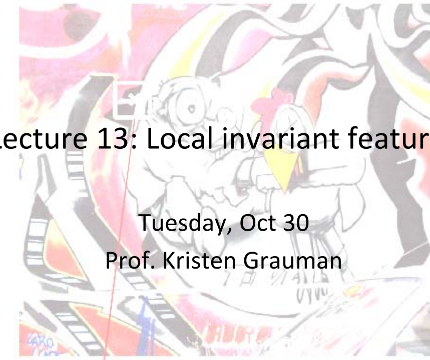


Lecture 13: Local invariant features

Tuesday, Oct 30

Prof. Kristen Grauman

Outline

- Types of transformations and invariance
  - Scale invariance
- Local features: detectors and descriptors
  - SIFT

- What would we like our image descriptions to be invariant to?

Geometric transformations

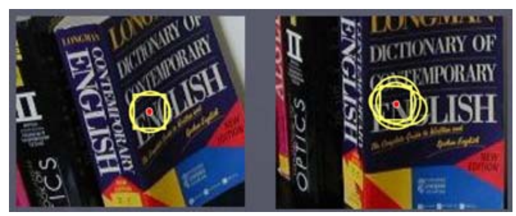


Figure from T. Tuytelaars ECCV 2006 tutorial

Photometric transformations

Figure from T. Tuytelaars ECCV 2006 tutorial

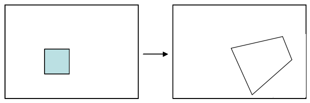
And other nuisances…

- Noise
- Blur
- Compression artifacts
- Appearance variation for a category

Classes of transformations

- **Euclidean/rigid**: Translation + rotation
- **Similarity**: Translation + rotation + uniform scale
- **Affine**: Similarity + shear
  - Valid for orthographic camera, locally planar object
- **(Projective**: Affine + projective warps)
- **Photometric**: affine intensity change
  - I -> aI + b

Projective transformation



Exhaustive search

A multi-scale approach

Slide from T. Tuytelaars ECCV 2006 tutorial

Exhaustive search

A multi-scale approach

Slide from T. Tuytelaars ECCV 2006 tutorial

Exhaustive search

A multi-scale approach

Slide from T. Tuytelaars ECCV 2006 tutorial

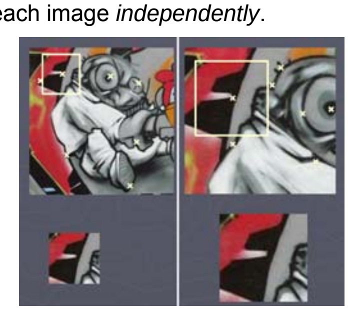
Exhaustive search

A multi-scale approach

Slide from T. Tuytelaars ECCV 2006 tutorial

Key idea of **invariance**

We want to extract the patches from each image *independently*.

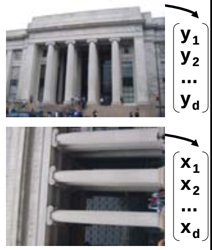


Slide adapted from T. Tuytelaars ECCV 2006 tutorial

Invariant local features

Subset of local feature types designed to be *invariant* to
- Scale
- Translation
- Rotation
- Affine transformations
- Illumination

1) Detect distinctive interest points
2) Extract invariant descriptors



[Mikolajczyk & Schmid, Matas et al., Tuytelaars & Van Gool, Lowe, Kadir et al.,…]

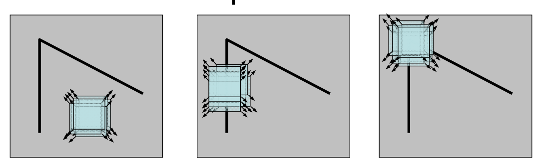
(Good) invariant local features

- Reliably detected
- Distinctive
- Robust to noise, blur, etc.
- Description normalized properly

Interest points: From stereo to recognition

- Feature detectors previously used for stereo, motion tracking
- Now also for recognition
  - Schmid & Mohr 1997
    - Harris corners to select interest points
    - Rotationally invariant descriptor of local image regions
    - Identify consistent clusters of matched features to do recognition

Review: corner detection as an interest operator



"flat" region: no change in all directions

"edge": no change along the edge direction

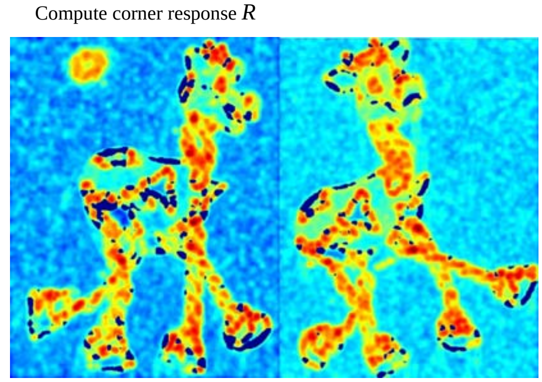
"corner": significant change in all directions

C.Harris, M.Stephens. "A Combined Corner and Edge Detector". 1988
[Slide credit: Darya Frolova and Denis Simakov]

Review: Harris Detector Workflow

Review: Harris Detector Workflow

Compute corner response R

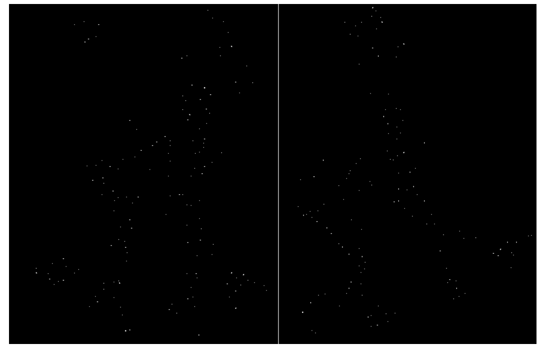


Review: Harris Detector Workflow

Find points with large corner response: R>threshold

Review: Harris Detector Workflow

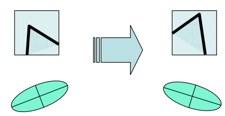
Take only the points of local maxima of R



Review: Harris Detector Workflow

Harris Detector

- Rotation invariance

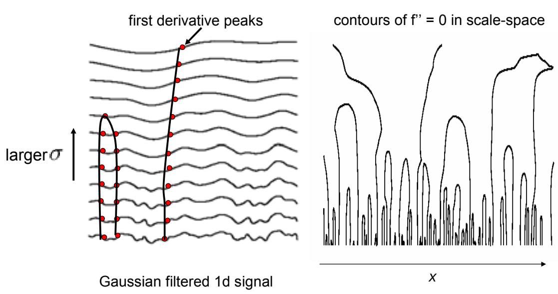


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

But, for corner detection we must search windows **at a pre-determined scale**.

Scale space (Witkin 83)



Adapted from Steve Seitz, UW

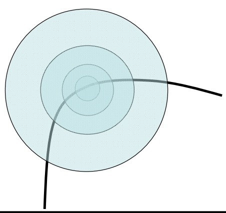
Scale space

Scale space insights:

- edge position may shift with increasing scale (σ)
- two edges may merge with increasing scale (edges can disappear)
- an edge may ***not*** split into two with increasing scale (new edges do not appear)

Scale Invariant Detection

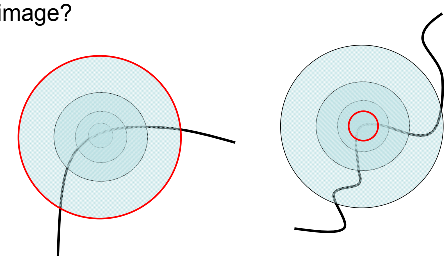
- Consider regions of different sizes around a point
- At the right scale, regions of corresponding content will look the same in both images



[Slides by Darya Frolova and Denis Simakov]

Scale Invariant Detection

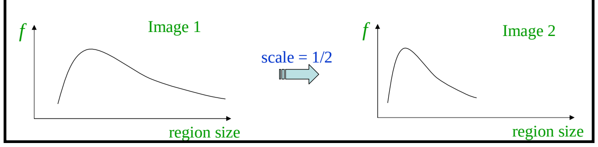
- The problem: how do we choose corresponding circles ***independently*** in each image?



Scale Invariant Detection

- Solution:
  - Design a function on the region (circle), which is "scale invariant" (*the same for corresponding regions, even if they are at different scales*)

    Example: average intensity. For corresponding regions (even of different sizes) it will be the same.
  - For a point in one image, we can consider it as a function of region size (circle radius)



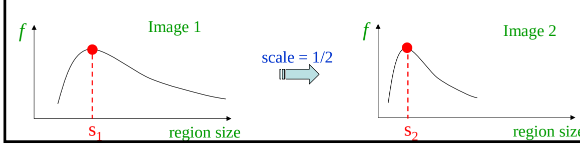
Scale Invariant Detection

- Common approach:

  Take a local maximum of this function

  Observation: region size, for which the maximum is achieved, should be *invariant* to image scale.

Important: this scale invariant region size is found in each image independently!

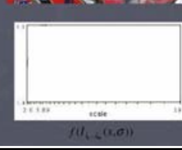


Scale Invariant Detection

[Images from T. Tuytelaars]

Automatic scale selection

Lindeberg et al., 1996



Following example was created by T. Tuytelaars, ECCV 2006 tutorial

Automatic scale selection

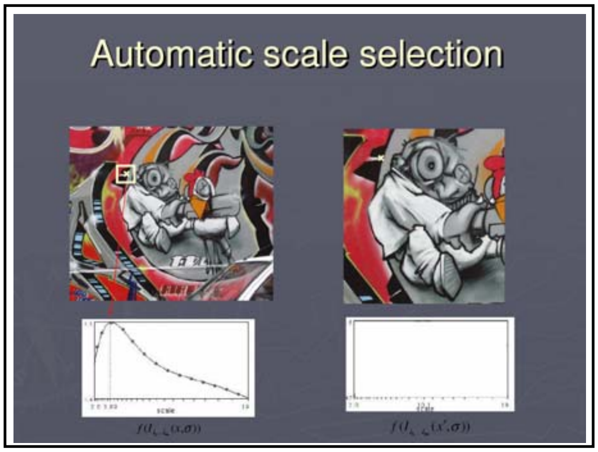
Automatic scale selection

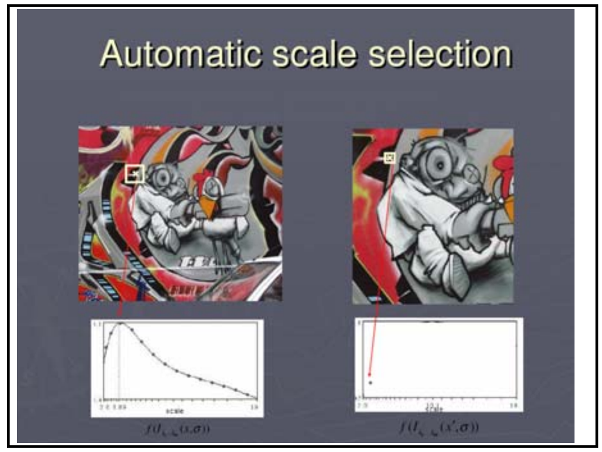
Automatic scale selection

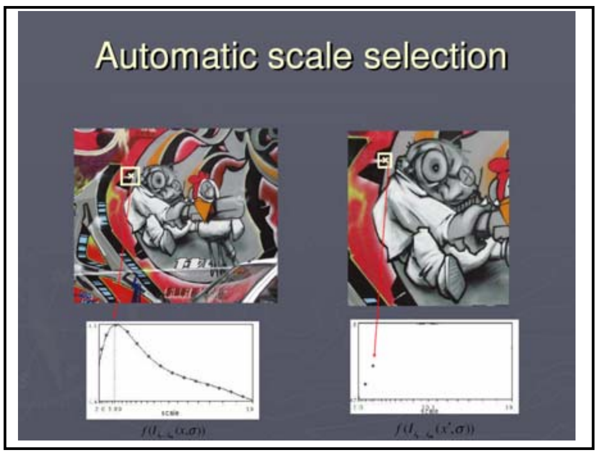
Automatic scale selection

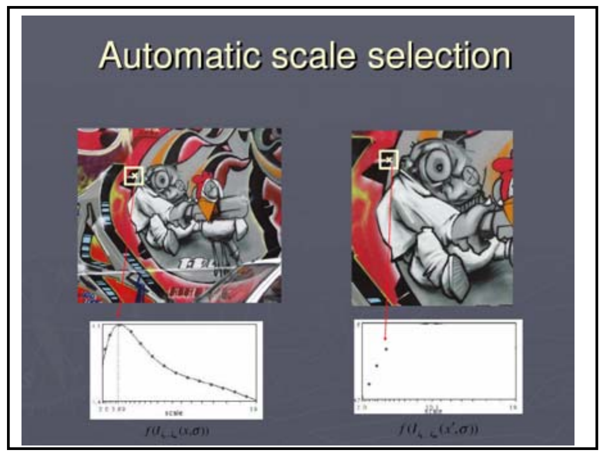
Automatic scale selection

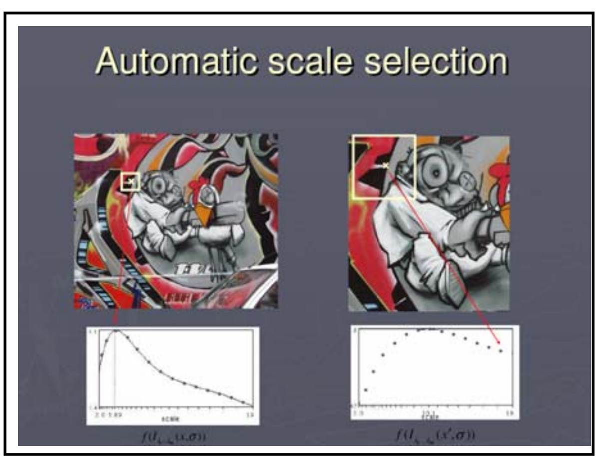
Automatic scale selection

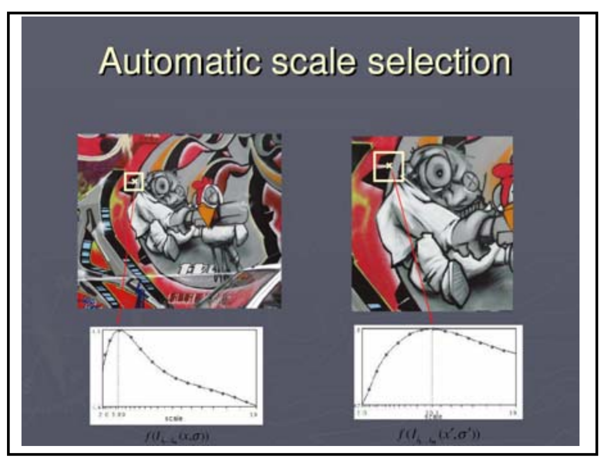

Automatic scale selection


Automatic scale selection


Automatic scale selection

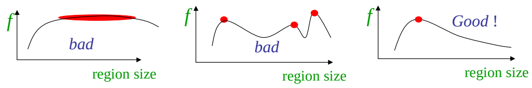

Automatic scale selection


Automatic scale selection


Automatic scale selection

Scale Invariant Detection

- A "good" function for scale detection: has one stable sharp peak



- For usual images: a good function would be a one which responds to contrast (sharp local intensity change)

Scale space

Scale space insights:

- edge position may shift with increasing scale (σ)
- two edges may merge with increasing scale (edges can disappear)
- an edge may ***not*** split into two with increasing scale (new edges do not appear)

What could be an approximation of an image's scale space?

Scale invariant detection

Requires a method to repeatably select points in location and scale:

- Only reasonable scale-space kernel is a Gaussian (Koenderink, 1984; Lindeberg, 1994)
- An efficient choice is to detect peaks in the difference of Gaussian pyramid (Burt & Adelson, 1983; Crowley & Parker, 1984)
- Difference-of-Gaussian is a close approximation to Laplacian

Slide adapted from David Lowe, UBC

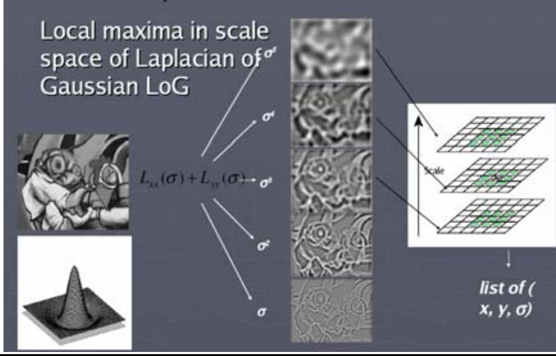
Scale selection principle

- Intrinsic scale is the scale at which normalized derivative assumes a maximum -- marks a feature containing interesting structure. (T. Lindeberg '94)

➔ Maxima/minima of Laplacian

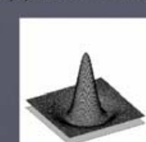
Scale invariant detectors
Laplacian of Gaussian

Local maxima in scale space of Laplacian of Gaussian LoG



Lowe's DoG

Difference of Gaussians as approximation of the Laplacian of Gaussian



Scale Invariant Detection

Kernels:

$$L = \sigma^2 \left(G_{xx}(x,y,\sigma) + G_{yy}(x,y,\sigma) \right)$$

(Laplacian)

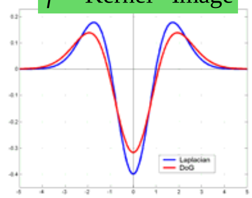
$$DoG = G(x,y,k\sigma) - G(x,y,\sigma)$$

(Difference of Gaussians)

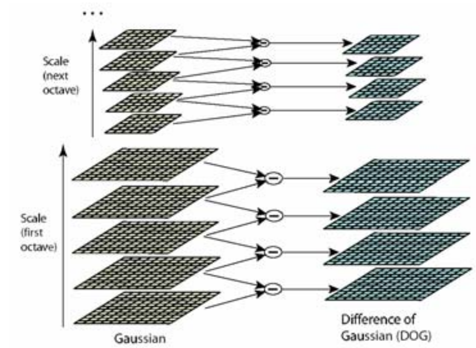
where Gaussian

$$G(x,y,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$f = \text{Kernel} * \text{Image}$$



[Slide by Darya Frolova and Denis Simakov]

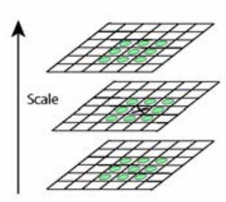


Scale space images: repeatedly convolve with Gaussian

Adjacent Gaussian images subtracted

SIFT: Key point localization

- Detect maxima and minima of difference-of-Gaussian in scale space
- Then reject points with low contrast (threshold)
- Eliminate edge responses (use ratio of principal curvatures)



Candidate keypoints: list of (x,y,σ)

Adapted from David Lowe, UBC

SIFT: Example of keypoint detection

Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)

(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures

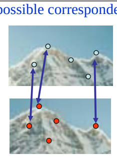
Slide from David Lowe, UBC

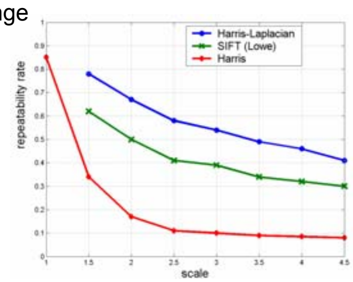
Scale Invariant Detectors

- Experimental evaluation of detectors w.r.t. scale change

Repeatability rate:

$$\frac{\#\ \text{correspondences}}{\#\ \text{possible correspondences}}$$





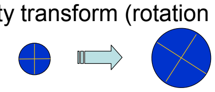
K.Mikolajczyk, C.Schmid. "Indexing Based on Scale Invariant Interest Points". ICCV 2001

Scale Invariant Detection: Summary

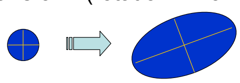
- Given: two images of the same scene with a large *scale difference* between them
- Goal: find *the same* interest points *independently* in each image
- Solution: search for *maxima* of suitable functions in *scale* and in *space* (over the image)

Affine Invariant Detection

- Above we considered:
  Similarity transform (rotation + uniform scale)

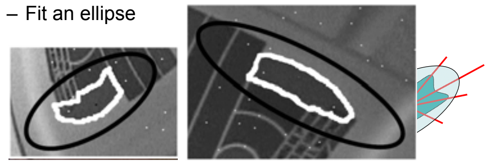


- Now we go on to:
  Affine transform (rotation + non-uniform scale)



Affine Invariant Detection

- Intensity-based regions (IBR):
  – Start from a local intensity extrema
  – Consider intensity profile along rays
  – Select maximum of invariant function f(t) along each ray
  – Connect local maxima
  – Fit an ellipse



T.Tuytelaars, L.V.Gool. "Wide Baseline Stereo Matching Based on Local, Affinely Invariant Regions". BMVC 2000.

Affine Invariant Detection

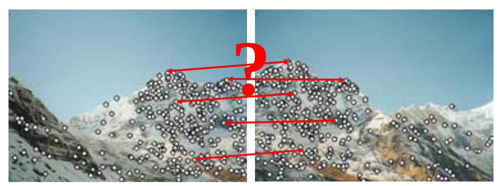
- Maximally Stable Extremal Regions (MSER)
  – *Threshold* image intensities: $I > I_0$
  – Extract *connected components* ("Extremal Regions")
  – Seek extremal regions that remain "Maximally Stable" under range of thresholds

Matas et al. Robust Wide Baseline Stereo from Maximally Stable Extremal Regions. BMVC 2002.

Point Descriptors

- We know how to detect points
- Next question:

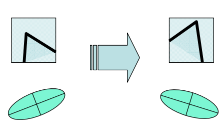
How to *describe* them for matching?



Point descriptor should be:
1. Invariant
2. Distinctive

Rotation Invariant Descriptors

- Harris corner response measure:
  depends only on the eigenvalues of the matrix *M*

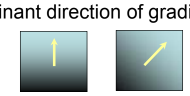


C.Harris, M.Stephens. "A Combined Corner and Edge Detector". 1988

Rotation Invariant Descriptors

- Find local orientation

  Dominant direction of gradient

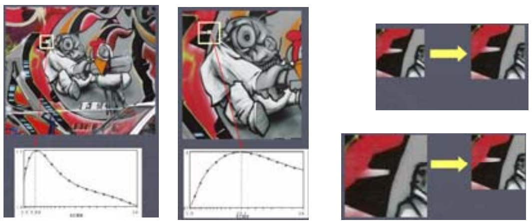


- Rotate description relative to dominant orientation

[1] K.Mikolajczyk, C.Schmid. "Indexing Based on Scale Invariant Interest Points". ICCV 2001
[2] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". Accepted to IJCV 2004

Scale Invariant Descriptors

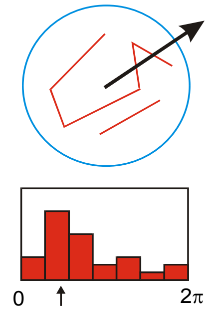
- Use the scale determined by detector to compute descriptor in a normalized frame



[Images from T. Tuytelaars]

SIFT descriptors: Select canonical orientation

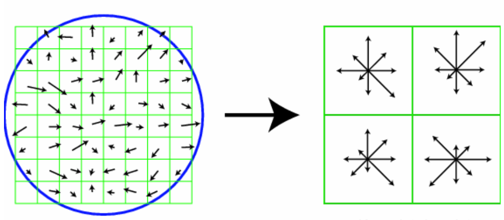
- Create histogram of local gradient directions computed at selected scale
- Assign canonical orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientation)



Slide by David Lowe, UBC

SIFT descriptors: vector formation

- Thresholded image gradients are sampled over 16x16 array of locations in scale space
- Create array of orientation histograms
- 8 orientations x 4x4 histogram array = 128 dimensions



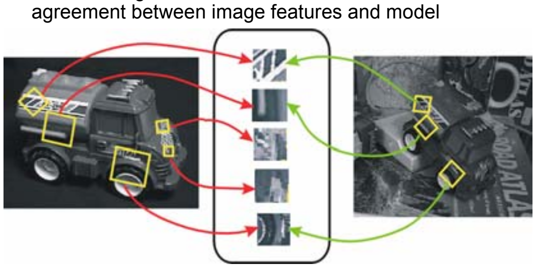
Slide by David Lowe, UBC

SIFT properties

- Invariant to
  - Scale
  - Rotation
- Partially invariant to
  - Illumination changes
  - Camera viewpoint
  - Occlusion, clutter

SIFT matching and recognition

- Index descriptors
- Generalized Hough transform: vote for object poses
- Refine with geometric verification: affine fit, check for agreement between image features and model



Adapted from David Lowe, UBC

Value of local (invariant) features

- Complexity reduction via selection of distinctive points
- Describe images, objects, parts without requiring segmentation
  - Local character means robustness to clutter, occlusion
- Robustness: similar descriptors in spite of noise, blur, etc.

Coming up

- Problem set 3 due 11/13
  - Stereo matching
  - Local invariant feature indexing
- Thursday: image indexing with bags of words
  - Read Video Google paper