

Linear filtering

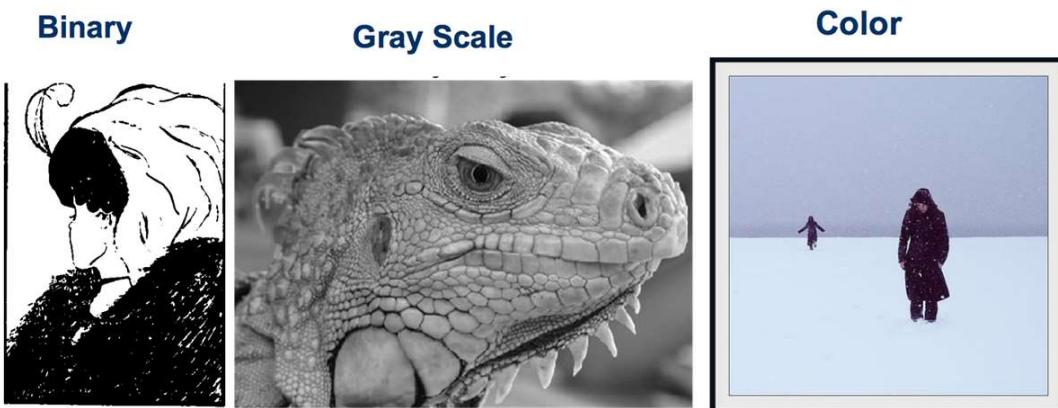
1

Roadmap

Machine Vision Technology							
Semantic information				Metric 3D information			
Pixels	Segments	Images	Videos	Camera		Multi-view Geometry	
Convolutions Edges & Fitting Local features Texture	Segmentation Clustering	Recognition Detection	Motion Tracking	Camera Model	Camera Calibration	Epipolar Geometry	SfM
?	?	?	?	?	?	?	?

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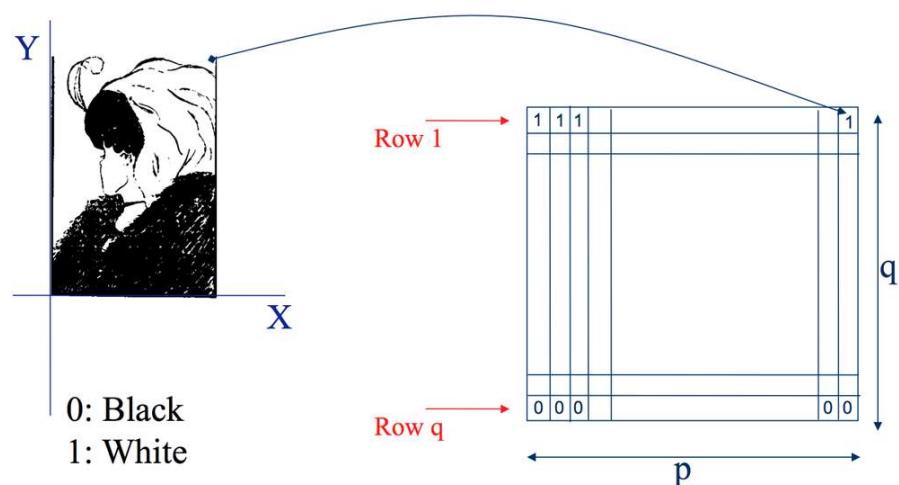
Types of Images



Source: Ulas Bagci

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Binary image representation

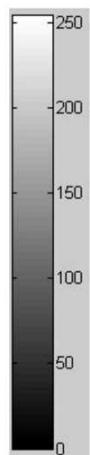
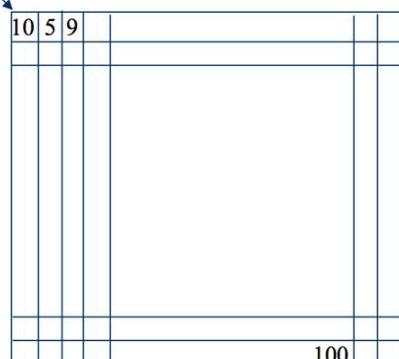
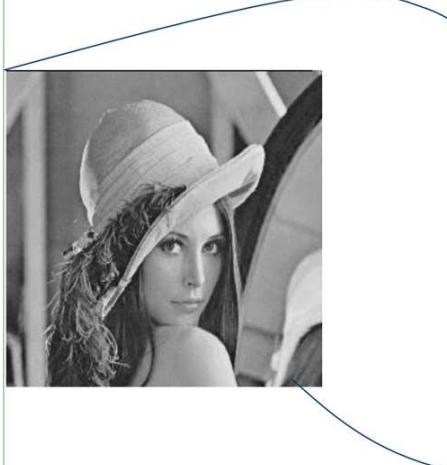


Source: Ulas Bagci

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Grayscale image representation

Slide credit:
Ulas Bagci



Source: Ulas Bagci

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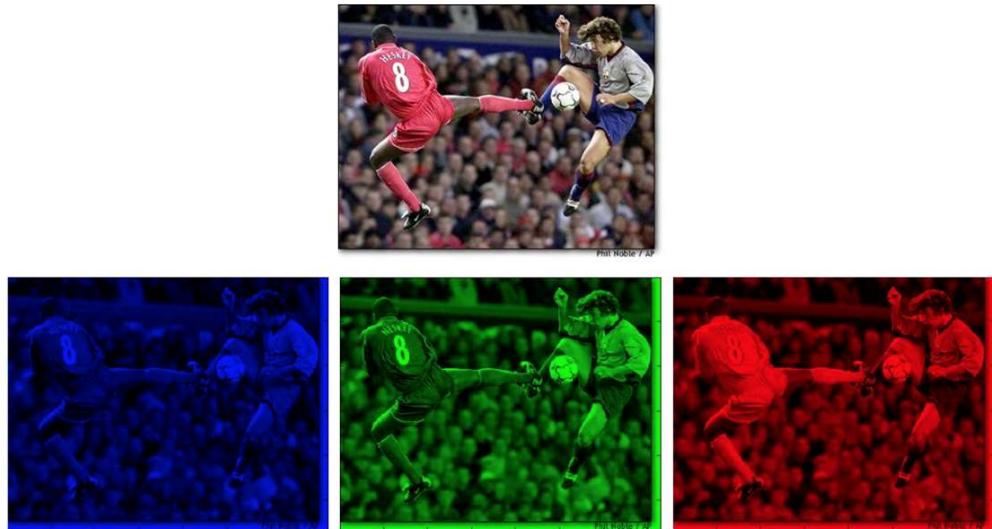
Color Image - one channel



Source: Ulas Bagci

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Color image representation



Source: Ulas Bagci

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Motivation: Image denoising

- How can we reduce noise in a photograph?



Source: S. Lazebnik

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Moving average

- Let's replace each pixel with a *weighted* average of its neighborhood
- The weights are called the *filter kernel*
- What are the weights for the average of a 3x3 neighborhood?

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

“box filter”

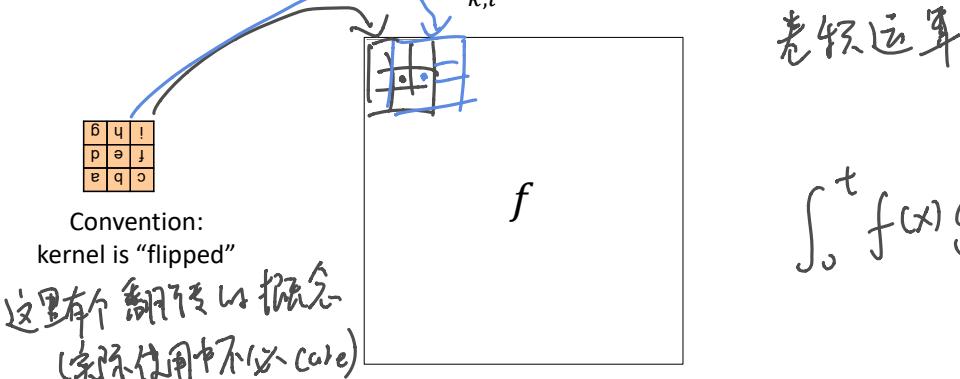
Source: S. Lazebnik

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Defining convolution

- Let f be the image and g be the kernel. The output of convolving f with g is denoted $f * g$.

$$(f * g)[m, n] = \sum_{k,l} f[m - k, n - l]g[k, l]$$



$$\int_0^t f(x) g(t-x) dx$$

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m, n 是核 g 在 f 中的坐标

k, l 是核 g 内的坐标

Key properties

- **Linearity:** $\text{filter}(f_1 + f_2) = \text{filter}(f_1) + \text{filter}(f_2)$
- **Shift invariance:** same behavior regardless of pixel location: $\text{filter}(\text{shift}(f)) = \text{shift}(\text{filter}(f))$
- Theoretical result: any linear shift-invariant operator can be represented as a convolution

Source: S. Lazebnik

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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 $e = [..., 0, 0, 1, 0, 0, ...]$,
 $a * e = a$

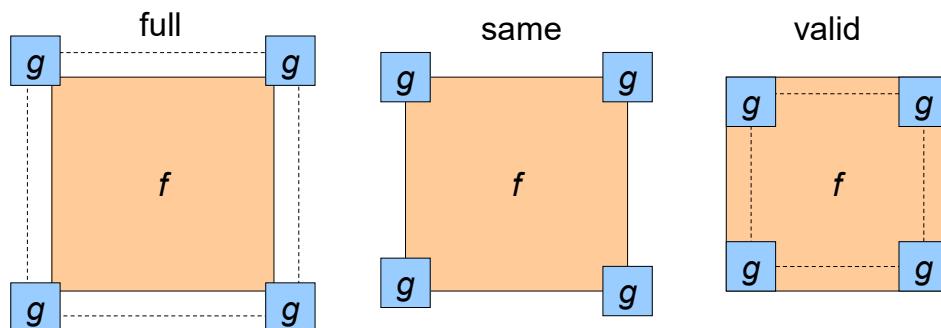
Source: S. Lazebnik

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Annoying details

What is the size of the output?

- MATLAB: `filter2(g, f, shape)`
 - `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



Source: S. Lazebnik

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Annoying details

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



Source: S. Marschner

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Annoying details

What about near the edge?

- the filter window falls off the edge of the image
- need to extrapolate
- methods (MATLAB):
 - clip filter (black): `imfilter(f, g, 0)`
 - wrap around: `imfilter(f, g, 'circular')`
 - copy edge: `imfilter(f, g, 'replicate')`
 - reflect across edge: `imfilter(f, g, 'symmetric')`

Source: S. Marschner

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Practice with linear filters



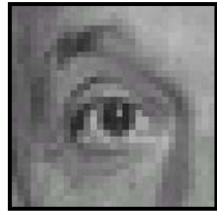
0	0	0
0	1	0
0	0	0

?

Source: D. Lowe

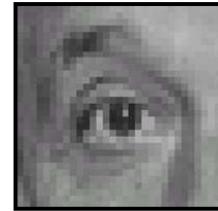
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Practice with linear filters



Original

0	0	0
0	1	0
0	0	0



Filtered
(no change)

Source: D. Lowe

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Practice with linear filters



Original

0	0	0
0	0	1
0	0	0

?

Source: D. Lowe

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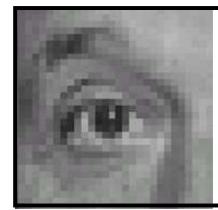
Practice with linear filters



Original

0	0	0
0	0	1
0	0	0

左移



Shifted *left*
By 1 pixel

Source: D. Lowe

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Practice with linear filters



Original

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

?

Source: D. Lowe

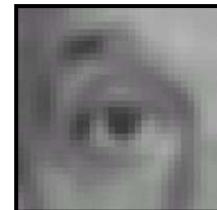
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Practice with linear filters



Original

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$



Blur (with a
box filter)

Source: D. Lowe

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Practice with linear filters



Original

$$\begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 0 & 2 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array} - \frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

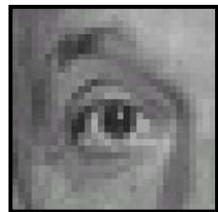
?

(Note that filter sums to 1)

Source: D. Lowe

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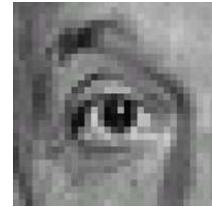
Practice with linear filters



Original

$$\begin{matrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix}$$

$$- \frac{1}{9} \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$



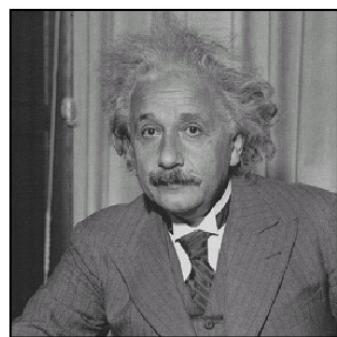
Sharpening filter

- Accentuates differences with local average

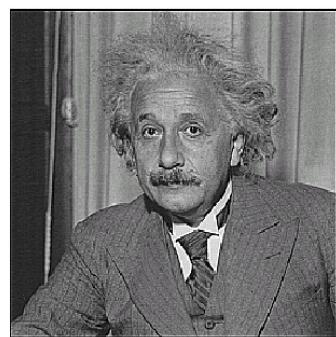
Source: D. Lowe

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Sharpening



before



after

Source: D. Lowe

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Sharpening

What does blurring take away?



原图

平滑

减弱了变化较大的地方 (轮廓边界)

相减后，就变留下轮廓

Source: D. Lowe

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Sharpening

What does blurring take away?

$$\text{src} * \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix} = \text{original} - \text{smoothed (5x5)} = \text{src} * (\text{E} - \text{G})$$

Let's add it back:

$$\text{src} * \text{E} + \text{src} * (\text{E} - \text{G}) = \text{src} * (2\text{E} - \text{G})$$

Source: D. Lowe

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原图

+

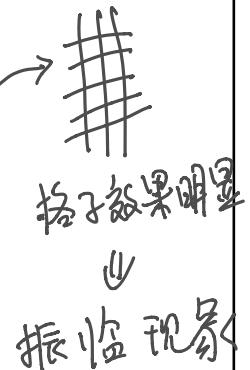
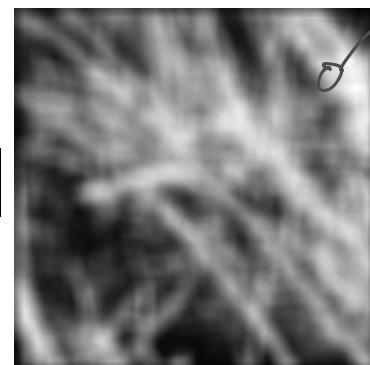
轮廓

=

锐化

Smoothing with box filter revisited

- What's wrong with this picture?
- What's the solution?

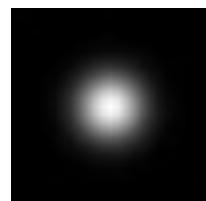


Source: D. Forsyth

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Smoothing with box filter revisited

- What's wrong with this picture?
- What's the solution?
 - To eliminate edge effects, weight contribution of neighborhood pixels according to their closeness to the center



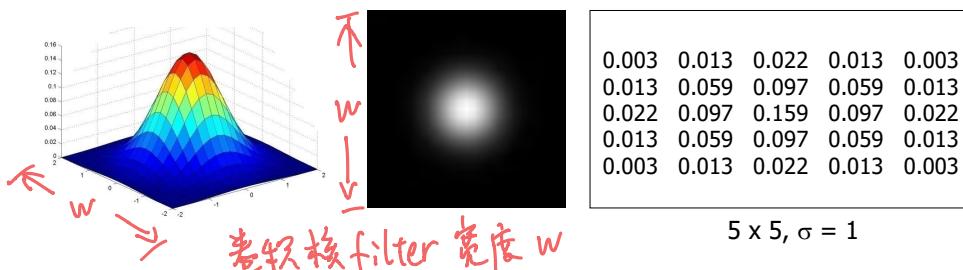
“fuzzy blob”

Source: S. Lazebnik

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Gaussian Kernel

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



- Constant factor at front makes volume sum to 1 (can be ignored when computing the filter values, as we should renormalize weights to sum to 1 in any case)

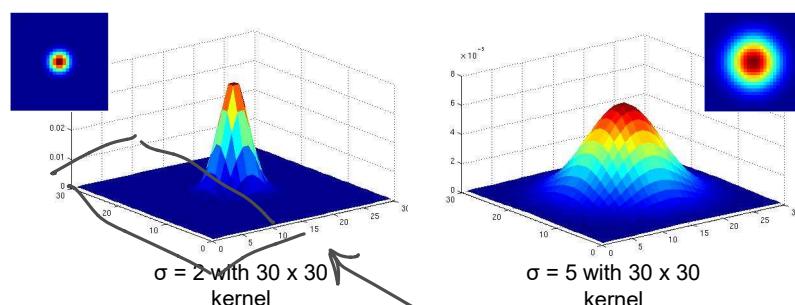
Source: C. Rasmussen

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标准差 σ / 方差 σ^2 与 w , 固定其一, 加大另一个, 会导致更平滑更模糊

Gaussian Kernel

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



- Standard deviation σ : determines extent of smoothing

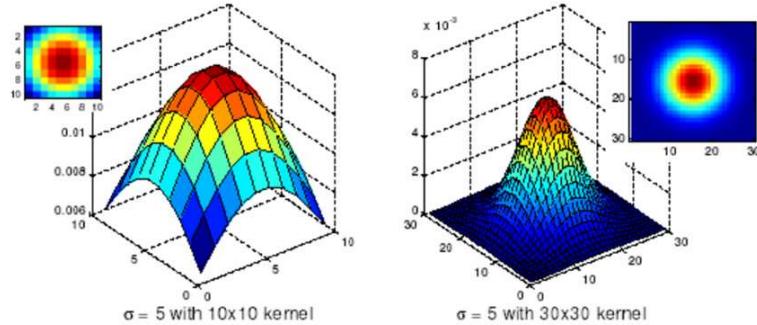
Source: K. Grauman

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一般 w 取 3 倍 σ , 否则 filter 外围都是 0, 意义不大

Choosing kernel width

- The Gaussian function has infinite support, but discrete filters use finite kernels

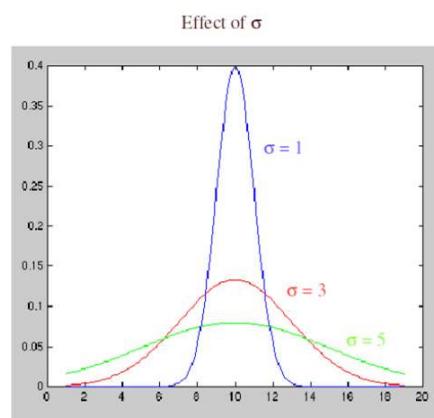


Source: K. Grauman

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Choosing kernel width

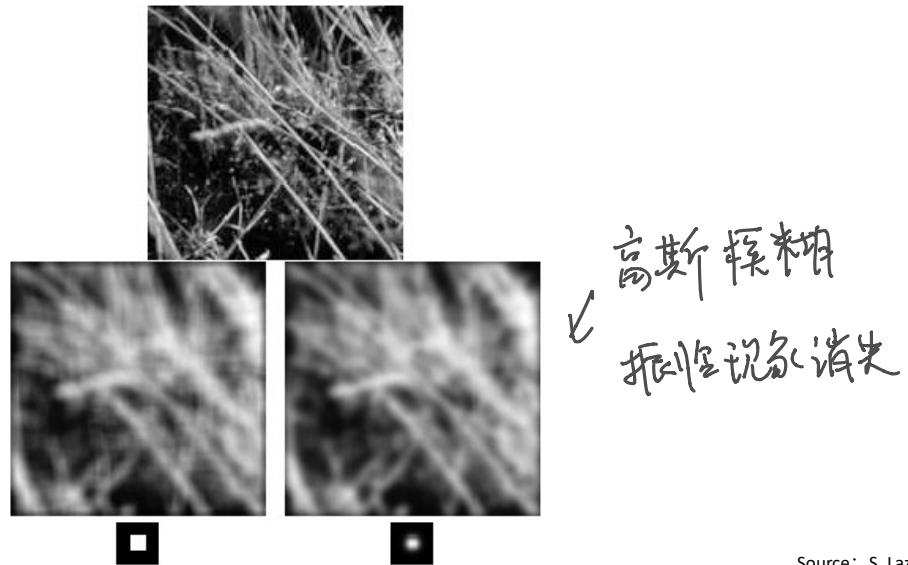
- Rule of thumb: set filter half-width to about 3σ



Source: S. Lazebnik

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Gaussian vs. box filtering



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Gaussian filters

- Remove “high-frequency” components from the image (low-pass filter)
- Convolution with self is another Gaussian
 - So can smooth with small- σ kernel, repeat, and get same result as larger- σ kernel would have
 - Convolving two times with Gaussian kernel with std. dev. σ is same as convolving once with kernel with std. dev. $\sigma\sqrt{2}$
- *Separable* kernel
 - Factors into product of two 1D Gaussians

Source: K. Grauman

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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

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Separability example

2D convolution
(center location only)

$$\begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline 2 & 3 & 3 \\ \hline 3 & 5 & 5 \\ \hline 4 & 4 & 6 \\ \hline \end{array}$$

卷积运算

= 65

The filter factors
into a product of 1D
filters:

$$\begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array} = \begin{array}{|c|} \hline 1 \\ \hline 2 \\ \hline 1 \\ \hline \end{array} \times \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline \end{array}$$

矩阵运算

Perform convolution
along rows:

$$\begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline \end{array} * \begin{array}{|c|c|c|} \hline 2 & 3 & 3 \\ \hline 3 & 5 & 5 \\ \hline 4 & 4 & 6 \\ \hline \end{array} =$$

卷积运算

$$\begin{pmatrix} 1 \\ 18 \\ 18 \end{pmatrix}$$

Followed by convolution
along the remaining column:

$$\begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} * \begin{pmatrix} 1 \\ 18 \\ 18 \end{pmatrix} = 65$$

Source: K. Grauman

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$$\vec{B} \cdot \vec{C} = A \quad \text{1是原因}$$

(矩阵乘法)

$$\underline{A * I} = \underline{\vec{B} * \vec{C} * I}$$

以**上**的做這題的運算量會變



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?
 - $O(n^2 m)$

Source: S. Lazebnik

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Noise



Original



Salt and pepper noise



Impulse noise



Gaussian noise

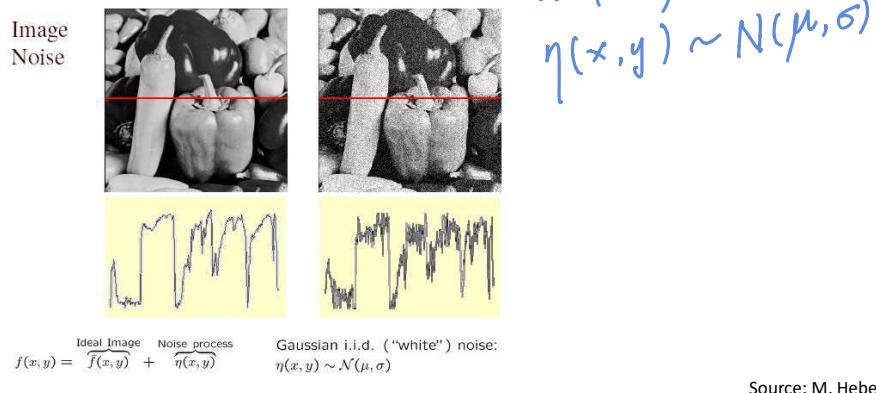
- **Salt and pepper noise:** contains random occurrences of black and white pixels
- **Impulse noise:** contains random occurrences of white pixels
- **Gaussian noise:** variations in intensity drawn from a Gaussian normal distribution

Source: S. Seitz

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Gaussian noise

- Mathematical model: sum of many independent factors
- Good for small standard deviations
- Assumption: independent, zero-mean noise

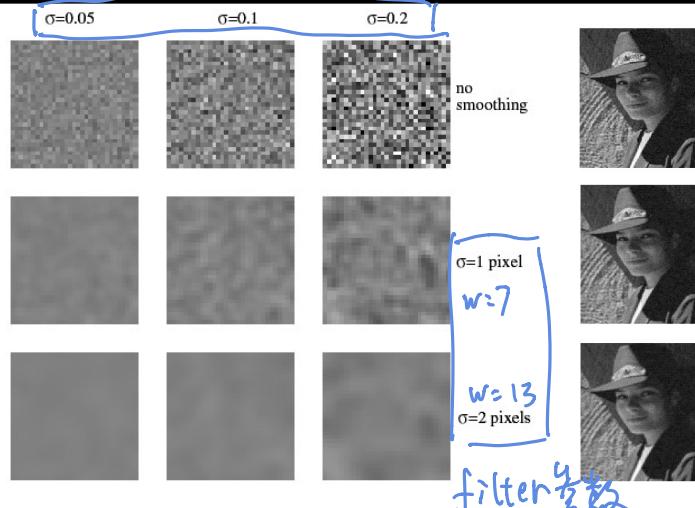


高斯噪聲
 $\eta(x, y) \sim \mathcal{N}(\mu, \sigma)$

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Reducing Gaussian noise

高斯噪聲 $N(\mu, \sigma)$ 參數



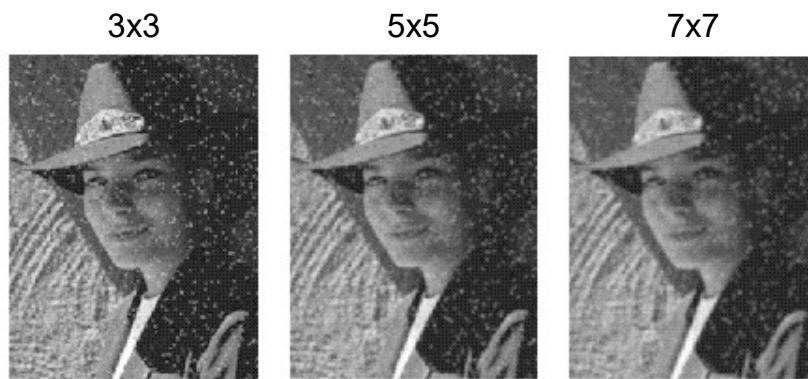
Smoothing with larger standard deviations suppresses noise, but also blurs the image

Source: S. Lazebnik

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由大的 σ 产生的 noise，可以用大的 σ 为參數的 filter 来降噪

Reducing salt-and-pepper noise



What's wrong with the results?

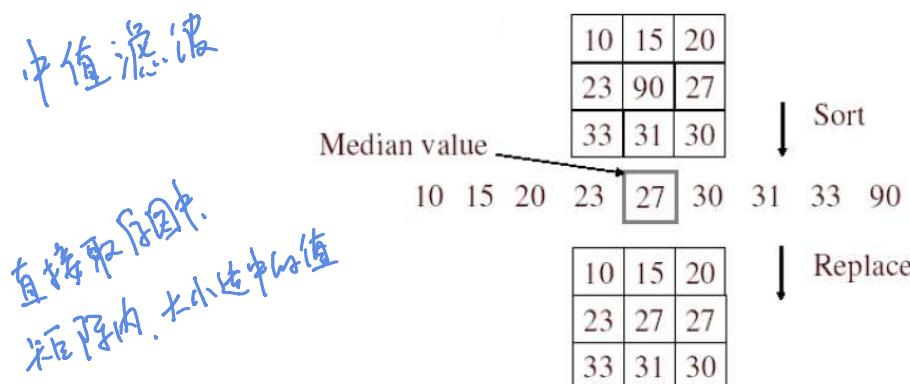
Gaussian 方法解决 盐噪

Source: S. Lazebnik

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Alternative idea: Median filtering

- A **median filter** operates over a window by selecting the median intensity in the window



- Is median filtering linear?

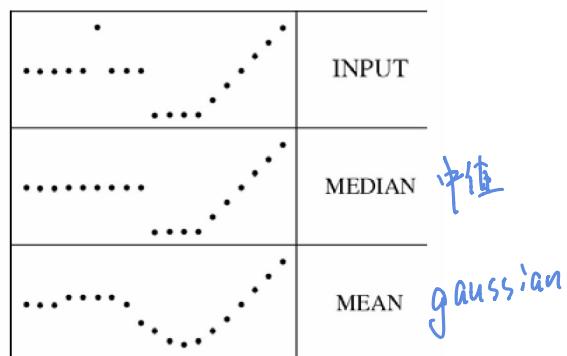
Source: K. Grauman

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Median filter

- What advantage does median filtering have over Gaussian filtering?
 - Robustness to outliers

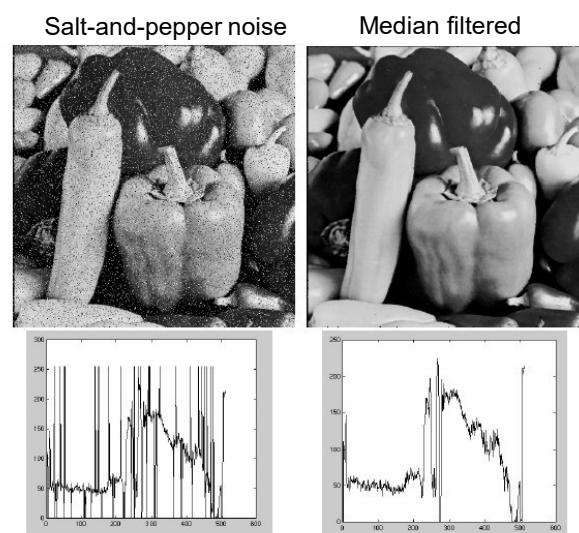
filters have width 5 :



Source: K. Grauman

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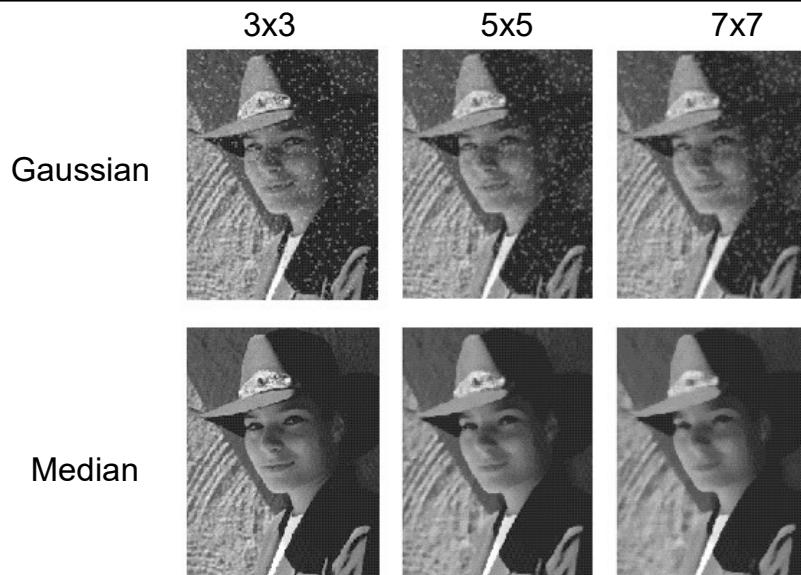
Median filter



Source: M. Hebert

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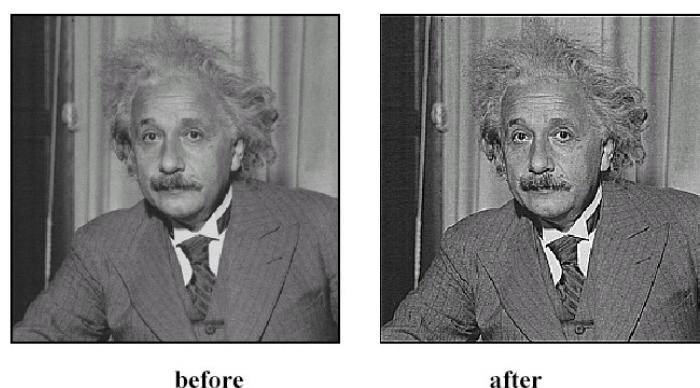
Gaussian vs. median filtering



Source: S. Lazebnik

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Sharpening revisited



Source: D. Lowe

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Sharpening revisited

What does blurring take away?



Let's add it back:

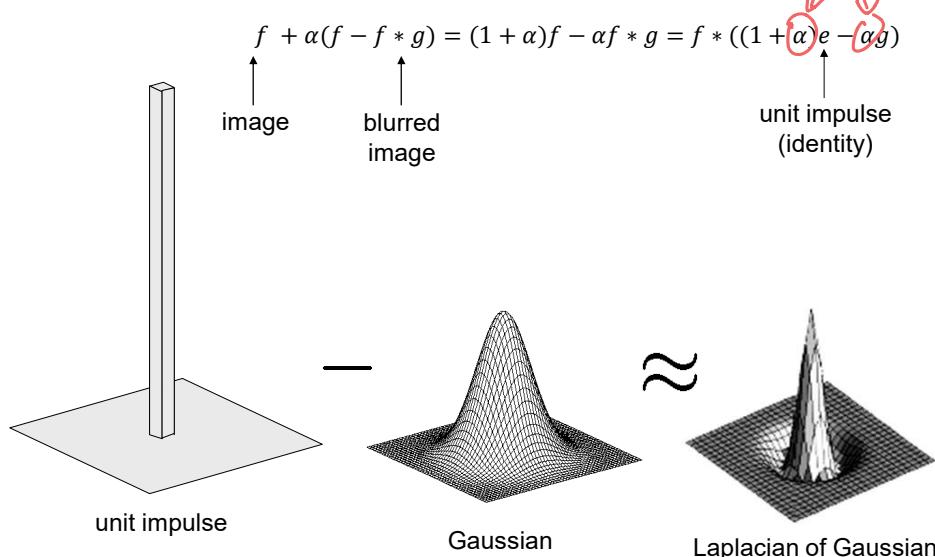


Source: S. Lazebnik

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Unsharp mask filter

控制锐化的强度



Source: S. Lazebnik

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