Corner Detection & Optical Flow

CSC420
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Slide credit: Babak Taati ←Ahmed Ashraf ←Sanja Fidler

TCIG
Toronto Computational Imaging Group

Logistics

- A2 due on Friday

- no lecture next Monday (reading week)

Overview

- Recap
- Image features
- Corner detection
- Optical flow

Recap

Review

- Images
  - what is an image?

Review

- Images
  - what is an image?
  - what do pixel values represent?

Review

- Filtering
  - what is correlation?

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- Filtering
  - what is correlation?
  - what is convolution?

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  - what is the convolution theorem?

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  - what is the Nyquist theorem?

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- Filtering
  - what is correlation?
  - what is convolution?
  - what is the convolution theorem?
  - what is the Nyquist theorem?
  - how do we “smooth” an image?

Review

- Edges
  - how do we extract edges from an image?

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- Edges
  - how do we extract edges from an image?
  - advantages of using edges vs. a conventional image for computer vision?

Review

- Image resizing
  - what is an image pyramid?

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  - what is an image pyramid?
  - what is aliasing?

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  - what is aliasing?
  - how do we downsample an image?

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- Image resizing
  - what is an image pyramid?
  - what is aliasing?
  - how do we downsample an image?
  - how do we upsample an image?

Image Features:
Interest Point (Keypoint) Detection

Image Features

- What skyline is this?

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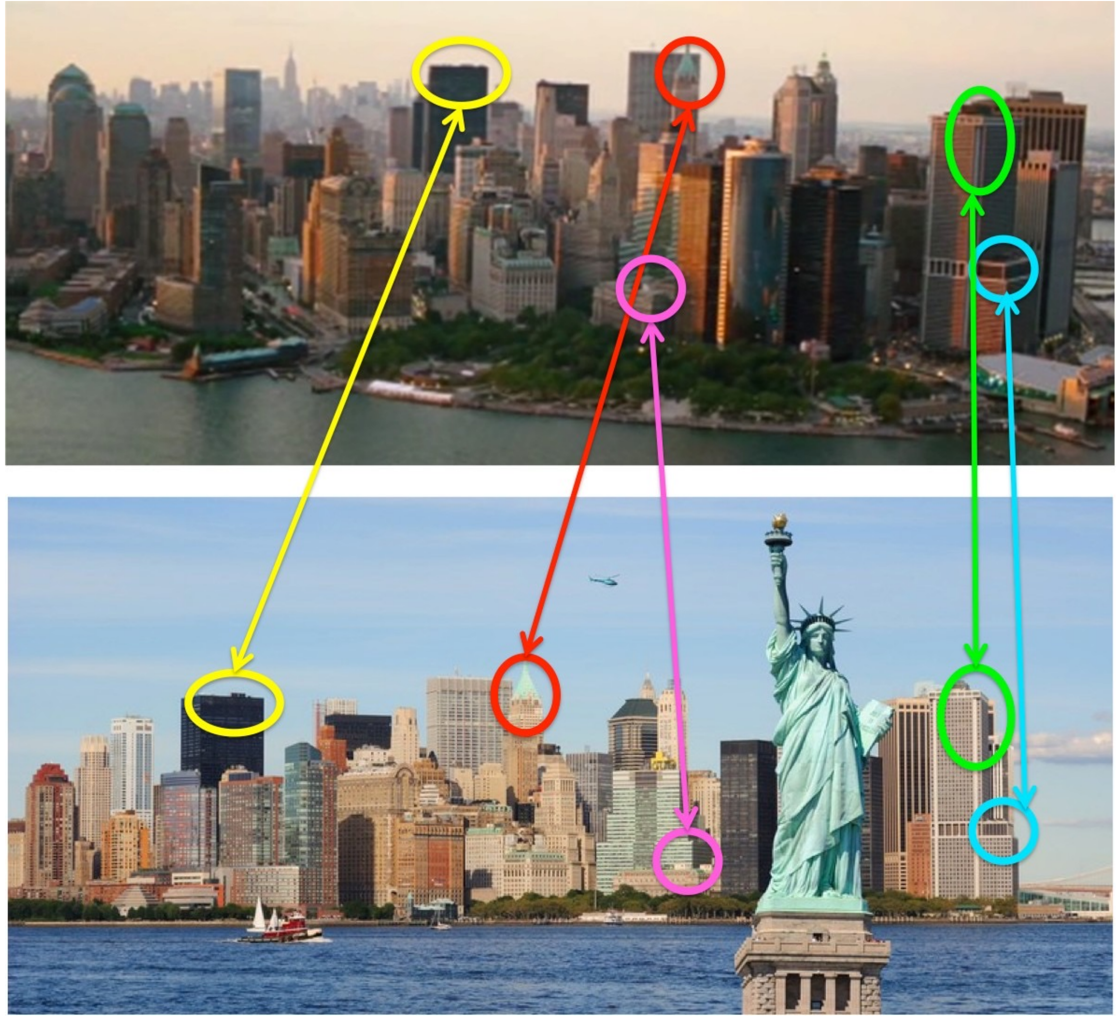
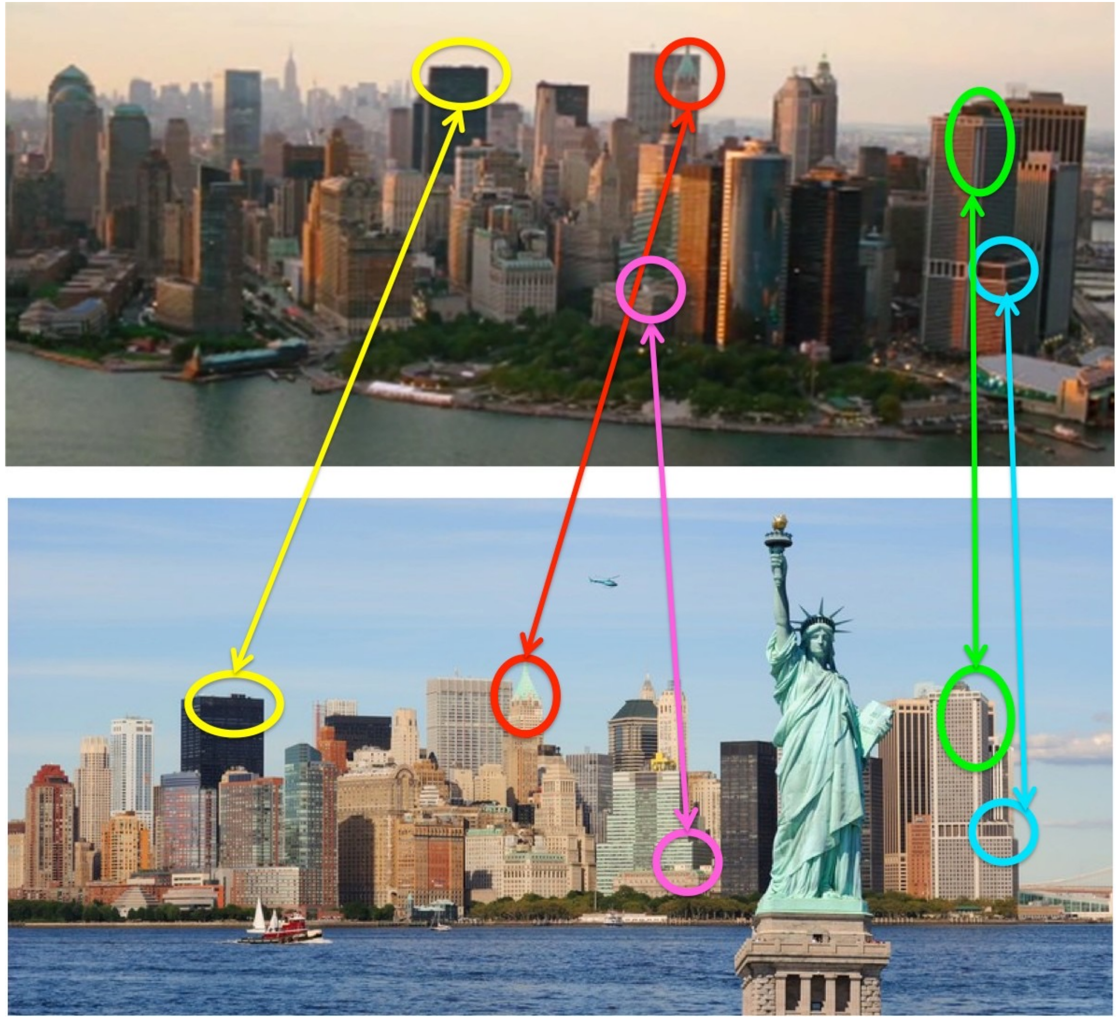


Image Features

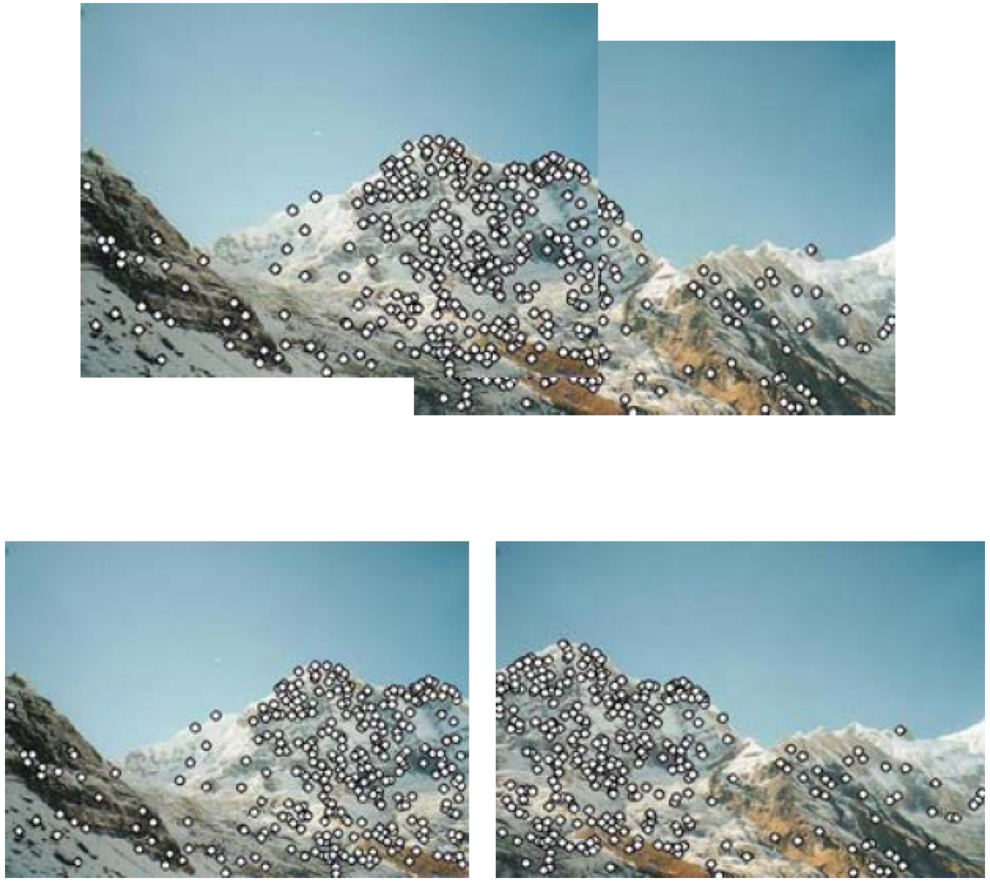
- What skyline is this?

We matched in:

- Distinctive locations: keypoints
- Distinctive features: descriptors



Application Example: Image Stitching



[Source: K. Grauman]

Application Example: Image Stitching

- Detection: Identify the interest points.

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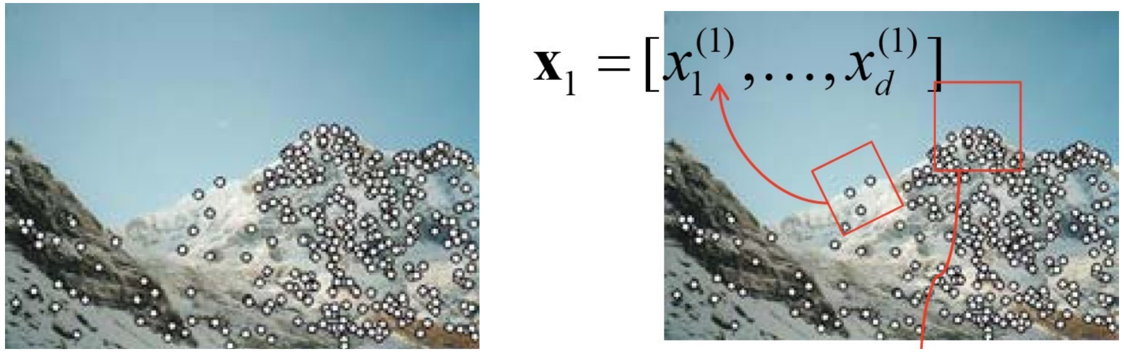
Application Example: Image Stitching

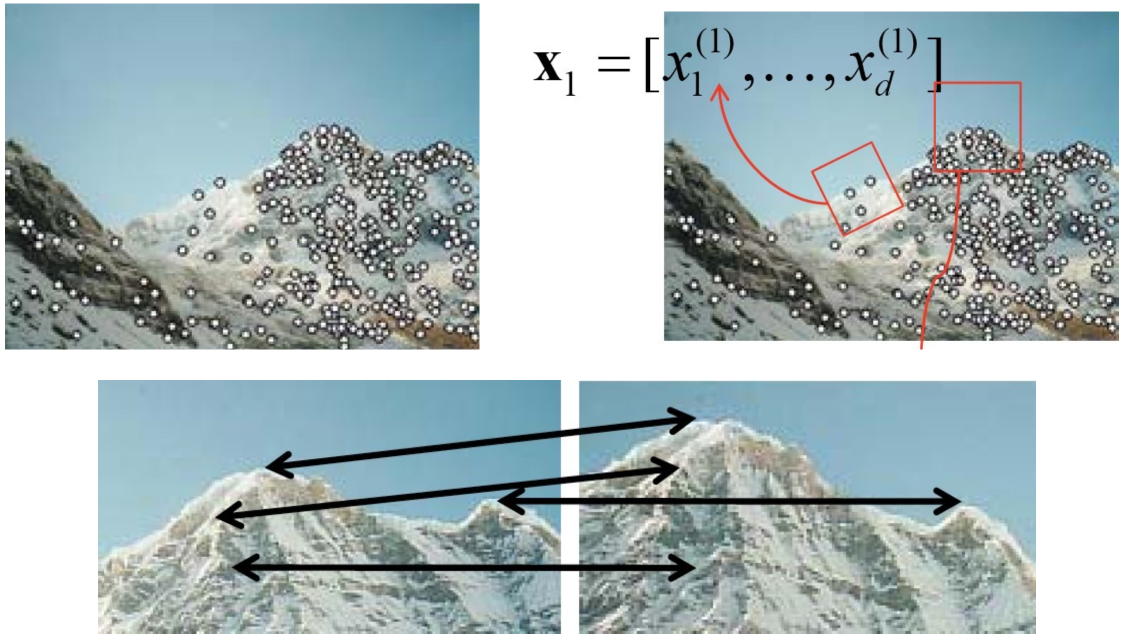
- Detection: Identify the interest points.
- Description: Extract feature vector descriptor around each interest point.



[Source: K. Grauman]

Application Example: Image Stitching

- Detection: Identify the interest points.
- Description: Extract feature vector descriptor around each interest point.
- Matching: Determine correspondence between descriptors in two views.



[Source: K. Grauman]

Goal: Repeatability of the Interest Point Operator

- Our goal is to detect (at least some of) the same points in both images
- We need to run the detection procedure independently per image

Figure: Too few keypoints → little chance to find the true matches

[Source: K. Grauman, slide credit: R. Urtasun]

Goal: Repeatability of the Interest Point Operator

- Our goal is to detect (at least some of) the same points in both images
- We need to run the detection procedure independently per image
- Is it better to detect more interest points or fewer interest points?

Figure: Too few keypoints → little chance to find the true matches

[Source: K. Grauman, slide credit: R. Urtasun]

What Points to Choose?

[Source: K. Grauman]

What Points to Choose for matching?

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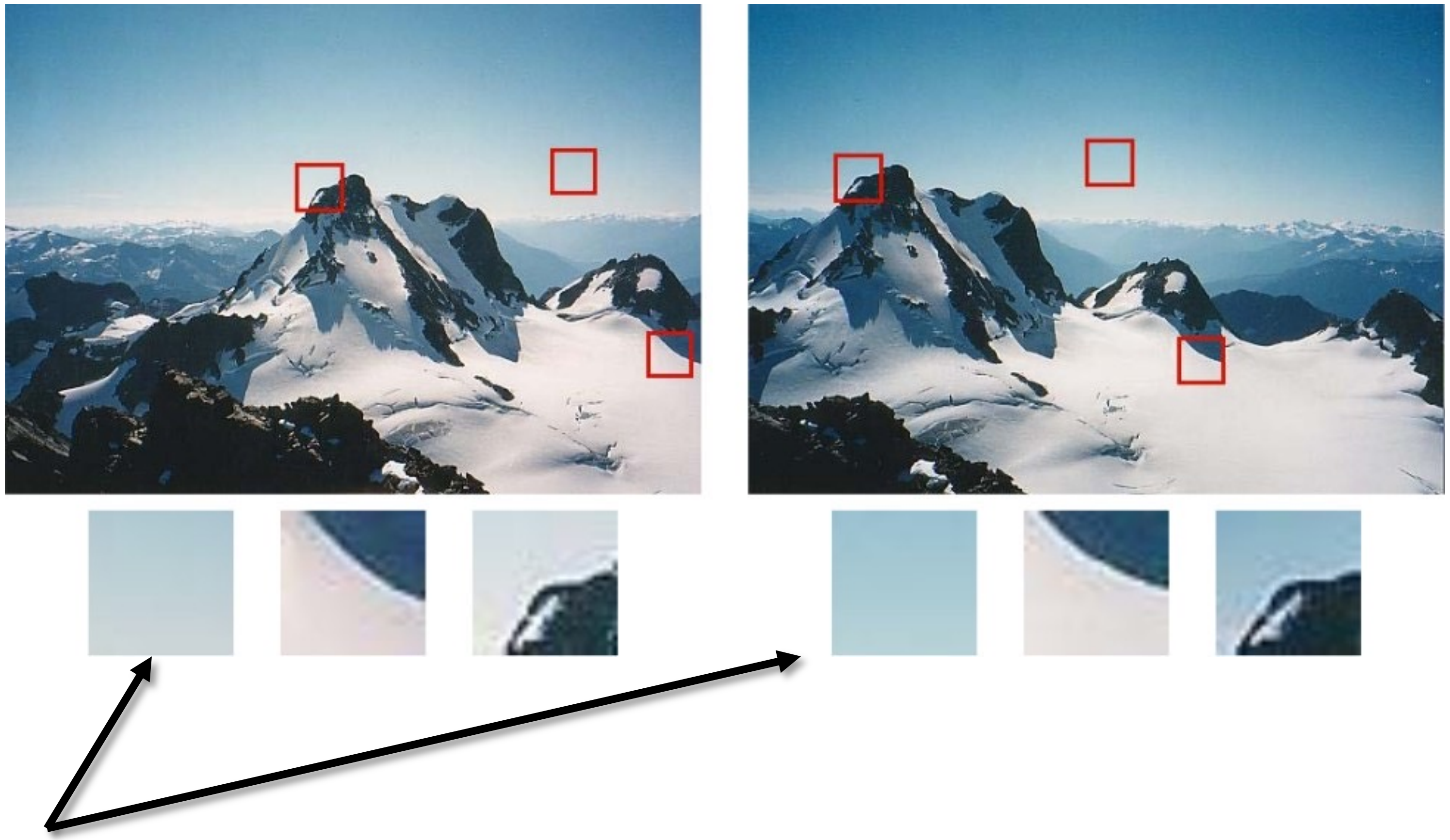
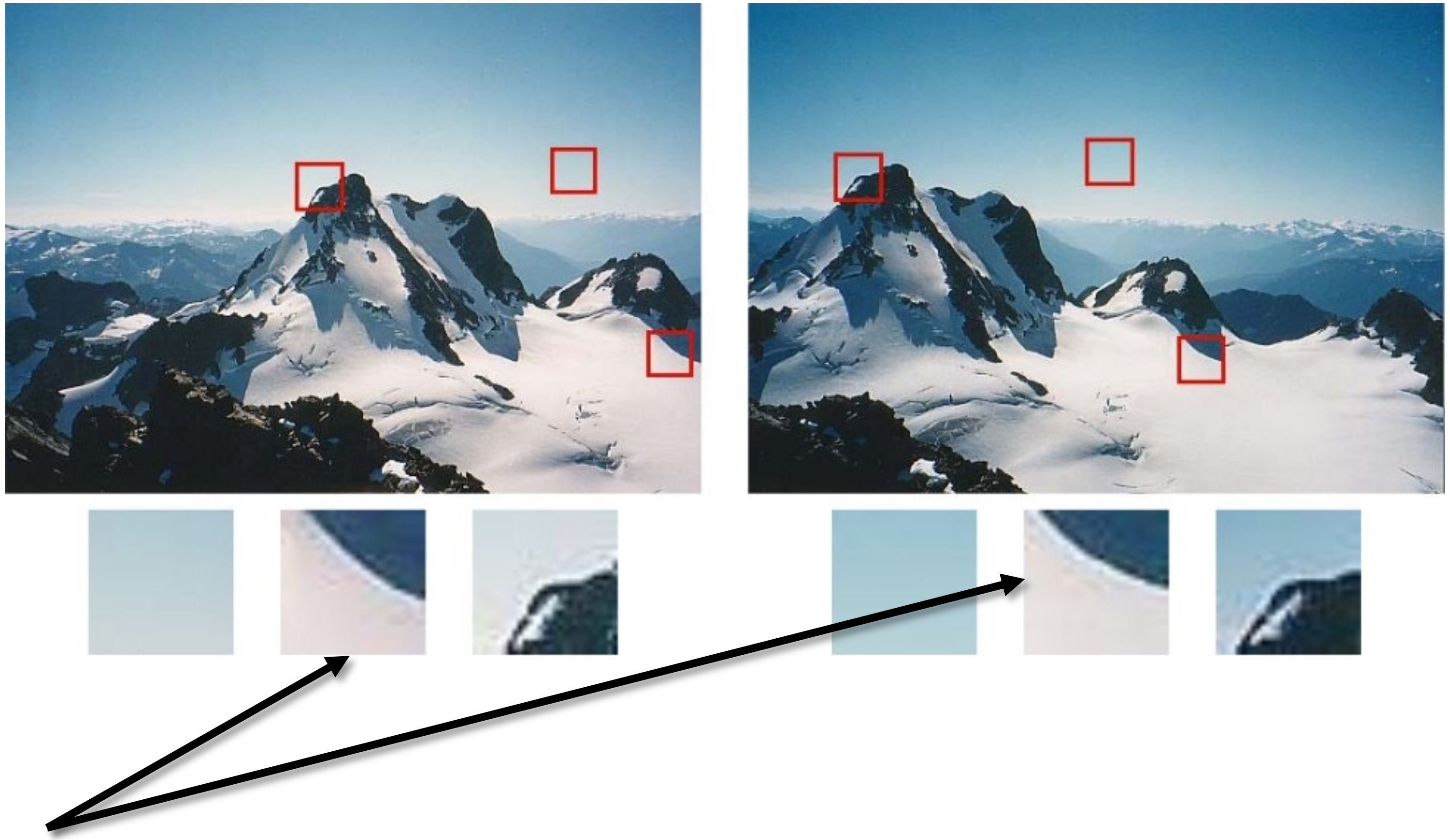


is this a good interest point?

[Adopted from: Szelski (Book)]

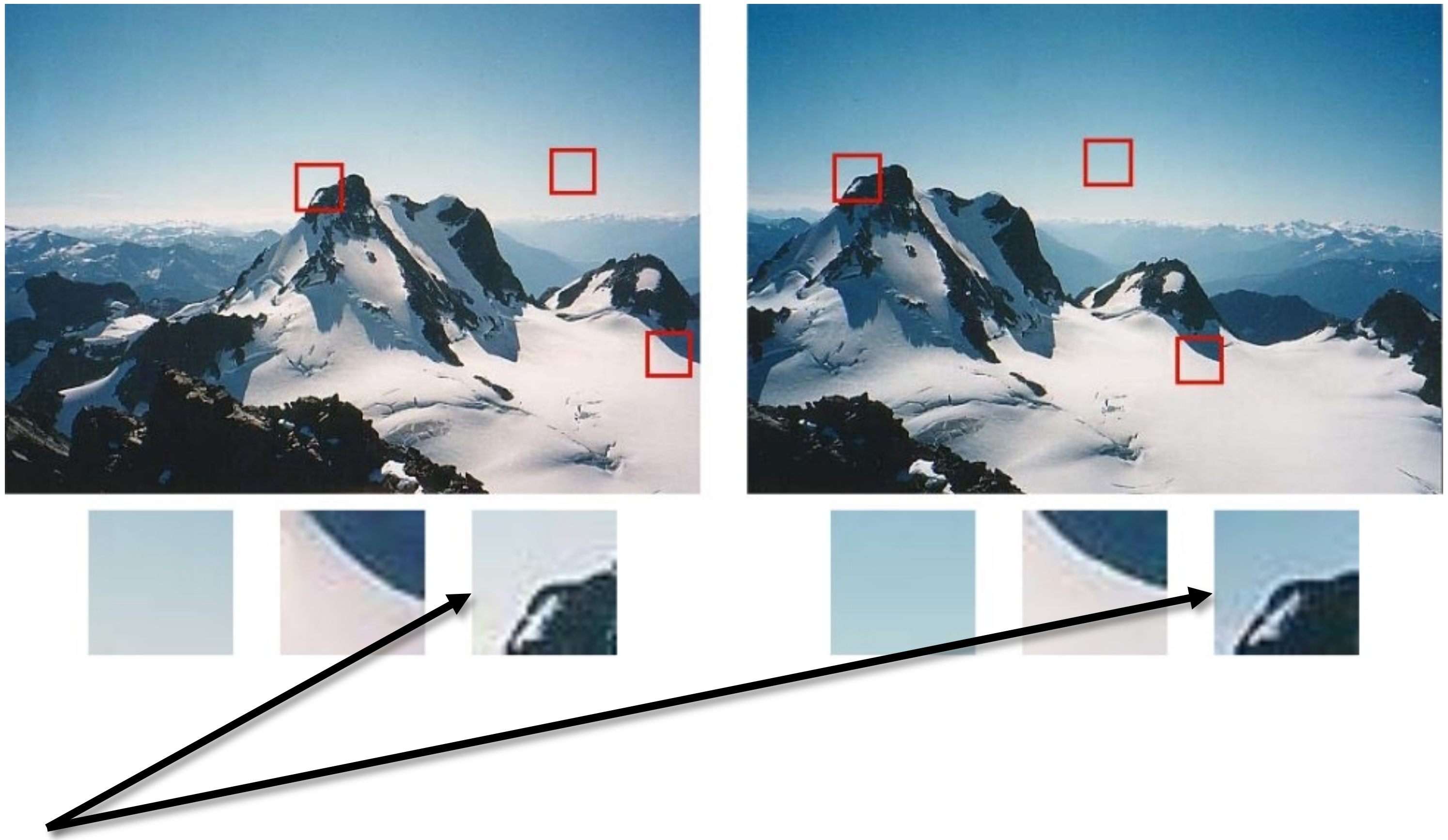
What Points to Choose for matching?



how about this one?

[Adopted from: Szelski (Book)]

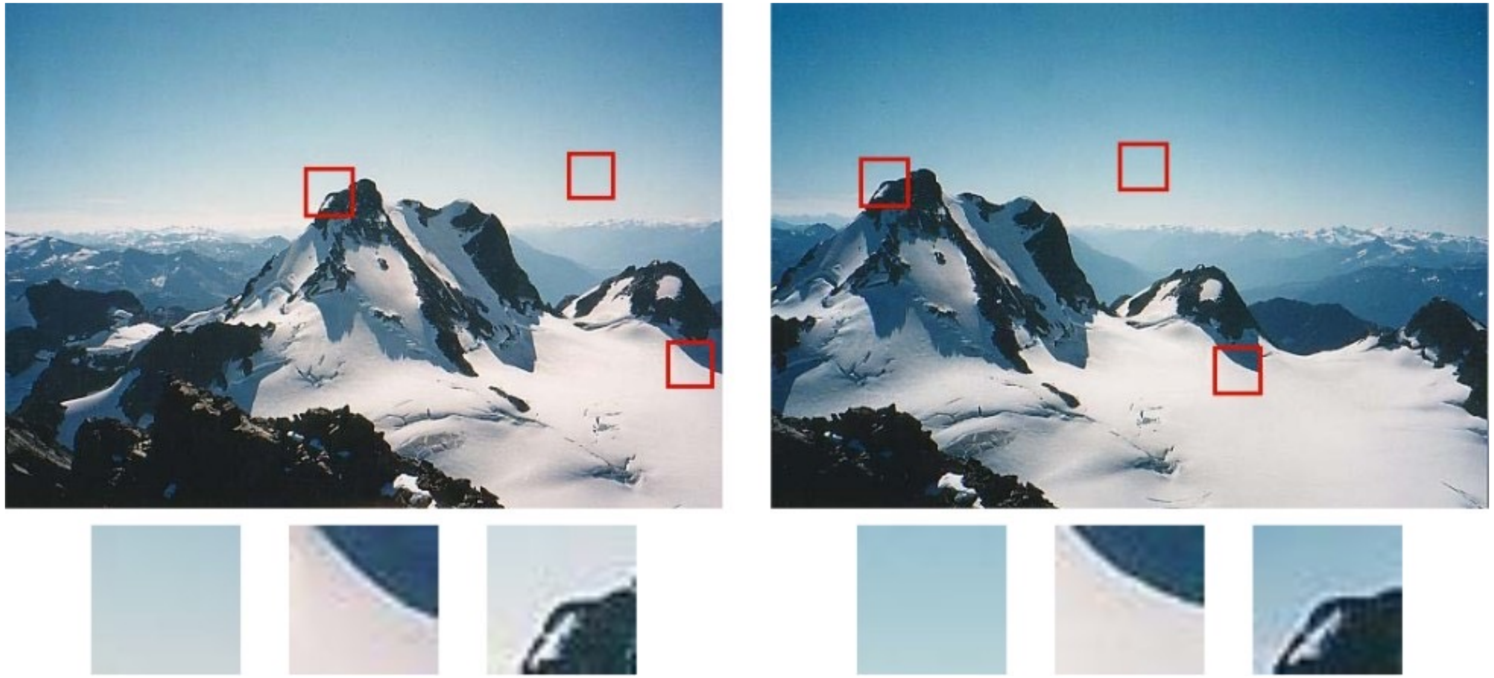
What Points to Choose for matching?



this one? which is best?

[Adopted from: Szelski (Book)]

What Points to Choose for matching?



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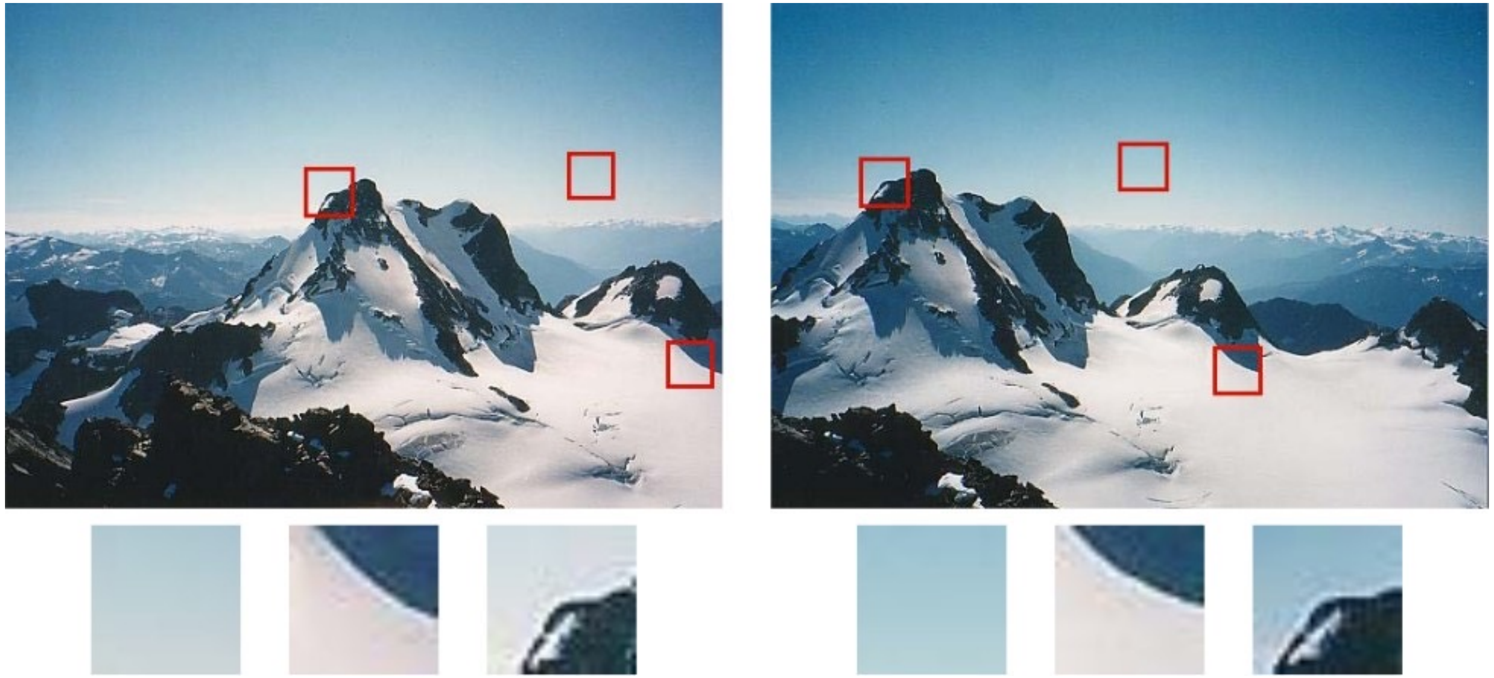

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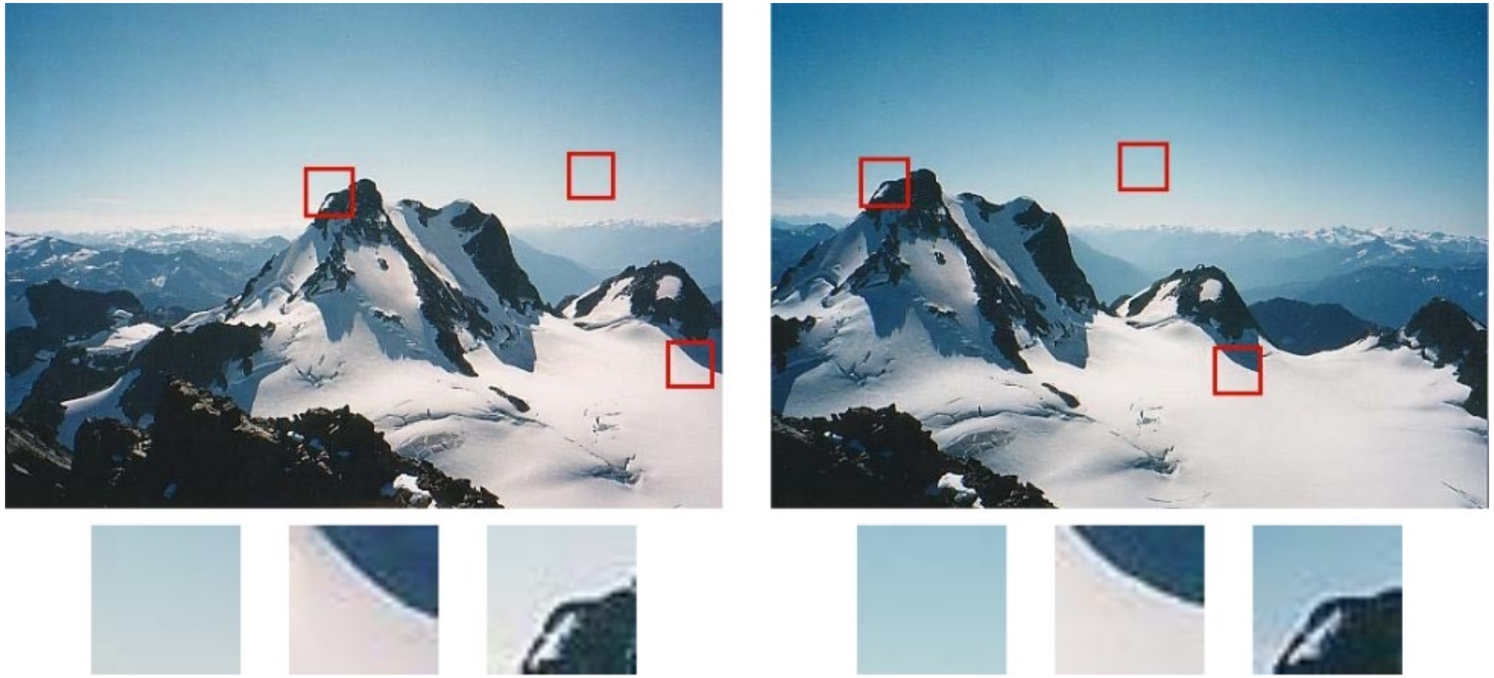

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    - can we localize with a single horizontal/vertical/diagonal edge?

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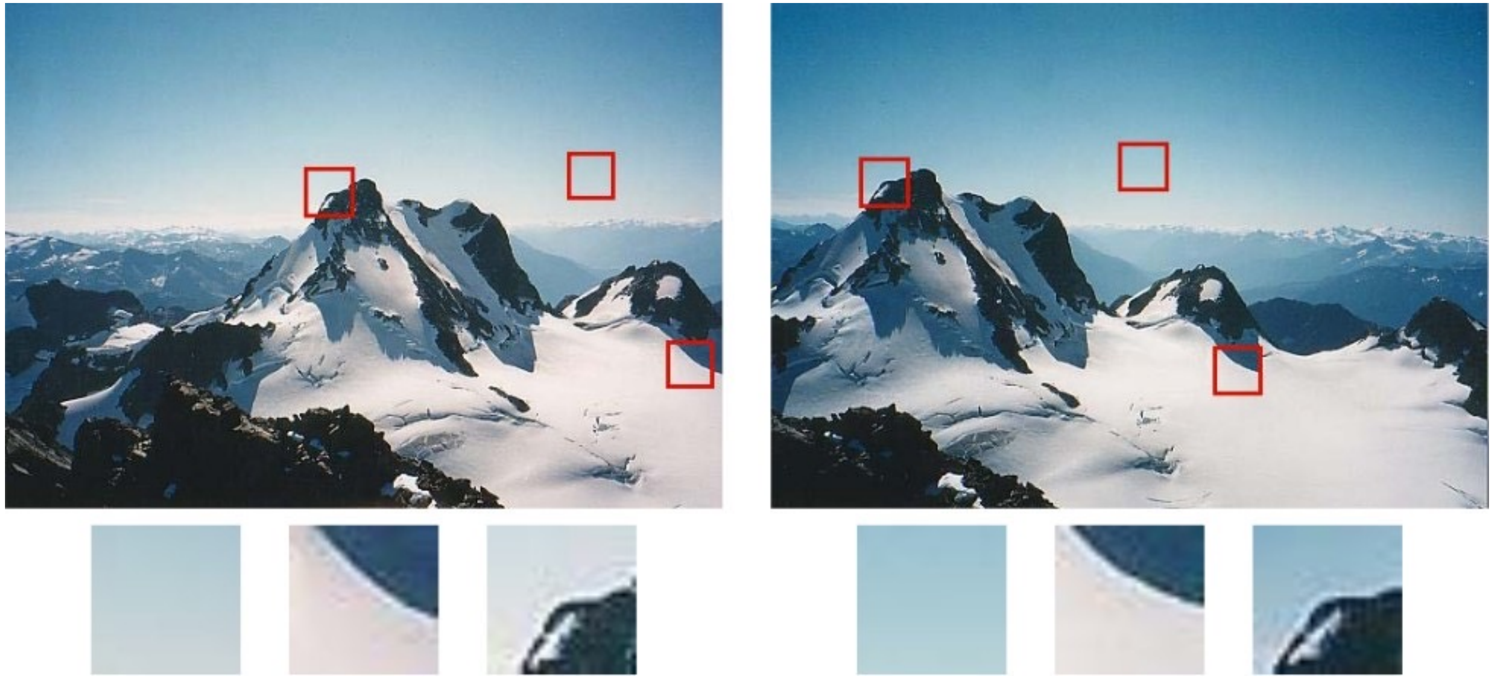
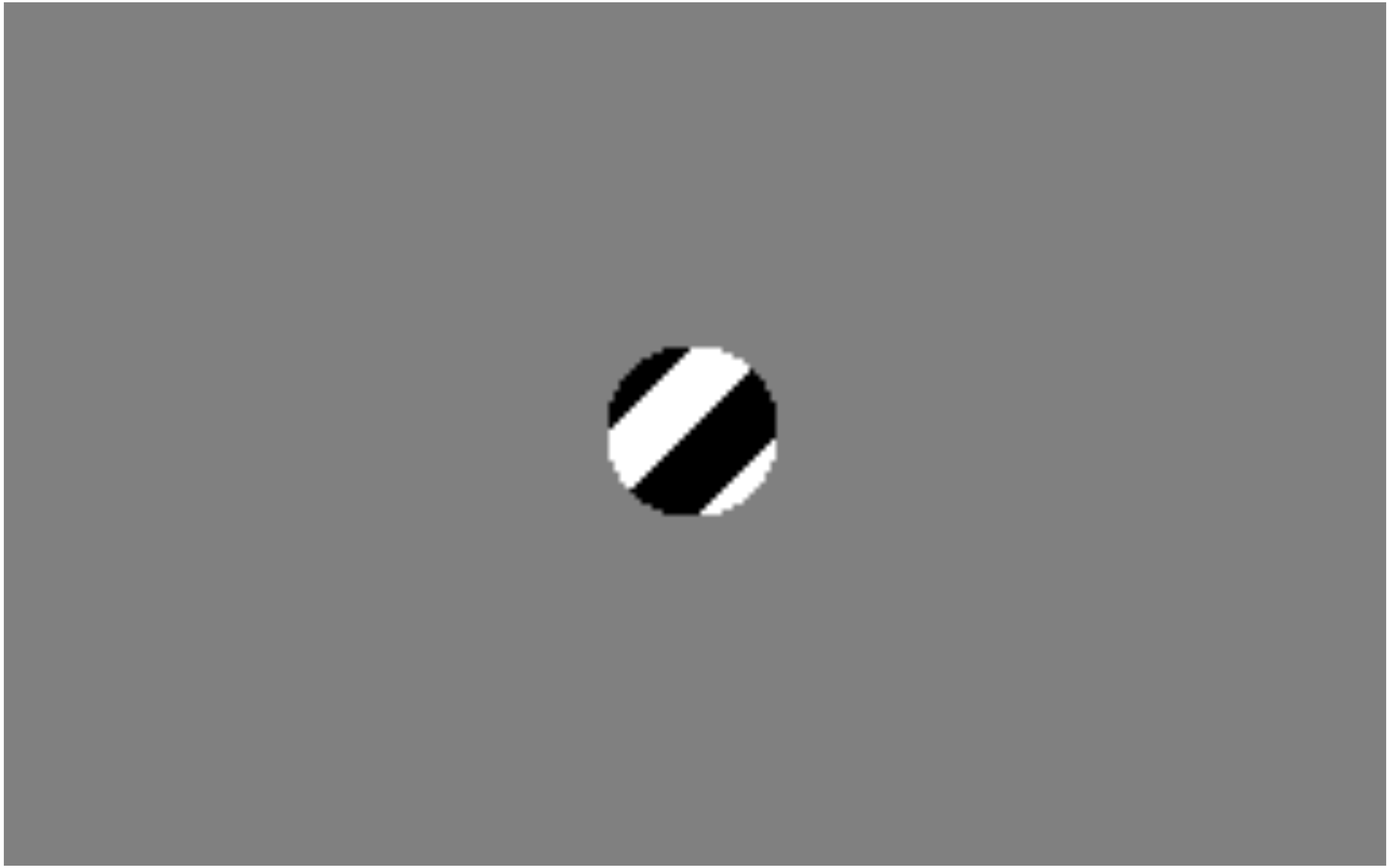


- textureless patches are nearly impossible to localize.
- large contrast changes (gradients) make it easier!
  - can we localize with a single horizontal/vertical/diagonal edge?
  - no—gradients with at least two orientations are easiest (corners)

[Adopted from: Szelski (Book)]

Aperture Problem

Aperture Problem



Aperture Problem

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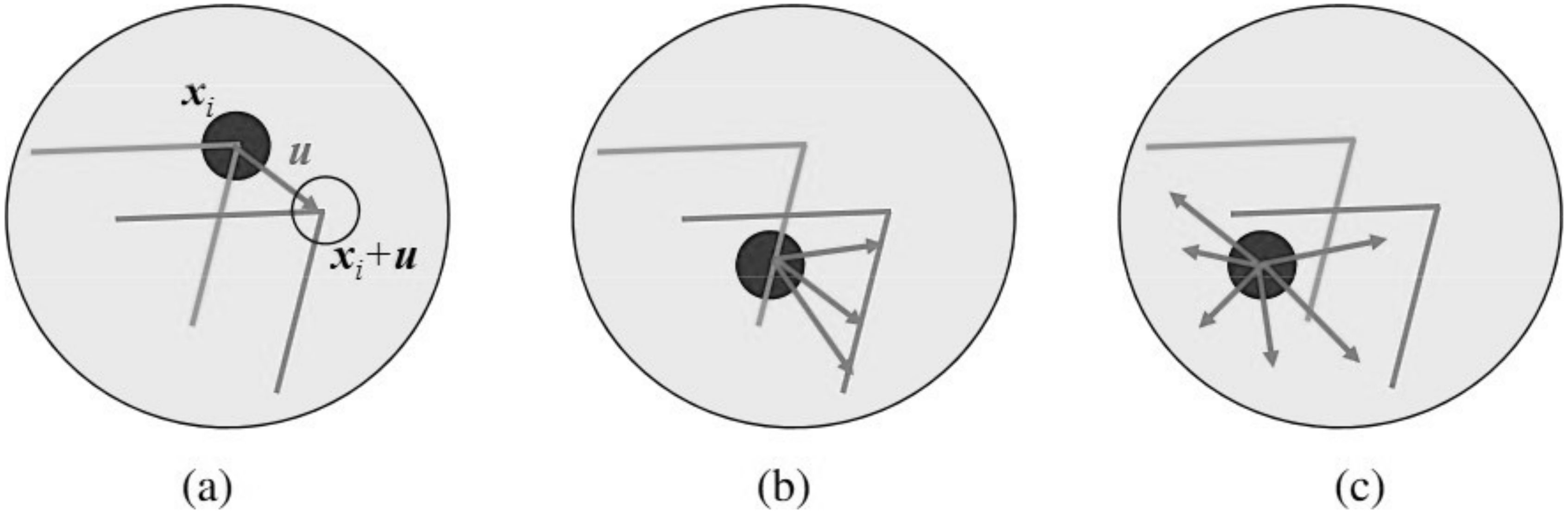


- "Corner-like" patch can be reliably matched
- A straight line patch can have multiple matches (Aperture Problem)
- Zero texture, useless, can have infinite matches

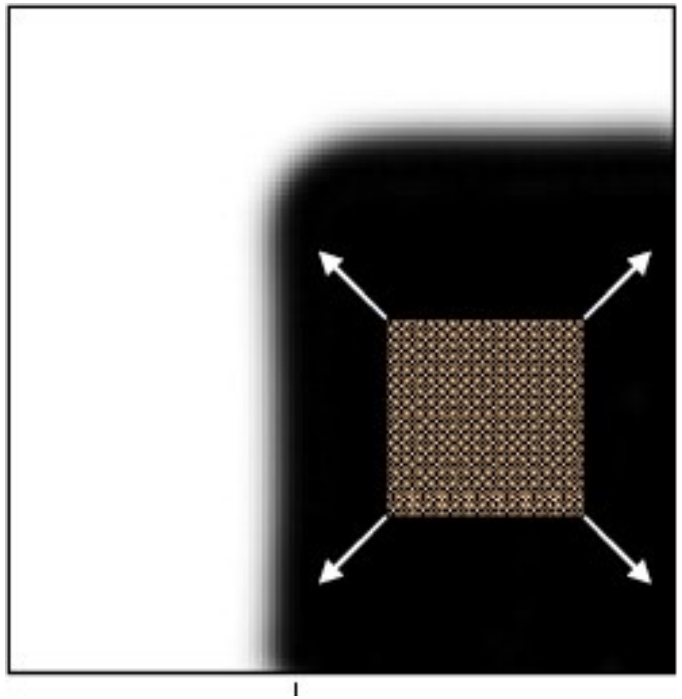
[Source: K. Grauman]

Corner Detection

Interest Points: Corners

- How can we find corners in an image?

Interest Points: Corners

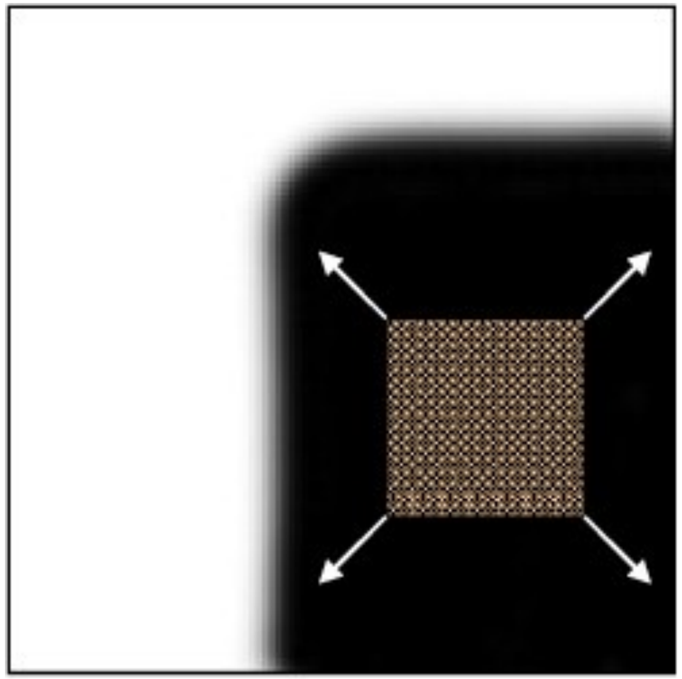


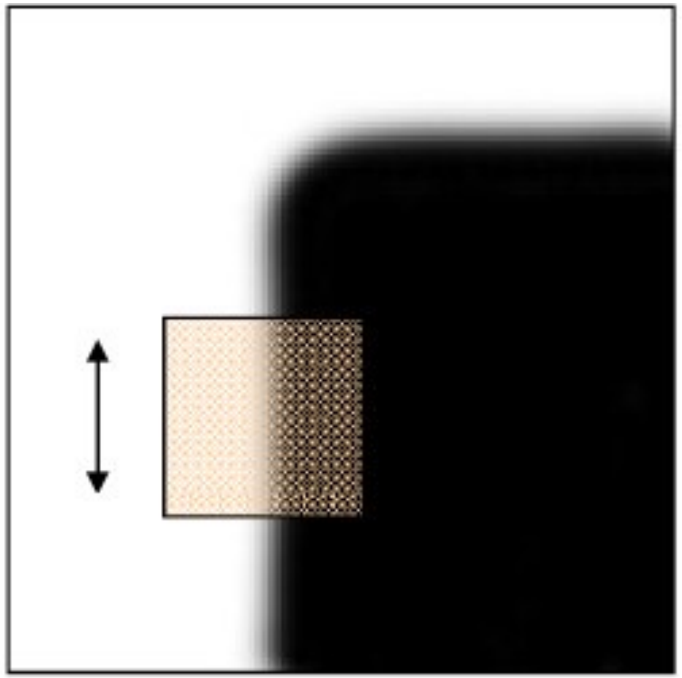
What if we use a small window?

What happens to the intensity variation within the window if we change it's location?

[Source: Alyosha Efros, Darya Frolova, Denis Simakov]

Interest Points: Corners





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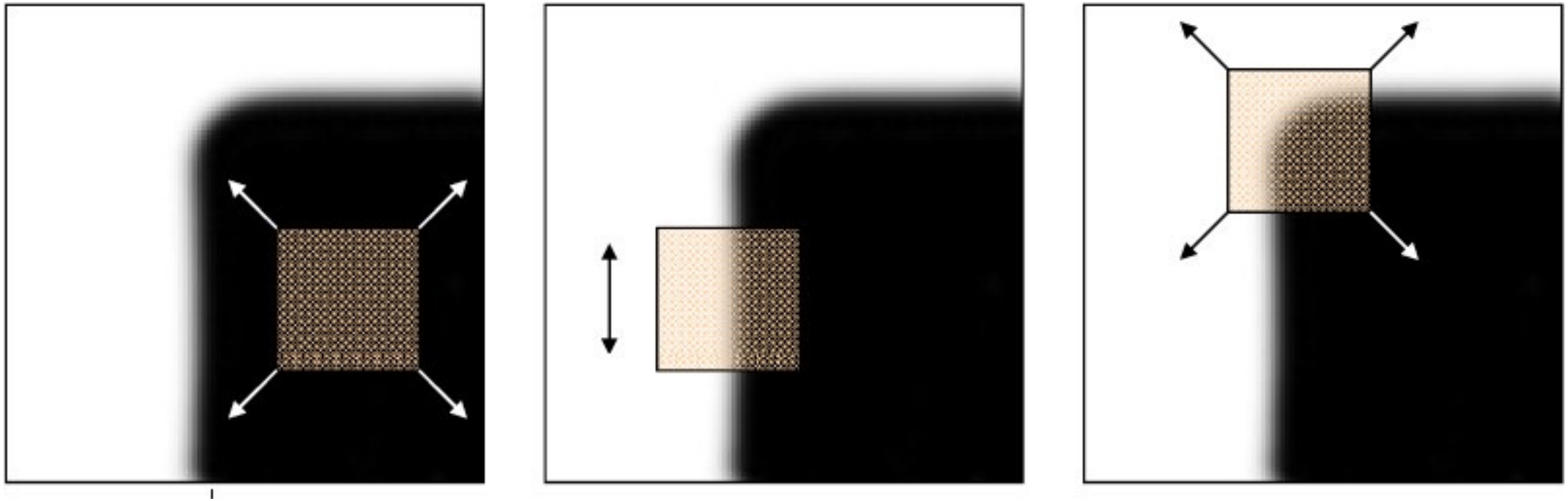

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Interest Points: Corners

- Compare two image patches using (weighted) summed square difference
- Measures change in appearance of window w(x, y) for the shift

[Source: J. Hays]

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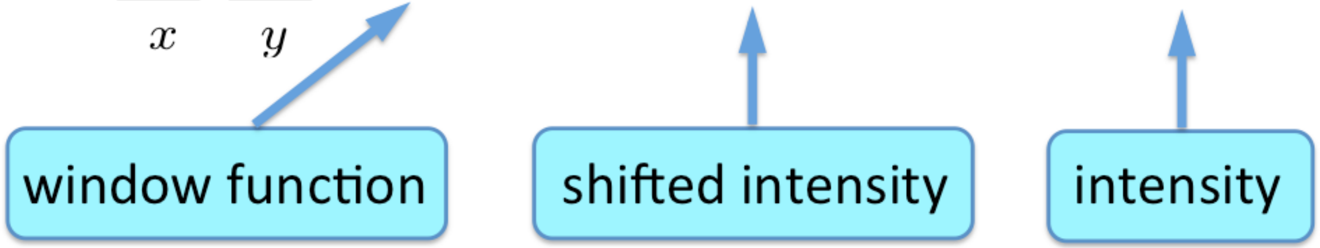
$$E_{\mathrm{WSSD}}(u, v) = \sum_x \sum_y w(x, y)[I(x + u, y + v) - I(x, y)]^2$$



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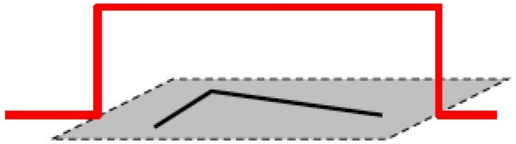
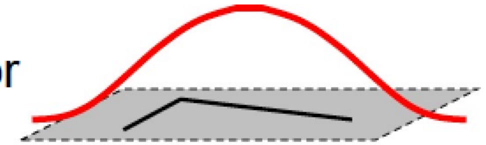
window function — shifted intensity — intensity

Window function $w(x,y)$ =



1 in window, 0 outside

or



Gaussian

[Source: J. Hays]

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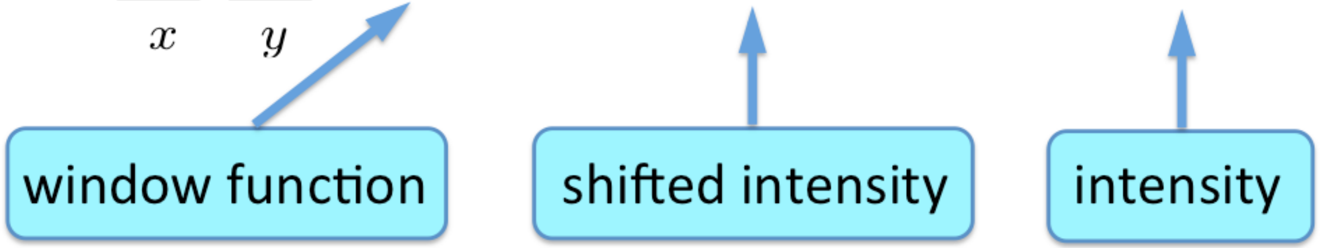

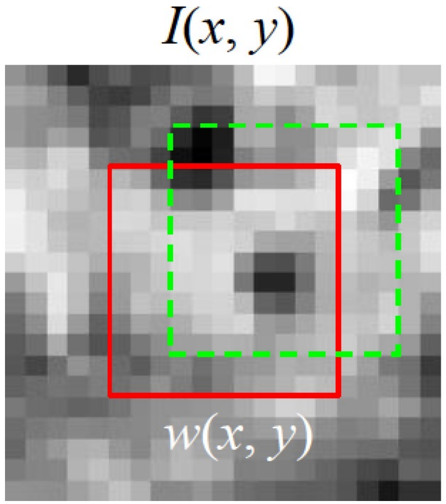

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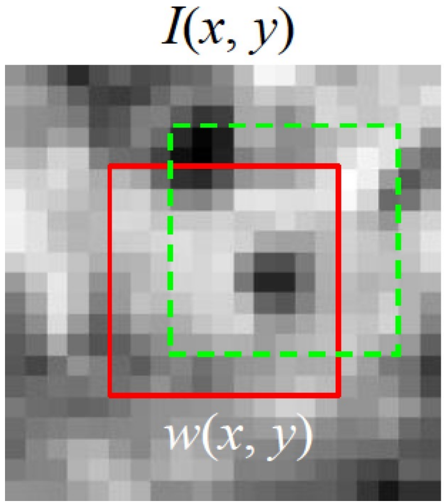
what does E_{WSSD} look like?

window function

shifted intensity

intensity



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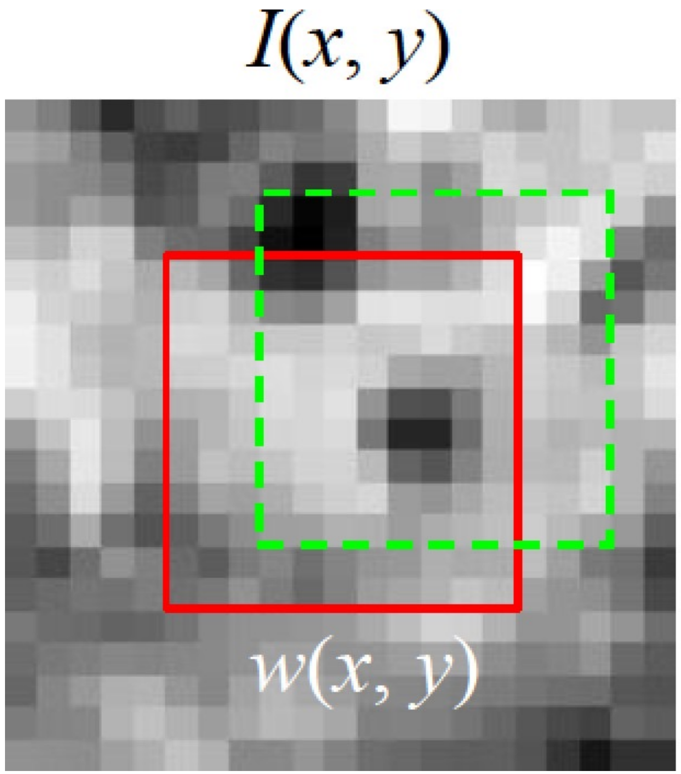
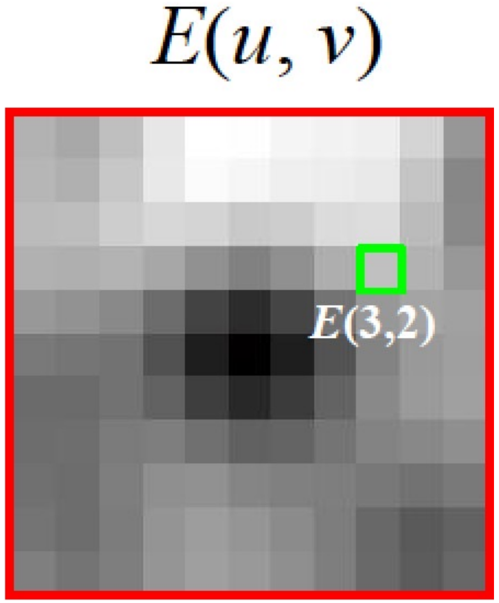
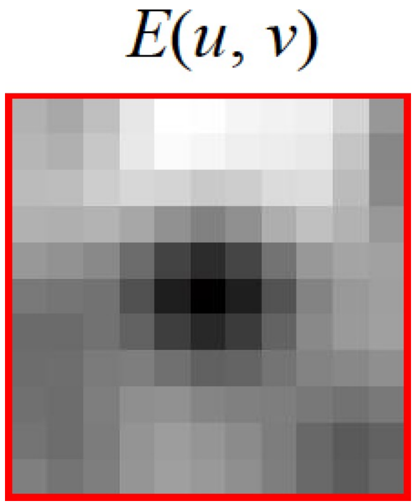




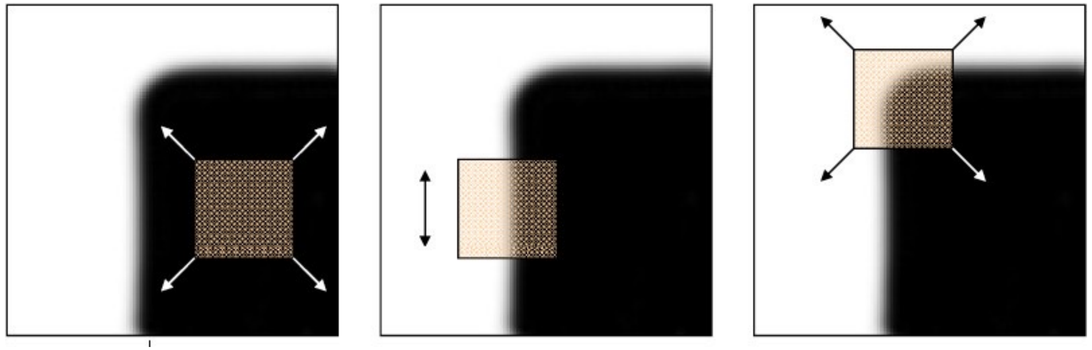
[Source: J. Hays]

Interest Points: Corners

- Let's look at E_{WSSD}
- We want to find out how this function behaves for small shifts



- Remember our goal to detect corners:



Interest Points: Corners

- Using a simple first order Taylor series expansion about *x, y* :

$$I(x+u, y+v) \approx I(x,y) + u \cdot \frac{\partial I}{\partial x}(x,y) + v \cdot \frac{\partial I}{\partial y}(x,y)$$

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- Using a series of polynomials to approximate I, more info on Taylor Series here
- And plugging it in our expression for E_{WSSD}:

$$E_{\text{WSSD}}(u,v) \quad = \quad \sum_x \sum_y w(x,y)\Big(I(x+u, y+v) - I(x,y)\Big)^2$$

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$$= \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

what is M?

Interest Points: Corners

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$$= \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

- M is a 2x2 second moment matrix computed from image gradients

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

How Do I Compute M ?

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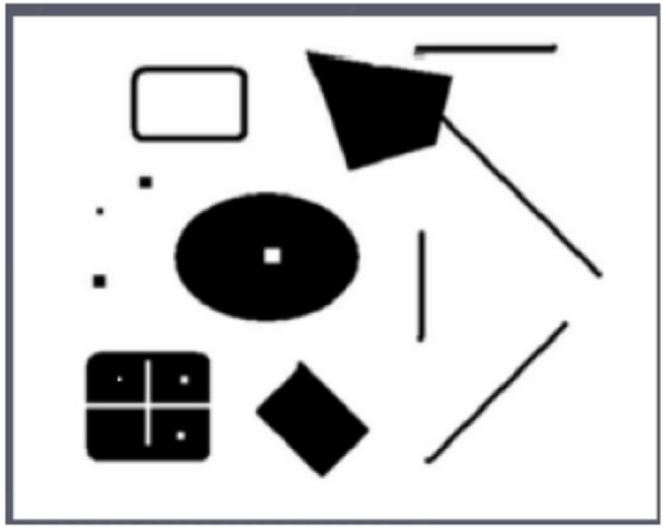
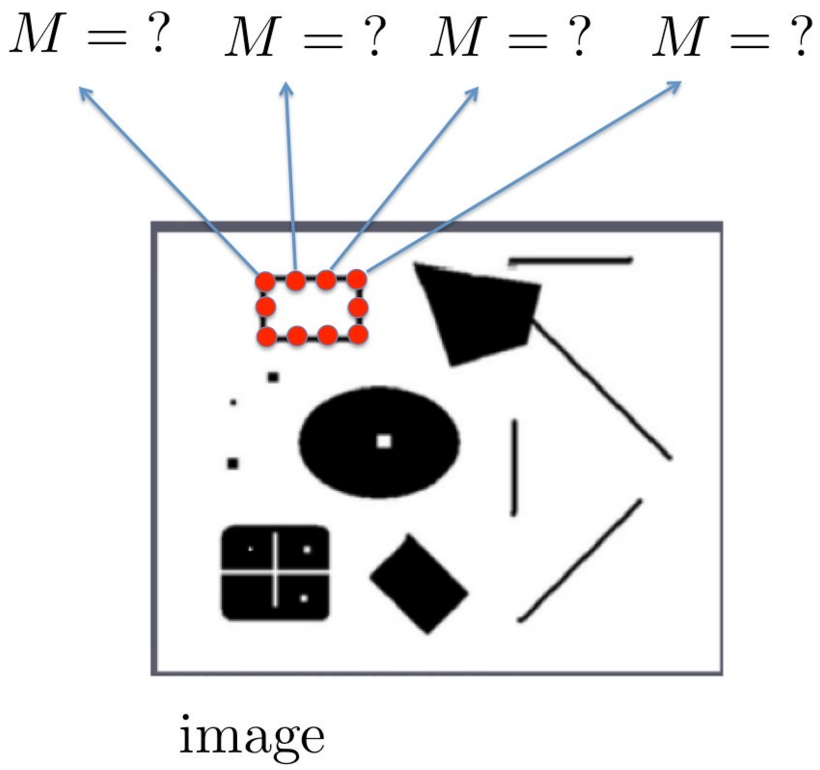
- Let’s say I have this image



image

How Do I Compute M ?

- Let's say I have this image
- I need to compute a 2 × 2 second moment matrix in each image location



How Do I Compute M ?

- Let's say I have this image
- I need to compute a 2 × 2 second moment matrix in each image location
- In a particular location I need to compute M as a weighted average of gradients in a window

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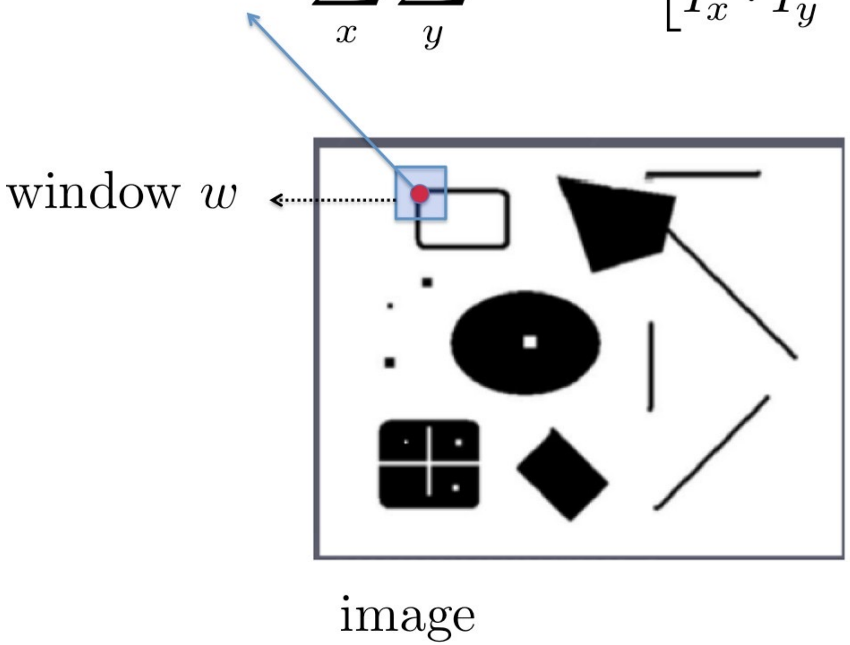

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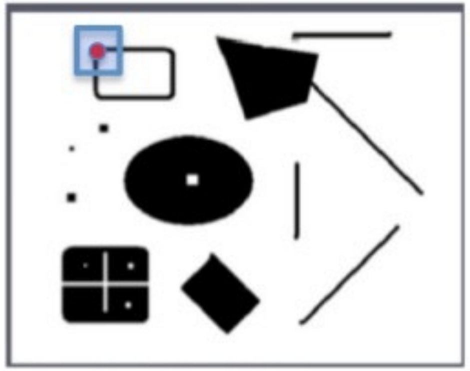
- I need to compute a 2 × 2 second moment matrix in each image location
- In a particular location I need to compute M as a weighted average of gradients in a window

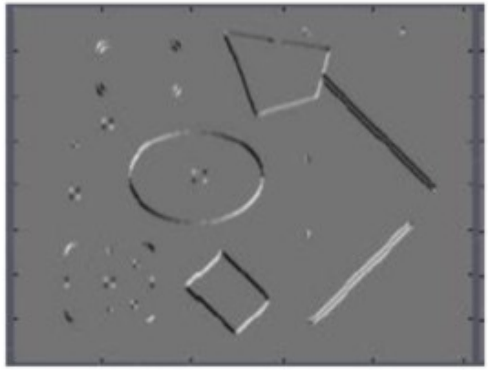
$$M = \sum_x \sum_y w(x,y) \begin{bmatrix} I_x^2 & I_x \cdot I_y \\ I_x \cdot I_y & I_y^2 \end{bmatrix}$$



image

$$I_x = \frac{\partial I}{\partial x}$$

$$I_y = \frac{\partial I}{\partial y}$$



$$I_x \cdot I_y$$

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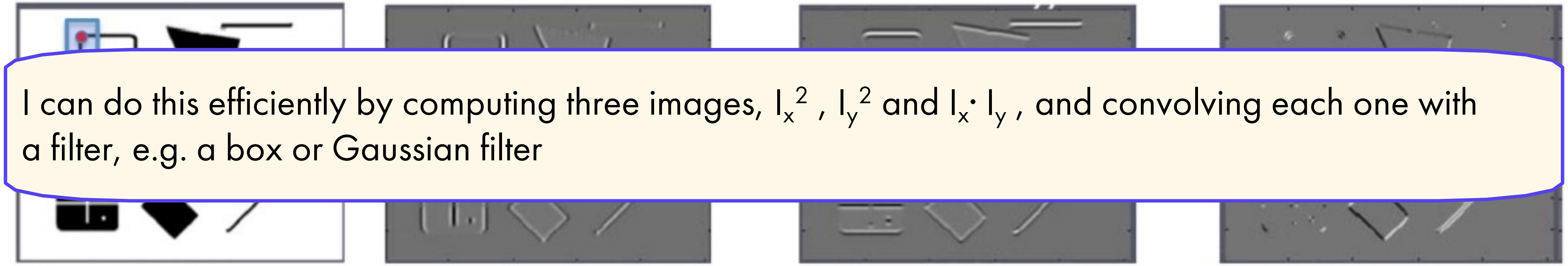

I can do this efficiently by computing three images, I_x^2 , I_y^2 and $I_x \cdot I_y$, and convolving each one with a filter, e.g. a box or Gaussian filter

image

$$I_x = \frac{\partial I}{\partial x} \qquad I_y = \frac{\partial I}{\partial y} \qquad I_x \cdot I_y$$

How Do I Compute M ?

- Let's take a "slice" of $E_{WSSD}(u, v)$:

$$\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$

what is this the equation for?

How Do I Compute M ?

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$$\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$

- This is the equation of an ellipse

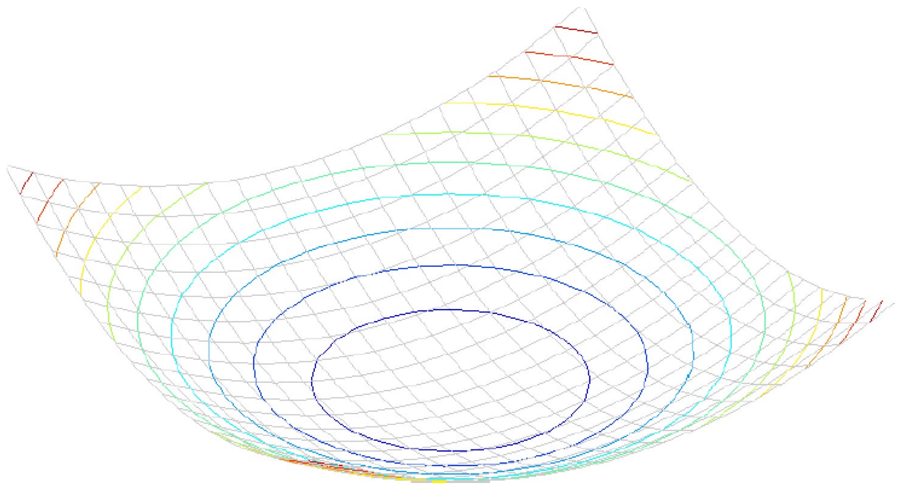


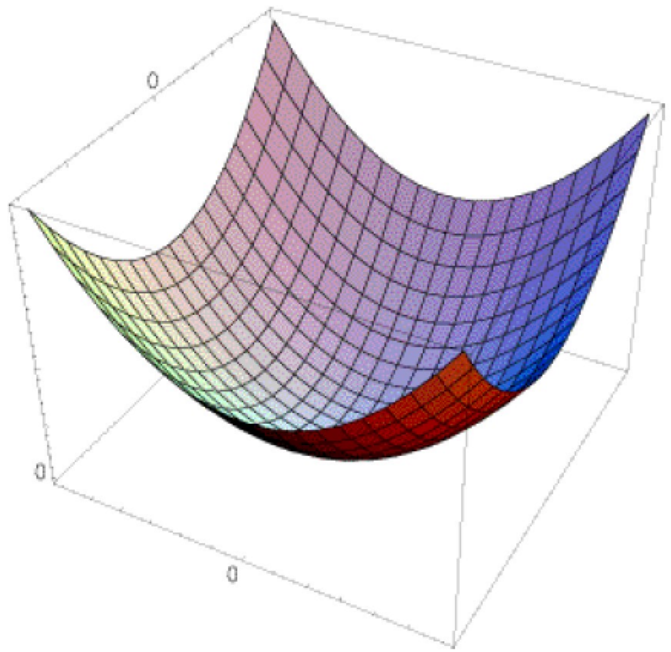
Figure: Different ellipses obtain by different horizontal "slices"

How Do I Compute M ?

- We now have *M* computed in each image location
- Our E_{WSSD} is a quadratic function where *M* implies its shape

$$E_{\text{WSSD}}(u, v) \;=\; \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

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



[Source: J. Hays]

How Do I Compute M ?

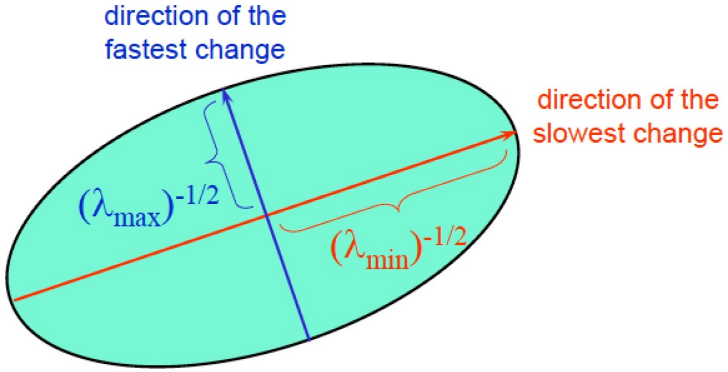
- Our matrix M is symmetric:

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

- And thus we can diagonalize it (in Matlab: [V,D] = eig(M)):

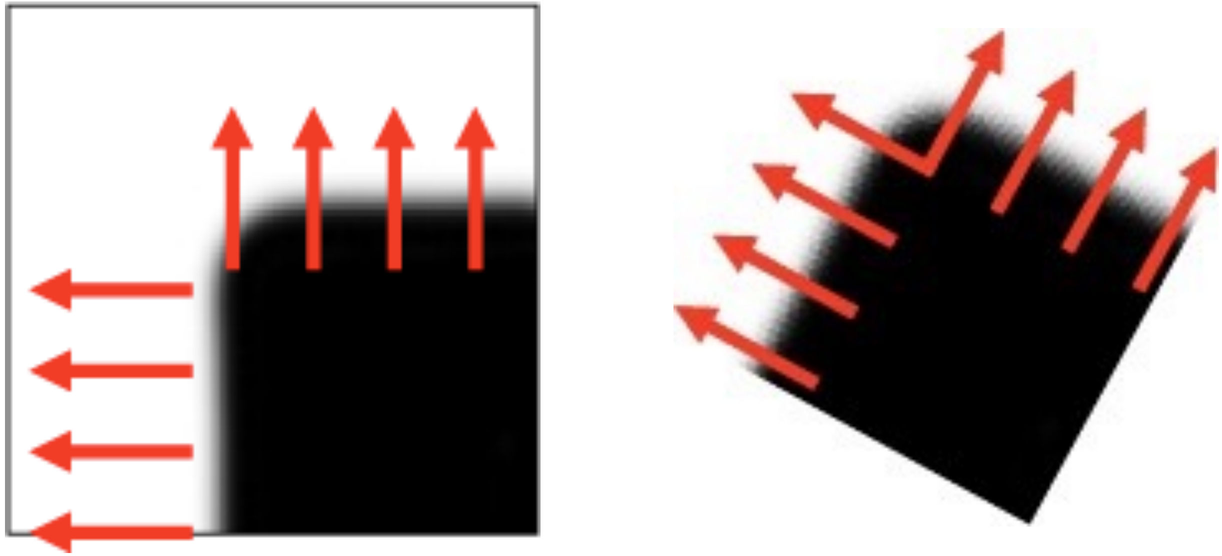
$$M = V \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} V^{-1}$$

- Columns of V are major and minor axes of ellipse, the lengths of the radii proportional to $\lambda^{-1/2}$



How Do I Compute M ?

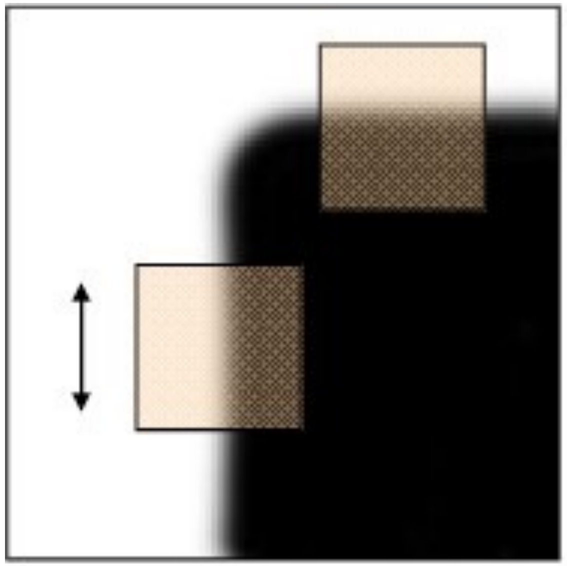
- for these images, what will the eigenvalues and eigenvectors look like?



[Source: R. Szeliski, slide credit: R. Urtasun]

How Do I Compute M ?

- how about for these windows?



[Source: K. Grauman, slide credit: R. Urtasun]

How Do I Compute M ?

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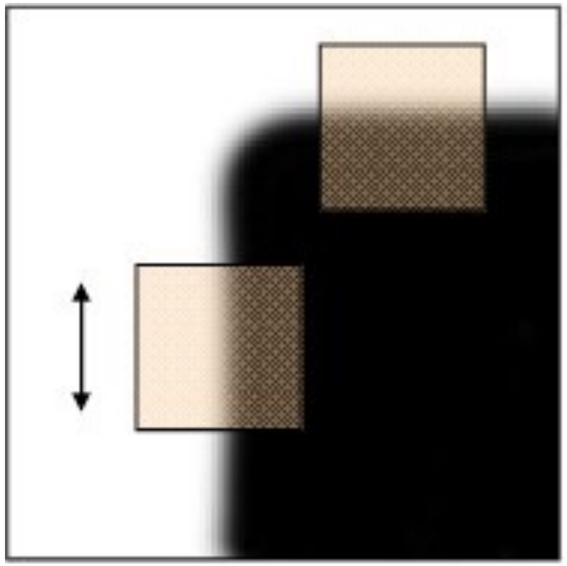

"edge":

$\lambda_1 >> \lambda_2$

$\lambda_2 >> \lambda_1$

[Source: K. Grauman, slide credit: R. Urtasun]

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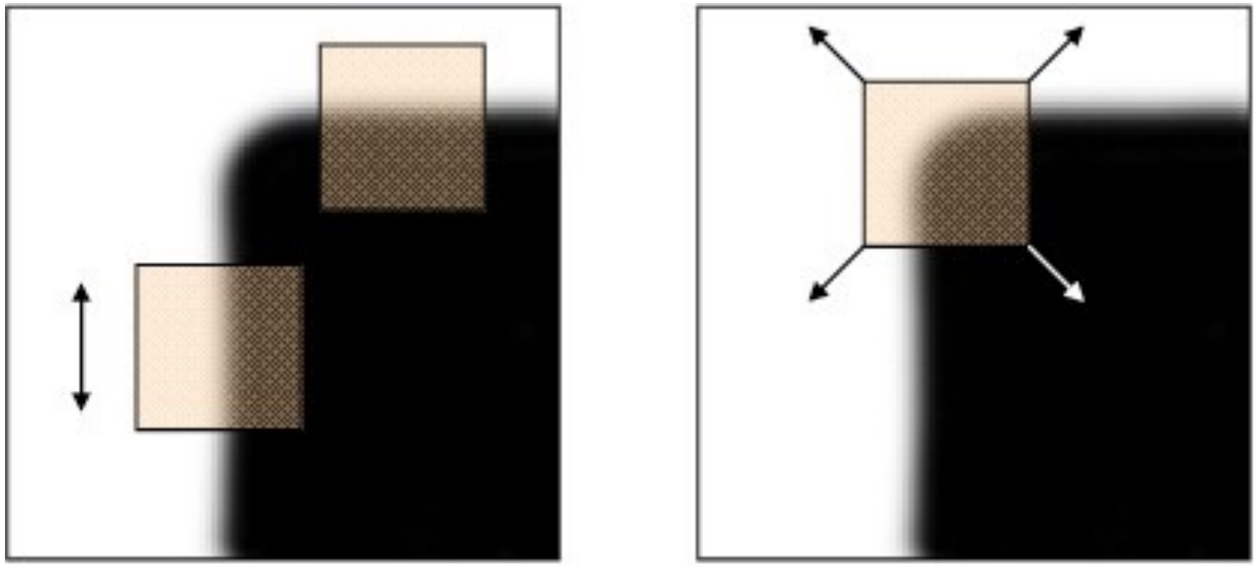

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[Source: K. Grauman, slide credit: R. Urtasun]

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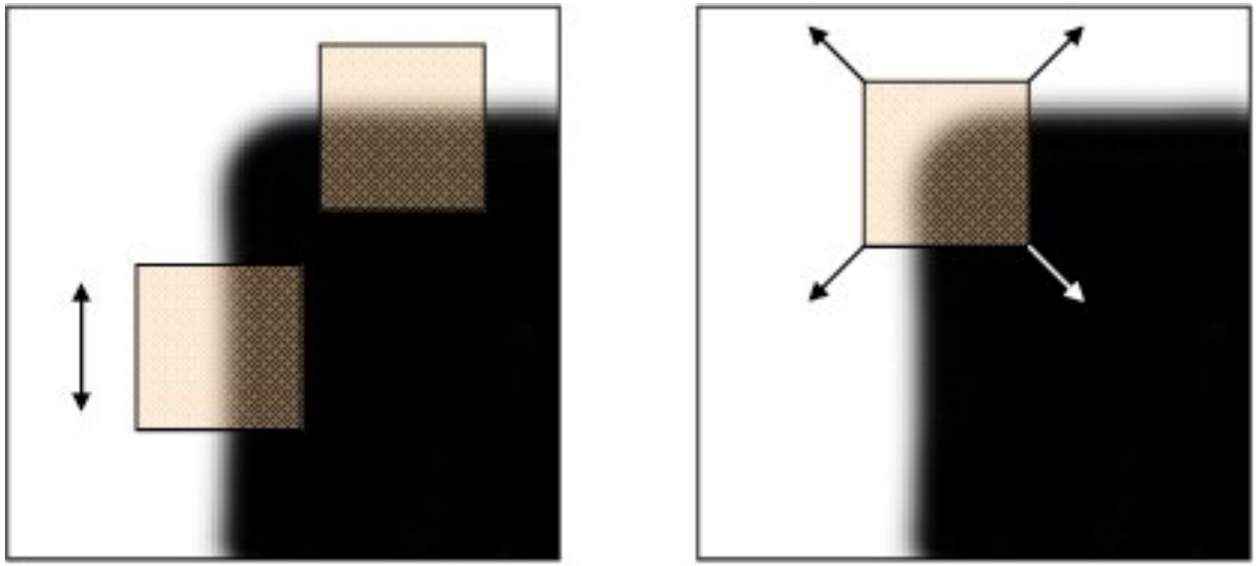

"edge":

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"corner":

λ_1 and λ_2 are large,

$\lambda_1 \sim \lambda_2$;

[Source: K. Grauman, slide credit: R. Urtasun]

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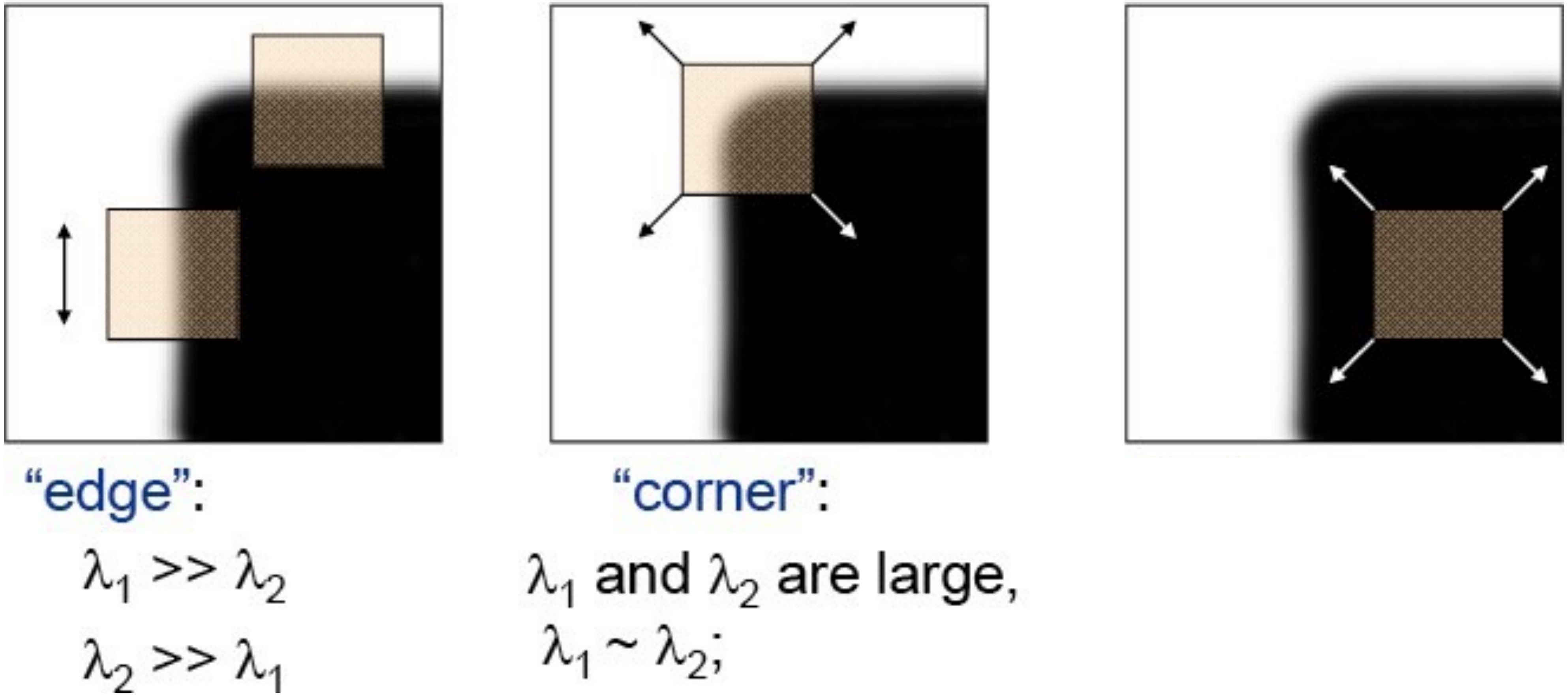

[Source: K. Grauman, slide credit: R. Urtasun]

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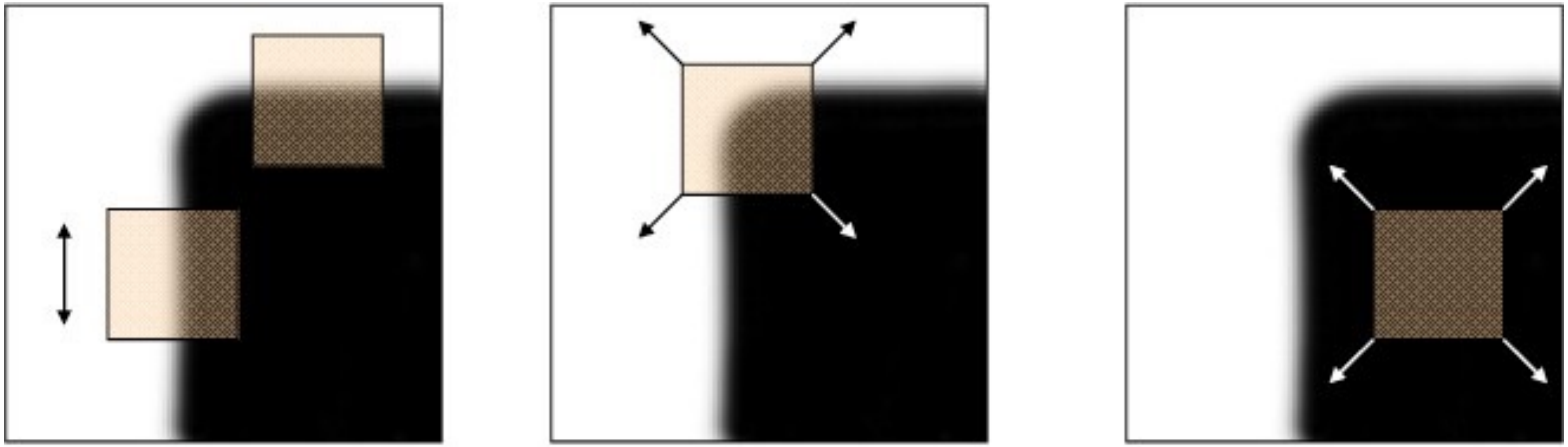


"edge":

$\lambda_1 >> \lambda_2$

$\lambda_2 >> \lambda_1$

"corner":

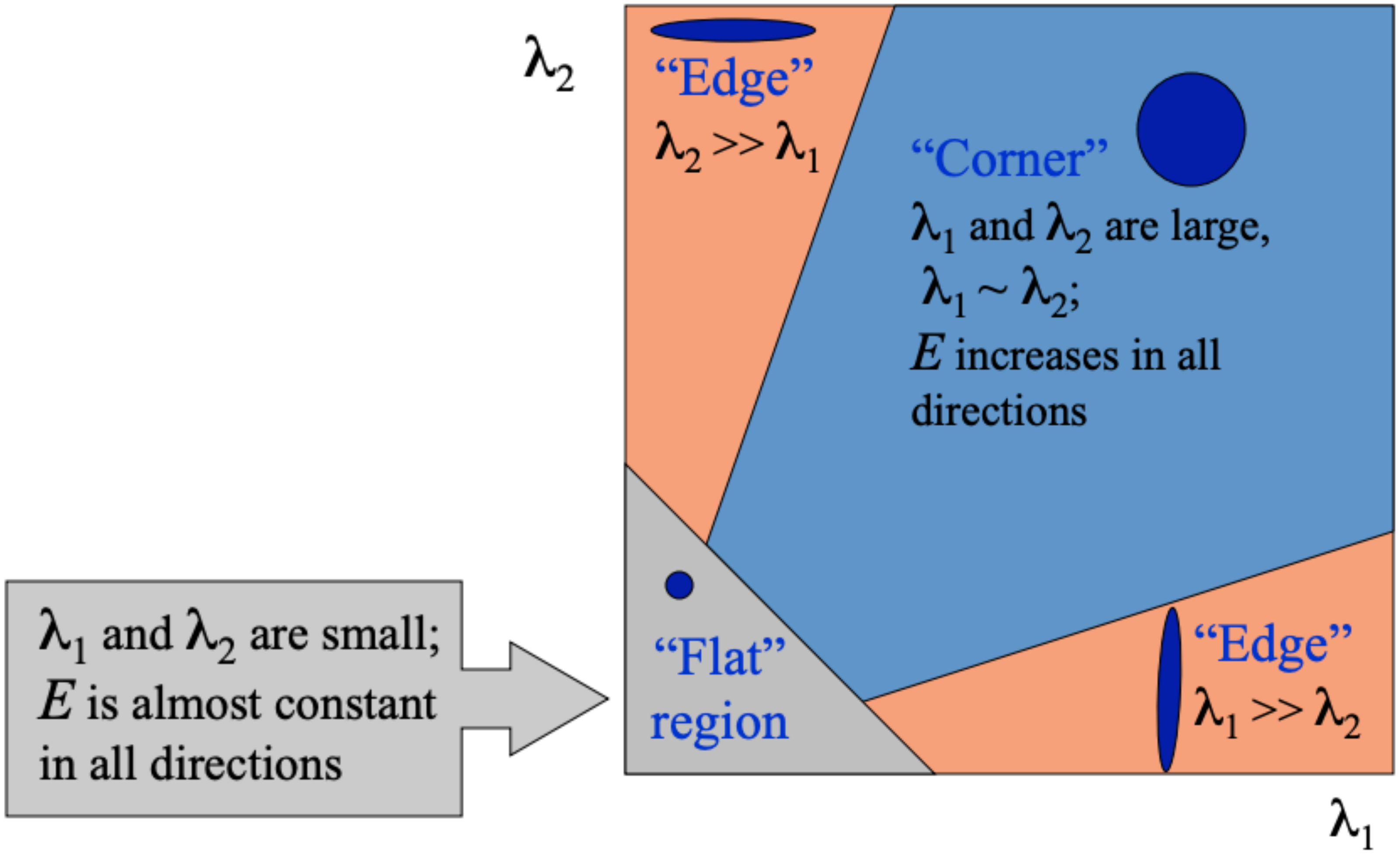
λ_1 and λ_2 are large, $\lambda_1 \sim \lambda_2$;

"flat" region

λ_1 and λ_2 are small;

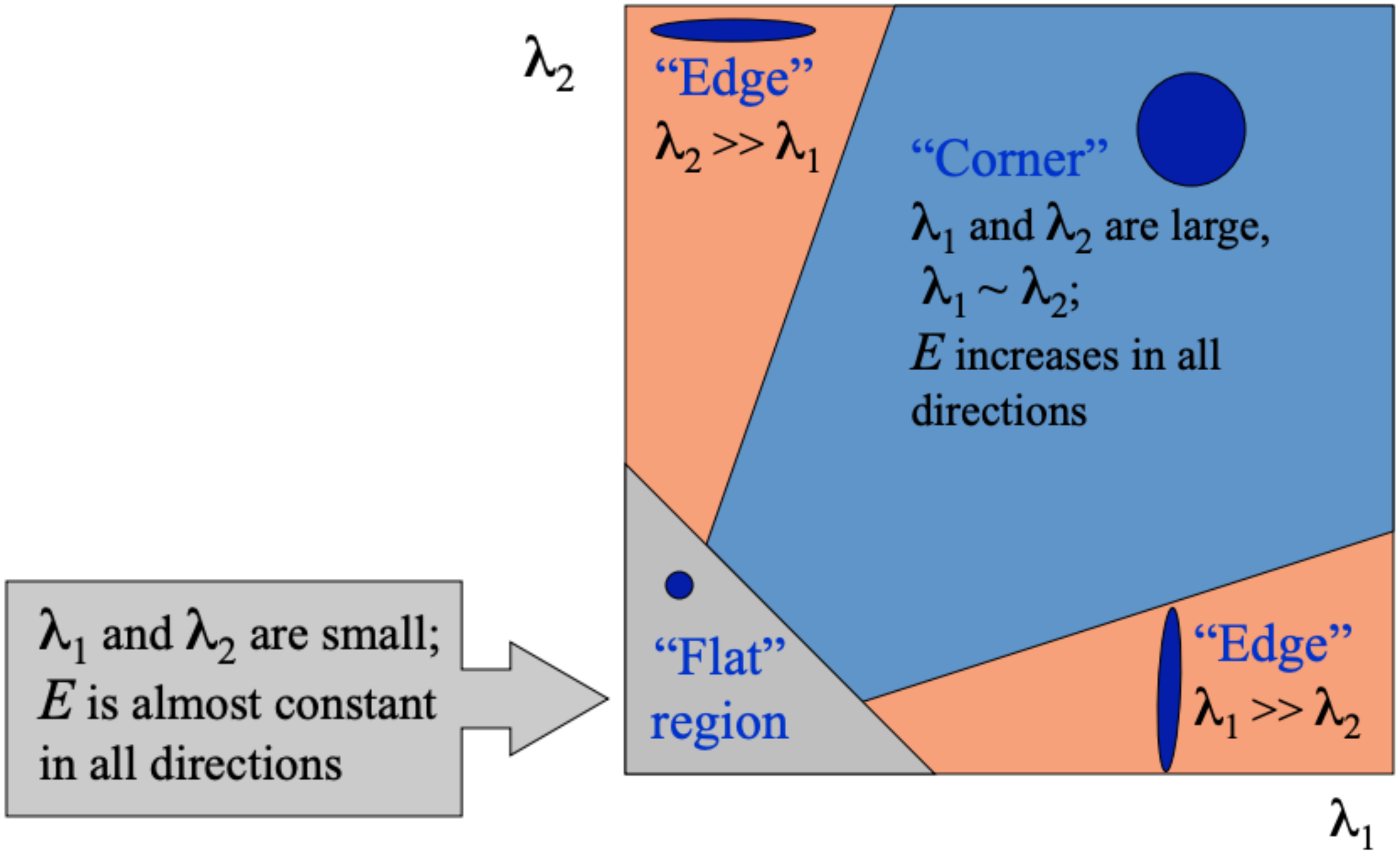
[Source: K. Grauman, slide credit: R. Urtasun]

Interest Points: Criteria to Find Corners



[Source: K. Bala]

Interest Points: Criteria to Find Corners



- can you write an equation that uses the eigenvalues to detect a corner?

[Source: K. Bala]

Interest Points: Criteria to Find Corners

- Harris and Stephens, '88, is rotationally invariant and downweighs edge-like features where $\lambda_1 \gg \lambda_0$

$$R = \lambda_0 \lambda_1 - \alpha(\lambda_0 + \lambda_1)^2 = \text{det}(M) - \alpha \cdot \text{trace}(M)^2$$

- α a constant (0.04 to 0.06)

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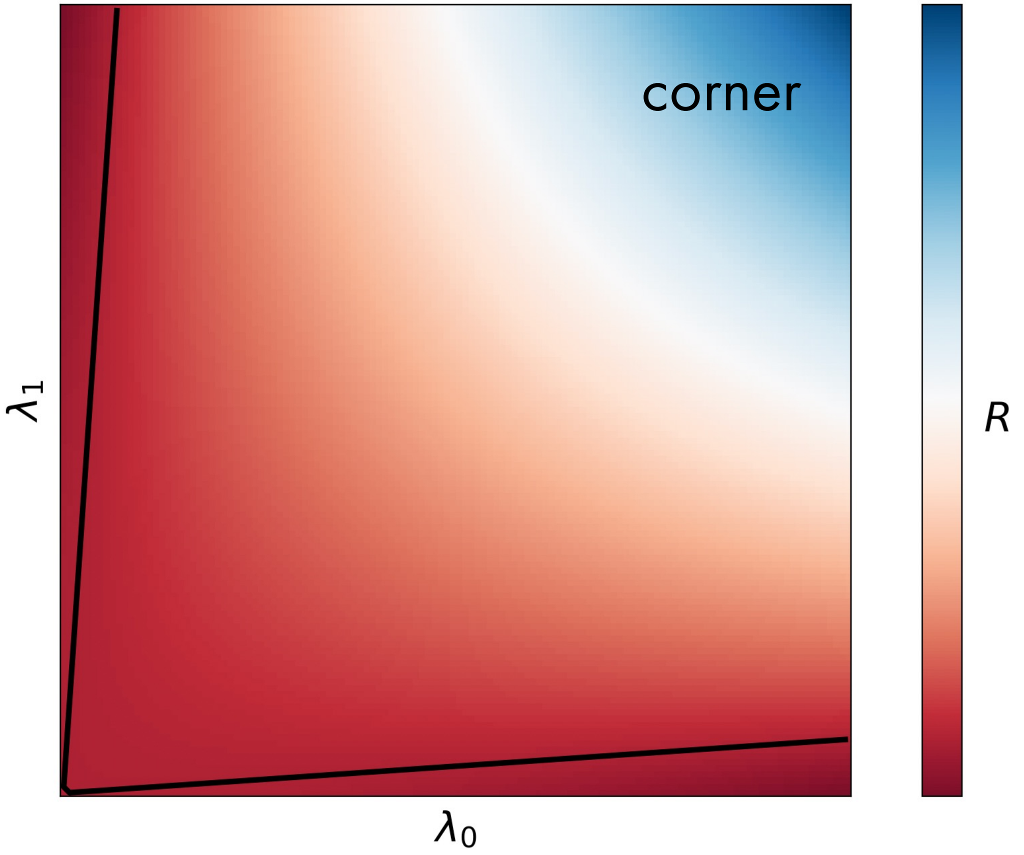

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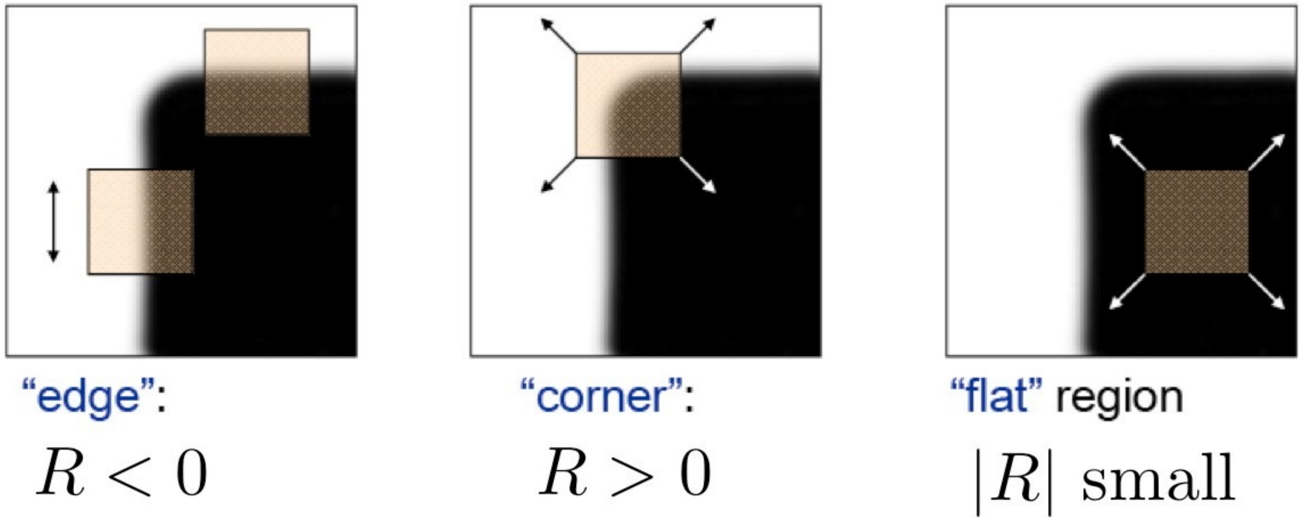


- The corresponding detector is called Harris corner detector

Interest Points: Criteria to Find Corners

- Harris & Stephens (1998)

$$R = \lambda_0 \lambda_1 - \alpha(\lambda_0 + \lambda_1)^2 = \mathrm{det}(M) - \alpha \cdot \mathrm{trace}(M)^2$$

- Kande & Tomasi (1994)

$$R = \min(\lambda_1, \lambda_2)$$

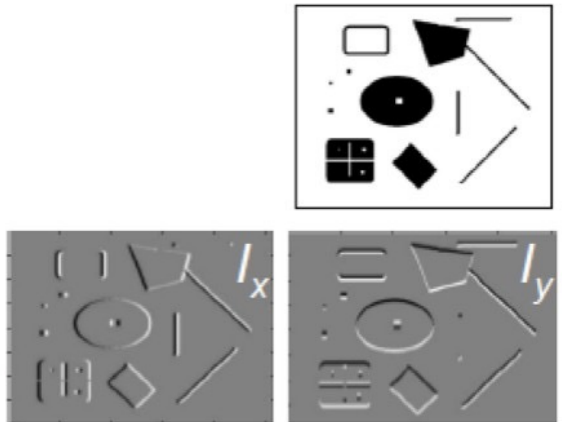
- Nobel (1998)

$$R = \frac{\det(M)}{\mathrm{trace}(M) + \epsilon}$$

[Source Mubarak Shah, Szelski]

Harris Corner detector

1. Compute gradients I_x and I_y



Harris Corner detector

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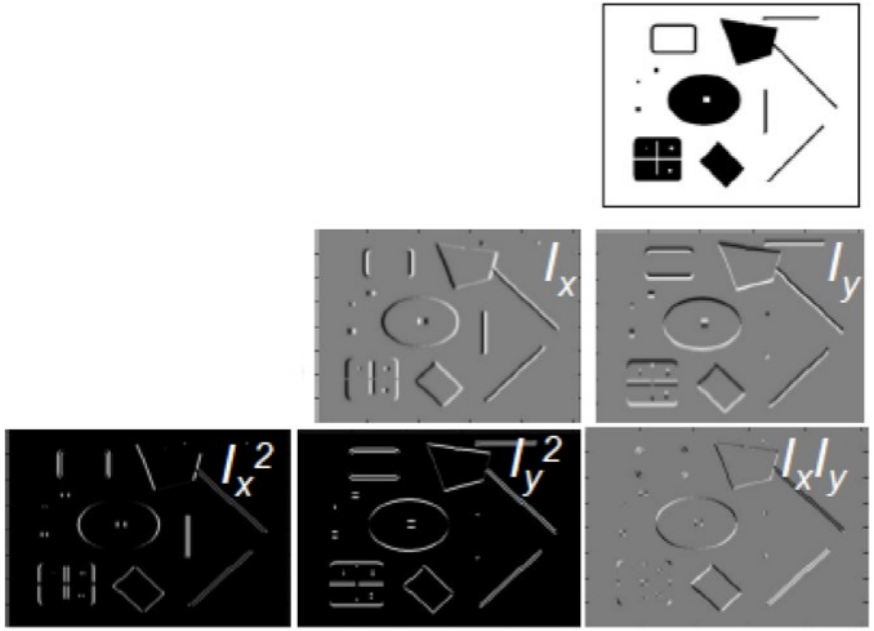
2. Compute I_x^2, I_y^2 , $I_x \cdot I_y$



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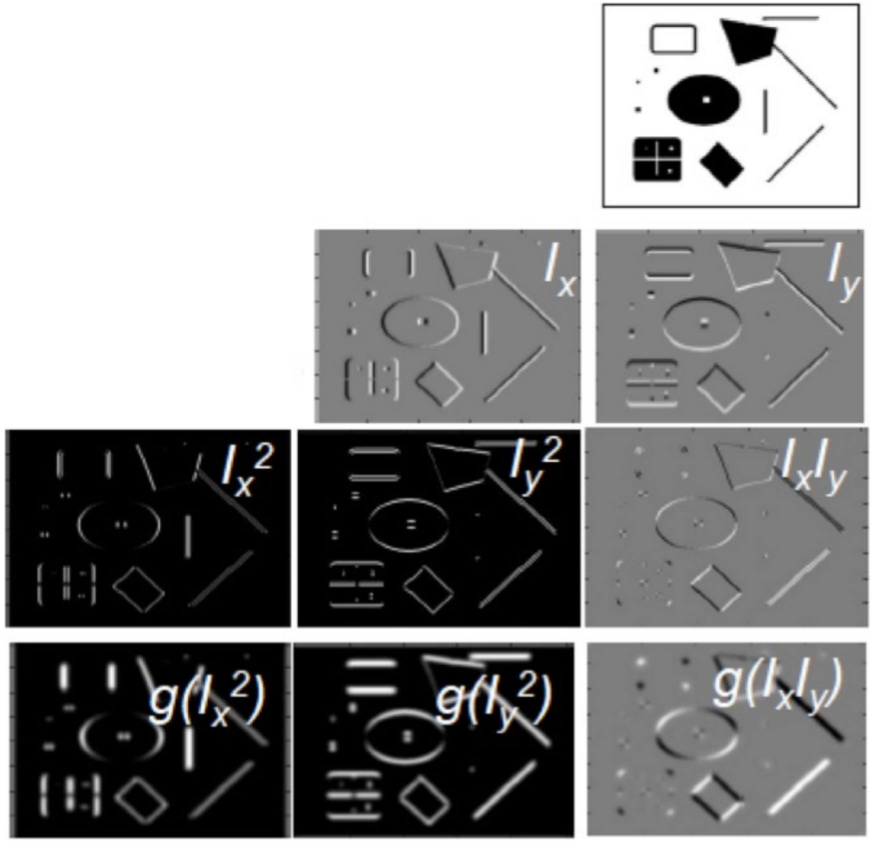

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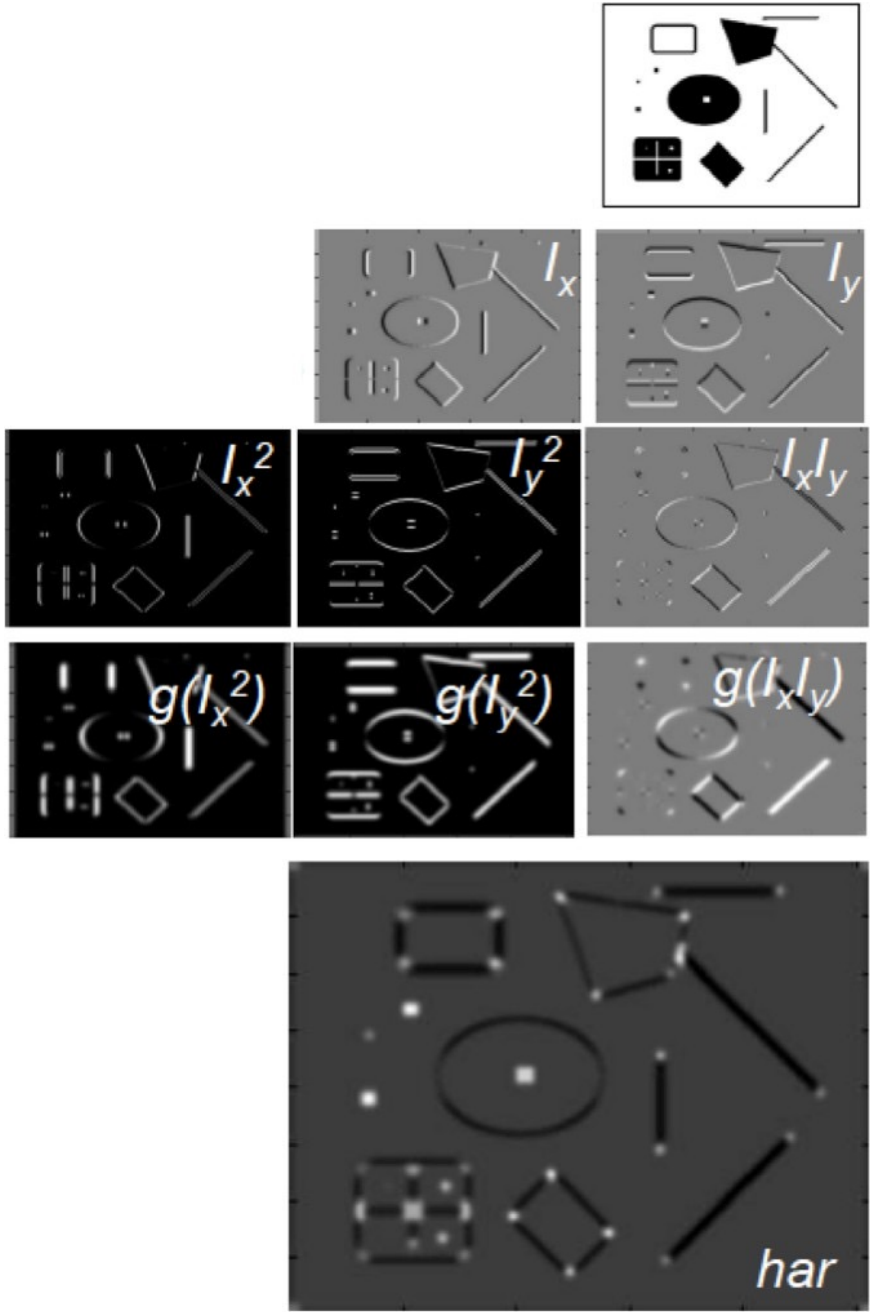

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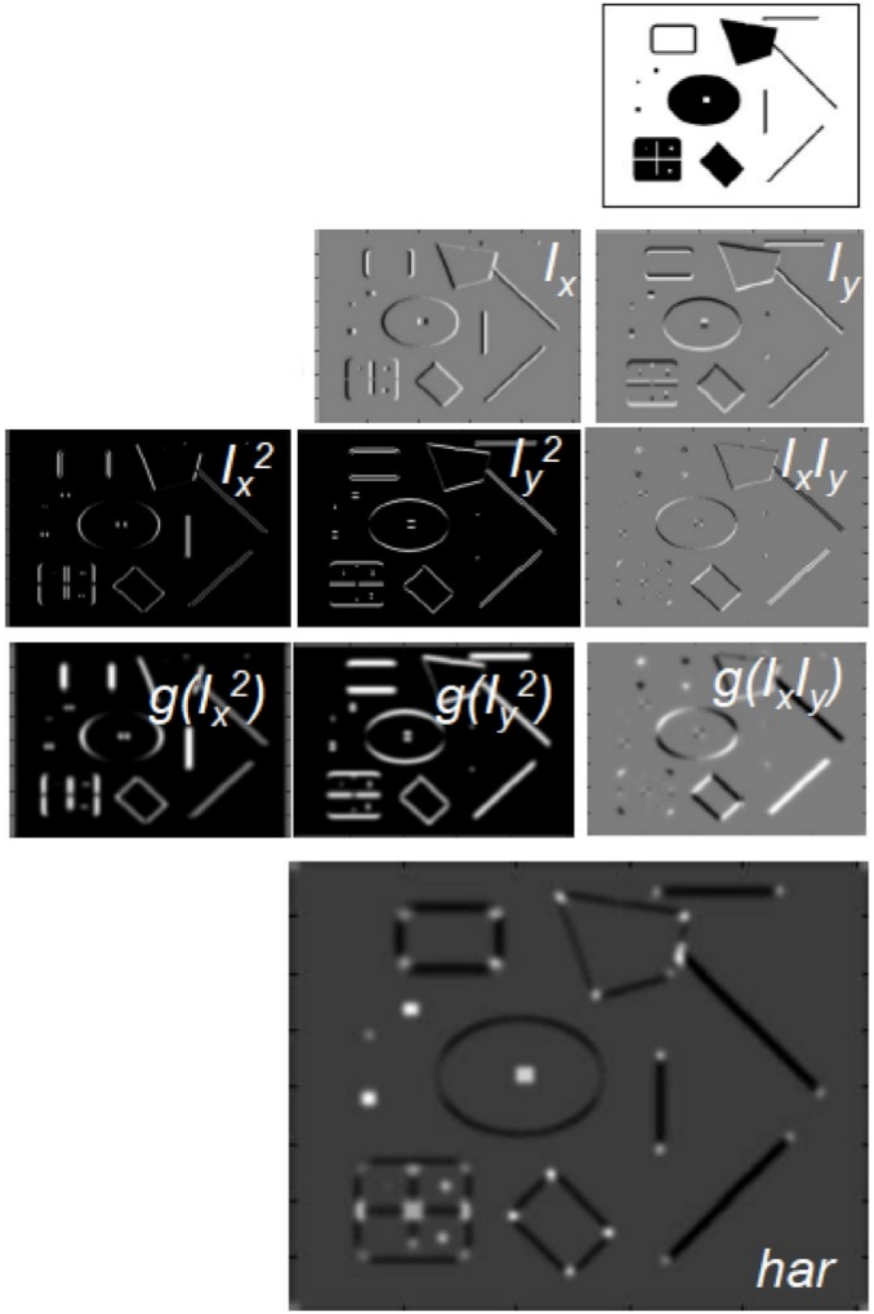

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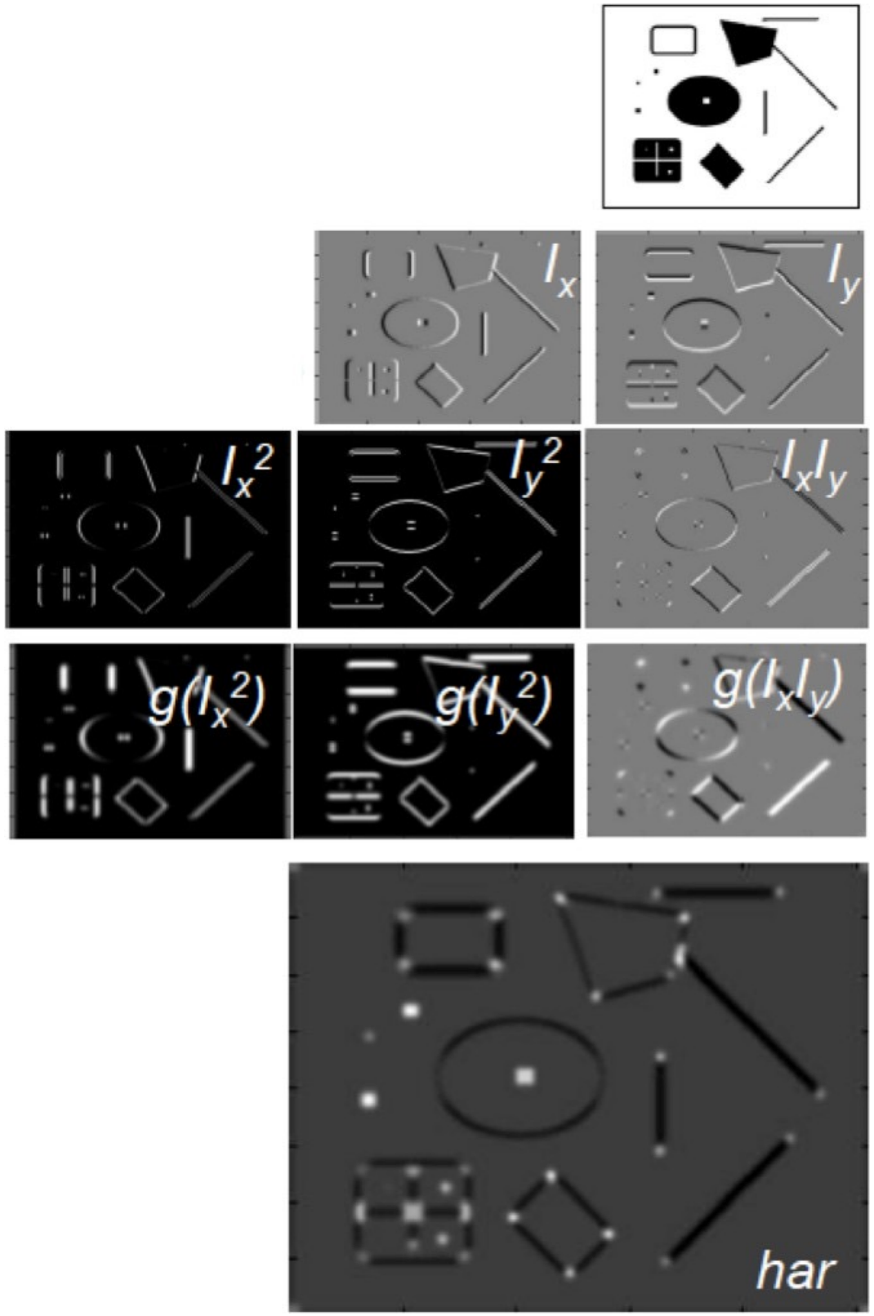
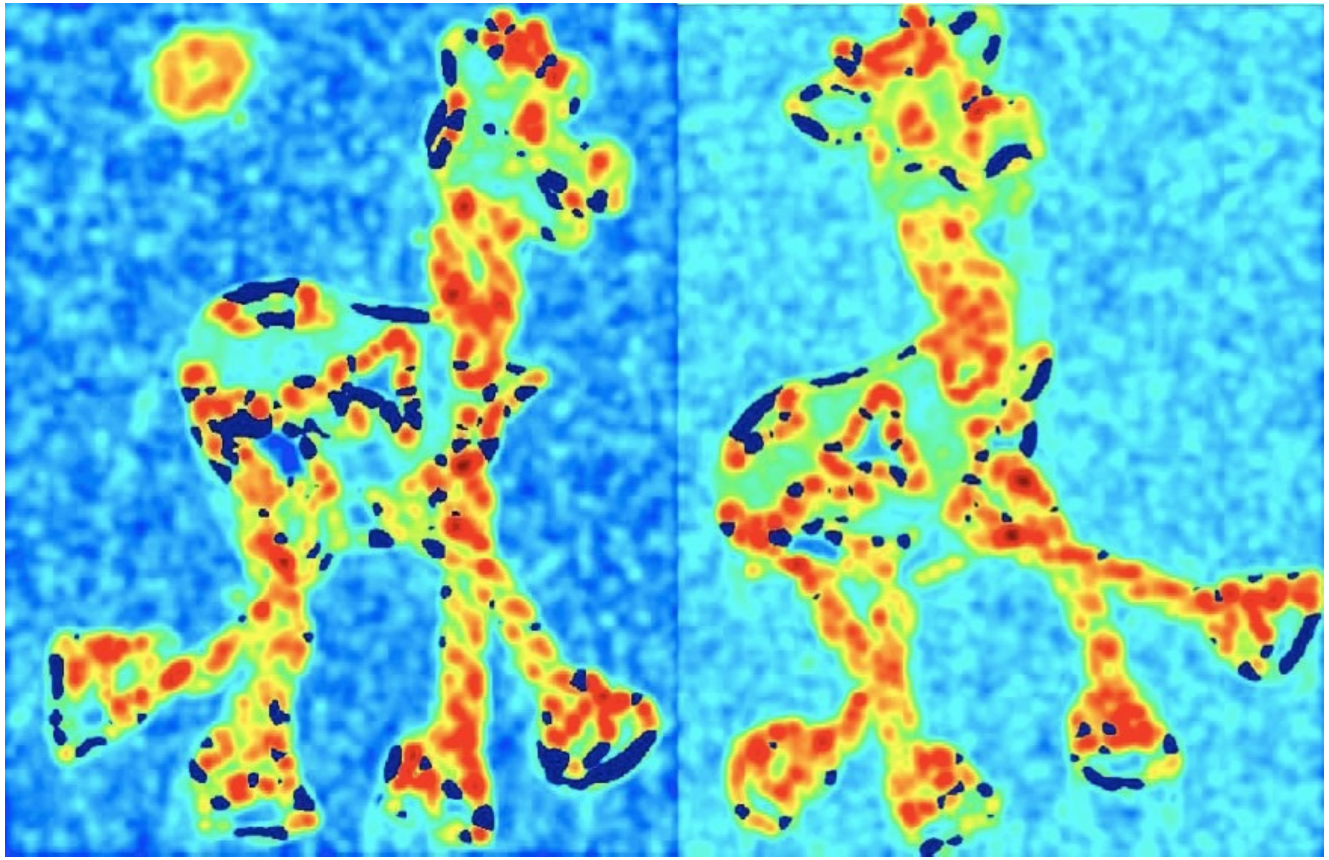
5. Find points with large R ($R >$ threshold).
6. Take only points of local maxima, i.e., perform non-maximum suppression



Example

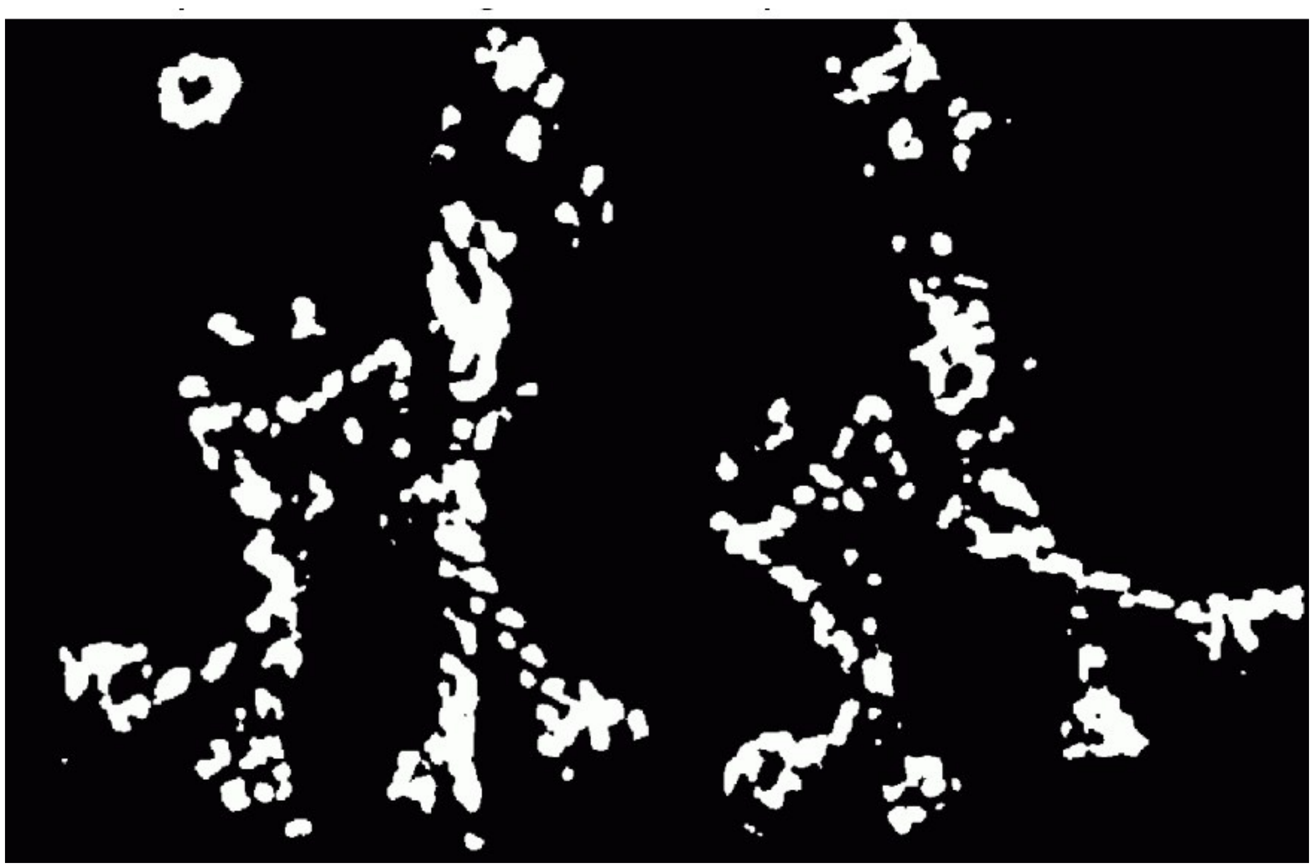
[Source: K. Grauman]

1) Compute Cornerness



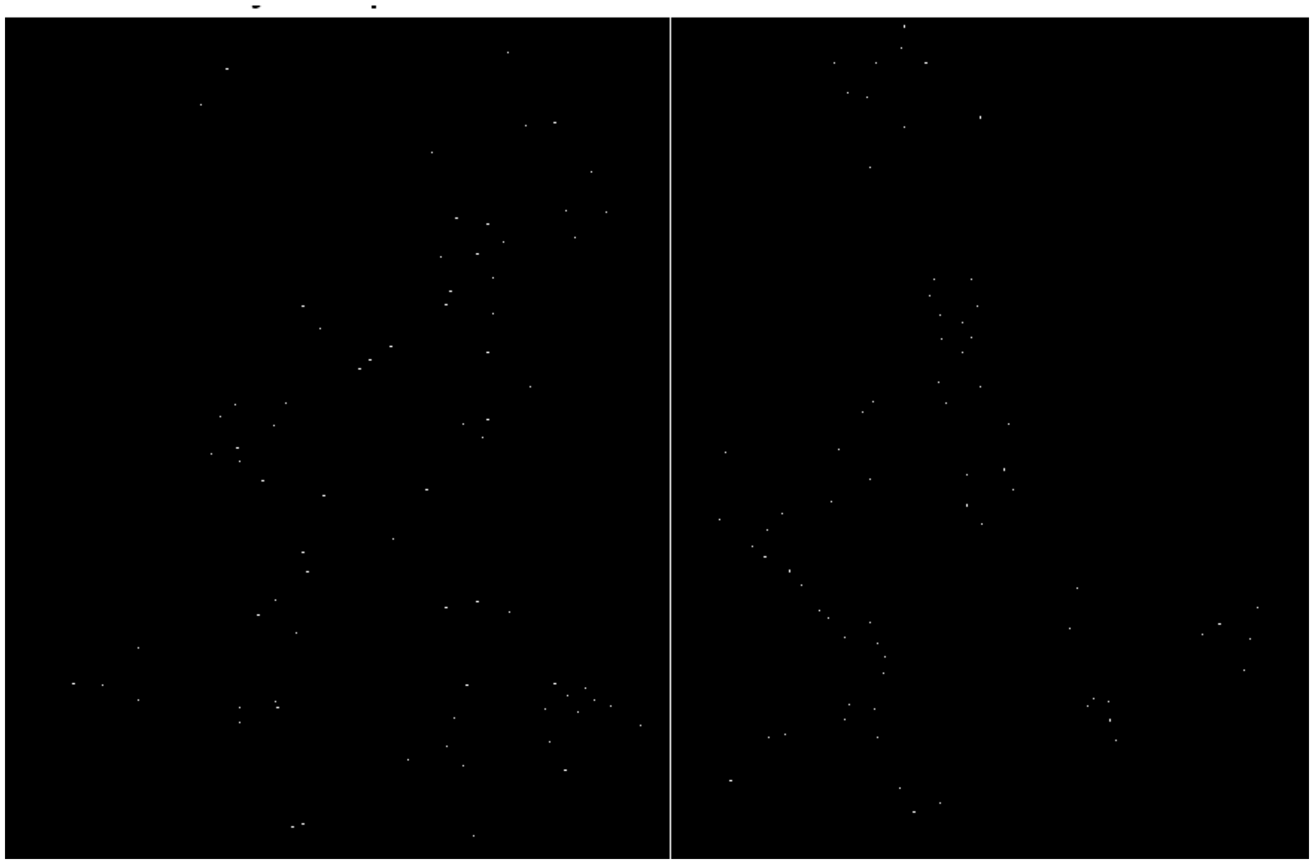
[Source: K. Grauman]

2) Find High Response



[Source: K. Grauman]

3) Non-maxima Suppresion



[Source: K. Grauman]

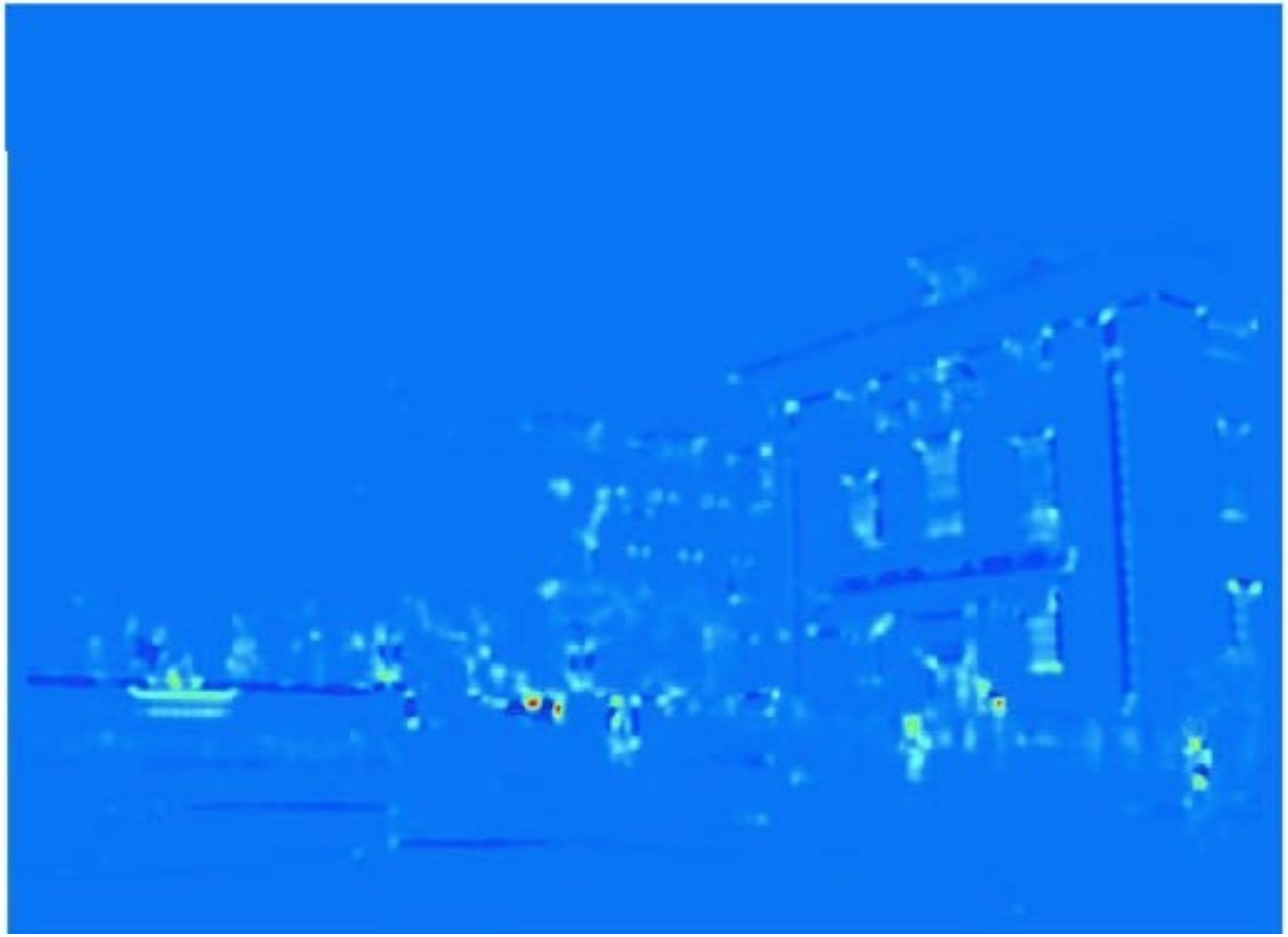
Results

[Source: K. Grauman]

Another Example

[Source: K. Grauman]

Cornerness



[Source: K. Grauman]

Interest Points

[Source: K. Grauman]

Properties of Harris Corner Detector

- Is the Harris corner detector rotation invariant? Shift invariant?

[Source: J. Hays]

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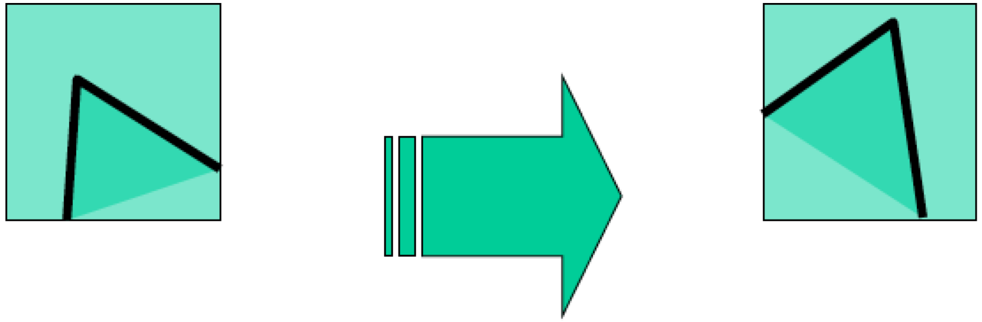

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Properties of Harris Corner Detector

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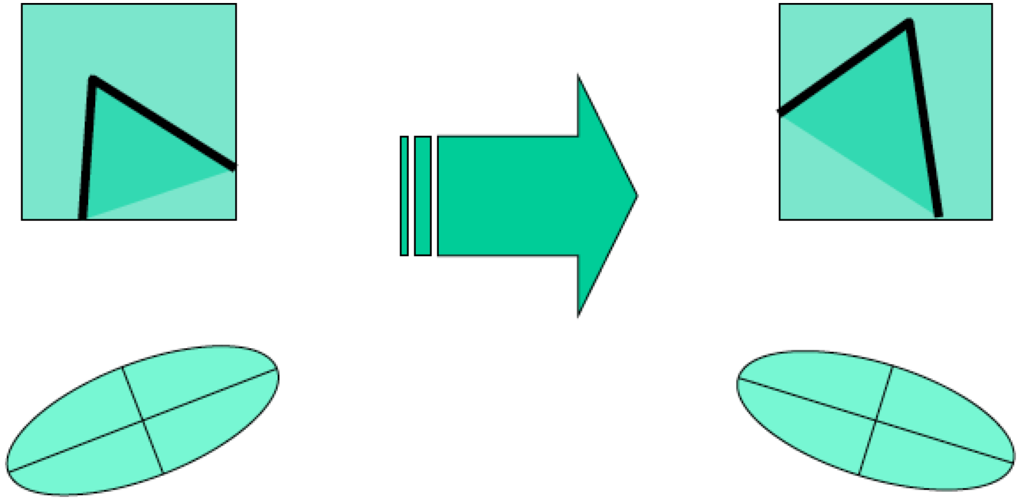
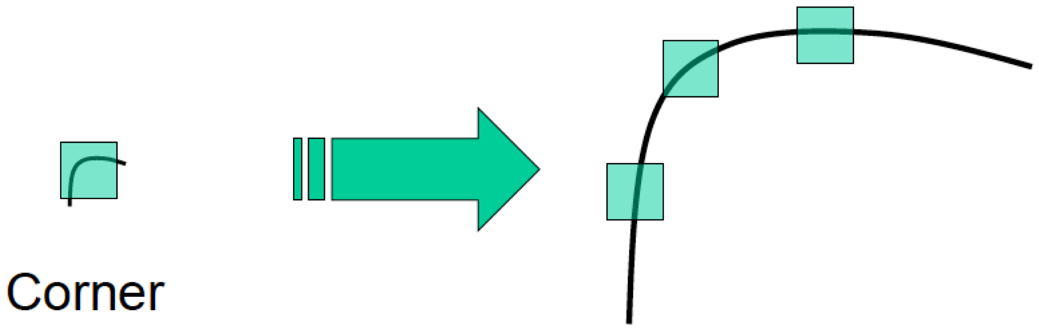


- Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same
- Harris corner detector is rotation-covariant
- what about scale?

[Source: J. Hays]

Properties of Harris Corner Detector

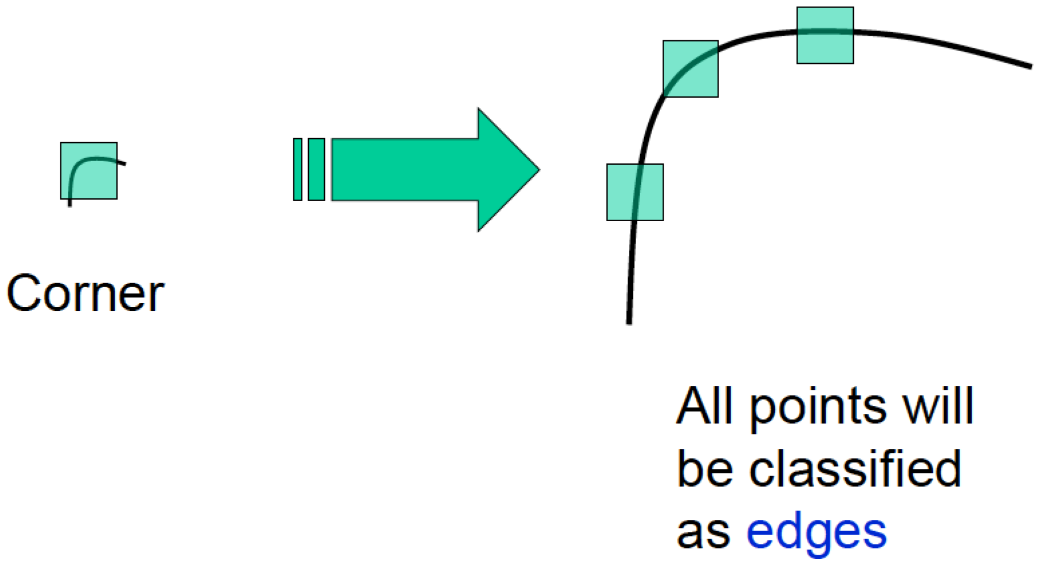
- Scale?



[Source: J. Hays]

Properties of Harris Corner Detector

- Scale?



- Corner location is not scale invariant/covariant!

[Source: J. Hays]

Optical Flow

Slide Credit: Ali Farhadi

We live in a moving world

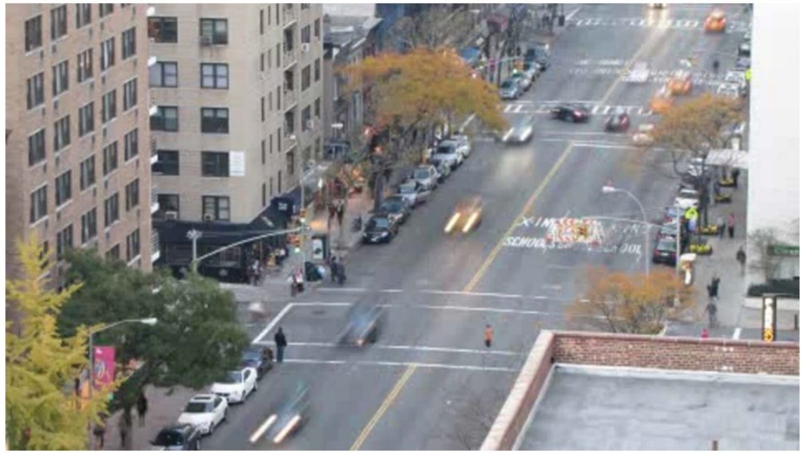
- Perceiving, understanding and predicting motion is an important part of our daily lives

Motion scenarios (priors)

Static camera, moving scene

Moving camera, static scene

Moving camera, moving scene



Static camera, moving scene, moving light

How can we recover motion?

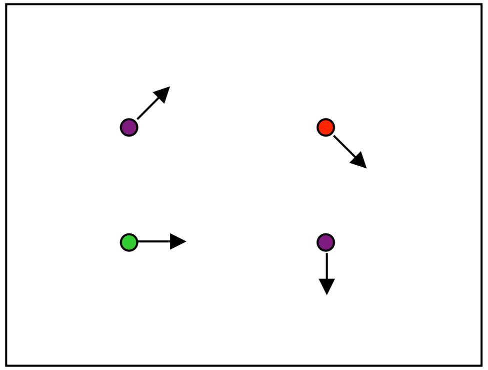
- Extract visual features (corners, textured areas) and “track” them over multiple frames.

- Recover image motion at each pixel from spatio-temporal image brightness variations (optical flow).

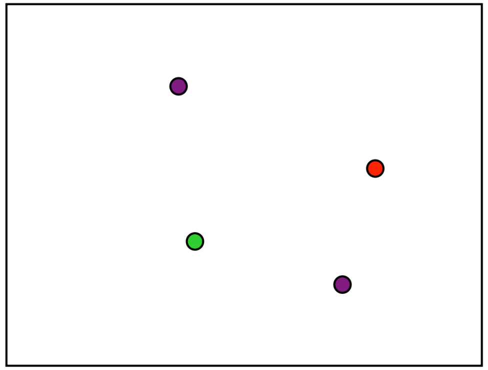
B. Lucas and T. Kanade. An iterative image registration technique with an application to stereo vision. In Proceedings of the International Joint Conference on Artificial Intelligence, pp. 674–679, 1981.

Jonschkowski et al. 2020]

Feature tracking



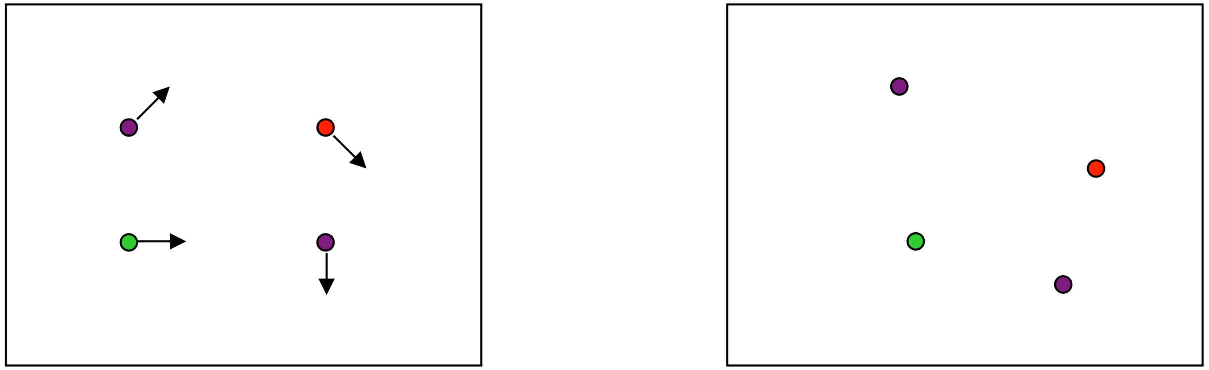
$I(x,y,t)$



$I(x,y,t+1)$

- Given two subsequent frames, estimate the point translation

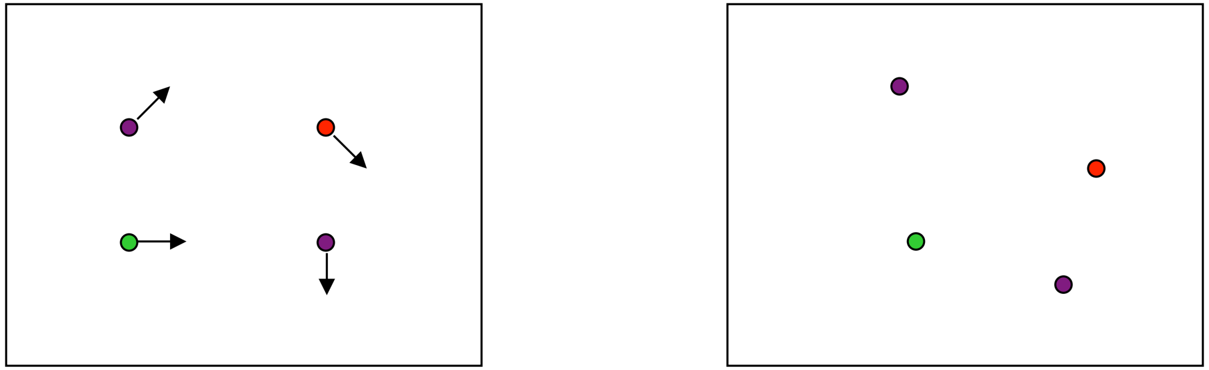
Feature tracking



$I(x,y,t)$ $I(x,y,t+1)$

- Given two subsequent frames, estimate the point translation
- Key assumptions:
  - Brightness constancy: projection of the same point looks the same in every frame
  - Small motion: points do not move very far
  - Spatial coherence: points move like their neighbors

Feature tracking



$I(x,y,t)$ $\quad$ $I(x,y,t+1)$

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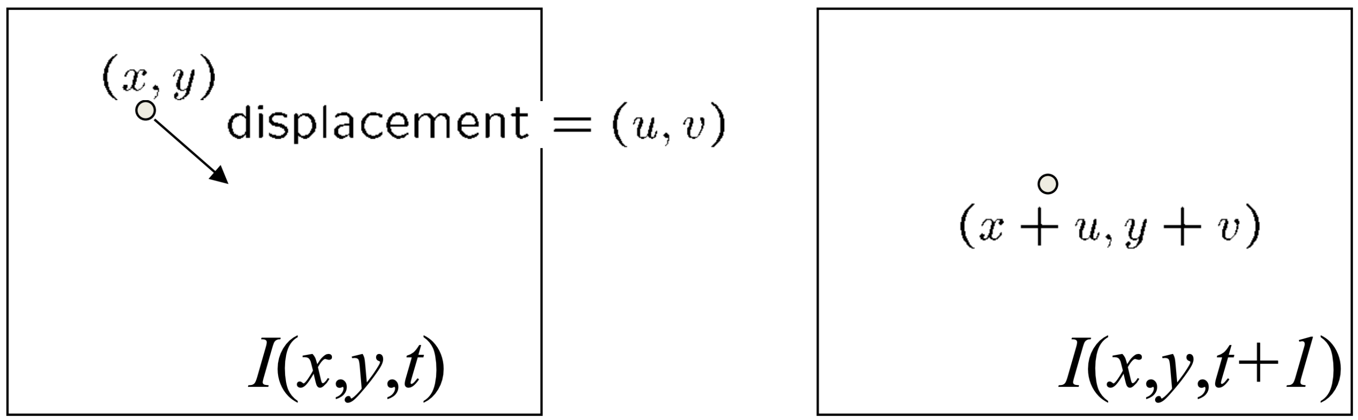
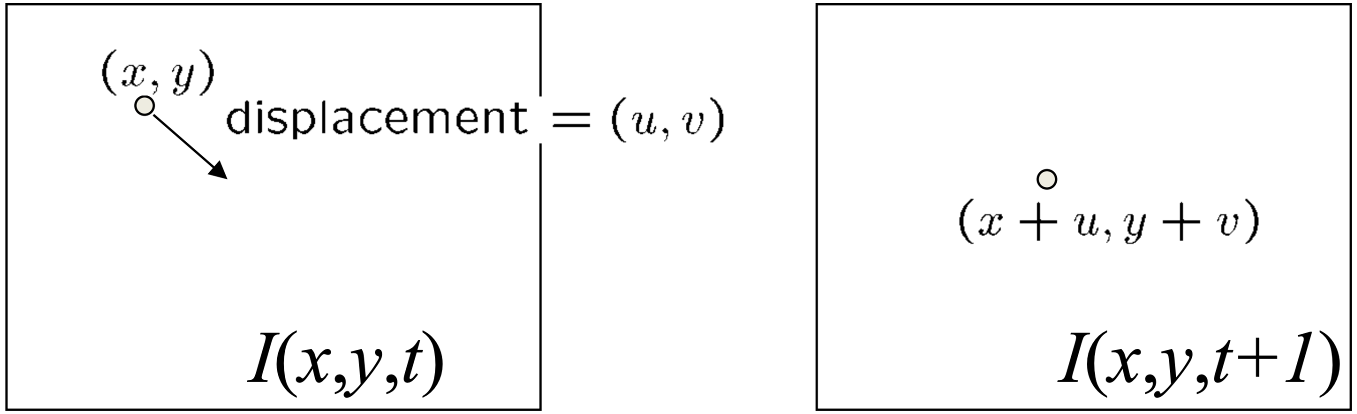
The brightness constancy constraint

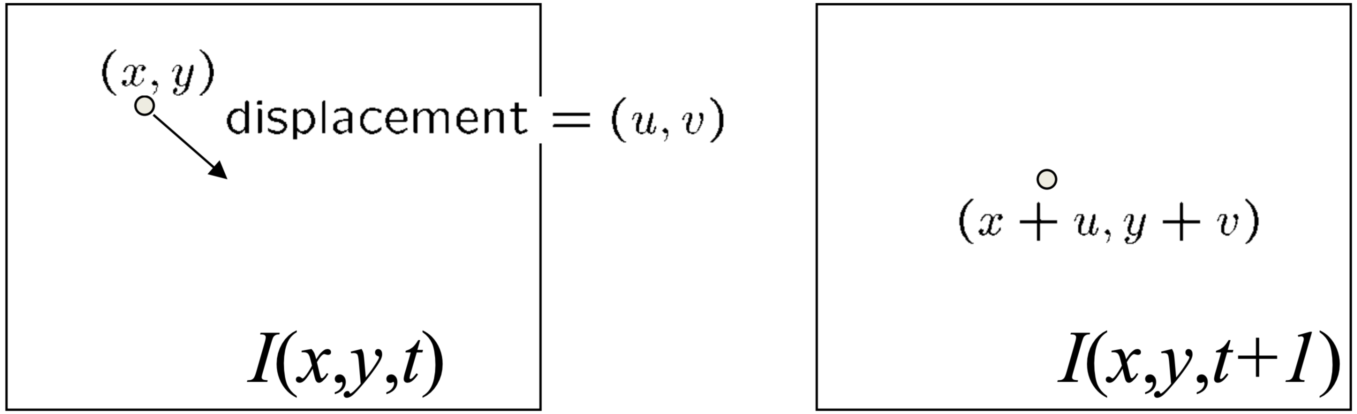


The brightness constancy constraint



Brightness Constancy Equation: $I(x, y, t) = I(x + u\ , y + v, t + 1)$

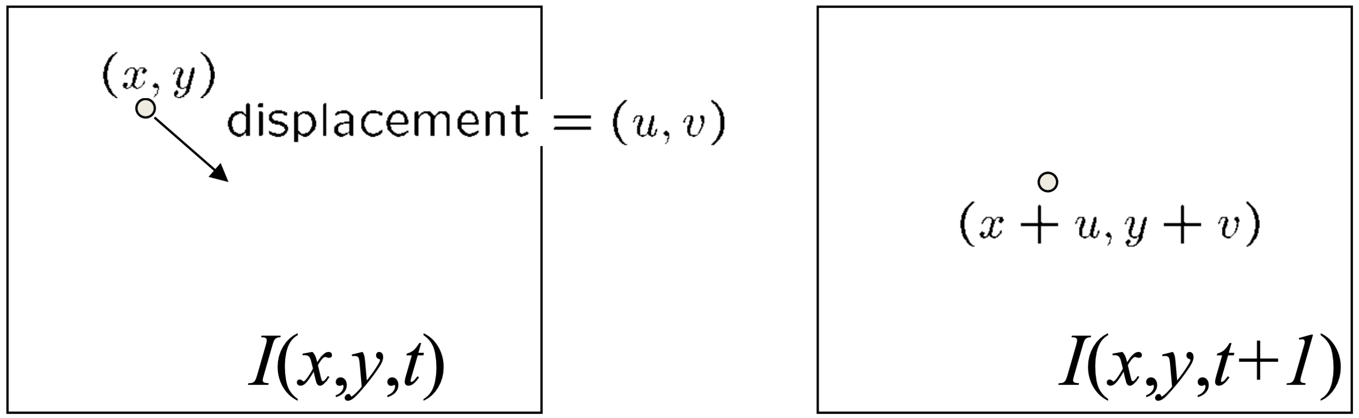
The brightness constancy constraint



Brightness Constancy Equation: $I(x, y, t) = I(x + u\ , y + v, t + 1)$

- Now, take the Taylor expansion of $I(x + u\ , y + v, t + 1)$ at (x, y, t) to linearize the right side

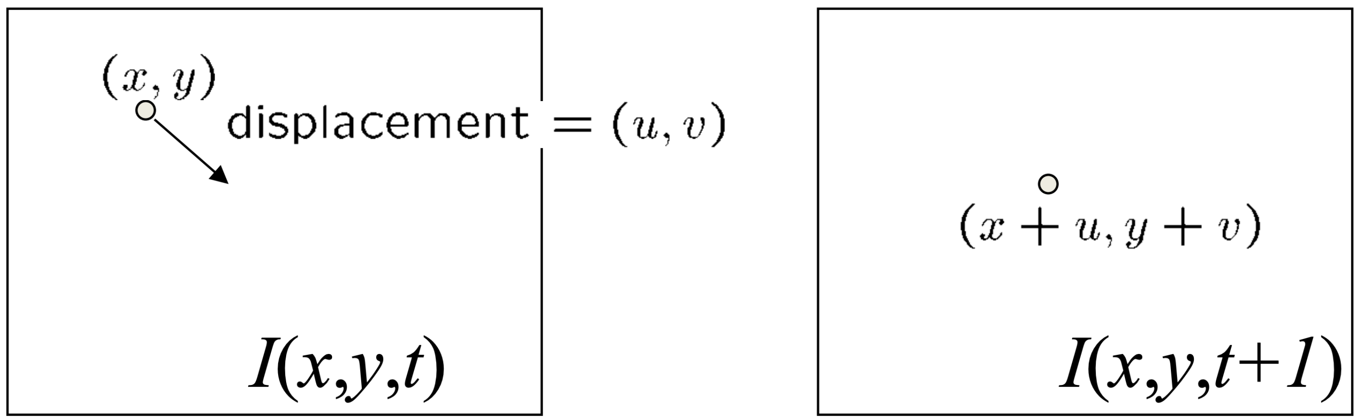
The brightness constancy constraint



Brightness Constancy Equation: $I(x, y, t) = I(x + u\ , y + v, t + 1)$

$$I(x + u\ , y + v, t + 1)\ \approx I(x, y, t) + I_x . u + I_y . v + I_t$$

The brightness constancy constraint



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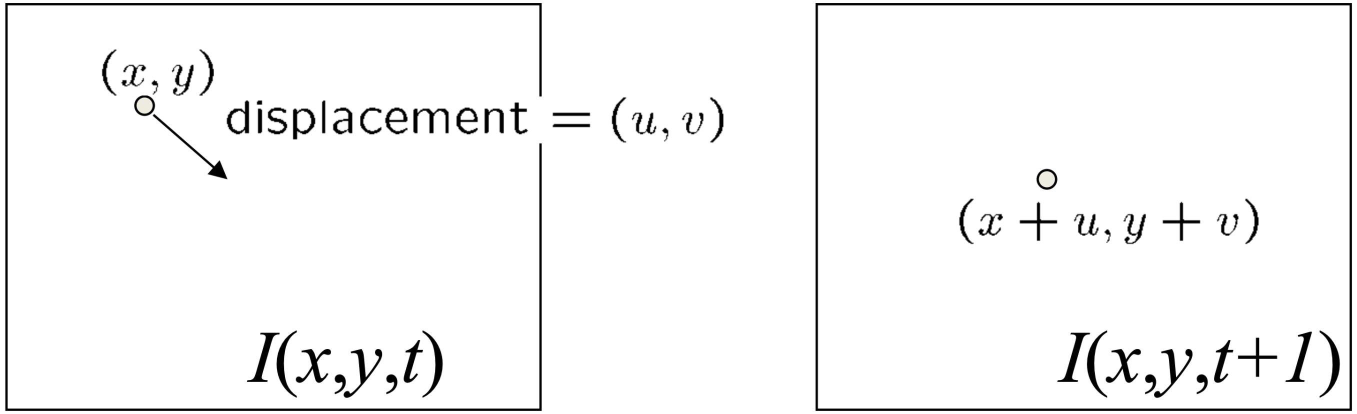
$$I(x + u\,, y + v, t + 1) - I(x, y, t) \approx I_x . u + I_y . v + I_t$$

The brightness constancy constraint



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$$I(x + u\ , y + v, t + 1) - I(x, y, t) \approx I_x . u + I_y . v + I_t$$

$$\nabla I \begin{bmatrix} u \\ v \end{bmatrix} + I_t = 0$$

The brightness constancy constraint

- Can we use this equation to recover image motion (u,v) at each pixel?

$$\nabla I \,.\begin{bmatrix} u \\ v \end{bmatrix} + I_t = 0$$

- How many equations and unknowns per pixel?

The brightness constancy constraint

- Can we use this equation to recover image motion (u,v) at each pixel?

$$\nabla I \, . \begin{bmatrix} u \\ v \end{bmatrix} + I_t = 0$$

- How many equations and unknowns per pixel?
- One equation (this is a scalar equation!), two unknowns (u,v)

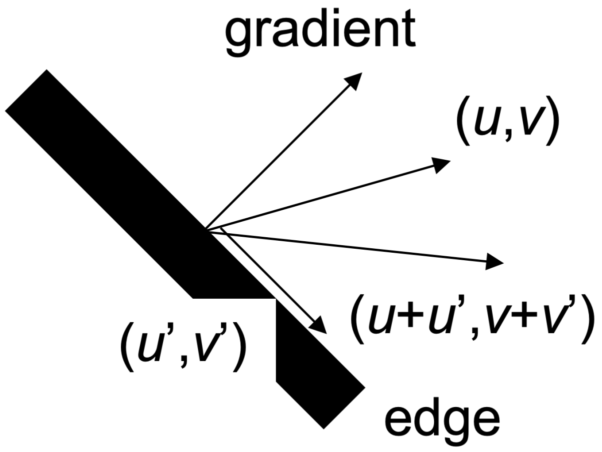
The brightness constancy constraint

- The component of the motion perpendicular to the gradient (i.e., parallel to the edge) cannot be measured.

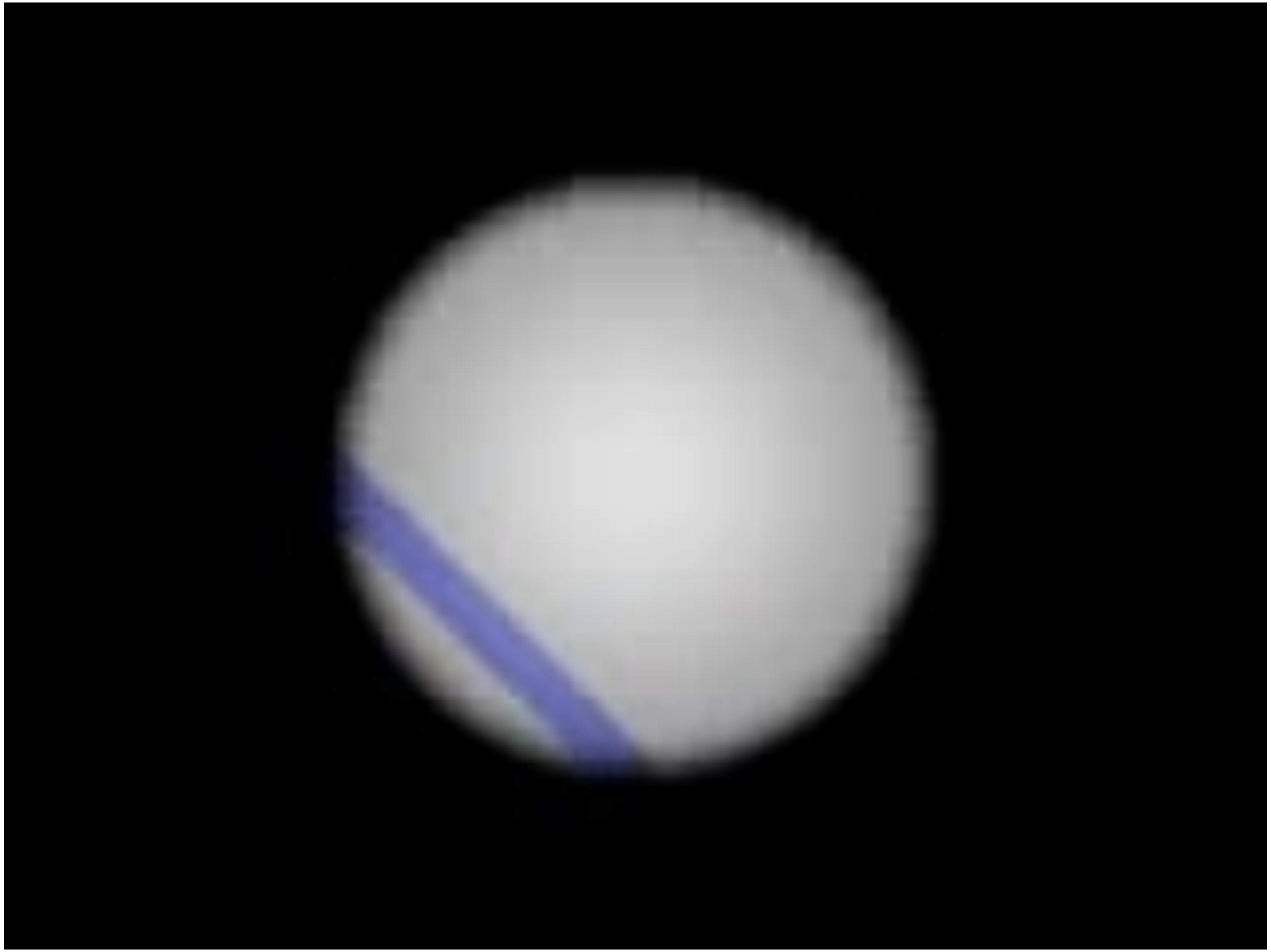
The brightness constancy constraint

- The component of the motion perpendicular to the gradient (i.e., parallel to the edge) cannot be measured.
  - If (u, v) satisfies the equation, so does $(u + u', v + v')$ if

$$\nabla I \cdot \begin{bmatrix} u' \\ v' \end{bmatrix} = 0$$



The aperture problem



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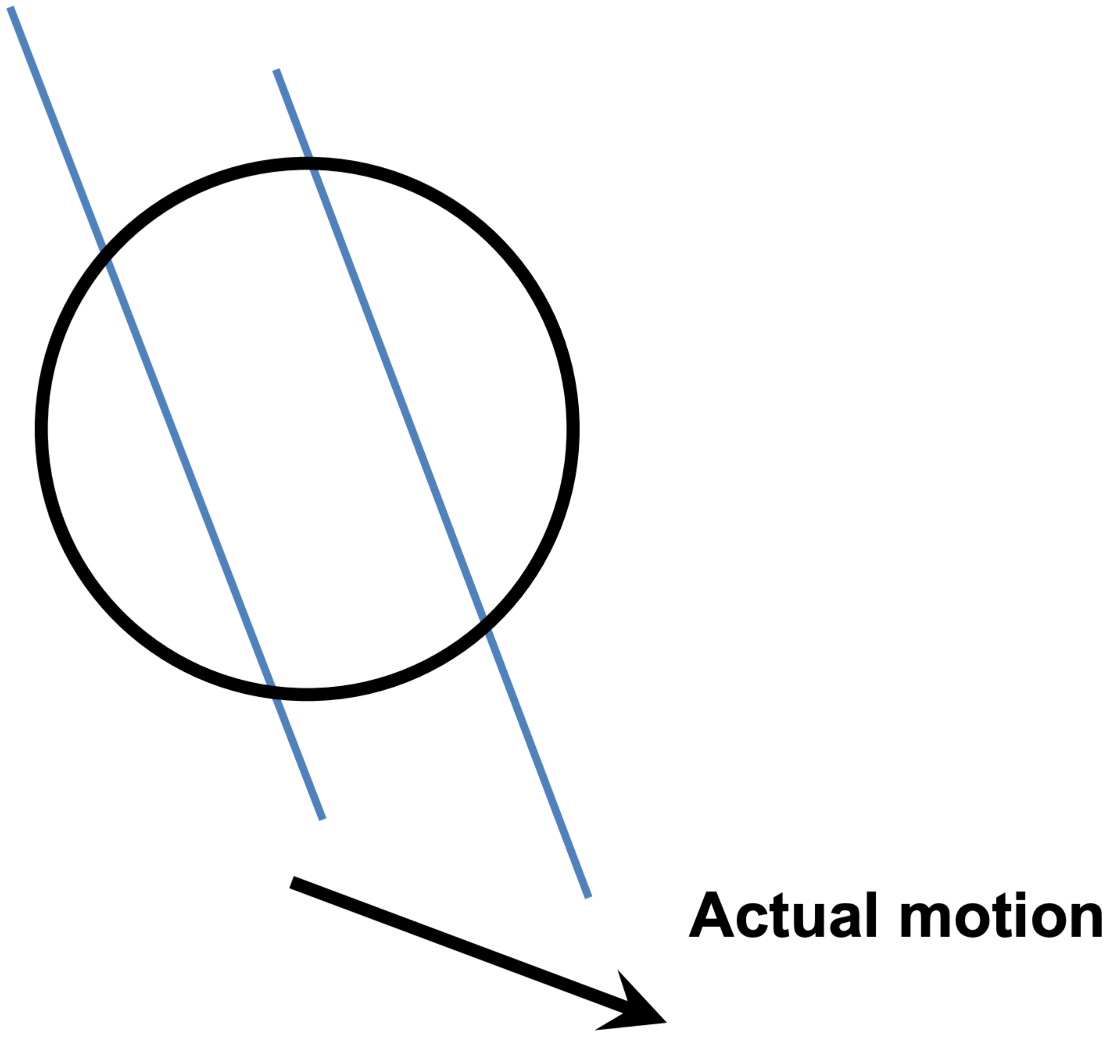

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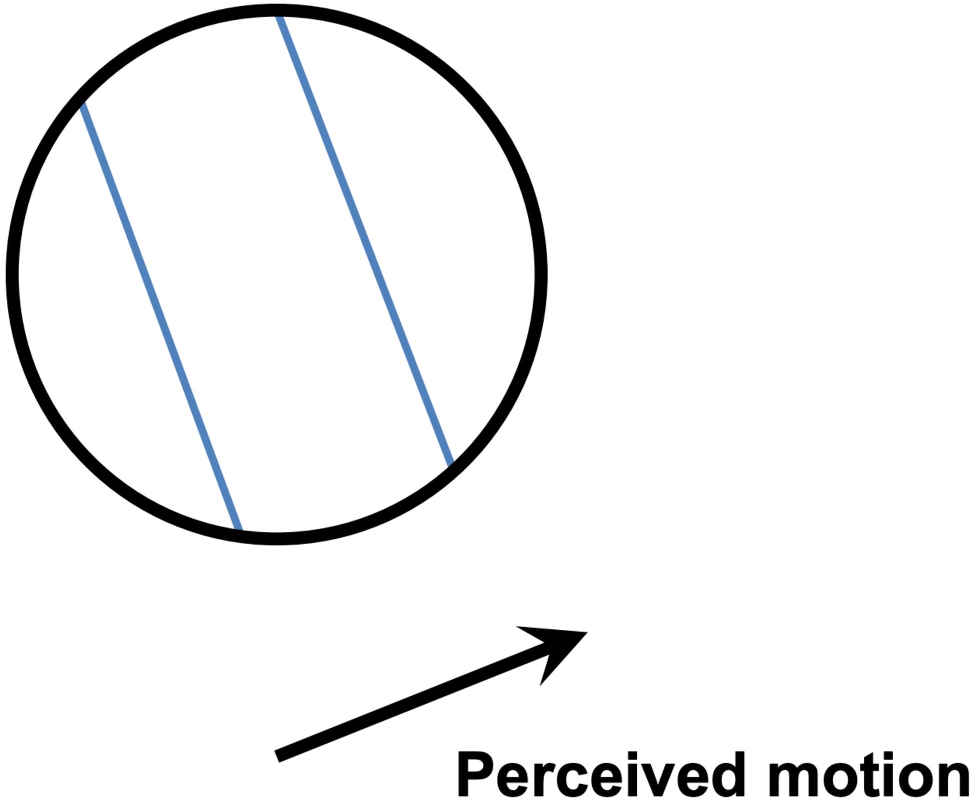

The barber pole illusion

Solving the ambiguity...

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- Assume the pixel's neighbors have the same (u, v)
  - If we use a 5x5 window, that gives us 25 equations per pixel

  - For $\forall_{p_i} : \nabla I(p_i) . \begin{bmatrix} u \\ v \end{bmatrix} + I_t(p_i) = 0$

Solving the ambiguity...

$$\begin{pmatrix} I_x(p_1) & I_y(p_1) \\ \vdots & \vdots \\ I_x(p_{25}) & I_y(p_{25}) \end{pmatrix} \begin{bmatrix} u \\ v \end{bmatrix} + \begin{pmatrix} I_t(p_1) \\ \vdots \\ I_t(p_{25}) \end{pmatrix} = 0$$

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$$A\,d = b$$

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how do we solve this?

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- Least squares solution for d given by

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does this look familiar?

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

Conditions for solvability

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- When is this solvable? I.e., what are good points to track?

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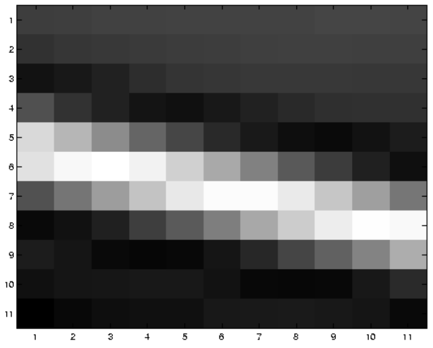
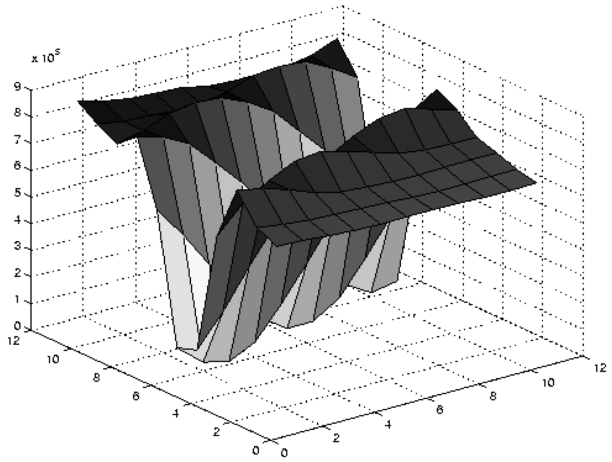
  - $A^T A$ should be well-conditioned
    - λ_1/λ_2 should not be too large (λ_1=larger eigenvalue)

Edges cause problems

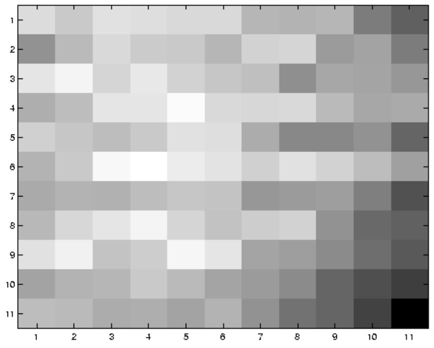


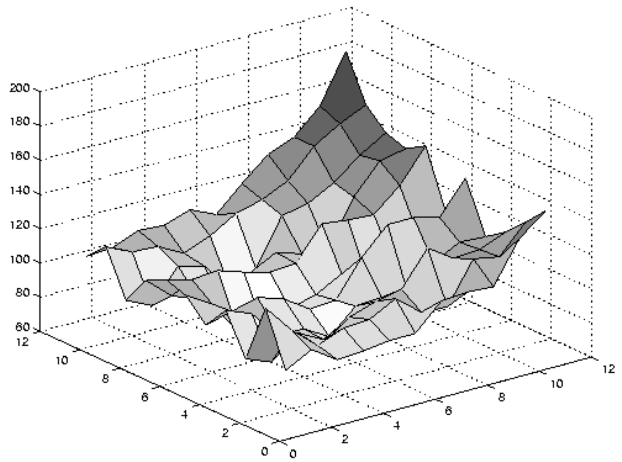


$$\sum \nabla I (\nabla I)^T$$

– large gradients, all the same
– large λ_1, small λ_2

Low texture regions don't work





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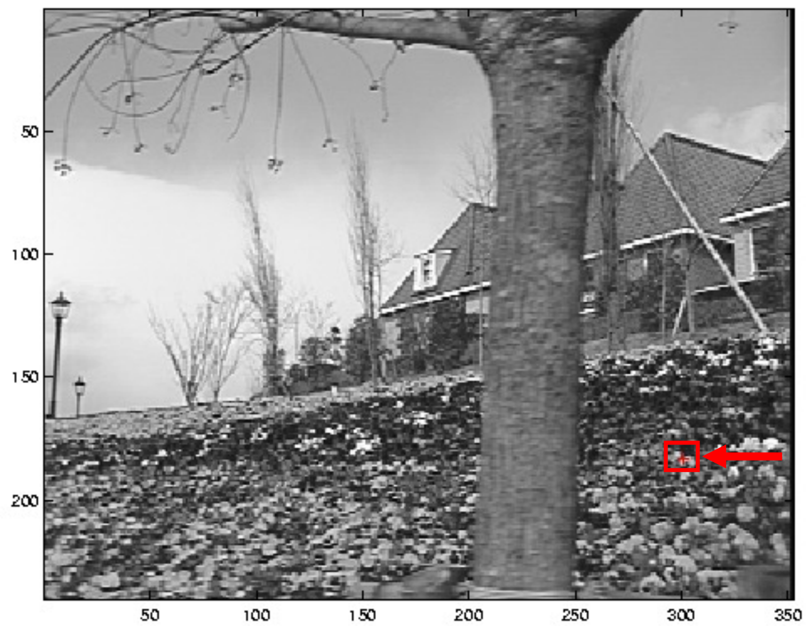
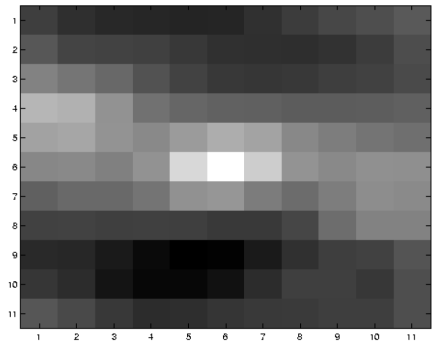
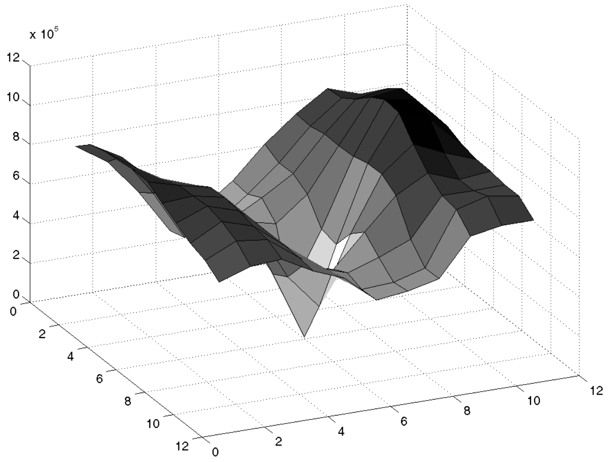
– gradients have small magnitude

– small λ_1, small λ_2

High textured region work best







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– gradients are different, large magnitudes

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- What are the potential causes of errors in this procedure?
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Dealing with larger movements: Iterative refinement

Original (x,y) position

$$I_t = I(x', y', t+1) - I(x, y, t)$$

1. Initialize $(x', y') = (x, y)$
2. Compute (u, v) by

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2nd moment matrix for feature patch in first image

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5. Repeat steps 2-4 until small change
   - Use interpolation for subpixel values

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Revisiting the small motion assumption

How might we solve this problem?

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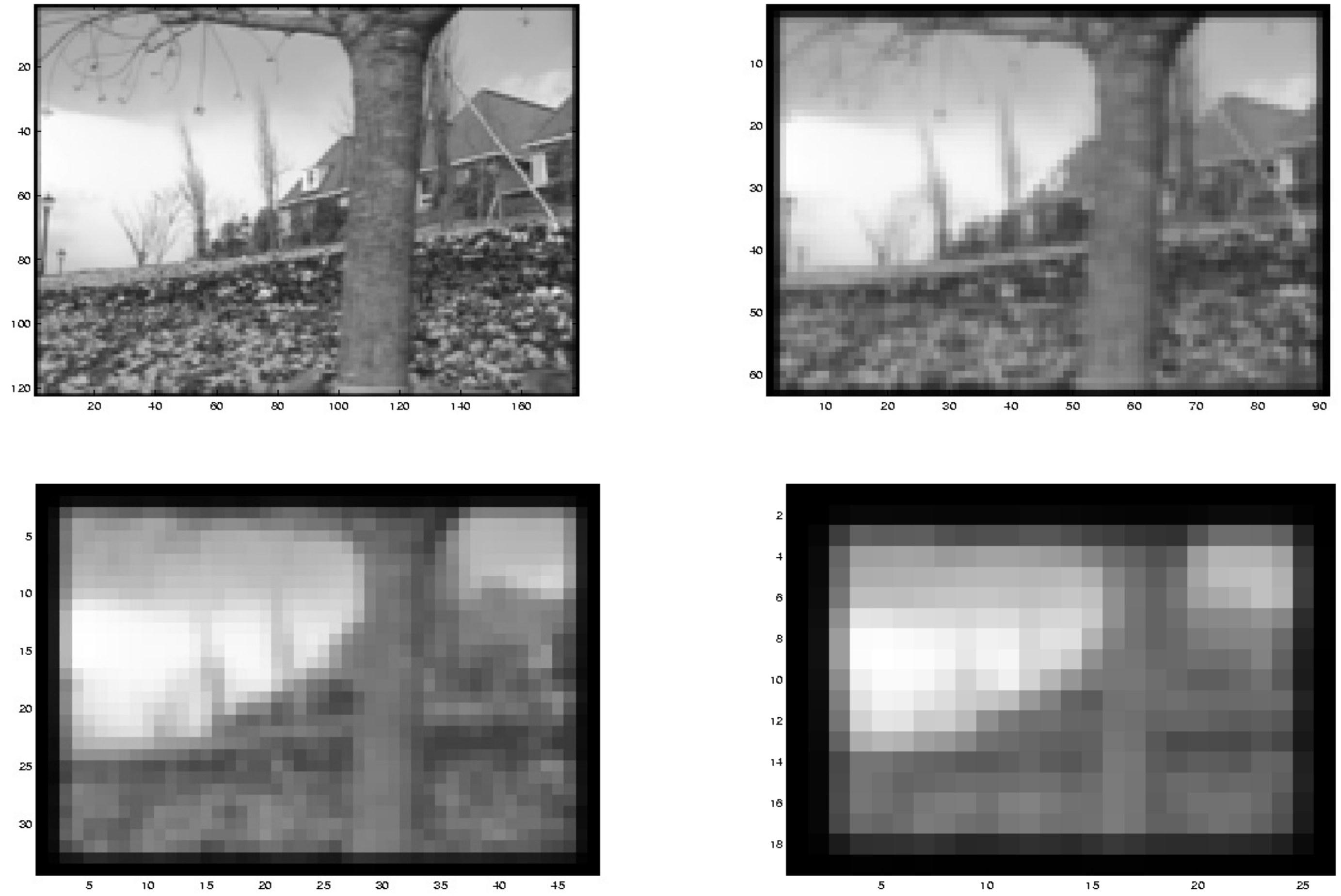
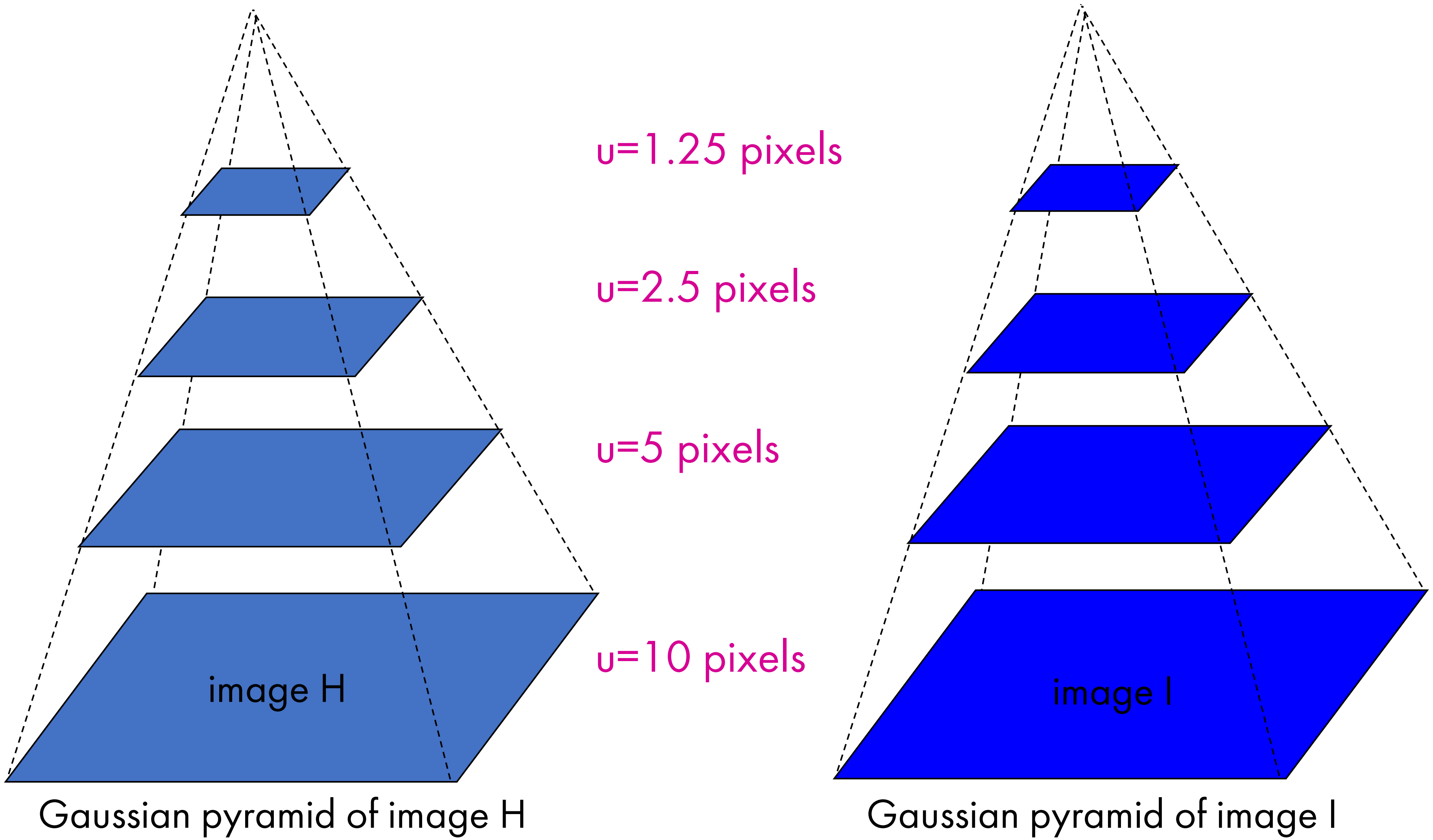
Reduce the resolution!



Coarse-to-fine optical flow estimation



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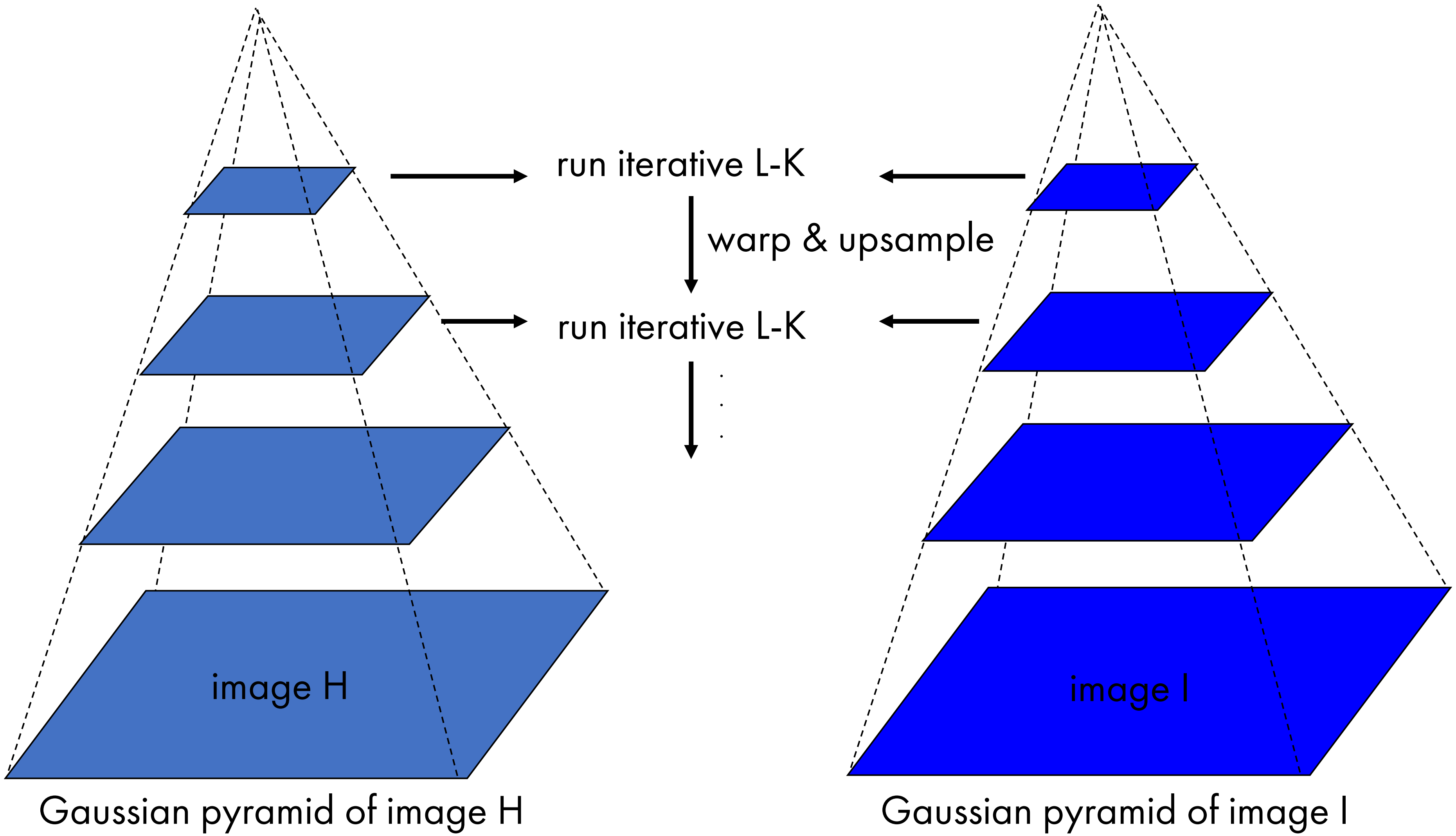

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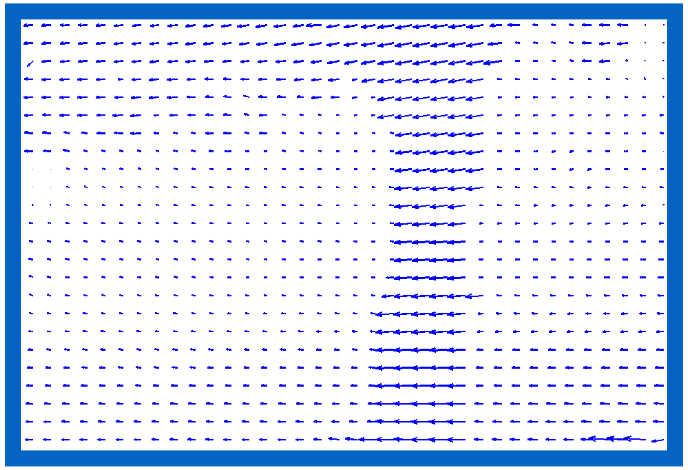
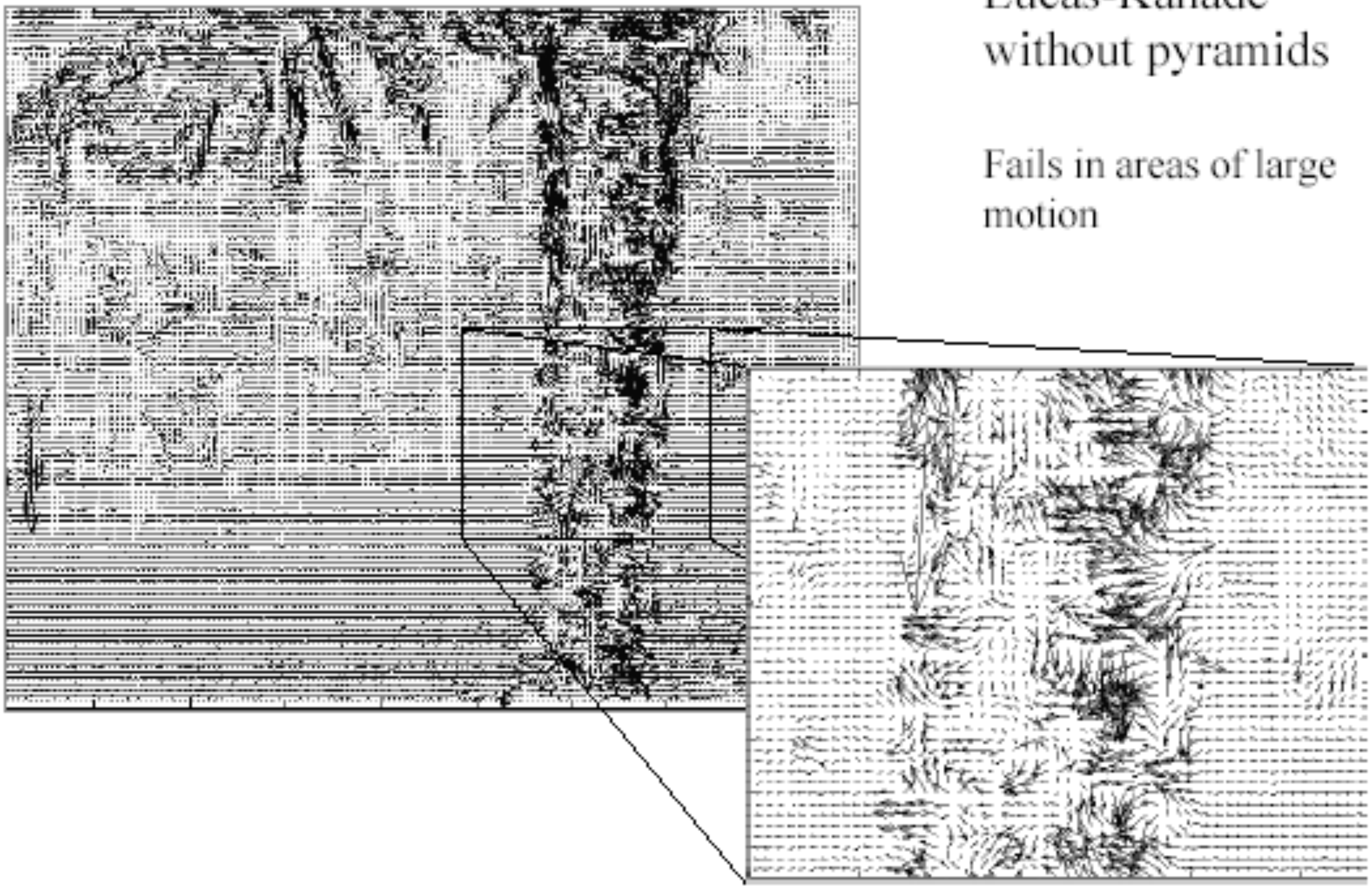
  - Apply this flow field to warp the first frame toward the second frame.
  - Rerun L-K and warping till convergence as above.
- Etc.

The Flower Garden Video

- What should the
- optical flow be?



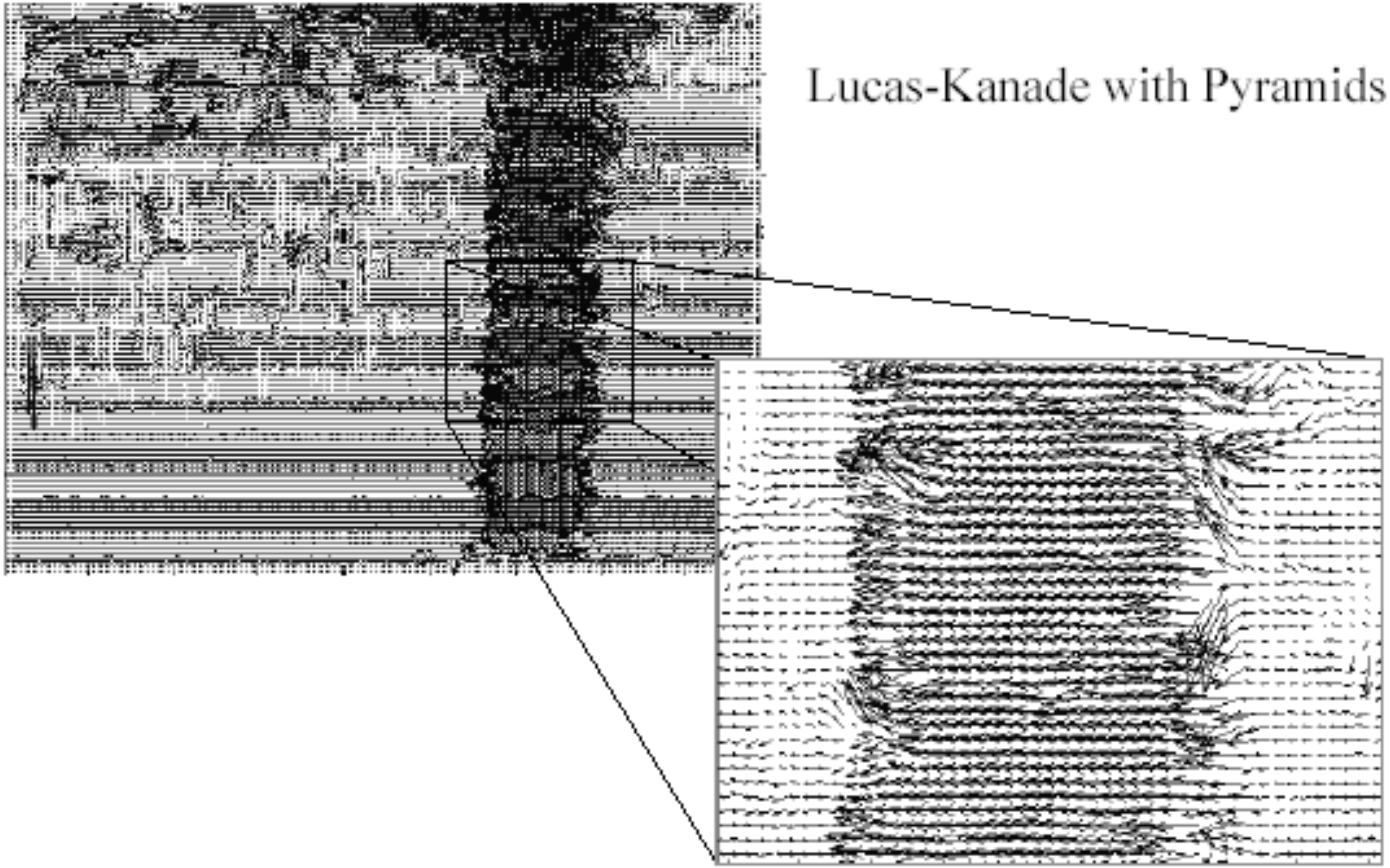
Optical Flow Results



Lucas-Kanade
without pyramids

Fails in areas of large
motion

Optical Flow Results



Lucas-Kanade with Pyramids

Next Time

- Can we also define keypoints that are shift, rotation, and scale invariant/covariant?
- What should be our description around keypoint?