CS688: Web-Scale Image Search Classical Keypoint Localization

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Course URL: http://sgvr.kaist.ac.kr/~sungeui/IR



Class Objective (Ch. 2 of My Draft)

- Get to know related conferences
- Understand locally invariant features
 - Key point localization
 - Harris detector
- At Last class:
 - Student activities including paper presentations and mid- and final-term project presentations
 - Grading policy



Homework for Every Class

- Preview the lecture slides first; just 5 min
- Come up with one question on what we have discussed today
 - 1 for typical questions (that were answered in the class)
 - 2 for questions with thoughts or that surprised me
- Write questions 3 times before the mid-term
 - Multiple questions in one time will be counted as one time
- Common questions are addressed at my draft
 - Some of questions will be discussed in the class
- If you want to know the answer of your question, ask me or TA on person



Homework for Every Class

- Go over recent papers on image search
 - High quality papers: Papers published at the top-tier conf.; e.g., CVPR, ICCV, ECCV, ACM ICMR, NeurIPS, ICML, MM, SIGGRAPH
 - Recent publication: papers published since 2017
 - Find and browse two papers, and submit two summaries before every beginning of the Tue. Class
 - Online submission is possible
- Think about possible team members
 - You can do the solo project, since we don't have many students in this class of 2021
 - Too late if you think them later...



Content-Based Image Retrieval (CBIR)

 Identify similar images given a userspecified image or other types of inputs

Extract image descriptors (e.g., CNN or SIFT)



Input







Output



Key Components of Image Search

- Image representations
- Indexing algorithms
- Matching methods
- Classification, Localization, etc.
 - Can improve image search or improve these techniques utilizing image search



Image Representations

- SIFT, GIST, CNN, etc.
 - Invariant to different transformations



Image Retrieval

 At pre-processing, build a database for efficient retrieval at runtime

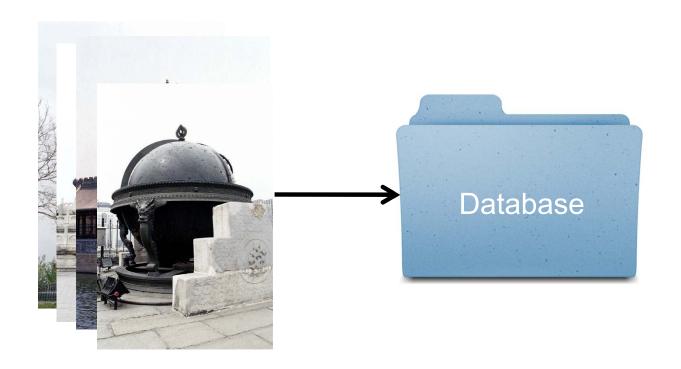
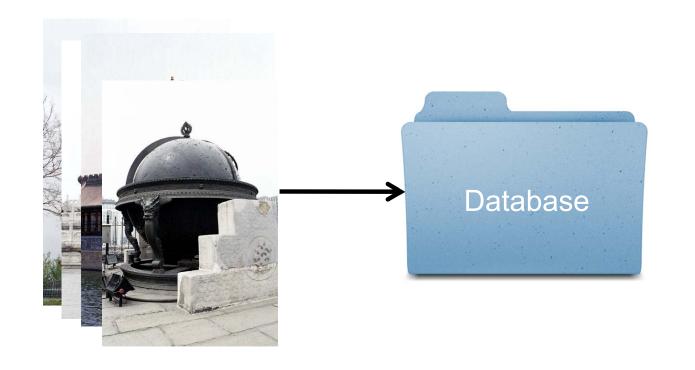




Image Retrieval

 At pre-processing, build a database for efficient retrieval at runtime



Index schemes: vocabulary trees, hashing, and inverted files



Image Retrieval: Runtime Procedure

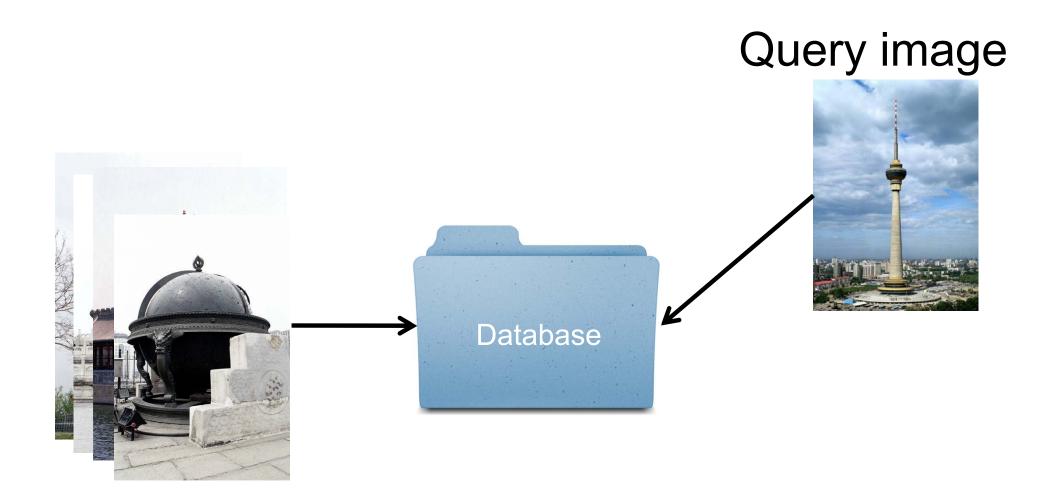
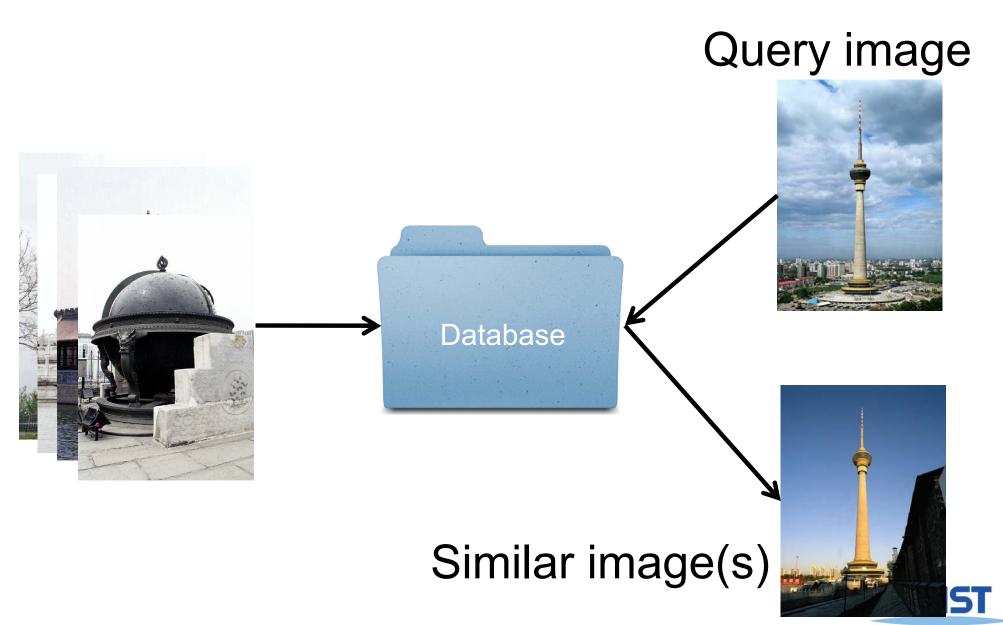




Image Retrieval: Runtime Procedure



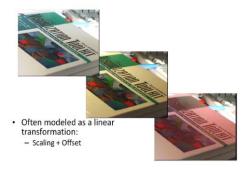
Post-Processing



Motivation for Image Descriptors

 RGB images are not robust for various changes (e.g., geometric and photometric transformations)





- Image descriptors are classified into:
 - Global feature encoding the overall context
 - Local features encoding different parts of objects
- Global and local features are useful, but we focus on local features for now
 - More robust to various changes



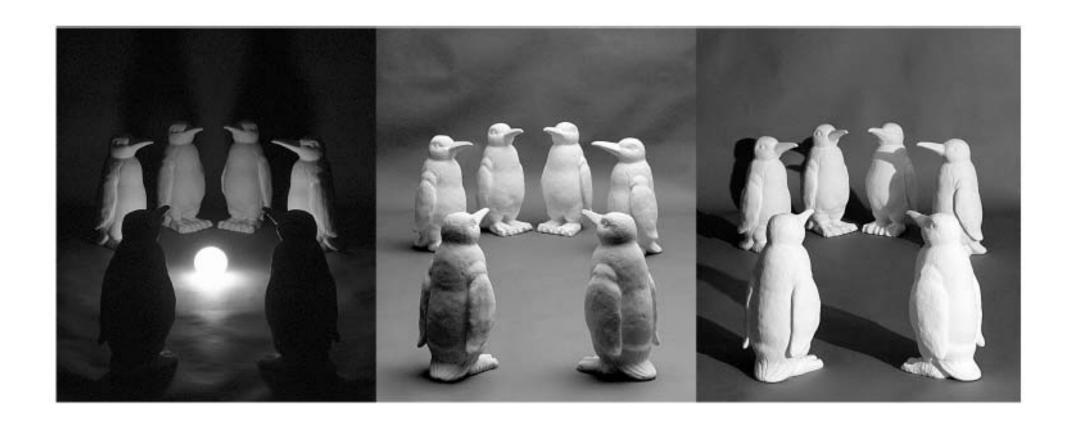
Challenges: viewpoint variation





Michelangelo 1475-1564

Challenges: illumination



Challenges: scale

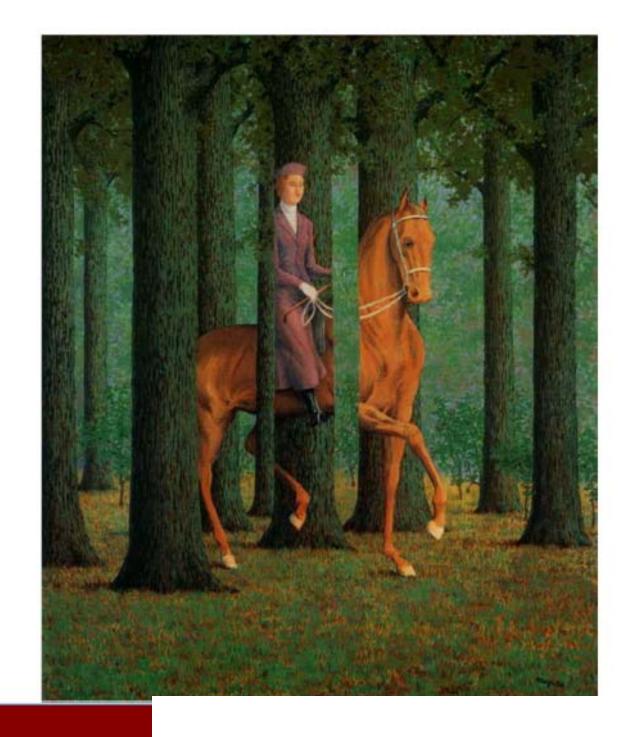


Challenges: deformation



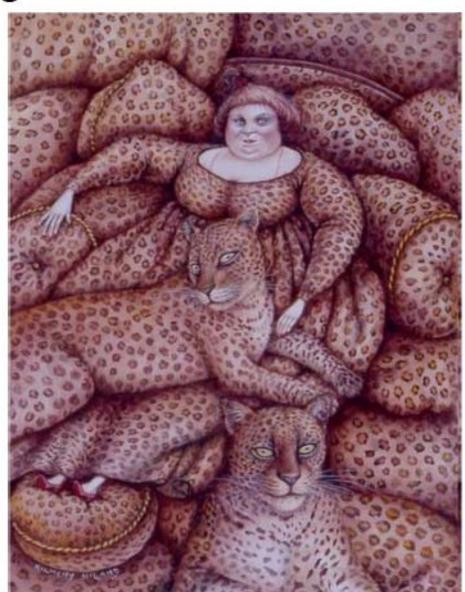


Challenges: occlusion



Magritte, 1957

Challenges: background clutter



Kilmeny Niland. 1995

Challenges: intra-class variation



Slide credit: Steve Seitz

Application: Image Matching



by Diva Sian



by swashford

Slide credit: Steve Seitz

Harder Case



by Diva Sian



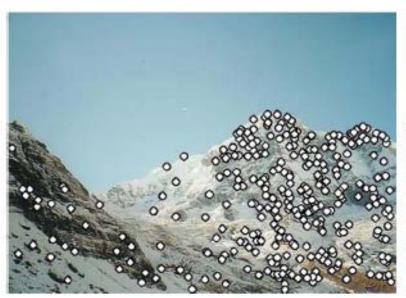
by scgbt

Application: Image Stitching





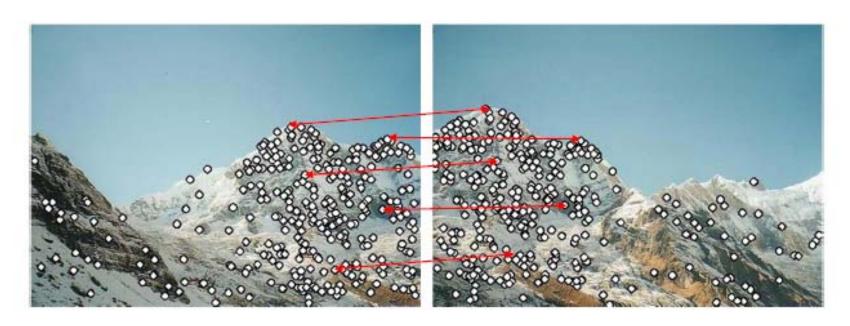
Application: Image Stitching





- · Procedure:
 - Detect feature points in both images

Application: Image Stitching



· Procedure:

- Detect feature points in both images
- Find corresponding pairs

Application: Image Stitching



· Procedure:

- Detect feature points in both images
- Find corresponding pairs
- Use these pairs to align the images

Common Requirements

- Problem 1:
 - Detect the same point independently in both images





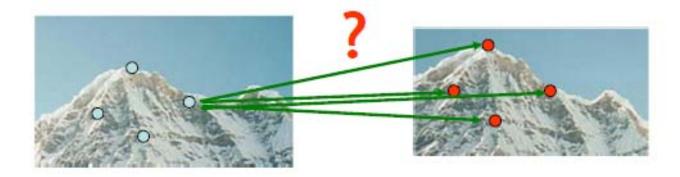
No chance to match!

This lecture

We need a repeatable detector!

Common Requirements

- Problem 1:
 - Detect the same point independently in both images
- Problem 2:
 - For each point correctly recognize the corresponding one



Next lecture

We need a reliable and distinctive descriptor!

Two Different Directions

- Classical approaches
 - Manually designed in image processing and computer vision fields
- Deep learning approaches
 - Learned approaches, but are inspired by many prior (manually crafted) approaches
- In this class
 - We first talk about the classical approaches, followed by deep learning approaches



Many Existing Detectors Available

- Hessian & Harris [Beaudet '78], [Harris '88]
- Laplacian, DoG [Lindeberg '98], [Lowe '99]
- Harris-/Hessian-Laplace [Mikolajczyk & Schmid '01]
- Harris-/Hessian-Affine [Mikolajczyk & Schmid '04]
- EBR and IBR [Tuytelaars & Van Gool '04]
- MSER [Matas '02]
- Salient Regions [Kadir & Brady '01]
- Others...
- Those detectors have become a basic building block for many recent applications in Computer Vision.

Slide credit: Bastian Leibe

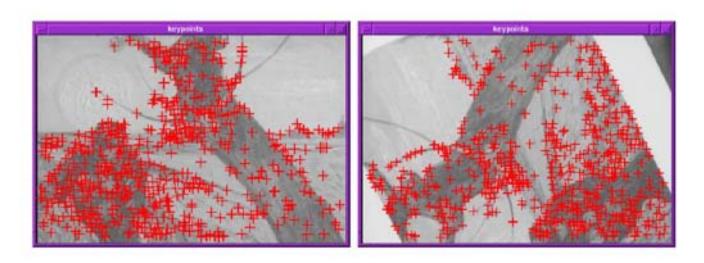
Keypoint Localization



- Goals:
 - Repeatable detection
 - Precise localization
 - Interesting content
 - ⇒ Look for two-dimensional signal changes

Slide credit: Svetlana Lazebnik

Finding Corners



- Key property:
 - In the region around a corner, image gradient has two or more dominant directions
- Corners are repeatable and distinctive

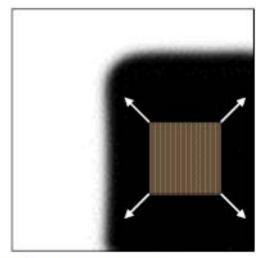
C.Harris and M.Stephens. "A Combined Corner and Edge Detector."

Proceedings of the 4th Alvey Vision Conference, 1988.

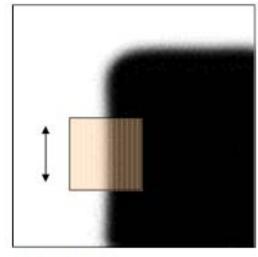
Slide credit: Alyosha Efros

Corners as Distinctive Interest Points

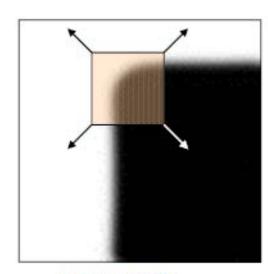
- Design criteria
 - We should easily recognize the point by looking through a small window (locality)
 - Shifting the window in any direction should give a large change in intensity (good localization)



"flat" region: no change in all directions



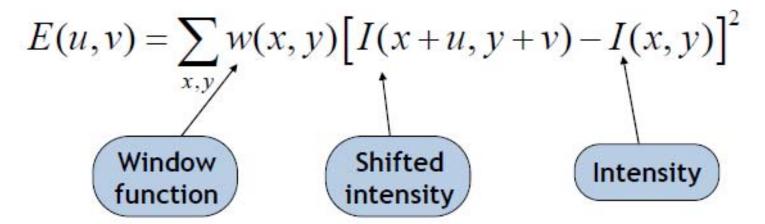
"edge": no change along the edge direction

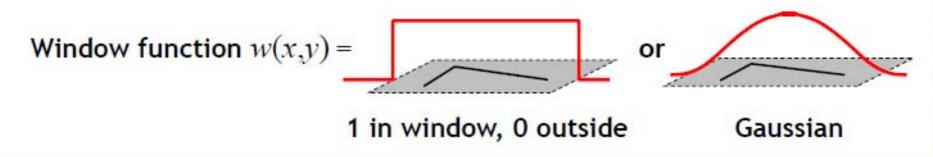


"corner": significant change in all directions

Harris Detector Formulation

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





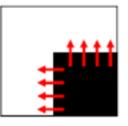
Slide credit: Rick Szeliski

Main Intuition of Harris Detector

• Approximated into the following:

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

• In the case of axis-aligned corner:



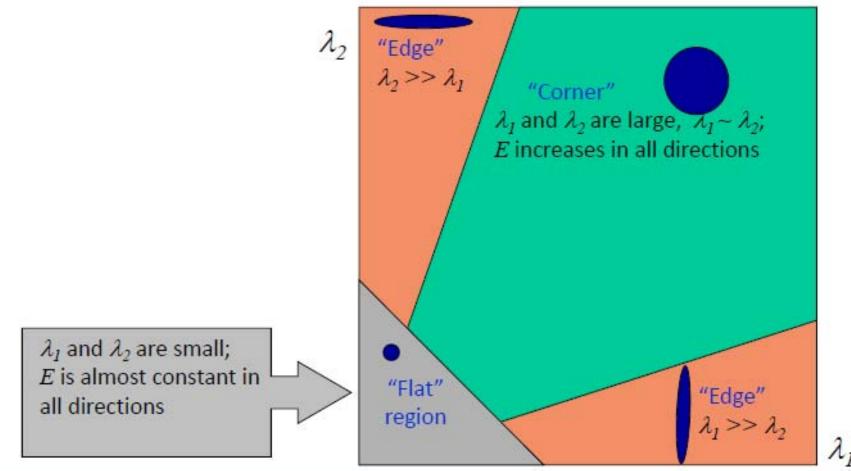
$$M = \sum_{(x,y)\in P} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

- λ corresponds gradient directions
- When both $\lambda_1 \& \lambda_2$ are non-zero, it is corner!
- Can be extended to rotated corners



Interpreting the Eigenvalues

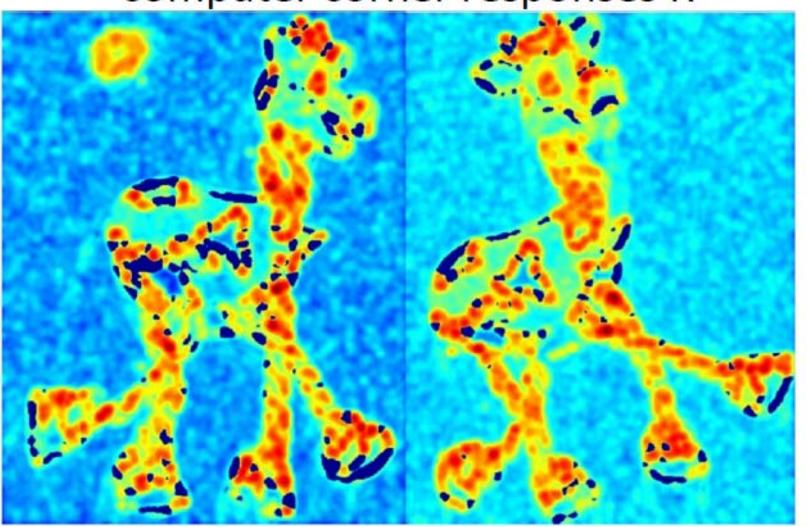
Classification of image points using eigenvalues of M:



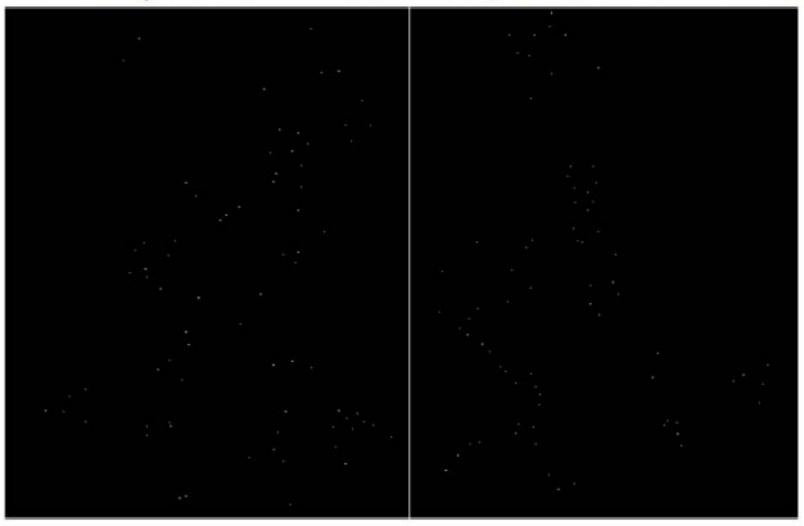
Slide credit: Kristen Grauman



- computer corner responses R



- Take only the local maxima of R, where R>threshold



- Resulting Harris points

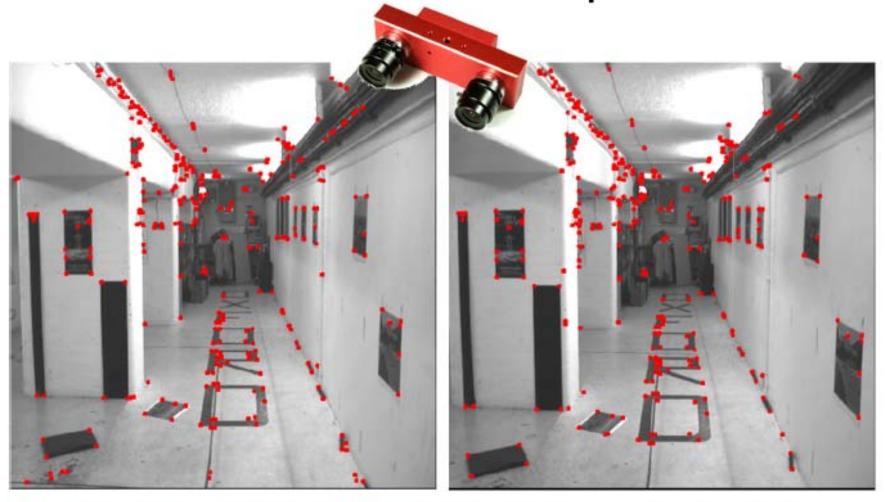


Harris Detector – Responses [Harris88]



Slide credit: Kristen Grauman

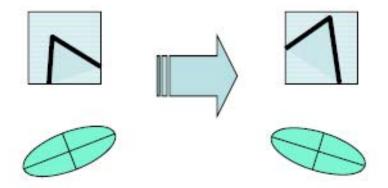
Harris Detector – Responses [Harris88]



· Results are well suited for finding stereo correspondences

Harris Detector: Properties

· Rotation invariance?

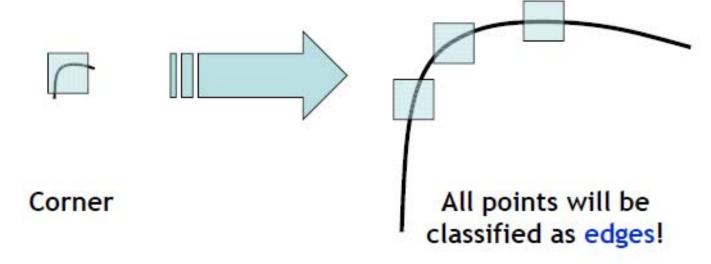


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner response R is invariant to image rotation

Harris Detector: Properties

- Rotation invariance
- Scale invariance?



Not invariant to image scale!

Class Objective were:

- Knew related conferences to our course theme
- Understand locally invariant features
 - Key point localization
 - Harris detector: manually designed detector
 automatically learned detector using deep learning



Next Time...

Scale invariant region selection



Homework for Every Class

- Go over the next lecture slides
- Come up with one question on what we have discussed today
 - https://forms.gle/7vqvJFAcBsebaQs68
- Go over recent papers on image search, and submit their summary
 - Just one or two (Korean or English) paragraphs are okay
 - Do not copy the abstract of the paper
 - https://forms.gle/yq19VqqLXwW7TyvZ9

