

# Digital Image Processing Using MATLAB

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## IMAGE RESTORATION

The main objective of restoration is to improve the quality of a digital image which has been degraded due to Various phenomena like:

- Motion
- Improper focusing of Camera during image acquisition.
- Atmospheric turbulence
- Noise

## Enhancement versus Restoration

- Both processes try to improve an image in some predefined sense
- Image enhancement is largely a subjective process, while image restoration is for the most part an objective process

### **Enhancement:**

- (1) Manipulating an image in order to take advantage of the psychophysics of the human visual system.
- (2) Techniques are usually “heuristic.”
- (3) Example: Contrast stretching, histogram equalization.

### **• Restoration:**

- (1) A process that attempts to reconstruct or recover an image that has been degraded by using some prior knowledge of the degradation phenomenon.
- (2) Involves modeling the degradation process and applying the inverse process to recover the original image.
- (3) A criterion for “goodness” is required that will recover the image in an optimal fashion with respect to that criterion.
- (4) Example: removal of blur by applying a deblurring function.

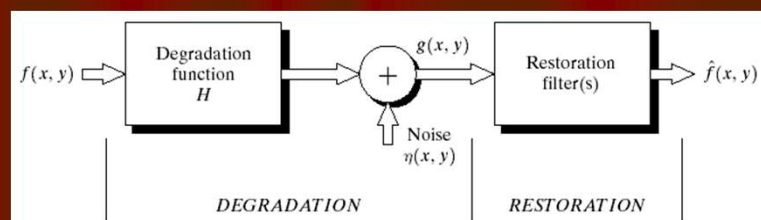
Problem:

- You want to know some image X.
- But you only have a corrupted version Y .
- How do you determine X from Y ?



### Blurring due to uniform motion

12-5996 New York, NY, Statue of Liberty with Stinson  
Aerials Only Gallery 508-295-5551(C) (E)



Degradation model:

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

where  $h(x, y)$  is a system that causes image distortion and  $\eta(x, y)$  is noise.

## 2-D Convolution (Spatial)

If  $H$  is a **linear, position-invariant** process, then the degraded image is given in the spatial domain by

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

## 2-D Convolution (Spatial)

$A = \begin{bmatrix} 17 & 24 & 1 & 8 & 15 \\ 23 & 5 & 7 & 14 & 16 \\ 4 & 6 & 13 & 20 & 22 \\ 10 & 12 & 19 & 21 & 3 \\ 11 & 18 & 25 & 2 & 9 \end{bmatrix}$

$H = \begin{bmatrix} 8 & 1 & 6 \\ 3 & 5 & 7 \\ 4 & 9 & 2 \end{bmatrix}$

To compute the (2,4) output pixel using three steps:

## 2-D Convolution (Spatial)

Rotate the convolution kernel 180 degrees about its center element.

```
>> p = rot90(H)
```

H =	[ 8	1	6
	3	5	7
	4	9	2]

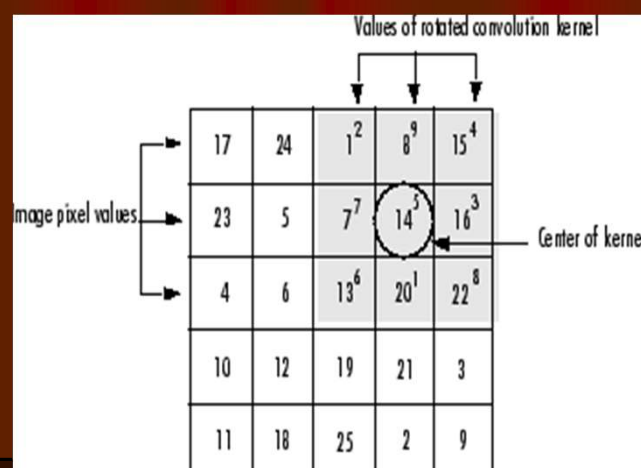
6	7	2
1	5	9
8	3	4

```
>> q = rot90(p)
```

2	9	4
7	5	3
6	1	8

## 2-D Convolution (Spatial)

Slide the center element of the convolution kernel so that it lies on top of the (2,4) element of A.



## 2-D Convolution (Spatial)

Multiply each weight in the rotated convolution kernel by the pixel of A underneath.

Sum the individual products from step 3.

$$1 \cdot 2 + 8 \cdot 9 + 15 \cdot 4 + 7 \cdot 7 + 14 \cdot 5 + 16 \cdot 3 + 13 \cdot 6 + 20 \cdot 1 + 22 \cdot 8 = 575$$

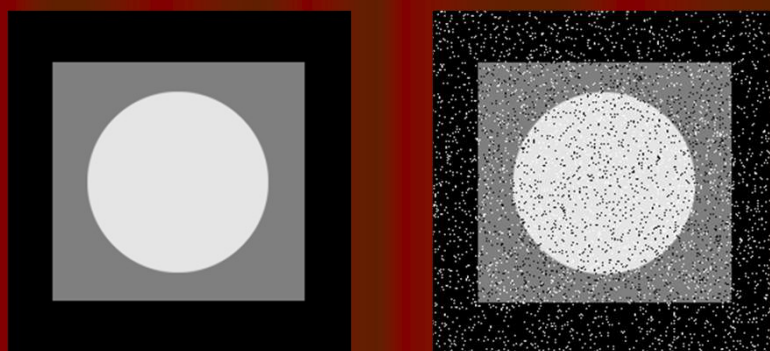
## Noise Sources

- The principal sources of noise in digital images arise during **image acquisition and/or transmission**
- Image acquisition  
e.g., light levels, sensor temperature, etc.
- Transmission  
e.g., lightning or other atmospheric disturbance in wireless network

## Noise probability density functions

- Noises are taken as random variables
- Random variables
  - Probability density function (PDF)

### Salt & Pepper Noise





## Noise Probability Distribution (Salt & Pepper Noise)

The PDF of (bipolar) impulse noise is given by

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

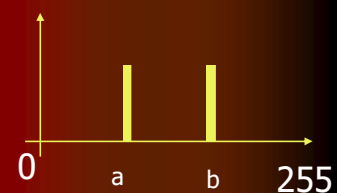
if  $b > a$ , gray-level  $b$  will appear as a light dot, while level  $a$  will appear like a dark dot.

If either  $P_a$  or  $P_b$  is zero, the impulse noise is called *unipolar*

## Noise Probability Distribution (Salt & Pepper Noise)

The PDF of (bipolar) impulse noise is given by

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



The CDF of (bipolar) impulse noise is given by

$$F(z) = \begin{cases} P_a & \text{for } a \leq z < b \\ P_a + P_b & \text{for } z \geq b \\ 0 & \text{Otherwise} \end{cases}$$

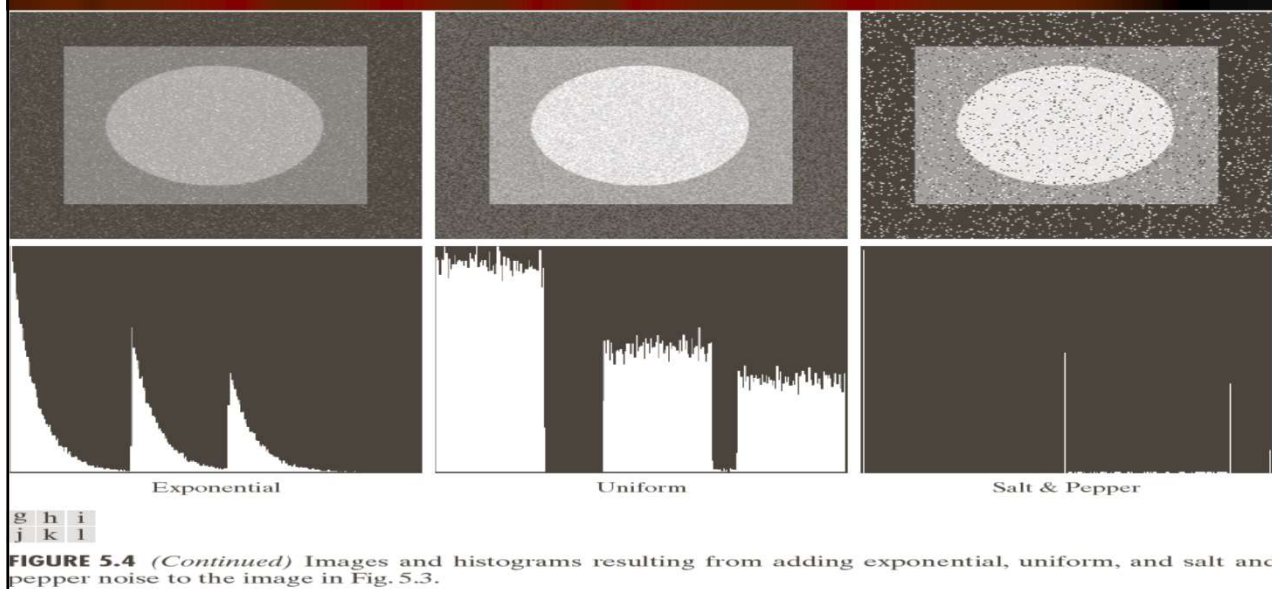
## Salt & Pepper Noise

```
➤ a = imread('C:\lake2.bmp');  
➤ a = double(a);  
➤ a = mat2gray(a);  
➤ imhist(a);  
➤ b = imnoise(a,'Salt & Pepper');  
➤ figure,imshow(b);  
➤ figure, imhist(b)
```

## Implementation: Salt & Pepper

```
function i= saltpepper(img1,a,b)  
[m,n]=size(img1);  
img1=mat2gray(double(img1));  
r= rand(m,n);  
x=find(r <=a);  
img1(x)=0;  
x=find(r >a & r <=(a+b));  
img1(x)=255;  
figure,imhist(img1);  
figure,imshow(img1);  
imwrite(img1,'C:\board_salt.tif');  
return i;
```

## Noise Patterns

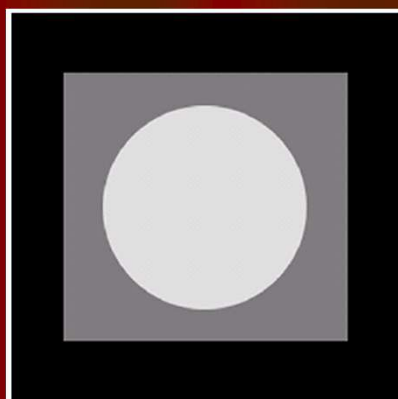
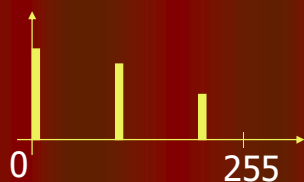


## Test for noise behavior

- Uniform noise

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

Its histogram:



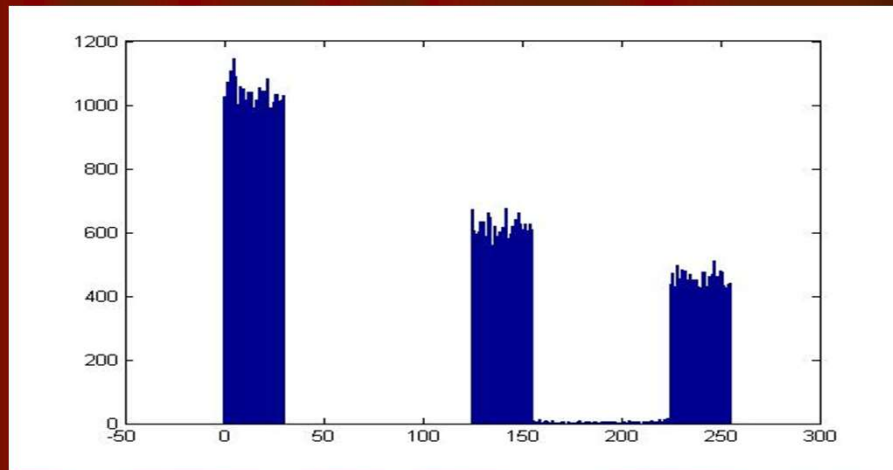
## Test for noise behavior

```
a1=(imread('Fig0503 (original_pattern).tif'));  
[m,n]=size(a1);  
z=uint8(randi([10,40],m,n));  
  
noisy_a=double(a1)+ double(z) ;  
noisy=imhist(mat2gray(noisy_a));  
original=imhist((a1));
```

## Test for noise behavior

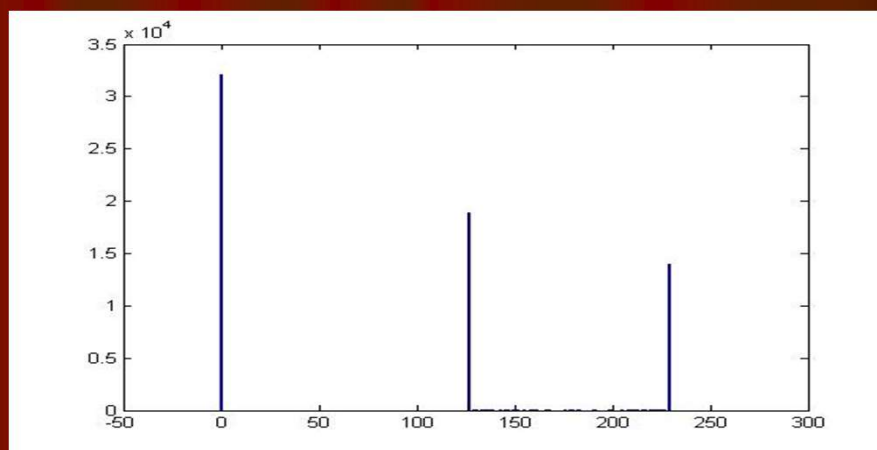
```
figure(1), bar(0:255,noisy)  
figure(2) , bar(0:255,original)  
figure (3)  
subplot(2,1,1)  
imshow(a1)  
title('original image')  
subplot(2,1,2)  
imshow(mat2gray(noisy_a))  
title('noisy image-uniform noise')
```

## Test for noise behavior



Noisy Image

## Test for noise behavior



Original Image

## Noise Probability Distribution (Uniform Noise)

The PDF of uniform noise is given by

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

The mean and variance of this density are given by

$$\bar{z} = (a+b)/2$$

$$\sigma^2 = (b-a)^2 / 12$$

The PDF of uniform noise is given by

$$p(z) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases}$$

## Uniform Noise

Shorthand  $X \sim U(a, b)$

Cumulative distribution function On the support  $a \leq x < b$

$$F(x) = \int_a^x \frac{1}{b-a} dw = \left[ \frac{w}{b-a} \right]_a^x = \frac{x-a}{b-a}$$

So

$$F(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & x > b \end{cases}$$

$$F(x) = P(X \leq x)$$

## Uniform Noise

$$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$E(X) = \int_{\text{all } x} x f(x) dx$$

$$E(X) = \int_a^b \frac{x}{b-a} dx$$

$$= \left[ \frac{x^2}{2(b-a)} \right]_a^b$$

$$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$= \frac{1}{2(b-a)} (b+a) (b-a)$$

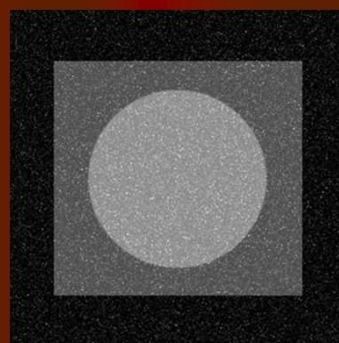
$$E(X) = \frac{a+b}{2}$$

The mean and variance of this density are given by

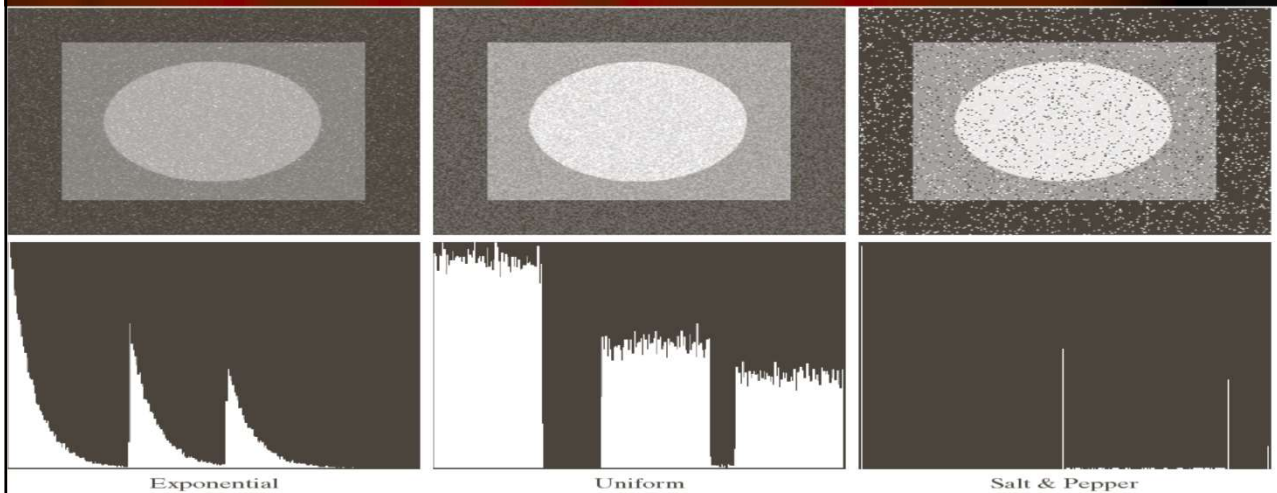
$$\bar{z} = (a+b)/2$$

$$\sigma^2 = (b-a)^2/12$$

## Exponential Noise



## Noise Patterns



g h i  
j k l

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

## Noise Probability Distribution (Exponential Noise)

The PDF of exponential noise is given by

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

The mean and variance of this density are given by

$$\bar{z} = 1/a$$

$$\sigma^2 = 1/a^2$$

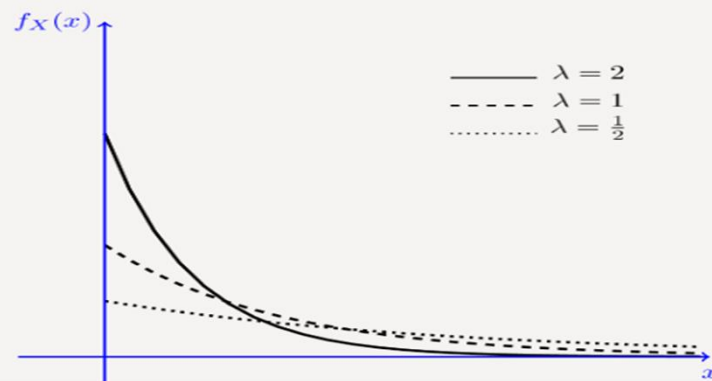


## Noise Probability Distribution (Exponential Noise)

A continuous random variable  $X$  is said to have an *exponential* distribution with parameter  $\lambda > 0$ , shown as  $X \sim \text{Exponential}(\lambda)$ , if its PDF is given by

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Figure 4.5 shows the PDF of exponential distribution for several values of  $\lambda$ .



## Noise Probability Distribution (Exponential Noise)

Let us find its CDF, mean and variance. For  $x > 0$ , we have

$$F_X(x) = \int_0^x \lambda e^{-\lambda t} dt = 1 - e^{-\lambda x}.$$

So we can express the CDF as

$$F_X(x) = (1 - e^{-\lambda x})u(x).$$

Let  $X \sim \text{Exponential}(\lambda)$ . We can find its expected value as follows, using integration by parts

$$\begin{aligned} EX &= \int_0^\infty x \lambda e^{-\lambda x} dx \\ &= \frac{1}{\lambda} \int_0^\infty y e^{-y} dy \quad \text{choosing } y = \lambda x \\ &= \frac{1}{\lambda} \left[ -e^{-y} - y e^{-y} \right]_0^\infty \\ &= \frac{1}{\lambda}. \end{aligned}$$

## Noise Probability Distribution (Exponential Noise)

Now let's find  $\text{Var}(X)$ . We have

$$\begin{aligned} EX^2 &= \int_0^\infty x^2 \lambda e^{-\lambda x} dx \\ &= \frac{1}{\lambda^2} \int_0^\infty y^2 e^{-y} dy \\ &= \frac{1}{\lambda^2} \left[ -2e^{-y} - 2ye^{-y} - y^2 e^{-y} \right]_0^\infty \\ &= \frac{2}{\lambda^2}. \end{aligned}$$

Thus, we obtain

$$\text{Var}(X) = EX^2 - (EX)^2 = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}.$$

If  $X \sim \text{Exponential}(\lambda)$ , then  $EX = \frac{1}{\lambda}$  and  $\text{Var}(X) = \frac{1}{\lambda^2}$ .

English (United States)  
English (India) keyboard  
to switch input method