Interest 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
Local features: main components

1) Detection: Identify the interest points

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

\[ \mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}] \]

\[ \mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}] \]

3) Matching: Determine correspondence between descriptors in two views
Goal: interest operator repeatability

• We want to detect (at least some of) the same points in both images.

No chance to find true matches!

• Yet we have to be able to run the detection procedure *independently* per image.

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Goal: descriptor distinctiveness

• We want to be able to reliably determine which point goes with which.

• Must provide some invariance to geometric and photometric differences between the two views.
Some patches can be localized or matched with higher accuracy than others.
Local features: main components

1) Detection: Identify the interest points

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

3) Matching: Determine correspondence between descriptors in two views
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

Basic Idea

“flat” region: no change in all directions

“edge”: no change along the edge direction

“corner”: significant change in all directions
Aperture Problem
Mathematics of Harris Detector

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

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

Auto-correlation

Window functions →
Auto-Correlation
Mathematics of Harris Detector

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

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

Taylor Series

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

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

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

\[ E(u, v) = \left( u \begin{pmatrix} I_x \\ I_y \end{pmatrix} \begin{pmatrix} I_x & I_y \end{pmatrix} \right) \left[ \begin{pmatrix} u \\ v \end{pmatrix} \right] = \left( u \begin{pmatrix} I_x \\ I_y \end{pmatrix} \begin{pmatrix} I_x & I_y \end{pmatrix} \right) \begin{pmatrix} u \\ v \end{pmatrix} \]
Mathematics of Harris Detector

\[ E(u,v) = (u \quad v)M \begin{pmatrix} u \\ v \end{pmatrix} \quad M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x I_x & I_x I_y \\ I_x I_y & I_y I_y \end{bmatrix} \]

- \( E(u,v) \) is an equation of an ellipse, where \( M \) is the covariance
- Let \( \lambda_1 \) and \( \lambda_2 \) be eigenvalues of \( M \)

\( \lambda_{\text{max}}^{-1/2} \)

\( \lambda_{\text{min}}^{-1/2} \)
Classification of image points using eigenvalues of $M$:

- $\lambda_1$ and $\lambda_2$ are small; $E$ is almost constant in all directions.
- $\lambda_1$ and $\lambda_2$ are large, $\lambda_1 \sim \lambda_2$; $E$ increases in all directions.
- $\lambda_1 \gg \lambda_2$; “Corner”
- $\lambda_1 \gg \lambda_2$; “Edge”
- $\lambda_1$ and $\lambda_2$ are large, $\lambda_1 \sim \lambda_2$; $E$ increases in all directions.
Mathematics of Harris Detector

- Measure of cornerness in terms of $\lambda_1, \lambda_2$

$$M = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

$$R = \det M - k(\text{trace}M)^2 \quad R = \lambda_1 \lambda_2 - k(\lambda_1 + \lambda_2)^2$$
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
Compute corner response
Find points with large corner response: $R > \text{threshold}$
Take only the points of local maxima of $R$
Other Interest Point Detectors

\[ R = \lambda_1 - \alpha \lambda_2 \]

Triggs

\[ R = \frac{\det(M)}{\text{trace}(M)} = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} \]

Szeliski

\[ R = \lambda_1 \]

Shi-Tomasi
\[ \lambda_2 \]

\[ \lambda_1 \]

- Harris
- Harmonic mean
- Shi-Tomasi
Algorithm

- Compute horizontal and vertical derivatives of image $I_x$ and $I_y$.
- Compute three images corresponding to three terms in matrix $M$.
- Convolve these three images with a larger Gaussian (window).
- Compute scalar cornerness value using one of the $R$ measures.
- Find local maxima above some threshold as detected interest points.