

# Computer Vision I

Bjoern Andres, Holger Heidrich

Machine Learning for Computer Vision  
TU Dresden



Winter Term 2022/2023

**Definition 1.** Let  $n_0, n_1 \in \mathbb{N}$ , let  $V = [n_0] \times [n_1]$  and let  $C \subseteq \mathbb{R}$ . 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  $d_c : C \times C \rightarrow \mathbb{R}_0^+$  and a decreasing  $w_c : \mathbb{R}_0^+ \rightarrow [0, 1]$
- ▶ 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  $\nu : C^V \rightarrow \mathbb{R}^V$ , called **normalization**, such that for any digital image  $f : V \rightarrow C$  and any pixel  $v \in V$ :

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

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

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

### Example.

- ▶  $d_s(v, v') = \|v - v'\|_2$  and, for a filter parameter  $\sigma_s > 0$ :

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

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

$$w_c(x) = \frac{1}{1 + \frac{x^2}{\sigma_c^2}} \quad (4)$$

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

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

### **Suggested self-study:**

- ▶ Implement a bilateral filter for gray-scale images
- ▶ Apply your implementation to a digital image
- ▶ 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

## Non-linear operators

**Definition 2.** Let  $n_0, n_1 \in \mathbb{N}$ , let  $V = [n_0] \times [n_1]$ , let  $C \subseteq \mathbb{R}$  and let  $N : V \rightarrow 2^V$  define for every pixel  $v \in V$  a set  $N(v) \subseteq V$  called the **spatial neighborhood** of  $v$ . The **median operator** wrt.  $N$  is the function  $M : C^V \rightarrow C^V$  such that for any  $f : V \rightarrow C$  and any  $v \in V$ :

$$M(f)(v) = \text{median } f(N(v)) \quad (6)$$

## Non-linear operators

Noisy image



$f$

Filtered image



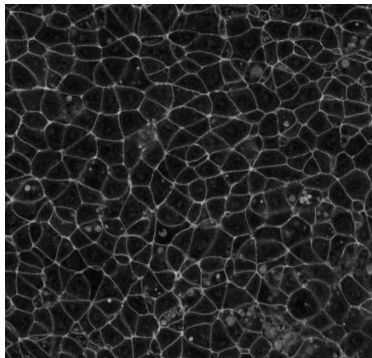
$M(f)$

## Morphological operators

- ▶ We may identify any **binary** infinite digital image  $f: \mathbb{Z}^2 \rightarrow \{0, 1\}$  with its support set  $f^{-1}(1) = \{v \in \mathbb{Z}^2 \mid f(v) = 1\}$ .
- ▶ This allows us to apply operations from the field of **binary mathematical morphology** to binary infinite digital images.

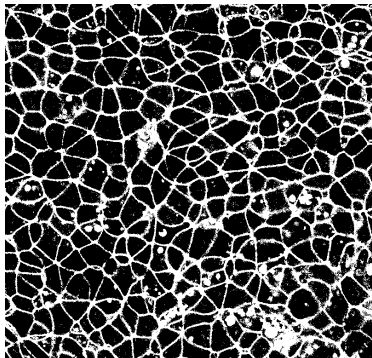
## Non-linear operators

Image<sup>1</sup>



$f$

Binary image



$f \geq 45$

---

<sup>1</sup>By courtesy of Stephan Grill and his lab at the MPI of Molecular Cell Biology and Genetics.



**Definition 3.** For any  $A, B \subseteq \mathbb{Z}^2$ , we define

$$A \ominus B := \{v \in \mathbb{Z}^2 \mid B + v \subseteq A\} \quad (7)$$

$$A \oplus B := \{v \in \mathbb{Z}^2 \mid -B + v \cap A \neq \emptyset\} \quad (8)$$

and call these operations **erosion** and **dilation**. Moreover, we call the operations

$$A \circ B := (A \ominus B) \oplus B \quad (9)$$

$$A \bullet B := (A \oplus B) \ominus B \quad (10)$$

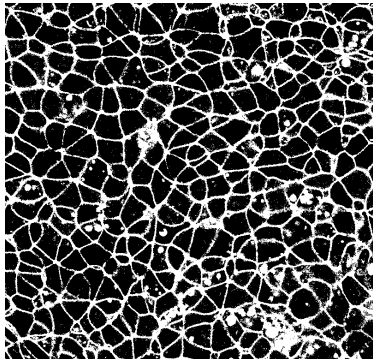
**opening** and **closing**.

**Definition 4.** For any (typically small) support set  $B$  called a **structuring element** and any morphological operation  $\otimes$ , the operator

$\varphi_{\otimes B}: \{0, 1\}^{\mathbb{Z} \times \mathbb{Z}} \rightarrow \{0, 1\}^{\mathbb{Z} \times \mathbb{Z}}$  such that for any (infinite binary digital image)  $f: \mathbb{Z}^2 \rightarrow \{0, 1\}$  and any (pixel)  $v \in \mathbb{Z}^2$ , we have  $\varphi_{\otimes B}(f)(v) = 1$  if and only if  $v \in f^{-1}(1) \otimes B$  is called the **morphological operator** wrt.  $\otimes$  and  $B$ .

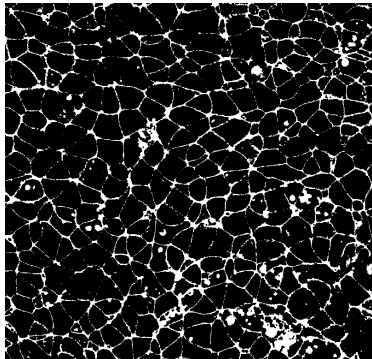
## Non-linear operators

Binary image



$f$

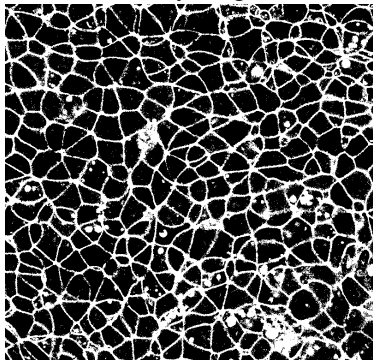
Erosion



$\varphi_{\ominus B}(f)$

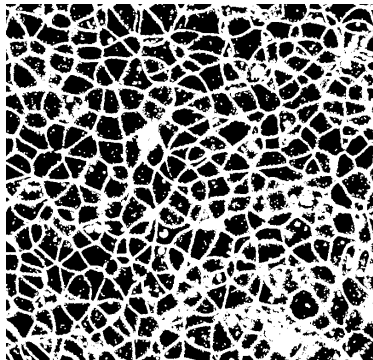
## Non-linear operators

Binary image



$f$

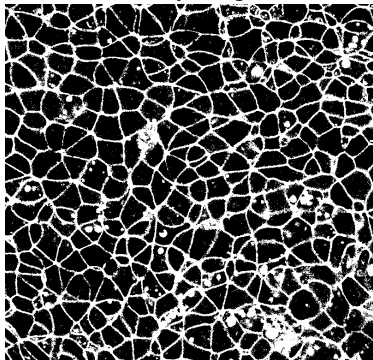
Dilation



$\varphi_{\oplus B}(f)$

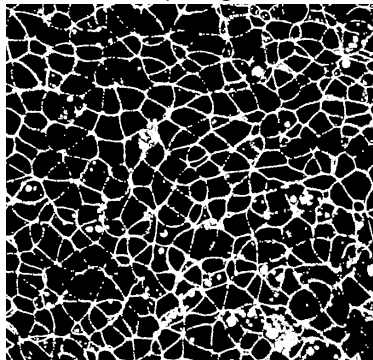
## Non-linear operators

Binary image



$f$

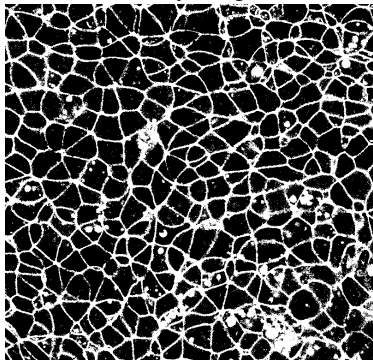
Opening



$\varphi \circ_B(f)$

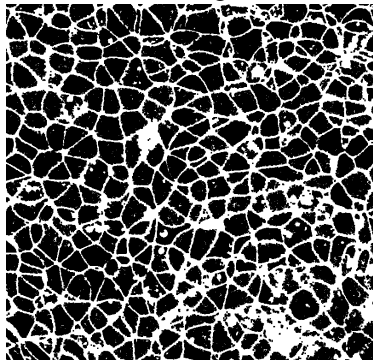
## Non-linear operators

Binary image



$f$

Closing

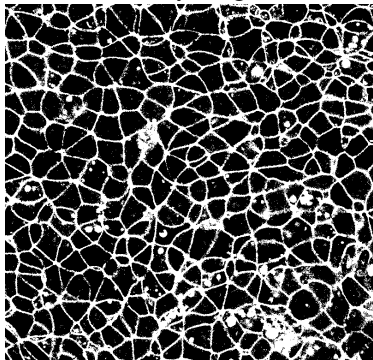


$\varphi_{\bullet B}(f)$

**Definition 5.** For any  $n_0, n_1 \in \mathbb{N}$ , the set  $V = [n_0] \times [n_1]$  and the pixel grid graph  $G = (V, E)$ , an operator  $\varphi: \mathbb{N}_0^V \rightarrow \mathbb{N}_0^V$  is called a **(connected) components operator** if for any digital image  $f: V \rightarrow \mathbb{N}_0$  and any pixels  $v, w \in V$ , we have  $\varphi(f)(v) = \varphi(f)(w)$  iff there exists a  $vw$ -path in  $G$  along which all pixels have the color zero.

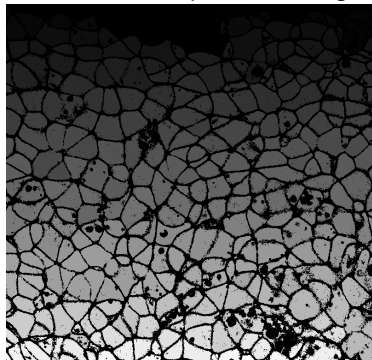
## Non-linear operators

Binary image



$f$

Connected component labeling



$\varphi(f)$

## Non-linear operators

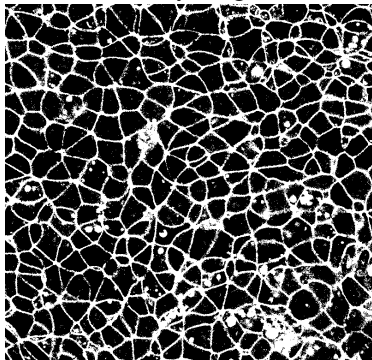
```
size_t componentsImage(
    Marray<size_t> const & image,
    Marray<size_t> & components
) {
    components.resize({image.shape(0), image.shape(1)});
    PixelGridGraph pixelGridGraph({image.shape(0), image.shape(1)});
    size_t component = 0;
    stack<size_t> stack;
    for(size_t v = 0; v < pixelGridGraph.numberOfVertices(); ++v) {
        Pixel pixel = pixelGridGraph.coordinate(v);
        if(image[pixel[0], pixel[1]] == 0
            && components[pixel[0], pixel[1]] == 0) {
            ++component;
            components[pixel[0], pixel[1]] = component;
            stack.push(v);
            while(!stack.empty()) {
                size_t const v = stack.top();
                stack.pop();
                for(auto it = pixelGridGraph.verticesFromVertexBegin(v);
                    it != pixelGridGraph.verticesFromVertexEnd(v); ++it) {
                    Pixel pixel = it.coordinate();
                    if(image[pixel[0], pixel[1]] == 0
                        && components[pixel[0], pixel[1]] == 0) {
                        components[pixel[0], pixel[1]] = component;
                        stack.push(*it);
                    }
                }
            }
        }
    }
    return component; // number of components
}
```



**Definition 6.** For any  $n_0, n_1 \in \mathbb{N}$ , the set  $V = [n_0] \times [n_1]$  and the pixel grid graph  $G = (V, E)$ , the **distance operator**  $\varphi: \mathbb{N}_0^V \rightarrow \mathbb{N}_0^V$  is such that for any digital image  $f: V \rightarrow \mathbb{N}_0$  and any pixel  $v \in V$ , the number  $\varphi(f)(v)$  is the minimum distance in the pixel grid graph from  $v$  to a pixel  $w$  with  $f(w) = 1$ .

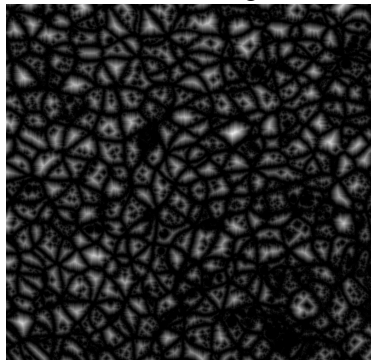
## Non-linear operators

Binary image



$f$

Distance image



$\varphi(f)$

## Non-linear operators

```
1 size_t distanceImage(  
2     Marray<size_t> const & image,  
3     Marray<size_t> & distances  
4 ) {  
5     distances.resize({image.shape(0), image.shape(1)}, 0);  
6     GridGraph pixelGridGraph({image.shape(0), image.shape(1)});  
7     size_t distance = 0;  
8     array<stack<size_t>, 2> stacks;  
9     for(size_t v = 0; v < pixelGridGraph.numberofVertices(); ++v) {  
10        Pixel pixel = pixelGridGraph.coordinates(v);  
11        if(image(pixel[0], pixel[1]) != 0)  
12            stacks[0].push(v);  
13    }  
14    ++distance;  
15    for(;;) {  
16        auto & stack = stacks[(distance - 1) % 2];  
17        if(stack.empty())  
18            return distance - 1; // maximal distance  
19        while(!stack.empty()) {  
20            size_t const v = stack.top();  
21            stack.pop();  
22            for(auto it = pixelGridGraph.verticesFromVertexBegin(v);  
23                it != pixelGridGraph.verticesFromVertexEnd(v); ++it) {  
24                Pixel pixel = it.coordinate();  
25                if(image(pixel[0], pixel[1]) == 0  
26                    && distances(pixel[0], pixel[1]) == 0) {  
27                    distances(pixel[0], pixel[1]) = distance;  
28                    stacks[distance % 2].push(*it);  
29                }  
30            }  
31        }  
32        ++distance;  
33    }  
34 }
```

## Non-linear operators

For any set  $V$  of pixels and neighborhood function  $N: V \rightarrow 2^V$ , **non-maximum suppression** is the operator  $\varphi_{\text{NMS}}: \mathbb{R}^V \rightarrow \mathbb{R}^V$  such that for each digital image  $f: V \rightarrow \mathbb{R}$  and all pixels  $v \in V$ :

$$\varphi_{\text{NMS}}(f)(v) = \begin{cases} f(v) & \text{if } f(v) = \max f(N(v)) \\ 0 & \text{otherwise} \end{cases} \quad (11)$$