



Math 3360: Mathematical Imaging

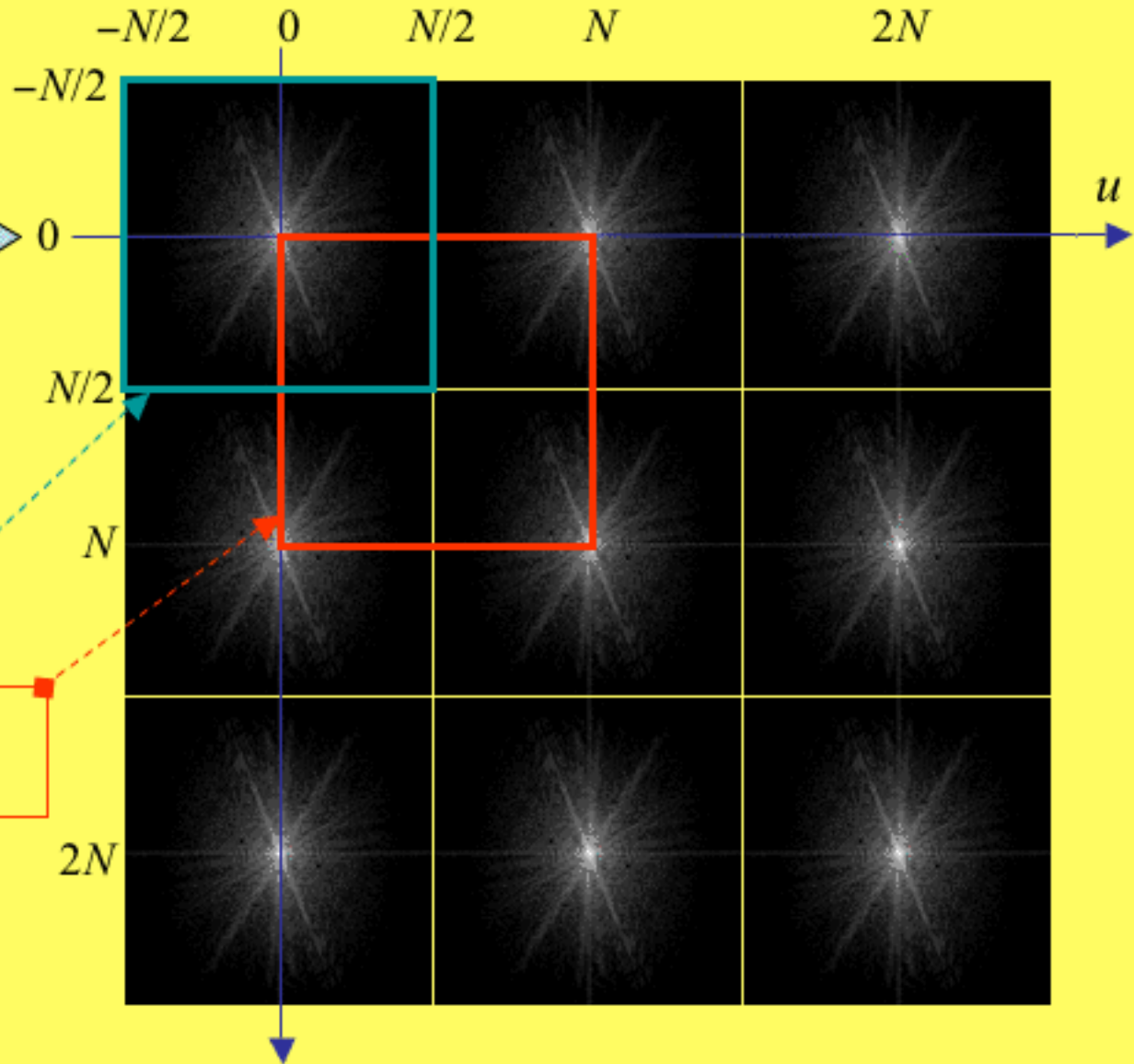
Lecture 12: Image Denoising/Deblurring in Frequency Domain

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Frequency spectrum of an image



DFT



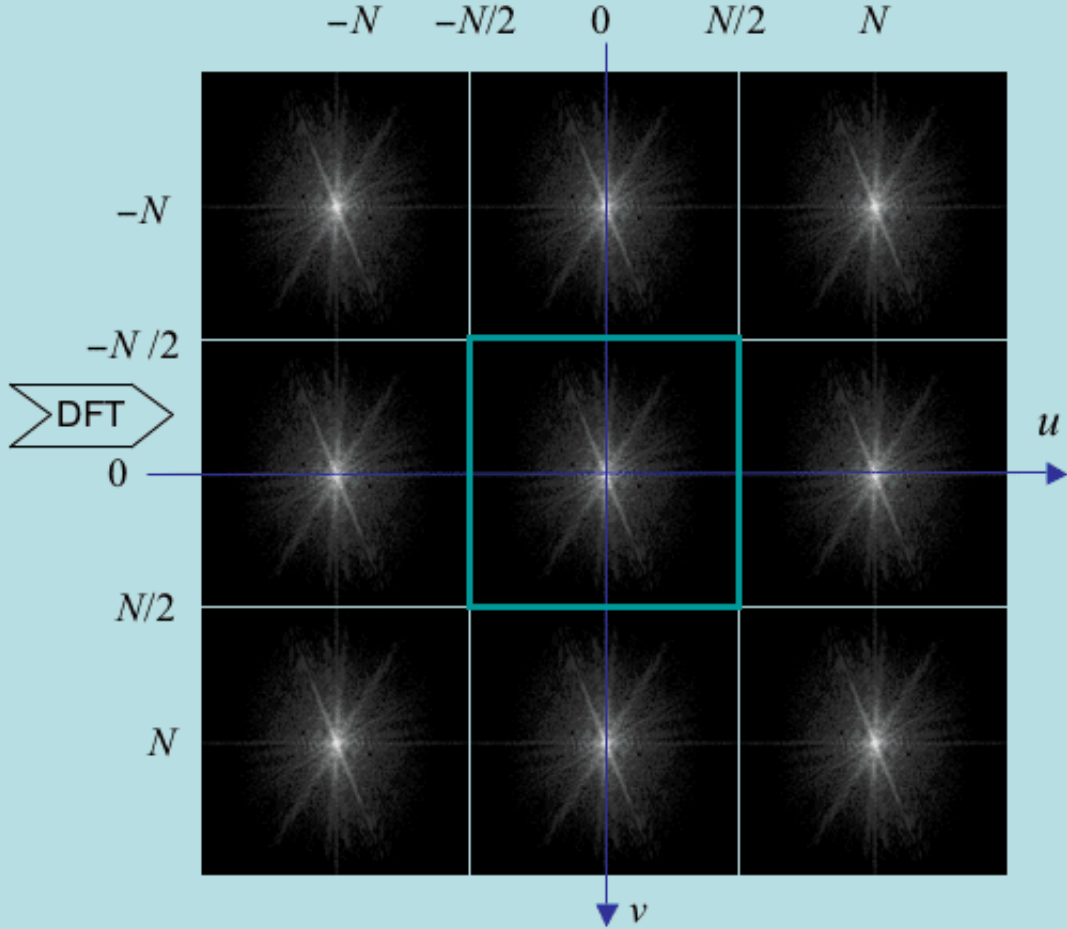
Representation of spectra
being easier to interpret

Single period of the spectrum
computed by a DFT

Frequency spectrum of an image



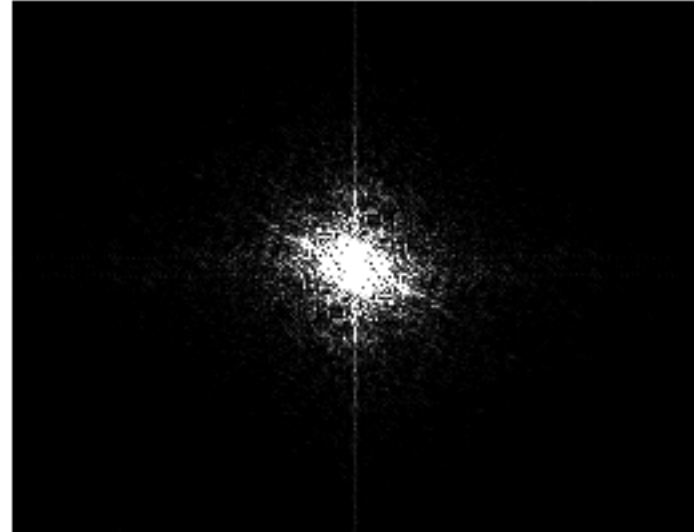
Spatial discontinuities caused by considering an image to be periodic



Frequency spectrum of an image

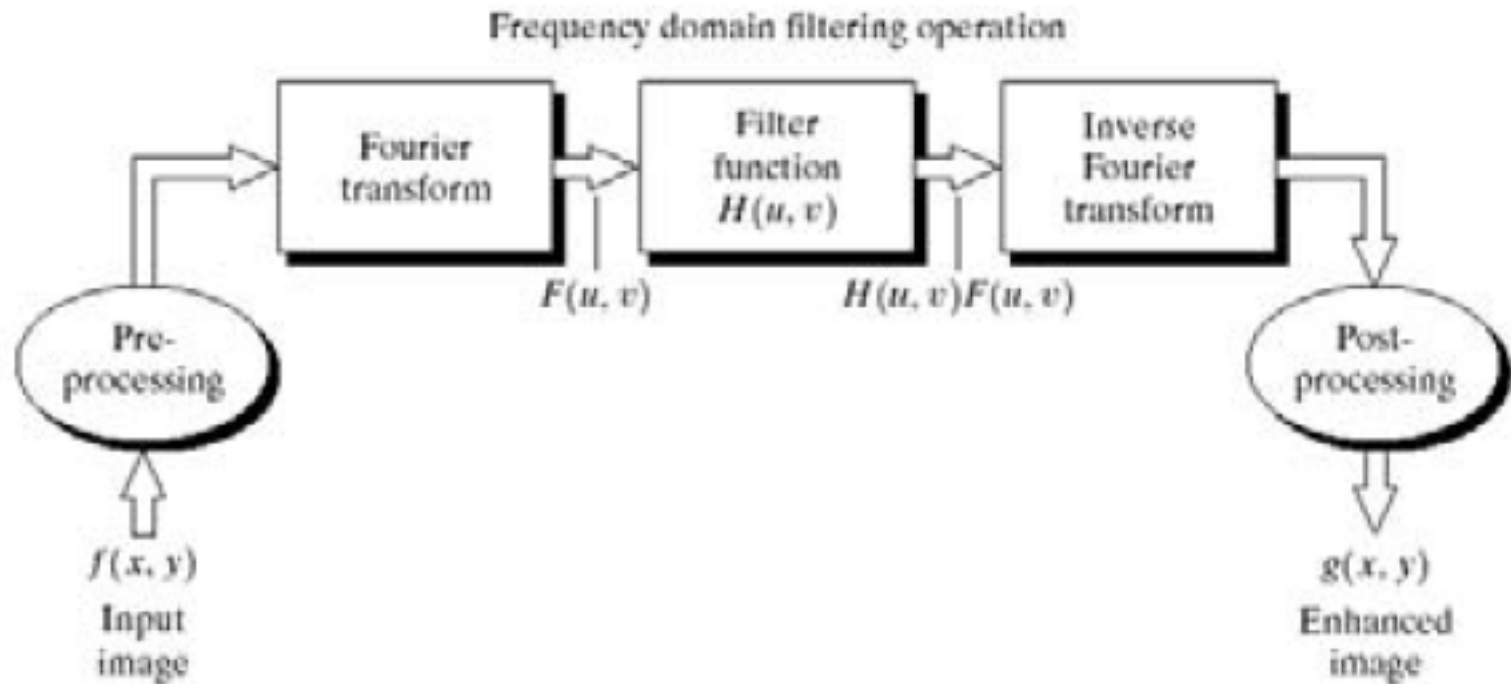


Original image

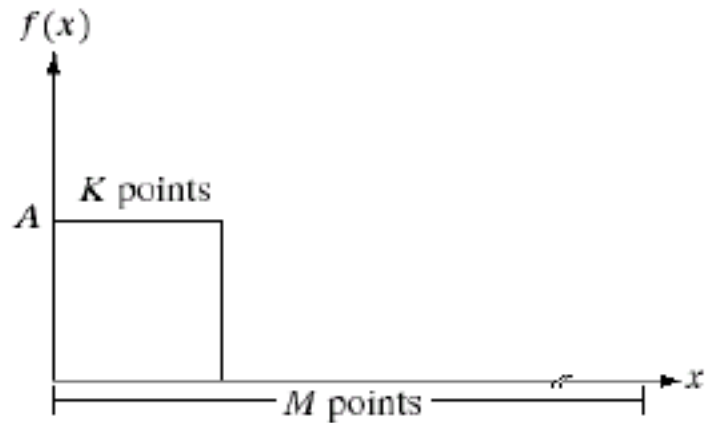


Spectrum

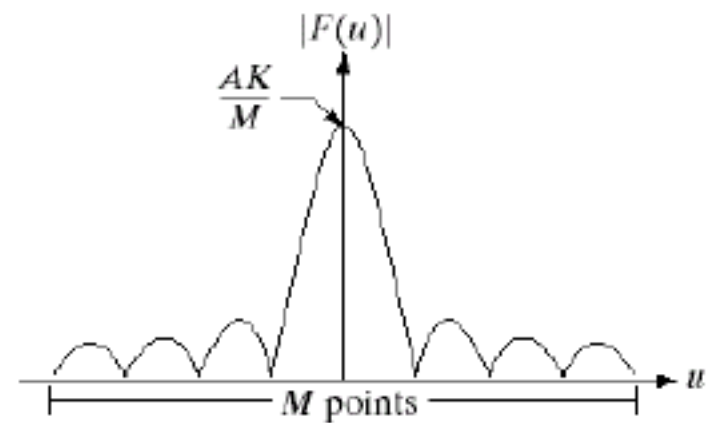
Key steps for image enhancement in the frequency domain



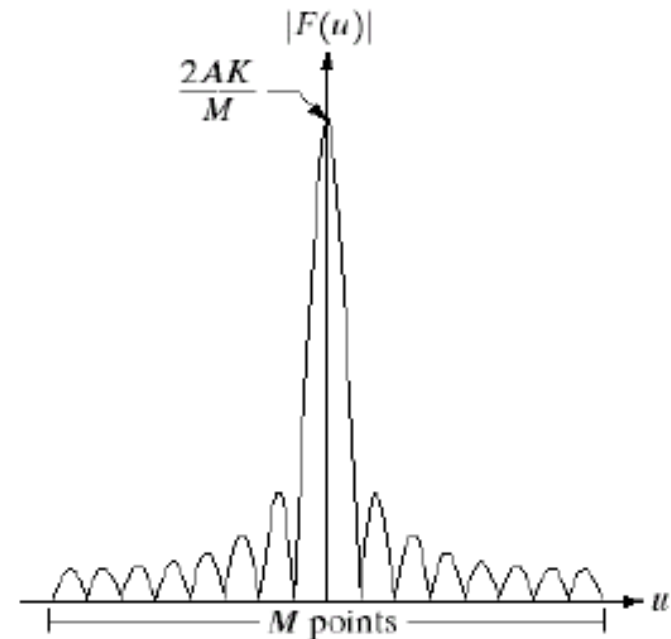
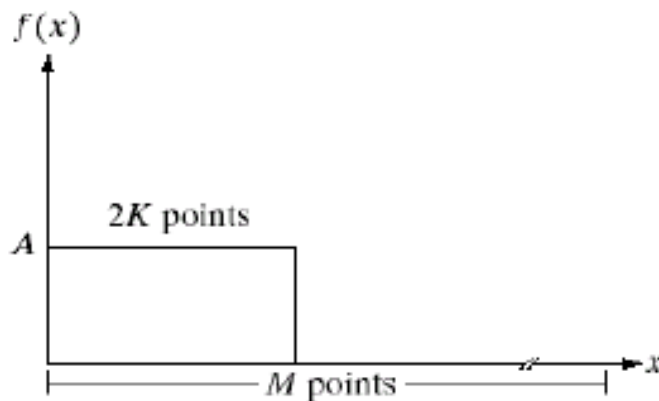
Relationship between spatial and frequency domain



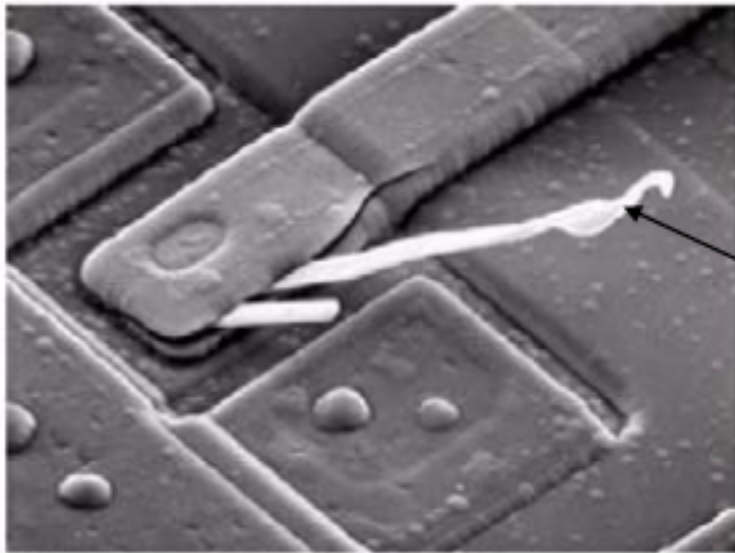
Flat filter



Low pass filtering



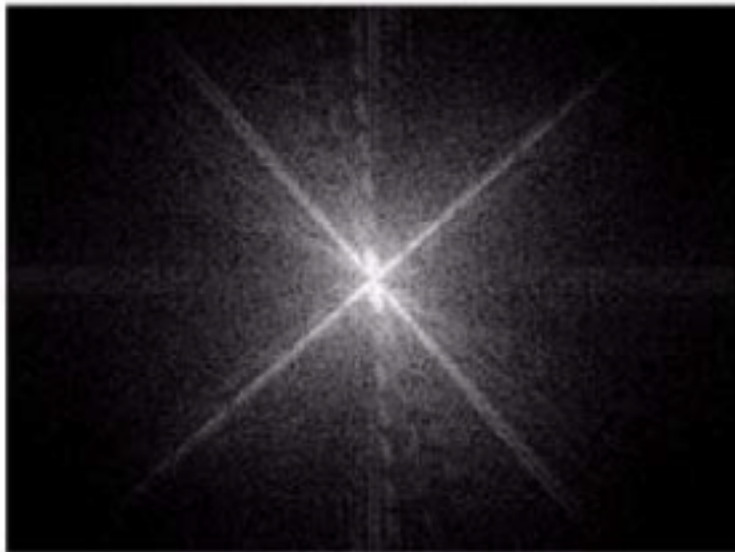
Spatial and frequency domain



protrusions

SEM: scanning electron
Microscope

(a) SEM image of a damaged integrated circuit.
(b) Fourier spectrum of (a).
(Original image courtesy of Dr. J. M. Hudak, Brockhouse Institute for Materials Research, McMaster University, Hamilton, Ontario, Canada.)

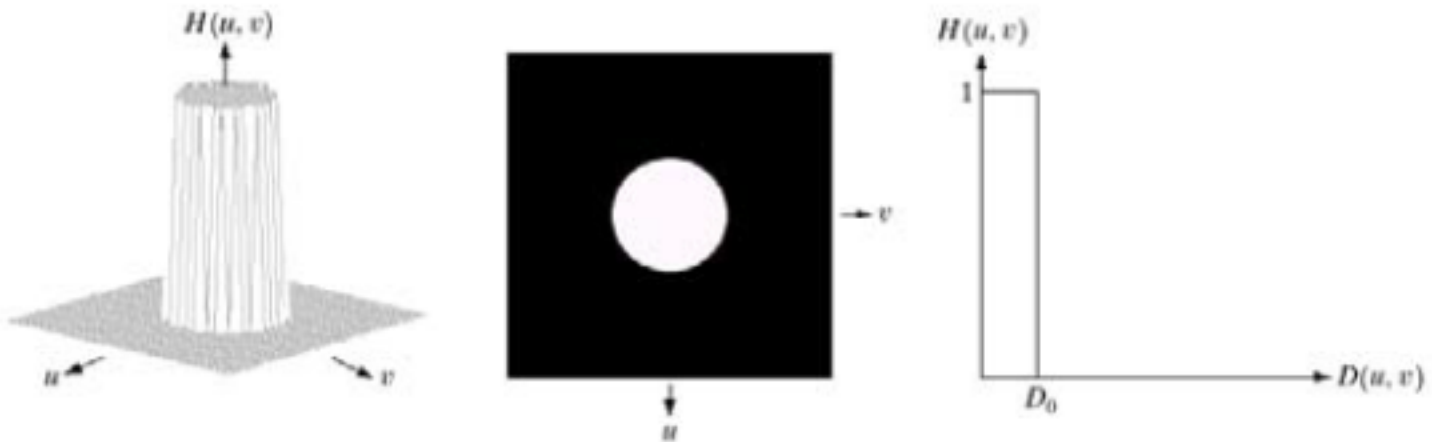


notice the $\pm 45^\circ$ components and the vertical component which is slightly off-axis to the left! It corresponds to the protrusion caused by thermal failure above. 4.29

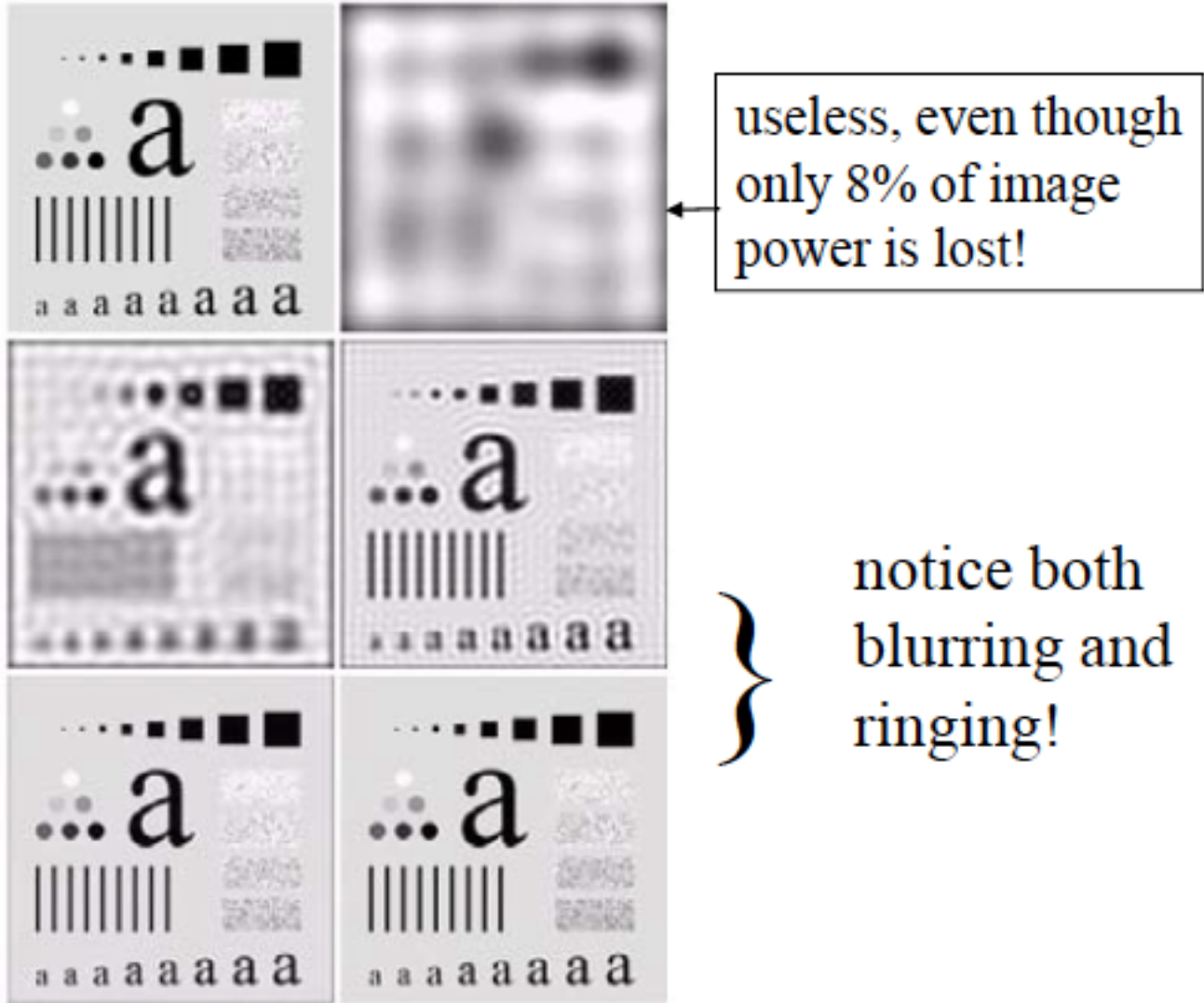
Ideal Low Pass Filter

Ideal low-pass filter $H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$

D_0 is the cutoff frequency and $D(u, v)$ is the distance between (u, v) and the frequency origin.



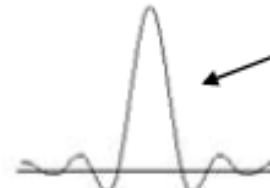
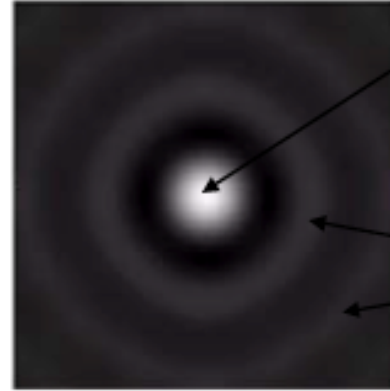
Ideal Low Pass Filter



Ideal Low Pass Filter with larger and larger radii D_0

Explanation of ringing effect

$H(u,v)$ of Ideal
Low-Pass Filter
(ILPF) with
radius 5



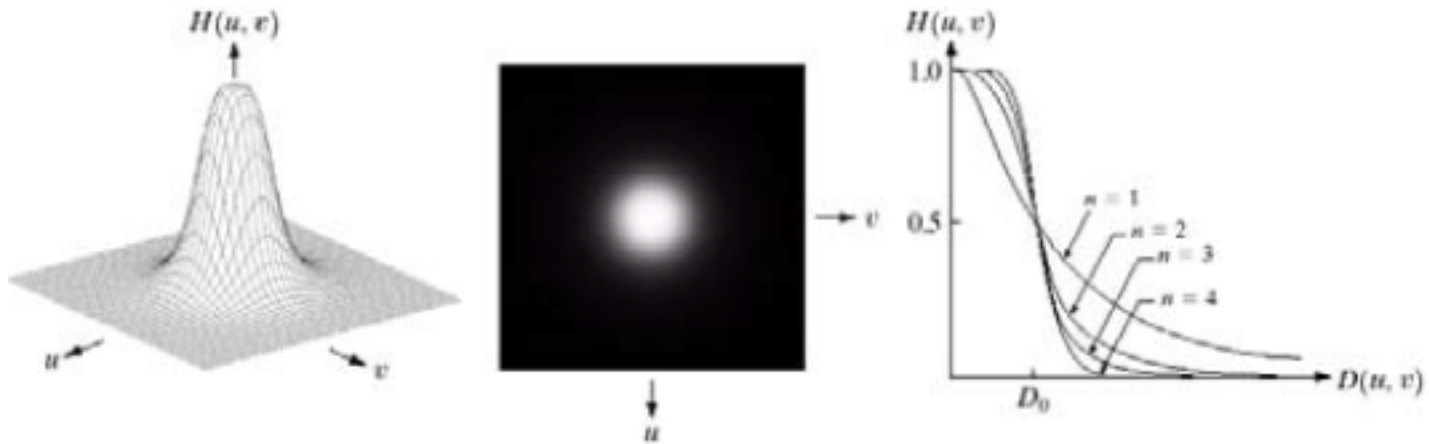
*a greylevel profile of a horizontal
scan line through the center*

$h(x,y)$ is the corresponding
spatial filter

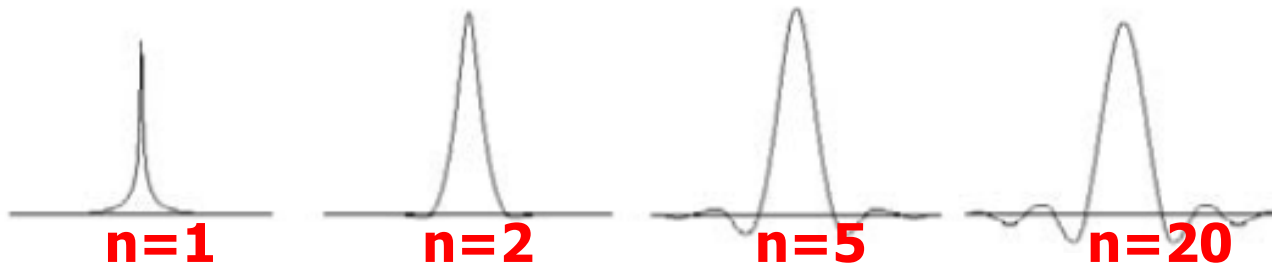
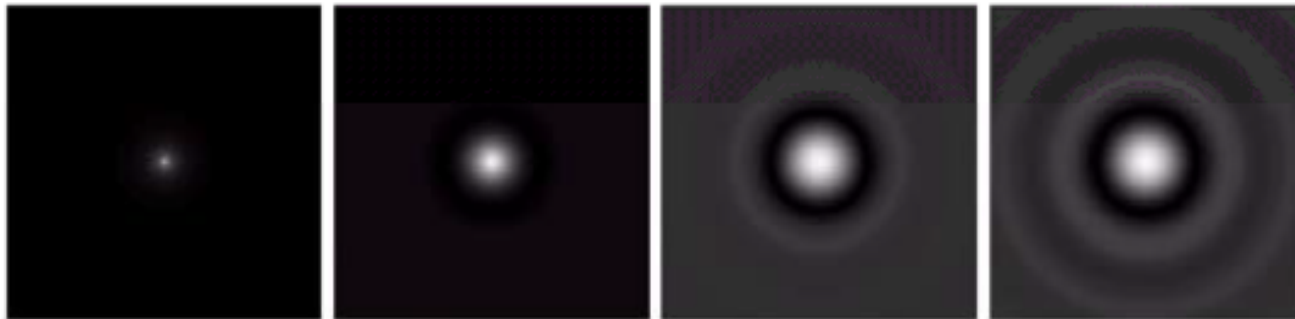
the center component is
responsible for blurring

the concentric components
are responsible for ringing

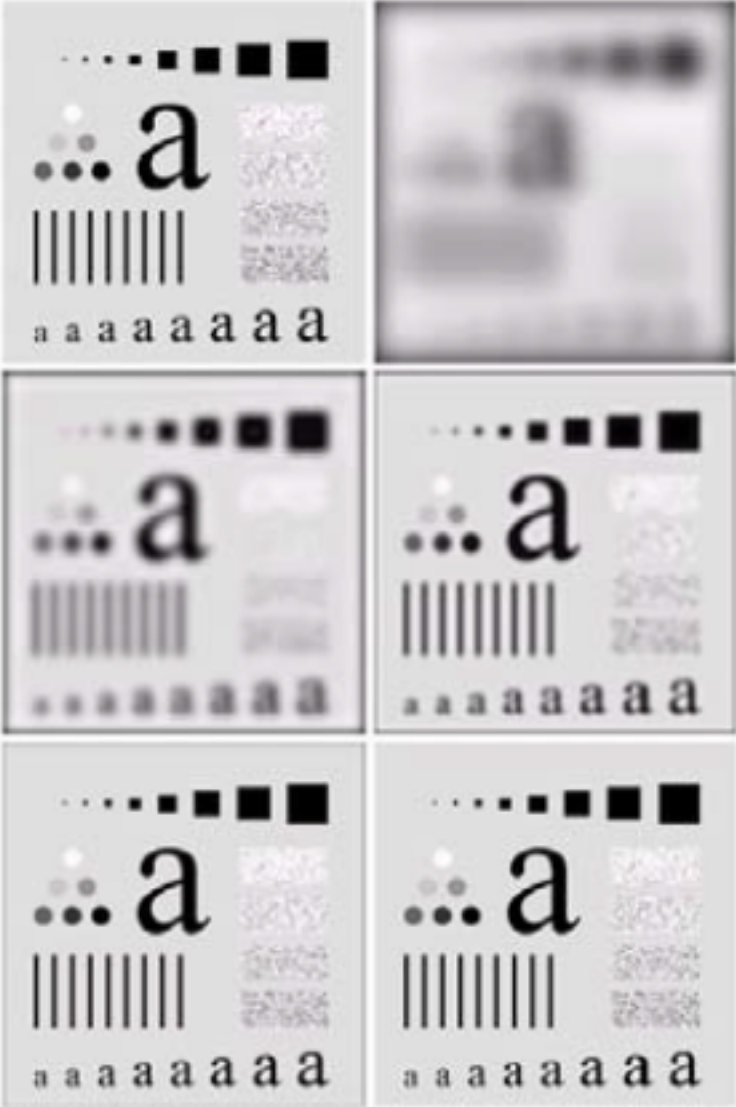
Butterworth Low Pass Filter



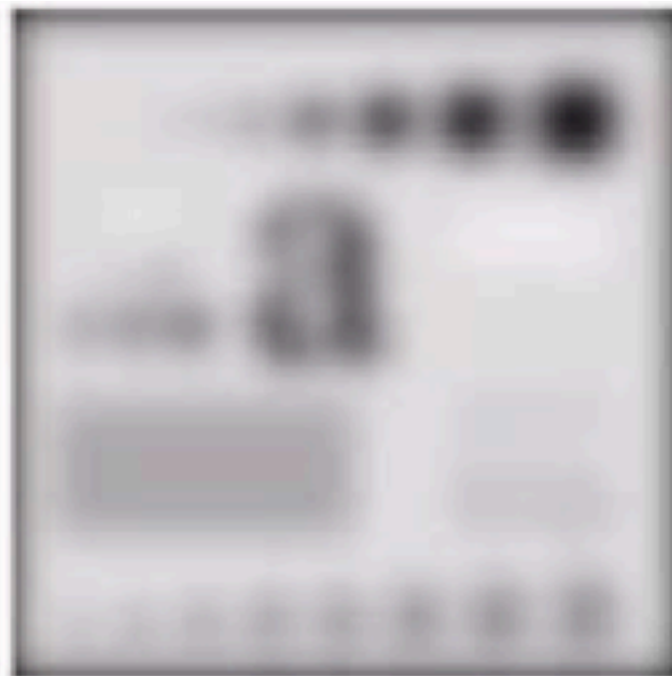
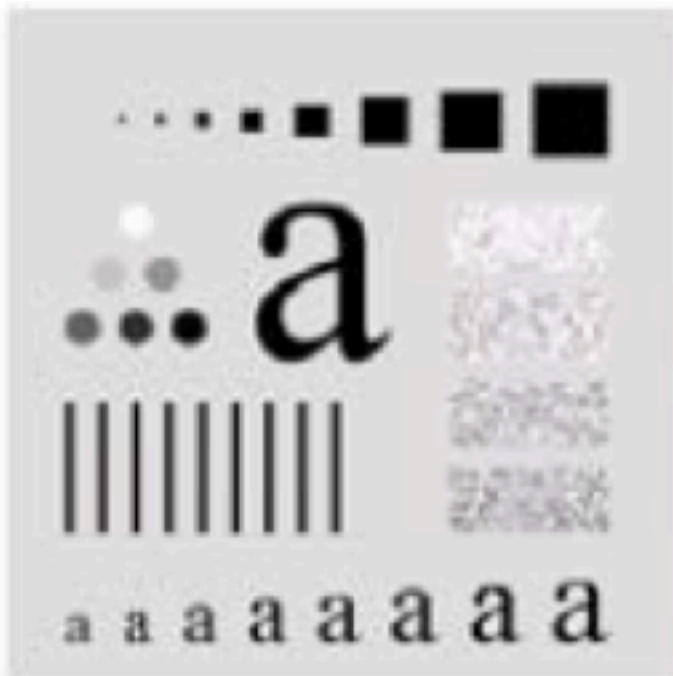
$$H(u, v) = \frac{1}{1 + [D(u, v) / D_0]^n}$$



Butterworth Low Pass Filter



Butterworth Low Pass Filter with larger and larger radii D_0



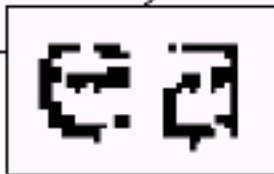
Gal

,

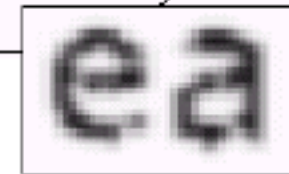
Gaussian Low Pass Filter

Applications: fax transmission, duplicated documents and old records.

Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.



Historically, certain computer programs were written using only two digits rather than four to define the applicable year. Accordingly, the company's software may recognize a date using "00" as 1900 rather than the year 2000.



GLPF with $D_0=80$ is used.

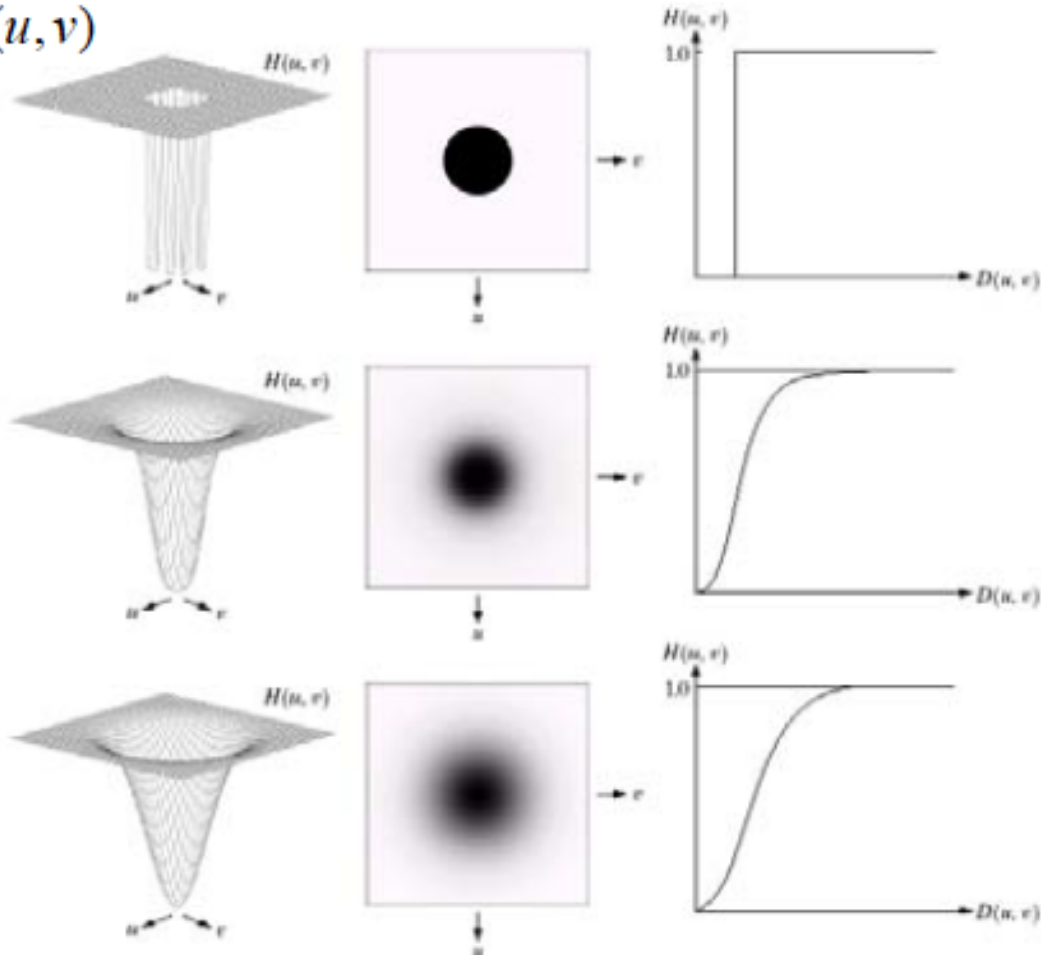
Application: Low Pass Filter

A LPF is also used in printing, e.g. to smooth fine skin lines in faces.



High Pass Filter

$$H_{hp}(u, v) = 1 - H_{lp}(u, v)$$

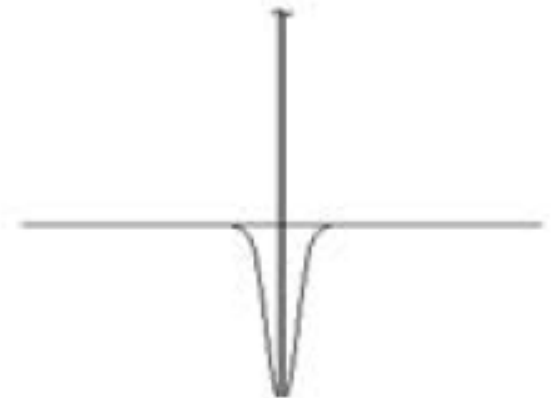
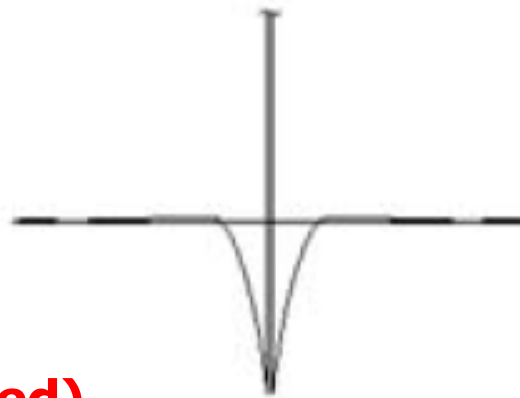
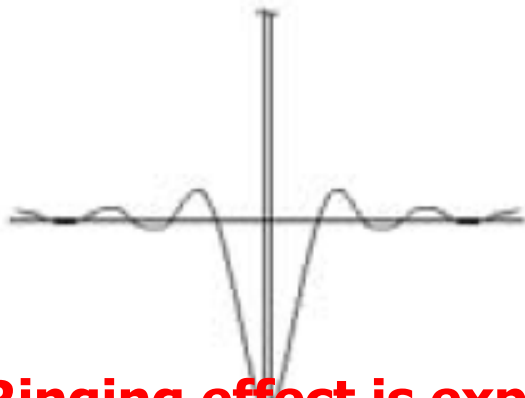
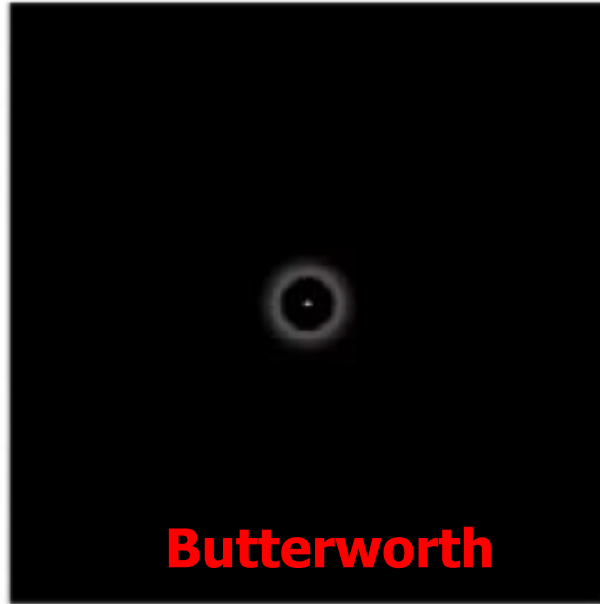
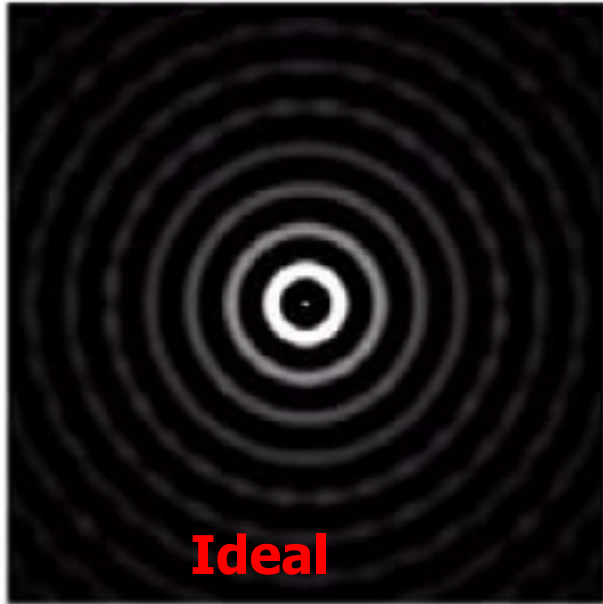


ideal high-pass filter

Butterworth high-pass

Gaussian high-pass

Spatial representation of High Pass Filter

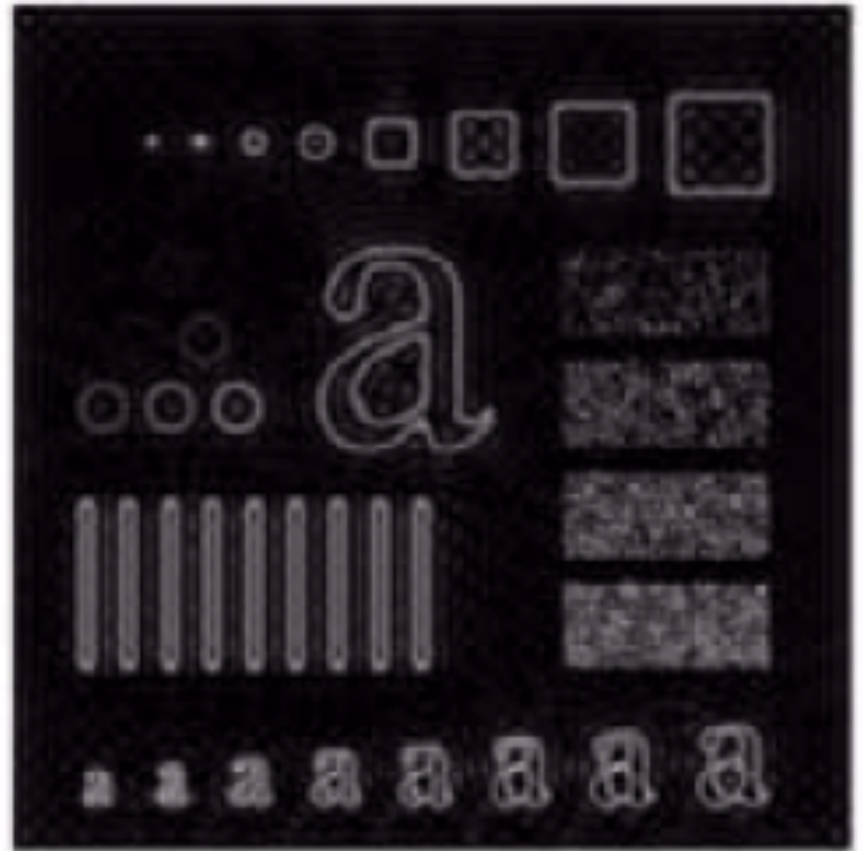


(Ringing effect is expected)

Ideal High Pass Filter



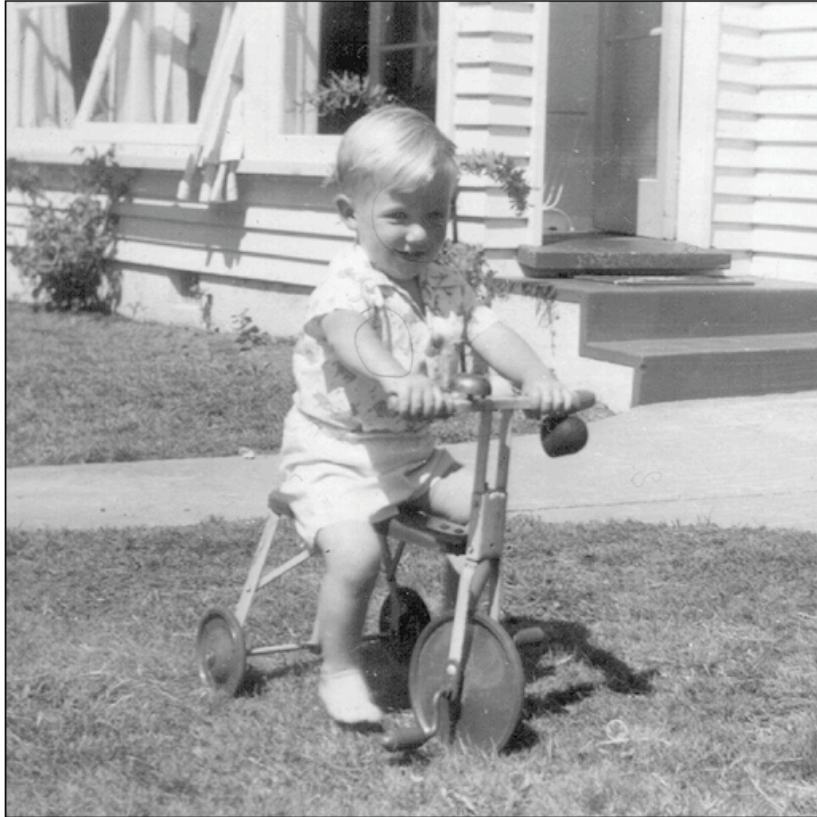
$D_0 = 15$



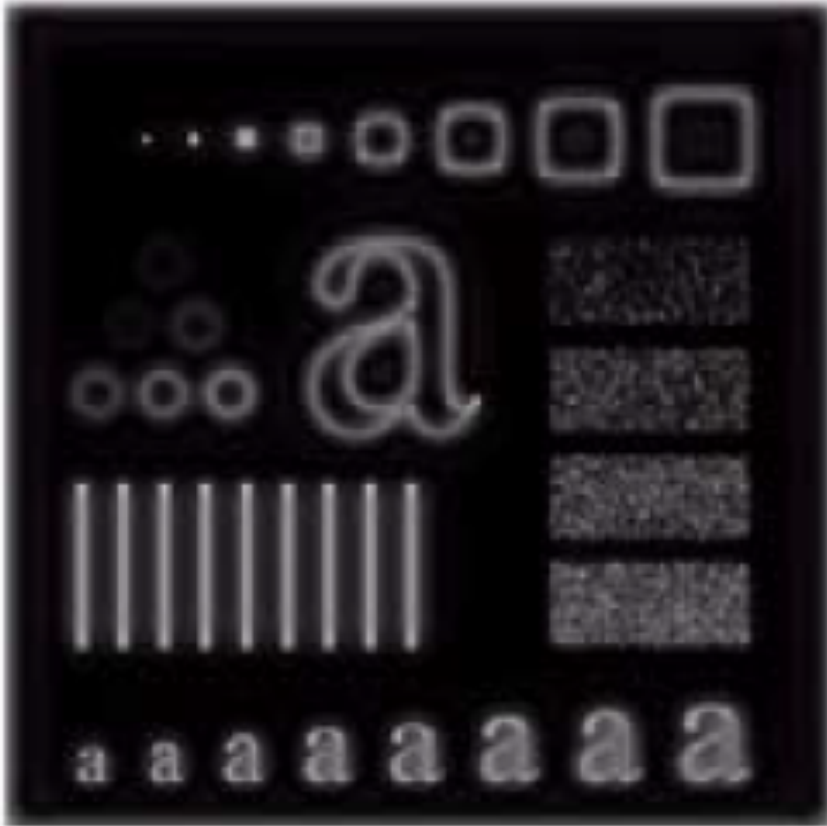
$D_0 = 30$

(Ringing effect is observed)

Ideal High Pass Filter



Butterworth High Pass Filter



$D_0 = 15$



$D_0 = 30$

Comparison: High Pass Filter



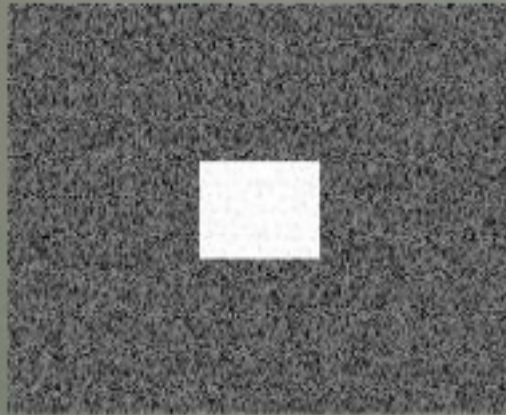
High-pass filtering



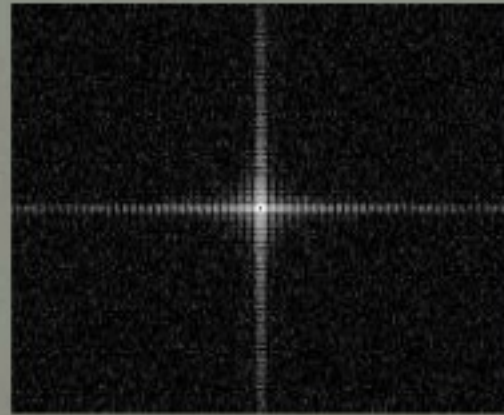
Low-pass filtering

Image denoising examples

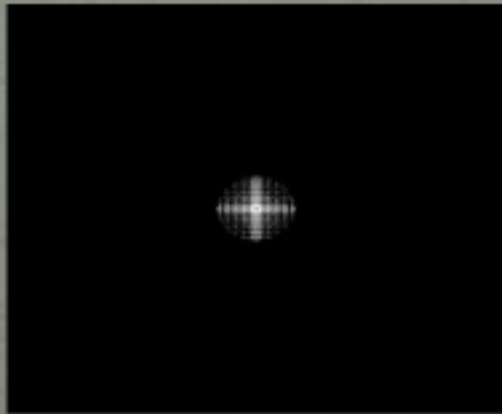
Ideal filtering



Original Image



Fourier Transform



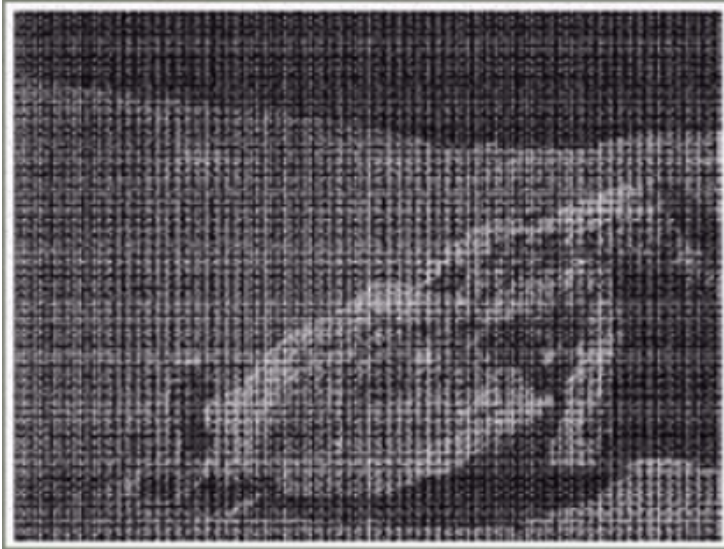
Apply LPF on FT



Inverse Fourier Transform

Image denoising examples

Ideal filtering



Noisy image



Frequency domain



Denoised

Image denoising examples

Butterworth filtering



Noisy

Image denoising examples

Butterworth filtering



Denoised

Image denoising examples

Gaussian filtering

noisy



denoised



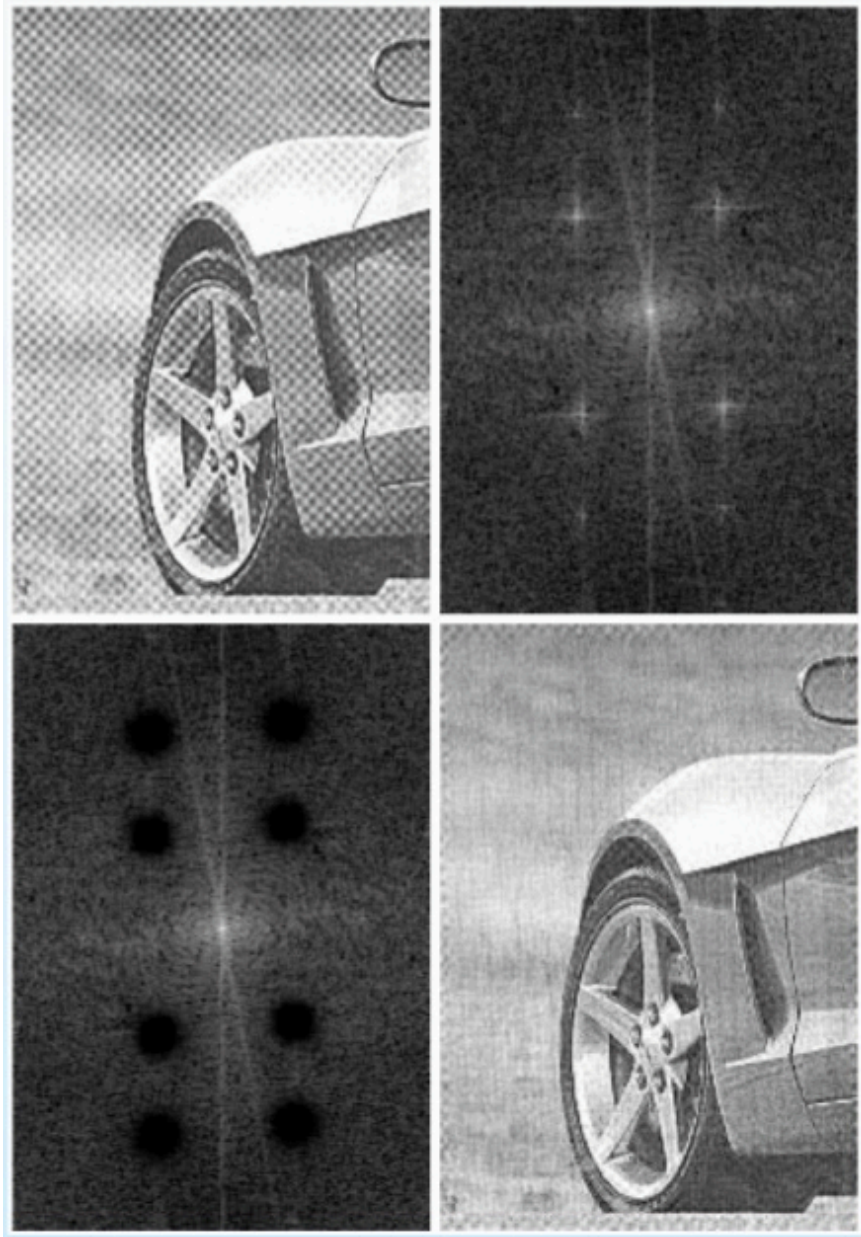
$(\sigma=1)$

denoised

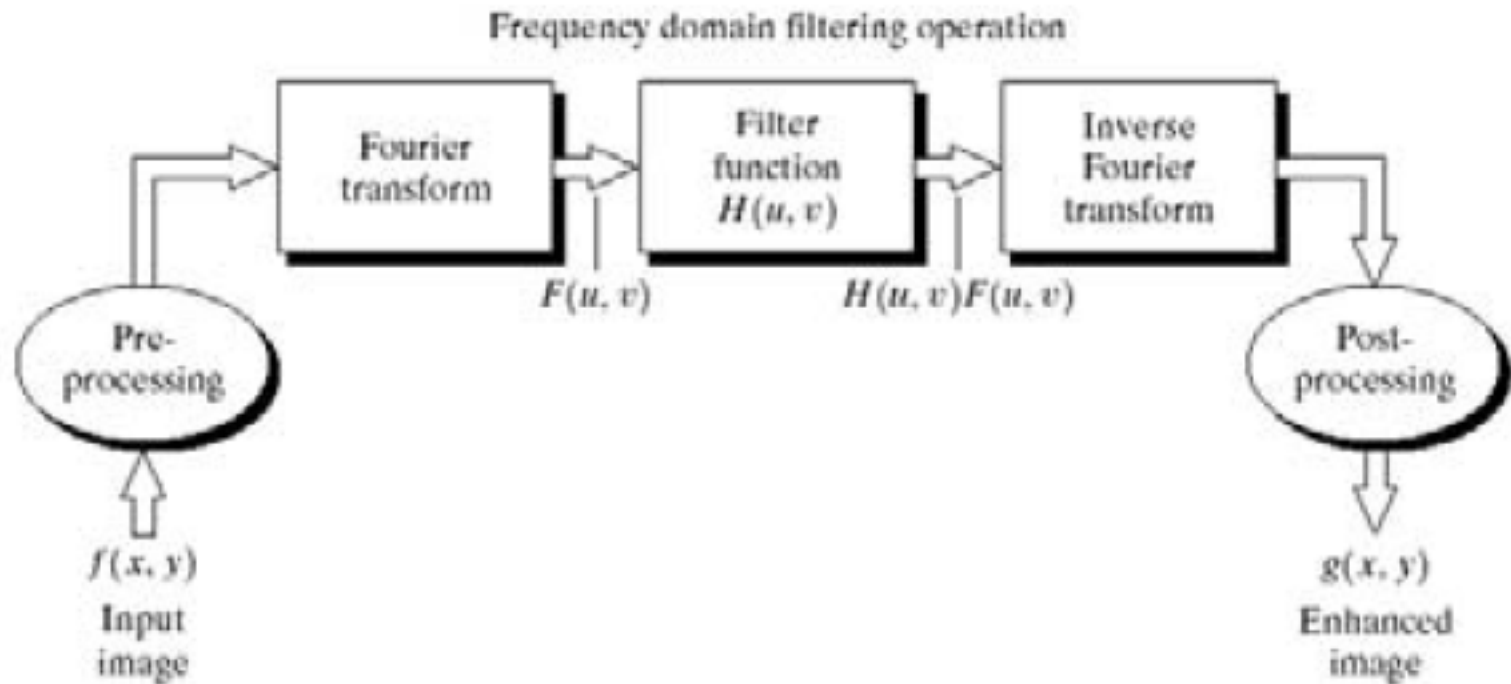


$(\sigma=1.5)$

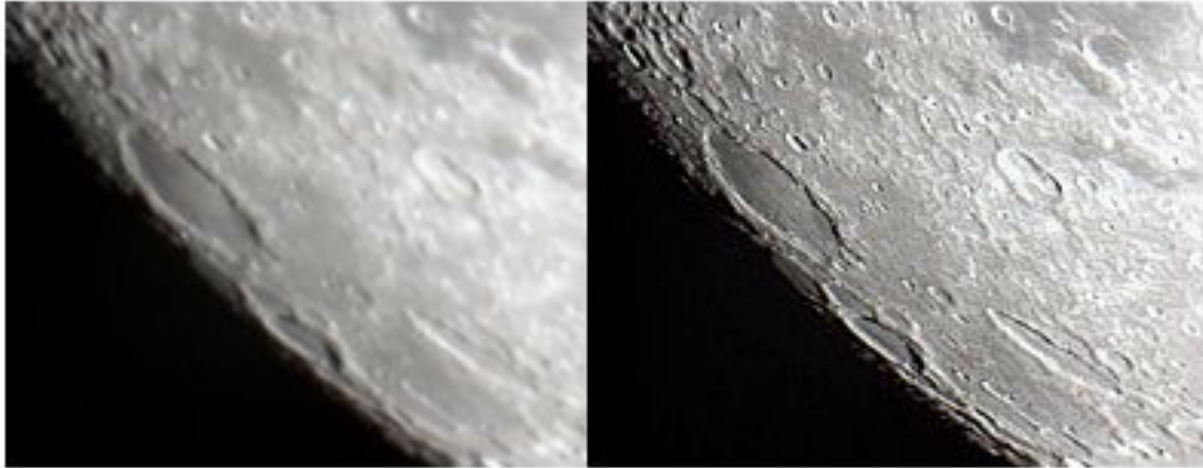
Image denoising examples



Key steps for image enhancement in the frequency domain

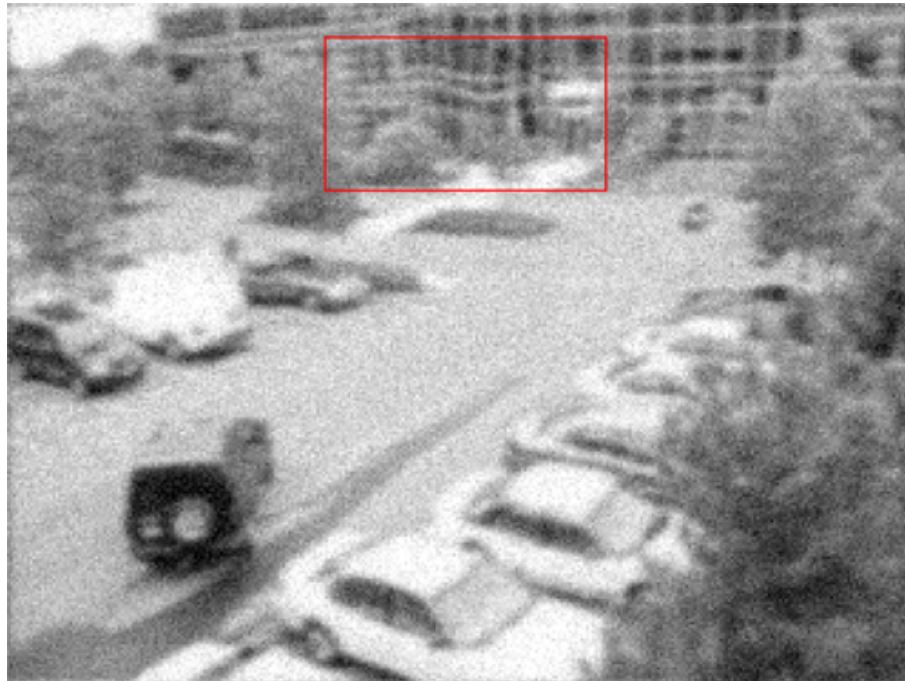


Example of turbulence blur



Blurry image

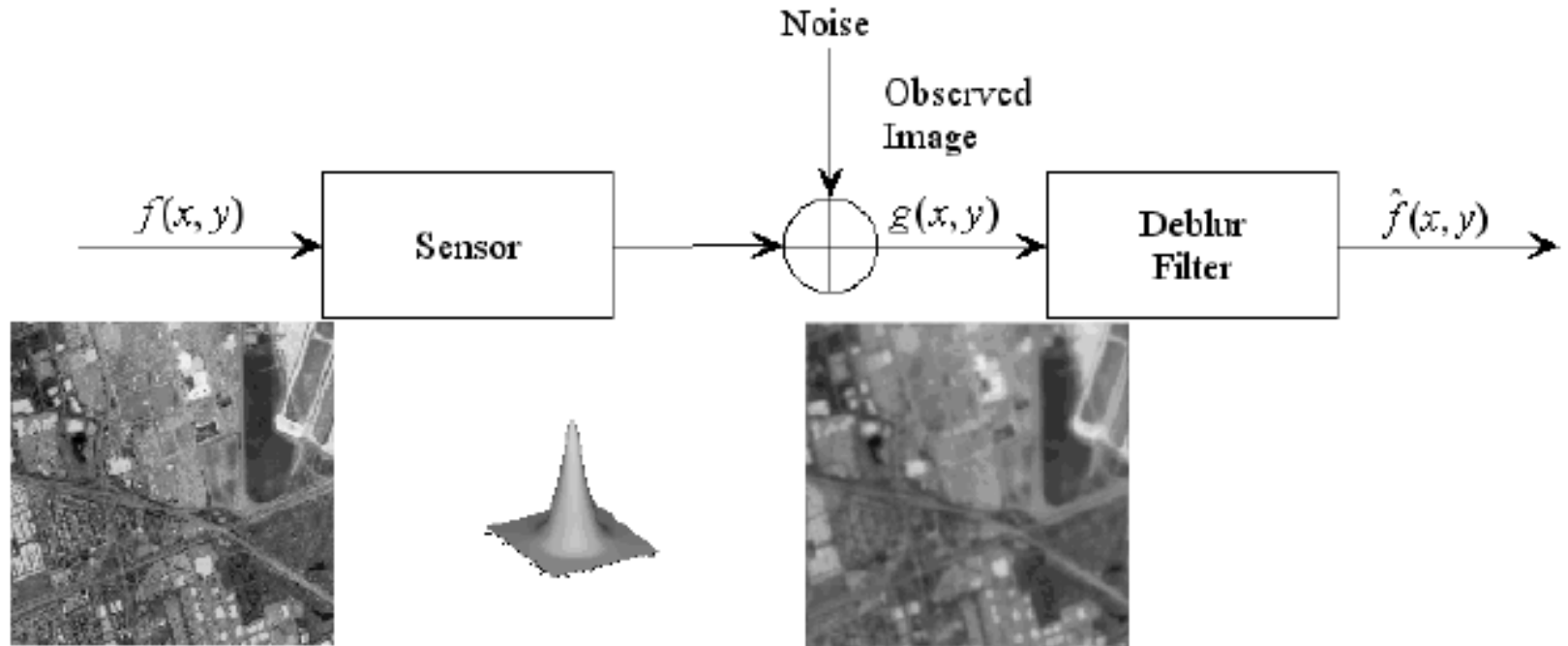
Deblurred image



Example of motion blur



Image deblur model



Linear model of observation system

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

Image filtering in the frequency domain

The observation equation can also be expressed in the frequency domain as

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

We can construct an estimate of $F(u, v)$ by filtering the observation $G(u, v)$. Let $T(u, v)$ be a linear shift-invariant reconstruction filter.

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

Our task is to find a filter $T(u, v)$ that provides a good estimate of the original image.

The solution must balance noise reduction and sharpening of the image. These are conflicting goals.

Direct inverse filter

$$T(u, v) = H^{-1}(u, v)$$

$$\hat{F}(u, v) = G(u, v)H^{-1}(u, v) = F(u, v) + \mathcal{N}(u, v)H^{-1}(u, v)$$

The result will be filtered noise added to the desired image.

The problem is that the inverse filter typically has very high gain at certain frequencies so that the noise term completely dominates the result.

Direct inverse filter



Original Image



Blurred Image

A small amount of noise saturates the inverse filter.

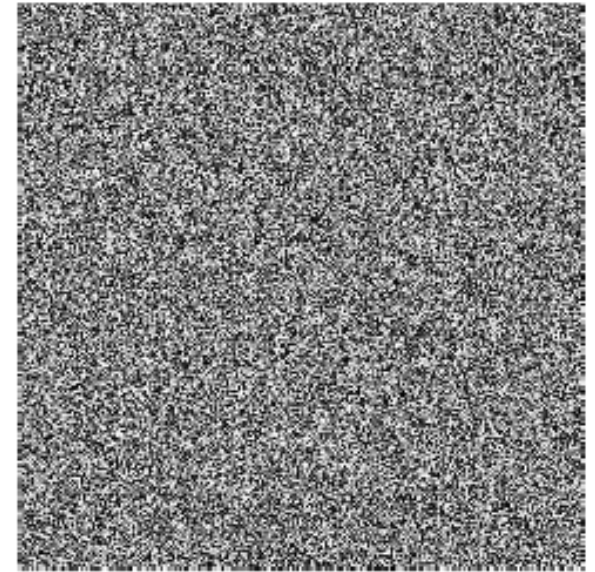
Direct inverse filter



Original Image



Blurred Image



Restored with $H^{-1}(u, v)$

A small amount of noise saturates the inverse filter.

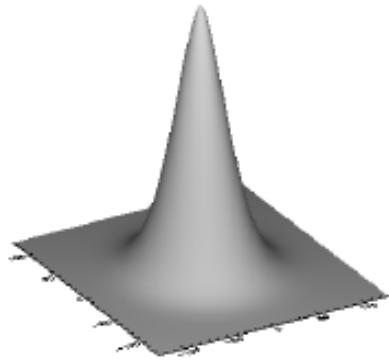
Modified inverse filter

$$B(u, v) = \frac{1}{1 + \left(\frac{u^2 + v^2}{D^2}\right)^n}$$

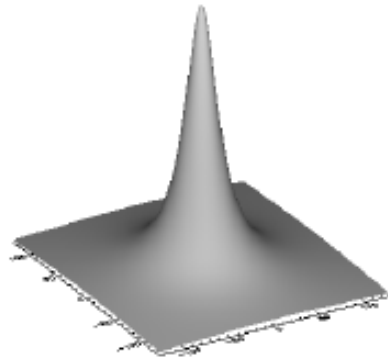
$$T(u, v) = \frac{B(u, v)}{H(u, v)}$$

$$\begin{aligned}\hat{F}(u, v) &= (F(u, v)H(u, v) + \mathcal{N}(u, v))T(u, v) \\ &= F(u, v)B(u, v) + \frac{\mathcal{N}(u, v)B(u, v)}{H(u, v)}\end{aligned}$$

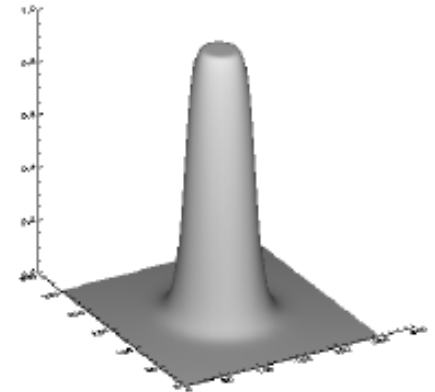
Modified inverse filter



$H(u, v)$



$B(u, v): R = 20, n = 1$



$R = 40, n = 1$



Blurred Image $G(u, v)$

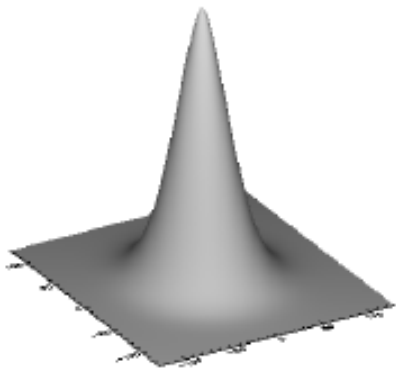


Restored using $R = 20$

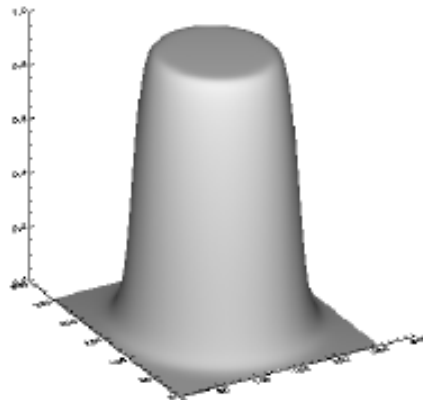


Restored using $R = 40$

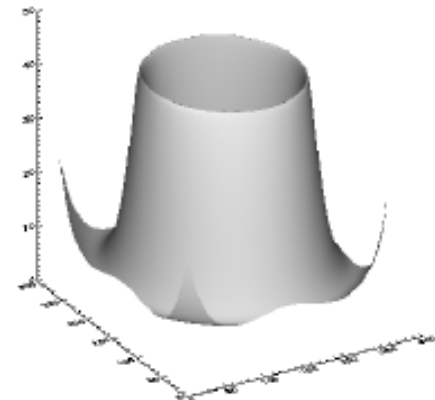
Modified inverse filter



$H(u, v)$



$B(u, v): R = 90, n = 8$



Inverse B/H



Original Image $G(u, v)$



Blurred using $R = 20$



Restored

Wiener filter

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

$$W(u, v) = \frac{H^*(u, v)}{|H(u, v)|^2 + K(u, v)}$$



Wiener filter

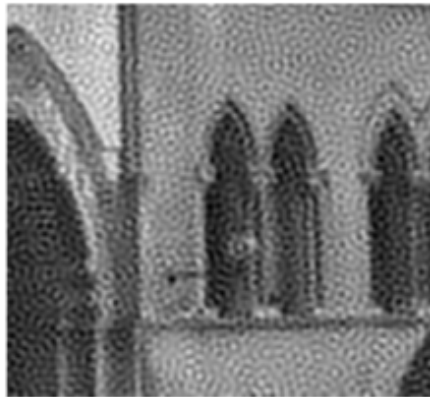
$g(x,y)$



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



$K = 1.0 e -5$



$K = 1.0 e -3$



$K = 1.0 e -1$



Wiener filter

$f(x,y)$



$g(x,y)$

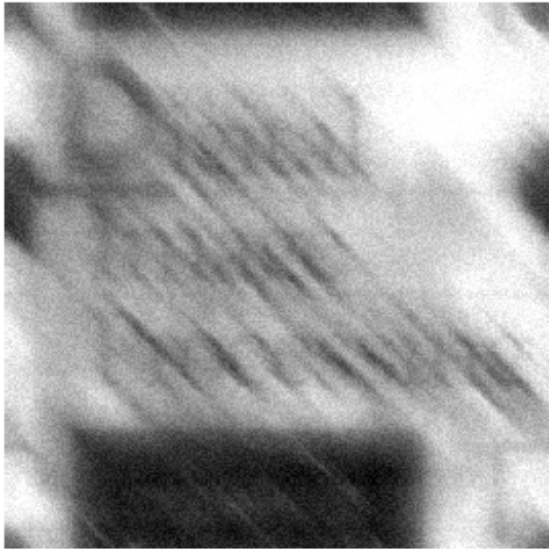


$\hat{f}(x,y)$



$K = 5.0 \text{ e } -4$

Wiener filter



Deblurred

High Noise

Medium Noise

Low Noise

Wiener filter

Comparison



Original



Wiener $K = 0.0001$



Inverse Butterworth $[90, 8]$

Wiener filter

Application



Algorithm

1. Rotate image so that blur is horizontal
2. Estimate length of blur
3. Construct a bar modelling the convolution
4. Compute and apply a Wiener filter
5. Optimize over values of K

Wiener filter

Application



Zoom-in

Algorithm

1. Rotate image so that blur is horizontal
2. Estimate length of blur
3. Construct a bar modelling the convolution
4. Compute and apply a Wiener filter
5. Optimize over values of K

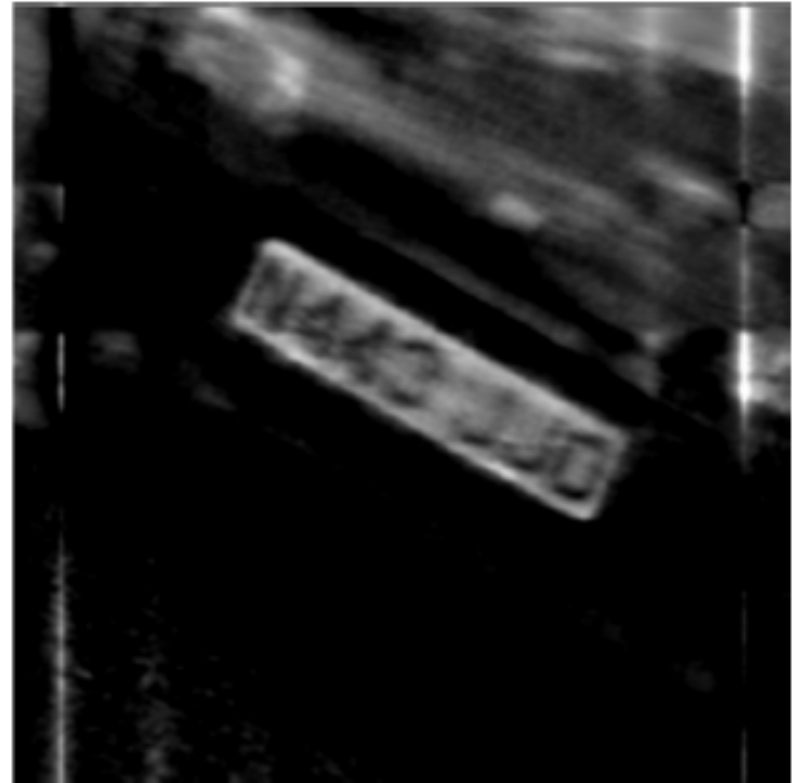
Wiener filter

Application

Blurry image

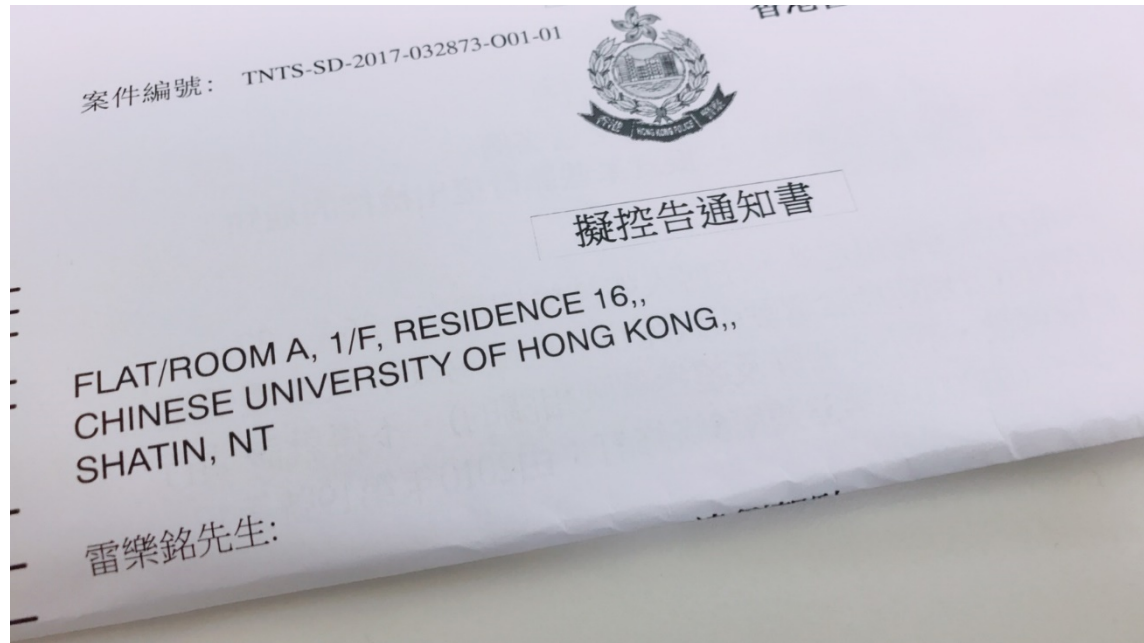
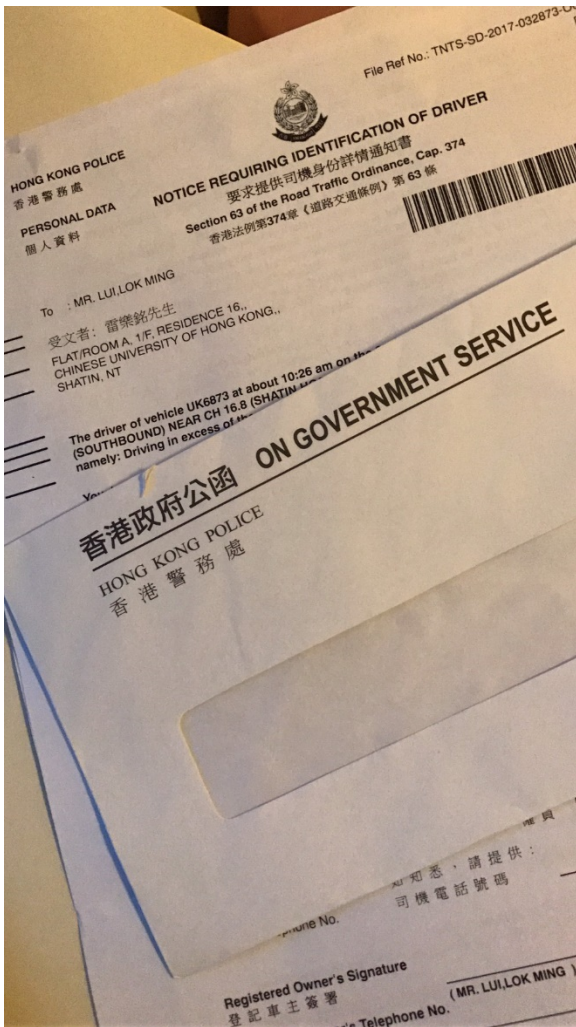


Deblurred image



Wiener filter

BUT sometimes it doesn't work!



Different image deblurring algorithms

Method 1: Direct inverse filtering

Let $T(u, v) = \frac{1}{H(u, v) + \varepsilon \operatorname{sgn}(H(u, v))}$. Compute $\hat{F}(u, v) = G(u, v)T(u, v)$. Find inverse DFT of $\hat{F}(u, v)$ to get an image $\hat{f}(x, y)$.

(Here, $\operatorname{sgn}(z) = 1$ if $\operatorname{Re}(z) \geq 0$ and $\operatorname{sgn}(z) = -1$ otherwise.)

Method 2: Modified inverse filtering

Let $B(u, v) = \frac{1}{1 + (\frac{u^2+v^2}{D^2})^n}$, and $T(u, v) = \frac{B(u, v)}{H(u, v) + \varepsilon \operatorname{sgn}(H(u, v))}$, then

$$\hat{F}(u, v) = T(u, v)G(u, v) \approx F(u, v)B(u, v) + \frac{N(u, v)B(u, v)}{H(u, v) + \varepsilon \operatorname{sgn}(H(u, v))}$$

$\frac{B(u, v)}{H(u, v) + \varepsilon \operatorname{sgn}(H(u, v))}$ suppresses the high-frequency gain.

Different image deblurring algorithms

Method 3: Wiener Filter

The Wiener Filter is defined (in the frequency domain) as:

$$T(u, v) = \frac{\overline{H(u, v)}}{|H(u, v)|^2 + S_n(u, v)/S_f(u, v)}$$

where $S_n(u, v) = |N(u, v)|^2$, $S_f(u, v) = |F(u, v)|^2$ (Add parameters to avoid singularities)

If $S_n(u, v)$ and $S_f(u, v)$ are not known, then we let $K = S_n(u, v)/S_f(u, v)$ to get

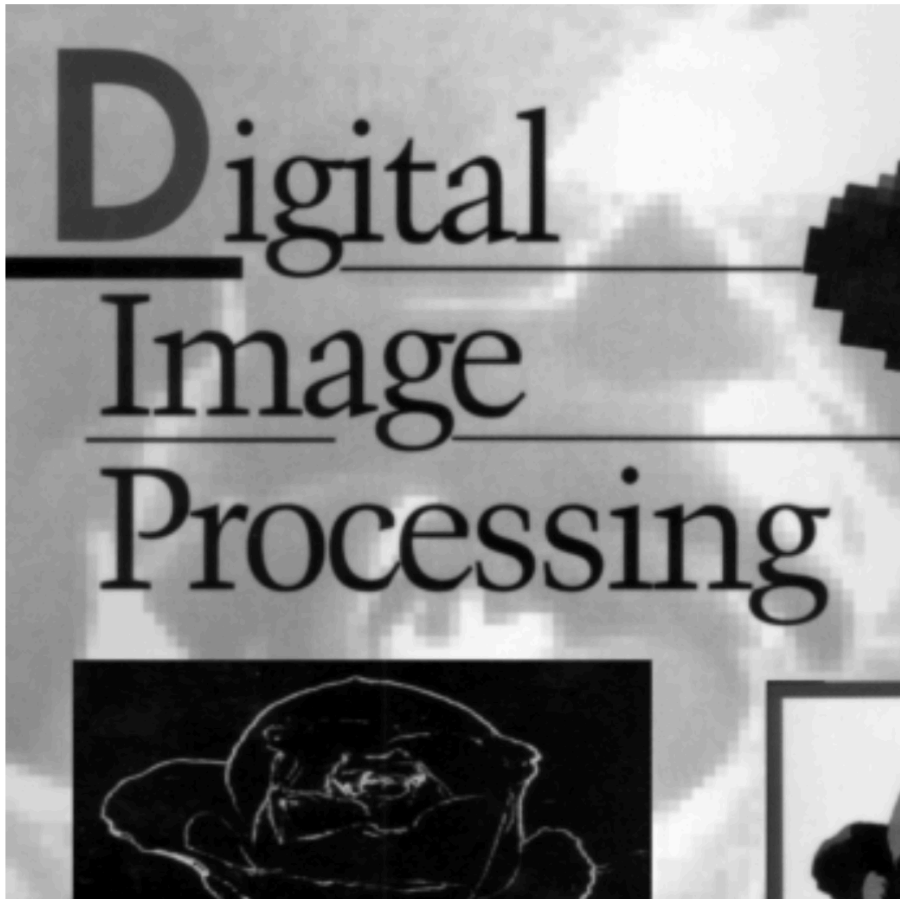
$$T(u, v) = \frac{\overline{H(u, v)}}{|H(u, v)|^2 + K}$$

Hence, Wiener Filter can be described as the inverse filtering as follows:

$$\hat{F}(u, v) = \left[\underbrace{\left(\frac{1}{H(u, v)} \right)}_{\text{direct inverse filter}} \underbrace{\left(\frac{|H(u, v)|^2}{|H(u, v)|^2 + K} \right)}_{\text{modifier}} \right] G(u, v)$$

Image deblur model

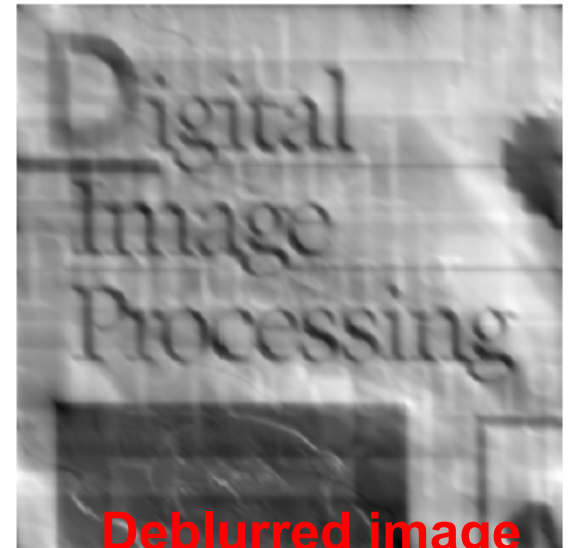
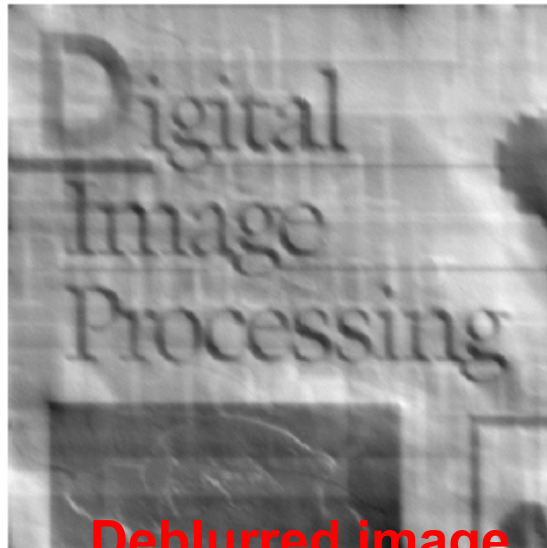
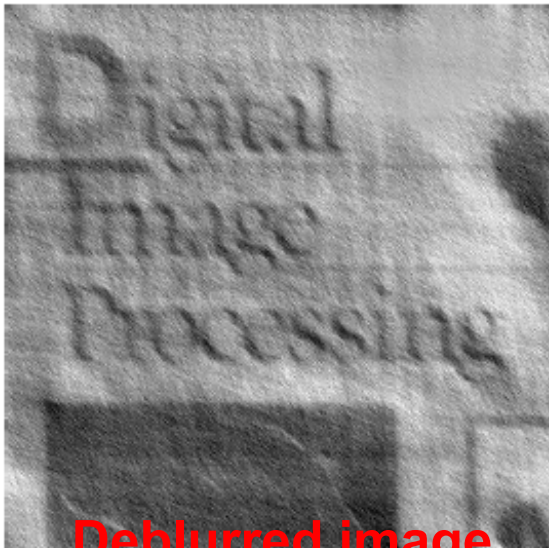
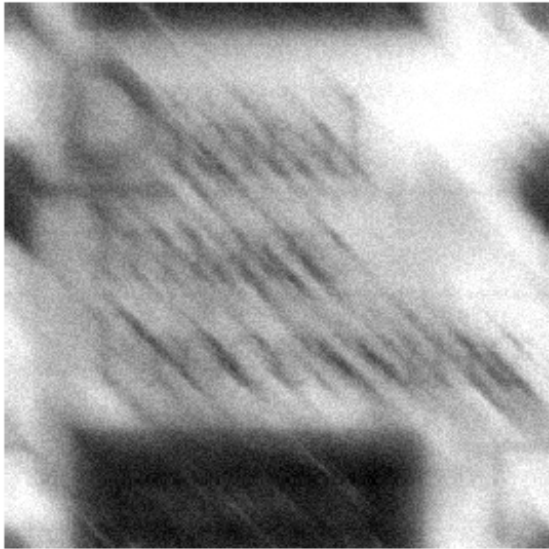
Original image



Blurred image



Wiener filter



Deblurred image
High Noise

Deblurred image
Medium Noise

Deblurred image
Low Noise

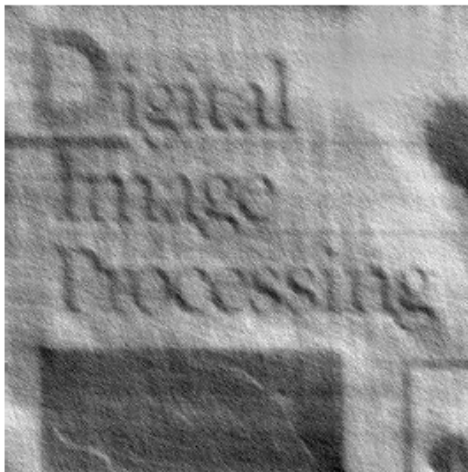
Constrained least square filtering

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

Constrained
Least
Square



Wiener
filter



High Noise

Medium Noise

Low Noise

Constrained least square filtering



Blurry image without noise

Constrained least square filtering



Blurry image without noise

Constrained least square filtering



Blurry images



Deblurred images