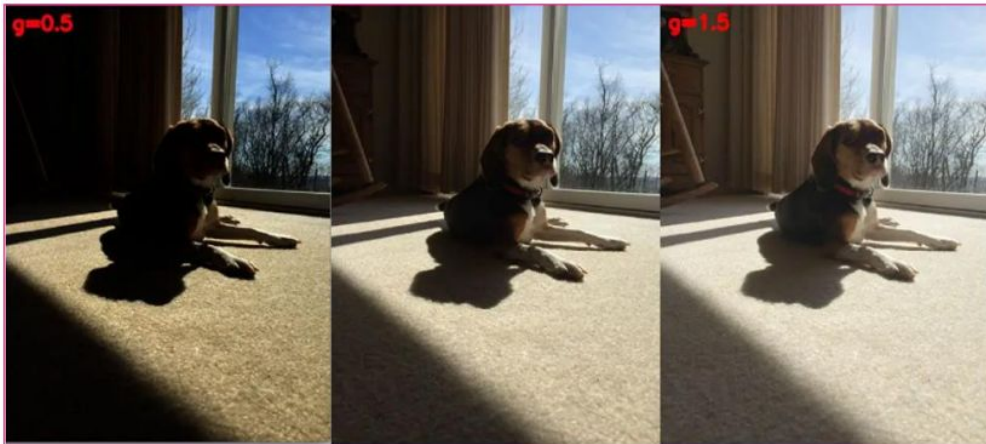


Image Enhancement



Introduction

- Intensity transformations



- Distribution transformation

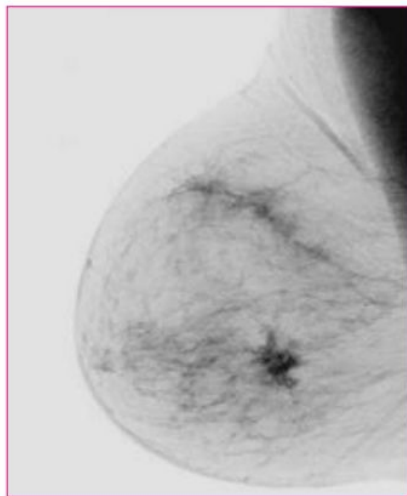
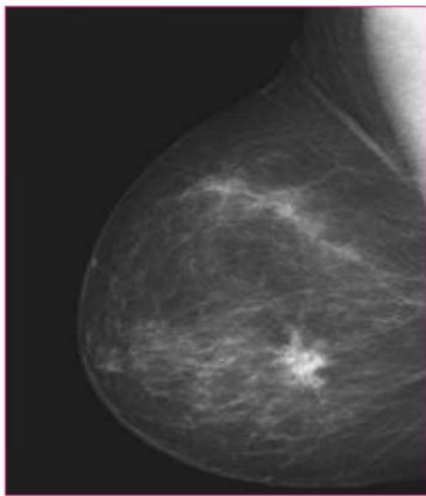


SPATIAL DOMAIN TRANSFORMATION

- Transformations
 - intensity transformations
 - negatives
 - logs
 - power-law (gamma)
 - contrast stretching
 - level slicing
 - bit-plane slicing
 - distribution transformations
 - histogram equalization
- Spatial filtering
 - image filtering

Negatives

$$s = L - 1 - r$$

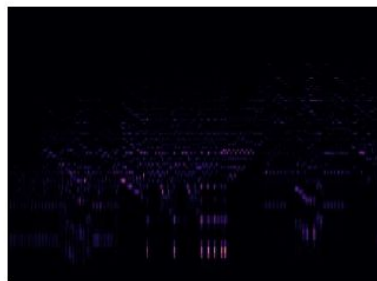


Logs

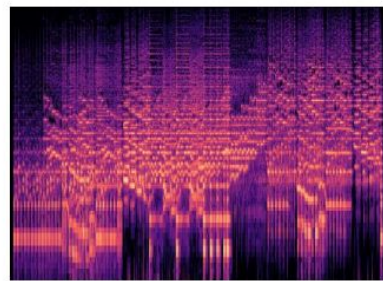
$$s = c \cdot \log(1 + r)$$

- Log transformations

- used to expand values of dark pixels
- simultaneously compressing bright pixels
- compresses dynamic range of images
 - Fourier spectrum



Without Log transform



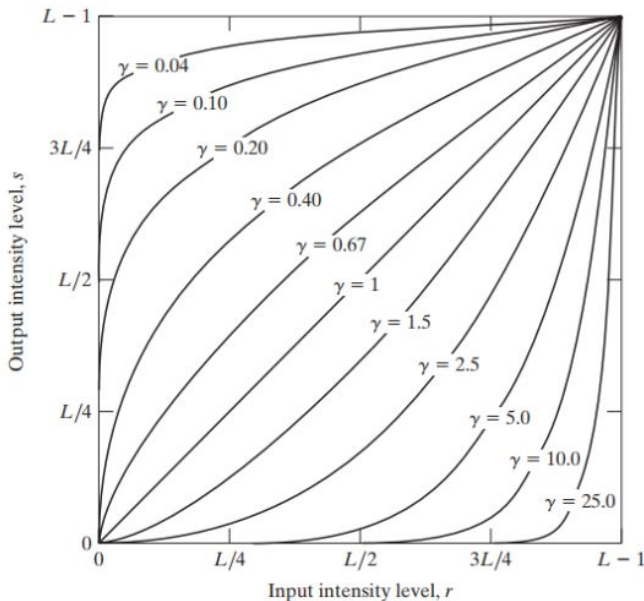
Log transform done on original image and then, it has been scaled up to 255, to form the image matrix

Gammas

$$s = c \cdot r^\gamma$$

■ Power-law transformations

- sensors respond according to power law
 - CMOS, scanners, printing, displays
 - CRT: intensity to voltage response as power function ($\gamma' = 1.8 \sim 2.5$)
- gamma correction
 - device dependent γ
 - γ variation also varies the color ratios
 - correct color reproduction needs knowledge of γ
- gamma injection
 - post image processing for contrast manipulation

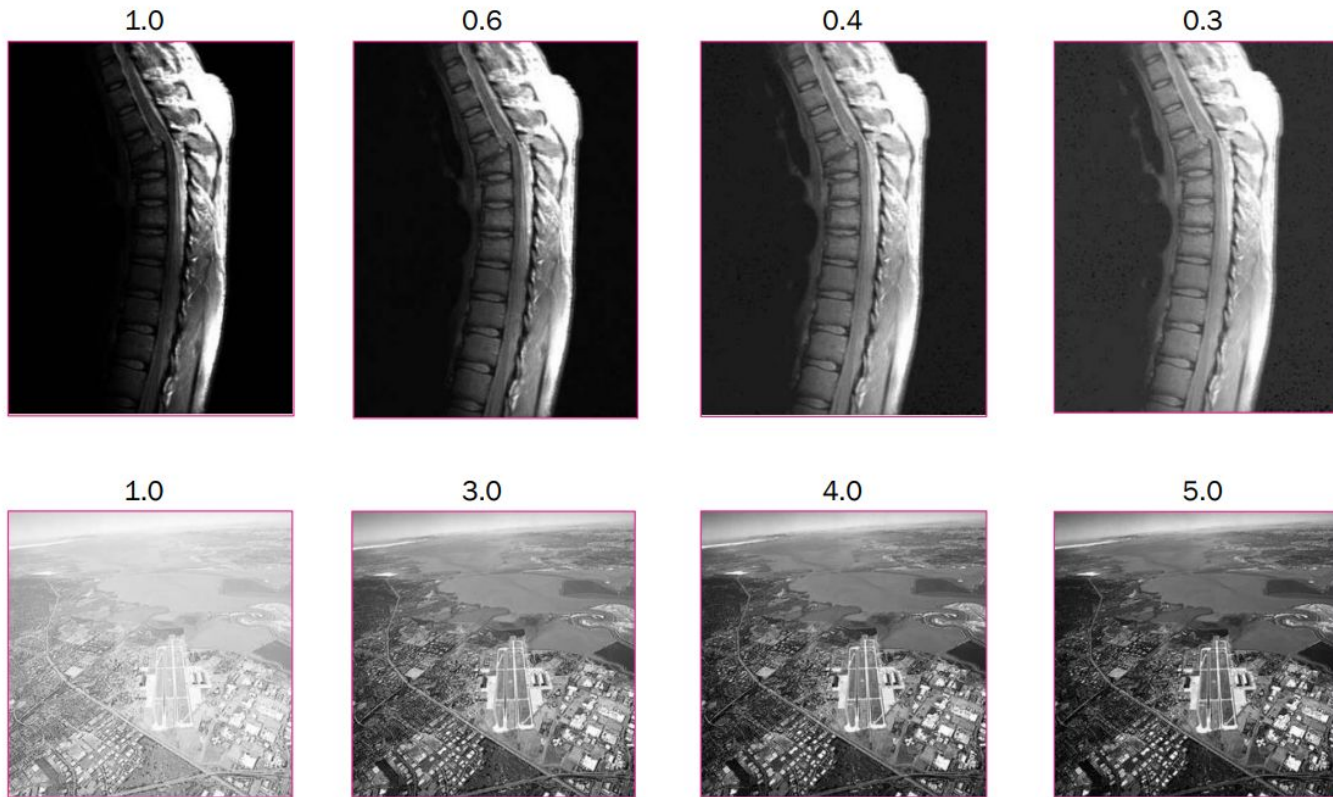


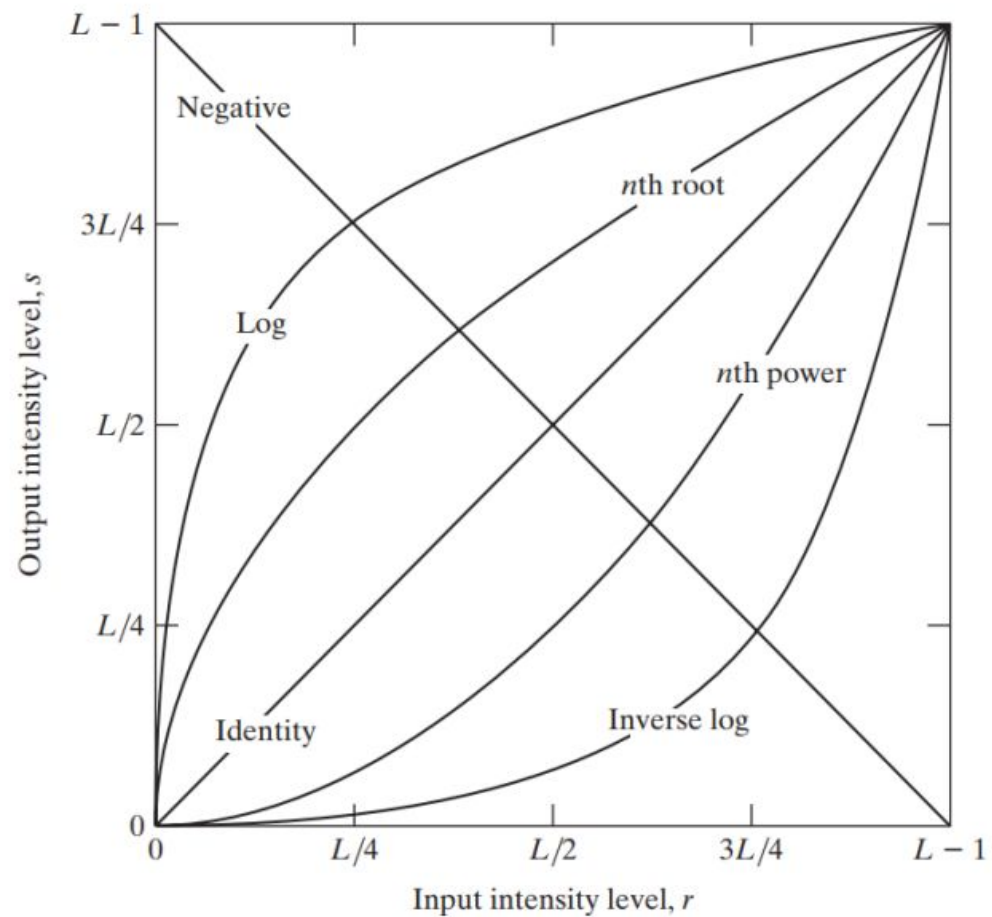
Gammas

$$s = c \cdot r^\gamma$$

■ γ injection

Enhances Contrast





Contrast stretching

■ Contrast

○ Low contrast images

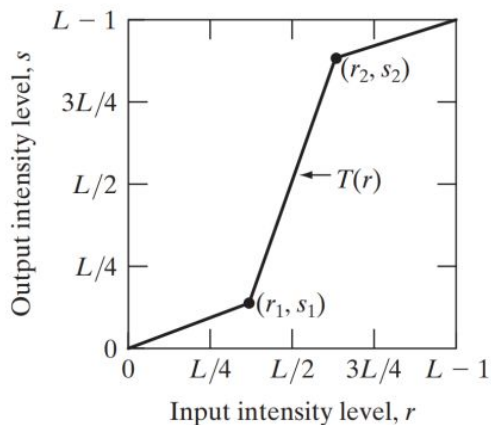
- due to poor illumination, low dynamic range sensors
- wrong setting of lens aperture

○ full range stretching

- $(r_1, s_1) = (r_{min}, 0)$
- $(r_2, s_2) = (r_{max}, L - 1)$

○ thresholding

- $r_1 = r_2, s_1 = 0, s_2 = L - 1$



70~140

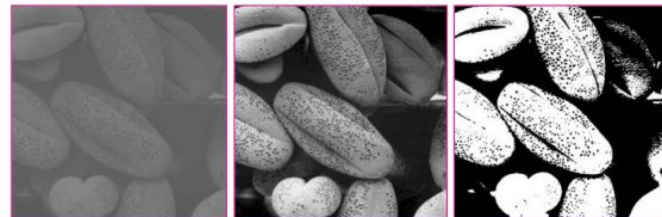
Contrast stretching

0~255

pixel ranges

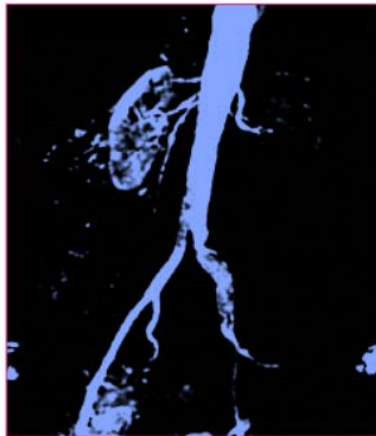
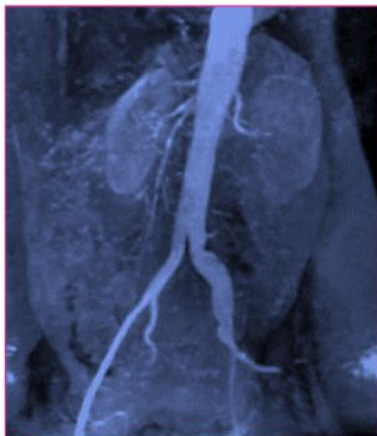
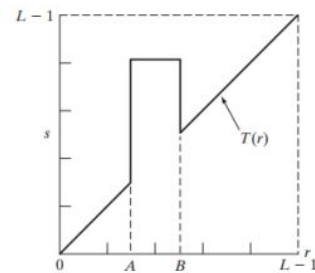
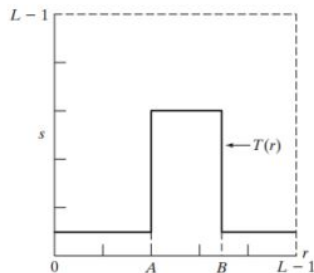


SEM image of pollen grains



Level slicing

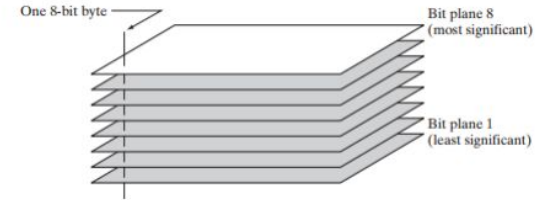
- Intensity levels
 - local thresholding, stretching
 - enhancing only specific intensities
 - e.g. detecting water, wetland in sat. images



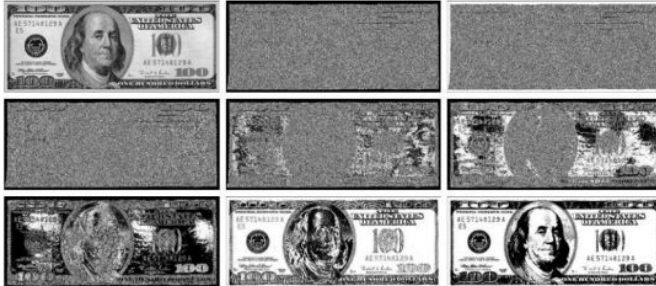
Bitplane slicing

■ Bitplanes

- contribution of each bit for total image appearance
- gives clue for a compression



○ slicing



○ reconstruction

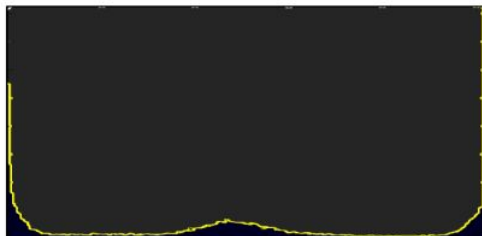
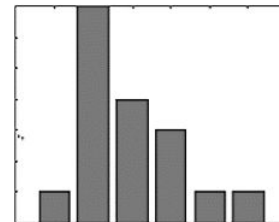


- bitplanes (8+7)
- bitplanes (8+7+6)
- bitplanes (8+7+6+5)

Histograms

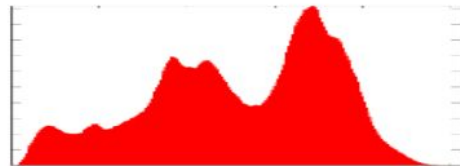
- distribution of discrete intensities
 - distribution is also discrete

4	1	3	2
3	1	1	1
0	1	5	2
1	1	2	2

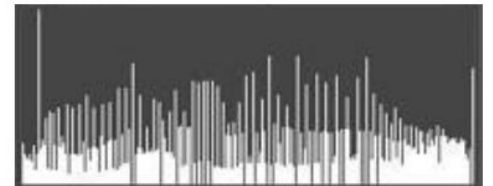
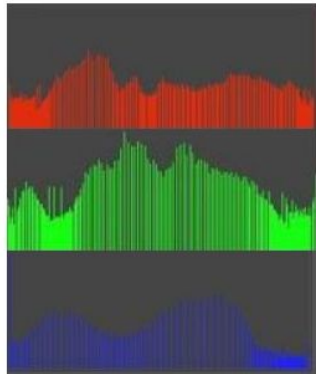
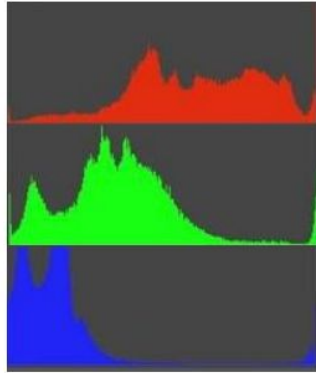


Histograms

- Color images



Histogram equalization



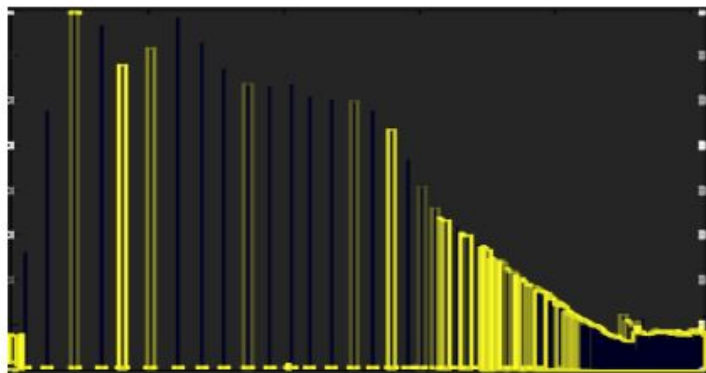
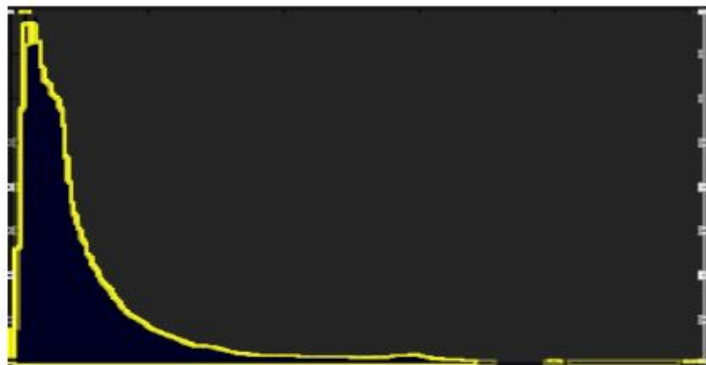


Image Filtering



Introduction

Input

Histeq

Noise

Filter-1

Filter-2

Filter-3



New filter

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

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

○ non-linear

- not satisfying above

■ 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

- Convolution

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

Correlation & Convolution

■ 2D correlation

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

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

W is the kernel. F is the image function

■ 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)

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

Correlation & Convolution

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

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

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

Filtering

- Image filtering

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

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

- Multistage filtering

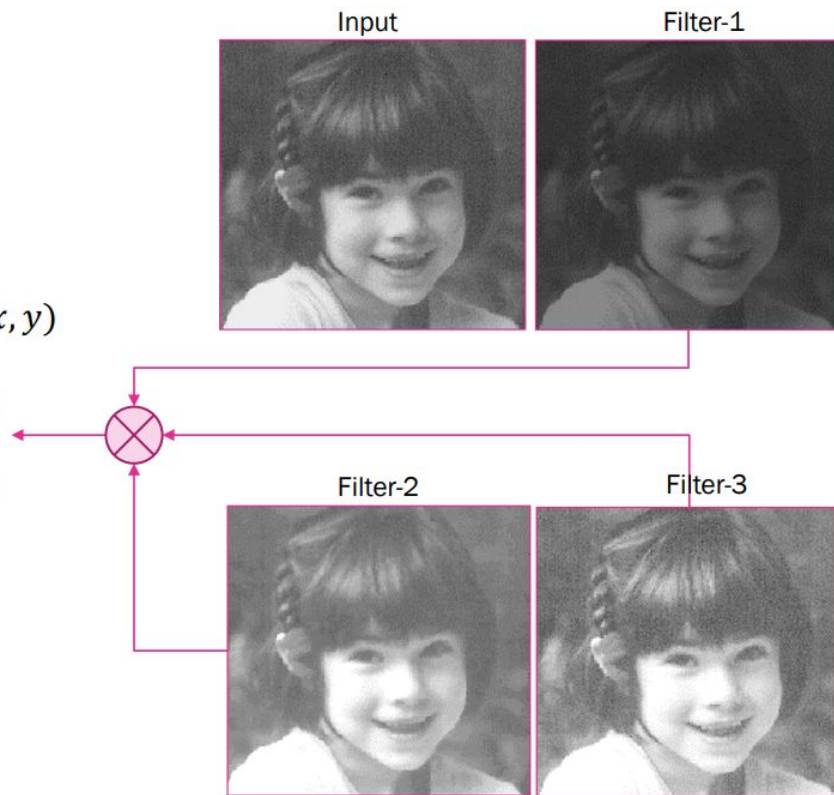
- filtering the filtered
- use properties
 - commutative & associative

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

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

$$g(x, y) = w \star f(x, y)$$

$$w = w_1 \star w_2 \star w_3$$



Filtering

■ Filter

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

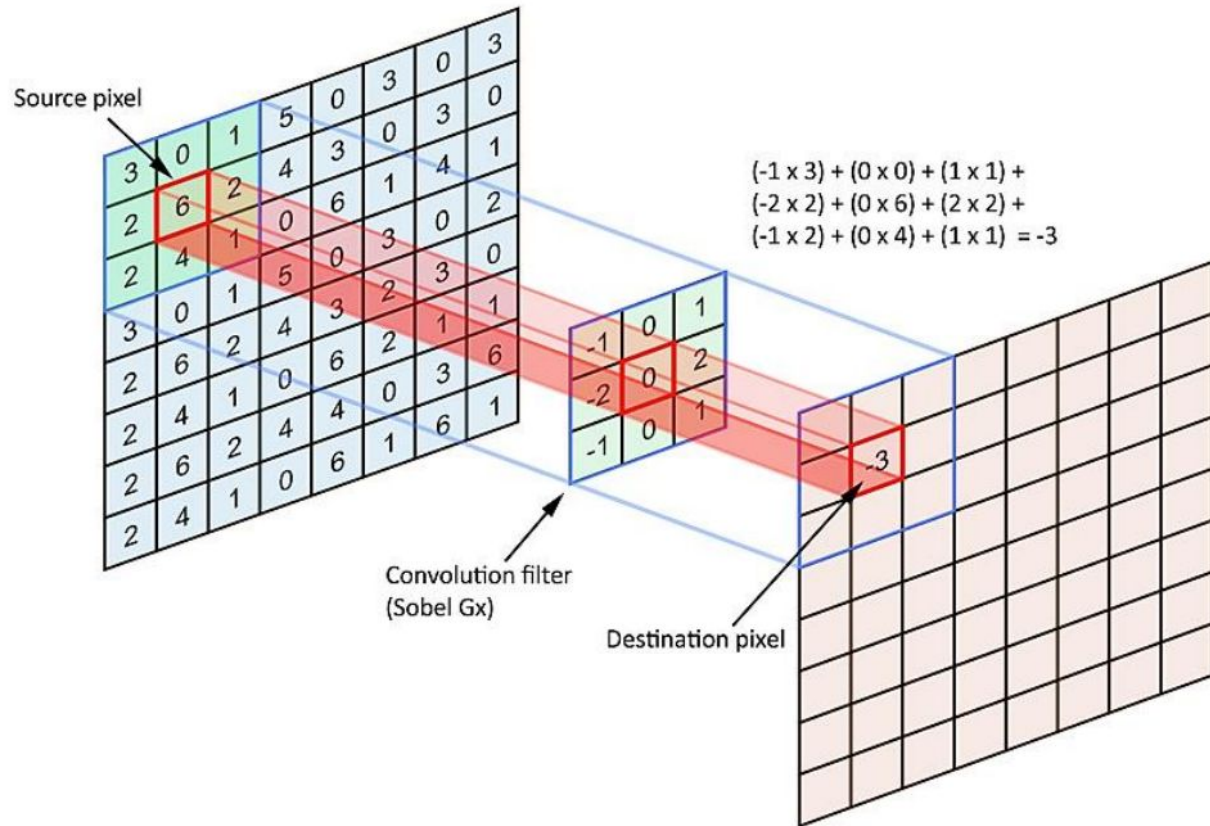
■ Nature of a filter

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

Filtering

■ Paddings

- zero
- mirror
- replicate



3. Mirror padding

- values outside the boundary of the image are obtained by mirror-reflecting the image across its border

- It is more applicable when the areas near the border contain image details

13	12	11	12	13	14	15	14	13
8	7	6	7	8	9	10	9	8
3	2	1	2	3	4	5	4	3
8	7	6	7	8	9	10	9	8
13	12	11	12	13	14	15	14	13
18	17	16	17	18	19	20	19	18
13	12	11	12	13	14	15	14	13
8	7	6	7	8	9	10	9	8

mirror padding

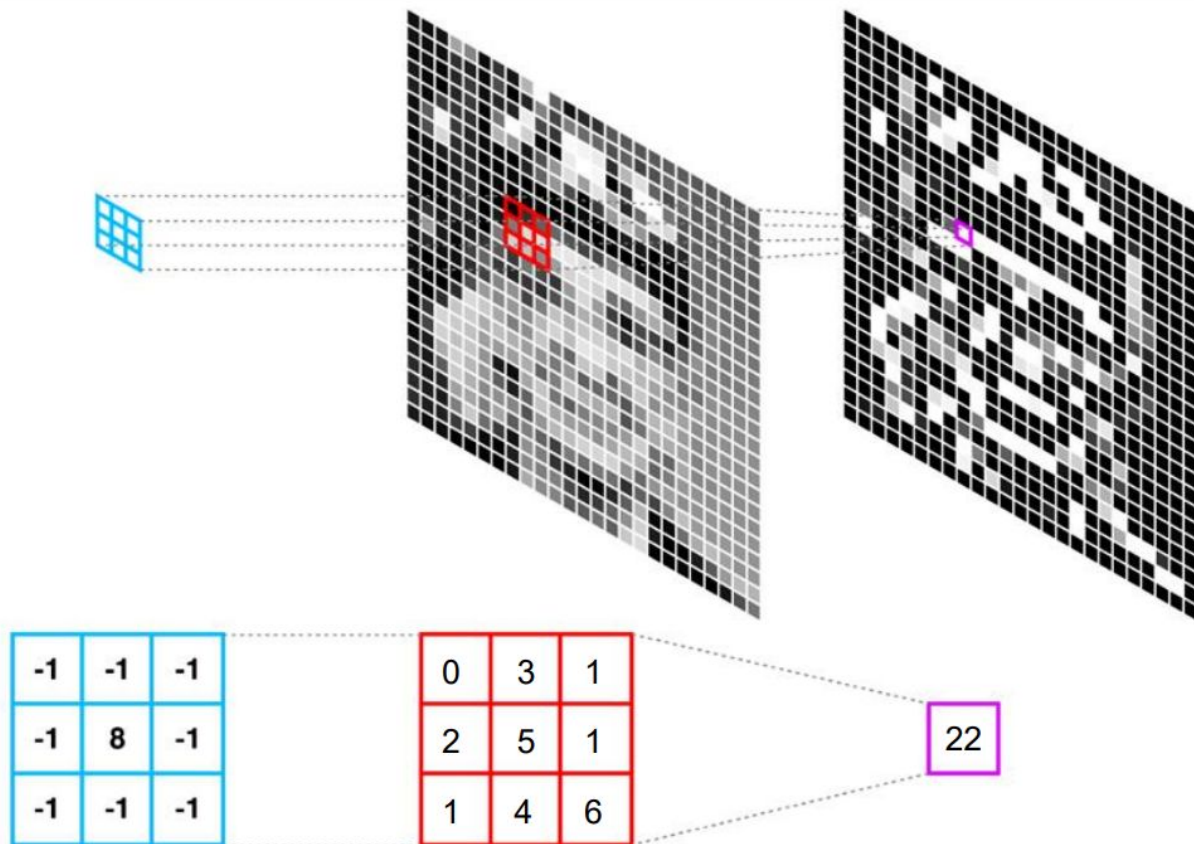
3	5	1
3	6	1
4	7	9

No padding

5	3	3	5	1	1	5
5	3	3	5	1	1	5
6	3	3	6	1	1	6
7	4	4	7	9	9	7
7	4	4	7	9	9	7

(1, 2) replication padding

Filtering



Filtering

- Separable kernels

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

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

$$\mathbf{c} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \mathbf{r} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

- Advantage: separable kernels

- computationally fast
 - outer product of vectors is same as their 2D conv

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

Filtering

- Box filter

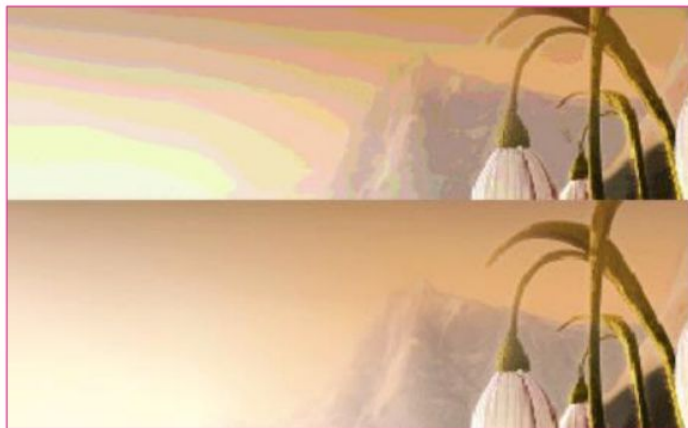
- smoothing filter
- lowpass filter
- averaging filter

- Use cases

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

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

1	1	1
1	1	1
1	1	1



Filtering

Box filter

- smoothing filter
- lowpass filter
- averaging filter

padding: $\frac{m-1}{2}$ **m represents Kernel size** (see 2.1.1)

input



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

m=3



m=11



m=21



Filtering

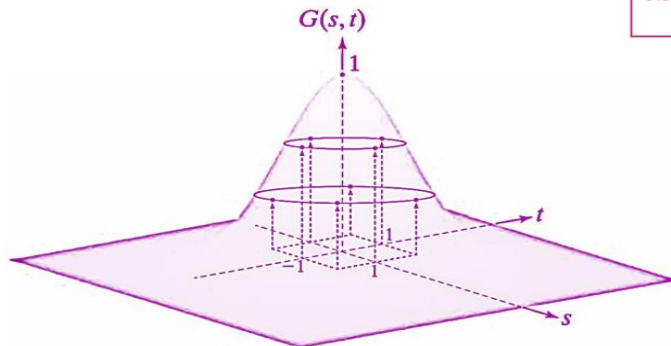
■ Gaussian filter

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

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

$$\frac{1}{4.8976} \times$$

0.3679	0.6065	0.3679
0.6065	1.0000	0.6065
0.3679	0.6065	0.3679



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



$m=85 \sigma=7$ Gauss



$m=43 \sigma=7$ Gauss



$m=21$ box



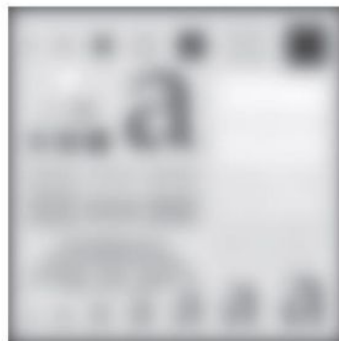
Filtering

- Padding effects

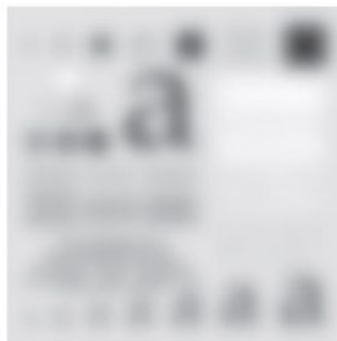
$m=187$ $\sigma=31$ Gauss

image 1024x1024

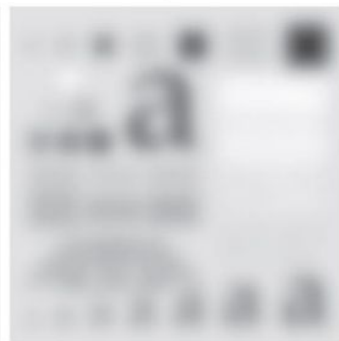
zero



mirror



replicate



- Relative size effect

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

image 4096x4096

$m=745$ $\sigma=124$ Gauss

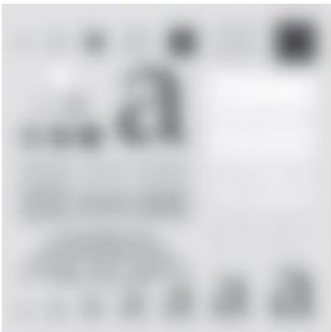
input



$m=187$ $\sigma=31$



$m=745$ $\sigma=124$



Filtering

- Relevant region extraction



filtering

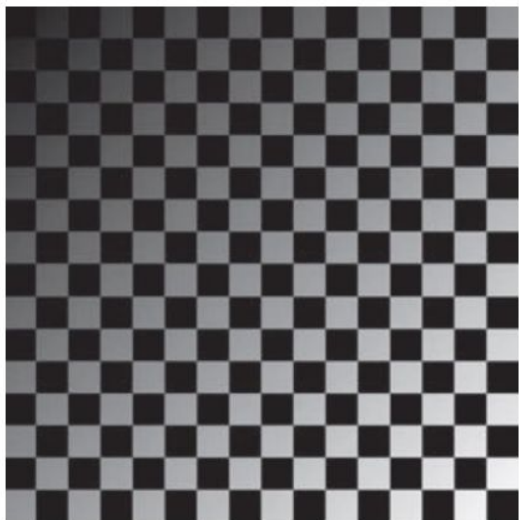


thresholding

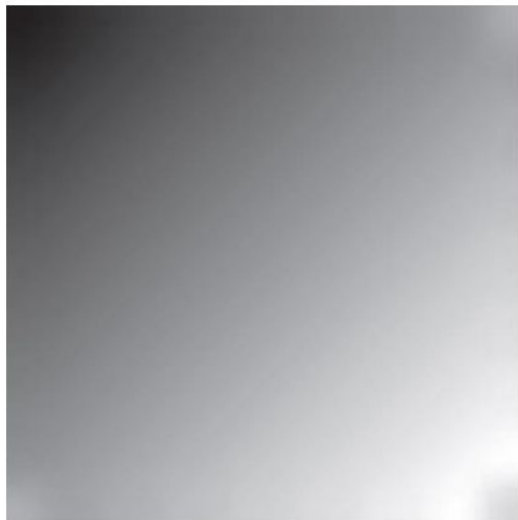


Filtering

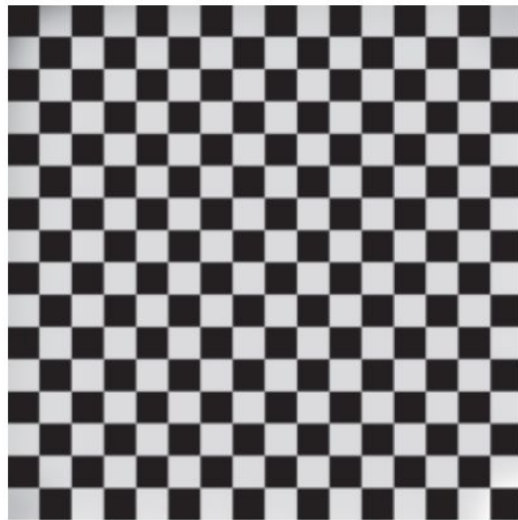
- Shading correction



filtering



scaling





THANK YOU