Motion Estimation
Pose Estimation
Object Recognition

[Workflow Diagram]

When handling objects
in Computed Vision,
Project Inference

Lecture 16
Harris Corner Detector: Basic Idea

Harris corner detector gives a mathematical approach for determining which case holds.

In all directions significant change, "corner".

In the edge direction no change along "edge".

In all directions no change in "har" region.

Many other features (e.g., keypoints)

Because it...
Change of intensity for the shift $[n, n']$:

$$\sum \left( \lambda', n \right) f \left( \lambda', x \right) \left[ \left( \lambda', x \right) I - \left( \lambda + \lambda', n + x \right) I \right] \left( \lambda', x \right) w \left( \lambda', x \right)$$
Hence... we want patches where $E(u,v)$ is large.

For very distinctive patches, this will be larger.

For nearly constant patches, this will be near 0.

\[
\sum\left[ (\lambda, x)I - (\lambda + \lambda, n + x)I \right] = (\lambda, n)E
\]

Change of intensity for the shift $[n,v]$:

Harris Detector: Intuition
First order approx

\[(\lambda x) f\Lambda + (\lambda x)^2 f n + (\lambda x) f = (\lambda + \lambda x n + x) f\]

Higher order terms

Third partial derivatives

\[\left[ (\lambda x)^3 f_\zeta \Lambda + (\lambda x)^2 f_\zeta n + (\lambda x) f_\zeta n + (\lambda x)^2 f_n n + (\lambda x)^3 f_n n \right] \frac{i\pi}{\iota!}

Second partial derivatives

\[+ \left[ (\lambda x)^2 f_\zeta \Lambda + \lambda x f_\zeta n + (\lambda x) f_\zeta n \right] \frac{i\pi}{\iota!}

First partial derivatives

\[+ (\lambda x)^2 f_\zeta \Lambda + (\lambda x)^2 f n + (\lambda x) f = (\lambda + \lambda x n + x) f\]
\[
\left[ \begin{array}{c}
\lambda \\
n
\end{array} \right] \left( \left[ \begin{array}{cc}
\mathcal{E} & \mathcal{E}^T \\
\mathcal{E}^T & \mathcal{E}^T + \frac{1}{\mathcal{E}} I
\end{array} \right] Z \right) \left[ \begin{array}{c}
\lambda \\
n
\end{array} \right] =
\]

Rewrite as matrix equation:

\[
\left[ \begin{array}{c}
\lambda \\
n
\end{array} \right] \left[ \begin{array}{cc}
\mathcal{E} & \mathcal{E}^T \\
\mathcal{E}^T & \mathcal{E}^T + \frac{1}{\mathcal{E}} I
\end{array} \right] \left[ \begin{array}{c}
\lambda \\
n
\end{array} \right] Z =
\]

\[
\frac{\mathcal{E}}{\mathcal{E}} I - \mathcal{E}^T \mathcal{E} n + \frac{1}{\mathcal{E}} I n Z =
\]

First order approx:

\[
Z \left[ \left( \mathcal{E}^T x \right) I - \mathcal{E}^T \mathcal{E} + \frac{1}{\mathcal{E}} I n \right] \approx
\]

\[
Z \left[ \left( \mathcal{E}^T x \right) I - \left( \lambda + \mathcal{E}^T n + x \right) I \right]
\]
Components of the gradient, \( \mathbf{v} \):

**Note:** these are just products of

\[
\begin{bmatrix}
\lambda I & \lambda x I \\
\lambda x I & \lambda x^2 I
\end{bmatrix}
\begin{bmatrix}
(x, x) W
\end{bmatrix}
= W
\]

where \( W \) is a \( 2 \times 2 \) matrix computed from image derivatives:

\[
\begin{bmatrix}
\lambda \\
n
\end{bmatrix}
\begin{bmatrix}
\lambda n \\
n
\end{bmatrix} = (\lambda, n) E
\]

For small shifts \([n, v]\) we have a linear approximation:

**Harris Detector:** Mathematics
Classification via Eigenvalues

Analyzing ellipse parameters for varying cases...

Fit an ellipse to a set of points via scatter matrix.

Fit a center of mass defined as being at (0,0).

Treat gradient vectors as a set of (dx,dy) points.

The distribution of x and y
\[ \text{Algorithm 1.} \]

1. Compute敬材値es of \( \mathcal{L} \) and \( x \in x_0 \)

2. Compute敬材 Image \( \mathcal{G} \)

3. Compute敬材 Smages \( \phi \)

4. Compurot \( \phi \) and \( \mathcal{G} \)
Harris Corner Detection Algorithm

1. Compute $x$ and $y$ derivatives of image

$I * \frac{\partial}{\partial x} = x_I \quad I * \frac{\partial}{\partial y} = y_I$

2. Compute products of derivatives at every pixel.

$I \cdot x_I = x_I \cdot x_I \quad I \cdot y_I = x_I \cdot y_I$

3. Compute the sums of the products of derivatives.

$x_I \cdot x_I = \bar{x}^2 \quad x_I \cdot y_I = \bar{xy} \quad y_I \cdot y_I = \bar{y}^2$

4. Define at each pixel $(\tilde{h} \cdot x)$ the matrix.

\[
\begin{bmatrix}
(\tilde{h} \cdot x) \bar{S}_x & (\tilde{h} \cdot x) \bar{S}_y \\
(\tilde{h} \cdot x) \bar{S}_y & (\tilde{h} \cdot x) \bar{S}_x
\end{bmatrix} = (\tilde{h} \cdot x) H
\]

5. Compute the response of the detector at each pixel.

\[
\rho(x) = \det(H) - \chi \cdot \text{trace}(H)^2
\]

6. Threshold on value of $\rho$. Compute nonmax suppression.
$$\gamma([x_I]_\delta + [y_I]_\delta) - \gamma([x_I]_\delta - [y_I]_\delta)$$

$$\gamma = \text{det}([o^T I o^T] - [o^T I o^T] \text{trace}([o^T I o^T]$$

**1. Image derivatives**

2. Square of derivatives

3. Gaussian filter $g(o)$
Solution:

Find local maxima in interest function above R_k criticize in neglect selection in neglect of higher contrast.

Local maxima ≠ AND

Value is significantly

\[ \text{WRMIN} \rightarrow \text{MRMIN} \]

\[ \text{FINN} \rightarrow \text{NMIN} \text{ Maxima Max} \]
Naras as Keytours
Many, many, many... different ways, e.g., gradients.

Gradient intensities are affected by illumination, but their orientations aren't.
In the blocks of the pitch, construct a histogram representing the distribution of blocks of size $m \times m$. Place $n \times n$ blocks of the patch into the patch of size $m \times m$. Find a point at the key point $c$. Histogram of curvature gradients.
Create an orientation histogram for the orientation of \( \Delta \).

Add a vote with weight \( \frac{\frac{\partial g}{\partial \Delta}}{\sqrt{\Delta}} \exp \frac{-\|\Delta\|^2}{2} \) to \( \Delta \).

Compute a weighted average of \( \Delta \) using bilinear weights centered at \( d \).

For each point in an \( m \times m \) subgrid spanning \( \delta \), create an orientation histogram.

Given a grid cell for patch with center \( c = (x, y, z) \) and radius \( \rho \),
$\mathcal{L} > (g f \circ v f) p$

I found features for key points.
vector is normalized again.

To construct a SIFT descriptor for a neighborhood, we place a grid over
\[(\omega^x)^{\ldots \cdot I} f = (\omega^x)^{\ldots \cdot I} f\]
Finally, each keyword will have a preferential radius.