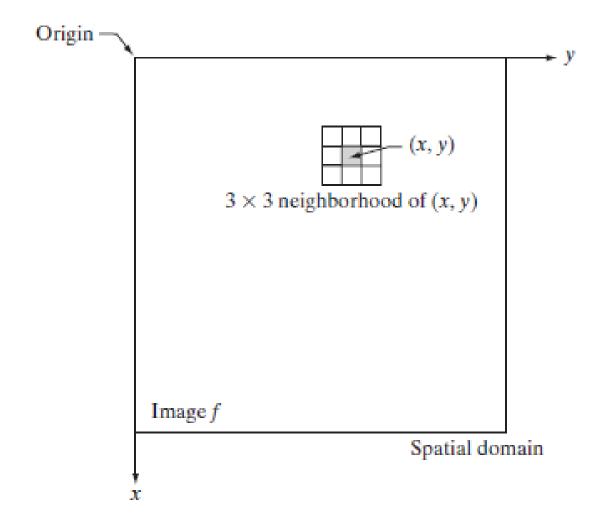
EE610 – Image Processing

Amit Sethi asethi, 7483

Spatial domain is defined as the domain of pixels in the image grid



A special case

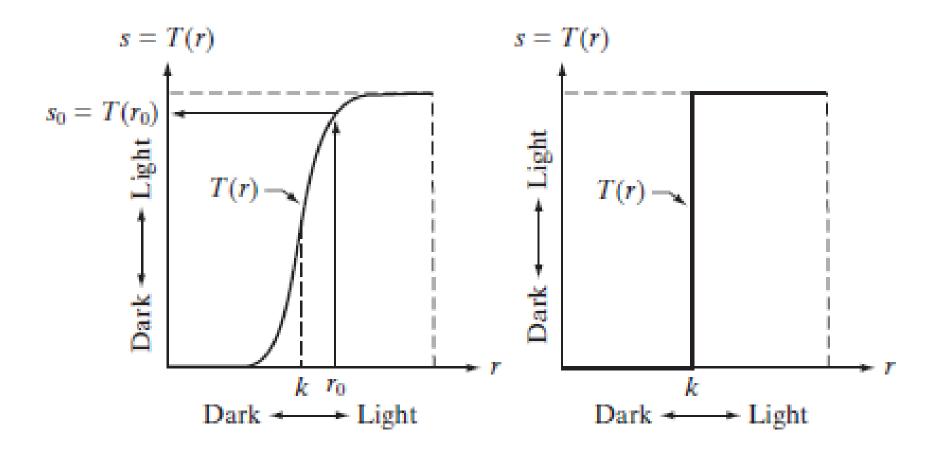
- Process each pixel with a W×W window around it
- W = 2M+1

- When M=0,
 - g(x,y) = T[f(x,y)]

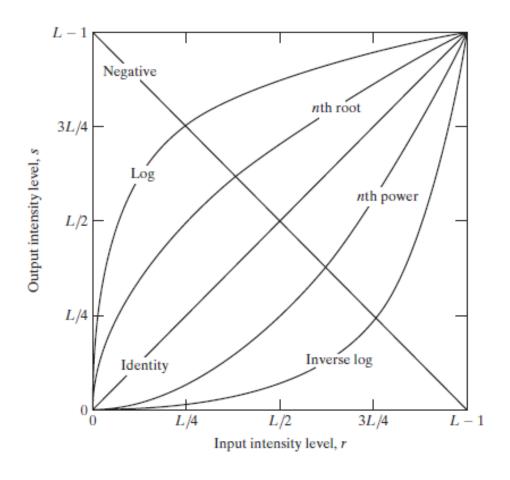
a.k.a. Intensity Transform

- Else,
 - $g(x,y) = T[N_f(x,y)]$

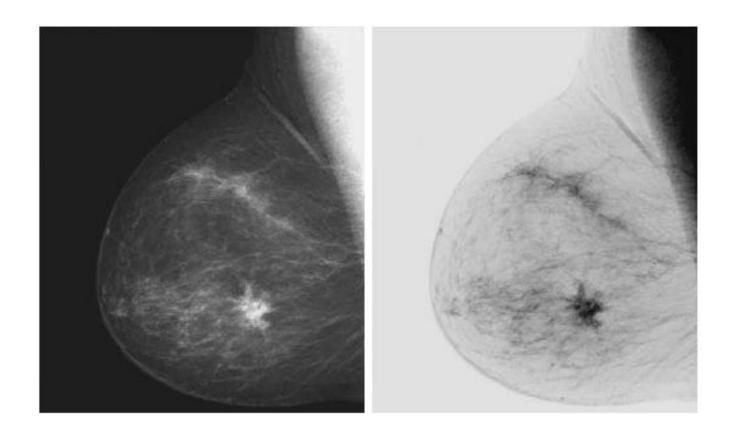
Contrast stretching and thresholding



Some basic intensity transformations

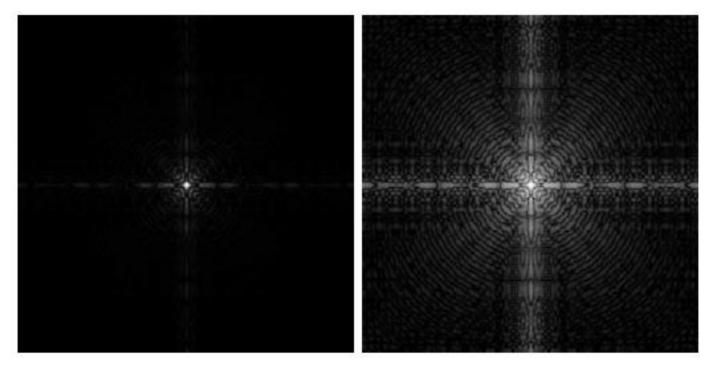


Negative of an image



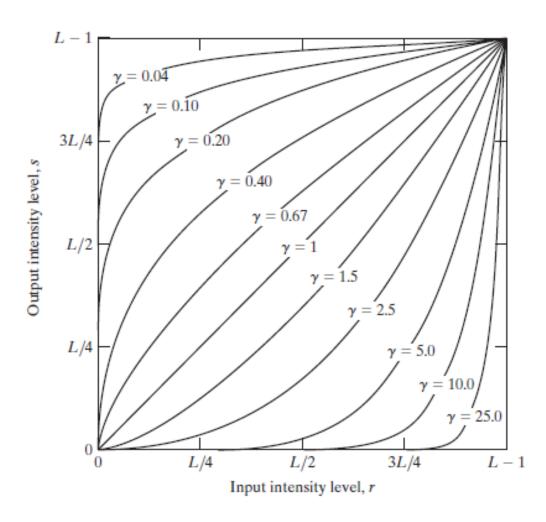
Log transformation in log domain

• $s = c \log (1+r)$

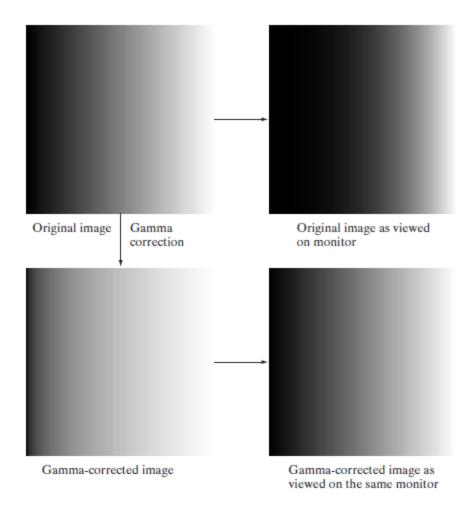


Power-law (gamma transformation)

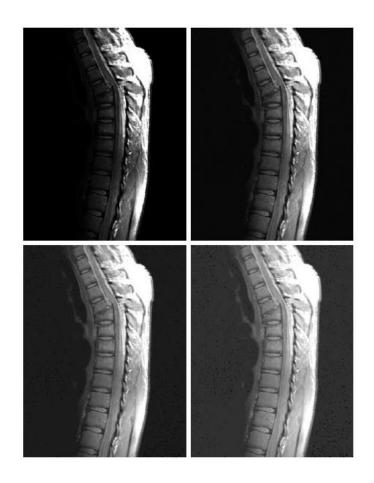
•
$$s = c r^{\gamma}$$



CRT's needed gamma correction



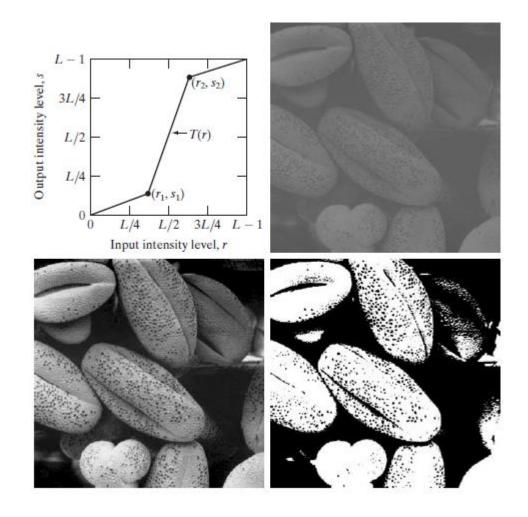
Gamma 1, .6, .4, .3



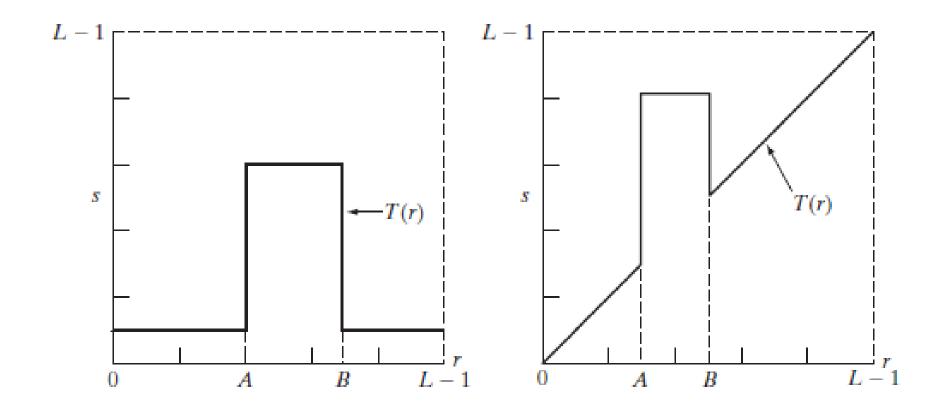
Gamma 1, 3, 4, 5



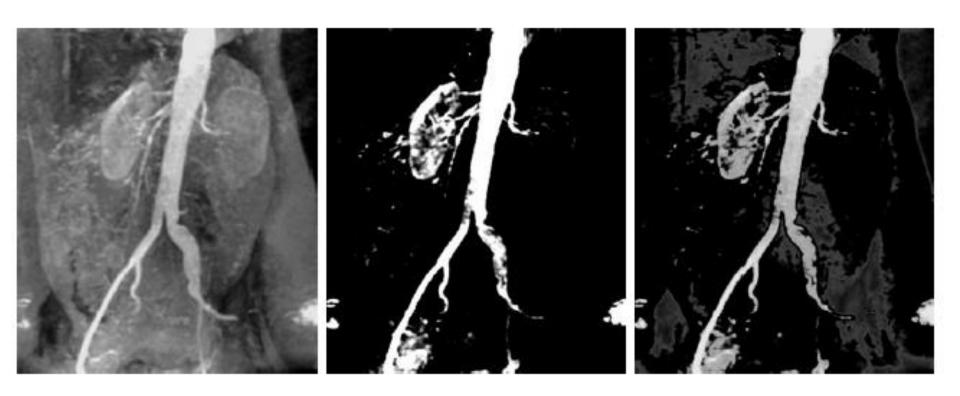
Contrast stretching vs. thresholding



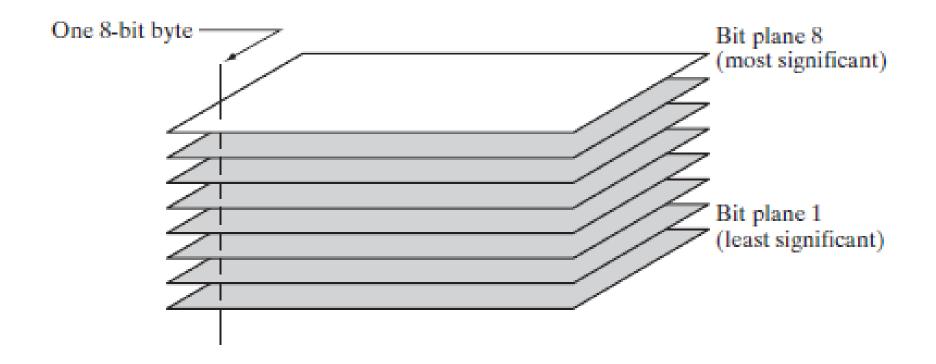
Highlighting a range of intensities



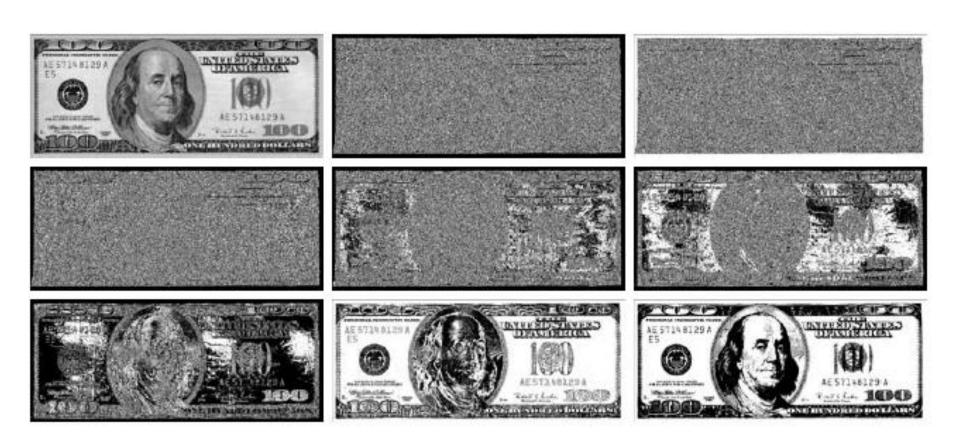
Some results of intensity highlighting



Bit-plane splicing



Different bit planes of an image



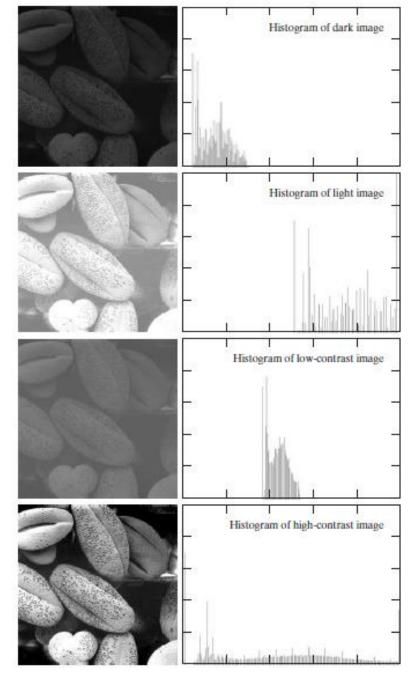
Higher bit planes contain the most information



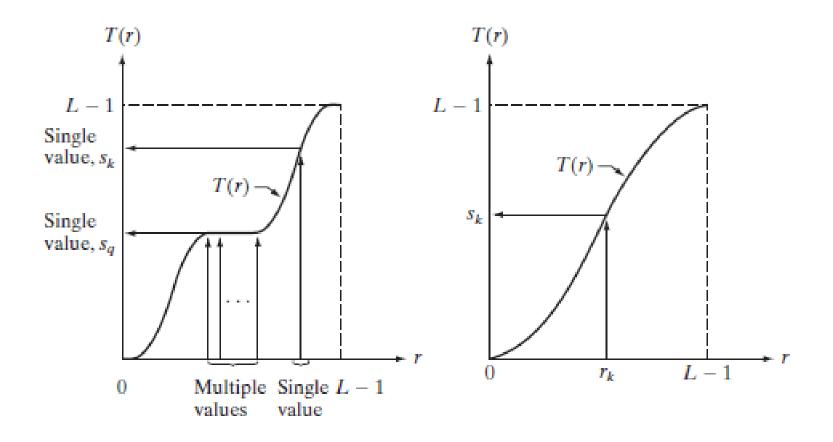




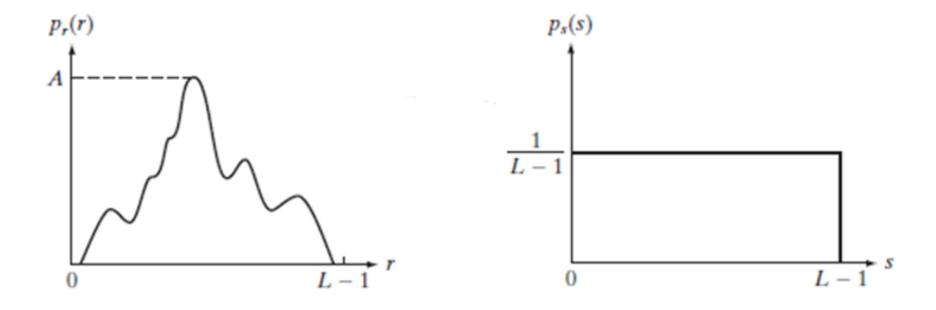
Image versions and their histograms



(Strictly) monotonically increasing functions for intensity transformations



Goal of histogram equalization



Relation between # pixels and probability of an intensity

r_k	n_k	$p_r(r_k) = n_k/MN$
$r_0 = 0$	790	0.19
$r_1 = 1$	1023	0.25
$r_2 = 2$	850	0.21
$r_3 = 3$	656	0.16
$r_4 = 4$	329	0.08
$r_5 = 5$	245	0.06
$r_6 = 6$	122	0.03
$r_7 = 7$	81	0.02

Relation between a random variable and its transform

$$s = T(r)$$

$$\frac{ds}{dr} = \frac{dT(r)}{dr}$$

$$p_s(s) = p_r(r) \left| \frac{dr}{ds} \right|$$

Transform for equalization

$$s = T(r) = (L - 1) \int_0^r p_r(w) dw$$

$$\frac{ds}{dr} = \frac{dT(r)}{dr}$$

$$= (L-1)\frac{d}{dr} \left[\int_0^r p_r(w) dw \right]$$

$$= (L-1)p_r(r)$$

$$= p_r(r) \left| \frac{1}{(L-1)p_r(r)} \right|$$

$$= \frac{1}{L-1} \quad 0 \le s \le L-1$$

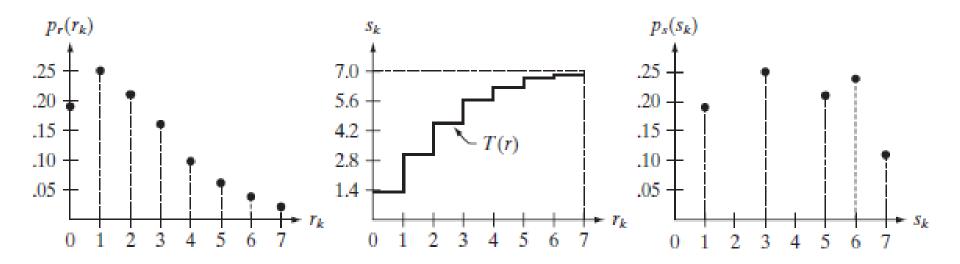
Discrete version of equalizing transformation

$$s_k = T(r_k) = (L - 1) \sum_{j=0}^k p_r(r_j)$$

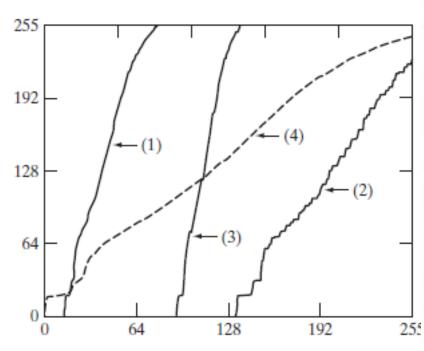
$$= \frac{(L-1)}{MN} \sum_{j=0}^{k} n_j \qquad k = 0, 1, 2, \dots, L-1$$

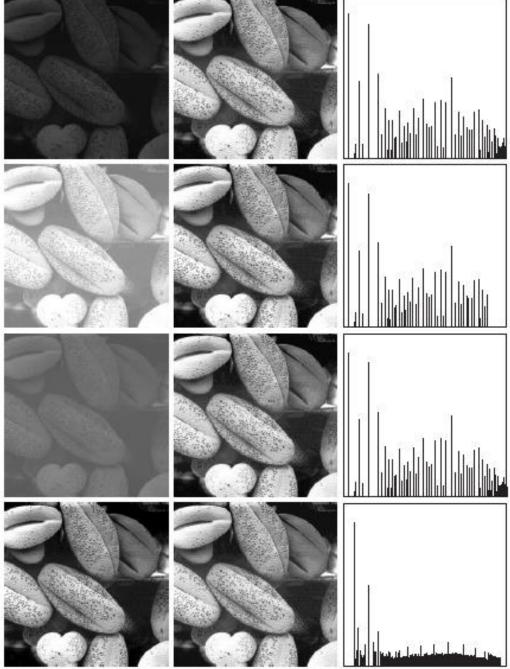
$$s = T(r) = (L - 1) \int_0^r p_r(w) dw$$

Equalizing a discrete histogram

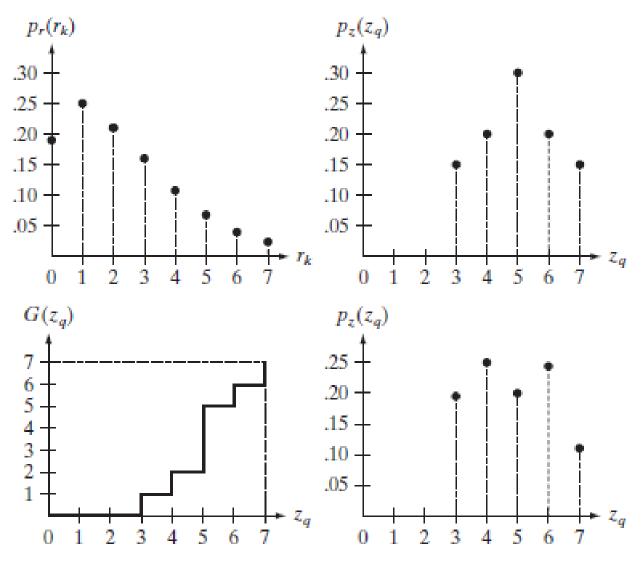


Histogram equalization on different starting images





One can also specify a histogram



Now we need two transformations

$$s = T(r) = (L - 1) \int_0^r p_r(w) dw$$

$$G(z) = (L - 1) \int_0^z p_z(t) dt = s$$

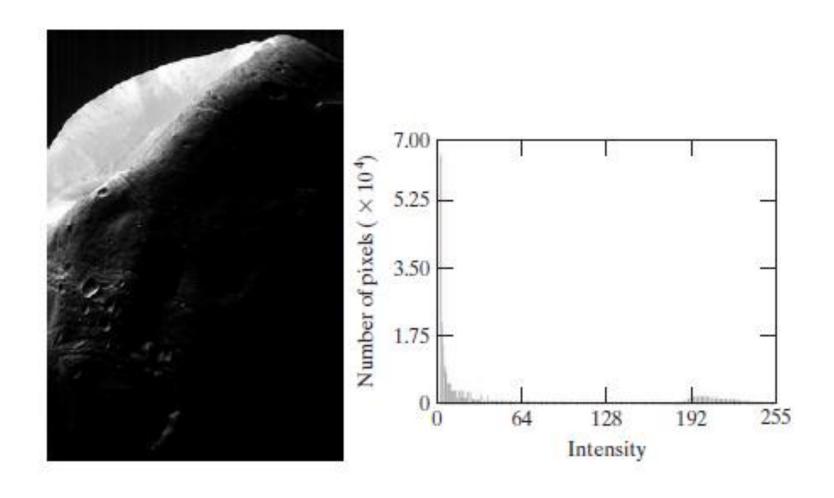
$$z = G^{-1}[T(r)] = G^{-1}(s)$$

- Obtain pdf
- Compute G(z)
- Compute *G*⁻¹(*s*)
- First equalize,
 then apply G⁻¹(s)

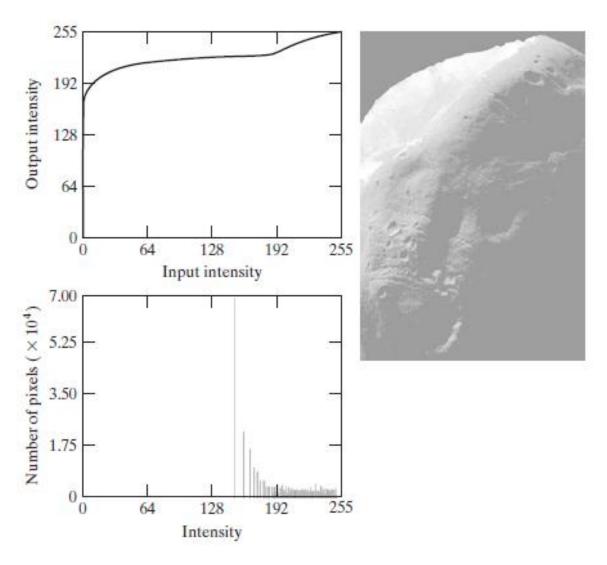
For discrete values, it cannot be perfect

z_q	Specified $p_z(z_q)$	Actual $p_z(z_k)$
$z_0 = 0$	0.00	0.00
$z_1 = 1$	0.00	0.00
$z_2 = 2$	0.00	0.00
$z_3 = 3$	0.15	0.19
$z_4 = 4$	0.20	0.25
$z_5 = 5$	0.30	0.21
$z_6 = 6$	0.20	0.24
$z_7 = 7$	0.15	0.11

Original image



Equalized image



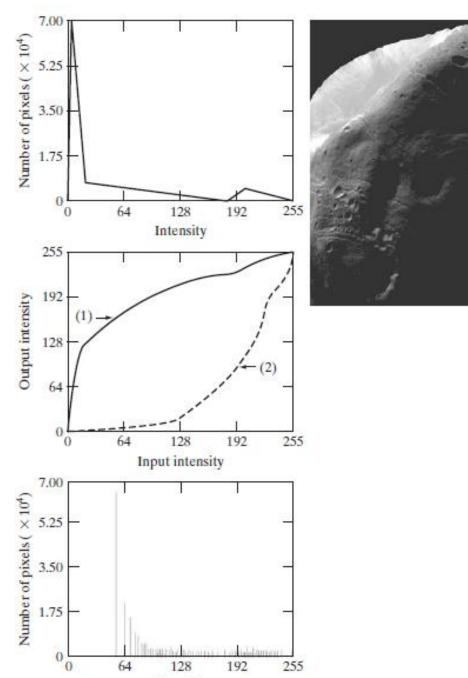
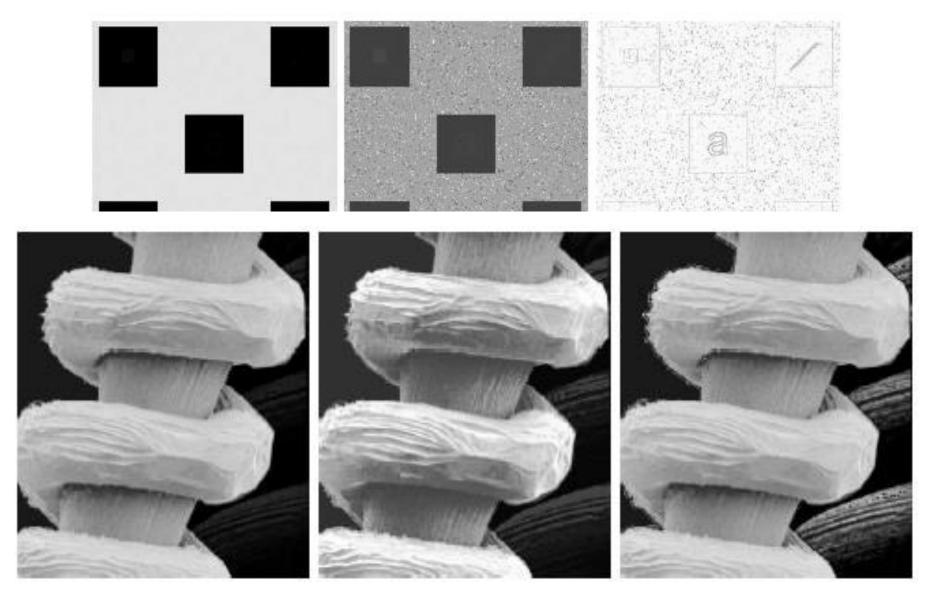
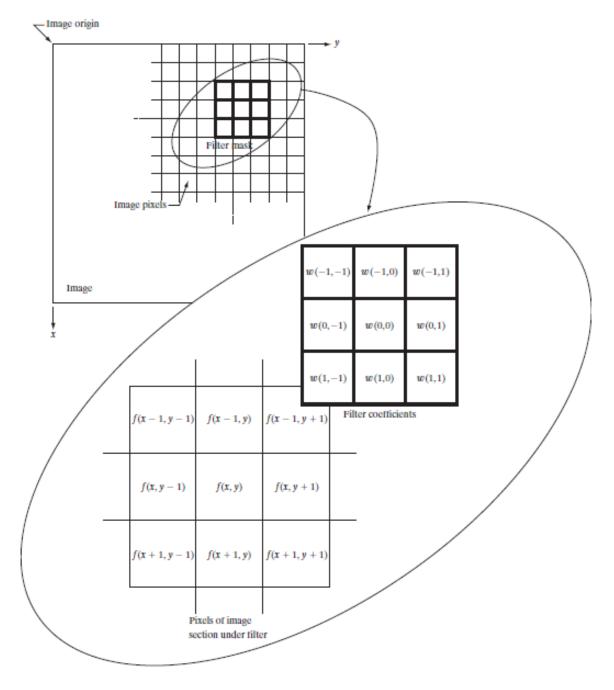


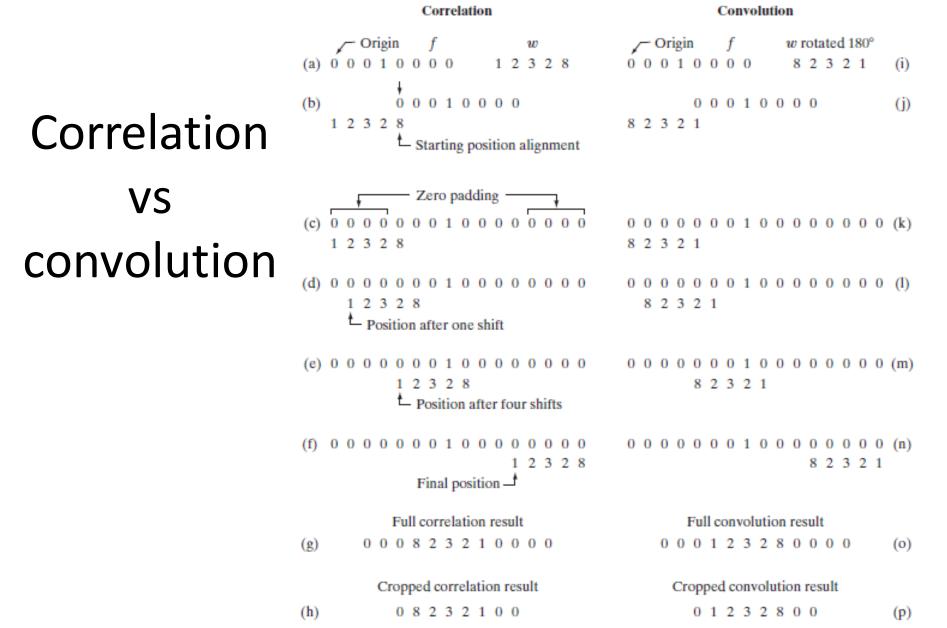
Image with histogram specification

Global vs local histogram equalization

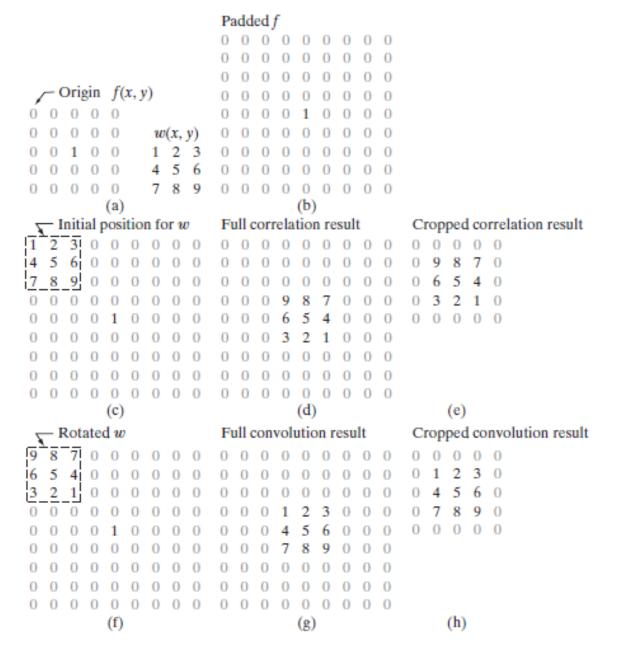


Basics of spatial filtering





Correlation and convolution in 2-D



Correlation vs. convolution in 2-D

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

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

Correlation as a vector operation

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

$$R = w_1 z_1 + w_2 z_2 + \dots + w_{mn} z_{mn}$$

$$= \sum_{k=1}^{mn} w_k z_k$$

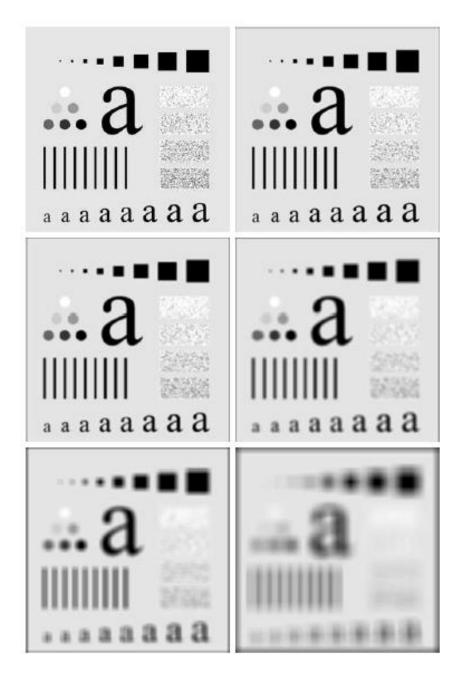
$$= \mathbf{w}^T \mathbf{z}$$

Smoothing (low pass filters)

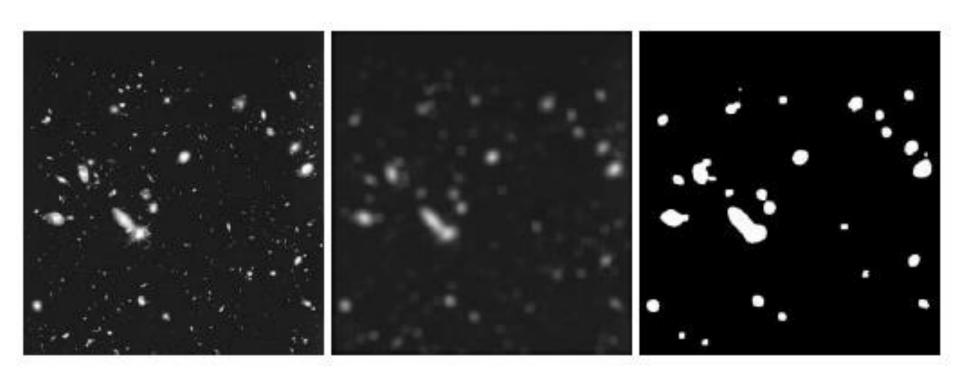
1/9 ×	1	1	1
	1	1	1
	1	1	1

$$h(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Averaging with box filters of sizes 1, 3, 5, 9, 15, and 35



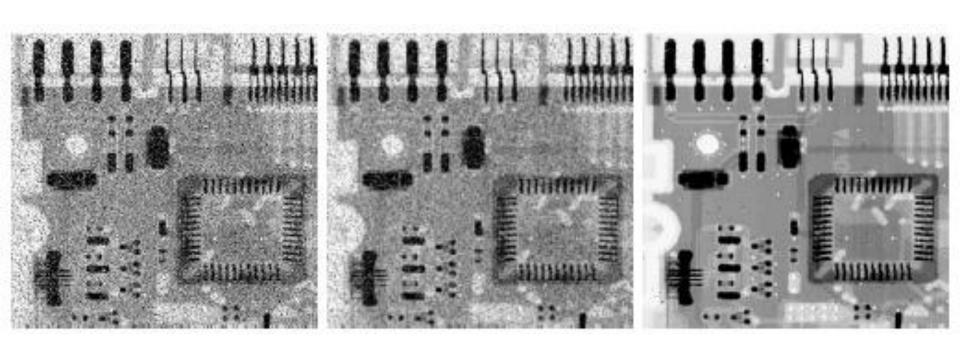
Filtering followed by thresholding



Filtering as weighted average

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

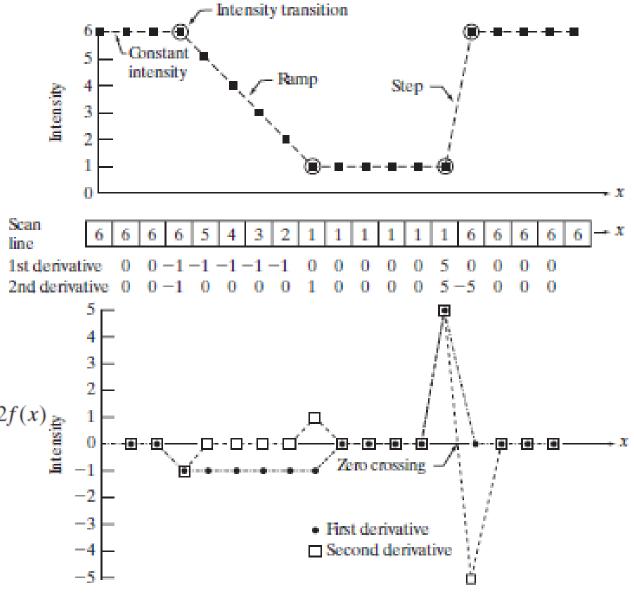
Nonlinear filters such as median filter (right) are better suited many times



Derivatives of intensity profiles

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x)$$



Sobel operators for directional edges

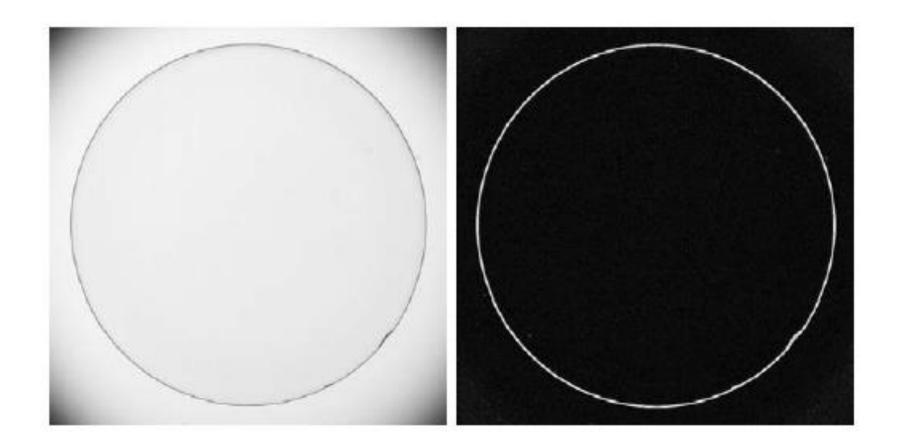
$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

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

Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Original and Sobel gradient



Laplacian as an isotropic second derivative

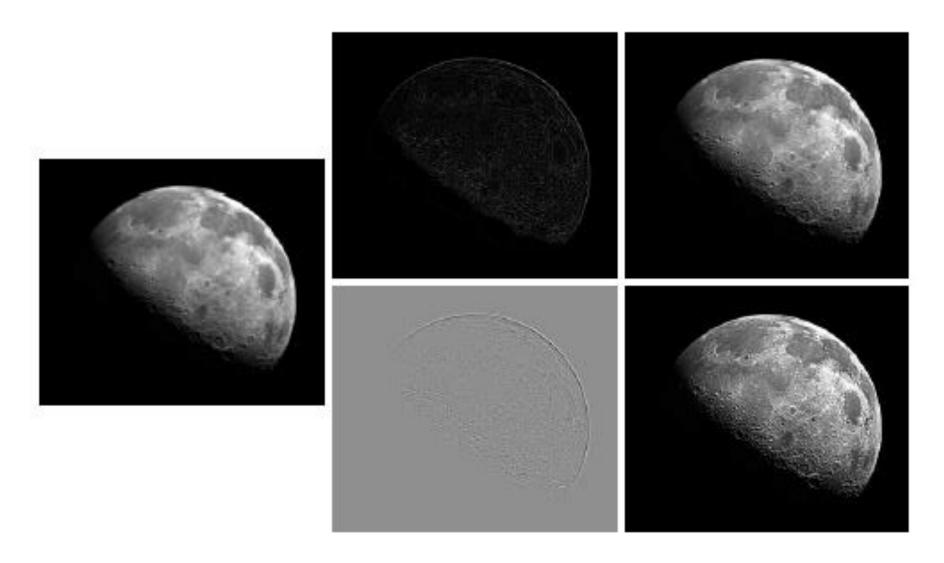
Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Practical implementation of Laplacian

0	-1	0	-1	-1	-1
-1	4	-1	-1	8	-1
0	-1	0	-1	-1	-1

$$g(x, y) = f(x, y) + c \left[\nabla^2 f(x, y) \right]$$

Results of sharpening



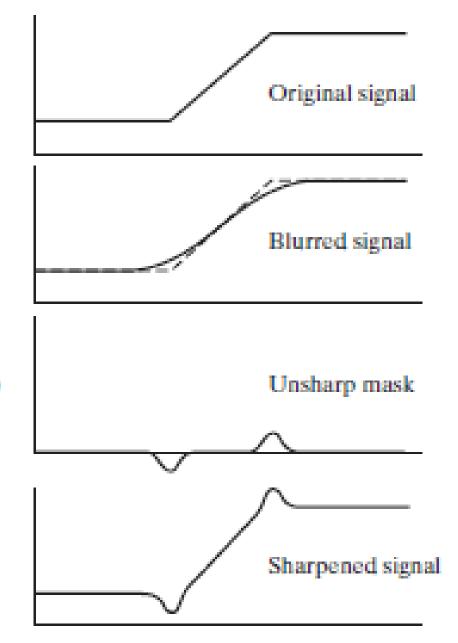
Source: Digital Image Processing, Gonzalez and Woods, Prentice Hall

Unsharp masking

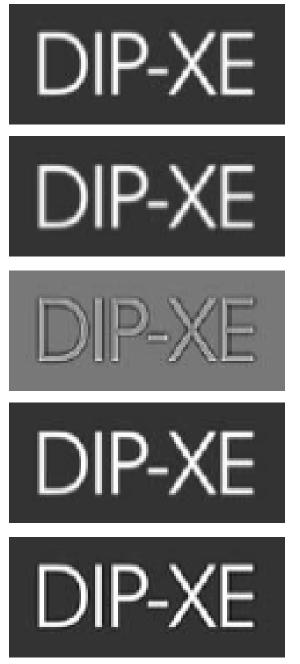
- Blur the original image.
- mask = original blurred
- output = original + mask

$$g_{\text{mask}}(x, y) = f(x, y) - \overline{f}(x, y)$$

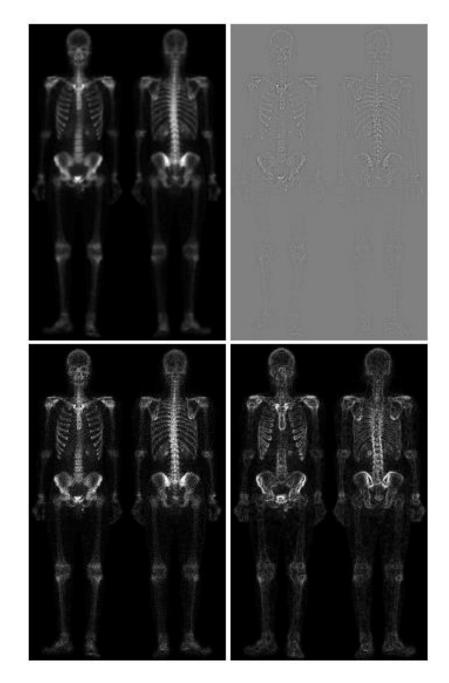
$$g(x, y) = f(x, y) + k * g_{\text{mask}}(x, y)$$



Sample results of unsharp masking



Original,
Laplacian,
Sharpened,
Sobel gradient



Smoothened Sobel, c*e, a+f, power law transformation

