Today

Early vision on a single image

- Features

Announcement

Homework #3 has been posted in Blackboard.

Due on 1:15pm EST, Tuesday, March 4.

Orientation Representations

The gradient magnitude is affected by illumination changes

- but its direction isn't

We can describe image patches by the swing of the gradient orientation

Important types:

- constant window
  - small gradient magnitudes
- edge window
  - few large gradient mags in one direction
- flow window
  - many large gradient mags in one direction
- corner window
  - large gradient magnitudes that swing

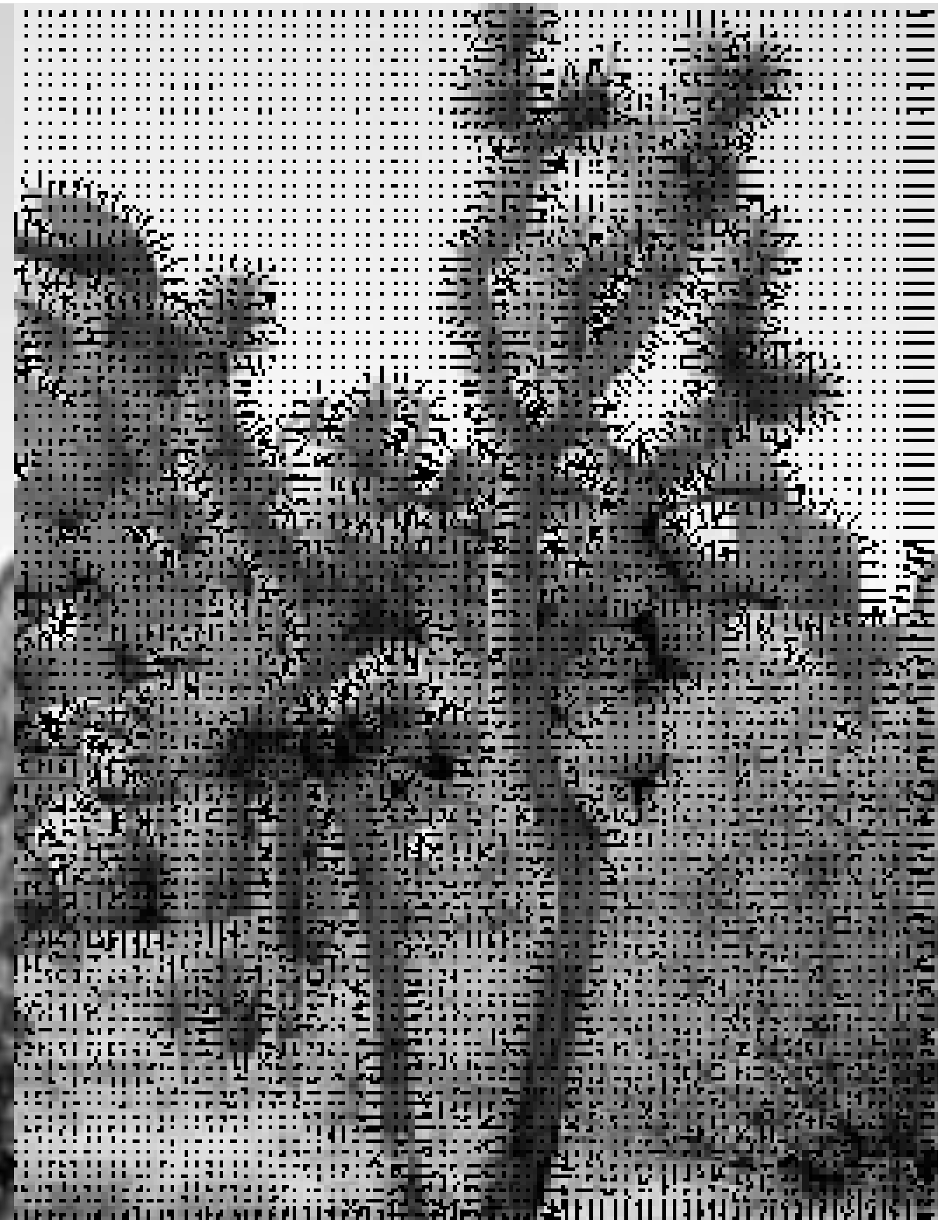
Representing Windows

Four Types

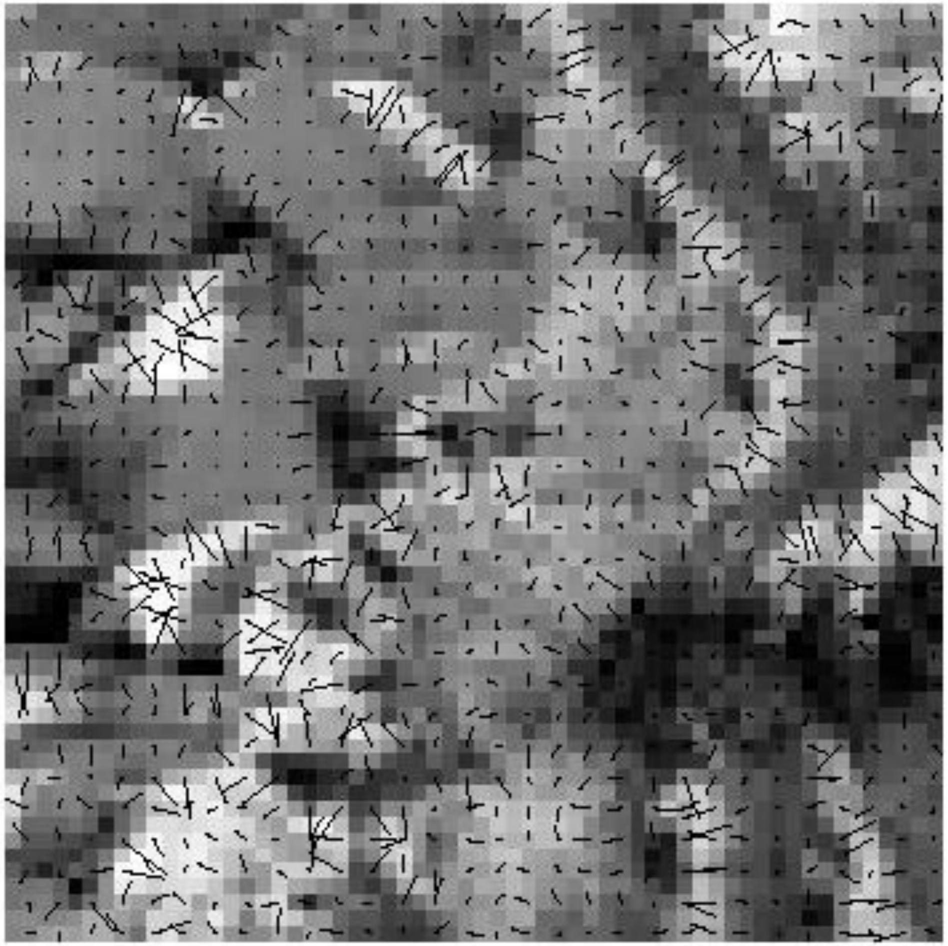
- constant
  - small eigenvalues
- Edge
  - one medium, one small
- Flow
  - one large, one small
- corner
  - two large eigenvalues

$$H = \sum_{window} (\nabla I)(\nabla I)^T$$

$$= \sum_{window} \begin{Bmatrix} \left(\frac{\partial G_\sigma}{\partial x} \otimes I\right)\left(\frac{\partial G_\sigma}{\partial x} \otimes I\right) & \left(\frac{\partial G_\sigma}{\partial x} \otimes I\right)\left(\frac{\partial G_\sigma}{\partial y} \otimes I\right) \\ \left(\frac{\partial G_\sigma}{\partial x} \otimes I\right)\left(\frac{\partial G_\sigma}{\partial y} \otimes I\right) & \left(\frac{\partial G_\sigma}{\partial y} \otimes I\right)\left(\frac{\partial G_\sigma}{\partial y} \otimes I\right) \end{Bmatrix}$$



Details



From Edges to Boundary

Object boundary is a closed curve

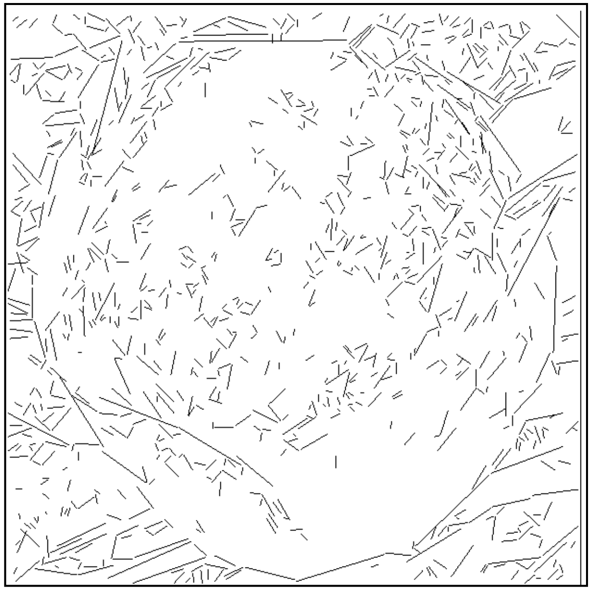
The detected edges are just segments of boundaries. They are not connected

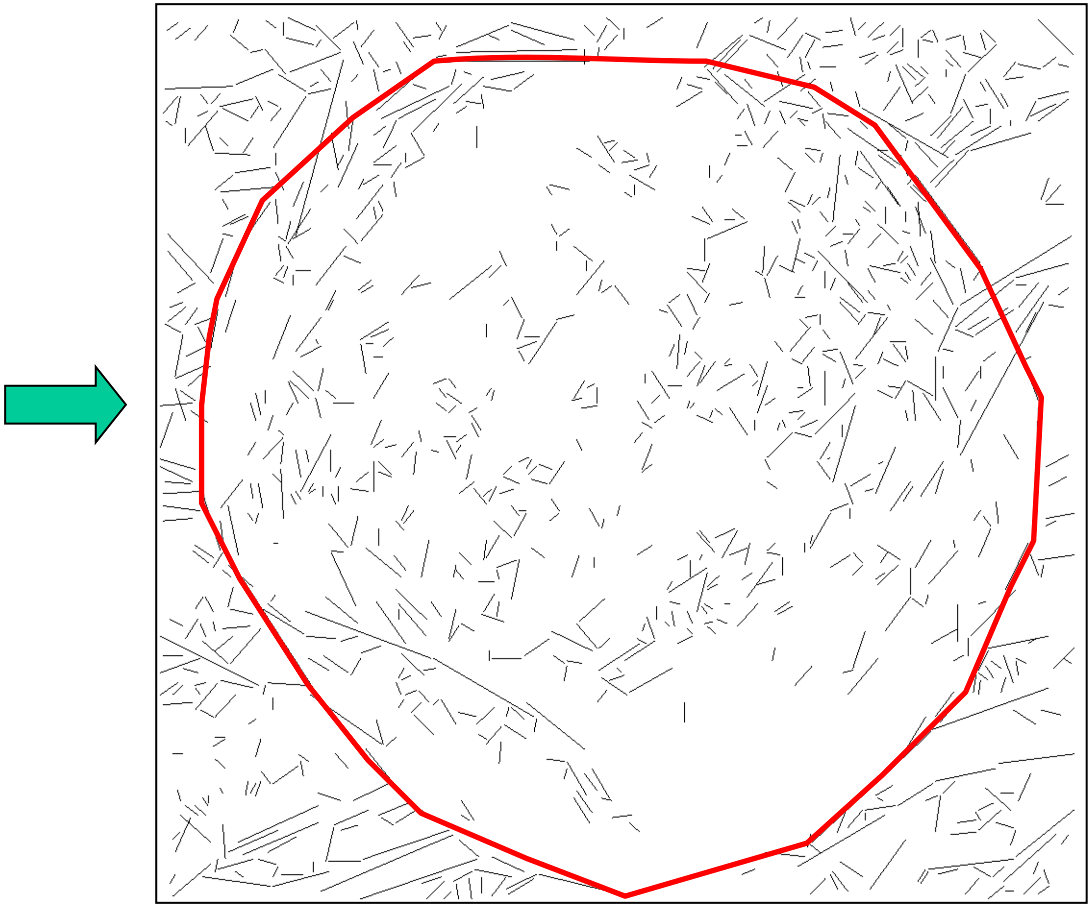
Edges may also come from noise

How to find the full object boundary from edge-detection output?

Edge-linking, edge-grouping, …

Brainstorm: How to Formulate and Solve this Problem?





Suggested Reading

S. Wang, T. Kubota, J. M. Siskind, J. Wang. Salient Closed Boundary Extraction with Ratio Contour, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 27(4):546-561, 2005

http://www.cse.sc.edu/~songwang/document/pami05.pdf

Corner Detection

Corners are important 2D geometrical features

- Applications in matching images, representing textures, representing objects

Corners are located in a region with large intensity variations

Good corners:

- High contrast ⟹ Large gradients
- Change direction sharply ⟹ Gradient direction changes

Corner detection procedure:

- Localize centers
- At each center, estimate scale, and then orientation

Corner Detection: Harris Corner Detector

Build a matrix for a point *p* in its neighborhood

$$G_x = \frac{\partial G_\sigma}{\partial x} \otimes I$$

$$H = \begin{bmatrix} \sum_{N(p)} G_x^2 & \sum_{N(p)} G_x G_y \\ \sum_{N(p)} G_x G_y & \sum_{N(p)} G_y^2 \end{bmatrix}$$

λ_1 **and** λ_2 **are two eigenvalues of *H***

If $\min(\lambda_1, \lambda_2) > threshold$ **, the point *p* is a corner**

How about one or both eigenvalues are zero?

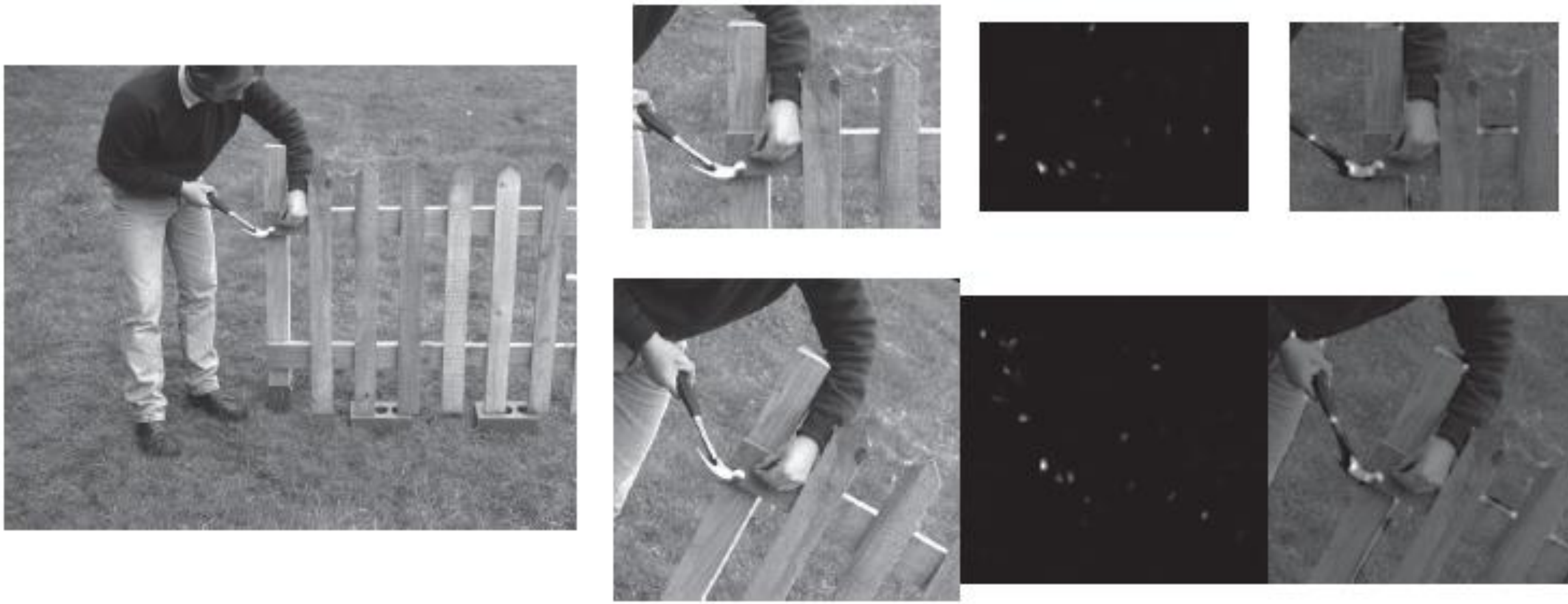
In practice, look for big values of

$$\det(\mathcal{H}) - k\left(\frac{\mathrm{trace}(\mathcal{H})}{2}\right)^2 \longrightarrow$$

Don't need eigenvalue decomposition

$$\det(H) = \lambda_1 \lambda_2 \qquad \mathrm{trace}(H) = \lambda_1 + \lambda_2$$

Examples



Invariant to scaling and rotation

Desired Feature Properties

Invariant to

- Translation, rotation, scale, illumination

Why? Robust matching or interest point detection in real world

SIFT Feature

Scale Invariant Feature Transform (SIFT)

- Invariant to uniform scaling and orientation
- Partially invariant to affine transformation and illumination changes

Algorithm overview

- Scale-space extrema detection
- Keypoint localization
- Keypoint descriptor

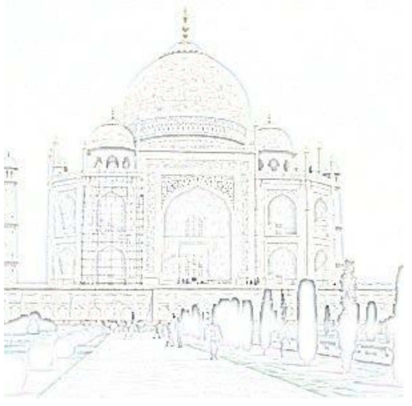
Scale-space Extrema Detection

Observations: features are scale-invariant if they appear in the feature maps at different scales

Scale-space is defined based on Difference of Gaussians (DoG)

$$H_{DOG}(x,y) = \frac{1}{2\pi\sigma_1^2} e^{-\frac{x^2+y^2}{2\sigma_1^2}} - \frac{1}{2\pi\sigma_2^2} e^{-\frac{x^2+y^2}{2\sigma_2^2}}, \quad \sigma_1 > \sigma_2$$

$$\Rightarrow \quad D(x,y) = I_{in} \otimes H_{DoG} = I_{in} \otimes G_1 - I_{in} \otimes G_2$$



Figures from http://gimp.open-source-solution.org/manual/plug-in-dog.html

Scale Space

Generate a Gaussian pyramid by down sampling the images and keep convolving them with a Gaussian kernel

For the first level

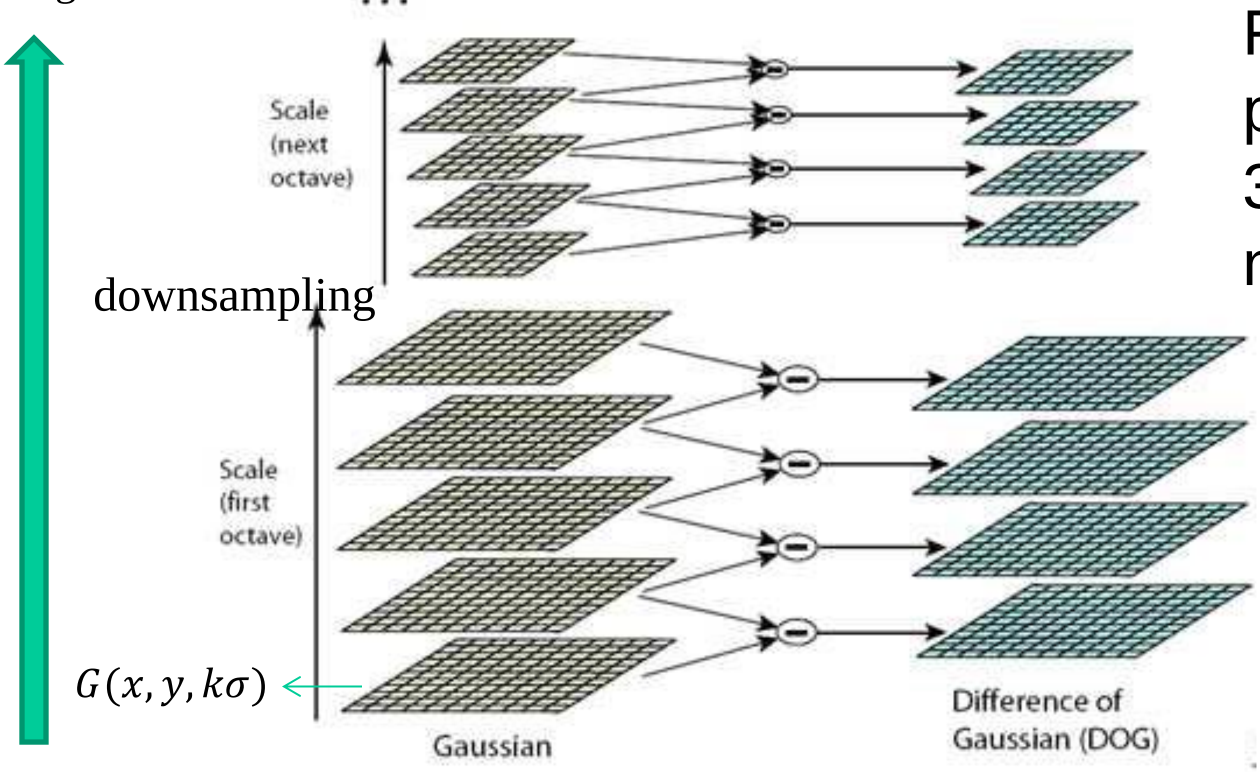
$$I_{L0}(x, y) = I_{orig}$$

For the other levels

$$I_{L_i}(x, y) = \sum_{u=-s}^{s} \sum_{v=-s}^{s} w(u, v) I_{L_{i-1}}(2x + u, 2y + v)$$

Extreme Point Detection in Scale-space

increasing σ for Gaussian filter



Lowe IJCV 2004

Find extreme points in 3x3x3 3D DoG neighborhood

Result in excessive interest points

Keypoint Localization

- **Obtain sub-pixel accuracy for keypoint localization**

$$\Delta\mathbf{x} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}} \qquad\qquad \mathbf{x} = [x, y, \sigma]^T$$

- **Eliminating extreme points with low contrast**
  - the interest point should be different from its neighbors
  - eliminate the point if the value at subpixel location is smaller than a threshold
- **Eliminating edge responses with poor localization ability**
  - The points along the edges are not robust for localization

Keypoint Localization

- **Eliminating edge responses with poor localization ability**

Hessian matrix $\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$

$$r = \frac{\lambda_1}{\lambda_2}$$

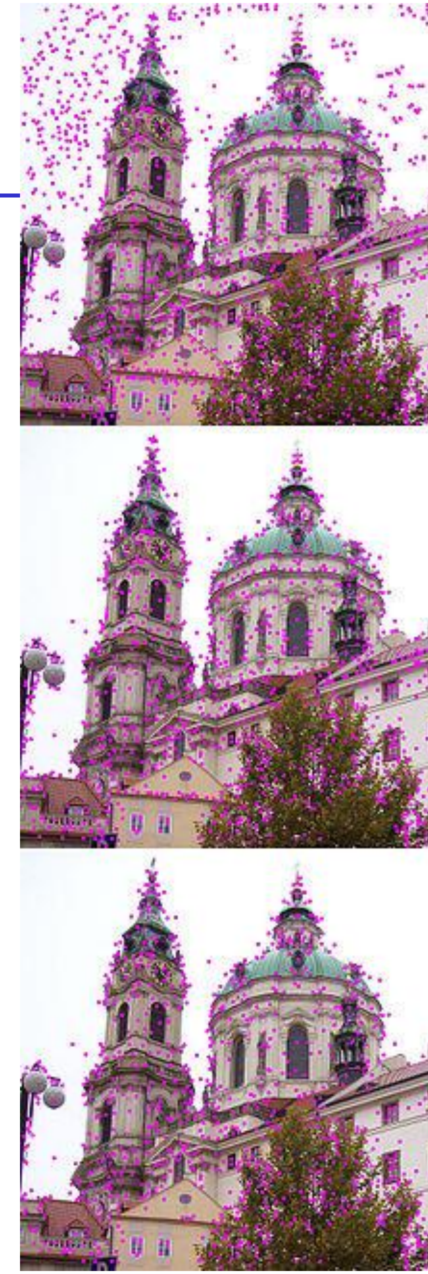
The larger eigenvalue of H

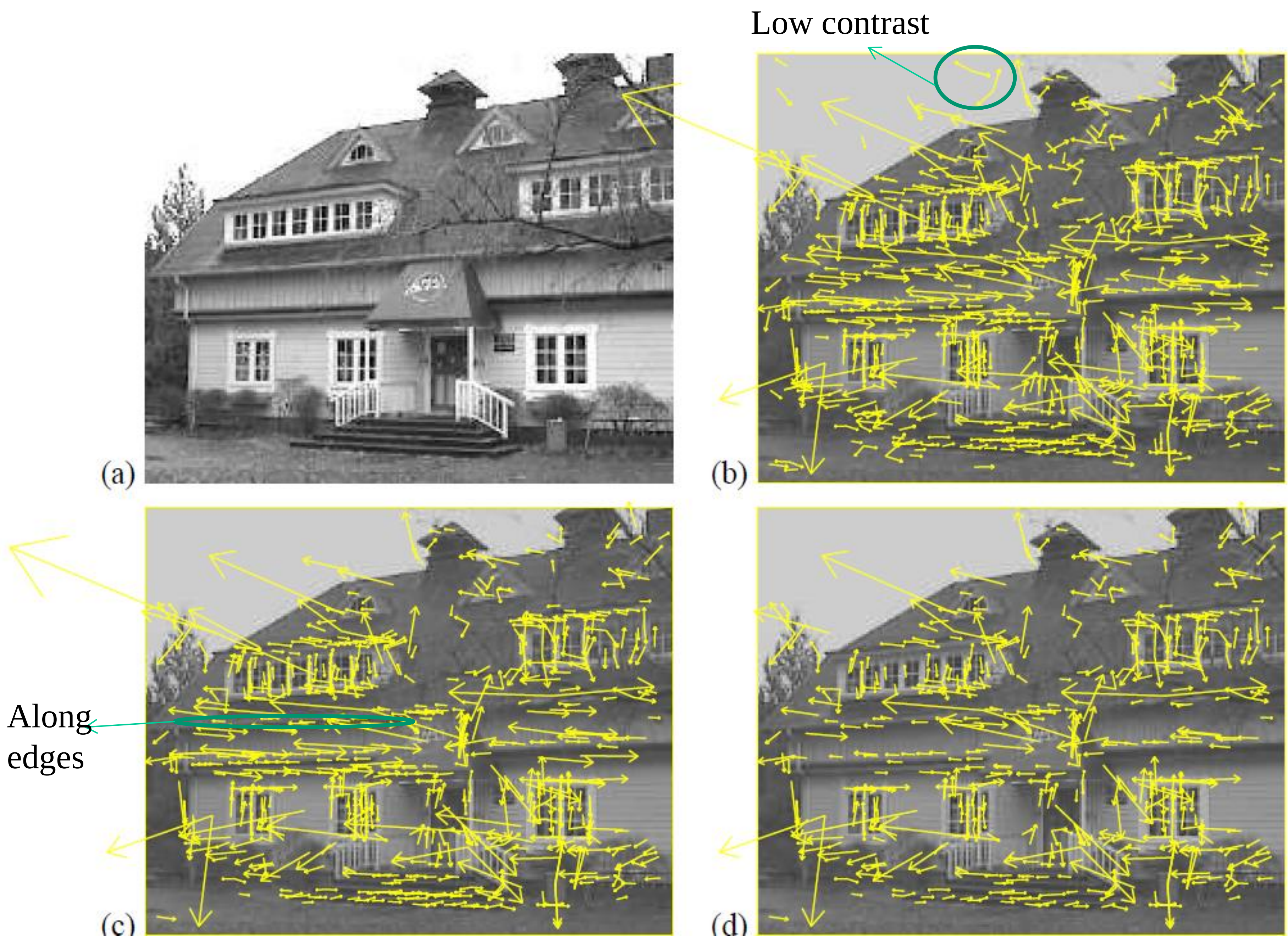
The smaller eigenvalue of H

- **Eliminate the points with**

$$\frac{(r+1)^2}{r} > \frac{(r_T+1)^2}{r_T}$$

threshold



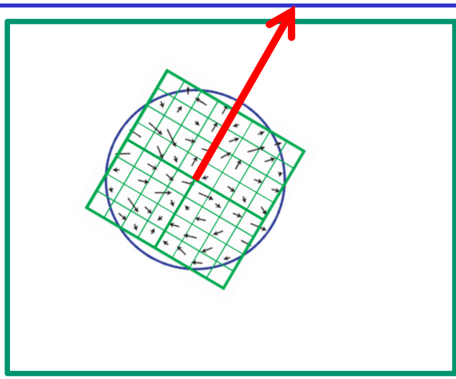


Lowe IJCV 2004

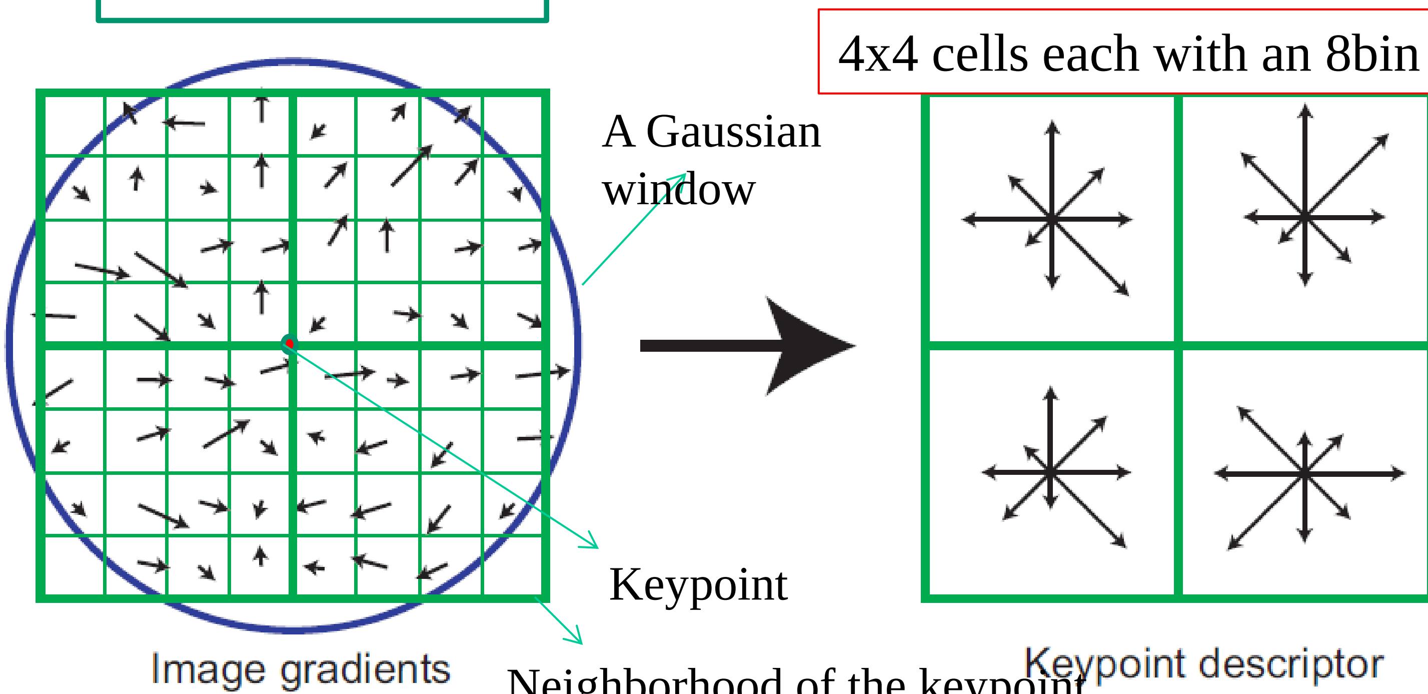
Orientation Assignment

- Compute gradient for Gaussian blurred image at the selected scale
- Create histograms (36 bins for 360°) of gradient directions weighted by gradient magnitude in a neighborhood of keypoint at the selected scale
- Localize the highest peak with height *h* and other local peaks (>=0.8*h*) as the orientations for the keypoint

Keypoint Descriptor



- Use the Gaussian blurred image at the closest scale
- Rotate the gradient map to align with the orientation of the keypoint ➡ Rotation invariance

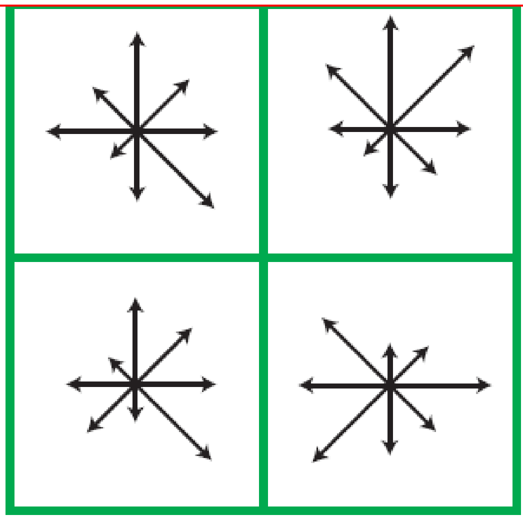


➡ Normalize histogram for illumination invariance

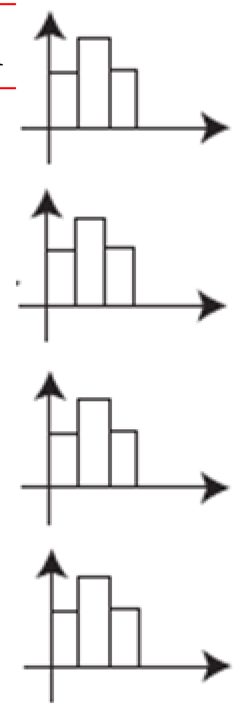
Lowe IJCV 2004

Keypoint Descriptor

4x4 cells each with a 8bin histogram



Keypoint descriptor



Weighted histogram based on gradient magnitude

Normalize histogram for illumination invariance

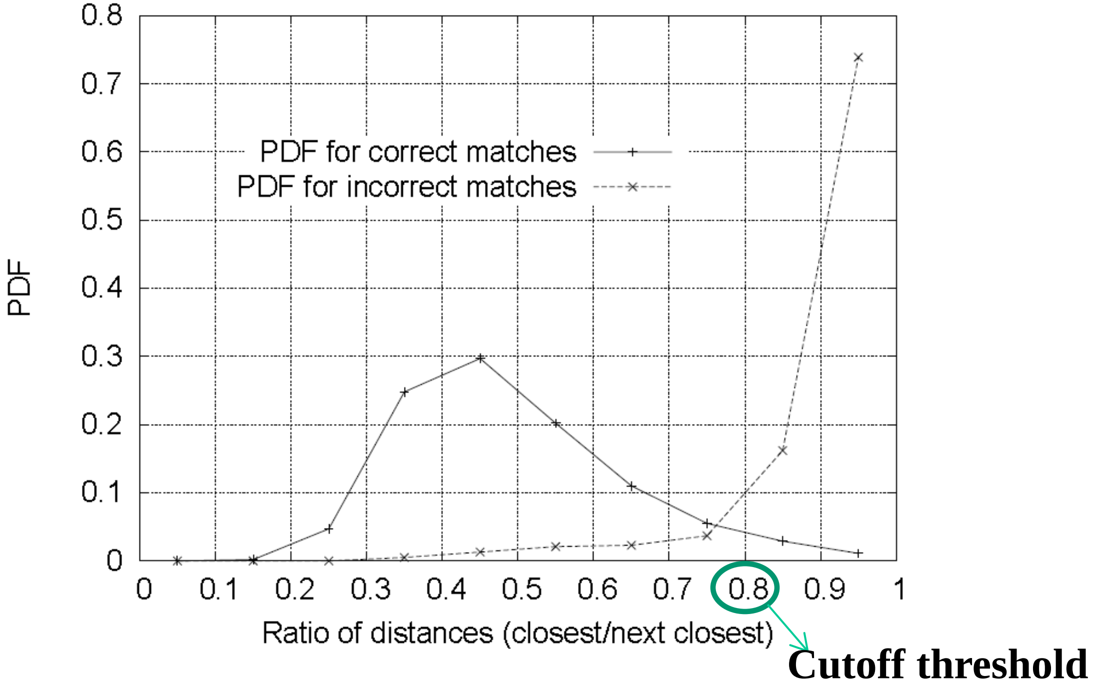
A descriptor with128 elements

Lowe IJCV 2004

Applications: Object Recognition

Keypoint matching:

- Best candidate match by searching nearest neighbors
  - Many false matches
- Reject false matches



Lowe IJCV 2004

Applications: Object Recognition

Testing

Training

Lowe IJCV 2004

Reading Assignments

- Chapter 5 in Forsyth and Ponce
- D. G. Lowe, “Distinctive Image Features from Scale-invariant Keypoints”, IJCV2004