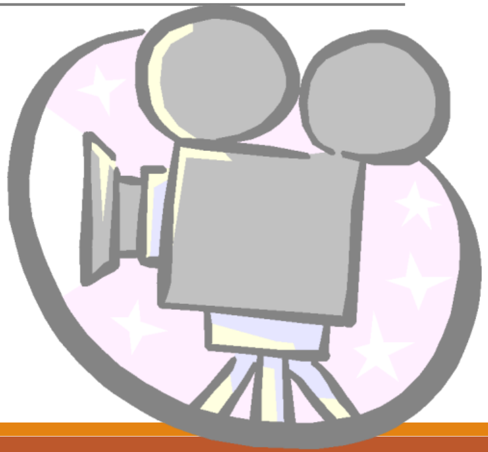
Image Processing

CS-317/CS-341



Outline

- Image Restoration
  - Noise Models
  - Image denoising

Image Restoration

- Restoration attempts to recover an image that has been degraded by using a priori knowledge of the degradation phenomenon.

- Restoration techniques are oriented towards modeling the degradation and applying the inverse process in order to recover the original image.

Image Restoration Example

- Contrast stretching is considered an enhancement technique because it is based primarily on the pleasing aspects, it might present to viewer.

- Removal of image blur by applying a deblurring function is considered a Restoration techniques.

Model of the Image Degradation

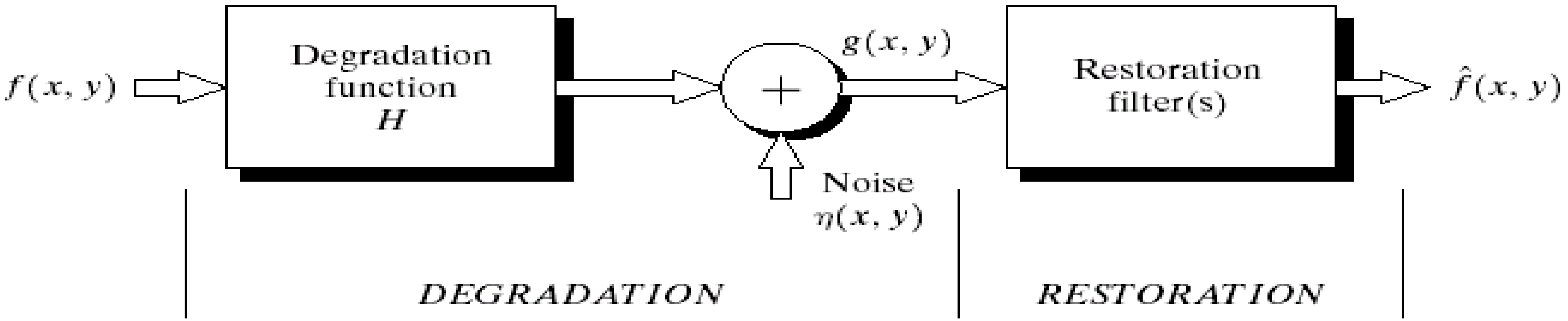


FIGURE 5.1 A model of the image degradation/ restoration process.

Model of the Image Degradation

Spatial Domain

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

$*$ Convolution Operator
h(x, y) is the spatial degradation function,
g(x, y) is degraded image

Frequency Domain

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

Objective of restoration To obtain an estimate $\hat{f}(x,y)$ of the original image, for given $g(x,y)$

Image Restoration

- Image Restoration
  - Denoising
  - Deblurring

Denoising

$$G(u,v) = F(u,v) + \eta(u,v)$$

Deblurring

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

Noise Model

- The principal sources of noise in digital images arise during image acquisition and/or transmission.

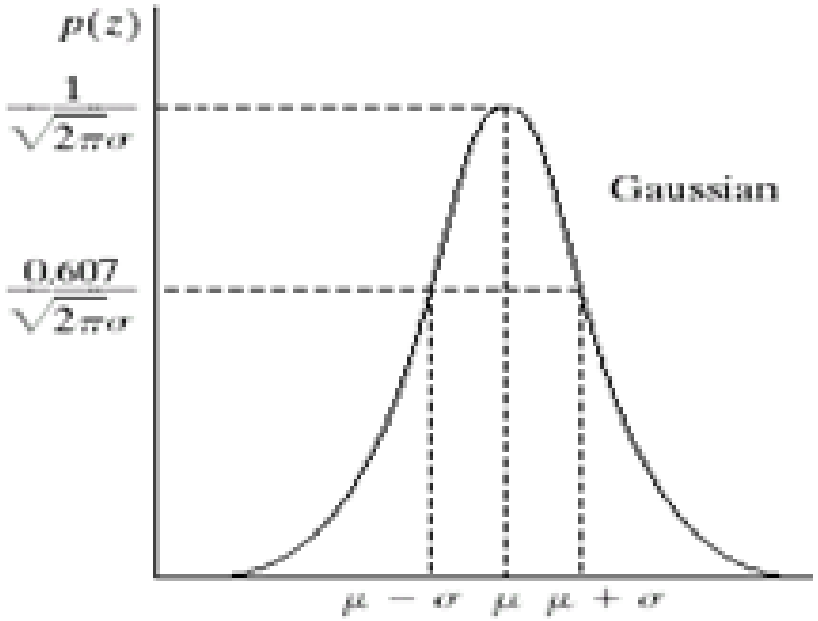
- The performance of imaging sensors is affected by a variety of factors such as environment condition during image acquisition and by the quality of sensing elements themselves.

- Images are corrupted during transmission principally due to interference in the channel used for transmission.

The spatial noise descriptor with which we shall be concerned is the statistical behavior of the intensity values in the noise component of the image restoration model .

These may be considered random variables characterized by a probability density function.

Noise Model



Gaussian noise:

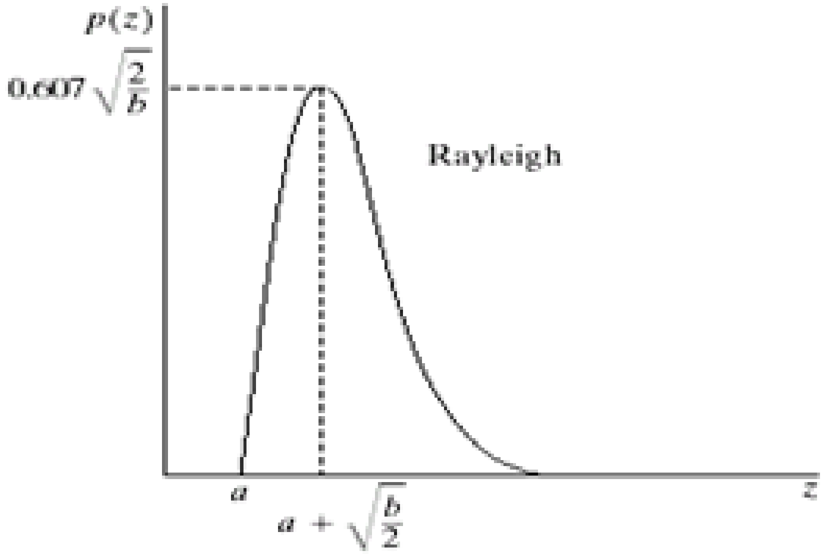
$$p(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2 / 2\sigma^2}$$

Z=intensity

Noise Model

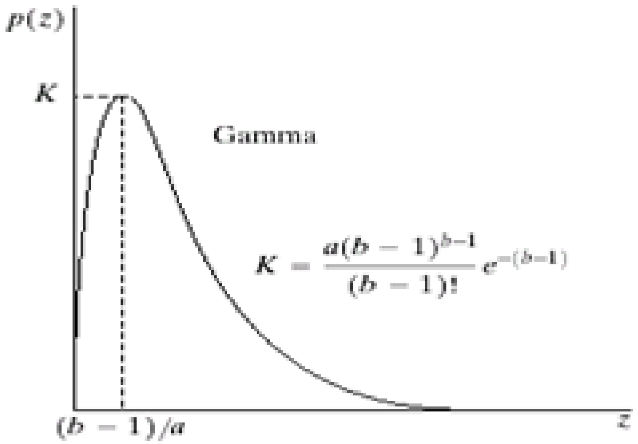
Rayleigh Noise:

$$p(z)=\begin{cases}\frac{2}{b}(z-a)e^{-(z-a)^2/b}, & for\ z\ge a\\ 0, & for\ z<a\end{cases}$$



$$\mu=a+\sqrt{\pi b/4}, \qquad \sigma^2=\frac{b(4-\pi)}{4}$$

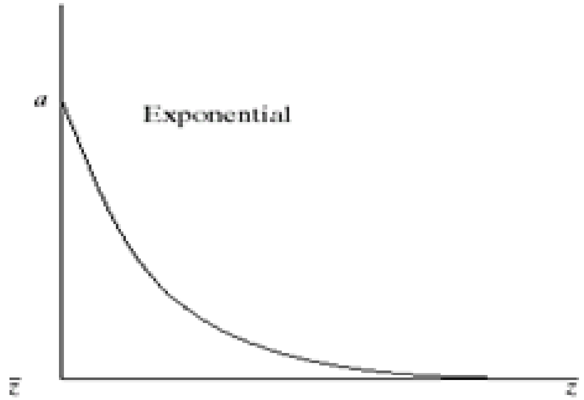
Erlang (Gamma) noise:



$$p(z) = \begin{cases} \frac{a^b z^{b-1}}{(b-1)!} e^{-az}, & for\ z \geq 0 \\ 0, \ \ for\ z < 0 \end{cases}$$

$$\mu = \frac{b}{a}, \qquad \sigma^2 = \frac{b}{a^2}$$

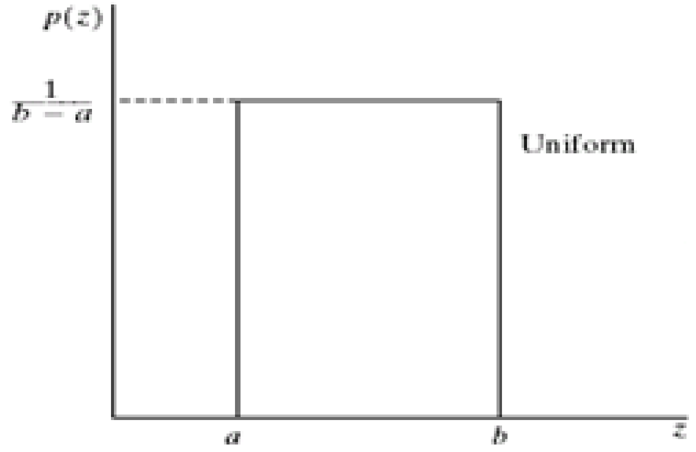
Exponential Noise:



$$p(z) = \begin{cases} ae^{-az}, & for\ z \geq 0 \\ 0, \ \ for\ z < 0 \end{cases}$$

$$\mu = \frac{1}{a}, \qquad \sigma^2 = \frac{1}{a^2}$$

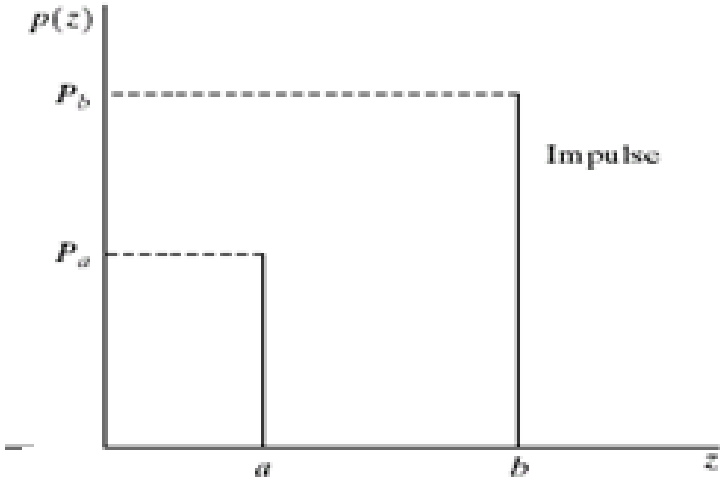
Special case of Erlang PDF ,with
b=1



Uniform noise:

$$p(z) = \begin{cases} \frac{1}{(b-a)}, & if \;\; a \le z \le b \\ 0, & \text{Otherwise} \end{cases}$$

$$\mu = \frac{a+b}{2}, \qquad \sigma^2 = \frac{(b-a)^2}{12}$$



Impulse (Salt – and –pepper) Noise:

$$p(z) = \begin{cases} P_a, & for \;\; z = a \\ P_b, & for \;\; z = b \\ 0, & Otherwise \end{cases}$$

$$\mu = \frac{1}{a}, \qquad \sigma^2 = \frac{1}{a^2}$$

Noise Model

Impulse (Salt – and –pepper) Noise:

$$p(z) = \begin{cases} P_a, & for\ z = a \\ P_b, & for\ z = b \\ 0, & Otherwise \end{cases}$$

$$\mu = \frac{1}{a}, \quad \sigma^2 = \frac{1}{a^2}$$

- *b*> *a*, gray level *b* will appear as light dot in the image. Conversely, level *a* will appear like dark dot.
- If either P_a or P_b is zero, the impulse noise is called unipolar.
- If neither probability is zero, and especially if they are approximately equal, impulse noise values will resemble salt-and-pepper granules randomly distributed over the image.
- Due to this reason bipolar noise is also called salt-and- pepper noise.
- Also Shot and spike noise term is used to refer this type of noise.

Noise Model

- ***Gaussian:*** Noise due to factors such as electronic circuit noise and sensor noise due to poor illumination and / or high temperature.
- ***Rayleigh:*** Rayleigh density is helpful in characterizing noise phenomena in range imaging.
- **Exponential and Gamma** density are found application in range imaging.
- **Impulse noise** is found in satuation where quick transients, such as faulty switching, takes place during imaging.
- **Uniform density** is useful as the basis for numerous random number generator.

Estimation of Noise Parameter

Noise is estimated using histogram

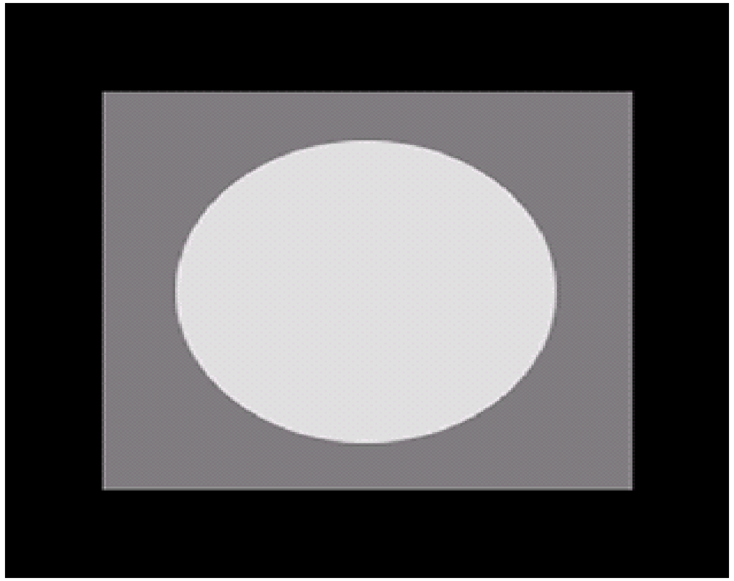


FIGURE 5.3 Test pattern used to illustrate the characteristics of the noise PDFs

$$\mu = \sum z_i p(z_i), \qquad \sigma^2 = \sum (z_i - \mu)^2 p(z_i)$$

Estimation of Noise Parameter

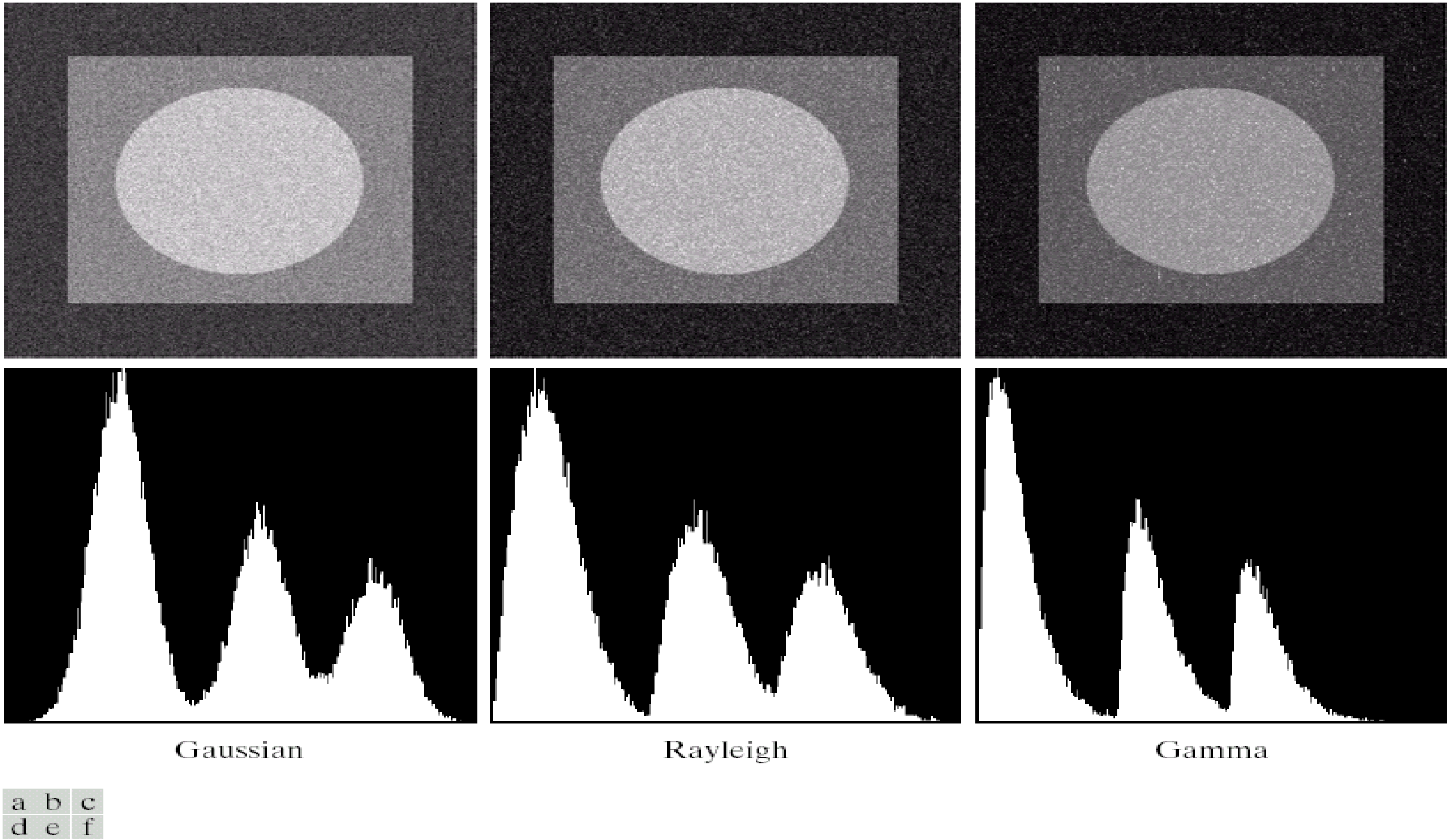


FIGURE 5.4 Images and histograms resulting from adding Gaussian, Rayleigh, and gamma noise to the image in Fig. 5.3.

Estimation of Noise Parameter

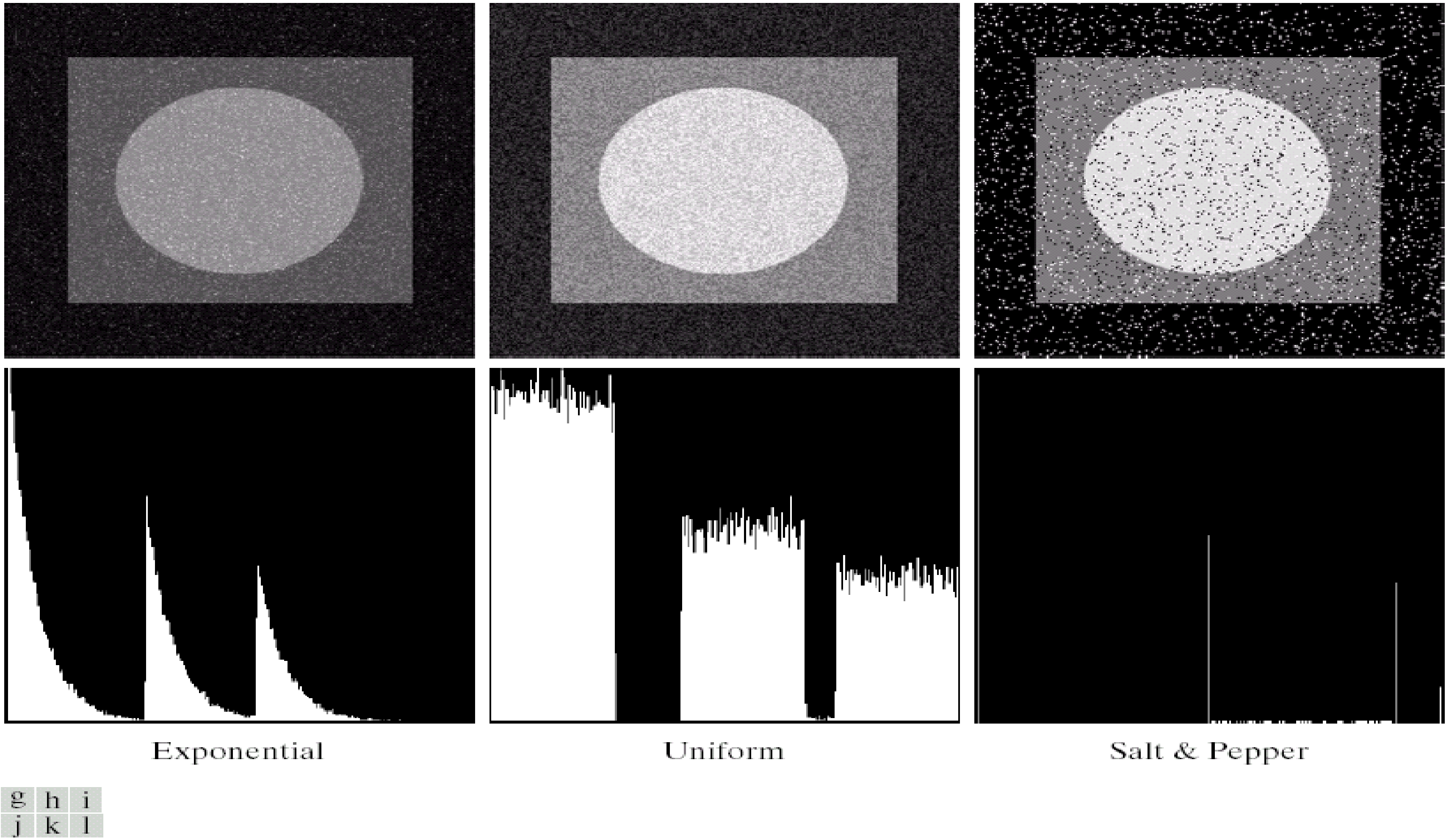


FIGURE 5.4 *(Continued)* Images and histograms resulting from adding exponential, uniform, and impulse noise to the image in Fig. 5.3.

De-noising using Spatial Filter

Spatial filtering is method of choice in situations when only additive noise is present.

$$g(x,y) = f(x,y) + \eta(x,y)$$

$$G(u,v) = F(u,v) + \eta(u,v)$$

Arithmetic Mean Filter

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

-Smoothes local variations in an image.

- Noise is reduced as a result of blurring

Harmonic Filter

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

-Works well for salt noise, Gaussian noise, but fails for pepper noise

Geometric Mean Filter

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

-Achieves smoothing comparable to the arithmetic mean filter.

-Lose less image detail in the process.

Contraharmonic Mean Filter

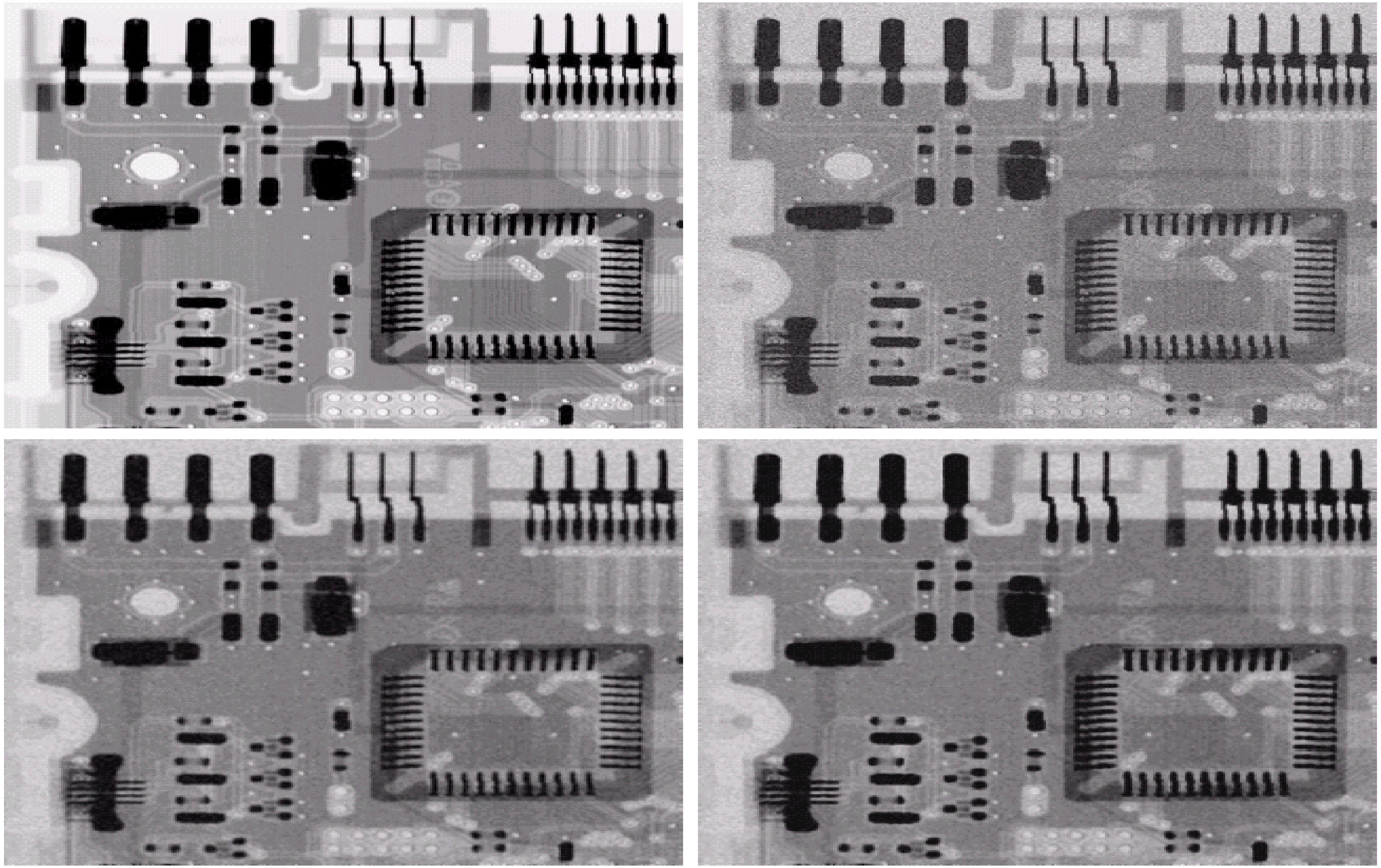
$$\hat{f}(x,y) = \frac{\sum_{s,t \in W_{mn}} g(s,t)^{Q+1}}{\sum_{s,t \in W_{mn}} g(s,t)^{Q}}$$

-This filter is well suited for salt-and- pepper noise. Q>0 for pepper and Q<0 for salt noise.

Q=0 , Arithmetic mean filter

Q=-1, Harmonic mean filter

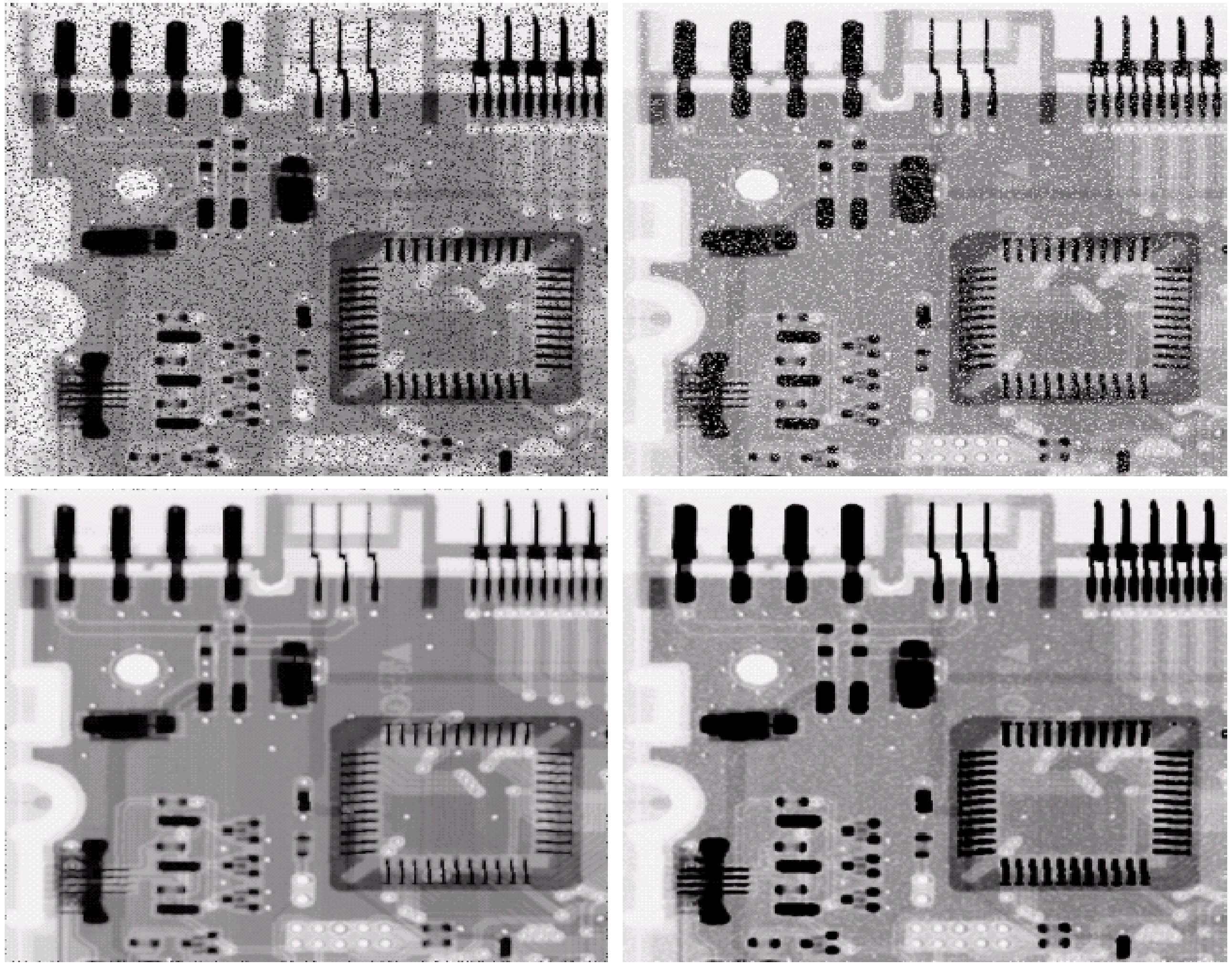
Arithmetic Mean and Geometric Mean Filter



a b
c d

FIGURE 5.7 (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 Filtering



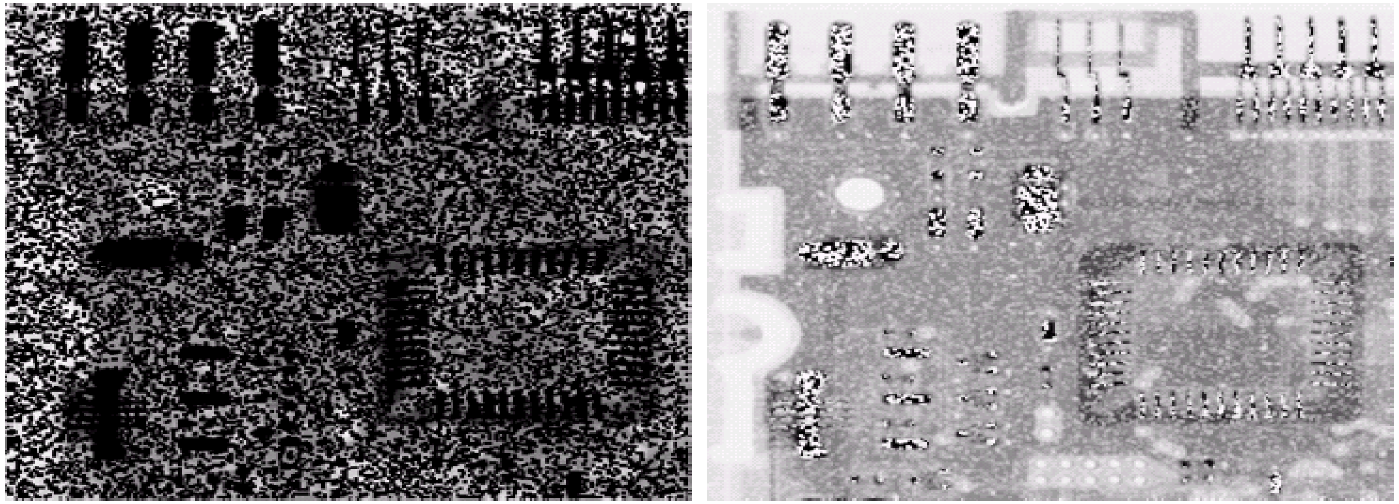
a b
c d

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 contraharmonic filter of order 1.5. (d) Result of filtering (b) with $Q = -1.5$.

-Positive-order filters did better job of cleaning the background, at the expense of blurring the dark areas.

- The opposite was true of the negative filter.

Contraharmonic Mean Filtering



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 $Q = 1.5$.

- Arithmetic mean and Geometric mean filters are well suited for random noise like Gaussian or uniform noise.

- The contraharmonic filter is well suited for impulse noise, but it has drawback that it must be known whether the noise is dark or light in order to select the proper sign for *Q*.

De-noising using Order -Statics Filters

Median Filter

$$\hat{f}(x,y) = \underset{s,t \in W_{mn}}{median}\{g(s,t)\}$$

-Provide excellent noise reduction capabilities, with considerably less blurring than linear smoothing filters of similar support.

Max and Min Filter

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

- This filter is useful for finding the brightest points in an image. Useful in reducing pepper noise.

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

- Useful for finding darkest point in an image. It reduces the salt noise.

Midpoint Filter

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

- Works best for randomly distributed noise, like Gaussian or uniform noise

De-noising using Order -Statics Filters

Alpha-trimmed Mean Filter

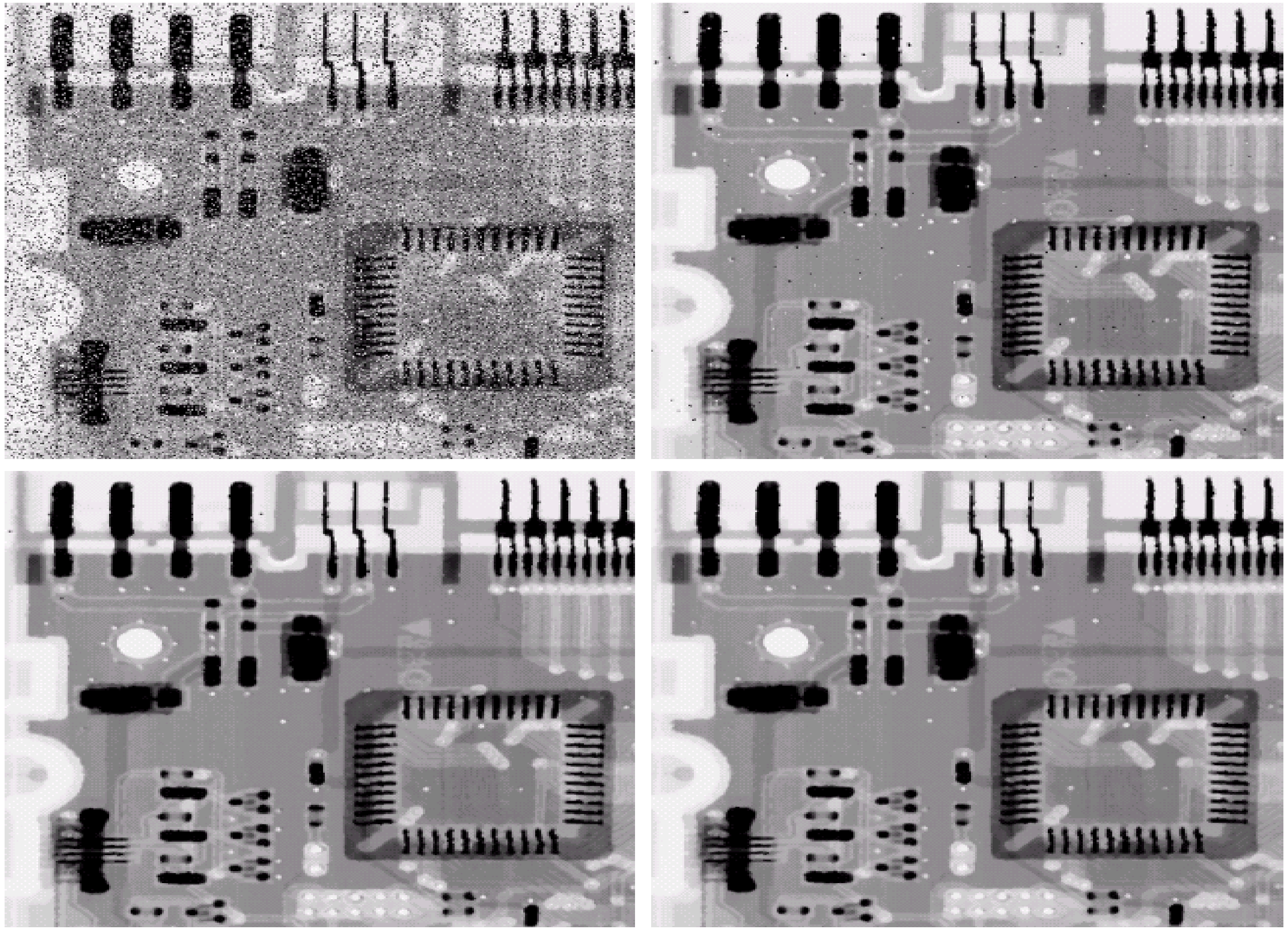
$$\hat{f}(x,y) = \frac{1}{mn-d} \sum_{s,t \in W_{mn}} g_r(s,t)$$

- *d* can range from *0* to *mn-1.*
- *d=0 alpha-trimmed mean filter reduces into mean filter.*
- *d= (mn-1)/2, the filter becomes median filter.*
- For other values of *d*, alpha-trimmed filter is useful in situations involving multiple type of noise, such as combination of salt-and-pepper and Gaussian noise.

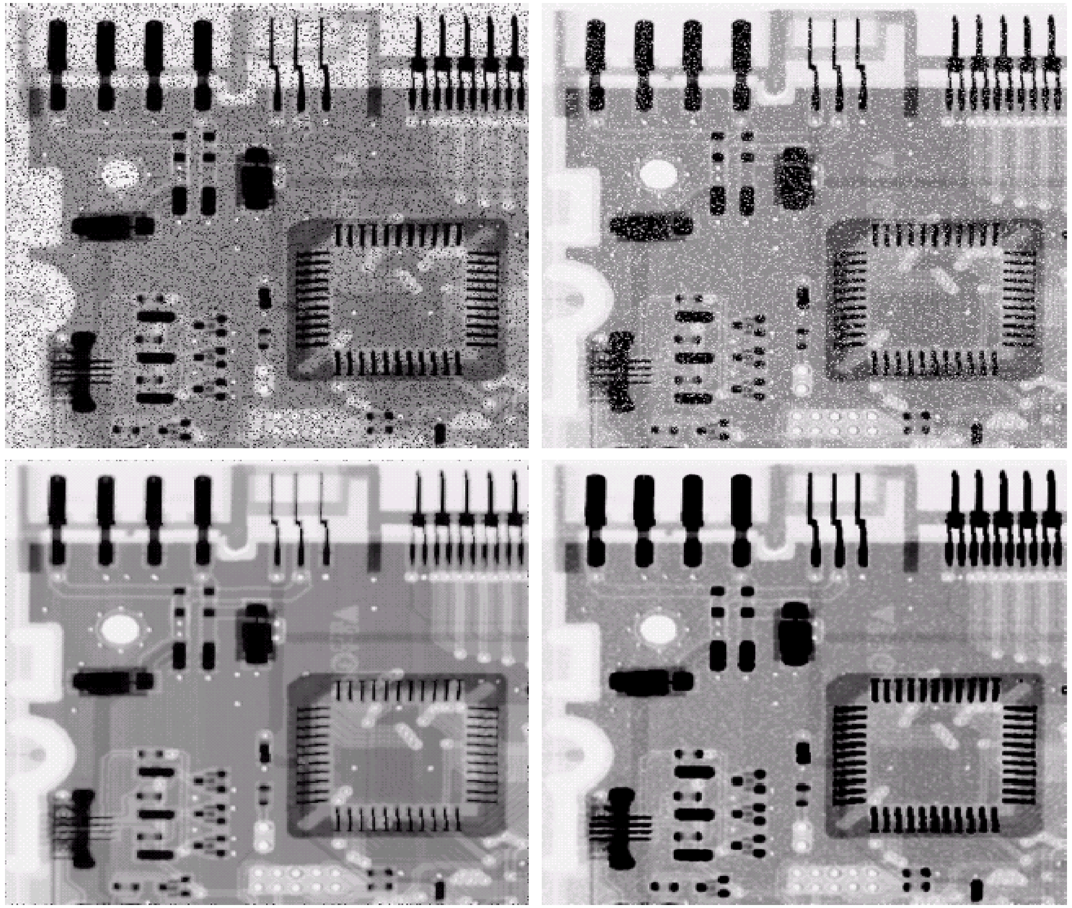
Median filter for salt-and-pepper noise

a	b
c	d

FIGURE 5.10 (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.

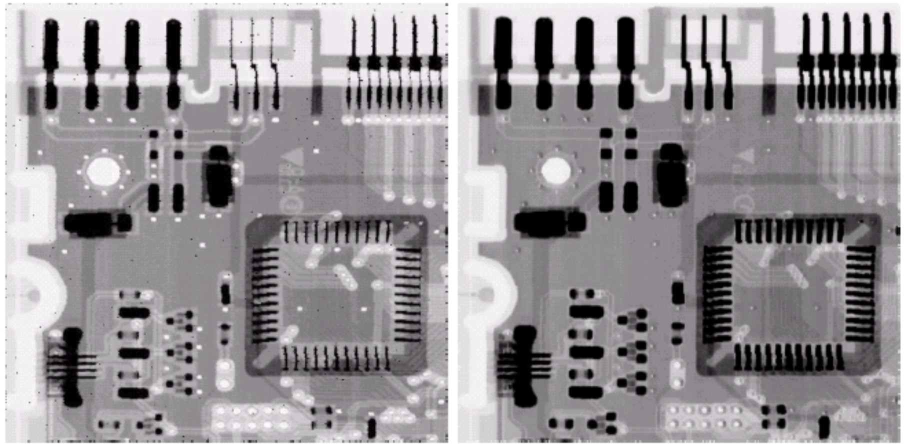


Max and Min Filter



a b
c d

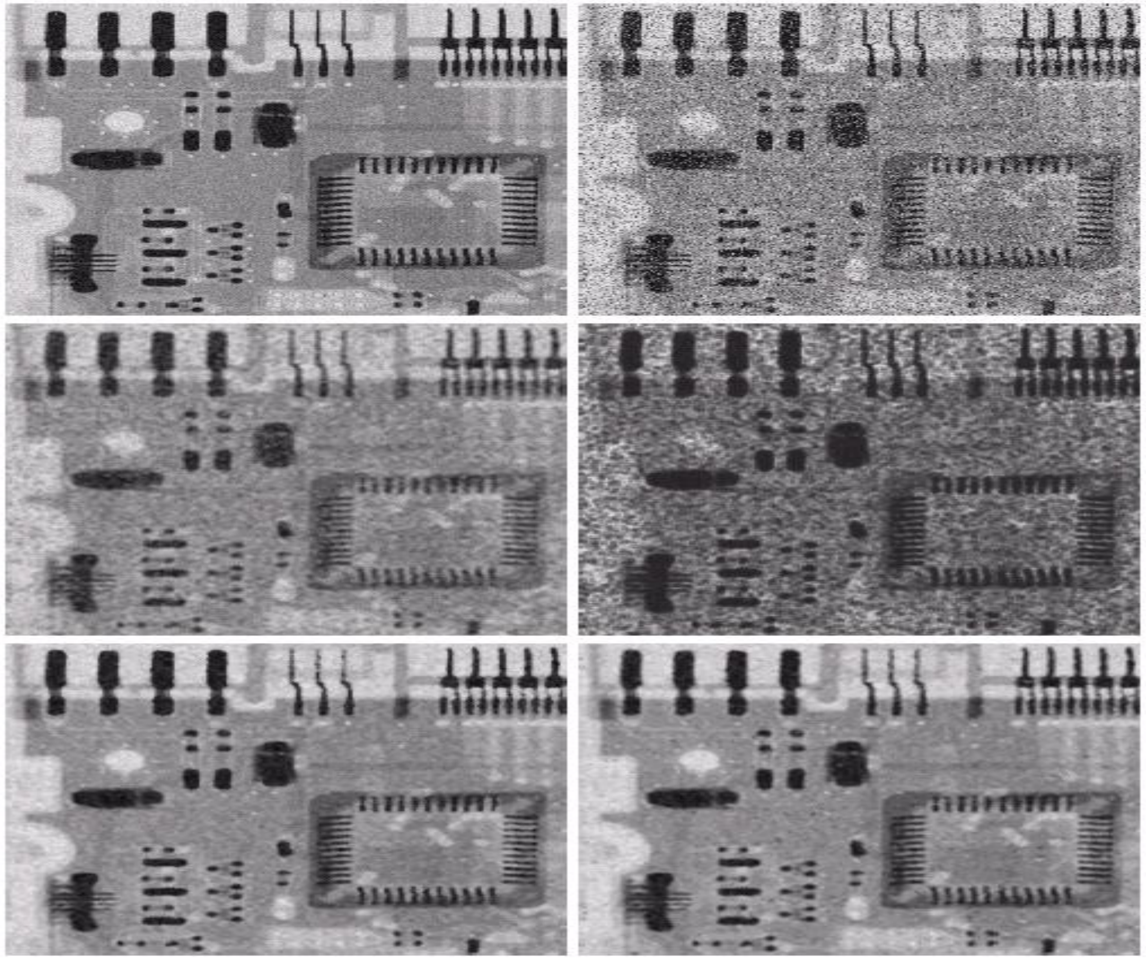
FIGURE 5.8
(a) Image corrupted by pepper noise with a probability of 0.1. (b) Image corrupted by salt noise with the same probability. (c) Result of filtering (a) with a 3×3 contraharmonic filter of order 1.5. (d) Result of filtering (b) with $Q = -1.5$.



a b

FIGURE 5.11
(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.

Filter Effect on Mixed Noise



a	b
c	d
e	f

FIGURE 5.12 (a) Image corrupted by additive uniform noise. (b) Image additionally corrupted by additive salt-and-pepper noise. Image in (b) filtered with a 5×5: (c) arithmetic mean filter; (d) geometric mean filter; (e) median filter; and (f) alpha-trimmed mean filter with $d = 5$.

Suggested Readings

- **Digital Image Processing by Rafel Gonzalez, Richard Woods, Pearson Education India, 2017.**

- **Fundamental of Digital image processing by A. K Jain, Pearson Education India, 2015.**

Thank you