Image Restoration

Image Processing

CSE 166

Lecture 8

Announcements

- Assignment 3 is due Apr 27, 11:59 PM
- Midterm exam is May 4
- Assignment 4 will be released May 4
  - Due May 11, 11:59 PM
- Reading
  - Chapter 5: Image Restoration and Reconstruction
    - Sections 5.1, 5.2, 5.3, 5.4, 5.6, and 5.7

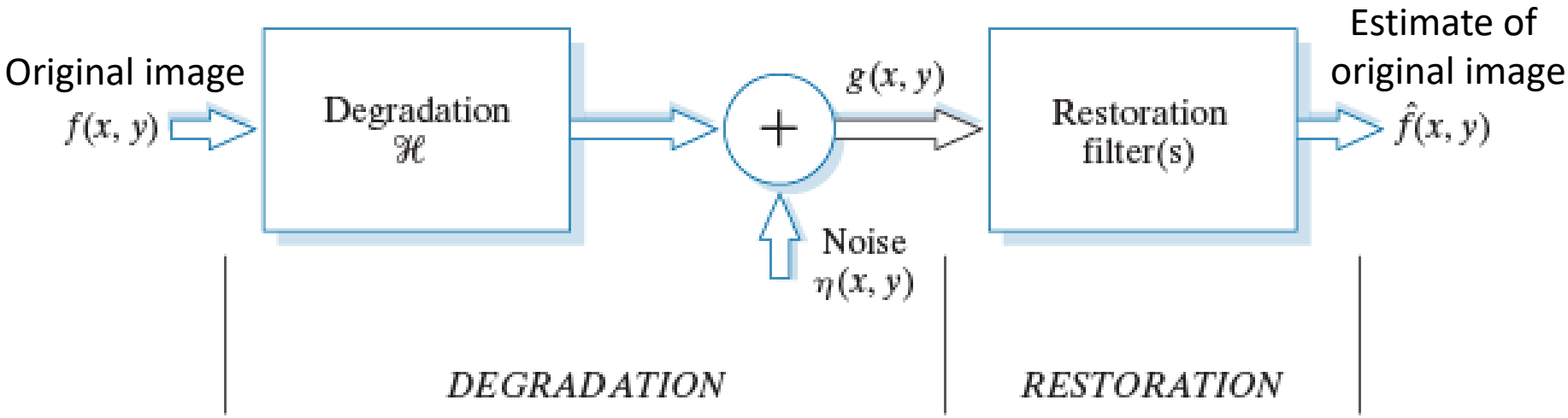
Model of image degradation

- Spatial domain

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

Degraded image	Degradation function	Original image	Noise image

Model of image degradation, then restoration

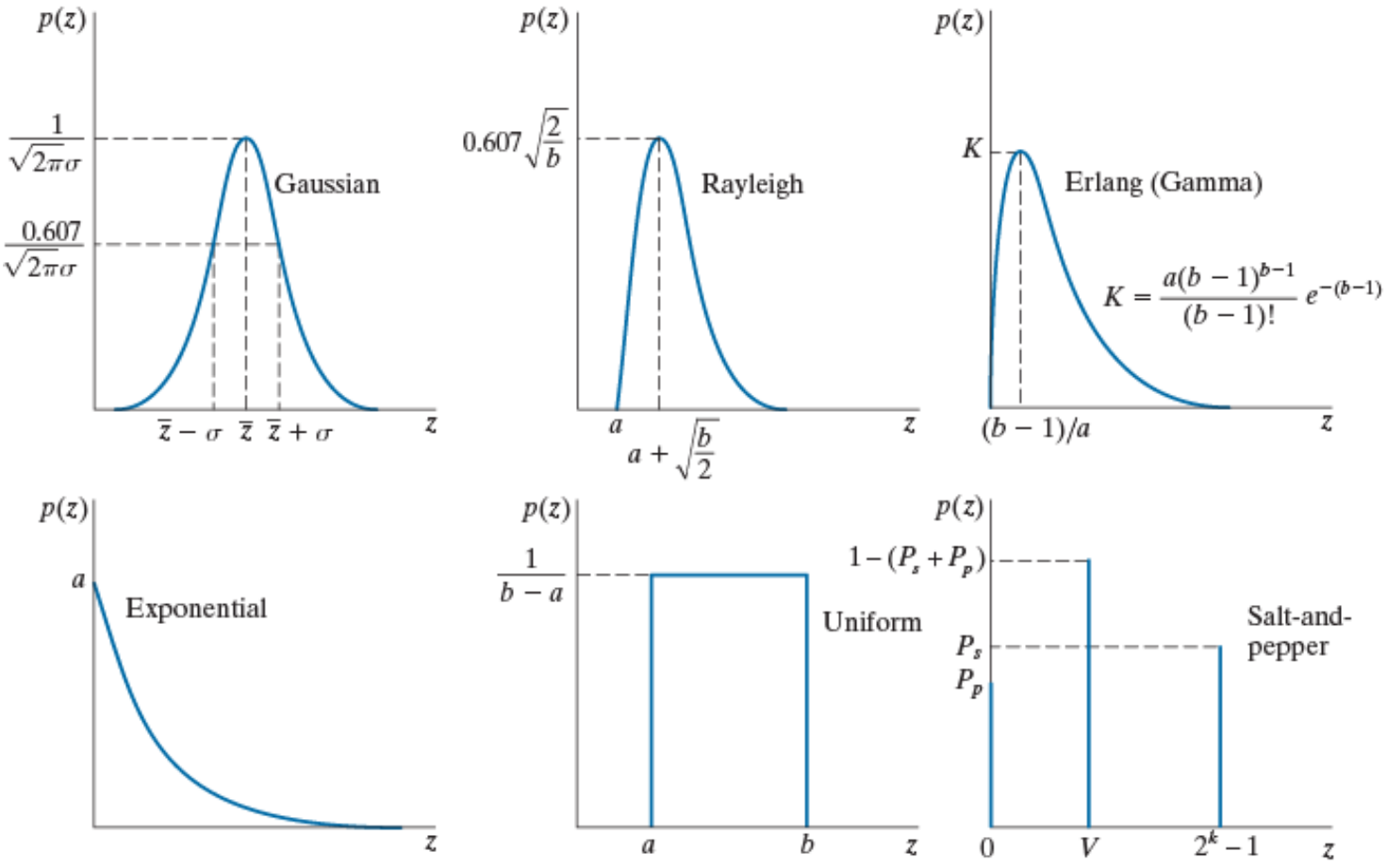


$$g(x, y) = h(x, y) \star f(x, y) + \eta(x, y)$$

Image restoration

1. Remove noise
2. Estimate original image
   - Deconvolution

Noise modeled as different probability density functions



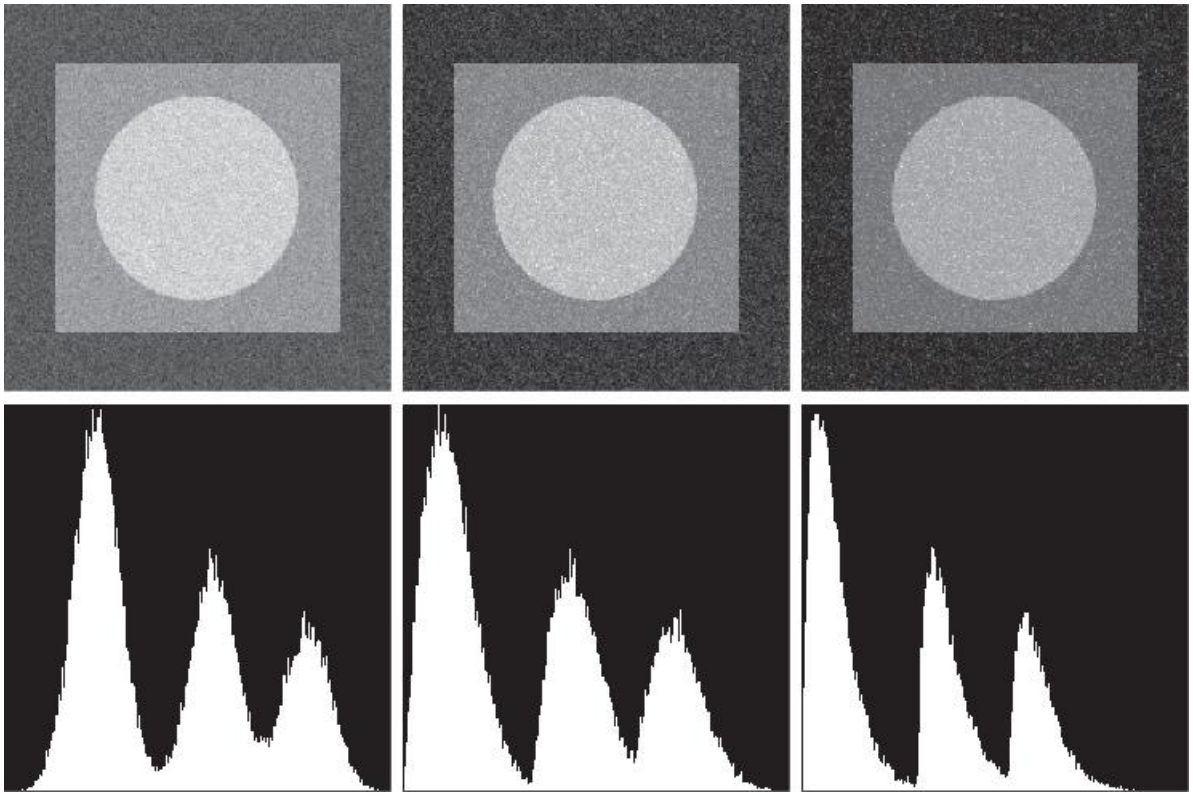
Adding noise from different models



Free of noise

$f(x, y)$

$g(x, y)$ $g(x, y)$ $g(x, y)$



Gaussian Rayleigh Gamma

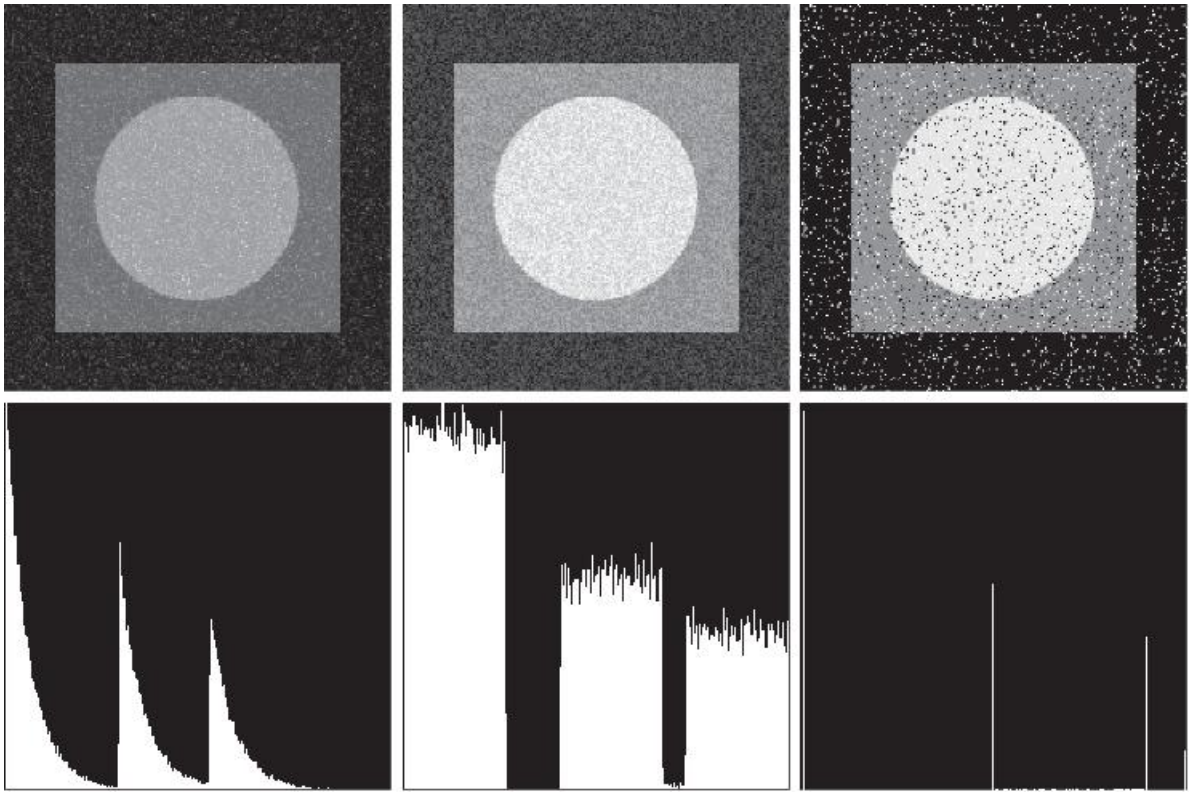
Adding noise from different models



Free of noise

$f(x, y)$

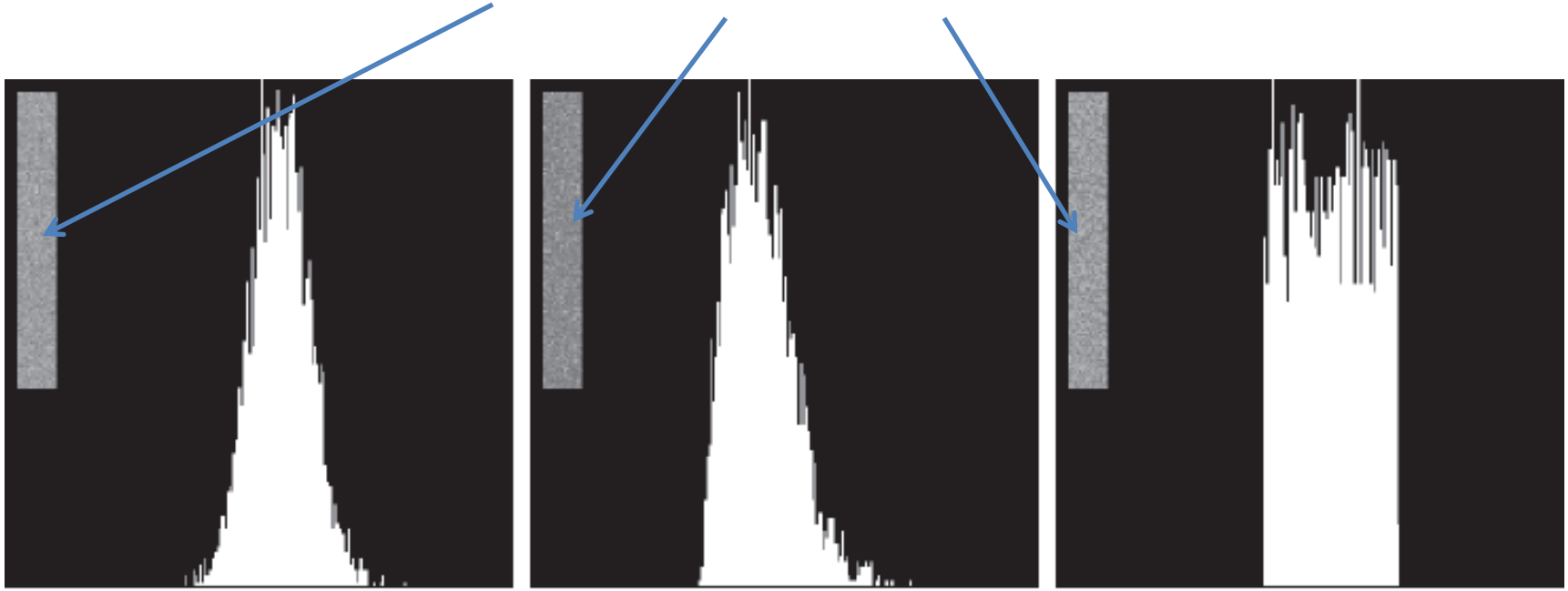
$g(x, y)$ $g(x, y)$ $g(x, y)$



Exponential Uniform Salt and pepper

Histograms of sample patches

1. Sample “flat” patches from images with noise



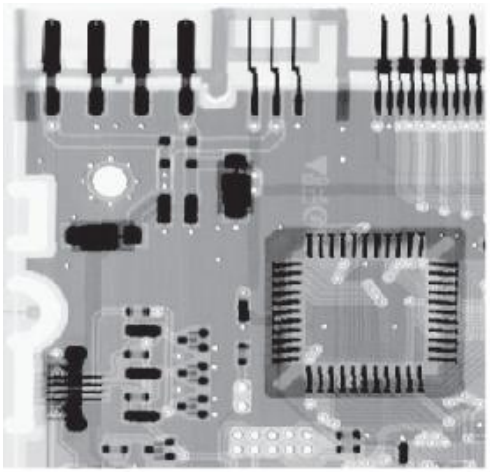
2. Identify closest probability density function (pdf) match

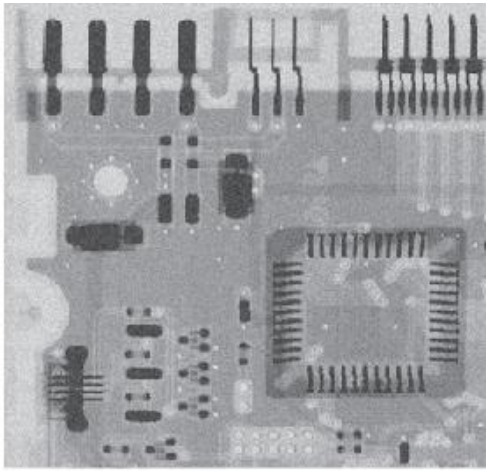
Gaussian Rayleigh Uniform

Mean filters

X-ray image

$f(x, y)$

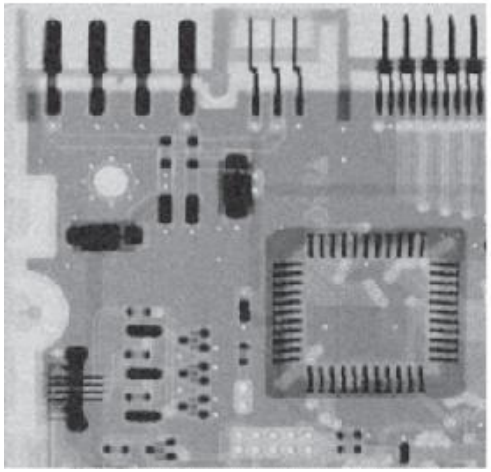


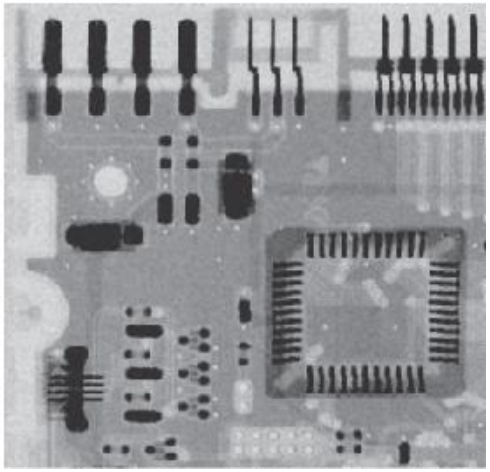


Additive Gaussian noise

$g(x, y)$

Arithmetic mean filtered





Geometric mean filtered

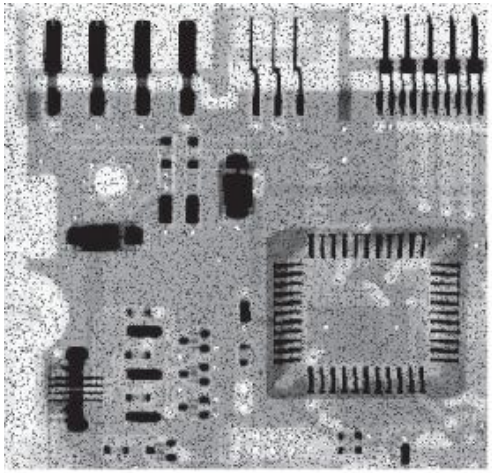
$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(r,c) \in S_{xy}} g(r, c)$$

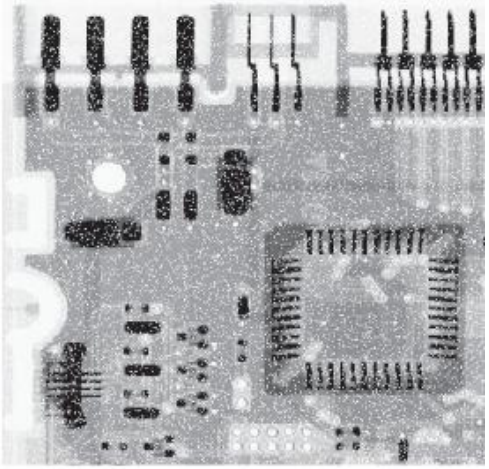
$$\hat{f}(x, y) = \left[\prod_{(r,c) \in S_{xy}} g(r, c) \right]^{\frac{1}{mn}}$$

Mean filters

Additive pepper noise

$g(x, y)$



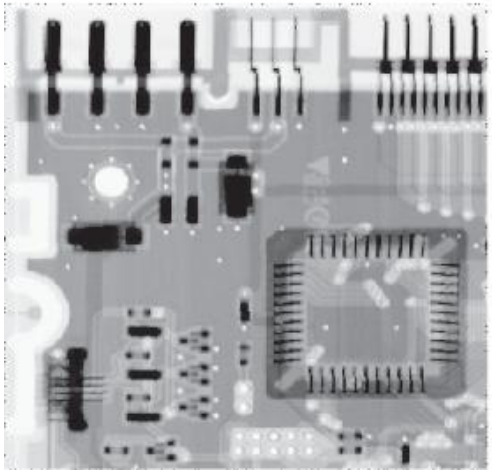


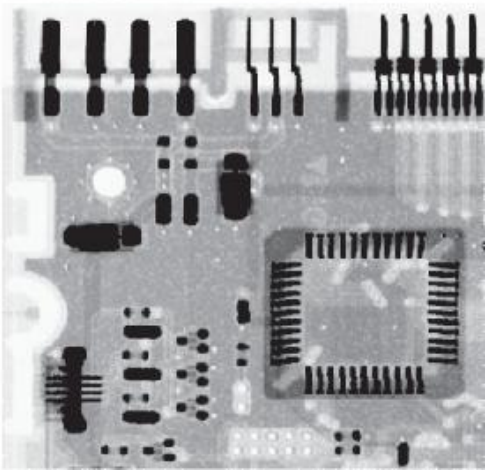
Additive salt noise

$g(x, y)$

Contraharmonic mean filtered

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





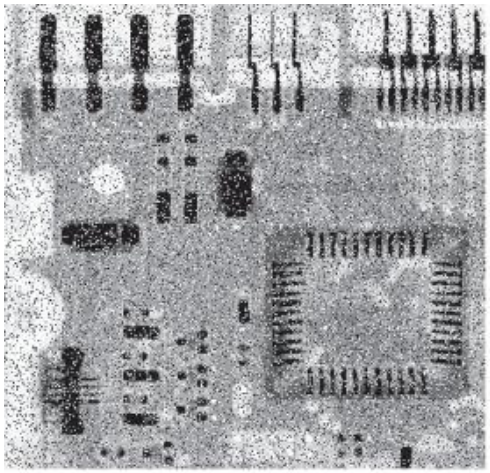
Contraharmonic mean filtered

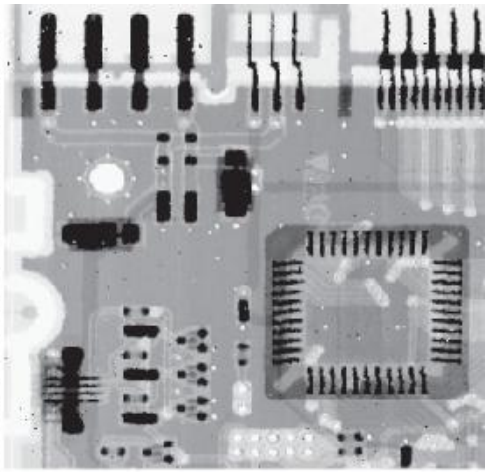
$\hat{f}(x, y)$

Order-statistic filters

Additive salt and pepper noise

$g(x, y)$



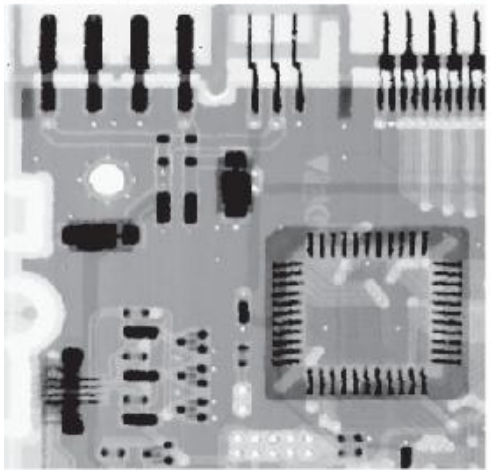


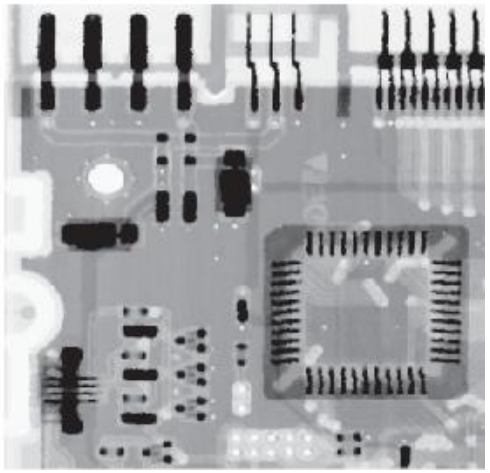
1x median filtered

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

2x median filtered

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





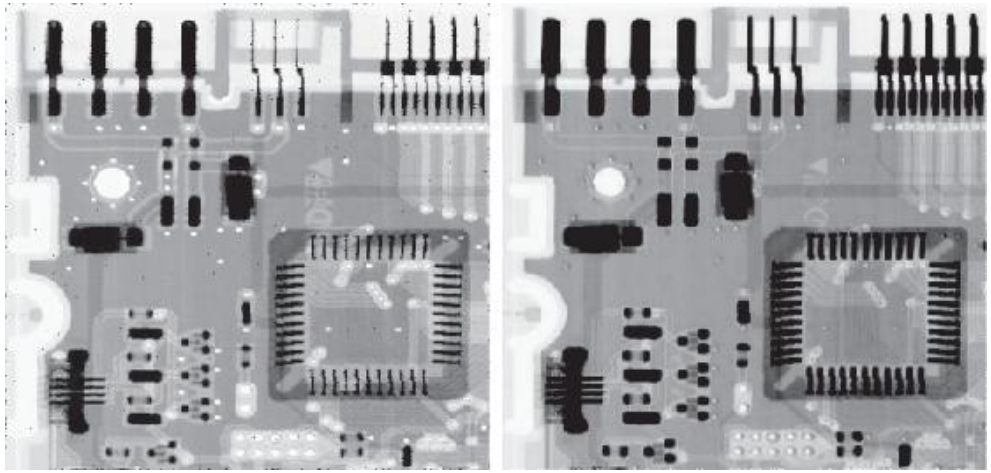
3x median filtered

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

Order-statistic filters

Max filtered

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

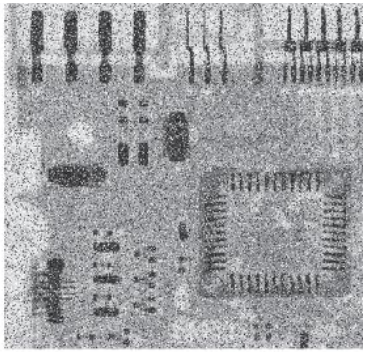


Min filtered

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

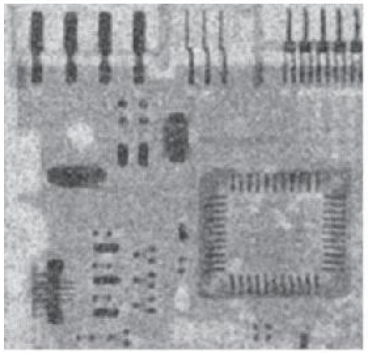
Comparing filters

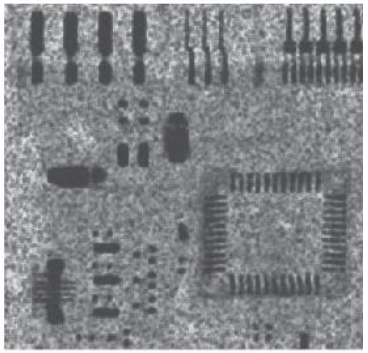
Additive uniform + $g(x,y)$ salt and pepper noise



Arithmetic mean filtered

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



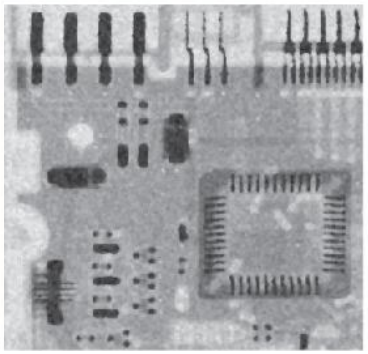


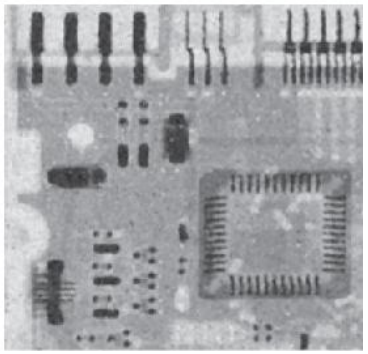
Geometric mean

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

Median filtered

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





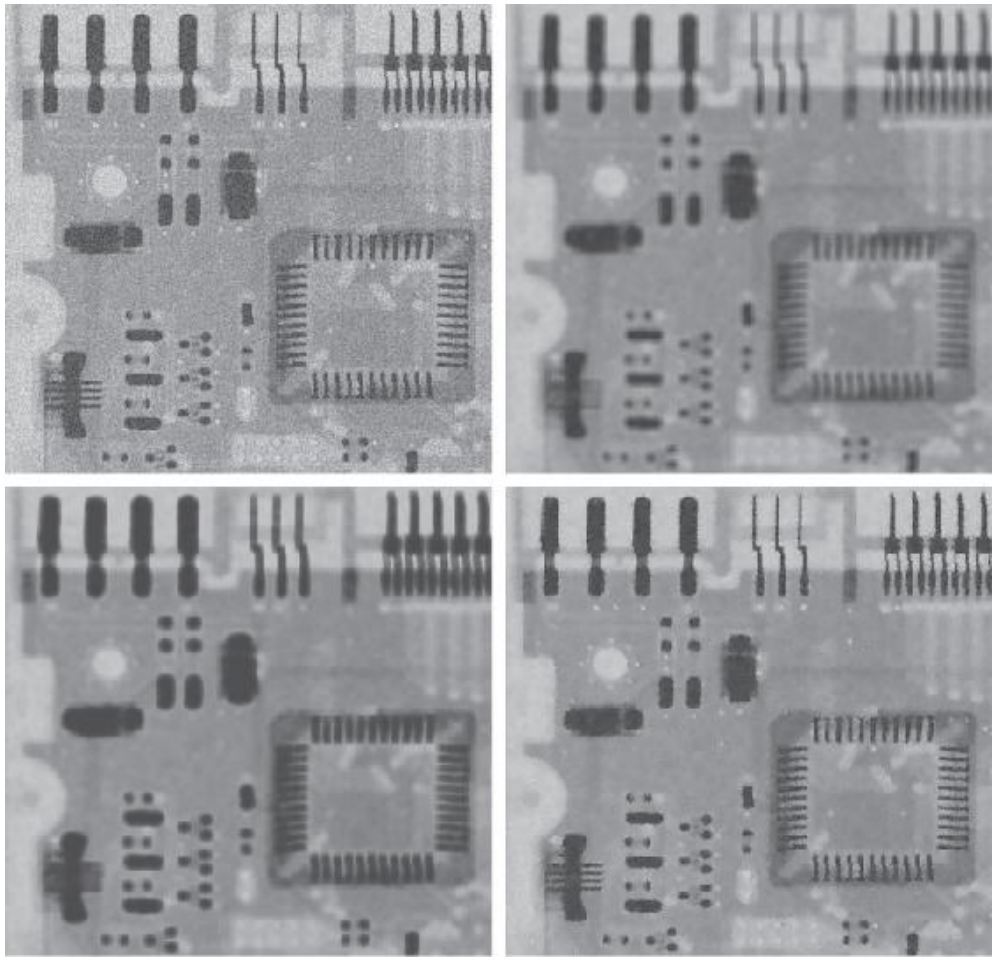
Alpha-trimmed mean filtered

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

Adaptive filters

Additive Gaussian noise

$g(x, y)$



Arithmetic mean filtered

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

Geometric mean filtered

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

Adaptive noise reduction filtered

$$\hat{f}(x,y) = g(x,y) - \min\left(1, \frac{\sigma_\eta^2}{\sigma_{S_{xy}}^2}\right)\left[g(x,y) - \bar{z}_{S_{xy}}\right]$$

Input: Overall noise variance

Local variance

Local mean (computed)

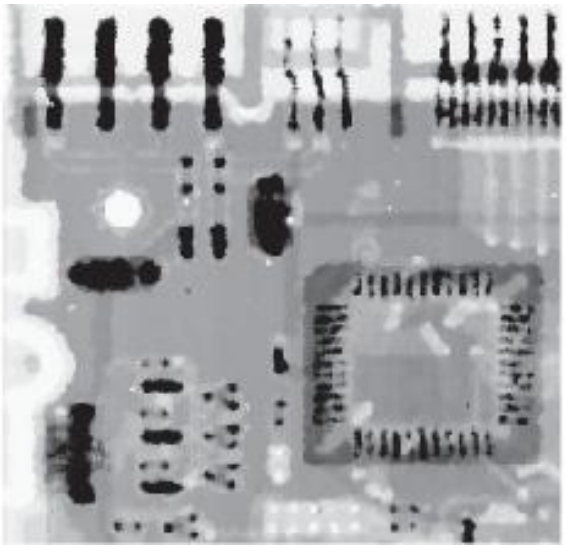
Adaptive filters

Additive salt and pepper noise



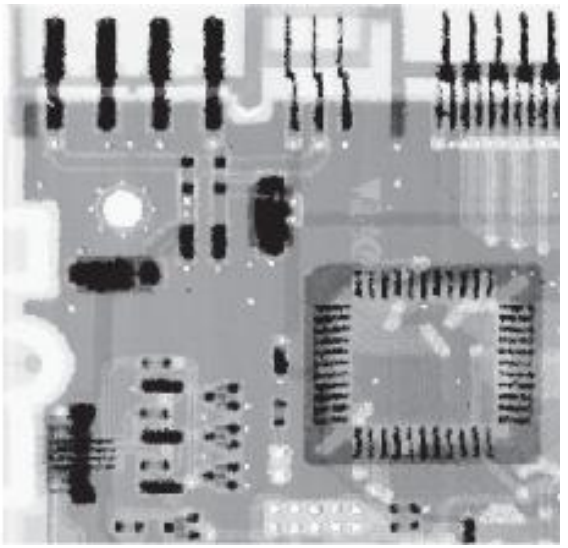
$g(x, y)$

Median filtered



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

Adaptive median filtered



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

Changes size of neighborhood according to noise density

Model of image degradation

- Spatial domain

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

Degraded image | Degradation function | Original image | Noise image

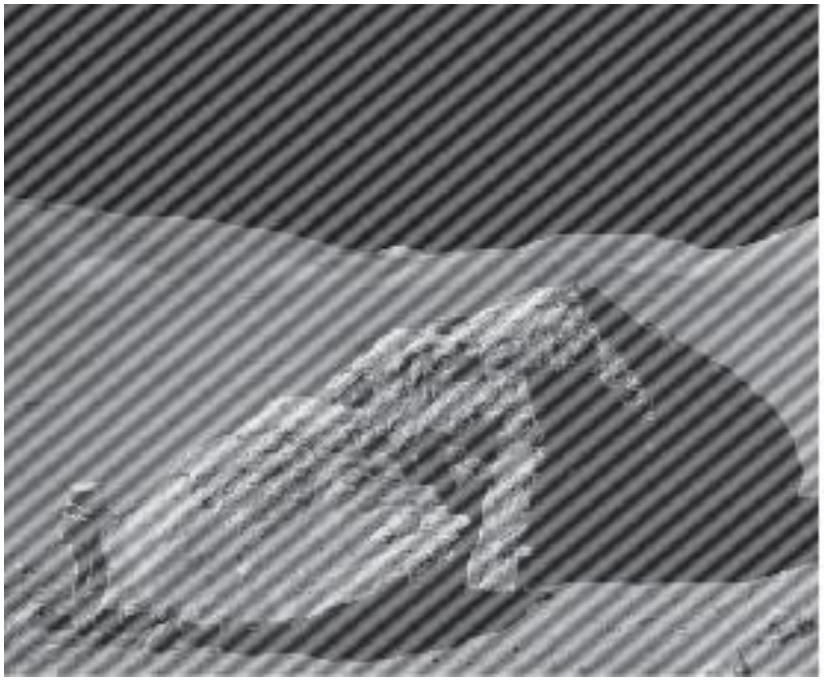
- Frequency domain

$$G(u,v) = H(u,v)F(u,v) + N(u,v)$$

Degraded image | Degradation function | Original image | Noise image

Periodic noise

DFT magnitude



Additive sinusoidal noise

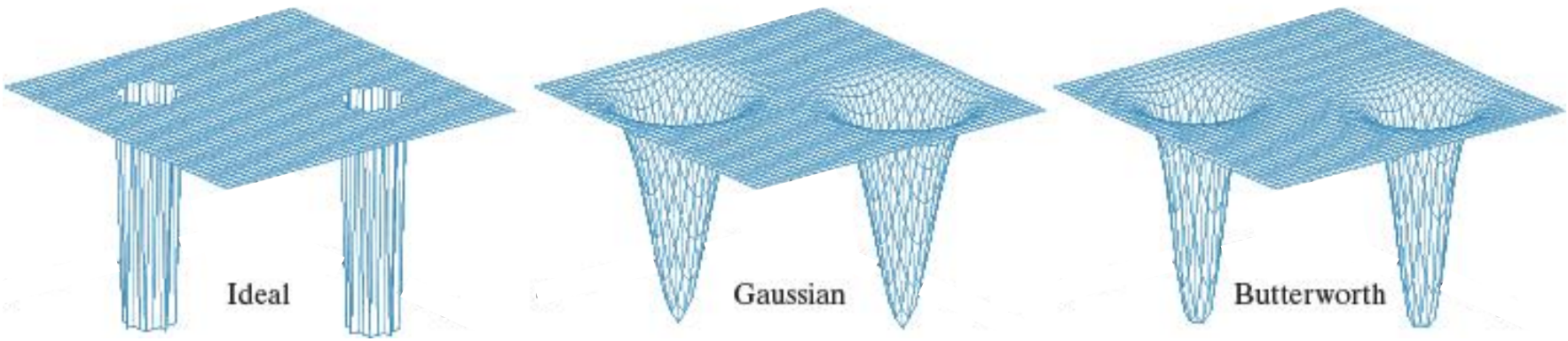
$g(x, y)$



Conjugate impulses

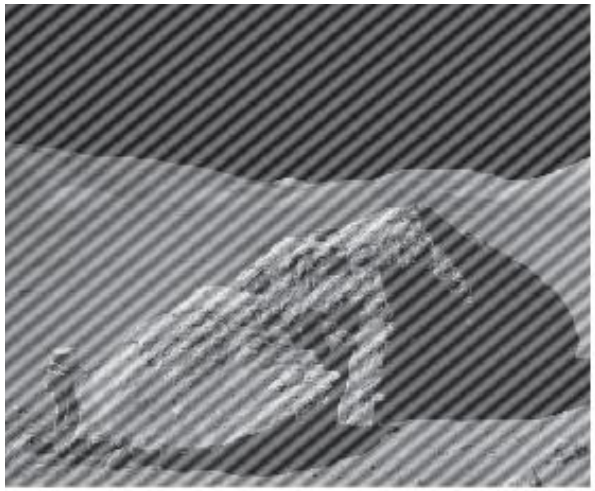
Notch reject filters

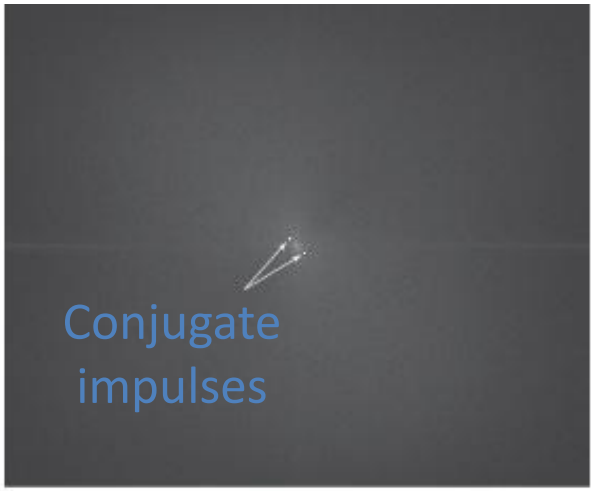
Band of frequencies, specific orientation(s)



Notch reject filter

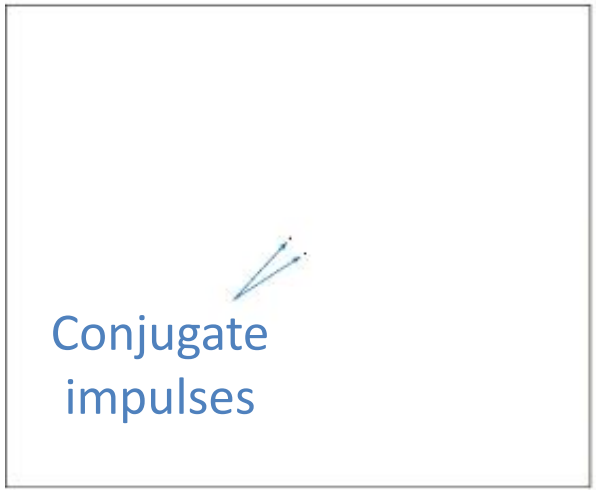
Degraded image
$g(x, y)$





DFT magnitude

Filter in frequency domain



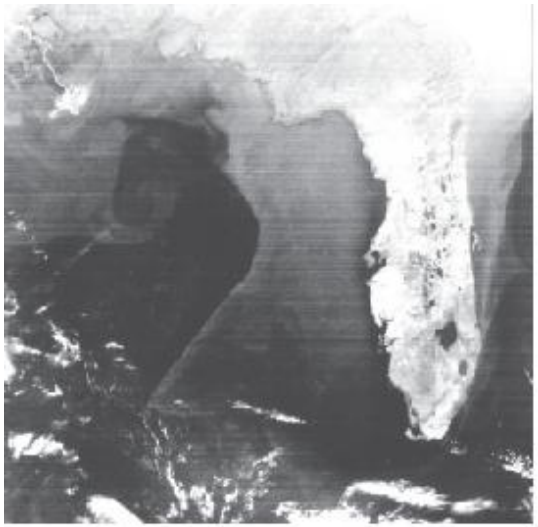


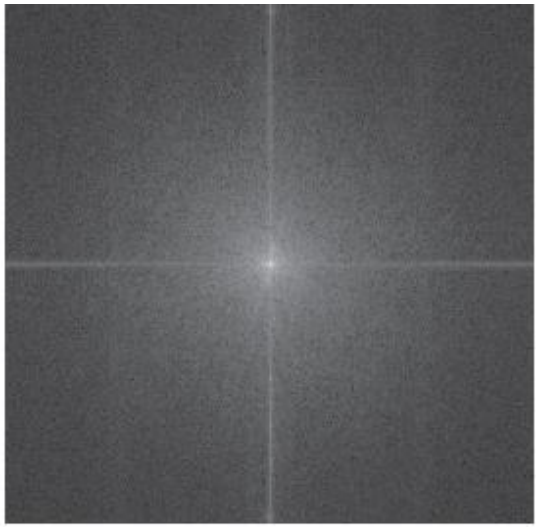
Estimate of original image
$\hat{f}(x, y)$

Notch reject filter

Degraded image

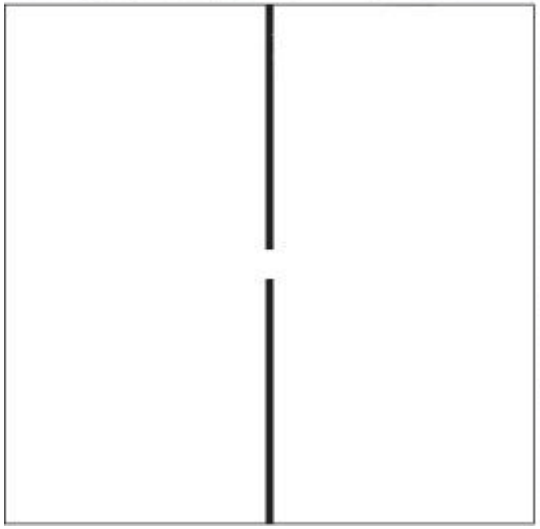
$g(x, y)$





DFT magnitude

Filter in frequency domain





Estimate of original image

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

Estimating the degradation function

- Methods
  - Observation
  - Experimentation
  - Mathematical modeling

Estimating the degradation function

- Observation

Manually process a subimage $g_s(x, y)$ of the degraded image $g(x, y)$ and let the result be our estimate of the original subimage $\hat{f}_s(x, y)$

$$g_s(x, y) = h_s(x, y) \bigstar \hat{f}_s(x, y), \text{ solve for } h_s(x, y)$$

This is called blind deconvolution because the true degradation function is not known. Solve in the frequency domain

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

then construct $H(u, v)$ for whole image with the same basic shape as $H_s(u, v)$

Estimating the degradation function

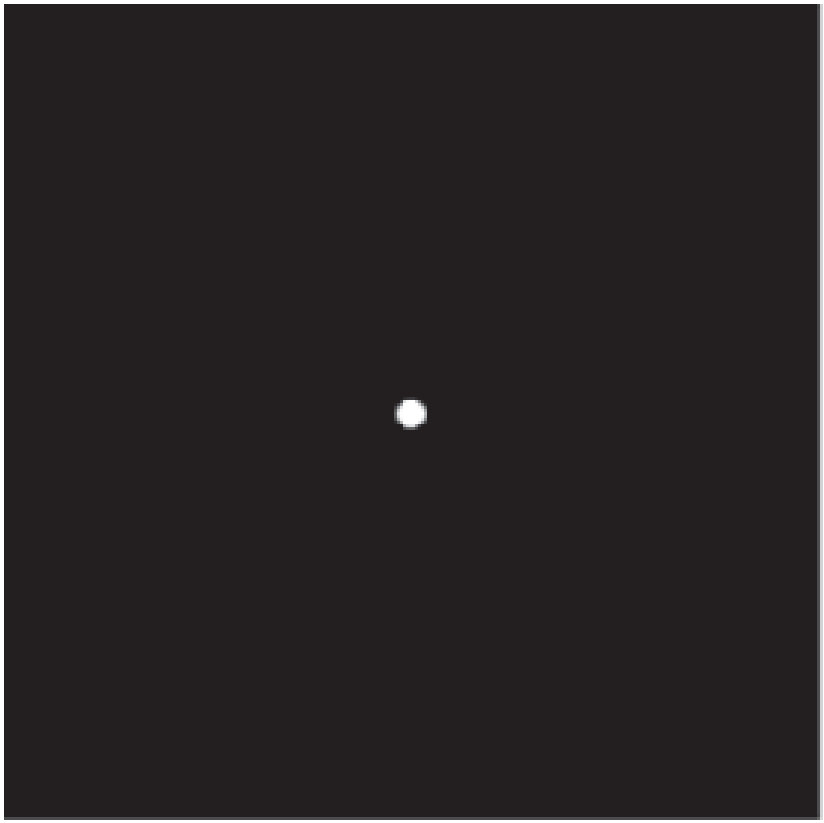
- Experimentation

If the imaging system is available, then obtain the impulse response of the degradation by imaging an impulse (i.e., a small dot of light, as bright as possible)

$H(u,v) = \frac{G(u,v)}{A}$, where A is a constant describing the strength of the impulse

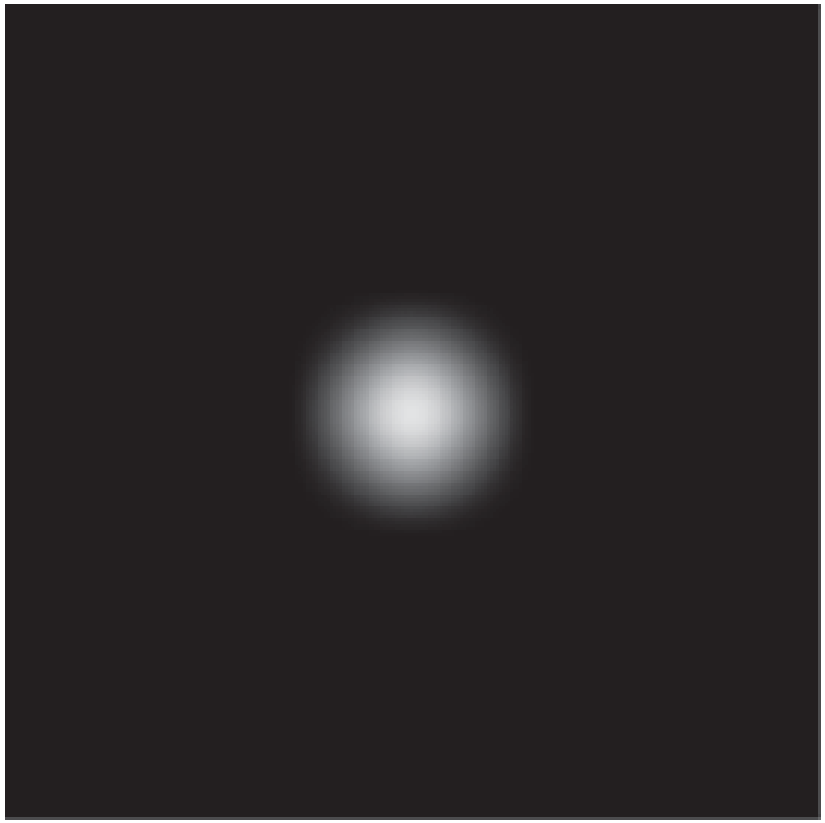
DFT of acquired, degraded image

Estimation of degradation function by experimentation



Impulse of light

$f(x, y)$



Imaged (degraded) impulse

$g(x, y)$

Estimating the degradation function

- Mathematical modeling

$$\text{Model } H(u, v) \text{ known parameters}$$

Estimation of degradation function by mathematical modeling

$f(x, y)$





Severe turbulence
$g(x, y)$

Atmospheric turbulence model

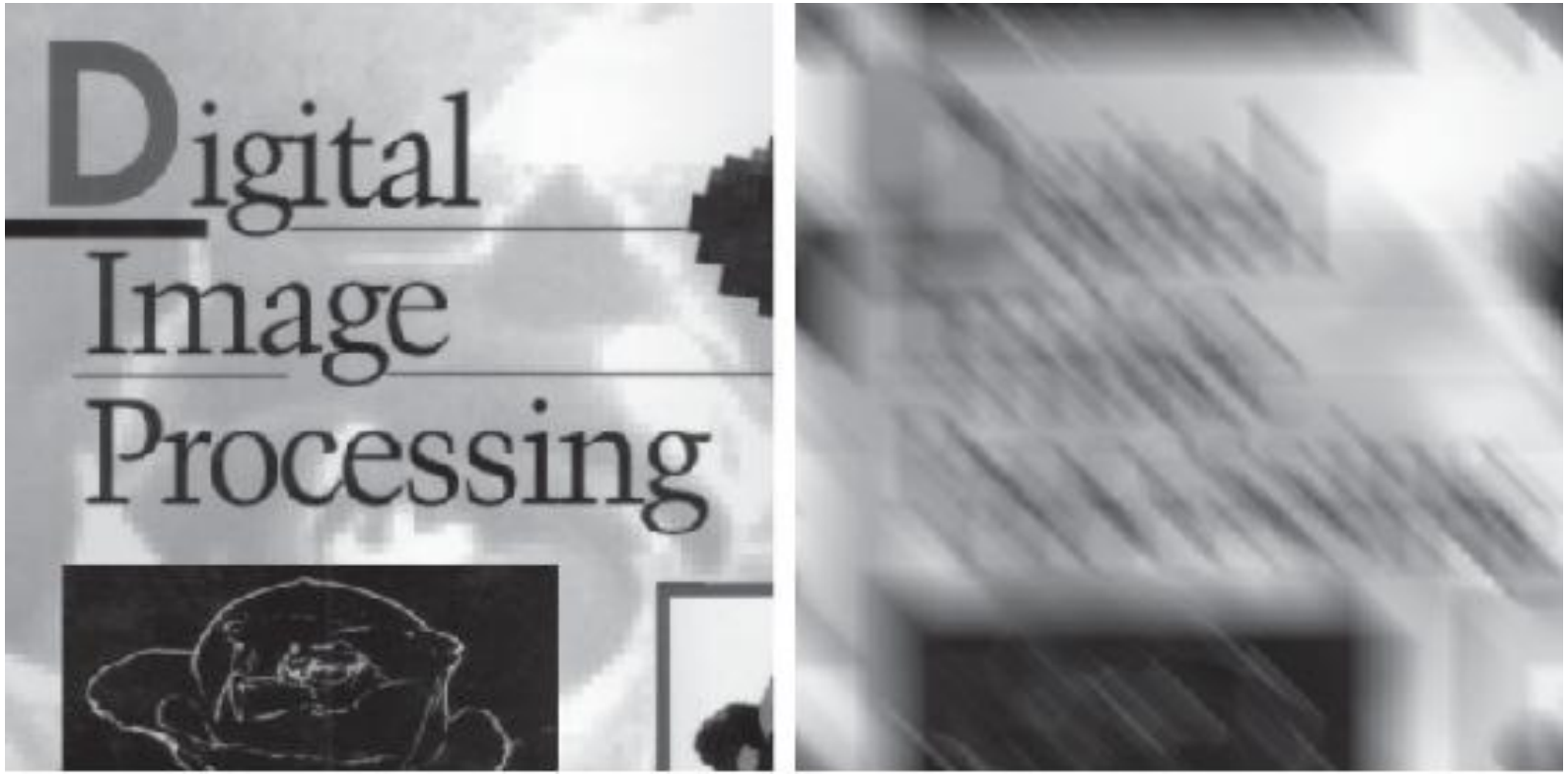
Mild turbulence
$g(x, y)$





Low turbulence
$g(x, y)$

Estimation of degradation function by mathematical modeling



$f(x, y)$ Motion blur model $g(x, y)$

Image restoration

- Inverse filtering

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

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

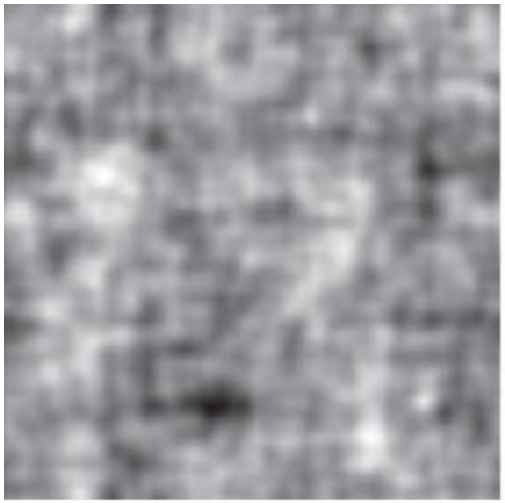
  - Mitigate divide by zero
    - Threshold *H(u,v)*
    - Ideal lowpass filter *H(u,v)*

$$\hat{F}(u,v) = \begin{cases} \frac{G(u,v)}{H(u,v)} & \text{if } |H(u,v)| \geq t \\ 0 & \text{otherwise} \end{cases}$$

Image restoration, inverse filtering

Full (i.e., no lowpass filter)

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





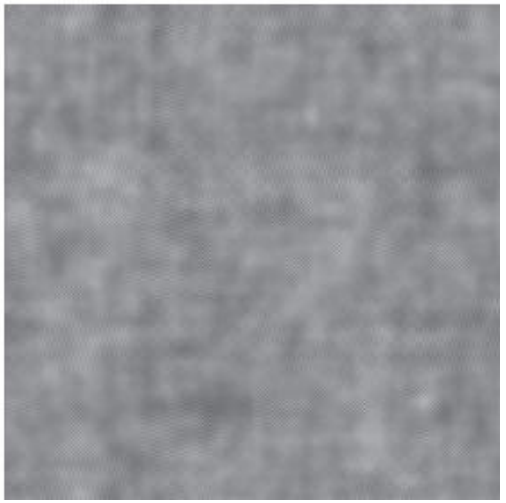
Lowpass filter limited to radius of 40

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

Lowpass filter limited to radius of 70

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





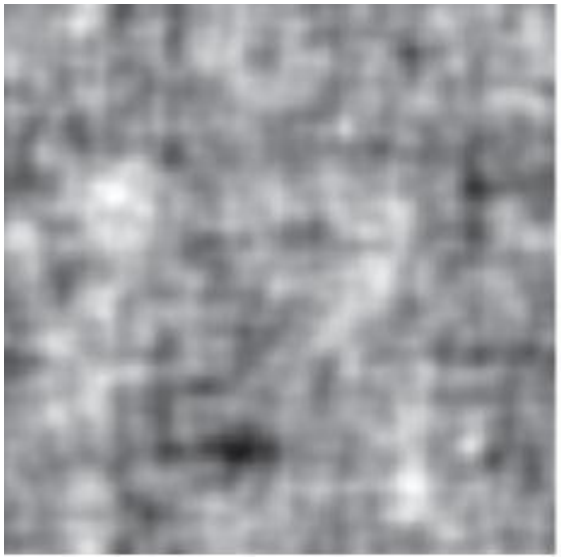
Lowpass filter limited to radius of 85

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

Image restoration, Wiener filtering

Inverse filtering

Wiener filtering







Full

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

Lowpass filter radially limited

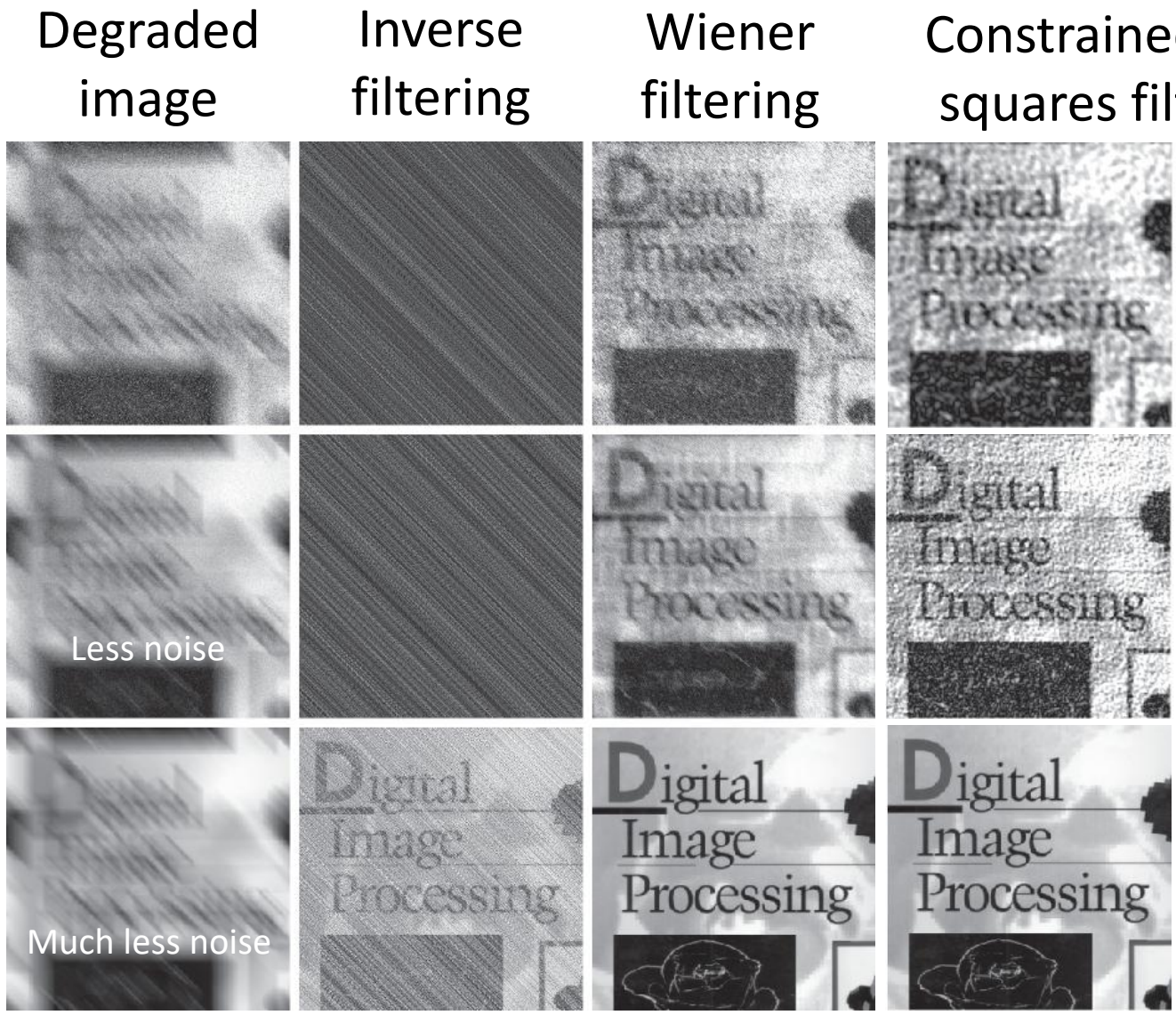
$\hat{f}(x,y)$

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

$e^2 = E\{(f - \hat{f})^2\}$

Minimum mean square error filter

Image restoration, constrained least squares filtering



Next Lecture

- Color image processing
- Reading
  - Chapter 7: Color Image Processing
    - Sections 7.1, 7.2, 7.3, 7.4, 7.5, and 7.6