Filters
(cont.)

CS 554 – Computer Vision
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Today’s topics

• **Image Formation**

• **Image filters in spatial domain**
  – Filter is a mathematical operation of a grid of numbers
  – Smoothing, sharpening, measuring texture

• **Image filters in the frequency domain**
  – Filtering is a way to modify the frequencies of images
  – Denoising, sampling, image compression

• **Templates and Image Pyramids**
  – Filtering is a way to match a template to the image
  – Detection, coarse-to-fine registration
Template matching

A toy example

Source: Darrell, Berkeley
Template matching

Detected template

Template

Source: Darrell, Berkeley
Template matching

Detected template

Correlation map

Source: Darrell, Berkeley
Where’s Waldo?

Source: Darrell, Berkeley
Where's Waldo?

Source: Darrell, Berkeley
Where’s Waldo?

Detected template

Correlation map

Source: Darrell, Berkeley
What if the template is not identical to some subimage in the scene?
Template matching

Match can be meaningful, if scale, orientation, and general appearance is right.

Source: Darrell, Berkeley
Application

Template matching

• Goal: find 🎉 in image

• Main challenge: What is a good similarity or distance measure between two patches?
  – Correlation
  – Zero-mean correlation
  – Sum Square Difference
  – Normalized Cross Correlation

Source: Hays, Brown
Matching with filters

• Goal: find \( \text{in image} \)

• Method 0: filter the image with eye patch

\[
h[m,n] = \sum_{k,l} g[k,l] f[m+k,n+l]
\]

What went wrong?

response is stronger for higher intensity

Source: Hays, Brown
Matching with filters

- **Goal:** find \( \text{in image} \)

- **Method 1:** filter the image with zero-mean eye

\[
h[m,n] = \sum_{k,l} (f[k,l] - \bar{f}) (g[m+k, n+l])
\]

Source: Hays, Brown
Matching with filters

• Goal: find 🕍 in image

• Method 2: SSD

\[ h[m, n] = \sum_{k, l} (g[k, l] - f[m + k, n + l])^2 \]

Source: Hays, Brown
Matching with filters

- **Goal:** find 🌟 in image
- **Method 2: SSD**

\[
h[m, n] = \sum_{k, l} (g[k, l] - f[m + k, n + l])^2
\]

What’s the potential downside of SSD?

SSD is sensitive to average intensity
Matching with filters

- **Goal**: find \( \begin{array}{c} \text{in image} \end{array} \)

- **Method 3**: Normalized cross-correlation

\[
h[m,n] = \frac{\sum_{k,l} (g[k,l] - \bar{g})(f[m-k,n-l] - \bar{f}_{m,n})}{\left(\sum_{k,l} (g[k,l] - \bar{g})^2 \sum_{k,l} (f[m-k,n-l] - \bar{f}_{m,n})^2\right)^{0.5}}
\]

**Matlab**: `normxcorr2(template, im)`

**Source**: Hays, Brown
Matching with filters

• Goal: find 🕍 in image

• Method 3: Normalized cross-correlation

Source: Hays, Brown
Matching with filters

- Goal: find eye in image
- Method 3: Normalized cross-correlation

Source: Hays, Brown
Q: What is the best method to use?

A: Depends

• SSD: faster, sensitive to overall intensity
• Normalized cross-correlation: slower, invariant to local average intensity and contrast

Source: Hays, Brown
Q: What if we want to find larger or smaller eyes?

Motivation for studying scale.
A: Image Pyramid

adapted from Michael Black, Brown University
Review of Sampling

Image $\xrightarrow{\text{Gaussian Filter}}$ Low-Pass Filtered Image $\xrightarrow{\text{Sample}}$ Low-Res Image
Gaussian Pyramid

adapted from Michael Black, Brown University
Gaussian pyramid

Source: Forsyth

Source: Hays, Brown
Template Matching with Image Pyramids

Input: Image, Template
1. Match template at current scale
2. Downsample image
3. Repeat 1-2 until image is very small
4. Take responses above some threshold, perhaps with non-maxima suppression

Source: Hays, Brown
Coarse-to-fine Image Registration

1. Compute Gaussian pyramid
2. Align with coarse pyramid
3. Successively align with finer pyramids
   - Search smaller range

Why is this faster?

Are we guaranteed to get the same result?

Source: Hays, Brown
Laplacian filter

unit impulse

Gaussian

Laplacian of Gaussian

Source: Lazebnik

Source: Hays, Brown
Laplacian pyramid

Source: Forsyth

Source: Hays, Brown
Computing Gaussian/Laplacian Pyramid

Can we reconstruct the original from the laplacian pyramid?

Source: Hays, Brown
Texture segmentation

Clues from Human Perception

- Early processing in humans filters for various orientations and scales of frequency
- Perceptual cues in the mid-high frequencies dominate perception
- When we see an image from far away, we are effectively subsampling it

Source: Hays, Brown