Image Features

CSE 576, Spring 2005

About me

- Ph. D., Carnegie Mellon, 1988
- Researcher, Cambridge Research Lab at DEC, 1990-1995
- Senior Researcher, Interactive Visual Media Group, Microsoft, 1995-
- Research interests:
  - computer vision (stereo, motion),
    computer graphics (image-based rendering),
    data-parallel programming

Today’s lecture

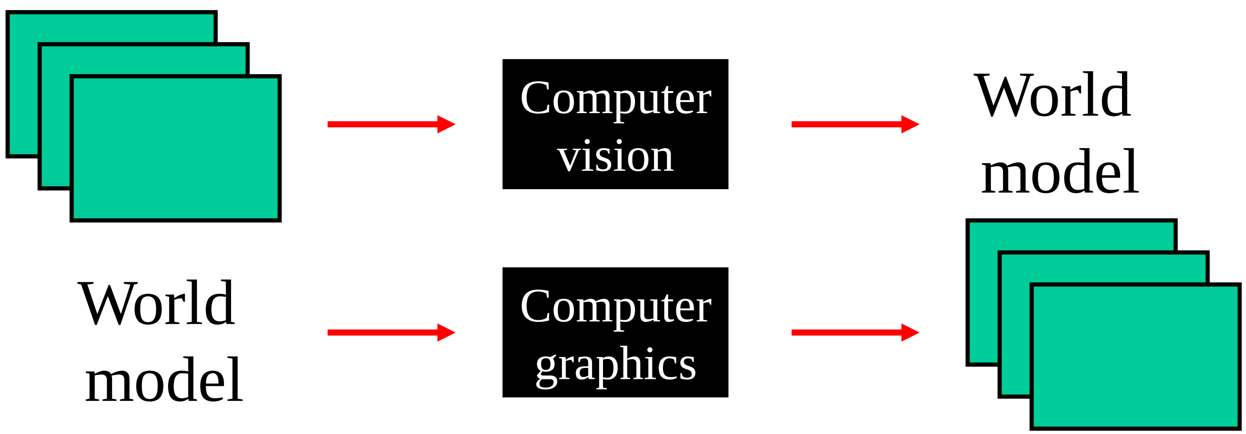
- What is computer vision?
- Scale-space and pyramids
- What are good features?
- Feature detection
- Feature descriptors
- (Next lecture: feature matching)

- Project 1description and demo [Ian Simon]

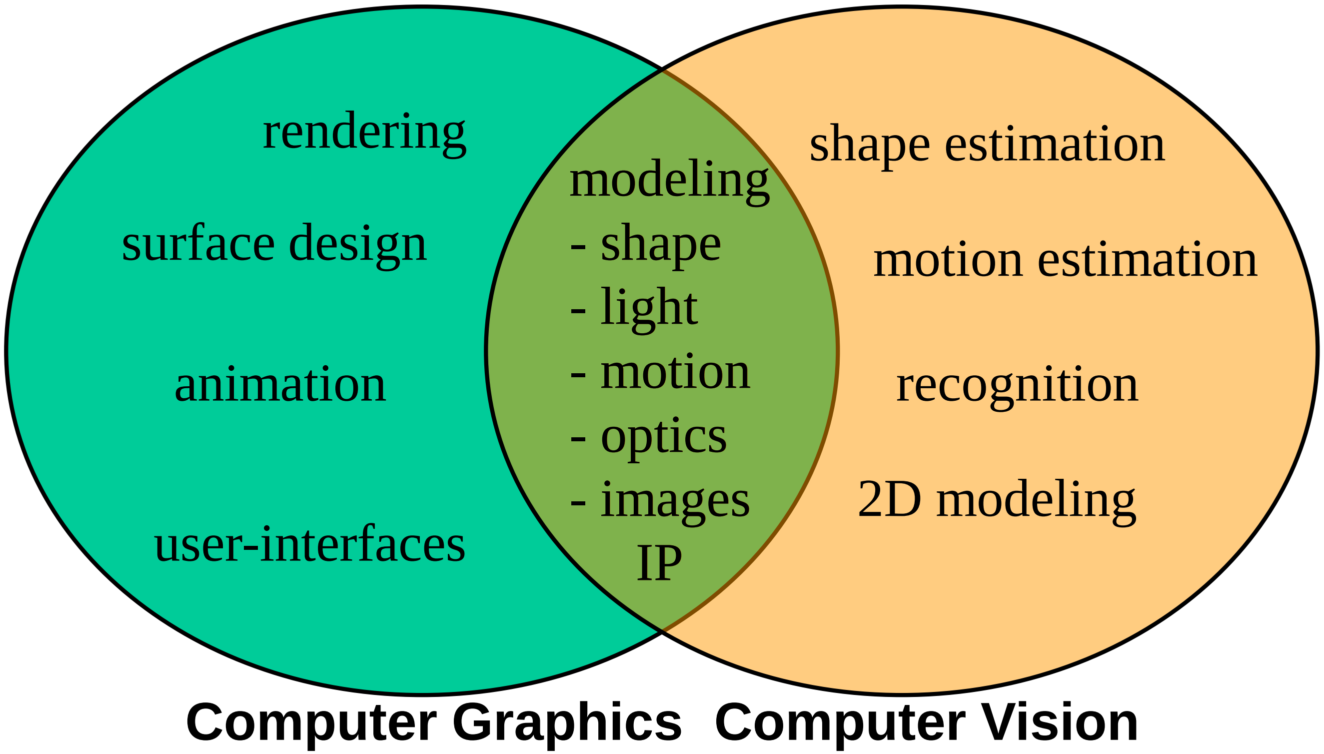
What is Computer Vision?

What is Computer Vision?

- Image Understanding (AI, behavior)
- A sensor modality for robotics
- Computer emulation of human vision
- Inverse of Computer Graphics



Intersection of Vision and Graphics



Computer Vision [Trucco&Verri'98]

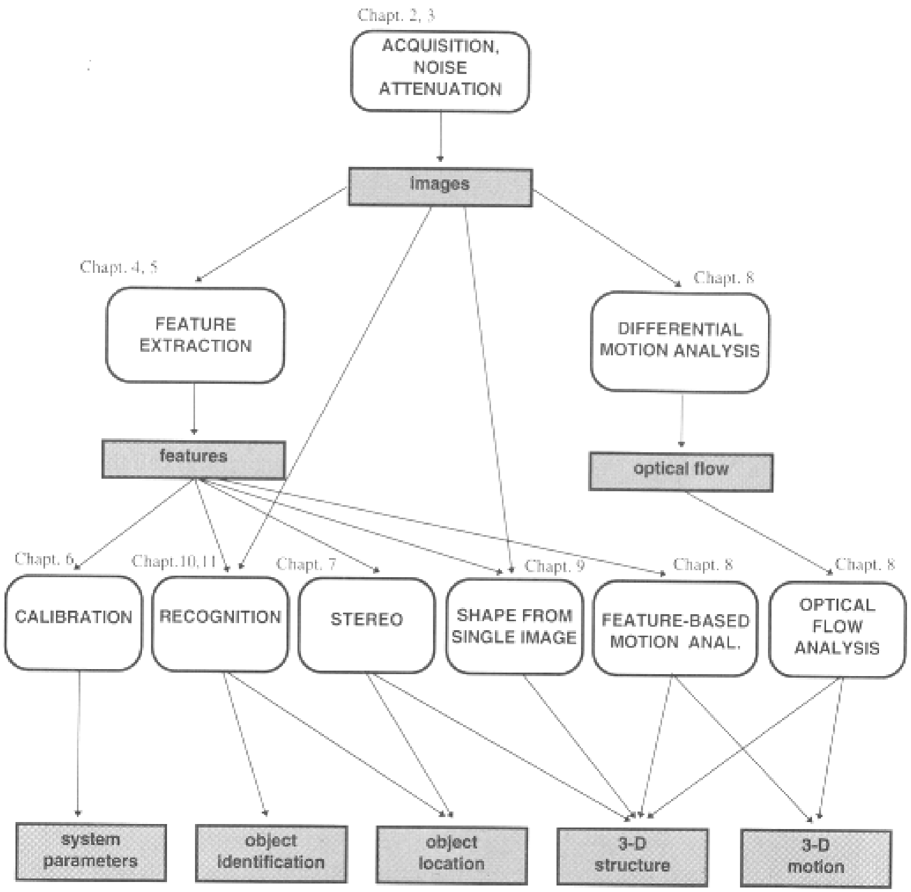
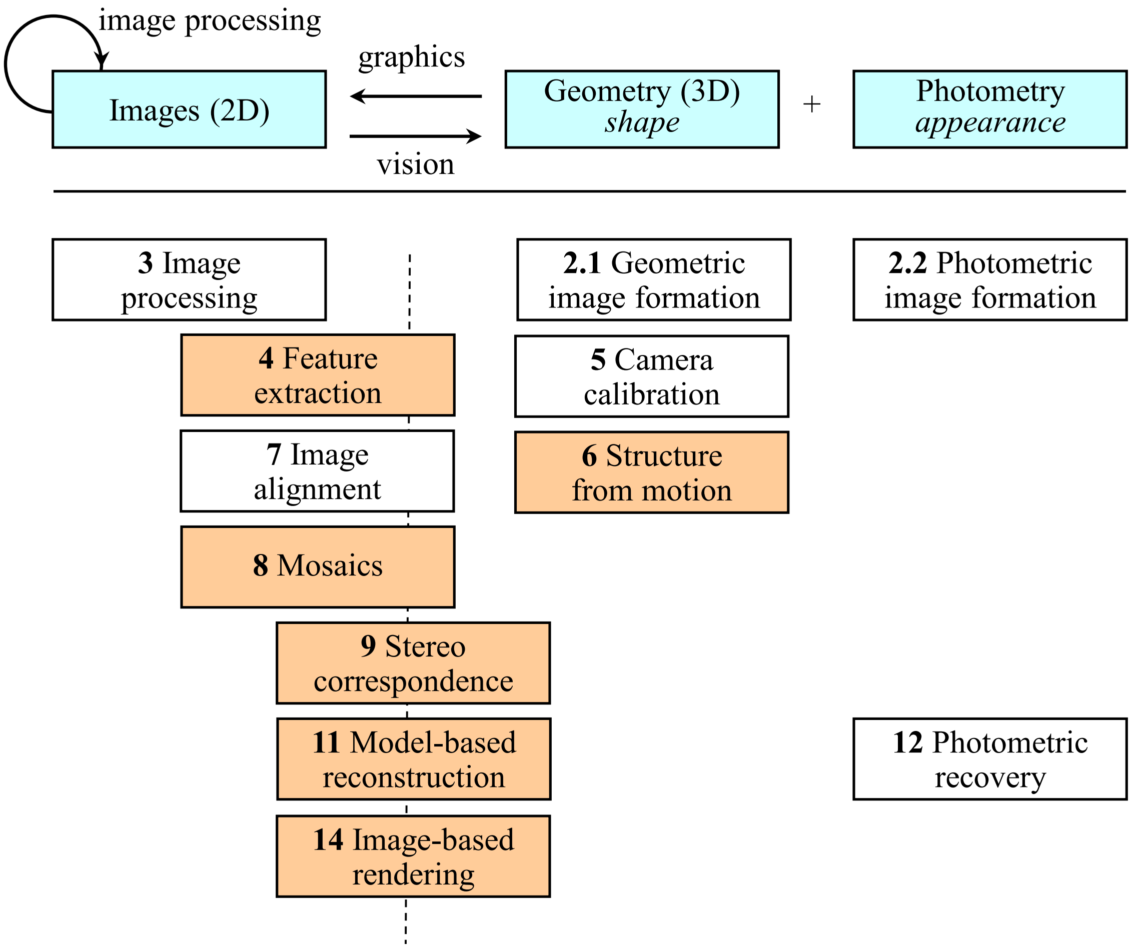


Figure 1.7 The book at a glance: method classes (white boxes), results (grey boxes), their interdependence, and where to find the various topics in this book.

Image-Based Modeling



Applications

- Geometric reconstruction: modeling, forensics, special effects (ILM, RealVis,2D3)
- Image and video editing (Avid, Adobe)
- Webcasting and Indexing Digital Video (Virage)
- Scientific / medical applications (GE)

Applications

- Tracking and surveillance (Sarnoff)
- Fingerprint recognition (Digital Persona)
- Biometrics / iris scans (Iridian Technologies)
- Vehicle safety (MobilEye)
- Drowning people (VisionIQ Inc)
- Optical motion capture (Vicon)

Image Morphing

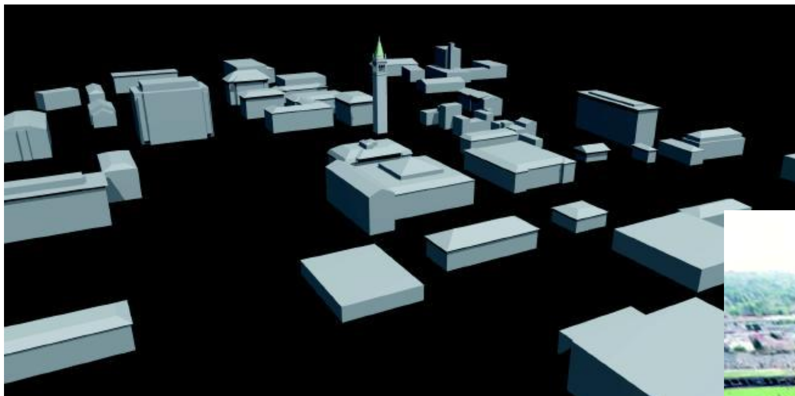
Panoramic Mosaics

+

+ … +

=

3D Shape Reconstruction

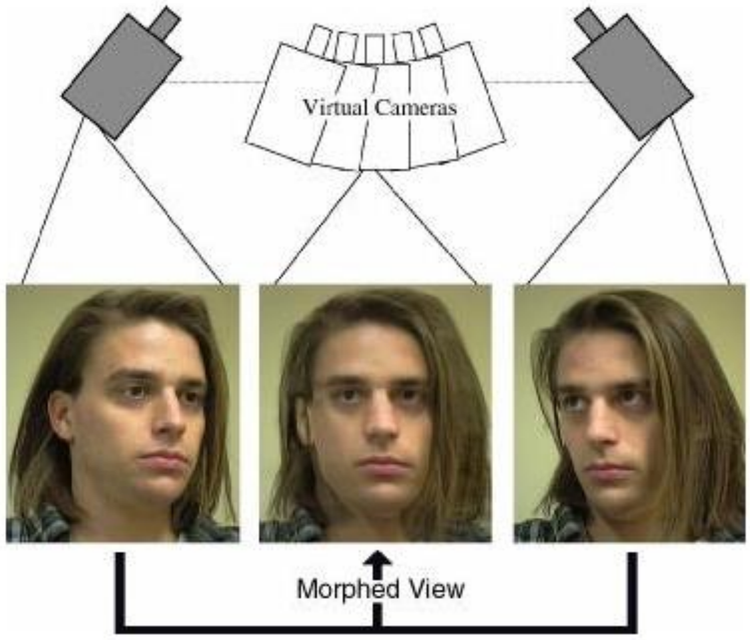


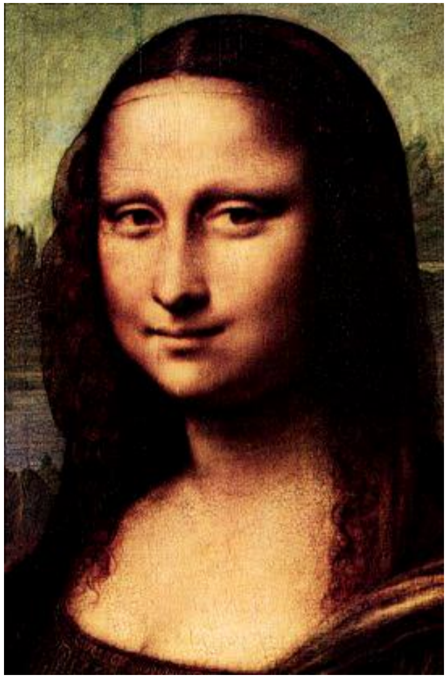
Debevec, Taylor, and Malik, SIGGRAPH 1996

Face Modeling

View Morphing

Morph between pair of images using epipolar geometry [Seitz & Dyer, SIGGRAPH'96]



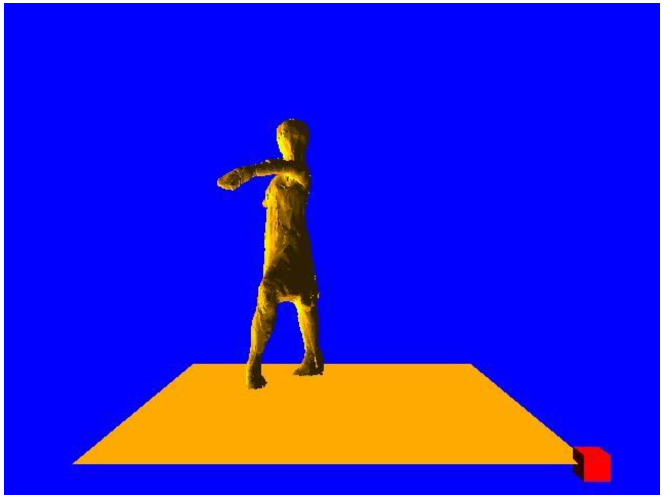


Virtualized Reality^{TM}

Takeo Kanade, CMU

- collect video from 50+ stream

reconstruct 3D model sequences

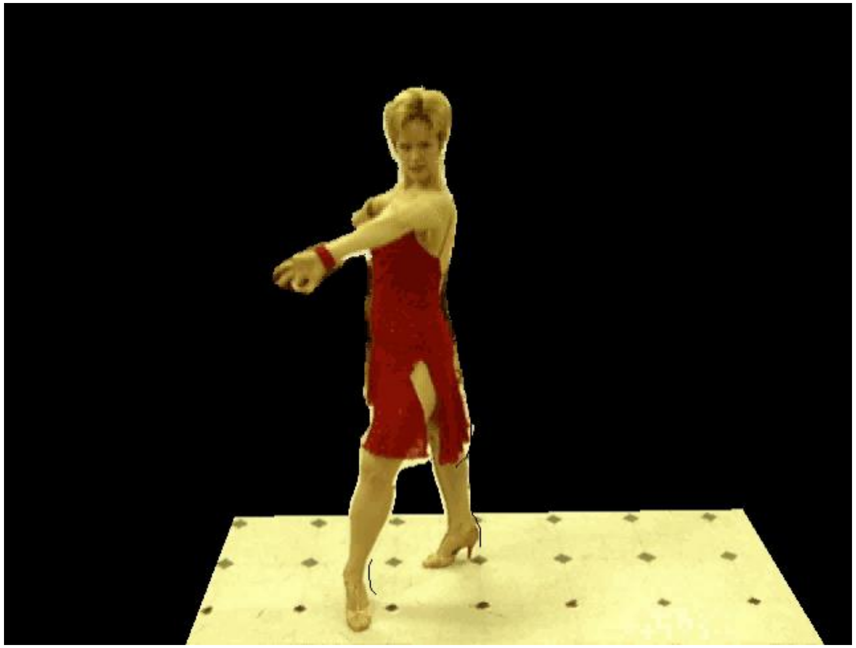


http://www.cs.cmu.edu/afs/cs/project/VirtualizedR/www/VirtualizedR.html

Virtualized Reality^{TM}

Takeo Kanade, CMU

- generate new video



- steerable version used for SuperBowl XXV "eye vision" system

Edge detection and editing

Elder, J. H. and R. M. Goldberg. "Image Editing in the Contour Domain,"
Proc. IEEE: Computer Vision and Pattern Recognition, pp. 374-381, June, 1998.

Image Enhancement

High dynamic range photography
[Debevec *et al*.'97; Mitsunaga & Nayar'99]

- combine several different exposures together

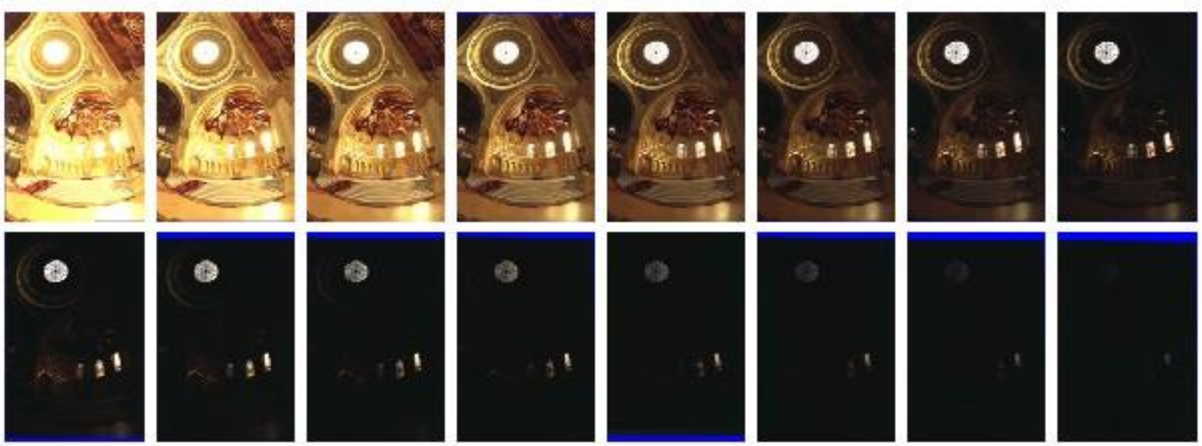


Figure 6: *Sixteen photographs of a church taken at 1-stop increments from 30 sec to [illegible] sec. The sun is directly behind the rightmost stained glass window, making it especially bright. The blue borders seen in some of the image margins are induced by the image registration process.*

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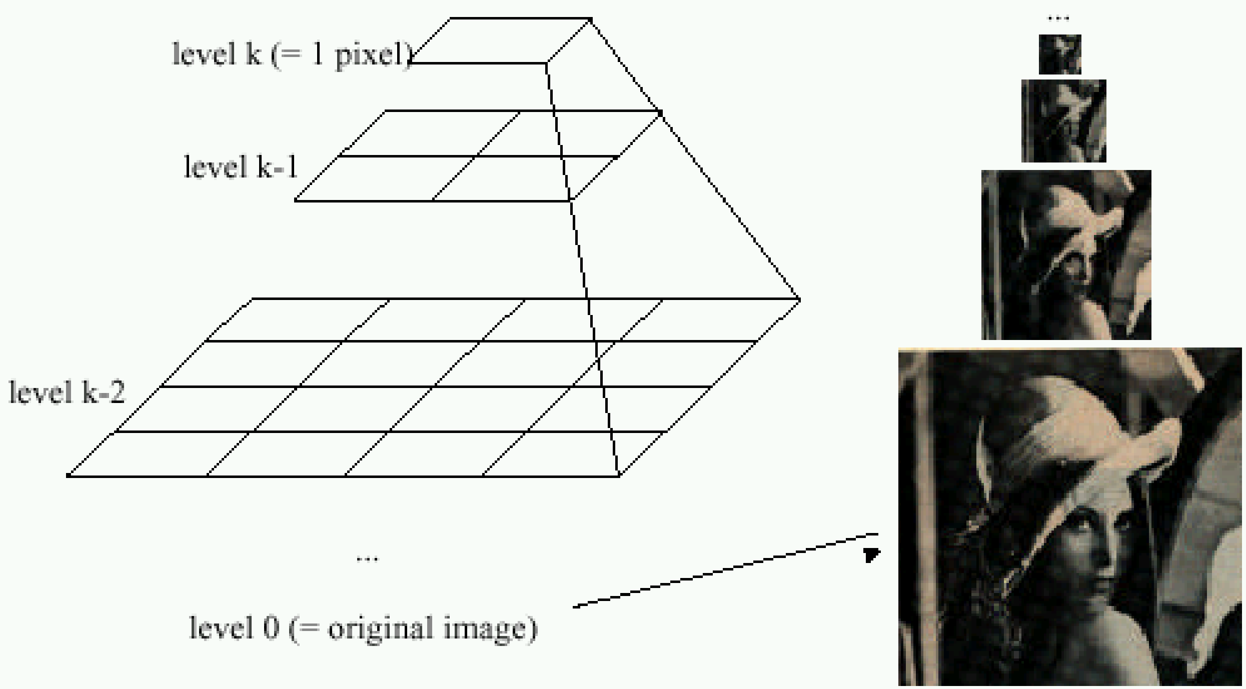
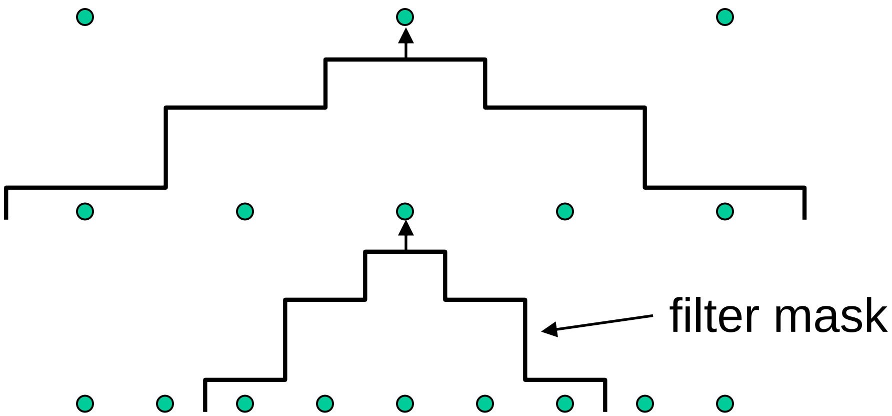
Image Pyramids

Image Pyramids

Idea: Represent NxN image as a “pyramid” of $1\mathrm{x}1$, $2\mathrm{x}2$, $4\mathrm{x}4$,…, $2^k\mathrm{x}2^k$ images (assuming $N=2^k$)



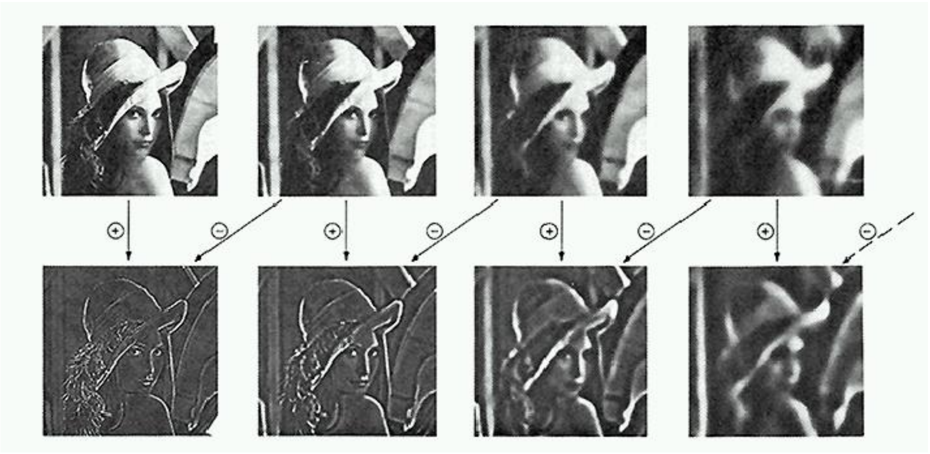
Pyramid Creation



“Gaussian” Pyramid

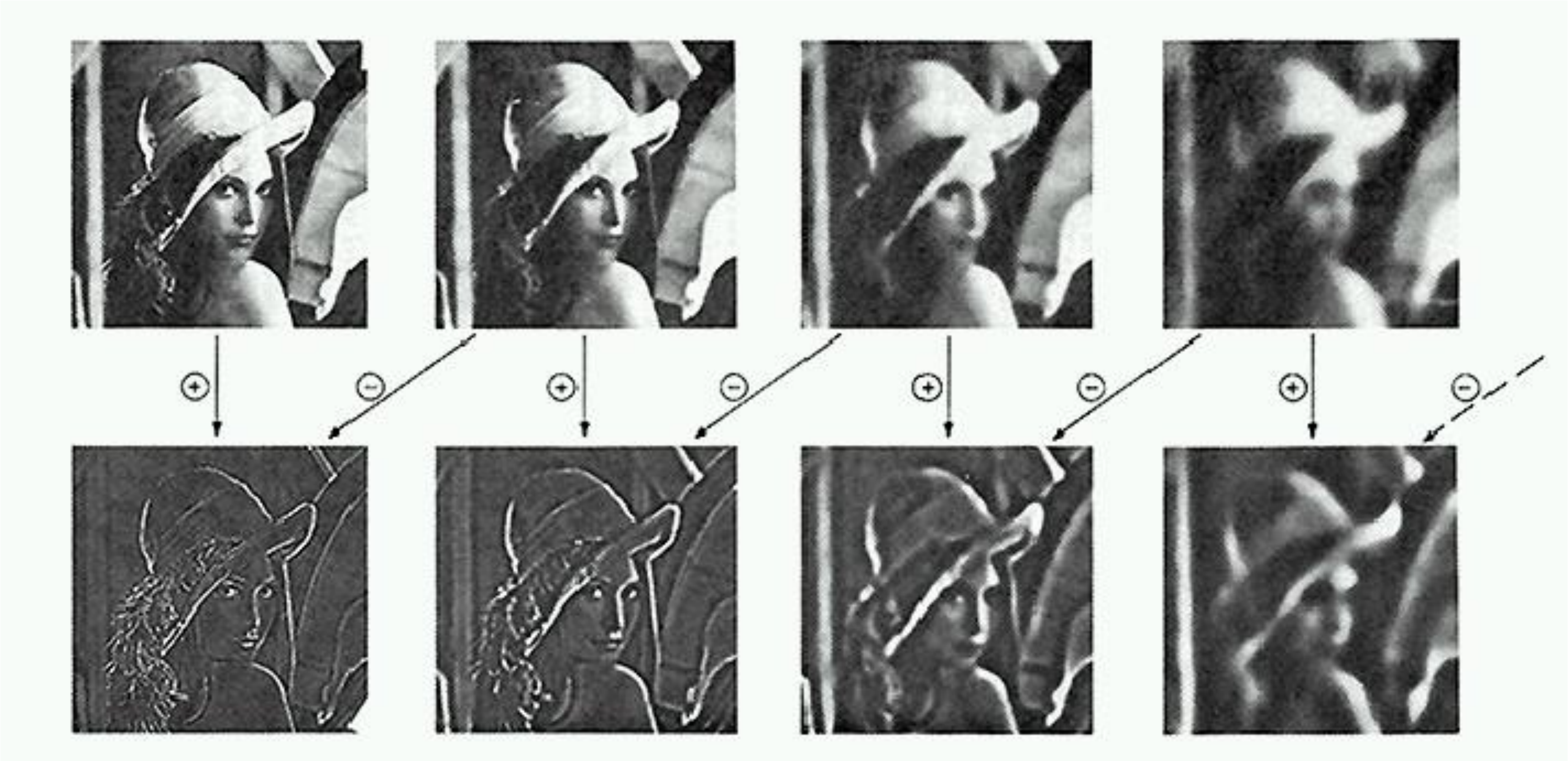
“Laplacian” Pyramid

- Created from Gaussian pyramid by subtraction $L_l = G_l - \text{expand}(G_{l+1})$



Octaves in the Spatial Domain

Lowpass Images



Bandpass Images

Pyramids

Advantages of pyramids

- Faster than Fourier transform
- Avoids “ringing” artifacts

Many applications

- small images faster to process
- good for multiresolution processing
- compression
- progressive transmission

Known as “MIP-maps” in graphics community

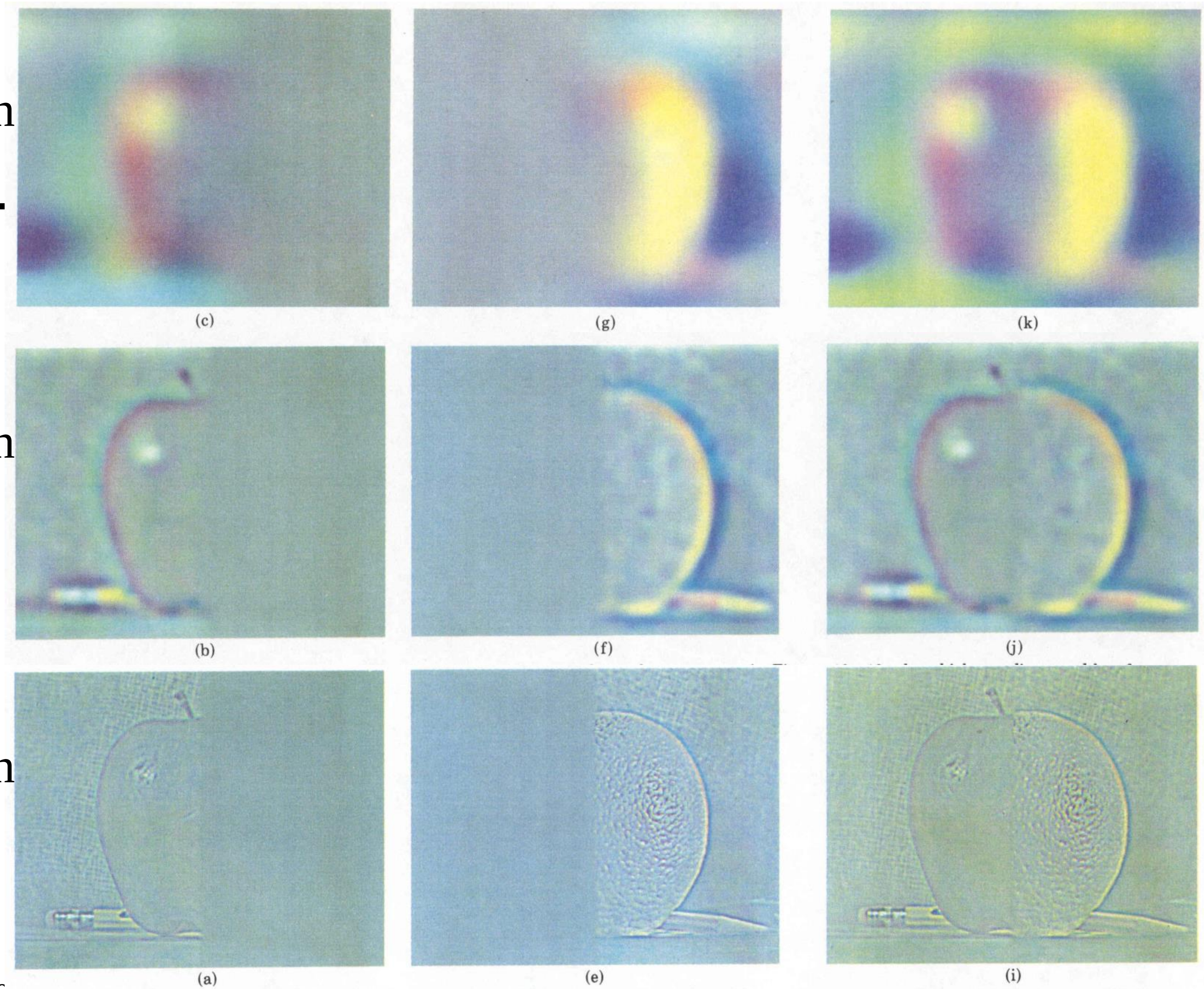
Precursor to wavelets

- Wavelets also have these advantages

Laplacian level 4

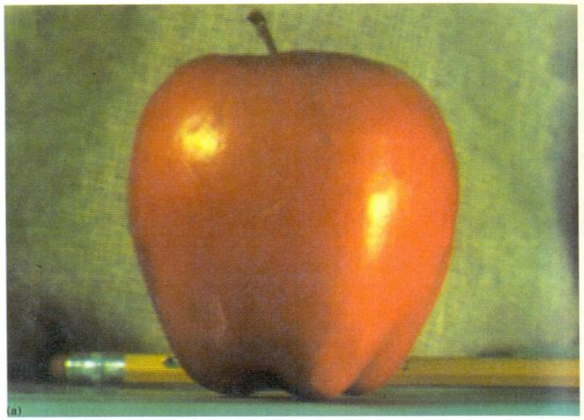
Laplacian level 2

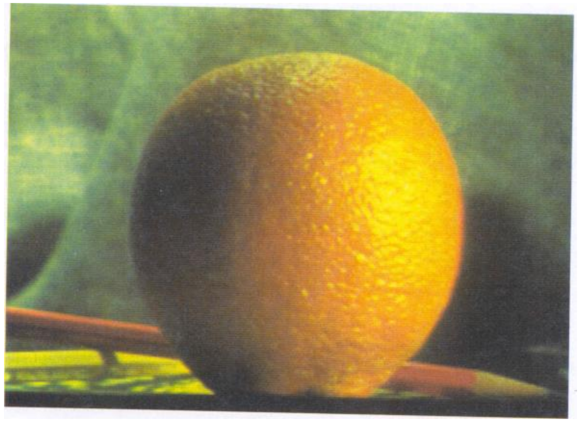
Laplacian level 0

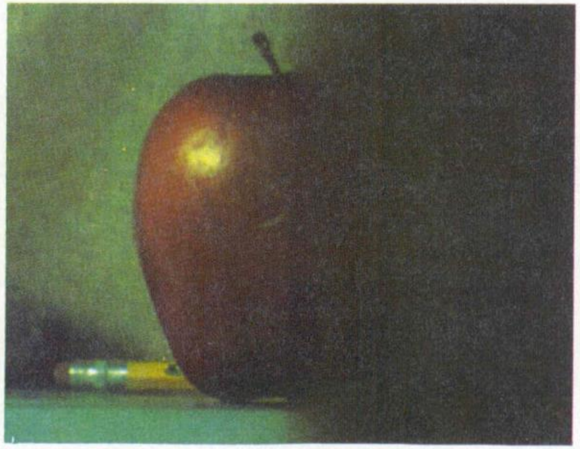


left pyramid | right pyramid | blended pyramid

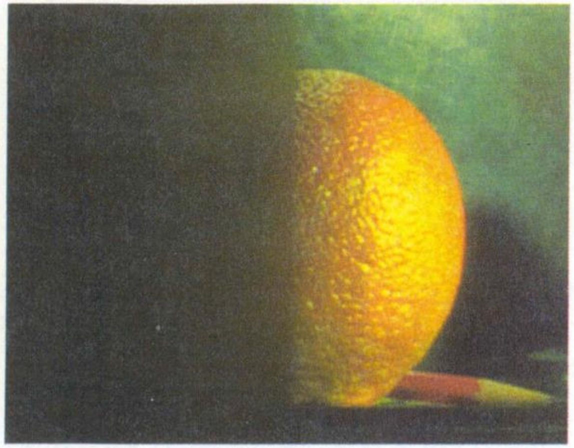
Pyramid Blending



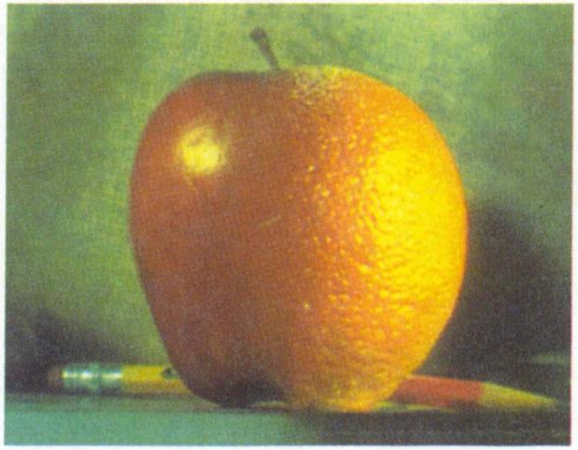




(d)



(h)



(l)

original

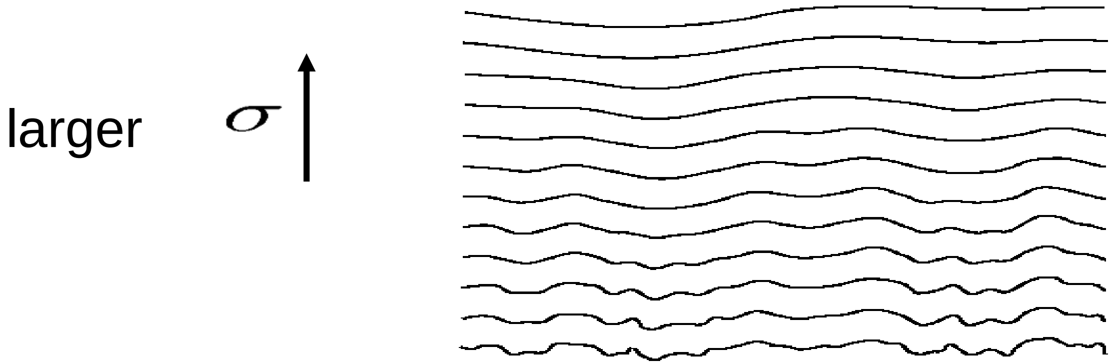
smoothed (5x5 Gaussian)

smoothed – original

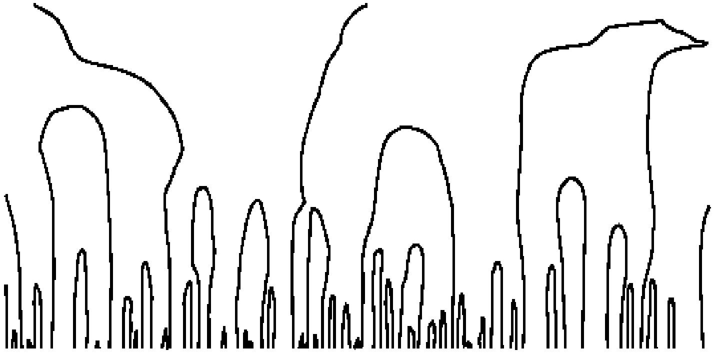
(scaled by 4, offset +128)

hy does
this work?

Scale space (Witkin 83)



Gaussian filtered signal

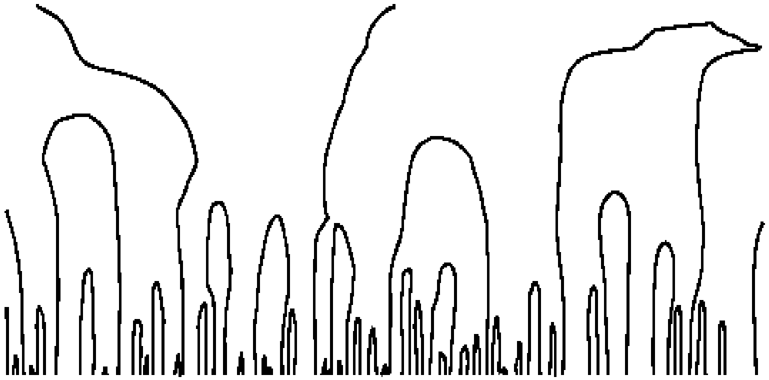


Zero crossings

Scale space: insights

As the scale is increased

- edge position can change
- edges can disappear
- new edges are not created



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These slides adapted from:

Matching with Invariant Features

Darya Frolova, Denis Simakov

The Weizmann Institute of Science

March 2004

and…

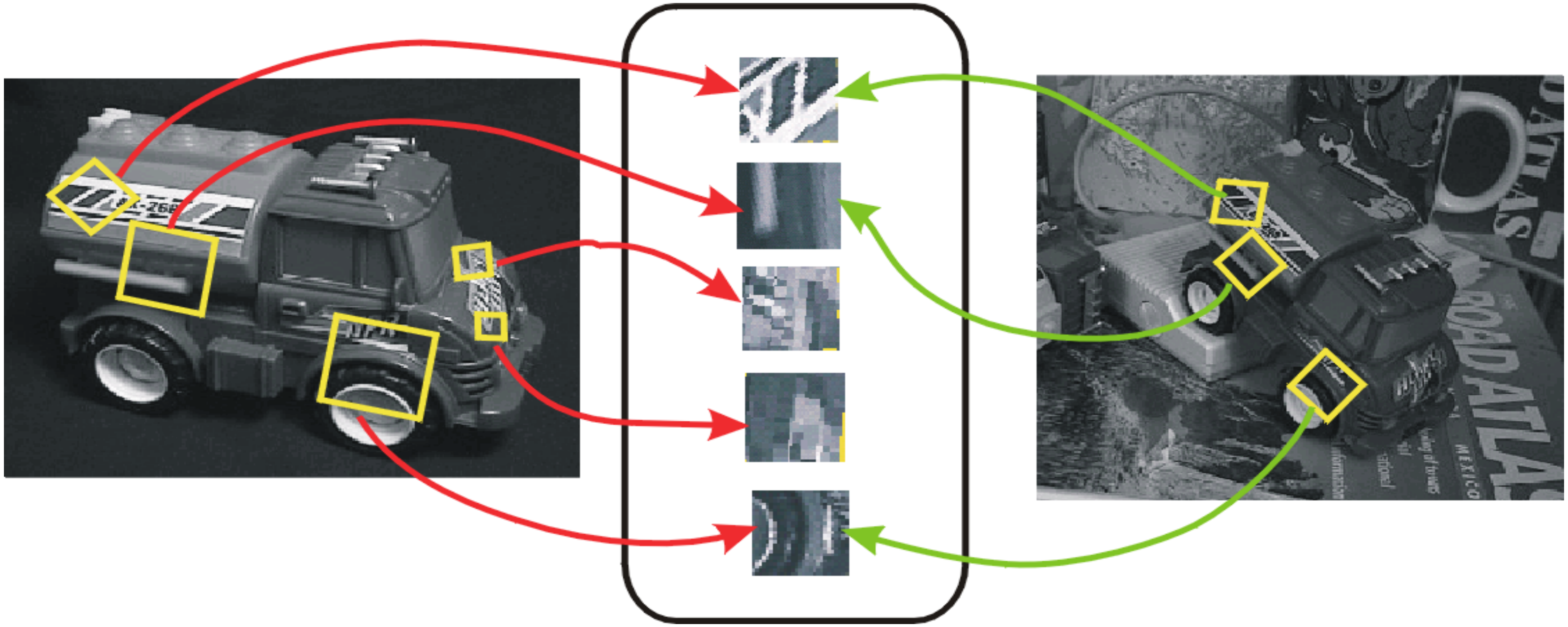
Real-time Object Recognition using Invariant Local Image Features

David Lowe
Computer Science Department
University of British Columbia

NIPS 2003 Tutorial

Invariant Local Features

Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



SIFT Features

Advantages of local features

Locality: features are local, so robust to occlusion and clutter (no prior segmentation)

Distinctiveness: individual features can be matched to a large database of objects

Quantity: many features can be generated for even small objects

Efficiency: close to real-time performance

Extensibility: can easily be extended to wide range of differing feature types, with each adding robustness

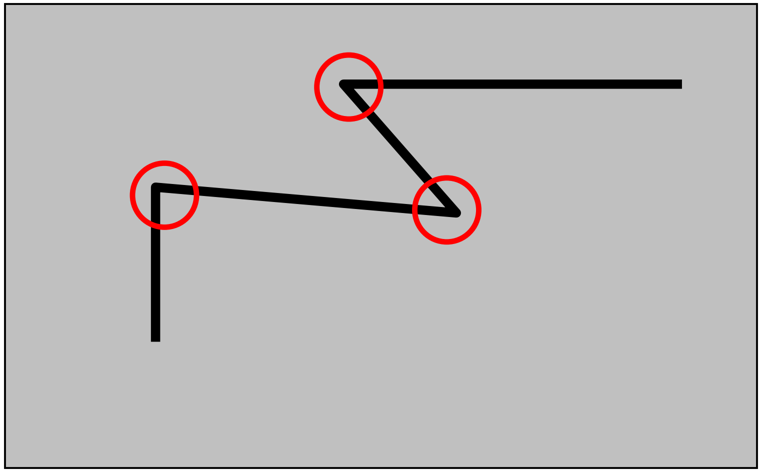
More motivation…

Feature points are used also for:

- Image alignment (homography, fundamental matrix)
- 3D reconstruction
- Motion tracking
- Object recognition
- Indexing and database retrieval
- Robot navigation
- … other

Harris corner detector

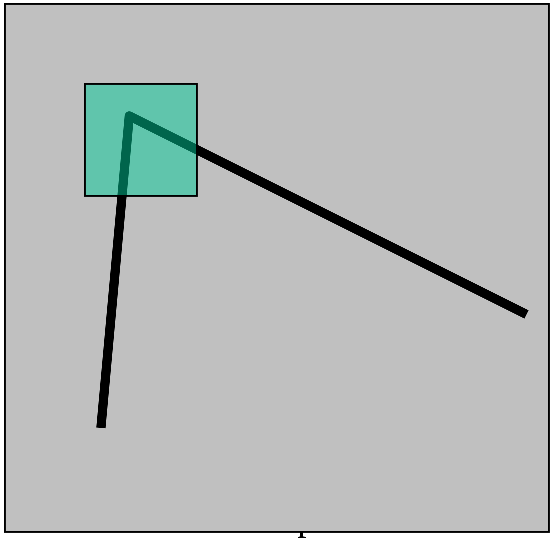
C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988



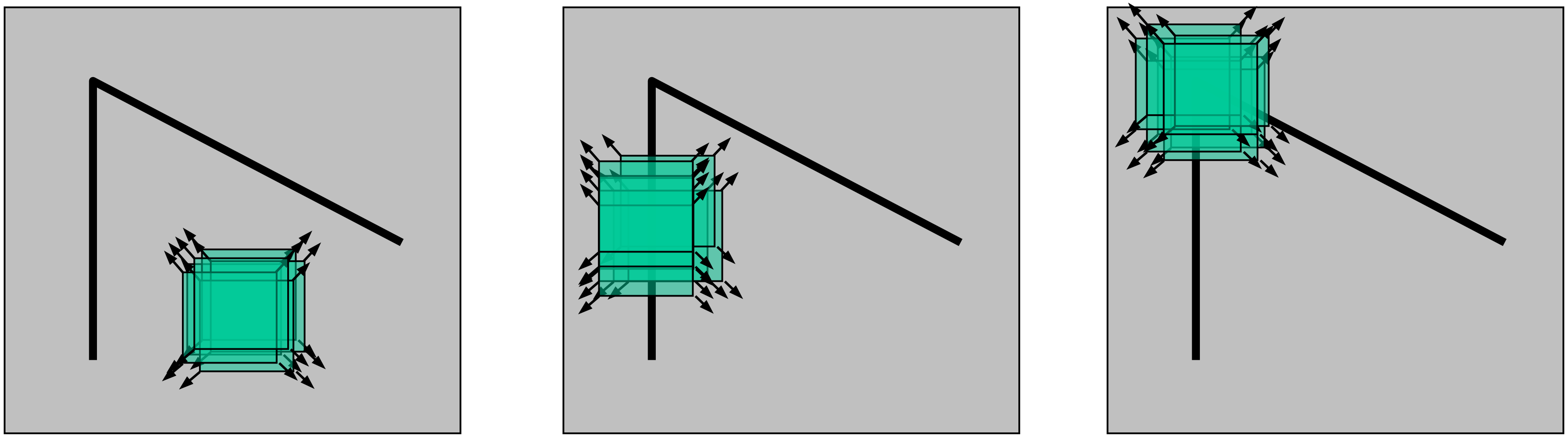
The Basic Idea

We should easily recognize the point by looking through a small window

Shifting a window in *any direction* should give *a large change* in intensity



Harris Detector: Basic Idea



“flat” region:
no change in
all directions

“edge”:
no change along
the edge direction

“corner”:
significant change
in all directions

Harris Detector: Mathematics

Change of intensity for the shift [u,v]:

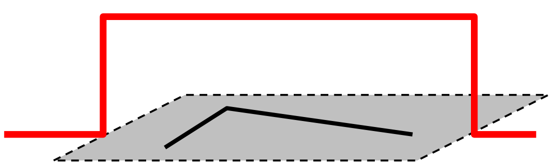
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

Window function

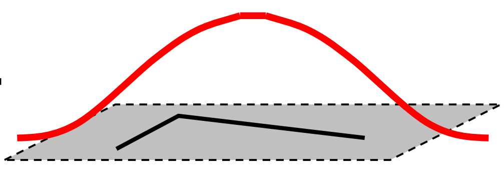
Shifted intensity

Intensity

Window function $w(x,y)$ =



or



1 in window, 0 outside

Gaussian

Harris Detector: Mathematics

For small shifts $[u,v]$ we have a *bilinear* approximation:

$$E(u,v) \cong [u,v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$$

where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

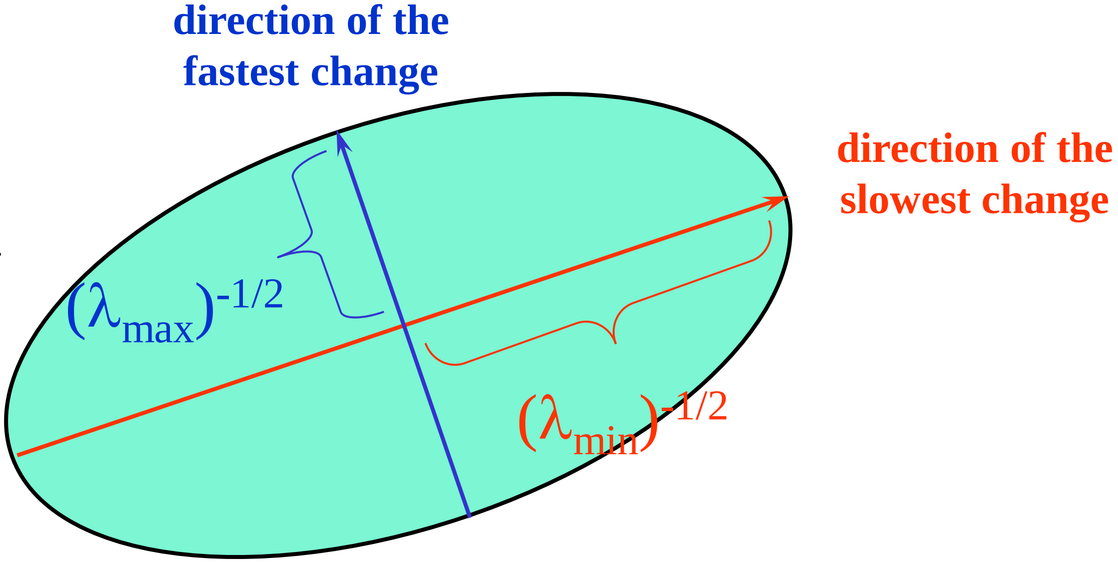
Harris Detector: Mathematics

Intensity change in shifting window: eigenvalue analysis

$$E(u,v) \cong [u,v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$$

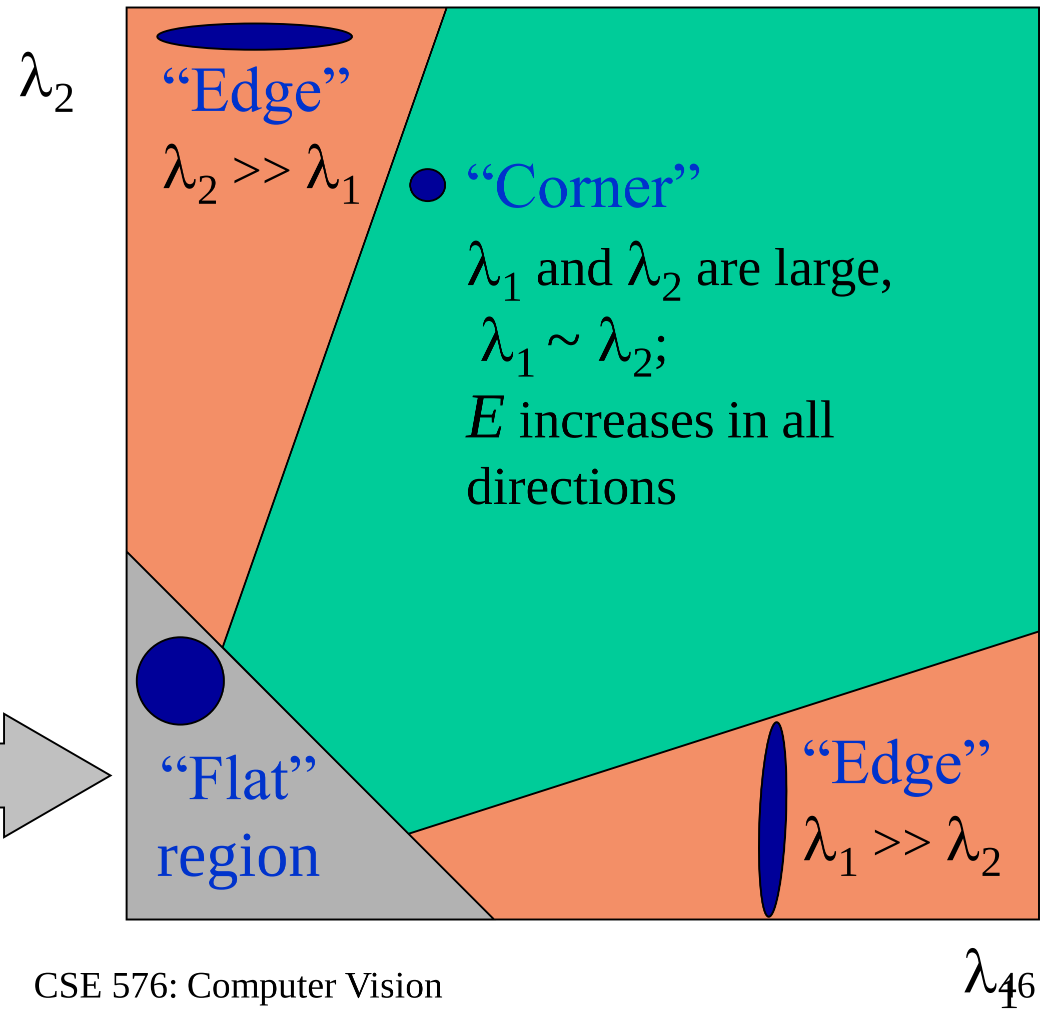
λ_1, λ_2 – eigenvalues of M

Ellipse $E(u,v)$ = const



Harris Detector: Mathematics

Classification of image points using eigenvalues of *M*:



λ_1 and λ_2 are small;
E is almost constant in all directions

Harris Detector: Mathematics

Measure of corner response:

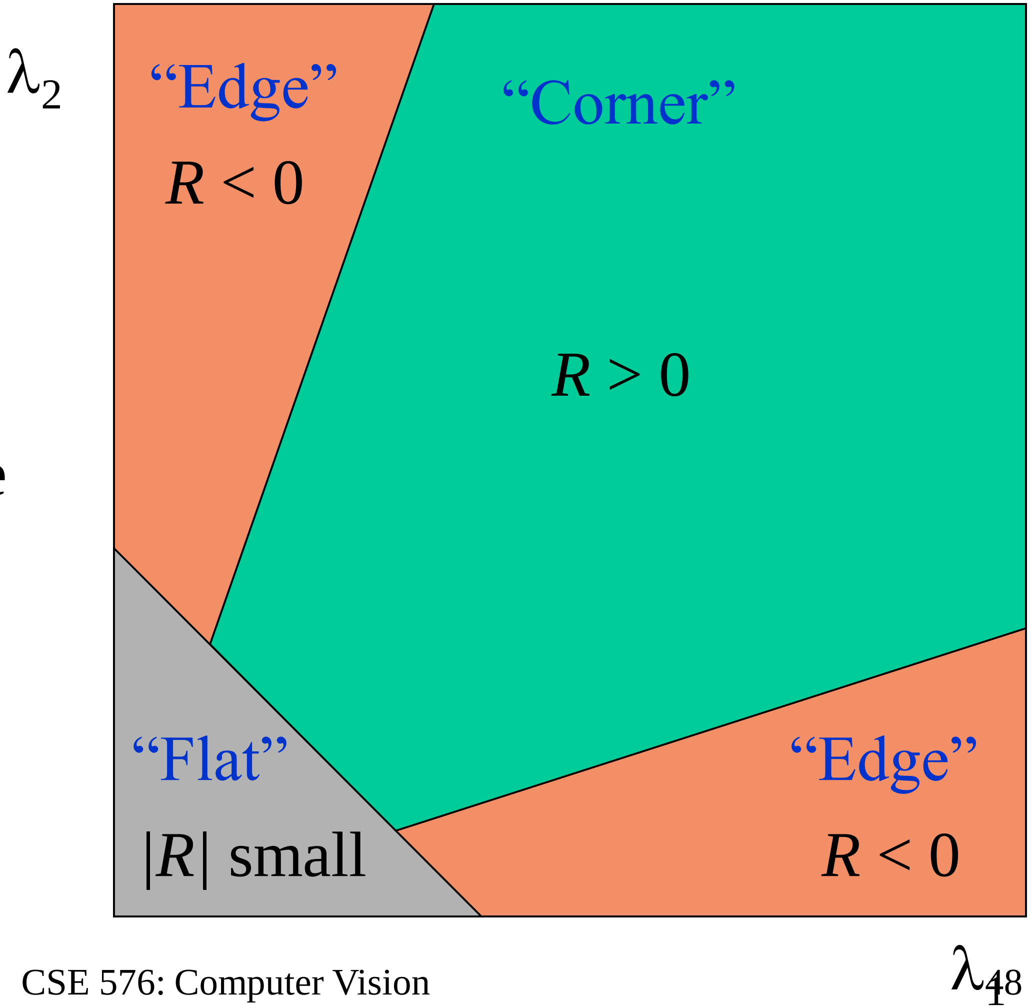
$$R = \det M - k\left(\operatorname{trace} M\right)^2$$

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

(k – empirical constant, k = 0.04-0.06)

Harris Detector: Mathematics

- R depends only on eigenvalues of M
- R is large for a corner
- R is negative with large magnitude for an edge
- $|R|$ is small for a flat region



Harris Detector

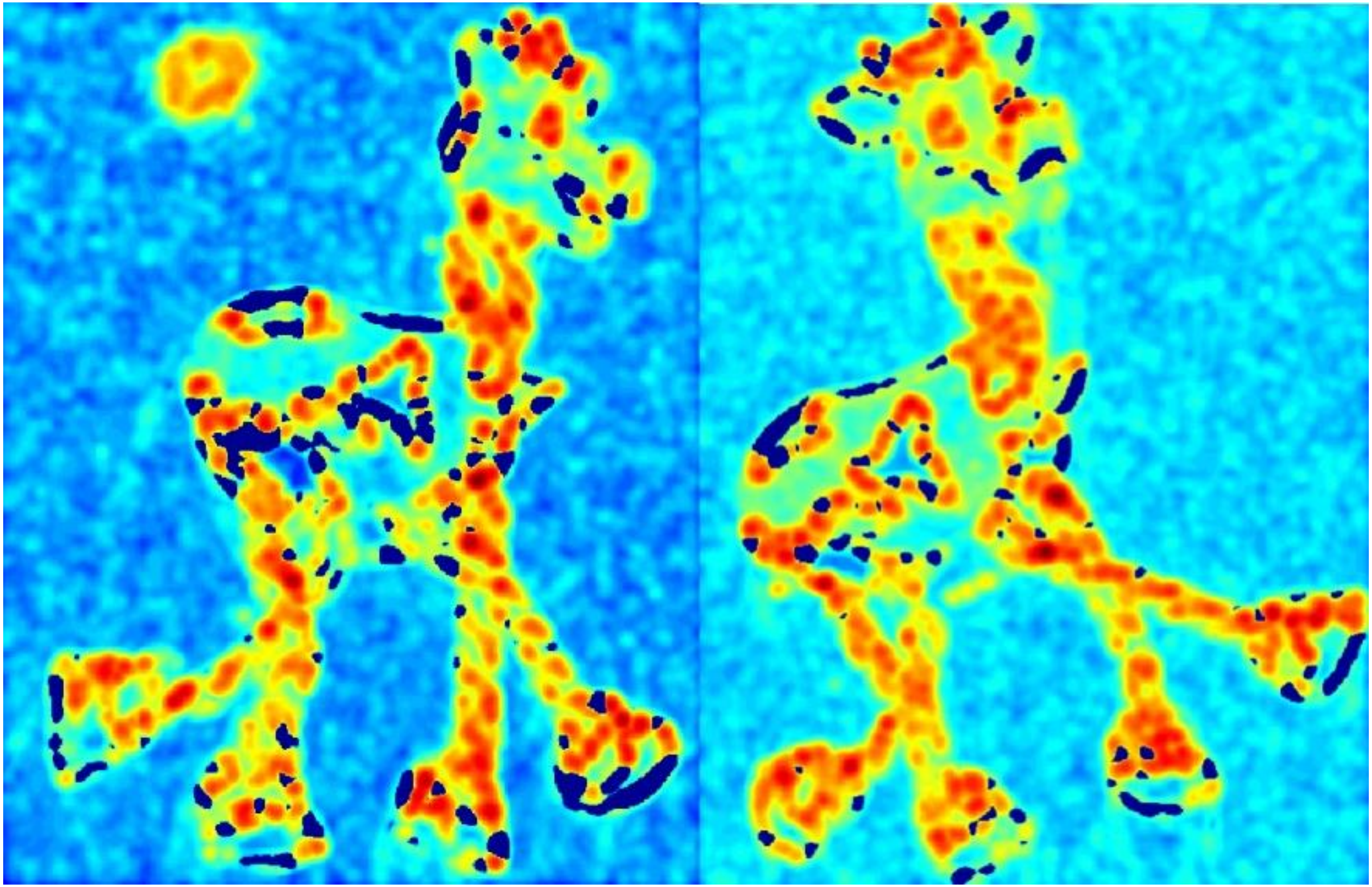
The Algorithm:

- Find points with large corner response function *R* (*R* > threshold)
- Take the points of local maxima of *R*

Harris Detector: Workflow

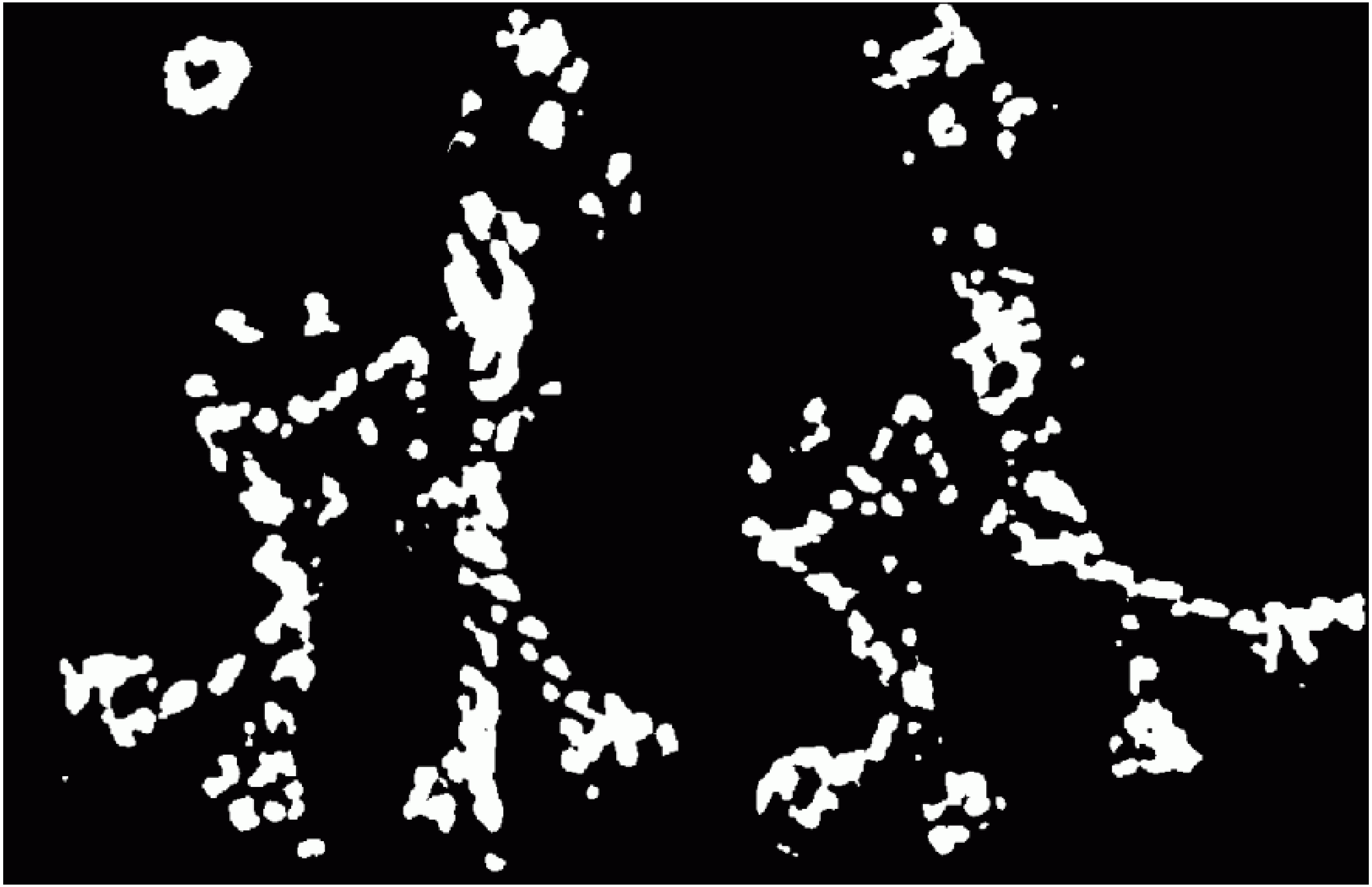
Harris Detector: Workflow

Compute corner response R



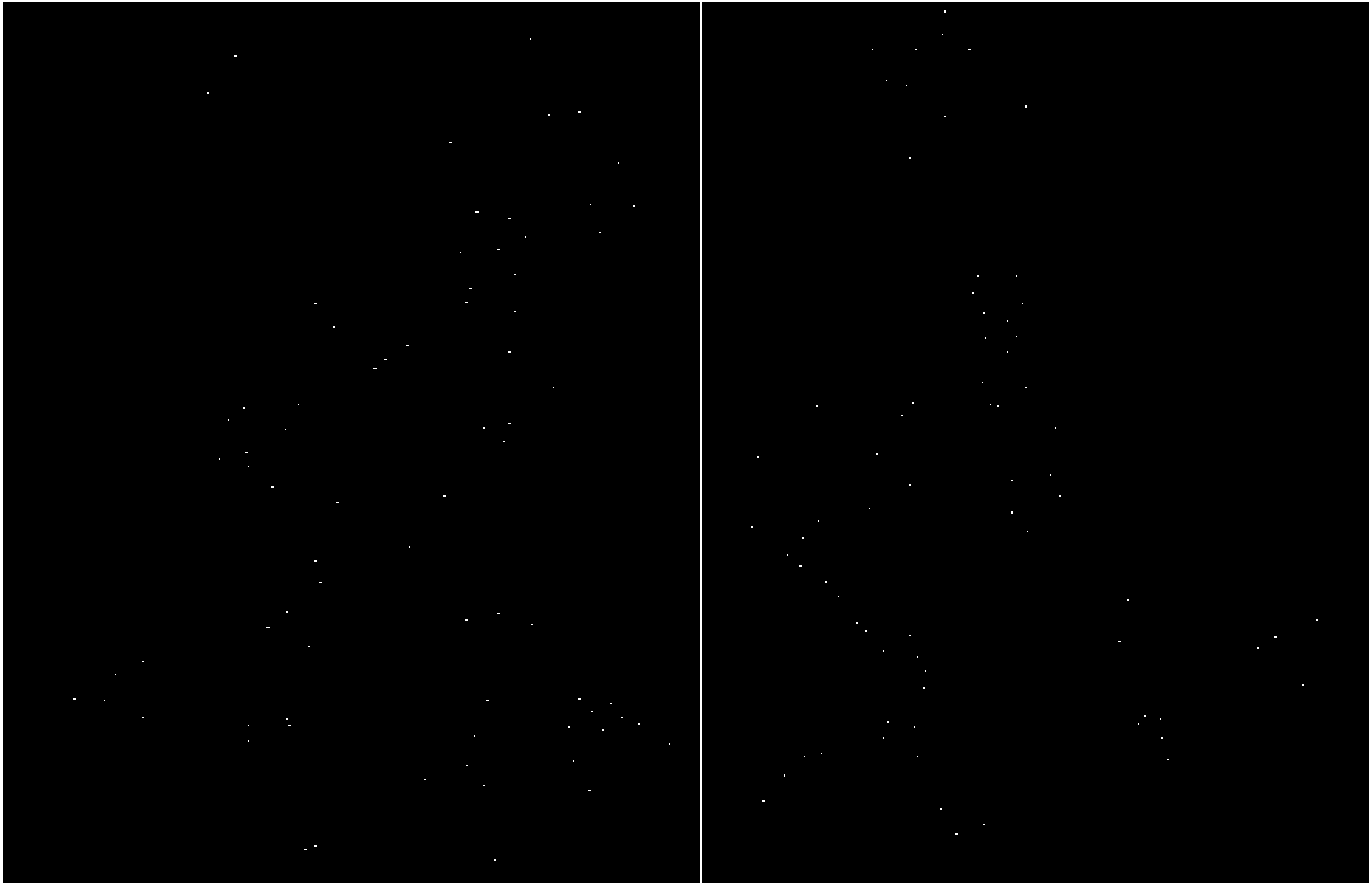
Harris Detector: Workflow

Find points with large corner response: R>threshold



Harris Detector: Workflow

Take only the points of local maxima of R



Harris Detector: Workflow

Harris Detector: Summary

Average intensity change in direction $[u,v]$ can be expressed as a bilinear form:

$$E(u,v) \cong [u,v] \; M \; \begin{bmatrix} u \\ v \end{bmatrix}$$

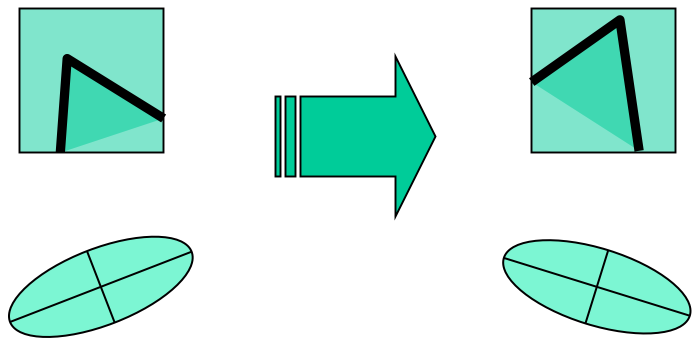
Describe a point in terms of eigenvalues of M:
measure of corner response

$$R = \lambda_1 \lambda_2 - k\left(\lambda_1 + \lambda_2\right)^2$$

A good (corner) point should have a *large intensity change* in *all directions*, i.e. R should be large positive

Harris Detector: Some Properties

Rotation invariance



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

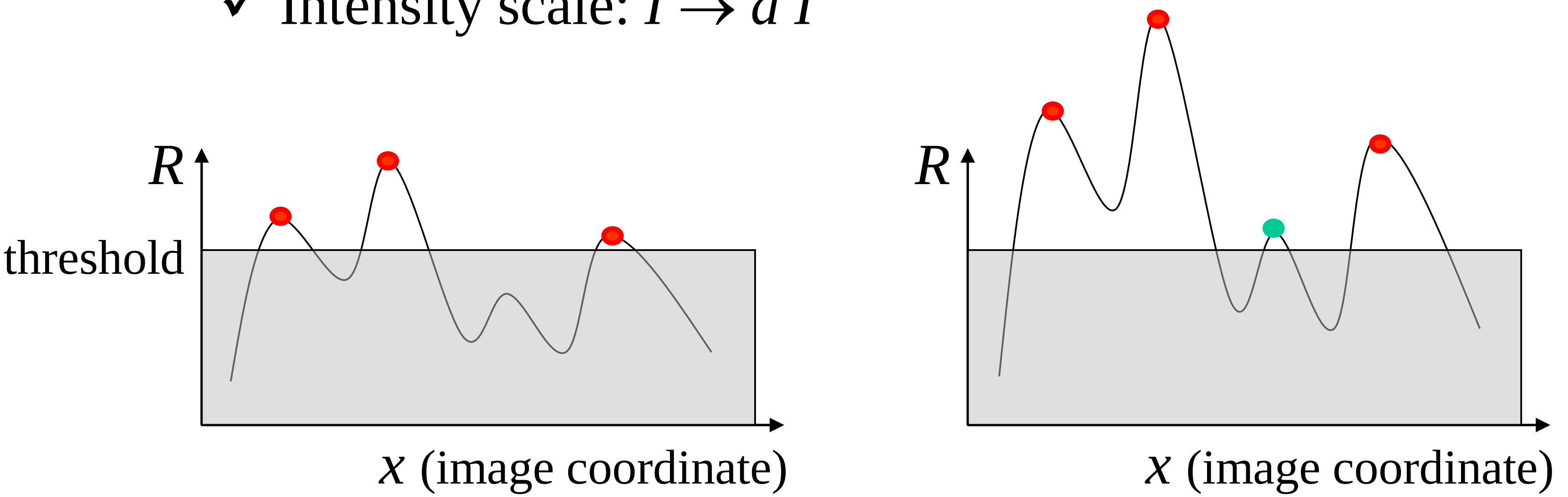
Corner response R is invariant to image rotation

Harris Detector: Some Properties

Partial invariance to *affine intensity* change

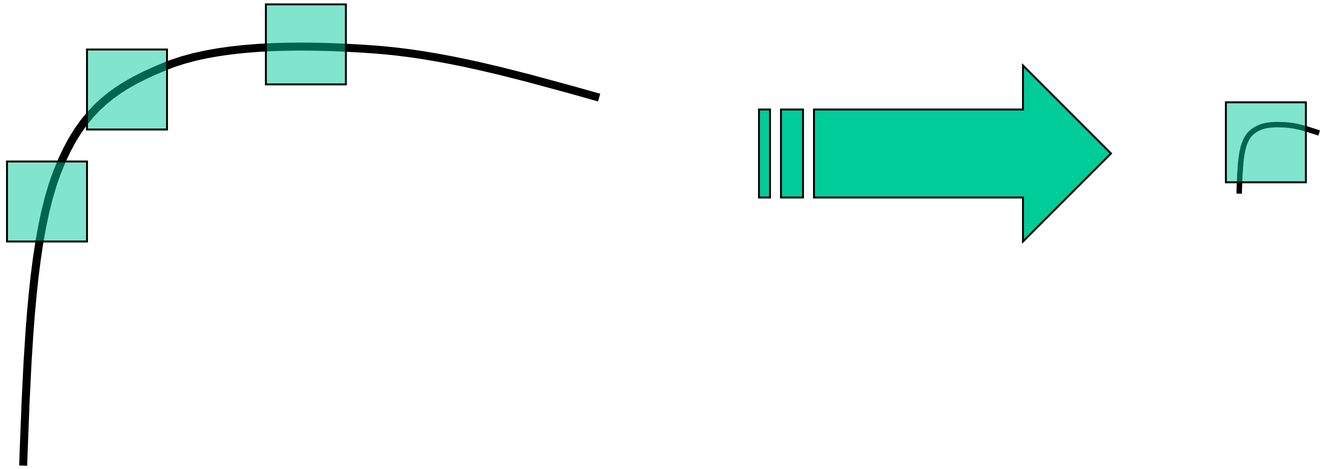
✓ Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$

✓ Intensity scale: $I \rightarrow a\,I$



Harris Detector: Some Properties

But: non-invariant to *image scale*!



All points will be classified as edges

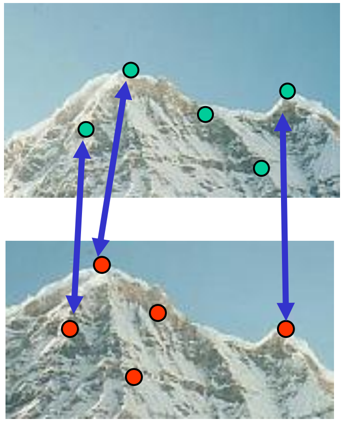
Corner !

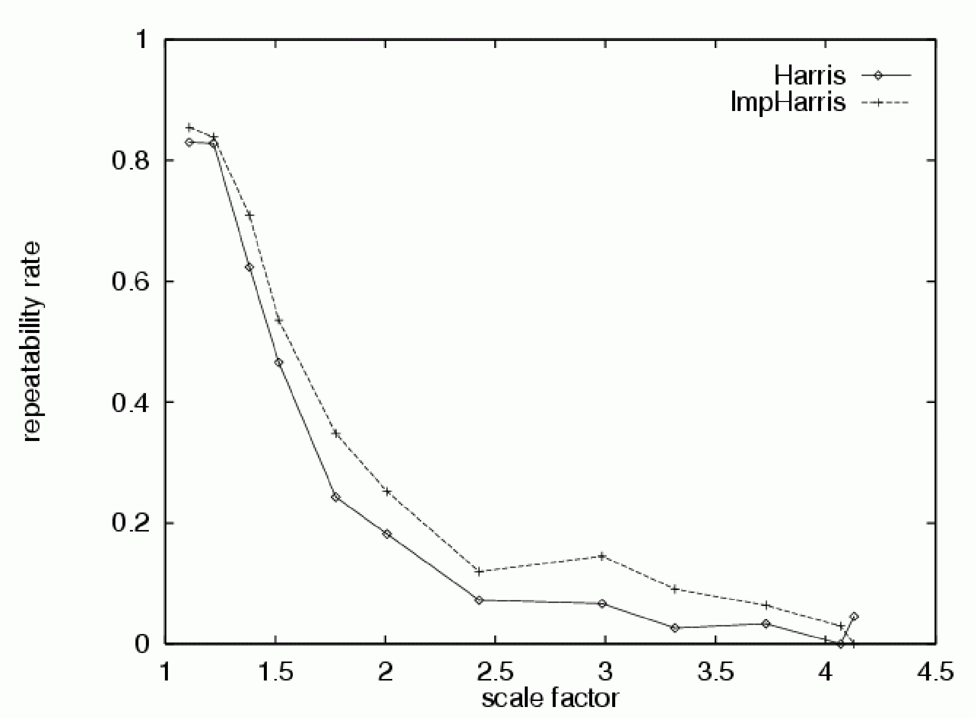
Harris Detector: Some Properties

Quality of Harris detector for different scale changes

Repeatability rate:

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



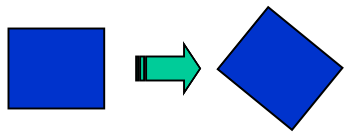


C.Schmid et.al. "Evaluation of Interest Point Detectors". IJCV 2000

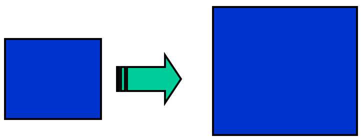
Models of Image Change

Geometry

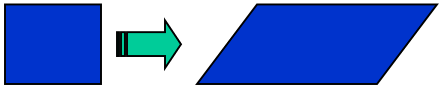
- Rotation



- Similarity (rotation + uniform scale)

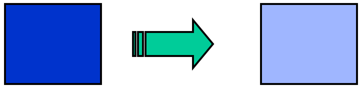


- Affine (scale dependent on direction)
  valid for: orthographic camera, locally planar object



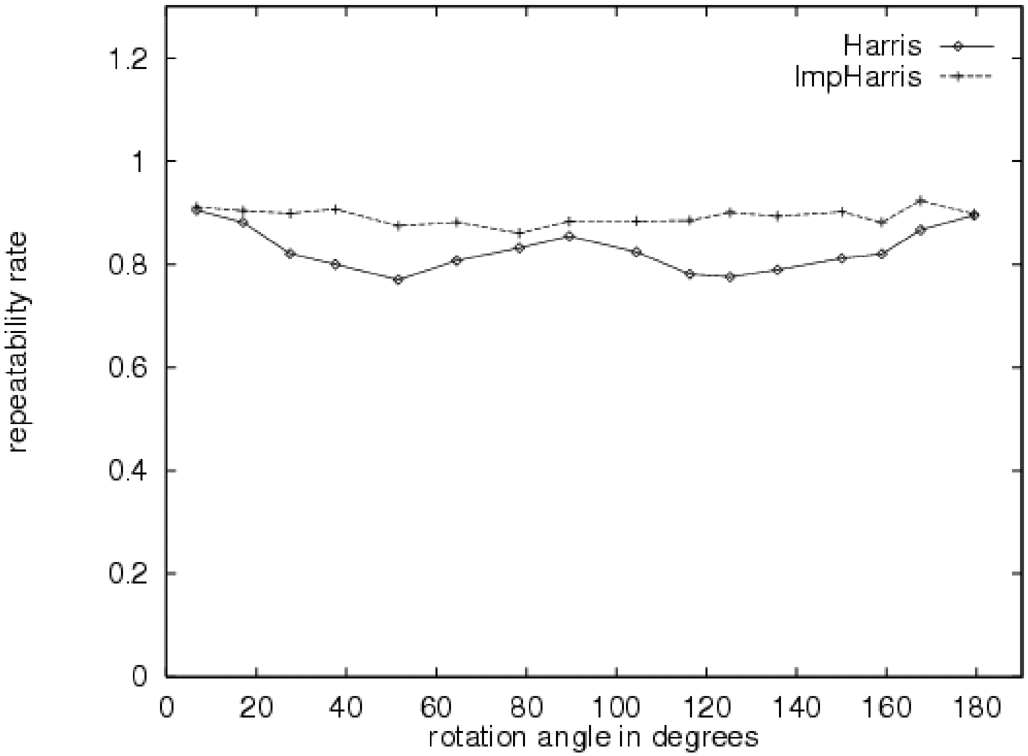
Photometry

- Affine intensity change ($I \rightarrow a\, I + b$)



Rotation Invariant Detection

Harris Corner Detector

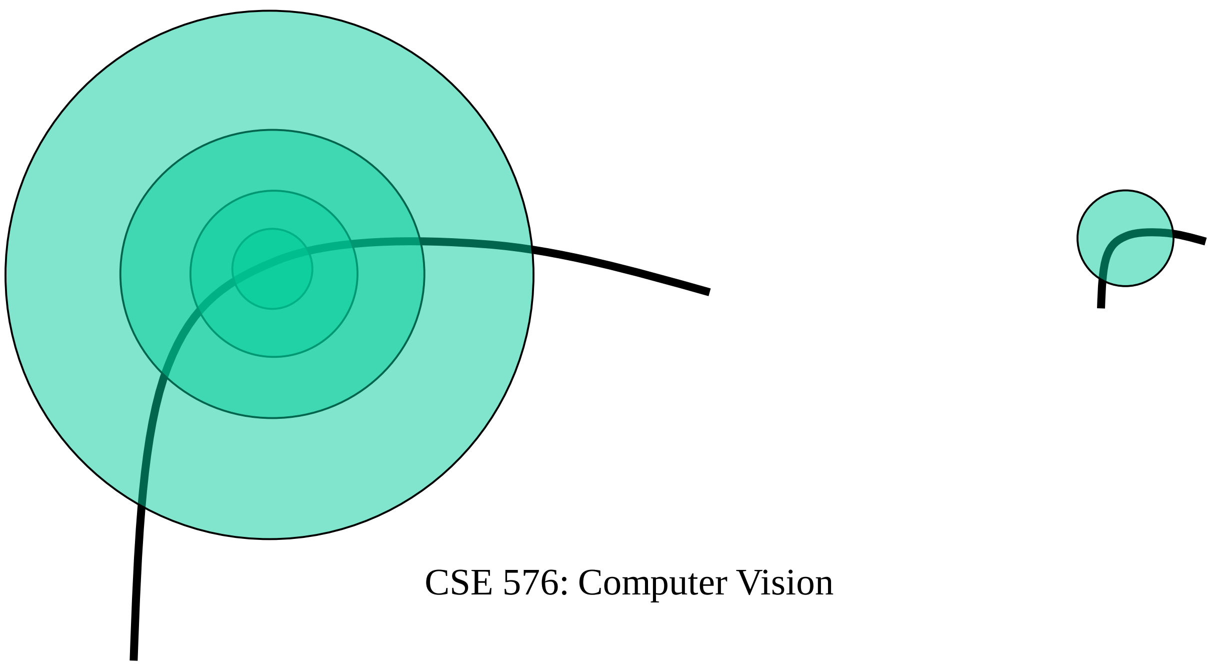


C.Schmid et.al. “Evaluation of Interest Point Detectors”. IJCV 2000

Scale Invariant Detection

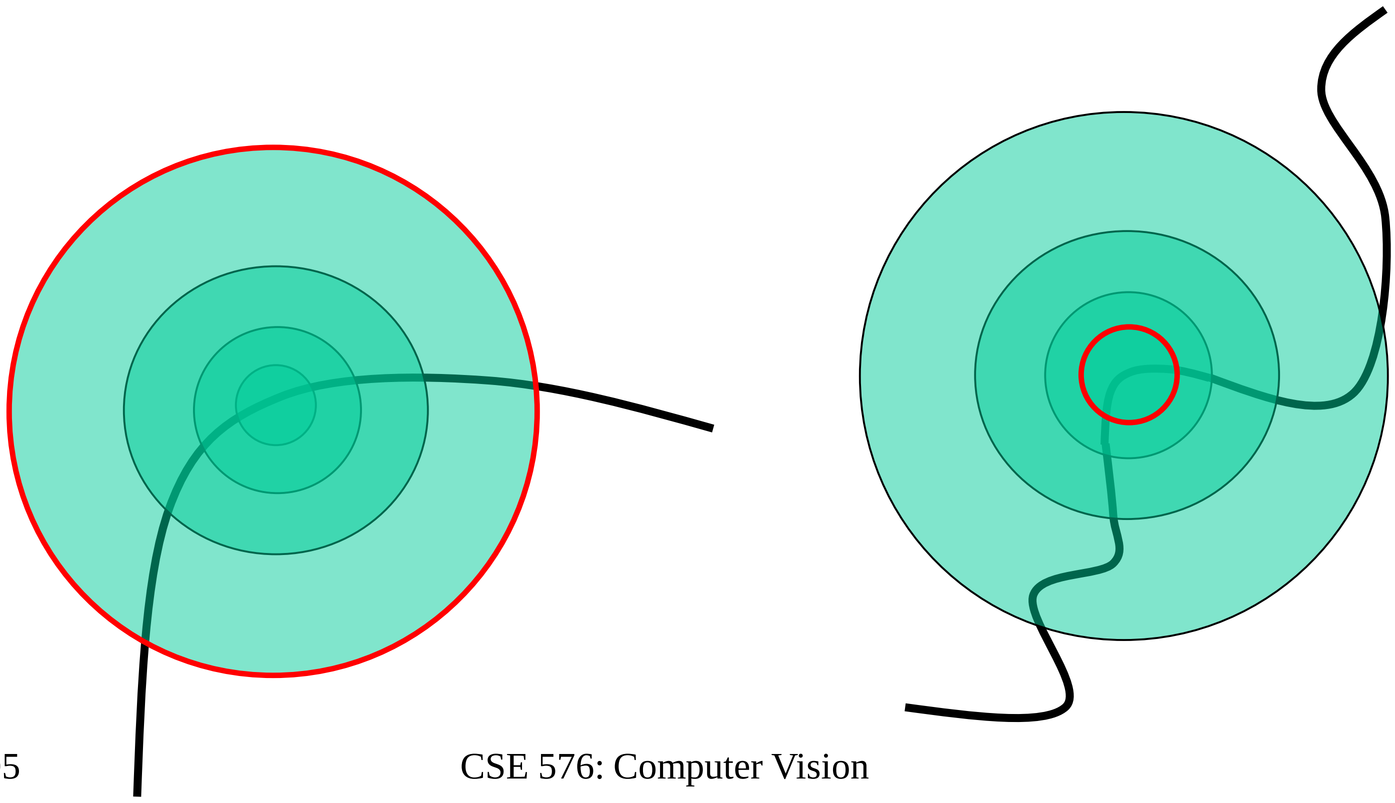
Consider regions (e.g. circles) of different sizes around a point

Regions of corresponding sizes will look the same in both images



Scale Invariant Detection

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



Scale invariance

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

The 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 – but examining more scales)

Difference-of-Gaussian with constant ratio of scales is a close approximation to Lindeberg's scale-normalized Laplacian (can be shown from the heat diffusion equation)

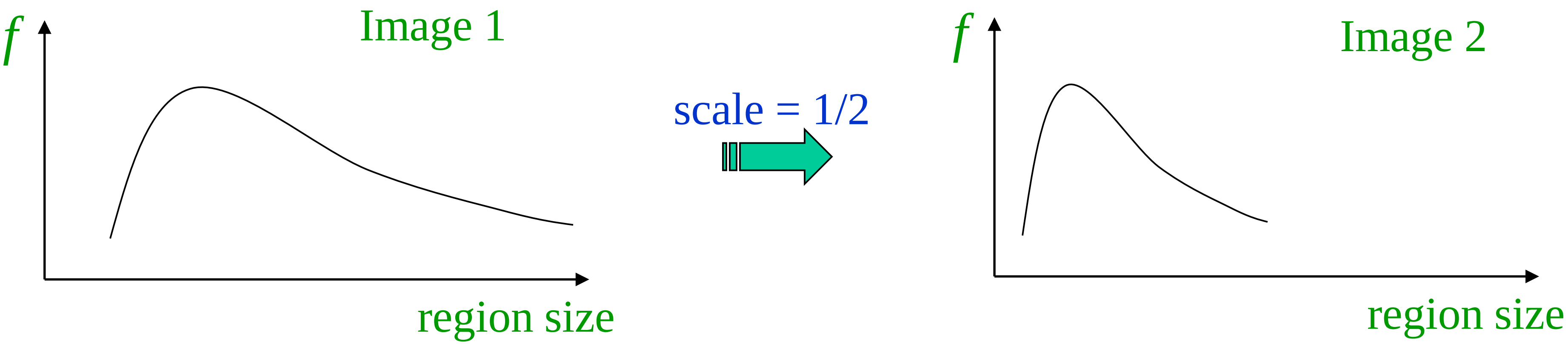
Scale Invariant Detection

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)



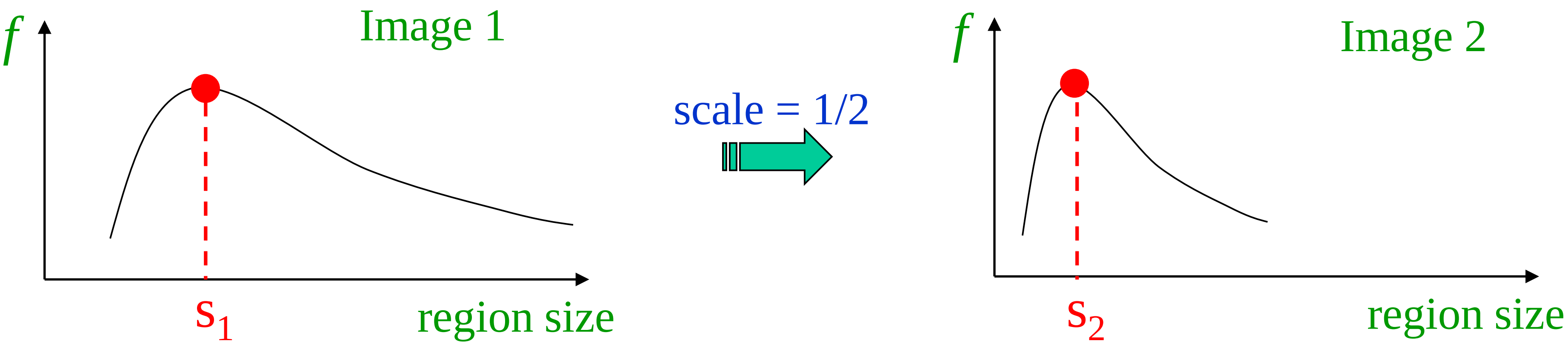
Scale Invariant Detection

Common approach:

Take a local maximum of this function

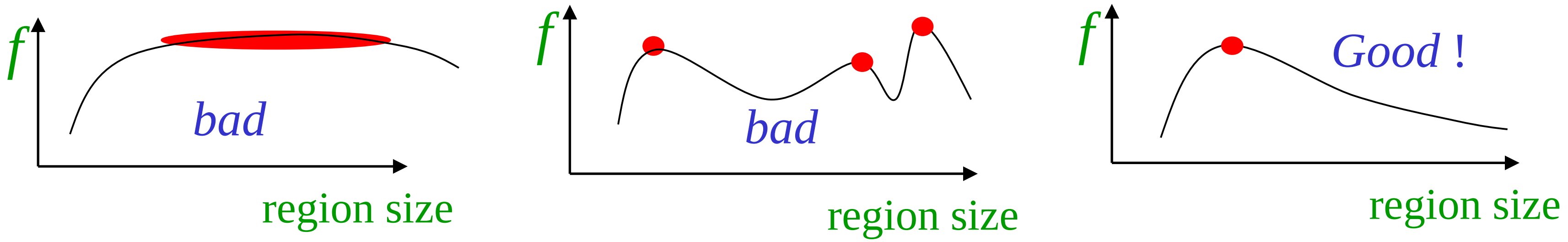
Observation: region size, for which the maximum is achieved, should be *invariant* to image scale.

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



Scale Invariant Detection

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 Invariant Detection

Functions for determining scale

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

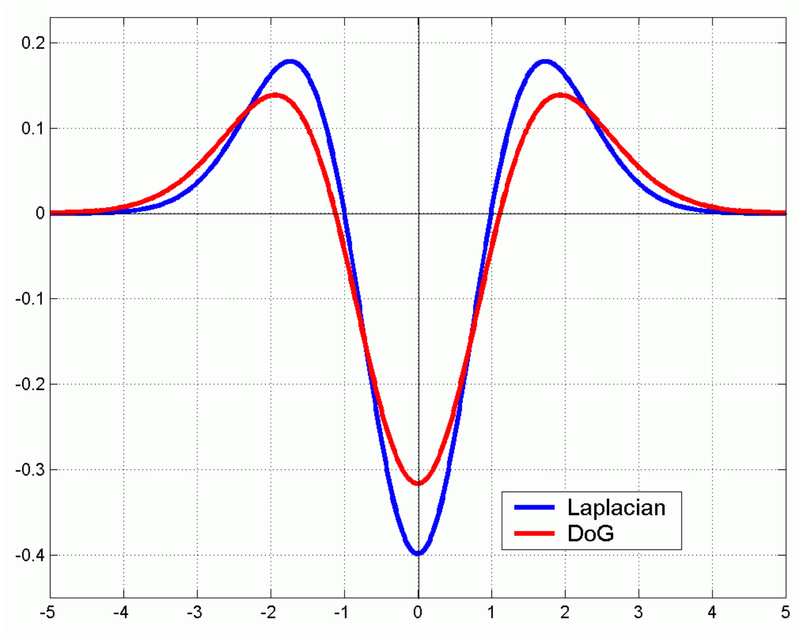
Kernels:

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

(Laplacian)

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

(Difference of Gaussians)

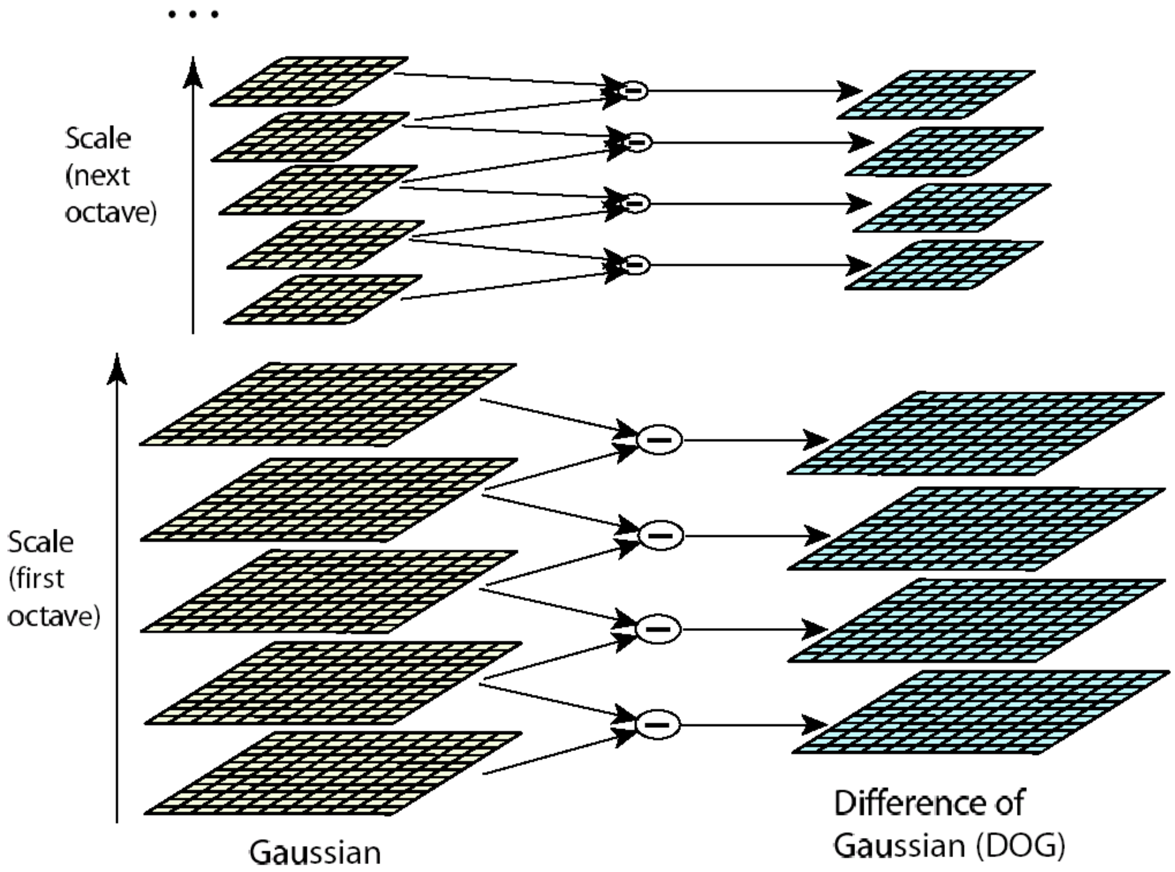


where Gaussian

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

Note: both kernels are invariant to *scale* and *rotation*

Scale space: one octave at a time



Key point localization

Detect maxima and minima of difference-of-Gaussian in scale space

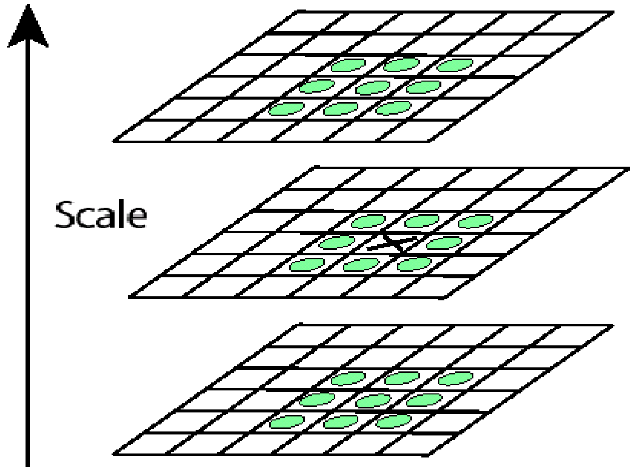
Fit a quadratic to surrounding values for sub-pixel and sub-scale interpolation (Brown & Lowe, 2002)

Taylor expansion around point:

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

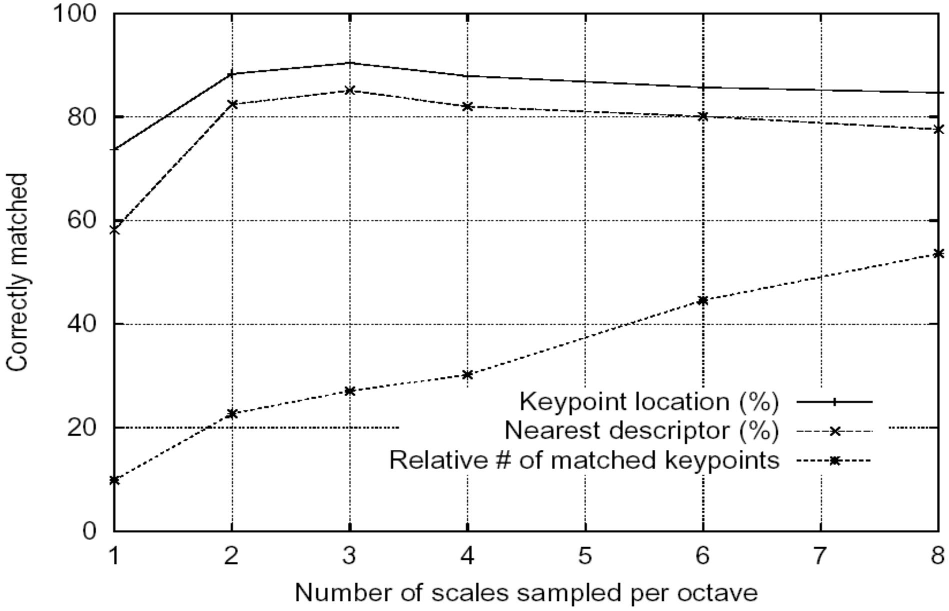
Offset of extremum (use finite differences for derivatives):

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



Sampling frequency for scale

More points are found as sampling frequency increases, but accuracy of matching decreases after 3 scales/octave



Eliminating unstable keypoints

Discard points with DOG value below threshold (low contrast)

However, points along edges may have high contrast in one direction but low in another

Compute principal curvatures from eigenvalues of 2x2 Hessian matrix, and limit ratio (Harris approach):

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

$$\mathrm{Tr}(\mathbf{H}) = D_{xx} + D_{yy} = \alpha + \beta,$$
$$\mathrm{Det}(\mathbf{H}) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha\beta.$$

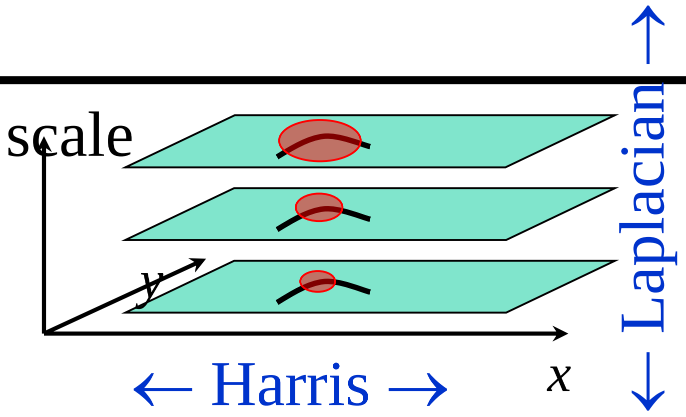
$$\frac{\mathrm{Tr}(\mathbf{H})^2}{\mathrm{Det}(\mathbf{H})} < \frac{(r+1)^2}{r}$$

Scale Invariant Detectors

Harris-Laplacian[1]

Find local maximum of:

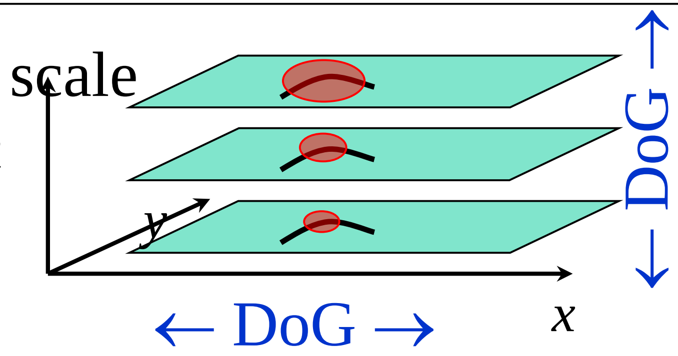
- Harris corner detector in space (image coordinates)
- Laplacian in scale



- SIFT (Lowe)[2]

Find local maximum of:

- – Difference of Gaussians in space and scale



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

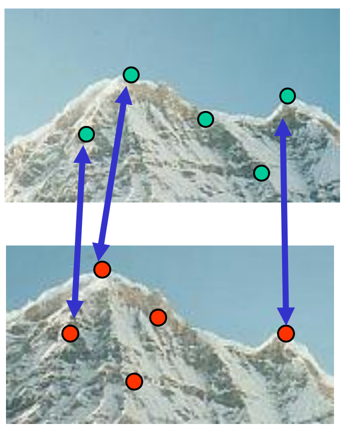
[2] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". Accepted to IJCV 200

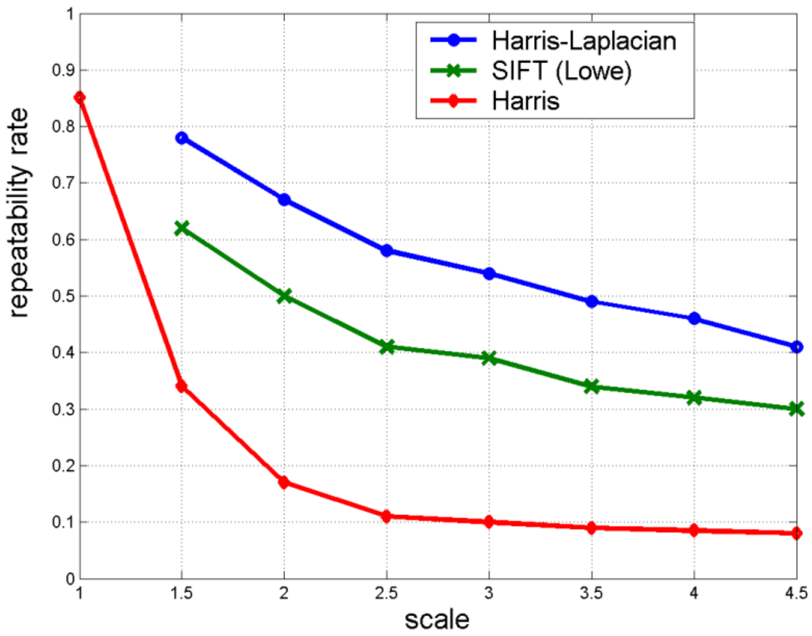
Scale Invariant Detectors

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

Affine Covariant Features - Microsoft Internet Explorer

Address: http://www.robots.ox.ac.uk/~vgg/research/affine/

Affine Covariant Regions

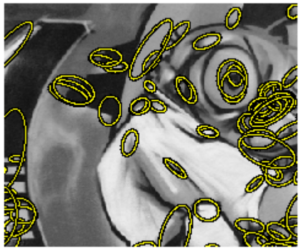


Image 1

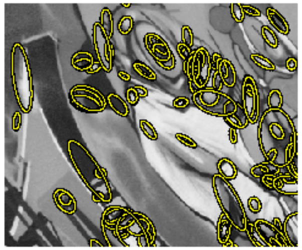


Image 2

Publications

Region detectors

- *Harris-Affine & Hessian Affine*: K. Mikolajczyk and C. Schmid, Scale and Affine invariant interest point detectors. In IJCV 1(60):63-86, 2004. PDF
- *MSER*: J.Matas, O. Chum, M. Urban, and T. Pajdla, Robust wide baseline stereo from maximally stable extremal regions. In BMVC p. 384-393, 2002. PDF
- *IBR & EBR*: T.Tuytelaars and L. Van Gool, Matching widely separated views based onaffine invariant regions. In IJCV 1 (59):61-85, 2004. PDF
- *Salient regions*: T. Kadir, A. Zisserman, and M. Brady, An affine invariant salient region detector. In ECCV p. 404-416, 2004. PDF

Region descriptors

- *SIFT*: D. Lowe, Distinctive image features from scale invariant keypoints. In IJCV 2(60):91-110, 2004. PDF

Performance evaluation

- K. Mikolajczyk, T. Tuytelaars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir and L. Van Gool, A comparison of affine region detectors. Technical Report, accepted to IJCV. PDF
- K. Mikolajczyk, C. Schmid, A performance evaluation of local descriptors. Technical Report, accepted to PAMI. PDF

Software

- Region detectors - Linux binaries for detecting affine covariant regions.
- Region descriptors - Linux binaries for computing region descriptors.
- Detectors evaluation - Matlab files to compute the repeatability.
- Descriptors evaluation - Matlab files to compute the matching score.

Test Data

The packages contain images in PPM format and homographies between image pairs. Data description.

Affine Covariant Features - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Address http://www.robots.ox.ac.uk/~vgg/research/affine/

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Blur

1000x700
6 images

Blur

1000x700
6 images

Viewpoint

800x640
6 images

Viewpoint

1000x700
6 images

Zoom+rotation

765x512
6 images

Zoom+rotation

800x640
6 images

Light

921x614
6 images

JPEG compression

800x640
6 images

Page maintained by km@robots.ox.ac.uk.
Last updated 26th November 2004

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)

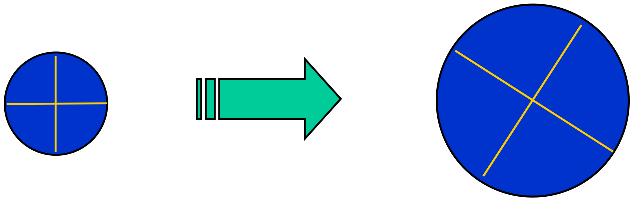
Methods:

1. Harris-Laplacian [Mikolajczyk, Schmid]: maximize Laplacian over scale, Harris' measure of corner response over the image
2. SIFT [Lowe]: maximize Difference of Gaussians over scale and space

Affine Invariant Detection

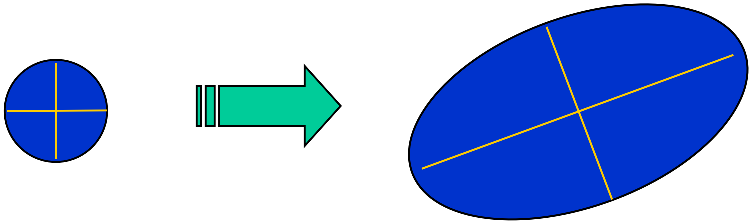
Above we considered:

Similarity transform (rotation + uniform scale)



- Now we go on to:

  Affine transform (rotation + non-uniform scale)

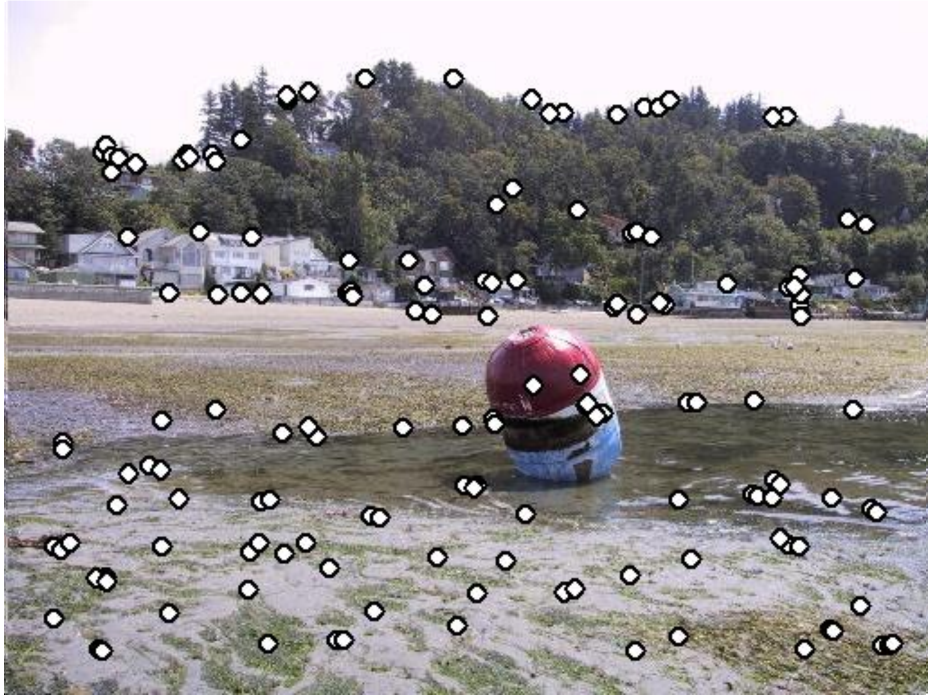


Affine invariant descriptors

… skip these slides (see handouts and on-line class notes) …

Feature selection

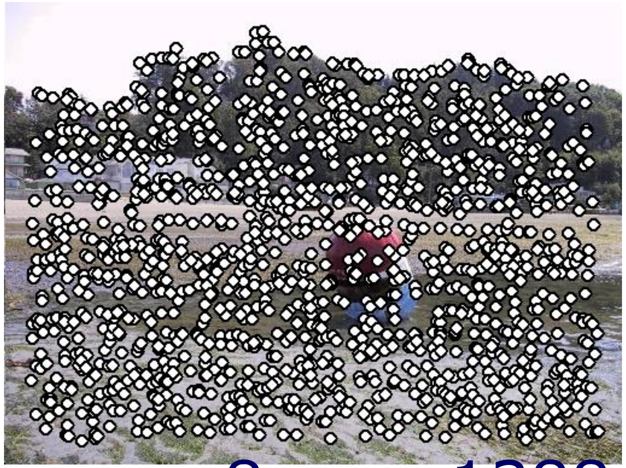
Distribute points evenly over the image



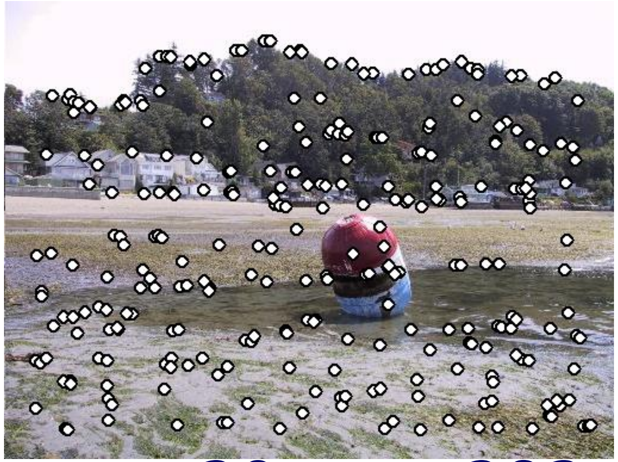
Adaptive Non-maximal Suppression

Desired: Fixed # of features per image

- Want evenly distributed spatially…
- Search over non-maximal suppression radius [Brown, Szeliski, Winder, CVPR'05]



r = 8, n = 1388



r = 20, n = 283

Today's lecture

- What is computer vision?
- Scale-space and pyramids
- What are good features?
- Feature detection
- Feature descriptors
- (Next lecture: feature matching)

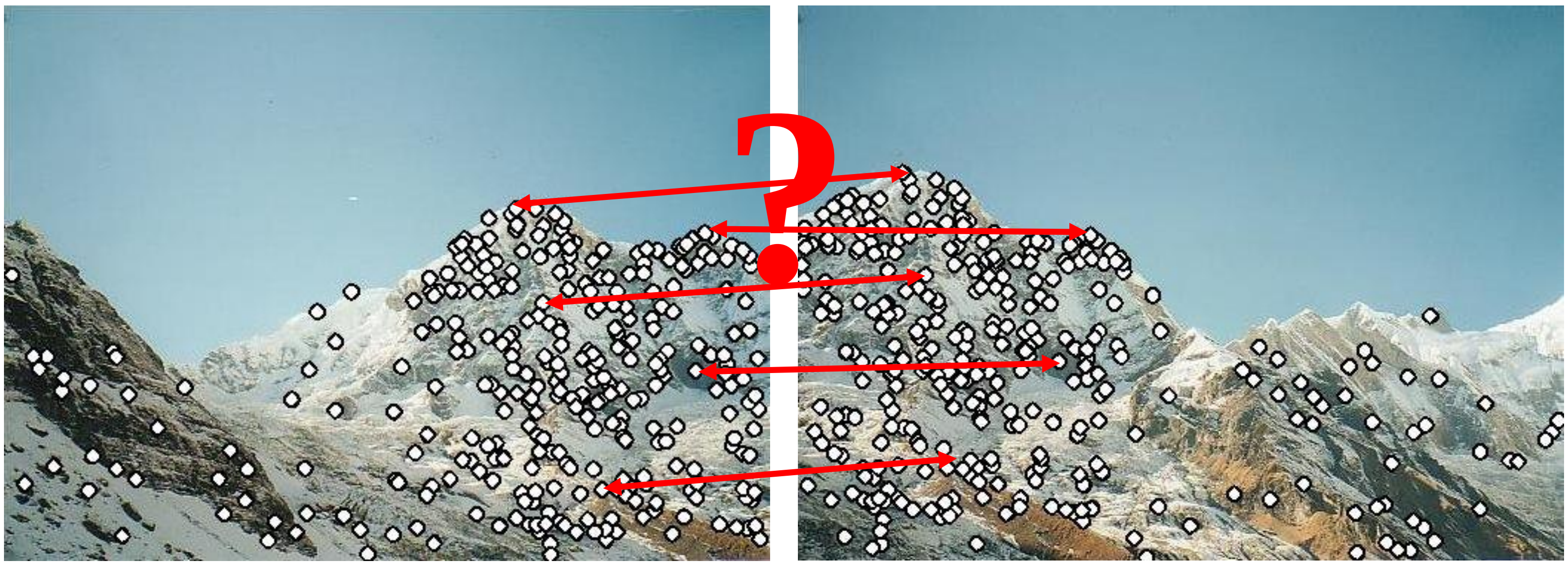
- Project 1description and demo [Ian Simon]

Point Descriptors

We know how to detect points

Next question:

How to match them?



Point descriptor should be:

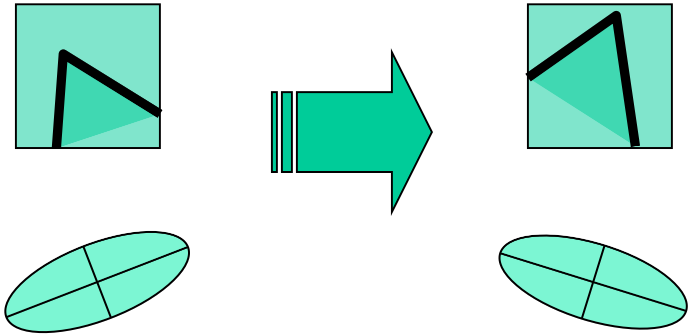
1. Invariant
2. Distinctive

Descriptors Invariant to Rotation

Harris corner response measure:

depends only on the eigenvalues of the matrix *M*

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



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

Multi-Scale Oriented Patches

Interest points

- Multi-scale Harris corners
- Orientation from blurred gradient
- Geometrically invariant to similarity transforms

Descriptor vector

- Bias/gain normalized sampling of local patch (8x8)
- Photometrically invariant to affine changes in intensity

Descriptor Vector

Orientation = blurred gradient

Similarity Invariant Frame

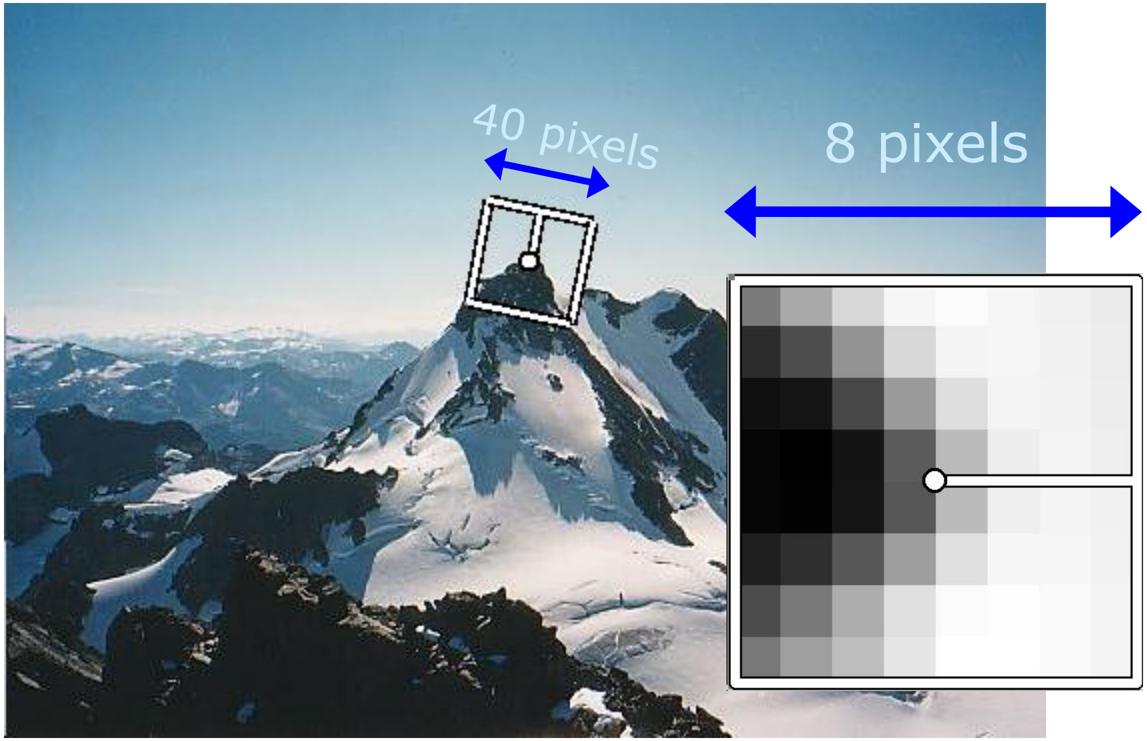
- Scale-space position (x, y, s) + orientation (θ)

MOPS descriptor vector

8x8 oriented patch

- Sampled at 5 x scale

Bias/gain normalisation: $I' = (I - \mu)/\sigma$



Descriptors Invariant to Rotation

Image moments in polar coordinates

$$m_{kl} = \iint r^k e^{-i\theta l} I(r,\theta)\, dr\, d\theta$$

Rotation in polar coordinates is translation of the angle:

$$\theta \to \theta + \theta_0$$

This transformation changes only the phase of the moments, but not its magnitude

Rotation invariant descriptor consists of magnitudes of moments:

$$|m_{kl}|$$

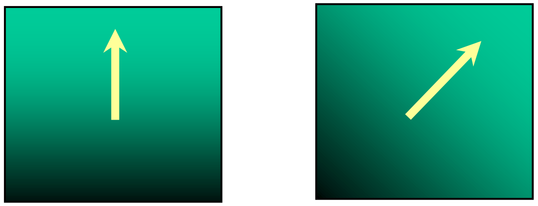
Matching is done by comparing vectors $[|m_{kl}|]_{k,l}$

J.Matas et.al. "Rotational Invariants for Wide-baseline Stereo". Research Report of CMP, 2003

Descriptors Invariant to Rotation

Find local orientation

Dominant direction of gradient



- Compute image derivatives relative to this 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

Descriptors Invariant to Scale

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

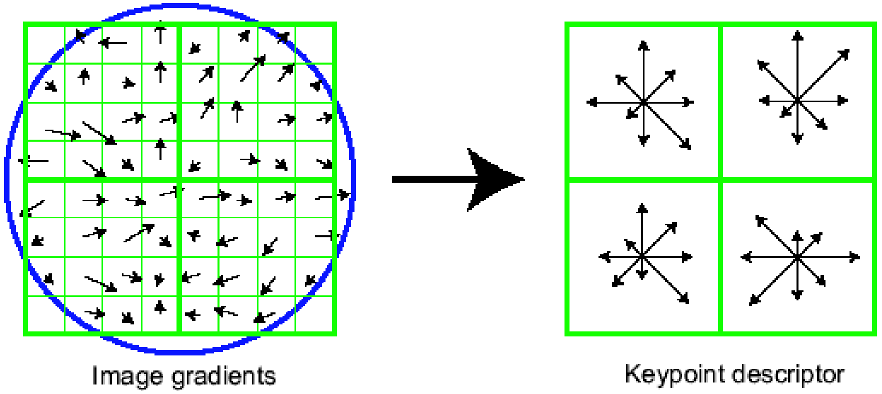
For example:

- moments integrated over an adapted window
- derivatives adapted to scale: sI_x

SIFT – Scale Invariant Feature Transform

Descriptor overview:

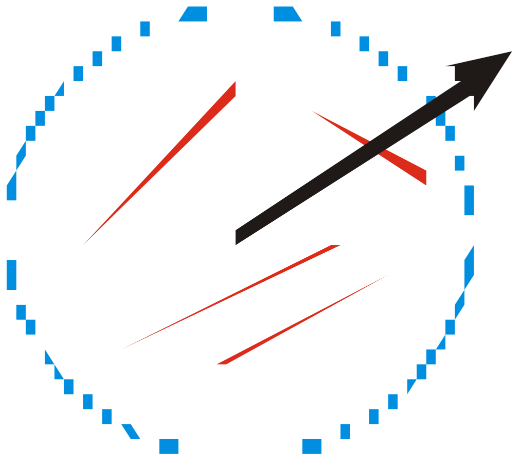
- Determine scale (by maximizing DoG in scale and in space), local orientation as the dominant gradient direction.
  Use this scale and orientation to make all further computations invariant to scale and rotation.
- Compute gradient orientation histograms of several small windows (128 values for each point)
- Normalize the descriptor to make it invariant to intensity change

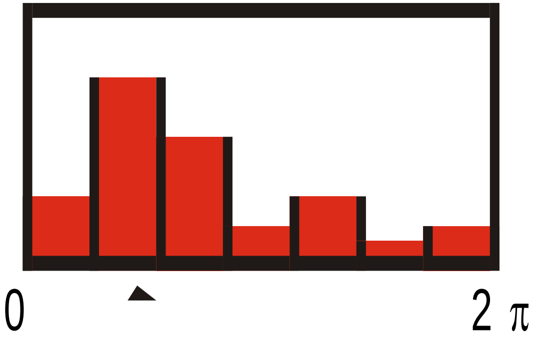


D.Lowe. “Distinctive Image Features from Scale-Invariant Keypoints”. IJCV 2004

Select canonical orientation

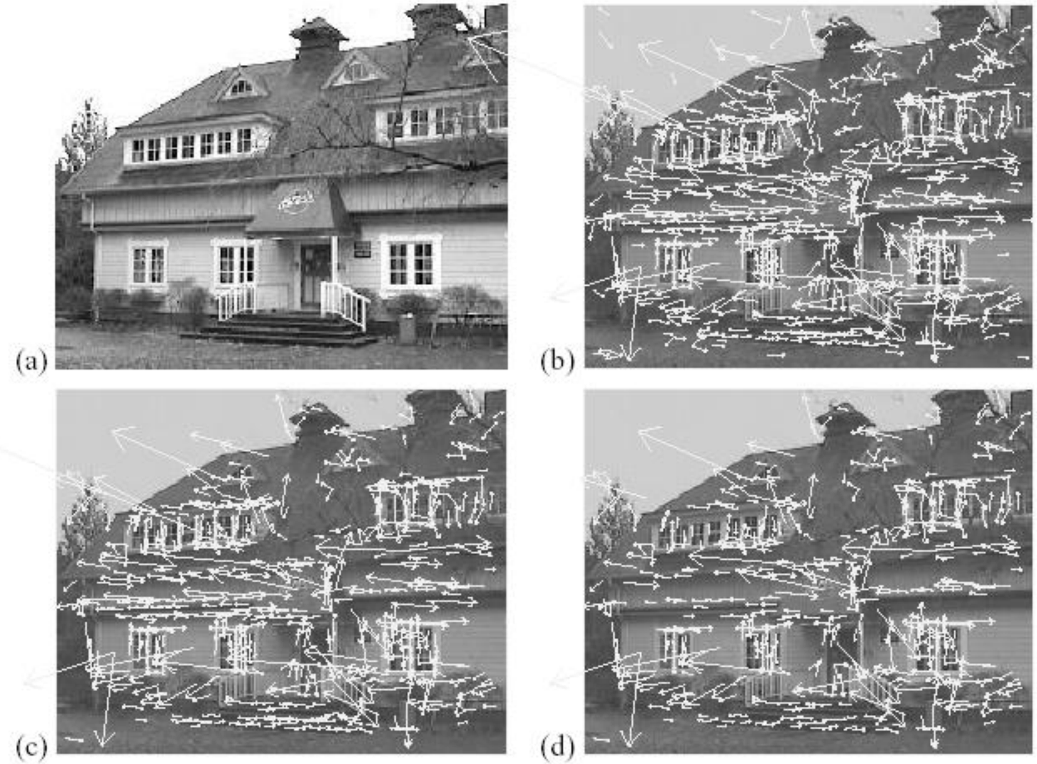
- Create histogram of local gradient directions computed at selected scale
- Assign canonical orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientation)





Example of keypoint detection

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



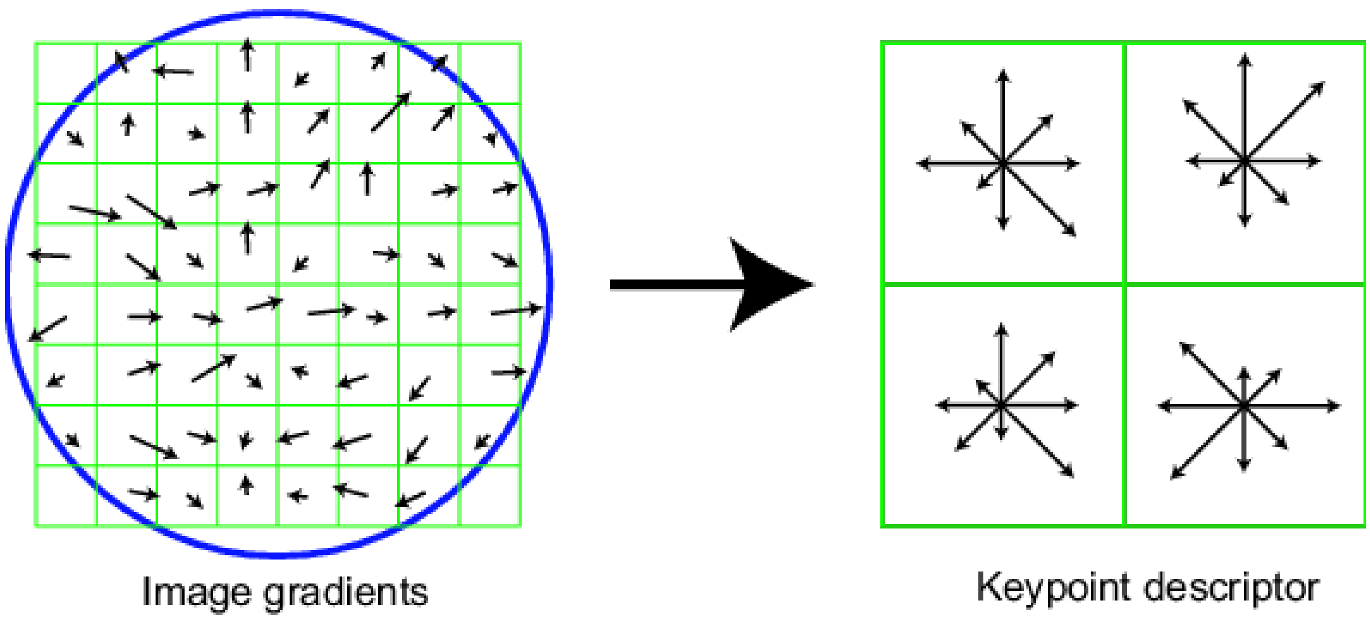
(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures

SIFT vector formation

Thresholded image gradients are sampled over 16x16 array of locations in scale space

Create array of orientation histograms

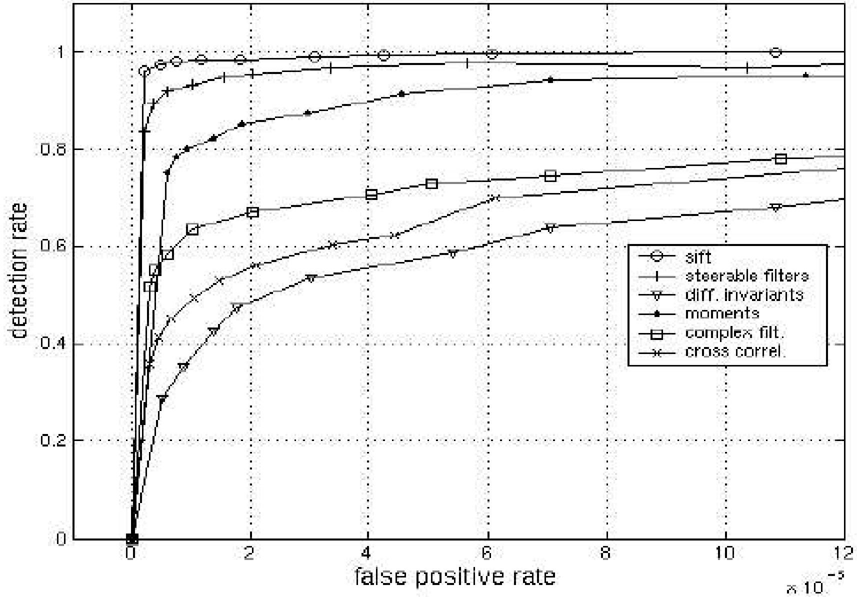
8 orientations x 4x4 histogram array = 128 dimensions



SIFT – Scale Invariant Feature Transform[1]

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] D.Lowe. "Distinctive Image Features from Scale-Invariant Keypoints". Accepted to IJCV 2004
[2] K.Mikolajczyk, C.Schmid. "A Performance Evaluation of Local Descriptors". CVPR 2003

Invariance to Intensity Change

Detectors

- mostly invariant to affine (linear) change in image intensity, because we are searching for *maxima*

Descriptors

- Some are based on derivatives => invariant to intensity shift
- Some are normalized to tolerate intensity scale
- Generic method: pre-normalize intensity of a region (eliminate shift and scale)

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