Spatial Filtering
Image Filtering

- **Image filtering**: computes a function of a *local neighborhood* at each pixel position
- Called “Local operator,” “Neighborhood operator,” or “Window operator”
- $f$: image $\rightarrow$ image
- **Uses:**
  - Enhance images
    - Noise reduction, smooth, resize, increase contrast, recolor, artistic effects, etc.
  - Extract features from images
    - Texture, edges, distinctive points, etc.
  - Detect patterns
    - Template matching, e.g., eye template

Slide credit: D. Hoiem
Filtering

- The name “filter” is borrowed from frequency domain processing (next week’s topic)
- Accept or reject certain frequency components
- Fourier (1807): Periodic functions could be represented as a weighted sum of sines and cosines
Signals

- A signal is composed of low and high frequency components

  - **Low frequency components:** smooth / piecewise smooth
    - Neighboring pixels have similar brightness values
    - You’re within a region

  - **High frequency components:** oscillatory
    - Neighboring pixels have different brightness values
    - You’re either at the edges or noise points
Low/high frequencies vs. fine/coarse-scale details

Original image

Low-frequencies (coarse-scale details) boosted

High-frequencies (fine-scale details) boosted
Signals – Examples

[Images of signals and graphs]
Motivation: noise reduction

- Assume image is degraded with an additive model.
- Then,

\[
\text{Observation} = \text{True signal} + \text{noise}
\]

\[
\text{Observed image} = \text{Actual image} + \text{noise}
\]

\[
\begin{align*}
\text{low-pass filters} & \quad \text{high-pass filters} \\
\downarrow & \\
\text{smooth the image}
\end{align*}
\]
Common types of noise

- **Salt and pepper noise:**
  random occurrences of black and white pixels

- **Impulse noise:**
  random occurrences of white pixels

- **Gaussian noise:**
  variations in intensity drawn from a Gaussian normal distribution
Gaussian noise

\[ f(x, y) = \overline{f(x, y)} + \overline{\eta(x, y)} \]

Gaussian i.i.d. ("white") noise:
\[ \eta(x, y) \sim \mathcal{N}(\mu, \sigma) \]

>> noise = randn(size(im)).*sigma;
>> output = im + noise;

What is the impact of the sigma?
Motivation: noise reduction

- Make multiple observations of the same **static** scene
- Take the average
- Even multiple images of the same static scene will not be identical.

Adapted from: K. Grauman
Motivation: noise reduction

- Make multiple observations of the same static scene
- Take the average
- Even multiple images of the same static scene will not be identical.

- What if we can’t make multiple observations?

*What if there’s only one image?*

Adapted from: K. Grauman
Image Filtering

• **Idea:** Use the information coming from the neighboring pixels for processing

• Design a transformation function of the local neighborhood at each pixel in the image
  – Function specified by a “filter” or mask saying how to combine values from neighbors.

• Various uses of filtering:
  – Enhance an image (denoise, resize, etc)
  – Extract information (texture, edges, etc)
  – Detect patterns (template matching)

Adapted from: K. Grauman
Filtering

- Processing done on a function
  - can be executed in continuous form (e.g. analog circuit)
  - but can also be executed using sampled representation
- Simple example: smoothing by averaging

Slide credit: S. Marschner
Linear filtering

• Filtered value is the linear combination of neighboring pixel values.

• Key properties
  – linearity: $\text{filter}(f + g) = \text{filter}(f) + \text{filter}(g)$
  – shift invariance: behavior invariant to shifting the input
    • delaying an audio signal
    • sliding an image around

• Can be modeled mathematically by convolution

Adapted from: S. Marschner
First attempt at a solution

- Let’s replace each pixel with an average of all the values in its neighborhood
- Assumptions:
  - Expect pixels to be like their neighbors (spatial regularity in images)
  - Expect noise processes to be independent from pixel to pixel
First attempt at a solution

• Let’s replace each pixel with an average of all the values in its neighborhood

• Moving average in 1D:

Slide credit: S. Marschner
Convolution warm-up

- Same moving average operation, expressed mathematically:

\[ b_{\text{smooth}}[i] = \frac{1}{2r + 1} \sum_{j=i-r}^{i+r} b[j] \]
Discrete convolution

• Simple averaging:

\[ b_{\text{smooth}}[i] = \frac{1}{2r + 1} \sum_{j=i-r}^{i+r} b[j] \]

– every sample gets the same weight

• Convolution: same idea but with *weighted* average

\[(a \ast b)[i] = \sum_{j} a[j] b[i - j] \]

– each sample gets its own weight (normally zero far away)

• This is all convolution is: it is a **moving weighted average**
Filters

- Sequence of weights $a[j]$ is called a filter
- Filter is nonzero over its region of support
  - usually centered on zero: support radius $r$
- Filter is normalized so that it sums to 1.0
  - this makes for a weighted average, not just any old weighted sum
- Most filters are symmetric about 0
  - since for images we usually want to treat left and right the same

Slide credit: S. Marschner
Convolution and filtering

• Can express sliding average as convolution with a box filter

\[ a_{box} = [..., 0, 1, 1, 1, 1, 1, 0, ...] \]

Slide credit: S. Marschner
Example: box and step
Convolution and filtering

• Convolution applies with any sequence of weights
• Example: bell curve (gaussian-like) \([…, 1, 4, 6, 4, 1, …]/16\)
And in pseudocode...

```plaintext
function convolve(sequence a, sequence b, int r, int i)
    s = 0
    for j = -r to r
        s = s + a[j] * b[i - j]
    return s
```

Slide credit: S. Marschner
Key properties

• **Linearity:** $\text{filter}(f_1 + f_2) = \text{filter}(f_1) + \text{filter}(f_2)$

• **Shift invariance:** $\text{filter}(\text{shift}(f)) = \text{shift}(\text{filter}(f))$
  - same behavior regardless of pixel location, i.e. the value of the output depends on the pattern in the image neighborhood, not the position of the neighborhood.

• Theoretical result: any linear shift-invariant operator can be represented as a convolution

Slide credit: S. Lazebnik
Properties in more detail

• Commutative: $a * b = b * a$
  – Conceptually no difference between filter and signal

• Associative: $a * (b * c) = (a * b) * c$
  – Often apply several filters one after another: $((a * b_1) * b_2) * b_3)$
  – This is equivalent to applying one filter: $a * (b_1 * b_2 * b_3)$

• Distributes over addition: $a * (b + c) = (a * b) + (a * c)$

• Scalars factor out: $ka * b = a * kb = k (a * b)$

• Identity: unit impulse $e = [..., 0, 0, 1, 0, 0, ...]$, $a * e = a$

Slide credit: S. Lazebnik
A gallery of filters

• Box filter
  – Simple and cheap

• Tent filter
  – Linear interpolation

• Gaussian filter
  – Very smooth antialiasing filter

Slide credit: S. Marschner
Box filter

\[ a_{\text{box},r}[i] = \begin{cases} 
1/(2r + 1) & |i| \leq r, \\
0 & \text{otherwise}. 
\end{cases} \]

\[ f_{\text{box},r}(x) = \begin{cases} 
1/(2r) & -r \leq x < r, \\
0 & \text{otherwise}. 
\end{cases} \]
Tent filter

\[ f_{\text{tent}}(x) = \begin{cases} 1 - |x| & |x| < 1, \\ 0 & \text{otherwise}; \end{cases} \]

\[ f_{\text{tent},r}(x) = \frac{f_{\text{tent}}(x/r)}{r}. \]
Gaussian filter

\[ f_g(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}. \]
Discrete filtering in 2D

• Same equation, one more index

\[(a \ast b)[i, j] = \sum_{i', j'} a[i', j']b[i - i', j - j']\]

– now the filter is a rectangle you slide around over a grid of numbers

• Usefulness of associativity

– often apply several filters one after another: \(((a \ast b_1) \ast b_2) \ast b_3)\)
– this is equivalent to applying one filter: \(a \ast (b_1 \ast b_2 \ast b_3)\)

Slide credit: S. Marschner
And in pseudocode...

```python
function convolve2d(filter2d a, filter2d b, int i, int j)
    s = 0
    r = a.radius
    for i' = -r to r do
        for j' = -r to r do
            s = s + a[i'][j'] * b[i - i'][j - j']
    return s
```
Moving Average In 2D

\[ F[x, y] \]

\[ G[x, y] \]
Moving Average In 2D

\[ F[x, y] \quad G[x, y] \]

Slide credit: S. Seitz
Moving Average In 2D

\[ F[x, y] \quad G[x, y] \]

Slide credit: S. Seitz
Moving Average In 2D

\[ F[x, y] \]

\[ G[x, y] \]

Slide credit: S. Seitz
Moving Average In 2D

$F[x, y]$

$G[x, y]$

Slide credit: S. Seitz
Moving Average In 2D

\[ F[x, y] \]

\[ G[x, y] \]
Image Correlation Filtering

• Center filter $g$ at each pixel in image $f$
• Multiply weights by corresponding pixels
• Set resulting value in output image $h$
• $g$ is called a filter, mask, kernel, or template
• Linear filtering is sum of dot product at each pixel position
• Filtering operation called cross-correlation
Correlation filtering

Say the averaging window size is $2k+1 \times 2k+1$:

$$G[i, j] = \frac{1}{(2k + 1)^2} \sum_{u=-k}^{k} \sum_{v=-k}^{k} F[i + u, j + v]$$

Attribute uniform weight to each pixel
Loop over all pixels in neighborhood around image pixel $F[i,j]$

Now generalize to allow different weights depending on neighboring pixel’s relative position:

$$G[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u, v] F[i + u, j + v]$$

Non-uniform weights

Slide credit: K. Grauman
Correlation filtering

\[ G[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u, v] F[i + u, j + v] \]

This is called cross-correlation, denoted \( G = H \otimes F \).

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter “kernel” or “mask” \( H[u, v] \) is the prescription for the weights in the linear combination.

Slide credit: K. Grauman
Correlation filtering

Scene

Template (mask)
Correlation filtering

Detected template

Correlation map
Cross correlation example

Left

Right

scanline

Norm. corr

Slide credit: Fei-Fei Li
Averaging filter

- What values belong in the kernel $H$ for the moving average example?

$$G = H \otimes F$$

Slide credit: K. Grauman
Smoothing by averaging

What if the filter size was 5 x 5 instead of 3 x 3?

Slide credit: K. Grauman
Boundary issues

• What is the size of the output?

• MATLAB: output size / “shape” options
  – $shape = 'full'$: output size is sum of sizes of $f$ and $g$
  – $shape = 'same'$: output size is same as $f$
  – $shape = 'valid'$: output size is difference of sizes of $f$ and $g$

Slide credit: S. Lazebnik
Boundary issues

• What about near the edge?
  – the filter window falls off the edge of the image
  – need to extrapolate
  – methods:
    • clip filter (black)
    • wrap around
    • copy edge
    • reflect across edge

Slide credit: S. Marschner
Boundary issues

• What about near the edge?
  – the filter window falls off the edge of the image
  – need to extrapolate
  – methods (MATLAB):
    • clip filter (black): \texttt{imfilter}(f, g, 0)
    • wrap around: \texttt{imfilter}(f, g, ‘circular’)
    • copy edge: \texttt{imfilter}(f, g, ‘replicate’)
    • reflect across edge: \texttt{imfilter}(f, g, ‘symmetric’)

Slide credit: S. Marschner
**Gaussian filter**

- What if we want nearest neighboring pixels to have the most influence on the output?

![Gaussian kernel](image)

This kernel is an approximation of a 2d Gaussian function:

\[ h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}} \]

- Removes high-frequency components from the image ("low-pass filter").

Slide credit: S. Seitz
Smoothing with a Gaussian

Slide credit: K. Grauman
Gaussian filters

- What parameters matter here?

- **Size** of kernel or mask
  - Note, Gaussian function has infinite support, but discrete filters use finite kernels

Slide credit: K. Grauman
Gaussian filters

• What parameters matter here?
• **Variance** of Gaussian: determines extent of smoothing

\[ \sigma = 2 \text{ with } 30 \times 30 \text{ kernel} \]

\[ \sigma = 5 \text{ with } 30 \times 30 \text{ kernel} \]

Slide credit: K. Grauman
Choosing kernel width

- Rule of thumb: set filter half-width to about $3\sigma$
Matlab

```matlab
>> hsize = 10;
>> sigma = 5;
>> h = fspecial('gaussian' hsize, sigma);

>> mesh(h);

>> imagesc(h);

>> outim = imfilter(im, h); % correlation
>> imshow(outim);
```

Slide credit: K. Grauman
Smoothing with a Gaussian

Parameter $\sigma$ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.

```matlab
for sigma=1:3:10
    h = fspecial('gaussian', fsize, sigma);
    out = imfilter(im, h);
    imshow(out);
    pause;
end
```

Slide credit: K. Grauman
Gaussian Filters

Slide credit: C. Dyer
Spatial Resolution and Color
Blurring the \textbf{G} Component

original \hspace{1cm} processed

Slide credit: C. Dyer
Blurring the R Component

original

processed

Slide credit: C. Dyer
Blurring the B Component

original
processed

Slide credit: C. Dyer
“Lab” Color Representation

A transformation of the colors into a color space that is more perceptually meaningful:

- **L**: luminance
- **a**: red-green
- **b**: blue-yellow

Slide credit: C. Dyer
Blurring L

original

processed

Slide credit: C. Dyer
Blurring a

original

processed

Slide credit: C. Dyer
Blurring b
Separability

- In some cases, filter is separable, and we can factor into two steps:
  - Convolve all rows
  - Convolve all columns
Separability of the Gaussian filter

\[ G_\sigma(x, y) = \frac{1}{2\pi \sigma^2} \exp \left( -\frac{x^2 + y^2}{2\sigma^2} \right) \]

\[ = \left( \frac{1}{\sqrt{2\pi \sigma}} \exp \left( -\frac{x^2}{2\sigma^2} \right) \right) \left( \frac{1}{\sqrt{2\pi \sigma}} \exp \left( -\frac{y^2}{2\sigma^2} \right) \right) \]

The 2D Gaussian can be expressed as the product of two functions, one a function of \( x \) and the other a function of \( y \).

In this case, the two functions are the (identical) 1D Gaussian.
Separability example

2D convolution (center location only)

Perform convolution along rows:

Followed by convolution along the remaining column:

The filter factors into a product of 1D filters:

Slide credit: K. Grauman
Why is separability useful?

• What is the complexity of filtering an $n \times n$ image with an $m \times m$ kernel?
  – $O(n^2 m^2)$

• What if the kernel is separable?
  – $O(n^2 m)$
Properties of smoothing filters

- **Smoothing**
  - Values positive
  - Sum to 1 → constant regions same as input
  - Amount of smoothing proportional to mask size
  - Remove “high-frequency” components; “low-pass” filter
Filtering an impulse signal

What is the result of filtering the impulse signal (image) $F$ with the arbitrary kernel $H$?

$F[x, y] \otimes H[u, v] \rightarrow G[x, y]$
Convolution

- Convolution:
  - Flip the filter in both dimensions (bottom to top, right to left)
  - Then apply cross-correlation

\[
G[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u, v] F[i - u, j - v]
\]

\[
G = H \ast F
\]

Notation for convolution operator

Slide credit: K. Grauman
Convolution vs. Correlation

• A **convolution** is an integral that expresses the amount of overlap of one function as it is shifted over another function.
  – convolution is a filtering operation

• **Correlation** compares the *similarity of two sets of data.* Correlation computes a measure of similarity of two input signals as they are shifted by one another. The correlation result reaches a maximum at the time when the two signals match best.
  – correlation is a measure of relatedness of two signals

Slide credit: Fei-Fei Li
Convolution vs. correlation

Convolution

\[ G[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u, v] F[i - u, j - v] \]

\[ G = H \star F \]

Cross-correlation

\[ G[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u, v] F[i + u, j + v] \]

\[ G = H \otimes F \]

For a Gaussian or box filter, how will the outputs differ?
If the input is an impulse signal, how will the outputs differ?
Predict the outputs using correlation filtering

\[
\begin{array}{c}
\text{Slide credit: K. Grauman}
\end{array}
\]
Practice with linear filters

Original

Slide credit: D. Lowe
Practice with linear filters

Original

Filtered (no change)

Slide credit: D. Lowe
Practice with linear filters

Original

Slide credit: D. Lowe
Practice with linear filters

Original

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Shifted left by 1 pixel with correlation

Slide credit: D. Lowe
Practice with linear filters

Original

1 1 1 1
1 1 1 1
1 1 1 1

1/9

?
Practice with linear filters

Original

\[
\begin{array}{ccc}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1 \\
\end{array}
\]

Blur (with a box filter)

Slide credit: D. Lowe
Practice with linear filters

Original

\[
\begin{array}{ccc}
0 & 0 & 0 \\
0 & 2 & 0 \\
0 & 0 & 0 \\
\end{array}
\quad - \quad \frac{1}{9}
\begin{array}{ccc}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1 \\
\end{array}
\]

?
Practice with linear filters

\[ \begin{bmatrix}
0 & 0 & 0 \\
0 & 2 & 0 \\
0 & 0 & 0 \\
\end{bmatrix} - \frac{1}{9} \begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1 \\
\end{bmatrix} \]

Sharpening filter: accentuates differences with local average

Slide credit: D. Lowe
Filtering examples: sharpening

before

after

Slide credit: K. Grauman
Sharpening

- What does blurring take away?

Let’s add it back:

Slide credit: S. Lazebnik
Unsharp mask filter

\[ f + \alpha(f - f \ast g) = (1 + \alpha)f - \alpha f \ast g = f \ast ((1 + \alpha)e - g) \]
Sharpening using Unsharp Mask Filter

Original

Filtered result

Slide credit: C. Dyer
Unsharp Masking

Slide credit: C. Dyer
Other filters

Slide credit: J. Hays
Other filters

Sobel

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Horizontal Edge (absolute value)

Slide credit: J. Hays
Median filters

• A **Median Filter** operates over a window by selecting the median intensity in the window.

• What advantage does a median filter have over a mean filter?

• Is a median filter a kind of convolution?

adapted from: S. Seitz
Median filter

- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise
- Non-linear filter

Slide credit: K. Grauman
Median filter

Salt and pepper noise

Median filtered

Plots of a row of the image

Matlab: `output im = medfilt2(im, [h w]);`

Slide credit: M. Hebert
Median filter

- What advantage does median filtering have over Gaussian filtering?
  - Robustness to outliers
  - Median filter is edge preserving

Slide credit: K. Grauman