# Linear Image Filtering

#### Introduction

We have a fairly good idea of what happens at the initial stages of human visual processing

It is similar to some of the filtering we will discuss

We will also talk about

- 1. Extracting low-level features (tokens)
- 2. How to enhance image structures
- 3. Remove variability

#### Introduction

- 1. **first stage** in most computer vision algorithms, namely the use of **image processing** to preprocess the image and convert it into a form **suitable for further analysis** 
  - a. exposure correction and
  - b. color balancing,
  - c. reducing image noise,
  - d. increasing sharpness, or
  - e. straightening the image by rotating it

# Signals and Images

- 1. "A signal is a measurement of some physical quantity (light, sound, height, temperature, etc.) as a function of another independent quantity (time, space, wavelength, etc.)."
- 2. "A system is a process/function that transforms a signal into another."
- 3. Continuous signals are sampled for processing by computers
- 4. The sampling equation:  $\ell / n = \ell / n \Delta T / n$

## Signals and Images

1.  $\ell \in \mathbb{R}^{M \times N}$  , height x width

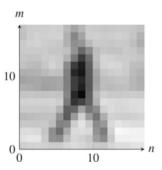
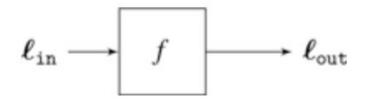


Figure 15.2: Grayscale image showing a person walking in the street. This tiny image has only  $18 \times 18$  pixels.

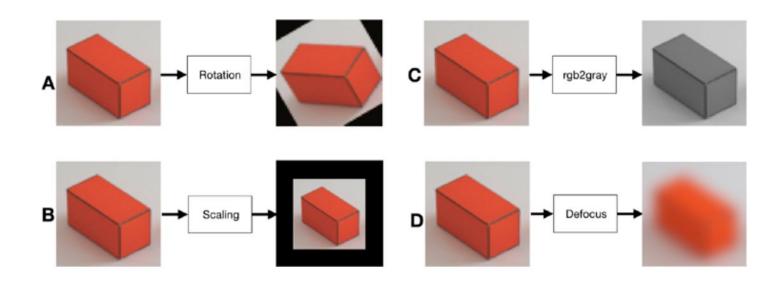


- Linear systems are capable of creating very interesting image transformations
- 2. "A function *f* is linear is it satisfies the following two properties:"

a. 
$$f(\ell_1 + \ell_2) = f(\ell_1) + f(\ell_2)$$

b.  $f(a\ell) = af(\ell)$  for any scalar a

1. Which of the following are linear transformations?



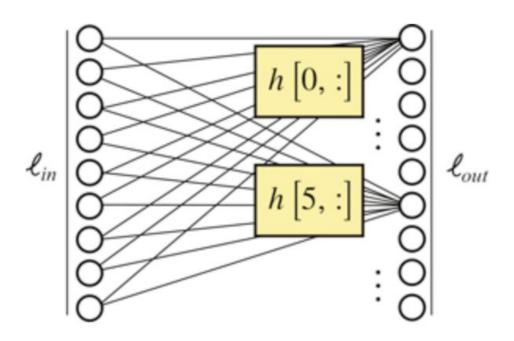
1. General form of a 1D linear system

$$\ell_{\text{out}}[n] = \sum_{k=0}^{N-1} h[n, k] \ell_{\text{in}}[k] \text{ for } n \in [0, M-1]$$

$$\begin{bmatrix} \ell_{\text{out}} [0] \\ \ell_{\text{out}} [1] \\ \vdots \\ \ell_{\text{out}} [n] \\ \vdots \\ \ell_{\text{out}} [M-1] \end{bmatrix} = \begin{bmatrix} h[0,0] & h[0,1] & \dots & h[0,N-1] \\ h[1,0] & h[1,1] & \dots & h[1,N-1] \\ \vdots & \vdots & \vdots & \vdots \\ h[M-1,0] & h[M-1,1] & \dots & h[M-1,N-1] \end{bmatrix} \begin{bmatrix} \ell_{\text{in}} [0] \\ \ell_{\text{in}} [1] \\ \vdots \\ \ell_{\text{in}} [k] \\ \vdots \\ \ell_{\text{in}} [N-1] \end{bmatrix}$$

$$\ell_{\text{out}} = H\ell_{\text{in}}$$

1. General form of a 1D linear system



General form of a 2D linear system

$$\ell_{\text{out}}[n,m] = \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} h[n,m,k,l] \,\ell_{\text{in}}[k,l]$$

 If we convert 2D images into a long 1D column vector, we can write

$$\ell_{\text{out}} = H\ell_{\text{in}}$$

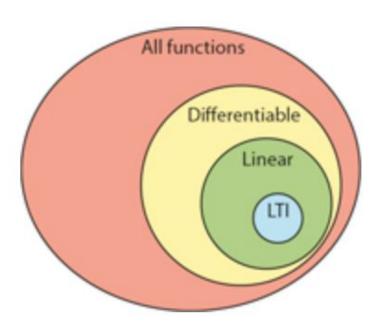
# "Linear Translation Invariant Systems"

- 1. Why LTI?
  - i. because we want to process the image in a spatially invariant manner
- 2. "A system is an LTI system if it is linear and when we translate the input signal by  $n_0$ ,  $m_0$ , then output is also translated by  $n_0$ ,  $m_0$ :"

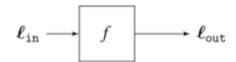
$$\ell_{\text{out}}[n-n_0, m-m_0] = f(\ell_{\text{in}}[n-n_0, m-m_0])$$

# "Linear Translation Invariant Systems"

1.



# **Analyzing LTI systems**



- 1. LTI systems transforms input signal into output signal
- 2. We want to understand how the system is carrying out the transformation
- 3. We want to determine how a system reacts to different inputs, like in electrical circuits and mechanical systems.

# **Analyzing LTI systems**

- 1. Every LTI system has a unique "impulse response," h(t).
- 2. The impulse response help us analyze the system
- 3. Imagine a basic circuit with a resistor (R) and a capacitor (C). This is an LTI system.
  - a. Impulse Response: The impulse response h(t) of this circuit is an exponential decay.

#### Convolution

- 1. Every LTI transformation can be represented by convolution.
- 2. All convolutions are LTI transformations
- 3. Convolution has widespread applications in engineering, physics, and computer science.

# **Applications of Convolution**

- 1. Convolution is a fundamental tool in system analysis because it helps us determine how an input signal transforms into an output.
- 2. The system in question is doing convolution to the input signal and giving us output.
- 3. We can design our own system and convolve it with an input signal to modify it in a controlled way.
- 4. In signal processing, convolution is used to filter signals, remove noise, and enhance features.
- 5. The idea is to apply a convolution filter (also called an **impulse** response) to modify the signal in a controlled way.

#### Convolution

1. Convolution between two continuous functions f and g

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - \tau) d\tau$$

#### Convolution

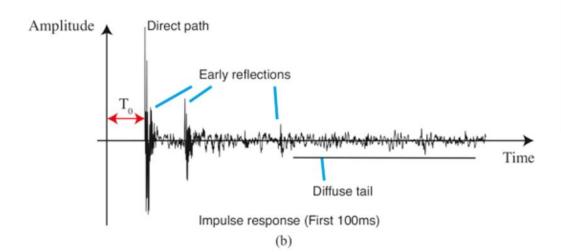
- 1. Practice convolution of continuous functions
- 2. Convolution demo
  - a. <a href="https://phiresky.github.io/convolution-demo/">https://phiresky.github.io/convolution-demo/</a>

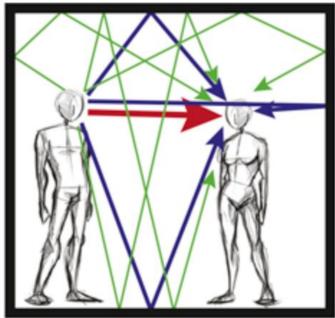
# **System Identification - Acoustics**

Direct-Path ("dry" sound)

1st-order reflections

2nd-order reflections



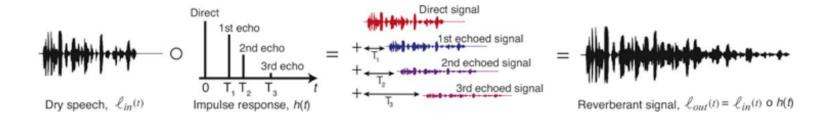


# **System Identification - Acoustics**

1.

$$h(t) = a_0 \delta(t) + a_1 \delta(t - T_1) + a_2 \delta(t - T_2) + a_3 \delta(t - T_3)$$

$$\ell_{\text{out}}(t) = \ell_{\text{in}}(t) \circ h(t) = a_0 \ell_{\text{in}}(t) + a_1 \ell_{\text{in}}(t - T_1) + a_2 \ell_{\text{in}}(t - T_2) + a_3 \ell_{\text{in}}(t - T_3)$$



#### **Noise Cancellation**

- 1. How can you cancel the noise when you have impulse response of a place?
- 2. Using Adaptive Filter
- 3. Taking a sample of the signal from the far end (before it goes to the speaker).
- 4. Passing this signal through its own internal filter. This filter has adjustable parameters (called coefficients or weights).
- 5. Comparing the output of its filter to the actual echo that's being picked up by the microphone.

#### **Hack Audio: Convolution Function**

- 1. Convolving audio with impulse response of a system that introduces echo
- 2. Convolving audio with impulse response of a system that introduces stereo effect
- 3. <a href="https://www.youtube.com/watch?v=NVSL9BcDKac">https://www.youtube.com/watch?v=NVSL9BcDKac</a>

#### **Convolution - Discrete**

1. "The convolution, denoted o, between a signal \(\ell\) in [n] and the convolutional kernel h [n] is defined as follows"

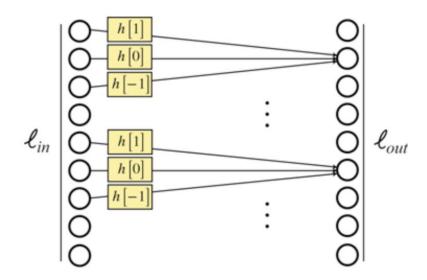
$$\ell_{\text{out}}[n] = h[n] \circ \ell_{\text{in}}[n] = \sum_{k=-\infty}^{\infty} h[n-k] \ell_{\text{in}}[k]$$

#### **Convolution - Discrete**

- 1. "The convolution operation can be described in words as:
  - a. first take the kernel h[k] and mirror it i.e. h[-k],
  - b. then shift the mirrored kernel so that the origin is at location n,
  - c. then multiply the input values around location n by the mirrored kernel and sum the result.
  - d. Store the result in the output vector  $\ell_{out}[n]$ ."

#### **Convolution - Discrete**

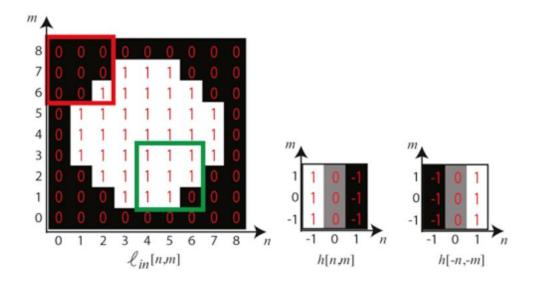
1. 
$$\begin{bmatrix} \ell_{\text{out}}[0] \\ \ell_{\text{out}}[1] \\ \ell_{\text{out}}[2] \\ \vdots \\ \ell_{\text{out}}[N-1] \end{bmatrix} = \begin{bmatrix} h[0] & h[-1] & 0 & \dots & 0 \\ h[1] & h[0] & h[-1] & \dots & 0 \\ 0 & h[1] & h[0] & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & h[0] \end{bmatrix} \begin{bmatrix} \ell_{\text{in}}[0] \\ \ell_{\text{in}}[1] \\ \ell_{\text{in}}[2] \\ \vdots \\ \ell_{\text{in}}[N-1] \end{bmatrix} (15.13)$$

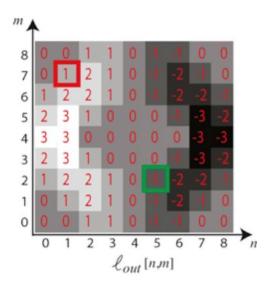


#### **Convolution - Two dimensional**

1.

$$\ell_{\text{out}}[n,m] = h[n,m] \circ \ell_{\text{in}}[n,m] = \sum_{k,l} h[n-k,m-l] \ell_{\text{in}}[k,l]$$





# Input Output \*

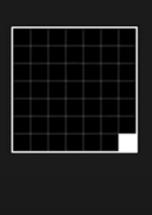
 $f(x,y) \qquad \qquad \delta(x,y) \qquad \qquad f(x,y)$ 

# Input



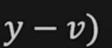


Output



f(x,y)

$$\delta(x-u,y-v)$$
  $f(x-u,y-v)$ 



# 



# Input Output







# Input

# Output



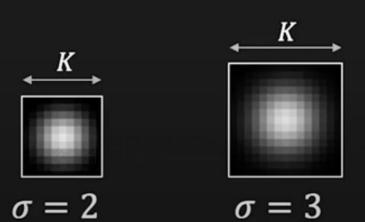


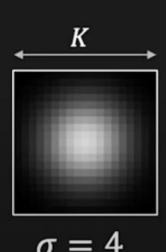


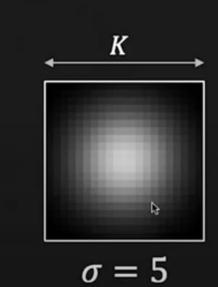
$$n_{\sigma}[i,j] = \frac{1}{2\pi\sigma^2} e^{-\frac{1}{2}\left(\frac{i^2+j^2}{\sigma^2}\right)}$$

$$\sigma^2$$
: Variance

$$\begin{bmatrix} 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$







### Gaussian Smoothing is Separable

$$g[i,j] = \frac{1}{2\pi\sigma^2} \sum_{k=1}^{K} \sum_{i=1}^{K} e^{-\frac{1}{2}\left(\frac{m^2+n^2}{\sigma^2}\right)} f[i-m,j-n]$$

$$g[i,j] = \frac{1}{2\pi\sigma^2} \sum_{m=1}^{K} e^{-\frac{1}{2}(\frac{m^2}{\sigma^2})} \cdot \sum_{m=1}^{K} e^{-\frac{1}{2}(\frac{n^2}{\sigma^2})} f[i-m,j-n]$$

Using One 2D Gaussian Filter ≡ Using Two 1D Gaussian Filters

# Gaussian Smoothing is Separable

Using One 2D Gaussian Filter ≡ Using Two 1D Gaussian Filters

$$f * \boxed{ } = f * \boxed{ } \stackrel{\uparrow}{\downarrow} * \boxed{ } \stackrel{\longleftarrow}{\longleftarrow} K \rightarrow$$

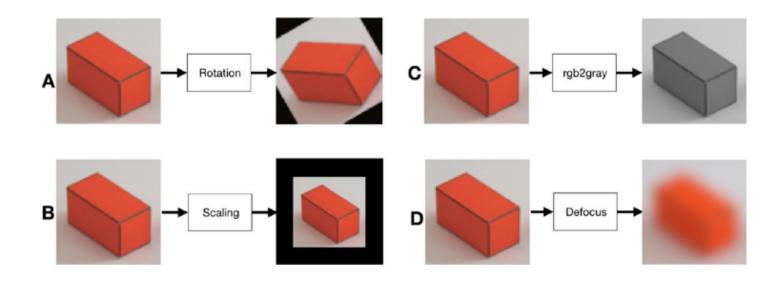
Which one is faster? Why?

 $K^2$  Multiplications

$$K^2 - 1$$
 Additions  $2(K - 1)$  Additions

2K Multiplications

1. Which of the following are LTI transformations?



# **Properties of Convolution**

1. Commutative

 $h[n] \circ \ell[n] = \ell[n] \circ h[n]$ 

2. Associative

 $\ell_1[n] \circ \ell_2[n] \circ \ell_3[n] = \ell_1[n] \circ (\ell_2[n] \circ \ell_3[n]) = (\ell_1[n] \circ \ell_2[n]) \circ \ell_3[n]$ 

3. Distributive

 $\ell_1[n] \circ (\ell_2[n] + \ell_3[n]) = \ell_1[n] \circ \ell_2[n] + \ell_1[n] \circ \ell_3[n]$ 

4. Shift

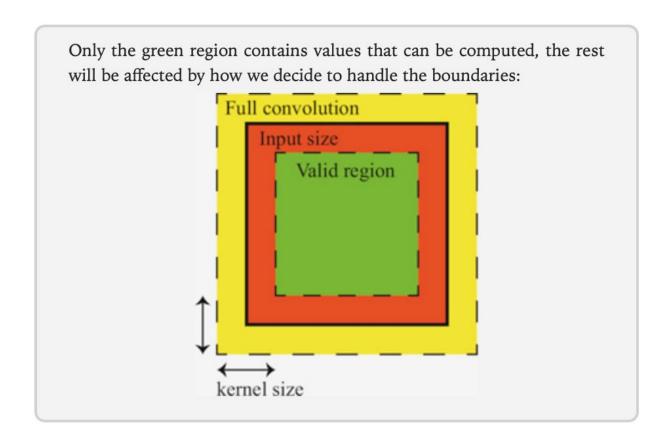
 $\ell_{\text{out}}\left[n-n_0\right] = h\left[n\right] \circ \ell_{\text{in}}\left[n-n_0\right]$ 

5. Identity

 $\delta [n] \circ \ell [n] = \ell [n]$   $\delta [n] = \begin{cases} 1 & \text{if } n = 0 \\ 0 & \text{if } n \neq 0 \end{cases}$ 

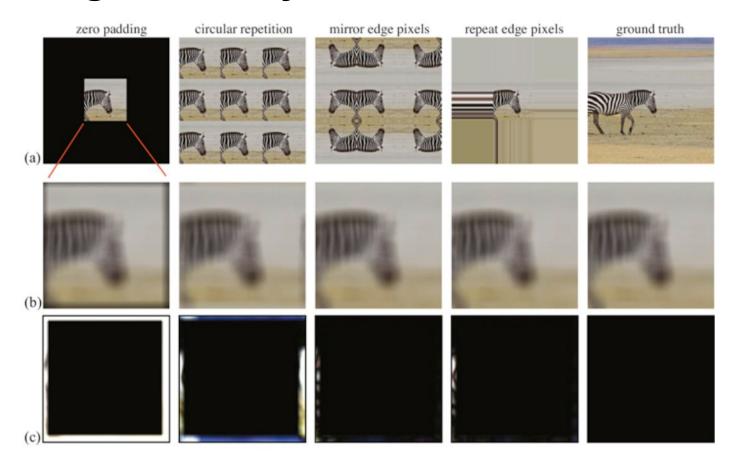
# **Handling Boundary Conditions**

1.



# **Handling Boundary Conditions**

1.



# **Template Matching**

1. How do we match a template with image?



#### 2. Minimize

$$E[n,m] = \sum_{k,l} (\ell_{in}[n+k, m+l] - T[k,l])^2$$

#### **Cross-Correlation vs Convolution**

Cross-Correlation

 $\ell_{\text{out}}[n,m] = \ell_{\text{in}} \star h = \sum_{l=N}^{N} \ell_{\text{in}}[n+k,m+l] h[k,l]$ 

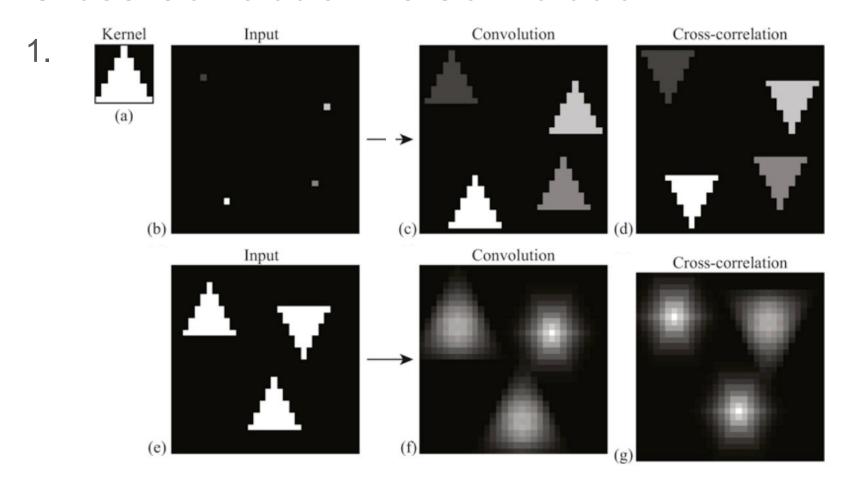
- a. Not Commutative
- b. Not Associative

2. Convolution

$$\ell_{\text{out}}[n, m] = \ell_{\text{in}} \circ h = \sum_{k,l=-N}^{N} \ell_{\text{in}}[n-k, m-l] h[k, l]$$

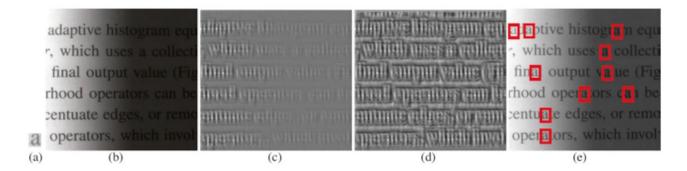
"cross-correlation and convolution outputs are identical when the kernel h has central symmetry."

#### **Cross-Correlation vs Convolution**



# **Template Matching and Normalized Correlation**

 "Normalized correlation will detect the object independently of location, but it will not be robust to any other changes such as rotation, scaling, and changes in appearance."



**Figure 15.13:** (a) Template. (b) Input image. (c) Correlation between input (b) and template (a). (d) Normalized correlation. e) Locations with cross-correlation above 75 percent of its maximum value.

#### References

- 1. Foundations of Computer Vision Chapter 15
- 2. <a href="https://www.iaincollings.com/signals-and-systems#h.2uort">https://www.iaincollings.com/signals-and-systems#h.2uort</a>
  <a href="https://www.iaincollings.com/signals-and-systems#h.2uort">dygbgqy</a>
- 3. <a href="https://phiresky.github.io/convolution-demo/">https://phiresky.github.io/convolution-demo/</a>
- 4. <a href="https://www.youtube.com/watch?v=NVSL9BcDKac">https://www.youtube.com/watch?v=NVSL9BcDKac</a>
- 5. Columbia University <a href="https://fpcv.cs.columbia.edu">https://fpcv.cs.columbia.edu</a>