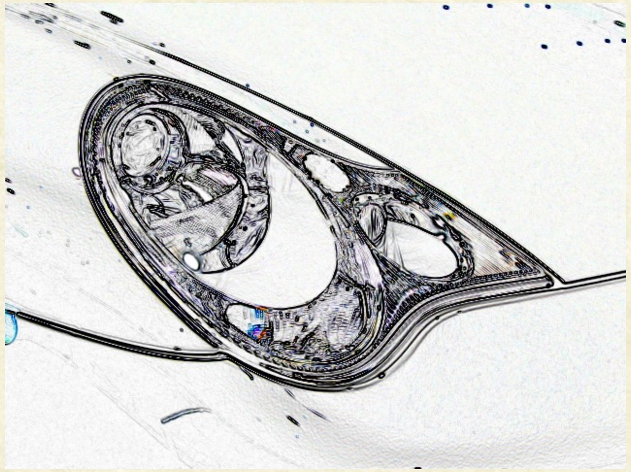
CS7.505: Computer Vision

Spring 2022: Feature Detection



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Stereo Examples





Image Matching

by Diva Sian

by swashford

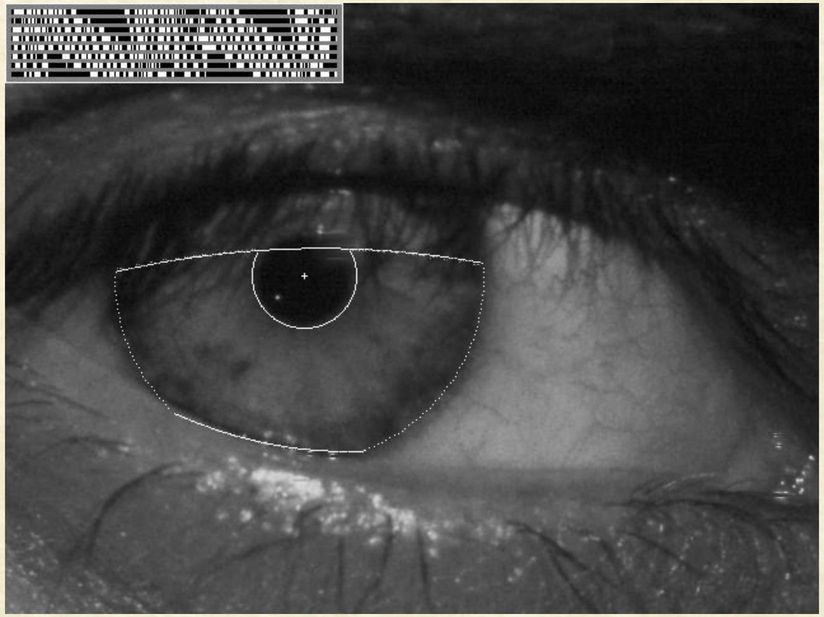
Harder Case

by Diva Sian

by scgbt

Even Harder Case

“*How the Afghan Girl was Identified by Her Iris Patterns*”
Read the story



Harder still?

NASA Mars Rover images

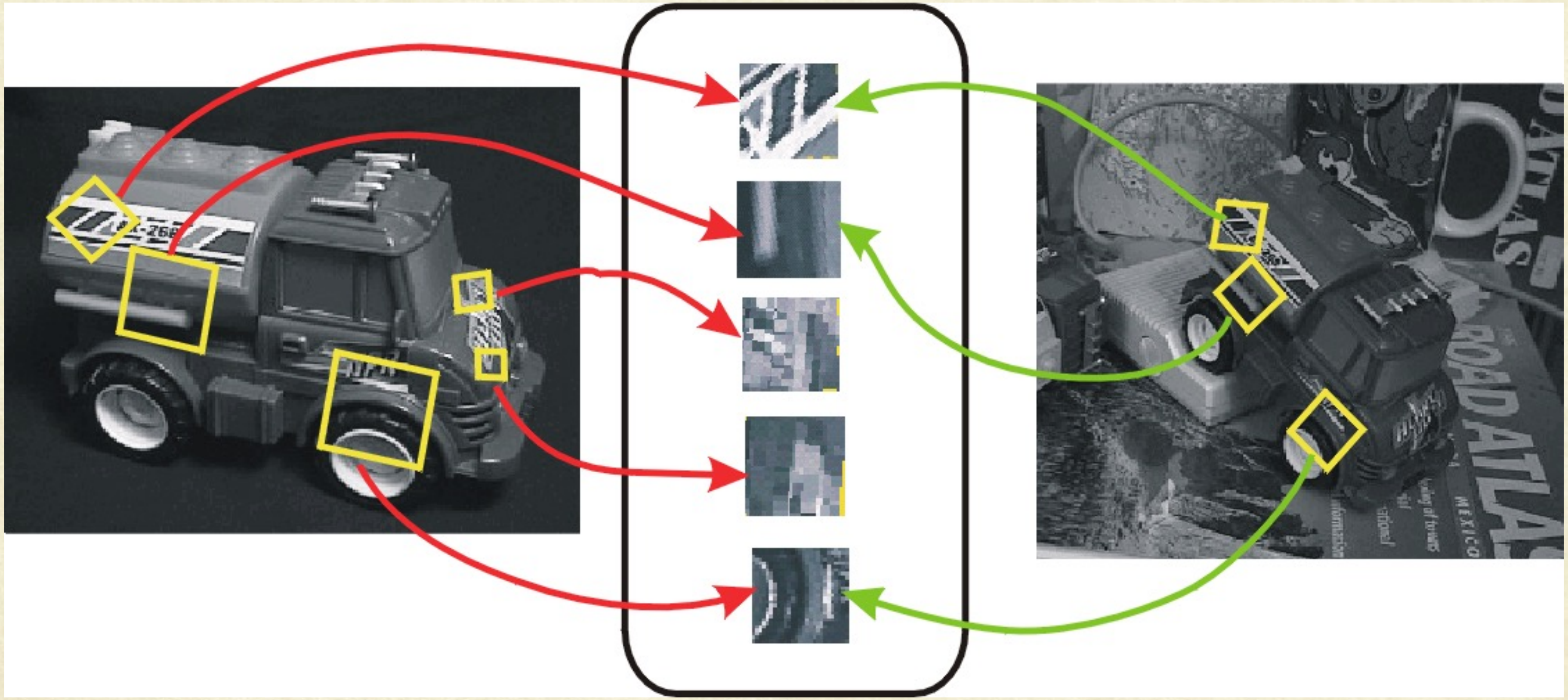
Answer below (look for tiny colored squares…)

NASA Mars Rover images with SIFT feature matches
Figure by Noah Snavely

Invariant Local Features

Find features that are invariant to transformations

- geometric invariance: translation, rotation, scale
- photometric invariance: brightness, exposure, …



Feature Descriptors

Advantages of Local Features

Locality
- features are local, so robust to occlusion and clutter

Distinctiveness:
- can differentiate a large set of objects

Quantity
- hundreds or thousands in a single image

Efficiency
- real-time performance achievable

Generality
- exploit different types of features in different situations

Applications:
- Image alignment (e.g., mosaics)
- 3D reconstruction
- Motion tracking
- Object recognition
- Indexing and database retrieval
- Robot navigation
- … other

Desirable Properties

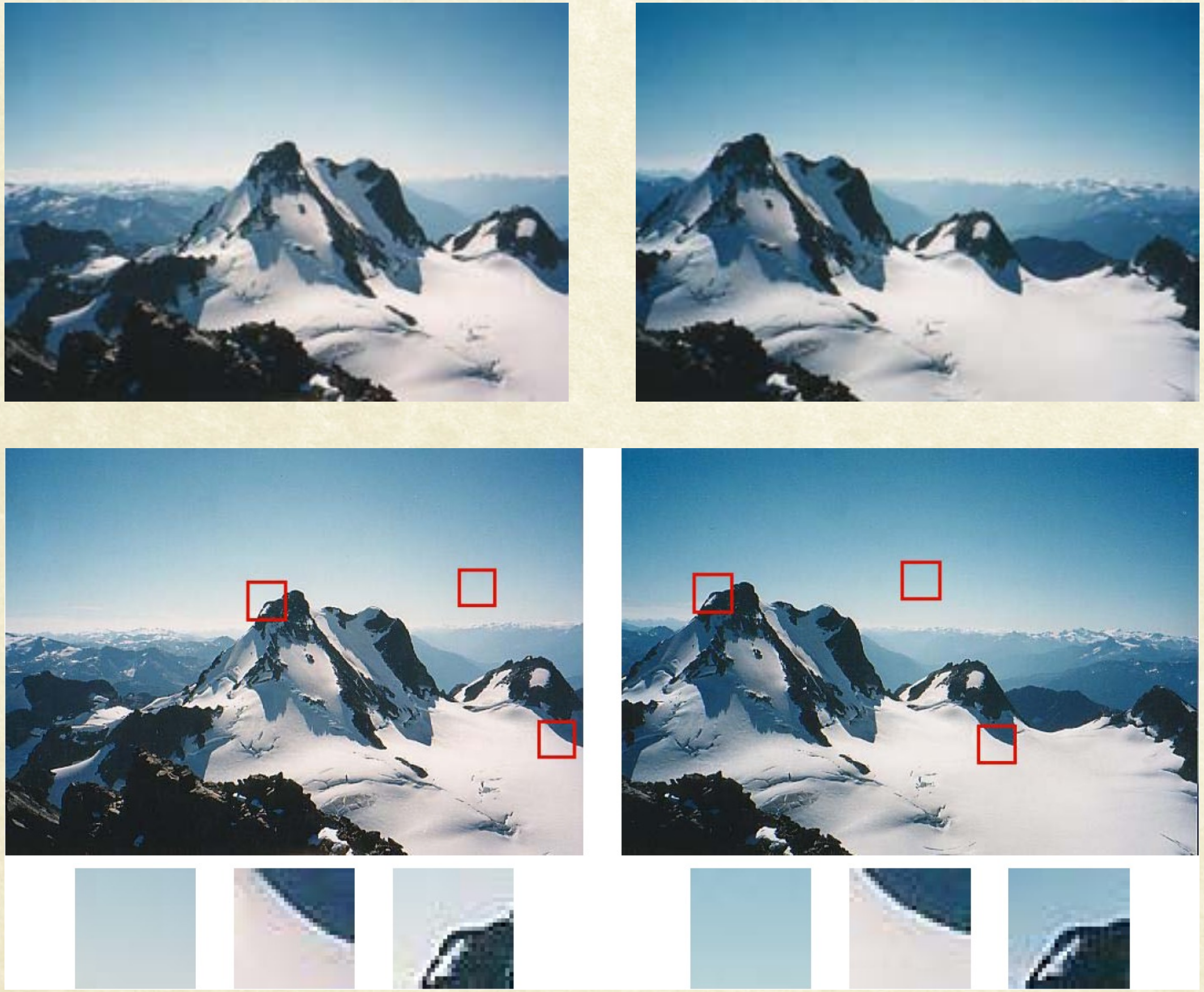
Detector

- Repeatable
- Efficient
- Invariant
- Localizing

Descriptor

- Discriminative
- Efficient
- Invariant
- Capture local geometry and appearance

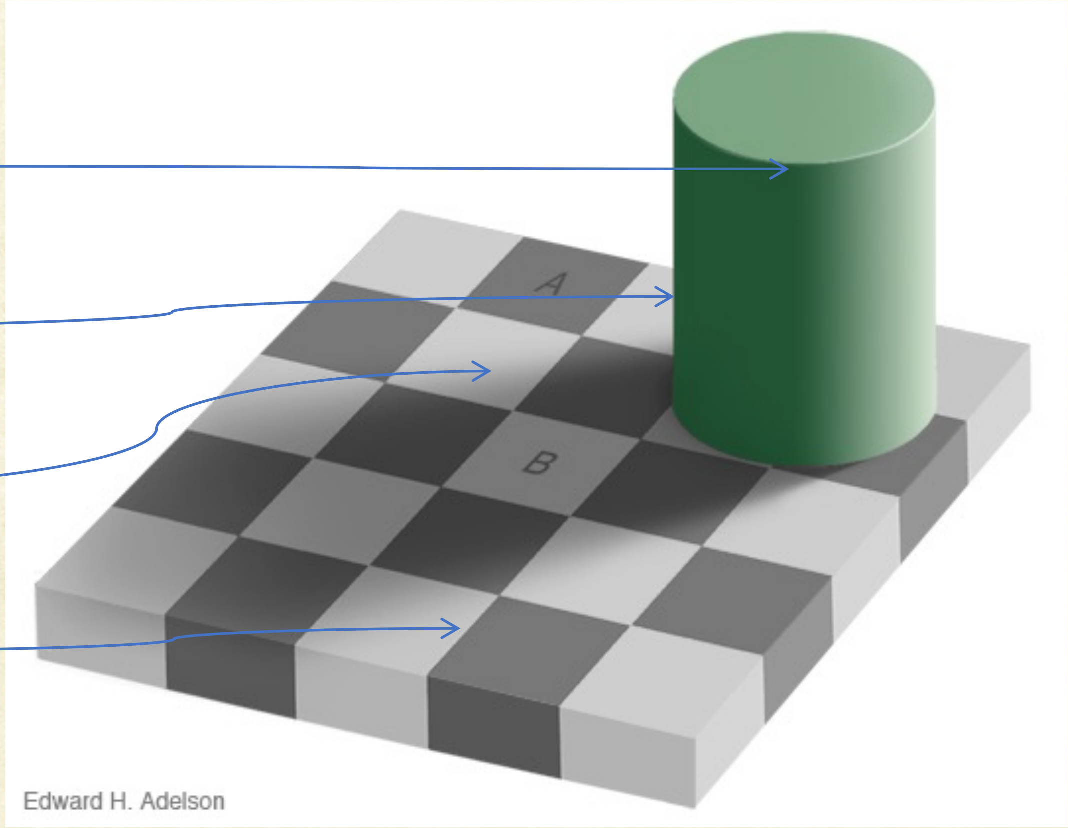
Features



- Point/patch,
- Edge/curve
- Region
- Want Uniqueness
  - Look for image regions that are unusual
  - Lead to unambiguous matches in other images
  - How to define “unusual”?

Edges

- Discontinuities in:
  - Surface Normal
  - Depth
  - Illumination
  - Surface Color

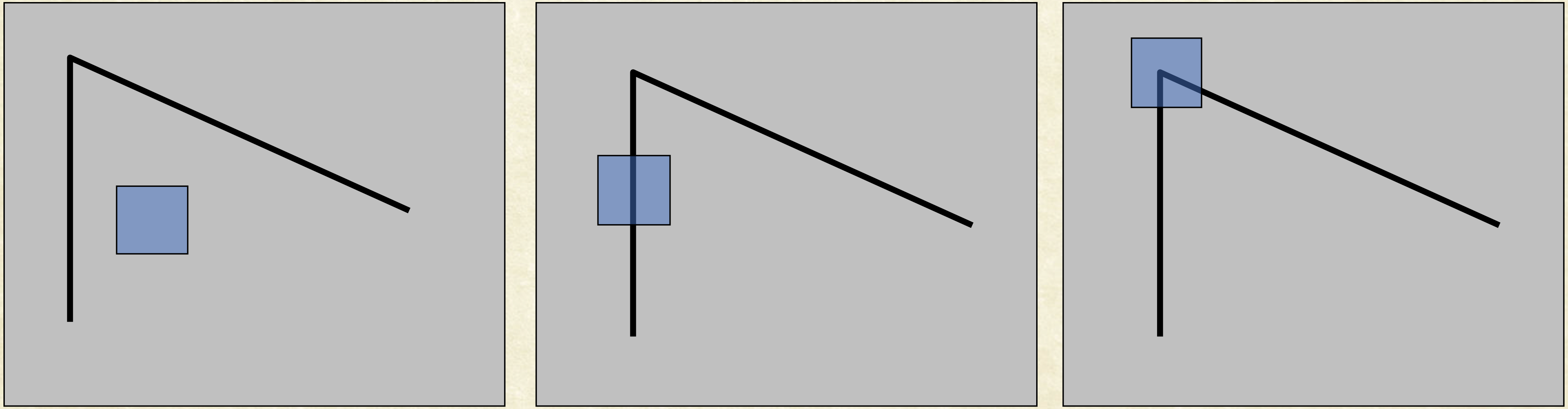


Edge Detection: DoG

Local measures of uniqueness

Suppose we only consider a small window of pixels

- What decides whether a feature is a good or bad?

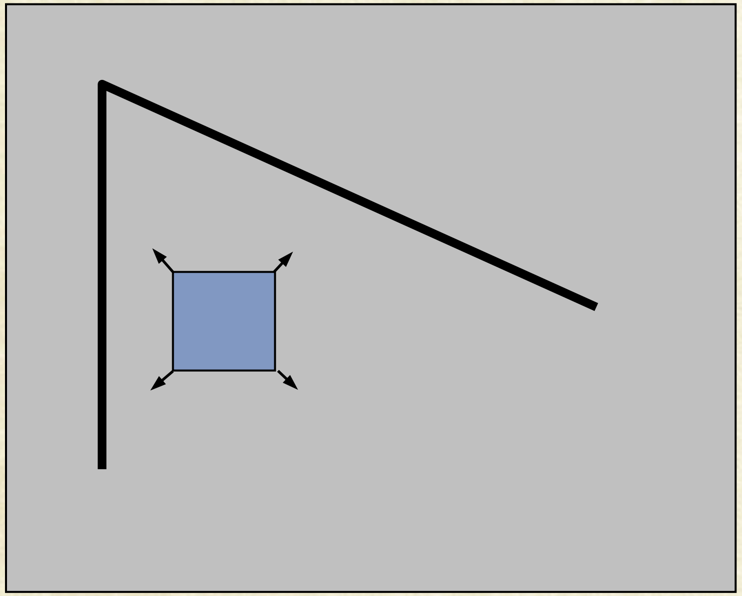


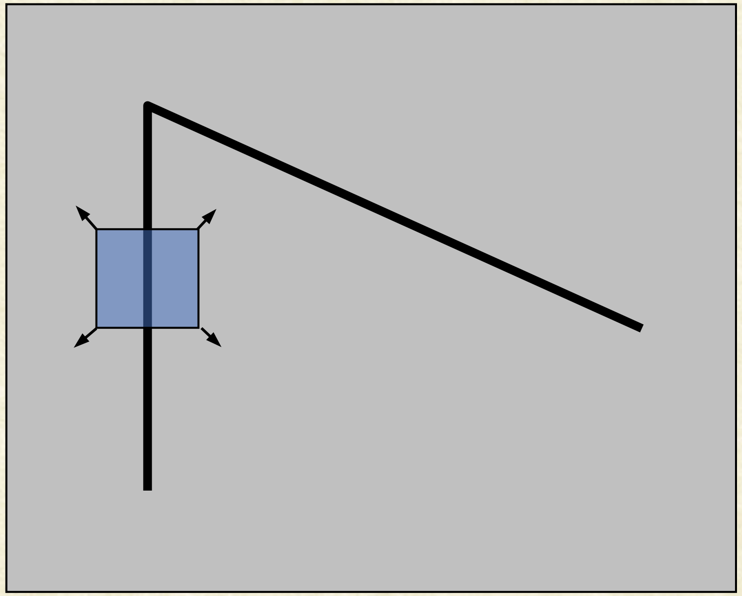
Slide adapted from Darya Frolova, Denis Simakov, Weizmann Institute.

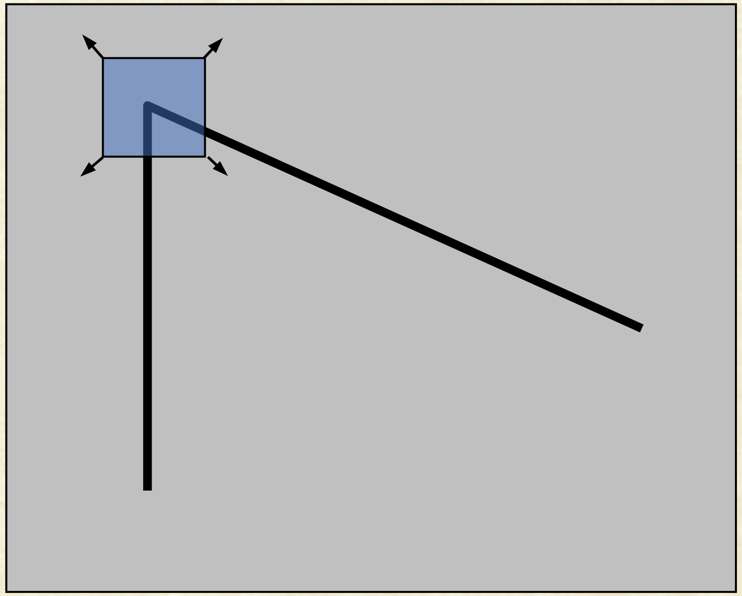
Feature Detection

Local measure of feature uniqueness

- How does the window change when you shift it?
- We need windows that exhibit a *big change* when *moved slightly* in *any direction*







"flat" region:
no change in all directions

"edge":
no change along the edge direction

"corner":
significant change in all directions

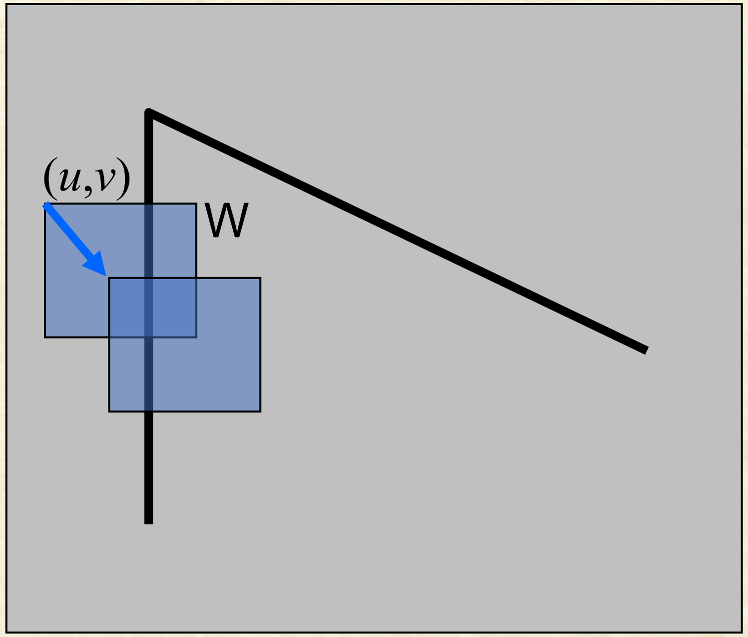
Slide adapted from Darya Frolova, Denis Simakov, Weizmann Institute.

Feature Detection: The Math

Consider shifting the window W by (u,v)

- How do the pixels in W change?
- Compare each pixel before and after by summing up the squared differences
- This defines an SSD “error” of $E(u,v)$:

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



Small Motion Assumption

Taylor Series expansion of I:

$$I(x+u, y+v) = I(x,y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \text{higher order terms}$$

For small motion (u, v), first order approximation is good:

$$i.e., \qquad I(x+u, y+v) \approx I(x,y) + \frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v$$

$$\approx I(x,y) + \begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$\text{shorthand:} \quad I_x = \frac{\partial I}{\partial x}$$

Plugging this into the formula on the previous slide…

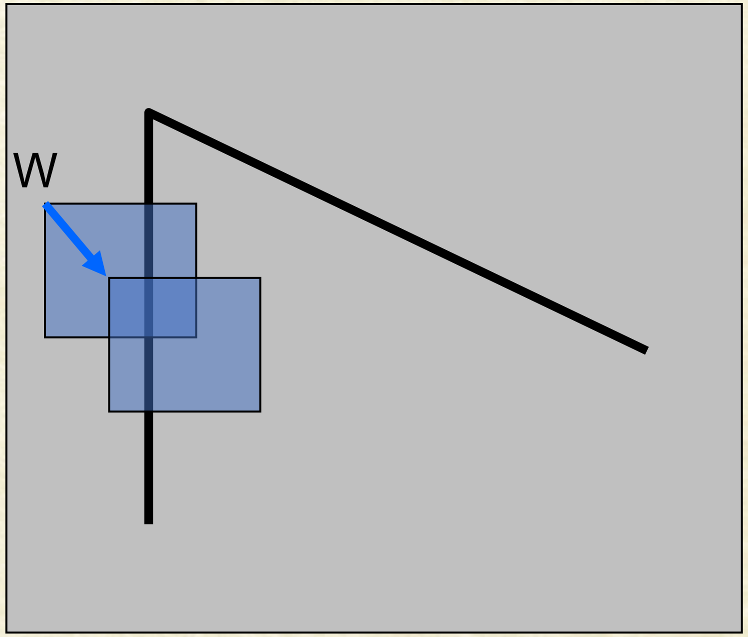
Feature Detection: The Math

SSD "error" of $E(u,v)$:

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

$$\approx \sum_{(x,y)\in W} \left[I(x,y) + [I_x \quad I_y]\begin{bmatrix} u \\ v \end{bmatrix} - I(x,y)\right]^2$$

$$\approx \sum_{(x,y)\in W} \left[[I_x \quad I_y]\begin{bmatrix} u \\ v \end{bmatrix}\right]^2$$

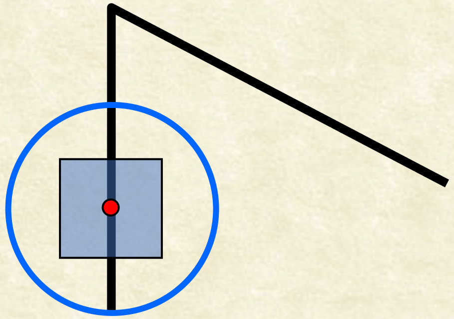


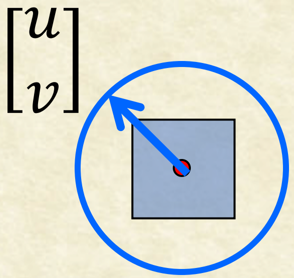
Note: $A^2 = A'A$

Feature Detection: The Math

This can be rewritten as:

$$E(u,v) = \sum_{(x,y)\in W} \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix}}_{H} \begin{bmatrix} u \\ v \end{bmatrix}$$



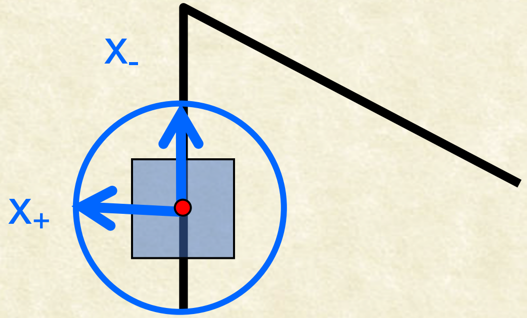


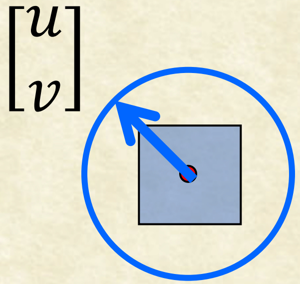
For the example above

- You can move the center of the gray window to anywhere on the blue unit circle
- Which directions will result in the largest and smallest E values?
- We can find these directions by looking at the eigenvectors of *H*

Feature Detection: The Math

$$E(u,v) = \sum_{(x,y)\in W} \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} I_x^2 & I_x I_y \\ I_y I_x & I_y^2 \end{bmatrix}}_{H} \begin{bmatrix} u \\ v \end{bmatrix}$$





Eigenvalues and eigenvectors of H define shifts with the smallest and largest change (E value):

- x_+ = direction of largest increase in E.
- λ_+ = amount of increase in direction x_+
- x_- = direction of smallest increase in E.
- λ_- = amount of increase in direction x_+

$$Hx_+ = \lambda_+ x_+$$
$$Hx_- = \lambda_- x_-$$

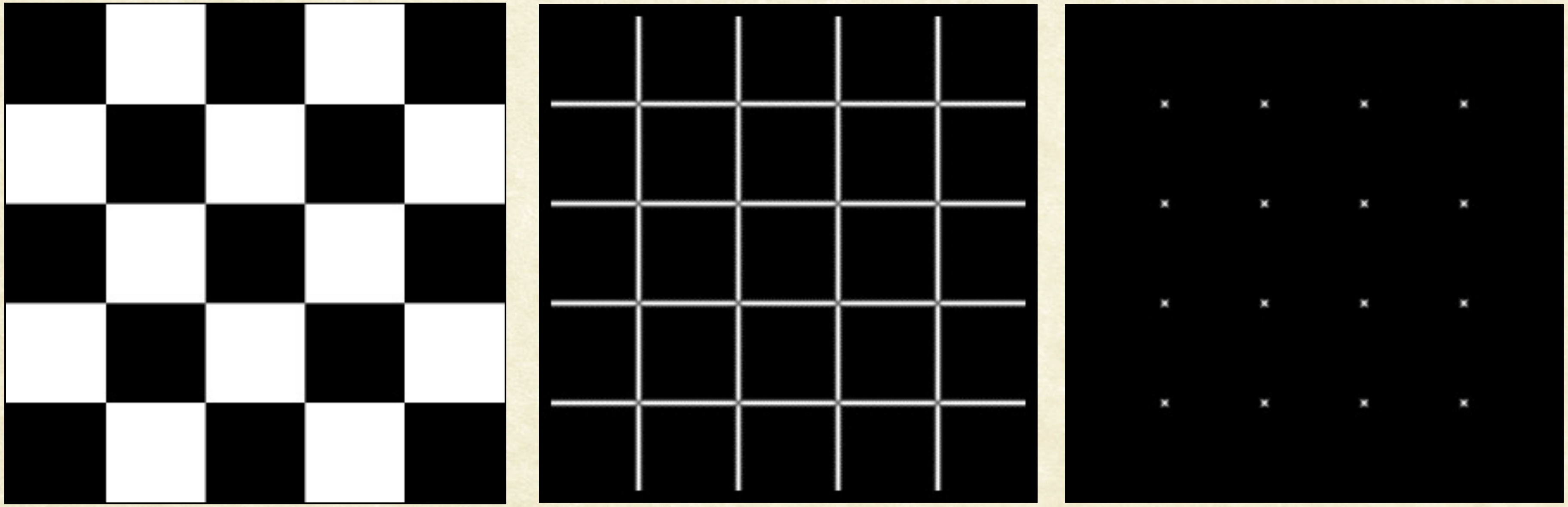
Feature Detection: The Math

How are λ_+, x_+, λ_-, and x_- relevant for feature detection?

- What is our feature scoring function?

Want *E(u,v)* to be *large* for small shifts in *all* directions

- the *minimum* of *E(u,v)* should be large, over all unit vectors [u v]
- this minimum is given by the smaller eigenvalue (λ_-) of *H*

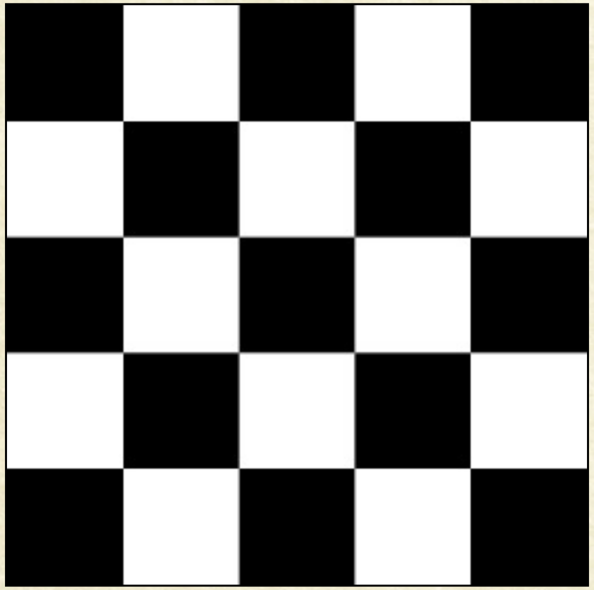


I λ_+ λ_-

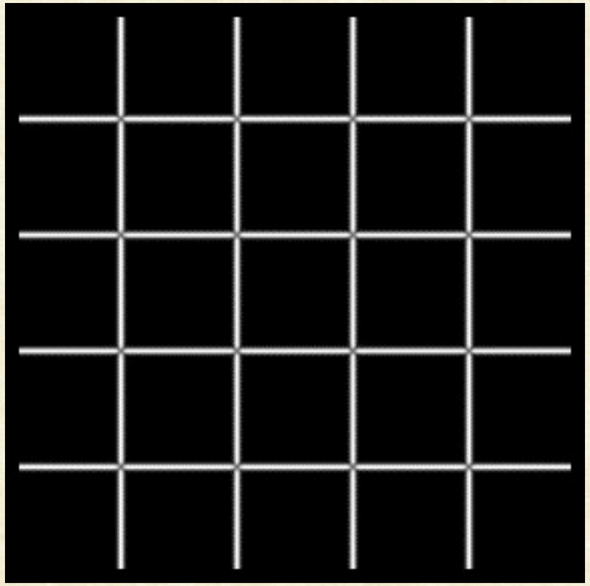
Feature Detection: Summary

Here is what you do

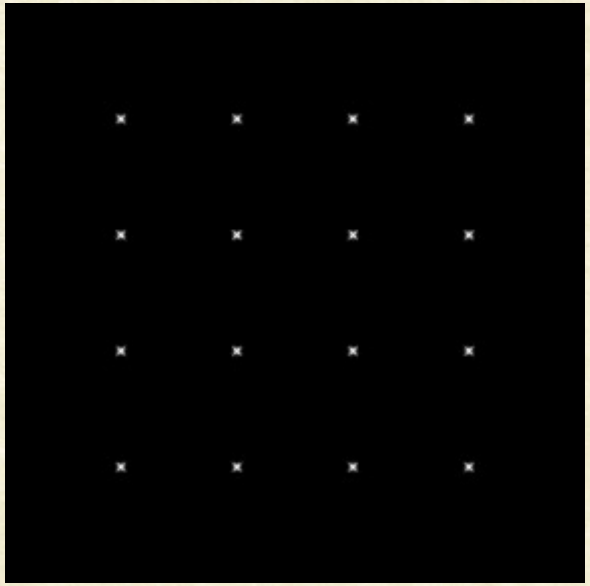
- Compute the gradient at each point in the image
- Create the *H* matrix from the entries in the gradient
- Compute the eigenvalues.
- Find points with large response (λ_- > threshold)
- Choose those points where λ_- is a local maximum as features



I



λ_+



λ_-

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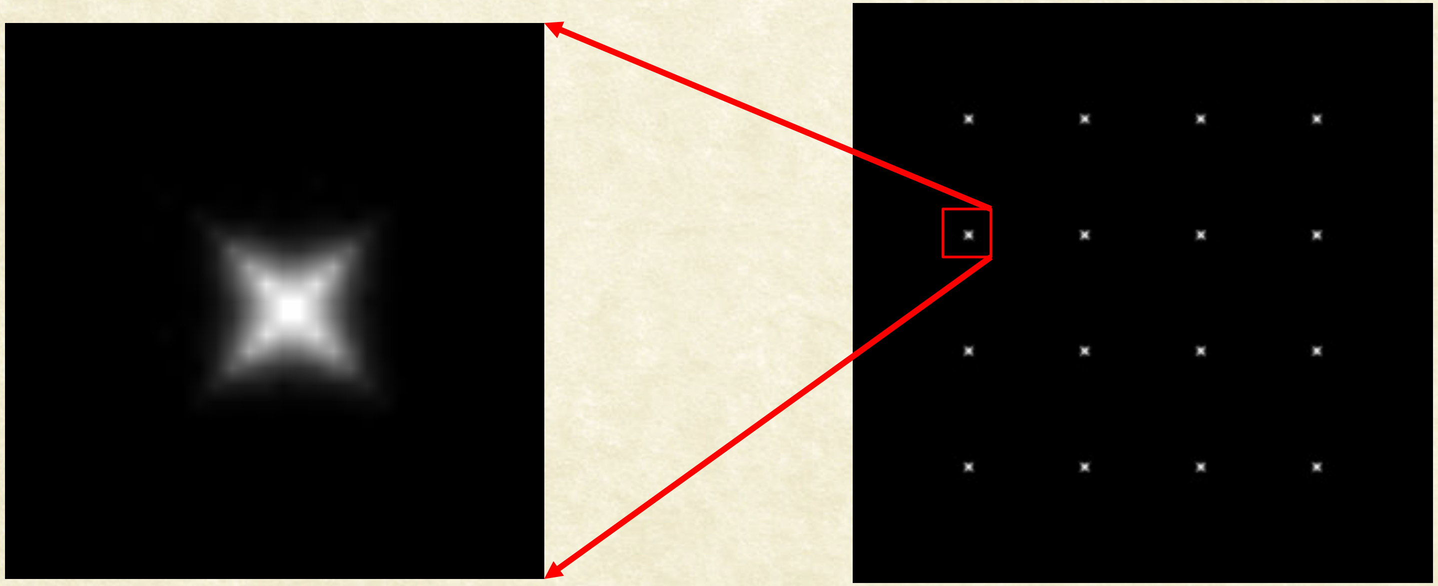


$\lambda\_$

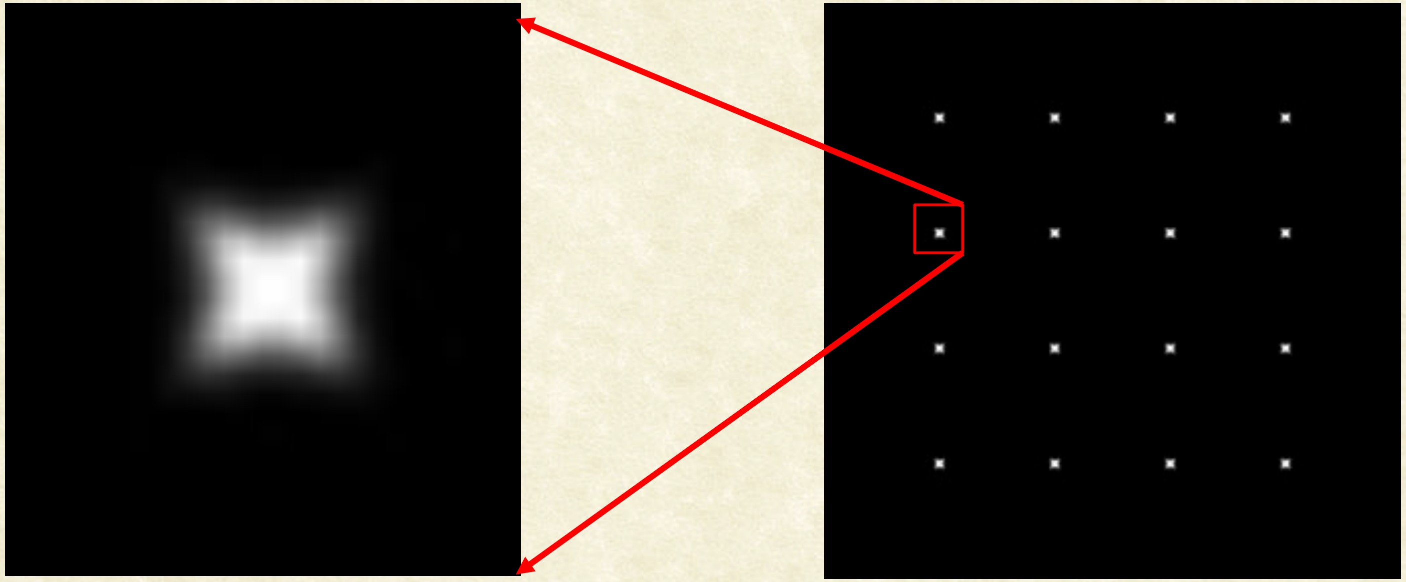
The Harris operator

λ_- is a variant of the "Harris operator" for feature detection

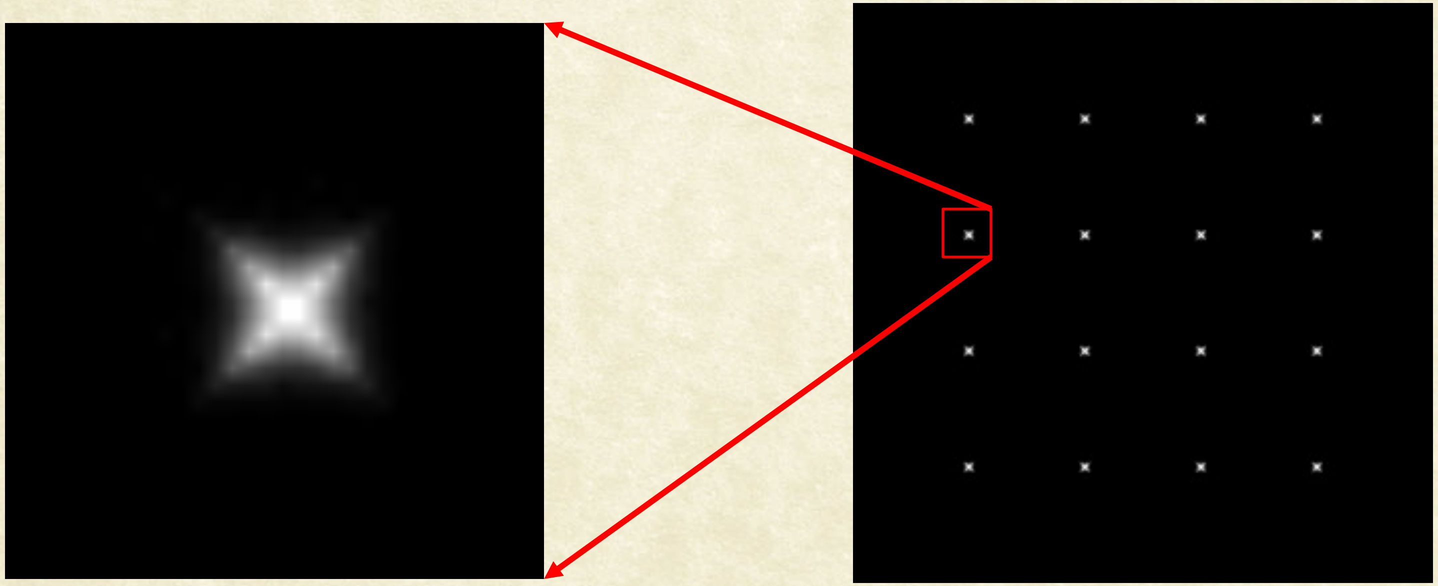
$$f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} = \frac{determinant(H)}{trace(H)}$$

- The *trace* is the sum of the diagonals, i.e., $trace(H) = h_{11} + h_{22}$
- Very similar to λ_- but less expensive (no square root)
- Called the "Harris Corner Detector" or "Harris Operator"
- Lots of other detectors, this is one of the most popular

The Harris operator



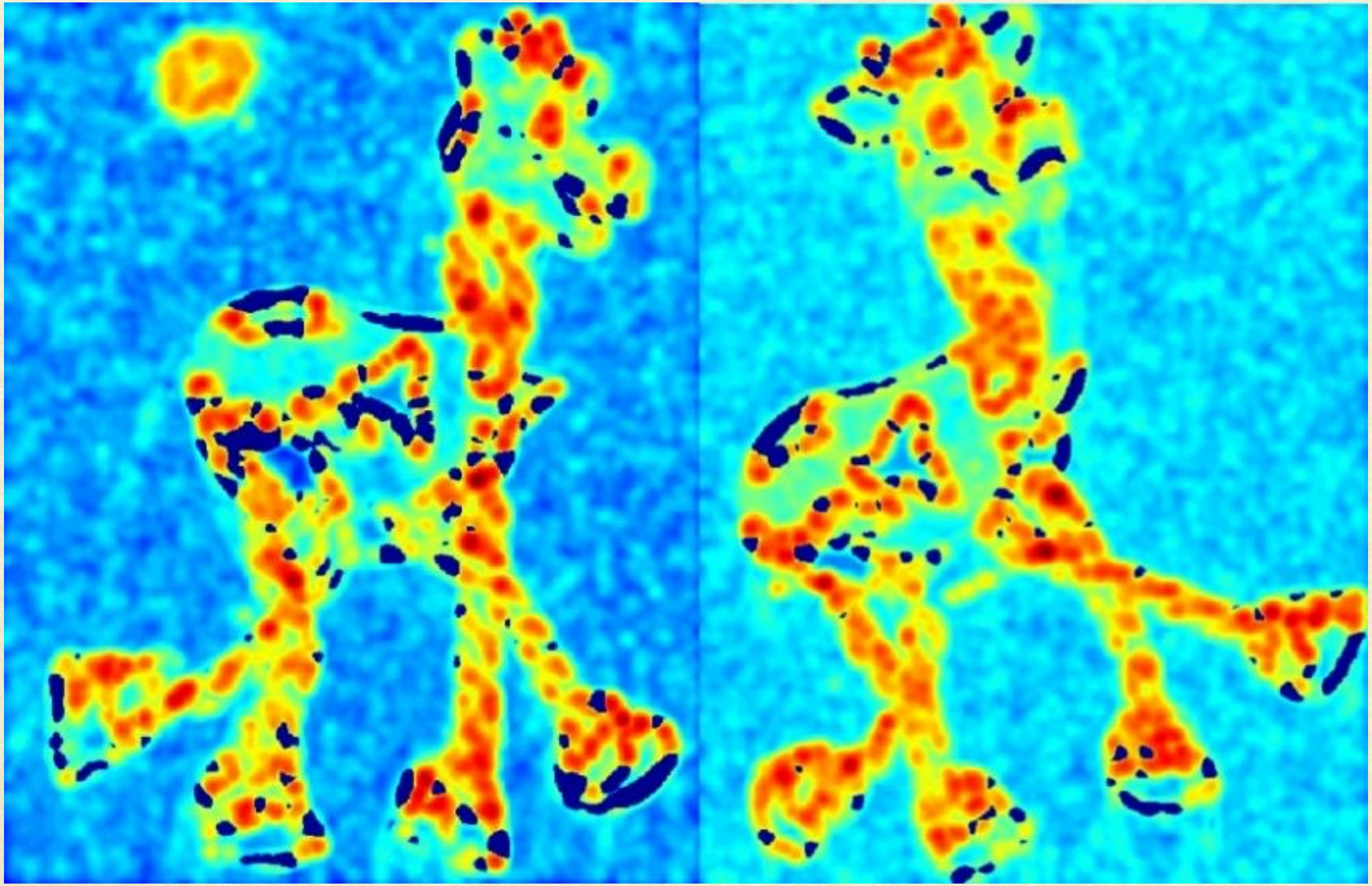
Harris operator



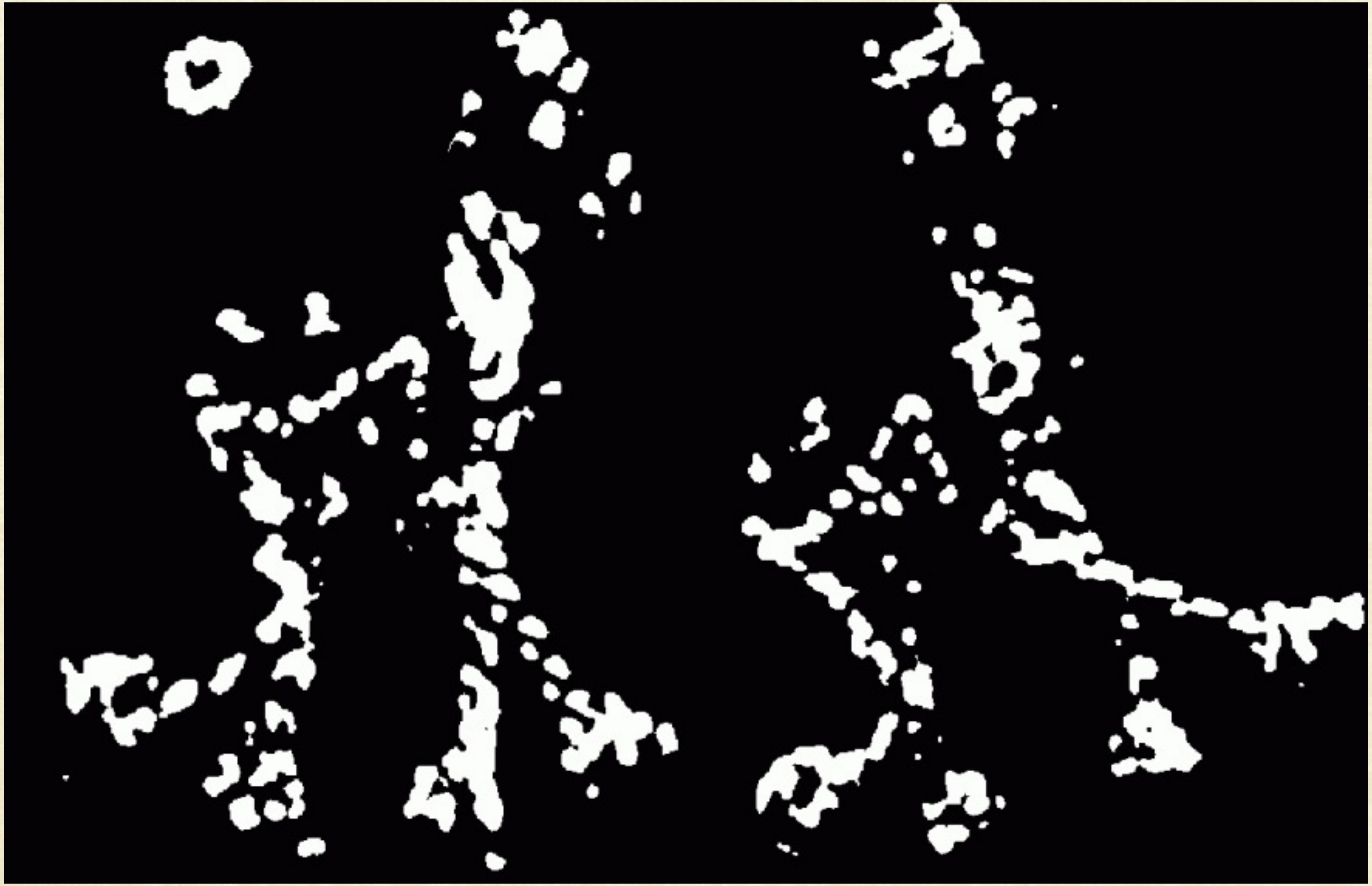
λ_-

Harris detector example

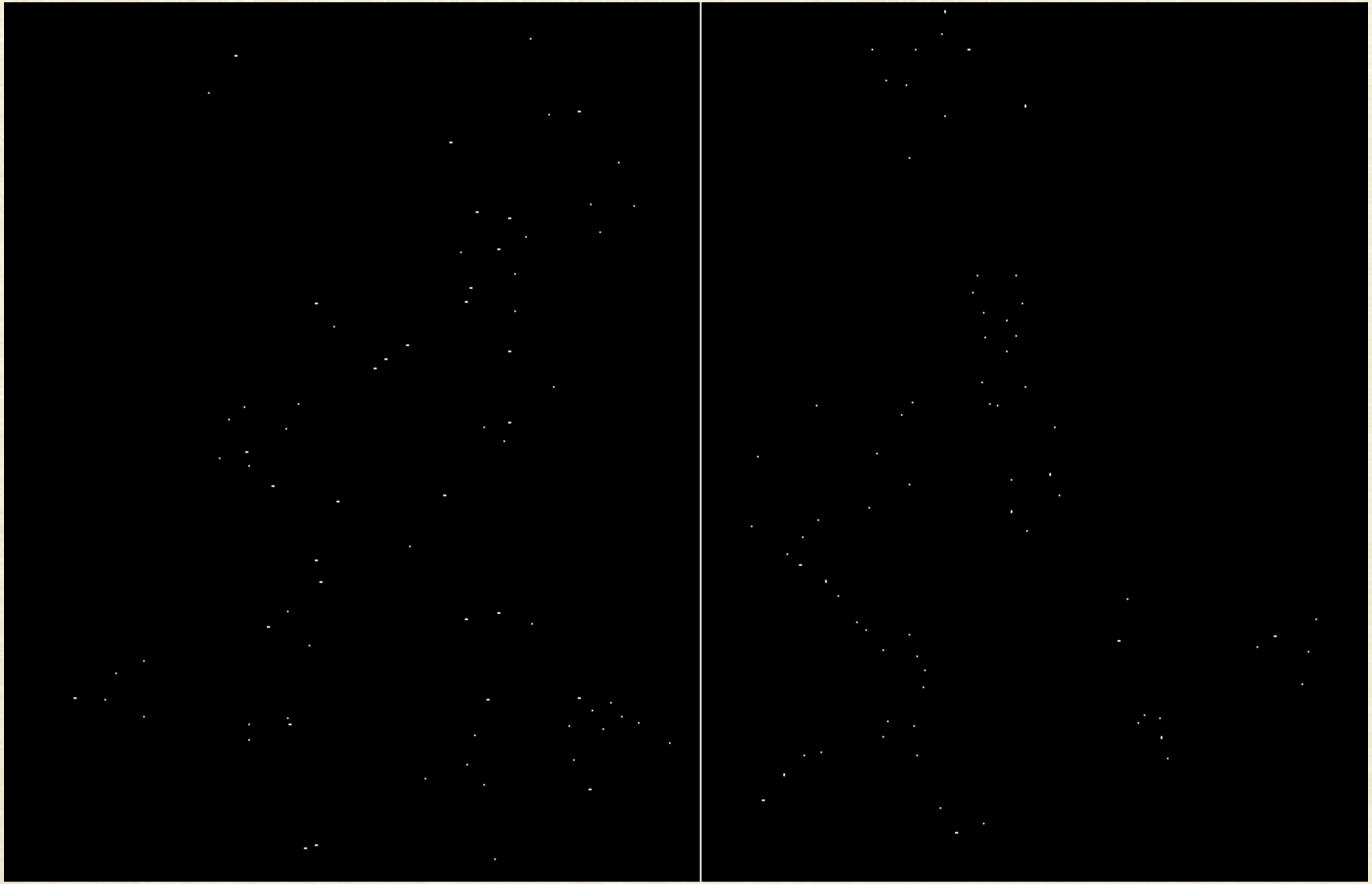
f value (red high, blue low)



Threshold (f > value)



Find local maxima of f



Harris features (in red)

The tops of the horns are detected in both images

Thank You