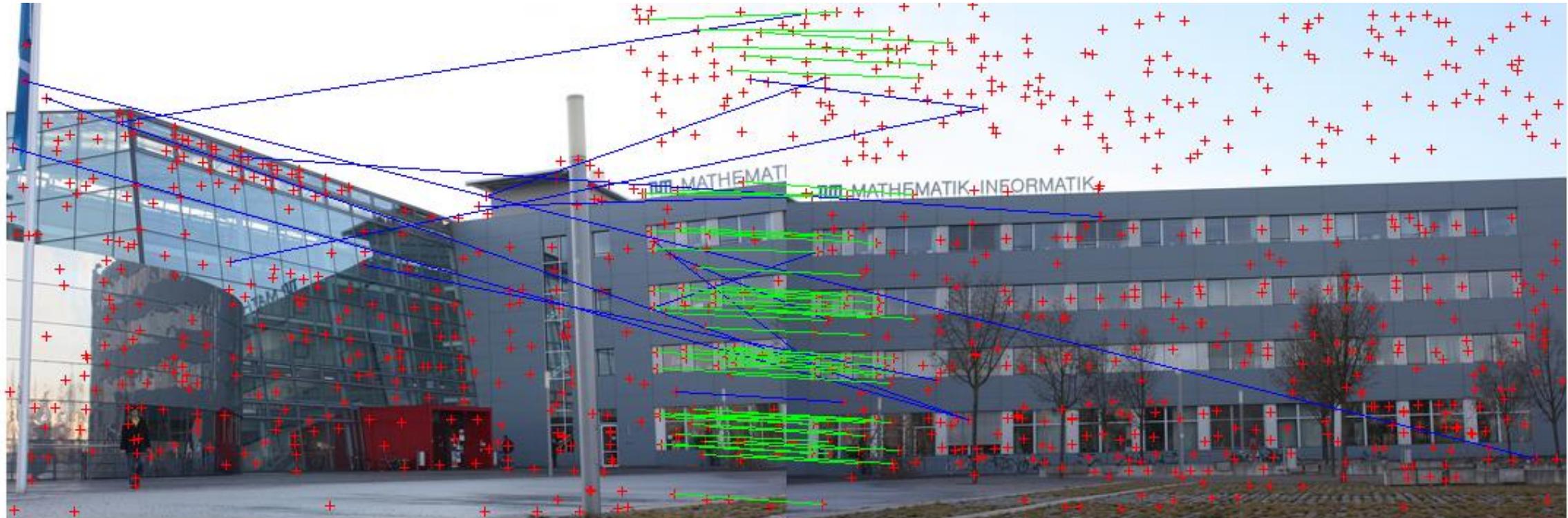


# Features



# References

- <http://szeliski.org/Book/>
- <http://www.cs.cornell.edu/courses/cs5670/2019sp/lectures/lectures.html>
- <http://www.cs.cmu.edu/~16385/>
- <https://towardsdatascience.com/sift-scale-invariant-feature-transform-c7233dc60f37>

# contents

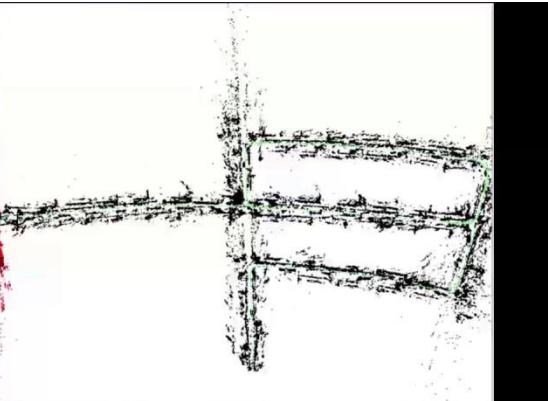
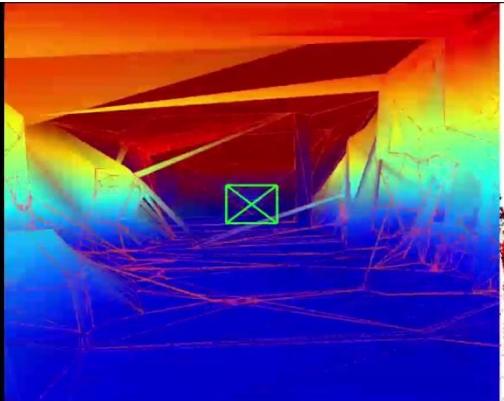
- **What and why we need features detection?**
- Feature detection
  - Blob detection
  - Harris corner detection
  - SIFT detector
- Feature description
  - HOG
  - SIFT descriptor
- SIFT feature matching
- Panoramas

# What is a feature?

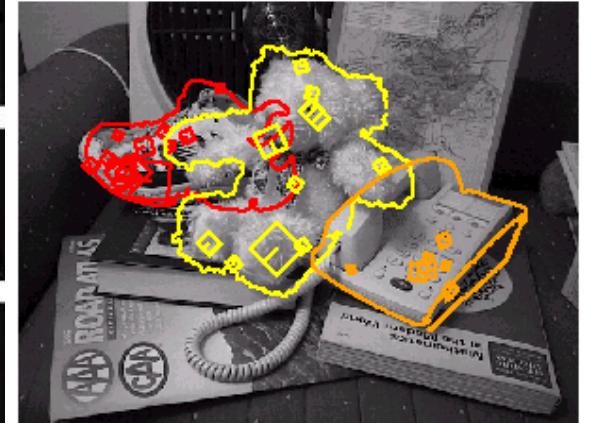
- There is no universal or exact definition of what constitutes a feature, and the exact definition often depends on the problem or the type of application.  
Given that, a feature is defined as an "**interesting**" part of an image.
  - [from: wikipedia]

# What can we do with features?

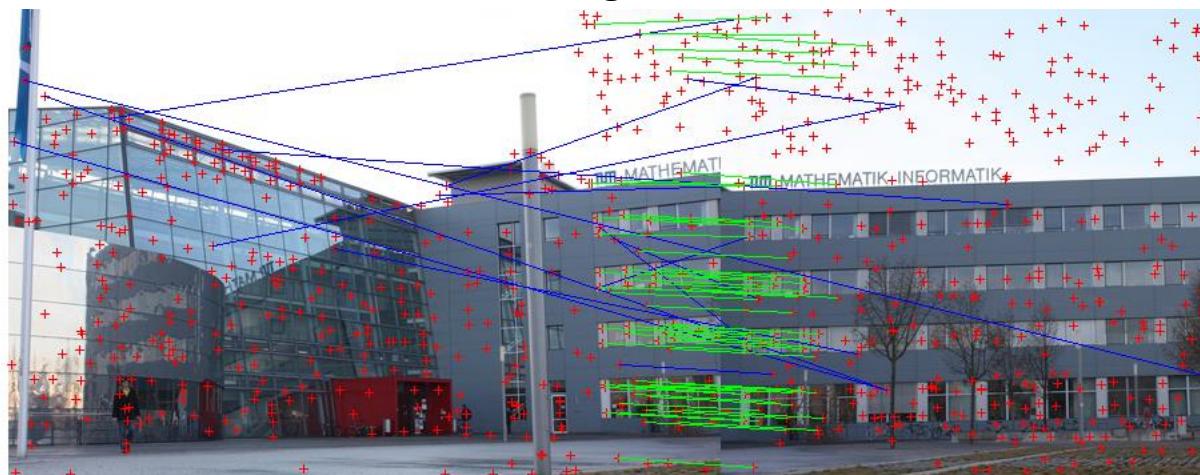
6x



Robot navigation



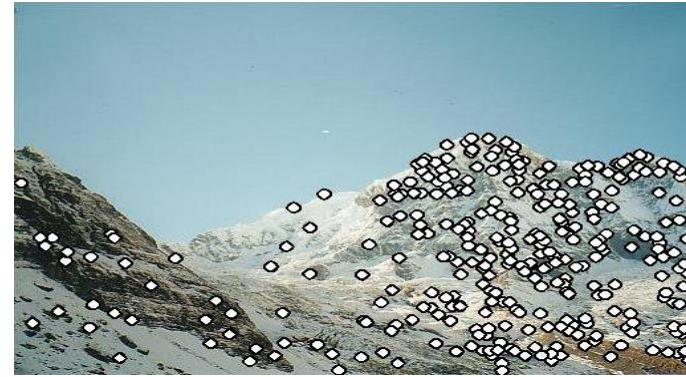
Object recognition



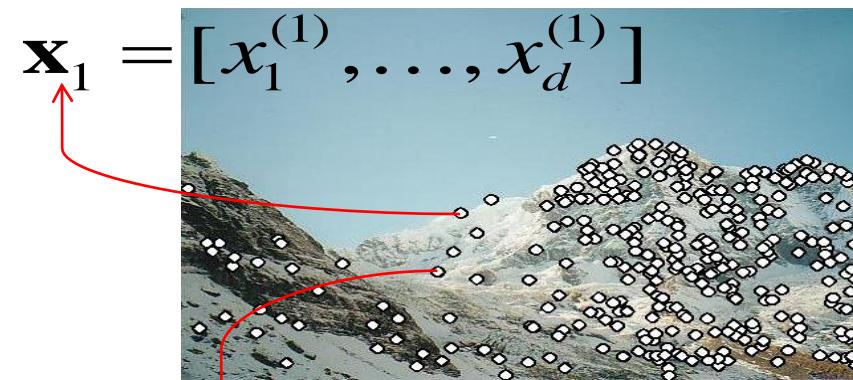
Panorama stitching

# Local features: main components

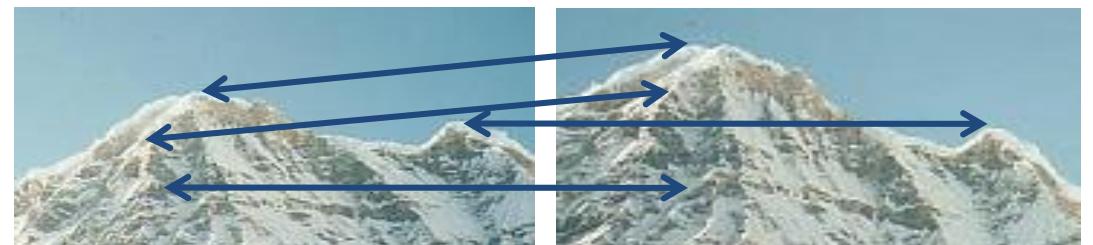
1. Detection: Identify the interest points (also called **keypoints**).



2. Description: Extract vector feature descriptor surrounding each interest point.



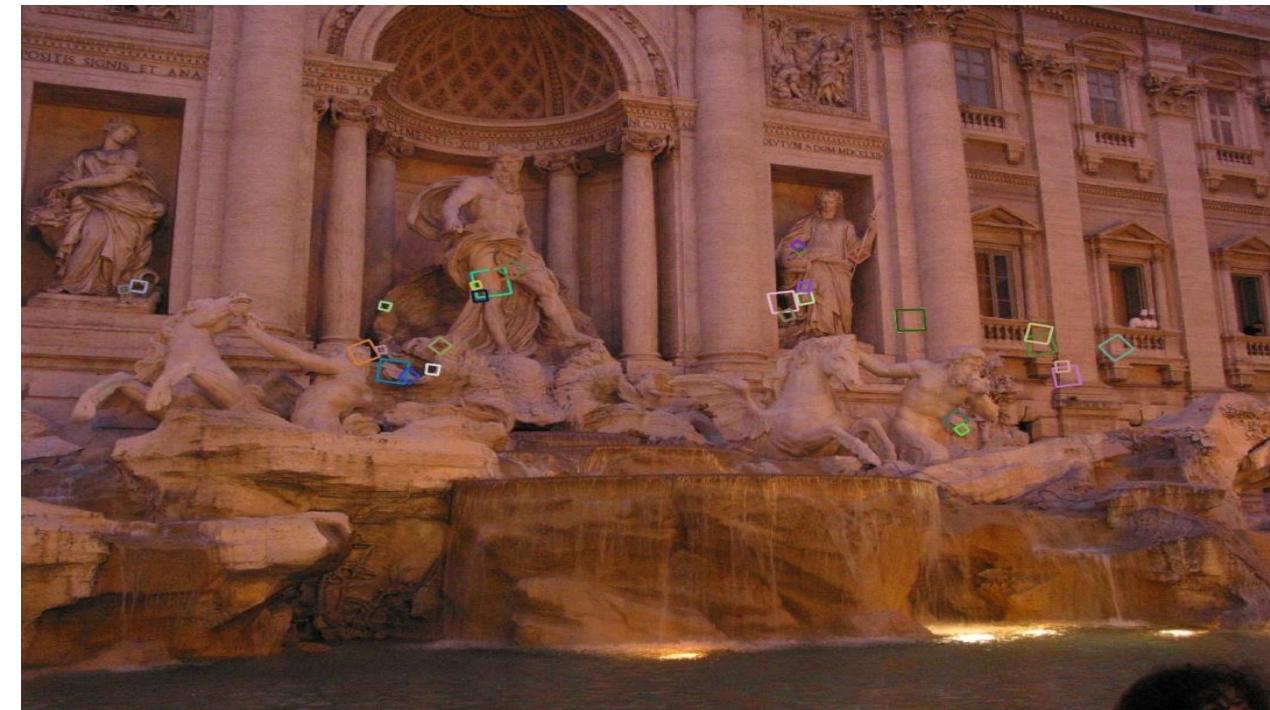
3. Matching: Determine correspondence between descriptors in two views.



# Properties of SIFT

- **SIFT: scale invariant feature transform.**
- Extraordinarily robust matching technique for local keypoint detection description and matching.
- Can handle changes in viewpoint: 3D change of POV, scale, rotation and translation.
  - Up to about 60 degree out of plane rotation.
- Can handle significant changes in illumination.
  - Sometimes even day vs. night.
- Fast and efficient—can run in real time.

# SIFT example



# contents

- What and why we need features detection?
- **Feature detection**
  - Blob detection
  - Harris corner detection
  - SIFT detector
- Feature description
  - HOG
  - SIFT descriptor
- SIFT feature matching
- Panoramas

# Advantages of local keypoints

Locality:

- features are local, so robust to occlusion and clutter => invariance to 3D change of viewpoint.

Quantity:

- hundreds or thousands in a single image

Distinctiveness:

- can differentiate a large database of objects

Efficiency

- real-time performance achievable

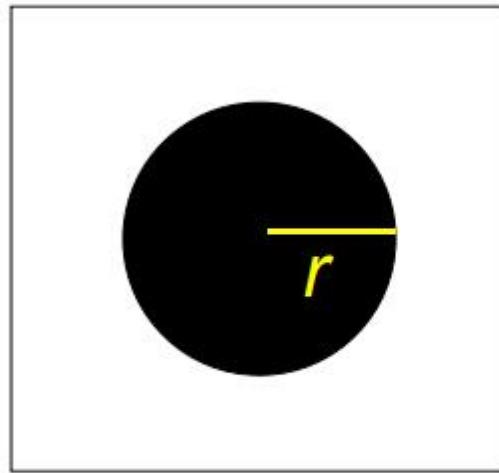
# contents

- What and why we need features detection?
- Feature detection
  - **Blob detection**
  - Harris corner detection
  - SIFT detector
- Feature description
  - HOG
  - SIFT descriptor
- SIFT feature matching
- Panoramas

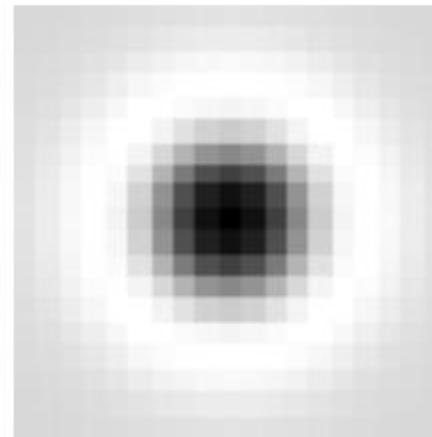
# Blob detection

- Like template matching- we are convolving a signal with a template of a LoG (Laplacian of Gaussian) to get the highest response when the template matches the signal.

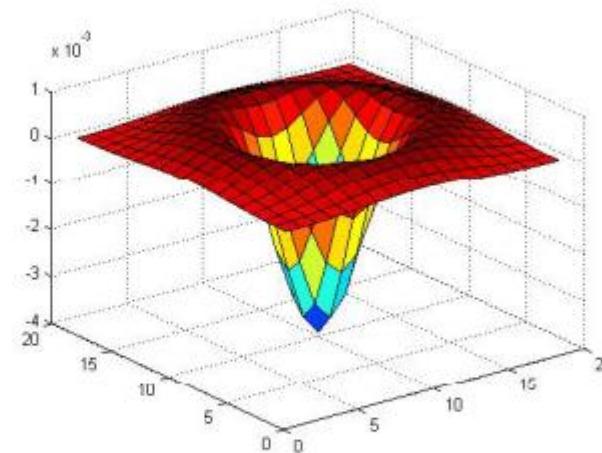
$$\text{LoG}(x, y; \sigma) = \Delta_{(x,y)} G(x, y; \sigma) = \frac{\partial^2 G(x, y; \sigma)}{\partial x^2} + \frac{\partial^2 G(x, y; \sigma)}{\partial y^2} = \frac{1}{\pi \sigma^4} \left( \frac{x^2 + y^2}{2\sigma^2} - 1 \right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$



image



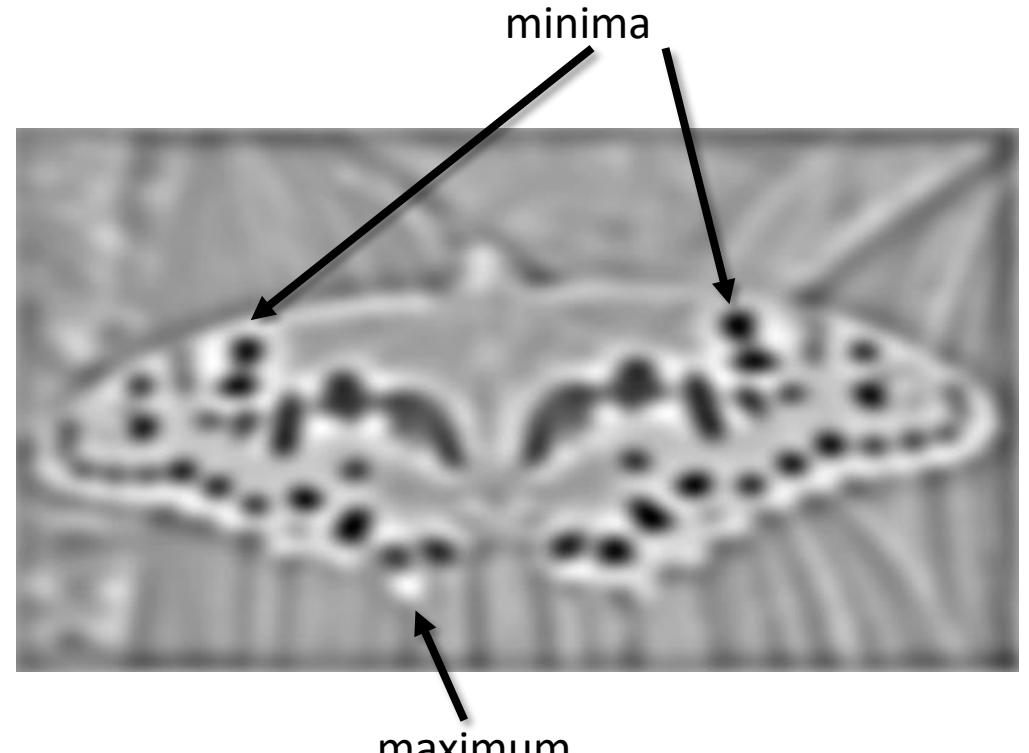
Laplacian



# Blob detection



$$* \quad =$$

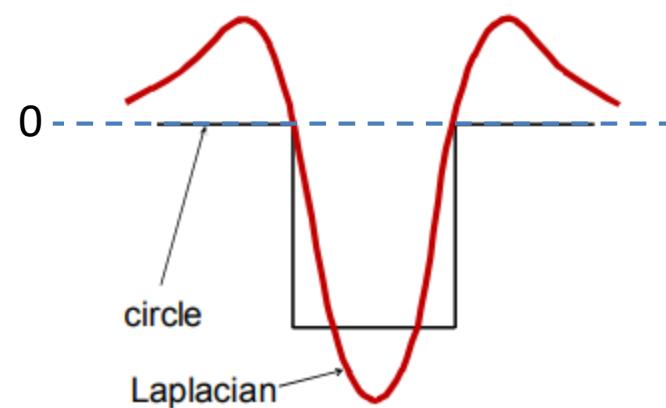
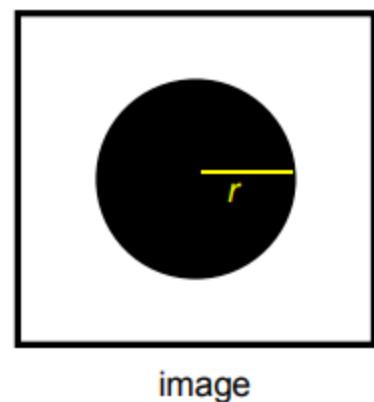


- Find maxima *and minima* of LoG operator in space and scale

# Blob detection

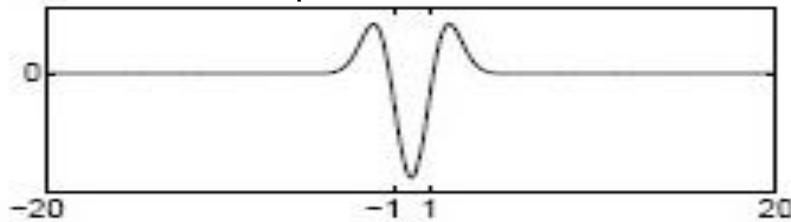
$$\text{LoG}(x, y; \sigma) = \Delta_{(x,y)} G(x, y; \sigma) =$$
$$\frac{\partial^2 G(x, y; \sigma)}{\partial x^2} + \frac{\partial^2 G(x, y; \sigma)}{\partial y^2} = \frac{1}{\pi \sigma^4} \left( \frac{x^2 + y^2}{2\sigma^2} - 1 \right) e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- Highest response occurs when the signal is exactly the width of the positive part of the LoG =>  $r = \sqrt{2}\sigma$ .

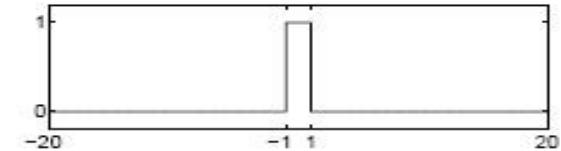
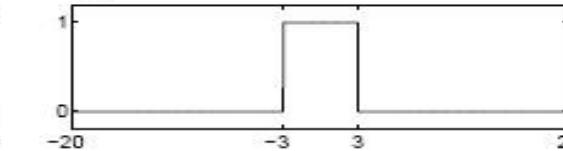
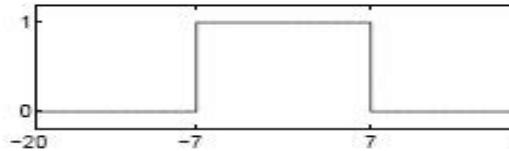
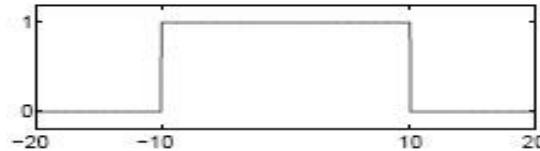


# Blob detection

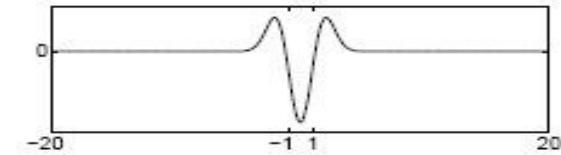
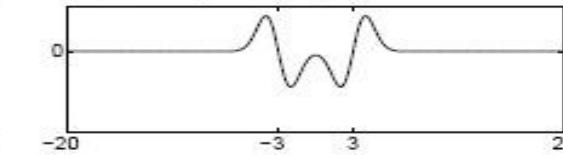
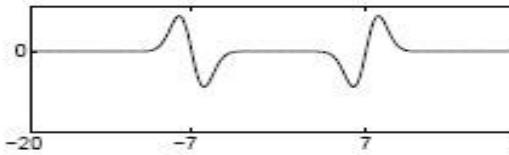
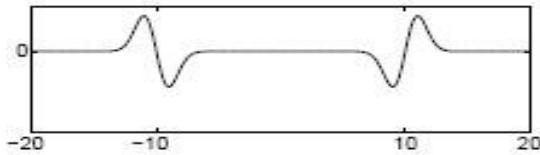
Laplacian filter



Original signal



Convolved with Laplacian ( $\sigma = 1$ )

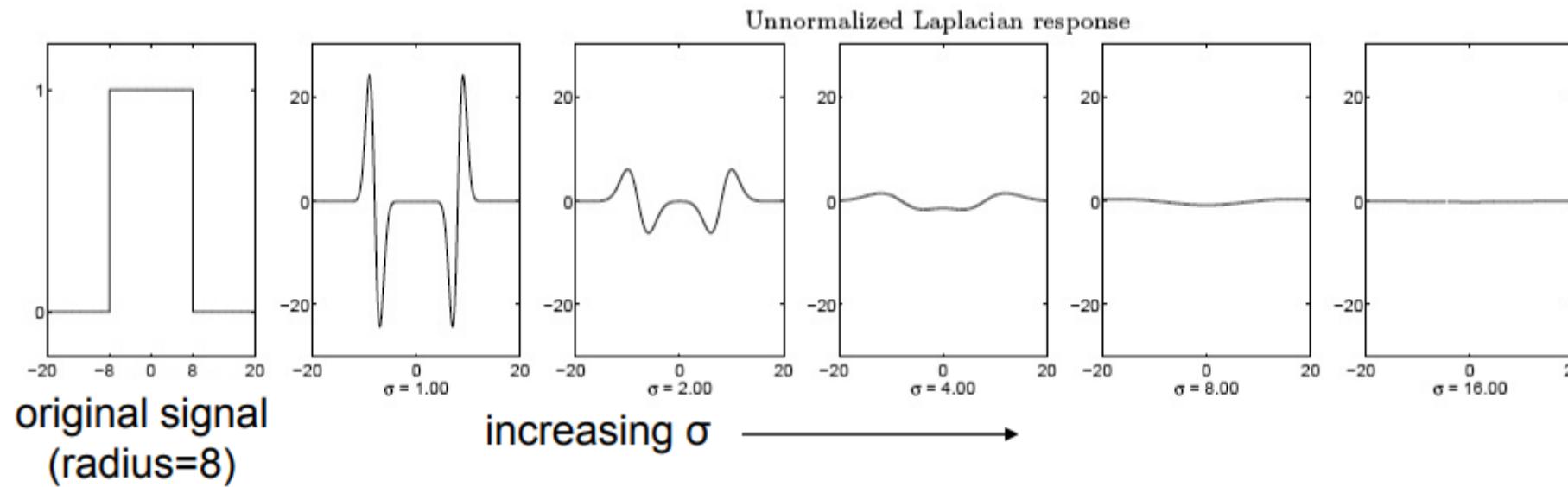


Highest absolute response when the signal has the same **characteristic scale** as the filter



# Blob detection- normalized LoG

- We want to find the characteristic scale of the blob by convolving it with LoGs at several scales and looking for the maximum response.
- However, LoG response decays as scale increases.



# Blob detection- normalized LoG

- We want that the maximum of the LoG will be always at the same value, so we are using the scale normalized LoG:

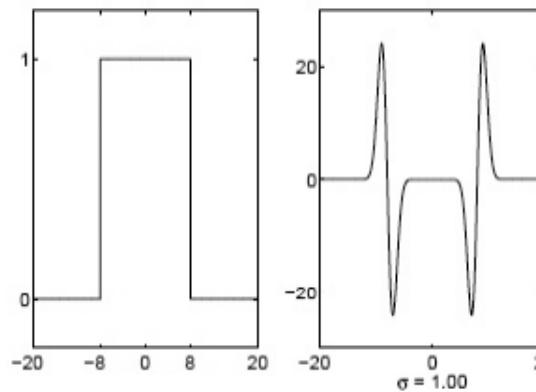
$$\text{normLoG}(x, y; \sigma) = \sigma^2 \Delta_{(x,y)} G(x, y; \sigma) = \sigma^2 \left( \frac{\partial^2 G(x, y; \sigma)}{\partial x^2} + \frac{\partial^2 G(x, y; \sigma)}{\partial y^2} \right)$$

- Full derivation is available here:

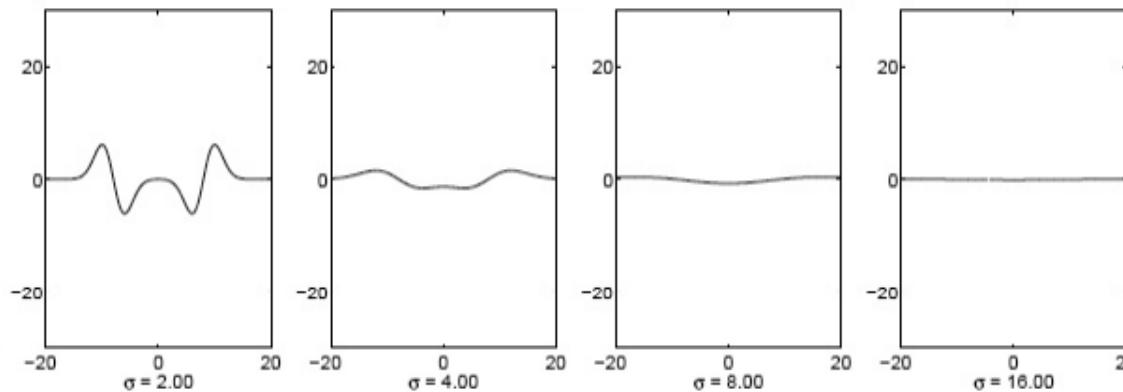
<http://www.cim.mcgill.ca/~langer/558/2009/lecture11.pdf>

# Blob detection- normalized LoG

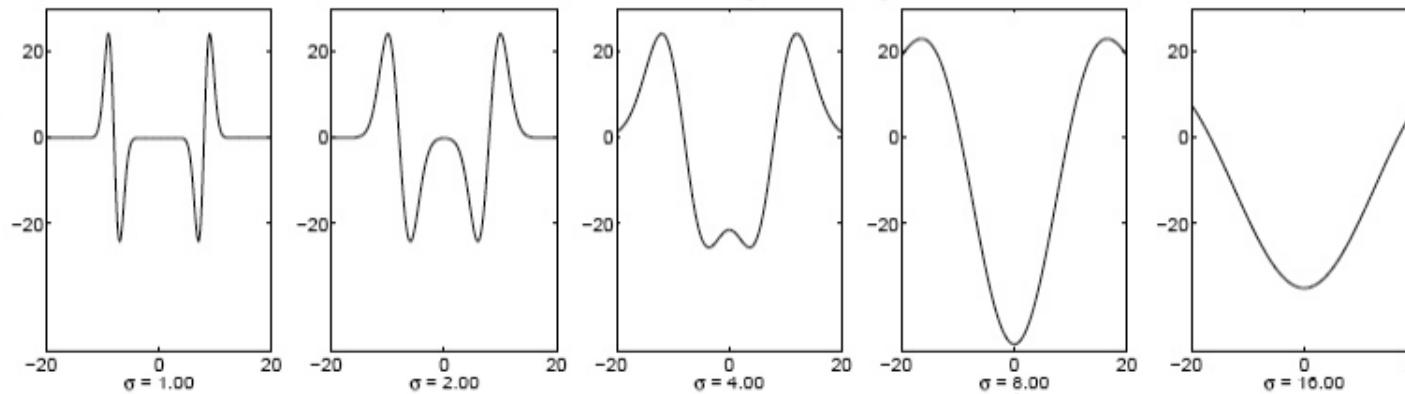
Original signal



Unnormalized Laplacian response



Scale-normalized Laplacian response

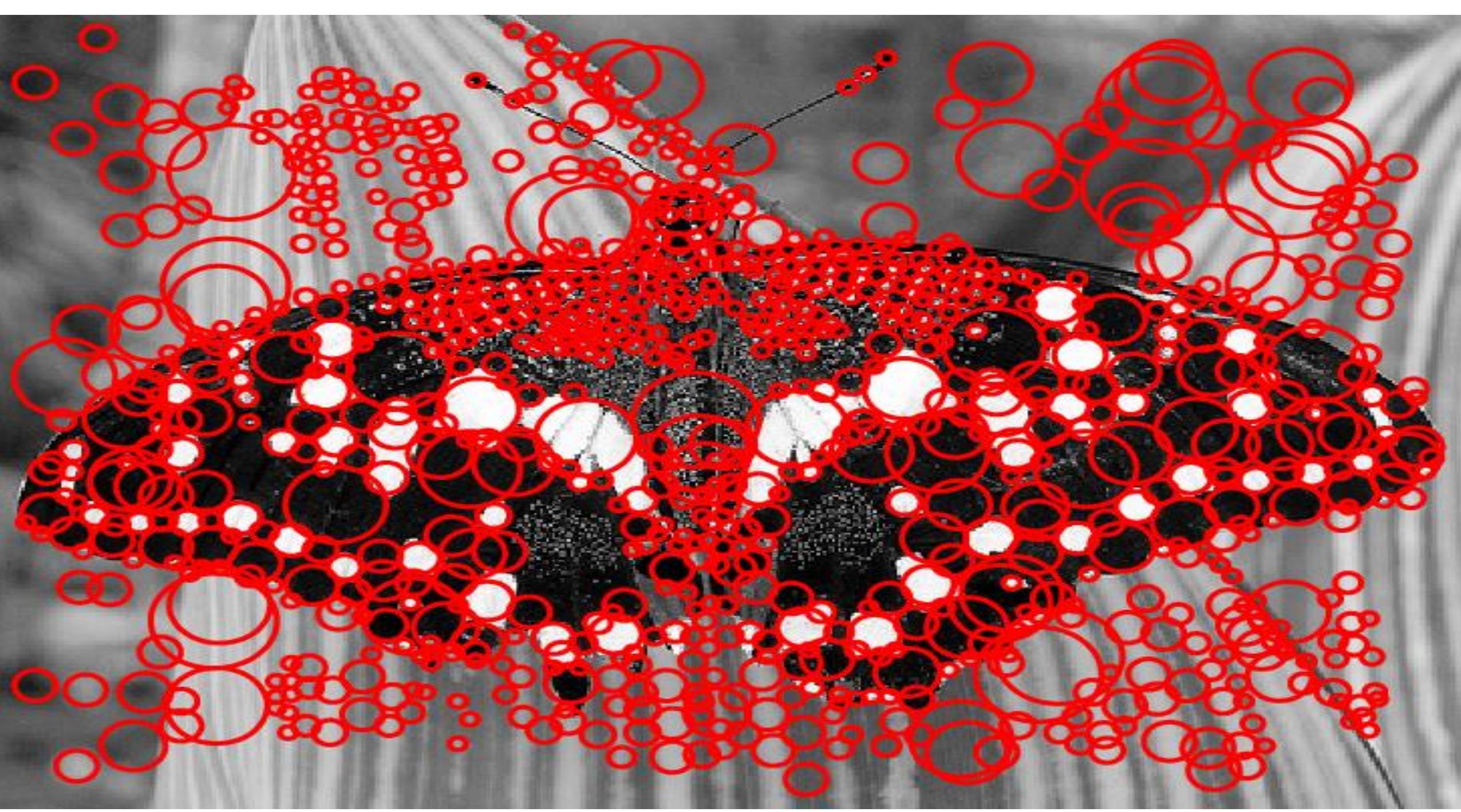


maximum

# **Blob detection- normalized LoG**

- An example of max responses:





# Normalized LoG

- responses of the same features at different scales are the same!

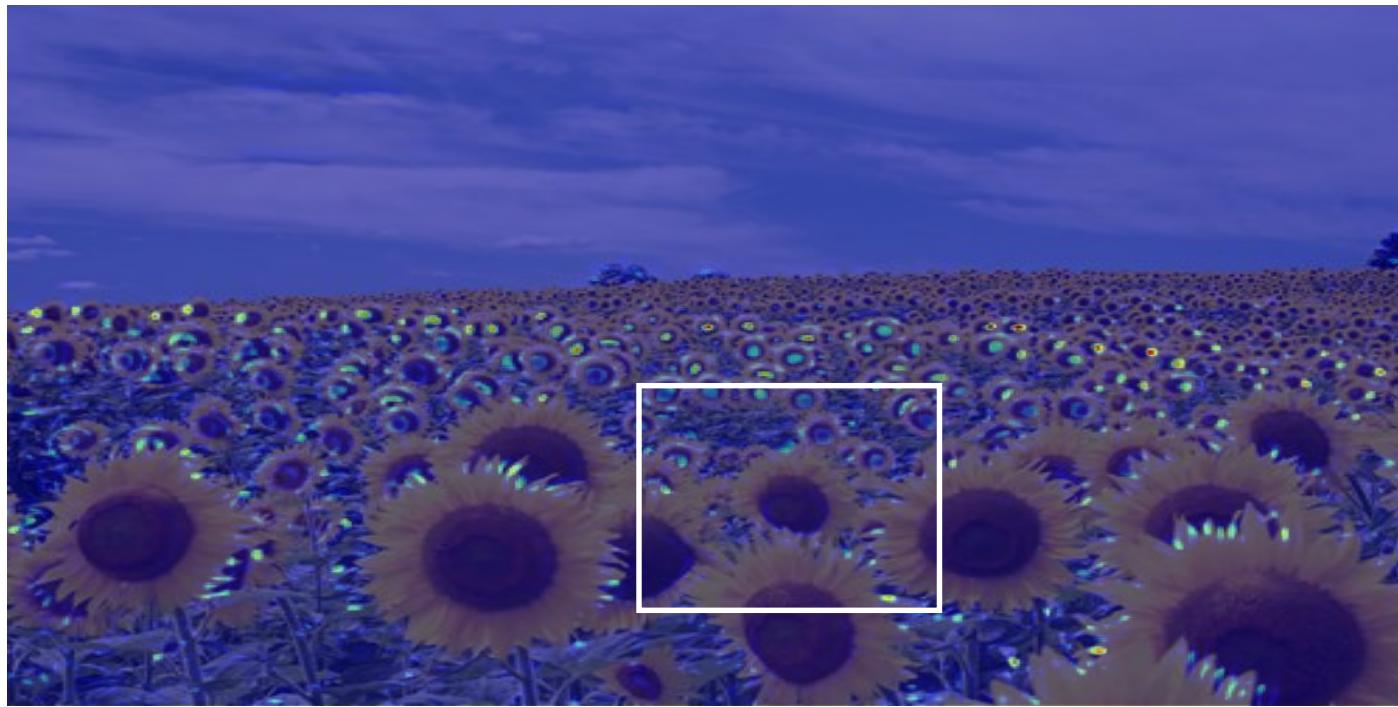
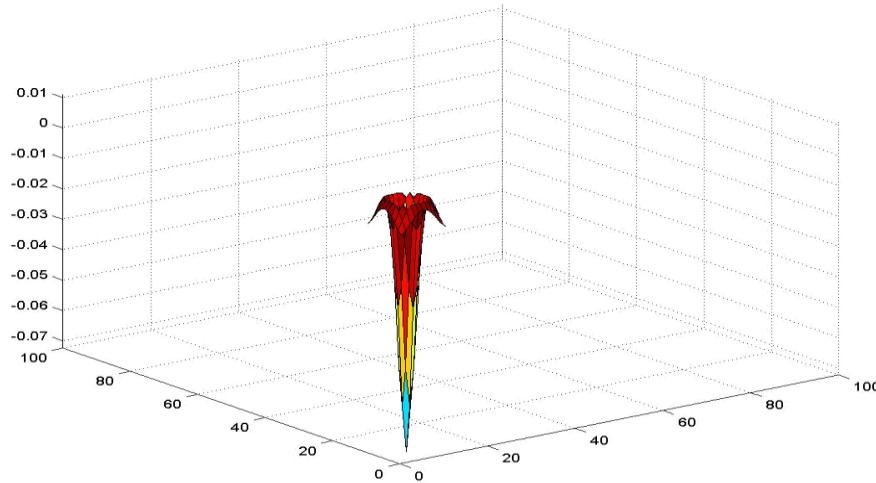
Full size



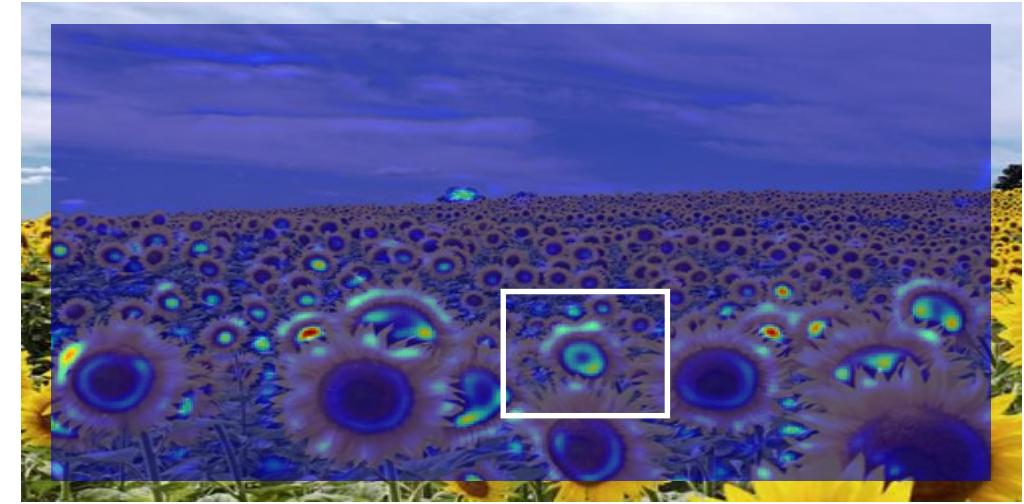
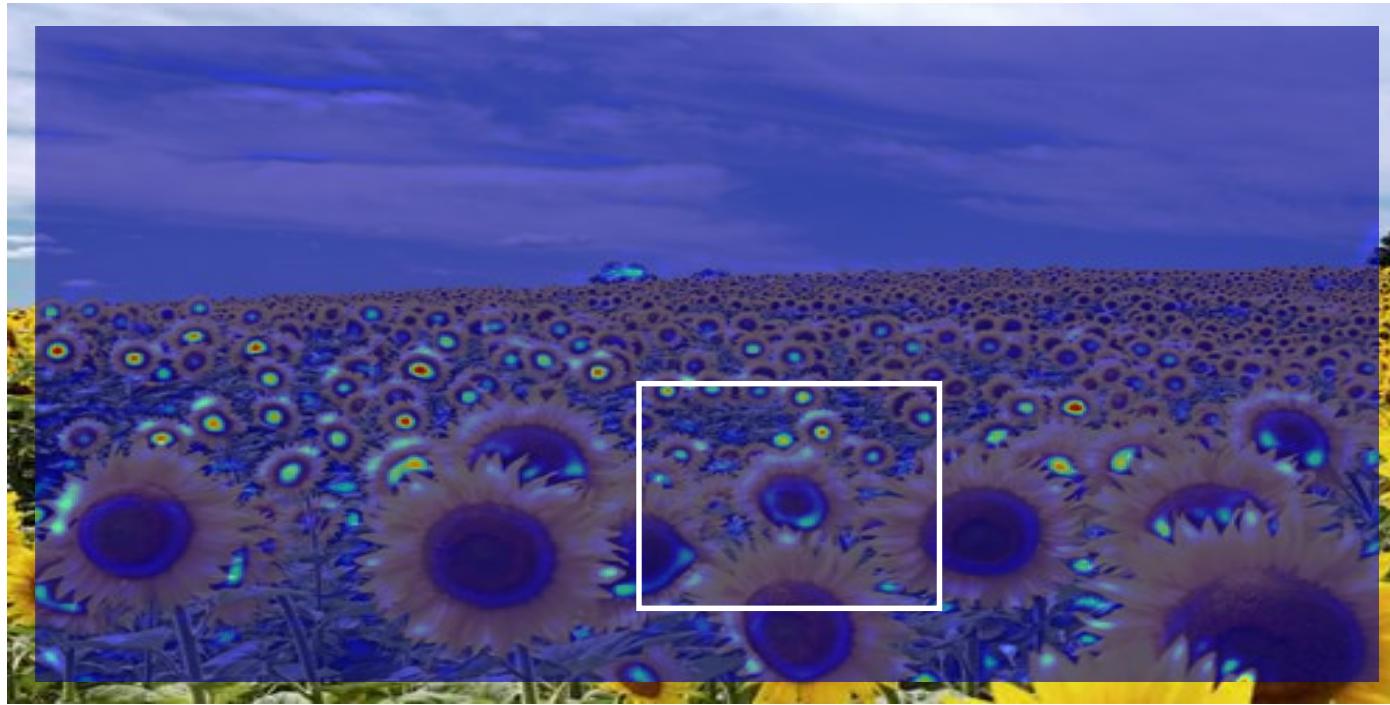
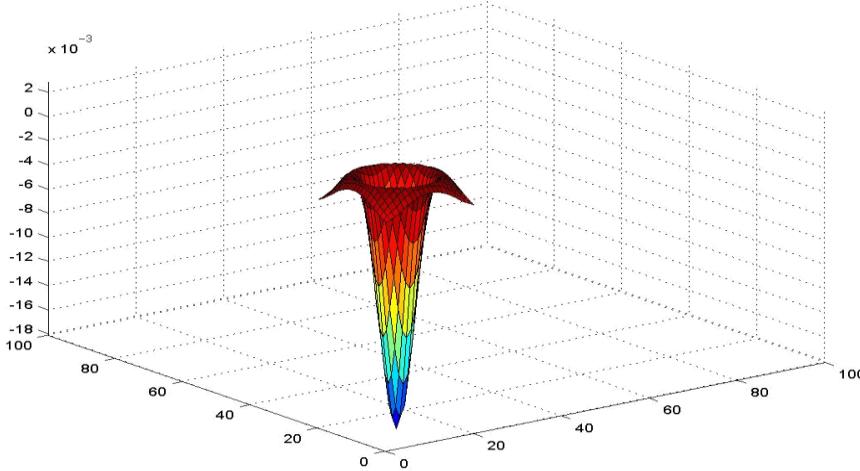
3/4 size

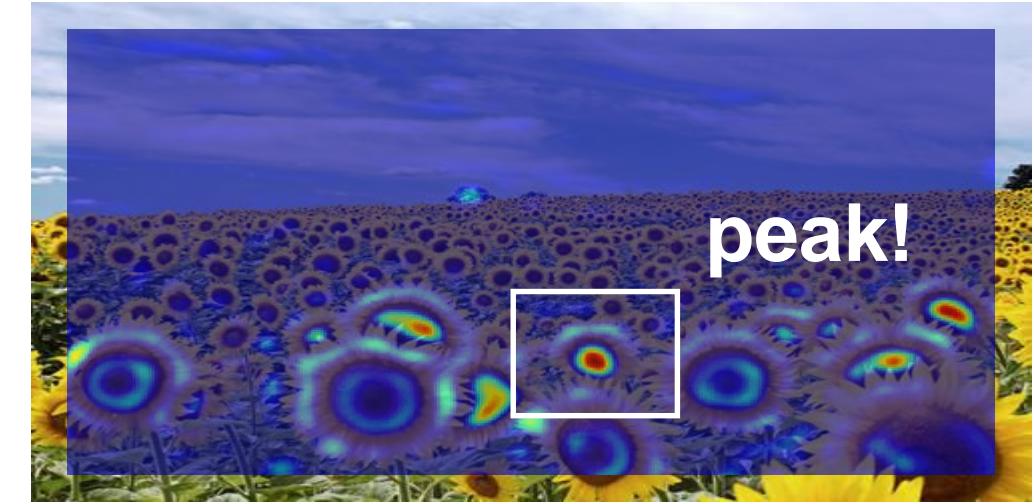
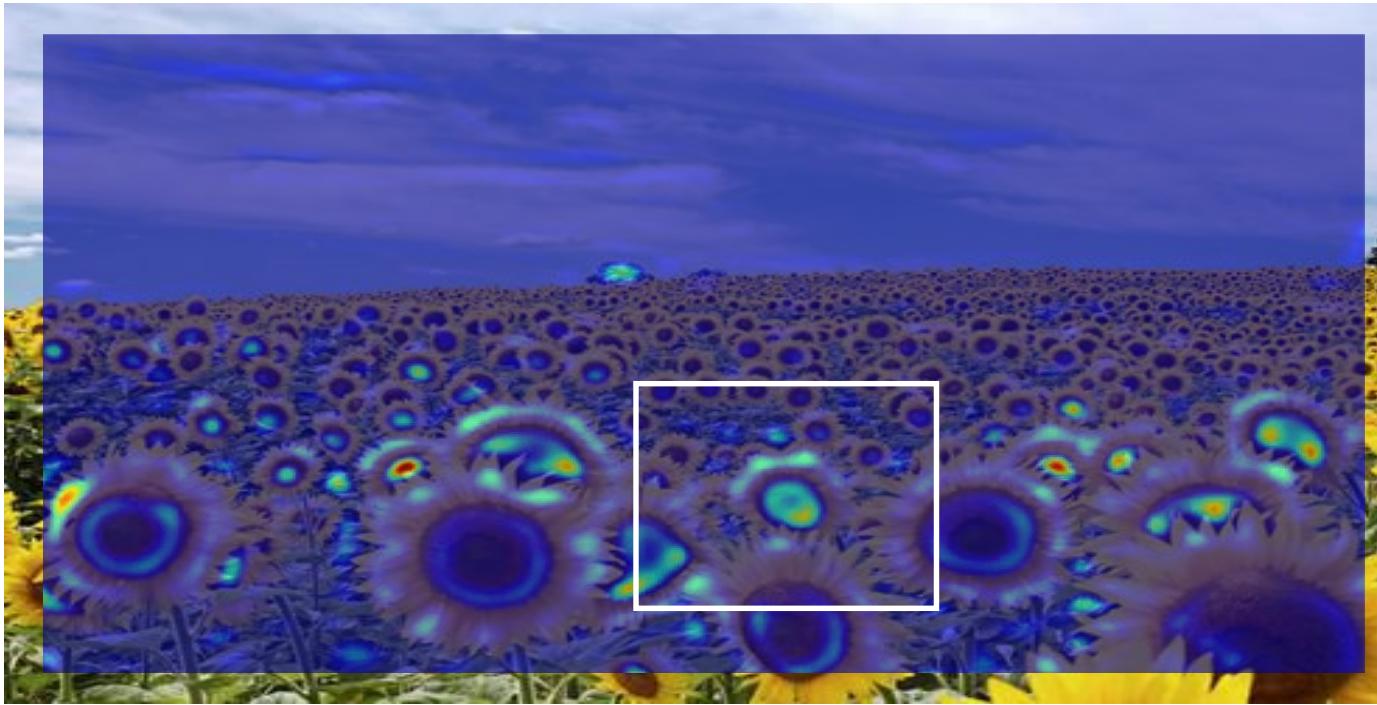
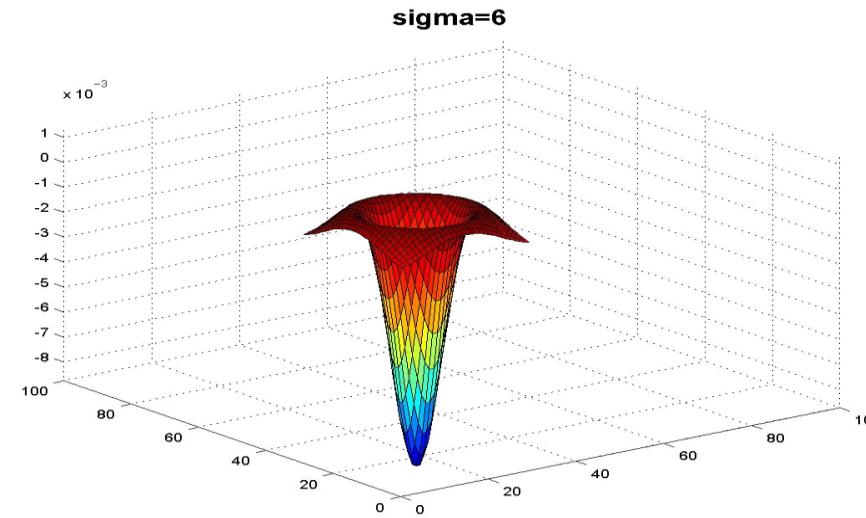


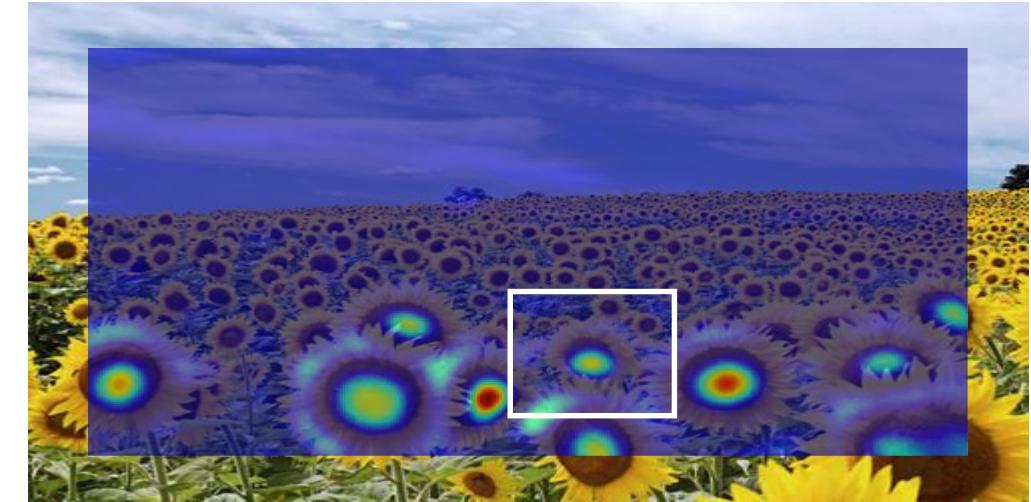
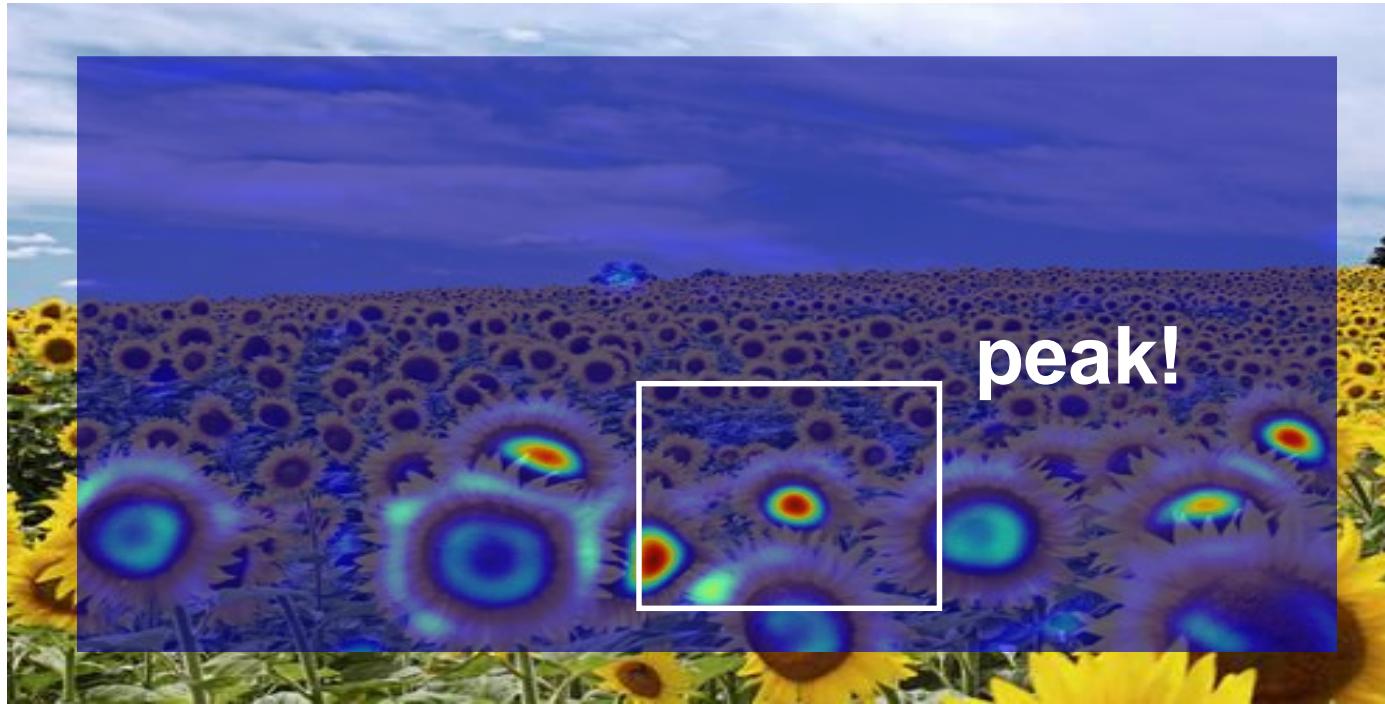
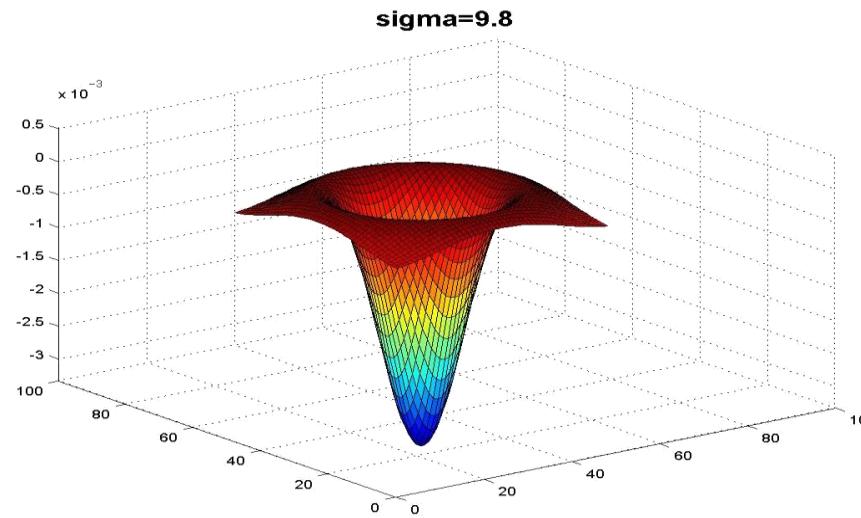
**sigma=2.1**



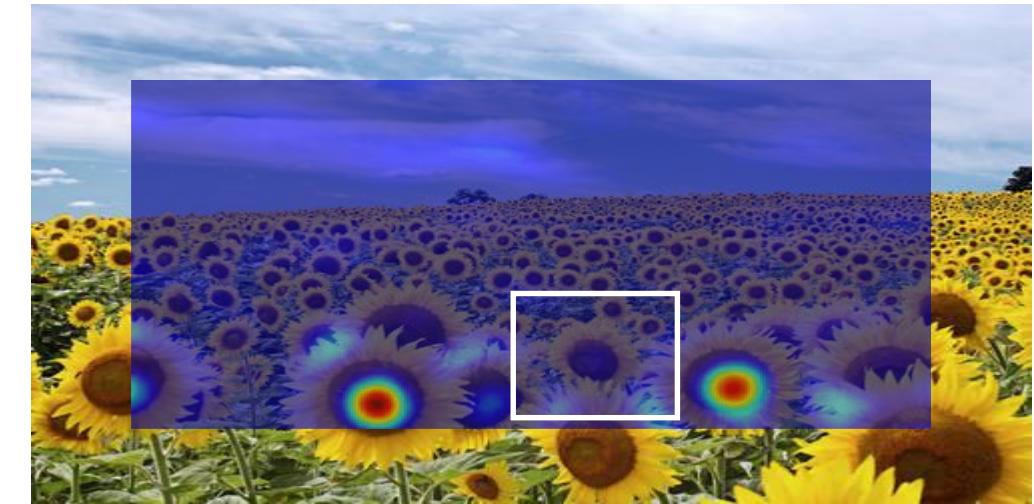
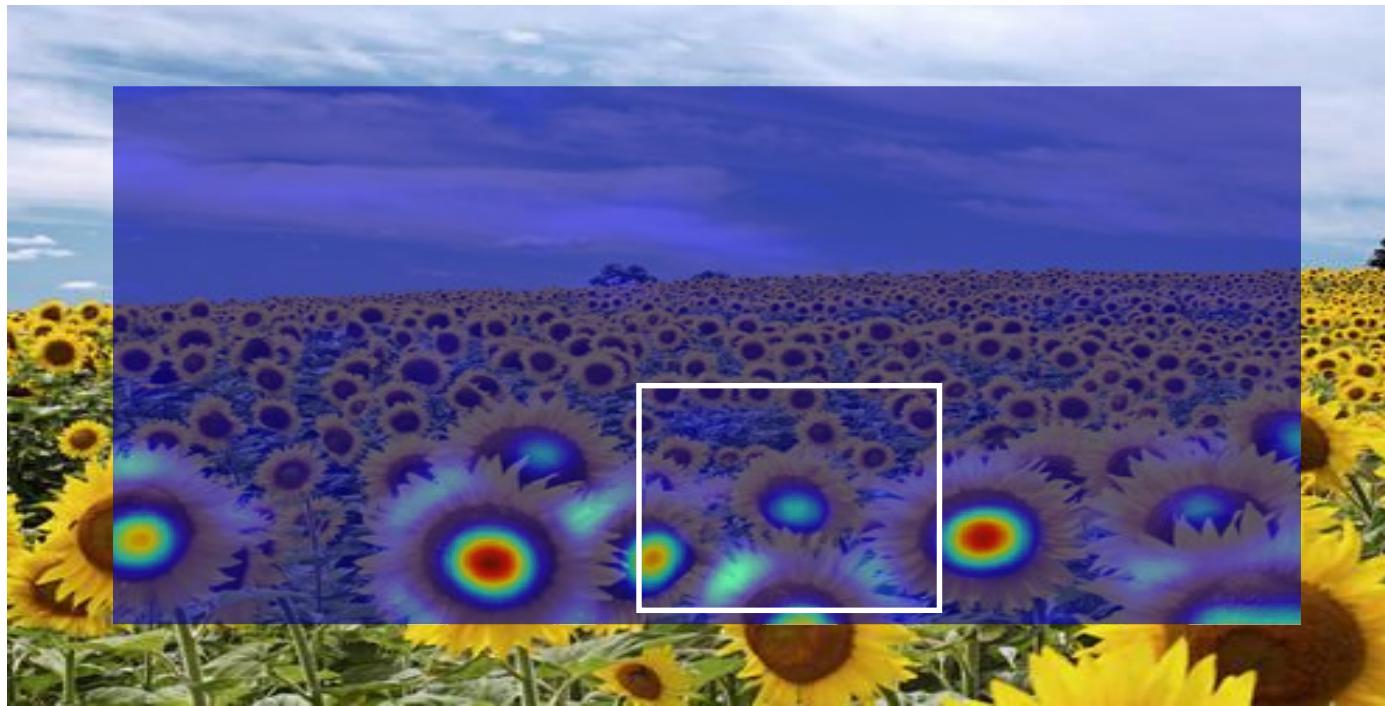
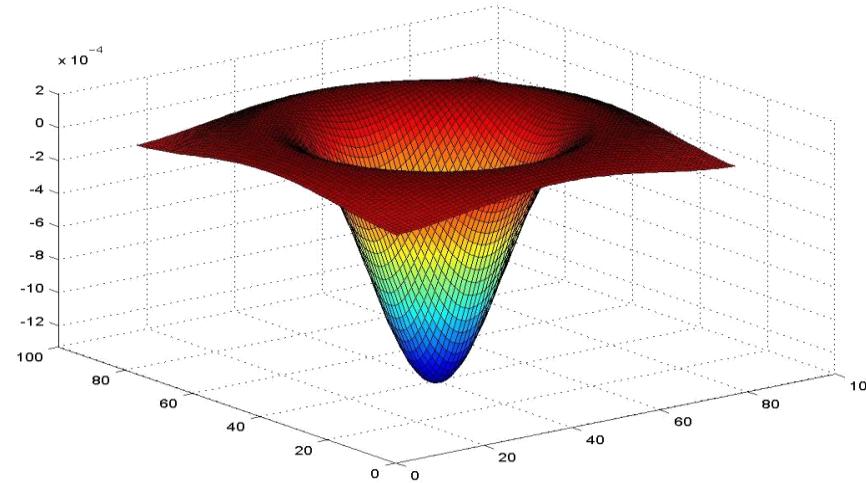
**sigma=4.2**

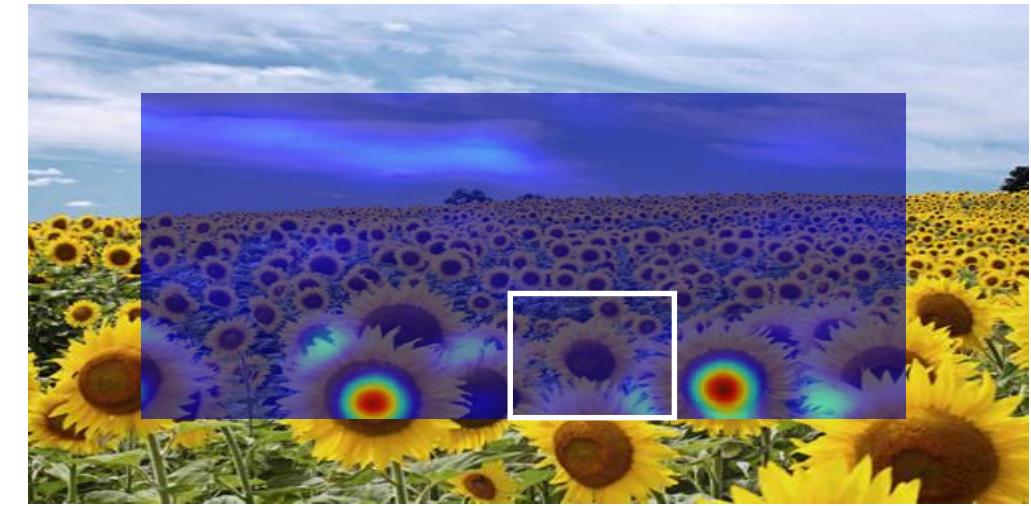
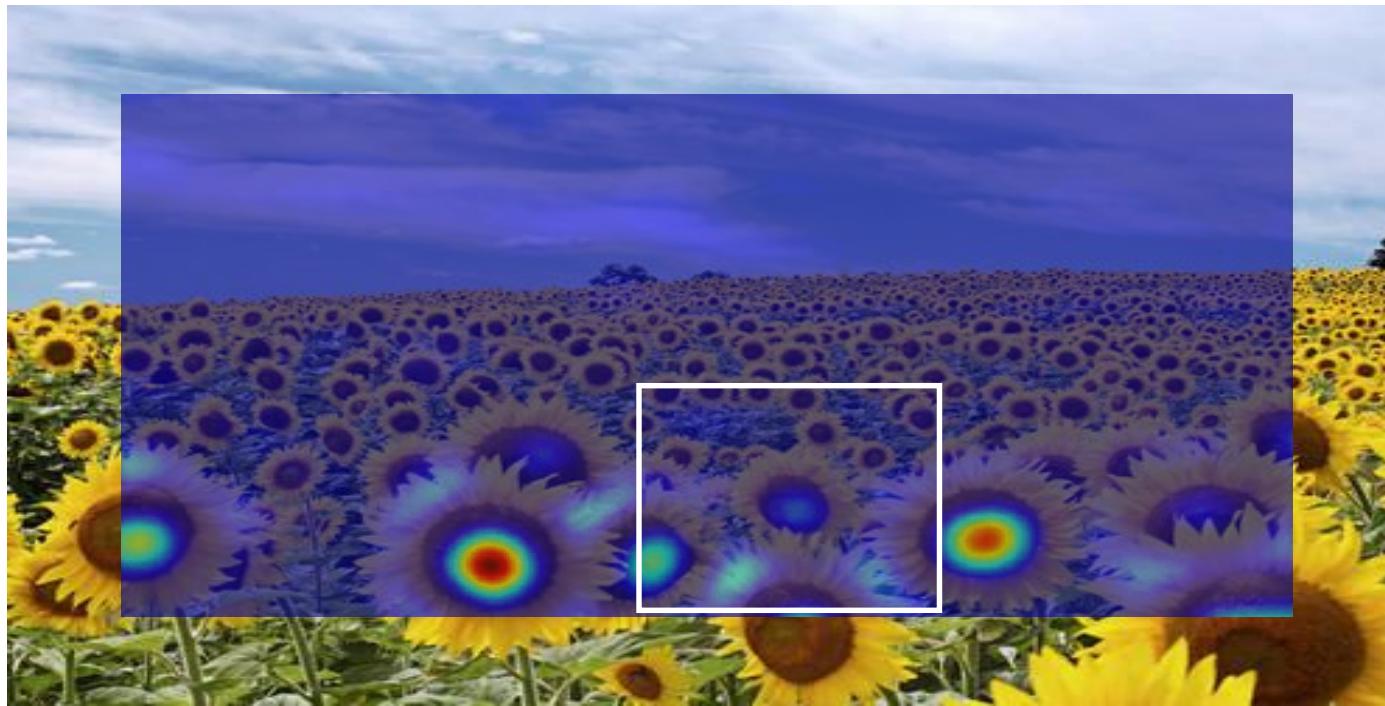
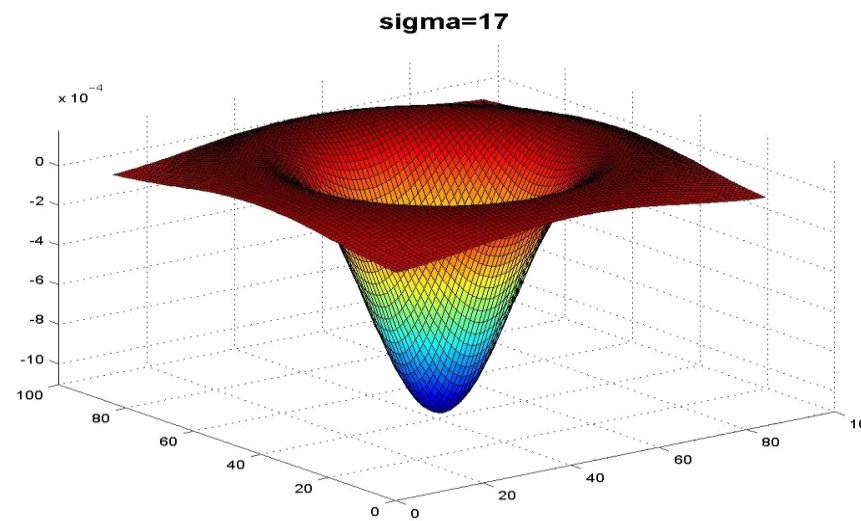






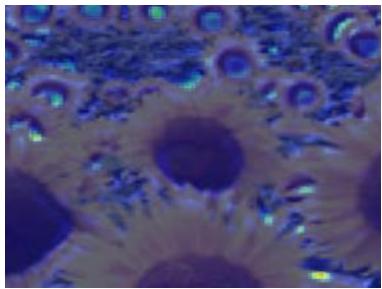
**sigma=15.5**



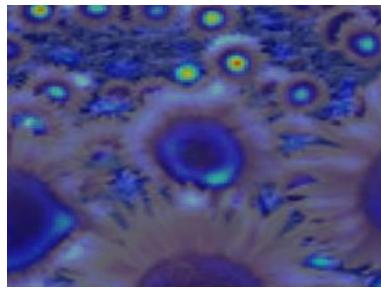


# optimal scale

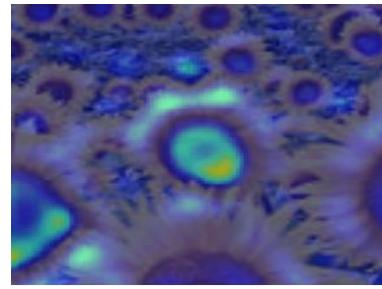
2.1



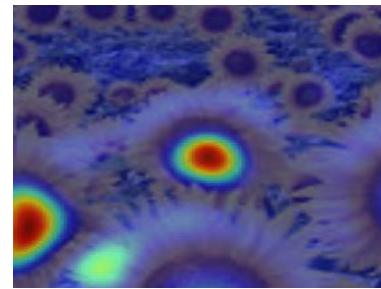
4.2



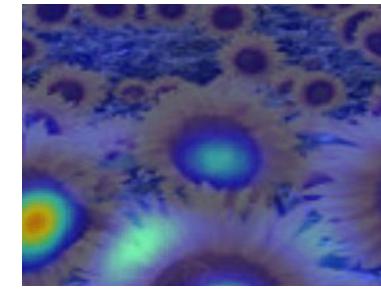
6.0



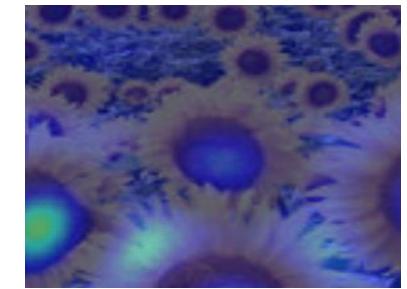
9.8



15.5

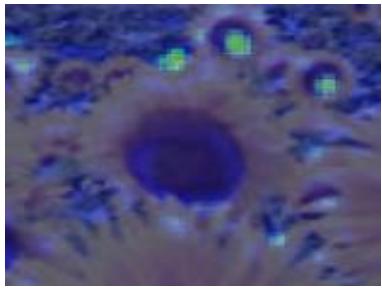


17.0

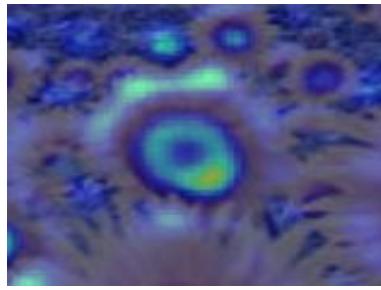


Full size image

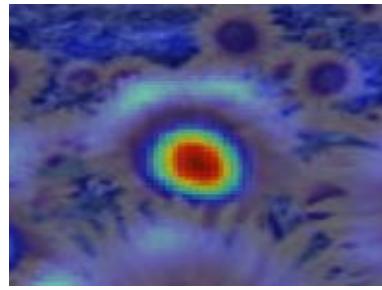
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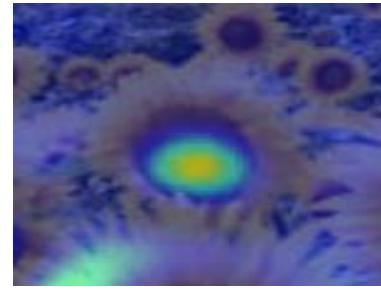
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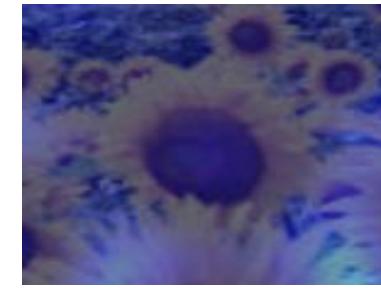
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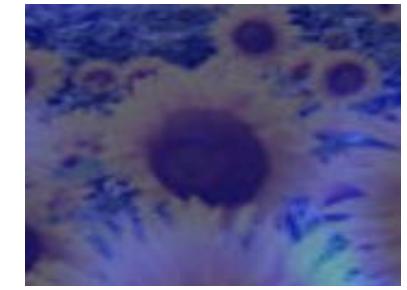
9.8



15.5



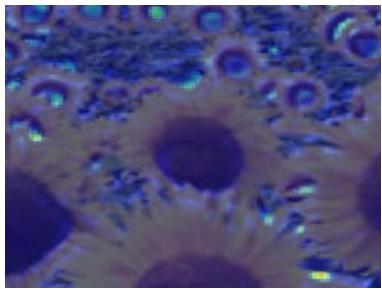
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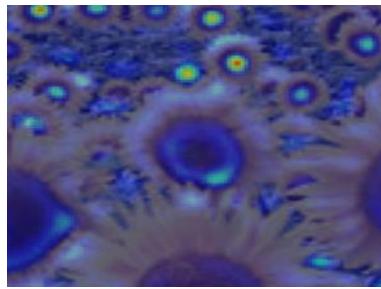
3/4 size image

# optimal scale

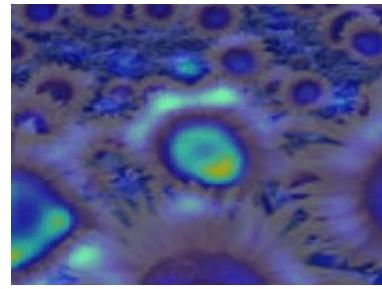
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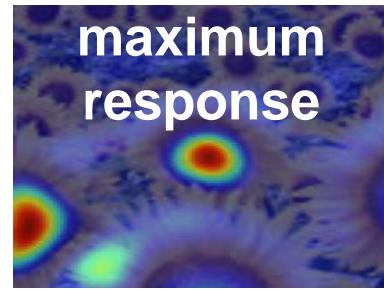
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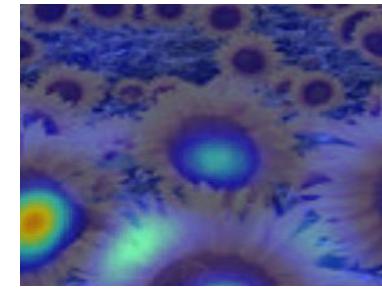
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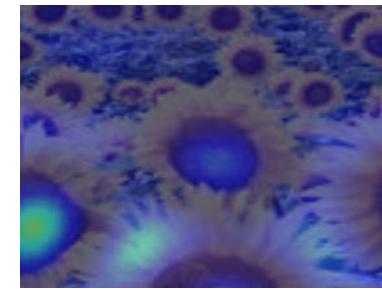
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15.5

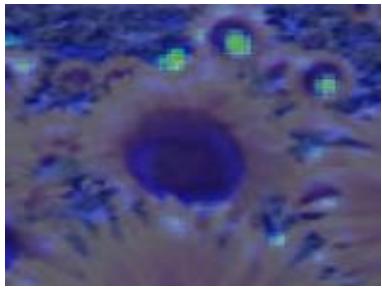


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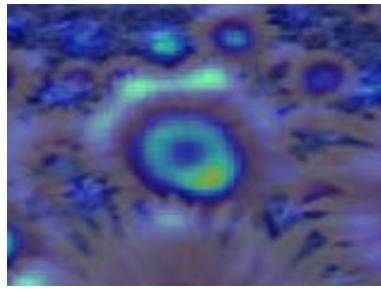


Full size image

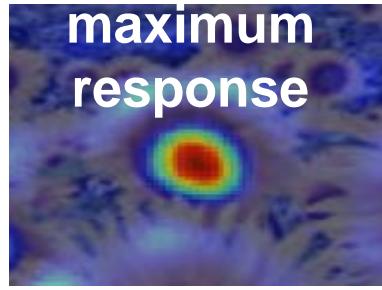
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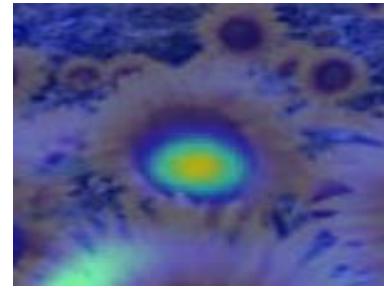
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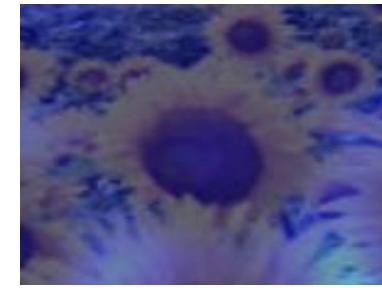
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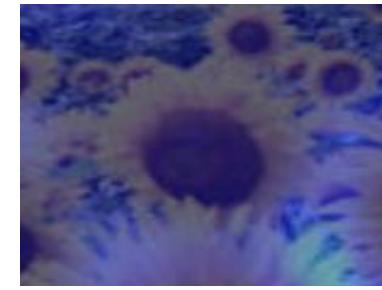
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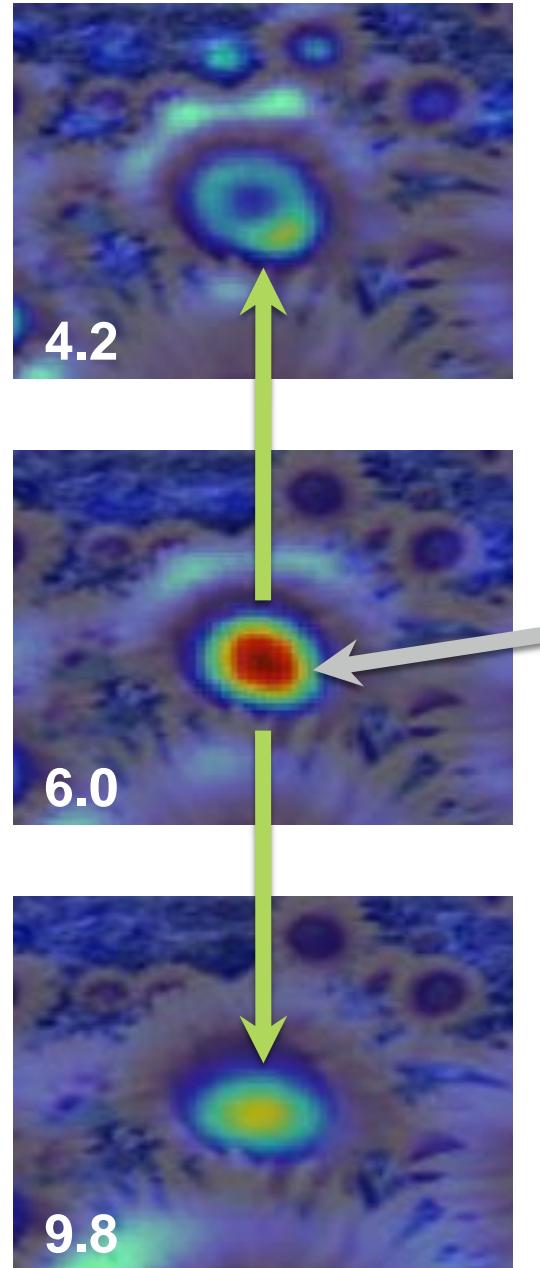


17.0



3/4 size image

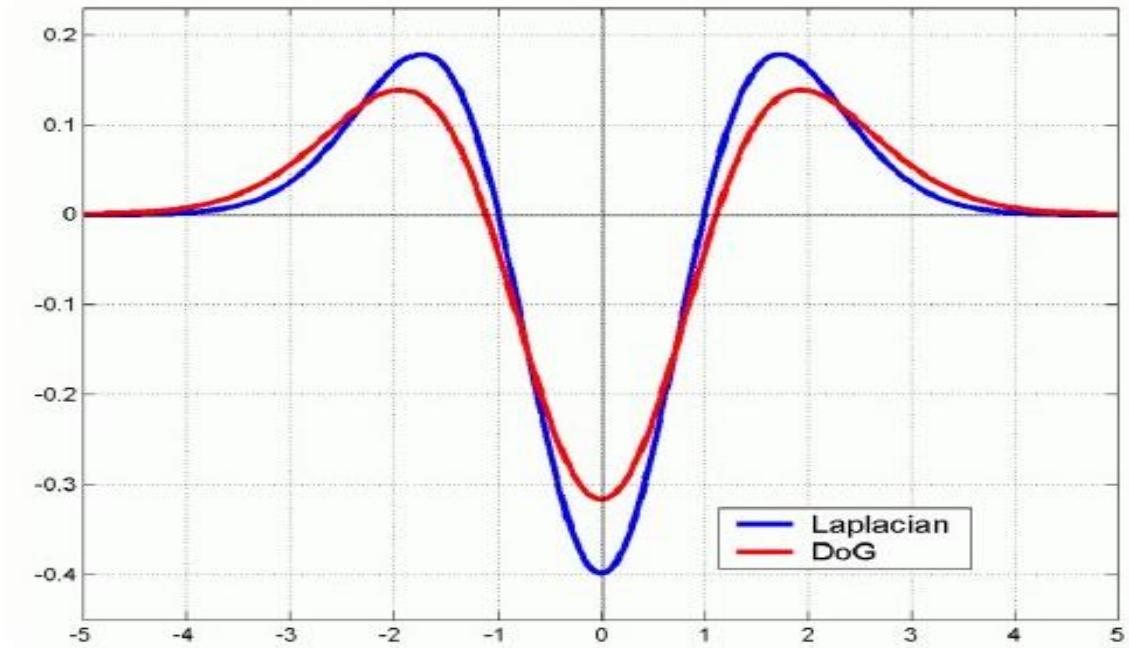
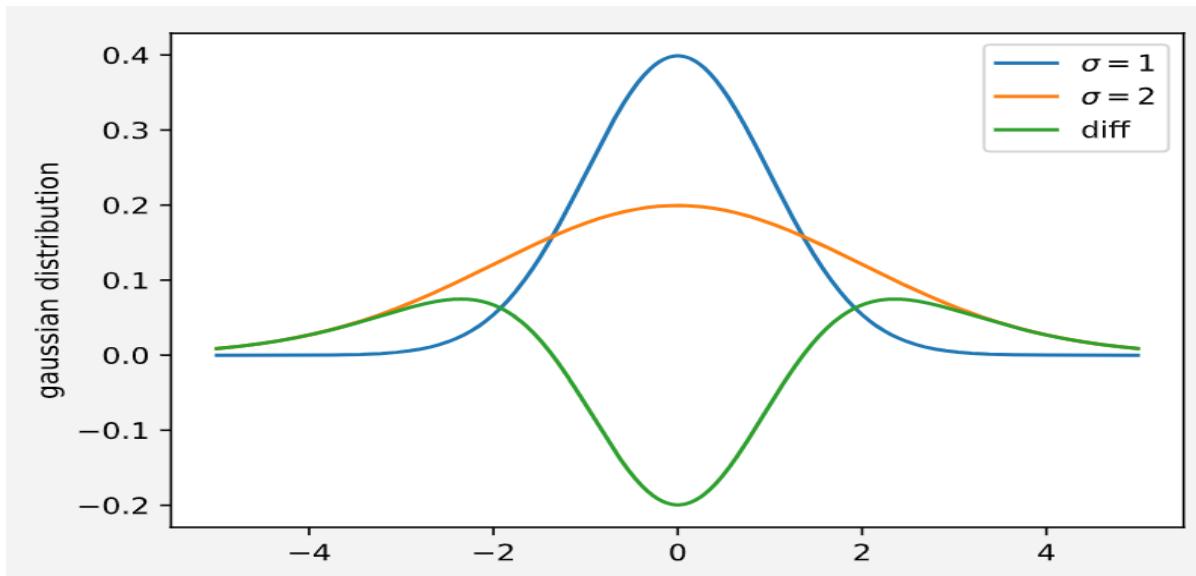
cross-scale maximum



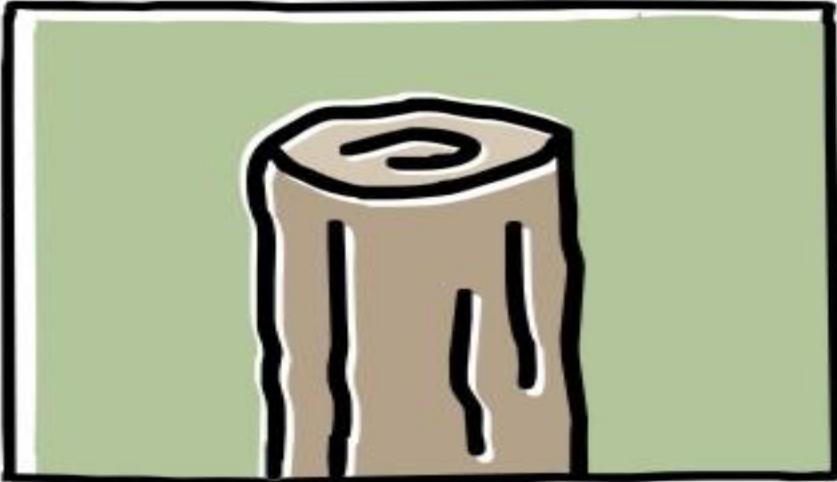
local maximum

# As seen in class- edges: DoG

- Can also use difference of Gaussians (DoG) to mimic LoG.
- Why do we want to do this? Faster computationally (explained here: <https://dsp.stackexchange.com/a/37675>)



# log vs. dog



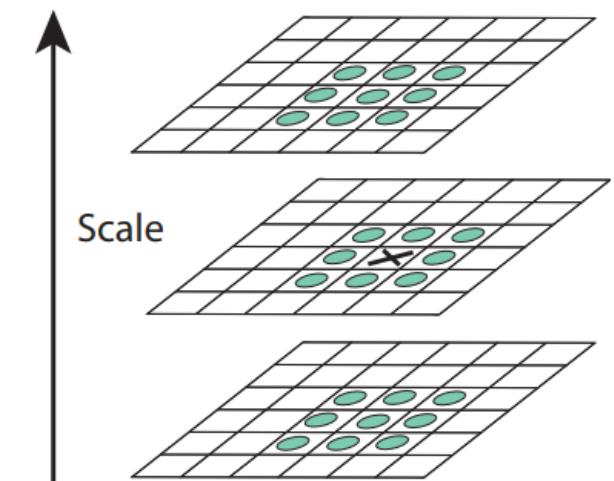
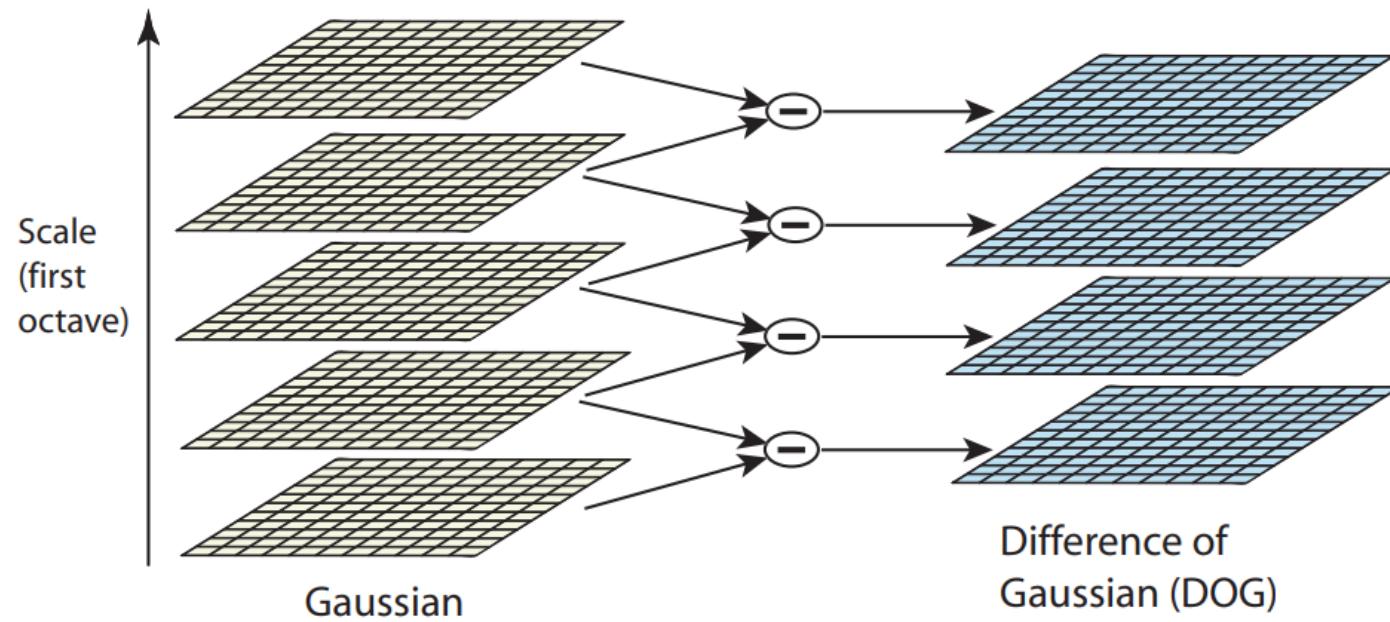
likes to be outside  
found near the fireplace  
gives warmth and comfort  
plays dead  
bark  
doesn't have a tail



likes to be outside  
found near the fireplace  
gives warmth and comfort  
plays dead  
bark  
can't be made into shelves

# Blob detection algorithm

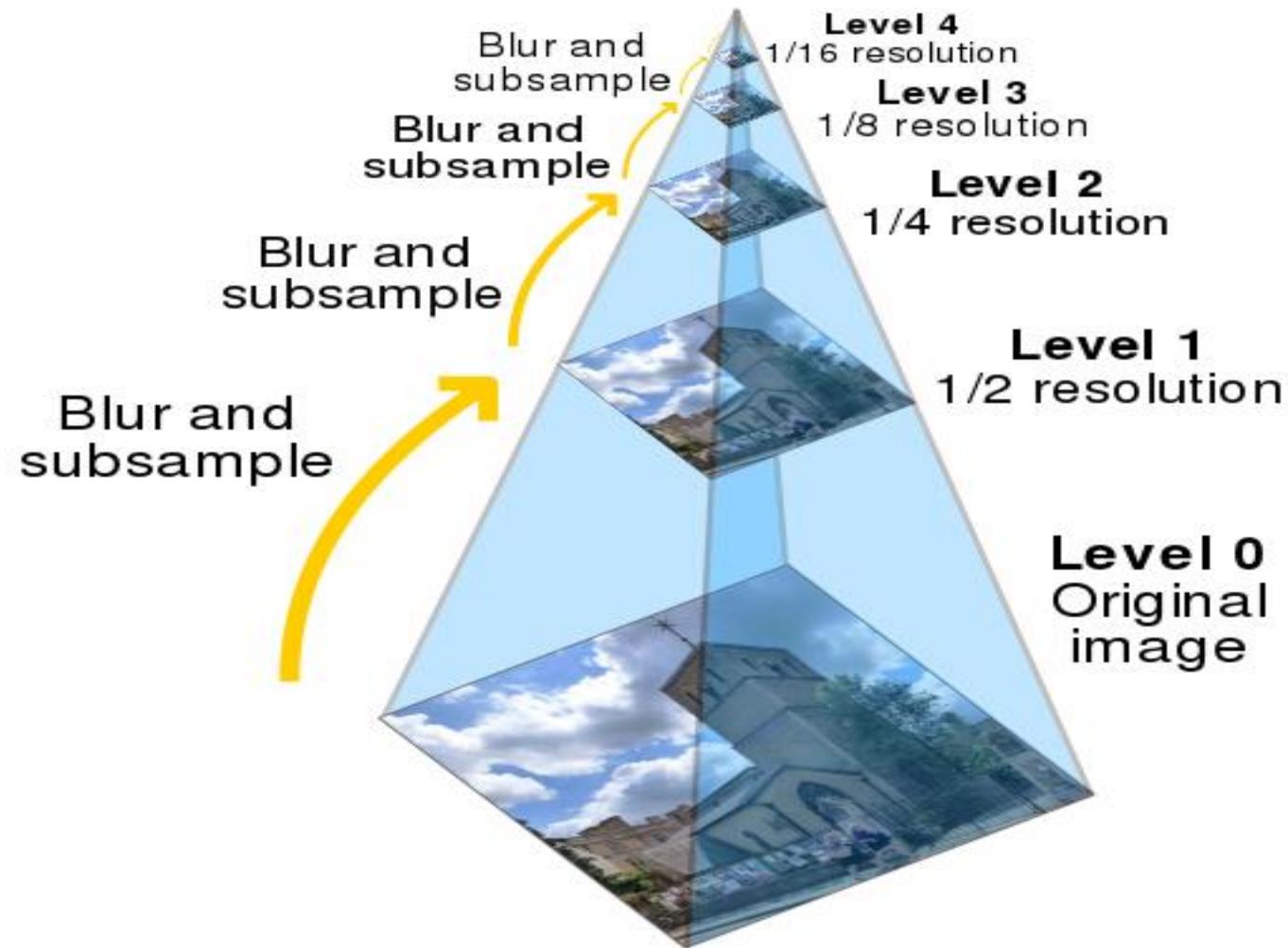
- Build DoG images.
- Search across different image scales the max response.



# Blob detection: summary

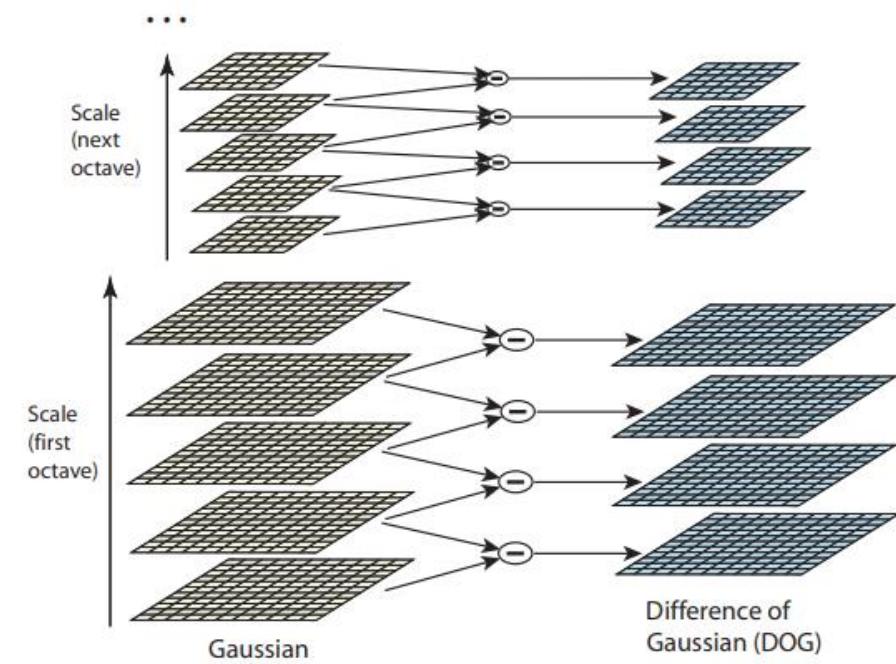
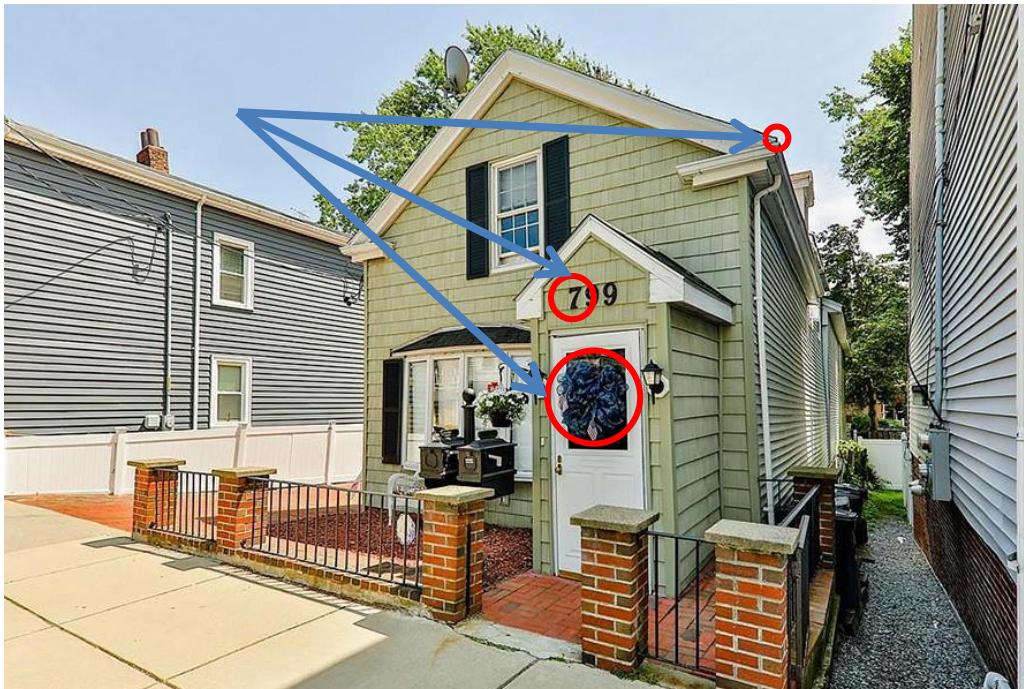
- Advantages:
  - Invariant to translation, rotation, scale and intensity shift  $I \rightarrow I + b$  (because we use only the derivatives).
- Disadvantages:
  - Can also find edges and not only corners (why is it bad? Next).

# Reminder: Gaussian pyramid



# Improved LoG blob detector

- Since the images is low-passed filter so much, we can decimate the image and not loose data in the process!
- We can build a Gaussian pyramid (as taught in image processing recap class) and run the entire algorithm on the different **octave scales**.
- **When using different octave scales we can get features from different image scale.**



# contents

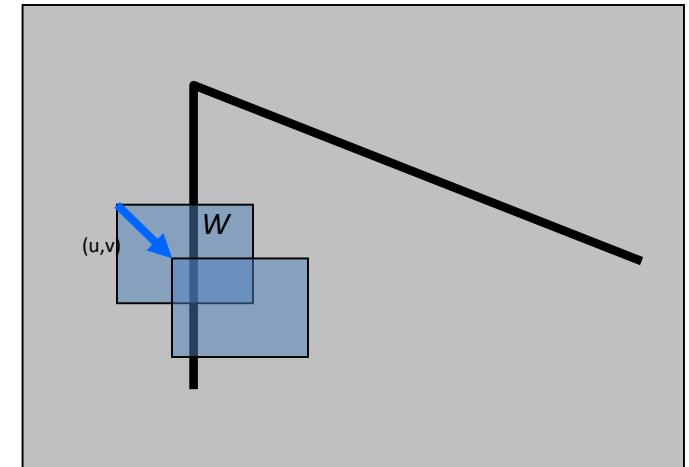
- What and why we need features detection?
- Feature detection
  - Blob detection
  - **Harris corner detection**
  - SIFT detector
- Feature description
  - HOG
  - SIFT descriptor
- SIFT feature matching
- Panoramas

# Harris corner detection

- Consider shifting the window  $W$  by  $(u, v)$ 
  - compare each pixel before and after by summing up the squared differences (SSD).
  - this defines an SSD “error”  $E(u, v)$ :

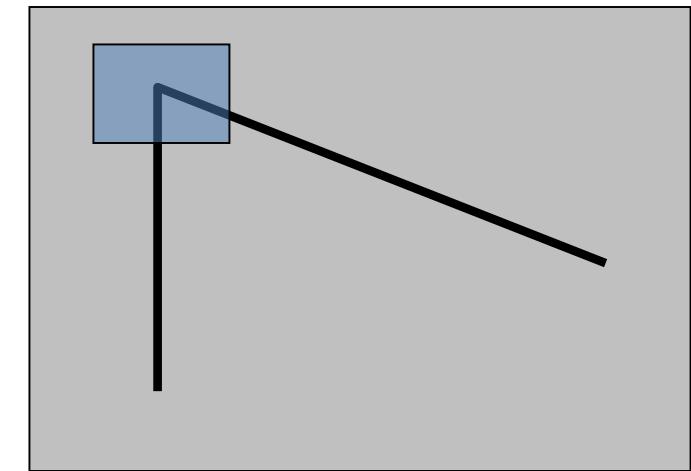
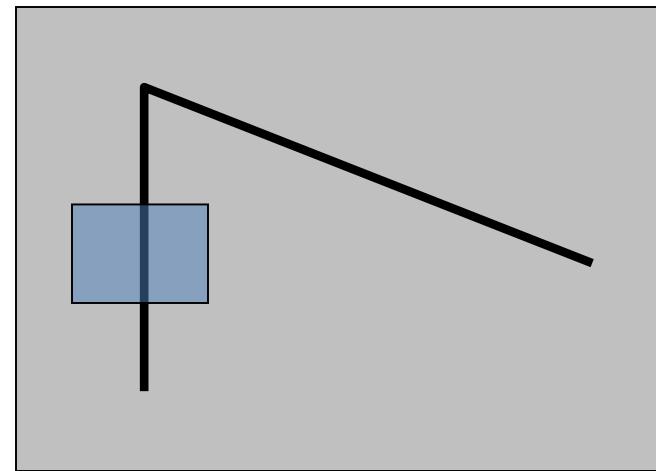
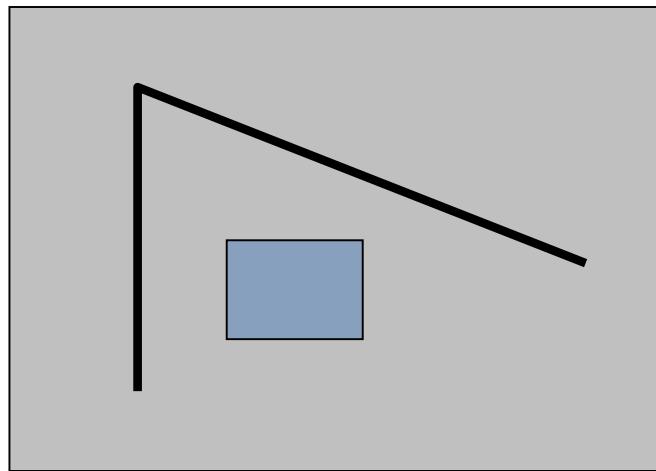
$$E(u, v) = \sum_{(x,y) \in W} [I(x + u, y + v) - I(x, y)]^2$$

- **We are happy if this error is high for all  $(u, v) \neq (0, 0)$**



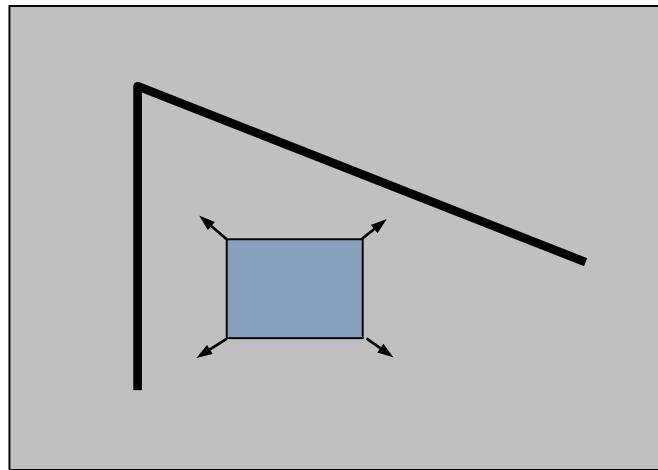
# Local measures of uniqueness

- Suppose we only consider a small window of pixels.
- How does the window change when you shift it?

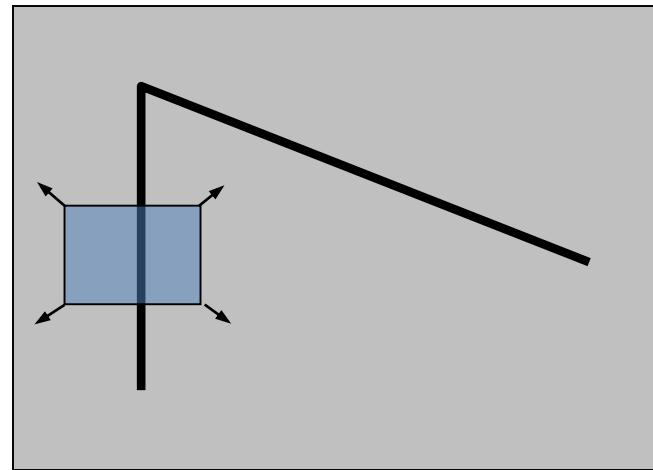


# Local measures of uniqueness

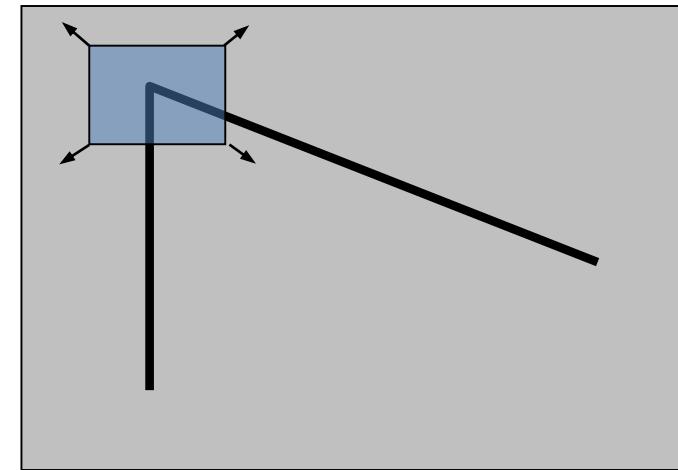
- Suppose we only consider a small window of pixels-
- How does the window change when you shift it?



“flat” region:  
no change in all  
directions



“edge”:  
no change along the edge  
direction



“corner”:  
significant change in all  
directions

# Harris corner detection

- Taylor Series expansion of  $I$ :

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

- If the motion  $(u, v)$  is small, then first order approximation is good

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

- Plug it into the SSD error term:

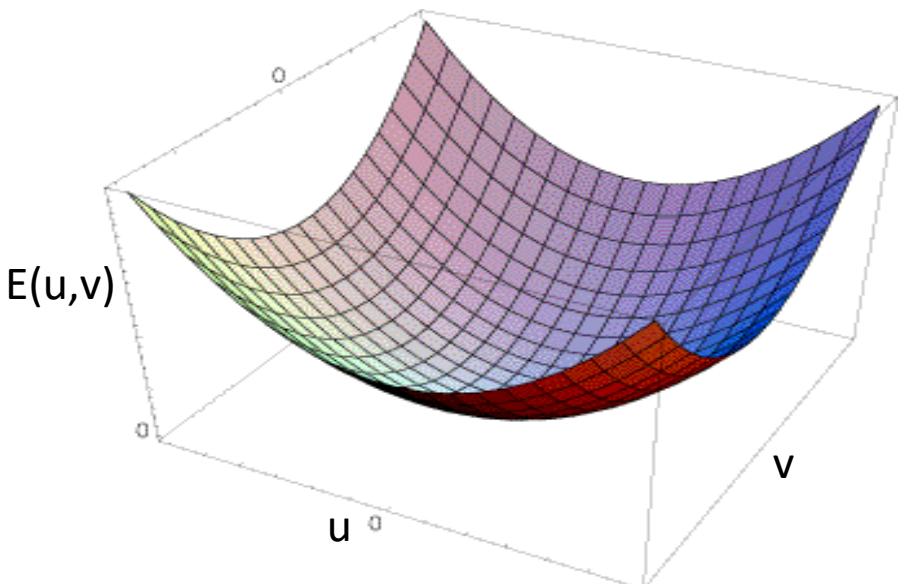
$$\begin{aligned} E(u, v) &= \sum_{(x,y) \in W} [I(x + u, y + v) - I(x, y)]^2 \\ &\approx \sum_{(x,y) \in W} [I(x, y) + I_x u + I_y v - I(x, y)]^2 \\ &\approx \sum_{(x,y) \in W} [I_x u + I_y v]^2 \end{aligned}$$

# Harris corner detection

$$\begin{aligned} E(u, v) &\approx \sum_{(x,y) \in W} [I_x u + I_y v]^2 \\ &\approx A u^2 + 2Buv + C v^2 \\ &\approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_H \begin{bmatrix} u \\ v \end{bmatrix} \end{aligned}$$

Also called **second-moments matrix**

$$\begin{aligned} A &= \sum_{(x,y) \in W} I_x^2 \\ B &= \sum_{(x,y) \in W} I_x I_y \\ C &= \sum_{(x,y) \in W} I_y^2 \end{aligned}$$



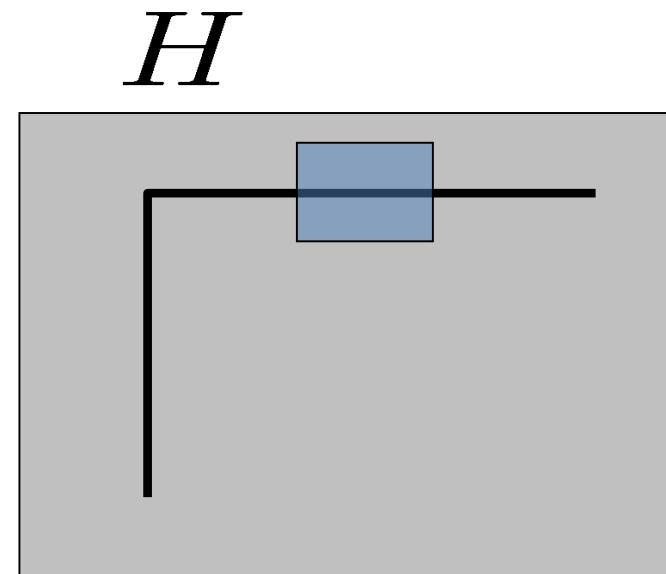
# Harris corner detection

$$E(u, v) \approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_{H} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$A = \sum_{(x,y) \in W} I_x^2$$

$$B = \sum_{(x,y) \in W} I_x I_y$$

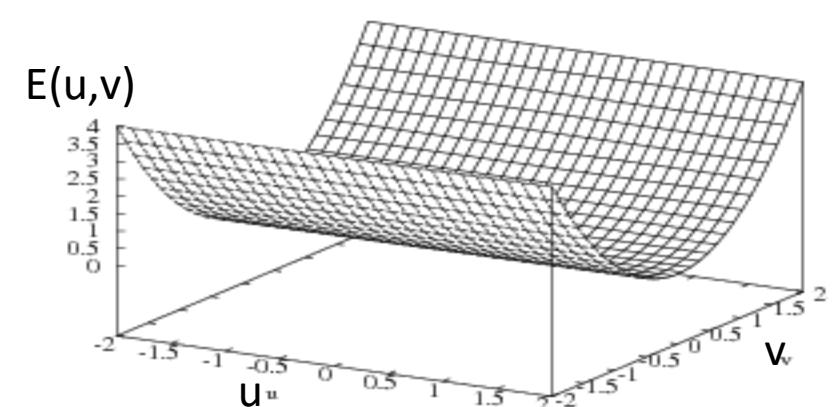
$$C = \sum_{(x,y) \in W} I_y^2$$



Horizontal edge:

$$I_x = 0$$

$$H = \begin{bmatrix} 0 & 0 \\ 0 & C \end{bmatrix}$$



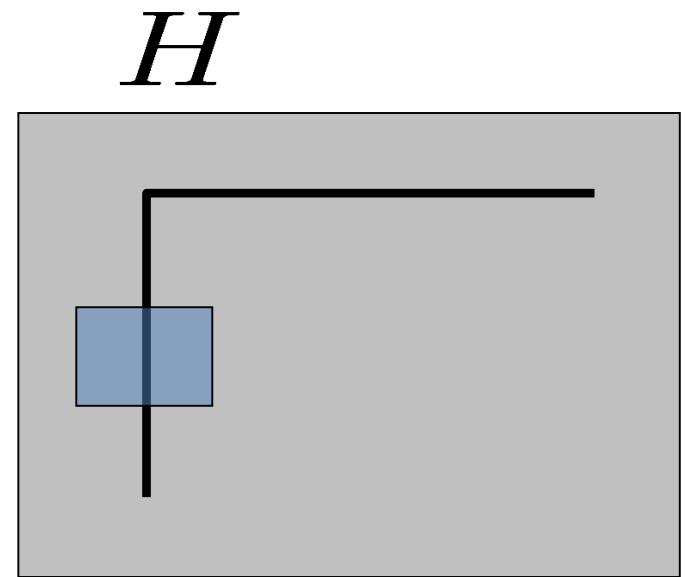
# Harris corner detection

$$E(u, v) \approx \begin{bmatrix} u & v \end{bmatrix} \underbrace{\begin{bmatrix} A & B \\ B & C \end{bmatrix}}_{H} \begin{bmatrix} u \\ v \end{bmatrix}$$

$$A = \sum_{(x,y) \in W} I_x^2$$

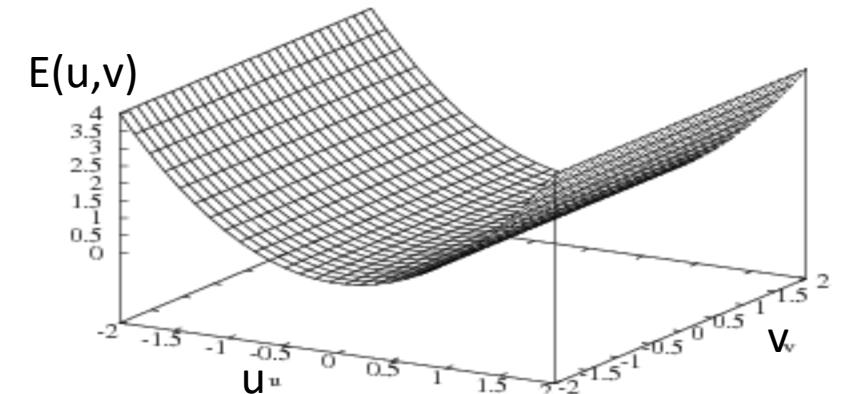
$$B = \sum_{(x,y) \in W} I_x I_y$$

$$C = \sum_{(x,y) \in W} I_y^2$$



Vertical edge:  $I_y = 0$

$$H = \begin{bmatrix} A & 0 \\ 0 & 0 \end{bmatrix}$$



# Harris corner detection: probabilistic interpretation

- A real symmetric matrix has an eigendecomposition of:

$$Av = \lambda v$$

$$AQ = Q\Lambda$$

$$A = Q\Lambda Q^{-1}$$

A is real symmetric matrix

$$\xrightarrow{} A = Q\Lambda Q^T$$

$$A = \begin{pmatrix} e_1 & e_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} e_1^T \\ e_2^T \end{pmatrix}$$

- Bonus: eigenvectors are orthonormal if A is real and symmetric.

# Harris corner detection

- An ellipse can have a matrix form of:

$$x^T (e_1 e_2) \begin{pmatrix} \lambda_1 & \\ & \lambda_2 \end{pmatrix} \begin{pmatrix} e_1^T \\ e_2^T \end{pmatrix} x = 1$$

$$\lambda_1 x^T e_1 e_1^T x + \lambda_2 x^T e_2 e_2^T x = 1$$

$$\frac{(e_1^T x)^2}{\left(\frac{1}{\sqrt{\lambda_1}}\right)^2} + \frac{(e_2^T x)^2}{\left(\frac{1}{\sqrt{\lambda_2}}\right)^2} = 1$$

- Which is exactly as a rotated ellipse with a center of (0,0):

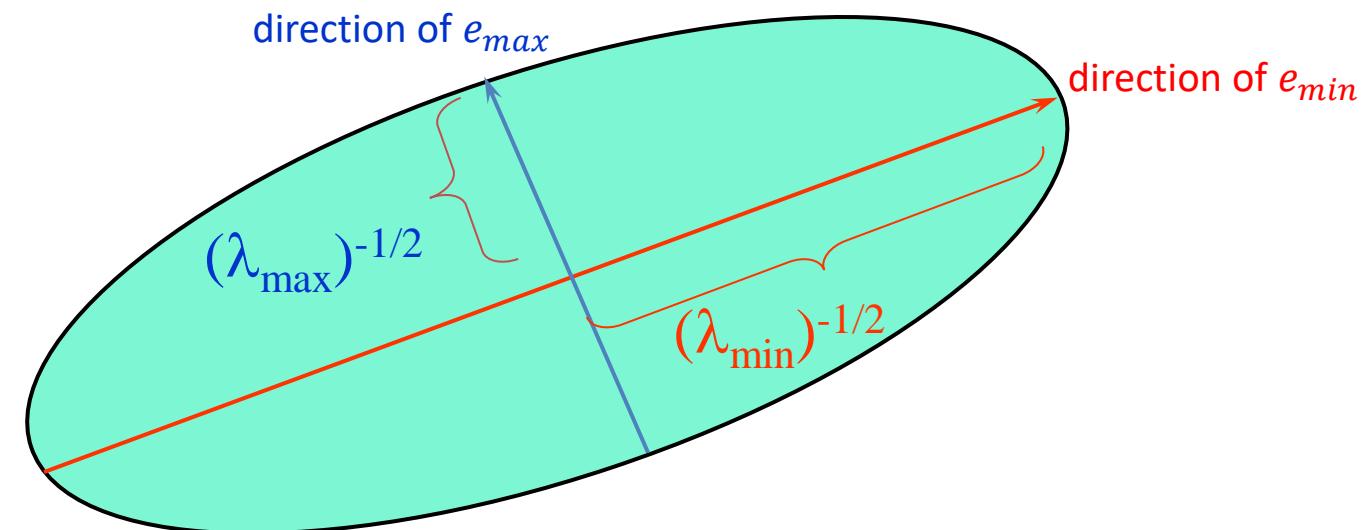
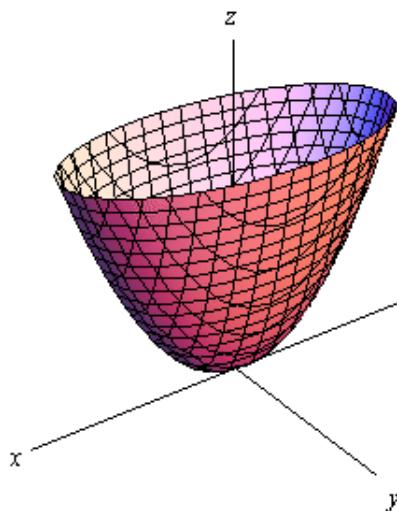
$$\frac{(x \cos(\theta) + y \sin(\theta))^2}{a^2} + \frac{(x \sin(\theta) - y \cos(\theta))^2}{b^2} = 1$$

# Harris corner detection

- Combining the two equations seen before we can conclude that when taking a cross-section from the error function, we can get an ellipsoid.

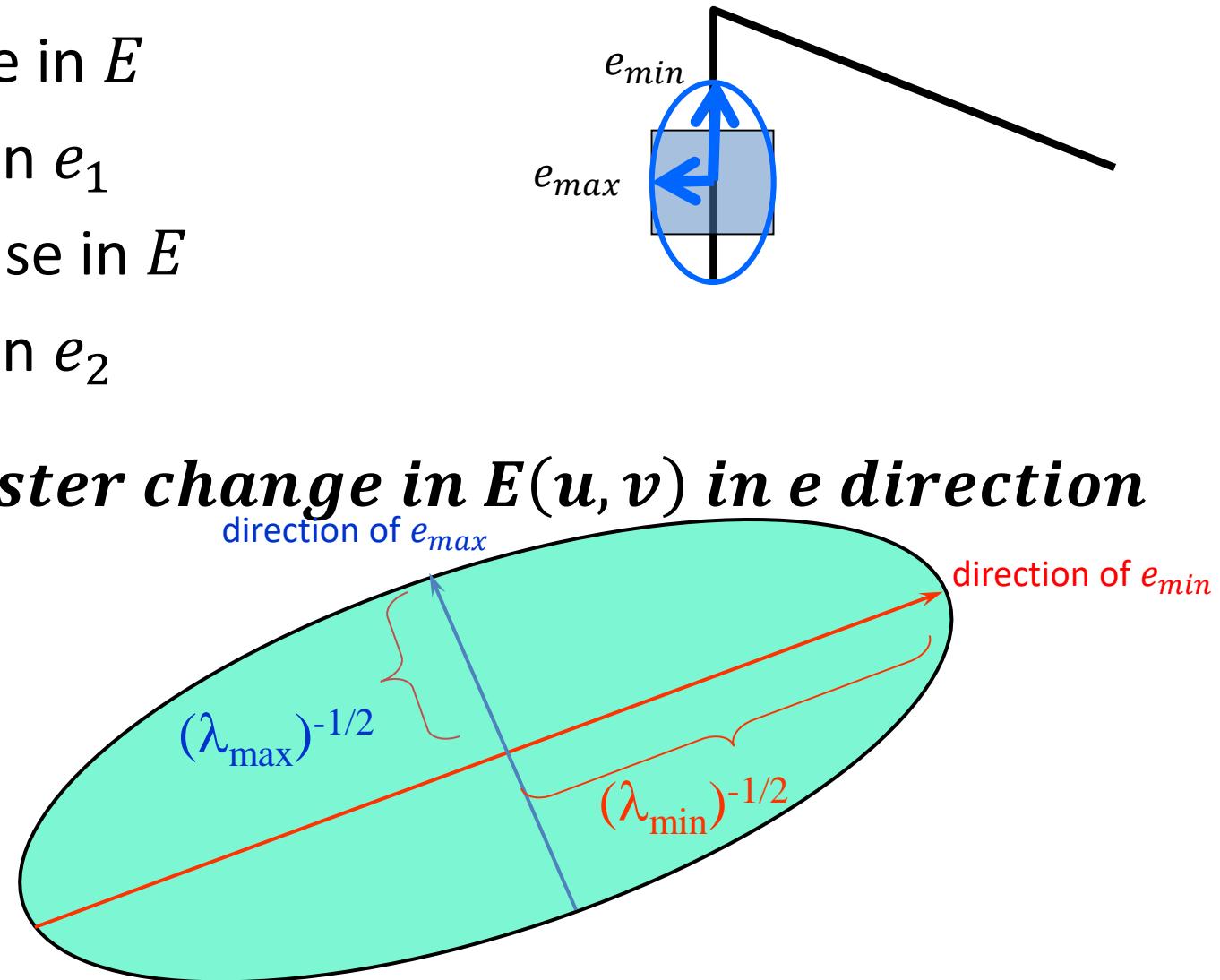
$$-[u \ v]H \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$

- Assume  $\lambda_1 > \lambda_2$



# Harris corner detection

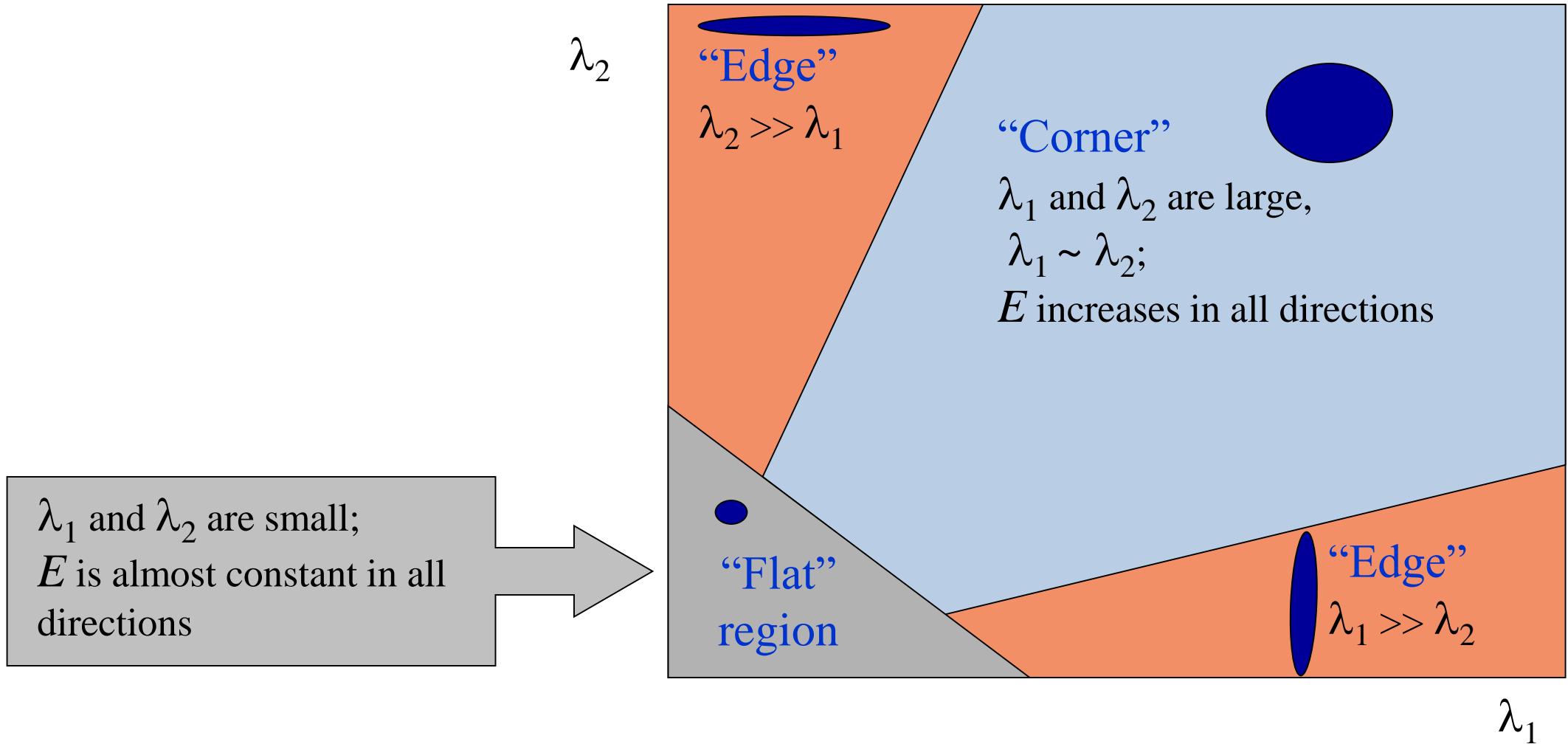
- Eigenvalues and eigenvectors of  $H$ 
  - $e_1$  = direction of largest increase in  $E$
  - $\lambda_1$  = relative increase in direction  $e_1$
  - $e_2$  = direction of smallest increase in  $E$
  - $\lambda_2$  = relative increase in direction  $e_2$
- $\lambda$  larger  $\leftrightarrow \lambda^{-\frac{1}{2}}$  smaller  $\leftrightarrow$  faster change in  $E(u, v)$  in  $e$  direction



# Interpreting the eigenvalues

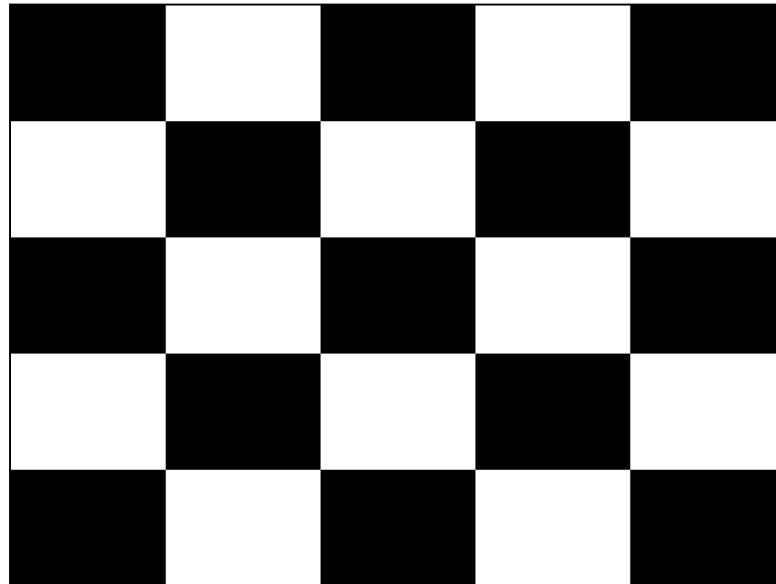
- A “good” corner will have a large  $R = \lambda_{min}$ , which means big change of  $E$  in both axis.
- Getting the eigenvectors and eigenvalues is computationally inefficient.
- Instead, use two tricks:
  - $\prod_i \lambda_i = \det(A)$
  - $\sum_i \lambda_i = \text{trace}(A)$
- Then we can more easily compute  $R$ :
  - $R = \det(A) - \kappa * \text{trace}(A)^2 \quad (\kappa \in [0.04, 0.06])$
  - $R = \frac{\det(A)}{\text{trace}(A)+\epsilon} = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2 + \epsilon}$

# Interpreting the eigenvalues

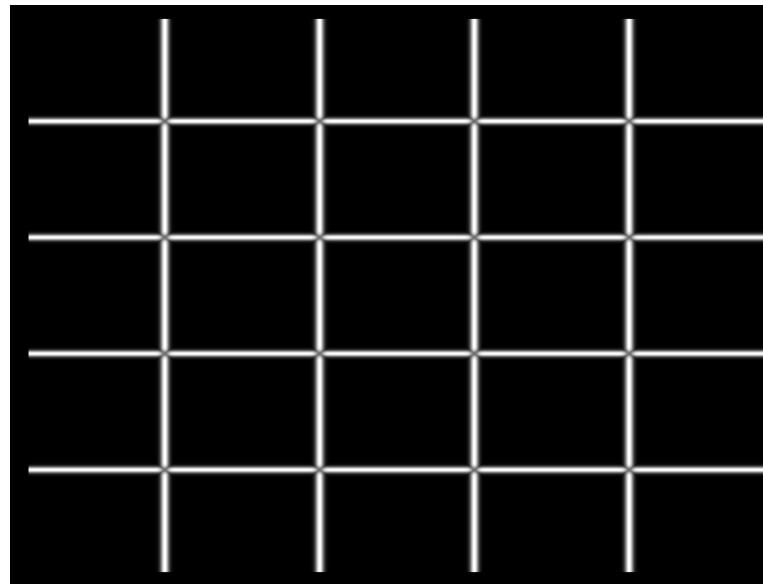


# Interpreting the eigenvalues

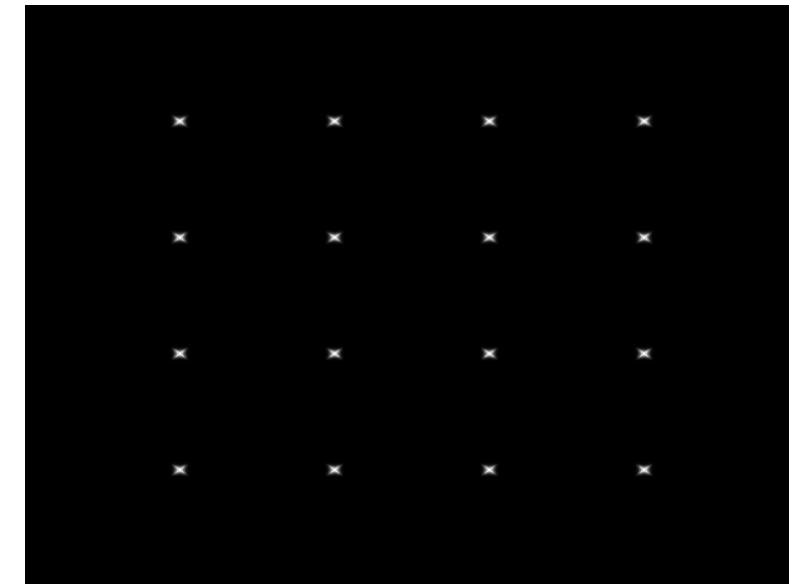
- A binary threshold of pixels above  $\lambda_{max}$  and  $\lambda_{min}$



$I$



$\lambda_{max}$



$\lambda_{min}$

# Harris corner detection

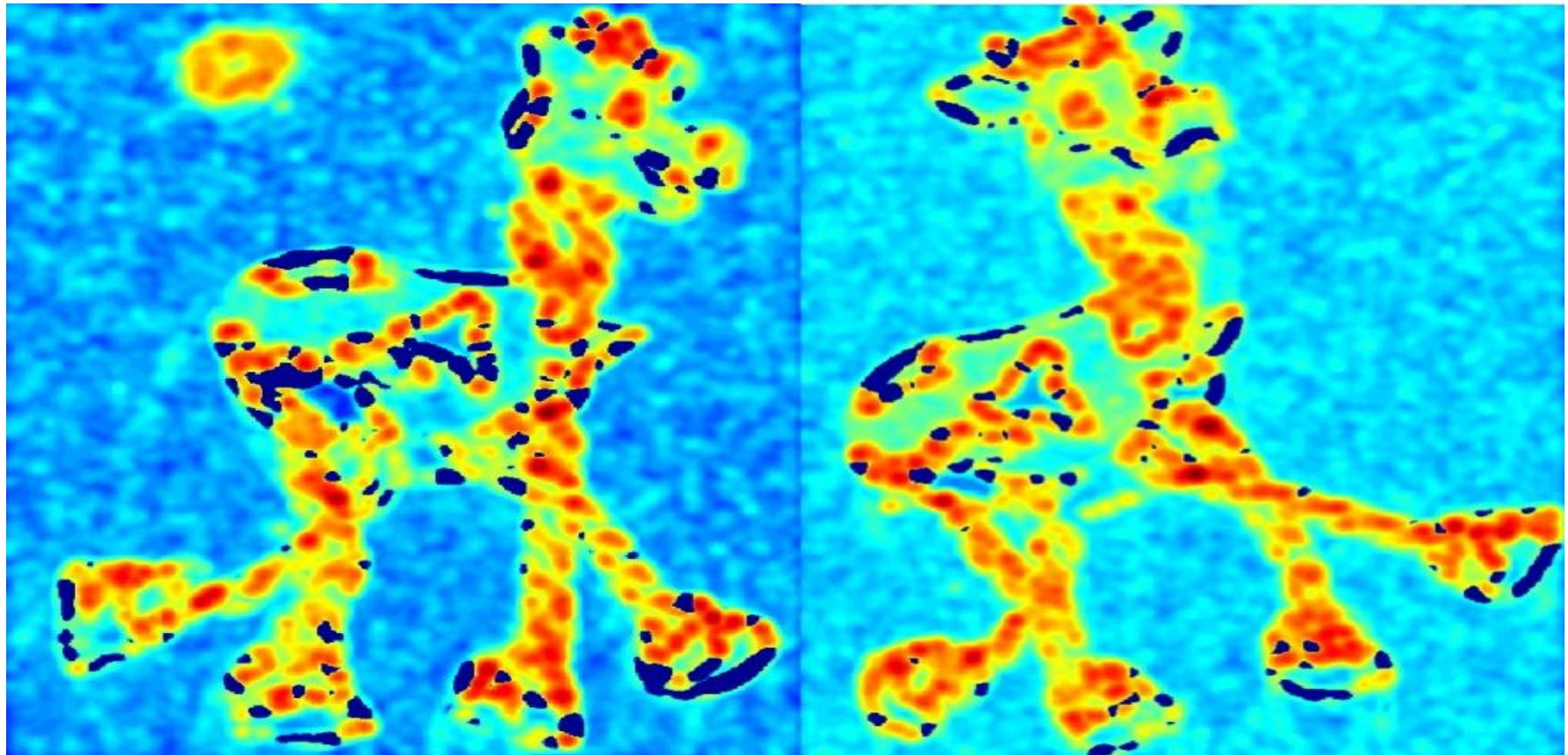
- Compute gradients of patch around each pixel.
- ~~Subtract the mean from each patch gradient.~~
- Compute the second-moment matrix.
- Compute eigendecomposition of covariance matrix.
- Use eigenvalues to find corners.

This is PCA (principal component analysis). Out of scope but really interesting!

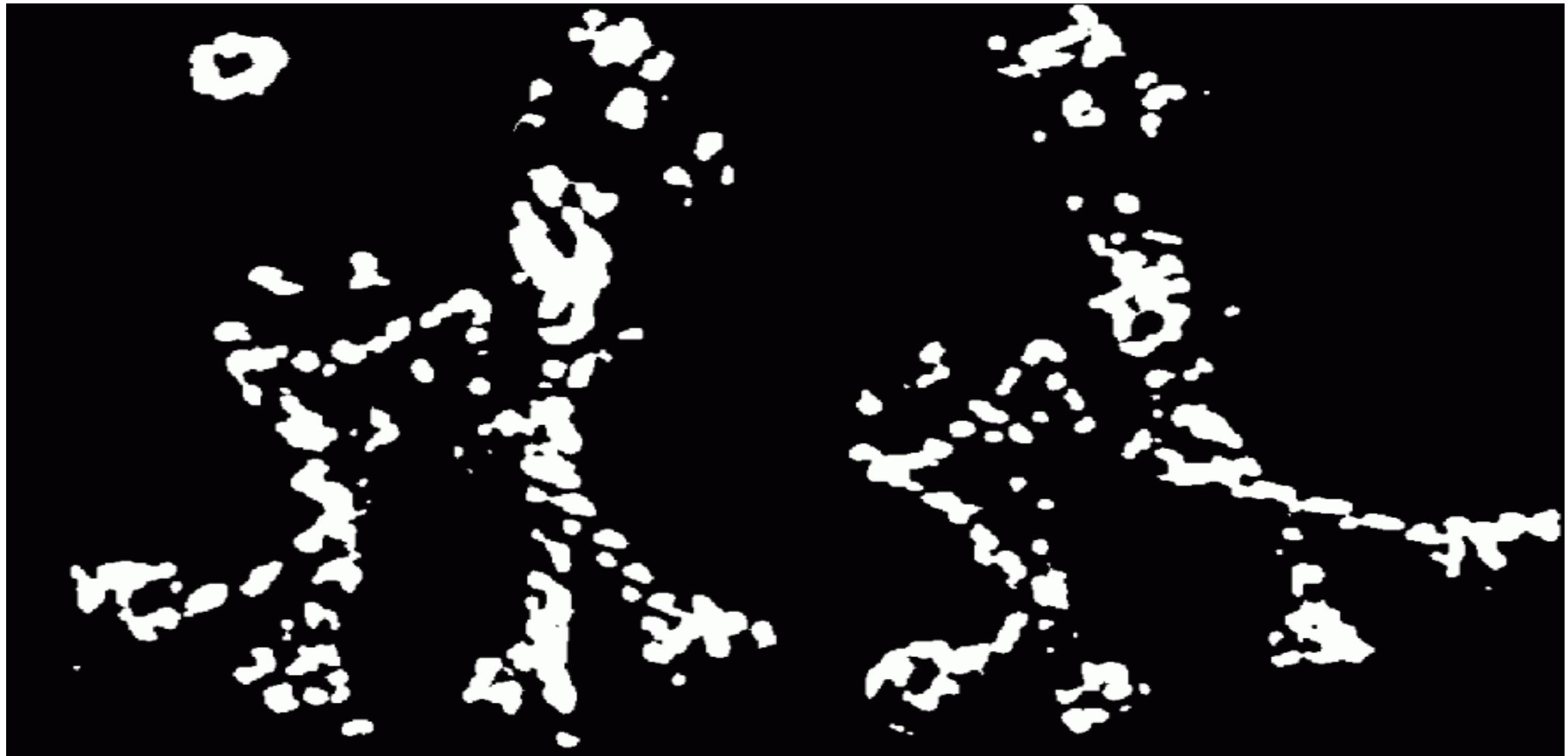
# Harris detector example



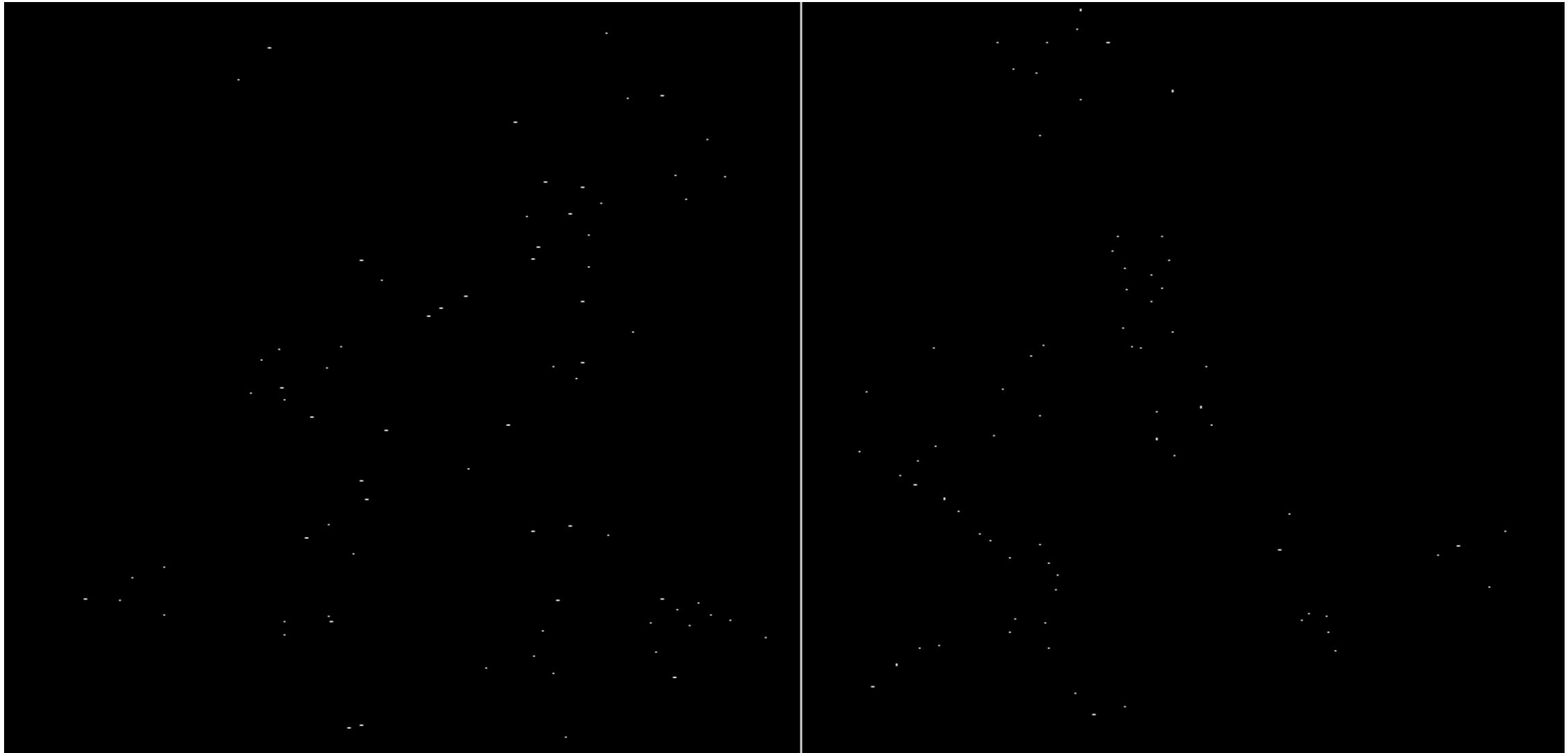
$f$  value (red high, blue low)



## Threshold ( $f > \text{value}$ )



# Find local maxima of $f$



# Harris features (in red)



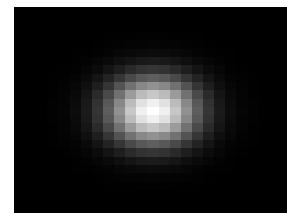
# Weighting the derivatives

- In practice, using a simple window  $W$  doesn't work too well

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

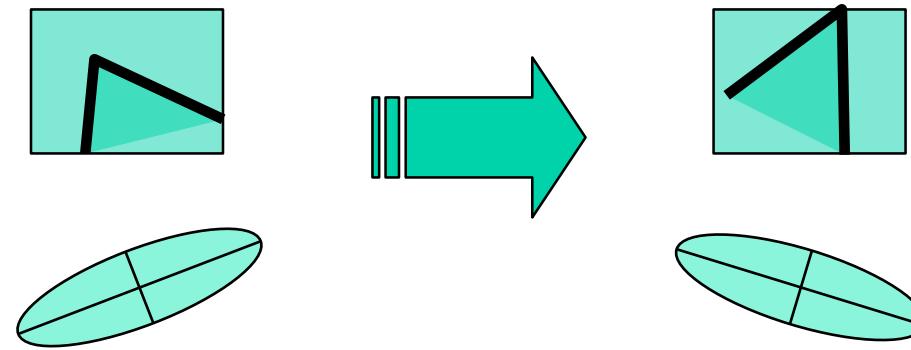
- Instead, we'll *weight* each derivative value based on its distance from the center pixel

$$H = \sum_{(x,y) \in W} w_{x,y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



$w_{x,y}$

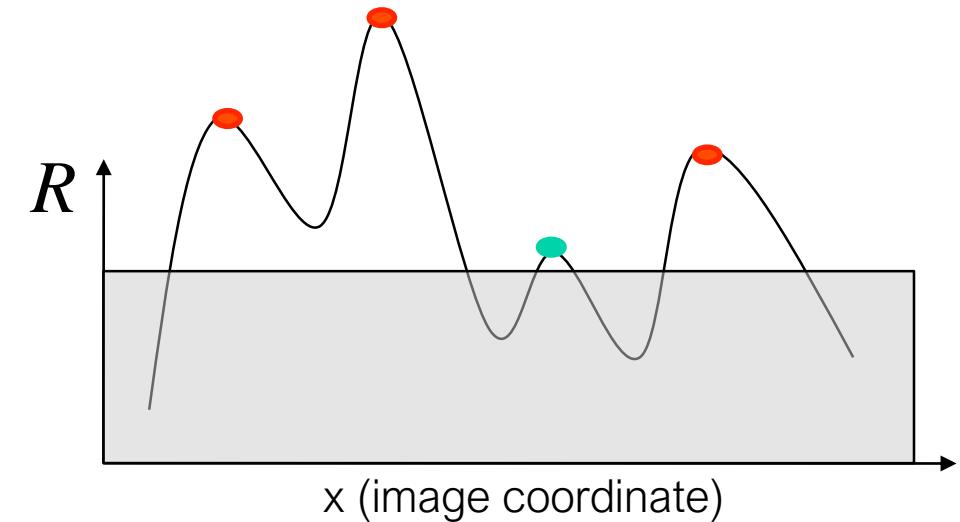
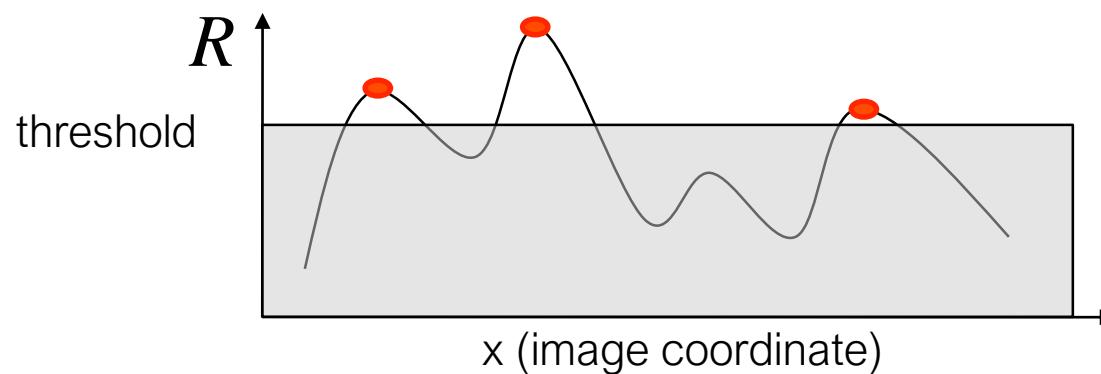
# Harris corner detector- rotation and translation



- Ellipse rotates but its shape (**eigenvalues**) remains the same => invariant to rotation!
- The feature is also translation invariant (easy to see).

# Harris corner detector- intensity

- Partial invariance to *affine intensity* change
- Only derivatives are used => invariance to intensity shift  $I \rightarrow I + b$
- Not completely invariance to Intensity scale:  $I \rightarrow a \cdot I$



# The Harris corner detector is not invariant to scale



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- What and why we need features detection?
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  - Harris corner detection
  - **SIFT detector**
- Feature description
  - HOG
  - SIFT descriptor
- SIFT feature matching
- Panoramas

# SIFT keypoint detection

- Find blobs using the improved blob detection (across different octave scale).
- Use interpolation to find exact peak of keypoint.
  - The interpolation takes place in **x, y and scale dimension.**
- Eliminate edge response with Harris corner detector variant (called **principal curvature**) around temp keypoints in interpolated space and scale.
- SIFT has the advantages of both previous technics and is invariance to: rotation, translation, scale, illumination shift and partially to 3D change of viewpoint since it is a local keypoint detector.

# contents

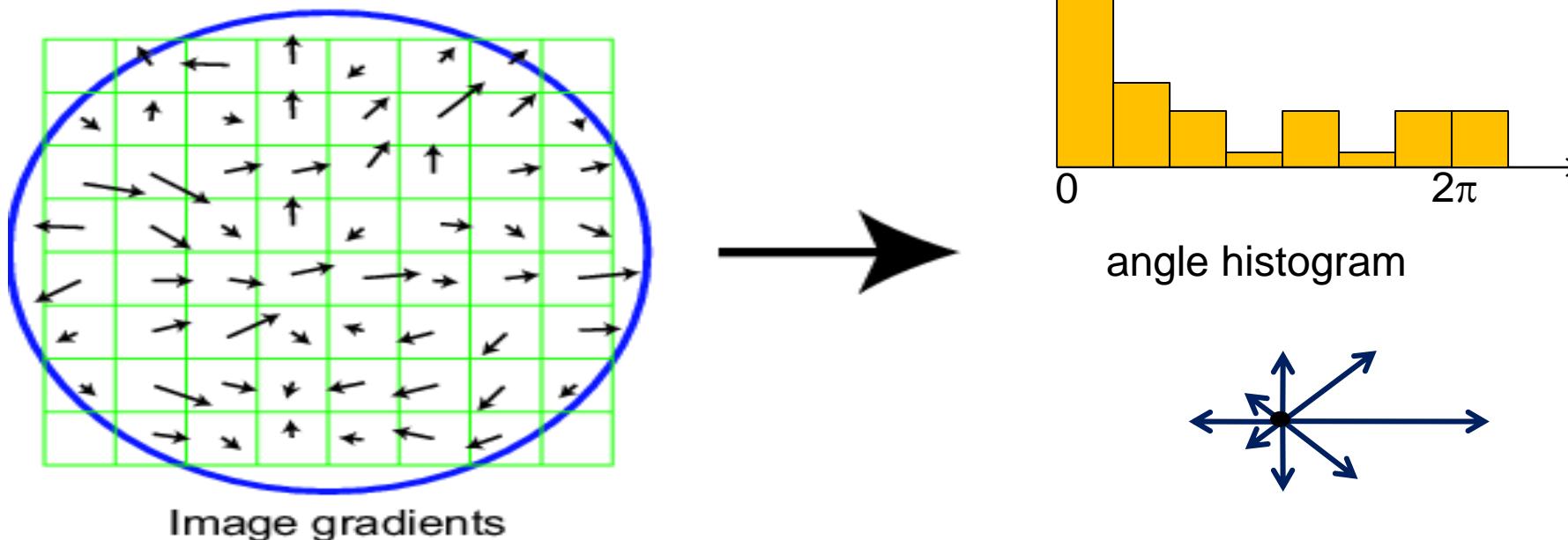
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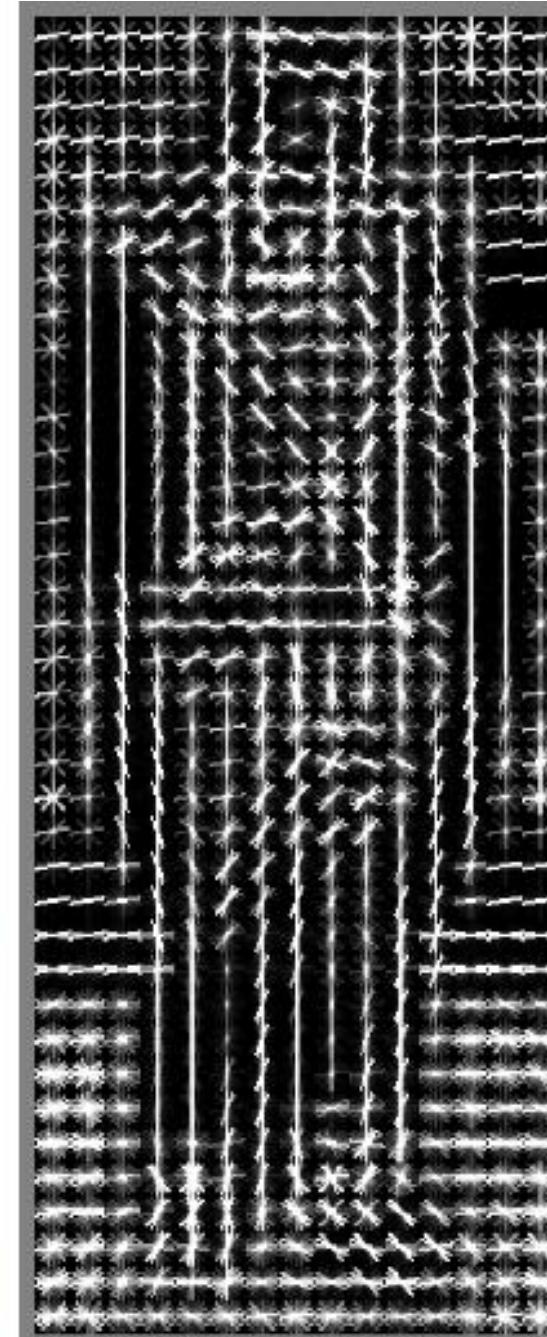
# HOG- Histogram of Oriented Gradients

- A dense representation of image as blocks, each with its own histogram of gradient directions, weighted by the gradient magnitude.
- Originally used to detect humans in images.
- Equations for gradient magnitude and orientation:

$$m(x, y) = \sqrt{(L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2}$$

$$\theta(x, y) = \tan^{-1}((L(x, y + 1) - L(x, y - 1)) / (L(x + 1, y) - L(x - 1, y)))$$





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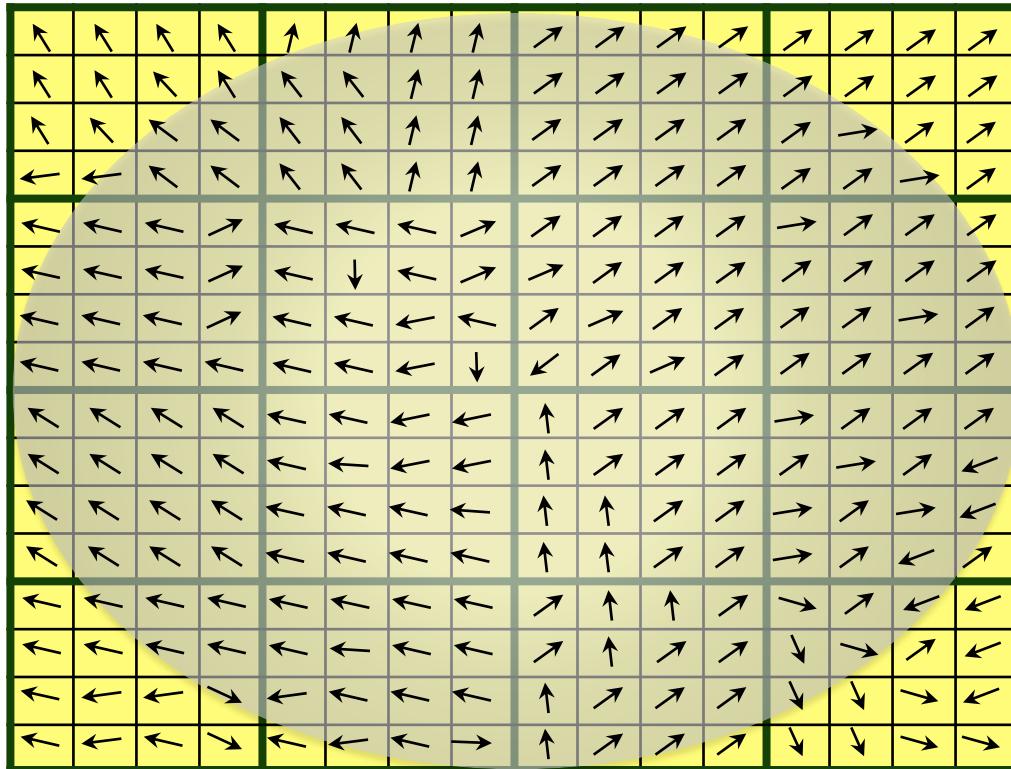
# HOG variation as SIFT keypoint descriptor

- First, find the main patch direction using a HOG on all gradients around keypoint at the selected scale, all further calculation is done around this direction (this is how to get a rotation invariance descriptor).
- Take 16x16 patch around detected feature, and calculate gradient orientation and magnitude to each pixel.
- Magnitude is also weighted by a Gaussian around the keypoint.
- Build sub-blocks of 4X4 of the patch.
- Create 8-bin histogram of edge orientations (weighted by Gaussian and magnitude of gradient) to each sub-block.
- Take the  $4 \times 4 \times 8 = 128$  results of histograms and concatenate them to a single feature vector. Normalize this vector to be invariance to illumination scale.

# HOG variation as SIFT keypoint descriptor

Image Gradients

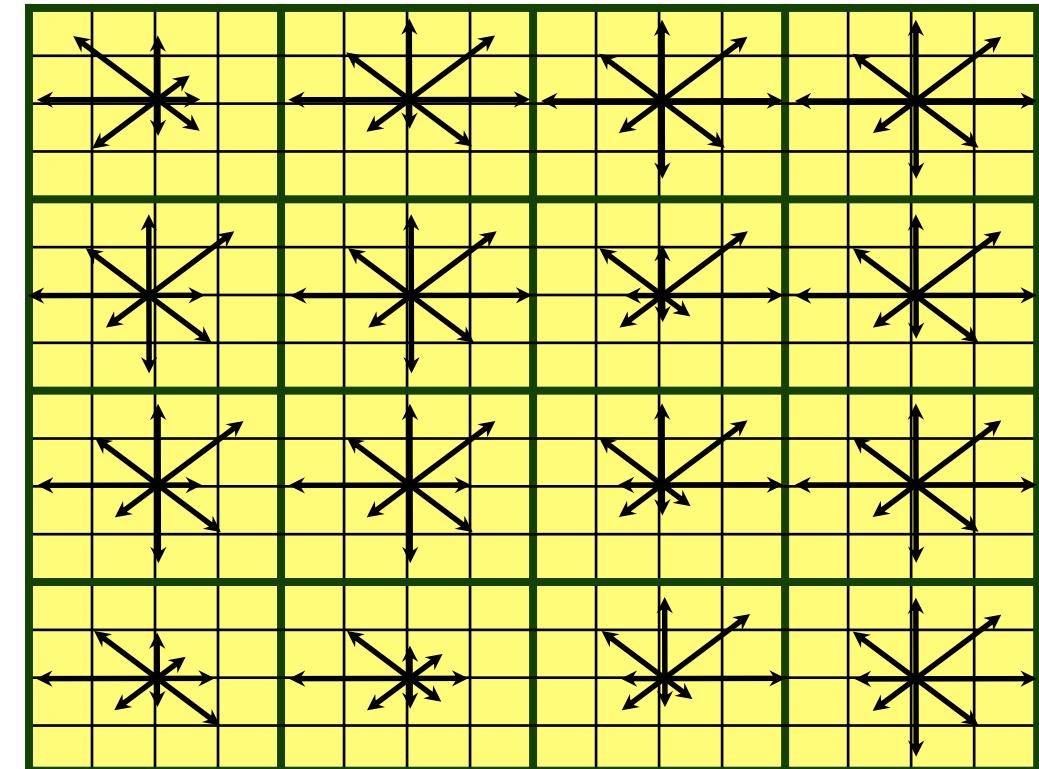
(4 x 4 pixel per cell, 4 x 4 cells)



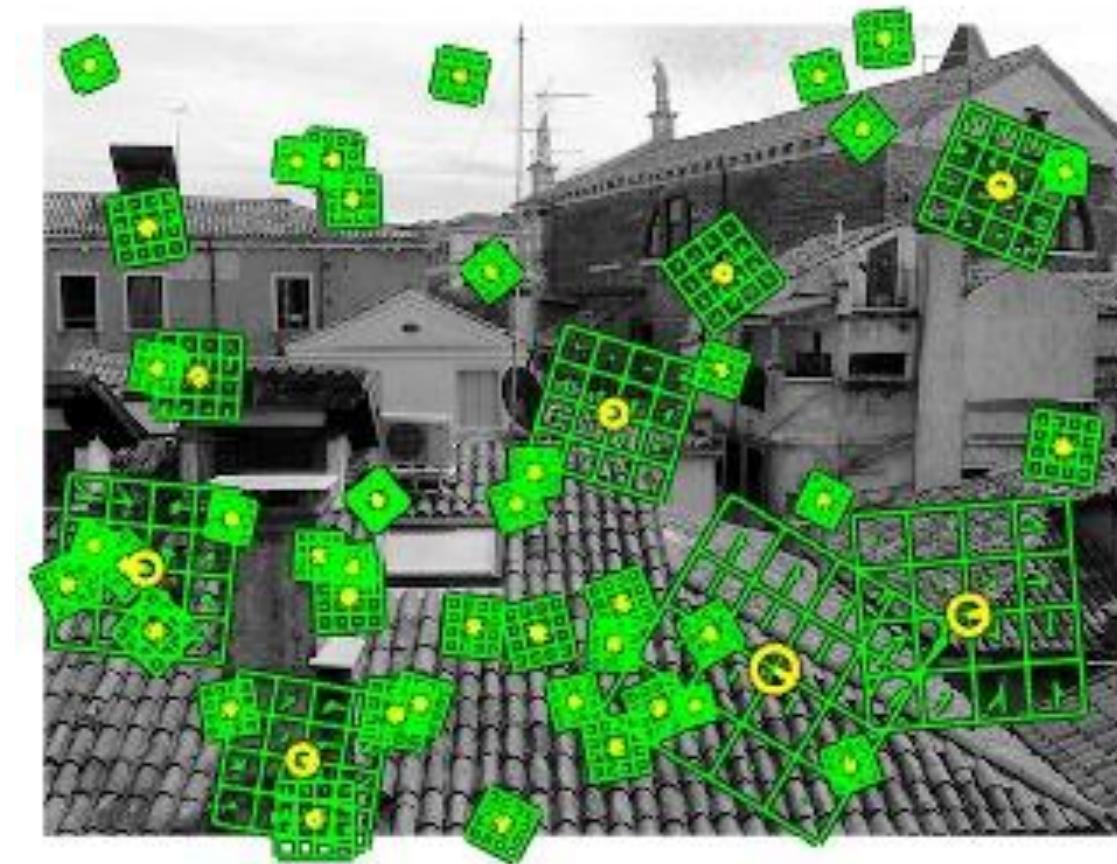
Gaussian weighting

SIFT descriptor

(16 cells x 8 directions = 128 dims)



# HOG variation as SIFT keypoint descriptor



# HOG variation as SIFT keypoint descriptor

- Invariant to:
  - Rotation (due to shifting of the histograms around the main direction).
  - Translation (easy to see).
  - Scale (build at a specific scale).
  - Illumination shift (only derivatives are used).
  - Illumination scale (normalize the feature vector).
  - 3D change of view (the descriptor is of local keypoints).

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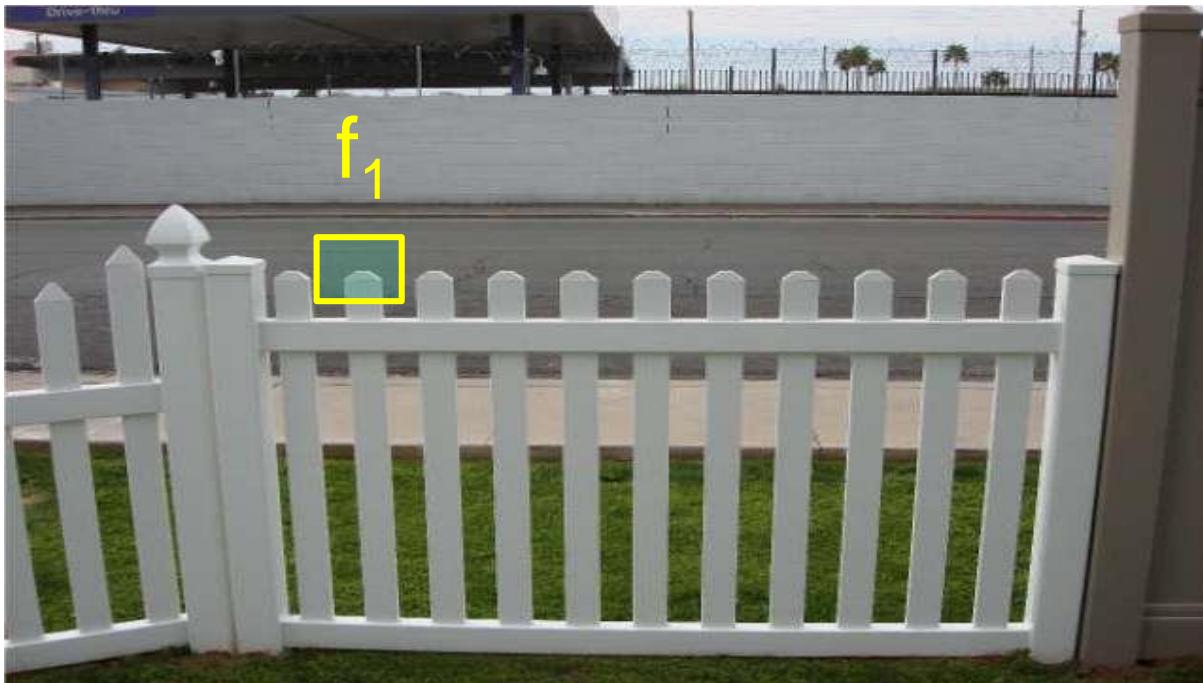
# SIFT Feature matching

- Given a feature in  $I_1$ , how to find the best match in  $I_2$ ?
  1. Define distance function that compares two descriptors
  2. Test all the features in  $I_2$ , find the one with min distance
- What distance function to use?

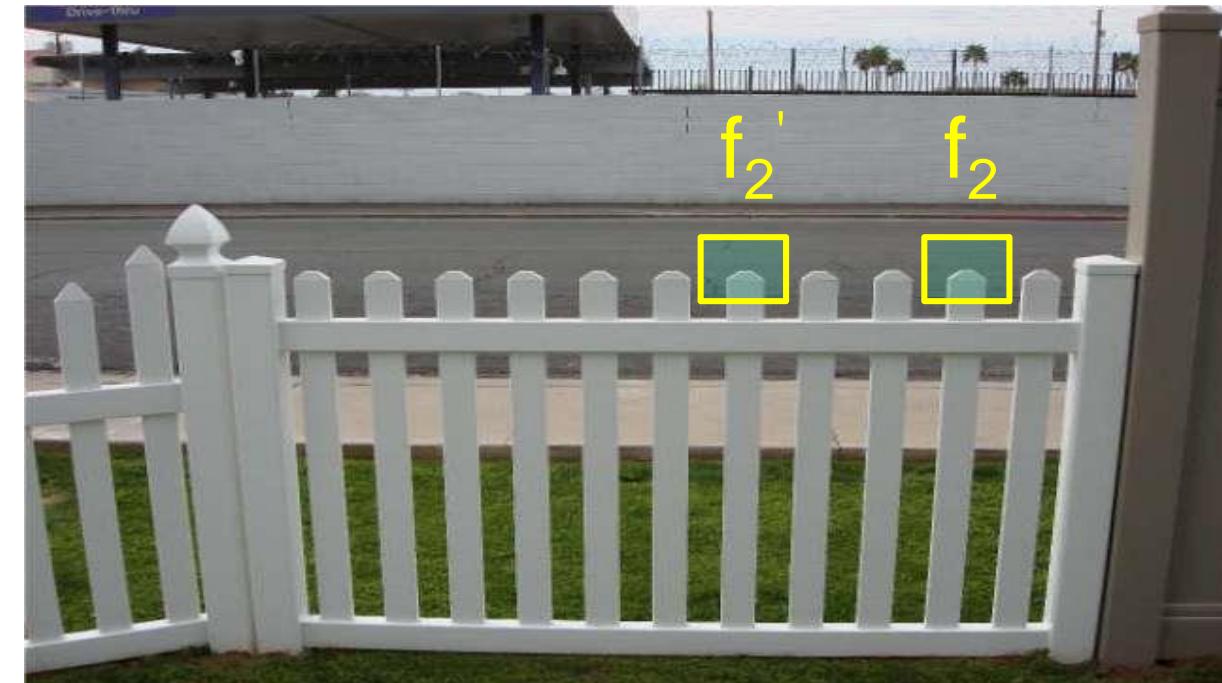
# SIFT Feature matching

- What distance function to use?

- Simple approach: L<sub>2</sub> distance,  $L_2 = ||f_1 - f_2|| = \sqrt{\sum_i (f_{1i} - f_{2i})^2}$
- can give small distances for ambiguous (incorrect) matches.



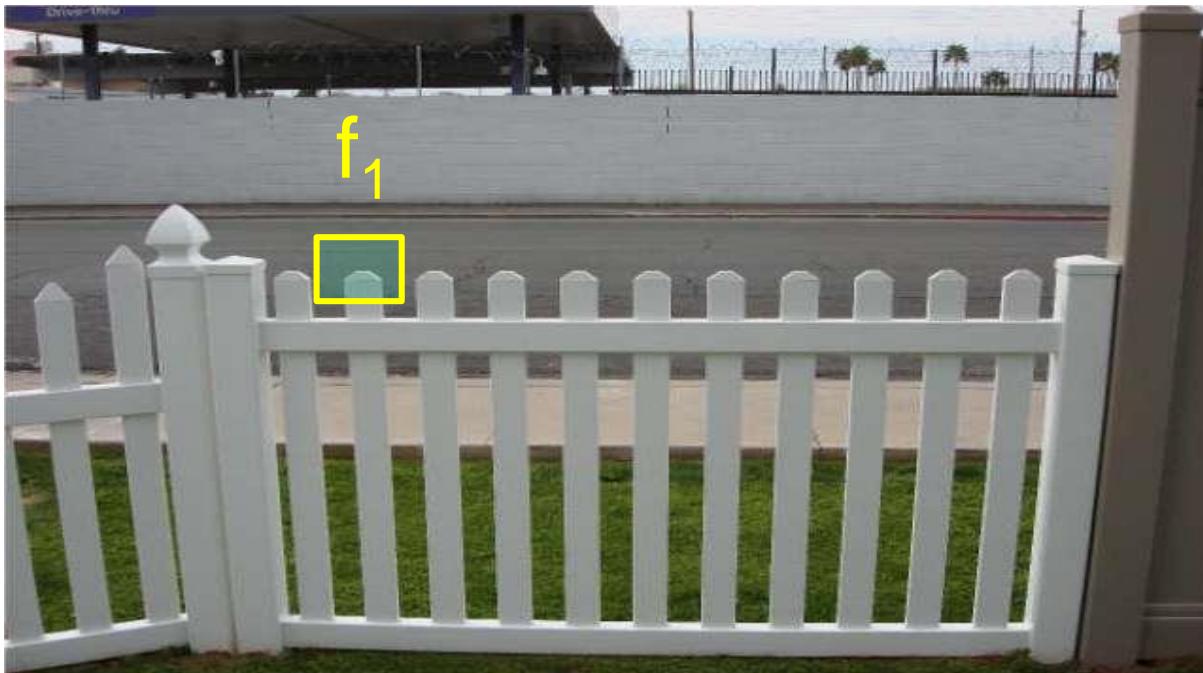
$I_1$



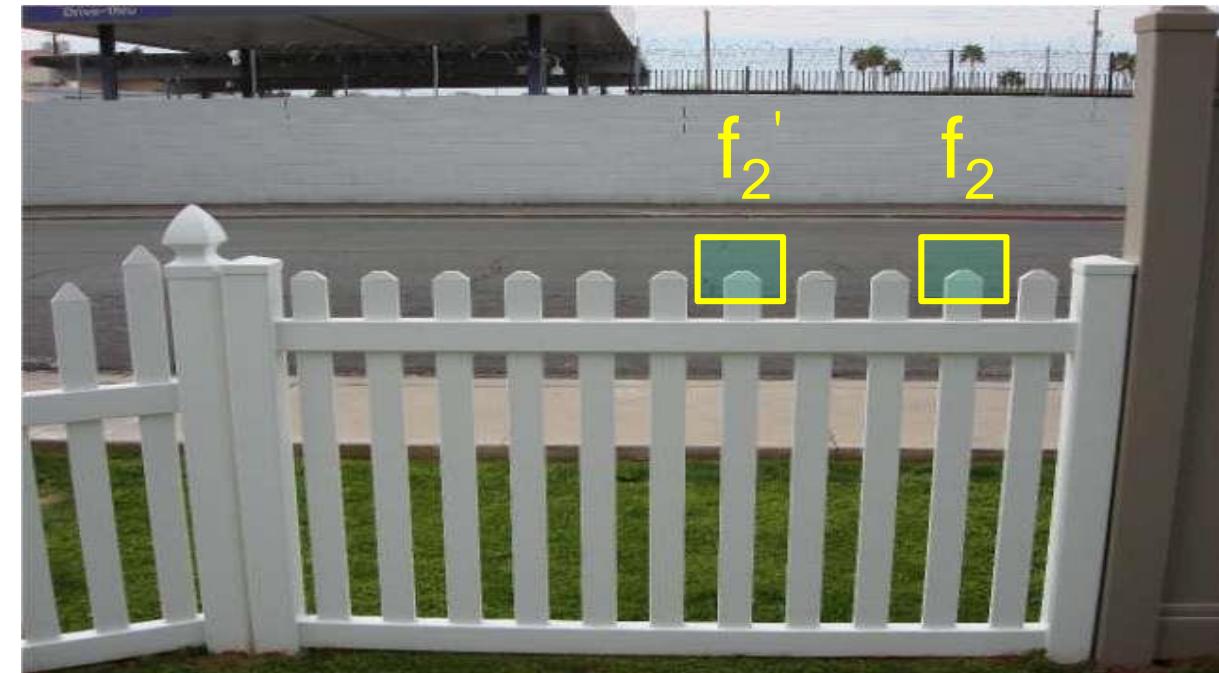
$I_2$

# SIFT Feature matching

- Better approach: ratio distance:  $\|f_1 - f_2\| / \|f_1 - f_2'\| < TH$ 
  - $f_2$  is best match to  $f_1$  in  $I_2$
  - $f_2'$  is 2<sup>nd</sup> best match to  $f_1$  in  $I_2$
  - gives larger values for distinct matches.



$I_1$



$I_2$

# What haven't been covered about SIFT

- Computational fast search of descriptors.
- A lot of minor engineering steps (e.g. thresholding of features).
- And more... this algorithm is 28 pages long article (with 52000 citations!!!)
  - <https://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf>

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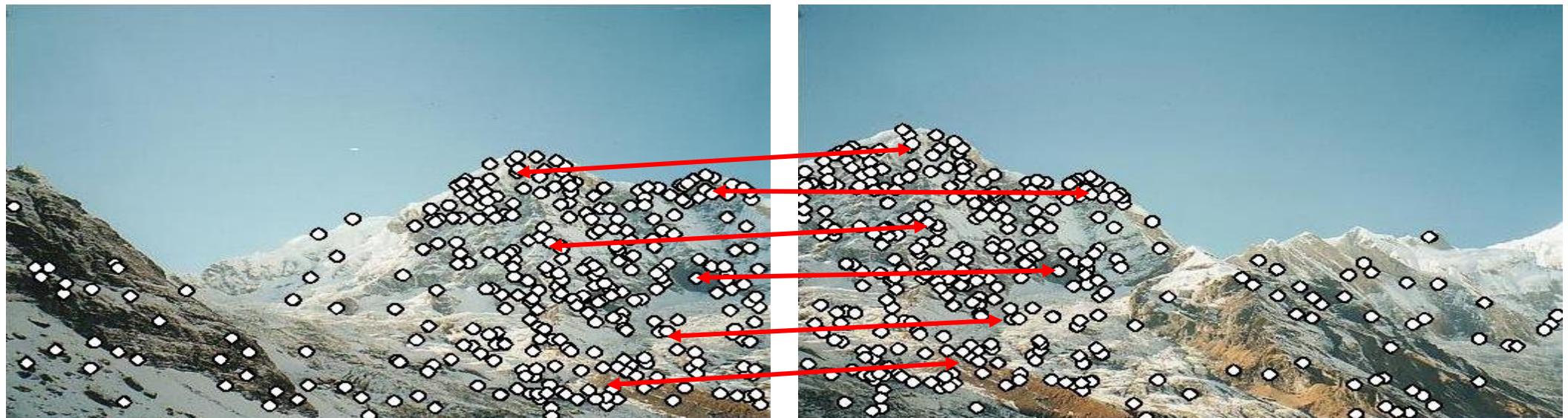
# Panoramas

- We have two images – how do we combine them?



# Panoramas

- Use SIFT to match descriptors of the two images.
- Between the two images there can be an unknown homographic transformation.
  - How do we align the two images?



# Panoramas

- Find the best homographic projection from  $I_2$  to  $I_1$  using RANSAC.
  - Finding this homographic projection is the same as finding the camera calibration matrix that we've seen, only with 3X3 matrix.
  - RANSAC is used to drop wrongly matched points (outliers). Only 3 points needed to be chosen at random to find a RANSAC projection.

