COMP 9517 Computer Vision

Image Processing

Image Analysis

- Manipulation of image data to extract the information necessary for solving an imaging problem
- Consists of preprocessing, data reduction and feature analysis
- Preprocessing removes noise, eliminates irrelevant information
- Data reduction extracts features for the analysis process
- During feature analysis, the extracted features are examined and evaluated for their use in the application

Image Preprocessing

- Input and output are intensity images
- Aim to improve image, by suppressing distortions and enhancing image features, so that result is more suitable for a specific application
- Exploit redundancy in image: for example, neighbouring pixels have similar brightness value.

Image Preprocessing

- Two types of image processing/image transformation:
 - Spatial domain
 - Transform domain (mainly frequency domain)

- Two principal categories in spatial processing:
 - Intensity transformation (on single pixels)
 - Spatial filtering (on pixel and its neighbours)

Spatial Domain Techniques

Operate directly on image pixels:

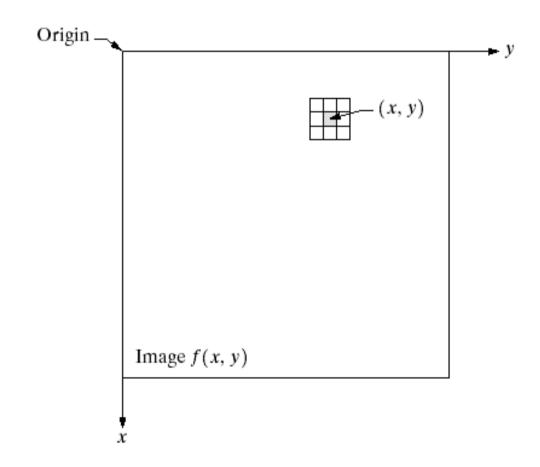
$$g(x,y) = T[f(x,y)]$$

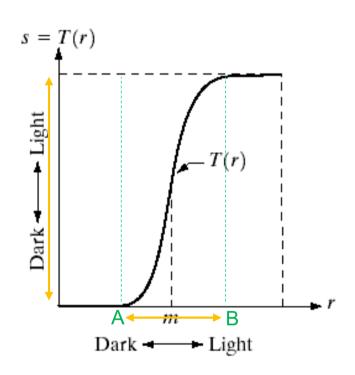
where:

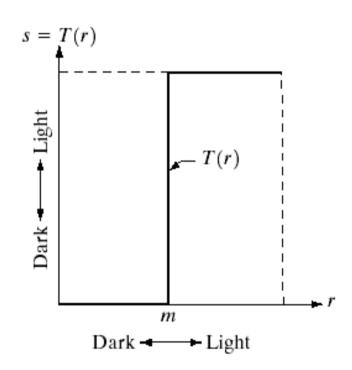
- f(x, y) is the input image
- -g(x,y) is the processed image
- T is an operator on f, over a pixel at (x, y), or a neighbourhood of (x, y)
- When T is of size 1×1 , T becomes a gray-level transformation function: s = T(r)
- Examples are contrast stretching, thresholding

FIGURE 3.1 A

 3×3 neighborhood about a point (x, y) in an image.







a b

FIGURE 3.2 Graylevel transformation functions for contrast enhancement.

Basic Gray-level Transformations

Image thresholding

- Replace each pixel with a black pixel if r < t and with a white pixel if r > t (t is a fixed value selected as cut-off)
- One of the simplest transformations which is used to segment the image into two binary classes of background and foreground
- Useful for segmentation to simplify the representation of an image to something easier for analysis
- Limitation: if histogram does not have bimodal distribution and it does not have a sharp valley, the determined threshold may not be very useful.

Otsu's method:

- Automatic image thresholding algorithm
- Output is a binary image (two classes)
- Exhaustively searches for a threshold that minimizes intra-class variance

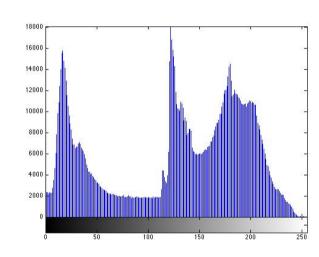
$$\sigma_w^2 = w_0(t)\sigma_0^2 + w_1(t)\sigma_1^2$$
. $w_0(t) + w_1(t) = 1$

equivalent to maximizing inter-class variance, and is much faster

$$\sigma_b^2 = \sigma^2 - \sigma_w^2 = w_0(t)w_1(t)[\mu_0(t) - \mu_1(t)]^2$$

Otsu's method:





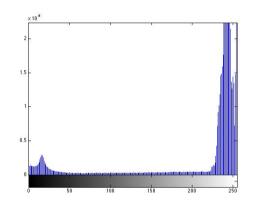


Balanced histogram thresholding:

- Automatic image thresholding algorithm
- Output is a binary image (two classes)
- Searches for a threshold that has equal weights on both sides of the histogram (this is equal to median point)

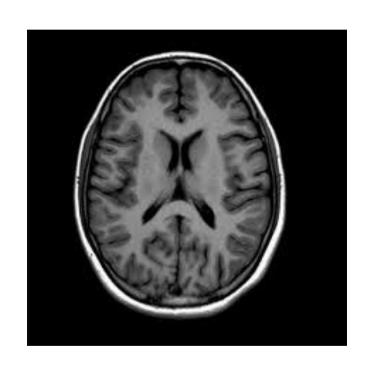
Balanced histogram thresholding:

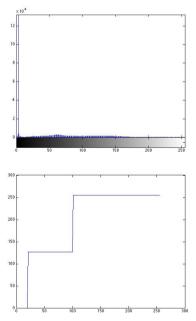


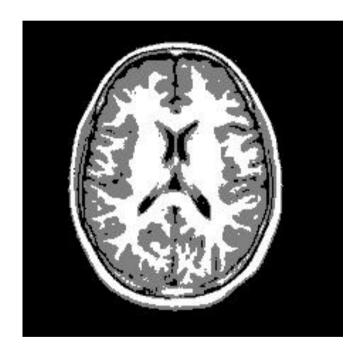




Multi-band thresholding:







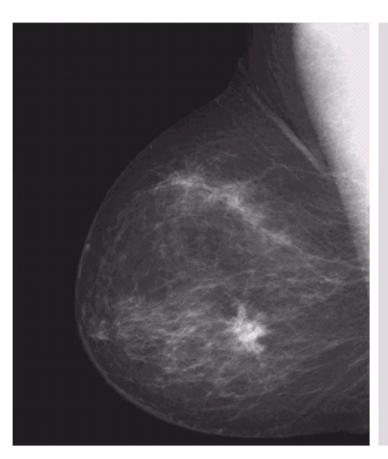
Basic Gray-level Transformations

Image Negatives

• For input image with gray levels in range [0, L-1], the negative transformation is

$$s = L - 1 - r$$

- Produces equivalent of a photo negative
- Useful for enhancing white or gray detail in dark regions of image, when black areas are dominant



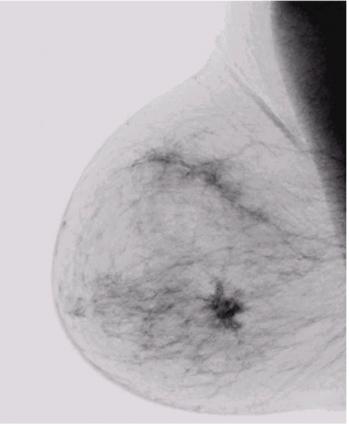


FIGURE 3.4 (a) Original digital mammogram. (b) Negative image obtained using the negative transformation in Eq. (3.2-1). (Courtesy of G.E. Medical Systems.)

Basic Gray level Transformations

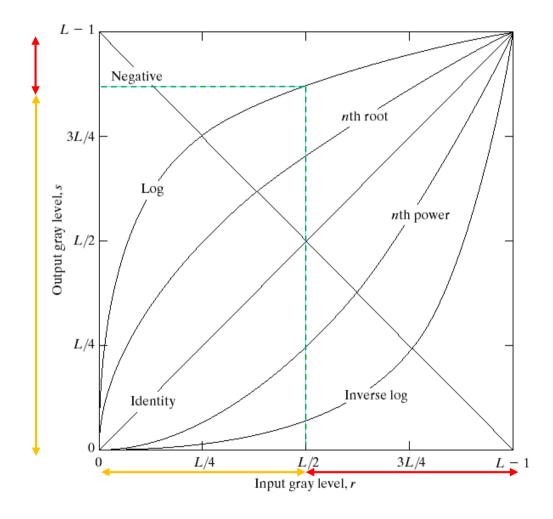
Log Transformations

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

where c is constant, r >= 0

Maps narrow range of low gray-level values into wider range of output values, also compresses dynamic range of images with large variations in pixel values.

FIGURE 3.3 Some basic gray-level transformation functions used for image enhancement.

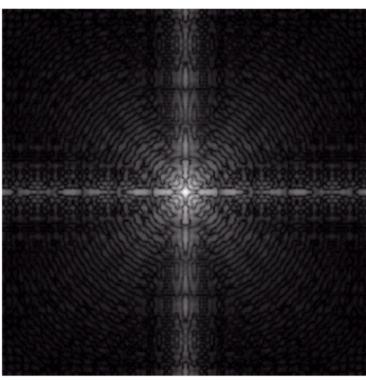


a b

FIGURE 3.5

(a) Fourier spectrum.
(b) Result of applying the log transformation given in Eq. (3.2-2) with c = 1.





Power-Law Transformations

- Given by $s = cr^{\gamma}$ where c, γ are constant
- Similar to log transformation on input-output
- Family of possible transformations by varying γ
- Useful in displaying an image accurately on a computer screen (for example on web sites!) by pre-processing images appropriately before display
- Also useful for general-purpose contrast manipulation

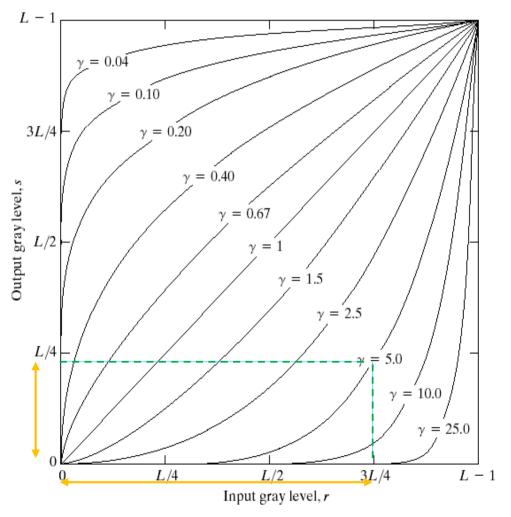
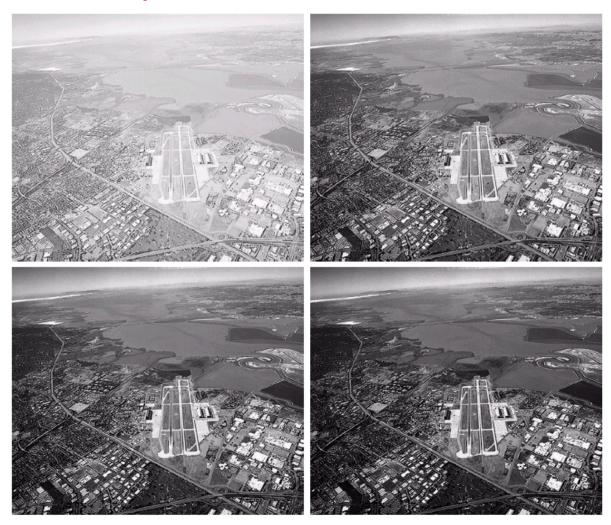


FIGURE 3.6 Plots of the equation $s = cr^{\gamma}$ for various values of γ (c = 1 in all cases).

a b c d

FIGURE 3.9

(a) Aerial image. (b)–(d) Results of applying the transformation in Eq. (3.2-3) with c = 1 and $\gamma = 3.0, 4.0$, and 5.0, respectively. (Original image for this example courtesy of NASA.)



Piecewise-linear Transformations

Why?

- Complementary to transformation-based methods
- Forms of piecewise functions can be complex
- However, require more user input

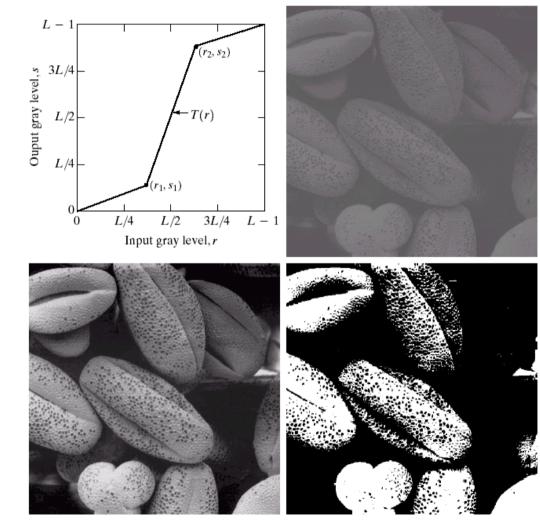
Piecewise-linear Transformations

Here we discuss 3 types of such transformation:

- Contrast stretching
- Gray-level slicing / intensity-level slicing
- Bit-plane slicing

Contrast Stretching

- One of the simplest piecewise linear transformations
- To increase the dynamic range of gray levels in image
- Used in display devices or recording media to span the full intensity range



a b c d

FIGURE 3.10

function. (b) A low-contrast image. (c) Result

(Original image

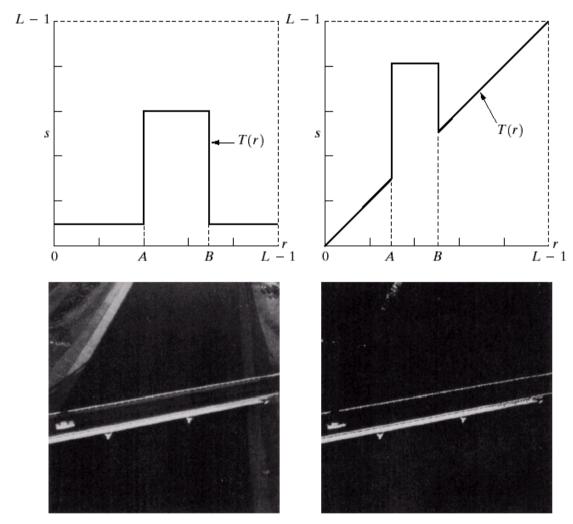
of contrast stretching. (d) Result of thresholding.

courtesy of Dr. Roger Heady, Research School of Biological Sciences, Australian National University, Canberra, Australia.)

Contrast stretching. (a) Form of transformation

Gray-level Slicing

- Highlighting of specific range of gray levels
- Display high value for all gray levels in range of interest, and low value for all others- produces binary image
- Brighten the desired range of gray levels, while preserving background and other gray-scale tones of image



a b c d

FIGURE 3.11

(a) This transformation highlights range [A, B] of gray levels and reduces all others to a constant level. (b) This transformation highlights range [A, B] but preserves all other levels. (c) An image. (d) Result of using the transformation in (a).

Bit-plane Slicing

- Highlights contribution made to total image appearance by specific bits
- Eg, for an 8-bit image, there are 8 1-bit planes
- Useful in compression

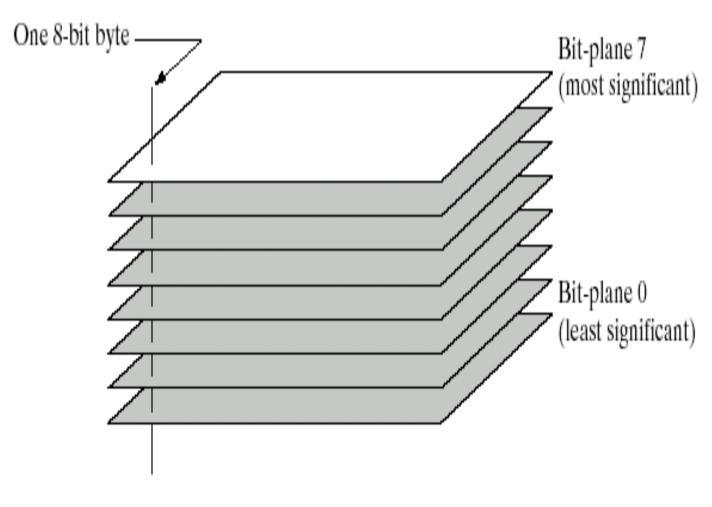


FIGURE 3.12

Bit-plane representation of an 8-bit image.

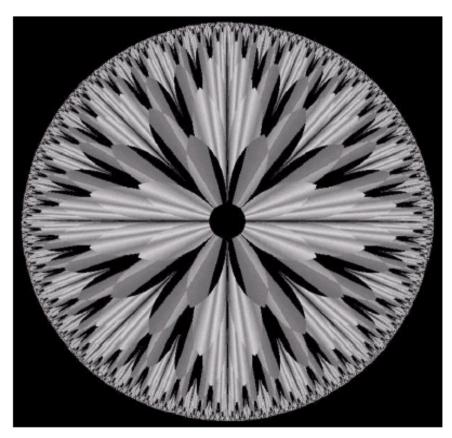


FIGURE 3.13 An 8-bit fractal image. (A fractal is an image generated from mathematical expressions). (Courtesy of Ms. Melissa D. Binde, Swarthmore College, Swarthmore, PA.)

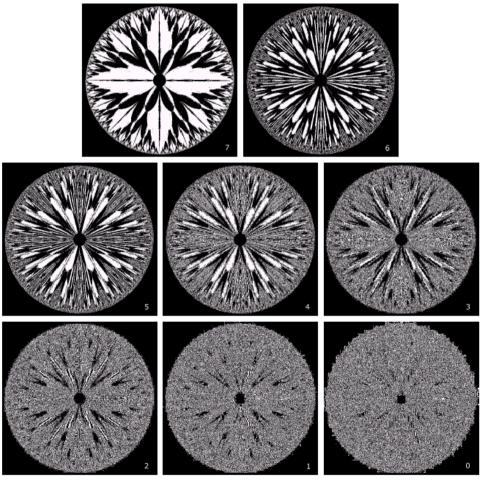


FIGURE 3.14 The eight bit planes of the image in Fig. 3.13. The number at the bottom, right of each image identifies the bit plane.

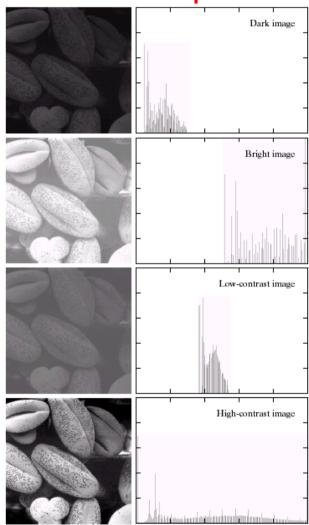
Histogram Processing

Histogram Equalization

Aim: To get an image with equally distributed brightness levels over the whole brightness scale.

Histogram Matching

Aim: To get an image with a specified histogram (brightness distribution)



a b

FIGURE 3.15 Four basic image types: dark, light, low contrast, high contrast, and their corresponding histograms. (Original image courtesy of Dr. Roger Heady, Research School of Biological Sciences, Australian National University, Canberra, Australia.)

Histogram equalization

Results: enhances contrast for brightness values near histogram maxima, decreases contrast near minima.

Let r represent grey levels of the image.

Let r be normalised in [0, L-1], where

r = 0 represents black

r = L - 1 represents white

Histogram equalization

We consider transformations of the form:

$$s = T(r), 0 \le r \le L - 1$$

Also assume that T(r) satisfies:

- a) T(r) is single-valued and monotonically increasing in $0 \le r \le L-1$
- b) $0 \le T(r) \le L-1$ for $0 \le r \le L-1$
- a) guarantees that the inverse transformation exists, and monotonicity preserves pixel order
- b) guarantees that output grey levels will be in the same range as input levels

Histogram equalization ctd

Let's assume that r & s are continuous intensities

- r and s may be viewed as random variables over [0, L-1], with PDFs $p_r(r)$ and $p_s(s)$

If $p_r(r)$ and T(r) are known and $T^{-1}(s)$ satisfies monotonocity, then, from probability theory:

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

If we choose:

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

This is the CDF of random variable r and this function satisfies (a) and (b)

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

$$p_{s(S)} = p_{r(r)} \left| \frac{1}{(L-1)p_r(r)} \right| = \frac{1}{L-1}, 0 \le s \le L-1$$

This is a uniform distribution!

Histogram equalization ctd

For discrete values, we get probabilities and summations instead of p.d.fs and integrals:

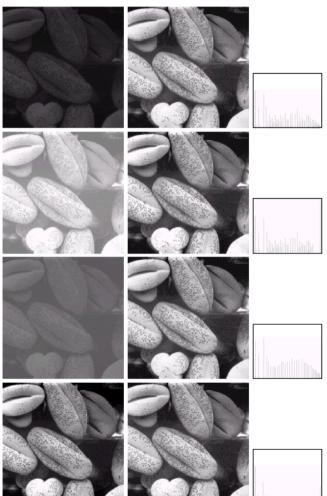
$$p_r(r_k) = n_k / MN, k = 0, 1, ..., L - 1$$

where MN is total number of pixels in image, n_k is number of pixels with gray level r_k and L is total number of gray levels

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

$$k = 0, 1, ..., L-1$$

This transformation is called *histogram equalization*. However, in practical applications, getting a perfectly uniform distribution (in discrete version) is rare.



a b c

FIGURE 3.17 (a) Images from Fig. 3.15. (b) Results of histogram equalization. (c) Corresponding histograms.

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Histogram Matching

Let's assume that r and s are continuous intensities and $p_z(z)$ is the target distribution for the output image.

- From before we know that

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

has uniform distribution

Similarly we can define a function G(z) as:

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

Therefore:

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

Histogram Matching ctd

For discrete values, we can write:

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

and

$$G(z_q) = (L-1)\sum_{i=1}^q p_z(z_i)$$

therefore:

$$z_q = G^{-1}(s_k)$$

Histogram Matching Example

r_k	n_k	$p_r(r_k) = \frac{n_k}{MN}$	
$r_0 = 0$	790	0.19	
$r_1 = 1$	1023	0.25	
$r_2 = 2$	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	

$$s_k = 7 * \sum_{j=0}^k p_r(r_j)$$



S_k	
1	
3	
5	
6	
6	
7	
7	
7	

Histogram Matching Example (ctd)

Z_q	$p_z(z_q)$
$z_0 = 0$	0.00
$z_1 = 1$	0.00
$z_2 = 2$	0.00
$z_3 = 3$	1.15
$z_4 = 4$	0.20
$z_5 = 5$	0.30
$z_6 = 6$	0.20
$z_7 = 7$	0.15

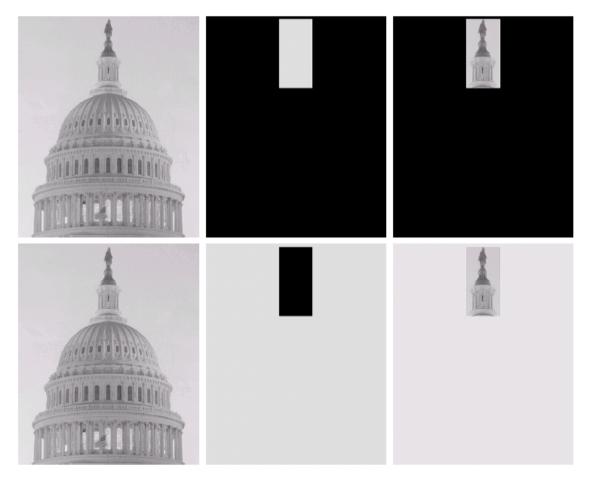
$$G(z_k) = 7 * \sum_{i=0}^q p_z(z_i)$$

Round the number

$G(z_q)$		s_k	Z_q
0		1	3
0		3	4
0		5	5
1		6	6
2		7	7
5			
6			
7	<i>y</i>		

Arithmetic/Logic Operations

- On pixel-by-pixel basis between 2 or more images
- AND and OR operations are used for maskingselecting subimages as Rol
- Subtraction and addition are the most useful arithmetic operations



a b c d e f

(a) Original image. (b) AND image mask. (c) Result of the AND operation on images (a) and (b). (d) Original image. (e) OR image mask. (f) Result of operation OR on images (d) and (e).

Image Averaging

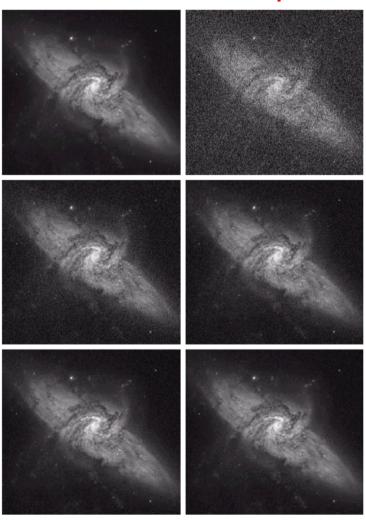
 Noisy image g (x, y) formed by adding noise n (x, y) to uncorrupted image f (x, y):

$$g(x, y) = f(x, y) + n(x, y)$$

- Assume that at each (x, y), the noise is uncorrelated and has zero average value.
- **Aim:** To obtain smoothed result by adding a set of noisy images $g_i(x, y)$, i = 1, 2, ..., K

$$g(x,y) \approx \frac{1}{K} \sum_{i=1}^{K} g_i(x,y)$$

- As K increases, the variability of the pixel values decreases
- Assumes that images are spatially registered



a b c d e f

FIGURE 3.30 (a) Image of Galaxy Pair NGC 3314. (b) Image corrupted by additive Gaussian noise with zero mean and a standard deviation of 64 gray levels. (c)–(f) Results of averaging K=8,16,64, and 128 noisy images. (Original image courtesy of NASA.)

References and Acknowledgements

- Chapter 3, Gonzalez and Woods 2002
- Szeliski 3.1-3.3
- Some slides and all images drawn from above resources