

# Computer Vision II

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# Notation

Throughout the course, we shall use the following notation:

- ▶ We write “iff” as shorthand for “if and only if”
- ▶ For any  $m \in \mathbb{N}$ , we define  $[m] = \{0, \dots, m - 1\}$ .
- ▶ For any set  $A$ , we denote by  $2^A$  the power set of  $A$
- ▶ For any set  $A$  and any  $m \in \mathbb{N}$ , we denote by  $\binom{A}{m} = \{B \in 2^A \mid |B| = m\}$  the set of all  $m$ -elementary subsets of  $A$
- ▶ For any sets  $A, B$ , we denote by  $B^A$  the set of all maps from  $A$  to  $B$

# Bilateral Filter

We recall from the course Computer Vision I operations (filters) on digital images by looking at the example of the bilateral filter. Bilateral filtering is a powerful tool for image de-noising and is implemented, e.g., in GIMP and Adobe Photoshop.

We consider:

- ▶ A grid graph  $G = (V, E)$  whose nodes we refer to as **pixels**.  
E.g., in case of a 2-dimensional grid of  $n_0 \cdot n_1$  pixels,  
 $V = [n_0] \times [n_1]$
- ▶ A non-empty set  $R$  whose elements we refer to as **intensities**, **gray values** or **colors**. E.g.,  $R = [0, 1] \subset \mathbb{R}$  or  $R = \{0, \dots, 255\}$
- ▶ A map  $f: V \rightarrow R$  called a **digital image**

# Bilateral Filter

Given

- ▶ a metric  $d_s : V \times V \rightarrow \mathbb{R}_0^+$  and a decreasing  $w_s : \mathbb{R}_0^+ \rightarrow [0, 1]$
- ▶ a metric  $d_r : R \times R \rightarrow \mathbb{R}_0^+$  and a decreasing  $w_r : \mathbb{R}_0^+ \rightarrow [0, 1]$
- ▶ a  $N : V \rightarrow 2^V$  that defines, for every pixel  $v \in V$ , a set  $N(v) \subseteq V$  called the **spatial neighborhood** of  $v$
- ▶ the  $\nu : R^V \rightarrow \mathbb{R}^V$ , called **normalization**, such that for any digital image  $f : V \rightarrow R$  and any pixel  $v \in V$ :

$$\nu(f)(v) = \sum_{v' \in N(v)} w_s(d_s(v, v')) w_r(d_r(f(v), f(v'))) , \quad (1)$$

the **bilateral filter** w.r.t.  $d_s, w_s, d_r, w_r$  and  $N$  is the  $\beta : R^V \rightarrow \mathbb{R}^V$  such that for any digital image  $f : V \rightarrow R$  and any pixel  $v \in V$ :

$$\beta(f)(v) = \frac{1}{\nu(f)(v)} \sum_{v' \in N(v)} w_s(d_s(v, v')) w_r(d_r(f(v), f(v'))) f(v') \quad (2)$$

# Bilateral Filter

## Example

- ▶  $n_0 = 768$ ,  $n_1 = 1024$ ,  $V = [n_0] \times [n_1]$ ,  $R = [0, 1] \subset \mathbb{R}$
- ▶  $d_s(v, v') = \|v - v'\|_2$  and, for a filter parameter  $\sigma_s > 0$ :

$$w_s(x) = \frac{1}{\sigma_s \sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma_s^2}\right) \quad (3)$$

- ▶  $d_r(g, g') = |g - g'|$  and, for a filter parameter  $\sigma_r > 0$ :

$$w_r(x) = \frac{1}{1 + \frac{x^2}{\sigma_r^2}} \quad (4)$$

- ▶ for a filter parameter  $n \in \mathbb{R}_0^+$ :

$$N(v) = \{v' \in V \mid d_s(v, v') < n\} \quad (5)$$

# Bilateral Filter

## **Suggested self-study:**

- ▶ Implement a bilateral filter for gray-scale images
- ▶ Apply your implementation to a digital picture of yours or from the web
- ▶ Try different metrics  $d_s, d_r$  and weighting functions  $w_s, w_r$
- ▶ Try iterating bilateral filtering
- ▶ Share and discuss your implementations, outputs and findings via OPAL

## **Advanced self-study:**

- ▶ Define, implement and apply bilateral filtering for color images
- ▶ Share and discuss your implementations, outputs and findings via OPAL