# Image Restoration

**Pengolahan Citra**

**Semester Gasal 2019/2020**

Laksmita Rahadianti, Aniati Murni

Fakultas Ilmu Komputer Universitas Indonesia

# Review

- We have previously studied **image enhancement** techniques.
- Image enhancement.. aims to improve the image heuristically until we achieve a result that is visually pleasing.

- We will now consider **image restoration**
- Image restoration.. attempts to recover a degraded image using prior knowledge of the distortion.

# Restoration vs Enhancement

- Image enhancement dilakukan secara heuristic, **trial and error,** sampai diperoleh image yang sudah **baik menurut kita**
- In image restoration usually **we know the model of distortion**

Image Enhancement

Image Restoration

# Before we continue....

- Convolution vs Correlation

  - Are both used in spatial and frequency filtering
  - Are not the same thing..

# Correlation

- The process of moving a filter mask over the image and computing the sum of products at each location.
  - Slide filter *g(x) by* image *f(x)*

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

filter

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

image

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 5 | 6 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 8 | 9 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Original position of filter

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 9 | 8 | 7 | 0 | 0 | 0 |
| 0 | 0 | 0 | 6 | 5 | 4 | 0 | 0 | 0 |
| 0 | 0 | 0 | 3 | 2 | 1 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Filtering result

# Convolution

- Rotating a filter mask by 180º and moving it over the image and computing the sum of products at each location.
  - Flip filter *g(x)*
  - Slide filter *g(x) by* image *f(x)*

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

filter

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

image

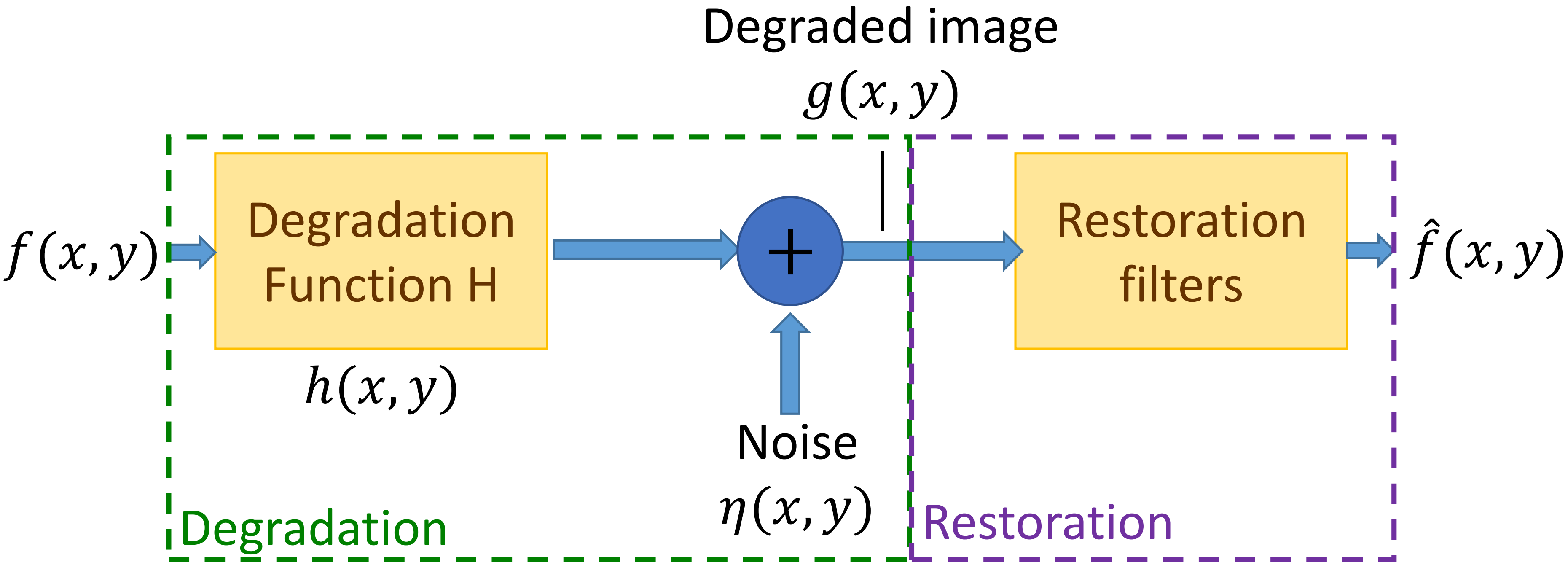
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 9 | 8 | 7 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 5 | 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Original position of filter

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 2 | 3 | 0 | 0 | 0 |
| 0 | 0 | 0 | 4 | 5 | 6 | 0 | 0 | 0 |
| 0 | 0 | 0 | 7 | 8 | 9 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Filtering result

# Model of Image Degradation



# Model of Image Degradation (2)

- Spatial domain

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

  - If the degradation function h is linear, and the noise is spatially independent

- Frequency domain

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

  - $g/G(x,y)$ : degraded image
  - $h/H(x,y)$ : degradation function
  - $f/F(x,y)$: original image
  - $\eta/N(x,y)$ : noise

# Which Domain to Use?

| | Spatial Restoration | Frequency Restoration |
|---|---|---|
| Type of Noise | Additive | Blur |
| Solution | Spatial Masks | Filter Masks |

# Restoring Images based on Noise Model

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

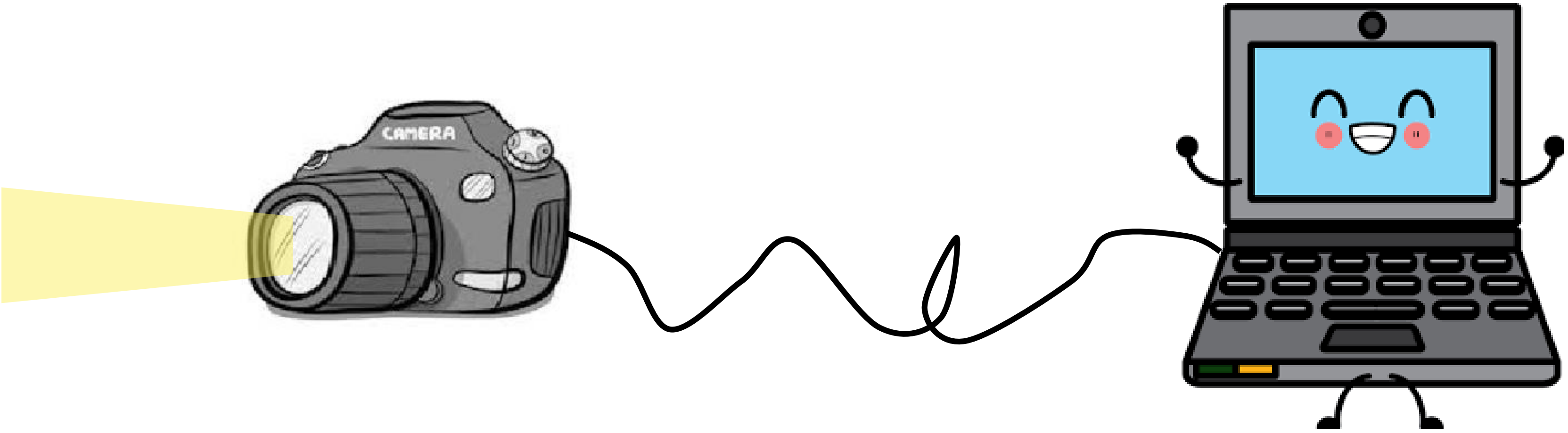
$$G(u,v) = H(u,v)F(u,v) + N(u,v)$$

- Recall:
  - Image restoration attempts to recover a degraded image using **prior knowledge** of the distortion.
- Assume:
  - Degradation function can be ignored

We focus on the noise model $\eta(x,y)$

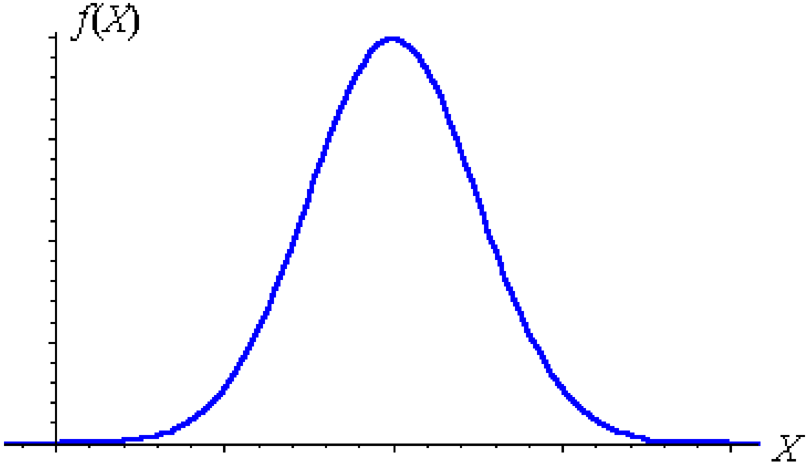
# Noise Model

- Noise in digital images occur during acquisition, such as:
  - Sensor errors: quality of electronics
  - Light levels
  - Sensor temperature
- Or during transmission, such as:
  - Interference in the transmission channel

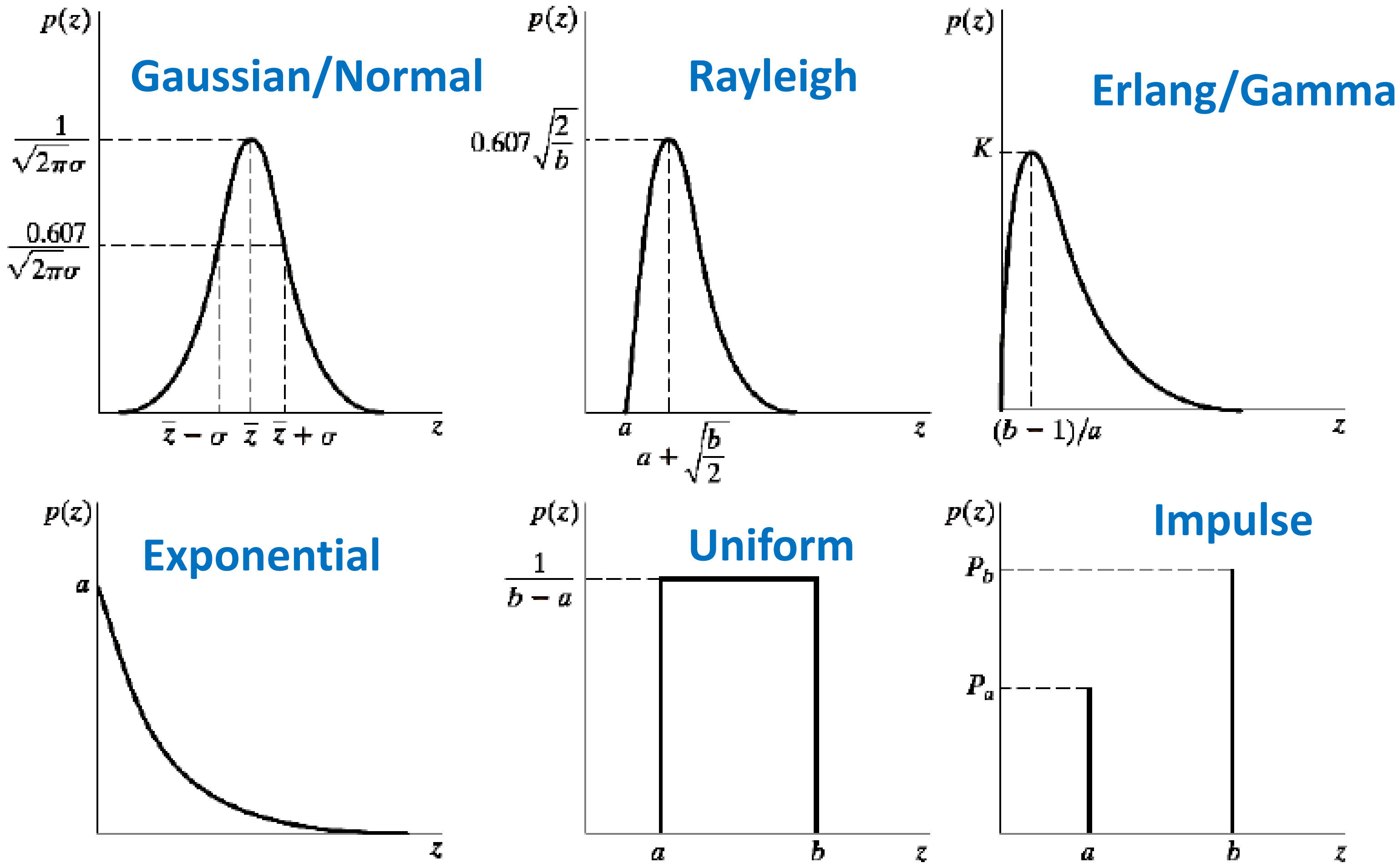


# Spatial Noise

- Can be described statistically as random variables
  - Hence we will consider them as probability density functions (PDF)
  - Probability Density Functions: A function that describes the distribution of a continuous random variable

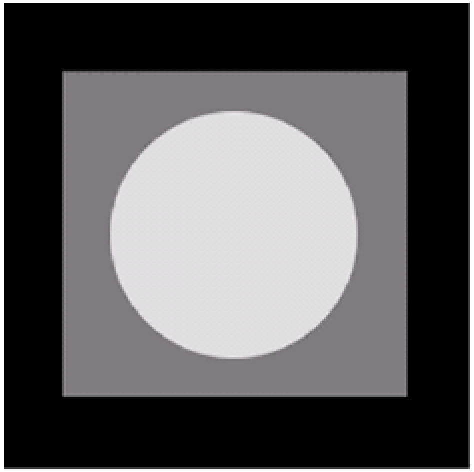


# Common PDFs in Images

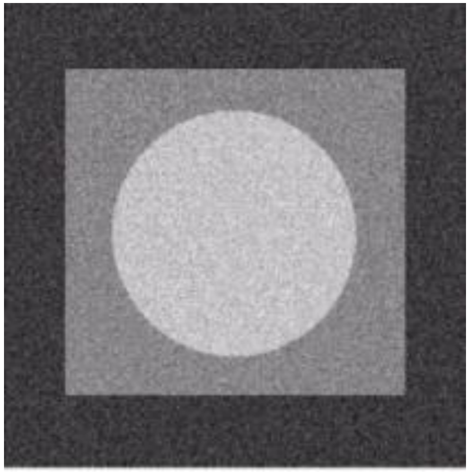


# Gaussian Noise

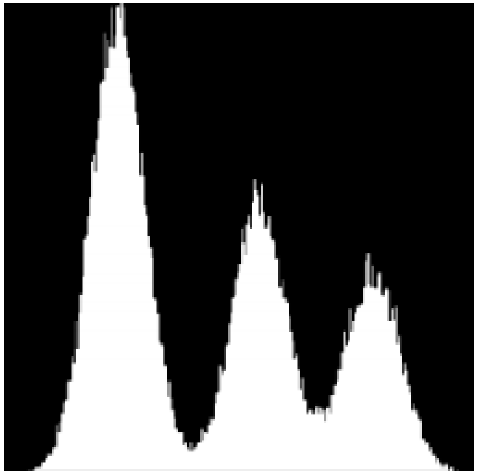
Clear Image



Degraded Image



Histogram of degraded image



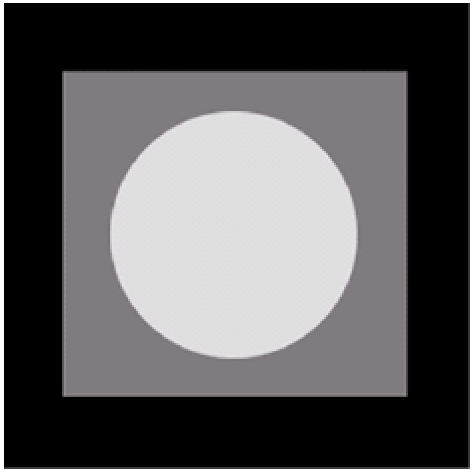
- Very commonly used to describe image noise

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

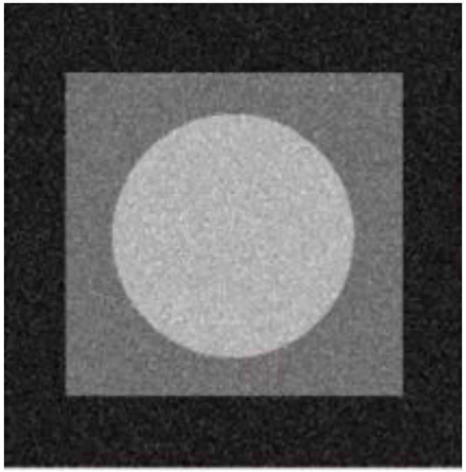
$z$ : intensity
$\bar{z}$: mean intensity
$\sigma$: standard deviation

# Rayleigh Noise

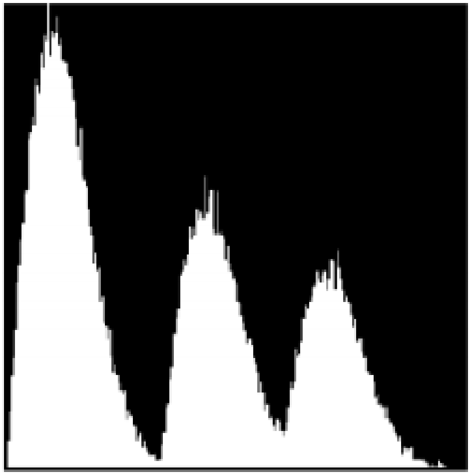
Clear Image



Degraded Image



Histogram of degraded image



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

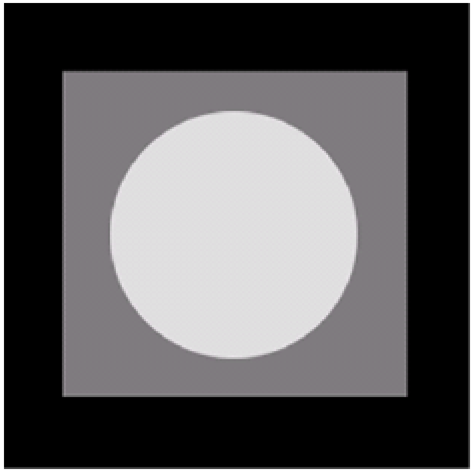
$z$ : intensity

$\bar{z}$: mean intensity = $a + \sqrt{\pi b/4}$

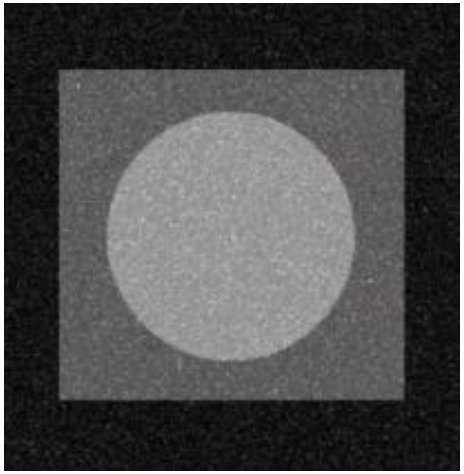
$a, b$ : certain values

# Erlang/Gamma Noise

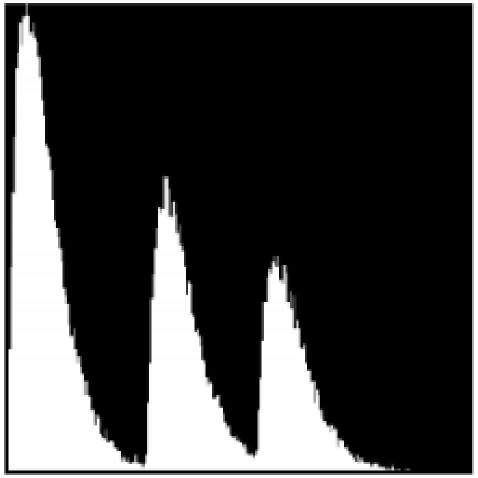
Clear Image



Degraded Image



Histogram of degraded image



- Can be called gamma noise only when the denominator is the gamma function

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

$z$ : intensity

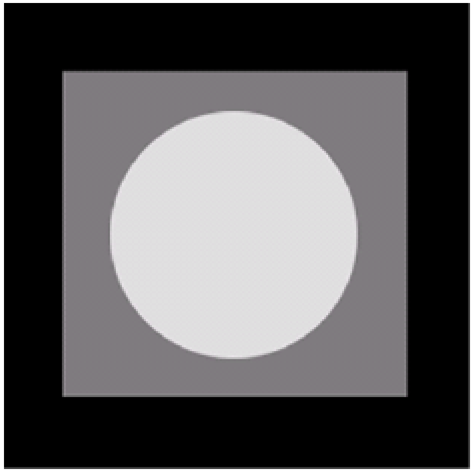
$\bar{z}$: mean intensity = $\frac{b}{a}$

$a, b$ : certain values

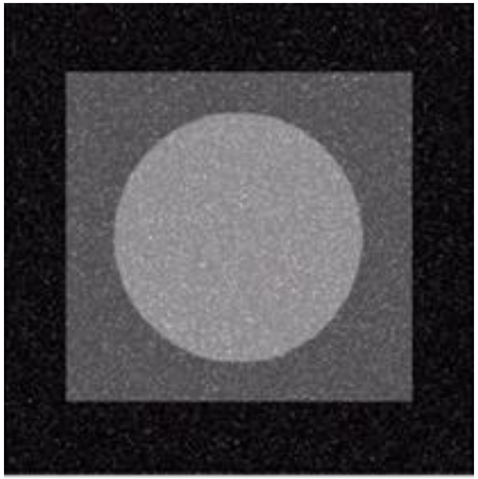
$a > 0$, $b$ is a positive integer

# Exponential Noise

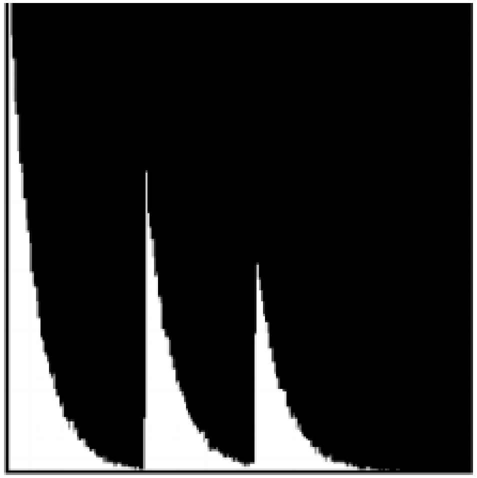
Clear Image



Degraded Image



Histogram of degraded image



- This is a special case of Erlang where $b = 1$

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

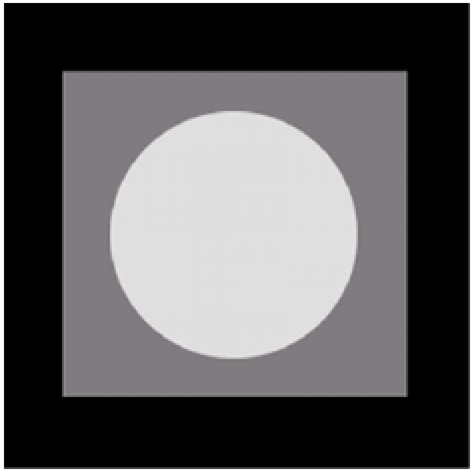
$z$ : intensity

$\bar{z}$: mean intensity = $\frac{1}{a}$

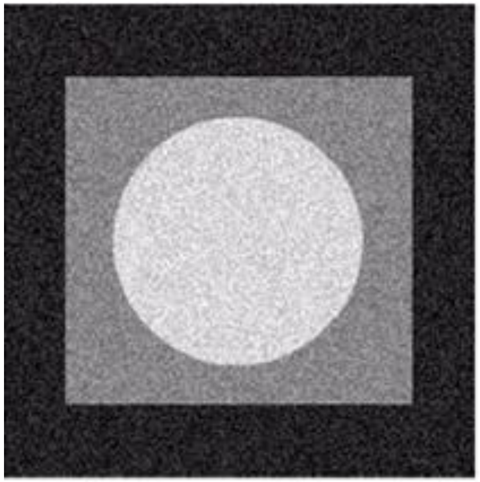
$a$ : certain value

# Uniform Noise

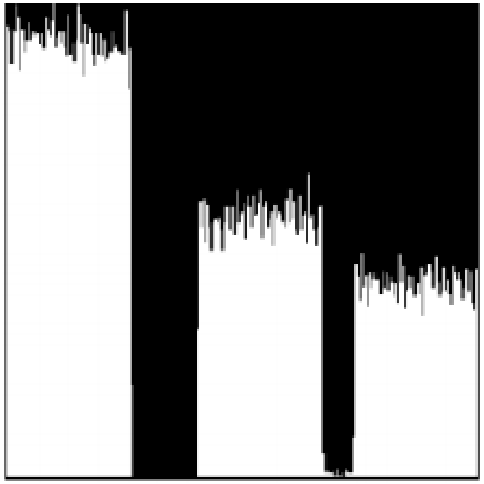
Clear Image



Degraded Image



Histogram of degraded image



- This noise is –as its name says- uniform

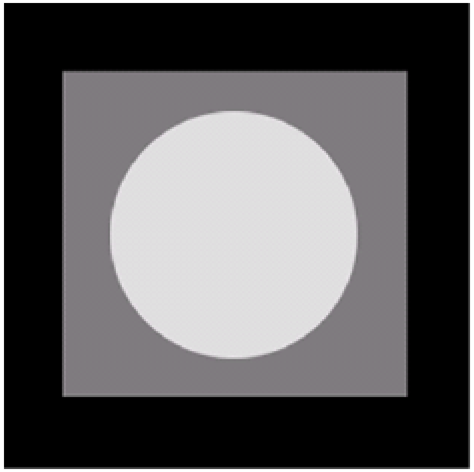
$$p(z) = \begin{cases} \dfrac{1}{b-a}, for\ a \le z \le b \\ 0, otherwise \end{cases}$$

$z$ : intensity

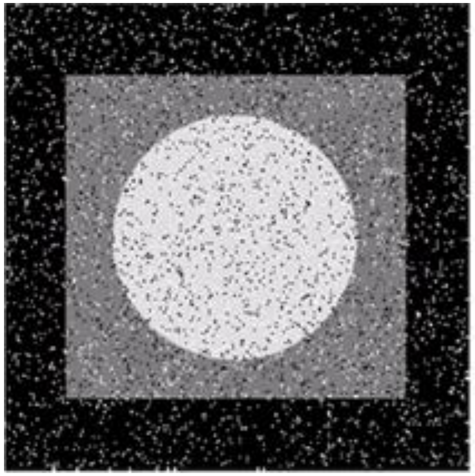
$\bar{z}$: mean intensity = $\frac{a+b}{2}$

# Impulse Noise

Clear Image



Degraded Image



Histogram of degraded image

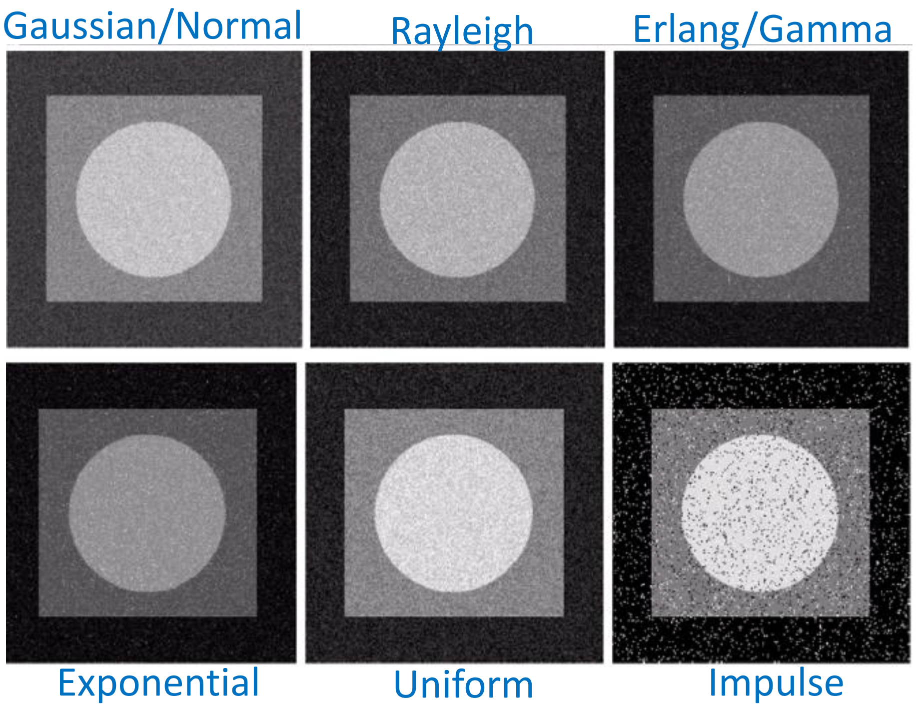
- Only gives peaks of noise: salt-and pepper noise

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

$a, b$ : certain values

# Statistical Noise

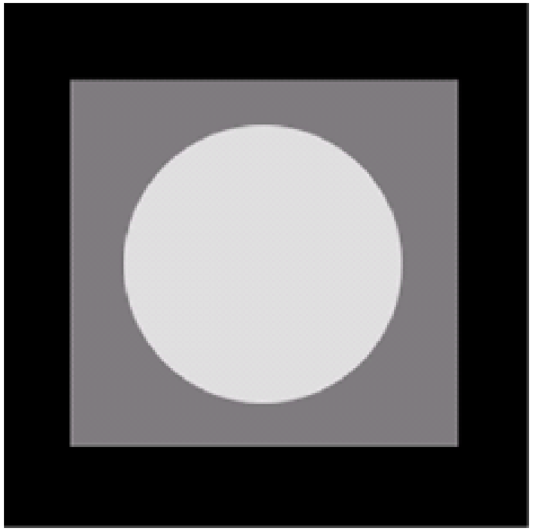
- What do all of the previously described noise have in common?
  - Gaussian
  - Rayleigh
  - Erlang
  - Exponential
  - Uniform
  - Impulse



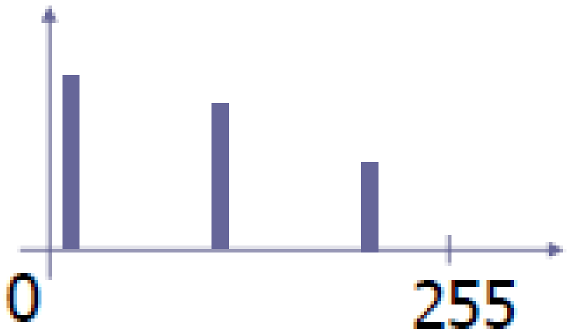

**Spatially Independent**

# Estimation of Noise

- What does a clear image look like?



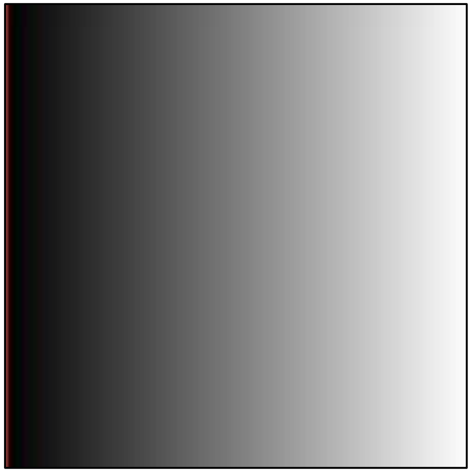
Clear Image




Histogram

# Noise Estimation: If the imaging system is available

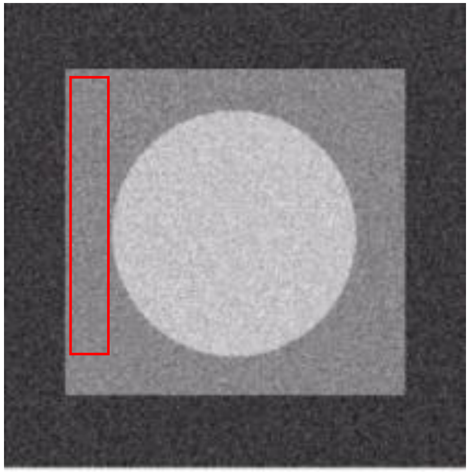
- Capture images of a “flat” environment
  - Capture a plain **known** surface
  - We can then see the pattern of the noise


Clear Image

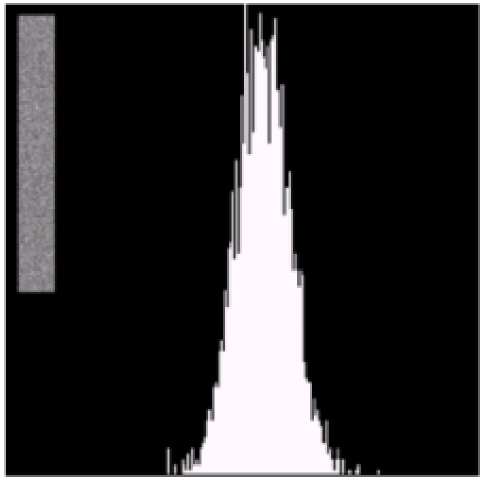

Captured Image

# Estimation of Noise (3)

- If the imaging system is **not** available
  - Use the captured images
  - Take strips of a reasonably constant intensity
  - Observe the histogram of the strips

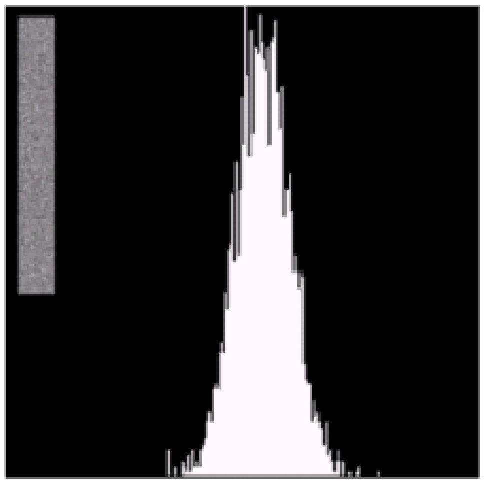


Captured Image



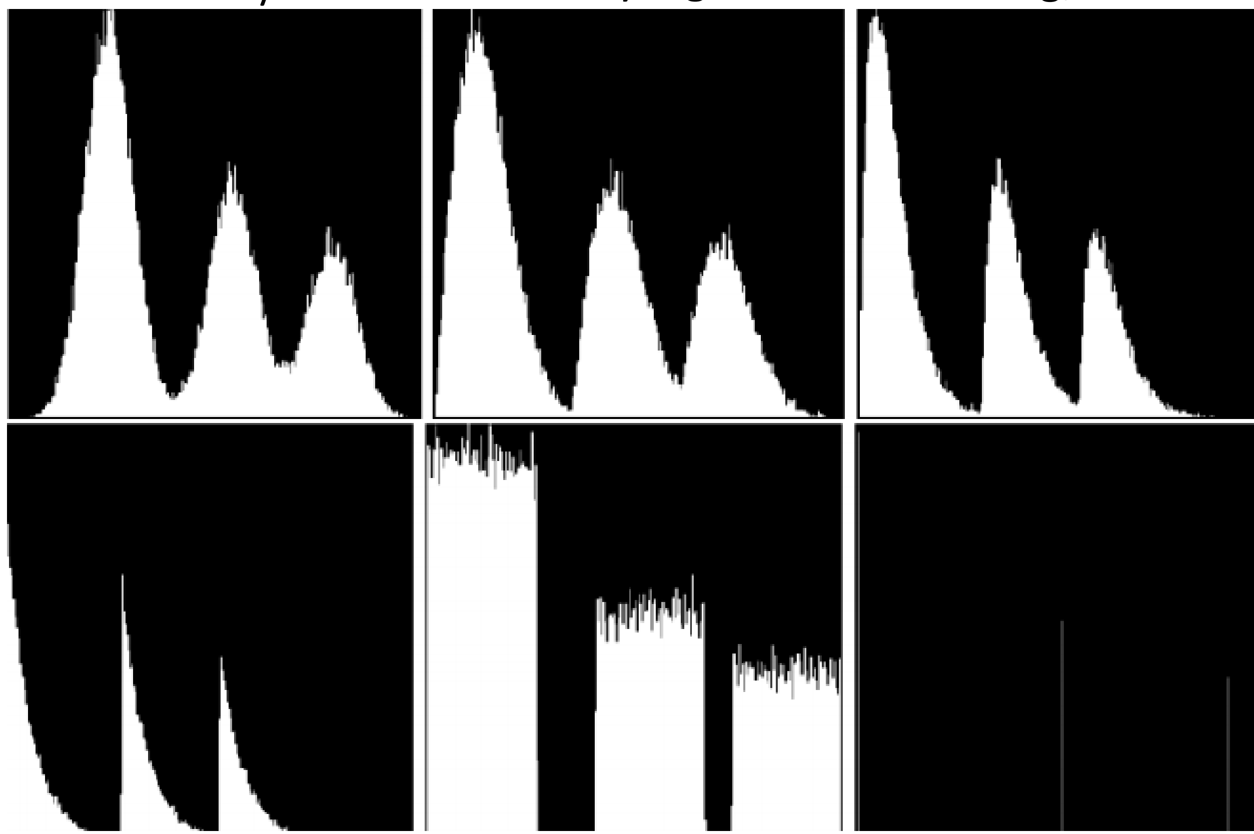
Histogram

# Which noise is this?



**Gaussian/Normal**

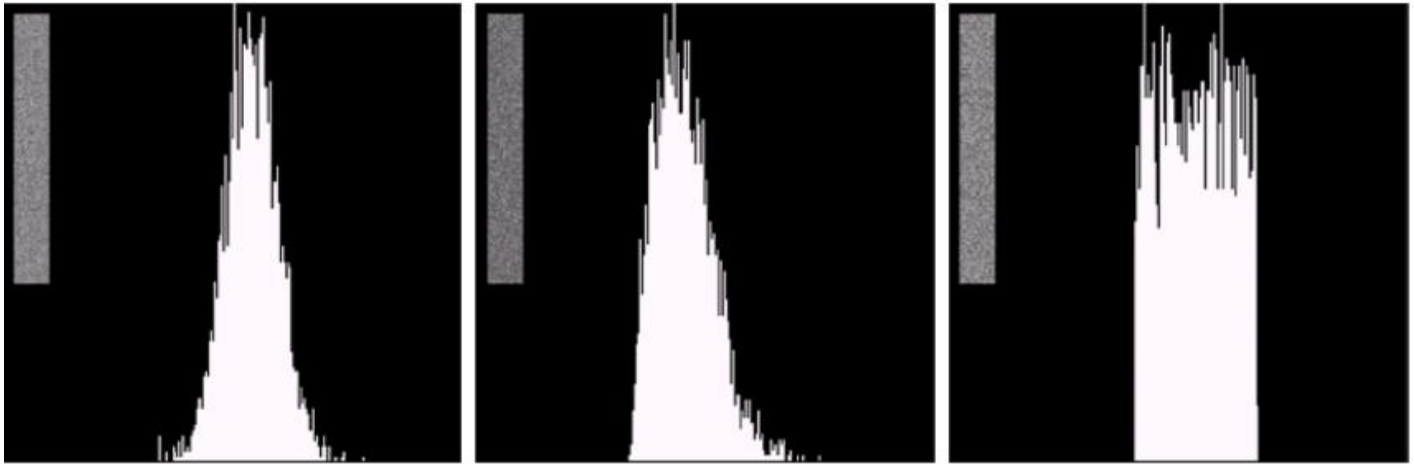
Gaussian/Normal    Rayleigh    Erlang/Gamma



Exponential    Uniform    Impulse

# Estimation of Noise (4)

- Indicators:
  - Mean intensity $\bar{z}$
  - Standard deviation $\sigma$



Gaussian/Normal Rayleigh Uniform

# Eliminating Additive Noise

We have assumed:

- Degradation function can be ignored
- Focus on the additive noise model $\eta(x, y)$

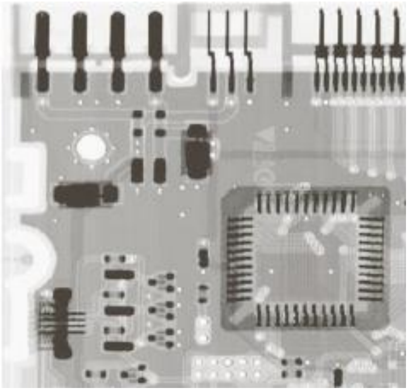
Spatial Filtering

# Arithmetic Mean Filter

- Smoothing and noise reduction
- Loss of detail

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

- $m \times n$ image
- $S_{x,y}$ kernel centered at $(x,y)$



Clear Image

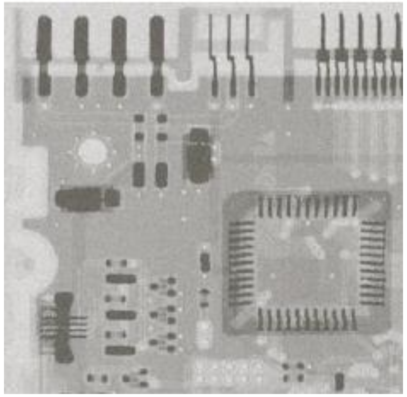
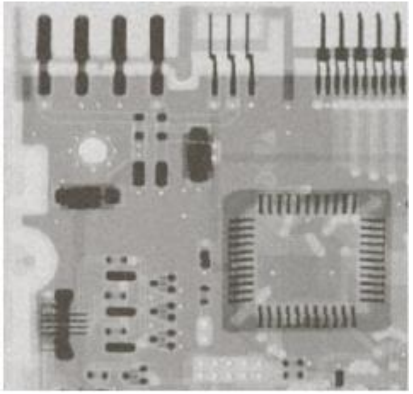


Image w/ Gaussian Noise



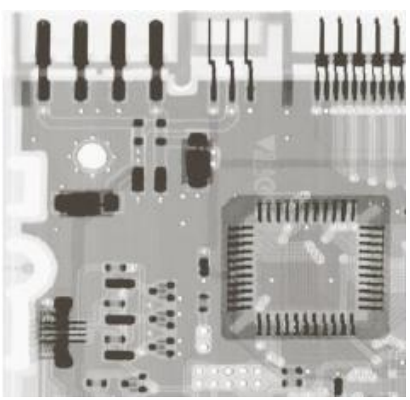
Restored Image with Arithmetic Mean Filter

# Geometric Mean Filter

- Smoothing and noise reduction
- Less loss of detail compared to arithmetic mean filter

$$\hat{f}(x,y) = \left[ \prod_{(s,t)\in S_{x,y}} g(s,t) \right]^{1/2}$$

- $m \times n$ image
- $S_{x,y}$ kernel centered at $(x,y)$



Clear Image

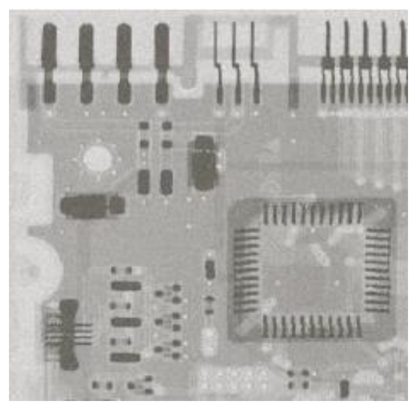
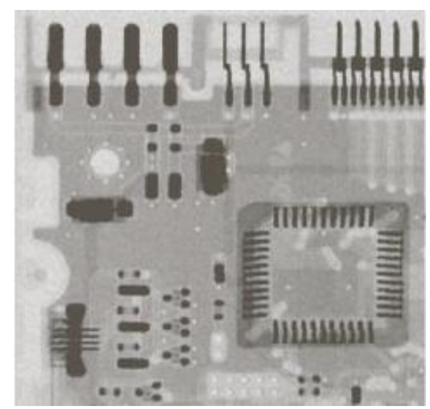


Image w/ Gaussian Noise



Restored Image with Geometric Mean Filter

# Harmonic Mean Filter

- Works especially well for salt noise (not pepper noise!)
- Works well for Gaussian noise and other noise types

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

- $m \times n$ image
- $S_{x,y}$ kernel centered at $(x,y)$

# Contraharmonic Mean Filter

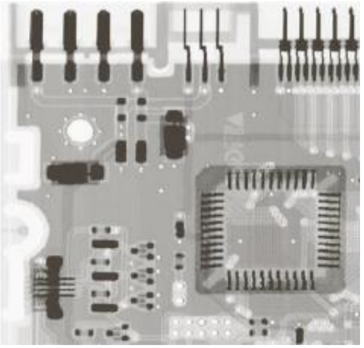
- Perfect for salt-and-pepper noise

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

- $m \times n$ image
- $S_{x,y}$ kernel centered at $(x,y)$

- $Q$ (filter order)
- $Q > 0$ eliminates pepper,
- $Q < 0$ eliminates salt

# Contraharmonic Mean Filter (2)



Clear Image

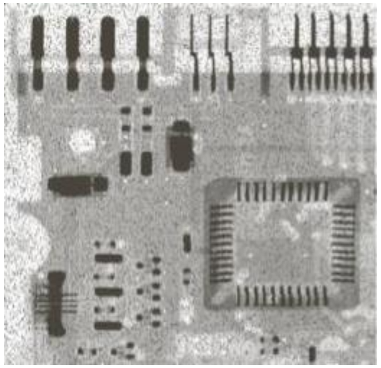


Image w/ Pepper Noise

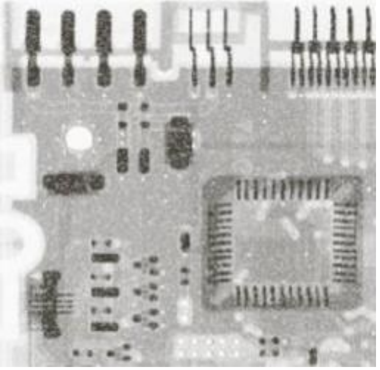
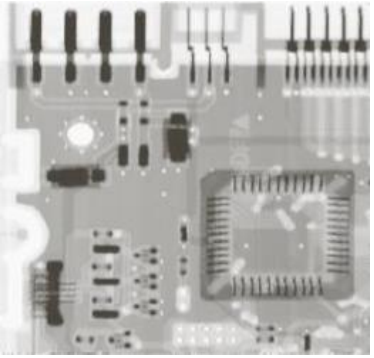
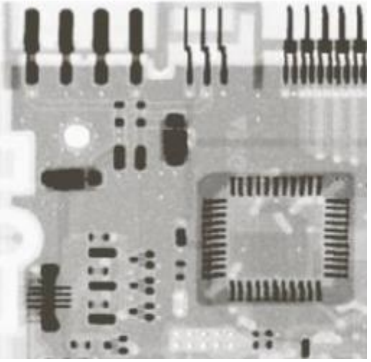


Image w/ Salt Noise



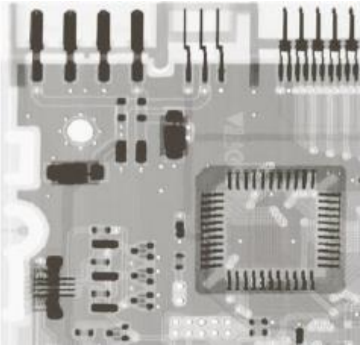
Restored Image (Q=1.5)



Restored Image (Q=-1.5)

# Contraharmonic Mean Filter (3)

- The choice of Q is crucial!



Clear Image

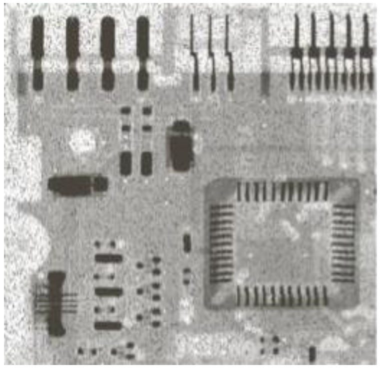
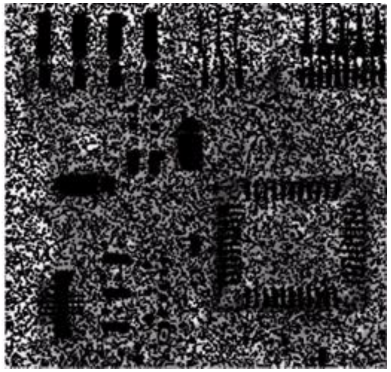


Image w/ Pepper Noise



Restored Image (Q=-1.5)

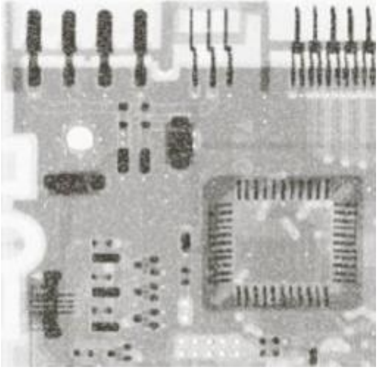
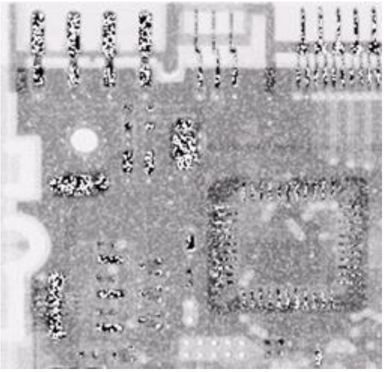


Image w/ Salt Noise



Restored Image (Q=1.5)

# Order-Statistic Filters

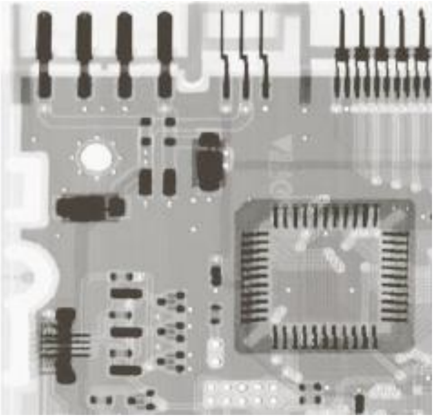
- Spatial filters based on ordering (ranking) the values of the pixels contained in the local image area encompassed by the filter.

  - Median Filters
  - Min/Max
  - Alpha Trimmed

# Order-Statistic Filters (2)

- Median Filters

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



Clear Image

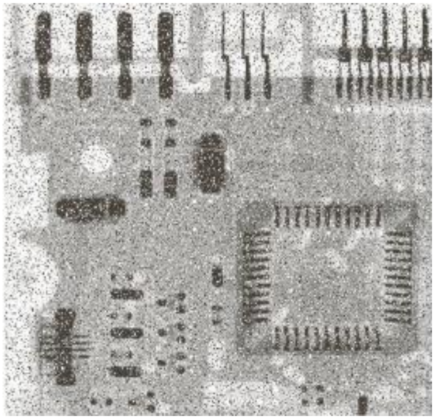
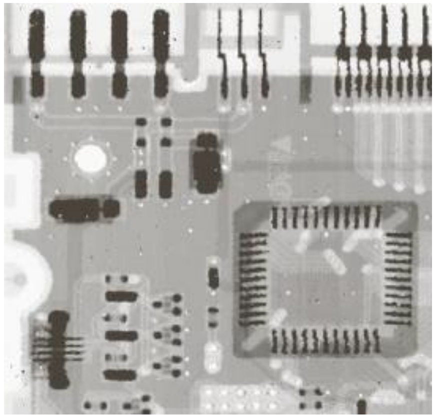
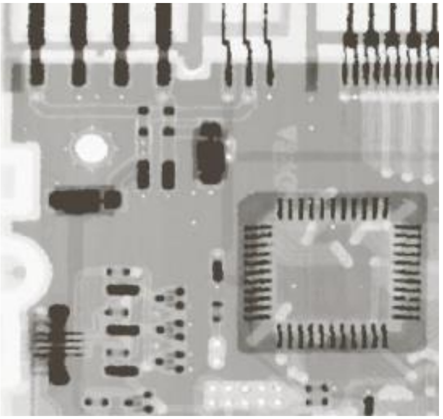


Image w/ Salt and Pepper Noise



Restored Image with 1 pass of Median Filter



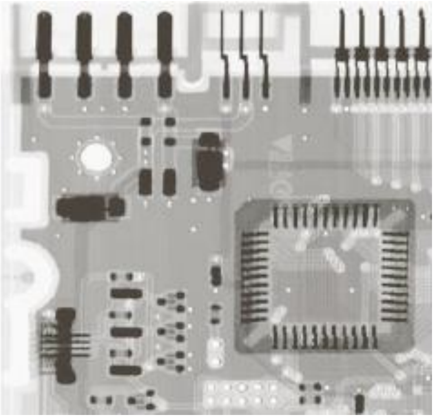
Restored Image with 3 passes of Median Filter

# Order-Statistic Filters (3)

- Min / Max Filters

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

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



Clear Image

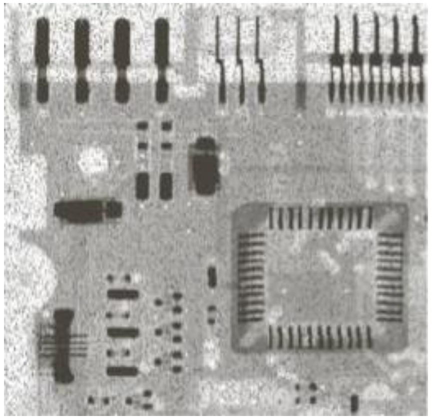
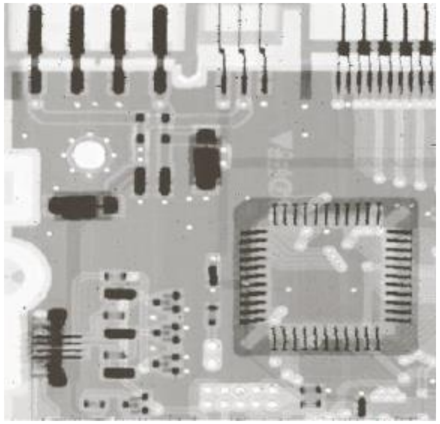
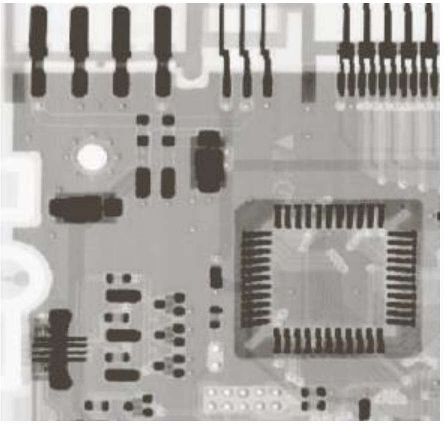


Image w/ Pepper Noise



Restored Image with Max Filter

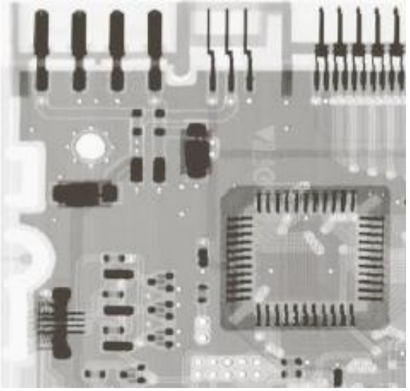


Restored Image with Min Filter

# Order-Statistic Filters (4)

- Alpha Trimmed Mean Filter

$$\hat{f}(x,y) = \frac{1}{mn-d} \sum_{(s,t)\in S_{x,y}} g(s,t) \quad d : \text{between 0 and } mn-1$$



Clear Image

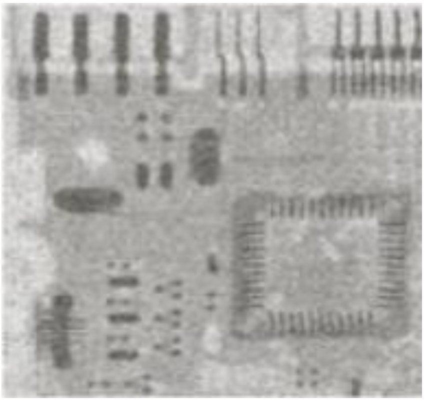
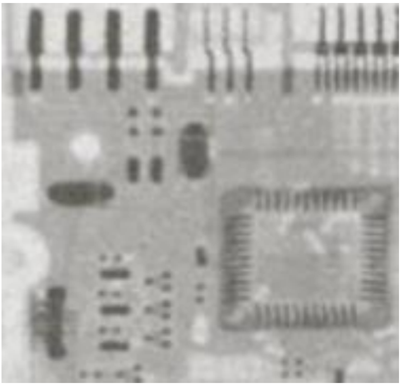
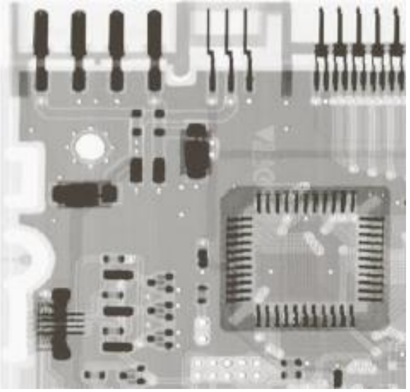


Image w/ Salt and Pepper Noise



Restored Image with Alpha-Trimmed Filter

# Image Restoration with Spatial Filters



Clear Image

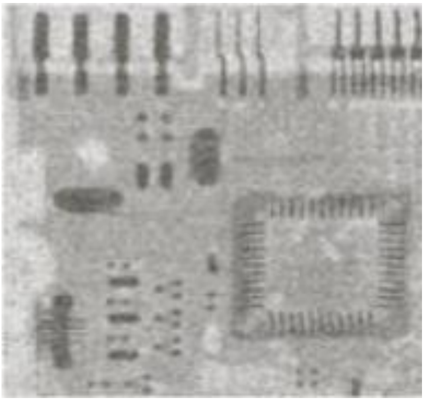
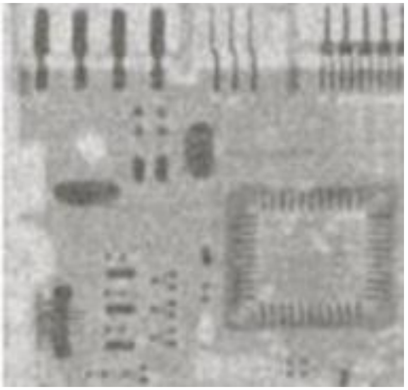
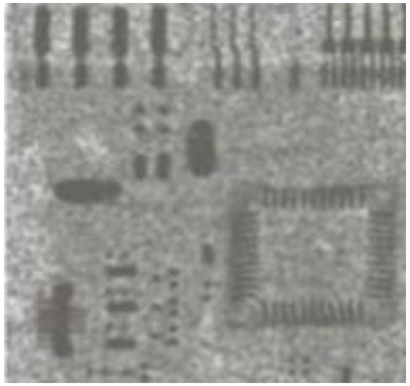


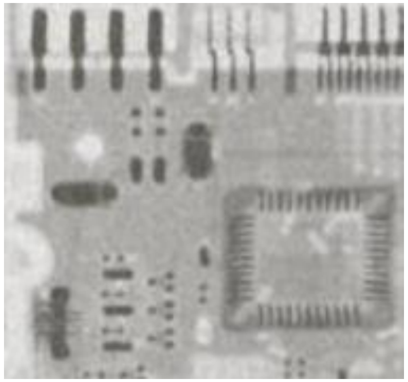
Image w/ Salt and Pepper Noise



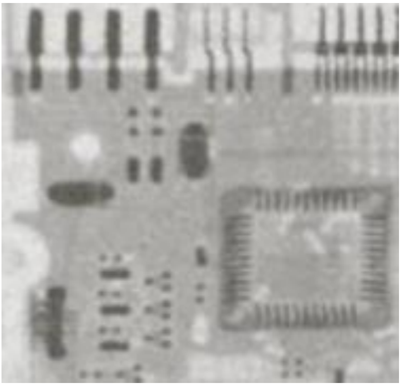
Restored Image with Arithmetic Mean Filter



Restored Image with Geometric Mean Filter



Restored Image with Median Filter



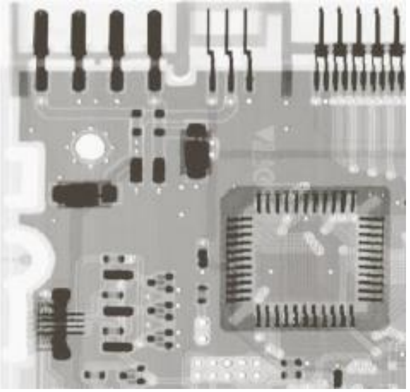
Restored Image with Alpha-Trimmed Filter

# Adaptive Local Noise Reduction Filter

- Changes its behavior based on the statistical characteristics of the image inside the filter region defined by the neighborhood.
  - Simplest statistical measurement
    - Mean and variance
  - Known parameters on local region $S_{x,y}$
    - $g(x, y)$: noisy image pixel value
    - $\sigma_\eta^2$: noise variance (assume known a prior)
    - $m_L$: local mean
    - ${\sigma^2}_L$: local variance

$$\hat{f}(x, y) = g(x, y) - \frac{\sigma_\eta^2}{{\sigma^2}_L}[g(x, y) - m_L]$$

# Adaptive Local Noise Reduction Filter (2)



Clear Image

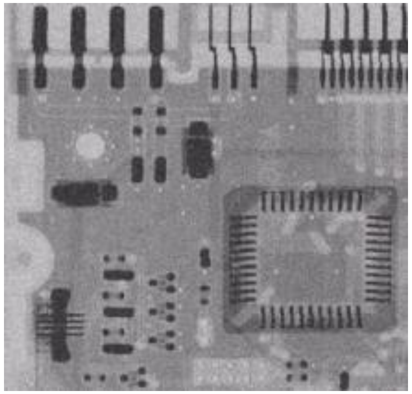
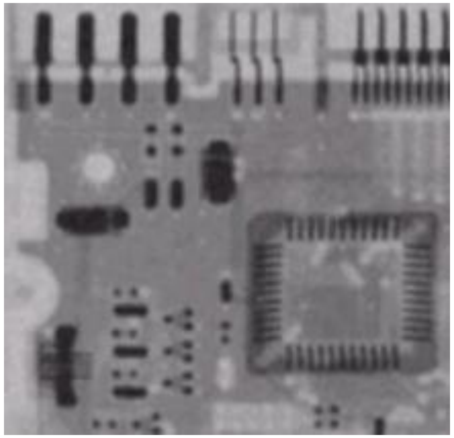
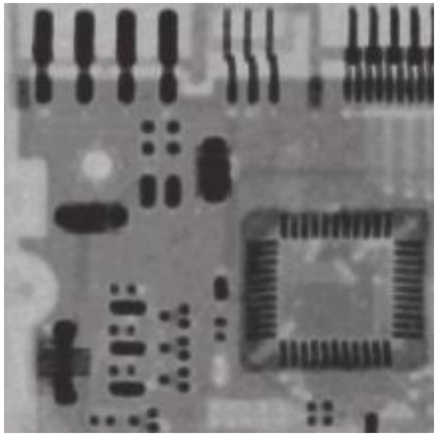


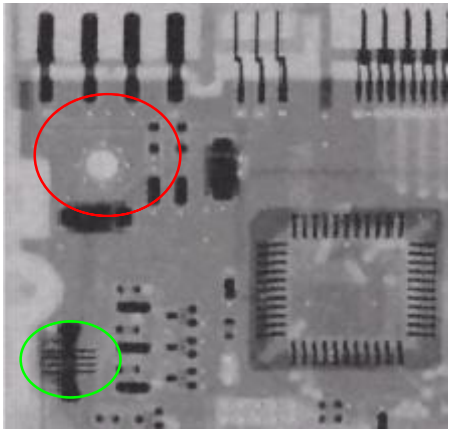
Image w/ Gaussian Noise



Restored Image with Arithmetic Mean Filter



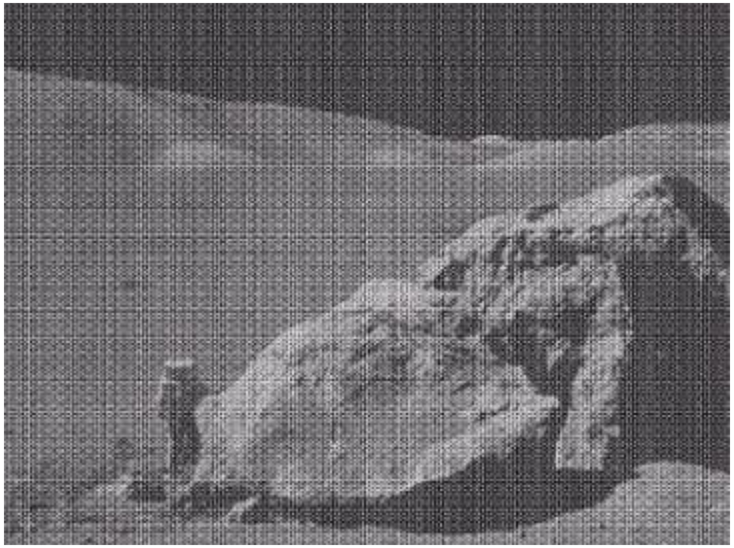
Restored Image with Geometric Mean Filter



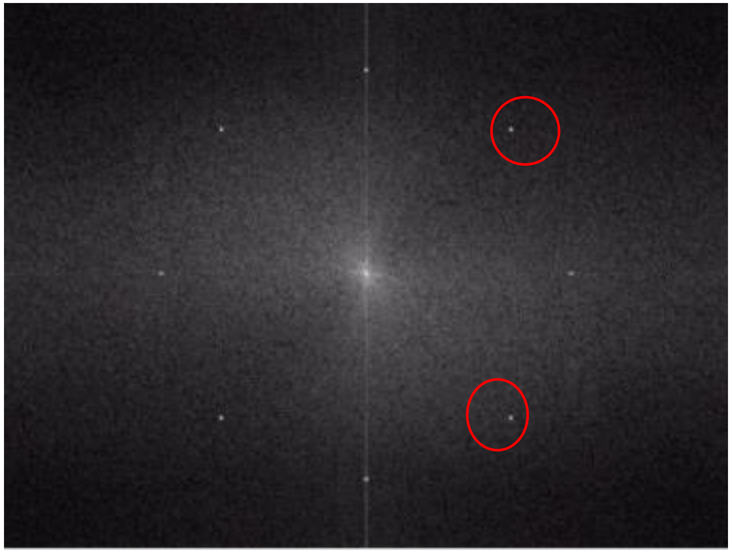
Restored Image with Adaptive Local Filter

# Periodic Noise

- Unlike previously, periodic noise is spatially dependent
- Can be handled well by frequency domain filtering



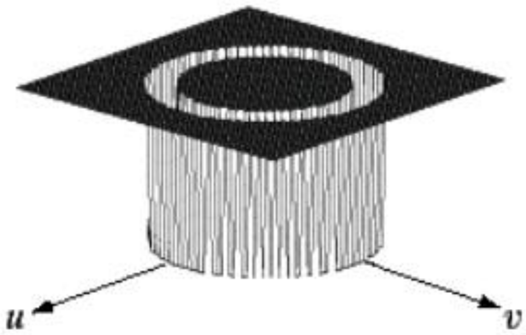
Spatial Image



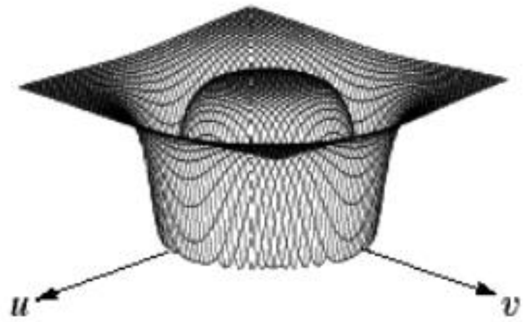
Fourier Transform

Band Reject Filters

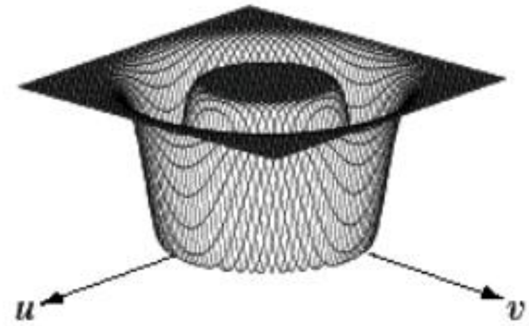
# Band Reject Filters




Ideal Bandreject Filter

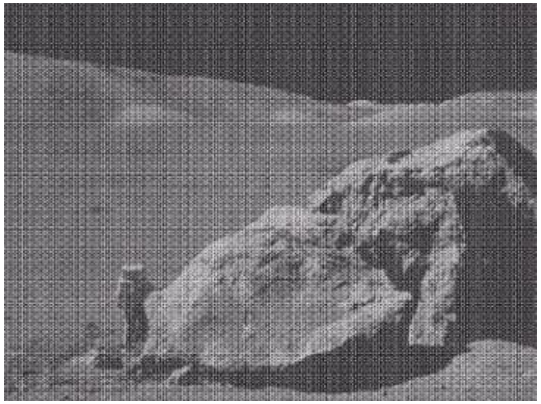



Butterworth Bandreject Filter

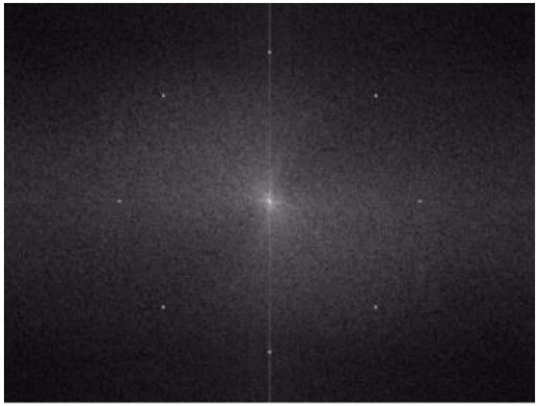



Gaussian Bandreject Filter

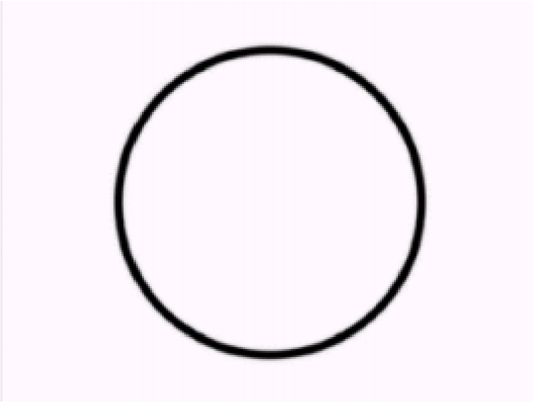
# Band Reject Filters (2)



Spatial Image



Fourier Transform



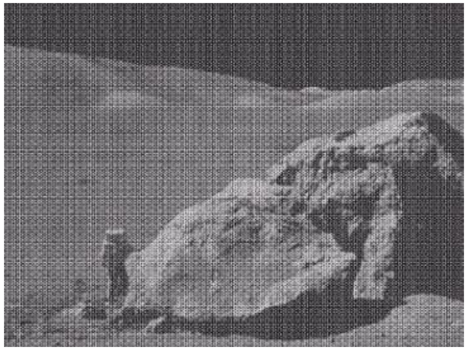
Band Reject Filter

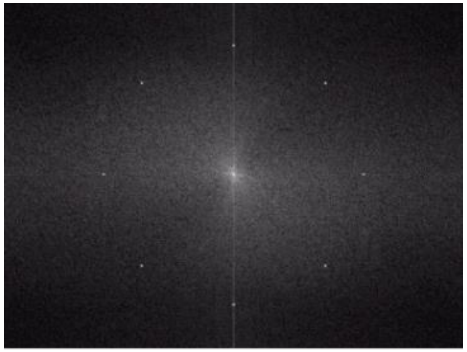
Restored Image

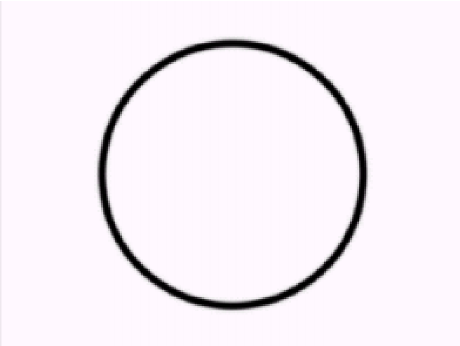
# Band Pass Filters

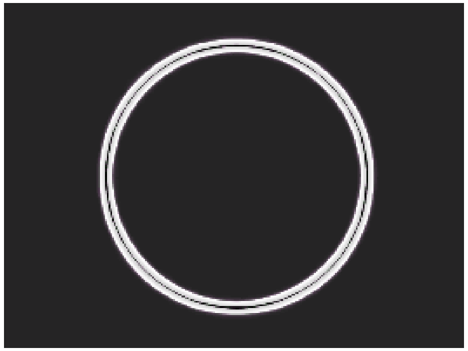
- The opposite of Band Reject Filters

$$H_{BP}(u,v) = 1 - H_{BR}(u,v)$$


Spatial Image

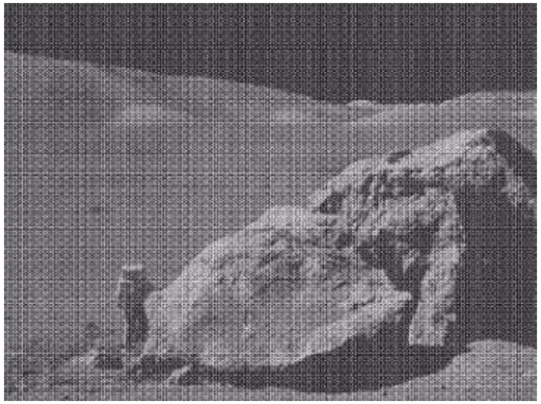

Fourier Transform


Band Reject Filter

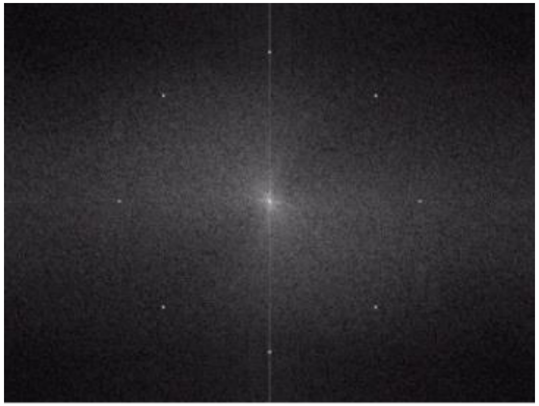

Band Pass Filter

- What will I obtain if I filter the image with the band pass filter?

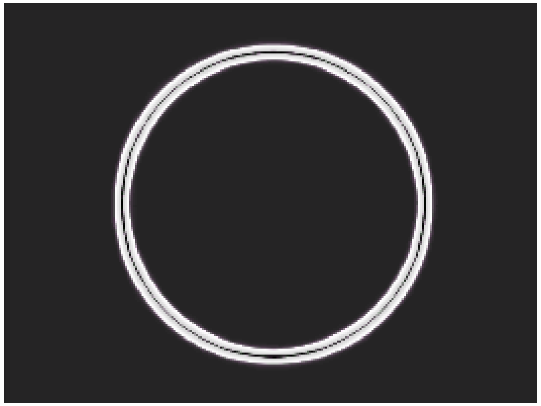
# Band Pass Filters (2)



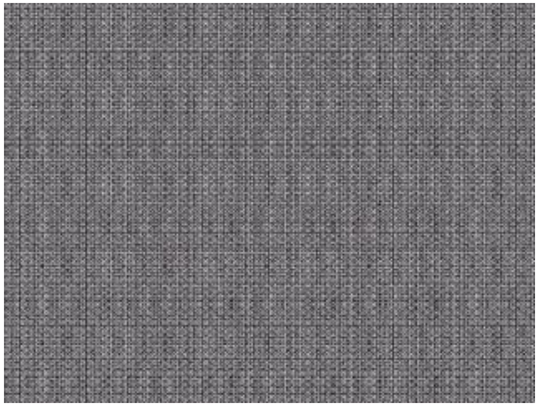
Spatial Image



Fourier Transform



Band Pass Filter



Noise Pattern of Image

# Restoring Images based on Degradation Model

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

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

- Previously we assumed:
  - Degradation function can be ignored

We focus now on the degradation model $H(u,v)$

# Estimating the Degradation Function

- Given a degraded image without any knowledge of the degradation.
- Assume a **linear, spatially independent** process.
- What can we do?
    - Observation
    - Experimentation
    - Mathematical Modeling.

# Estimation By Image Observation

- Take a local window in the degraded image $G_s(u,v)$

  →simple structure, strong signal
- Estimate the original image in the window $\widehat{F}_s(u,v)$
- Use the degraded and the estimated "clear" window

$$H(u,v) = \frac{G_s(u,v)}{\widehat{F}_s(u,v)}$$

# Estimation By Image Observation (2)

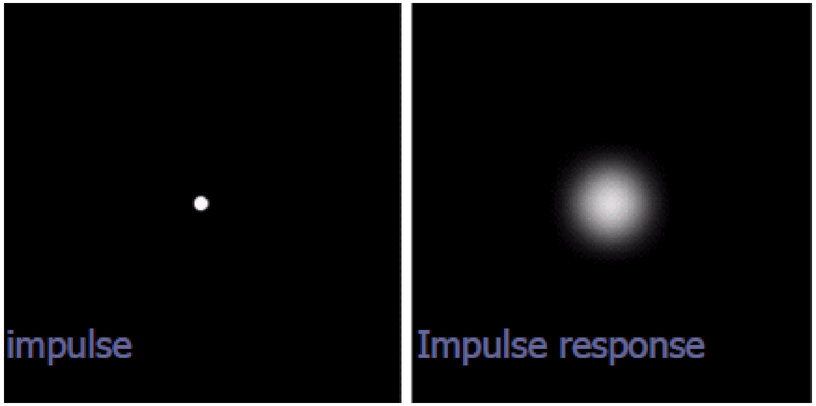
- Example:
  - We have a blurred image
  - Take a small rectangular section of background
  - Attempt to enhance the image → any ideas how?
- Thus, we approximate the degradation by assuming position invariance

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

# Estimation By Experimentation

- If we can obtain similar equipment to that used in the image acquisition.
  - Capture an image of a single impulse
  - The fourier transform of a single impulse is a constant, A
- Thus, we can estimate

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



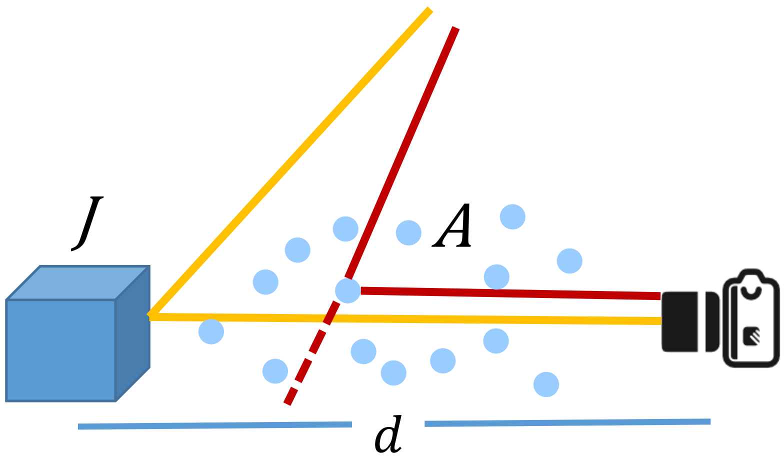
# Estimation By Mathematical Modelling

- Can be used to estimate environmental effects to image capture
- Example in the frequency domain: Atmospheric effects

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

# Estimation By Mathematical Modelling (2)

- Example in the spatial domain: Photometric scattering effects




$$I = JT + A(1 - T)$$

- Transmission
  - Beer-lambert law

$$T = e^{-cd}$$

$c$ : Attenuation coefficient of media
$d$ : Distance of object and camera
$J$ : Original intensity of scene
$A$ : Airlight (The color of surrounding media, composed solely of scattering effects.)

Rahadianti, L., Sakaue, F., Sato, J. "Time-to-Contact in Scattering Media based on Statistical Priors". ITE Transactions on Media Technology and Applications. October 2017.

# Inverse Filtering

- Using the previous estimation methods, we obtain

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

- Back to our degradation model

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

- We obtain

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

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

We still need $N(u,v)$ .
If $H(u,v)$ is close to 0, $N(u,v)$ will dominate the estimate $\hat{F}(u,v)$.

# Inverse Filtering(2)

- To avoid near-zero values:
  - Limit filter frequencies near the origin
  - Manual adjustments to restoration
  - Experimental approaches to set parameters

# Wiener Filter

- N. Wiener (1942)
- Also known as:
  - Minimum mean square filter
  - Least square error filter
- What does it do:
  - Considers both degradation function and statistical noise
  - The objective is to find the estimate $\hat{f}$ for a clear image $f$ with the mean square error between them is minimized

# Wiener Filter (2)

- The objective is to find the estimate $\hat{f}$ for a clear image $f$ with the mean square error between them is minimized

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + \frac{S_\eta(u,v)}{S_f(u,v)}}\right] G(u,v)$$

$H(u,v)$: degradation function
$H^*(u,v)$: complex conjugate of $H(u,v)$
$|H(u,v)|^2$: $H^*(u,v)\ H(u,v)$
$S_\eta(u,v)$ : power spectrum of noise
$S_f(u,v)$: $\boxed{\text{power spectrum of the original image}}$

Usually unknown

# Wiener Filter (3)

- Constant $K$ as an estimate

$$\hat{F}(u,v) = \left[\frac{1}{H(u,v)} \frac{|H(u,v)|^2}{|H(u,v)|^2 + K}\right] G(u,v)$$

$H(u,v)$: degradation function
$H^*(u,v)$: complex conjugate of $H(u,v)$
$|H(u,v)|^2$: $H^*(u,v)\ H(u,v)$
$K$: constant chosen for the best visual result

# Wiener Filter Results


Clear Image

Image w/ Motion Blur and Additive Noise

Wiener Filter Results with various noise variance

# Additional Reading

- Inverse Filtering and its applications
- Wiener Filter and its applications
- Constrained Least Squares Filtering
- Image Quality Measures

# Image Quality

Pedersen, Marius & Yngve Hardeberg, Jon. (2012). Full-Reference Image Quality Metrics: Classification and Evaluation. Foundations and Trends in Computer Graphics and Vision.

AHMED, ISMAIL T., Chen Soong Der, and BARAA TAREQ HAMMAD. "A Survey of Recent Approaches on No-Reference Image Quality Assessment with Multiscale Geometric Analysis Transforms."

# Image Quality

- Image Quality
  - The level of accuracy in which digital systems display the signals that form an image.
  - The weighted combination of all of the visually significant attributes of an image.
- Image Quality Methods, Image Quality Metrics, Image Quality Assessment
- Ways to assess image quality
  - Subjective methods
  - Objective methods

# Image Quality Metrics (1)

- Objective methods:
  - **Full-reference (FR) methods** – The image quality is computed by comparing it with a reference image that is assumed to have perfect quality
  - **Reduced-reference (RR) methods** – The image quality is measured based on a features extracted from the reference image.
  - **No-reference (NR) methods** – The image quality is measured without any reference to the original one.

# Image Quality Metrics

- Based on the information used:
  - **Pixel difference-based** which uses the difference of value of each pixel.
  - **Correlation-based measures:** correlation of pixels or vector angular directions.
  - **Edge-based measures:** displacement of edge positions or their consistency across resolution levels.
  - **Spectral distance-based measures:** the Fourier magnitude and/or phase spectral discrepancy on a block basis.
  - **Context-based measures:** based on various functionals of the multidimensional context probability.
  - **HVS-based measures**, based on the human visual system (HVS) weighted spectral distortion measures or (dis)similarity criteria used in image-based browsing functions.

# A Non-Exhaustive List of Image Quality Measures

- Full/Reduced Reference
  - Signal to Noise Ratio
  - Mean Square Error / Root Mean Square Error
  - Structural Similarity (SSIM)
  - $\Delta E^*_{ab}, \Delta E^*_{94}$, etc: color difference methods
  - Adaptive Image Difference
  - Universal Image Quality Index
- No-Reference
  - Blind Image Spatial Quality Evaluator (BRISQUE)
  - Natural Image Quality Evaluator (NIQE)
  - Perception based Image Quality Evaluator (PIQE)