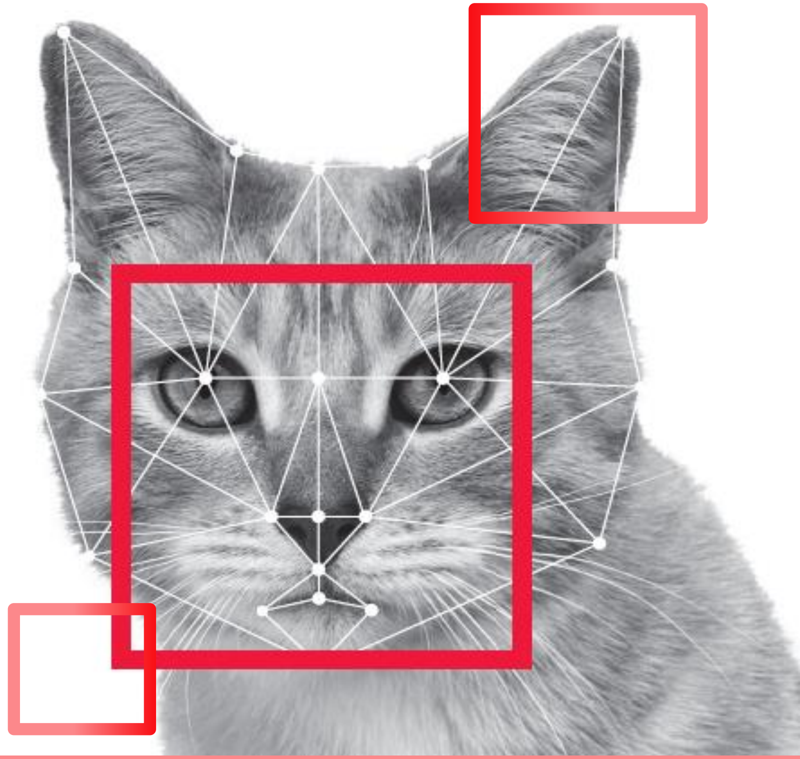
한빛아카데미 Hanbit Academy, Inc.

COMPUTER VISION 컴퓨터 비전

기본 개념부터 최신 모바일 응용 예까지



2장. 영상 처리

각 절에서 다루는 내용

1. 영상 처리의 세 가지 기본 연산

2.4 영상 처리의 세 가지 기본 연산

2.4.1 점 연산

- 오직 자신의 명암값에 따라 새로운 값을 결정

2.4.2 영역 연산

- 이웃 화소의 명암값에 따라 새로운 값 결정

2.4.3 기하 연산

- 일정한 기하 연산으로 결정된 화소의 명암값에 따라 새로운 값 결정

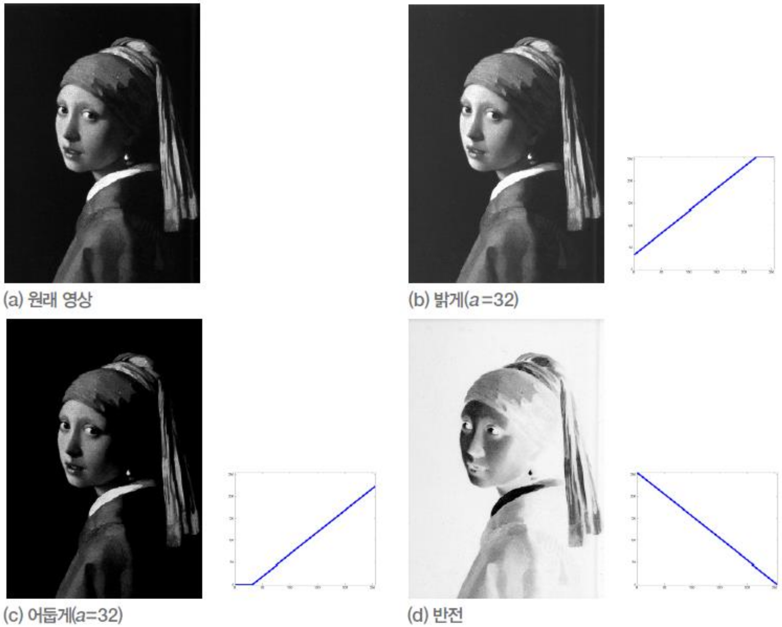
2.4.1 점 연산

- 점 연산을 식으로 쓰면,
  - 대부분은 k=1 (즉 한 장의 영상을 변환)

$$f_{out}(j,i) = t(f_1(j,i),\ f_2(j,i), \cdots f_k(j,i)) \qquad (2.10)$$

- 선형 연산
  - 예)

$$f_{out}(j,i) = t(f(j,i))$$
$$= \begin{cases} \min(f(j,i)+a, L-1), & (\text{밝게}) \\ \max(f(j,i)-a, 0), & (\text{어둡게}) \\ (L-1)-f(j,i), & (\text{반전}) \end{cases}$$



(a) 원래 영상 (b) 밝게(a=32) (c) 어둡게(a=32) (d) 반전

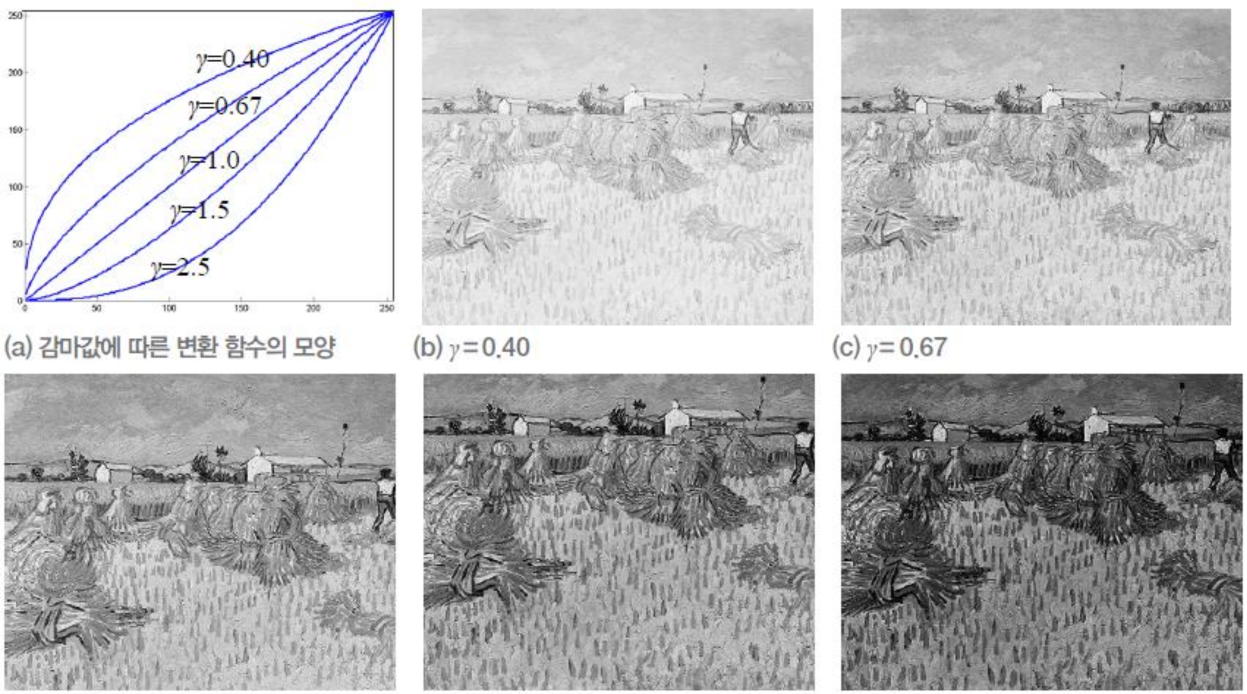
그림 2-18 여러 가지 선형 점 연산

2.4.1 점 연산

비선형 연산

- 예) 감마 수정 (모니터나 프린터 색상 조절에 사용)

$$f_{out}(j,i) = (L-1) \times (\hat{f}(j,i))^{\gamma} \quad \text{이때} \quad \hat{f}(j,i) = \frac{f(j,i)}{(L-1)}$$



(a) 감마값에 따른 변환 함수의 모양 (b) $\gamma=0.40$ (c) $\gamma=0.67$

(d) $\gamma=1.0$(원본 영상) (e) $\gamma=1.5$ (f) $\gamma=2.5$

그림 2-19 감마 수정

2.4.1 점 연산

- 디졸브
  - k=2인 경우

$$f_{out}(j,i) = \alpha f_1(j,i) + (1-\alpha) f_2(j,i) \quad (2.13)$$

그림 2-21 디졸브 효과

2.4.2 영역 연산 (filtering)

- Image filters in spatial domain (영상평면에서의 연산)
  - Filter is a mathematical operation of a grid of numbers
  - Smoothing, sharpening, measuring texture

- Image filtering: compute function of local neighborhood at each position

- Really important!
  - Enhance images
    - Denoise, resize, increase contrast, etc.
  - Extract information from images
    - Texture, edges, distinctive points, etc.
  - Detect patterns
    - Template matching

2.4.2 영역 연산

상관

- 원시적인 매칭 연산 (물체를 윈도우 형태로 표현하고 물체를 검출)
- 아래 예에서는 최대값 29를 갖는 위치 6에서 물체가 검출됨

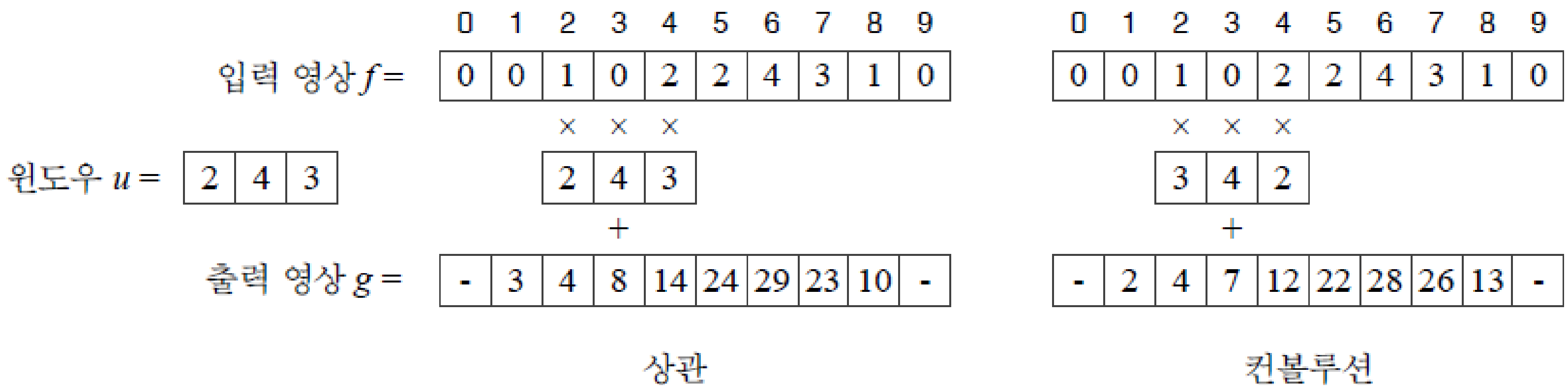


그림 2-22 상관과 컨볼루션의 원리

컨볼루션

- 윈도우를 뒤집은 후 상관 적용
- 임펄스 반응

2.4.2 영역 연산

2차원

입력 영상 $f=$

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

윈도우 $u=$

-1	0	1	
1	2	3	-1
4	5	6	0
7	8	9	1

1	2	3
4	5	6
7	8	9

9	8	7
6	5	4
3	2	1

$\downarrow$

출력 영상 $g=$

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	9	8	7	0	0	0	0
0	6	5	4	0	0	0	0
0	3	2	1	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

상관

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	2	3	0	0	0	0
0	4	5	6	0	0	0	0
0	7	8	9	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

컨볼루션

그림 2-23 2차원 상관과 컨볼루션

2.4.2 영역 연산

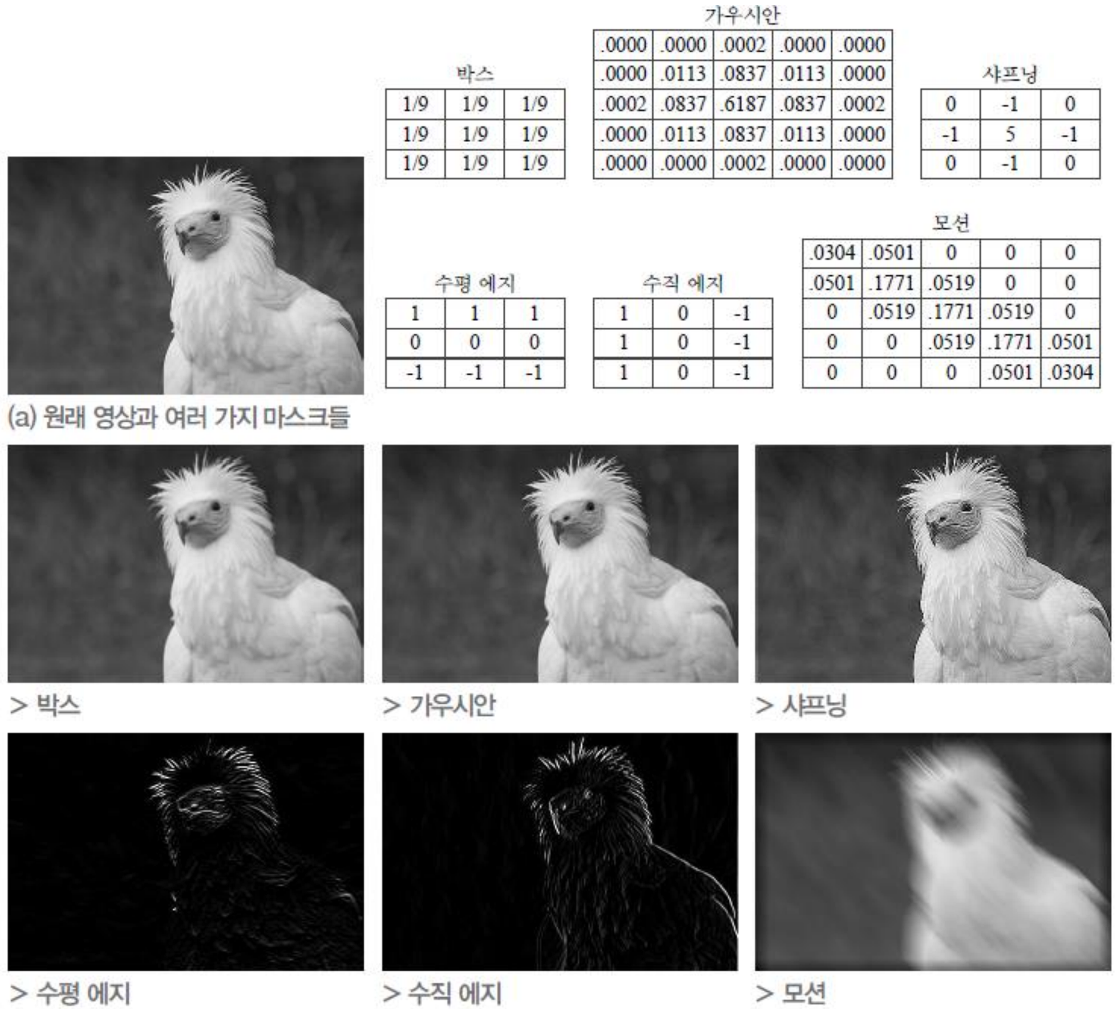
- 수식으로 쓰면,

$$
\begin{aligned}
&\left.\begin{aligned}
\text{상관 } g(i) &= u \otimes f = \sum_{x=-(w-1)/2}^{(w-1)/2} u(x) f(i+x) \\
\text{컨볼루션 } g(i) &= u \circledast f = \sum_{j=-(w-1)/2}^{(w-1)/2} u(x) f(i-x)
\end{aligned}\right] \text{1차원} \\
&\left.\begin{aligned}
\text{상관 } g(j,i) &= u \otimes f = \sum_{y=-(h-1)/2}^{(h-1)/2} \sum_{x=-(w-1)/2}^{(w-1)/2} u(y,x) f(j+y, i+x) \\
\text{컨볼루션 } g(j,i) &= u \circledast f = \sum_{y=-(h-1)/2}^{(h-1)/2} \sum_{x=-(w-1)/2}^{(w-1)/2} u(y,x) f(j-y, i-x)
\end{aligned}\right] \text{2차원}
\end{aligned}
\tag{2.14}
$$

- 이 책은 둘 구분하지 않고 컨볼루션이라는 용어를 사용

2.4.2 영역 연산

- 컨볼루션 예제
  - 박스와 가우시안은 스무딩 효과
  - 샤프닝은 명암 대비 강조 효과
  - 수평 에지와 수직 에지는 에지 검출 효과
- 컨볼루션은 선형 연산



박스

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

가우시안

.0000	.0000	.0002	.0000	.0000
.0000	.0113	.0837	.0113	.0000
.0002	.0837	.6187	.0837	.0002
.0000	.0113	.0837	.0113	.0000
.0000	.0000	.0002	.0000	.0000

샤프닝

0	-1	0
-1	5	-1
0	-1	0

수평 에지

1	1	1
0	0	0
-1	-1	-1

수직 에지

1	0	-1
1	0	-1
1	0	-1

모션

.0304	.0501	0	0	0
.0501	.1771	.0519	0	0
0	.0519	.1771	.0519	0
0	0	.0519	.1771	.0501
0	0	0	.0501	.0304

(a) 원래 영상과 여러 가지 마스크들

(b) 다양한 마스크로 컨볼루션한 영상들

그림 2-24 다양한 마스크와 컨볼루션 효과

Example: box filter

$$g[\cdot\,,\cdot\,]$$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Slide credit: David Lowe (UBC)

Image filtering

$$g[\cdot,\cdot]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

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

Credit: S. Seitz

Image filtering

$$g[\cdot,\cdot] \quad \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

	0	10							

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

Credit: S. Seitz

Image filtering

$g[\cdot,\cdot]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f[.,.]$

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

$h[.,.]$

	0	10	20						

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

Credit: S. Seitz

Image filtering

$$g[\cdot\,,\cdot\,]\ \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

	0	10	20	30					

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

Credit: S. Seitz

Image filtering

$g[\cdot\,,\cdot\,]\ \frac{1}{9}$

1	1	1
1	1	1
1	1	1

$f\,[.,.]$

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

$h[.,.]$

	0	10	20	30	30				

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

Credit: S. Seitz

Image filtering

$$g[\cdot,\cdot]\ \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

	0	10	20	30	30				
				?					

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

Credit: S. Seitz

Image filtering

$$g[\cdot,\cdot]\ \frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

	0	10	20	30	30				
						?			
				50					

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

Credit: S. Seitz

Image filtering

$$g[\cdot\,,\cdot\,] \quad \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$f[.,.]$

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

$h[.,.]$

	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	

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

Credit: S. Seitz

Box Filter

What does it do?

- Replaces each pixel with an average of its neighborhood

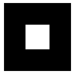
- Achieve smoothing effect (remove sharp features)

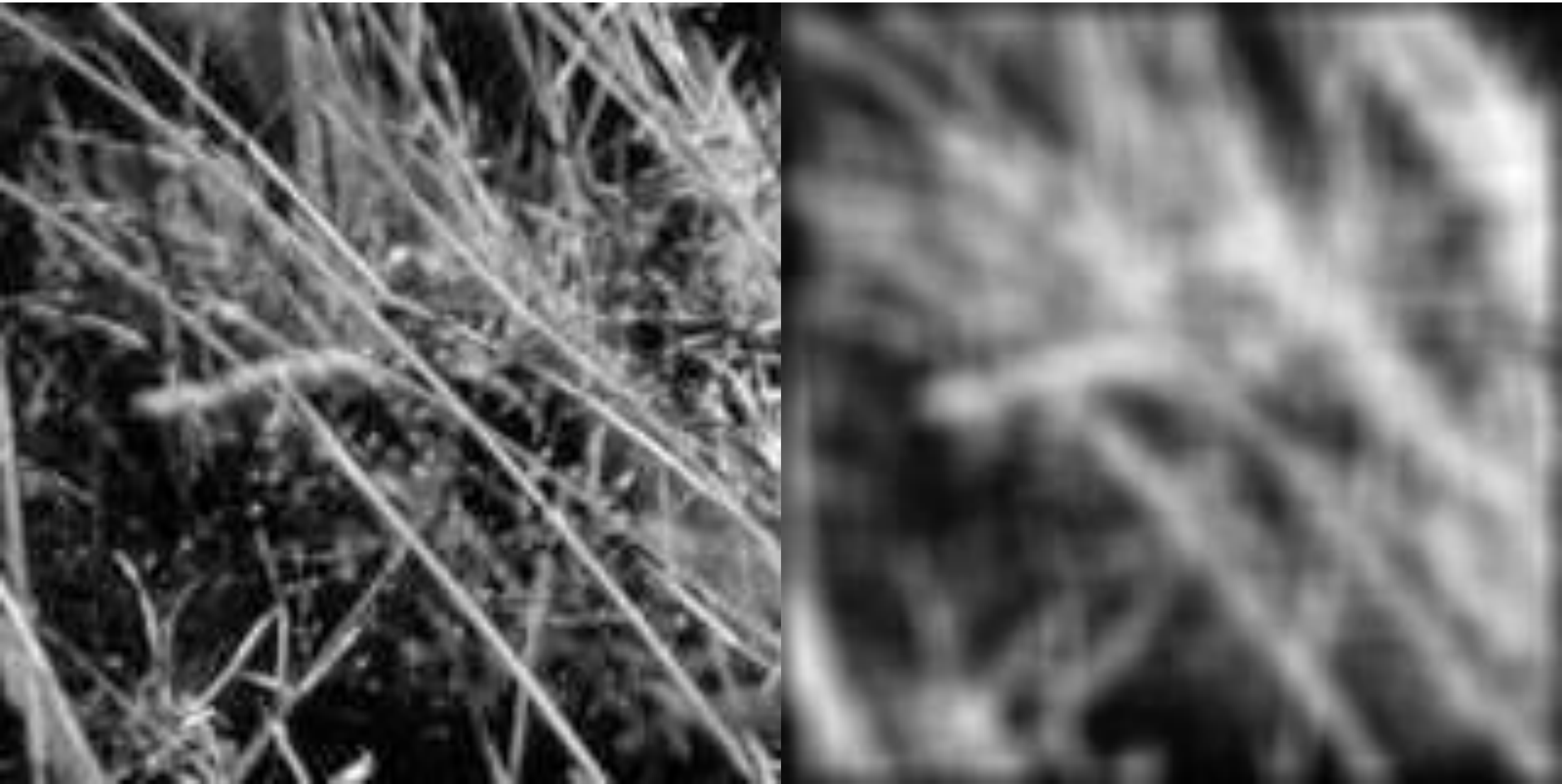
$$g[\cdot,\cdot]$$

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

Slide credit: David Lowe (UBC)

Smoothing with box filter





Practice with linear filters

Original

0	0	0
0	1	0
0	0	0

?

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	1	0
0	0	0

Filtered
(no change)

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	0	1
0	0	0

?

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	0	1
0	0	0

Shifted left
By 1 pixel

Source: D. Lowe

Practice with linear filters

Original

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

(Note that filter sums to 1)

?

Source: D. Lowe

Practice with linear filters

Original

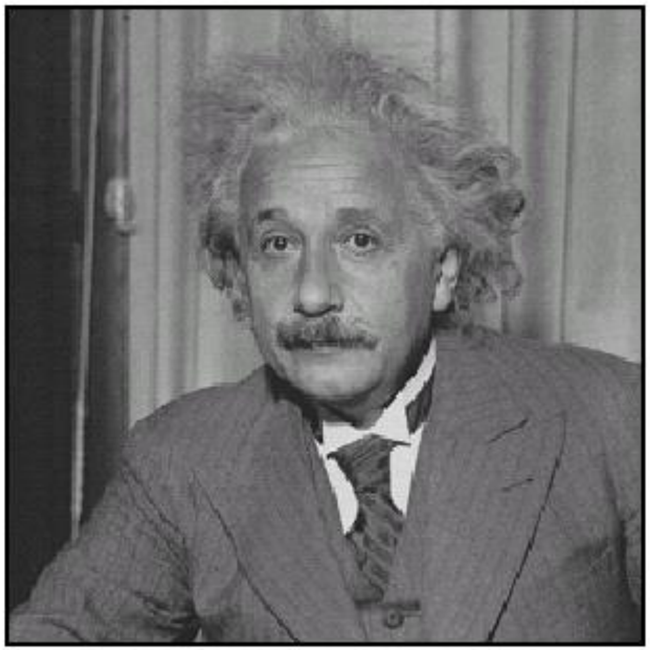
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Sharpening filter

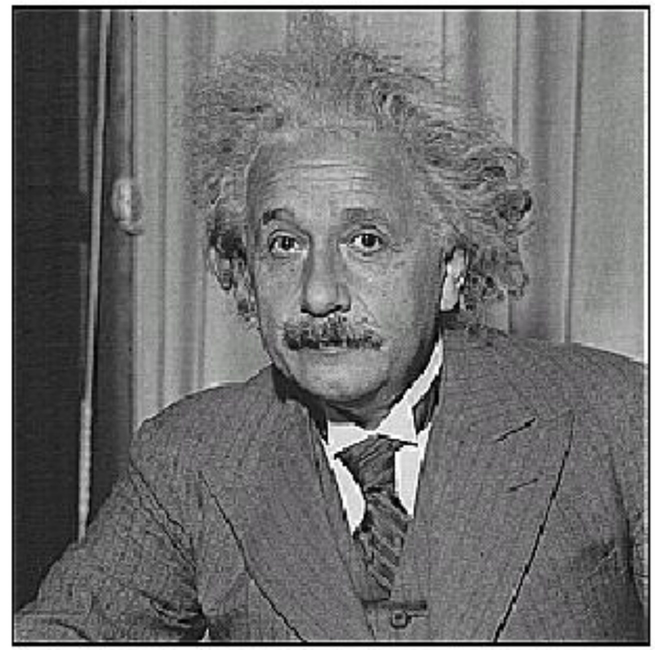
- Accentuates differences with local average

Source: D. Lowe

Sharpening



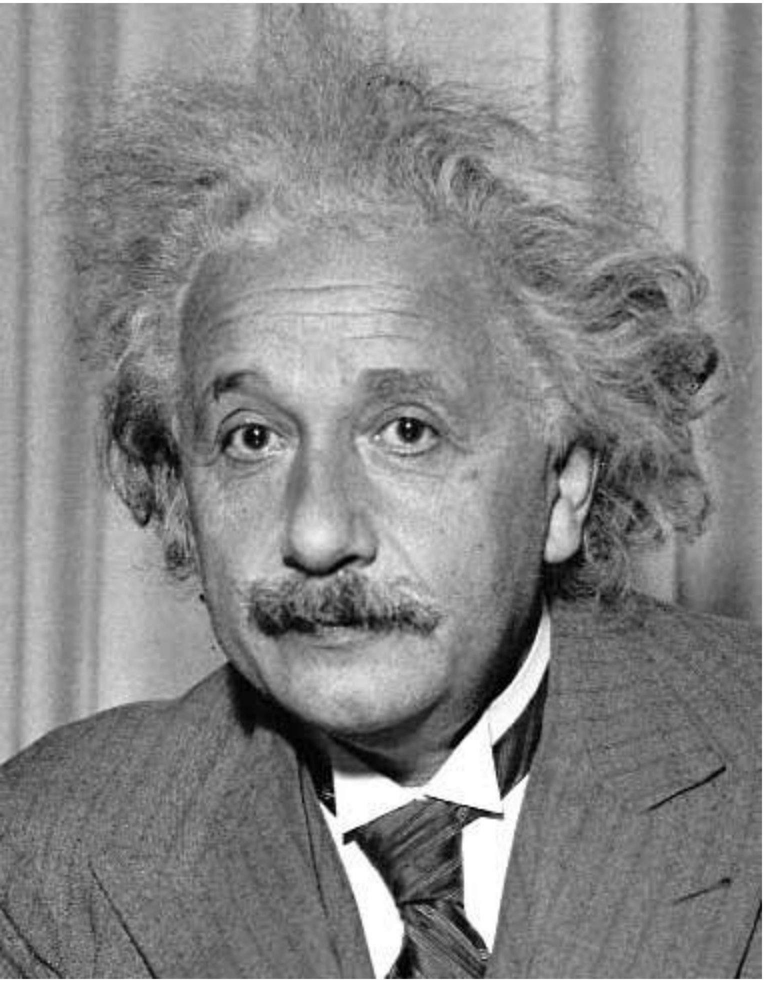
before



after

Source: D. Lowe

Other filters

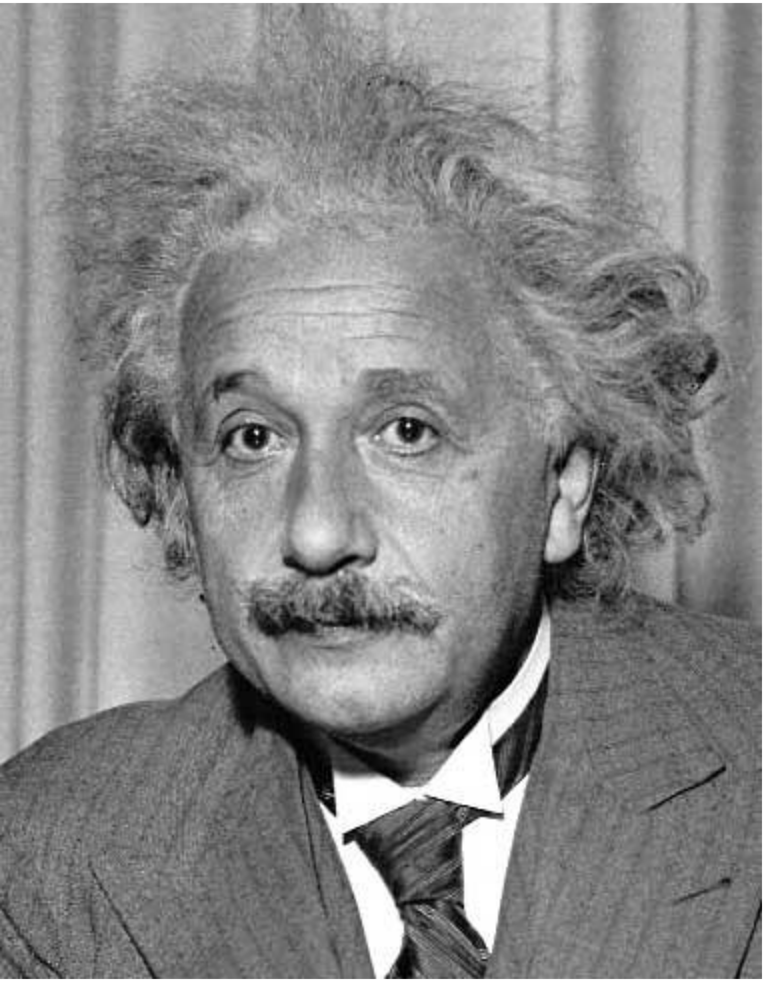


1	0	-1
2	0	-2
1	0	-1

Sobel

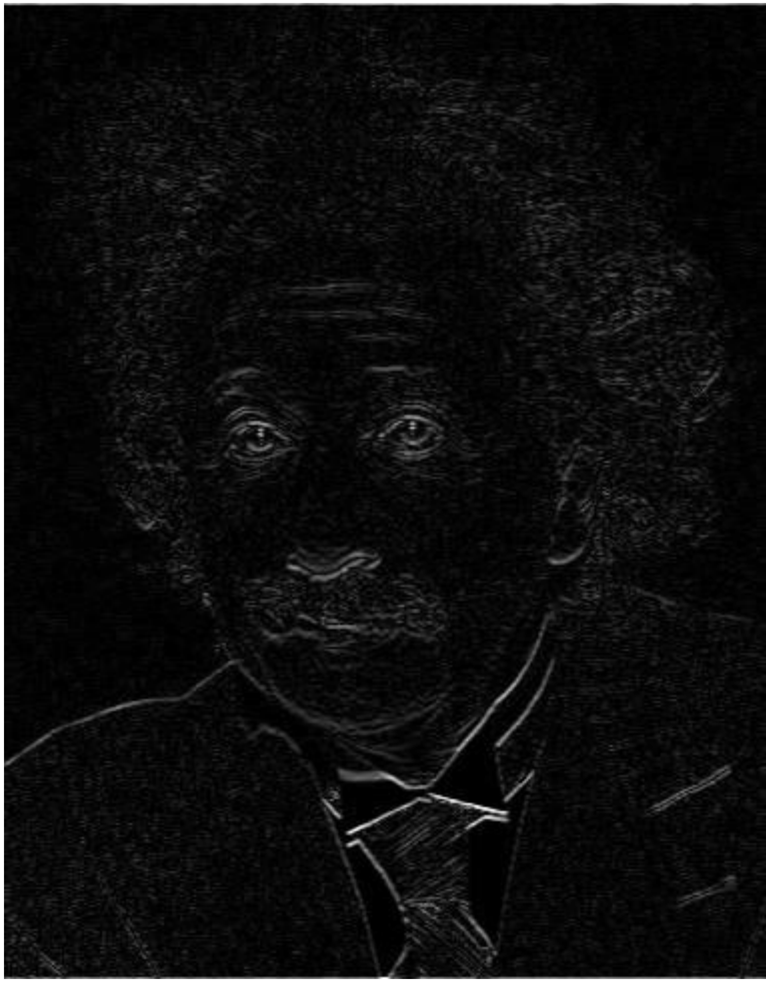
Vertical Edge
(absolute value)

Other filters



1	2	1
0	0	0
-1	-2	-1

Sobel



Horizontal Edge
(absolute value)

Key properties of linear filters

Linearity:

`filter(f`$_1$` + f`$_2$`) = filter(f`$_1$`) + filter(f`$_2$`)`

Shift invariance: same behavior regardless of pixel location

`filter(shift(f)) = shift(filter(f))`

Any linear, shift-invariant operator can be r epresented as a convolution

Source: S. Lazebnik

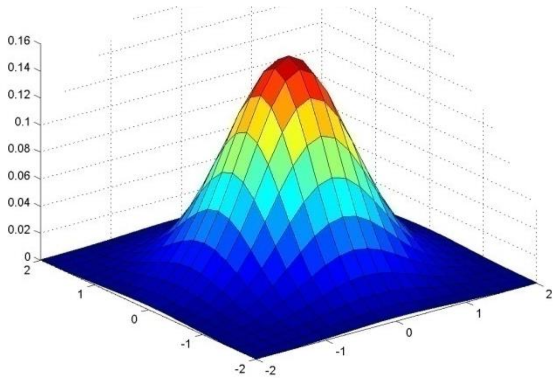
More properties

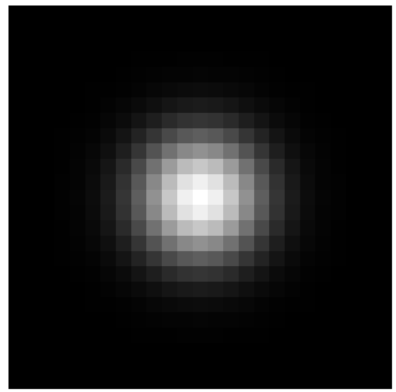
- Commutative: $a * b = b * a$
  - Conceptually no difference between filter and signal
  - But particular filtering implementations might break this equality
- Associative: $a * (b * c) = (a * b) * c$
  - Often apply several filters one after another: $(((a * b_1) * b_2) * b_3)$
  - This is equivalent 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 $e = [0, 0, 1, 0, 0]$,
  $a * e = a$

Source: S. Lazebnik

Important filter: Gaussian

- Weight contributions of neighboring pixels by nearness





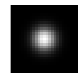
0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

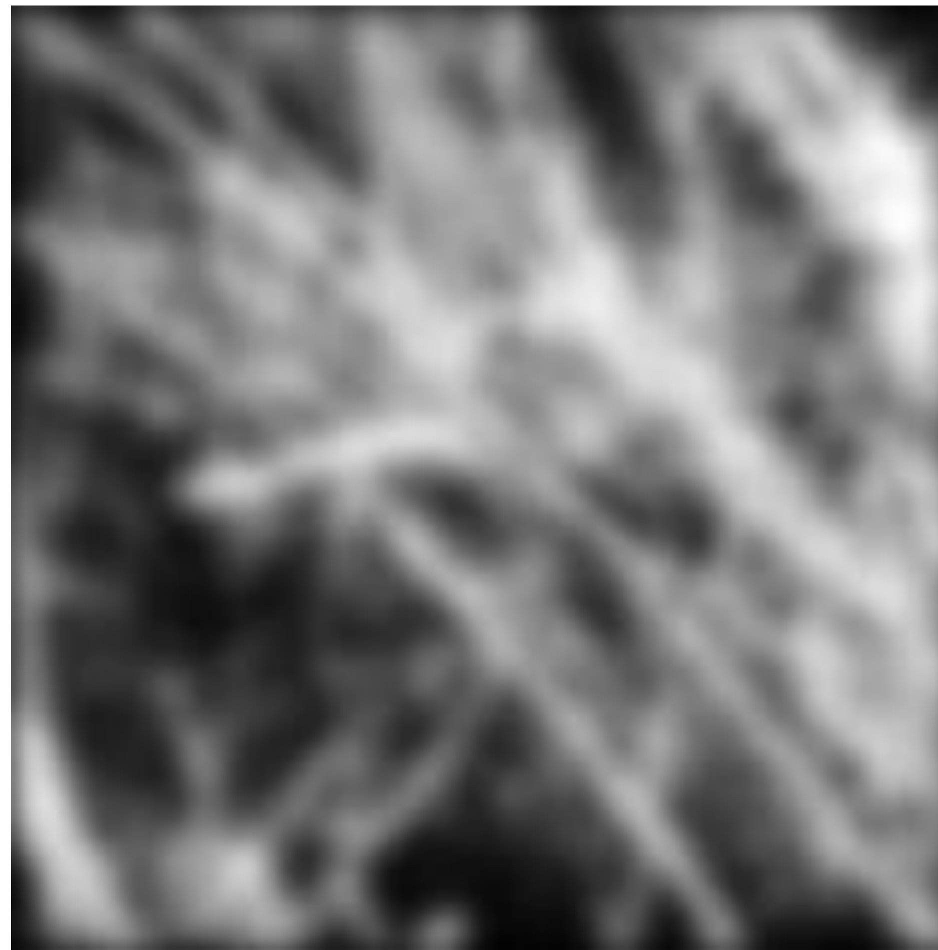
5 x 5, σ = 1

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

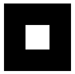
Slide credit: Christopher Rasmussen

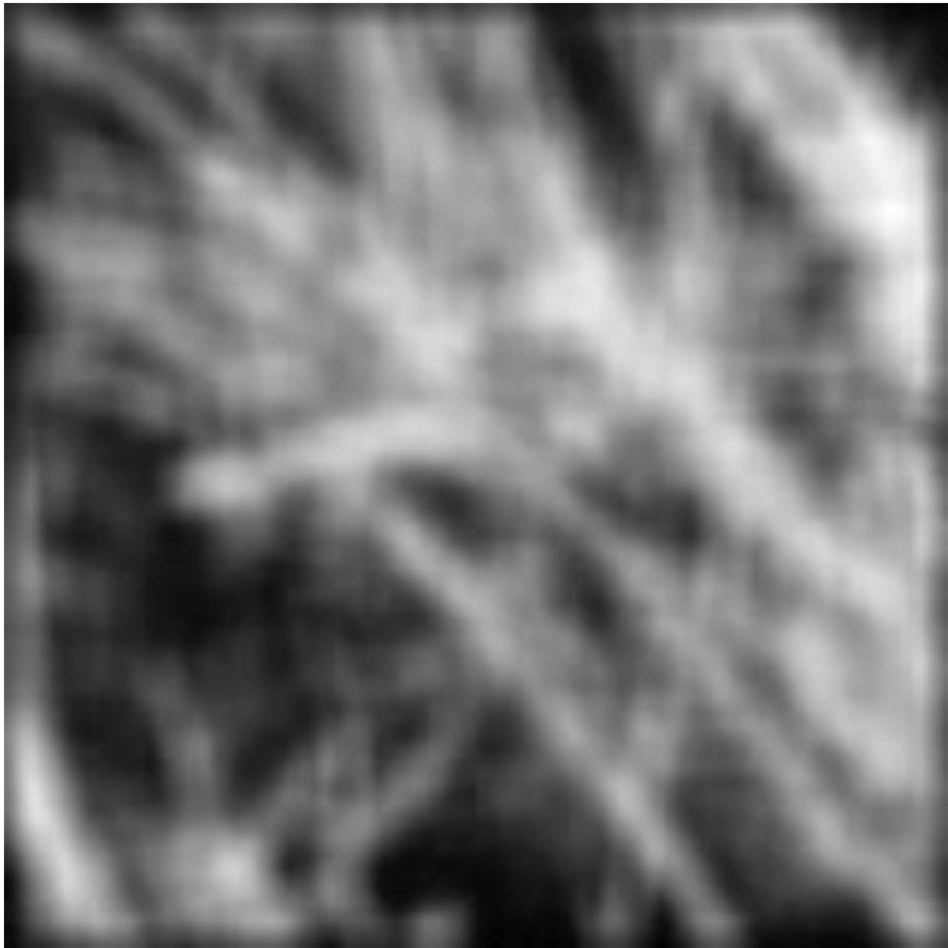
Smoothing with Gaussian filter





Smoothing with box filter





Gaussian filters

- Remove "high-frequency" components from the image (low-pass filter)
  - Images become more smooth
- Convolution with self is another Gaussian
  - So can smooth with small-width kernel, repeat, and get same result as larger-width kernel woul d have
  - Convolving two times with Gaussian kernel of w idth σ is same as convolving once with kernel of width $\sigma\sqrt{2}$
- *Separable* kernel
  - Factors into product of two 1D Gaussians

Source: K. Grauman

Separability of the Gaussian filter

$$
\begin{aligned}
G_\sigma(x,y) &= \frac{1}{2\pi\sigma^2}\exp^{-\frac{x^2+y^2}{2\sigma^2}} \\
&= \left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{x^2}{2\sigma^2}}\right)\left(\frac{1}{\sqrt{2\pi}\sigma}\exp^{-\frac{y^2}{2\sigma^2}}\right)
\end{aligned}
$$

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

Separability example

2D convolution
(center location only)

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 2 & 3 & 3 \\ 3 & 5 & 5 \\ 4 & 4 & 6 \end{bmatrix}$$

The filter factors
into a product of 1D
filters:

$$\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 1 \end{bmatrix}$$

Perform convolution
along rows:

$$\begin{bmatrix} 1 & 2 & 1 \end{bmatrix} * \begin{bmatrix} 2 & 3 & 3 \\ 3 & 5 & 5 \\ 4 & 4 & 6 \end{bmatrix} = \begin{bmatrix} & 11 & \\ & 18 & \\ & 18 & \end{bmatrix}$$

Followed by convolution
along the remaining column:

Source: K. Grauman

Separability

- Why is separability useful in practice?

2.4.2 영역 연산

- 비선형 연산
  - 예) 메디안 필터
    - 솔트페퍼 잡음에 효과적임
    - 메디안은 가우시안에 비해 에지 보존 효과 뛰어남

(a) 원래 영상 (b) 솔트페퍼 잡음

(c) 가우시안 필터 (d) 메디안 필터

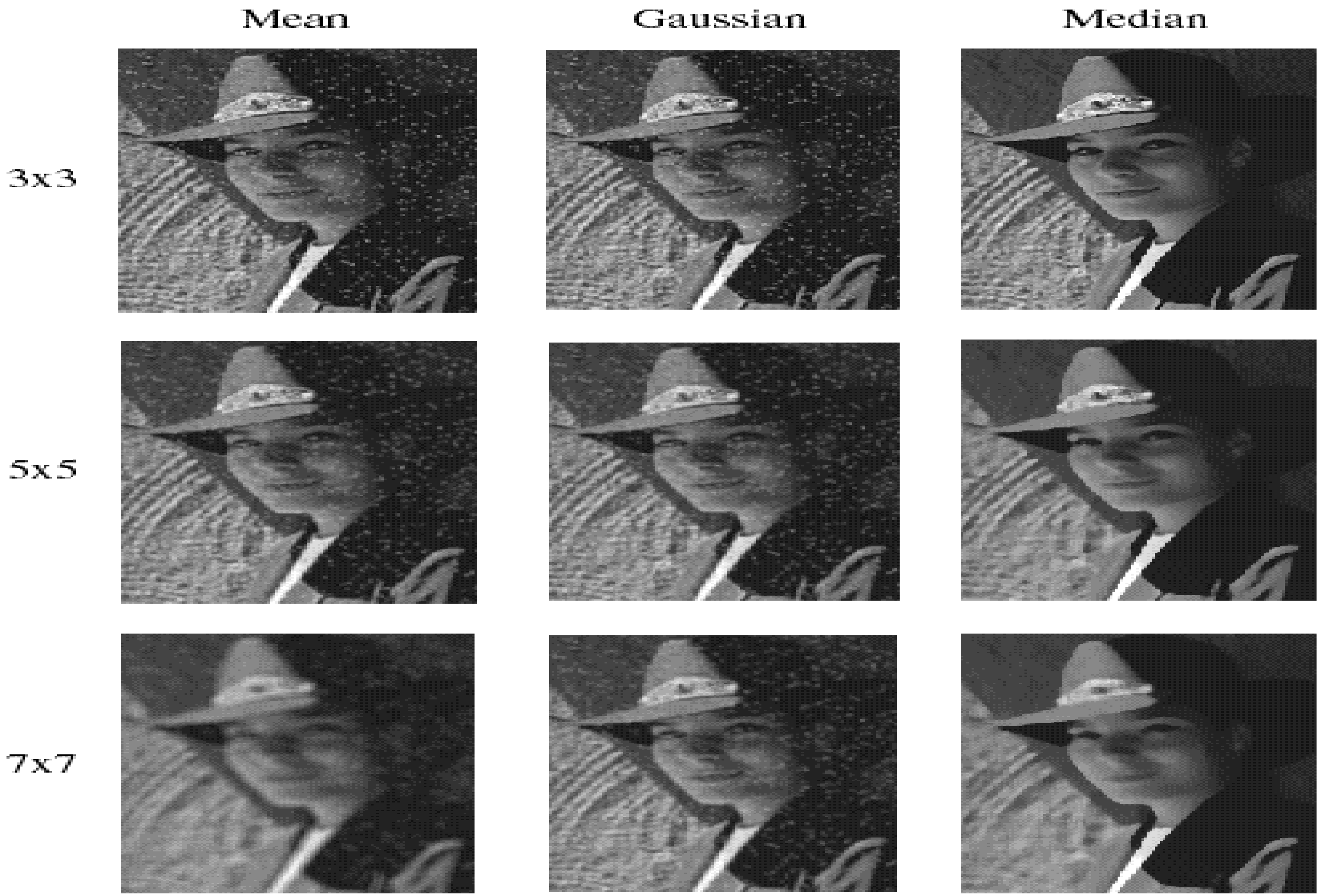
그림 2-25 가우시안과 메디안 필터의 비교

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?

Slide by Steve Seitz

Comparison: salt and pepper noise



Slide by Steve Seitz