CS688/WST665: Web-Scale Image Retrieval
Scale Invariant Region Selection

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Course URL:
http://sglab.kaist.ac.kr/~sungeui/IR
What we will learn today?

- Local invariant features
  - Motivation
  - Requirements, invariances
- Keypoint localization
  - Harris corner detector
  - Hessian detector
- Scale invariant region selection
  - Automatic scale selection
  - Laplacian-of-Gaussian detector
  - Difference-of-Gaussian detector
  - Combinations
- Local descriptors
  - An intro
From Points to Regions...

• The Harris and Hessian operators define interest points.
  – Precise localization
  – High repeatability

• In order to compare those points, we need to compute a descriptor over a region.
  – How can we define such a region in a scale invariant manner?

• i.e. how can we detect scale invariant interest regions?
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size

\[ d(f_A, f_B) \]

Slide credit: Krystian Mikolajczyk
Naïve Approach: Exhaustive Search

- Multi-scale procedure
  - Compare descriptors while varying the patch size

\[ d(f_A, f_B) \neq \]
Naïve Approach: Exhaustive Search

• Multi-scale procedure
  – Compare descriptors while varying the patch size
Naïve Approach: Exhaustive Search

- Comparing descriptors while varying the patch size
  - Computationally inefficient
  - Inefficient but possible for matching
  - Prohibitive for retrieval in large databases
  - Prohibitive for recognition
Automatic Scale Selection

- Solution:
  - Design a function on the region, which is “scale invariant” (the same for corresponding regions, even if they are at different scales)
    
    Example: average intensity. For corresponding regions (even of different sizes) it will be the same.

  - For a point in one image, we can consider it as a function of region size (patch width)
Automatic Scale Selection

- Common approach:
  - Take a local maximum of this function.
  - Observation: region size for which the maximum is achieved should be *invariant* to image scale.
Automatic Scale Selection

- Function responses for increasing scale (scale signature)
Automatic Scale Selection

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- Function responses for increasing scale (scale signature)
Automatic Scale Selection

- Normalize: Rescale to fixed size
What Is A Useful Signature Function?

- Laplacian-of-Gaussian = “blob” detector
Characteristic Scale

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

Laplacian-of-Gaussian (LoG)

- Interest points:
  - Local maxima in scale space of Laplacian-of-Gaussian

\[ L_{xx}(\sigma) + L_{yy}(\sigma) \]

Fei-Fei Li

Lecture 11 - 64
Laplacian-of-Gaussian (LoG)

• Interest points:
  – Local maxima in scale space of Laplacian-of-Gaussian

\[ L_{xx}(\sigma) + L_{yy}(\sigma) \]
Laplacian-of-Gaussian (LoG)

- Interest points:
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Laplacian-of-Gaussian (LoG)

- Interest points:
  - Local maxima in scale space of Laplacian-of-Gaussian

\[ L_{xx}(\sigma) + L_{yy}(\sigma) \]

\[ \Rightarrow \text{List of } (x, y, \sigma) \]
LoG Detector: Workflow
LoG Detector: Workflow

\[ \text{sigma} = 11.9912 \]
LoG Detector: Workflow
Technical Detail

- We can efficiently approximate the Laplacian with a difference of Gaussians:

\[ L = \sigma^2 \left( G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right) \]  
(Laplacian)

\[ DoG = G(x, y, k\sigma) - G(x, y, \sigma) \]  
(Difference of Gaussians)
Difference-of-Gaussian (DoG)

- Difference of Gaussians as approximation of the LoG
  - This is used e.g. in Lowe’s SIFT pipeline for feature detection.

- Advantages
  - No need to compute $2^{nd}$ derivatives
  - Gaussians are computed anyway, e.g. in a Gaussian pyramid.
Key point localization with DoG

- Detect maxima of difference-of-Gaussian (DoG) in scale space
- Then reject points with low contrast (threshold)
- Eliminate edge responses

Candidate keypoints: list of \((x, y, \sigma)\)
DoG – Efficient Computation

- Computation in Gaussian scale pyramid
Results: Lowe’s DoG
Example of Keypoint Detection

(a) 233x189 image
(b) 832 DoG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures (removing edge responses)
Harris-Laplace [Mikolajczyk '01]

1. Initialization: Multiscale Harris corner detection
Harris-Laplace  [Mikolajczyk ‘01]

1. Initialization: Multiscale Harris corner detection
2. Scale selection based on Laplacian
   (same procedure with Hessian ⇒ Hessian-Laplace)

Harris points

Harris-Laplace points
Summary: Scale Invariant Detection

- **Given**: Two images of the same scene with a large *scale difference* between them.
- **Goal**: Find the *same* interest points *independently* in each image.
- **Solution**: Search for *maxima* of suitable functions in *scale* and in *space* (over the image).

- Two strategies
  - Laplacian-of-Gaussian (LoG)
  - Difference-of-Gaussian (DoG) as a fast approximation
  - These can be used either on their own, or in combinations with single-scale keypoint detectors (Harris, Hessian).
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  – Laplacian-of-Gaussian detector
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  – Combinations

• Local descriptors
  – An intro
Local Descriptors

- We know how to detect points
- Next question:
  
  How to *describe* them for matching?

⇒ Next lecture...
Local Descriptors

- We know how to detect points
- Next question:

  How to describe them for matching?

Point descriptor should be:
1. Invariant
2. Distinctive
Next Time

- Local descriptors (e.g., SIFT)
Homework for Every Class

- Go over the next lecture slides
- Come up with one question on what we have discussed today
  - 1 for typical questions (that were answered in the class)
  - 2 for questions with thoughts or that surprised me
- Write questions at least 4 times
  - Write a question about one out of every four classes
  - Multiple questions in one time will be counted as one time
- Common questions are compiled at the Q&A file
  - Some of questions will be discussed in the class
- If you want to know the answer of your question, ask me or TA on person