

Image Enhancement

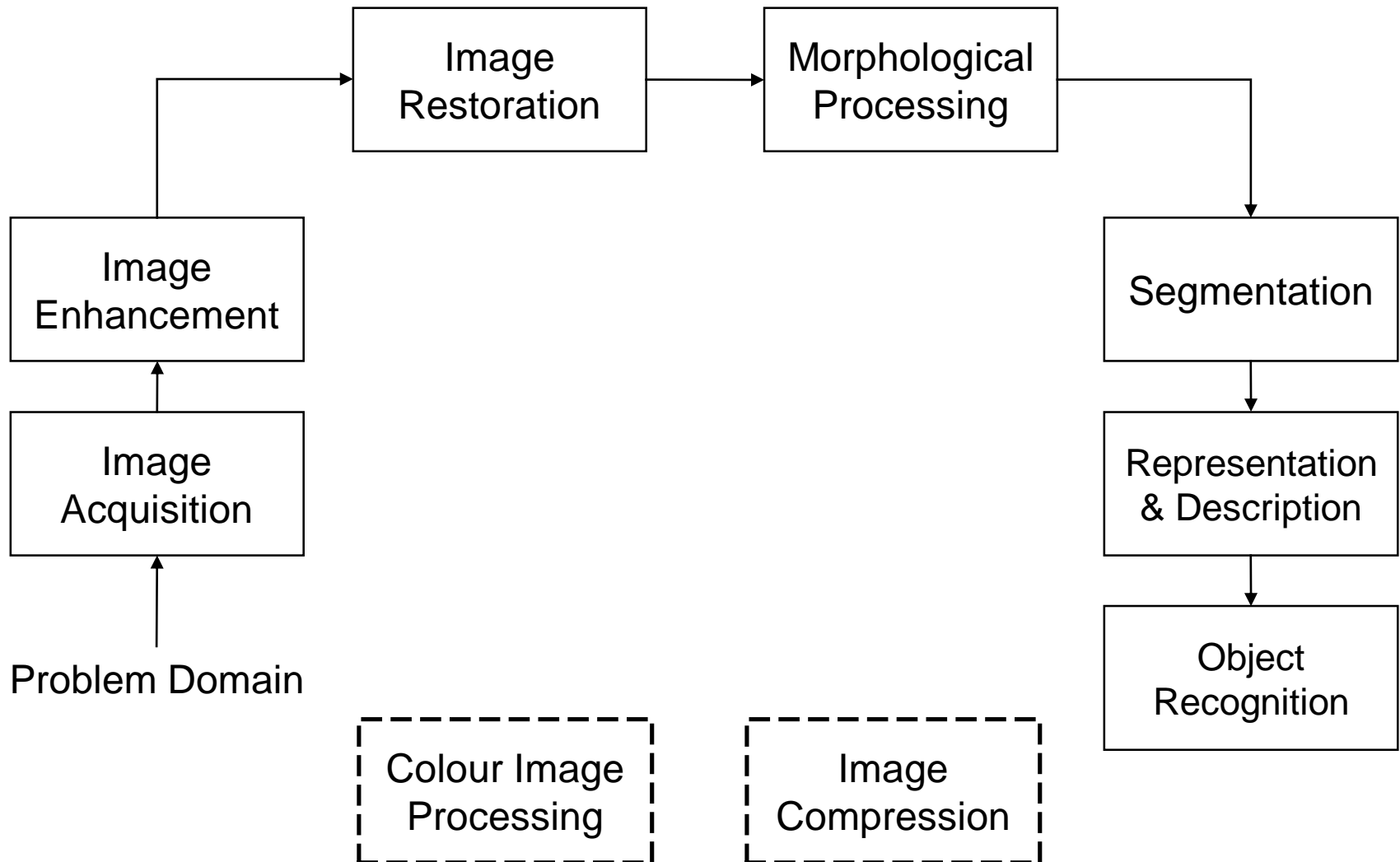
In Frequency Domain

Partially Adopted from Brian Mac Namee

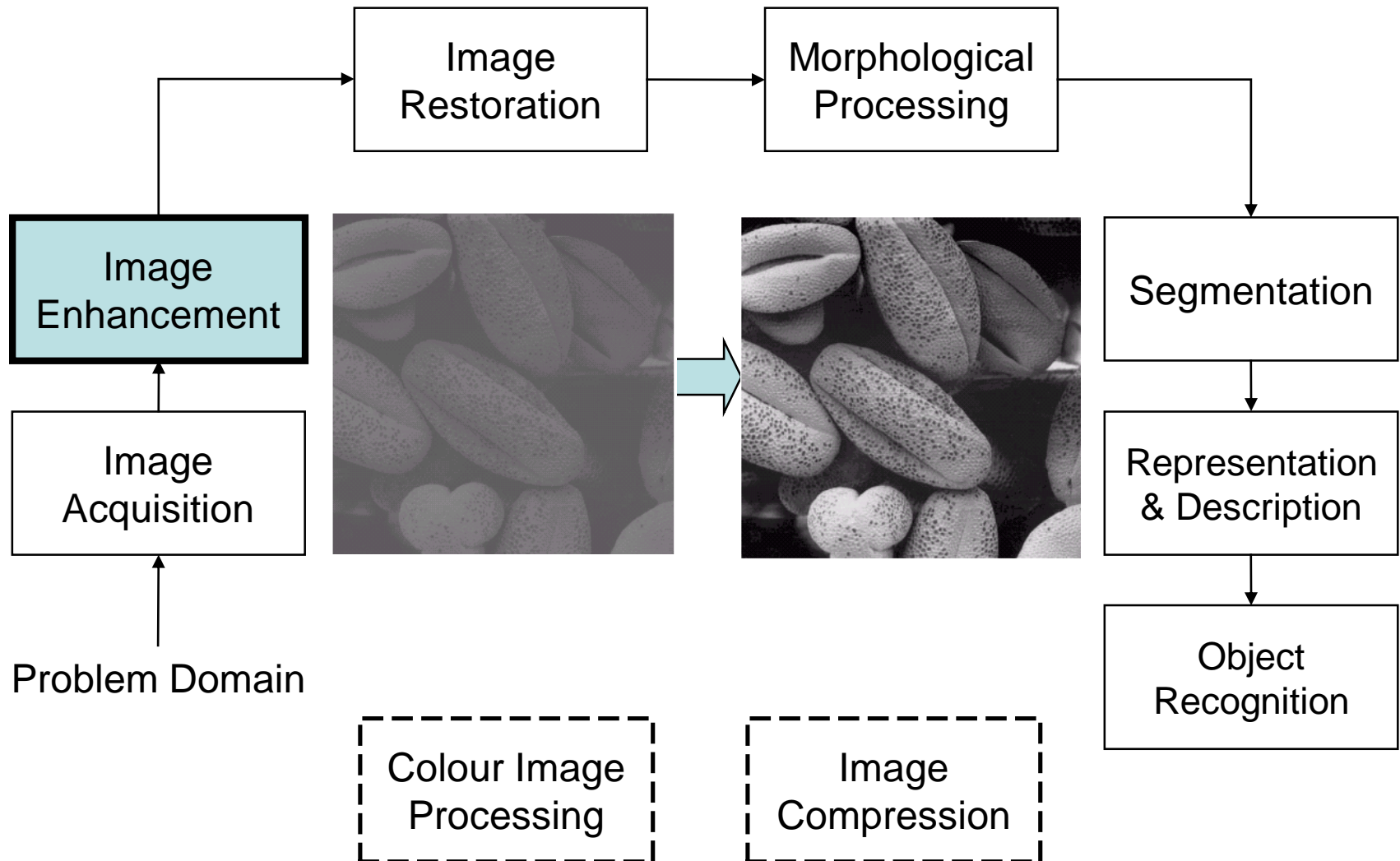
Contents

- ✓ Jean Baptiste Joseph Fourier
- ✓ The Fourier Series & the Fourier Transform
- ✓ Image Processing in the Frequency Domain
 - Image smoothing
 - Image sharpening
- ✓ Fast Fourier Transform

Phases of Digital Image Processing



Phases of Digital Image Processing: Image Enhancement



Jean Baptiste Joseph Fourier



Fourier was born in Auxerre, France in 1768.

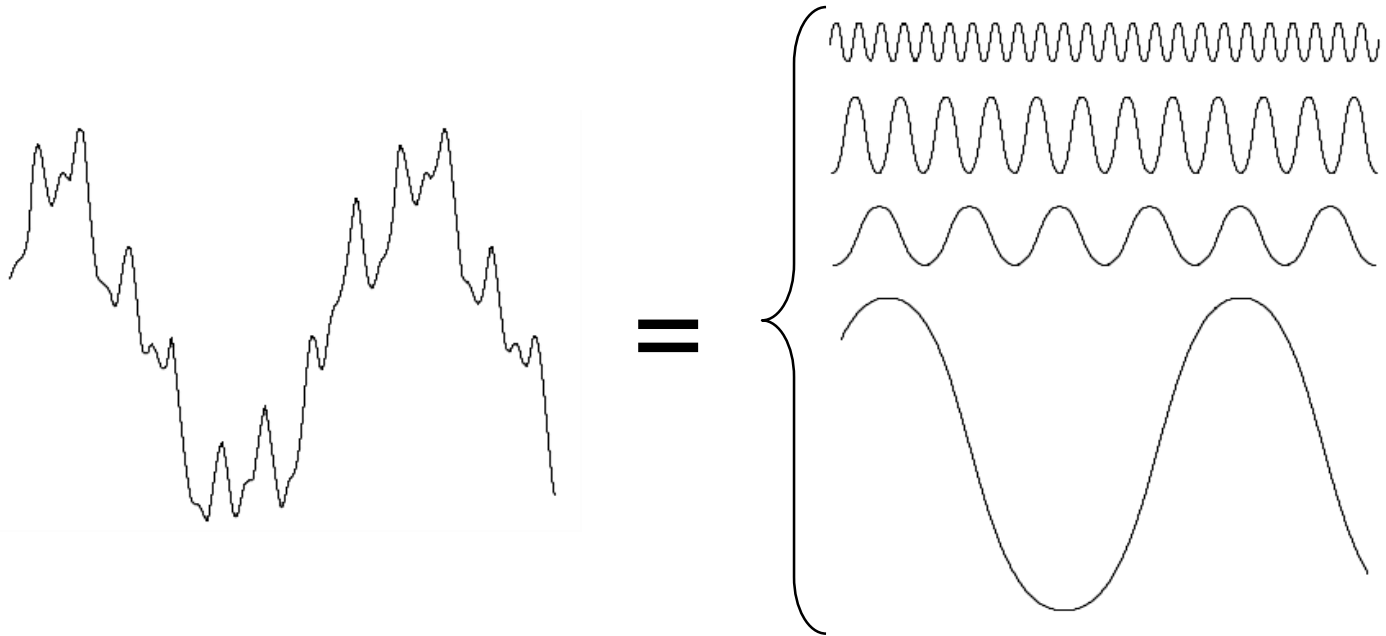
Most famous for his work "*La Théorie Analytique de la Chaleur*" published in 1822.

Translated into English in 1878 by Freeman: "*The Analytic Theory of Heat*".

Nobody gave much attention when the work was first published.

One of the most important mathematical theories in Modern Engineering / Science.

Theoretical View



Any function that periodically repeats itself can be expressed as the sum of sines and/or cosines of different frequencies, each multiplied by a different coefficient – a Fourier series.

Theoretical View

Even function that are not periodic (but whose area under the curve is finite) can be expressed as the integral of sines and/or cosines multiplied by a weighing function – a Fourier transform.

Its utility is even greater than the Fourier series in most practical problems.

A function, expressed in either Fourier series or Fourier transform, can be reconstructed completely via an inverse function, with no loss of information.

The One-Dimensional Fourier Transform and its Inverse

The Fourier transform, $F(u)$, of a single variable, continuous function, $f(x)$ is defined by:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-j2\pi ux} dx, \text{ where } j = \sqrt{-1}.$$

Conversely, given $F(u)$, we can obtain $f(x)$ by means of the inverse Fourier transform

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{j2\pi ux} du, \text{ where } j = \sqrt{-1}.$$

The two-Dimensional Fourier Transform and its Inverse

$$F(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) e^{-j2\pi(ux+vy)} dx dy$$

$$f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u, v) e^{j2\pi(ux+vy)} du dv$$

The Discrete Fourier Transform (DFT)

The *Discrete Fourier Transform* of $f(x, y)$, for $x = 0, 1, 2 \dots M-1$ and $y = 0, 1, 2 \dots N-1$, denoted by $F(u, v)$, is given by the equation:

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(ux/M + vy/N)}$$

for $u = 0, 1, 2 \dots M-1$ and $v = 0, 1, 2 \dots N-1$.

The Discrete Fourier Transform (DFT)

- Fourier Spectrum:

$$|F(u, v)| = [R^2(u, v) + I^2(u, v)]^{1/2}$$

- Phase Angle / Phase Spectrum:

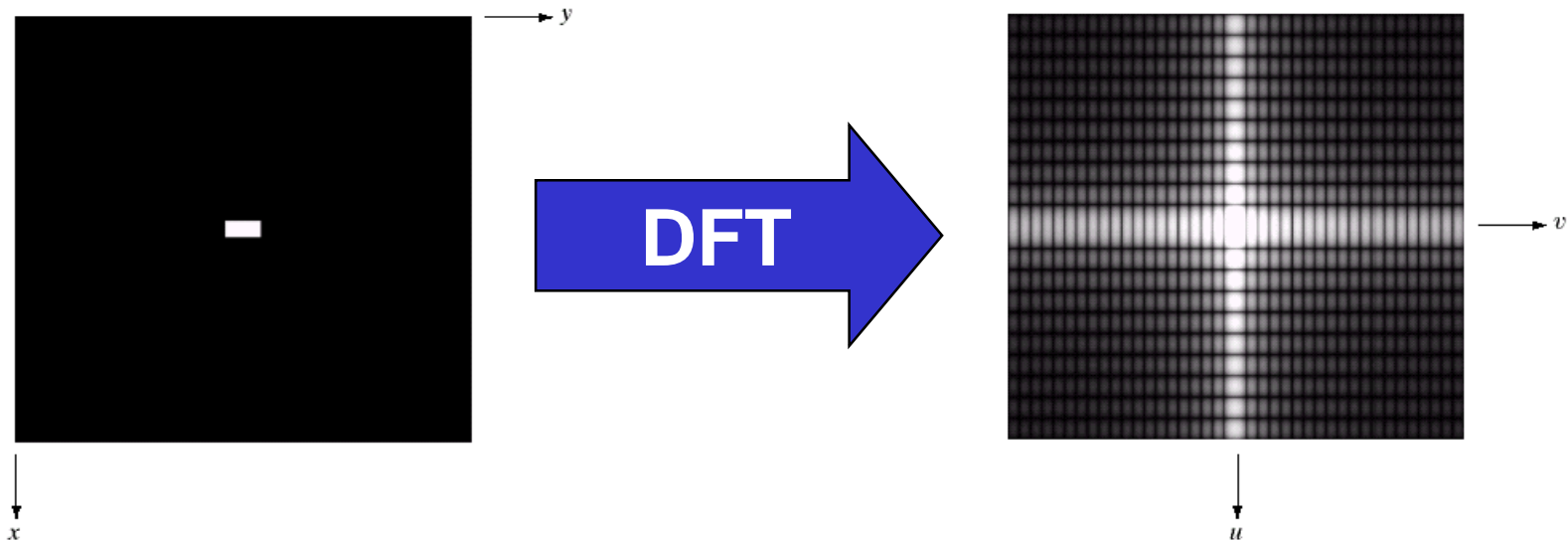
$$\phi(u, v) = \tan^{-1} \left[\frac{I(u, v)}{R(u, v)} \right]$$

- Power Spectrum:

$$P(u, v) = |F(u, v)|^2 = R^2(u, v) + I^2(u, v)$$

DFT of an Image

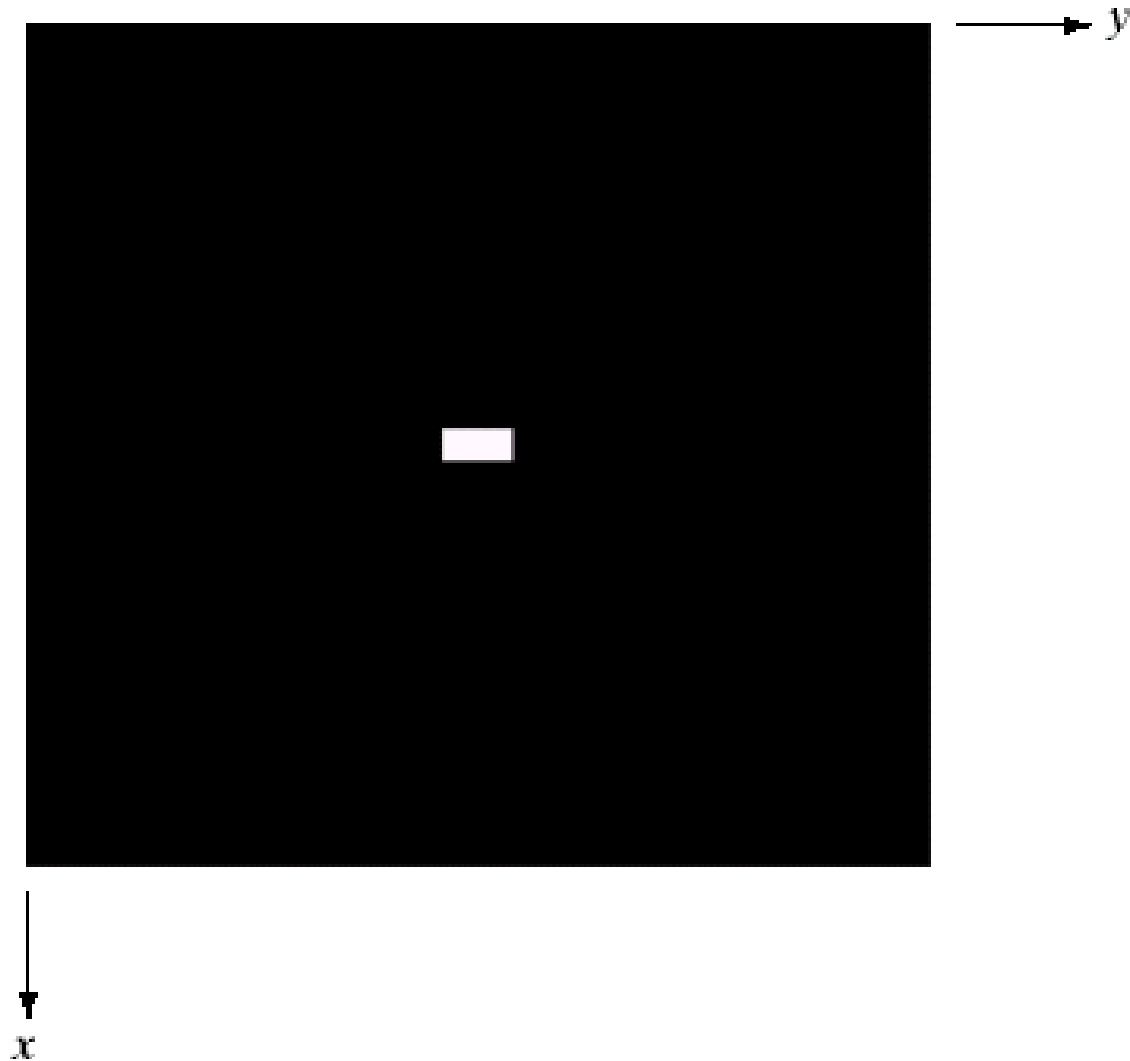
The DFT of a two dimensional image can be visualised by showing the spectrum of the image component frequencies.



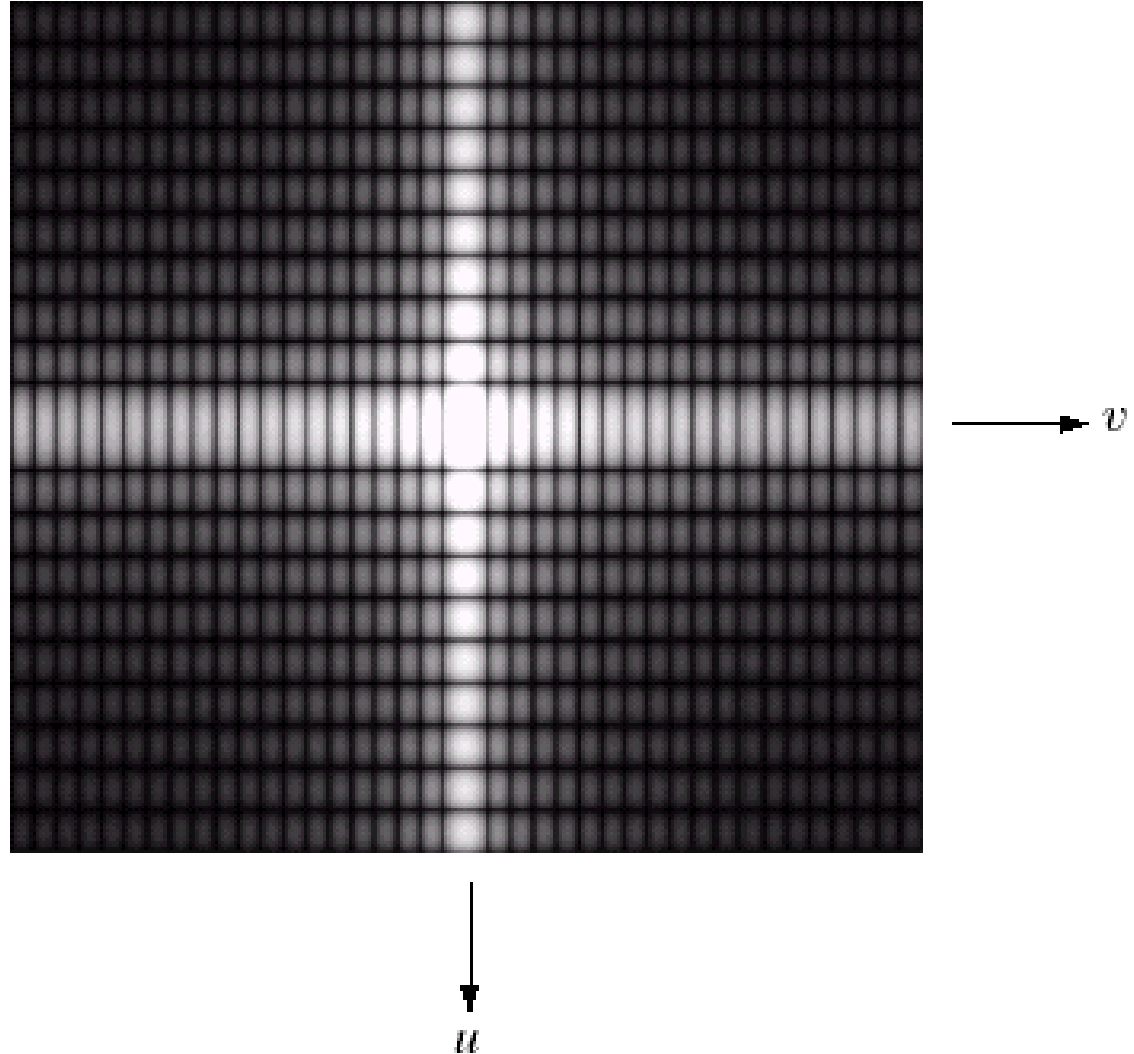
It is common practice to multiply the input image function by $(-1)^{x+y}$ prior to computing Fourier transform.

This operation shifts the origin of FT of $f(x,y)(-1)^{x+y}$ (i.e. $F(0,0)$) to $[M/2, N/2]$.

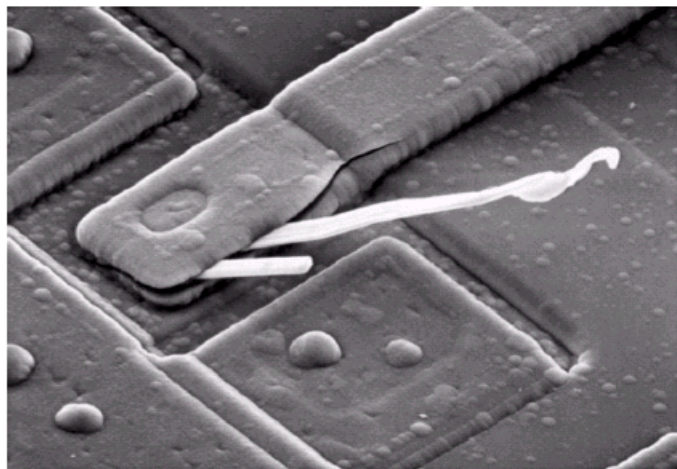
DFT of an Images



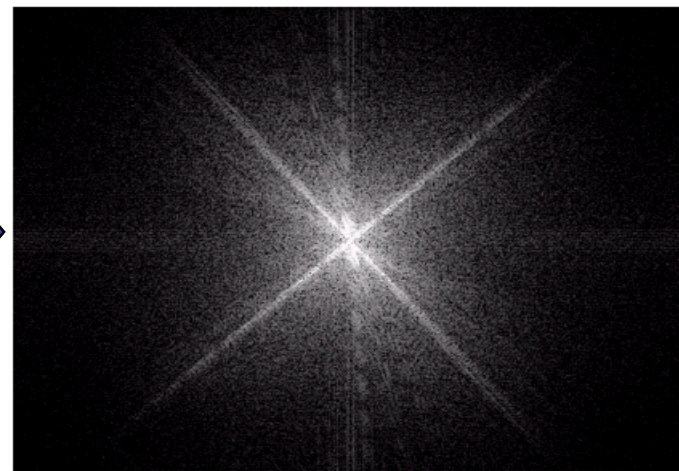
DFT of an Image



DFT of an Image

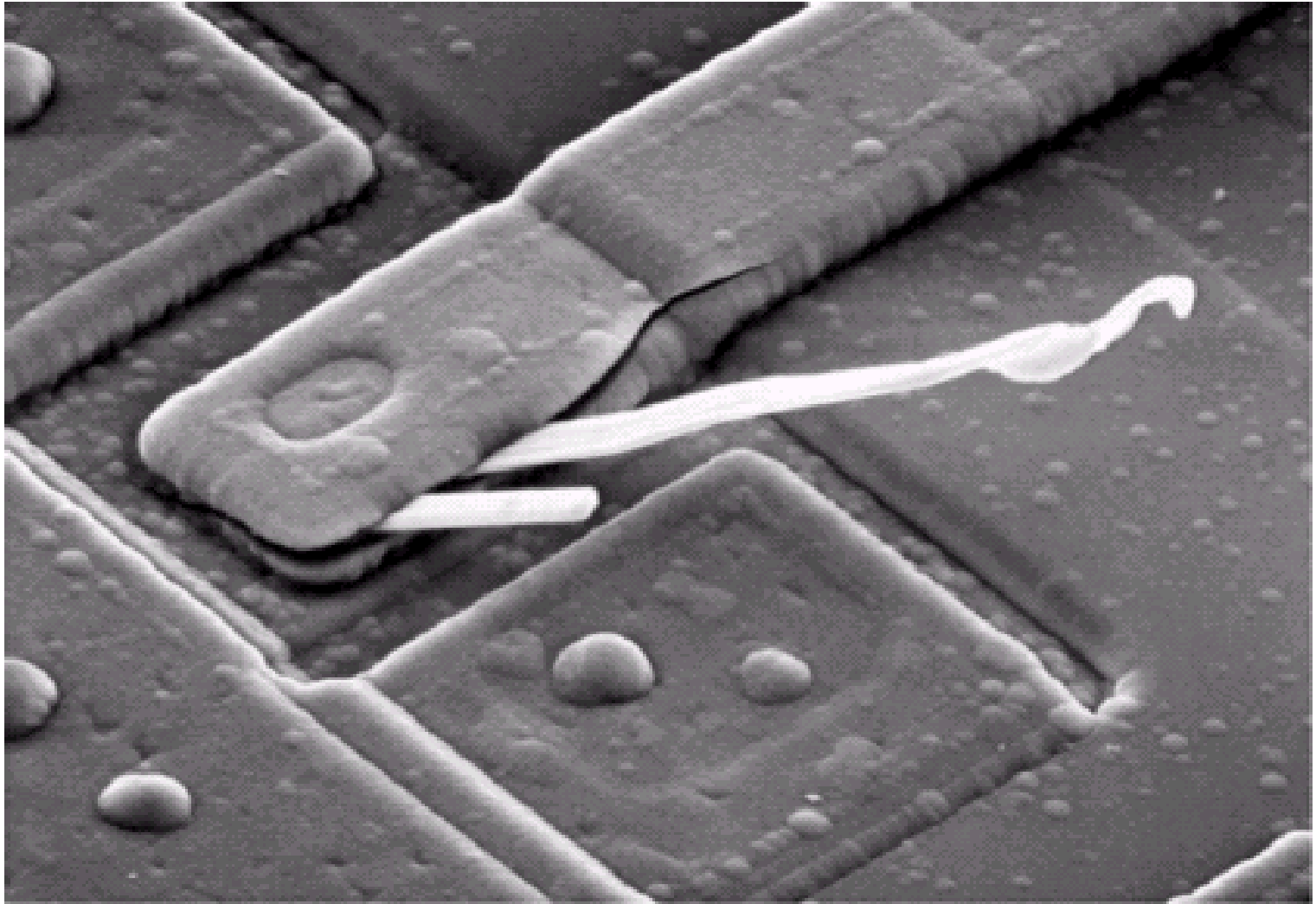


Scanning electron microscope image of an integrated circuit magnified ~2500 times

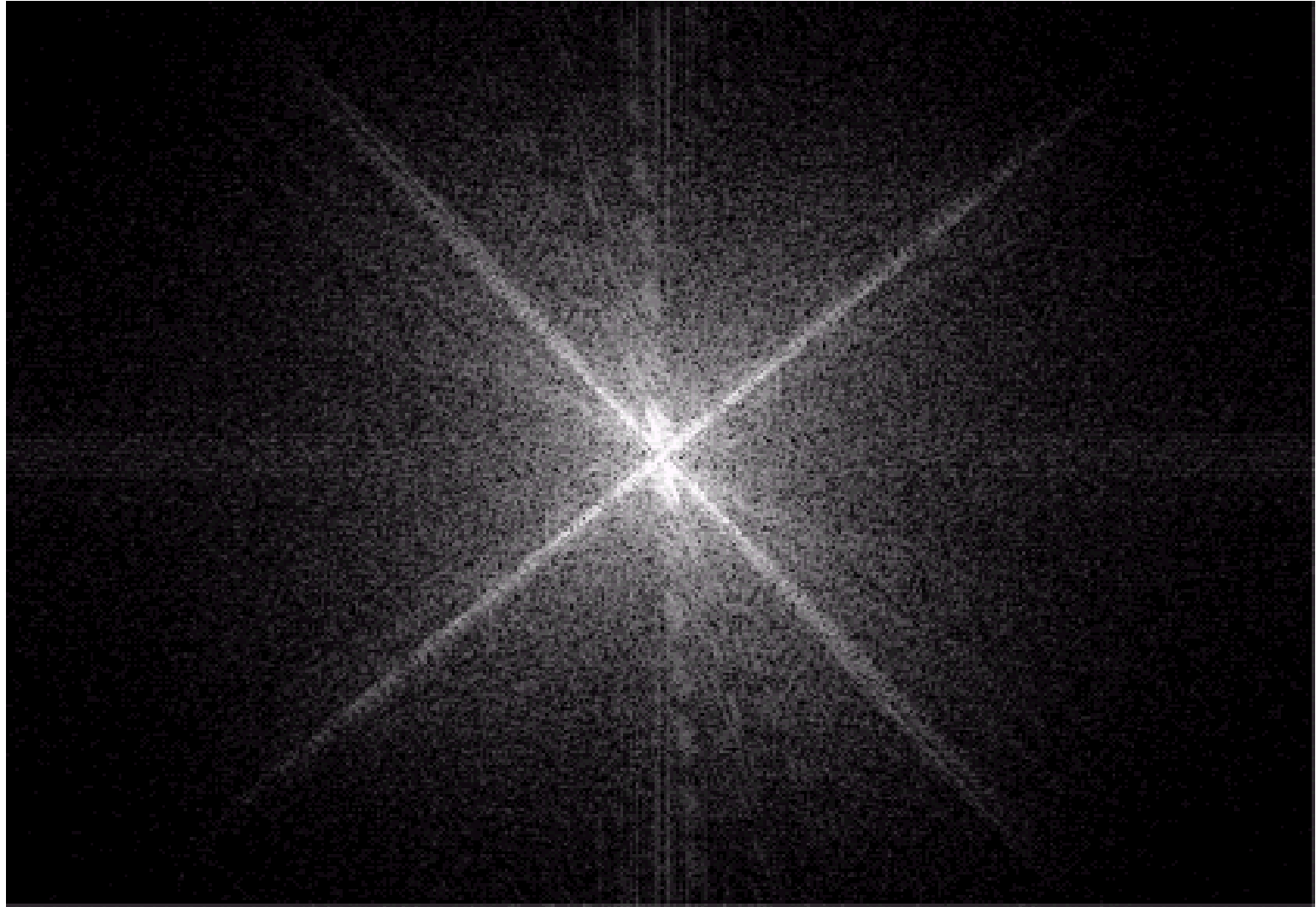


Fourier spectrum of the image

DFT of an Image



DFT of an Image



The Inverse DFT

It is really important to note that the Fourier transform is completely **reversible**.

The inverse DFT is given by:

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{j2\pi(ux/M + vy/N)}$$

for $x = 0, 1, 2 \dots M-1$ and $y = 0, 1, 2 \dots N-1$

Basics of Filtering in Frequency Domain

To filter an image in the frequency domain:

1. Multiply the input image by $(-1)^{x+y}$ to center the transform, as indicated in

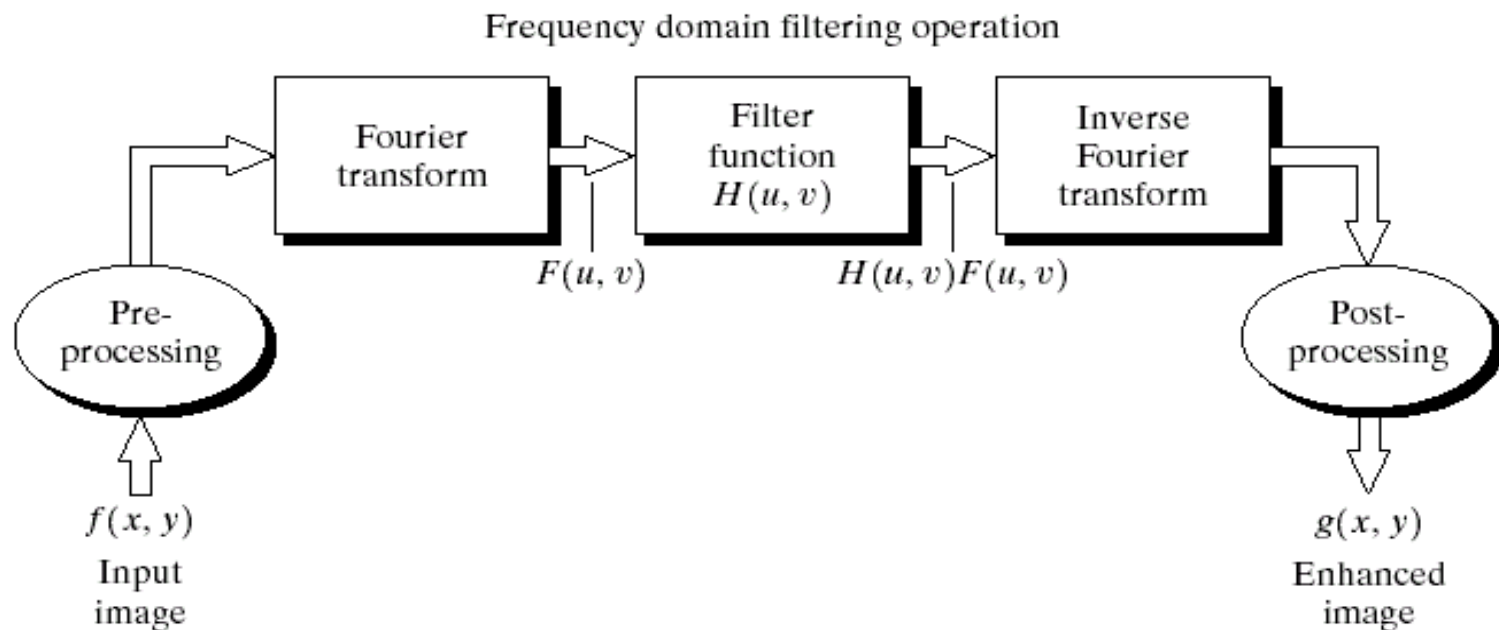
$$\mathfrak{F}[f(x, y)(-1)^{x+y}] = F(u - M/2, v - N/2).$$

It states that the origin of the Fourier transform of $f(x, y)(-1)^{x+y}$ [i.e., $F(0,0)$] is located at $u = M/2$ and $v = N/2$.

2. Compute $F(u, v)$, the DFT of the image from (1).
3. Multiply $F(u, v)$ by a filter function $H(u, v)$.

Basics of Filtering in Frequency Domain

4. Compute the inverse DFT of the result in (3).
5. Obtain the real part of the result in (4).
6. Multiply the result in (5) by $(-1)^{x+y}$.

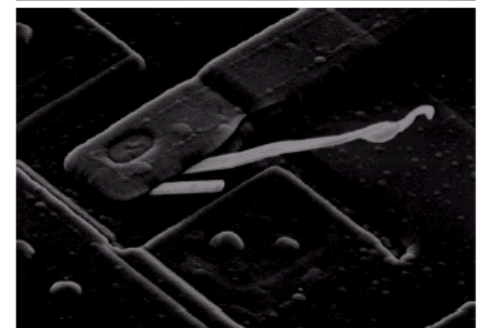
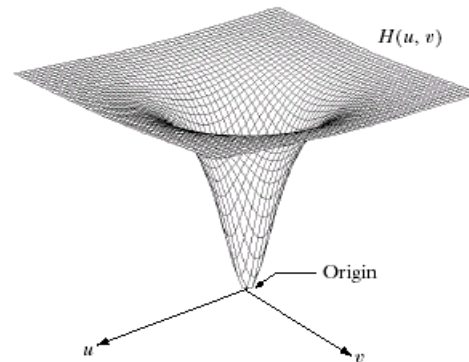
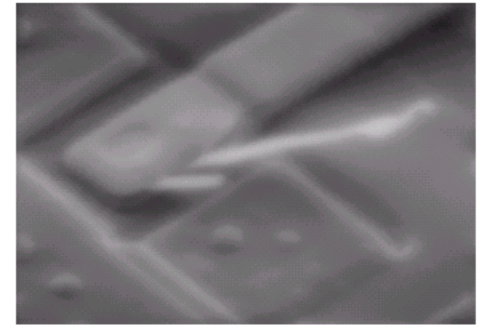
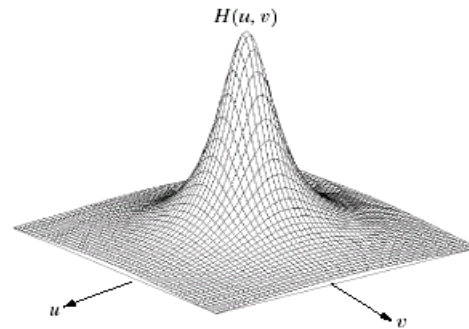
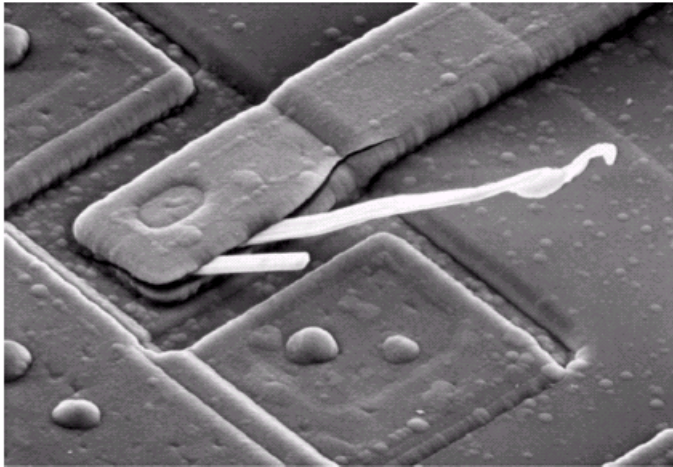


Basics of Filtering in Frequency Domain

- Each component of H multiplies both the real and imaginary parts of the corresponding components in F .
- This type of filters are called zero-phase-shift filters.

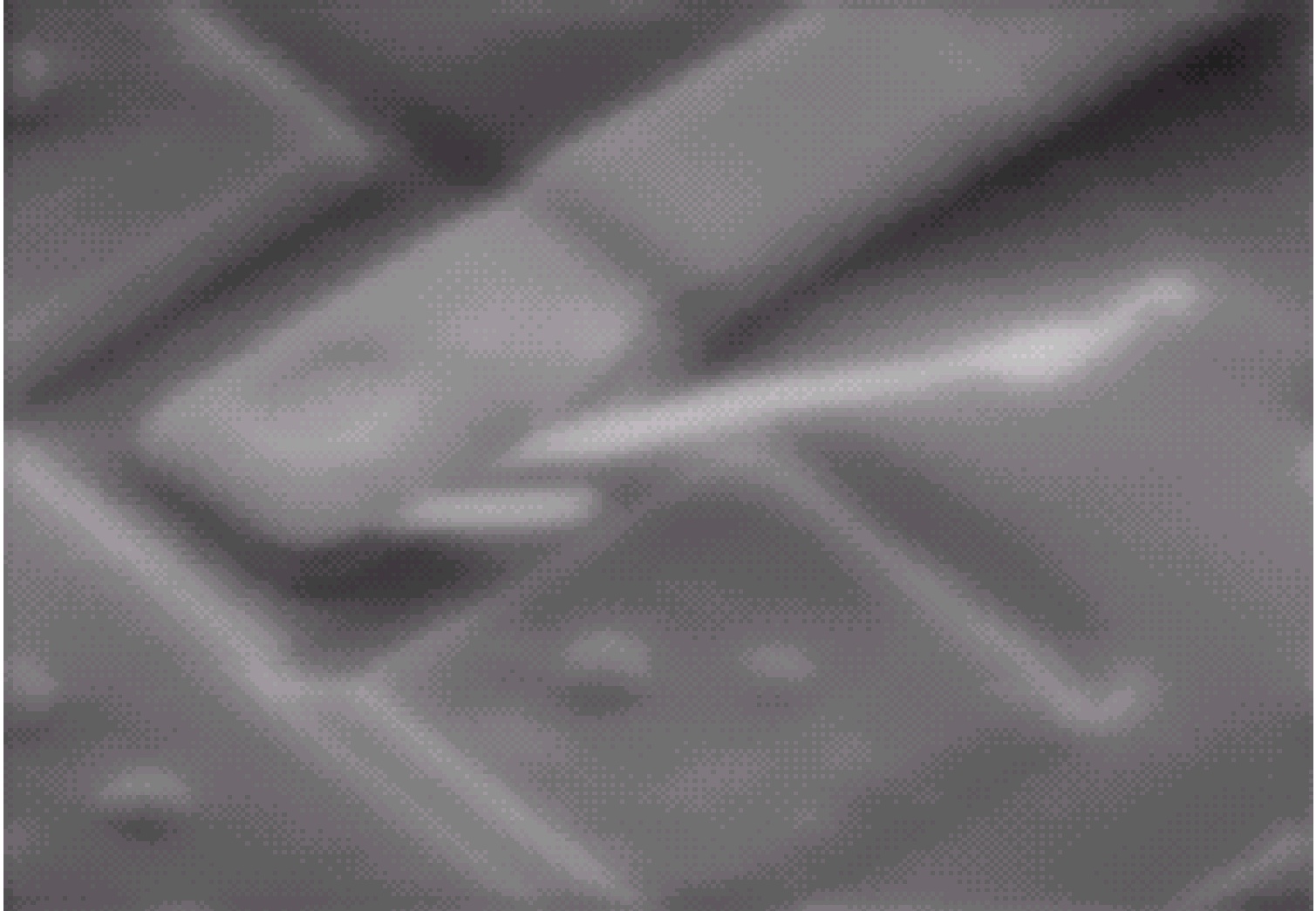
Some Basic Frequency Domain Filters

Low Pass Filter

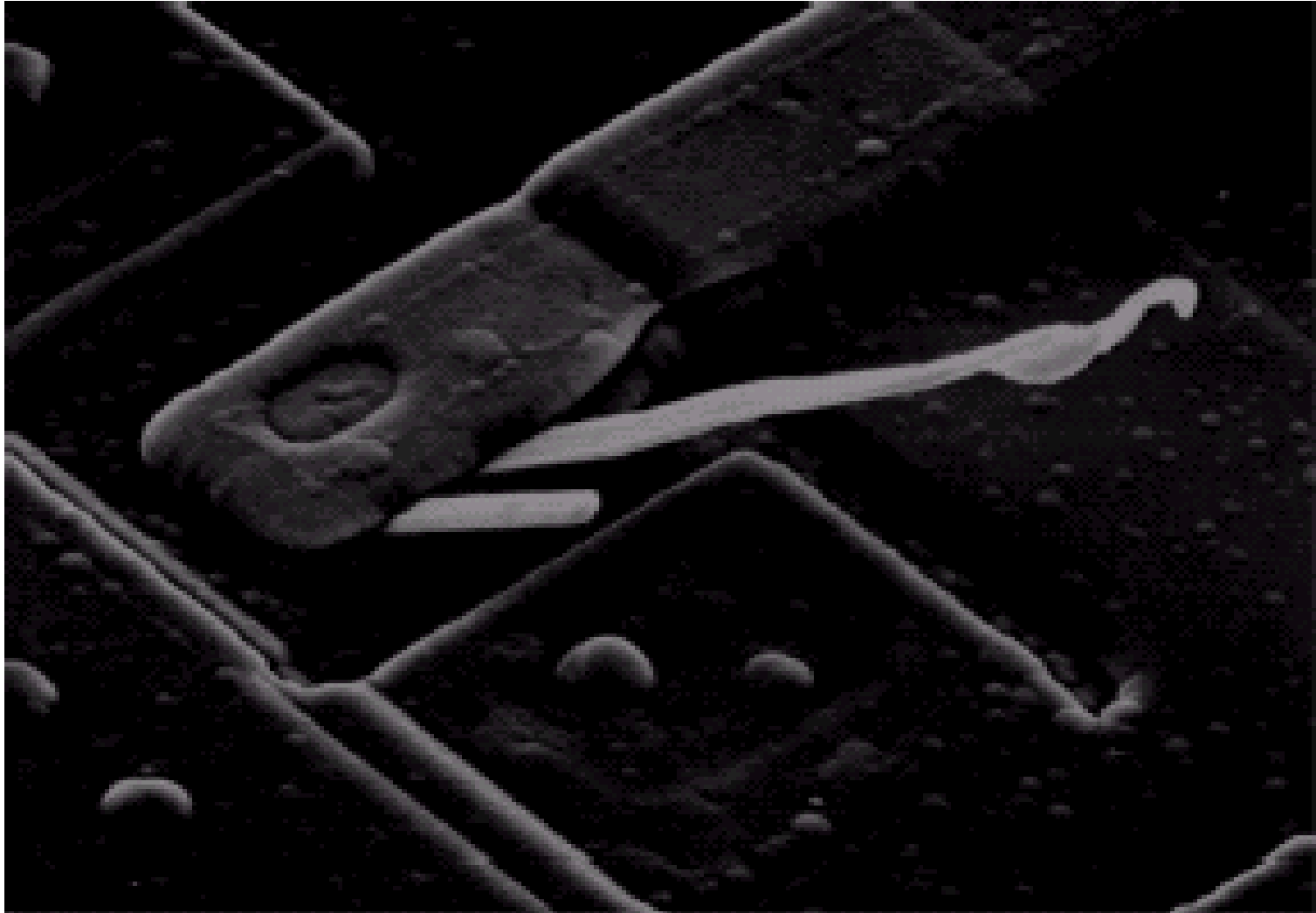


High Pass Filter

Some Basic Frequency Domain Filters



Some Basic Frequency Domain Filters



Filters in Frequency Domain

- ✓ Image Smoothing Filters
 - Ideal Low Pass Filter
 - Butterworth Low Pass Filter
 - Gaussian Low Pass Filter

- ✓ Image Sharpening Filters
 - Ideal High Pass Filter
 - Butterworth High Pass Filter
 - Gaussian High Pass Filter

Smoothing Frequency Domain Filters

Smoothing is achieved in the frequency domain by dropping out the high frequency components.

The basic model for filtering is:

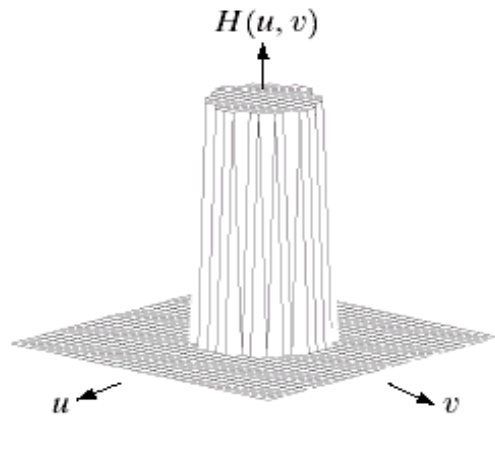
$$G(u,v) = H(u,v)F(u,v)$$

where $F(u,v)$ is the Fourier transform of the image being filtered and $H(u,v)$ is the filter transform function.

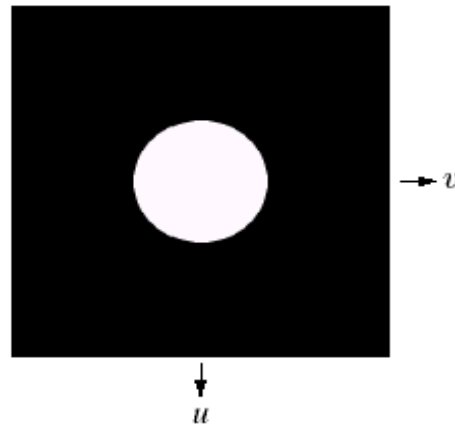
Low pass filters – only pass the low frequencies, drop the high ones.

Ideal Low Pass Filter

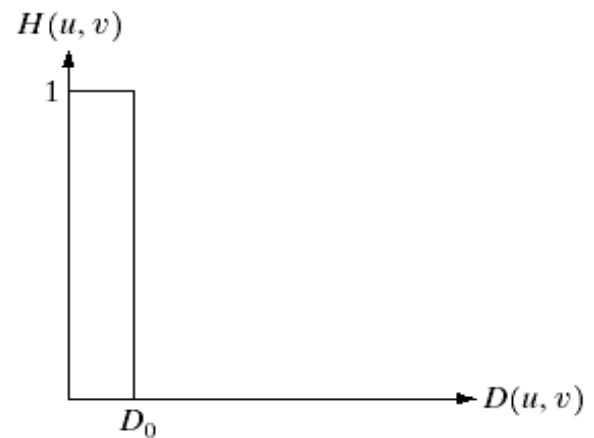
Simply cut off all high frequency components that are a specified distance D_0 from the origin of the transform.



Perspective plot
of the transfer function



Displayed as an
image



Radial cross section

Changing the distance changes the behaviour of the filter.

Ideal Low Pass Filter

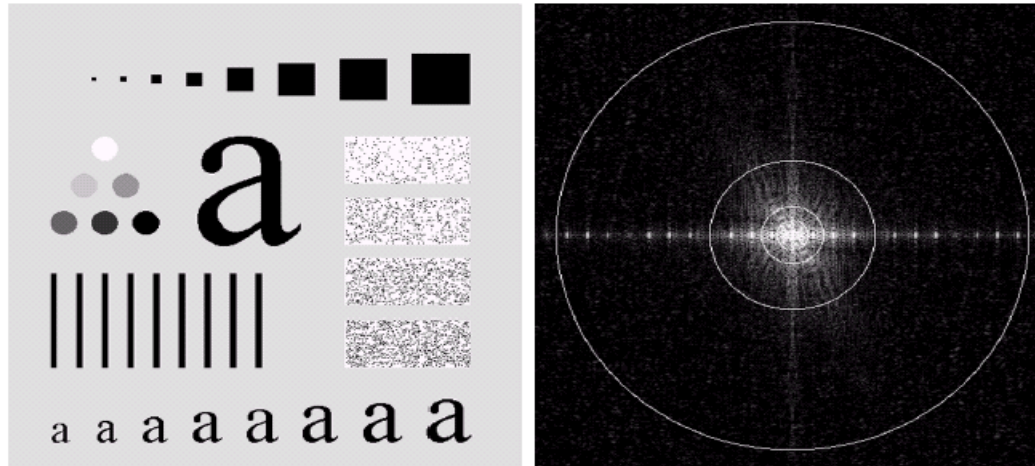
The transfer function for the ideal low pass filter can be given as:

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

where $D(u, v)$ is given as:

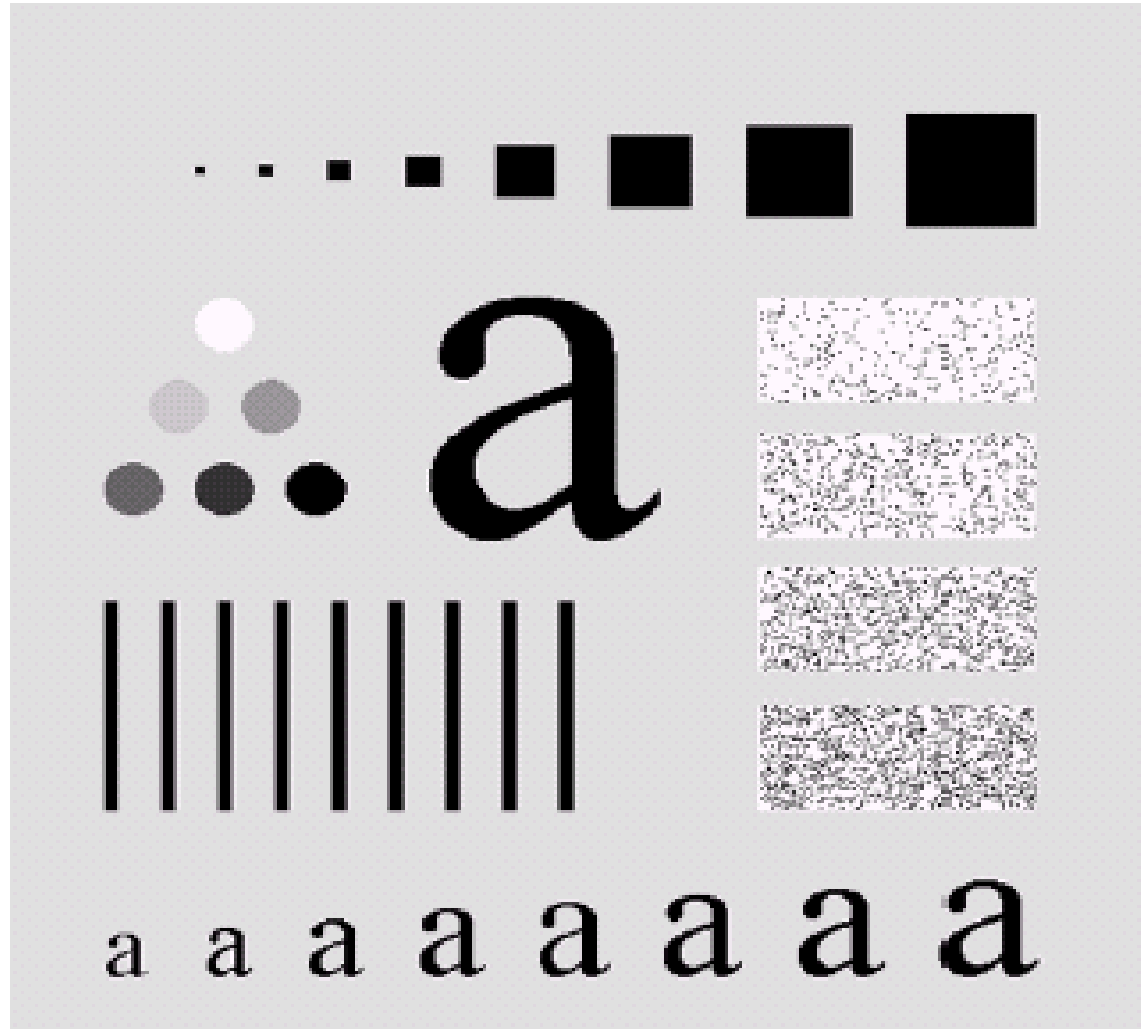
$$D(u, v) = [(u - M / 2)^2 + (v - N / 2)^2]^{1/2}$$

Ideal Low Pass Filter

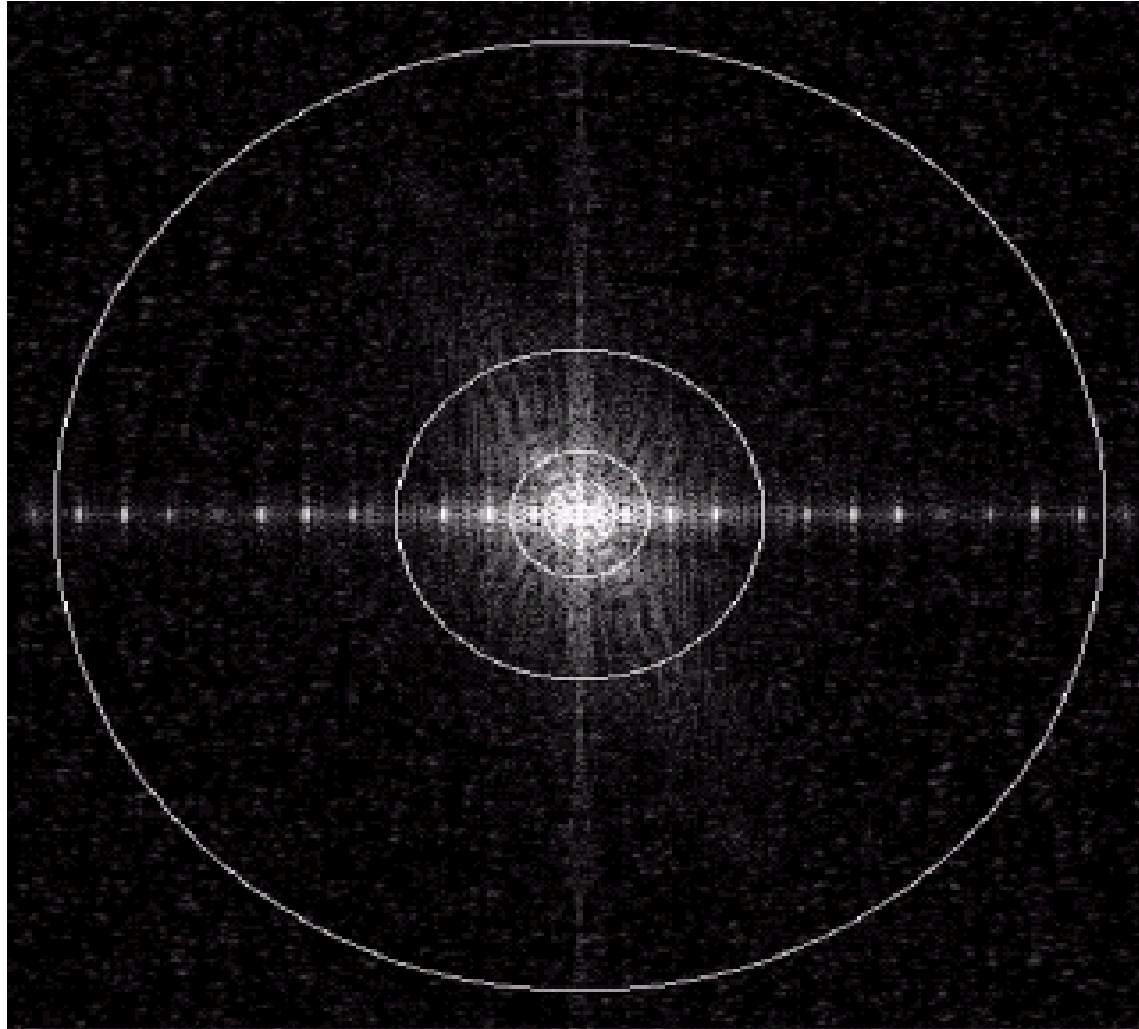


An image, it's Fourier spectrum and a series of ideal low pass filters of radius 5, 15, 30, 80, and 230 superimposed on top of it.

Ideal Low Pass Filter

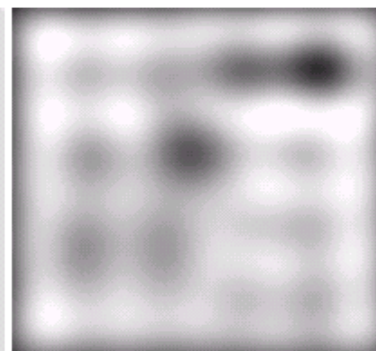
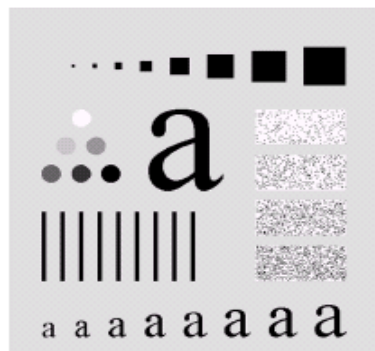


Ideal Low Pass Filter



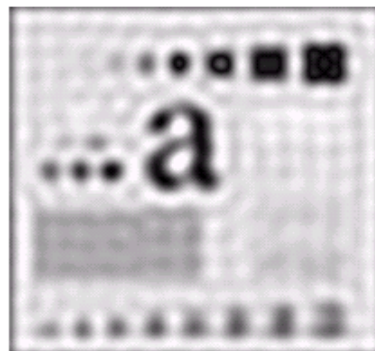
Ideal Low Pass Filter

Original
image



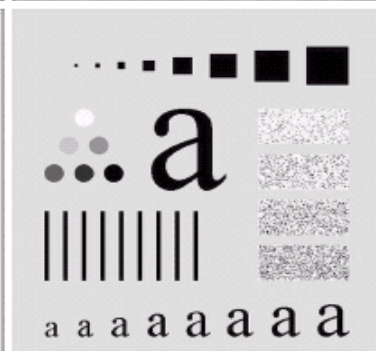
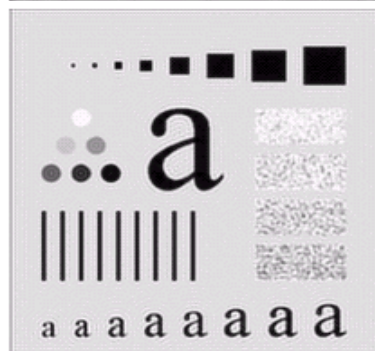
Result of filtering
with ideal low pass
filter of radius 5

Result of filtering
with ideal low pass
filter of radius 15



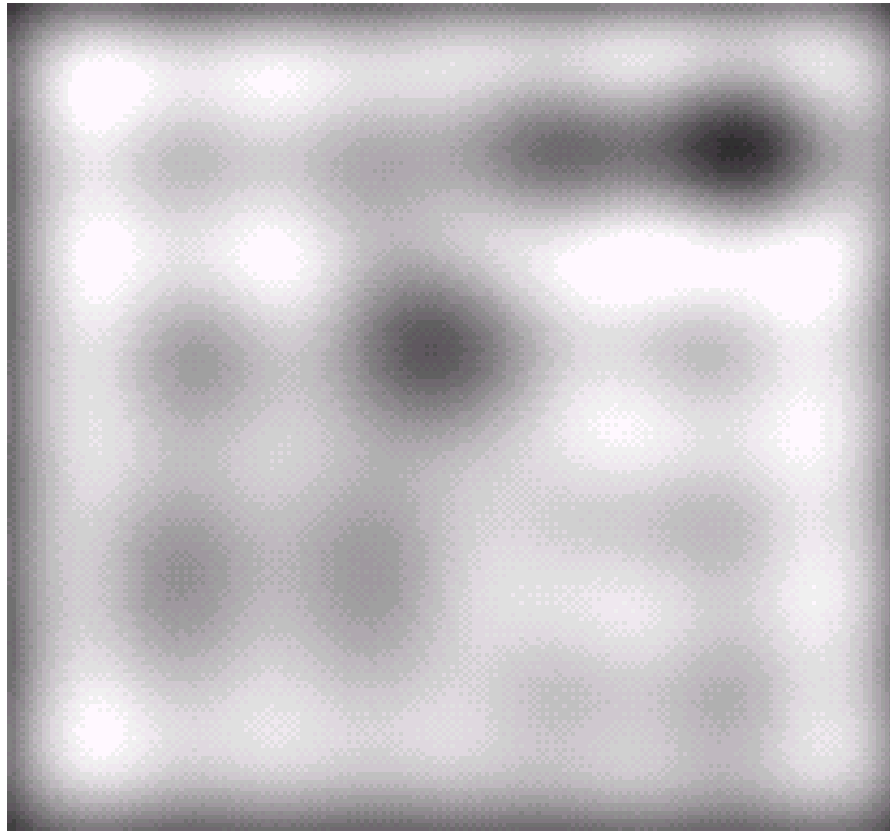
Result of filtering
with ideal low pass
filter of radius 30

Result of filtering
with ideal low pass
filter of radius 80



Result of filtering
with ideal low pass
filter of radius 230

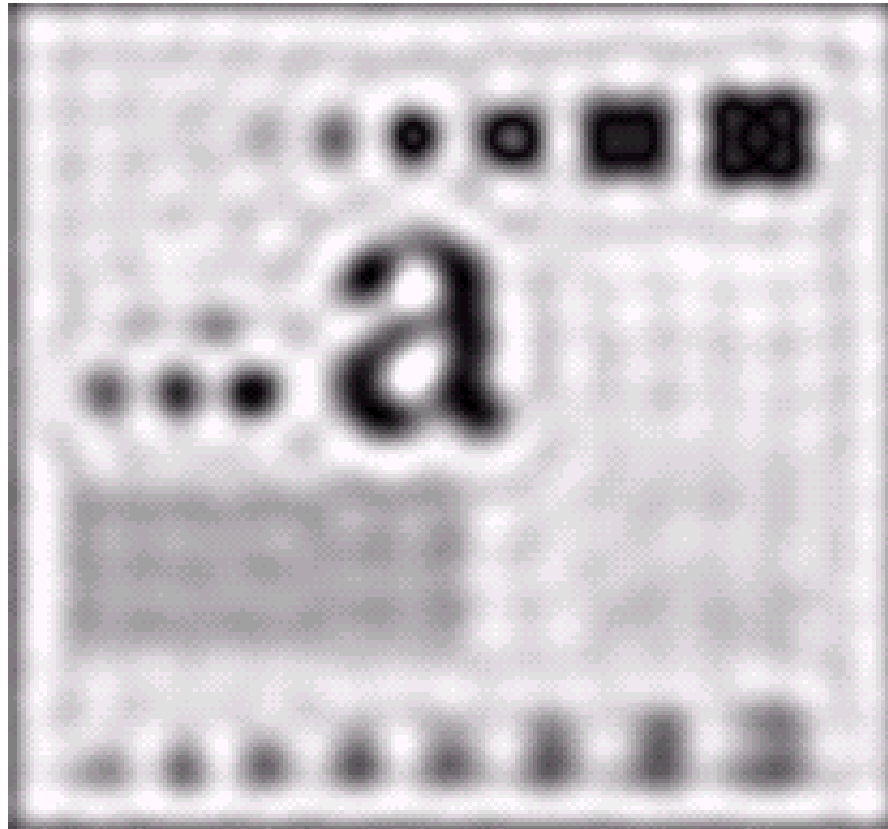
Ideal Low Pass Filter



Result of filtering
with ideal low pass
filter of radius 5

Suffered by Ringing
artifact.

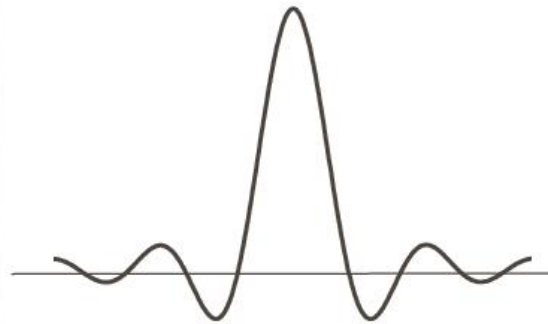
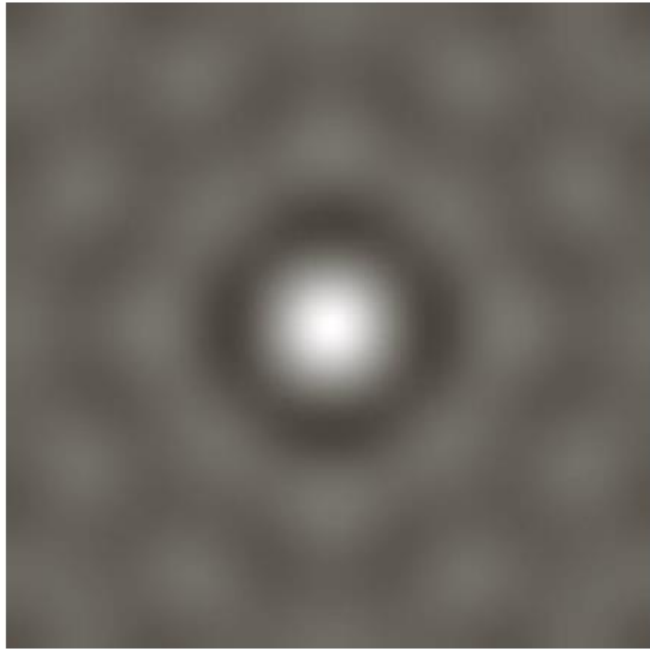
Ideal Low Pass Filter



Result of filtering
with ideal low pass
filter of radius 15

Suffered by Ringing
artifact.

Ideal Low Pass Filter



a b

FIGURE 4.43

(a) Representation in the spatial domain of an ILPF of radius 5 and size 1000×1000 .

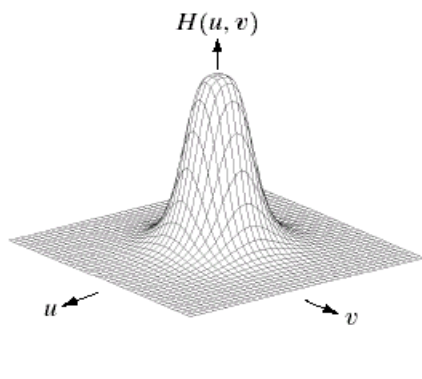
(b) Intensity profile of a horizontal line passing through the center of the image.

Butterworth Low Pass Filter

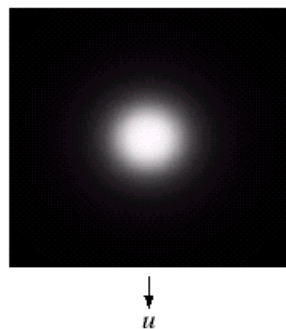
The transfer function of a Butterworth lowpass filter of order n with cutoff frequency at distance D_0 from the origin is defined as:

$$H(u, v) = \frac{1}{1 + [D(u, v) / D_0]^{2n}}$$

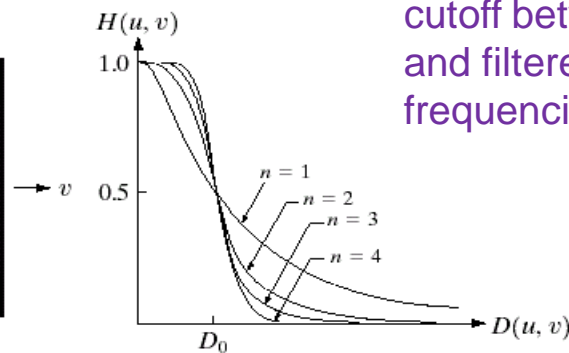
Unlike the ILPF, the BLPF transfer function does not have a sharp discontinuity that establishes a clear cutoff between passed and filtered frequencies.



Perspective plot
of the transfer function



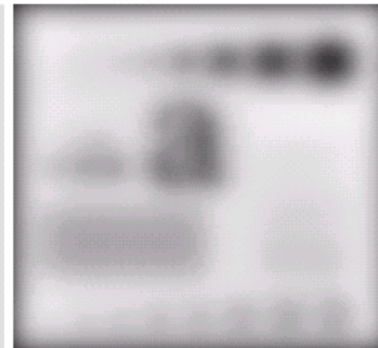
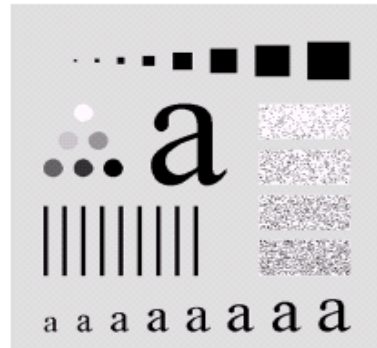
Displayed as an
image



Radial cross section

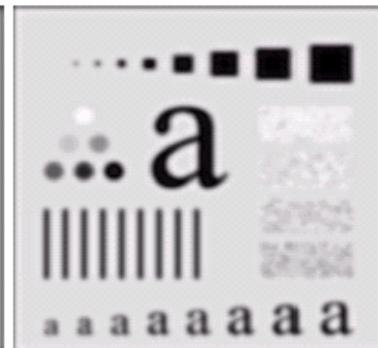
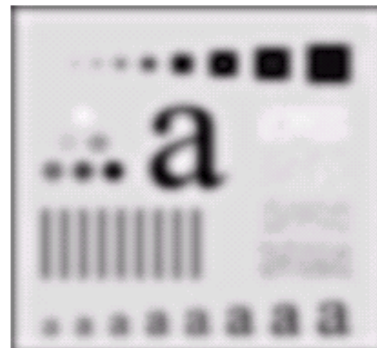
Butterworth Low Pass Filter

Original
image



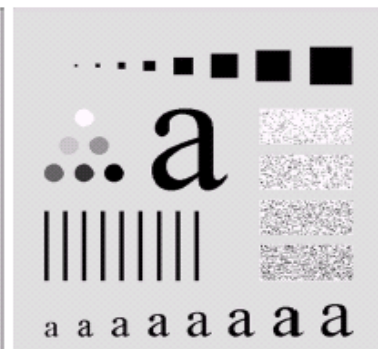
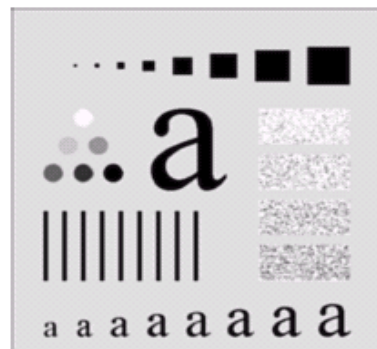
Result of filtering
with Butterworth
filter of order 2 and
cutoff radius 5

Result of filtering with
Butterworth filter of
order 2 and cutoff
radius 15



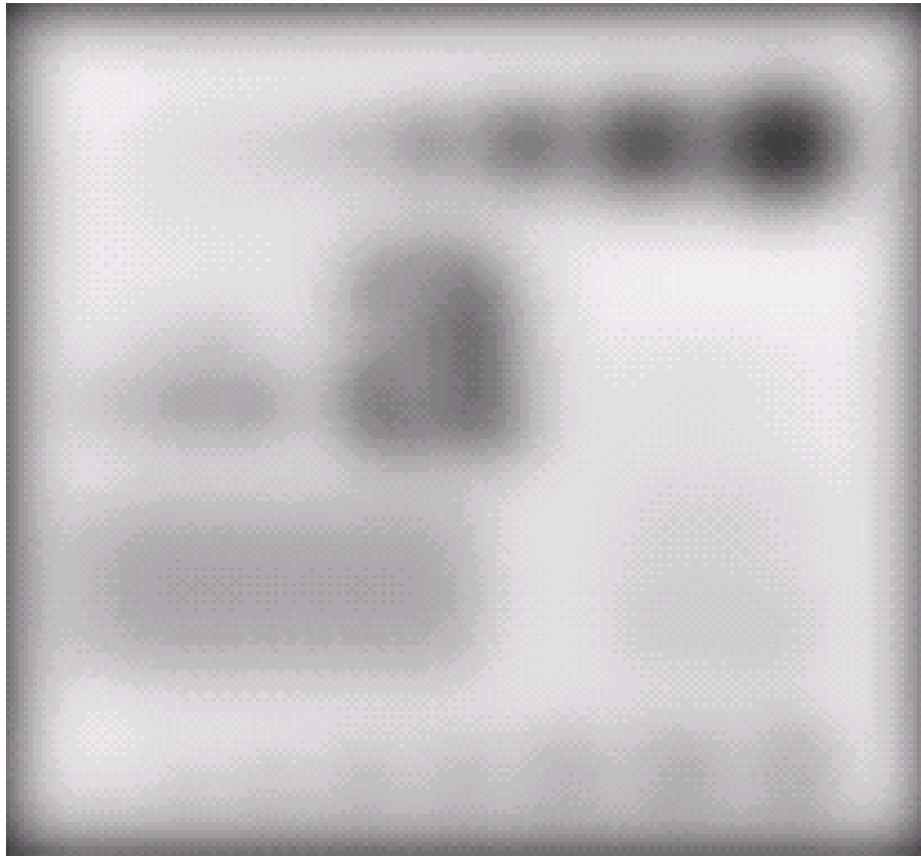
Result of filtering
with Butterworth
filter of order 2 and
cutoff radius 30

Result of filtering with
Butterworth filter of
order 2 and cutoff
radius 80



Result of filtering
with Butterworth
filter of order 2 and
cutoff radius 230

Butterworth Low Pass Filter



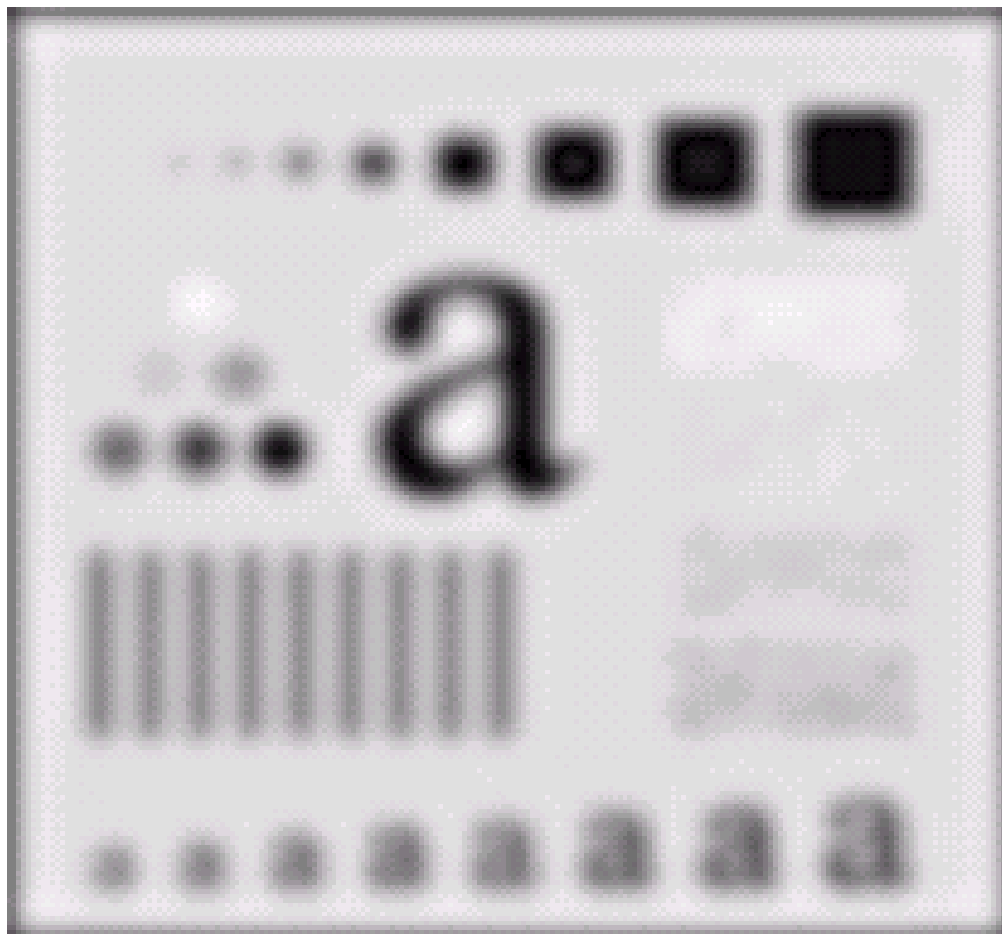
Result of filtering
with Butterworth
filter of order 2 and
cutoff radius 5

No Ringing artifact.

Butterworth Low Pass Filter

Result of filtering with
Butterworth filter of
order 2 and cutoff
radius 15

No Ringing artifact.



Butterworth Low Pass Filter

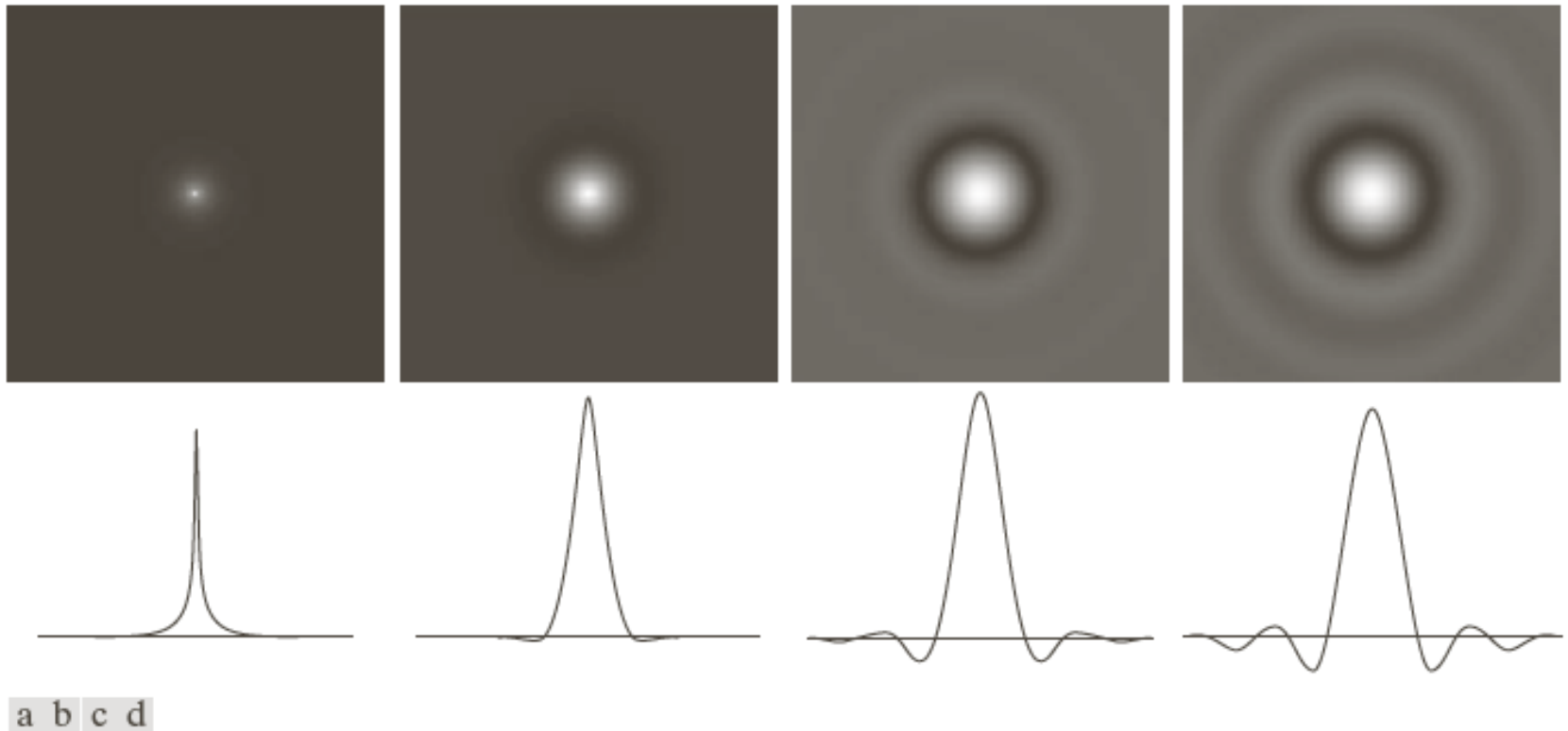
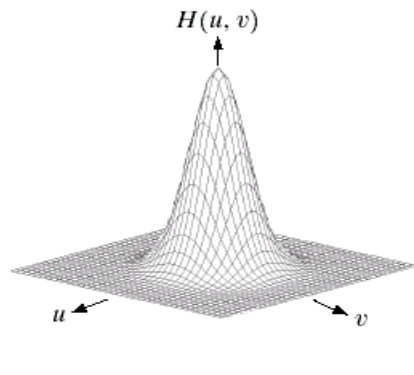


FIGURE 4.46 (a)–(d) Spatial representation of BLPFs of order 1, 2, 5, and 20, and corresponding intensity profiles through the center of the filters (the size in all cases is 1000×1000 and the cutoff frequency is 5). Observe how ringing increases as a function of filter order.

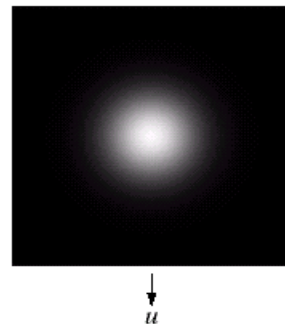
Gaussian Low Pass Filter

The transfer function of a Gaussian lowpass filter is defined as:

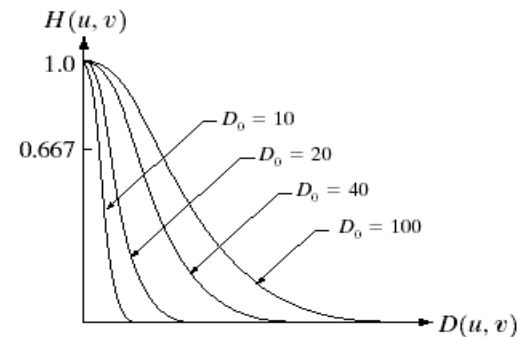
$$H(u, v) = e^{-D^2(u, v) / 2D_0^2}$$



Perspective plot
of the transfer function



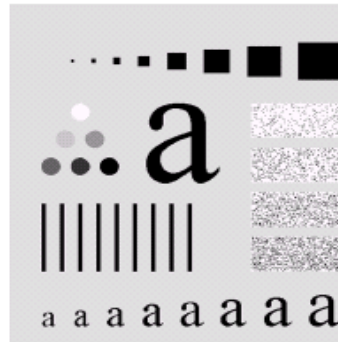
Displayed as an
image



Radial cross section

Gaussian Low Pass Filter

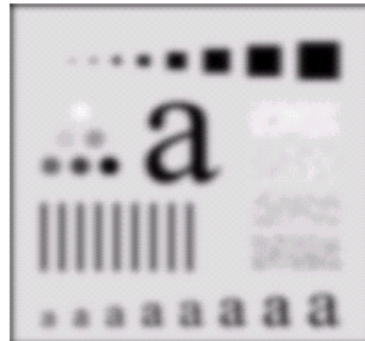
Original
image



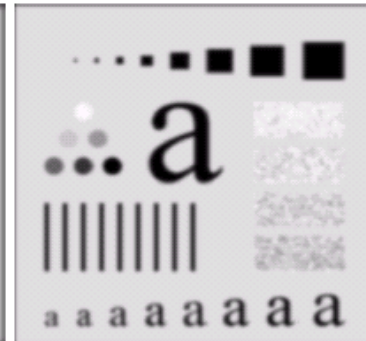
Result of filtering
with Gaussian filter
with cutoff radius 5



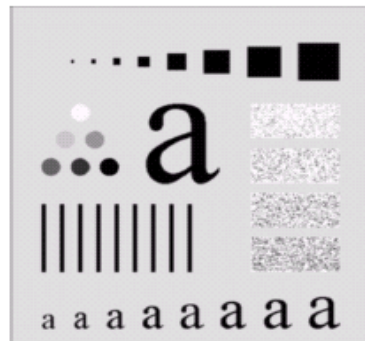
Result of filtering
with Gaussian
filter with cutoff
radius 15



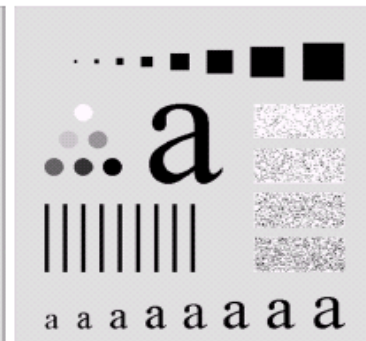
Result of filtering
with Gaussian filter
with cutoff radius 30



Result of filtering
with Gaussian
filter with cutoff
radius 85

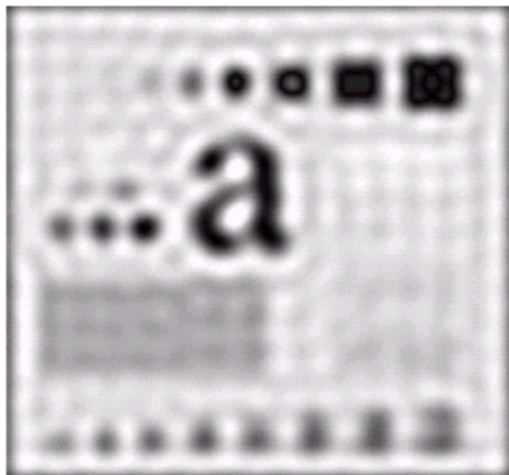


Result of filtering
with Gaussian filter
with cutoff radius
230

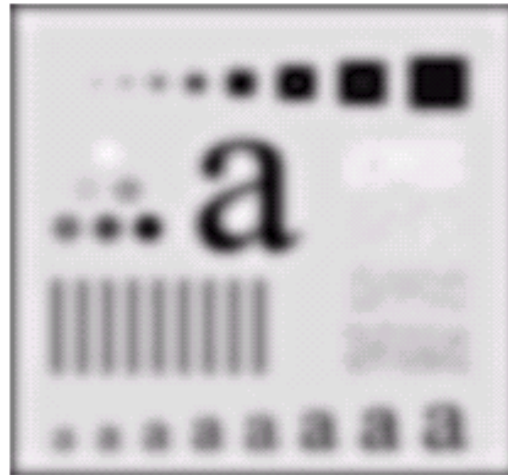


Low Pass Filters Comparison

Result of filtering
with ideal low pass
filter of radius 15



Result of filtering
with Butterworth
filter of order 2
and cutoff radius
15



Result of filtering
with Gaussian
filter with cutoff
radius 15



Gaussian filter did not
achieve as much
smoothing as the
Butterworth filter.

However, the results are quite comparable in general, as
we are assured no ringing in the case of GLPF.

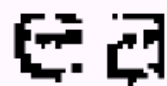
This is an important characteristics in practice, especially
in situations where any type of artifact (e.g., medical
imaging) is not acceptable.

This is happened
because the profile of
Gaussian is not as “tight”
as the profile of the
Butterworth filter.

Low Pass Filtering Example

A low pass Gaussian filter is used to connect broken text.

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.



ea

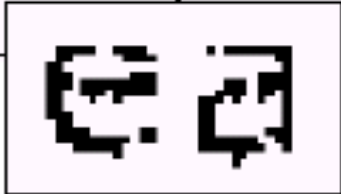
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ea

Low Pass Filtering Example

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ea

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ea

Low Pass Filtering Example

Different lowpass Gaussian filters used to remove blemishes (small mark) in a photograph.



Low Pass Filtering Example

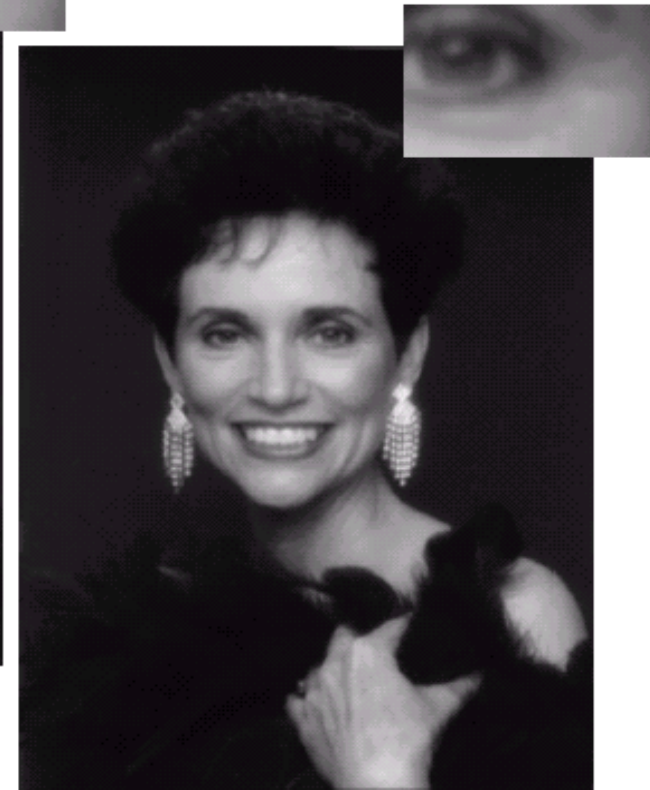
Reduction in skin lines in the magnified sections of the filtered images.



Original image of size 1028×732



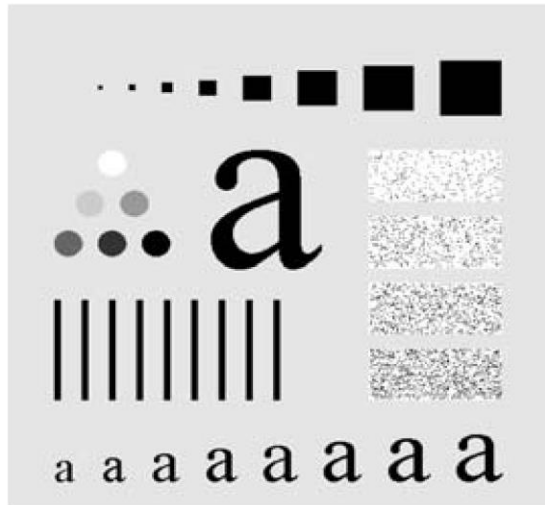
Filtered with a GLPF with $D_0 = 100$



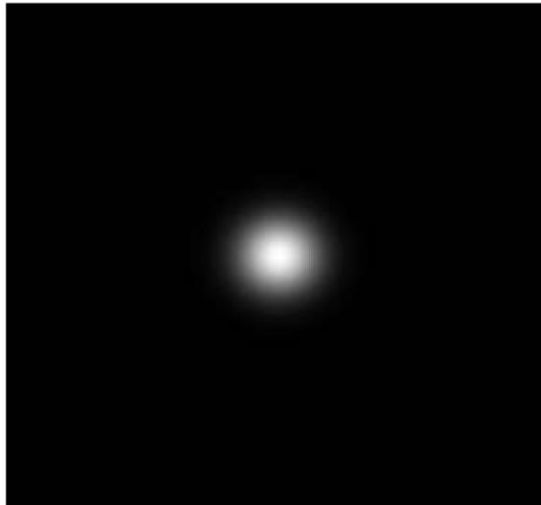
Filtered with a GLPF with $D_0 = 80$

Low Pass Filtering Example

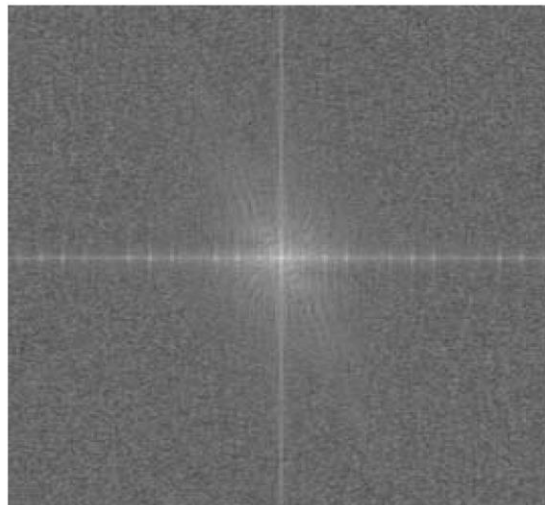
Original image



Gaussian lowpass filter



Spectrum of original image



Processed image



Sharpening in the Frequency Domain

Edges and fine detail in images are associated with high frequency components.

High pass filters – only pass the high frequencies, drop the low ones.

High pass frequencies are precisely the reverse of low pass filters as:

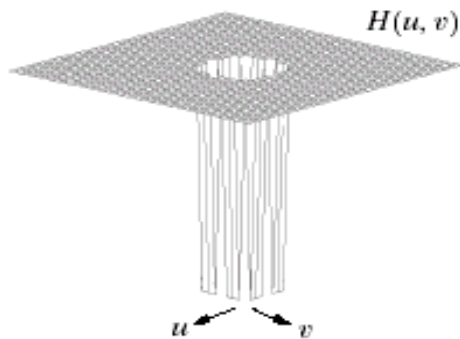
$$H_{hp}(u, v) = 1 - H_{lp}(u, v)$$

Ideal High Pass Filter

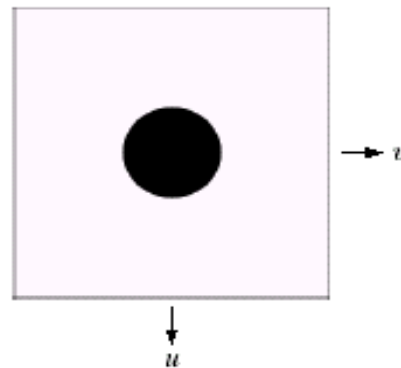
The ideal high pass filter is given as:

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

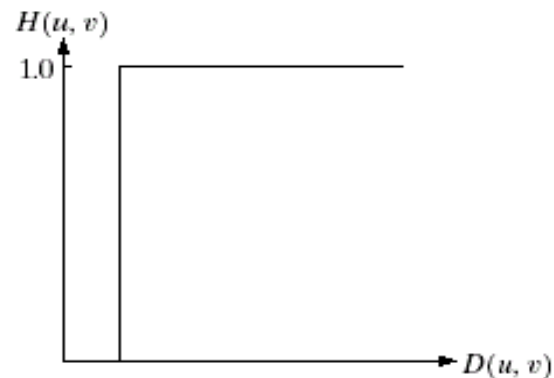
where D_0 is the cut off distance as low pass filter.



Perspective plot
of the transfer function



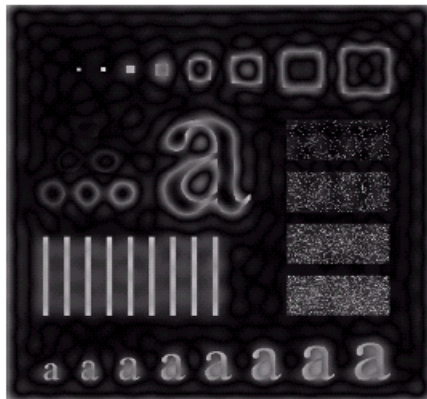
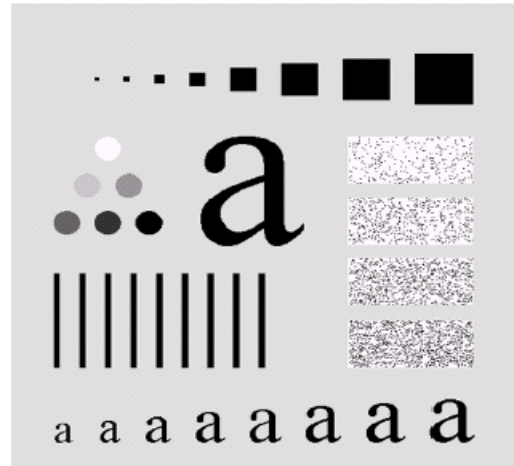
Displayed as an
image



Radial cross section

Ideal High Pass Filter

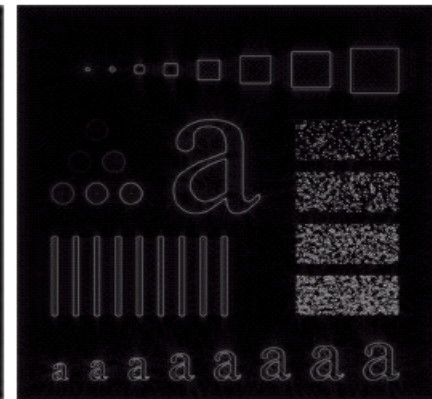
The ringing is so severe that it produced distorted, thickened object boundaries.



Results of ideal high pass filtering with $D_0 = 15$



Results of ideal high pass filtering with $D_0 = 30$



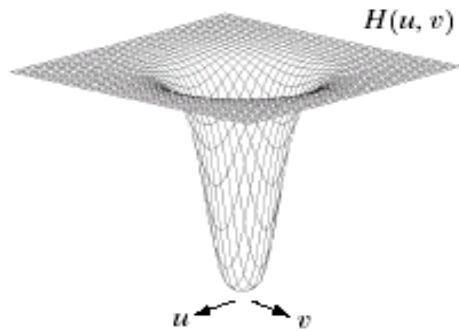
Results of ideal high pass filtering with $D_0 = 80$

Butterworth High Pass Filter

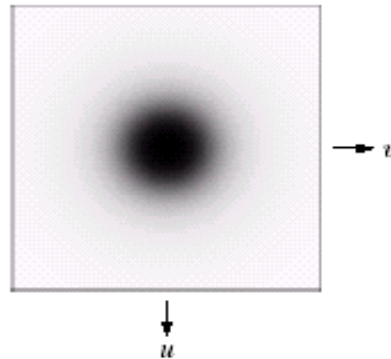
The Butterworth high pass filter is given as:

$$H(u, v) = \frac{1}{1 + [D_0 / D(u, v)]^{2n}}$$

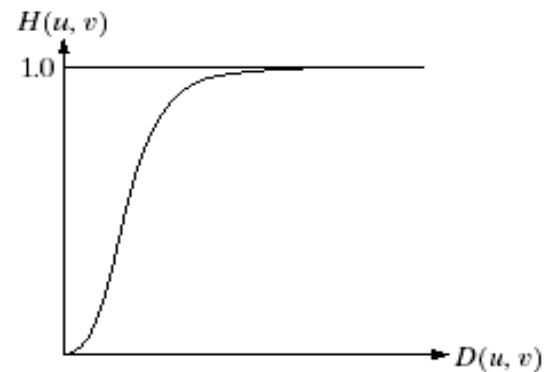
where n is the order and D_0 is the cut off distance as low pass filter.



Perspective plot
of the transfer function



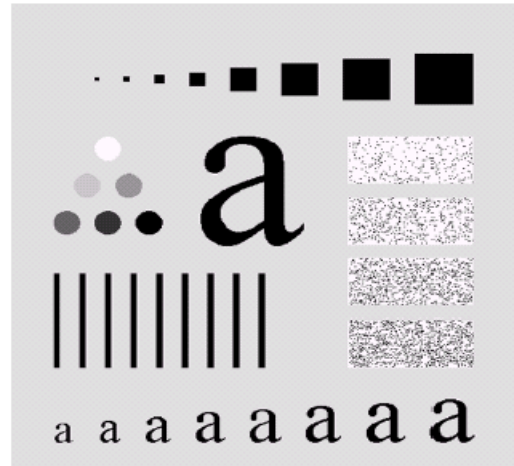
Displayed as an
image



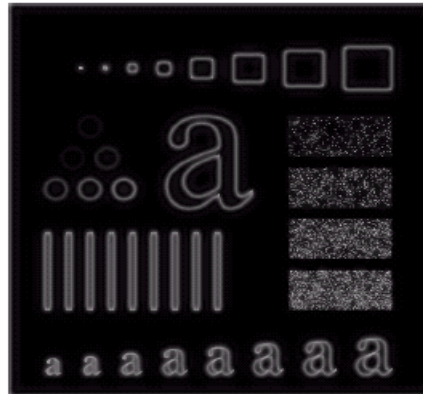
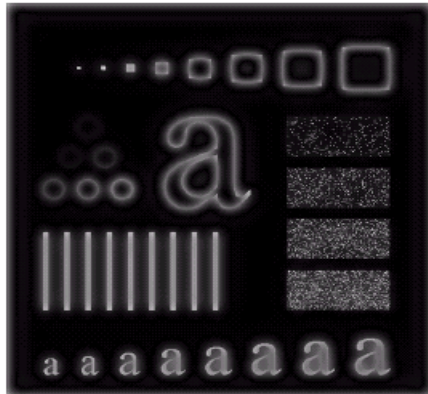
Radial cross section

Butterworth High Pass Filter

The boundaries are much less distorted than the outcome of IHPF.



Results of Butterworth high pass filtering of order 2 with $D_0 = 15$



Results of Butterworth high pass filtering of order 2 with $D_0 = 30$



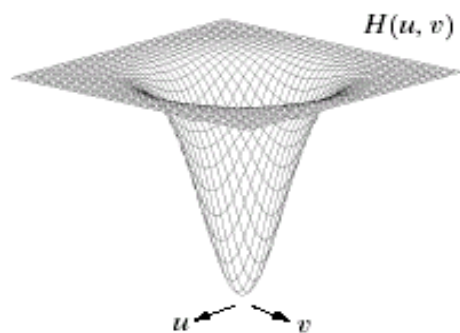
Results of Butterworth high pass filtering of order 2 with $D_0 = 80$

Gaussian High Pass Filter

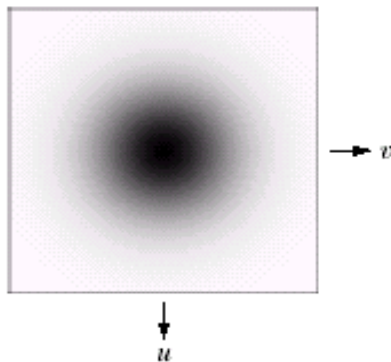
The Gaussian high pass filter is given as:

$$H(u, v) = 1 - e^{-D^2(u, v) / 2D_0^2}$$

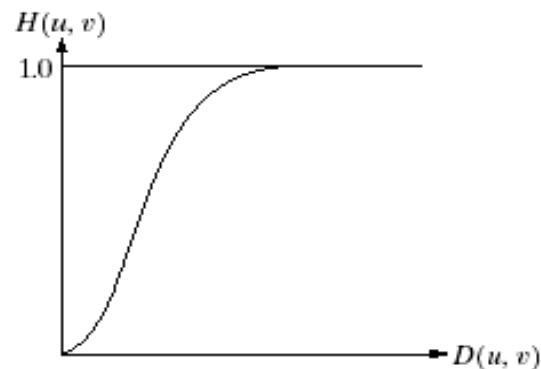
where D_0 is the cut off distance as before.



Perspective plot
of the transfer function

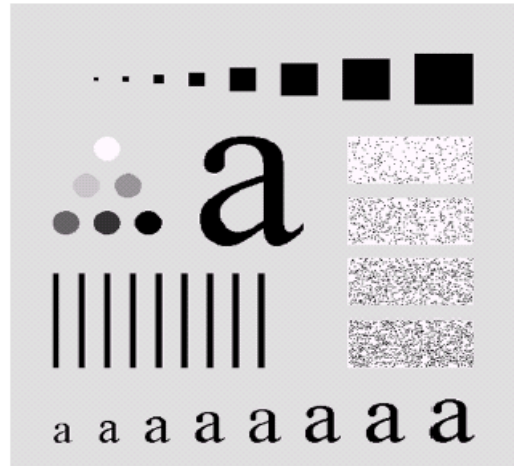


Displayed as an
image

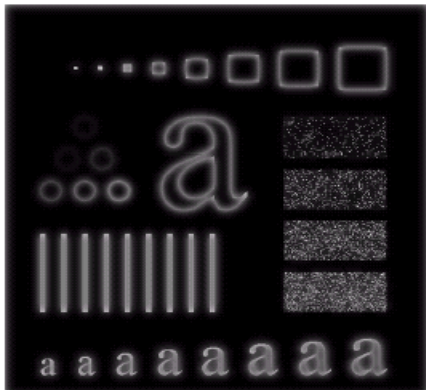


Radial cross section

Gaussian High Pass Filter



Results of
Gaussian
high pass
filtering with
 $D_0 = 15$



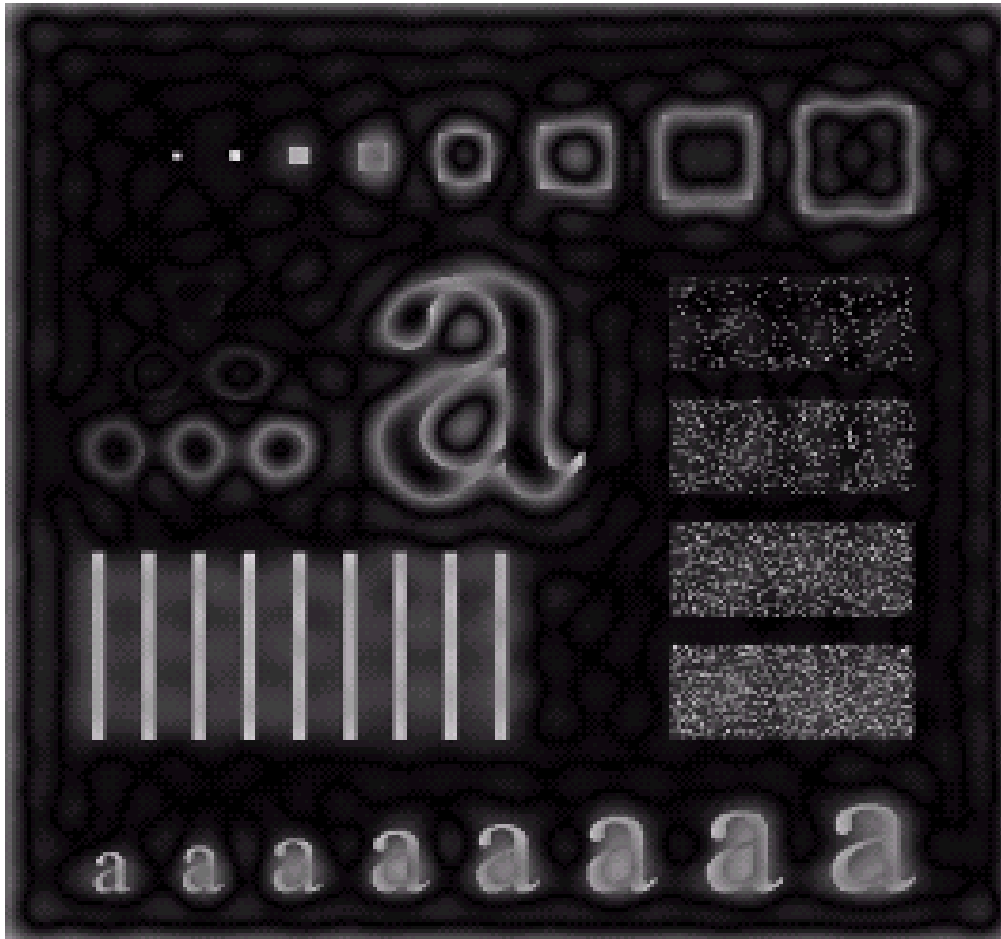
Results of
Gaussian high
pass filtering with
 $D_0 = 30$



Results of
Gaussian
high pass
filtering with
 $D_0 = 80$



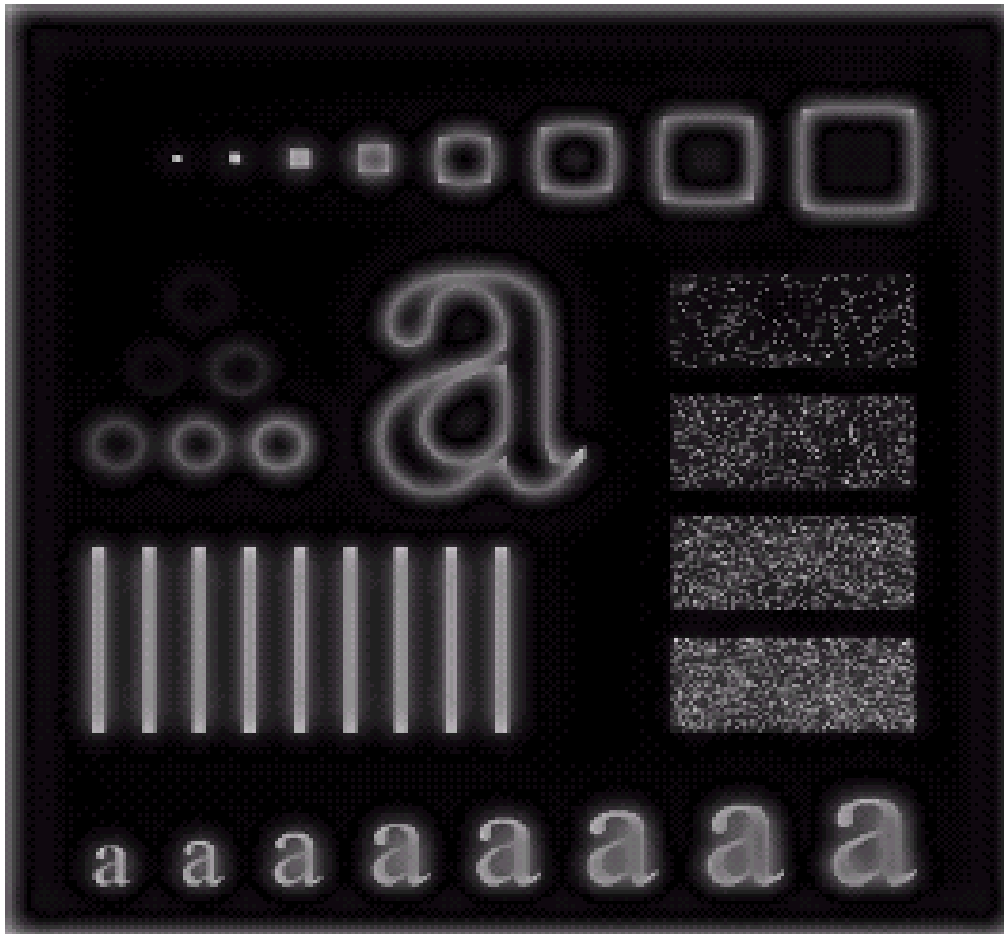
Highpass Filter Comparison



Results of ideal
high pass filtering
with $D_0 = 15$

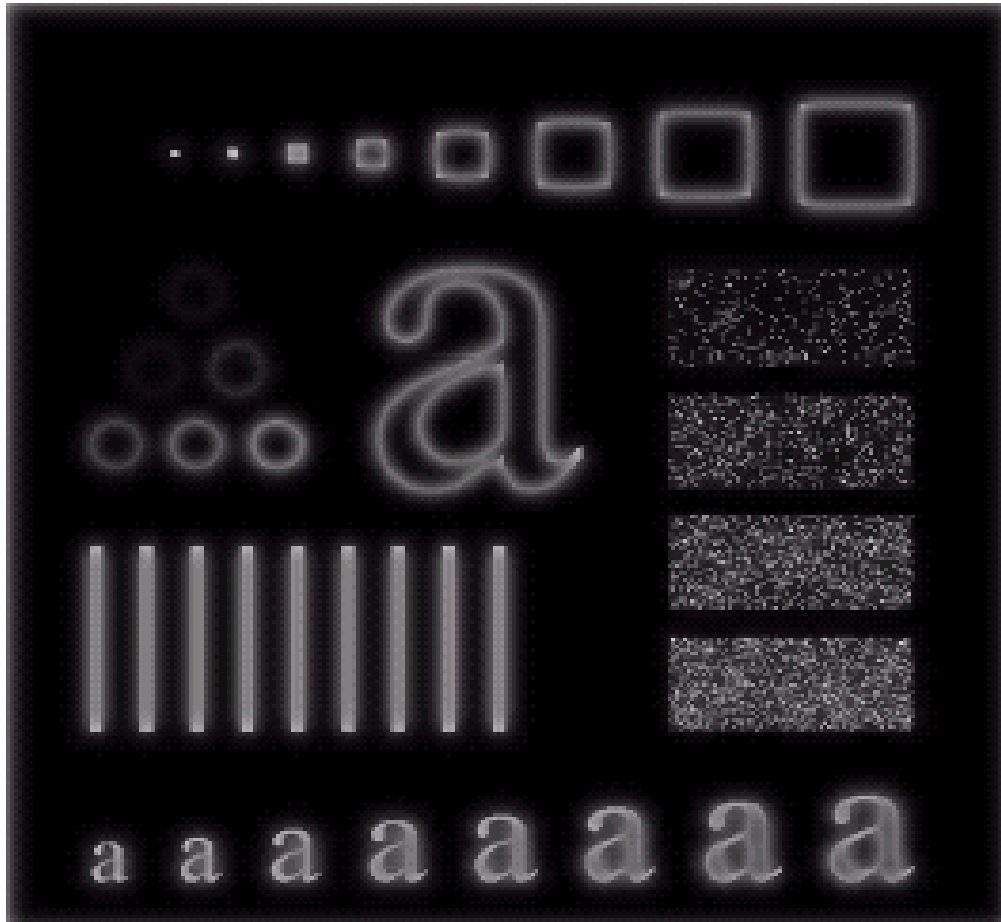
Distorted thickened
object boundary.

Highpass Filter Comparison



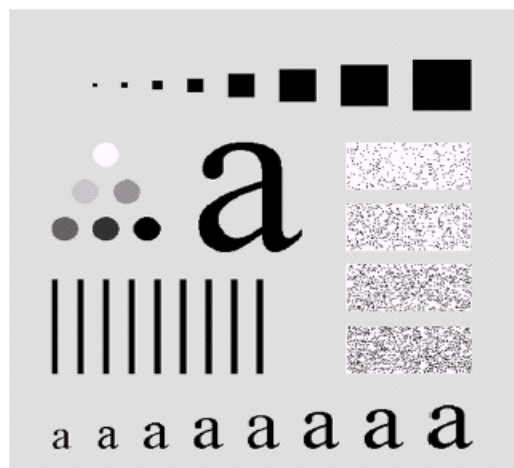
Results of Butterworth
high pass filtering of order
2 with $D_0 = 15$

Highpass Filter Comparison



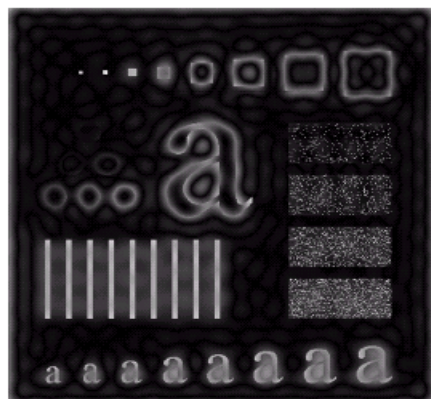
Results of Gaussian
high pass filtering with
 $D_0 = 15$

Highpass Filter Comparison

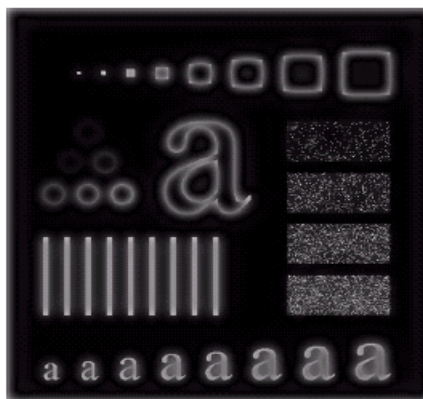


The results obtained by Gaussian filter are smoother than with the other two filters.

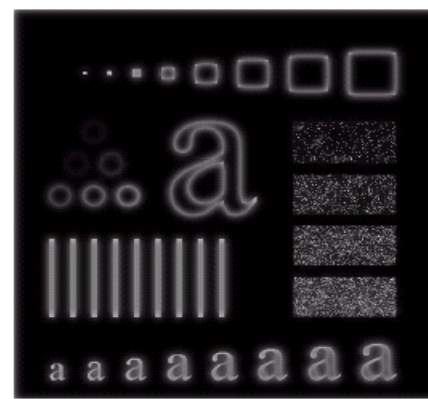
Even the filtering of the smaller objects and thin bars is clear with this filter.



Results of ideal high pass filtering with $D_0 = 15$



Results of Butterworth high pass filtering of order 2 with $D_0 = 15$



Results of Gaussian high pass filtering with $D_0 = 15$

Highpass Filter Comparison

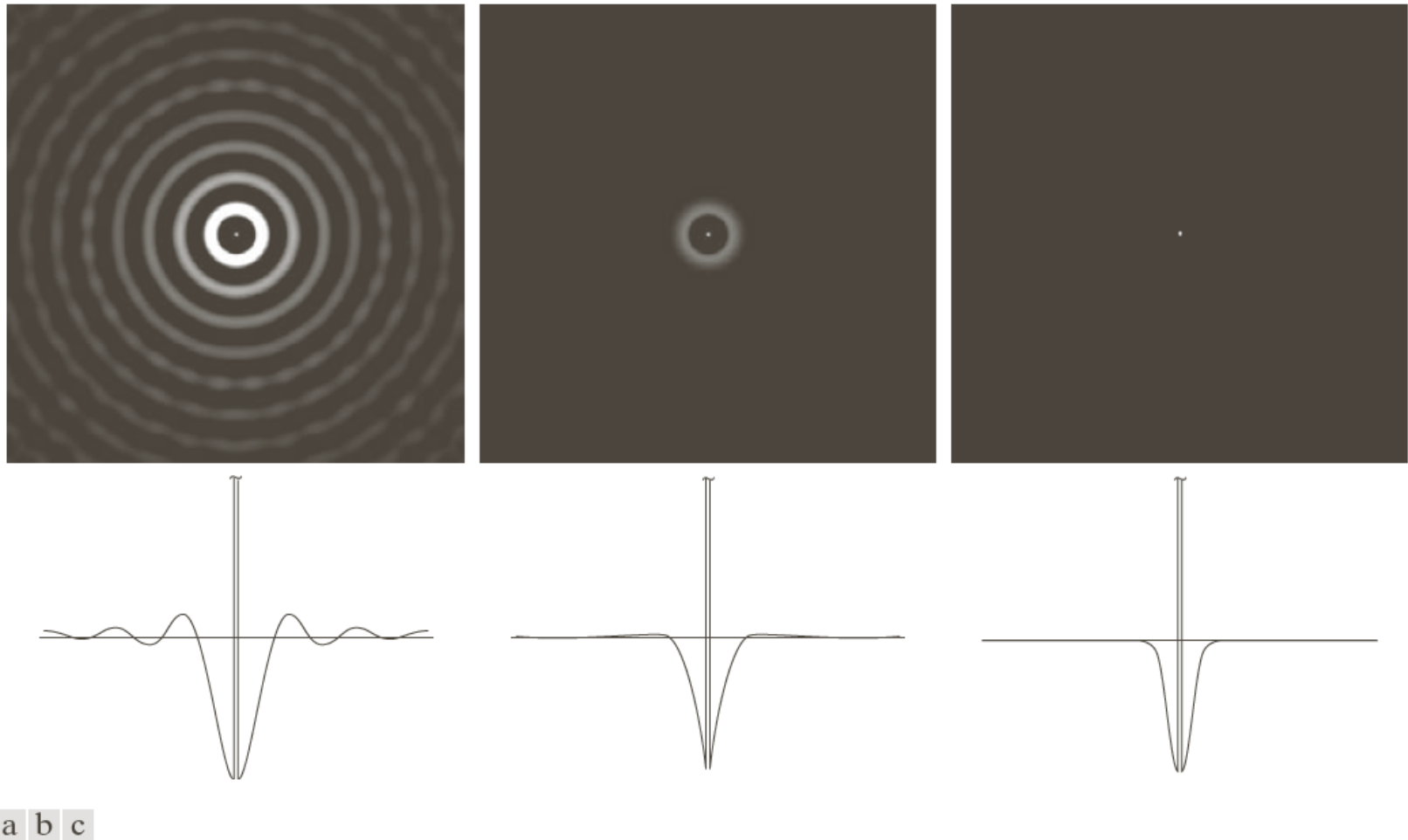


FIGURE 4.53 Spatial representation of typical (a) ideal, (b) Butterworth, and (c) Gaussian frequency domain highpass filters, and corresponding intensity profiles through their centers.

Highpass Filtering Example

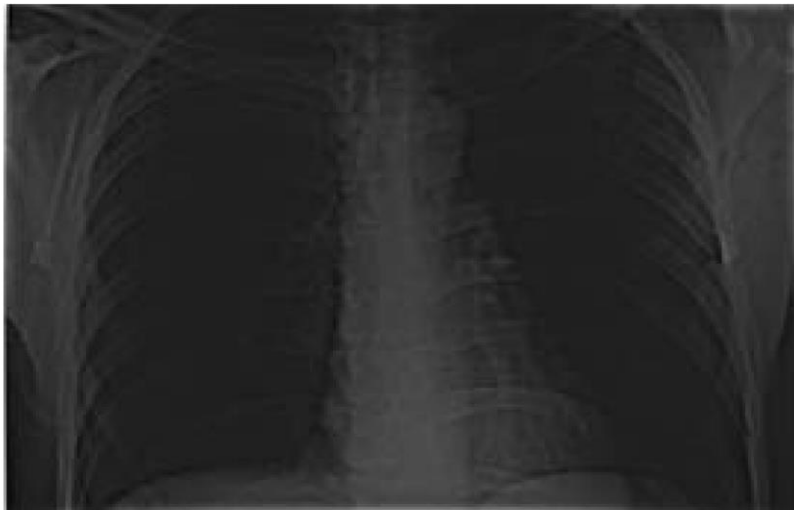
Original image



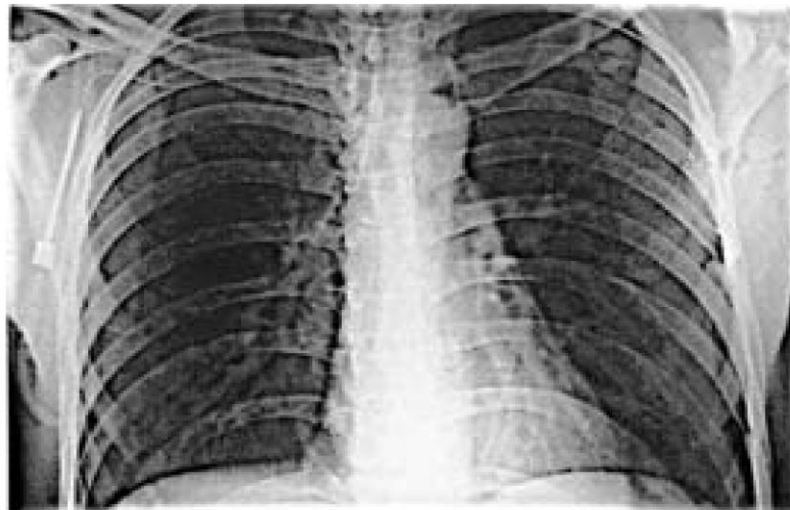
Highpass filtering result



High frequency
emphasis result



After histogram
equalisation



Convolution

$$f(x, y) * h(x, y) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) h(x - m, y - n)$$

$$f(x, y) * h(x, y) \Leftrightarrow F(u, v) H(u, v)$$

The double arrow is used to indicate that the expression on the left (spatial convolution) can be obtained by taking the inverse Fourier transform of the expression on the right [the product $F(u, v)H(u, v)$ in the frequency domain].

$$f(x, y) h(x, y) \Leftrightarrow F(u, v) * H(u, v)$$

Convolution theorem defines the correspondence between filtering in the spatial domain and frequency domain.

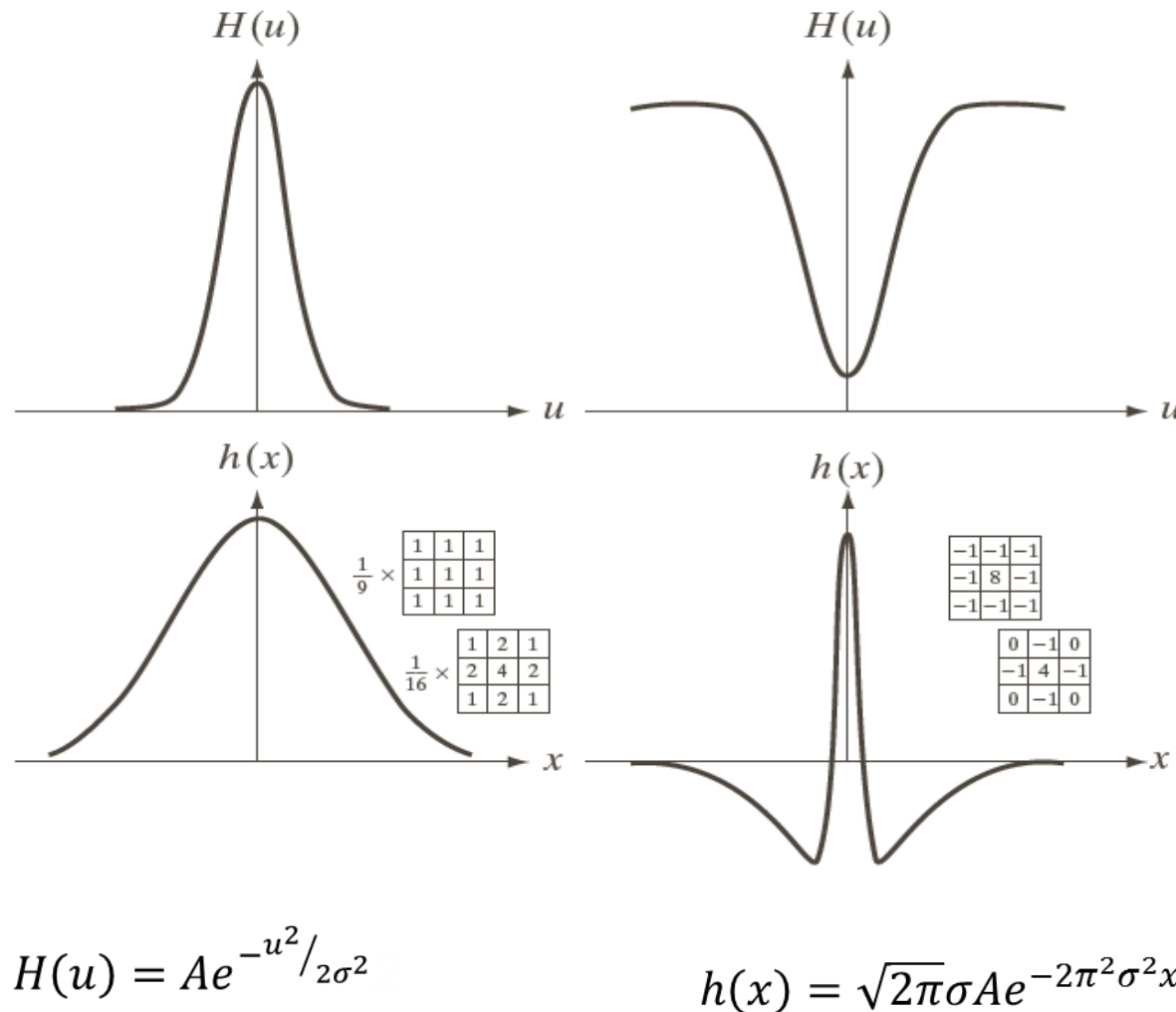
Convolution

Convolution equation is nothing more than an implementation for

- (1) flipping one function about origin;
- (2) shifting that function with respect to the other by changing the values of (x, y) ; and
- (3) Computing a sum of products over all values of m and n , for each displacement (x, y) .

The displacements (x, y) are integer increments that stop when the function no longer overlap.

Correspondence between Filtering in the Spatial domain and Frequency Domain

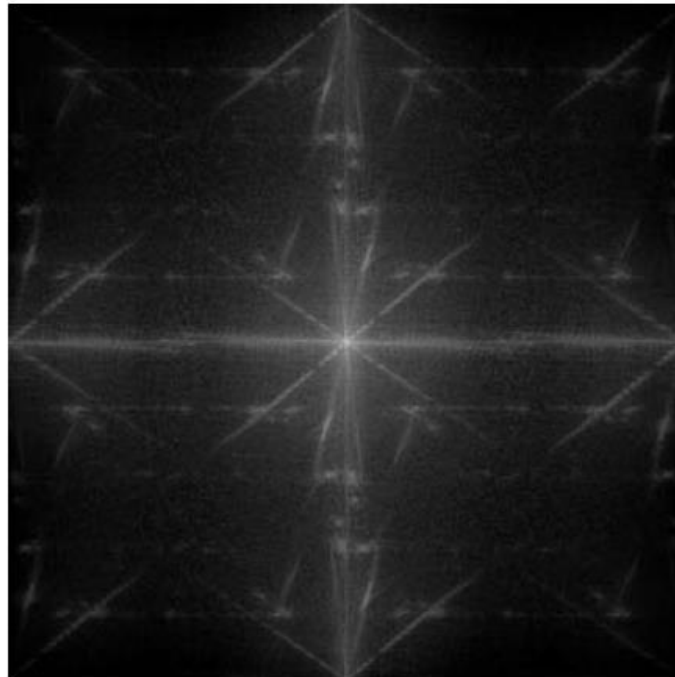


a c
b d

FIGURE 4.37

(a) A 1-D Gaussian lowpass filter in the frequency domain. (b) Spatial lowpass filter corresponding to (a). (c) Gaussian highpass filter in the frequency domain. (d) Spatial highpass filter corresponding to (c). The small 2-D masks shown are spatial filters we used in Chapter 3.

Correspondence between Filtering in the Spatial domain and Frequency Domain

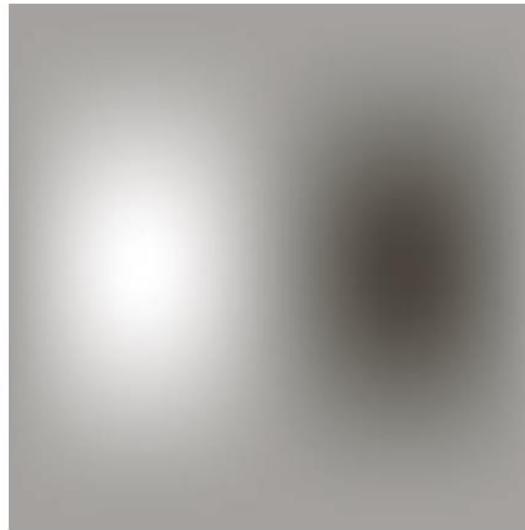
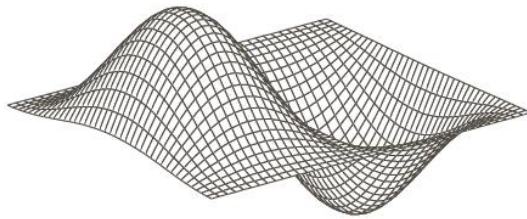


a b

FIGURE 4.38
(a) Image of a building, and
(b) its spectrum.

Correspondence between Filtering in the Spatial domain and Frequency Domain

-1	0	1
-2	0	2
-1	0	1



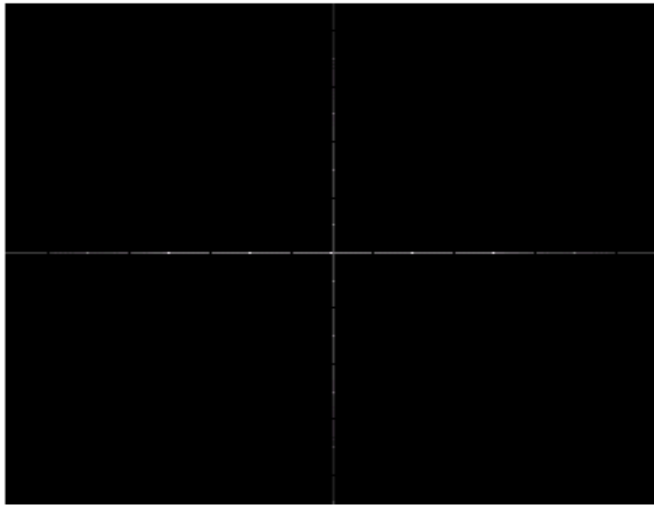
a	b
c	d

FIGURE 4.39

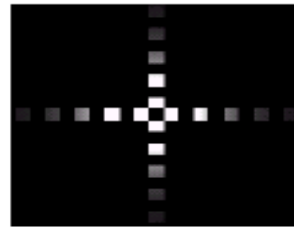
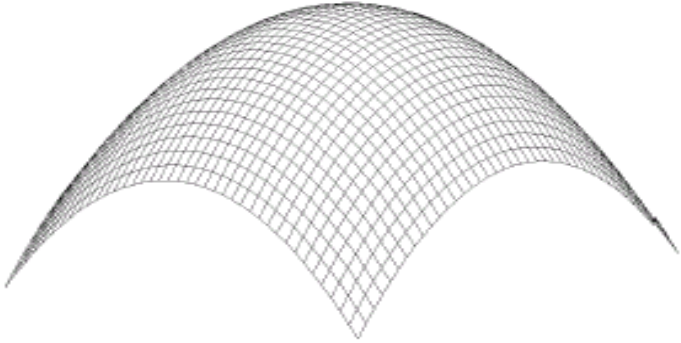
(a) A spatial mask and perspective plot of its corresponding frequency domain filter. (b) Filter shown as an image. (c) Result of filtering Fig. 4.38(a) in the frequency domain with the filter in (b). (d) Result of filtering the same image with the spatial filter in (a). The results are identical.

Laplacian In The Frequency Domain

Inverse DFT of
Laplacian in the
frequency domain



Laplacian in the
frequency domain



0	1	0
1	-4	1
0	1	0

Zoomed section of
the image on the
left compared to
spatial filter

2-D image of Laplacian
in the frequency
domain

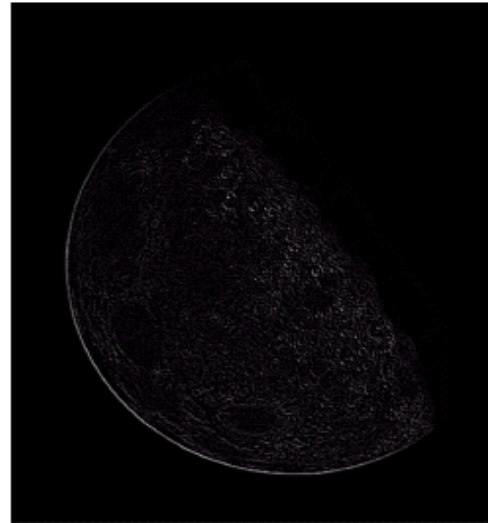


Frequency Domain Laplacian Example

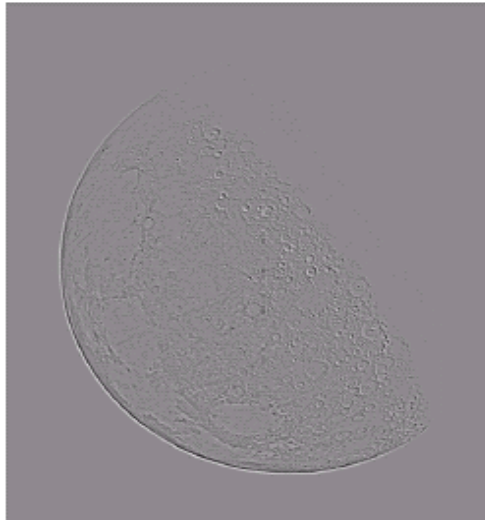
Original
image



Laplacian
filtered
image



Laplacian
image
scaled



Enhanced
image



Correlation

$$f(x, y) \circ h(x, y) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f^*(m, n) h(x + m, y + n)$$

$$f(x, y) \circ h(x, y) \Leftrightarrow F^*(u, v) H(u, v)$$

$$f^*(x, y) h(x, y) \Leftrightarrow F(u, v) \circ H(u, v)$$

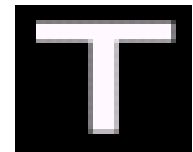
If $f = x + iy$ then $f^ = x - iy$*

f^* denotes the complex conjugate of f . We normally deal with real functions (images), in which case $f^* = f$.

Application of Correlation



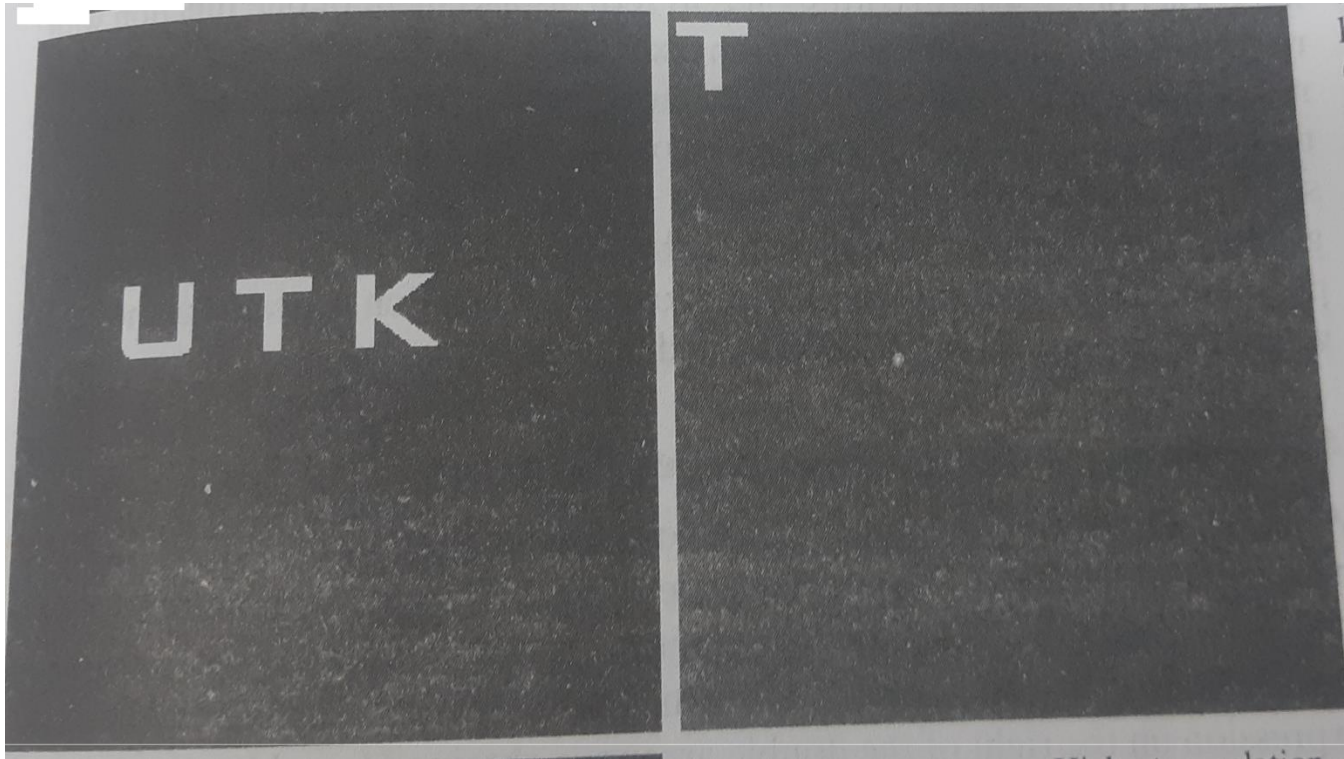
The principal use of correlation is for matching.



Template of
size 38×42

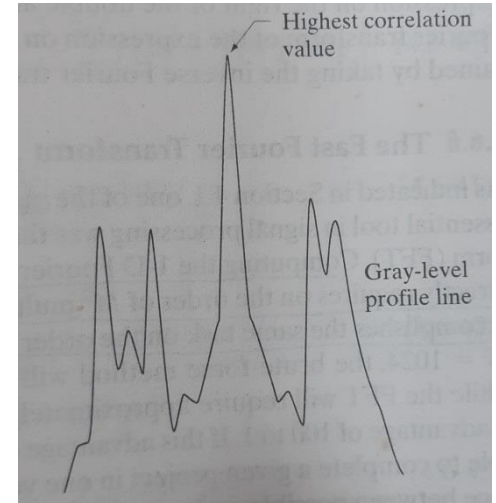
Input Image of
size 256×256

Application of Correlation



Size of both the images is 298×298

Application of Correlation



Correlation
function displayed
as an image

Fast Fourier Transform (FFT)

The reason that Fourier based techniques have become so popular is the development of the *Fast Fourier Transform (FFT)* algorithm.

Allows the Fourier transform to be carried out in a reasonable amount of time.

Reduces the amount of time required to perform a Fourier transform by a factor of 100 – 600 times!

Frequency Domain Filtering & Spatial Domain Filtering

- Similar jobs can be done in the spatial and frequency domains.
- Filtering in the spatial domain can be easier to understand.
- Filtering in the frequency domain can be much faster – particularly for large images.