Image Restoration

Restoration vs Enhancement

- Restoration attempts to recover an image that has been degraded by using a priori knowledge of the degradation phenomenon.
- Restoration techniques are oriented towards modelling the degradation and applying the inverse process in order to recover the original image.
- In contrast, enhancement techniques basically are heuristic procedures designed to manipulate an image in order to take advantage of the psychophysical aspects of the HVS.
- For example, contrast stretching is an contrast enhancement technique because it is based primarily on the pleasing aspects it might present to the viewer.
- Removal of blur is considered a restoration technique.

Example

$\underline{y} = D\underline{H}\underline{x} + n$

LR

$D = I \rightarrow$ Deblurring

$DH = I \rightarrow$ Denoising

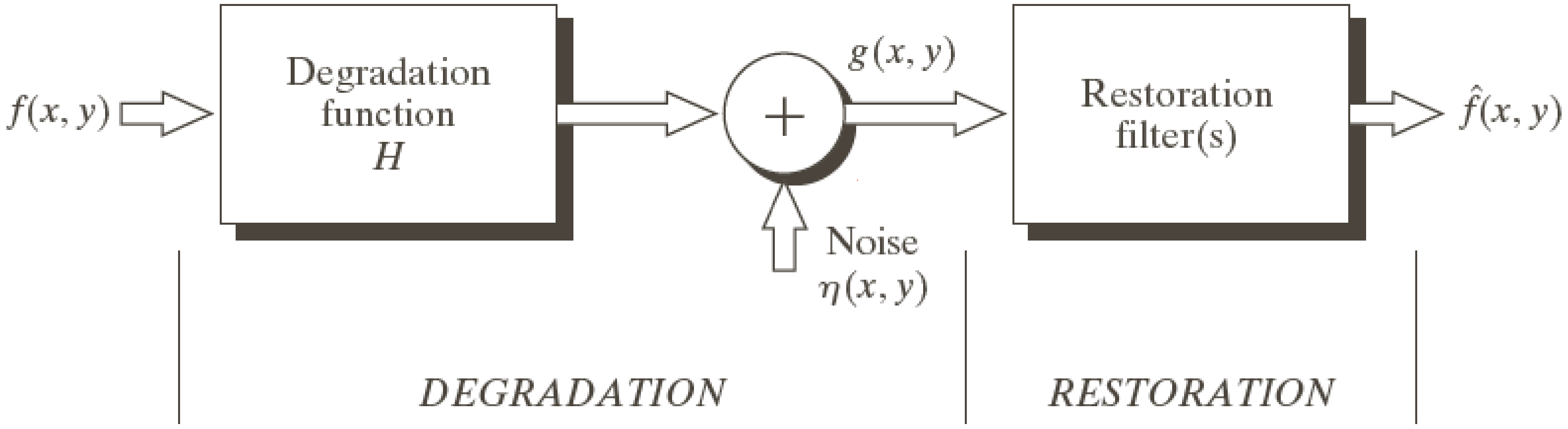
else

x from $y \rightarrow$ SR

A Model of the Image Degradation/Restoration Process

- Spatial Domain: $g(x,y) = h(x,y) \circledast f(x,y) + \eta(x,y)$
- Frequency Domain: $G(u,v) = H(u,v)F(u,v) + N(u,v)$

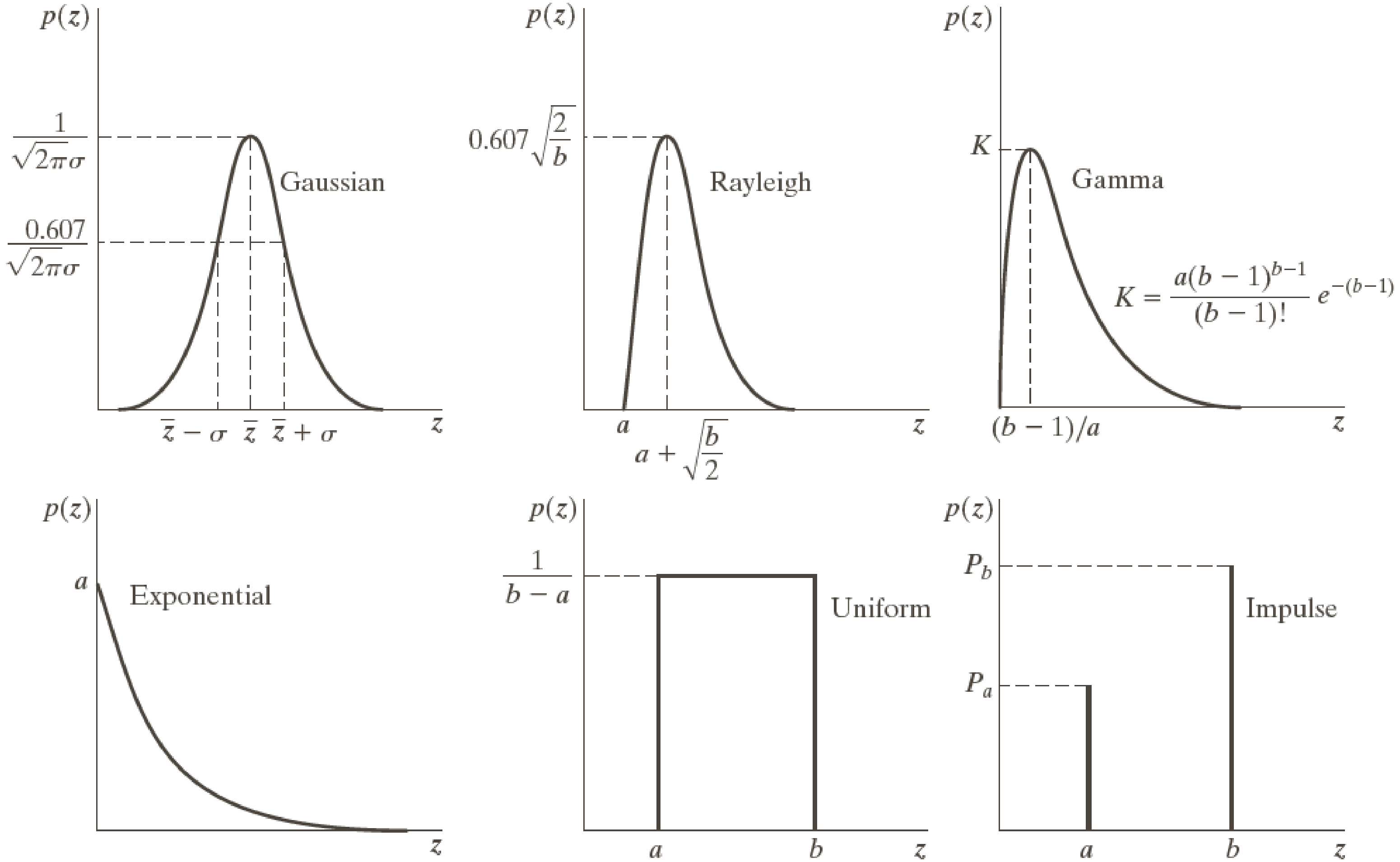
FIGURE 5.1 A model of the image degradation/restoration process.



Noise Sources

- The main sources of noise in image are during acquisition and transmission.
- Light level and sensor temperature are major factors affecting the amount of noise in acquisition.
- Images are corrupted during transmission principally due to interference in the channel used for transmission
- Lightning or other atmospheric disturbances.

Noise Models



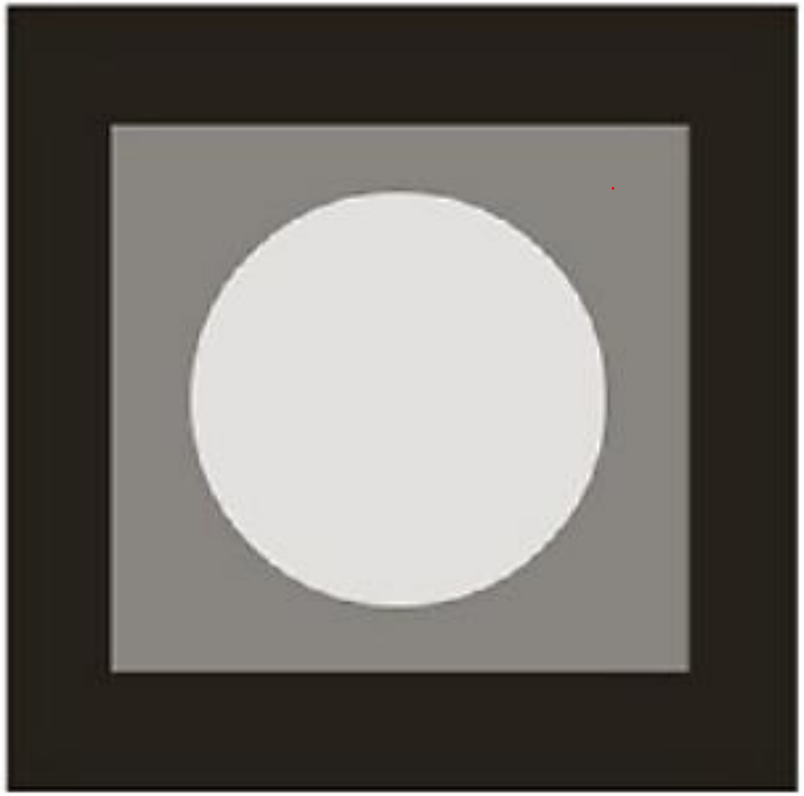
a b c
d e f

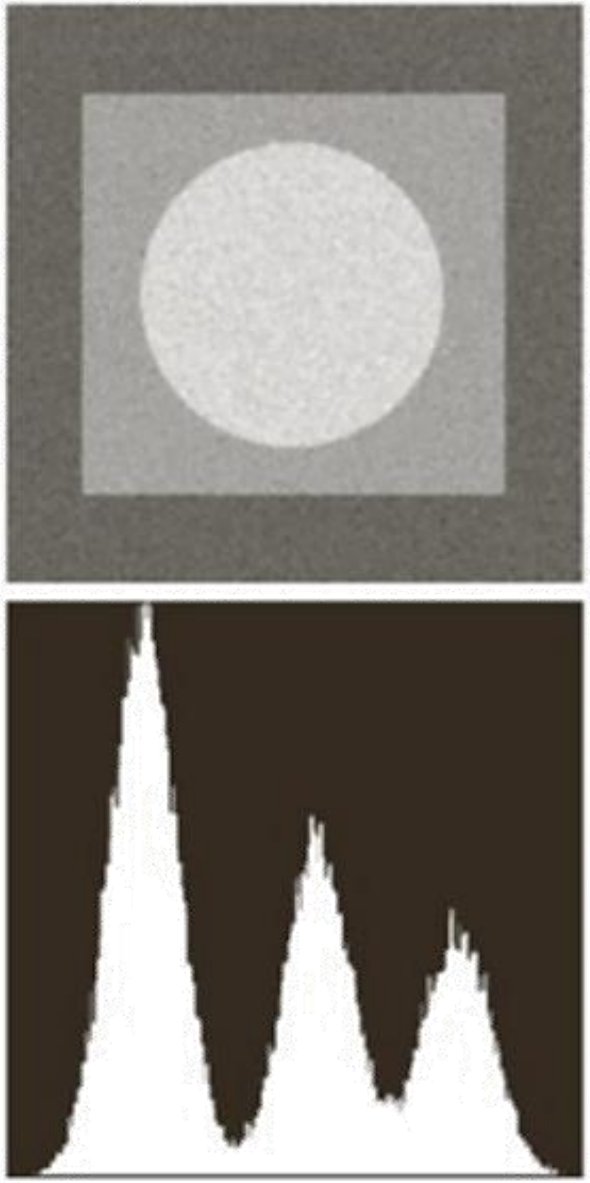
FIGURE 5.2 Some important probability density functions.

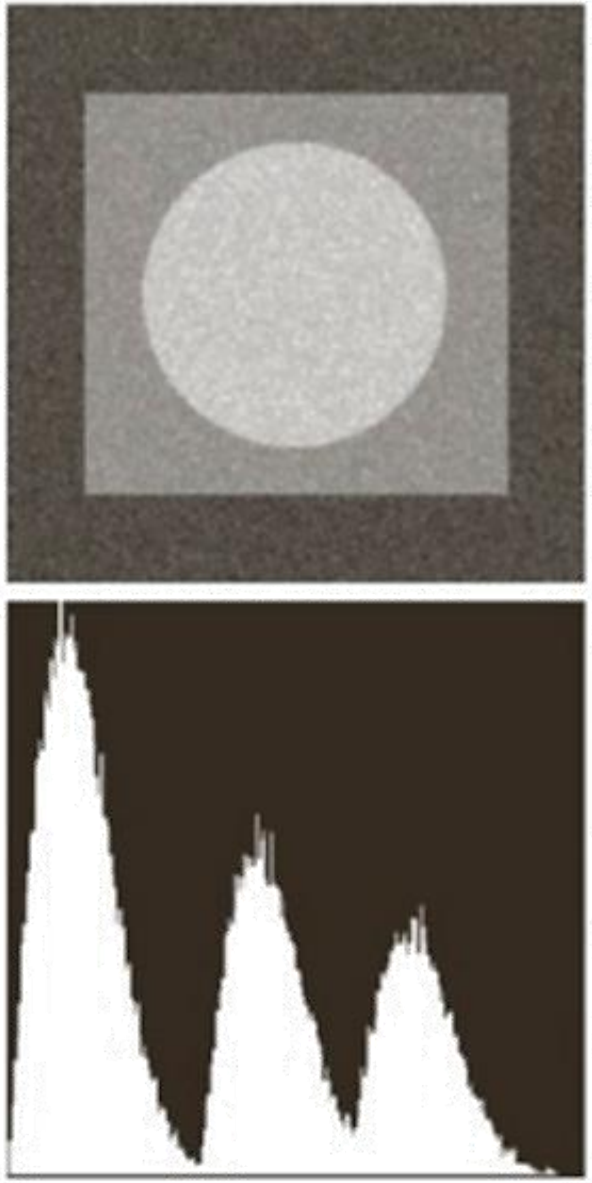
Applications of Noise Models

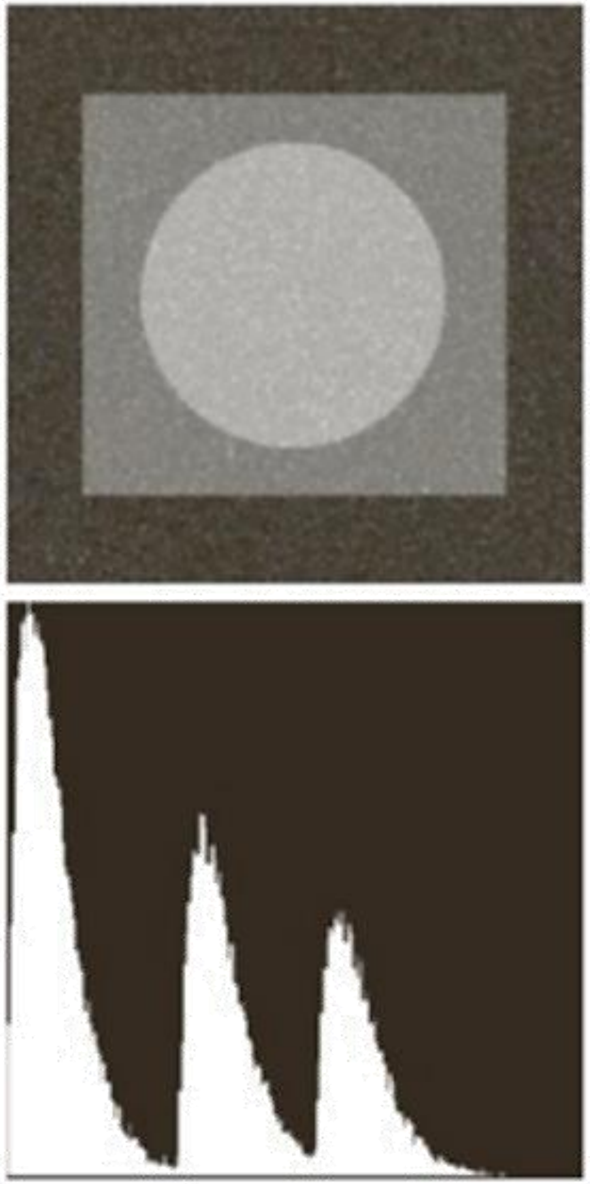
- Gaussian noise arises in an image due to factors such as electronic circuit noise and sensor noise due to poor illumination and/or high temperature.
- Rayleigh density is helpful in characterizing noise phenomenon in range imaging
- The exponential and gamma densities have application in laser imaging.
- Impulse noise is found in situations where quick transients, such as faulty switching, take place during recording.
- Uniform is the least descriptive of practical situations (helpful for random number generators that are used in simulations)

Noise model: Visualization

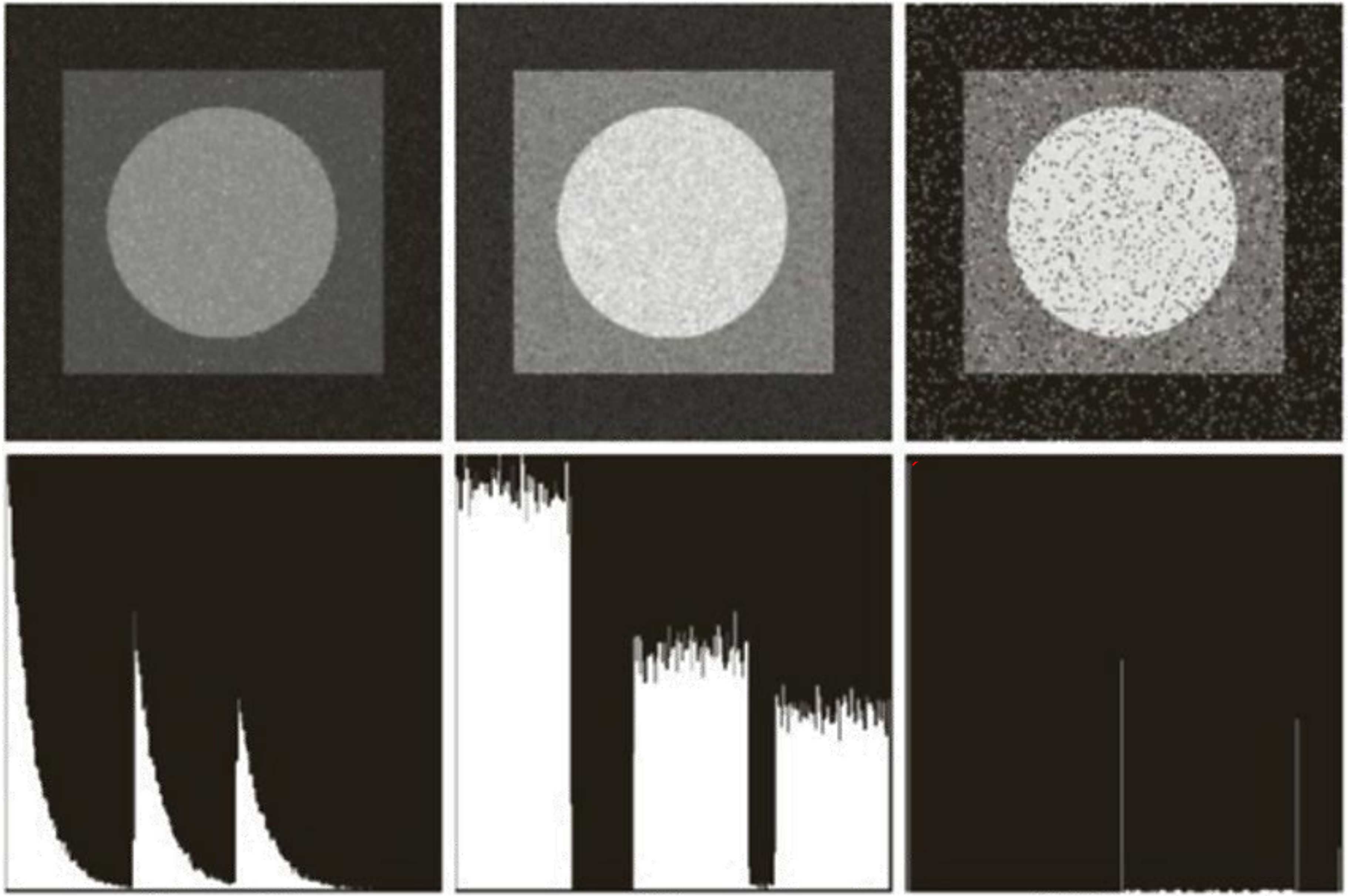








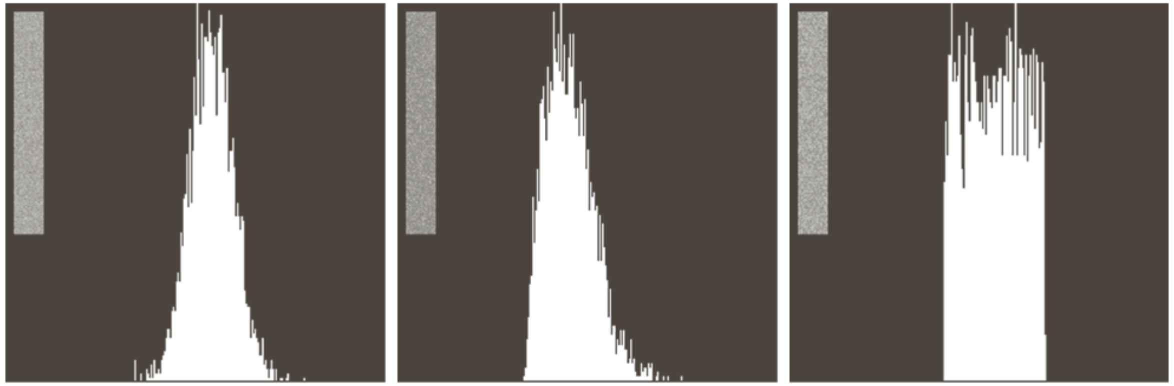
Gaussian Rayleigh Gamma



Exponential Uniform Salt & Pepper

Estimation of Noise Parameter- The basic way

- Consider a small vertical strip of reasonably constant background intensity.



a b c

FIGURE 5.6 Histograms computed using small strips (shown as inserts) from (a) the Gaussian, (b) the Rayleigh, and (c) the uniform noisy images in Fig. 5.4.

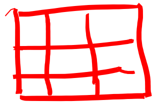
- Compute $p_s(z_i), \mathrm{i} = 1,2, \ldots, \mathrm{L} - 1$ (normalized histogram values of the intensities of the strip)
- $\bar{z} = \sum_{i=0}^{L-1} z_i p_s(z_i)$ & $\sigma^2 = \sum_{i=0}^{L-1} (z_i - \bar{z})^2 p_s(z_i)$

Restoration in the presence of Noise only

- Mean filters
  - Arithmetic mean filter
  - Geometric mean filter
  - Contraharmonic mean filter
- Order statistic filters
  - Median Filter
  - Max and Min filter
  - Mid point Filter
- Noise removal by frequency domain filters

Arithmetic and Geometric Mean Filters

S_{xy}



- Arithmetic mean filter

$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s, t)$$

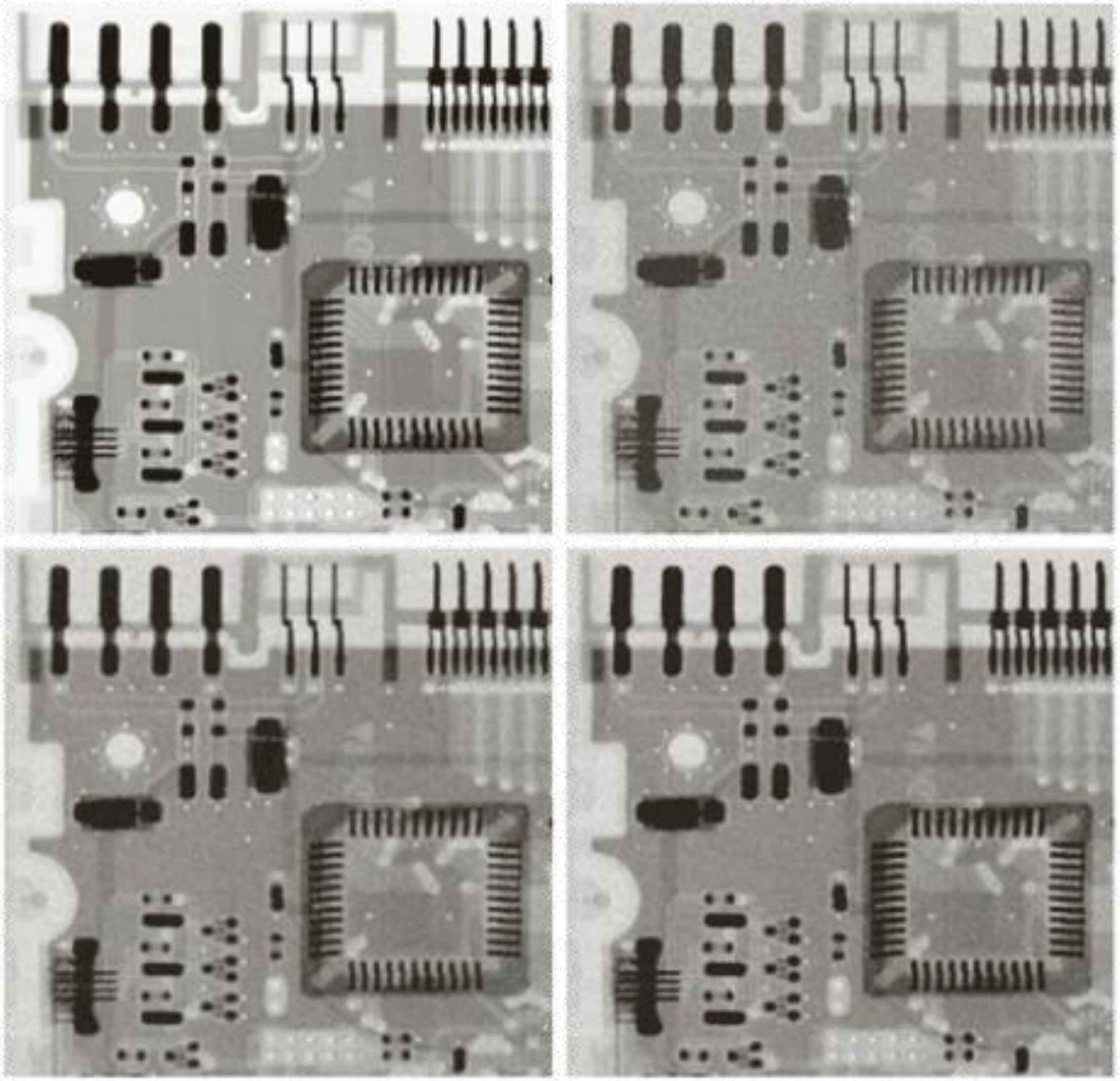
- Geometric mean filter

$$\hat{f}(x, y) = \left[\prod_{(s,t) \in S_{xy}} g(s, t) \right]^{\frac{1}{mn}}$$

Results

a b
c d

FIGURE
(a) X-ray image. (b) Image corrupted by additive Gaussian noise. (c) Result of filtering with an arithmetic mean filter of size 3 × 3. (d) Result of filtering with a geometric mean filter of the same size. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)



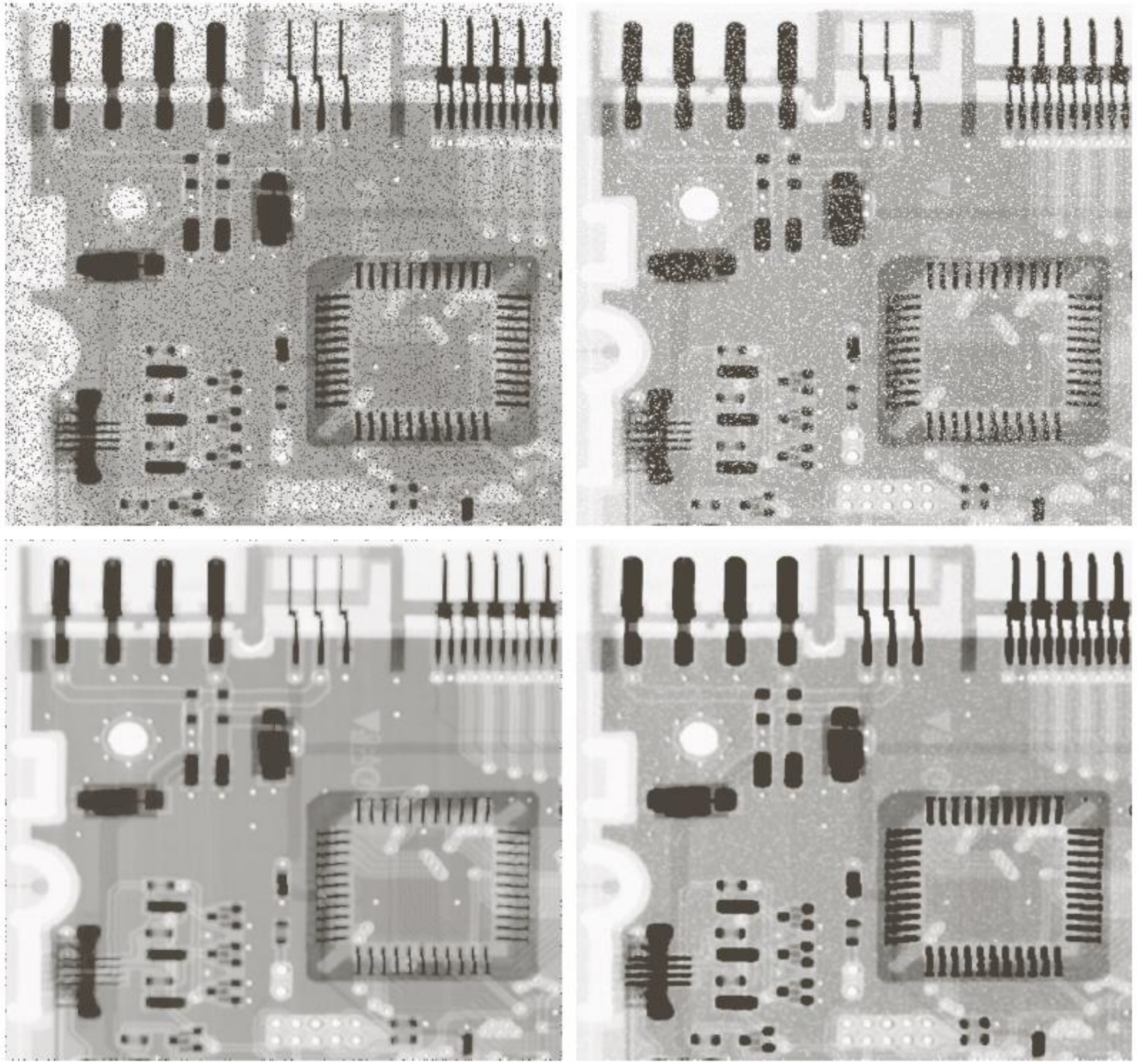
Contraharmonic Mean Filter

- It restores image based on the expression

$$\hat{f}(x, y) = \frac{\sum_{(s,t)\in S_{xy}} g(s,t)^{Q+1}}{\sum_{(s,t)\in S_{xy}} g(s,t)^{Q}}$$

- For Q>0, it eliminates pepper noise
- For Q<0, it eliminates salt noise
- For Q=0, it becomes arithmetic mean filter
- For Q=-1, it becomes harmonic mean filter (works well for salt noise but fails for pepper noise)

Results



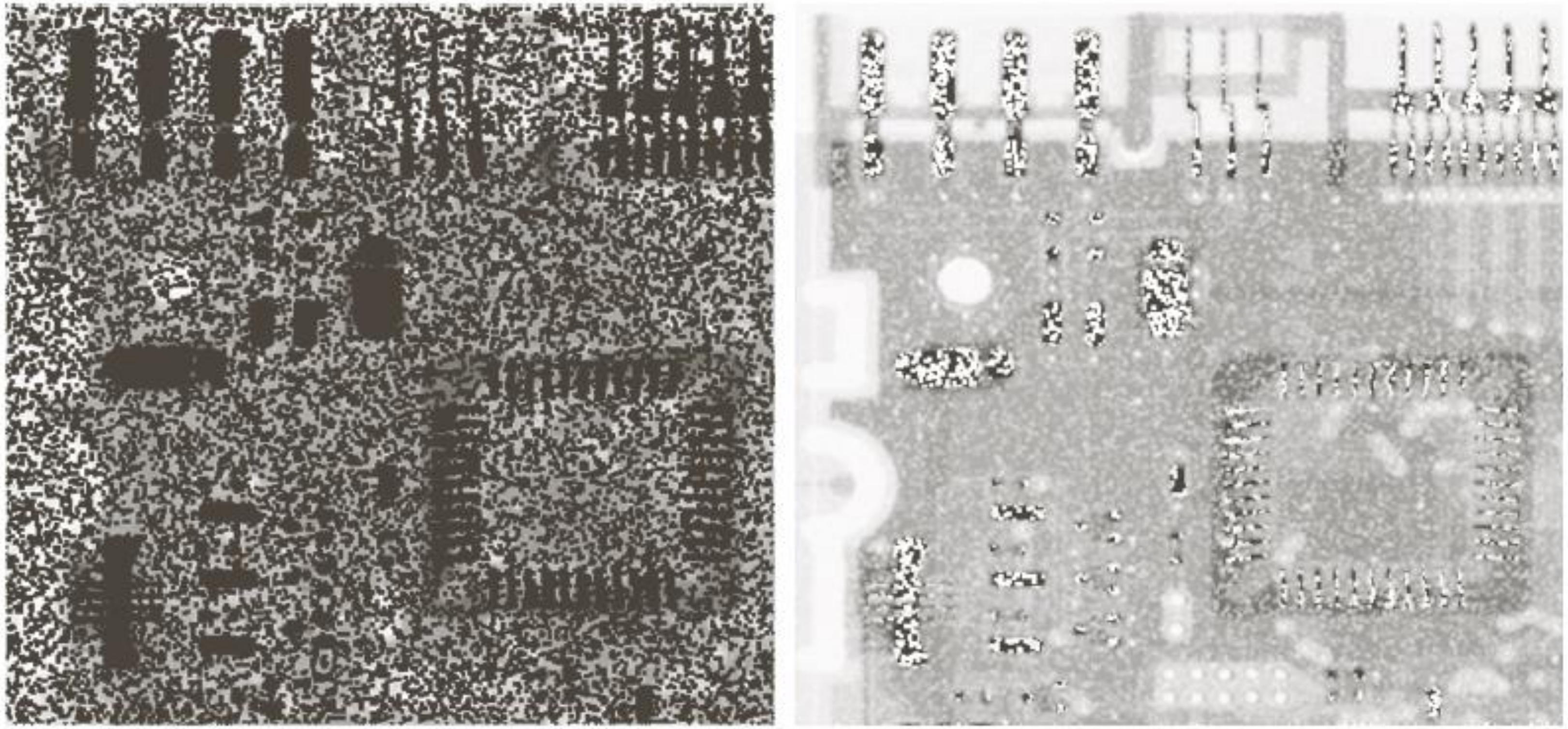
a b
c d

FIGURE 5.8 (a) Image corrupted by pepper noise with a probability of 0.1. (b) Image corrupted by salt noise with the same probability. (c) Result of filtering (a) with a 3 × 3 contra-harmonic filter of order 1.5. (d) Result of filtering (b) with $Q = -1.5$.

Q = 1.5

Q = -1.5

Results



a b

FIGURE 5.9 Results of selecting the wrong sign in contraharmonic filtering. (a) Result of filtering Fig. 5.8(a) with a contraharmonic filter of size 3×3 and $Q = -1.5$. (b) Result of filtering 5.8(b) with $Q = 1.5$.

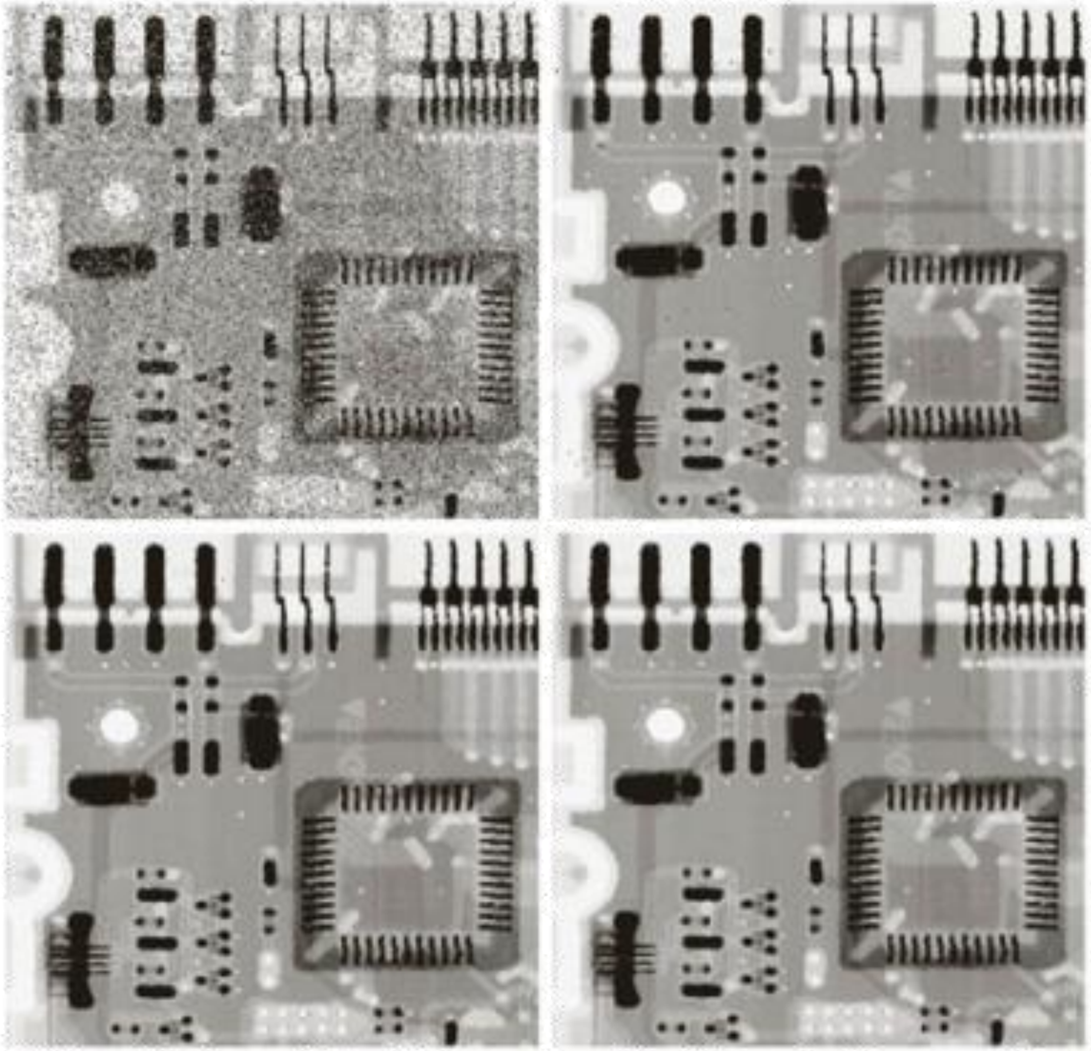
Order-Statistic Filter

- Median Filter
  - Replaces the value of a pixel by the median of the intensity levels in the neighborhood of that pixel

$$\hat{f}(x, y) = \underset{(s,t) \in S_{xy}}{\text{median}}\{g(s, t)\}$$

  - Median filters are practically effective in the presence of both bi-polar and unipolar impulse noise.

Results



a b
c d

FIGURE (a) Image corrupted by salt-and-pepper noise with probabilities $P_a = P_b = 0.1$. (b) Result of one pass with a median filter of size 3×3. (c) Result of processing (b) with this filter. (d) Result of processing (c) with the same filter.

Max, Min and Midpoint Filters

- Pepper noise can be reduced by max filter

$$\hat{f}(x, y) = \max_{(s,t)\in S_{xy}} \{g(s, t)\}$$

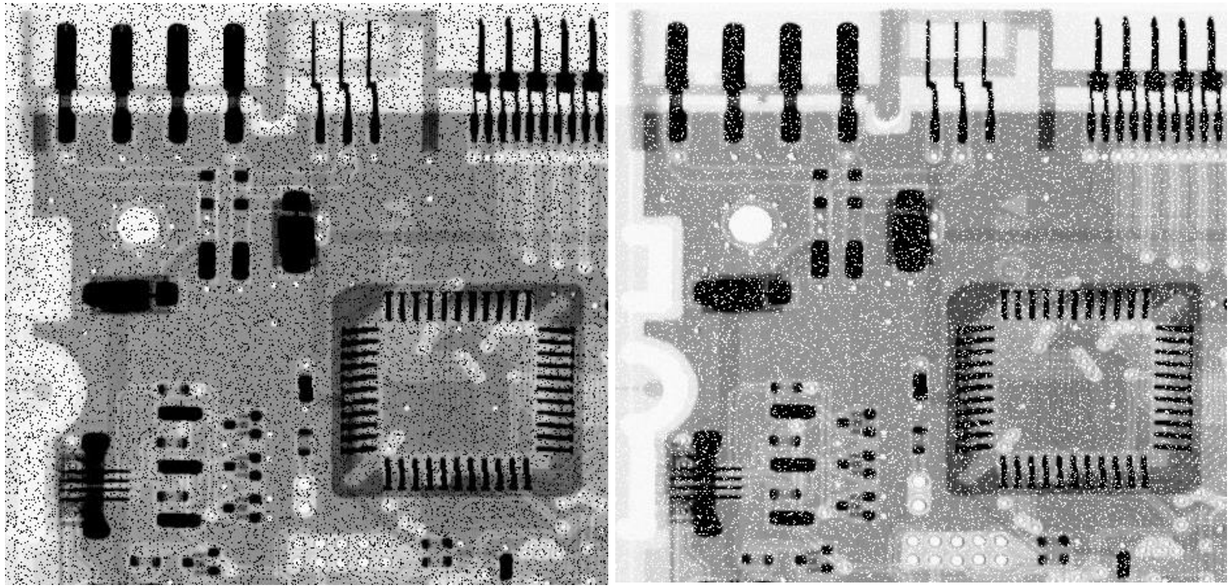
- Salt noise can be reduced by min filter

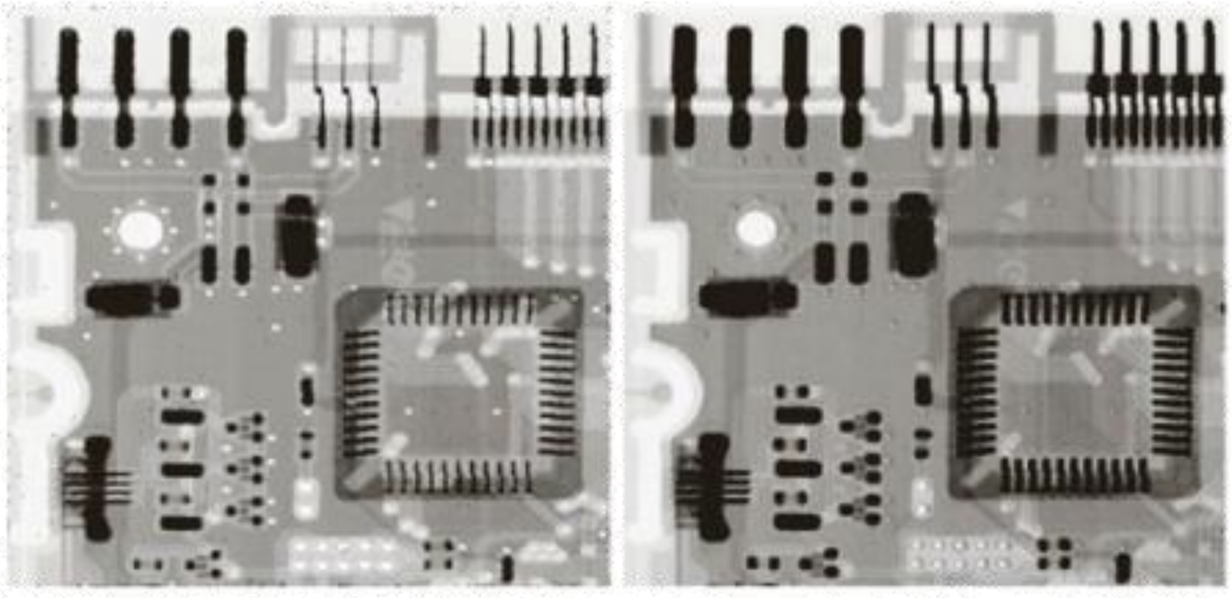
$$\hat{f}(x, y) = \min_{(s,t)\in S_{xy}} \{g(s, t)\}$$

- Midpoint filter computes the midpoint between max and in values in the area encompasses by the filter:

$$\hat{f}(x, y) = \frac{1}{2}\left[\max_{(s,t)\in S_{xy}} \{g(s, t)\} + \min_{(s,t)\in S_{xy}} \{g(s, t)\}\right]$$

Results





a b

FIGURE
(a) Result of filtering Fig. 5.8(a) with a max filter of size 3 × 3. (b) Result of filtering 5.8(b) with a min filter of the same size.

$$\hat{f}(x,y) = g(x,y) - \frac{\sigma_n^2}{\sigma_L^2}\left[g(x,y) - m_L\right]$$

Results of adaptive filter

S_{xy}

(i) $g(x,y)$: noisy pixel's ima

(ii) σ_n^2 : variance of noise.

(iii) m_L : mean of a local region

(iv) σ_L^2 : local variance

(a) $\hat{f}(x,y) = g(x,y)$ if $\sigma_n^2 \to 0$

(b) $\sigma_L^2 > \sigma_n^2$

$\hat{f}(x,y) \approx g(x,y)$

(c) $\sigma_L^2 == \sigma_n^2$

$\hat{f}(x,y) = m_L$

a	b
c	d

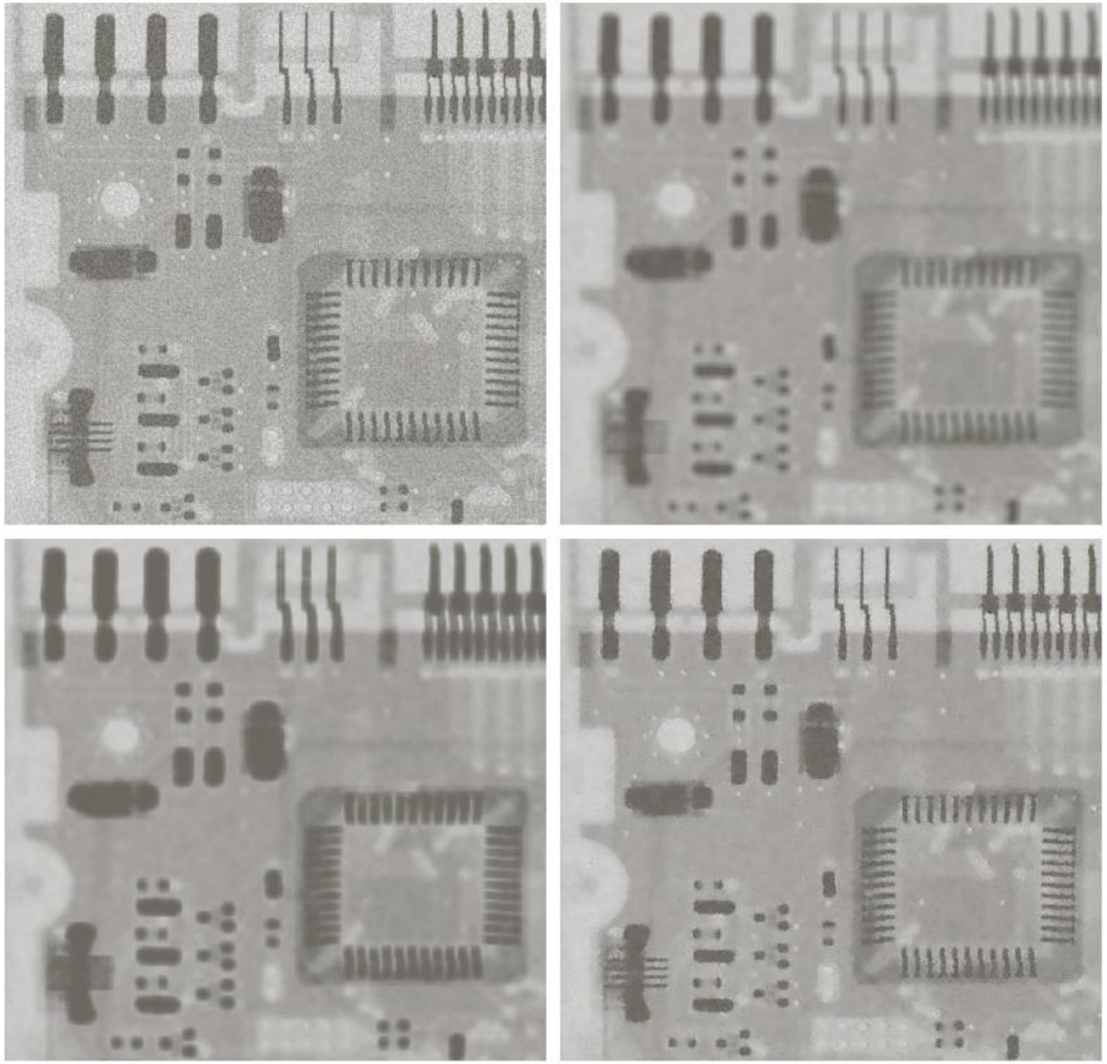
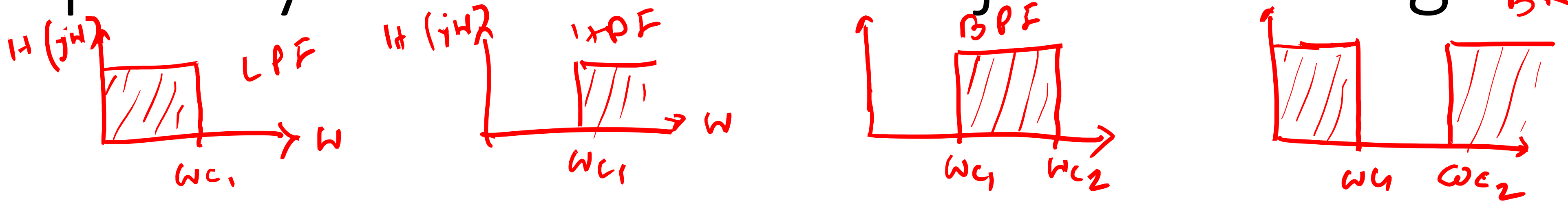


FIGURE 5.13 (a) Image corrupted by additive Gaussian noise of zero mean and variance 1000. (b) Result of arithmetic mean filtering. (c) Result of geometric mean filtering. (d) Result of adaptive noise reduction filtering. All filters were of size 7 × 7.

Frequency Domain-Band Reject Filtering

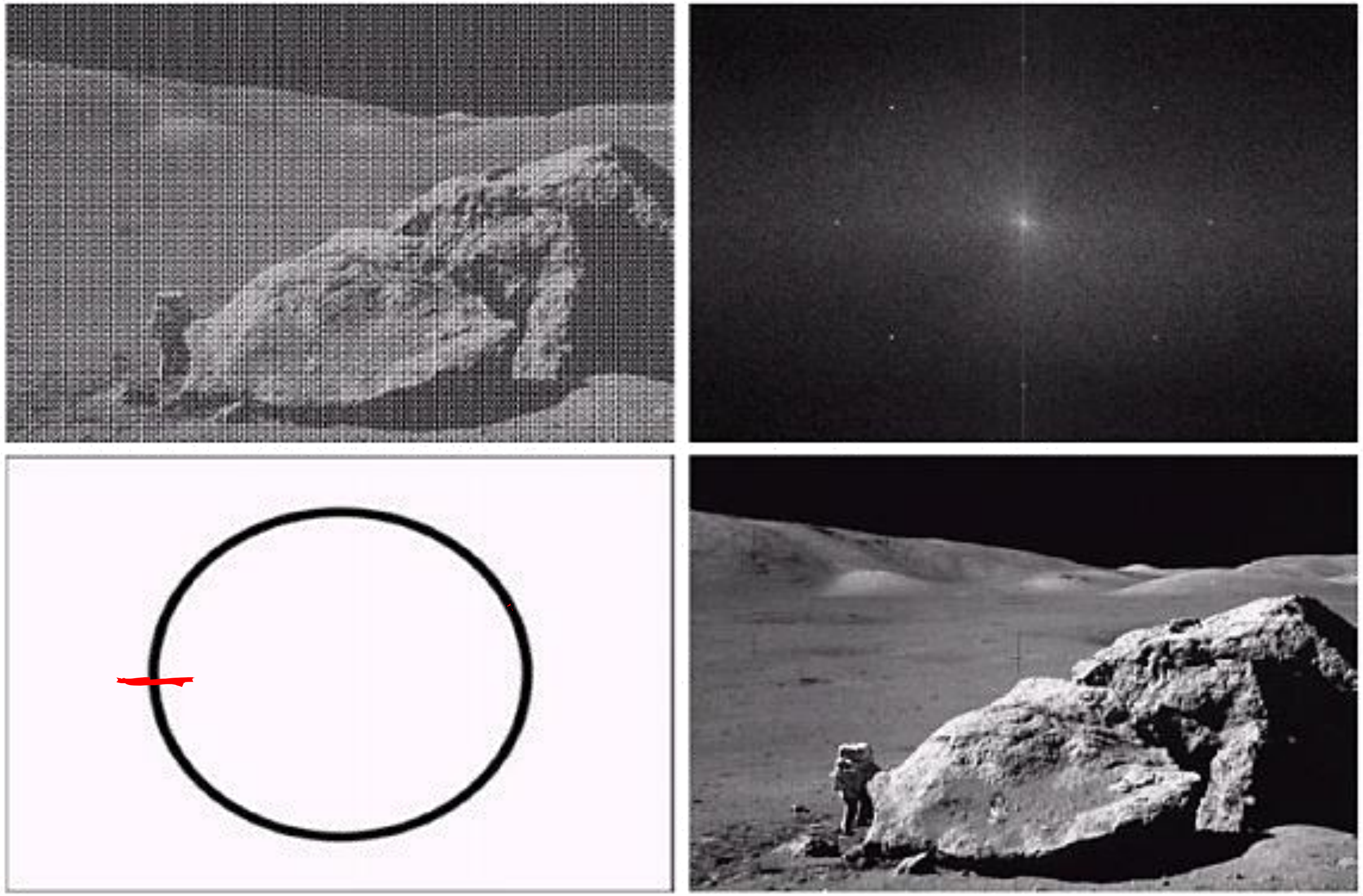
BRF / BSF



a b c

FIGURE 5.15 From left to right, perspective plots of ideal, Butterworth (of order 1), and Gaussian bandreject filters.

Results

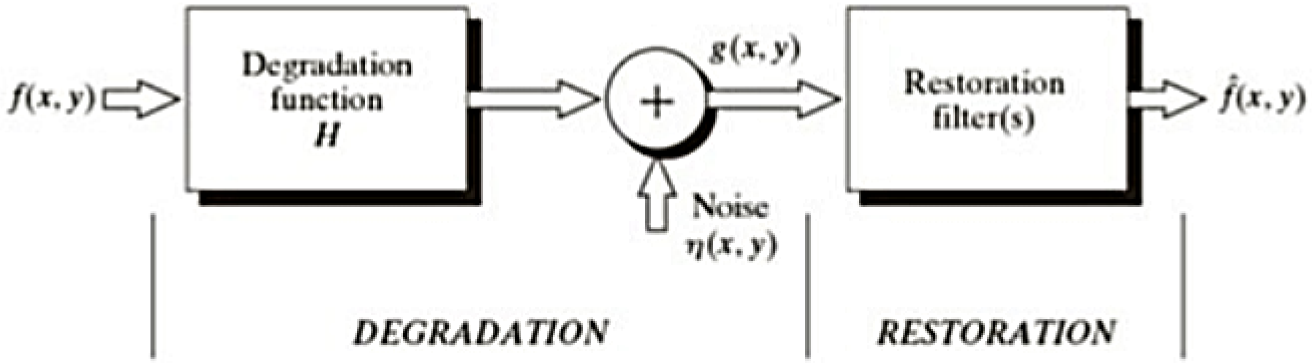


a b
c d

(a) Image corrupted by sinusoidal noise. (b) Spectrum of (a). (c) Butterworth bandreject filter (white represents 1). (d) Result of filtering. (Original image courtesy of NASA.)

The Model

$g(x,y) = \underline{f(x,y) * h(x,y)} + \underline{\eta(x,y)}$



Estimation of Degradation Function

- Estimation by image observation
- Estimation by experimentation
- Estimation by modeling

Estimation by image observation

$G(u,v) = H(u,v)\,F(u,v)$

$H(u,v) = \frac{G(u,v)}{F(u,v)}$

- Looking for an area, in which signal content is strong.
- Process that area to make it as clean as possible.
- Let the observed part is $g_s(x, y)$ and let the processed part is $\widehat{f_s}(x, y)$

$$H_s(u, v) = \frac{G_s(u, v)}{\hat{F}_s(u, v)}$$

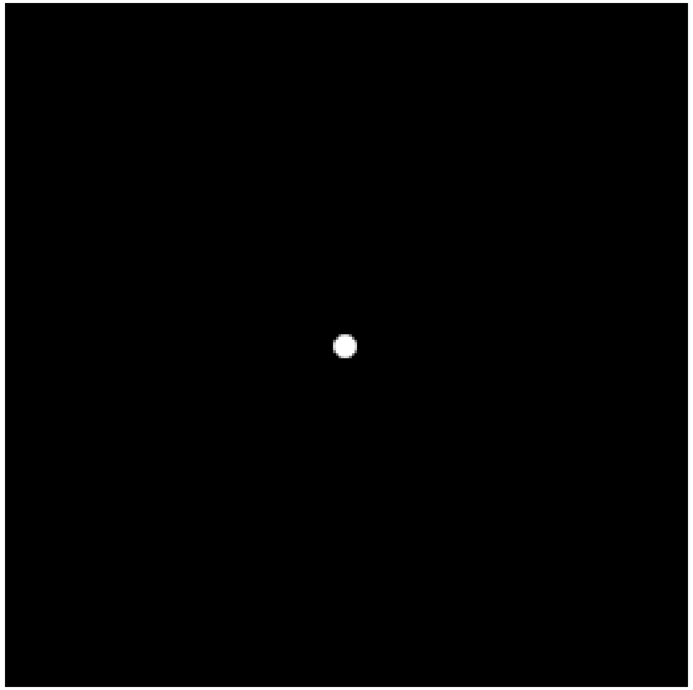
- Complete degradation function H(u,v) can be deduced.

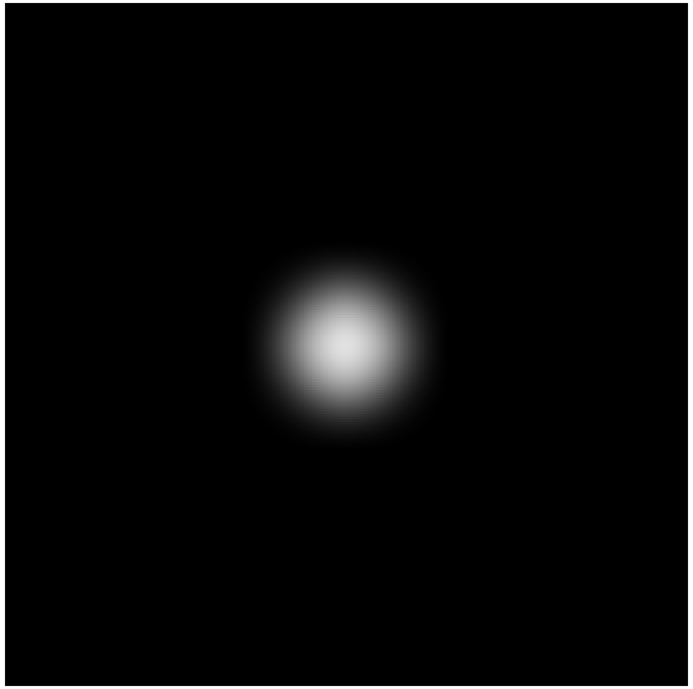
Estimation by Experimentation

- If equipment similar to the equipment used to capture the degraded image, it is possible to estimate the degradation function.
- Manipulate some of the settings of your image capturing device to capture an image, which is degraded as the observed one.
- Using same system settings capture the impulse response, which will be constant value A in frequency domain.

$$H(u, v) = \frac{G(u, v)}{A}$$

Degradation Estimation by Impulse





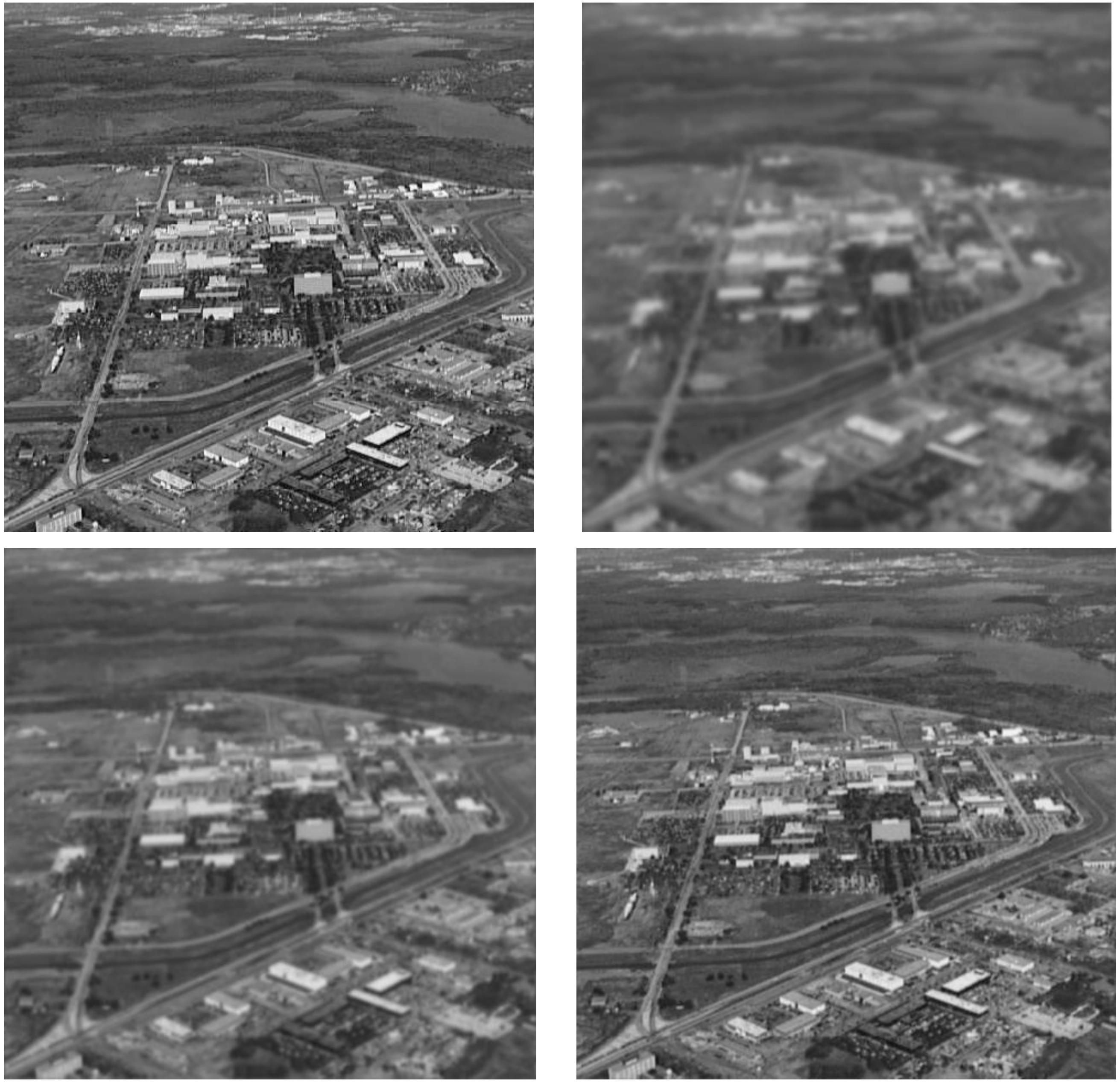
Estimation by modeling

- Model can take into account environmental conditions that cause degradations.
- Hufnagel and Stanley [1964] proposed a degradation model based on the physical characteristics of atmospheric turbulence. This model has the form:

$$H(u, v) = e^{-k(u^2+v^2)^{5/6}}$$

Results

Illustration of the atmospheric turbulence model. (a) Negligible turbulence. (b) Severe turbulence, $k = 0.0025$. (c) Mild turbulence, $k = 0.001$. (d) Low turbulence, $k = 0.00025$. (Original image courtesy of NASA.)



Results

a b

FIGURE 5.26 (a) Original image. (b) Result of blurring using the function in Eq. (5.6-11) with $a = b = 0.1$ and $T = 1$.

Mathematical Modeling of Motion Blur:-

$$\begin{array}{ccc} f(x,y) & \longrightarrow & y_0(t) \\ \downarrow & & \\ x_0(t) & & \end{array}$$

$$g(x,y) = \int_0^T f\left[x - x_0(t),\; y - y_0(t)\right] dt$$

F. T

$$G(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x,y)\, e^{-j2\pi(ux+vy)}\, dx\, dy = \iint_{-\infty}^{\infty} \left[\int_0^T f\left[x - x_0(t),\; y - y_0(t)\right] dt\right] e^{-j2\pi(ux+vy)}\, dx\, dy$$

$$G(u,v) = \int_0^T \left[\iint_{-\infty}^{+\infty} f\left[x - x_0(t),\; y - y_0(t)\right] e^{-j2\pi(ux+vy)}\, dx\, dy\right] dt.$$

$$= \int_0^T F(u,v)\, e^{-j2\pi(ux_0(t) + vy_0(t))}\, dt.$$

$$G(u,v) = F(u,v) \underbrace{\int_0^T e^{-j2\pi(ux_0(t) + vy_0(t))}\, dt.}_{H(u,v)}$$

$x_0(t) = at/T$. $y_0(t) = 0$

$$H(u,v) = \int_0^T e^{-j2\pi u x_0(t)}\, dt$$

$$= \int_0^T e^{-j2\pi u \frac{at}{T}}\, dt$$

$$=$$