

Discrete Fourier Transform

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CS 663

Fourier Transform

- You have so far studied the Fourier transform of a 1D or 2D continuous (analog) function.
- The functions we deal with in practical signal or image processing are however discrete.
- We need an equivalent of the Fourier transform of such discrete signals.

Towards the Discrete Fourier Transform

- Given a continuous signal $f(t)$, we will consider signal $g(t)$, obtained by sampling $f(t)$ at equally-spaced time instants.
- So $g(t)$ is the pointwise product of $f(t)$ with an impulse train $s_{\Delta T}(t)$ given by:

$$s_{\Delta T}(t) = \sum_{n=-\infty}^{\infty} \delta(t - n\Delta T)$$

$$g(t) = f(t)s_{\Delta T}(t)$$

The impulse functions here are Dirac delta functions.

Towards the Discrete Fourier Transform

$$G(\mu) = \mathcal{F}(g(t)) = \mathcal{F}(f(t)s_{\Delta T}(t)) = F(\mu) * S(\mu)$$

where $S(\mu) = \frac{1}{\Delta T} \sum_{n=-\infty}^{\infty} \delta(\mu - n/\Delta T)$

Check the book
for the derivation
for this

$$\begin{aligned} \therefore G(\mu) &= \int_{-\infty}^{\infty} F(\tau) S(\mu - \tau) d\tau = \frac{1}{\Delta T} \int_{-\infty}^{\infty} F(\tau) \sum_{n=-\infty}^{\infty} \delta(\mu - \tau - n/\Delta T) d\tau \\ &= \frac{1}{\Delta T} \sum_{n=-\infty}^{\infty} F(\mu - n/\Delta T) \end{aligned}$$

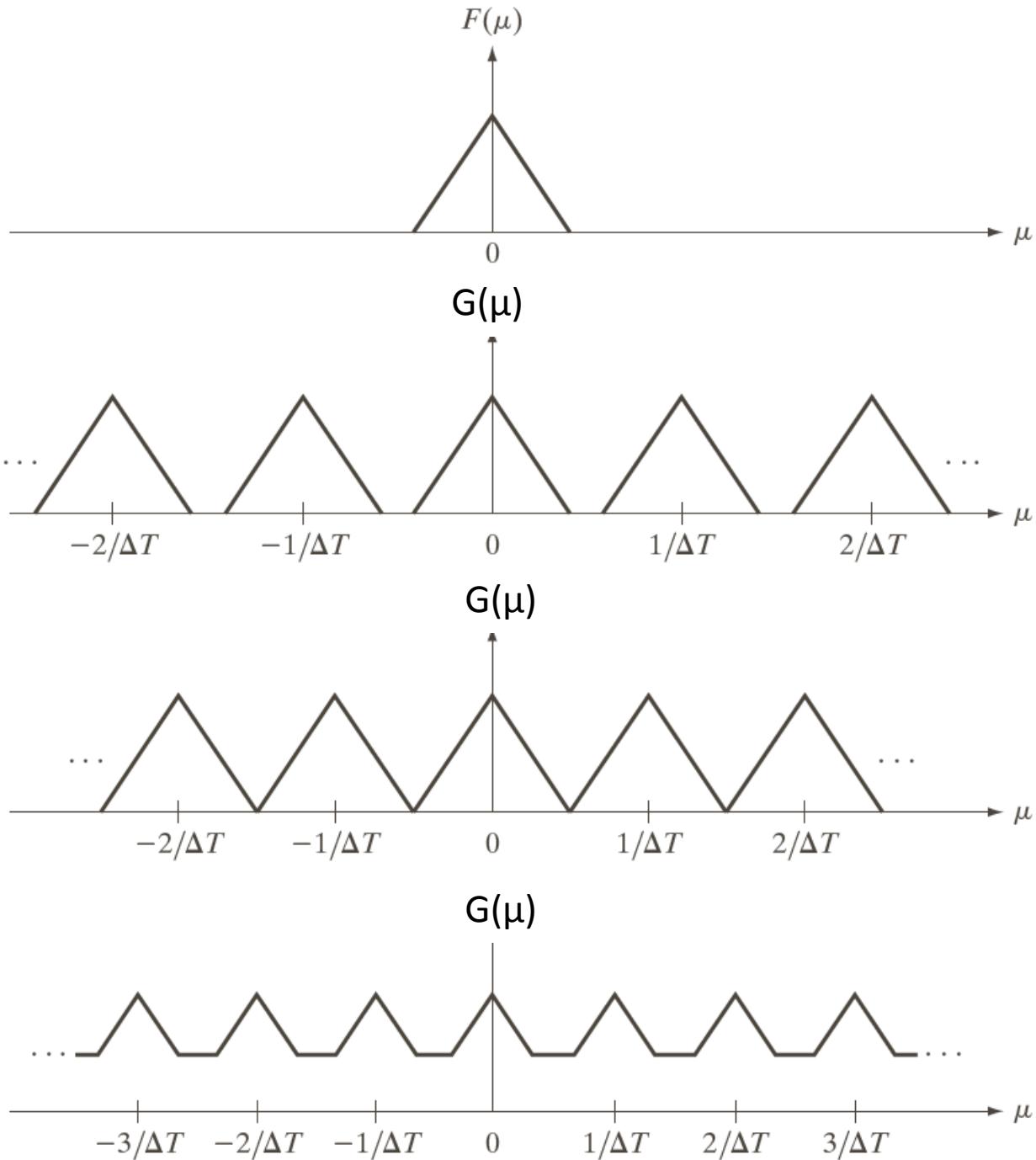
This shows that the Fourier transform $G(\mu)$ of the sampled signal $g(t)$ is an infinite periodic sequence of copies of $F(\mu)$ which is the Fourier transform of $f(t)$. The periodicity of $G(\mu)$ is given by the sampling period ΔT . Also though $g(t)$ is a sampled function, its Fourier transform is continuous.

a
b
c
d

FIGURE 4.6

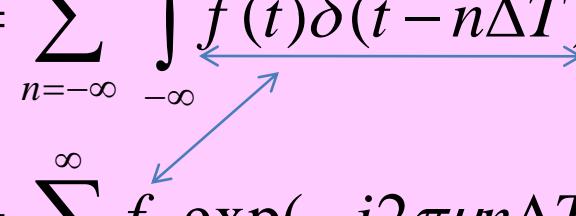
(a) Fourier transform of a band-limited function.

(b)–(d)
Transforms of the corresponding sampled function under the conditions of over-sampling, critically-sampling, and under-sampling, respectively.



Towards the Discrete Fourier Transform

- Let us now try to derive $G(\mu)$ directly in terms of $g(t)$ instead of $F(\mu)$.

$$\begin{aligned} G(\mu) &= \mathcal{F}(g(t)) = \int_{-\infty}^{\infty} g(t) \exp(-j2\pi\mu t) dt \\ &= \int_{-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(t) \delta(t - n\Delta T) \exp(-j2\pi\mu t) dt \\ &= \sum_{n=-\infty}^{\infty} \int_{-\infty}^{\infty} f(t) \delta(t - n\Delta T) \exp(-j2\pi\mu t) dt \\ &= \sum_{n=-\infty}^{\infty} f_n \exp(-j2\pi\mu n\Delta T) \end{aligned}$$


$f(t)\delta(t-n\Delta T)$ is the sampled function (a Dirac impulse weighted by $f(t)$). To get the actual sample values (the strength of the impulse), we do an integration, i.e. of the following form:

$$f_n = \int_{-\infty}^{\infty} f(t) \delta(t - n\Delta T) dt = f(n\Delta T)$$

Towards the Discrete Fourier Transform

- We have seen earlier that the Fourier transform of $g(t)$ is periodic with period ΔT , so it is of interest to characterize one period.
- Consider that we take some M equally spaced samples of $G(\mu)$ over one period from $\mu = 0$ to $1/\Delta T$.
- This gives us frequencies of the form $\mu = u/M\Delta T$ where $u = 0, 1, 2, \dots, M-1$.

Towards the Discrete Fourier Transform

- Plugging these values for μ we now have:

$$G(u) = F_d(u) = \sum_{n=0}^{M-1} f_n \exp(-j2\pi un / M)$$

- This is called the Discrete Fourier Transform of the sequence $\{f_n\}$ where $n = 0, 1, \dots, M-1$.
- Given the sequence $\{F_d(u)\}$ where $u = 0, 1, \dots, M-1$, we can recover $\{f_n\}$ using:

$$f(n) = f_n = \frac{1}{M} \sum_{u=0}^{M-1} F_d(u) \exp(j2\pi un / M)$$

This is the inverse Discrete Fourier Transform (IDFT).

Towards the Discrete Fourier Transform

- Consider:

$$G(u) = F_d(u) = \sum_{n=0}^{M-1} f_n \exp(-j2\pi un / M)$$

$$f(n) = \frac{1}{M} \sum_{u=0}^{M-1} F_d(u) \exp(j2\pi un / M)$$

- It can be proved that plugging in the expression for $f(n)$ into the expression for $F_d(u)$ yields the identity $F_d(u) = F_d(u)$.
- Also plugging in the expression for $F_d(u)$ into the expression for $f(n)$ yields the identity $f(n) = f(n)$.

Towards the Discrete Fourier Transform

- In some books, the following expressions are used:

$$F_d(u) = \frac{1}{\sqrt{M}} \sum_{n=0}^{M-1} f_n \exp(-j2\pi un / M)$$

$$f(n) = \frac{1}{\sqrt{M}} \sum_{u=0}^{M-1} F_d(u) \exp(j2\pi un / M)$$

MATLAB does NOT follow this convention – it follows the one on the earlier slide.

- Note that the above expressions can be written in the following matrix vector format:

$$\mathbf{f} = \mathbf{U} \mathbf{F}_d$$

Vectors of size M by 1

$$\mathbf{F}_d = \mathbf{U}^T \mathbf{f}$$

\mathbf{U} turns out to be an **orthonormal** M by M matrix – called the *discrete Fourier basis matrix* or *DFT matrix*. The square root of M in the denominator is required for \mathbf{U} to be orthonormal, else it would be proportional to an orthonormal matrix.

$$\mathbf{f} = \mathbf{U}\mathbf{F}_d$$

$$\mathbf{F}_d = \mathbf{U}^T \mathbf{f}$$

Vectors of size M by 1

\mathbf{U} is an orthonormal M by M matrix – called the discrete Fourier basis matrix or DFT matrix. The square root of M is required for \mathbf{U} to be orthonormal, else it would be proportional to an orthonormal matrix.

$\mathbf{f} = \mathbf{U}\mathbf{F}_d, \mathbf{f} \in \mathbf{R}^M, \mathbf{F}_d \in \mathbf{C}^M, \mathbf{U} \in \mathbf{C}^{M \times M}; \mathbf{C} = \text{complex domain}, \mathbf{R} = \text{real domain}$

$$\begin{pmatrix} f(0) \\ f(1) \\ \vdots \\ \vdots \\ f(M-1) \end{pmatrix} = \frac{1}{\sqrt{M}} \begin{pmatrix} e^{j2\pi(0)(0)/M} & e^{j2\pi(0)(1)/M} & \dots & e^{j2\pi(0)(M-1)/M} \\ e^{j2\pi(1)(0)/M} & e^{j2\pi(1)(1)/M} & \dots & e^{j2\pi(1)(M-1)/M} \\ \vdots & \vdots & \ddots & \vdots \\ e^{j2\pi(M-1)(0)/M} & e^{j2\pi(M-1)(1)/M} & \dots & e^{j2\pi(M-1)(M-1)/M} \end{pmatrix} \begin{pmatrix} F_d(0) \\ F_d(1) \\ \vdots \\ \vdots \\ F_d(M-1) \end{pmatrix}$$

$$= \frac{1}{\sqrt{M}} \begin{pmatrix} e^{j2\pi(0)(0)/M} \\ e^{j2\pi(1)(0)/M} \\ \vdots \\ \vdots \\ e^{j2\pi(M-1)(0)/M} \end{pmatrix} F_d(0) + \frac{1}{\sqrt{M}} \begin{pmatrix} e^{j2\pi(0)(1)/M} \\ e^{j2\pi(1)(1)/M} \\ \vdots \\ \vdots \\ e^{j2\pi(M-1)(1)/M} \end{pmatrix} F_d(1) + \dots + \frac{1}{\sqrt{M}} \begin{pmatrix} e^{j2\pi(0)(M-1)/M} \\ e^{j2\pi(1)(M-1)/M} \\ \vdots \\ \vdots \\ e^{j2\pi(M-1)(M-1)/M} \end{pmatrix} F_d(M-1)$$

Notice in the last equality how the signal \mathbf{f} is being represented as a linear combination of column vectors of the DFT matrix. The coefficients of the linear combination are the *discrete Fourier coefficients*!

Sampling in time and frequency

- Remember that the function $g(t)$ was created by sampling $f(t)$ with a period of ΔT .
- And the spacing between the samples in the frequency domain (to get the DFT from $G(\mu)$) is $1/ \Delta T$ since $\mu = u/M\Delta T$ where $u = 0,1,2,\dots,M-1$.
- Likewise the *range of frequencies* spanned by the DFT is also inversely proportional to ΔT .

DFT properties

- Linearity: $\mathcal{F}(af+bg)(u) = a\mathcal{F}(f)(u) + b\mathcal{F}(g)(u)$
- Periodicity: $F(u) = F(u + kM)$ for integer k ,
- And so is the inverse DFT since $f(n) = f(n+kM)$.
- The DFT is in general complex. Hence it has a *magnitude* $|F(u)|$ and a *phase*.

Clarification about DFT

- We have seen earlier that the Fourier transform $G(\mu)$ of the sampled version $g(t)$ of analog signal $f(t)$ is continuous.
- We also saw earlier that we take some M equally spaced samples of $G(\mu)$ over one period from $\mu = 0$ to $1/\Delta T$.
- This way the DFT and the discrete signal both were vectors of M elements.
- Obtaining the DFT given the signal (or the signal given its DFT) is an efficient operation owing to the orthonormality of the discrete Fourier matrix (why efficient? Because for an orthonormal matrix, inverse = transpose).
- Why don't we take more than M samples in the frequency domain?
- If we did, the aforementioned computational efficiency would be lost. The inverse transform would require a matrix pseudo-inverse which is costly.
- Also the columns of the orthonormal matrix \mathbf{U}^T (size $M \times M$) constitute a basis: i.e. any vector in M -dimensional space can be **uniquely** represented using linear combination of the columns of that matrix. If you took more than M samples in the frequency domain, that **uniqueness** would be lost as \mathbf{U}^T would now have size $M' \times M$ where $M' > M$.

Convolution of discrete signals

- Discrete equivalent of the convolution is:

$$(f * h)(n) = \sum_{m=0}^{M-1} f(m)h(n-m)$$

- Due to the periodic nature of the DFT and IDFT, the convolution will also be periodic.
- The above formula represents one period of that periodic resultant signal.

Convolution of discrete signals

- The convolution theorem from continuous signals has an extension to the discrete case as well:

$$\mathcal{F}(f * h)(u) = F(u)H(u)$$

- Therefore discrete convolution can be implemented using product of DFTs followed by an IDFT.
- But in doing so, one has to account for **periodicity issues** to avoid *wrap-around artifacts* (see next slide).

Convolution of discrete signals

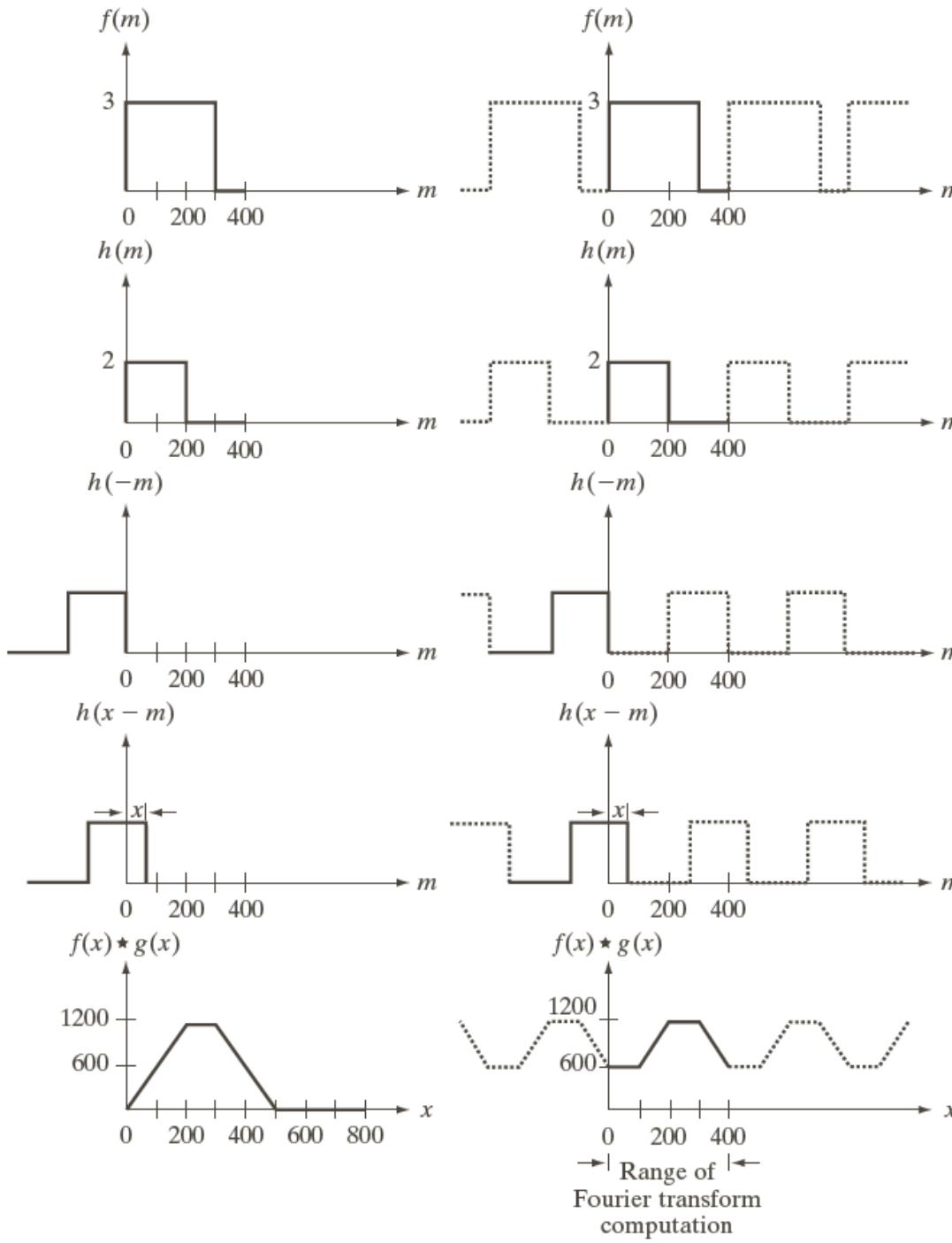
- Consider the discrete convolution:

$$(f * h)(n) = \sum_{l=0}^{M-1} f(l)h(n-l)$$

- To convolve f with h , you need to (1) flip h about the origin, (2) translate the flipped signal by an amount n , and (3) compute the sum in the above formula.
- Steps 2 and 3 are repeated for each value of n .
- The variable n ranges over all integers required to completely slide h over f .
- If h and f have size M , then n has to range up to $2M-1$.

Convolution of discrete signals

- In other words, the resultant signal must have length of $2M-1$.
- The convolution can be implemented in the time/spatial domain – and MATLAB has a routine called **conv** which does the job for you!
- Now imagine you tried to implement the convolution using a DFT of M -point signals followed by an M -point IDFT.
- Owing to the assumed periodicity, you would get an undesirable wrap-around effect. See next slide for an illustration.



a	f
b	g
c	h
d	i
e	j

FIGURE 4.28 Left column: convolution of two discrete functions obtained using the approach discussed in Section 3.4.2. The result in (e) is correct. Right column: Convolution of the same functions, but taking into account the periodicity implied by the DFT. Note in (j) how data from adjacent periods produce wraparound error, yielding an incorrect convolution result. To obtain the correct result, **function padding** must be used.

Convolution of discrete signals

- How does one deal with this conundrum?
- If \mathbf{f} has length M and \mathbf{h} has length K , then you should zero-pad both sequences so that they now have length at least $M+K-1$.
- Then compute $M+K-1$ point DFT for both, multiply the DFTs and compute the $M+K-1$ point IDFT.

Convolution of discrete signals: 2 methods

- Consider you want to convolve signal f having N elements with signal h having K elements.
- You can use the **conv** routine in MATLAB – which by default produces a signal of $N+K-1$ elements for you. It takes care of zero-padding internally for you.
- The other (equivalent) alternative is to:
 - Append f with $K-1$ zeros.
 - Append h with $N-1$ zeros.
 - Compute the $N+K-1$ point DFT of f and h (using **fft**).
 - Multiply the two DFTs point-wise.
 - Compute the IDFT of the result – this gives you a signal with $N+K-1$ elements.
- In both cases, you may wish to extract the first N elements of the resultant signal (note that the trailing $K-1$ elements may not be zeros!).

Why convolution using Fourier transforms?

- The time complexity of computing the convolution of a signal of length M with another of length M is $O(M^2)$.
- With a DFT computed naively, it would remain $O(M^2)$ – the complexity of multiplying a $M \times M$ matrix with a $M \times 1$ vector.

$$\mathbf{f} = \mathbf{U}\mathbf{F}_d$$

$$\mathbf{F}_d = \mathbf{U}^T \mathbf{f}$$

Why convolution using Fourier transforms?

- But there's a smarter way of doing the same which computes the DFT in $O(M \log M)$ time.
- That is called the **Fast Fourier Transform**, discovered by Cooley and Tukey in 1965.
- It is based on a **divide and conquer** algorithmic strategy.
- The same strategy can be used to compute the IDFT in $O(M \log M)$ time.
- Hence convolution can now be computed in $O(M \log M)$ time.

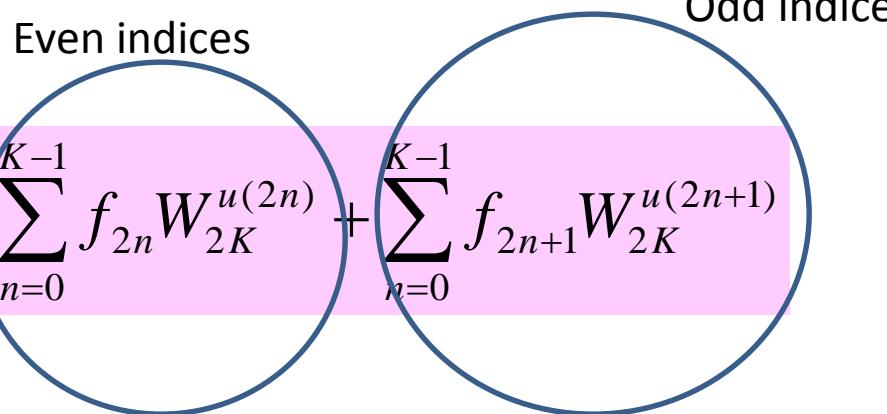
Towards the Fast Fourier Transform

$$F(u) = \sum_{n=0}^{M-1} f_n \exp(-j2\pi un/M) = \sum_{n=0}^{M-1} f_n W_M^{un}$$

where $W_M = \exp(-j2\pi/M)$

Let $M = 2^n = 2K$

$$F(u) = \sum_{n=0}^{2K-1} f_n W_{2K}^{un} = \sum_{n=0}^{K-1} f_{2n} W_{2K}^{u(2n)} + \sum_{n=0}^{K-1} f_{2n+1} W_{2K}^{u(2n+1)}$$



$$\therefore F(u) = \sum_{n=0}^{K-1} f_{2n} W_K^{u(n)} + \sum_{n=0}^{K-1} f_{2n+1} W_K^{u(n)} W_{2K}^u \xrightarrow{\therefore W_{2K}^{u(2n)} = W_K^{u(n)}}$$

Towards the Fast Fourier Transform

$$\therefore F(u) = \sum_{n=0}^{K-1} f_{2n} W_K^{u(n)} + \sum_{n=0}^{K-1} f_{2n+1} W_K^{u(n)} W_{2K}^u$$

Define $F_{even}(u) = \sum_{n=0}^{K-1} f_{2n} W_K^{u(n)}$, $F_{odd}(u) = \sum_{n=0}^{K-1} f_{2n+1} W_K^{u(n)}$

$$\therefore F(u) = F_{even}(u) + F_{odd}(u) W_{2K}^u \text{ for } u = 0, 1, \dots, K-1$$

$$\text{and } F(u+K) = F_{even}(u) - F_{odd}(u) W_{2K}^u \text{ for } u = 0, 1, \dots, K-1$$

$$\text{as } W_{2K}^{u+K} = W_{2K}^u W_{2K}^K = W_{2K}^u \exp(-j2\pi K / 2K) = -W_{2K}^u$$

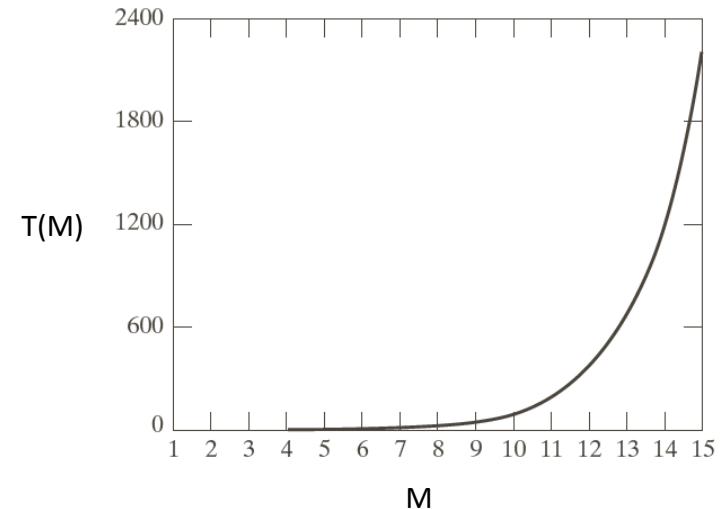
The M -point DFT computation for F is split up into **two halves**. The **first half** requires two $M/2$ -point DFT computations – one for F_{even} , one for F_{odd} . The **second half** follows directly without any additional transform evaluations once F_{even} and F_{odd} are computed. Now F_{even} and F_{odd} can be further split up **recursively**.

Towards the Fast Fourier Transform

The M -point DFT computation for F is split up into **two halves**. The **first half** requires two $M/2$ -point DFT computations – one for F_{even} , one for F_{odd} . The **second half** follows directly without any additional transform evaluations once F_{even} and F_{odd} are computed. Now F_{even} and F_{odd} can be further split up **recursively**.

This gives:

$$\begin{aligned}T(1) &= c \text{ (constant)} \\T(M) &= 2T(M/2) + M \\&= 2(2T(M/4) + M/2) + M = 2^2T(M/2^2) + 2M \\&= \dots \\&= 2^kT(M/2^k) + kM \\&= O(M \log M)\end{aligned}$$



There is also a fast inverse Fourier transform which works quite similarly in $O(M \log M)$ time. The speedup achieved by the fast Fourier transform over a naïve DFT computation is rather dramatic for large M !

MATLAB implementation

- The Fast Fourier Transform is implemented in MATLAB directly – there are the routines **fft** and **ifft** for the inverse.

2D-DFT

- Given a 2D discrete signal (image) $f(x,y)$ of size W_1 by W_2 , its DFT is given as:

$$F_d(u, v) = \frac{1}{\sqrt{W_1 W_2}} \sum_{x=0}^{W_1-1} \sum_{y=0}^{W_2-1} f(x, y) \exp(-j2\pi(ux/W_1 + vy/W_2))$$

$$f(x, y) = \frac{1}{\sqrt{W_1 W_2}} \sum_{u=0}^{W_1-1} \sum_{v=0}^{W_2-1} F(u, v) \exp(j2\pi(ux/W_1 + vy/W_2))$$

2D-DFT computation

- Given a 2D discrete signal (image) $f(x,y)$ of size W_1 by W_2 , its DFT is given as:

$$F_d(u,v) = \frac{1}{\sqrt{W_1 W_2}} \sum_{x=0}^{W_1-1} \sum_{y=0}^{W_2-1} f(x,y) \exp(-j2\pi vy/W_2) \exp(-j2\pi ux/W_1)$$

Compute row-wise FFT, followed by a column-wise FFT. Overall complexity is $W_1 W_2 \log(W_1 W_2)$.

$$f(x,y) = \frac{1}{\sqrt{W_1 W_2}} \sum_{u=0}^{W_1-1} \sum_{v=0}^{W_2-1} F(u,v) \exp(j2\pi(ux/W_1 + vy/W_2))$$

MATLAB implementation

- The FFT for 2D arrays or images is implemented in MATLAB routines **fft2** and **ifft2**.

2D-DFT properties

- Linearity: $\mathcal{F}(af+bg)(u,v) = a\mathcal{F}(f)(u,v) + b\mathcal{F}(g)(u,v)$ where a and b are scalars.
- Periodicity: $F(u,v) = F(u + k_1 W_1, v) = F(u, v + k_2 W_2) = F(u + k_1 W_1, v + k_2 W_2)$ for integer k_1 and k_2 .
- And so is the inverse DFT since $f(x,y) = f(x + k_1 W_1, y) = f(x, y + k_2 W_2) = f(x + k_1 W_1, y + k_2 W_2)$ for integer k_1 and k_2 .

2D-DFT: Magnitude and phase

- The phase carries very critical information.
- If you retain the magnitude of the Fourier transform of an image, but change its phase, the appearance drastically changes.



IFT (Magnitude of FT
of Salman Khan times
phase of P V Sindhu)



IFT (Magnitude of FT
of P V Sindhu times
phase of Salman
Khan)



2D-DFT properties

- Translation:

$$\mathcal{F}(f(x - x_0, y - y_0))(u, v) = F(u, v) \exp(-j2\pi(ux_0/W_1 + vy_0/W_2))$$
$$F(u - u_0, v - v_0) = f(x, y) \exp(j2\pi(xu_0/W_1 + yv_0/W_2))$$

- Note that translation of a signal does not change the magnitude of the Fourier transform – only its phase.

2D-DFT properties

- The Fourier transform of a rotated image yields a rotated version of its Fourier transform

$$\begin{aligned}\mathcal{F}(f(x, y))(u, v) &= F(u, v) \rightarrow \\ \mathcal{F}(f(x \cos \phi - y \sin \phi, x \sin \phi + y \cos \phi))(u, v) &= \\ F(u \cos \phi - v \sin \phi, u \sin \phi + v \cos \phi)\end{aligned}$$

- If you consider conversion to polar coordinates, then we have:

$$\begin{aligned}x &= r \cos \theta, y = r \sin \theta \\ u &= \omega \cos \theta, v = \omega \sin \theta\end{aligned}$$

$$\begin{aligned}\mathcal{F}(f(x, y))(u, v) &= F(u, v) \rightarrow \\ \mathcal{F}(f(r \cos(\theta + \phi), r \sin(\theta + \phi)))(u, v) &= \\ F(\omega \cos(\theta + \phi), \omega \sin(\theta + \phi))\end{aligned}$$

2D-DFT visualization in MATLAB

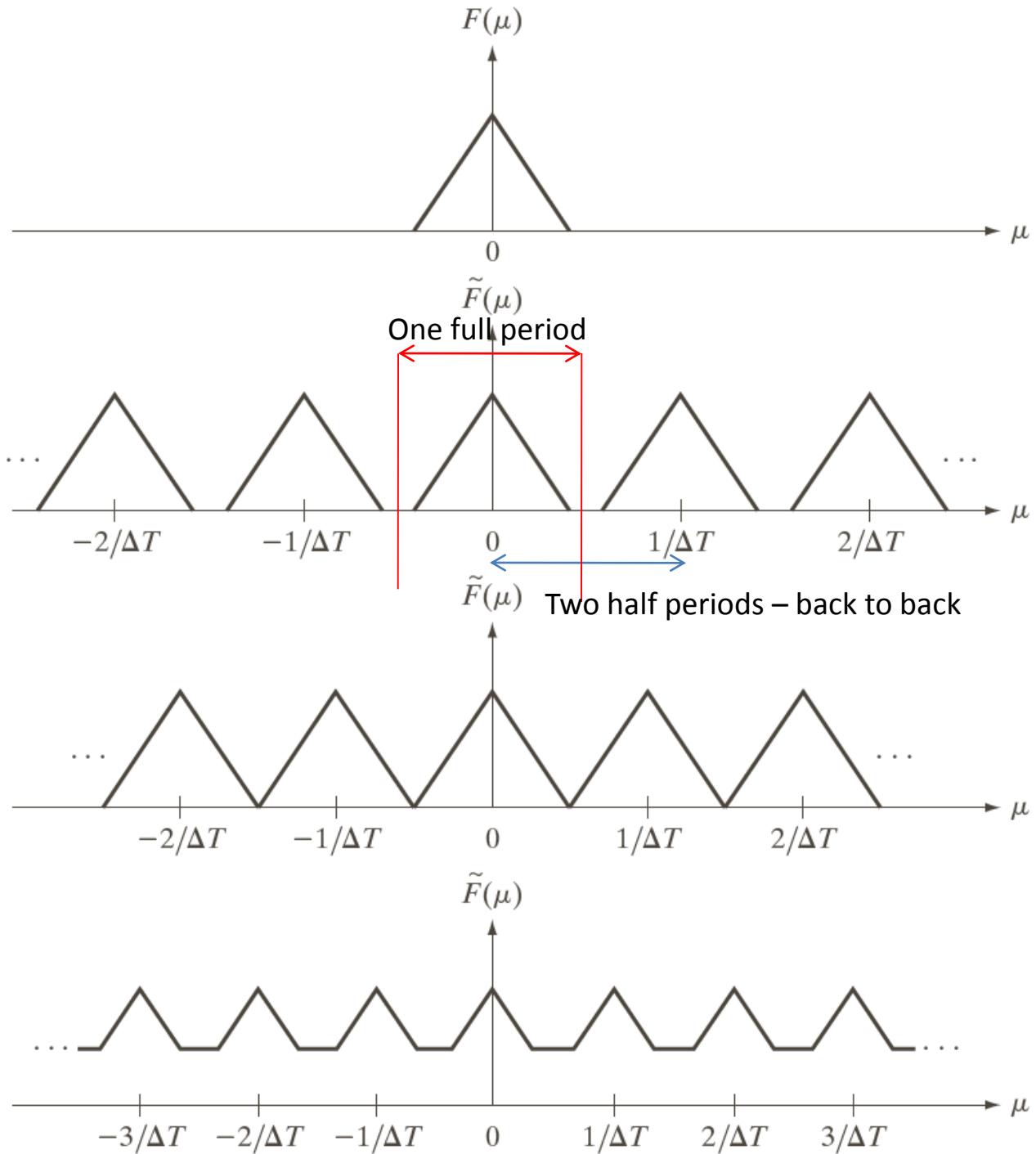
- In the formula for the DFT, the frequency range from $u = 0$ to $u = M-1$ actually represents two half periods back to back meeting at $M/2$ (see next slide).
- It is more convenient to instead view a complete period of the DFT instead.
- For that purpose we visualize $F(u-M/2)$ instead of $F(u)$ in 1D, and $F(u-W_1/2, v-W_2/2)$ instead of $F(u, v)$ in 2D.
- Thereby frequency $u = 0$ or $u = v = 0$ now occurs at the center of the displayed Fourier transform.
- Note that $F(u-W_1/2, v-W_2/2) = \mathcal{F}(f(x, y)(-1)^{x+y})(u, v)$, so the centering operation is easy to implement.

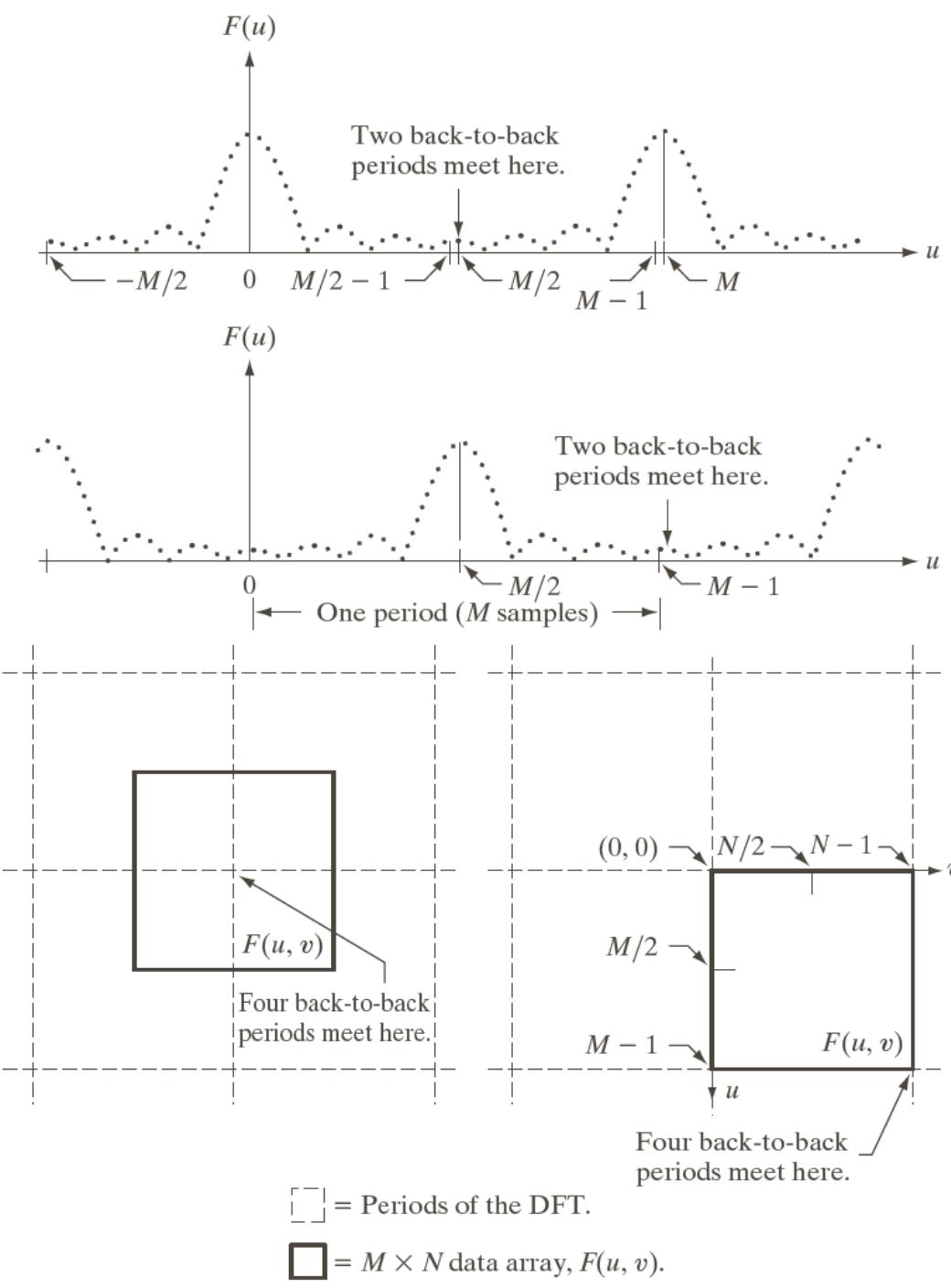
a
b
c
d

FIGURE 4.6

(a) Fourier transform of a band-limited function.

(b)–(d)
Transforms of the corresponding sampled function under the conditions of over-sampling, critically-sampling, and under-sampling, respectively.





a
b
c d

FIGURE 4.23
Centering the Fourier transform.
 (a) A 1-D DFT showing an infinite number of periods.
 (b) Shifted DFT obtained by multiplying $f(x)$ by $(-1)^x$ before computing $F(u)$.
 (c) A 2-D DFT showing an infinite number of periods. The solid area is the $M \times N$ data array, $F(u, v)$, obtained with Eq. (4.5-15). This array consists of four quarter periods.
 (d) A Shifted DFT obtained by multiplying $f(x, y)$ by $(-1)^{x+y}$ before computing $F(u, v)$. The data now contains one complete, centered period, as in (b).

2D-DFT visualization in MATLAB

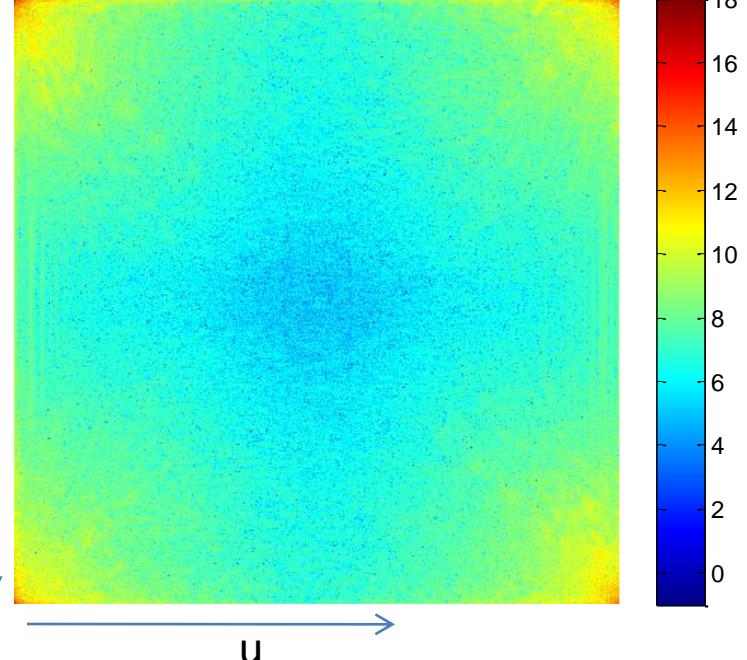
- To visualize the DFT of an image, we visualize the magnitude of the DFT.
- The Fourier transform is first centered as mentioned on the previous slide.
- Due to the large range of magnitude values, the DFT magnitudes are visualized on a logarithmic scale, i.e. we view $\log(|F(u,v)|+1)$ where the 1 is added for stability.



Without centering the fft

```
fim2 = fft2(im2);
absfim2 = log(abs(fim2)+1);
imshow(absfim1,[-1 18]);
colormap (jet); colorbar;
```

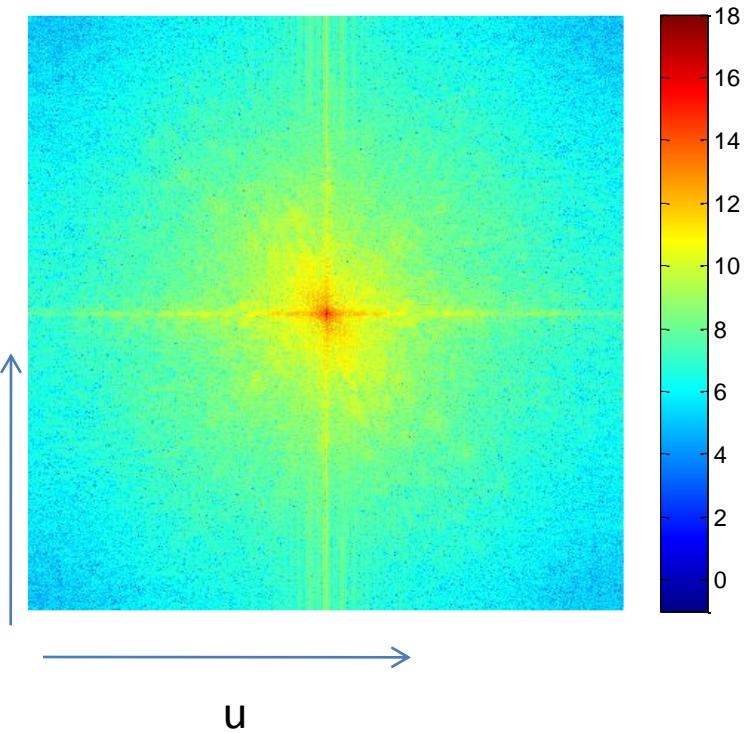
The (0,0) frequency lies at the top left corner



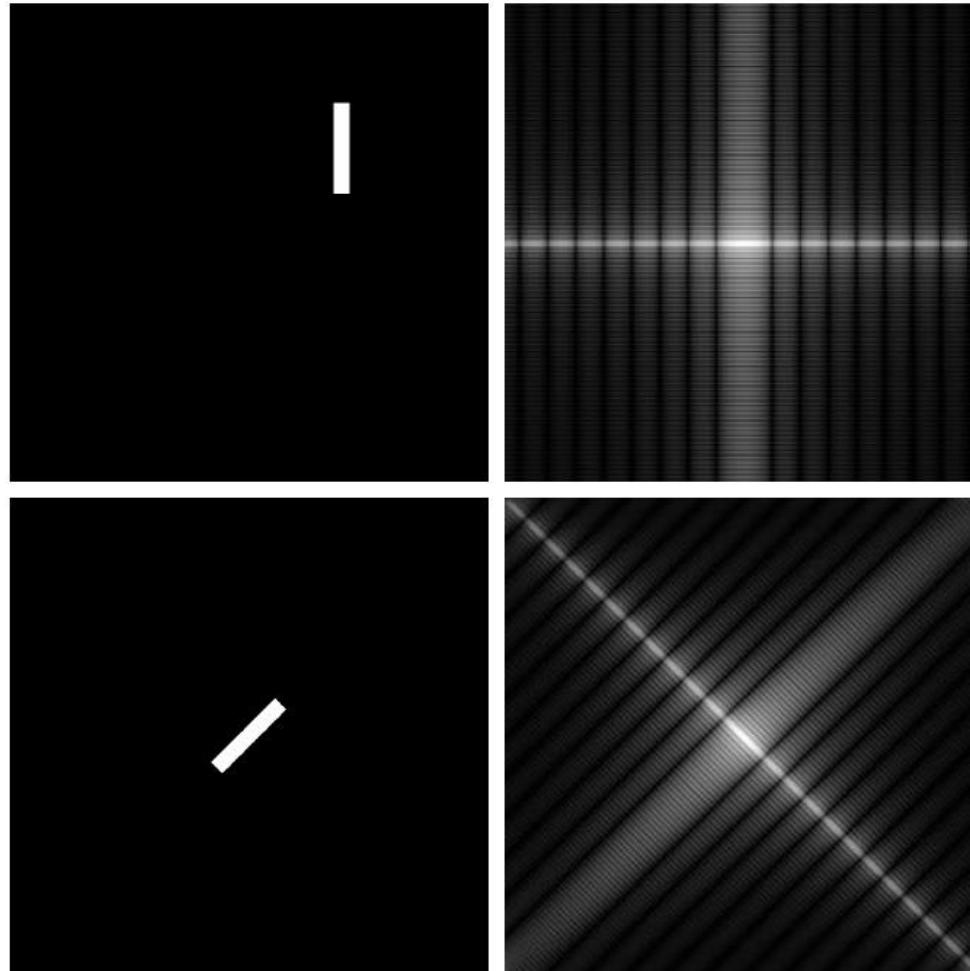
With centering the fft

```
fim2 = fftshift(fft2(im2));
absfim2 = log(abs(fim2)+1);
imshow(absfim1,[-1 18]);
colormap (jet); colorbar;
```

The (0,0) frequency lies in the Center.



“Viewing” the rotation property of the DFT



a	b
c	d

FIGURE 4.25

(a) The rectangle in Fig. 4.24(a) translated, and (b) the corresponding spectrum. (c) Rotated rectangle, and (d) the corresponding spectrum. The spectrum corresponding to the translated rectangle is identical to the spectrum corresponding to the original image in Fig. 4.24(a).

2D convolution

- In MATLAB, 2D convolution can be implemented using the routine **conv2**.
- This can be very expensive if the signals you wish to convolve another with, are of large size.
- Hence one resorts to the convolution theorem which holds in 2D as well.

2D convolution

- The convolution theorem applies to 2D-DFTs as well:

$$\mathcal{F}(f * h)(u, v) = F(u, v)H(u, v)$$

- Consider an image f of size $W_1 \times W_2$ which you want to convolve with a kernel k of size $K_1 \times K_2$ using the DFT method.
- Then you should symmetrically zero-pad f and k so that they acquire size $W_1+K_1-1 \times W_2+K_2-1$.
- Compute the DFTs of the zero-padded images using the FFT algorithm, point-wise multiply them and obtain the IDFT of the result.
- Extract the central $W_1 \times W_2$ portion of the result – for the final answer.

Image Filtering: Frequency domain

- You have studied image filters of various types: mean filter, Gaussian filter, bilateral filter, patch-based filter.
- The former two are linear filters and the latter two aren't.
- Linear filters are represented using convolutions and hence have a frequency domain interpretation as seen on the previous slides.

Image Filtering: Frequency domain

- Hence such filters can also be designed in the frequency domain.
- In certain applications, it is in fact more intuitive to design filters directly in the frequency domain.
- Why? Because you get to design directly which frequency components to weaken/eliminate and which ones to boost, and by how much.

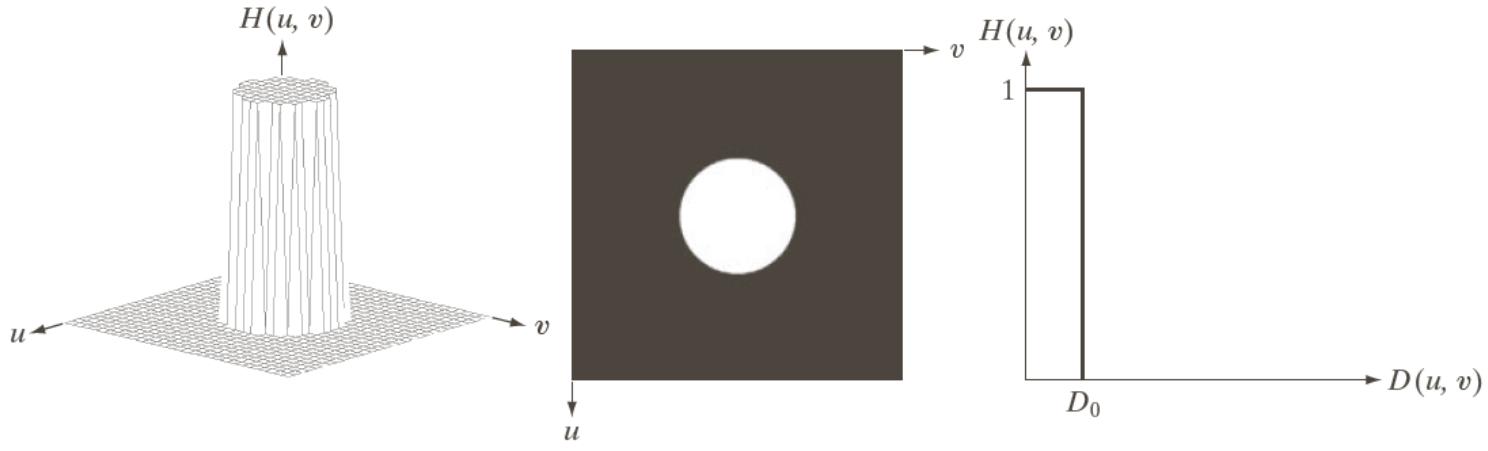
Low pass filters

- Edges and fine textures in images contribute significantly to the high frequency content of an image.
- When you smooth/blur an image, these edges and textures are weakened (or removed).
- Such filters allow only the low frequencies to remain intact and are called as **low pass filters**.
- In the frequency domain, an ideal low pass filter can be represented as follows:

$$H(u, v) = \begin{cases} 1, & \text{if } u^2 + v^2 \leq D^2 \\ 0, & \text{otherwise} \end{cases}$$

Note: we are assuming (0,0) to be the center (lowest) frequency. Frequencies outside a radius of D from the center frequency are eliminated.

Low pass filters



a | b | c

FIGURE 4.40 (a) Perspective plot of an ideal lowpass-filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross section.

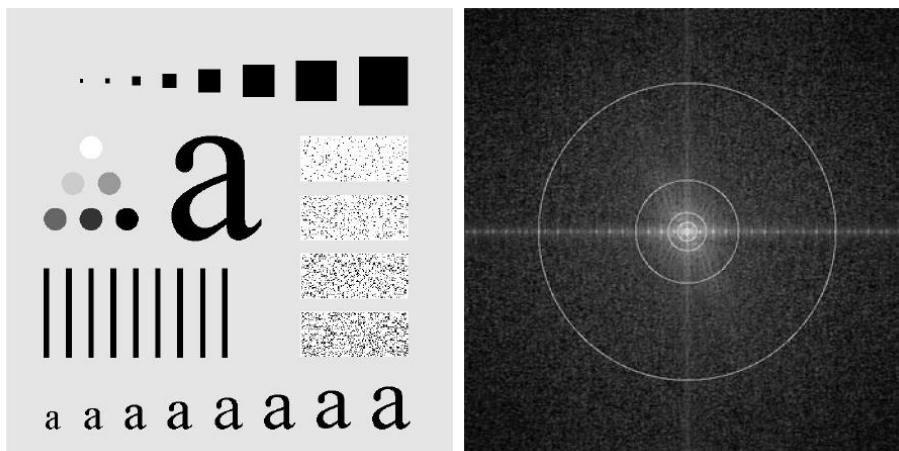
Low pass filters

- To apply such a filter to an image f to create a filtered image g , we do as follows:

$$\begin{aligned} H(u, v) &= 1, \text{ if } u^2 + v^2 \leq D^2 \\ &= 0 \text{ otherwise} \\ G(u, v) &= F(u, v)H(u, v) \end{aligned}$$

- D is a design parameter of the filter – often called the **cutoff frequency**.
- This is called the **ideal** low pass filter as it completely eliminates frequencies outside the chosen radius.

Low pass filters



a b

FIGURE 4.41 (a) Test pattern of size 688×688 pixels, and (b) its Fourier spectrum. The spectrum is double the image size due to padding but is shown in half size so that it fits in the page. The superimposed circles have radii equal to 10, 30, 60, 160, and 460 with respect to the full-size spectrum image. These radii enclose 87.0, 93.1, 95.7, 97.8, and 99.2% of the padded image power, respectively.

Notice the ringing artifacts around the edges!

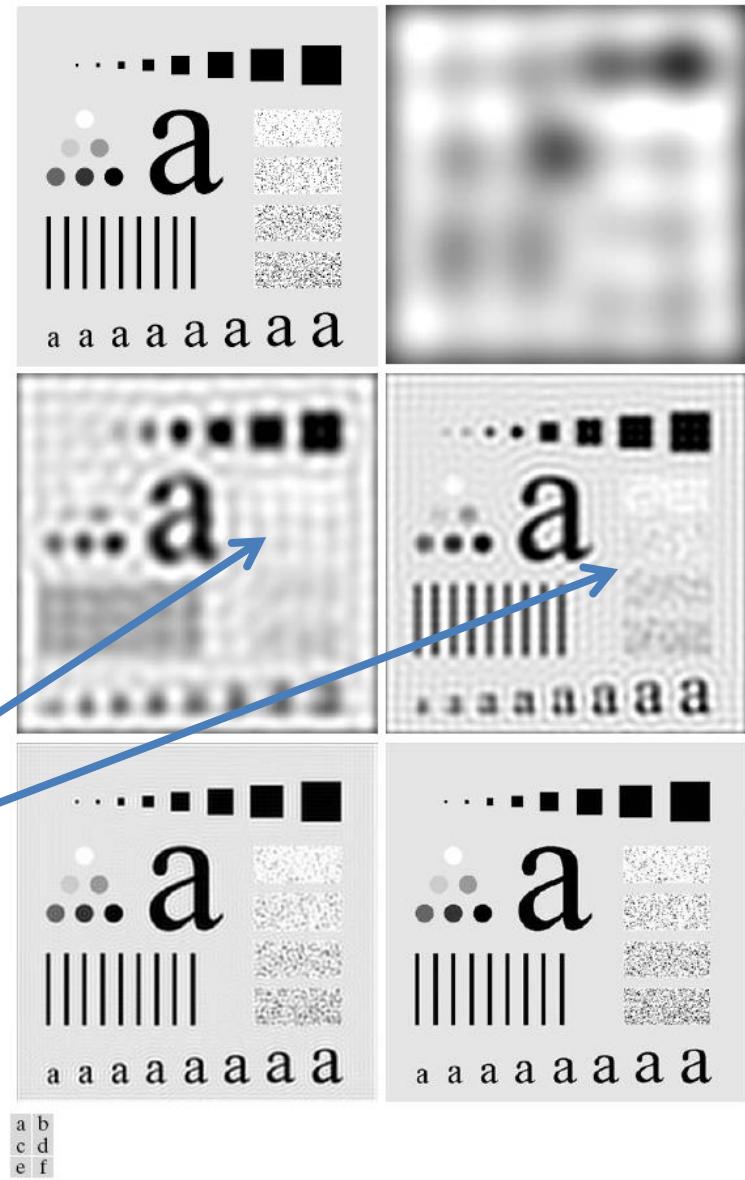
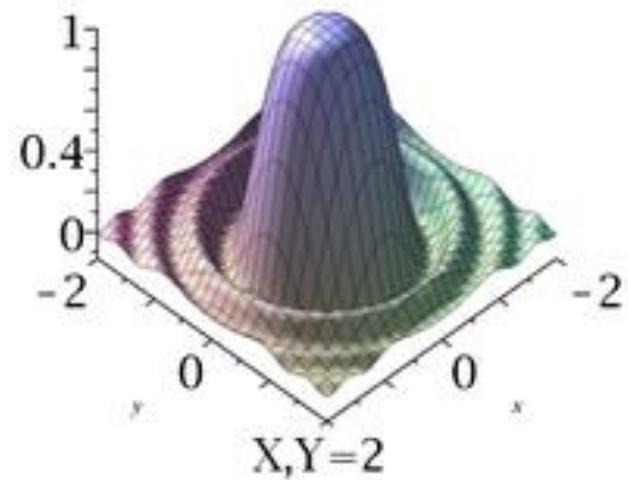


FIGURE 4.42 (a) Original image. (b)–(f) Results of filtering using ILPFs with cutoff frequencies set at radii values 10, 30, 60, 160, and 460, as shown in Fig. 4.41(b). The power removed by these filters was 13, 6.9, 4.3, 2.2, and 0.8% of the total, respectively.

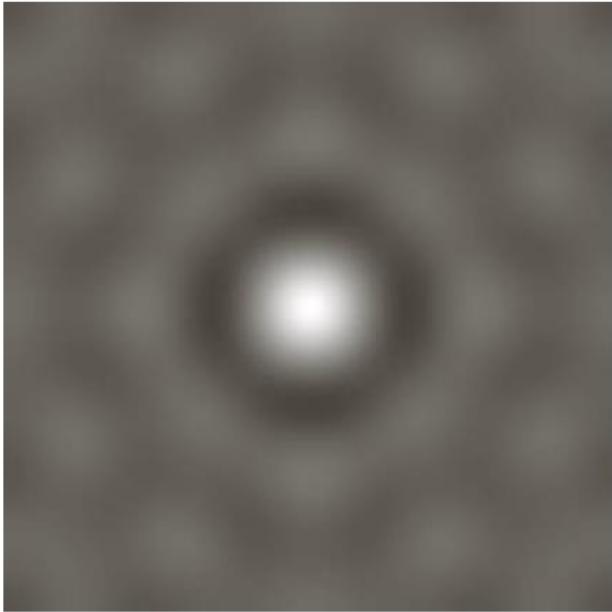
Low pass filters

- The ringing artifacts can be explained by the convolution theorem.
- The corresponding spatial domain filter is called the **jinc** function.
- The jinc is a 2D and circularly symmetric version of the sinc function – see also the next slide.
- Any cross section of the jinc is basically a sinc function.

Sombrero function



[https://en.wikipedia.org/
wiki/Sombrero_function](https://en.wikipedia.org/wiki/Sombrero_function)



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.

An image can be regarded as a weighted sum of Kronecker delta functions (impulses). Convolving with a sinc function means placing copies of the sinc function at each impulse. The central lobe of the sinc function causes the blurring and the smaller lobes give rise to the “ripple artifacts” or ringing.

Low pass filters: other types

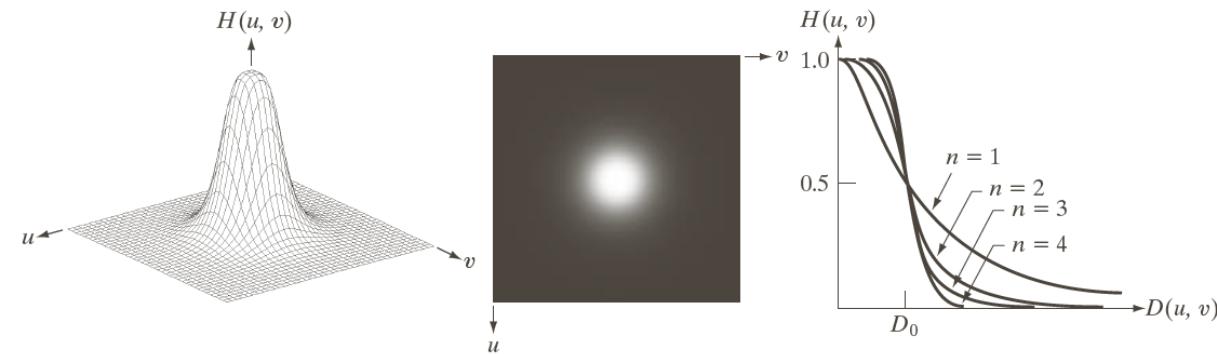
- These ringing artifacts can be quite undesirable.
- Hence the ideal low pass filter is replaced by other types of low pass filters which **weaken** but do not totally eliminate the higher frequencies.
- For example:

$$H(u, v) = \frac{1}{1 + (\sqrt{u^2 + v^2} / D)^{2n}}, (n, D) = \text{filter parameters}$$

Butterworth filter:
 D = cutoff frequency,
 n = order of the filter

$$H(u, v) = \exp(-(u^2 + v^2) / (2\sigma^2)), (\sigma) = \text{filter parameters}$$

Gaussian filter



a b c

FIGURE 4.44 (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.

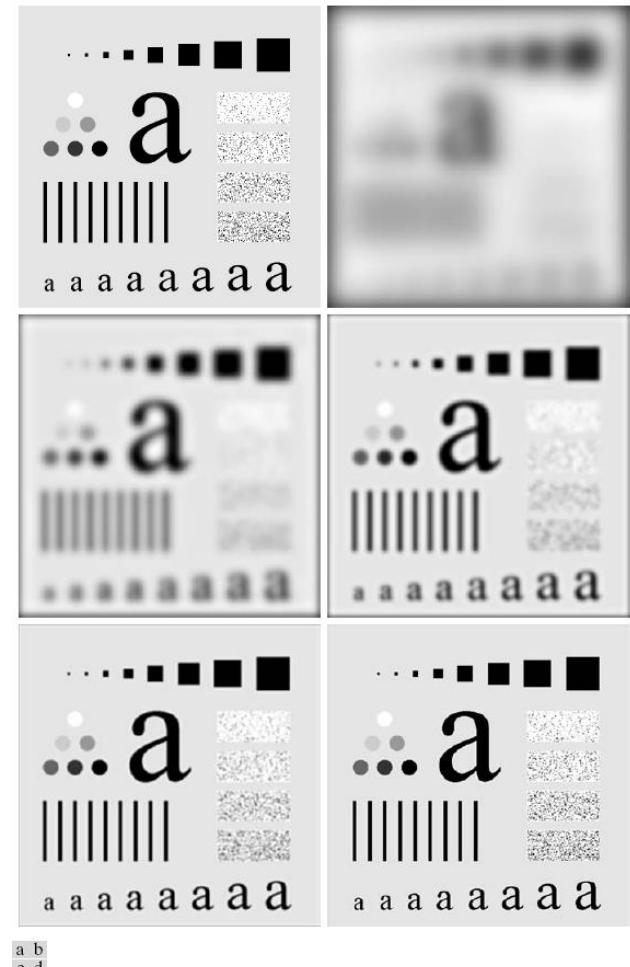
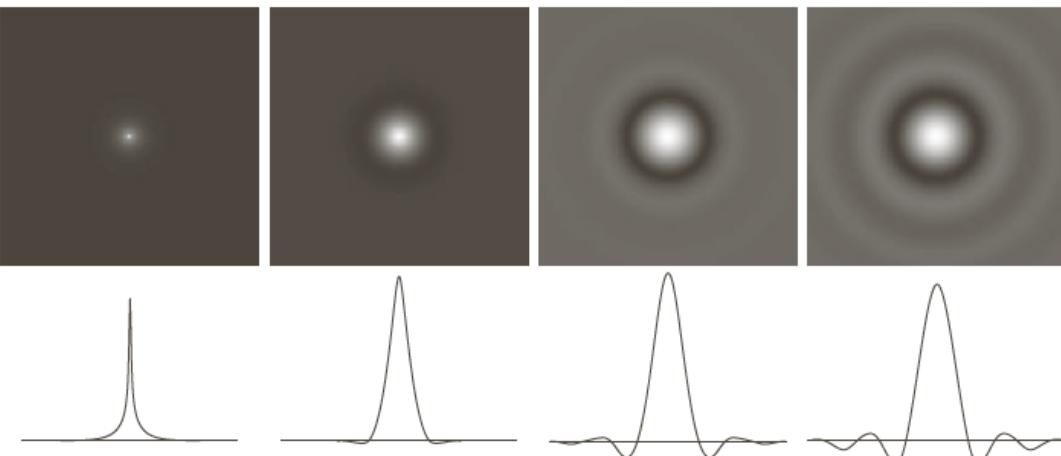


FIGURE 4.45 (a) Original image. (b)–(f) Results of filtering using BLPFs of order 2, with cutoff frequencies at the radii shown in Fig. 4.41. Compare with Fig. 4.42.

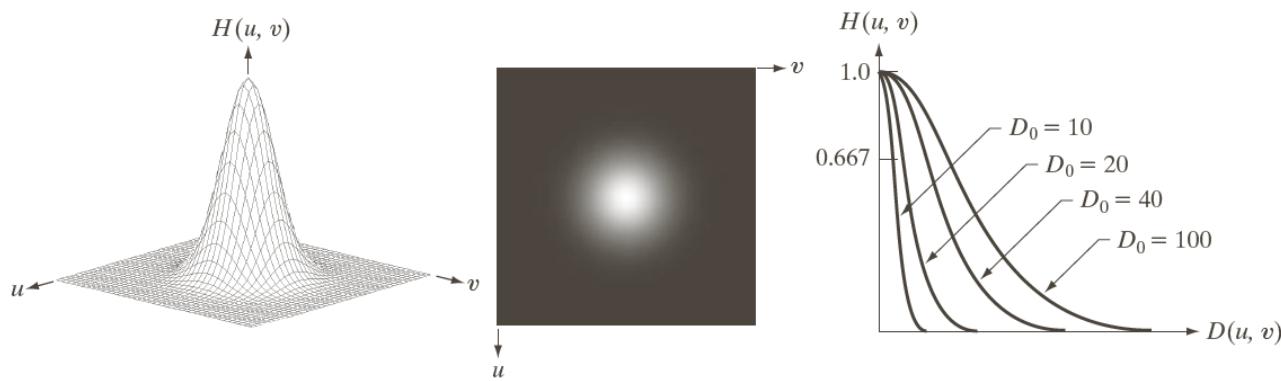


a b c d

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.

Low pass filters: Butterworth

- As D increases, the Butterworth filter allows more frequencies to pass through without weakening (see previous slide).
- As the order n increases, the Butterworth filter weakens the higher frequencies more aggressively (why?) – which actually increases ringing artifacts (see previous slide).



a b c

FIGURE 4.47 (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 .



a b c

FIGURE 4.50 (a) Original image (784×732 pixels). (b) Result of filtering using a GLPF with $D_0 = 100$. (c) Result of filtering using a GLPF with $D_0 = 80$. Note the reduction in fine skin lines in the magnified sections in (b) and (c).

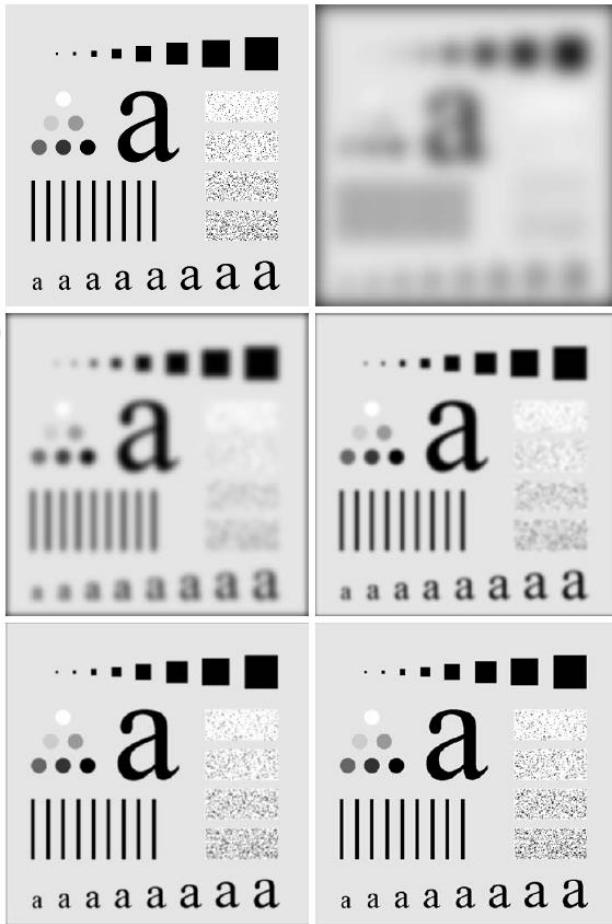


FIGURE 4.48 (a) Original image. (b)–(f) Results of filtering using GLPFs with cutoff frequencies shown in Fig. 4.41. Compare with Figs. 4.42 and 4.45.

Low pass filters: Gaussian

- The spatial domain representation for the Gaussian LPF is basically a Gaussian.
- In fact, the following are Fourier transform pairs:

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-x^2}{2\sigma^2}\right) \leftrightarrow G(u) = \exp\left(\frac{-u^2}{2(1/\sigma^2)}\right)$$

http://www.cse.yorku.ca/~kosta/CompVis_Notes/fourier_transform_Gaussian.pdf

Notice from the equations that a spatial domain Gaussian with high standard deviation corresponds to a frequency domain Gaussian with low cut off frequency! The extreme case of this is a constant intensity signal (Gaussian with very high standard deviation – infinite as such) whose Fourier transform is an impulse at the origin of the Frequency plane). Another extreme case is a spatial domain signal which is just an impulse – its Fourier transform has constant amplitude everywhere.

High pass filter

- It is a filter that allows high frequencies and eliminates or weakens the lower frequencies.
- The equation for the frequency response of an ideal high pass filter is given as:

$$\begin{aligned} H(u, v) &= 0, \text{ if } u^2 + v^2 \leq D^2 \\ &= 1 \text{ otherwise} \end{aligned}$$

- In fact, given an LPF, an HPF can be constructed from it using:

$$H_{HP}(u, v) = 1 - H_{LP}(u, v)$$

TABLE 4.5

Highpass filters. D_0 is the cutoff frequency and n is the order of the Butterworth filter.

Ideal	Butterworth	Gaussian
$H(u, v) = \begin{cases} 1 & \text{if } D(u, v) \leq D_0 \\ 0 & \text{if } D(u, v) > D_0 \end{cases}$	$H(u, v) = \frac{1}{1 + [D_0/D(u, v)]^{2n}}$	$H(u, v) = 1 - e^{-D^2(u, v)/2D_0^2}$

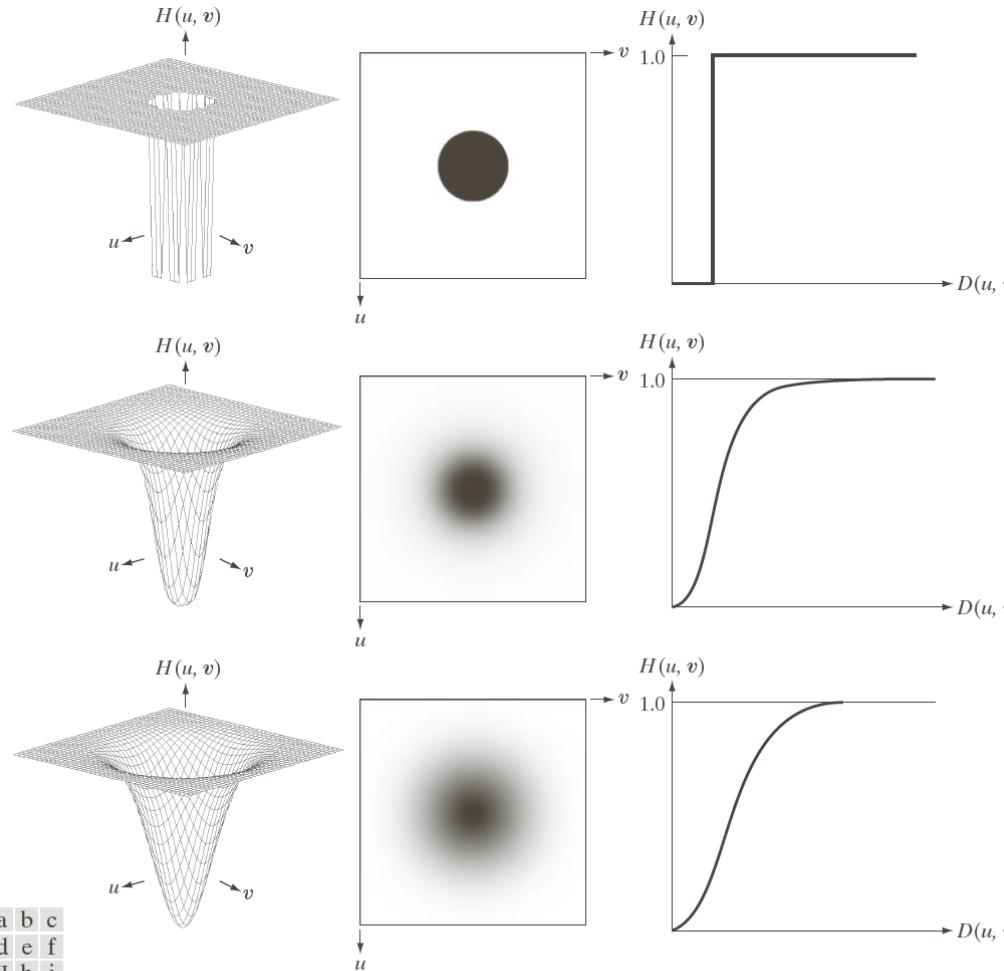
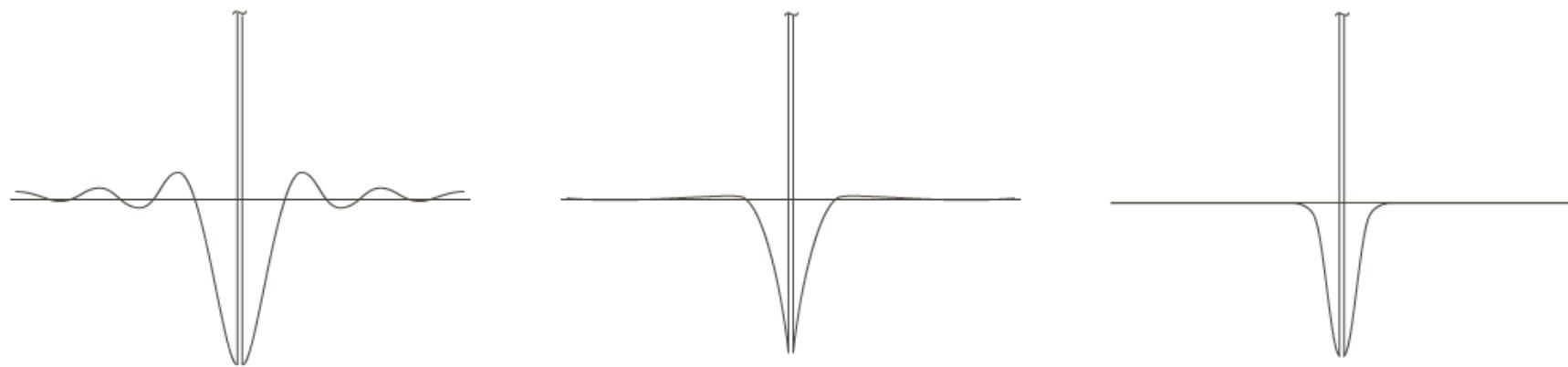
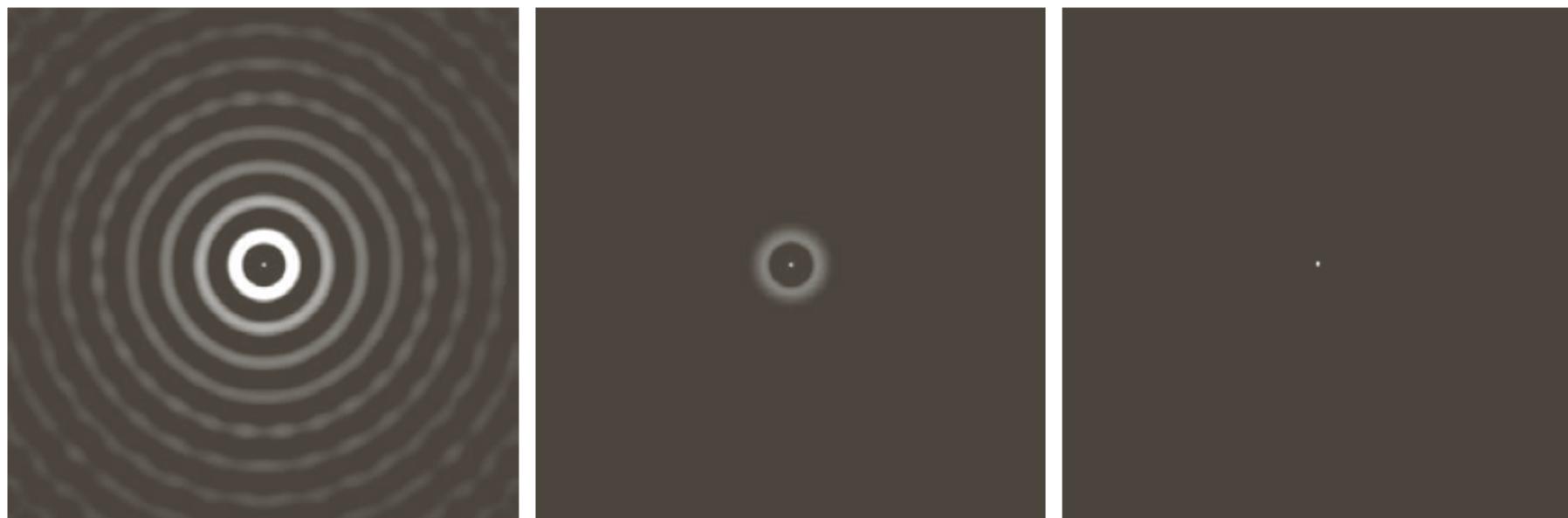


FIGURE 4.52 Top row: Perspective plot, image representation, and cross section of a typical ideal highpass filter. Middle and bottom rows: The same sequence for typical Butterworth and Gaussian highpass filters.



a b c

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.

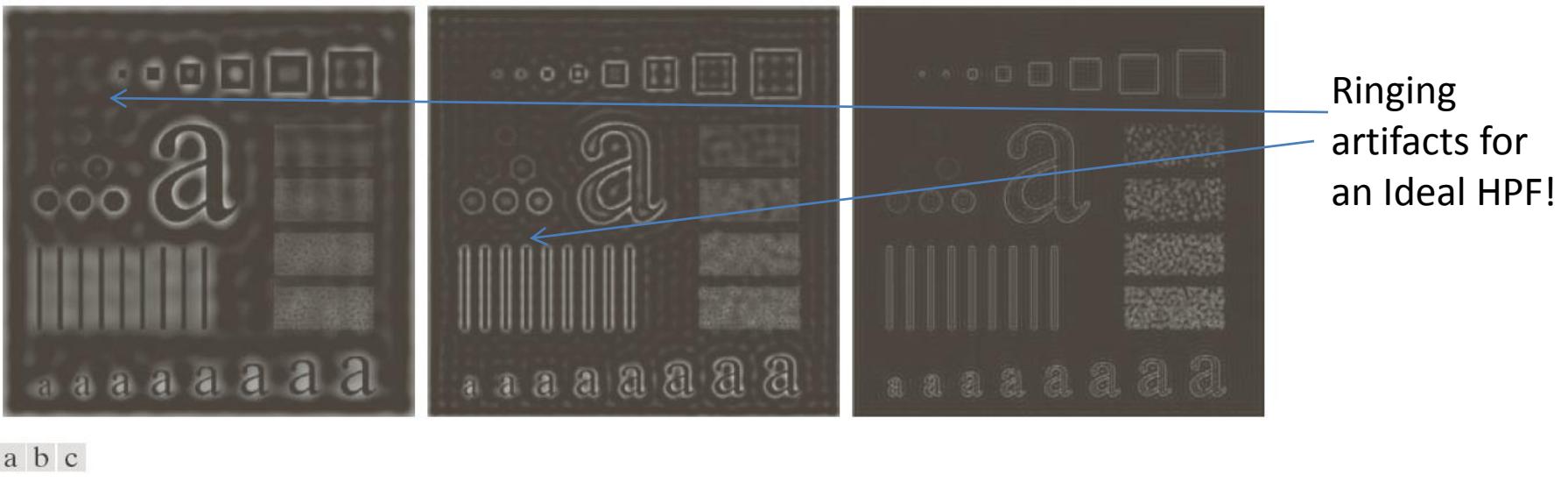


FIGURE 4.54 Results of highpass filtering the image in Fig. 4.41(a) using an IHPF with $D_0 = 30, 60$, and 160 .

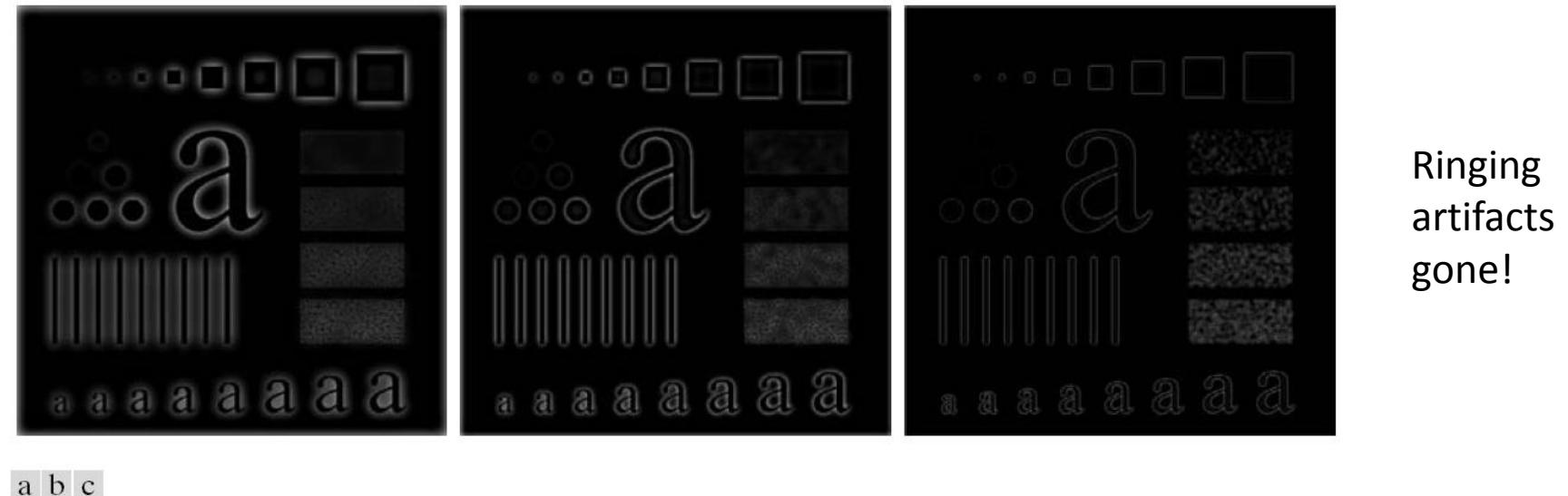


FIGURE 4.55 Results of highpass filtering the image in Fig. 4.41(a) using a BHPF of order 2 with $D_0 = 30, 60$, and 160 , corresponding to the circles in Fig. 4.41(b). These results are much smoother than those obtained with an IHPF.

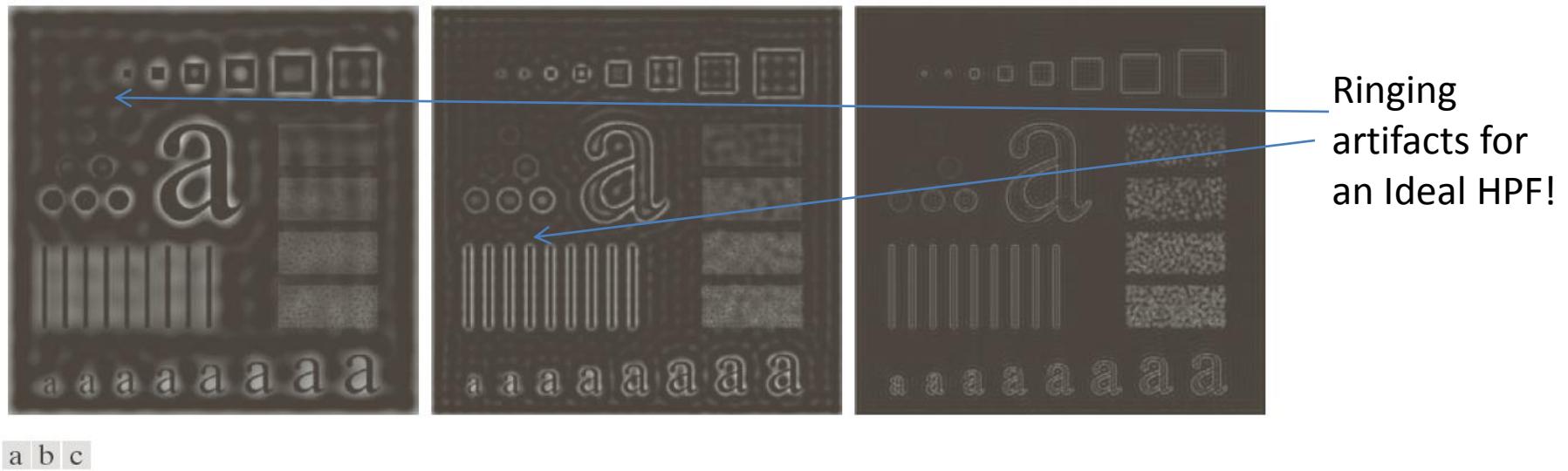


FIGURE 4.54 Results of highpass filtering the image in Fig. 4.41(a) using an IHPF with $D_0 = 30, 60$, and 160 .

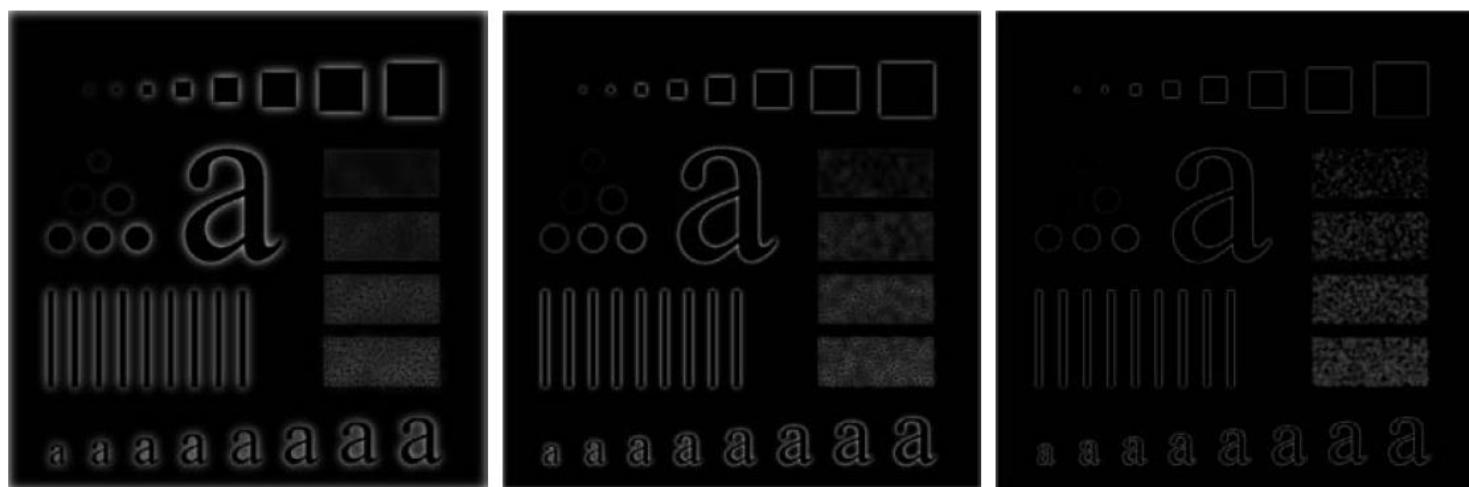


FIGURE 4.56 Results of highpass filtering the image in Fig. 4.41(a) using a GHPF with $D_0 = 30, 60$, and 160 , corresponding to the circles in Fig. 4.41(b). Compare with Figs. 4.54 and 4.55.

High pass filters

- Note that any gradient-based operation on images is essentially a type of high-pass filter.
- This includes first order derivative filters or the Laplacian filter.
- Why? Consider the first order derivative filter in y direction.

$$\begin{aligned} g(x, y) &= I(x, y+1) - I(x, y) \\ G(u, v) &= I(u, v)(1 - e^{-j2\pi v/M}) \end{aligned} \quad \xrightarrow{\hspace{10em}} \quad G(u, 0) = 0$$

High pass filters

- Consider the Laplacian filter:

$$g(x, y) = (I(x, y + 1) + I(x + 1, y) + I(x, y - 1) + I(x - 1, y) - 4I(x, y)) / 4$$

$$G(u, v) = \frac{(e^{-j2\pi v/M} + e^{-j2\pi u/M} + e^{j2\pi v/M} + e^{j2\pi u/M} - 4)}{4} I(u, v)$$

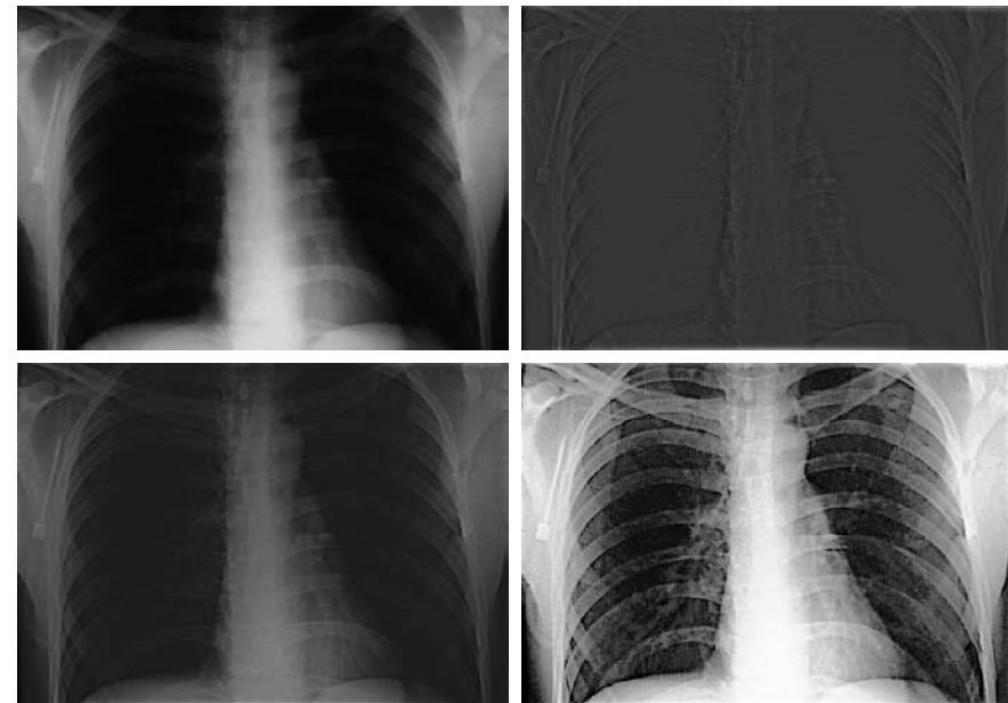


$$G(0,0) = 0$$

Boosting high frequencies

- In some applications, you neither wish to weaken the higher frequencies nor the lower frequencies.
- For example, in image sharpening applications you wish to **boost** the edges or textures (basically higher frequencies).
- In that case you wish to perform operations of the following form:

$$g(x, y) = \mathcal{F}^{-1}(1 + kH_{HP}(u, v))F(u, v)$$



a
b
c
d

FIGURE 4.59 (a) A chest X-ray image. (b) Result of highpass filtering with a Gaussian filter. (c) Result of high-frequency-emphasis filtering using the same filter. (d) Result of performing histogram equalization on (c). (Original image courtesy of Dr. Thomas R. Gest, Division of Anatomical Sciences, University of Michigan Medical School.)

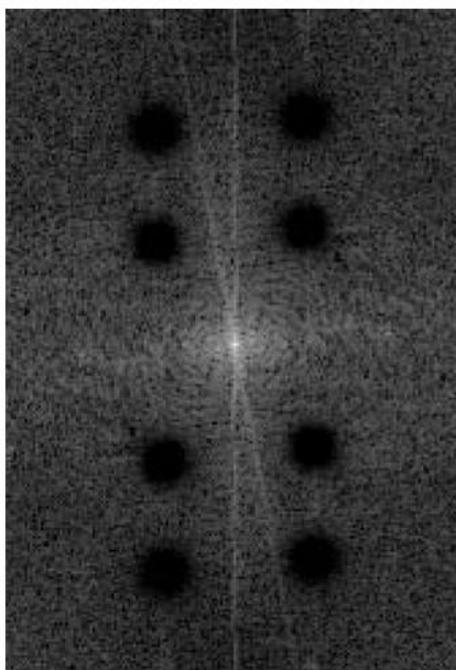
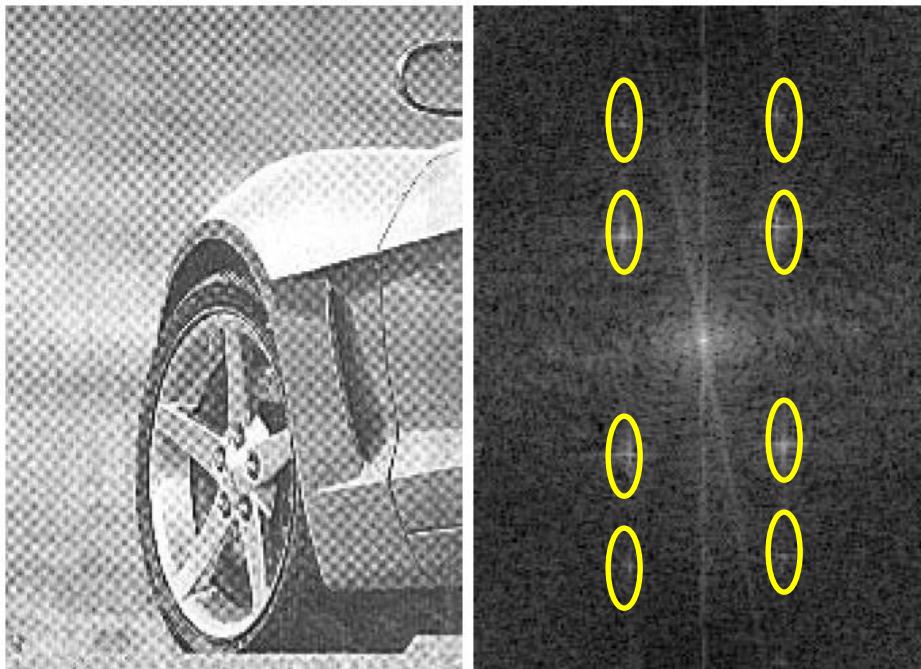


a
b

FIGURE 4.58
(a) Original, blurry image.
(b) Image enhanced using the Laplacian in the frequency domain. Compare with Fig. 3.38(e).

Notch filters

- There are applications where images are presented with **periodic noise patterns** – e.g. images scanned from old newspapers (see next slide).
- Usually, the amplitudes of the Fourier components of natural images are seen to decay with frequency.
- The Fourier transform of images with periodic patterns show unnatural peaks – unlike ordinary natural images.
- Such images can be restored using **notch filters**, which basically weaken or eliminate these unnatural frequency components (or any frequency components specified by the user).

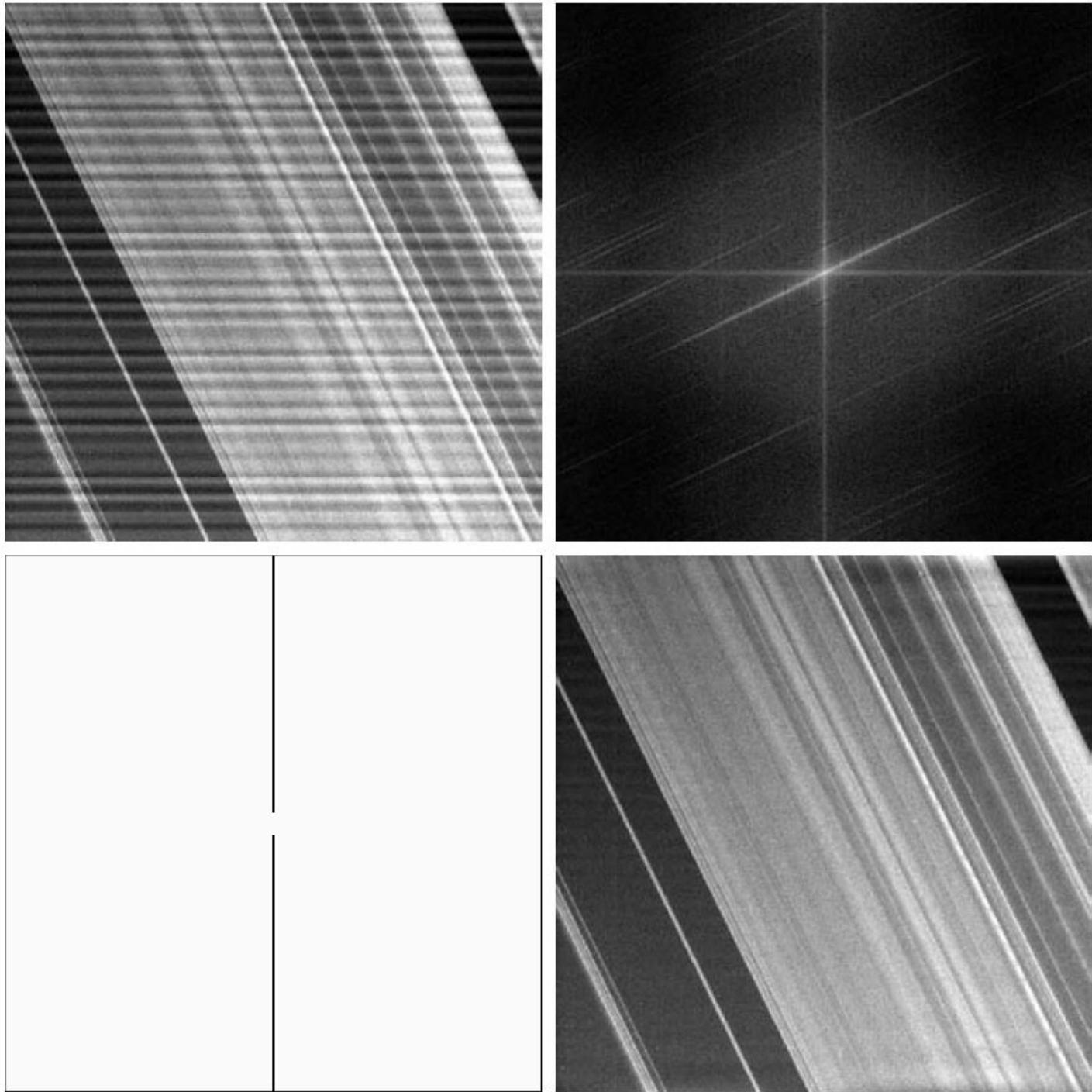


a	b
c	d

FIGURE 4.64

- (a) Sampled newspaper image showing a moiré pattern.
- (b) Spectrum.
- (c) Butterworth notch reject filter multiplied by the Fourier transform.
- (d) Filtered image.

The yellow ellipses indicate unnatural peaks in the Fourier transform of the image with the superimposed interfering pattern. These are unnatural because typical images do not have such Fourier transforms. Therefore one can apply a notch filter to remove the interfering pattern.



a b
c d

FIGURE 4.65

(a) 674×674 image of the Saturn rings showing nearly periodic interference.

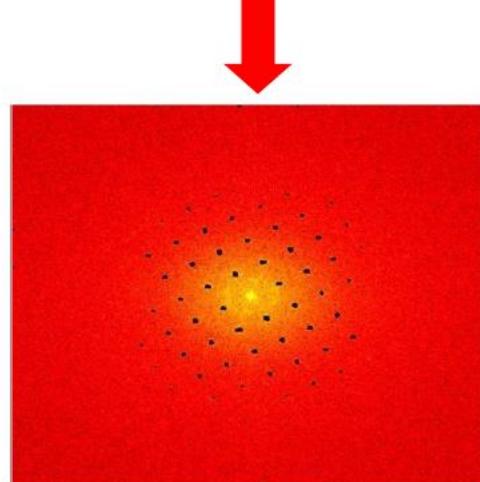
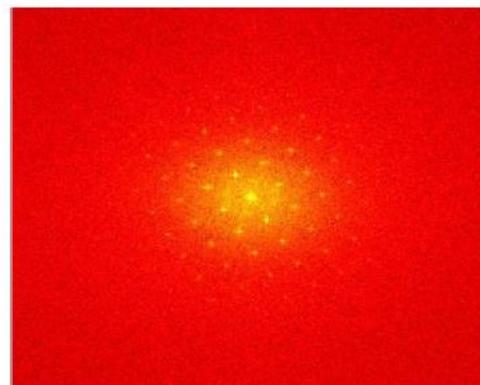
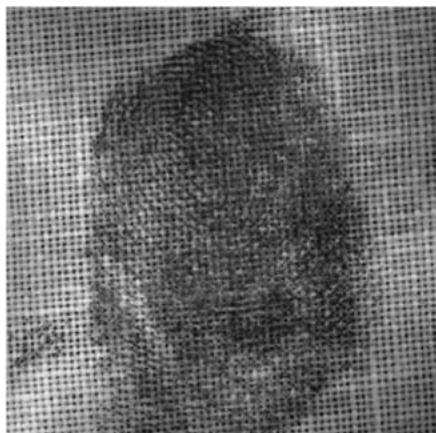
(b) Spectrum: The bursts of energy in the vertical axis near the origin correspond to the interference pattern.

(c) A vertical notch reject filter.

(d) Result of filtering. The thin black border in (c) was added for clarity; it is not part of the data.

(Original image courtesy of Dr. Robert A. West, NASA/JPL.)

Example – Forensic application

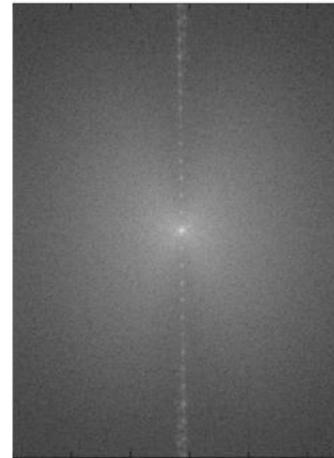
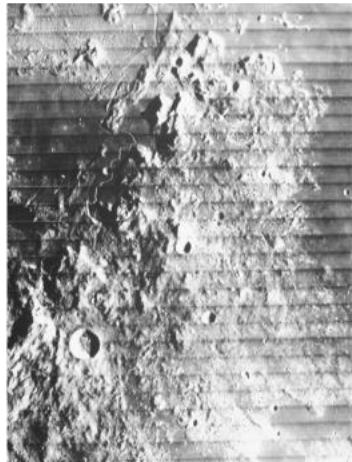


Periodic background removed

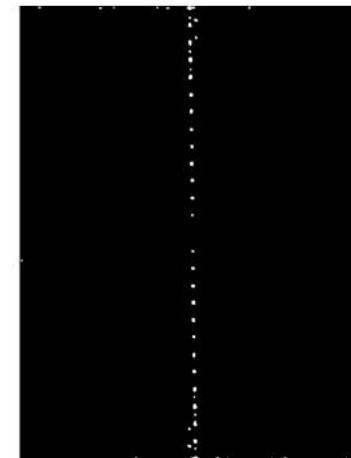
Courtesy: <http://www.robots.ox.ac.uk/~az/lectures/ia/lect2.pdf>

Example – Image processing

Lunar orbital image (1966)



$$|F(u,v)|$$



remove
peaks



join lines
removed

Notch filters

- The expression for a notch filter frequency response is given as follows (Q = number of frequency components to suppress):

$$H_{NR}(u, v) = \prod_{i=1}^Q H_N(u, v; u^{(i)}, v^{(i)}, R)$$

$$H_{NR}(u, v; u^{(i)}, v^{(i)}, R) = 0 \text{ if } (u - u^{(i)})^2 + (v - v^{(i)})^2 \leq R^2 \\ = 1 \text{ otherwise}$$

Ideal notch reject filter

$$H_{NR}(u, v; u^{(i)}, v^{(i)}, R) = 1 - \exp\left(-((u - u^{(i)})^2 + (v - v^{(i)})^2) / R^2\right)$$

Gaussian notch reject filter

Algorithm for frequency domain filtering

- Consider you have to filter an image f of size $H \times W$ using one of the filters described in these slides.
- Zero pad the image symmetrically to create a new image f' of size $2H \times 2W$.
- Compute the Fourier transform of f' and center it using `fftshift`. Let the Fourier transform be $F'(u,v)$.
- Design a frequency domain filter $H(u,v)$ of size $2H \times 2W$ with the zero frequency at index (H,W) of the 2D filter array.
- Compute the product $F'(u,v)H(u,v)$.
- Compute the inverse Fourier transform of the product after applying `ifftshift` (to undo the effect of `fftshift`).
- Consider only the real part of the inverse Fourier transform and extract the central portion of size $H \times W$.
- That gives you the final filtered image.
- Note that the zero padding is important. To understand the difference, see the results on the next slide with and without zero-padding.



Original image



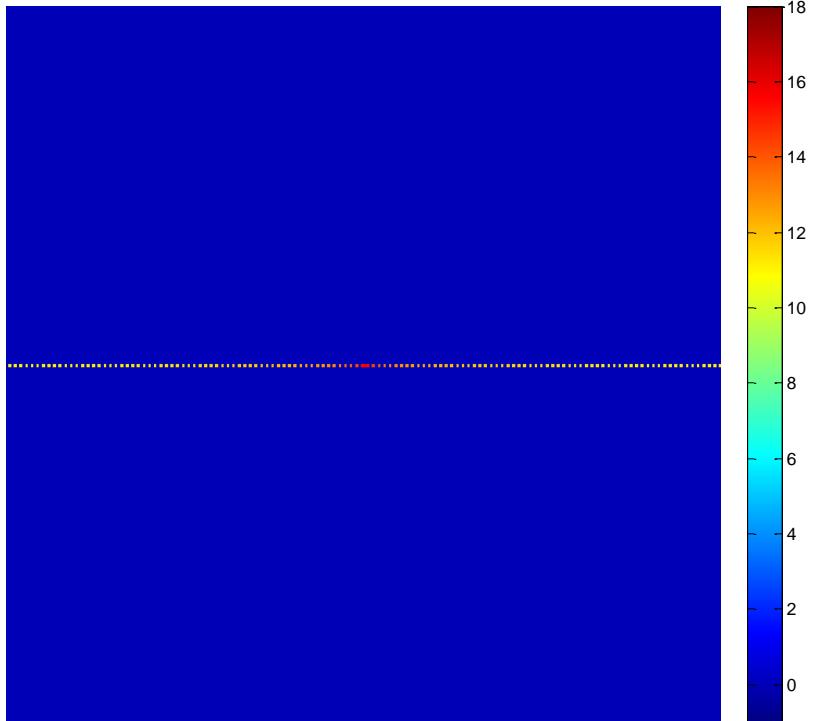
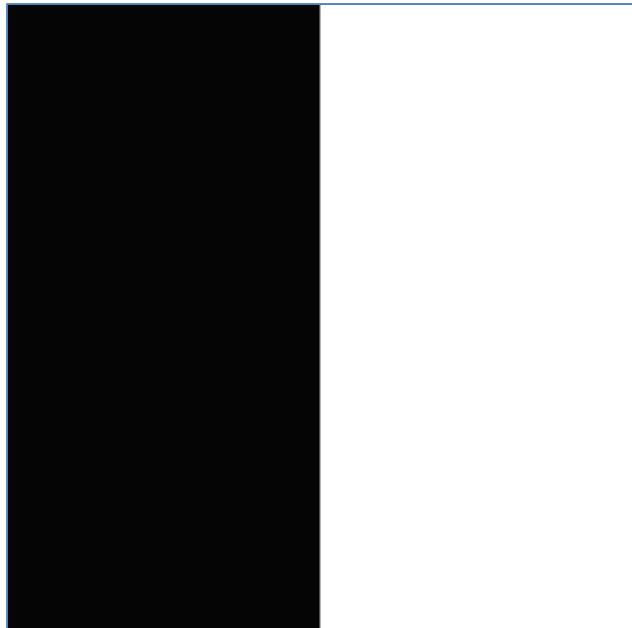
Effect of Gaussian LPF
with appropriate zero
padding



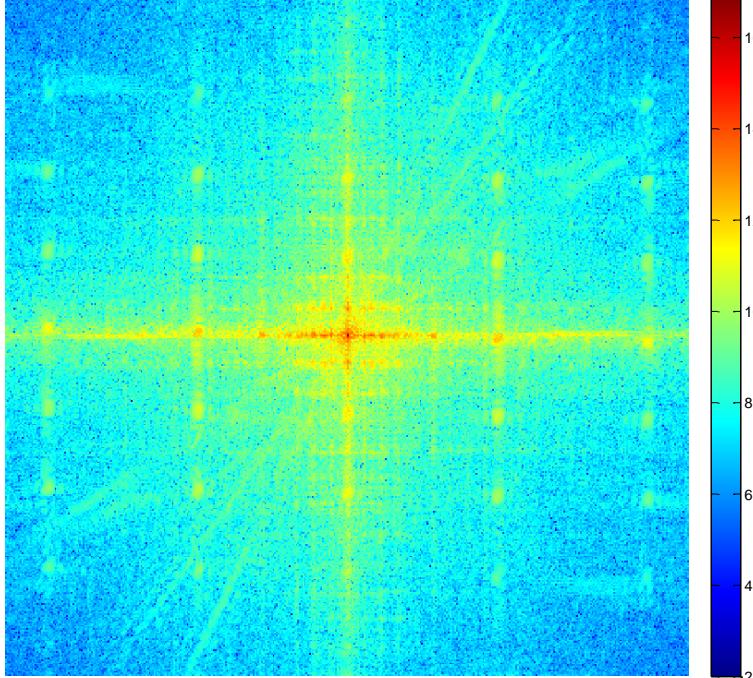
Effect of Gaussian LPF
without appropriate zero
padding – zero the
border artifacts!

Interpreting the DFT of Natural Images

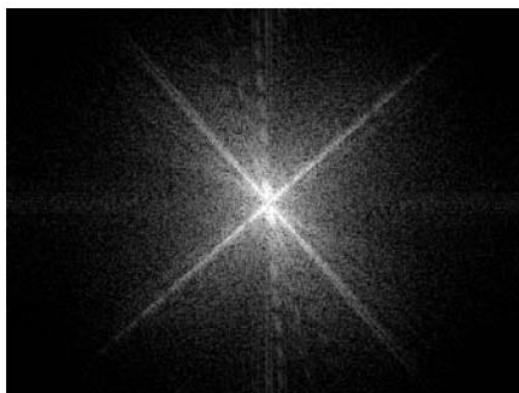
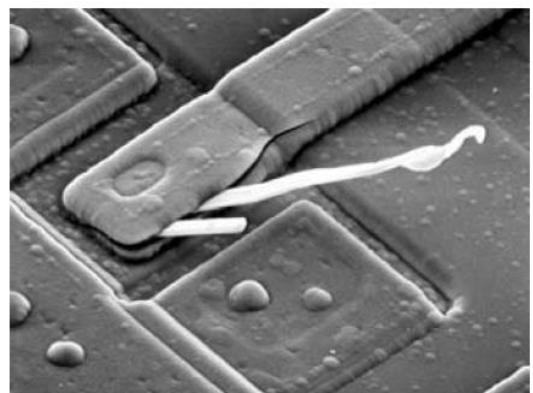
- In a few cases, one can guess some structural properties of an image by looking at its Fourier transform.
- Most natural images have stronger low frequency components as compared to higher frequency components. This is generally true, although its not a strictly monotonic relationship.
- For example, how does the DFT of a vertical edge image look like?



There is a sinc function along the u axis!



Strong horizontal and vertical edges = strong responses along u and v axes in the Fourier plane!



a b

FIGURE 4.29 (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.)

A strong edge in direction θ in XY plane = a strong response in the direction perpendicular to θ in UV plane

Interpreting the DFT

- For an image (or any 2D array) with Fourier transform $F(u,v)$, $F(0,0)$ is proportional to the average value of the image intensity – why?
- The DFT of a non-zero constant intensity image is basically an impulse at the zero frequency. What is the height of the impulse?

DFT limitations

- A strong response at frequency (u,v) (i.e. a large magnitude for $F(u,v)$) indicates the presence of a sinusoid with frequency (u,v) and with large amplitude *somewhere* in the image.
- In general, the Fourier transform *cannot* and *does not* tell us *where* in the image the sinusoid is located (read section 1 of <http://users.rowan.edu/~polikar/WAVELETS/WTpart1.html>).
- For that, you need to compute separate Fourier transforms over smaller regions of the image (Short time Fourier transform) – that will tell you which region(s) contained a particular sinusoidal component.

Fun with Fourier: Hybrid images

- Hybrid images are a superposition of an image J_1 with **strong low frequency components** and *weak higher frequency components*, and an image J_2 with **stronger higher frequency components** and weak lower frequency components.
- J_1 = apply LPF with some cutoff frequency D on an image.
- J_2 = apply HPF with some cutoff frequency D on another image.
- The appearance of the hybrid image changes with viewing distance!



a)



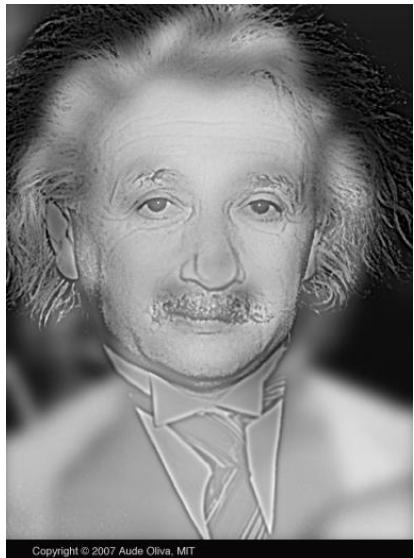
b)



c)

Figure 3: Perceptual grouping between edges and blobs. The three images are perceived as a tiger when seen up-close and as a cheetah from far away. The differences among the three images is the degrees of alignment between the edges and blobs. Image a) contains two images superimposed without alignment. In image b), the eyes are aligned. And in image c), the head pose and the locations of eyes and mouth are aligned. Under proper alignment, the residual frequency band does not manage to build a percept. When seen up-close, it is difficult to see the cheetah's face, which is perfectly masked by the tiger's face. From far away, the tiger's edges are assimilated to the cheetah's face.

Tiger – when seen up-close, Cheetah – when seen from far



Einstein from nearby,
Marilyn Monroe from
far away (or if you
squint)!

Refer to:

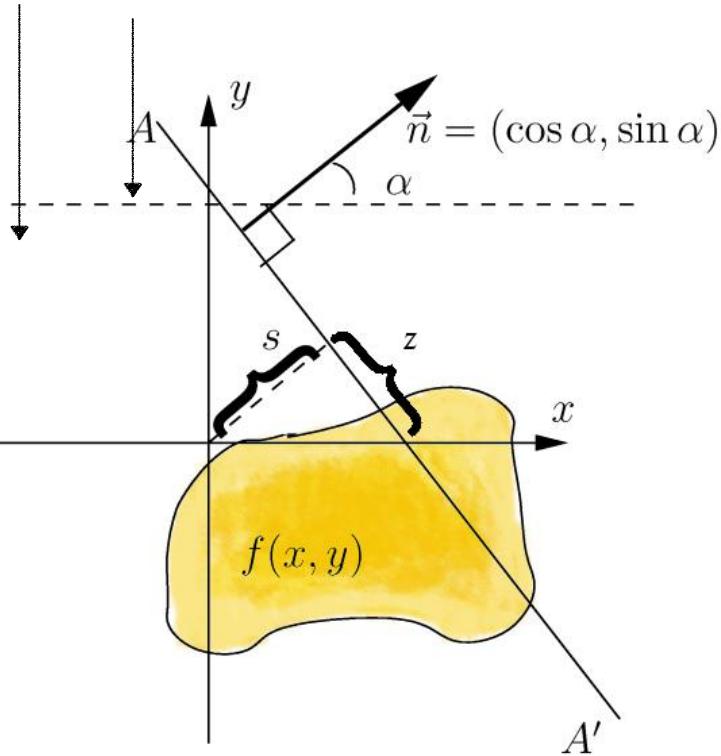
http://cvcl.mit.edu/hybrid_gallery/monroe_einstein.html

http://cvcl.mit.edu/publications/OlivaTorralb_Hybrid_Siggraph06.pdf (paper from a graphics journal!)

Fourier in action: tomographic reconstruction

- Tomography refers to the process of estimation of the internal structure of an object (tomos in Greek means interior).
- This is different from photographic imaging which images only the object surface.
- Tomography is typically accomplished via X Rays and the so called Radon transform.

Radon transform



Imagine a line was drawn through the 2D image in a certain direction α , and you integrated the intensity values along that line.

Now you repeat this for lines parallel to the original one but at different offsets.

Each such summation produces a “**bin**” of the “**tomographic projection**”.

The collection of bins form a 1D array which is called the **tomographic projection** or the **Radon transform** of the object in the direction α .

Reconstruction from the Radon Transform

- The Radon transform computation can be similarly repeated for multiple angles.
- The aim of tomographic reconstruction is to reconstruct the 2D image from a collection of its 1D tomographic projections in different angles.

Fourier transform of the Radon Transform

- The Radon transform is given as:

$$R(f) = g(\rho, \theta) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - \rho) dx dy$$

- Its 1D Fourier transform w.r.t. ρ (keeping Θ fixed to some value) is given by:

$$\begin{aligned} G(\mu, \theta) &= \int_{-\infty}^{+\infty} g(\rho, \theta) \exp(-j2\pi\mu\rho) d\rho \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - \rho) \exp(-j2\pi\mu\rho) dx dy d\rho \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \left[\int_{-\infty}^{+\infty} \delta(x \cos \theta + y \sin \theta - \rho) \exp(-j2\pi\mu\rho) d\rho \right] dx dy \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \exp(-j2\pi\mu(x \cos \theta + y \sin \theta)) dx dy \end{aligned}$$

$G(\mu, \theta)$ is the Fourier transform of the projection of $f(x, y)$ along some direction Θ .

Fourier transform of the Radon Transform

- Its 1D Fourier transform w.r.t. ρ (keeping Θ fixed) is given by:

$$\begin{aligned} G(\mu, \theta) &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \exp(-j2\pi(x\mu \cos \theta + y\mu \sin \theta)) dx dy \\ &= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y) \exp(-j2\pi(xu + yv)) dx dy \end{aligned}$$

where we define $u = \mu \cos \theta, v = \mu \sin \theta$

$$\therefore G(\mu, \theta) = [F(u, v)]_{u=\mu \cos \theta, v=\mu \sin \theta} = F(\mu \cos \theta, \mu \sin \theta) \longrightarrow$$

The RHS of this equation is a slice of the 2D Fourier transform of $f(x, y)$, i.e. $F(u, v)$, along the angle Θ in the frequency plane, and passing through the origin

This equation above is called the **Projection Slice Theorem** or the **Fourier Slice Theorem**. It states that the Fourier transform of a projection of the 2D object along some direction Θ (i.e. $G(\mu, \Theta)$) is equal to a slice of the 2D Fourier transform of the object along the same direction Θ (in the frequency plane), passing through the origin.

Reconstruction from the Radon transfer

- The projection slice theorem thus tells you that you can fill up the 2D Fourier transform of the original image – since the 1D Fourier transform of the projection at angle θ is equal to a slice of the 2D Fourier transform of the image at the angle θ through the origin of the (u,v) plane.
- Thus given different projections, each at different angles, you can fill up the Fourier transform of the original image. The final inverse Fourier transform gives you a reconstruction of the image.