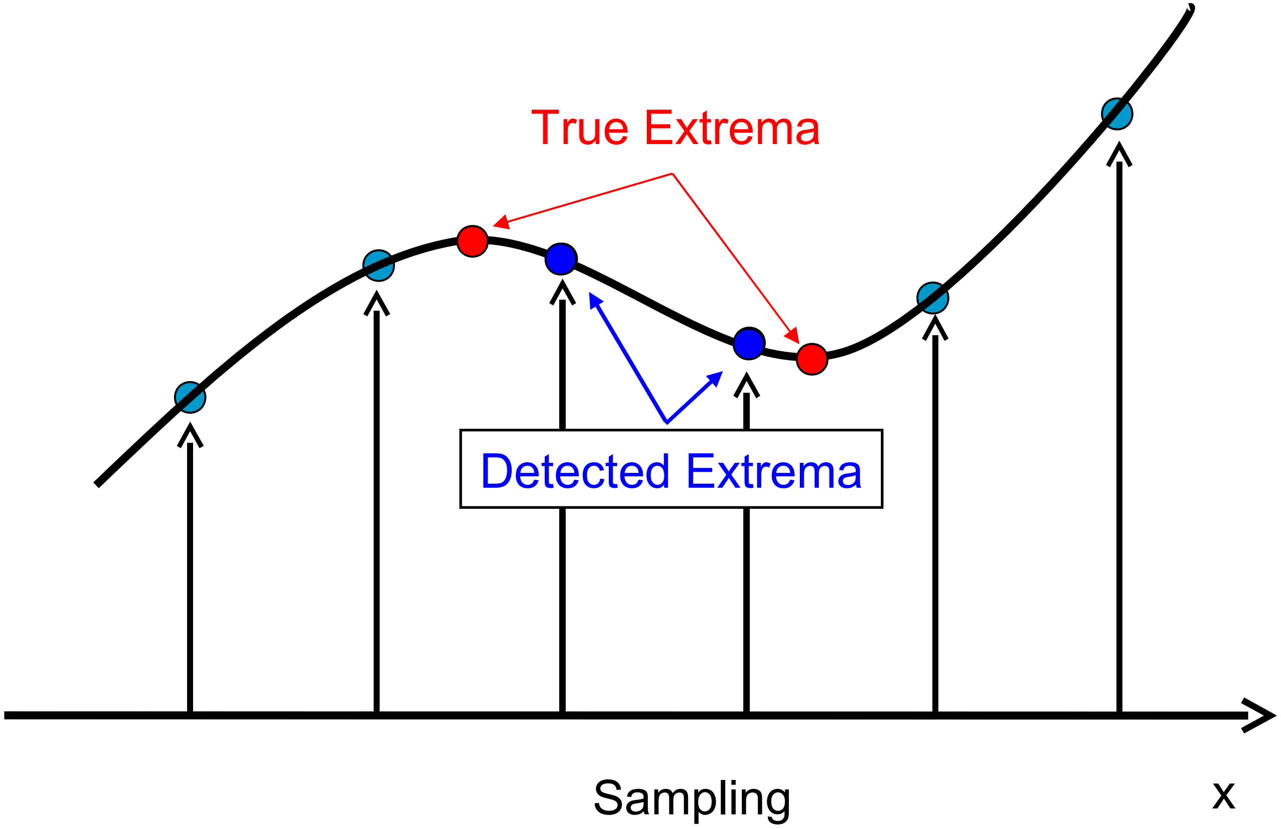
Keypoint Localization & Filtering

- 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:

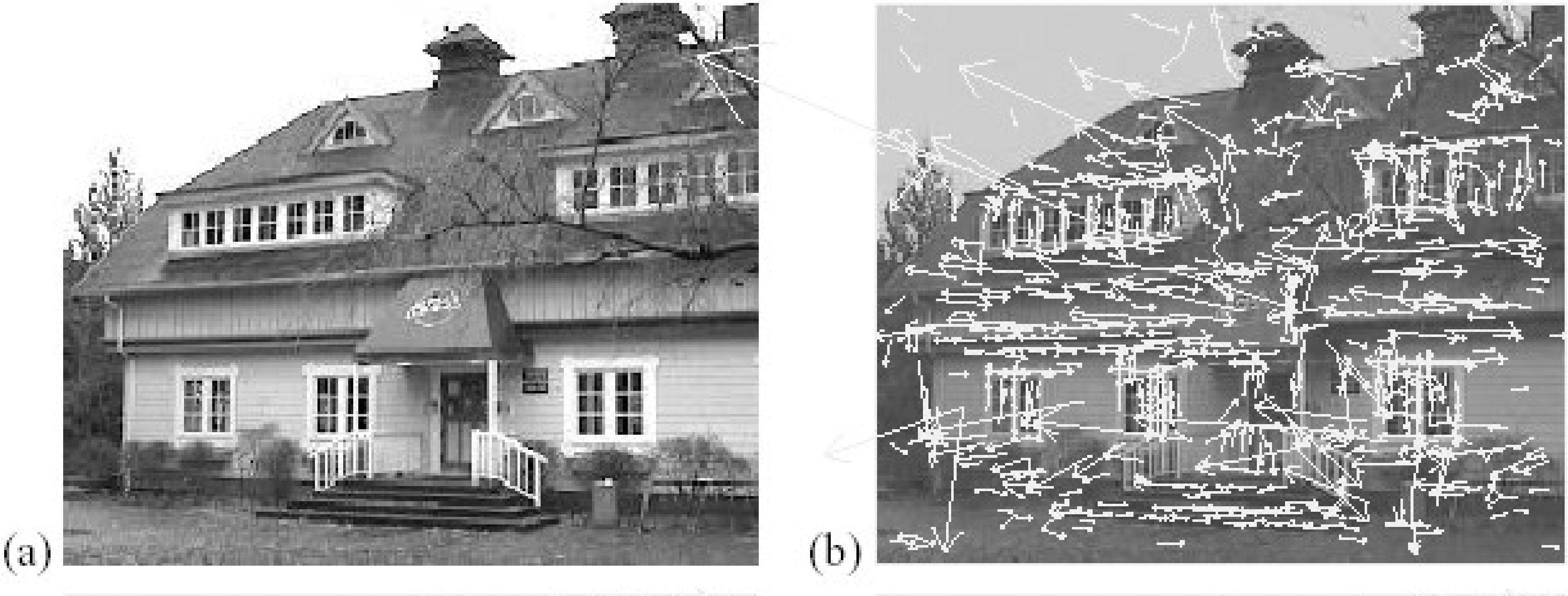
$$D(\vec{x}) = D + \frac{\partial D^T}{\partial \vec{x}}\vec{x} + \frac{1}{2}\vec{x}^T \frac{\partial^2 D^T}{\partial \vec{x}^2}\vec{x}$$

  - Minimize to get true location of extrema:

$$\hat{x} = -\frac{\partial^{٢} D}{\partial \vec{x}^{٢}}^{-١} \frac{\partial D}{\partial \vec{x}}$$

Brown & Lowe 2002

Keypoints



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

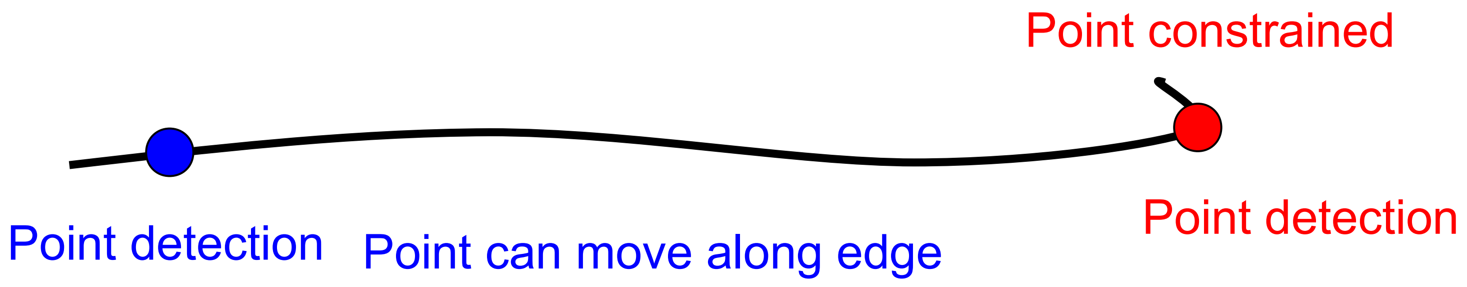
Keypoint Filtering - Low Contrast

- 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



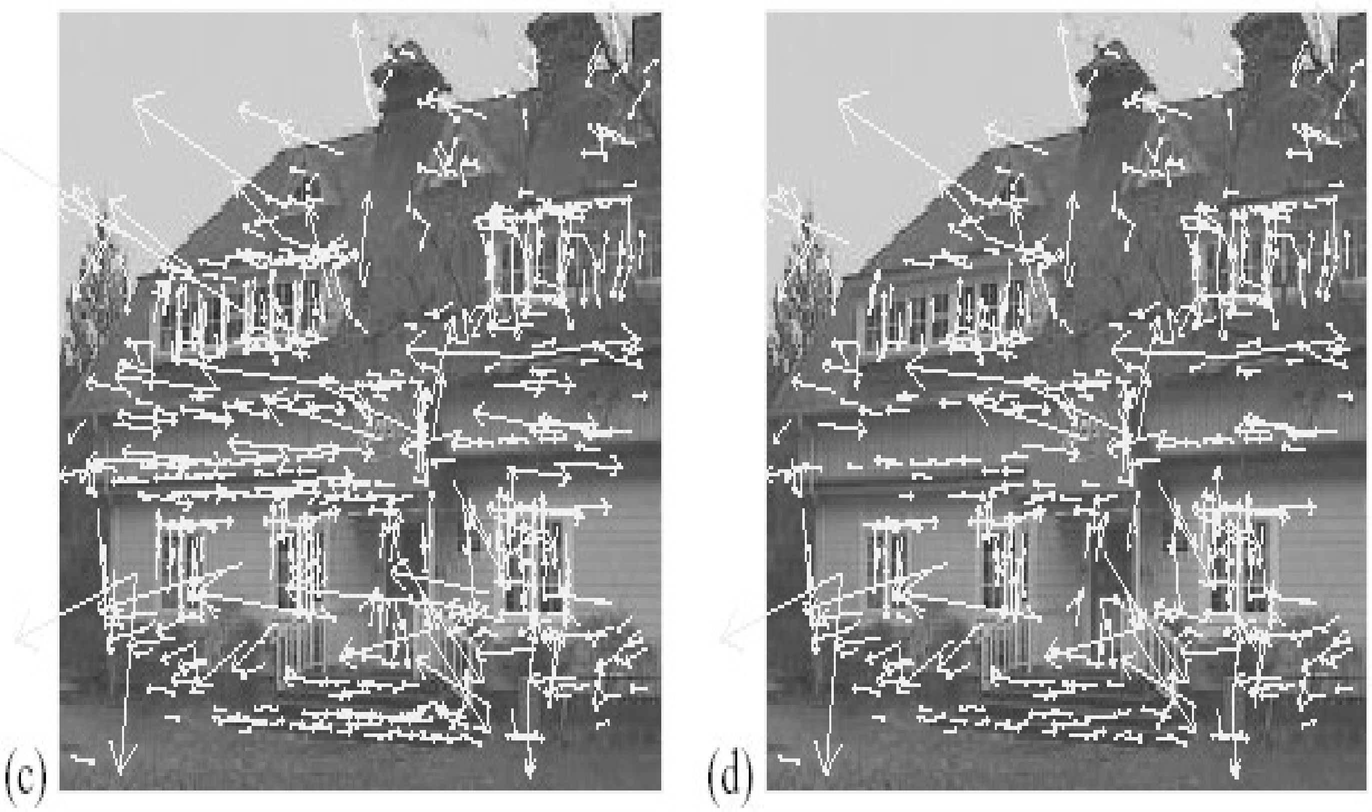
Keypoint Filtering - Edges

- 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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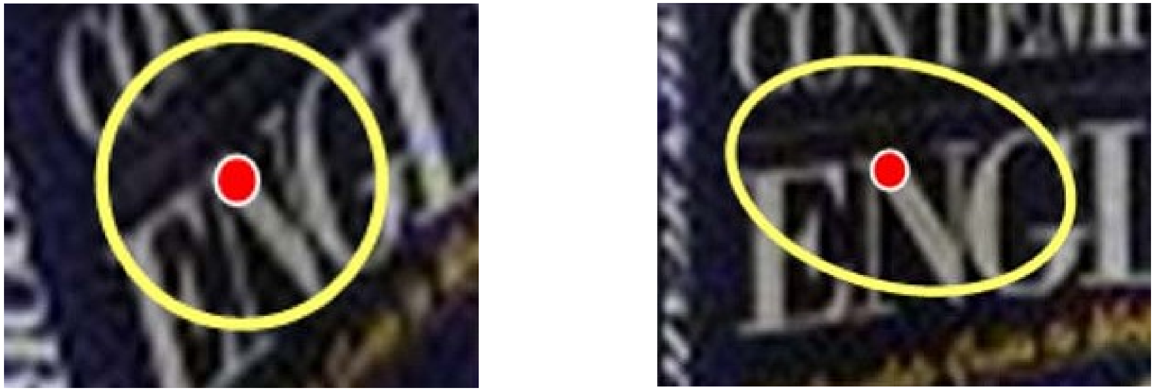
Orientation Assignment

- 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:

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

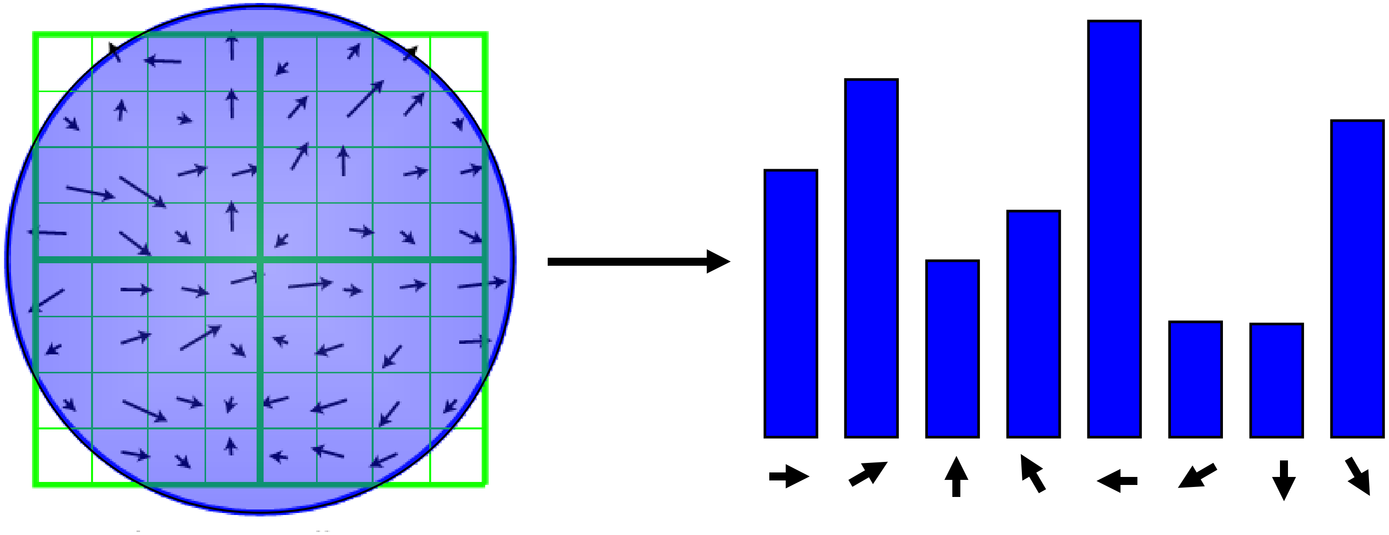
- Compute gradient magnitude and orientation using finite differences:

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

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

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

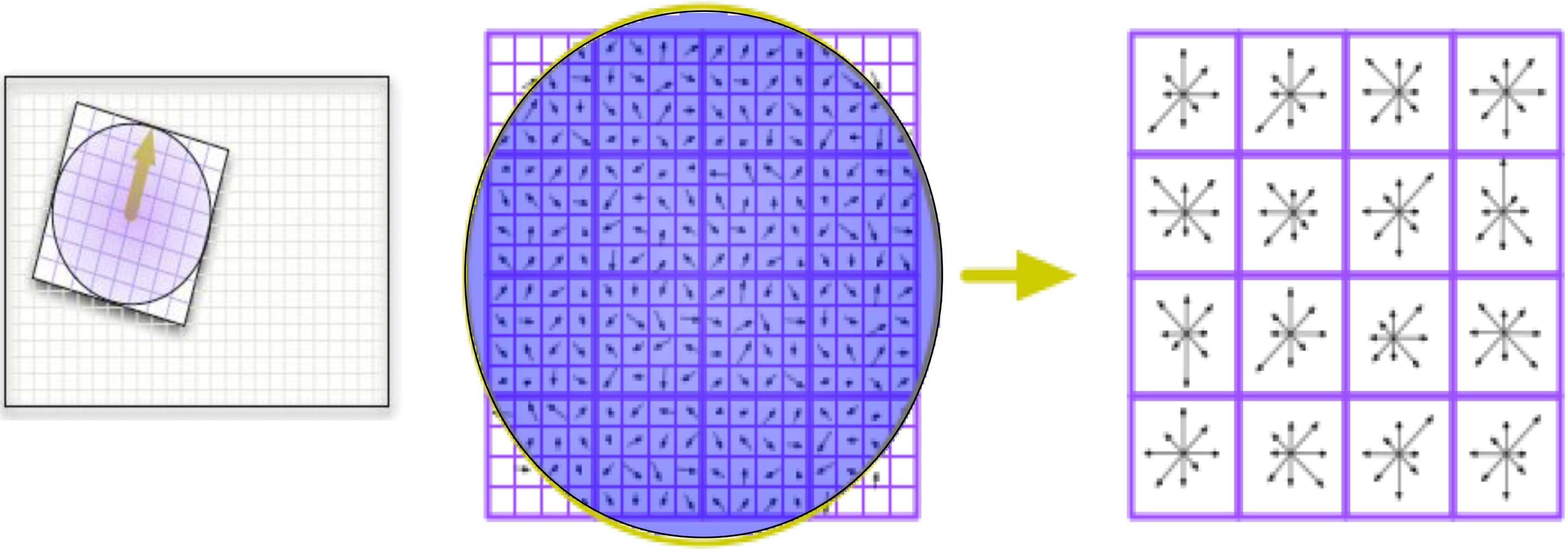


Image gradients

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

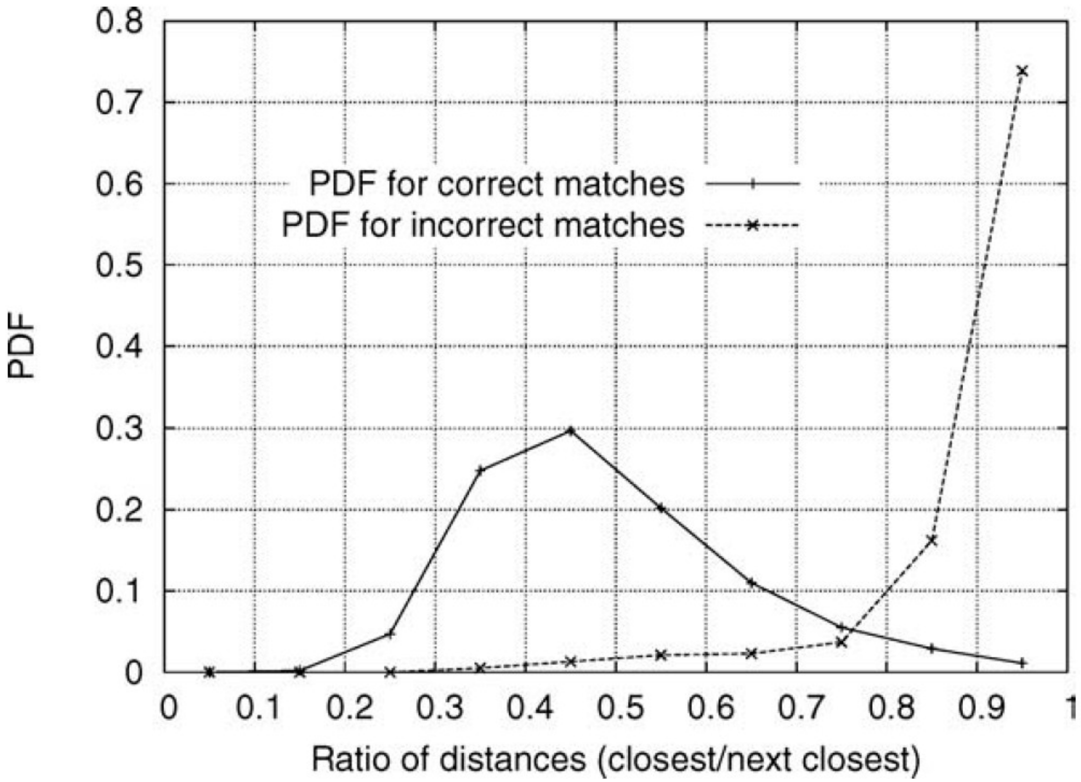
- Very robust
  - 80% Repeatability at:
    - 10% image noise
    - 45° viewing angle
    - 1k-100k keypoints in database
- Best descriptor in [Mikolajczyk & Schmid 2005]'s extensive survey
- 3670+ citations on Google Scholar

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 a match
  3. Verify matches
     - Geometry
     - Hough transform

Matching Descriptors

- Threshold on Distance – bad performance
- Nearest Neighbor – better
- Ratio Test – best performance



Matching Descriptors - Distance

- L_2 norm – used by Lowe
- $\text{SIFT}_{\text{DIST}}$: linear time EMD algorithm that adds robustness to orientation shifts

  Pele and Werman, ECCV 2008

Ratio Test

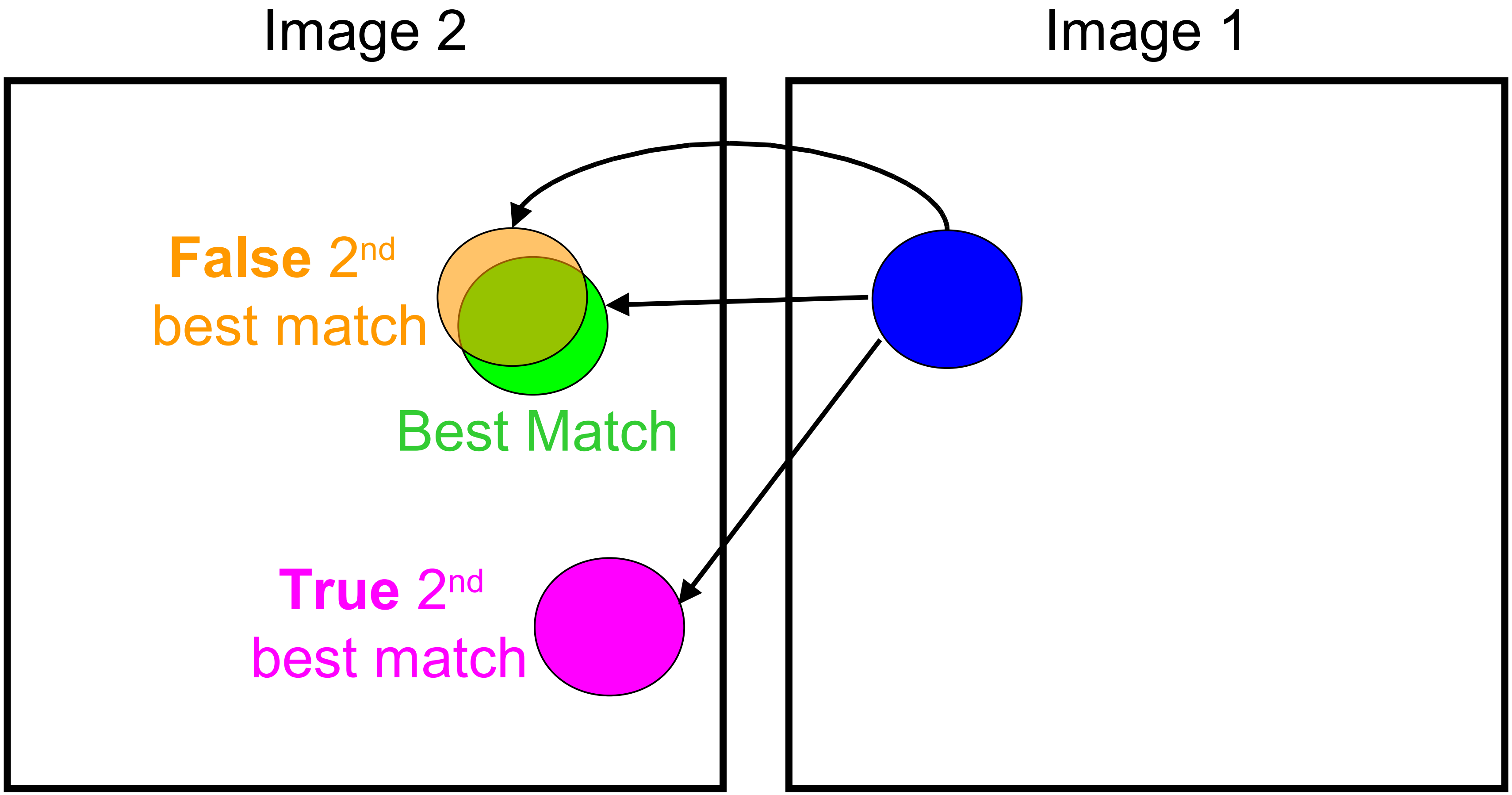


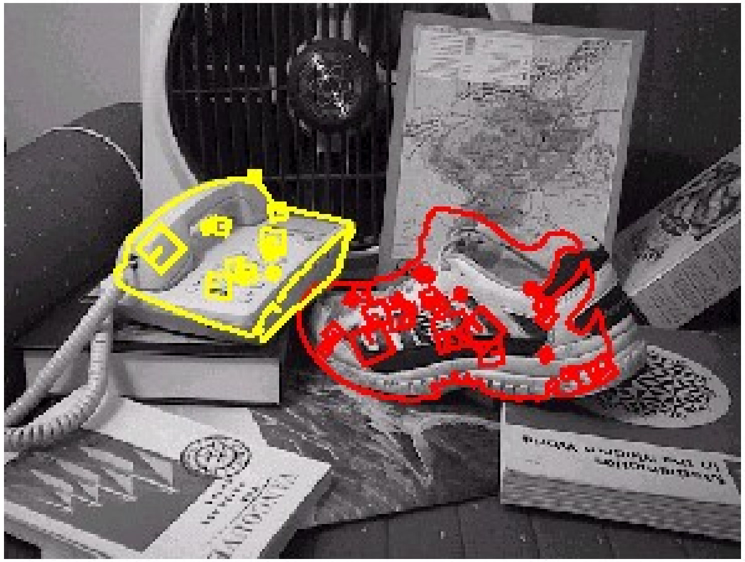
Image 2
Image 1
False 2nd best match
Best Match
True 2nd best match

Fast 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

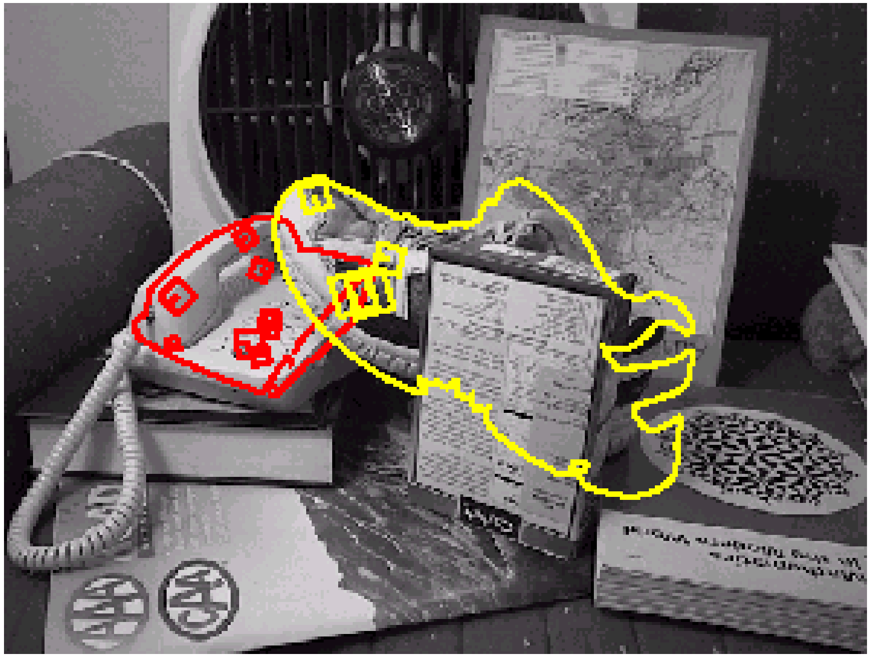
- **Result:** Can give speedup by factor of 1000 while finding nearest neighbor (of interest) 95% of the time

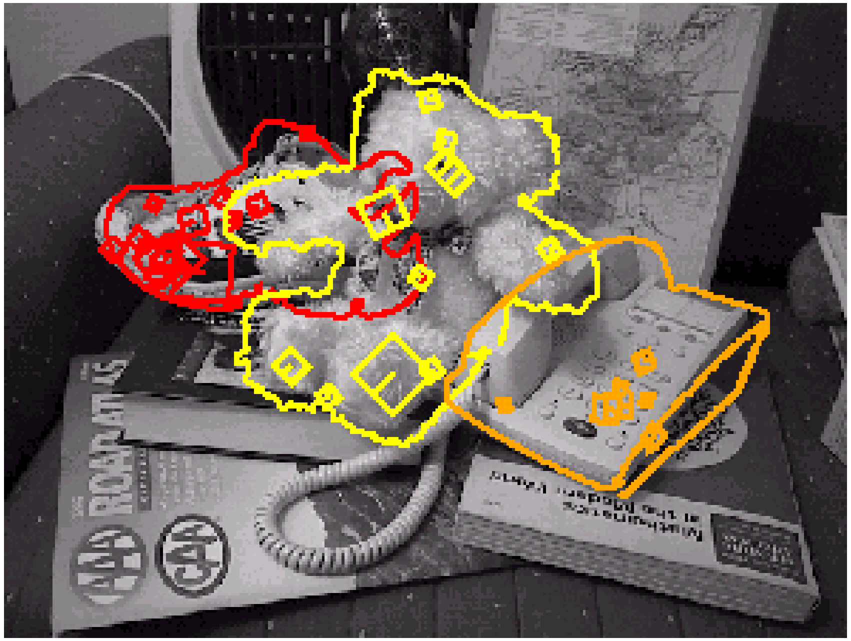
3D Object Recognition



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

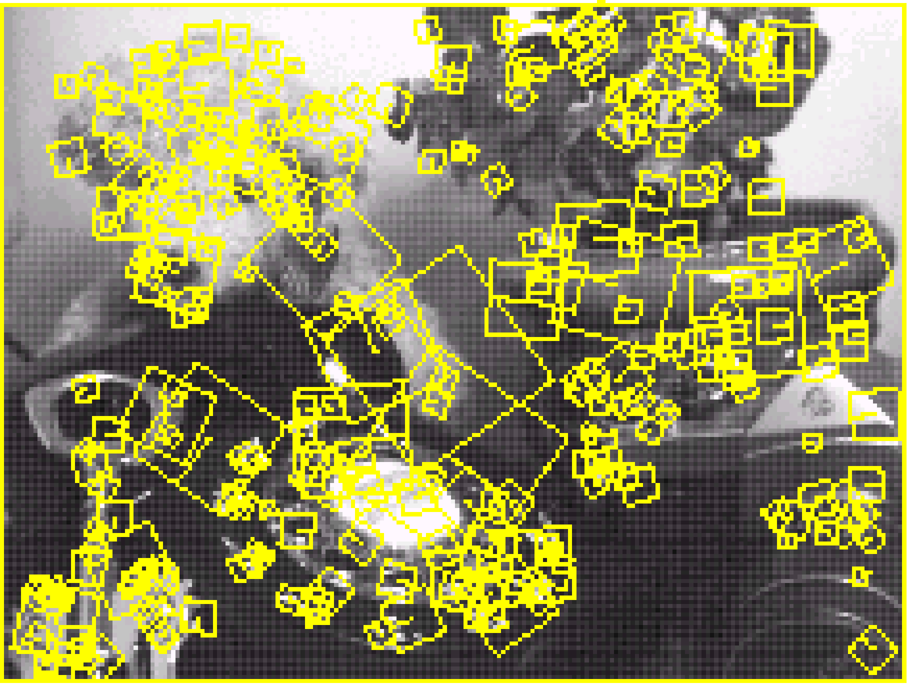
Recognition under occlusion





Test of illumination Robustness

- Same **image** under differing illumination



273 keys verified in final match

Location recognition

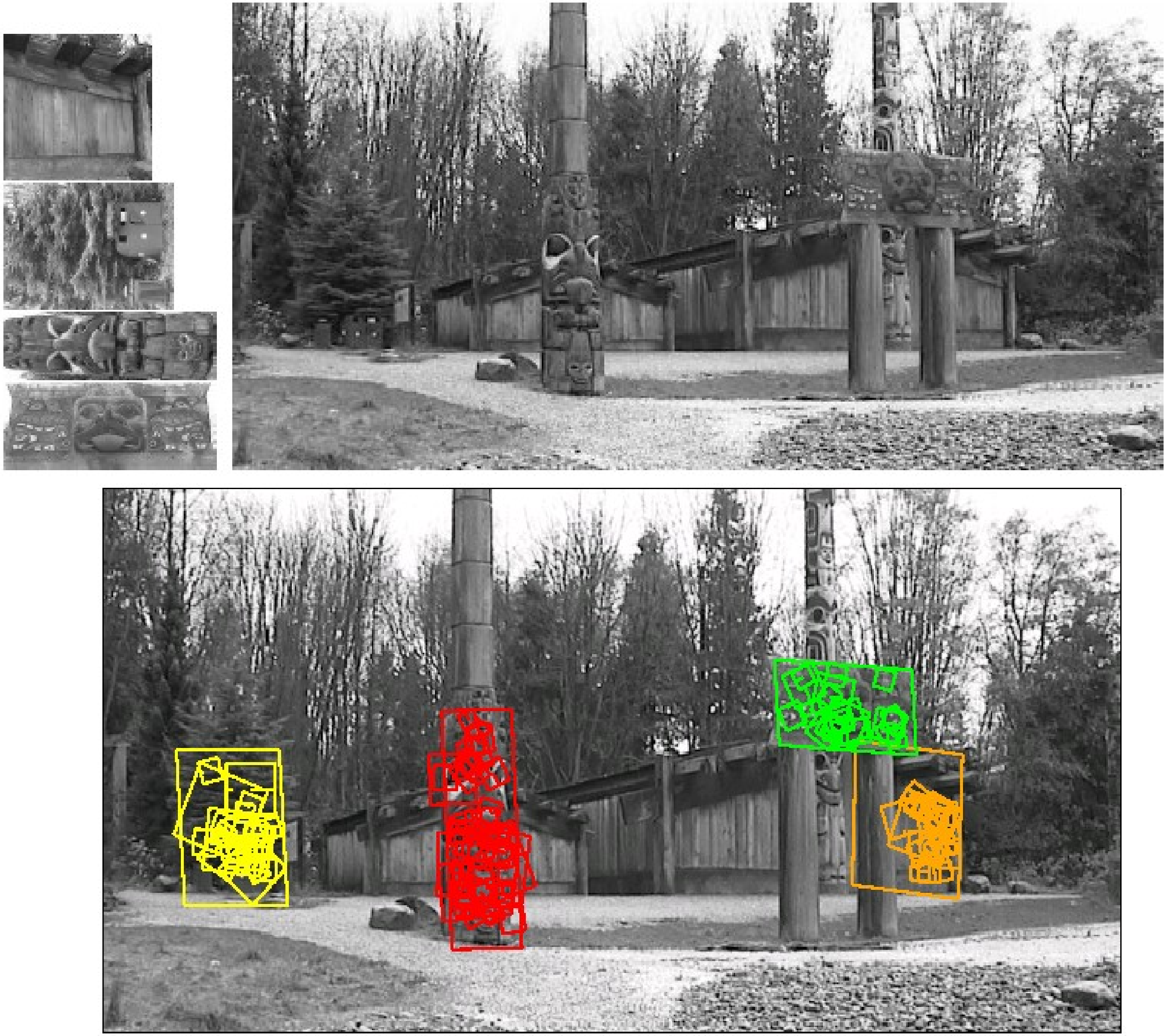
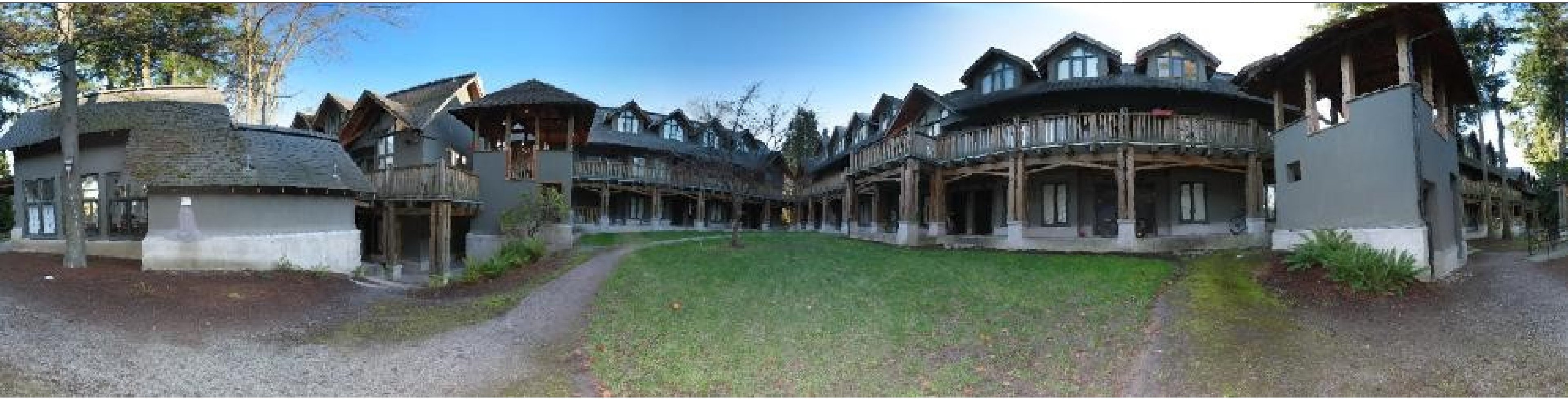


Image Registration Results

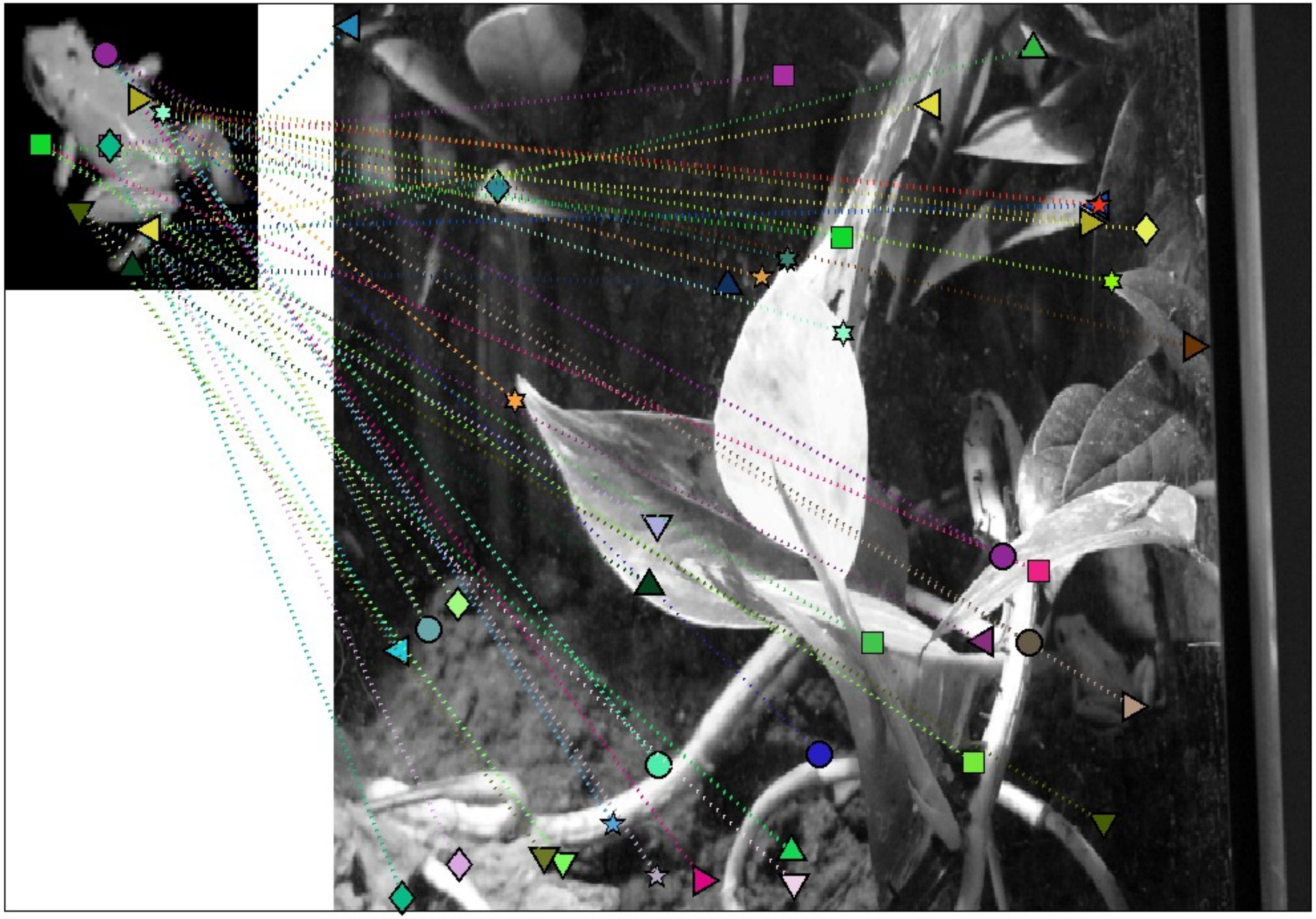


[Brown & Lowe 2003]

Cases where SIFT didn’t work

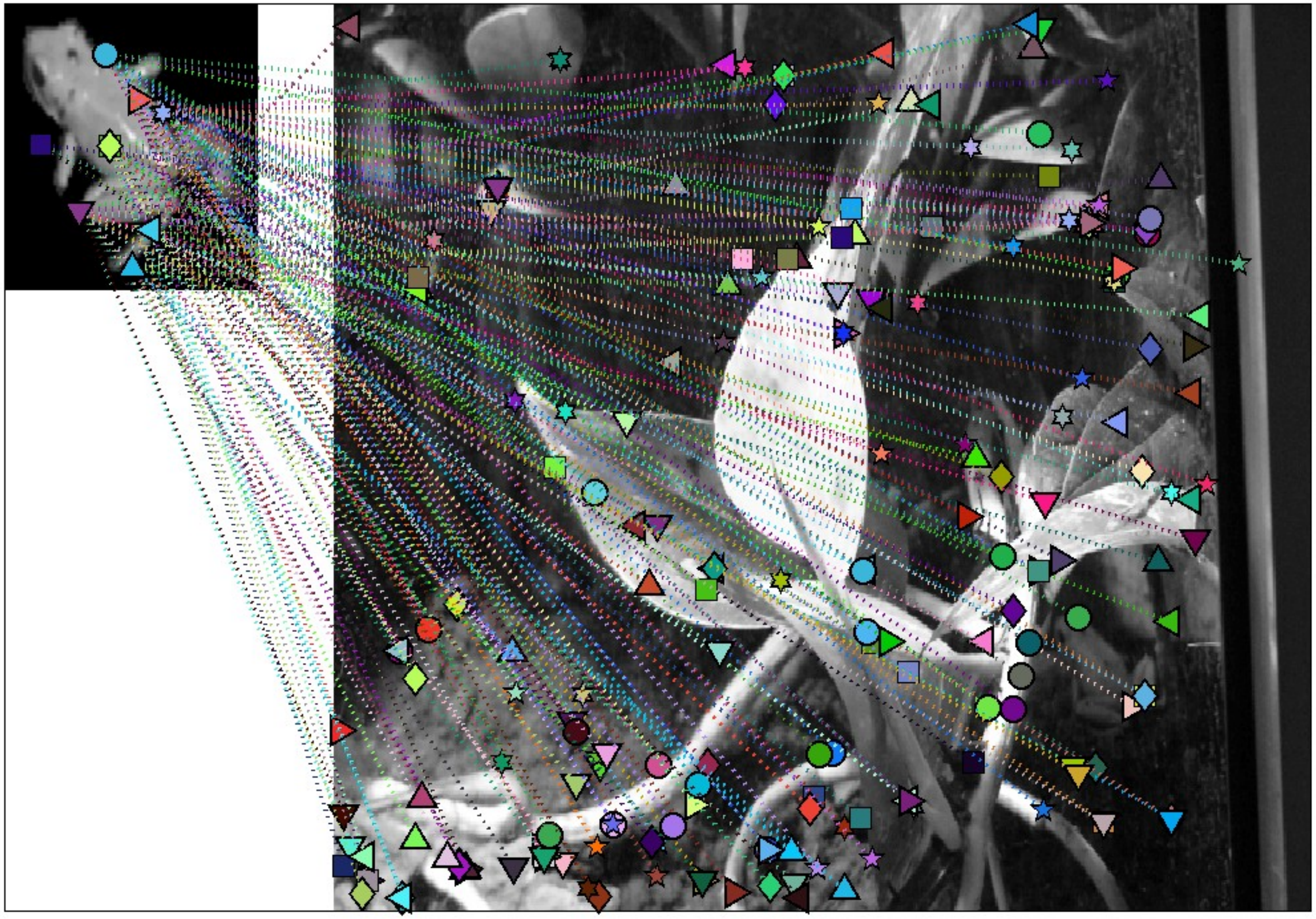
Large illumination change

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



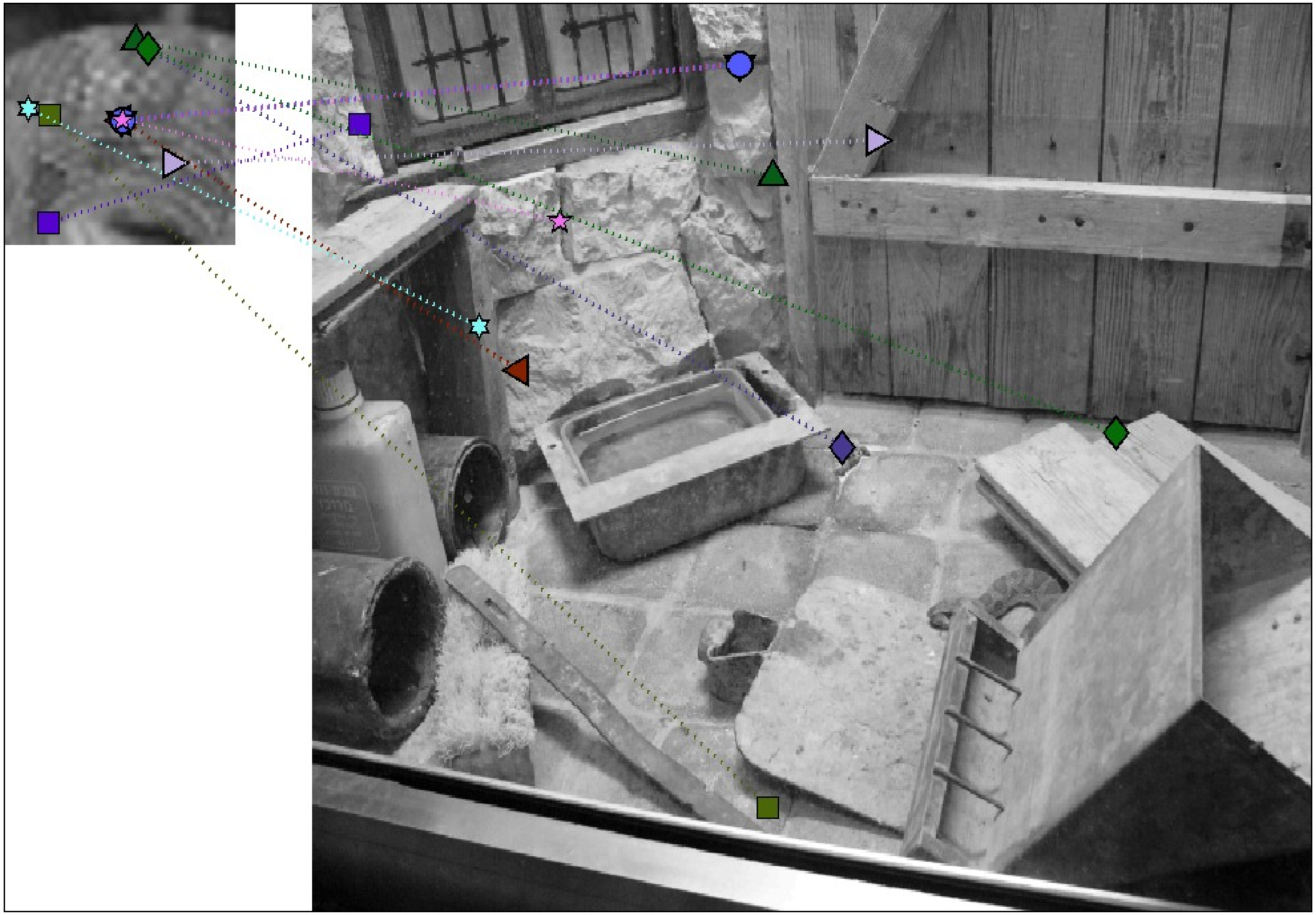
Large illumination change

- 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)



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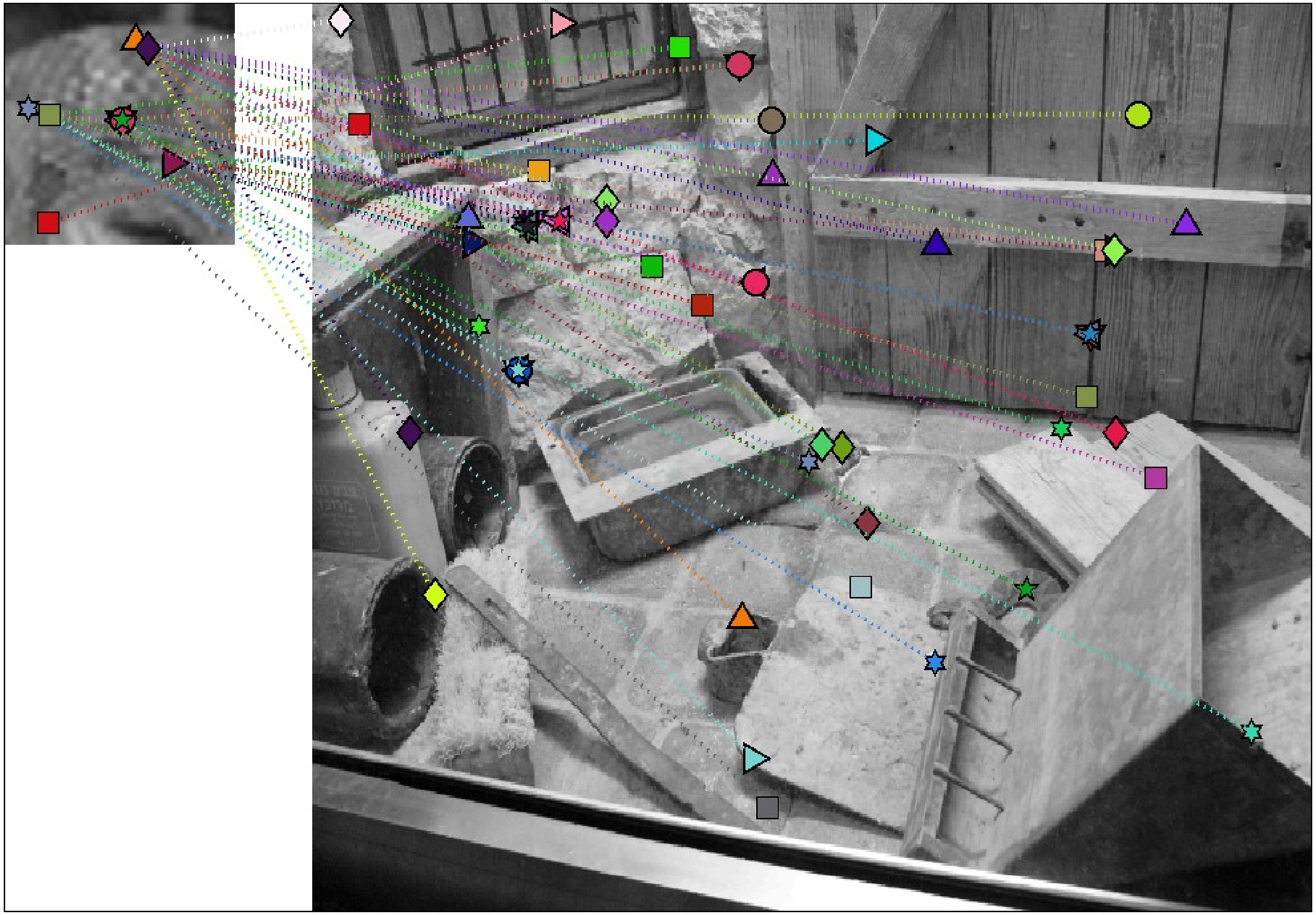


Conclusion: SIFT

- 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

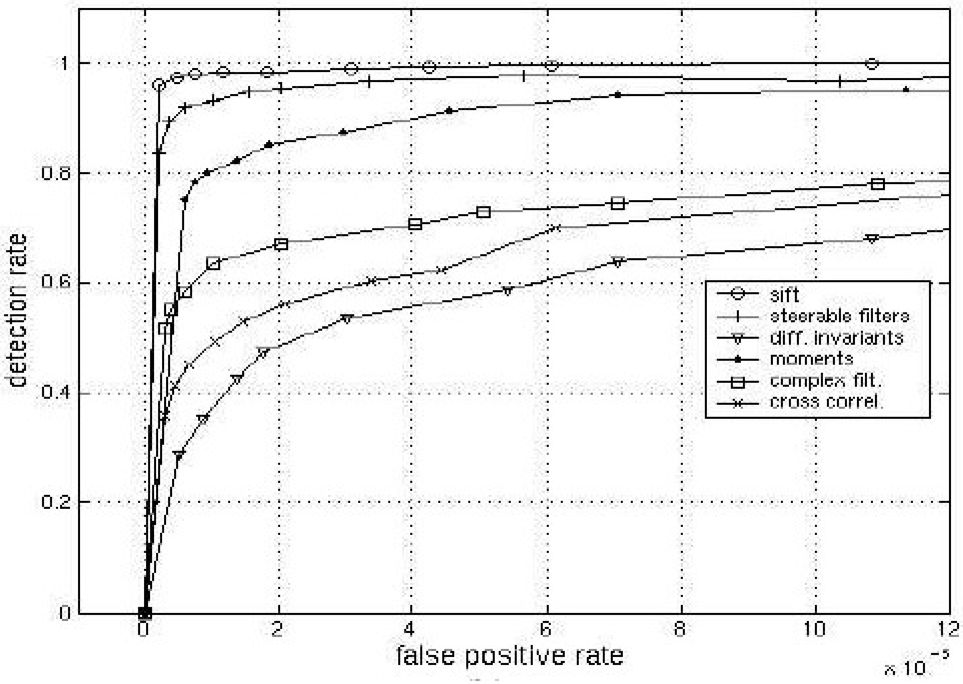
Conclusion: SIFT

- 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, robust to *image rotation*, *scale*, *intensity change*, and to moderate *affine* transformations

Scale = 2.5
Rotation = 45^0



[1] Mikolajczyk & Schmid 2005

A note regarding invariance/robustness

- There is a tradeoff between invariance and distinctiveness.
- For some tasks it is better not to be invariant
- Local *features* and kernels for classification of texture and object categories: An in-depth study - *Zhang*, Marszalek, Lazebnik and *Schmid*. IJCV 2007.
- 11 color names - J. van de Weijer, C. Schmid, Applying Color Names to Image Description. ICIP 2007

Conclusion: Local features

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

SIFT extensions

Color

- Color SIFT - G. J. Burghouts and J. M. Geusebroek. Performance evaluation of local colour invariants. *Comput. Vision Image Understanding*, 2009
- Hue and Opponent histograms - J. van de Weijer, C. Schmid. Coloring Local Feature Extraction.

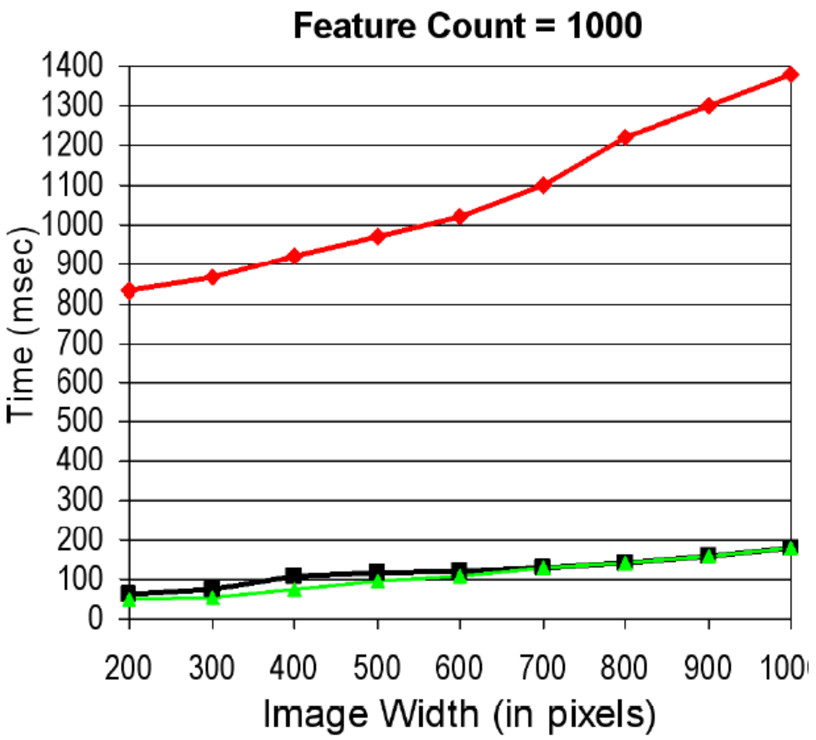
  ECCV 2006
- 11 color names - J. van de Weijer, C. Schmid, Applying Color Names to Image Description. ICIP 2007

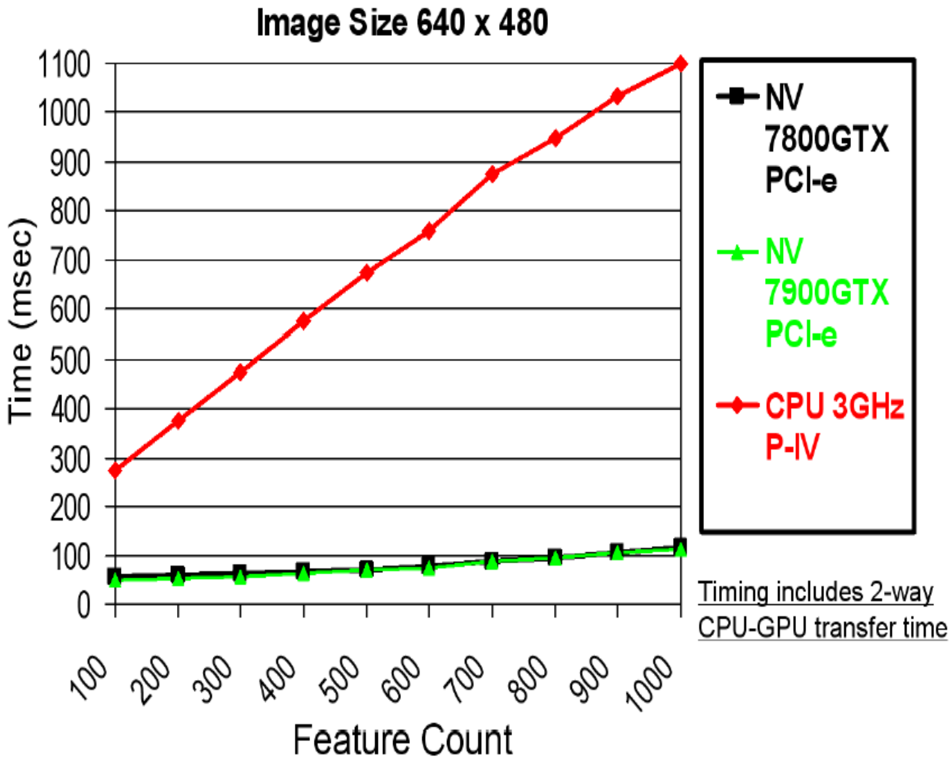
PCA-SIFT

- 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

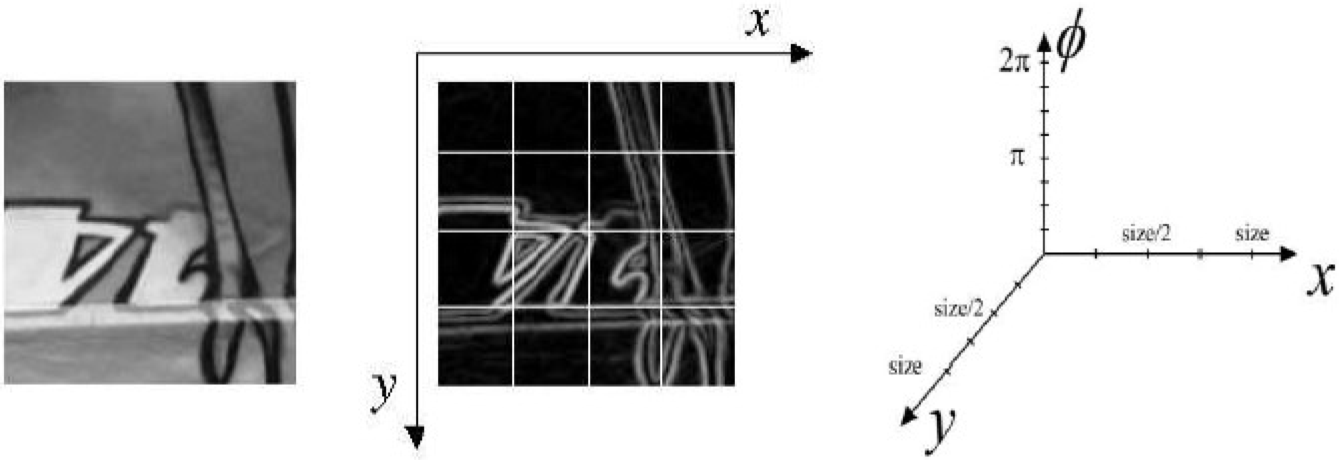
- SURF - Bay et al. 2006
- Approx SIFT - Grabner et al. 2006
- GPU implementation - Sudipta N. Sinha et al. 2006



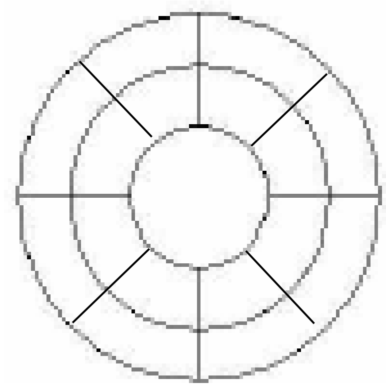


Timing includes 2-way CPU-GPU transfer time

GLOH (Gradient location-orientation histogram)



SIFT



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