

Advanced Digital Image Processing

Chapter 4: : Image Enhancement in the Frequency Domain

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Outline

- 1 Introduction to Fourier Transform
- 2 Frequency Domain Filtering
- 3 Smoothing Frequency-Domain Filters
- 4 Sharpening Frequency-Domain Filters
- 5 Homomorphic Filtering



Fourier Transform

1-D Fourier Transform

Definition

_____:

$$F(u) = \frac{1}{M} \sum_{x=0}^{M-1} f(x) e^{-j2\pi \frac{ux}{M}} \quad u = 0, 1, 2, \dots, M-1,$$

$$f(x) = \sum_{u=0}^{M-1} F(u) e^{j2\pi \frac{ux}{M}} \quad x = 0, 1, 2, \dots, M-1.$$



Fourier Transform

2-D Fourier Transform

Definition

_____:

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

$$u = 0, 1, \dots, M-1, v = 0, 1, \dots, N-1$$

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

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



Fourier Transform

DC Coefficient

Definition

The _____ $F(0,0)$ is,

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

Reason: The right side is the **average of $f(x,y)$** .
Therefore, $F(0,0)$ is _____ of the spectrum.



Property of Fourier Transform

Separability

Property

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

where

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

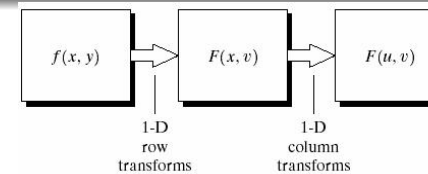


FIGURE 4.35
Computation of the 2-D Fourier transform as a series of 1-D transforms.



Property of Fourier Transform

Conjugate Symmetry & Rotation Invariant

Theorem

If $f(x,y)$ is **real**,

$$F(u,v) = F^*(-u,-v)$$

$F(u,v)$ is _____

Theorem

_____:

- Rotating $f(x,y)$ by an angle θ_0 rotates $F(u,v)$ by the same angles.
- Rotating $F(x,y)$ by an angle θ_0 rotates $f(u,v)$ by the same angles.

$$f(r, \theta + \theta_0) \Leftrightarrow F(\omega, \phi + \theta_0)$$



Property of Fourier Transform

Scaling

Theorem

_____ : Let $\Delta x, \Delta y$ be sampling space in spatial domain, $\Delta u, \Delta v$ are sampling space in freq, i.e.,

$$\begin{aligned} f(x,y) &\triangleq f(x_0 + x\Delta x, y_0 + y\Delta y) \\ F(u,v) &\triangleq F(u\Delta u, v\Delta v) \end{aligned}$$

Then, the samples are **inversely related**.

$$\begin{aligned} \Delta u &= \frac{1}{M\Delta x} \\ \Delta v &= \frac{1}{M\Delta y} \end{aligned}$$

Property of Fourier Transform

Periodicity

Theorem

_____:

$$F(u, v) = F(u + M, v) = F(u, v + N) = F(u + M, v + N)$$

_____:

$$f(x, y) = f(x + M, y) = f(x, y + N) = f(x + M, y + N)$$



Property of Fourier Transform

Shifting in Frequency

Theorem

_____:

$$f(x, y)e^{j2\pi(u_0x/M + v_0y/N)} \Leftrightarrow F(u - u_0, v - v_0)$$

Example

When $u_0 = M/2$, $v_0 = N/2$,

$$e^{j2\pi(u_0x/M + v_0y/N)} = e^{j\pi(x+y)} = (-1)^{x+y}.$$

Therefore,

$$f(x, y)(-1)^{x+y} \Leftrightarrow F(u - M/2, v - N/2)$$

It is common practice to **multiply the image by $(-1)^{x+y}$ to shift the origin of $F(u, v)$ to frequency coordinates $(M/2, N/2)$** . (M, N should be even number to make coordinate integer)

Property of Fourier Transform

Convolution Theorem

Definition

_____:

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

Theorem

_____:

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

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



Property of Fourier Transform

Correlation Theorem

Definition

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

Theorem

_____:

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

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

Theorem

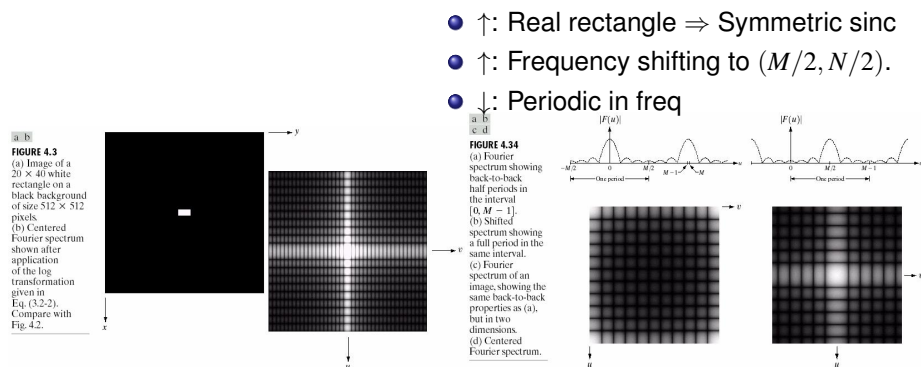
_____:

$$f(x, y) \circ f(x, y) \Leftrightarrow |F(u, v)|^2$$

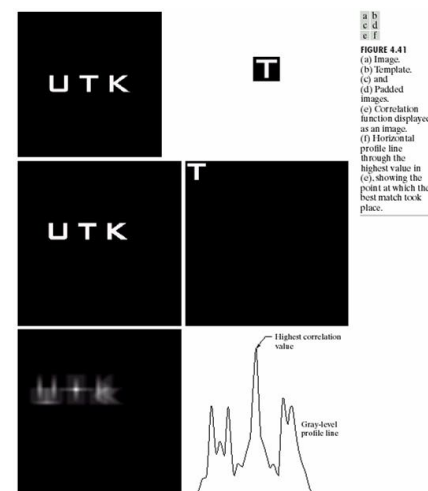
$$|f(x, y)|^2 = F(u, v) \circ F(u, v)$$

Property Demonstration

Symmetry+Periodity+Frequency Shifting



Property Demonstration



- **Padding** avoid aliasing during **circular convolution**
- Convolution **peak** location show the best match

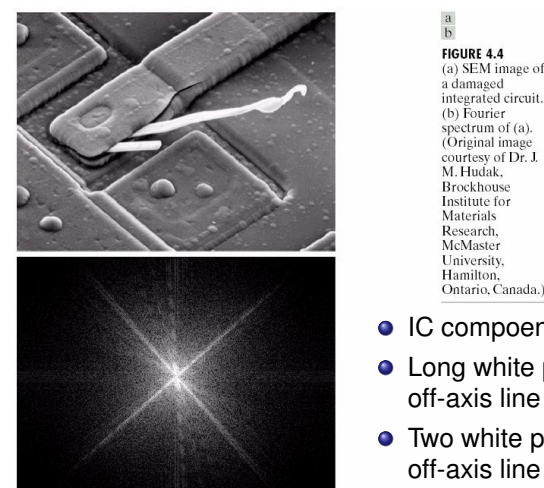
Association between Spatial and Frequency domains

Frequency is related to **rate of change**

⇒ Fourier Transform is related to **intensity variations in an image**

- (at origin): **Slowest** varying frequency component
 $((u, v) = (0, 0))$ is related to the **average gray level** of an image.
- (near origin): Characterized by **smooth area** in gray level
- (away from origin): Characterized by **abrupt changes** in gray level (**edge, noise**).

Example



- IC component $45^\circ \Rightarrow$ DFT 45°
- Long white protrusion \Rightarrow Vertical off-axis line
- Two white protrusions \Rightarrow Strong vertical off-axis line near origin

Filtering in Frequency Domain

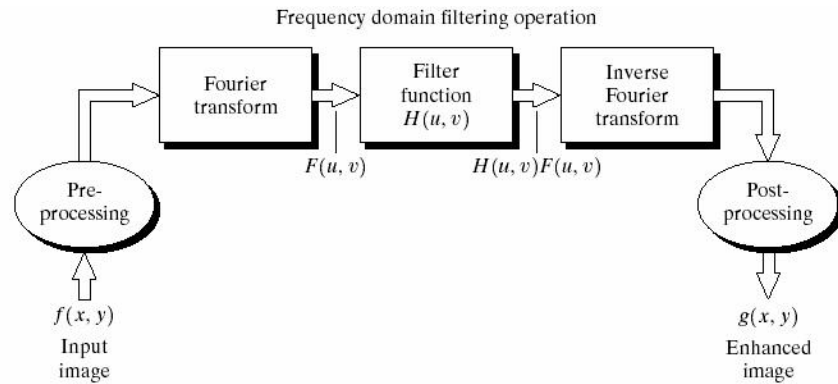


FIGURE 4.5 Basic steps for filtering in the frequency domain.



Notch Filter

Definition

: Rejects (Passes) freqs in predefined neighborhoods **about a center freq.**

Example

An example of notch filter is

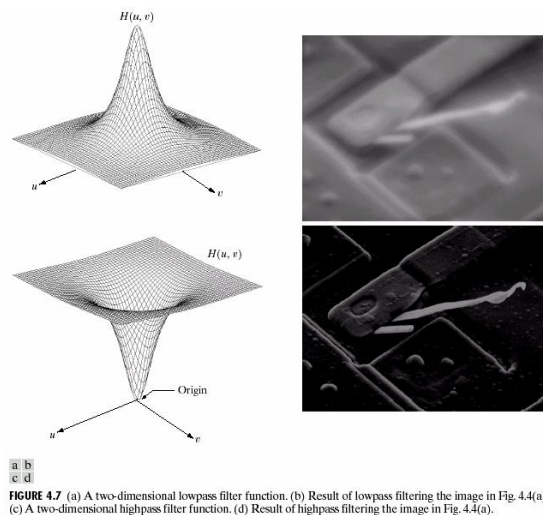
$$H(u, v) = \begin{cases} 0 & \text{if } (u, v) = (M/2, N/2) \\ 1 & \text{otherwise} \end{cases}$$

FIGURE 4.6 Result of filtering the image in Fig. 4.4(a) with a notch filter that set to 0 the $F(0, 0)$ term in the Fourier transform.



- Set $F(0, 0) = 0$ and make prominent **edges** stand out.
- In reality, the displayed image **cannot be with $F(0, 0) = 0$**
Reason: Avg value=0 \Rightarrow Negative pixel intensity somewhere)

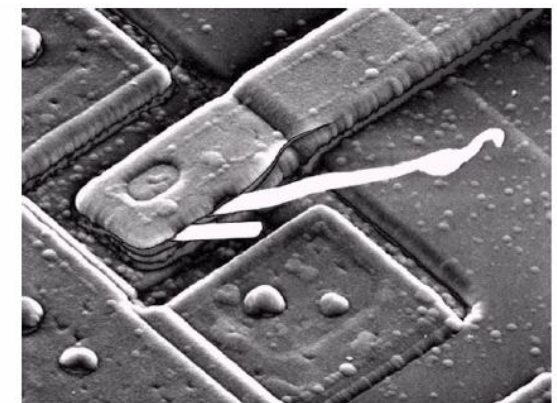
HPF & LPF



Modified HPF

Add a constant to the filter so that it will not completely eliminate $F(0, 0)$.

FIGURE 4.8 Result of highpass filtering the image in Fig. 4.4(a) with the filter in Fig. 4.7(c), modified by adding a constant of one-half the filter height to the filter function. Compare with Fig. 4.4(a).



Frequency Filtering versus Spatial Masking

Theorem

Masking in Time = Filtering in Frequency

That is, $h(x, y) \Leftrightarrow H(u, v)$

Proof.

By Convolution Theorem:

$$\begin{aligned} f(x, y) * h(x, y) &\Leftrightarrow F(u, v)H(u, v) \\ \delta(x, y) * h(x, y) &\Leftrightarrow \mathcal{F}[\delta(x, y)]H(u, v) \\ h(x, y) &\Leftrightarrow H(u, v) \end{aligned}$$



Frequency Filtering versus Spatial Masking

Gaussian Low-pass Filter

Example

1-D Gaussian LPF:

$$h(x) = \sqrt{2\pi}\sigma A e^{-2\pi^2\sigma^2 x^2} \Leftrightarrow H(u) = A e^{-u^2/2\sigma^2}$$

- Fourier Transform of **real Gaussian** is still **real Gaussian**
- Spatial and Frequency behave **reciprocally**:
 $H(u)$ has **broad** profile (**large σ**), $h(x)$ has a **narrow** profile, vice versa.



Frequency Filtering versus Spatial Masking

Gaussian High-pass Filter

Example

1-D Gaussian HPF:

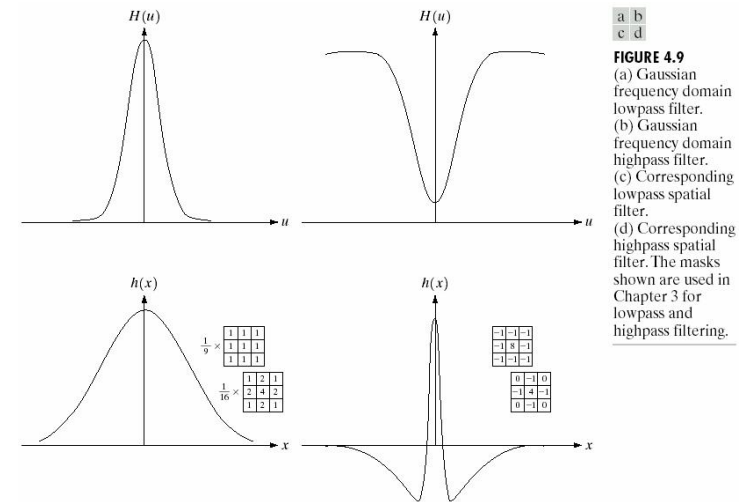
$$\begin{aligned} h(x) &= \sqrt{2\pi}\sigma A e^{-2\pi^2\sigma_1^2 x^2} - \sqrt{2\pi}\sigma B e^{-2\pi^2\sigma_2^2 x^2} \\ \Leftrightarrow H(u) &= A e^{-u^2/2\sigma_1^2} - B e^{-u^2/2\sigma_2^2} \end{aligned}$$

- Gaussian HPF is constructed as **a difference of Gaussian LPF**.



Frequency Filtering versus Spatial Masking

Gaussian Filters



Frequency Filtering versus Spatial Masking

Pros and Cons

Frequency approach:

- **More intuitive**
- **Computational complexity** is better when mask size is larger.
Ex: 1-D, Freq with FFT is faster than Spatial with mask if the number of points is greater than 32



Two-Dimensional Low-pass Filters

Three Types of LPFs:

- _____
- _____
- _____



Ideal Low-Pass Filter

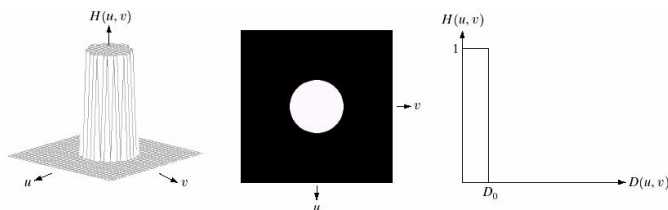
Definition

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

where

$$D(u, v) = \sqrt{(u - M/2)^2 + (v - N/2)^2}$$

and D_0 is _____



(a) (b) (c)



Ideal Low-Pass Filter

Performance Metrics

The performance of different LPFs at **the same cutoff frequency** are compared by computing _____,

$$\alpha = 100 \left[\sum_u \sum_v P(u, v) / P_T \right]$$

where

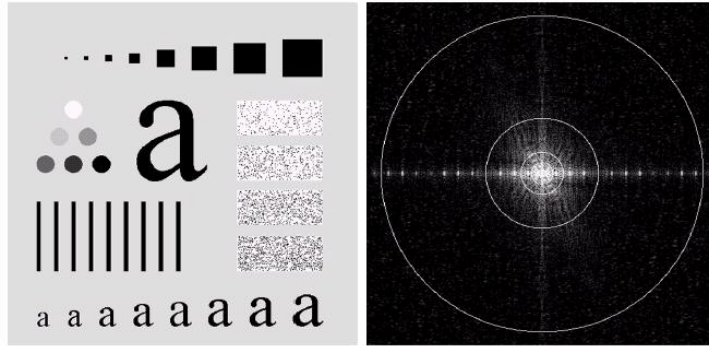
P_T is the _____ before filtering

$$P_T = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} |F(u, v)|^2 = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} P(u, v)$$



Ideal Low-Pass Filter

Performance Metrics



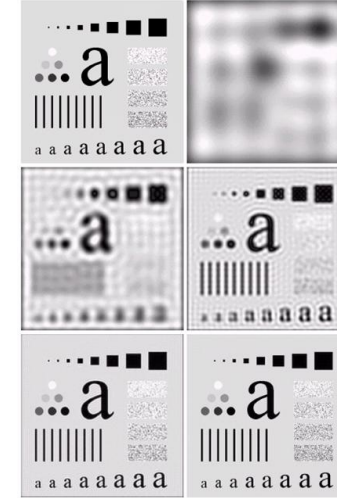
a b

FIGURE 4.11 (a) An image of size 500×500 pixels and (b) its Fourier spectrum. The superimposed circles have radii values of 5, 15, 30, 80, and 230, which enclose 92.0, 94.6, 96.4, 98.0, and 99.5% of the image power, respectively.



Ideal Low-Pass Filter

Performance Metrics



Ideal Low-Pass Filter

Ringing and Blurred

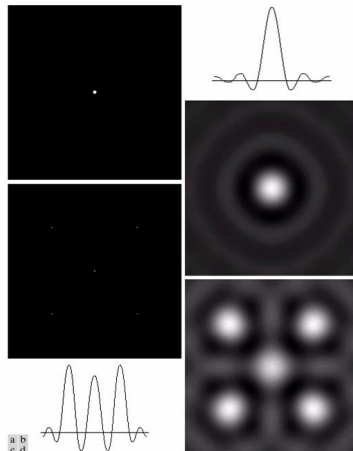


FIGURE 4.13 (a) A frequency-domain ILPF of radius 5. (b) Corresponding spatial filter (note the ringing). (c) Five impulses in the spatial domain, simulating the values of five pixels. (d) Convolution of (b) and (c) in the spatial domain.

- h & H is reciprocal \Rightarrow
The narrower filter in freq, the more blurred and ringing image.

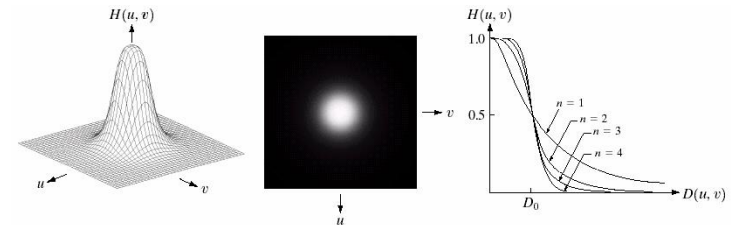


Butterworth LPF

Definition

Butterworth Low-pass filter (BLPF):

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



a b c

FIGURE 4.14 (a) Perspective plot of a Butterworth lowpass filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross sections of orders 1 through 4.



Butterworth LPF

Filter order

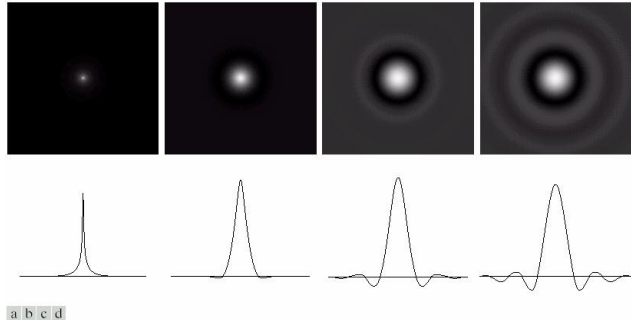


FIGURE 4.16 (a)–(d) Spatial representation of BLPFs of order 1, 2, 5, and 20, and corresponding gray-level profiles through the center of the filters (all filters have a cutoff frequency of 5). Note that ringing increases as a function of filter order.

- filter order = 1 : **No ringing**
- filter order $\rightarrow \infty$: Larger **ringing and blurring**/Close to **ideal LPF**
- filter order $\rightarrow 1$: Close to **Gaussian LPF**
- BLPF behaves in between two **extremes ILPF and GLPF**



Butterworth LPF

Cut-off frequency

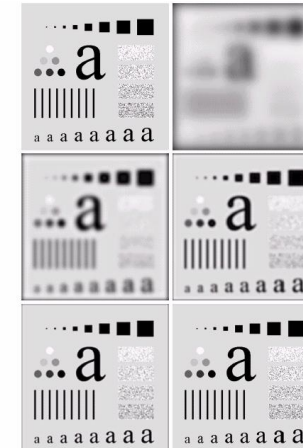


FIGURE 4.15 (a) Original image. (b)–(f) Results of filtering with BLPFs of order 2, with cutoff frequencies at radii of 5, 15, 30, 60, and 200, as shown in Fig. 4.11(b). Compare with Fig. 4.12.



Gaussian LPF

Definition

Gaussian Low-pass filter (GLPF):

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

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

Note: Gaussian Filter (in freq domain) also means a **spatial Gaussian filter**.

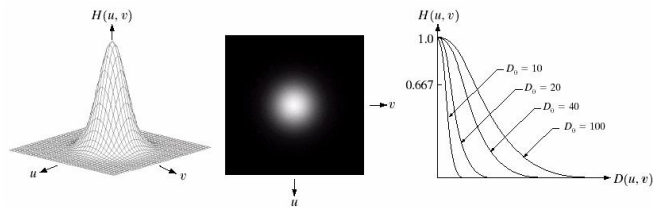


FIGURE 4.17 (a) Perspective plot of a GLPF transfer function. (b) Filter displayed as an image. (c) Filter radial cross sections for various values of D_0 .



Gaussian LPF

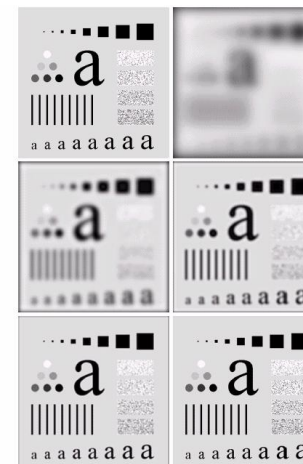


FIGURE 4.15 (a) Original image. (b)–(f) Results of filtering with BLPFs of order 2, with cutoff frequencies at radii of 5, 15, 30, 60, and 200, as shown in Fig. 4.11(b). Compare with Fig. 4.12.



Compare to BLPF of order 2 at the same value of D_0 , GLPF does **not achieve as much smoothing as BLPF**.
Reason: Because GLPF is **not as tight** as BLPF of order 2)

Gaussian LPF

Example

a b

FIGURE 4.19
(a) Sample text of poor resolution (note broken characters in magnified view).
(b) Result of filtering with a GLPF (broken character segments were joined).

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.

e a

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.

e a



Gaussian LPF

Example



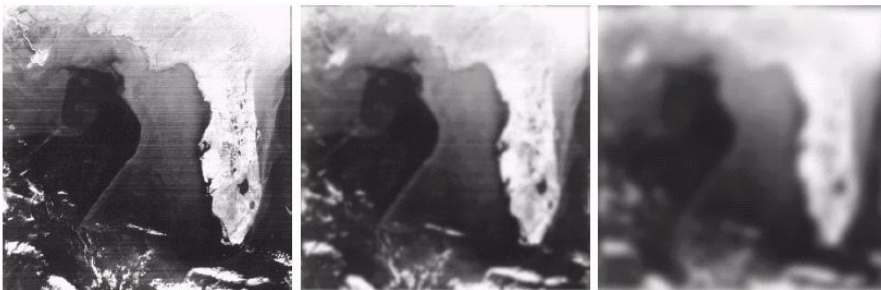
a b c

FIGURE 4.20 (a) Original image (1028 × 732 pixels). (b) Result of filtering with a GLPF with $D_0 = 100$. (c) Result of filtering with a GLPF with $D_0 = 80$. Note reduction in skin fine lines in the magnified sections of (b) and (c).



Gaussian LPF

Example



a b c

FIGURE 4.21 (a) Image showing prominent scan lines. (b) Result of using a GLPF with $D_0 = 30$. (c) Result of using a GLPF with $D_0 = 10$. (Original image courtesy of NOAA.)



High-Pass Filter

Definition

_____ : Achieve image **sharpening**

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

- Ideal HPF
- Butterworth HPF
- Gaussian HPF



High-Pass Filter

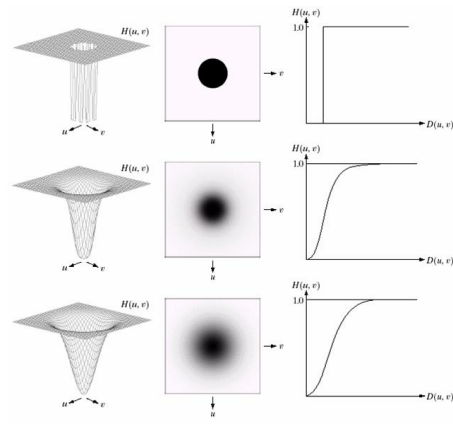


FIGURE 4.22 Top row: Perspective plot, image representation, and cross section of a typical ideal highpass filter. Middle and bottom rows: The same sequence for typical Butterworth and Gaussian highpass filters.



High-Pass Filter Ringing

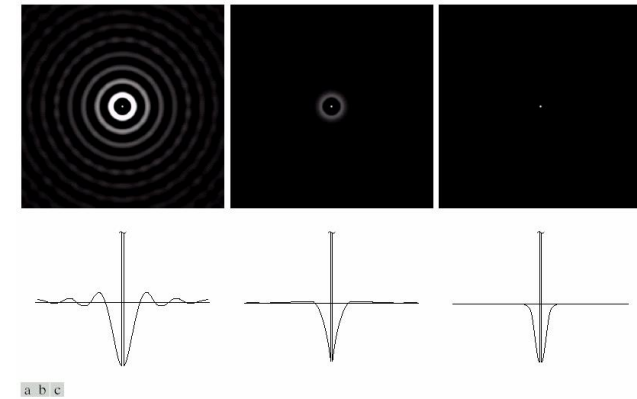


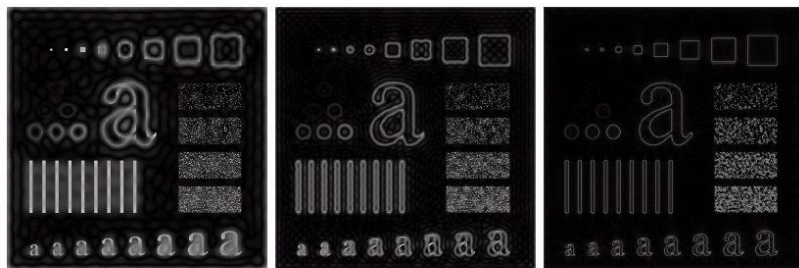
FIGURE 4.23 Spatial representations of typical (a) ideal, (b) Butterworth, and (c) Gaussian frequency domain highpass filters, and corresponding gray-level profiles.



Ideal HPF

Definition

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



a b c

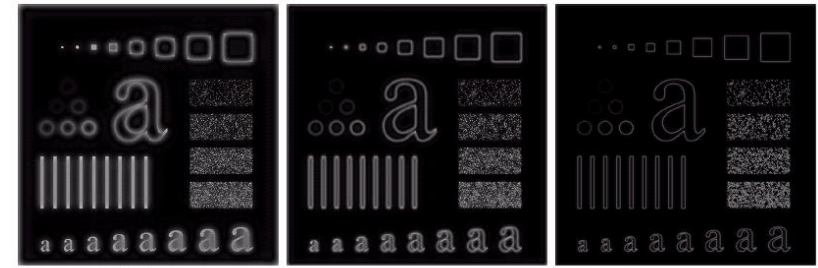
FIGURE 4.24 Results of ideal highpass filtering the image in Fig. 4.11(a) with $D_0 = 15, 30$, and 80 , respectively. Problems with ringing are quite evident in (a) and (b).



Butterworth HPF

Definition

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



a b c

FIGURE 4.25 Results of highpass filtering the image in Fig. 4.11(a) using a BHPF of order 2 with $D_0 = 15, 30$, and 80 , respectively. These results are much smoother than those obtained with an ILPF.

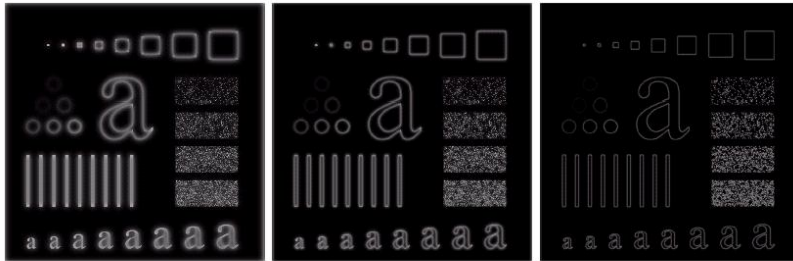


Gaussian HPF

Definition

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

Note: Another way: **Diff** of two GLPF (**More control**)



a b c

FIGURE 4.26 Results of highpass filtering the image of Fig. 4.11(a) using a GHPF of order 2 with $D_0 = 15$, 30, and 80, respectively. Compare with Figs. 4.24 and 4.25.



Laplacian Filter in Frequency Domain

Definition

is

$$H(u, v) = -[(u - M/2)^2 + (v - N/2)^2]$$

Proof.

$$\therefore \frac{\partial^2 f(x, y)}{\partial x^2} + \frac{\partial^2 f(x, y)}{\partial y^2} \xrightarrow{\mathcal{F}} (ju)^2 F(u, v) + (jv)^2 F(u, v)$$

$$\therefore \nabla^2 f(x, y) \xrightarrow{\mathcal{F}} -(u^2 + v^2) F(u, v)$$

Considering the **origin shifting**,

$$\nabla^2 f(x, y) \xrightarrow{\mathcal{F}} -((u - M/2)^2 + (v - N/2)^2) F(u, v)$$

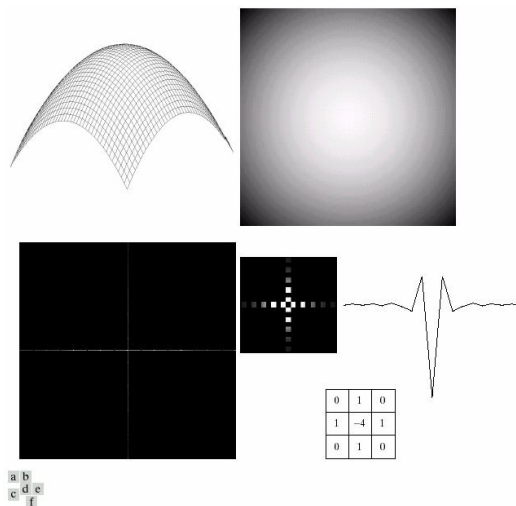
Laplacian Filter in Frequency Domain
versus Laplacian Filter in Spatial Domain

FIGURE 4.27 (a) 3-D plot of Laplacian in the frequency domain. (b) Image representation of (a). (c) Laplacian in the spatial domain obtained from the inverse DFT of (b). (d) Zoomed section of the origin



Original plus Laplacian in Frequency Domain

Definition

The _____ in frequency domain is

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

Proof.

Because Laplacian filter $H(u, v)$ is **negative**, the enhanced image $g(x, y)$ is

$$g(x, y) = f(x, y) - \nabla^2 f(x, y)$$

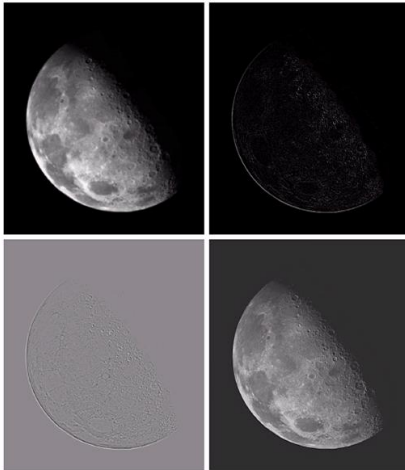


Original plus Laplacian in Frequency Domain

Example

All are processed in **freq domain**

FIGURE 4.28
(a) Image of the North Pole of the moon.
(b) Laplacian filtered image.
(c) Laplacian image scaled.
(d) Image enhanced by using Eq. (4.4-12).
(Original image courtesy of NASA.)



Unsharp Masking

Definition

in Frequency Domain:

$$H_{hp}(x, y) = 1 - H_{lp}(x, y)$$

Proof.

Unsharp masking in Spaital Domain:

$$f_{hp}(x, y) = f(x, y) - f_{lp}(x, y)$$



High-boost Filtering

Definition

in Frequency Domain:

$$H_{hp}(x, y) = (A - 1) - H_{lp}(x, y)$$

Proof.

High-boost filtering in Spaital Domain:

$$\begin{aligned} f_{hp}(x, y) &= Af(x, y) - f_{lp}(x, y) \\ &= (A - 1)f(x, y) + [f(x, y) - f_{lp}(x, y)] \\ &= (A - 1)f(x, y) + f_{hp}(x, y) \end{aligned}$$

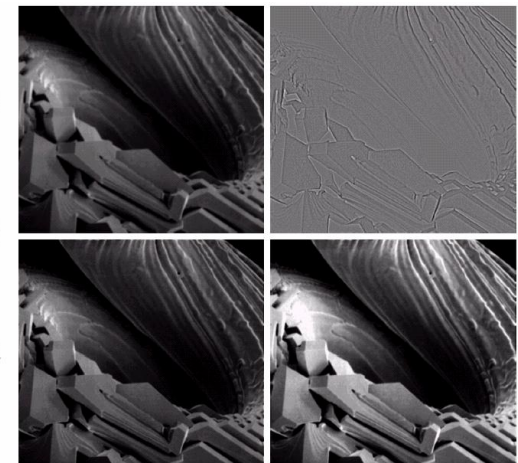


High-boost Filtering

Example

All are processed in **freq domain**

FIGURE 4.29
Same as Fig. 3.43, but using frequency domain filtering. (a) Input image. (b) Laplacian of (a). (c) Image obtained using Eq. (4.4-17) with $A = 2$. (d) Same as (c), but with $A = 2.7$. (Original image courtesy of Mr. Michael Shaffer, Department of Geological Sciences, University of Oregon, Eugene.)



High-Frequency Emphasis Filtering

Definition

_____ is to enhance the high-frequency components of an image.

This can be done by

- Multiplying a HPF by a constant
- Add an offset so that zero frequency term is not eliminated by the filter

$$H_{hfe}(u, v) = a + bH_{hp}(u, v)$$

- $a \geq 0$ from 0.25 to 0.5, $b > a$ from 1.5 to 2.0.
- If $b > 1$, the high frequencies are emphasized
- $a = (A - 1)$ and $b > 1$: High-boost filtering



Homomorphic System

Definition

_____ is to design filter $H(u, v)$ for the **logarithm of the input image**.

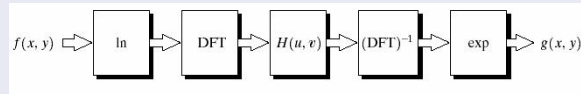


FIGURE 4.31
Homomorphic filtering approach for image enhancement.

Why

Recall

$$f(x, y) = i(x, y)r(x, y)$$

where $i(x, y)$ and $r(x, y)$ are **illumination** and **reflection**

$$\mathcal{F}\{\ln f(x, y)\}H(u, v) = \mathcal{F}\{\ln i(x, y)\}H(u, v) + \mathcal{F}\{\ln r(x, y)\}H(u, v)$$

$$g(x, y) = e^{\mathcal{F}^{-1}\{\mathcal{F}\{\ln i(x, y)\}H(u, v)\}} e^{\mathcal{F}^{-1}\{\mathcal{F}\{\ln r(x, y)\}H(u, v)\}}$$

High-Frequency Emphasis Filtering

Example

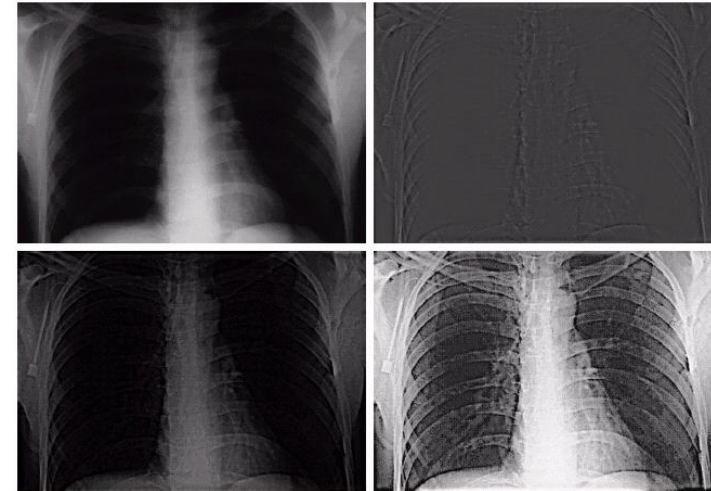


FIGURE 4.30
(a) A chest X-ray image. (b) Result of Butterworth highpass filtering. (c) Result of high-frequency emphasis filtering. (d) Result of performing histogram equalization on (c). (Original image courtesy Dr. Thomas R. Gest, Division of Anatomical Sciences, University of Michigan Medical School.)

Homomorphic filter function $H(u, v)$

- _____: **Slow spatial variations**
⇒ **Low frequency** of the Fourier transform of the logarithm of an image.
- _____: **Vary abruptly** (junctions of dissimilar objects)
⇒ **High frequency** of the Fourier transform of the logarithm of an image.

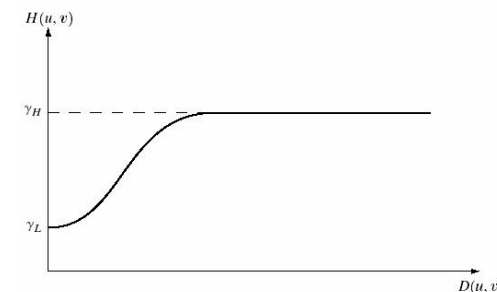


FIGURE 4.32
Cross section of a circularly symmetric filter function. $D(u, v)$ is the distance from the origin of the centered transform.



Homomorphic filter function $H(u, v)$

The curve shape of _____ can be approximated by **modified Gaussian HPF**

$$H(u, v) = (r_H - r_L)[1 - e^{-c(D^2(u, v)/D_0^2)}] + r_L$$

And choose,

- $r_L < 1$ to decrease the illumination contribution
- $r_H > 1$ to amplify reflectance
- c is to control the sharpness of **the slope** of the filter function as it transitions between r_L and r_H .

Note: $r_L < 1$ and $r_H > 1$ achieve simultaneous **dynamic range compression** and **contrast enhancement**



Homomorphic filtering: Example

a b

FIGURE 4.33
(a) Original image. (b) Image processed by homomorphic filtering (note details inside shelter). (Stockham.)

