Image Filtering

Week – 2B

Announcement

- Mathematics Reference Book: Linear algebra, probability
  - https://mml-book.github.io/book/mml-book.pdf
  - eg. CDF (cumulative distribution function, see chapter 6.2 discrete and continuous distribution function)

- Lecture Series by Prof. Shree Nayar, Professor of Computer Science in the School of Engineering at Columbia University, Senior researcher in computer vision with high profile.
  - https://fpcv.cs.columbia.edu/

Outline

- Image Noise
- Linear filter
  - Gaussian filter
  - Edge detection
- Non-linear filter
  - median filter
  - bilateral filter

Outline

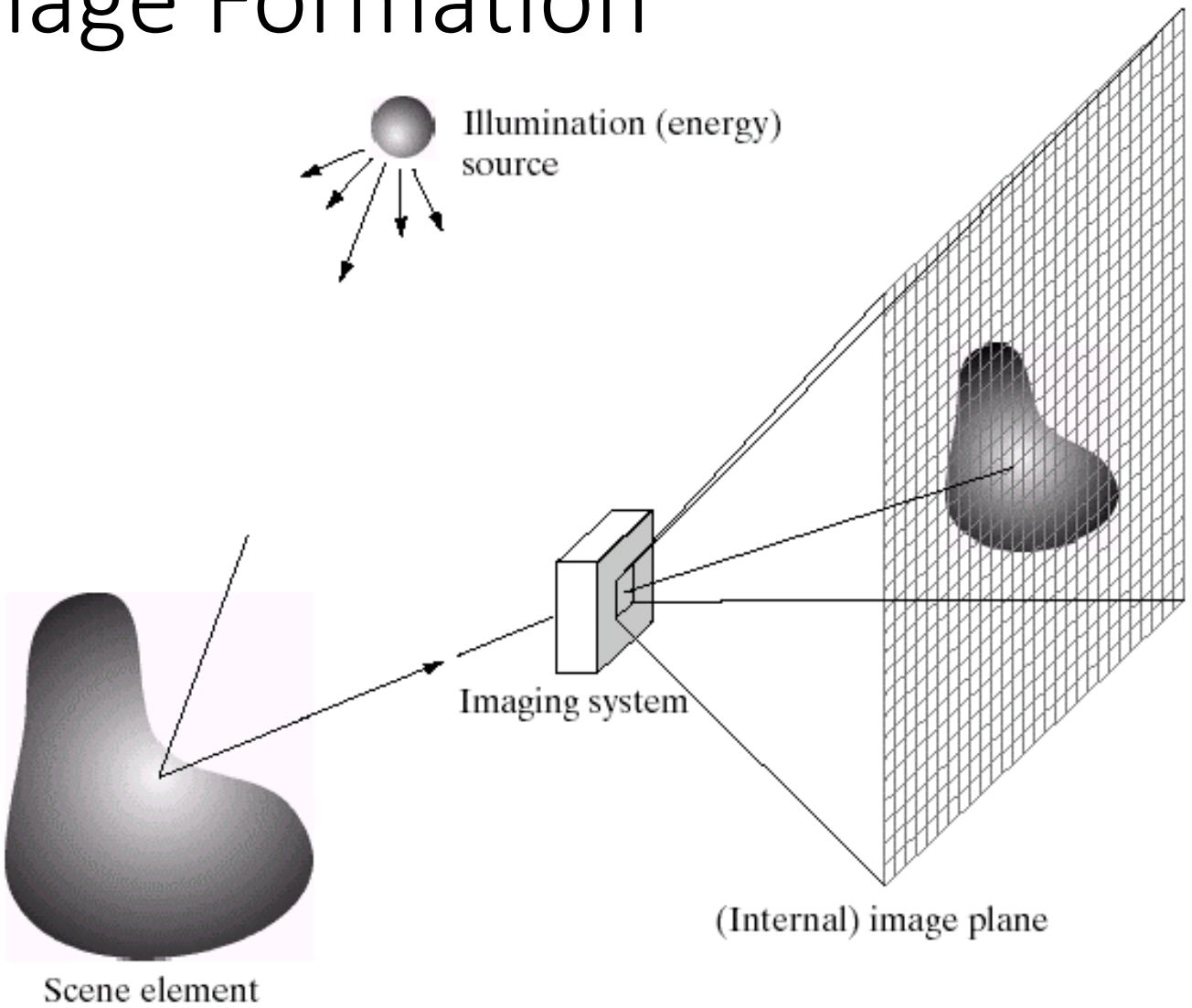
- Image Noise
- Linear filter
  - Gaussian filter
  - Edge detection
- Non-linear filter
  - median filter
  - bilateral filter

Image Filtering

- Filtering (correlation, convolution)
- Gaussian filter
- Application of filters (denoising, edge, contour, corner, texture, template matching and tracking ...,)

Image Noise

Recall: Image Formation



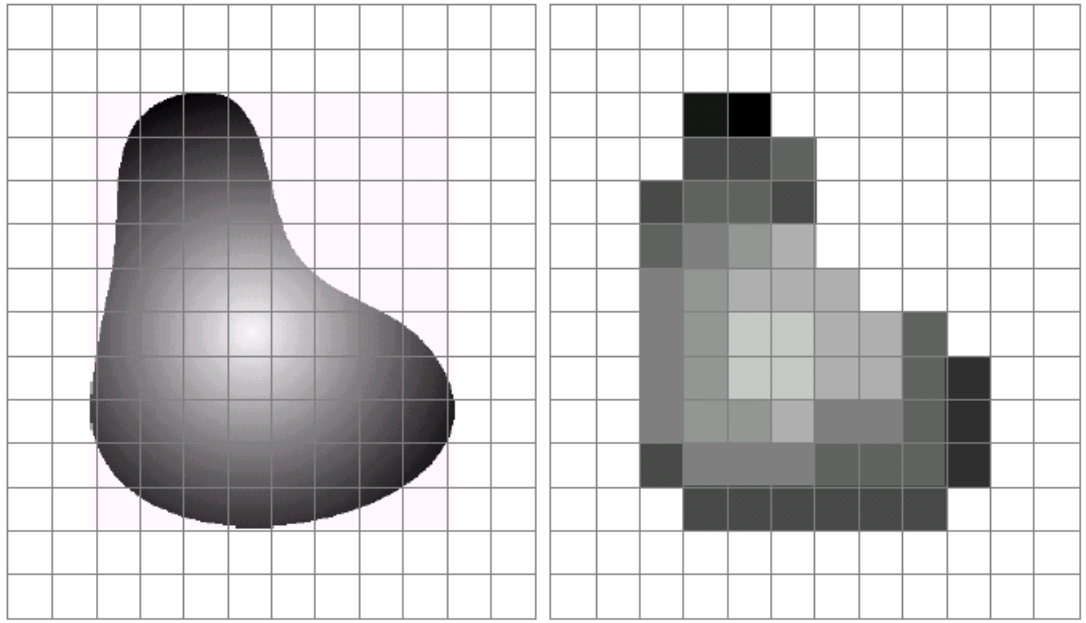
Recall: Digital camera

A digital camera replaces film with a sensor array

- Each cell in the array is light-sensitive diode that converts photons to electrons
- http://electronics.howstuffworks.com/digital-camera.htm

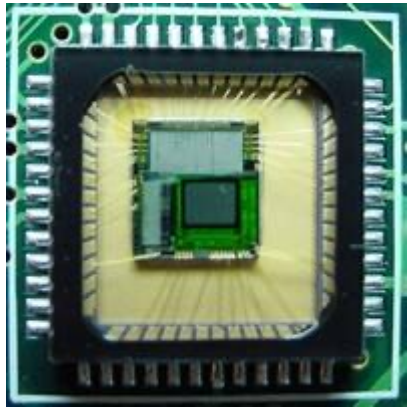
Slide by Steve Seitz

Digital images



a b

FIGURE 2.17 (a) Continuos image projected onto a sensor array. (b) Result of image sampling and quantization.



Recall: Images as functions

- We can think of an image as a function, *f*, from R^2 to R: Input: coordinate output: intensity value
  - $f(x, y)$ gives the intensity at position (x, y)
  - Realistically, we expect the image only to be defined over a rectangle, with a finite range:
    - $f: [a,b] \times [c,d] \rightarrow [0, 255]$

limit intensity

- A color image is just three functions pasted together. We can write this as a "vector-valued" function:

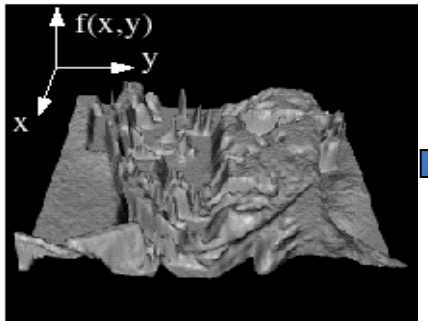
$$f(x,y) = \begin{bmatrix} r(x,y) \\ g(x,y) \\ b(x,y) \end{bmatrix}$$

Source: S. Seitz

Recall: Digital images

- **Sample** the 2D space on a regular grid
- **Quantize** each sample (round to nearest integer)

- Image is thus represented as a matrix of integer values.

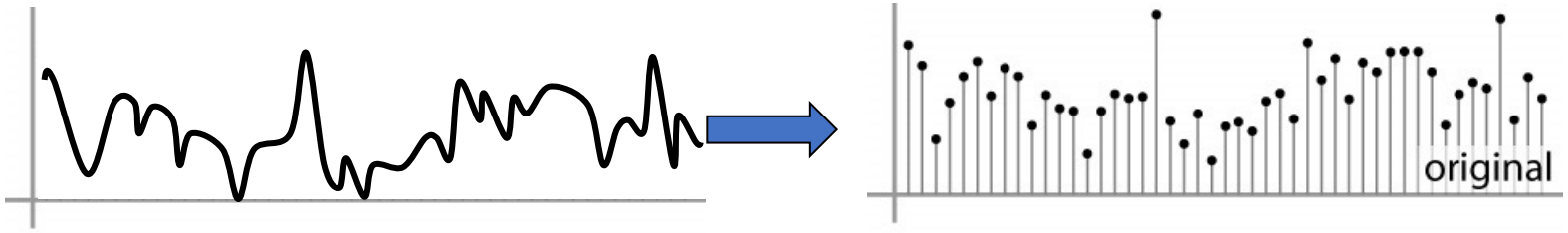


x

y

62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	197	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

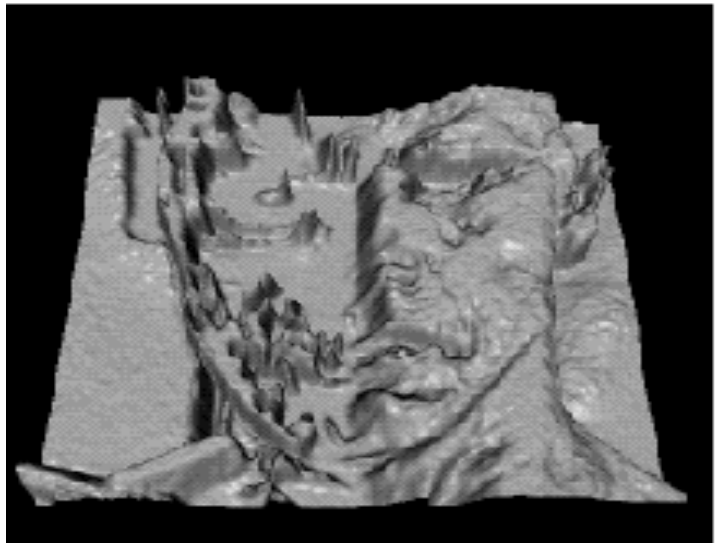
2D

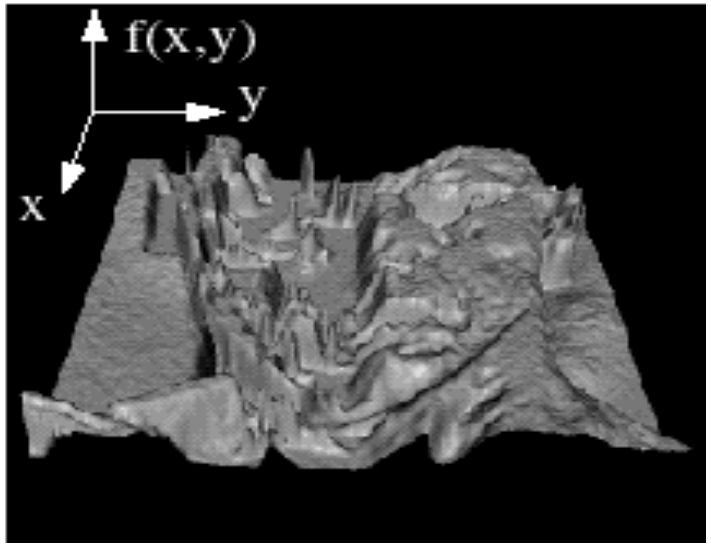


1D

Adapted from S. Seitz

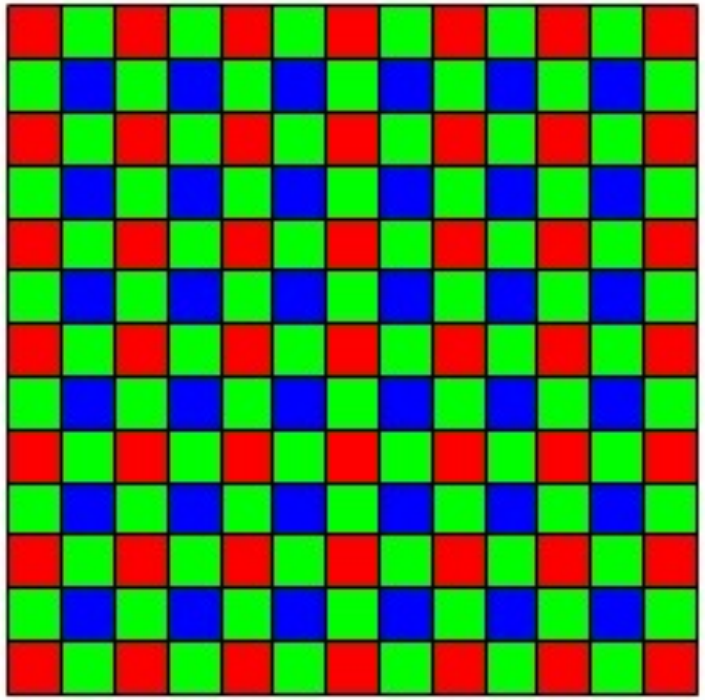
Recall: Images as functions





Source: S. Seitz

Digital color images



Bayer filter

Slide credit: Kristen Grauman

Recall: Digital color images

Color images, RGB color space

R

G

B

Common types of noise

- **Salt and pepper noise**: random occurrences of black and white pixels
- **Impulse noise:** random occurrences of white pixels, sometimes, it is also referred to as Salt and pepper noise.
- **Gaussian noise**: variations in intensity drawn from a Gaussian normal distribution

Original

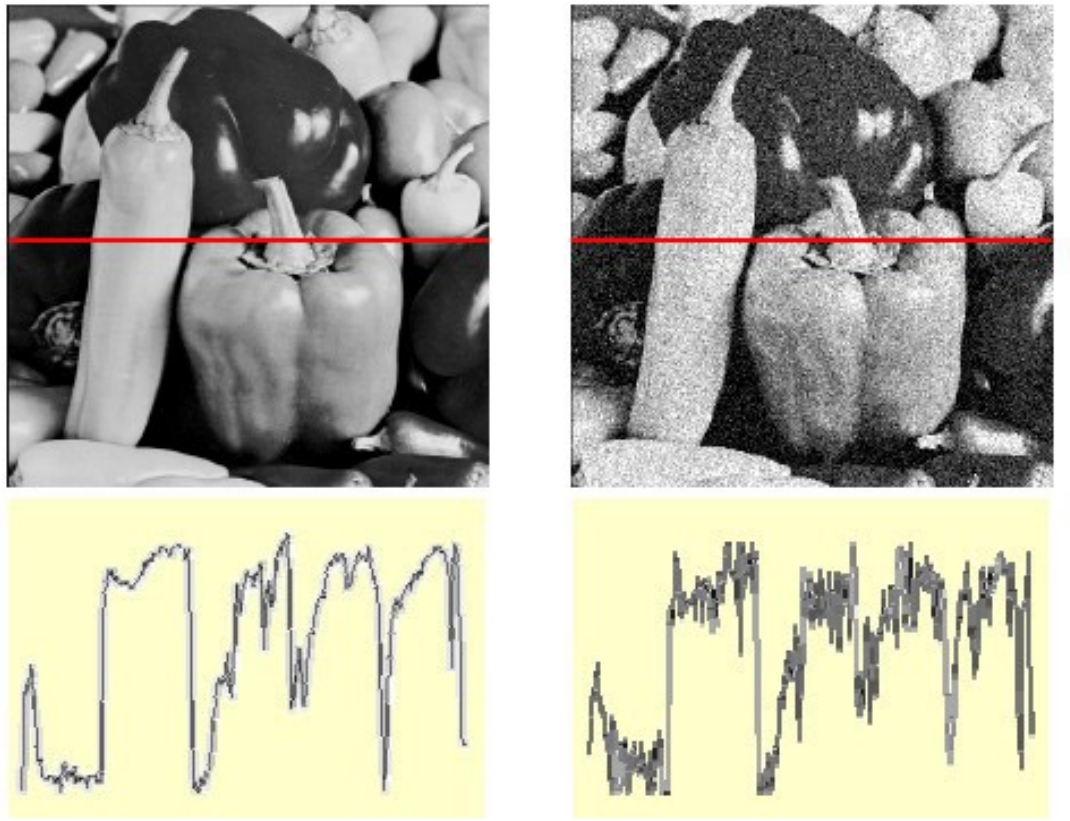
Salt and pepper noise

Impulse noise

Gaussian noise

Source: S. Seitz

Gaussian noise



$$f(x,y) = \overbrace{\bar{f}(x,y)}^{\text{Ideal Image}} + \overbrace{\eta(x,y)}^{\text{Noise process}}$$

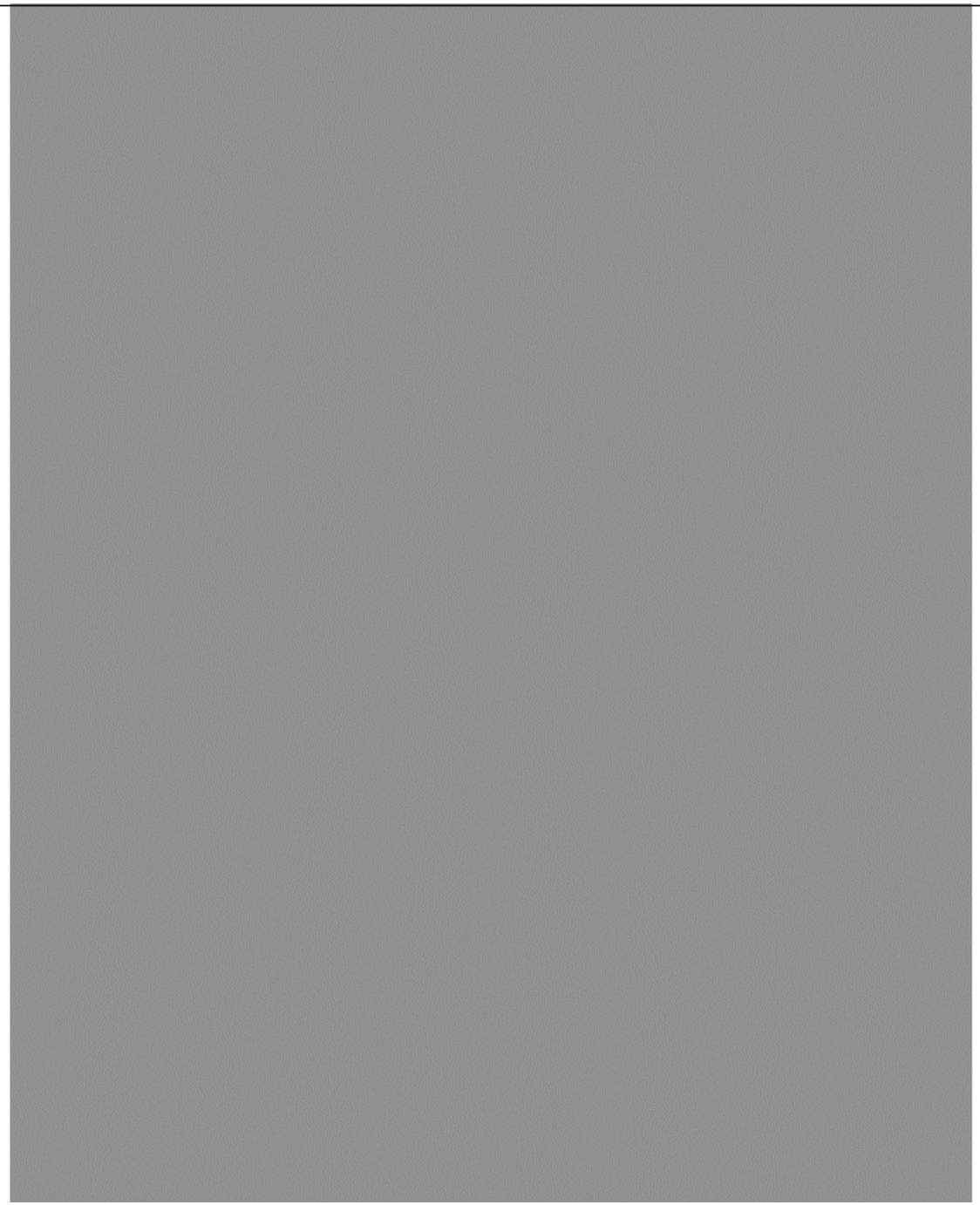
Gaussian i.i.d. ("white") noise:
$\eta(x,y) \sim \mathcal{N}(\mu,\sigma)$

```
>> noise = np.random.normal(mean, std_dev, shape)
>> output = im + noise;
```

What is the impact of the sigma?

Fig: M. Hebert

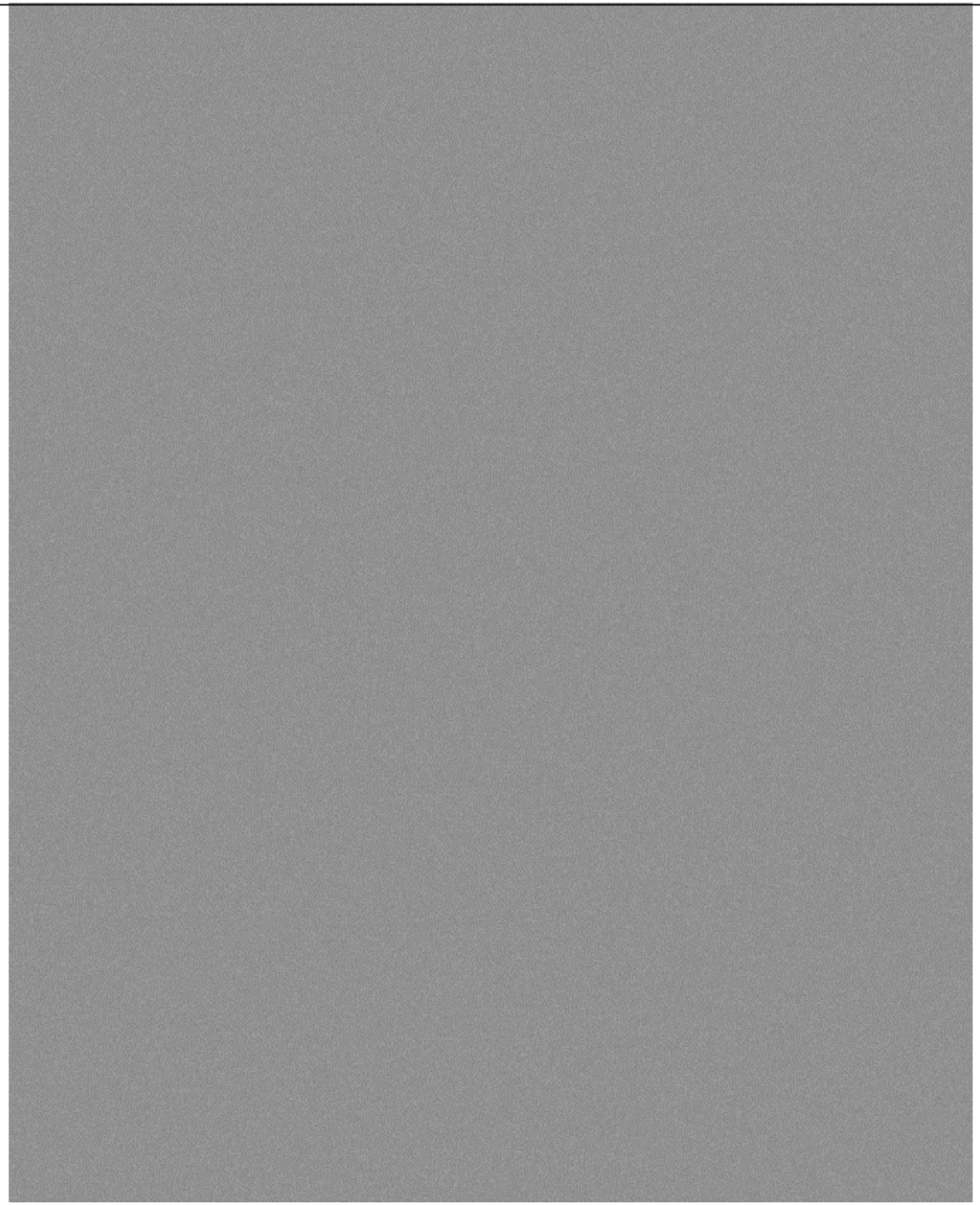
sigma=1



Effect of sigma on Gaussian noise:

Image shows the noise values themselves.

sigma=4



Effect of sigma on Gaussian noise:

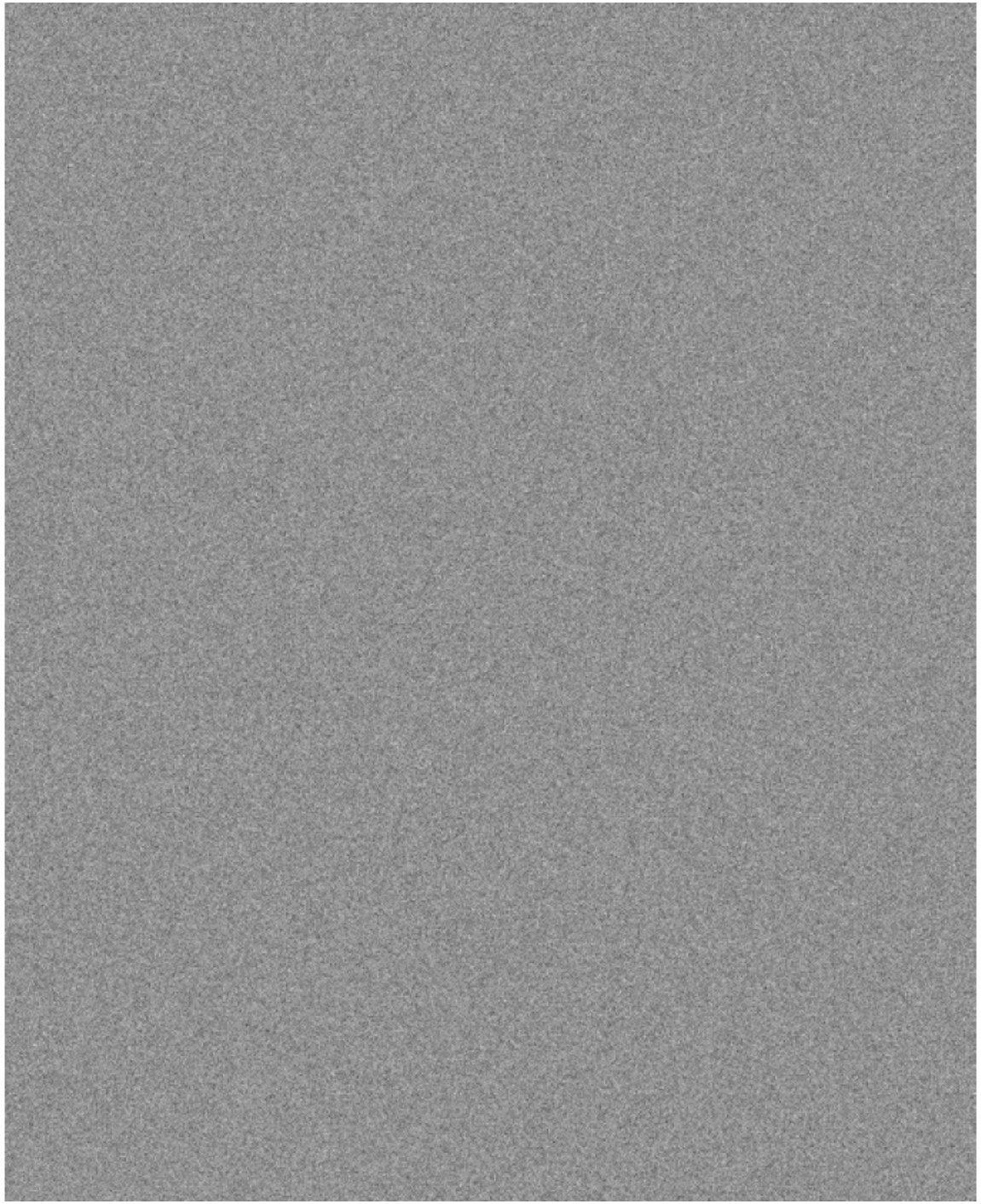
Image shows the noise values themselves.

sigma=1

Effect of sigma on Gaussian noise:

This shows the noise values added to the raw intensities of an image.

sigma=
16



Effect of sigma on Gaussian noise:

Image shows the noise values themselves.

sigma=16

Effect of sigma on Gaussian noise

This shows the noise values added to the raw intensities of an image.

Noise Reduction

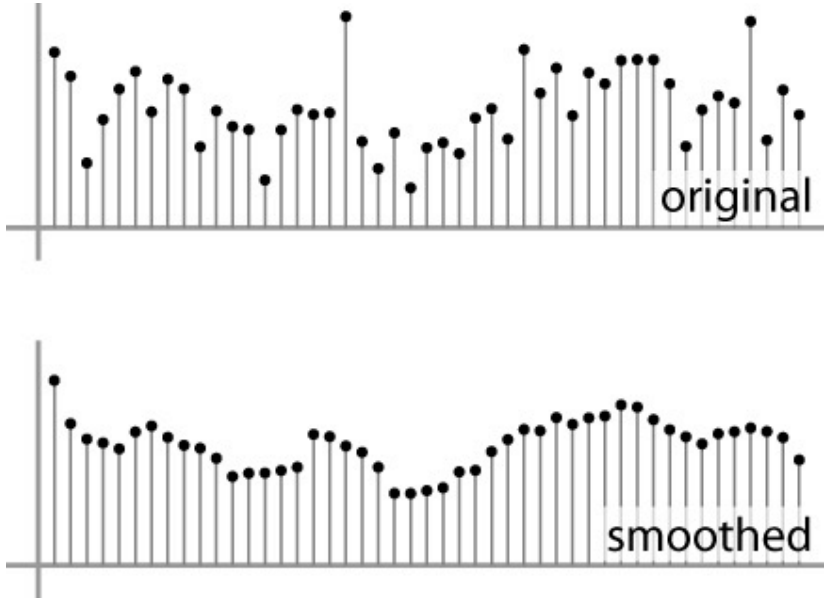
- How should we reduce the noise?

First attempt at a solution

- Let's replace each pixel with an average of all the values in its neighborhood (neighborhood operation)
- Assumptions:
  - Expect pixel to be like their neighbors
  - Expect noise processes to be independent from pixel to pixel

First attempt at a solution

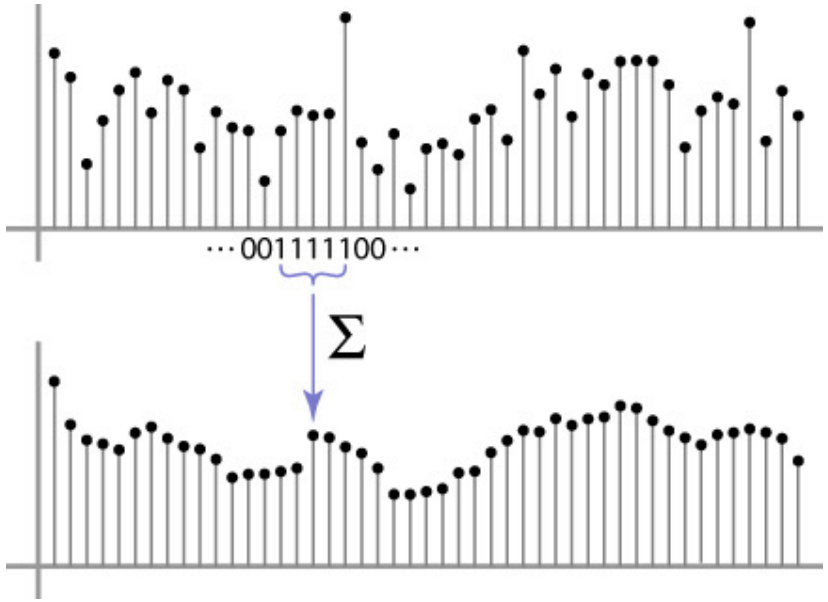
- Let’s replace each pixel with an average of all the values in its neighborhood
- Moving average in 1D:



•Source: S. Marschner

Weighted Moving Average

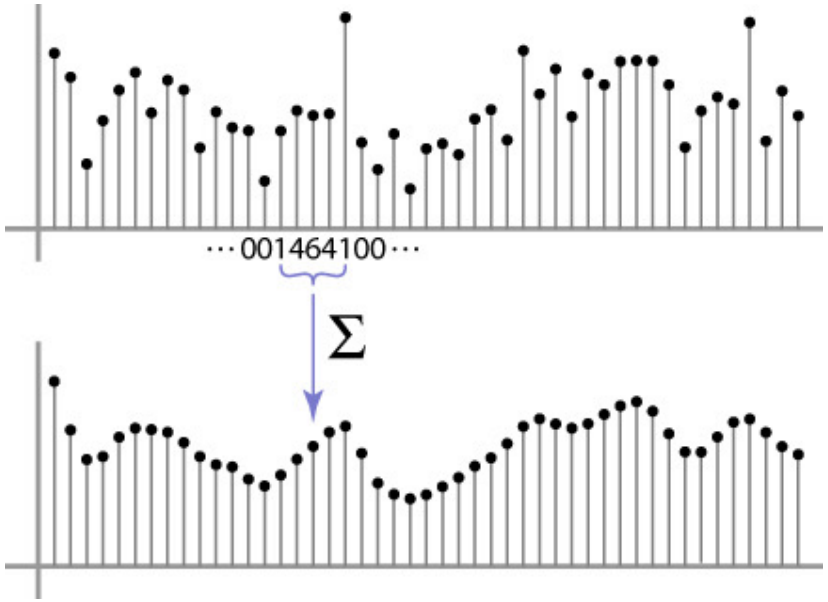
- Can add weights to our moving average
- *Weights* [1, 1, 1, 1, 1] / 5



•Source: S. Marschner

Weighted Moving Average

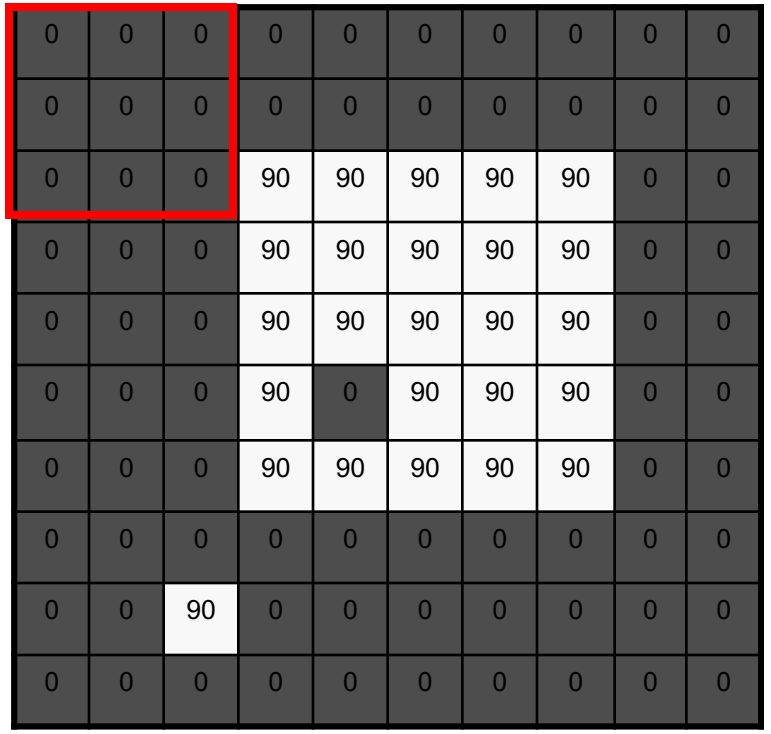
- Non-uniform weights [1, 4, 6, 4, 1] / 16



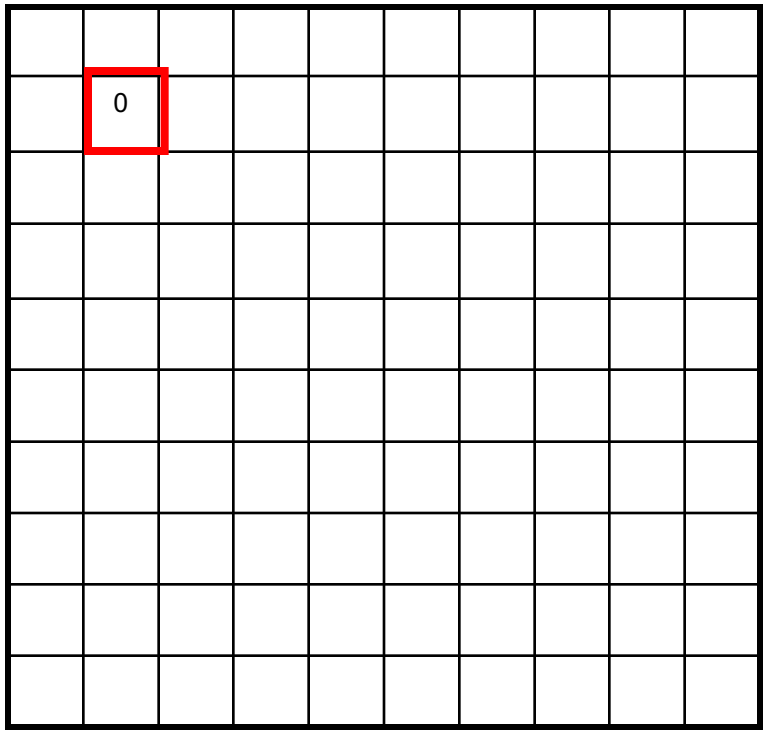
•Source: S. Marschner

Moving Average In 2D

$F[x, y]$



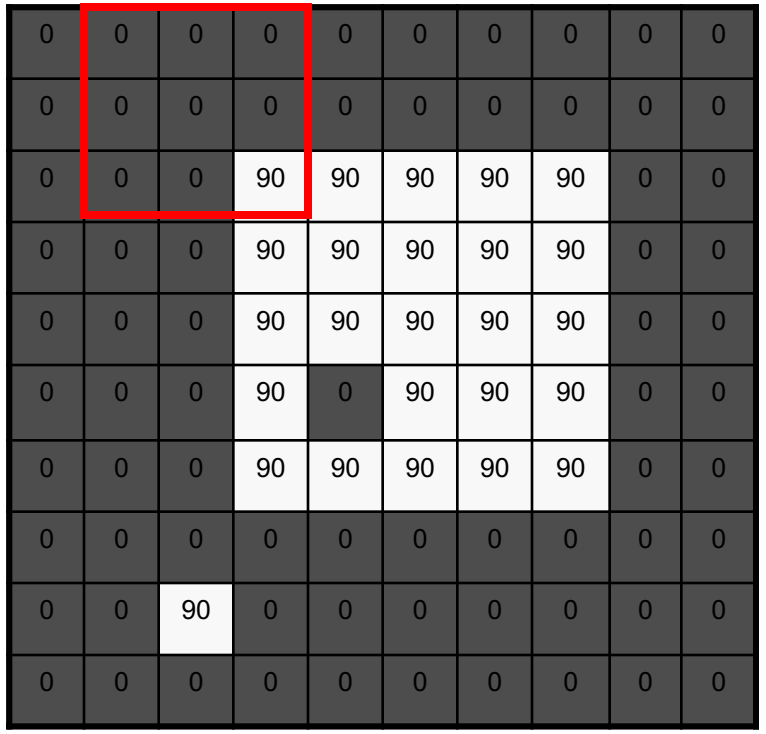
$G[x, y]$



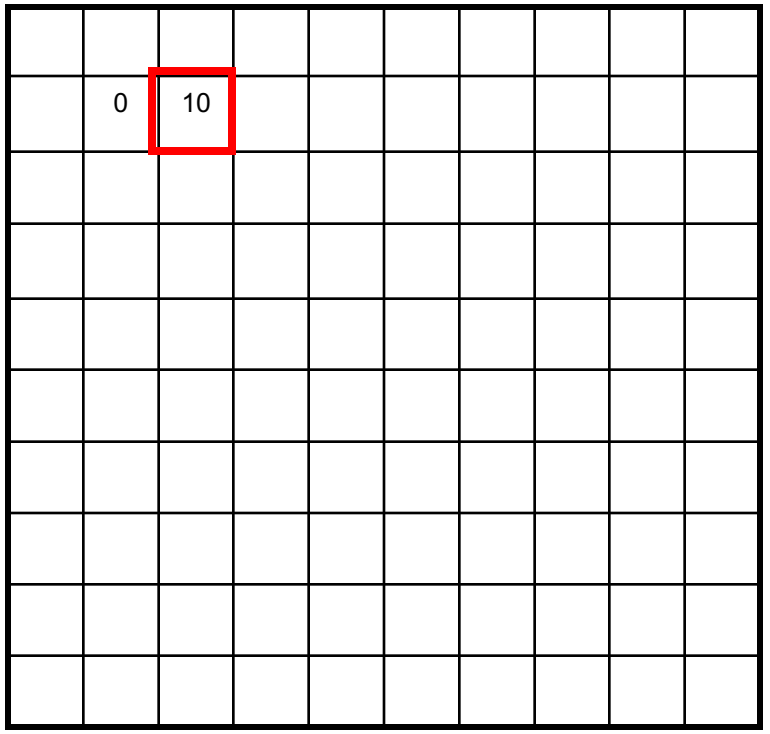
•Source: S. Seitz

Moving Average In 2D

$F[x, y]$



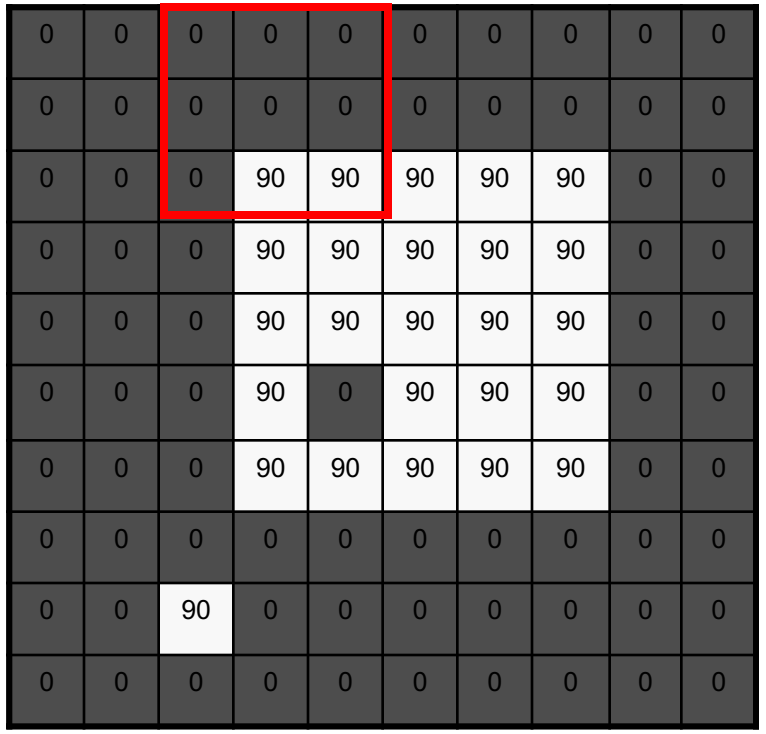
$G[x, y]$



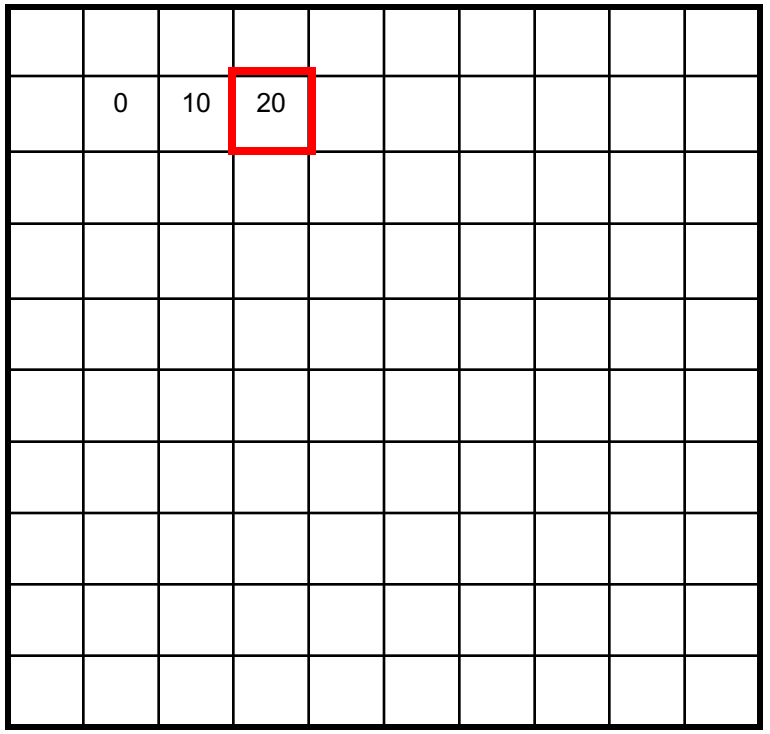
•Source: S. Seitz

Moving Average In 2D

$F[x, y]$



$G[x, y]$



•Source: S. Seitz

Moving Average In 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30					

•Source: S. Seitz

Moving Average In 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30	30				

•Source: S. Seitz

Moving Average In 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

•Source: S. Seitz

Correlation filtering

Say the averaging window size is (2k+1) x (2k+1):

$$G[x,y] = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \underbrace{\sum_{u=-k}^{k}\sum_{v=-k}^{k} F[x+u, y+v]}_{\text{Loop over all pixels in neighborhood around image pixel F[x,y]}}$$

average over the window

Now we can generalize to allow **different weights** depending on neighboring pixel's relative position:

$$G[x,y] = \sum_{u=-k}^{k}\sum_{v=-k}^{k} \underbrace{H[u,v]}_{\text{Non-uniform weights}} F[x+u, y+v]$$

Slide credit: Kristen Grauman

Correlation filtering

u, v define the size of window

after $$G[x,y] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[x+u, y+v]$$ before

kernel/mask that depands on the coordinates in the window

moving across the pixels in the window

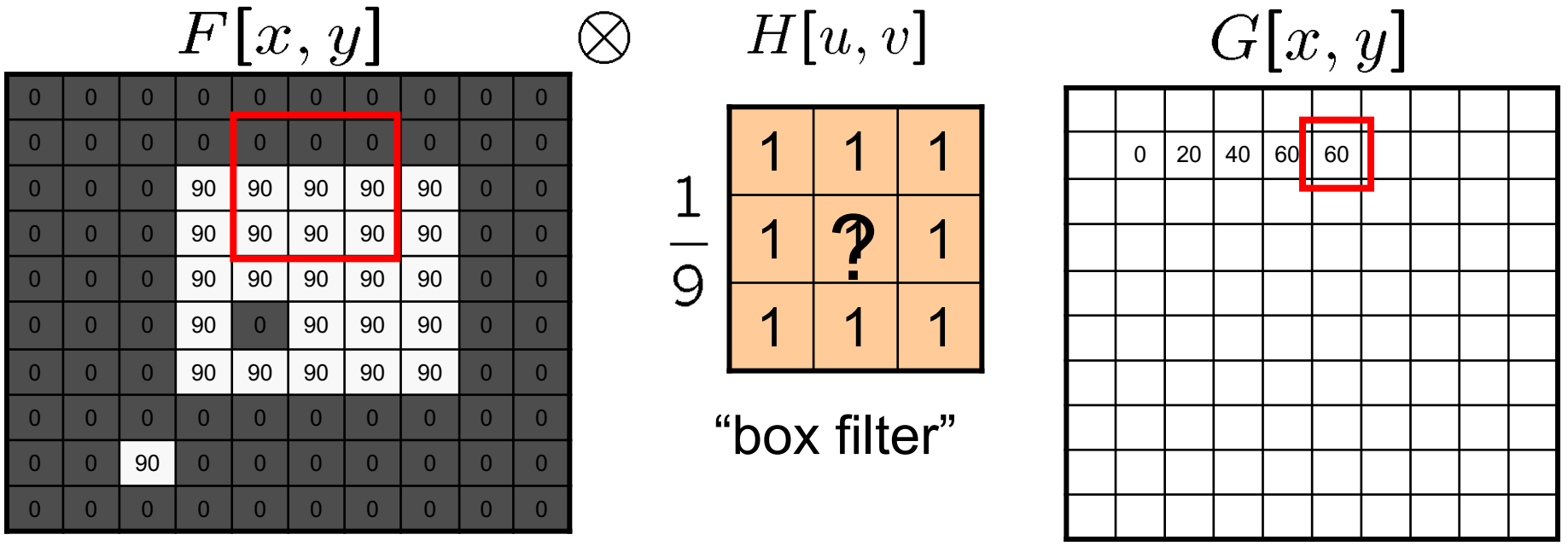
This is called cross-correlation, denoted $$G = H \otimes F$$

- Filtering an image: replace each pixel with a linear combination of its neighbors.
- The filter "kernel" or "mask" $H[u,v]$ defines the weights in the linear combination.

Slide credit: Kristen Grauman

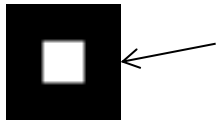
Averaging filter

- What values belong to the kernel *H* for the moving average example?



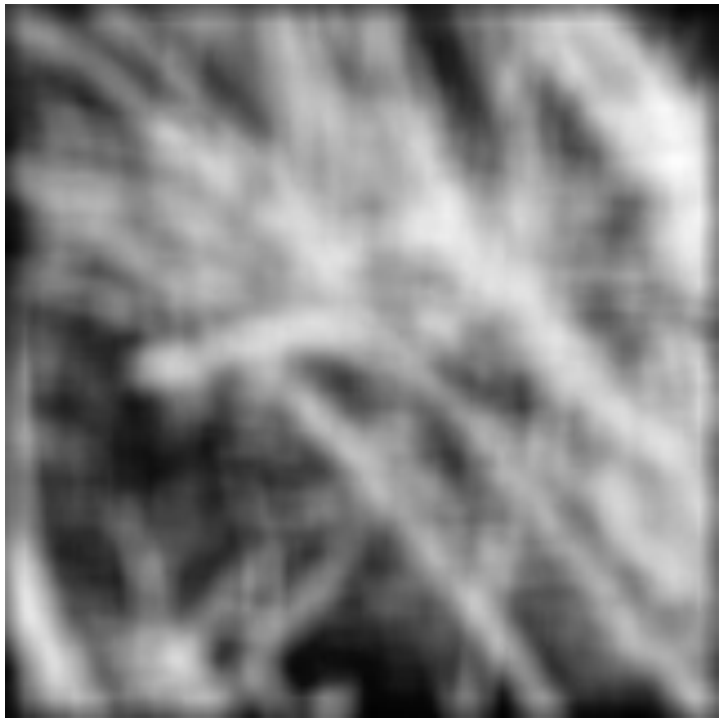
$$G = H \otimes F$$

Smoothing by averaging



depicts box filter:
white = high value, black = low value

original



filtered

We can see the ‘Block’ effect on the filtered image.

Image Filtering

- Image filtering: compute the function value of local neighbourhood at each pixel.
- Very useful
  - **Enhance images**
    - De-noise, resize, increase contrast, etc.
  - **Extract information from images**
    - Texture, edges, distinctive points, etc.
  - **Detect patterns**
    - Template matching

Gaussian filter

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

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$

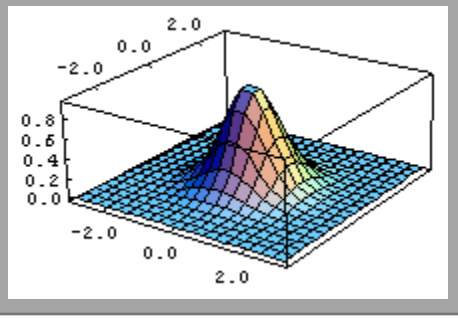
$$\frac{1}{16}$$

1	2	1
2	4	2
1	2	1

$H[u, v]$

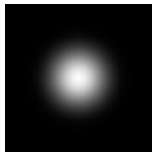
- This kernel is an approximation of a 2d Gaussian function:

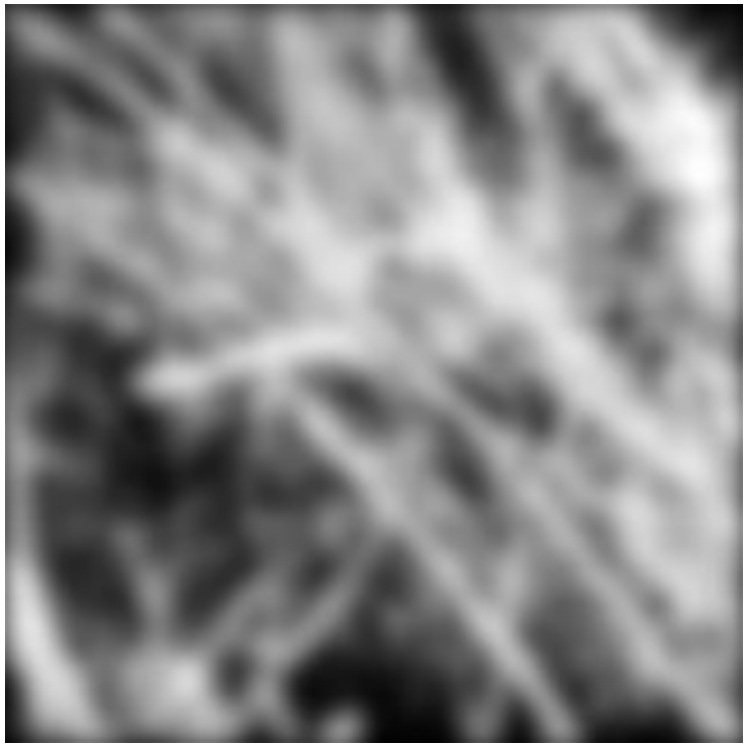
$$h(u, v) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{u^2+v^2}{2\sigma^2}}$$



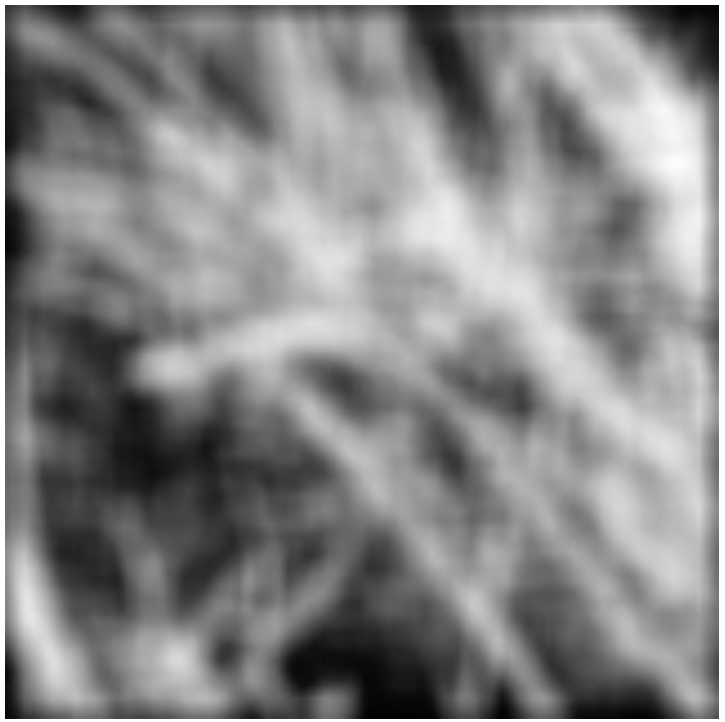
Source: S. Seitz

Smoothing with a Gaussian

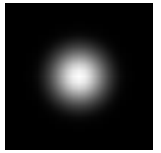


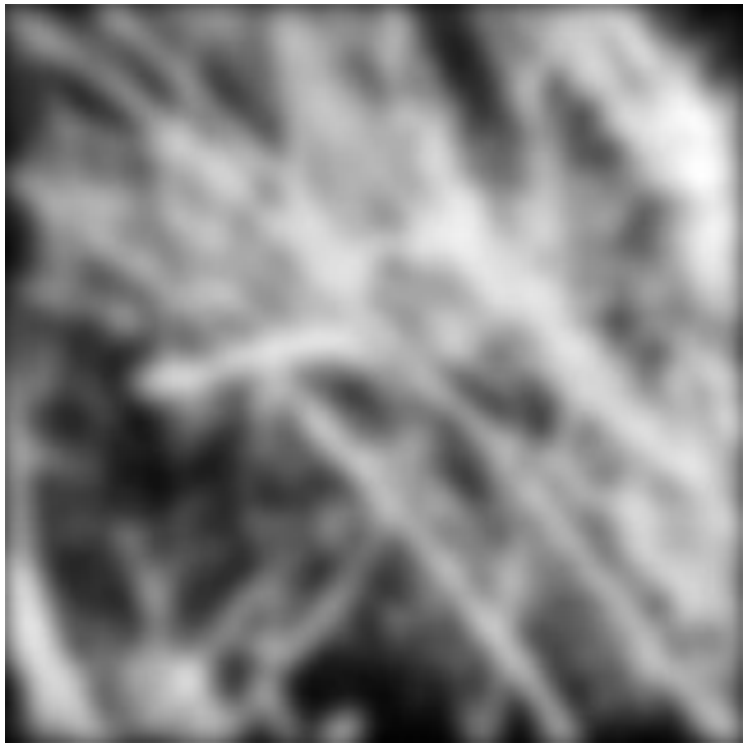


Compare box filter with Gaussian filter effects



Smoothed image by box filter



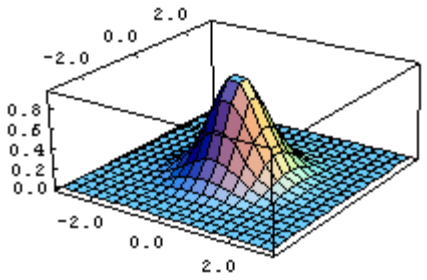


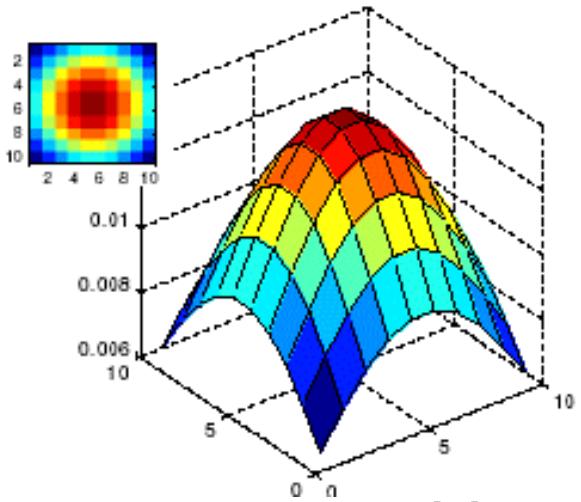
Smoothed image by Gaussian filter

Gaussian filters

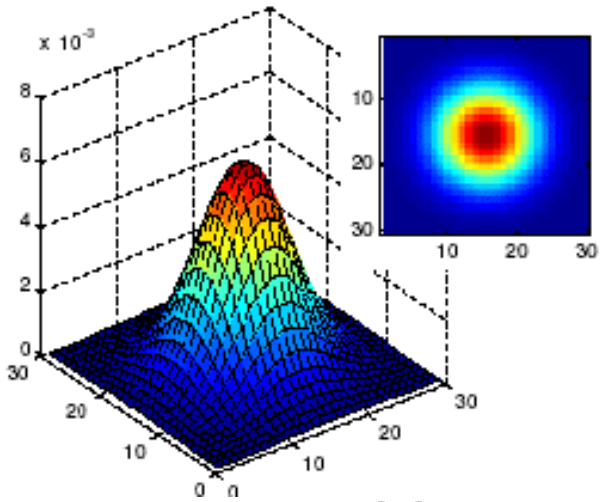
- What parameters matter here?
- **Size** of kernel or mask
  - Note, Gaussian function has infinite support, but discrete filters use finite kernels

$$h(u,v) = \frac{1}{2\pi\sigma^2}\exp^{-\frac{u^2+v^2}{2\sigma^2}}$$





σ = 5 with 10x 10 kernel

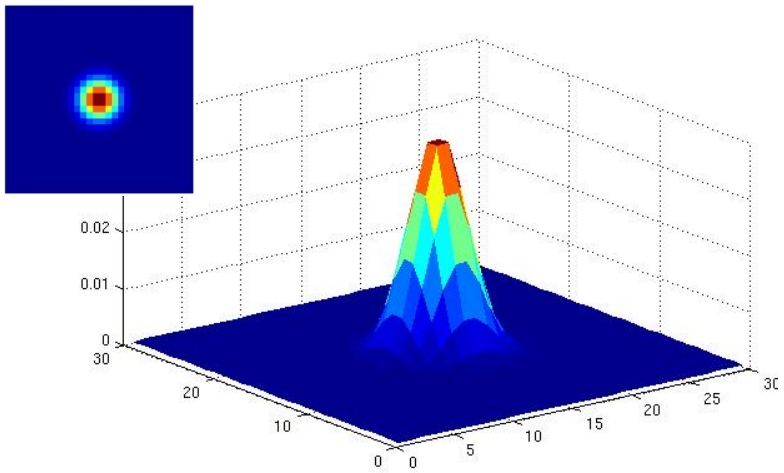


σ = 5 with 30 x 30 kernel

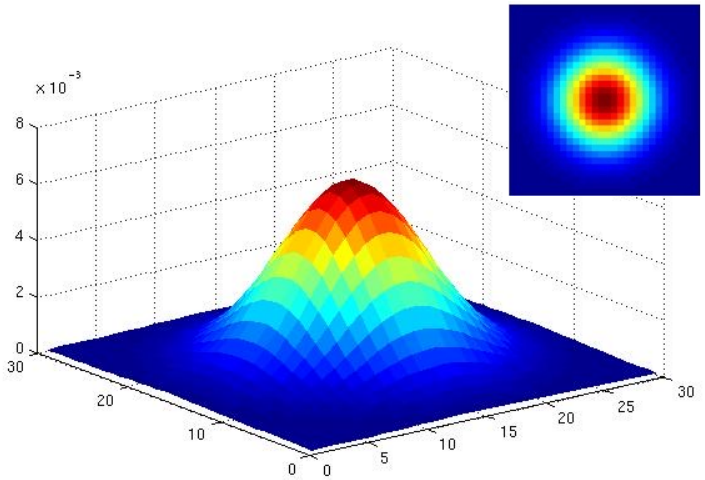
•Slide credit: Kristen Grauman

Gaussian filters

- What parameters matter here?
- **Variance** of the Gaussian function : determines extent of smoothing



σ = 2 with 30 x 30 kernel

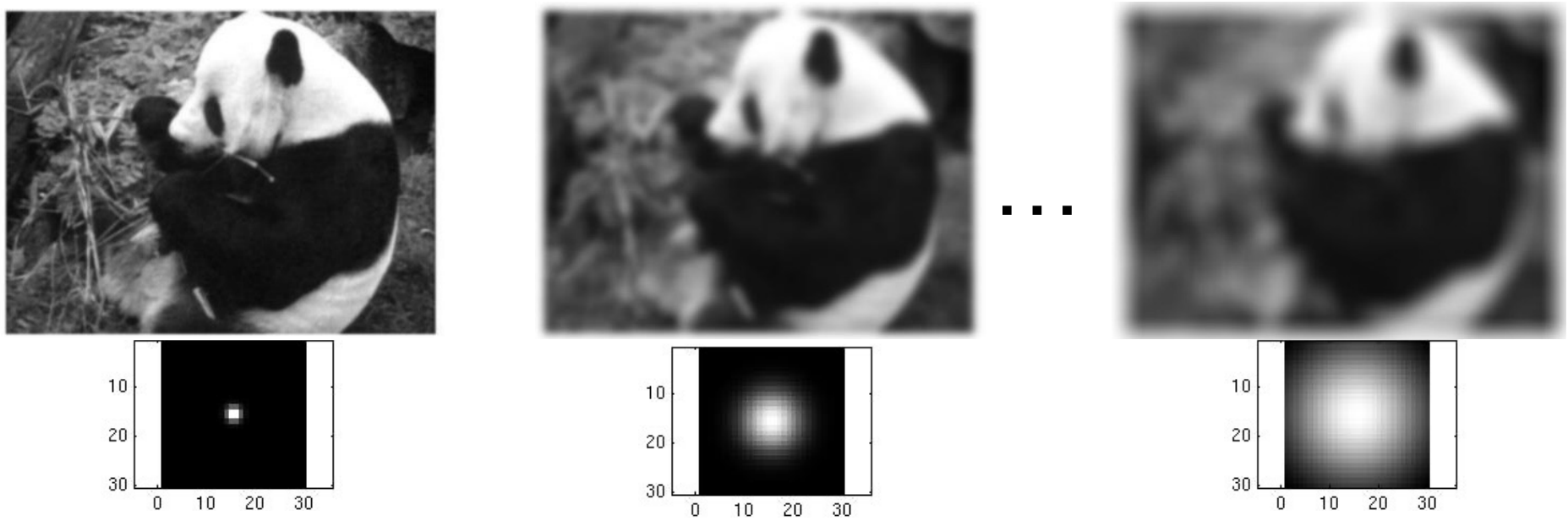


σ = 5 with 30 x 30 kernel

•Slide credit: Kristen Grauman

Smoothing with a Gaussian

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



. . .

•Slide credit: Kristen Grauman

Convolution

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

$$G[x,y] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[x-u,y-v]$$

$$G = H \star F$$

Notation for convolution operator

Convolution

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

$$G(x,y) = \sum_{u=0}^{M} \sum_{v=0}^{N} F(u,v) H(x-u, y-v)$$

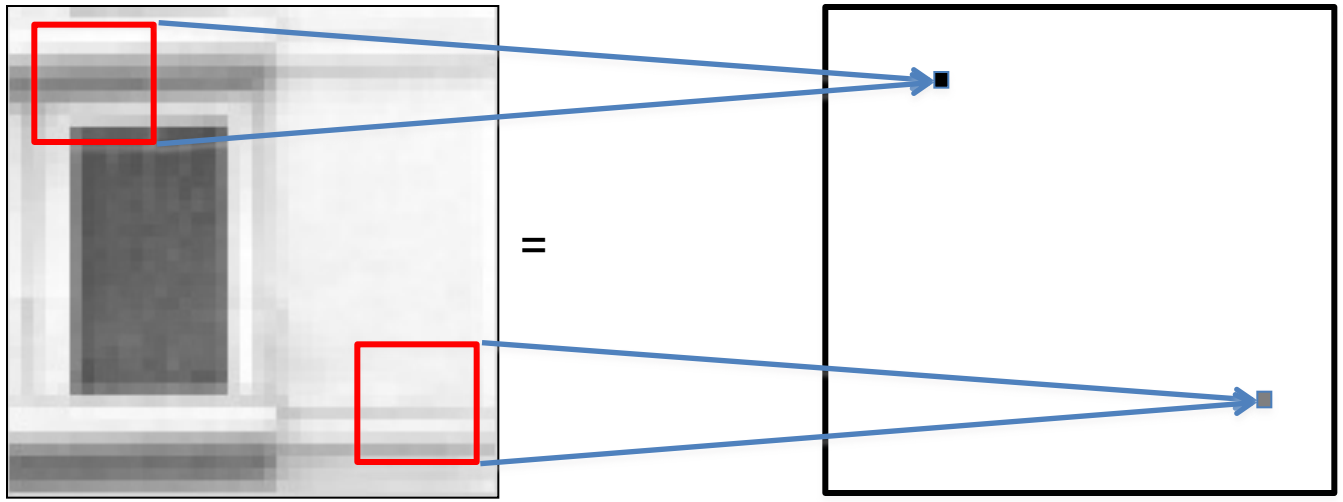
$$G = F \star H$$

Notation for convolution operator

Discrete linear system

In vision, many times, we are interested in operations that are spatially invariant.
For a linear spatially invariant system:

$$g(m,n) = h \star f = \sum_{u=-k}^{u=k} \sum_{v=-k}^{v=k} f(m-u, n-v) h(u,v)$$



Properties of convolution

- **Shift invariant:**
  - Operator behaves the same everywhere, i.e. the value of the output depends on the pattern in the image neighborhood, not the position of the neighborhood.

Properties of convolution

- Commutative:

  $f * g = g * f$

- Associative

  $(f * g) * h = f * (g * h)$

- Distributes over addition

  $f * (g + h) = (f * g) + (f * h)$

- Scalars factor out

  $kf * g = f * kg = k(f * g)$

- Identity:

  unit impulse e = […, 0, 0, 1, 0, 0, …]. $f * e = f$

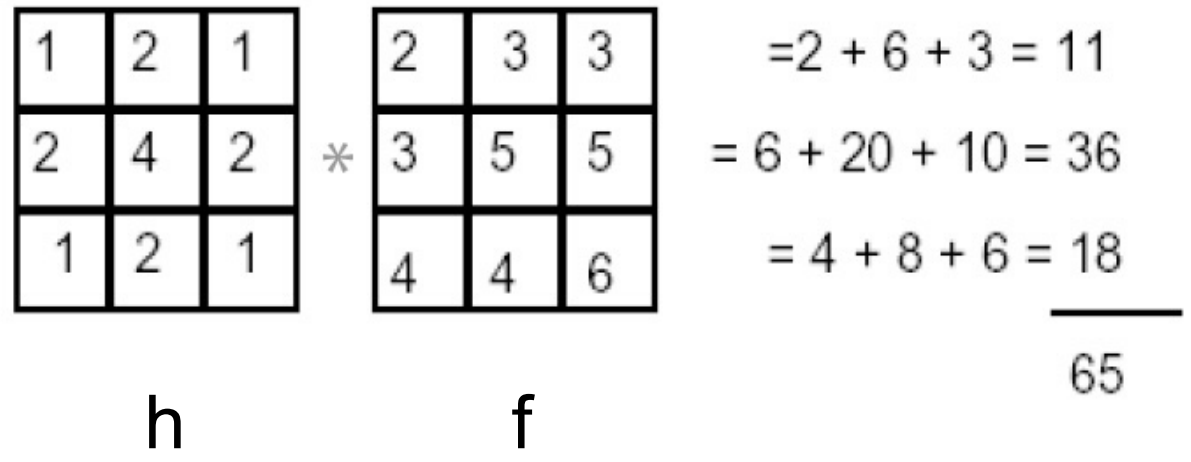
Separability

- In some cases, the filter is separable, and we can factor into two steps:
  - Convolve all rows with a 1D filter
  - Convolve all columns with a 1D filter

$$\begin{bmatrix} \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{3} & 0 \\ 0 & \frac{1}{3} & 0 \\ 0 & \frac{1}{3} & 0 \end{bmatrix} \circ \begin{bmatrix} 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 0 \end{bmatrix}$$

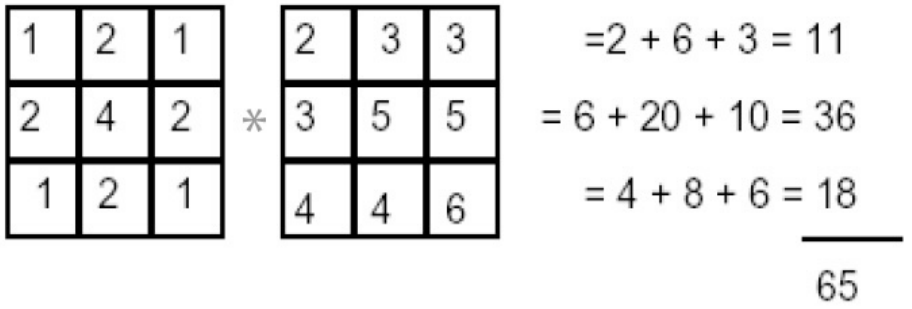
Separability example

- 2D convolution (center location only)(65)

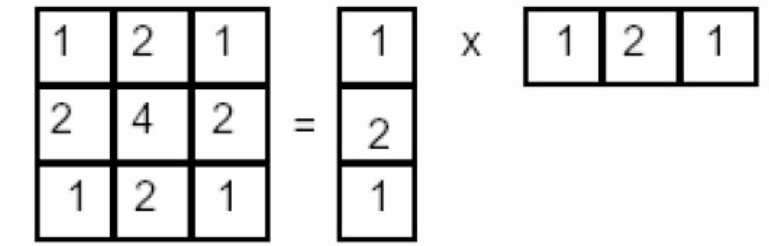


Source: K. Grauman

Separability example

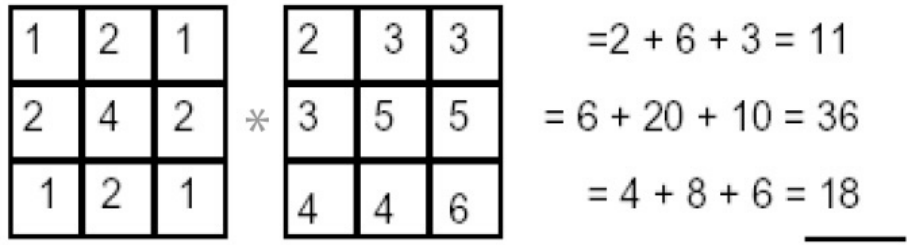


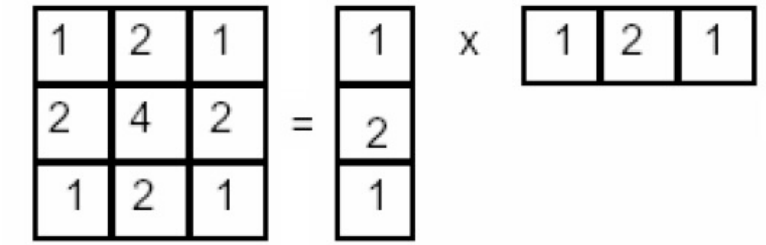
- The filter is factored into a product of 1D filters.



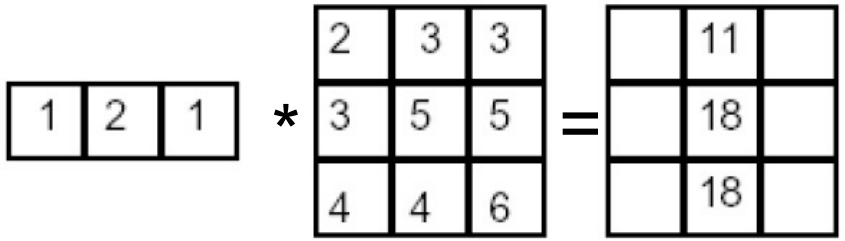
Source: K. Grauman

Separability example



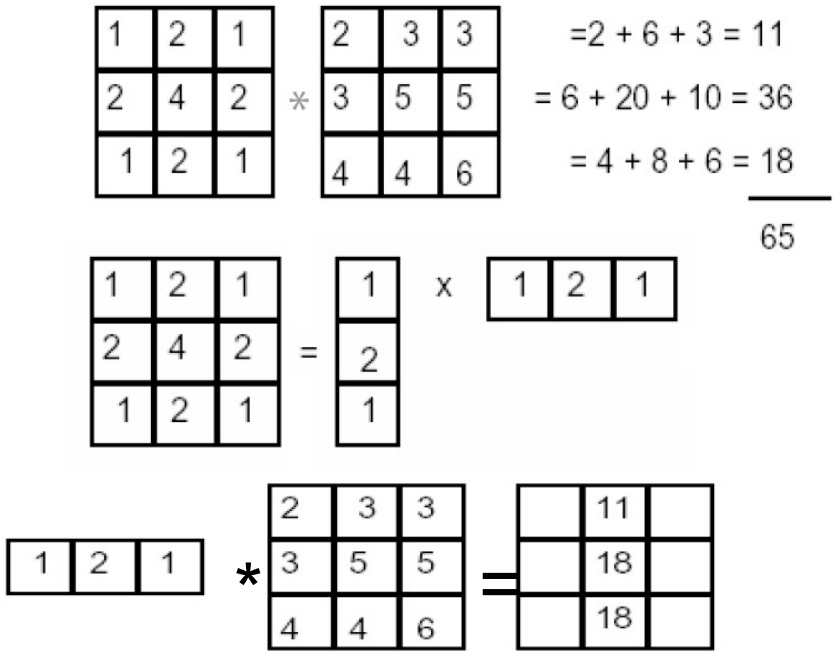


- Perform convolutions along rows.

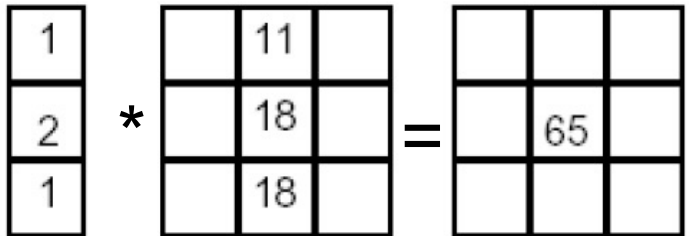


Source: K. Grauman

Separability example



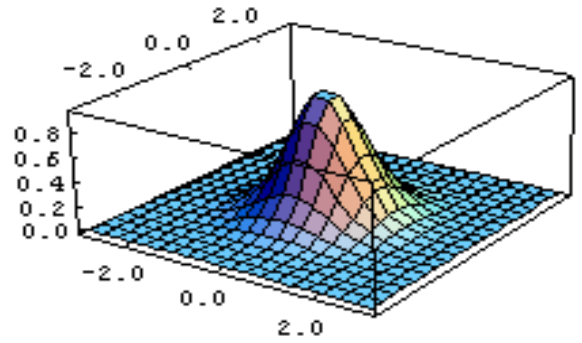
- Perform convolutions along columns.



Source: K. Grauman

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

$$h(u,v) = \frac{1}{2\pi\sigma^2} \exp^{-\frac{u^2+v^2}{2\sigma^2}}$$



Properties of Gaussian filter

- Rotational symmetry treats features of all orientations equally (isotropy).
- Convolution with self gives another Gaussian
  - So can smooth with small-width kernel, repeat, and get same result as larger-width kernel would have
  - Convolving two times with Gaussian kernel of width σ is same as convolving once with kernel of width $\sigma\sqrt{2}$
- *Separable* kernel
  - Factors into the product of two 1D Gaussians

Source: K. Grauman

Separability of the Gaussian filter

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2}\exp^{-\frac{x^2+y^2}{2\sigma^2}}$$

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

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

Source: D. Lowe

- What is the complexity of filtering an n×n image with an m×m kernel?
    - $O(n^2 m^2)$
- What if the kernel is separable?
    - $O(n^2 m)$

Readings

- Computer Vision: Algorithms and Applications, Chapter 3.1, 3.2 and 3.3