



Image Restoration



Preview

- Goal of **image restoration**
 - Improve an image in some **predefined** sense
 - Difference with **image enhancement** ?
- Features
 - Image restoration v.s image enhancement
 - Objective process v.s. subjective process
 - A prior knowledge v.s heuristic process
 - A prior knowledge of the **degradation phenomenon** is considered
 - **Modeling the degradation** and apply the **inverse process** to recover the original image



Preview (cont.)

- Target

- Degraded digital image
- Sensor, digitizer, display degradations are less considered

- Spatial domain approach

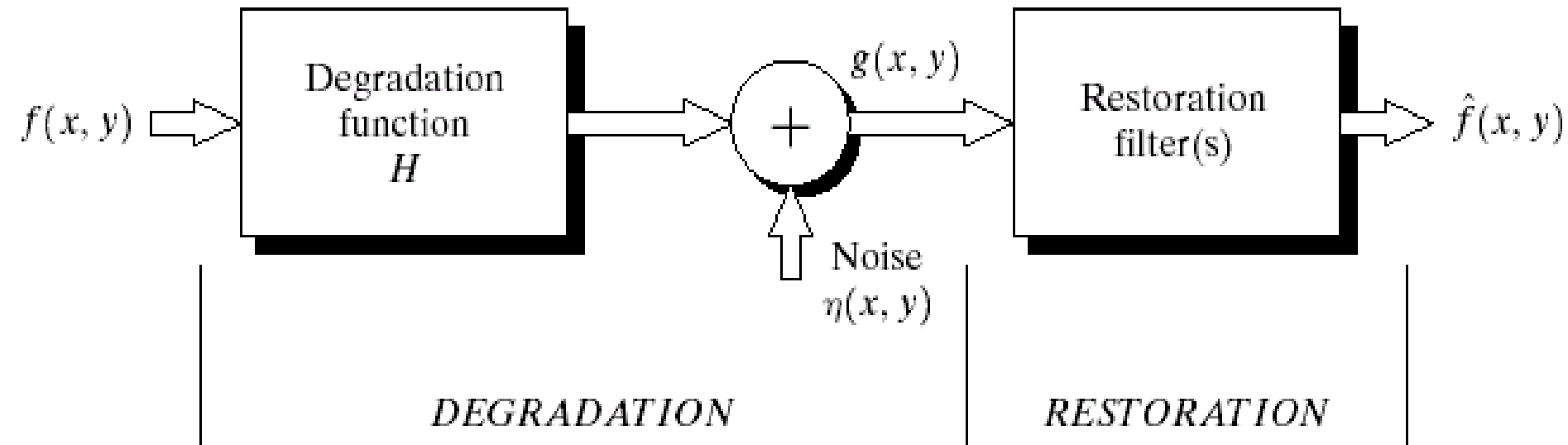
- Frequency domain approach



Outline

- A model of the image degradation / restoration process
- Noise models
- Restoration in the presence of noise only – spatial filtering
- Periodic noise reduction by frequency domain filtering
- Linear, position-invariant degradations
- Estimating the degradation function
- Inverse filtering

A model of the image degradation/restoration process



$$\left\{ \begin{array}{l} g(x,y)=f(x,y)*h(x,y)+\eta(x,y) \\ G(u,v)=F(u,v)H(u,v)+N(u,v) \end{array} \right.$$



Noise models

- Source of noise
 - Image acquisition (digitization)
 - Image transmission
- Spatial properties of noise
 - **Statistical behavior** of the gray-level values of pixels
 - Noise parameters, correlation with the image
- Frequency properties of noise
 - Fourier spectrum
 - Ex. **white** noise (a constant Fourier spectrum)



Noise probability density functions

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



Gaussian noise

- Math. tractability in spatial and frequency domain
- Electronic circuit noise and sensor noise

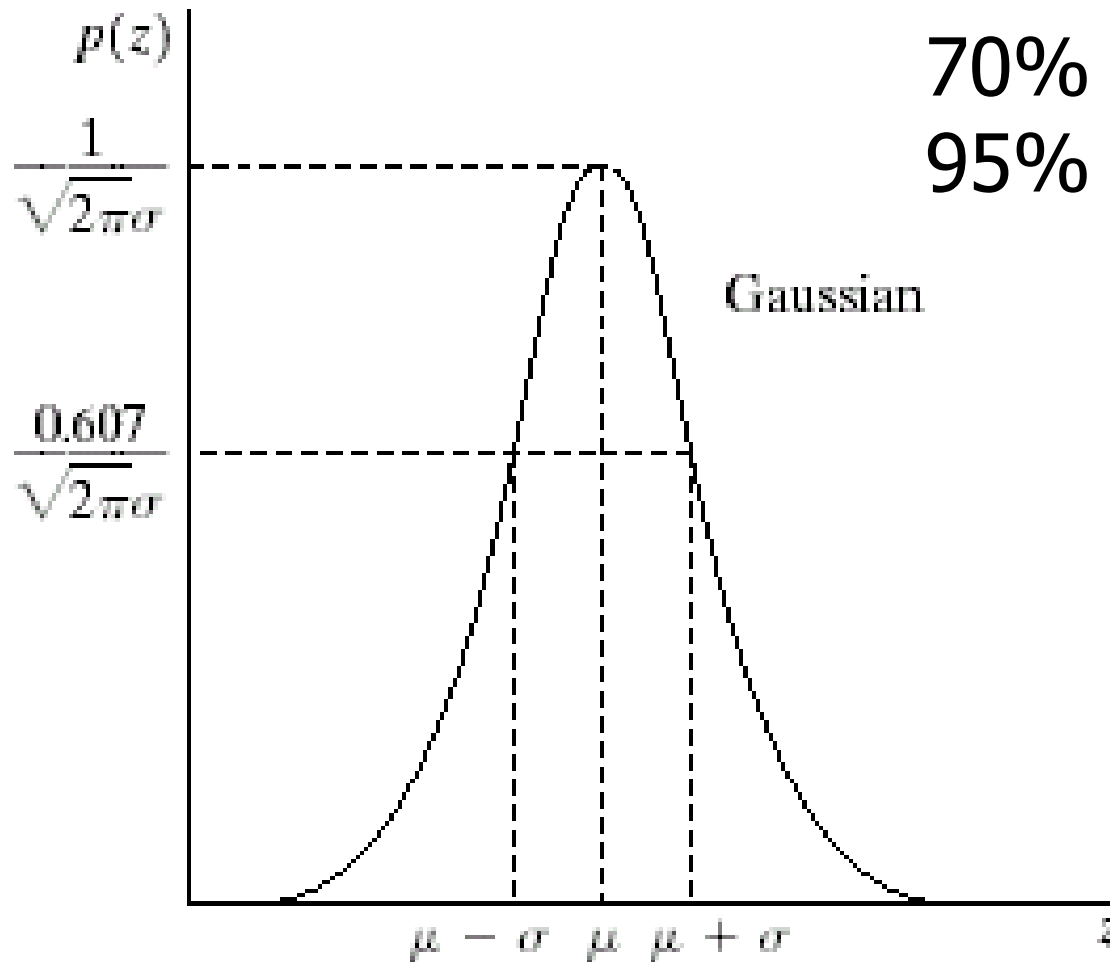
$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\mu)^2 / 2\sigma^2}$$

Diagram illustrating the Gaussian distribution formula with annotations:

- A red arrow points from $\sqrt{2\pi}\sigma$ down to the integral equation below.
- A red arrow points from μ up to the word "mean".
- A red arrow points from σ^2 up to the word "variance".

Note: $\int_{-\infty}^{\infty} p(z) dz = 1$

Gaussian noise (PDF)





Uniform noise

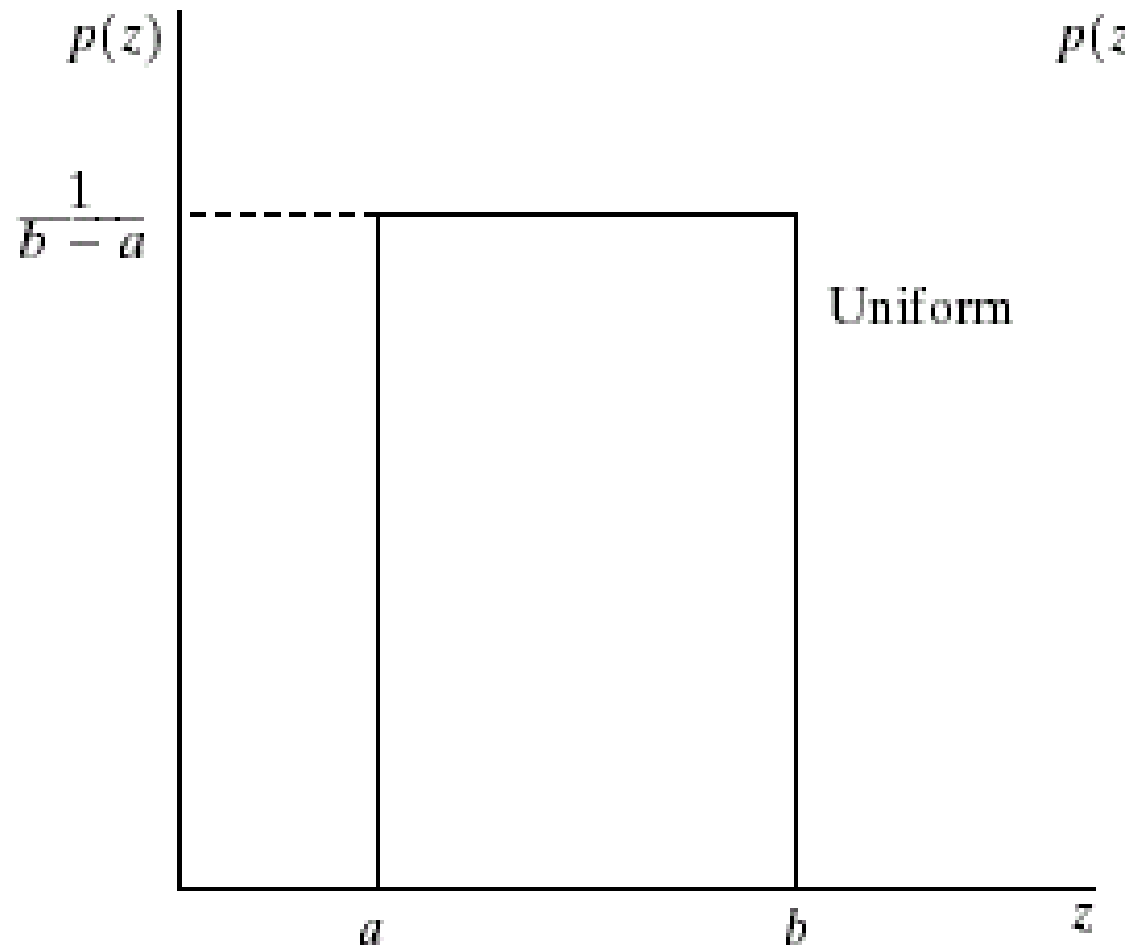
- Less practical, used for random number generator

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

$$\text{Mean: } \mu = \frac{a+b}{2}$$

$$\text{Variance: } \sigma^2 = \frac{(b-a)^2}{12}$$

Uniform PDF





Impulse (salt-and-pepper) noise

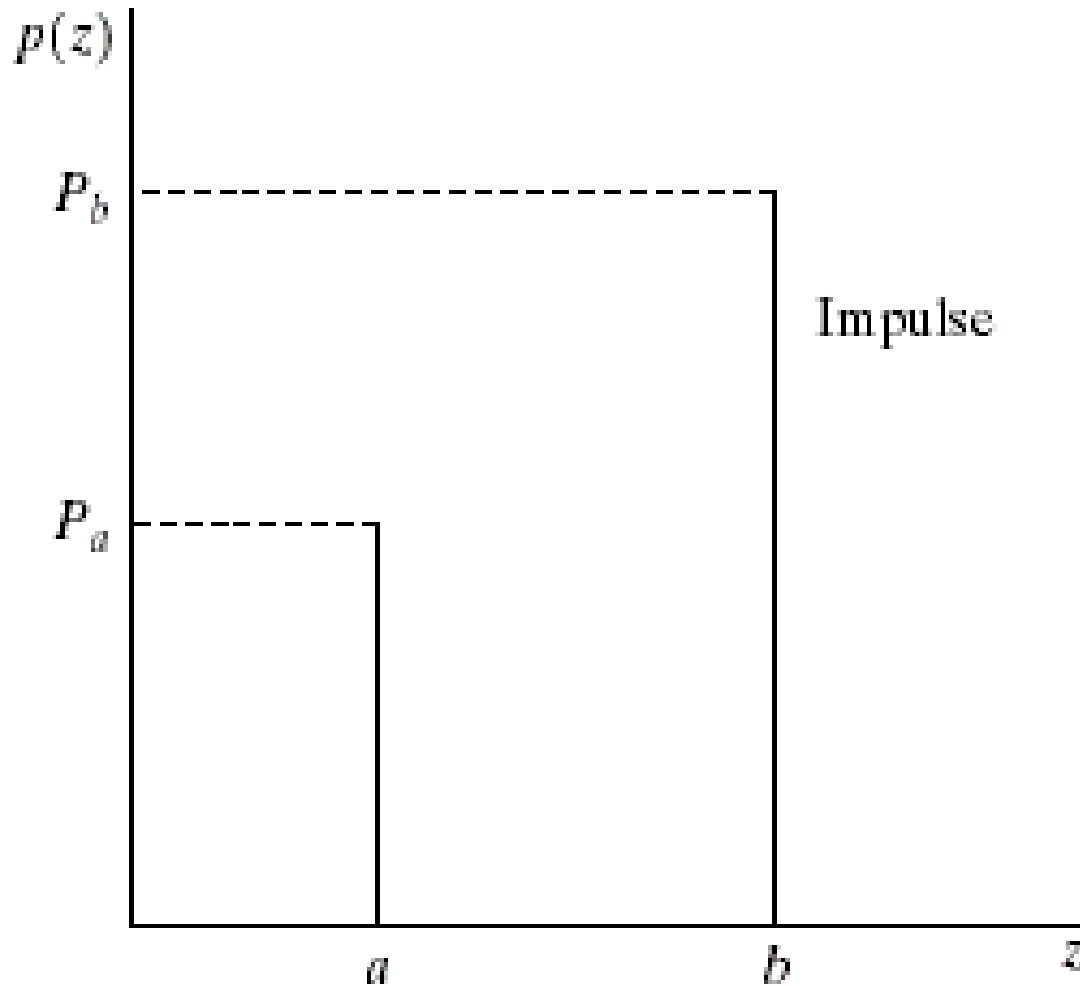
- Quick transients, such as faulty switching during imaging

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

If either P_a or P_b is zero, it is called *unipolar*.
Otherwise, it is called *bipolar*.

- In practical, *impulses* are usually stronger than image signals. Ex., $a=0$ (black) and $b=255$ (white) in 8-bit image.

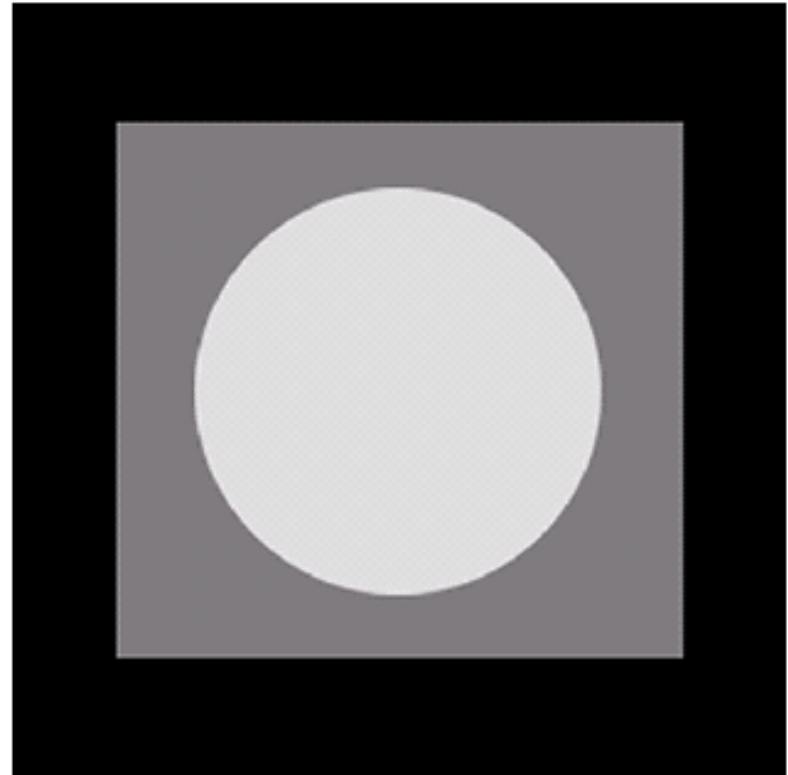
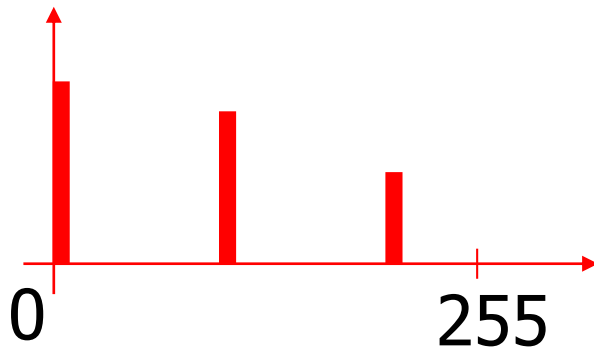
Impulse (salt-and-pepper) noise PDF

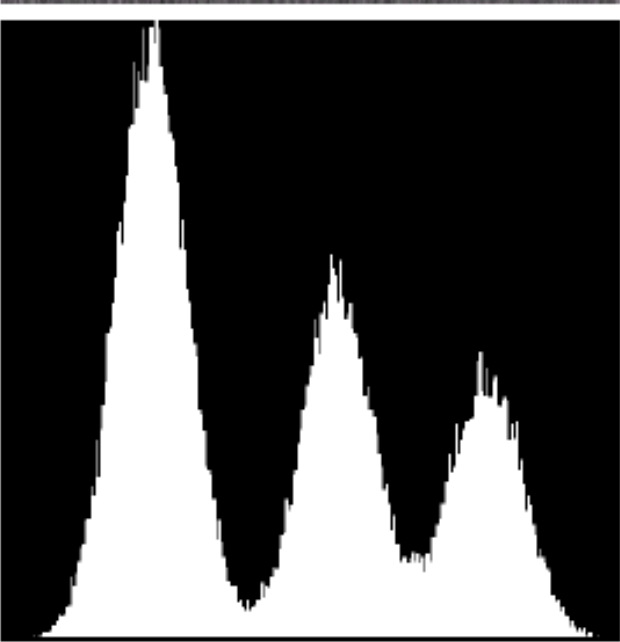
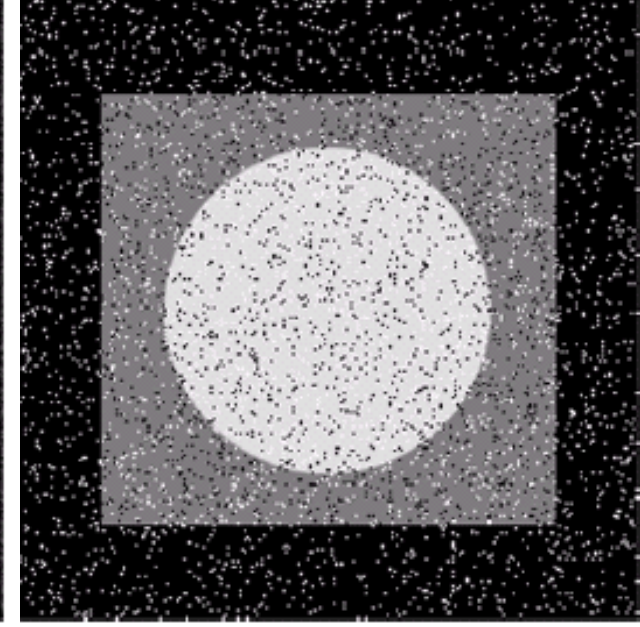
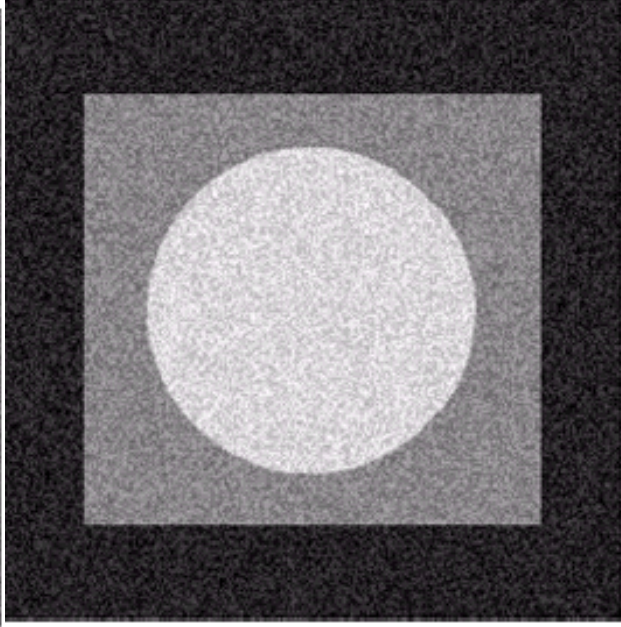
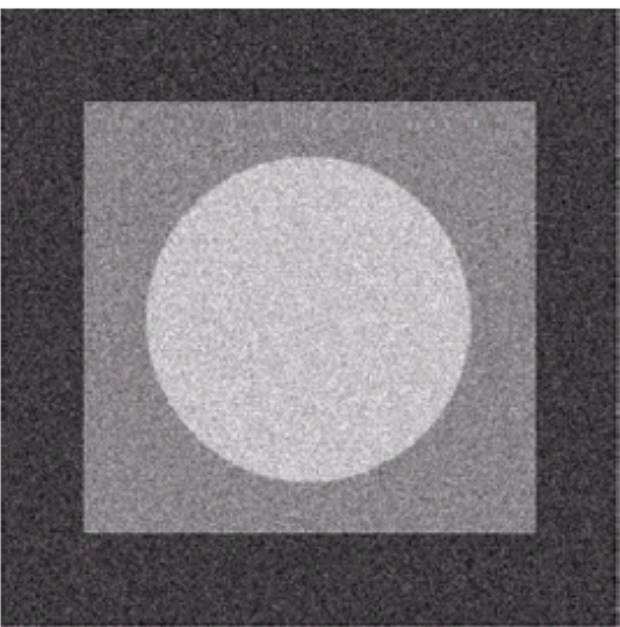


Test for noise behavior

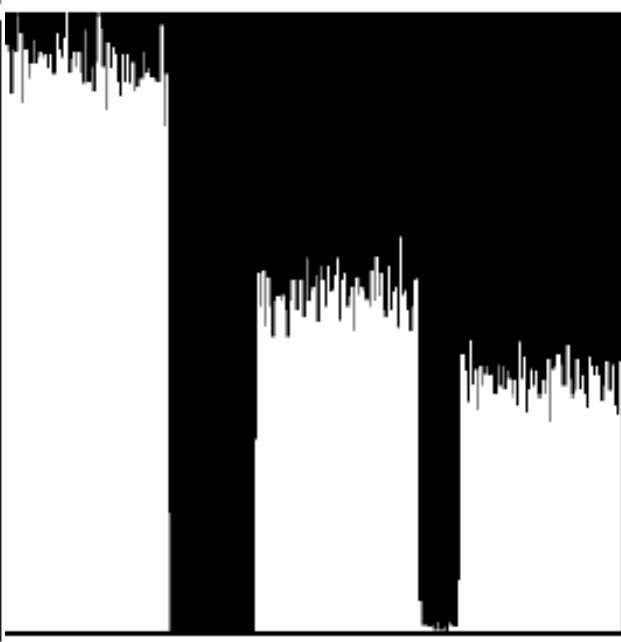
- Test pattern

Its histogram:

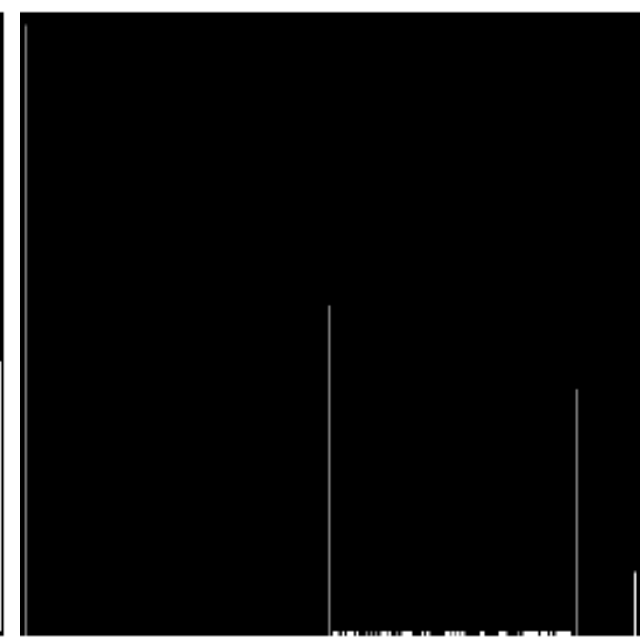




Gaussian



Uniform

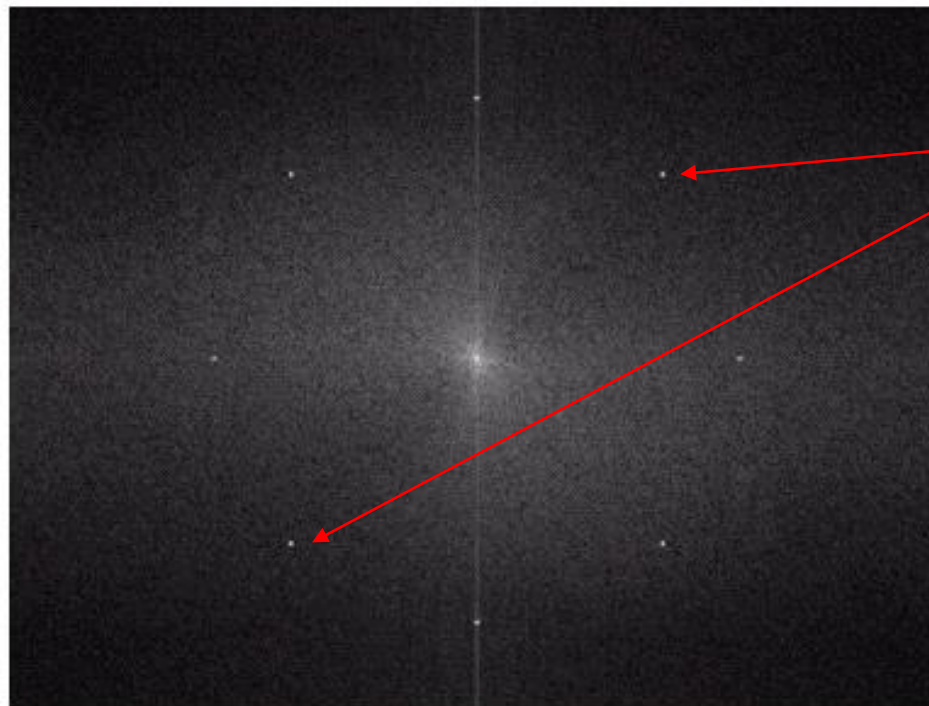
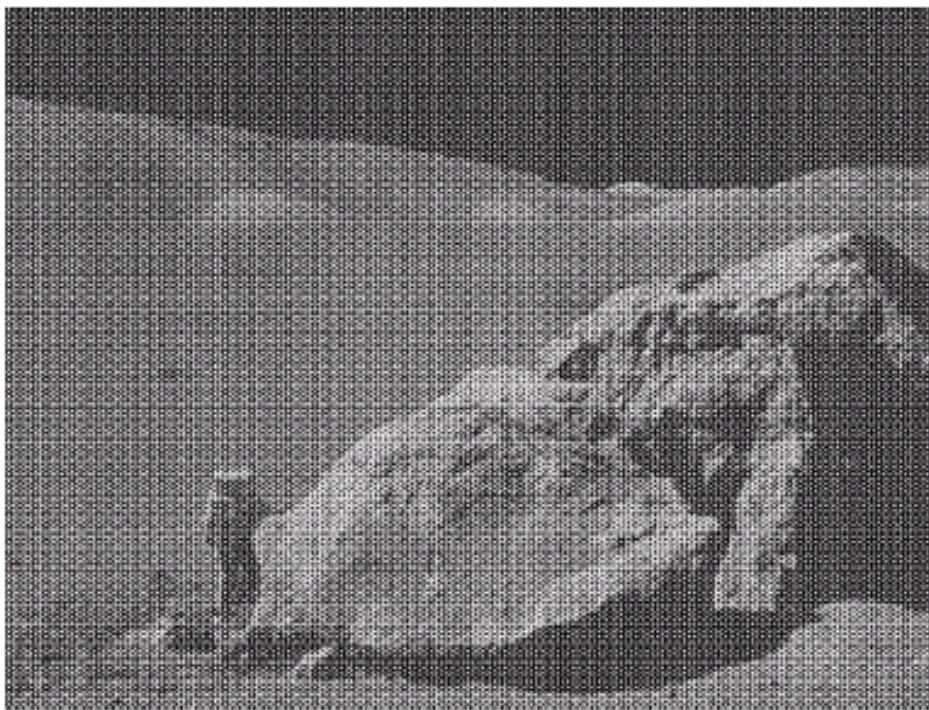


Salt & Pepper



Periodic noise

- Arise from electrical or electromechanical interference during image acquisition
- Spatial dependence
- Observed in the frequency domain



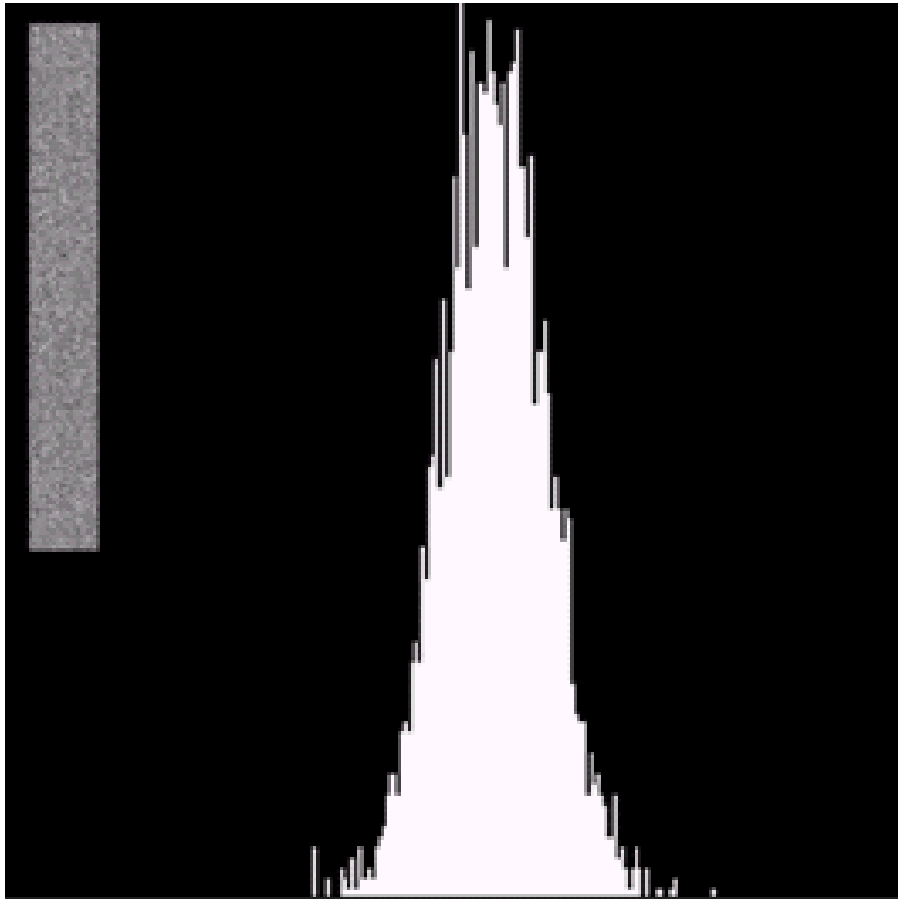
Sinusoidal noise:
Complex conjugate
pair in frequency
domain



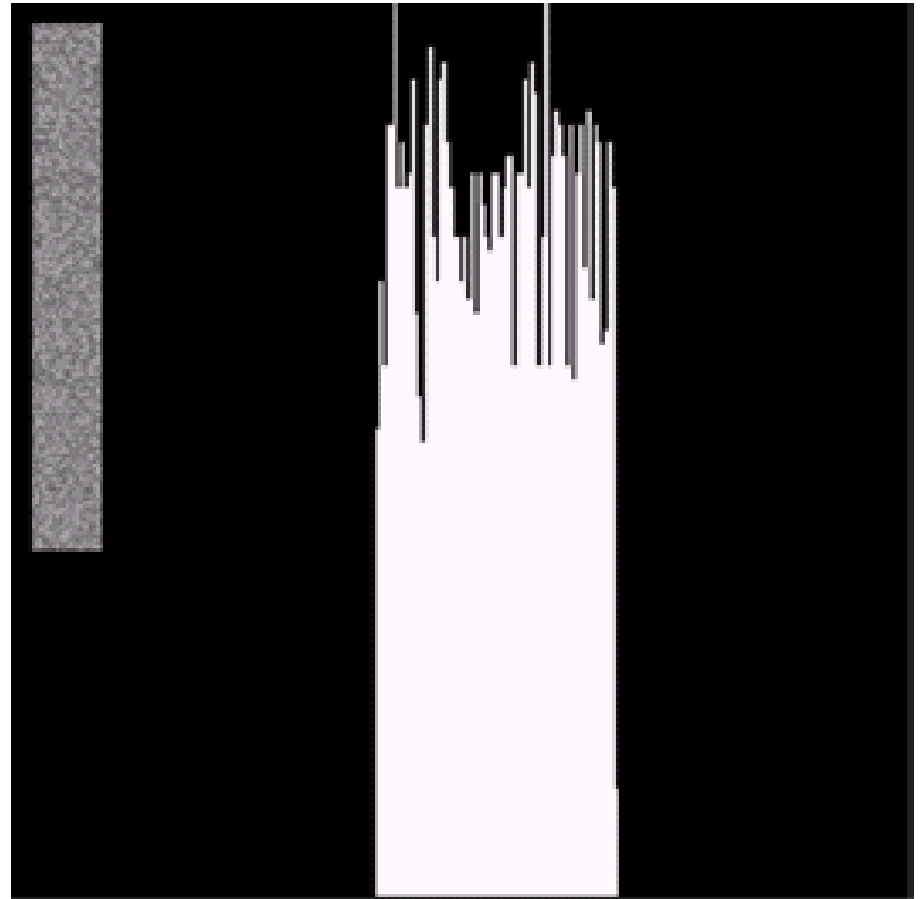
Estimation of noise parameters

- Periodic noise
 - Observe the **frequency spectrum**
- Random noise with unknown PDFs
 - Case 1: imaging system is available
 - Capture images of **"flat"** environment
 - Case 2: noisy images available
 - Take a strip from **constant area**
 - Draw the **histogram** and observe it
 - Measure the **mean and variance**

Observe the histogram



Gaussian



uniform



Measure the mean and variance

- Histogram is an estimate of PDF

$$\left\{ \begin{array}{l} \mu = \sum_{z_i \in S} z_i p(z_i) \\ \sigma^2 = \sum_{z_i \in S} (z_i - \mu)^2 p(z_i) \end{array} \right.$$



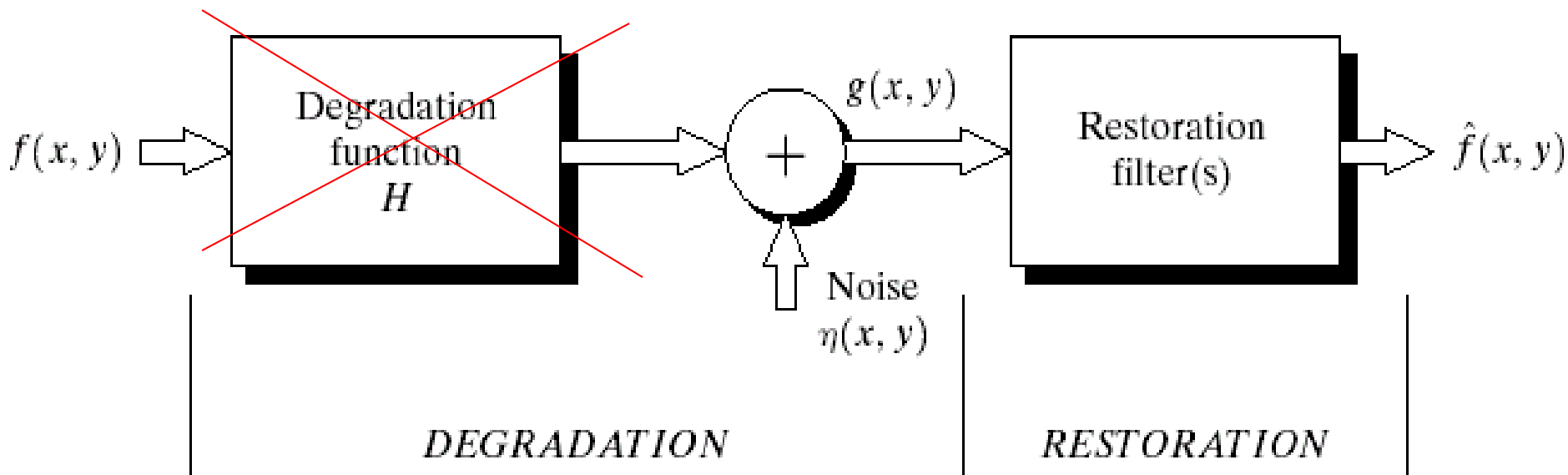
Gaussian: μ, σ
Uniform: a, b



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Additive noise only



$$\left\{ \begin{array}{l} g(x, y) = f(x, y) + \eta(\mathbf{x}, \mathbf{y}) \\ G(u, v) = F(u, v) + N(u, v) \end{array} \right.$$



Spatial filters for de-noising additive noise

- Skills similar to image enhancement
- Mean filters
- Order-statistics filters
- Adaptive filters



Mean filters

- Arithmetic mean

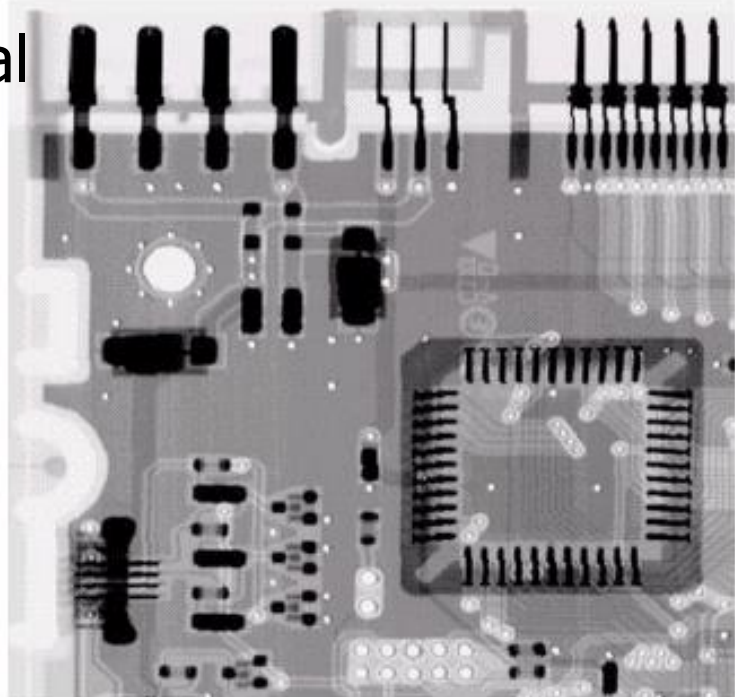
$$\hat{f}(x, y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s, t)$$

Window centered at (x,y)

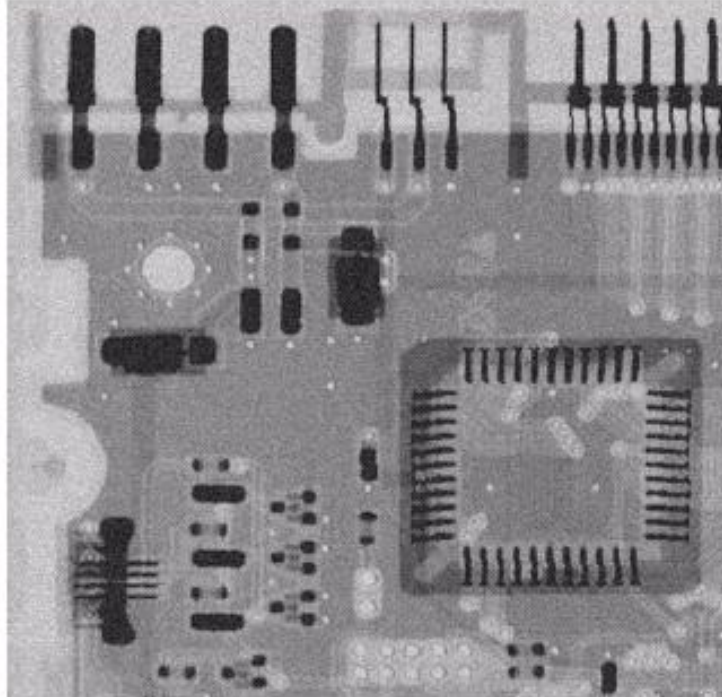
- Geometric mean

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

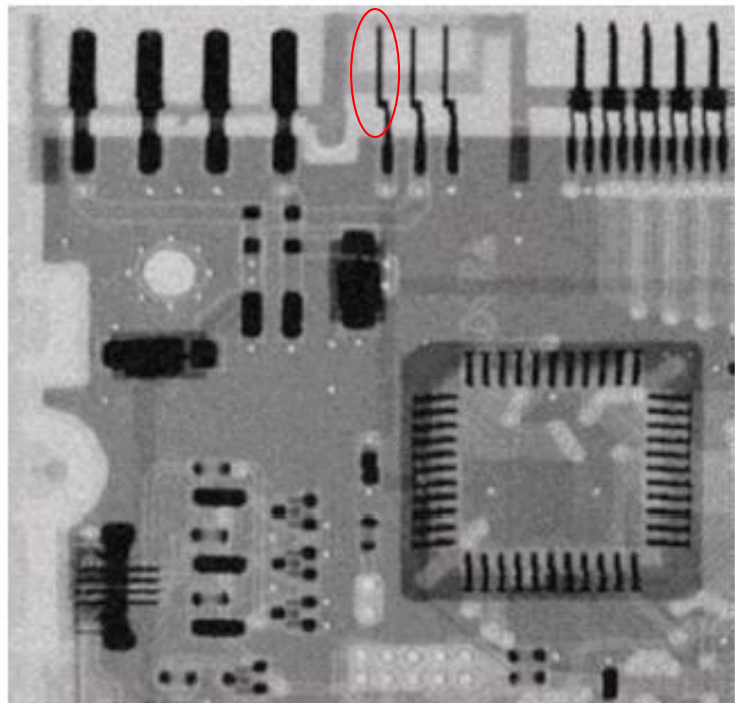
original



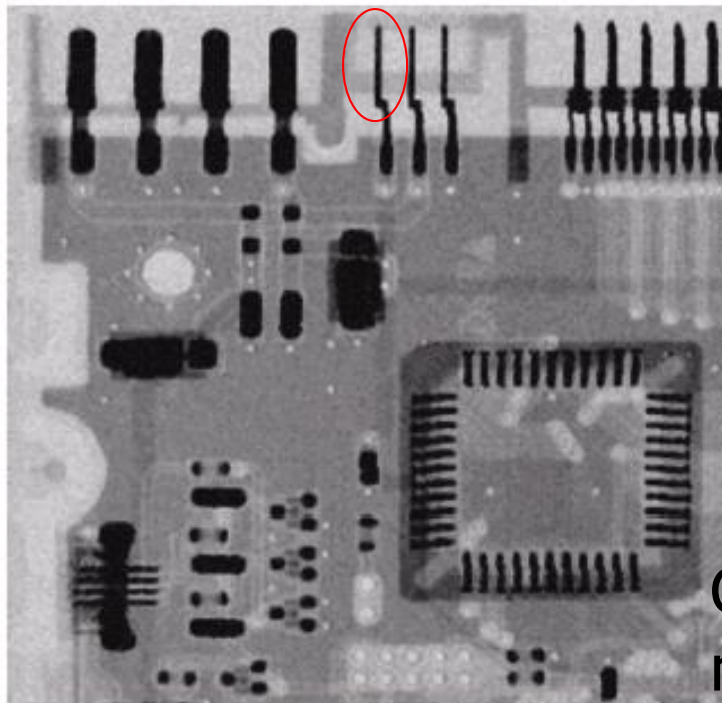
Noisy
Gaussian
 $\mu=0$
 $\sigma=20$



Arith.
mean



Geometric
mean





Mean filters (cont.)

- Harmonic mean filter

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

- Contra-harmonic mean filter

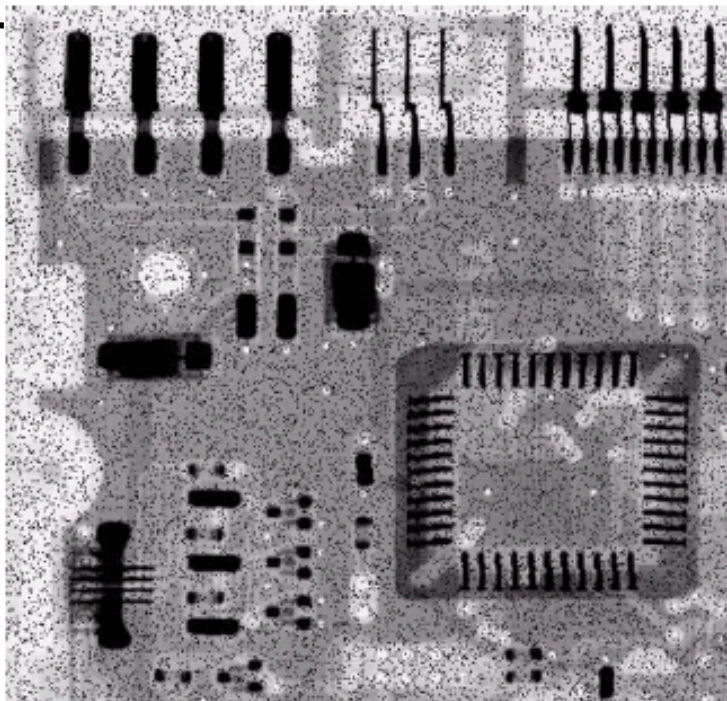
$$\hat{f}(x, y) = \frac{\sum_{(s,t) \in S_{xy}} g(s,t)^{Q+1}}{\sum_{(s,t) \in S_{xy}} g(s,t)^Q}$$

Q=-1, harmonic

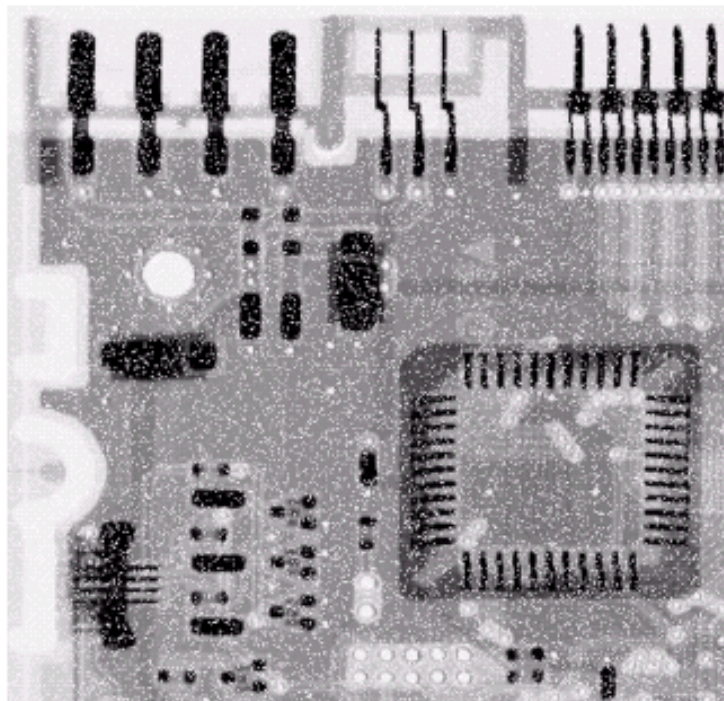
Q=0, airth. mean

Q=+, ?

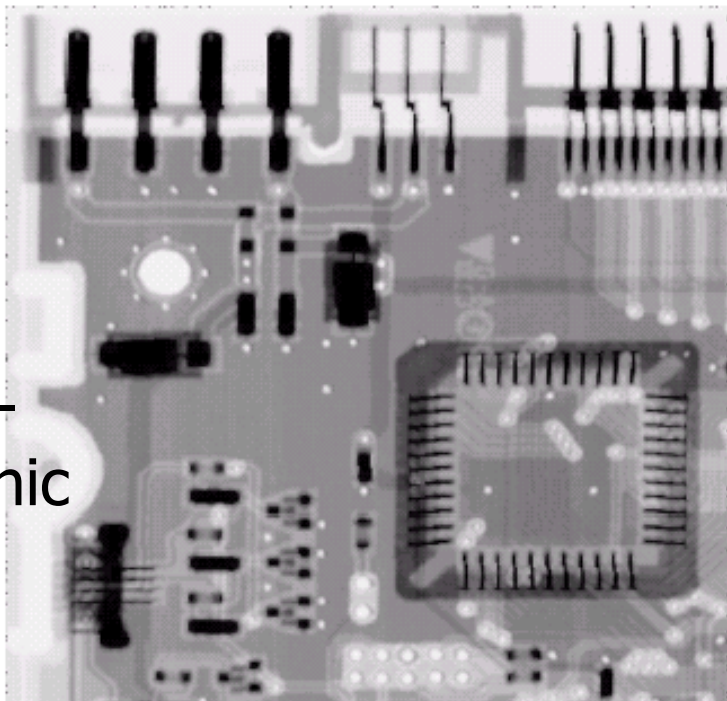
Pepper
Noise
黑點



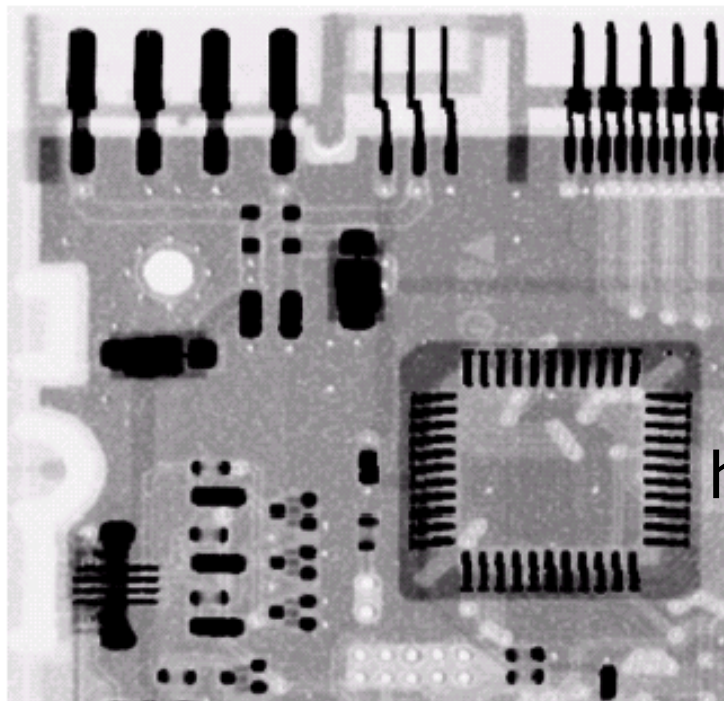
Salt
Noise
白點



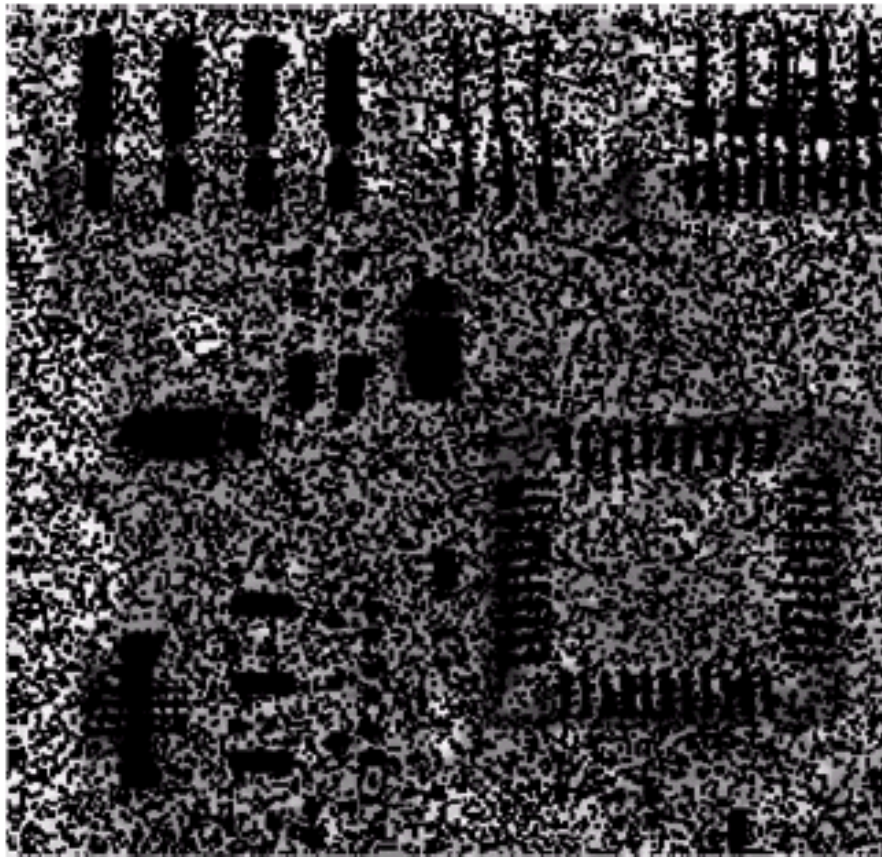
Contra-
harmonic
 $Q=1.5$



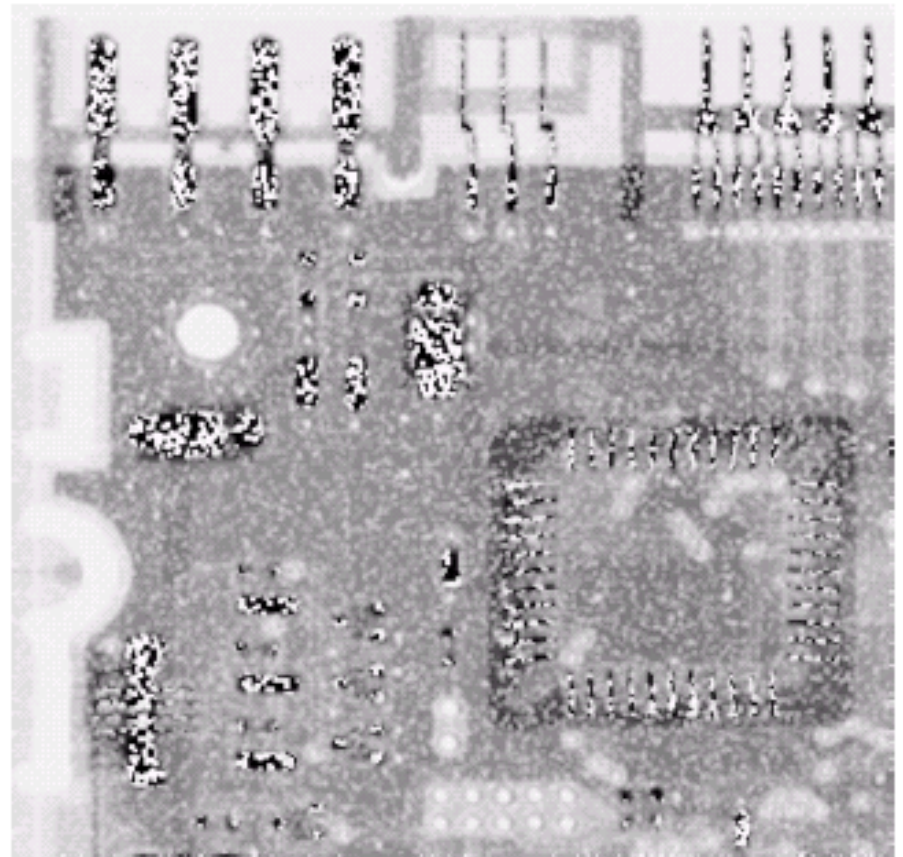
Contra-
harmonic
 $Q=-1.5$



Wrong sign in contra-harmonic filtering



$Q=-1.5$



$Q=1.5$



Order-statistics filters

- Based on the ordering(ranking) of pixels
 - Suitable for unipolar or bipolar noise (salt and pepper noise)
- Median filters
- Max/min filters
- Midpoint filters
- Alpha-trimmed mean filters



Order-statistics filters

- Median filter

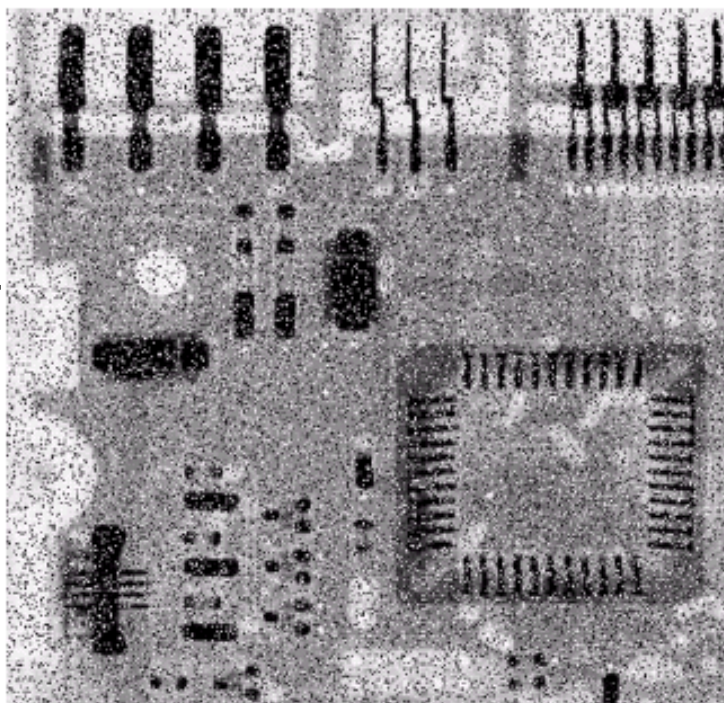
$$\hat{f}(x, y) = \underset{(s,t) \in S_{xy}}{\text{median}} \{g(s, t)\}$$

- Max/min filters

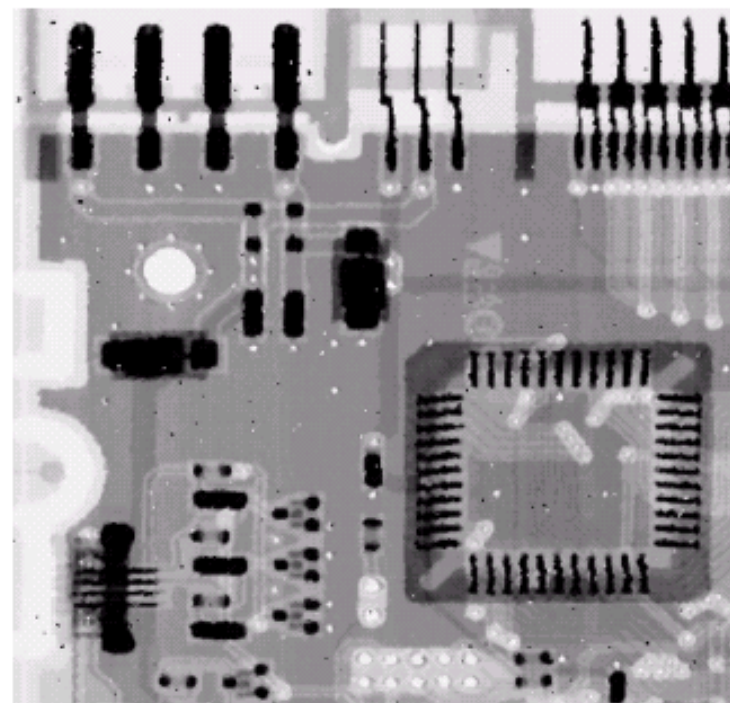
$$\hat{f}(x, y) = \max_{(s,t) \in S_{xy}} \{g(s, t)\}$$

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

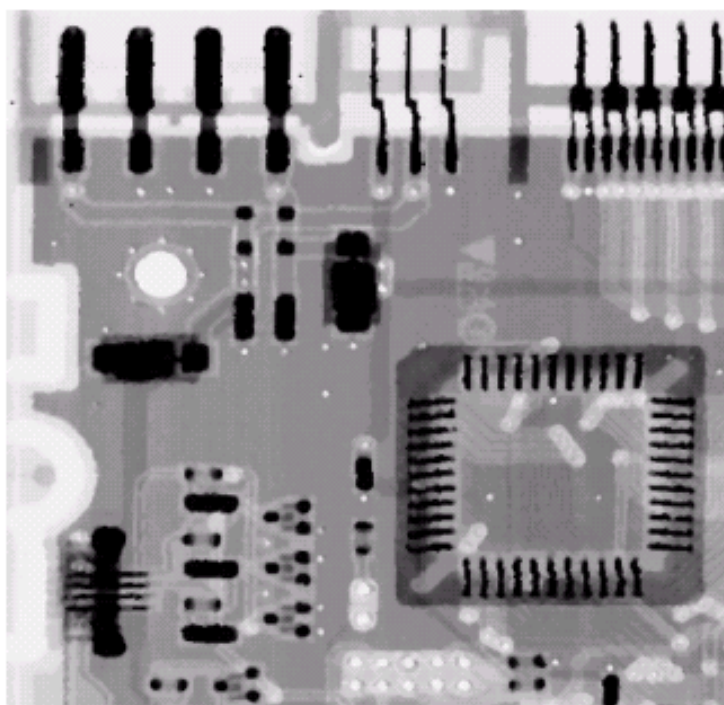
bipolar
Noise
 $P_a = 0.1$
 $P_b = 0.1$



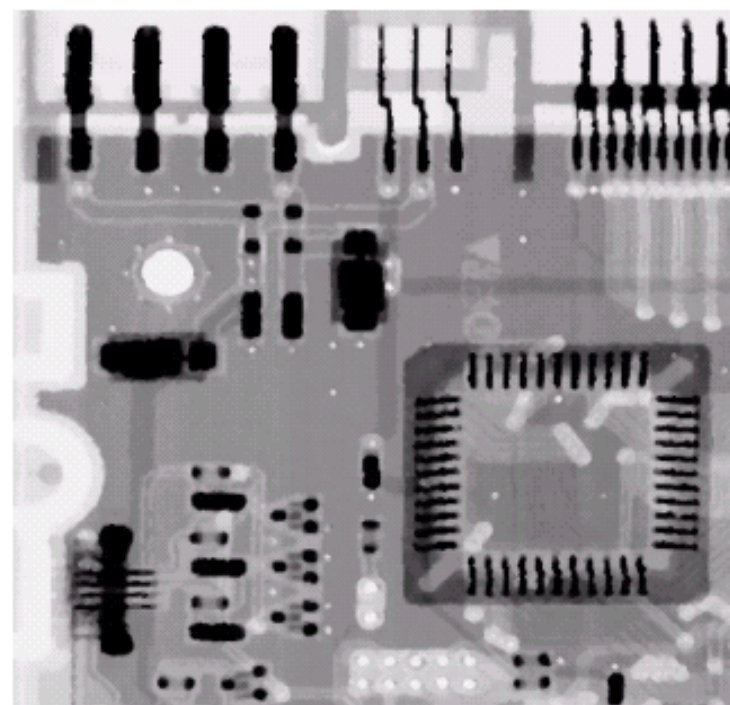
3x3
Median
Filter
Pass 1



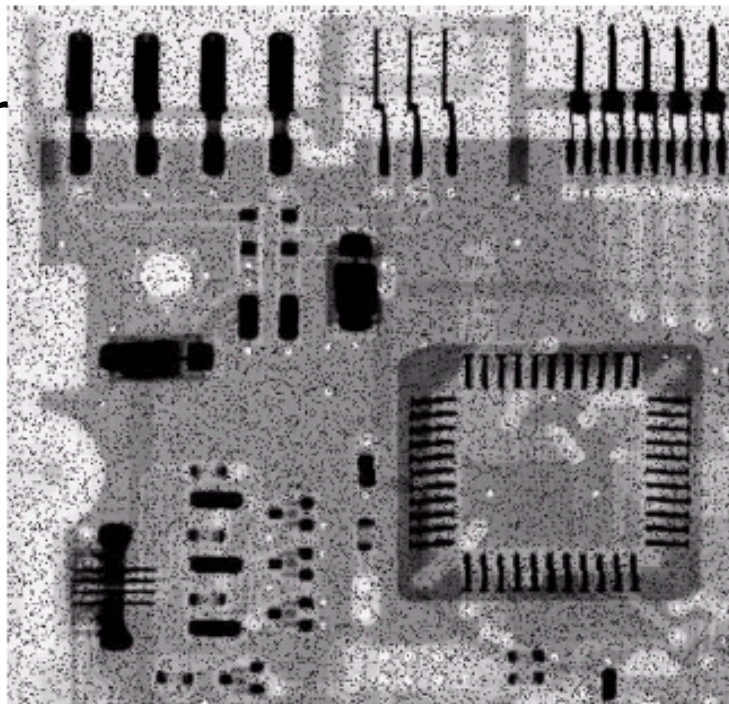
3x3
Median
Filter
Pass 2



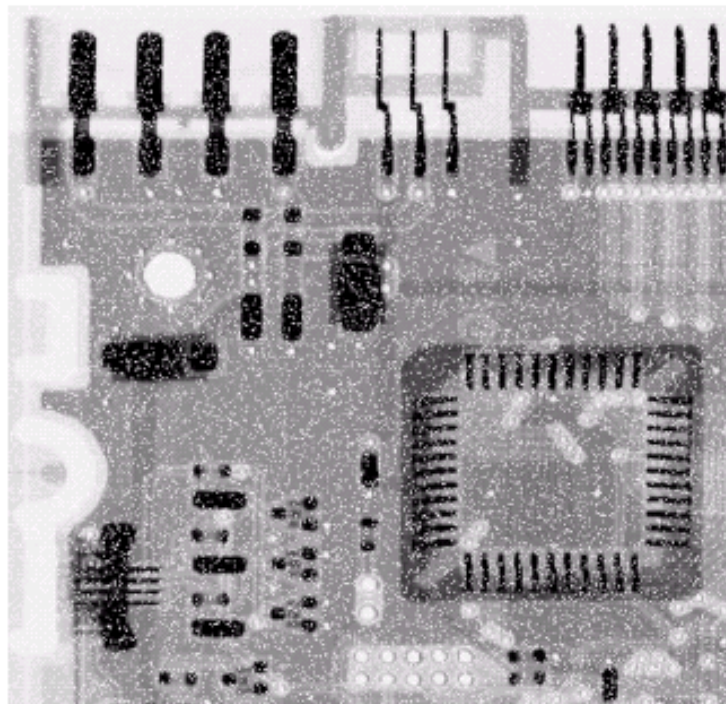
3x3
Median
Filter
Pass 3



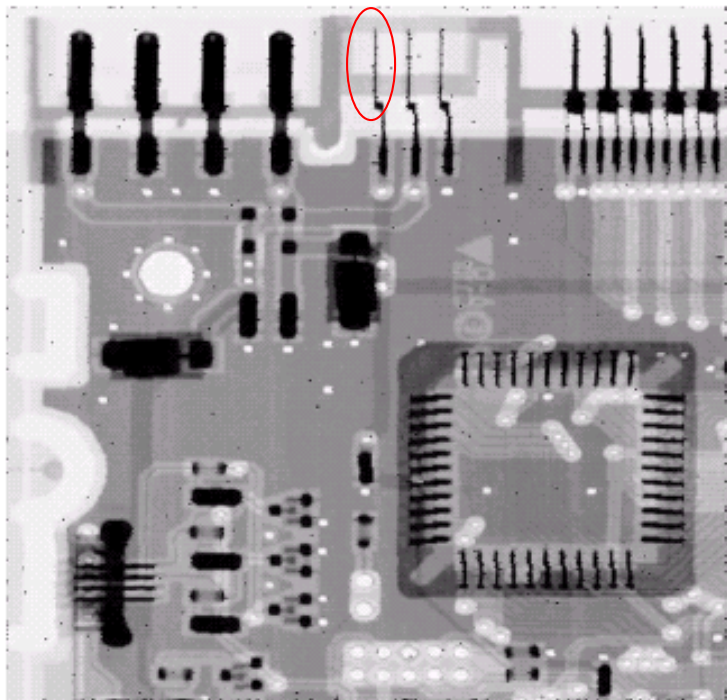
Pepper
noise



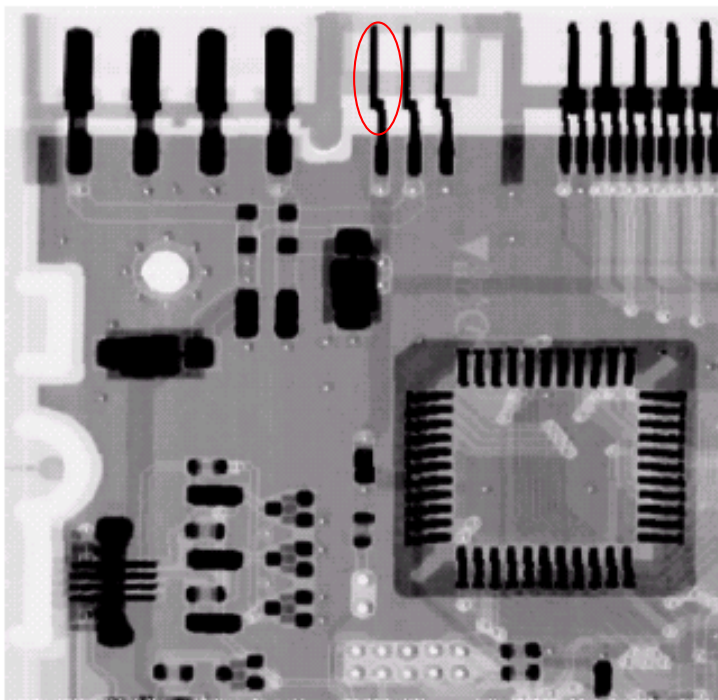
Salt
noise



Max
filter



Min
filter





Order-statistics filters (cont.)

■ Midpoint filter

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

■ Alpha-trimmed mean filter

- Delete the $d/2$ lowest and $d/2$ highest gray-level pixels

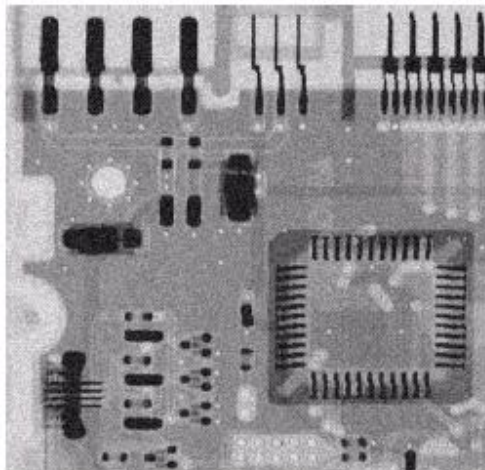
$$\hat{f}(x, y) = \frac{1}{mn - d} \sum_{(s,t) \in S_{xy}} g_r(s, t)$$

← Middle ($mn-d$) pixels

Uniform noise

$$\mu=0$$

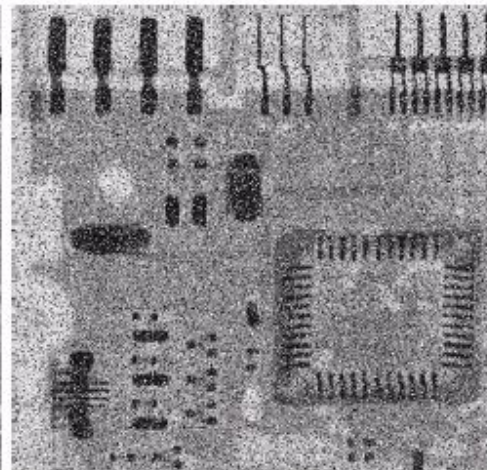
$$\sigma^2=800$$



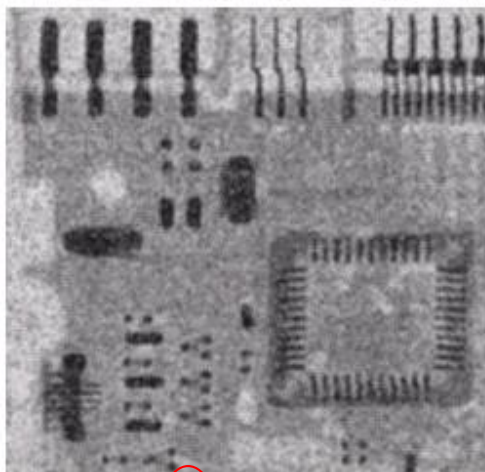
Left +
Bipolar Noise

$$P_a = 0.1$$

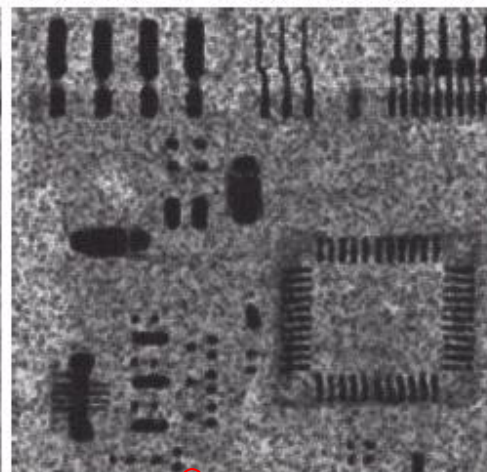
$$P_b = 0.1$$



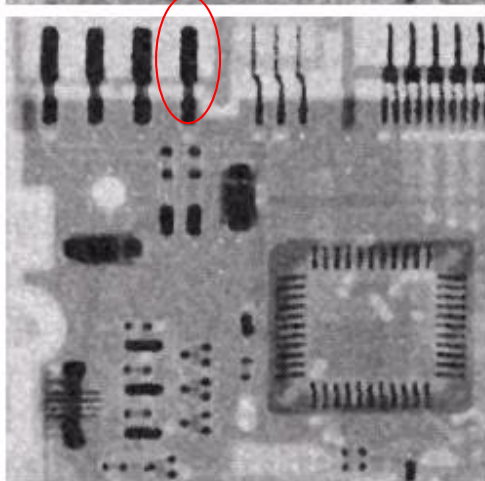
5x5
Arith. Mean
filter



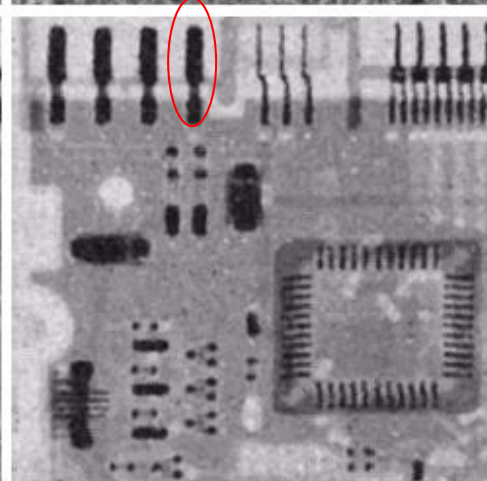
5x5
Geometric
mean



5x5
Median
filter



5x5
Alpha-trim.
Filter
 $d=5$





Adaptive filters

- Adapted to the behavior based on the **statistical characteristics** of the image inside the filter region S_{xy}
- Improved performance v.s increased complexity
- Example: **Adaptive local noise reduction filter**



Adaptive local noise reduction filter

- Simplest statistical measurement
 - Mean and variance
- Known parameters on local region S_{xy}
 - $g(x,y)$: noisy image pixel value
 - σ^2_{η} : noise variance (assume known a prior)
 - m_L : local mean
 - σ^2_L : local variance

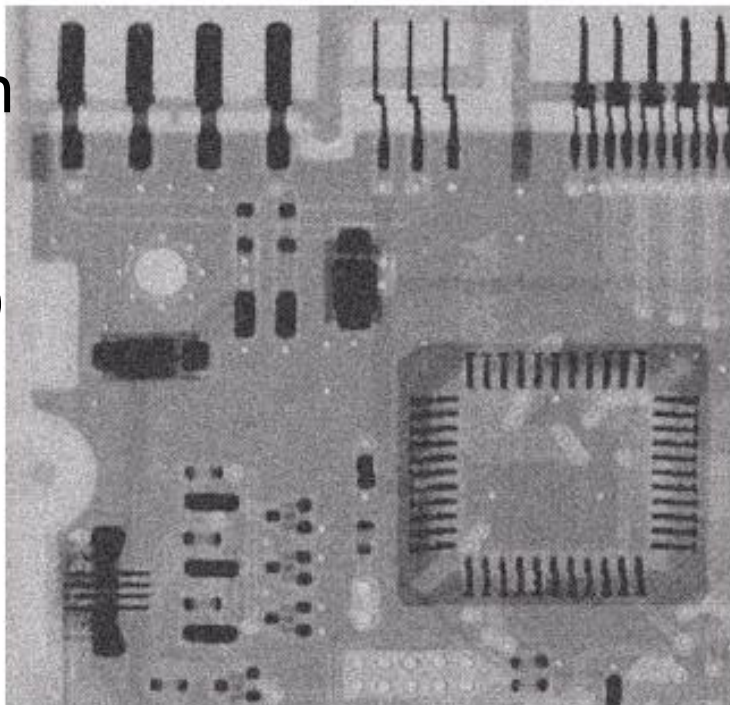


Adaptive local noise reduction filter (cont.)

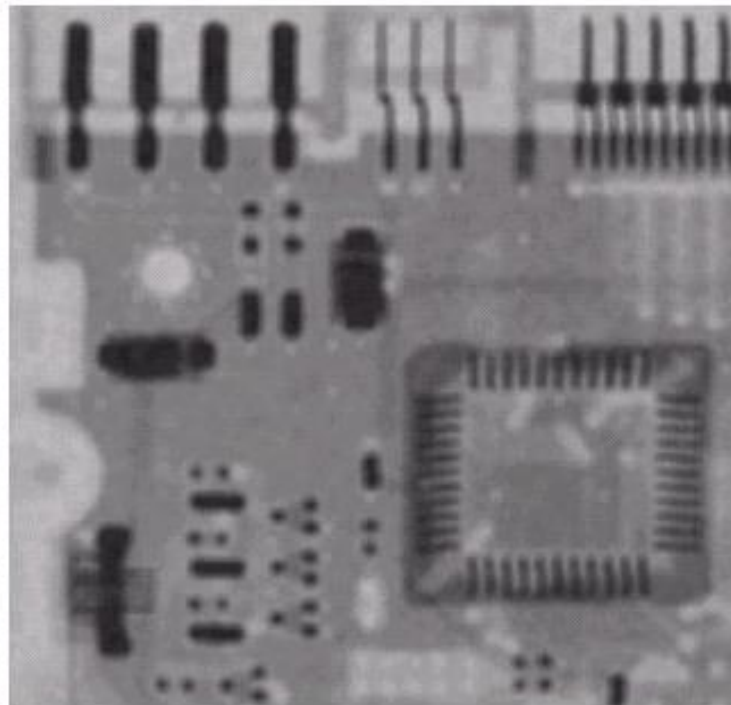
- Analysis: we want to do
 - If σ_{η}^2 is zero, return $g(x,y)$
 - If $\sigma_L^2 > \sigma_{\eta}^2$, return value close to $g(x,y)$
 - If $\sigma_L^2 = \sigma_{\eta}^2$, return the arithmetic mean m_L
- Formula

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

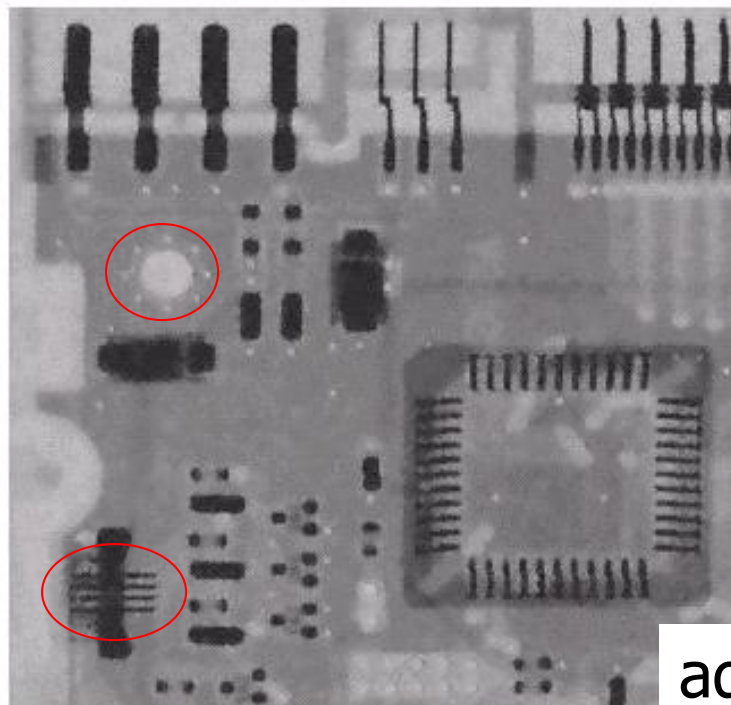
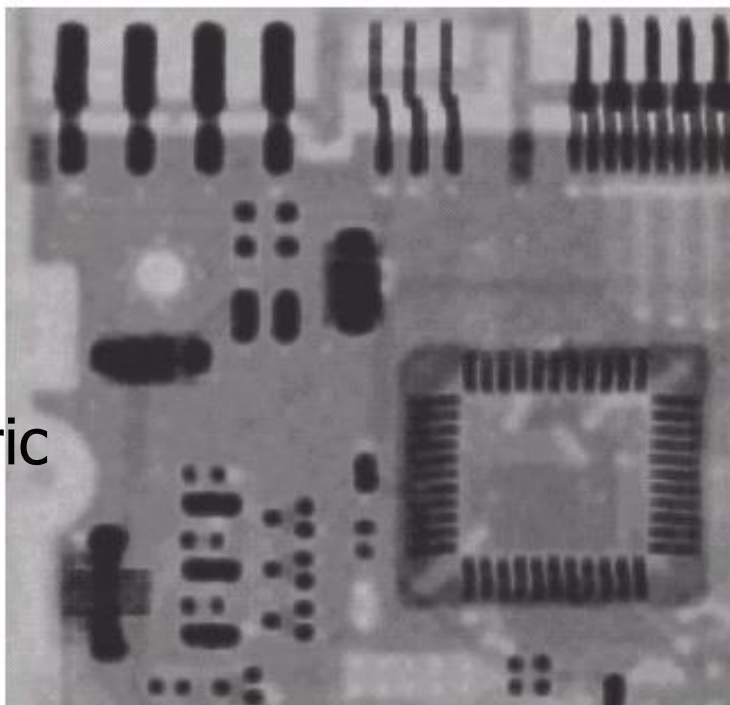
Gaussian
noise
 $\mu=0$
 $\sigma^2=1000$



Arith.
mean
7x7



Geometric
mean
7x7



adaptive



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Periodic noise reduction

- Pure sine wave

- Appear as a **pair of impulse** (conjugate) in the frequency domain

$$f(x, y) = A \sin(u_0 x + v_0 y)$$

$$F(u, v) = -j \frac{A}{2} \left[\delta\left(u - \frac{u_0}{2\pi}, v - \frac{v_0}{2\pi}\right) - \delta\left(u + \frac{u_0}{2\pi}, v + \frac{v_0}{2\pi}\right) \right]$$



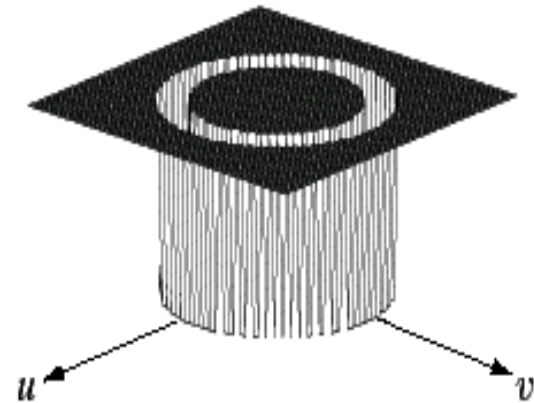
Periodic noise reduction (cont.)

- Bandreject filters
- Bandpass filters
- Notch filters
- Optimum notch filtering

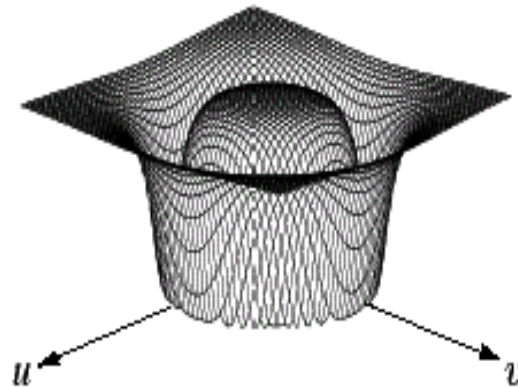
Bandreject filters

* Reject an **isotropic** frequency

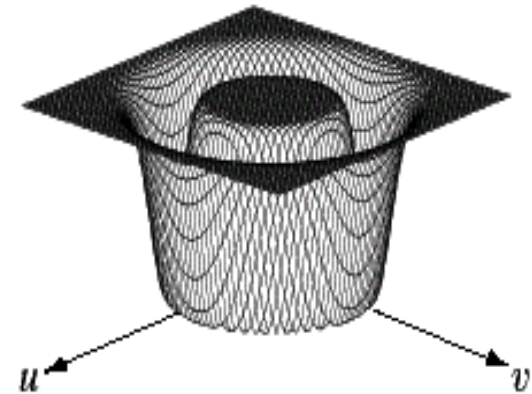
ideal



Butterworth

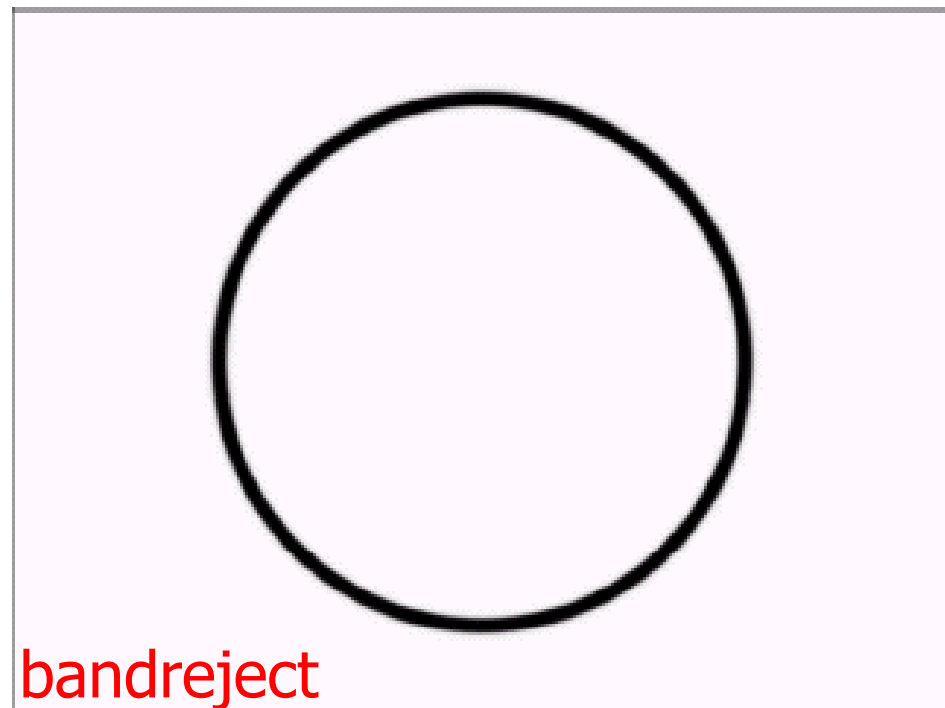
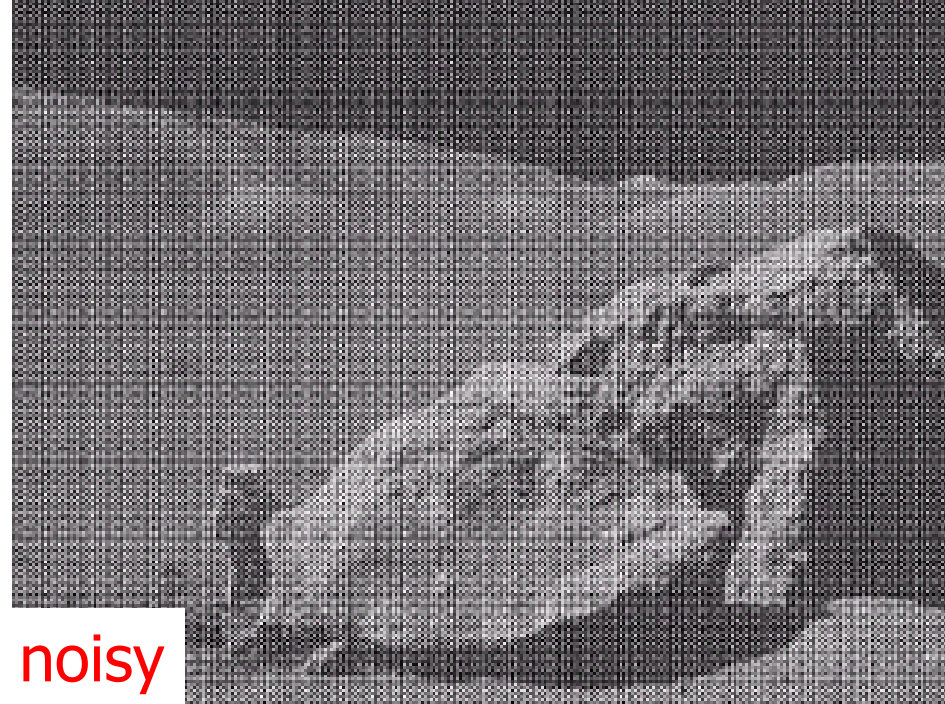


Gaussian



a b c

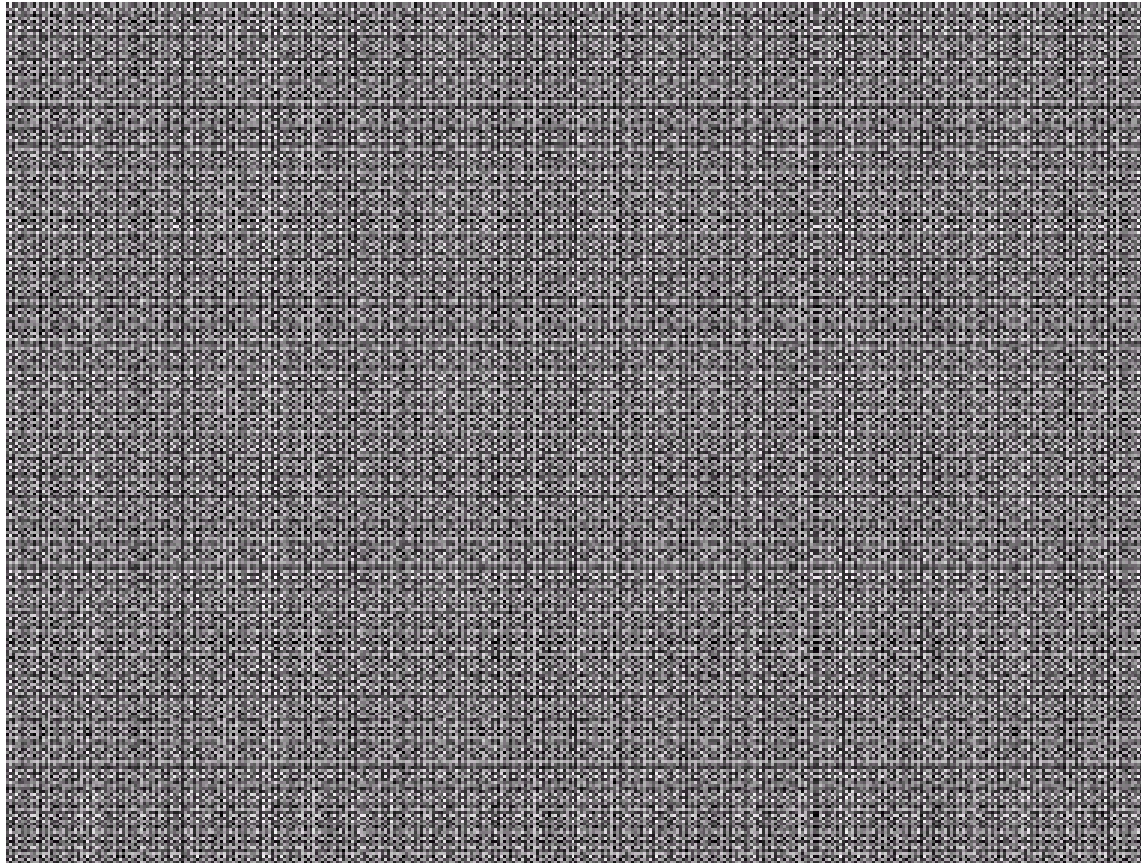
FIGURE 5.15 From left to right, perspective plots of ideal, Butterworth (of order 1), and Gaussian bandreject filters.





Bandpass filters

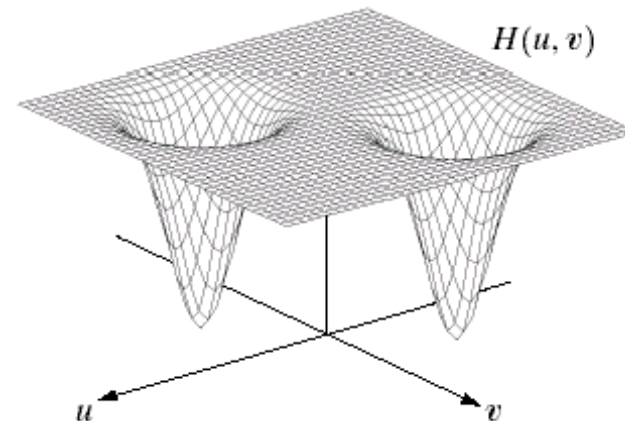
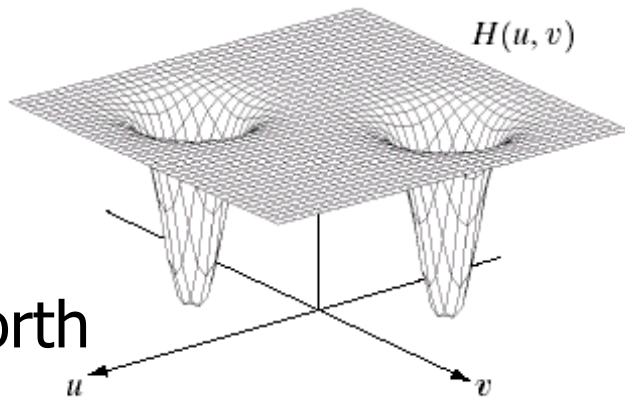
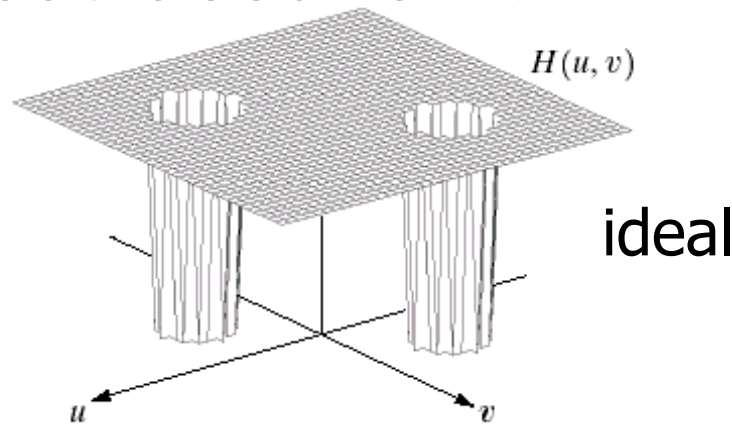
- $H_{bp}(u,v) = 1 - H_{br}(u,v)$



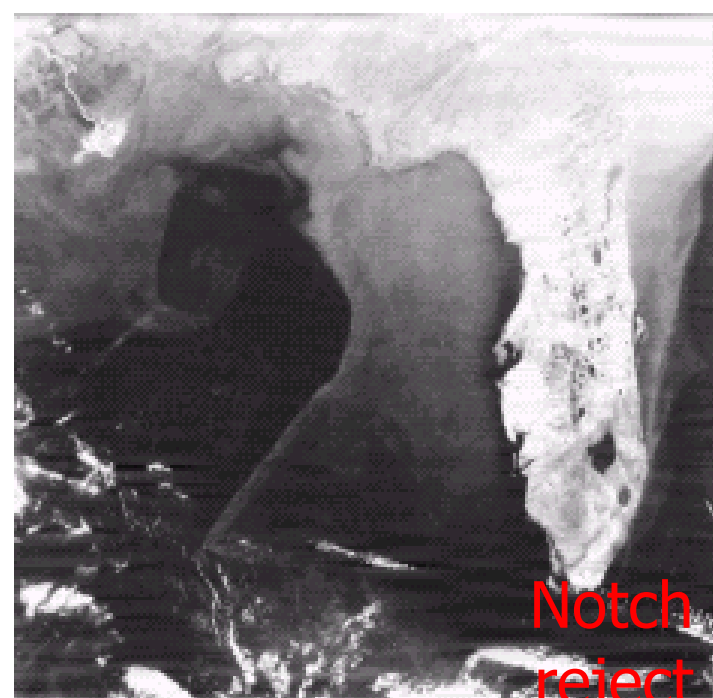
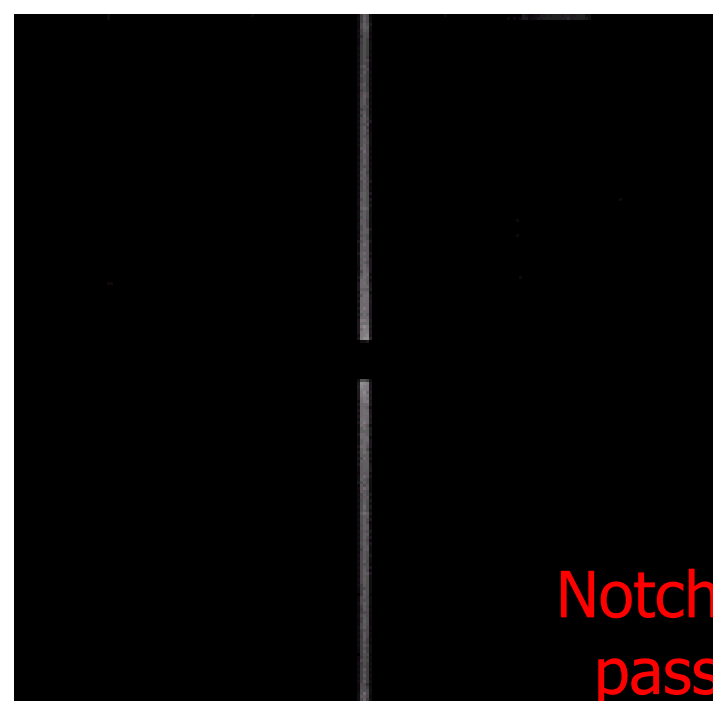
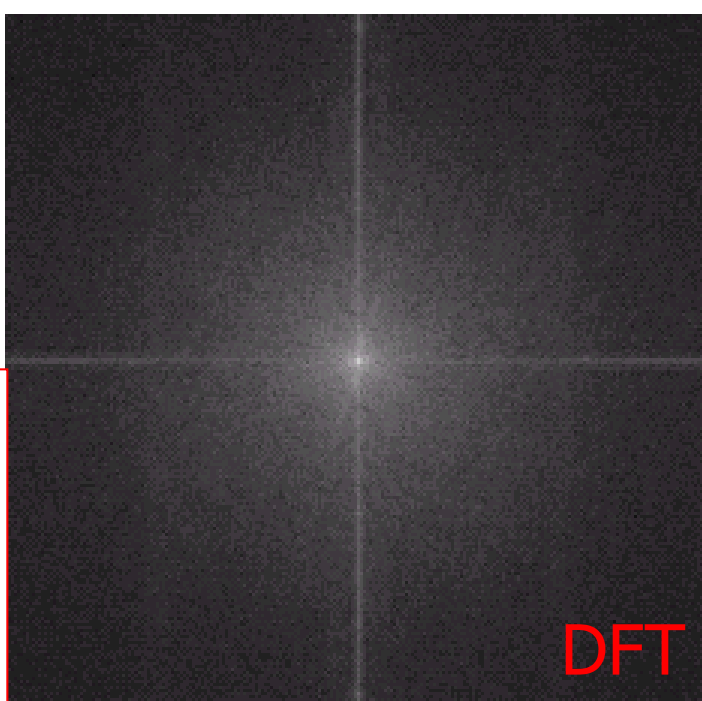
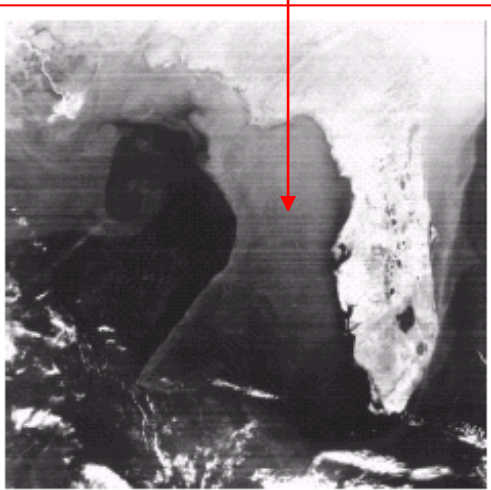
$$\mathcal{F}^{-1}\{G(u,v)H_{bp}(u,v)\}$$

Notch filters

- Reject(or pass) frequencies in predefined neighborhoods about a **center frequency**



Horizontal
Scan lines

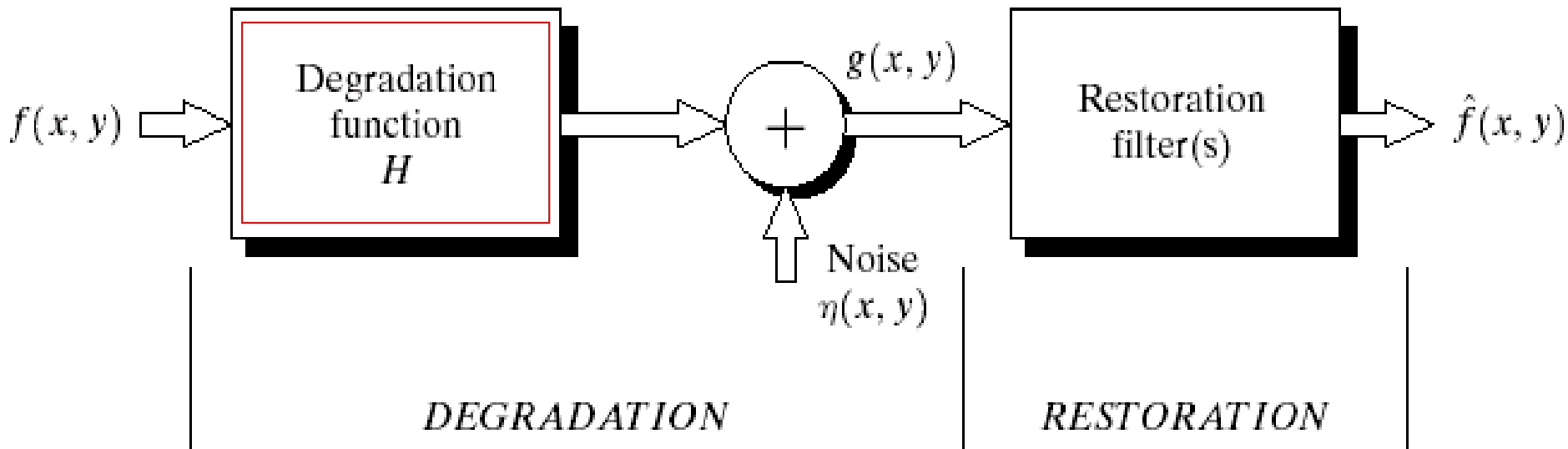




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A model of the image degradation /restoration process



$$\left\{ \begin{array}{l} g(x,y)=f(x,y)*h(x,y)+\eta(x,y) \\ G(u,v)=F(u,v)H(u,v)+N(u,v) \end{array} \right.$$

If linear, position-invariant system



Linear, position-invariant degradation

Properties of the degradation function H

- **Linear system**

- $H[af_1(x,y)+bf_2(x,y)]=aH[f_1(x,y)]+bH[f_2(x,y)]$

- **Position(space)-invariant system**

- $H[f(x,y)]=g(x,y)$

- $\Leftrightarrow H[f(x-\alpha, y-\beta)]=g(x-\alpha, y-\beta)$

- **c.f. 1-D signal**

- LTI (linear time-invariant system)



Linear, position-invariant degradation model

- Linear system theory is ready
- Non-linear, position-dependent system
 - May be general and more accurate
 - Difficult to solve computationally
- Image restoration: find $H(u,v)$ and apply
inverse process
 - Image deconvolution



Estimating the degradation function

- Estimation by Image observation
- Estimation by experimentation
- Estimation by modeling



Estimation by image observation

- Take a window in the image
 - Simple structure
 - Strong signal content
- **Estimate the original image** in the window

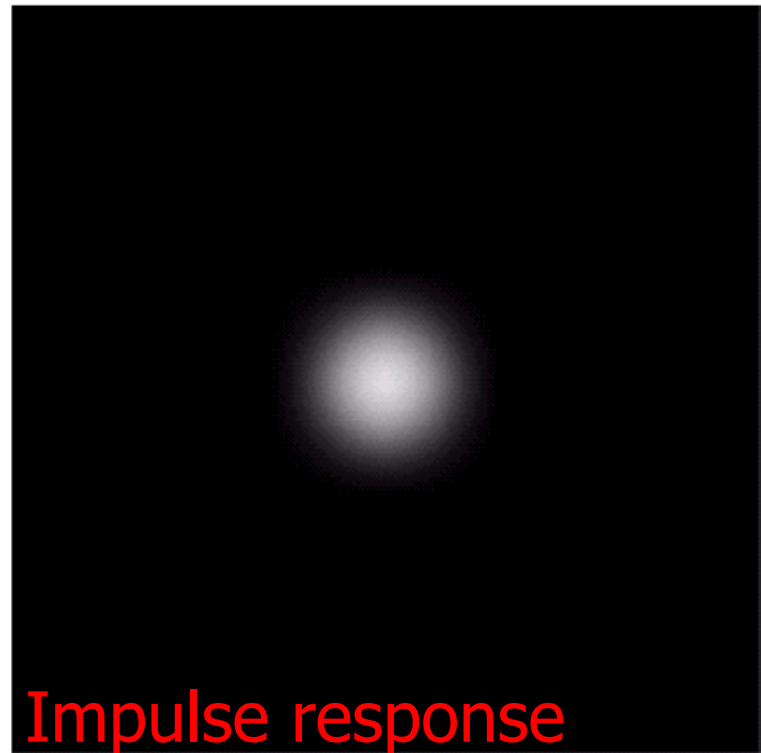
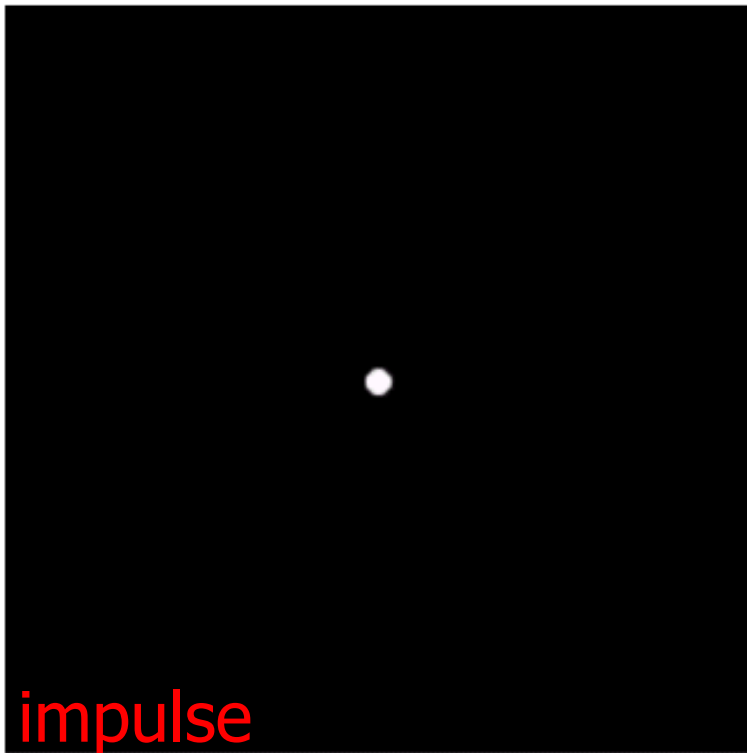
$$H_s(u, v) = \frac{G_s(u, v)}{\hat{F}_s(u, v)}$$

known

estimate

Estimation by experimentation

- If the image acquisition system is ready
- Obtain the **impulse response**



Estimation by modeling (1)

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

original



k=0.0025



k=0.001



k=0.00025





Estimation by modeling (2)

- Derive a **mathematical model**
- Ex. Motion of image

$$g(x, y) = \int_0^T f(x - x_0(t), y - y_0(t)) dt$$

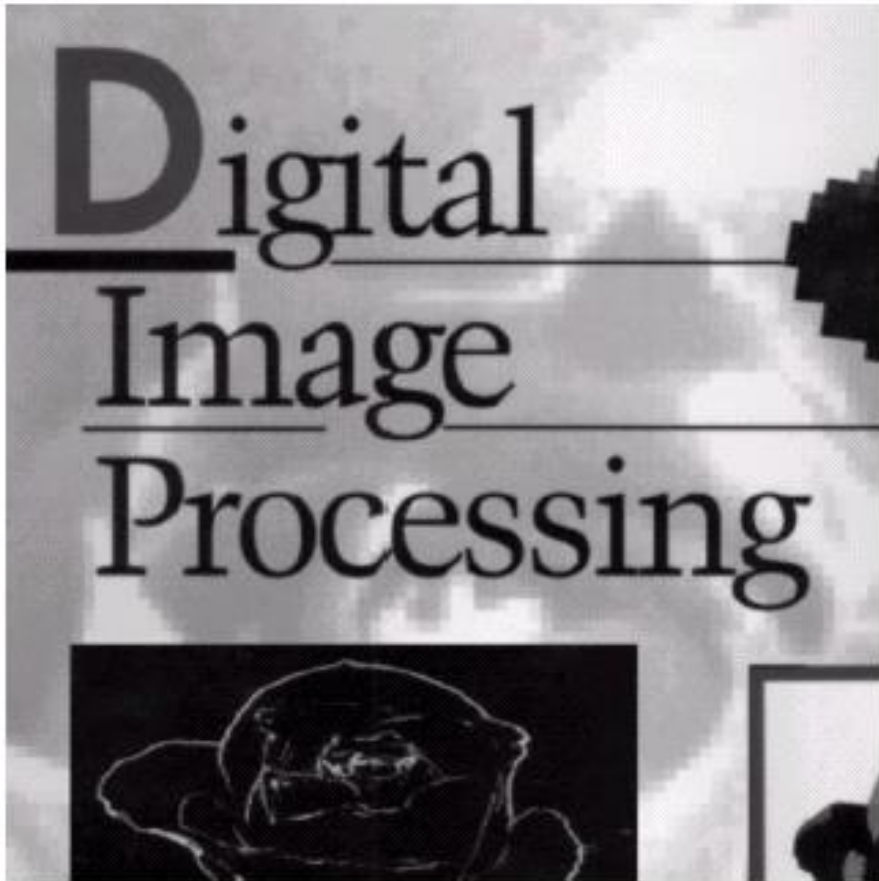
Fourier
transform

Planar motion

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

Estimation by modeling: example

original



Apply motion model





Inverse filtering

- With the estimated degradation function $H(u,v)$

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

Unknown
noise

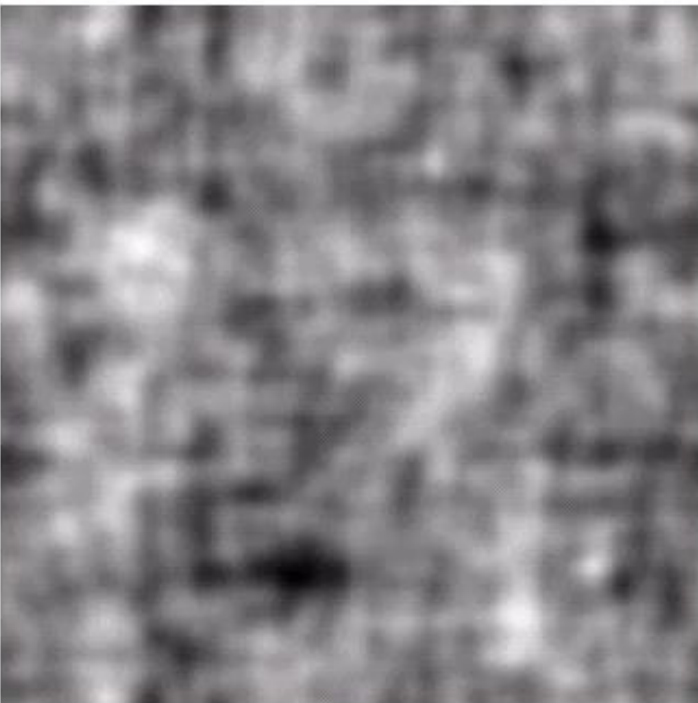
$$\Rightarrow \hat{F}(u,v) = \frac{G(u,v)}{H(u,v)} = F(u,v) + \frac{N(u,v)}{H(u,v)}$$

↑
Estimate of
original image

↑
Problem: **0** or **small values**

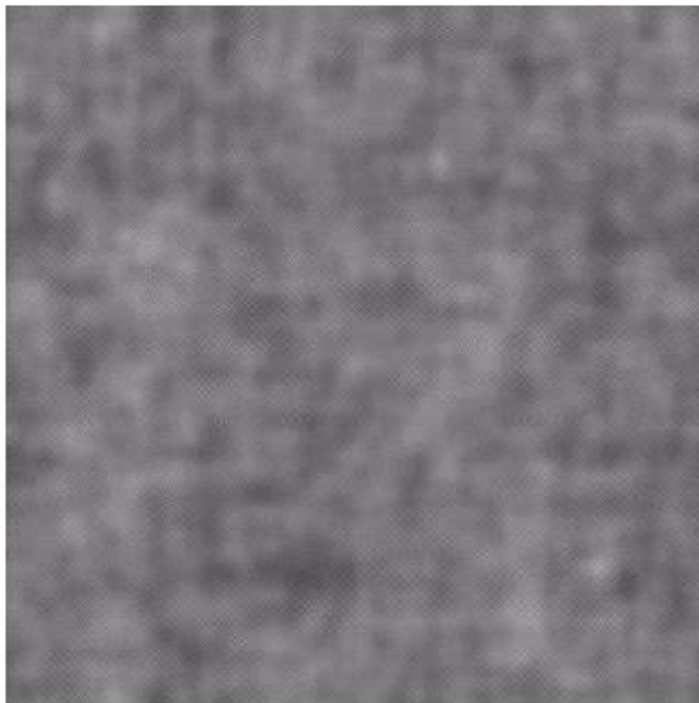
Sol: limit the frequency
around the origin

Full
inverse
filter
for
 $k=0.0025$



Cut
Outside
40%

Cut
Outside
70%



Cut
Outside
85%