

Digital Image

(B4M33DZO)

Lecture 3:

Convolution

<https://cw.fel.cvut.cz/wiki/courses/dzo/start>

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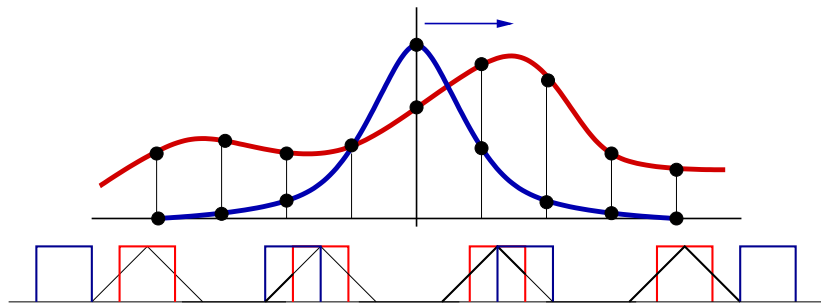


Convolution

Sliding average of function f weighted by function g :

Definition

$$(f * g)(t) = \int_{-\infty}^{\infty} f(x) \cdot g(t - x) dx$$



Interesting Properties

- ▶ **Commutativity:**

$$f * g = g * f$$

- ▶ **Associativity:**

$$f * (g * h) = (f * g) * h$$

- ▶ **Distributivity:**

$$f * (g + h) = (f * g) + (f * h)$$

- ▶ **Differentiation:**

$$(f * g)' = f' * g = f * g'$$

- ▶ **Convolution theorem:**

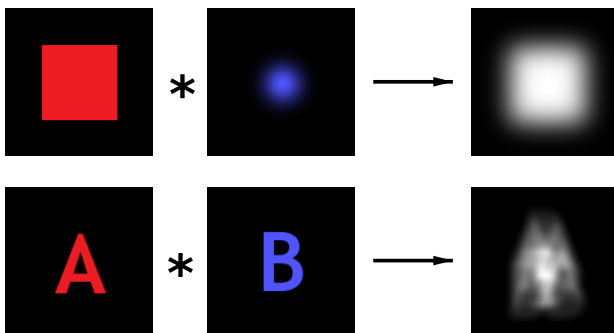
$$f * g = \mathcal{F}^{-1}\{\mathcal{F}\{f\} \cdot \mathcal{F}\{g\}\}$$

Convolution (in 2D) — Continuous Case

Extension of 1D case (image F , convolution kernel G):

Definition

$$(F * G)(s, t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(x, y) \cdot G(s - x, t - y) dx dy$$



Convolution (in 2D) — Discrete Case

Discrete convolution (for image F and kernel G):

$$(F * G)[s, t] = \sum_x \sum_y F[x][y] \cdot G[s - x][t - y]$$

Computational complexity: $\mathcal{O}(|F| \cdot |G|)$

Would it be possible to compute it faster?

Methods:

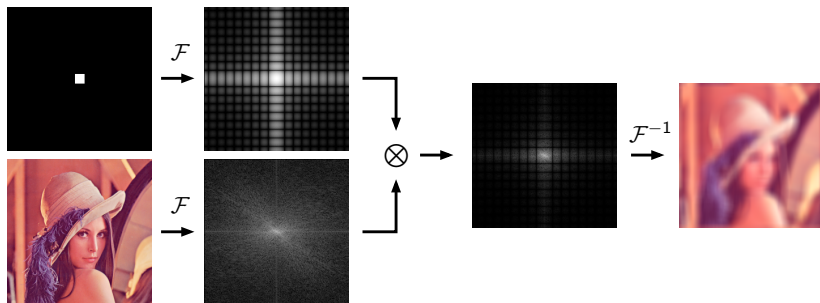
Method	Accuracy	Kernel	Complexity
Fourier Transform	Exact	Arbitrary	$\mathcal{O}(F \cdot \log F)$
Separable Kernel	Exact	Limited	$\mathcal{O}(F \cdot \sqrt{ G })$
Integral Image	High	Limited	$\mathcal{O}(F)$

Fourier Transform

Convolution Theorem:

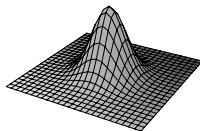
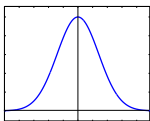
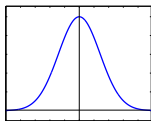
Theorem

$$\mathcal{F}\{F * G\} = \mathcal{F}\{F\} \cdot \mathcal{F}\{G\}$$



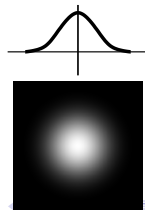
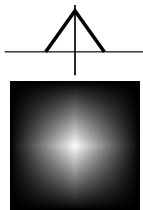
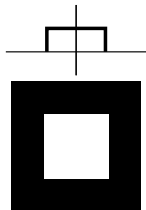
Separable Kernel

$$G(x, y) = g_x(x) \cdot g_y(y)$$



Separable Convolution

$$(F * G)(s, t) = \int_{-\infty}^{\infty} g_y(t - y) \left(\int_{-\infty}^{\infty} F(x, y) \cdot g_x(s - x) dx \right) dy$$



Integral Image

Summed Area Table (SAT):

$$S[x, y] = \sum_{x' \leq x} \sum_{y' \leq y} I[x', y']$$

2	3	2	1
3	0	1	2
1	3	1	0
1	4	2	2

Image *I*

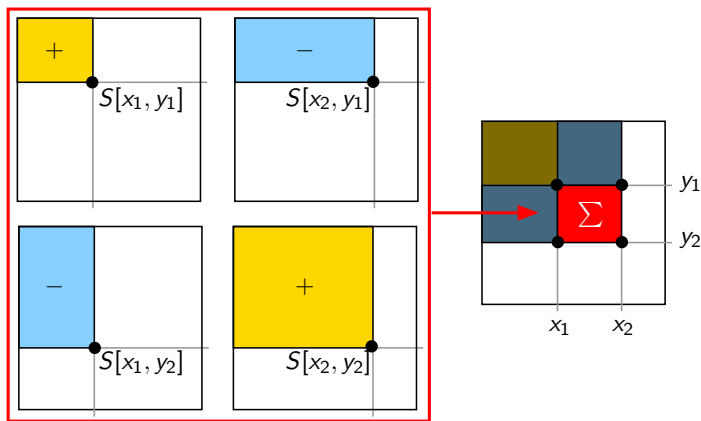
2	5	7	8
5	8	11	14
6	12	16	19
7	17	23	28

SAT *S*

Integral Image

Region Sum:

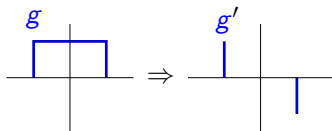
$$\Sigma = S[x_2, y_2] - S[x_1, y_2] - S[x_2, y_1] + S[x_1, y_1]$$



Integral Image — Extension

Basic Idea

$$f * g = [\int f] * [g']$$



Extension for more complex kernels:

Generalized Form

$$f * g = [\int^{(n)} f] * [g^{(n)}]$$

Equivalently,

$$\underbrace{(g * g * \dots * g)}_n^{(n)} = \underbrace{g' * g' * \dots * g'}_n$$

Integral Image — Extension

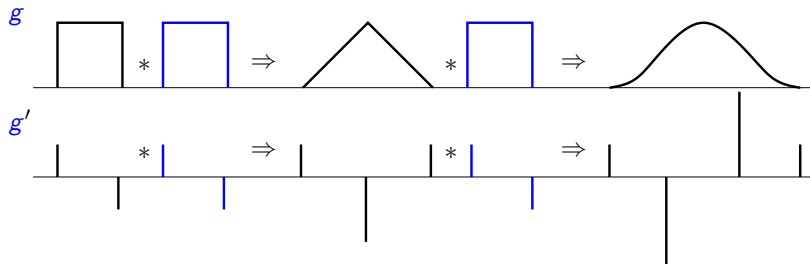
Extension for more complex kernels:

Generalized Form

$$\mathbf{f} * \mathbf{g} = \left[\int^{(n)} \mathbf{f} \right] * [\mathbf{g}^{(n)}]$$

Equivalently,

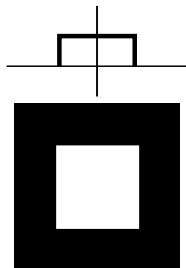
$$\underbrace{(g * g * \dots * g)}_n^{(n)} = \underbrace{g' * g' * \dots * g'}_n$$



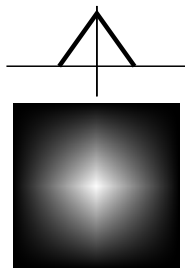
Integral Image — Kernel Examples

Examples of convolution kernels:

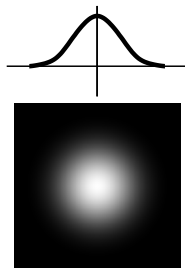
$$\begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix}$$



$$\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$



$$\begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -9 & 9 & -3 \\ -3 & 9 & -9 & 3 \\ 1 & -3 & 3 & -1 \end{bmatrix}$$



Fourier Transform — Pros and Cons

Advantages:

- ▶ Arbitrary kernel shape
- ▶ Accurate convolution
- ▶ Suitable for large kernels
- ▶ Independent of kernel width

Disadvantages:

- ▶ Two FFTs per convolution
- ▶ Slow for small kernels

Separable Kernel — Pros and Cons

Advantages:

- ▶ Accurate convolution
- ▶ Speed-up for large kernels

Disadvantages:

- ▶ Limited kernel shape
- ▶ Still slow for very large kernels
- ▶ Requires extra memory and two passes

Integral Image — Pros and Cons

Advantages:

- ▶ Fast
- ▶ High accuracy

Disadvantages:

- ▶ Limited numeric precision (when approximation is used)
- ▶ Limited kernel shapes