Image Filtering

Dr. Tushar Sandhan

Input



Input





Input

Histeq





Input

Histeq







Input Histeq Noise







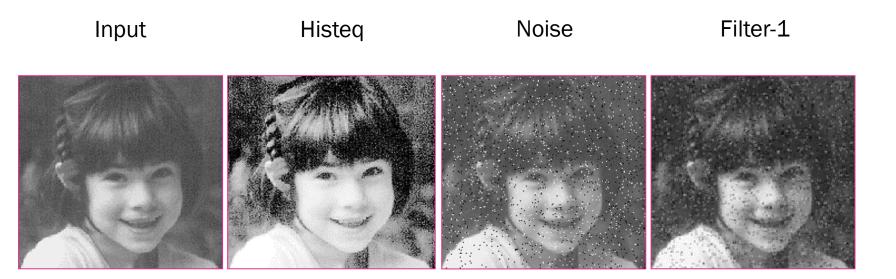
Input Histeq Noise

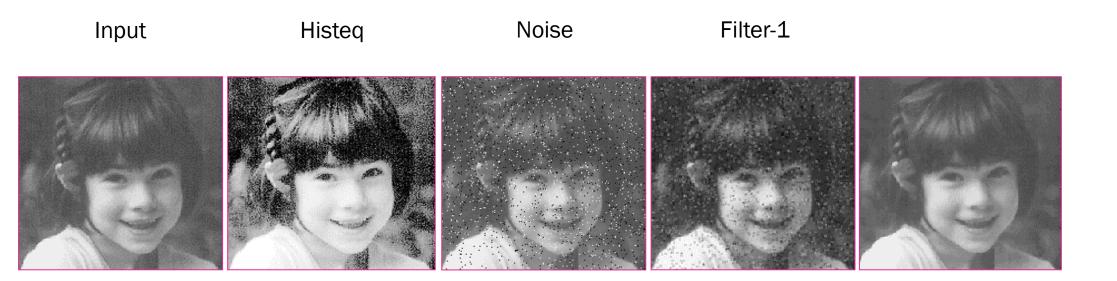


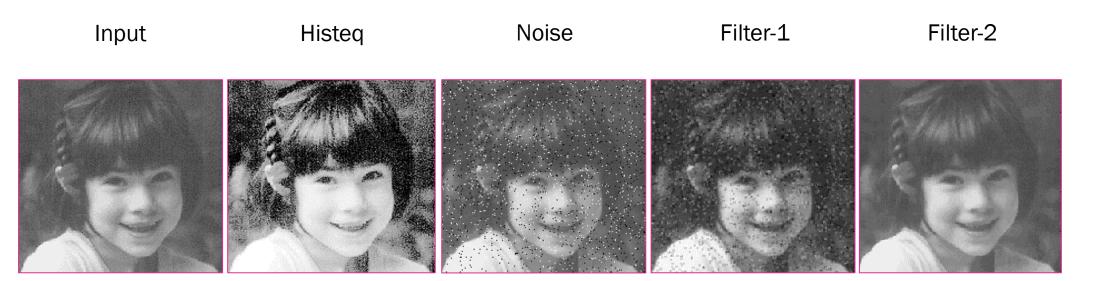


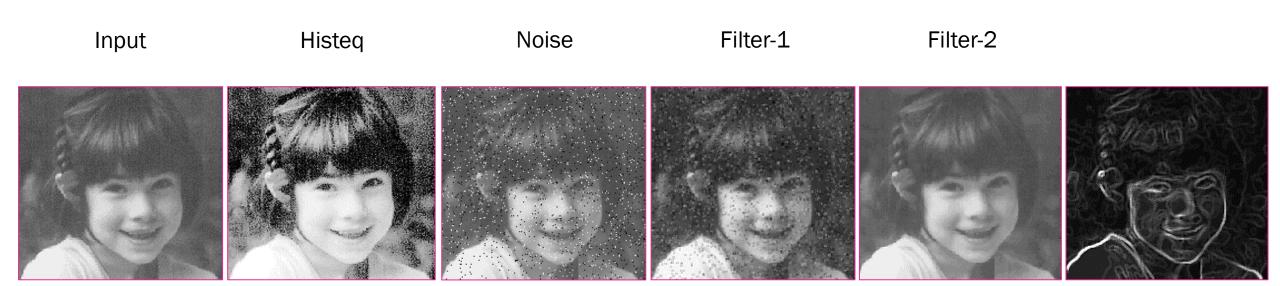


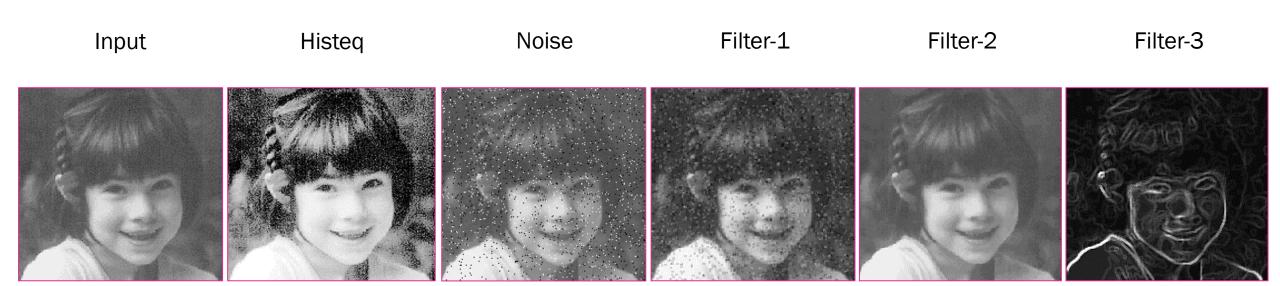


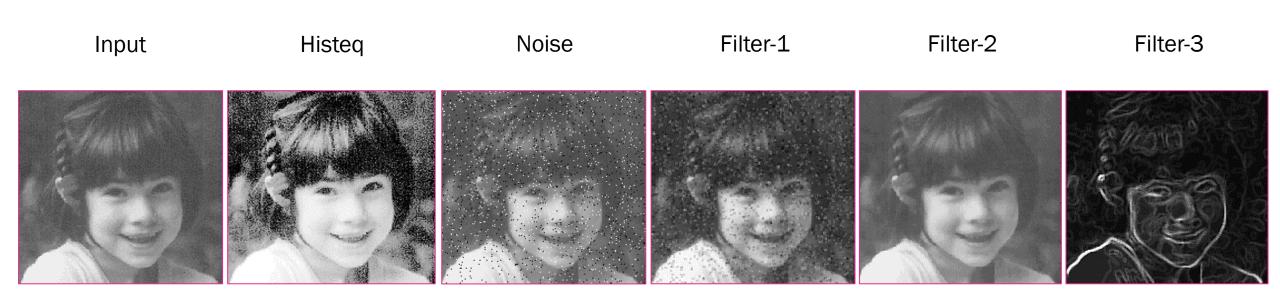




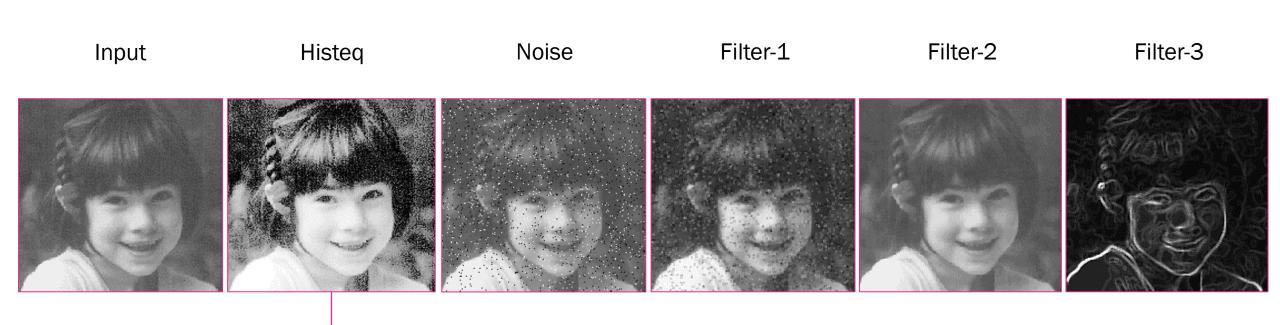


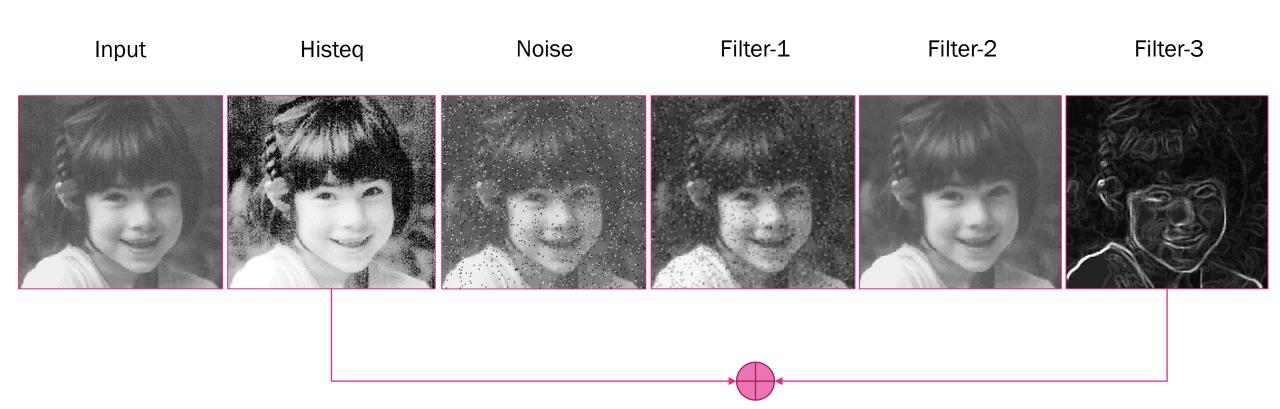


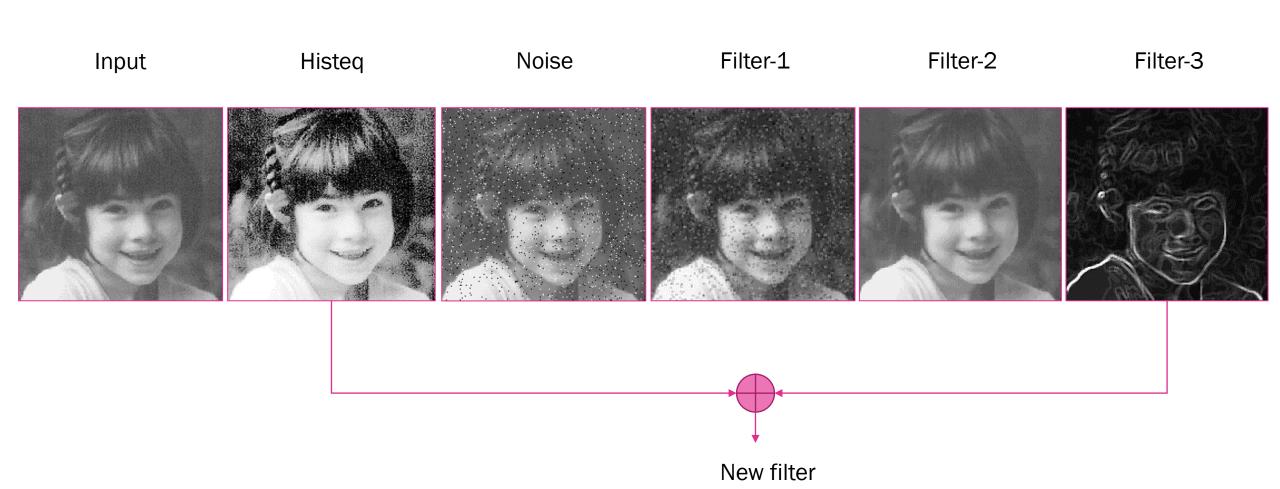


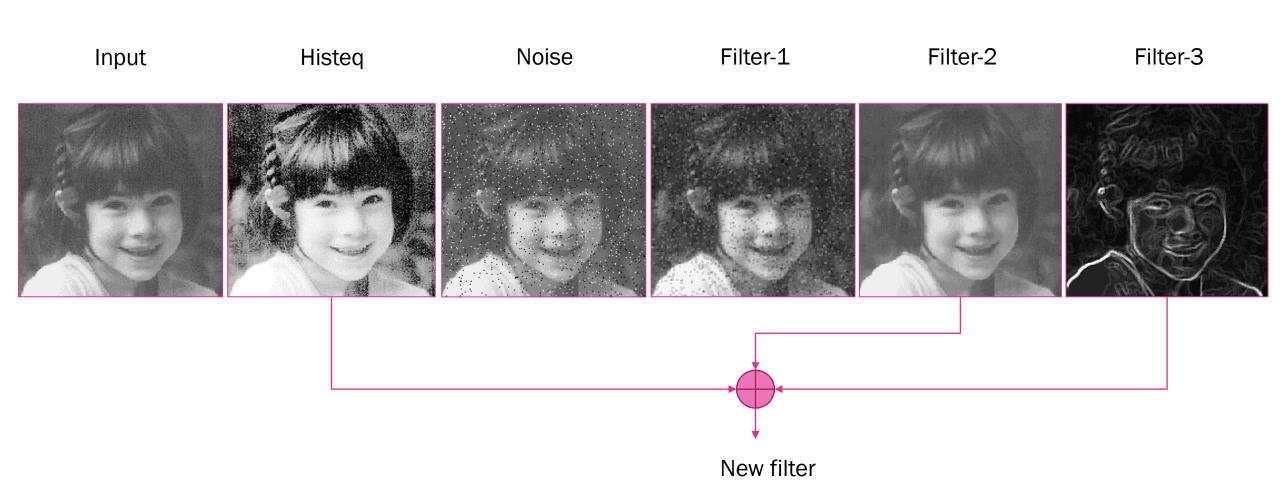












Linearity

- Operations
 - linear
 - additivity

$$\mathcal{T}[a \cdot f_1(x, y) + b \cdot f_2(x, y)] = \mathcal{T}[a \cdot f_1(x, y)] + \mathcal{T}[b \cdot f_2(x, y)]$$

homogeneity

$$\mathcal{T}[a \cdot f_1(x, y)] = a \cdot \mathcal{T}[f_1(x, y)]$$

- o non-linear
 - not satisfying above

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- o non-linear
 - not satisfying above
- Examples
 - linear
 - negatives
 - o non-linear
 - gammas

Correlation

- measures similarity between the two signals
- windowed signal (kernel) is not reversed
- sliding vectors dot product
- o orthogonal signals are uncorrelated

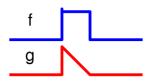
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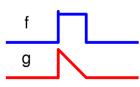
Convolution

- measure the effect of one signal on the another
- windowed signal (kernel) is reversed
 - for symmetric kernels convolution = correlation

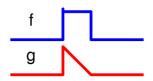
Correlation



Convolution



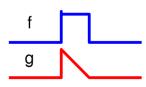
Correlation



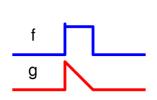
$$R(x) = f(x) * g(x)$$

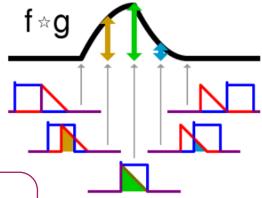
$$R(x) = \int_{-\infty}^{\infty} f(z)g(x+z)dz$$

Convolution



Correlation

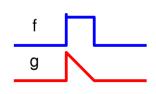




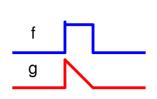
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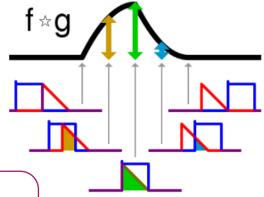
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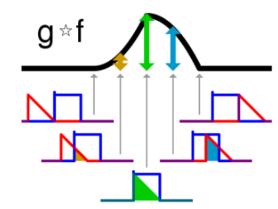
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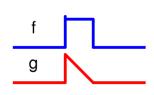


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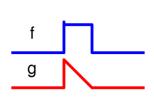
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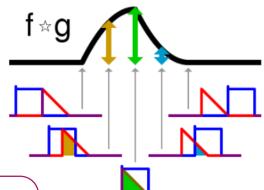


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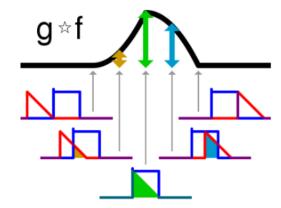
Correlation



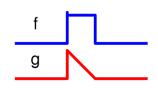


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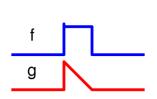
Convolution

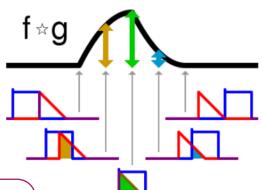


$$G(x) = f(x) * g(x)$$

$$G(x) = \int_{-\infty}^{\infty} f(z)g(x-z)dz$$

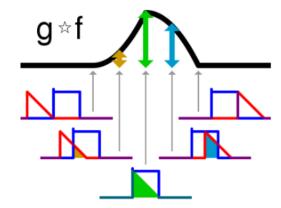
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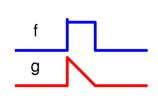


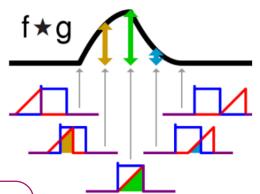
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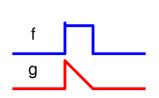


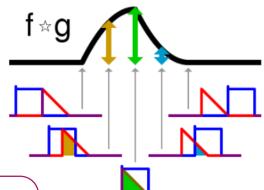


$$G(x) = f(x) \star g(x)$$

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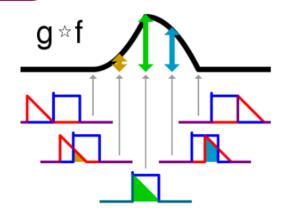
Correlation



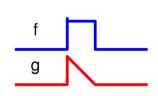


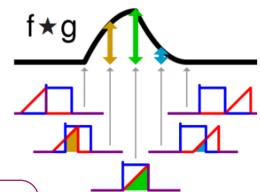
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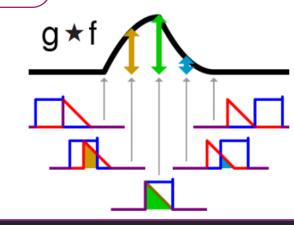
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- 2D correlation
 - cross-correlation
 - o filtering algos internally use it
 - w need to be appropriately reflected before filtering

$$(w \stackrel{\wedge}{\approx} f)(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s,y+t)$$

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$$(w \star f)(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s, t) f(x - s, y - t)$$

- 2D correlation
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2D convolution

$$\circ w \rightarrow m \times n$$

$$a = \frac{m-1}{2}, b = \frac{n-1}{2}$$

- a, b are assumed to be odd integers
- note the kernels do not depend on (x, y)

$$(w \stackrel{\wedge}{\approx} f)(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s,y+t)$$

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$$(w \approx f)(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s,y+t) \qquad (w \star f)(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x-s,y-t)$$

Property	Correlation	Convolution
Commutative	_	$f \star g = g \star f$
Associative		$f \star (g \star h) = (f \star g) \star h$
Distributive	$f \Leftrightarrow (g+h) = (f \Leftrightarrow g) + (f \Leftrightarrow h)$	$f \star (g + h) = (f \star g) + (f \star h)$

- Image filtering
 - spatial filtering
 - o convolving a kernel with an image
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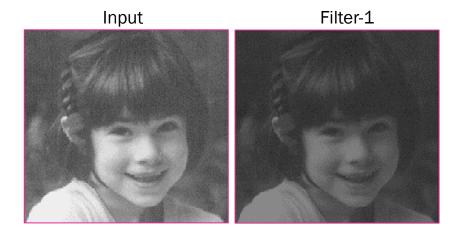
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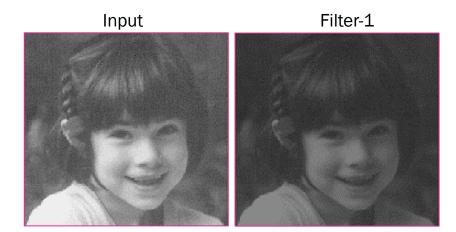
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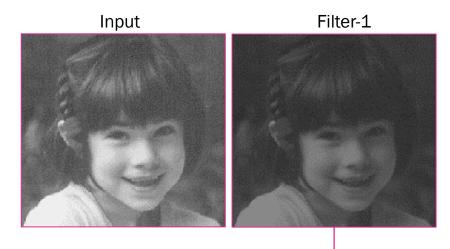


Filter-2



- Image filtering
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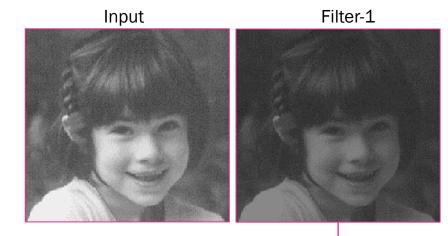


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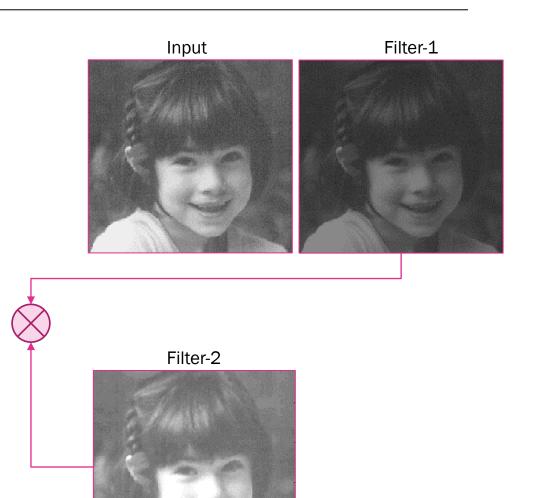






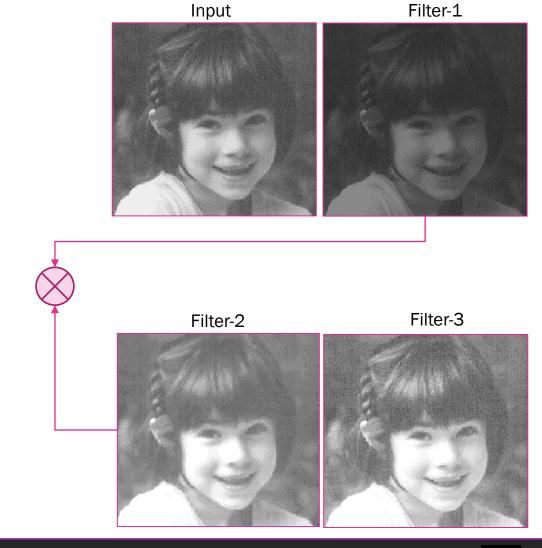
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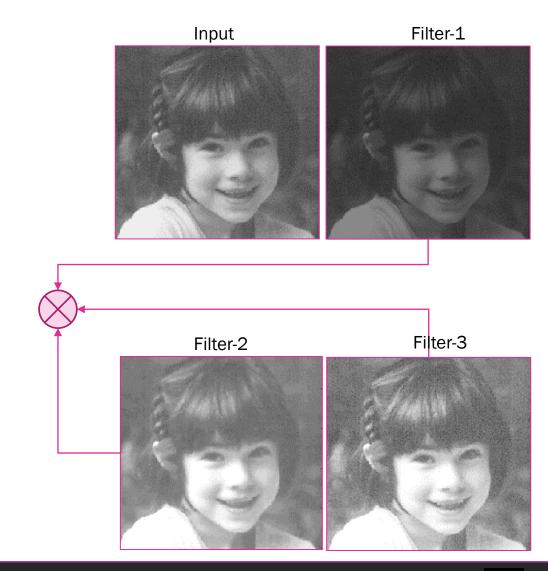
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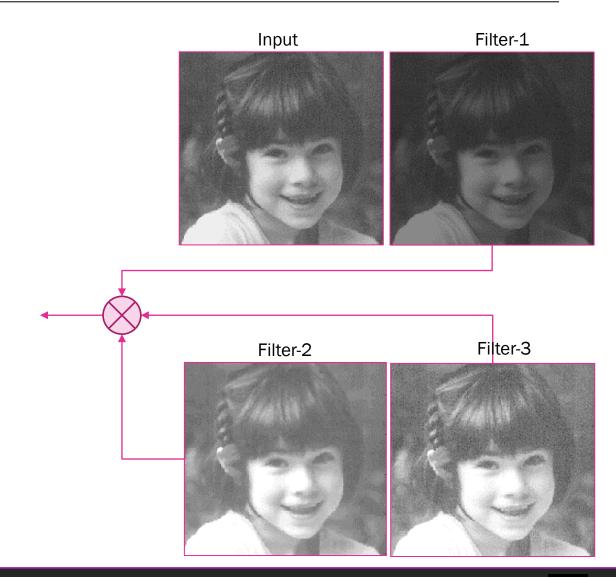
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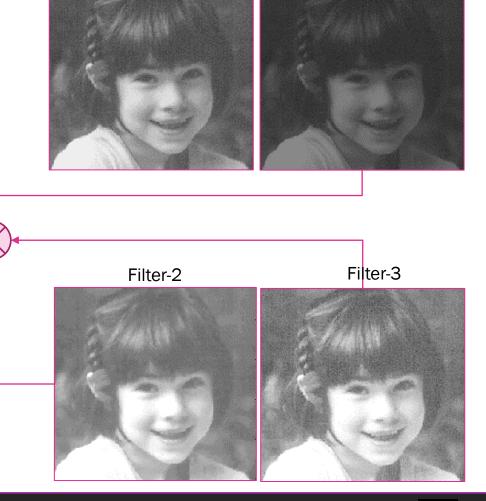
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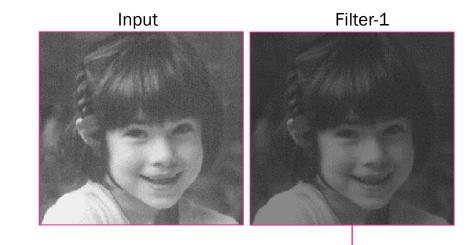
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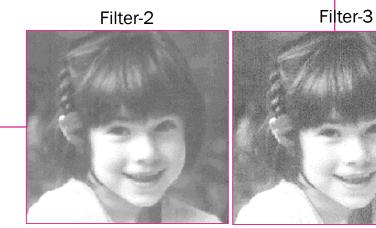
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 $(w_3 \star w_2 \star w_1) \star f(x, y)$

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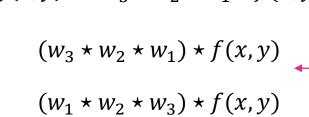


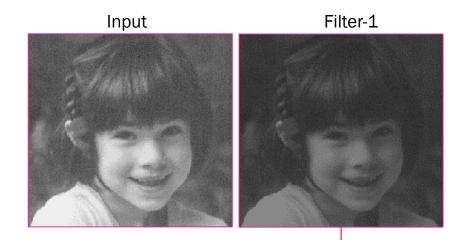


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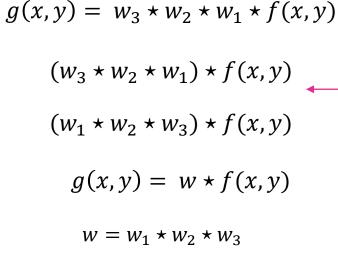


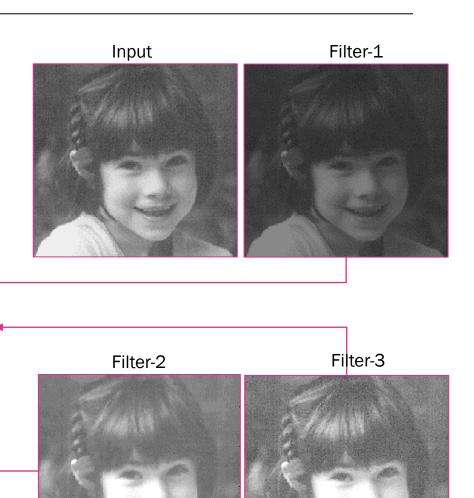




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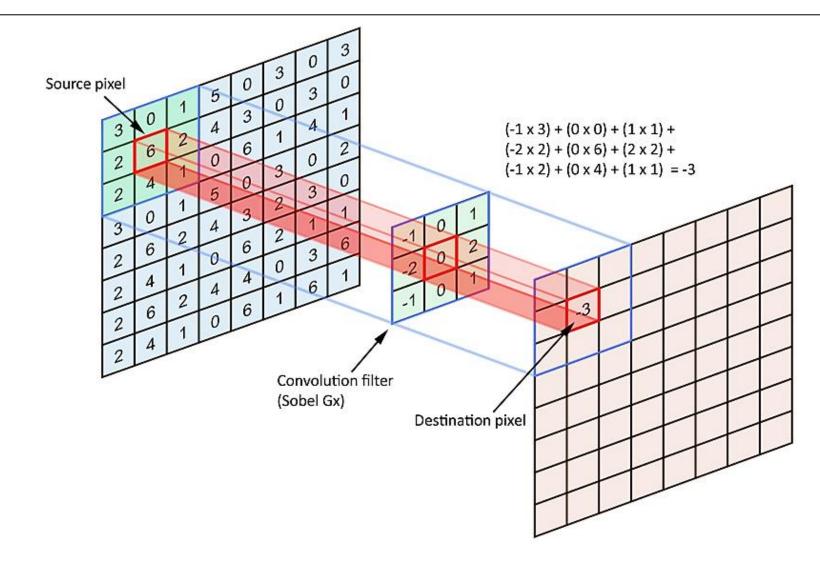




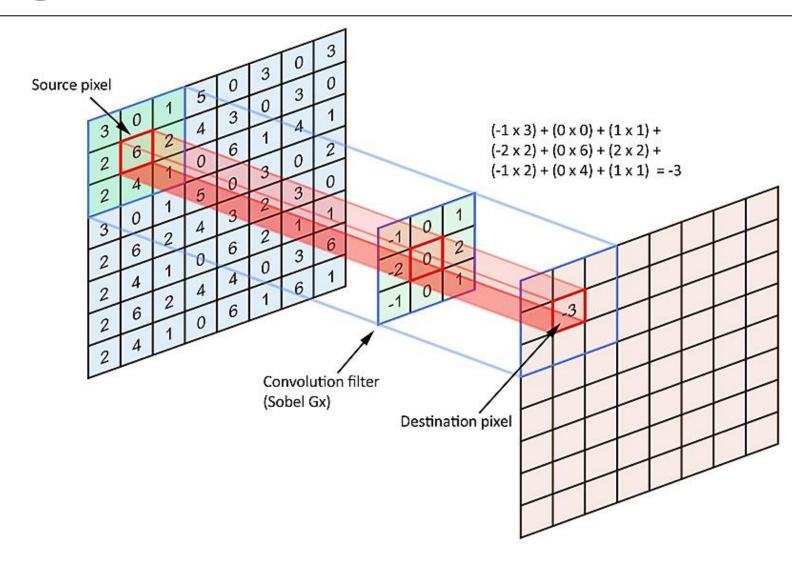
- Filter
 - o kernel, mask, window, template
 - ow(i,j) or k(i,j) ∀ $i,j ∈ N_K$, K-kernel size
 - *K* : determine neighbourhood of operation
 - w(i,j): filter coefficients determine nature of the filter

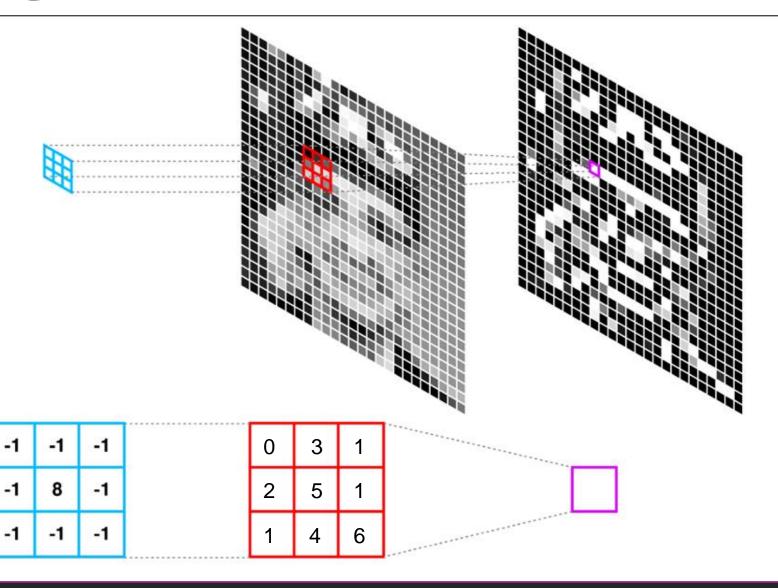
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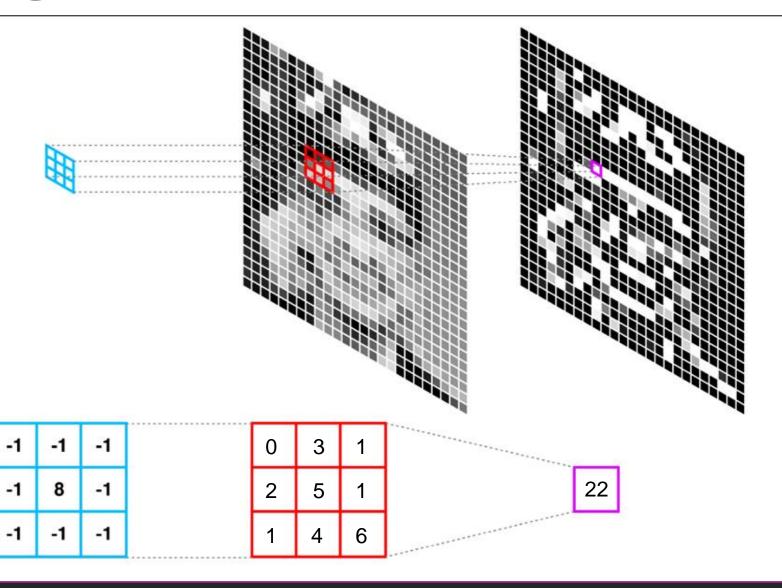
- Nature of a filter
 - neighbour interactions
 - o filter coefficients define severity of interaction
 - smoothing
 - sharpening
 - noise handling capacity



- Paddings
 - zero
 - mirror
 - replicate







Separable kernels

- a kernel in a matrix form can be represented as outer product of two vectors
- $ow = uv^T$
 - $u \in m \times 1$
 - $v \in n \times 1$
 - sq. kernels $w = uu^T$, $w \in m \times m$

$$w = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

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$$\mathbf{c} \, \mathbf{r}^T = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \mathbf{w}$$

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$$=(w_2 \star w_1) \star f$$

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- $\circ w = uv^T$
 - $u \in m \times 1$
 - $v \in n \times 1$
 - sq. kernels $w = uu^T$, $w \in m \times m$
- Advantage: separable kernels
 - computationally fast
 - outer product of vectors is same as their 2D conv
 - image: $M \times N$

$$w = w_1 \star w_2$$

$$w \star f = (w_1 \star w_2) \star f$$

$$=(w_2 \star w_1) \star f$$

$$= w_2 \star (w_1 \star f)$$

Separable kernels

- a kernel in a matrix form can be represented as outer product of two vectors
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$$=(w_1\star f)\star w_2$$

Separable kernels

- a kernel in a matrix form can be represented as outer product of two vectors
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- Advantage: separable kernels
 - computationally fast
 - outer product of vectors is same as their 2D conv
 - image: $M \times N$
 - advantage factor = $\frac{mn}{m+n}$

$$w = w_1 \star w_2$$

$$w \star f = (w_1 \star w_2) \star f$$

$$=(w_2 \star w_1) \star f$$

$$= w_2 \star (w_1 \star f)$$

$$= (w_1 \star f) \star w_2$$

- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter

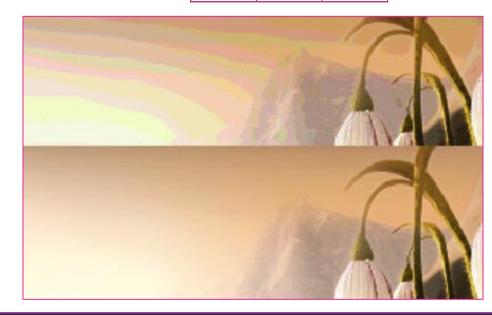
	1	1	1
$\frac{1}{9}$ ×	1	1	1
	1	1	1

- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter
- Use cases
 - o random noise reduction
 - reducing sharp transitions in intensity
 - favours blurring along perpendicular directions
 - reduce aliasing
 - smoothing prior to resampling
 - o reduce quantization noise
 - o reduce false contours of intensities
 - o essential in composite filtering
 - multistage filters

	1	1	1
$\frac{1}{9} \times$	1	1	1
	1	1	1

- Box filter
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- Use cases
 - o random noise reduction
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	1	1	1
$\frac{1}{9}$ ×	1	1	1
	1	1	1

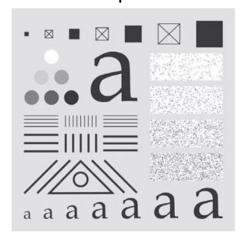


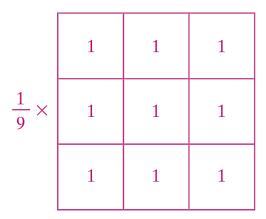
- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter

	1	1	1
$\frac{1}{9}$ ×	1	1	1
	1	1	1

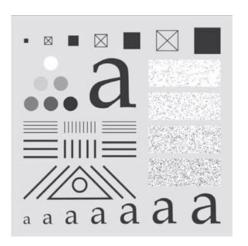
- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter

input

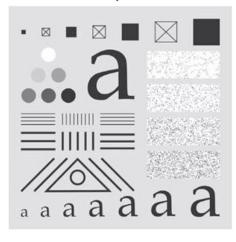




- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter



input



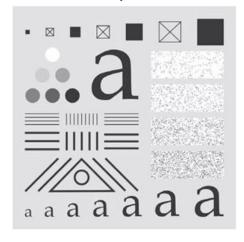
	1	1	1
$\frac{1}{9}$ ×	1	1	1
	1	1	1

EE604: IMAGE PROCESSING

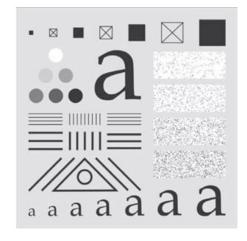
m=3

- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter





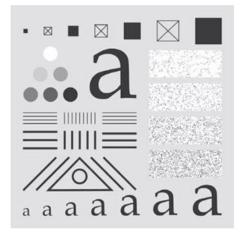
m=3



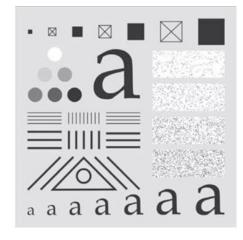
m=11

- Box filter
 - smoothing filter
 - lowpass filter
 - averaging filter

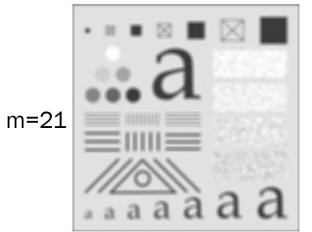
input



m=3



m=11



- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric

$$w(s,t) = G(s,t) = Ke^{-\frac{s^2+t^2}{2\sigma^2}}$$

$\frac{1}{4.8976} \times$	0.3679	0.6065	0.3679
	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

- Gaussian filter
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	$s^2 + t^2$
$w(s,t) = G(s,t) = Ke^{-s}$	$2\sigma^2$

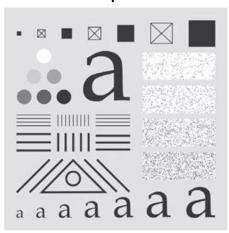
	0.3679	0.6065	0.3679
<	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

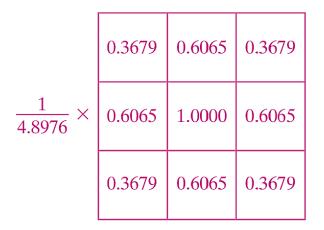
G(s,t)	
1	
s	

- Gaussian filter
 - smoothing filter
 - o defocused lens approximators
 - o isotropic
 - response is independent of orientation
 - circularly symmetric

$\frac{1}{4.8976} \times$	0.3679	0.6065	0.3679
	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric

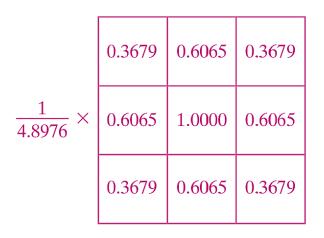




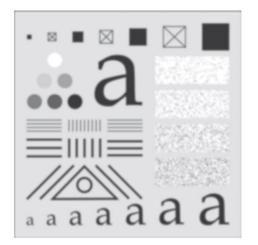
- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric

input



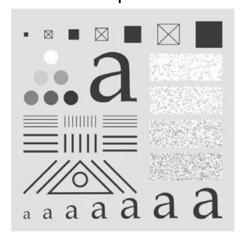


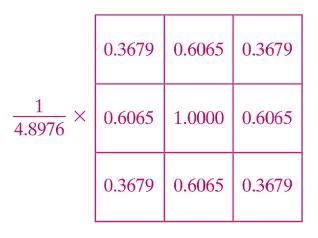
m=21 σ =3.5 Gauss



- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric

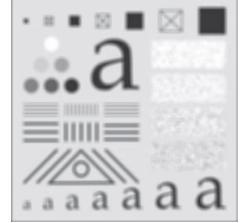
input





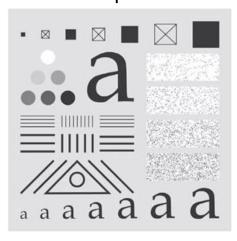
m=21 box

m=21 σ =3.5 Gauss



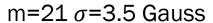


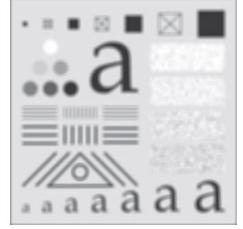
- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
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$\frac{1}{4.8976} \times$	0.3679	0.6065	0.3679
	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

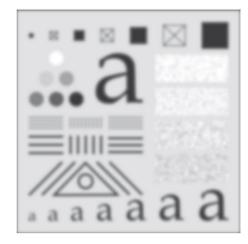
$$m=21 box$$



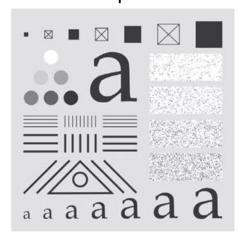




m=43 σ =7 Gauss



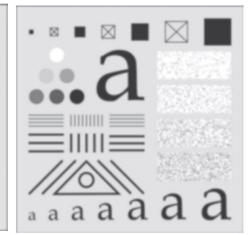
- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric



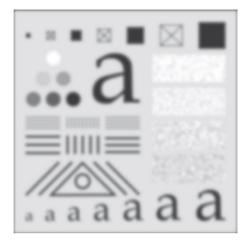
$\frac{1}{4.8976} \times$	0.3679	0.6065	0.3679
	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

$$m=21 box$$

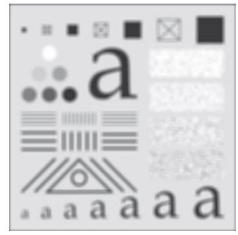
m=21 σ =3.5 Gauss



m=43 σ =7 Gauss



m=21 box

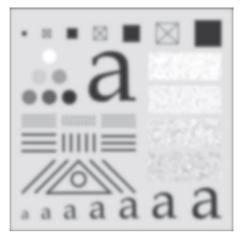


- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - circularly symmetric

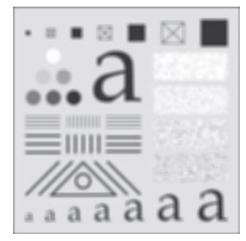


$\frac{1}{4.8976} \times$	0.3679	0.6065	0.3679
	0.6065	1.0000	0.6065
	0.3679	0.6065	0.3679

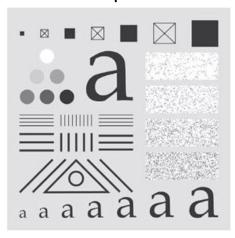
m=43 σ =7 Gauss

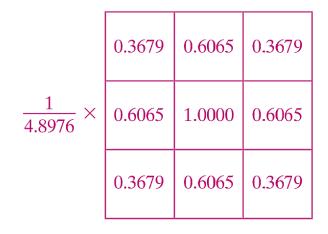


m=21 box

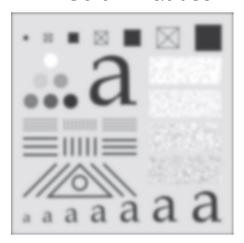


- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
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 - circularly symmetric

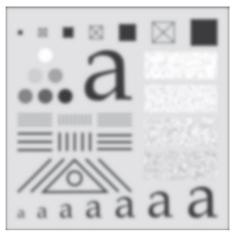




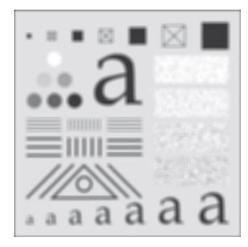
m=85 σ =7 Gauss



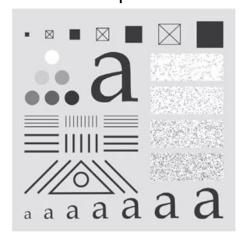
m=43 σ =7 Gauss

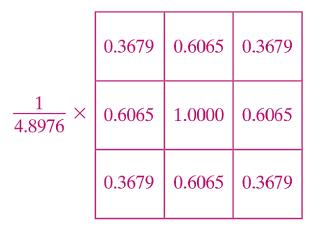


m=21 box

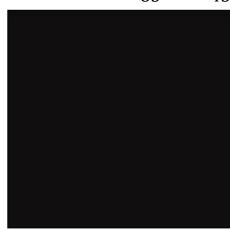


- Gaussian filter
 - smoothing filter
 - defocused lens approximators
 - isotropic
 - response is independent of orientation
 - · circularly symmetric

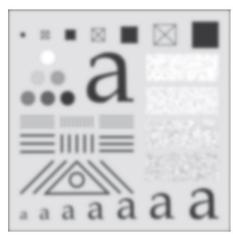




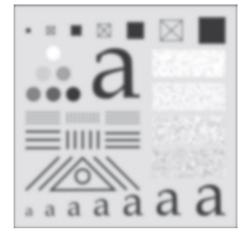
difference $m_{85} - m_{43}$



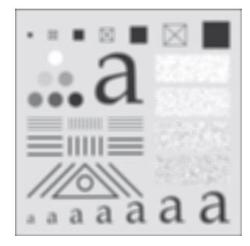
m=85 σ =7 Gauss



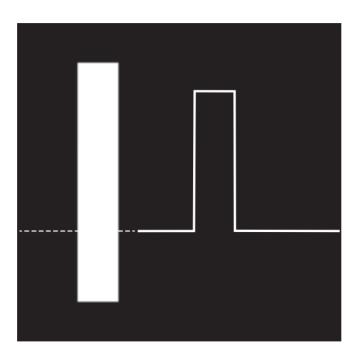
m=43 σ =7 Gauss



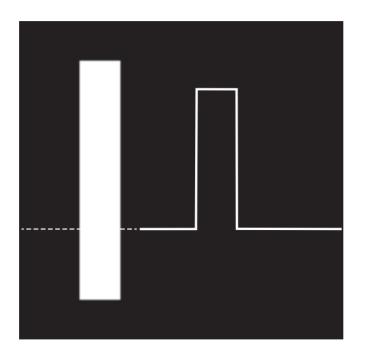
m=21 box

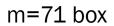


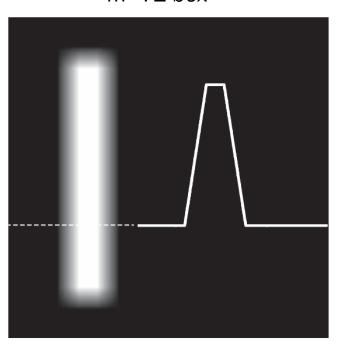
- Box vs Gaussian
 - o blur profile
 - o blurred rects having same shape



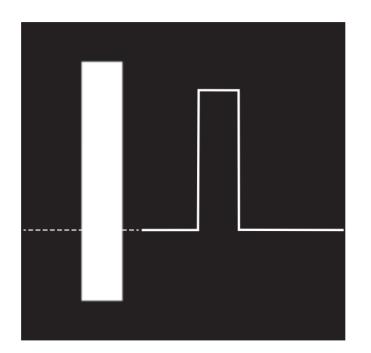
- Box vs Gaussian
 - o blur profile
 - o blurred rects having same shape

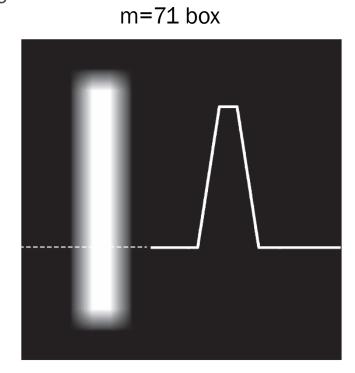


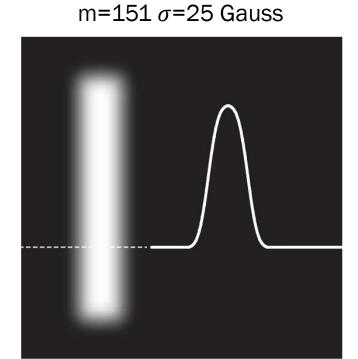




- Box vs Gaussian
 - o blur profile
 - o blurred rects having same shape



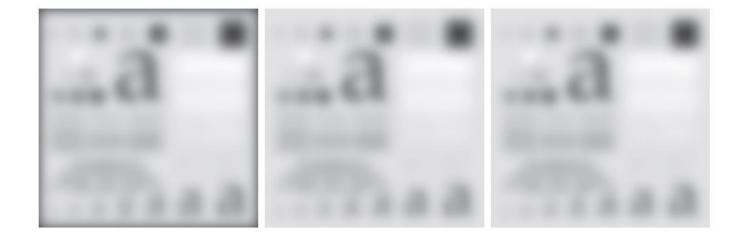




Padding effects

m=187 σ =31 Gauss

image 1024x1024



Padding effects

m=187 σ =31 Gauss

image 1024x1024



Padding effects

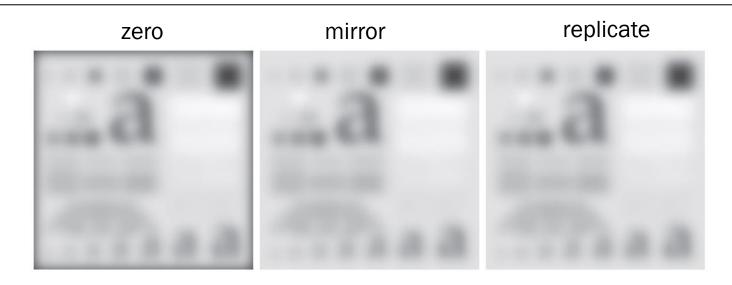
m=187
$$\sigma$$
=31 Gauss

image 1024x1024

Relative size effect

m=187 σ =31 Gauss

image 4096x4096



Padding effects

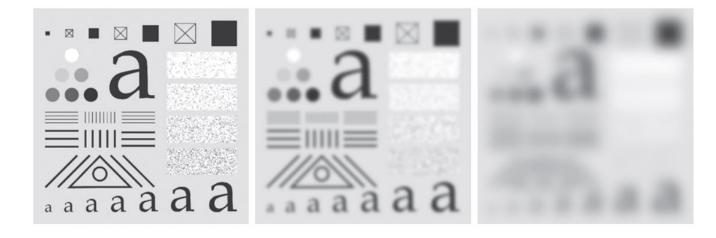
m=187 σ =31 Gauss image 1024x1024

Relative size effect

m=187 σ =31 Gauss

image 4096x4096





Padding effects

m=187 σ =31 Gauss image 1024x1024

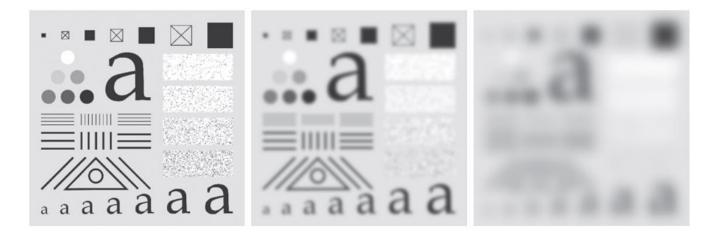
Relative size effect

m=187 σ =31 Gauss

image 4096x4096

m=745 σ =124 Gauss





Padding effects

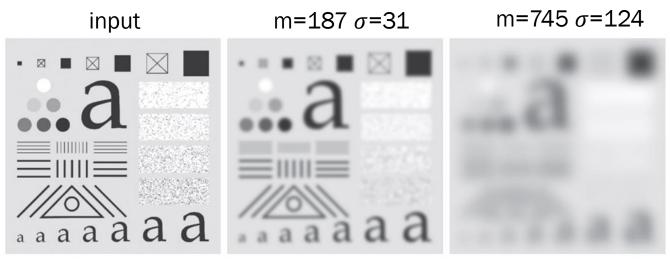
m=187
$$\sigma$$
=31 Gauss image 1024x1024

Relative size effect

m=187 σ =31 Gauss image 4096x4096

 $m=745 \sigma=124 Gauss$





Relevant region extraction

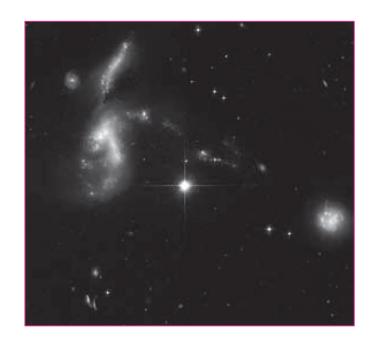


Relevant region extraction

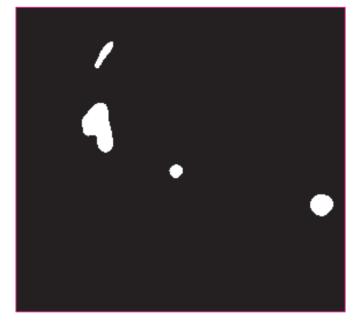




Relevant region extraction







Relevant region extraction







thresholding



Shifting





Shifting



filter output



Shifting



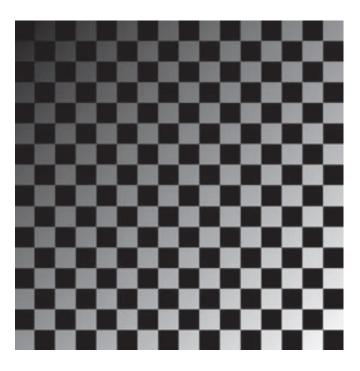
filter

output

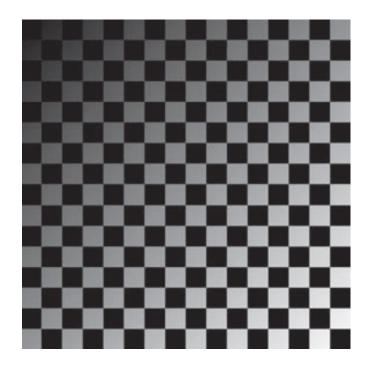




Shading correction

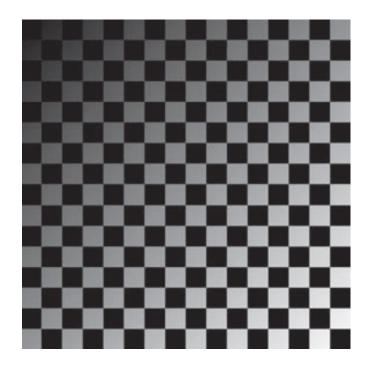


Shading correction

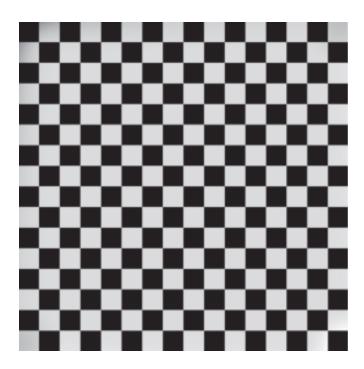




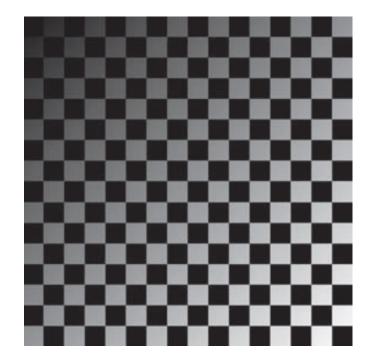
Shading correction



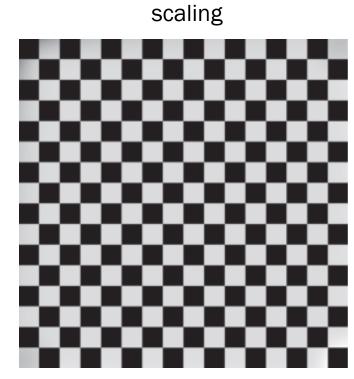




Shading correction







Conclusion

- Filtering
 - Separable kernels
 - Correlation Vs Convolution
 - Filter properties
 - Smoothing filters

