Lecture 19: SIFT cont., HOG, SURF
Menu for Today (October 22, 2018)

Topics:
- SIFT continued
- HOG, SURF descriptors
- Object detection with SIFT
- RANSAC intro

Readings:
- Today’s Lecture: Forsyth & Ponce (2nd ed.) 5.4, 10.4.2
  “Distinctive Image Features for Scale-Invariant Keypoints"
- Next Lecture: Forsyth & Ponce (2nd ed.) 10.1, 10.2

Reminders:
- Assignment 3: Texture Synthesis is out, due on October 29th
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Today’s “fun” Example: Recognizing Panoramas

Figure Credit: Matthew Brown and David Lowe
Lecture 18: Re-Cap

— We motivated SIFT for identifying locally distinct keypoints in an image (detection)

— SIFT features (description) are invariant to translation, rotation, and scale; robust to 3D pose and illumination

1. Multi-scale extrema detection
2. Keypoint localization
3. Orientation assignment
4. Keypoint descriptor
Lecture 18: Re-Cap

**Keypoint** is an image location at which a descriptor is computed

- Locally distinct points
- Easily localizable and identifiable

The feature **descriptor** summarizes the local structure around the key point

- Allows us to (hopefully) unique matching of keypoints in presence of object pose variations, image and photometric deformations

**Note**, for repetitive structure this would still not give us unique matches.
Lecture 18: Re-Cap

**Keypoint** is an image location at which a descriptor is computed

- Locally distinct points
- Easily localizable and identifiable

The feature **descriptor** summarizes the local structure around the key point

- Allows us to (hopefully) unique matching of keypoints in presence of object pose variations, image and photometric deformations

**Note**, for repetitive structure this would still not give us unique matches.
Lecture 18: Re-Cap

Keypoint is an image location at which a descriptor is computed
— Locally distinct points
— Easily localizable and identifiable

The feature descriptor summarizes the local structure around the key point
— Allows us to (hopefully) unique matching of keypoints in presence of object pose variations, image and photometric deformations

Note, for repetitive structure this would still not give us unique matches.
Lecture 18: Re-Cap

**Keypoint** is an image location at which a descriptor is computed
- Locally distinct points
- Easily localizable and identifiable

The feature **descriptor** summarizes the local structure around the key point
- Allows us to (hopefully) unique matching of keypoints in presence of object pose variations, image and photometric deformations

**Note**, for repetitive structure this would still not give us unique matches.
Lecture 18: Re-Cap

Keypoint is an image location at which a descriptor is computed
— Locally distinct points
— Easily localizable and identifiable

The feature descriptor summarizes the local structure around the key point
— Allows us to (hopefully) unique matching of keypoints in presence of object pose variations, image and photometric deformations

Note, for repetitive structure this would still not give us unique matches.
Lecture 18: Re-Cap

— We motivated SIFT for identifying locally distinct keypoints in an image (detection)

— SIFT features (description) are invariant to translation, rotation, and scale; robust to 3D pose and illumination

1. Multi-scale extrema detection
2. Keypoint localization
3. Orientation assignment
4. Keypoint descriptor
1. Multi-scale Extrema Detection

**First octave**

- Gaussian

**Second octave**

- Half the size

**Difference of Gaussian (DoG)**

*Slide Credit:* Ioannis (Yannis) Gkioulekas (CMU)
1. Multi-scale Extrema Detection

Detect maxima and minima of Difference of Gaussian in scale space

\[ \sigma = 2^{1/s} \]

Difference of Gaussian (DoG)

Selected if larger than all 26 neighbors

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
1. Multi-scale Extrema Detection

Detect maxima and minima of Difference of Gaussian in scale space

— Responds to blob-line and corner-like structures

— Could also give strong responses at edges
2. Keypoint Localization

— After keypoints are detected, we remove those that have low contrast or are poorly localized along an edge.

How do we decide whether a keypoint is poorly localized, say along an edge, vs. well-localized?

\[
C = \begin{bmatrix}
\sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\
\sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y
\end{bmatrix}
\]
3. Orientation Assignment

— Create **histogram** of local gradient directions computed at selected scale

— Assign **canonical orientation** at peak of smoothed histogram

— Each key specifies stable 2D coordinates (x, y, scale, orientation)
4. SIFT Descriptor

— Thresholded image gradients are sampled over $16 \times 16$ array of locations in scale space (weighted by a Gaussian with sigma half the size of the window)
— Create array of orientation histograms
— 8 orientations $\times 4 \times 4$ histogram array
How many dimensions are there in a SIFT descriptor?

(Hint: This diagram shows a 2 x 2 histogram array but the actual descriptor uses a 4 x 4 histogram array)
Demo
Descriptor is **normalized** to unit length (i.e. magnitude of 1) to reduce the effects of illumination change

— if brightness values are scaled (multiplied) by a constant, the gradients are scaled by the same constant, and the normalization cancels the change

— if brightness values are increased/decreased by a constant, the gradients do not change
Feature Stability to **Noise**

Match features after random change in image scale & orientation, with differing levels of image noise

Find nearest neighbour in database of 30,000 features
Feature Stability to **Affine Change**

Match features after random change in image scale & orientation, with differing levels of image noise

Find nearest neighbour in database of 30,000 features
Distinctiveness of Features

Vary size of database of features, with 30 degree affine change, 2% image noise

Measure % correct for single nearest neighbour match
Summary

Four steps to SIFT feature generation:

1. **Scale-space representation and local extrema detection**
   - use DoG pyramid
   - 3 scales/octave, down-sample by factor of 2 each octave

2. **Keypoint localization**
   - select stable keypoints (threshold on magnitude of extremum, ratio of principal curvatures)

3. **Keypoint orientation assignment**
   - based on histogram of local image gradient directions

4. **Keypoint descriptor**
   - histogram of local gradient directions — vector with $8 \times (4 \times 4) = 128$ dim
   - vector normalized (to unit length)
Histogram of Oriented Gradients (HOG) Features

Dalal, Triggs. Histograms of Oriented Gradients for Human Detection. CVPR, 2005

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
Histogram of Oriented Gradients (HOG) Features

Pedestrian detection

1 cell step size

128 pixels
16 cells
15 blocks

15 x 7 x 4 x 36 = 3780

64 pixels
8 cells
7 blocks

Redundant representation due to overlapping blocks

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)
‘Speeded’ Up Robust Features (SURF)

Each cell is represented by 4 values:

$$ \left[ \sum d_x, \sum d_y, \sum |d_x|, \sum |d_y| \right] $$

Haar wavelets filters
(Gaussian weighted from center)

How big is the SURF descriptor?
64 dimensions
‘Speeded’ Up Robust Features (SURF)