

Digital Image Processing

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Last Exercise - Theory

1. What is a digital image?

→ A projection of the continuous 3D world into a discrete 2D map.
An image maps spatial coordinates $(x, y) \in \mathbb{N}$ to discrete intensity values $f(x, y)$, e.g. $f(x, y) \in \mathbb{N}^c$, where c the number of channels.

2. What does the paradigm “bottom-up processing” mean?

→ Bottom-up processing refers to a data-driven processing scheme, where low-level features are successively grouped into complex structures and thus accumulating object evidence.

3. State at least three fundamentally different image sources!

→ Optical cameras:

passive sensor, visible part of the spectrum, object position depends on angle of visual ray

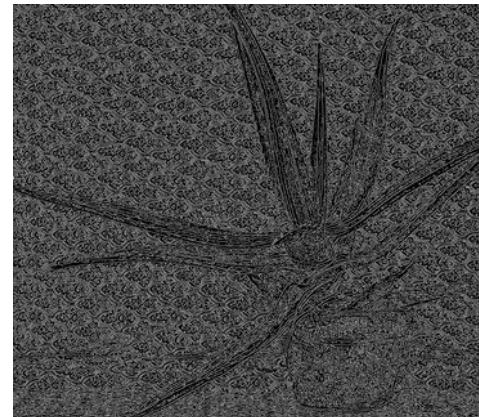
→ SAR:

active sensor, micro-waves, object position depends on distance

→ Ultrasound:

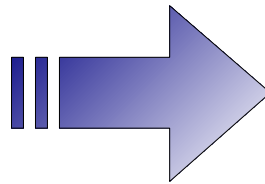
Active sensor, based on high-frequency sound pulses

Last Exercise - Examples

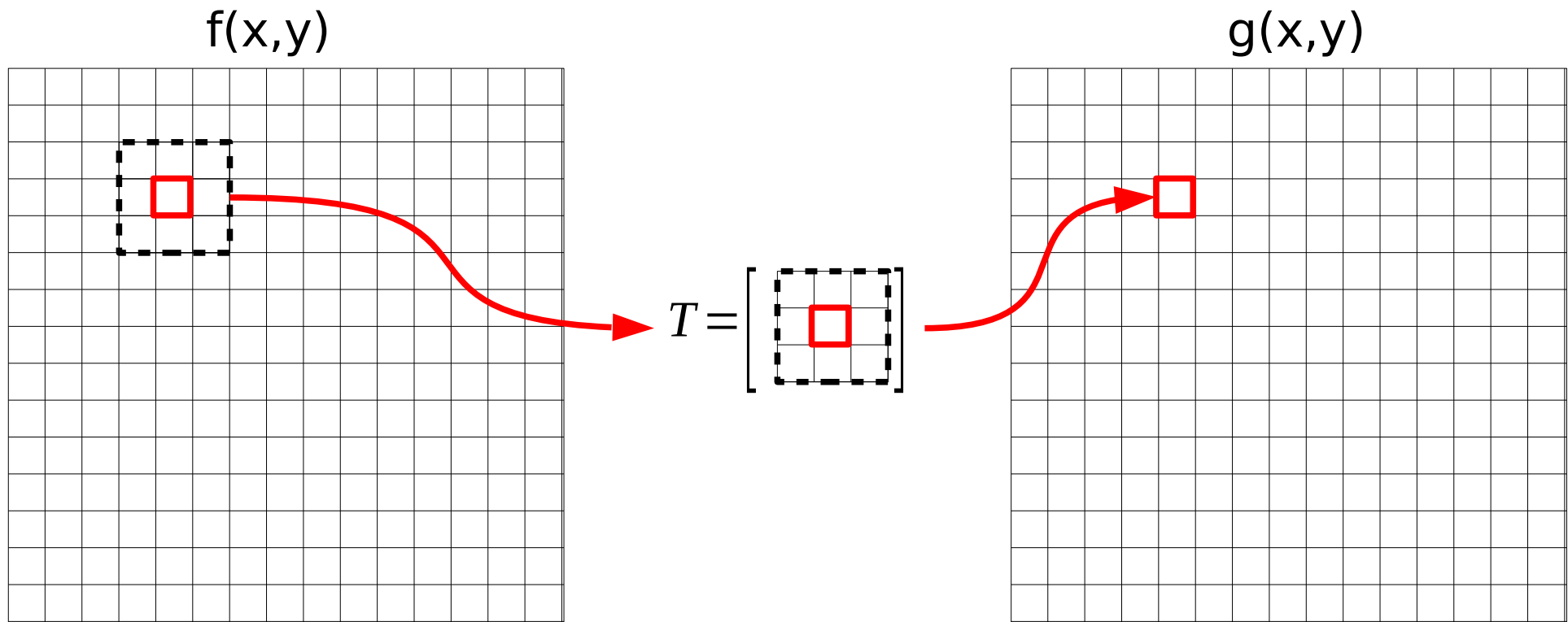


Purpose of Digital Image Processing

Image restoration: Improving *objective* image quality
e.g. noise suppression



Sliding Window

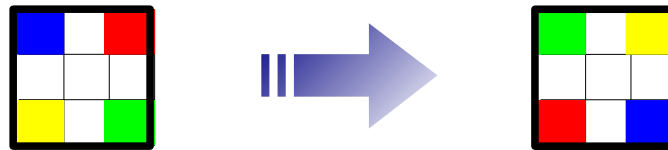


- Operator T takes into account only local information
- Result in g is based on pixel intensity and intensities of neighbours
 - '*Filter size*' refers to size of neighbourhood (e.g. 3x3 pixels)

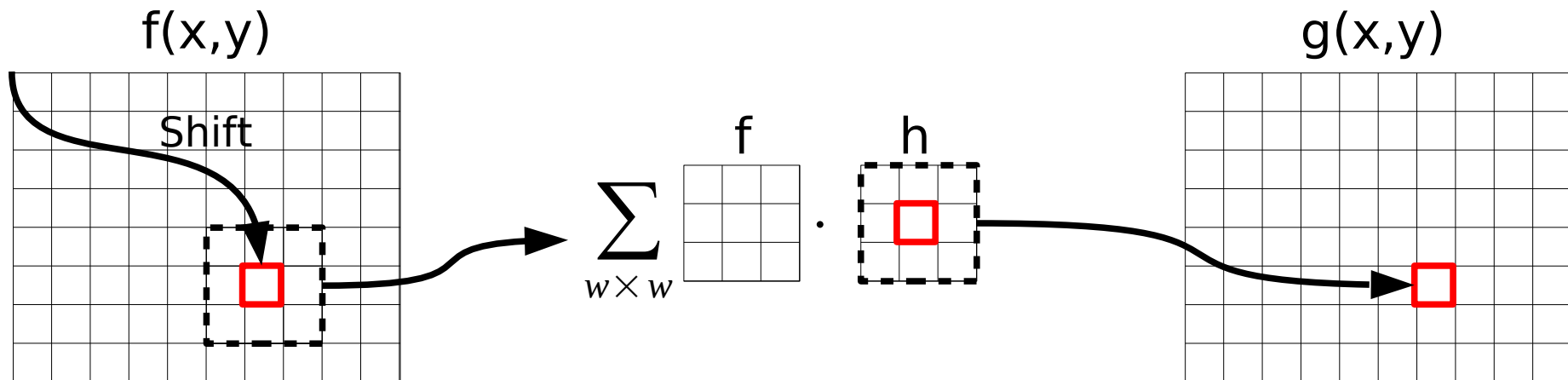
Convolution

$$g(\alpha, \beta) = \sum_{x=1}^N \sum_{y=1}^M f(x, y) \cdot h(x - \alpha, y - \beta)$$

1. Flip filter kernel (about the filter centre)



2. Shift (re-centre), **Multiply** and **Integrate**



Convolution

- Filter consists of coefficients and has a **anchor point**:

$$h(r, s) = \begin{pmatrix} h(-1, -1) & h(0, -1) & h(1, -1) \\ h(-1, 0) & \boxed{h(0, 0)} & h(1, 0) \\ h(-1, 1) & h(0, 1) & h(1, 1) \end{pmatrix}$$

- Linear filters are applied by *convolution*:

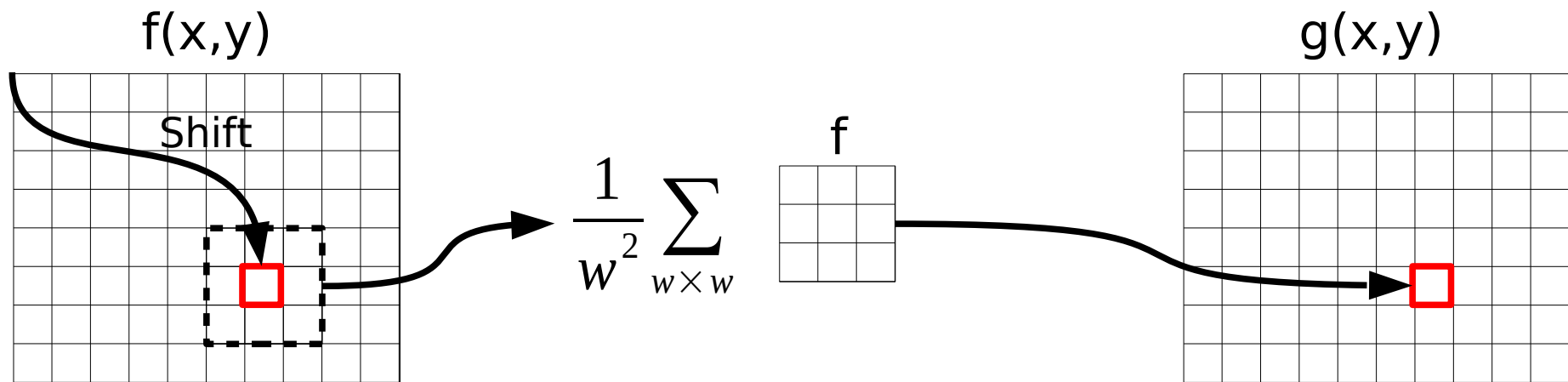
$$g(x, y) = (f * h)(x, y) = \sum_{3 \times 3} \begin{pmatrix} f(x-1, y-1)h(1,1) & f(x, y-1)h(0,1) & f(x+1, y-1)h(-1,1) \\ f(x-1, y)h(1,0) & f(x, y)h(0,0) & f(x+1, y)h(-1,0) \\ f(x-1, y+1)h(1,-1) & f(x, y+1)h(0,-1) & f(x+1, y+1)h(-1,-1) \end{pmatrix}$$

Filter Techniques

Example: Noise Suppression by Moving Average Filter

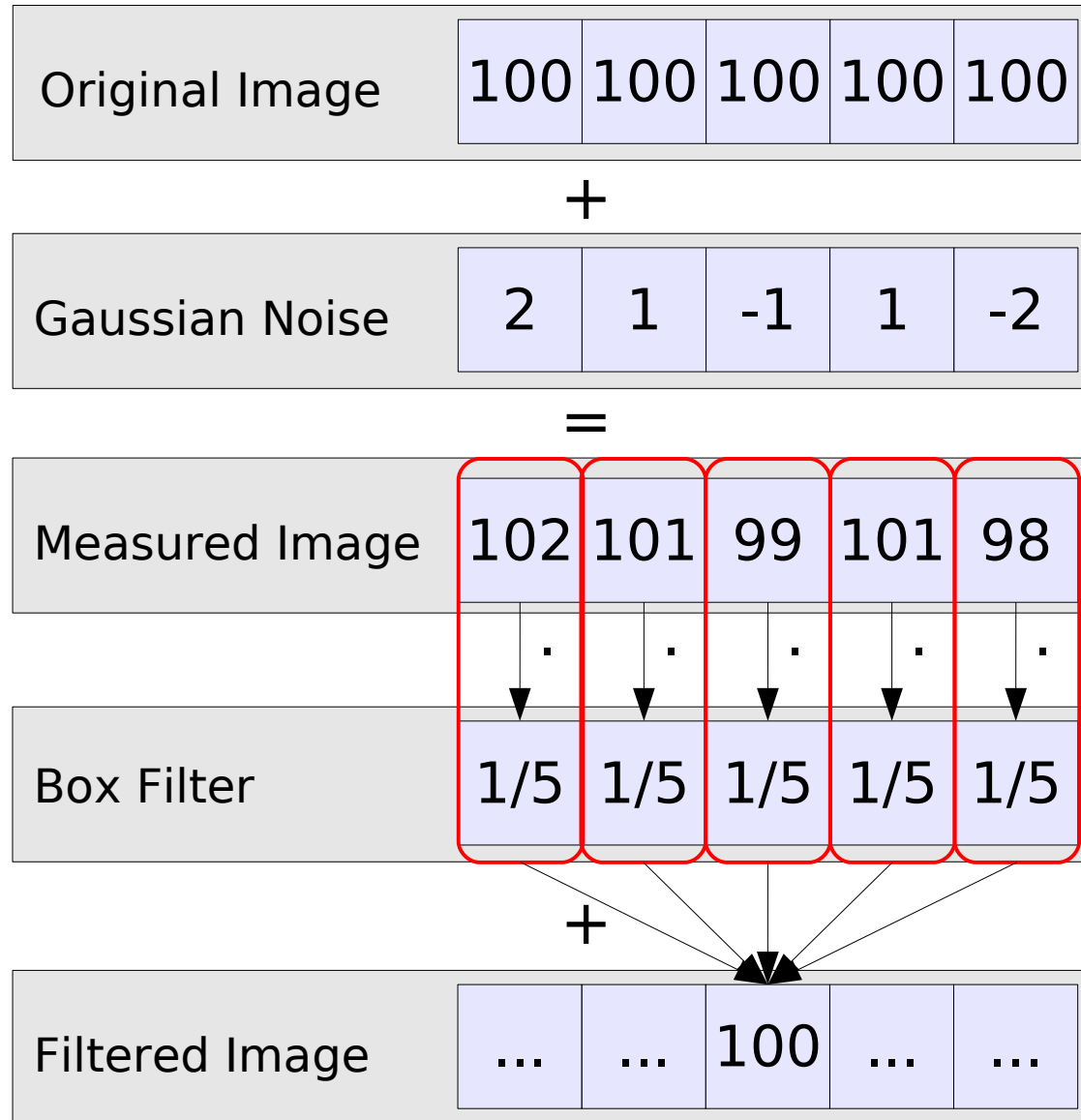
$$h(x, y) = \frac{1}{w^2} \begin{pmatrix} 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ 1 & 1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \quad (w \times w \text{ Filter Kernel})$$

- Each pixel intensity is replaced by the local average...



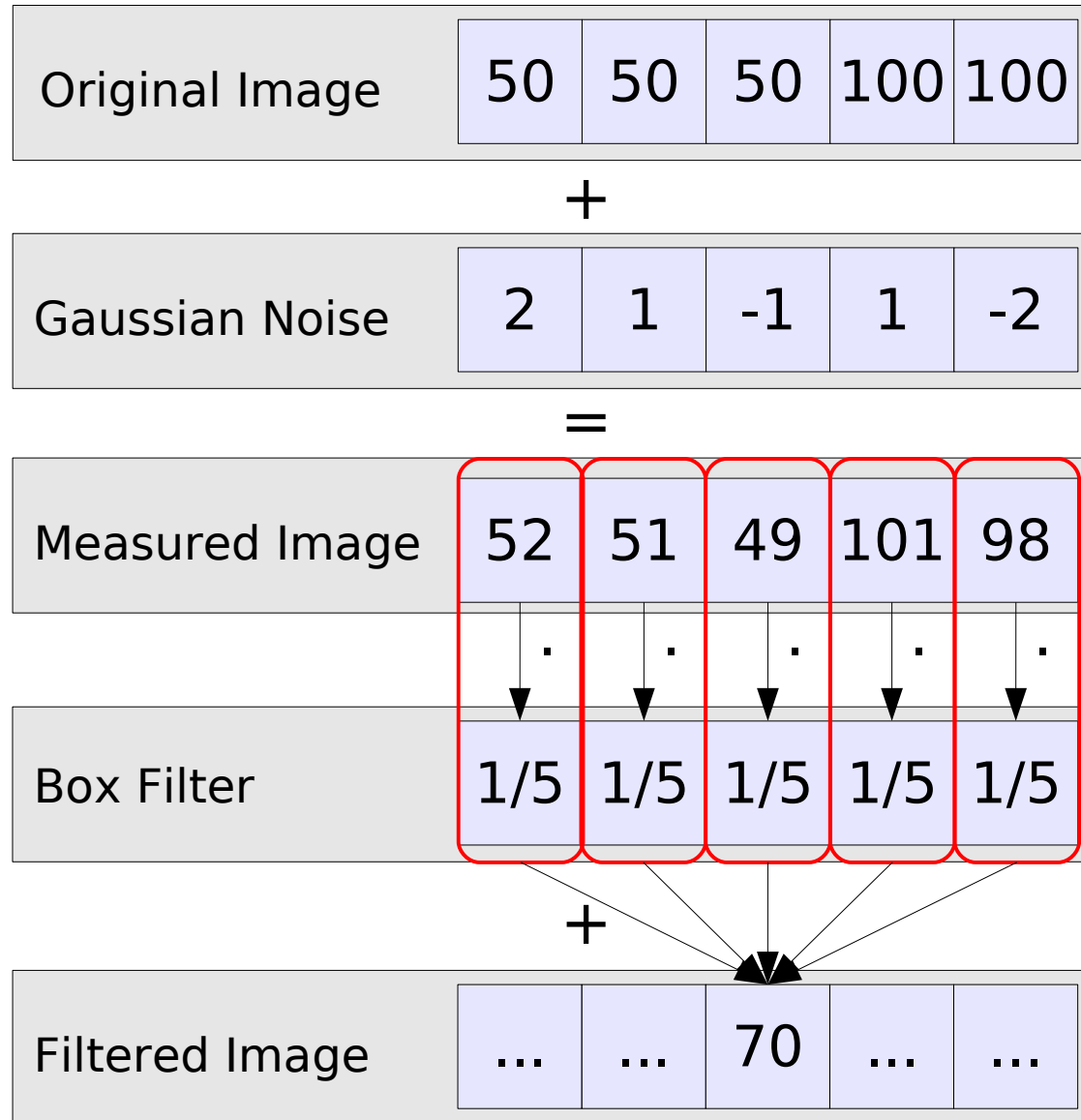
Filter Techniques

Example: Noise Suppression by Moving Average Filter



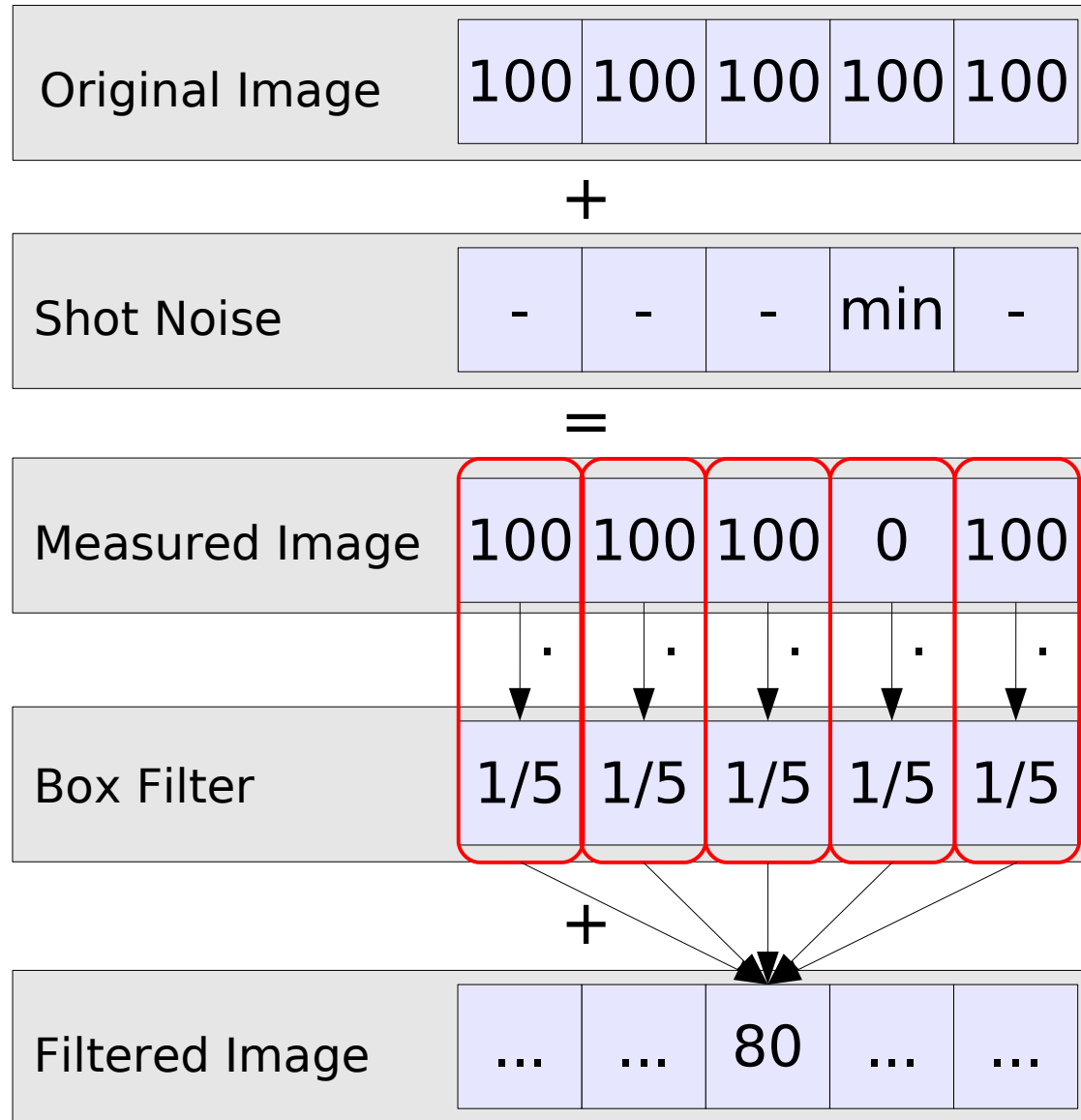
Filter Techniques

Example: Noise Suppression by Moving Average Filter



Filter Techniques

Example: Noise Suppression by Moving Average Filter



Filter Techniques

Example: Noise Suppression by Moving Average Filter

Gaussian Noise



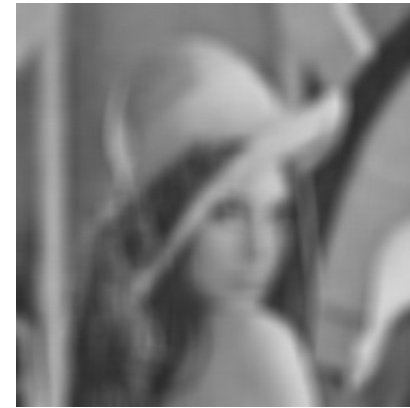
f



w=5



w=11



w=25

Shot Noise



f



w=5



w=11



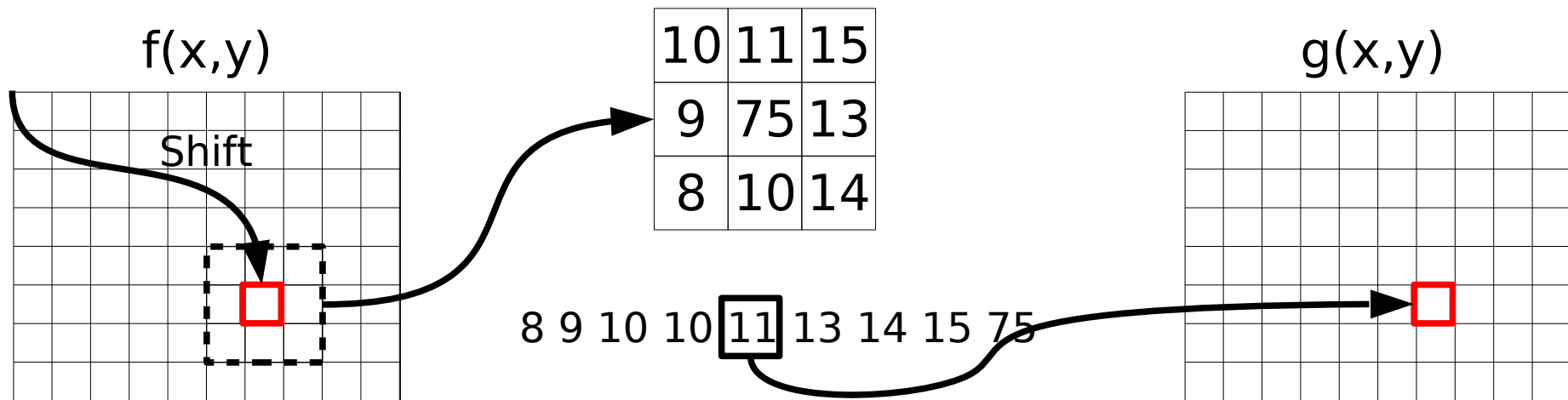
w=25

Filter Techniques

Example: Noise Suppression by Median Filter (NOTE: No convolution)

1. Consider intensities in a local $N \times N$ window
2. Sort intensities
3. Select middle value (median) as result

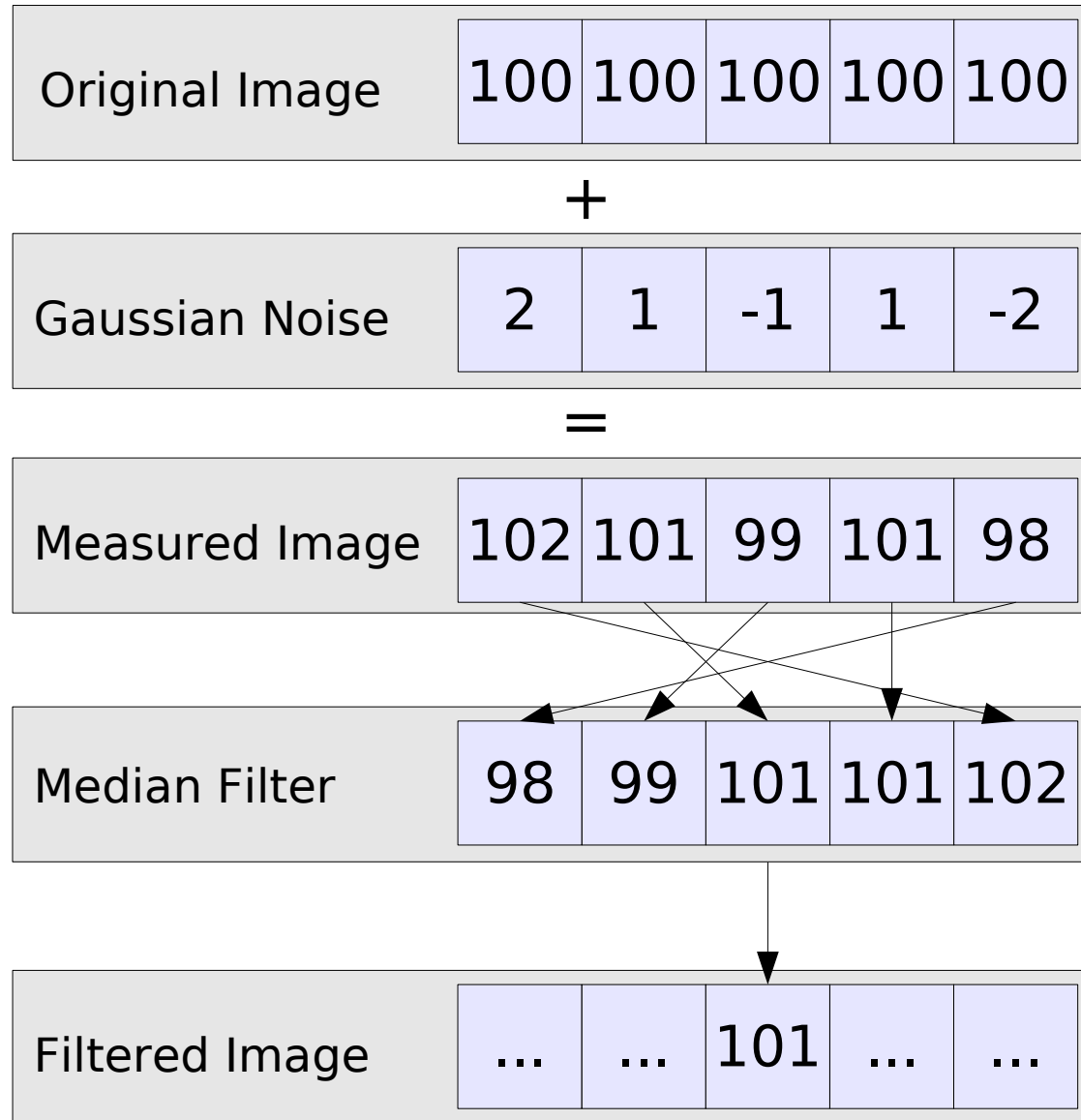
- Each pixel intensity is replaced by the local median...



- Effectively removes outliers
- Preserves sufficiently large ($\gg w \times w$) image structures

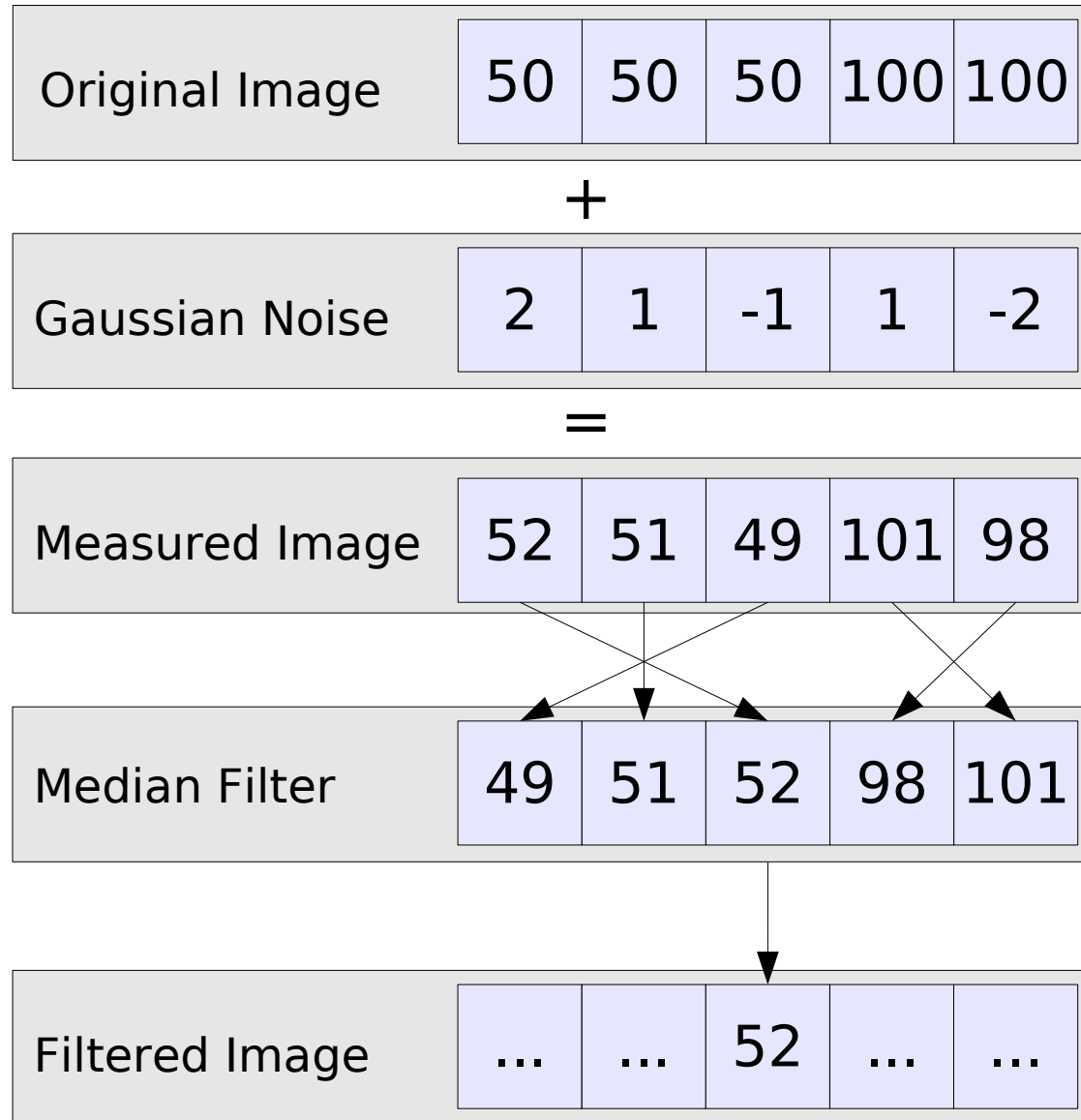
Filter Techniques

Example: Noise Suppression by Median Filter



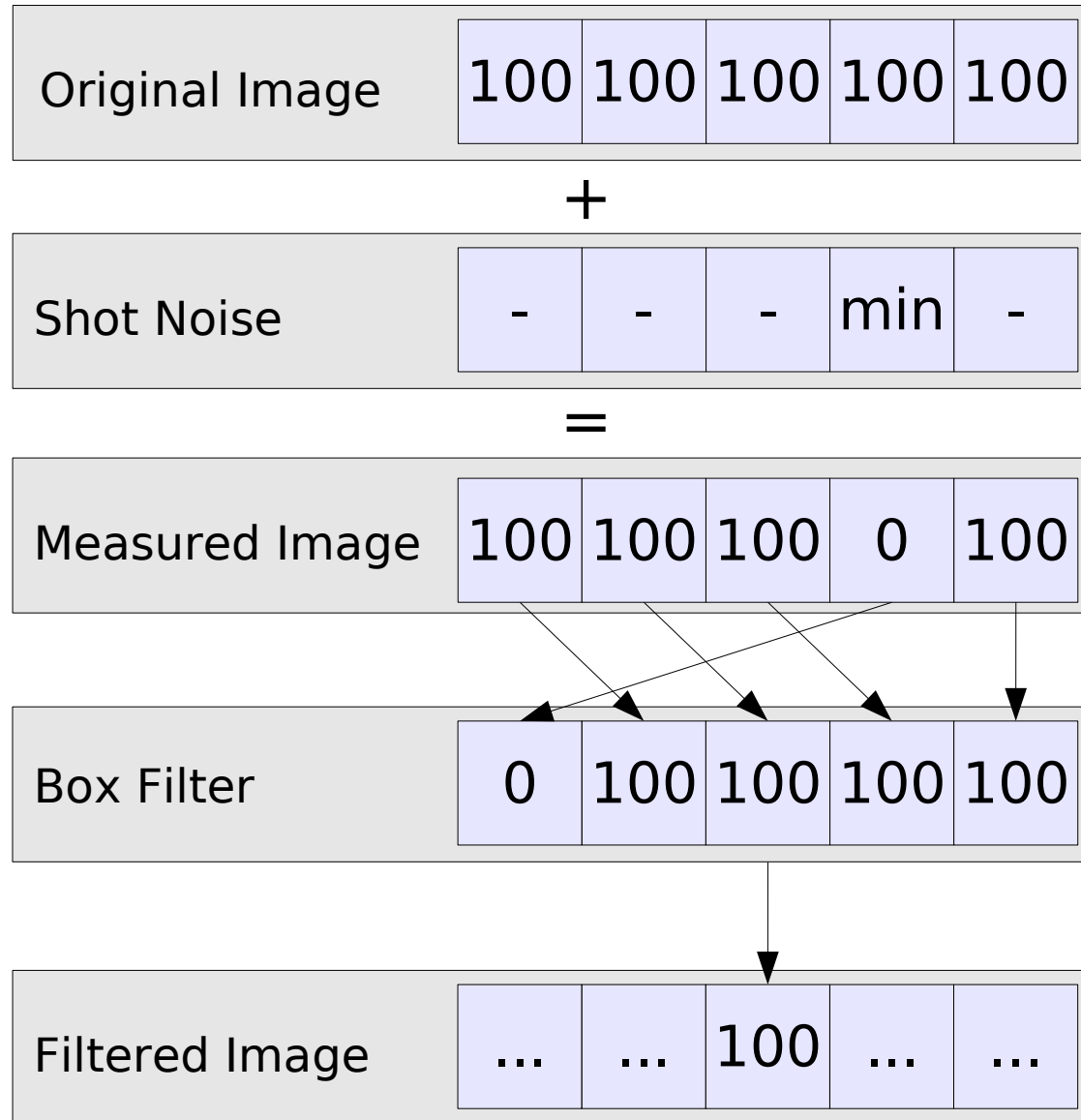
Filter Techniques

Example: Noise Suppression by Median Filter



Filter Techniques

Example: Noise Suppression by Median Filter



Filter Techniques

Example: Noise Suppression by Median Filter

Gaussian Noise



f



w=5



w=11

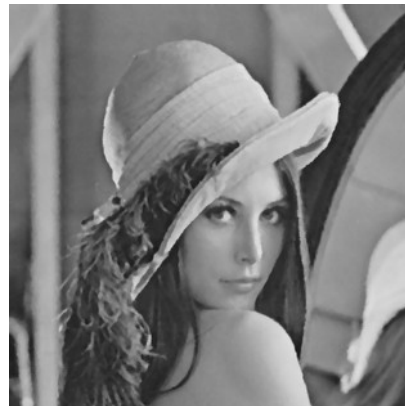


w=25

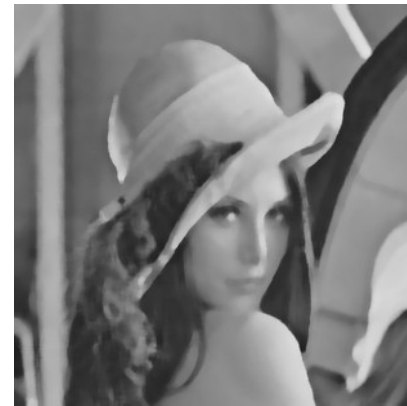
Shot Noise



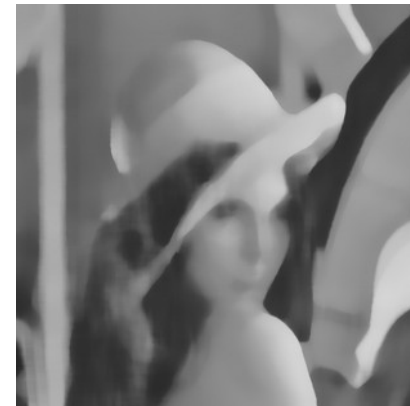
f



w=5



w=11



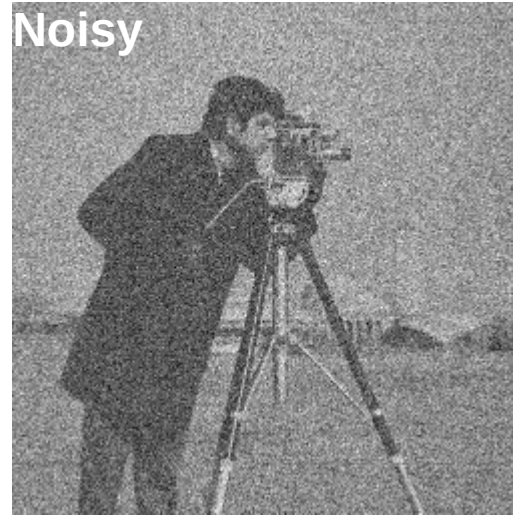
w=25

Noise Suppression vs. Resolution

Original



Noisy



Moving average filtering

3x3



5x5



7x7



Bilateral Filter

Spatial Weight:

$$h_{spat}(r, s) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(r-\mu)^2 + (s-\mu)^2}{2\sigma^2}\right)$$



Radiometric Weight:

$$h_{rad}(p, q) = \frac{1}{2\pi\sigma_p^2} \exp\left(-\frac{(p-q)^2}{2\sigma_p^2}\right)$$



Combined:

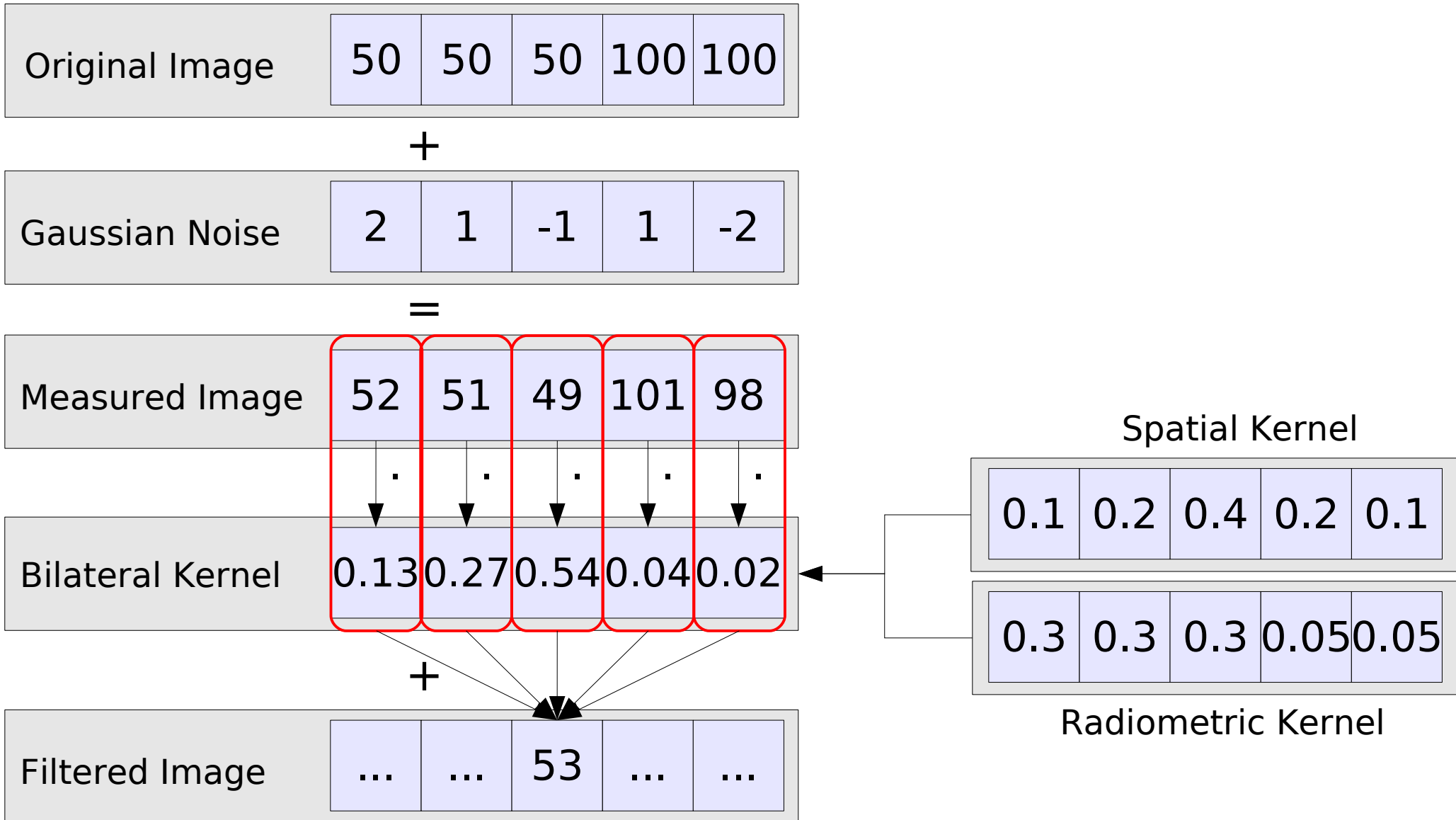
$$h(r, s, f(x, y)) = h_{spat}(r, s) \cdot h_{rad}(f(x, y))$$

Output:

$$g(\vec{x}) = \frac{1}{Z(\vec{x})} \sum_{\vec{x}' \in N(\vec{x})} \exp\left(-\frac{(\vec{x}' - \vec{x})^2}{2 \cdot \sigma_1^2}\right) \cdot \exp\left(-\frac{(f(\vec{x}') - f(\vec{x}))^2}{2 \cdot \sigma_2^2}\right) \cdot f(\vec{x}')$$

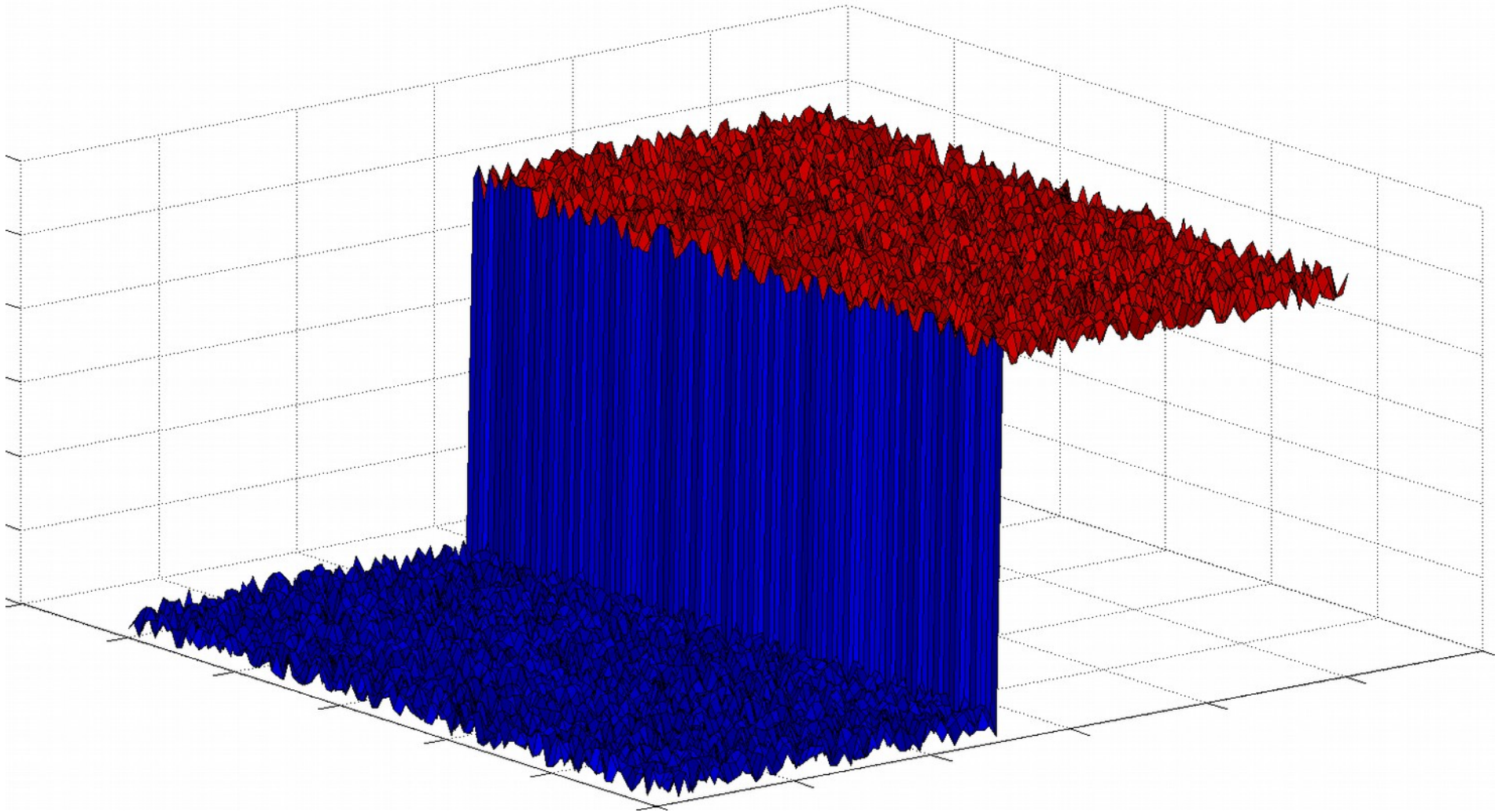
Bilateral Filter

Example: Noise Suppression by Bilateral Filter



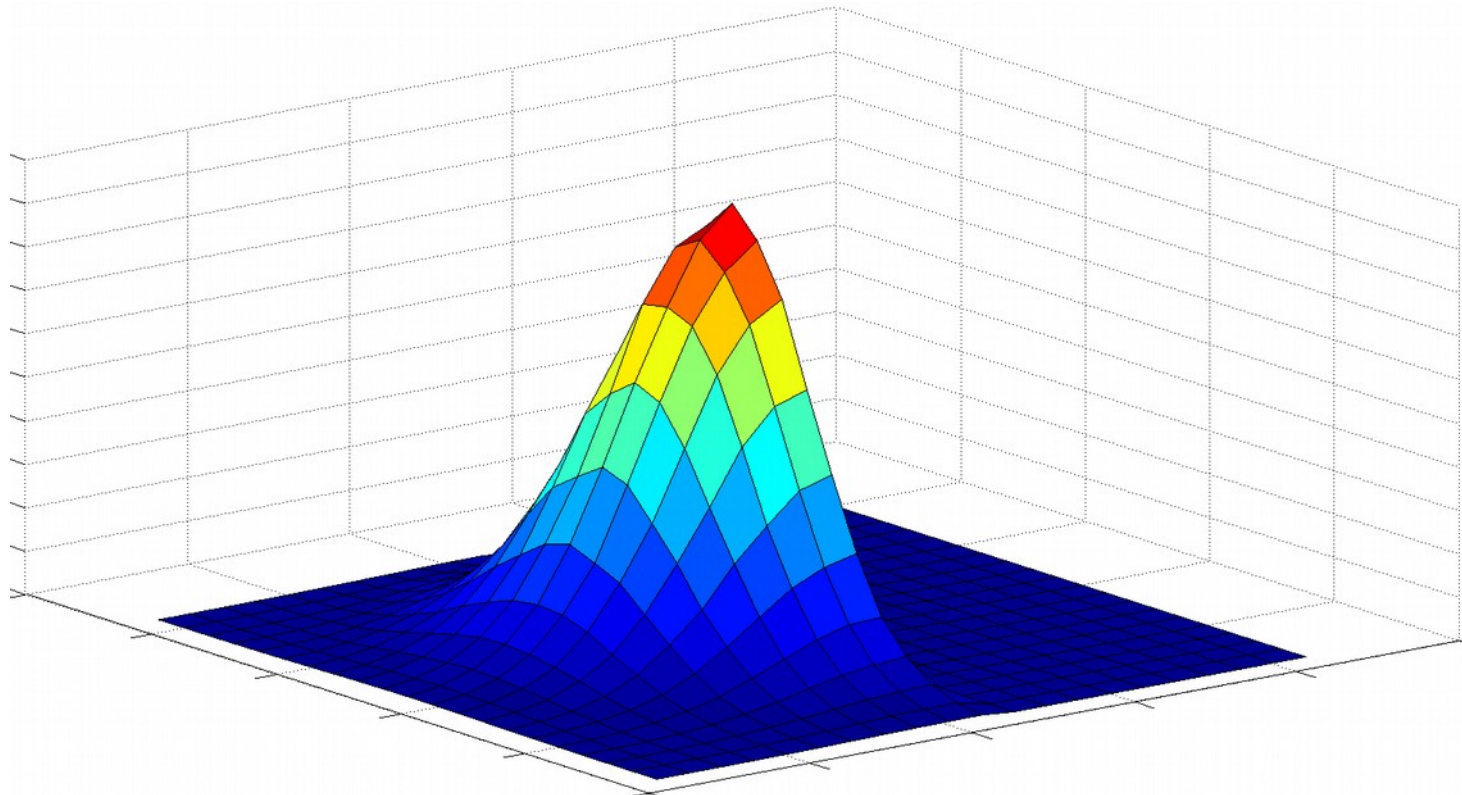
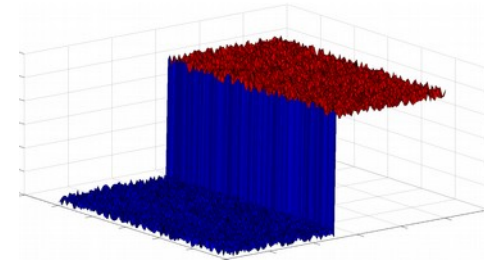
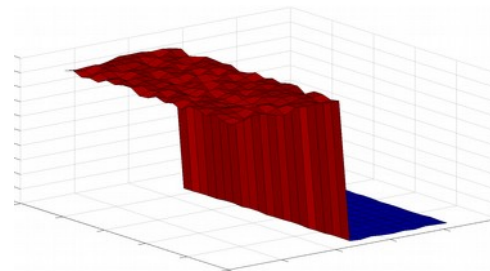
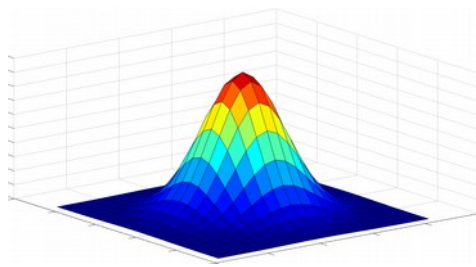
Bilateral Filter

$$g(\vec{x}) = \frac{1}{Z(\vec{x})} \sum_{\vec{x}' \in \mathcal{O}_{\vec{x}}} \exp\left(-\frac{(\vec{x}' - \vec{x})^2}{2 \cdot \sigma_1^2}\right) \cdot \exp\left(-\frac{(f(\vec{x}') - f(\vec{x}))^2}{2 \cdot \sigma_2^2}\right) \cdot f(\vec{x}')$$



Bilateral Filter

$$g(\vec{x}) = \frac{1}{Z(\vec{x})} \sum_{\vec{x}' \in \mathcal{O}_{\vec{x}}} \exp\left(-\frac{(\vec{x}' - \vec{x})^2}{2 \cdot \sigma_1^2}\right) \cdot \exp\left(-\frac{(f(\vec{x}') - f(\vec{x}))^2}{2 \cdot \sigma_2^2}\right) \cdot f(\vec{x}')$$



Bilateral Filter

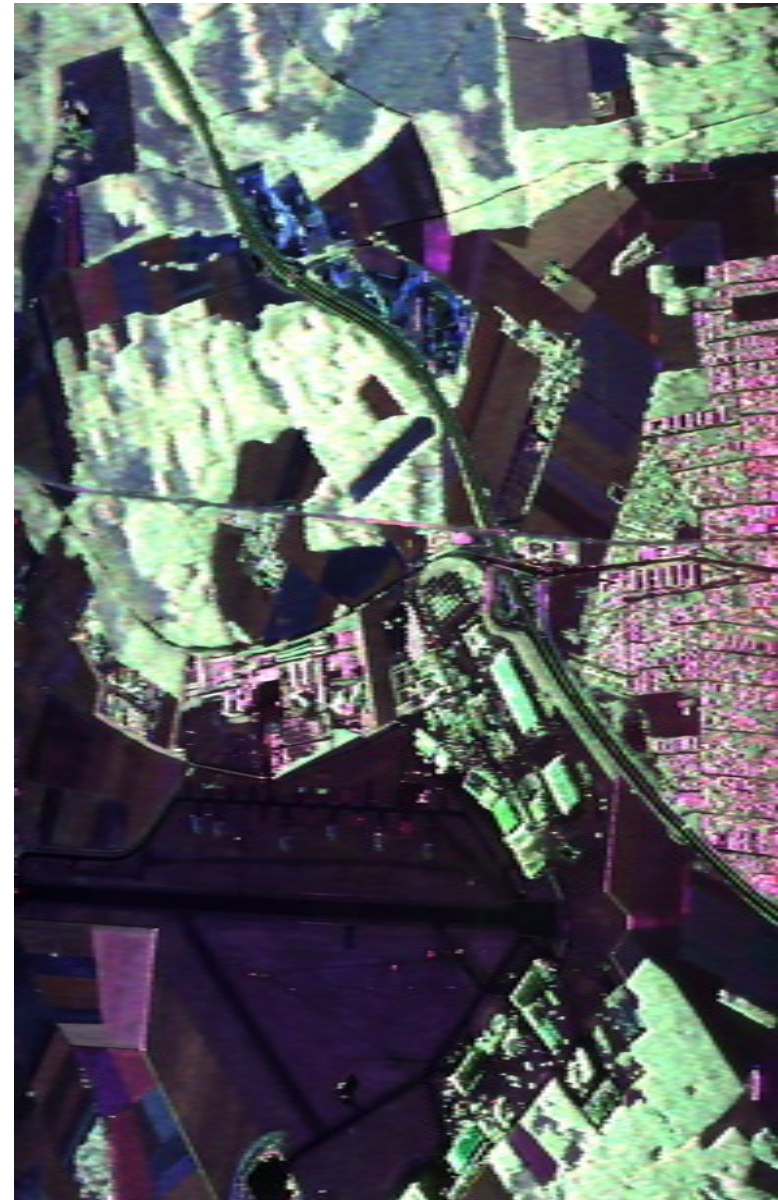
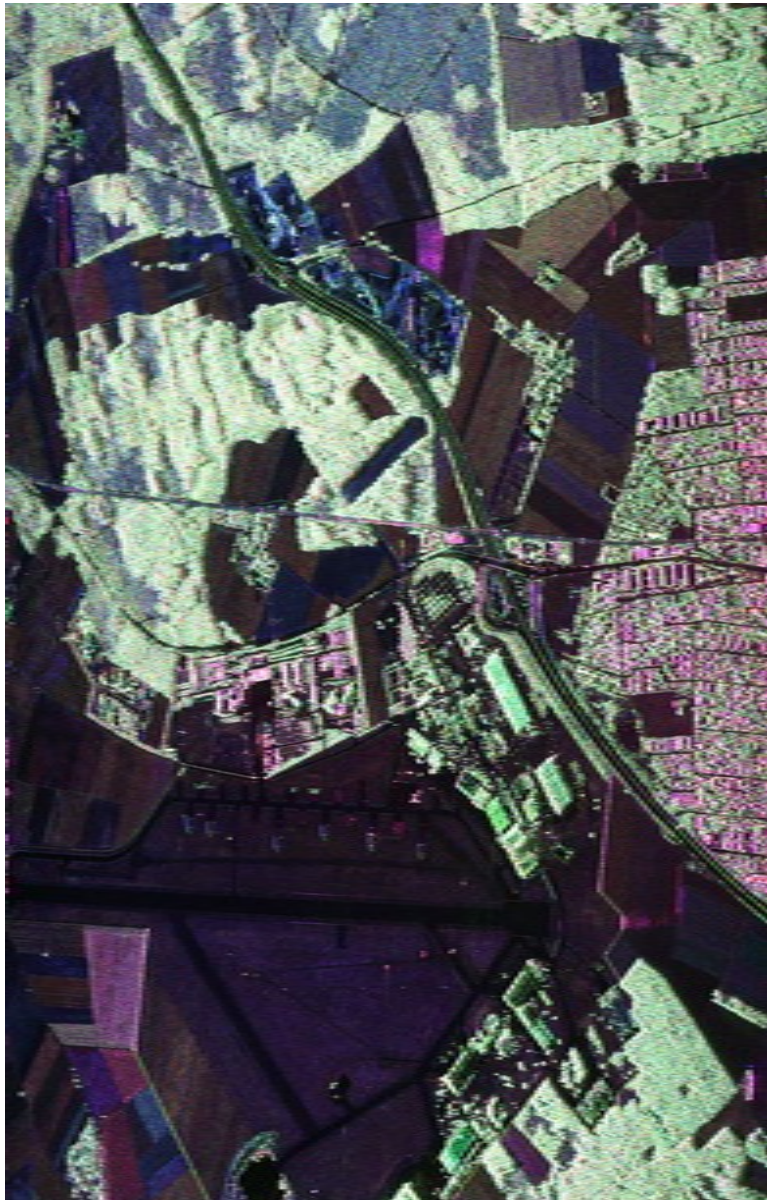


Original



Filter Result

Bilateral Filter



Bilateral Filter

$$g(\vec{x}) = \frac{1}{Z(\vec{x})} \sum_{\vec{x}' \in \mathcal{O}(\vec{x})} \exp\left(-\frac{(\vec{x}' - \vec{x})^2}{2 \cdot \sigma_1^2}\right) \cdot \exp\left(-\frac{(f(\vec{x}') - f(\vec{x}))^2}{2 \cdot \sigma_2^2}\right) \cdot f(\vec{x}')$$

What happens for $\sigma_1^2 \rightarrow \infty$?

Excursus: Non-Local Means

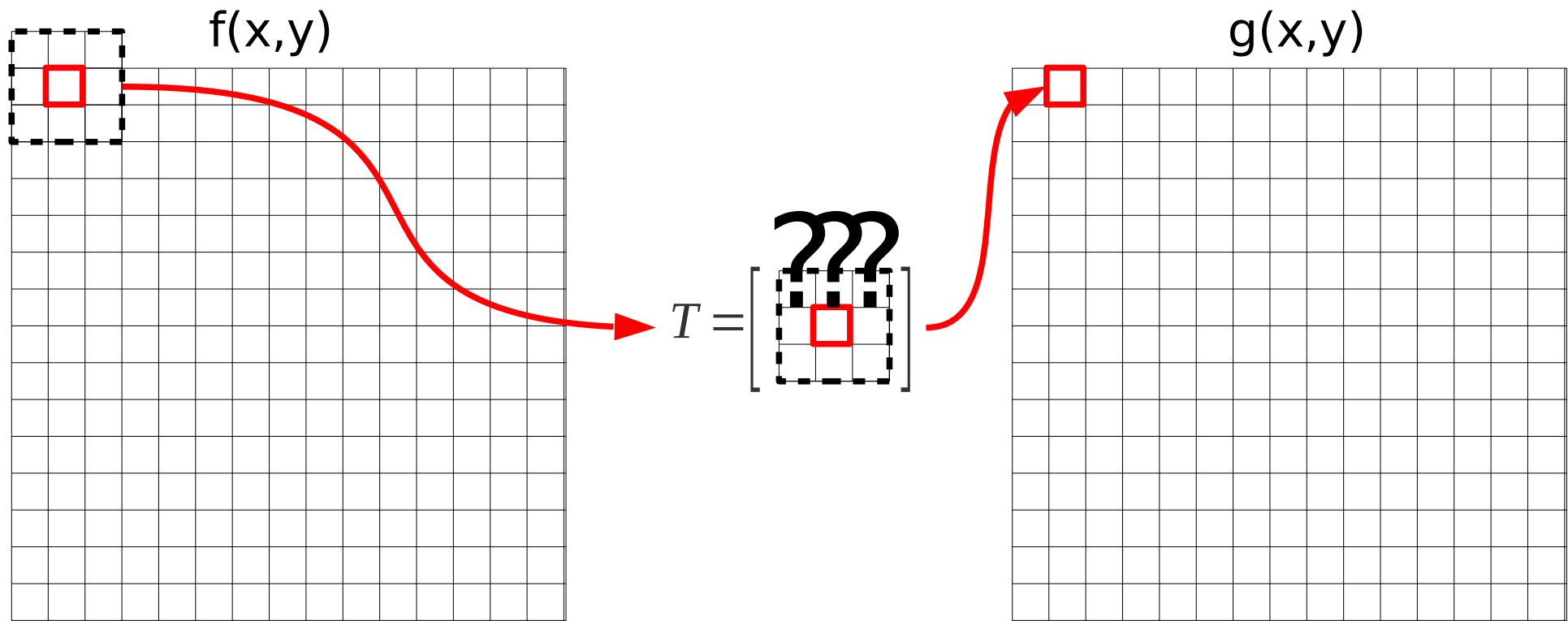
$$g(\vec{x}) = \frac{1}{Z(\vec{x})} \sum_{\vec{x}' \in \Omega} w(\vec{x}', \vec{x}) \cdot f(\vec{x}')$$

Important design questions:

- Which search region?
 - Often restricted
(computational complexity)
- Which pixel selection strategy?
 - Patch-based similarity measures
- Which averaging strategy?
 - Weighted average
 - Thresholding, normalizing



Border handling



- Problem: Unknown image values beyond image borders
- Possible solution
 - “Shrink” output image using only available information
 - Adapt kernel shape
 - Use “default” values (0, 255)
 - Use other image information (e.g. mirroring, wrapping)

2. Exercise – Noise Suppression

→ **Part I - Theoretical**

→ **Part II - Practical**

- Moving Average Filter
- Median Filter
- Bilateral Filtering

- Optional: Non-Local Means

2. Exercise - Theory

1. When should the median filter be applied to an image and when the moving average filter?
2. **Explain** your answer to question 1.
3. Is there a **general** better choice than the moving average filter?
4. **Explain** your answer to question 3.

2. Exercise - Given Functions

FILE: main.cpp

```
int main(int argc, char** argv)
```

- Main function

- Usage:

- ./main path_to_image

- For 2 noise types:

- Generates and saves noisy images

- Runs multiple denoising algorithms on noisy images

- Saves all resulting images and computes PSNR

FILE: unit_test.cpp


```
int main(int argc, char** argv)
```

- Unit tests

- Usage: ./unit_test

2. Exercise - To Do

`Mat spatialConvolution(Mat& src, Mat& kernel)`

- Parameter:
 - `src` : source image
 - `kernel` : kernel of the convolution 
 - `return` : output image
- Applies convolution in spatial domain
- One method of border handling: `size(src) == size(return)`
- Input / output single channel (greyscale)
- Do **NOT** use convolution functions of OpenCV

2. Exercise - To Do

Mat averageFilter(Mat& src, int kSize)

- Parameter:
 - **src** : noisy source image
 - **kSize** : Kernel size
 - **return** : output image
- Uses convolution to calculate local average
- Calls spatialConvolution(...)

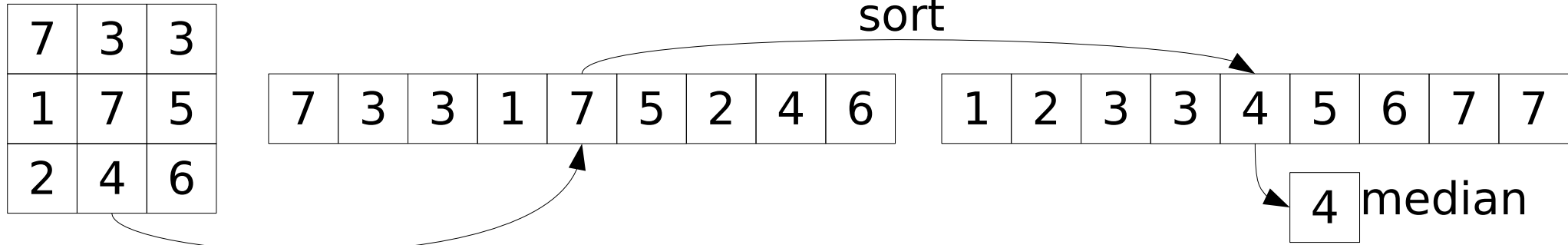


Mat medianFilter(Mat& src, int kSize)

- Parameter:
 - **src** : noisy source image
 - **kSize** : Kernel size
 - **return** : output image
- Applies local median filtering



2. Exercise - Median



```
#include <iostream>
#include <algorithm>
```

```
int main() {
    std::vector<int> array = { 23, 5, -10, 0, 0, 321, 1, 2, 99, 30 };
    std::sort(array.begin(), array.end());
    for (int i : elements)
        std::cout << i << ' ';
}
```

2. Exercise - To Do

```
Mat bilateralFilter(Mat& src, int kSize,  
                  float sigma_spatial, float sigma_radiometric)
```

- Parameter:
 - **src** : noisy source image
 - **kSize** : size of spatial kernel
 - **sigma_spatial** : Std-dev of spatial kernel
 - **sigma_radiometric** : Std-dev of radiometric kernel
 - **return** : output image
- Implements bilateral filter




2. Exercise - To Do

```
enum NoiseType {  
    NOISE_TYPE_1,  
    NOISE_TYPE_2,  
    NUM_NOISE_TYPES  
};
```

```
enum NoiseReductionAlgorithm {  
    NR_MOVING_AVERAGE_FILTER,  
    NR_MEDIAN_FILTER,  
    NR_BILATERAL_FILTER,  
    NUM_FILTERS  
};
```

```
Mat denoiseImage(Mat &src, NoiseType noiseType,  
                 NoiseReductionAlgorithm noiseReductionAlgorithm)
```

- Parameter: 
 - **src** : noisy source image
 - **noiseType** : type of noise in this image
 - **noiseReductionAlgorithm** : Which algorithm to use
- Denoises an image with the implemented filters
- Choose reasonable parameters (kernel size etc.) here

2. Exercise - To Do

```
enum NoiseType {  
    NOISE_TYPE_1,  
    NOISE_TYPE_2,  
    NUM_NOISE_TYPES  
};
```

```
enum NoiseReductionAlgorithm {  
    NR_MOVING_AVERAGE_FILTER,  
    NR_MEDIAN_FILTER,  
    NR_BILATERAL_FILTER,  
    NUM_FILTERS  
};
```

NoiseReductionAlgorithm chooseBestAlgorithm(NoiseType noiseType)

- Which reduction algorithm is best (in general) for the type of noise?
- Look at the noisy images and deduce the noise type

2. Exercise – Optional

Mat nlmFilter(Mat& src, int searchSize, double sigma)

- Parameter:
 - **src** : noisy source image
 - **searchSize** : size of search region
 - **sigma** : Optional parameter for weighting function
 - **return** : output image
- Implements non-local means filter (optional)

Reminder

Deadline: 12th of November

**But: We meet again in 1 week
(5th of November, H1028)**