COL783: Digital Image Processing

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Fourier Transform

Main Idea: A periodic function can be decomposed into a summation of sine and cosine functions

It may be easier and natural to apply some operations in the frequency domain

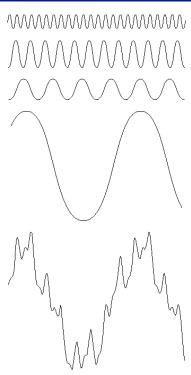


FIGURE 4.1 The function at the bottom is the sum of the four functions above it. Fourier's idea in 1807 that periodic functions could be represented as a weighted sum of sines and cosines was met with skepticism.

Fourier Transform

In continuous domain

$$F(u) \equiv \Im\{f(x)\} = \int_{-\infty}^{\infty} f(x)e^{-j2\pi ux} dx$$

F(u) and f(x) form a Fourier pair.

$$f(x) \equiv \mathfrak{I}^{-1}\{F(u)\} = \int_{-\infty}^{\infty} F(u)e^{j2\pi ux} du$$

1-D:

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

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

Discrete Fourier Transform

Suppose

$$\mathbf{f} = [f_0, f_1, f_2, \dots, f_{N-1}]$$

is a sequence of length N

$$\mathbf{F} = [F_0, F_1, F_2, \dots, F_{N-1}]$$

where

$$F_u = \frac{1}{N} \sum_{x=0}^{N-1} \exp\left[-2\pi i \frac{xu}{N}\right] f_x$$

Discrete Fourier Transform

 For M x N matrix, forward and inverse fourier transforms can be written

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \exp\left[-2\pi i \left(\frac{xu}{M} + \frac{yv}{N}\right)\right].$$

$$f(x,y) = \frac{1}{MN} \sum_{y=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) \exp\left[2\pi i \left(\frac{xu}{M} + \frac{yv}{N}\right)\right].$$

where

- x indices go from 0... M − 1 (x cycles over distance M)
- y indices go from 0... N − 1 (y cycles over distance N)

Discrete Fourier Transform

$$\begin{split} F(u,v) &= \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \exp\left[-2\pi i \left(\frac{xu}{M} + \frac{yv}{N}\right)\right]. \\ f(x,y) &= \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) \exp\left[2\pi i \left(\frac{xu}{M} + \frac{yv}{N}\right)\right]. \end{split}$$

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Discrete Fourier Transform

 DFT as spatial filter: These values are just basis functions (are independent of f and F)

$$\exp\left[\pm 2\pi i \left(\frac{xu}{M} + \frac{yv}{N}\right)\right]$$

- Can be computed in advance, put into formulas later
- Implies each value F(u,v) obtained by multiplying every value of f(x,y)
 by a fixed value, then adding up all results (similar to a filter!)

Discrete Fourier Transform

2-D DFT

Often it is convenient to consider a symmetric transform:

$$v(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} u(n) W_N^{kn} \quad \text{and}$$
$$u(n) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} v(k) W_N^{-kn}$$

In 2-D: consider a NXN image

$$v(k,l) = \frac{1}{N} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} u(m,n) W_N^{km} W_N^{ln},$$

$$u(m,n) = \frac{1}{N} \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} v(k,l) W_N^{-km-ln}$$

Properties

 Notice that Fourier transform "filter elements" can be expressed as products

Seperability

$$\exp\left[2\pi i\left(\frac{xu}{M} + \frac{yv}{N}\right)\right] = \exp\left[2\pi i\frac{xu}{M}\right] \exp\left[2\pi i\frac{yv}{N}\right]$$
2D DFT 1D DFT (row) 1D DFT (column)

 Formula above can be broken down into simpler formulas for 1D DFT

$$F(u) = \sum_{x=0}^{M-1} f(x) \exp\left[-2\pi i \frac{xu}{M}\right],$$

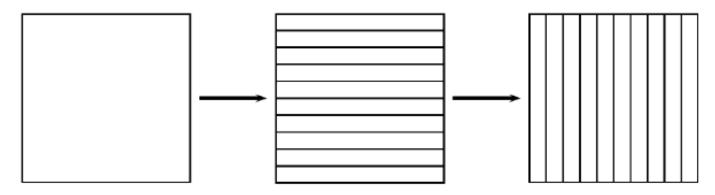
$$f(x) = \frac{1}{M} \sum_{u=0}^{M-1} F(u) \exp\left[2\pi i \frac{xu}{M}\right]$$

Properties

$$F(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} exp[-\frac{2i\pi ux}{N}] \sum_{y=0}^{N-1} f(x,y) exp[-\frac{2i\pi vy}{N}]$$

 Using their separability property, can use 1D DFTs to calculate rows then columns of 2D Fourier Transform

Seperability



(a) Original image

(b) DFT of each row of (a)

(c) DFT of each column of (b)

Properties

 Linearity: DFT of a sum is equal to sum (or multiplication) of the individual DFT's

$$\mathcal{F}(f+g) = \mathcal{F}(f) + \mathcal{F}(g)$$

 $\mathcal{F}(kf) = k\mathcal{F}(f)$ k is a scalar

 Useful property for dealing with degradations that can be expressed as a sum (e.g. noise)

$$d = f + n$$

Where f is original image, n is the noise, d is degraded image

We can find fourier transform as:

$$\mathcal{F}(d) = \mathcal{F}(f) + \mathcal{F}(n)$$

Noise can be removed/reduced by modifying transform of n

Properties

Translation

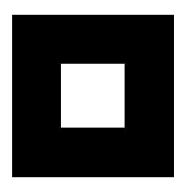
$$f(x,y)exp[\frac{2i\pi(u_0x+v_0y)}{N}] \Leftrightarrow F(u-u_0,v-v_0)$$

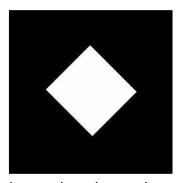
$$f(x-x_0,y-y_0) \Leftrightarrow F(u,v)exp[-\frac{2i\pi(ux_0+vy_0)}{N}]$$

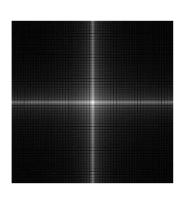
Properties

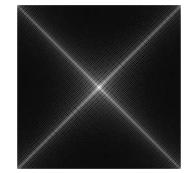
Rotation

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









Source: https://web.cs.wpi.edu/~emmanuel/courses/cs545/S14/slides/lecture10.pdf

Digital Image Processing

Properties

Not commutative

$$\mathcal{F}[f_1(x,y).f_2(x,y)] \neq \mathcal{F}[f_1(x,y)].\mathcal{F}[f_2(x,y)]$$

Properties

Periodicity and Conjugate Symmetry

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

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

Properties

Recall that:

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \exp \left[-2\pi i \left(\frac{xu}{M} + \frac{yv}{N} \right) \right]$$

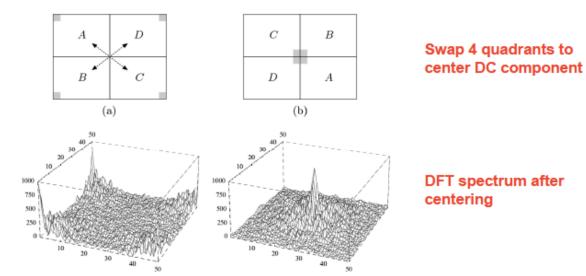
- The value F(0,0) of the DFT is called the dc coefficient
- If we put u = v = 0, then

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

Essentially F(0,0) is the sum of all terms in the original matrix

Properties

- F(0,0) at top left corner
- For display, convenient to have DC component in center
- Just swap four quadrants of Fourier transform



Source: https://web.cs.wpi.edu/~emmanuel/courses/cs545/S14/slides/lecture10.pdf

Digital Image Processing

Properties

Convolution

$$f(x)*h(x) = \int\limits_{-\infty}^{\infty} f(lpha)h(x-lpha)dlpha$$

$$f(x) * h(x) = \sum f(\alpha)h(x - \alpha)$$

$$\mathcal{F}[f(x) * h(x)] = \mathcal{F}[f(x)].\mathcal{F}[h(x)]$$

TABLE 4.1Summary of some important properties of the 2-D Fourier

transform.

Property	Expression(s)
Fourier transform	$F(u,v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi(ux/M + vy/N)}$
Inverse Fourier transform	$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u, v) e^{j2\pi(ux/M + vy/N)}$
Polar representation	$F(u,v) = F(u,v) e^{-j\phi(u,v)}$
Spectrum	$ F(u,v) = [R^2(u,v) + I^2(u,v)]^{1/2}, R = \text{Real}(F) \text{ and } I = \text{Imag}(F)$
Phase angle	$\phi(u,v) = \tan^{-1} \left[\frac{I(u,v)}{R(u,v)} \right]$
Power spectrum	$P(u,v) = F(u,v) ^2$
Average value	$\overline{f}(x,y) = F(0,0) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)$
Translation	$f(x,y)e^{j2\pi(u_0x/M+v_0y/N)} \Leftrightarrow F(u-u_0,v-v_0)$
	$f(x - x_0, y - y_0) \Leftrightarrow F(u, v)e^{-j2\pi(ux_0/M + vy_0/N)}$ When $y = y_0$ and $y = y_0$ then
	When $x_0 = u_0 = M/2$ and $y_0 = v_0 = N/2$, then
	$f(x, y)(-1)^{x+y} \Leftrightarrow F(u - M/2, v - N/2)$
	$f(x - M/2, y - N/2) \Leftrightarrow F(u, v)(-1)^{u+v}$

Conjugate symmetry	$egin{aligned} F(u,v) &= F^*(-u,-v) \ F(u,v) &= F(-u,-v) \end{aligned}$
Differentiation	$\frac{\partial^n f(x,y)}{\partial x^n} \Leftrightarrow (ju)^n F(u,v)$
	$(-jx)^n f(x,y) \Leftrightarrow \frac{\partial^n F(u,v)}{\partial u^n}$
Laplacian	$\nabla^2 f(x, y) \Leftrightarrow -(u^2 + v^2) F(u, v)$
Distributivity	$\Im[f_1(x, y) + f_2(x, y)] = \Im[f_1(x, y)] + \Im[f_2(x, y)]$ $\Im[f_1(x, y) \cdot f_2(x, y)] \neq \Im[f_1(x, y)] \cdot \Im[f_2(x, y)]$
Scaling	$af(x, y) \Leftrightarrow aF(u, v), f(ax, by) \Leftrightarrow \frac{1}{ ab } F(u/a, v/b)$
Rotation	$x = r \cos \theta$ $y = r \sin \theta$ $u = \omega \cos \varphi$ $v = \omega \sin \varphi$ $f(r, \theta + \theta_0) \Leftrightarrow F(\omega, \varphi + \theta_0)$
Periodicity	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)
Separability	See Eqs. (4.6-14) and (4.6-15). Separability implies that we can compute the 2-D transform of an image by first computing 1-D transforms along each row of the image, and then computing a 1-D transform along each column of this intermediate result. The reverse, columns and then rows, yields the same result.

TABLE 4.1 (continued)

- one reason for using Fourier transform in image processing is due to convolution theorem
- Spatial convolution can be performed by element-wise multiplication of the Fourier transform by suitable "filter matrix"

Frequency domain filtering operation

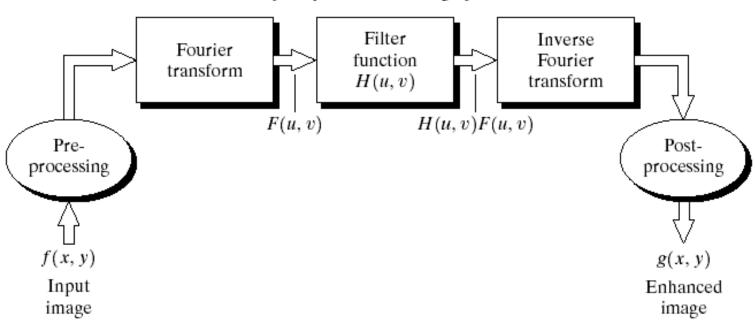
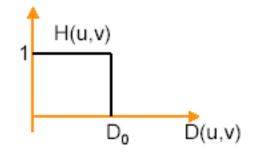


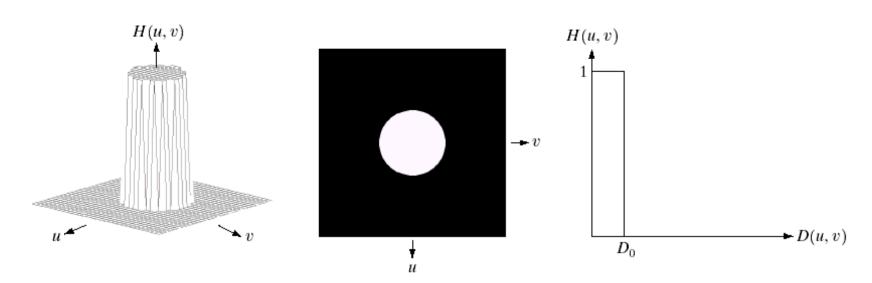
FIGURE 4.5 Basic steps for filtering in the frequency domain.

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

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

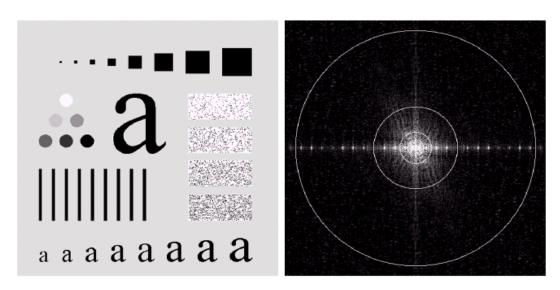
$$D(u,v) = \sqrt{u^2 + v^2} \quad \text{(Circularly symmetric)}$$





a b c

FIGURE 4.10 (a) Perspective plot of an ideal lowpass filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross section.



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.

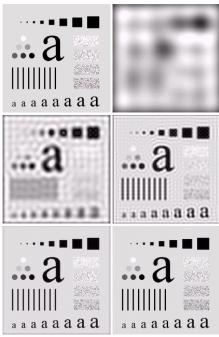
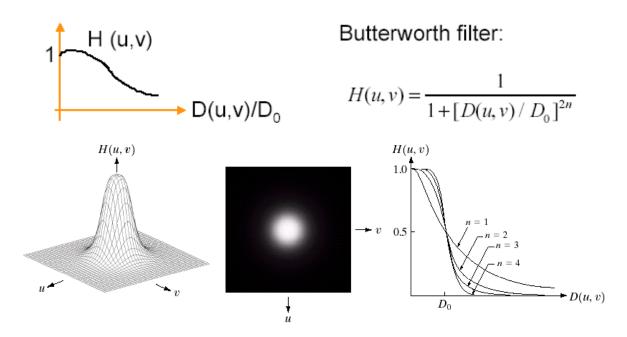


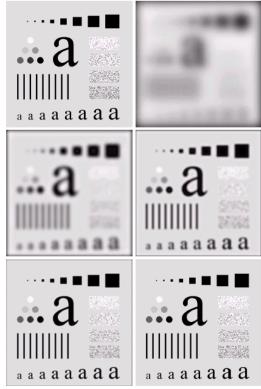
FIGURE 4.12 (a) Original image. (b)–(f) Results of ideal lowpass filtering with cutoff frequencies set at radii values of 5, 15, 30, 80, and 230, as shown in Fig. 4.11(b). The power removed by these filters was 8, 5.4, 3.6, 2, and 0.5% of the total, respectively.

(Source: Gonzalez and Woods)



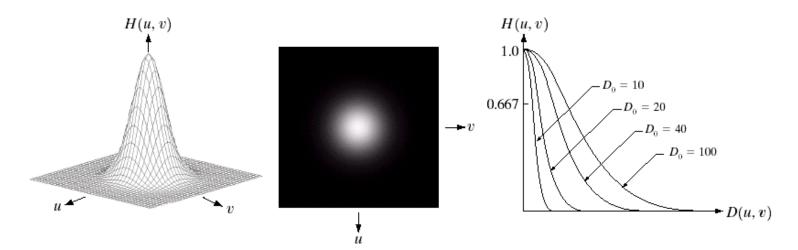
a b c

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.



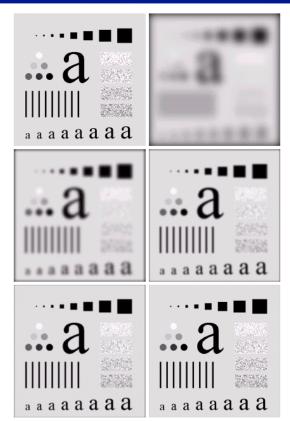
a b | FIGURE 4.15 (a) Original image. (b)–(f) Results of filtering with BLPFs of order 2, with cutoff frequencies at radii of 5, 15, 30, 80, and 230, as shown in Fig. 4.11(b). (STUTTEE: 4Gonzalez and Woods)

$$H(u,v) = \exp(-D^2(u,v)/2\sigma^2)$$



a b c

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 .



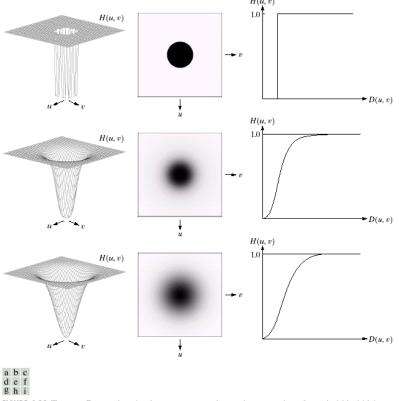
(Source: Gonzalez and Woods)

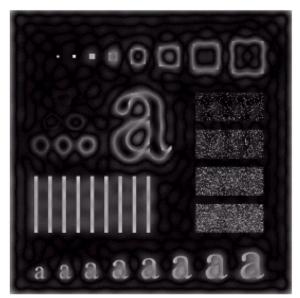
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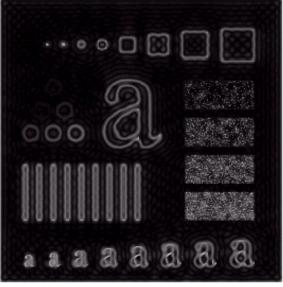
HPF:
$$H(u, v) = \begin{cases} 0 & \text{if } D(u, v) \le D_0 \\ 1 & \text{if } D(u, v) > D_0 \end{cases}$$

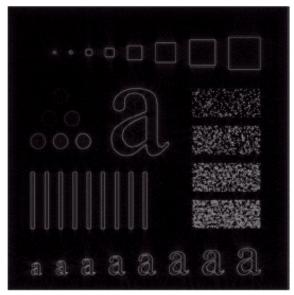
Butterworth filter:

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



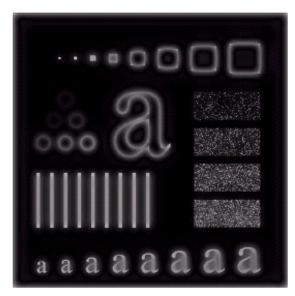


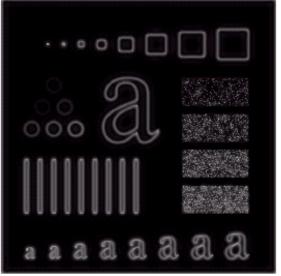


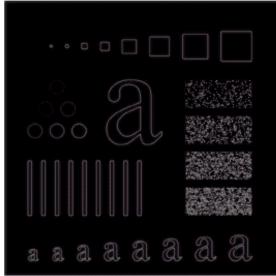


a b c

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).

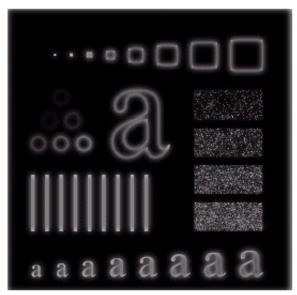






a b c

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.







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.

Fast Fourier Transform

- Many ways to compute DFT quickly
- Fast Fourier Transform (FFT) algorithm is one such way
- One FFT computation method
 - Divides original vector into 2
 - Calculates FFT of each half recursively
 - Merges results