CAP6411
Computer Vision Systems
Lecture 4

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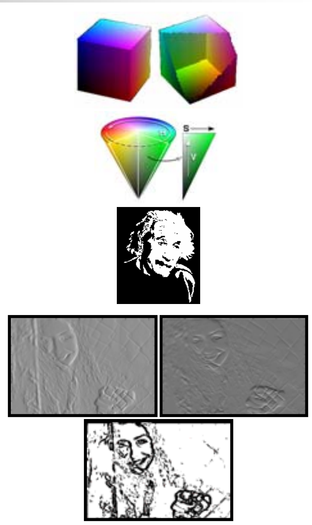
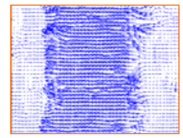
Recap
Typical Visual Features

- Color
  - RGB,
  - HSV,
  - Binary, IR
- Edges
  - Sobel, Canny

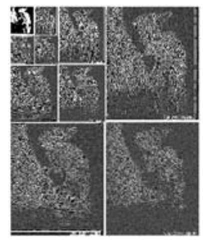


Recap
Typical Visual Features

- Optical flow $uI_x + vI_y + I_t = 0$
  - Lucas Kanade



- Texture
  - GLCM,
  - Law's texture
  - Wavelets, Steerable pyramids
  - Energy, entropy, kurtosis…



Object Detection

Object Detection

Categories
Point detectors
Segmentation
Background Modeling
Supervised Classifiers

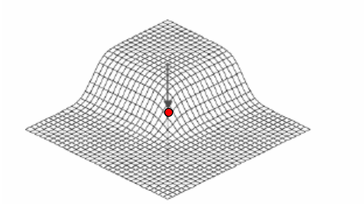
Point Detection

Where can we use it?

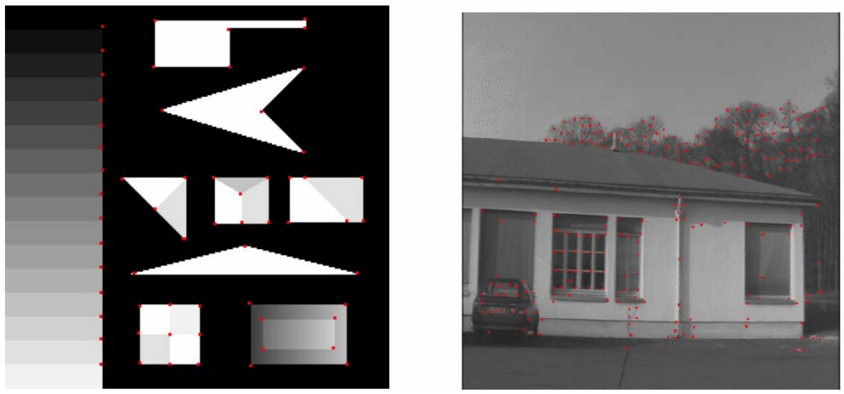
- Automate object tracking
- Point matching for computing disparity
- Stereo calibration
  - Estimation of fundamental matrix
- Motion based segmentation
- Recognition
- 3D object reconstruction
- Robot navigation
- Image retrieval and indexing

What is an interest point

- Expressive texture
  - The point at which the direction of the boundary of object changes abruptly
  - Intersection point between two or more edge segments



Synthetic & Real Interest Points



Corners are indicated in red

Properties of Interest Point Detectors

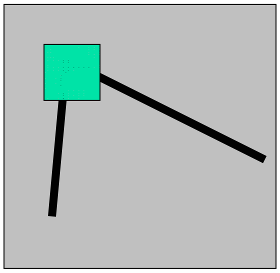
- Detect all (or most) true interest points
- No false interest points
- Well localized.
- Robust with respect to noise.
- Efficient detection

Possible Approaches to Corner Detection

- Based on brightness of images
  - Usually image derivatives
- Based on boundary extraction
  - First step edge detection
  - Curvature analysis of edges

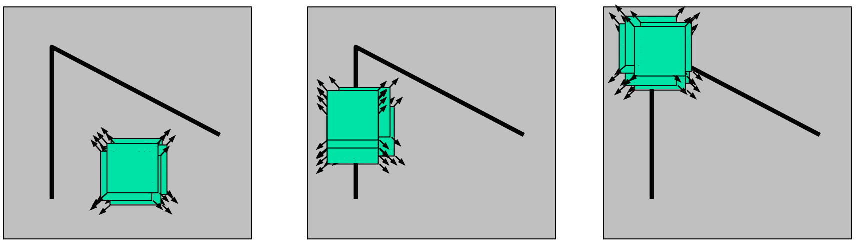
Harris Corner Detector

- Corner point can be recognized in a window
- Shifting a window in any direction should give a large change in intensity



C.Harris, M.Stephens. “A Combined Corner and Edge Detector”. 1988

Basic Idea



"flat" region:
no change in
all directions

"edge":
no change along
the edge direction

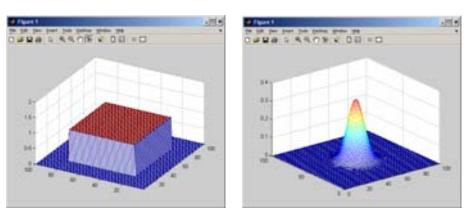
"corner":
significant change
in all directions

Mathematics of Harris Detector

- Change of intensity for the shift (u,v)

$$E(u,v)=\sum_{x,y}\underbrace{w(x,y)}_{\text{window function}}\;[\underbrace{I(x+u,y+v)}_{\text{shifted intensity}}-\underbrace{I(x,y)}_{\text{intensity}}]^2$$

Window functions →



Mathematics of Harris Detector

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

$$E(u,v)=\sum_{x,y} w(x,y)[uI_x+vI_y]^2$$

$$E(u,v)=\sum_{x,y} w(x,y)\left[\begin{pmatrix}u & v\end{pmatrix}\begin{pmatrix}I_x\\ I_y\end{pmatrix}\right]^2$$

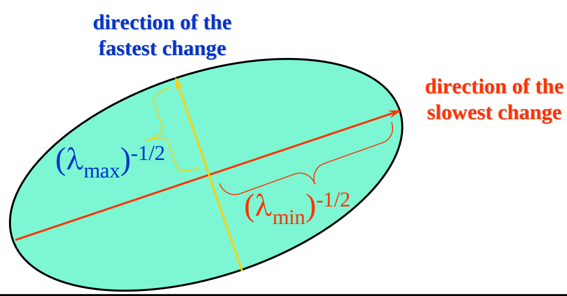
$$E(u,v)=\sum_{x,y} w(x,y)\begin{pmatrix}u & v\end{pmatrix}\begin{pmatrix}I_x\\ I_y\end{pmatrix}\begin{pmatrix}I_x & I_y\end{pmatrix}\begin{pmatrix}u\\ v\end{pmatrix}$$

$$E(u,v)=\begin{pmatrix}u & v\end{pmatrix}\left[\sum_{x,y} w(x,y)\begin{pmatrix}I_x\\ I_y\end{pmatrix}\begin{pmatrix}I_x & I_y\end{pmatrix}\right]\begin{pmatrix}u\\ v\end{pmatrix}$$

Mathematics of Harris Detector

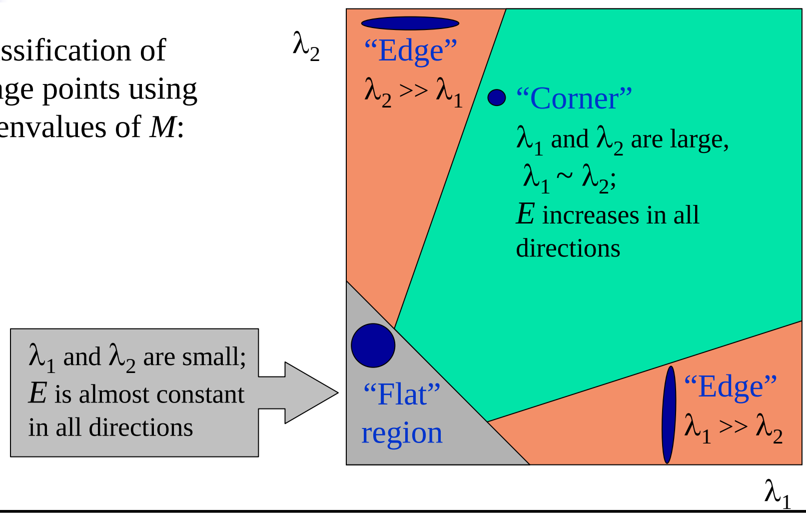
$$E(u,v)=\begin{pmatrix}u & v\end{pmatrix}M\begin{pmatrix}u\\ v\end{pmatrix} \qquad M=\sum_{x,y} w(x,y)\begin{bmatrix}I_xI_x & I_xI_y\\ I_xI_y & I_yI_y\end{bmatrix}$$

- E(u,v) is an equation of an ellipse, where M is the covariance
- Let λ_1 and λ_2 be eigenvalues of M



Mathematics of Harris Detector

Classification of image points using eigenvalues of *M*:



Mathematics of Harris Detector

- Measure of cornerness in terms of λ_1, λ_2

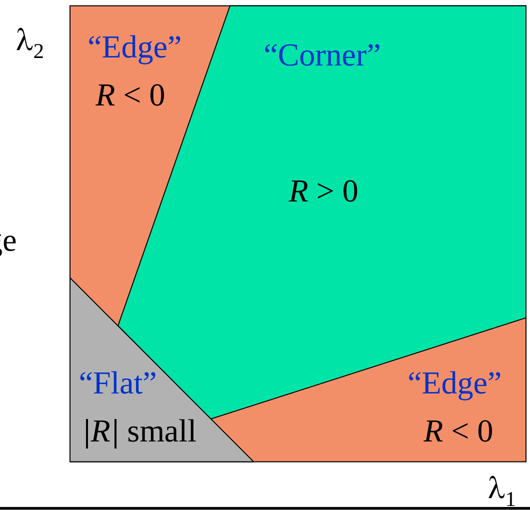
$$\det(M - I\lambda) = 0$$

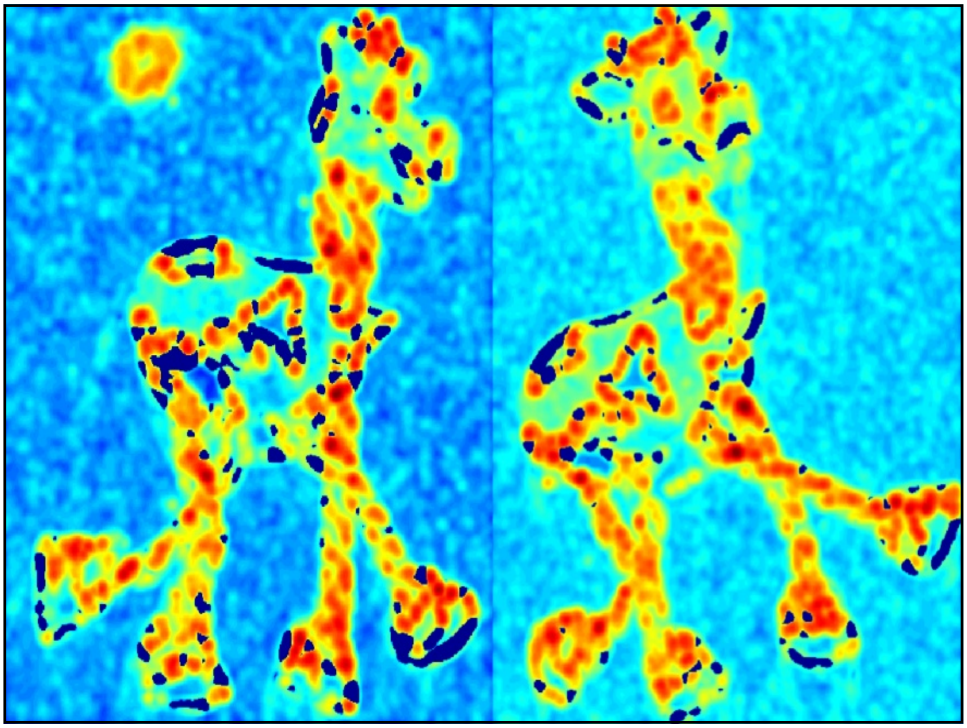
$$\vdots$$

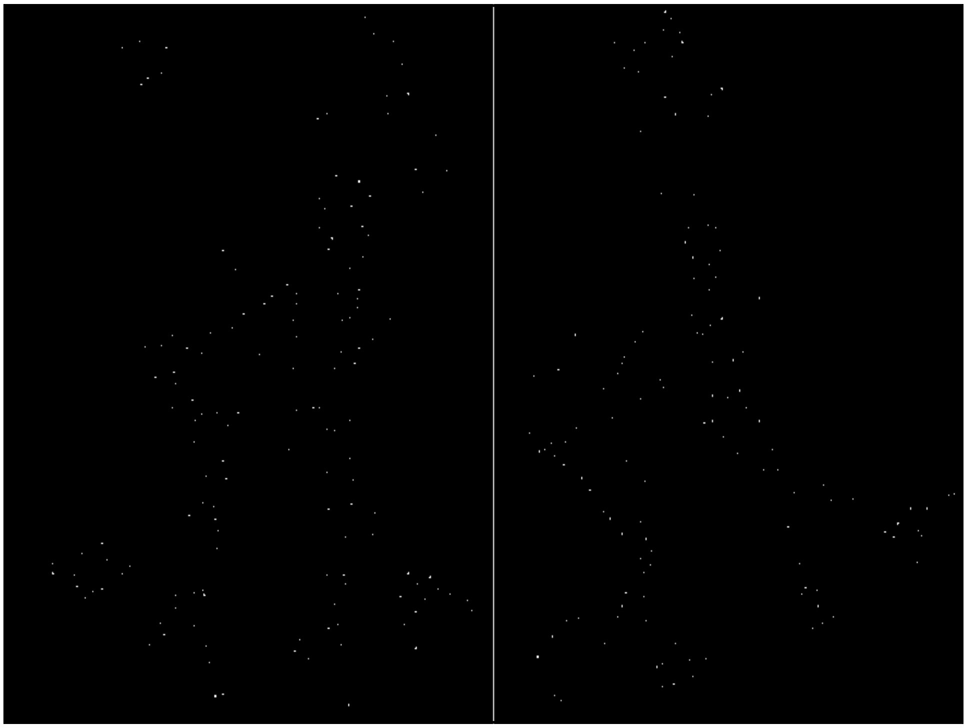
$$R = \det M - k(\operatorname{trace} M)^2$$

Mathematics of Harris Detector

- R depends only on eigenvalues of M
- R is large for a corner
- R is negative with large magnitude for an edge
- $|R|$ is small for a flat region

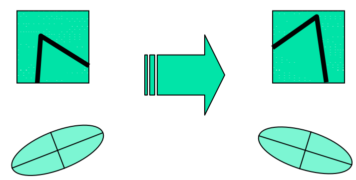






Properties of Harris Detector

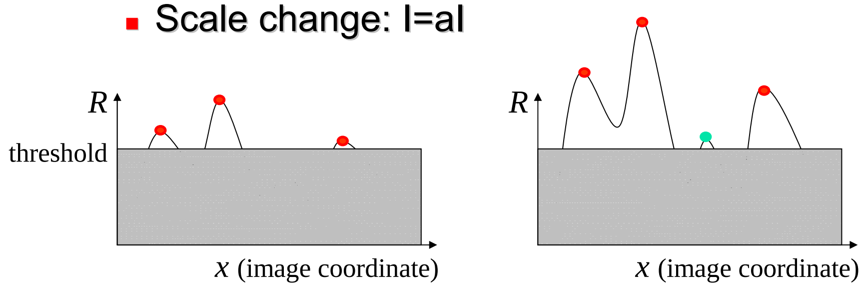
- Rotation invariance (Homework: Algebraically prove this)



- Ellipse rotates but its shape remains same
  - Hence, Harris is rotation invariant

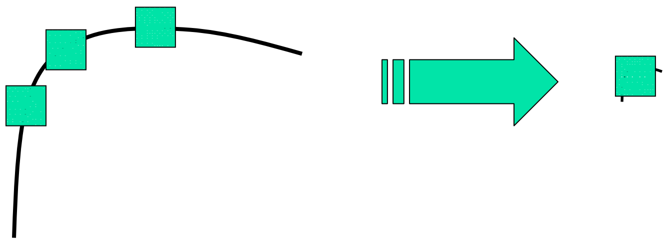
Properties of Harris Detector

- Invariance to conformal changes in intensities
  - Translation change: I=I+b
  - Scale change: I=aI



Properties of Harris Detector

- Varies with image scaling



All points will be classified as edges

Corner !

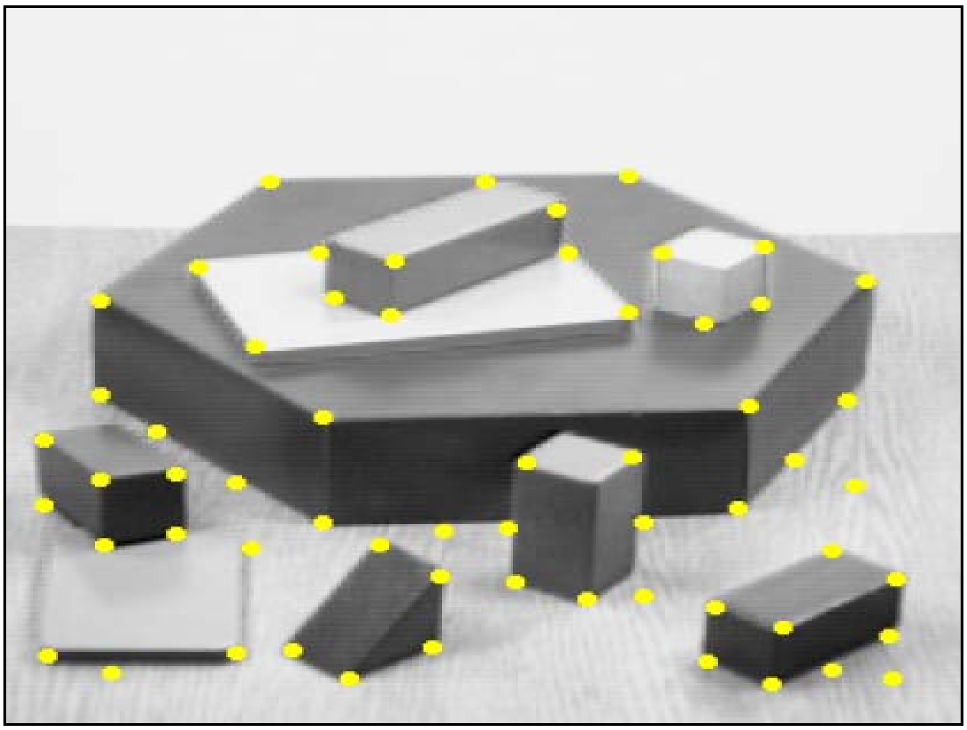
Scale Invariant Harris Corners

- Build Gaussian Pyramids
- Start from the biggest scale and apply Harris
- Keep points that are also detected in smaller scales.
- Hence Harris becomes rotation and isotropic scale invariant

KLT Corner Detector

- Same as the Harris only difference is use of eigenvalues directly
- Threshold is applied to lowest eigenvalue
  - The threshold λ_{thr} can be estimated from the histogram of λ_2
- Window size effects closeness of features

J. Shi and C. Tomasi. *Good features to track*. In Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR94), Seattle, June 1994.



SUSAN Detector

- Proposed by Smith and Brady in 1995
- SUSAN stands for Smallest "**U**nivalue **S**egment **A**ssimilating **N**ucleus (USAN)"
- It doesn't use any derivatives
- It is based on the fact that each point within an image is associated with it a local area of comparable brightness

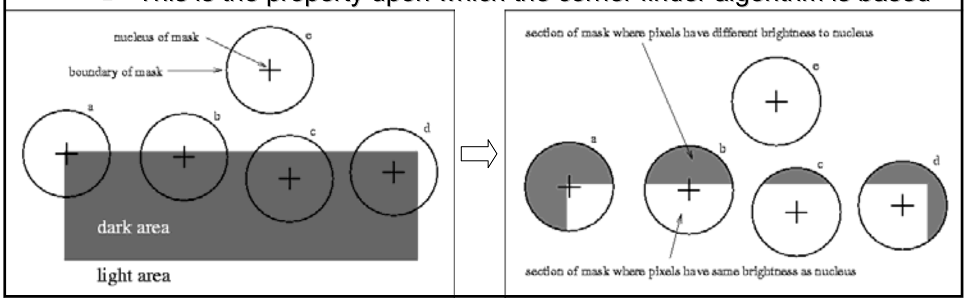
S.M. Smith. SUSAN - *a new approach to low level image processing*. Internal Technical Report TR95SMS1, Defence Research Agency, Chobham Lane, Chertsey, Surrey, UK, 1995.

Principle

- Considered in a circular mask around a pixel
- Comparison of intensity in a neighborhood
  - Area with similar intensities is called **USAN**
- Repeat the procedure for each pixel

The SUSAN Detector

- USAN area varies with respect to **features** of the image
- USAN area
  - is maximum within the rectangular area
  - falls to a **minimum at an edge**
  - smaller value corresponding to a **local minimum at a corner**
- This is the property upon which the corner finder algorithm is based



Algorithm

1. Determine a circular mask
   - Typically 37 pixels around each pixel (nucleus)
2. Calculate the brightness difference between each pixel in the mask with its nucleus

$$c(r, r_0) = \begin{cases} 1 & \text{if } |I(r) - I(r_0)| \le t \\ 0 & \text{otherwise} \end{cases}$$

3. Sum the number of pixels with similar intensity levels to that of the nucleus

$$n(r_0) = \sum_r c(r, r_0)$$

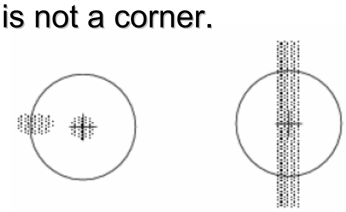
Algorithm

4. Compare *n* with *g*, the *geometric threshold* which is set to half of the maximum value that *n* can be ($n_{max}/2$)
5. At a perfect corner the USAN area will always be less than half the size of the mask area, and will be a local minimum

$$R(r_0) = \begin{cases} g - n(r_0) & \text{if } n(r_0) < g \\ 0 & \text{otherwise} \end{cases}$$

Problems

- Strong edges and noise results in false detection
- (Left figure) The USAN is not continuous. Obviously nucleus is not a corner, even though the function shows it is the local maxima.
- (Right figure) Nucleus lies in a long thin area, which depicts USAN is also very small. However, the value is high, which contradicts the fact that the point in question is not a corner.

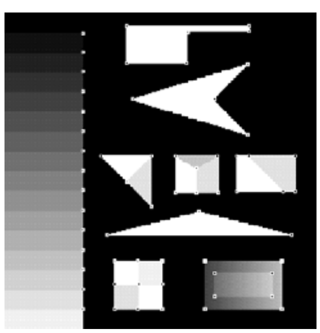


Improving SUSAN Detector

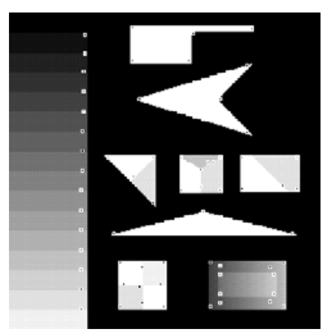
- Two rules
  - Find centroid of USAN area and distance from nucleus. point cannot become a corner if the distance is small.
  - One of the pixels on the line connecting centroid to center of circular region can be a corner

Benefits

- Accuracy, speed and localization



Output of the **SUSAN** corner detector (**t**=10) given the test image. (0.3 sec)



Output of the **Plessey** corner detector (**o** =2.0) given the test image. (3.5 sec)

But we want more!!

- Affine invariance
  - Not only rotation, isotropic scaling but also shearing, and anisotropic scaling