

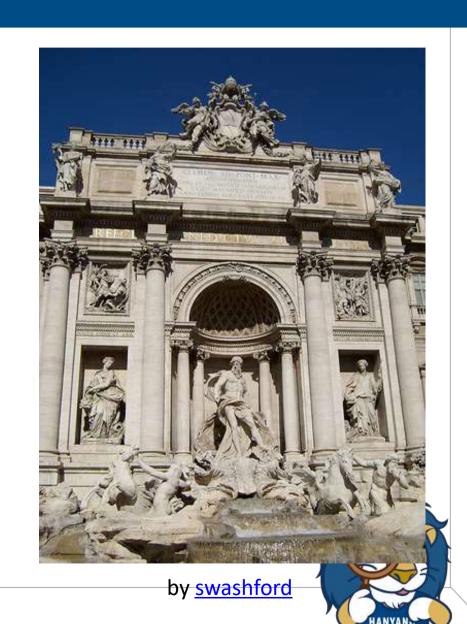
Feature Detection

automatic 32 DH21 10;103





by <u>Diva Sian</u>

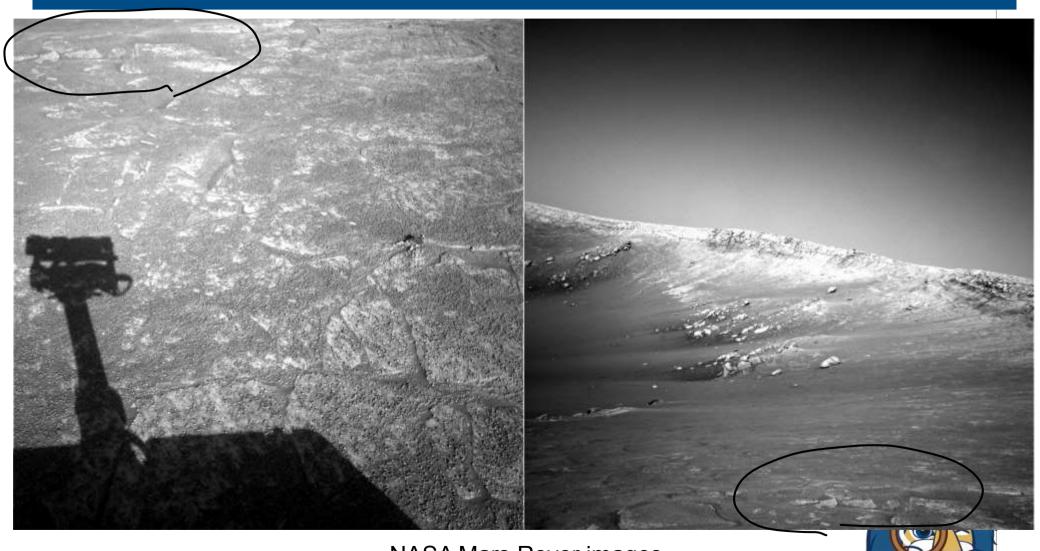


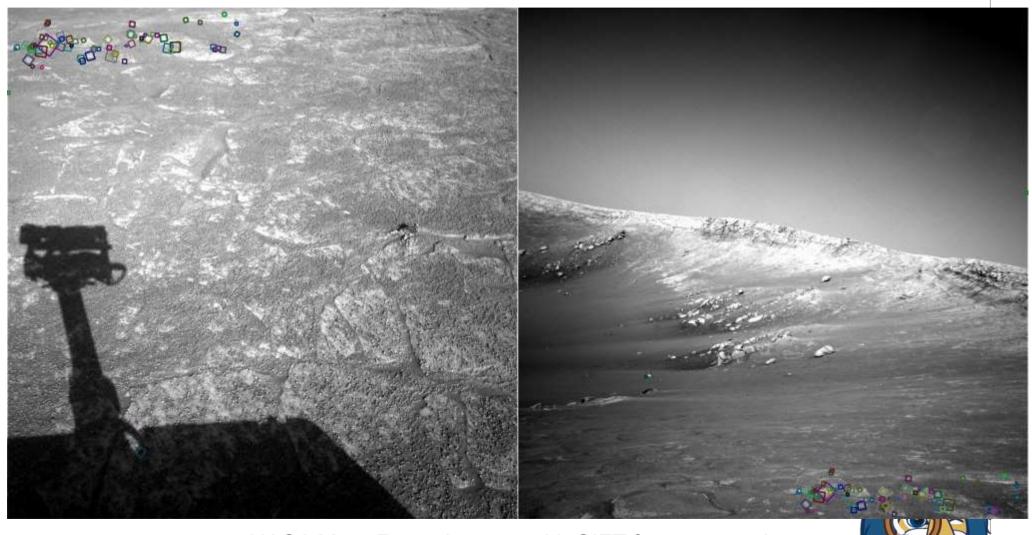




by <u>Diva Sian</u> by <u>scgbt</u>







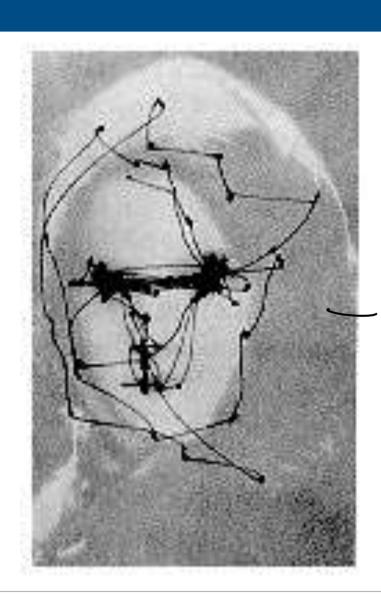
NASA Mars Rover images with SIFT feature matches

Figure by Noah Snavely

How to Match?

Human eye movements

What catches your interest?





Yarbus eye tracking

How to Match?

Corresponding points





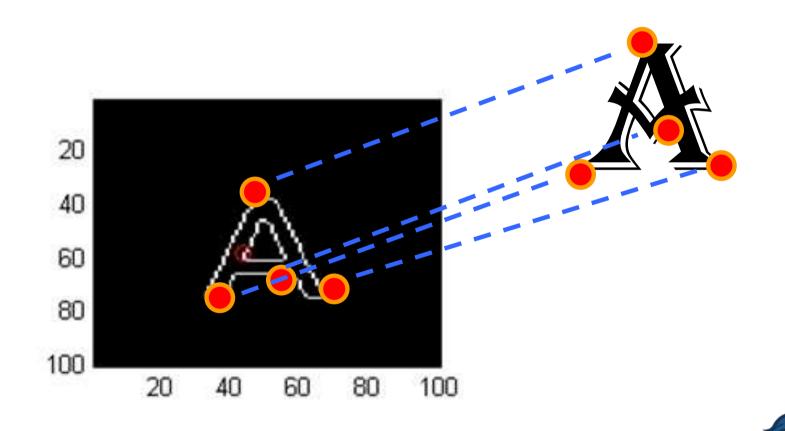
Example: automatic panoramas



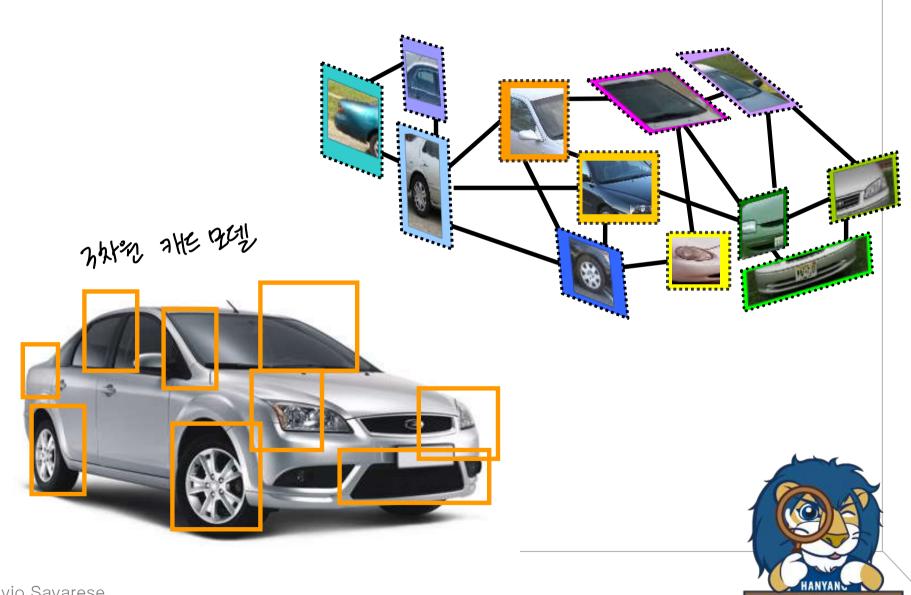


Credit: Matt Brown

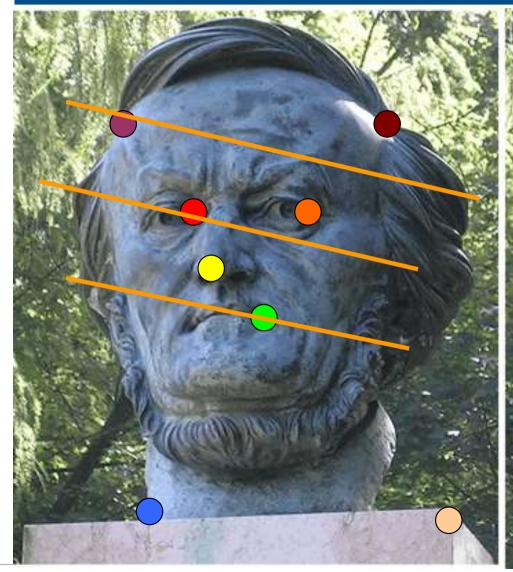
Example: fitting an 2D shape template

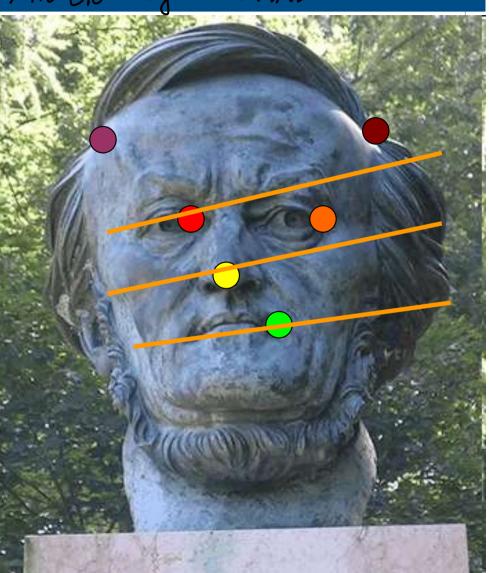


Example: fitting a 3D object model



Example: estimating homography/fundamental matrix that corresponds two views hard and anexal analysis of the corresponding the corresponding the corresponding to the correspondi





Example: visual tracking



Tracking over consecutive video frames

30 fecture \$501 (2011, Ghape..)

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Other Applications

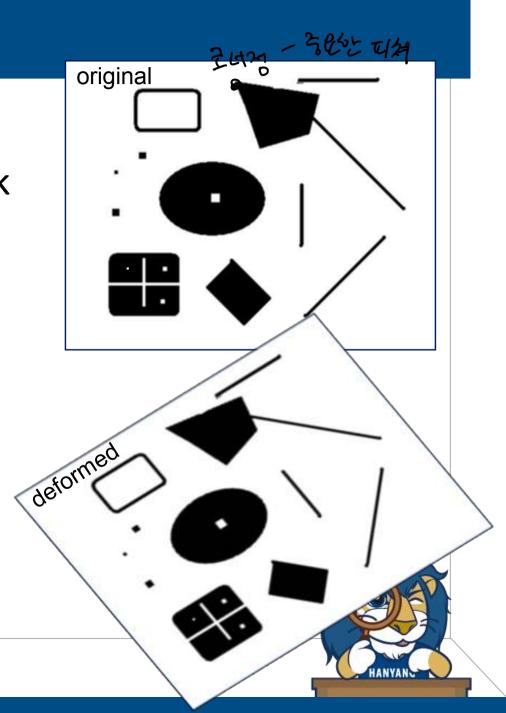
- Key (feature) points are used for:
 - Image alignment
 - 3D reconstruction
 - Motion tracking
 - Robot navigation
 - Indexing and database retrieval
 - Object recognition
- Almost everywhere in computer vision



Choosing Interest Points

- Which points would you choose?
 - Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again.

corner detector



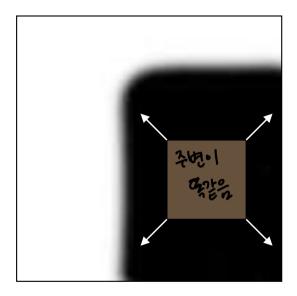
Intuition

Good features to match

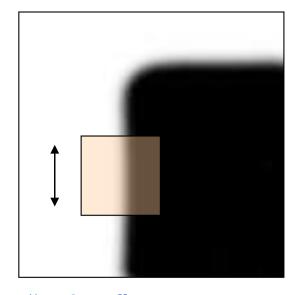


Corners

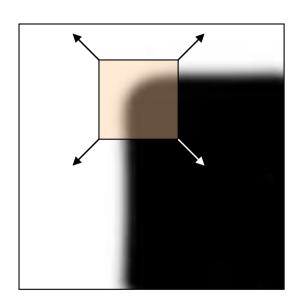
How does the window change when you shift it?



"flat" region: no change in all directions



"edge": no change along the edge direction



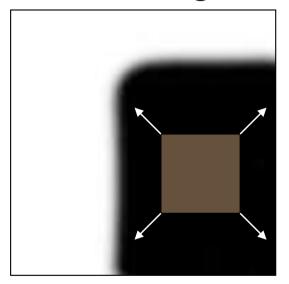
"corner":
significant
change in all
directions

Corners

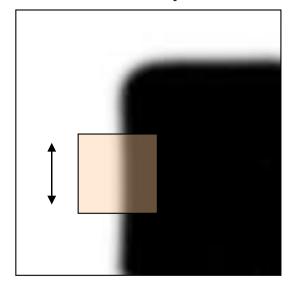
- Why Corners?
- A W A C
- A+B+C
 -> cornerts orce to the agriculture of the ag

olt ultsez corner detection

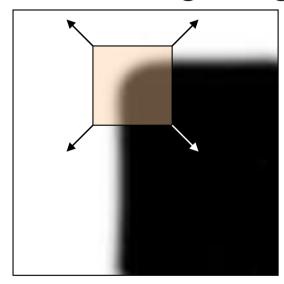
Shifting the window in any direction causes a big change



"flat" region: no change in all directions

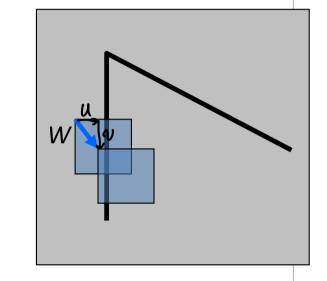


"edge": no change along the edge direction



"corner":
significant
change in all
directions

- Consider shifting the window W by (u,v)
 - how do the pixel values in W change?
 - compare each pixel before and after by summing up the squared differences (SSD)



– this defines an SSD "error" E(u,v):

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



Small motion assumption (small u, v)

Taylor Series expansion of *I*:

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

If the motion (u,v) is small, then first order approximation is good enough;

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



linear, 22/19/24/2 ZALTIE

군사가 유민가 교내 : 기+ U ≈ U : U기 말잖기 작을 때 Under small motion assumption

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

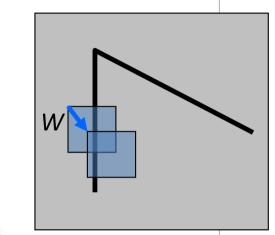
$$\approx \sum_{(x,y)\in W} (I(x,y) + I_x(x,y)u + I_y(x,y)v - I(x,y))^2$$

$$\approx \sum_{(x,y)\in W} (I_x(x,y)u + I_y(x,y)v)^2$$



• E(u,v) is locally approximated as a *quadratic form*

$$E(u,v) \approx \sum_{(x,y)\in W} (I_x(x,y)u + I_y(x,y)v)^2$$



$$\approx \sum_{(x,y)\in W} \left(I_x^2 u^2 + 2I_x I_y uv + I_y^2 v^2\right)$$

$$\approx Au^2 + 2Buv + Cv^2$$

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

U. V7+ 313 7524 265%

Harris corner detection: the math



가까운 때생들에서 가는





$$\approx$$

$$E(u,v) \approx Au^2 + 2Buv + Cv^2$$

$$\approx \left[\begin{array}{ccc} u & v \end{array}\right] \left[\begin{array}{ccc} A & B \\ B & C \end{array}\right] \left[\begin{array}{ccc} u \\ v \end{array}\right]$$





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

 $A = \sum_{x} I_x^2$ মঙ্গুড়া গুলায়ে I_x^2

 $(x,y)\in W$ birish is applied biring to H

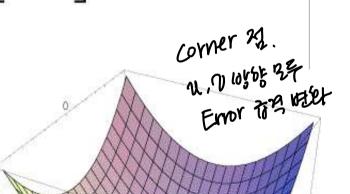
$$\dot{H}$$



 $B = \sum I_x I_y$ $(x,y)\in W$

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

Let's try to understand its shape.



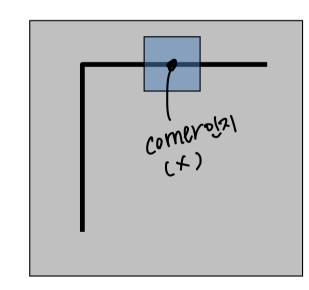
At horizontal edges

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

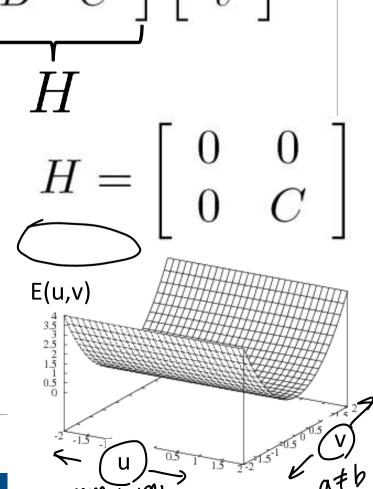
$$A = \sum_{(x,y)\in W} I_x^2$$

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

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



Horizontal edge:
$$I_x = 0$$
 $-$





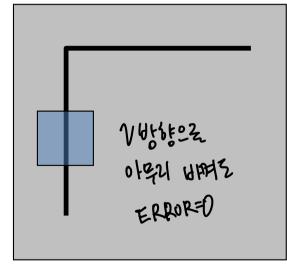
At vertical edges

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

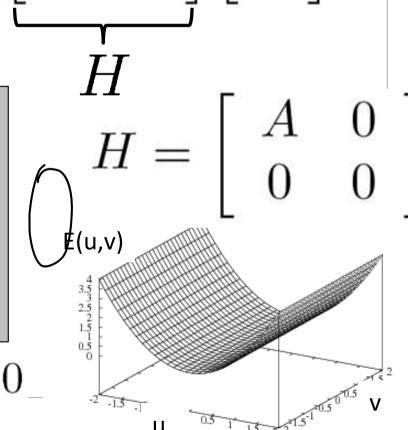
$$A = \sum_{(x,y)\in W} I_x^2$$

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

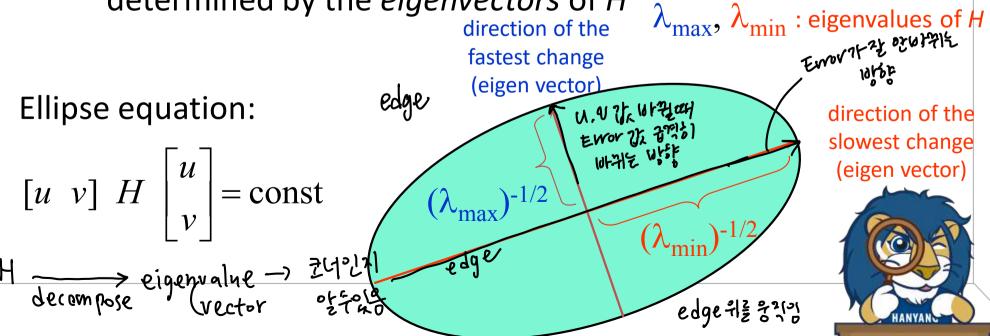
$$C = \sum_{(x,y)\in W} I_y^2$$



Vertical edge: $I_y=0$



- General case
 - Shape of H tells us something about the distribution of gradients around a pixel
 - We can visualize H as an ellipse where the axis lengths determined by the eigenvalues of H, and orientations determined by the eigenvectors of H



$$E(u,v) \approx \left[\begin{array}{ccc} u & v \end{array}\right] \left[\begin{array}{ccc} A & B \\ B & C \end{array}\right] \left[\begin{array}{c} u \\ v \end{array}\right]$$

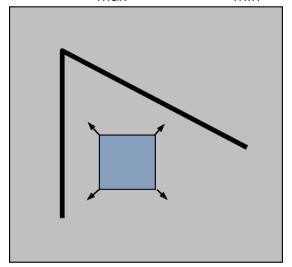
$$H_{2 \times 2} \quad Hx_{\max} = \lambda_{\max} x_{\max}$$

$$Hx_{\min} = \lambda_{\min} x_{\min}$$

- Eigenvalues and eigenvectors of H
 - Define shift directions with the smallest and largest change in error
 - x_{max} = direction of largest change in E eigen vector X:

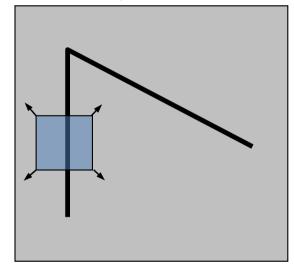
 Error পুনি আয়া সময় আয়
 - λ_{max} = amount of change in direction x_{max} eigenvalue 入: 転換 ななしたな なり 理想
 - x_{min} = direction of smallest change in E
 - λ_{min} = amount of change in direction x_{min}

Small λ_{max} & small λ_{min}



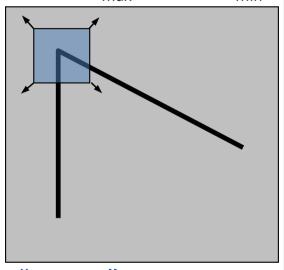
"flat" region: no change in all directions

Large λ_{max} & small λ_{min}



"edge": no change along the edge direction

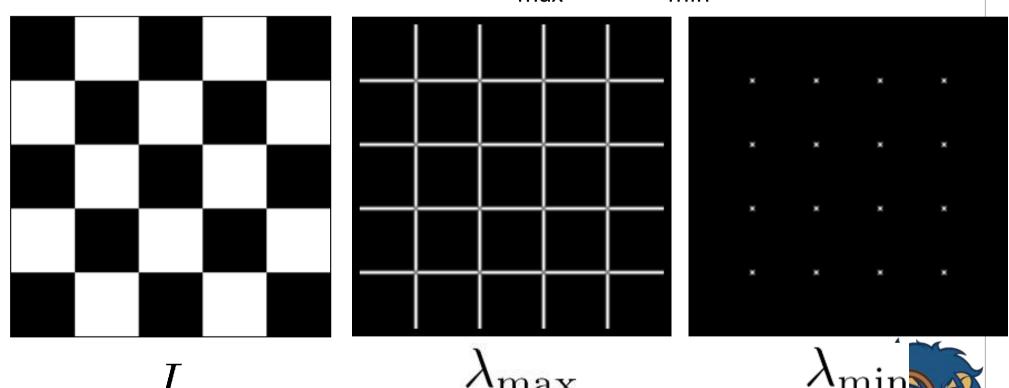
Large λ_{max} & large λ_{min}



"corner": significant change in all directions

eigenvalue sorting

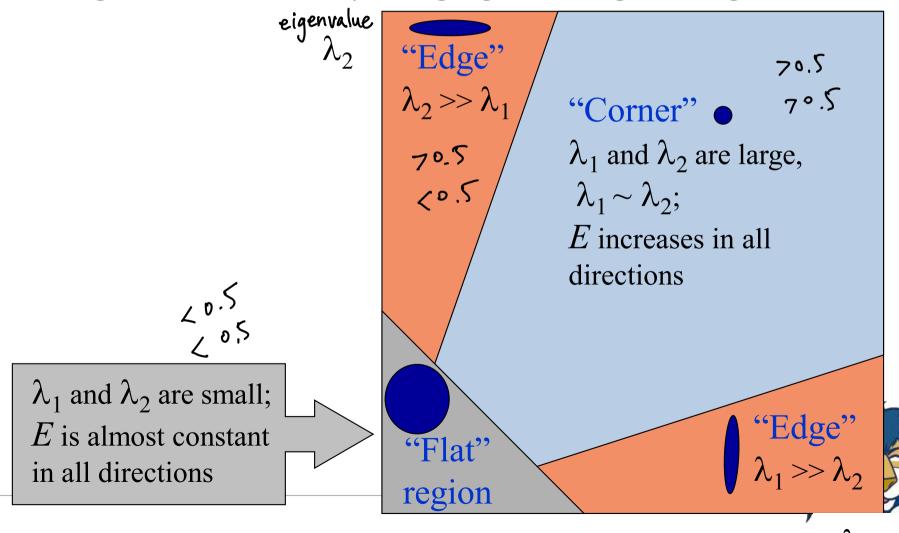
- Real Example
 - At corner points, both λ_{max} and λ_{min} are large



— edge, corder娛妈似

Cornerollyof

• Two eigen values and corresponding region in the given image



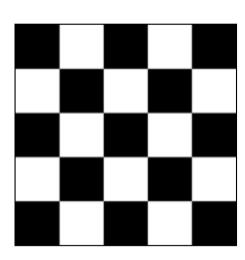
- Harris operator (metric)
 - Called the "Harris Corner Detector" or "Harris Operator"
 - Shi-Tomasi corner detector: λ_{\min}
 - Harris and Stephens: $det(H) \alpha \cdot trace(H)$
 - Harmonic mean: det(H)/trace(H)
 - Among lots metrics, this is one of the most popular
 - Harris response

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

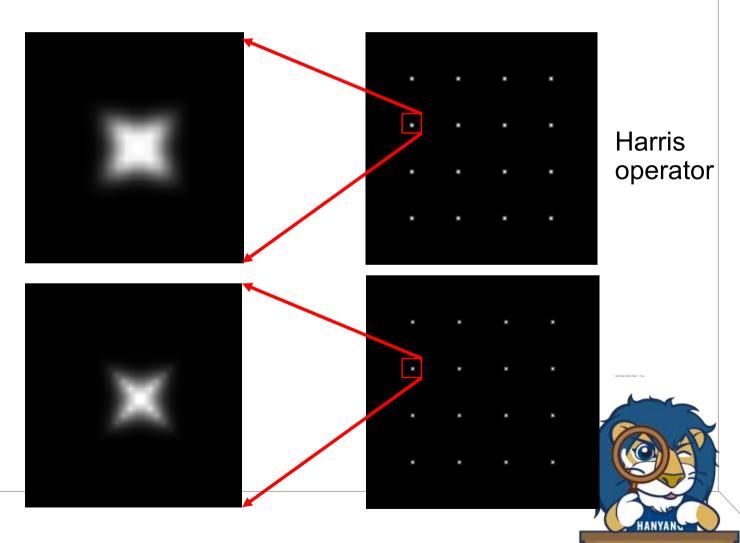


• Harris operator value f $pprox \lambda_{\min}$

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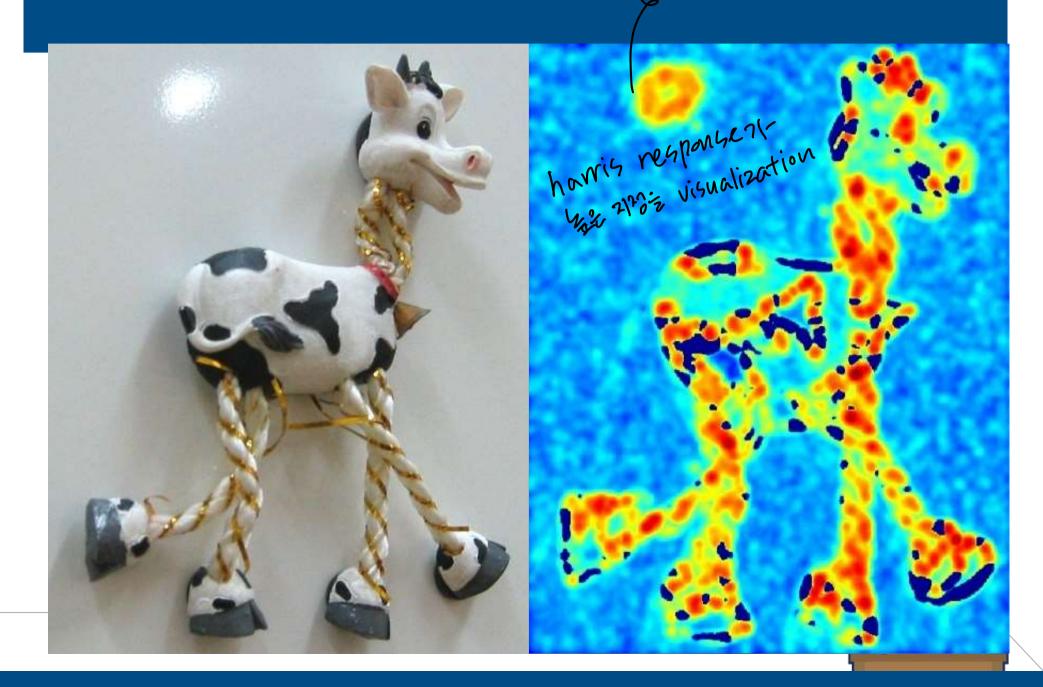


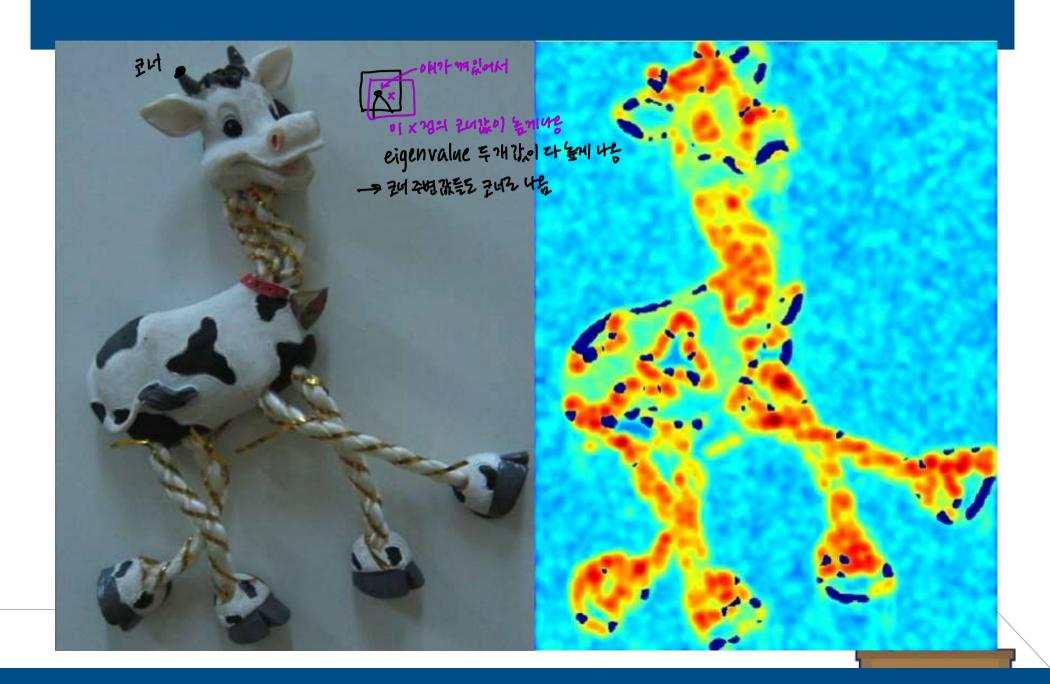
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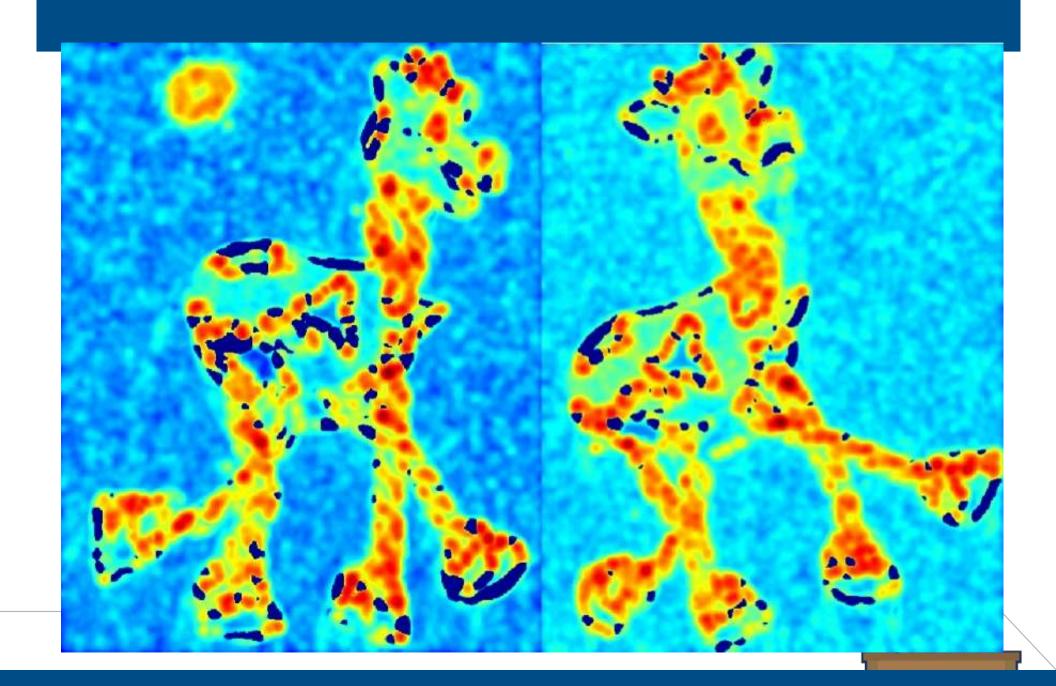




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Local maxima of f

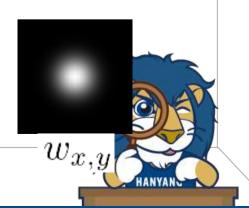


- Weighting the derivatives
 - In practice, using a simple and equally weighted window W doesn't work too well

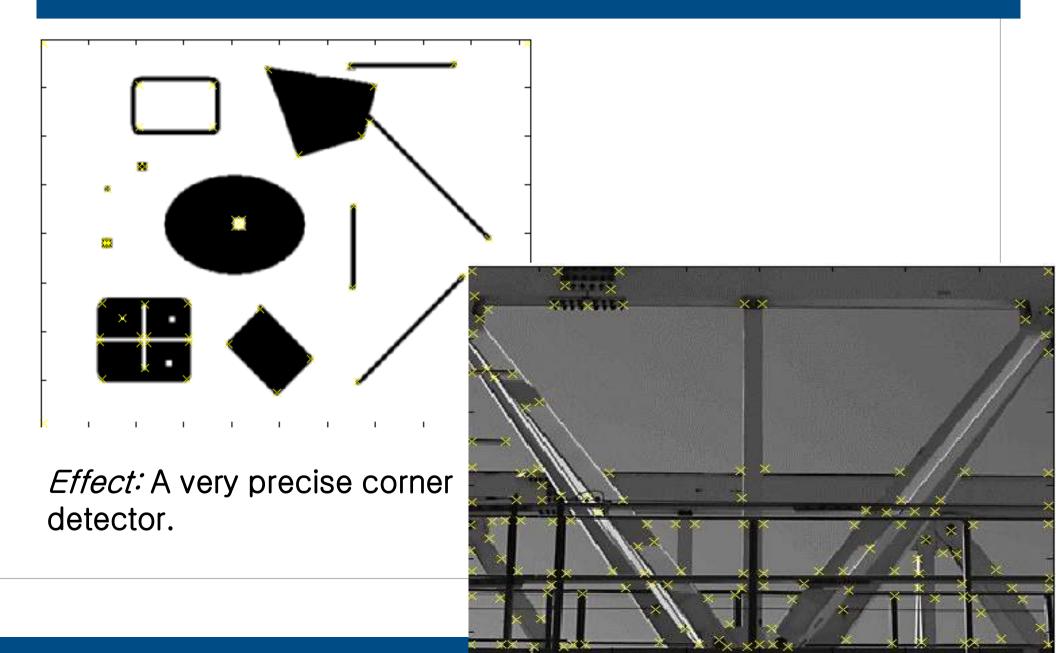
$$H = \sum_{(x,y)\in W} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

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

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



Harris detector: results

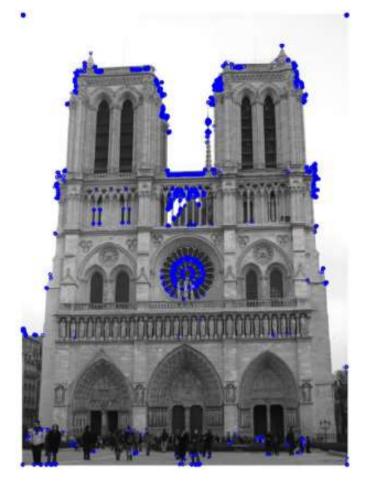


Harris detector: results



Adaptive Non-maximal Suppression (CVPR'05)

- To be a feature, it must be
 - A local maxima
 - Response (f) value is significantly greater than neighbors



Harris corner detection result



Adaptive Non-maximal Suppression (CVPR'05)

- Local Non-Maximum suppression
 - Slide a 3x3 window
 through the image and
 suppressing all the key
 points except for the key
 point with maximum
 confidence



Local Non-Maximum suppression

Adaptive Non-maximal Suppression (CVPR'05)

- Adaptive Non-Maximal Suppression
 - Apply Local non-maximum suppression
 - Keep track of the minimum distance to a larger magnitude interest point per point
 - Sort the list of interest points by descending radius and take the top N



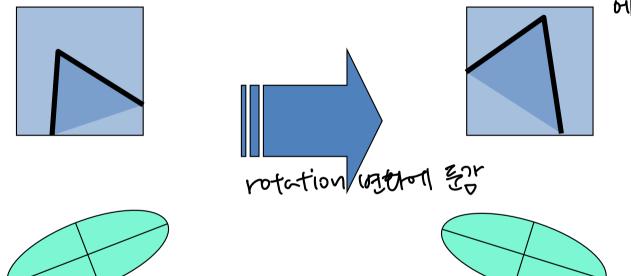
Adaptive Non-Maximal Suppression

Harris Detector: Invariance Properties

Translation and rotation invariance

Harris Corner Detector & rotation, translation

에 관계했기 코너 강출

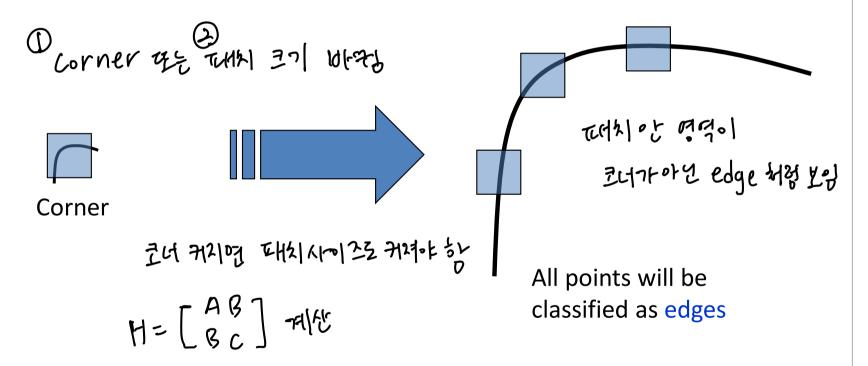


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response is invariant to image rotation

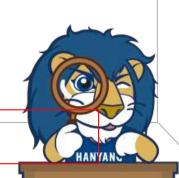
Harris Detector: Invariance Properties

Scaling

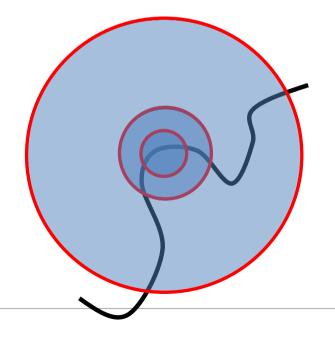


scale useral ors

Not invariant to scaling



- Suppose you're looking for corners
 - Key idea: find scale that gives local maximum of f in both position and scale
 - One definition of f: the Harris operator



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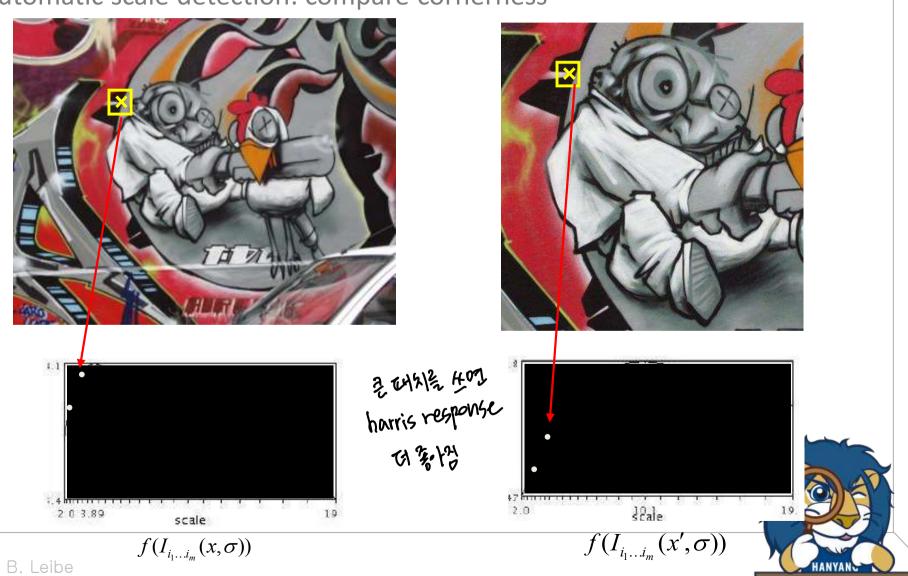
Real example

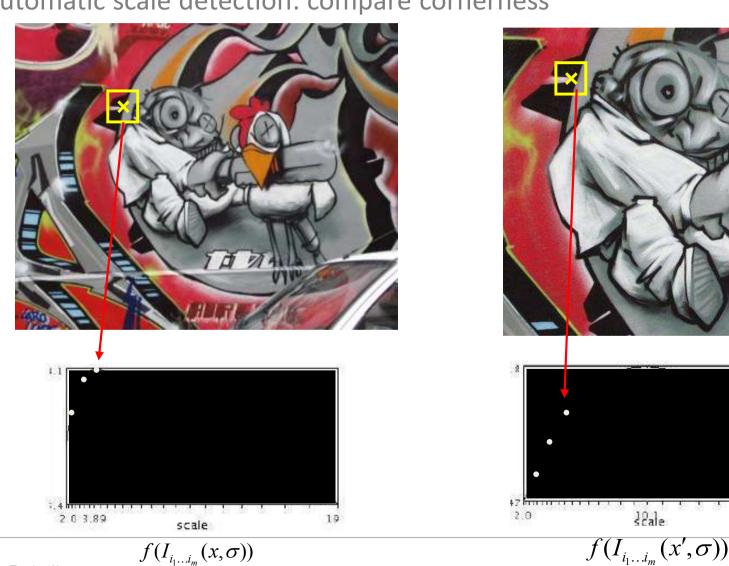


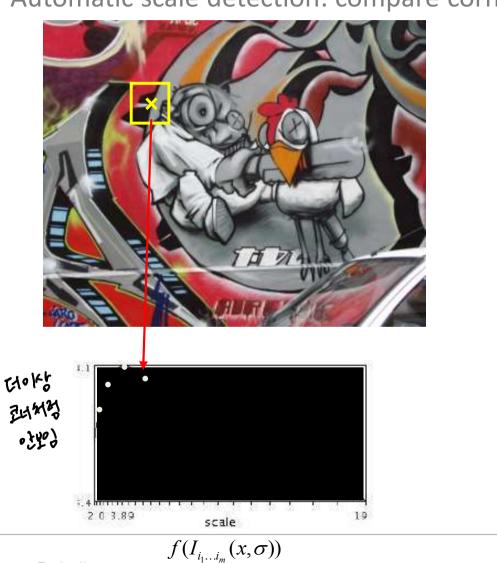
$$f(I_{i_1...i_m}(x,\sigma)) = f(I_{i_1...i_m}(x',\sigma'))$$

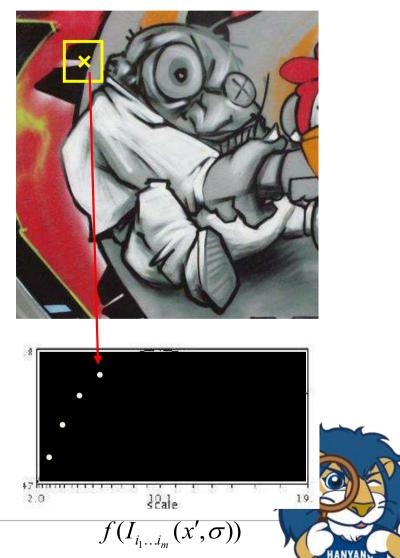






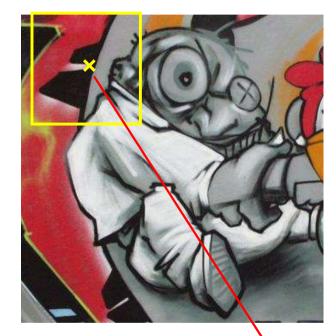


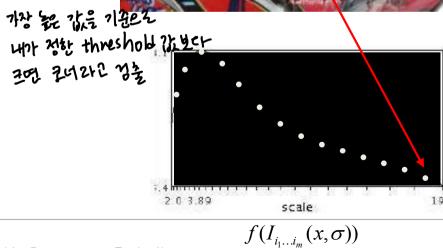




• Automatic scale detection: compare cornerness







Cornornessor

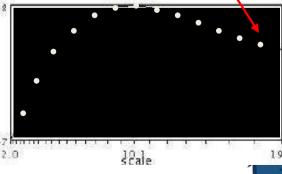
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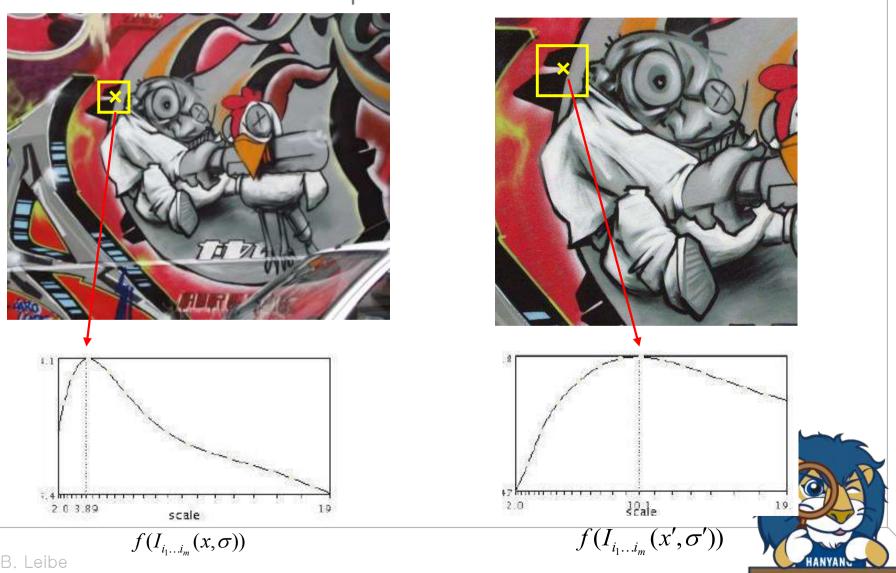
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 $f(I_{i_1...i_m}(x',\sigma))$



Practical implementation

그김 사이스틱 줄임 ㅋ 제산 속면 이걸

 Instead of computing f with larger windows, implement using a fixed window size with an image pyramid









Original image size



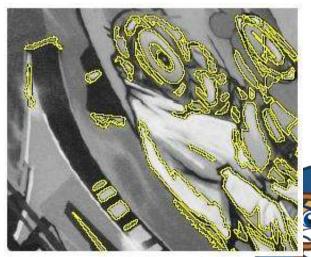
Other Detectors

- Scale-invariant feature transform (SIFT)
 - Lowe. ICCV'99
 - Find local maxima in position-scale space of Difference-of-Gaussian



SIFT result

- Maximally Stable Extremal Regions (MSER)
 - Matas et al. BMCV'02
 - Based on Watershed segmentation algorithm
 - Select regions that stay stable over a large parameter range



MSER result

Summary

- Why interest (feature) points?
 - Used in many applications for matching
- Harris corner detector
 - Traditional approach
 - Give motivation in many follow-up studies
- Invariant properties of Harris corner feature
 - Rotation invariant
 - Partially invariant to affine changes of brightness
 - Originally not invariant to scaling
 - But can be overcome by comparing cornerness in different scale

Matlab

- Download (licensed ver.)
 - https://iic.hanyang.ac.kr/office365
- Quick guide (official)
 - FYI
 - https://kr.mathworks.com/videos/introduction-to-matlab-81592.html
- HW1 (09/20~09/25)
 - Check out our course website
 - Linear image filtering



Thank you!

