Interest Points

Galatea of the Spheres
Salvador Dali

Computational Photography

Derek Hoiem, University of Illinois

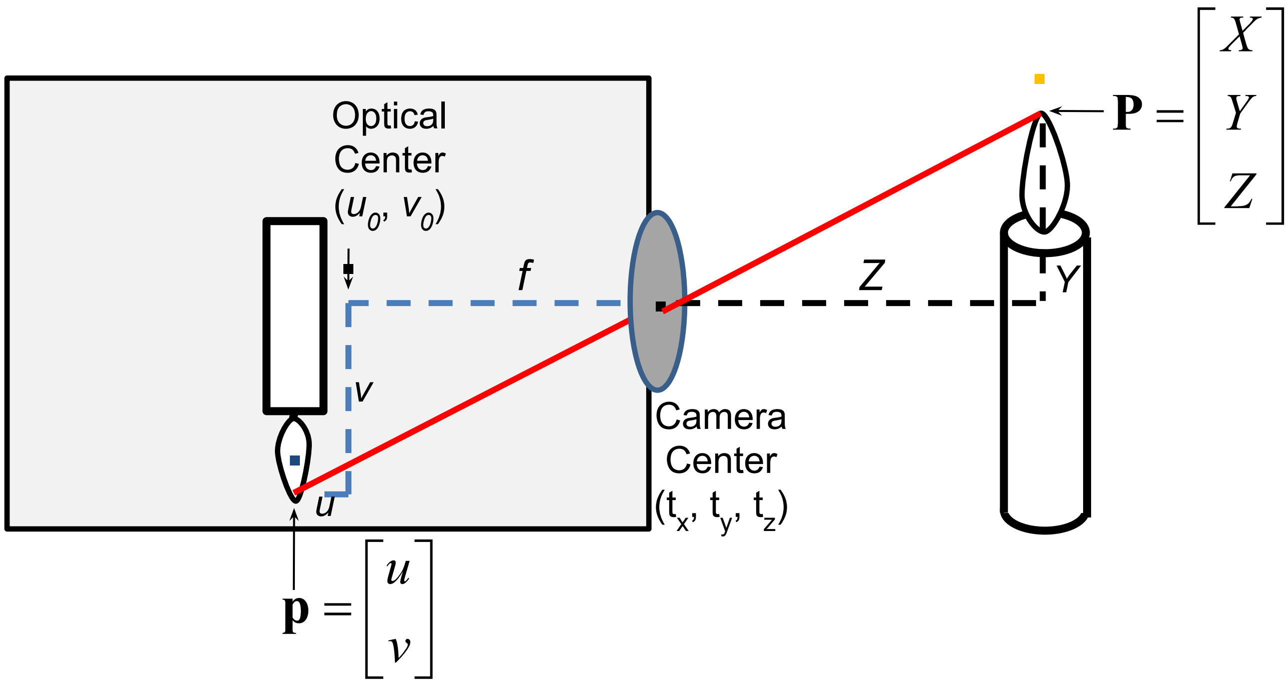
Today’s class

- Review of “Modeling the Physical World”
- Interest points

Pinhole camera model

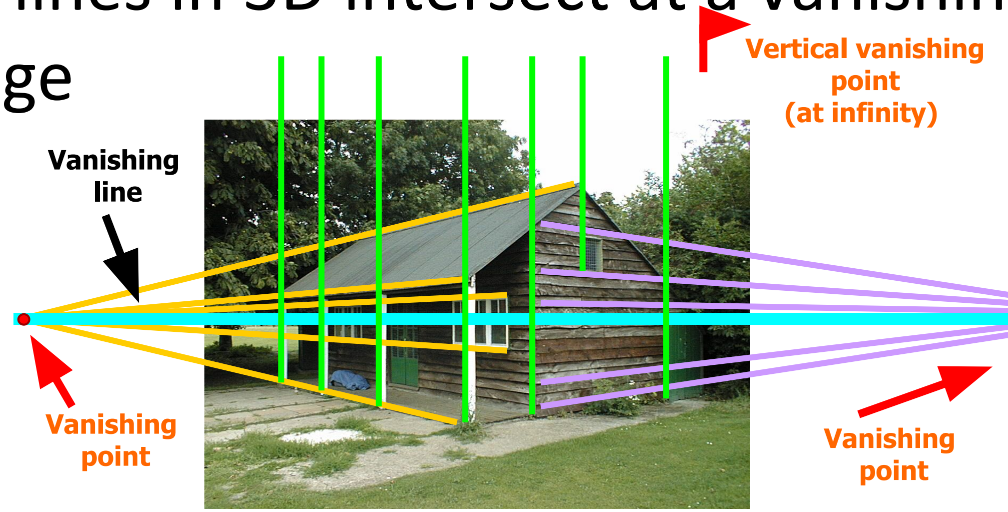
- Linear projection from 3D to 2D
  - Be familiar with projection matrix (focal length, principal point, etc.)

$$\mathbf{x} = \mathbf{K}\begin{bmatrix}\mathbf{R} & \mathbf{t}\end{bmatrix}\mathbf{X}$$

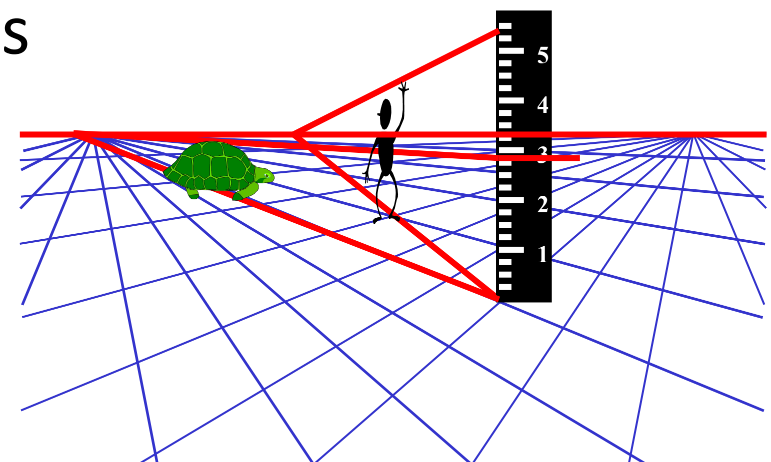


Vanishing points and metrology

- Parallel lines in 3D intersect at a vanishing point in the image

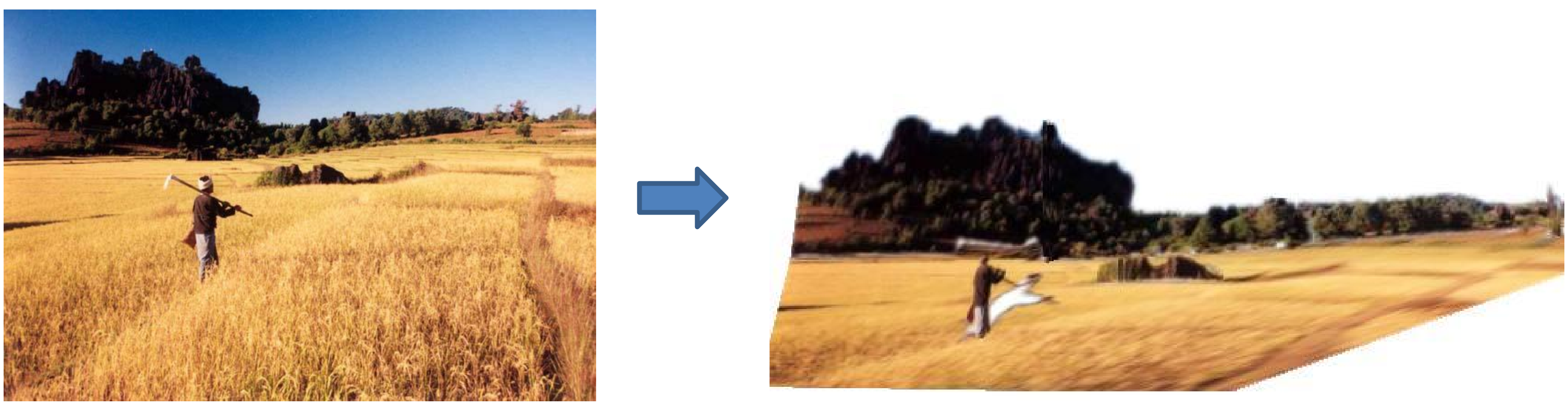


- Can measure relative object heights using vanishing point tricks



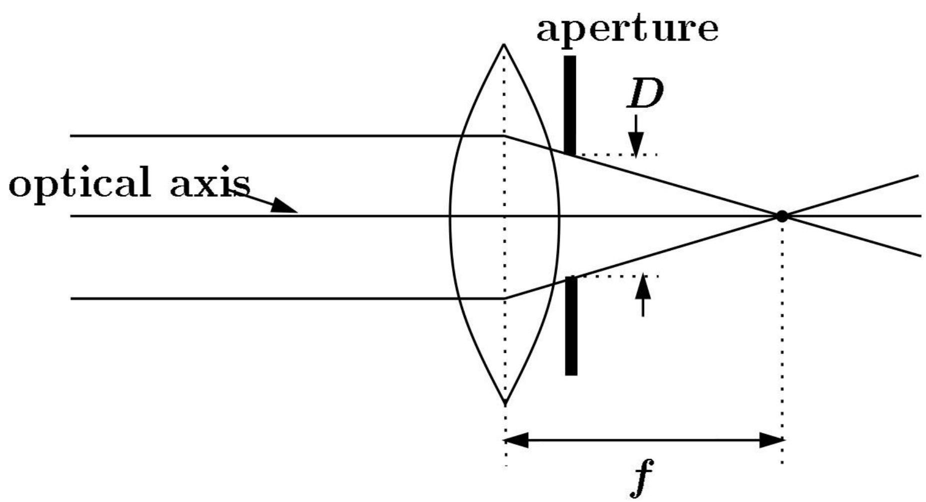
Single-view 3D Reconstruction

- Technically impossible to go from 2D to 3D, but we can do it with simplifying models
  - Need some interaction or recognition algorithms
  - Uses basic VP tricks and projective geometry



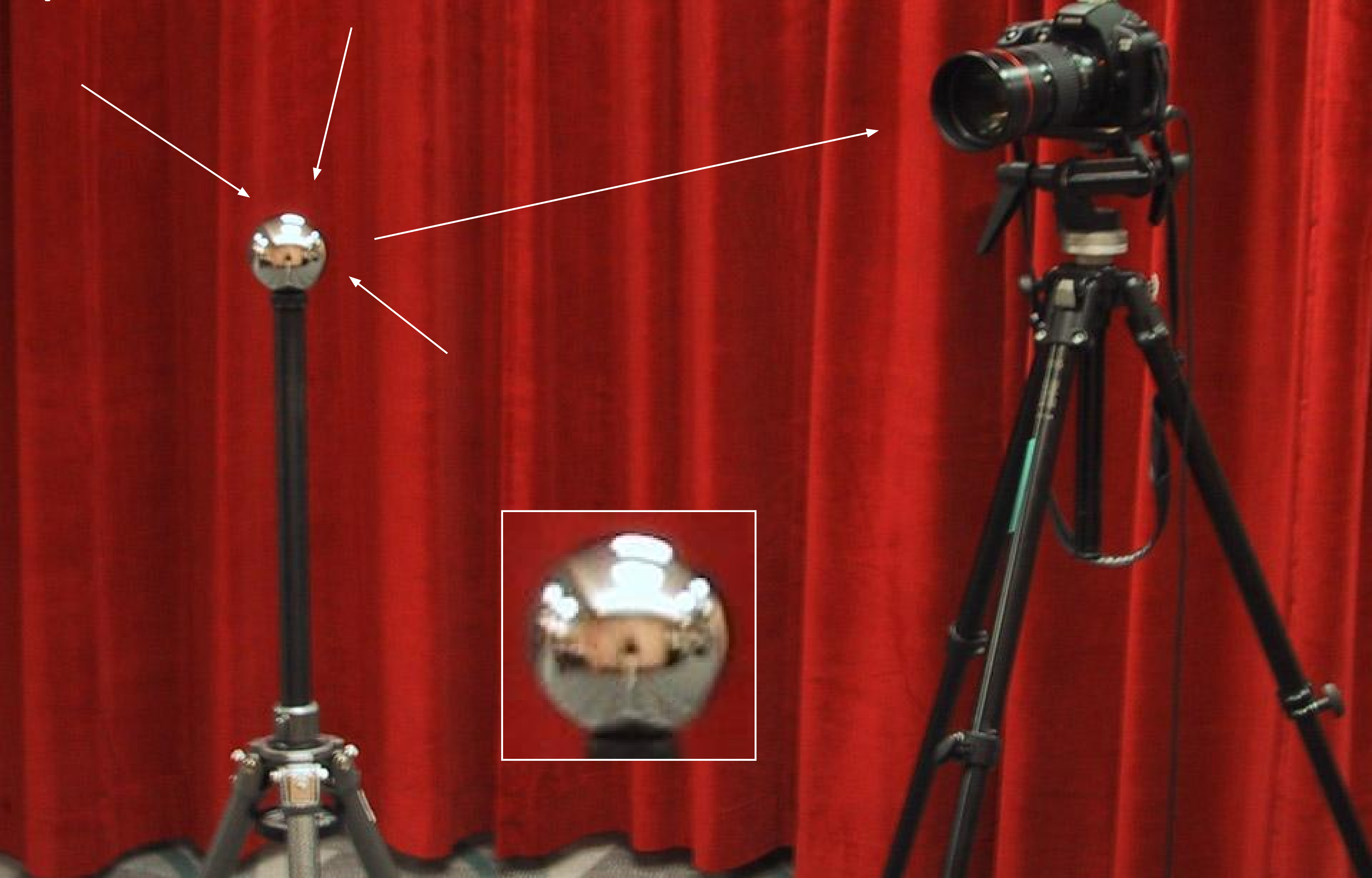
Lens, aperture, focal length

- Aperture size and focal length control amount of exposure needed, depth of field, field of view



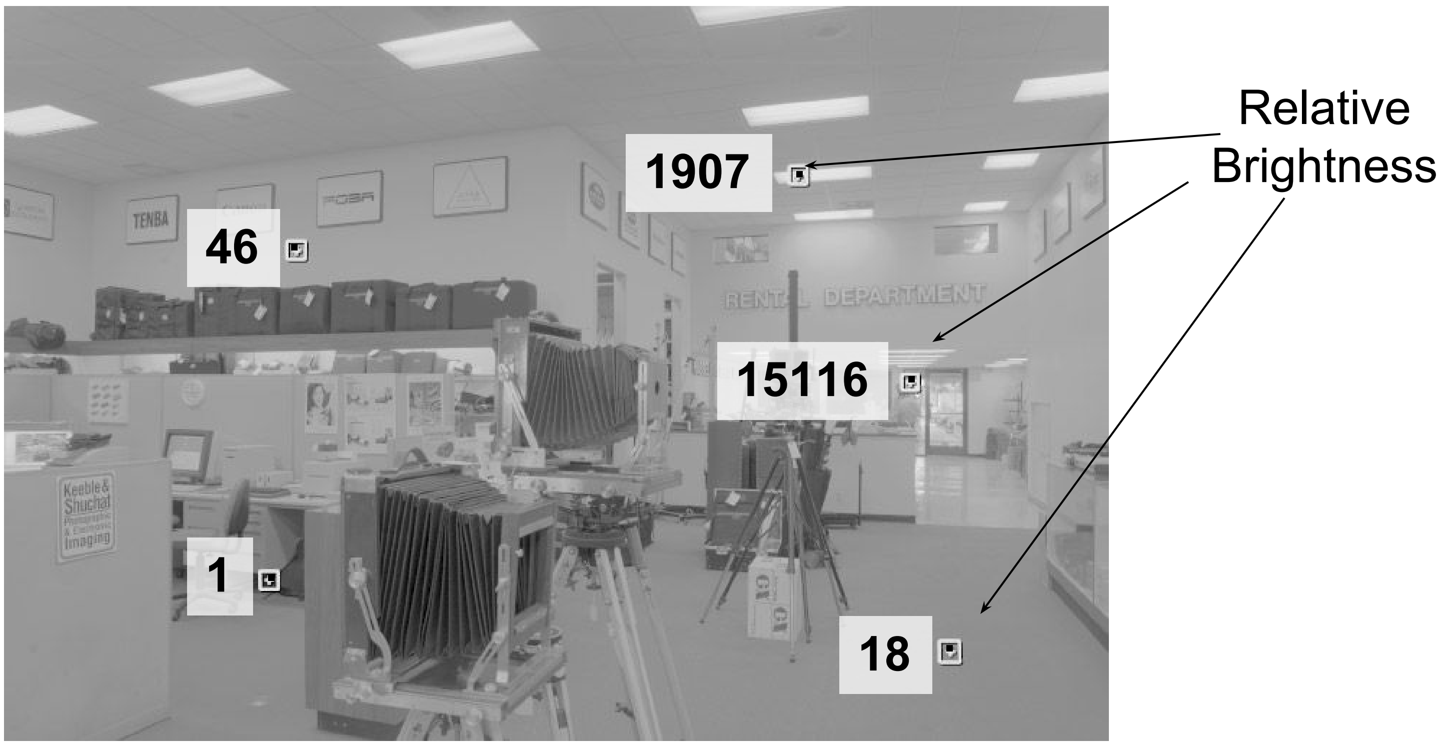
Good explanation: http://www.cambridgeincolour.com/tutorials/depth-of-field.htm

Capturing light with a mirrored sphere



One small snag

- How do we deal with light sources? Sun, lights, etc?
  - They are much, much brighter than the rest of the environment



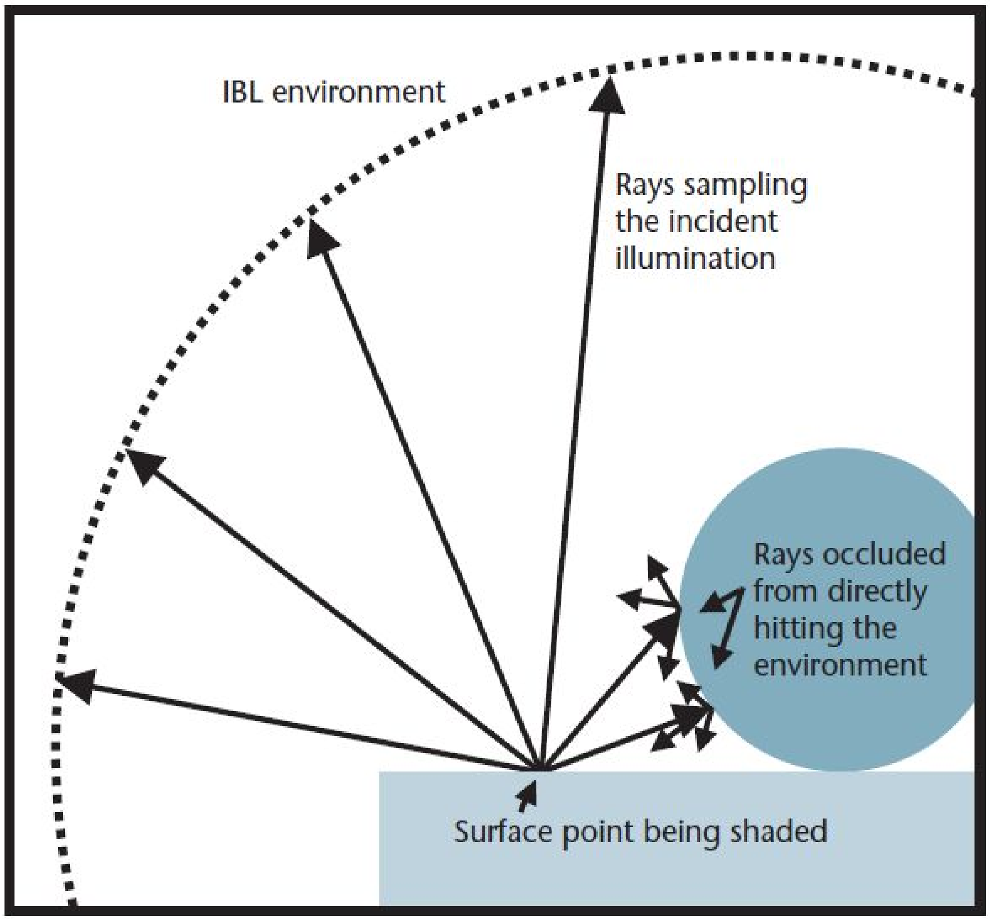
- Use High Dynamic Range photography

Key ideas for Image-based Lighting

- Capturing HDR images: needed so that light probes capture full range of radiance

Key ideas for Image-based Lighting

- Relighting: environment map acts as light source, substituting for distant scene



Next section of topics

- Correspondence
  - How do we find matching patches in two images?
  - How can we automatically align two images of the same scene?
  - How do we find images with similar content?
  - How do we tell if two pictures are of the same person's face?
  - How can we detect objects from a particular category?

- Applications
  - Photo stitching
  - Object recognition
  - 3D Reconstruction
  - Tracking

How can we align two pictures?

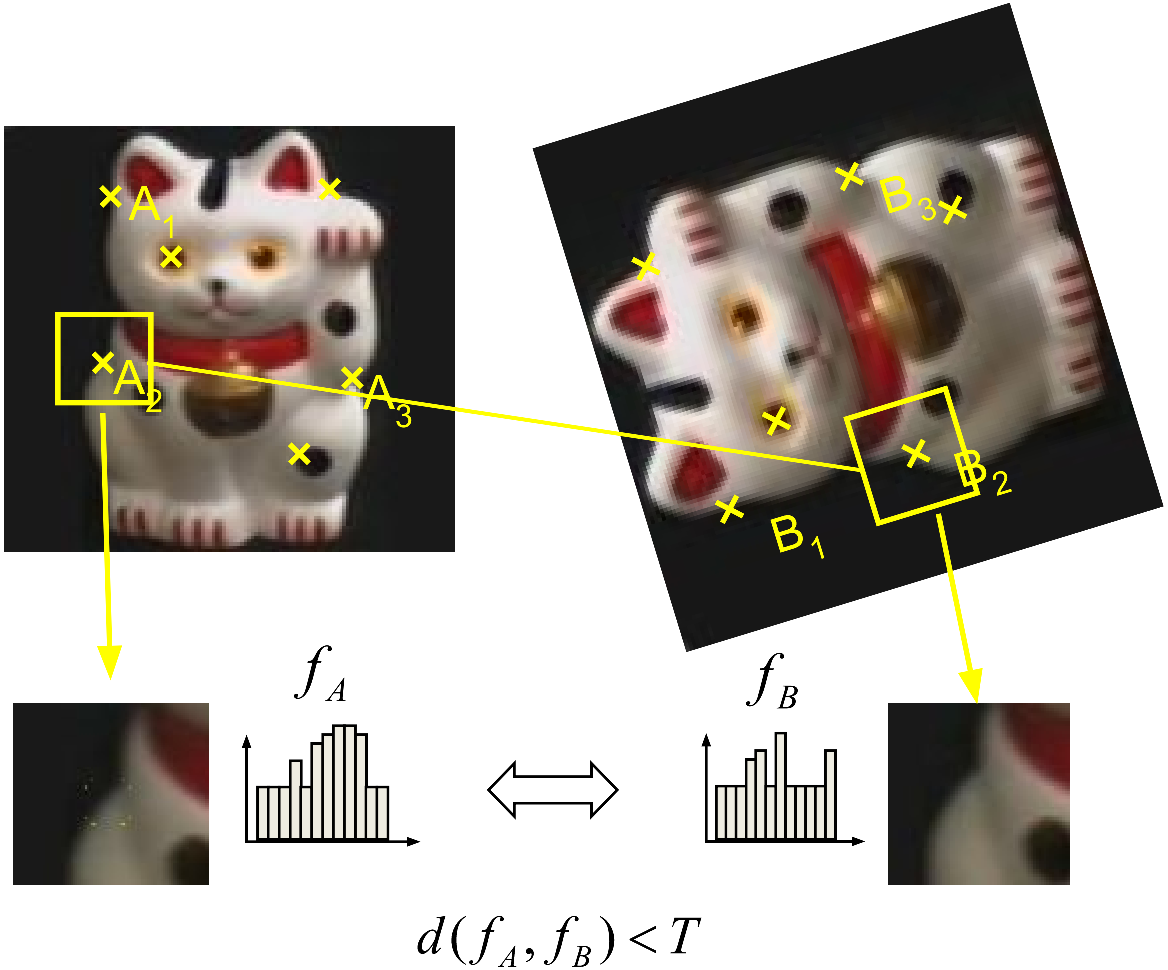
- Case of global transformation

How can we align two pictures?

- Global matching?
  - But what if
    - Not just translation change, but rotation and scale?
    - Only small pieces of the pictures match?

Today: Keypoint Matching



$$f_A \qquad f_B$$

$$d(f_A, f_B) < T$$

1. **Find a set of distinctive key-points**
2. **Define a region around each keypoint**
3. **Extract and normalize the region content**
4. **Compute a local descriptor from the normalized region**
5. **Match local descriptors**

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Main challenges

- Change in position, scale, and rotation
- Change in viewpoint
- Occlusion
- Articulation, change in appearance

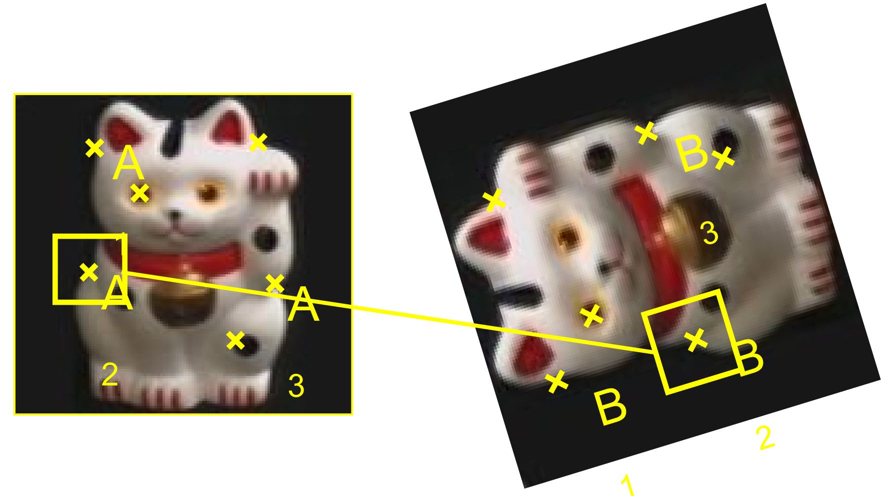
Question

- Why not just take every patch in the original image and find best match in second image?

Goals for Keypoints

Detect points that are *repeatable* and *distinctive*

Key trade-offs



Localization

More Points

Robust to occlusion
Works with less texture

More Repeatable

Robust detection
Precise localization

Description

More Robust

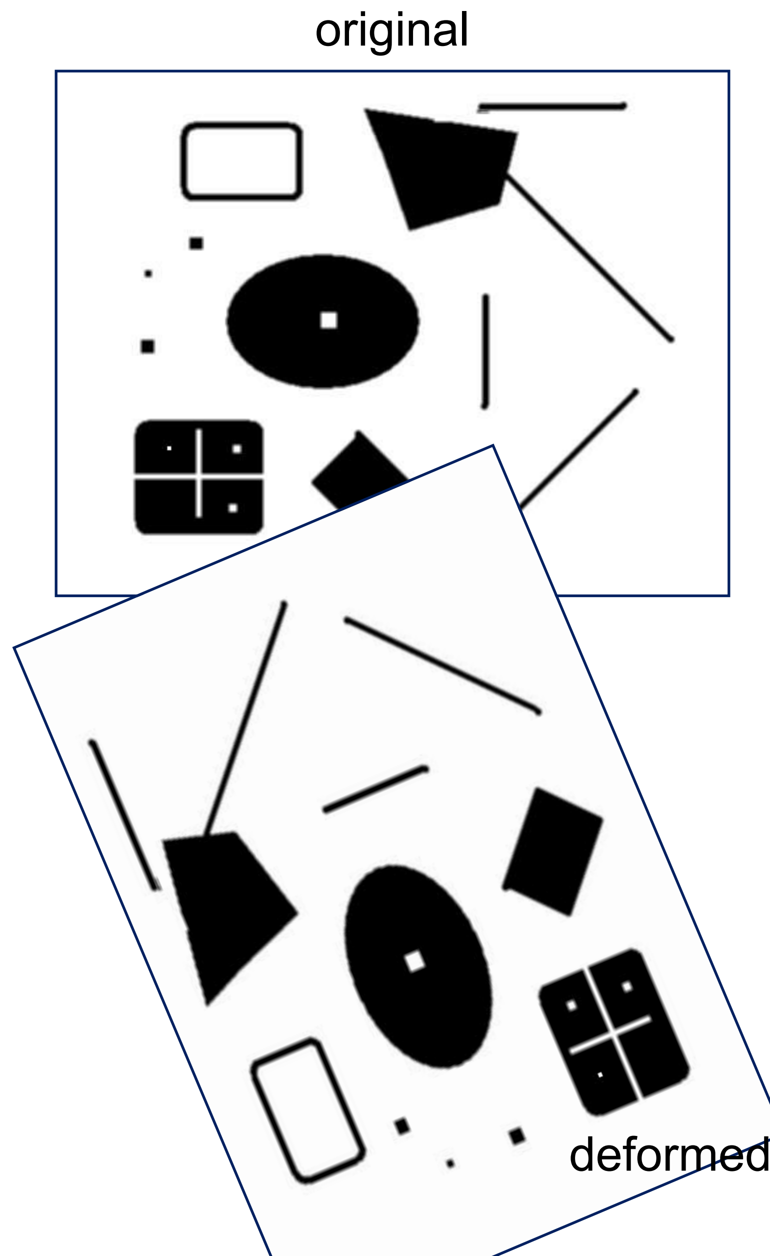
Deal with expected variations
Maximize correct matches

More Selective

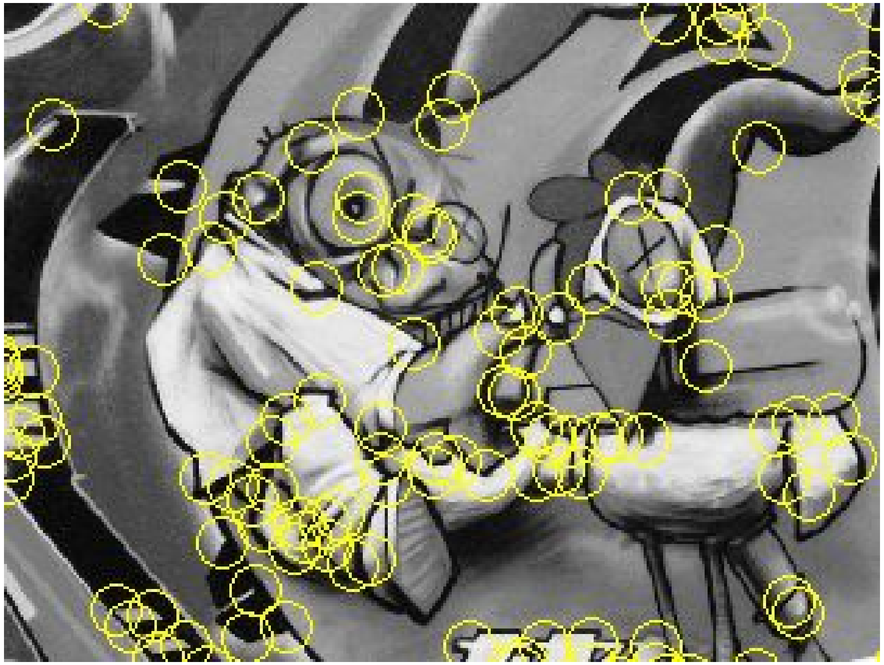
Minimize wrong matches

Keypoint localization

- Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again.
  - Which points would you choose?



Keypoint localization



- Goals:
  - Repeatable detection
  - Precise localization
  - Interesting content

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Choosing interest points

Where would you tell your friend to meet you?

Choosing interest points

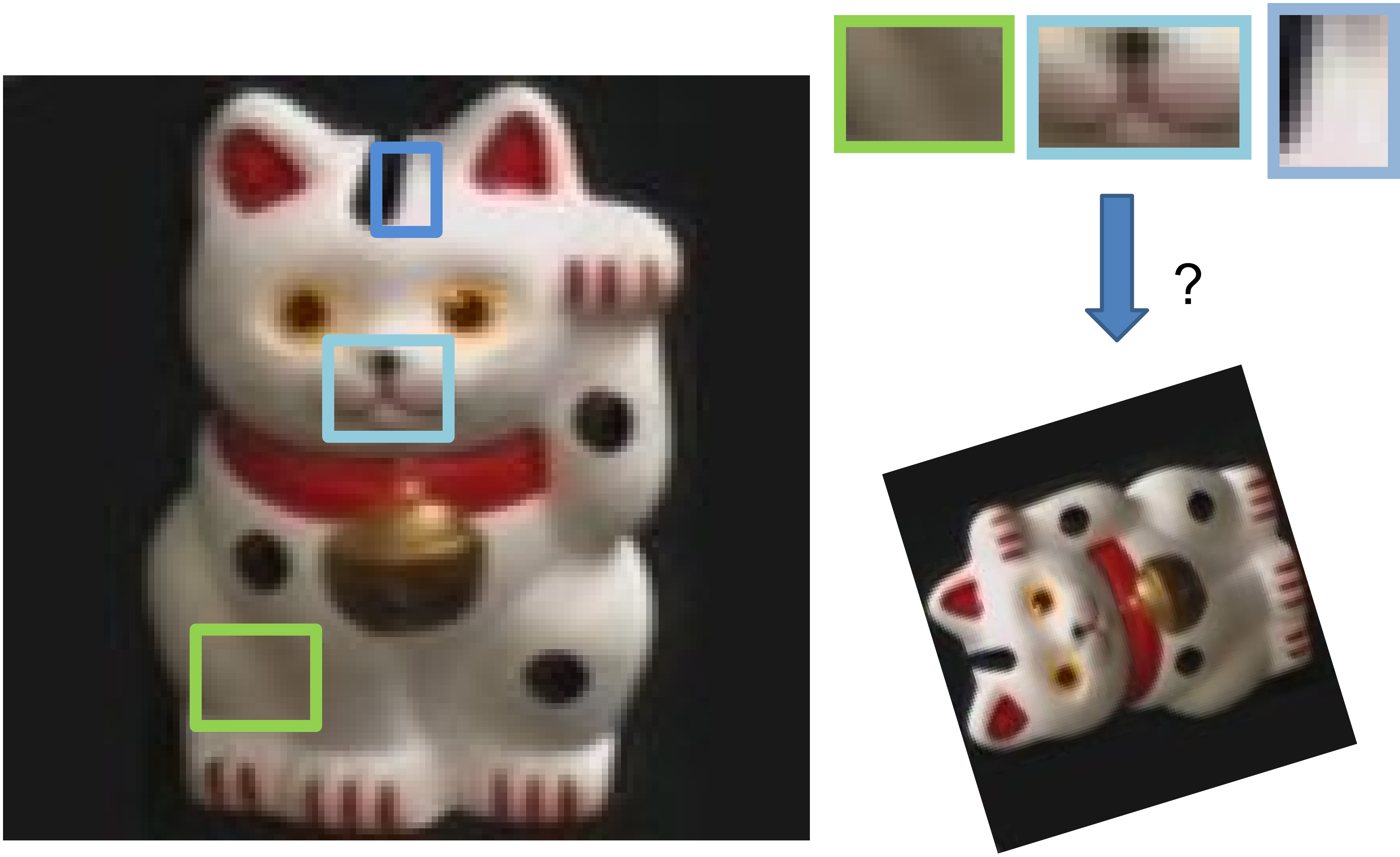
Where would you tell your friend to meet you?

Choosing interest points

- Corners

- Peaks/Valleys

Which patches are easier to match?



Choosing interest points

- If you wanted to meet a friend would you say
  a) "Let's meet on campus."
  b) "Let's meet on Green street."
  c) "Let's meet at Green and Wright."

- Or if you were in a secluded area:
  a) "Let's meet in the Plains of Akbar."
  b) "Let's meet on the side of Mt. Doom."
  c) "Let's meet on top of Mt. Doom."

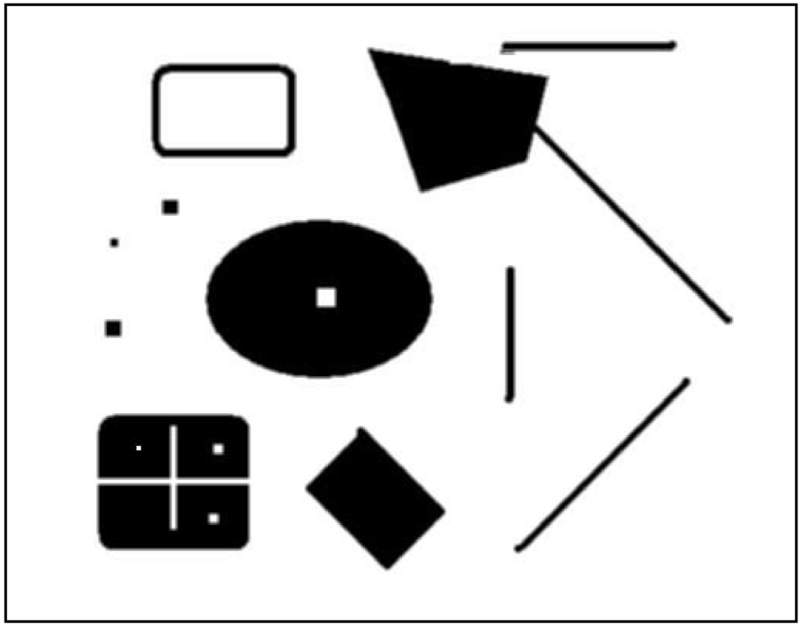
Many Existing Detectors Available

Hessian & Harris	[Beaudet ‘78], [Harris ‘88]
Laplacian, DoG	[Lindeberg ‘98], [Lowe 1999]
Harris-/Hessian-Laplace	[Mikolajczyk & Schmid ‘01]
Harris-/Hessian-Affine	[Mikolajczyk & Schmid ‘04]
EBR and IBR	[Tuytelaars & Van Gool ‘04]
MSER	[Matas ‘02]
Salient Regions	[Kadir & Brady ‘01]
Others…	

Harris Detector [Harris88]

Second moment matrix

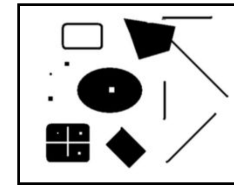
$$\mu(\sigma_I, \sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_x I_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$



Intuition: Search for local neighborhoods where the image gradient has two main directions (eigenvectors).

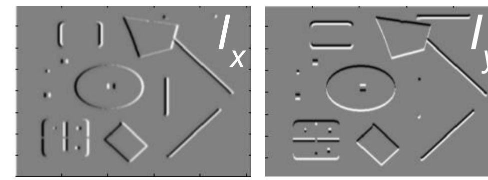
Harris Detector [Harris88]

Second moment matrix

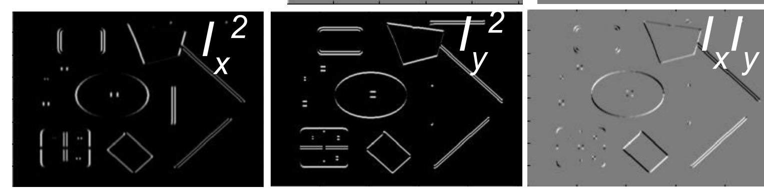


$$\mu(\sigma_I, \sigma_D) = g(\sigma_I) * \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_x I_y(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix}$$

1. Image derivatives

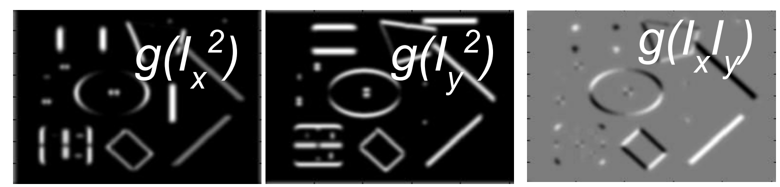


2. Square of derivatives



$$\det M = \lambda_1 \lambda_2$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

3. Gaussian filter $g(\sigma_I)$



4. Cornerness function – both eigenvalues are strong

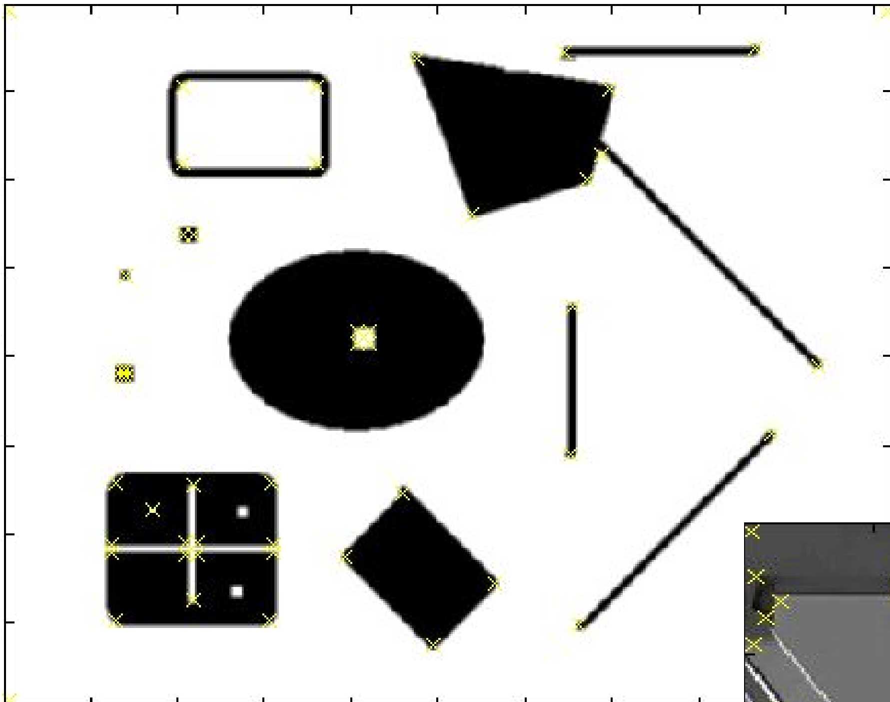
$$har = \det[\mu(\sigma_I, \sigma_D)] - \alpha[\operatorname{trace}(\mu(\sigma_I, \sigma_D))^2] =$$
$$g(I_x^2)g(I_y^2) - [g(I_x I_y)]^2 - \alpha[g(I_x^2) + g(I_y^2)]^2$$

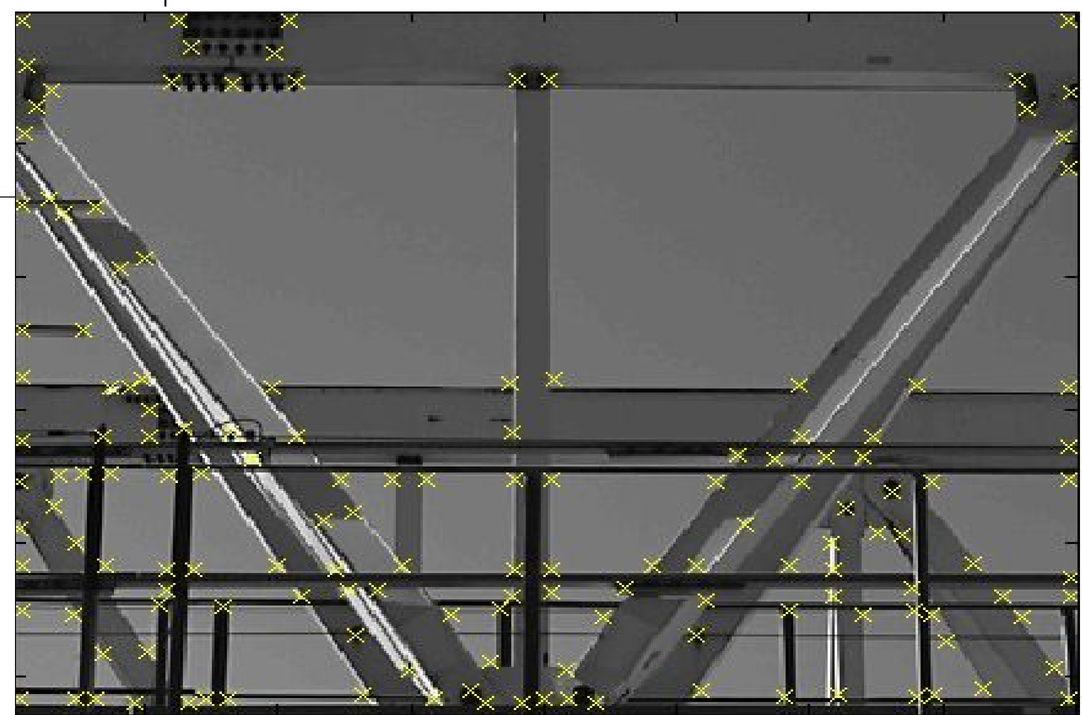
5. Non-maxima suppression

Matlab code for Harris Detector

```
function [ptx, pty] = detectKeypoints(im, alpha, N)

% get harris function
gfil = fspecial('gaussian', [7 7], 1); % smoothing filter
imblur = imfilter(im, gfil); % smooth image
[Ix, Iy] = gradient(imblur); % compute gradient
Ixx = imfilter(Ix.*Ix, gfil); % compute smoothed x-gradient sq
Iyy = imfilter(Iy.*Iy, gfil); % compute smoothed y-gradient sq
Ixy = imfilter(Ix.*Iy, gfil);
har = Ixx.*Iyy - Ixy.*Ixy - alpha*(Ixx+Iyy).^2; % cornerness

% get local maxima within 7x7 window
maxv = ordfilt2(har, 49, ones(7)); % sorts values in each window
maxv2 = ordfilt2(har, 48, ones(7));
ind = find(maxv==har & maxv~=maxv2);

% get top N points
[sv, sind] = sort(har(ind), 'descend');
sind = ind(sind);
[pty, ptx] = ind2sub(size(im), sind(1:min(N, numel(sind))));
```

Harris Detector – Responses [Harris88]



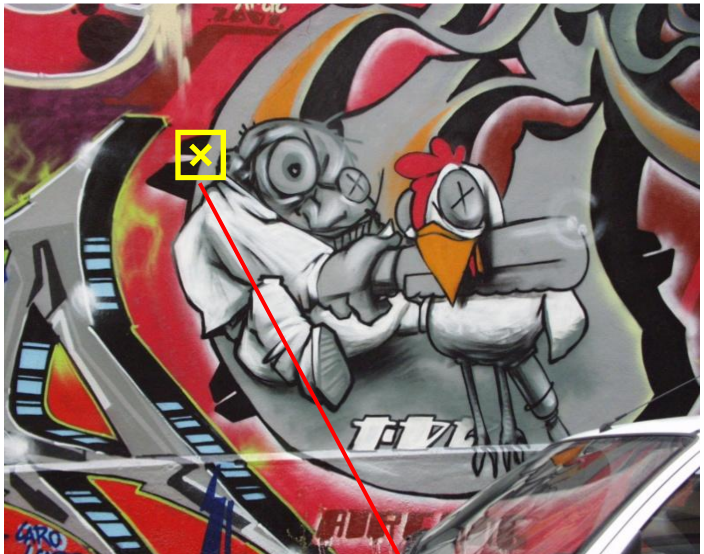


Effect: **A very precise corner detector.**

Harris Detector – Responses [Harris88]

So far: can localize in x-y, but not scale

Automatic Scale Selection



$$f(I_{i_1 \ldots i_m}(x,\sigma)) = f(I_{i_1 \ldots i_m}(x',\sigma'))$$

How to find corresponding patch sizes?

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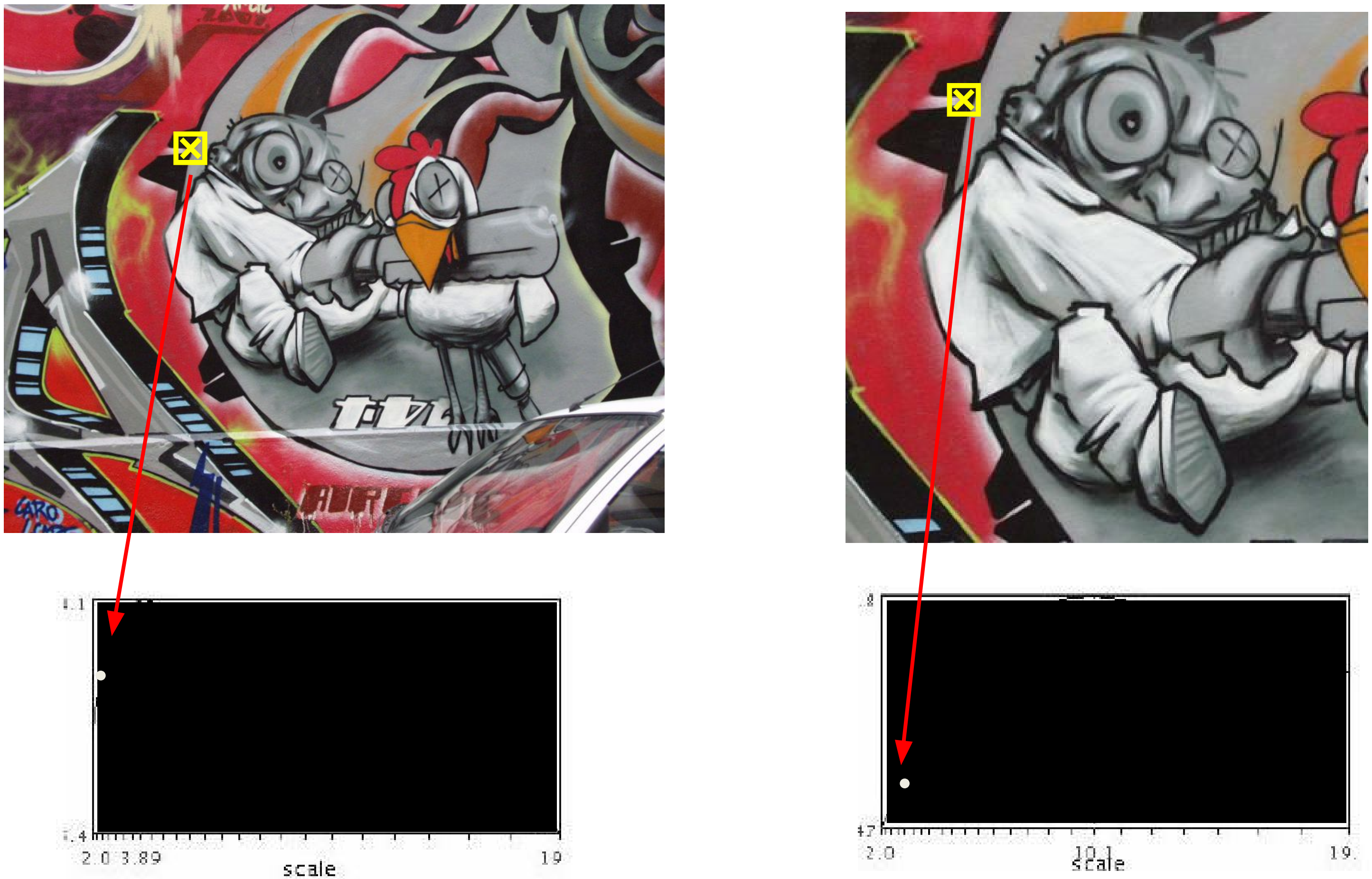
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x,\sigma))$ $f(I_{i_1 \dots i_m}(x',\sigma))$

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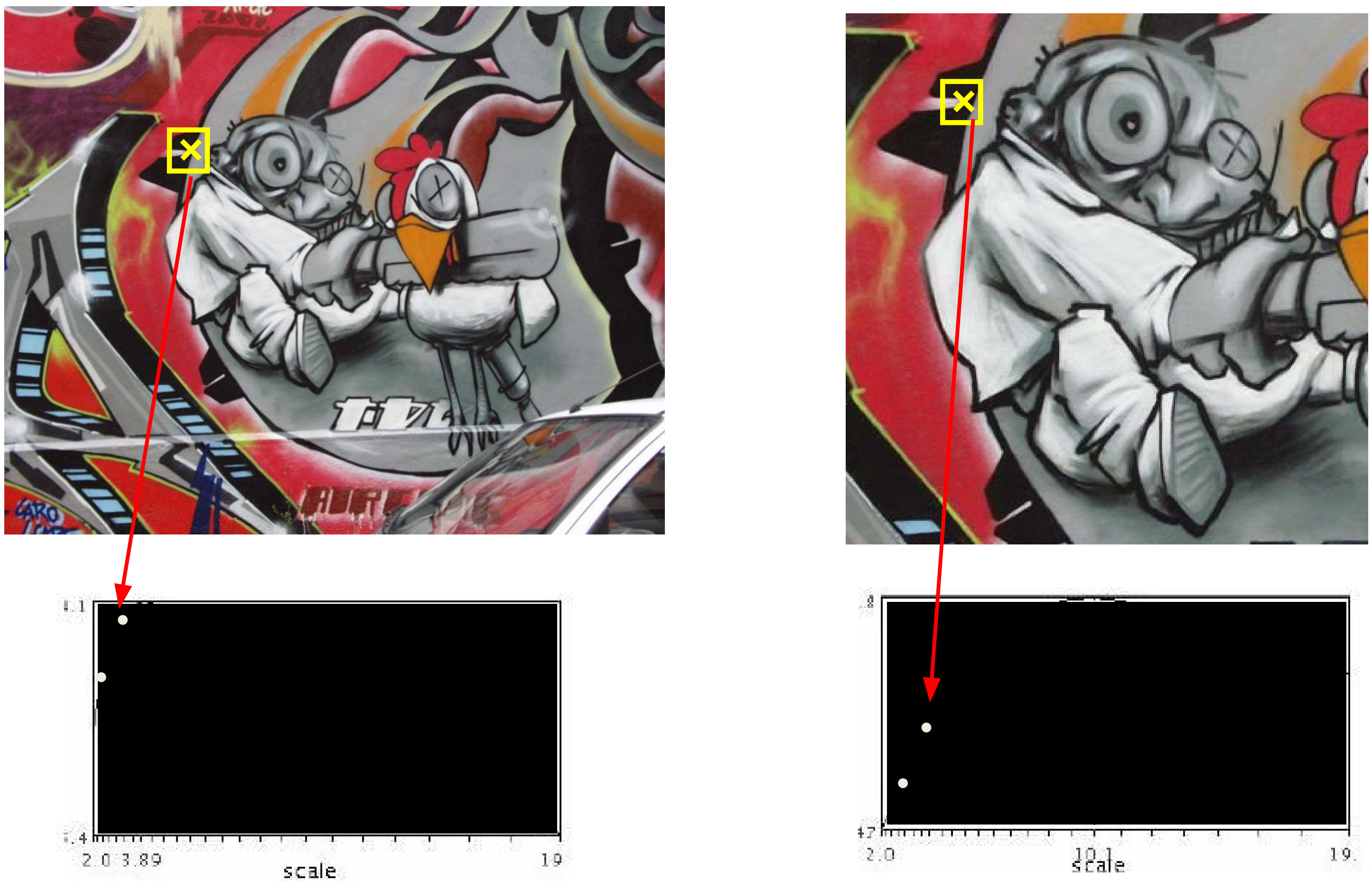
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x,\sigma))$ $f(I_{i_1 \dots i_m}(x',\sigma))$

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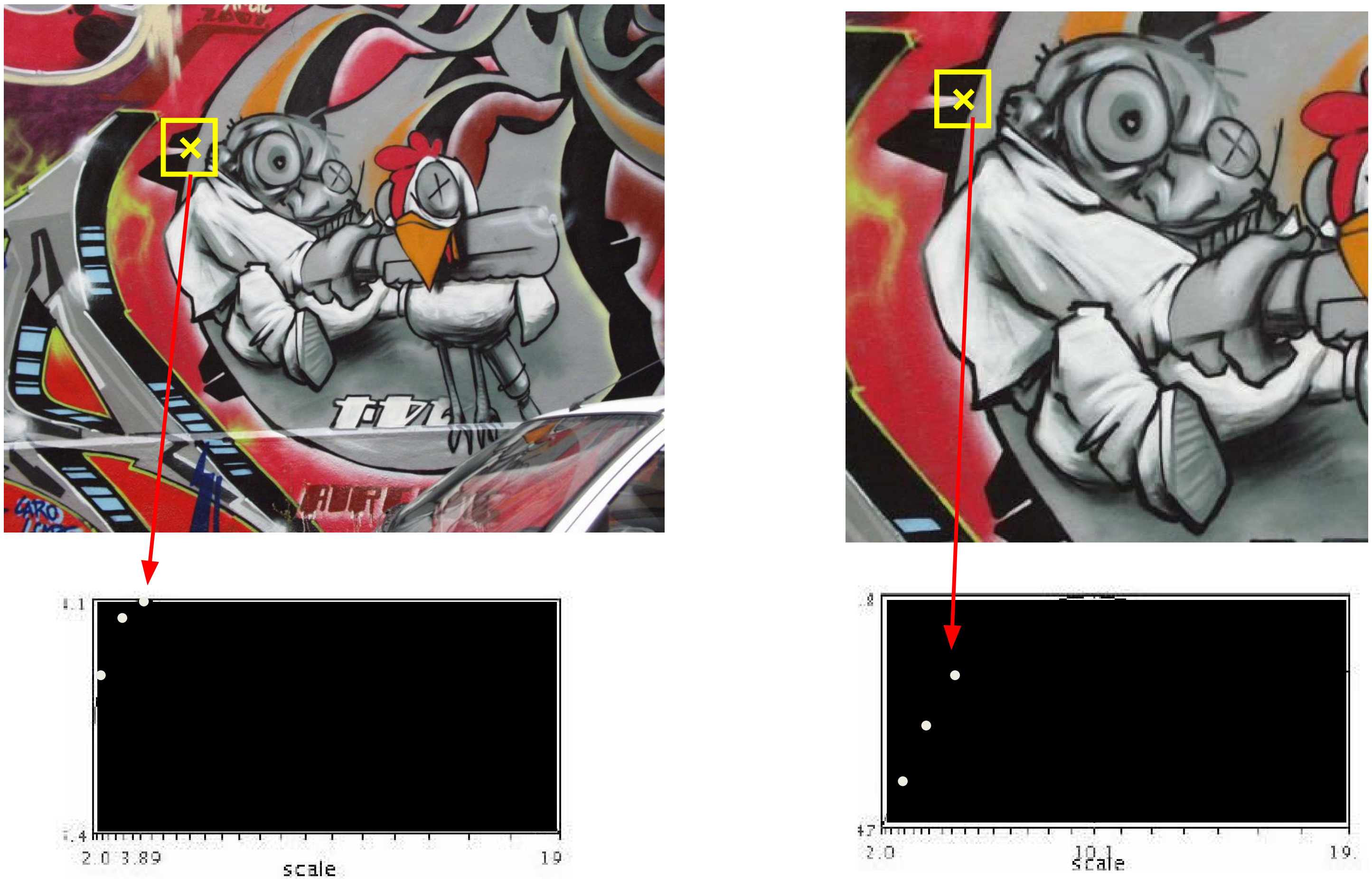
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x,\sigma))$ $\quad$ $f(I_{i_1 \dots i_m}(x',\sigma))$

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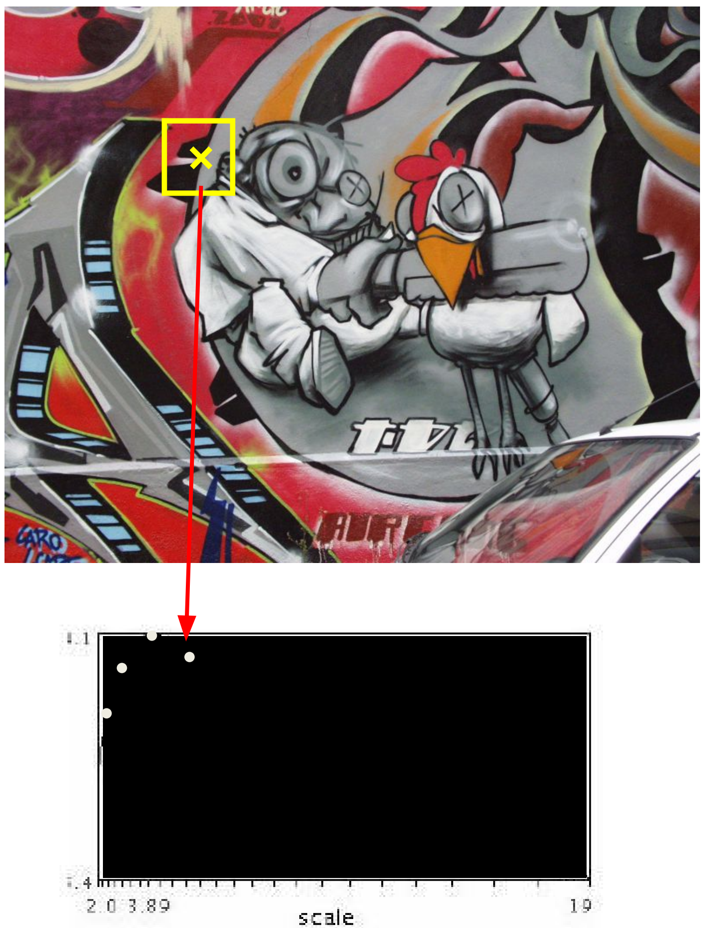
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x,\sigma))$

$f(I_{i_1 \ldots i_m}(x',\sigma))$

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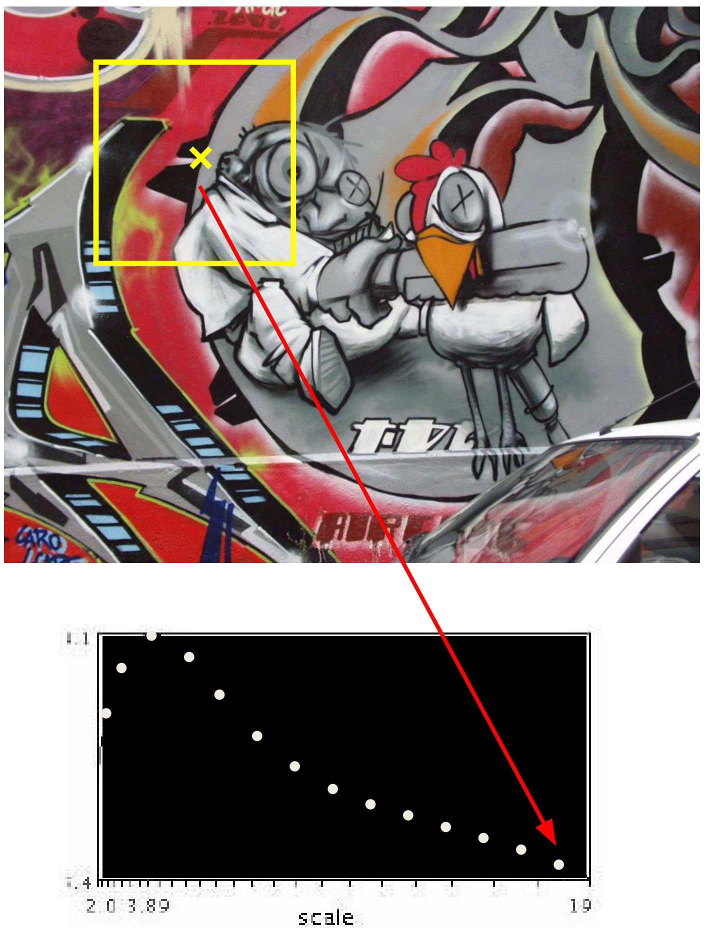
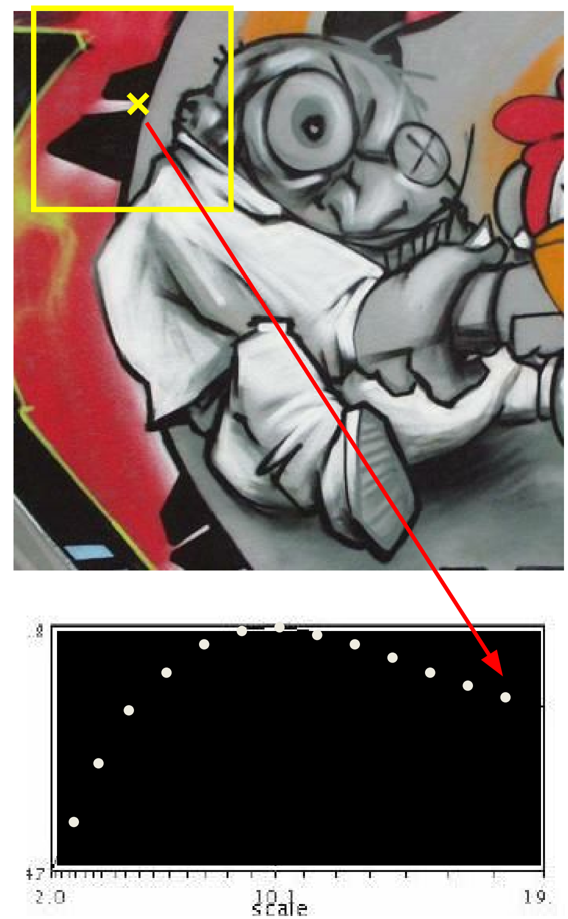
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x,\sigma))$



$f(I_{i_1 \ldots i_m}(x',\sigma))$

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Automatic Scale Selection

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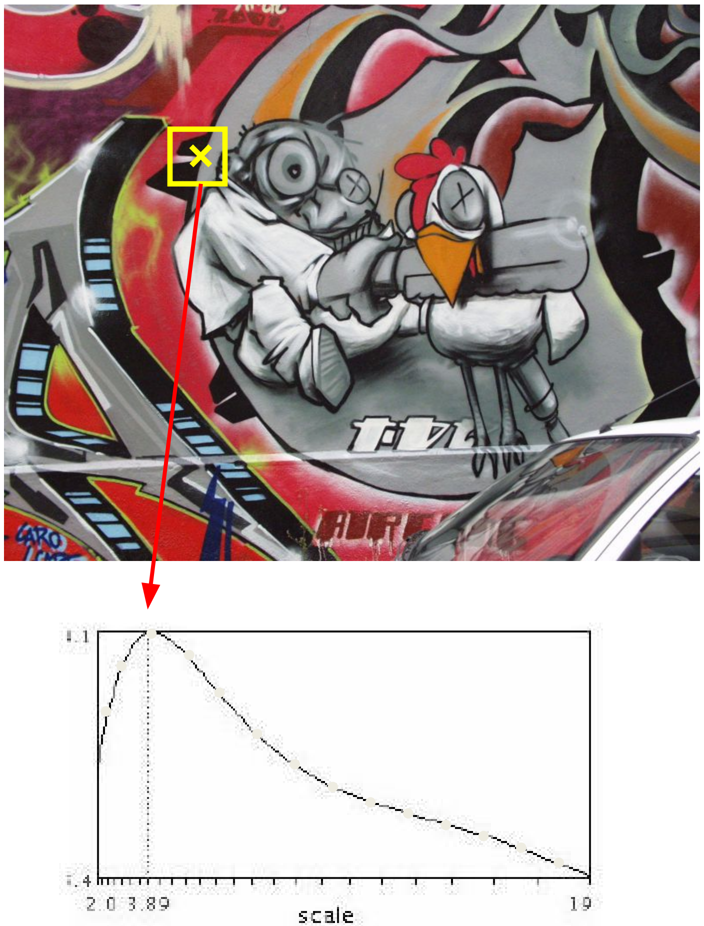
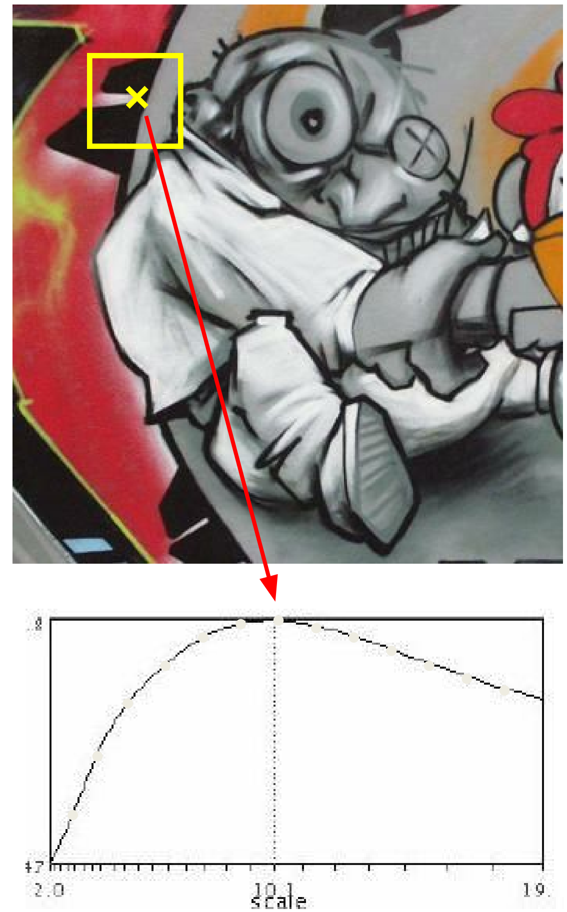


$$f(I_{i_1 \ldots i_m}(x,\sigma))$$



$$f(I_{i_1 \ldots i_m}(x',\sigma'))$$

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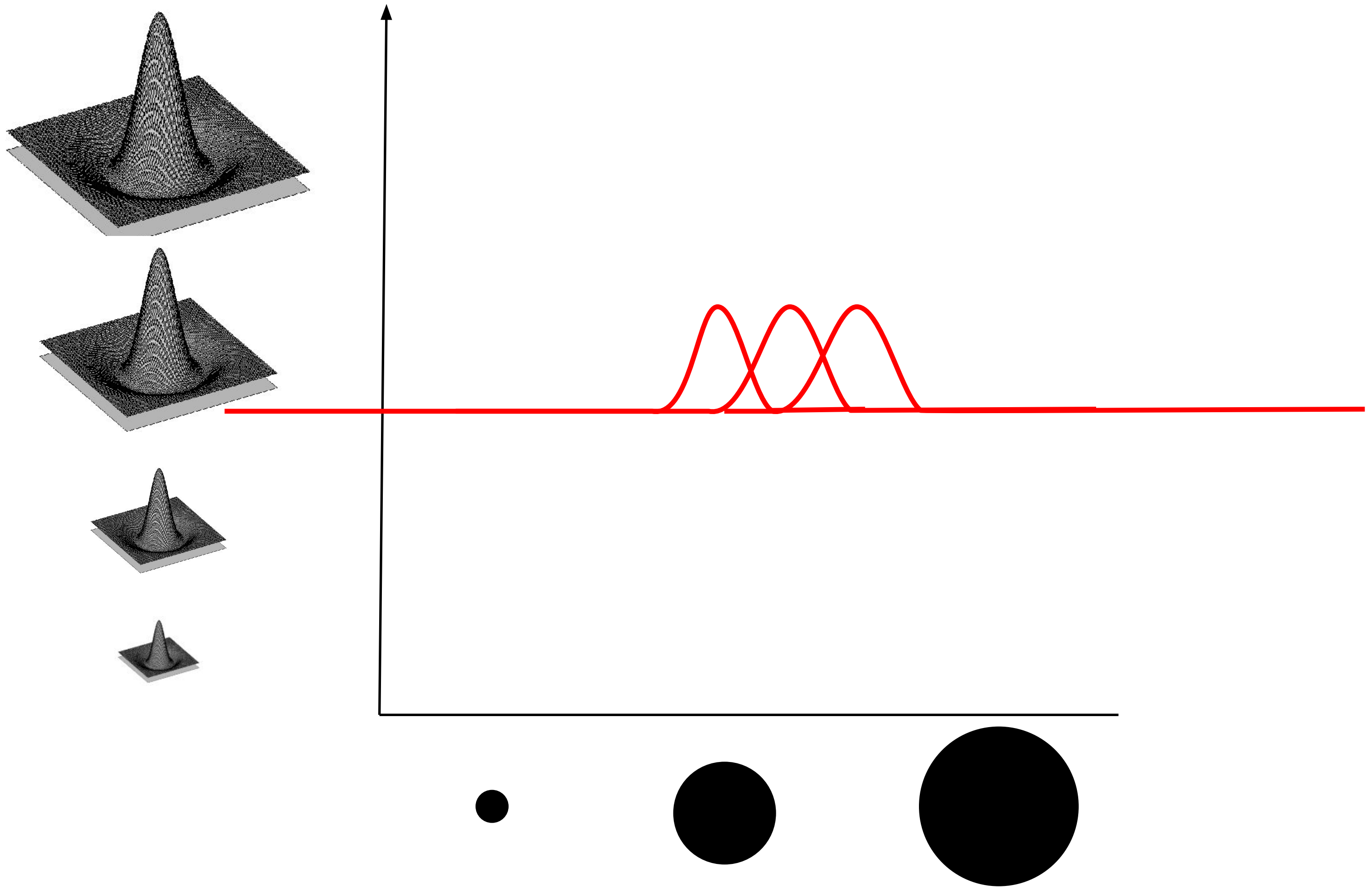
What Is A Useful Signature Function?

- Difference of Gaussian = "blob" detector



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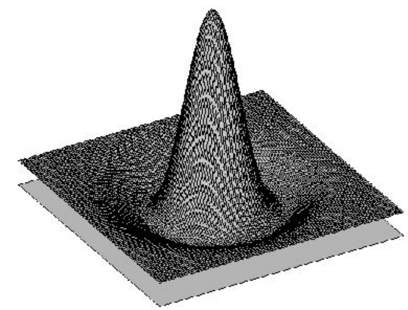
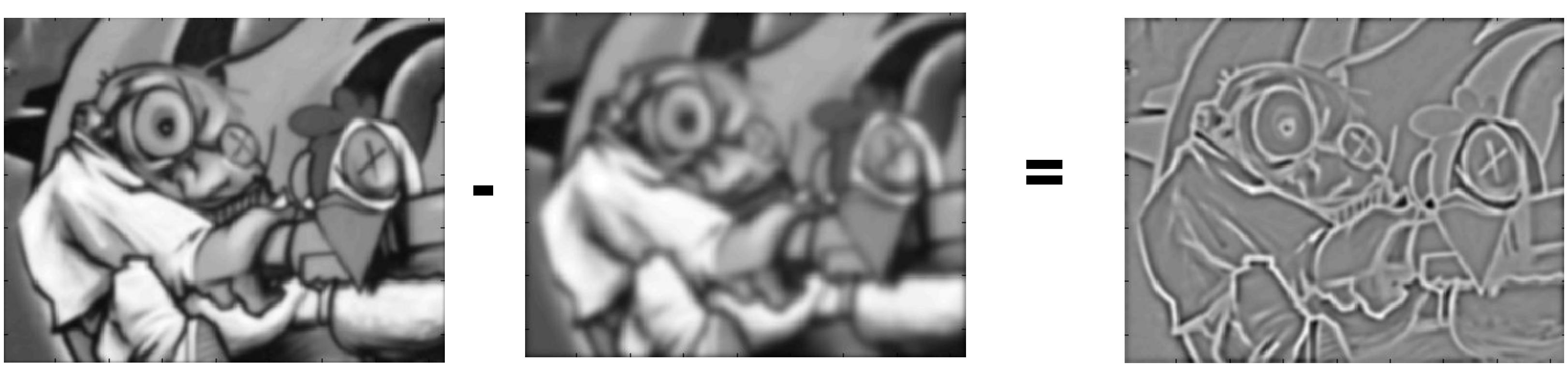
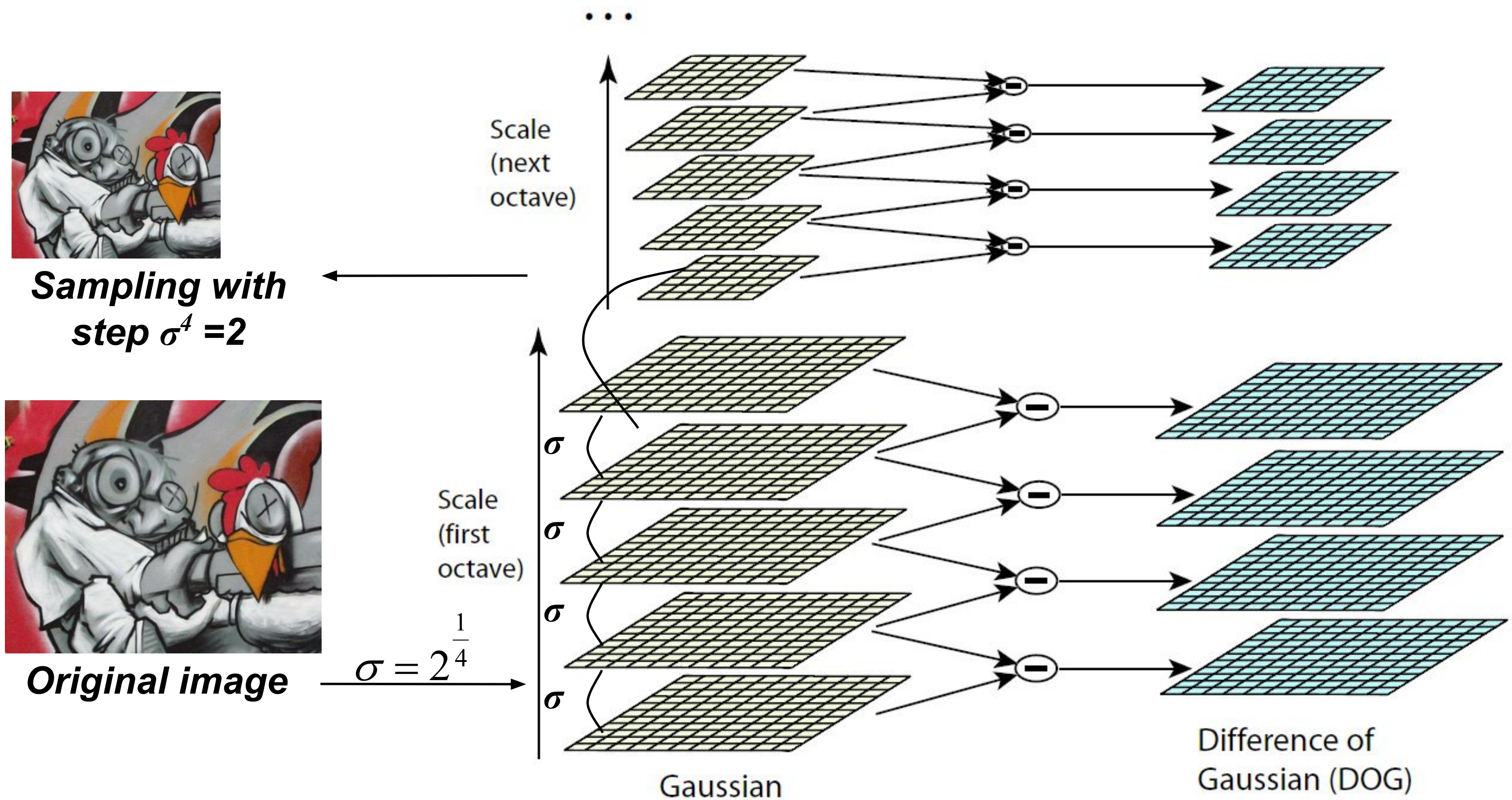
Difference-of-Gaussian (DoG)





DoG – Efficient Computation

- Computation in Gaussian scale pyramid



Results: Lowe's DoG

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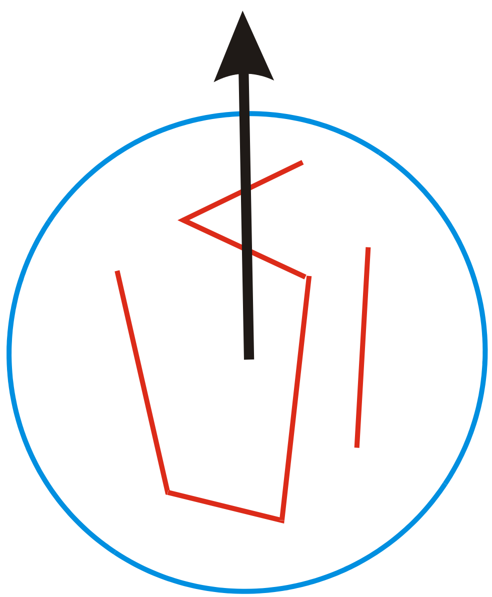
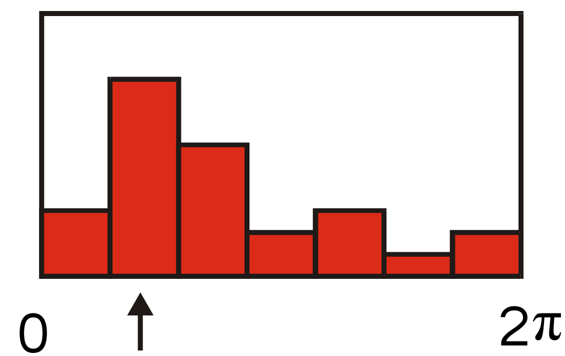
Orientation Normalization

- Compute orientation histogram
- Select dominant orientation
- Normalize: rotate to fixed orientation

[Lowe, SIFT, 1999]





Available at a web site near you…

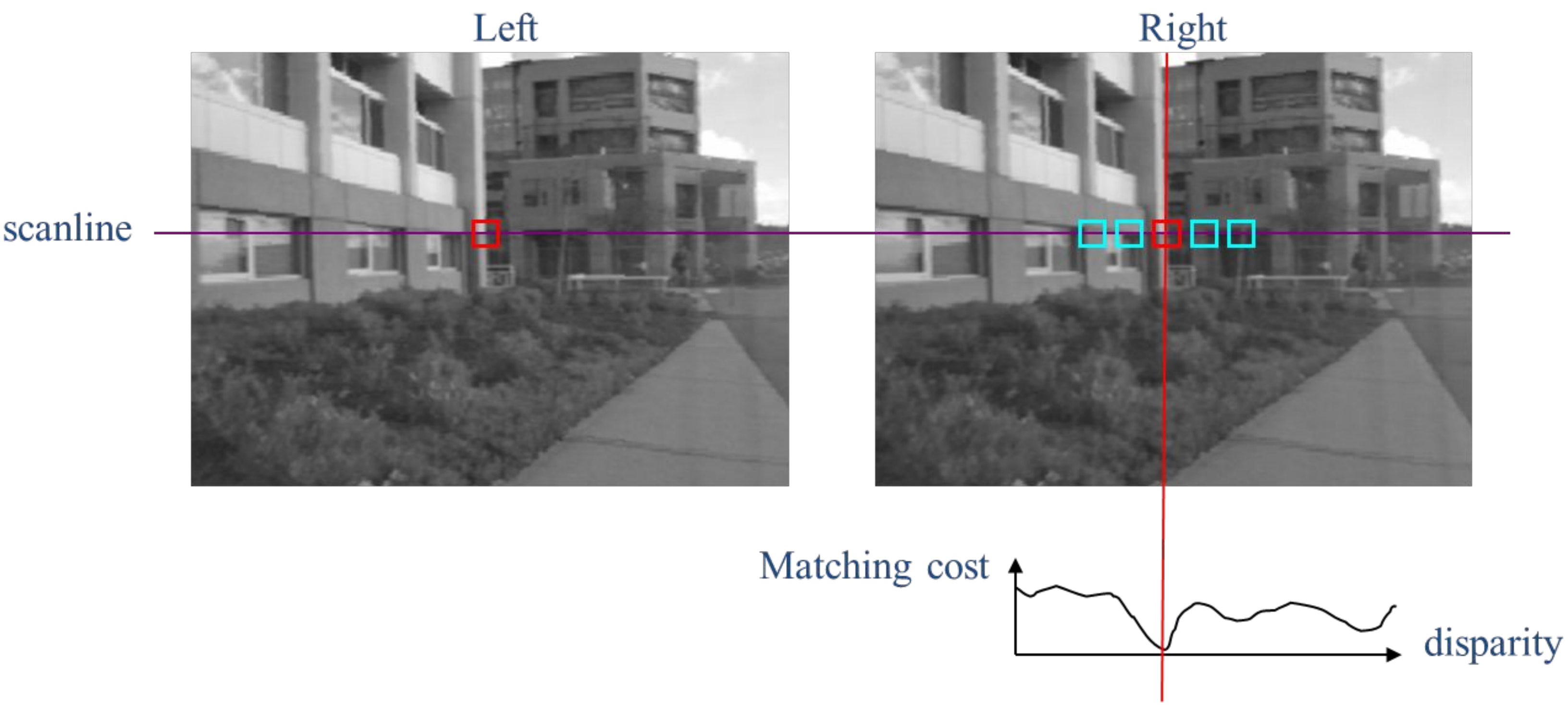
- For most local feature detectors, executables are available online:
  - http://robots.ox.ac.uk/~vgg/research/affine
  - http://www.cs.ubc.ca/~lowe/keypoints/
  - http://www.vision.ee.ethz.ch/~surf

How do we describe the keypoint?

Descriptors for local matching

- Image patch (plain intensities or gradient-based features)

Example of patch-based matching for stereo



Local descriptors for matching different views/times

- The ideal descriptor should be
  - Robust to expected deformation
  - Distinctive
  - Compact
  - Efficient to compute

- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color rarely used

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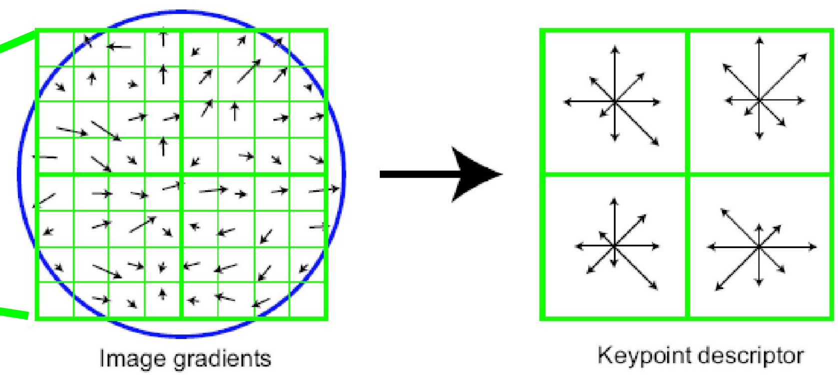
Local Descriptors: SIFT Descriptor



Histogram of oriented gradients

- **Captures important texture information**
- **Robust to small translations / affine deformations**

[Lowe, ICCV 1999]

Details of Lowe's SIFT algorithm

- Run DoG detector
  - Find maxima in location/scale space
  - Remove edge points
- Find all major orientations
  - Bin orientations into 36 bin histogram
    - Weight by gradient magnitude
    - Weight by distance to center (Gaussian-weighted mean)
  - Return orientations within 0.8 of peak
    - Use parabola for better orientation fit
- For each (x,y,scale,orientation), create descriptor:
  - Sample 16x16 gradient mag. and rel. orientation
  - Bin 4x4 samples into 4x4 histograms
  - Threshold values to max of 0.2, divide by L2 norm
  - Final descriptor: 4x4x8 normalized histograms

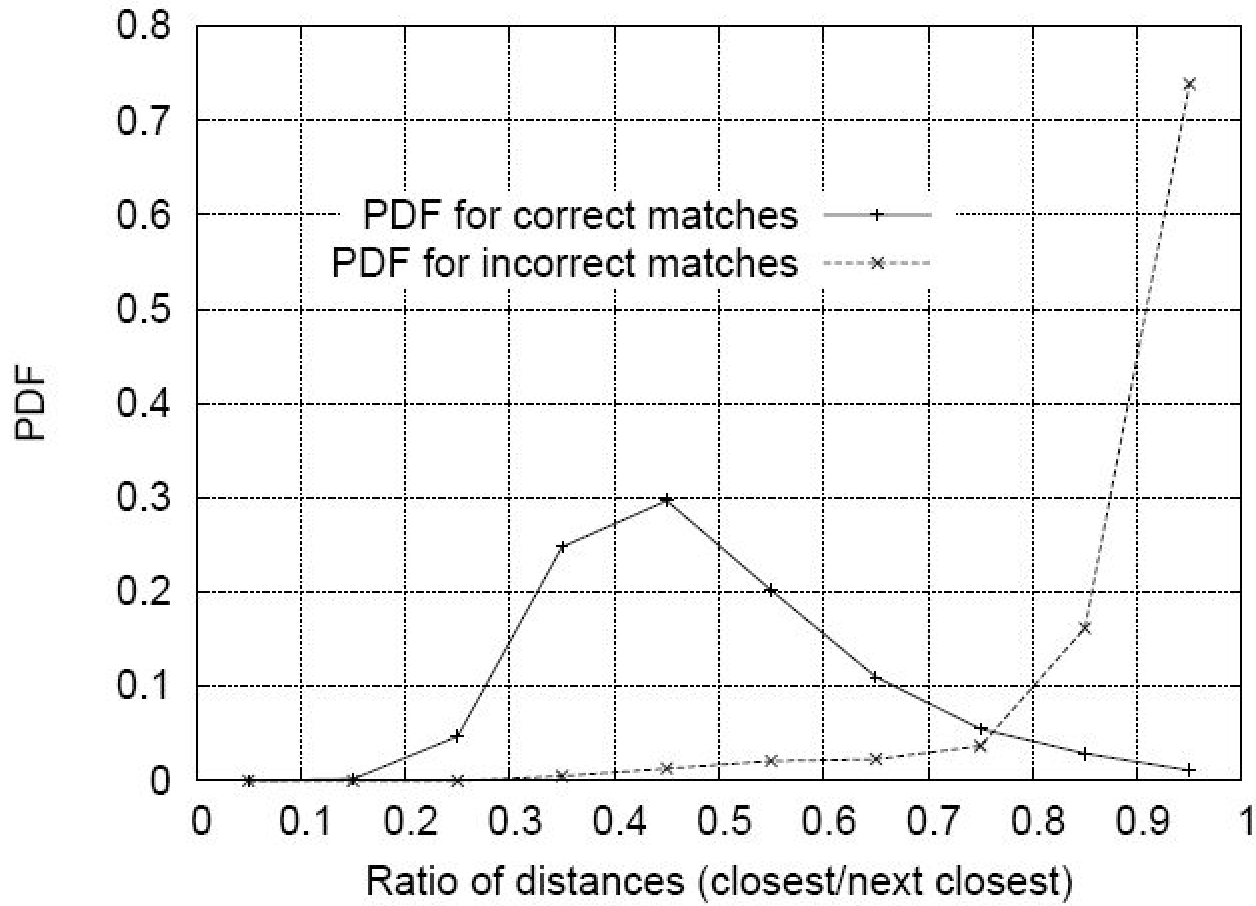
$$\mathrm{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

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

Lowe IJCV 2004

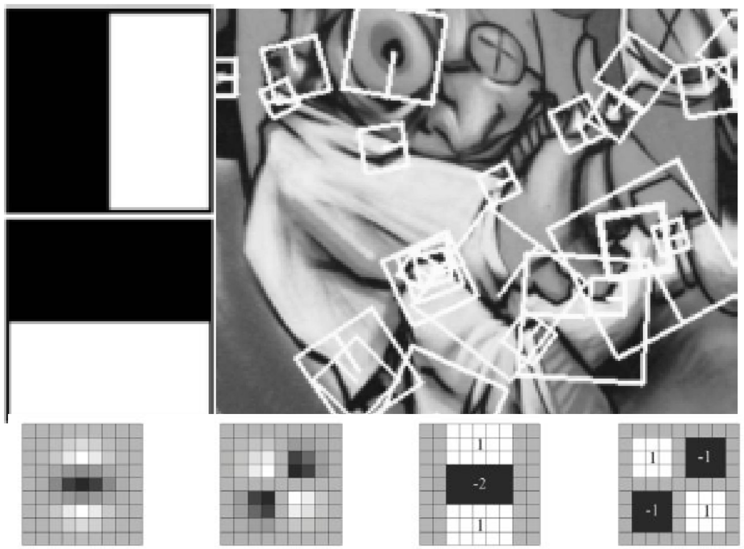
Matching SIFT Descriptors

- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



Lowe IJCV 2004

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]

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What to use when?

Detectors

- Harris gives very precise localization but doesn’t predict scale
  - Good for some tracking applications
- DOG (difference of Gaussian) provides ok localization and scale
  - Good for multi-scale or long-range matching

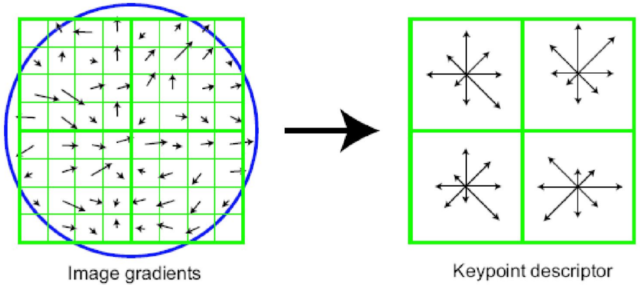
Descriptors

- Intensity patch: suitable for precise local search
- SIFT: good for long-range matching, general descriptor

Things to remember

- Keypoint detection: repeatable and distinctive
  - Corners, blobs
  - Harris, DoG

- Descriptors: robust and selective
  - SIFT: spatial histograms of gradient orientation



Next time: Panoramic Stitching