Lecture 10: Image Features
Harris Detector: Computing it
Feature Descriptors
Announcements
Goals

• Know how to compute Harris corners

• Understand the concept of invariance as it pertains to detectors and descriptors

• Understand how to compute the MOPS feature descriptor

• Understand the gist of the SIFT descriptor
Running motivational example: Panorama Stitching
Harris Corners: TL;DM

- **Goal**: Find "unique" patches.  
  Proxy for uniqueness: not like neighboring patches

- **Approach**: Eigenanalysis of SSD error on locally-linearized image windows.

- **Upshot**:  
The smaller eigenvalue of this 2x2 matrix indicates cornerishness:

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

\[
I_x = \frac{\partial I}{\partial x}
\]

\[
W \in \text{window}
\]
Harris Corners: TL;DM

Algorithm:

1. Use Sobel filter to estimate gradients $I_x, I_y$

2. Compute $I_x^2, I_y^2, I_xI_y$ \(\text{n^p ops}\)

3. Filter each with a K x K mean filter

4. Approximate smallest eigenvalue as:
   \[
   \frac{\det(H)}{\text{tr}(H)}
   \]
   \[
   h = \frac{AC - BB}{A + C}
   \]

   $\det(H) = A*C - B*B$

   $\text{tr}(H) = A+C$
Corner Detection: Upshot

- The **smaller** eigenvalue of $H$ is **large** when the patch is centered on a corner.
Input
Smallest eigenvalue
Thresholded
Keep only Local Maxima
Resulting Corners
Harris Corners: TL;DM

Algorithm:

1. Use Sobel filter to estimate gradients $I_x, I_y$

2. Compute $I_x^2, I_y^2, I_xI_y$

3. Filter each with a $K \times K$ mean filter

4. Approximate smallest eigenvalue as:
   $\frac{\text{det}(H)}{\text{tr}(H)}$

5. Threshold $h[\text{h < t}] = 0$

6. Maximum filter $np\text{.maximum\_filter}$
Two desirable properties:

- **Uniqueness**: features *shouldn't* match if they're from different points in the scene.

- **Invariance**: features *should* match if they do come from the same point in the scene.
Invariance
Invariance: Hard mode
Invariance: Mars Mode
Invariance: Mars Mode
Invariance

• Suppose we're comparing two images of the same scene. What kinds of transformations could relate the two images if:

  • They are part of a panorama sequence?
  
  • They were taken at different times of day?
  
  • They were taken by different cameras?
  
  • They were taken from different viewpoints?

  - translation
  - rotation
  
  - brightness/exposure
  - intensity changes
  - color
  
  - lighting, shadows
  - focal length(?)
  
  - noise
  
  - viewpoint-dependent appearance
  
  - magnification
Desirable Invariances

- Geometric transformations
  - Rotation
  - Translation
  - Scale
  - Shear

- Photometric transformations:
  - brightness shift $I \leftarrow I + 20$
  - brightness scale $I \leftarrow I \cdot 1.02$
  - contrast
Harris detector: invariance

- Invariant to intensity shift?

\[ I' = I + 20 \]
Harris detector: invariance

- Invariant to scaling?  
  \[ \text{No} \]

\[ \text{I} \]
Harris detector: invariance

- Invariant to scaling?
Features - Overview

1. Detect
   detect *unique* points

2. Describe
   describe using *invariant* representation
   \[ \mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}] \]

3. Match
   match them *robustly*
Feature Descriptors
Feature Descriptors

Simple starting point: window of pixels around the point.
Feature Descriptors

- Starting with a window of pixels, let's add invariances:
  - Brightness (scale and/or shift - "affine invariance")

\[
\begin{align*}
\chi_1 &= \frac{X_1 - \mu_{X_1}}{\sigma_{X_1}} \\
\chi_2 &= \frac{X_2 - \mu_{X_2}}{\sigma_{X_2}} \\
\chi_2' &= \chi_1 \cdot \delta + t
\end{align*}
\]
Feature Descriptors

- Starting with a window of pixels, let's add invariances:
  - Brightness (scale and/or shift - "affine invariance")
  - Rotation
Feature Descriptors

- Starting with a window of pixels, let's add invariances:
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Feature Descriptors

- Starting with a window of pixels, let's add invariances:
  - Scale
Feature Descriptors

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Feature Descriptors

- Starting with a window of pixels, let's add invariances:
  - Scale
Multiscale Oriented PatcheS: The MOPS Descriptor

- Scale to 1/5 size
- Rotate to horizontal
- Normalize intensity:
  - subtract mean
  - divide by standard dev
- Run it on a Gaussian pyramid
Fancy, industrial-strength feature descriptors: SIFT

- Take a 16x16 window
- Compute edge orientation at each pixel
- Discard weak edges
- Create a histogram of remaining edge orientations
Scale Invariant Feature Transform: SIFT

Real-deal, industrial-strength feature descriptors.

- Take a 16x16 window
- Compute edge orientation at each pixel
- Discard weak edges
- Create a histogram of remaining edge orientations
- Actually do this for each of 4 quadrants of the window

4 histograms - unroll into vector
SIFT: Example
SIFT: Properties

Remarkably invariant to:

- Viewpoint, illumination, rotation, scale (via pyramid)