



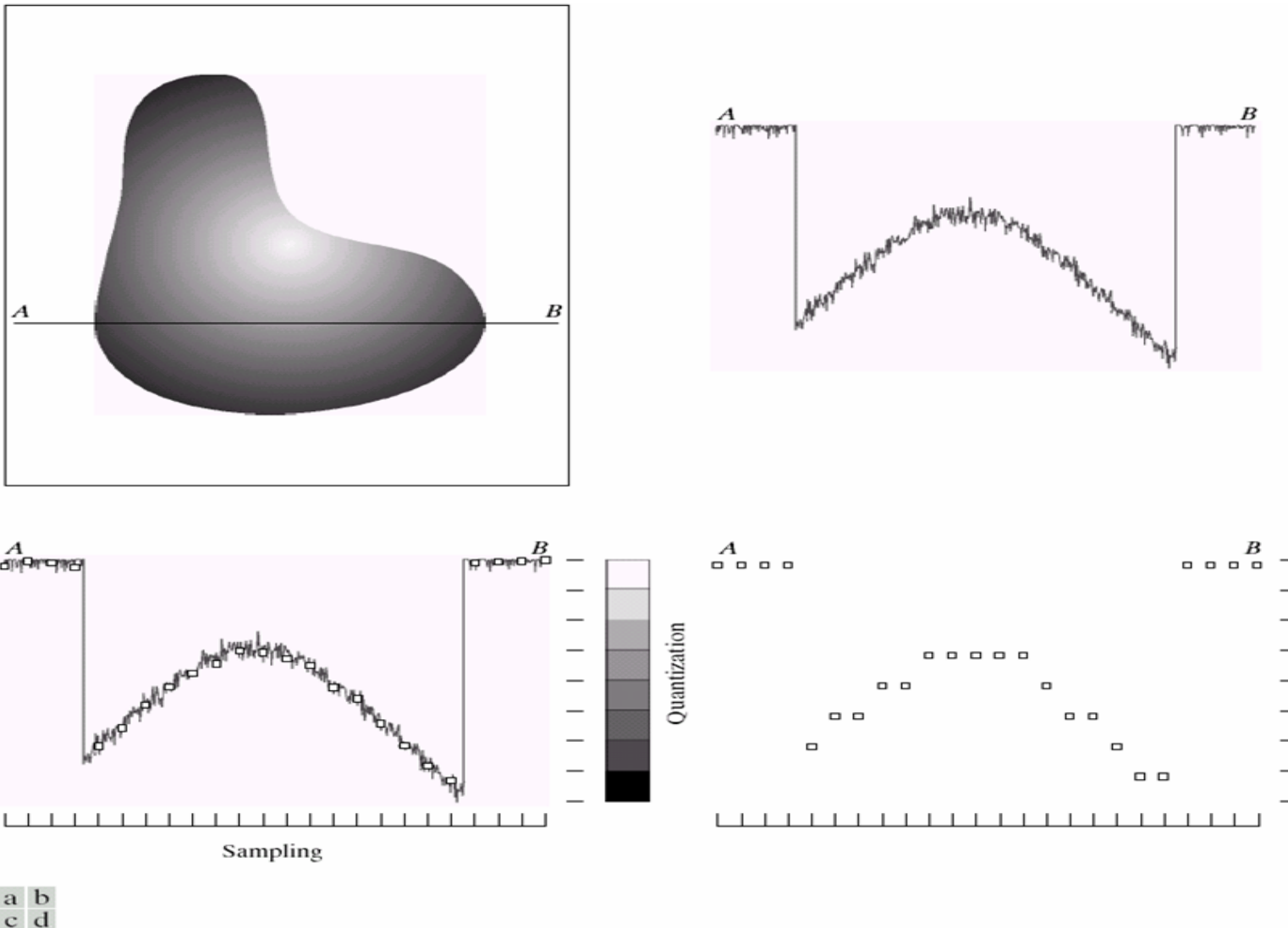
# Digital Image Processing

## Sampling

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# Sampling and Quantization



**FIGURE 2.16** Generating a digital image. (a) Continuous image. (b) A scan line from *A* to *B* in the continuous image, used to illustrate the concepts of sampling and quantization. (c) Sampling and quantization. (d) Digital scan line.

# 2-D Function

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- Continuous function (analog image)

$$f(x, y) : x, y \in \mathbb{R}$$

- Discrete function (sampled image)

$$u(m, n) : m, n \in \mathbb{Z}$$

# Delta Function in 1-D Discrete Case

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- Delta function

$$\delta(n) = \begin{cases} 1 & \text{if } n = 0, \\ 0 & \text{otherwise.} \end{cases}$$

- Arbitrary function as sum of shifted delta functions

$$u(n) = \sum_{\bar{n}=-\infty}^{\infty} u(\bar{n})\delta(n - \bar{n})$$

# Delta Function in 2-D Discrete Case

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- Delta function

$$\delta(m, n) = \delta(m) \cdot \delta(n)$$

- Arbitrary function as sum of shifted delta functions

$$u(m, n) = \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n}) \delta(m - \bar{m}, n - \bar{n})$$

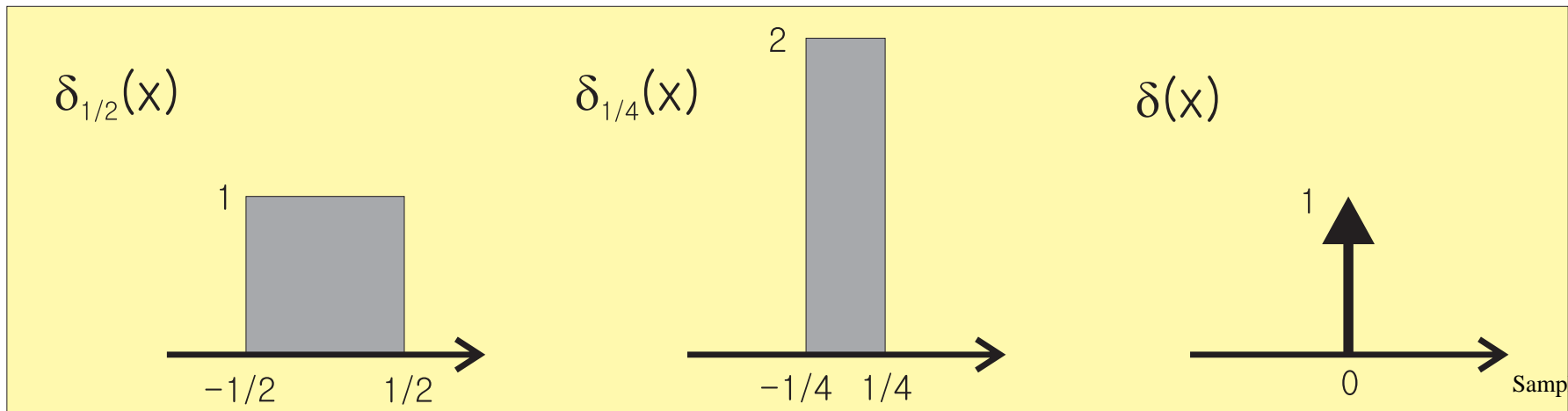
# Delta Function in 1-D Continuous Case

- Approximate delta function

$$\delta_{\epsilon}(x) = \begin{cases} \frac{1}{2\epsilon} & \text{if } |x| < \epsilon, \\ 0 & \text{otherwise.} \end{cases}$$

- Delta function

$$\delta(x) = \lim_{\epsilon \rightarrow 0} \delta_{\epsilon}(x)$$



# Delta Function in 1-D Continuous Case

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- Arbitrary function as sum (integral) of shifted delta functions

$$f(x) = \int_{-\infty}^{\infty} f(\bar{x})\delta(x - \bar{x})d\bar{x}$$

- Proof

$$\begin{aligned} \int_{-\infty}^{\infty} f(\bar{x})\delta(x - \bar{x})d\bar{x} &= \lim_{\epsilon \rightarrow 0} \int_{-\infty}^{\infty} f(\bar{x})\delta_{\epsilon}(x - \bar{x})d\bar{x} \\ &= \lim_{\epsilon \rightarrow 0} \frac{1}{2\epsilon} \int_{x-\epsilon}^{x+\epsilon} f(\bar{x})d\bar{x} \\ &= f(x) \end{aligned}$$

# Delta Function in 2-D Continuous Case

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- Delta function

$$\delta(x, y) = \delta(x) \cdot \delta(y)$$

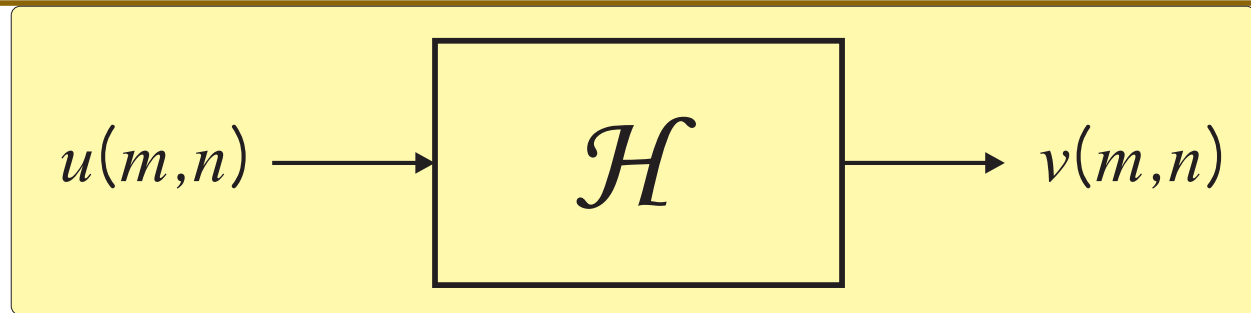
- Arbitrary function as sum of shifted delta functions

$$f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\bar{x}, \bar{y}) \delta(x - \bar{x}, y - \bar{y}) d\bar{x} d\bar{y}$$



# Linear Shift Invariant System

## ■ Linearity



$$\mathcal{H}[u_1(m, n)] = v_1(m, n),$$

$$\mathcal{H}[u_2(m, n)] = v_2(m, n)$$

$$\begin{aligned} \Rightarrow \mathcal{H}[a_1 u_1(m, n) + a_2 u_2(m, n)] \\ = a_1 v_1(m, n) + a_2 v_2(m, n) \end{aligned}$$

## ■ Shift Invariance

$$\mathcal{H}[u(m, n)] = v(m, n)$$

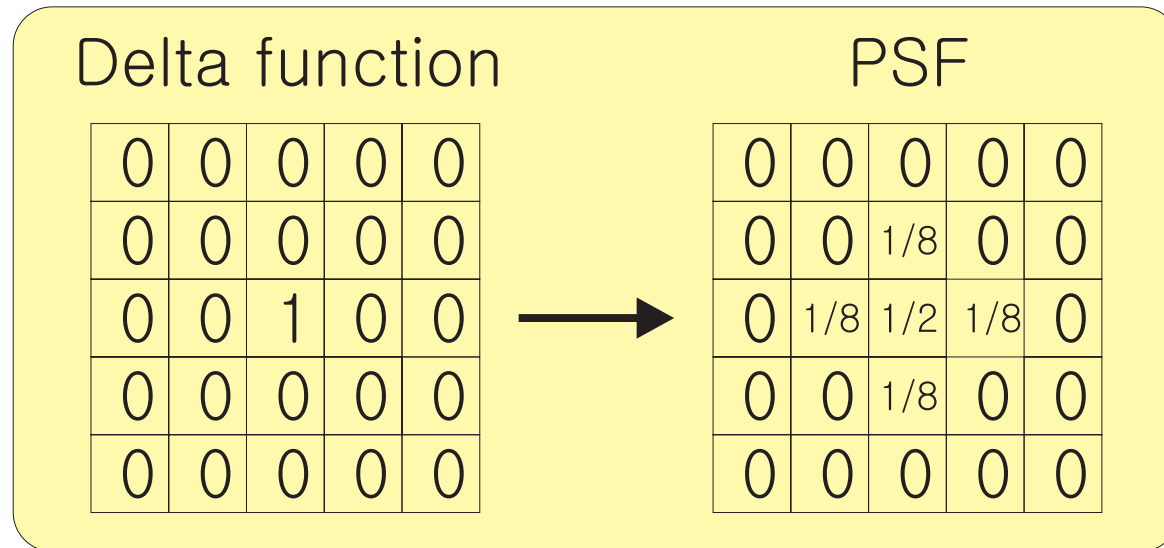
$$\Rightarrow \mathcal{H}[u(m - \bar{m}, n - \bar{n})] = v(m - \bar{m}, n - \bar{n})$$

# Impulse Response

- Consider an LSI system  $\mathcal{H}$  such that

$$\mathcal{H}(\delta(m, n)) = h(m, n)$$

- $h(m, n)$  is called
  - impulse response
  - point spread function (PSF)



# Convolution

- Given an LSI system  $\mathcal{H}$  with PSF  $h(m, n)$  and an arbitrary input  $u(m, n)$ , what is the output  $v(m, n)$ ?
- Recall that

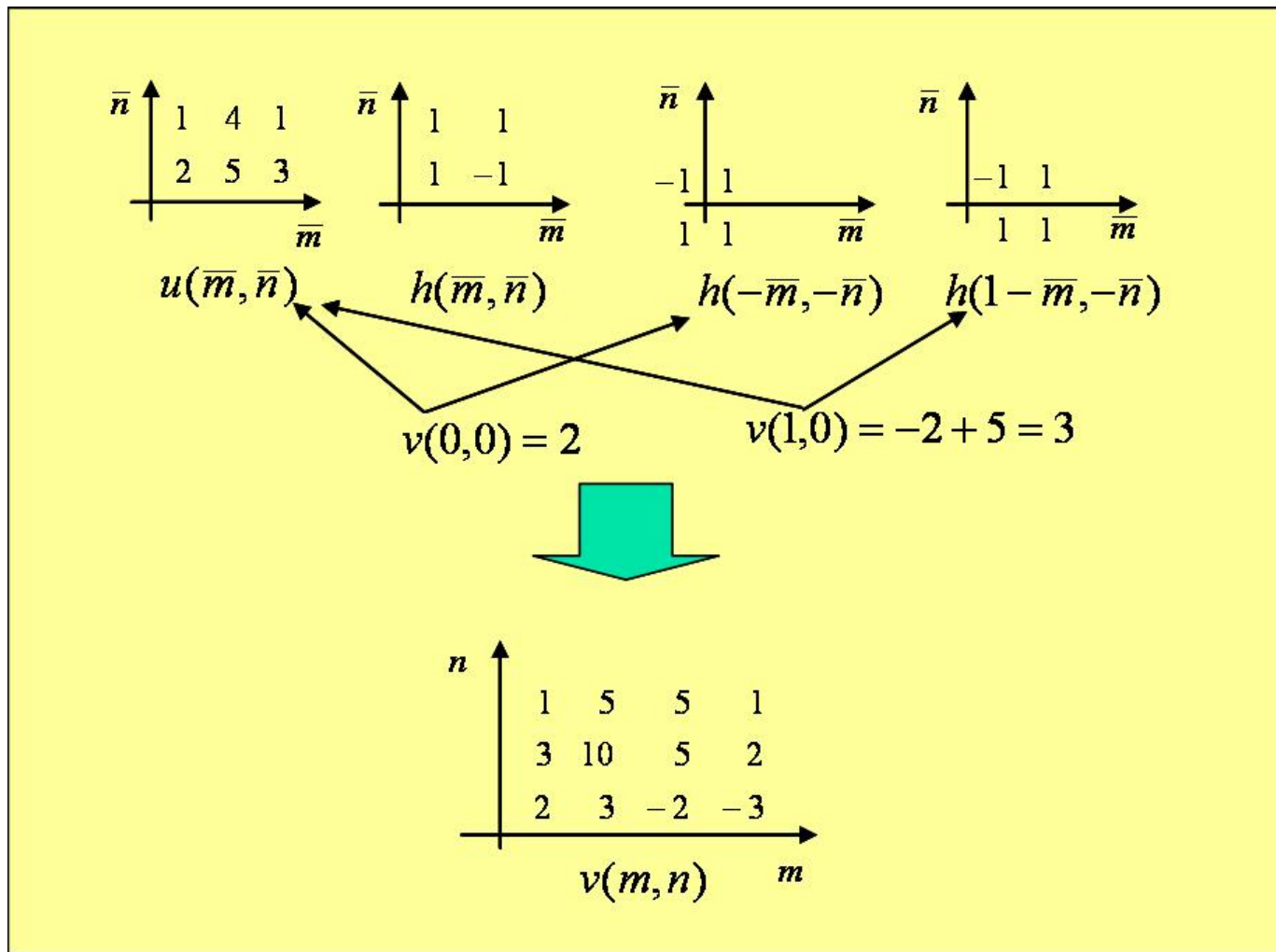
$$u(m, n) = \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n}) \delta(m - \bar{m}, n - \bar{n})$$

- Hence

$$\begin{aligned} v(m, n) &= \mathcal{H} \left[ \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n}) \delta(m - \bar{m}, n - \bar{n}) \right] \\ &= \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n}) \mathcal{H}[\delta(m - \bar{m}, n - \bar{n})] \\ &= \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n}) h(m - \bar{m}, n - \bar{n}) \\ &\doteq u(m, n) * h(m, n) \end{aligned}$$

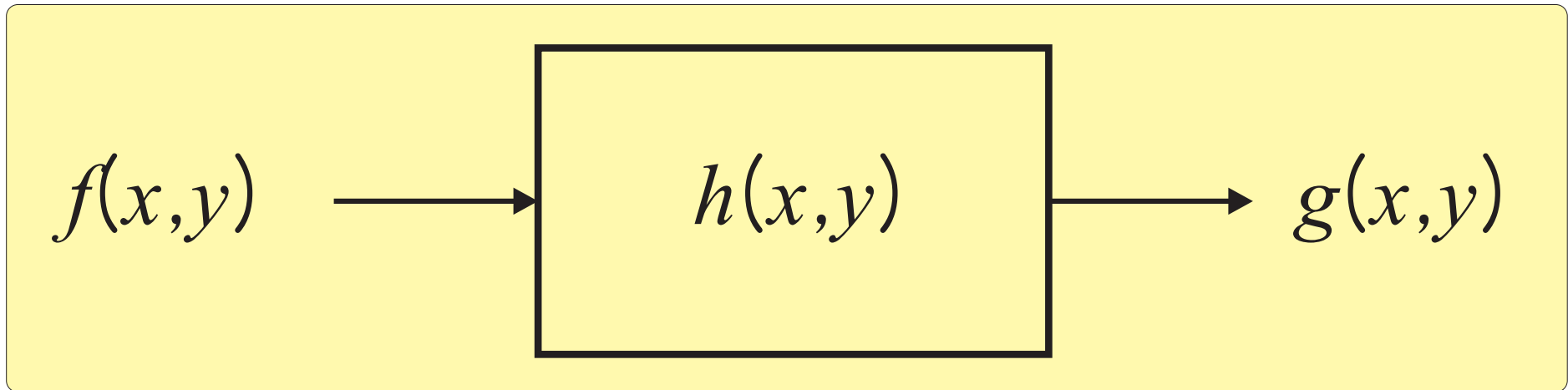
# Convolution Example

$$v(m, n) = u(m, n) * h(m, n) = \sum_{\bar{m}=-\infty}^{\infty} \sum_{\bar{n}=-\infty}^{\infty} u(\bar{m}, \bar{n})h(m - \bar{m}, n - \bar{n})$$



# Convolution of Continuous Functions

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## ■ Convolution

$$\begin{aligned} g(x, y) &= f(x, y) * h(x, y) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\bar{x}, \bar{y}) h(x - \bar{x}, y - \bar{y}) d\bar{x} d\bar{y} \end{aligned}$$

# Fourier Transform

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- Fourier transform pair

$$F(\xi_1, \xi_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \exp[-j2\pi(x\xi_1 + y\xi_2)] dx dy$$

$$f(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(\xi_1, \xi_2) \exp[j2\pi(x\xi_1 + y\xi_2)] d\xi_1 d\xi_2$$

- Fourier transform is an one-to-one mapping from function space to function space (information preserving).

- $\exp[j2\pi(x\xi_1 + y\xi_2)]$

- large  $\xi_1$  or  $\xi_2 \rightarrow$  fast varying in  $x$  or  $y$  direction

- $(\xi_1, \xi_2)$ : horizontal and vertical frequencies

- $F(\xi_1, \xi_2)$ : the amount of frequency component  $(\xi_1, \xi_2)$ , which is contained within  $f(x, y)$

# Fourier Transform

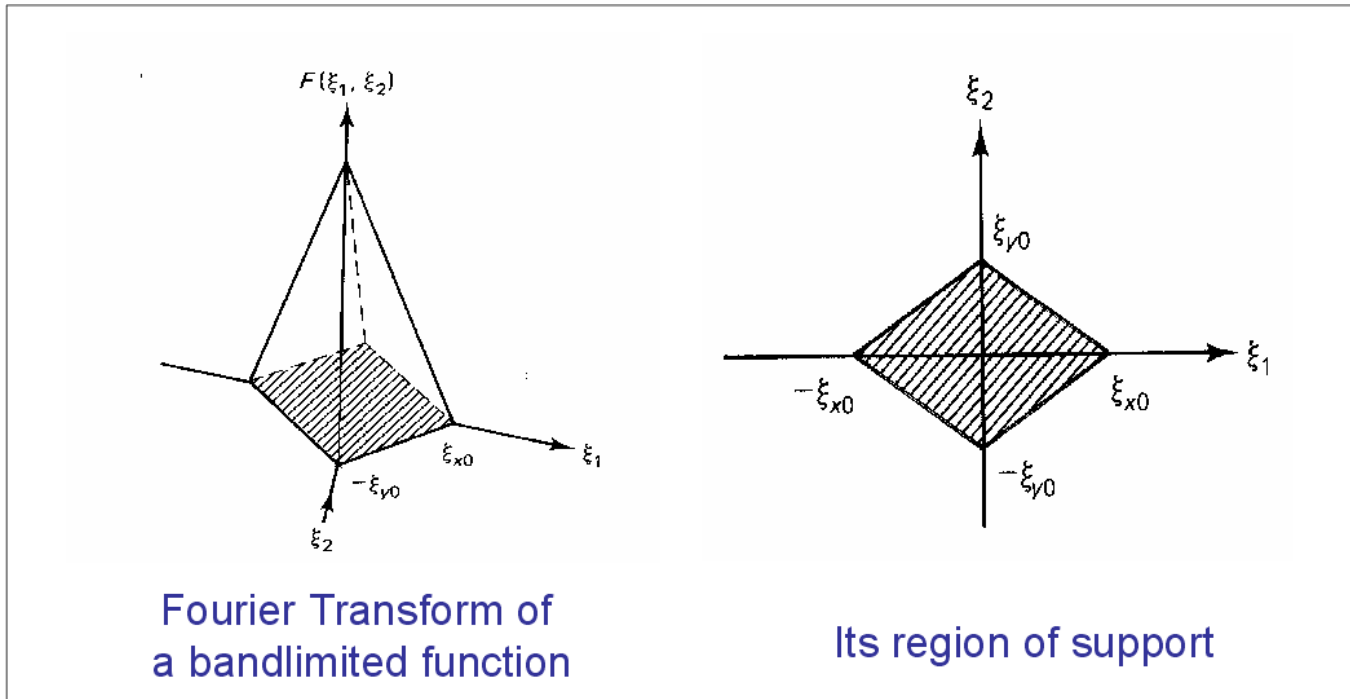
## Properties of 2-D Fourier Transform

	Function	Its Fourier Transform
Linearity	$a f(x, y) + b g(x, y)$	$a F(\xi_1, \xi_2) + b G(\xi_1, \xi_2)$
Convolution	$f(x, y) * g(x, y)$	$F(\xi_1, \xi_2) G(\xi_1, \xi_2)$
Multiplication	$f(x, y) g(x, y)$	$F(\xi_1, \xi_2) * G(\xi_1, \xi_2)$
Comb function	$\sum_{m, n=-\infty}^{\infty} \delta(x - m\Delta x, y - n\Delta y)$	$\frac{1}{\Delta x \Delta y} \sum_{k, l=-\infty}^{\infty} \delta(\xi_1 - k \frac{1}{\Delta x}, \xi_2 - l \frac{1}{\Delta y})$
Lowpass filter	$f(x, y) = \text{sinc}(\alpha x) \text{sinc}(\beta y)$	$F(\xi_1, \xi_2) = \begin{cases} \frac{1}{\alpha \beta}, &  \xi_1  < \frac{1}{2}\alpha,  \xi_2  < \frac{1}{2}\beta \\ 0, & \text{otherwise} \end{cases}$

Note:  $\text{sinc}(x) = \frac{\sin \pi x}{\pi x}$

# Sampling

## ■ Bandlimited Images



## ■ $f(x, y)$ is called bandlimited if

$$F(\xi_1, \xi_2) = 0 \quad \text{when } |\xi_1| > \xi_{x0} \text{ or } |\xi_2| > \xi_{y0}$$



# Multiplying by Comb Function

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- Sampling on a rectangular grid with spacing  $\Delta x, \Delta y$
- Comb function

$$\text{comb}(x, y; \Delta x, \Delta y) \doteq \sum_{m, n=-\infty}^{\infty} \delta(x - m\Delta x, y - n\Delta y)$$

- Sampled image  $f_s(x, y)$

$$\begin{aligned} f_s(x, y) &= f(x, y) \text{comb}(x, y; \Delta x, \Delta y) \\ &= \sum_{m, n=-\infty}^{\infty} f(m\Delta x, n\Delta y) \delta(x - m\Delta x, y - n\Delta y) \end{aligned}$$

# Multiplying by Comb Function

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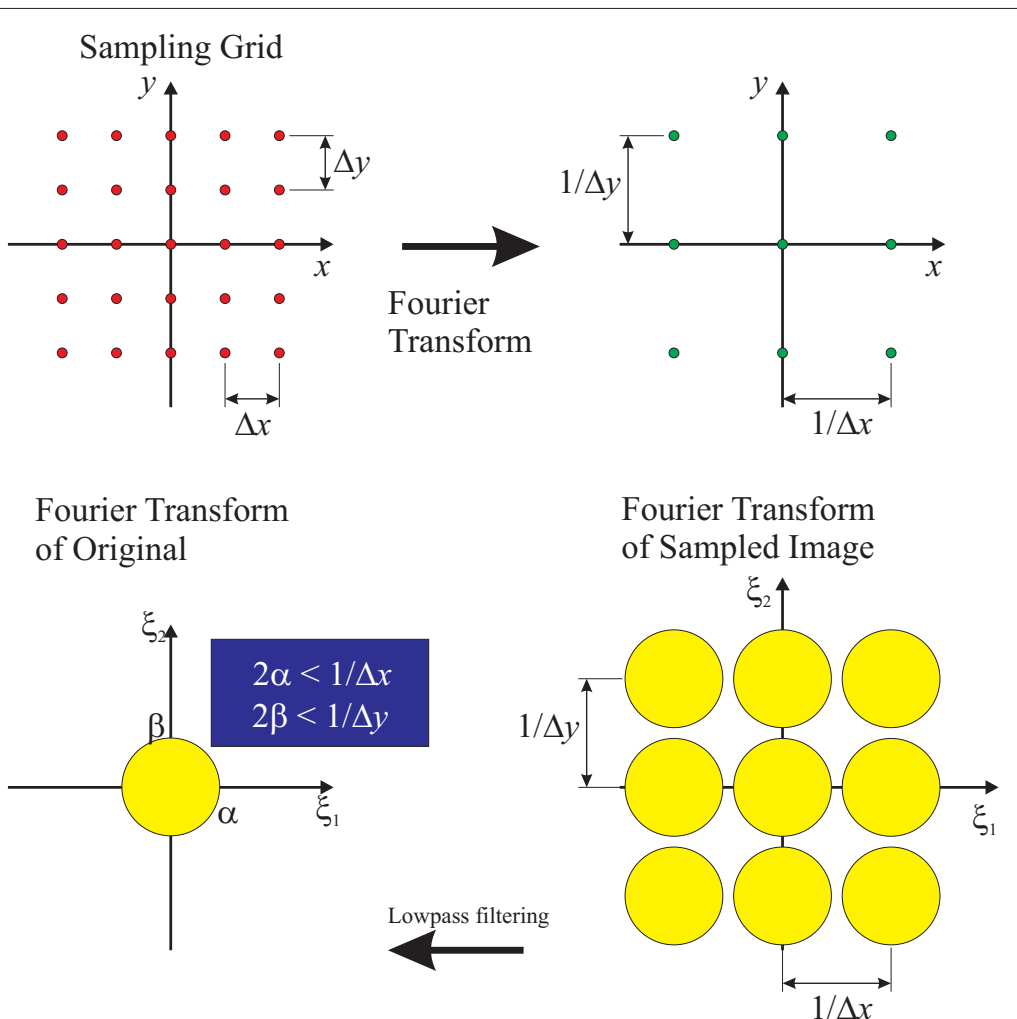
- Frequency Domain

$$\begin{aligned} F_s(\xi_1, \xi_2) &= F(\xi_1, \xi_2) * \mathcal{FOURIER}[\text{comb}(x, y; \Delta x, \Delta y)] \\ &= \frac{1}{\Delta x \Delta y} \sum_{k, l = -\infty}^{\infty} F(\xi_1, \xi_2) * \delta\left(\xi_1 - k \frac{1}{\Delta x}, \xi_2 - l \frac{1}{\Delta y}\right) \\ &= \frac{1}{\Delta x \Delta y} \sum_{k, l = -\infty}^{\infty} F\left(\xi_1 - k \frac{1}{\Delta x}, \xi_2 - l \frac{1}{\Delta y}\right) \end{aligned}$$

- Periodic replication of original transform on a grid with spacing  $\left(\frac{1}{\Delta x}, \frac{1}{\Delta y}\right)$

# Nyquist Sampling Theorem

$$F_s(\xi_1, \xi_2) = \frac{1}{\Delta x \Delta y} \sum_{k, l = -\infty}^{\infty} F\left(\xi_1 - k \frac{1}{\Delta x}, \xi_2 - l \frac{1}{\Delta y}\right)$$



■  $(\Delta x, \Delta y)$  in space  $\Rightarrow (\frac{1}{\Delta x}, \frac{1}{\Delta y})$  in frequency

■ Nyquist Sampling Theorem

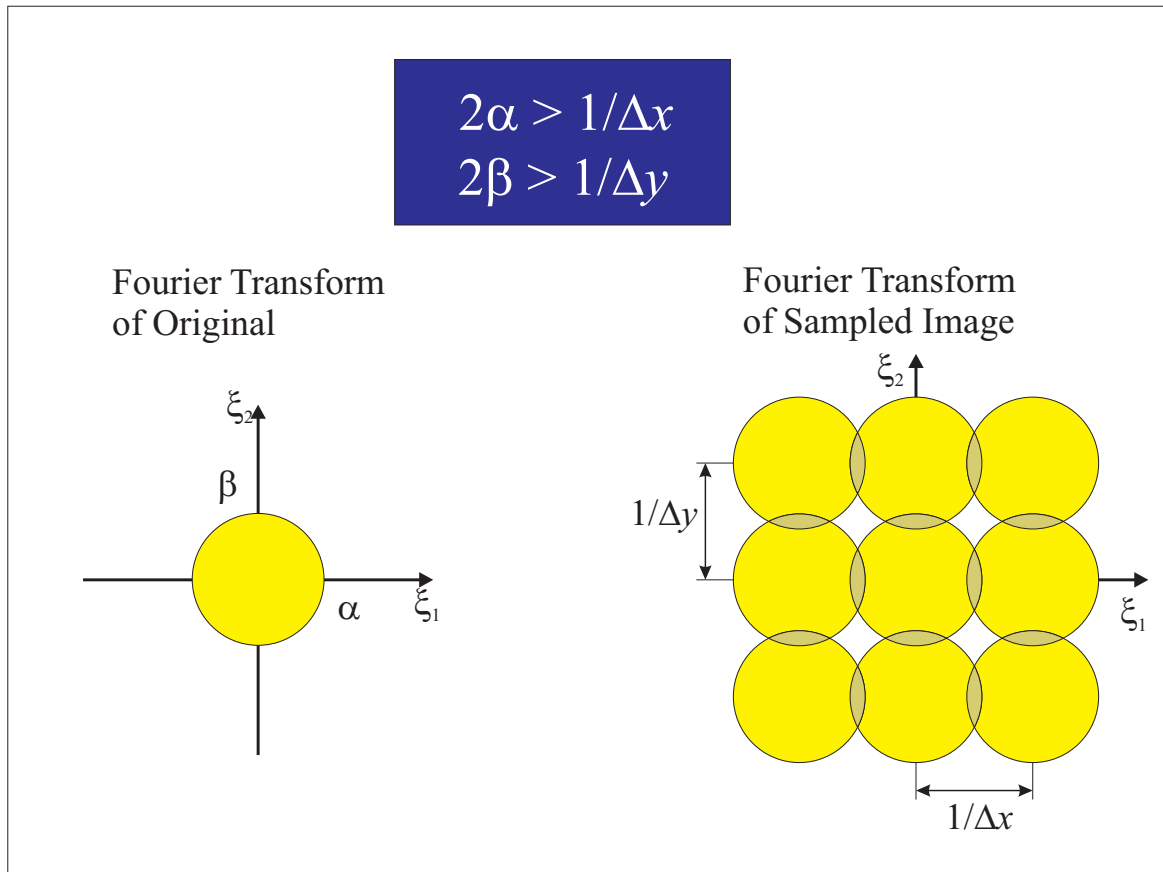
$$\xi_{xs} \doteq \frac{1}{\Delta x} > 2\alpha$$

$$\xi_{ys} \doteq \frac{1}{\Delta y} > 2\beta$$

■ Perfect reconstruction filter

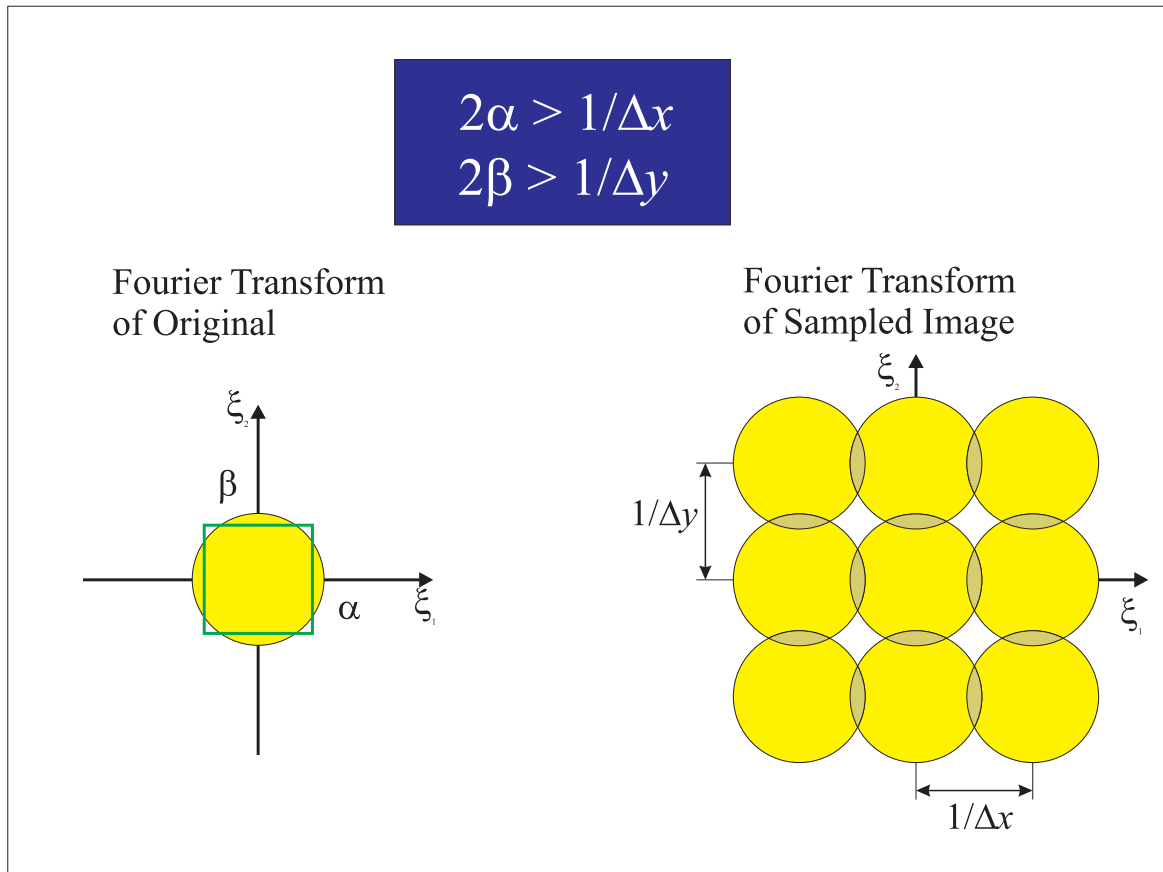
$$H(\xi_1, \xi_2) = \begin{cases} \Delta x \Delta y & |\xi_1| < \frac{1}{2\Delta x}, |\xi_2| < \frac{1}{2\Delta y} \\ 0 & \text{otherwise} \end{cases}$$

# Aliasing



- Folding (addition) happens between two consecutive replicas of original transform
- Thus, original transform (and image) cannot be reconstructed
- For example, let  $a + b = c$ . Can you recover  $a$  and  $b$  from  $c$ ?

# Pre-filtering

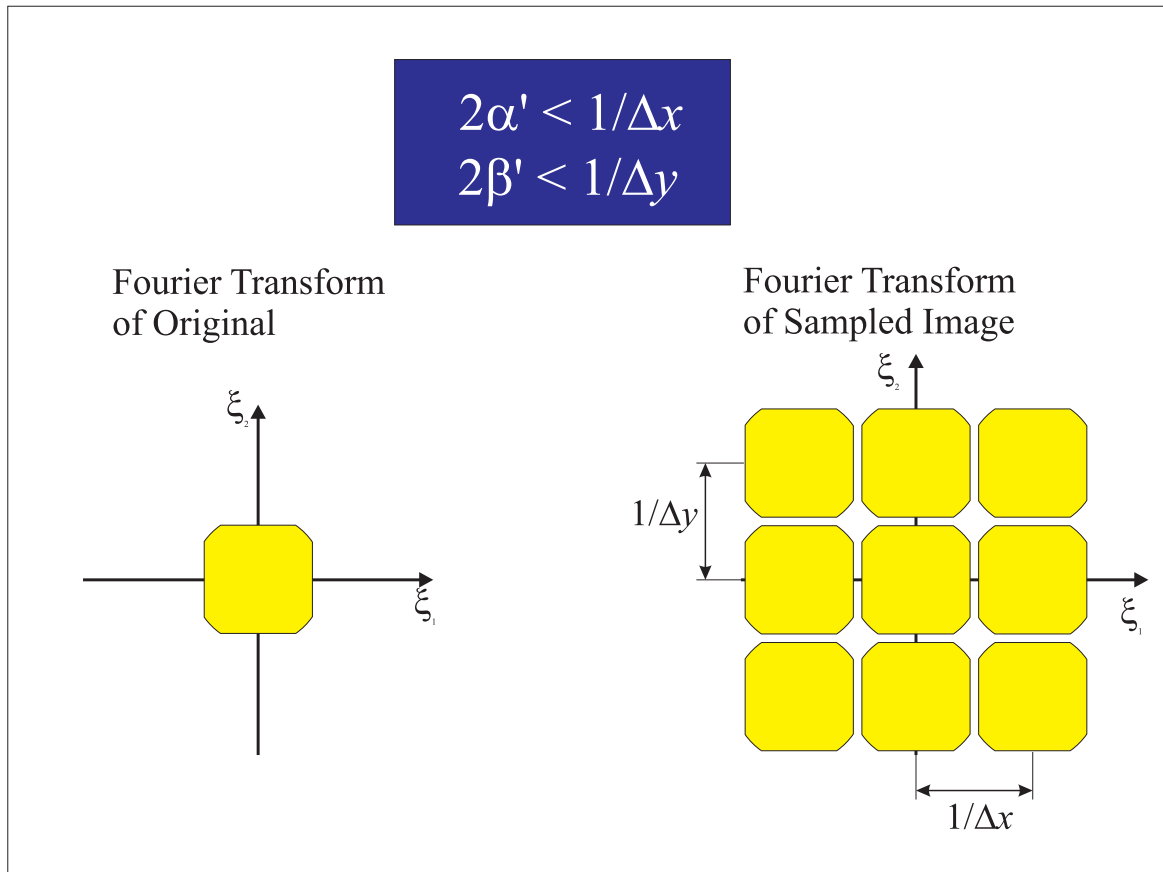


■ Before sampling, use a lowpass filter with cutoff frequencies  $(c_x, c_y)$

■  $c_x < \frac{1}{2\Delta x}$

■  $c_y < \frac{1}{2\Delta y}$

# Pre-filtering



- No aliasing due to pre-filtering
- Loss of high frequency information
- Pre-filtering is used in some applications because aliasing is unpredictable but the information loss is predictable.

# Perfect Reconstruction Filter

$$\times f_s(x, y) = \sum_{m, n=-\infty}^{\infty} f(m\Delta x, n\Delta y) \delta(x - m\Delta x, y - n\Delta y)$$

$$\Rightarrow F_s(\xi_1, \xi_2) = \frac{1}{\Delta x \Delta y} \sum_{k, l=-\infty}^{\infty} F(\xi_1 - k \frac{1}{\Delta x}, \xi_2 - l \frac{1}{\Delta y})$$

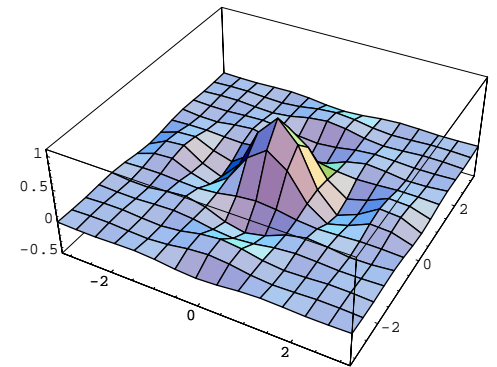
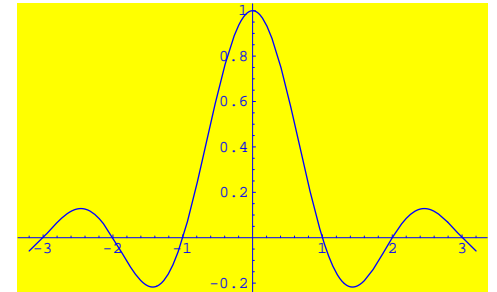
$$\times H(\xi_1, \xi_2) = \begin{cases} \Delta x \Delta y & |\xi_1| < \frac{1}{2\Delta x}, |\xi_2| < \frac{1}{2\Delta y} \\ 0 & \text{otherwise} \end{cases}$$

$$\Rightarrow h(x, y) = \text{sinc}\left(\frac{x}{\Delta x}\right) \text{sinc}\left(\frac{y}{\Delta y}\right)$$

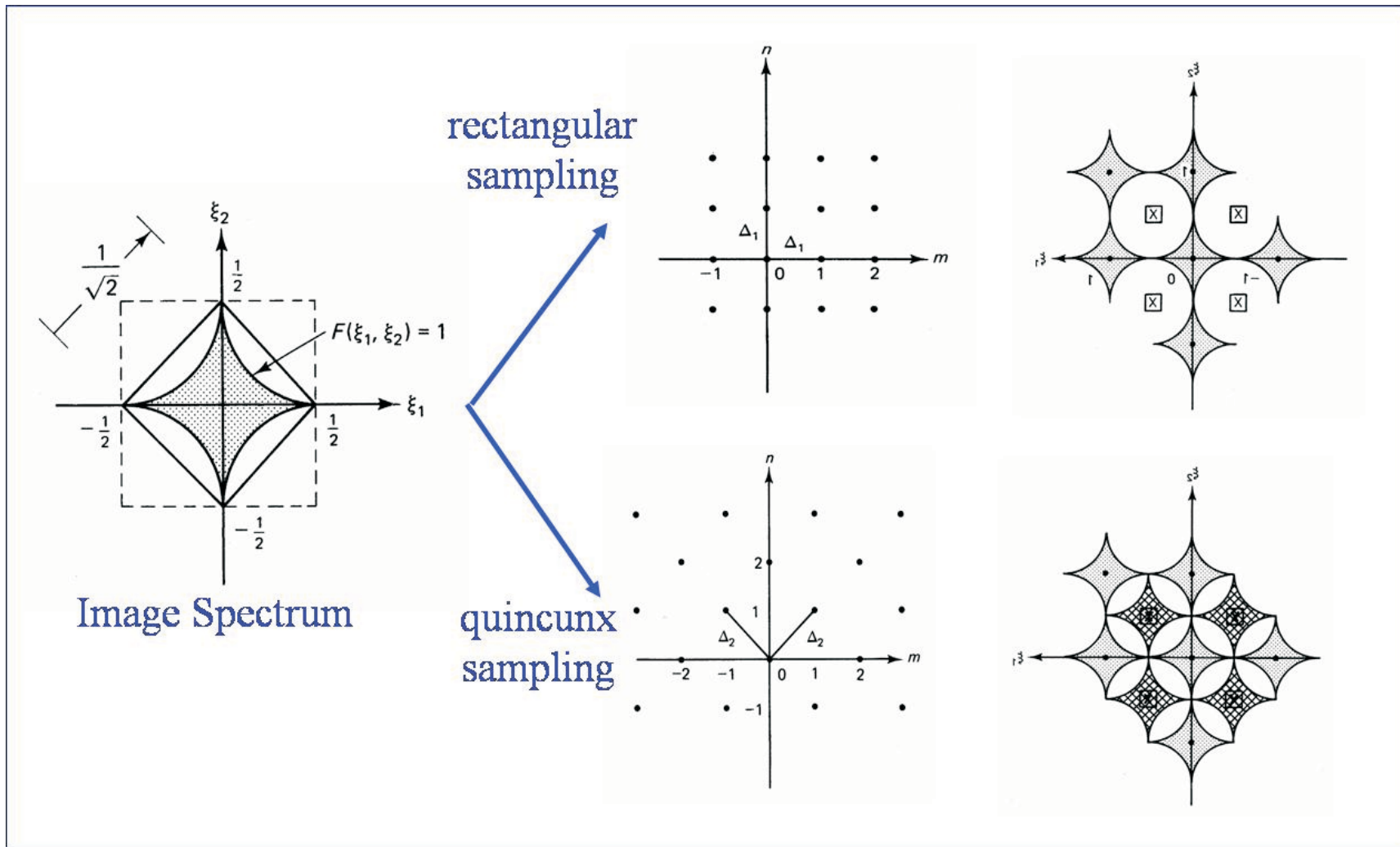
$$\times f(x, y) = f_s(x, y) * h(x, y)$$

$$= \sum_{m, n=-\infty}^{\infty} f(m\Delta x, n\Delta y) \delta(x - m\Delta x, y - n\Delta y) * \text{sinc}\left(\frac{x}{\Delta x}\right) \text{sinc}\left(\frac{y}{\Delta y}\right)$$

$$= \sum_{m, n=-\infty}^{\infty} f(m\Delta x, n\Delta y) \text{sinc}\left(\frac{x - m\Delta x}{\Delta x}\right) \text{sinc}\left(\frac{y - n\Delta y}{\Delta y}\right)$$



# Nonrectangular Grid Sampling and Interlacing

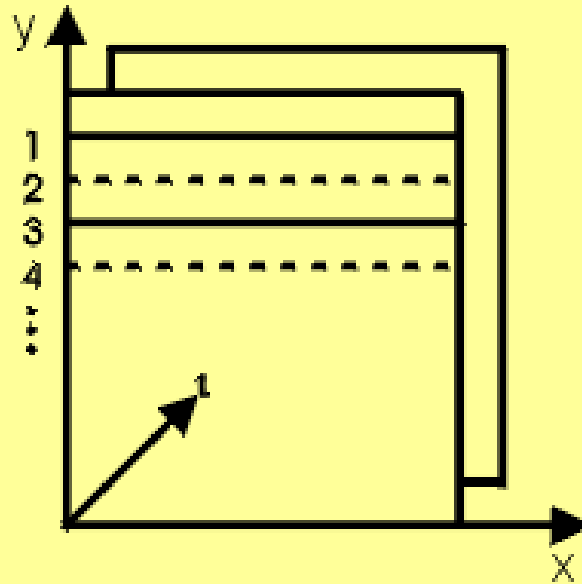


Sampling resolution can be reduced by a factor of 2 by using quincunx sampling lattice



# Nonrectangular Grid Sampling and Interlacing

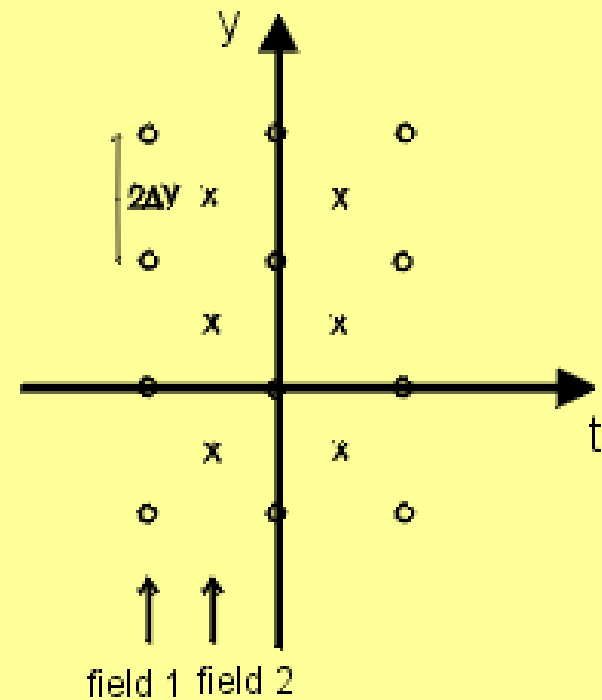
- Interlacing scan in TV system



TV : 2-to-1 interlace scan (sampling in  $y$  direction)

field 1 : scan odd numbered lines

field 2 : scan even numbered lines



Sampling structure in  
vertical/temporal plane

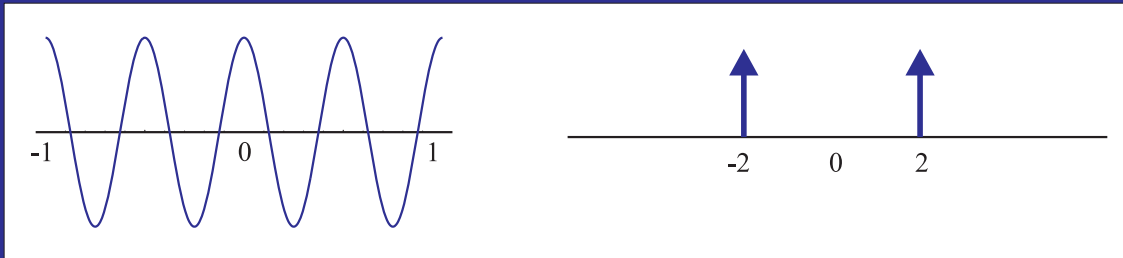
# Practical Limitations in Sampling and Reconstruction

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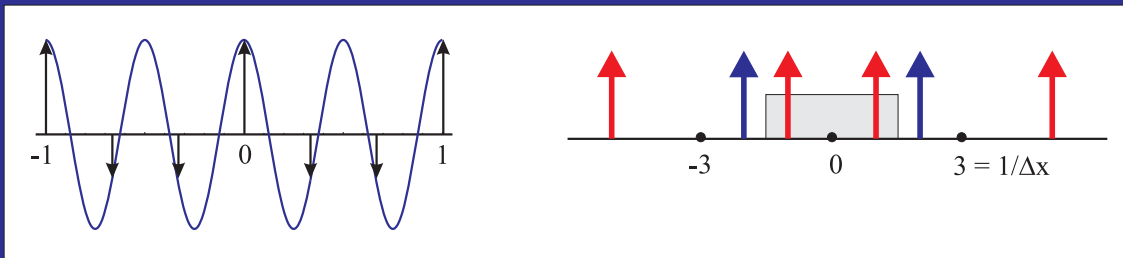
- Real image signal - not bandlimited
  - aliasing is inevitable
- Low-pass filtering before sampling
  - can alleviate aliasing
  - but attenuate higher spatial frequency information (image blurring)
- Non-ideal reconstruction filter (display or printer)

# Example of Aliasing

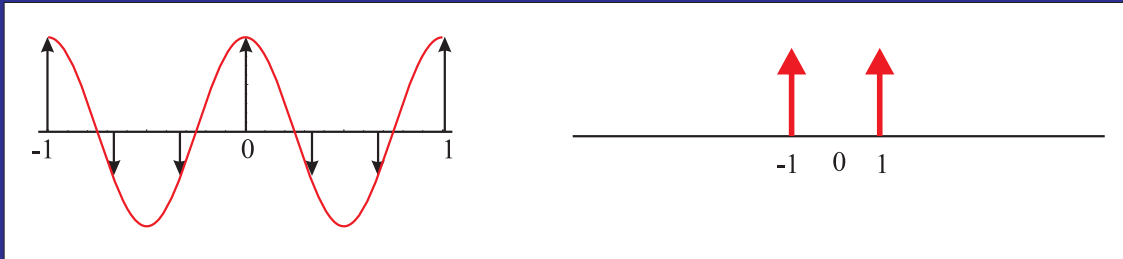
Original Signal:  $f(x) = \cos 4\pi x$



Sampling:  $\Delta x = 1/3$



Reconstructed Signal:  $f(x) = \cos 2\pi x$



■ Bandwidth of the original signal = 2

■ Nyquist sampling rate

$$\frac{1}{\Delta x} > 2 \cdot 2 = 4, \quad \Delta x < \frac{1}{4}$$

■ By mistake, one assume that the bandwidth is less than 1.5 and use the sampling distance  $\Delta x = \frac{1}{3}$

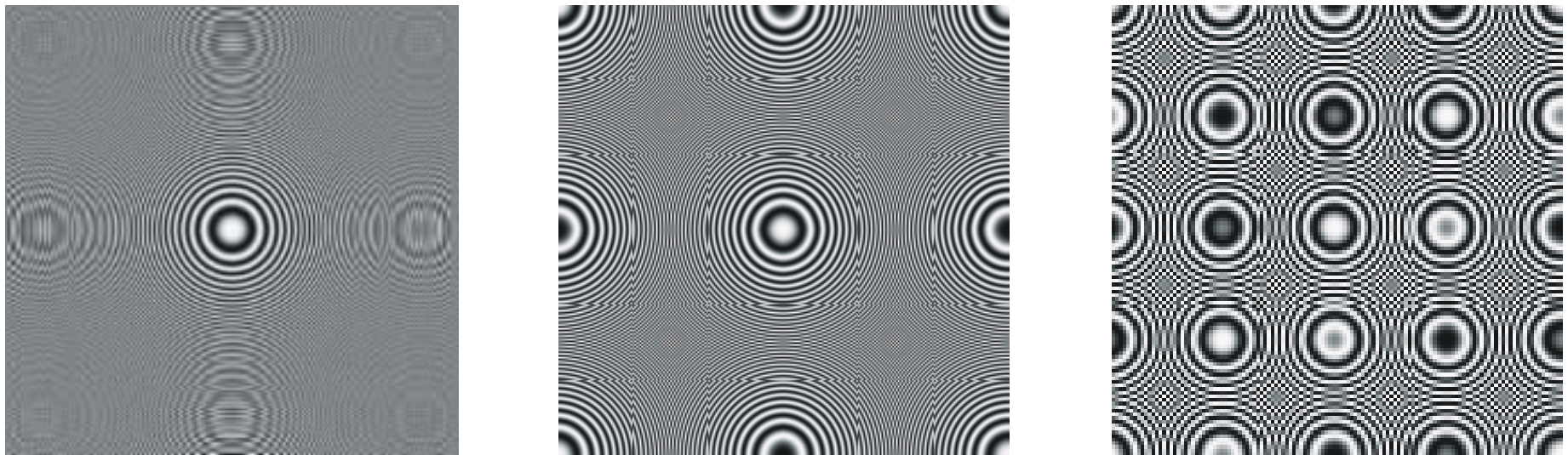
■ Reconstruction filter yields frequencies higher than 1.5

■ Aliasing causes totally wrong reconstruction

# Example of Aliasing (Cont'd)

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- Cocentric circles



High

Low

• Sampling frequency

# Low-pass Filtering

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- Aliasing can be alleviated by low-passing original image before sampling



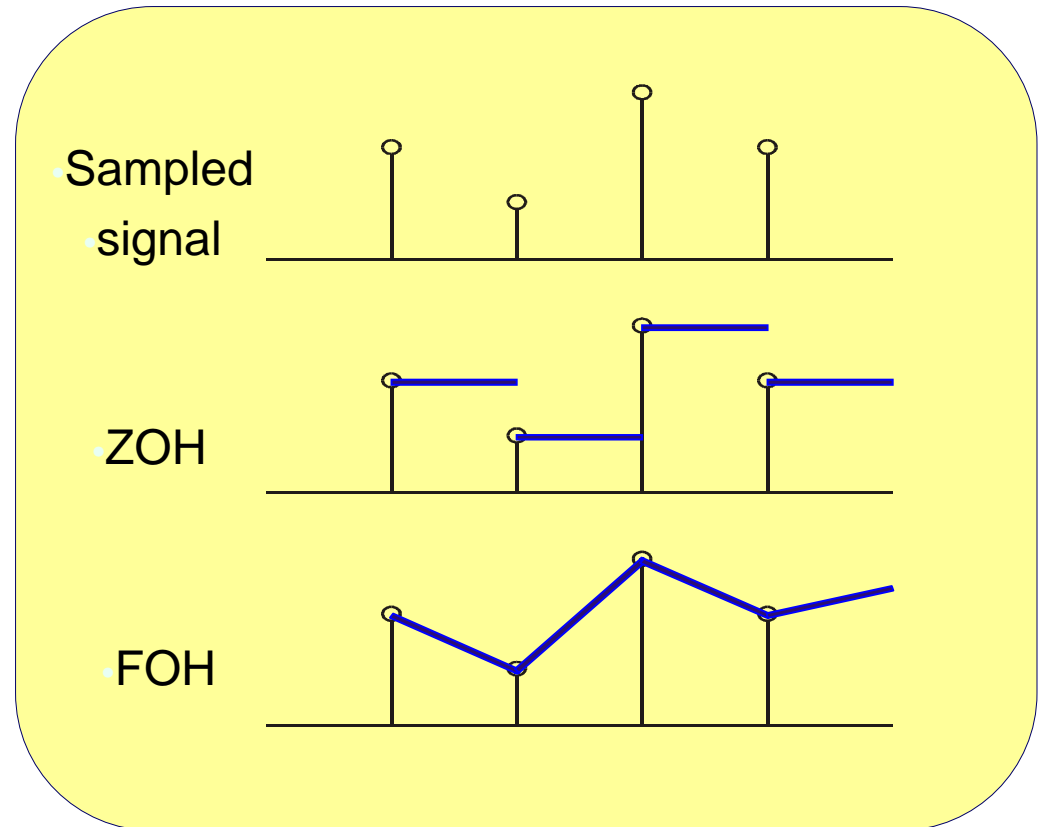
With pre-filtering



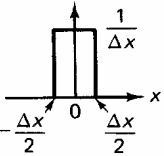
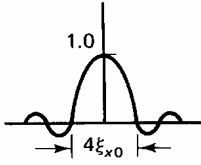
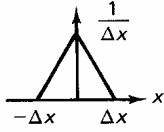
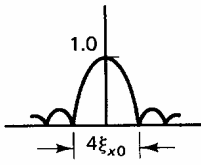
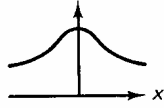
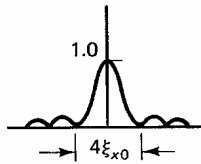
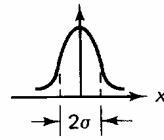
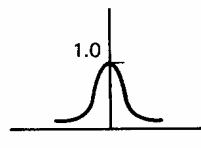
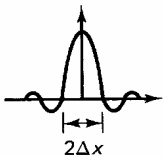
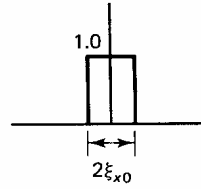
Without pre-filtering

# Practical Interpolation Filter

- Ideal filter – **sinc** function
  - ▶ not implemetable
  - ▶ infinite duration
  - ▶ negative lobe
- Repetition or zero-order holding (ZOH)
- Linear interpolation or first-order holding (FOH)
- Quadratic
- Cubic spline
- Gaussian



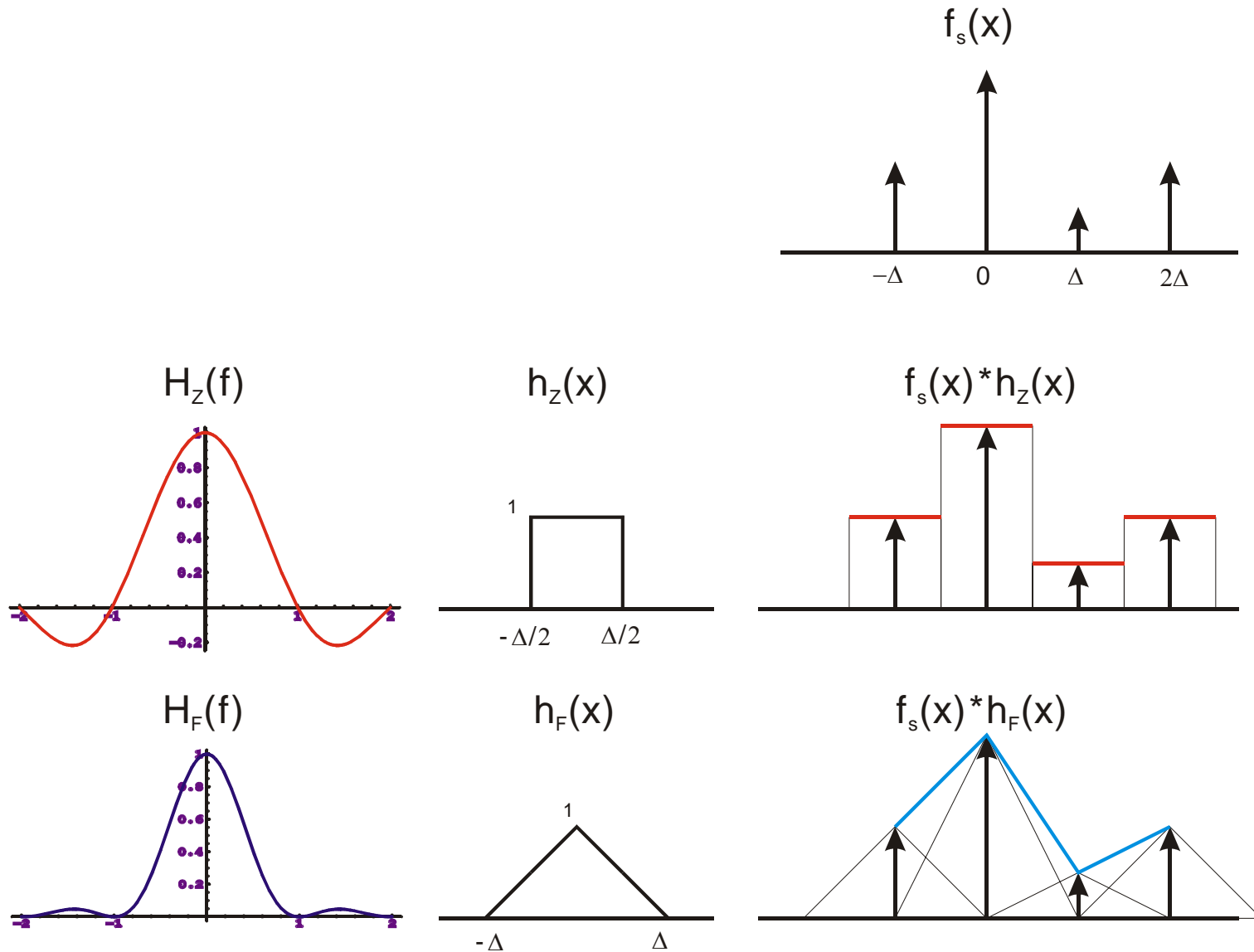
# Practical Interpolation Filter

One-dimensional interpolation function	Diagram	Definition $p(x)$	Two-dimensional interpolation function $p_d(x, y) = p(x)p(y)$	Frequency response $P_d(\xi_1, \xi_2)$	$P_d(\xi_1, 0)$
ZOH		$\frac{1}{\Delta x} \text{rect}\left(\frac{x}{\Delta x}\right)$	$p_o(x)p_o(y)$	$\text{sinc}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{2\xi_{y0}}\right)$	
FOH		$\frac{1}{\Delta x} \text{tri}\left(\frac{x}{\Delta x}\right)$ $p_o(x) \oplus p_o(x)$	$p_1(x)p_1(y)$	$\left[\text{sinc}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{2\xi_{y0}}\right)\right]^2$	
NOH		$p_o(x) \oplus \dots \oplus p_o(x)$ $n$ convolutions	$p_n(x)p_n(y)$	$\left[\text{sinc}\left(\frac{\xi_1}{\xi_{x0}}\right)\text{sinc}\left(\frac{\xi_2}{\xi_{y0}}\right)\right]^{n+1}$	
Gaussian		$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{x^2}{2\sigma^2}\right]$	$\frac{1}{2\pi\sigma^2} \exp\left[-\frac{(x^2+y^2)}{2\sigma^2}\right]$	$\exp[-2\pi^2\sigma^2(\xi_1^2 + \xi_2^2)]$	
Ideal		$\frac{1}{\Delta x} \text{sinc}\left(\frac{x}{\Delta x}\right)$	$\frac{1}{\Delta x \Delta y} \text{sinc}\left(\frac{x}{\Delta x}\right)\text{sinc}\left(\frac{y}{\Delta y}\right)$	$\text{rect}\left(\frac{\xi_1}{2\xi_{x0}}\right)\text{rect}\left(\frac{\xi_2}{2\xi_{y0}}\right)$	

less aliasing, more information loss



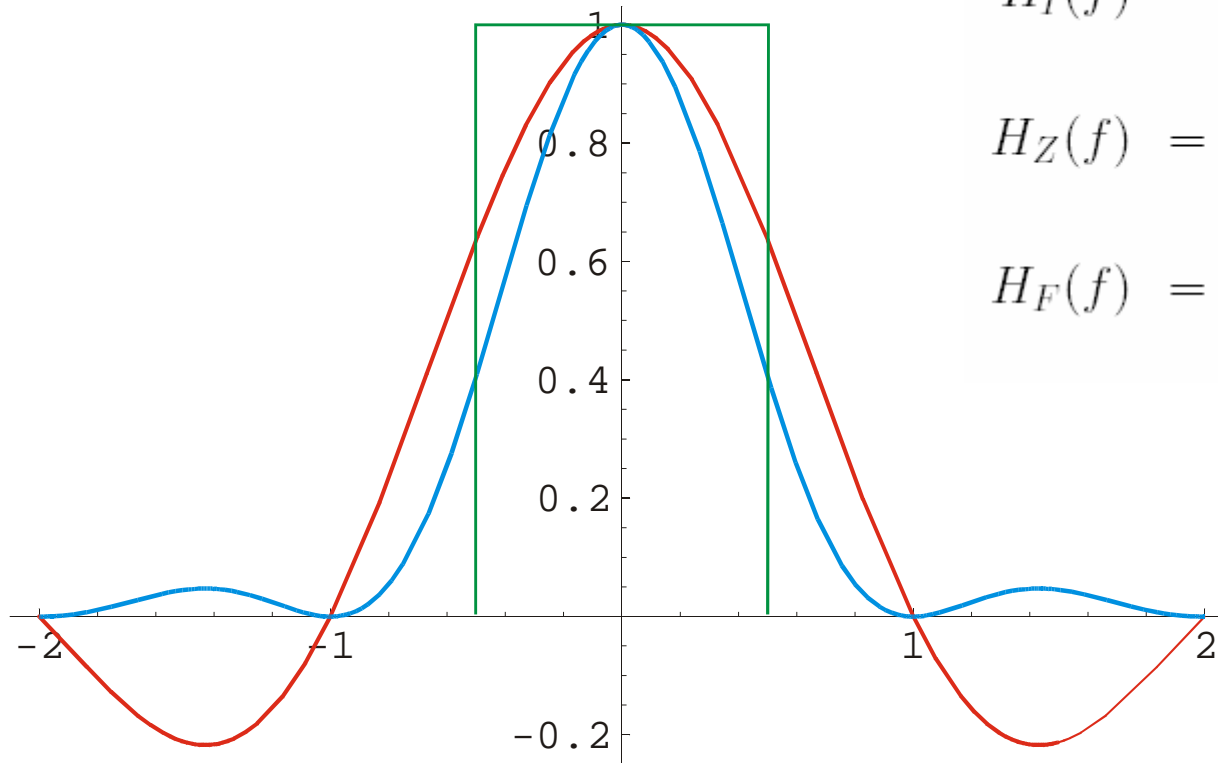
# ZOH vs FOH





# ZOH vs FOH

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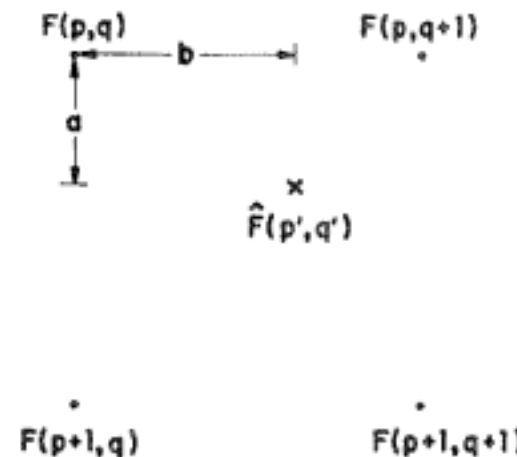
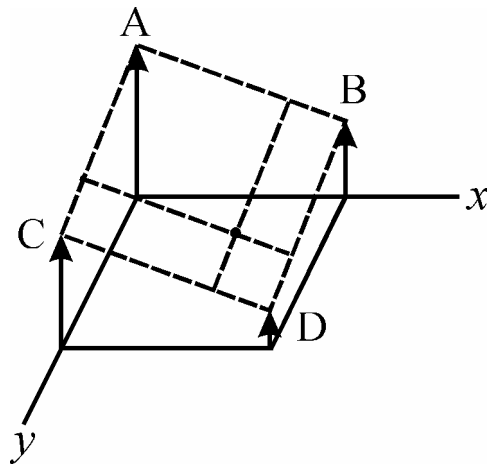
$$H_I(f) = \begin{cases} \Delta & \text{if } |f| < \frac{1}{2\Delta} \\ 0, & \text{otherwise} \end{cases}$$

$$H_Z(f) = \frac{\sin(\pi f \Delta)}{\pi f}$$

$$H_F(f) = \frac{1}{\Delta} \left( \frac{\sin(\pi f \Delta)}{\pi f} \right)^2$$

# Practical Interpolation Filter

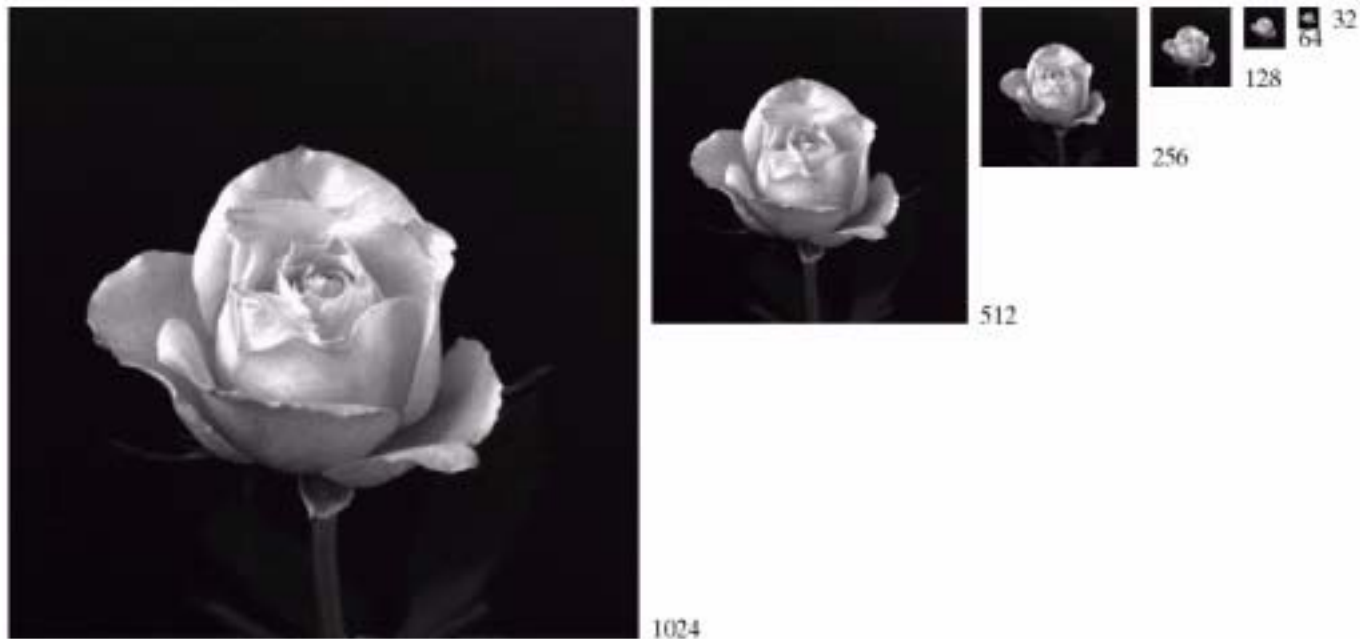
- FOH is a good compromise between information loss and aliasing suppression
- 2D FOH – bilinear interpolation



$$\hat{F}(p',q') = (1-a)[(1-b)F(p,q) + bF(p,q+1)] \\ + a[(1-b)F(p+1,q) + bF(p+1,q+1)]$$

# Example – Step 1. Sampling

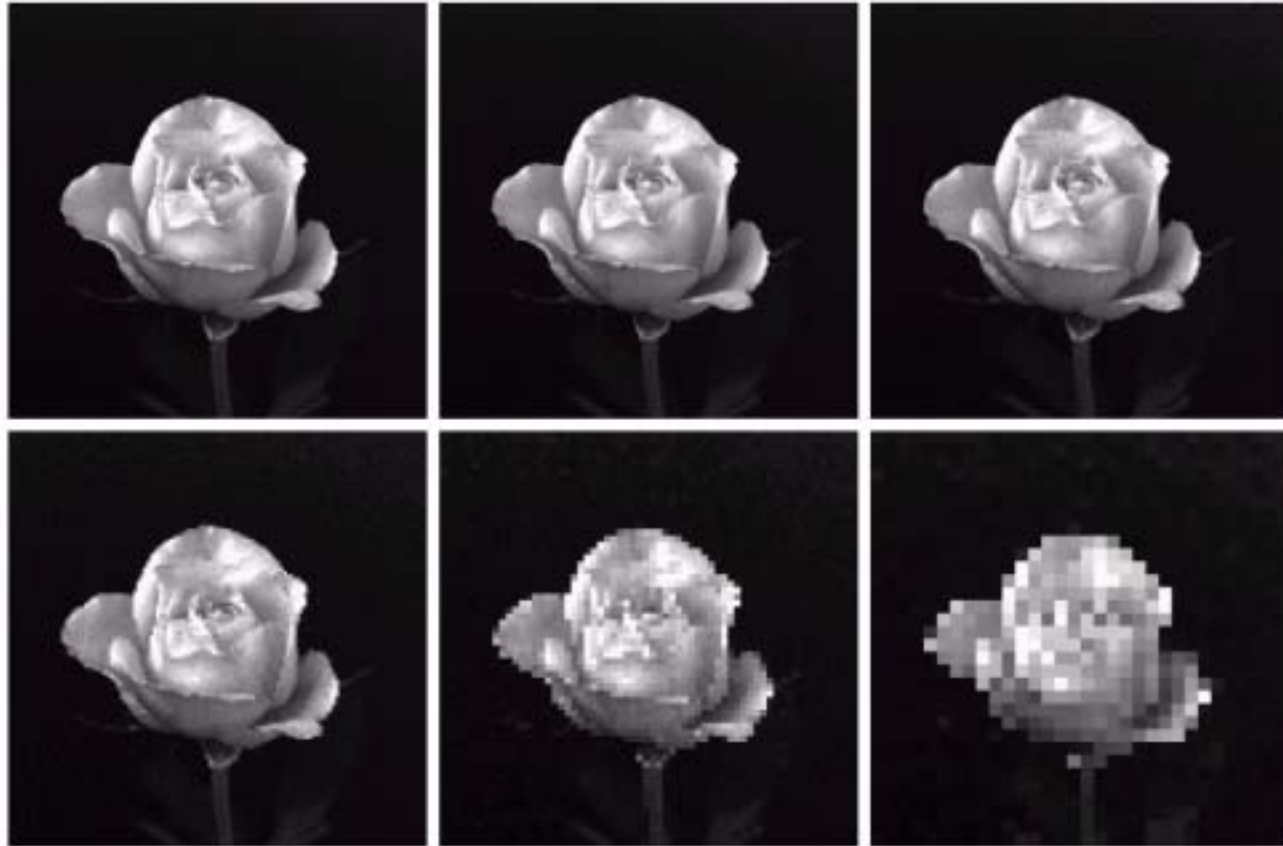
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**FIGURE 2.19** A  $1024 \times 1024$ , 8-bit image subsampled down to size  $32 \times 32$  pixels. The number of allowable gray levels was kept at 256.

# Example – Step 2. Interpolation (ZOH)

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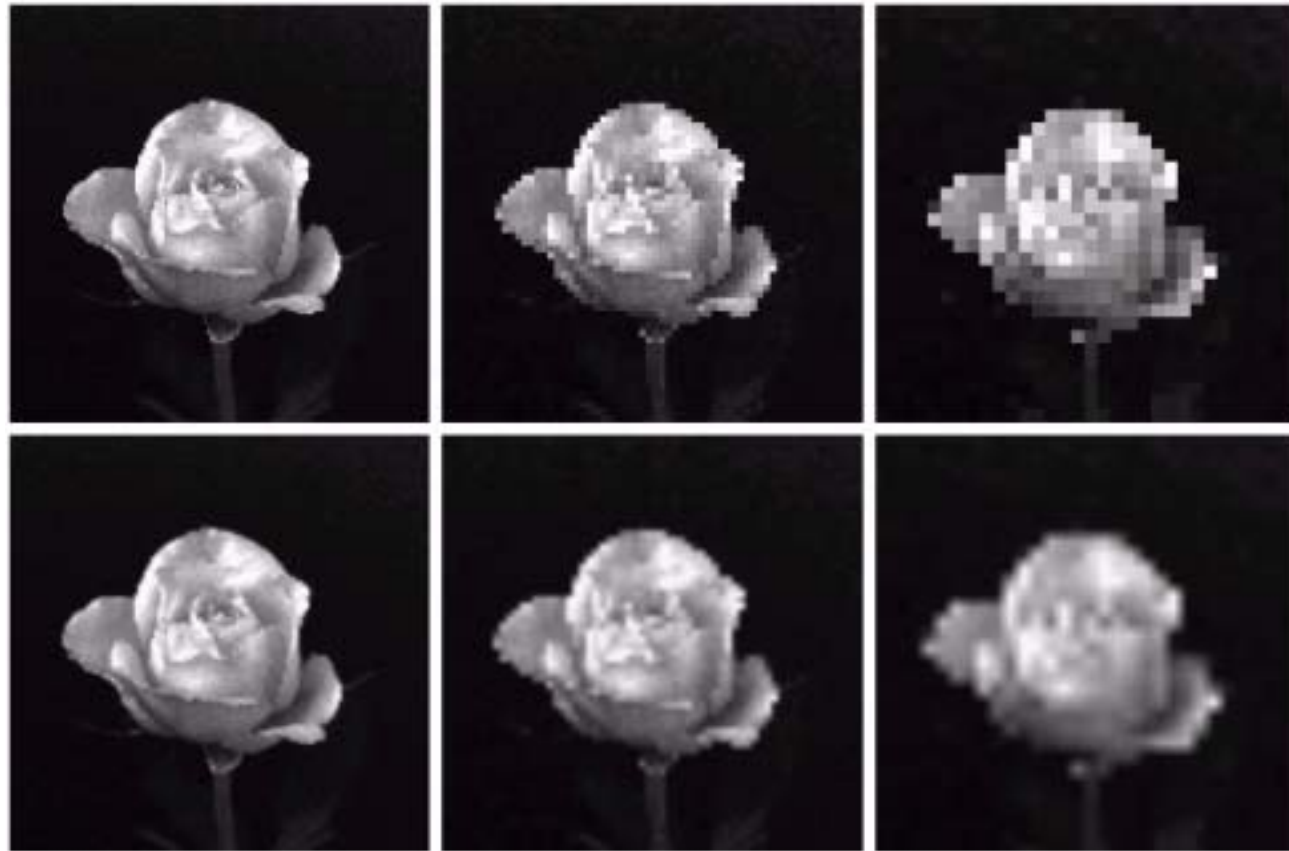


a b c  
d e f

**FIGURE 2.20** (a)  $1024 \times 1024$ , 8-bit image. (b)  $512 \times 512$  image resampled into  $1024 \times 1024$  pixels by row and column duplication. (c) through (f)  $256 \times 256$ ,  $128 \times 128$ ,  $64 \times 64$ , and  $32 \times 32$  images resampled into  $1024 \times 1024$  pixels.

# Example –ZOH vs. FOH

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a b c  
d e f

**FIGURE 2.25** Top row: images zoomed from  $128 \times 128$ ,  $64 \times 64$ , and  $32 \times 32$  pixels to  $1024 \times 1024$  pixels, using nearest neighbor gray-level interpolation. Bottom row: same sequence, but using bilinear interpolation.

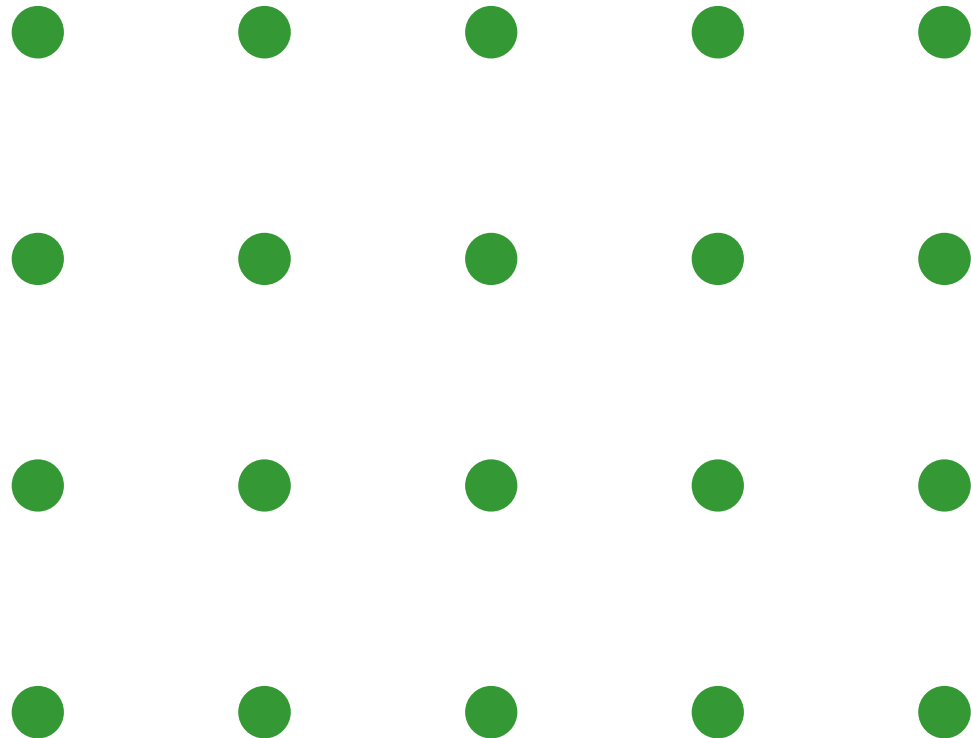
# Zooming and Shrinking Digital Images

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- Resolution conversion from  $(M_1, N_1)$  to  $(M_2, N_2)$ 
  - $M_1/M_2$  and  $N_1/N_2$  can be arbitrary
- 1. Digital-to-Analog conversion (e.g. bilinear interpolation)
- 2. Resampling

## Zooming Case

$M_1/M_2 = N_1/N_2 = 2/3$



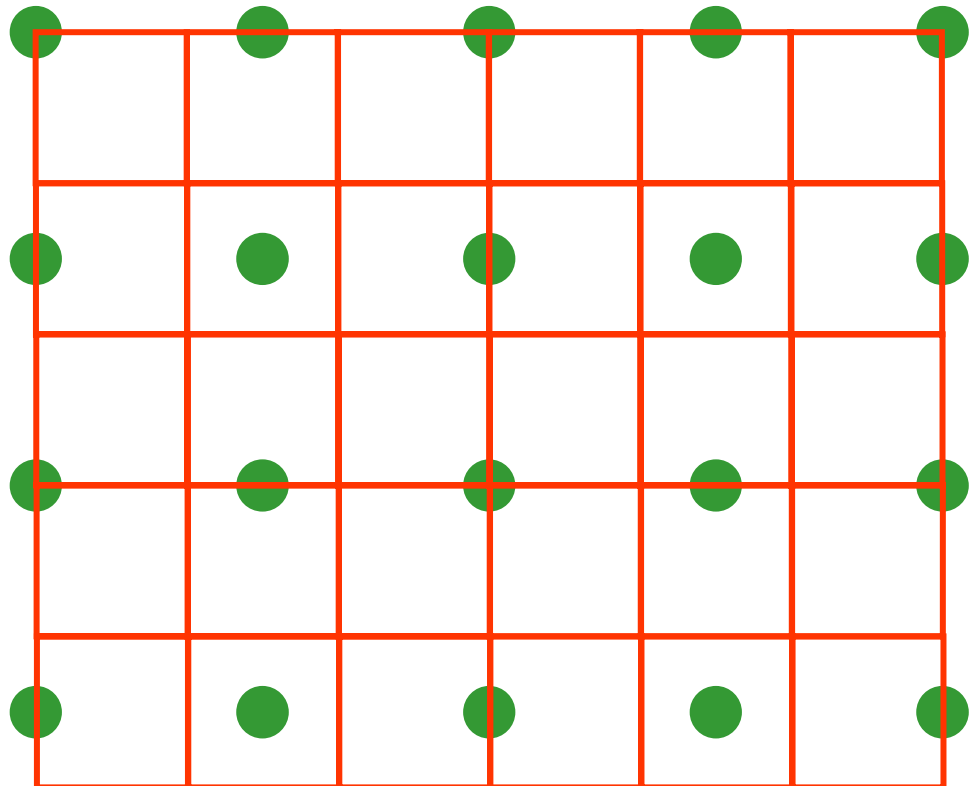
# Zooming and Shrinking Digital Images

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- Resolution conversion from  $(M_1, N_1)$  to  $(M_2, N_2)$ 
  - $M_1/M_2$  and  $N_1/N_2$  can be arbitrary
- 1. Digital-to-Analog conversion (e.g. bilinear interpolation)
- 2. Resampling

## Zooming Case

$$M_1/M_2 = N_1/N_2 = 2/3$$



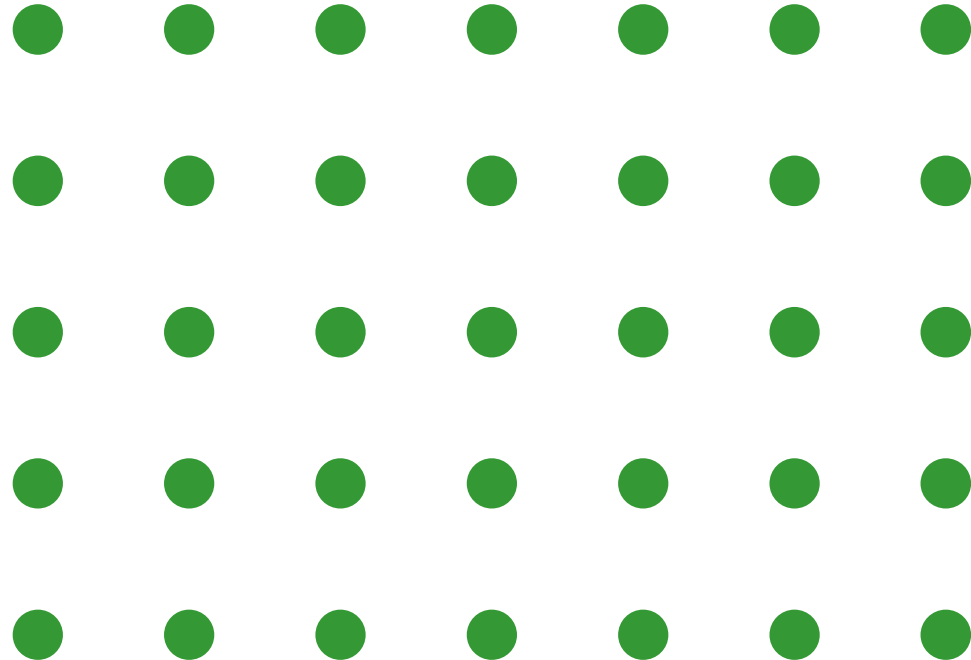
# Zooming and Shrinking Digital Images

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- Resolution conversion from  $(M_1, N_1)$  to  $(M_2, N_2)$ 
  - $M_1/M_2$  and  $N_1/N_2$  can be arbitrary
- 1. Digital-to-Analog conversion (e.g. bilinear interpolation)
- 2. Resampling

## Shrinking Case

$M_1/M_2 = N_1/N_2 = 3/2$





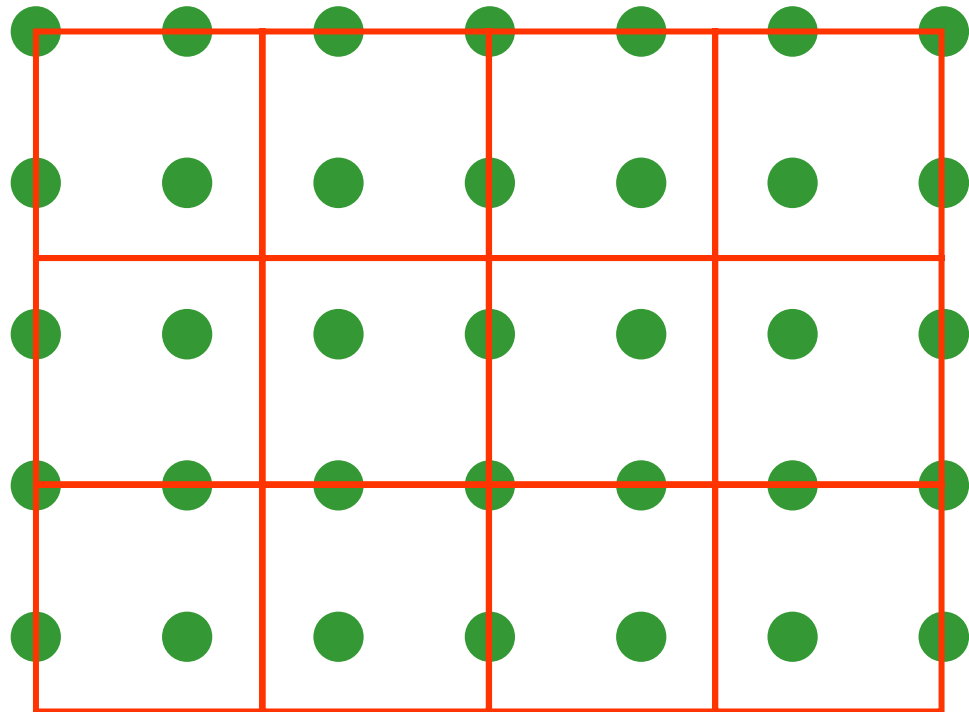
# Zooming and Shrinking Digital Images

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- Resolution conversion from  $(M_1, N_1)$  to  $(M_2, N_2)$ 
  - $M_1/M_2$  and  $N_1/N_2$  can be arbitrary
- 1. Digital-to-Analog conversion (e.g. bilinear interpolation)
- 2. Resampling

## Shrinking Case

$$M_1/M_2 = N_1/N_2 = 3/2$$



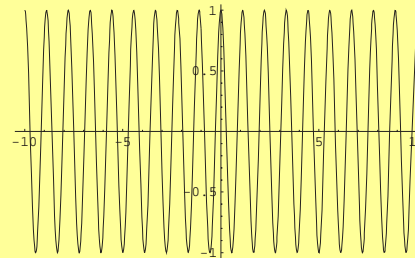
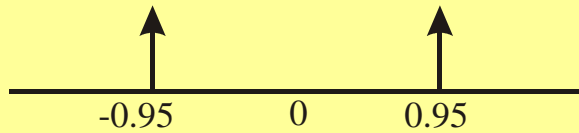
# Moiré Effect

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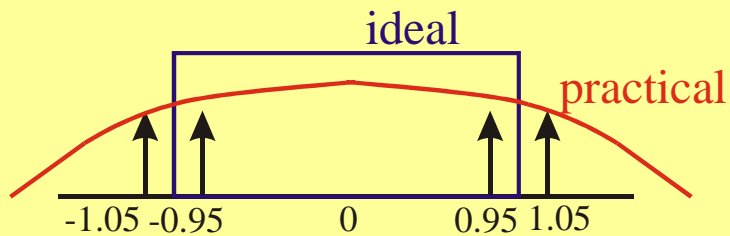
- Moiré pattern arises if
  - ▶ image contains periodicities that are close to half the sampling frequencies, and
  - ▶ reconstruction filter cutoff extends beyond the ideal low-pass filter cutoff
  - ▶ e.g. small display spot size => large cutoff frequency

# Moiré Effect – 1D example

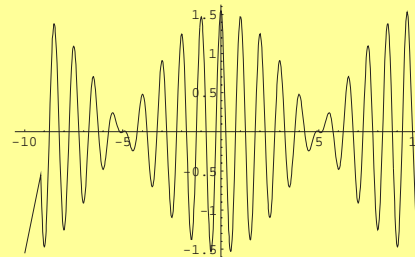
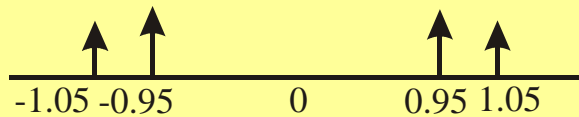
Original signal  $f(x) = \cos 2\pi(0.95)x$



Sampling:  $\Delta x = 1/2$



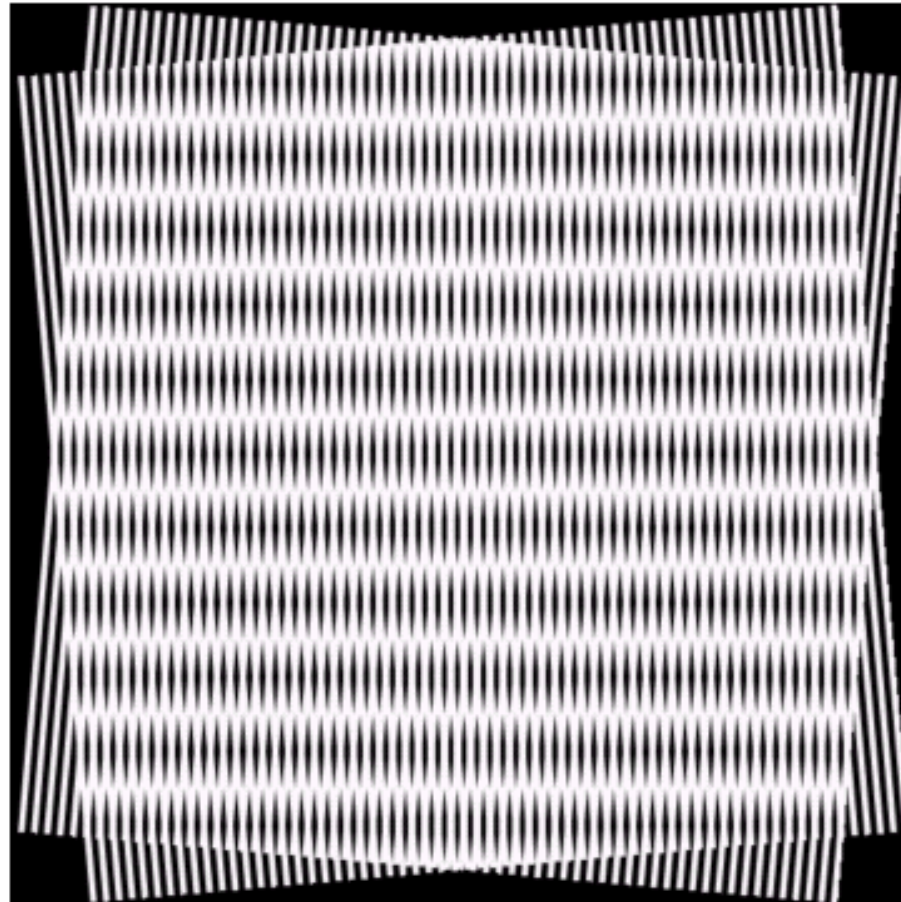
Reconstruction  $g(x) = 0.8 \cos 2\pi(0.95)x + 0.75 \cos 2\pi(1.05)x$



- Amplitude modulated signal

# Moiré Effect – 2D Example

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corrugated tin loop

**FIGURE 2.24** Illustration of the Moiré pattern effect.

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