Lecture 7:
Features 2: Invariance and blob detection

Announcements

• Demos today
  – In Upson 317
  – IMPORTANT: Please come early and setup your machine to demo in time for your slot

• No demo time works? Please email us.
Reading

- Szeliski: 4.1

Feature extraction: Corners and blobs
Harris Detector: Invariance Properties

• Rotation

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

Corner response is invariant to image rotation

Harris Detector: Invariance Properties

• Affine intensity change: \( I \rightarrow aI + b \)

✓ Only derivatives are used => invariance to intensity shift \( I \rightarrow I + b \)
✓ Intensity scale: \( I \rightarrow aI \)

Partially invariant to affine intensity change
Harris Detector: Invariance Properties

- Scaling

Not invariant to scaling

Scale invariant detection

Suppose you’re looking for corners

Key idea: find scale that gives local maximum of $f$
  - in both position and scale
  - One definition of $f$: the Harris operator
Automatic scale selection

Lindeberg et al., 1996
Automatic scale selection

\[ f(I_{i,j}(x,\sigma)) \]
Automatic scale selection

Normalize: rescale to fixed size
Implementation

• Instead of computing $f$ for larger and larger windows, we can implement using a fixed window size with a Gaussian pyramid

Another common definition of $f$

• The Laplacian of Gaussian (LoG)

\[ \nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \]

(very similar to a Difference of Gaussians (DoG) – i.e. a Gaussian minus a slightly smaller Gaussian)
Laplacian of Gaussian

• “Blob” detector

• Find maxima and minima of LoG operator in space and scale

Scale selection

• At what scale does the Laplacian achieve a maximum response for a binary circle of radius $r$?
Characteristic scale

- We define the characteristic scale as the scale that produces peak of Laplacian response.


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Scale-space blob detector: Example
Scale-space blob detector: Example

\[ \text{sigma = 11.9912} \]
Questions?

Feature descriptors

We know how to detect good points
Next question: **How to match them?**

**Answer:** Come up with a *descriptor* for each point, find similar descriptors between the two images
Feature descriptors

We know how to detect good points
Next question: How to match them?

Lots of possibilities (this is a popular research area)
- Simple option: match square windows around the point
- State of the art approach: SIFT

Invariance vs. discriminability

- Invariance:
  - Descriptor shouldn’t change even if image is transformed

- Discriminability:
  - Descriptor should be highly unique for each point
Invariance

• Most feature descriptors are designed to be invariant to
  – Translation, 2D rotation, scale

• They can usually also handle
  – Limited 3D rotations (SIFT works up to about 60 degrees)
  – Limited affine transformations (some are fully affine invariant)
  – Limited illumination/contrast changes

How to achieve invariance

Need both of the following:
1. Make sure your detector is invariant
2. Design an invariant feature descriptor
   – Simplest descriptor: a single 0
     • What’s this invariant to?
   – Next simplest descriptor: a square window of pixels
     • What’s this invariant to?
   – Let’s look at some better approaches...
Rotation invariance for feature descriptors

- Find dominant orientation of the image patch
  - This is given by $\mathbf{x}_{\text{max}}$, the eigenvector of $\mathbf{H}$ corresponding to $\lambda_{\text{max}}$ (the larger eigenvalue)
  - Rotate the patch according to this angle

Multiscale Oriented PatcheS descriptor

Take 40x40 square window around detected feature
- Scale to 1/5 size (using prefiltering)
- Rotate to horizontal
- Sample 8x8 square window centered at feature
- Intensity normalize the window by subtracting the mean, dividing by the standard deviation in the window

Adapted from slide by Matthew Brown
Detections at multiple scales

Figure 1. Multi-scale Oriented Patches (MOPS) extracted at five pyramid levels from one of the Matter images. The boxes show the feature orientation and the region from which the descriptor vector is sampled.