

# Image Processing

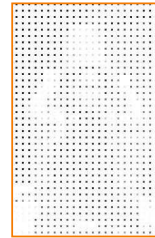
Tom Funkhouser  
Princeton University  
COS 426, Spring 2007

## What is an Image?

- An image is a discrete array of samples representing a continuous 2D function

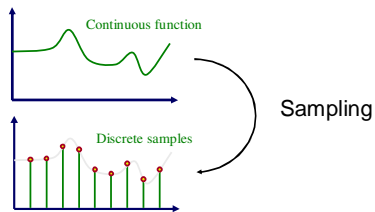


Continuous function

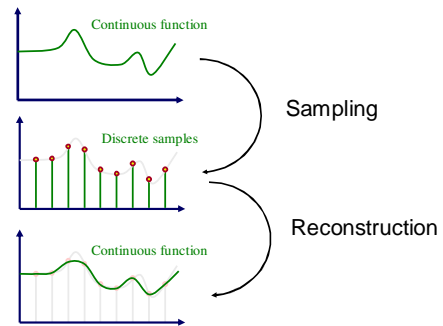


Discrete samples

## Sampling and Reconstruction



## Sampling and Reconstruction



## Sampling and Reconstruction

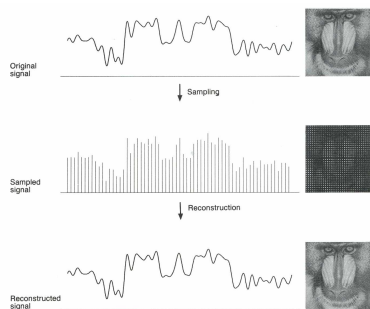
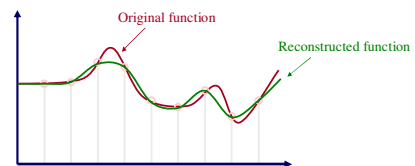


Figure 19.9 FvDFH

## Sampling Theory

- How many samples are enough?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Sampling Theory



- What happens when use too few samples?
  - Aliasing

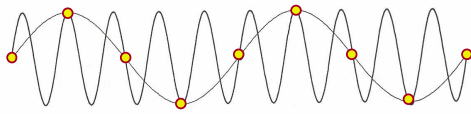
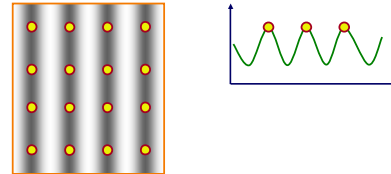


Figure 14.17 FvDFH

## Sampling Theory



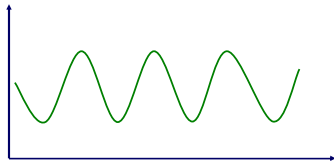
- What happens when use too few samples?
  - Aliasing



## Sampling Theory



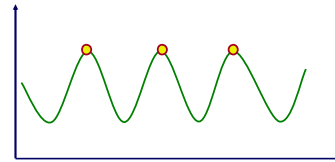
- How many samples are enough to avoid aliasing?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Sampling Theory



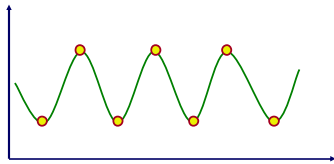
- How many samples are enough to avoid aliasing?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Sampling Theory



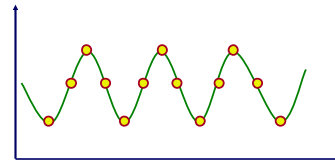
- How many samples are enough to avoid aliasing?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Sampling Theory



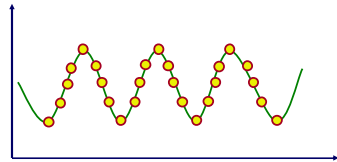
- How many samples are enough to avoid aliasing?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Sampling Theory



- How many samples are enough to avoid aliasing?
  - How many samples are required to represent a given signal without loss of information?
  - What signals can be reconstructed without loss for a given sampling rate?



## Spectral Analysis



- Spatial domain:
  - Function:  $f(x)$
  - Filtering: convolution
- Frequency domain:
  - Function:  $F(u)$
  - Filtering: multiplication



Any signal can be written as a sum of periodic functions.

## Fourier Transform

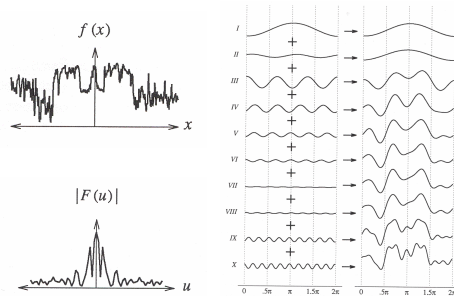


Figure 2.6 Wolberg

## Fourier Transform



- Fourier transform:

$$F(u) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi xu} dx$$

- Inverse Fourier transform:

$$f(x) = \int_{-\infty}^{\infty} F(u) e^{+i2\pi ux} du$$

## Sampling Theorem



- A signal can be reconstructed from its samples, if the original signal has no frequencies above 1/2 the sampling frequency - Shannon
- The minimum sampling rate for bandlimited function is called "Nyquist rate"

A signal is bandlimited if its highest frequency is bounded. The frequency is called the bandwidth.

## Image Processing



- Pixel operations
  - Add random noise
  - Add luminance
  - Add contrast
  - Add saturation
- Filtering
  - Blur
  - Detect edges
  - Sharpen
  - Emboss
  - Median
- Quantization
  - Uniform Quantization
  - Floyd-Steinberg dither
- Warping
  - Scale
  - Rotate
  - Warp
- Combining
  - Composite
  - Morph

## Adjusting Brightness



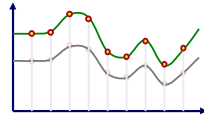
- Simply scale pixel components
  - Must clamp to range (e.g., 0 to 1)



Original



Brighter



## Adjusting Contrast



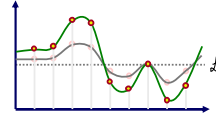
- Compute mean luminance  $\bar{L}$  for all pixels
  - $\text{luminance} = 0.30 \cdot r + 0.59 \cdot g + 0.11 \cdot b$
- Scale deviation from  $\bar{L}$  for each pixel component
  - Must clamp to range (e.g., 0 to 1)



Original



More Contrast



## Image Processing

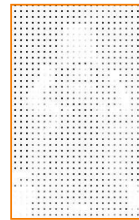


- Pixel operations
  - Add random noise
  - Add luminance
  - Add contrast
  - Add saturation
- Filtering
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  - Detect edges
  - Sharpen
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  - Morph

## Linear Filtering



- Convolution
  - Each output pixel is a linear combination of input pixels in neighborhood with weights prescribed by a filter



Input Image



Filter

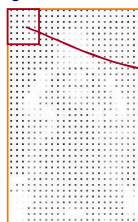


Output Image

## Linear Filtering



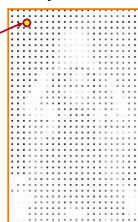
- Convolution
  - Each output pixel is a linear combination of input pixels in neighborhood with weights prescribed by a filter



Input Image



Filter



Output Image

## Linear Filtering



- Convolution
  - Each output pixel is a linear combination of input pixels in neighborhood with weights prescribed by a filter



Input Image



Filter

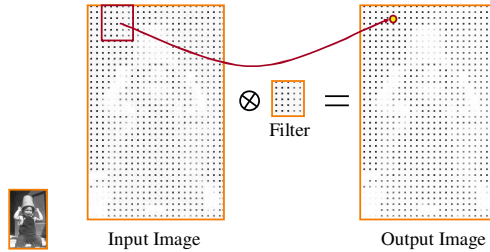


Output Image

## Linear Filtering



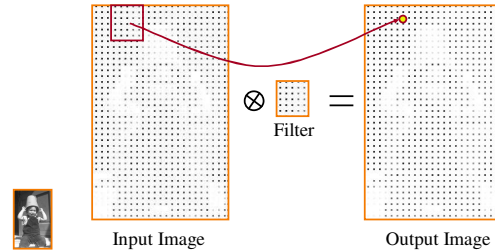
- Convolution
  - Each output pixel is a linear combination of input pixels in neighborhood with weights prescribed by a filter



## Linear Filtering



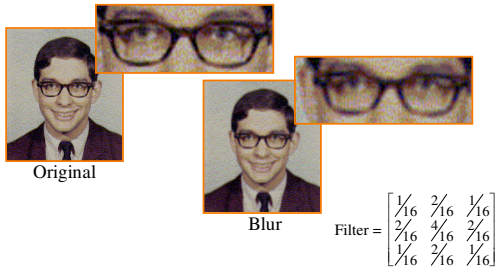
- Convolution
  - Each output pixel is a linear combination of input pixels in neighborhood with weights prescribed by a filter



## Adjust Blurriness



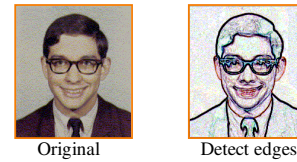
- Convolve with a filter whose entries sum to one
  - Each pixel becomes a weighted average of its neighbors



## Edge Detection



- Convolve with a filter that finds differences between neighbor pixels

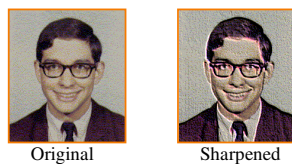


$$\text{Filter} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & +8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

## Sharpen



- Sum detected edges with original image

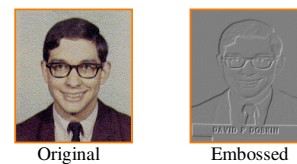


$$\text{Filter} = \begin{bmatrix} -1 & -1 & -1 \\ -1 & +9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

## Emboss



- Convolve with a filter that highlights gradients in particular directions



$$\text{Filter} = \begin{bmatrix} -1 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

## Non-Linear Filtering



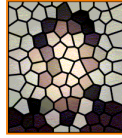
- Each output pixel is a non-linear function of input pixels in neighborhood (filter depends on input)



Original



Oil



Stain Glass

## Image Processing

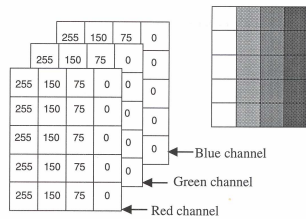


- Pixel operations
  - Add random noise
  - Add luminance
  - Add contrast
  - Add saturation
- Filtering
  - Blur
  - Detect edges
  - Sharpen
  - Emboss
  - Median
- Quantization
  - Uniform Quantization
  - Floyd-Steinberg dither
- Warping
  - Scale
  - Rotate
  - Warp
- Combining
  - Composite
  - Morph

## Quantization



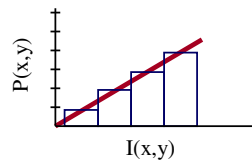
- Reduce intensity resolution
  - Frame buffers have limited number of bits per pixel
  - Physical devices have limited dynamic range



## Uniform Quantization



$P(x, y) = \text{round}(I(x, y))$   
where  $\text{round}()$  chooses nearest value that can be represented.



$I(x,y)$



$P(x,y)$   
(2 bits per pixel)

## Uniform Quantization



- Images with decreasing bits per pixel:



8 bits



4 bits



2 bits



1 bit

Notice contouring.

## Reducing Effects of Quantization



- Dithering
  - Random dither
  - Ordered dither
  - Error diffusion dither
- Halftoning
  - Classical halftoning

## Dithering



- Distribute errors among pixels
  - Exploit spatial integration in our eye
  - Display greater range of perceptible intensities



Original  
(8 bits)



Uniform  
Quantization  
(1 bit)

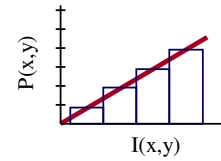
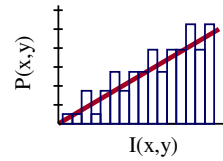


Floyd-Steinberg  
Dither  
(1 bit)

## Random Dither



- Randomize quantization errors
  - Errors appear as noise



$$P(x, y) = \text{round}(I(x, y) + \text{noise}(x, y))$$

## Random Dither



Original  
(8 bits)



Uniform  
Quantization  
(1 bit)



Random  
Dither  
(1 bit)

## Ordered Dither



- Pseudo-random quantization errors
  - Matrix stores pattern of thresholds

$$i = x \bmod n$$

$$j = y \bmod n$$

$$e = I(x, y) - \text{trunc}(I(x, y))$$

$$\text{threshold} = (D(i, j) + 1) / (n^2 + 1)$$

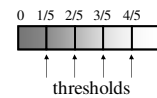
if ( $e > \text{threshold}$ )

$$P(x, y) = \text{ceil}(I(x, y))$$

else

$$P(x, y) = \text{floor}(I(x, y))$$

$$D_2 = \begin{bmatrix} 3 & 1 \\ 0 & 2 \end{bmatrix}$$



## Ordered Dither



- Bayer's ordered dither matrices

$$D_n = \begin{bmatrix} 4D_{n/2} + D_2(1,1)U_{n/2} & 4D_{n/2} + D_2(1,2)U_{n/2} \\ 4D_{n/2} + D_2(2,1)U_{n/2} & 4D_{n/2} + D_2(2,2)U_{n/2} \end{bmatrix}$$

$$D_2 = \begin{bmatrix} 3 & 1 \\ 0 & 2 \end{bmatrix}$$

$$D_4 = \begin{bmatrix} 15 & 7 & 13 & 5 \\ 3 & 11 & 1 & 9 \\ 12 & 4 & 14 & 6 \\ 0 & 8 & 2 & 10 \end{bmatrix}$$

## Ordered Dither



Original  
(8 bits)



Random  
Dither  
(1 bit)

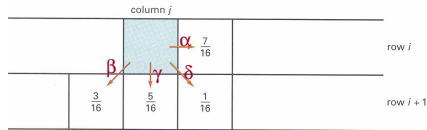


Ordered  
Dither  
(1 bit)

## Error Diffusion Dither



- Spread quantization error over neighbor pixels
  - Error dispersed to pixels right and below



$$\alpha + \beta + \gamma + \delta = 1.0$$

Figure 14.42 from H&B

## Error Diffusion Dither



Original  
(8 bits)

Random  
Dither  
(1 bit)

Ordered  
Dither  
(1 bit)

Floyd-Steinberg  
Dither  
(1 bit)

## Reducing Effects of Quantization



- Dithering
  - Random dither
  - Ordered dither
  - Error diffusion dither

### Ø Halftoning

- Classical halftoning

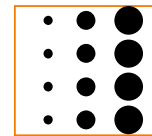
## Classical Halftoning



- Use dots of varying size to represent intensities
  - Area of dots proportional to intensity in image

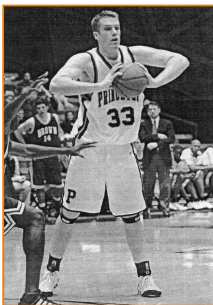


$I(x,y)$

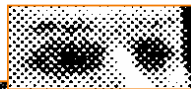


$P(x,y)$

## Classical Halftoning



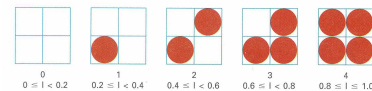
From Town Topics, Princeton



## Halftone patterns



- Use cluster of pixels to represent intensity
  - Trade spatial resolution for intensity resolution



0  $0 \leq I < 0.2$  1  $0.2 \leq I < 0.4$  2  $0.4 \leq I < 0.6$  3  $0.6 \leq I < 0.8$  4  $0.8 \leq I \leq 1.0$

Q: In this case, would we use four "halftoned" pixels in place of one original pixel?

Figure 14.37 from H&B



## Image Processing



- Pixel operations
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- Quantization
  - Uniform Quantization
  - Floyd-Steinberg dither
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  - Warp
- Combining
  - Composite
  - Morph

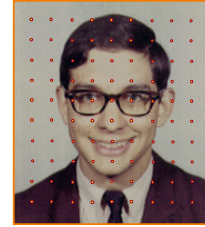
## Image Processing



- Consider reducing the image resolution



Original image

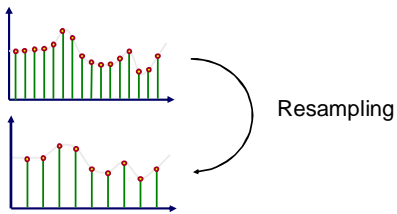


1/4 resolution

## Image Processing



- Image processing is a resampling problem

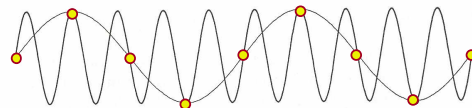


## Sampling Theorem



- A signal can be reconstructed from its samples, if the original signal has no frequencies above  $1/2$  the sampling frequency - Shannon

Aliasing will occur if the signal is under-sampled



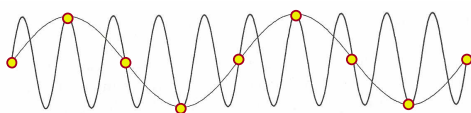
Under-sampling

Figure 14.17 FvDFH

## Aliasing



- In general:
  - Artifacts due to under-sampling or poor reconstruction
- Specifically, in graphics:
  - Spatial aliasing
  - Temporal aliasing



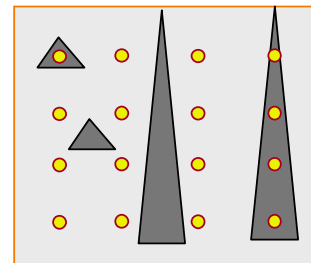
Under-sampling

Figure 14.17 FvDFH

## Spatial Aliasing



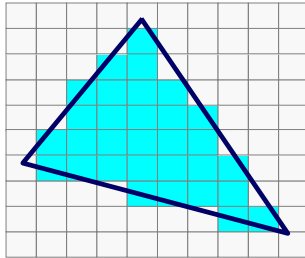
- Artifacts due to limited spatial resolution



## Spatial Aliasing



- Artifacts due to limited spatial resolution

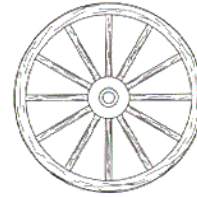


“Jaggies”

## Temporal Aliasing



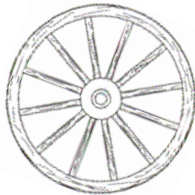
- Artifacts due to limited temporal resolution
  - Strobging
  - Flickering



## Temporal Aliasing



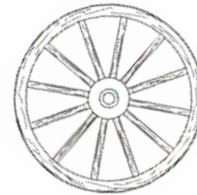
- Artifacts due to limited temporal resolution
  - Strobging
  - Flickering



## Temporal Aliasing



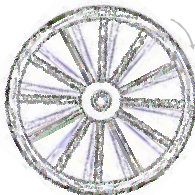
- Artifacts due to limited temporal resolution
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## Temporal Aliasing



- Artifacts due to limited temporal resolution
  - Strobging
  - Flickering

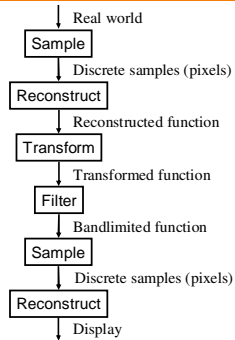


## Antialiasing

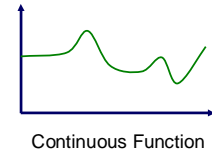
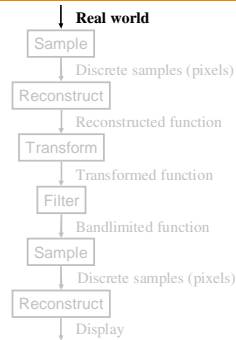


- Sample at higher rate
  - Not always possible
  - Doesn't always solve problem
- Pre-filter to form bandlimited signal
  - Form bandlimited function using low-pass filter
  - Trades aliasing for blurring

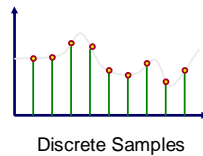
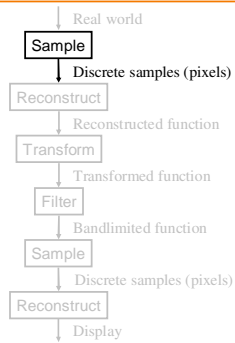
## Image Processing



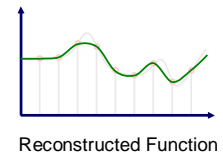
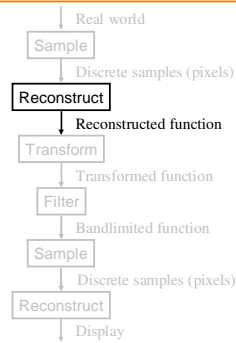
## Image Processing



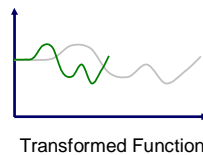
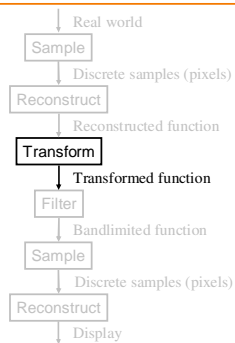
## Image Processing



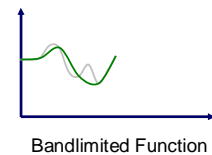
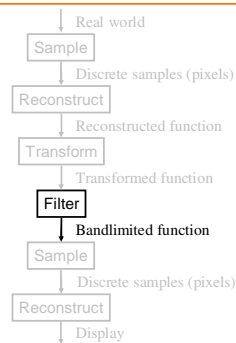
## Image Processing



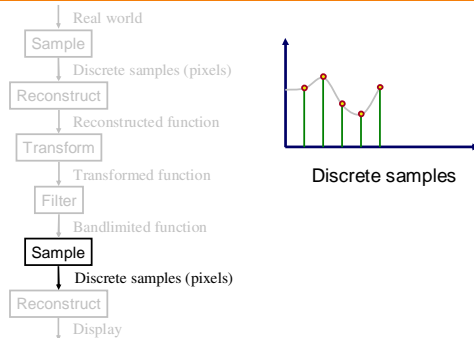
## Image Processing



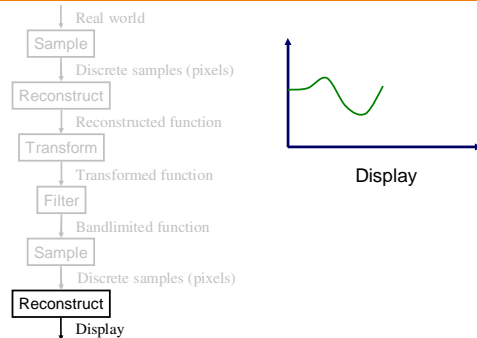
## Image Processing



## Image Processing



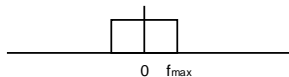
## Image Processing



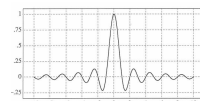
## Ideal Bandlimiting Filter



- Frequency domain



- Spatial domain



$$\text{Sinc}(x) = \frac{\sin \pi x}{\pi x}$$

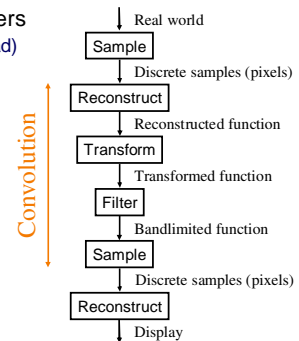
Figure 4.5 Wolberg

## Practical Image Processing



- Finite low-pass filters

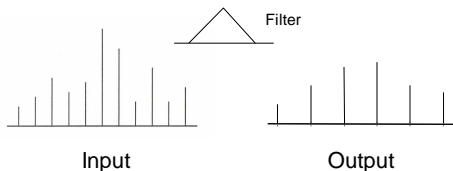
- Point sampling (bad)
- Triangle filter
- Gaussian filter



## Convolution



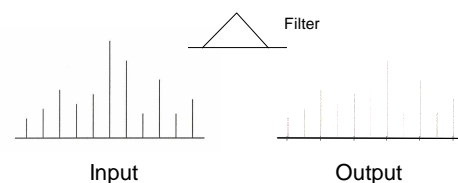
- Spatial domain: output pixel is weighted sum of pixels in neighborhood of input image
- Pattern of weights is the "filter"



## Convolution with a Triangle Filter



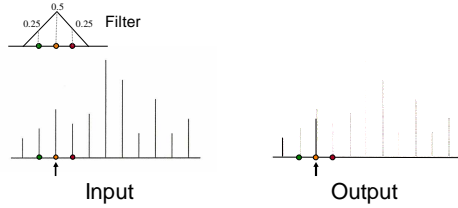
- Example 1:



## Convolution with a Triangle Filter



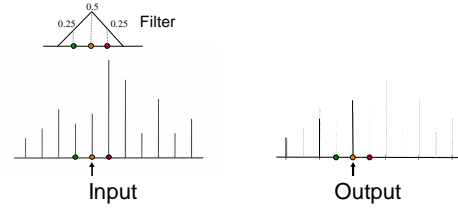
- Example 1:



## Convolution with a Triangle Filter



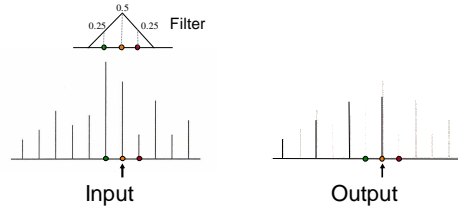
- Example 1:



## Convolution with a Triangle Filter



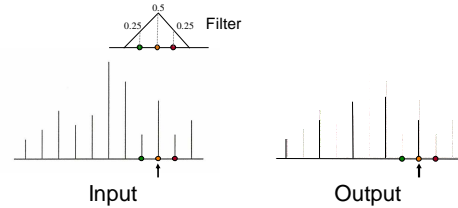
- Example 1:



## Convolution with a Triangle Filter



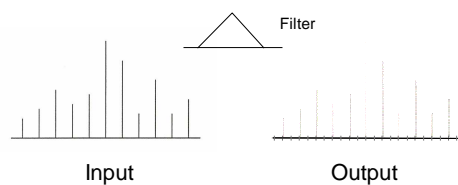
- Example 1:



## Convolution with a Triangle Filter



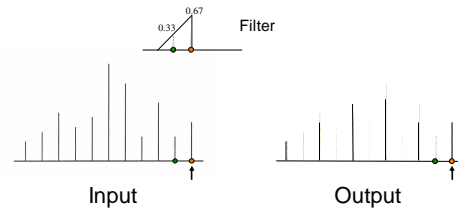
- Q: What if the filter runs off the end?



## Convolution with a Triangle Filter



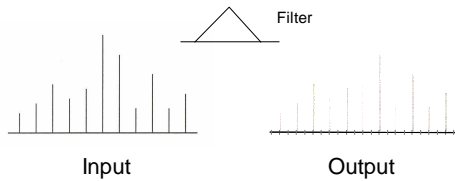
- Example 1:



### Convolution with a Triangle Filter



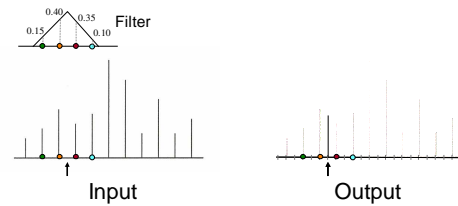
- Q: what if the filter is not centered on a sample?



### Convolution with a Triangle Filter



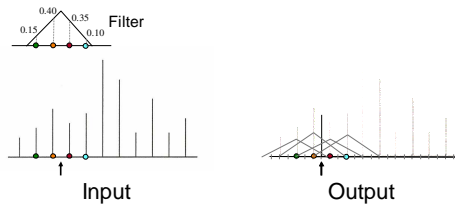
- Example 2:



### Convolution with a Triangle Filter



- Example 2:



### Convolution with a Triangle Filter



- Example 3 (triangle filter of radius 1):

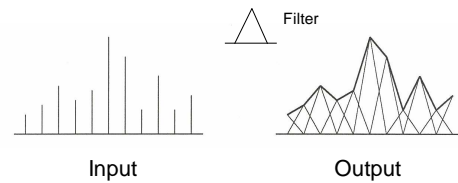


Figure 2.4 Wolberg

### Convolution with a Gaussian Filter



- Example 4:

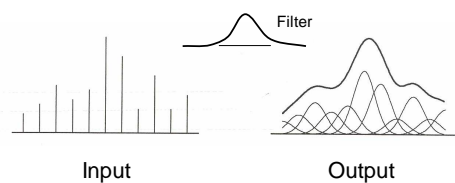


Figure 2.4 Wolberg

### Image Processing



- Pixel operations
  - Add random noise
  - Add luminance
  - Add contrast
  - Add saturation
- Filtering
  - Blur
  - Detect edges
  - Sharpen
  - Emboss
  - Median
- Quantization
  - Uniform Quantization
  - Floyd-Steinberg dither
- Warping
  - Scale
  - Rotate
  - Warp
- Combining
  - Composite
  - Morph

## Scaling



- Resample with triangle or Gaussian filter

More on this next lecture!



Original



1/4X  
resolution



4X  
resolution

## Summary



- Image filtering
  - Compute new values for image pixels based on function of old values
- Halftoning and dithering
  - Reduce visual artifacts due to quantization
  - Distribute errors among pixels
    - » Exploit spatial integration in our eye
- Sampling and reconstruction
  - Reduce visual artifacts due to aliasing
  - Filter to avoid undersampling
    - » Blurring is better than aliasing