Image Filtering

Dr. Tushar Sandhan

Introduction

Input

Introduction

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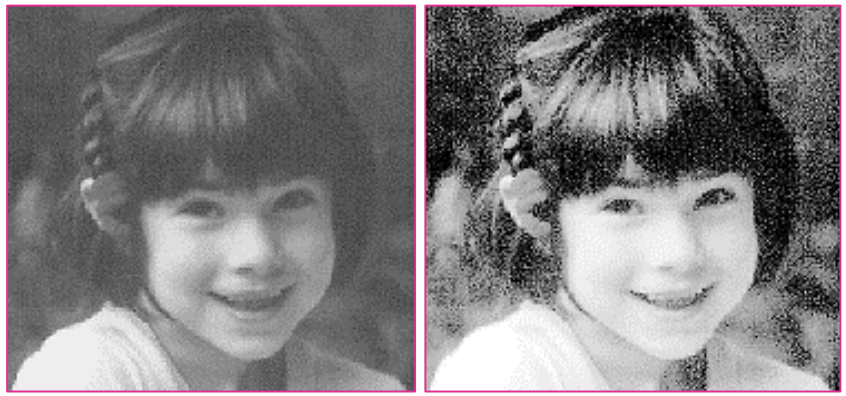

Introduction

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Histeq

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Noise

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Input Histeq Noise

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Input Histeq Noise Filter-1

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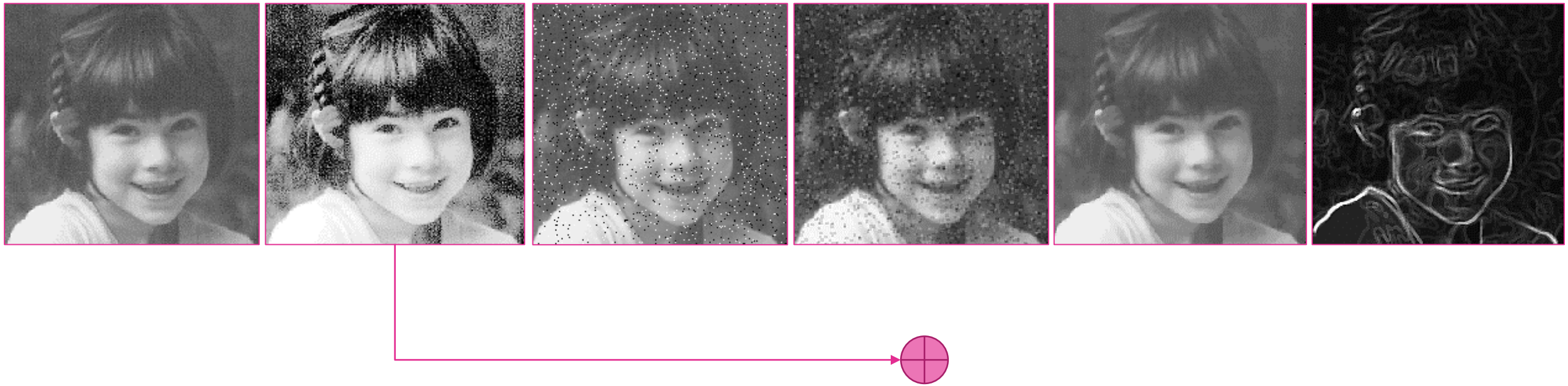

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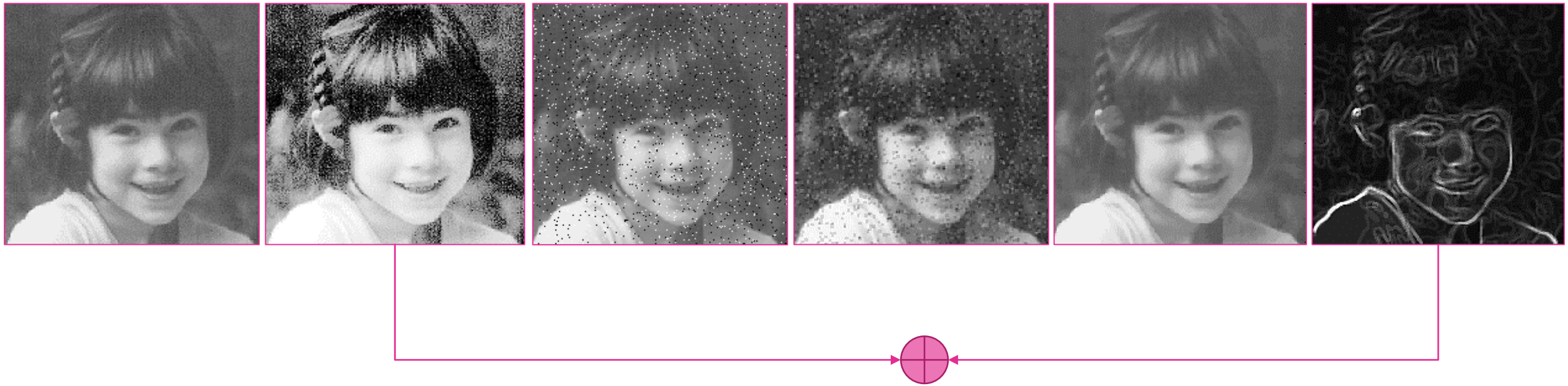

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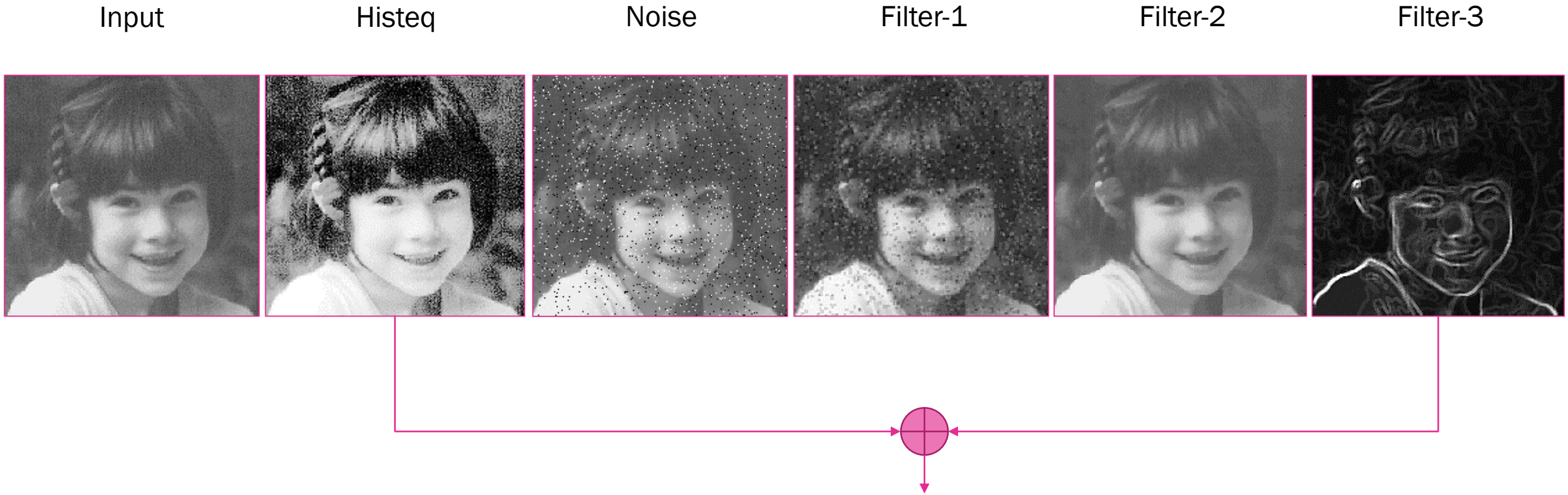

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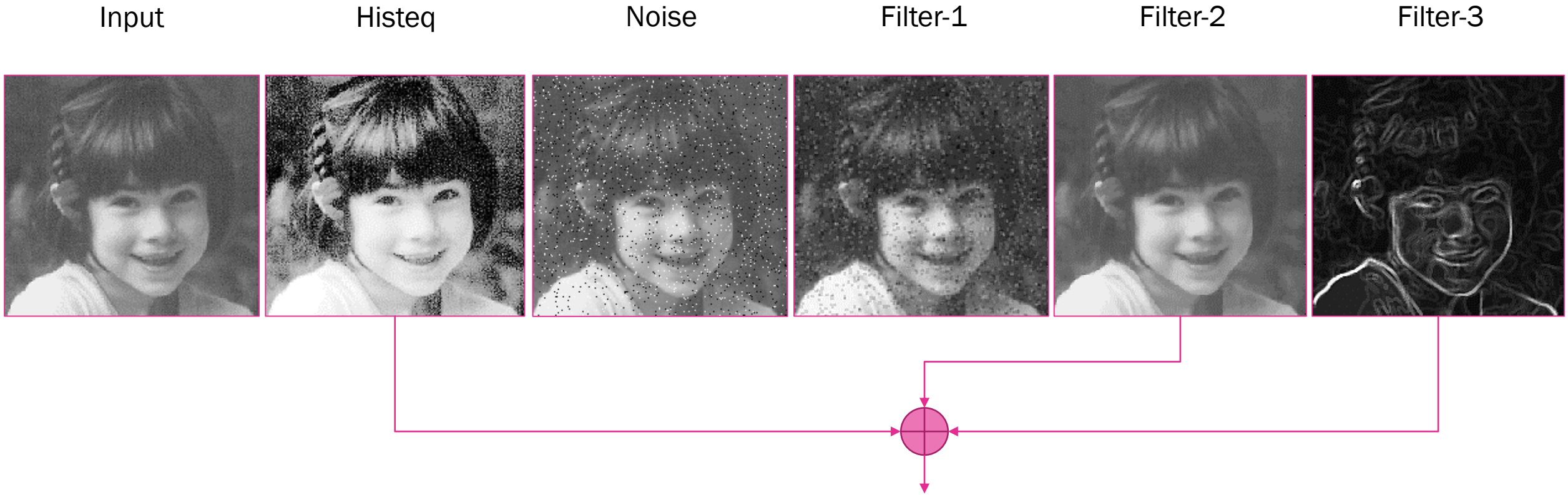

Linearity

- 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

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- Examples
  - linear
    - negatives
  - non-linear
    - gammas

Correlation & Convolution

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

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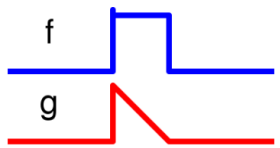
- Convolution
  - measure the effect of one signal on the another
  - windowed signal (kernel) is reversed
    - for symmetric kernels convolution = correlation

Correlation & Convolution

- Correlation



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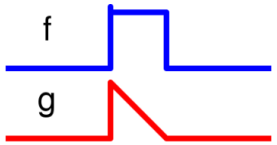

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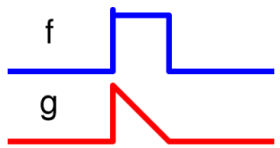

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$$R(x) = \int_{-\infty}^{\infty} f(z)g(x+z)dz$$

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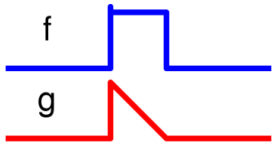

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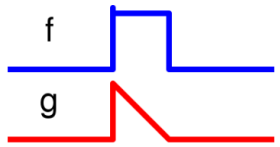

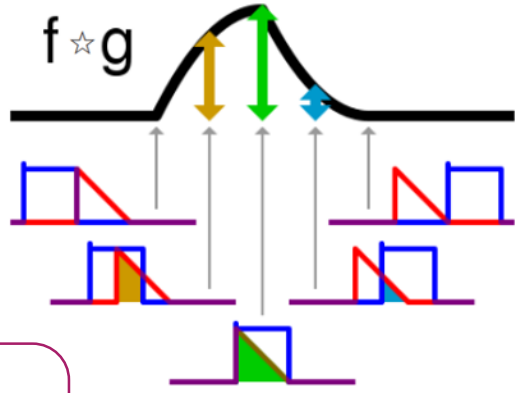

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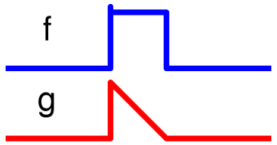

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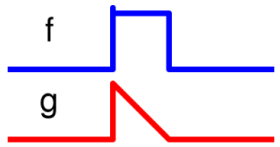

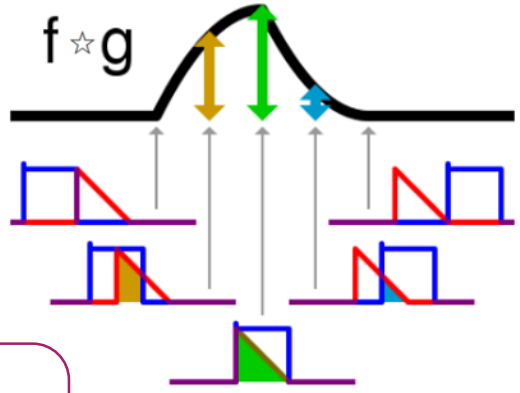

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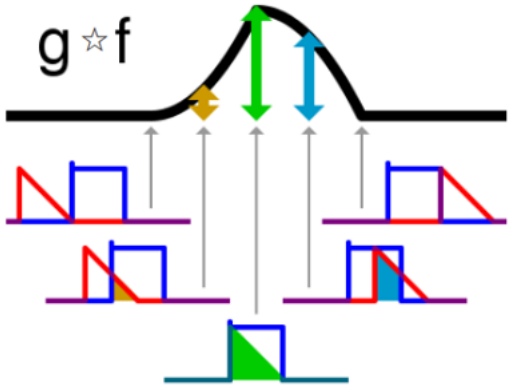

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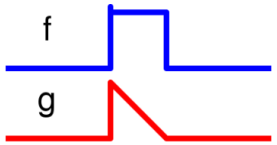

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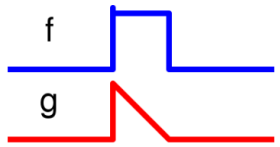

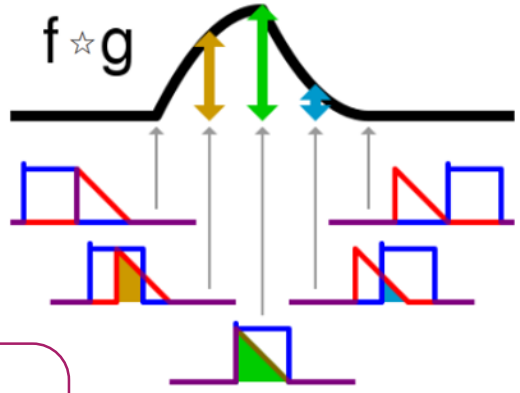

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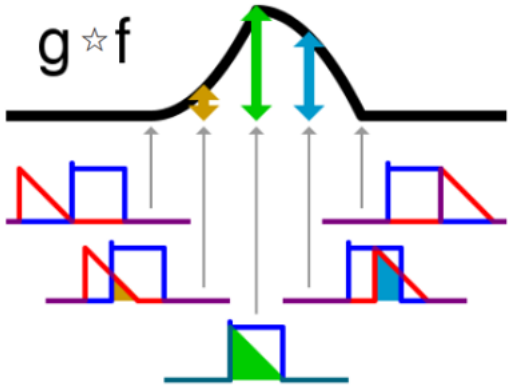

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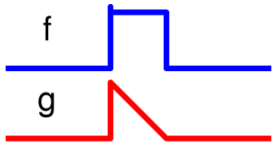

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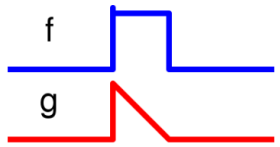

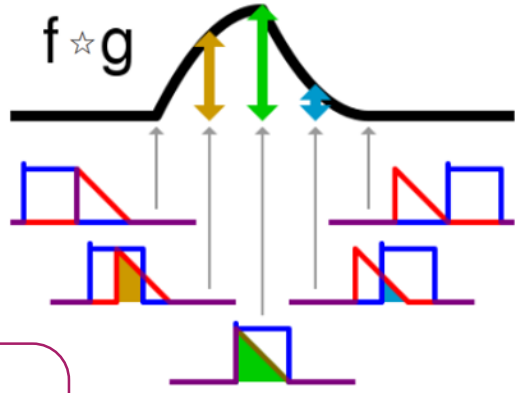

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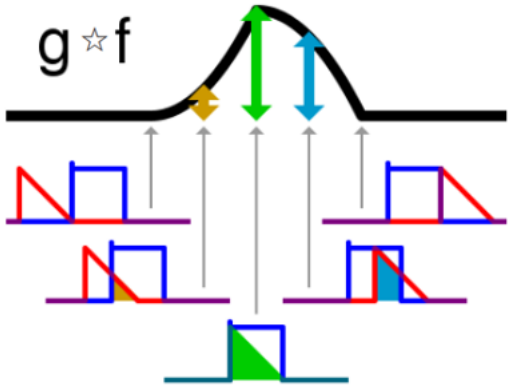

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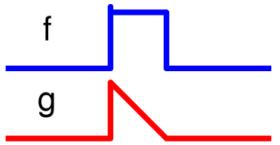

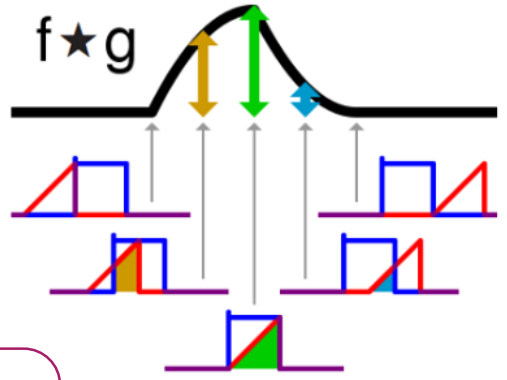

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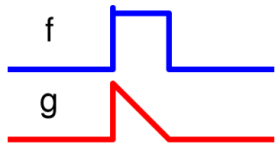

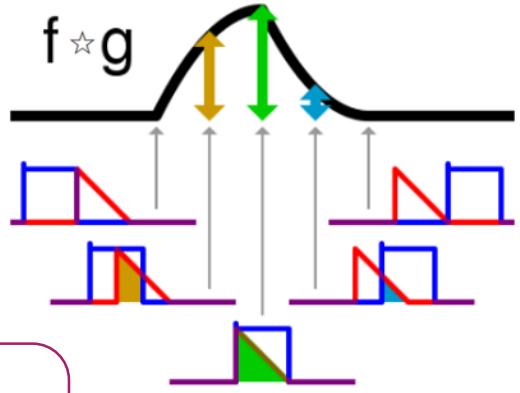

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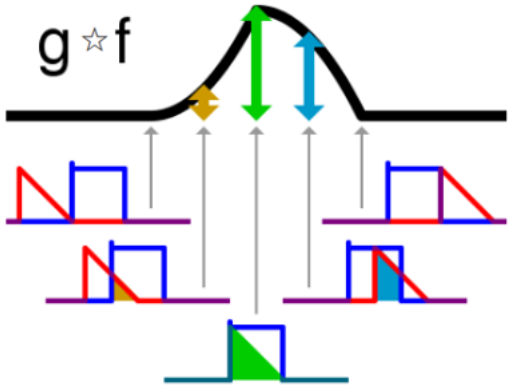

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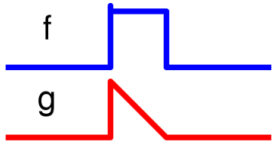

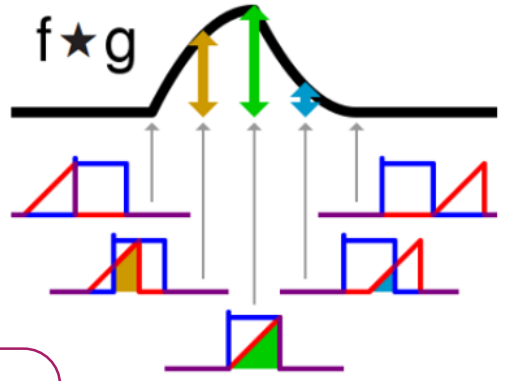

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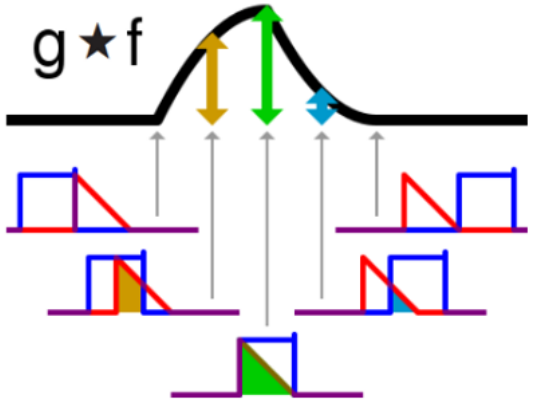

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Correlation & Convolution

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

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- 2D convolution
  - $w \rightarrow m \times n$
  - $a = \frac{m-1}{2}, b = \frac{n-1}{2}$
    - a, b are assumed to be odd integers
    - note the kernels do not depend on (x, y)

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

Filtering

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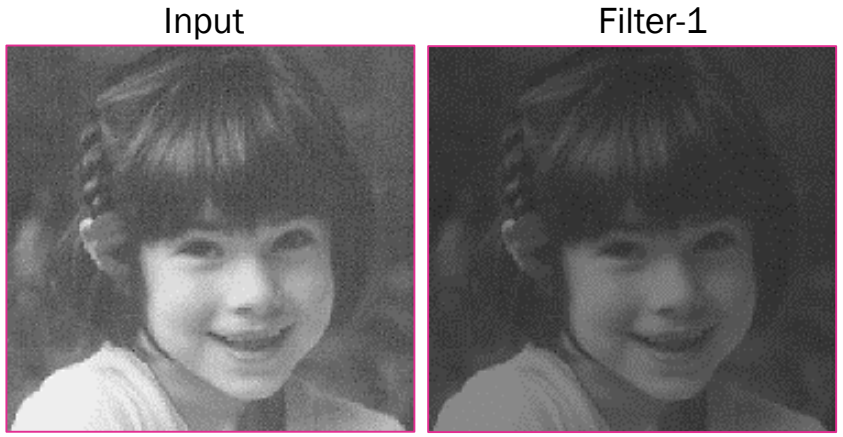

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Filter-2

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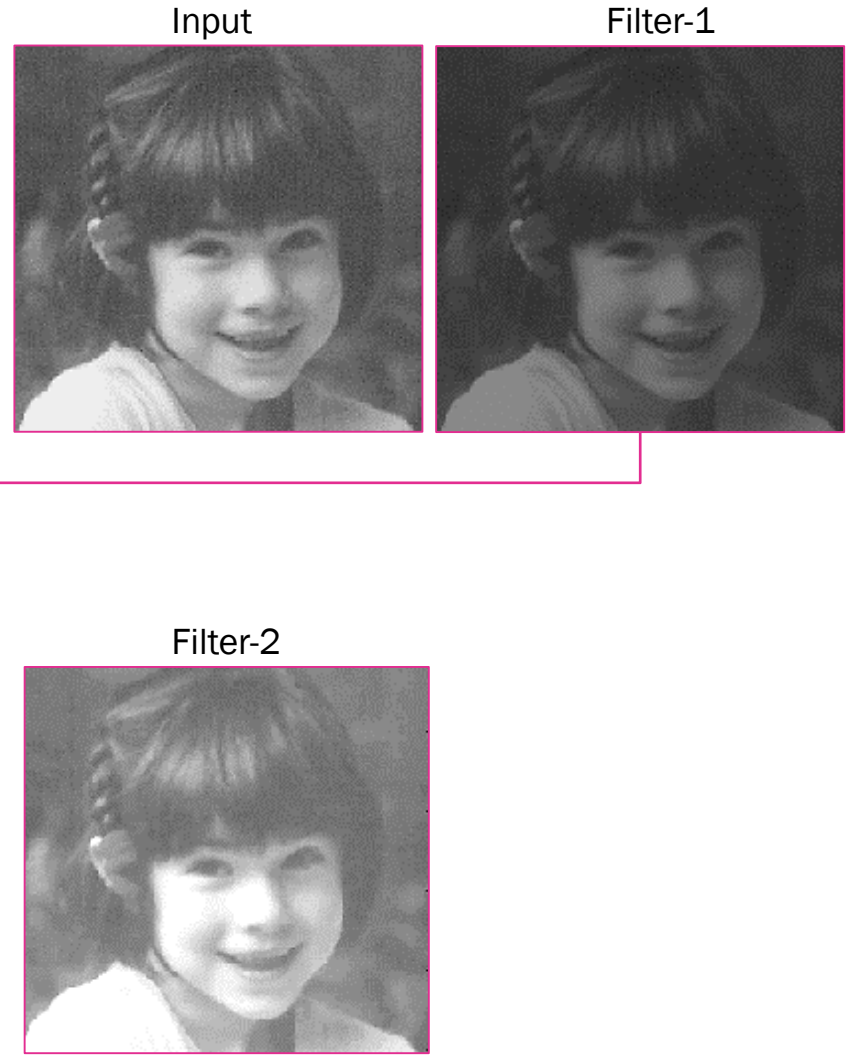

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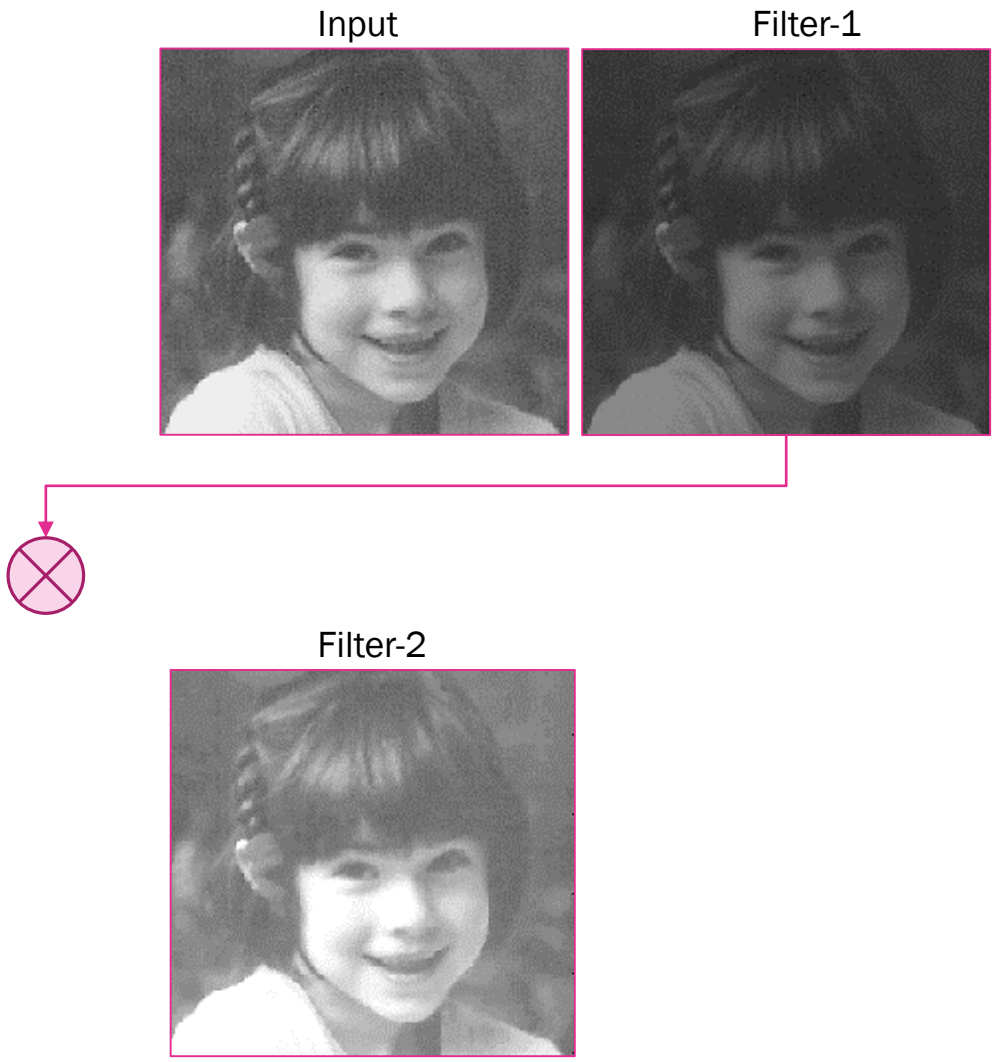

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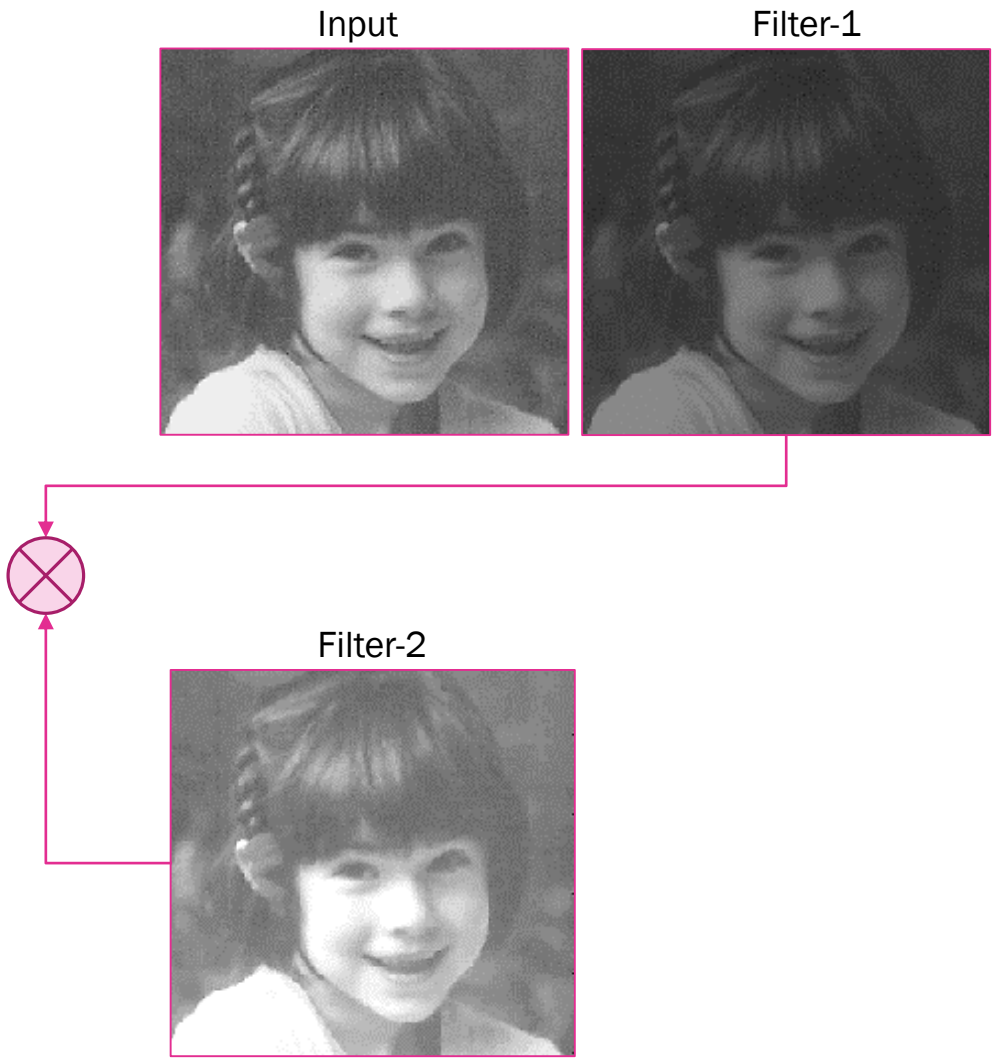

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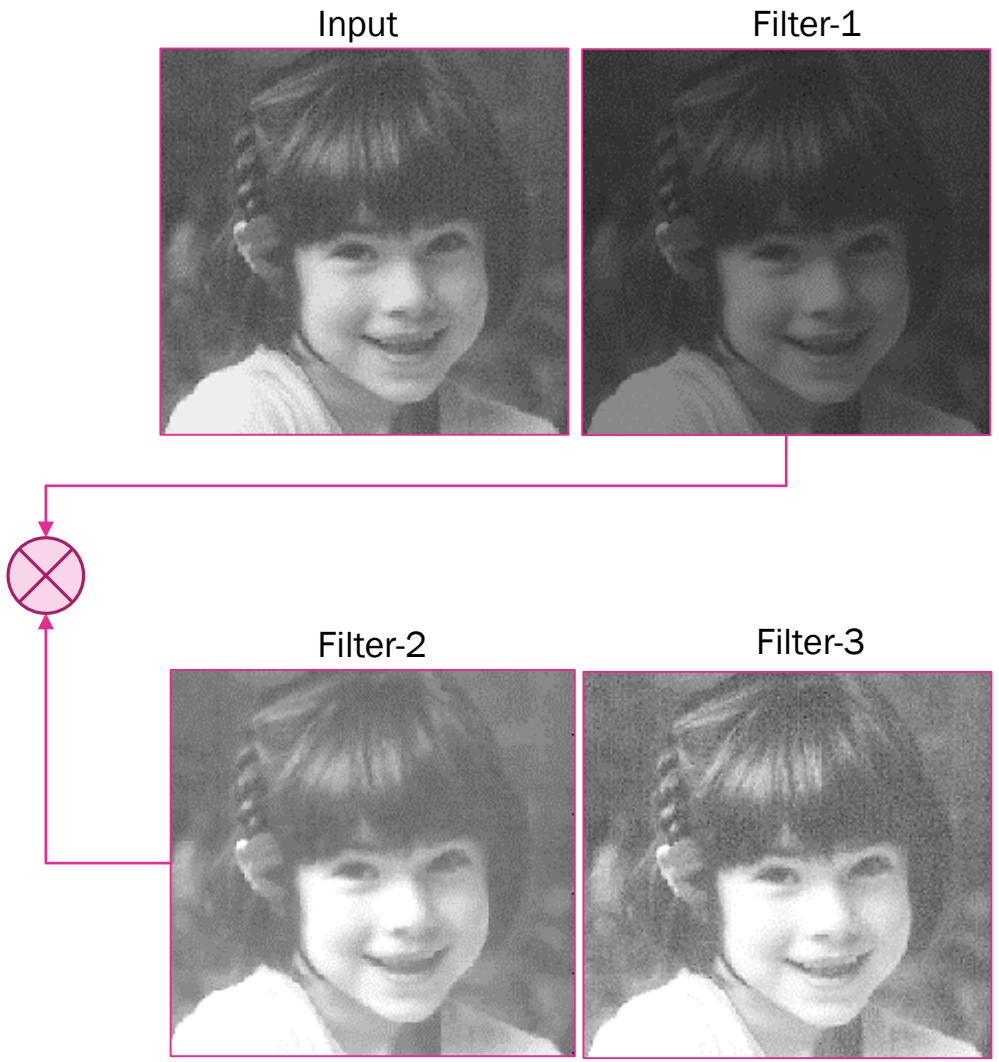

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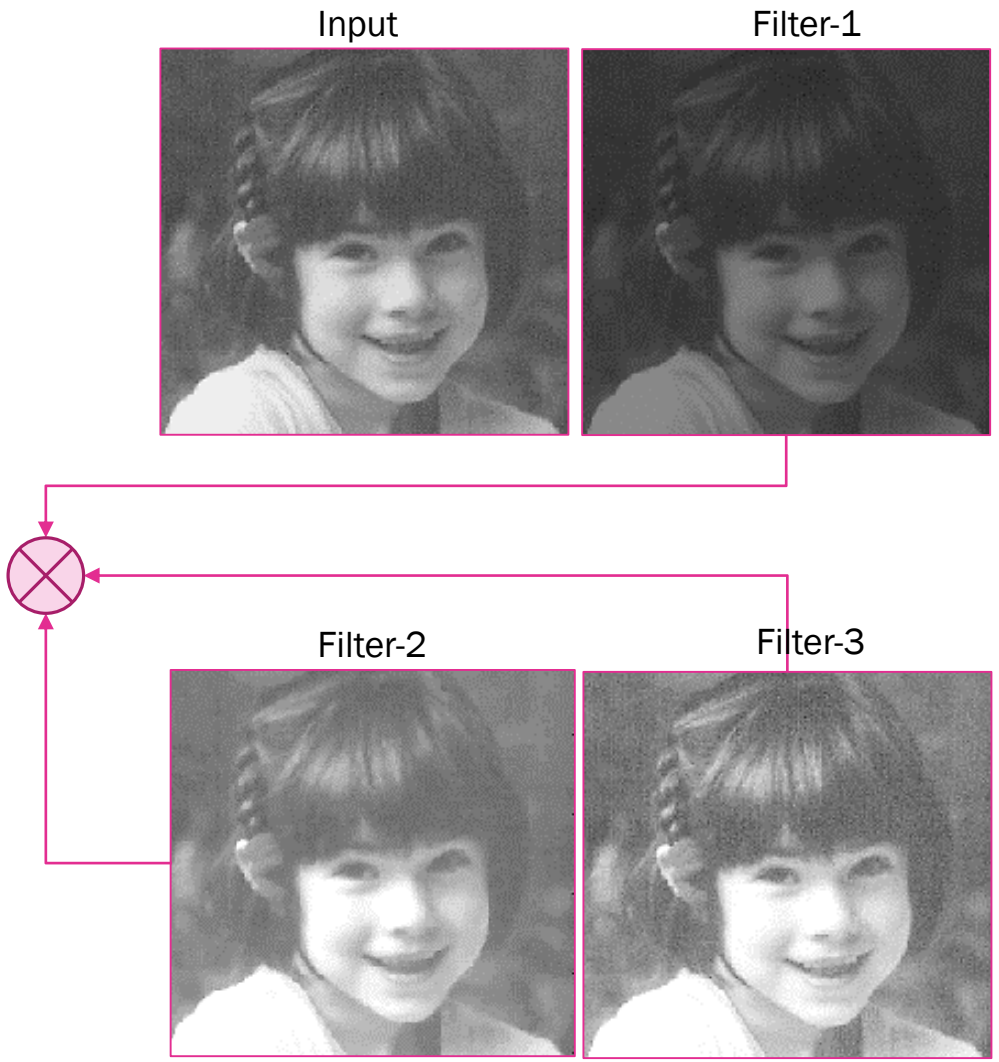

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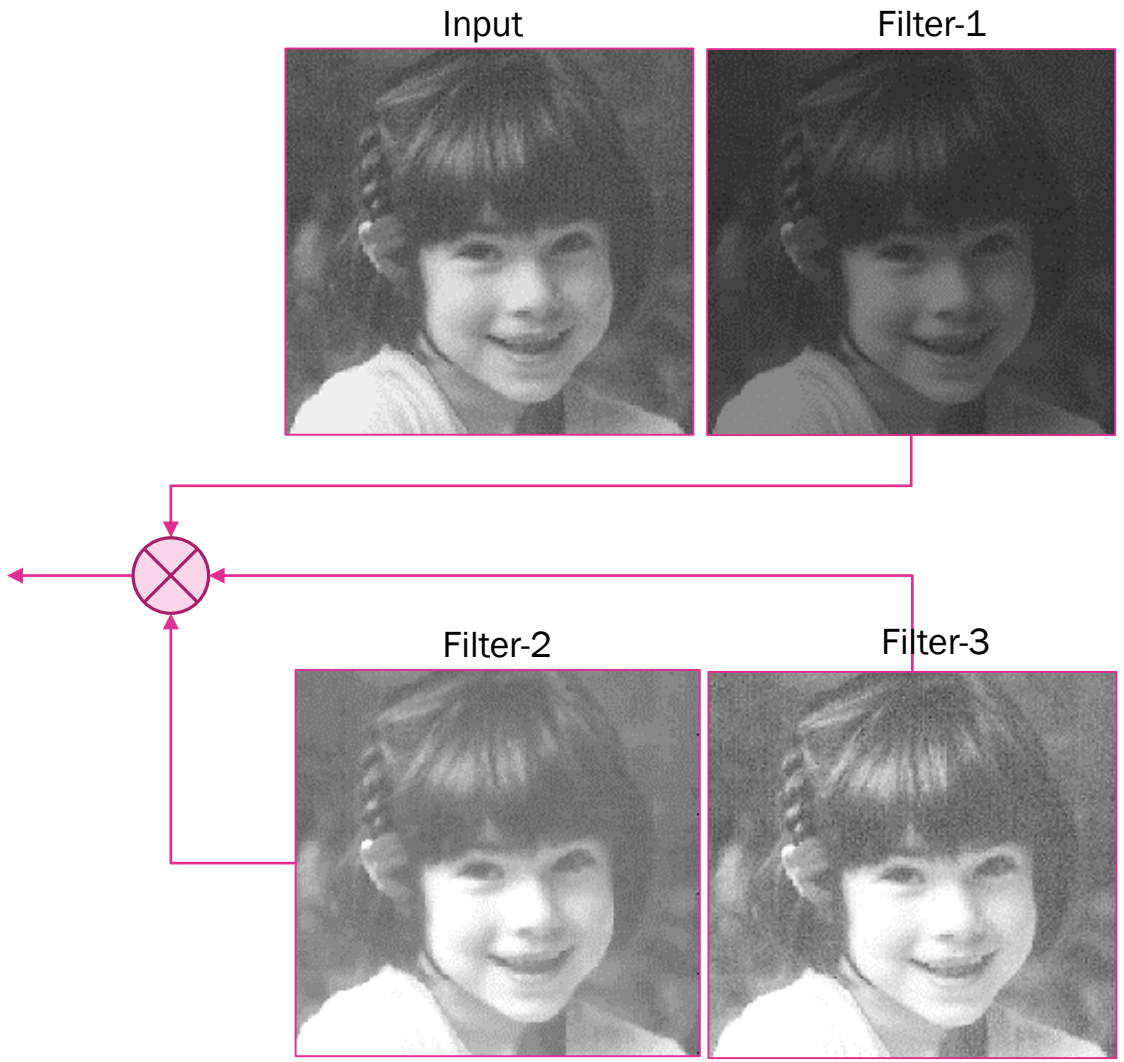

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$$g(x,y) = w_3 \star w_2 \star w_1 \star f(x,y)$$

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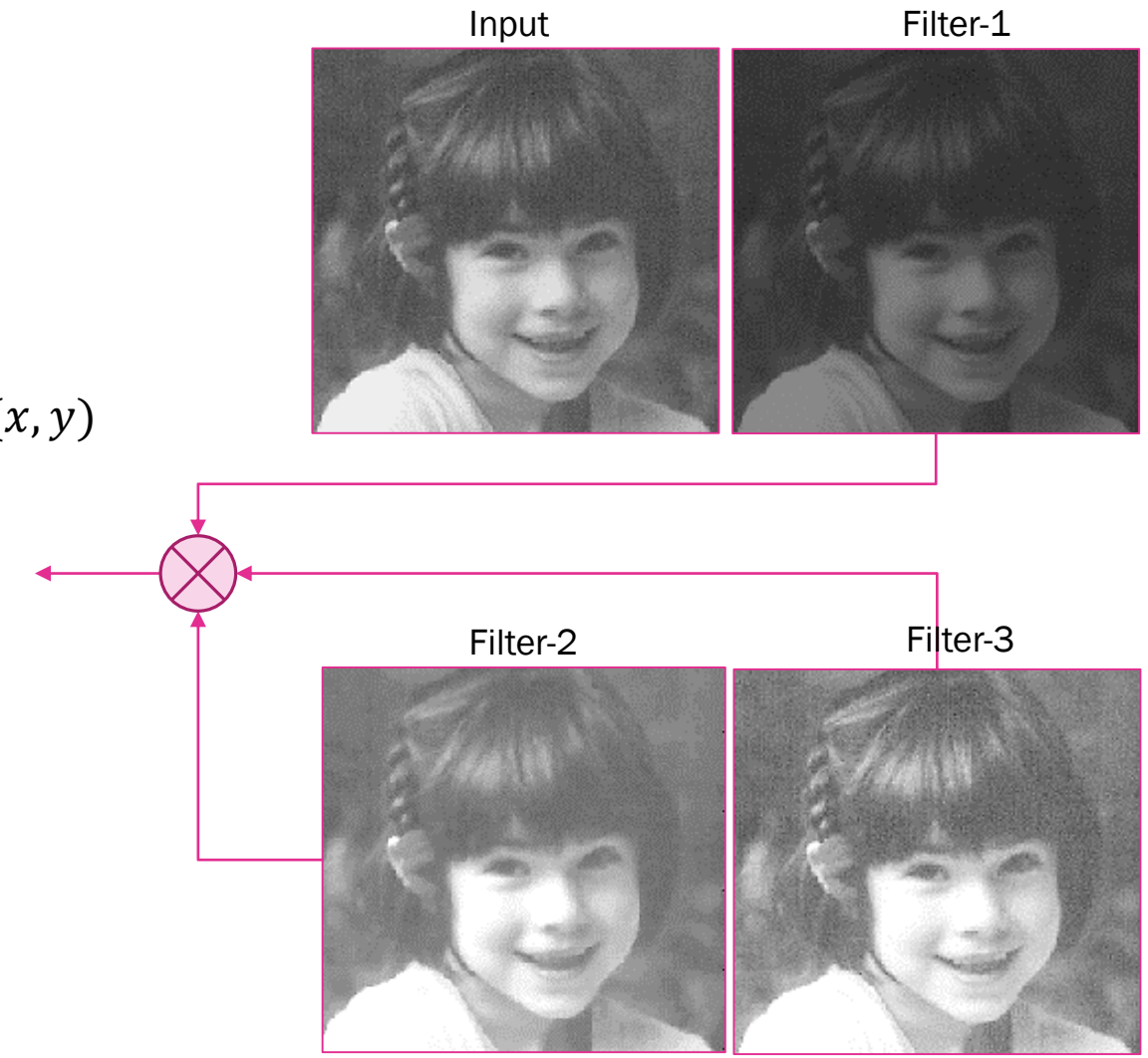

Filtering

- Image filtering
  - spatial filtering
  - convolving a kernel with an image
  - filtering: $g(x,y) = (w \star f)(x,y)$

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

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- Multistage filtering
  - filtering the filtered
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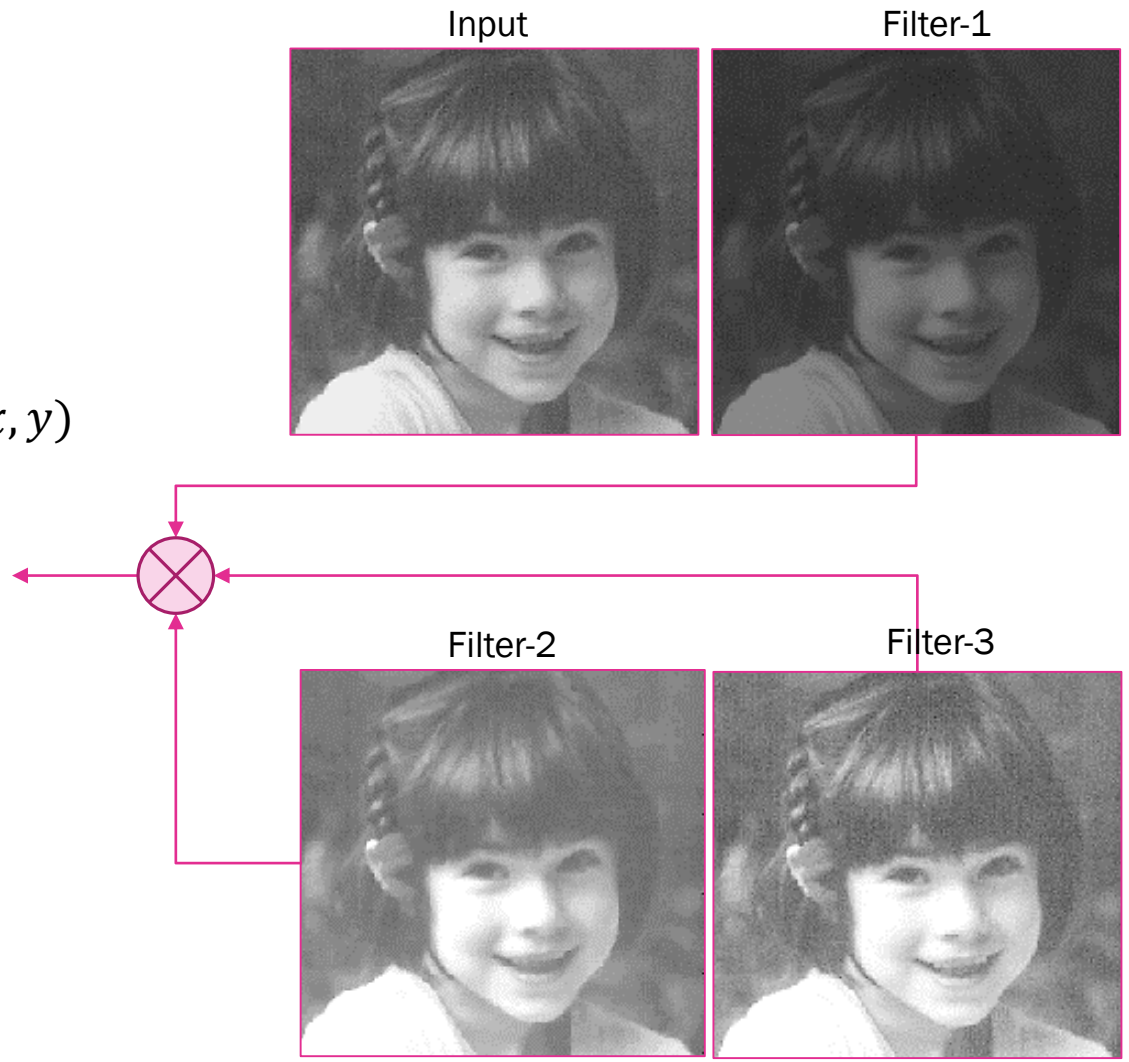

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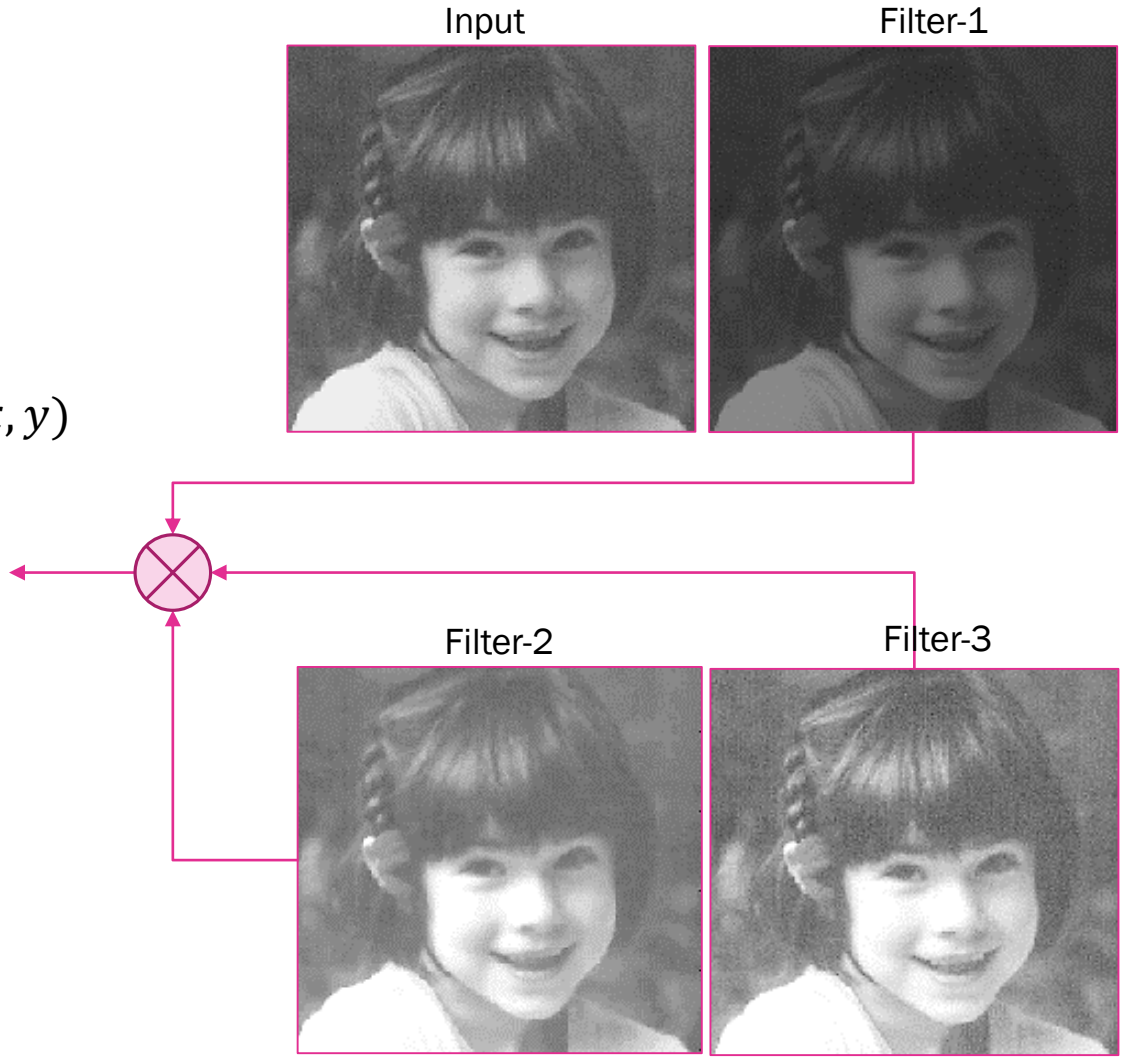

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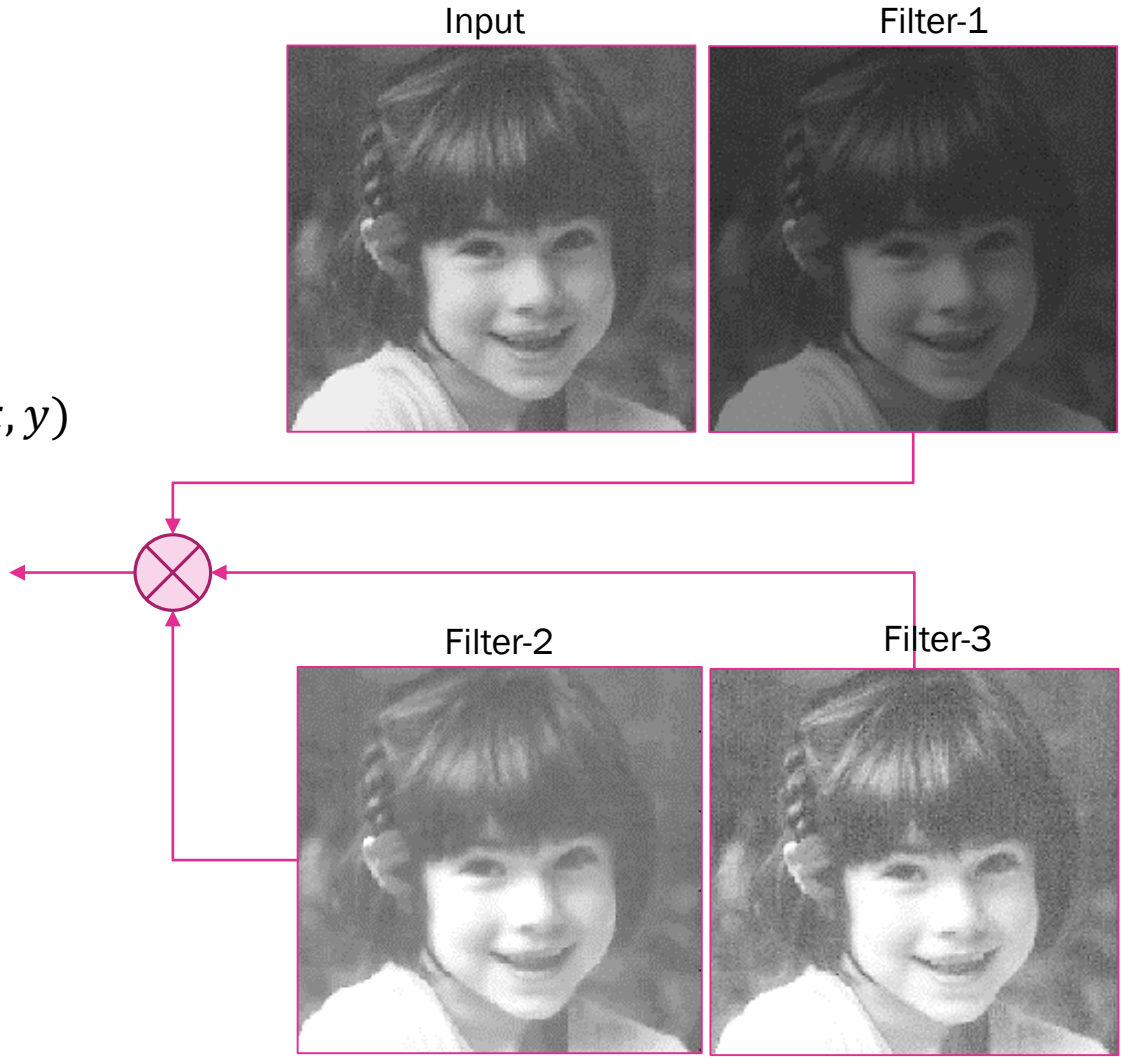

Filtering

- Filter
  - kernel, mask, window, template
  - $w(i,j)$ or $k(i,j)$ $\forall\ i,j \in N_K$, K- kernel size
    - K : determine neighbourhood of operation
    - $w(i,j)$: filter coefficients – determine nature of the filter

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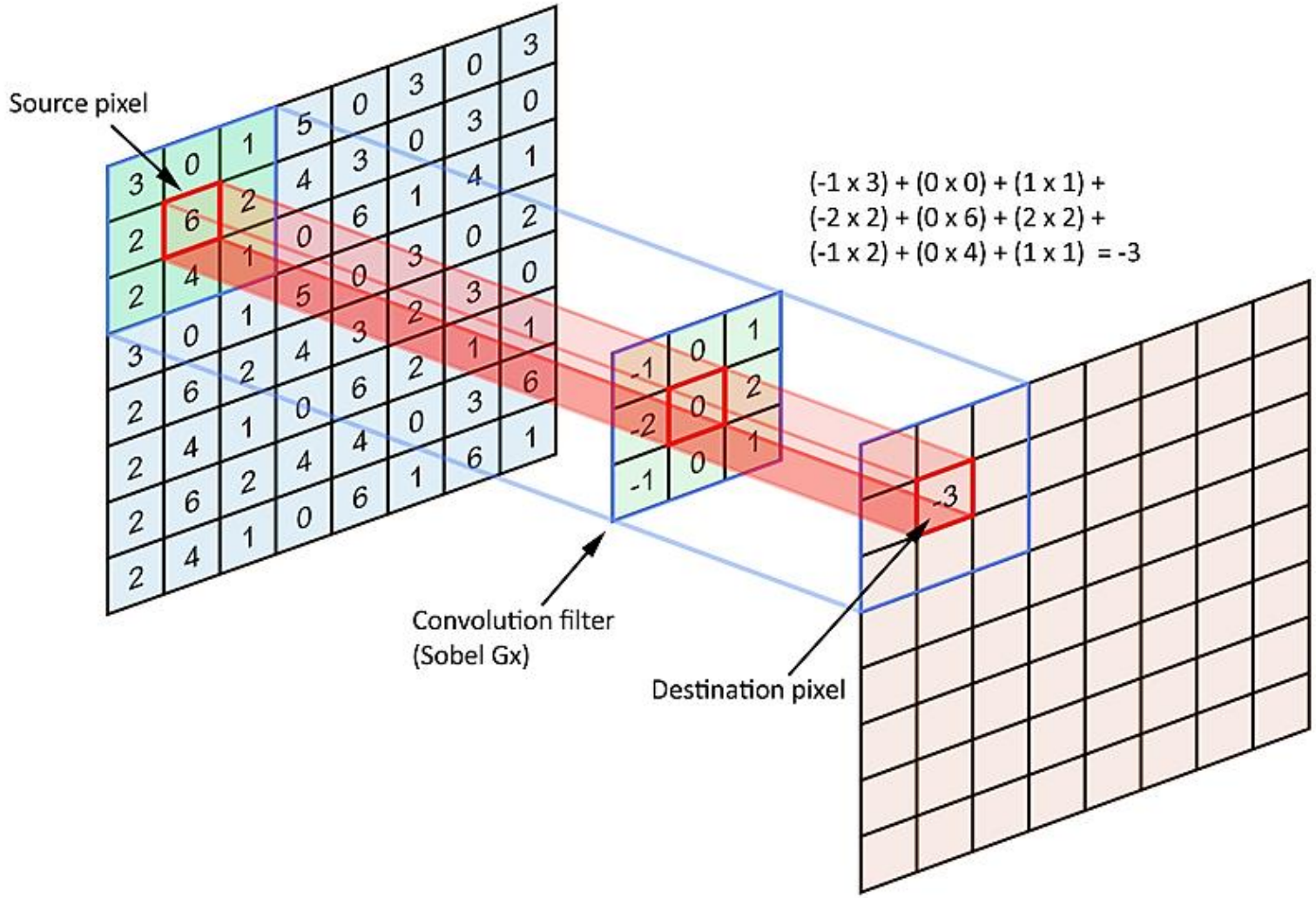
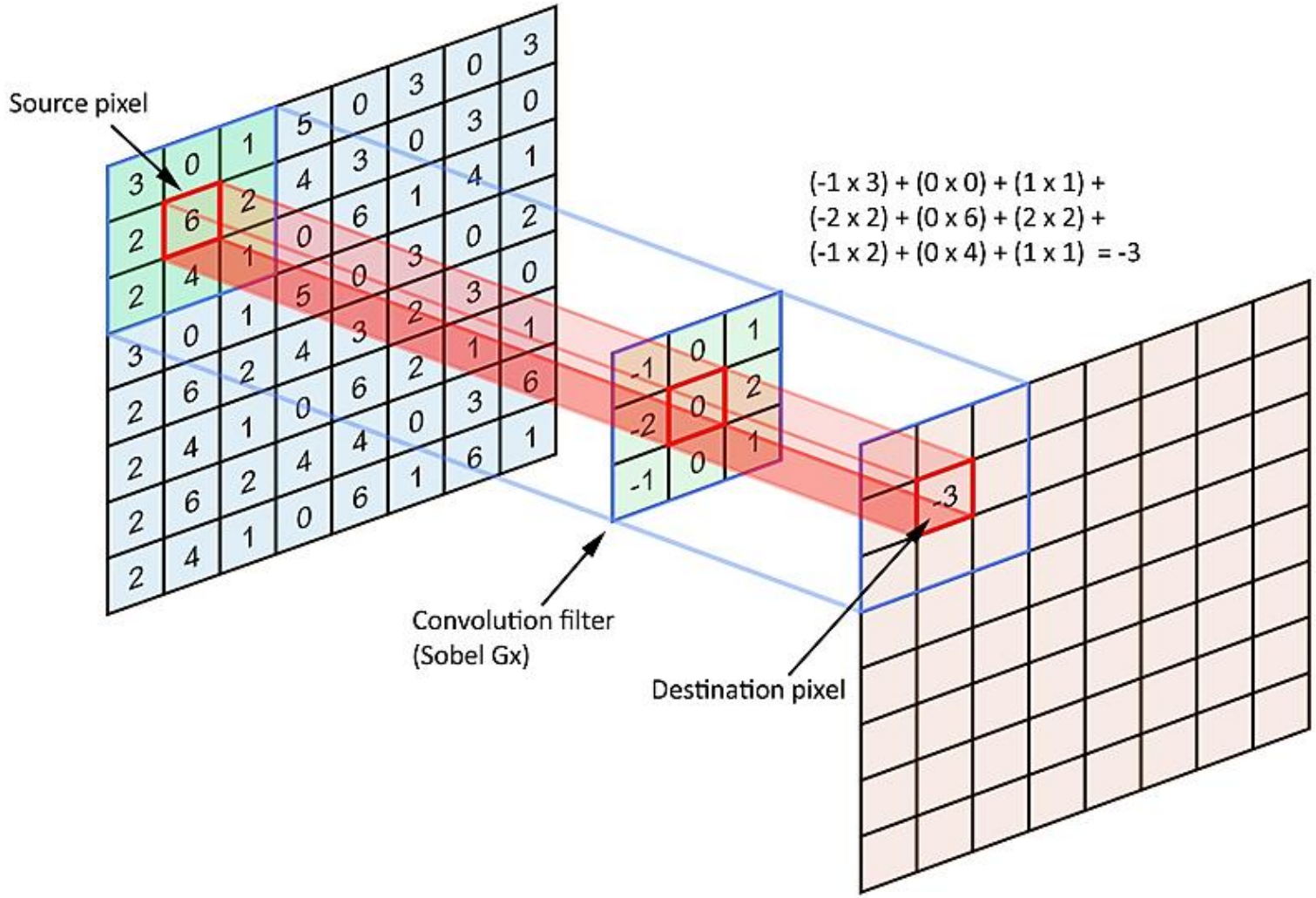
- Nature of a filter
  - neighbour interactions
    - filter coefficients define severity of interaction
  - smoothing
  - sharpening
  - noise handling capacity

Filtering


Source pixel
(-1 x 3) + (0 x 0) + (1 x 1) +
(-2 x 2) + (0 x 6) + (2 x 2) +
(-1 x 2) + (0 x 4) + (1 x 1) = -3
Convolution filter
(Sobel Gx)
Destination pixel
-3

Filtering

- Paddings
  - zero
  - mirror
  - replicate



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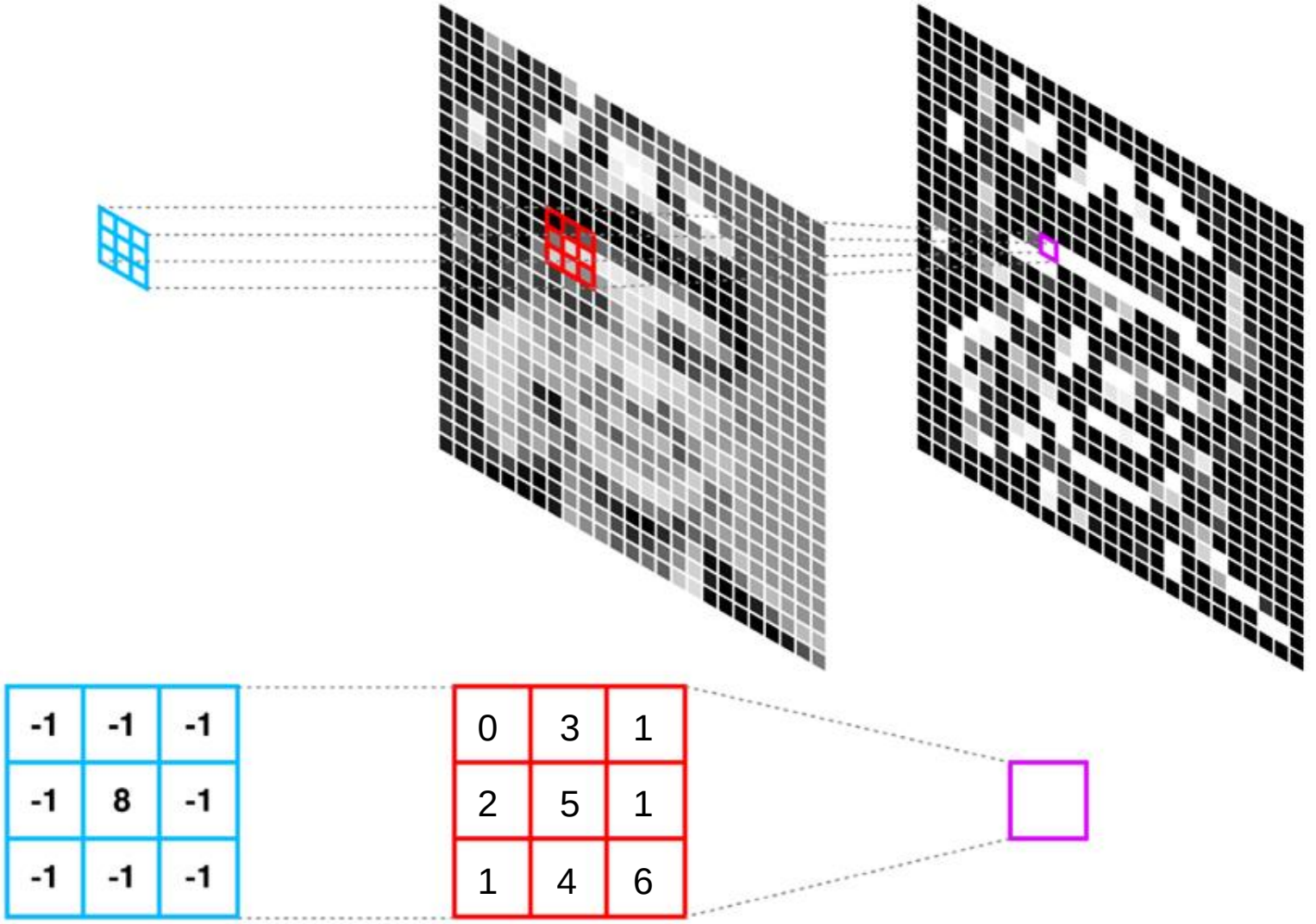

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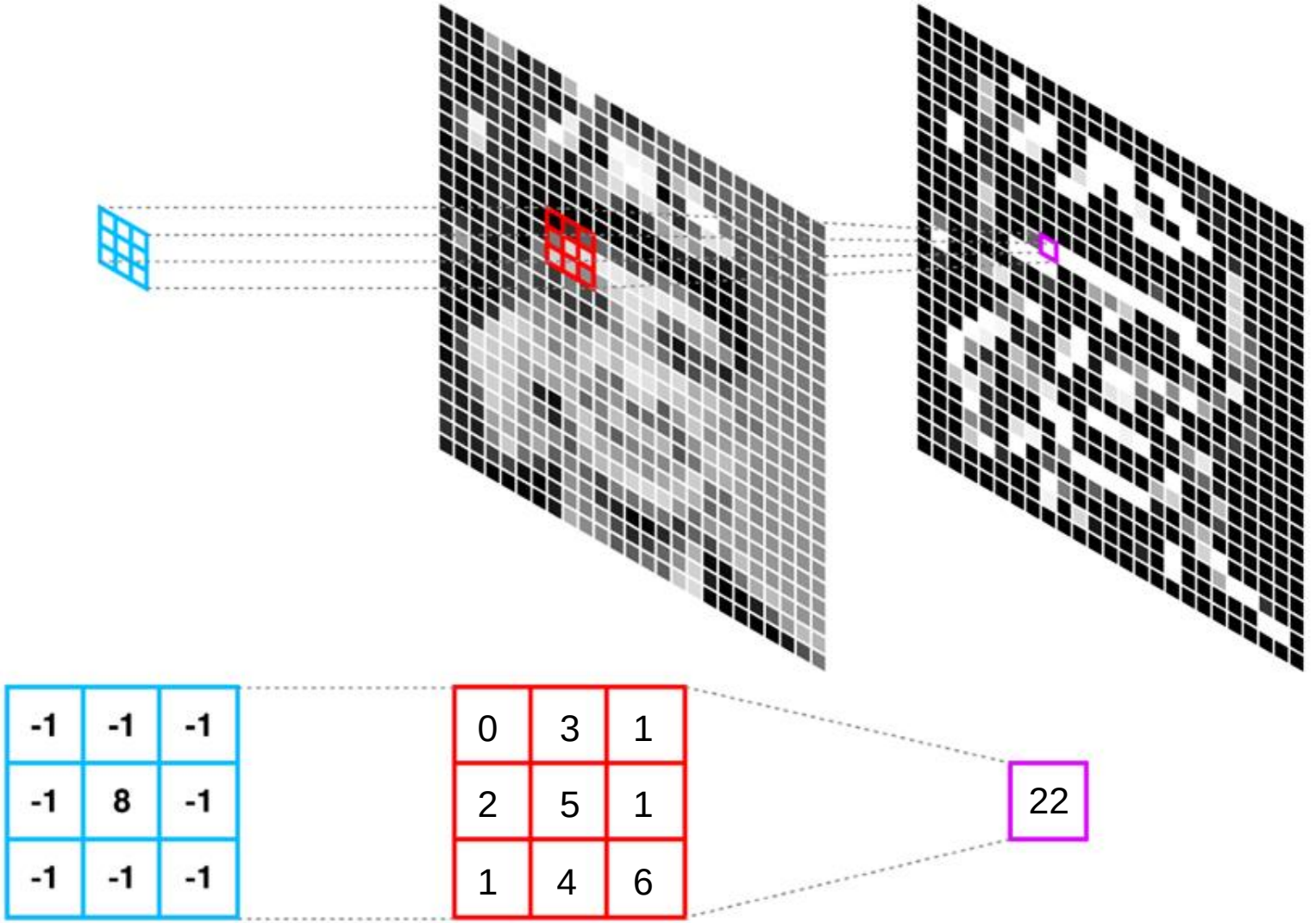

Filtering

- Separable kernels
  - a kernel in a matrix form can be represented as outer product of two vectors
  - $w = uv^T$
    - $u \in m \times 1$
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    - 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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$$\mathbf{c}\,\mathbf{r}^T = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = w$$

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    - advantage factor $= \dfrac{mn}{m+n}$

Filtering

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

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

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    - reducing sharp transitions in intensity
    - favours blurring along perpendicular directions
  - reduce aliasing
    - smoothing prior to resampling
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    - reduce false contours of intensities
  - essential in composite filtering
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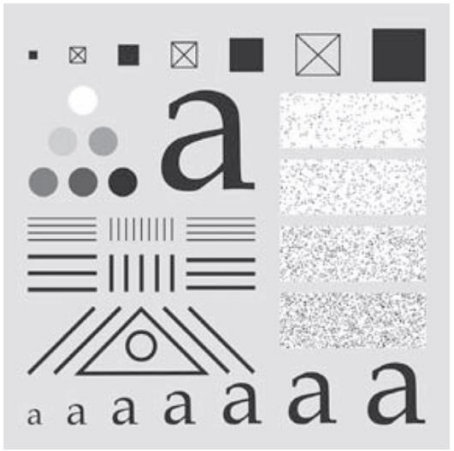

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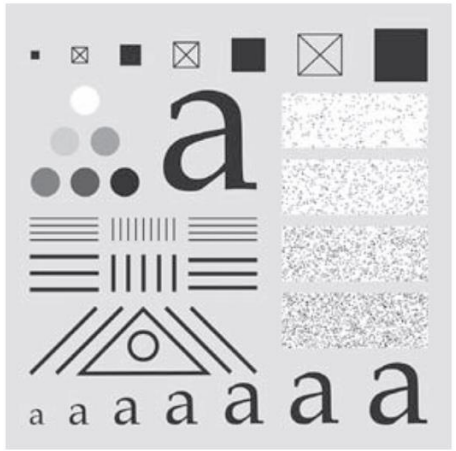

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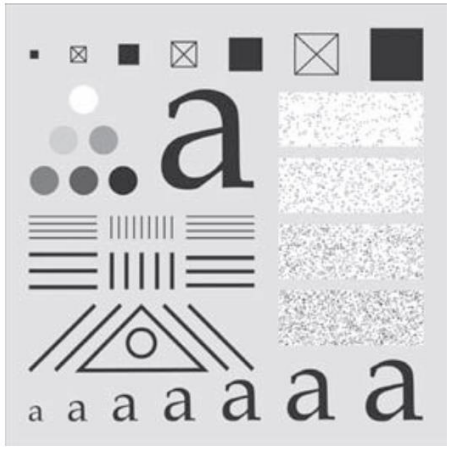
m=3



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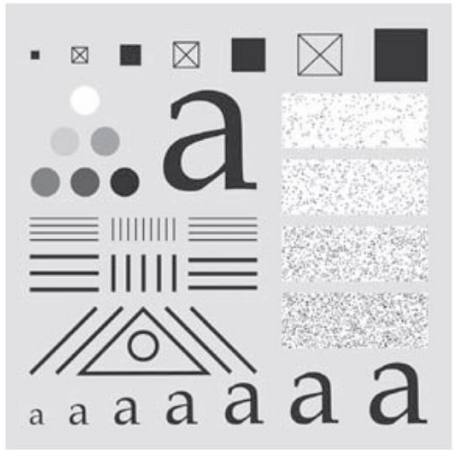

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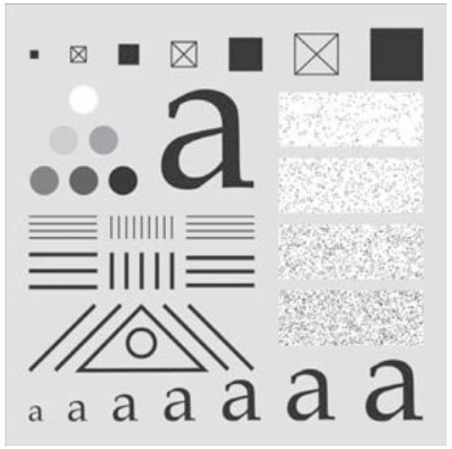

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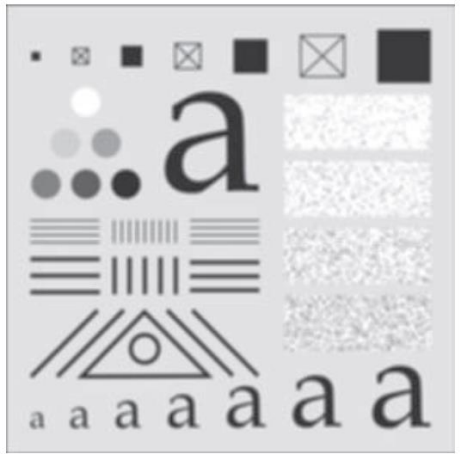

Filtering

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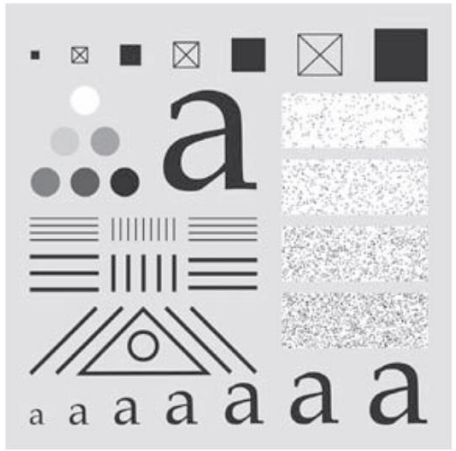

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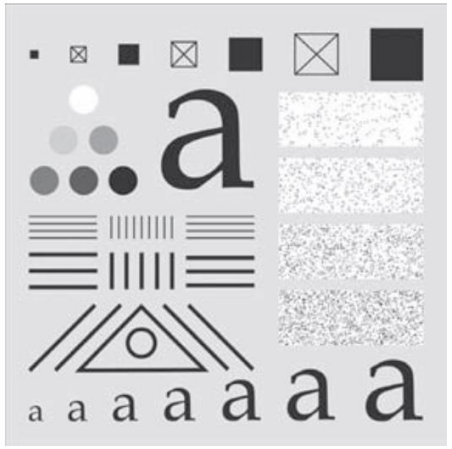

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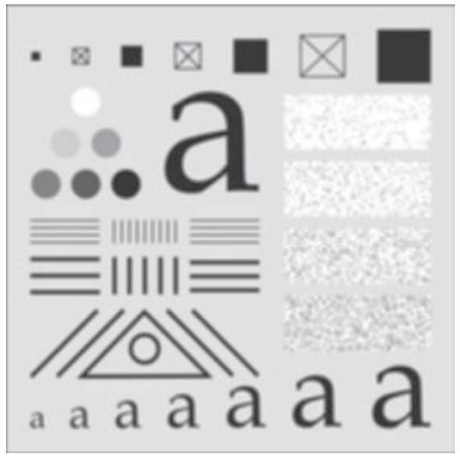
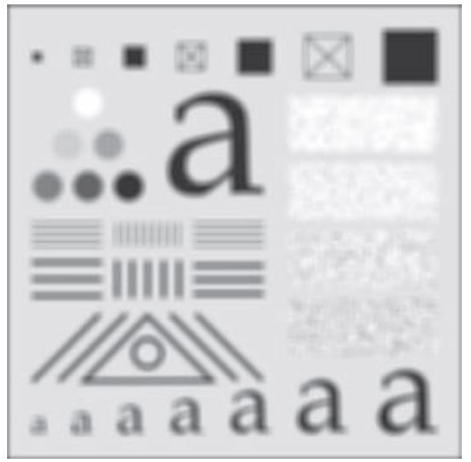


m=21



Filtering

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

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

$$\frac{1}{4.8976} \times \begin{bmatrix} 0.3679 & 0.6065 & 0.3679 \\ 0.6065 & 1.0000 & 0.6065 \\ 0.3679 & 0.6065 & 0.3679 \end{bmatrix}$$

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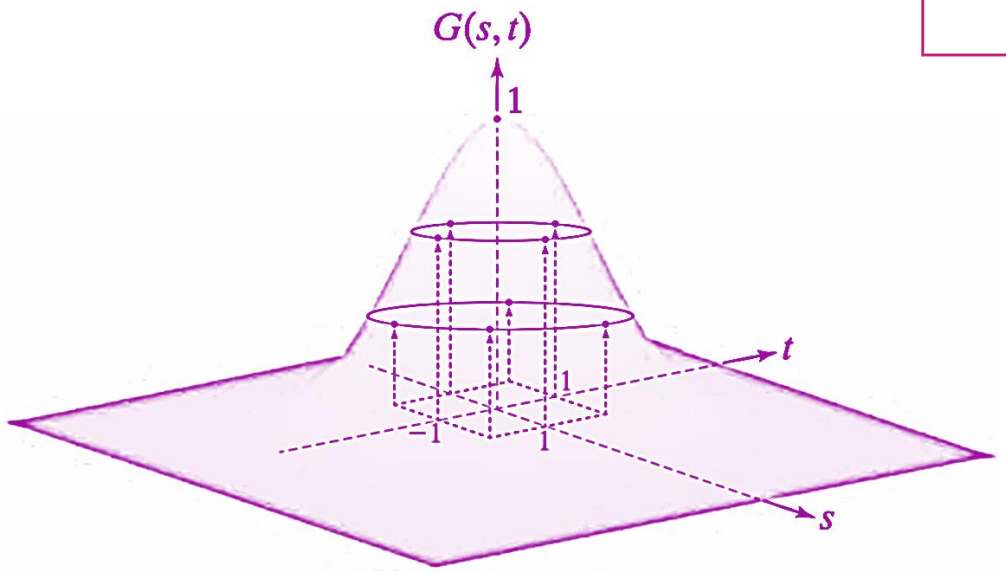

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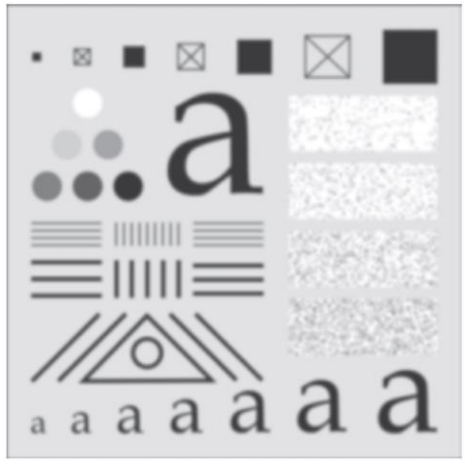

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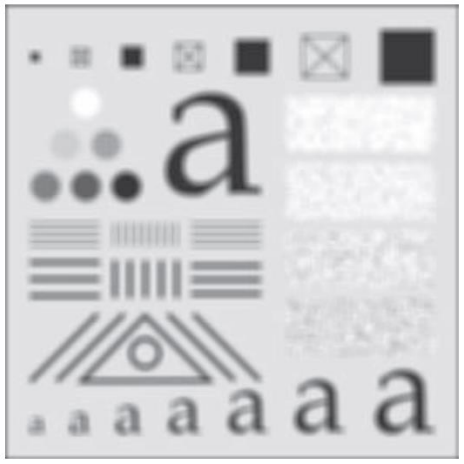
m=21 box



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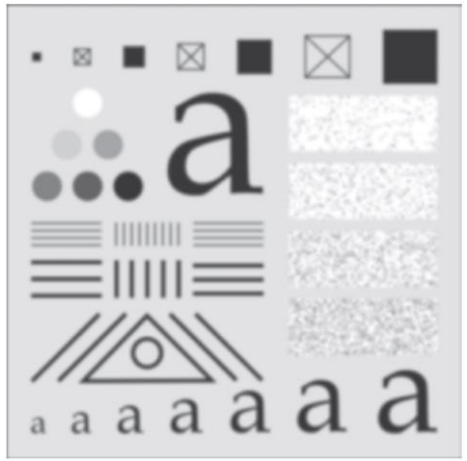

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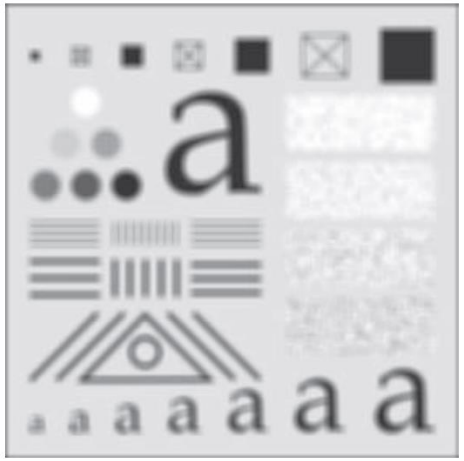

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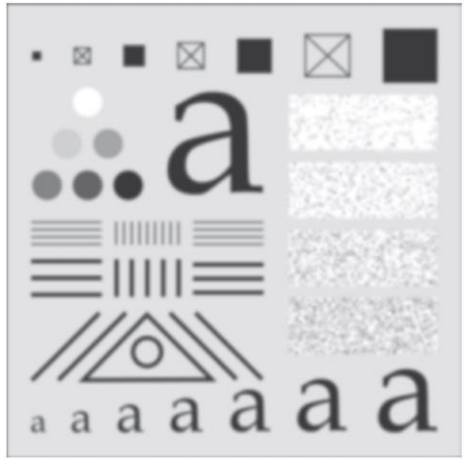

m=43 σ=7 Gauss

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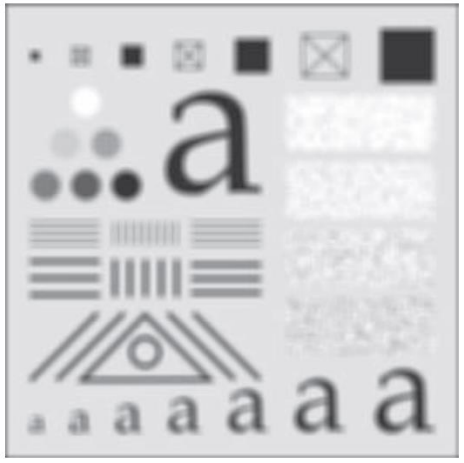
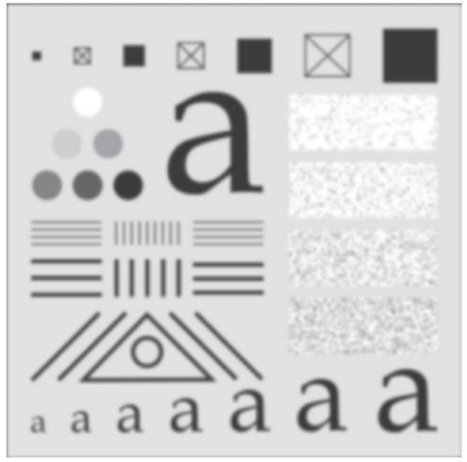
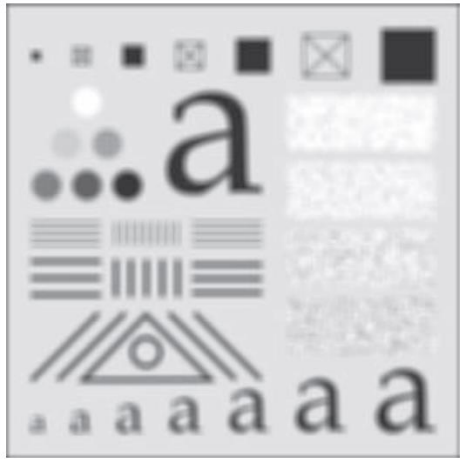


m=21 σ=3.5 Gauss



m=43 σ=7 Gauss

m=21 box



Filtering

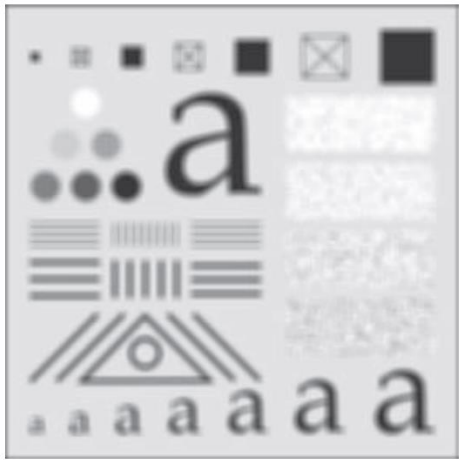
- Gaussian filter
  - smoothing filter
  - defocused lens approximators
  - isotropic
    - response is independent of orientation
    - circularly symmetric

input

$$\frac{1}{4.8976} \times \begin{bmatrix} 0.3679 & 0.6065 & 0.3679 \\ 0.6065 & 1.0000 & 0.6065 \\ 0.3679 & 0.6065 & 0.3679 \end{bmatrix}$$

m=43 σ=7 Gauss

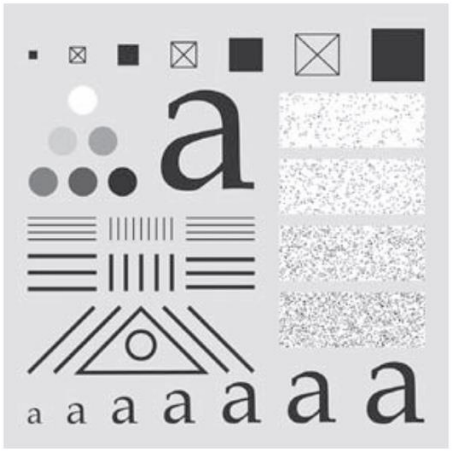
m=21 box



Filtering

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

input

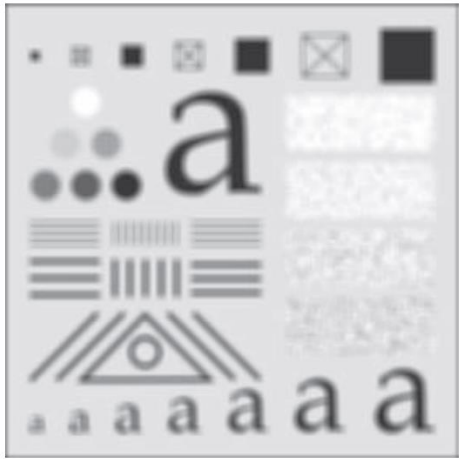


$$\frac{1}{4.8976} \times \begin{bmatrix} 0.3679 & 0.6065 & 0.3679 \\ 0.6065 & 1.0000 & 0.6065 \\ 0.3679 & 0.6065 & 0.3679 \end{bmatrix}$$

m=85 σ=7 Gauss

m=43 σ=7 Gauss

m=21 box



Filtering

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

input

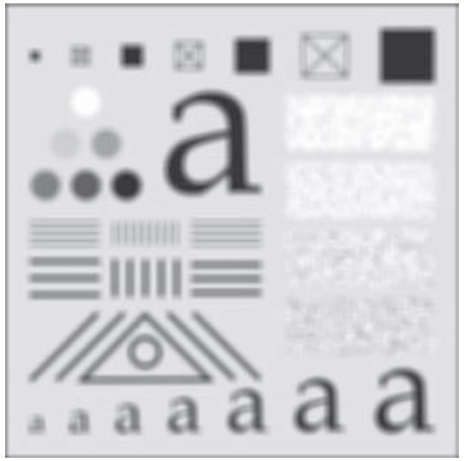
$$\frac{1}{4.8976} \times \begin{bmatrix} 0.3679 & 0.6065 & 0.3679 \\ 0.6065 & 1.0000 & 0.6065 \\ 0.3679 & 0.6065 & 0.3679 \end{bmatrix}$$

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

m=85 σ=7 Gauss

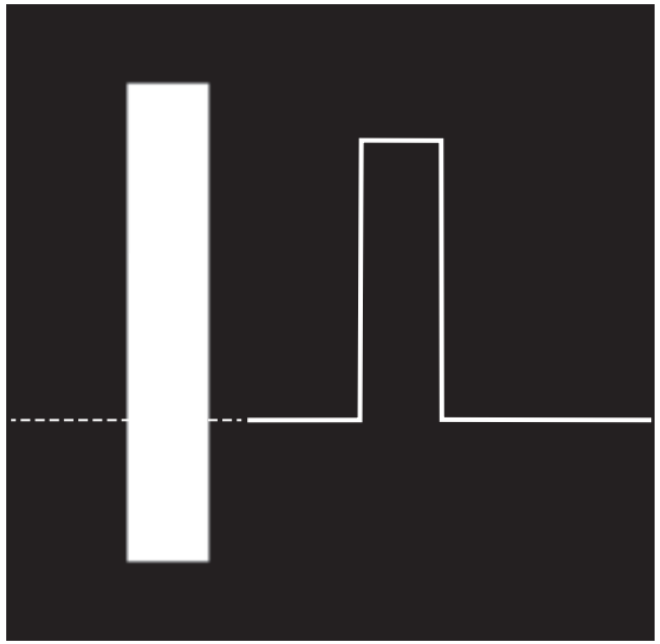
m=43 σ=7 Gauss

m=21 box



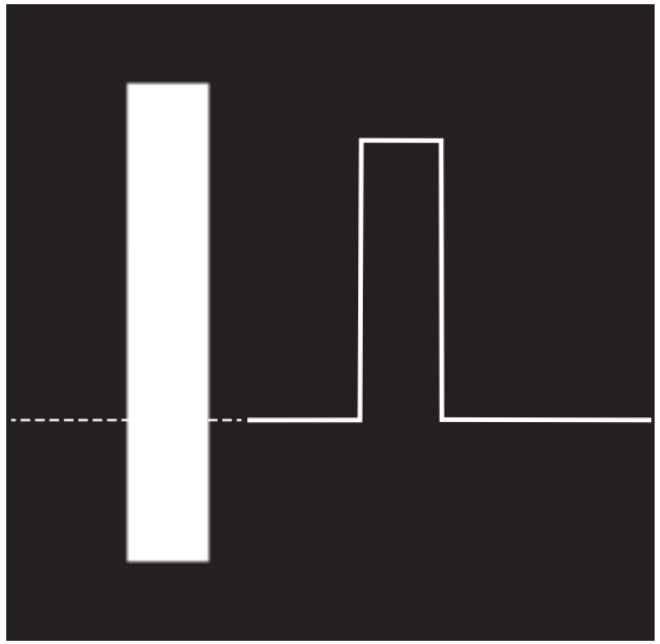
Filtering

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

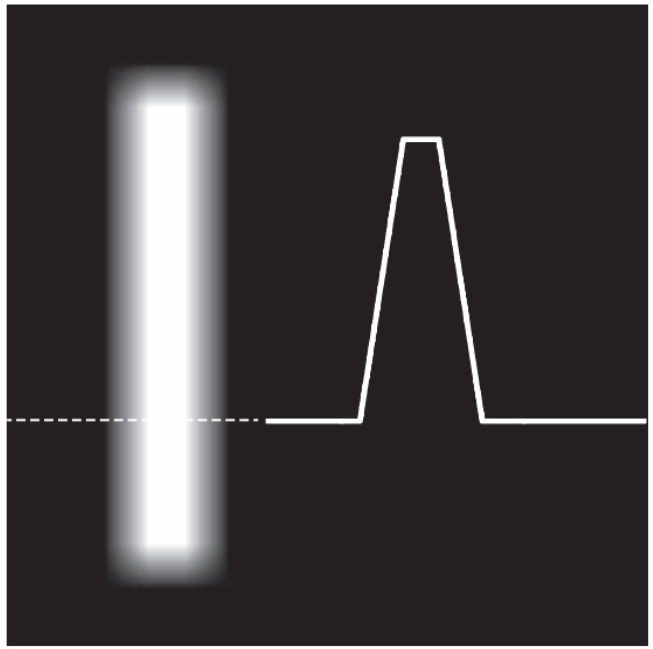


Filtering

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

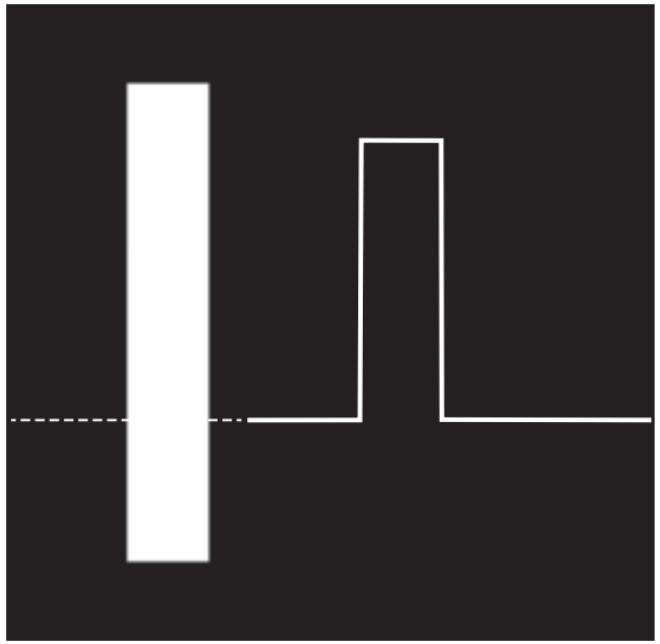


m=71 box

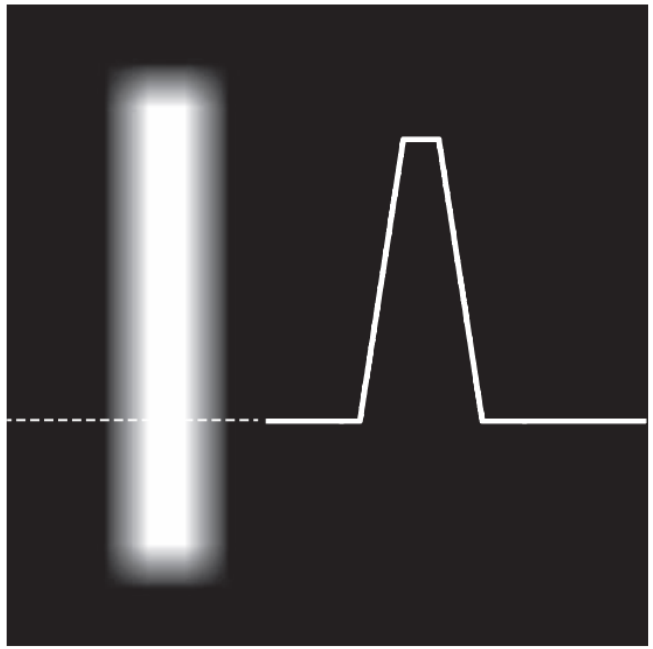


Filtering

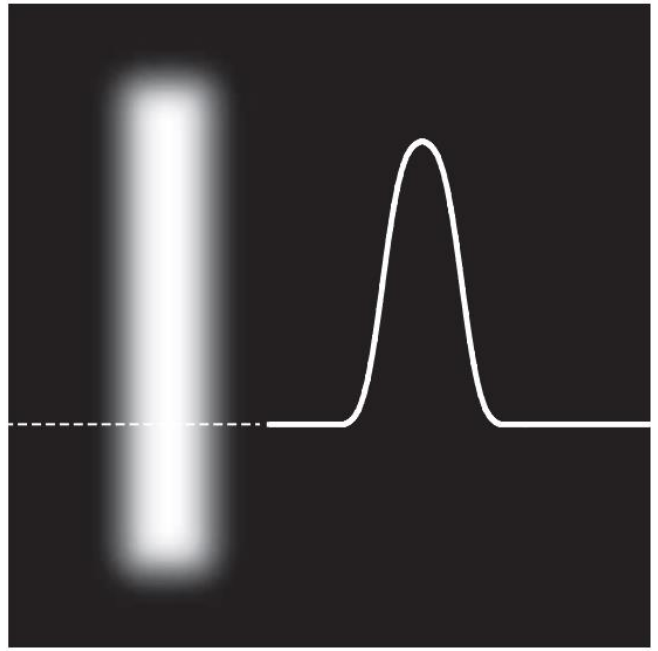
- Box vs Gaussian
  - blur profile
  - blurred rects having same shape



m=71 box



m=151 σ=25 Gauss

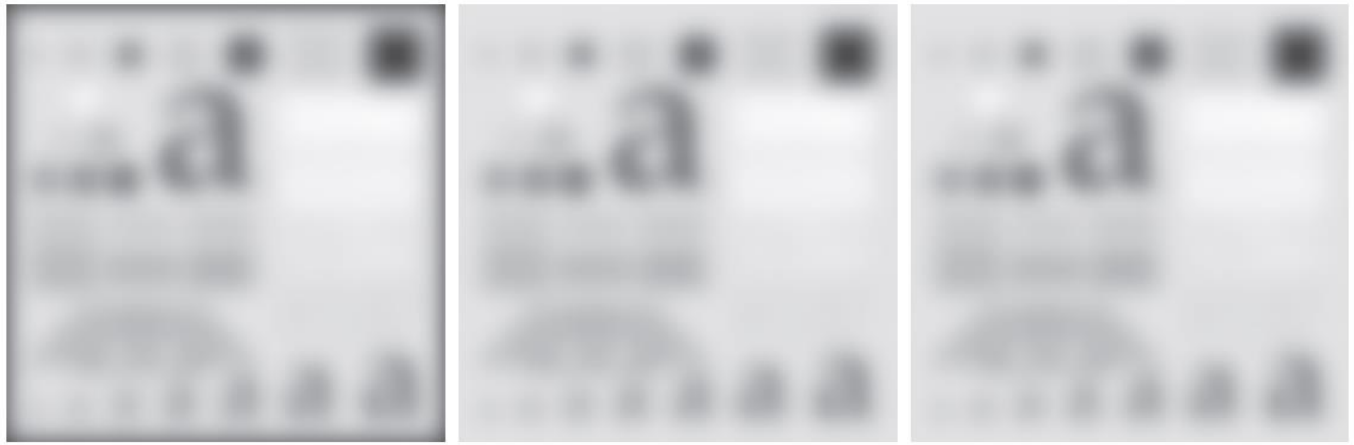


Filtering

- Padding effects

m=187 σ=31 Gauss

image 1024x1024



Filtering

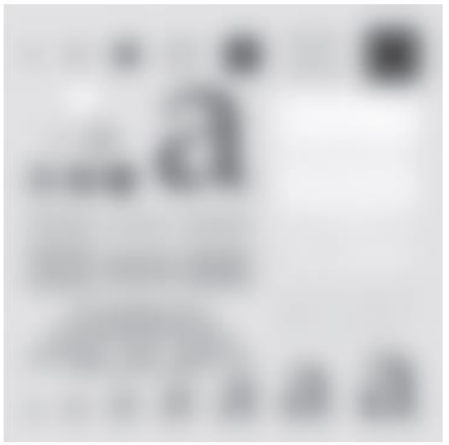
- Padding effects

m=187 σ=31 Gauss

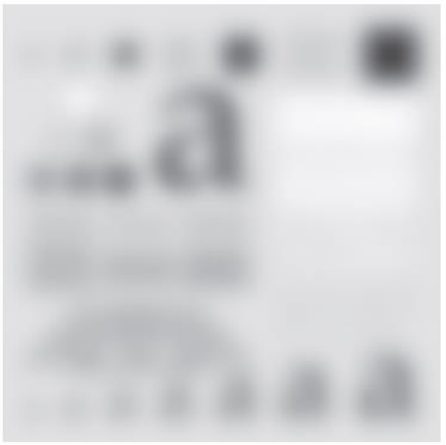
image 1024x1024

zero

mirror



replicate



Filtering

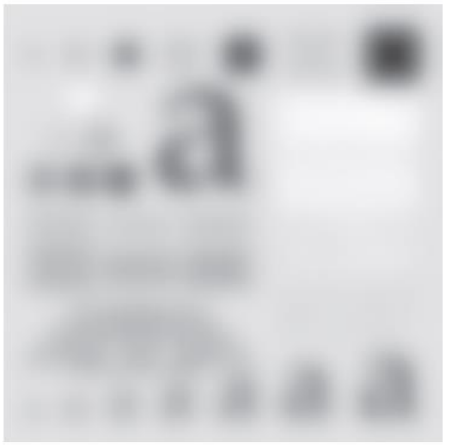
- Padding effects

m=187 σ=31 Gauss

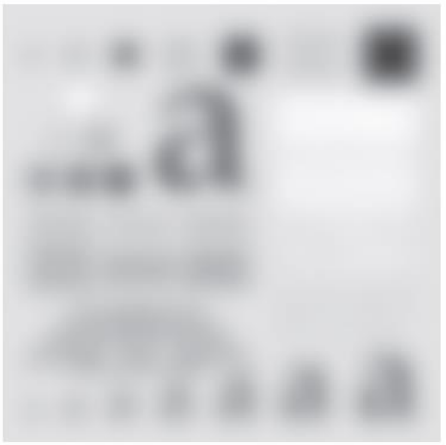
image 1024x1024

zero

mirror



replicate



- Relative size effect

m=187 σ=31 Gauss

image 4096x4096

Filtering

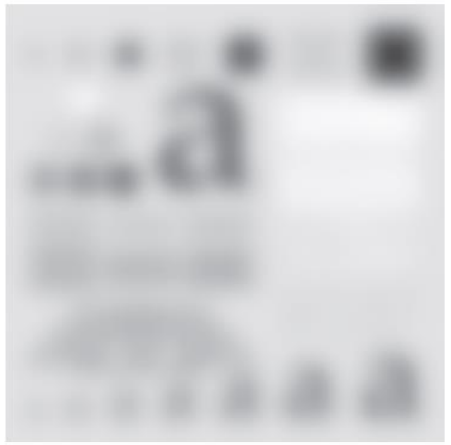
- Padding effects

m=187 σ=31 Gauss

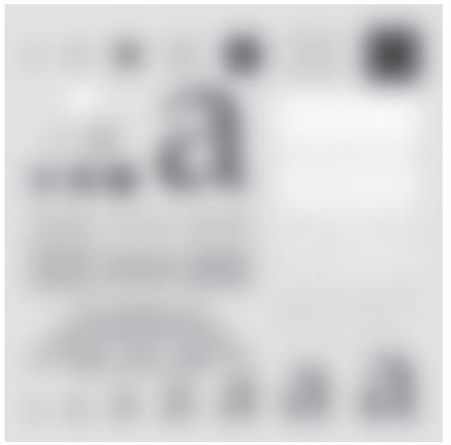
image 1024x1024

zero

mirror



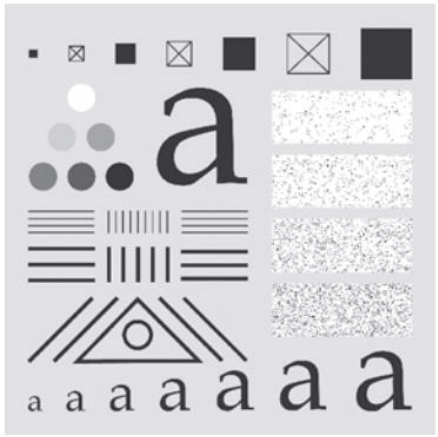
replicate

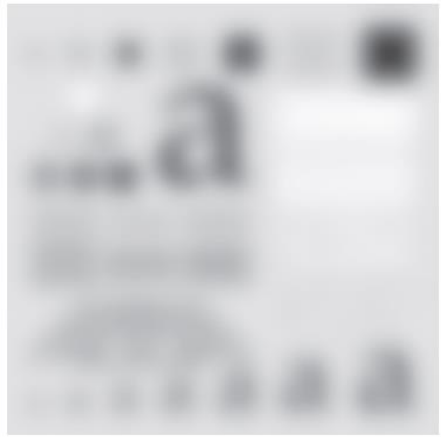


- Relative size effect

m=187 σ=31 Gauss

image 4096x4096





Filtering

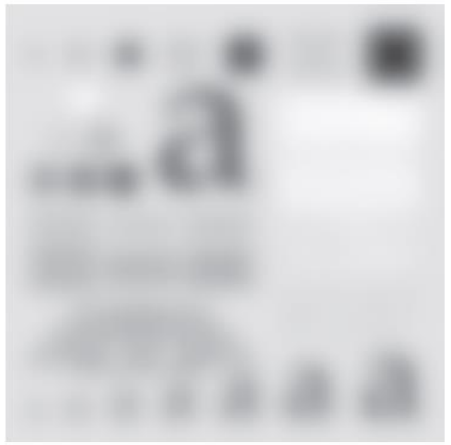
- Padding effects

m=187 σ=31 Gauss

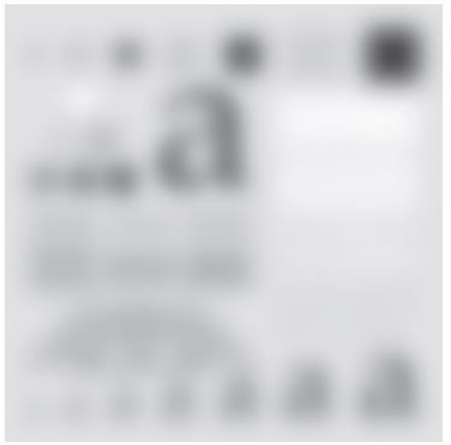
image 1024x1024

zero

mirror



replicate

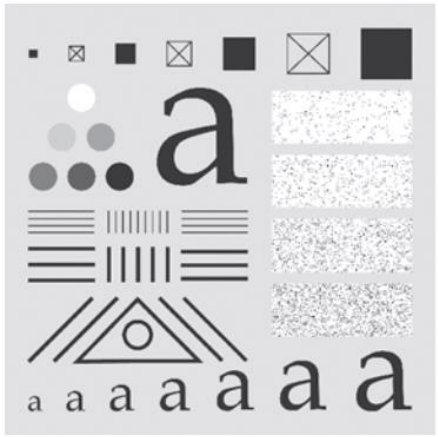


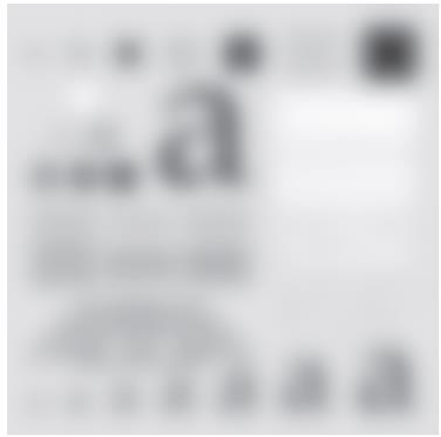
- Relative size effect

m=187 σ=31 Gauss

image 4096x4096

m=745 σ=124 Gauss





Filtering

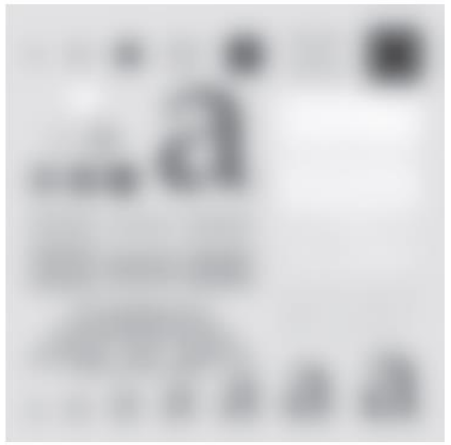
- Padding effects

m=187 σ=31 Gauss

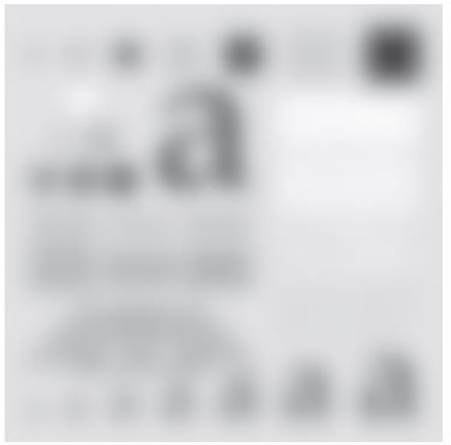
image 1024x1024

zero

mirror



replicate



- Relative size effect

m=187 σ=31 Gauss

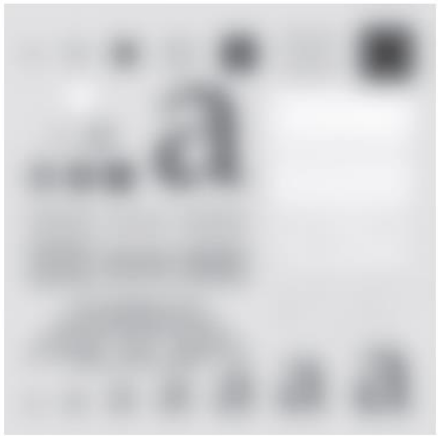
image 4096x4096

m=745 σ=124 Gauss

input

m=187 σ=31

m=745 σ=124



Filtering

- Relevant region extraction

Filtering

- Relevant region extraction

Filtering

- Relevant region extraction

Filtering

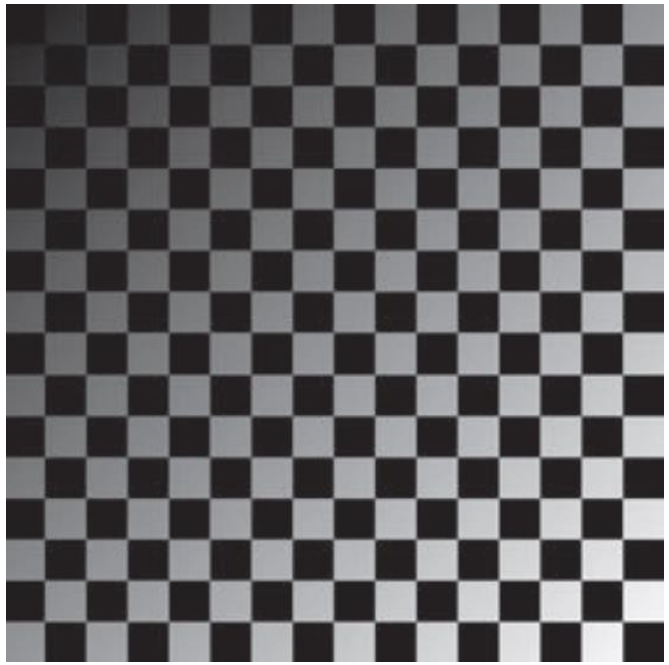
- Relevant region extraction

filtering

thresholding

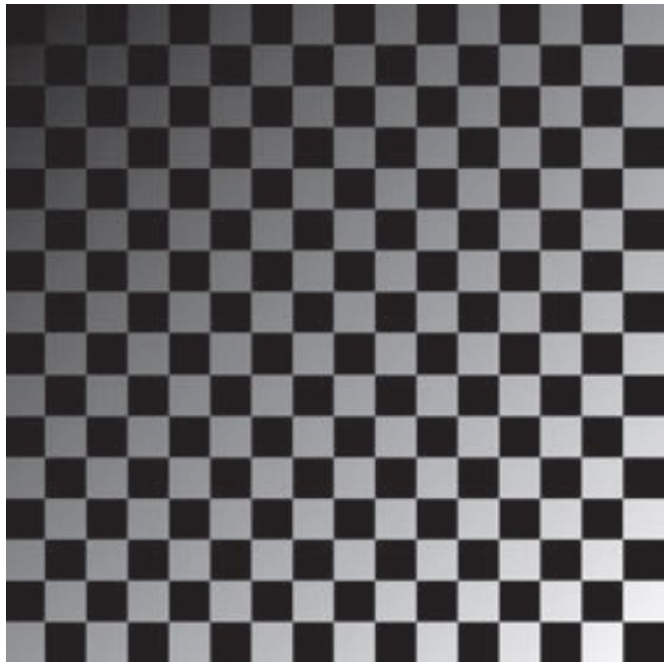
Filtering

- Shading correction



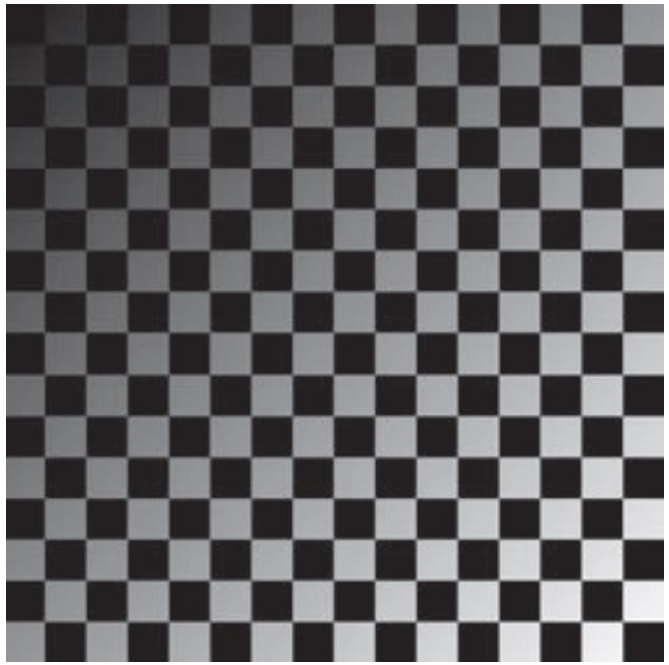
Filtering

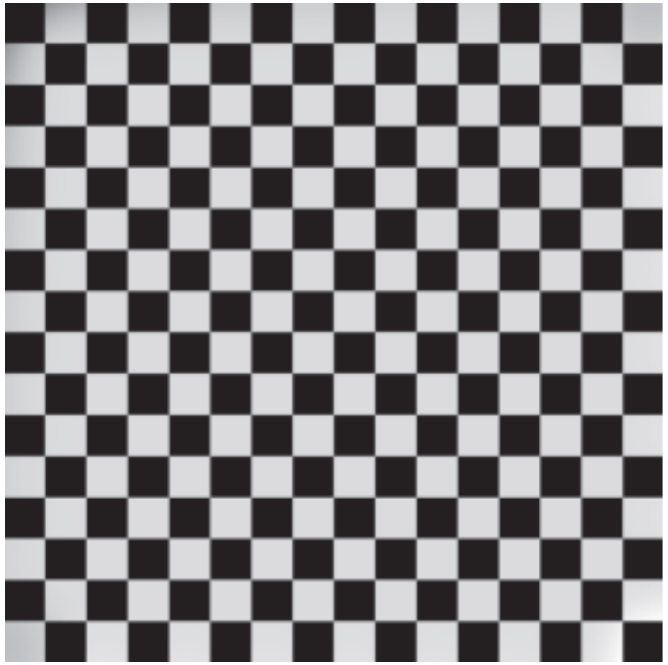
- Shading correction



Filtering

- Shading correction



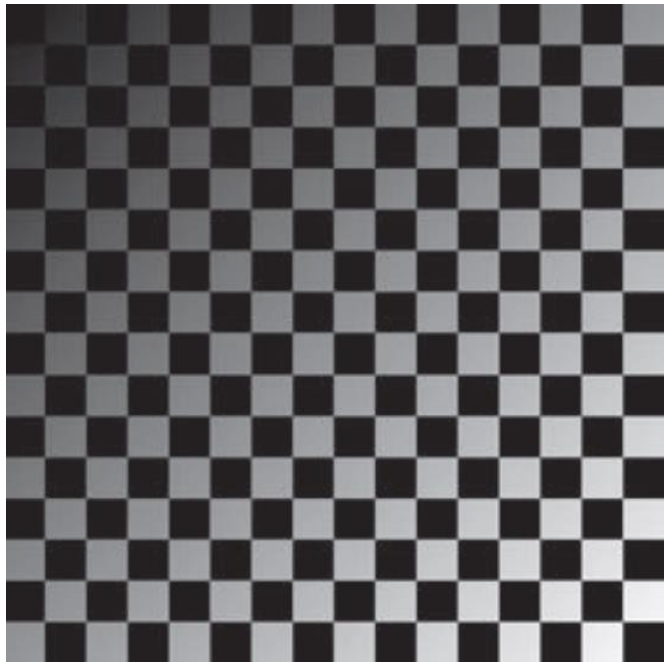


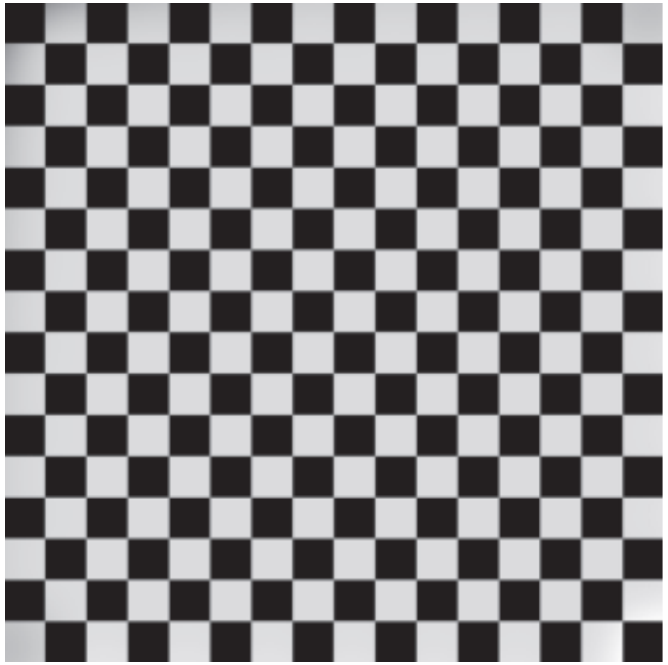
Filtering

- Shading correction

filtering

scaling





Conclusion

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

Filtering