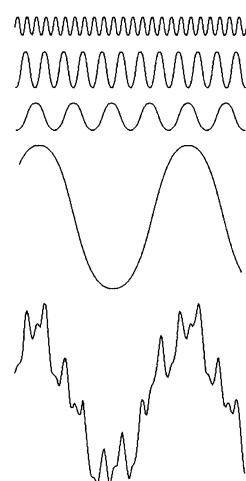




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} sum of above
four functions
gives this noisy looking signal.

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.

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1-D Fourier transform:

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

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

2-D Fourier transform

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

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

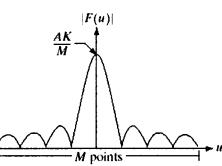
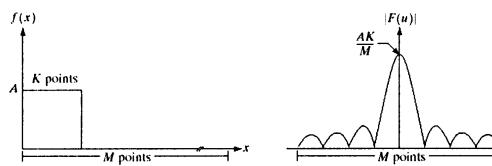
Discrete Fourier Transform

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

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



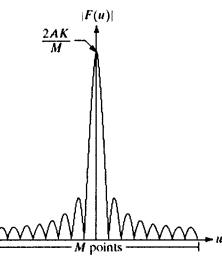
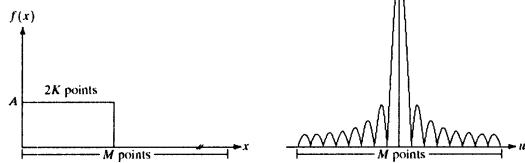
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a b

c d

FIGURE 4.2 (a) A discrete function of M points and (b) its Fourier spectrum. (c) A discrete function with twice the number of nonzero points, and (d) its Fourier spectrum.



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For above figure $A = 1$
 $M = 1024$
 $K = 8$

As the width of the function increased by 2 the area under the curve increases by 2 and the peak value increases by 2. Also note that the number of zero's in the transform also increases by 2.

In the future,

$$f(x) \triangleq f(x_0 + x \Delta x)$$

$$F(u) \triangleq F(u \Delta u) \text{ for } u=0, 1, 2, \dots, M-1$$

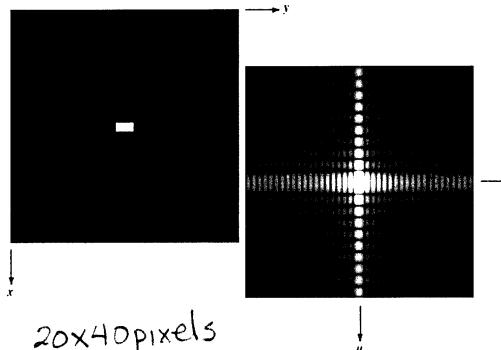
$$\Delta u = \frac{1}{m \Delta x}$$



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a b
FIGURE 4.3
(a) Image of a 20×40 white rectangle on a black background of size 512×512 pixels.
(b) Centered Fourier spectrum shown after application of the log transformation given in Eq. (3.2-2). Compare with Fig. 4.2.



20x40 pixels

centered
probably $|F(u;v)|$
 $0.5 \log(1+r)$ transform

Note twice as many zeros in u as compared to v .

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$$\text{2-D DFT} \quad F(u,v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi \left(\frac{ux}{M} + \frac{vy}{N}\right)}$$

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

Fourier spectrum

$$|F(u,v)| = \sqrt{R^2(u,v) + I^2(u,v)}$$

phase angle

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

power spectra

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

Multiply input image by $(-1)^{x+y}$ to center transform.

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

i.e. $F(0,0)$ is located at $u = \frac{M}{2}, v = \frac{N}{2}$

GWE 4.1

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

where u, v are frequency variables

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

Fourier coefficients

$$\text{If } f(x, y) \text{ is real } F(u, v) = F^*(-u, -v)$$

$$\Rightarrow |F(u, v)| = |F(-u, -v)|$$

By substitution

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

\Rightarrow infinitely periodic in u & v

From the inverse DFT $f(x, y)$ is periodic in x and y .

$$f(x, y) = f(x+m, y) = f(x, y+n) = f(x+m, y+n)$$

Some properties of the 2-D Fourier Transform

Translation

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

$$f(x-x_0, y-y_0) \Leftrightarrow F(u, v) e^{-j2\pi \left(\frac{u_0 x}{M} + \frac{v_0 y}{N} \right)}$$

Incidentally if we put $u_0 = \frac{M}{2}$ and $v_0 = \frac{N}{2}$ we get

$$F(u - \frac{M}{2}, v - \frac{N}{2}) \text{ and}$$

$$e^{j2\pi \left(\frac{u_0 x}{M} + \frac{v_0 y}{N} \right)} = e^{j2\pi \left(\frac{x}{2} + \frac{y}{2} \right)} = e^{j\pi(x+y)} = (-1)^{x+y}$$

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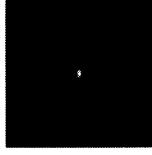
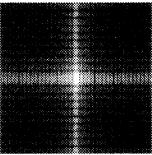
MATLAB/Image Processing Toolbox

MATLAB Fourier transforms

```

>> f=imread('Figure_Rectangle.jpg'); % load in spatial rectangle
>> F=fft2(f); % do 2D FFT
>> S=abs(F); % determine magnitude for display
>> imshow(S, [ ]); % shows in four corners of display
>> Fc=fftshift(F); % shift FFT to center
>> imshow(abs(Fc), [ ]); % show magnitude of FFT in center
% much tougher to do display transform
>> g=im2uint8(mat2gray(log(1+double(f)))); % double converts the image to double precision floating point
% mat2gray brings the values to the range [0,1]
% im2unit8 brings the values back to the range [0,255]

% general log transform
>> g=im2uint8(mat2gray(c*log(1+double(f))));
```

SEE GWE, Section 4.2 Computing and Visualizing the 2-D DFT in MATLAB
GWE, Section 3.2.2 Logarithmic and Contrast Stretching Transformations

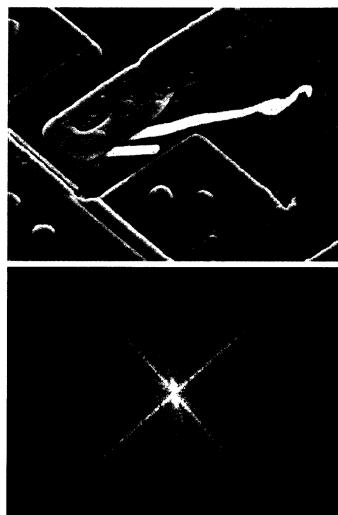
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a
b
FIGURE 4.4
(a) SEM image of
a damaged
integrated circuit.
(b) Fourier
spectrum of (a).
(Original image
courtesy of Dr. J.
M. Hudak,
Brockhouse
Institute for
Materials
Research,
McMaster
University,
Hamilton,
Ontario, Canada.)

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value $F(0,0) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)$ which is the average image intensity

Note that $|F(u,v)| = |F(-u,-v)|$

In this figure the strong axes of $|F(u,v)|$ correspond to the approximate $\pm 45^\circ$ edges in the SEM image.

The angle of the white oxide extrusions wrt horizontal roughly corresponds to the short white off-center line in the transform.

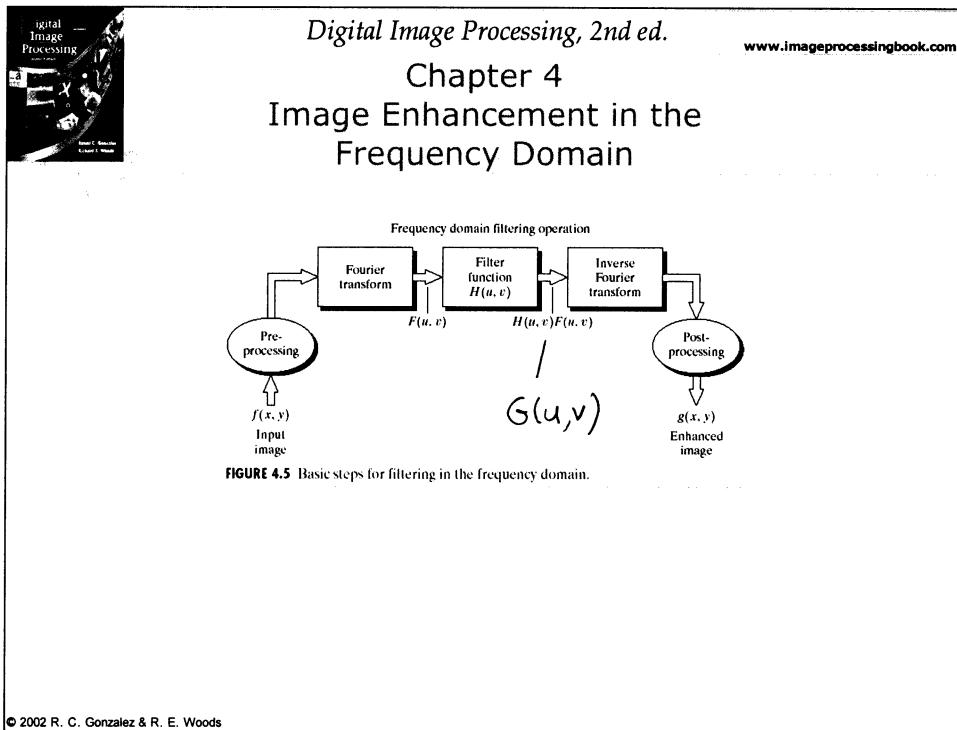


FIGURE 4.5 Basic steps for filtering in the frequency domain.

Preprocessing examples

- $(-1)^{x+y}$ multiplication
- cropping image to even dimension
- gray level scaling
- conversion to floating point

H is known as a zero-phase filter. In general, filters for imaging are real and do not change the phase of $F(u, v)$

Notch filter

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

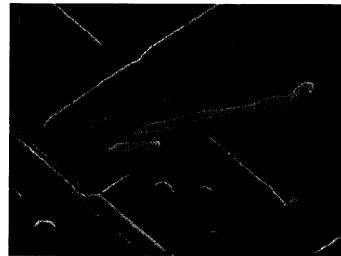
Such a filter is called a notch filter because it removes only $F(0,0)$ which is the average value of the image.



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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.



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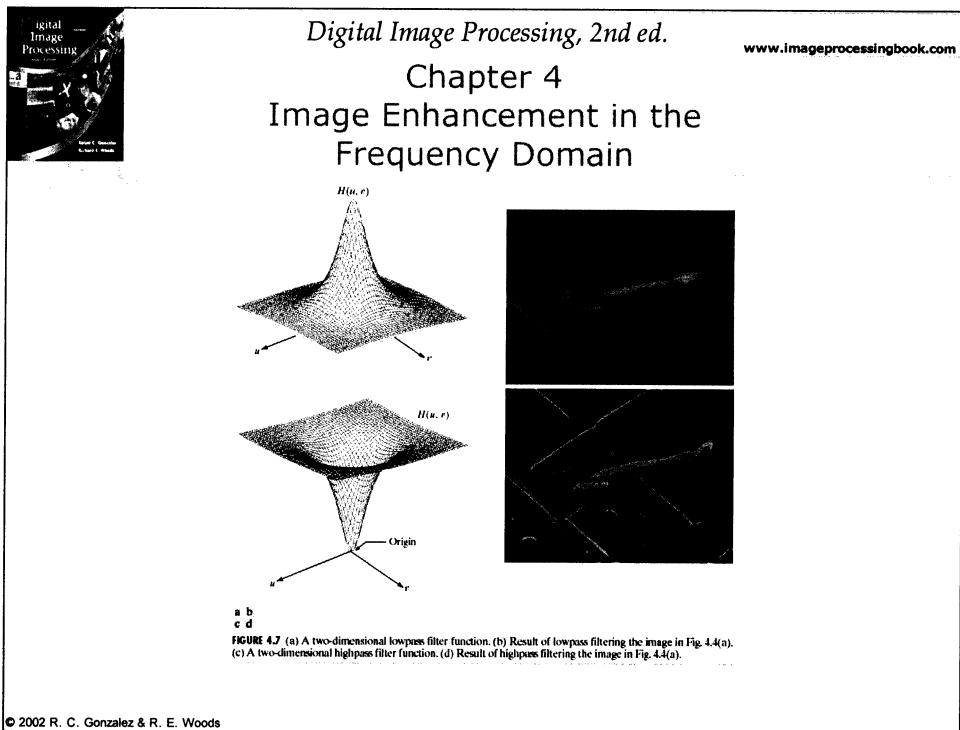
This is an example of a displayed image after $F(0,0)$ was removed by a notch filter.

Since a display cannot show negative values the image has been shifted so that the most negative value corresponds to zero, i.e. black.

Other kinds of filters:

low pass - attenuates high frequencies while passing low frequencies which come from the large, smooth areas in the image, will show less gray scale variation.

high-pass - attenuates low frequencies while passing high frequencies which come from image detail such as edges and noise

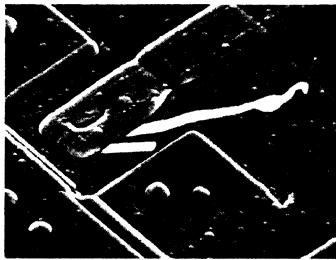


- (a) blurred image with high frequency detail missing due to low-pass filter
- (b) high-pass filter.
 sharp image with prominent edge information
 dark because negative information not being shown.



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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).



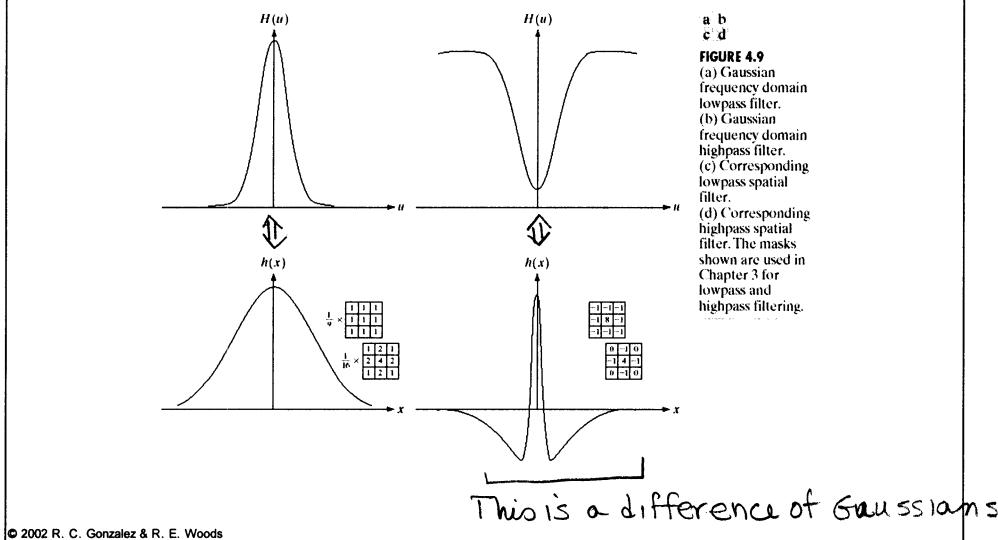
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Result of adding a constant to the high-pass filtered image. Adding a constant shifts previously negative values from black into perceivable gray scale.



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The Gaussian filter can be shown to be an optimal filter under certain conditions and has the property that both the forward and reverse transform of a Gaussian is a Gaussian.

$$h(x) = \sqrt{2\pi} \sigma A e^{-\frac{x^2}{2\sigma^2}}$$

$$H(u) = A e^{-\frac{u^2}{2\sigma^2}}$$

} both real
construct using
Pascal's triangle

$$\frac{1}{9} \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

low-pass

$$\frac{1}{16} \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

weighted average filter from 3.6.1

Difference of Gaussians

$$h(x) = \sqrt{2\pi} \sigma_1 A e^{-\frac{x^2}{2\sigma_1^2}} - \sqrt{2\pi} \sigma_2 B e^{-\frac{x^2}{2\sigma_2^2}}$$

We usually design a filter in the frequency domain and implement it in the spatial domain.



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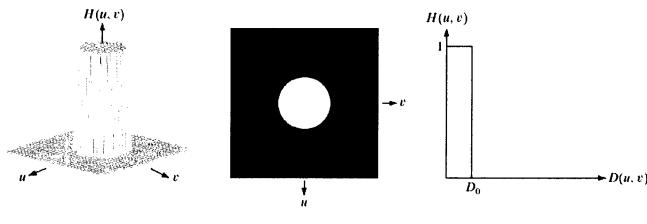


FIGURE 4.10 (a) Perspective plot of an ideal lowpass filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross section.

Ideal Low Pass Filter

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Two-dimensional ideal low-pass filter

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

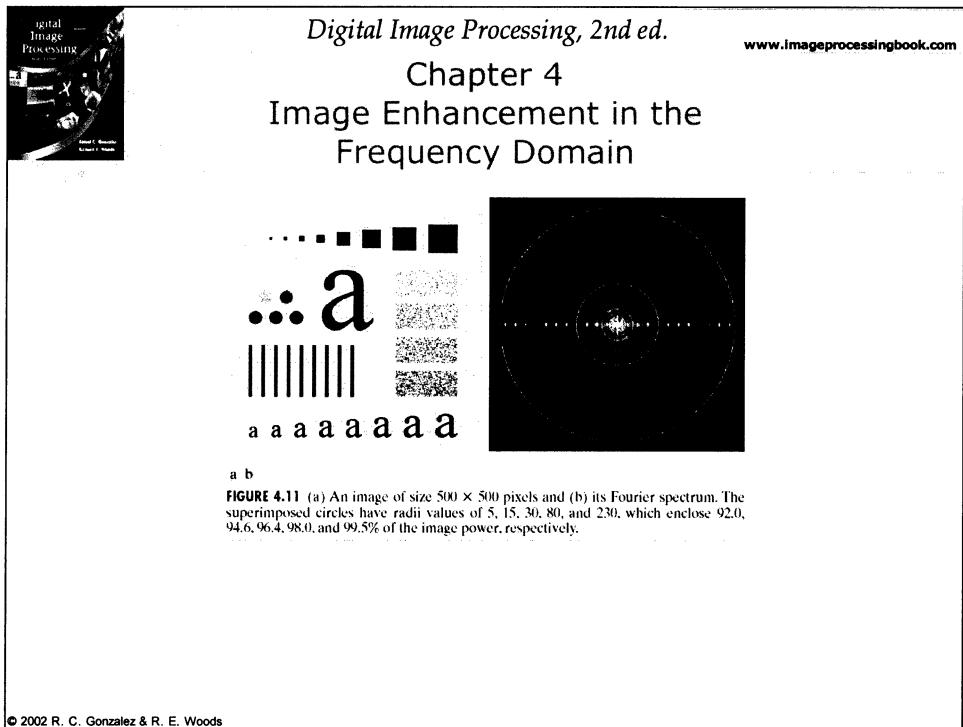
where $D(u,v) = \sqrt{(u - \frac{M}{2})^2 + (v - \frac{N}{2})^2}$ D_0 is the cutoff frequency.

Pick cutoff frequencies based upon fraction of image power they remove.

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

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

$$\% \text{ of image power} \quad \alpha = 100 \left[\sum_u \sum_v \frac{P(u,v)}{P_T} \right]$$



There are five circles shown in the Fourier transform of this test image. These correspond to $\alpha = 92.0, 94.6, 96.4, 98$ & 99.5% . The corresponding u, v are $5, 15, 30, 80$ & 230 .

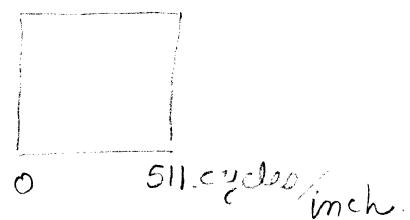
The results of using each filter are shown in the next figure.

$$\Delta u = \frac{1}{M \Delta x}$$

↑

spatial interval. Say $\frac{512 \text{ pixels}}{\text{inch}}$ Then $\frac{1 \text{ inches}}{512 \text{ pixels}}$

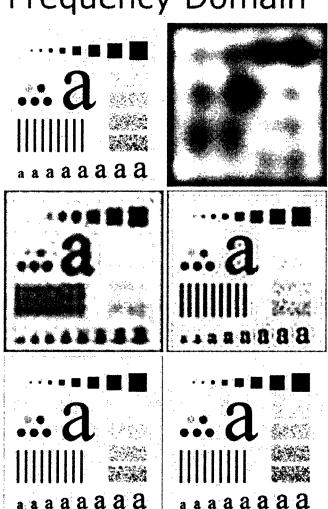
$$\Delta u = \frac{1}{512 \times 0.001953} = \frac{1}{\text{inch}} = 0.001953 \frac{\text{m}}{\text{pix}}$$



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"ringing" shown in all images.



a b 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.
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pretty useless
 except for blurring
 all edge information contained in
 upper 8% of image power.

← Little edge information in
 upper 0.5% of power

Lowpass filtering



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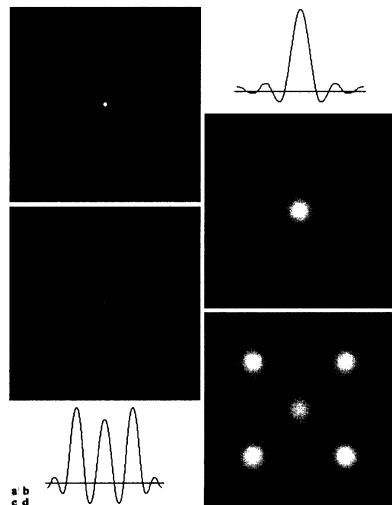


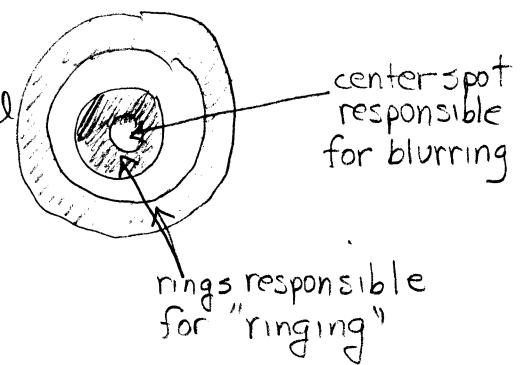
FIGURE 4.13 (a) A frequency-domain ILPF of radius 5. (b) Corresponding spatial filter (note the ringing). (c) Five impulses in the spatial domain, simulating the values of five pixels. (d) Convolution of (b) and (c) in the spatial domain.

← illustrates "ringing" due to ILPF

- (a) ideal low pass filter of radius 5 pixels
(b) corresponding spatial filter is computed
$$(-1)^{u+v} H(u,v) \text{ for centering}$$

inverse DFT
$$(-1)^{x+y} \text{Re}[\text{inverse DFT}]$$

re-centers \uparrow take real part since it should be real
As pixel radius of (a) increases
the radius of the spatial rings decreases.
- (c) 5 pixels in spatial domain
"impulses"
- (d) convolution of (b) with (c)
showing "shifting" property





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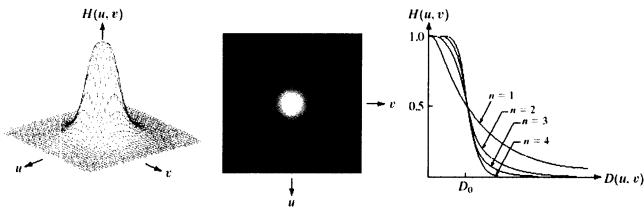


FIGURE 4.14 (a) Perspective plot of a Butterworth lowpass filter transfer function. (b) Filter displayed as an image. (c) Filter radial cross sections of orders 1 through 4.

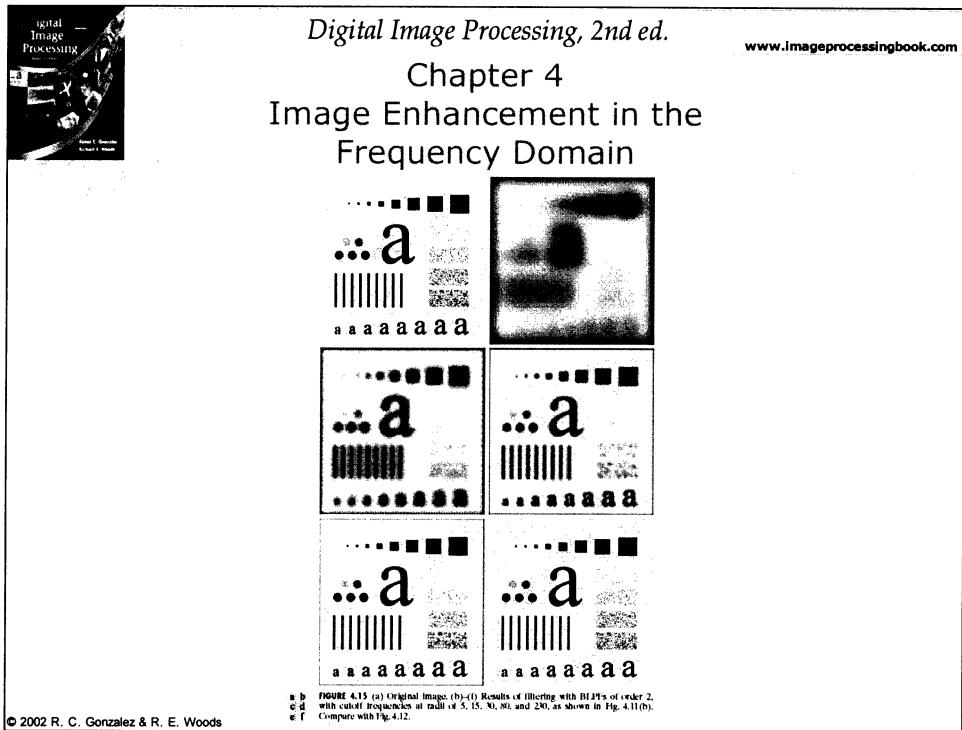
Butterworth LPF

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Ringing will increase as n increases.

$n=1$ no ringing

$n=2$ bare perceptible

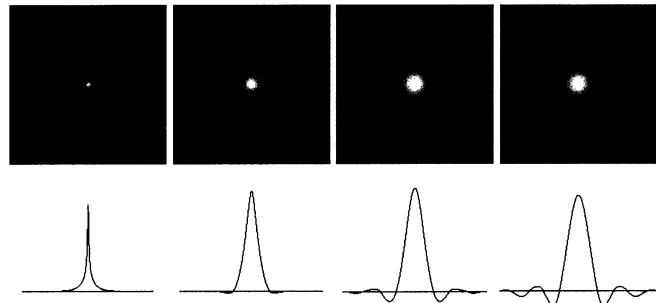


Results of $n=2$ Butterworth low pass filter
Using same radii (D_0) as for ideal low-pass filter.

Blurring linearly decreases as radius increases,
No ringing visible.



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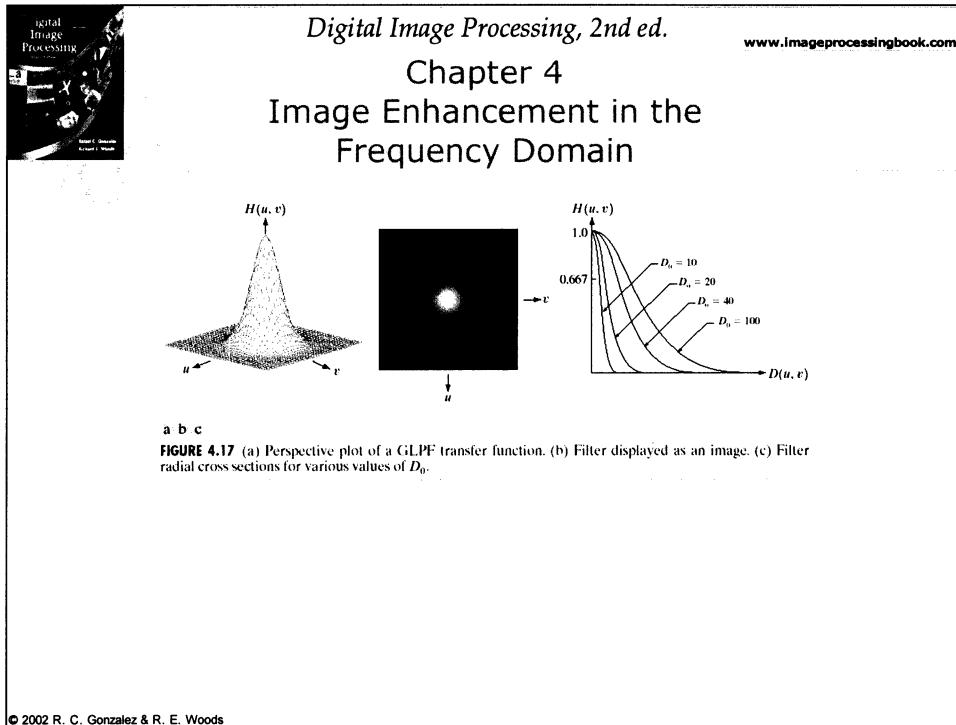
a b c d

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.

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Spatial implementations of Butterworth low-pass filters. All filters have $D_0 = 5$.

Note that ringing increases with n .



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Gaussian Low Pass filter

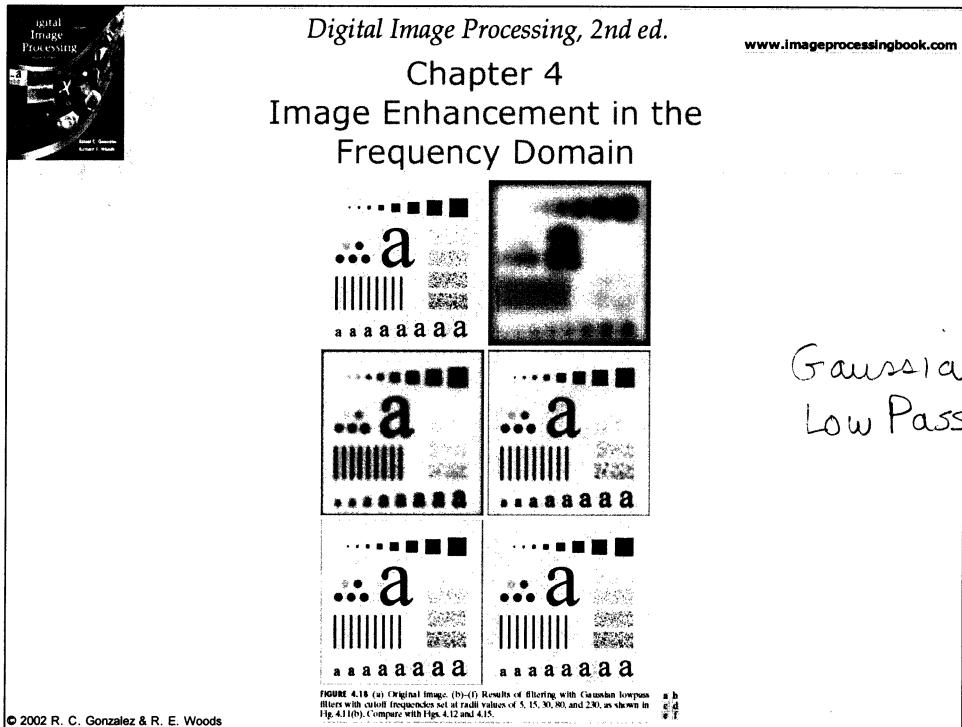
$$H(u, v) = e^{-\frac{D^2(u, v)}{2\sigma^2}}$$

↑
note constant is 1 for consistency with other filter types

PICK $\sigma = D_0$

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

Since it's always positive we expect no ringing in the resulting image.



Blurring linearly decreases as radius (D_0) increases
No ringing visible

Compare 4.18(c) Gaussian ← picture looks better
to 4.15(c) Butterworth so not as much smoothing



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a

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.



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.



broken
characters
are bad.

fuller and more filled
In Images using
GLPF with $D_0 = 80$

444 x 508 pixels.

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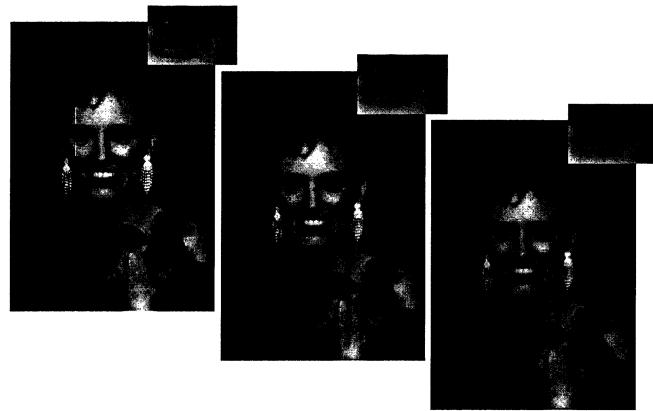
Example of using Gaussian LPF to improve
text for OCR.



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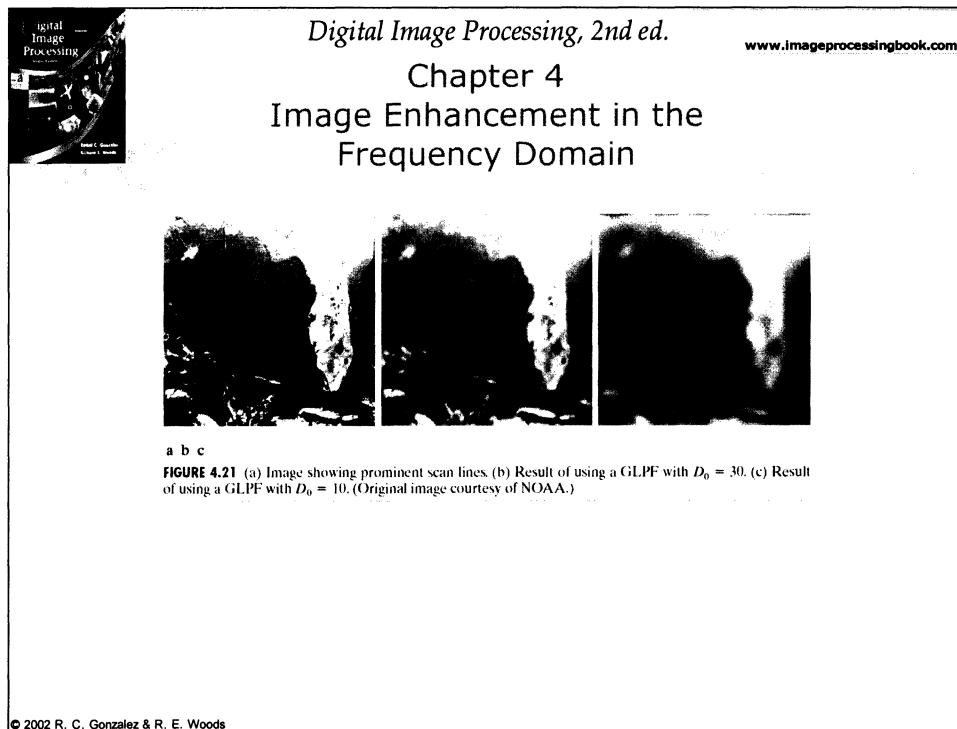


a b c

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).

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Another commercial application of low pass filtering.
Apply a GLPF to eliminate skin lines and blemishes
by selectively smoothing images.

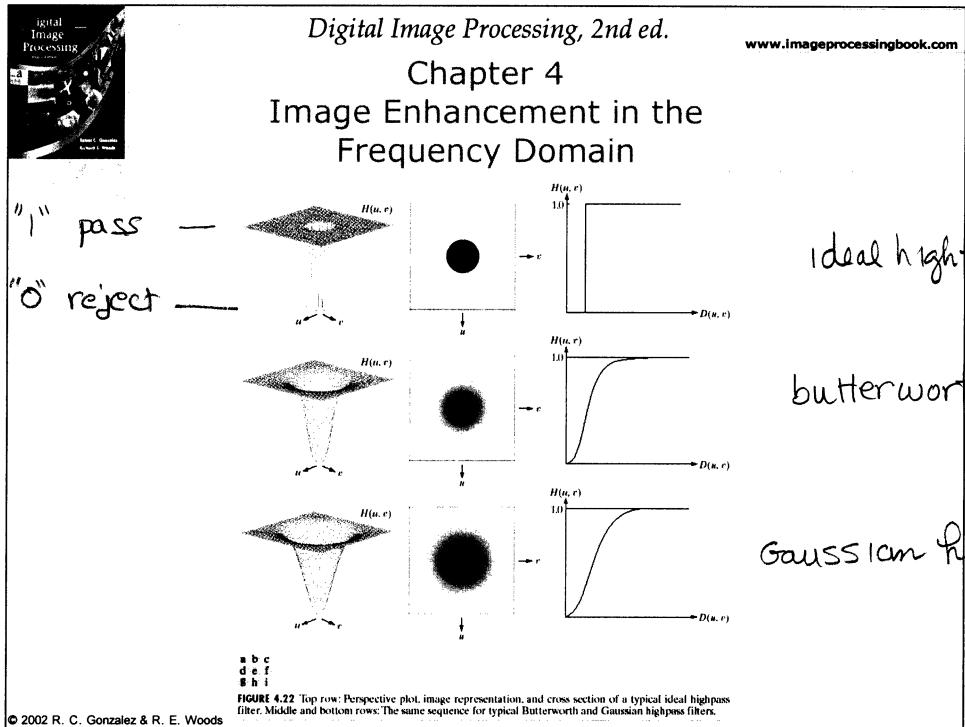


588 x 600 pixel original

GLPF $D_0 = 30$

GLPF $D_0 = 10$

might use this image for registration with a map



In the spatial domain we did unsharp masking as

$$f_s(x,y) = f(x,y) - \underbrace{\bar{f}(x,y)}_{\substack{\uparrow \\ \text{sharpened} \\ \text{detail}}} \quad \text{by subtracting} \\ \text{averaged image}$$

In the frequency domain we can write something roughly comparable

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

Generate spatial masks by

1. multiply $H(u,v)$ by $(-1)^{u+v}$ to center

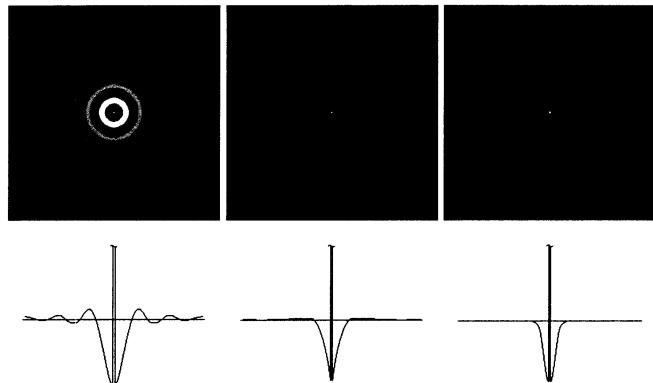
2. compute inverse DFT

3. multiply real part of inverse DFT by $(-1)^{x+y}$



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a b c

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

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Spatial filters generated by $H(u,v)$

1. multiply $H(u,v)$ by $(-1)^{u+v}$ to center
2. inverse DFT
3. multiply inverse DFT by $(-1)^{x+y}$

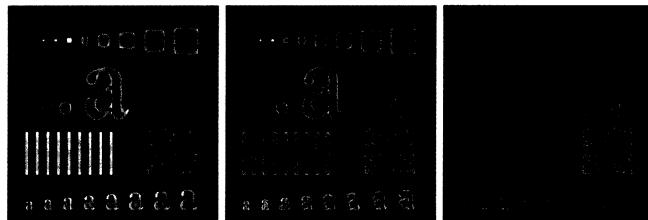


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original
test image
 500×500
Pixels

{



a b c

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

$D_0 = 15$

$D_0 = 30$

$D_0 = 80$

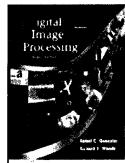
Nice edges
Good

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2D ideal high-pass filter (IHPF)

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

high-pass filtering emphasizes edge discontinuity information



Chapter 4

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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.

$D_0 = 15$

$D_0 = 30$

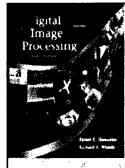
$D_0 = 80$

Much less ringing for small D_0 than IHPE

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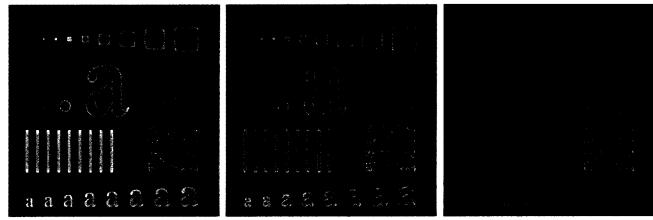
Butterworth high pass filter (BHPF) of order n

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



Chapter 4

Image Enhancement in the Frequency Domain



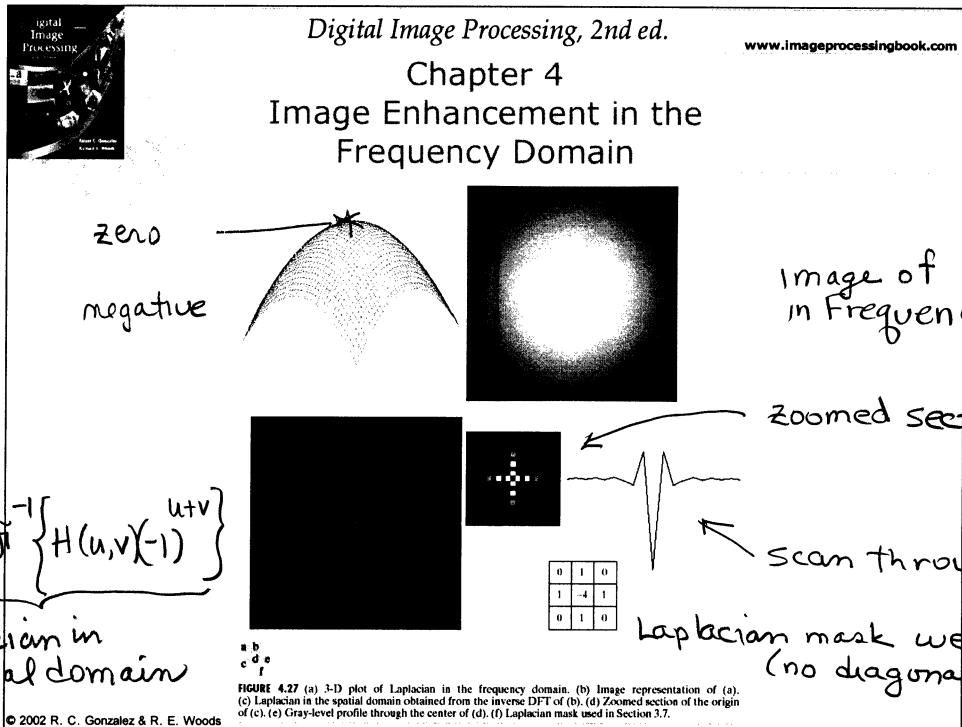
a b c

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.

$$\underbrace{D_0=15}_{\text{Very clean and smooth results.}} \quad \underbrace{D_0=30}_{\text{Very clean and smooth results.}} \quad \underbrace{D_0=80}_{\text{Very clean and smooth results.}}$$

Gaussian high-pass filter (GHPF)

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



What does the Laplacian look like in the frequency domain?

Using $\mathcal{F}\left[\frac{d^n f(x)}{dx^n}\right] = (j\omega)^n F(u)$

we can write $\mathcal{F}\left[\frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}\right] = (ju)^2 F(u,v) + (jv)^2 F(u,v)$

or $\mathcal{F}\left[\nabla^2 f(x,y)\right] = -(u^2 + v^2) F(u,v)$

We shift this to the center by multiplying $f(x,y)$ by $(-1)^{x+y}$ before we Fourier transform

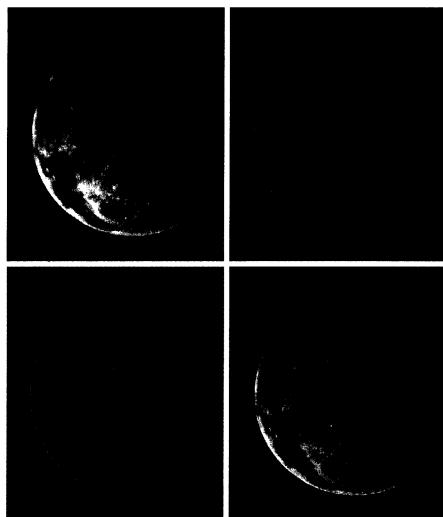
$$\Rightarrow \underbrace{\nabla^2 f(x,y)}_{\text{multiply by } (-1)^{x+y}} \Leftrightarrow - \left[\left(u - \frac{m}{2}\right)^2 + \left(v - \frac{N}{2}\right)^2 \right] F(u,v)$$

Laplacian plotted in (a)



Chapter 4 Image Enhancement in the Frequency Domain

a b
c d
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.)



scaled image
most positive $\rightarrow 1$
most negative $\rightarrow 0$

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laplacian
Filtering in the (u, v) domain

$$\nabla^2 f(x, y) = \mathcal{F}^{-1} \left\{ -[(u - \frac{M}{2})^2 + (v - \frac{N}{2})^2] F(u, v) \right\}$$

$$(4.4-12)$$

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

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

use one frequency domain mask

$$H(u, v) = 1 - \left[(u - \frac{M}{2})^2 + (v - \frac{N}{2})^2 \right]$$

be careful in scaling since these can be $\gg 1$

This result is the same one as done before in the spatial domain EXCEPT now done in the frequency domain.



Chapter 4 Image Enhancement in the Frequency Domain

a

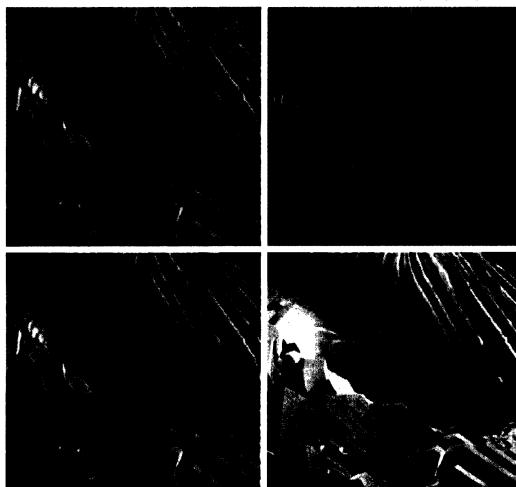
b

c

d

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-boost image
with $A=2$



high-pass filtered
image
with A increased to 2.7

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unsharp masking

$$f_{hp}(x,y) = f(x,y) - f_{lp}(x,y) \quad (1)$$

high boost filtering

$$f_{hb} = Af(x,y) - f_{lp}(x,y)$$

re-writing

$$f_{hb} = (A-1)f(x,y) + \underbrace{f(x,y) - f_{lp}(x,y)}_{f_{hp}(x,y)}$$

In the frequency domain

we can use a composite filter $H_{hb}(u,v) = (A-1)H(u,v) + H_{hp}(u,v)$ where $A \geq 1$

This is slightly different than previous spatial domain results because this frequency domain representation of the Laplacian does not include diagonal components.



Chapter 4 Image Enhancement in the Frequency Domain

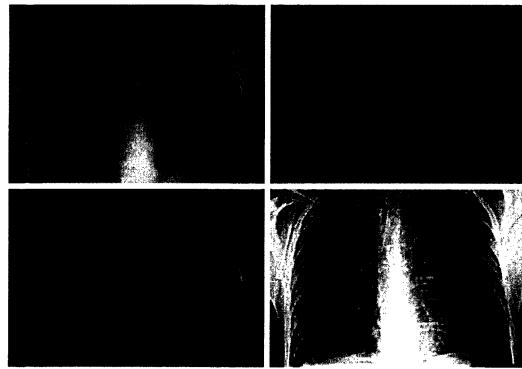


FIGURE 4.30
(a) A chest X-ray image. (b) Result of Butterworth highpass filtering.
(c) Result of high-frequency emphasis filtering.
(d) Result of performing histogram equalization on (c). (Original image courtesy Dr. Thomas R. Gest, Division of Anatomical Sciences, University of Michigan Medical School.)

high frequency
emphasis
 $a = 0.5$ $b = 2$
keeps low freq.
tones

histogram
equalization
of high frequency emphasis image

butterworth high pass
 $n=2$

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$$\text{high boost} \quad H_{hb}(u,v) = (A^{-1})f(x,y) + H_{hp}(u,v)$$

high-frequency emphasis

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

\uparrow multiply high frequencies by a constant
 \uparrow
add an offset so zero frequency term is
not eliminated

typically $1.25 < a < .5$ $1.5 < b < 2.0$

when $b=1$ this reduces to high-frequency boost

$b > 1$ this emphasizes high frequencies



Chapter 4 Image Enhancement in the Frequency Domain

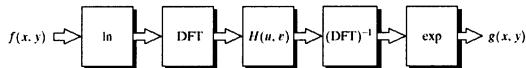


FIGURE 4.31
Homomorphic filtering approach for image enhancement.

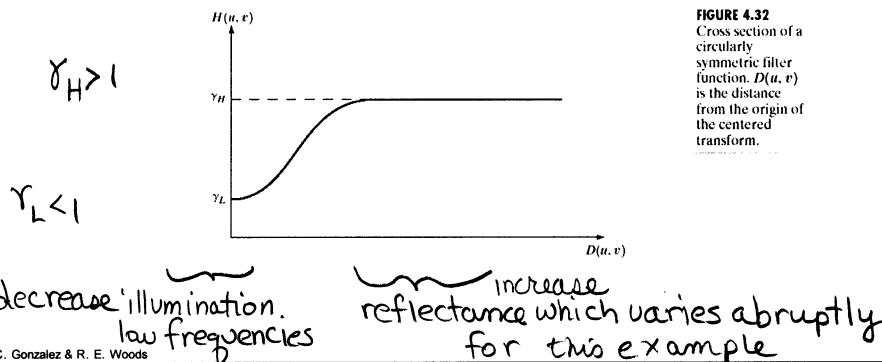


FIGURE 4.32
Cross section of a circularly symmetric filter function $H(u,v)$. $D(u,v)$ is the distance from the origin of the centered transform.

- simultaneous:
- ① dynamic range compression
- ② contrast enhancement

incident
reflected
object

$$f(x,y) = \underbrace{i(x,y)}_{\text{illumination}} \underbrace{r(x,y)}_{\text{reflectance from object}}$$

define $z(x,y) = \ln(f(x,y)) = \ln i(x,y) + \ln r(x,y)$
(Used log to separate i and r)
Fourier transform $\mathcal{F}\{z(x,y)\} = \mathcal{F}\{\ln i(x,y)\} + \mathcal{F}\{\ln r(x,y)\}$

$$Z(u,v) = F_i(u,v) + F_r(u,v)$$

Now process by a filter $H(u,v)$

$$S(u,v) = H(u,v)Z(u,v) = \underbrace{H(u,v)F_i(u,v)}_{\text{low frequencies}} + \underbrace{H(u,v)F_r(u,v)}_{\text{high frequencies}}$$

Inverse transforming

$$s(x,y) = \mathcal{F}^{-1}\{S(u,v)\} = \underbrace{\mathcal{F}^{-1}\{H(u,v)F_i(u,v)\}}_{i'(x,y)} + \underbrace{\mathcal{F}^{-1}\{H(u,v)F_r(u,v)\}}_{r'(x,y)}$$

$$s(x,y) = i'(x,y) + r'(x,y)$$

Use exponential to invert original logarithm

$$g(x,y) = e^{s(x,y)} = e^{i'(x,y)} e^{r'(x,y)} = i_0(x,y) r_0(x,y)$$

where $i_0(x,y) = e^{i'(x,y)}$ and $r_0(x,y) = e^{r'(x,y)}$

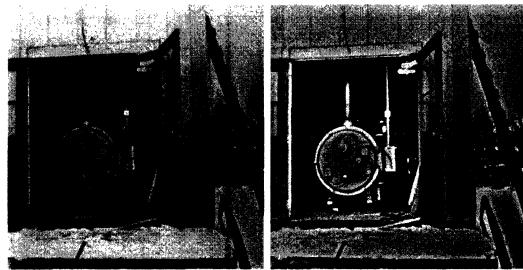


Chapter 4

Image Enhancement in the Frequency Domain

a-b

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



$$\gamma_L = 0.5$$

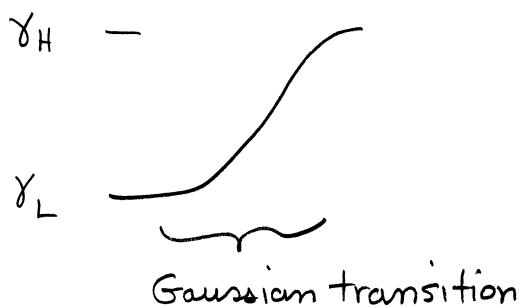
$$\gamma_H = 2$$

similar to high-frequency emphasis filter

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Result of homomorphic processing:

$$H(u,v) = (\gamma_H - \gamma_L) \left[1 - e^{-c \frac{D^2(u,v)}{D_0^2}} \right] + \gamma_L$$





Chapter 4 Image Enhancement in the Frequency Domain

centered on origin due to symmetry

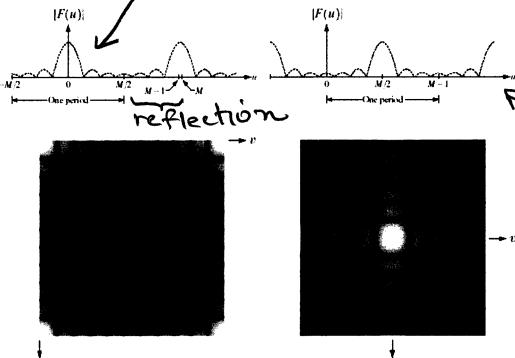
a

b

c

d

FIGURE 4.34
(a) Fourier spectrum showing back-to-back half periods in the interval $[0, M - 1]$.
(b) Shifted spectrum showing a full period in the same interval.
(c) Fourier spectrum of an image, showing the same back-to-back properties as (a), but in two dimensions.
(d) Centered Fourier spectrum.



This is the result
of `fft2`

This is what you see after using
`FFTSHIFT`

multiply by $(-1)^X$ before
taking transform.

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The DFT is periodic: $F(u, v) = F(u + M, v) = F(u, v + N) = F(u + M, v + N)$

The inverse DFT is periodic

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

The DFT is also symmetric

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

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

(a) In (a) we see $F(u)$ is periodic with a period of length M

$$F(u) = \frac{1}{m} \sum_{x=0}^{m-1} f(x) e^{-j \frac{2\pi u x}{m}}$$

(b) shows the result of premultiplying by $(-1)^X$
which is simply a shift.

$$F(u) = \frac{1}{m} \sum_{x=0}^{m-1} (-1)^x f(x) e^{-j \frac{2\pi u x}{m}} = \frac{1}{m} \sum_{x=0}^{m-1} f(x) e^{-j \frac{\pi}{2} x} e^{-j \frac{2\pi u x}{m}}$$

↑
since $-1 = e^{-j \frac{\pi}{2}}$

$$= \frac{1}{m} \sum_{x=0}^{m-1} f(x) e^{-j \frac{2\pi u x}{m} - j \frac{m\pi x}{2m}} = \frac{1}{m} \sum_{x=0}^{m-1} f(x) e^{-j \left(2\pi u + \frac{m}{2}\right) \frac{x}{m}}$$

Shifted by
 $\frac{m}{2}$



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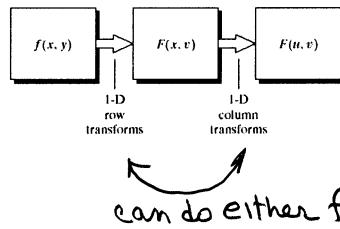


FIGURE 4.35
Computation of the 2-D Fourier transform as a series of 1-D transforms.

This argument also works for the inverse DFT.

SEPARABILITY

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This is one of the most common 2-D DFT implementations

①

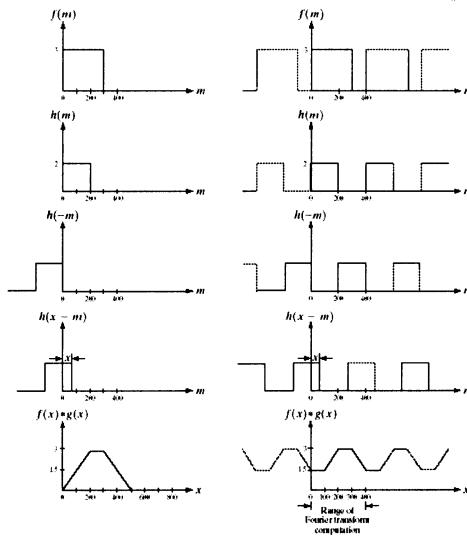
$$\begin{aligned}
 F(u, v) &= \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi \left(\frac{ux}{M} + \frac{vy}{N}\right)} \\
 &= \frac{1}{M} \sum_{x=0}^{M-1} e^{-j2\pi \frac{ux}{M}} \underbrace{\left[\sum_{y=0}^{N-1} f(x, y) e^{-j2\pi \frac{vy}{N}} \right]}_{\text{This is the 1-D DFT of } f(x, y)} \\
 &= \frac{1}{M} \sum_{x=0}^{M-1} F(x, v) e^{-j2\pi \frac{vx}{N}} \underbrace{F(x, v)}_{\text{This is the column DFT of } f(x, y)} \\
 &\quad \underbrace{x \text{ going from 0 to } M}_{\text{This is the subsequent row DFT}}
 \end{aligned}$$

② The DFT of the DFT yields $\frac{1}{MN} f^*(x, y)$
Since f is real this is not a problem. Multiply by MN to get $f(x, y)$



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FIGURE 4.36 Left: convolution of two discrete functions. Right: convolution of the same functions, taking into account the implied periodicity of the DFT. Note in (j) how data from adjacent periods corrupt the result of convolution.



Note: period
is 400

the wraparound
error comes from
Overlap of the
periodic functions

analytical convolution

Note that if f and g
are 400 points

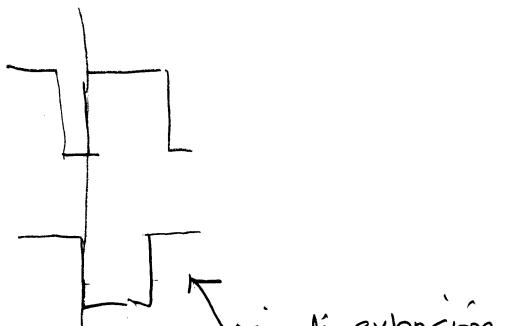
$f * g$ goes out to
800 points

DFT makes functions
periodic so
we are really convolving
periodic functions

Convolution:

$$\text{continuous: } f(x) * h(x) = \int_{-\infty}^{+\infty} x(\tau) h(t-\tau) d\tau$$

$$\text{discrete: } f(x) * h(x) = \frac{1}{M} \sum_{m=0}^{M-1} f(m) h(x-m)$$



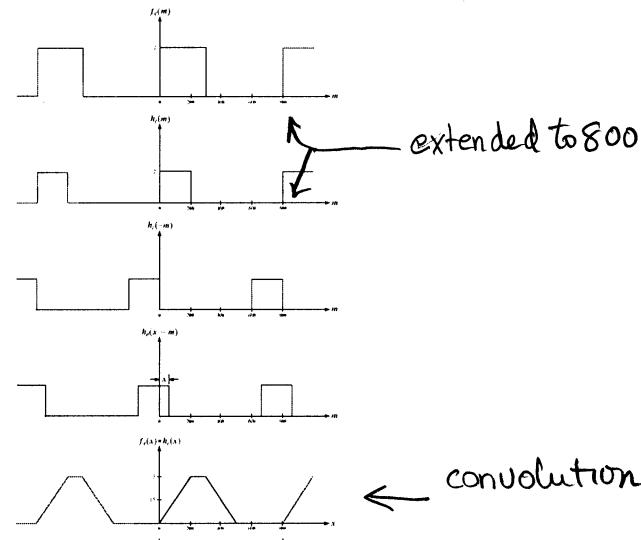
integral non-zero here

Get rid of this non-zero overlap
by simply adding zeros to both functions
until the overlap term goes away.



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FIGURE 4.37
Result of performing convolution with extended functions. Compare Figs 4.37(c) and 4.38(c).

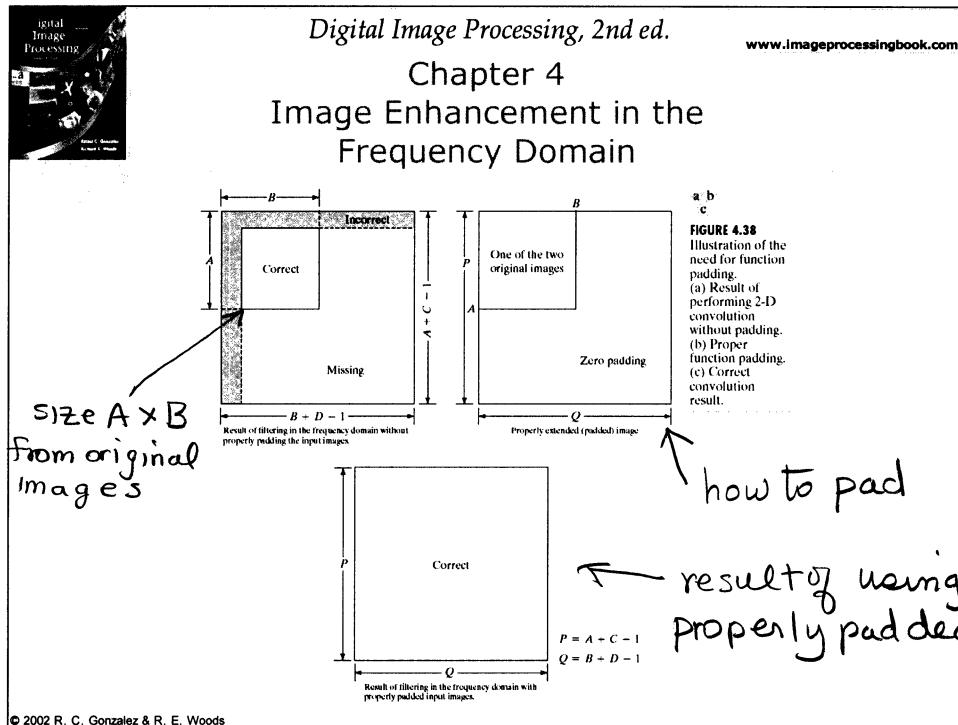


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$$\text{Padded functions } \begin{aligned} f_e(x) &= \begin{cases} f(x) & 0 \leq x \leq A-1 \\ 0 & A \leq x \leq P \end{cases} \\ g_e(x) &= \begin{cases} g(x) & 0 \leq x \leq B-1 \\ 0 & B \leq x \leq P \end{cases} \end{aligned} \quad \left. \right\} \text{ both have period } P \text{ after padding}$$

P is the new extended (or padded) period

If $P = A + B - 1$ there will be no wrap-around area



(a) f, h are square and the same size

This is the result of $\text{ifft2} [\text{fft2}(f) * \text{fft2}(h)]$

There is a band of wrap around error.

(b) f, h are properly padded

$$P \geq A + C - 1$$

$$Q \geq B + D - 1$$

for images $A \times B$ and $C \times D$



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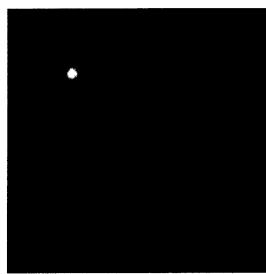


FIGURE 4.39 Padded lowpass filter in the spatial domain (only the real part is shown).

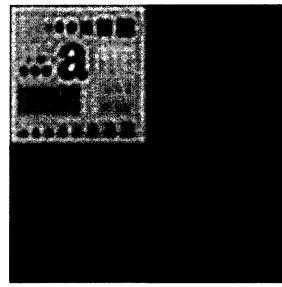


FIGURE 4.40 Result of filtering with padding. The image is usually cropped to its original size since there is little valuable information past the image boundaries.

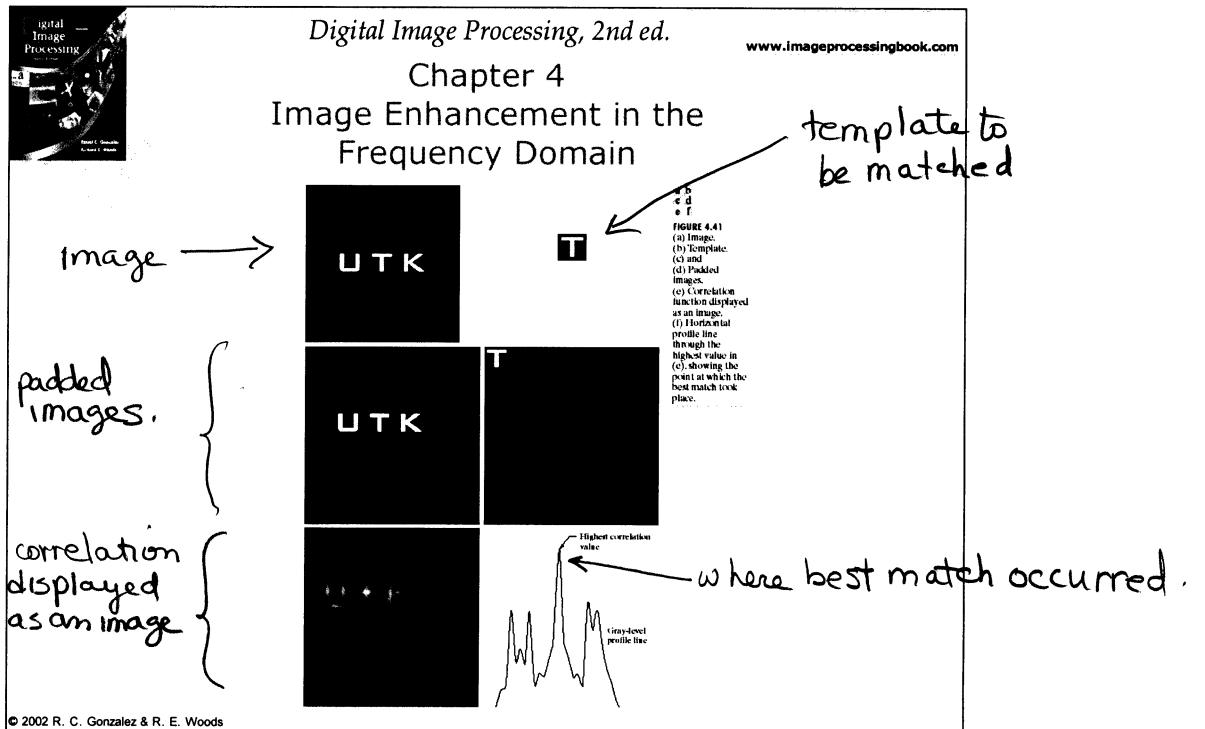
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properly padded
low pass filter



result of filtering (using padded filter)
a padded test image

Crop back to size
of original image



discrete convolution

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

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

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

discrete correlation

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

Since images are usually real
this doesn't affect us

not mirrored about origin

correlation theorem

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

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